EVALUATING THE ACCURACY OF SATELLITE-DERIVED SUGARCANE CANOPY COVER ESTIMATES FOR TWO DIVERSE PRODUCTION REGIONS IN SOUTH AFRICA FOR POTENTIAL USE IN CROP ESTIMATION

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Introduction

Accurate sugarcane yield and production estimates are needed to optimise operational and resource use efficiencies along the supply chain. The South African Sugarcane Research Institute (SASRI) uses the Canesim® crop forecasting system (CCFS) to simulate sugarcane production as affected by the climatic potential and, where applicable, irrigation water supply (Bezuidenhout and Singels, 2007). Practical considerations require that assumptions be made regarding important input factors such as local weather conditions, soil properties, agronomic management and crop and soil health. A possible solution to fill these information gaps is to incorporate remotely sensed (RS) indicators of crop status into weather-based simulations (Morel et al., 2014; Moulin et al., 1998). This has become more feasible as the resolution of these data improve and costs decline over time. Jarmain et al. (2014) improved the accuracy of CCFS yield estimates by up to 8.5% by using RS surface energy balance and crop canopy information. Other studies (e.g. Bappel et al., 2005, Morel et al., 2014) have also shown that correcting sugarcane canopy simulations with SPOT information can significantly improve yield predictions. These examples made use of the strong relationship between fractional interception of photosynthetically active radiation (FIPAR) by green leaves and RS vegetation indices (VIs) such as the normalised difference vegetation index (NDVI). However, these relationships can be influenced by atmospheric factors, canopy and soil conditions (Rahman and Lamb, 2017). The source of the satellite imagery from which VI is derived also affects the relationship. This may restrict the application of a single generic FIPAR-VI relationship to large areas where crops are grown under diverse conditions as is the case with sugarcane production in South Africa, hence the need to derive and test FIPAR-VI relationships in different regions.

The objective of this study was to determine the accuracy of RS derived canopy cover, as indicated by FIPAR, in two diverse sugarcane production regions in South Africa. Various VIs derived from Landsat-8 imagery were compared to field measurements of FIPAR and also assessed for robustness for application in operational Canesim® yield estimation.
Methods

Field measurements

Twenty fields in two diverse sugarcane growing regions in KwaZulu-Natal, South Africa, were selected for field measurements of canopy cover from June 2015 to October 2016. Half the fields were in Pongola in the irrigated northern region, where sugarcane fields are relatively large while the other half were in Sezela in the rainfed South Coastal region where narrow, elongated fields, shaped around contours, are predominant.

FIPAR was estimated by measuring incident photosynthetically active radiation (IPAR) above the crop canopy and transmitted (TPAR) below the lowest green leaf, using a portable line quantum sensor (Model AccuPar LP80, Decagon Devices, Pullman, USA) at approximately monthly intervals on five fixed positions in each field. Measurements were taken between 11h00 and 13h00 on cloud free days. FIPAR was then calculated as:

\[
FIPAR = 1 - \frac{TPAR}{IPAR}
\]

Reflection of PAR from soil and leaves was assumed to be negligible.

Measurements were discontinued after cane lodged, flowered or became too tall (lowest green leaf above shoulder level). Measurements were also discontinued in one field that became heavily infested with weeds.

FIPAR measurements for a given date were aggregated per field to produce a mean field value. Only sampling positions that were 15 m or further away from field edges were considered.

Landsat-8 imagery collection and preparation

A total of 28 Landsat-8 images relevant to the study were pre-processed (atmospheric correction and pan-sharpening) to 15 m resolution. Seven of these images were affected by could cover and were excluded from further analysis. A number of VIs were generated for the purpose of modelling FIPAR, but for this paper the focus was on three, viz:

- Normalised difference vegetation index (NDVI) (Rouse et al., 1973)
- Normalised difference moisture index (NDMI) (Gao, 1996)
- Aerosol free vegetation index (AFRI) (Karnieli et al., 2001).

NDMI and AFRI were based on the short wave infrared 1 (SWIR1) spectral band.

Mean field VI values were generated, with a 15 m buffer inside field boundaries to reduce the effect of mixed pixels on field edges.

Regression model development and evaluation

Regression analyses were used to develop linear, quadratic and cubic FIPAR-VI relationships using measurements made between June 2015 and June 2016. Data from the two study areas were analysed separately, as well as combined. Goodness of fit was quantified with the coefficient of determination (R²).

Accuracy of RS estimates of FIPAR was quantified using the root mean square error (RMSE) between RS and field estimates of FIPAR for the period July to October 2016, which were not used for regression model development.
Results and Discussion

RS estimates of FIPAR correlated well with field estimates for Pongola and Sezela. Results of the three regression models of FIPAR show that the correlation was stronger in Pongola, with $R^2$ values ranging from 0.94 to 0.96, than Sezela where $R^2$ values ranged between 0.69 and 0.87 (data not shown here, but fully reported in Muller et al., 2019). There were no significant differences in the relationship between the different VIs for Pongola, whereas for Sezela, the SWIR1 based AFRI and NDMI, had better $R^2$ values than NDVI. The SWIR region of the electromagnetic spectrum is known for monitoring moisture status of vegetation and the results therefore suggest that they are more accurate, than NDVI, in predicting sugarcane FIPAR in rainfed areas where large soil water variations occur.

The RMSE values (Table 1) confirmed again that the models were more accurate for Pongola than for Sezela. This is ascribed to the fields being larger and more homogenous in Pongola than in Sezela.

In general, the linear models performed on par (both $R^2$ and RMSE values) with the more complex quadratic and cubic models, and because they are easier to implement, are consequently recommended for operational purposes.

The NDVI regression models developed in this study were compared to those developed elsewhere by Morel et al. (2014), Zhang et al. (2015) and Bastiaanssen and Ali (2003) and performed better in both study areas (Table 1). This further emphasises the benefit of local calibration of RS FIPAR models.
Table 1. Linear regression modelling between field measured fractional interception of photosynthetically active radiation (FIPAR) and remotely sensed vegetation indices; normalised difference vegetation index (NDVI), aerosol free vegetation index (AFRI) and normalised difference moisture index (NDMI). The root mean square error (RMSE) is a measure of model accuracy on independent data recorded in this study.

<table>
<thead>
<tr>
<th>Region</th>
<th>Source</th>
<th>Regression model</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pongola</td>
<td>This Study</td>
<td>FIPAR = 1.45 NDVI - 0.31</td>
<td>0.084</td>
</tr>
<tr>
<td></td>
<td></td>
<td>FIPAR = 1.63 AFRI - 0.27</td>
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<tr>
<td></td>
<td></td>
<td>FIPAR = 1.36 NDMI + 0.25</td>
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</tr>
<tr>
<td></td>
<td>Morel et al. (2014)</td>
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<td>0.099</td>
</tr>
<tr>
<td></td>
<td>Zhang et al. (2015)</td>
<td>FIPAR = 1.31 NDVI - 0.19</td>
<td>0.102</td>
</tr>
<tr>
<td></td>
<td>Bastiaanssen and Ali (2003)</td>
<td>FIPAR = 1.26 NDVI - 0.16</td>
<td>0.109</td>
</tr>
<tr>
<td>Sezela</td>
<td>This Study</td>
<td>FIPAR = 1.50 NDVI - 0.35</td>
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<td></td>
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<td>FIPAR = 1.67 AFRI - 0.26</td>
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<td>Combined</td>
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<td></td>
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<td>FIPAR = 1.64 AFRI - 0.26</td>
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<td>FIPAR = 1.37 NDMI + 0.26</td>
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<tr>
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<td></td>
<td>Bastiaanssen and Ali (2003)</td>
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</table>

**Conclusion**

Field measured FIPAR and Landsat-8 imagery derived VIs were quantitatively analysed using regression analyses and showed strong relationships between the two variables in Pongola and Sezela. Estimation accuracy was consistently better for Pongola than for Sezela. Complex models were only marginally more accurate than simple linear regression models. SWIR-based vegetation indices (NDMI and AFRI) were more robust, with better accuracy in Sezela and the combined set, than NDVI based estimates. Based on these findings, the authors recommend the use of either NDMI or AFRI, in addition to NDVI (due to its wide use in crop RS applications) as a basis for canopy correction on operational Canesim® crop estimates in these two areas.

The results of this study emphasised the importance of local calibration to achieve the accurate estimates of FIPAR in different regions. More work is required to establish how the FIPAR models developed in KwaZulu Nalal perform in other regions of the South African sugar industry.
REFERENCES


