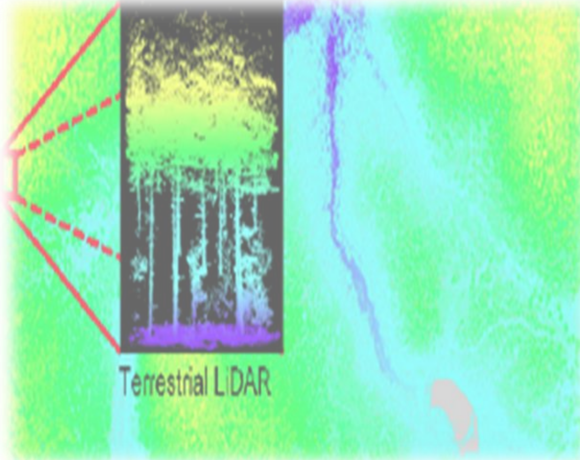
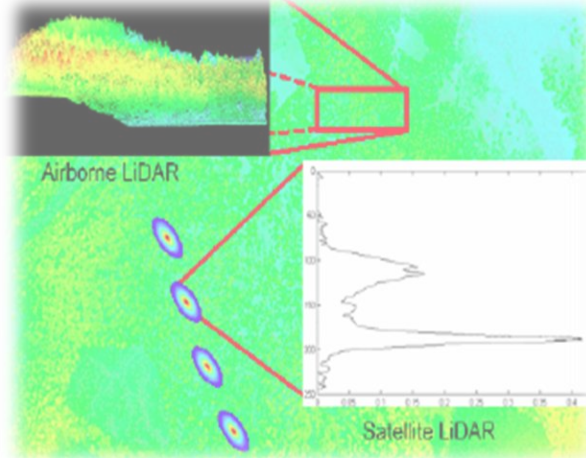
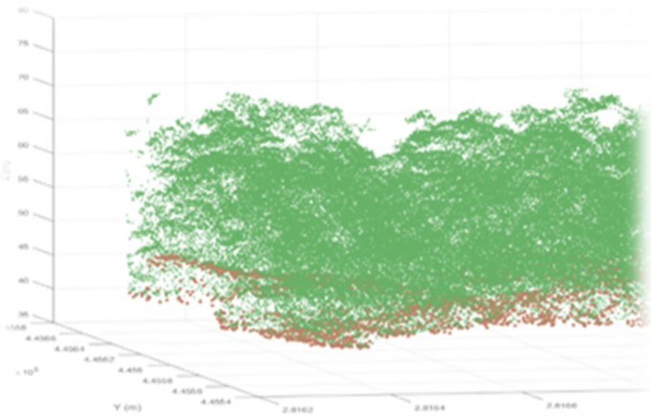
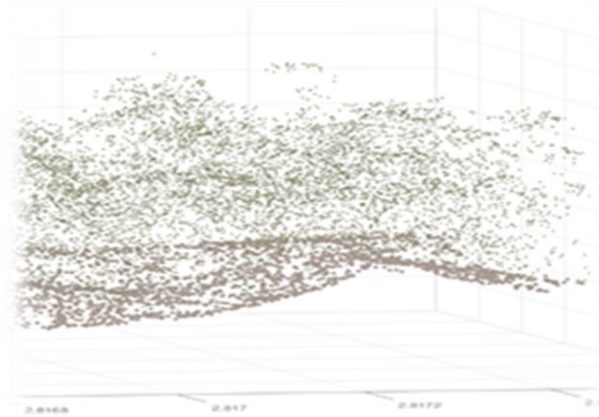


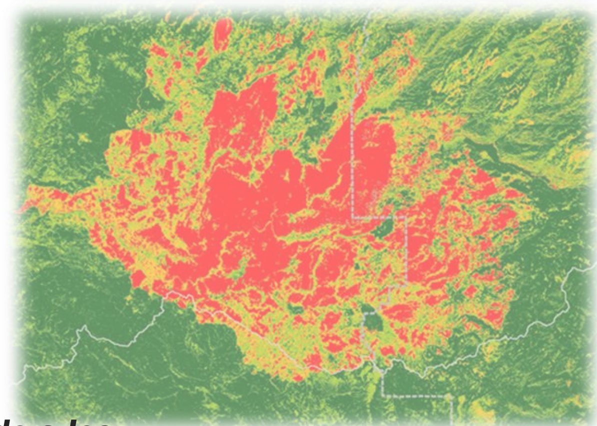


Integrating LiDAR and Landsat data for the extrapolation of canopy fuel properties

M. García[1,2,3], S. Saatchi[3], A. Casas[4], A. Koltunov[5], S. Ustin[5], C. Ramírez[6] & H. Balzter[2,7]
[1]Universidad de Alcalá, [2] University of Leicester, [3] Jet Propulsion Laboratory, [4] The Climate Corporation, [5] University of California Davis, [6] USFS, [7] National Center for Earth Observation







III Taller del Grupo de Incendios Forestales de la AET. LiDAR aplicado a los incendios forestales
Alcalá de Henares - 19 de octubre de 2018

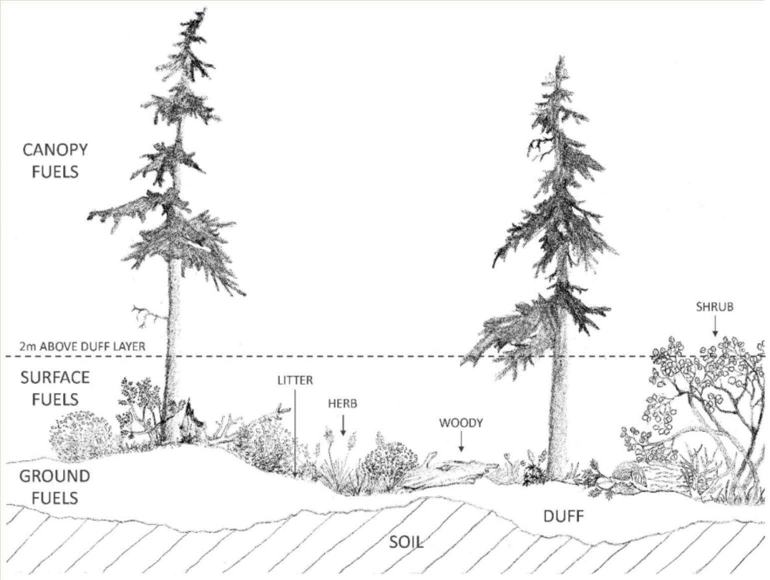
OUTLINE

- Introduction
- Objectives
- Study site and datasets
- Methodology
- Results and discussion
- Concluding remarks

INTRODUCTION

- Why canopy fuels?

Important in assessing fire risk because they represent fuel layer supporting crown fire spread.



source: Keane, R.E., 2016. *Forests*, *7*(7), 29; https://doi.org/10.3390/f7070129

Crown fires are more difficult to control than surface fires due to the increase in the rate of spread, intensity, and spotting.

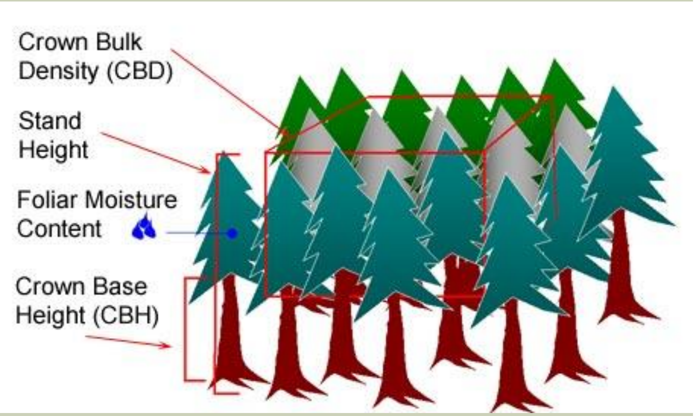
Crown fire effects are more severe and lasting than surface fires.

Information on canopy fuels is required for appropriate fire planning and management activities (predicting fire behavior and effects; designing fuel treatment)

Used in fire management decision support systems: BehavePlus, FlamMAP, FOFEM.

INTRODUCTION

- What canopy fuels properties?



source: www.fire.org

Canopy base height (CBH); canopy cover (CC); canopy fuel load (CFL); canopy bulk density (CBD)

CC (%): vertical projection of crowns on the ground. Provides a representation of the horizontal distribution of fuels. Affects the development and propagation of crown fires.

CFL (t/ha): amount of fuel that is potentially available for combustion.

CBD (kg/m^3): the mass of available canopy fuel per unit canopy volume that would burn in a crown fire (Scott & Reinhardt, 2001).

INTRODUCTION

- How?

Field methods: direct (destructive sampling) or indirect methods (optical and/or measurements readily available to forest managers)

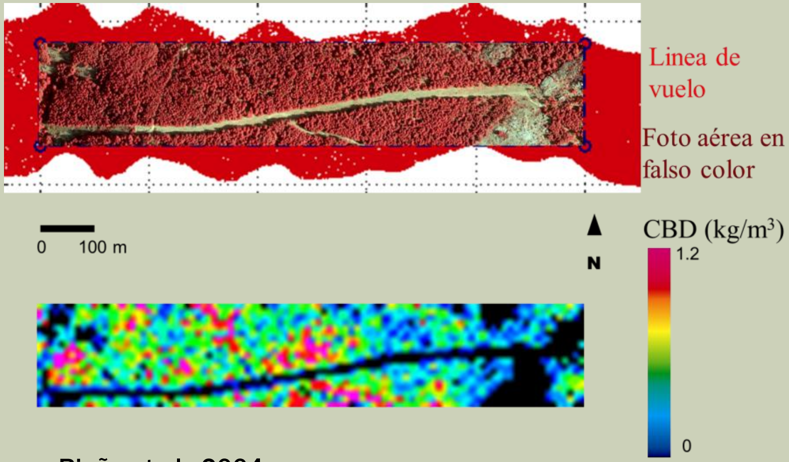
Images courtesy of B. Schlelgel and Dr. Riaño

Can provide accurate information on fuel properties but are difficult to implement operationally, limited spatial and temporal coverage. Yet, needed for calibration and validation of models that allow spatially explicit estimates of canopy fuel properties.

Remote sensing, particularly LiDAR, has proved great potential to estimate canopy fuel properties such as CBH, CBD, CC, CFL (*see Gajardo et al., 2014 for a review*).

INTRODUCTION

- **How?**



Riaño et al., 2004

Previous research based on airborne LiDAR focusing on fine spatial scales and small geographical extents, with limited temporal coverage.

Information on forest fuels is required at multiple spatial scales.

Satellite systems (ICESat-I y II; GEDI) can help to overcome these limitation but do not provide continuous sampling.

Landsat data has been commonly used to estimate canopy fuel properties relying on empirical relationships between field estimates and spectral information.

Optical sensors limited sensitivity to vegetation height and vertical vegetation distribution → CC successfully estimated but poorer results for CBD.

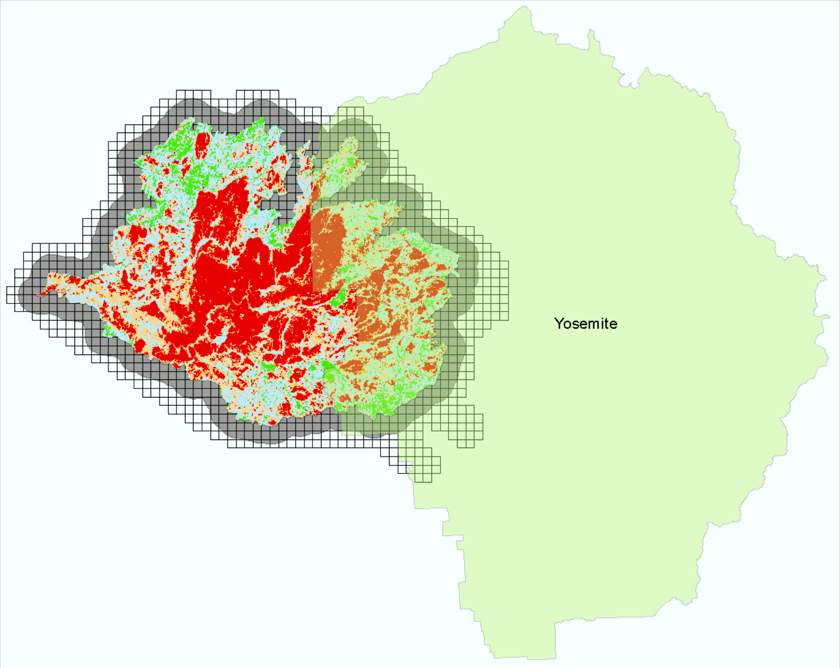
INTRODUCTION

Need to develop methods that allow to provide large-scale estimates of canopy fuel properties from satellite LiDAR sensors or to extrapolate airborne LiDAR based estimates over larger geographical extents

- ## Objectives

1. To estimate CFL, CC, and CBD from LiDAR data.
2. To extrapolate these LiDAR-based estimates over a larger area based on a statistical approach using a Landsat image.
3. To quantify the uncertainty associated with each pixel.

Study area



Rim fire burned 257,314 acres (104,131,28 ha).

The fire started on **August 17, 2013**, in Stanislaus National Forest, Sierra Nevada Region.

It was fully contained on **October, 24, 2013**.

Estimated cost of the fire is > $127 M

García et al., 2017

Field work

- 67 field plots
- R=16.92 = 0.09 ha (1 Landsat pixel)
- DBH & species
- Ht estimated from DBH
- AGB and FB estimated from Ht and DBH using National Biomass Estimator Library

Datasets

LiDAR data

Optech Gemini Airborne Laser Terrain Mapper (ALTM)

Flight elevation 2200 m above sea level

Scan angle ± 14°

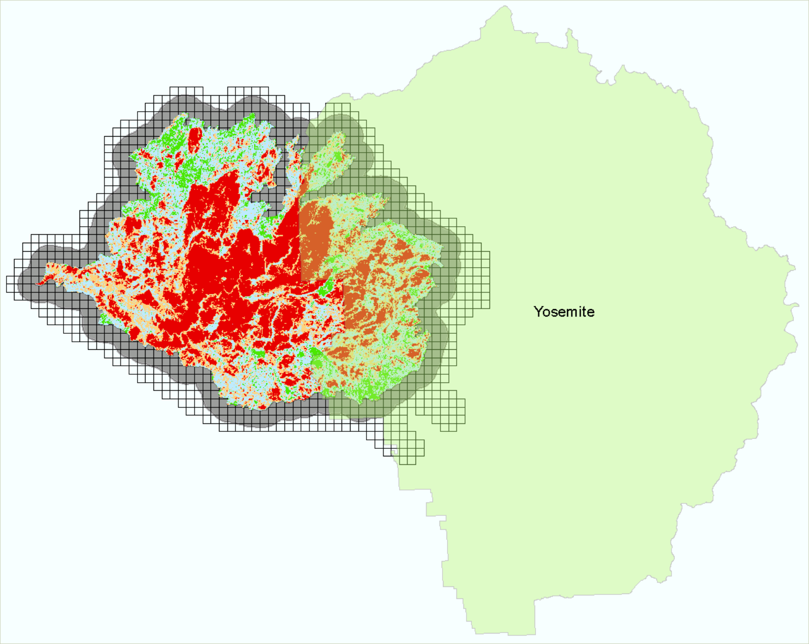
Overlap 50%

Point density 20 p/m^2

Landsat data

Landsat 8 OLI (Operational Land Imager) scene from 30th July 2013

Landsat 8 Surface Reflectance Code (LaSRC) product (Vermote et al., 2016) downloaded from the USGS Earth Explorer web site

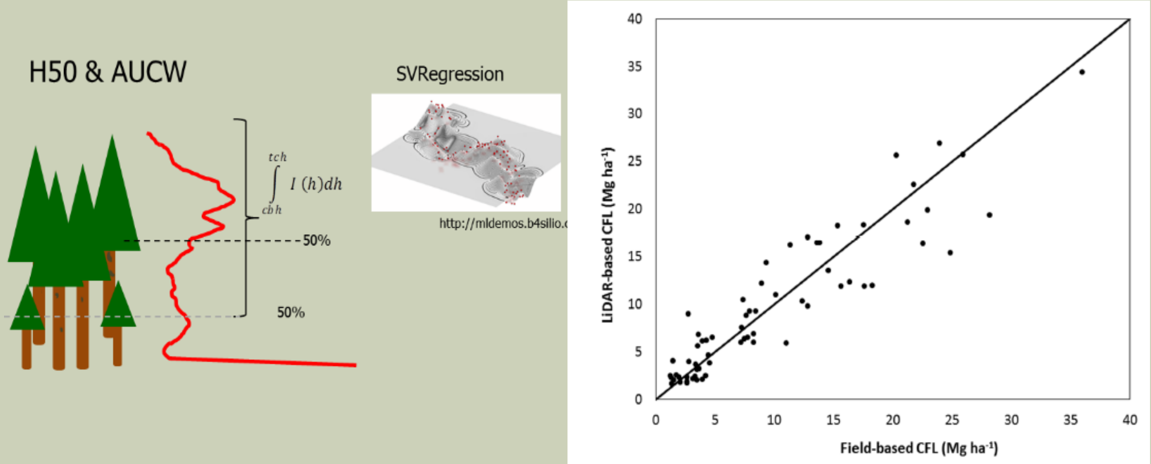


García et al., 2017

Methods

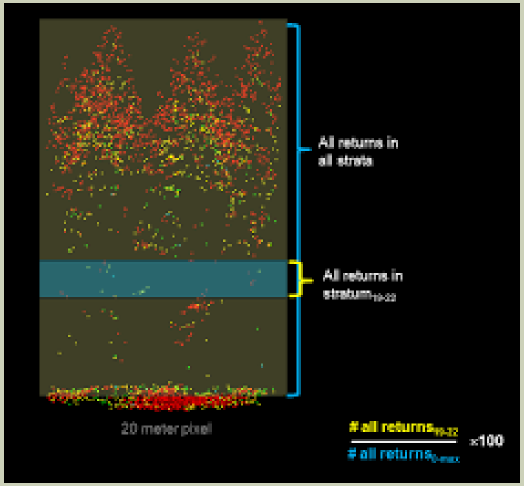
Estimation of canopy fuel properties from LiDAR data

CFL

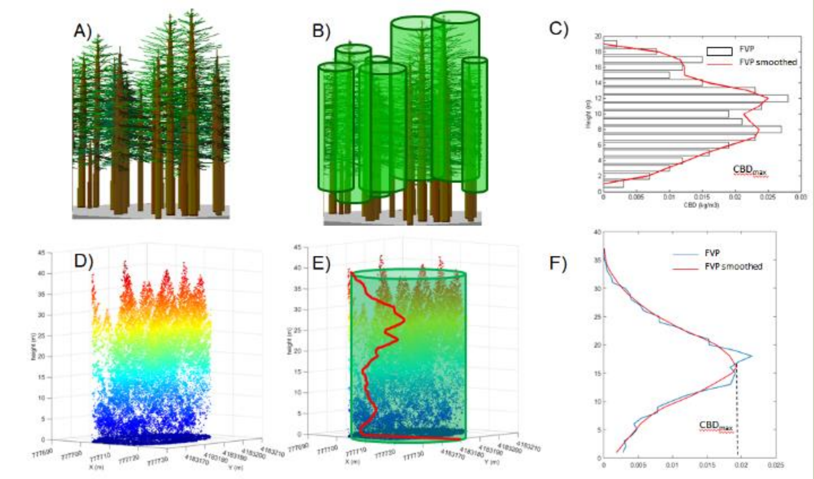


García et al., 2017

CC



CBD



Gajardo et al., 2014

Methods

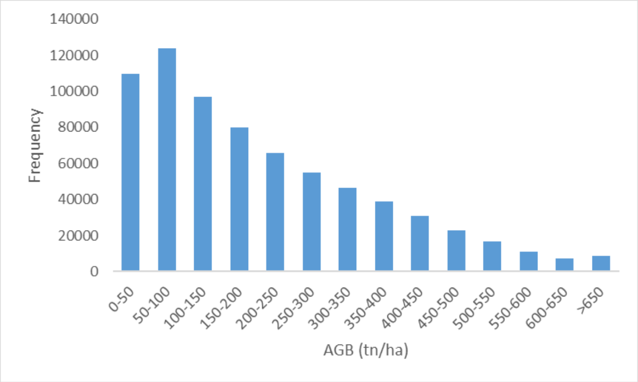
Extrapolation of canopy fuel properties using Landsat data

Assumption: buffer area is representative of inner area.

Stratified random sampling (>500 samples)

SVR for each variable

- 60%/40% calibration-validation
- Feature selection
- Model evaluation (R^2; R^2-adj, RMSE, RRMSE)



- Error assessment: $\sigma^2_{model} = RMSE^2_{LiDAR} + RMSE^2_{Landsat}$

  CFL_{LiDAR}: evaluated against field estimates

  CC_{LiDAR}: error assumed to be 18% (Morsdorf et al., 2006; Hopkinson & Chasmer, 2009)

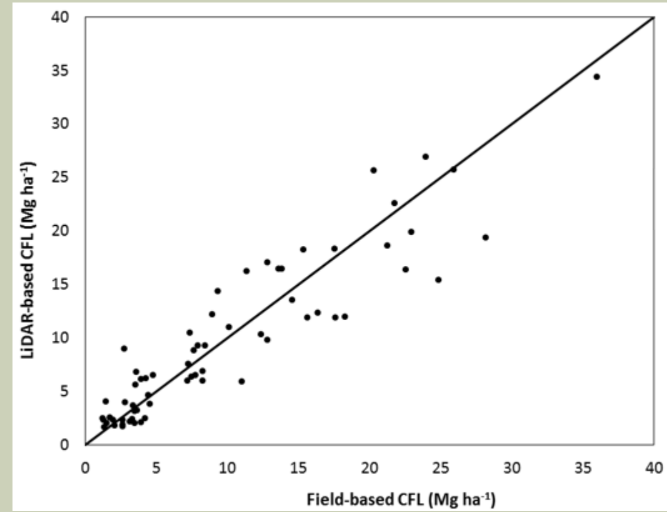
  CBD_{LiDAR}: main source of error CFL. Several studies found no statistically significant differences between LiDAR-derived and field-based canopy profiles

- 95% CI using a bootstrapping pairs approach with 500 samples.

Results and discussion

1st step: Field-LiDAR

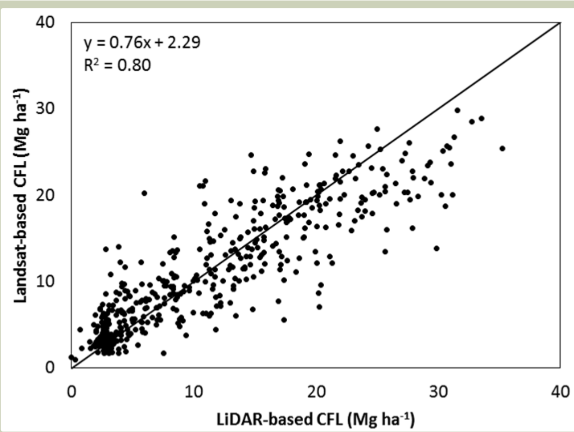
Feature Selection	Selected variables	R^2	R^2-adj	RMSE ($Mg\ ha^{-1}$)	RRMSE (%)
Expert Knowledge	AUCW H_{50}	0.87	0.86	3.01	30.40
		0.81	0.79	3.28	33.68
		0.85	**0.84**	**3.08**	**31.25**

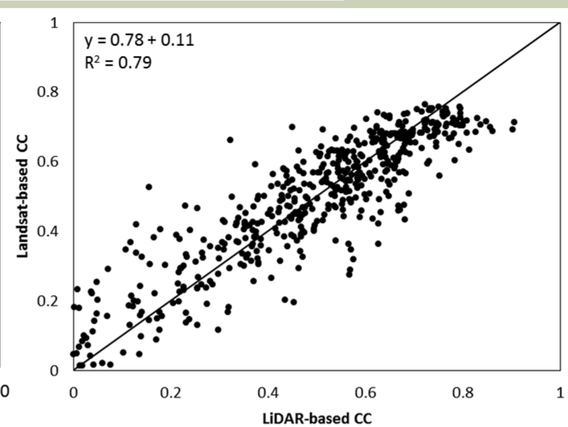


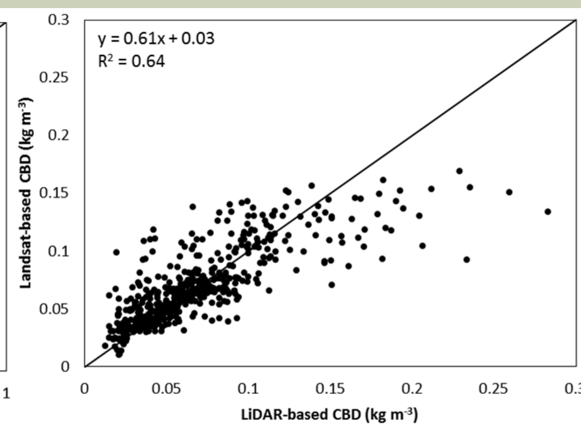
2nd step: LiDAR- Landsat

Variable	Metrics selected	R^2	R^2-adj	RMSE	RRMSE (%)
CFL	B2-B6, NDII, Elevation, Slope	0.85	0.85	3.24	31.04
		0.72	0.71	4.43	41.80
		0.80	**0.79**	**3.72**	**35.37**
CC	B6	0.79	0.79	0.09	18.88
		0.78	0.78	0.10	19.40
		0.79	**0.79**	**0.09**	**19.09**
CBD	Brightness, Wetness, Elevation	0.66	0.65	0.03	36.71
		0.60	0.60	0.03	37.23
		0.64	**0.63**	**0.03**	**36.92**

García et al., 2017

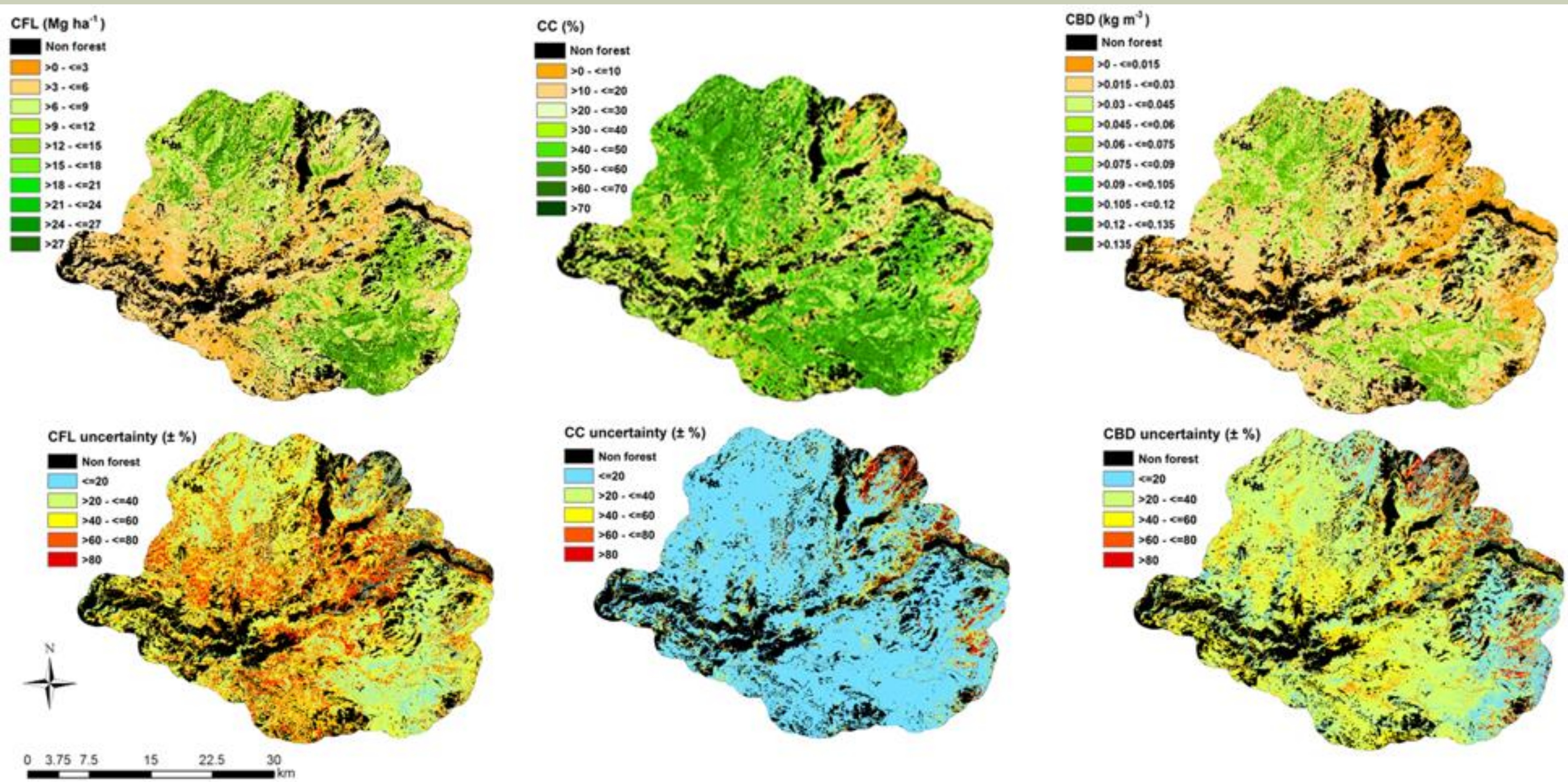






Results and discussion

Final errors:
$RMSE_{CBD}$= 0.033 kg m^{-3} ($RRMSE_{CBD}$= 46.73%); $RMSE_{CFL}$= 4.82 Mg ha^{-1} ($RRMSE_{CFL}$= 47.64%);
$RMSE_{CC}$= 0.20 ($RRMSE_{CC}$= 26.24%).



García et al., 2017

Conclusions

- LiDAR-based canopy fuel properties can be extrapolated to larger regions using Landsat data.
- The uncertainty of the estimates was provided at the pixel level.
- Our approach is relevant for fuel and resource management planning:
    - Accurate LiDAR-based canopy fuel properties extrapolated to provide improved continuous spatial information on canopy fuel properties over large regions.
    - Landsat data used, but the same approach could be applied to Sentinel 2.
- Our results show improved performance against other studies based on Landsat data alone. This is of considerable importance since the results of fire behavior and fire effect models depend on the quality of the fuel products used as inputs


Thank you