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SOME PROCEDURES USED IN YIELD PREDICTION OF SOY-BEAN GROWN ON SANDY SOIL IN EGYPT

[42]

Nemat A. Noureldin[1]; Samiha A. Ouda[2] and M.F. Hamed[1]

ABSTRACT

Yield prediction is an important part of decision making process in soybean production and is accomplished by either yield prediction equations or simulation models. In this research both multiple linear regression analysis and SOYGRO simulation model were used to predict soybean yield grown on sandy soil in Egypt. Two field experiments were carried out in 1999 growing season at Nubaria Research Station and El-Faregh Valley Experimental Station, to determine variables, which can be used for more accurate prediction in soybean and validation of SOYGRO model. Four soybean cultivars, i.e. Southern State No. 517, Manokin, Wicomico and Giza 82 were planted in a randomized complete block design with two replications. Total biomass was determined at R_4, R_6, R_7 and R_8 stages. Seed yield, pod yield, individual seed weight, seed number pod^{-1}, seed number m^{-2} and total biomass m^{-2} were also measured at harvest. Data collected on plant and environmental factors were used to develop four different yield prediction equations based on the following parameters: (1) night length, night temperature and biomass measurements, (2) biomass at R_8 and growing-degree days, (3) mean biomass duration and mean relative growth rate between R_6 and R_7 stages and (4) sand percent in the soil. It was found that soybean yield prediction equation using sand percent is the earliest procedure of yield prediction because it can be done before planting. Moreover, prediction yield using night length and night temperature was more accurate than using biomass duration. Using SOYGTO model made it possible to determine the most suitable variety to be planted at both locations.

Key words: Yield prediction, SOYGRO, Sandy soils, Weather factors, Growth analysis

INTRODUCTION

Plant climate and soil are very complicated systems consisting of numerous factors, which influence crop yield. Prediction equations or simulation models have been developed as important tools used in decision making in soybean pro-

1- Agronomy Department, Faculty of Agriculture, Ain Shams University, Shoubra El-Kheima, Cairo, Egypt.

2- Central Laboratory for Experimental Design and Statistical Analysis, Agricultural Research Center, Giza, Egypt

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duction. The classical approach for prediction is the multiple linear regression (**Draper and Smith, 1987**), which is employed in identifying the most important yield attributes that are used as components of prediction equation. Different equations can be developed to predict soybean yield using either climate, plant, or soil factors.

Soybean seed yield is highly sensitive to the prevailing conditions at different growth stages. Two environmental variables, photoperiod and temperature, affect soybean seed development. Soybean is a quantitative short-day plant, where most soybean cultivars flowers sooner under long night (**Borthwick and Parker, 1938**). They added that night temperatures also exert a more dominant effect than day temperature. In addition, all reproductive stages from R1 to R7 are sensitive to photoperiod and temperature. Whereas, the final stage, R7 to R8, is basically a temperature sensitive only (**Johnson *et al* 1960 and Jones *et al*** 1991). Therefore, the effect of both photoperiod and temperature could be included in an equation to predict soybean yield.

Growth analysis examines the individual rate of plant development through time as a result of the interaction between plant and environment (**Hunt, 1982**). Two growth analysis parameters, biomass duration and relative growth rate may be used to predict soybean yield. Biomass duration is a measurement of biomass persistence with time. It is defined as the area under the time curve of biomass production (**Gardner *et al* 1985**). this parameter is related to total yield by the mean of relative growth rate. Relative growth rate is a productive efficiency of unit amounts of dry matter, which expresses the dry matter increase in a time interval in relation to the initial weight (**Hunt, 1982**).

Soil plays a critical role in meeting human food need. Soil may be defined as the natural media for plant growth. Soil supplies water, air and mechanical support for plant roots as well as heat to enhance chemical reactions (**Brady, 1984**).

Recently, simulation model, which is a more advanced technique, has been used in yield prediction. Simulation is a representation of all relevant processes of a system, usually embodied in the form of computer program (**Penning de Vries *et al*** 1989). Simulation can also be partially used in determined optimum management practices to capitalize on precision farming (**Allen *et al*** 1996). SOYGRO (**International Benchmark Sites Network for Agrotechnology Transfer, IBSNAT,** 1989) is one of the most important crop models for soybean (**Wilkerson *et al* 1983; Jones *et al* 1987 and IBSNAT,** 1989). It is physiological crop model that simulates growth and yield of soybean under various soils, weather and management conditions. The model includes a component that predicts development of the crop, which is the basis for changes in partitioning of dry matter. The dry matter production and partitioning in SOYGRO model are controlled mainly by the plant's physiological time scale (**Jones *et al*** 1991). Earlier versions of soybean models that were used to study economic risks of irrigation management (**Swaney *et al*** 1987; Boggess ***et al* 1983**) were also incorporated into pest management models (**Wilkerson *et al* 1983; Szmedra *et al*** 1987; **Batchelor *et al* 1993**). Furthermore, SOYGRO model was used to accurately predict grain yield in Iowa, USA (**Allen *et al*** 1996).

The objective of this research is to evaluate factors that accurately predict seed yield of soybean grown on sandy soil using both multiple linear Regression analysis and SOYGRO simulated model.

MATERIAL AND METHODS

Field experiments were carried out in 1999 growing season at Nubaria Research Station (29° 57′ E, 31° 12′N) and El-Faregh Valley Experimental Station (31°24′E, 30°08′ N), Higher Institute for Agricultural Cooperation to evaluate factors that could be used in yield prediction and to validate SOYGRO. Physical and chemical analysis of soil in both locations were done before planting (Tables 1).

Four soybean cultivars, Southern states No. 517, Manokin, Wicomico and Giza 82, were planted in a randomized complete block design at each location.

The plot consisted of 6 ridges each measuring 4 m long and 0.7 and planting spacing was 10 cm between hills with two-plants $hill^{-1}$. Planting was done by hand. Both conventional fertilization and hand weeding were practiced to ensure optimum plant growth and yield. Total biomass (BioM1) was harvested at four reproductive stages: R_4, R_6, R_7, R_8. These reproductive stages are defined as follows **(Richie *et al* 1997).**

Table 1. Physical and chemical analysis of soil at for Nubaria and El-Faregh Valley

Nubaria			
Physical properties		Chemical properties	
Sand %	54.4	Mean pH	8.21
Silt+clay %	45.6	Ec (dS/m^{-1})	1.00
Organic	0.83	Available N $\mu g/g^{-1}$	44.5
Matter %		Available P $\mu g/g^{-1}$	24.0
Texture	Silty clay	Available K $\mu g/g^{-1}$	314.2
El-Faegh Valley			
Physical properties		Chemical properties	
Sand %	95.5	Mean pH	8.27
Silt+clay %	4.50	Ec (dS/m^{-1})	1.20
Organic	0.60	Available N $\mu g/g^{-1}$	54.61
Matter %		Available P $\mu g/g^{-1}$	17.50
Texture	Sandy	Available K $\mu g/g^{-1}$	135.0

R_4 : the pod is 2 cm (3/4 inch) long at one of the four uppermost nodes on the main stem with a fully developed leaf

R_6 : the pod contains a green seed that fills the pod cavity at one of the four uppermost nodes on the main stem a fully developed leaf

R_7 : one normal pod on the main stem has reached its mature pod color, normally brown or tan, depending on variety.

R_8 : Ninety-five percent of the pods have reached their mature pod color.

Furthermore, at harvest, data were collected on seed yield (SY, kg ha^{-1}), pod yield (PY, kg ha^{-1}), individual seed weight (SW, g), seed number pod^{-1} (S/P), seed number m^{-2} , and total biomass at harvest (BioM1, kg ha^{-1}).

Statistical analysis

Yield prediction using multiple linear regression analysis

The aim of this part is to collect different data sets known (from literature) by its contribution to soybean yield. Correlation coefficients were calculated between different data sets to determine their contribution to soybean yield. Both multiple linear regressions, full and stepwise models, were used to calculate two parameters, coefficient of determination (R^2) and standard error of estimates (SE%). In order to obtain a precise prediction, R^2 should be near to one and SE% should be near to zero. R^2 is the amount of variability due to all independent variables and SE% is a measurement of precision i.e. closeness of predicted and observed yield to each other. The use of stepwise multiple linear regression was to remove multicolinearity between different yield attributes and screen independent factors to minimum that had the highest partial correlation with yield **(Draper and Smith, 1987).** Four prediction equations were developed using weather data, biomass measurements and soil parameters.

Night length (NL, h), night temperature (NTEMP, °C), and biomass measurements (BioM1, kg ha^{-1}) in the period between R_4 and R_7 were used to predict seed yield and to determine the most suitable stage to be used in that matter. Biomass measurements between R_7 and R_8 stages were used together with growing degree days to predict soybean yield. Growing degree-days (GDD) is calculated by subtracting daily mean temperature (MT, °C) from base temperature for soybean (BT, 8°C). Base temperature is the temperature under which no growth occurs.

Biomass measurements were also used to calculate two growth analysis parameters; biomass duration (BMD, kg d^{-1}) and relative growth rate (RGR, kg d^{-1}). Both BMD and RGR in the phase between R_4 to R_7 were used to predict seed yield (SY, kg ha^{-1}) and also to determine the most suitable stage to be used for that matter. BMD, RGR and SY were calculated using the following equations.

$$BMD = [(W2 + W1)/2] * (T2-T1)$$
(Gardner *et al* 1985)

$$RGR = (\ln W2 - \ln W1)/(T2 - T1)$$
(Gardner *et al* 1985)

$$SY = BMD * RGR$$
(Hunt, 1982)

Soil variables were determined before planting and were used to predict soybean yield. Correlation matrix was used to identify soil variables that had high correlation coefficients with yield. The studied variables were electric conductivity, calcium carbonate content sand percent, silt percent, clay percent, ammonium nitrate ($\mu g g^{-1}$) and potassium ($\mu g g^{-1}$).

Stepwise multiple linear regression analysis was done to reduce the number of attributes predicting yield.

Soygro validation

Season length, crop yield and demand for irrigation water were estimated by the model. Texture, albedo and water related specific characteristics of the soils of the two locations were adequately represented by the genetic soil provided for the study. For simulation purposes, the field schedule irrigation option was chosen to provide the crops with water as field schedule and also considered water and nitrogen balances. The soil profile taken before sowing was included in the model inputs to provide initial soil moisture content and soil nitrogen level in the two forms (NO_3 and NH_4). Monthly maximum and minimum temperatures, and solar radiation data were obtained for the two locations and also used in the validation.

SOYGRO model was validated against plant, weather and soil data for each location. Predicted values for yield and its attributes were compared to the measured values of the model. Accuracy was validated using percent error averaged over time (PE). PE is a measure of the average percent difference between predicted and measured values, averaged overall observation for an experiment This determines the average percentage error for a plant component for the entire season and it is calculated by the following equation (**Allen *et al* 1996).**

$$PE = \frac{\sum_{i=1}^{n} \left(\frac{Y - Y^{\backslash}}{Y} \right) X\ 100}{n}$$

Where:

Y = measured value

$Y^{\backslash}$ = predicted value

n = number of observations per experiment

RESULTS AND DISCUSSION

Prediction equations using weather data

The highest R^2 (0.7648) and the lowest SE% (6.33) were obtained for the growth stage between R_6 to R_7 (Table 2). Furthermore, stepwise multiple linear regression analysis revealed that night length was negatively correlated with yield ($R^2 = 0.3951$, data not shown). This result could be attributed to the fact that long nights may cause early flowering, which reduce growth period and final yield (**Borthwick and Parker, 1938 and Jones *et al* 1991).** Similarly, GDD was correlated negatively with final yield at R_7-R_8 growth stage. There is an opposite relationship between the length of GDD and the duration between R7 and R8 (the stages of pod formation), which in turn caused a lower number of mature pods. This result is in agreement with that obtained by **Johnson *et al*** (1960) and **Jones *et al*** (1991).

Table 2. Best yield prediction equations for four soybean cultivars using weather data at different growth stages.

Stages	R^2	SE%	Yield prediction equation
R_4-R_8	0.1387	10.33	Not application*
R_4-R_6	0.2106	11.60	Not applicable*
R_6-R_7	0.7648	6.33	$Y^\backslash$ = 8273.6783 + 0.1729 BIOM1- 718.4834 NL + 115.6908 NTEMP
R_7-R_8	0.6308	7.87	$Y^\backslash$ = 6619.0612 + 0.1962 BioM1 – 1.7562 GDD

* R^2 is very low (see Materials and Methods)

Prediction equations using growth analysis parameters

Growth analysis technique analyzes of plant community growth, since it represents the accumulation of economic yield. Thus, in our experiments, mean biomass duration (BMD kg/d) and mean relative growth rate (RGR) were used to predict the final seed yield of soybean. The full model of multiple linear regression revealed that the highest R^2 (0.7654) and the lowest SE% (8.89) were obtained between R_6 and R_7 growth stage. Because of the low relative contribution of RGR to soybean seed yield, it was removed from the equation by stepwise multiple linear regression (Table 3), where R^2 was slightly reduced (0.7436) and the accuracy of estimate was increased (SE% = 7.82). The relatively low contribution of RGR in the yield of soybean might be attributed to the fact that it is fluctuated greatly with environmental variables such as inadequate supply of light or unsuitable temperature regime **(Hunt, 1982).**

Table 3. Best yield equation for four soybean cultivars using biomass duration (BMD) at different growth stages.

Stages	R^2	SE%	Yield prediction equation
R_4-R_8	0.0746	12.84	Not applicable*
R_4-R_6	0.5411	9.91	Not applicable*
R_6-R_7	0.7436	7.87	$Y^\backslash$ = 1011.6874 + 0.0363 BMD
R_7-R_8	0.0206	8.08	Not applicable *

* R^2 is very low (see Material and Methods)

Prediction equations using soil parameters

Six soil parameters were used in the full model of linear regression analysis (see Materials and Methods). Stepwise multiple linear regression showed that sand percent (Sand) was found to be the most important soil parameter that influenced soybean yield. Furthermore, the analysis showed that R^2 for the full model was 0.6887, whereas it was 0.6785 for stepwise model. Thus, in our experiment, the additive effect of soil parameters other than sand was very low; equals to 0.0102 (R^2 for the full model minus R^2 for the stepwise model). Similarly, SE% for the stepwise model was also decreased when the other five soil parameters was removed from the model (SE% for the full model = 2.2198 and for the stepwise model = 1.9320). The relationship is expressed in the following equation.

$$Y' = 2771.6573 - 3.6045\ Sand$$

R^2 for the full model = 0.6887
SE% for the full model = 2.2198
R^2 for the stepwise model = 0.6785
SE% for the stepwise model = 1.9320

Sand percent was negatively correlated with soybean yield, where the higher the sand percent in the soil the lower were silt, clay and yield. Soil dominated by sand, possess good drainage and aeration, but may be drought prone **(Brady, 1984).** Thus, in our experiment, sand percent in the soil was the earliest possible soybean yield predictor, because it can be done before planting.

SOYGRO Prediction

SOYGRO prediction for both days to anthesis and physiological maturity were precise for both locations (Tables 4 and 6). Furthermore, pod yield (PY), seed number pod^{-1} (S/P) and seed yield (SY) were accurately predicted in both locations (Tables 5 and 7). Yield is the product of two principal components; individual seed weight and number per unit area. The two components are interrelated; an increase in one component leads to a decrease in the other. Although, the value of PE for seed number m^{-2} (S#) was high for both locations, it was low for individual seed weight (SW), which led to low value of PE for yield. The highest R^2 between predicted and measured values was found for seed yield at Nubaria (R^2 = 0.9691), with SE% = 0.0192. Whereas, R^2 was 0.7876 for El-Faregh Valley, with SE% = 0.2323 (Table 5 and 7). SOYGRO model was able to determine the most suitable variety, which has low percent error averaged over time (PE) for seed yield, to be planted in both locations. The PE for Wicomico and Giza 82 were 1.04 (Table 5) and 1.84 (Table 7) for Nubaria and El-Faregh Valley, respectively.

Table 4. Predicted versus measured days to athesis and physiological maturity for four soybean cultivars planted at Nubaria.

Cultivars	Days to anthesis		Days to physiological maturity	
	Predicted	Measured	Predicted	Measured
Southern States No. 517	36	36	135	135
Manokin	35	35	135	135
Wicomico	36	36	135	135
Giza 82	35	35	126	125

Table 5. Mean percent error average over time (PE) between predicted and measured yield and its components for four soybean cultivars planted at Nubaria.

Cultivars	BioM1 (kg ha^{-1})	PY (kg ha^{-1})	SP^{-1}	SW (g)	S#	BioM2 (kg ha^{-1})	SY (kg ha^{-1})
Southern States No. 517	18.10	7.00	4.59	29.03	47.44	3.69	3.07
Manokin	6.85	1.57	4.60	2.85	35.98	2.32	2.97
Wicomico	2.98	0.05	10.80	7.02	36.46	6.57	1.04
Giza 82	12.00	9.45	10.81	9.00	22.04	18.48	5.95
R2	0.3883	0.4571	0.6450	0.6090	0.1202	0.4015	0.9691
SE %	0.0040	0.0421	0.0315	0.0942	0.2993	0.0581	0.0192

Table 6. Predicted versus measured days to anthesis and physiological maturity for four soybean cultivars planted at El-Faregh Valley.

Cultivars	Days to anthesis		Days to physiological maturity	
	Predicted	Measured	Predicted	Measured
Southern States No. 517	36	36	135	136
Manokin	35	35	135	135
Wicomico	36	36	135	135
Giza 82	36	36	126	125

Table 7. Mean percent error average over time (PE) between predicted and measured yield and its components for four soybean cultivars planted at El-Faregh Valley.

Cultivars	BioM1 (kg ha^{-1})	PY (kg ha^{-1})	SP^{-1}	SW (g)	S#	BioM2 (kg ha^{-1})	SY (kg ha^{-1})
Southern States No. 517	16.32	8.00	4.59	20.77	50.29	1.68	10.63
Manokin	12.56	1.19	4.58	5.54	38.28	1.08	6.83
Wicomico	14.60	3.79	5.80	3.50	41.38	12.70	2.22
Giza 82	12.28	2.85	10.81	4.00	34.48	6.37	1.84
R2	0.255	0.636	0.111	0.940	0.129	0.977	0.787
SE %	0.004	0.079	0.034	0.045	0.382	0.007	0.232

CONCLUSION

Regression analysis could be a very useful tool for early prediction of yield, which is sometimes important to be known as early as possible during growing season. Furthermore, it is an easy procedure and does not required intensive training as simulation models. However, simulation models provide better prediction of the behavior of the crop for immediate use in improving crop management, which can not be attained by regression analysis. Therefore, either technology could be used depending on its availability.

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بعض الطرق المستخدمة في التنبؤ بمحصول فول الصويا في الأراضى الرملية في مصر

[٤٢]

نعمت عبد العزيز نور الدين[١] – سميحة أبو الفتوح عودة[٢] – محمد فوزى حامد[١]

١– قسم المحاصيل – كلية الزراعة – شبرا الخيمة – القاهرة – مصر

٢– المعمل المركزى لبحوث التصميم والتحليل الإحصائى – مركز البحوث الزراعية

يعتبر التنبؤ بالمحصول أداه مهمة لعملية اتخاذ القرار في انتاج فول الصويا ، ويمكن إجراءه إما باستخدام معادلات التنبؤ أو باستخدام برامج المحاكاه. في هذا البحث استخدم كلا من أسلوب الانحدار الخطى المتعدد وبرنامج SOYGRO للتنبؤ بمحصول فول الصويا بالأراضى الرملية. أقيمت تجربتان حقليتان في عام ١٩٩٩ في محطة بحوث النوبارية ومحطة بحوث وادى الفارغ التابعة لمعهد التعاون الزراعى لتحديد بعض المتغيرات التى يمكن استخدامها في التنبؤ بمحصول فول الصويا ولإجراء اختبارات البيئايرة والتأكيد لبرنامج SOYGRO. زرعت أربعة أصناف من فول الصويا وهى : الولاية الجنوبية رقم ٥١٧ ، مونكن ، واكومكو ، جيزة ٨٢ في تصميم القطاعات الكاملة العشوائية في مكررين. أخذت عينات لوزن النبات الكلى في أربعة مراحل نمو في مرحلة النمو الثمرى (R_5, R_6, R_7 and R_8) بالإضافة إلي وزن البذور ووزن القرون ووزن البذرة الواحدة وعدد البذور / م² والوزن الكلى للنبات عند الحصاد. وتم عمل أربعة معادلات للتنبؤ كالآتى :١) طول الليل وحرارة الليل ووزن النبات الكلى (٢) وزن النبات الكلى في R_8 والحرارة المتجمعه للنمو (٣) فترة استمرار النمو ومعدل النمو

النسبى في R_6, R_7 (٤) نسبة الرمل في التربة. وقد اتضح أن استخدام نسبة الرمل في التربة يمكن أن يكون تنبؤ مبكر لأنه يمكن أن يتم قبل الزراعة بينما استخدام طول الليل وحرارة الليل كان أكثر دقة لارتفاع معامل التقدير عن استخدام فترة استمرار النمو في التنبؤ بمحصول فول الصويا. بالإضافة إلي أن استخدام برنامج SOYGRO أمكننا من تحديد أنسب صنف يمكن زراعته في أى من الموقعين.

تحكيم: ا.د عبد العظيم أحمد عبد الجواد

ا.د جابر عبد اللطيــف ســارى