Comparing the precision of biomass estimates from a *sample based* forest inventory and a *model-assisted* approach utilizing small footprint LiDAR data

-A case study from a tropical peat swamp forest in Central Kalimantan-

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Introduction

- Forests receive public attention as multifunctional *carbon sinks*, as host of *biodiversity* and as a source of *renewable energy.*
- International policy processes address these issues by setting economic incentives and the establishment of markets.
- Estimates of above ground biomass (AGB) are important and highly demanded by many entities and groups.
- Often these entities request not only the actual estimate but an information on it's precision as well as a wall-to-wall map

UN-REDD
PROGRAMME

United Nations
Framework Convention on
Climate Change

Convention on
Biological Diversity

UNDP

UNEP

Introduction

Remote Sensing

- produce wall-to-wall maps also for remote locations
- cannot provide information on the precision of the estimate

Field inventories

- provide estimates of AGB
- provide information on the precision of the estimates
- cannot provide maps and is difficult / impossible to implement in remote locations

Model-Assisted Approaches

In the last decades new concepts were developed which allow to combined the well established concepts of design-based forest inventories with remote sensing based modelling approaches (e.g. Gregoire et al. 2011, McRoberts et al. 2013, Næsset et al. 2011, Särndal et al 1992)

Objectives

- Development a model to predict AGB for the study area in Kalimantan based on small footprint **L**ight **D**etection **A**nd **R**anging (LiDAR) data

- Comparison of the precision of AGB estimates derived from:
    - a) design-based inventory
    - b) model-assisted approach

Research Question:

1. Can small footprint LiDAR data be used to predict AGB in a tropical peat swamp forests in central Kalimantan?
2. Can the precision of AGB estimates be improved by using LiDAR data when compared to field inventories?

Material

The terrestrial survey was conducted in 2013 by different field teams

- A systematic sampling design (grid width=500m)
- *n*=35 plots
- Three concentric circular plots of size 50.3 m²; 201 m²radii and 804 m²
- Recorded Variables:
  - DBH, Basal Area, Azimuth, Distance, Tree species, Tree height, … .

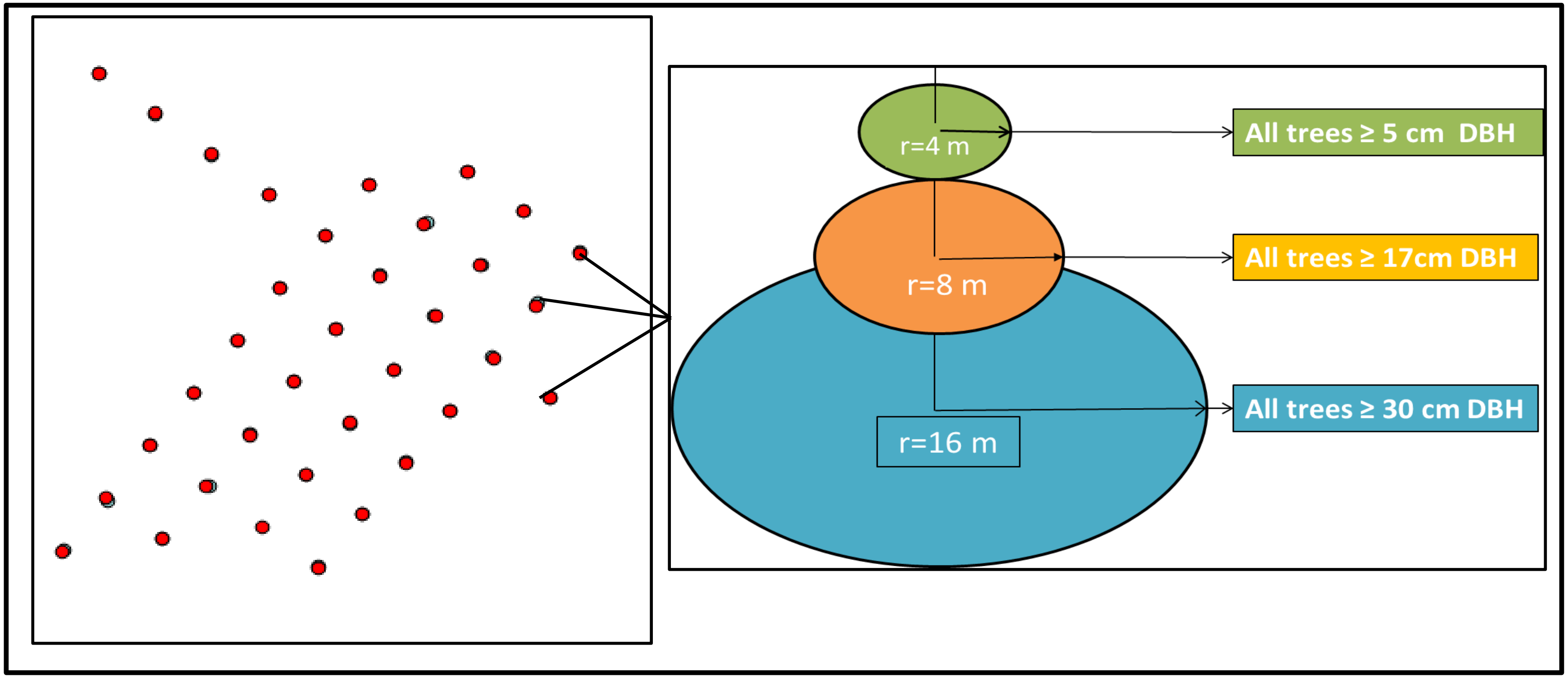


Fig.1 Sample design (left) and plot design (right) in the HIL experimental area

LiDAR (**L**ight **D**etection **A**nd **R**anging)

- Active remote sensing system mounted on aircrafts
- Sends pulses in a high frequency from the sensor to the earth surface
- The pulses are either absorbed or reflected by the earth surface (e.g. tree leaves)
- The energy and time traveled of each return is recorded and a 3d position calculated

Material

The LiDAR data was acquired by Surtech Ltd. in two flights

- Acquisition dates: 10/11/2011 & 10/13/2011
- Full-waveform laser
- Sensor: Optech Orion M200
- Average point density : 2.6 pts /m²
- Beam width: approx. 20 cm
- Features recorded:
    - intensity, angle, x, y, z-coordinates, ….

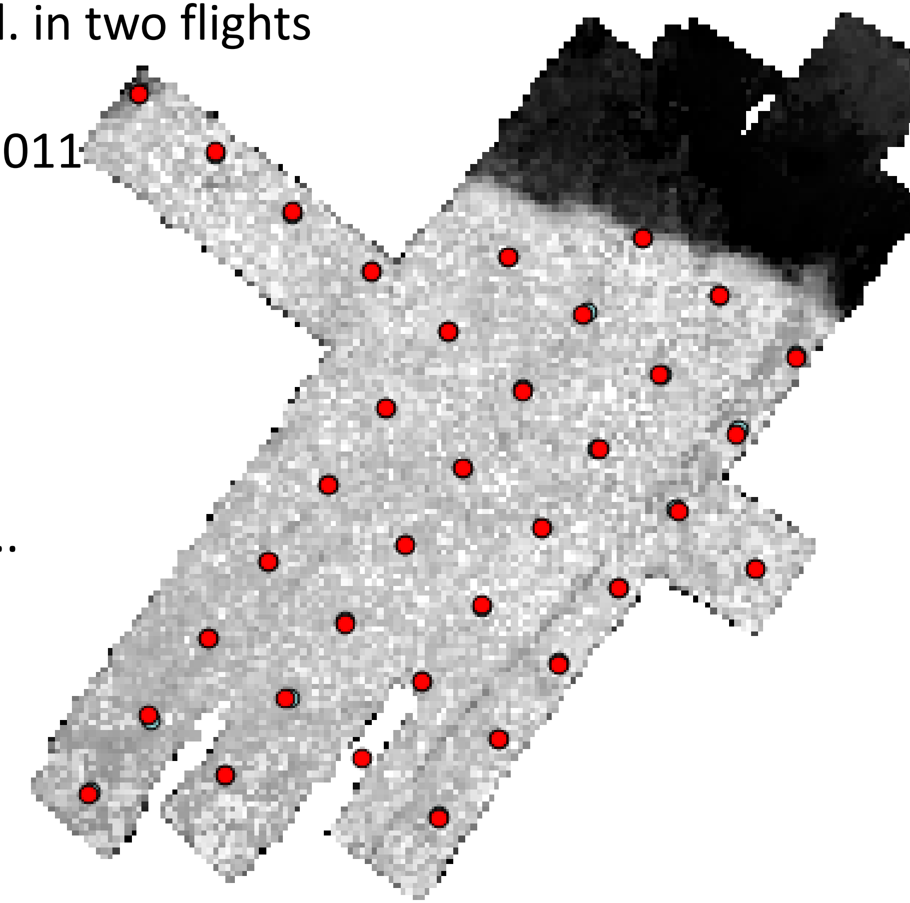
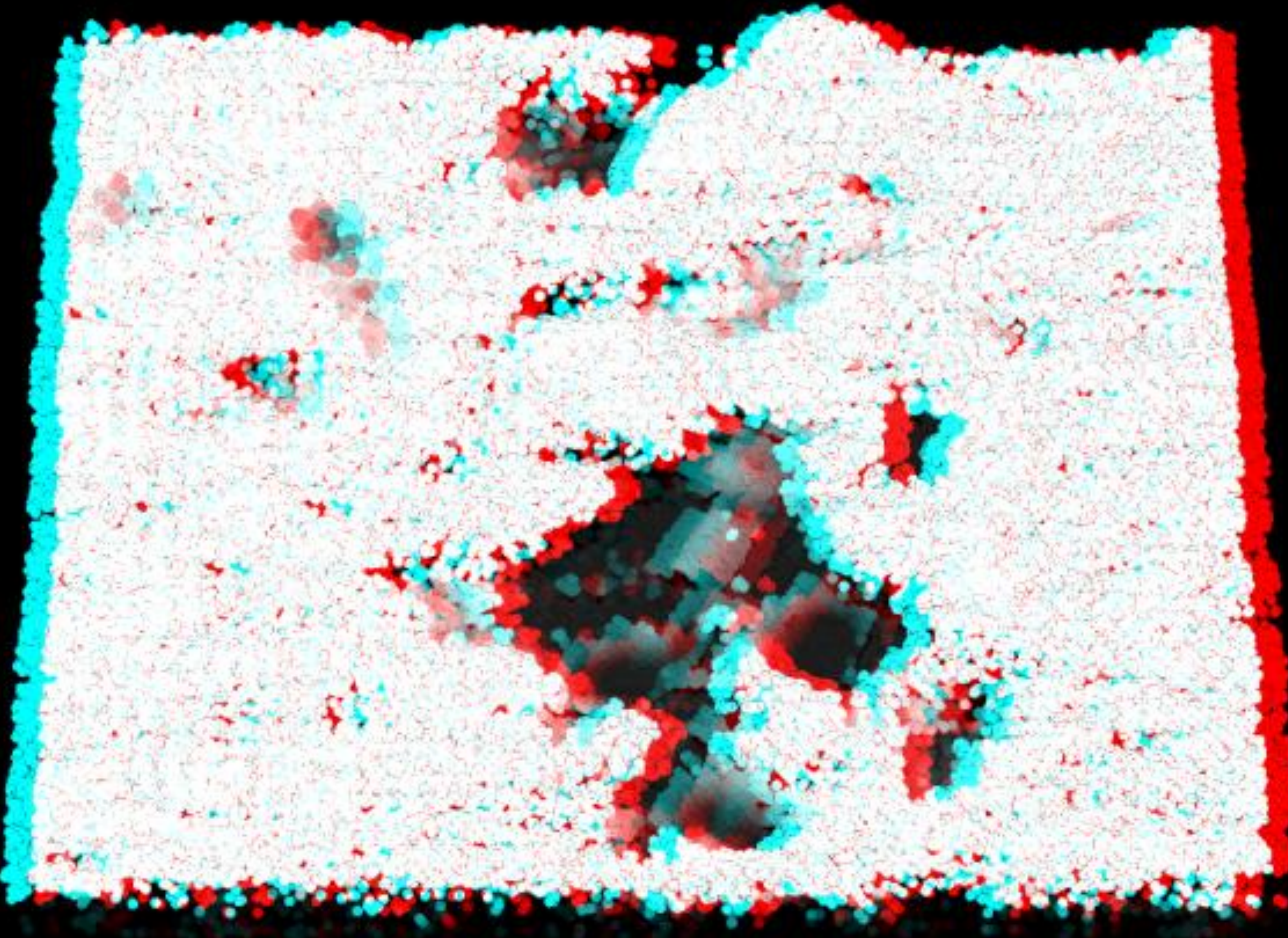
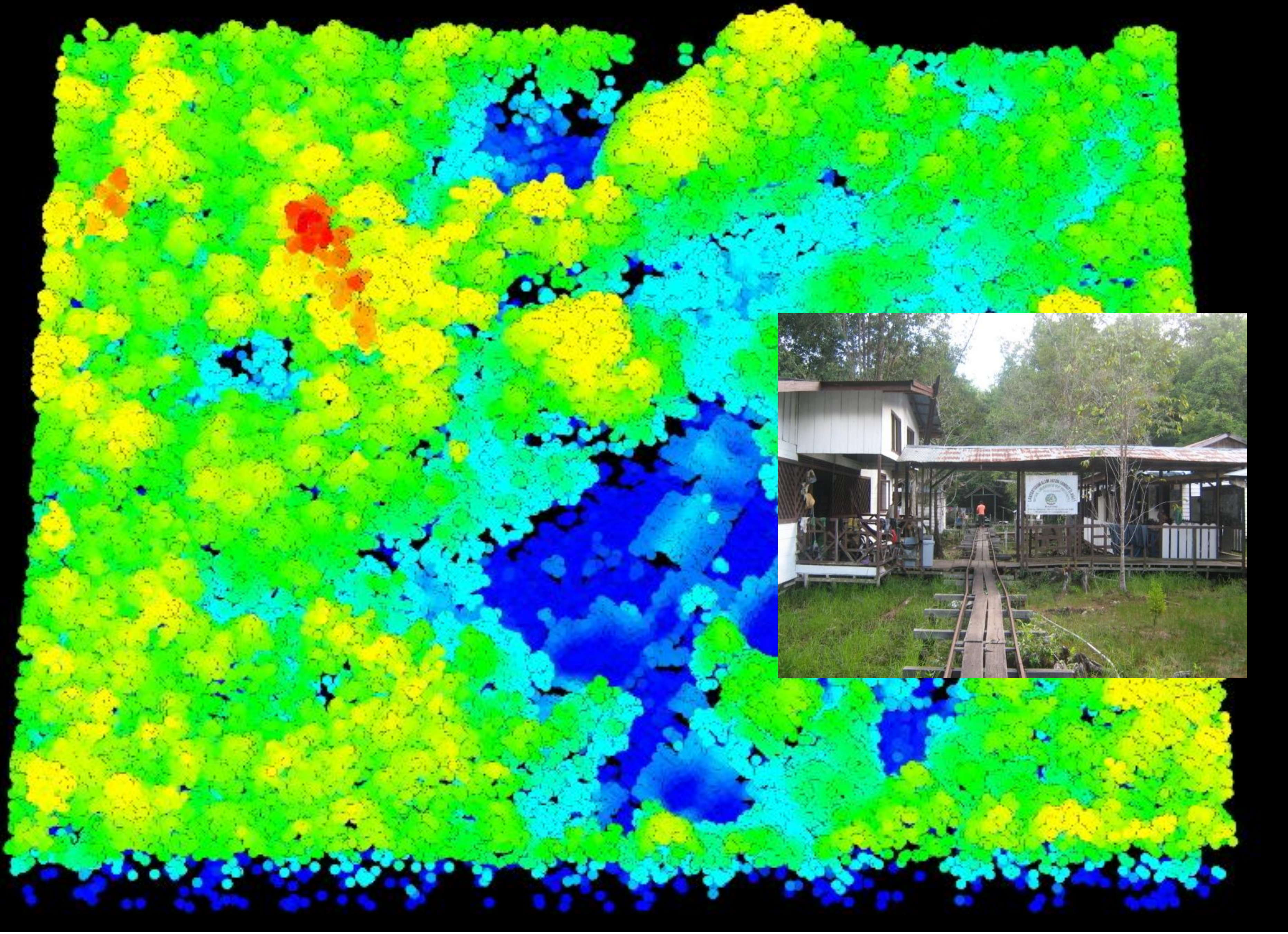
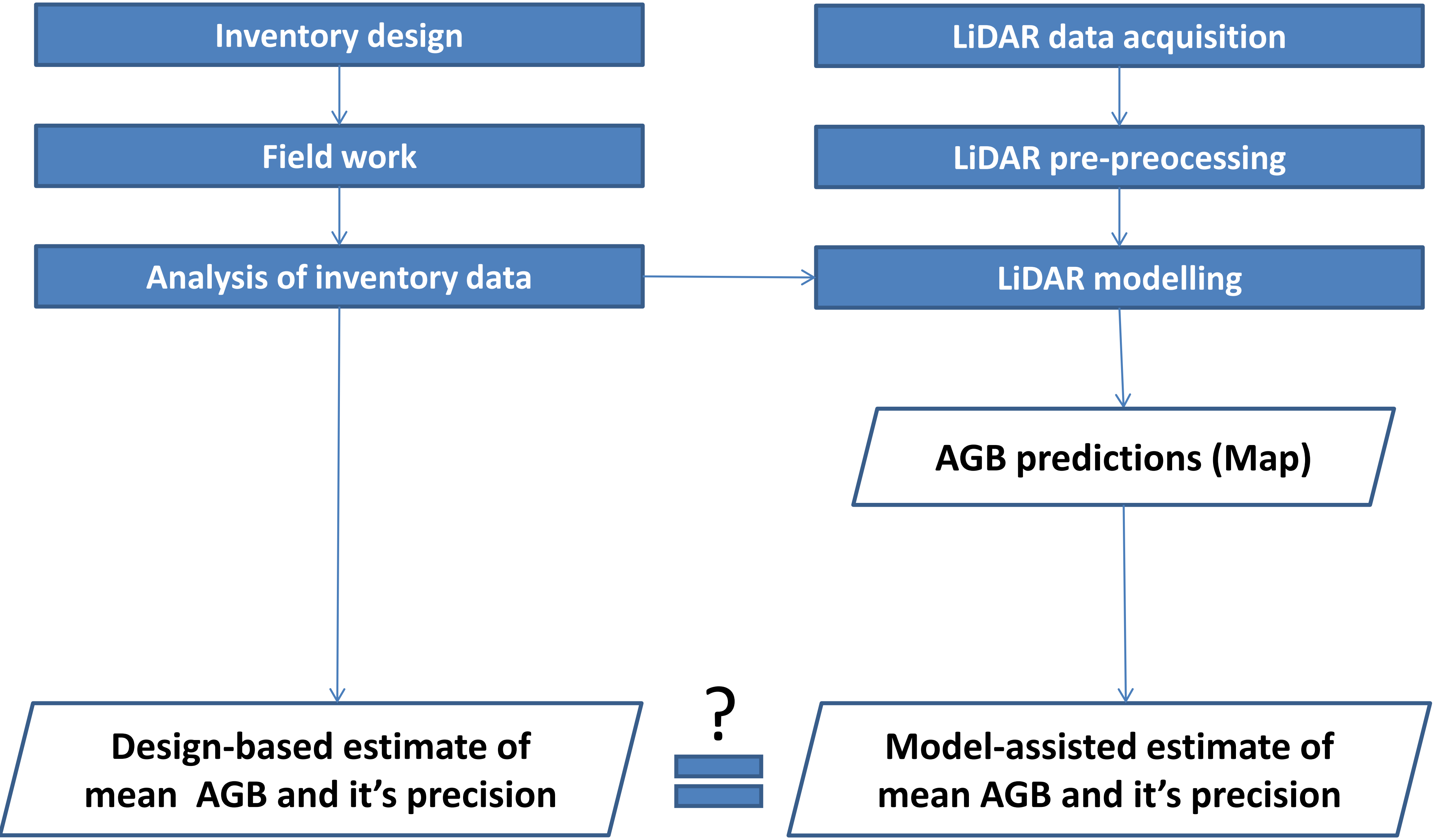


Fig.2 LiDAR coverage of the study area. Brightness values based on the intensity





Methods


Inventory design
Field work
Analysis of inventory data
LiDAR data acquisition
LiDAR pre-preocessing
LiDAR modelling
AGB predictions (Map)
Design-based estimate of mean AGB and it's precision
?
Model-assisted estimate of mean AGB and it's precision

Methods

- The biomass of each tree was modeled using the DBH and the general allometric model for moist tropical forests (Brown S., 1997)

- The single tree biomass values were aggregated on a plot level and rescaled to t/ha

- The mean AGB (μ) and it's error variance $var(\mu)$ was estimated using the standard Simple Random Sampling (SRS) estimators.

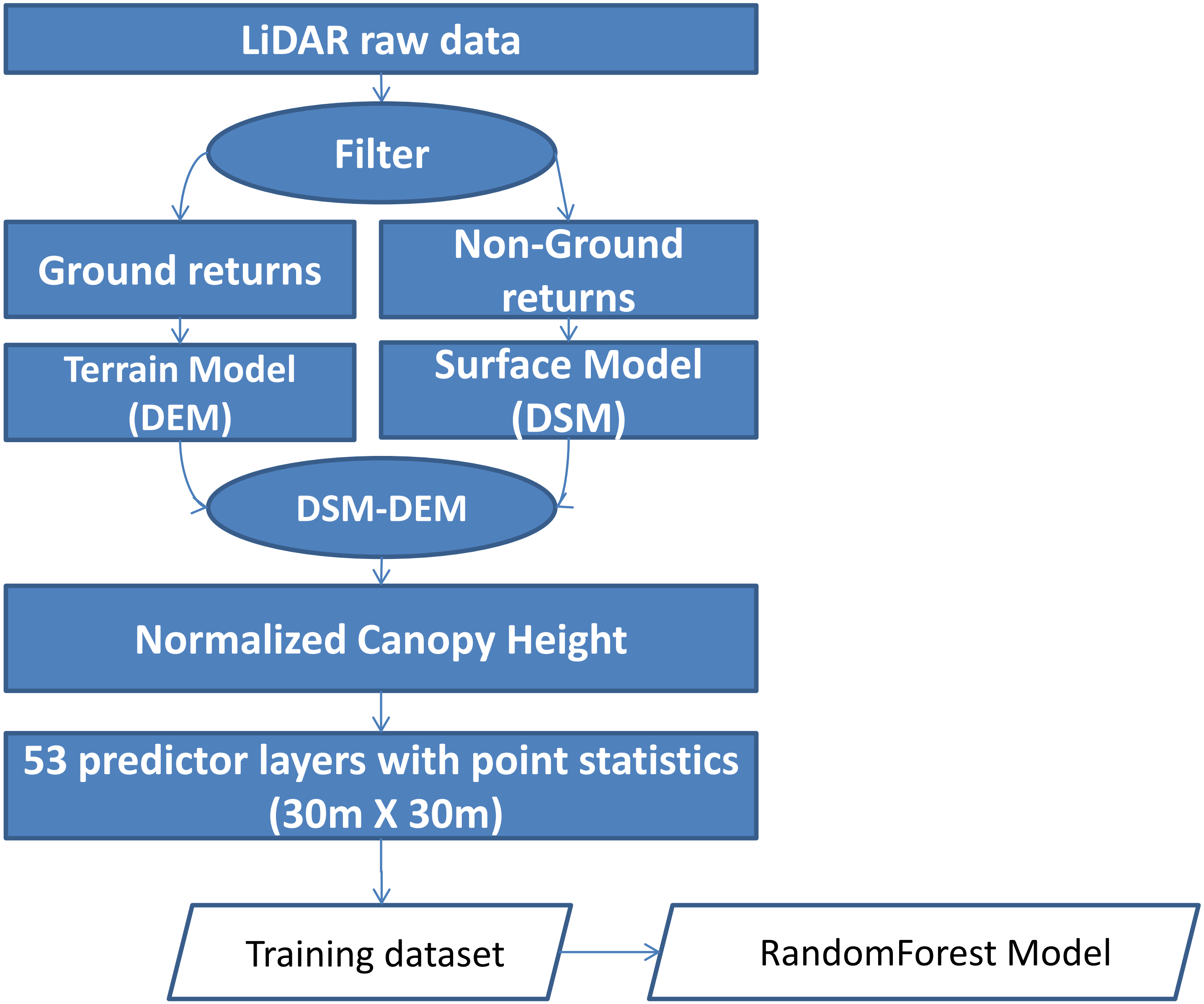
Mean AGB in t/ha :

$$\hat{\mu}_{SRS} = \frac{1}{n}\sum_{i=1}^{n} y_i$$

Error variance of mean AGB in t/ha:

$$v\hat{a}r(\hat{\mu}_{SRS}) = \frac{\sum_{i=1}^{n}(y_i - \hat{\mu}_{SRS})^2}{n(n-1)}$$

Methods


LiDAR raw data
Filter
Ground returns
Non-Ground returns
Terrain Model (DEM)
Surface Model (DSM)
DSM-DEM
Normalized Canopy Height
53 predictor layers with point statistics (30m X 30m)
Training dataset
RandomForest Model

Methods

- The mean biomass of each grid cell was predicted using the RandomForests model which resulted in a AGB map
- The mean AGB (μ_{MA}) and it's error variance var_{MA} estimated using the model-assisted estimators of Särndal et al. (1992)

Mean of the model predictions over all population elements N

Mean AGB in t/ha :

$$\hat{\mu}_{MA} = \frac{1}{N}\sum_{i=1}^{N}\hat{y}_i - \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)$$

Model Bias

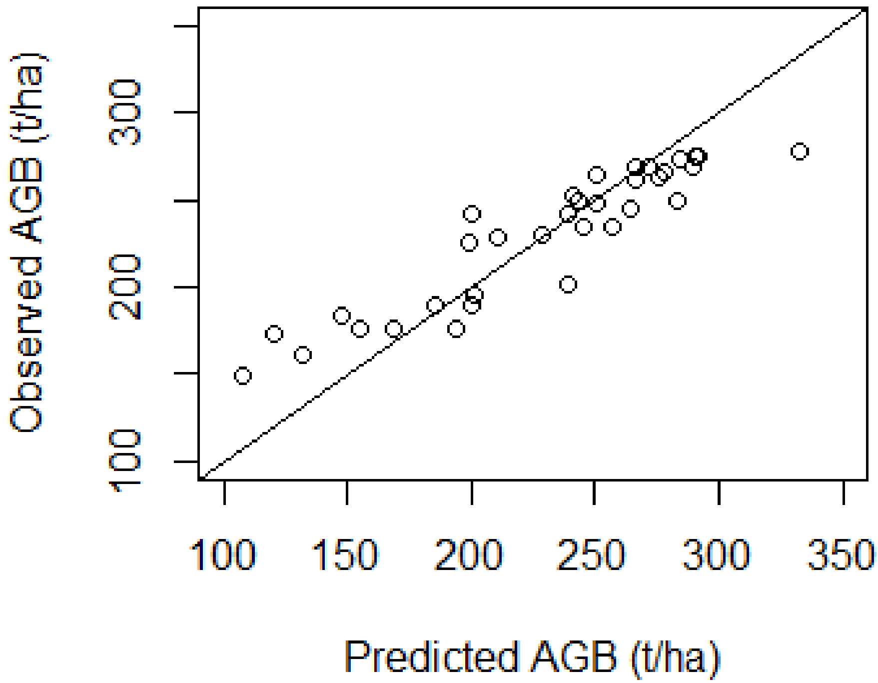
$$\varepsilon_i = \hat{y}_i - y_i$$

Error variance of mean AGB in t/ha:

$$v\hat{a}r(\hat{\mu}_{MA}) = \frac{1}{n(n-1)}\sum_{i=1}^{n}(\epsilon_i - \bar{\varepsilon})^2$$

The notation is follows McRoberts et al. (2013)

Results



RMSE: 45.53 t/ha

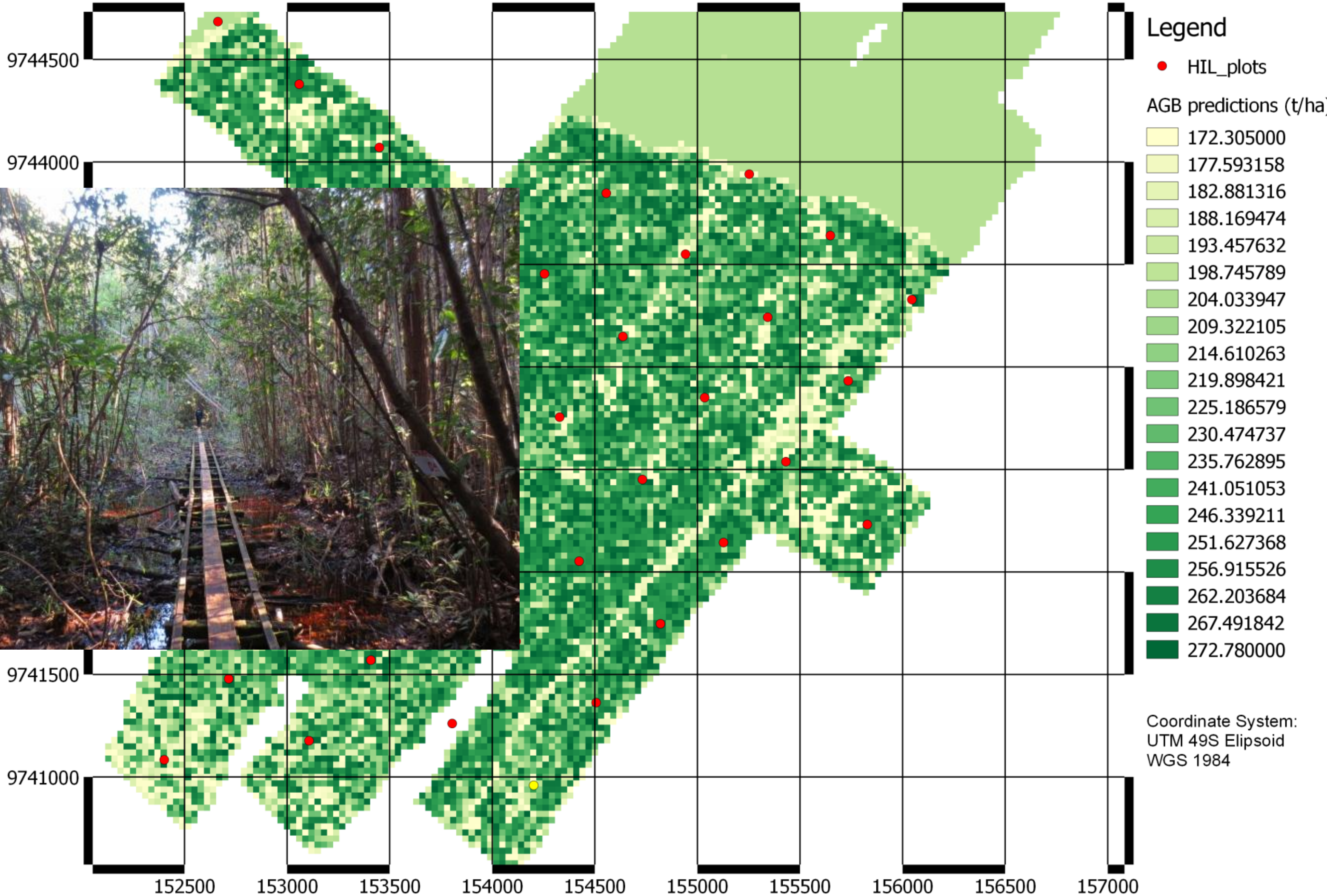
Variance explained: 30.7 %

Predictors selected for the model:

- Elevation Mode
- The height the top 70% of returns (Percentile 0.7)
- The height the top 75% of returns (Percentile 0.75)
- The height the top 80% of returns (Percentile 0.8)
- The height the top 95% of returns (Percentile 0.95)

Results

AGB Map



Results

Table 1: Comparison of the AGB estimates by both approaches

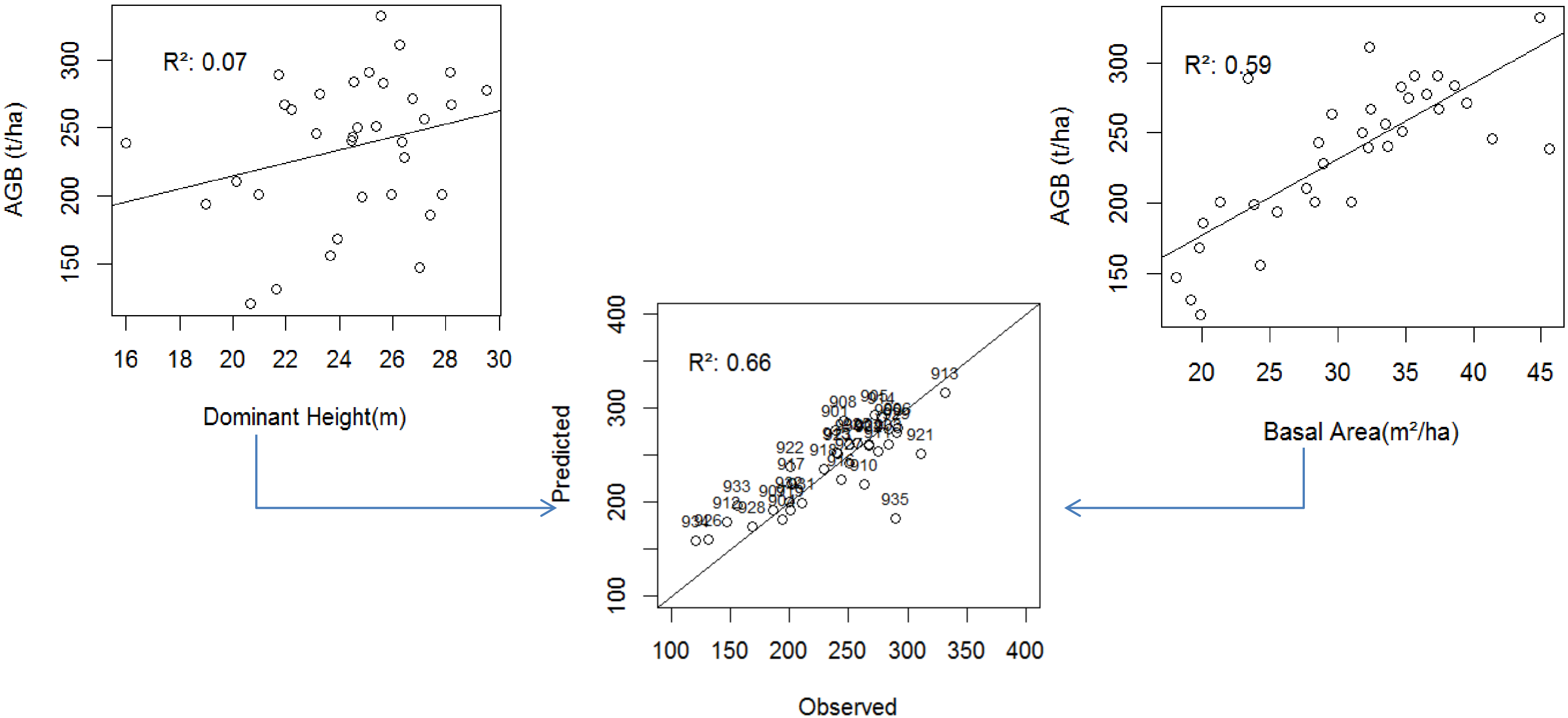
Approach	n	N	$\hat{\mu}$ (t/ha)	$v\hat{a}r(\hat{\mu})$	$SE(\hat{\mu})$ (t/ha)	$v\hat{a}r(\hat{\mu})$ relative
Design-based	33	-	230.63	93.48	9.66	4.2%
Model- assisted	33	12294	230.81	64.48	8.02	3.47%

- The standard error of the model-assisted estimator is 1.64 t/ha less then for the design-based estimator

Discussion

- The quality of the AGB model was lower than found in other types of forests.
- But studies working in the same peat swamp forest report similar values of R^2 0.3 (Kronseder et al. 2012)

Why is the correlation between LiDAR metrics and AGB in peat-swamp forest areas low?



Conclusions & Outlook

Research Question:

1. Can small footprint LiDAR data be used to predict AGB in a tropical peat swamp forests in central Kalimantan?
2. Can the precision of AGB estimates be improved by using LiDAR data when compared to field inventories?

- The RandomForest model used to predict the AGB is in general suitable even thought there are many options for improvement
- Using the model-assisted approach resulted smaller error variances than the design-based estimator
- The investment into LiDAR data and processing can not be justified by the increase in precision of AGB estimates in our study area
- If LiDAR data should become operational more applications need to be integrated e.g.   degradation mapping, forest structure analysis

Wrap up & Outlook Kalimantan Project

- In the last 15 month we developed and implemented the experimental design and we are almost finished with the collection of the field data which is potentially the first such dataset for the Sabangau Forest.
- The data was / is continuously quality controlled and stored in a central database to increase the consistency between the different data users.
- Furthermore a rich collection of GIS and remote sensing products have been acquired (still ongoing)
- First research results of the team members are presented at this workshop

Where to go from here?

1) Improve the quality of model-assisted estimation utilizing the LiDAR models and test alternative remote sensing products (e.g. RapidEye, Péiades and Landsat)
2) Analyze effects of biomass model selection and /or tree species misidentification on the precision of AGB estimates.
3) Continue the research on the mono-temporal detection of degradation by linking to remote sensing

If you are interested in research and thesis work contact us!

Acknowledgements

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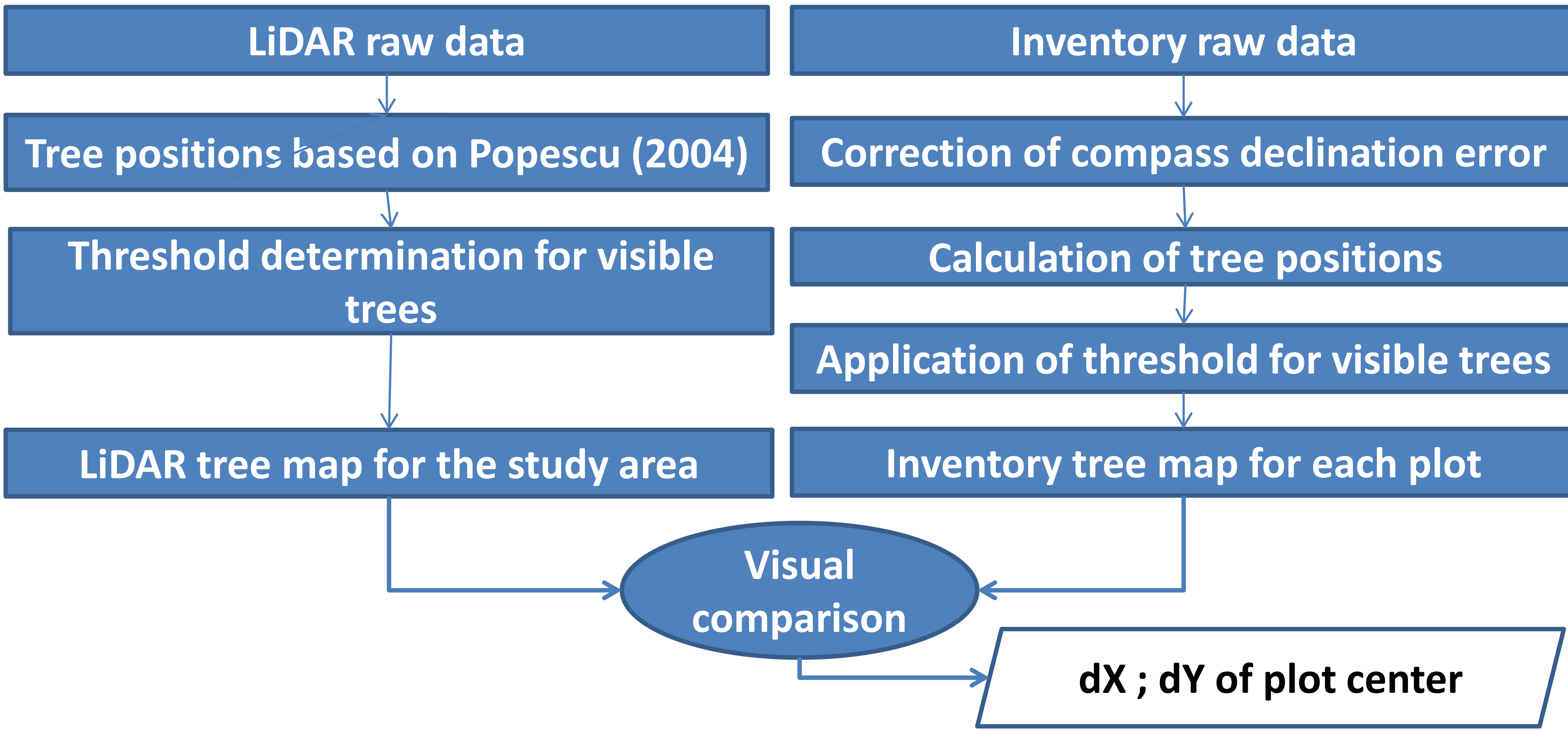
Methods

LiDAR Pre-Processing

LiDAR Co-Registration:

- The exact co-registration between the LiDAR and the field inventory is a critical prerequisite
- We developed a semi automatic approach based on the comparison of single tree positions in both data sets.



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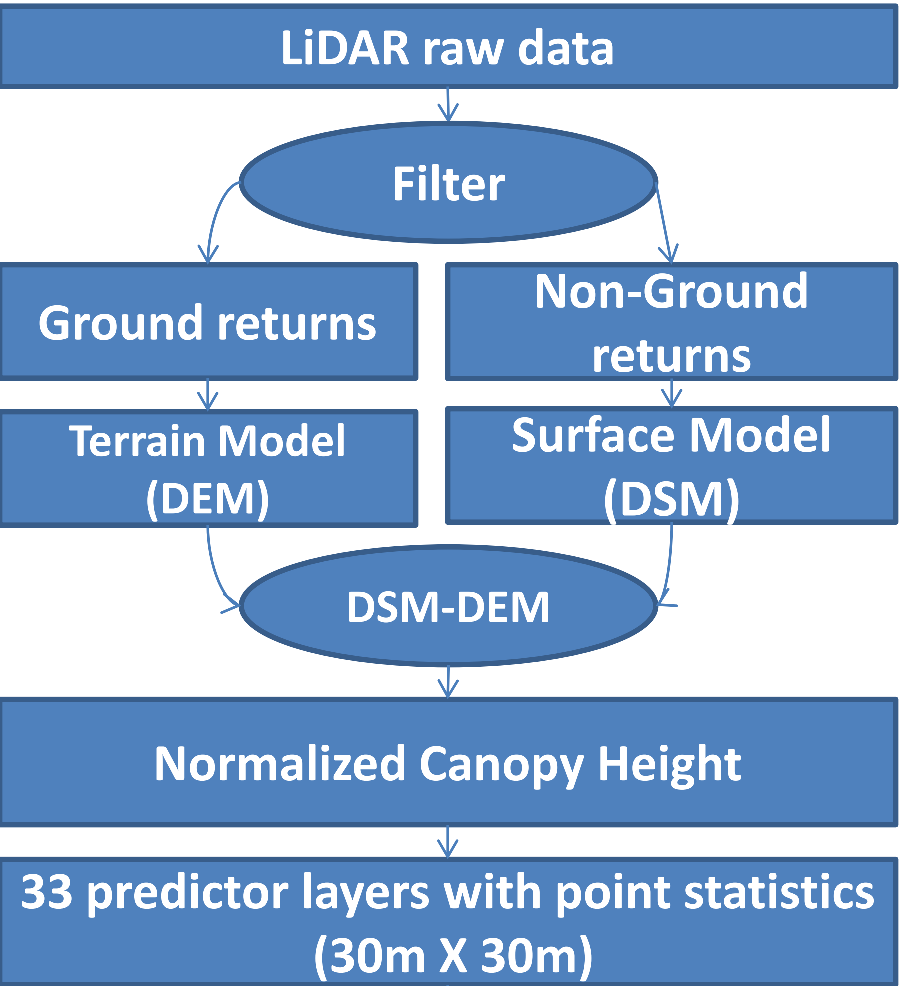
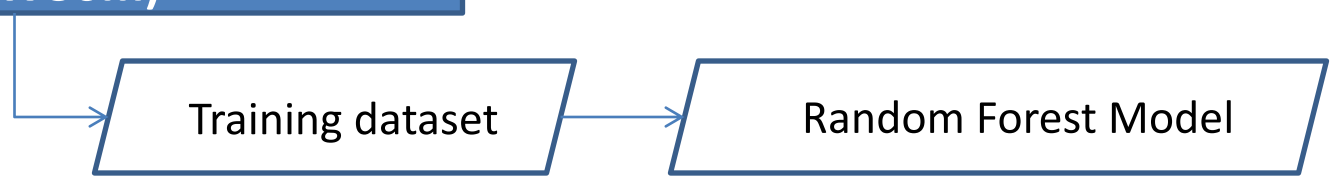
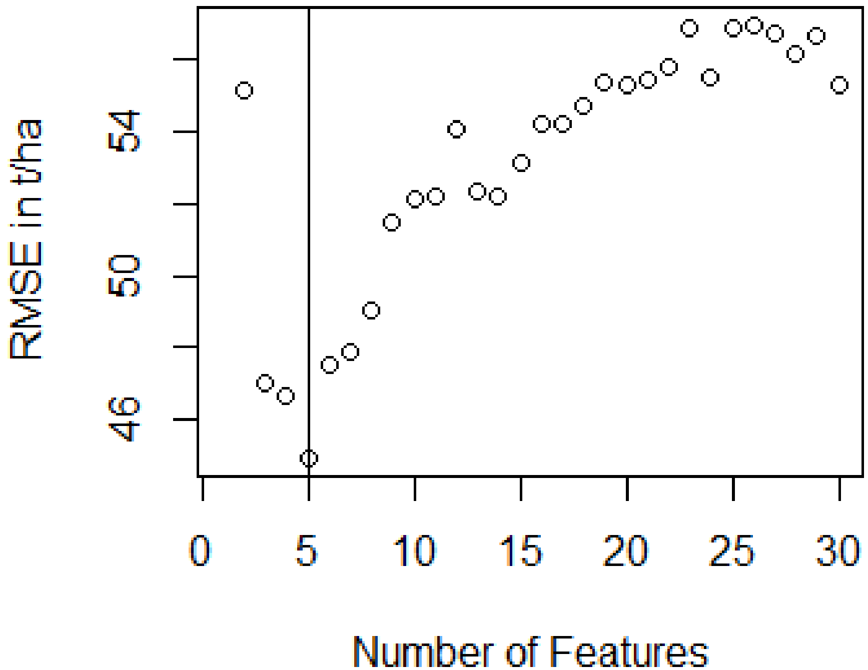


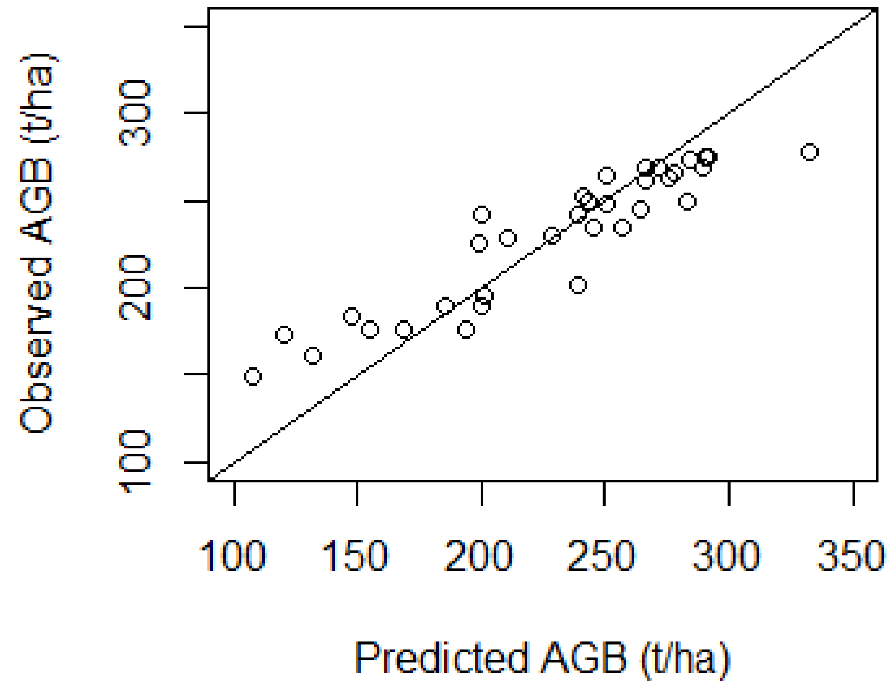
- For the modelling we used a non-parametric Random Forests model as developed by Breiman (2001)

- Feature selection was done in two steps:
  1. by a visual analysis the predictor layers with no or little variance were excluded
  2. the remaining variables were selected using the mean decrease accuracy (MDA) statistic in a bootstrap approach
- Finally we selected the *n*=5 features with the highest MDA values and grow a Random Forests model with *n*=500 trees



Results





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