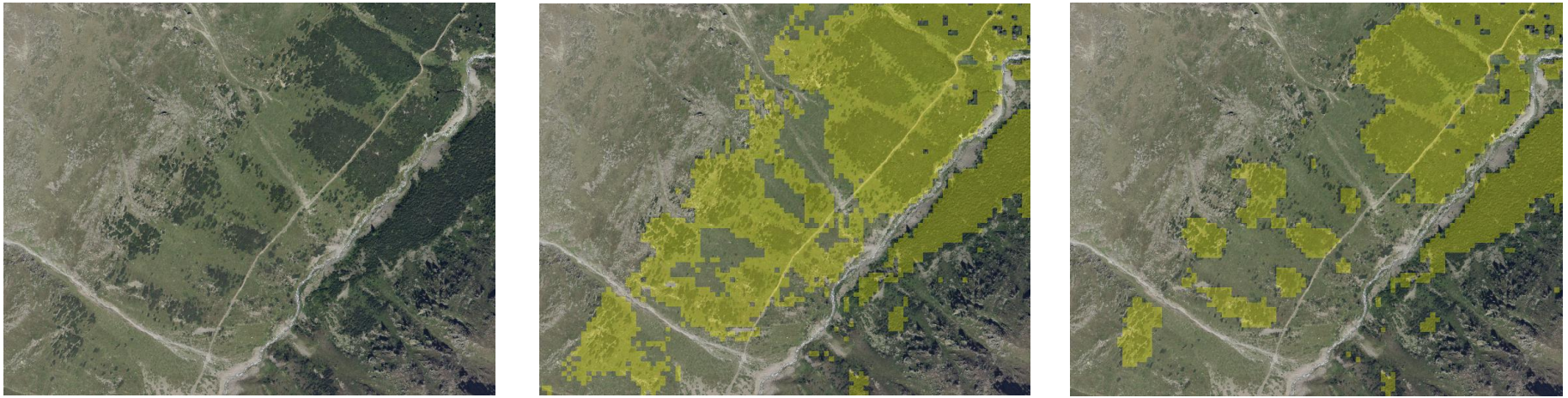
Wide-area shrub forest map based on multi-sensor data and active learning



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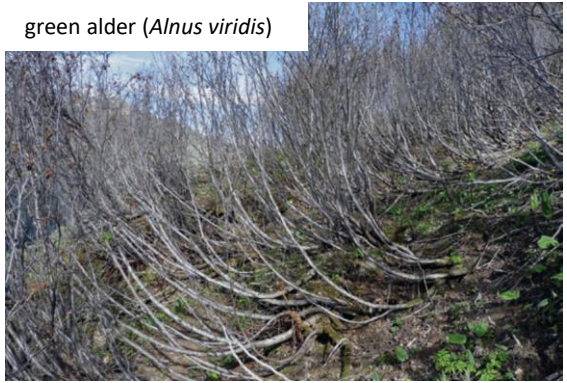
Motivation to map shrub forests countrywide

- Shrub forest in Switzerland
  - 5 % of forest; dominated by green alder 68 % and dwarf mountain pine 19 % (National Forest Inventory (NFI) 4; Cioldi et al., 2020)
  - FAO definition: ‘other wooded land’ (FAO, 2018)
- Increase in area in the past few decades
  - ~3’500 ha (5 %) from NFI 3 – 4 (~10 years) (Cioldi et al., 2020)
  - mainly due to agricultural land abandonment in the mountains but also climate change (Gehrig-Fasel et al., 2007)
- Influence on
  - soil and hydrological parameters (e.g. Hunziker et al., 2017)
  - biodiversity and succession (e.g. Zehnder et al., 2020)
  - protection forest (e.g. Bühlmann et al., 2014; Brožová et al., 2020)

green alder (*Alnus viridis*)



dwarf mountain pine (*Pinus mugo*)

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So far statistics from NFI plots (samples on systematic grid), no area-wide information

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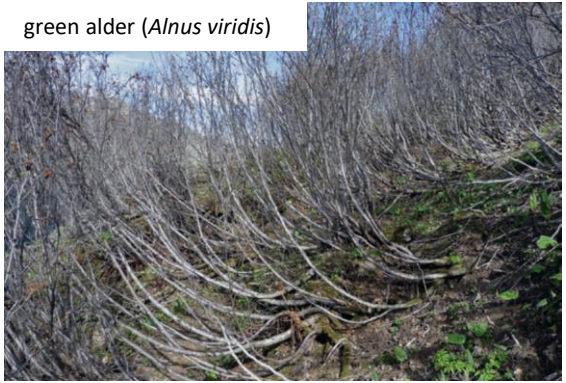

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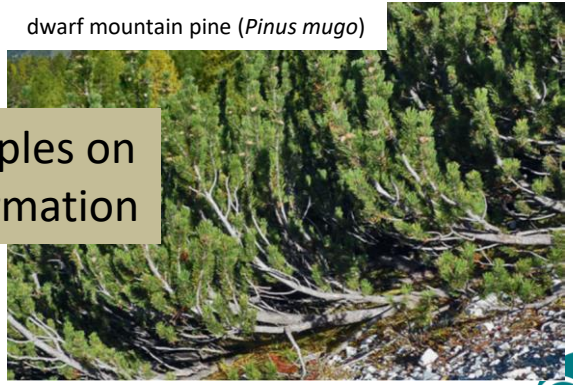

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Motivation to use remote sensing (RS)

- RS enables area-wide products with the possibility for monitoring at low costs
- Increasing RS data availability and processing efficiency in the past two decades
  - Sentinel data through Copernicus programme
  - Aerial stereo imagery through open data policy
- RS data from multiple sensors and technologies sensitive to vegetation

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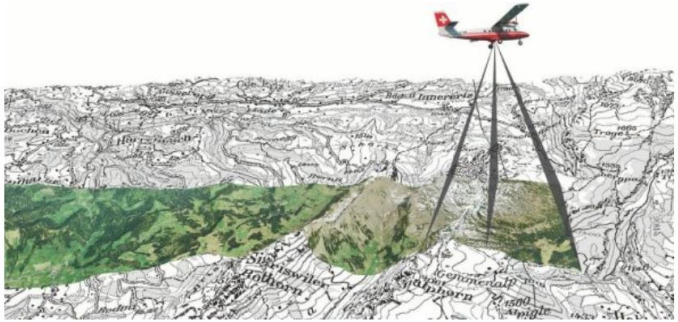

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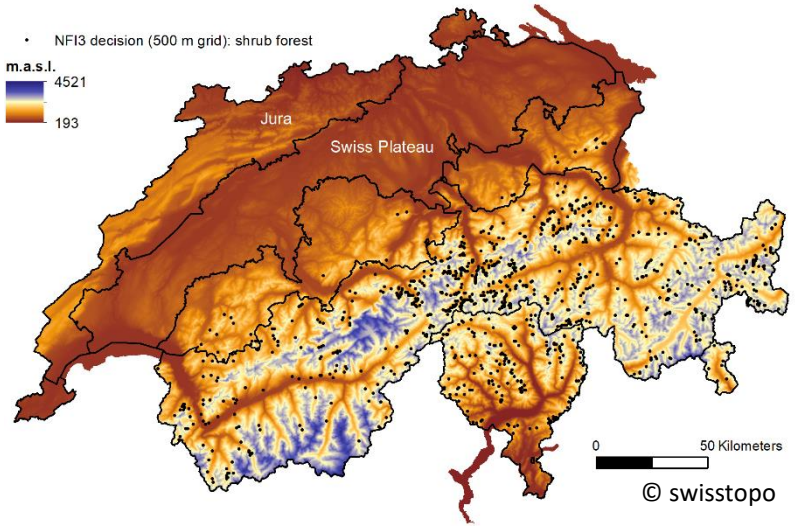
Reference data

- Challenge with shrub forest
  - Scarce and heterogenous distribution within study area (1 % of area)
- Initial training data (Initial RF model)
  - Guided by NFI3 aerial image interpretation
  - Aerial image interpretation of shrub forest areas
  - Non-probabilistic sampling



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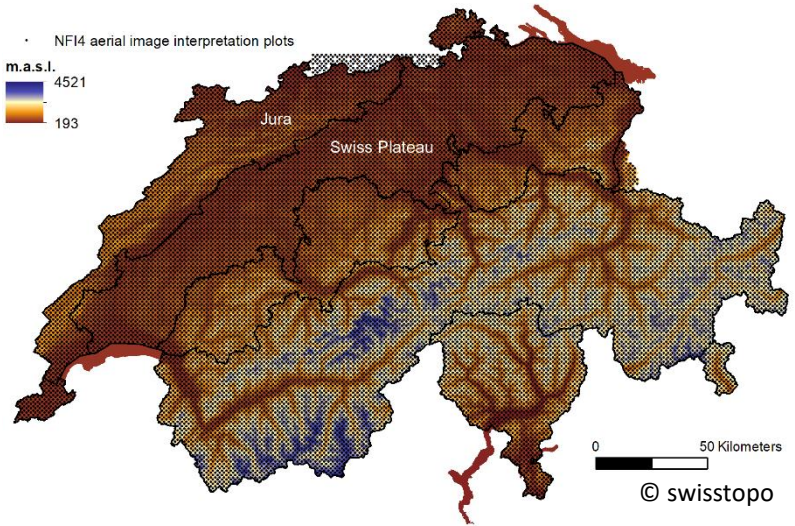
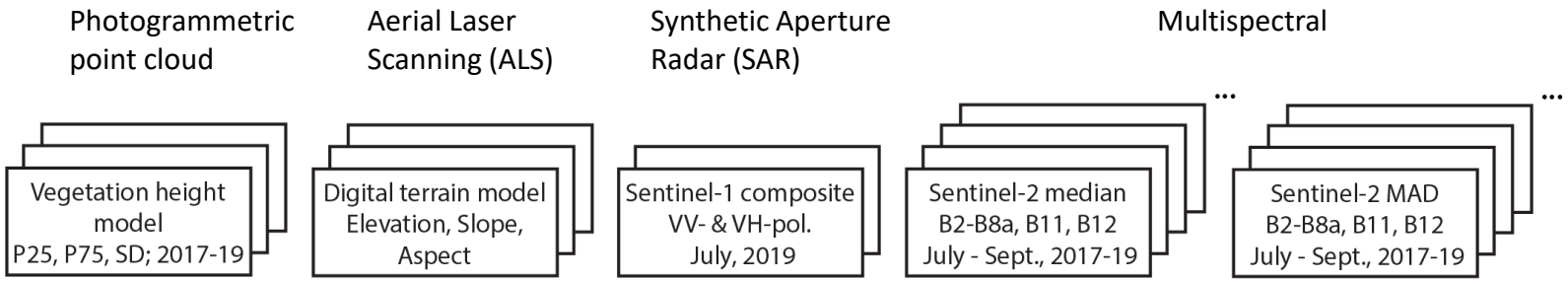
  - Non-probabilistic sampling
- Tuning data
  - Share of shrubs per NFI plot (NFI4 aerial image interpretation, systematic 1.4 km grid)



Multi-sensor predictors

- Beneficial use of different RS technologies that complement each other by their diverse sensitivity to properties of shrub forests

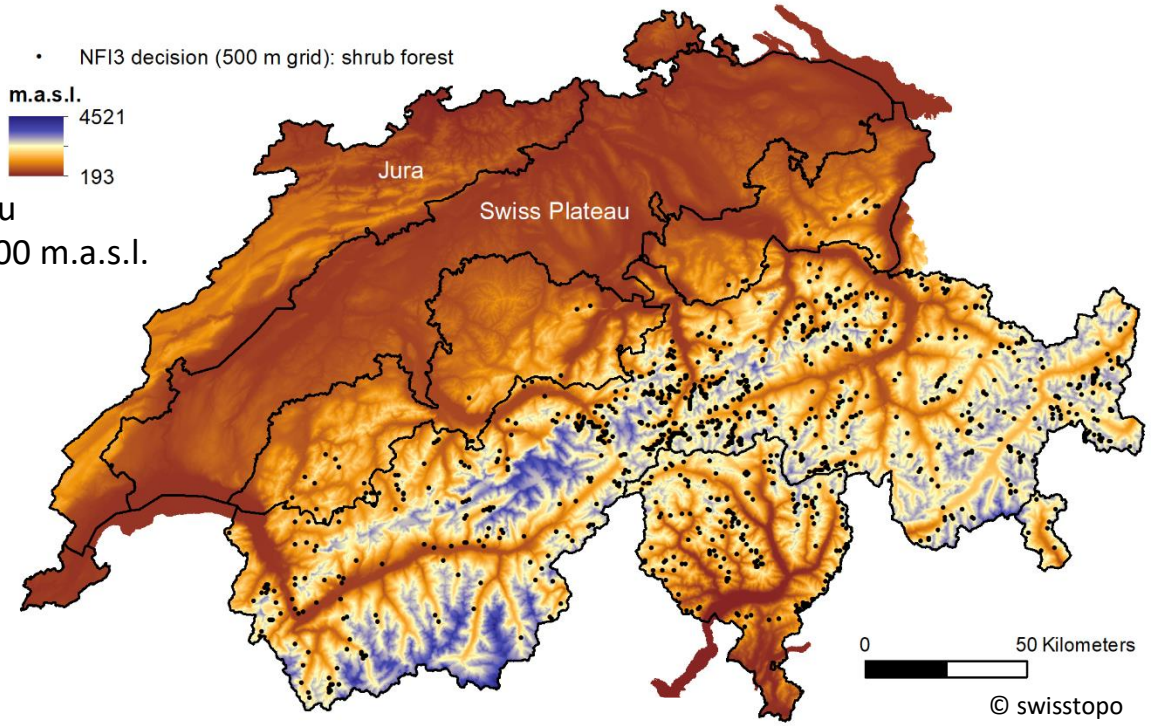


- Total of 29 predictors, each at a sample interval of 10 m

Expert rule

- Based on observed occurrence of shrub forest

1) Not within Jura or Swiss Plateau
2) 2’400 m.a.s.l. > elevation > 1’000 m.a.s.l.



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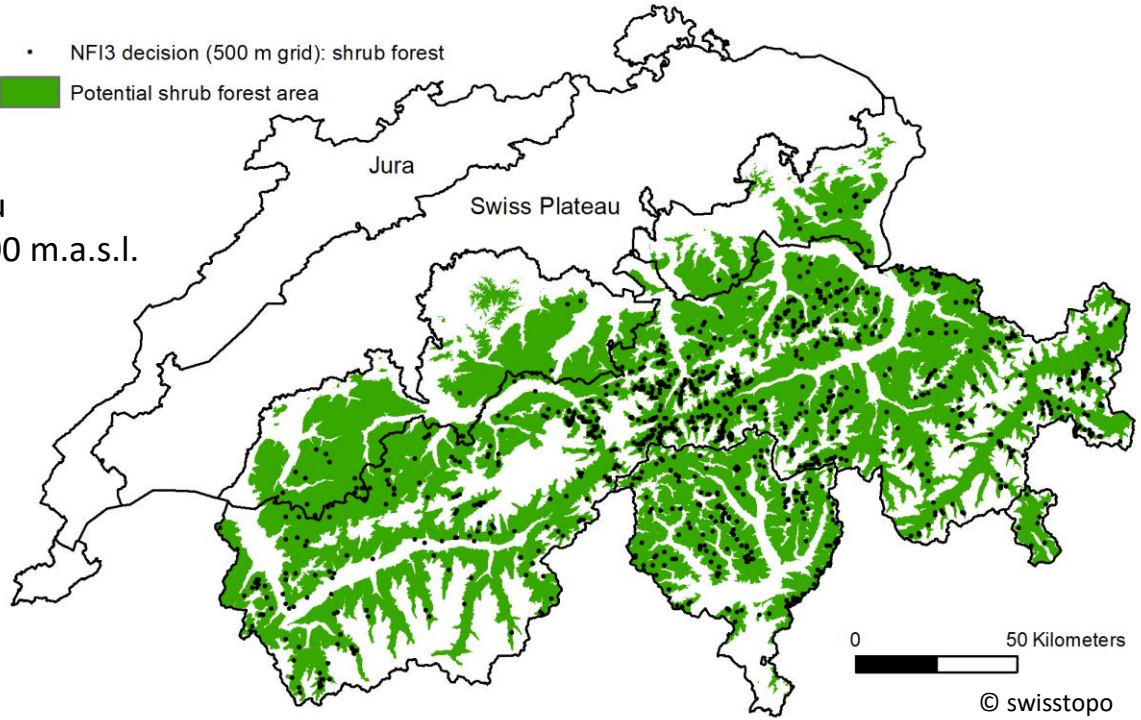
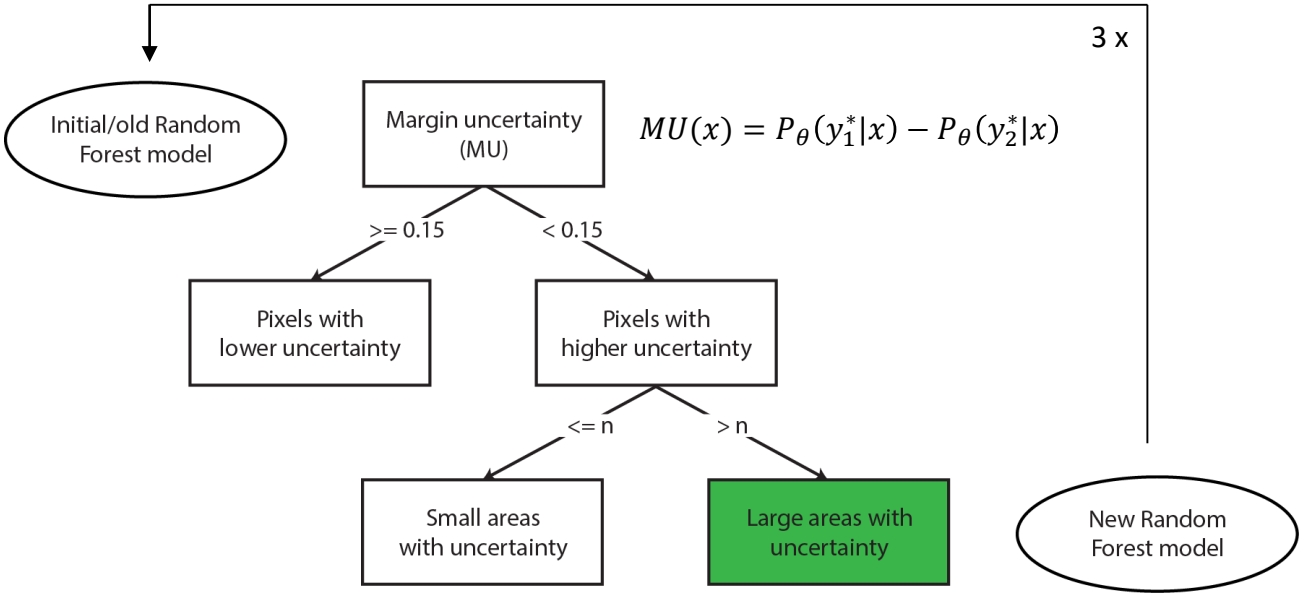


Semi-automatic active learning

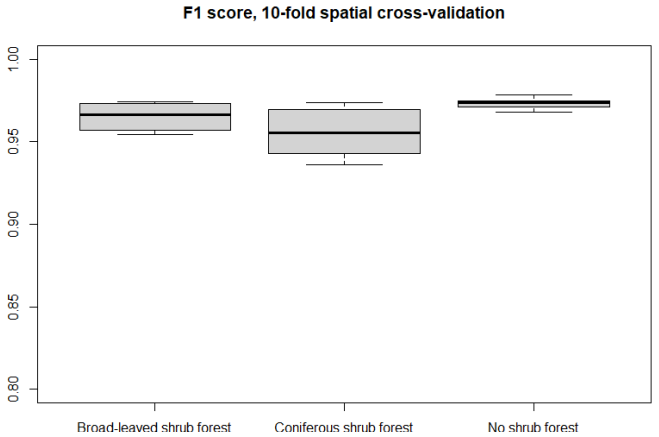
- New training data in areas of model uncertainty (Scheffer et al., 2001; Demir et al., 2011)



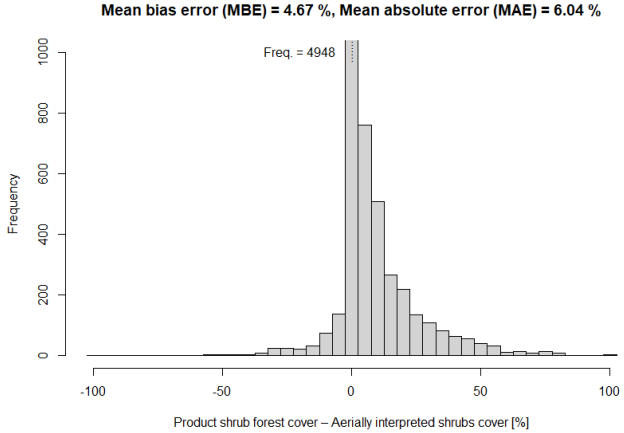
- Supervision with the tuning data

Result (without active learning)

- Within domain of training data
  - # of reference samples: 61’208, but non-probabilistic sampling → bias?
  - F1 scores of each class very high



- Within study area domain (7’640 NFI plots)
  - Comparison of map to the tuning data (share of shrubs per NFI plot)
  - Comparison with NFI4 area estimation
    - NFI4: 71’900 ha (Cioldi et al., 2020)
    - Shrub forest map: 127’703 ha (**+ 78 %**)



Result (benefit of active learning)

	Without active learning	After round 1	After round 2	After round 3
Reference samples	61’208	100’313 (+ 39’105)	110’775 (+ 10’462)	119’276 (+ 8’501)
Mean bias error [%]	4.67	0.87	0.3	-0.3
Mean absolute error [%]	6.04	3.33	2.87	2.69
Area [ha]	127’703	71’056	61’750	52’496

dwarf mountain pine stands

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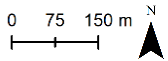

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green alder stands

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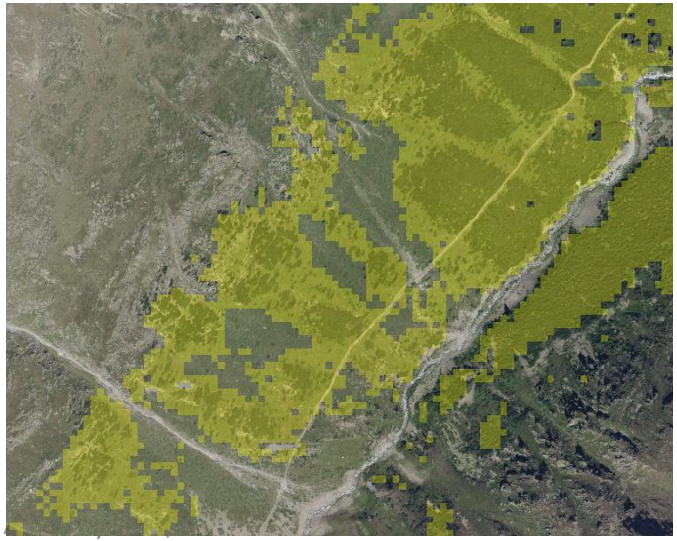

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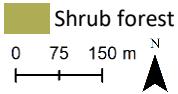

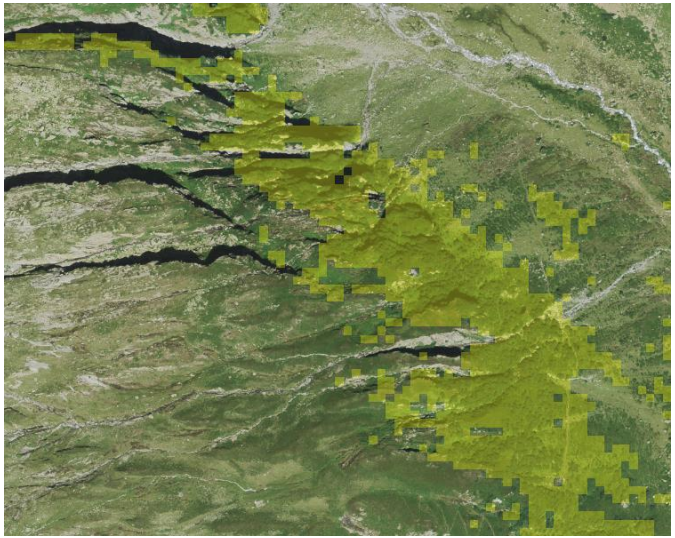

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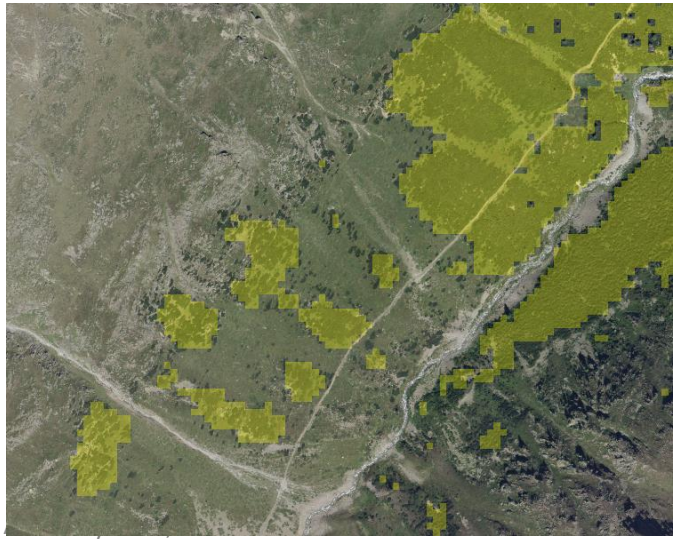

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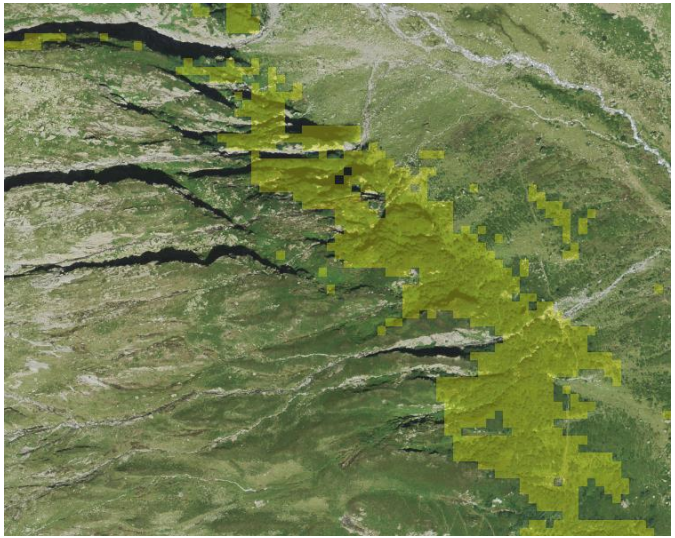
After round 3

Shrub forest

0 75 150 m

N



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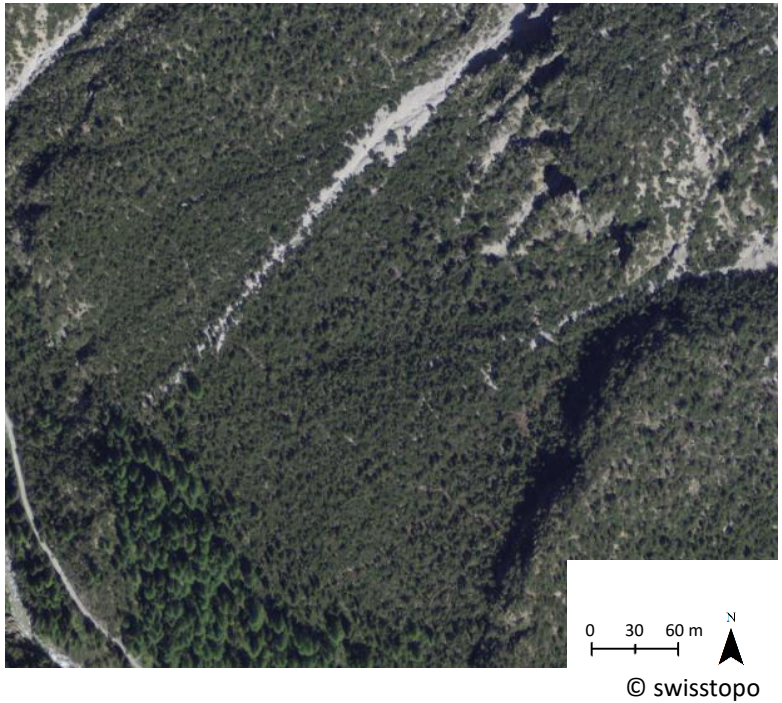
green alder stands

Challenges and next steps

- Distinction hard in transition areas from shrub to high mountain pine forest
- Reproducibility for monitoring applications? (e.g. with data from 2020-2022)

- Post-production for final product
  - Underestimation -> Increase areas at the edges
  - Filtering -> Generalisation, minimum mapping unit (MMU)
- Comparison of product with Swiss land cover survey (100 m grid, > 4 M points)



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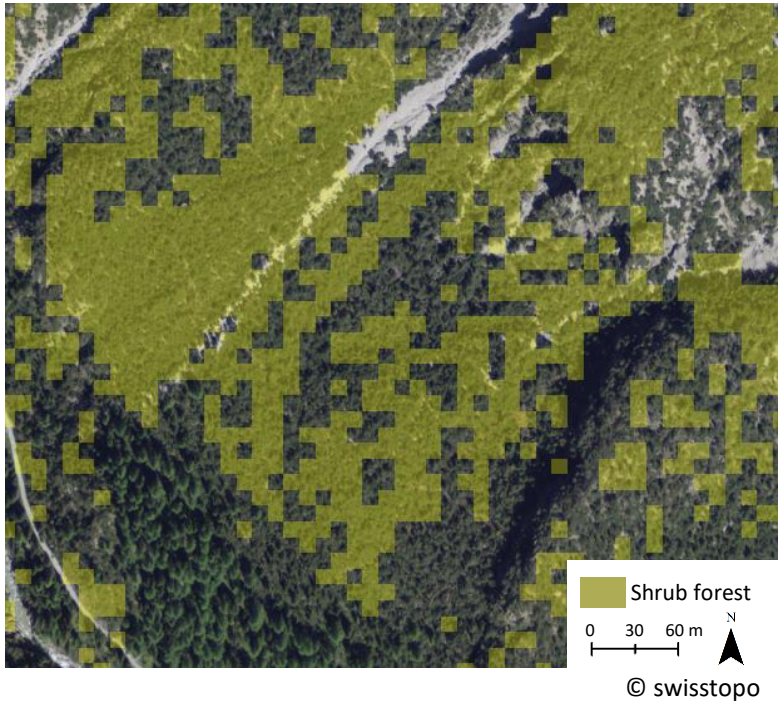

Conclusions

- Feasible to map shrub forest on the countrywide scale using data from several remote sensing sources of three years (2017-2019)

- Sampling bias has to be addressed in case of non-probabilistic training data collection

- An active learning technique benefits from RF model probability estimates and enables to increase the model performance in an efficient way (MAE ~-3 %)

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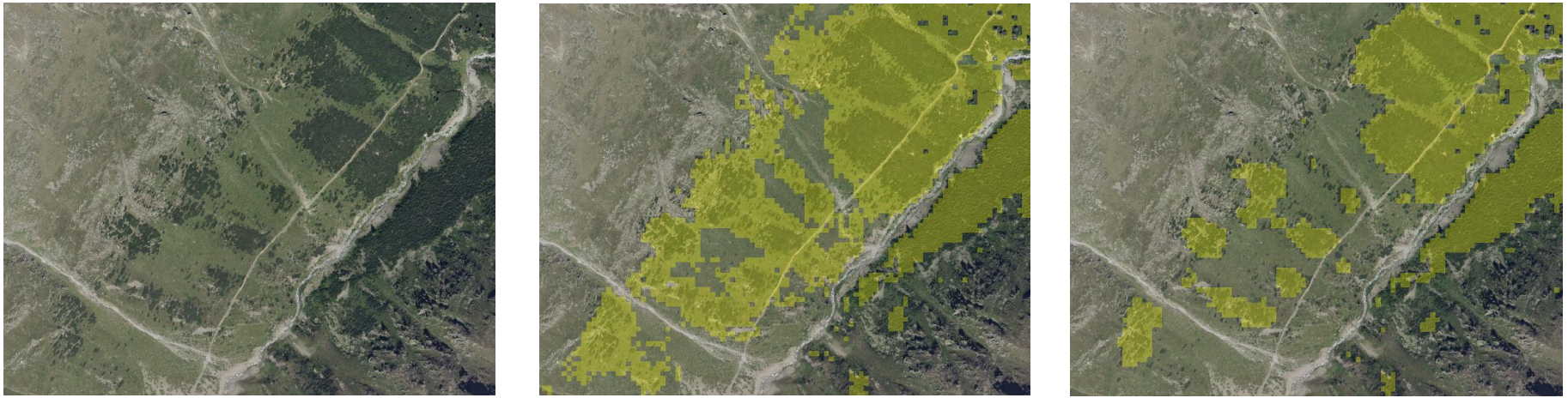

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