LiDAR aplicado a los incendios forestales

III Taller del Grupo de Incendios Forestales de la AET

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Spatial modelling of crown fuels: Comparing methods based on LiDAR data

Introduction

Introduction

Background

→ Wildfire risk prevention: fuel management

→ Crown fires: high severity on forest ecosystems

→ Strategic fuel treatment planning based on simulations

- wildfire behavior potential
- high vulnerability areas
- spatial information on fuels needed

Introduction

Background

→ Collaboration between INIA and AGRESTA

→ Research focused on forest structure characterization

- ***GEPRIF*** **- forest fuels**
- ***SCALYFOR*** **- forest dynamics**

→ Different types of sensors (imagery, ALS, TLS, ForeStereo)

GEPRIF Project

"Fire Severity Reduction through New Tools and Technologies for Integrated Forest Fire Protection Management"

SCALYFOR Project

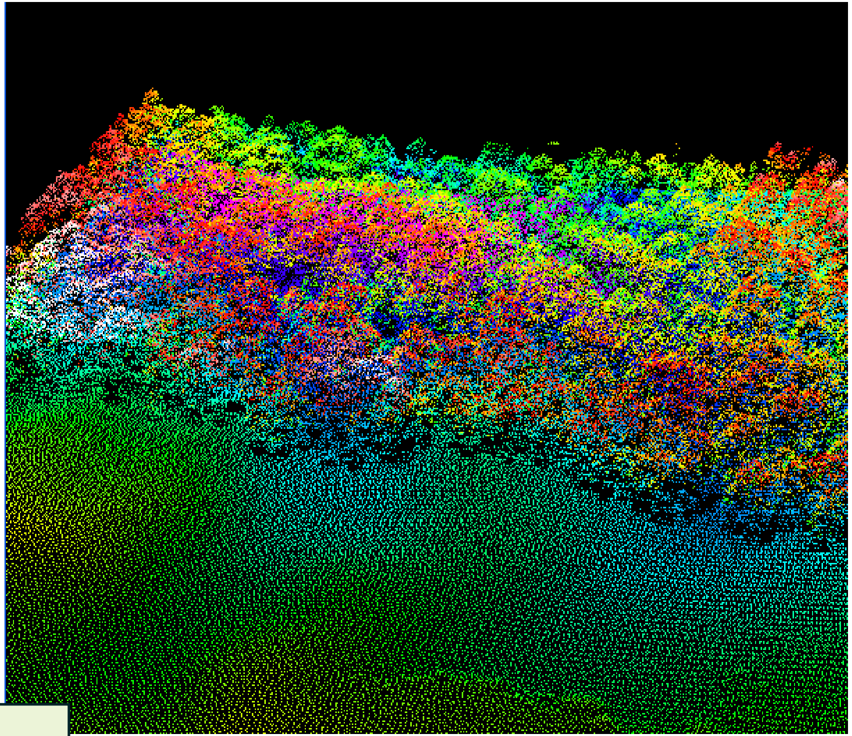
"Forest management facing the change in forest ecosystems dynamics: a multiscale approach"

Introduction

Airborne LiDAR

- Very useful to characterize 3D forest structure
- Revolution on data gathering at large scale
- PNOA – free data available in Spain
- Increasingly used in forest monitoring
- Previous studies providing different methods for fuel characterization

Which are the **best methods** to get information on the spatial distribution of **crown fuels**?



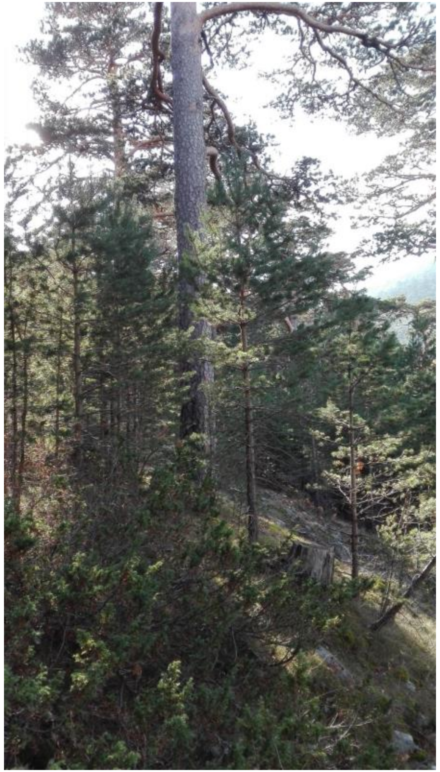
Introduction

Study objectives

→ Assessment of different methods for crown fuel modelling

→ Focused on 3 critical variables related to crown fire behaviour

- Crown Base Height – CBH
- Crown Fuel Load – CFL
- Crown Bulk Density – CBD



→ Methodology

Methodology

Study area

- Valsaín in Sierra de Guadarrama National Park (Segovia, central Spain)
- Mountain forest area (wide altitude range, steep slopes)
- 7448 ha dominated by natural *Pinus sylvestris* stands
- Sustainable forest management since 1889
- Different types of forest structure (tall mature stands, dense young stands, excellent regeneration)

Methodology

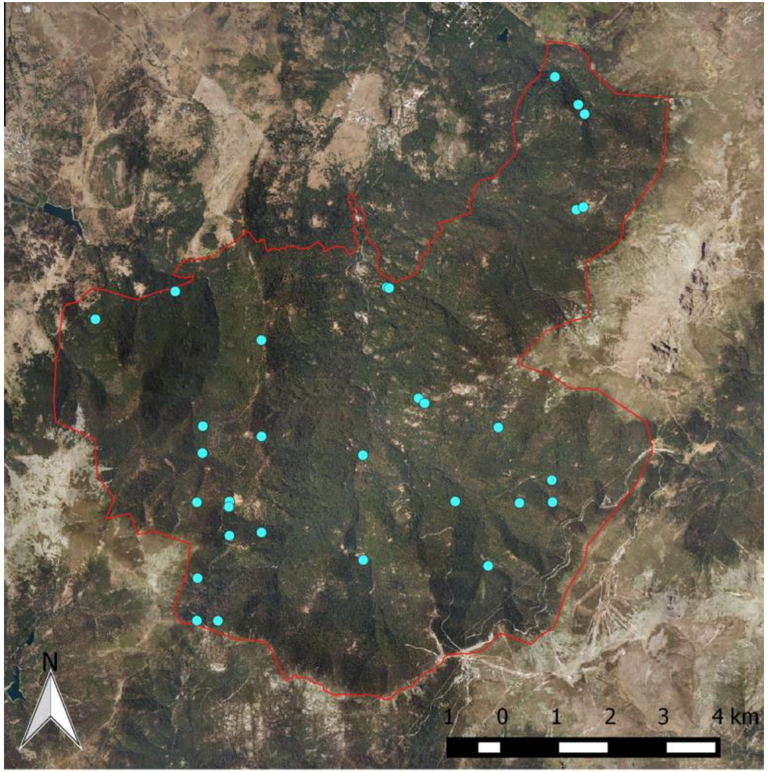
Field inventory

→ 30 circular plots (r = 14 m)

- Diameters (DBH) of all trees > 7.5 cm
- Random sampling of 10 trees/plot
  - Tree height
  - Crown base height (CBH)

→ GPS location of plot center

- submetric accuracy in post-processing



Crown fuel variables at plot level

→ **Crown fuel load (CFL, kg/m^2)**

- Allometric equations for *Pinus sylvestris* from Sierra de Guadarrama (Montero et al. 2005)

  Dry biomass (kg) = $CF\ e^a\ D^b$

  $CF = e^{(SEE^2/2)}$

  D = diameter

- Fine fuels:

  CFL Foliar biomass (only leaves)

→ **Crown bulk density (CBD, kg/m^3)**

- Calculated from crown fuel load (CFL) and crown lenght (H_{mean}-CBH)

Methodology

LiDAR data

Classification → Normalization → LiDAR metrics

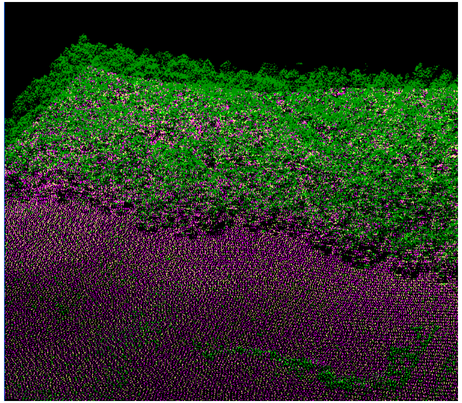
Classification: Soil, Vegetation

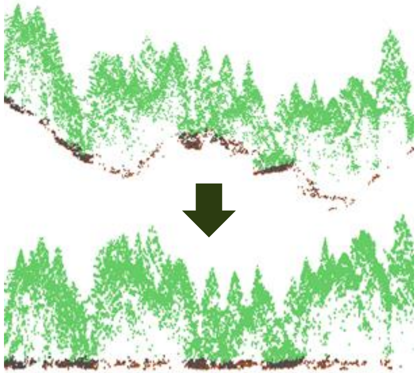
Normalization: Heights = DSM - DTM

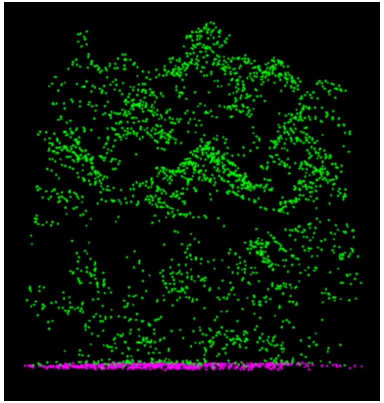
LiDAR metrics: Plots, Raster 25m

Pulse density

1.5 – 5 p/m²







Methodology

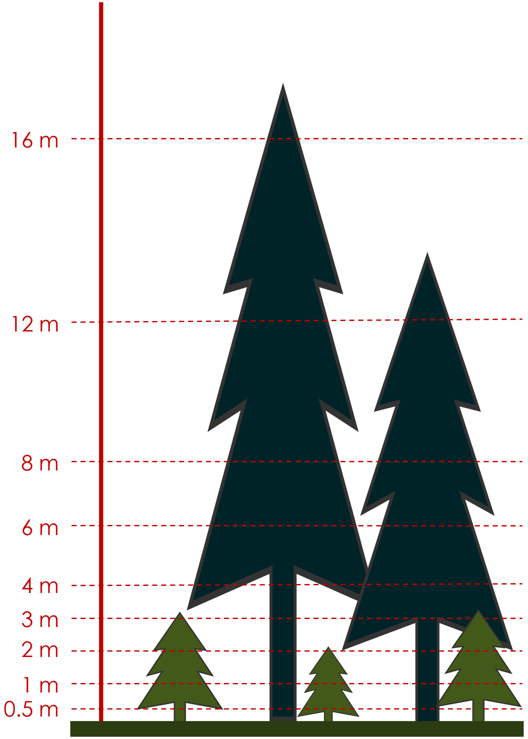
LiDAR metrics

Returns above 0.5 m

- → Percentiles (P05, P10, … , P99)
- → Elevation statistics (h_min, h_max, h_mean, h_CV, etc.)
- → Canopy Relief Ratio (CRR)
- → Percentage of first (PFR) and all returns (PAR)
- → Proportion of returns normalized by height strata (PRN)

Additional threshold levels for CRR, PFR and PAR

- → 2 m and 4 m



Methodology

Statistical analysis

Performance of different methods for crown fuel modelling

→ **Parametric regression**

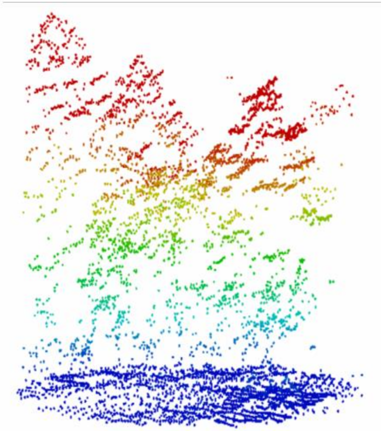
- Linear, potential & exponential models

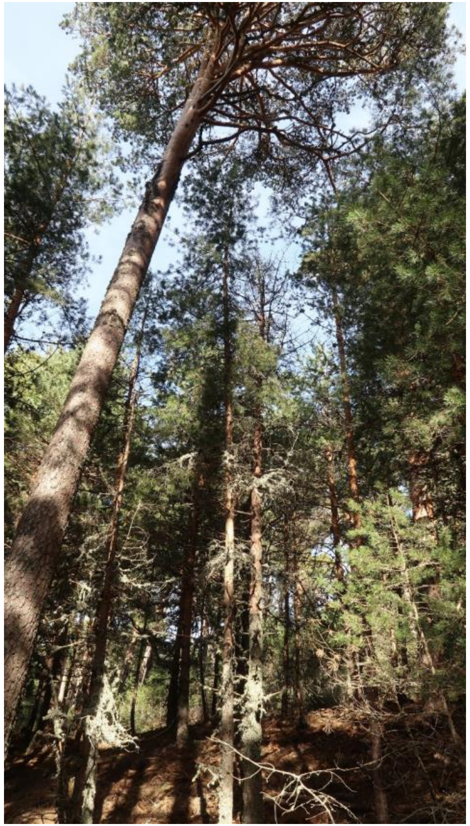
→ **Non-parametric regression**

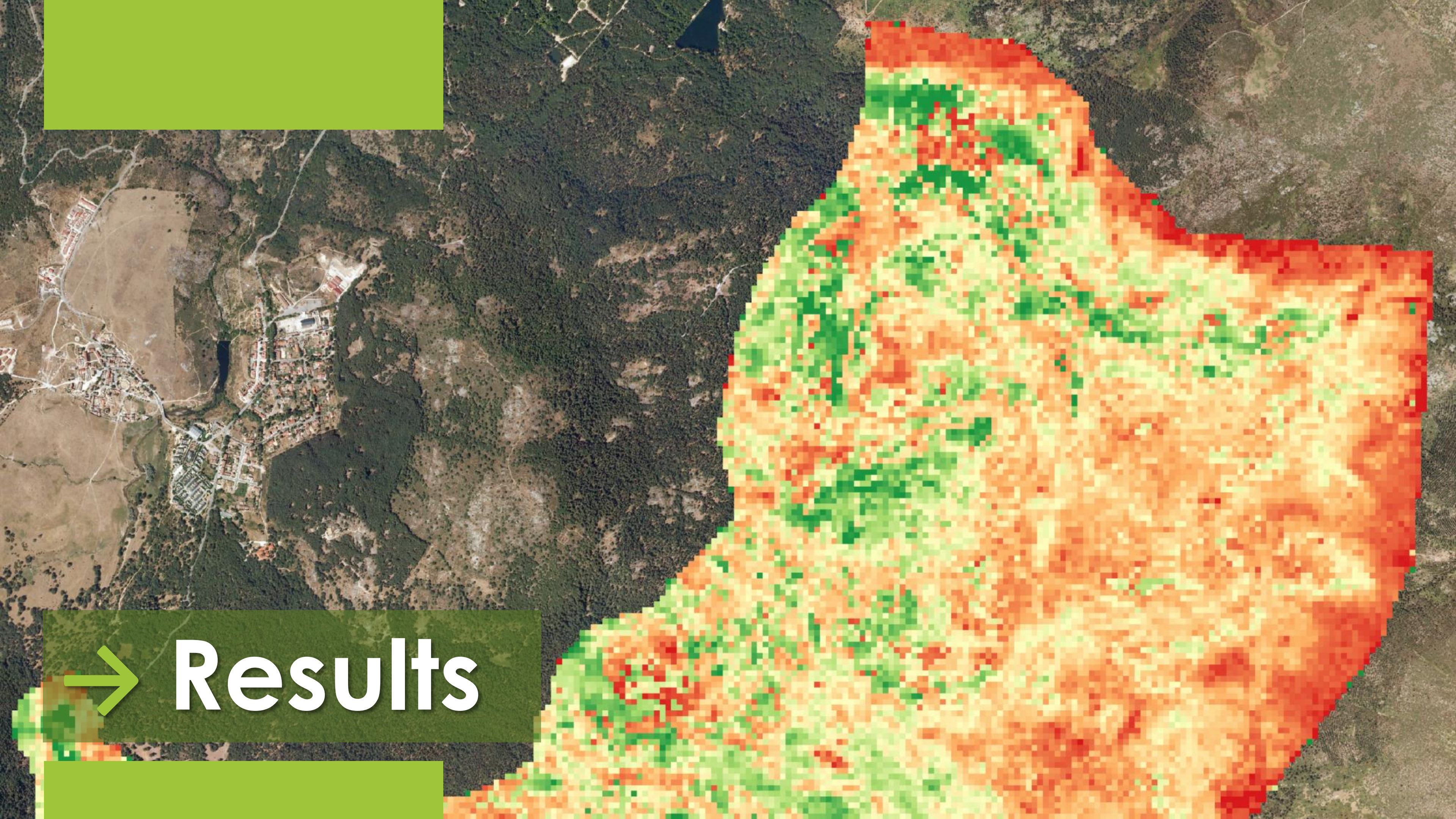
- Random Forest

→ **Geoestatistics**

- Universal Kriging







Results

Results

Parametric regression

→ **Model fitting**

- Stepwise (forward& backward)
- Additional combination of metrics

→ **Model selection**

- LiDAR metrics: p-values of β coefficients
- Overall model significance: p-value
- adjusted R^2 and RMSE (crossvalidation)

R Software

Packages:

rms

lmtest

Results

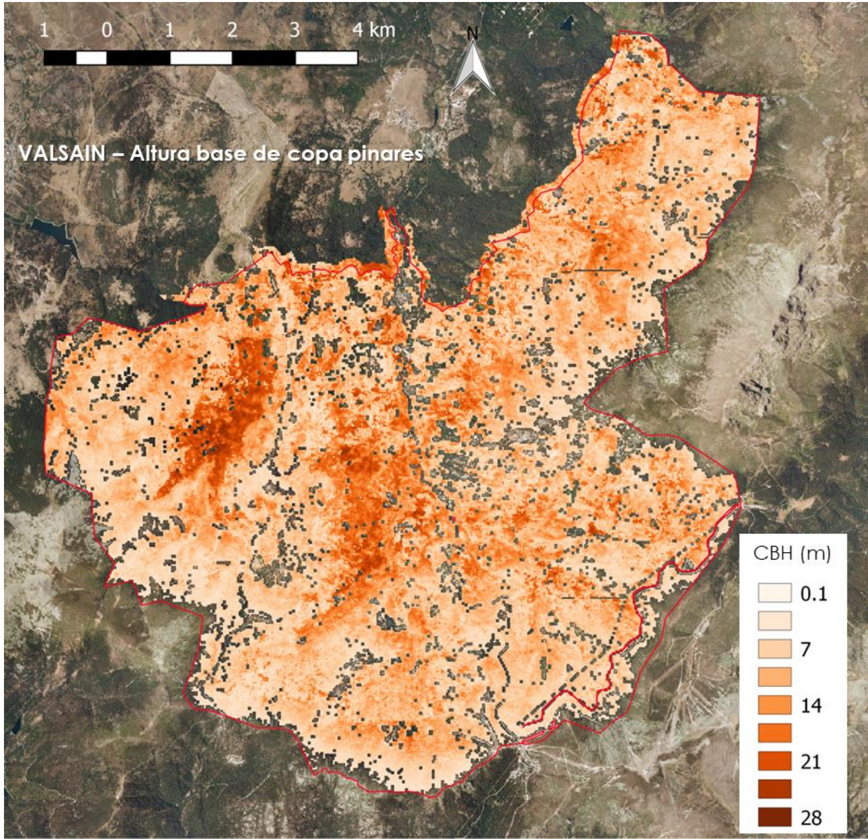
Parametric regression

Crown Base Height (CBH)

→ Best model: **linear**

→ **Inputs**: LiDAR metrics changing with different formulation

Model type	LiDAR metrics	R^2 (adjusted)	RMSE	p-value
Linear	**P10** **P50** **CRR_a4**	**0.89**	**1.42**	**< 0.0001**
Potential	h_CV h_L4 P60 PRN_6a8	0.87	3.57	< 0.0001
Exponential		n.a.	n.a.	n.a.



Results

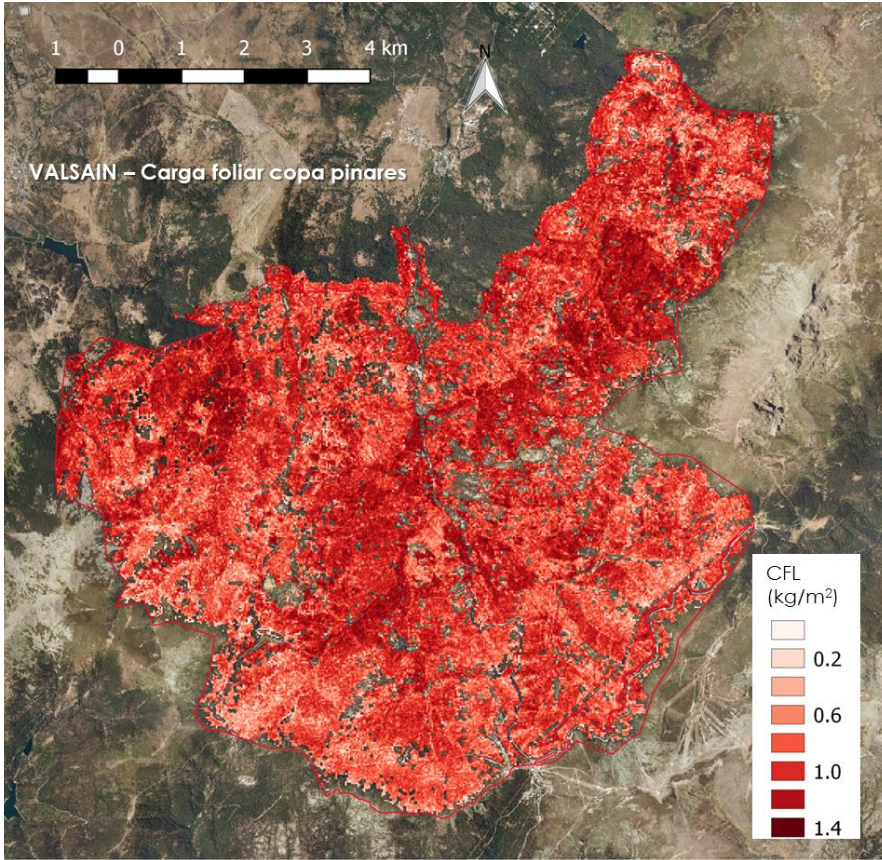
Parametric regression

Crown Fuel Load (CFL)

→ Best model: **linear**

→ **Inputs**: same LiDAR metrics with different formulation

Model type	LiDAR metrics	R^2 (adjusted)	RMSE	p-value
Linear	**PFR_a05**	**0.71**	**0.16**	**< 0.0001**
Potential	PFR_a05	0.69	0.15	< 0.0001
Exponential		n.a.	n.a.	n.a.



Results

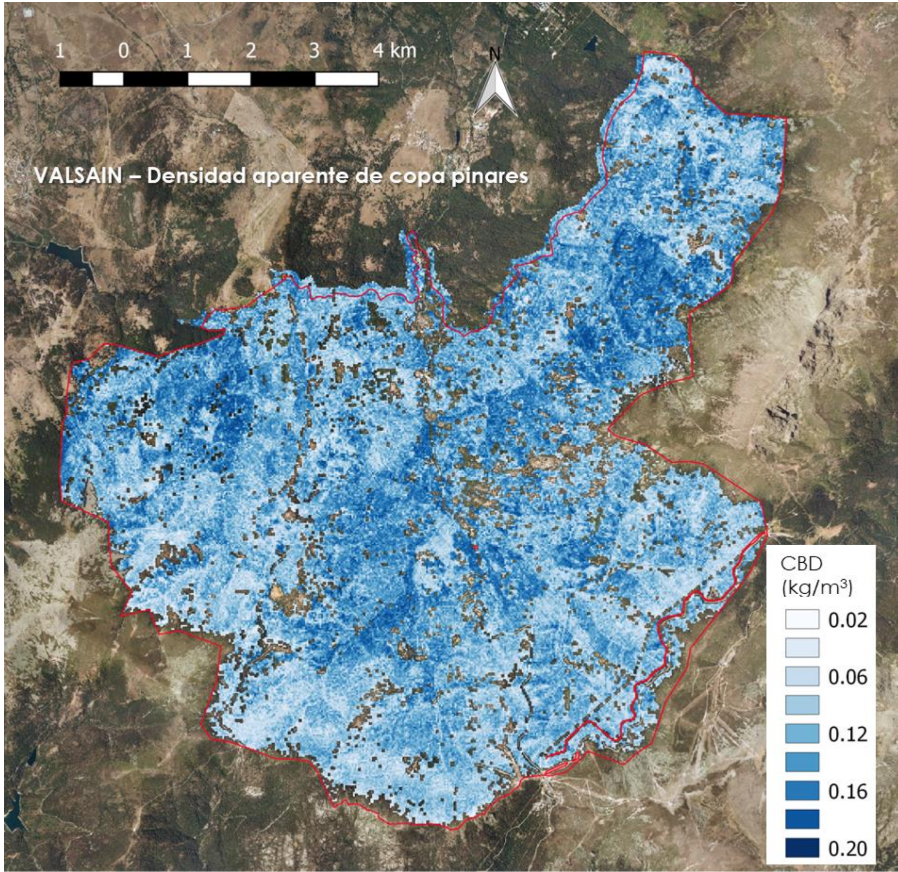
Parametric regression

Crown Bulk Density (CBD)

→ Best model: **exponential**

→ **Inputs**: same LiDAR metrics with different formulation

Model type	LiDAR metrics	R^2 (adjusted)	RMSE	p-value
Linear	n.a.	n.a.	n.a.	n.a.
Potential	PFR_a05	0.57	0.05	< 0.0001
Exponential	**PFR_a05**	**0.61**	**0.03**	**< 0.0001**



Random Forest

→ **Model fitting**

- input metrics optimized
- 1000 trees
- Importance of variable

→ **Model selection**

- pseudo R^2 (% variability explained)
- RMSE

R Software

Packages:

randomForest

rfUtilities

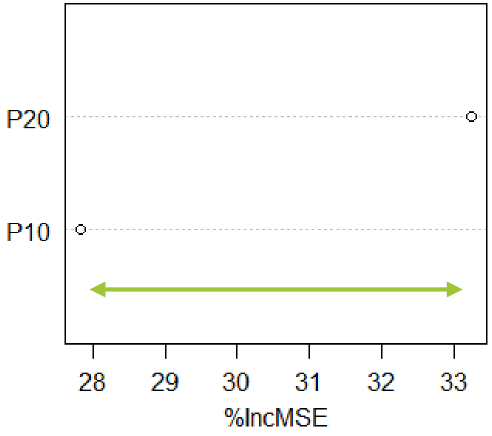
VSURF

Random Forest

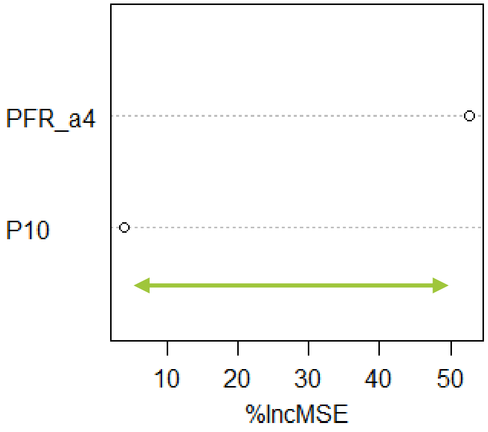
Model	LiDAR metrics	pseudo R^2	RMSE
CBH	P10, P20	0.79	2.11
CFL	PFR_a4, P10	0.63	0.19
CBD	PFR_a05, PFR_a2, PFR_a4, PRN_8a12, h_IQ, h_MADmedian	0.65	0.03

Random Forest – Importance of variables

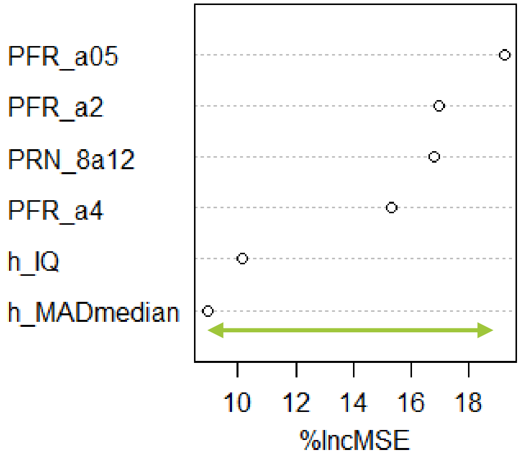
Crown Base Height (CBH)



Crown Fuel Load (CFL)



Crown Bulk Density (CBD)



Geoestatistics

→ **Universal Kriging**

- Neuman-Jacobson method
- Input data: 30 sampling plots
- LiDAR as auxiliary data
- Variogram fit: spherical

→ **Model selection**

- LiDAR metrics: p-values of β coefficients
- Crossvalidation

Software GEOSTAT

Matlab application developed in

INIA-CIFOR for geostatistical analysis

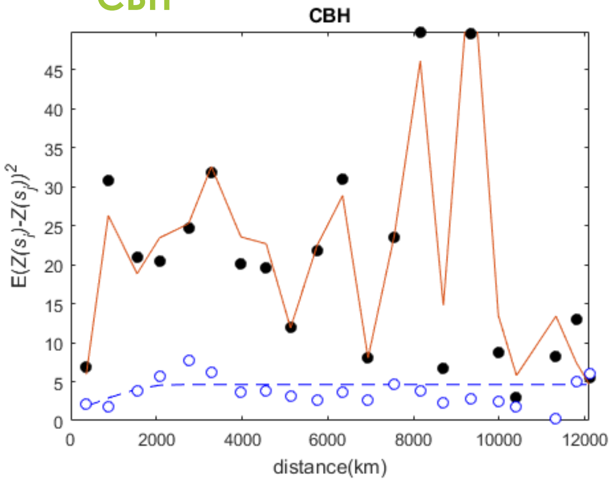
Results

Geostatistics

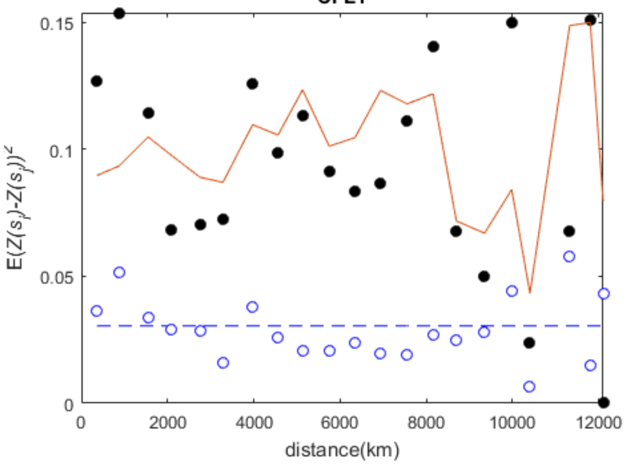
→ Universal Kriging

- CBH: excellent variogram fit
- High correlation with LiDAR data

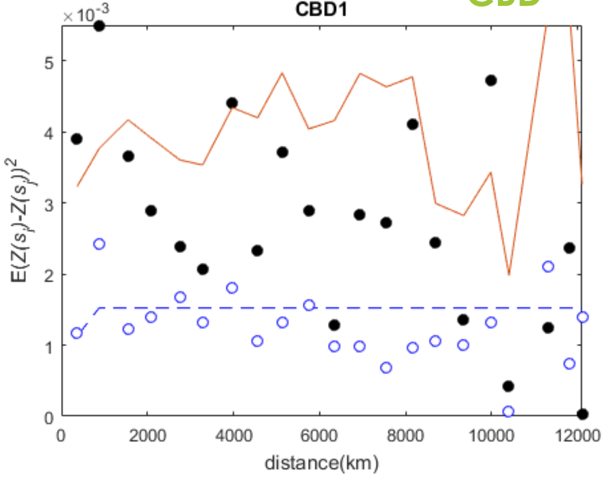
CBH



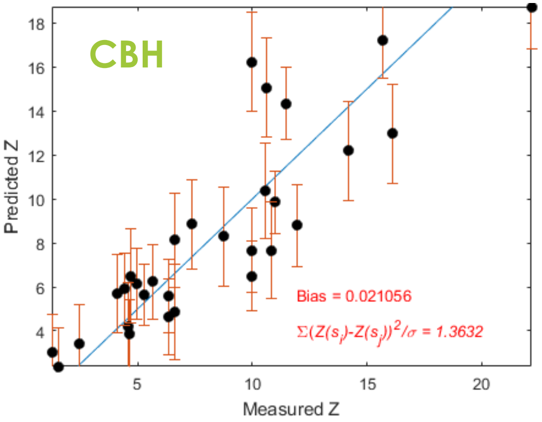
CFL

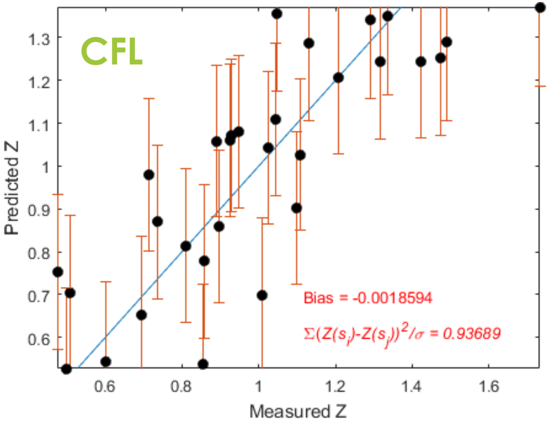


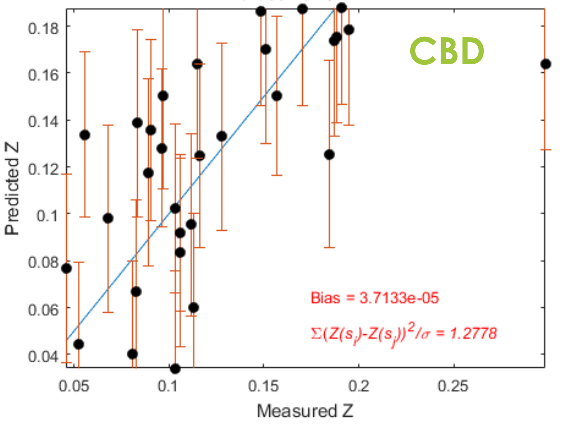
CBD



Results







Geoestatistics

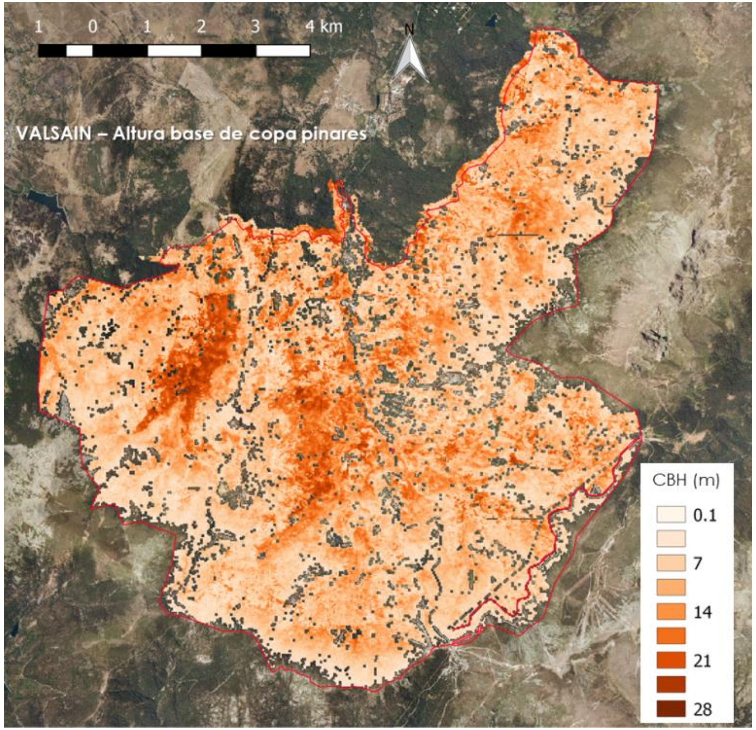
→ Crossvalidation

- good accuracy (RMSE)
- low bias

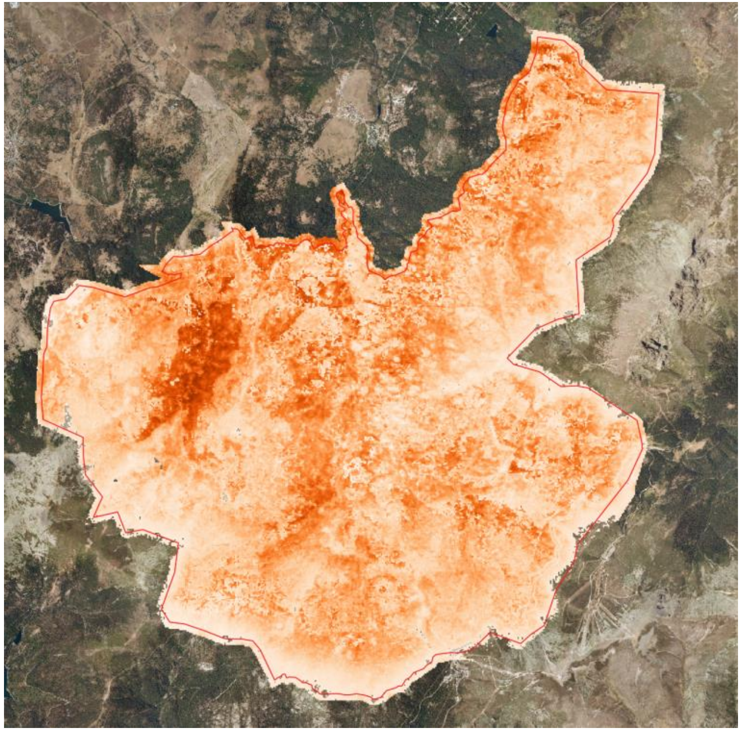
UK model	LiDAR metric	p-value	Nugget	Sill	Range	RMSE
CBH	P25	< 0.0001	0.98	3.64	2377.6	2.31
	CRR_05	0.0217				
CFL	PFR_a05	< 0.0001	0.03	<0.0001	862.5	0.18
CBD	PFR_a05	< 0.0001	0.004	0.001	800.0	0.04

Results

Linear regression



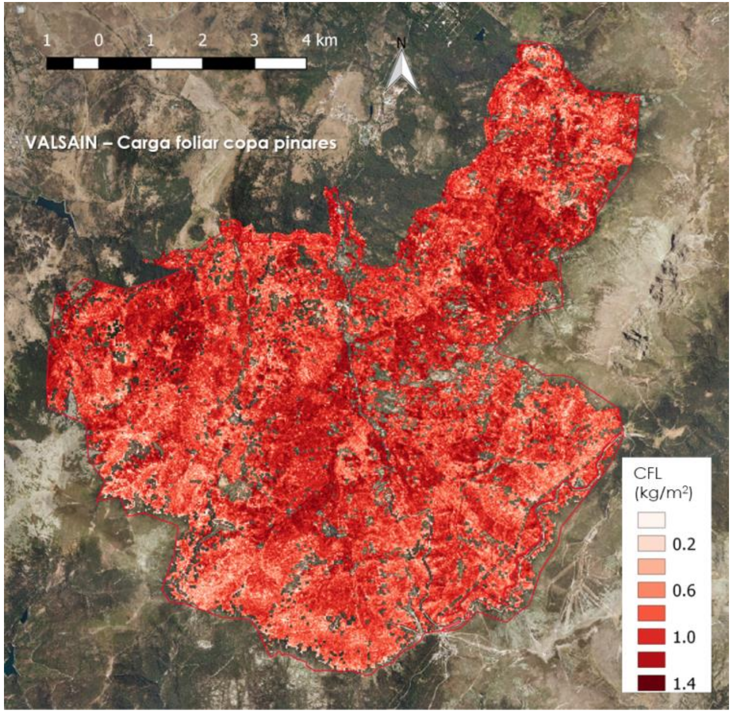
Geostatistics



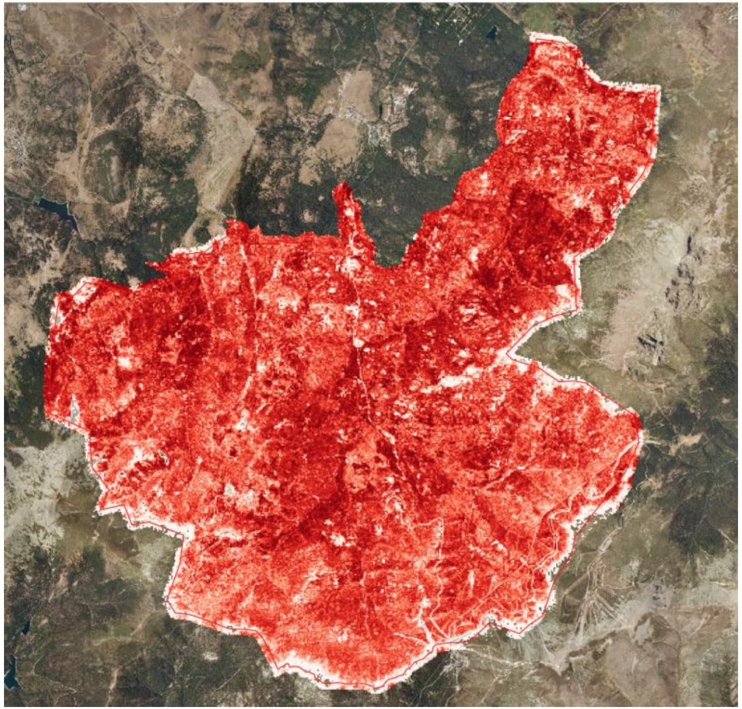
Crown Base Height (CBH)

Results

Linear regression



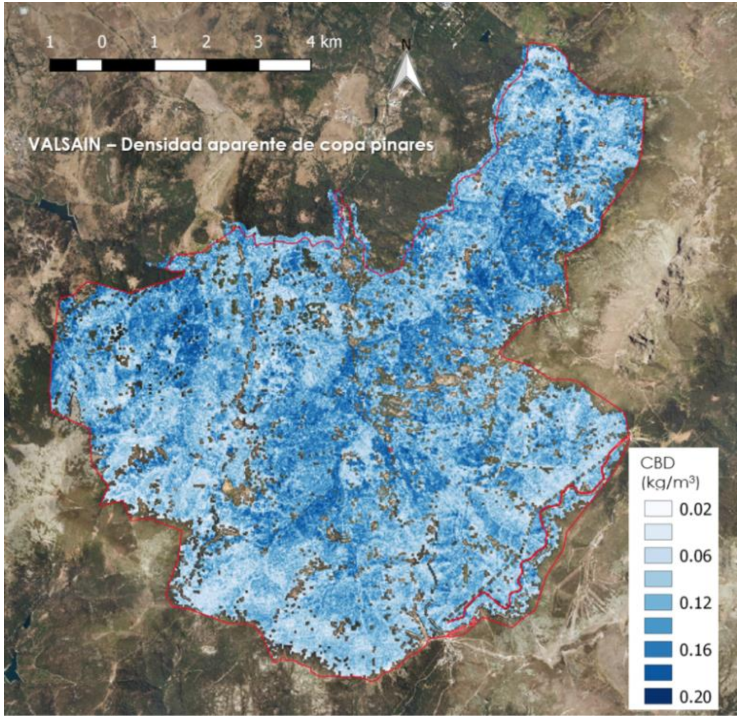
Geostatistics



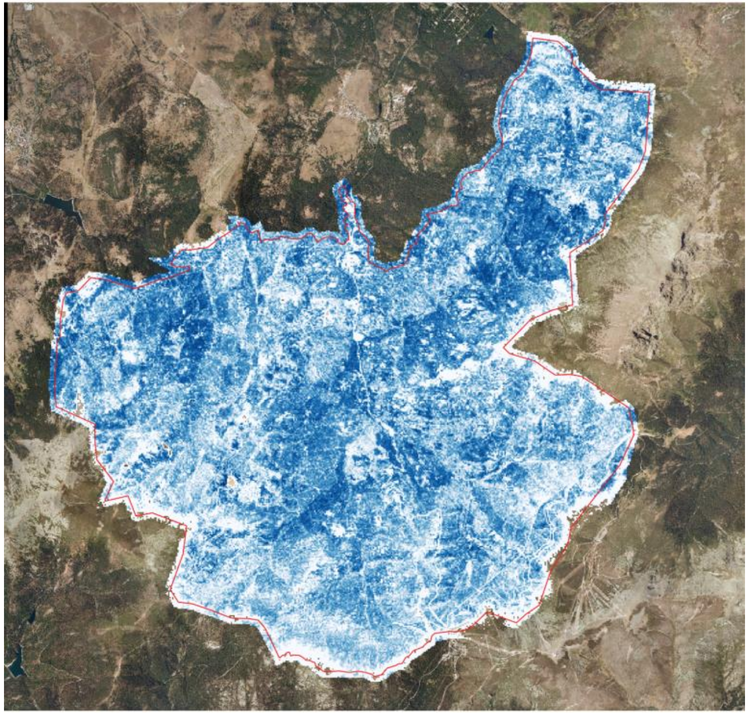
Crown Fuel Load (CFL)

Results

Linear regression



Geostatistics



Crown Bulk Density (CBD)

Comparison of methods

- → Main RMSE differences observed in CBH
- → Better performance of parametric regression, except CBD (similar to RF)
- → CBD: more difficult to model

Model	RMSE (%)		
	Parametric regression	Random Forest	Geostatistic (UK)
CBH	1.42 (17%)	2.11 (25%)	2.31 (28%)
CFL	0.16 (16%)	0.19 (19%)	0.18 (18%)
CBD	0.03 (24%)	0.03 (24%)	0.04 (32%)

→ Conclusions

Conclusions

Parametric regression

→ the best modelling approach for the crown fuel variables tested

Random Forest

→ robust and accurate alternative for crown fuel modelling when parametric regression is not applicable

Geostatistics

→ promising technique for field and LIDAR data integration, but increased sampling density is required to better account spatial correlation agresta

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