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SORGHUM YIELD AND ASSOCIATED SATELLITE-DERIVED METEOROLOGICAL PARAMETERS IN SEMI-ARID BOTSWANA

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ABSTRACT

Africa has sparse meteorological stations, hence it is increasingly common to use satellite-derived meteorological parameters, where *in-situ* measuremnts are not available. The objective of this study was to determine if there is a relationship between sorghum yield and meteorological parameters (measured and satellite-derived). Sorghum (*Sorghum bicolor*) yield for five seasons (2005/6 to 2009/10) from the Botswana Department of Crop Production Station in Pandamatenga, actual rainfall from the Botswana Meteorologial Services, and Normalised Difference Vegetation Index (NDVI) and Satellite Rainfall Estimates (RFEs) data from Famine Early Warning Systems Network (FEWSNET) were used in this study to determine relationships between the yield and satellite derived estimates. Although the NDVI and RFEs data were available for 2005 to 2011 (6 seasons), the limiting factor was the actual yield data which were only available for 2005 to 2010 (5 seasons). The Pearson Correlations Coefficient between seasonal rainfall and seasonal NDVI was 0.77 and seasonal RFE and seasonal NDVI was -0.19. Further correlation coefficient between sorghum yield and seasonal NDVI is 0.88. The correlation coefficient between sorghum yield and seasonal rainfall was 0.53; while correlation coefficient between sorghum yield and seasonal RFEs was -0.38. The sorghum NDVI signature reacted positively to the the seasonal rainfall, while sorghum NDVI signature was not correlated with the 1 Km resolution RFEs data. Furthermore, there was good correlation between sorghum yield and both the seasonal NDVI and seasonal rainfall, the seasonal NDVI seemed to predict yield slightly better than the seasonal rainfall. There seem to be a potential to use RFEs to predict yield though there are still problems associated with RFEs.

Key Words: Coefficient of determination, NDVI, Pearson correlation

RÉSUMÉ

L'Afrique a des stations météorologiques rares où il est de plus en plus courant d'utiliser des paramètres provenant de satellites météorologiques, où in situ measuremnts ne sont pas disponibles. L'objectif de cette étude était de déterminer se il y avait une relation entre le rendement du sorgho et des paramètres météorologiques (mesurées et obtenues par satellite). Du sorgho (Sorghum bicolor) rendement pendant cinq saisons (2005/6-2009/10) du ministère du Botswana de la station de la production agricole à Pandamatenga, précipitations réelle de la Meteorologial services Botswana, et indice de végétation normalisé (NDVI) et Satellite précipitations estimations (RFE) données de Famine Early Warning Systems Network (FEWSNET) ont été utilisés dans cette étude pour déterminer les relations entre le rendement et le satellite estimations tirées. Bien que les données de NDVI et RFEs étaient disponibles pour 2005-2011 (6 saisons), le facteur limitant était les données de rendement réels qui ne était disponible pour 2005-2010 (5 saisons). Les corrélations Pearson Coefficient entre les précipitations saisonnières et NDVI saisonnière était de 0,77 et RFE saisonnière et saisonnière NDVI était -0,19. En outre coefficient de corrélation entre le rendement du sorgho et NDVI saison est de 0,88. Enfin, le coefficient de corrélation entre le rendement de sorgho et précipitations saisonnière était de 0,53; tandis que le coefficient de corrélation entre le rendement de sorgho et RFE saisonniers était -0,38. La signature sorgho NDVI a réagi positivement à l'pluies saisonnières, tandis que la signature sorgho NDVI ne est pas corrélée avec les 1 km de résolution RFEs données. En outre, il y avait une bonne corrélation entre le rendement de sorgho et à la fois le NDVI saison et des précipitations saisonnières, le NDVI saison semblait prédire le rendement légèrement meilleur que les pluies saisonnières. Il semble y avoir un potentiel d'utiliser RFE à prédire le rendement se il ya encore des problèmes liés à RFE.

Mots Clés: coefficient de détermination, NDVI, corrélation de Pearson

INTRODUCTION

Most of southern Africa is sensitive to climatic extremes, resulting in poor crop yields. The sensitivity is compounded by a strong dependence upon agriculture, high population growth rates, and unstable economic conditions (Martin, 1998). Due to southern Africa's position in the sub-tropics, it experiences predominantly high pressure and arid conditions. Air rising from the low pressure of the equator, drops its moisture in the Inter-Tropical Convergence Zone before traveling southward and sinking over southern Africa, creating the dry high-pressure system (Martin, 1998; Nicholson, 2001).

In a review of a decade of sorghum production (2000 – 2010) from Pandamatenga farms, the average production of sorghum was 1.87 t ha^{-1}. Given the agro-climatic conditions of Pandamatenga, its productivity could be higher if it was not for the challenges such as periodic flooding and seasonal outbreaks of *quelea* birds (African Development Bank, 2008).

In 1979, sorghum accounted for a little less than 40 percent of cultivated area, in Botswana and maize for about 30 percent. By 1988, the share of sorghum was estimated at 75 percent. During the same period, the ratio of maize cultivated area fell from 30 percent to about 15 percent (African Development Bank, 2008).

One major challenge for operational crop monitoring and yield forecasting using crop models, is to find spatially representative meteorological input data due to low density of weather station networks in developing countries (Teo, 2006; Rojas, 2007).

Remote sensing data acquired by satellites have a wide scope for agricultural applications, owing to their synoptic and repetitive coverage. Spectral indices deduced from visible (VIS) and Near Infra-Red (NIR) remote sensing data have been extensively used in crop characterisation, biomass estimation and crop yield monitoring and forecasting. NDVI has been used as indicator of the vigour of vegetative activity as represented by indirectly observable chlorophyll activity (Hastings and Emery, 1992). Weissteiner *et al.* (2004) used Maximum Value Composites (MVC) to estimate barley yield, accumulating NDVI at the maximum photosynthetic activity period (ear emergence to yellow ripeness or grain filling period) gave improved correlation between NDVI and grain yield.

There are challenges in using NDVI, namely data loss due to cloud cover, data response to atmospheric moisture and spatial heterogeneity, calibration mismatches between satellites and within sensor calibration drift (Holben, 1986; Gutman, 1991). Lu (2006) looked into the potential and challenges of remote sensing-based biomass estimation, and concluded that more research work is needed to focus on data integration (optical and radar), the use of multi-source data and the selection of suitable variables and algorithms for biomass estimation.

Rojas (2007), developed operational spectro-agrometeorological yield model for maize, using a spectral index, Normalised Difference Vegetation Index (NDVI) derived from the SPOT-VEGETATION, meteorological data obtained from the European Centre for Medium-Range Weather Forecast (ECMWF) model and crop-water status indicators estimated by the Crop Specific Water Balance model (CSWB). Many studies modeling crop growth and yield forecasting have been carried with mixed results. De Wit and van Deepen (2006) used MeteoSat meteorological observations to run the WOrld Food STudies

(WOFOST) crop growth model, and concluded that it was not easy to calibrate the evapotranspiration related parameters since satellite based potential evaporation was on average 30 percent smaller to the standard Penman reference evapotranspiration.

The comparison of *in-situ* rainfall data with satellite rainfall estimates (RFEs) from FEWS NET archive and daily precipitation fields from the National Center for Atmospheric Research (NCAR) reanalysis data, gave a coefficient of regression was 0.8 and 0.2, respectively (Funk and Verdin, 2003).

Overall, the NDVI – rainfall relationship becomes much weaker when studied at the inter-annual time scale; moreover, the study showed that factors influencing the rainfall–NDVI relationship differ between time scales, with field characteristics (topography, vegetation composition and structure), having a major influence only at the seasonal time scale (Chamaille-James *et al*., 2006).

Satellite images have been used in Italy to spatially estimate Fraction of Absorbed Photosynthetically Active Radiation (fAPAR) and key phenological rice stages that control biomass accumulation. The maps of rice yield estimates for the year 2002, 2003 and 2004 were compared with official statistics and showed a good agreement with an inter-annual relative RMSE, ranging from 15 to 17% (Boschetti *et al*., 2011).

Janowiak *et al*. (2007) found that satellite estimates of precipitation exhibited a substantial positive bias over semi-arid regions, during the warm season due to evaporation of rain before it reaches the ground surface. Teo (2006) used Tropical Application of Meteorological Satellite (TAMSAT) RFEs and gauge rainfall in a crop model to forecast groundnut yield. It was concluded that RFE are able to capture the intraseasonal variability of rainfall better that total seasonal amount.

Although there has been progress in the applications of RFE to replace rainfall gauge observations, there are still accuracy issues to be resolved and several studies have been carried out to improve the accuracy of RFE (Xie and Arkin, 1996; Grimes *et al*., 1999; Teo, 2006)

Jones 1987 developed mathematical relations between yield parameter, plant populations and rainfall for Botswana, it was concluded that yield differences were unrelated to rainfall. The objective of this study was to determine if there was a relationship between sorghum yield and meteorological parameters (measured and satellite-derived).

MATERIALS AND METHODS

Figure 1 shows the study area, Pandamatenga is a commercial arable farming area situated north-northeastern Botswana, at the 17°49'S 28°38'E and at 1071 m above sea level. Pandamatenga is one of the most suitable areas for rain fed farming because of its relatively high rainfall of 600 mm per annum and inherently fertile PellicVertisols (dark cracking clay soils). The farming area is situated on predominantly flat lacustrine clay plains which are poorly drained (Moganane *et al*., 1990).

Despite the physical characteristics of the Pandamatenga soils which present a challenge in management, this area is considered the highest producer of commercial sorghum grain annually. In 1984, the Government of Botswana allocated 25 074 ha of farmland to the country's arable crop production (African Development Bank, 2008) This area was subsequently increased to 47,686 ha in 2011 to increase participation of farmers in commercial arable production.

Sorghum yield for the season 2005/6 to 2009/10 seasons from the Botswana Department of Crop Production station in Pandamatenga, actual rainfall from the Botswana Meteorological Services and NDVI and RFEs data from FEWSNET, were used in this study.

The Integrated Land and Water Information System (ILWIS) © 52° North Initiative for Geospatial Open Source Software Gmbh, was used to process FEWSNET RFEs and NDVI time series data. ILWIS is a remote sensing and GIS software, which integrates image, vector and thematic data in one unique and powerful package on the desktop.

The polygon to raster operation was used to rasterise the study area into a polygon map. The class names, IDs, or values in the polygon map

Figure 1. Study area map for Pandamatenga in Botswana.

were also used in the raster map. The domain of the polygon map was also the domain of the raster map. Figure 2 shows the raterised map of the study site.

A map list is a set of raster maps, for example the bands of a satellite image. In the study, the map lists were used to store data (NDVI and RFEs) for each of the six seasons. All raster maps in the map list must have the same georeference and the same domain. A map list is used to present multi-temporal changes in maps as a slide show, to apply the same Map Calculation formula on all raster maps in the map list, or to perform an operation on all raster maps in the map list. Map lists made up of dekadal data (NDVI or RFEs) for each of the six seasons were produced for further cross analysis.

Cross operations were performed between project raster image and either seasonal NDVI or seasonal RFEs map lists. A cross operation performs an overlay of two raster maps: pixels on the same positions in both maps are compared; the occurring combinations of class names,

Figure 2. Study area raster map for Pandamatenga, Botswana.

identifiers or values of pixels in the first input map and those of pixels in the second input map are stored. These combinations give an output cross map and a cross table. The cross table includes the combinations of input values, classes or IDs, the number of pixels that occur for each combination and the area for each combination.

RESULTS AND DISCUSION

Figure 3 shows six seasonal NDVI for 2005/6, 2006/7, 2007/8, 2008/9, 2009/10 and 2010/11 seasons. Dark green indicates higher NDVI values; while orange/brown indicates lower NDVI values. Each Figure is made up by the composition (average) of NDVI values for all dekades (September to August) for each season.

Figure 4 shows seasonal RFEs for seasons 2005/6, 2006/7, 2007/8, 2008/9, 2009/10 and 2010/11. Darker blue indicates higher RFES values; while lighter blue indicates lower RFEs values. Each Figure is made up by the composition (average) of RFEs values for all dekades (September to August) for each season.

Sorgum yield for the season 2005/6 to 2009/10 seasons from the Botswana Department of Crop Production station in Pandamatenga, actual rainfall from the Botswana Meteorologial Services and NDVI and RFEs data from FEWSNET were used in this study to determine any relationships between the yield and satellite derived estimates. Pearson correlations coefficient between Seasonal Rainfall and seasonal NDVI is 0.77 (r2=0.6) as shown in Figure 5 and Figure 6. Seasonal RFE and seasonal NDVI was -0.19 (r^2=0.03).

As expected, the sorghum NDVI signal is positively correlated to the the seasonal rainfall. Besides aerosol and water vapour related

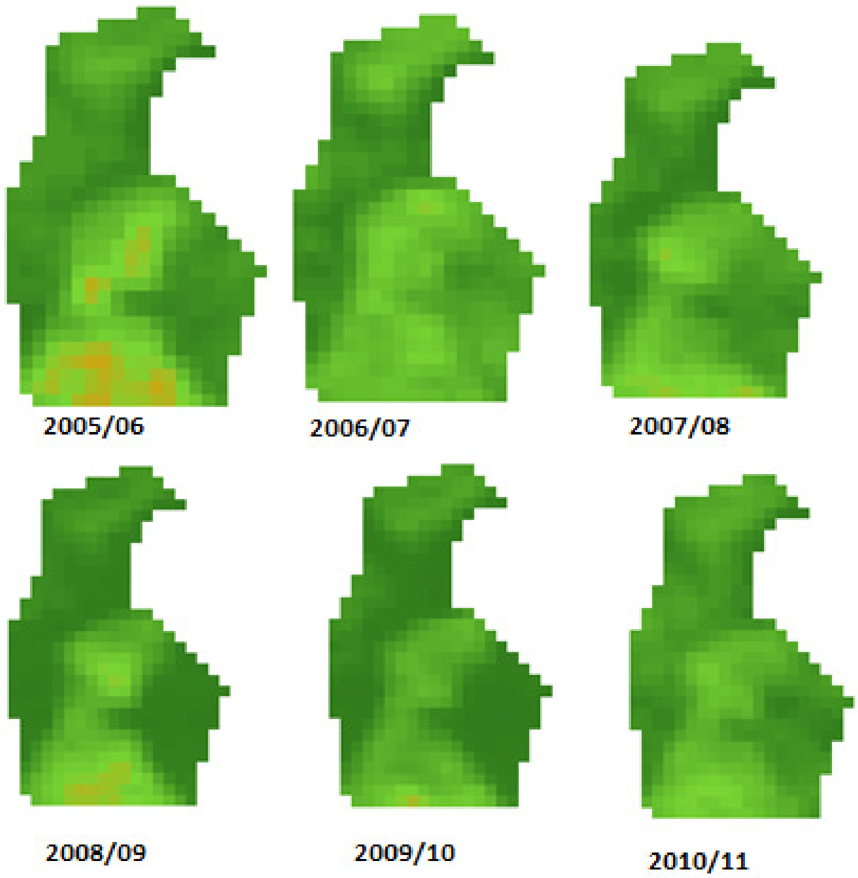

Figure 3. Seasonal NDVI for Pandamatenga, Botswana.

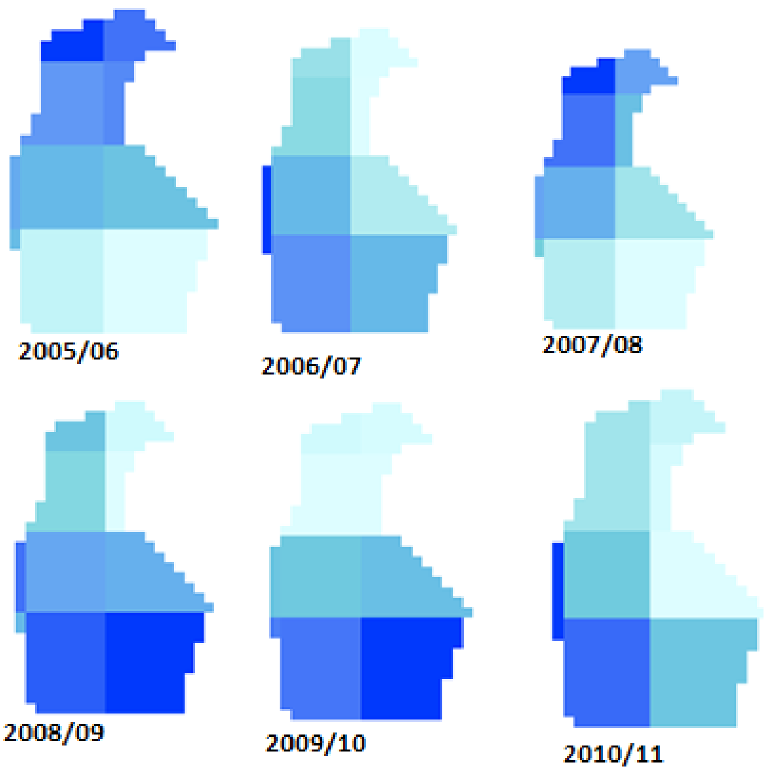

Figure 4. Seasonal RFEs for Pandamatenga, Botswana.

problems, cloud contamination (especially during the raining season) remains the biggest problem for low resolution NDVI satellite images. The sorghum NDVI signature is not correlated to the 1km resolution RFEs data as indicated by the weak correlation coefficient (r^2), this observation indicates that RFEs are not a very reliable rainfall proxy in this study area.There are several reasons for this, namely, these are estimates based on cloud temperature hence contain errors (eg. Rainfall from lower clouds is not adequtely accounted for), the 1km cell resolution is too coarse and also these have not been validated or calibrated fully due to the lack of sufficient number of ground rainfall measurements. Furthermore, satellite retrieval relies on inference of surface rainfall from irradiances measured by the satellite sensors operating at visible, thermal infrared, or microwave regions of the electromagnetic spectrum. The visible radiometric measurement is a function of the cloud albedo, while the thermal infrared radiometric measurement is a function of cloud top temperature. These are all indirect measurement of rainfall.

Correlation coefficient for the sorghum yield and seasonal NDVI is 0.88 (r^2=0.77) as shown in Figure 7 and Figure 8. This observation cofirms that there is a relationship between the sorghum yield and the satellite borne spectrometric biomass data.

There was a strong correlation between sorghum yield and seasonal NDVI (r =0.88) as shown in Figure 6. Finally, the correlation coefficient between the sorghum yield and seasonal rainfall was 0.53, this result is lower than the expected mainly due to the fact that the rainfall of 2010/2011 was a record low 474 mm; while the LongTerm Average rainfall is over 800 mm (removing this anormally increases the correlation to 0.88 as shown in Figure 8).

The correlation coefficient between sorghum yield and seasonal RFEs was weak (r= -0.38) as shown in Figure 13. This was due to problems

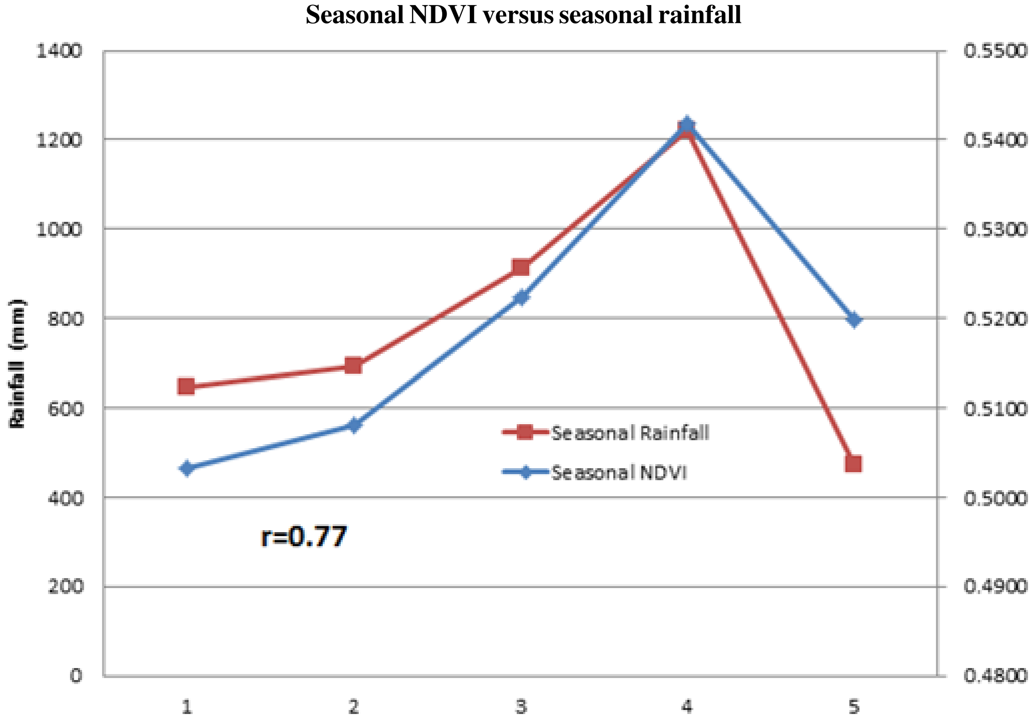

Figure 5. Seasonal NDVI and seasonal rainfall versus the five (5) seasons.

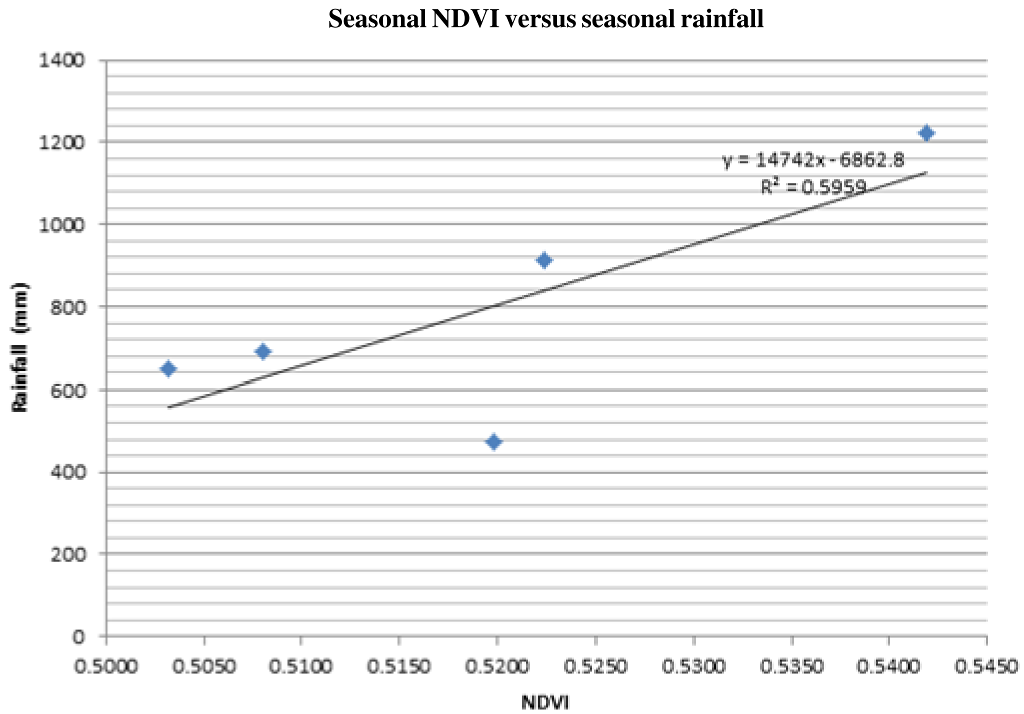

Figure 6. Seasonal NDVI versus seasonal rainfall.

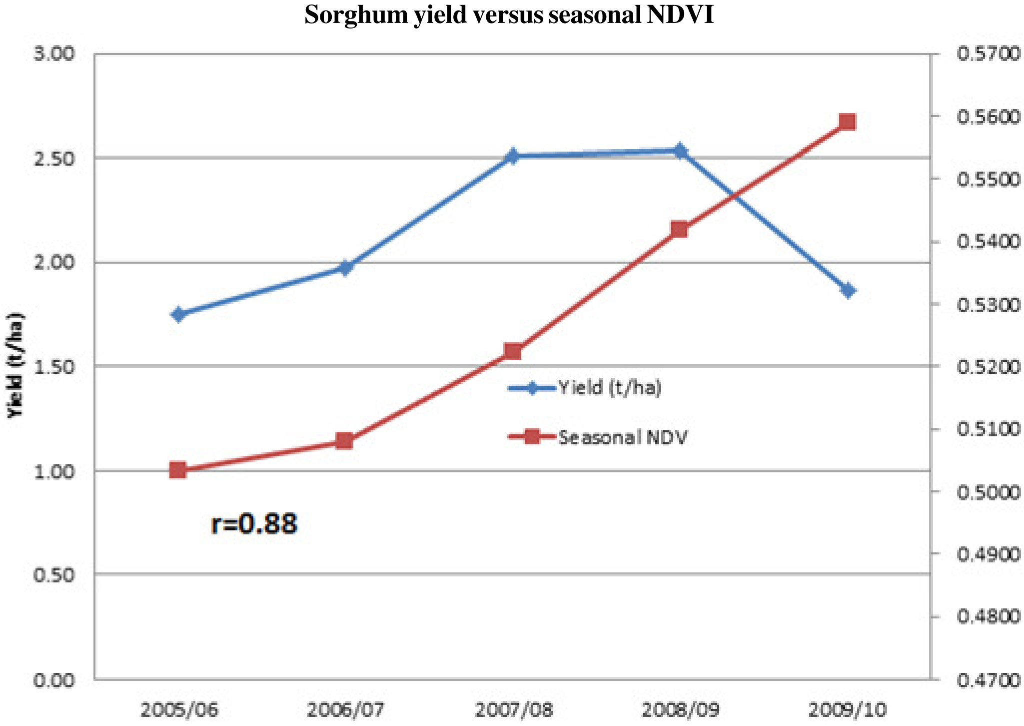

Figure 7. Sorghum yield and seasonal NDVI versus five (5) seasons.

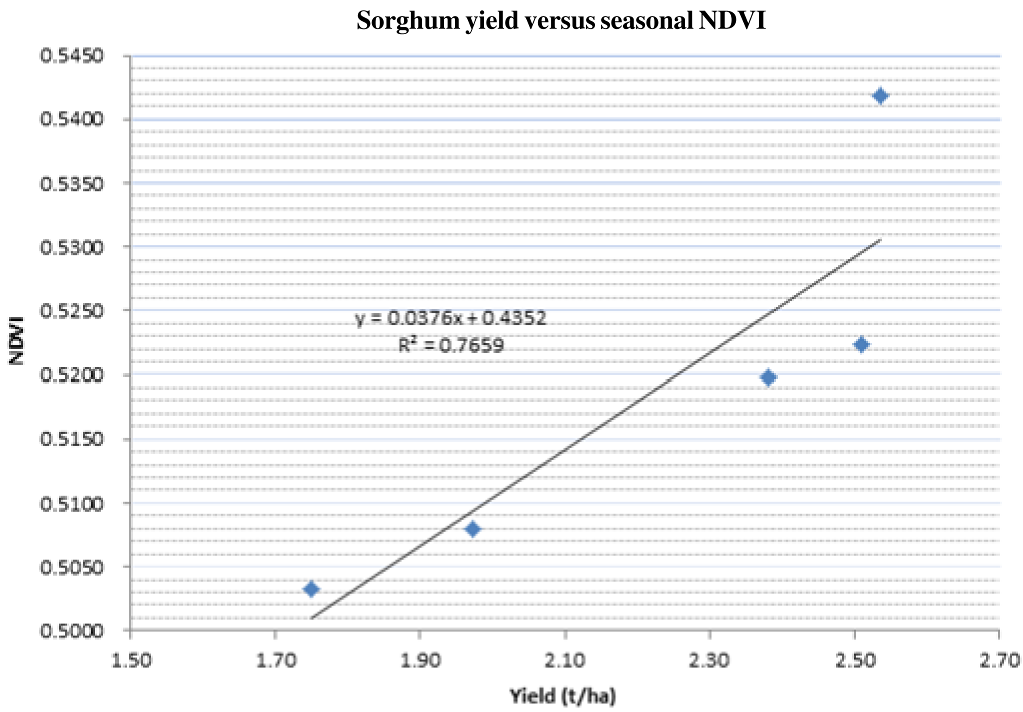

Figure 8. Sorghum yield versus seasonal NDVI.

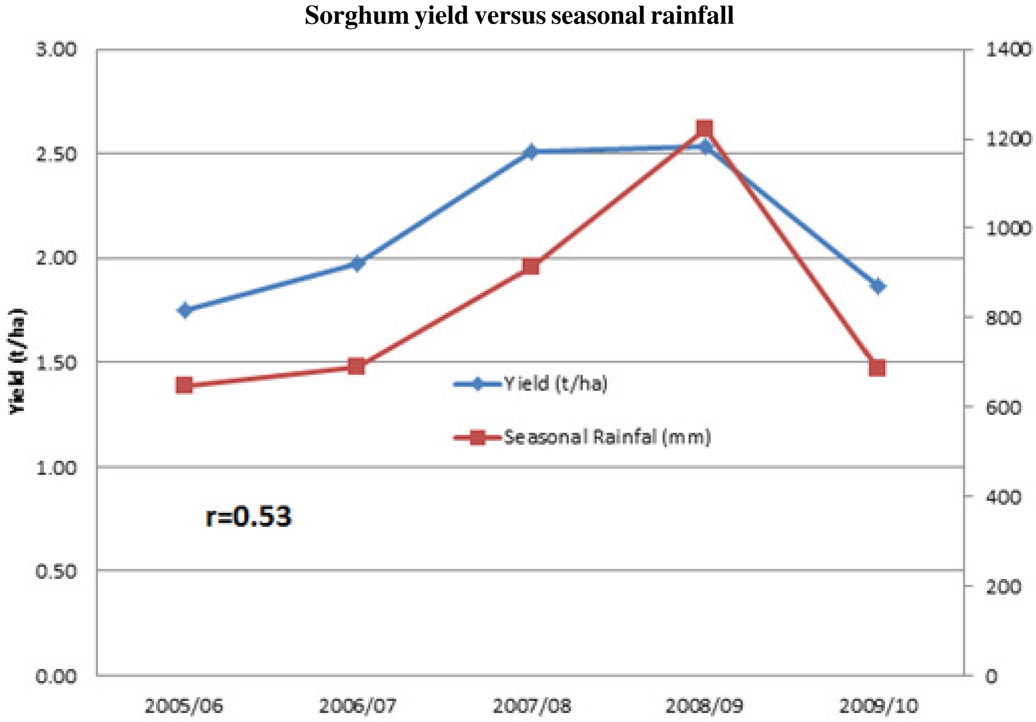

Figure 9. Sorghum yield, seasonal rainfall versus five (5) seasons.

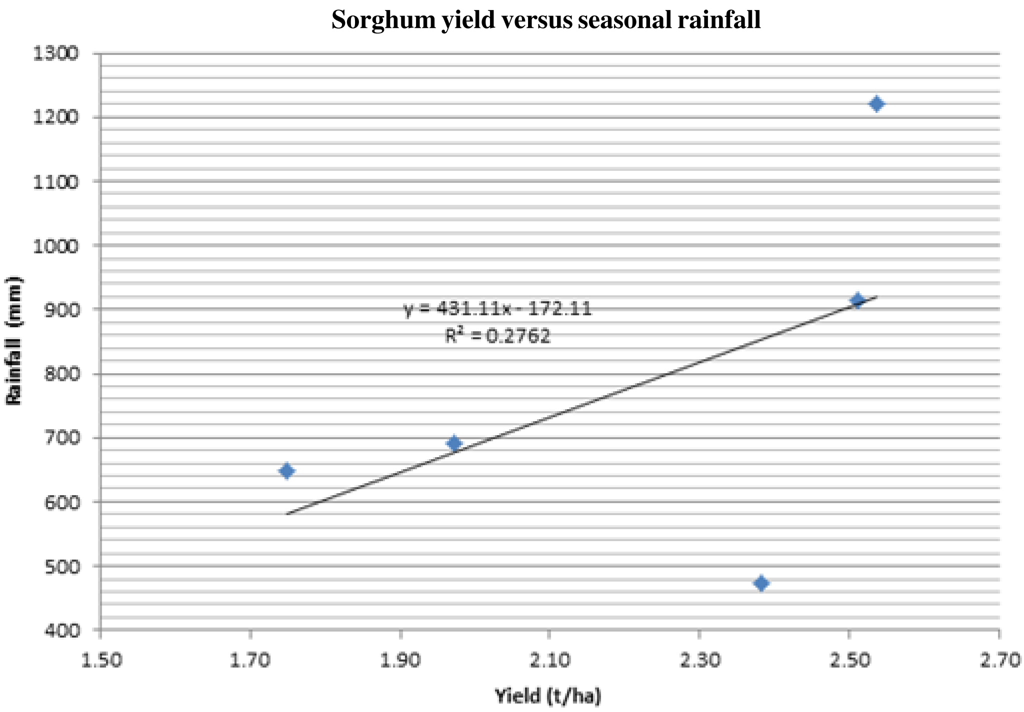

Figure 10. Sorghum yield versus seasonal rainfall.

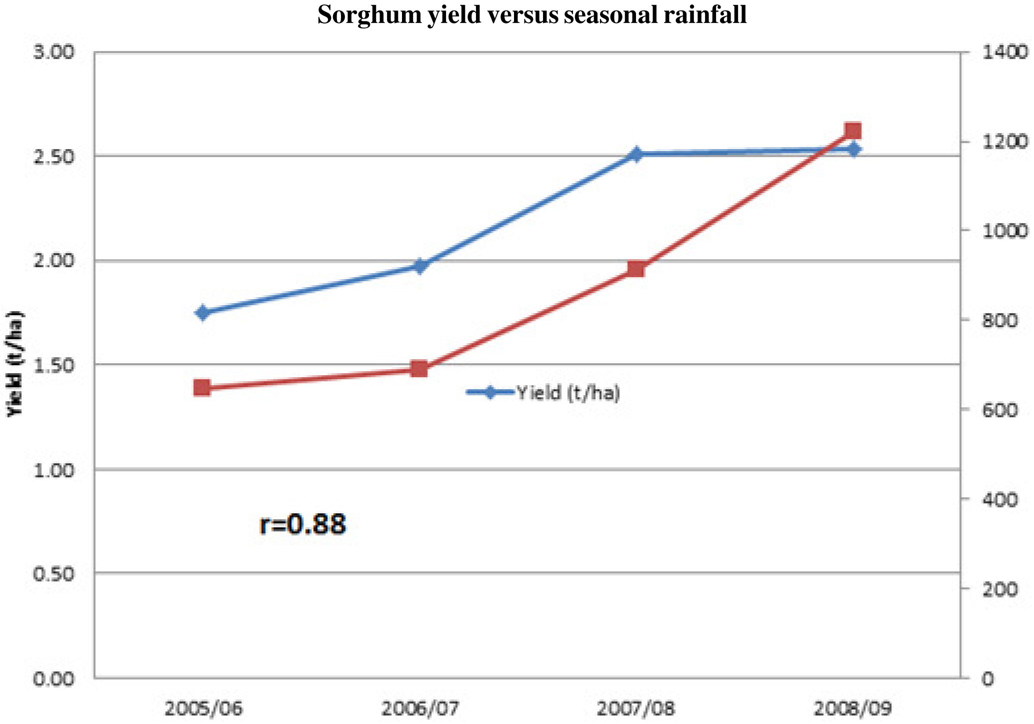

Figure 11. Sorghum yield, seasonal rainfall versus five (5) seasons (excluding the anomaly).

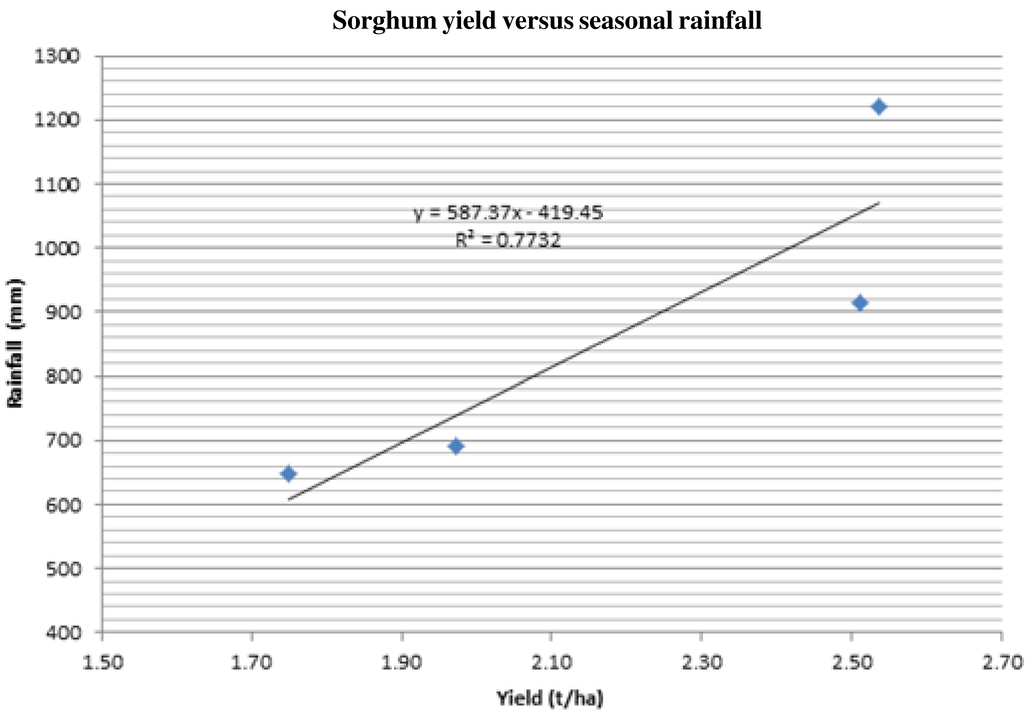

Figure 12. Sorghum yield versus seasonal rainfall (excluding the anomaly).

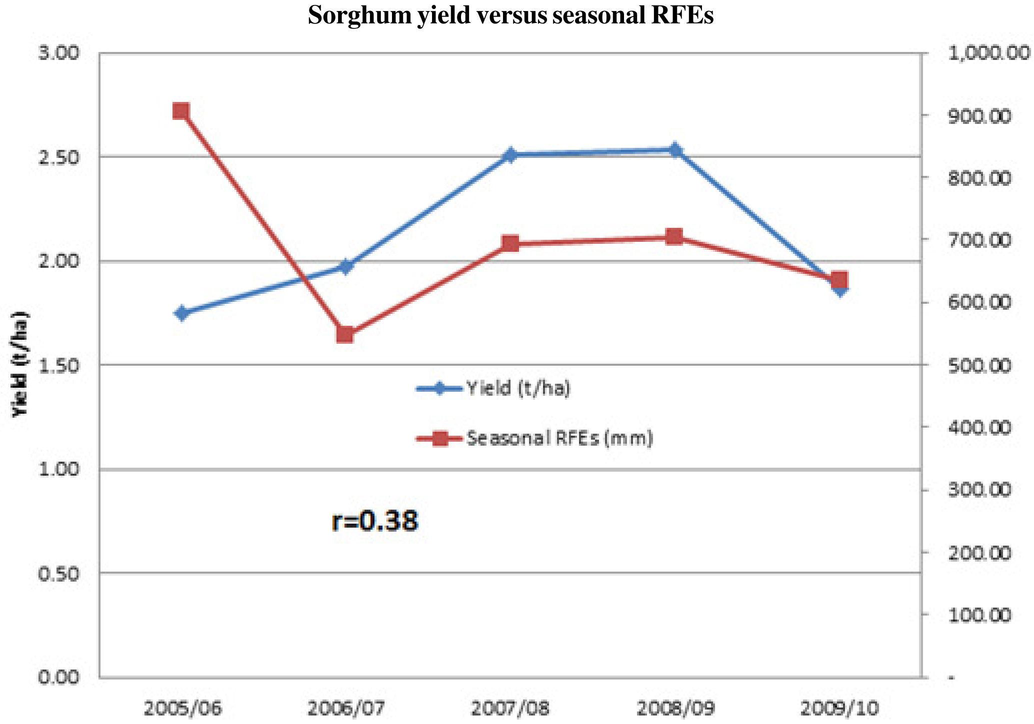

Figure 13. Sorghum yield, seasonal RFEs versus five (5) seasons.

associated with RFEs as has been discussed previously. Looking at the data closely shows that 2005/06 season might be errorneous. By removing the data, improves both the correlation to 0.95. Not withstanding all the shortcomings of satellite estimated precipitation, this could indicate that RFEs have potential for yield prediction, espacially in regions where *in-situ* rainfall measurements are sparse or non-existent. The seasonal NDVI (satellite base index) seem to predict the yield slightly better that the seasonal rainfall (point *insitu* data).

Finally, the correlation coefficient between the sorghum yield and seasonal rainfall is 0.53 (r2=0.28) and shown in Figure 9 and Figure 10, this result is lower than the expected mainly due to the fact that the rainfall of 2010/2011 was a record low 474mm while the LongTerm Average rainfall is over 800mm (removing this anormally increases the correlation to 0.88 and r2=0.77 as shown in Figure 11 and Figure 12).

The correlation coefficient between sorghum yield and seasonal RFEs was -0.38 (R2=0.15) as shown in Figure 13 and Figure 14, this is due to the problems associated with RFEs as has been discussed previously. Looking the data closely shows that the data for 2005/06 season might be errorneous, by removing it, improves both the correlation to 0.95 and (r2=90) as shown in Figure 15 and Figure 16. Not withstanding all the shortcomings of satellite estimated precipitation, this could indicate that RFEs have potential in yield prediction, espacially in regions where in-situ rainfall measurements are sparse or non-existent. The seasonal NDVI (satellite base index) seem to predict the yield slightly better that the seasonal rainfall (point insitu data). Because of the sparcity of meteorological observation points, there was only one rainfall gauging station used in th study area.

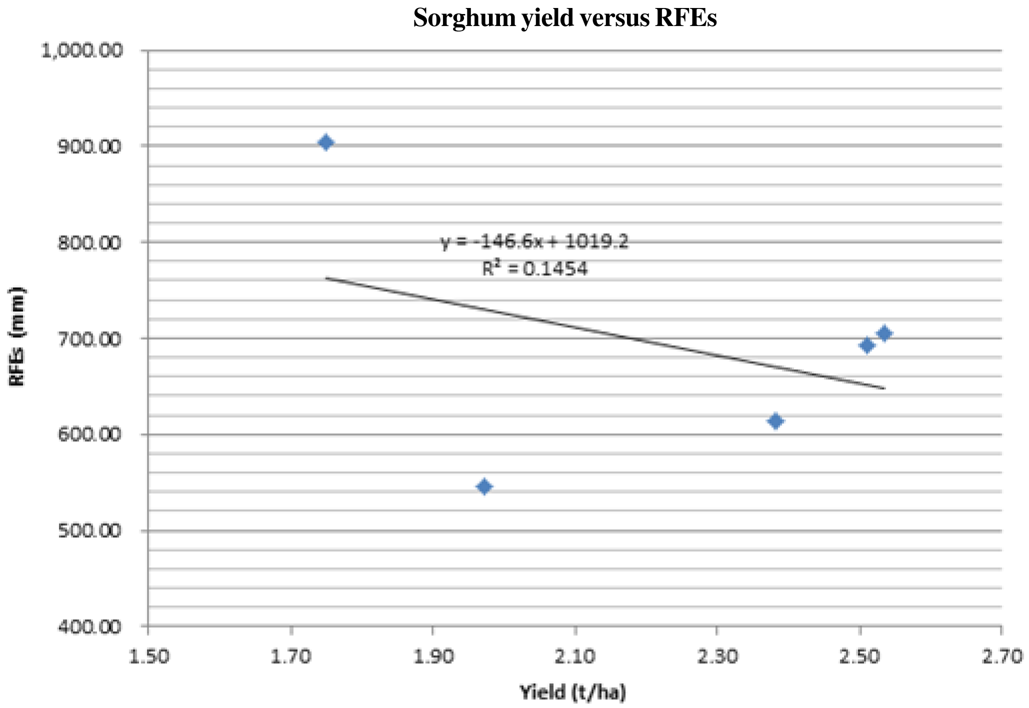

Figure 14. Sorghum yield versus RFEs.

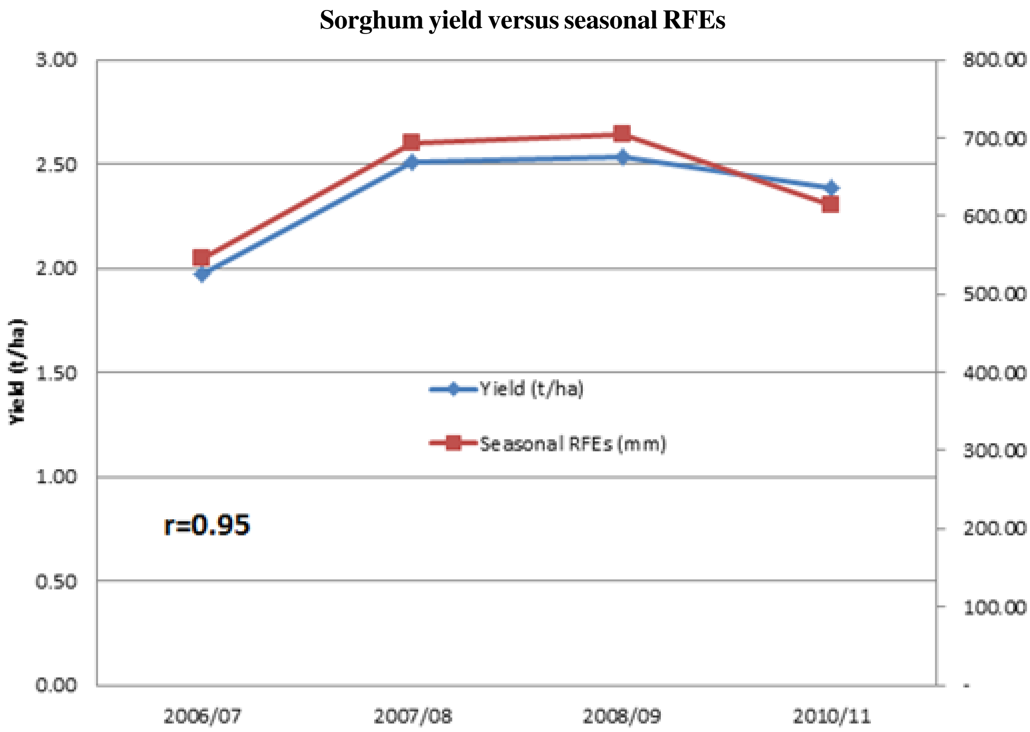

Figure 15. Sorghum yield, seasonal RFEs versus four (4) seasons (excluding the anomaly).

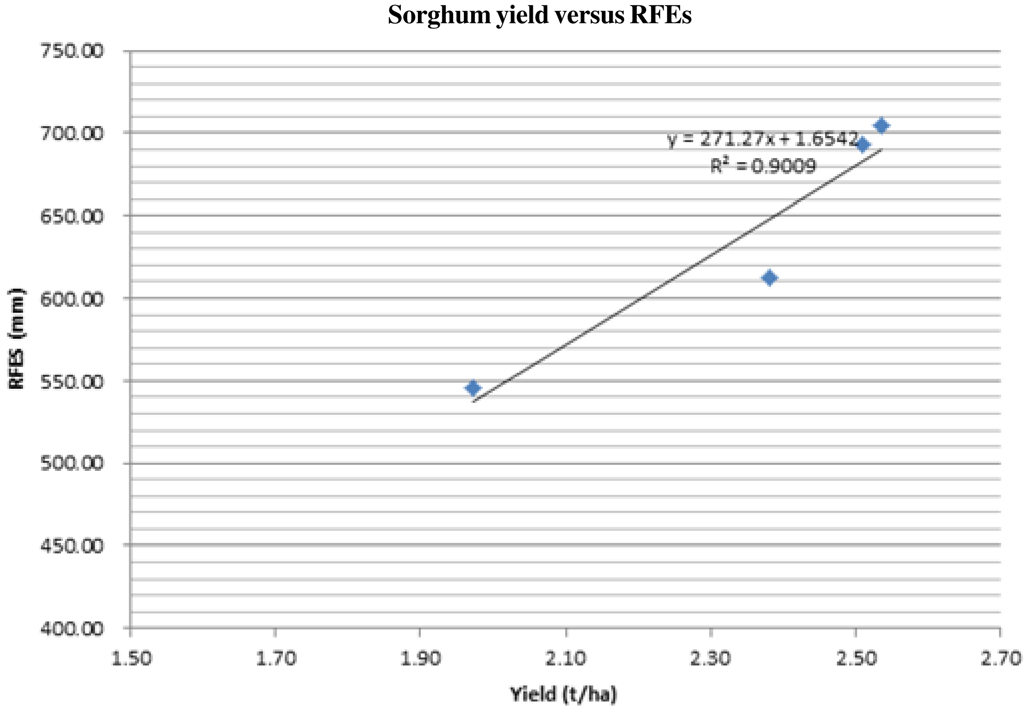

Figure 16. Sorghum yield versus RFEs (excluding the anomaly).

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