Research Application Summary

Measuring maize (*Zea mays* L.) genetic coefficients for modeling water-limited potential yield and yield gaps in the Wami-Ruvu river basin, Tanzania: An overview

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Abstract

This research establishes observed data for validating an artificial neural network model for estimating the cultivar coefficients for the popular maize varieties in Tanzania. The genetic coefficients are fundamental in calibrating the DSSAT crop system model for estimating potential yield and yield gap under rain fed conditions. Leaf area index, plant height, aboveground biomass and grain growth rate varied significantly among the maize varieties. This paper summarizes the obtained results.

Key words: DSSAT, modeling, potential yield, yield gap, *Zea mays*

Résumé

Cette recherche établit les données observées pour valider un modèle de réseau neural artificiel afin d'estimer les coefficients de cultivars pour les variétés de maïs populaires en Tanzanie. Les coefficients génétiques sont fondamentaux pour calibrer le modèle de système cultural DSSAT afin d'estimer le rendement potentiel et l'écart de rendement dans les conditions pluviales. L'indice de la surface foliaire, la hauteur des plantes, la biomasse au-dessus du sol et le taux de croissance des grains ont varié significativement pour les variétés de maïs. Le présent article résume les résultats obtenus.

Mots clés: DSSAT, modélisation, rendement potentiel, écart de rendement, *Zea mays*

Background

Determining the crop yield potential by classical methods requires long term and costly experimentation which, in most cases, may not be feasible in situations where resources are limiting. However, using soil and weather databases and knowledge of crop physiological process, potential yield and thus the yield gap can be determined by dynamic crop models (Lobell *et al*., 2009). The importance of knowing the crop potential yield and yield gap is twofold; first, it enables us to project the future crop yields and second, it facilitates the knowledge and understanding of the biophysical constraints to maximum yield (Lobell *et al*., 2009).

Accurate estimation of model parameters for crop, soil and weather is an entry point in crop modelling for estimating crop potential yield and yield gap in any location under any crop production setting. Cultivar coefficients are input parameters in crop models that account for cultivar differences either in the duration of developmental phases or in the response of a specific plant process to a change in environmental factors. The coefficients summarize the way in which a specific crop cultivar divides up its life cycle, responds to different aspects of its environment (e.g. day-length, temperature, moisture stress, disease organism) or appears/changes morphologically. An elusive, yet important step in crop modelling has been the estimation of cultivar coefficients. In the current Decision Support System for Agro-technology Transfer (DSSAT) ver. 4.5 (Hoogenboom *et al*., 2010) the calculation of cultivar coefficients is still done through conventional, heuristic search techniques or with cultivar coefficient calculator (GENCALC) program (Hunt *et al*., 1993). Conventionally, the process for estimation of cultivar coefficients is tedious and labour intensive, somewhat subjective and sometimes criticized as 'tweaking' the model. To tackle this problem, a number of techniques have been proposed, including genetic algorithm and simulation annealing (Mavromatis *et al*., 2001) to mention but a few. The setbacks to these techniques are that they are not adaptive; unable to process all the data and give outputs at once but rather few outputs at a time.

Furthermore, available techniques are computationally inefficient, requiring longer computer times. Artificial Neural Networks (ANNs) which are highly parallel data processing systems and particularly suited to learn ill defined or fuzzy input-output relations (Porto and Pazos, 2006) may be instrumental in solving this problem. In Tanzania, crop simulation models have not been widely employed as research or decision support tools probably because of the difficulty in measuring crop cultivar coefficients for major cultivated crops. For example, of the 75 registered maize varieties in Tanzania, none had genetic coefficients determined.

The purpose of this work therefore was to develop a technique for estimation of maize cultivar coefficients for use in the DSSAT crop system model, using readily available data from official variety trials and ultimately use the model calibrated with local maize cultivars to estimate maize potential yield and yield gap under varying climate, soil and management strategies for selected locations in the Wami-Ruvu River basin, Tanzania. Reported in this paper are experimental data with which to validate the ANN model to be developed afterwards for estimation of the genetic coefficients for maize.

Literature Summary

For calibration of CERES-Maize (V4.5) crop system model, information on six main coefficients is required. Four of these relate to development and the progression through the lifecycle while two relate to growth aspects.

Length of juvenile phase P1. The juvenile stage is defined as the pre-induction stage when the plant is not sensitive to variation is photoperiod. The cultivar variation in the length of a juvenile stage gives rise to the classification of cultivars in in terms of maturity types (Ritchie *et al*., 1998). The duration of juvenile stage is controlled by temperature, thus a single cultivar specific coefficient (P1) can be determined to describe the duration of the juvenile period (from emergence to the end of juvenile phase) in thermal time given as eq 1

$$t_d = \sum_{i=1}^{n} (\overline{T}_a - T_b) \quad \text{..........................} \; 1$$

Where $\overline{T}_a$ is daily mean air temperature, T_b is the base temperature at which development stops and n is the number of days of temperature observations used in the summation.

Delay of development due to photoperiod (P2). The cultivar specific coefficient P2 refers to an extent to which development (expressed in days) is delayed. This increases for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate (considered to be 12.5 hours).

Silking to physiological maturity phase (P5). Thermal time from silking to physiological maturity (expressed in degree days above a base temperature of 10^oC).

Grain number (G2). Grain number per unit area that will make mature kernels are usually the most critical determinant of crop yield. Under optimal conditions, there is cultivar variability in final grain weight and grain number. To account for this variability, the coefficient G2 is used to convert from the weight of all or part of a plant organ such as the ear or stem to grain number.

Grain filling rate (G3). For the CERES-maize model, the filling rate per grain (kernel) is calculated daily using a source-sink reserve procedure. A sink capacity is calculated based on temperature and is related to a cultivar coefficient G3, which is the potential daily single kernel growth rate (in mg/day) at optimum temperature.

Leaf appearance rate (PHINIT). The leaf appearance rate in the CERES models is also primarily temperature-driven. With the exception of the period of formation for the first two to three leaves, CERES assumes a constant thermal requirement for a single leaf to appear. The thermal time for a single leaf-tip to appear, the phyllochron interval (PHINT), is a cultivar-specific coefficient expressed also in degree days (°C).

Study Description

The validation field experiment was carried out at Sokoine University of Agriculture where four (4) maize cultivars namely *Situka, TMV1, Staha* and *Pioneer* were planted in a randomized block design with three replications. Row spacing was 75cm and inter-row spacing was 30 cm, equivalent to 4.4 plants m^{-2}. Sowing took place on 07/03/2012 or 12067 day of the year (DOY). The crop was grown under near-optimum conditions of Nitrogen and water, whereas 80kg/ha N (as DAP) was applied, 50% of which was applied at planting and another 50% at 45^{th} day after sowing. Other nutrient elements were supplied as per recommendations. Depleted water was replenished through furrow irrigation as per crop demand. Daily weather data including precipitation, minimum and maximum air temperature were collected using automated weather station (Umwelt - Geräte – Technik, GmbH, Müncheberg, Germany). Crop phasic developmental stages were recorded for each cultivar as required (Hoogenboom *et al.*, 2010).

Leaf area index was calculated using a procedure by Montgomery, (1911) by multiplying the leaf length (L) (measured from leaf tip to the point of attachment to the collar), leaf width (W) (at the widest point) and a factor of 0.75 (Eq. 2)

$$LAI = L \times W \times 0.75 \quad \text{...} \quad (2)$$

Leaf number was counted as the number of all completely opened leaves. Plant height was measured from the ground level to the tip of the top most leaf or the tassel by a measuring tape after harvest sampling. Grain development rate was determined by weekly measuring the grain biomass. Fifty grains were extracted from the centre of the cob, oven dried and weighed.

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Daily weather. Daily maximum temperature ranged from 23°C to 26.1°C whereas minimum temperature ranged from 22 to 25C. Daily precipitation ranged from 0 to 43mm, showing a declining trend as the season advanced (Fig .1).

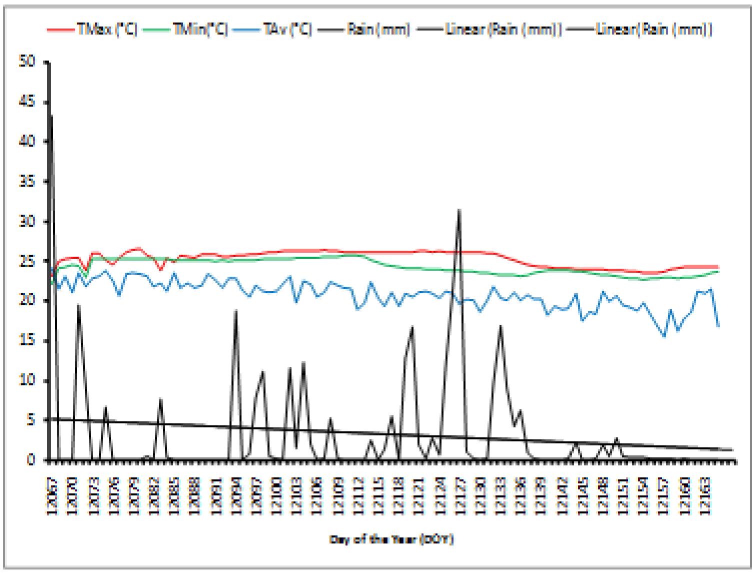

Figure 1. Daily weather information from the day of planting.

Leaf area index (LAI). There was significant difference (P<0.05) between maize varieties with respect to the leaf area index. For all varieties, this variable increased at increasing rate during the juvenile phase and stagnating and at decreasing rate afterwards and LAI declining as maize plants approached maturity (Fig. 2). Variety *Staha* exhibited on average high LAI whereas *Pioneer* had the lowest LAI.

Plant height. There was significant (P<0.05) variability among the maize varieties with respect to the crop height. This variable also increased with time, although *Situka* ceased elongation earlier than any other variety and *Staha* continued elongation

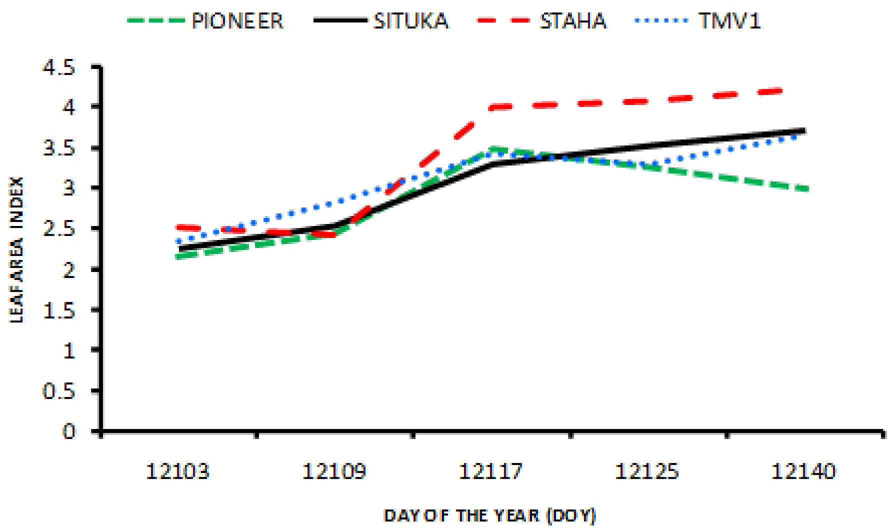

Figure 2. Development of Leaf area Index (LAI) for the four maize varieties.

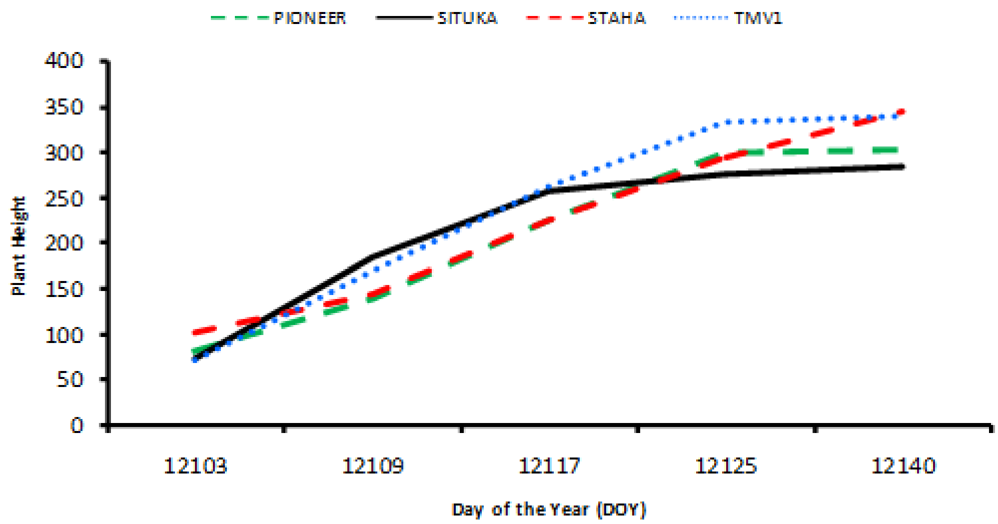

Figure 3. Plant height development pattern for maize varieties.

60 days after sowing (Fig. 3). Overall, *Situka*'s canopy was the shortest whereas TMV's canopy was the highest.

Above-ground biomass. The rate of biomass accumulation did not significantly ($P<0.05$) differ among the four maize varieties. The total biomass increased as the plant growth progressed. The total above-ground biomass ranged from 116.7g for *Pioneer* to 146.4 g for *Situka* . The pattern exhibited by the varieties indicates that the rate of biomass accumulation was more or less similar during the juvenile stage, diverging later during the reproductive stage. During this latter stage, *Situka* has high rate of biomass increase while *Pioneer* has the lowest rate of biomass accumulation (Fig. 4).

Grain growth rate. The rate at which grain weight increased varied significantly (P<0.05) among the four maize varieties, with high and low rate for *Staha* and *Situka* respectively. The growth rate is still increasing since the crop is in grain filling phase (Fig. 5).

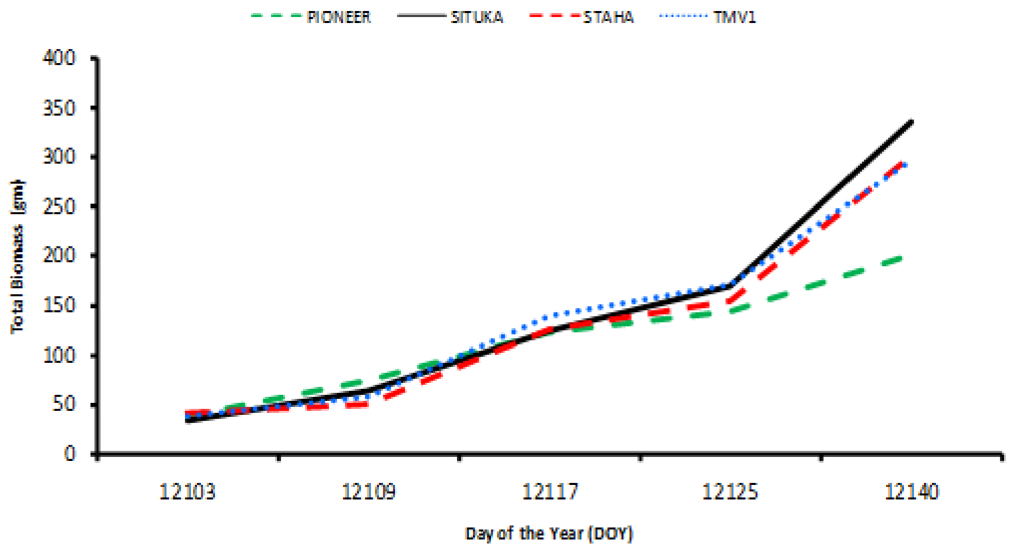

Figure 4. Above-ground biomass accumulation.

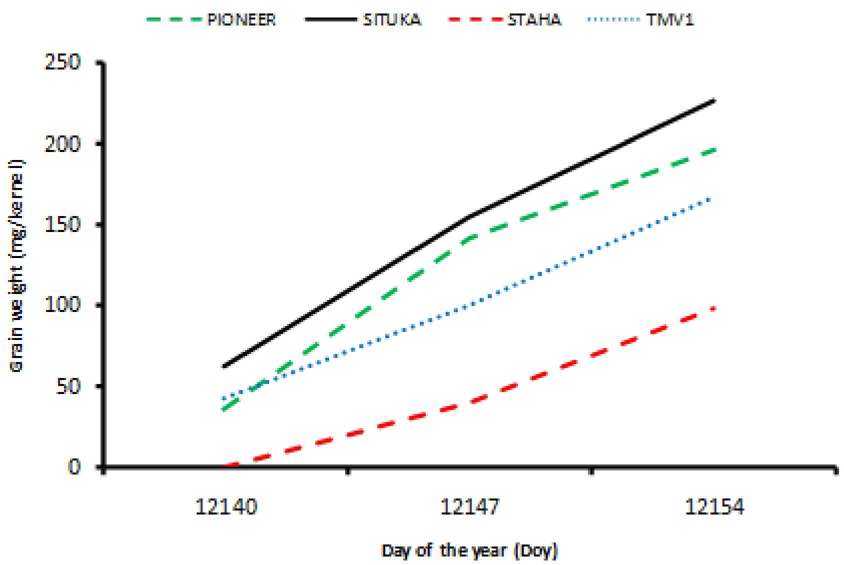

Figure 5. Grain growth rate.

The results from this study indicate that the maize varieties are uniquely different such that they perform differently under similar growing conditions. When their genetic coefficients are determined, they can be used to calibrate the DSSAT model to guide research and decision making in maize productivity improvement under varying management and climatic scenarios.

Acknowledgement

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