Combining multispectral and texture imagery features to assess health condition in priority riparian forests by means of unmanned aerial systems

Patricia María Rodríguez González¹, Juan Guerra-Hernández², Ramon Alberto Díaz-Varela³, Juan Gabriel Álvarez-González⁴

¹Centro de Estudos Florestais, Instituto Superior de Agronomia, Universidade de Lisboa, Portugal, (patri@isa.ulisboa.pt)
²3edata, Lugo, Spain (juanguerra@isa.ulisboa.pt)
³Departamento de Botánica (GI-1809-BioAplic), Escola Politécnica Superior, Universidade de Santiago de Compostela, Spain (ramon.diaz@usc.es)
⁴Unidade de Xestión Forestal Sostible (GI-1837-UXFS), Departamento de Producción Vexetal e Proxectos de Enxeñaría, Escola Politéctica Superior, Universidade de Santiago de Compostela (juangabriel.alvarez@usc.es)
Background: Importance and threats to riparian forests

IMPORTANCE

Riparian systems: ecological importance in relation to their surface area extent

THREATS

Historical - floodplain degradation depleting ecosystem functions and services

Currently - Emerging global threats
- Climate change
- Pests and pathogens causing extensive decline worldwide
Background: Decline of alder forests across Europe

- *Alnus glutinosa* L. Gaertn (alder) forests – Foundation species in riparian zones (N\textsubscript{2} fixing sp)
- 91E0* habitat – priority for conservation at EU
- Substantial decline across Europe caused by *Phytophthora alni* species complex

Bjelke et al 2016
Challenge:
• Management requires accurate assessment of health status
• UAV offers new potential tools yet mapping disease-induced defoliation is particularly challenging in high density ecosystems with high spectral variability due to canopy heterogeneity

• GOALS OF THE STUDY
  ✓ Improve classification methods of health status in alder forests
  ✓ Exploring a set of new image attributes including Texture and spectral variables
Methods (I)

Field survey

Tree sampling

- 81 trees
- x,y, submetric GPS (Astech Mobile Mapper 100)
- Health condition: defoliation, presence of canker, injuries
- Dbh, h, #alive and dead trunks

Unmanned Aerial Vehicle (UAV): two types of data

- Structure from Motion image processing
- Georeferenced with 9 GCP submetric GPS

Study site: NW Portugal
Natura 2000 SCI Rio Lima PTCON0020
Methods (II)
Remote sensing data acquisition:
34 variables extracted from images including

• MULTISPECTRAL SENSOR
  ✓ Multispectral orthomosaic used for vegetation index calculation
    • 4 multispectral bands: green, red, near-infrared, red-edge (4 variables)
    • set of vegetation indices (VI) (8 variables)
    • texture features from NDVI (8 variables)

• RGB SENSOR
  ✓ Digital Aerial Photogrammetry-derived structural from Digital Surface Model (DSM) at crown level.
    • topographic variables from DSM (6 variables)
    • texture features from DSM (8 variables)

library(raster, glcm)
Methods (III)
Data analyses:

Response variable $\rightarrow Y=\text{Health condition classes}$  
Candidate predictor variables $\rightarrow Xi= \text{all 34 variables from spectral and RGB sensors}$

Two approaches for modelling health condition classification

• **Random Forests:**
  ✓ Variable importance measure on the impurity reduction of splits (Mean Decrease Gini)

```r
library(randomForest)
```

• **Robust three-step logistic modelling:**
  ✓ Model performance based on $R^2$ adjusted (Nagelkerke (1991))

```r
function glm
```

---
Results (I)

**Random Forests (4 classes)**

The most important variables:
- Textural spectral variables from NDVI,
- Spectral indices (e.g. NDVI, RERNDVI)
- \texttt{dsm\_Glc\_variance} form DSM

```r
library(randomForest)
```
### Results (II)

#### Random Forests

<table>
<thead>
<tr>
<th>Health status</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>Σ</th>
<th>PA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Healthy</td>
<td>24</td>
<td>4</td>
<td>2</td>
<td>0</td>
<td>30</td>
<td>0.80</td>
</tr>
<tr>
<td>10-50</td>
<td>7</td>
<td>4</td>
<td>1</td>
<td>0</td>
<td>12</td>
<td>0.33</td>
</tr>
<tr>
<td>&gt;50</td>
<td>3</td>
<td>3</td>
<td>2</td>
<td>6</td>
<td>14</td>
<td>0.14</td>
</tr>
<tr>
<td>Dead</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>24</td>
<td>25</td>
<td>0.96</td>
</tr>
<tr>
<td>Σ</td>
<td>34</td>
<td>11</td>
<td>6</td>
<td>30</td>
<td>54</td>
<td></td>
</tr>
</tbody>
</table>

| UA            | 0.71| 0.36| 0.33| 0.80|     | 0.67|

*Kappa*=0.52

Image classification accuracy by group in four classes where A = number of healthy trees, B= number of defoliated trees less than 50%, C= number of defoliated trees more than 50% and D= death trees, PA = producer’s accuracy, UA = user’s accuracy, **bold values** = overall accuracy.
Results (III)

Logistic Models

- **Logistic model 1** (probability of the tree belongs to category A)

\[
\pi(A) = \frac{\exp(-17.085 + 29.038 \cdot GNDVI - 18.669 \cdot DSM_{GLCM_dissimilarity})}{1 + \exp(-17.085 + 29.038 \cdot GNDVI - 18.669 \cdot DSM_{GLCM_dissimilarity})}
\]

- **Logistic model 2** (probability of the tree belongs to category D, discriminate between the group D (death trees) and the group of defoliated trees (B and C))

\[
\pi(D) = \frac{\exp(-11.8445 + 39.6708 \cdot NDVI_{GLCM_{contrast}} + 0.02244 \cdot DSM_{GLCM_{variance}})}{1 + \exp(-11.8445 + 39.6708 \cdot NDVI_{GLCM_{contrast}} + 0.02244 \cdot DSM_{GLCM_{variance}})}
\]

- **Logistic model 3** (probability of the tree belongs to category B)

\[
\pi(B) = \frac{\exp(-14.7280 + 38.2480 \cdot NGRVI)}{1 + \exp(-14.7280 + 38.2480 \cdot NGRVI)}
\]
Image classification accuracy by group in four classes where A = number of healthy trees, B = number of defoliated trees less than 50%, C = number of defoliated trees more than 50% and D = death trees, PA = producer’s accuracy, UA = user’s accuracy, **bold values** = overall accuracy.

Kappa=0.74
Discussion

- The **logistic three step robust approach** performed better (Kappa=0.74) than the RF (Kappa= 0.52)
- Notably, **Texture variables** (spectral and derived from DSM) offered promising results
- **healthy class** was better predicted by variables related with **vegetation indices** (such as NDVI)
- **dead trees** were better discriminated from **infected trees** by **heterogeneity in texture** (spectral and from DSM)

- Prospects:
  - ✔ Rapid and effective assessment of areas affected by the disease
  - ✔ Alternative robust classification method to forest and conservation managers,
  - ✔ Application: planning of control and restoration measures aimed at reducing these forests vulnerability and black alder mortality
  - ✔ Potential application to other species
ACKNOWLEDGEMENTS
Patricia M Rodríguez-González is funded by Portuguese Foundation for Science and Technology, through UID/AGR/00239/2019, through Investigador FCT programme IF/00059/2015. And through LIFE FLUVIAL (LIFE16 NAT/ES/000771) “Improvement and sustainable management of river corridors of the Iberian Atlantic Region”.

Juan Guerra Hernández is co-funded by the Spanish Ministry of Science and Innovation. Torres Quevedo Programme (PTQ).