Earth Observation models help management of tropical dry savannah forests in the Okavango-Zambezi transfrontier conservation zone (KAZA) region of Southern Africa.

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Outline

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Background: Why KAZA?

• The KAZA is the World’s largest conservation area with an enclosed area the size of Sweden (519,912 km²), characterized by savannah grassland forest, woodland and protected lands.

• Vegetation types range from low herbaceous to high density woody cover, facing exacerbating pressures from wildlife, climate change (see fig. 1) and humans.

• Forest loss and degradation are major concerns which directly impact wildlife species distributions and a growing human populations.

Figure 1: Shows (a) Projected biome change b) Vulnerability of ecosystems to biome shifts (2071–2100). Source: IPCC (Niang et al., 2014).
Aim and objectives

• The aim of the current study was to establish a link between remote sensing Landsat 8 OLI data derivatives (indices and biophysical parameters) and ground characteristics from a comprehensive field dataset of measured field plots to improve precision of AGB and forest area estimates in savannah forest at a regional level.

• The research focused on Chobe National Park, Botswana, as the savannah forests in these areas are under-studied and their forest habitats are known to be most vulnerable and sensitive to climate forcing and fire, which directly impact wildlife species distributions.

• Presented here, are the results from Chobe National Park and Landsat 8 OLI data
Study Site

Figure 2: Study area with field data and examples of collected ground truth plots in the savannah forest and some recent degradation activities captured during a field campaign in Chobe National Park, March 2019.
Methods:

- Comprehensive field work was conducted during 2019 winter growing season.
- A generalized linear model (GLM) were coupled with feature selection approach to identify the most relevant Landsat 8 predictors in savanna forest for the final model.
- For multi-collinearity among dependent variables, the Person’s correlation coefficient ($\rho$) and variance inflation factor (VIF) was used to find most important and uncorrelated factor.
- Different Landsat 8 OLI spectral indices were calculated, some shown in Eqs. 1, 2).

Table 1: Applied spectral Indices derived from Landsat 8 spectral band reflectance values

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

$$\text{GNDVI} = \frac{\text{NIR} - \text{GREEN}}{\text{NIR} + \text{GREEN}}$$

- The AGB of each sampled tree in the plot were estimated using the Dry forest stands allometric biomass model developed by Chave et al., 2005 shown in eq. 3

$$\text{AGB}_{\text{est}} = \exp(-2.187 + 0.916 \times \ln(pD^2H))$$
$$\equiv 0.112 \times (pD^2H)^{0.916}$$

- Where D is dbh in (cm) and H is height in (m)
Methods

- Model evaluation was based on root mean square error (RMSE) and absolute bias (Eqs. 4, 5)

\[
\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(X_{\text{obs},i} - X_{\text{sensor},i})^2}{n}}
\]

\[
\text{bias} = \frac{1}{n} \sum_{i=1}^{n}(X_{\text{obs},i} - X_{\text{sensor},i})
\]

- The final predictors were determined by calculating several models (e.g. stepwise regression and backward selection in each run) and comparing the Akaike Information Criterion (AIC) eq. 6.

\[
\text{AIC} = -2 \ln L [\hat{\theta}] + 2k,
\]
Results

- Using the best selected model, a map of the above-ground biomass for the study area was generated (fig.3).

- The estimated AGB of the savanna forest range from 0 Mg/ha to 328 Mg/ha with an average of 31 Mg/ha.

- The RMSE of the model is low 0.67 mg/ha, with the $r^2$ of 0.61 and the Variance of Inflation (VIF) is less than 6 for both predictors.

- GNDVI performed better than NDVI and other indices in the study.

Table 2: The selected best multiple regression model (Shown here is the best selected model).

<table>
<thead>
<tr>
<th>Response</th>
<th>Predictors</th>
<th>Equation</th>
<th>$r^2$</th>
<th>RMSE error (mg/ha)</th>
<th>AIC</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Above-ground</td>
<td>B3, gndvi</td>
<td>Y = -3.673 - 9.037 B3 + 14.303 gndvi</td>
<td>0.61</td>
<td>0.67</td>
<td>101.1</td>
<td>5.4</td>
</tr>
<tr>
<td>Biomass (AGB)</td>
<td></td>
<td></td>
<td></td>
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</tbody>
</table>
Figure 4: a) Scatterplot between field measured AGB and the predicted AGB  b) residuals distribution between of the selected biomass prediction model.
Results

Figure 5: a) Biomass map for the selected model derived from Landsat 8 OLI data (30m spatial resolution), b) RapidEye (5 m resolution), c) Sentinel 2 data (10 m spatial resolution)
Summary

✓ Although most previous AGB mapping efforts in Africa focused on tropical humid forests, with little attention on tropical and subtropical savannah forest, the high total AGB value from savannah forest in the study area highlight the importance of the savannah-forest mosaic as a biomass storage and carbon pool.

✓ Landsat 8 derivatives and comprehensive field data can yield suitable auxiliary information of AGB in the savannah forest and in areas with habitats vulnerable and sensitive to climate forcing.

✓ Such regional models and results can compare biomass maps of less studied areas such as Chobe National Park with global derived biomass maps

✓ The study helps provide biomass spatial explicit information to aid natural resource management at varied spatial scales.

References: