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

Farai Kuri a, b, *, Amon Murwira b, Karin S. Murwira a, Mhosisi Masocha b

a Scientific and Industrial Research and Development Centre, Geo-information and Remote Sensing Institute, 1574 Alpes Road, Hatcliffe, Harare, Zimbabwe
b University of Zimbabwe, Department of Geography and Environmental Science, P.O. Box MP167, Mount Pleasant, Harare, Zimbabwe

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A B S T R A C T
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 estimates 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.

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 Mehta, 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
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: $VCI = \frac{1}{n} \sum_{i=1}^{n} \left( \frac{NDVI_i - NDVI_{\text{min}}}{(NDVI_{\text{max}} - NDVI_{\text{min}})} \right) \times 100\%$ where $NDVI_i$ is the dekadal $NDVI$, $NDVI_{\text{max}}$ and $NDVI_{\text{min}}$ 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 ith 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 different 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$^\circ$ S and 15.6071$^\circ$ S and between Longitude 25.2376$^\circ$ E and 33.0672$^\circ$ E and it covers an area of 390,757 km$^2$ 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$^\circ$C on the Highveld to 23$^\circ$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
suitable for extensive livestock production or game ranching. Main crops grown in Zimbabwe include maize, tobacco, cotton, wheat, sorghum, millet and soybeans (Chenje et al., 1998; Vincent and Thomas, 1960).

Soils in Zimbabwe are grouped into 8 classes based on soil structure, texture, depth and chemistry. The regosols and lithosols have low agricultural potential. The sodic soils are delicate and easily exhausted leading to infertility and are mainly found in the Zambezi valley. Vertisols are the most fertile soils in the low rainfall areas but are intractable. The siallitic group contains fertile moisture retaining soils which have good agricultural value. The ferralsitic red clay is the most productive soil in Zimbabwe and mainly supports large-scale commercial farming (Chenje et al., 1998). Many areas in Zimbabwe are naturally highly susceptible to erosion because of poor soils. An estimated 60–65% of the country’s total area is covered by sandy soils whose parent materials is igneous rocks and metamorphosed igneous rocks (Thompson and Purves, 1978). Generally natural soils in Zimbabwe are infertile and deficient in nitrogen and phosphorous.

Zimbabwe is divided into administrative wards which is the third administrative level after provincial and district levels. The field data used in this study was recorded at ward level which is a detailed representation of maize yield in Zimbabwe and allows a detailed analysis of the relationship between the maize yield and number of dry dekads. We used the ward as the unit of analysis because the maize yield data was recorded at ward level.

2.2. Remote sensing data

We used SPOT S10 NDVI data in this study. The SPOT S10 NDVI dataset consists of 10-day maximum NDVI value composites from the SPOT VEGETATION 1 and VEGETATION 2 instruments on board SPOT 4 and SPOT 5 Satellites respectively. These instruments measure reflectance in four spectral bands which are Blue (0.43–0.47 μm), Red (0.61–0.68 μm), Near Infrared (NIR) (0.78–0.89 μm) and Shortwave Infrared (SWIR) (1.58–1.75 μm). NDVI is calculated from the Red and the NIR bands as follows: 

$$\text{NDVI} = \frac{\text{NIR - Red}}{\text{NIR + Red}}$$

NDVI is a dimensionless index which shows green vegetation density and vigour (Tarpley et al., 1984; Tucker, 1979). The SPOT NDVI data was downloaded from the Flemish Institute for Technological Research (VITO) Product Distribution Portal (http://www.vito-eodata.be), African Monitoring of Environment for Sustainable Development (AMESD) stations and from Devocast (http://www.devocast.eu). The dataset has a spatial resolution 1 km and a temporal frequency of 10 days. The SPOT NDVI data comes together with status maps which indicate on a pixel basis, the NDVI quality, i.e., presence/absence of cloud, shadow, snow and/or water bodies (Etienne, 2006). We used the status maps to mask out bad pixels from the SPOT NDVI images. Although SPOT NDVI time series have been pre-processed to minimize noise there are almost always disturbances in this dataset due to cloud contamination, atmospheric variability and bi-directional effects (Chen et al., 2004). To reduce the effect of these disturbances, we smoothed the SPOT NDVI time series using the Savitzky Golay filter implemented in the Timesat software (Ekblund and Jönsson, 2011; Jönsson and Ekblund, 2002, 2004).

A cultivation mask was derived from the VegRIS land-use/cover map which was developed by the Forestry Commission of Zimbabwe in 2005. The VegRIS land-use/cover map was produced through visual image interpretation and digitizing from the Landsat images as well as extensive ground truthing. This is the best land-use/cover map available for Zimbabwe. The land-use map was rasterized to match the spatial resolution of the of the SPOT NDVI dataset. Only pixels identified in the land-use map as cultivated were used in further analysis.

2.3. Calculating Vegetation Condition Index (VCI)

From the smoothed SPOT NDVI long-term time series (1998–2013) we calculated the Vegetation Condition Index (VCI) for four wet seasons 2009/10, 2010/11, 2011/12 and 2012/13, each wet season starting in October and ending in March. VCI values range from 0% for extremely unfavourable vegetation conditions to 100% for optimal conditions (Kogan, 1995b; Singh et al., 2003). VCI is calculated using the following equation:

$$\text{VCI} = \frac{(\text{NDVI}_i - \text{NDVI}_{\text{min}})}{(\text{NDVI}_{\text{max}} - \text{NDVI}_{\text{min}})} 	imes 100\%$$

where $\text{NDVI}_i$ is the dekadal NDVI, $\text{NDVI}_{\text{max}}$ and $\text{NDVI}_{\text{min}}$ 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.

2.4. Calculating number of dry dekads

We used a VCI threshold value of 35% (Kogan, 1995b) to define a dry dekad (ten day period) whereby all dekads with a VCI value of less than 35% are considered dry. For each of the seasons considered in this study, we calculated on a pixel basis, the total number of dry dekads that occurred in that season based on the 35% VCI threshold value. The cultivation mask was applied on the sum of dry dekads map to exclude non-cultivated areas from analyses. We also masked out irrigation schemes from the analysis to focus on rain-fed agriculture only. We calculated spatially defined median number of dry dekads for each ward and weighted the number of dry dekads by number of pixels in the ward in order to get a representation of all the pixels in that ward. Within the period from October to March there are 18 dry dekads. The developed model is valid from 0 to 17 dry dekads which give us positive yield values.

2.5. Maize yield data

We used official maize yield statistics data from the Ministry of Agriculture, Mechanization and Irrigation Development (MAMID) for the period from 2009 to 2013. This data is collected by experienced ward-based Agricultural Technical and Extension Services (AGRITEX) Officers through sample-based field surveys in all rural wards and is the most relied on in situ maize yield data in Zimbabwe. However, error associated with this data is not statistically reported. But, the data is verified by the national crop and livestock assessment team by visiting all rural districts and farming sectors in the country to observe field crops and discuss with farmers and field extension officers. Wards are sub-district administrative units in Zimbabwe. The ward administrative boundaries vector data was obtained from the Surveyor General’s Office. The ward boundaries were used for the zonal statistics calculation of the remote sensing data.

2.6. Regression analysis

The average yield for all wards with the same number of dry dekads was calculated for each of the seasons considered in this study. We tested whether average maize yield data was normally distributed using the Shapiro–Wilk test (Shapiro and Wilk, 1965). Next, we tested for correlation between the average maize yield and number of dry dekads using Spearman’s Rho correlation coefficient. We used linear regression to relate the median number of dry dekads experienced in a particular wet season to the corresponding maize yield that was harvested at the end of that season. Analysis was conducted for four wet seasons, i.e., 2009/10, 2010/11, 2011/12 and 2012/13. We tested for normality of the residuals (Poole and O’Farrell, 1971) of the regression of dry dekads and maize yield.
to establish whether the relationship between the dry dekads and maize yield is linear or nonlinear.

We statistically tested whether one global (shared) regression model fits all the data points (four seasons) better than separate regression models for each separate season, i.e., 2009/10, 2010/11, 2011/12 and 2012/13 using the extra sum-of-squares F-Test (Motulsky and Christopoulos, 2004). This test also tests whether there are significant differences among the Y-intercepts and slopes for the four regression functions corresponding to the four seasons from 2009/10 to 2012/13. The result of this test would establish whether the relationship between the median number of dry dekads and average maize yield was consistent over the four wet seasons considered in this study.

In order to evaluate the use of dry dekads to forecast maize yield we used the leave-one-out cross validation technique (Mkhabela et al., 2011; Schut et al., 2009; Snee, 1977; Teh et al., 2010). From the four seasons’ data the yield prediction model is trained on three seasons’ data and then tested on the data that was left out. This process is repeated four times until every season in the dataset was excluded once as a cross-validation instance. The root mean square error of prediction (RMSEP) and correlation coefficients the for each instance were calculated and the results were averaged across the four instances to estimate the model’s prediction accuracy (Teh et al., 2010). The RMSEP is defined as the square root of the mean squared error: \( RMSEP = \sqrt{\frac{\sum_{i=1}^{n}(X_{\text{obs},i} - X_{\text{pred},i})^2}{n}} \) where \( X_{\text{obs},i} \) is measured values, \( X_{\text{pred},i} \) is predicted values at time/place \( i \) and \( n \) is the number of cases (Fox, 1981; Willmott, 1982).

3. Results

Fig. 2 illustrates the distribution of dry dekads (based on the VCI threshold value of 35%) over cropped areas in Zimbabwe for the four wet seasons from 2009 to 2013. We observe that the VCI derived number of dry dekads range from 0 to 18 with south eastern parts of Zimbabwe experience the highest number of dry dekads.

The Shapiro–Wilk test for normality showed that the data (average yield for all wards with the same number of dry dekads) is not normally distributed and the Spearman’s Rho correlation test indicated that there is high correlation between the average maize yield and number of dry dekads. The test for normality of the residuals of the regression also showed that the number of dry dekads and maize yield are linearly related. Fig. 3 illustrates significant \( P < 0.01 \) linear relationships between the ward based average maize yield and the number of dry dekads over four consecutive...
growing seasons, i.e., from 2009 to 2013. We observe the strongest relationship between the average maize yield and dry dekads in the 2011/12 wet season when the number of dry dekads explains 90% of variance in average maize yield over Zimbabwe. The least strong relationship is observed in the 2009/10 growing season where 75% of the variance in maize yield is explained. We also observe that yield ranges from 0.64 tonnes/ha to 0.79 tonnes/ha when the number of dry dekads equals zero and that the slopes of the regression lines range from −0.05 to −0.04.

The extra sum-of-squares F-Test indicated that there is no compelling evidence ($P > 0.05$) that the four separate seasonal models (Fig. 3) define the relationship between ward based maize yield and number of dry dekads for the 2009–2013 wet seasons in Zimbabwe better than the global (shared) model illustrated in Fig. 5. Overlap of the 95% confidence intervals (error bars) for the $Y_0$ and slope values for the four growing seasons illustrated in Fig. 4 also indicates that there is no compelling evidence ($P > 0.05$) of differences among the estimated parameters for all the growing seasons considered in this study.

Fig. 5 illustrates the global linear model to estimate average maize yield for future seasons. One linear regression function was estimated for the maize yield and number of dry dekads for the 2009–2013 wet seasons.
fitted on the four seasons’ datasets with a coefficient of determination of 0.80. Table 1 illustrates the parameters of the four global (shared) linear models developed using the leave-one-out approach (Schut et al., 2009; Teh et al., 2010). A similarity of slope and Y-intercept values of the four linear models is observed in Table 1.

Fig. 6 illustrates scatter plots of the measured yield against yield predicted from the global (shared) models developed using the leave-one-out approach. The perfect prediction (y=x) line is also plotted for reference (Willmott, 1982). We observe RMSE values ranging from 0.11 to 0.19 with an average RMSE of 0.14 tonnes/ha and correlation coefficient values ranging from 0.85 to 0.95 with an average correlation coefficient of 0.90.

4. Discussion

The results of this study indicate that there is a consistently significant negative linear relationship between the number of dry dekads and average maize yield for four consecutive wet seasons considered in this study, i.e., from 2009 to 2013. The negative relationship between the number of dry dekads and maize yield is not surprising. This is because a dry dekad, being a ten-day period with a VCI value below 35% (Liu and Kogan, 1996), is linked with crops experiencing drought related stress. In other words, the higher the number of dry dekads experienced during the crop growing season, the higher the drought related stress that crop experiences resulting in poor crop yield being evidence that dry spells are a major limiting factor on rain-fed agriculture (Mafakheri et al., 2010). The models were developed over the wet season consisting of 18 dekads, meaning a season can only have a maximum of 18 dekads of which, if they are all dry yields are zero.

Since VCI is a direct indicator of crop performance as it takes into account many factors which may affect maize yield, including soil type, crop management practices, crop variety and others (Kogan, 1995a). The VCI derived number of dry dekads are a more direct measure of the influence of dry spells on crop yield as it is derived from crop greenness unlike other drought indices (such as SPI) that are based on weather parameters only. In addition, VCI derived number of dry dekads have an easier physical interpretation than VCI. This result is supported by numerous studies which have shown that Vegetation Condition Index (VCI) is correlated with crop yield (Hayes and Decker, 1998; Liu and Kogan, 1996; Prasad et al., 2006; Salazar et al., 2008; Unganai and Kogan, 1998) which also show a significant inverse relationship between maize yield and drought. In this study we successfully used the VCI derived number of dry dekads as a predictor of crop yield and the development of a consistent regression model to estimate maize

<table>
<thead>
<tr>
<th>Training data seasons</th>
<th>Regression equation</th>
<th>Std. error of estimate</th>
<th>$R^2$</th>
<th>$P$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010/11, 2011/12, 2012/13</td>
<td>$\text{Yield} = -0.04 \times \text{drydekads} + 0.71$</td>
<td>0.09</td>
<td>0.83</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>2009/10, 2011/12, 2012/13</td>
<td>$\text{Yield} = -0.04 \times \text{drydekads} + 0.66$</td>
<td>0.09</td>
<td>0.82</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>2009/10, 2010/11, 2012/13</td>
<td>$\text{Yield} = -0.04 \times \text{drydekads} + 0.72$</td>
<td>0.10</td>
<td>0.79</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>2009/10, 2010/11, 2011/12</td>
<td>$\text{Yield} = -0.04 \times \text{drydekads} + 0.69$</td>
<td>0.11</td>
<td>0.79</td>
<td>&lt;0.01</td>
</tr>
</tbody>
</table>
yield based on the number of VCI-derived dry dekads in this study is novel.

Evaluation of the global (shared) crop yield estimation models with independent data indicated that we can significantly predict average maize yield from VCI-derived number of dry dekads with a root mean square error of prediction (RMSEP) of 0.14 tonnes/ha which translates to 33% error. Even though the SPOT VGT products with a 1 km coarse spatial resolution are used over maize fields that can be as little as 1 hectare in some areas and therefore consisting of mixed pixels of maize crop and other crops as well as non-crop vegetation, the regression model between dry dekads and maize yield is significant. The model developed in this study can predict maize yield at the end of March which is 4–6 weeks before harvesting which normally starts in April.

Although NDVI used to calculate the VCI in this study is known to saturate in closed canopy situations, in this study we deemed that NDVI would not saturate considering that the study area is largely sparse savanna vegetation. However, in the event that saturation happens, it is one of the limitations of using NDVI in this study. There are other parameters such as Enhanced vegetation index (EVI) from MODIS and Leaf Area Index (LAI) which may provide better yield estimation. These can be important for future studies, however, in this study we used the SPOT NDVI product as it was readily available and also has a higher temporal frequency of ten days making it suitable for monitoring growth of the maize crop more precisely and hence is more likely to produce reliable yield forecasts.

Although the model developed in this study was successfully evaluated in the four seasons, there is need to continue evaluating the performance of the model using data from other seasons. Improving on the spatial resolution of images used in the calculation of dry dekads and using a crop-specific crop mask may improve the reliability of the model.

5. Conclusion

The regression analysis significance tests and prediction validation of this study demonstrate a significant relationship between average maize yield and the VCI based number of dry dekads that occurred during the wet season. Based on the analysis done in Zimbabwe this study shows that maize yield can be predicted from the remotely sensed number of dry dekads recorded during the wet season 4–6 weeks before harvest. Unlike previous studies in this study we used VCI derived number of dry dekads which is a more direct indicator to measure the impact of dry spells on crop yield. We therefore conclude that remotely sensed drought indices, particularly, the Vegetation Condition Index-derived frequency of dry dekads recorded over the wet season can explain, as well as predict maize crop yield in Zimbabwe.

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References


