

# Predicting bilberry yields using ALS and other auxiliary data combined with NFI field plots

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## 1. Introduction

Wild berries are the most utilized non-wood forest products by Nordic people (e.g. Kardell 1980, Turtiainen 2015) and essential nutriment of many animal species. Predicting and mapping non-wood forest products has been challenging because of the characteristics of non-wood products like small size, seasonality, rarity, difficult location, etc. In addition collecting field data for modelling is laborious and expensive. In the earlier studies field measurements of bilberries and accurate description of tree stock and site type have been used to model berry yields (Miina et al. 2009, Turtiainen 2015). However the general drawback of field measurements based approaches is that accurate field data is typically not available for the applications of the elaborated models.

Since 2003 worldwide unique berry yield data has been collected annually in the Swedish National forest inventory (NFI) (Fridman et al. 2014). The number of bilberries and cowberries are counted in small vegetation plots, inside the NFI plots and the annual berry yields of ripen berries kg ha<sup>-1</sup> are estimated to national and to county level. This unique time series of bilberry and cowberry data also offers high possibilities for spatial and temporal studies of berry yields in Sweden. That data combined with wall-to-wall remote sensing data (e.g. McRoberts et al. 2010), such as airborne laser scanning (ALS) data describing the forest structure and terrain variables and satellite and aerial images describing the forest types and tree species, offers possibilities to improve the forecasting of berry yields and maps in landscape level, of high interest to many users.

In this study we combined bilberry data from Swedish NFI with nationwide ALS data to predict bilberry yields. The specific aims were 1) to develop general prediction model for bilberry yield based on ALS data and other existing wall-to-wall data and 2) to identify laser based structural features of forest that can be linked to locations of the highest yield, highly interesting by the berry pickers. This information can be used for multi-objective forest planning, developing the next generation berry yield forecasting applications and mapping berry yields in forest landscape.

## 2. Data and methods

We used bilberry yield data from the Swedish NFI from 2007 to 2016 covering whole Sweden. Detailed berry inventory was done in two 0.25m<sup>2</sup> circular berry plots inside the NFI plot and the sum of flowers and berries of two berry plots was calculated. The final number of plots used for modelling was 13 715 and varied between years and geographical locations of laser scanning.

The number of flowers and berries is depended on the inventory day of the growing season. The time difference between middle of July (bilberries expected to be ready for picking) and Julian day of field data collection was used as one predictor variables in the models. This variable indicated the change in berry amount (% per day) over the season.

We used ALS data from Swedish National Land Survey from 2009 to 2014. All ALS based and other wall-to-wall metrics calculated were extracted from the 7 m buffer around the center of the NFI field plots (corresponds the size of temporary NFI plots). ALS point cloud data were extracted from each NFI plot and point cloud metrics were calculated using the FUSION software (McGaughey 2021). Percentage of first echoes above height limit of 2 meter called “canopy cover”, Elev.P95 (height, where 95 % of the first echoes are accumulated) called “tree height” and “shrub cover” from first echo data

((percentage of echoes below 2 meter – percentage of echoes below 0.5 m)/(percentage of echoes below 2 meter), %), were selected to identify the critical structural differences in presence/absence data (high berry yield/no berries) to locate the highest bilberry yields. Other auxiliary data used on models included e.g. ALS based terrain variables, bioclimatic variables (worldclim.com), tree species variables from SLU forest map, Corine-land cover map, and soiltype and soildepth maps. The mean and standard deviation of raster cells (continues variables) or the maximum (categorical variables) were extracted from each plot to represent the predictor variables for the models.

Models were created for bilberry yields (number of berries) using generalized linear mixed effect models. Models for bilberry counts were expressed by the log-link function with Poisson response. The hierarchy and unbalanced structure of the data was taken account by random effects at different levels (county, laser-block, cluster). Mixed effect models were fitted using glmmPQL function of the R-software (<https://www.r-project.org/>) and bias-correction was applied in prediction for new dataset.

The structural differences of commonly used ALS based variables were demonstrated in histograms of presence/absence (high bilberry yield /no berries) data. Only bilberry plots with ripen berries were included. Five percent of the plots with the highest berry amount was selected to represent the high bilberry yield.

### 3. Results

The ALS based canopy cover was found to be important variable in bilberry model. Other significant variables were e.g. ALS based height variance, shrub cover, height above sea, slope, soil wetness and terrain ruggedness, satellite based species specific volume and percentage, seasonality of temperature and precipitation and annual precipitation, inventory year, soil type and land use class. The time difference between Julian day when berries were expected to be ripen and inventory day was also significant predictor variable and this variable showed 1,5 % decrease for bilberry per day during the season.  $R^2$  was 0.4 for the full bilberry model and 0.08 for the fixed part and there was high variation between plots in the prediction accuracy. Model underestimated especially the higher berry yields.

Based on our study the highest bilberry yield was identified in forests with canopy cover of 50 % (Figure 1, left), the canopy height of 15 meter and the shrub cover close to zero. Even though our model could not give very accurate estimates for the berry yields, the model can be used as an effective tool for predicting the most potential locations for the berry yields in forest landscape. To demonstrate this we predicted the most potential locations of bilberry yields in small study area (Figure 1, right).

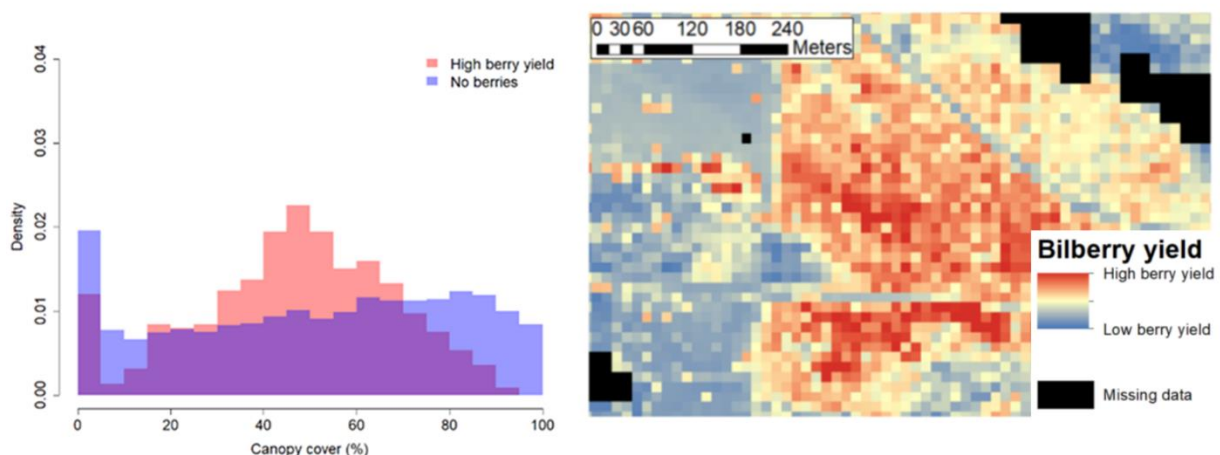


Figure 1: Density distribution of ALS based canopy cover in plots with high bilberry yield and no berries (left) and predicted potential locations of bilberry yields in forest landscape (right).

### 4. Discussion and conclusions

This is the first study where ALS and other wall-to-wall remote sensing variables were used to model bilberry yields and also first berry yield models done in Sweden. Here we also obtained valuable information about suitable remote sensing based variables for predicting bilberry yields and about the ALS based structural features which are reflecting the locations of the highest bilberry yield. Our maps

of potential berry yields are much needed as input for e.g. land-use planning at landscape level (e.g. European Commission 2016). For local berry pickers, the berry yield maps makes it easier to find the berries in the forest landscape.

Our results are supporting the earlier findings, which have showed that best bilberry yield can be found in mature stands with conifer dominance which are not too dense (e.g. Raatikainen et al. 1984, Miina et al. 2009, Turtiainen 2015). In addition more important than e.g. tree species is the light reaching bilberry stand. It has been found that the crown density of 10–50 % allows bilberry to flower and produce berries optimally (e.g. Raatikainen et al. 1984). This supports especially the usability of ALS based canopy cover in prediction of bilberry yields.

Our study also supports the earlier findings that accurate prediction of berry yields is difficult because of the complexity of berry yield production; variables used in the models can not catch the spatial and temporal variation of berry yields for accurate berry yield modelling. But models can be used as an effective tool for predicting the most potential locations for the berry yields.

More accurate wall-to-wall prediction of berry yields would demand more accurate information about tree species and especially site fertility, which has been critical variable in earlier berry yield models (e.g. Miina et al. 2009, Turtiainen 2015), but not accurately available in wall-to-wall data yet. To improve the yearly prognoses of berry yields more accurate temporal and spatial data, such as weather, pollination, site type and operational history data together with localized observations of berry yield developments could improve estimates.

Despite the difficulties of modelling bilberry yields, our model could be imported to the forest planning system, like Heureka in Sweden (Wikström et al. 2011) and then the stand level prognosis of bilberry yield development under different forest management alternatives could be produced (e.g. Turtiainen 2015). This would support the forest owners growing interest for integrating multiple aspects of forest in management planning. So far no berry yield models have been integrated in forest planning systems in Sweden.

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