

living planet | BONN symposium | 23-27 May 2022

TAKING THE PULSE
OF OUR PLANET FROM SPACE



Temporal deep learning for mapping temperate forest tree species in Flanders using Sentinel-2 time series

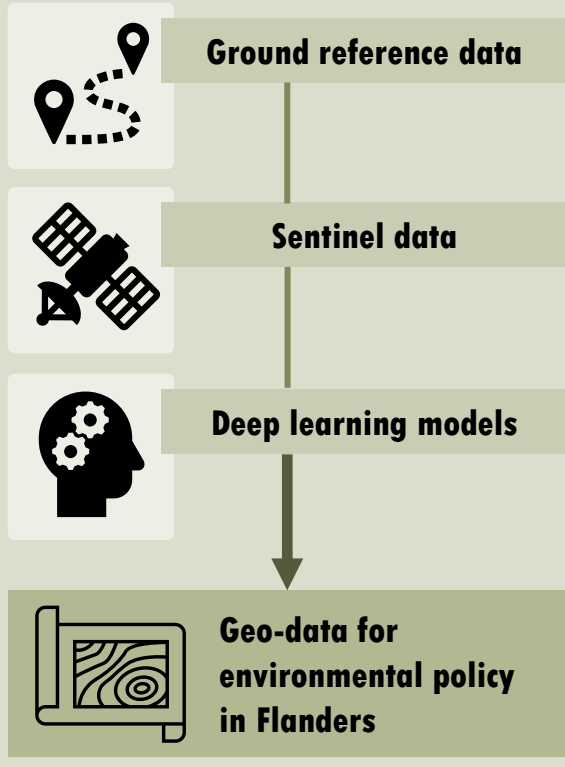
Margot Verhulst, Stien Heremans, Matthew Blaschko, Ben Somers

27/05/2022

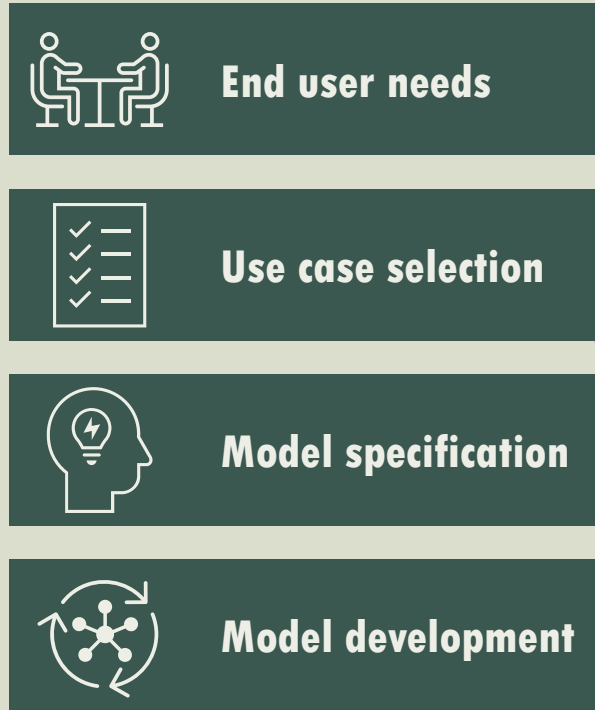
KU Leuven

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CONCEPT



PROJECT WORKFLOW

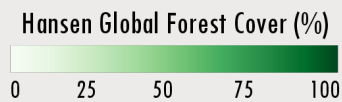
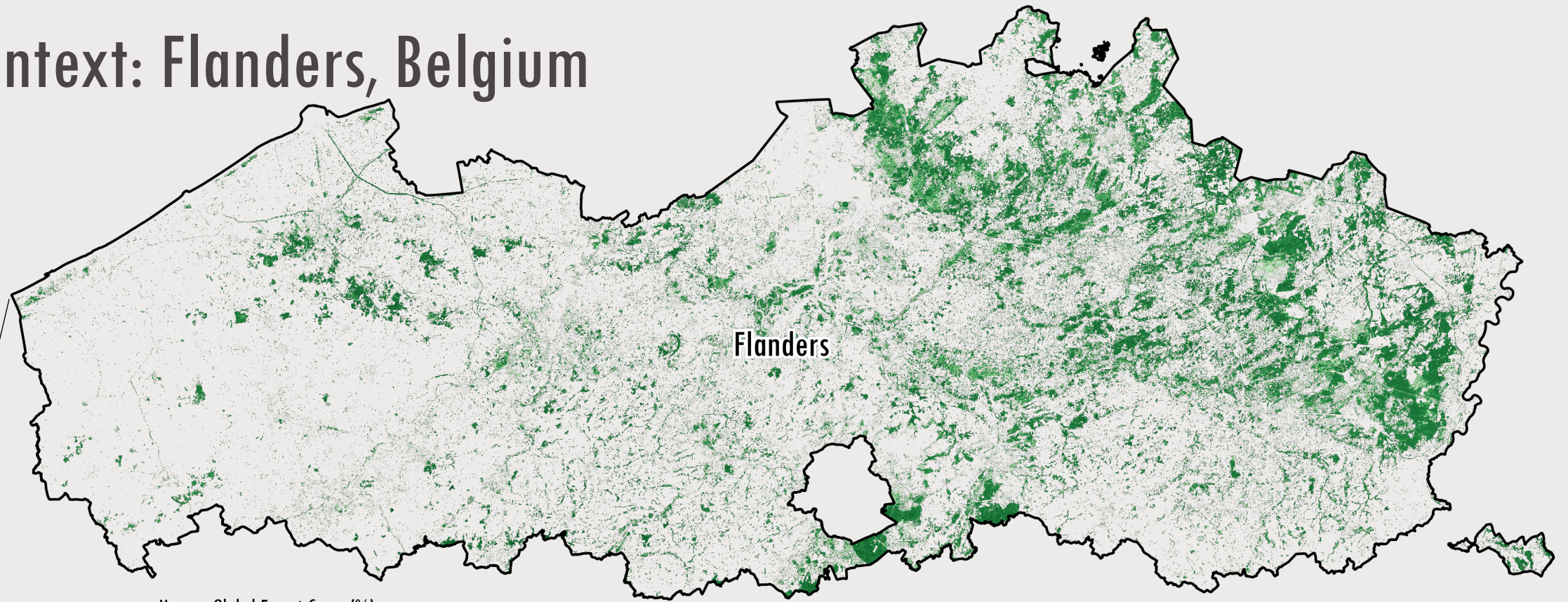


USE CASES

A grid of nine use cases, each with a representative image and a text label:

- Biological Valuation Map**: Image of a green map with a winding path.
- Forest monitoring**: Image of tall trees in a forest.
- Crop damage by wild boar**: Image of two wild boars in a field.
- Buffer zone watercourses**: Image of a river flowing through a grassy field.
- Catch crops**: Image of a circular tree in a field.
- Algae blooms**: Image of green algae in water.
- Fire hazard in heathlands**: Image of dry, brown grass.
- GEO.INFORMED**: A central icon representing the project, featuring a satellite, a neural network, a water drop, and a leaf.
- Water detection**: Image of water reflecting trees in a field.

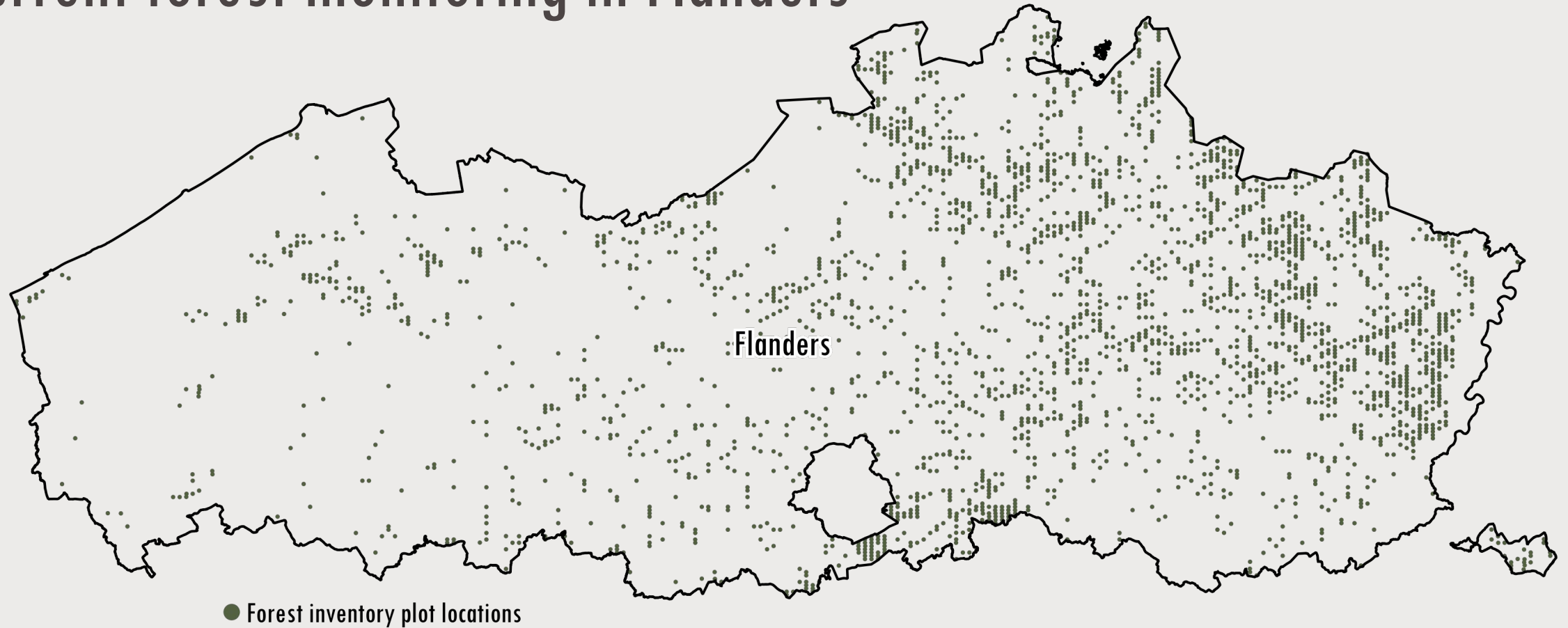
Context: Flanders, Belgium



- Highly urbanized & fragmented landscape
- Forest cover percentage ~10 % of area
- Shift in policy focus
 - Wood production → multifunctionality
 - Increase average stand age & structural diversity



Current forest monitoring in Flanders



- National forest inventory → Tree characteristics (diameter, height), presence native/exotic species, dead wood
- But only allows for statistical evaluation on regional level over decadal time period
- Need for information: frequent updates and spatially-explicit

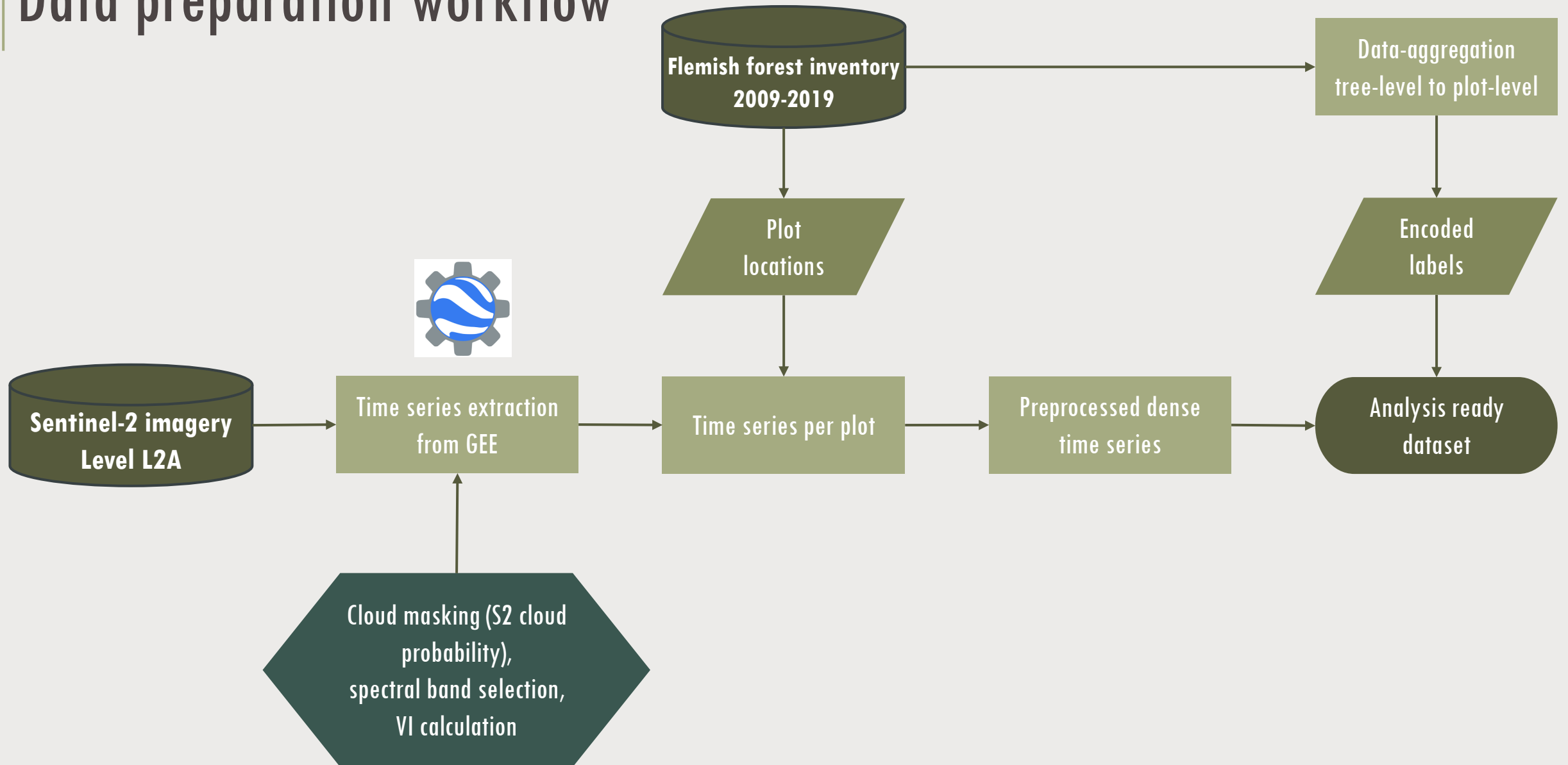
Objectives and challenges

- Can we use national forest inventory data in Flanders to train supervised ML/DL algorithms?

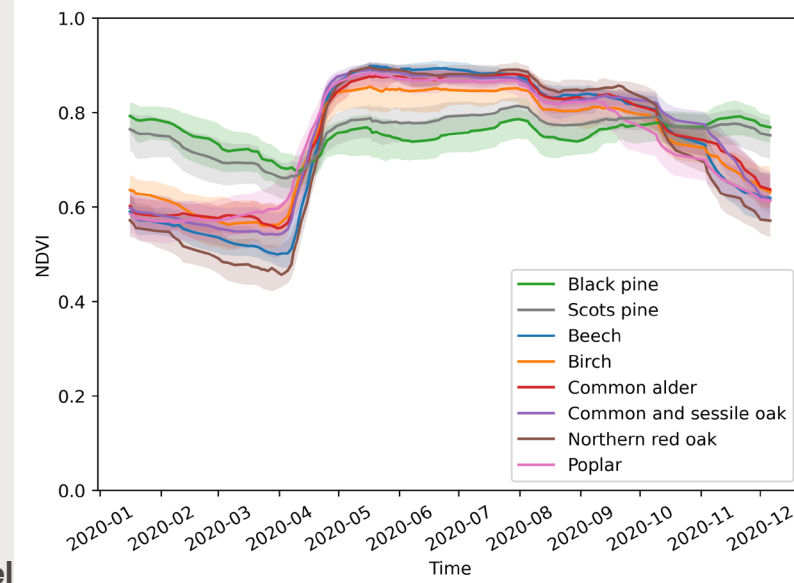
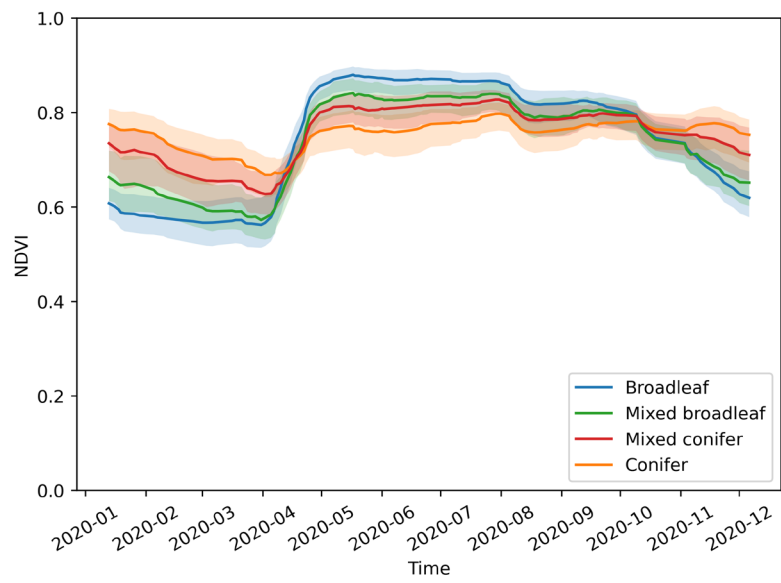
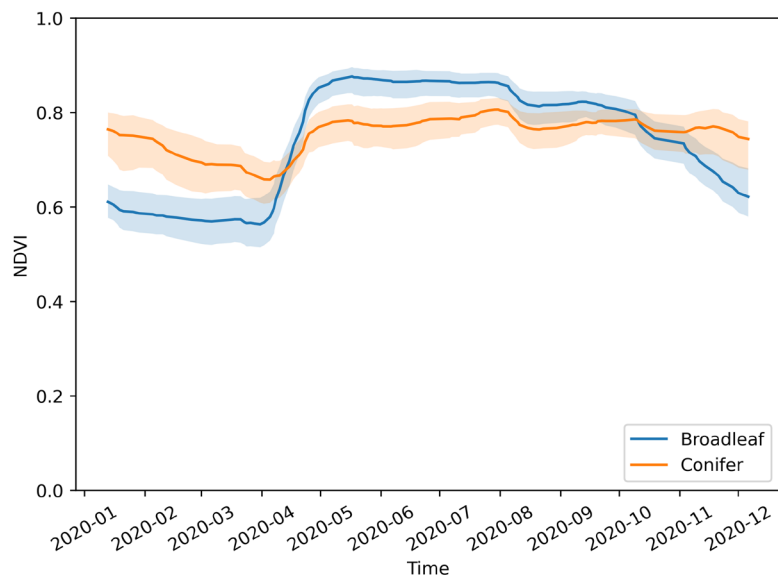
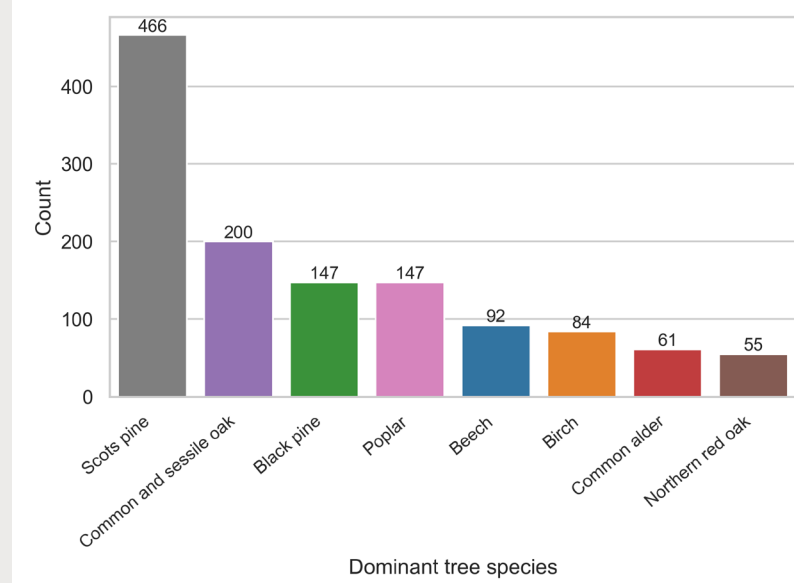
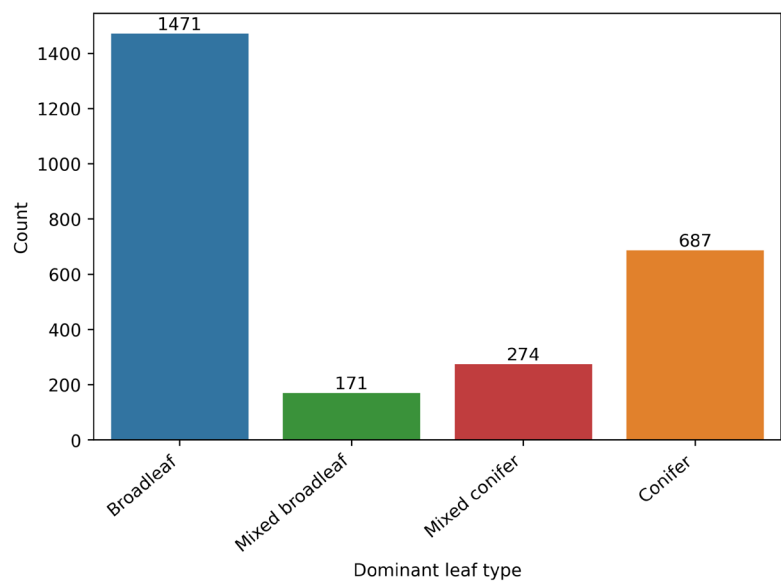
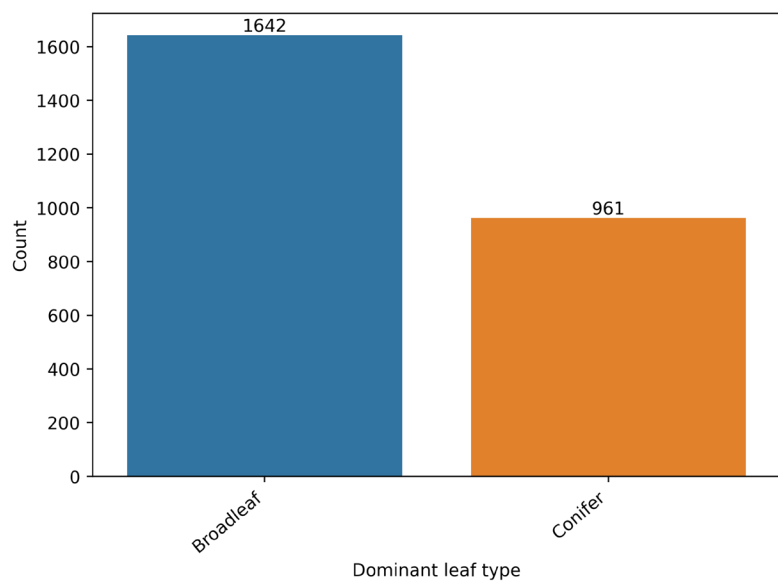
Challenges

- Temporal mismatch between data collection and Sentinel-2 data
- Limited size of inventory (~ 2600 plots in one measurement cycle)
- Highly imbalanced datasets

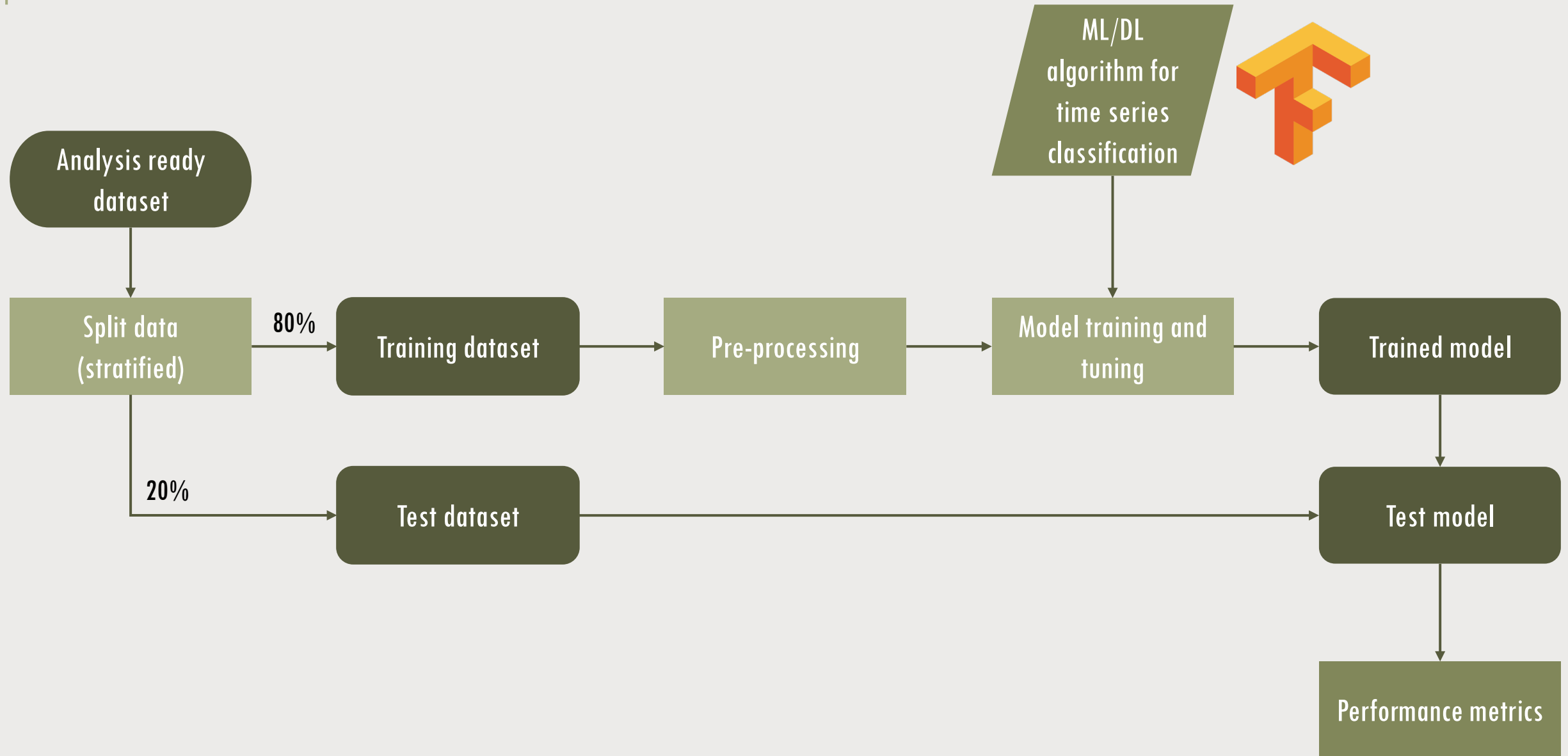
Data preparation workflow



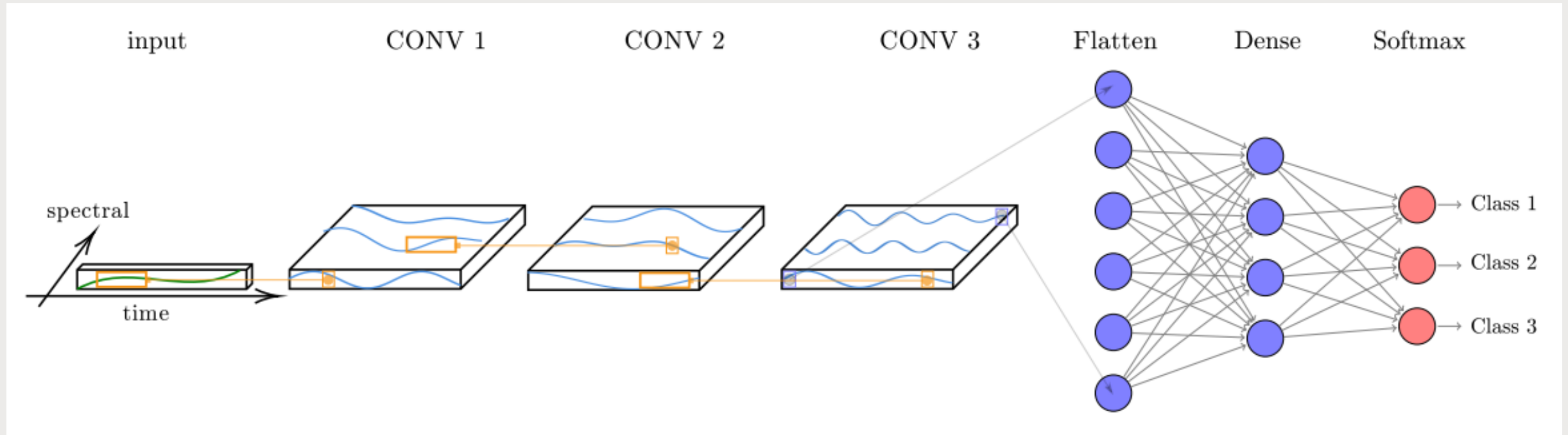
Datasets



Model training workflow



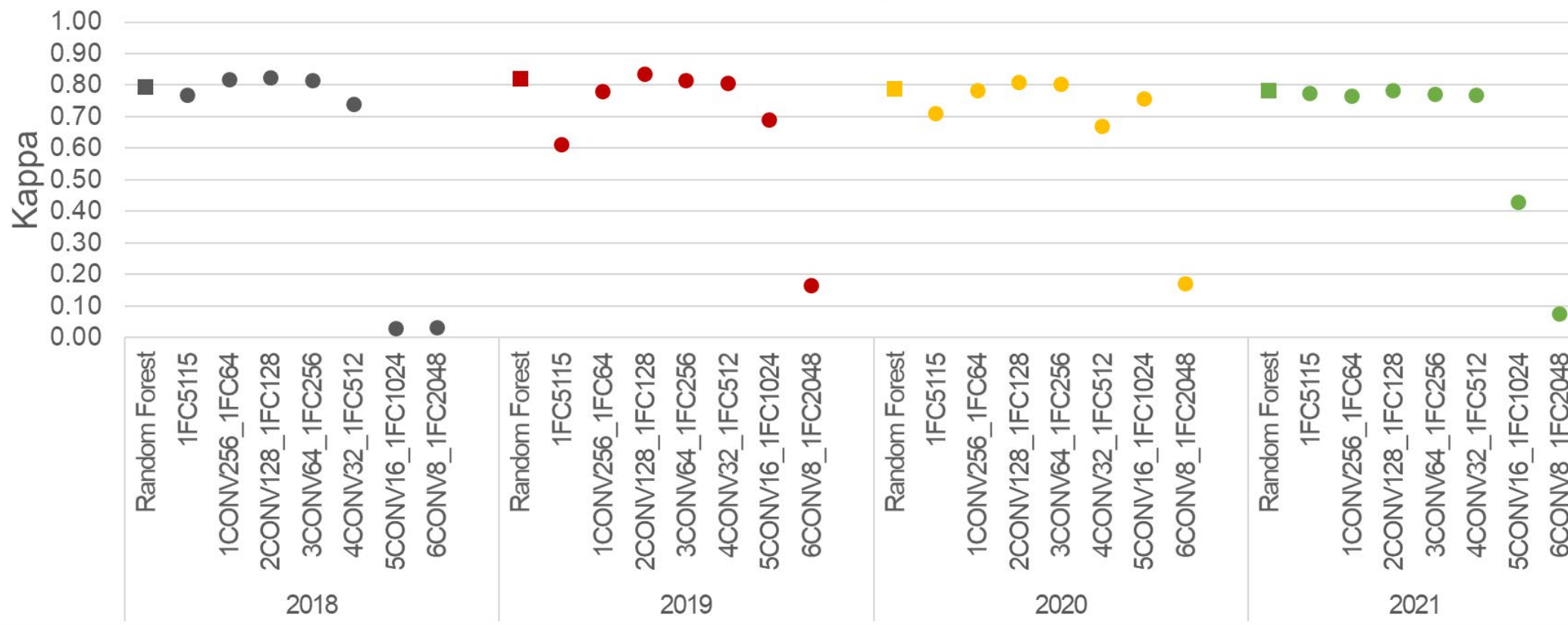
Temporal convolutional neural network (tempCNN)



- Architecture proposed by Pelletier et al. (2019)
- Applies the idea of temporal convolutions
- Previously applied to crop type mapping
- Compare with random forest

Results

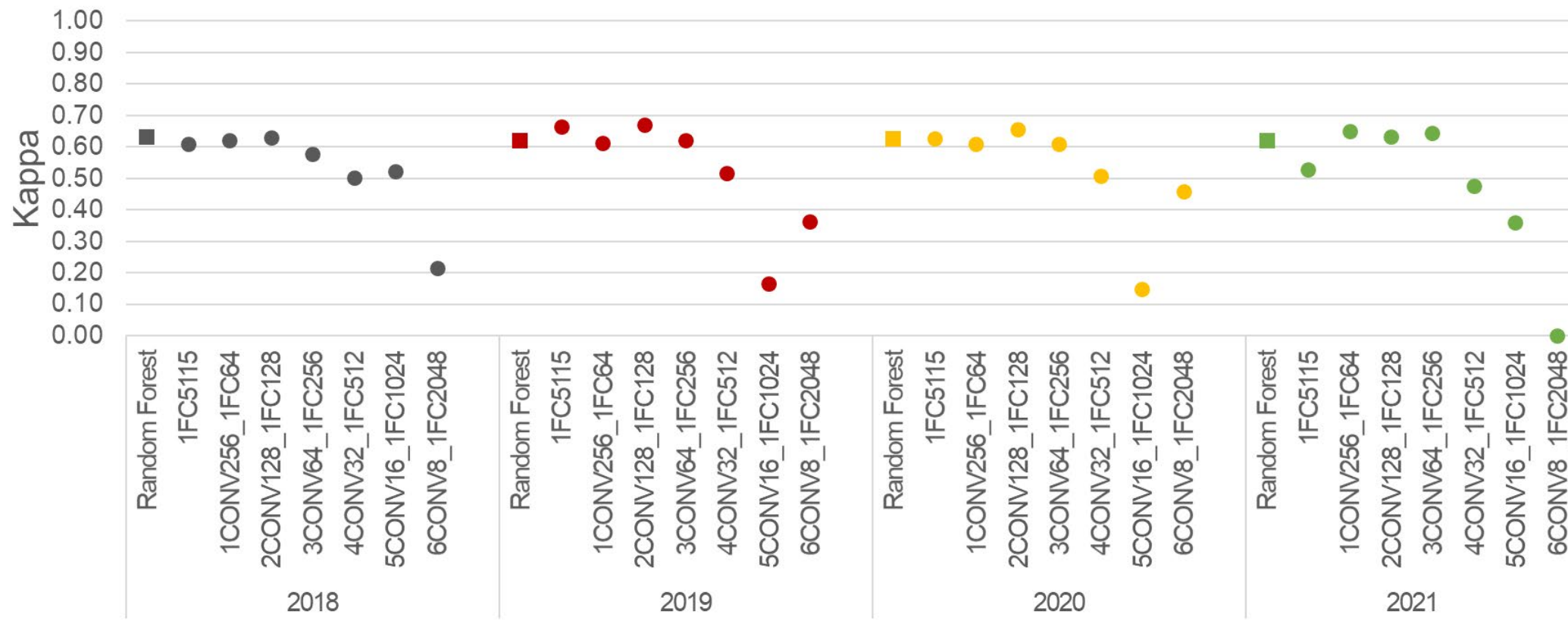
Dominant leaf type (2 classes)



Highest overall accuracy
92%

Results

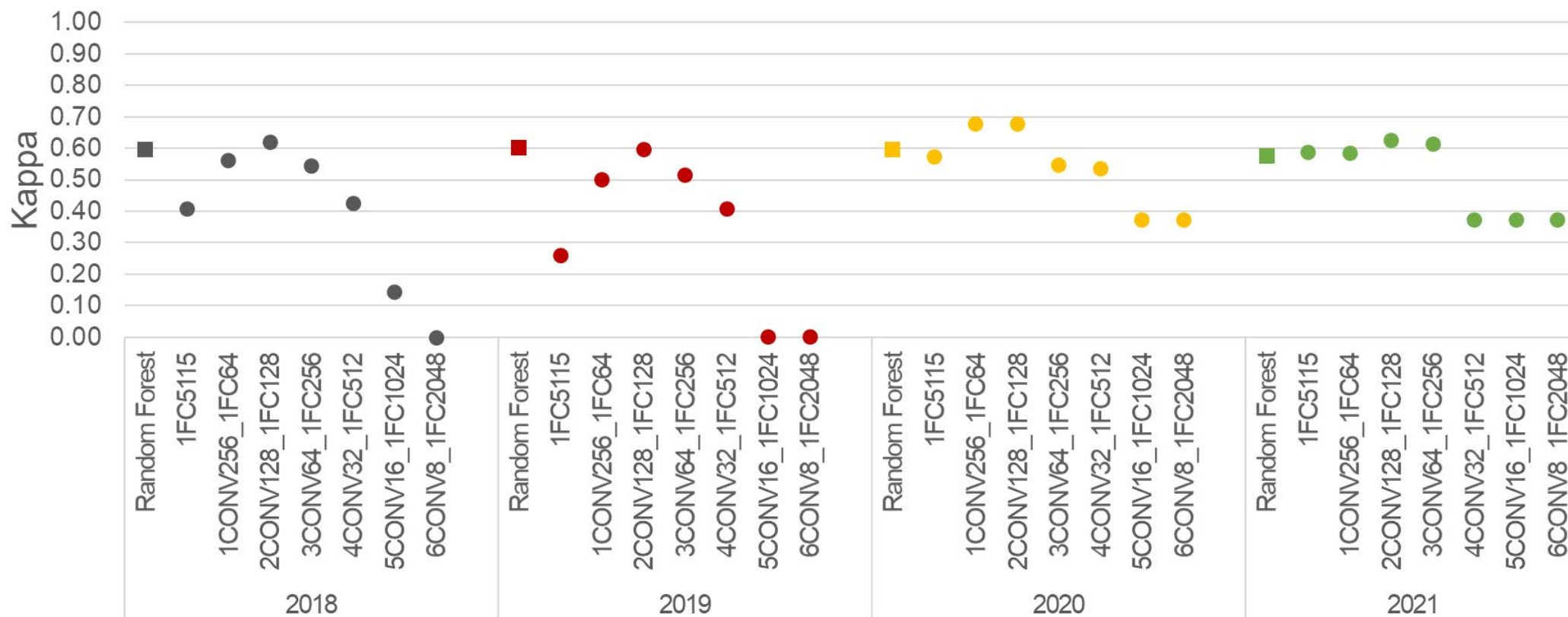
Dominant leaf type (4 classes)



Highest overall accuracy
82%

Results

Dominant tree species (8 classes)



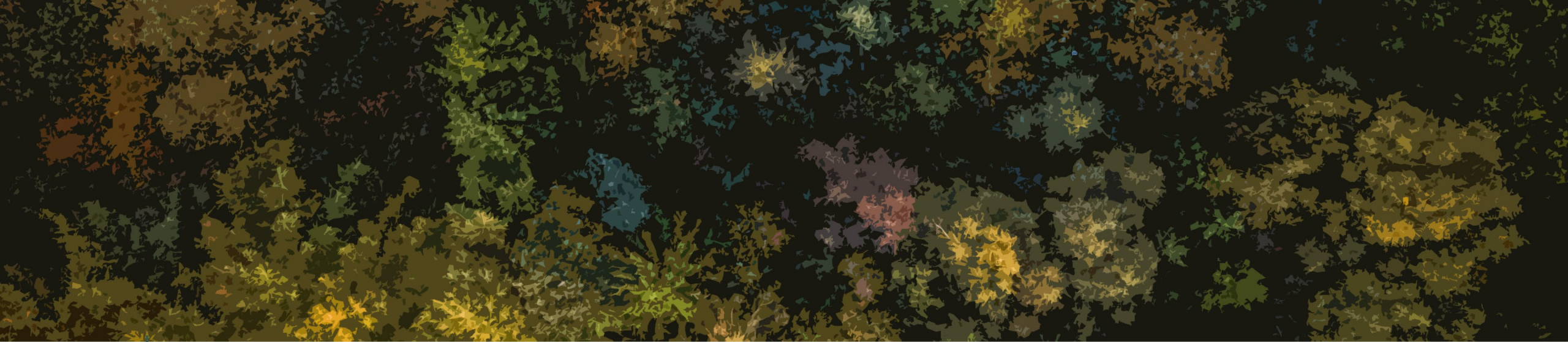
Highest overall accuracy
70%

Findings

- Optimal number of convolutional layers: 2 or 3
 - Certain configurations with too many layers may lead to under-performance
- TempCNN vs RF
 - RF performance is often on similar level as best-performing TempCNN configuration
 - Training and testing time
- Performance across years seems similar
 - Transferability across years?

Next steps

- Run additional experiments with TempCNN
- Repeat experiments to check robustness of accuracies
- Class imbalance
- Move towards prediction of percentages of classes



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