Canopy gap analysis using LiDAR-derived variables

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Introduction
Background

• Canopy gaps in plantations occur due artificial and natural disturbances

• Natural disturbances caused by:
  – wind, snowfall, disease, drought, climate change, and fires

Source: https://www.flickr.com/photos/natureserve/
Background

- Canopy gap is seen as a **small-scale opening or ‘hole’** in the forest canopy
- Remote sensing has been explored as a means to detect and quantify canopy gaps
- Passive sensors generally struggle to discriminate small to medium sized gaps
- Active sensors (e.g. **LiDAR**) overcomes many obstacles faced by passive sensors

Source: http://proyectojuanchacon.blogspot.co.za/
Background

• A review of the literature reveals that no study to date has used LiDAR derivatives, within an OBIA environment, to model forest canopy gaps in a commercial plantation in South Africa.

• These analyses can assist foresters and forest managers in better understanding the mechanisms underpinning the formation and distribution of forest canopy gaps.
Aim and objectives

- The overall aim of this study was to model and spatially characterise forest canopy gaps using a LiDAR-derived CHM and an intensity raster.
- To achieve this aim, the specific objectives of the study were to:
  1. Detect and delineate forest canopy gaps using a canopy height model (CHM) and intensity raster (IR) within an object-based image analysis (OBIA) environment
  2. Spatially characterise forest canopy gaps using Getis-Ord Gi* and FRAGSTATS
Study area
Methods
Overview

Objective 1

Data

Image Segmentation

MRS:
- Shape: 0.1
- Compactness: 0.5
- Scale: 20, 10, & 5

Rule-based using SEaTH thresholds

Image Classification

Objective 2

Data

CHM & IR

Spatial analysis

MRS:
- Shape: 0.1
- Compactness: 0.5
- Scale: 20, 10, & 5

Getis-Ord Gi*:
- z-score
- p-value

FRAGSTATS
- PLAND
- Shape Index
- PD
- LSI

Output maps

Accuracy assessment

Output maps

Software used:
eCognition v9,
ArcMap v10.3.1 &
FRAGSTATS v4.2
<table>
<thead>
<tr>
<th>Metric</th>
<th>Analysis level</th>
<th>Equation</th>
</tr>
</thead>
</table>
| Percentage of Landscape (PLAND)    | Class level                  | \[ P_i = \frac{\sum_{j=1}^{n} a_{ij}}{A} \times 100 \] \[ P_i = \text{percentage of landscape occupied by patch type } i \]
|                                    |                              | \[ a_{ij} = \text{area of patch } ij \ (m^2) \]
|                                    |                              | \[ A = \text{total area of the landscape (m}^2) \]                       |
| Shape Index                        | Patch level & Class level    | \[ SHAPE = \frac{0.25 P_{ij}}{\sqrt{a_{ij}}} \]
|                                    |                              | \[ P_{ij} = \text{perimeter of patch } ij \ (m) \]
|                                    |                              | \[ a_{ij} = \text{area of patch } ij \ (m^2) \]                          |
| Patch Density (PD) (per 100 hectares) | Class level                  | \[ PD = \frac{n_i}{A} \times 10000 \times 100 \]
|                                    |                              | \[ n_i = \text{number of patches in the landscape for class } i \]        |
| Landscape Shape Index (LSI)        | Class level                  | \[ LSI = \frac{0.25 E^*}{\sqrt{A}} \]
|                                    |                              | \[ E^* = \text{total length (m) of edge in landscape; includes the entire landscape boundary and some or all background edge segments} \]
|                                    |                              | \[ A = \text{total landscape area (m}^2) \]                             |
Results
### Multiresolution segmentation (MRS)

<table>
<thead>
<tr>
<th>Datasets/ Scale factors</th>
<th>20</th>
<th>10</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CHM</strong></td>
<td><img src="image1.png" alt="Image" /></td>
<td><img src="image2.png" alt="Image" /></td>
<td><img src="image3.png" alt="Image" /></td>
</tr>
<tr>
<td><strong>IR</strong></td>
<td><img src="image4.png" alt="Image" /></td>
<td><img src="image5.png" alt="Image" /></td>
<td><img src="image6.png" alt="Image" /></td>
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<tr>
<td><strong>CHM + IR</strong></td>
<td><img src="image7.png" alt="Image" /></td>
<td><img src="image8.png" alt="Image" /></td>
<td><img src="image9.png" alt="Image" /></td>
</tr>
<tr>
<td>Features</td>
<td>JM</td>
<td>Threshold</td>
<td>Notes</td>
</tr>
<tr>
<td>-----------------</td>
<td>-----</td>
<td>-----------</td>
<td>---------------------</td>
</tr>
<tr>
<td>Mean CHM</td>
<td>1.996</td>
<td>9.965</td>
<td>CHM &lt; 9.965</td>
</tr>
<tr>
<td>Mean Intensity</td>
<td>1.810</td>
<td>9.070</td>
<td>intensity &gt; 9.070</td>
</tr>
</tbody>
</table>

![Separability and threshold analysis (SEaTH)](image)
### Positional accuracy

<table>
<thead>
<tr>
<th></th>
<th>F1</th>
<th>F3a</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CHM</td>
<td>Intensity</td>
</tr>
<tr>
<td><strong>Overall</strong></td>
<td>96.3</td>
<td>95.0</td>
</tr>
<tr>
<td>accuracy (%)</td>
<td></td>
<td></td>
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<tr>
<td><strong>KHAT</strong></td>
<td>0.90</td>
<td>0.86</td>
</tr>
<tr>
<td></td>
<td>0.90</td>
<td>0.86</td>
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</tbody>
</table>
Area-based accuracy

<table>
<thead>
<tr>
<th></th>
<th>CHM</th>
<th>Intensity</th>
<th>Combined</th>
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</thead>
<tbody>
<tr>
<td>F1</td>
<td>74.51</td>
<td>85.82</td>
<td>95.01</td>
</tr>
<tr>
<td>F3a</td>
<td>78.85</td>
<td>83.58</td>
<td>91.5</td>
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</table>
Hotspot Analysis (Getis-Ord Gi*)
<table>
<thead>
<tr>
<th>Metrics</th>
<th>E Block</th>
<th>F Block</th>
<th>Combined block</th>
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</thead>
<tbody>
<tr>
<td>Class level</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PLAND</td>
<td>1.27</td>
<td>3.02</td>
<td>2.02</td>
</tr>
<tr>
<td>PD</td>
<td>42.23</td>
<td>125.39</td>
<td>77.93</td>
</tr>
<tr>
<td>LSI</td>
<td>11.84</td>
<td>20.57</td>
<td>23.55</td>
</tr>
<tr>
<td>Mean Shape Index</td>
<td>1.79</td>
<td>1.84</td>
<td>1.82</td>
</tr>
</tbody>
</table>
An operational framework

• LiDAR has attracted attention in **forestry**
• OBIA is useful, particularly when features are analysed using LiDAR
• Natural disturbance processes are possible models for silviculture operations
• LiDAR datasets can be utilized for effective forest canopy gap delineation
• Forest managers can implement these methodologies to detect forest canopy gaps and incorporate gap-based silviculture
• Further, accurate forest gap detection influence the analysis of spatial characteristics
Conclusions
Conclusion

- The primary aim of this study was to model canopy gaps within a commercial *Eucalyptus grandis* plantation using LiDAR derived variables, i.e. a CHM and an intensity raster.

- The results of this study highlight that using a combined CHM and intensity raster provides improved accuracies for modelling forest canopy gaps within a commercial *E. grandis* forest.

- The overall results show promise as a viable methodology that can be operationalized for modelling canopy gaps within a commercial forestry environment.
Acknowledgements

• National Research Foundation: Funding
• SAPPI: Data
• ESRI: ArcGIS online 50 cm colour imagery

THANK YOU!

Source: http://www.slideshare.net/
Key references


