AGU FALL MEETING
Online Everywhere | 1–17 December 2020

Plant Structure and Carbon Storage Assessment Utilizing Drone-Borne Lidar and Deep Learning Technologies in a Danish Agricultural Expanse

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ABSTRACT

The increase of vegetation greenness in the Northern latitudes suggests a rise in the fixation of CO2 by photosynthesis, but the observed upward trends in respiration could compensate for elevated uptake by photosynthesis, necessitating the monitoring of variation in vegetation structure and carbon (C) storage at very high spatio-temporal resolution. Compared to passive optical remote sensing, Light Detection and Ranging (Lidar) scanners may improve the quantification of C sink by providing 3D information of plant structures without apparent sign of saturation of spectral response over dense canopies. We evaluate a novel approach to precisely map C sequestration and key metrics describing the 3D canopy structure of a temperate agricultural expanse by implementing drone-borne Lidar scanner technology and deep learning (DL) architectures potentially capable of detecting individual plants and associated geometrical properties while deriving their above ground biomass (AGB) from point cloud datasets originated from the scanner. An intensive aerial and field campaign was carried out over an Integrated Carbon Observation System (ICOS) class 1 station site (60 ha) in Denmark to remotely measure the horizontal and vertical canopy structure at 15-day intervals during the vegetation growing period, and to collect ground truth data of crop growth in terms of height, density, AGB and green area index of more than 1200 plants. The point cloud data are pre-processed using pattern recognition tools to remove noise. Then, several regression models are implemented for AGB prediction. Two DL models (PointNet-based methods) specifically designed to handle the irregular structure of raw point clouds are trained to extract features of vegetation by labeling the processed point cloud data; DL's suitability for assigning semantic information on 3D data representing cropland is assessed by validating them with the field-based observations. In combination with tower-based flux data, the application of Lidar and DL technologies appear to offer a characterization of the dynamic interaction between

climatic conditions, vegetation growth, C sink, water and CO2 fluxes suitable to the challenge of assessing the rapidly changing northern landscapes.

OBJECTIVE & APPROACH

Objective

- We aim at developing a new method to assess **above-ground biomass (AGB**) and estimate **carbon (C) storage** in agricultural fields.

Why using this approach?

- Changes in AGB are a strong indicator for plant growth, water and nutrient status, as well as C-storage under given climatic and management conditions.
- High-density lidar point cloud data (PCD) provide accurate estimates of canopy volume and development stage.
- Machine learning (ML) and in particular deep learning (DL) methods are successfully used in other domains [1, 2] for automated interpretation of 3D point cloud data.

STUDY SITE & INSTRUMENTATION

[VIDEO] https://www.youtube.com/embed/B8-d0rU7GDY?rel=0&fs=1&modestbranding=1&rel=0&showinfo=0

Video 1: UAV in operation at study site.

Study site

- We study an agricultural field (13 ha of extension), where the cultivated crops (*Hordeum Vulgare L.*) are subject to conventional management practice.

Fig 1. Location of the study site (**A** symbol on the map, Mid Jutland, Denmark). Source: icos-cp.eu

Instrumentation

- Unmanned aerial vehicle (UAV) with mounted lidar sensor (LidarSwiss Nano M8).

Fig 2. UAV-lidar.

- Eddy-covariance (EC) ecosystem station (ICOS class-1), located at the center of the study site (56º, 02' N; 9º, 09' E).

Fig 3. Eddy-covariance station.

METHODS & CURRENT WORKFLOW

Current workflow

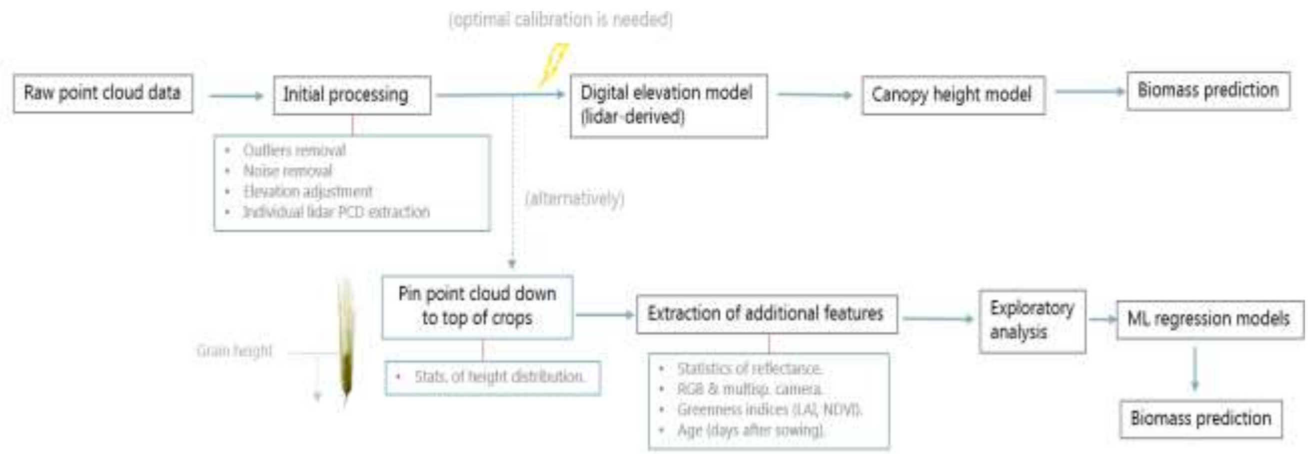

Fig. 4. Flowchart of current work.

Point cloud data (PCD) derived from UAV-lidar

[VIDEO]
https://www.youtube.com/embed/WIf7CG-w3aI?rel=0&fs=1&modestbranding=1&rel=0&showinfo=0
Video 2. Extraction of individual lidar samples from PCD scene. Software: Lidar360.

Fig. 5. Location of sampling points (n=104) in the study site. Several samples were taken close to each location shown on the map (+ symbols).

Fig. 6. Example of a biomass sampling point.

AGB and C content

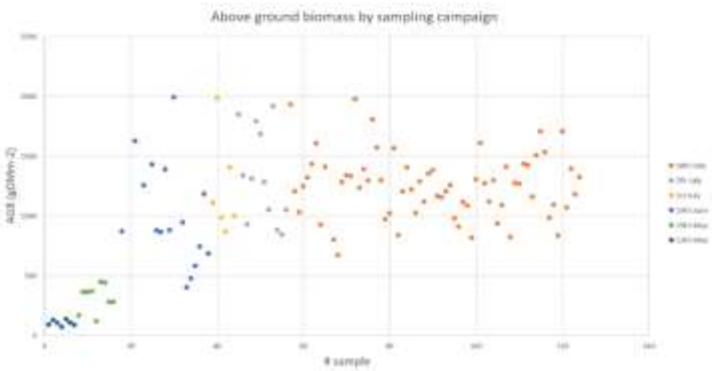

Fig. 7. AGB of all biomass samples in each campaign.

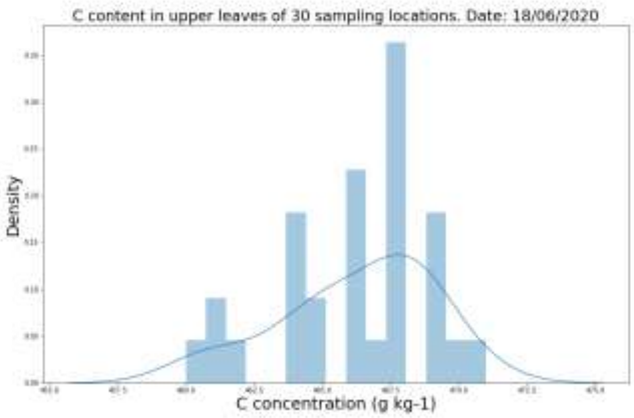

Fig. 8. Carbon concentration sampled at 30 locations. The solid line (*kernel density est.*) is inferred from the histogram for probability density estimation. Sampling date: 18/06/2020.

Data collection

- The data collection was conducted during the crops' **growing period**: April-July 2020. Random georeferenced locations were selected, in **6 sampling campaigns.**

- **Two simultaneous sampling methods**: (i) UAV-lidar scanning, and (ii) destructive biomass sampling.

- The simultaneous sampling allowed the comparative analysis between **AGB** and extracted features from the **PCD**.

UAV-lidar scanning

- The study site was scanned at every campaign in 6 individual flights, flying at 40m of altitude.

Biomass sampling

- 1 m long AGB samples were taken at random locations in the direction of the sowing lines and later oven-dried (65 °C for 72 h.)

AGB PREDICTION: ML REGRESSION MODELS

Comparison of different models

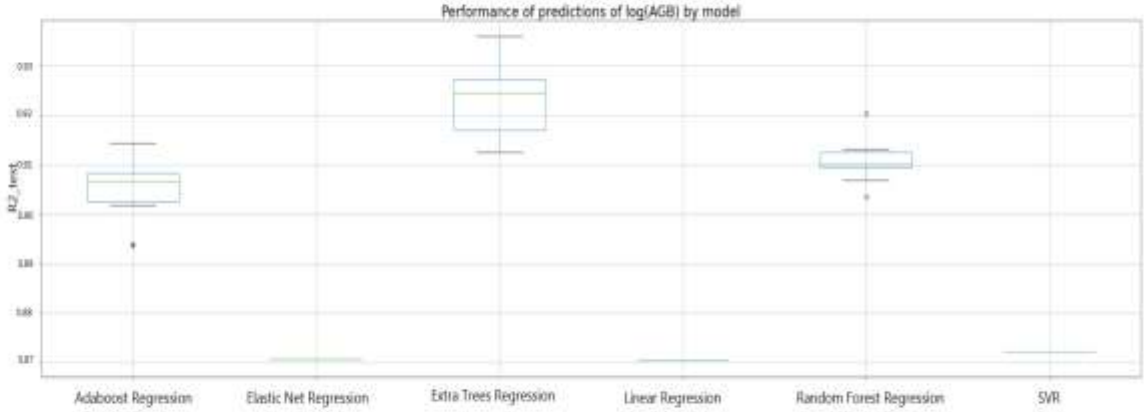

Fig. 9. Boxplot: comparative of performance of models using R^2 (test data) on nat. log(AGB), after 10 runs per model.

Best biomass prediction model

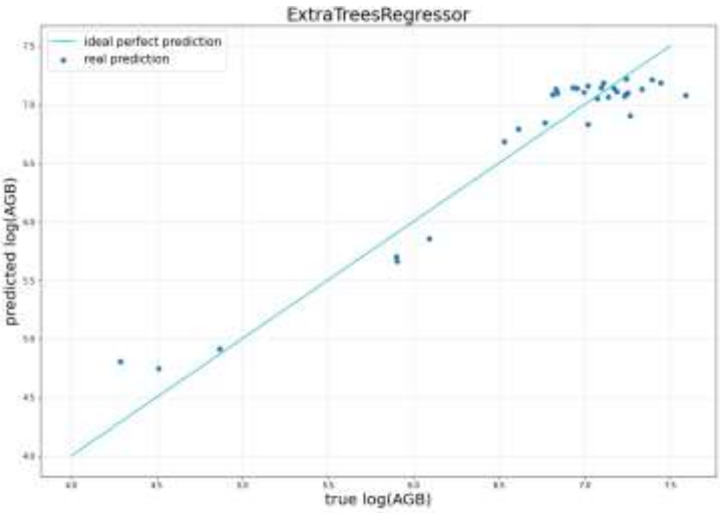

Fig. 10.Prediction by ExtraTrees regression.

Prediction of log(AGB), R^2 test :**0.92**

Prediction of AGB, R^2 test : **0.76**

Data preparation

- **Split** of training (70%) and test data (30%).
- **Stratification** of data (6 subsets, equal to the number of sampling campaigns).
- All data was **normalized** according to training distribution.

Data specifications

- The total **dataset** contains **104 data points**, each corresponding to an individual sampling location.
- Each data point is characterized by a group of **features** extracted from the plant development stage as well as lidar points' reflectances and heights. The feature importances (**i**) for the best model are shown in brackets:
    - Days after sowing; the age of crops in days **[i: 0.330]**.
    - Growing degree days (°C) [3,4] **[i:0.066].**
    - Mean intensity of reflectance **[i:0.014]**.
    - The standard deviation of reflectance **[i:0.006]**.
    - Mean of lidar points' height distribution **[i:0.15].**
    - Median of height distribution **[i:0.143]**.
    - Percentile 75 of height distribution **[i:0.227]**.
    - The standard deviation of height distribution **[i:0.059]**.
    - Kurtosis of height distribution **[i:0.006]**.

Training and evaluation

- For each model, we performed a search of optimal parameters on the training data set (*cross-validation*).
- We evaluated the predictive performance with all available features.
- Iteratively, the features with the lowest importance with respect to the prediction were removed.

Which models have been tested?

- **ExtraTrees regression**
- Random Forest regression
- Support Vector regression
- Nearest Neighbor regression
- AdaBoost regression.

- Elastic Net regression.
- Linear regression

Other models tested

- The performance of other models is described based on mean R^2 (on test data) after 10 runs.

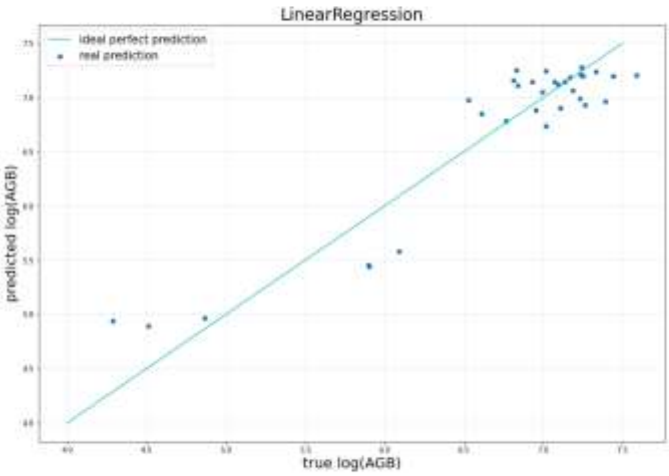

Fig. 11. Linear regression.

Prediction of log(AGB), R^2 test: 0.87

Prediction of AGB, R^2 test: 0.69

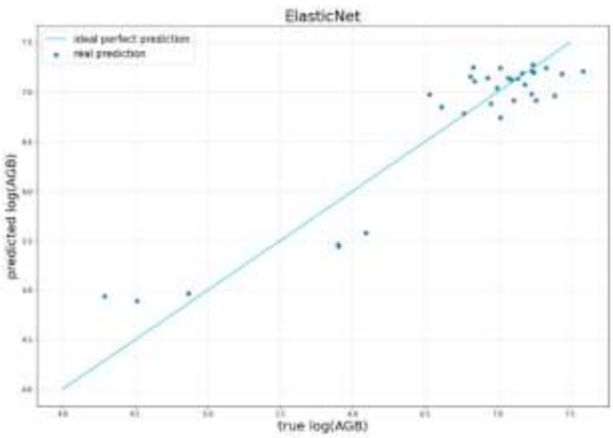

Fig. 12. Elastic Net regression.

Prediction of log(AGB), R^2 test: 0.87

Prediction of AGB, R^2 test: 0.69

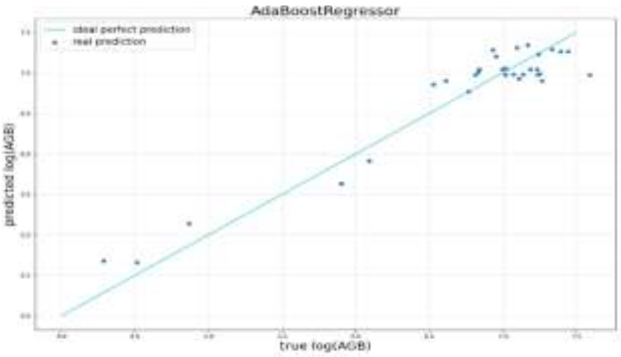

Fig. 13. AdaBoost regression

Prediction of log(AGB), R^2 test:0.90

Prediction of AGB, R^2 test: 0.65

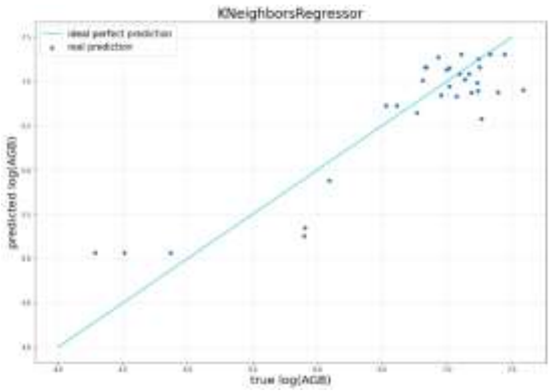

Fig. 14.Nearest Neighbor regression

Prediction of log(AGB), R^2 test: 0.82

Prediction of AGB, R^2 test: 0.55

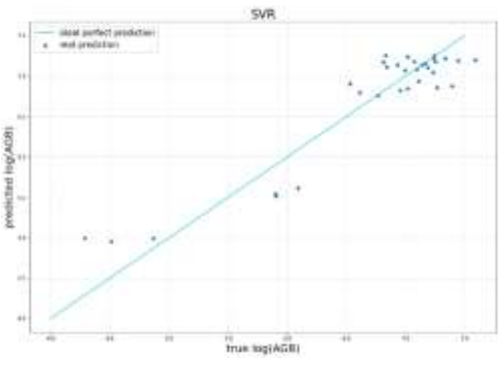

Fig. 15. Support Vector regression.

Prediction of log(AGB), R^2 test: 0.87

Prediction of AGB, R^2 test: 0.69

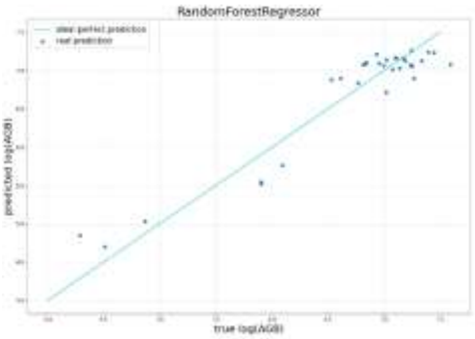

Fig. 16.Random Forest regression.

Prediction of log(AGB), R^2 test: 0.91

Prediction of AGB, R^2 test: 0.72

DL APPLIED TO AGB PREDICTION & SEGMENTATION OF LIDAR-PCD

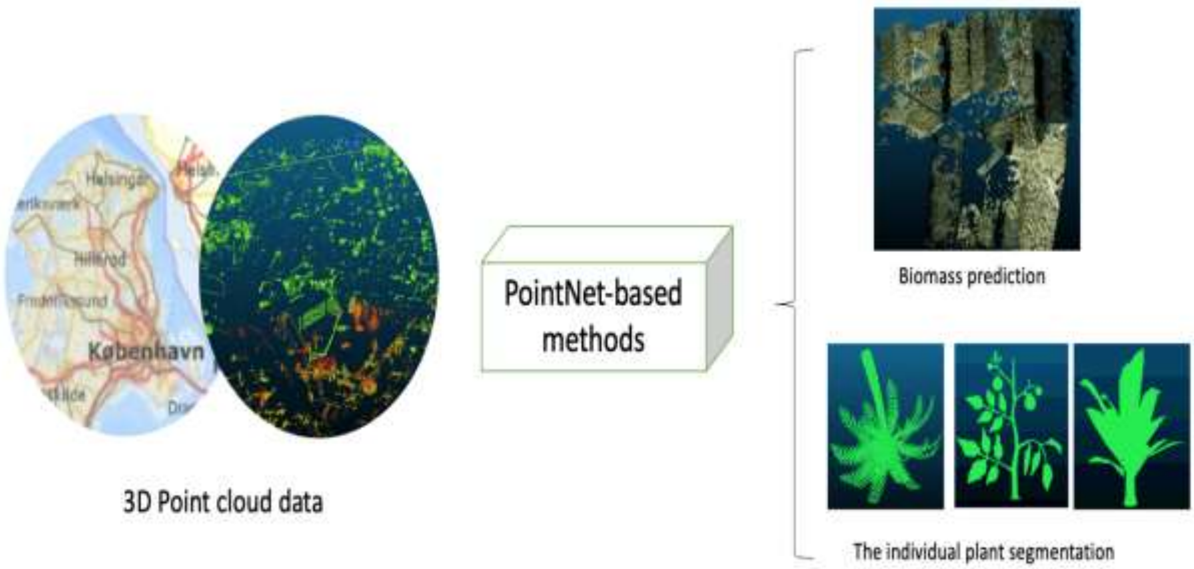

Fig. 17. DL approach to AGB prediction and plant segmentation.

Current work focuses on the implementation of DL models for the task of biomass prediction and plant segmentation. Two models are currently being evaluated:

i) PointNet [5].

ii) PointNet++ [6].

The implementation of these models seems a promising option for outperforming ML models [*].

CONCLUSIONS & OUTLOOK, ACKNOWLEDGMENTS & REFERENCES

Conclusions

- The predictive performance of the ML models is satisfactory at this stage of the project. However, enhancements are expected by further tuning and adding features such as classic vegetation indices (e.g. NDVI, LAI) derived from multispectral imagery.

- Best performance is found when including some background meteorological and growth stage parameters (e.g. growing degree days).

- Among the ML regression models evaluated, the best predicting performance was achieved with Extra Trees regression (R^2 on test data ln(AGB): 0.92 and AGB: 0.76).

Outlook

- In the next step, we will evaluate the development of **AGB against NPP** values from eddy covariance-based flux measurements of CO_2.

- The overarching objective is to obtain a **time-series map** of C-storage, as well as CO_2 fluxes of ecosystems based on UAV-lidar technology.

- DL approach seems to be the way ahead to analyze and interpret large amounts of LiDAR data.

Acknowledgments

- [*] Lei Li, recently incorporated into the project, is currently working along these lines.
- This project is supported by a Strategic grant from the University of Copenhagen, a Villum Experiment grant by the Velux foundations, and the Horizon2020 Marie Sklodowska-Curie COFUND Doctoral Programme.

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