Mapping health status of chestnut forest stands using Sentinel-2 images

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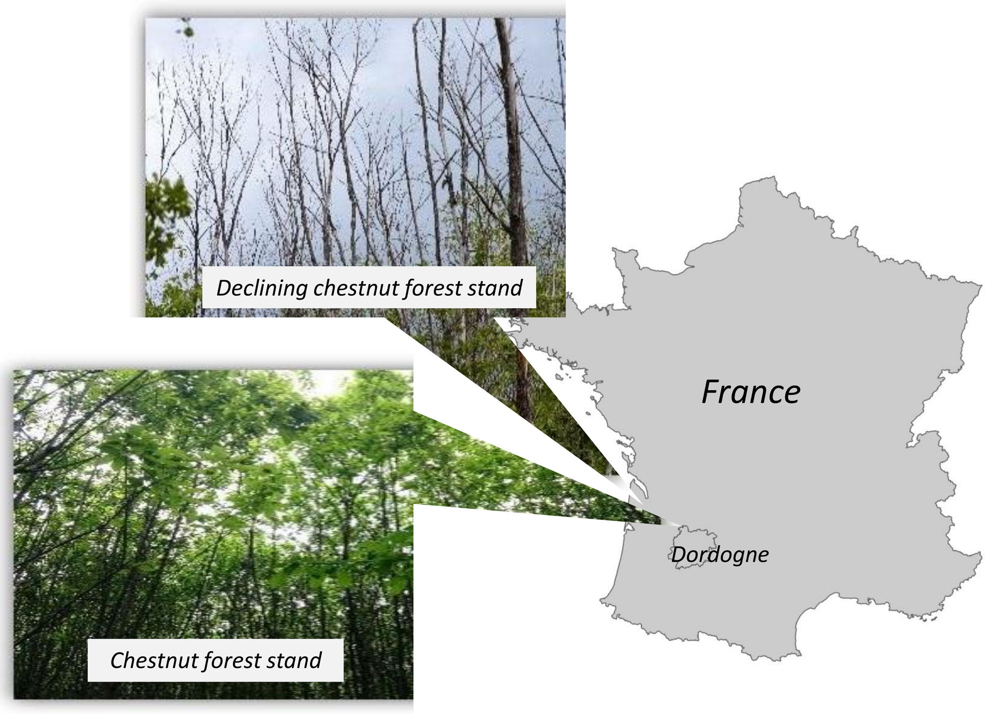
Context - Objectives

Health status diagnosis of chestnut forest stands is a crucial concern for forest managers. These stands are made vulnerable by numerous diseases and sometimes unadapted forestry practices. Moreover, since last years, they were submitted to several droughts. In Dordogne province (France), the economic stakes are important. For example, about 2/3 of the chestnut forest area are below the optimal production level, and most of the forest stands of this area show a high proportion of dry branches. The actual extent of declining forest remains unknown. Sentinel-2 images show an interesting potential to map declining stands over a wide area and to monitor their evolutions. This study aim to propose a method to discriminate healthy chestnut forest stands from the declining ones with several levels of withering intensity, over the whole Dordogne province (9 000 km²).



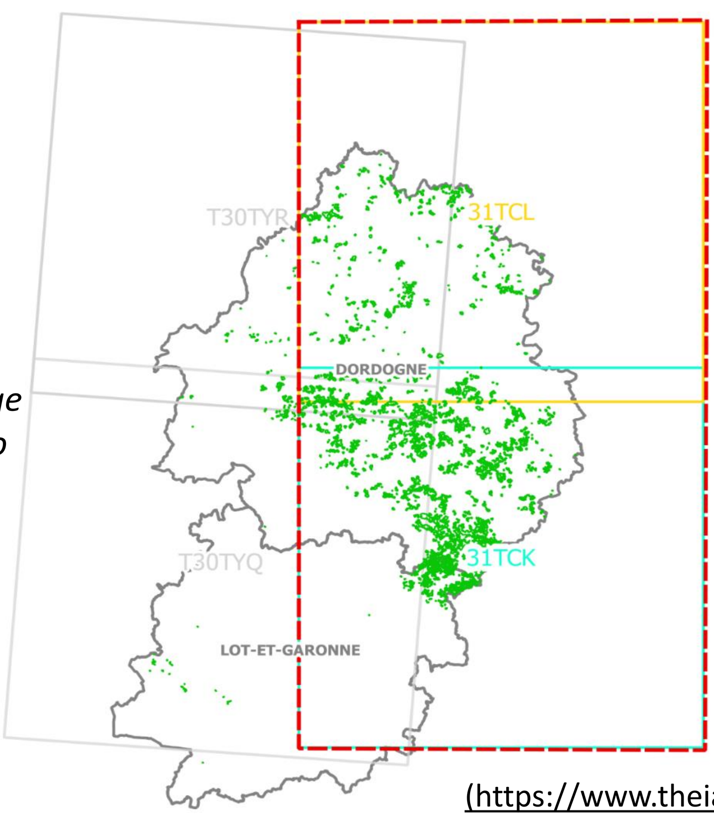
Data

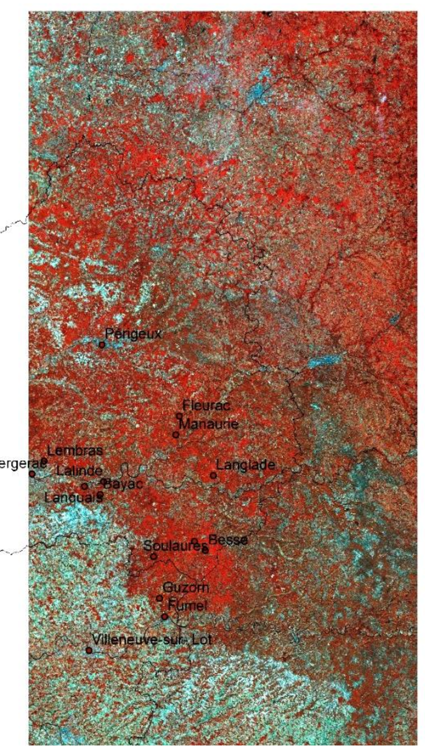
In this study, Sentinel-2 images (10 bands at 10 and 20 m spatial resolution) acquired during the growing season of 2016 have been processed. Due to insufficient data quality related to atmospheric conditions, only 2 cloud-free images were analyzed (one in July and one in September)

2 dates images

- *07/30/2016*
- *09/28/2016*

Remark : Image to image registration shows up to 1.5 pixel error





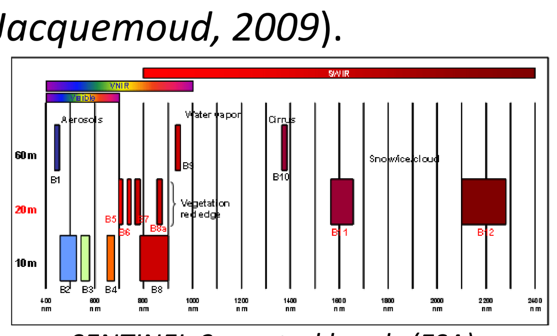
(https://www.theia-land.fr, https://sentinel.esa.int)

Method

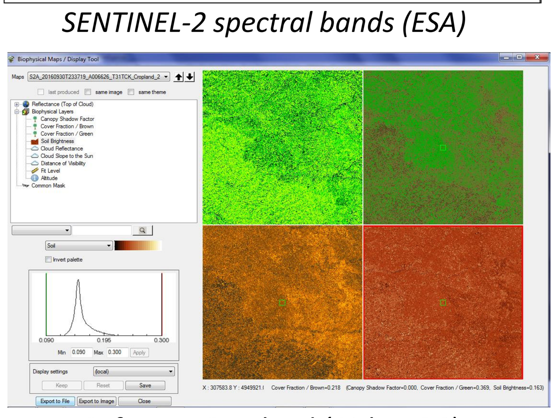
The proposed method is **the development of statistical models integrating in a parsimonious manner several vegetation indices and biophysical parameters.**
The statistical approach is based on an ordered polytomous regression to which are applied various technics of models' selection *(Agresti, 2003)*.

The three processing steps are : 1 – Selection of the best remote sensing variables
2 – Models calculation and selection
3 – Mapping selected models and validation

Remote sensing variables : 36 vegetation indices were calculated from THEIA-MAJA L2A products and 5 biophysical parameters were processed from ESA level 1C product (*Poilvé, 2010*). These last parameters have been obtained by inverting a canopy reflectance model with the Overland software (developed by Airbus DS Geo-Intelligence). This software couples the PROSPECT leaf model and the scattering by arbitrary inclined leaves (SAIL) canopy model (*Jacquemoud, 2009*).



SENTINEL-2 spectral bands (ESA)



Software Overland (Airbus DS)

- 10 spectral bands (resampled at 10m spatial resolution)
  - B2, B3, B4, B5, B6, B7, B8, B8a, B11 et B12
- 36 vegetation indices
  - NDVI, EVI, NDII, $NDVI_{RedEdge}$, MCARI, DVI, Clgreen, CRI2, NBR, PSRI ….
- 5 Biophysical parameters
  - BLCV : Cover fraction of brown vegetation
  - GLCV : Cover fraction of green vegetation
  - fAPAR : Fraction of Absorbed Photosynthetically Active Radiation
  - GLAI : Green Leaf Area Index
  - WAT : Leaf Water Content

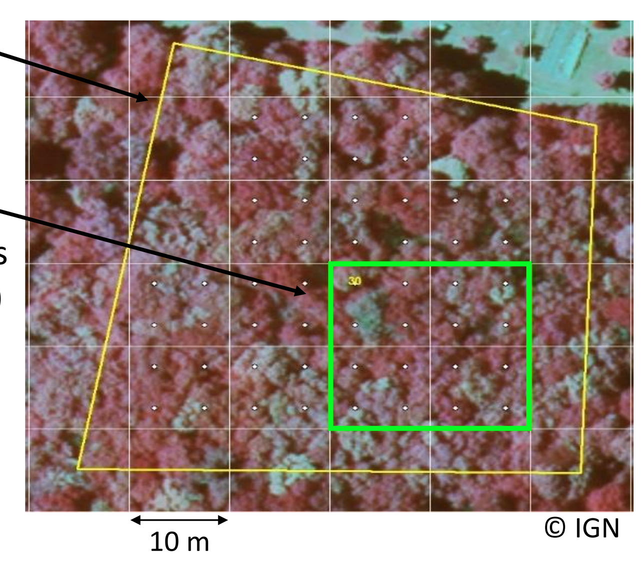
Field data for calibration and validation of the predictive models are based on health status data. Plots have been surveyed by foresters. The chestnut trees health status has been described by using two protocols (ARCHI and Expert knowledge) (*Lambert,2013*) : 50 for calibration, 102 for validation.

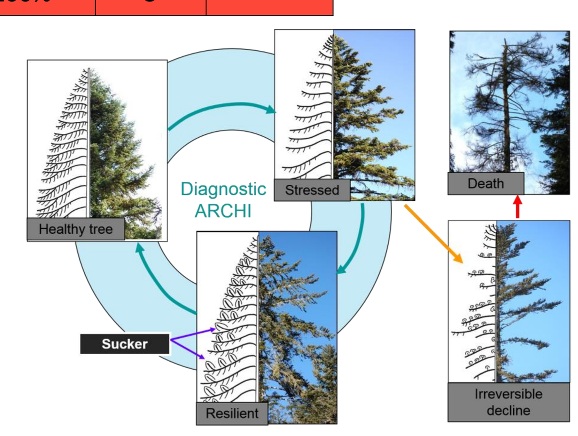
Decline value of forest plots

Chestnut forest health status (% of declining trees)	*Class of decline (5 levels)*	*Class of decline (3 levels)*
0-10%	1	1
10%-30%	2	2
30%-50%	3	
50%-80%	4	3
80%-100%	5	

Plots area for **Expert Knowledge** observations

Plots area for **ARCHI** observations (30 trees in 4 pixels)

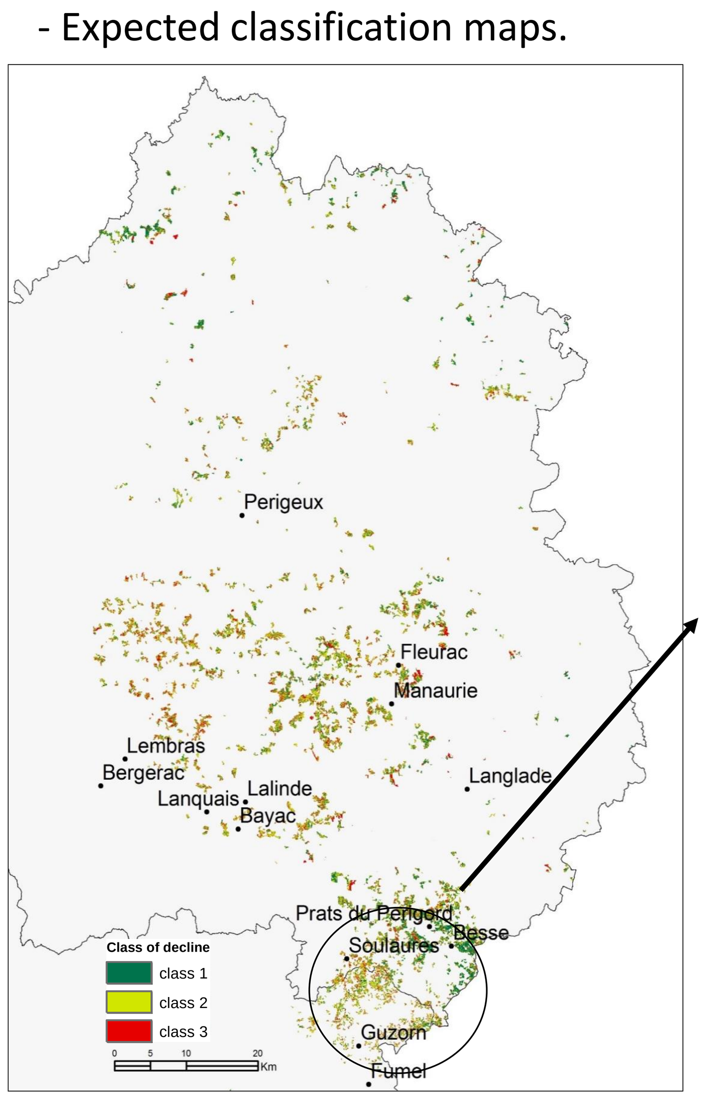


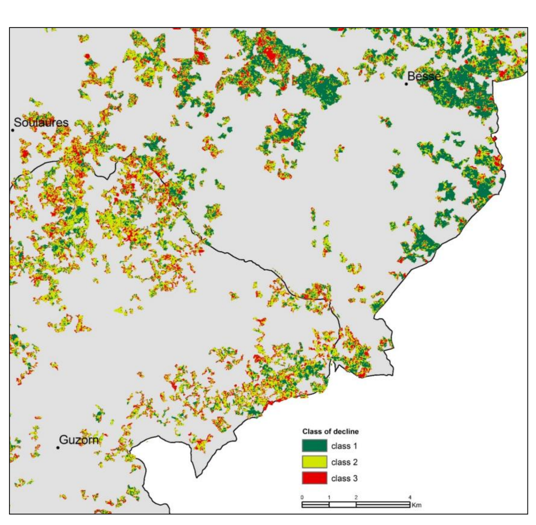


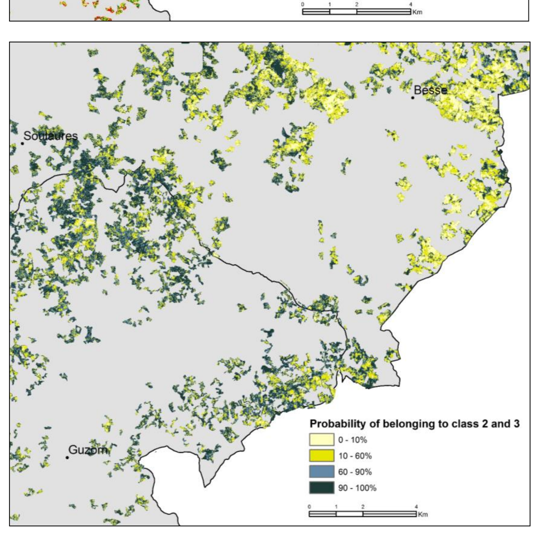
Diagnostic ARCHI method
(C. Drenou, CNPF)

Results

- The **best remote sensing variables** according to AIC and cross validation :
  - Vegetation Red Edge and NIR spectral bands : B8a, B8, B7, B6…
  - Vegetation indices : NDVIre2n, NDII, DVI, NBR, GNDVI, NDWI, MTCI, IRECI, S2REP…
  - Biophysical parameters : GLAI and GLCV.
- The **selected models** using for 2 to 5 variables, and using single date images (July and Sept) or both combined : **57** selected models according to AIC and CHI², then **12** selected models according to quality indices (Kappa, Tau, Overall accuracy, RMSE) using validation observations.
- The **Maps** of probability of belonging to a class of decline,
  - Maps of probability of belonging to a class of decline,
  - Expected classification maps.

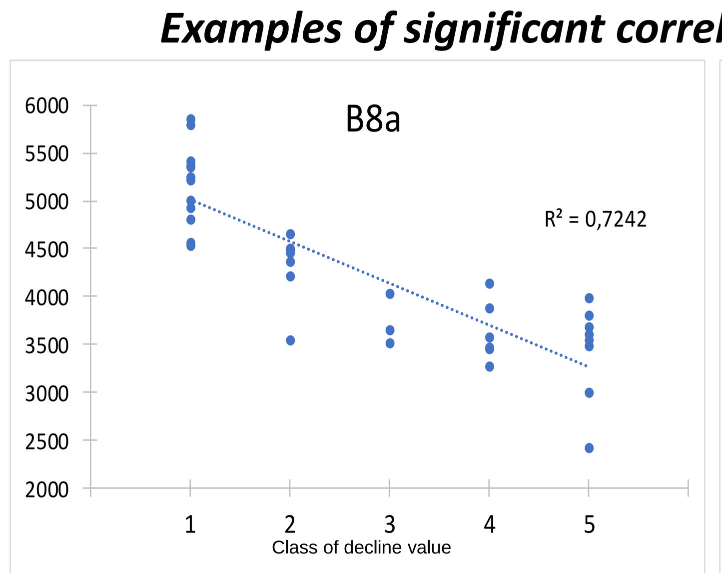


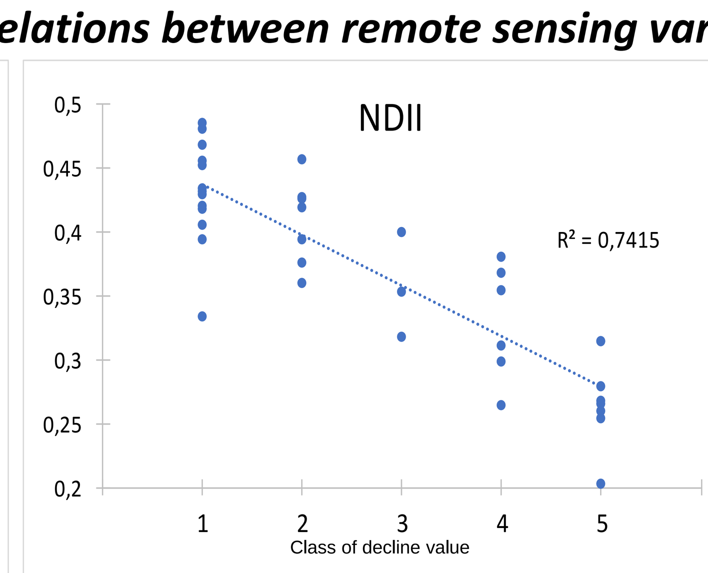


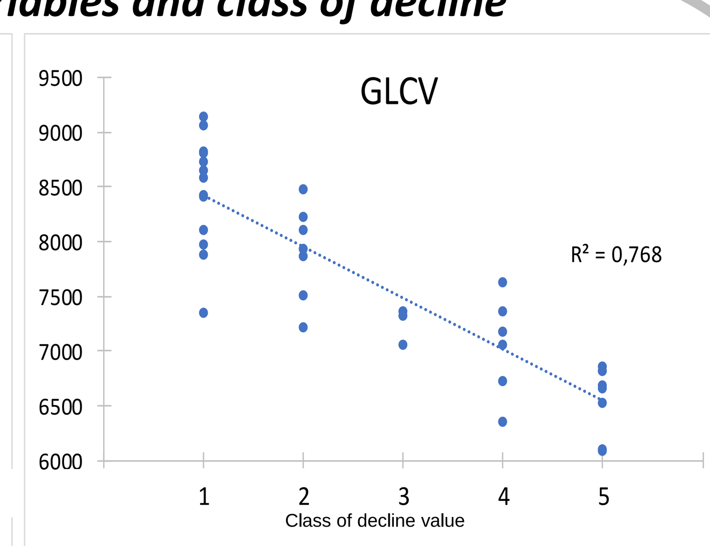


Example of classification map and probability of belonging to a class of decline

Examples of significant correlations between remote sensing variables and class of decline







Selected models and quality assessment

Validation with Expert knowledge observations (n=87)
Single date : July

Model	Kappa index	Overall accuracy	Tau index	RMSE
(-3.73*B8a) + (-1.47*NDII)	0.61	0.80	0.61	0.44
(-3.66*B6) + (-2.67*NDVIre2n)	0.56	0.78	0.56	0.47
(-3.84*B8a) + (-1.96*NDVIre2n)	0.54	0.77	0.54	0.48

Validation with Expert knowledge observations (n=87)
Two dates : July (J) and Sept (S)

Model	Kappa index	Overall accuracy	Tau index	RMSE
(3.707*B8a(J)) + (-1.106*DVI(S))	0.62	0.81	0.62	0.44
(-0.536*NDII(S)) + (-3.611*B6(J)) + (-2.801*NDVIre2n(J))	0.59	0.79	0.59	0.45
(-9.289 *GLAI(J)) + (-0.379*B6(S))	0.49	0.74	0.49	0.50

Validation with ARCHI observations (n=77)
Single date : July

Model	Kappa index	Overall accuracy	Tau index	RMSE
(-5.46*NBR) + (5.06*GNDVI) + (8.7*B8) + (-12.87*B8a)	0.65	0.84	0.68	0.40
(1.41*GNDVI) + (-4.05*B8a) +	0.57	0.80	0.61	0.44
(-1.36*NDWI) + (-3.98*B8a)	0.56	0.80	0.61	0.44

Validation with ARCHI observations (n=77)
Two dates : July (J) and Sept (S)

Model	Kappa index	Overall accuracy	Tau index	RMSE
(-1.20*MTCI(S)) + (-2.49*B6(J))	0.60	0.82	0.63	0.43
(-2.11*B8a(J)) + (-1.22*IRECI(S))	0.56	0.79	0.58	0.46
(-2.624*GLAI(J)) + (-0.766*S2REP(S))	0.54	0.79	0.58	0.46

Remote sensing variables	Formula
NDVIre2n	*(B8a-B6)/B8a+B6)*
NDII	*(B8-B11)/(B8+B11)*
DVI	*B8-B4*
NBR	*(B8-B12)/B8+B12)*
GNDVI	*(B7-B3)/(B7+B3)*
NDWI	*(B3-B8)/B3+B8)*
MTCI	*(B6-B5)/(B5-B4)*
IRECI	*((B7−B4)*B6)/B5*
S2REP	*705+35*(((B7+B4)/2)−B5)/(B6−B5))*
GLAI	*Green Leaf Area Index*

Conclusion

- The kappa index of the 57 models varies from **0.2** to 0.6 ; the kappa index of the 12 best models varies from 0.49 to **0.65**.
- The contribution of the image of September is not significant.
- The biophysical parameter **GLAI** contributes to two of the best models.

- Agresti A. (2003), Categorical Data Analysis, Second Edition, 2002 Wiley, 710p.
- Poilvé H. (2010), Geoland2 BioPar Methods Compendium MERIS FR Biophysical Products; Technical Report BP-RP-BP038; VITO: Toulouse, France.
- Jacquemoud S., W. Verhoef, F. Baret, C. Bacour, P.J. Zarco-Tejada, G.P. Asner, C. François, S.L. Ustin (2009), PROSPECT+ SAIL models : A review of use for vegetation characterization. Remote Sens. Environ., 113, S56–S66.
- Lambert J., C. Drénou, J. P. Denux, G. Balent, V. Chéret (2013), Monitoring forest decline through remote sensing time series analysis, Giscience & Remote Sensing, vol. 50 (4), pp. 437-457.