Assessment of Fine-Tuned Canopy Height Maps from Satellite Imagery: A Case Study in the Czech Republic

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Abstract: This study evaluates the performance of a lightweight convolutional Long Short-Term Memory (ConvLSTM)-based deep learning model for estimating canopy height across three test areas in the Czech Republic using Sentinel-2 time series data. The model, initially trained on forest data from Germany and Switzerland, incorporate uncertainty quantification techniques and was fine-tuned and evaluated using dense airborne laser scanning (ALS) data collected between 2022 and 2024. Results show that fine-tuning reduced mean absolute error (MAE) from 4.26 m to 2.74 m in the primary test area, with similar improvements across other regions. Species-specific uncertainties were also analyzed, highlighting performance variations between deciduous and coniferous forests.

1 INTRODUCTION

Accurate estimation of forest canopy height is crucial for understanding forest structure, carbon storage potential, and biodiversity (Zhang et al., 2016; Mao et al., 2019; Lang et al., 2023). Traditionally, high-resolution airborne laser scanning (ALS) has been the benchmark for obtaining accurate canopy height data (Brovkina et al., 2017; Douss and Farah, 2022; Fischer et al., 2024). However, ALS is resource-intensive and limited in spatial and temporal coverage. The alternative approaches are developing that make use of readily available satellite data (Potapov et al., 2021; Lang et al., 2023; Tolan et al., 2024). Recent advancements in deep learning models have enabled indirect estimation of canopy height using satellite imagery, particularly time-series data from Sentinel-2. Although Sentinel-2 does not provide height information directly, its multispectral and temporal characteristics allow for canopy structure inference when combined with appropriate machine learning models. Nevertheless, challenges remain in adapting models trained on one geographic region to new areas with different ecological and distributional characteristics. Fine-tuning models with local ALS data is a promising strategy for improving transferability and accuracy. In this study, we leverage dense ALS-derived canopy height maps as ground-truth data to train and validate a deep learning model that predicts canopy height from Sentinel-2 time-series imagery.

This study contributes to the developing deep-learning approaches for canopy height estimation from satellite imagery. It evaluates the performance of Convolutional Long Short-Term Memory (ConvLSTM) based models on three Czech test areas. The models process 40 or more Sentinel-2 (S-2) time-frames spanning an entire year and provide uncertainty estimates using deep ensembles with isotonic regression calibration (Alagialoglou et al., 2022). Ground-truth data for training were sourced from the Bohemian Forest and Switzerland, and fine-tuning was performed on site-specific data.

We aim to provide insights into the reliability of Sentinel-2 derived canopy height maps for local ap-

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plications. The objectives of this study are to:

- Assess the performance of fine-tuned ConvLSTM models for estimating canopy height in Czech forests.
- Compare the accuracy of fine-tuned models with their pretrained counterparts.
- Quantify species-specific uncertainties for deciduous and coniferous trees.

2 MATERIALS & METHODS

2.1 Study Areas

The three test areas are located in the Moravian region of the Czech Republic spanning 3.5 km^2, 11 km^2, and 3 km^2, as shown in figure 1. The three study areas were selected to represent different forest compositions and ecological conditions, allowing us to assess model performance across diverse environments. The forests in Test Areas 1 and 2 are predominantly deciduous, with a small mixture of spruce and pine. Test Area 3 consists mostly of coniferous forest (Fig. 2).

2.2 ALS and Sentinel-2 Data

Airborne laser scanning (ALS) data were acquired using the Riegl LMS Q780 airborne full-waveform laser scanner, which was mounted on the Flying Laboratory of Imaging Systems (FLIS) operated by CzechGlobe (https://olc.czechglobe.cz/en/home-en/). ALS data were collected during the years 2023, 2022, and 2024, for the test areas 1, 2, 3 respectively. The acquisition details, including point cloud density and Sentinel-2 availability, are summarized in Table 1. Fine-tuning of the model was conducted on a 1.4 km^2 subset of Test Area 2, marked in pink color on figure 1. The acquisition details are summarized in Table 1, with some additional information of the available Sentinel-2 imagery of the specific study areas. Despite variations in the point cloud density of the acquired ALS data across the test areas, they are considered dense ground truth maps due to their significantly higher density compared to the interpolated resolution of the smallest Sentinel-2 ground sampling distance (10 m).

The ALS data processing workflow included trajectory calculation, georeferencing, relative orientation of individual flight lines, and export. These steps were conducted using a combination of software tools provided by the scanner manufacturer (POSPac 8.7, RiPROCESS 1.9.2, RiUNITE, GeoSysManager 2.2.4) and the LAStools software suite. The resulting laser point clouds were exported and further processed into digital surface models (DSM).

The processed ALS data provide highly accurate canopy height information and serve as dense ground truth references for model training and evaluation. The derived DSM spatial resolution is 0.5 m, ensuring detailed spatial representation of the forest canopy.

A sequence of Sentinel-2 (S-2) Level-1C products, representing top-of-atmosphere reflectance, of the study areas is downloaded for the years of each ALS data acquisition, from the Copernicus Dataspace Ecosystem. The number of available products for each area is given in table 1. Sentinel-2 imagery was collected across all seasons without cloud filtering, ensuring coverage throughout the year. All model inputs and outputs were resampled to a 10 m spatial resolution to match Sentinel-2's highest available resolution.

Tree species classifications were derived from the Forest Management Institute (FMI) dataset for 2022[1].

2.3 Model Architecture

The ConvLSTM models combine convolutional layers with long short-term memory (LSTM) networks to effectively process spatial and temporal data. The models were initially trained on Sentinel-2 imagery, using 40 timeframes per year, and calibrated with isotonic regression to produce uncertainty maps. Training data included regions in the Bavarian Forest and forested areas in the whole area of Switzerland. Further details on the training dataset and neural network architecture are available in our previous study (Alagialoglou et al., 2022).

The ensemble of models is fine-tuned on a subset of Test Area 2, specifically for the year 2022, as depicted in Figure 1. Fine-tuning employs the Gaussian Negative Log Likelihood loss function, as recommended in our earlier work (Alagialoglou et al., 2022). Optimization is performed using the AdamW optimizer with a weight decay regularization coefficient of 1×10^{-3} and a learning rate of 1×10^{-4}, over 100 epochs.

During inference, the model processes 40 uniformly distributed timeframes for a given year without applying any cloud filtering. In practice, more timeframes are utilized by ensembling the results of 150 runs, with each run using a different set of 40 inputs.

[1] https://geoportal.uhul.cz/mapy/MapyDpz.html

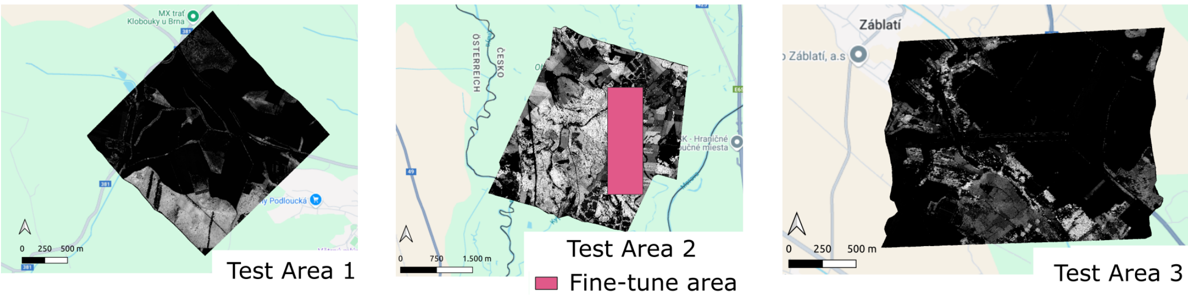

Figure 1: Overview of three test areas in the Czech Republic, covering 3.6 km^2, 10 km^2, and 3 km^2, respectively. ALS reference data were collected in 2023, 2022, and 2024. Fine-tuning was performed on a 1.4 km^2 subset of Test Area 2, highlighted in pink. The central coordinates of each test area are: Test Area 1 – (16.833260, 49.004164), Test Area 2 – (16.945512, 48.681688), and Test Area 3 – (16.180660, 49.313461).

Table 1: Overview of parameters for the three study areas, including ALS data acquisition and Sentinel-2 acquisitions. * The fine-tuning area is a small sub-region within study area 2, as shown in Figure 1.

Study Area	**Acquisition Date**	**Area [km^2]**	**Cloud Point Density [points/m^2]**	**Total Sentinel-2 Scenes**
1	28.05.2023	3.6	10	145
2 *	13.07.2022	10.0	8	144
3	30.04.2024	3.0	10	65

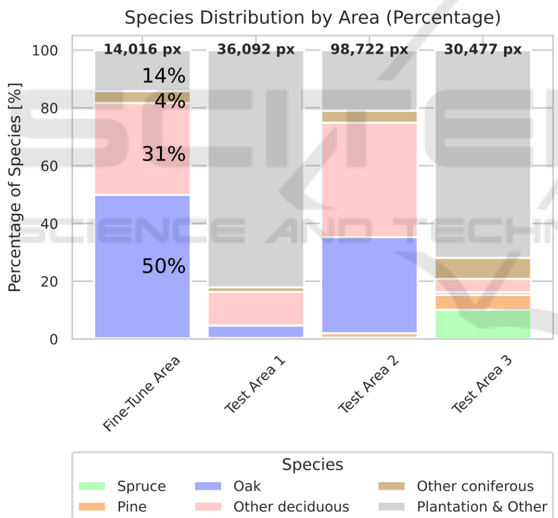

Figure 2: Species distribution in the test areas 1-3 and the fine-tune area.

2.4 Experimental Design

Two experimental setups were evaluated:

1. **Pretrained Models:** These models were applied without fine-tuning, resulting in higher estimation errors.
2. **Fine-Tuned Models with Dense Ground-Truth:** These models were fine-tuned using dense LiDAR data covering approximately 1.4 km^2. The fine-tuning area corresponds to a subregion of Test Area 2, as shown in Figure 1. In terms of species representation, this sub-region follows similar species distribution with the total Test Area 2. However, it is very different to the species distribution of Test Area 3. With this choice we aim to examine the fine-tuned model performance on test areas with both similar as well as different forest type characteristics.

Species-specific uncertainties were computed using tree species maps provided by the Forest Management Institute (FMI) for the reference year 2022. Exploratory statistics of species distributions across the three study areas are illustrated in Figure 2. The species map, originally a vector layer, was rasterized to match the Sentinel-2 resolution with a ground sampling distance of 10 m, using nearest-neighbor interpolation.

The performance of the canopy height models was evaluated using three quantitative metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2).

- MAE: average absolute difference between the predicted and observed values. MAE provides an intuitive measure of overall error, expressed in meters.
- RMSE: square root of the average squared differences between the predicted and observed values. RMSE penalizes larger errors more heavily, making it sensitive to outliers, and is also expressed in meters.

- R^2: Represents the proportion of variance in the observed data that is explained by the model. An R^2 value close to 1 indicates strong agreement between the predicted and observed values, while values near 0 suggest poor predictive performance.

3 RESULTS

Figure 3 presents canopy height estimation results for the three test areas, including absolute error maps and quantitative metrics such as mean absolute error, root mean square error and R^2. These figures provide a visual comparison of the errors associated with the pretrained and fine-tuned models across the test areas. Specifically, for Test Area 1, the fine-tuned model achieved a MAE of 1.09m, RMSE of 2.09m, and R^2 of 0.88, compared to the pretrained model's MAE of 1.27m, RMSE of 2.24m, and R^2 of 0.87. In Test Area 2, the fine-tuned model achieved a MAE of 2.69m, RMSE of 3.63m, and R^2 of 0.83, compared to the pretrained model's MAE of 4.45m, RMSE of 5.52m, and R^2 of 0.62. Similarly, in Test Area 3, the fine-tuned model achieved a MAE of 1.48m, RMSE of 2.51m, and R^2 of 0.66, compared to the pretrained model's MAE of 2.04m, RMSE of 3.18m, and R^2 of 0.46. The visual comparison further underscores the improvement, with reduced absolute error maps for fine-tuned models.

Based on the quantitative results and visual analysis shown in Figure 3, the fine-tuned model is overall accurate for all three test areas in different years, comparing to the state-of-the-art (Alagialoglou et al., 2022; Lang et al., 2023; Tolan et al., 2024), with as little as $1.4km^2$ fine-tuning ground-truth area. Furthermore, the fine-tune model consistently demonstrated superior performance compared to the pretrained model across all test areas and all vegetation types, as evidenced by all three metrics: MAE, RMSE, and R^2. This consistent trend across all test areas validates the efficacy of the fine-tuning process in improving model performance.

Similar conclusions are demonstrated in tables 3 and 4. Test Area 2 showed the most significant reductions in the overall MAE and RMSE for the fine-tuned models, particularly for deciduous species. This can be attributed to two factors:

1. The fine-tuning area is a subregion of Test Area 2 for the same year, allowing the models to better adapt to the specific distribution characteristics of the area and time.
2. Test Areas 1 and 3 contain large regions dominated by the "Plantation/Other" class, which generally exhibits lower canopy height values and, consequently, smaller errors and lower margin for improvement.

Detailed quantitative results for each species across the three test areas are summarized in Tables 3 and 4. These tables demonstrate that the fine-tuned model consistently outperforms the pretrained model across all test areas and species, with significant reductions in both MAE and RMSE. The results show metrics for six species categories, as well as overall metrics for each test area. Species categories include Spruce, Pine, Oak, Other Deciduous, Other Coniferous, and Plantation/Other. The metrics are provided for both pretrained and fine-tuned models to enable direct comparison.

The Oak class, representing approximately 50% of the fine-tuning dataset, dominates the model's learning and exhibits the most consistent accuracy improvements across all test areas with sufficient land cover percentages. For instance, in Test Area 2, the fine-tuned model achieves a MAE of 2.89 m, compared to 5.13 m for the pretrained model. Similarly, in Test Area 1, which corresponds to a different year, the fine-tuned model yields a MAE of 3.23 m, outperforming the pretrained model's MAE of 4.51 m. This trend is also evident in Figure 4. In Test Area 2, the MAE difference between the pretrained and fine-tuned models for shorter oak trees (1–4 meters) exceeds 1.5 times the actual canopy height. In contrast, the "Other deciduous" and "Plantation & Other" classes show MAE improvements closer to 1 times the actual canopy height. Additionally, the fine-tuned model demonstrates consistent accuracy improvements for the class Oak across all canopy height bins, as seen in the left panel of Figure 4. This improvement aligns with the class proportions in the fine-tuning dataset, where Oak dominates (50%), followed by "Plantation & Other" and "Other Deciduous".

Test Area 2, at 10 km^2, is significantly larger than Test Area 1 (3.6 km^2) and Test Area 3 (3 km^2). The species distribution in Test Areas 1 and 2 primarily incudes deciduous trees, while Test Area 3 is mostly coniferous, excluding the "Plantation/Other" class. For this reason, the analysis focuses on the dominant forest classes, avoiding those with small sample sizes. It is noted that the performance of classes with few pixels, such as the oak in Test Area 3 or the spruce and pine in Test Area 1, should not be taken into consideration. Due to the limited number of pixels available for these classes, results are likely affected by label noise in the species classification map. However, although oak is generally absent in Test Area 3, similarly to spruce and pine in Test Area 1, the results

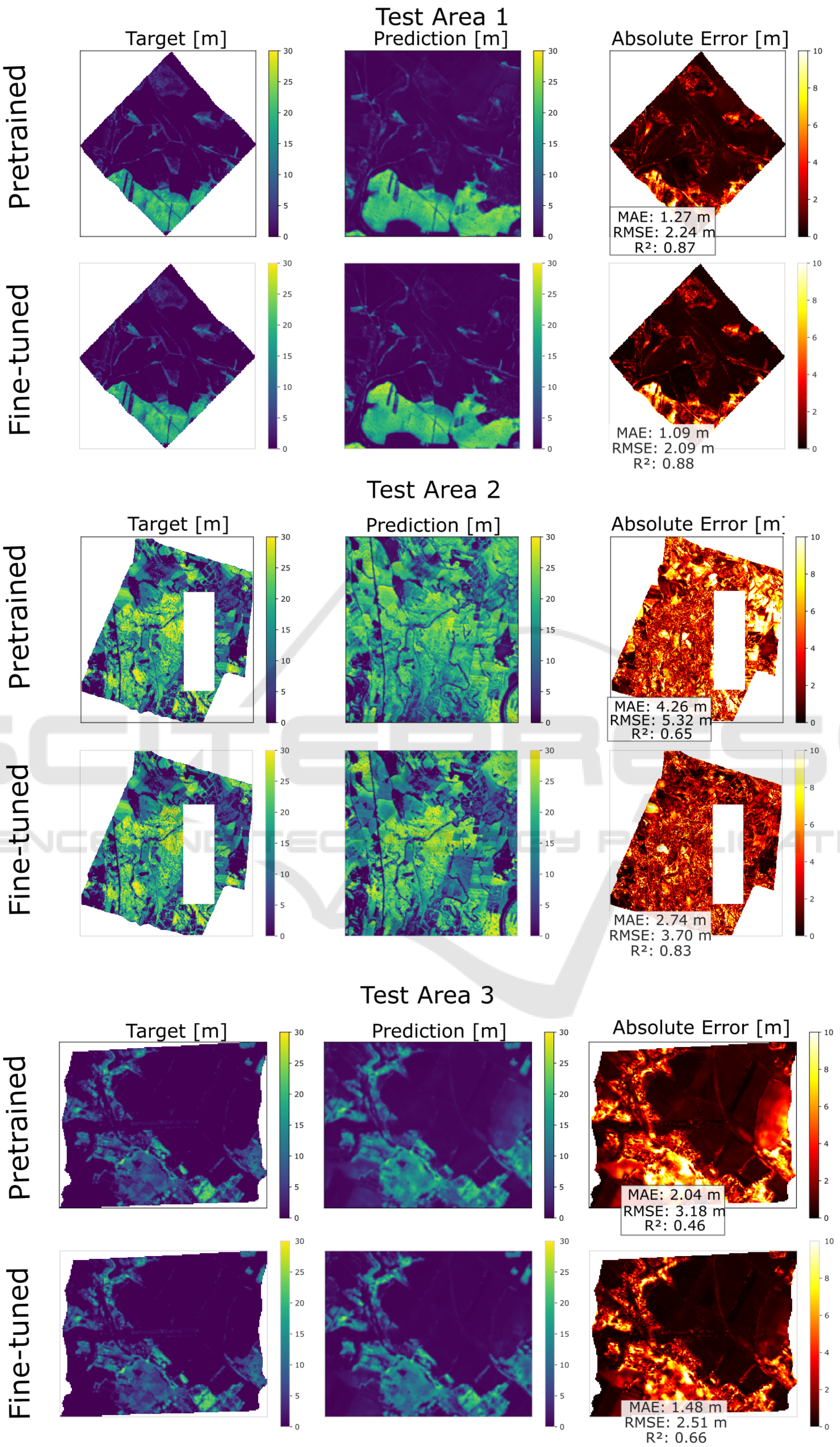

Figure 3: Results for the tree test areas: pretrained and fine-tuned models.

Table 2: Mean and Standard Deviation (std) for ALS measurements and predictions (Pretrained and Fine-tuned), along with number of pixels (n), by Class and Test Area.

Class	Test Area 1				Test Area 2				Test Area 3			
	ALS mean (std)	**Pretrained** mean (std)	**Fine-tuned** mean (std)	**n**	**ALS** mean (std)	**Pretrained** mean (std)	**Fine-tuned** mean (std)	**n**	**ALS** mean (std)	**Pretrained** mean (std)	**Fine-tuned** mean (std)	**n**
Spruce	5.73 (5.27)	5.26 (4.12)	5.37 (4.60)	83	5.16 (5.22)	6.95 (4.08)	6.28 (4.66)	485	6.28 (4.52)	9.52 (5.08)	8.39 (5.12)	3084
Pine	11.48 (3.63)	9.60 (3.54)	9.77 (3.59)	56	11.53 (3.56)	13.54 (3.28)	12.25 (3.16)	1514	11.24 (6.10)	13.69 (4.21)	13.85 (5.17)	1567
Oak	16.18 (4.61)	20.59 (3.36)	18.17 (3.36)	1541	15.02 (7.18)	18.64 (4.58)	15.80 (6.03)	32837	6.26 (2.90)	15.80 (3.03)	12.09 (2.80)	284
Other Deciduous	14.96 (6.00)	17.50 (6.43)	16.47 (6.40)	4193	16.65 (8.09)	16.14 (5.71)	17.29 (7.15)	39060	6.58 (4.60)	11.21 (4.89)	10.08 (5.06)	1414
Other Coniferous	13.03 (5.88)	15.49 (7.03)	14.61 (6.79)	582	11.30 (7.74)	11.66 (6.22)	11.42 (6.89)	4115	6.72 (4.56)	10.36 (4.66)	9.63 (5.06)	2215
Plantation/Other	0.68 (1.54)	0.93 (1.22)	0.75 (1.29)	29637	1.98 (3.61)	4.71 (4.53)	2.93 (3.86)	20711	0.39 (1.33)	1.49 (2.18)	1.03 (1.92)	21913
Overall	3.23 (6.15)	4.59 (7.70)	4.07 (7.12)	36092	12.67 (9.00)	14.71 (7.51)	13.36 (8.33)	98722	2.35 (4.31)	4.03 (5.25)	3.45 (5.12)	30477

Table 3: MAE and number of pixels (n) for Pretrained and Fine-tuned Models by Class and Test Area.

Class	Test Area 1			Test Area 2			Test Area 3		
	Pretrained MAE [m]	**Fine-tuned** MAE [m]	**n**	**Pretrained** MAE [m]	**Fine-tuned** MAE [m]	**n**	**Pretrained** MAE [m]	**Fine-tuned** MAE [m]	**n**
Spruce	1.74	1.60	83	3.33	2.73	485	3.80	2.76	3084
Pine	2.35	2.39	56	2.91	2.62	1514	3.96	3.67	1567
Oak	4.51	3.23	1541	5.13	2.89	32837	9.61	5.90	284
Other Deciduous	3.51	3.44	4193	4.23	3.23	39060	4.93	3.91	1414
Other Coniferous	3.54	3.32	582	3.73	3.23	4115	4.23	3.55	2215
Plantation/Other	0.74	0.60	29637	3.17	1.49	20711	1.15	0.72	21913
Overall	1.27	1.09	36092	4.26	2.74	98722	2.04	1.48	30477

Table 4: RMSE and number of pixels (n) for Pretrained and Fine-tuned Models by Class and Test Area.

Class	Test Area 1			Test Area 2			Test Area 3		
	Pretrained RMSE [m]	**Fine-tuned** RMSE [m]	**n**	**Pretrained** RMSE [m]	**Fine-tuned** RMSE [m]	**n**	**Pretrained** RMSE [m]	**Fine-tuned** RMSE [m]	**n**
Spruce	2.32	2.06	83	3.97	3.52	485	4.51	3.47	3084
Pine	2.58	2.62	56	3.81	3.23	1514	4.74	4.40	1567
Oak	5.57	4.51	1541	6.14	3.78	32837	10.31	6.42	284
Other Deciduous	4.50	4.44	4193	5.22	4.16	39060	5.83	4.75	1414
Other Coniferous	4.71	4.45	582	4.70	4.22	4115	5.12	4.40	2215
Plantation/Other	1.09	1.02	29637	4.28	2.35	20711	1.83	1.31	21913
Overall	2.24	2.09	36092	5.32	3.70	98722	3.18	2.51	30477

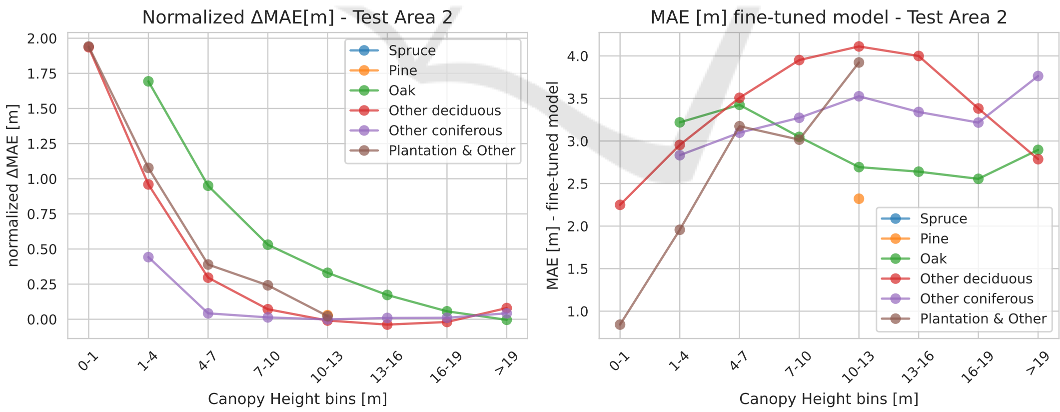

Figure 4: Left: Difference between the fine-tuned model's MAE and the pretrained model's MAE, normalized by ground-truth canopy height, for each tree species class across bins of ground-truth canopy height. Right: MAE for each tree species class across bins of ground-truth canopy height. Tree species with less than 200 pixels per height bin are not plotted for clarity.

in tables 2, 3 and 4 are included for completeness.

The left part of Figure 4 presents the difference in MAE between the fine-tuned model and the pretrained model, normalized by ground-truth canopy height, for each tree species class across bins of ground-truth canopy height. The higher the normalized ΔMAE, the more significant the improvement achieved by fine-tuning with this specific dataset. On the right side of the figure, the MAE for each species class is displayed across the same bins. In both figures, classes with less than 200 pixels per height bin are not plotted for clarity.

Using the normalized MAE difference shown in Figure 4, we observe that in Test Area 2, the Oak class exhibits the most significant improvement, followed by the "Plantation & Other" and "Other deciduous" classes, which improve similarly. The "Other coniferous" class shows the least improvement. This order corresponds to the class proportions in the fine-tuning dataset: Oak accounts for 50%, "Plantation & Other" for 31%, "Other deciduous" for 14%, and "Other coniferous" for only 4%. Although these results align with expectations based on the dataset composition, one should be cautious, since tree species representation in the fine-tuning dataset is an important factor but not the sole determinant of model performance.

4 CONCLUDING REMARKS

The fine-tuned model demonstrates high accuracy across all three test areas in different years, outperforming state-of-the-art approaches with as little as 1.4 km² of fine-tuning ground-truth data. It consistently surpasses the pretrained model in all test areas and vegetation types, with particularly notable accuracy improvements in the Oak class across all canopy height bins, likely due to its dominance in the fine-tuning dataset. Moreover, species showing the most significant improvements correspond to their proportions in the fine-tuning data, reinforcing expectations based on dataset composition. However, caution is needed, as species representation is a crucial factor but not the sole determinant of model performance. This study underscores the importance of evaluating the distribution characteristics of fine-tuning datasets to ensure reliable and localized conclusions.

Recent studies showed that the accuracy of CHMs derived from satellite data varies between deciduous and coniferous forests due to differences in canopy structure, spectral reflectance, and other biophysical properties. For instance, (Alvites et al., 2024) reported that CHM accuracy differed significantly between forest types, with the highest RMSE as a percentage of the mean observed data reaching 17.79% in broadleaf forests and 26.58% in coniferous forests, indicating higher errors in canopy height estimation for coniferous forests. Our research does not offer such insights however offers the perspective of the correlation between the model's performance and the characteristics of the initial training data and the fine-tuning area distribution. This highlights the critical importance of assessing the distribution characteristics of training datasets to draw reliable, localized conclusions.

The "Plantation/Other" class, dominant in Test Areas 1 and 3, typically shows low errors, leading to smaller improvements for the fine-tuned models (Tables 3 and 4). As shown in Table 2, the mean height values for this class are very low, indicating minimal or no vegetation. Both pretrained and fine-tuned models perform well in these low-vegetation regions. Plantations typically consist of evenly spaced, same-aged trees, leading to a more uniform canopy. This homogeneity simplifies the modeling process, potentially reducing errors (Schwartz et al., 2024).

These findings highlight the effectiveness of fine-tuning in adapting models to site-specific conditions while adding an explainability dimension to uncertainty quantification, particularly in relation to tree species distribution in fine-tuning datasets and target regions. This contributes to improving wide covering canopy height estimation for operational forest inventories. Although this study is a preliminary exploration of species-specific uncertainties, future work will involve experiments with diverse fine-tuning datasets to further evaluate the impact of species-representativeness on the fine-tuning dataset, as well as the effect of specific species on the model's accuracy. Additionally, addressing the challenge of fine-tuning local-scale canopy height models with limited datasets or sparse ground-truth measurements, i.e., field measurements, is crucial for both research and forest industry applications. To tackle this, we plan to explore few-shot learning approaches, such as semi-supervised and active learning techniques.

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REFERENCES

Alagialoglou, L., Manakos, I., Heurich, M., Červenka, J., and Delopoulos, A. (2022). A learnable model with calibrated uncertainty quantification for estimating canopy height from spaceborne sequential imagery. *IEEE Transactions on Geoscience and Remote Sensing*, 60:1–13.

Alvites, C., O'Sullivan, H., Francini, S., Marchetti, M., Santopuoli, G., Chirici, G., Lasserre, B., Marignani, M., and Bazzato, E. (2024). High-resolution canopy height mapping: Integrating nasa's global ecosystem dynamics investigation (gedi) with multi-source remote sensing data. *Remote Sensing*, 16(7):1281.

Brovkina, O., Novotny, J., Cienciala, E., Zemek, F., and Russ, R. (2017). Mapping forest aboveground biomass using airborne hyperspectral and lidar data in the mountainous conditions of central europe. *Ecological Engineering*, 100:219–230.

Douss, R. and Farah, I. R. (2022). Extraction of individual trees based on canopy height model to monitor the state of the forest. *Trees, Forests and People*, 8:100257.

Fischer, F. J., Jackson, T., Vincent, G., and Jucker, T. (2024). Robust characterisation of forest structure from airborne laser scanning—a systematic assessment and sample workflow for ecologists. *Methods in ecology and evolution*, 15(10):1873–1888.

Lang, N., Jetz, W., Schindler, K., and Wegner, J. D. (2023). A high-resolution canopy height model of the earth. *Nature Ecology & Evolution*, 7(11):1778–1789.

Mao, L., Bater, C. W., Stadt, J. J., White, B., Tompalski, P., Coops, N. C., and Nielsen, S. E. (2019). Environmental landscape determinants of maximum forest canopy height of boreal forests. *Journal of plant ecology*, 12(1):96–102.

Potapov, P., Li, X., Hernandez-Serna, A., Tyukavina, A., Hansen, M. C., Kommareddy, A., Pickens, A., Turubanova, S., Tang, H., Silva, C. E., et al. (2021). Mapping global forest canopy height through integration of gedi and landsat data. *Remote Sensing of Environment*, 253:112165.

Schwartz, M., Ciais, P., Ottlé, C., De Truchis, A., Vega, C., Fayad, I., Brandt, M., Fensholt, R., Baghdadi, N., Morneau, F., et al. (2024). High-resolution canopy height map in the landes forest (france) based on gedi, sentinel-1, and sentinel-2 data with a deep learning approach. *International Journal of Applied Earth Observation and Geoinformation*, 128:103711.

Tolan, J., Yang, H.-I., Nosarzewski, B., Couairon, G., Vo, H. V., Brandt, J., Spore, J., Majumdar, S., Haziza, D., Vamaraju, J., et al. (2024). Very high resolution canopy height maps from rgb imagery using self-supervised vision transformer and convolutional decoder trained on aerial lidar. *Remote Sensing of Environment*, 300:113888.

Zhang, J., Nielsen, S. E., Mao, L., Chen, S., and Svenning, J.-C. (2016). Regional and historical factors supplement current climate in shaping global forest canopy height. *Journal of Ecology*, 104(2):469–478.