SEMINARIO
CARTOGRAFÍA DE LOS HABITATS ESPAÑOLES
16-17 DE OCTUBRE DE 2017

GOBIERNO DE ESPAÑA
MINISTERIO DE AGRICULTURA Y PESCA, ALIMENTACIÓN Y MEDIO AMBIENTE

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http://geoforest.unizar.es/

Seguimiento y evaluación de espacios forestales: SERGISAT y aplicaciones LiDAR-PNOA

GEOFOREST-IUCA

Universidad de Zaragoza

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Universidad Zaragoza

Geoforest

ERTAlab

Departamento de Geografía y Ordenación del Territorio
Universidad Zaragoza

CUD Zaragoza

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Geoforest-IUCA

Presentación: Líneas de trabajo

GEOFOREST-IUCA

http://geoforest.unizar.es/

Presentación | Personal | Publicaciones | Líneas y proyectos de investigación | Enlaces | Equipamiento | Resultados/Transferencia | Galería de Imágenes | Contacto

Español | English

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GEOFOREST-IUCA

ERTAlab -- *Laboratorio de Espectro-Radiometría y Teledetección Ambiental de la Universidad de Zaragoza* (Subprograma de proyectos de infraestructura científico-tecnológica cofinandados por FEDER-DGA, UNZA10-4E-488)

Infraestructura cofinanciada

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MINISTERIO DE ECONOMÍA Y COMPETITIVIDAD

Unión Europea

Fondo Europeo de Desarrollo Regional

"Una manera de hacer Europa"

GOBIERNO DE ARAGON

GEOFOREST-IUCA

Research areas in the 90s: Forest management / Erosion processes / Vegetation dynamic / Landscape dynamic-analysis / LU-LC digital classification

Present research areas, methods and techniques

- Forest fires
  - Fire risk modeling
    - Fire ocurrence ....Spatial statistics / Point pattern analysis – GIS – Model.
    - Fuel moisture content ....Field work – Mspect – GIS – Model.
    - Fuel mapping .... Field work – MSpect / SpectRad / SAR / LiDAR – GIS – Model.
    - Human fire risk ....Machine learning / GWR – GIS – Model.
    - Ecologic vulnerability ....Map algebra / Inductive models – GIS – Model.
  - Post-fire environmental dynamic monitoring and modelling
    - Fire severity .... Field work – MSpect / SpectRad / SAR / LiDAR
    - Vegetation recovery ... Field (Exp.) work – FDARE – MSpect / SpectRad / SAR/LiDAR – Model.
    - Hydro-geomorpho-edaphic processes
      - Soil disturbances ...Field (Exp.) work – FDARE / SpectRad
      - Erosion predictive models .... Field work – MSpect – GIS – Model.
- Enviornmental variables cartography and modelling
  - Measuring of vegetation parameters
    - Biomass estimation........................ Field work – MSpect / SAR / LiDAR – GIS – Model.
    - Dasometry (forest measurements) .... Field work – MSpect / SAR / LiDAR – GIS – Model.
    - Biophysical parameters of mediterranean vegetation .... Field work – MSpect / HypSpect / Thermal – GIS
  - Geo-hazards and Geo-resources mapping.. Field work – Ortoph / MSpect – GIS / 3D – Model.
  - Landscape mapping and diagnosis .... Field work – Ortoph – GIS / 3D – Model.
  - Species distribution pattern ....Mspect – GIS – Model.

Seguimiento y evaluación de espacios forestales:
SERGISAT y aplicaciones LiDAR-PNOA

SERGISAT

SEVERIDAD Y REGENERACION EN GRANDES INCENDIOS FORESTALES MEDIANTE TELEDETECCION Y S.I.G.

SERGISAT

DATOS BÁSICOS DEL PROYECTO

TITULO: SEVERIDAD Y REGENERACION EN GRANDES INCENDIOS FORESTALES MEDIANTE TELEDETECCION Y S.I.G. (SERGISAT)

Referencia: CGL2014-57013-C2

Organismo/Centro: Departamento de Geología, Geografía y Medio Ambiente. Universidad de Alcalá; Departamento de Geografía y Ordenación del Territorio, Universidad de Zaragoza

Modalidad: B **Individual / Coordinado:** Coordinado

IP1/2 (SP1): Emilio Chuvieco Salinero / Inmaculada Aguado Suárez

IP1 (SP2): Juan de la Riva.

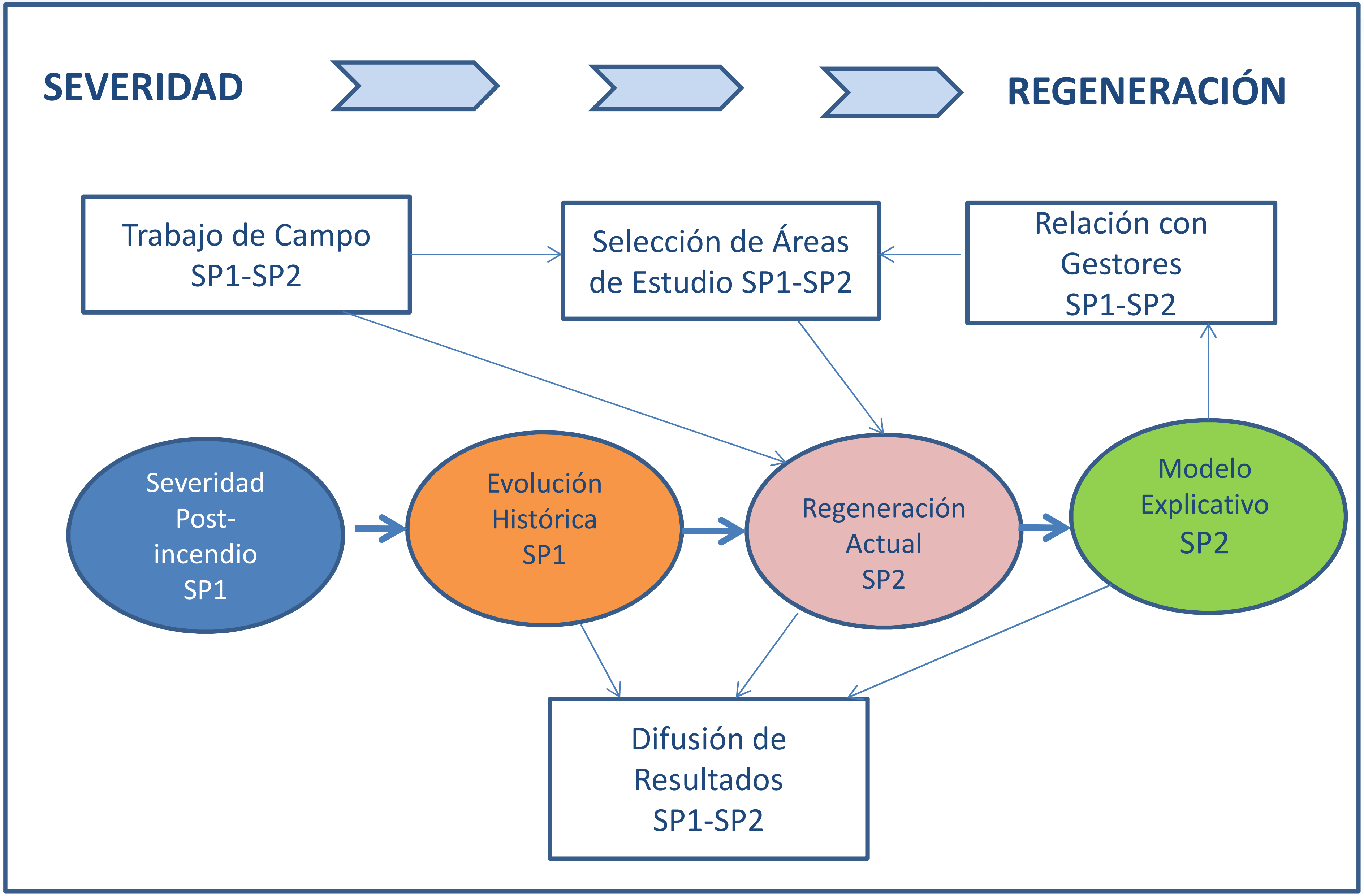
SERGISAT

• MOTIVACIÓN, HIPÓTESIS Y ESTRATEGIA DEL PROYECTO

MOTIVACIÓN CIENTÍFICA:
Mejorar la estimación de los daños causados por grandes incendios forestales, analizando los procesos de regeneración post-fuego en función de los distintos escenarios de severidad.

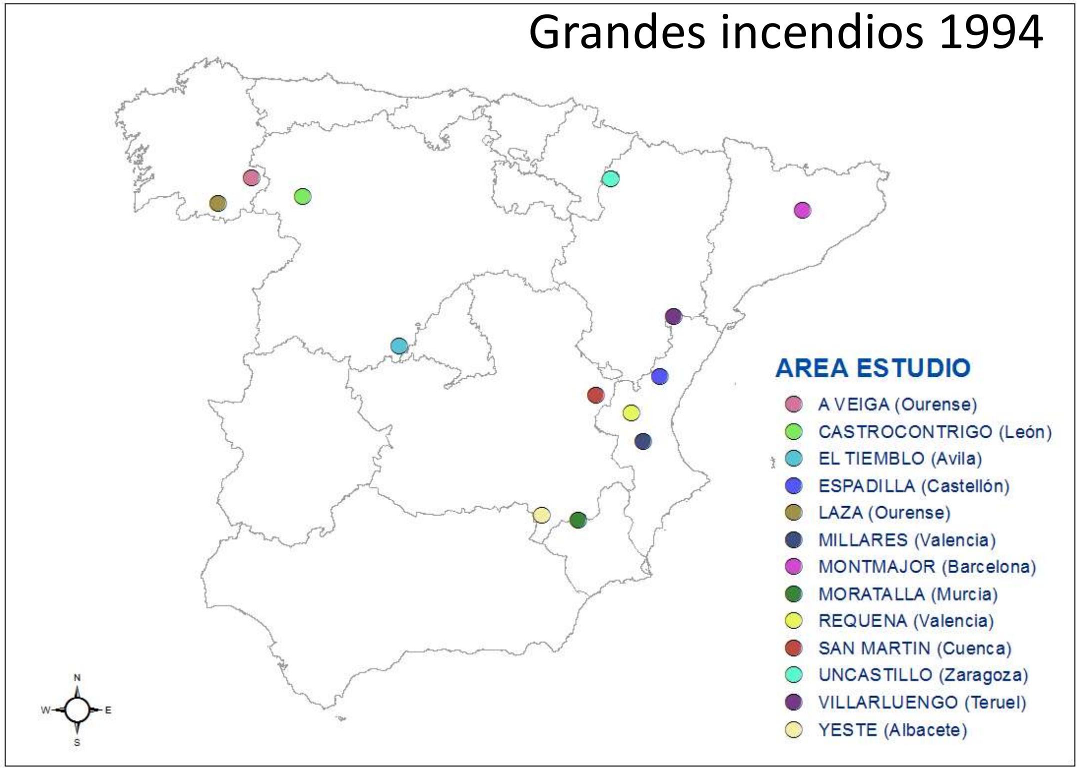
HIPÓTESIS DE PARTIDA:
La severidad del fuego afecta a la regeneración de la zona afectada. Por tanto, podemos estimar la regeneración en una superficie quemada a partir de su severidad.

SERGISAT

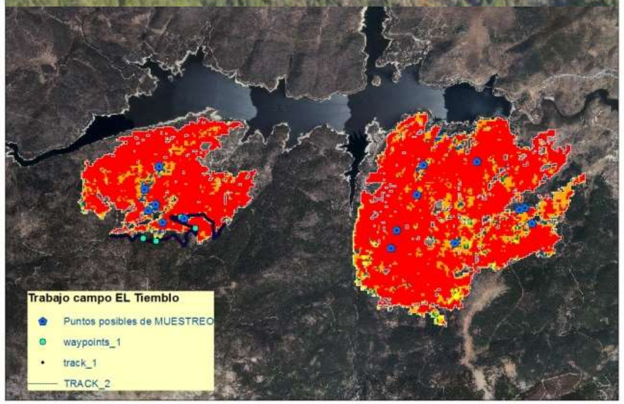

SEVERIDAD
REGENERACIÓN
Trabajo de Campo SP1-SP2
Selección de Áreas de Estudio SP1-SP2
Relación con Gestores SP1-SP2
Severidad Post-incendio SP1
Evolución Histórica SP1
Regeneración Actual SP2
Modelo Explicativo SP2
Difusión de Resultados SP1-SP2

SERGISAT

SELECCIÓN DE LAS ÁREAS DE ESTUDIO



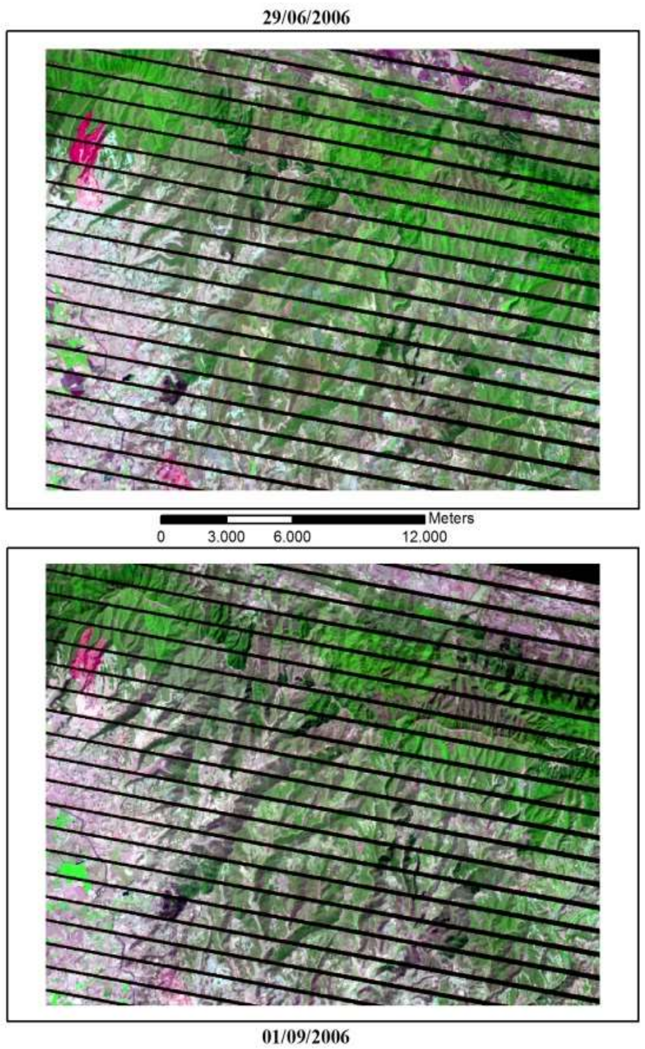
- >500 ha
- Distintos ambientes geográficos



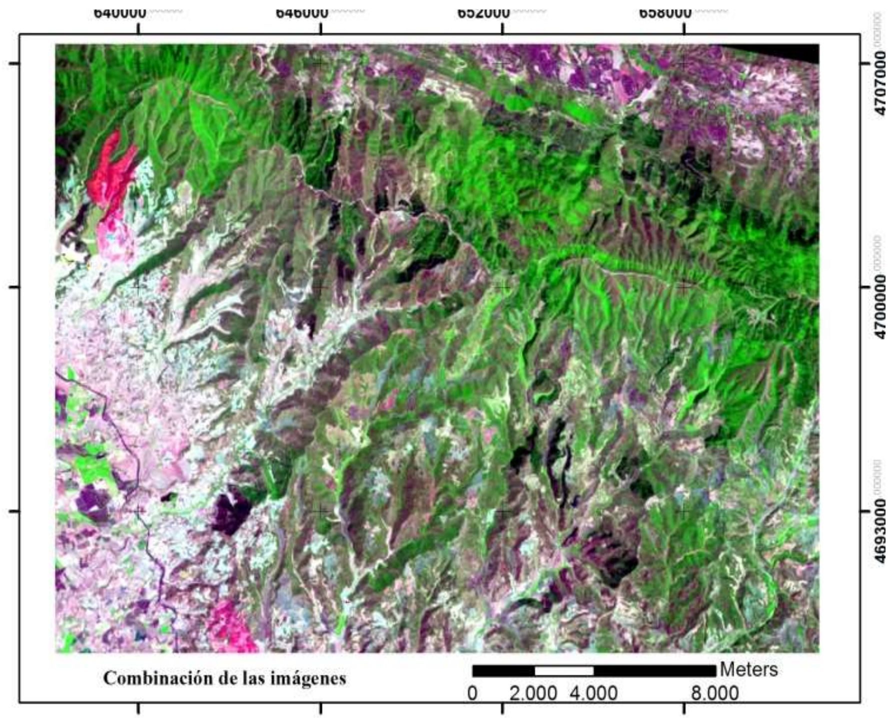
Incendio de
“El Tiemblo” (Ávila)

SERGISAT

Cartografía de los niveles de severidad en grandes incendios.



Preprocesado de las imágenes Landsat-TM
(Incendio de “Uncastillo”)
Se han procesado en total mas de 450 imágenes

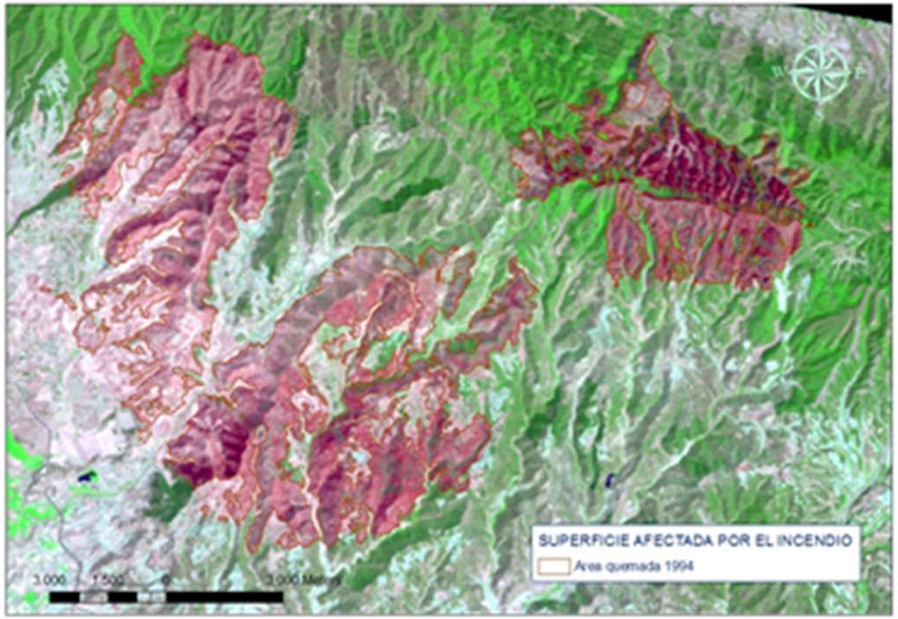


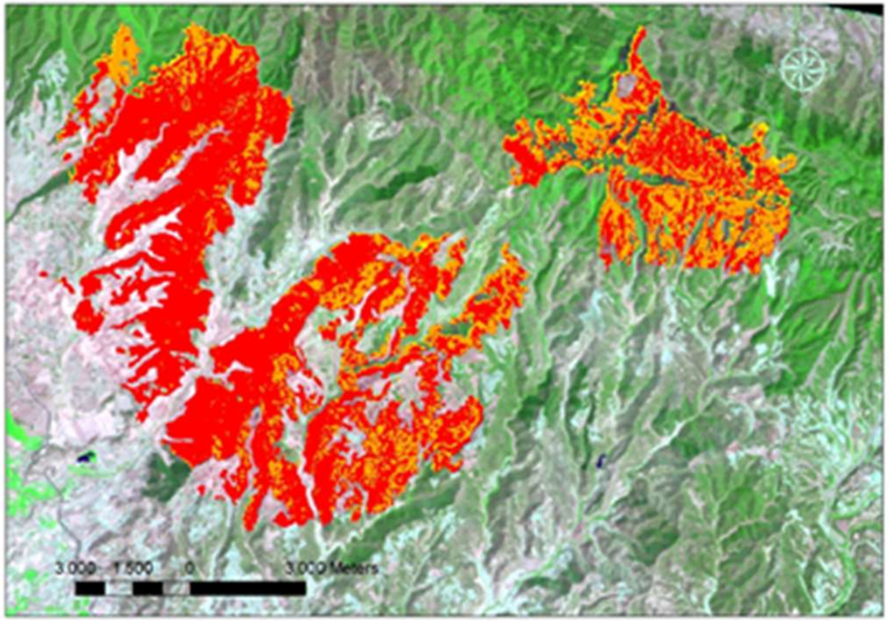
Sist. Coordenadas: WGS84 UTM Zone 30N
Composición RGB: 732

Fuente: USGS GloVis

SERGISAT

Cartografía de los niveles de severidad en grandes incendios.



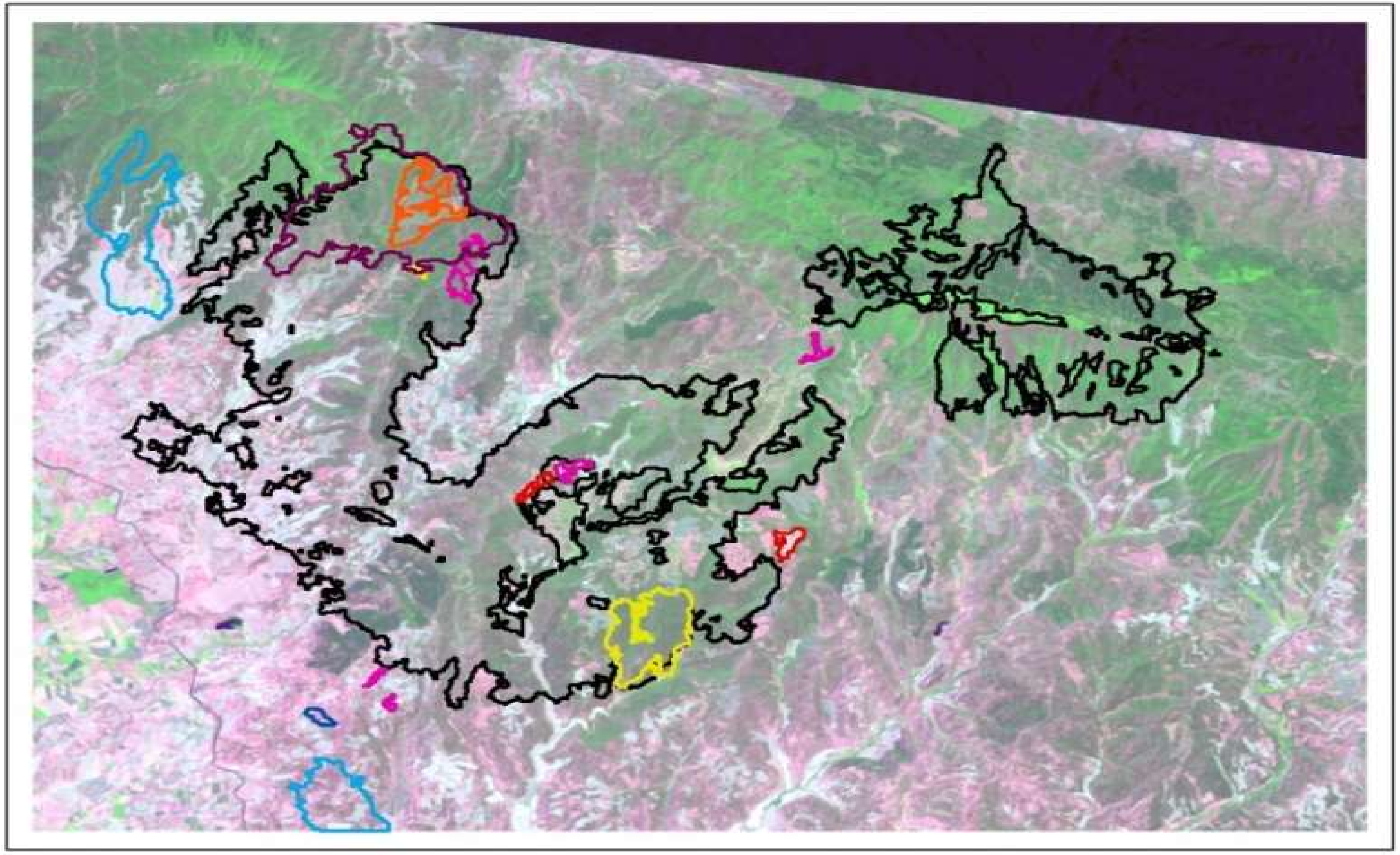


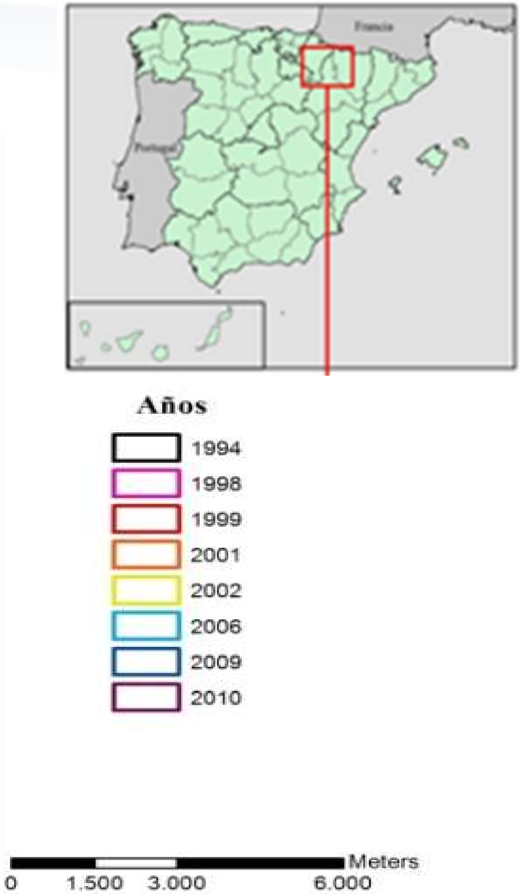
Generado a partir de modelos de transferencia radiativa desde imágenes Landsat-TM (Incendio de “Uncastillo”)

Todos los incendios están disponibles en http://www.sergisat.es/

SERGISAT

Recurrencia del fuego en grandes incendios.



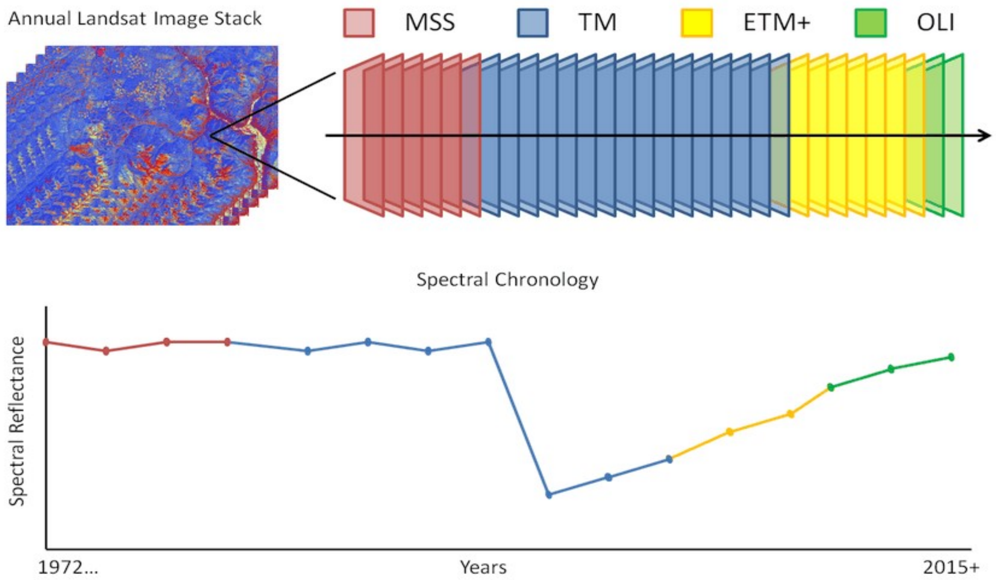


Incendio de Uncastillo

SERGISAT

Reconstruir la evolución post-incendio en grandes incendios

Generado a partir de series temporales de imágenes con LandTrendr

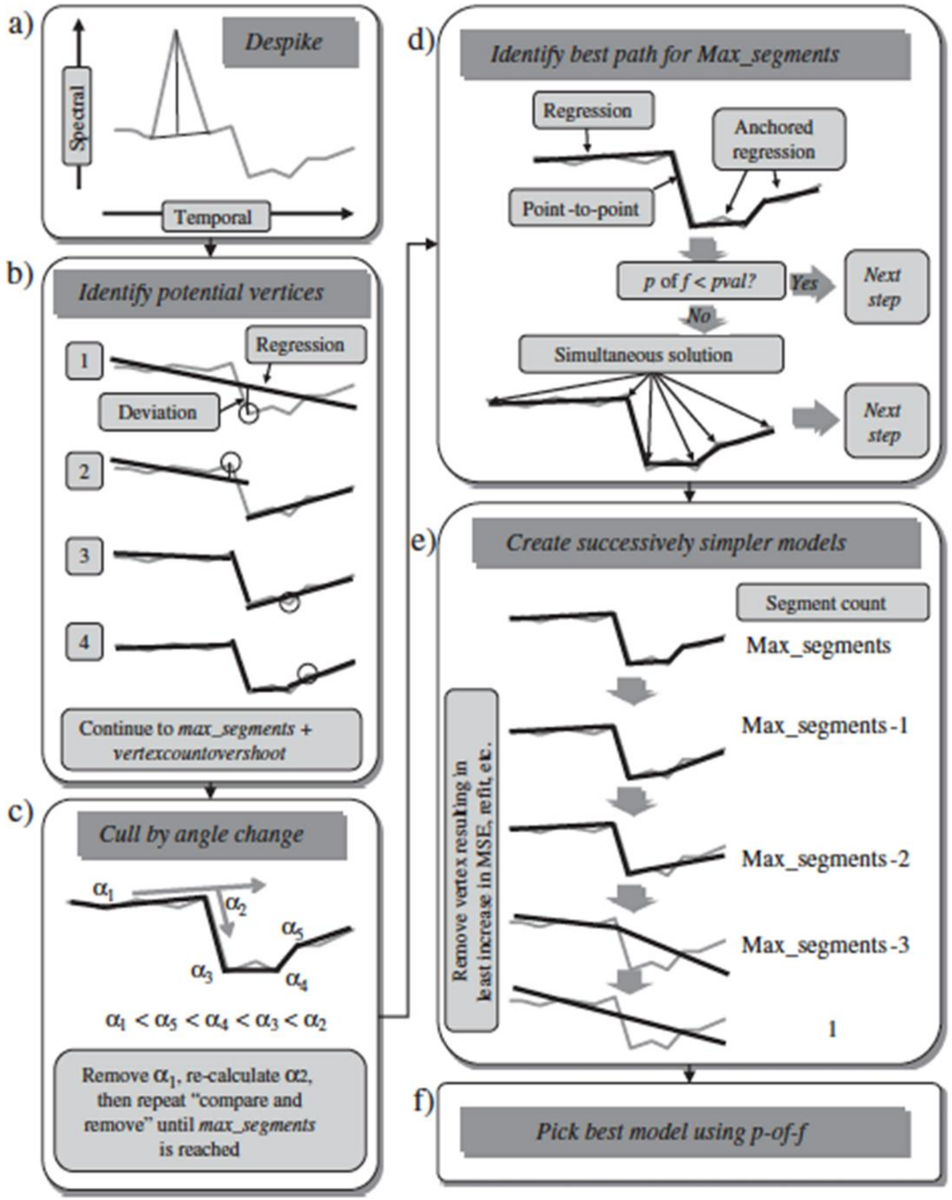


Representación conceptual de LandsatLinkr: stack de imágenes y perfil espectral a lo largo de la serie multitemporal.
Fuente: http://landsatlinkr.jdbcode.com/guide.html

1. Descompresión de las imágenes.
2. Reprojección.
3. Generación de composiciones de bandas.
4. Creación de máscaras de nubes.
5. Mejora de la geolocalización de las imágenes MSS.
6. Aplicaciones de corrección atmosférica (si es necesario).
7. Calibración espectral de las imágenes MSS a las imágenes TM.
8. Calibración espectral de las imágenes OLI a las imágenes ETM+.
9. Creación de composiciones anuales de bandas libres de nubes.

SERGISAT

Proceso de segmentación en LandTrendr

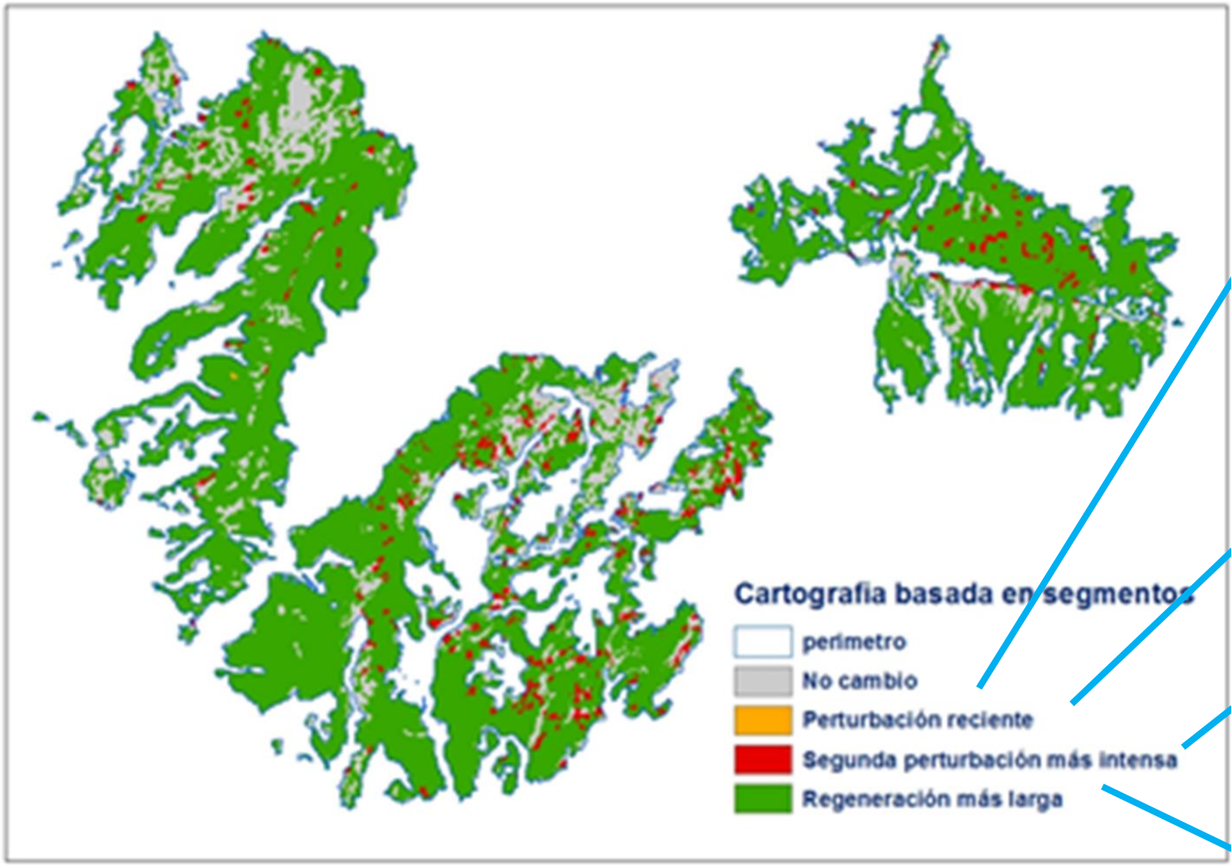


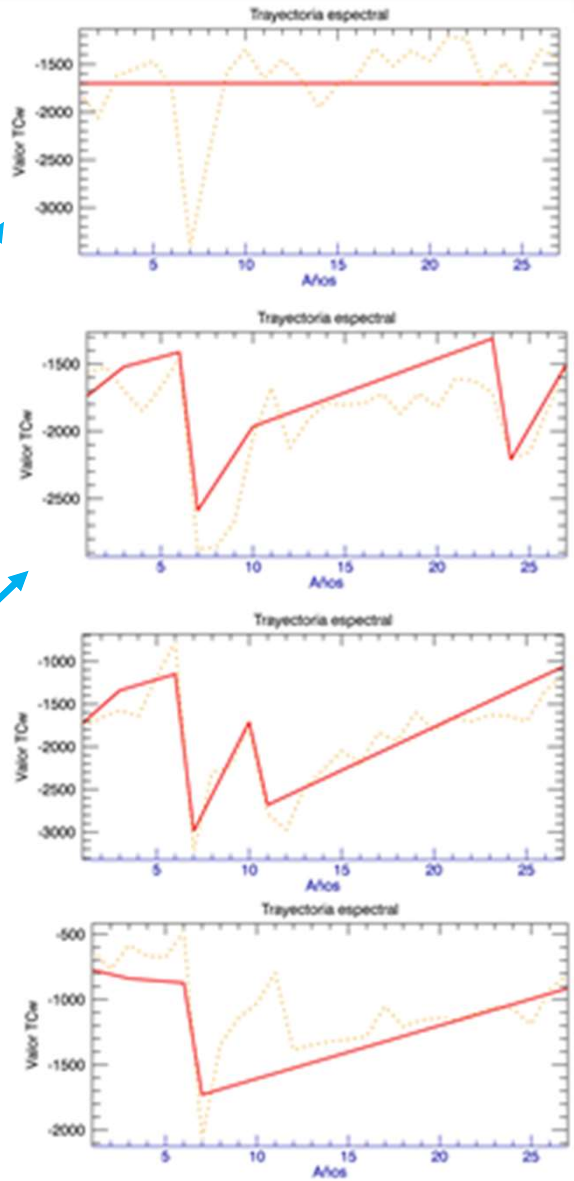
a) Eliminación de picos.
b) Identificación de vértices en la serie multitemporal.
c) Extracción de vértices extraños.
d) Identificación de la mejor línea de tendencia entre los vértices.
e) Simplificación de la serie multitemporal.
f) Selección del mejor modelo utilizando estadísticas de ajuste simple.

SERGISAT

Reconstruir la evolución post-incendio en grandes incendios

Generado a partir de series temporales de imágenes con LandTrendr

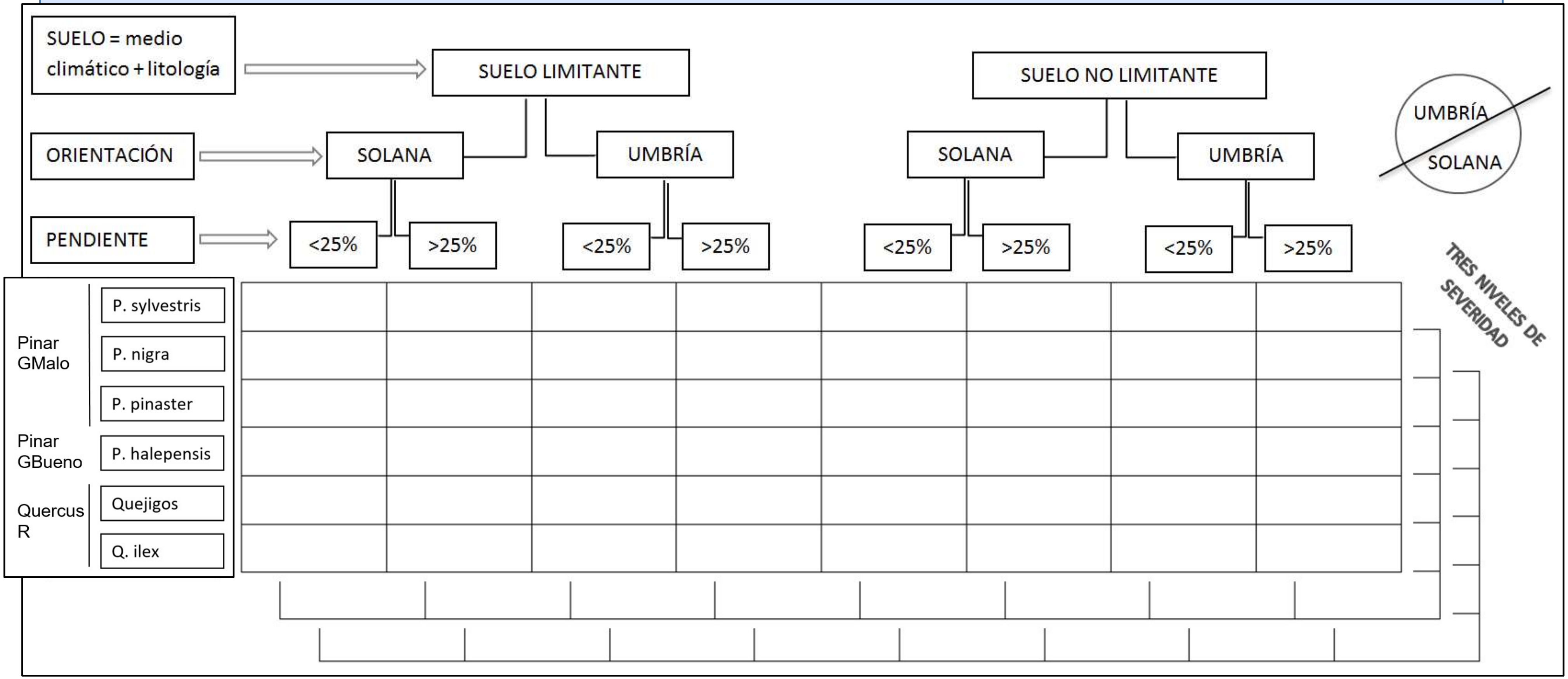




Landsat-TM (Incendio de "Uncastillo")

SERGISAT

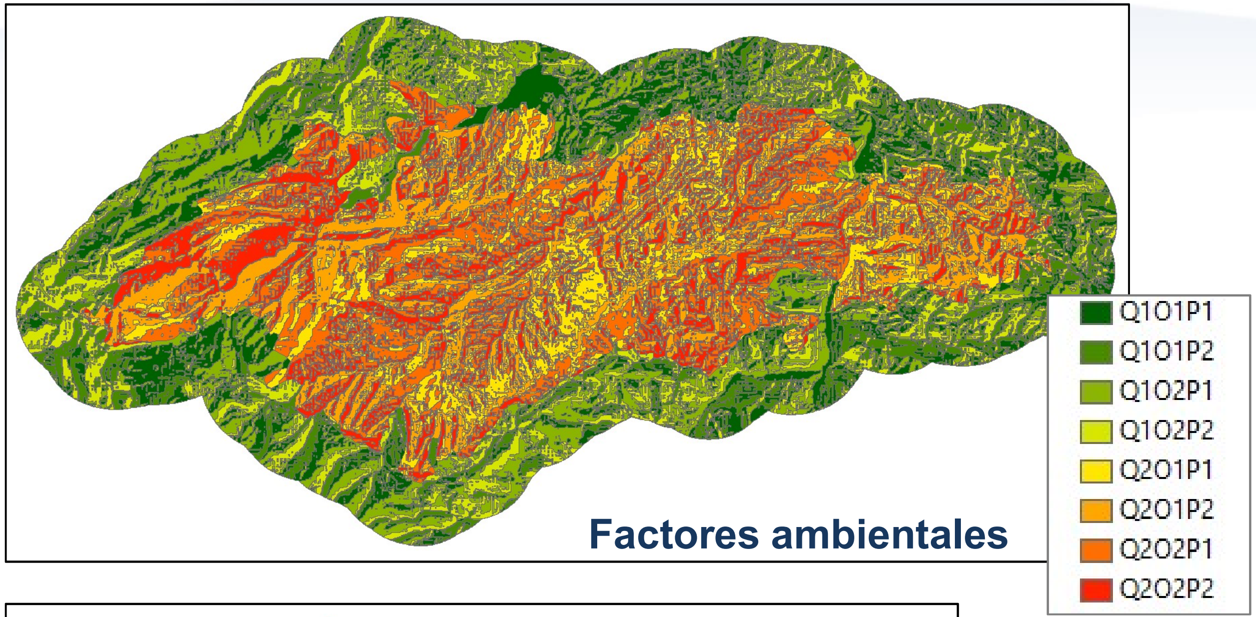
Factores ambientales para el modelado de la regeneración



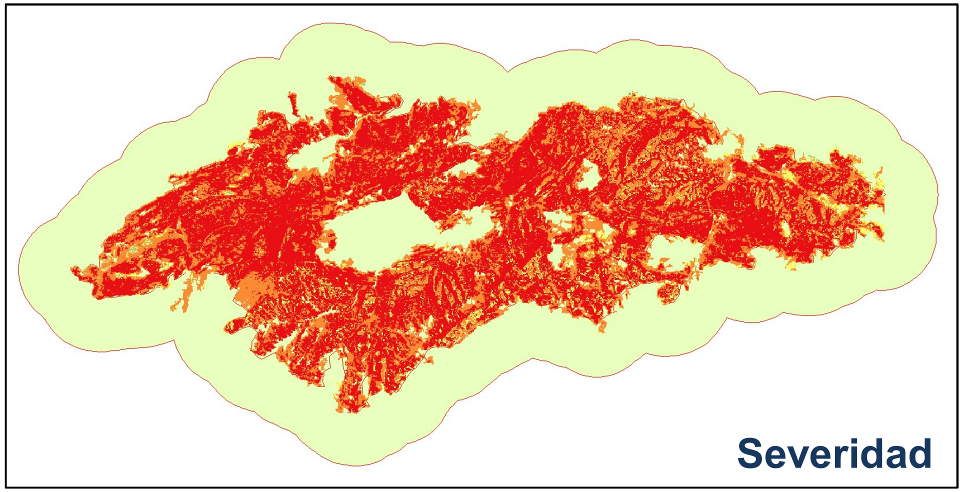
SERGISAT

Análisis exploratorio… factores ambientales – severidad – especie – estrategia reproductiva

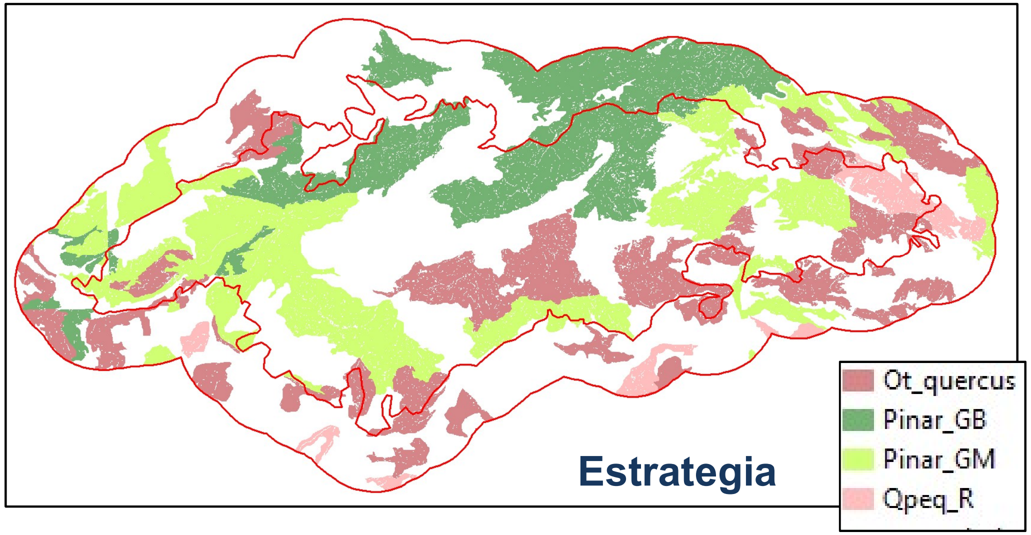
Incendio de Villarluengo



Factores ambientales

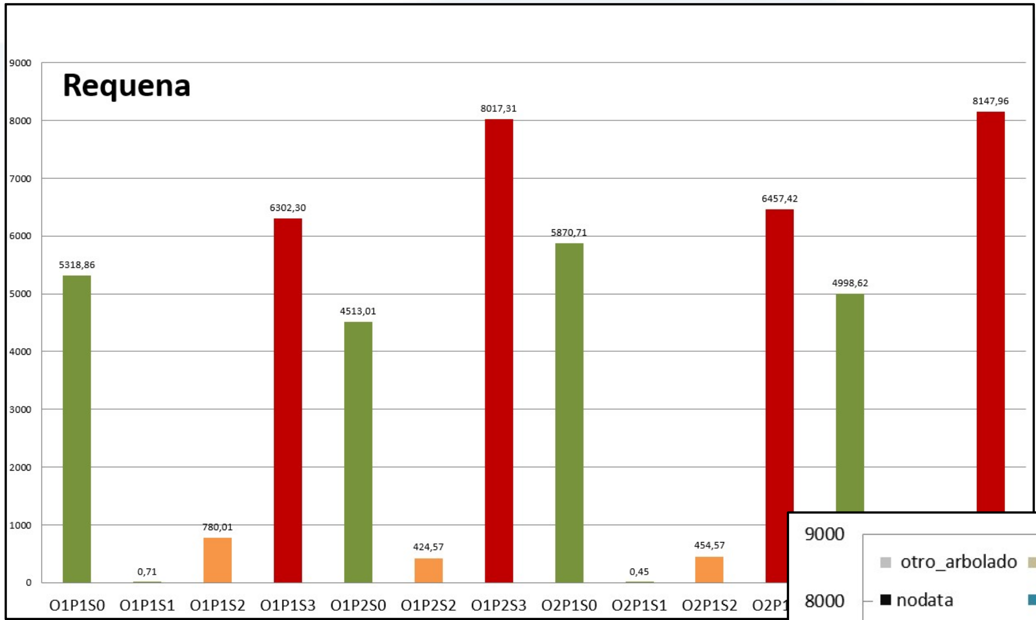


Severidad

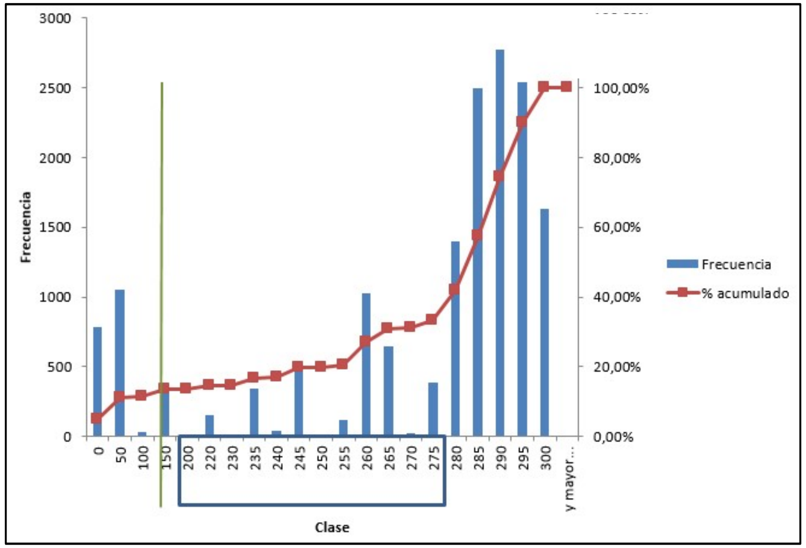


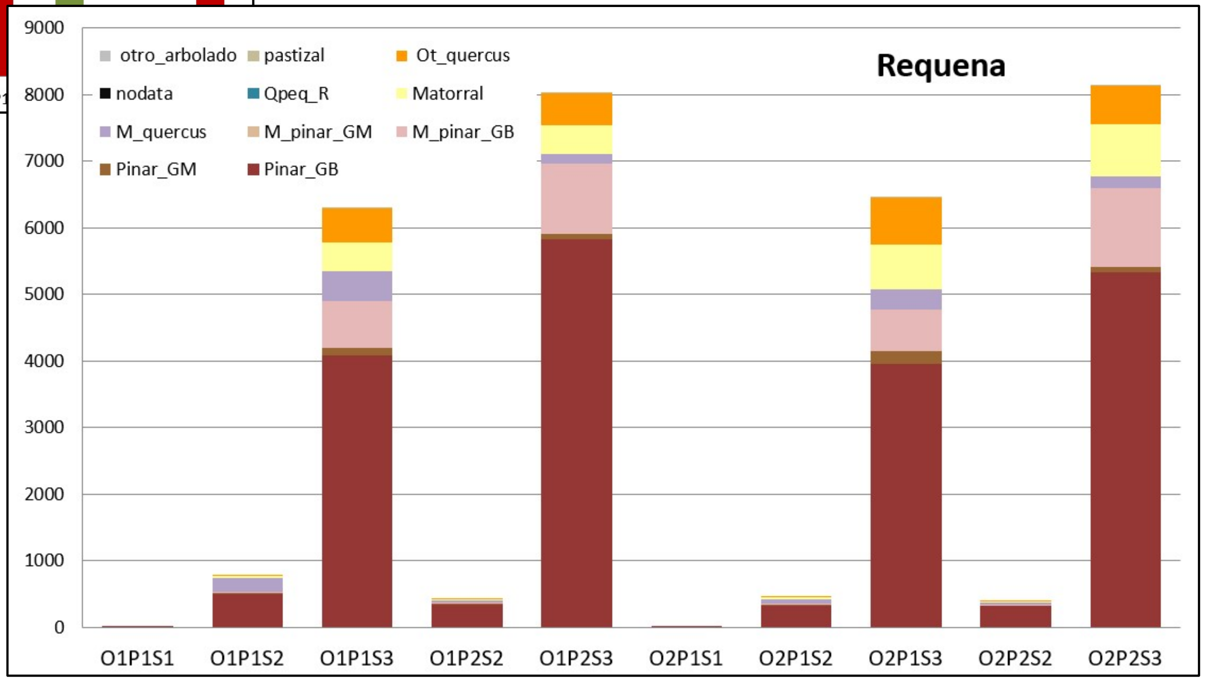
Estrategia

SERGISAT



Análisis exploratorio… factores ambientales – severidad – especie – estrategia reproductiva





SERGISAT

		Pinar_GB	Pinar_GM	Quejigos_R	Encina-carrasca_R
CONDICIONANTE CLIMA-SUELO BAJO	L1O1P1S1		_5_ (PS-PP)		
	L1O1P1S2		_5_ (PS-PP)		
	L1O1P1S3		_5_ (PS-PP) - _2_ (PP) - _1_ (PS) - _3_ (PP)		
	L1O1P2S1		_5_ (PS-PP)		
	L1O1P2S2		_5_ (PS-PP) - _3_ (PP)		
	L1O1P2S3		_5_ (PS-PP) - _2_ (PP) - _1_ (PS) - _3_ (PP)	_1_	_1_
	L1O2P1S1		_5_ (PS-PP)		
	L1O2P1S2		_5_ (PS-PP)		
	L1O2P1S3		_5_ (PS-PP) - _2_ (PP) - _1_ (PS) - _3_ (PP)		_1_
	L1O2P2S1				
	L1O2P2S2		_5_ (PS-PP)		
	L1O2P2S3		_5_ (PS-PP) - _2_ (PP) - _1_ (PS) - _3_ (PP)		_1_
CONDICIONANTE CLIMA-SUELO ALTO	L2O1P1S1		_7_ (PN)		
	L2O1P1S2	_9_		_11_	
	L2O1P1S3	_13_ - _11_ - _9_ - _8_ - _6_ - _4_ - _12_ - _10_	_13_ (PP-PN) - _11_ (PN) - _9_ (PP) - _4_ (PP) - _12_ (PN) - _10_ (PP-PN) - _7_ (PN)	_11_ - _12_ - _7_	_13_ - _11_ - _9_ - _4_ - _12_ - _10_ - _7_
	L2O1P2S1		_7_ (PN)		
	L2O1P2S2	_9_	_11_ (PN)	_11_	
	L2O1P2S3	_13_ - _11_ - _9_ - _8_ - _6_ - _4_ - _12_ - _10_	_13_ (PP-PN) - _11_ (PN) - _9_ (PP) - _4_ (PP) - _12_ (PN) - _10_ (PP-PN) - _7_ (PN)	_11_ - _12_ - _7_	_13_ - _11_ - _9_ - _4_ - _12_ - _7_
	L2O2P1S1		_7_ (PN)		
	L2O2P1S2	_9_	_13_ (PP-PN)		
	L2O2P1S3	_13_ - _11_ - _9_ - _8_ - _6_ - _4_ - _12_ - _10_	_10_ (PP-PN) - _13_ (PP-PN) - _11_ (PN) - _9_ (PP) - _4_ (PP) - _12_ (PN) - _7_ (PN)	_12_ - _7_	_13_ - _11_ - _9_ - _4_ - _12_ - _10_ - _7_
	L2O2P2S1		_7_ (PN)		
	L2O2P2S2	_9_		_11_	
	L2O2P2S3	_13_ - _11_ - _9_ - _8_ - _6_ - _4_ - _12_ - _10_	_13_ (PP-PN) - _11_ (PN) - _9_ (PP) - _4_ (PP) - _12_ (PN) - _10_ (PP-PN) - _7_ (PN)	_11_ - _12_ - _7_	_13_ - _11_ - _9_ - _4_ - _12_ - _7_

Combinaciones resultantes:

- **Pinar germinador bueno – P. halep**
- **Pinar germinador malo – P. sylvestris – P. nigra – P. pinaster**
- **Quercíneas rebrotadoras – Quejigos – Q. ilex**

SERGISAT

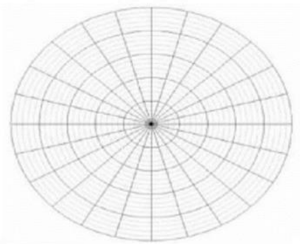
Incendio:		Autores:		Fecha:
Nº parcela:		Nº Fotos:		Hora inicio:
Coordenadas:				Hora fin:

Estrato	FCC %
5 Arbóreo > 5 m:	
4 Arborescente 3-5 m:	
3 Arbustivo 1-3 m:	
2 Subarbustivo <1m:	
1 Herbáceo:	
Pedregosidad:	

Modelo de combustible

Prometheus:	
Rothermel:	

Prof. Horizonte 0:	
Prof. horizonte A:	
Nº muestras suelo:	



Estrato	Especie	Abundancia dominancia por especie

Datos generales de la parcela

Tipo de erosión	Intensidad: Alta (A), Media(M), Baja(B)	% sup. en 1/4 de parcela (<1; 1- 5; 5-10; > 10-25; > 25)
Rills		
Laminar		
Enlosado		
Pedestales		
Mov. Masa		

Estado general del arbolado/vegetación

Daños (Viento, hongos, perforadores, defoliadores, muérdago...)	Nivel (0: Sin daños, 1: <25% pies, 2: 25-50% p., 3: 50-75% p., 4:>75% p.)	Especies afectadas

Observaciones:

Diagnóstico de regeneración:

- **biodiversidad**
- **estructura vertical de la vegetación y biomasa contenida**
- **grado de cobertura**

Incendio:	Autores:	Nº parcela:

Datos de inventario

	Especie/ Forma	ØM (cm)	Øm (cm)	H (m)	H 1ª rama v. (m)		Especie/ Forma	ØM (cm)	Øm (cm)	H (m)	H 1ª rama v. (m)
1						36					
2						37					
3						38					
4						39					
5						40					
6						41					
7						42					
8						43					
9						44					
10						45					
11						46					

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16-17 DE OCTUBRE DE 2017

Seguimiento y evaluación de espacios forestales: SERGISAT y aplicaciones LiDAR-PNOA

LIDAR-PNOA

Aplicaciones forestales del laser escáner aeroportado (ALS)

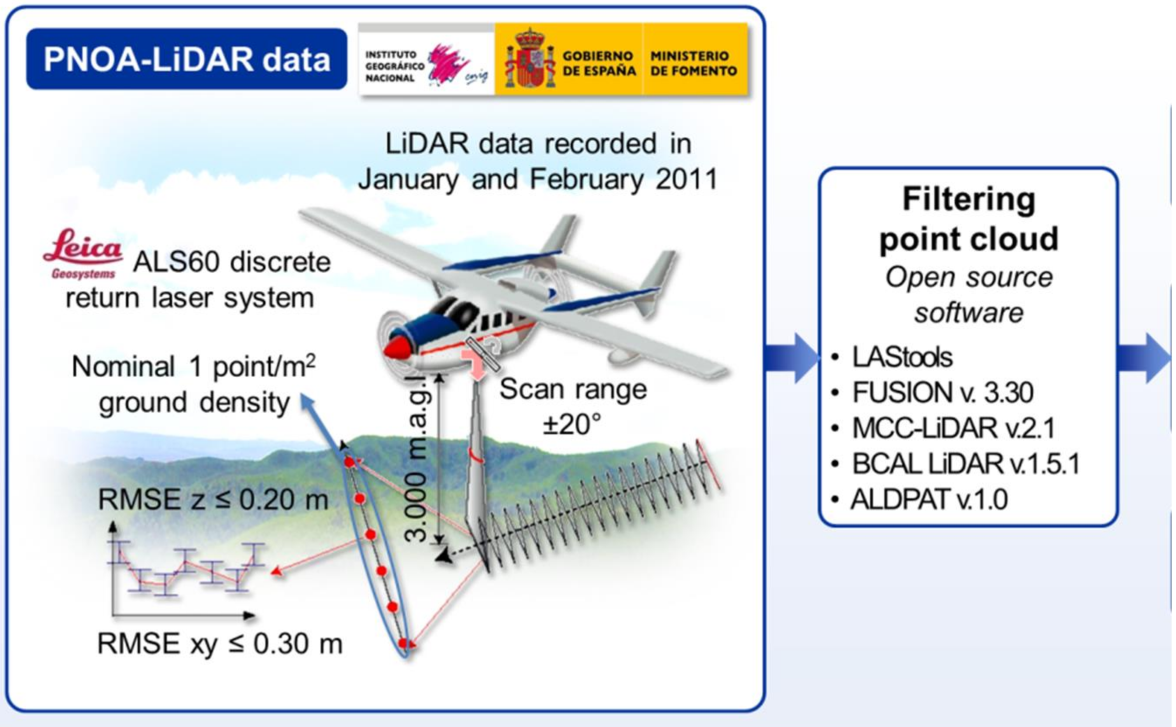
LiDAR-PNOA

Point cloud classification

4072 IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING, VOL. 8, NO. 8, AUGUST 2015

A Comparison of Open-Source LiDAR Filtering Algorithms in a Mediterranean Forest Environment

Antonio Luis Montealegre, María Teresa Lamelas, and Juan de la Riva



Instituto Universitario de Investigación en Ciencias Ambientales de Aragón Universidad Zaragoza

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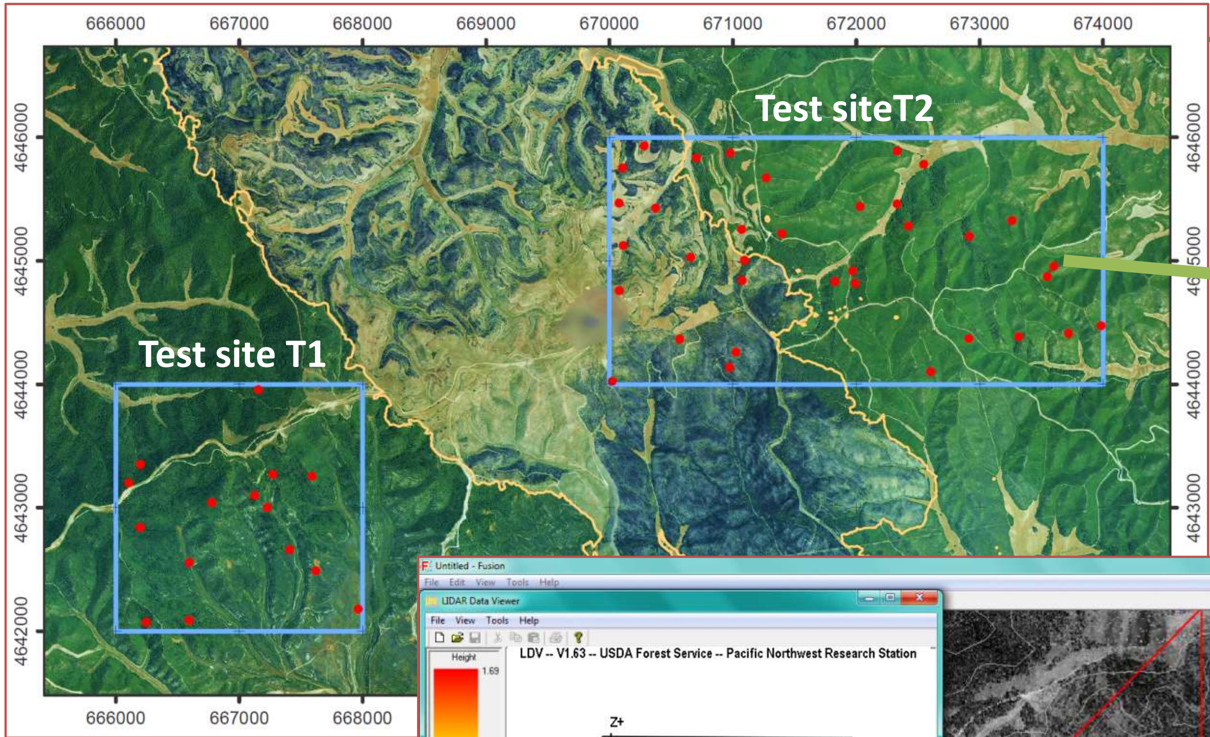
CUD Zaragoza

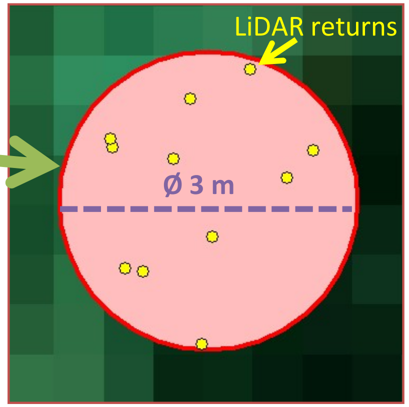
LiDAR-PNOA

Point cloud classification

1º) Random selection of 50 points in two test sites T1 y T2

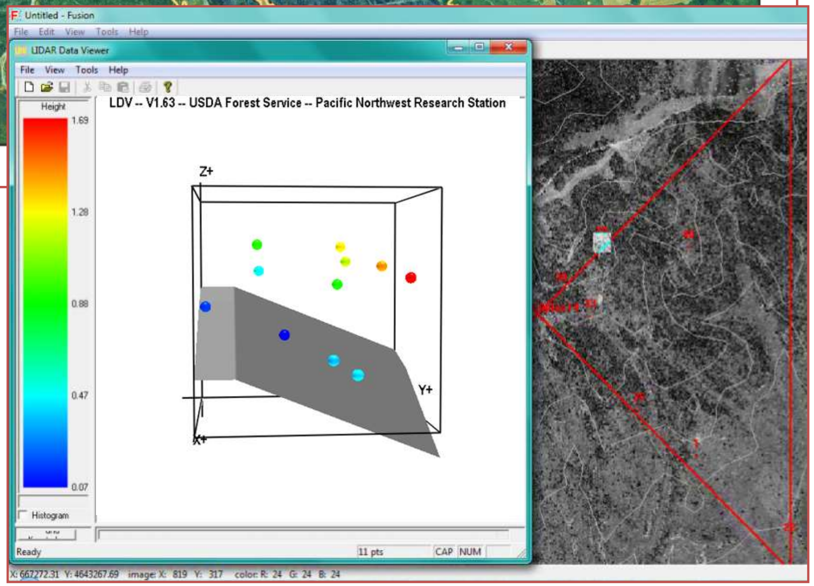


Two sample zones, T1 (2 km x 2 km) and T2 (4 km x 2 km). Topography characterized by a hilly relief, elevation ranging from 400 to 750 m.a.s.l. Forest is dominated by Aleppo pine (*Pinus halepensis* Mill.) and evergreen shrub vegetation.



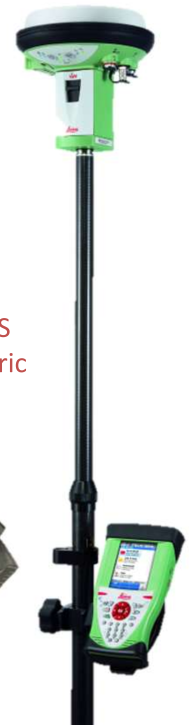
2º) 50 Plots Ø 3 m
424 LiDAR returns:
185 in T1 y
239 in T2

3º) Manual classification supported by 3D visor, Ortophoto, LiDAR intensity image …



4º) Field work to help manual classification of returns

GPS-GNSS centimetric precision



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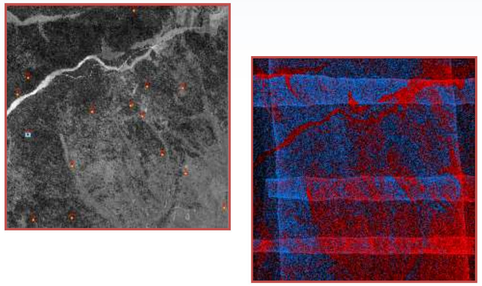
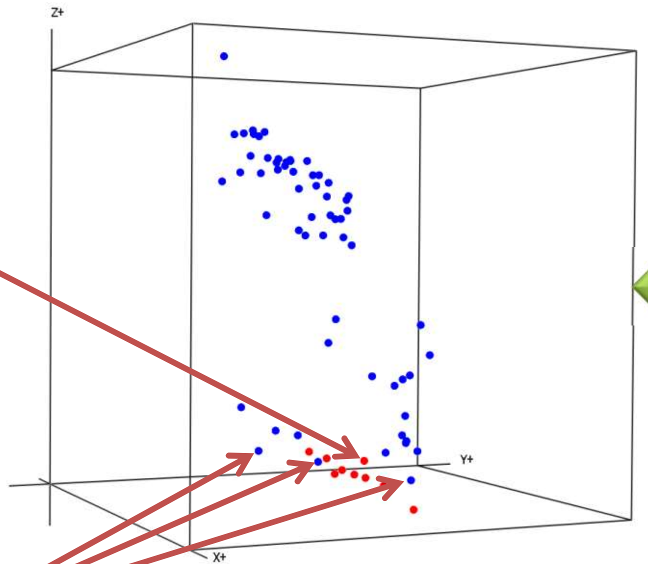
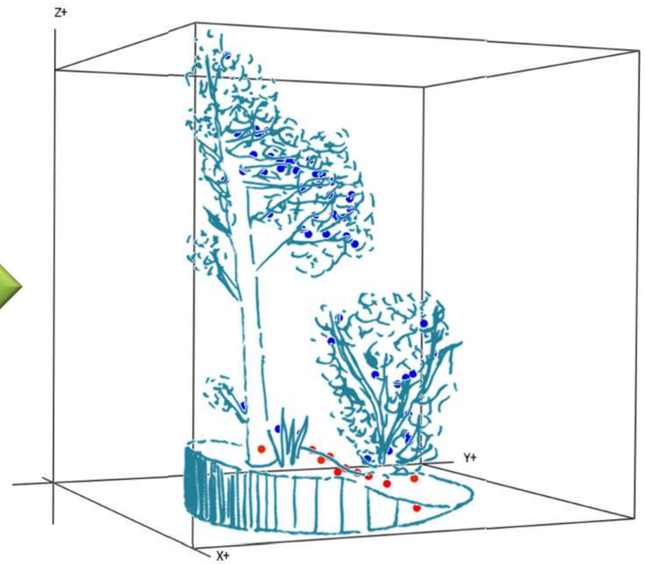
Point cloud classification



Cluster of points automatically classified



Cluster of points manually classified



Type II errors
Points classified as ground being vegetation

Type I errors
Points classified as vegetation being ground

ESTATISTICAS ASSESSMENT
Por correspondencia espacial entre puntos

IBM SPSS Statistics 20

LiDAR-PNOA

Point cloud classification

Filtering methods/tools		(%) Error Type I	(%) Error Type II	(%) Overall accuracy	Kappa index (k)
MCC	-s 1 -t 0,3	12,7	20,8	83,3	0,67
	-s 1 -t 0,4	8,0	34,0	79,0	0,58
	-s 1 -t 0,5	3,3	35,8	80,4	0,61
	-s 1,5 -t 0,3	16,5	21,2	81,1	0,62
LAS Tools	Defecto	24,1	11,8	82,1	0,64
	Fina	20,8	13,7	82,8	0,66
FUSION	w2 g-2,5 1	60,8	7,1	66,0	0,32
	w2 g-2,5 2	61,3	2,8	67,9	0,36
ALDpat	ALDpat Zhang y Whitman (2005)	35,8	31,6	66,3	0,33
	ALDpat Zhang et al. (2003)	39,6	14,6	72,9	0,46
	ALDpat Vosselman (2000)	75,0	0,0	62,5	0,25
BCAL	Inverse distance 1^{st} order	38,2	7,5	77,1	0,54
	Inverse distance 2^{nd} order	40,6	8,0	75,7	0,51
	Inverse distance 3^{rd} order	38,2	10,8	75,5	0,51
	Linear	67,5	4,7	63,9	0,28
	Natural neighbour	64,2	4,7	65,6	0,31
	Nearest neighbour	33,0	19,3	73,8	0,48
	Polinomial regresion 2^{nd} order	56,1	3,8	70,0	0,40
	Polinomial regresion 3^{rd} order	55,7	4,2	70,0	0,40

- **Best overall accuracy:** MCC -s 1 -t 0.3 (83,3%),

- **Worst overall accuracy :** Vosselman (2000) (62,5%).

- **Type I errors from** 3,3% (MCC -s 1 -t 0,5) to 75% (ALDpat Vosselman (2000)).

-**Type II errors from** 0% (ALDpat Vosselman (2000)) to 35,8% (MCC -s 1 -t 0,5).

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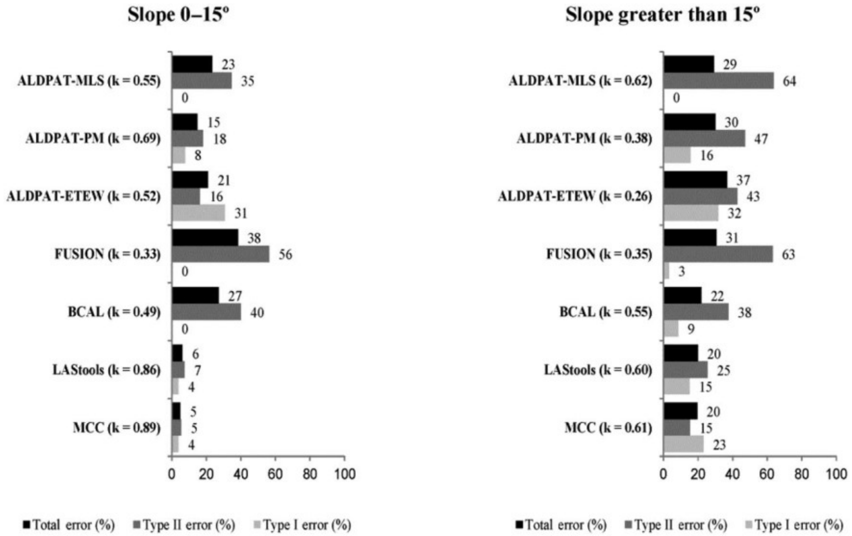
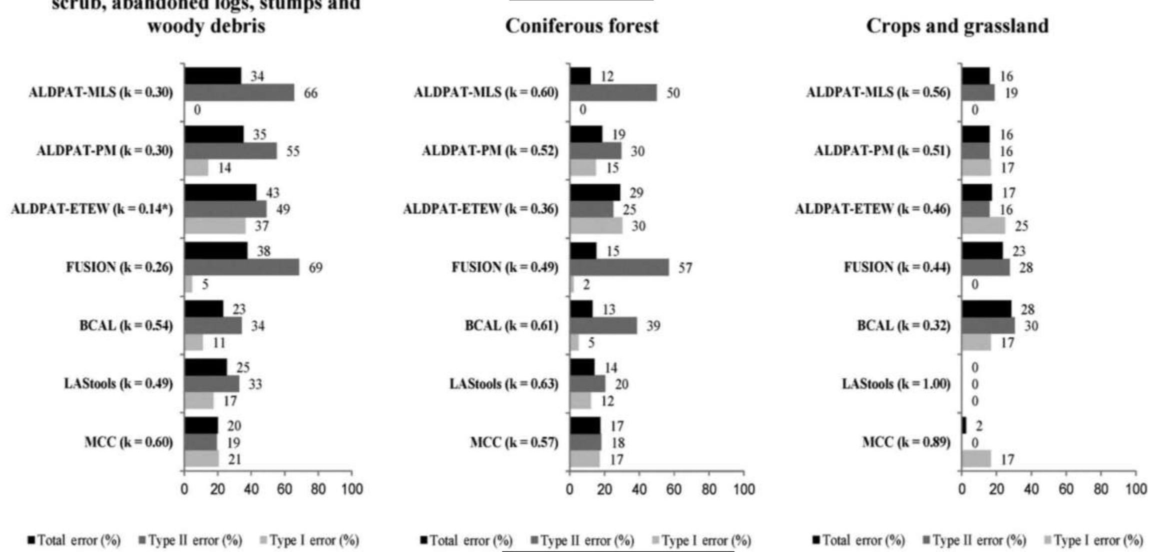
Point cloud classification

Sprouted scrub, stumps, and woody debris were the more problematic cover type in filtering, as well as terrain slopes higher than 15◦. However, less firm conclusions can be drawn from point density and scan angle variables, because morphological methods are less sensitive to these factors.

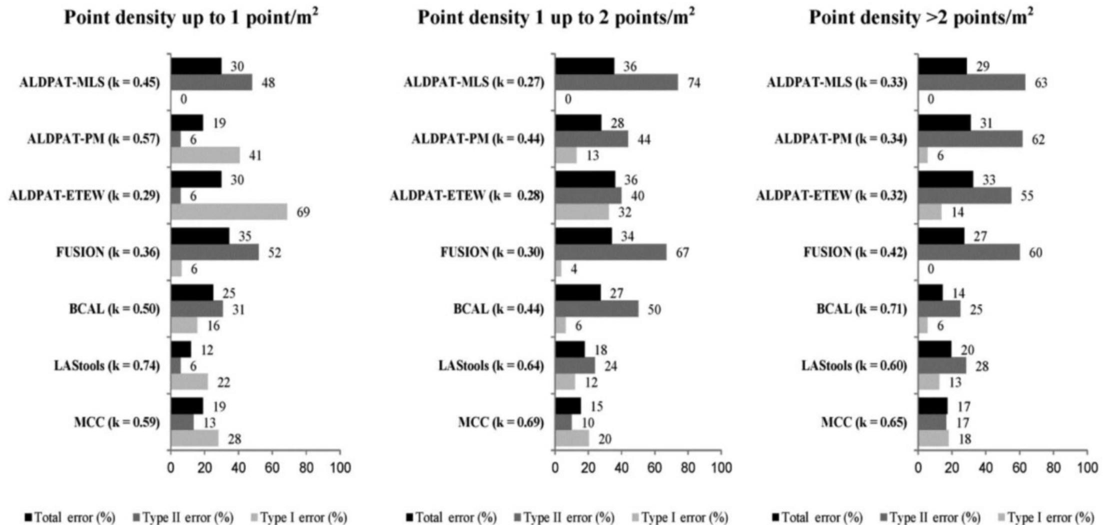
Slope



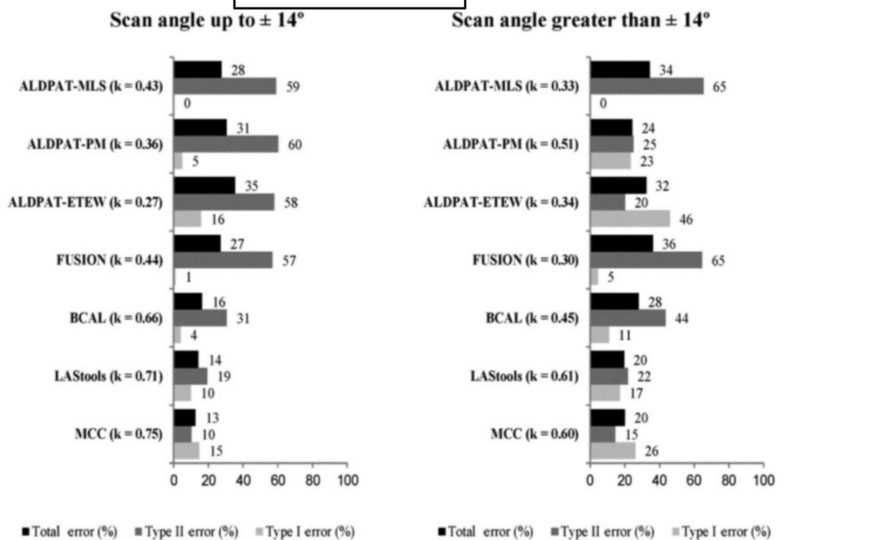
Cover



Point density



Scan angle



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Point cloud classification and interpolation routine assessment

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Article

Interpolation Routines Assessment in ALS-Derived Digital Elevation Models for Forestry Applications

Antonio Luis Montealegre [1,*], María Teresa Lamelas [1,2,†] and Juan de la Riva [1,†]

Filtering point cloud
Open source software
- LAStools
- FUSION v. 3.30
- MCC-LiDAR v.2.1
- BCAL LiDAR v.1.5.1
- ALDPAT v.1.0

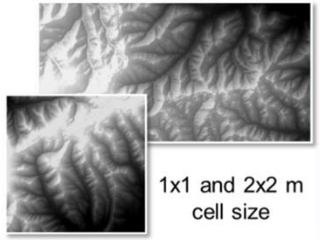
Random sampling of ground points

Training dataset (80%)

Test dataset (20%)

Interpolation of training dataset
- Natural Neighbours (NN)
- TIN to raster (TR)
- Inverse Distance Weighting (IDW)
- ANUDEM
- Ordinary Kriging (OK)
- Point to raster (PR)

LiDAR-derived DEMs



1x1 and 2x2 m cell size

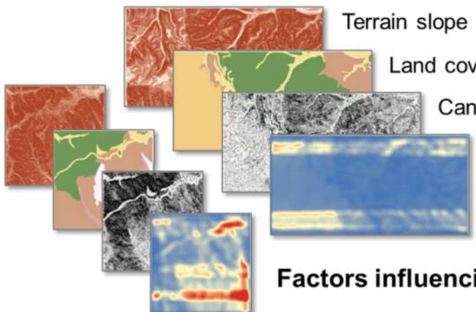
Accuracy assessment

GPS checkpoints

55 high-accuracy control points collected on foot with the Leica VIVA GS15 CS10 GNSS real-time kinematic GPS.
Vertical and horizontal accuracy of 2.38 cm and 1.32 cm, respectively.

DEM validation

For each DEM, vertical errors were calculated using this equation: $E(x,y) = P_z(x,y) - M_z(x,y)$
Where E is the error, P_z is the predicted value, and M_z is the measured value from the validation datasets at location *(x,y)*. Global statistics to quantify DEM error were computed: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).



Factors influencing DEM accuracy

Error prediction

A Classification And Regression Tree (CART) analysis was performed using IBM SPSS Statistics 20, to uncover those factors having the most influence on DEM error. These conditional rules generated by the decision tree were implemented in ArcGIS 10.1 software using map algebra to produce a categorical prediction uncertainty map.

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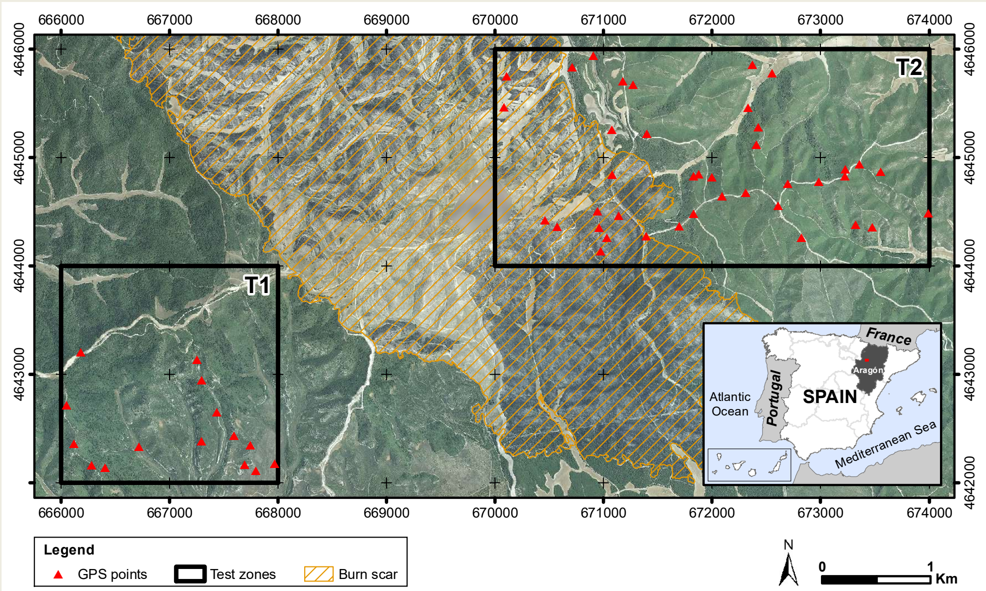

Better accuracy of DEMs created with the combination of MCC-LiDAR v.2.1 surface-based filter and TIN to raster interpolation method (RMSE of 2.68 cm) in a 1 m.

DEM validation

Interpolation method	DEM pixel (m)	DEM validation with LiDAR test dataset – Filtering method: MCC-LiDAR v.2.1	LAS tools	BCAL LiDAR v.1.5.1	ALDPAT v.1.0	FUSION v. 3.30	DEM validation with GPS checkpoints – Filtering method: MCC-LiDAR v.2.1	LAS tools	BCAL LiDAR v.1.5.1	ALDPAT v.1.0	FUSION v. 3.30
TR	1	2.68	3.69	8.04	2.99	17.69	42.80	44.02	42.10	44.18	44.26
	2	5.48	6.30	10.88	6.05	20.30	47.10	47.54	42.94	46.71	47.05
NN	1	2.95	4.02	8.53	2.99	19.41	40.40	41.58	39.09	43.93	40.85
	2	5.52	7.47	10.37	6.52	19.73	46.00	44.79	43.95	48.21	46.34
ANUDEM	1	2.99	3.75	8.05	2.83	18.62	45.40	44.30	40.44	44.83	40.67
	2	5.42	5.74	10.30	5.75	17.38	42.70	47.25	42.84	45.86	48.58
IDW	1	3.64	4.21	16.02	3.06	28.93	37.10	37.15	37.50	45.70	42.07
	2	5.74	6.05	17.18	5.87	28.38	40.60	50.44	43.09	47.35	49.90
OK	1	3.91	4.02	7.55	3.39	16.20	38.10	44.94	44.85	41.68	43.51
	2	5.25	5.86	9.34	6.00	16.61	44.10	50.29	45.34	46.01	48.79
PR	1	6.64	7.36	20.94	7.55	39.15	50.90	53.79	44.98	52.56	59.77
	2	17.67	17.70	28.20	19.91	37.25	63.00	63.77	62.67	59.31	57.28

RMSE (cm) for combinations of filtering algorithm and interpolation method for two spatial resolutions (1 and 2 m cell size) using the validation datasets.

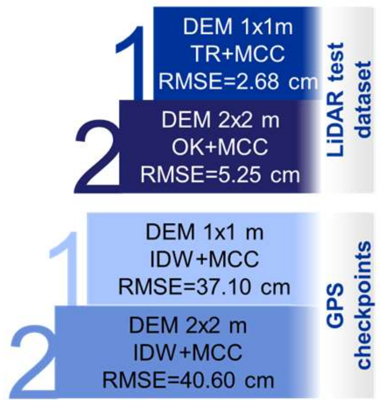

Fig.7 Ranking of the best DEMs validated.

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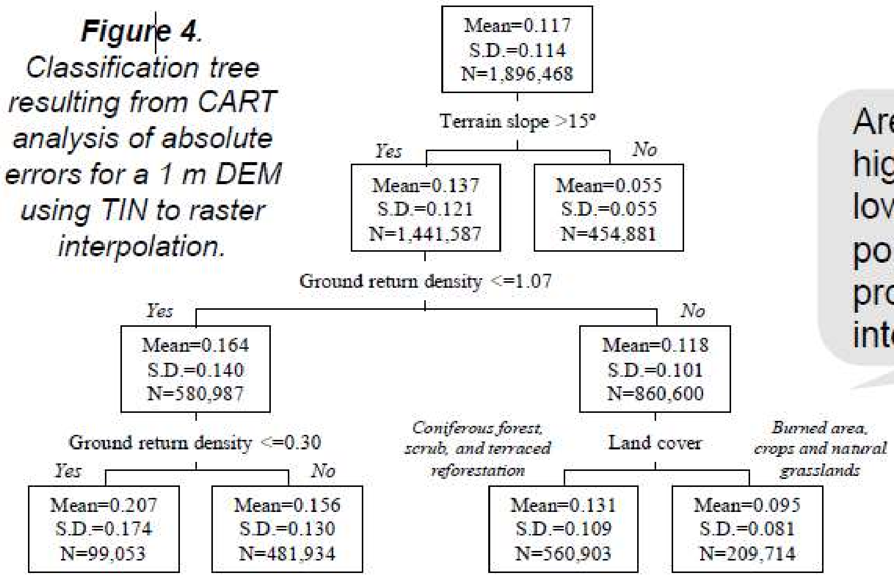
Error prediction

Figure 4. Classification tree resulting from CART analysis of absolute errors for a 1 m DEM using TIN to raster interpolation.



Areas with a combination of high slope (above 15º) and low point density (below 0.3 points/m^2) are the most prone to present high interpolation errors.

Conversely, if terrain slope is less than 15º, prediction uncertainty is very low.

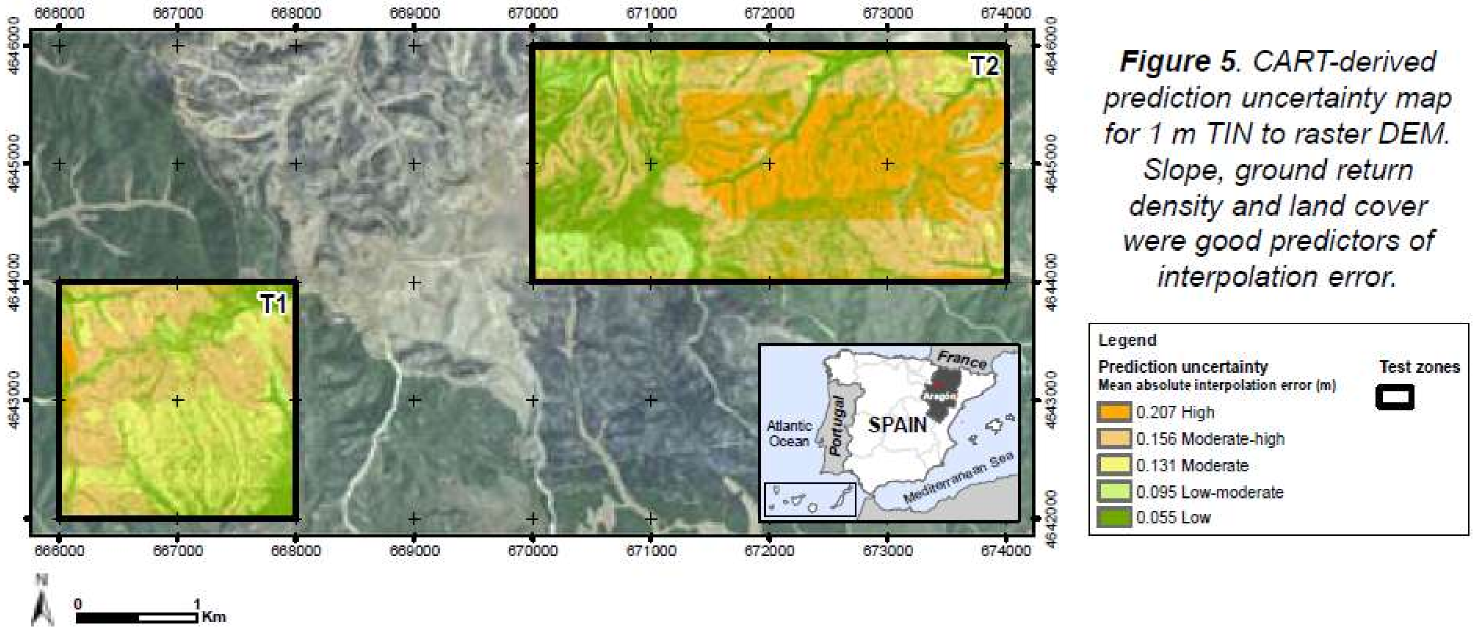
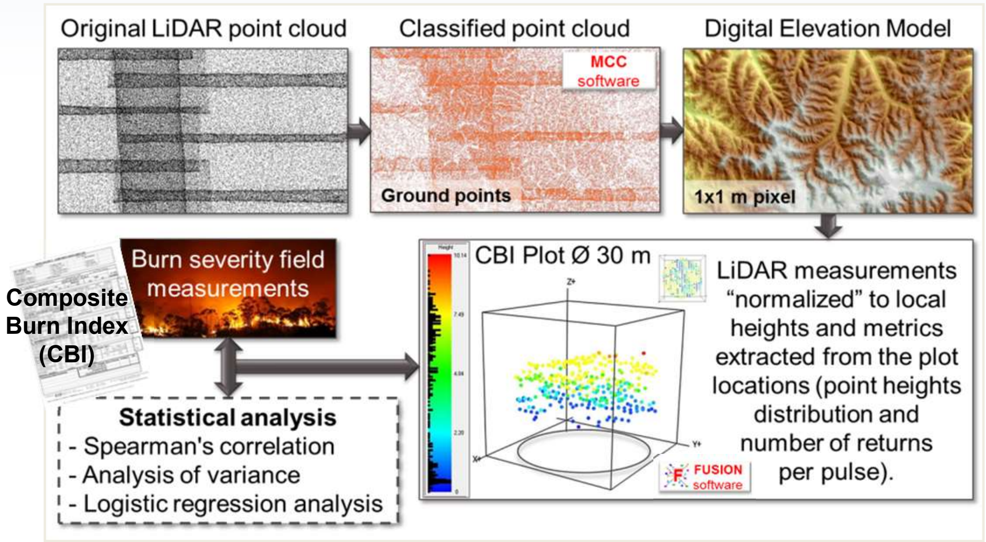


Figure 5. CART-derived prediction uncertainty map for 1 m TIN to raster DEM. Slope, ground return density and land cover were good predictors of interpolation error.

LiDAR-PNOA

Forest fire severity assessment

Methodological steps



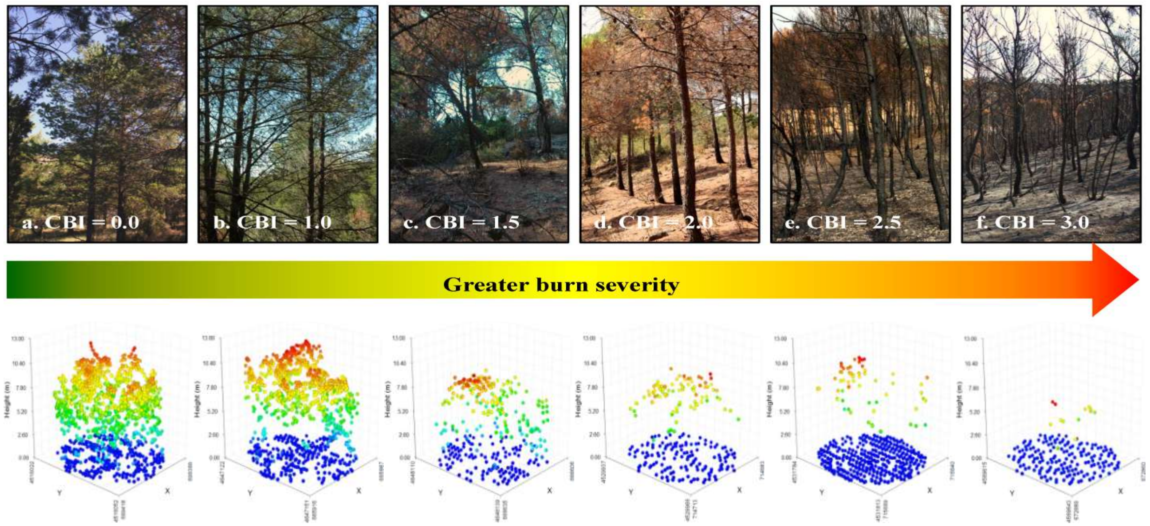


Fig. 8 ALS point clouds at plot level and their correspondence with the CBI values.

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Article

Forest Fire Severity Assessment Using ALS Data in a Mediterranean Environment

Antonio Luis Montealegre [1,*], María Teresa Lamelas [1,2], Mihai A. Tanase [3] and Juan de la Riva [1]

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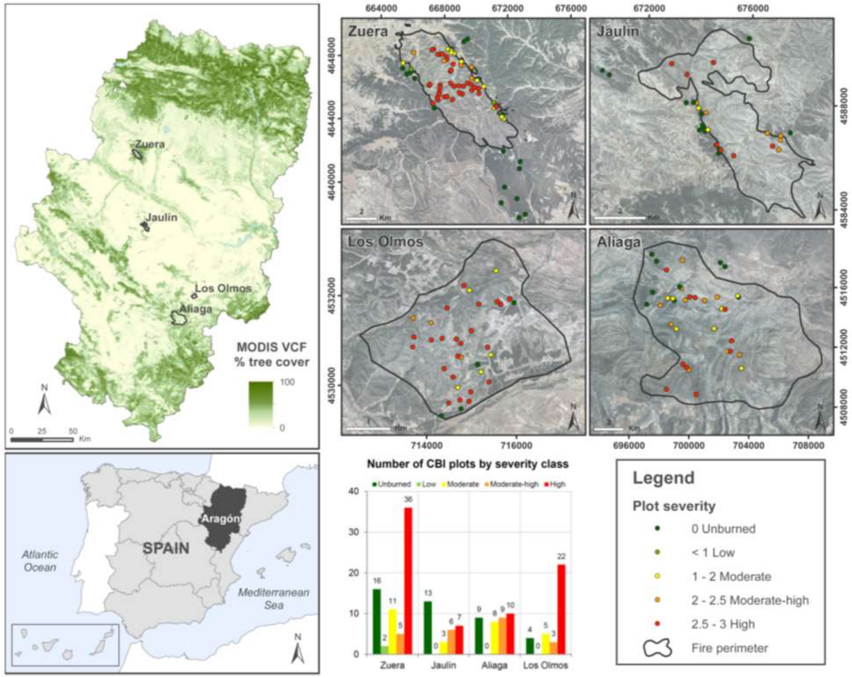
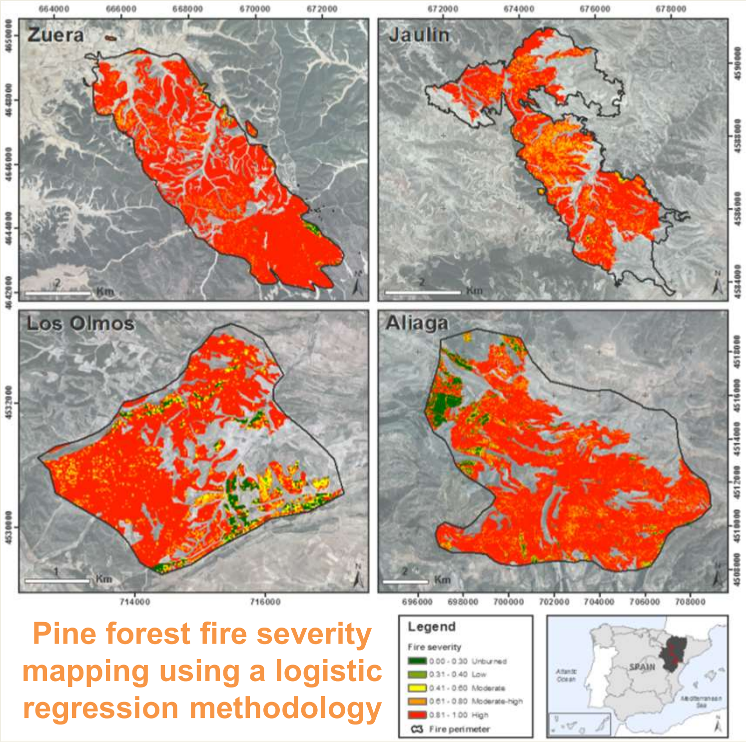
2nd María Teresa Lamelas · Centro Universitario de la Defensa

3rd Mihai A. Tanase · University of Alcalá

4th Juan De la Riva · University of Zaragoza



LiDAR-PNOA



Pine forest fire severity mapping using a logistic regression methodology

Table 5. Spearman's coefficient (Rho) and Kruskal–Wallis (K.W.) chi-square values for selected variables with a statistical significance level p-value ≤ 0.01.

ALS Variables	Rho	K.W. Chi^2	ALS Variables	Rho	K.W. Chi^2
Elev_kurtosis	0.788	54.169	Percentage first returns above 3.00	−0.690	39.927
Elev_P25	−0.767	64.776	Ratio_All_returns_3m	−0.690	39.797
Elev_P30	−0.764	63.550	Elev_mean	−0.684	34.138
%_All_returns_1m	−0.757	56.715	Elev_P60	−0.674	42.868
Elev_P20	−0.754	68.566	%_First_returns_mean	−0.673	62.590
Elev_P40	−0.752	63.802	Canopy relief ratio	−0.671	57.964
Elev_skewness	0.747	64.611	Ratio_All_returns_mean	−0.661	64.776
%_First_returns_1m	−0.744	52.460	Elev_P70	−0.653	33.988
Ratio_All_returns_1m	−0.742	51.915	Elev_P75	−0.649	29.533
%_All_returns_2m	−0.736	51.570	Elev_IQ	−0.637	29.544
%_Class_Unassigned	−0.729	54.131	Elev_P80	−0.631	24.535
%_Class_Ground	0.729	54.131	%_All_returns_mean	−0.630	67.337
Elev P50	−0.728	57.146	%_num_of_ret 1	0.623	30.906
%_First_returns_2m	−0.723	47.116	%_num_of_ret 2	−0.622	31.020
Ratio_All_returns_2m	−0.722	46.904	Elev_AAD	−0.614	16.834
Percentage all returns above 3.00	−0.702	43.290	Elev_P90	−0.608	16.450

Observed and predicted fire severity cross-tabulation for both training and validation datasets, Kappa index (K) and ROC curves.

	Training Dataset				Validation Dataset				
	Predicted				Predicted				
Observed		Low	High	Sum	%	Low	High	Sum	%
Low	32	6	38	84.2	Low	8	5	13	61.9
High	11	69	80	86.3	High	3	35	38	92.1
Sum	43	75	118	85.6	Sum	11	40	51	84.3

K = 0.68 **K** = 0.56

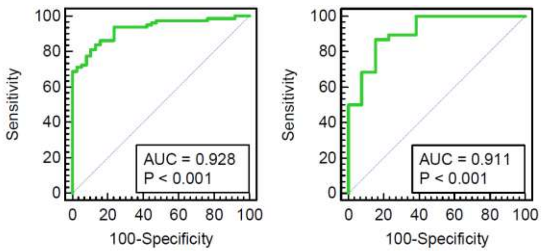
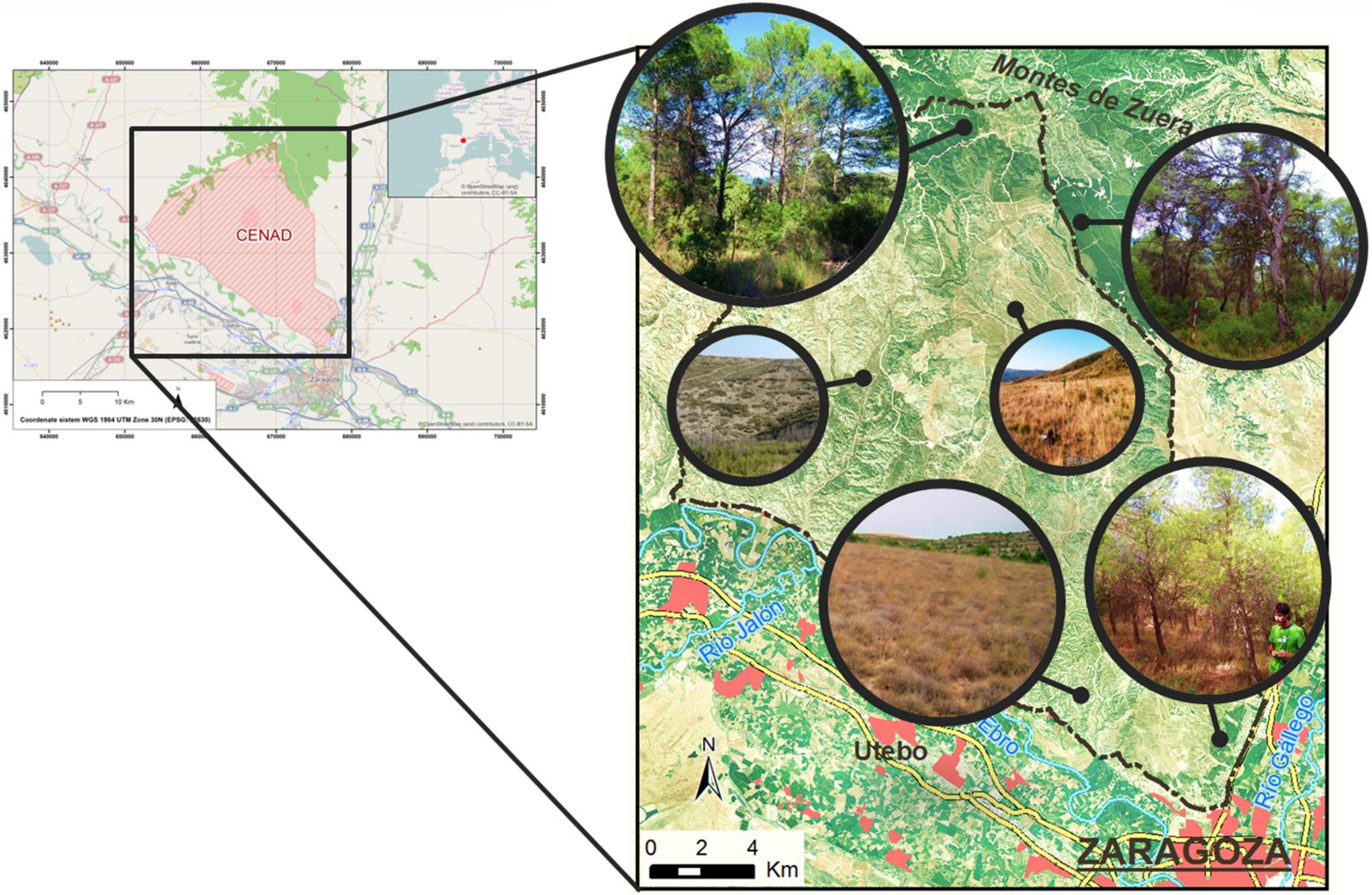


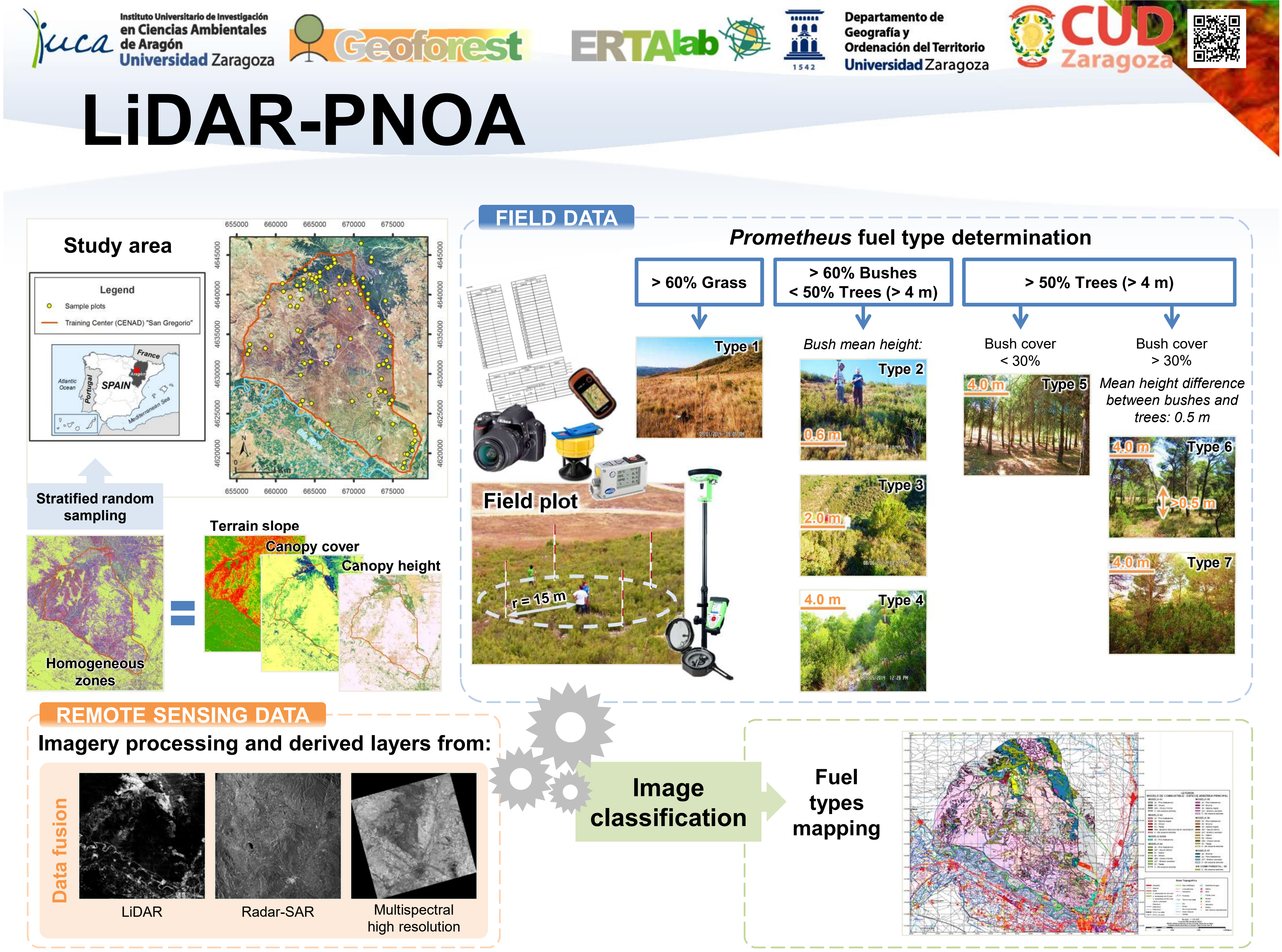
Table 8. β coefficients, Walt test values, degrees of freedom ($d.f.$) and their significance $p \leq 0.05$ computed for the variables of the selected regression model.

Independent Variables	β	Standard Error	Wald Test	$d.f.$	Signif.
Canopy relief ratio	−12.236	3.451	12.571	1	0.000
Percentage all returns above 1.00	−0.055	0.013	17.620	1	0.000
Constant	6.925	1.566	19.546	1	0.000

LiDAR-PNOA

Fuel types mapping using LiDAR, SAR and high resolution multispectral images





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LiDAR-PNOA
Study area
Legend
Sample plots
Training Center (CENAD) "San Gregorio"
France
Atlantic Ocean
Portugal
SPAIN
Aragón
Mediterranean Sea
Stratified random sampling
Homogeneous zones
Terrain slope
Canopy cover
Canopy height
FIELD DATA
Prometheus fuel type determination
> 60% Grass
> 60% Bushes
< 50% Trees (> 4 m)
> 50% Trees (> 4 m)
Type 1
Bush mean height:
Type 2
0.6 m
Type 3
2.0 m
Type 4
4.0 m
Bush cover
< 30%
Type 5
4.0 m
Bush cover
> 30%
Mean height difference between bushes and trees: 0.5 m
Type 6
4.0 m
>0.5 m
Type 7
4.0 m
Field plot
r = 15 m
REMOTE SENSING DATA
Imagery processing and derived layers from:
Data fusion
LiDAR
Radar-SAR
Multispectral
high resolution
Image classification
Fuel types mapping

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Spanish National Plan for Aerial Orthophotography (PNOA PROJECT)

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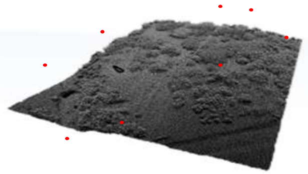
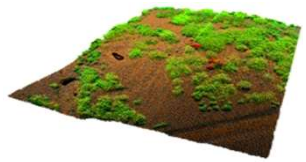
ALS point clouds captured 23st January and 2th February 2011

Delivered in 2 km x 2 km tiles of raw data points in LAS format v. 1.2, containing X, Y, Z coordinates, with up to 4 returns measured per pulse. Nominal point density of the study area **1 point/m^2** with a vertical accuracy higher than 0.20 m.

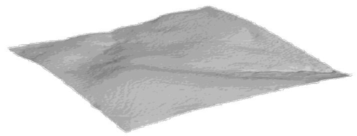
Outlier and noise removal



Filtering using the multiscale curvature classification algorithm (Evans and Hudak, 2007), implemented in MCC 2.1 command-line tool



Digital Elevation Model (DEM) 1 m resolution applying *"Point-TIN-Raster"* interpolation method to ground returns

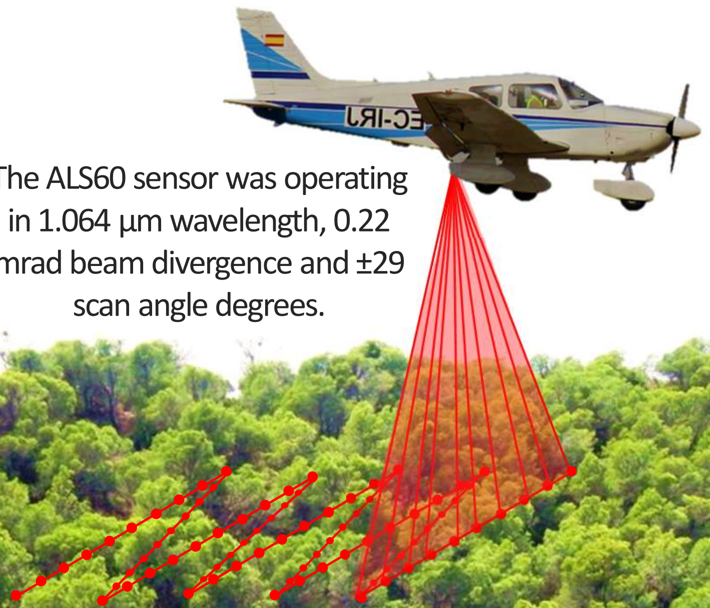


Normalized return heights and **ALS-derived metrics** with *"GridMetrics"* and *"CSV2Grid"* commands implemented in FUSION LDV 3.30

A total of 29 ALS-derived metrics were obtained: height percentiles, several metrics which describe the laser returns height distribution, and percentages of returns above a height threshold.

Height bin approach following Mutlu et al. (2008) using *"DensityMetrics"* command. Series of grids where each grid contains density information for a specific range of heights above ground.

A total of 8 ALS height bins were obtained: 0-0.5 m (HB1), 0.5-1 m (HB2), 1-2 m (HB3), 2-4 m (HB4), >4 m (HB5), 3-3.5 m (HB6), 3.5-4 m (HB7) y 1-4 m (HB8).



The ALS60 sensor was operating in 1.064 µm wavelength, 0.22 mrad beam divergence and ±29 scan angle degrees.

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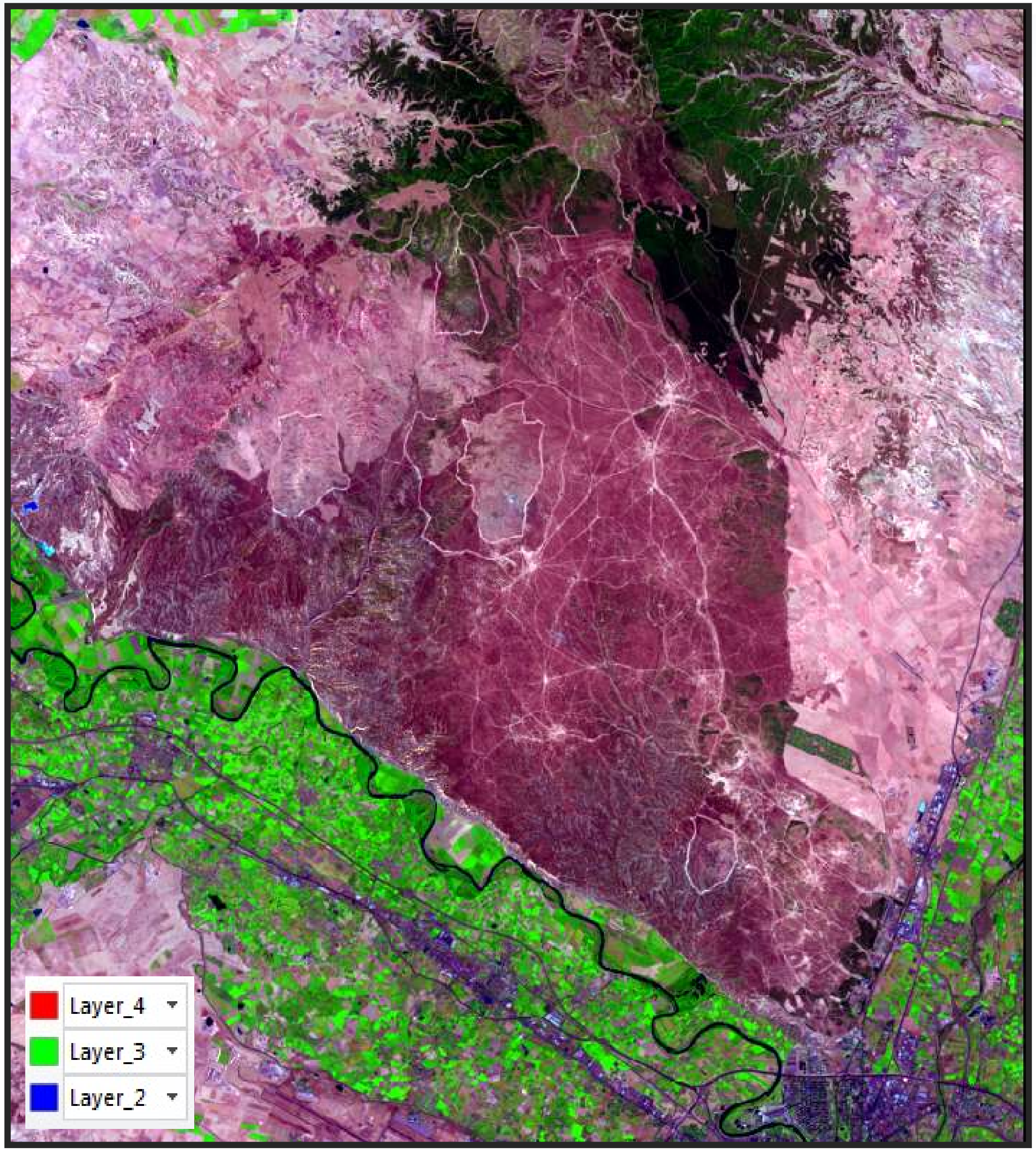
LiDAR-PNOA

Launch Date	May 3, 2002
Launch Vehicle	Ariane 4
Launch Location	Guiana Space Centre, Kourou, French Guyana
Orbital Altitude	822 kilometers
Orbital Inclination	98.7°, sun-synchronous
Speed	7.4 Km/second (26,640 Km/hour)
Equator Crossing Time	10:30 AM (descending node)
Orbit Time	101.4 minutes
Revisit Time	2-3 days, depending on latitude
Swath Width	60 Km x 60 Km to 80 Km at nadir
Metric Accuracy	< 50m horizontal position accuracy (CE90%)
Digitization	8 bits

Platform	Acquisition date
SPOT-5 satellite	29-08-2010

Band 1: Green (0.50 – 0.59 µm)
Band 2: Red (0.61 – 0.68 µm)
Band 3: Near infrared (0.78 – 0.89 µm)
Band 4: Short wave infrared (1.58 – 1.75 µm)

Additionally, **NDVI** (Normalized Difference Vegetation Index) and **NDII** (Normalized Difference Infrared Index) were calculated.



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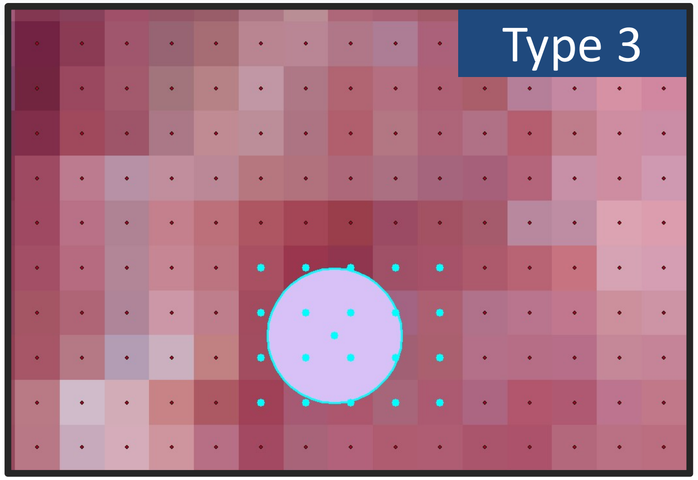
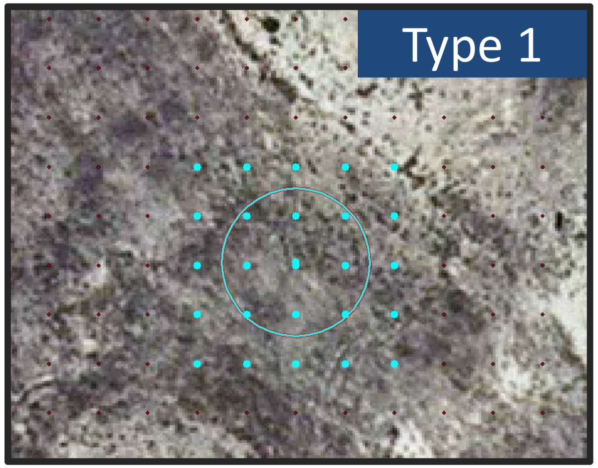
LiDAR-PNOA

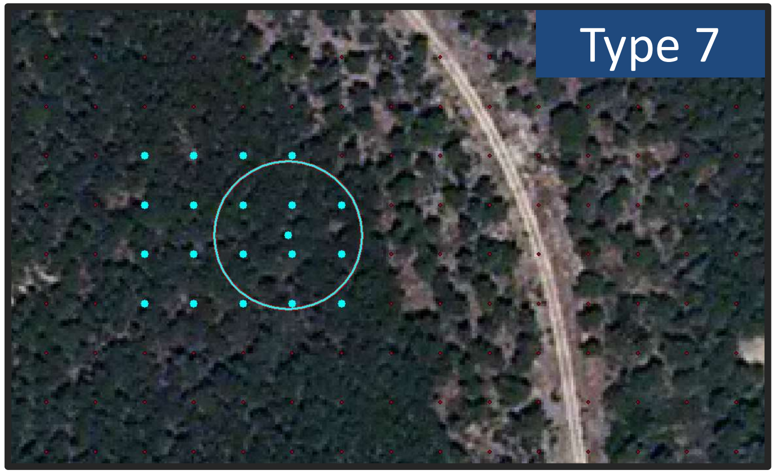
Training and validation samples

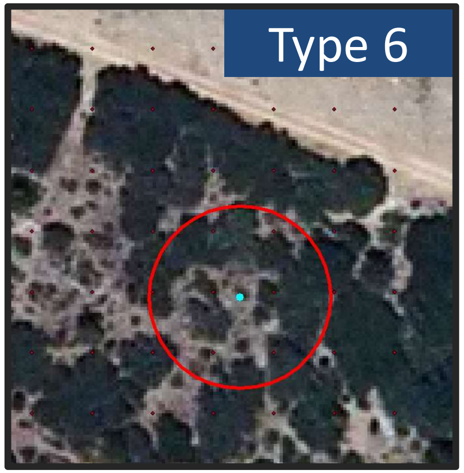
Fuel type	Field plots	Pixels for training	Pixels for validation	TOTAL
1	14	321	36	357
2	24	445	50	495
3	15	198	20	218
4	9	175	18	193
5	23	507	56	563
6	9	181	18	199
7	14	260	29	289
Bare ground	…	352	40	392
TOTAL	**108**	**2439**	**267**	**2706**



Considering the centroids of the plots, a total of **2314 pixels** were selected at which the **fuel** was allocated manually. **392 pixels** corresponding to **bare ground** were included in the sample.
10% of the total sample was randomly selected for validation and **90%** was used in the training phase.



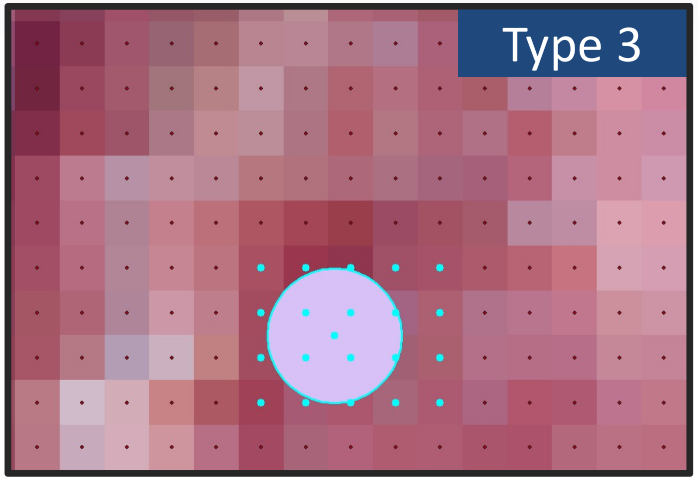




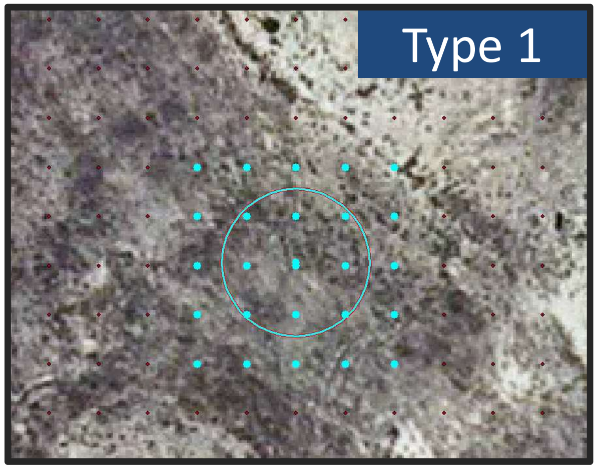
LiDAR-PNOA

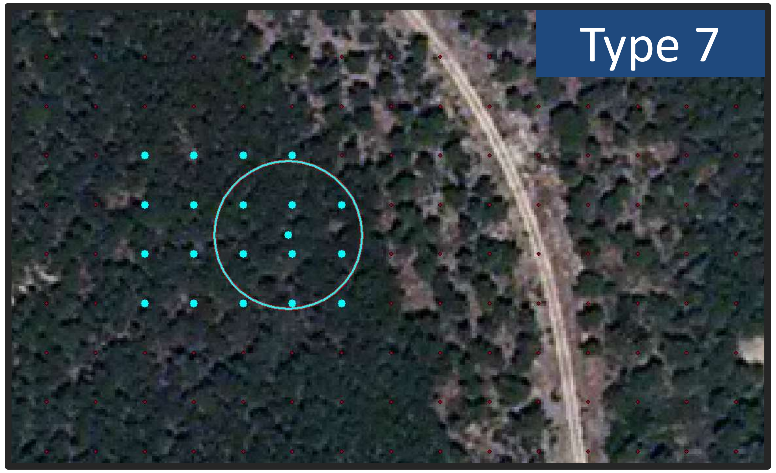
Training and validation samples

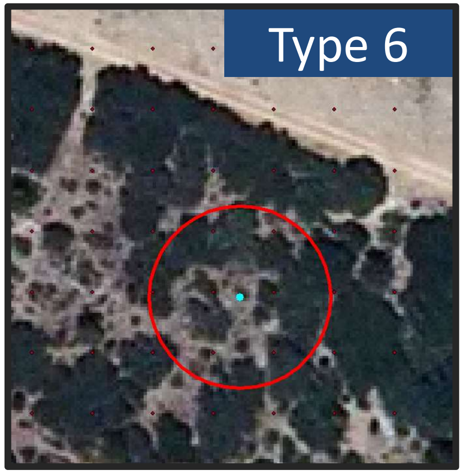
Fuel type	Field plots	Pixels for training	Pixels for validation	TOTAL
1	14	321	36	357
2	24	445	50	495
3	15	198	20	218
4	9	175	18	193
5	23	507	56	563
6	9	181	18	199
7	14	260	29	289
Bare ground	…	352	40	392
TOTAL	**108**	**2439**	**267**	**2706**



Considering the centroids of the plots, a total of **2314 pixels** were selected at which the **fuel** was allocated manually. **392 pixels** corresponding to **bare ground** were included in the sample.
10% of the total sample was randomly selected for validation and **90%** was used in the training phase.





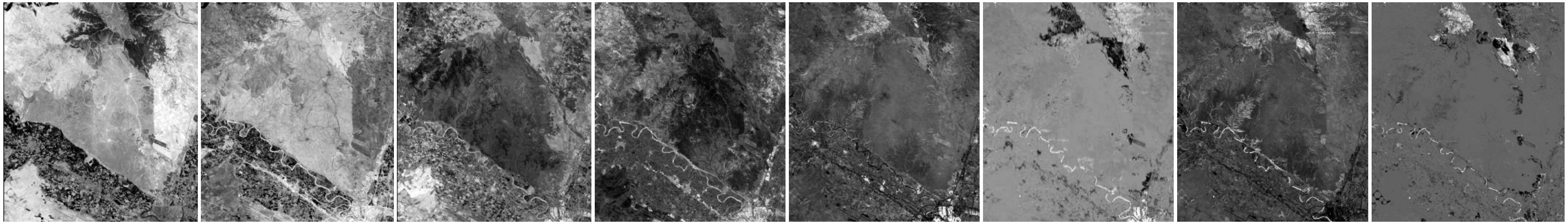


LiDAR-PNOA

Source of information	Bands	*Chi*-square
SPOT-5 image	NDVI	2000.8
ALS point clouds	HB 1	1993.1
	Elev. Mean (EM)	1993.0
	75th percentile (P_{75})	1974.9
	Variance (V)	1949.2
SPOT-5 image	Band 4	1948.2
	Band 2	1925.2
	Band 1	1854.4
ALS point clouds	HB 5	1731.9
	HB 8	1595.1
	HB 4	1570.9
	HB 7	1363.8
SPOT-5 image	Band 3	1318.6
ALS point clouds	HB 6	1317.7
	Percentage of first returns above mean height (%Ret)	1316.4
	Terrain slope model	812.0
	DEM	718.2

Multiband	Success rate (%)	Kappa coefficient (k)
SPOT-5 bands	59.2	0.5
PCA components 1 to 9 derived from (SPOT-5 bands + NDVI + HB1,4,5,6,7,8 + ME, P_{75}, V, %Ret) + DEM + Terrain slope model	70.8	0.7
SPOT-5 bands+ NDVI + HB 1,4,5,6,7,8 + EM, P_{75}, V, %Ret	72.7	0.7
SPOT-5 bands+ HB 1,4,5,6,7,8 + EM, P_{75}, V, %Ret + DEM + Terrain slope model	74.9	0.7
MNF components 1 to 8 derived from (SPOT-5 bands+ HB 1,4,5,6,7,8 + EM, P_{75}, V, %Ret) + NDVI + DEM + Terrain slope model	76.8	0.7

LiDAR-PNOA



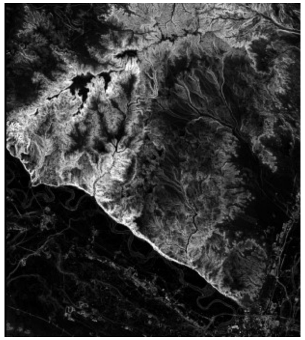
MNF component 1 | MNF component 2 | MNF component 3 | MNF component 4 | MNF component 5 | MNF component 6 | MNF component 7 | MNF component 8

MNF components derived from SPOT-5 bands; ALS height bins 1,4,5,6,7,8; Elev. Mean; 75_{th} percentile; Elev. Variance; percentage of first returns above mean height.

Component	Eigenvalues	% of total variance	Cumulative
CP1	70,083	53,262	53,262
CP2	25,163	19,123	72,386
CP3	7,408	5,630	78,015
CP4	6,318	4,802	82,817
CP5	4,351	3,306	86,124
CP6	3,696526	2,809	88,933
CP7	3,508181	2,666	91,599
CP8	2,570352	1,953	93,553
CP9	1,964258	1,493	95,046
CP10	1,459451	1,109	96,155
CP11	1,425	1,083	97,238
CP12	1,306632	0,993	98,231
CP13	1,182918	0,899	99,130
CP14	1,144812	0,870	100,000
	TOTAL	100,000	

NDVI

DEM



Terrain slope model

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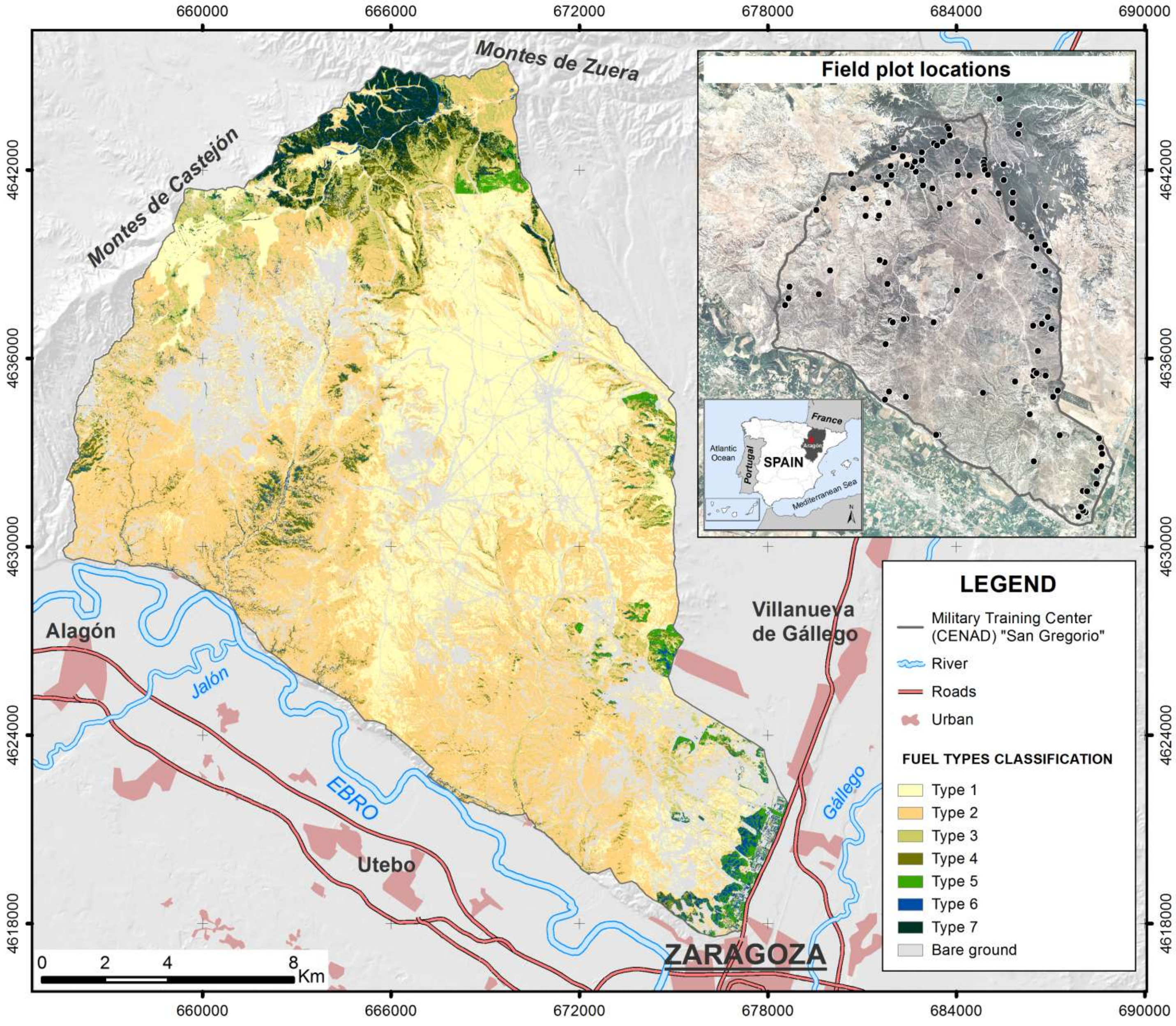

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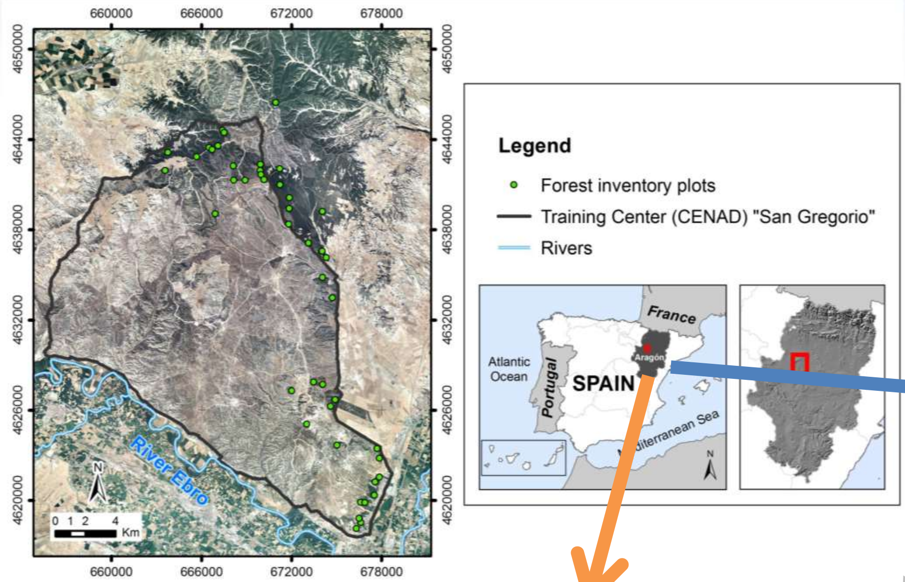
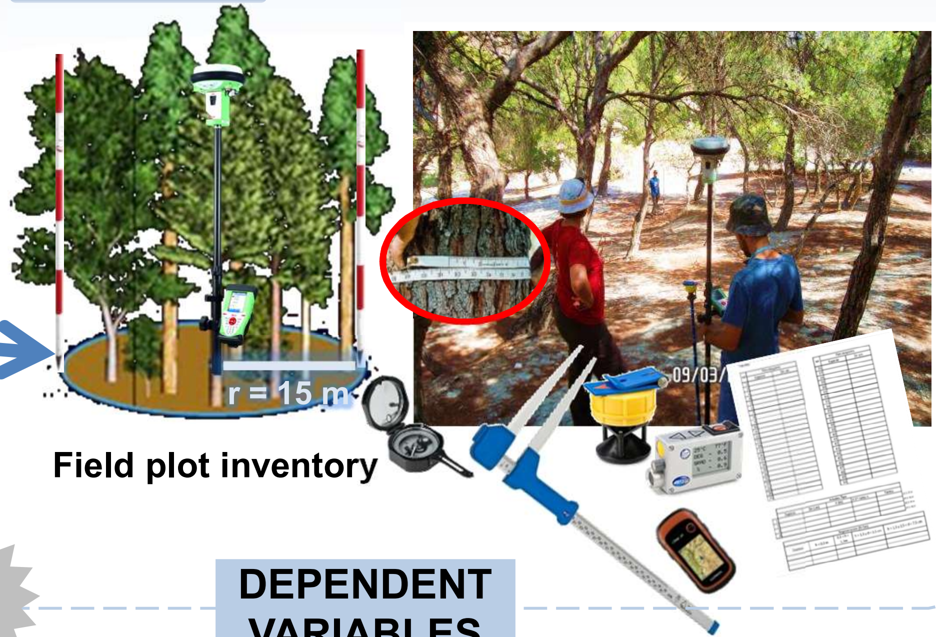
Structural variables estimation in Aleppo pine forest



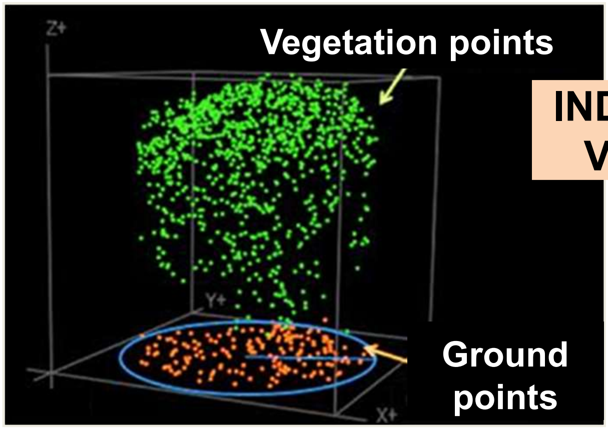
FIELD DATA



Field plot inventory

REMOTE SENSING DATA

LiDAR point cloud statistics at plot-level



INDEPENDENT VARIABLES

DEPENDENT VARIABLES

Results

Multiple regression analysis in order to develop Aleppo pine mean height (m), basal area (m^2/ha), timber volume (m^3/ha) density (stem/ha) and above ground biomass.

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Institute of Chartered Foresters
Forestry 2016; 0, 1–10, doi:10.1093/forestry/cpw008

Use of low point density ALS data to estimate stand-level structural variables in Mediterranean Aleppo pine forest

A. L. Montealegre[1,2]*, M. T. Lamelas[2,3], J. de la Riva[1,2], A. García-Martín[2,3] and F. Escribano[3]

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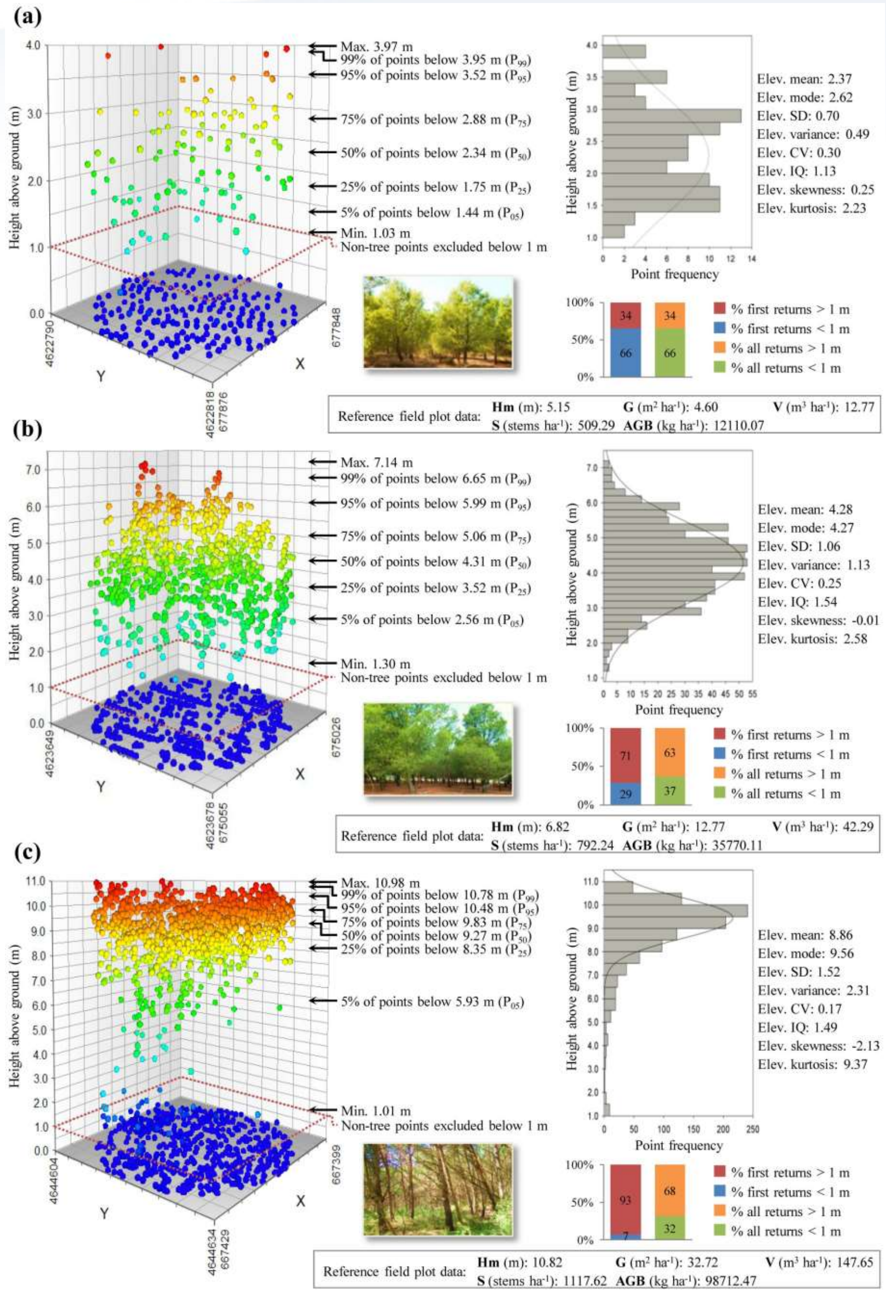

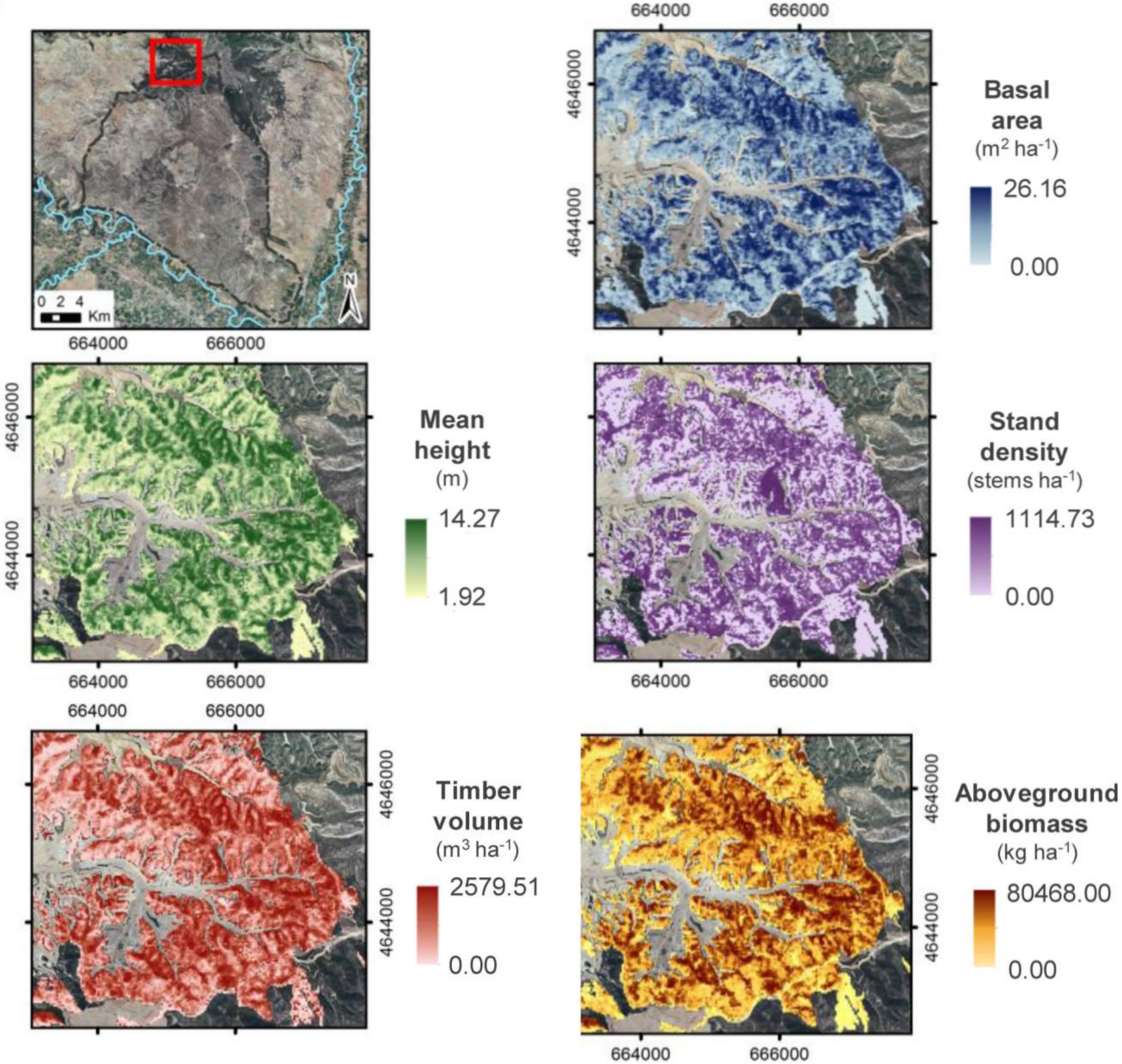

Dependent variable	Predictive model	Cross-validation		
		R^2	RMSE	Bias
Hm (m)	1.88+0.75* P_{99}	0.87	0.72	0.00
G (m² ha⁻¹)	-4.37+1.13*Elev. maximum-4.32*Elev. skewness+0.13*% first returns above 1 m	0.89	2.40	0.03
V (m³ ha⁻¹)	-67.29+9.71*P_{95}+8.18*Elev. kurtosis+0.52*% all returns above 1 m	0.89	10.99	0.03
S (stems ha⁻¹)	496.20-1391.99*Elev. CV+10.38*% all returns above 1 m	0.48	187.32	-0.91
AGB (kg ha⁻¹)	-16440.68+5222.70*P_{95}-14759.52*Elev.skewness+315.81*% all returns above 1 m	0.89	7326.12	2.03

Seguimiento y evaluación de espacios forestales: SERGISAT y aplicaciones LiDAR-PNOA

Muchas gracias

¿?