Télédétection et habitats d'espèces en forêt

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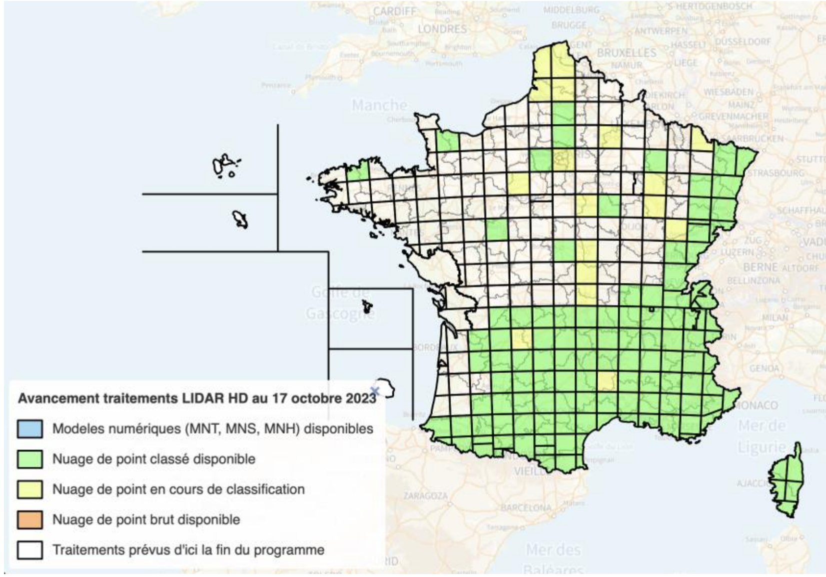
Take home message and overview

- LiDAR becomes increasingly accessible*
- Airborne LiDAR is a powerful tool for habitat modelling
- We need LiDAR metrics that are robust, interpretable and have a clear link to management
- Impactful analyses need more than good remote sensing data



- Capercaillie case study
- Principles of species distribution modelling
- LiDAR metrics – area-based vs object-oriented
- Model results: performance of different LiDAR metrics, optimal values of forest structure
- LiDAR-based habitat modeling and management

*https://gitlab.irstea.fr/jean-matthieu.monnet/lidartree_tutorials/-/wikis/Forest-structure-metrics-mapping
https://forgemia.inra.fr/jean-matthieu.monnet/lidarHD

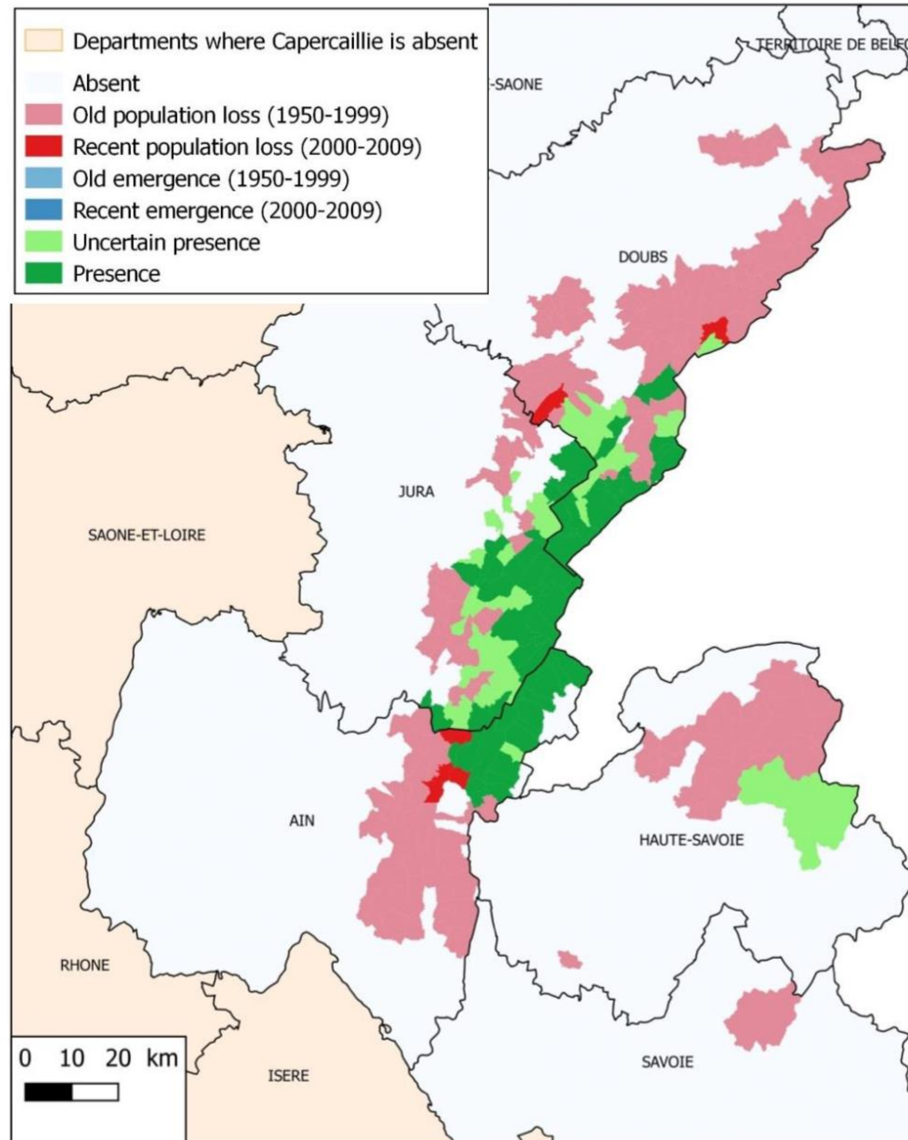
A locally endangered species

Capercaillie (*Tetrao urogallus*)

Habitat

- Structured mixed beech-fir stand
- Feeds on Scots pine (winter), bilberries (summer, autumn)

Working hypothesis:
Jura population threatened by habitat loss and human disturbances
-> Focus on these variables



Management support objectives of habitat model

Capercaillie

- Map suitable habitat
- Target beech regeneration areas
- Inform monitoring efforts

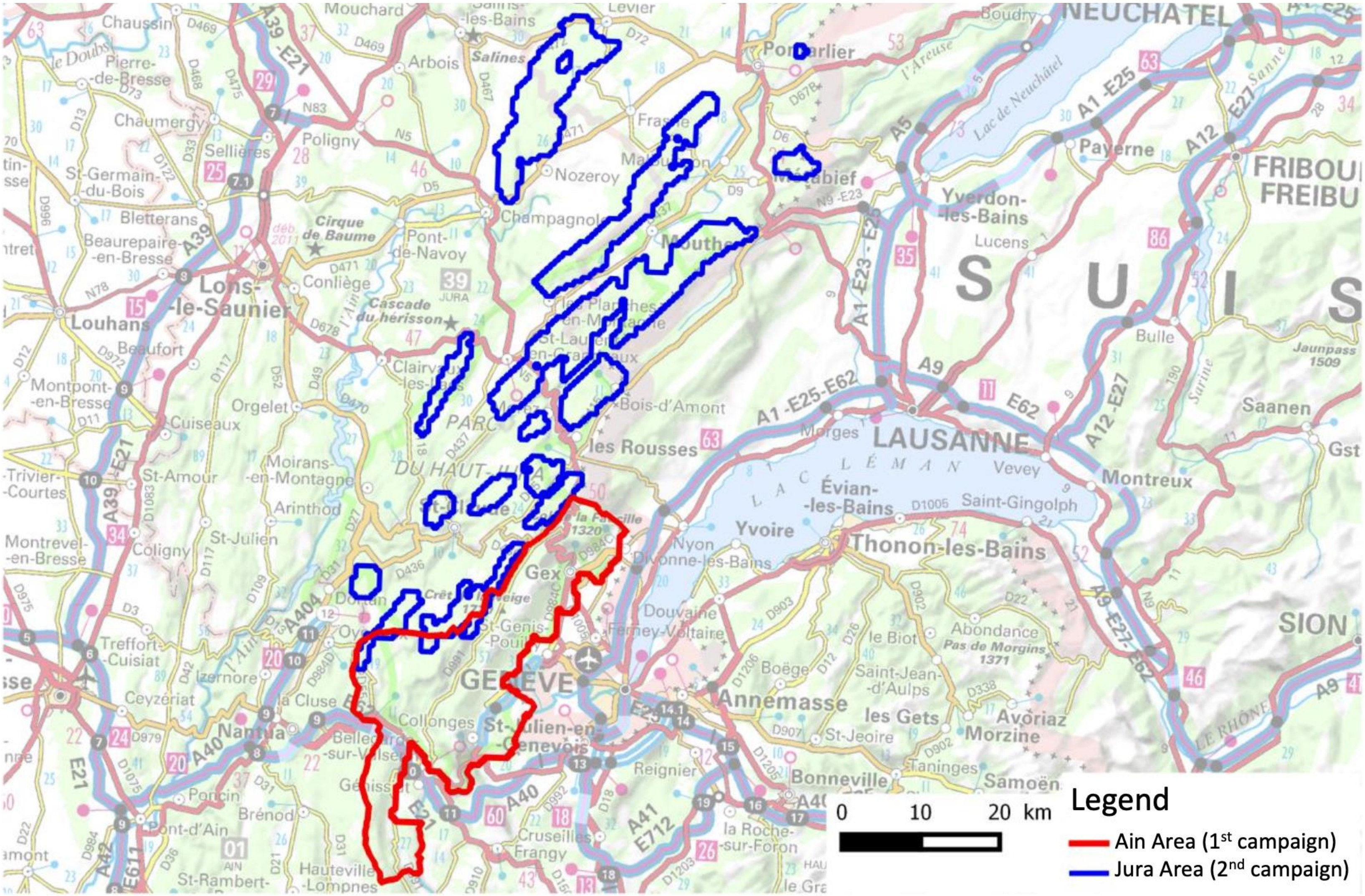
Vegetation characteristics define habitat suitability

Unsuitable habitat

Suitable habitat

Role of human disturbance in habitat suitability

Study areas: Ain and Jura

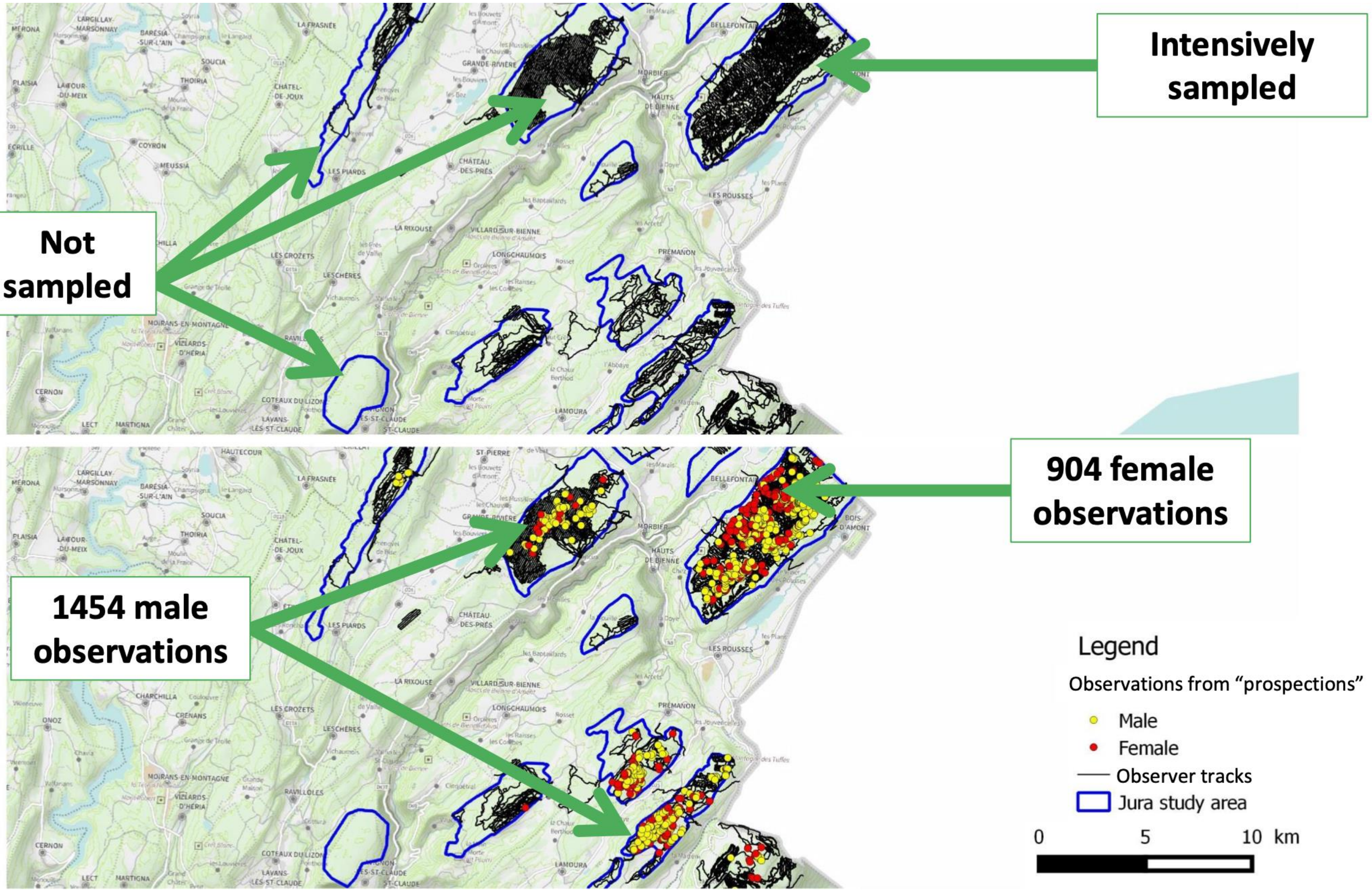


Autumn 2014 (21 points/m^2)

Summer 2016 (18 points/m^2)

Capercaillie observations

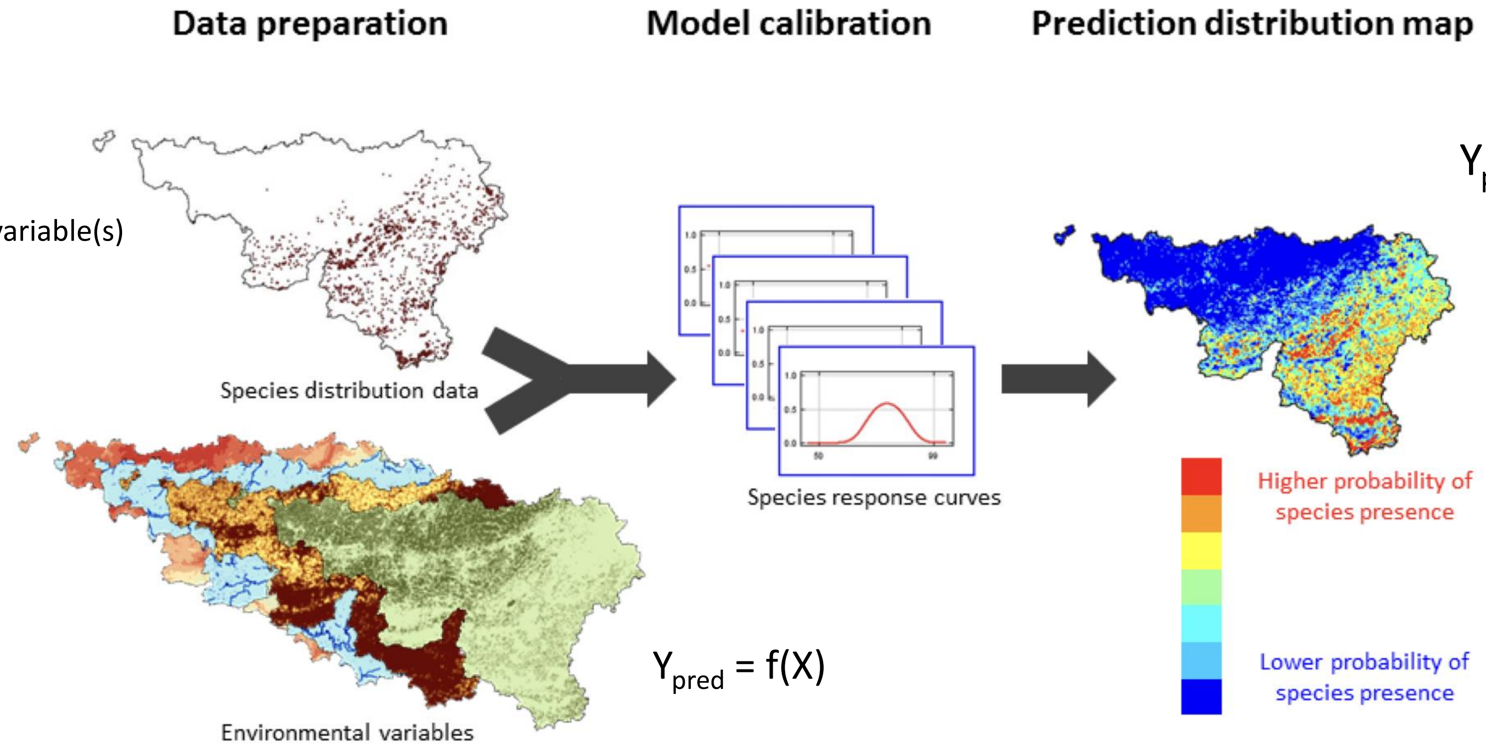
Observations and observer trajectories (winter)



- All (forest structures) x (lidar acquisition configurations) should be sampled so that the model does not extrapolate in mapping
- With presence only data in particular the sampling effort has to be known to avoid biased models

Species distribution modelling - Principles

Y_{obs}
Dependent variable(s)



Y_{pred}

X_{obs}
Predictor variable(s)
Features

$Y_{pred} = f(X)$

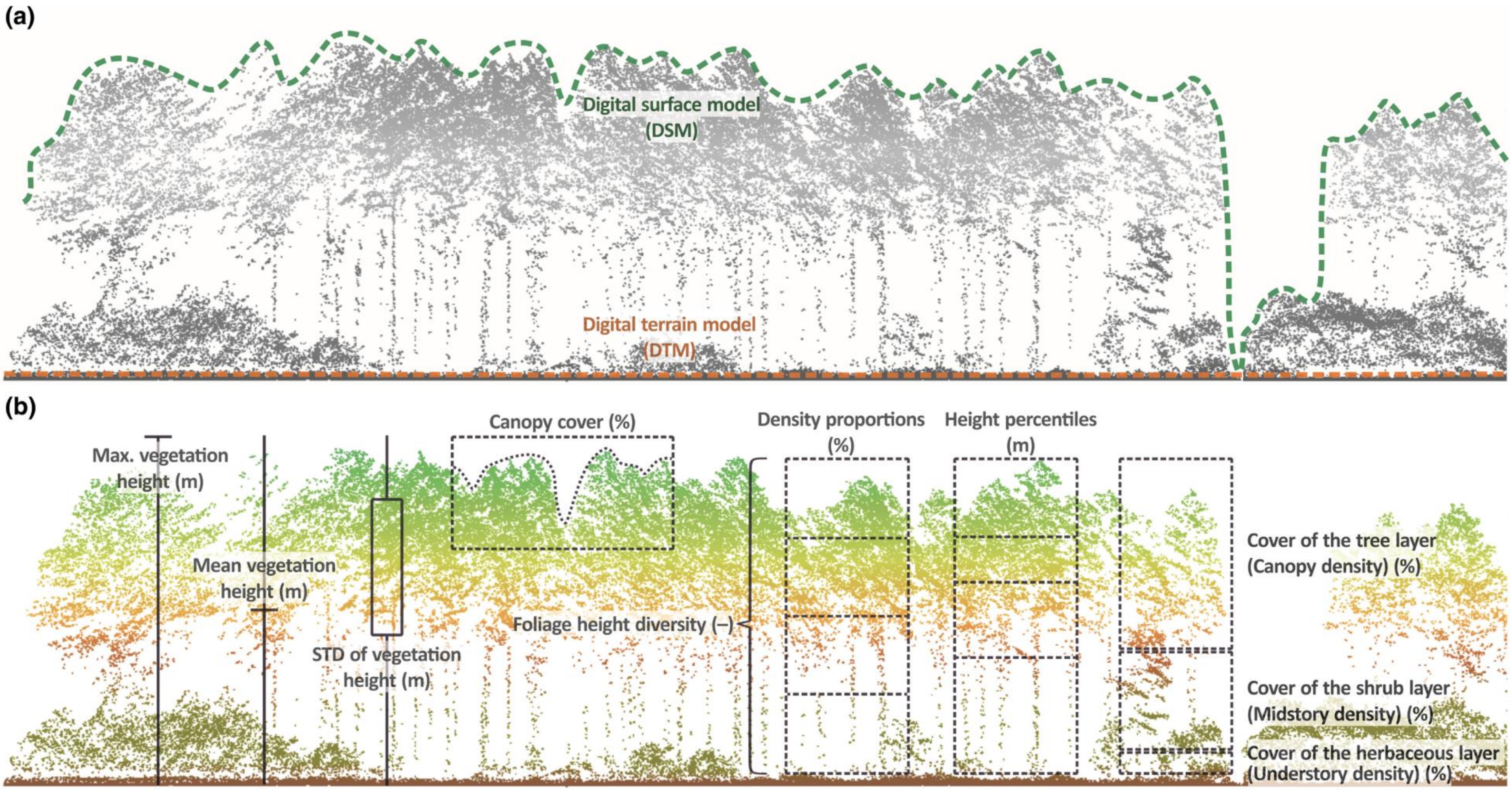
Find parameters of model f such that a measure of divergence between Y_{obs} and Y_{pred} becomes minimized

The model estimates the expected number of detected indices of presence
Key assumptions:
- Detected presence is an unbiased indicator of habitat quality
- Predictors keep their meaning in different contexts

Applications: mapping; predicting; explaining

https://www.tdx.cat/bitstream/handle/10803/667947/Toasr1de1.pdf

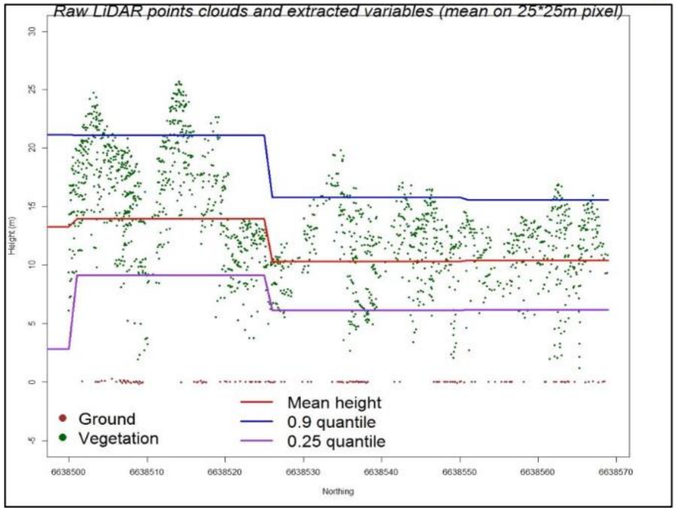
LiDAR metrics: From point clouds to rasters



Moudry et al. 2023 Diversity & Distributions

Point-cloud vs object-oriented metrics

Point-cloud



- Proportion of echoes
- Point density
- Penetration ratio
- Quantile for height

Zellweger *et al.* 2013
Kortmann *et al.* 2018
Melin *et al.* 2016, 2018

→ **Can be difficult to interpret**

Recent studies proposed to use Oriented-Object metrics instead of Point-clouds area-based metrics

Object-oriented

- Gaps
- Percentages of deciduous trees
- Edge length

Kortmann *et al.* 2018
Rechsteiner *et al.* 2017

→ **Can be designed to fit managers needs**

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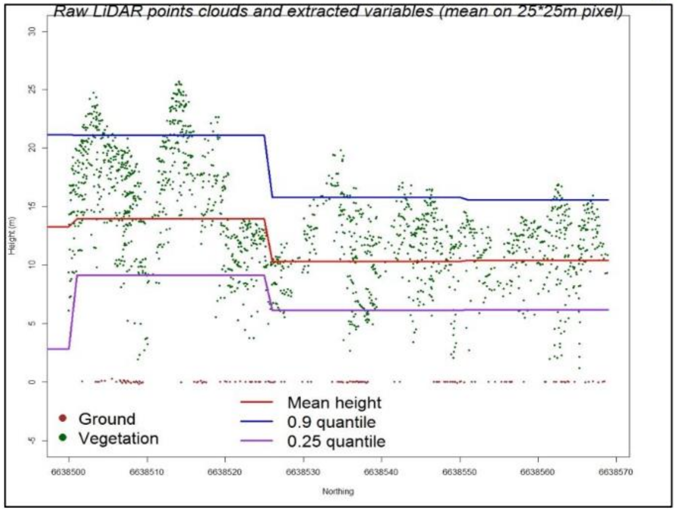
Point-cloud vs object-oriented metrics



Point-cloud

- Proportion of echoes
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→ **Can be difficult to interpret**

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Melin *et al.* 2016, 2018

Modelled values: e.g. basal area

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Kortmann *et al.* 2018
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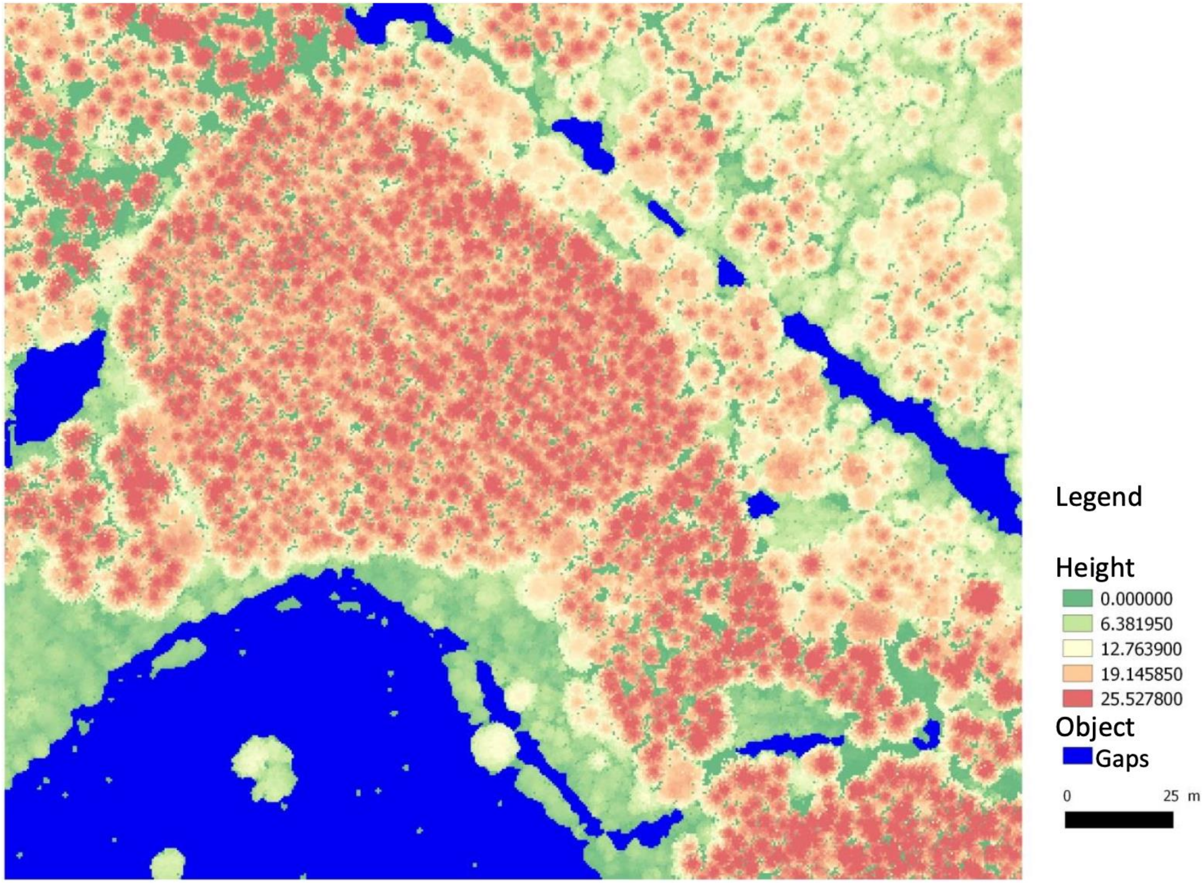
Object-oriented metrics (OO)

Landscape

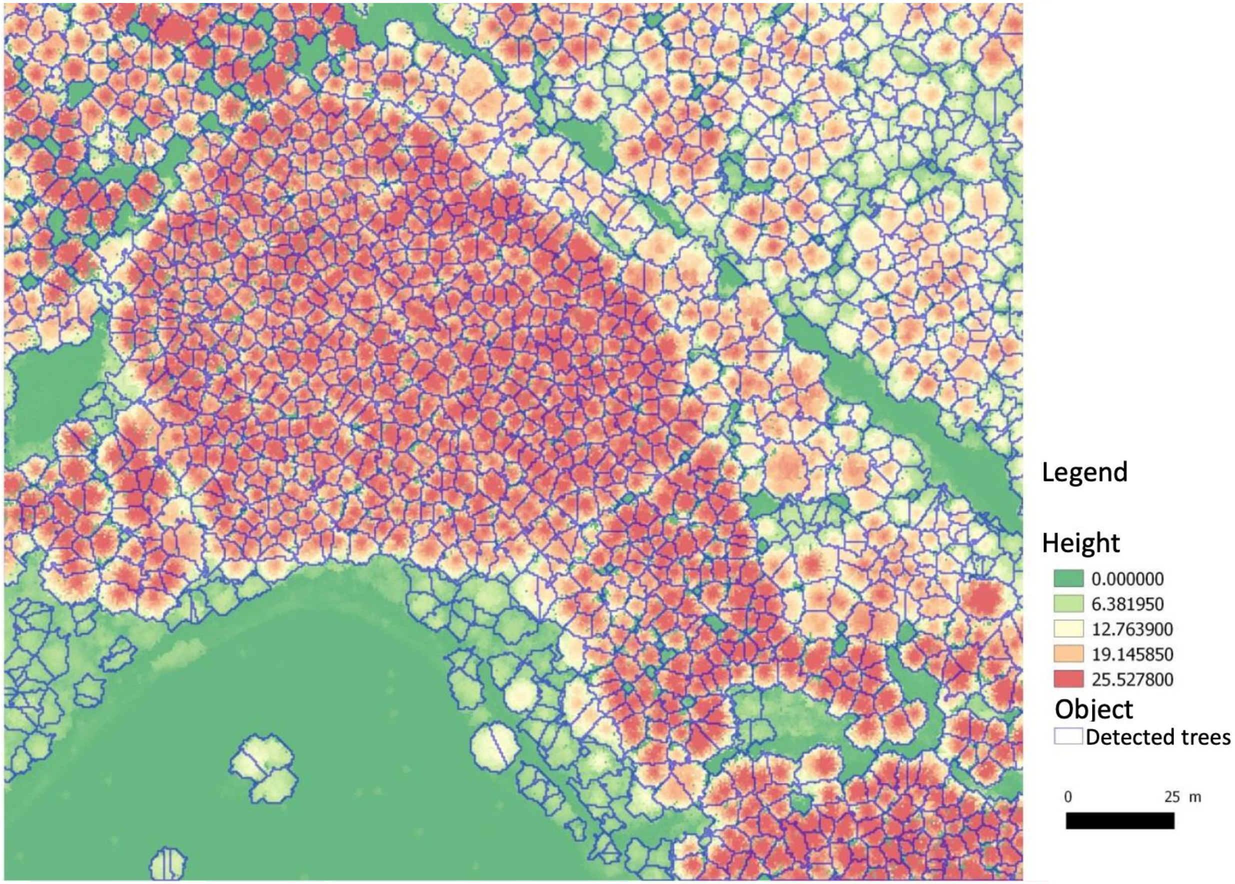
Gap detection



Object-oriented metrics (OO)

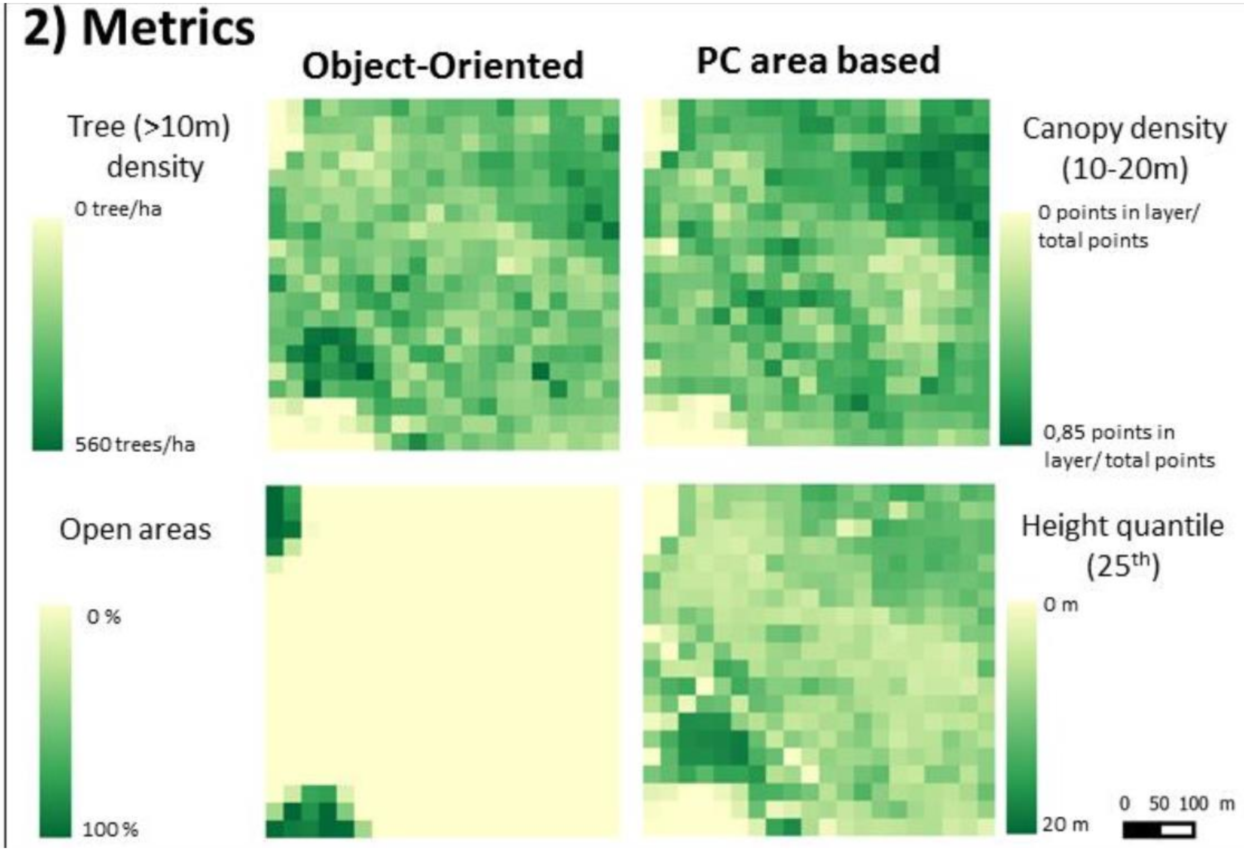
Landscape

Tree detection



Point cloud and object oriented metrics

Landscape

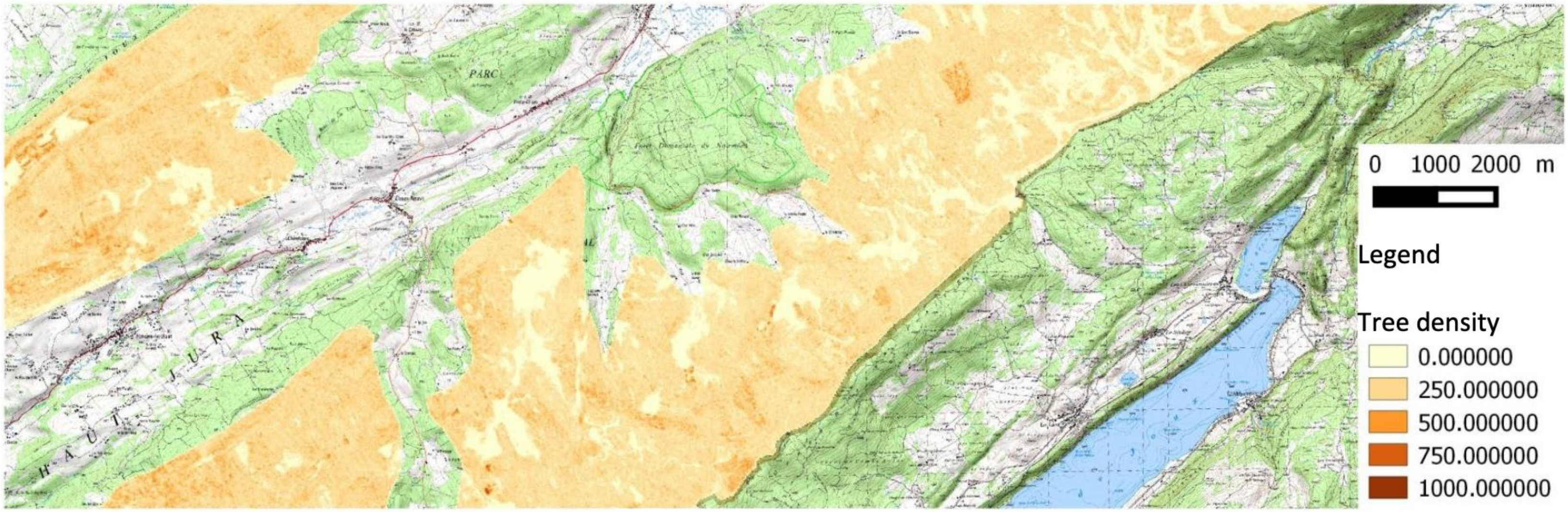


Glad et al. (2020) Remote Sensing in Ecology and Conservation

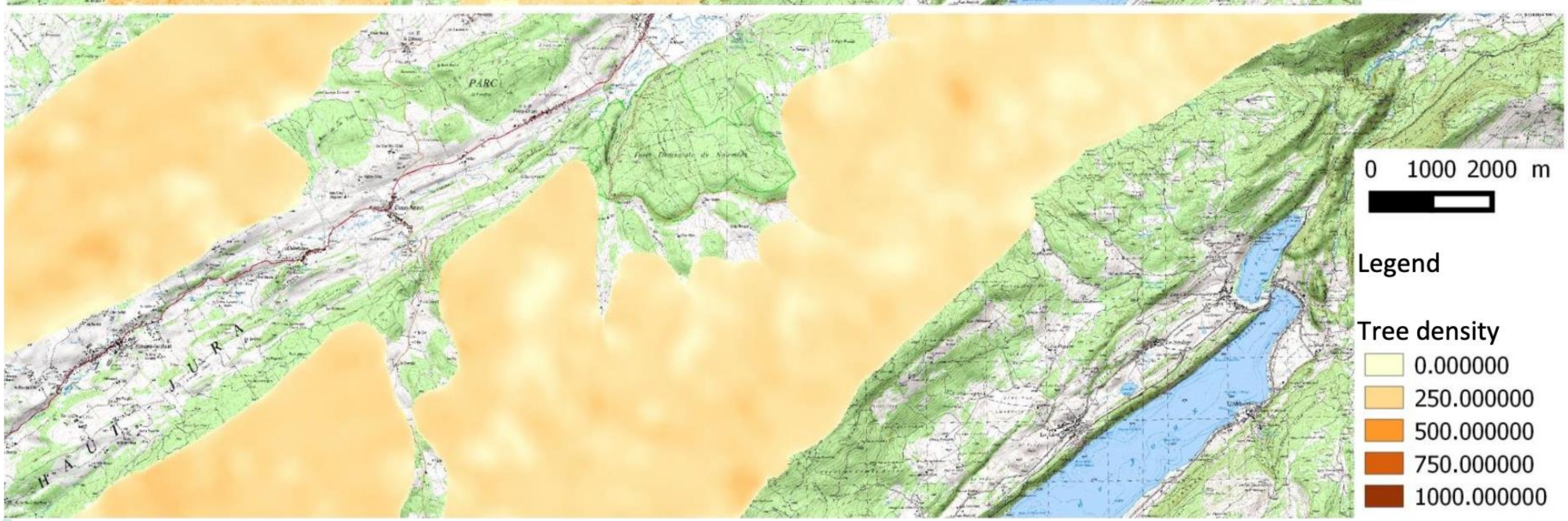
Contextual metrics - Scales

Moving window analysis (mean and sd) - grain stays constant (25 m x 25 m)

0.31 ha



15.8 ha



Method overview

Sex: male and female

Scales (mean and standard deviation of metrics)

0.31 ha (microhabitat); 0.81, 1.8 ha (patch); 15.8, 27.5, 56 ha (homerange)

Model: Maxent with linear and quadratic features, correction for observation pressure

Type of metrics	Metric name	Description
PC	Relative density of the 10–20-m canopy	Point relative density for the height layer 10- to 20-m
	SD relative density of the 20–30-m canopy	The standard deviation of the canopy density for the height layer 20- to 30-m
	SD penetration ratio 2–5 m	Penetration ratio standard deviation for the 2- to 5-m height layer
	Penetration ratio 2–5 m	Penetration ratio for the 2- to 5-m height layer
	Q25	25th Quantile of height of vegetation and unclassified points
	Simpson index	Simpson index for canopy height
OO	Tree density (5–10 m)	Density of trees shorter than 10 m but taller than 5 m (number/ha)
	Tree density (>10 m)	Density of trees taller than 10 m (number/ha)
	SD Tree density (>20 m)	Standard deviation of density of trees taller than 20 m (number/ha)
	Gini index	Tree height Gini index
	Open area	Proportion in the pixel that contains that contains a grassland object (surface <1000 m^2 and vegetation height <1 m) (%)
	Medium gap	Proportion in the pixel that contains a large gap object from 200 m^2 to 1000 m^2 (Height is <1 m and half height of surrounding trees is less than half of the gap width) (%)
	SD small gap	Standard deviation of the proportion in the pixel that contains an object large gap from 25 m^2 to 200 m^2 (Height is <1 m and half the height of surrounding trees is less than half the gap width) (%)

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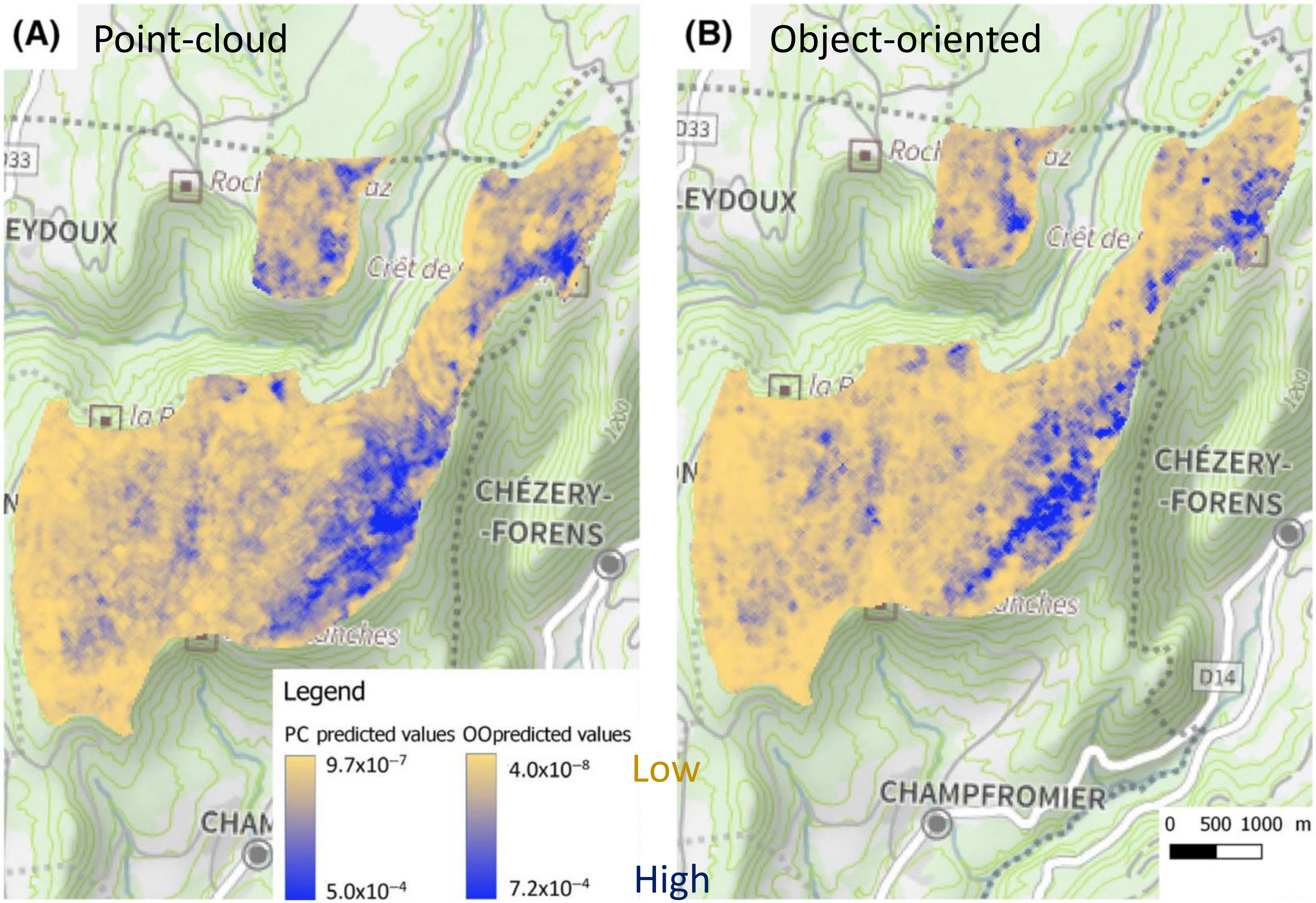
Model predictions

Male, Champfromier (Ain) study area, 0.81 ha scale



AUC (10-fold CV): 0.75

AUC (10-fold CV): 0.78

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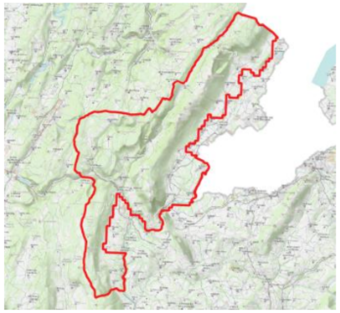
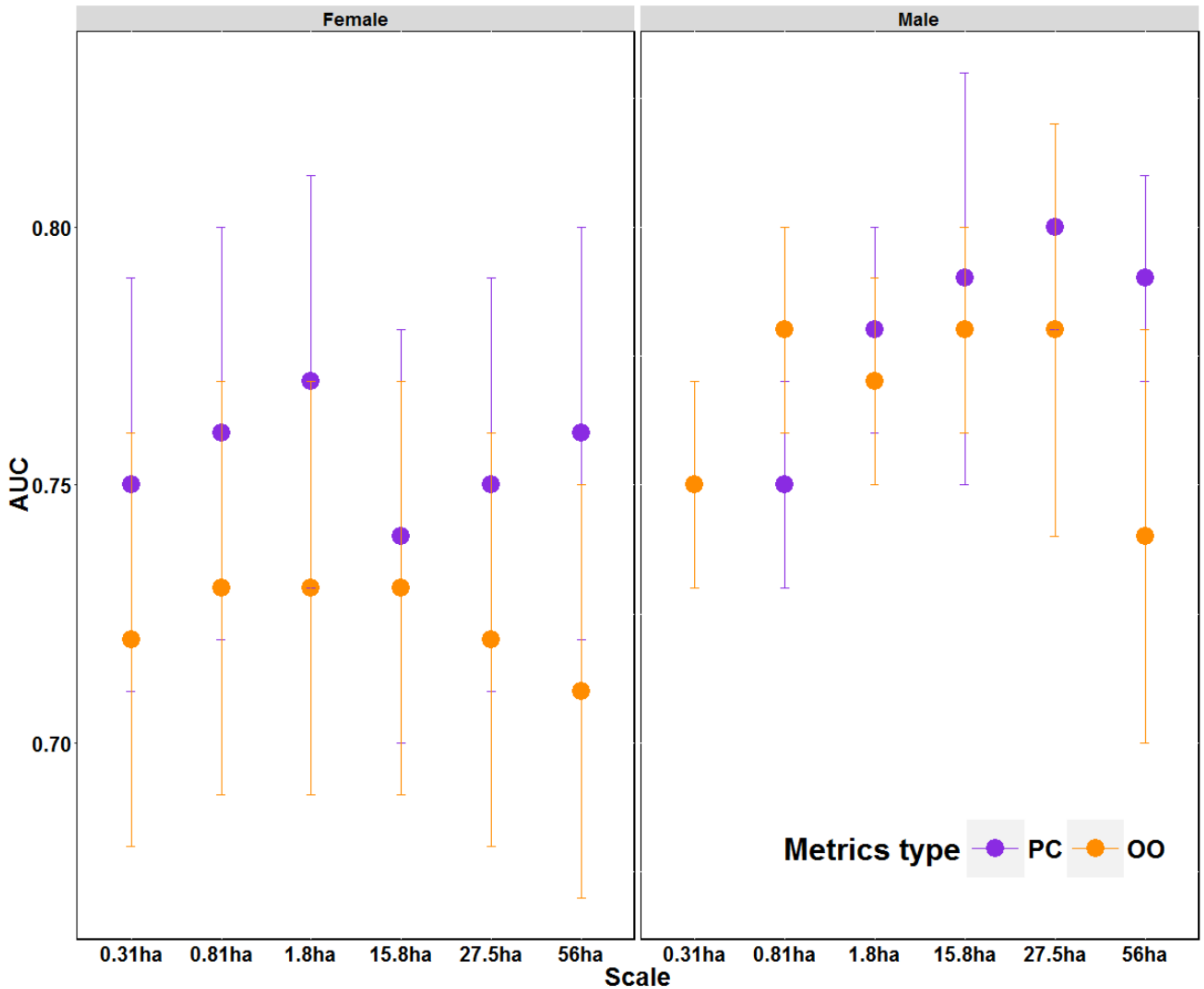
PC models have higher performance



AIN LiDAR campaign



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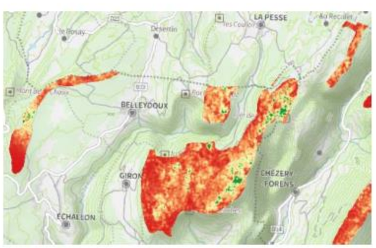
OO models are more robust across LiDAR campaigns

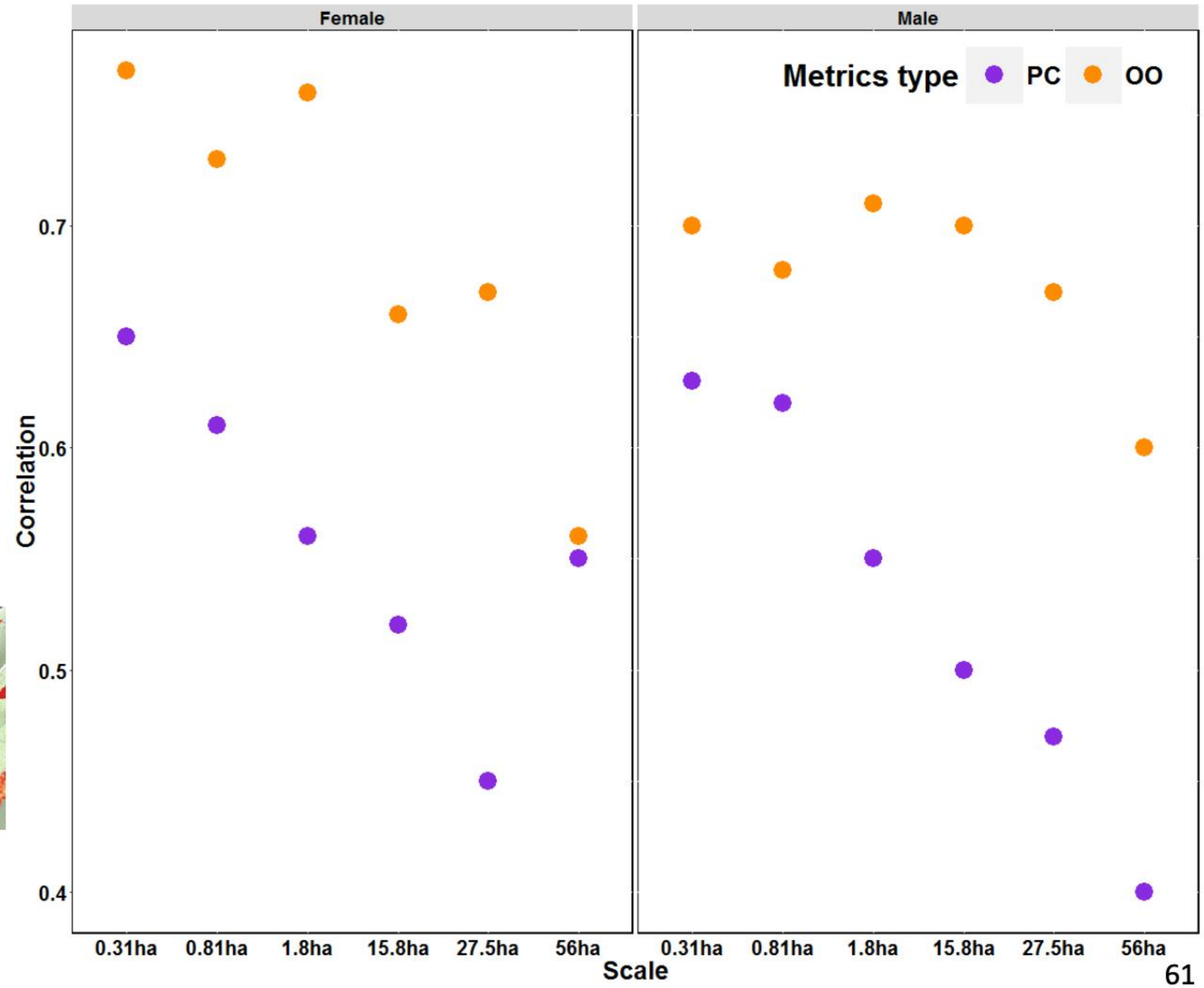
1st campaign

2nd campaign

Common area
(4 km²)



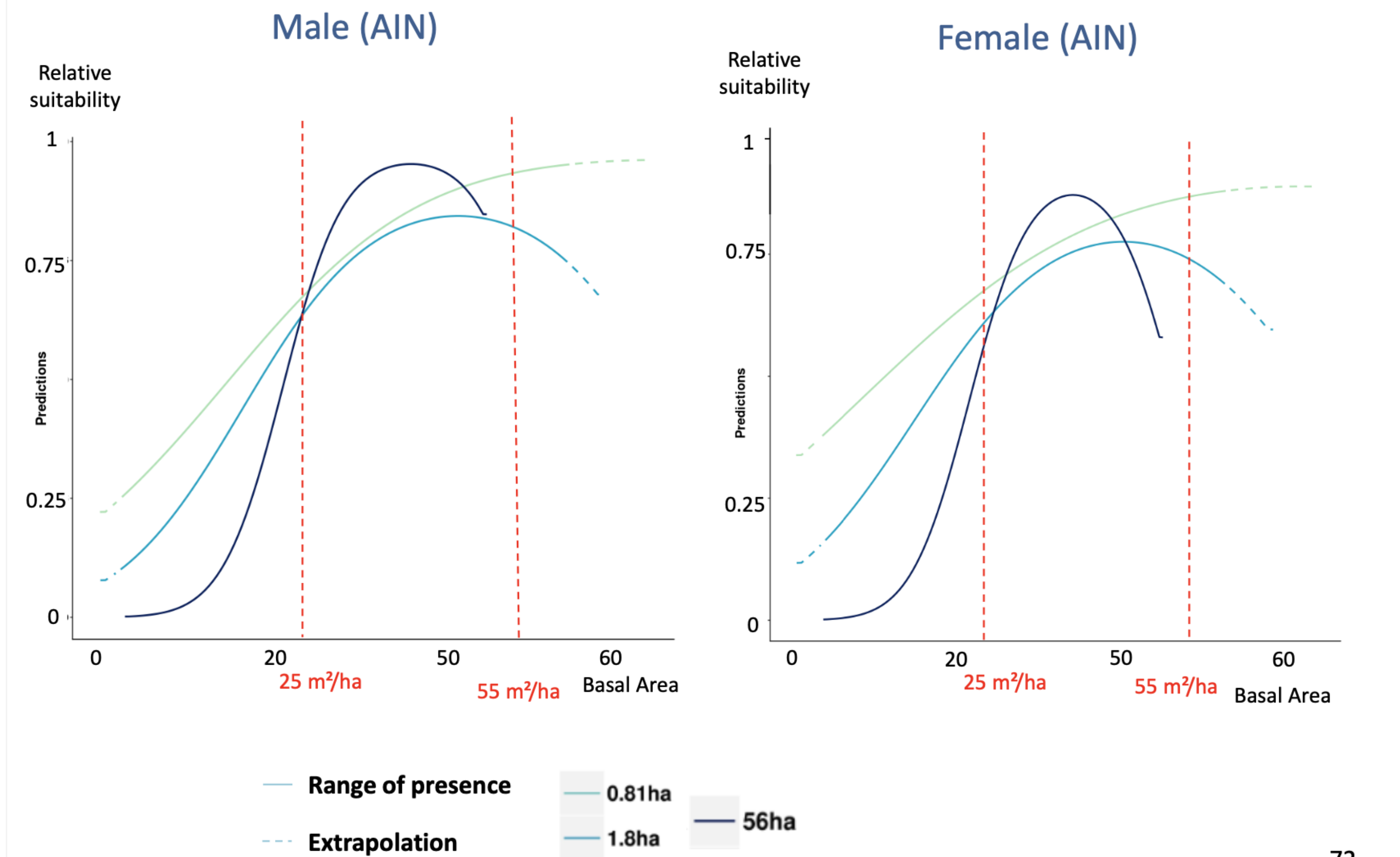
e.g. Predicted
map (Ain)



Models fitted to 2014 campaign data
Predictions compared for 2014 and for 2016 campaign data

Glad et al. (2020) Remote Sensing in Ecology and Conservation

Optimal values of basal area: 25-55 m^2 ha^{-1}



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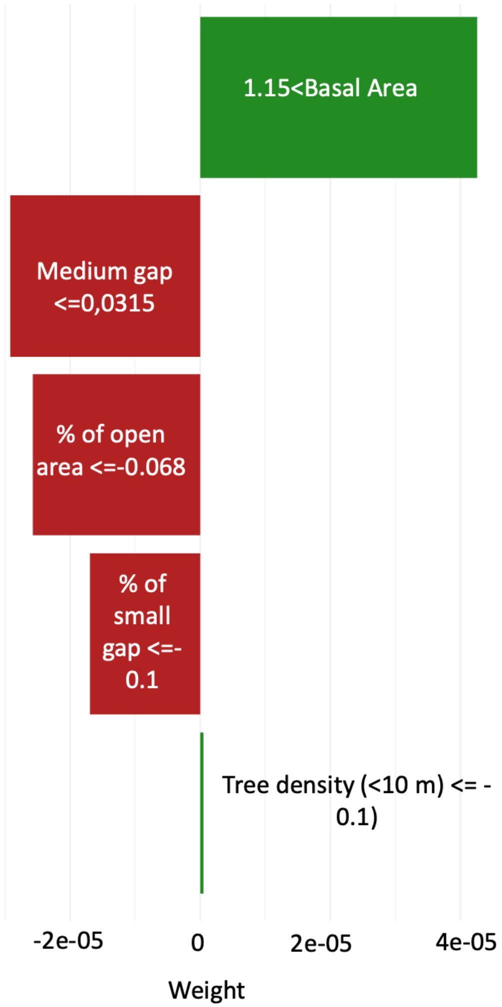
Comparison across scales suggests that high basal areas are good habitats for small patches but when considering large patches forests should have lower mean values

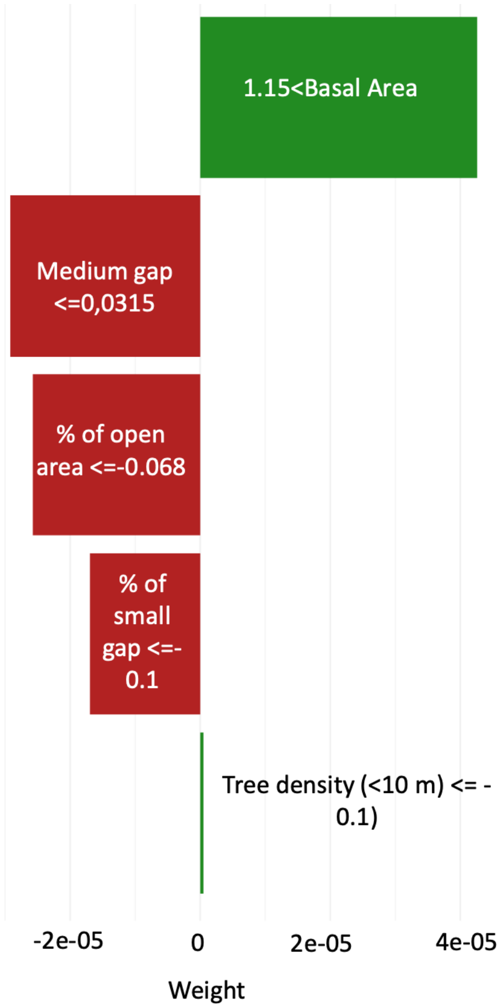
Management related challenges: interpretation



While the basal area value is suitable,
the absence of canopy gaps
results in a prediction of low habitat quality

Local Interpretable Model-agnostic Explanation (LIME) (Ribeirio et al. 2016)

Management related challenges: interpretation



This is not good enough!

- Too abstract
- Variables not independent
- How do they change with management?

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the absence of canopy gaps
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Local Interpretable Model-agnostic Explanation (LIME) (Ribeirio et al. 2016)

Challenges

LiDAR related

- Improve LiDAR analysis
  - 3D point clouds (Oehmcke et al. 2023)
  - Intensity calibration -> better use for cover type / tree species
  - Understorey (vegetation profiles – voxelisation; stage JM Monnet)
- Simplify use of LiDAR for habitat modelling (e.g. Moudry et al. 2023)

We need LiDAR metrics that are robust, interpretable and link to management

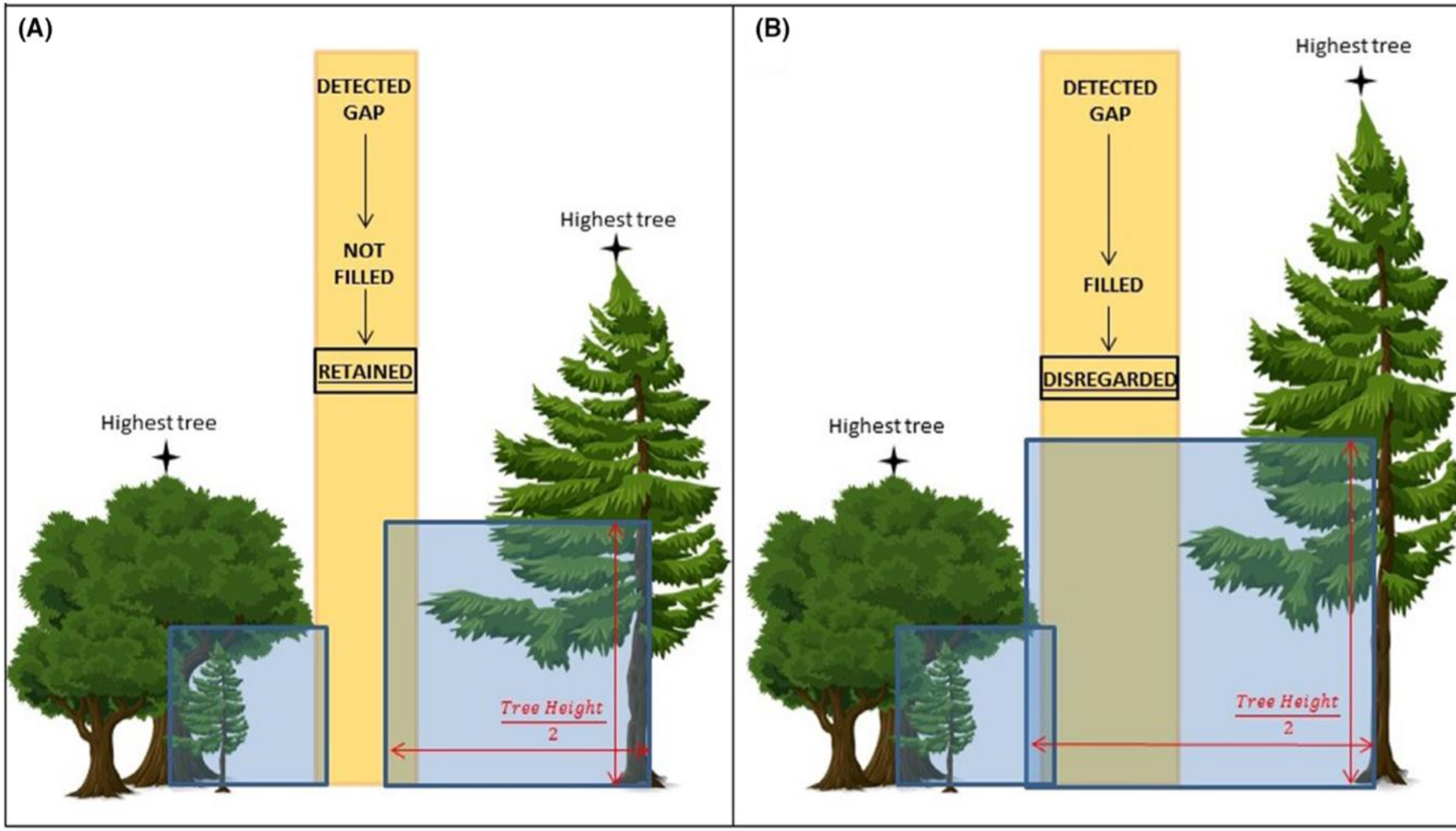
- Robustness across LiDAR campaigns
- Interpretability: LiDAR metrics -> forest structure
- Management link: Mangement -> LiDAR metrics -> Habitat suitability

Impactful analyses need more than good remote sensing data

- Better handling of scales & interactions between predictors
- Missing predictors (e.g. predators, climate change)
- Climate change
  - Direct impact on species
  - Impact on forest (trees, soil, ground vegetation)
- Beyond (relative) abundance

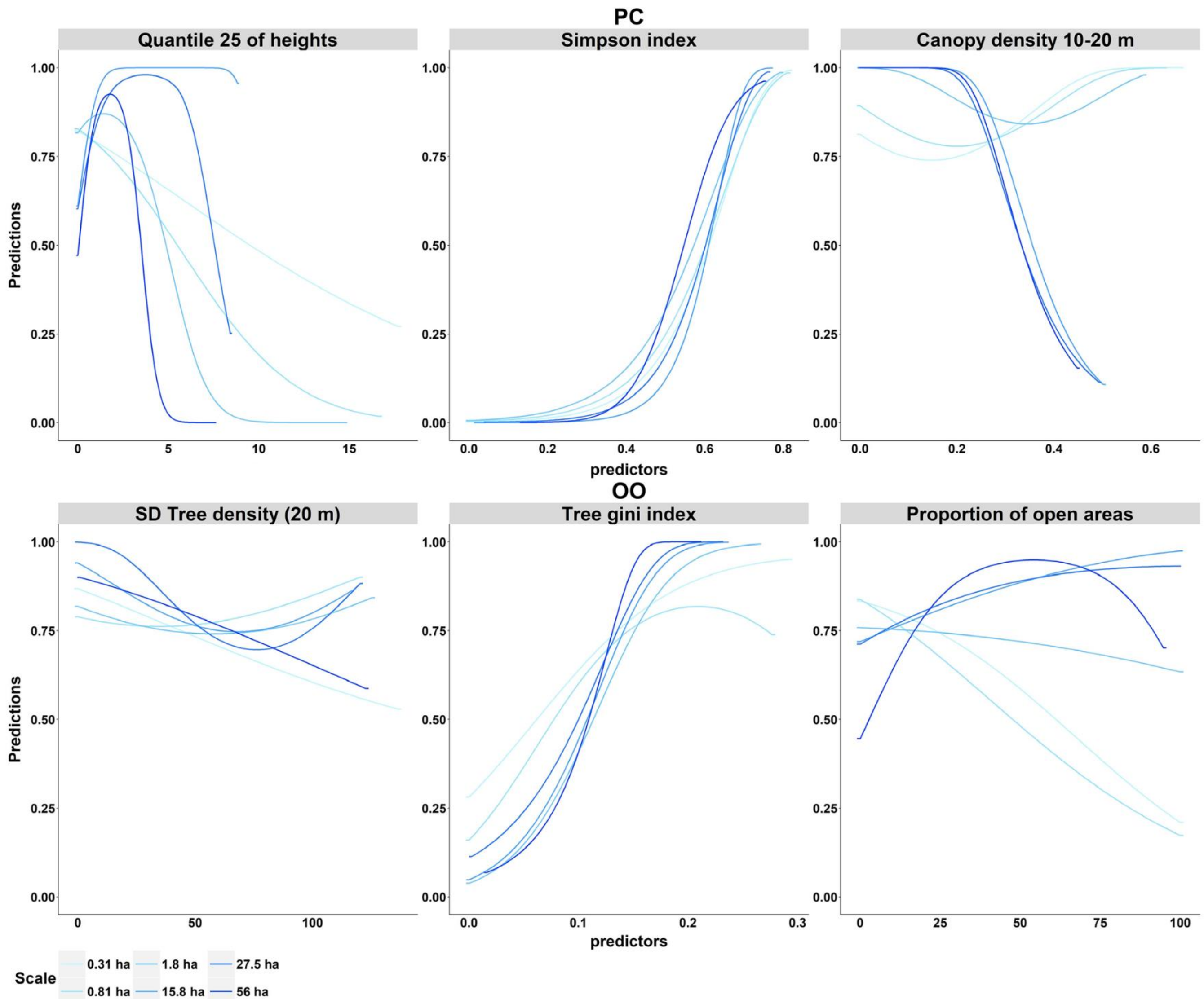
Oehmcke et al. (2023). http://arxiv.org/abs/2112.11335

Selection process of gap objects



Glad et al. (2020) Remote Sensing in Ecology and Conservation

Male response curves



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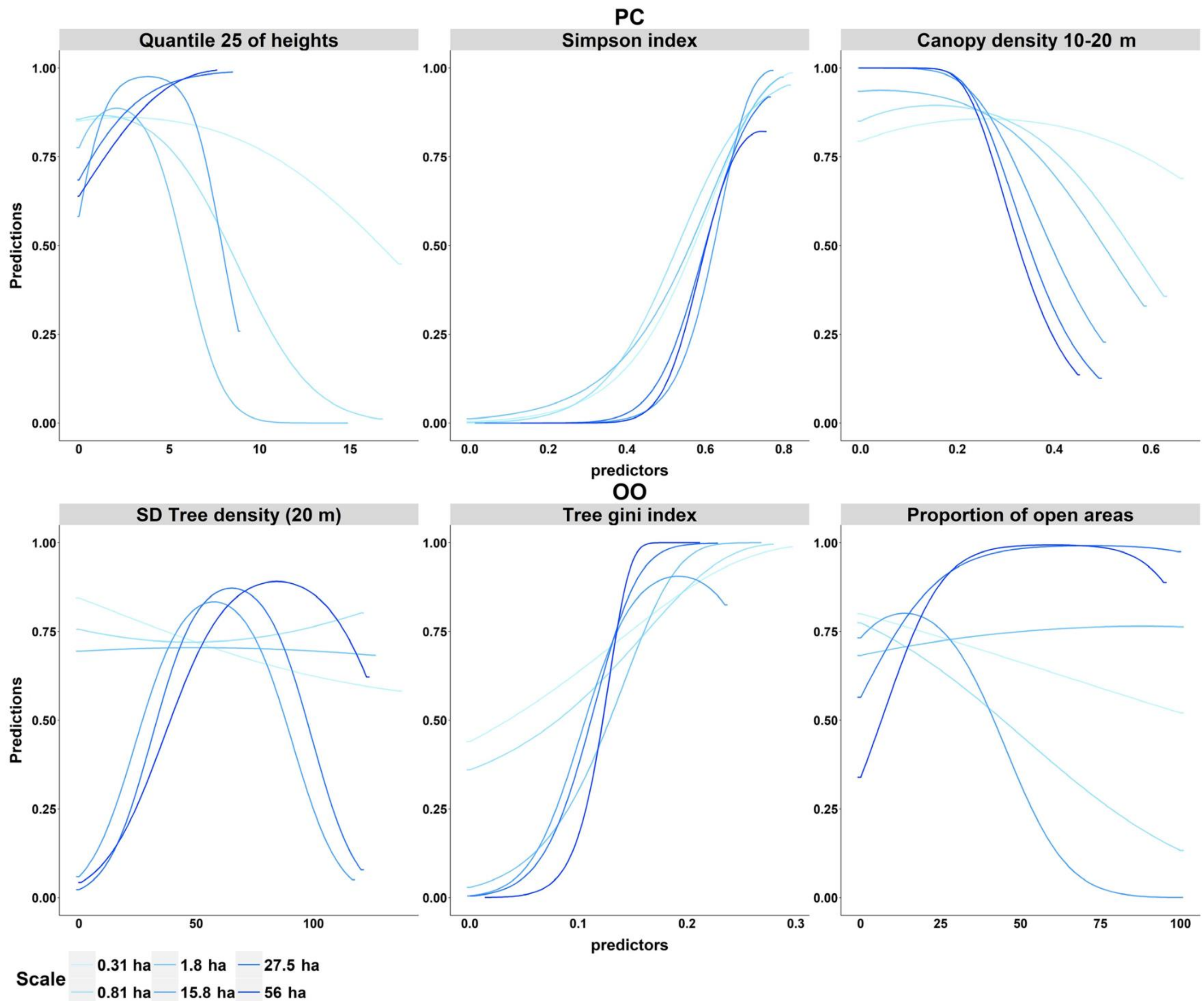
Female response curves



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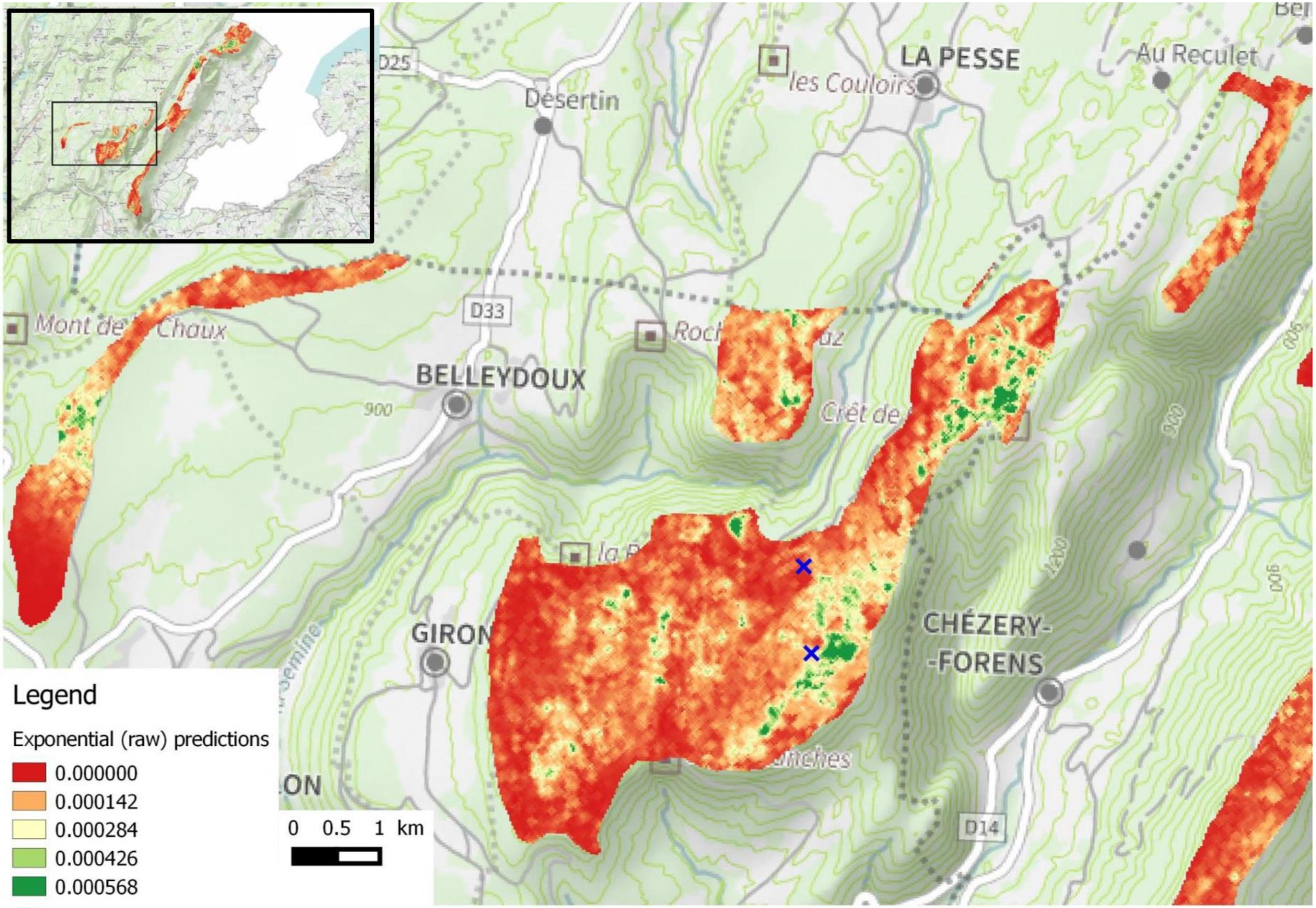
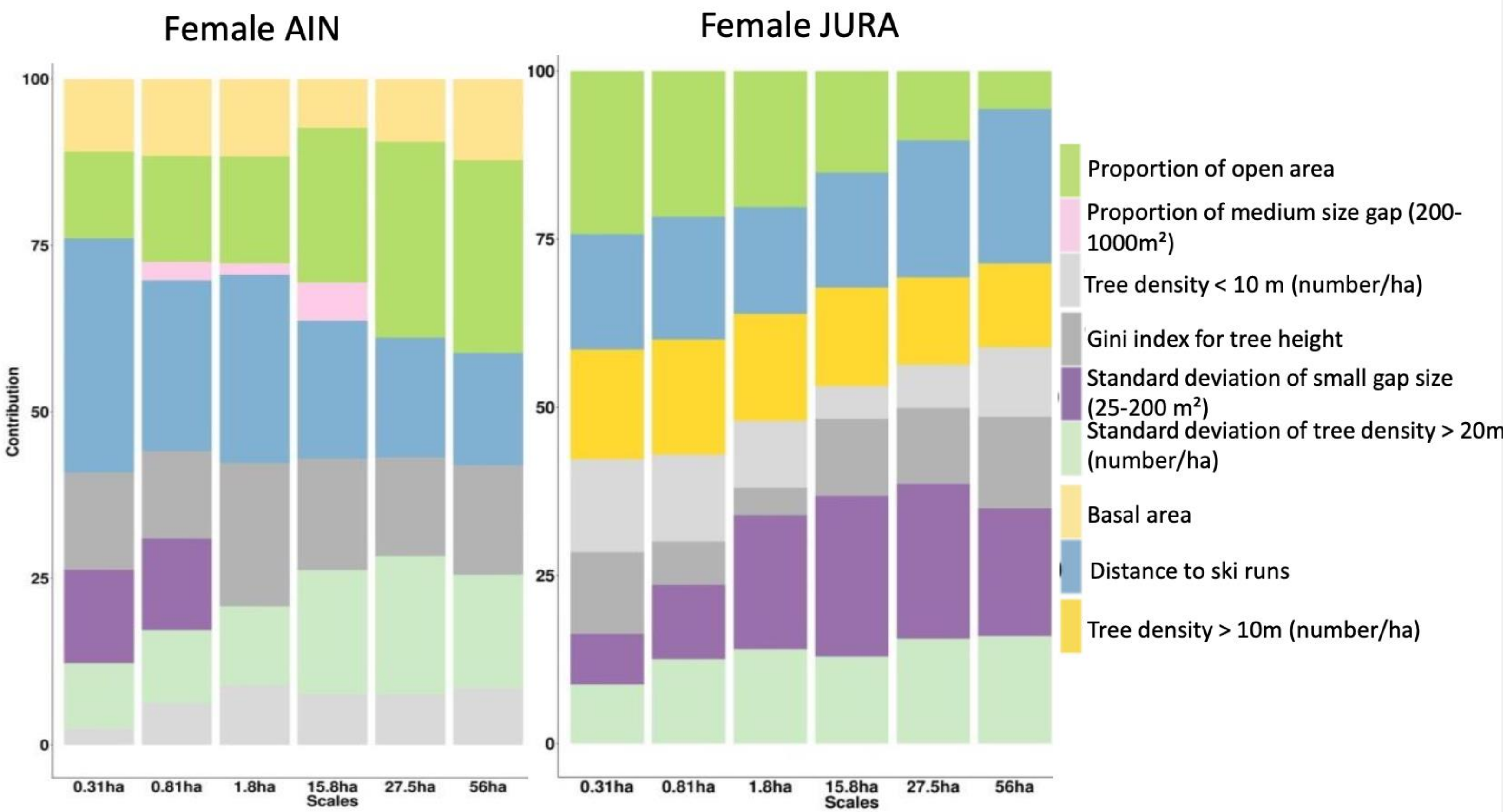
Model predictions



Females, Ain study area, 0.31 ha scale AUC: 0.72

Variable contributions vary across scales



Basal area is contributing at all scales