

# Potential value of combining CNN, GEDI and multi-source remote sensing data to improve the estimate of aboveground forest carbon storage in northeast China

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## Introduction

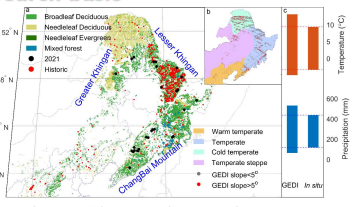
### Background

Quantifying forest biomass carbon stock is critical for determining the regional carbon balance, but a lack of both field observations spanning large climatic gradients and proper upscaling methods which take the spatial pattern into account, means there is little knowledge regarding forest C stock at high spatial resolutions.

### Motivation

- Propose a framework that could combine GEDI footprints and multi-source spectral remote sensing data using CNN.
- The potential climatic drivers and processes of the spatial distribution of forest above-ground carbon density (ACD) were investigated;
- Project the future forest carbon sink (circa 2060) and decipher size of carbon sink due to forest age and climate change.

## Research basis

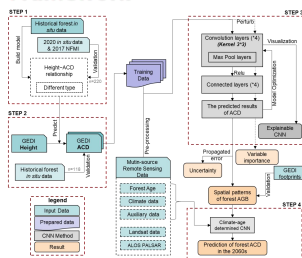


**Figure 1.** Distribution of in situ measurements and GEDI footprint. (a) Regional forest type and in situ measurements. The background shows the forest type provided by the 1:1,000,000 vegetation map of China (Editorial Board of Vegetation Map of China, 2007). The red and black points show locations of in situ measurements for the historic for the 2020s, respectively. (b) Distribution of GEDI footprint (2019-2021), with the background revealing the eco-regions provided by the vegetation regionalization of China. (c) Temperature and precipitation range for both GEDI footprint and in situ measurements.

## REFERENCE:

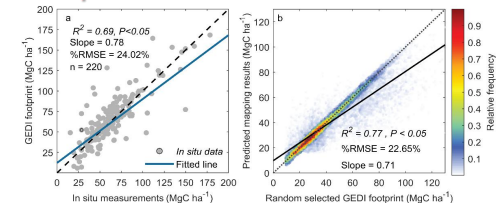
Dubayah, R., Hofton, M., Blair, J., Armstrong, J., Tang, H., Luthcke, S., 2021. GEDI L2A Elevation and Height Metrics Data Global Footprint Level V002 (Data set). In: NASA EOSDIS Land Processes DAAC. Fang, J., Chen, A., Peng, C., Zhao, S., & C. L. (2001). Changes in forest biomass carbon storage in China between 1949 and 1998. *Science*, 292(5525), 2320-2322. Forster, P. M., Maycock, A. C., McKenna, C. M., & Smith, C. J. (2020). Latest climate models confirm need for urgent mitigation. *Nature Climate Change*, 10(11), 7-10. Segal-Rozenzheim, M., Li, A., Das, K., & Chirayath, V. (2020). Cloud detection algorithm for multi-modal satellite imagery using convolutional neural-networks (CNN). *Remote Sensing of Environment*, 237, 111448.

## Framework



**Figure 2.** Scheme for estimating regional forest aboveground biomass carbon density from CNN, GEDI, and multi-source remote sensing data.

## Model performance

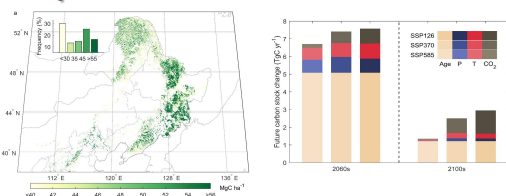


**Figure 3.** Validation of forest carbon density at GEDI footprint (a, Step 1 in Figure 2) versus in situ data at site level. (b) indicates the result of the CNN model validated using 20,000 independent GEDI footprint points without training, and the color indicates the distribution density of GEDI footprint points in the graph. The dashed line is the 1:1 line, and the solid blue line is the linearly fitted line.  $R^2$ , root mean square error (RMSE), and  $P$  value were used to evaluate our model.

## Why CNN is essential?

- Traditional methods ignore important spatial and texture information, which mirrors the roughness, shadowing, and species distribution;
- Deep Convolutional Neural Network, can extract multi-level features from raw images without any human supervision and is excellent at solving complex problems using a large amount of data.;
- The ability to analyze big data is the key for CNN to realize the combination of GEDI footprints and multi-source spectral remote sensing data.

## Benchmark of forest ACD, and potential carbon sink in 2060s



**Figure 4.** The spatial distribution of forest aboveground carbon density. The inserted panel reveals frequency of forest ACD and mean value in terms of different forest types.

**Figure 5.** Contributions of forest age, precipitation (P), temperature (T), and increased  $CO_2$  concentration to the cumulative changes of forest stocks in Northeast China in the 2060s and 2100s, respectively.

## Conclusions

- GEDI could provide systematic sampling across spatially variable environment conditions.
- CNN could make full use of big data sources and boost forest ACD prediction accuracy.
- Regional forest aboveground C stock is estimated to be  $1.80 \pm 0.10$  PgC circa 2020.
- The potential forest C sink is projected to be 5.56 TgC year<sup>-1</sup> before 2060, with age-related and climate change-induced C sequestration contributing 67.65% and 32.35%, respectively.



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