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Predicting grain yield of maize using drought tolerance traits

Shaibu A. S.*, Adnan A. A. and Umar I. R.

Department of Agronomy, Bayero University, Kano, Nigeria.

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Two experiments (field and pot) were conducted to evaluate the ability of partial least square regression (PLSR) using physiological and root traits to predict grain yield of maize. The genetic materials used for the experiments were six maize genotypes. Data was recorded on some growth, physiological and root traits. Data was analyzed using PLSR model of XLSTAT. There was a good prediction of grain yield of maize using phenological traits (R^2 = 0.99 and RMSE = 17.73). The model gave a good fit in predicting grain yield with Sammaz 14 having the best prediction. Prediction model of grain yield using root and seedling traits also gave a good fit (r^2 = 0.96). Sammaz 14 and TZE-COMP 5 had better fits. Prediction of grain yield of maize using some physiological traits of maize also produced a good fit (R^2 = 0.86 and RMSE = 90.94). Prediction accuracy for Sammaz 14 was higher than the other genotypes. The good fits observed for all the predictions indicates the ability and usefulness of PLSR in predicting grain yield of maize and this can reduce the time of breeding programs in developing maize varieties that are tolerant to drought.

Key words: Partial least square, maize, drought, root, and physiological traits.

INTRODUCTION

Maize is the third most important food grain for humankind after rice and wheat. It is mostly grown under rain-fed conditions and among the cereals, it is the second most susceptible to drought next to rice. Drought is a rising threat of the world. Most of the countries of the world are facing the problem of drought. It is the creeping disaster, slowly taking hold of an area and tightening its grip with time (Misra et al., 2002). Constitutive variation for root traits is an important adaptation under drought prone conditions (Nguyen et al., 2011). Water is an integral part of plant body and it plays an important role in growth initiation, maintenance of developmental process of plant life and hence has pivotal function in crop production. Drought stress has deleterious effects on the seedling establishment, vegetative growth, photosynthesis, root growth, anthesis, anthesis-silking interval, pollination and grain formation in maize crop (Aslam et al., 2012). Annual maize yield loss due to drought is estimated to be 15% in West and Central Africa and losses may be higher in the marginal areas where the annual rainfall is below 500 mm and soils are sandy or shallow (Edmeades et al., 1995). The effect of selection under stress on yield performance of genotypes under optimal conditions and vice versa has been an ongoing debate among plant breeders for decades. Secondary traits can improve the precision with which

*Corresponding author. E-mail: asshuaibu.agr@buk.edu.ng

Table 1. List of genotypes used for the study.

Entry	Genotype	Maturity
1	SAMMAZ 14	Late
2	SAMMAZ 29	Extra-Early
3	2009 EVDT	Early
4	2009 TZE-W	Early
5	TZE-COMP 5	Early
6	2009 TZEE	Extra-Early

drought tolerant genotypes are identified, compared with measuring only grain yield under drought stress. Secondary traits such as canopy temperature, stomata conductance, ears per plant and anthesis silking interval have been found to possess strong correlations with grain yield under drought conditions and have been used to select for higher levels of tolerance to drought (Badu-Apraku et al., 2011). Predictions of grain yield of maize using secondary traits that are of significance to drought tolerance have not been fully exploited in Nigeria.

Recently, partial least square regression (PLSR) has been employed for predicting plant biomass, LAI, nitrogen and Chlorophy ll concentration and density of wheat using reflectance measurement of wheat canopy (Hansen and Schjoerring, 2003). The PLSR has been widely used to assess N related indicators of crops in homogeneous areas (Nguyen and Lee, 2006; Soderstrom et al., 2010). Limited research has been conducted to estimate grain yield of maize fields with different growth stages and cultivars. In general, studies reported so far have confirmed that PLS appeared as one of the most efficient method in extracting and creating reliable models in wide range of fields (Nguyen and Lee, 2006).

Partial least square can easily treat data matrices in which each object is described by several hundreds of variables (Galadi and Kowalski, 1986; Haaland and Thomas, 1988). This technique can extract the relevant part of the information for the very large data matrices and produce the most reliable models compared to other calibration methods (Thomas and Haaland, 1990). Partial least square regression has been successfully applied to NIR spectral data for predicting soil nitrate (R^2 = 0.94–0.95) (Ehsani et al., 1999), sodium chloride content of commercial king and hot smoked salmon fish (R^2 = 0.82–0.85) (Lin et al., 2003), and several chemical components of sunflower seeds (R^2 = 0.90–0.96) (Fassio and Cozzolino, 2003). PLSR overcomes the problems of co-linearity and "over-fitting" compared to step linear regression analysis if optimally choosing a suitable number of principal components and deleting the noise bands (Herrmann et al., 2011). However, the small number of sampling may limit the number of latent variables in the PLSR model and reduce the calibration accuracy (Van Der Heijden et al., 2007). The objective of this study was to assess the predicting power of the relationship between physiological, shoot, and root traits with grain yield of maize using partial least square regression using.

MATERIALS AND METHODS

Two experiments (Screen House and Field) were conducted in the 2014 wet season at the Research and Teaching Farm of Department of Agronomy, Bayero University, Kano Nigeria (Lat 11°58'N, Long 8°25'E and 475 m above sea level). The experimental treatments consisted of six maize genotypes of varying maturity groups (Table 1). The treatments were laid out in a Completely Randomized Design (CRD) and Randomized Complete Block Design (RCBD) for the screen house and field experiments, respectively each replicated three times. The screen house experiment was maintained for 30 days and fully irrigated using watering can. Two seeds were sown per plot and later thinned to one per pot. Fertilizer was split applied at planting and two weeks after sowing using recommended rates. Data collected for the pot experiment were; root length, root fresh weight, shoot fresh weight, fresh root shoot ratio, dry root weight, dry shoot weight and dry root shoot ratio. In the field experiment, a single row plot of 4 m long was used. Three seeds were sown at 40 cm × 70 cm intra and inter row spacing, respectively. The seeds were later thinned to two plants per stand. NPK 15-15-15 was split applied at 2 and 6 weeks after sowing. Data were recorded on plant height at maturity, ear height, days to anthesis, days to silking, plant aspect and number of leaves. Drought tolerance related data collected includes: stomatal conductance and leaf temperature using leaf porometer (Decagon Devices), canopy temperature using infrared thermometer, and Chlorophy ll content using SC1 Handheld SPAD meter from Konica Minolta.

Partial least squares regression

In many situations, when the number of variables (S) is much larger than the number of observations (N), and there is high co-linearity among variables, the usual methods for fitting regressions based on ordinary least squares are not adequate. In this situation, partial least squares regression seems to be a more appropriate alternative. Details of PLS theory (Helland, 1988) and its similarities to principal components regression and stepwise multiple linear regression are described in Aastveit and Martens (1986). A description of univariate and multivariate PLS and their algorithms was given in Vargas et al. (1998). Partial least square (PLS) regression was carried out using the PLS module of the XLSTAT software (Addinsoft, 2009) to predict grain yield from three set of data collected (root, agronomical and physiological).

Model quality

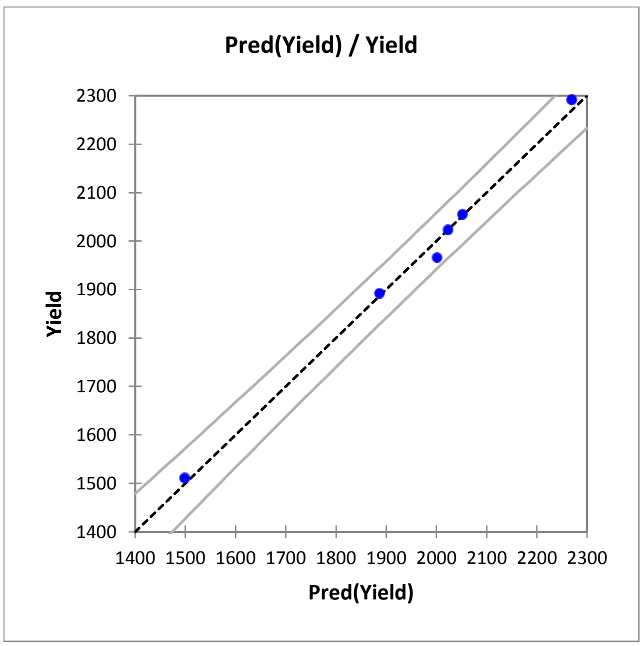
The performance of the model is measured by coefficient of determination of the model (R^2) and the root mean square error (RMSE) that is an indicator of the average error in the analysis expressed in original measurement unit (Kvalheim, 1987). The higher the R^2 and the lower the RMSE, the higher the precision and accuracy of the model to predict the grain yield.

RESULTS AND DISCUSSION

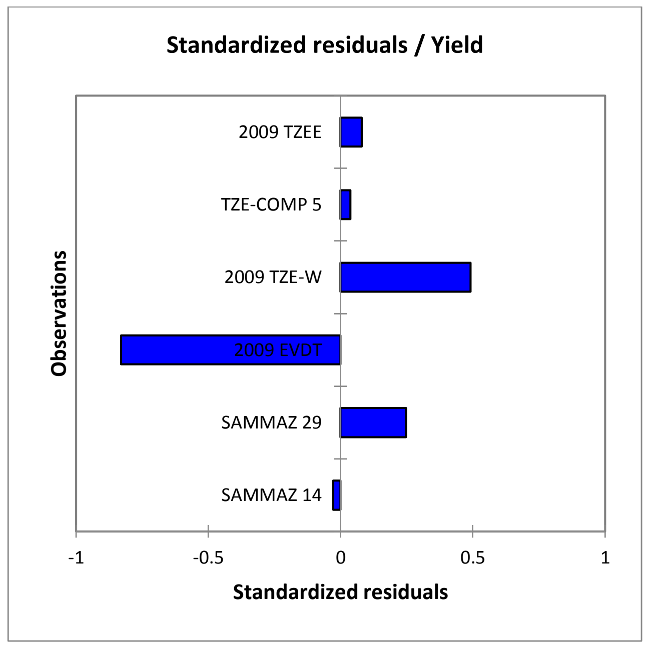
The prediction of grain yield of maize using plant height

Table 2. Prediction of grain yield of maize using phenological traits.

Variable	Yield
Intercept	4175.407
Days to anthesis	18.856
Days to silking	-3.974
Anthesis silking interval	47.534
Plant aspect a	-281.952
Plant aspect b	-649.283
Plant height	-0.204
Ear height	2.833
Leaf number	-137.618
R^2	0.99
RMSE	17.73



(a)



(b)

Figure 1. a) Plot of predicted yield against observed yield using phenological traits b) Standardized residual plots.

at maturity, ear height, days to anthesis, days to silking, plant aspect and number of leaves are presented in Table 2. The R^2 value was high (0.99) with a relatively low RMSE (17.73) indicating a good fit for yield prediction using these traits. From the Table, days to silking and plant aspect have negative contributions in the model. Anthesis silking interval had the highest positive value (47.534). Figure 1a also shows a good accuracy of prediction of grain yield for all the genotypes used. Grain yield of Sammaz 14 was predicted more accurately and had the least standardized residual (Figure 1b). The prediction of grain yield of 2009 EVDT and 2009 TZEW were fairly accurate because of the high residuals observed.

Table 3 shows the prediction of grain yield using root traits. The R^2 value (0.96) obtained indicates a good fit for prediction of grain yield. A low RMSE value was also obtained. Fresh root shoot ratio had the highest positive contribution in the model. A good fit was observed generally in all the prediction for the different genotypes (Figure 2a). However, Sammaz 29 and TZE-COMP 5 gave better fit in the prediction while Sammaz 14 and 2009 TZEW were fairly predicted (Figure 2b). Prediction of grain yield of maize using leaf temperature, canopy

Table 3. Prediction of grain yield of maize using root traits.

Variable	Yield
Intercept	8255.874
Dry root shoot ratio	-330.825
Dry root weight	11.227
Dry shoot weight	-7.946
Fresh root shoot ratio	260.936
Fresh root weight	-1.427
Fresh shoot weight	-12.642
Leaf number	-933.711
Root length	2.433
R^2	0.96
RMSE	44.16

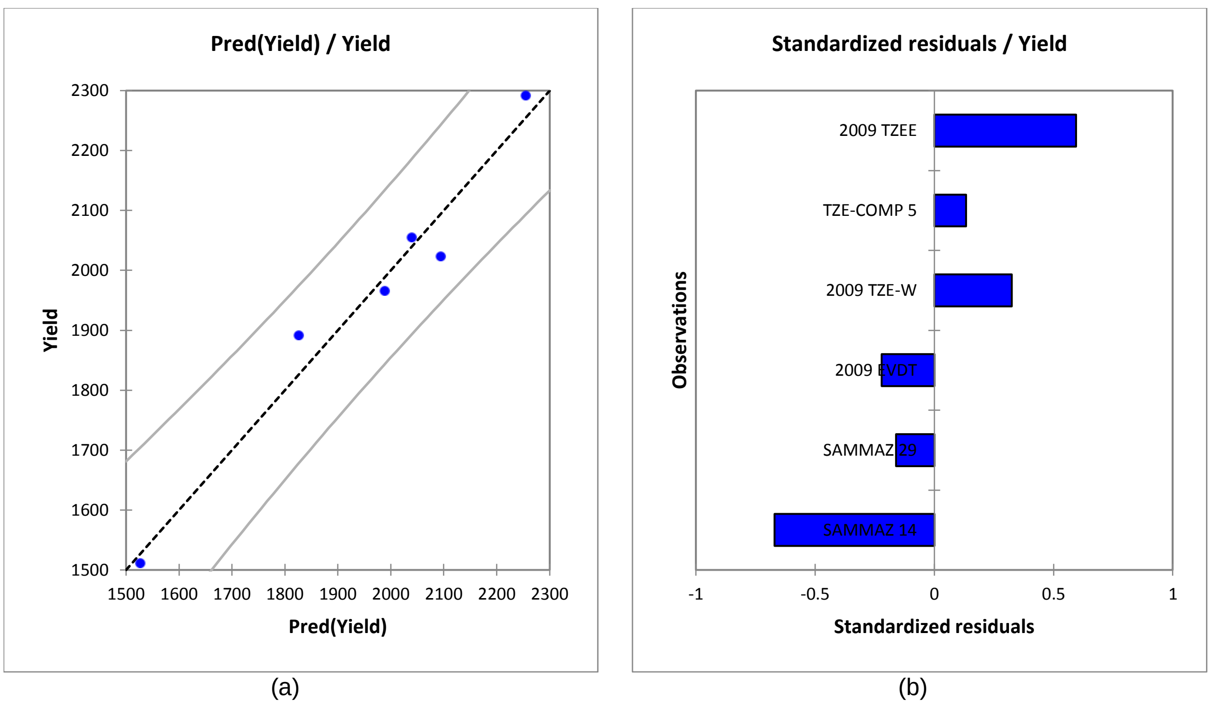


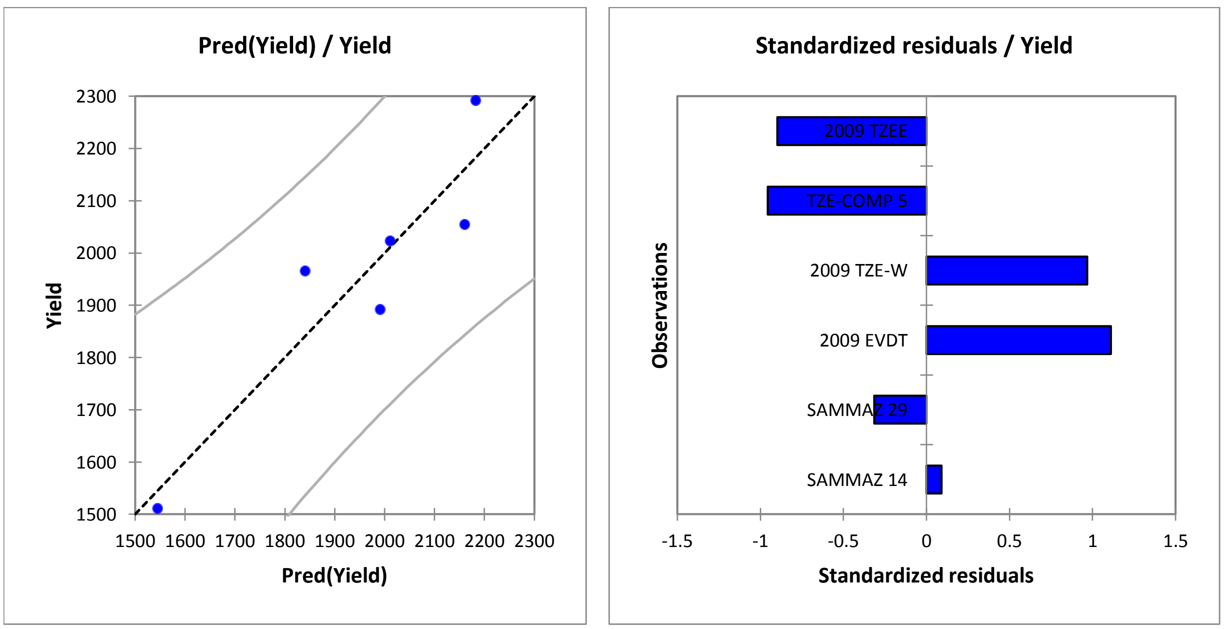
Figure 2. a) Plot of predicted yield against observed yield using root traits b) Standardized residual plots

temperature, stomatal conductance and Chlorophy ll content are presented in Table 4. These traits had negative contribution to grain yield. The R^2 value was 0.85 with RMSE of 90.94, thus, indicating a fair accuracy of prediction. The grain yield of Sammaz 14 was better predicted than the other genotypes (Figure 3a and b).

Generally, there was a good fit for predictions using above ground traits. However, prediction using root traits was fairly accurate. This finding is similar to the report of Nguyen and Lee (2006), and Li et al. (2014) who reported a good fit for prediction of rice leaf growth and canopy nitrogen of wheat, respectively using PLSR. Sammaz 14 was accurately predicted when agronomic and physiological (drought related) traits were used. This may be attributed to the late maturity of the genotype (110 days) when compared to other genotypes that are either extra early or early maturing. However, in terms of prediction using root traits, Sammaz 29 was better predicted followed by TZE-COMP 5. Vargas et al. (1998) used the PLSR in interpreting the genotype by environment interaction of wheat and observed that the PLS was effective in detecting environmental and cultivar explanatory variables associated with factors that explained large portions of the interaction. Further

Table 4. Prediction of grain yield of maize using physiological traits.

Variable	Yield
Intercept	20371.068
Leaf temperature	-428.334
Canopy temperature	-70.626
Stomatal conductance	-0.775
Chlorophy ll content	-17.001
R^2	0.85
RMSE	90.94



(a) (b)

Figure 3. a) Plot of predicted yield against observed yield using physiological traits b) Standardized residual plots.

research is recommended to evaluate the predicting power of PLS using drought tolerant related traits that are less tedious to measure as this can enhance screening and selection of drought tolerant maize genotypes at early stages.

Conflict of Interest

The authors have not declared any conflict of interest.

REFERENCES

Aastveit H, Martens H (1986). ANOVA interactions interpreted by partial least square regression. Biometrics 42:829-844.

Addinsoft (2009). XLSTAT. France: Addinsoft. http://www.xlstat.com/en/products/xlstat-pls/

Aslam M, Zamir MSI, Afzal I, Yaseen M, Mubeen M, Shoaib A (2012). Drought stress, its effect on maize production and development of drought tolerance through potassium application. Cercetări Agron. Moldova 46:99-114.

Badu-Apraku B, Akinwale RO, Ajala SO, Menkir A, Fakorede MAB, Oyekunle M (2011). Relationships among traits of tropical early maize cultivars in contrasting environments. Agron. J. 103:717-729.

Edmeades GO, Banziger M, Chapman SC, Ribaut JM, Bolanos J (1995). Recent advances in breeding for drought tolerance in maize. pp. 24-41. In B. Badu-Apraku B, Menkir A, Fakorede MAB, Ajala S, Elis-Jones J (eds.) Contributing to Food Self-sufficiency: Maize Research and Development in West and Central Africa. Proc. Regional Maize Workshop. 28 May-2 June 1995. IITA-Cotonou, Benin Republic. IITA, Ibadan, Nigeria

Ehsani MR, Upadhyaya SK, Slaughter D (1999). A NIR technique for rapid determination of soil mineral nitrogen. Precision. Agric. 1:217-234.

Fassio A, Cozzolino D (2003). Non-destructive prediction of chemical composition in sunflower seeds by near infrared spectroscopy. Industrial. Crops Prod. 20:321-329.

Li F, Mistele B, Hu Y, Chen X, Schmidhalter U (2014). Reflectance estimation of canopy nitrogen content in winter wheat using optimised hyperspectral spectral indices and partial least squares regression. Eur. J. Agron. 52:198-209.

Galadi P, Kowalski BR (1986). Partial least square regression: a tutorial. Analytica Chimica. Acta, 1-17.

Haaland DM, Thomas EV (1988). Partial least-squares methods for spectral analyses. 1. Relation to other quantitative calibration methods and the extraction of qualitative information. Anal. Chem. 60:1193-1202.

Hansen PM, Schjoerring JK (2003). Reflectance measurement of canopy biomass and nitrogen status in wheat crops using normalized difference vegetation indices and partial least squares regression. Remote Sens. Environ. 86:542-553.

Helland IS (1988). On the structure of partial least square regression. Commun. Statistics-Simul. Comput. 17:581-607.

Herrmann I, Pimstein A, Karnieli A, Cohen Y, Alchanatis V, Bonfil DJ (2011). LAI assessment of wheat and potato crops by VEN mu S and Sentinel-2 bands. Remote Sens. Environ. 115:2141-2151.

Lin M, Cavinato AG, Huang Y, Rasco BA (2003). Predicting sodium chloride in commercial king (*Oncorhynchus tshawytscha*) and chum (*O. keta*) hot smoked salmon fillet portions by short-wavelength near-infrared (SW-NIR) spectroscopy. Food Res. Int. 36:761-766.

Misra AN, Biswal AK, Misra M (2002). Physiological, biochemical and molecular aspects of water stress responses in plants and the biotechnological applications. Proceed. Natl. Acad. Sci. India 72B:115-134.

Nguyen HT, Lee BW (2006). Assessment of rice leaf growth and nitrogen status by hyperspectral canopy reflectance and partial least square regression. Eur. J. Agron. 24:349-356.

Nguyen HT, Manavalan, LP, Musket T (2011). Natural genetic variation for root traits among diversity lines of maize (*Zea mays* L.). Maydica 56:1-10.

Soderstrom M, Borjesson T, Pettersson CG, Nissen K, Hagner O (2010). Prediction of protein content in malting barley using proximal and remote sensing. Precis. Agric. 11:587-599.

Thomas EV, Haaland DM (1990). Comparison of multivariate calibration methods for quantitative spectral analysis. Anal. Chem. 62:1091-1099.

Van der Heijden G, Clevers J, Schut AGT (2007). Combining close-range and remote sensing for local assessment of biophysical characteristics of arable land. Int. J. Remote Sens. 28:5485-5502.

Vargas M, Crossa J, Sayre K, Reynolds M, Ramirez ME, Talbot M (1998). Interpreting genotype × environment interaction using partial least square regression. Crop Sci. 38:679-689.