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ENHANCING RESPONSE FARMING FOR STRATEGIC AND TACTICAL MANAGEMENT OF RISKS OF SEASONAL RAINFALL VARIABILITY

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ABSTRACT

Seasonal rainfall variability, particularly the uncertainty with respect to the direction and extent that variability will assume in a given season, forms the greatest source of risk to crop production in semi-arid areas of Ethiopia. Equipping vulnerable communities, in advance, with the expected date of onset of a cropping season, is crucial for smallholder farmers to better prepare to respond and manage the uncertainties. Therefore, rainfall prediction, particularly development of models that can foretell the date of onset of next cropping season is crucial in facilitating strategic agronomic planning and tactical management of in-season risks. A twenty-four-year climatic data study was conducted for Melkassa Agricultural Research Centre (MARC) in semi arid Ethiopia, to develop onset date prediction models that can improve strategic and tactical response farming (RF). A sequential simulation model for a build up of 15 to 25 mm soil water by April 1st, was conducted. Simulation results revealed a build up of soil water up to 25 mm, to be the most risk-wise acceptable time of season onset for planting of a 150-day maize crop. In the context of response farming, this was desirable as it offers the opportunity for farmers to consider flexible combination production of maize (*Zea mays* L.) varieties of 120 and 90 days in the event of failure of earliest sown 150-day maize crop. Thus, to allow for flexible combination production of the three maize varieties, predictive capacity was found crucial for April onset of the next crop season. Accordingly, based on the consideration of pre-onset rainfall parameters, the first effective rainfall date varied considerably with the date of onset of rainfall. Regression analyses revealed the first effective rainfall date to be the best predictor of the date of onset ($R^2 = 62.5\%$), and a good indicator of the duration of next season ($R^2 = 42.4\%$). The identified strategic predictor, the first effective rainfall date, enabled prediction of time of season onset and season length by a lead time of two to three months. This markedly improved Stewart's RF. The date of onset of the next crop season was also found to be a useful predictor of season duration ($R^2 = 87.3\%$). Strategic agronomic planning should be adjusted according to the first effective rain date, and tactically according to what date of rainfall onset informs us about expectations in the duration and total season water supply.

Key Words: Ethiopia, semiarid, strategic predictor, *Zea mays*

RÉSUMÉ

La variabilité saisonnière de la pluviométrie, particulièrement l'incertitude en rapport avec la direction et l'ampleur de cette variabilité au cours d'une saison donnée est un grand risque à la production agricole dans les zones semi-arides de l'Ethiopie. La provision à l'avance d'information sur les dates correspondantes aux débuts des saisond culturales s'avère cruciale pour que les communautés dans des zones vulnérables puissent gérer les risques liés à la variabilité saisonière de la pluviométrie Par conséquent, la prédiction de la pluviométrie, en particulier le développement des modèles pouvant prévoir à l'avance la date du début de la prochaine saison culturale est cruciale pour faciliter une planification stratégique de la saison culturale et une gestion tactique des risques au cours de la saison culturale. Une étude des données climatiques de vingt quatre années était menée au Centre de

Recherche Agricole de Melkassa situé dans la zone semi-aride de l'Ethiopie afin de développer des modèles de prédiction des débuts de saisons culturales pouvant améliorer la réponse stratégique et tactique aucours des saisons culturales. Un modèle de simulation séquentiel pour une accumulation de 15 à 25 mm d'eau dans le sol au 1er Avril était développé. Les résultats de cette simulation ont révélé qu'une accumulation de 25mm d'eau dans le sol constitue le niveau de risque le plus acceptable pour le début de la saison culturale et le semis d'une culture de maïs à maturité de 150 jours. Dans le contexte de développer une agriculture adaptée aux variabilités saisonnières, cette strratégie est appropriée car elle offre aux agriculteurs une opportunité d'être flexible et d'envisager de semer des combinaisons de 3 variétes de maîs pouvant inclure des variétés à 90, 120 et 150 jours de maturation pour s'assurer d'avoir une récolte satisfaisante en cas d'échec de la variété à 150 jours. Ainsi, pour permettre une combinaison flexible de production de ces trois variétés de maïs, la capacité de prédire le début de la prochaine la saison culturale d'Avril était jugée cruciale. Par conséquent, sur base des paramètres pré-pluviométriques, la date de la première pluie différait considérablement avec la date effective du début de la saison des pluies. Les analyses de régression ont révélé cependant que la date de la première pluie est le meilleur prédicateur de la date du début de la saison culturale (R^2=62.5), et un bon indicateur de la durée de la prochaine saison culturale (R^2=42.4%). L'indicateur stratégique identifiée qu'est la date de la première pluie permet de prédire la date effective du début de la saison culturale et de la longueur de la saison culturale 2 à 3 mois à l'avance. Ceci a amélioré remaquablement le modèle d'adaptation de la saison culturale à la variabilité climatique de Steward (modèle RF de Steward). La date du début de la prochaine saison culturale s'est aussi avéré être un prédicateur utile de la durée de saison culturale (R^2=87.3%). Cette étude montre que la planification stratéqique de la saison culturale devrait être ajustée sur base de la date de la première pluie, et tactiquement, ajustée sur base des informations que la date effective du début de la saison des pluies donne en rapport avec la durée de la saison et la pluviométrie totale au cours de la saison.

Mots Cles: Ethiopie, semi-aride, prédicateur stratégique*, Zea mays*

INTRODUCTION

Seasonal rainfall variability and its uncertainty with respect to the direction and extent that variability will assume in any given season, form the greatest source of risk to crop yield in Ethiopia's semiarid lands (Admassu *et al*., 2011). The high risk of low rainfall and the associated poor crop yields have been major disincentives to adoption of yield improving recommendations in Ethiopia (Admassu *et al*., 2010). This, together with farmers' reliance on traditional farming practices have resulted in acute shortage of food and pasture and depletion of assets contributing to enhanced societal vulnerability, mass migration and loss of life (Fujisaka *et al*., 1996; Admassu *et al*., 2013).

Under this condition, the need for dynamic cropping strategies that utilise climate forecasts is critical (Sadras *et al*., 2003). Thus, the prediction capacity for the onset of next crop season assumes key importance for vulnerable communities to better prepare, respond and manage the uncertainties presented by highly variable rainfall. Without such practical actions to reduce crop failure and improve the capacity to adapt, the gradual and sudden changes associated with climate change will increase vulnerability in many areas (Admassu *et al*., 2012; 2013). The objective of this study was to predict the date of onset of the next cropping season and other seasonal rainfall parameters for improving strategic planning and tactical RF under the semi-arid agricultural systems of Ethiopia.

MATERIALS AND METHODS

The study area. This study was conducted at the Melkassa Agricultural Research Centre (MARC) in the Central Rift Valley of Ethiopia. The Centre is located at Latitude 08^o.1' N and Longitude 39^o.3' E; lying at an altitude of 1578 m above sea level. The area is characterised by erratic and undependable rainfall (Reddy and Kidane, 1993), making crop production a risky enterprise.

Research procedure

Establishing date of onset to be predicted. The World Hunger Alleviation, through Response Farming (WHARF) Computer Programme was used for iterative simulation analyses of 24 years

(1977-2000) of daily rainfall (Stewart *et al.*, 1995) in order to determine the most risk-wise acceptable dates of onset for which predictive capacity was required. Based on a detailed season by season study of daily rainfall for the study area by Admassu (2004), and analysis of farmers perceptions by Fujisaka *et al.* (1996), WHARF Simulation Programme analytical inputs used designated the first day of January as the first acceptable date of soil water accumulation; the first day of April as the first acceptable onset; the 15th of April as the first normal onset; and 31st August as the last acceptable onset. The last search date for final rainfall was set at 15th October; a final rainfall criterion was set at 70 mm and a minimum season-end intensity index of 2 mm day^{-1}, based on the final days rainfall intensity in the study area (Admassu, 2004).

The study soil was a sandy loam texture (predominant in the study area) with water holding capacity at field capacity of 100 mm (Admassu, 2004). Simulation analyses accepting three onset criteria (maintaining the above input factors) were separately conducted (15, 20 and 25 mm). The analyses based on designation of 15 and 20 mm soil water build up as onset criteria resulted in a higher failure rate to a 150-day maize crop, and denied sufficient lead time and maximum possible flexibility desired for consideration of the growing of three maize varieties during early to median onset seasons. The outputs from the simulation designating 25 mm onset criterion was found desirable as it offered maximum flexibility.

WHARF rainfall analytical outputs, based on the 25 mm onset criterion, were exported to MINITAB statistical software, version 16 (MINITAB Incorporated, 2008) for determination of historical variability in various pre-onset rainfall parameters. Predictors were selected from among pre-onset rainfall parameters based on exhibits of extreme inter-seasonal variability. The date of onset then was regressed on the most variable pre-onset rainfall parameters using MINITAB. Assessments of model capability in predicting the onset of next crop season was done using MINITAB version 16 that applies a one-year-out cross validation technique. Graphical outputs to determine the goodness-of-fit of the observed and predicted observations were developed to confirm the findings.

RESULTS AND DISCUSSION

Establishing the date of onset and onset criterion for next crop season. Of all the simulations, a buildup of 25 soil water was found the most risk-wise acceptable date of rainfall season. The results presented in Table 1 summarise the characteristics of pre-onset and date of onset and other seasonal rainfall characteristics at Melkassa during 1977 - 2000 as limited by date of onset and the 25 mm onset criterion. The probability for onset for the month of April was the greatest (33%). This implies considerable potential for growing high yielding drought tolerant medium maturing crops in early seasons switching to lower yielding shorter maturing cultivars in late seasons (Admassu, 2010). Thus, development of predictive capacity for April onset to maximise the benefits from higher yield during April onset (during early seasons), and reduce failure during late season by bringing into play a 120-day and 90 day maize during median and late season was evident.

Predicting the date of onset for next crop season. Figure 1 presents a scatter diagram of individual years bounded by a prediction interval giving a

TABLE 1. Characteristics of pre-onset and date of onset and main season rainfall at Melkassa Research Centre in Ethiopia during 1977 – 2007

Variable	Mean	Median	SD	C.V (%)	Minimum	Maximum	Range
First effective rain date (Julian day)	109	105	61	55	18	194	176
Pre-onset rain (mm)	107	88	68	63	33	263	231
Season duration (days)	122	124	38	31	69	185	116
Total season water (mm)	590	553	139	23	339	966	626
Date of onset (Julian)	145	149	38	26	91	197	106

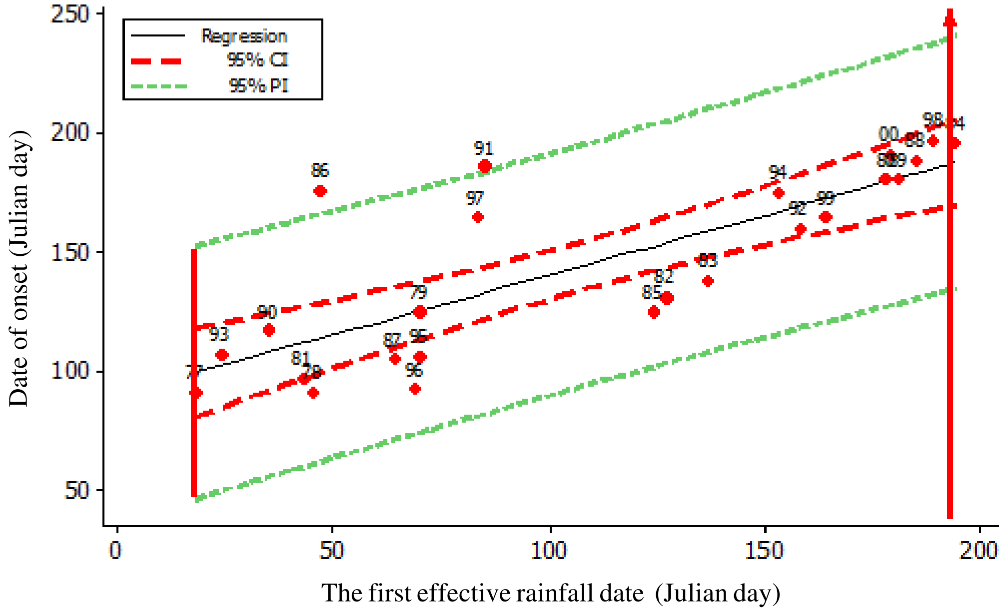

Figure 1. Twenty four seasosns relationship between the date of onset and the first effective rainfall date at Melkassa (1977 – 2000).

flag-like picture that droops away from the flag pole to the left. The R^2 value of 62% implies that the slightly more than 62% of the likely variation in the date of onset is explained by the variation in the first effective rainfall date (P <0.001). At the Research Centre (MARC), on average, the date of onset is extended by 12 hours per day that passes without its first effective rainfall (slope = 0.5013). The developed prediction model is:

Date of onset (Julian day) = 90.53 + 0.5013x

Where:

x = the first effective rainfall date in Julian day.

Cross validation results, relating the observed and the predicted date of onset has a correlation coefficient (r) of 0.75 (P <0.001, Fig. 2). This suggests that the model is good in predicting the dates of onset and has potential application for strategic agronomic planning purposes in reducing risk of variable season onset dates. The standard error of the developed prediction model for the date of onset using the prediction equation above is ±24 days. Taking the 24-seasons mean date of onset of 145 Julian days into account, the estimation error would have been close to17% either above or below it. This implies that the prediction model is acceptable.

As has been shown, the date of onset significantly varies with the first effective rainfall date (Table 1). The above relationship between the first effective rainfall date and the date of onset can be attributed to the fact that the dates when the first effective rainfall having significant contribution for onset are received are highly variable, making the date of onset considerably dependent on the first effective rainfall date.

The above observation clearly contradicts the conclusion by Mamo (2004), who reported a near complete unpredictability of the date onset under semi-arid conditions. The first effective rainfall date as the predictor of the date of onset makes it possible to get good insights into the expected season dates of onset at a lead time of two to three months. This can lay a foundation for strategic selection of crop types to emphasise during the up-coming season and credit to be sought for purchase of desired production inputs. This study has revealed for the first time the use of the first effective rainfall date as a predictor of the date of onset of next season.

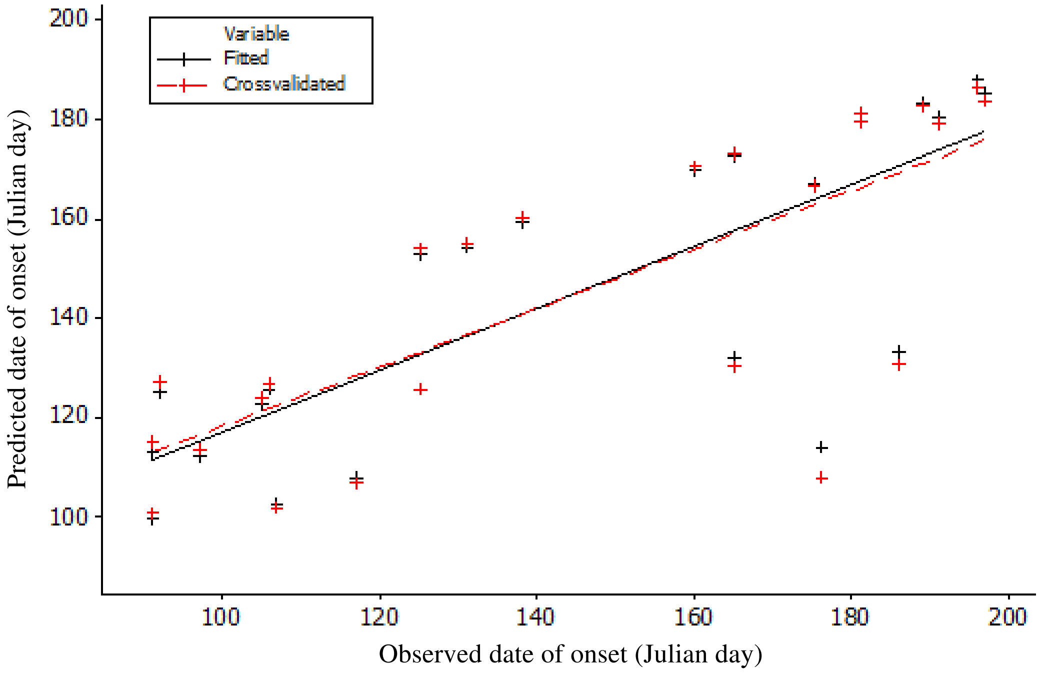

Figure 2. Observed *versus* predicted date of onset using the first effective rain date as a predictor of the date of onset.

Predicting season duration using the first effective rainfall date. Results for regression of season duration on its respective first effective rainfall date during the past 24 seasons (Fig. 3) have a R^2 value that indicates slightly more than 42% of the likely variation in the season duration with the variation in the first effective rainfall date. The developed prediction model is:

Season duration (days) = 167.2 - 0.4124x

Where:

x = the first effective rainfall date in Julian day.

Analysis of variance showed the R^2 to be significant ($P < 0.0001$). A flag like picture (Fig. 3) droops away from the pole to the right. At MARC, on average, the season duration is foreshortened by nearly half day per day that passes without its first effective rainfall (slope = 0.41).

The SE for predicting season duration using regression equation is ±30 days. Taking the 24 seasons mean season duration of 122 days, the estimation error is about 24% either above or below it.

Cross validation results relating both the observed and the predicted date of onset has r value of 0.65 (Fig. 4). This suggests that the model is fair in capturing future dates of onset and promise its operational use for strategic agronomic planning purposes.

At MARC, significant delay in the first effective rainfall date would result in shorter season duration. The apparent reason for such relationship is that the dates for receiving the first effective rainfall are highly variable, making season duration dependent on them. Similarly, as the first effective rainfall date is delayed, the date of onset is delayed implying shortening tendency in season duration. The variation expected in season duration is lower than that of the date of onset because of the precedence of the first effective rainfall date in time of occurrence compared to season duration.

Predicting season duration using the date of onset for next crop season. For tactical management of seasonal rainfall variability, regression analyses to predict seasonal rainfall characteristics using the date of onset revealed the date of onset to be the surest predictor of

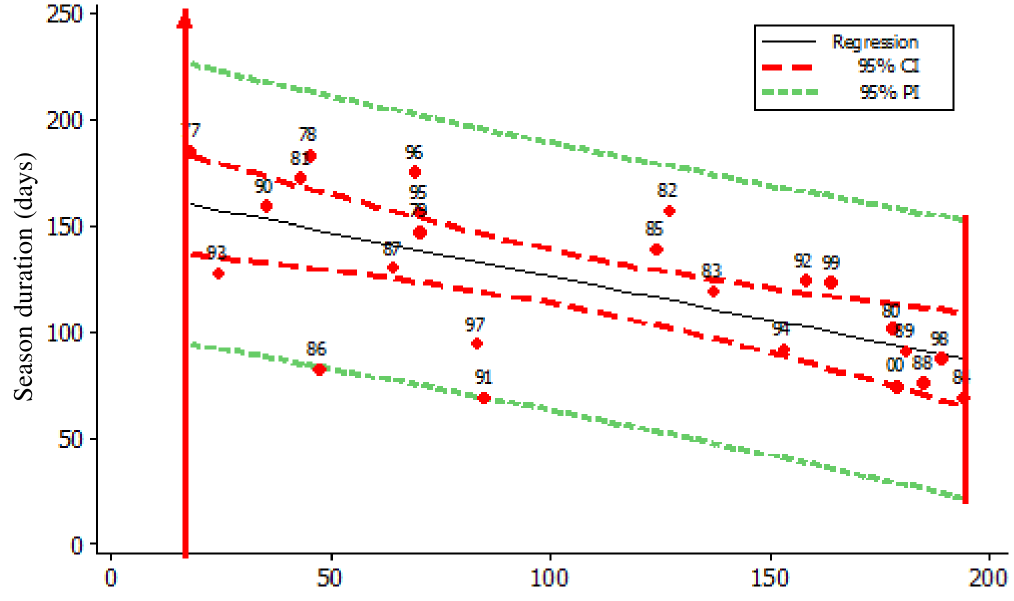

Figure 3. Twenty four years relationship between the season duration and the first effective rainfall date at Melkassa Research Centre in Ethiopia (1977 – 2000).

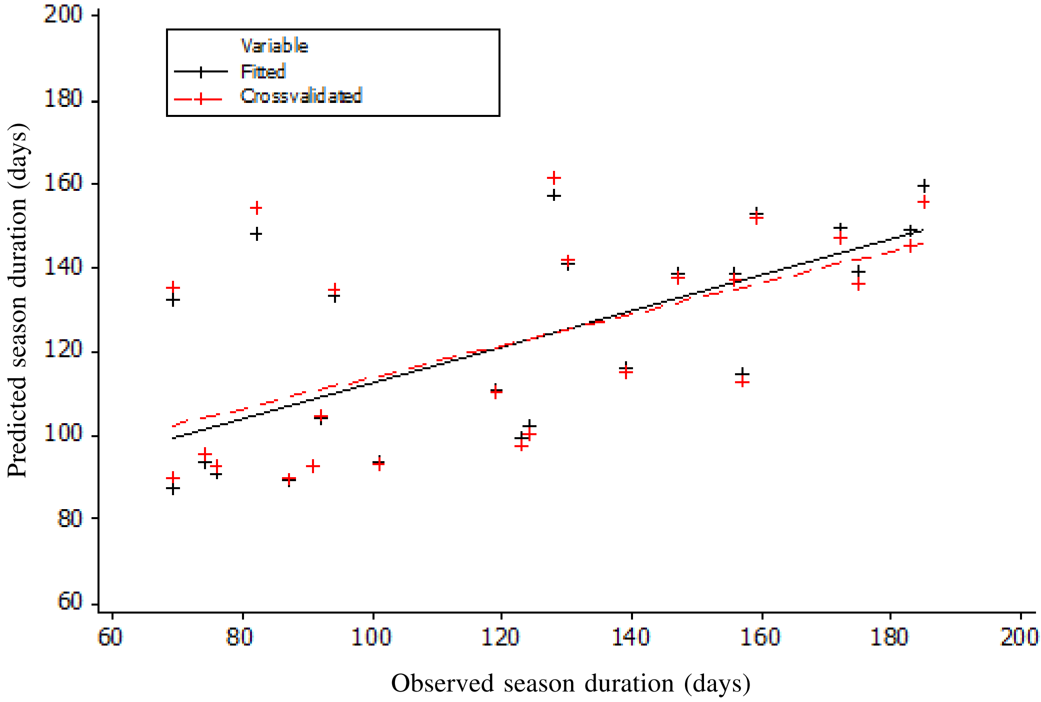

Figure 4. Observed *versus* predicted season duration using the first rain date as a predictor.

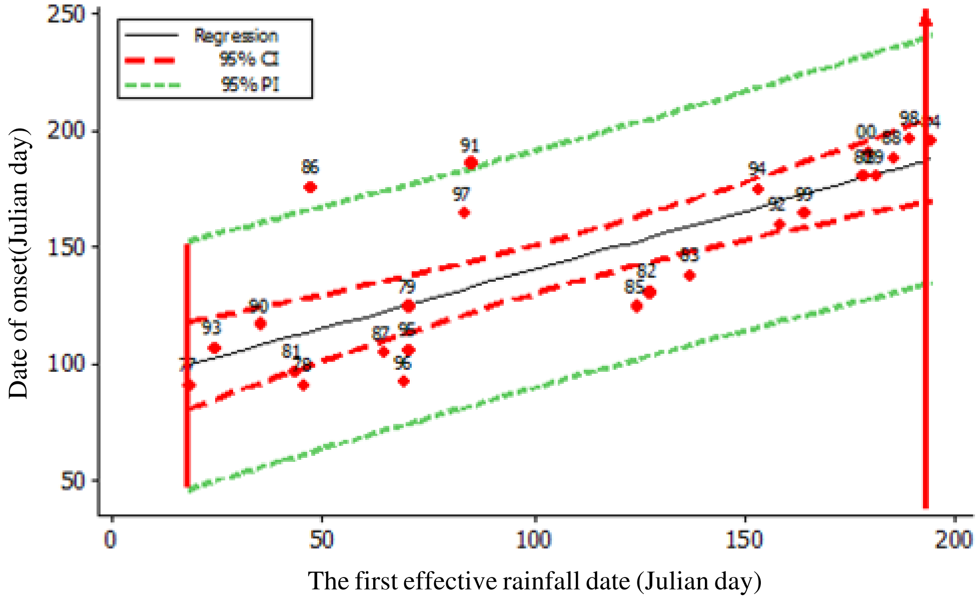

Figure 5. Twenty four years relationship between the date of onset and the duration of rainy period at MARC.

season duration (Fig. 5) as explained by the R^2 value of 87.3% ($P < 0.001$). The result shows that for every day that passes without onset, the duration of rainy period is foreshortened by nearly one day. The developed regression model is:

Season duration (days) = $257.7 - 0.9327x$

Where:

x = the date of onset in Julian day.

Cross validation results relating the predicted against the observed season duration has r = 0.93 (Fig. 6). This indicates that the model is good for predicting the duration of the next crop season. Stewart (1988) and Sivakumar (1990) found a similar relationship for many semi-arid areas in Africa. Sivakumar (1988) earlier used such a relationship and developed relay cropping recommendation for Sahel region of West Africa. The findings from this study promise potential application for developing seasonally flexible agronomic package that will minimise cropping season during seasons that vary in their season duration.

Historical relations of the amounts of total season water (TSW) with the date of onset of rainy seasons. Total season water was regressed on its respective date of onset at MARC. The resulting regression equation is:

TSW (mm) = $823 - 1.60x$

Where:

x = the date of onset in Julian day.

The R^2 relating to both TSW and the date of onset is small (20%), but statistically significant ($P < 0.030$). Moreover, the regression coefficient for the constant intercept was also statistically significant ($P < 0.001$). Although the very low R^2 value indicates that total seasonal rainfall bears little relationship with the date of onset, the large intercept indicates that seasons with earliest onset dates would have significant amount of TSW. On the other hand, the slope of the predictor was also statistically significant ($P < 0.030$); indicating a good example of the dichotomy, which can occur between the practical application and the statistical significance in that a slope of

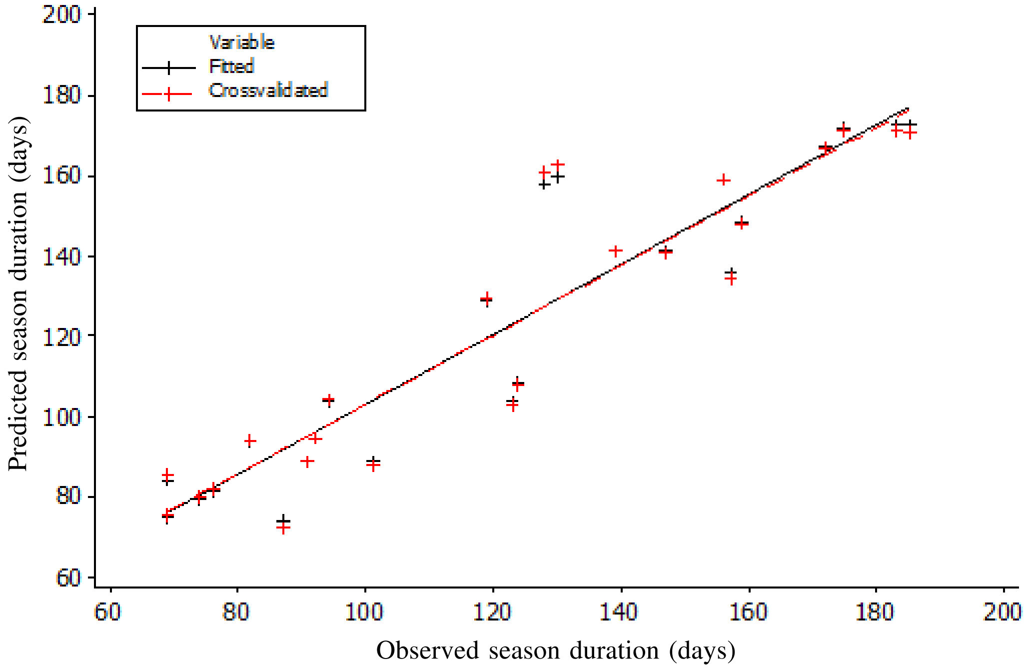

Figure 6. Comparison of predicted *versus* observed season duration based on model developed using date of onset as a predictor.

close to -2 means that rainfall expectation, is reduced by about 2 mm per day that passes without onset. Thus, this equation can be used to gain initial insight into TSW expectation.

The developed predictive capacity has good potential for localised strategic agronomic planning and decision making purposes compared to the crude down-scaled forecasts that are issued by meteorological service agencies today. In order to make use of the predictors, portable rain gauges can be locally installed and monitored to detect the first effective rainfall dates. These are economically feasible and are less demanding knowledge wise.

The developed predictive capacity encourages resource poor households to look for sources of credit in advance and prepare well to exploit the advantages inherent in early seasons. It also encourages lenders to give credits to farmers, and input suppliers too to deliver the required inputs (seed, fertiliser, herbicides and pesticides) in a very good time. In forecast of very delayed onset which bear high risk of too short season and too low water supply, farmers can be advised early enough to wait and sow lower water demanding short duration crops. In forecast of extremely delayed onset, they can also be advised to look for other off-farm remittances.

The scientific community concerned with rainfall prediction using numerical indices and other indicators often have implied a near total unpredictability of date of onset in semi-arid areas (Mamo, 2004). Reviewed literature shows no evidence of success in developing predictors for onset for localized agronomic planning of farm operations and decision making purposes. What is evident in literature is some exhibit of capability for detection of onset at regional scales (Ati *et al.*, 2002; Tadros *et al.*, 2005). Thus, the major challenge of the lack of site specific predictors for the date of onset as well as the problem of time of prediction which usually starts at onset (Stewart, 1988; Tadros *et al.*, 2005) has been successfully addressed through this study.

CONCLUSION

The first effective rainfall date as a predictor for the date of onset markedly improved our predictive capability for the date of onset by advancing time of prediction by a lead time of 3 months. This has several practical advantages: first, it is generated for decision making for local level using the data from the location where it is intended for use. This makes it site specific and, hence relevant. The first effective rainfall date turned the good predictor for date of onset onset. This is useful for strategic advance planning of farm operations. Moreover, the ability to predict the duration of next crop season is useful in tactical terms this is good to enable initial decision on types of varieties to sow at or following onset. The date of onset was also proved best predictor of duration of rainy period, and fair indicator of total season water. These are useful as they can facilitate rapid changes in on-farm tactics leading to reduction of risks. Hence, key agronomic risk management decisions need to be organised in a multi-staged decision array: first strategically using first rain effective rainfall date, and second tactically according to what date of onset of the current season informs us. Field validation and calibration of the predictors' performance, and further research to sharpen the predictions and possibly advance time of prediction using off-season rainfall are recommended. Wider application of RF warrants further investment decisions by governments to improve the overall low crop productivity and ensure food security in the semi-arid areas.

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