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DEVELOPING AN AI TOOL FOR FOREST MONITORING: INTRODUCING SYLVAMIND AI

Mohamed I. KESKES[1]   Mihai D. NIȚĂ[1]

Abstract: *Global forests face increasing threats from deforestation, biodiversity loss, and climate change, necessitating innovative tools for effective monitoring and management. Traditional forest monitoring methods, which rely heavily on manual fieldwork and labor-intensive data processing, are often inadequate for addressing the scale and complexity of these challenges. Advanced tools leveraging artificial intelligence (AI) and remote sensing have emerged as critical solutions, offering timely, accurate, and actionable insights to enable efficient ecosystem monitoring, threat detection, and sustainable management practices. This paper introduces SylvaMind AI, an advanced platform that integrates satellite imagery, deep learning frameworks, and geospatial analysis within a user-friendly interface, which was built using Python for backend systems and deep learning pipelines, alongside tools like Pandas, Rasterio, and TensorFlow for data preprocessing and predictive modelling. The platform processes high-resolution data from Sentinel-2 and Landsat missions for feature extraction and predictive modelling. SylvaMind AI offers two modelling approaches: an automated option for non-technical users and a customizable feature for researchers with specialized needs. Using these approaches, we developed a predictive canopy height model for a study area. The results demonstrated the platform's ability to capture underlying forest patterns and provide detailed insights into canopy height distribution, particularly for medium to high canopies (>25m). This underscores its strength in modeling structural complexity in dense forests. However, the model showed limitations in representing smaller trees, attributed to insufficient training data. SylvaMind AI holds immense potential in transforming forest monitoring by leveraging advanced geospatial data, AI, and intuitive design to address critical challenges in sustainable forest management.*

[1] Department of Forest Engineering, Forest Management Planning and Terrestrial Measurements, Faculty of Silviculture and Forest Engineering, Transilvania University of Brasov, Şirul Beethoven 1, 500123, Brasov, Romania;
Correspondence: Mohamed Islam Keskes; email: mohamed.keskes@unitbv.ro.

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1. Introduction

Managing forests effectively requires continuous and comprehensive monitoring of ecosystems to maintain biodiversity, prevent deforestation, combat illegal logging, and ensure the sustainable use of forest resources [9]. These tasks are critical in addressing global environmental concerns such as climate change, habitat loss, and declining biodiversity, making efficient and accurate monitoring methods increasingly essential [1, 26].

For instance, according to the Global Forest Watch [13], the world lost 4.1 million hectares of primary tropical forests in 2022 alone, releasing 2.7 gigatonnes (Gt) of carbon dioxide emissions, equivalent to India's annual fossil fuel emissions. This highlights the urgency of implementing advanced monitoring solutions to mitigate deforestation and its environmental impacts. According to official data from the National Institute for Space Research's (INPE) Legal Amazon Deforestation Satellite Monitoring Project (PRODES), the Amazon experienced an annual deforestation rate of 11,568 km^2 in 2022, further exacerbating biodiversity loss and carbon emissions [21]. These alarming trends underscore the need for real-time, scalable monitoring tools to combat such threats effectively.

Traditional approaches to forest management rely heavily on manual labour, including extensive field visits and on-site data collection, which are often limited by time, resources, and accessibility [1]. Such methods, while invaluable for ground-truthing, require significant effort to process and analyze data, leading to delays in decision-making and a lack of real-time information [40, 41]. Additionally, the scalability of traditional methods is limited, making it challenging to monitor large, forested regions or respond quickly to emerging threats like forest fires or illegal land encroachment [41, 3].

AI has demonstrated wide-ranging applications in forestry, addressing different key challenges methods [18, 38]. Studies have utilized deep learning for detecting forest disturbances [28], integrating LiDAR data for biomass estimation [42], and carbon stocks assessment [14]. AI tools also demonstrate their efficacity in tree attribute prediction [6], pest detection, fire monitoring, and wind damage assessment [2, 16, 33]. By leveraging satellite imagery, drone data, and ground-based sensors, AI-driven methods offer unparalleled efficiency and accuracy in forest management [18, 27].

Despite these advancements, a significant barrier to the widespread adoption of AI-driven tools in forestry remains; many platforms are designed for specialized use cases and require advanced technical expertise to operate [30, 20]. This creates challenges for forestry professionals, particularly those without a background in AI or programming, limiting their ability to fully utilize these powerful tools [20, 31, 8]. As a result, the potential of AI in forestry management often remains confined to research institutions or highly skilled technical teams, leaving many practical applications out of reach for everyday forestry professionals. Bridging this gap is crucial to ensure that the benefits of AI technology are accessible to a broader audience [20].

To address this challenge, there is a growing need for AI platforms that combine robust analytical capabilities with user-friendly interfaces [19]. Such platforms should enable forestry professionals to analyze complex data, generate actionable insights, and develop predictive models without requiring extensive technical training [22]. By lowering the barriers to entry, these tools can democratize access to advanced forest management techniques, empowering a wider range of stakeholders, including policymakers, landowners, and local communities, to participate in sustainable forest management [17, 18].

The aim of this paper is to introduce SylvaMind AI, a user-friendly AI platform that integrates advanced technologies such as geospatial analysis, deep learning, and interactive tools suitable for forest monitoring. Additionally, the paper validates the platform's automated modelling capabilities by using field data from Brașov County to generate and evaluate predictive canopy height model, demonstrating its practical applicability in real-world forestry scenarios.

2. Material and Method

2.1. Study Area

The study area covers the forested regions of Brașov County in the Carpathian Mountains (Figure 1), comprising a variety of tree species, including European beech (*Fagus sylvatica* L.), Norway spruce (*Picea abies* L., H. Karst.), and silver fir (*Abies alba* Mill.), and representing a mix of deciduous and coniferous vegetation [24]. These forests, found at elevations from 500 to over 2,500 meters, serve important ecological roles in soil conservation, water regulation, and carbon storage [11, 34]. The region's continental temperate climate and altitude variations create diverse vegetation zones, with deciduous species at lower elevations and conifers at higher elevations [11].

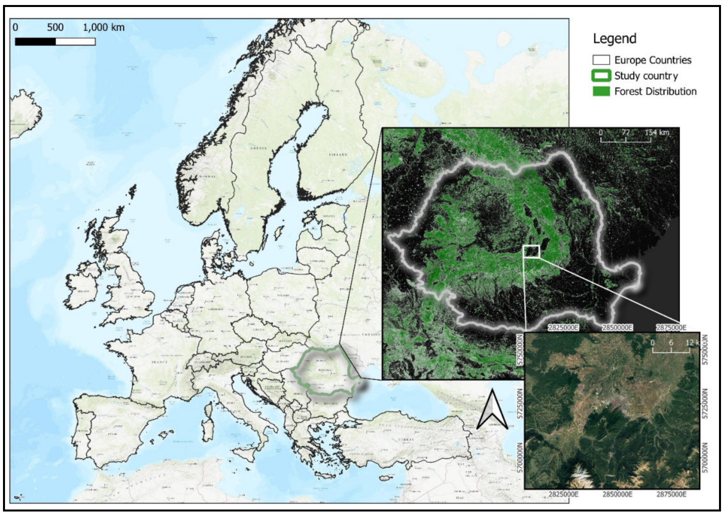

Fig. 1. *Geographic location of the study area*

2.2. Field Data Collection

In this research, we used data collected from field measurements taken in different forested areas of Romania. The basic tree information (e.g., DBH, H, position, species) was collected either with traditional forest inventory tools, such as the Vertex logger IV for tree H and forestry tape for measuring DBH, or with modern techniques, such as those based on a mobile LiDAR device and VirtSilv software [29]. The field survey was conducted from June 2023 to September 2023. The Vol, BA, DBH, and H of the plot used in the model were calculated using the national formulas [12] and extrapolated per hectare for all samples based on the circle area of 300 sqm.

2.3. Platform Building

2.3.1. Satellite Imagery

The development of SylvaMind AI relied on a combination of diverse technologies, datasets, and a systematic methodology to create a scalable and user-friendly platform for forest monitoring and management.

The platform leverages satellite data from the missions: Sentinel-2 and Landsat. Each contributes unique and critical information about forest ecosystems. Sentinel-2, part of the European Space Agency's Copernicus Program, supplies high-resolution multispectral optical imagery with spatial resolutions ranging from 10 to 60 meters [7]. Its 13 spectral bands enable the calculation of various vegetation indices like the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) [4]. These indices are crucial for monitoring plant health, chlorophyll content, and photosynthetic activity. Sentinel-2's frequent revisit time (every five days at the equator) allows SylvaMind AI to perform near-real-time monitoring of forest conditions, detect changes rapidly, and support timely decision-making [5].

Landsat satellites, operated by NASA and the U.S. Geological Survey, offer a historical archive of Earth observation data spanning over four decades [41]. With a spatial resolution of 30 meters, Landsat's multispectral imagery is instrumental for long-term change detection, land cover classification, and deforestation monitoring [32]. The temporal depth of Landsat data enables the platform to analyze trends over time, assess the impacts of human activities, and evaluate the effectiveness of conservation efforts [39].

2.3.2. Programing and Scripting Languages

Programing and scripting languages formed the technical foundation of SylvaMind AI, enabling backend processes, data workflows, and geospatial analysis. Python was the primary language used for developing the backend systems and Deep learning pipelines. Its flexibility and extensive library ecosystem made it ideal for efficiently preprocessing satellite imagery and inventory data, building AI workflows for predictive modelling, and integrating APIs, geospatial libraries, and visualization tools.

In addition to Python, the platform’s web development incorporated HTML and CSS for designing and structuring the user interface. HTML provided the framework for building the interactive web elements, while CSS was used to style and customize the interface, ensuring a visually appealing and intuitive user experience. Together, these technologies enabled the creation of a cohesive platform that is both functionally powerful and user-friendly, making SylvaMind AI accessible to a wide range of users.

2.3.3. Data Preprocessing and Analysis Libraries Tools

Data preprocessing and geospatial libraries were integral to ensuring that datasets uploaded by the users were clean, harmonized, and optimized for modelling and visualization. A suite of Python tools facilitated efficient handling of both tabular and raster data, streamlining the entire data workflow.

Pandas and NumPy served as the primary libraries for handling tabular and numerical data, such as forest inventory records and environmental datasets. These tools enabled robust data cleaning, imputation of missing values, normalization, and preparation of datasets for integration into machine learning workflows.

For raster data, Rasterio was critical for reading, writing, and editing GeoTIFFs and other raster formats, allowing seamless handling of satellite imagery. GDAL (Geospatial Data Abstraction Library) complemented this by supporting advanced raster operations like reprojection, resampling, and conversion between formats. These tools ensured the geospatial datasets were compatible with the platform's analytical pipelines.

GeoPandas extended Pandas capabilities to vector data, enabling the processing and visualization of shape files and other geospatial vector formats. It was essential for overlaying spatial data, performing geometric operations, and merging vector and raster datasets. Shapely further enhanced these workflows by providing advanced geometric editing tools, such as buffering, intersections, and spatial joins.

2.3.4. Deep Learning Frameworks

Deep learning frameworks formed the backbone of SylvaMind AI's predictive modelling capabilities, enabling advanced analysis and tailored model-building for forest monitoring applications. TensorFlow, one of the most cutting-edge frameworks, was instrumental in developing SylvaMind's AI models. It powered the training of convolutional neural networks (CNNs), such as ResNet-50, which were used to extract features from high-resolution satellite imagery for forest structure analysis. TensorFlow also facilitated the implementation of custom neural network architectures tailored to specific user needs such as predicting forest attributes like Above Ground Biomass (AGB).

With built-in support for GPU and TPU acceleration, TensorFlow was employed to enhance the efficiency of training processes, allowing SylvaMind AI to handle large-scale datasets seamlessly.

2.3.5. Mapping and Visualization Tools

The interactive map of the platform was powered by Folium library, a Python wrapper for Leaflet, enabled integration with Python-based workflows. This library allowed us to easily incorporate geospatial data into the interactive map, rendering GeoJSON files, raster overlays, and markers with Python code. Folium simplified the creation of dynamic maps by handling complex geospatial visualizations directly within the platform's Python environment.

Matplotlib and Plotly, two versatile Python libraries, were central to creating both static and interactive visualizations. These tools were employed to generate statistical plots, which gives the users clear insights into the model performance.

3. Results

3.1. SylvaMind Interface

3.1.1. SylvaMind Overview

Figure 2 represents the interface of the SylvaMind AI platform, showcasing a user-friendly design tailored for forestry and geospatial analysis. The platform is structured into two primary sections: the Main Map Panel and the sidebar.

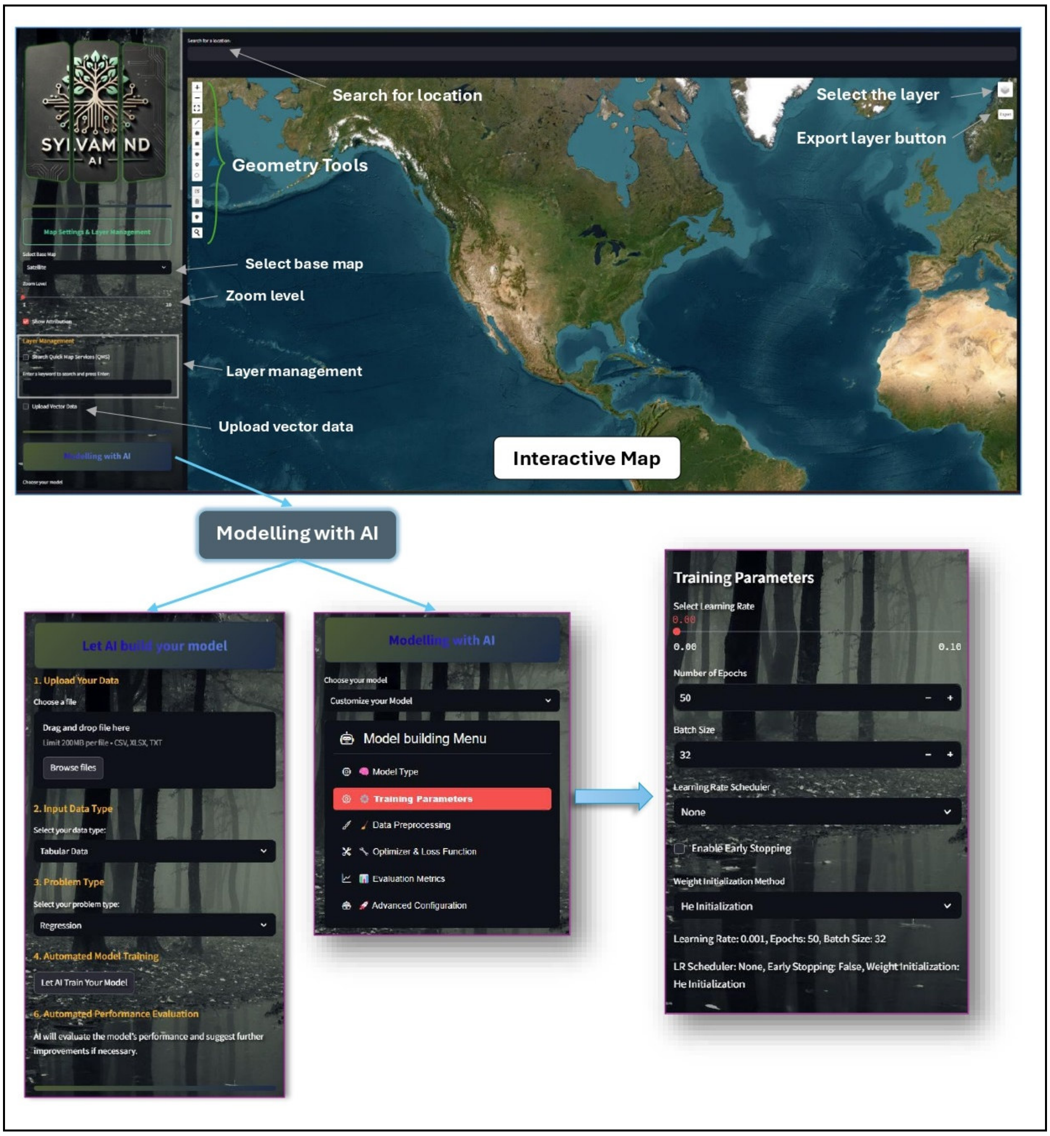

Fig. 2. *SylvaMind AI User Interface overview*

The Map Panel serves as the primary workspace for visualizing and interacting with geospatial data. A vertical toolbar on the left edge offers essential tools, including zoom controls, a pan tool, layer selection for adding or toggling overlays, and measurement tools for calculating distances or areas. This panel emphasizes usability and functionality, making it ideal for forestry analysis and geospatial tasks.

The **Left Sidebar**, as depicted in Figure 2, serves as the central hub for navigation and control within the platform. Designed with an intuitive layout, it ensures users can seamlessly access the platform's core features and personalize their analysis experience. It has two key components. The first one is the **Map Settings & Layer Management** section which allows users to configure the map and manage data layers. The second section from the sidebar, labelled "**Modelling with AI**" provides access to the platform's AI tools for predictive modelling and data analysis. The platform integrates two distinct modelling approaches, each designed to provide practical solutions based on the user's experience in modelling and the type of data available.

3.1.2. Let the AI Build Your Model

The advanced features of the "**Let the AI Build Your Model**" section in SylvaMind AI streamline the entire modelling process, making it highly accessible and efficient. The AI ensures that uploaded datasets meet analysis requirements by checking for missing values, resolving inconsistencies, aligning geospatial data to a unified coordinate system, and imputing missing data using statistical methods (Figure 3). The feature extraction and image processing for the selected area and the given time is fully automated. Using Deep learning algorithms, the platform selects the most appropriate model architecture based on the type, size, and complexity of the dataset, as well as the task objectives, such as biomass estimation or tree species classification.

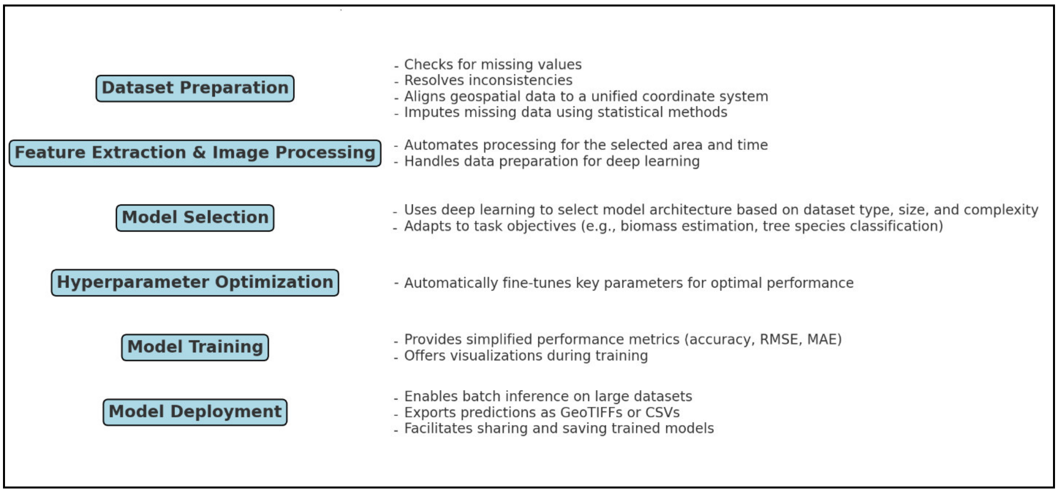

Fig. 3. *Workflow of the automated feature of SylvaMind AI*

Hyperparameter optimization is automated, employing techniques to fine-tune the key parameters for optimal model performance. During training, the platform offers simplified performance metrics like accuracy, RMSE, and MAE, along with visualizations. Once training is complete, the platform enables users to deploy models for batch inference on larger datasets, export spatial predictions such as GeoTIFFs or summary results as CSVs and share trained models with collaborators or save them for future use.

3.1.3. Customize Your Model

The feature provides a structured, step-by-step approach for users to customize their model. Each section focuses on a critical aspect of neural network configuration (Table 1).

Key Configurable Sections and Features of SylvaMind AI's Model Customization Interface Table 1

Section	Description	Key Features
Model Type	Select the base architecture or design a custom neural network tailored to the task.	• Pre-configured options: ResNet-50, EfficientNet; • Design custom models with layer-by-layer flexibility; • Transfer Learning with fine-tuning capabilities.
Training Parameters	Configure essential training parameters to optimize the learning process.	• Set number of epochs and batch size; • Adjust learning rate; • Configure training-validation-test splits.
Data Preprocessing	Tools for preparing and augmenting data for optimal model performance.	• Normalize and scale tabular data; • Augmentation for images (rotation, flips, brightness adjustment); • Missing data handling and dataset alignment.
Optimizer & Loss Function	Define how the model updates its weights and minimizes errors during training.	• Optimizers: Adam, SGD, RMSProp; • Loss functions: MSE, Cross-Entropy; • Support for task-specific functions (e.g., IoU for segmentation).
Evaluation Metrics	Select metrics to measure model performance and accuracy.	• Regression metrics: R^2, RMSE, MAE; • Classification metrics: Precision, Recall, F1-Score; • Segmentation metrics: IoU, pixel-level accuracy.

3.2. Predicting the Canopy Height of the Study Area

Using the platform's modelling capabilities, we employed the automated AI approach to generate a predictive canopy height model for the study area. Figure 4 highlights the results of this modelling process, showcasing SylvaMind AI's ability to produce a wall-to-wall map for forest H within the validation area.

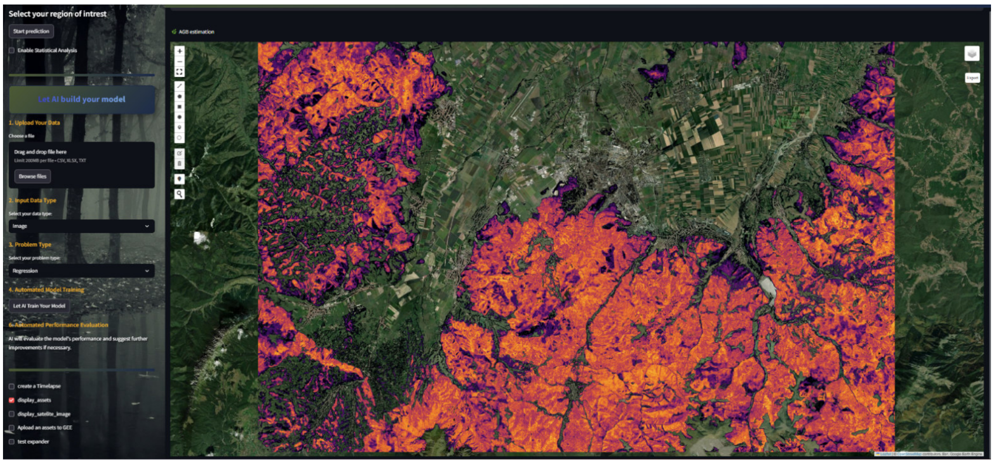

Fig. 4. *SylvaMind AI's Predicted Canopy Height for the Study Area*

Figure 5 presents a comparison between the canopy height models produced by SylvaMind AI (a) and the Meta Project, as published by Tolan et al. [37] (b) for the study area, highlighting their ability to capture spatial patterns and variations in forest structure.

SylvaMind AI successfully captured the underlying forest patterns, offering detailed insights into canopy height distribution, particularly in regions with medium to high canopy heights (>25m). This performance emphasizes its capability to model structural complexity in dense forested areas. However, the model shows limitations in accurately representing smaller trees, likely due to insufficient representation of such data during the training phase. In contrast, the Meta model provides a broader, smoother distribution of canopy height, capturing overall patterns effectively but lacking the granularity needed for areas with highly heterogeneous structures. This generalization is particularly evident for lower canopy heights (<15m), where variations are less distinct compared to SylvaMind AI's predictions.

4. Discussion

4.1. AI-Driven Solutions for Forest Monitoring with SylvaMind AI

The development of the SylvaMind AI platform represents a step forward in the integration of geospatial data and AI for forest ecosystem monitoring and management. This achievement addresses critical gaps in existing tools and provides a versatile, scalable, and user-friendly solution for a wide range of stakeholders.

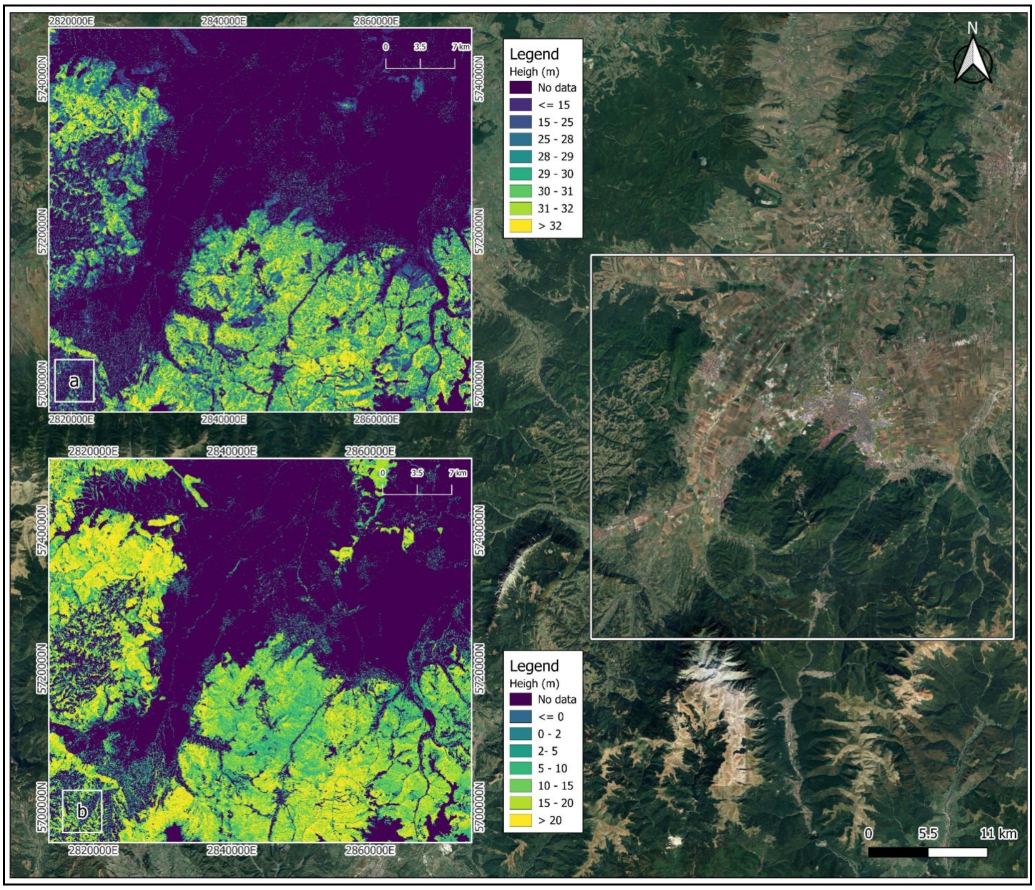

Fig. 5. *Comparison of Predicted Canopy Height Models: a. SylvaMind AI Prediction; b. Meta product Prediction*

One of the platform's most notable strengths is its accessibility to diverse user groups, from non-technical individuals to advanced researchers. For users who have data but may lack technical expertise in modelling, it offers a fully automated solution with the "**Let the AI Build Your Model**" feature. This approach is ideal for users who want to tailor a model to their specific needs without handling the intricacies of model design and training. Users simply upload their data, and the platform's AI-driven engine analyzes the input, selects optimal parameters, and constructs a model tailored to their requirements. This feature adapts to various data types - whether it is imagery, environmental data, or inventory records - and builds a model that can deliver insights relevant to the user's objectives.

The ''**Customize Your Model**'' option is designed for users who seek a high level of control over their model-building process, allowing them to adjust parameters, choose specific datasets, and fine-tune the model according to their specific needs. This option is particularly valuable for experienced users, such as researchers or advanced forest managers, who have specialized datasets or require tailored models to address unique environmental conditions or specific research questions. Users can specify the input data sources, set training parameters, and adjust model structures to optimize accuracy and relevance for their objectives. This approach is highly flexible, accommodating advanced customization and fine-tuning, which allows users to maximize the model's performance in a targeted setting.

Despite its strengths, SylvaMind AI faces certain limitations that need to be addressed for broader scalability and usability. For instance, the platform's reliance on computationally intensive deep learning frameworks may pose challenges for users with limited hardware resources. High-performance GPUs or cloud computing environments are often required to achieve optimal performance, which can be a barrier for stakeholders in regions with limited technological infrastructure [25]. This is a common challenge in AI-driven platforms, as noted by Kattenborn et al. [23], where the hardware requirements for training and inference can limit accessibility for users in resource-constrained settings.

Additionally, while SylvaMind AI is designed to process diverse datasets, scalability can still be an issue when dealing with very large datasets, such as nationwide forest monitoring projects or global analyses. Although cloud-based solutions mitigate some of these challenges, they often incur additional costs, which may limit adoption by smaller organizations or individual users. This aligns with findings by Gorelick et al. [15], who highlighted similar cost and scalability issues in platforms like Google Earth Engine (GEE).

Moreover, the platform's performance in complex environments with sparse or low-quality training data—such as regions dominated by understory vegetation or areas with limited field inventory data—may be constrained. Models built on insufficient or biased datasets may struggle to capture fine-scale variations, particularly for smaller trees or heterogeneous canopy structures [10]. These limitations indicate the need for continuous refinement of the platform, including the integration of diverse training datasets and complementary data sources like LiDAR, as suggested by Zolkos et al. [42].

In comparison to existing tools, SylvaMind AI offers a unique combination of geospatial processing, AI-driven modelling, and user-centric design, bridging the gap between traditional GIS-based analysis and dynamic predictive modelling. Its ability to automate workflows while also accommodating advanced customization positions it as a versatile and accessible platform for forest ecosystem monitoring. However, addressing limitations related to hardware requirements, scalability, and data availability will be crucial for ensuring its adoption by a wider audience and enhancing its utility for global-scale applications.

4.2. Evaluating AI-Driven Canopy Height Models: Insights from SylvaMind AI and Meta product Comparisons

The comparison between the SylvaMind AI model and the Meta Project model highlights the strengths and limitations of AI-driven approaches for predicting forest canopy height. Our product demonstrates a strong capability to capture localized patterns and variations in canopy height, particularly in areas with medium to high tree canopies (>25m). This aligns with findings from recent studies emphasizing the value of deep learning models in leveraging high-resolution geospatial data to provide detailed spatial predictions [35, 36]. By integrating satellite imagery with advanced modelling techniques, SylvaMind AI successfully maps forest height while accounting for the structural complexity of dense forest regions.

However, the model struggles to accurately predict the height of smaller trees, which can be attributed to the limited representation of such features in the training data. This limitation has been widely noted in forestry applications of AI, where the availability of ground truth data for smaller and understory trees is often insufficient [23]. Without diverse training datasets encompassing all canopy layers, predictive models may overgeneralize or fail to capture fine-scale variations in shorter vegetation.

In contrast, the Meta model exhibits a broader, smoother representation of canopy height distribution, which is effective for capturing general patterns but lacks the detail necessary for heterogeneous forest structures. This outcome reflects the trade-off between model generalization and specificity, a challenge often discussed in the literature. For instance, Hansen et al. [18] emphasized that smoother predictions are better suited for large-scale assessments but may miss localized variations critical for precision forestry and conservation efforts.

Both models highlight the importance of high-quality input data in achieving accurate canopy height predictions. The integration of multispectral data from Sentinel-2 and Landsat in the SylvaMind AI model likely contributed to its enhanced ability to capture medium-to-high canopy heights. Research has shown that multispectral imagery provides valuable information on forest structure and biomass, enabling models to distinguish between different canopy heights [14]. However, the absence of ground truth data for smaller trees underscores the need for comprehensive field-based measurements to improve model performance across all forest layers.

This analysis underscores the potential of AI-driven platforms like SylvaMind AI for advancing sustainable forest management. The ability to generate detailed, wall-to-wall canopy height maps provides valuable insights for applications such as biomass estimation, carbon stock assessment, and biodiversity monitoring. Nevertheless, future work should focus on improving model training datasets by incorporating diverse forest conditions and understory vegetation to address the observed limitations. Moreover, integrating LiDAR data, as suggested by Zolkos et al. [42], could further enhance the accuracy of height predictions, particularly for shorter vegetation and mixed forest types.

5. Conclusion

SylvaMind AI holds immense potential in transforming forest monitoring by leveraging advanced geospatial data, AI, and intuitive design to address critical challenges in sustainable forest management. It was built to streamline the training and deployment of models and AI applications in forestry. The platform emphasizes a user-friendly experience, enabling forest managers and conservationists to monitor and analyze forest data effectively. Its dynamic modelling capabilities, ranging from automated workflows to fully customizable options, ensure accessibility for non-technical users while providing advanced features for researchers and forest managers.

Looking to the future, SylvaMind AI aims to further enhance its capabilities by integrating additional data sources, such as LiDAR and hyperspectral imagery, to improve accuracy and support multi-layered forest ecosystem analysis. Planned developments also include optimizing the platform for large-scale applications through advanced cloud computing and edge processing, ensuring scalability for global forest monitoring initiatives. Moreover, the introduction of real-time monitoring features, predictive analytics for climate resilience, and collaborative tools for team-based projects will expand its functionality, making SylvaMind AI an indispensable tool for tackling evolving forestry challenges. These advancements will continue to position SylvaMind AI at the forefront of innovation in sustainable forest management.

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