



Predicting maize yield in Zimbabwe using dry dekads derived from remotely sensed Vegetation Condition Index



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ABSTRACT

Maize is a key crop contributing to food security in Southern Africa yet accurate estimates of maize yield prior to harvesting are scarce. Timely and accurate estimates of maize production are essential for ensuring food security by enabling actionable mitigation strategies and policies for prevention of food shortages. In this study, we regressed the number of dry dekads derived from VCI against official ground-based maize yield estimates to generate simple linear regression models for predicting maize yield throughout Zimbabwe over four seasons (2009–10, 2010–11, 2011–12, and 2012–13). The VCI was computed using Normalized Difference Vegetation Index (NDVI) time series dataset from the SPOT VEGETATION sensor for the period 1998–2013. A significant negative linear relationship between number of dry dekads and maize yield was observed in each season. The variation in yield explained by the models ranged from 75% to 90%. The models were evaluated with official ground-based yield data that was not used to generate the models. There is a close match between the predicted yield and the official yield statistics with an error of 33%. The observed consistency in the negative relationship between number of dry dekads and ground-based estimates of maize yield as well as the high explanatory power of the regression models suggest that VCI-derived dry dekads could be used to predict maize yield before the end of the season thereby making it possible to plan strategies for dealing with food deficits or surpluses on time.

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1. Introduction

Maize is the staple and the key cereal crop grown in Southern Africa and other parts of the world, providing the primary calorific and nutritional source for millions of people (Unganai and Kogan, 1998). Therefore an ability to predict maize yield before harvesting helps in ensuring regional food security (Justice and Becker-Reshef, 2007) by providing information relevant for the distribution, storage and marketing of the crop (Agrawal and Meht, 2007). Maize yield estimates are traditionally obtained after surveys are done by field staff who use eyeballing and pace along the edges of sample maize fields to estimate area under maize and expected yield (Casley and Kumar, 1988; Fermont and Benson, 2011). This approach is well accepted and widely utilized but it requires more time of field work. This makes it costly and slow especially when

yield estimates are needed for national planning. Thus, the development of fast and less costly crop assessment methods that give reliable and timely maize forecasts at national scale is vital.

Numerous studies have explored alternative methods for conducting crop assessments for large areas to obtain crop yield estimates. For example, crop yield models have been developed based on field measurements of yield that are regressed against meteorological observations to generate yield estimation models (FAO, 1992). Manatsa et al. (2011) used rainfall estimates as input into a crop water balance model to calculate water requirement satisfaction index (WRSI) and developed maize yield estimation models based on linear regression between the WRSI values with historical yield data. While such models do not require many hours of field work, their use has limited applicability in developing countries as they are based on rainfall data acquired from a sparse network of weather stations (Unganai and Kogan, 1998).

Satellite remote sensing which is capable of providing spatial information at large spatial extents, as well as high temporal frequency (Seiler et al., 2000) can overcome the limitations of ground-based surveys. This applies to the remote sensing of rainfall and other weather parameters as well as remote sensing of

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vegetation cover. Using a remotely sensed vegetation cover as a crop predictor has an advantage in that it also captures the effect of soil type, relief, climate, vegetation type (Kogan, 1995a) and other socio-economic factors that influence crop performance such as management practices adopted by farmers. Among the major achievements, in the use of remote sensing in agricultural monitoring is its ability to be calibrated by in situ data to predict crop yield. To this end, the use of remote sensing for crop monitoring especially using remotely sensed vegetation indices such as Normalized Difference Vegetation Index (NDVI) has increased (Huang et al., 2013; Mkhabela et al., 2005, 2011; Ren et al., 2008).

Medium spatial resolution images like Landsat based vegetation indices have been used to predict crop yield (Dubey et al., 1994; Pinter et al., 1981). Medium spatial resolution satellite images can distinguish different fields however they have a low temporal resolution of 16 days or more which makes them less appropriate for monitoring frequent changes that occur in crops due to the influence of dry spells as the season progresses. Because of the low temporal resolution of medium spatial resolution images, previous studies used single date images (Dubey et al., 1994; Pinter et al., 1981) to predict crop yield before harvesting. Vegetation indices based on single date images may not account for the cumulative effects of weather on the crops throughout the growing season.

The Vegetation Condition Index (VCI) (Kogan, 1990), mainly based on low spatial resolution but high temporal resolution satellite data has been used to predict crop yield ahead of harvesting (Hayes and Decker, 1996; Salazar et al., 2008; Seiler et al., 2007; Unganai and Kogan, 1998). To do this, a time series of end of season maize yield for multiple years and the corresponding VCI values were regressed. The average district VCI for each week of the growing season was often used. Regression was performed for each week in the growing season and then the appropriate model was selected on the basis of the highest R^2 value. VCI is a drought index derived from NDVI and capable of capturing the impact of weather on crops in different ecological regions (Unganai and Kogan, 1998). However most studies that use VCI for crop yield forecasting, spatially aggregated the yield data (e.g., average yield in large administrative district units or ecological zones) to calibrate regression models hence these models do not show spatial variations in yield at finer scales (Hayes and Decker, 1996; Seiler et al., 2007; Unganai and Kogan, 1998). Hayes and Decker (1996) developed Crop Reporting Districts (CRD)-specific crop yield models based on direct relationship between VCI time series and crop yield time series.

Although the utility of satellite-derived VCI to forecast yield before harvesting has been demonstrated, in its current form VCI is difficult to interpret. We therefore hypothesize that calculating the number of dry dekads using VCI and relating these to yield data may generate simple crop yield models that are easier to interpret since the number of dry dekads (ten-day periods) is related with dry spells which have a direct effect on crop performance and are widely understood by farmers and decision-makers. Following Kogan (1995b) a dry dekad can be defined as a ten-day period with VCI value below 35%. VCI is computed from a time-series NDVI data as follows: $VCI = ((NDVI_i - NDVI_{min}) / (NDVI_{max} - NDVI_{min})) \times 100\%$ where $NDVI_i$ is the dekadal NDVI, $NDVI_{max}$ and $NDVI_{min}$ are the absolute long-term maximum and minimum NDVI respectively calculated for each pixel and dekad from multi-year NDVI data and i defines the NDVI for the i th dekad.

Having been derived from the electromagnetic spectral response of the crop and being of high temporal resolution, VCI based number of dry dekads (ten day period with VCI below 35% (Kogan, 1995b)) could be a more direct method of estimating the impact of weather on crop yield as it takes into account, not only the cumulative impact of dry dekads on the crop but also the effect of soil type, crop management practices and other factors. Because VCI is capable of comparing the impact of weather on crops in

deferent ecological regions and we used VCI-derived number of dry dekads, the prediction model developed in this study covers the whole country without stratification by ecological regions.

In this study, we test whether and to what extent maize yield can be predicted from VCI derived number of dry dekads recorded over the wet season. We also test whether the relationship between the VCI based number of dry dekads and maize yield does not differ significantly over four wet seasons (2009–2013).

2. Materials and methods

2.1. Study area

The study area covers Zimbabwe's cultivated areas (Fig. 1). Zimbabwe lies between latitude 22.421° S and 15.6071° S and between Longitude 25.2376° E and 33.0672° E and it covers an area of 390 757 km² which fall into four physiographic regions. These are the Eastern Highlands (1500–2600 m), high veld (1500–1800 m), the middle veld (600–1200 m) and the low veld (below 600 m) (Chenje et al., 1998). Zimbabwe has distinct wet and dry seasons with the rainy season spanning from November to March. The average annual temperature ranges from 18 °C on the Highveld to 23 °C on the Lowveld while rainfall varies from below 400 mm in the southern parts to over 1000 mm in the north-eastern parts of the country (Chenje et al., 1998).

Zimbabwe is divided into five agro-ecological regions indicating agricultural potential. Region 1 is in the eastern highlands covering less than 2% of the country and is suitable for forestry and intensive diversified farming including tea, coffee, deciduous fruit and intensive livestock production. Region 2 covers the eastern high veld and is suitable for intensive cropping and livestock production. Region 3 mainly covers the midlands and is characterized by mid-season dry spells and high temperatures. In this region drought resistant crops are grown; livestock and intensive farming are practised. Region 4 occupies the low-lying areas in the northern and southern parts of the country and is characterized by seasonal droughts and severe dry spells during the rainy season. It is unsuitable for rain-fed agriculture but for livestock production. Region 5 covers the low-lands and receives below 650 mm of annual rainfall. It is

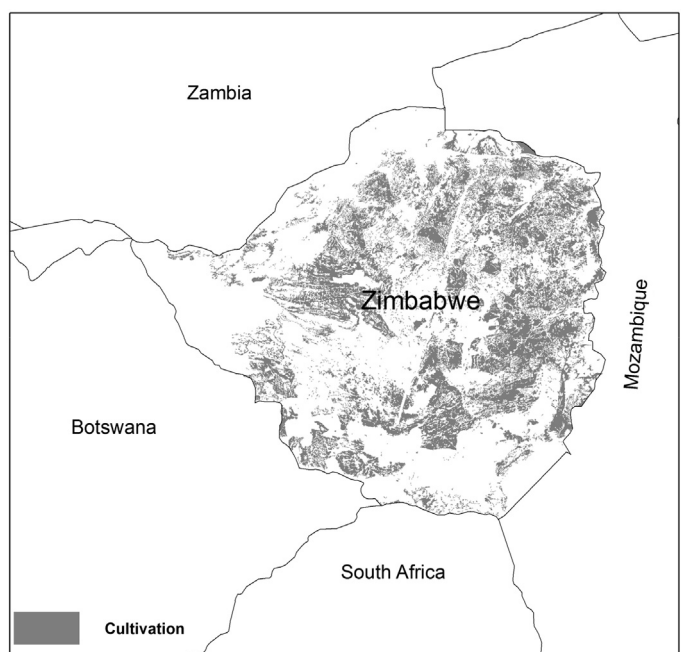


Fig. 1. Study area.

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