# SIMPLE MODELS FOR PREDICTING SORGHUM GRAIN YIELD USING ENVIRONMENTAL FACTORS

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(Received: December, 1983)

#### SUMMARY

Data on sorghum growth and yield, soil water at critical growth stages and daily climatic variables were collected from 9 locations in India during 1979-82. Regression models that included one or more of the indepndent variables namely soil water at planting (SW), rainfall, mean temperature, solar radiation, evapotranspiration (ET) for the whole growing season and for three growth stages were developed from 48 data sets. Stepwise regression technique and Mallow's Cp criterion were also utilized to develop models. Results showed that rainfall, mean temperature and their product for three growth stages together explained 68% yield variation. SW, rainfall×mean temperature in GS2, rainfall × ET in GS2 and GS3, and rainfall × solar radiation in GS2 explained 73% yield variation. These two models when tested with 11 independent data sets, the former model explained only 36% yield variation while the later explained 59% yield variation.

Keywords: Sorghum bicolor (L.) Moench; Regression model; crop-simulation-model; Collaborative multilocation experiments; Phenology.

## Introduction

Regression-type crop yield prediction models have been utilized by many researchers to predict crop yield using environmental factors. Gangopadhyaya and Sarkar [6] applied the curvilinear correlation technique to study the effect of weather factors such as rainfall, maximum and minimum temperature on the growth and yield of sugarcane. Multiple regression analyses were used by Thompson [12] to determine the influence of selected weather factors in the production of maize in

the USA. Brown and Vanderlip [1] utilized stepwise multiple regression models to investigate the relationships between winter wheat yields and monthly weather variables at several locations in Kansas State, USA. Using Fisher's [5] orthogonal polynominal technique, Huda et al. [8] studied the relationship between weekly weather variables such as rainfall, humidity, temperature, and rice production in the Tarai regions of India. All of these researchers agreed that weather data when included for specific growth periods are better than monthly data to explain variations in crop yield.

The location-specificity problem of regression type yield prediction models is well recognized. Problems associated with the use of climatecrop-yield models in an operational system were described by LeDuc et al. [9]. Crop-simulation models with sound physical and physiological bases are better research tools to quantify the effects of environmental factors on crop growth and development. However, the relatively simpler data requirements of the regression type model make it simple to use for large-scale yield prediction. To predict wheat grain yields on a large scale without the benefit of direct measurements of plant characteristics, mathematical models were developed by Feyerherm and Paulsen [4]. These models require only a modest amount of historical data for application on a real-time basis to geographical regions other than the one where the models were developed. In this paper, an attempt has been made to develop regression-type yield prediction models using different environmental variables collected from collaborative multilocation sorghum modeling experiments coordinated by the authors. These experiments were aimed at developing a better understanding of the physicaland physiological processes involved in sorghum production.

### Data and Models

Data for this study were obtained from collaborative sorghum modeling experiments conducted under adequate management practice at nine locations in India (11-31°N) during 1979-82 to quantify the effects of environmental factors on sorghum growth and development. The locations were Ludhiana, Hissar, Delhi, Parbhani, Rahuri, Pune, Solapur, Patancheru and Coimbatore. Data on soil, crop, weather and management factors were collected from the experiments from planting to maturity. Data included daily rainfall, solar radiation, open-pan evaporation, maximum and minimum temperature, soil water at planting and at other critical growth stages (panicle initiation, anthesis and physiological maturity), leaf area, phenological data such as dates of emergence, panicle initiation and physiological maturity, total dry matter and dry weights of leaf, culm, and head + grain.

There were 59 data sets in total from different locations, and seasons. From these data sets, 48 were randomly selected to develop the relations between environmental factors and sorghum grain yield, referred to as models in this paper; the remaining 11 were utilized as independent data sets for testing the models.

Eight models are reported in this paper (Table I). Models 1 to 4 were

TABLE 1—DESCRIPTION OF MODELS WITH THEIR COEFFICIENT OF DETERMINATION (R\*) AND ROOT MEAN SQUARE ERROR (RMSE)

Number	Model	R**	RMSE (kg ha)
	2	<b>3</b>	4:
1 Y=	$= 1913.71 + 5.1664 SW - 1.1777 R1$ $(2.3551) \bullet (0.9515)$ $+ 5.0313 R2 + 4.4864 R3$ $(1.4638) (1.1812)$	0.53	748
2 · Y =	= 478.83 - 1.5737 ET1 + 13.82 ET2 + 18.426 ET3  (4.1570) (5.0584) (3.2959)	0.52	7 <b>5</b> 8
3 Ÿ=	= -1017.1 - 37.9141 R1 + 31.3804 R2 + 33.6311 R3  (13.9815) (13.4277) (23.8986)  -145.42 T1 + 185.993 T2 + 129.522 T3 +  (104.375) (154.548) (109.582)  1.1928 R1T1 - 1.069 R2T2 - 1.143 R3T3  (0.4630) (0.5319) (0.9382)	0:68	635
4 Y:	= -6015.56 - 3.1597 R1 + 7.3877 R2 + 5.3287 R3 $(1.5694)$	0.66	642
· 5 · Y	= -455.3 + 5.3326 SW - 2.9756 TR - 0.11 R2ET2  (2.0405)	ö.76	540
ĠŶ	= 561.39 - 0.241 SWTR - 0.0701 R2ET2  (0.1245)	0.64	656

<b>_</b>	2	3	4.
	-2996.65 + 45.2459 R3 + 5.1302 SR3 + 0.5130 R1T1  (13.7164)	0.81.	474
	- 1.9849, R3T3 - 0.0782 R2ET2 + 0.1011 R3ET3 (0.5631), (0.0314) (0.0339) - 0.0420 R1SR1 + 0.0418 R2SR2 + 0.2952 T2SR2 (0.0137) (0.0105) (0.7662)		
8 Y=	782.11 + 7.8741  SW - 0.2403  R2T2 - 0.1232  R2ET2 $(1.9345)  (0.132)  (0.0354)$ $+ 0.0539  R3ET3 + 0.0719  R2SR2$ $(0.009)  (0.1322)$	0.73	572

\*Figure in parenthesis refers to standard errors.

Where Y =Observed grain yield (kg/ha)

SW = Available soil water (mm) at planting

TR = Total rainfall (mm) for the whole crop growing season

R1 = Total rainfall (mm) during GS1

R2 = Total rainfall (mm) during GS2

R3 = Total rainfall (mm) during GS3

ET = Total evapotranspiration (mm) for the whole crop growing season

ET1 = Total evapotranspiration (mm) during GS1

ET2 = Total evapotranspiration (mm) during GS2

ET3 = Total evapotranspiration (mm) during GS3

T1 = Mean temperature in °C during GS1

T2 = Mean temperature in °C during GS2

T3 = Mean temperature in °C during GS3

SR1 = Mean solar radiation (ly/day) during GS1

SR2 = Mean solar radiation (ly/day) during GS2

SR3 = Mean solar radiation (ly/day) during GS3

developed by selecting one or more independent variables, namely, soil water at planting (SW), rainfall (R), mean temperature (T), open-pan evaporation (E), solar radiation (SR), estimated evapotranspiration (ET) (computed after Ritchie [11]) for the whole growing season and for the three growth stages defined by Eastin [3]. These growth stages are from emergence to panicle initiation (GS1), from panicle initiation to anthesis (GS2), and from anthesis to physiological maturity (GS3). Several combinations of these variables—product and inverse relations—were made. A stepwise regression technique was used, and models 5 and 6 were selected based on  $R^2$  values.

Models 7 and 8 were selected using the Mallow's (Daniel and Wood, [2]) Cp criterion. This criterion is defined as  $Cp = (RSS/s^2) - (N-2p)$  where RSS = residual sum of square for the best subset being tested; p = number of variables in the subset (including the intercept, if any);  $s^2$  = residual mean square based on the regression using all independent

variables. Neter and Wasserman [10] described that the model which has the smallest Cp value should be selected. Thus model 7 was selected because it had the lowest Cp value of 0.2. Neter and Wasserman [10] further described that the bias component of the models should also be examined to select the best model. This can be done by plotting the Cp values for all possible models against the number of parameters (p) used in the respective models. The model which has little bias component tends to fall near the line Cp = p. Those models with substantial bias will tend to fall above this line. Thus the relationship between Cp and p was plotted in Figure 1. Model 8 was selected as it had 6 parameters (p) and was close to the line Cp = p with 4.9 as Cp value.

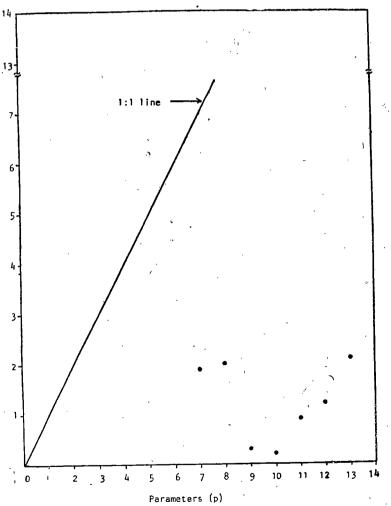


Figure 1. Relationship between Cp and parameters (p) used in several possible regression models.

## **Model Tests**

The correlation coefficients between observed and predicted yield using these 8 models (Table 1) for 11 independent data sets were 0.59, 0.46, 0.60, 0.72, 0.72, 0.71, 0.72, and 0.77 respectively. These results show that only five models (4, 5, 6, 7, and 8) could explain the 50% to 59% variability in the yield data; the RMSE values for these models ranged from 851 to 994 kg/ha. The other three models had very low  $r^2$  and high RMSE values. The actual grain yield for these 11 data sets were compared using model 8 simulated values (Fig. 2), as this model provided high  $r^2$  values (0.59) and lowest RMSE values (851 kg/ha) when tested with independent data sets.

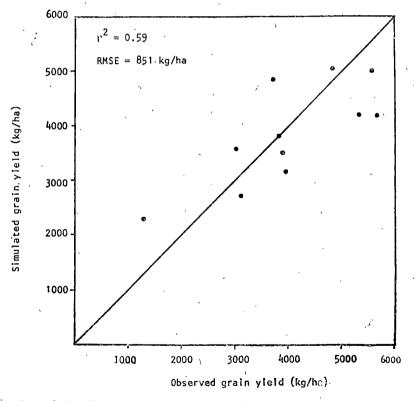


Figure 2. Relationship between observed and simulated grain yield of sorghum (model 8 test results with independent data set).

### . Discussion

Total rainfall for the entire growing season could only explain 29%

variability, but rainfall for GS1, GS2 and GS3 explained 53% variability. Similarly, evapotranspiration for the three growth stages gave higher  $R^2$  values (0.52) compared to the seasonal total ET ( $R^2 = 0.37$ ). Rainfall, mean temperature and their product for three growth stages (model 3) explained 68% variability in yield. Models 3, 4, and 6 gave similar  $R^2$  values (0.64 and 0.68). Model 7 gave the highest ( $R^2$ ) values (0.81).

Model 8 simulates 79 kg of additional grain yield if the available soil water at planting exceeds by 10 mm from its mean values of 92 mm. This is expected as soil moisture at planting helps in crop establishment and particularly for the postrainy season crop when sorghum is mainly raised on residual moisture stored in the soil profile. Reduction in grain yield due to additional rainfall in GS2 increases with the increase in temperature and evapotranspiration rate during this period. However, the beneficial effect of additional rainfall in the grain-filling period increases with increased ET rate during GS3. Probably these results have some basis, for example, in GS2 high ET means a higher vegetative growth rate and, thus, with additional rainfall, the crop tends to add vegetative parts causing a negative effect on grain yield. On the other hand, additional rainfall in GS3 along with high ET rate provides more green leaf and also probably a longer grain filling period thus resulting in increased grain yield.

Models 4 and 6 have lower  $R^2$  values compared with that of models 5, 7, and 8 (Table 1) but all these models except model 8 provided similar  $R^2$  values (0.50 to 0.53) when tested with independent data sets. Model 8 had  $R^2$  value of 0.59. These results are in agreement with that of Gardner (7) that the performance of a prediction equation is better in the sample from which it is obtained than in a second independent sample. Comparing the data requirements of these models, we would suggest that model 4 could be used for prediction purposes as it requires only data on rainfall, temperature and solar radiation. The other four models need information on soil water and ET, which in turn requires leaf area data. If these data are available, model 8 should be used for yield prediction.

### Conclusion

One of the eight models developed in this study (model 4) that requires rainfall, temperature and solar radiation data is recommended for yield prediction purposes in areas where growth simulation type models can not be applied because of data limitations. If data on soil moisture and evapotranspiration are available in addition to rainfall, temperature and solar radiation, model 8 can be used for yield prediction.

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