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

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Background: Importance and threats to riparian forests

IMPORTANCE

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

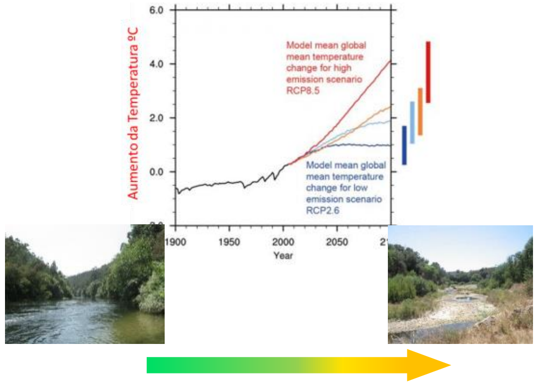
THREATS

Historical - floodplain degradation

depleting ecosystem functions and services

Currently - Emerging global threats

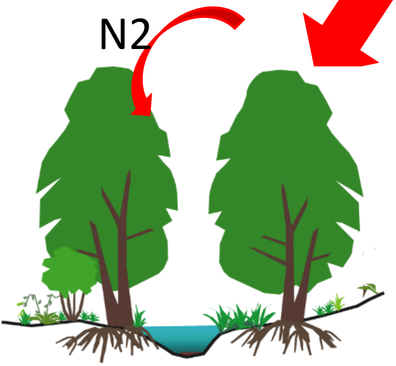
- Climate change
- Pests and pathogens causing extensive decline worldwide



Background: Decline of alder forests across Europe

- *Alnus glutinosa* L. Gaertn (alder) forests – Foundation species in riparian zones (N_2 fixing sp)
- 91E0* habitat – priority for conservation at EU
- Substantial decline across Europe caused by *Phytophthora alni* species complex

Loss of ecological functions



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)

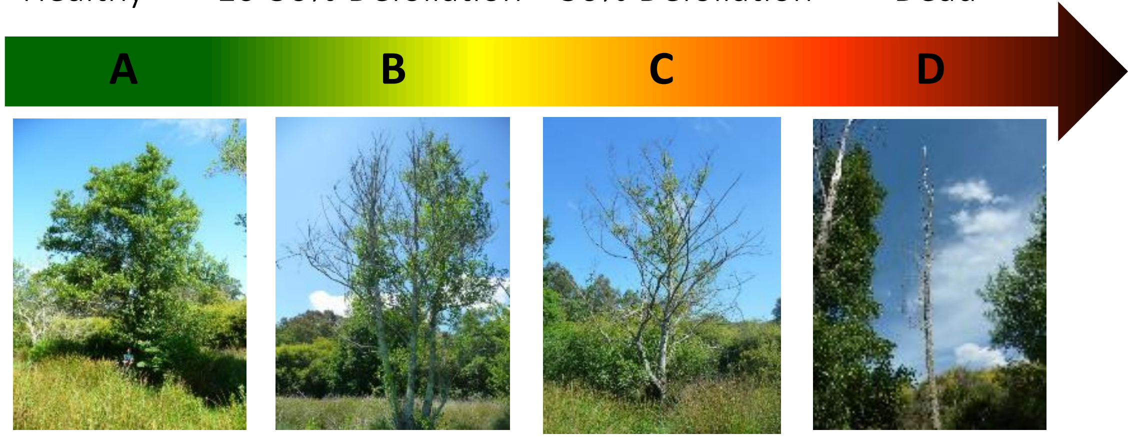
Field survey

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

4 Health condition categories

Healthy 10-50% Defoliation >50% Defoliation Dead

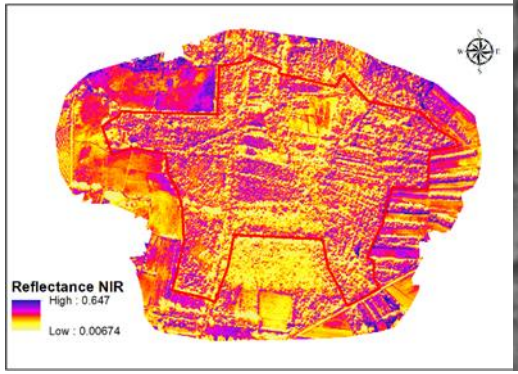


***Study site**: NW Portugal Natura 2000 SCI Rio Lima PTCON0020*

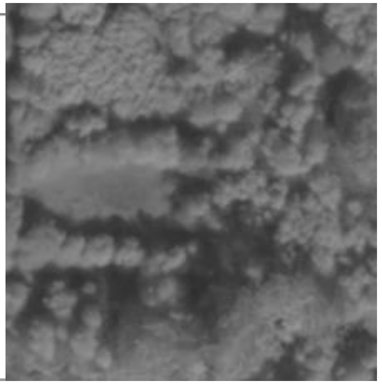
Unnmaned Aerial Vehicle (UAV): two types of data

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

multispectral Parrot Sequoia

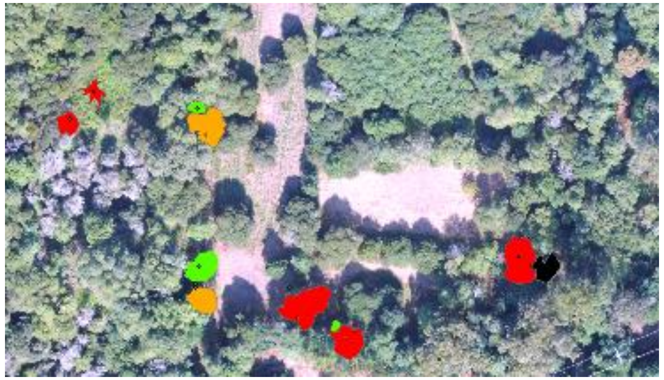


NIR reflectacnce



Red edge reflectance

RGB-UAV-data



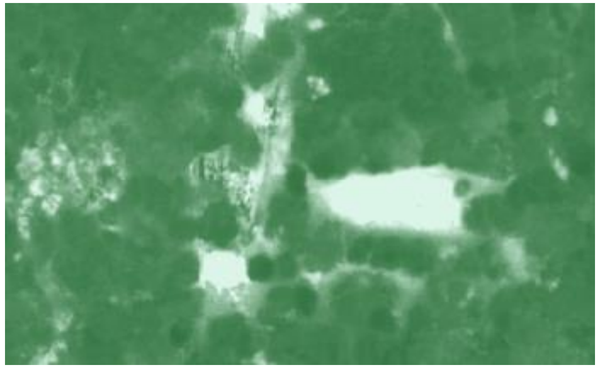
Crown delineation

Methods (II)

Remote sensing data acquisition:

34 variables extracted from images including

ndvi



- 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)

DSM

library(raster, glcm)

Methods (III)
Data analyses:

Response variable → Y=Health condition classes A B C D

Candidate predictor variables →Xi= all 34 variables from spectral and RGB sensors

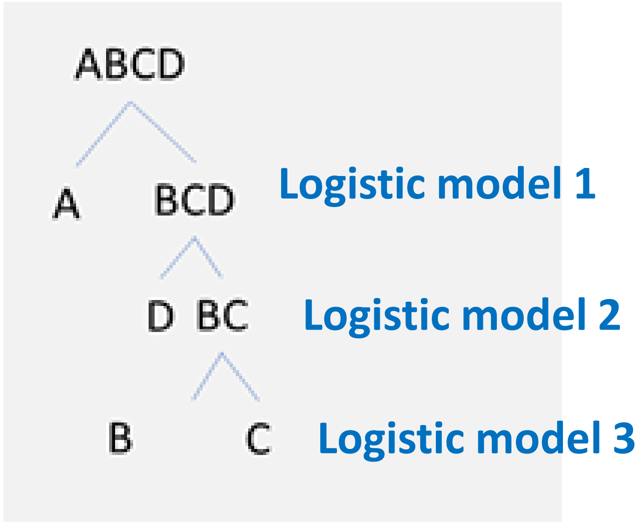
Two approaches for modelling health condition classification

- **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)

    sas THE POWER TO KNOW. R function glm



Nagelkerke, N. J. D. (1991). A note on a general definition of the coefficient of determination.Biometrika,78, 691-692.

Results (I)

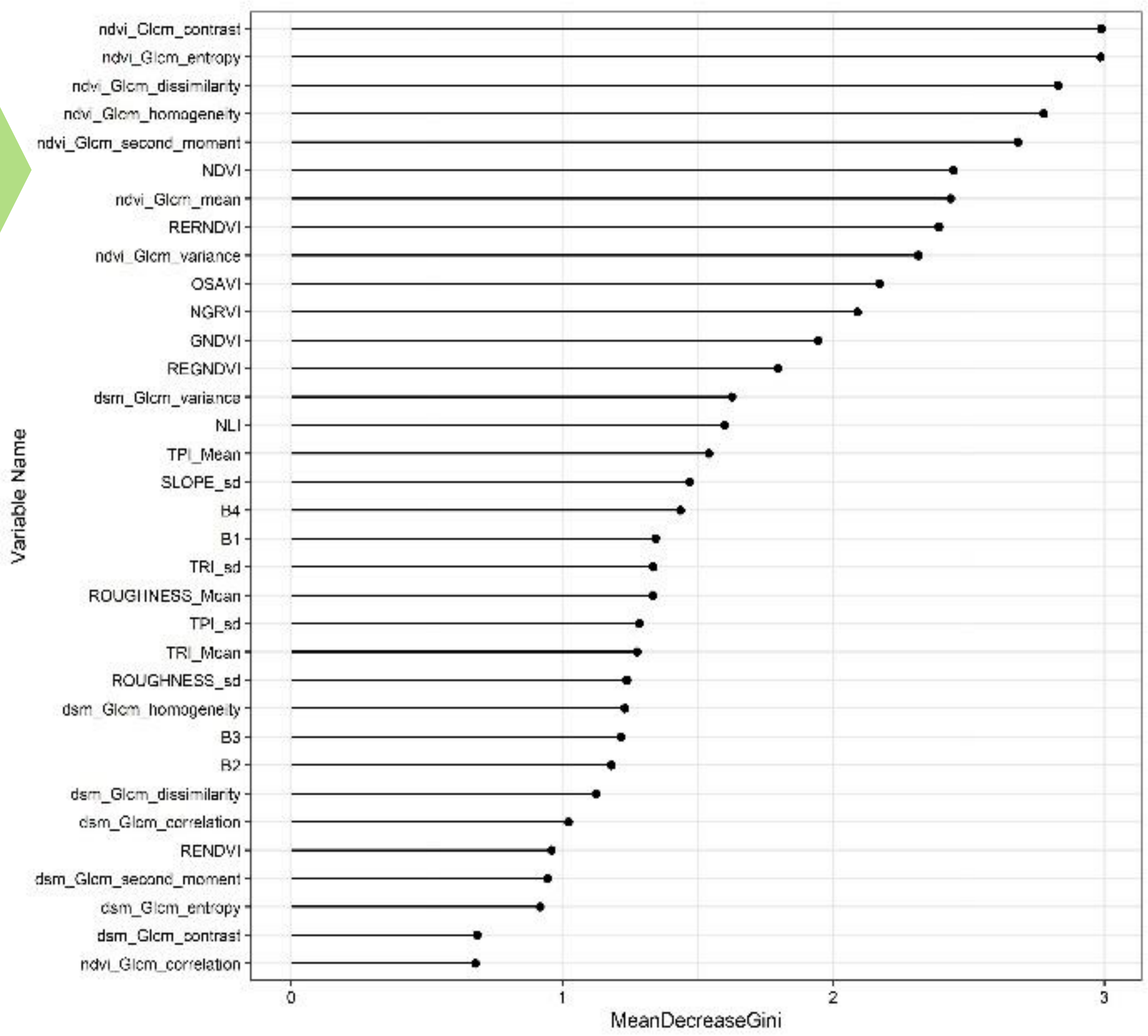
Random Forests (4 classes)

The most important variables:

- textural spectral variables from NDVI,
- spectral indices (e.g. NDVI, RERNDVI)
- *dsm_Glcm_variance* form DSM

library(randomForest)

relative ranking of the remote sensing features



Results (II)
Random Forests

Healthy *10-50* *>50* *Dead*

Total references

	Health status	A	B	C	D	∑	PA
Healthy	**A**	24	4	2	0	30	0.80
10-50	**B**	7	4	1	0	12	0.33
>50	**C**	3	3	2	6	14	0.14
Dead	**D**	0	0	1	24	25	0.96
	∑	34	11	6	30	54	
	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)**

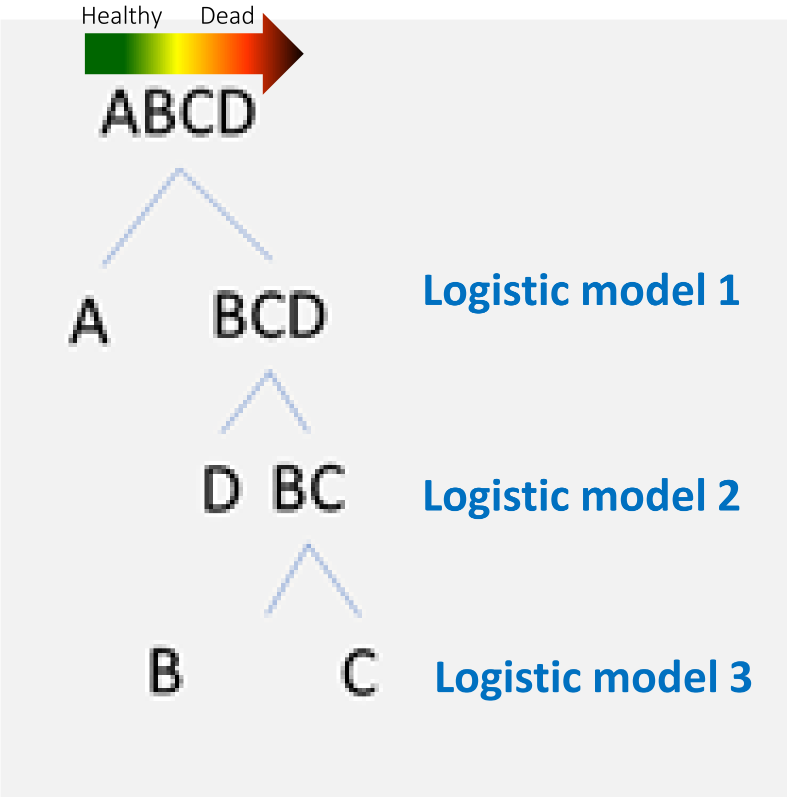
$$\pi(A) = \frac{\exp(-17.085 + 29.038 \cdot GNDVI - 18.669 \cdot DSM_{GLCM_{dissimilarity}})}{1 + \exp(-17.085 + 29.038 \cdot GNDVI - 18.669 \cdot DSM_{GLCM_{dissimilarity}})}$$

- **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)**

$$\pi(B) = \frac{\exp(-14.7280 + 38.2480 \cdot NGRVI)}{1 + \exp(-14.7280 + 38.2480 \cdot NGRVI)}$$



Results (IV)

Logistic Models

Healthy 10-50 >50 Dead

Total references

Health status	A	B	C	D	∑	PA
A	28	0	0	0	28[1]	0.93
B	7	3	2	0	12	0.25
C	3	0	10	1	14	0.71
D	0	0	0	21	21[2]	0.84
∑	38	3	12	22	62	
UA	0.79	0.78	0.64	0.96		**0.76**

[1] Missing 2 could be in groups B or C

[2] Missing 4 could be in groups A, B or C

Kappa=0.74

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.

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

Thank you for your attention!!

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