Mapping potential location for bilberry picking with remote sensing, local field data and phone-application

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AIM: Develop a practical method for identifying potential locations for bilberry picking in forest landscape with help of remote sensing, local field data and phone-application for supporting the development of the local berry value chain

WALL-TO-WALL REMOTE SENSING DATA AND METRICS

- Sentinel 2 image from 2021 -> spectral metrics
- Airborne laser scanning (ALS) data from 2020 -> structural forest and terrain metrics
- SLU-forest map of tree species (based on aerial images and NFI plots)
- National forest attribute map (based on ALS data and NFI plots)
- Site-index and soil moisture map (based on ALS data and NFI plots)
- Land use classification map (based on satellite data)

- All metrics were extracted from the 10 m radius circular buffer around the field plots

- NFI = National forest inventory

MODELLING

- Modelling the relationship between remote sensing metrics and shrub cover and berry yield classes using 2021 data
- Logistic and ordinal regression model for bilberry shrub and yield classes (3 and 2 classes were tested)
- All the variables (max 5) selected into models had to be logical and statistically significant and no high correlation was allowed between variables
- Model validation and annual calibration was done using 2022 data

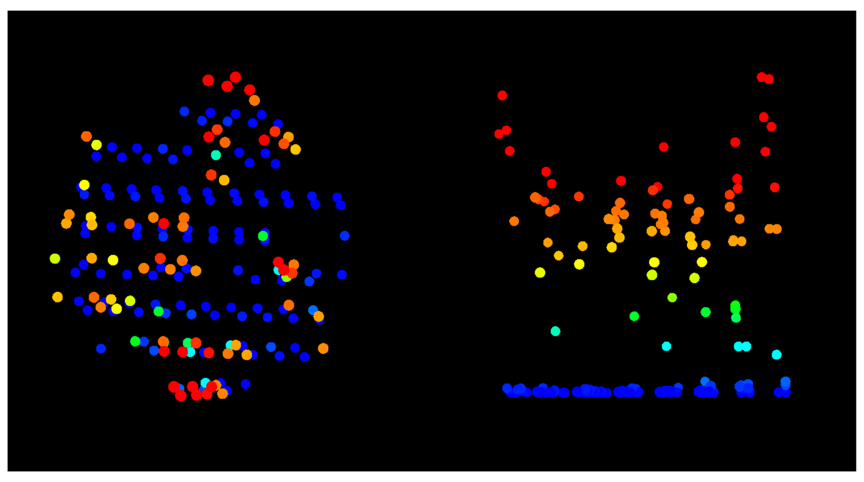

Fig. 4. Example of laser point cloud from a field plot (left:above, right:side).

RESULTS

- The best models included both ALS based forest structural metrics (e.g. canopy openness) and spectral metrics but also e.g. volume of pine, soil moisture and site-index for pine were selected
- The 2-class logistic model for berry yields (0=no or little, 1=medium or lot) performed best producing medium high accuracies (OA /AUC over 0.7 and kappa over 0.4) in all cases
- Calibration of the models improved annual predictions
- Best models were applied over the study area -> validation of raster maps produced similar accuracies with training data for bilberry yield but lower for bilberry shrub

Model	A. Training, 2021			B. Validation, 2022		
	OA	kappa	AUC	OA	kappa	AUC
Yield 3 class	0.71	0.41	0.75	0.59 (0.60)	0.28 (0.30)	0.60 (0.61)
Yield 2 class	0.78	0.51	0.75	0.70 (0.74)	0.40 (0.46)	0.70 (0.73)
Shrub 2 class	0.83	0.51	0.73	0.68 (0.68)	0.23 (0.24)	0.60 (0.61)
Model	C. Annual calibration, 2022			D. General calibration, 2022		
	OA	kappa	AUC	OA	kappa	AUC
Yield 3 class	0.61	0.21	0.58	0.63 [0.66]	0.30 [0.31]	0.60 [0.67]
Yield 2 class	0.71	0.40	0.70	0.70 [0.74]	0.39 [0.43]	0.69 [0.71]
Shrub 2 class	0.71	0.36	0.67	0.69 [0.76]	0.26 [0.38]	0.62 [0.67]

Table 1. Prediction accuracies (overall accuracy, kappa and AUC values) of the best classification models A) in 2021 training data, B) in 2022 validation data, C) in 2022 data using annual calibration and D) in 2022 data with general calibration based on combined data 2021 and 2022. Values in round brackets show the plot level accuracies based on raster cells in wall-to-wall prediction. Values in square brackets show the plot level accuracies in combined data of 2021 and 2022 data.

FIELD DATA

- Local forest landscape 25x45 km in Västerbotten, Sweden
- Training data: 503 plots in 2021. Validation/calibration data: 525 plots in 2022
- Potential for berry picking observed by four shrub cover and berry yield classes
- Plots were placed inside the forest representing the berry potential of the surrounding forest
- Data collection and GPS positioning via specially developed phone-application

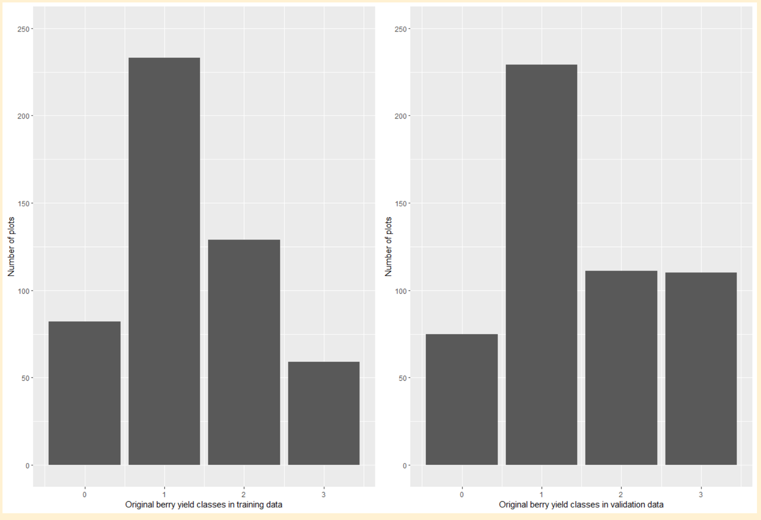

Fig. 1. Distribution of plots for berry yield classes (1=no, 2=little, 3=medium, 4=high amount of berries in 2021 (left) and 2022 data (right)

Fig. 2 Counting raw berries in 1 m² square plot

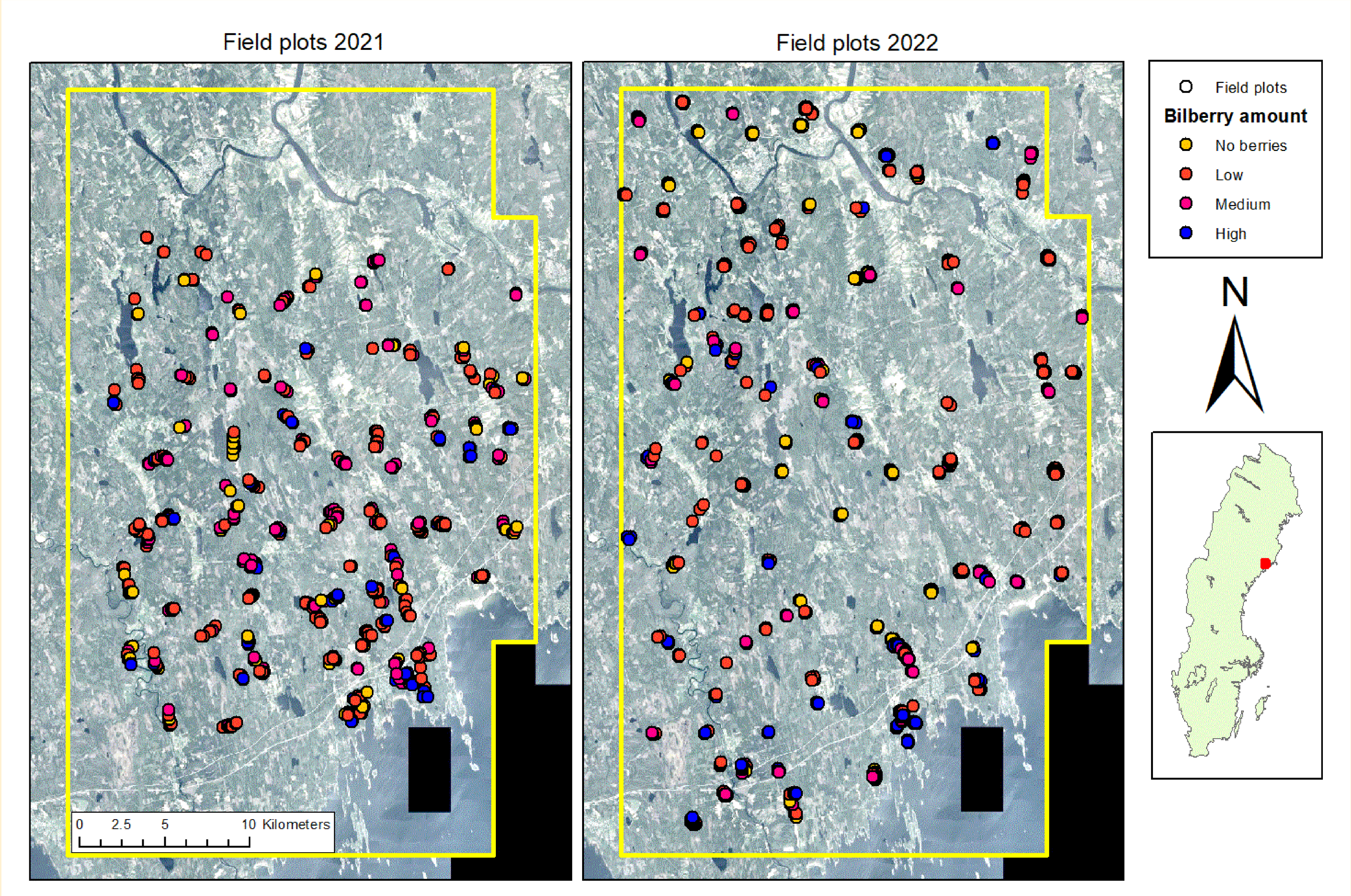

Fig. 3. Plots were located over study area in different forest types with different amount of berries

CONCLUSIONS

- **Practical method for locating potential berry locations was demonstrated ➡ berry pickers can easier find the berries ➡ development of the local berry value chain**
- We got valuable information about challenges and possibilities of predicting berry yields using remote sensing
- To receive higher prediction accuracies would demand more accurate information on the spatial and temporal variation of berry yields including e.g. weather effects
- Models could also be used for multi-objective forest planning

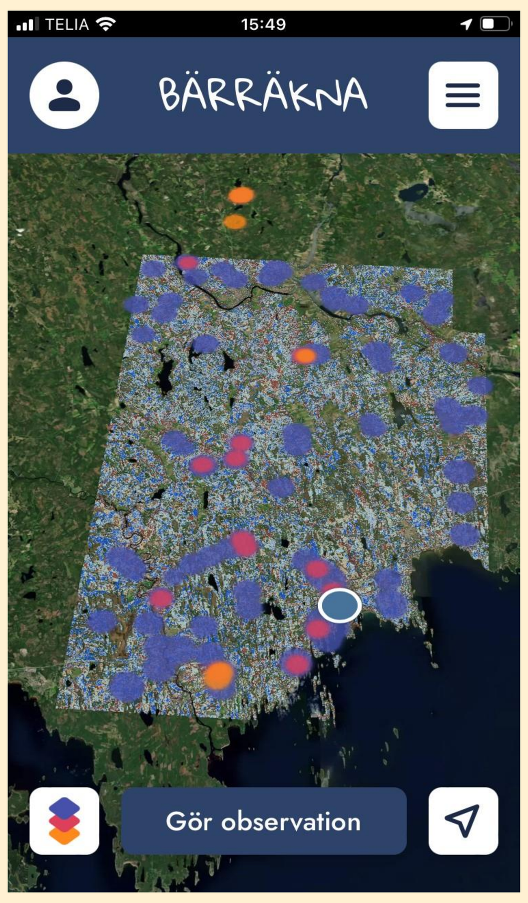

Fig. 5. Field measured berry locations and the best model for potential locations for bilberry picking was demonstrated in dedicated phone application

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