Combining and Processing Airborne Laser Scanning and Crowdsourced Terrestrial Images for Bilberry High-Yield Maps

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ABSTRACT: Forests provide essential ecosystem services beyond timber, yet locating high-yield areas for non-wood forest products such as bilberries (*Vaccinium myrtillus*) remains a challenge for both recreational and commercial pickers. By integrating Airborne Laser Scanning (ALS), Geographical Information System (GIS) data, and crowdsourced terrestrial imagery analyzed via deep learning (YOLO), we developed a predictive system optimized for identifying high-yield hotspots. We demonstrate that YOLO detection remains highly accurate, but plant height significantly contributes to berry omission. However, this limitation can be mitigated by selecting the maximum berry count from multi-angle terrestrial images. Using a Random Forest classifier across a 36-km² study area in Nuuksio, Finland, we achieved a precision of 58% for the highest yield category. This represents a 20-fold increase in the probability of encountering a high-yield area compared to random searching. Extensive user testing over two years validated the practical utility of the system, showing a 22.5% increase in harvested yield and a 36.5% reduction in time required to locate hotspots. Furthermore, 97% of users reported that the platform provided an accurate big picture of bilberry yield. These results highlight the potential of combining crowdsourced citizen science with advanced LiDAR metrics to create digital twins of forest ecosystems that enhance human interaction with nature and optimize the sustainable harvest of wild food resources.

1. Introduction

Beyond economic value, forests contribute significantly to human health, well-being, and cultural identity, with aesthetic and recreational benefits playing a central role for millions of people. In Finland, nearly 60% of the population participates in berry picking annually, and 96% of the adult population engage in some form of forest outdoor activity (Neuvonen et al., 2022). Bilberries (*Vaccinium myrtillus*) and lingonberries (*Vaccinium vitis-idaea*) are among the most important non-wood forest products in the Nordic region. The right of public access allows anyone to pick berries for both personal use and sale. However, nowadays, many live in urban areas and lack the knowledge to locate areas with high bilberry yields, making a system that identifies optimal picking locations valuable. The corresponding system would also benefit those who harvest large quantities of berries, especially for commercial purposes. Thus, there is a clear need for a fully automated system for bilberry yield modelling using accurate forest and Geographical Information System (GIS) data developed in this study.

This work presents outcomes of the user tests using a novel automated workflow to produce high-resolution bilberry yield maps from integrated Airborne Laser Scanning (ALS) data and crowdsourced terrestrial images. The main idea of the workflow was to assist the pickers to find high-yield, Figure 1, picking places.

2. Related Works

Early models and NFI-based empirical modelling - Initial bilberry yield models relied either on expert knowledge or empirical data and used site and stand characteristics as explanatory variables (see e.g. Pukkala, 2002). Ihalainen et al. (2005) used questionnaire data, confirming that medium-fertility sites yield the highest potential. Turtiainen et al. (2005) refined these models with large empirical berry yield datasets and utilized National Forest Inventory (NFI) data to provide national berry yield estimates. The next phase adopted robust statistical methods, primarily Generalized Linear Mixed Models (GLMMs), which are still used. Turtiainen (2015) confirmed that mature, moderately sparse stands offered the best yields. Miina et al. (2009) used GLMMs to model bilberry coverage, yield, and annual variation, finding higher yields in pine-dominated stands compared to spruce stands. Miina et al. (2021) provided an international comparison, confirming bilberry coverage increases with forest age. Turtiainen et al. (2016) developed models to predict bilberry coverage based on forest site and stand characteristics (Model 1) and its annual yield variation (Model 2) using permanent sample plots from the Finnish National Forest Inventory (NFI). The highest coverage was found in mesic heath and fell forests, with lower but significant coverage on certain mire types. Annual bilberry yield indices derived from Model 2 showed strong correlation with previous estimates, demonstrating a promising approach for predicting total annual bilberry yields. Kilpeläinen et al. (2016) determined that berry yield predictions using multi-source National Forest Inventory (MS-NFI) data were comparably suitable to predictions based on field-measured inventory data. However, the input data from either source must be updated to account for final cuttings conducted after the inventory date. Only a relatively small proportion of the total yield variation could be explained, and model uncertainty remained high, with typical root mean square errors (RMSE%) ranging from 150% to 200% (Kilpeläinen et al., 2016).

Obsie et al. (2020) investigated how weather factors and the composition of bee species influence wild blueberry yield. To

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perform this analysis, the researchers utilized yield data from a validated, spatially explicit pollination model, which served as the foundation for training and comparing several machine learning techniques, including multiple linear regression, boosted decision trees, random forest, and extreme gradient boosting.

Figure 1. Example of “*plenty of berries*” area.

Two existing Finnish applications, Satokausi and Karttaselain, offer comprehensive bilberry maps covering all of Finland. While the specific technical methodologies and data used to generate these maps have not been publicly disclosed, both organizations indicate that their platforms are designed to highlight potential growing sites for bilberries across the country.

Using ALS to depict forest structure – More detailed forest structural measures derived from ALS data, particularly canopy cover, have also been utilized to investigate the occurrence of wild berries (Barber et al., 2016; Nielsen et al., 2020). Detailed data shifted also modelling from inventory plots to wall-to-wall mapping. Bohlin et al. (2021) combined ALS metrics with other wall-to-wall datasets and Swedish National Forest Inventory (NFI) field data. The resulting models, which used Generalized Linear Mixed Models (GLMMs), identified ALS-based canopy cover as a key structural predictor, with bilberry yields peaking around 50% cover and 15m height. Furthermore, Bohlin et al. (2021) found that bilberry yields increased as shrub cover decreased, suggesting that understory vegetation may limit productivity. The study also identified terrain coarseness as a significant factor, with higher surface coarseness positively associated with greater berry yields.

Use of Deep Learning (DL) for Automating Reference Berry Counting - Recent studies integrate DL for automating field reference counting, which has been traditionally labour-intensive. Akiva et al. (2020) achieved improvements in cranberry counting. Riz et al. (2024) introduced the WildBe dataset for four Finnish wild berries, identifying GLIP/DINO as top-performing models. Hyyppä et al. (2026) found that while YOLOv8 is superior to SAM-RF (Segment Anything Model combined with RF classifier), the main errors are berry omission and poor image quality, pointing to fundamental data challenges over algorithmic refinement.

A fully automated system for bilberry yield modelling, integrating automatic image-based berry counting into final predictive models using ALS, is required. Earlier studies have not achieved this level of automation, apart from the work of Hyyppä (2025) and coming papers, such as Matikainen et al. (forthcoming) and Hyyppä et al. (forthcoming), from the same Horizon Europe Ferox project (Fostering and Enabling AI, Data and Robotics Technologies for Supporting Human Workers in Harvesting Wild Food). Matikainen et al. (forthcoming) introduced a multimodal approach by integrating ALS with geospatial databases and automatically interpreted terrestrial imagery. Applying a random forest algorithm, the model yielded a root mean square error (RMSE%) of 94%. Hyyppä et al. (forthcoming) developed large-scale bilberry yield maps by integrating crowdsourced training data with ALS and GIS-derived features. This study compared modelling strategies optimized for overall accuracy versus high-yield precision, assessed alternative reference data collection methods, and tested the temporal transferability of models across contrasting moisture regimes over two years.

3. Methodology

The integrated solution for bilberry yield mapping combines ALS and GIS data with crowdsourced terrestrial image analysis. The developed overall solution included

- collecting plot level data including location of the plot, Figure 2, and 10 terrestrial images taken with a smartphone,
- berry counting from smartphone imagery,
- creating and selecting features,
- implementing the yield model,
- producing the final bilberry yield map, and
- presenting it in a Web Application.

Then the wild berry yield maps in a Web Application, Figure 3, were tested by the users. Yield maps were produced both in 2024 and 2025 in Nuuksio, Finland. A 36-km^2 study area was established in the Nuuksio region of southern Finland (Figure 4). Site selection was based on the availability of national laser scanning data (5 points/m^2), the proximity to Nuuksio National Park boundaries, and preliminary assessments of bilberry shrub cover.

The process began with collecting image data to train a model that detects bilberries in the images. In 2023 and 2024, 500 images were taken for training of the berry counting algorithms based on YOLO (Jocher et al., 2023) and additional 245 images were taken to further study the omission error reported in Hyyppä et al. (2026). For about 400 images, the real number of ripe berries inside the frame was manually counted. Hyyppä et al. (2026) identified occlusion as the primary source of error in bilberry counting, surpassing detection model inaccuracies. However, that study utilized sites with low-growing plants where berries were more visible. To investigate how increased vegetation height impacts berry omission, a new dataset was collected at the Nuuksio site, where bilberry plants are typically taller. From the 245 images collected, a subset of 150 was selected to evaluate how plant height impacts berry occlusion. This subset comprised 50 images from each of three height categories: short (0–20 cm), moderately tall (20–40 cm), and tall (40–60 cm).

To train the yield model for the selected test site, a crowdsourcing approach was employed in Nuuksio in 2024 and 2025. Data collection involved crowdsourced smartphone imagery, supplemented by visual mean yield estimates provided by field collectors in 2025. A foldable berry plot frame of 0.5 × 0.5 m^2 was built for the data collection to be able to calculate the number of berries per unit area. In 2024 around 20 people participated in the reference image collection for the pipeline, resulting in a total of 9765 images. In 2025, eight people participated in the collection of 12 377 images. Ten images were taken in both years from each plot that corresponds to an area of approximately 16 × 16 m^2.

The data used for yield modelling was collected using a Web Application developed by FGI. The application allows data collectors to place test points on a digital map to record coordinates for berry images collected within each test plot, Figures 2 and 4. Collectors also visually estimated the mean bilberry yield for each specific location. To assist with navigation and spatial context, the application utilizes GNSS positioning and offers background layers such as topographic maps and orthophotos (National Land Survey of Finland, 2025). Both of them were used to allow georeferencing adequate for 16 m pixel level. By utilizing a crowdsourcing platform, multiple collectors are able to conduct fieldwork efficiently and simultaneously. All plots and yield estimates added to the database are synchronized across the map view for all surveyors at one-minute intervals. This real-time visibility of the current fieldwork status ensures that different forest areas within the test site are covered more systematically and evenly.

The YOLO model, used for detecting bilberries from images, was trained using over 500 images (18 464 annotated ripe bilberries). The images used for training and testing were annotated using a Computer Vision Annotation Tool (CVAT, Sekachev et al., 2024). To make the annotation process slightly less laborious, Language Segment Anything Model (LangSAM, Liu et al., 2023; Kirillov, et al., 2023) was used to detect the bilberries using a text prompt “blueberry”. Another YOLO model was developed for segmentation of the berry frames to filter out the bilberries detected outside the frames. The obtained berry counts from YOLO were divided into four categories (*few berries*, *some berries*, *many berries* and *plenty of berries*).

The second step in the automatic processing flow is the development of a method for yield modelling. Random forest classifier was selected and about 70 features were implemented from ALS and GIS data. This study applied six distinct feature categories to estimate bilberry yields, including

- topographic features,
- area-based forest metrics,
- individual tree-level (ITD) forest attributes,
- neighborhood spatial characteristics of forests,
- lake features,
- soil type, and site characteristics data.

The primary data sources for these features were national ALS data, with a point density of 5 points/m^2, and pre-existing GIS data. All features were in raster format and had a pixel size of 16 m × 16 m.

Random forest was then trained to classify berry yield into four separate classes stated above. Five-fold cross-validation was used to apply feature selection and evaluate the performance of the models. The feature selection was applied through a greedy forward selection approach that started with an empty set of features, and at each step, a new feature that provides the greatest improvement in precision of the class of *plenty of berries* (class 4) was added to the feature set, and the corresponding precision was recorded. In 2024, the yield maps were created using the number of berries counted by YOLO as a reference, whereas in 2025 both YOLO-counted number of berries and visually estimated number of berries were used. For user tests, maps that provided a broader view of the yields were used. Such maps are also shown in Figure 5.

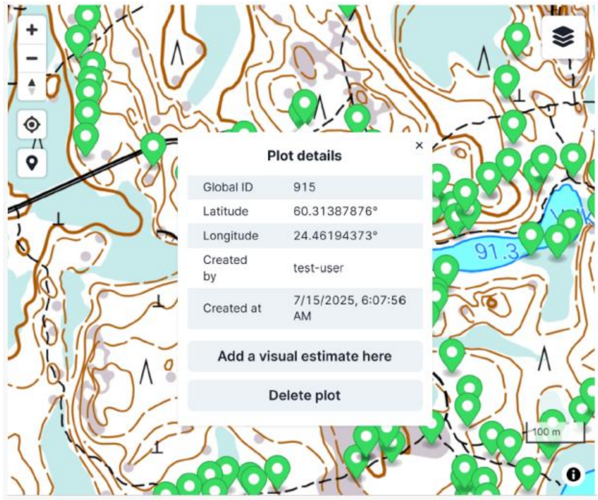

Figure 2. Representative screenshots of the Web App crowdsourcing platform utilized for test plot data (test plots in green) recording and yield map visualization.

Figure 3. Web App and an example yield map on the screen. Blue dot shows the current location of the test user.

Plots and images were collected during 8-18 July 2024 and 9-16 July 2025 in Nuuksio. Yield maps were tested with the Web App in Nuuksio 3 - 16 August 2024 by 18 FGI persons and in 21 July - 8 August 2025 by 32 FGI personnel, FEROX partners, and pickers organized by the FEROX consortium. In 2024, sample size was 18, and in 2025 about 170, since several persons repeated the tests in new locations. The following user tests were performed:

- Reduction in time required to locate hotspots (2024).

- Increase in yield: Berries were first picked without the Web App and yield map for 5 minutes and then with the Web App and yield map for 5 minutes. Yields were weighted. (2024)

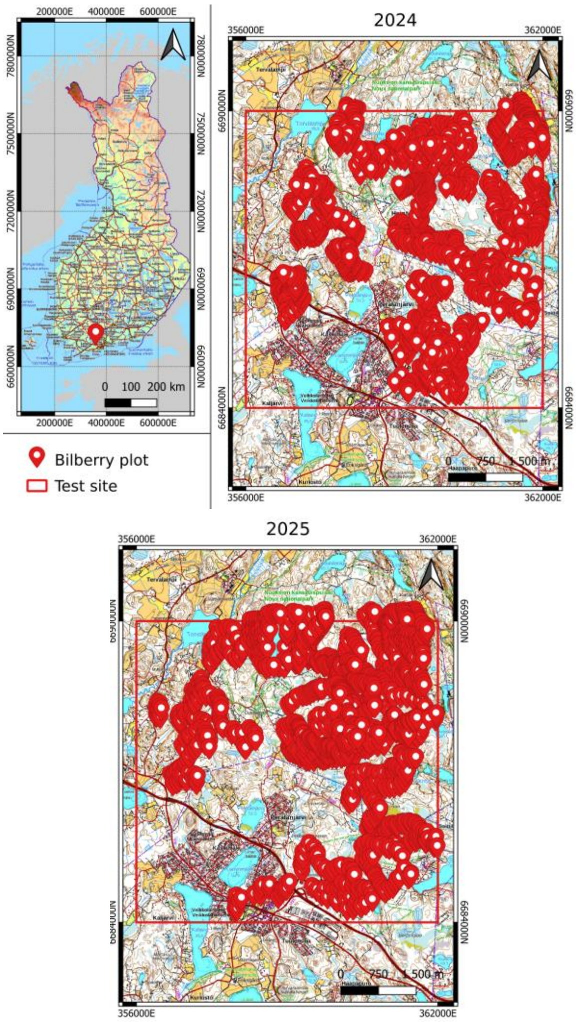

Figure 4. Locations of the test plots in Nuuksio 2024-2025. Contains data from the National Land Survey of Finland topographic map 2025.

- Test users walked in Nuuksio, picking berries and searching for hotspots. Then test users were asked to answer three questions: 1) “Did the Web App and the bilberry yield map increase your efficiency?”, 2) “How much did the Web App and the bilberry yield map Improve the time to reach a certain yield?”, and 3) “How much the Web App did increase your ability to find places with enough number of berries or lots of berries” (2024).
- Test persons walked in Nuuksio for several hours, picking berries and searching for hotspots, after which they answered two questions: 1) “Did you get a correct big picture of bilberry yields in Nuuksio using the Web App and related bilberry yield map?”, and 2) “How much did the Web App increase your ability to find places with enough number of berries or lots of berries?” (2025).
- Test persons walked in Nuuksio for several hours, picking berries and searching for hotspots, navigating through different stands of varying complexity. Then they answered to two questions: 1) “To what extent did the Web App increase your capacity to navigate and position yourselves in a forest (time saving in moving from place A to B) (by positioning yourself with GPS and map)?”, and 2) “Would you be lost in Nuuksio forests without the Web App?” (2025).

As a background information, users were asked with the following background questions:

- Your expertise in walking and navigating in forests (orienteering etc.). A) expert, B) weekly, C) monthly, D) few times a year, E) very rare or newer.
- Your expertise in collecting wild berries and mushrooms: A) more than 250 L/year, B) more than 50 L/year, C) more than 10 L/year, D) less than that or never

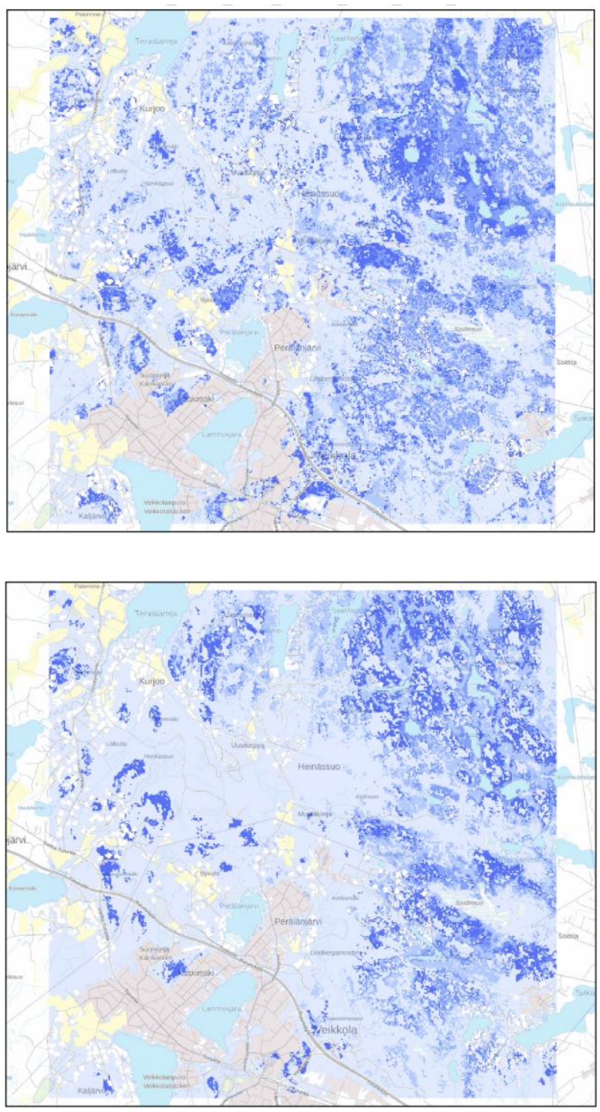

Figure 5. Produced example bilberry maps for 2024 (above) and 2025 (below). Contains data from the National Land Survey of Finland topographic map 2025. The darker the blue, the higher number of berries predicted.

4. Results and discussion

4.1 Berry omission and effect of the height of bilberry plants

Linear regression analysis by height category showed that while YOLO detection remained accurate across all bilberry plant heights ($R^2 \geq 0.91$), berry visibility decreased significantly as plants grew taller. Short plants (0–20 cm) exhibited the strongest correlation between image annotations and field counts ($R^2=0.944$), but this relationship weakened in moderately tall ($R^2=0.819$) and tall plants ($R^2=0.787$). These results indicate that occlusion in taller vegetation is the primary driver of berry omission, consistently exceeding YOLO detection errors, leading to a systematic underestimation in image-based counts.

Since five images were captured for each test plot with different viewing angles, we made an analysis where the highest annotated berry count was compared with the plot-level yield to minimize occlusion-related underestimation. Linear regression analysis demonstrated a strong correlation between YOLO-predicted and manually annotated counts ($R^2=0.93$). While selecting the image with the highest visible berry count reduced omission errors, these errors still exceeded detection inaccuracies. Ultimately, this confirms that crowdsourcing reliability is enhanced by capturing images from multiple angles and selecting the viewpoint with maximum berry visibility, as proposed by Hyyppä et al. (2026).

4.2 Yield maps

From about 70 features, fifteen were selected through greedy forward selection. Forward selection iteratively adds features that yield the greatest improvement in the precision of class *plenty of berries*, since it identifies the high-yield berry-picking locations. We highlight here that all previous yield models published have been optimized for overall accuracy. The best precision for class *plenty of berries* was obtained especially when ITD forest attributes, neighborhood spatial characteristics of forests, and lake features were applied. Best precision of 0.58 for class *plenty of berries* with 4 classes was obtained, meaning that 58 % of the instances predicted as class *plenty of berries* are actually class *plenty of berries*. Using the trained random forest model, a bilberry yield map was generated for the Nuuksio area. More details of the feature selection can be read from Matikainen et al. (forthcoming) and Hyyppä et al. (forthcoming).

We prioritized optimizing the precision of *plenty of berries* data, as it offers significant advantages to map users. For example, assuming that class *plenty of berries* represents about 3% of Nuuksio's areal extent, as indicated by our research for year 2024, and we achieved a precision of 58%, an inexperienced berry picker has 20-fold increase in the probability of encountering a high-yield area compared to a random search. Even taking into account the travelling, the map provides substantial benefits, which was tested by users.

Results also confirmed that optimal yields occur at a canopy cover of about 50% and with minimal understory shrub, aligning with the findings of Bohlin et al. (2021).

4.3 User tests

Based on user tests, we achieved the following results:

2024 (18 replies):

- The bilberry yield in Nuuksio when using the Web App and bilberry yield map increased 22.5% (measured).
- 36.5% time saving to find hotspots (measured). The Web App and bilberry yield map increased the pickers' ability to find good picking places by 58% (questionnaire).
- The Web App increased pickers' trust in navigating in the forests by 60%. Several cases happened where test pickers would have got lost in dense forest without the help. Users with expertise levels A-C reported a 45% increase in navigational confidence, while those in levels D-E reported a 66% increase.
- The Web App and the bilberry yield map increased pickers efficiency by 62 %.

2025 (166 replies):

- 97% of test users stated they gained a correct big picture of the bilberry yield in the test site by using the Web App and predicted yield map
- The increased ability to find hotspots was 78% with a standard deviation of 22%. Surprisingly, experienced pickers ("level 2" of expertise) benefitted the most, although the sample size for such pickers was small (7 persons). In general, there was no significant correlation with experience. Standard deviation was highest with cases having low experience in picking berries. This may suggest that less experienced users remained closer to access points, and did not walk 30 minutes into the deep forest, where there were more berries.
- The Web App increased users' capacity to navigate and position themselves in a forest by 72%.
- 42% of the pickers reported they would have got lost in test site without the Web App.

5. Conclusions

This work utilized a new workflow which integrates multi-modal multi-resolution data and processes with AI methods to derive high-resolution bilberry yield maps. These maps are a valuable support for optimal picking locations.

In accordance with Hyyppä et al. (2026), omission was identified as the primary source of error, a trend that became increasingly evident with greater bilberry plant height. Selecting the image with the highest visible berry count effectively mitigated this omission error.

Finally, user evaluations validated the practical utility of the yield maps and the crowdsourcing Web Application. Participants, regardless of their foraging experience, reported an improved ability to navigate forest environments and successfully locate productive bilberry patches. Impressively, 97% of test users stated they gained a correct big picture of bilberry yield with the new tools.

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