Work Package 5

Modelling activities to support plant breeding

Simon Fiil Svane
Per Abrahamsen

Section for Agrohydrology

KØBENHAVNS UNIVERSITET

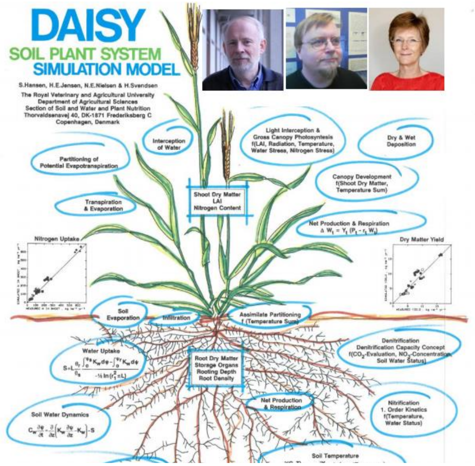
Work Package 5: Modelling activities to support plant breeding

Main research question

Will mechanistic modelling improve the understanding of relationships between crop traits and environment?

Activities

- Environmental characterization of all breeder sites
- Test experiment with spring barley at three sites (Graminor, Sejet and Lantmannen)
- Integration of UAV data collected by breeders with the Daisy model.



Open Source: Mechanistic simulation of agricultural fields

Objectives

Mechanistic crop models provides information of “E” and “M” in “GxExM” interactions:

- link specific traits or genetic markers to certain environmental conditions (Daisy=nitrogen stress and water stress)
- Identify ideotypes for the future climate conditions
- Improve the understanding of collected UAV imaging data

limitations

Mechanistic crop models often needs calibration and are not user friendly.

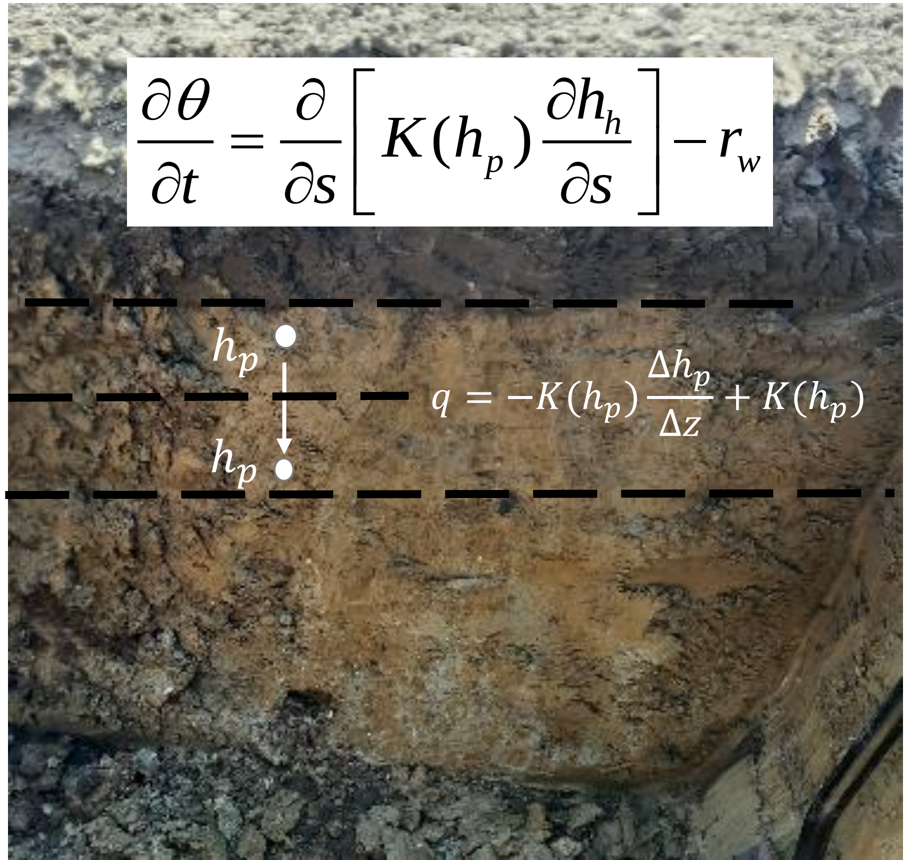
Lack of N

Lack of Water

Too much Water!

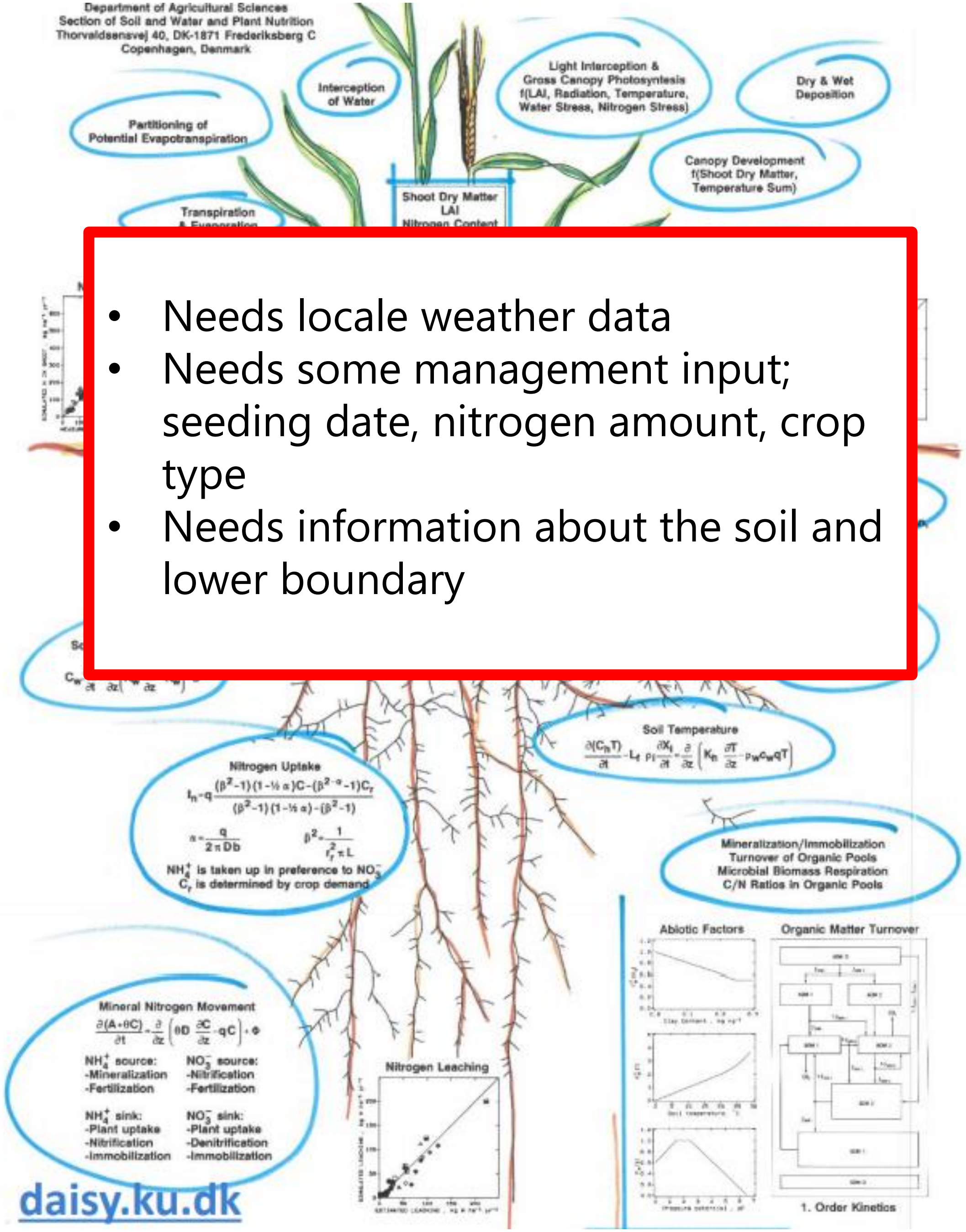
The daisy crop model

The daisy model simulates soil water flow using the Richards equation, it also simulate changes in soil organic carbon and are directly coupled to a plant atmosphere model simulating evapotranspiration and photosynthesis regulated by water and N stress



$$\frac{\partial\theta}{\partial t}=\frac{\partial}{\partial s}\left[K(h_p)\frac{\partial h_h}{\partial s}\right]-r_w$$

$$q=-K(h_p)\frac{\Delta h_p}{\Delta z}+K(h_p)$$

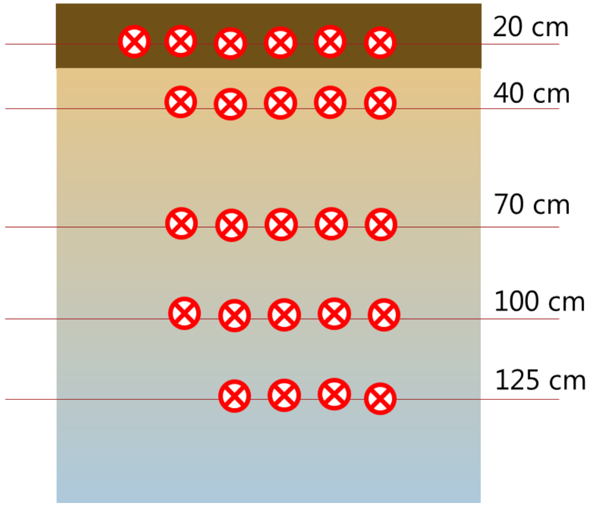


- Needs locale weather data
- Needs some management input; seeding date, nitrogen amount, crop type
- Needs information about the soil and lower boundary

Environmental characterization (soil data)

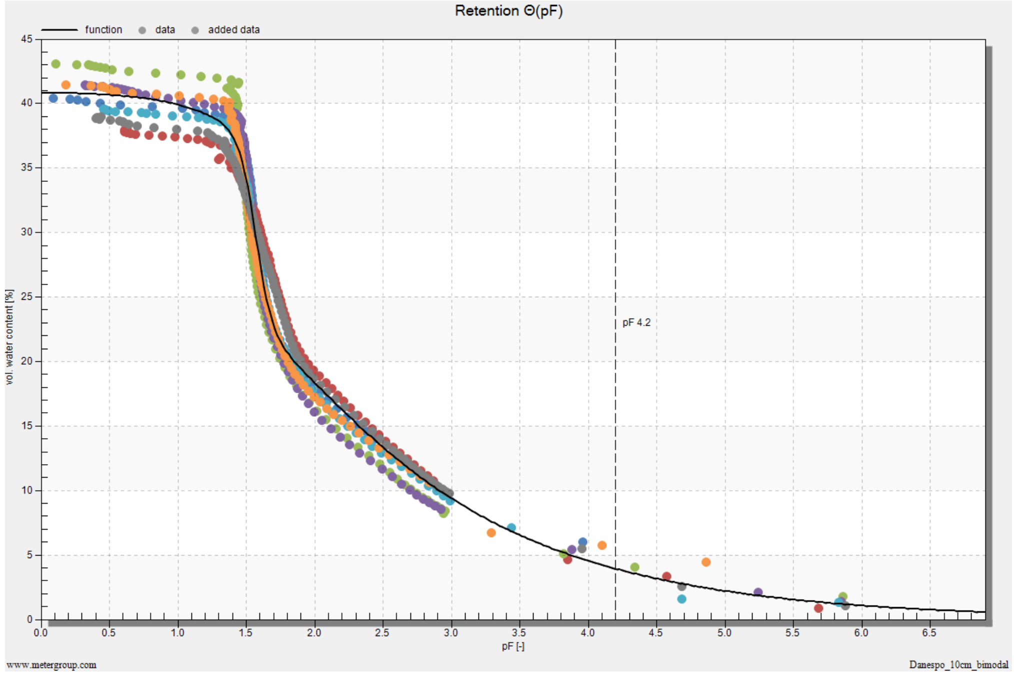
Soil profile investigation

- Soil horizon description
- Ring coring at each layer
- Soil texture data
- P,Mg and K content
- Soil (pH)
- Soil water retention
- Soil hydraulic conductivity



Environmental characterization (soil data)

Measurement of soil physical properties using the hyprop system



Data fitted using bimodal constrained Van Genutchen model (Durner 1994)

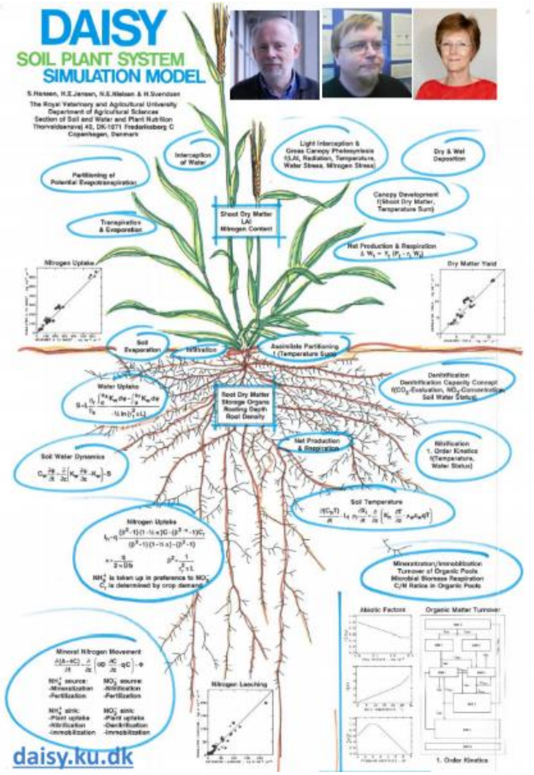
Environmental characterization (soil data)

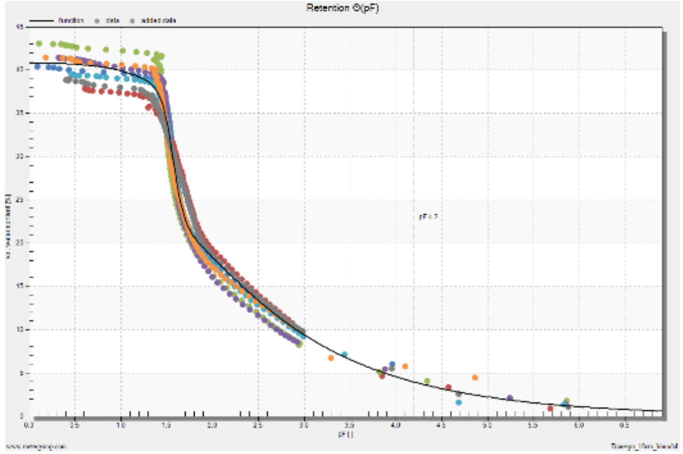
Daisy soil column files made for all sites

```
;;Description of the soilprofile
(defcolumn "Profile" default
    (Soil
    (MaxRootingDepth 100.00)
          (horizons (   -30.00 Ap)
                    (   -40.00 Bs_plowPan)
                    (   -60.00 Bs)
                    (   -200.00 C)))
  (Groundwater deep)
    (Chemistry low_denit))
```

```
(defhorizon Ap USDA3 (normalize true)
;0-30 cm
      (clay 3.9 [%])
      (silt 6.4 [%])
      (sand 87.0 [%])
      (humus 2.8 [%])
      (C_per_N 14.2)
(dry_bulk_density 1.47)
(root_homogeneity 0.5)
(hydraulic M_BivG
                (alpha1 0.026 [cm^-1])
                (n1 1.315 [])
                (Theta_res 0.000 [])
                (Theta_sat 0.409 [])
                (alpha2 0.0277 [cm^-1])
                (n2 7.689 [])
                (w2 0.357 [])
                (K_sat 200 [cm/d])
                (l 1.509 []))
)
```

Ap



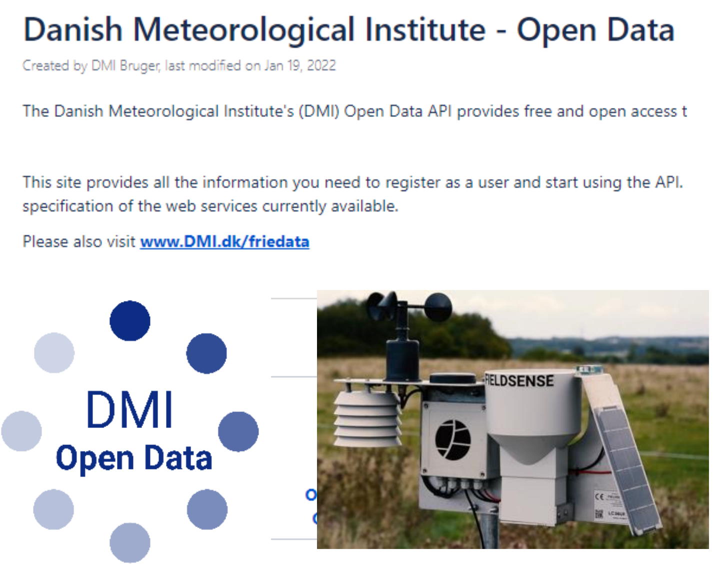


Environmental characterization (weather data)

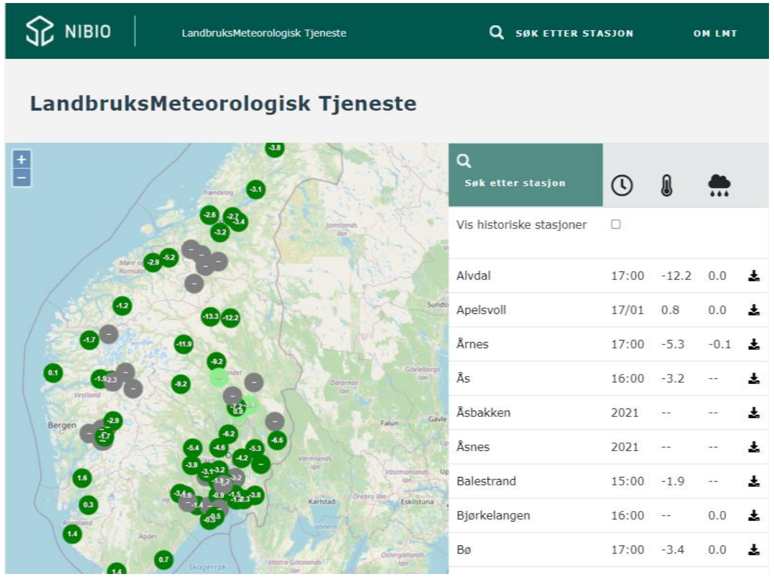
Weather data obtained from various sources

Different ontology and large variation in data quality

Denmark
DMI/FieldSense/Breeder stations



Norway
LandbruksMeteorologisk Tjeneste

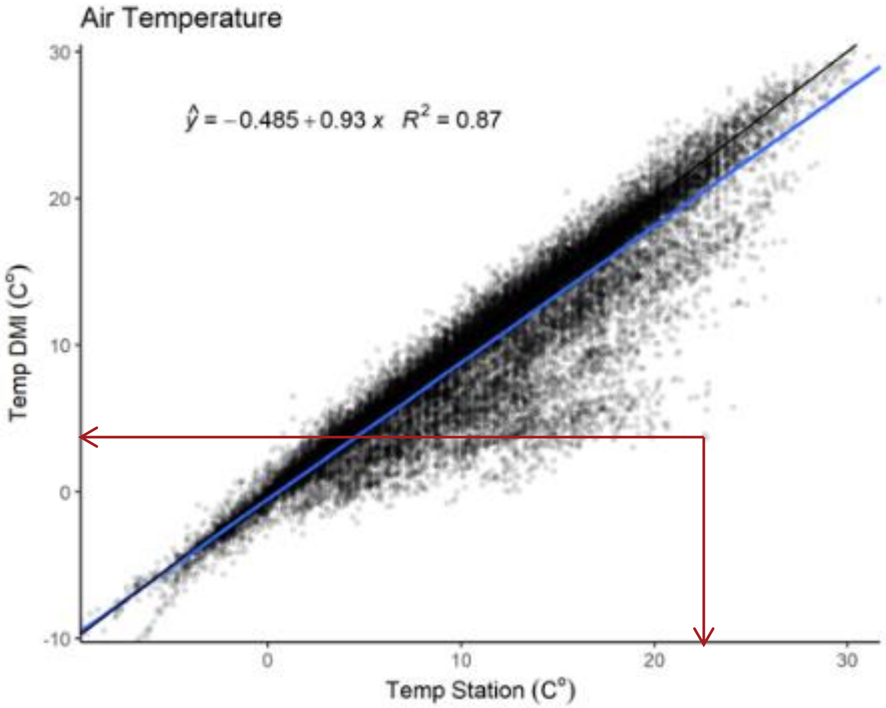


Sweden
SMHI/Lantmet

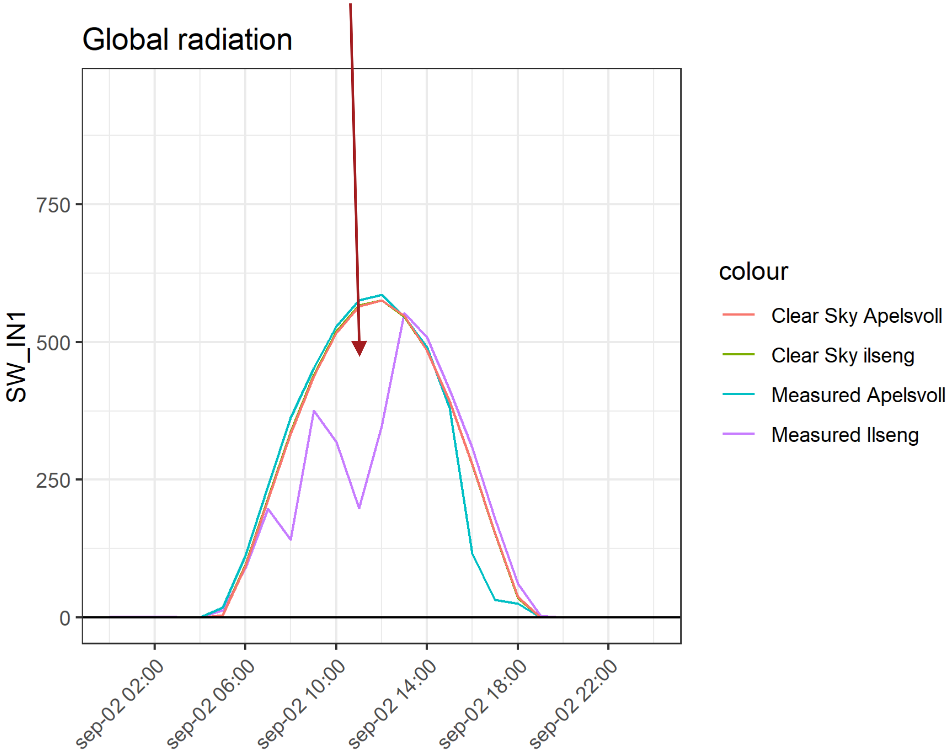
Quality control of weather data

- Data comparison to nearby stations
- Some sensors at breeder stations were unreliable
- Bad data and missing values were replaced with data from nearby stations

Mowing shadows from trees



Difference of 19 C° (Distance 16 km)



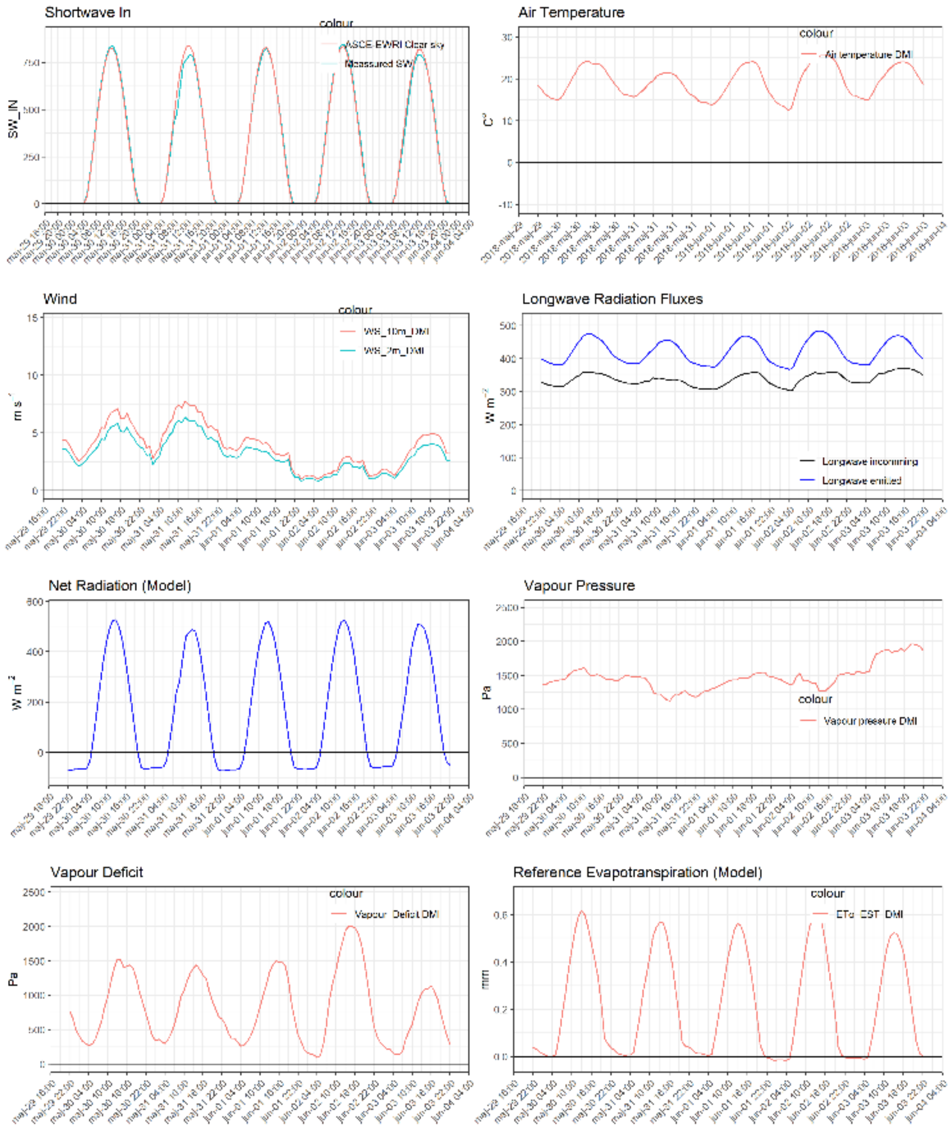
Environmental characterization (weather data)

Daisy hourly weather files created for all sites

Reference Evapotranspiration Method:

- FAO-penman method for hourly data (Allen et al. 2006)
- Net-radiation estimated according to (ASCE 2005)
- Cloudiness function for Sub-humid climates (Kjærsgaard et al. 2008)

```
--------------------------------------------------------------------------------
Year    Month   Day     Hour    AirTemp RelHum  Wind    GlobRad Precip  RefEvap
year    month   mday    hour    dgC     %       m/s     W/m^2   mm/h    mm/h
2011    1       1       0       2.8     90.3    7.731   0       0.1     0.005932
2011    1       1       1       3.1     92.8    8.63    0       0.1     0.004012
2011    1       1       2       3.2     94.3    7.731   0       0.2     0.002151
2011    1       1       3       3.4     90.5    7.641   0       0       0.005222
2011    1       1       4       3.2     82.5    7.91    0       0       0.012
2011    1       1       5       3.1     80.7    8.27    0       0       0.01351
2011    1       1       6       2.9     82.2    8       0       0       0.01163
2011    1       1       7       2.7     82.5    6.652   0       0       0.009822
2011    1       1       8       2.6     81.5    6.203   3       0       0.009964
```



Spring barley case

Providing information of “E” and “M” in “GxExM” interactions

Modelling water and nitrogen stress

Six cultivars, at three sites, in 2 seasons.

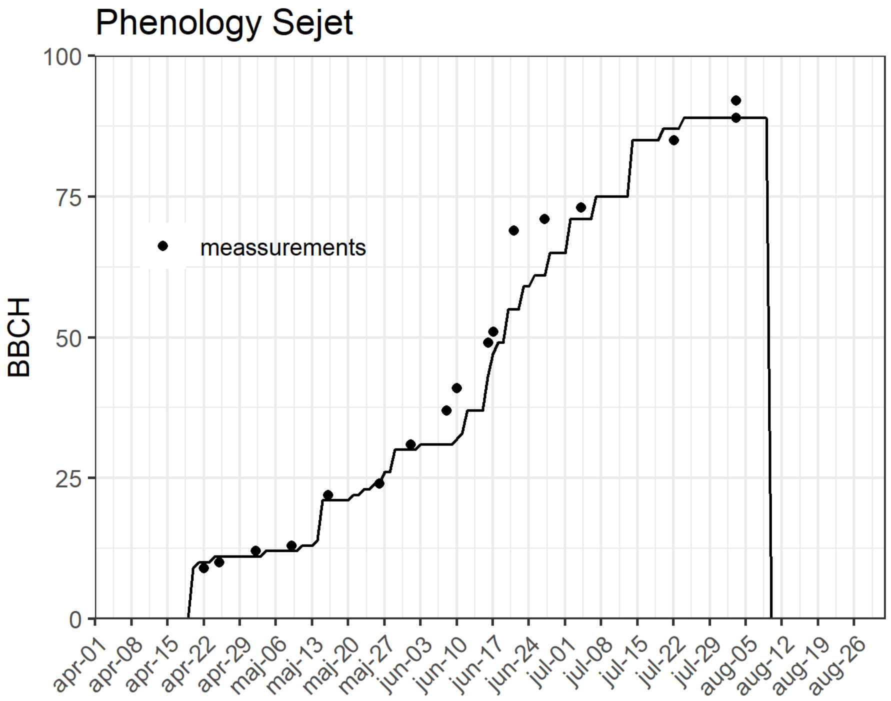
- Plant count
- Phenology observations
- Weekly UAV imaging
- Grain Yield
- At some locations measurements by sensors (Water potential/groundwater)

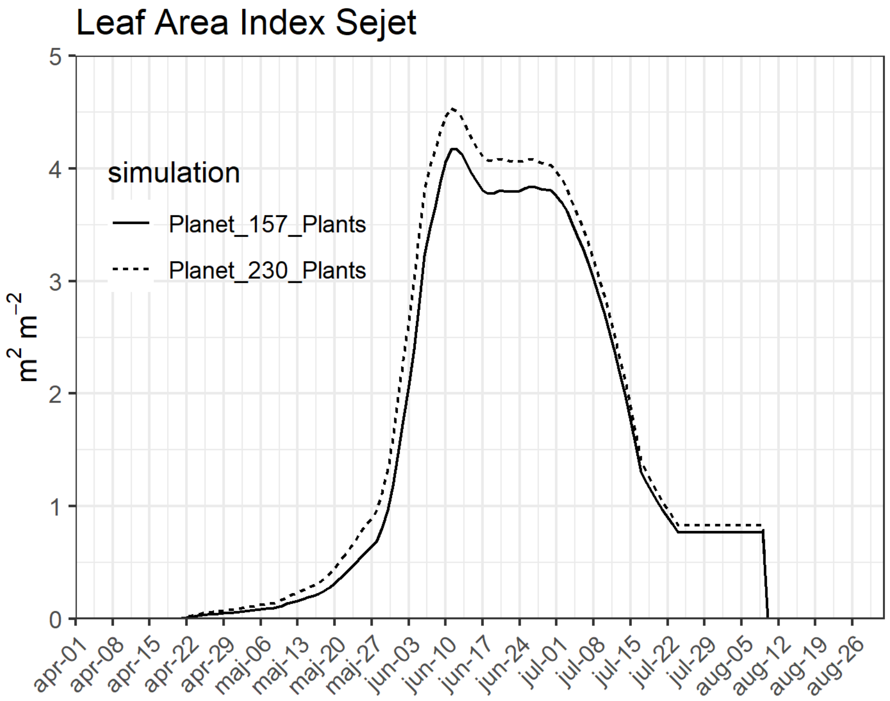
Janus Asbjørn Schatz-Jakobsen (Sejet)
Johan Lundmark (Lantmannen)
Constantin Jansen (Graminor)

Modelling spring barley development using Daisy

Example with different plant densities (Sejet)

RGT Planet grown at 157 and 230 plants/m^2



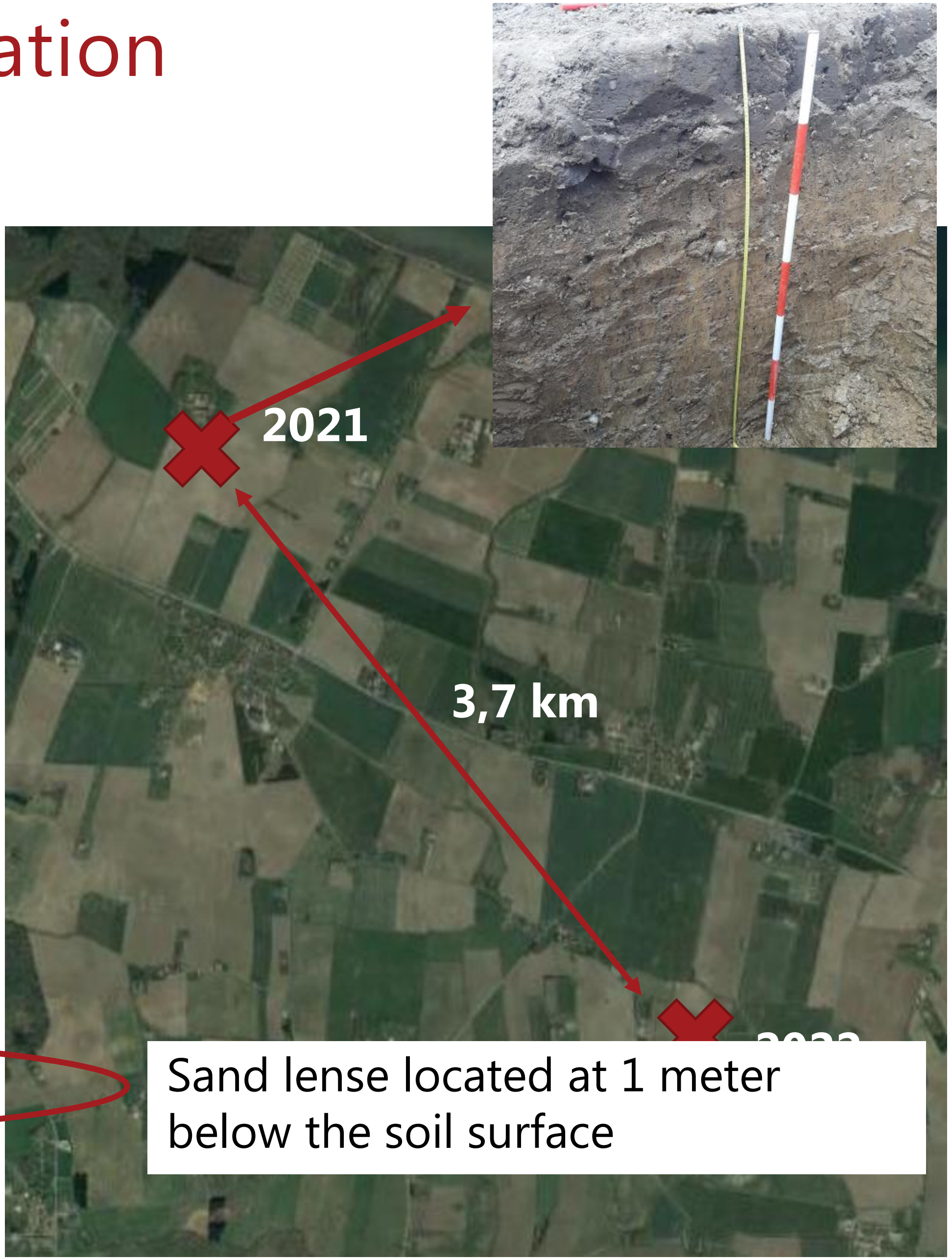


Experiments at sejet made at two location

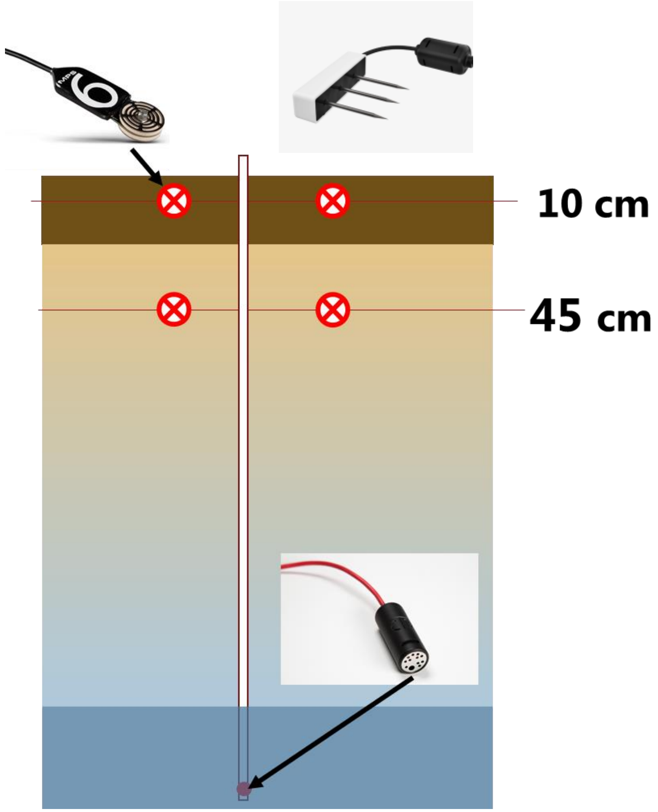
Soil profile characterisation made in 2021

In 2022 soil texture data were analysed to confirm similar soil conditions.

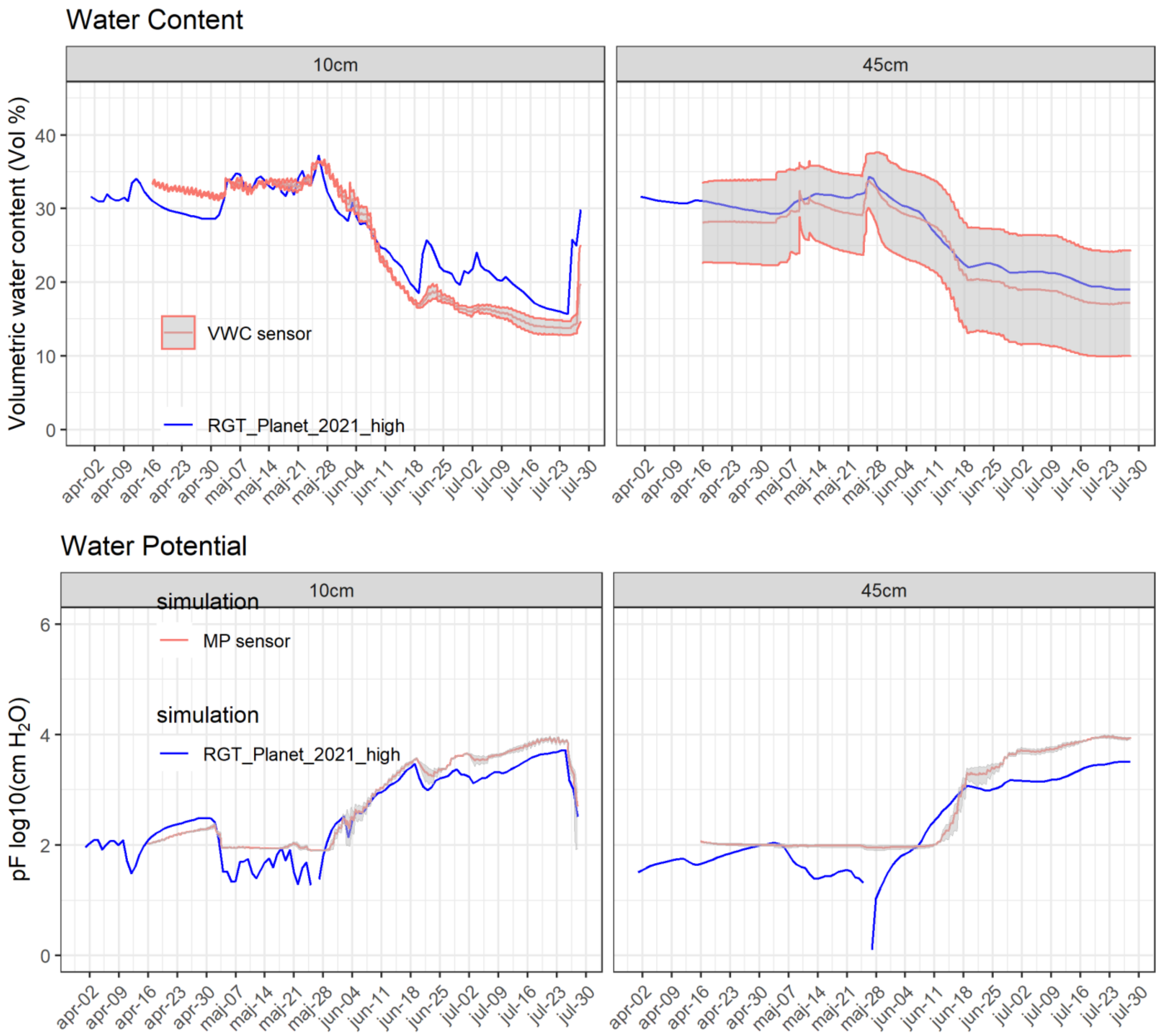
Year	Soil depth	clay	silt	Coarse silt	Fine sand	Coarse sand
	cm	<2 um	2-20um	20-60um	60-200 um	200-2000 um
2021	15	13.5	7.4	8.3	20.5	48.4
2021	35	10.3	6.4	4.8	14.5	63.5
2021	50	17.4	12.7	6.3	17.3	45.9
2021	100	25.7	10.3	6.4	15.6	41.9
2022	0-30	12.8	14.1	13.4	32.0	27.7
2022	40-80	11.0	8.2	7.2	26.6	46.9
2022	90-110	0.5	2.3	10.4	58.9	27.9
2022	130-160	6.8	15.8	41.1	20.5	15.9
2022	180-220	16.3	14.5	27.4	22.4	19.4



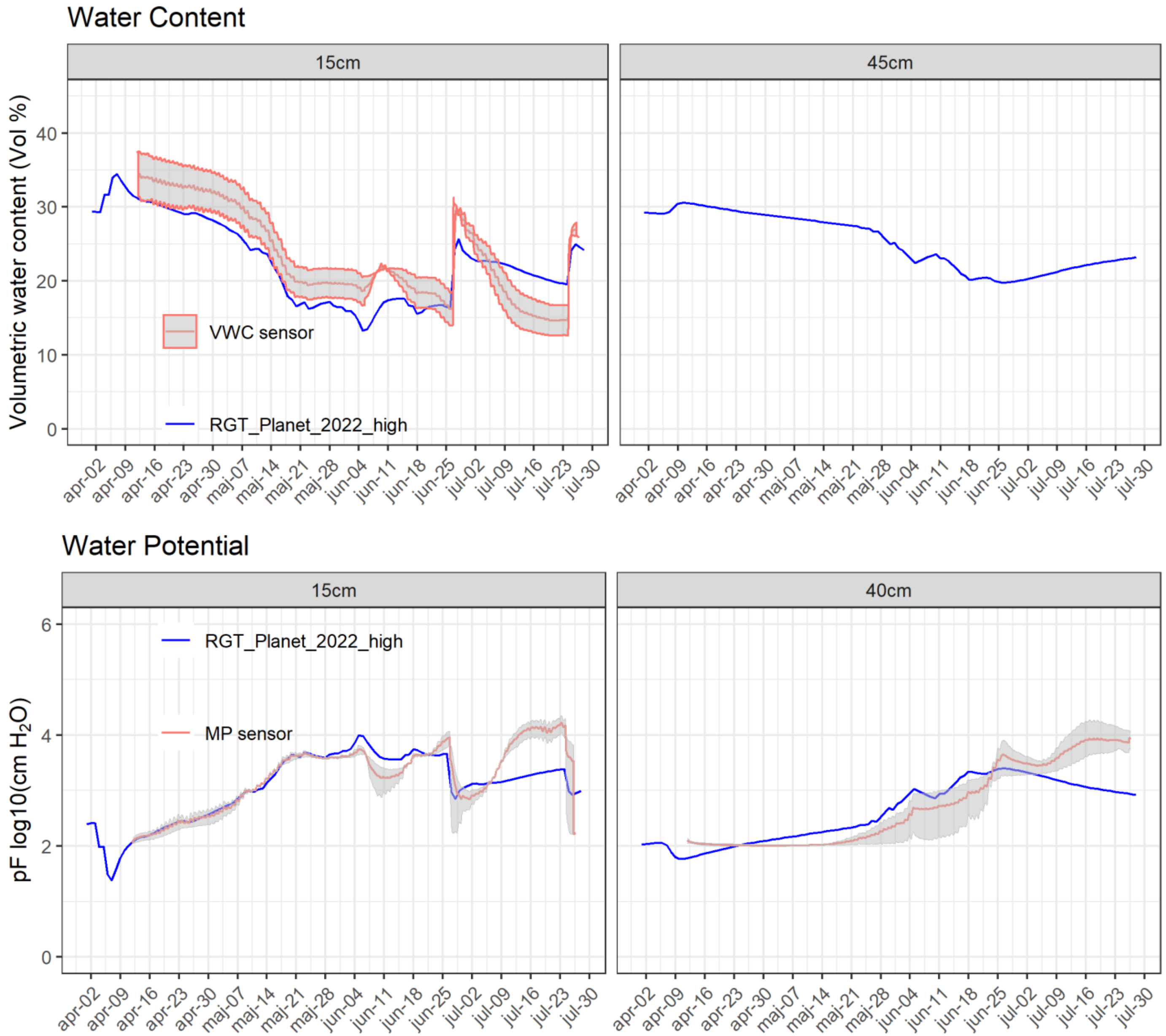
Validating the model using soil water sensors



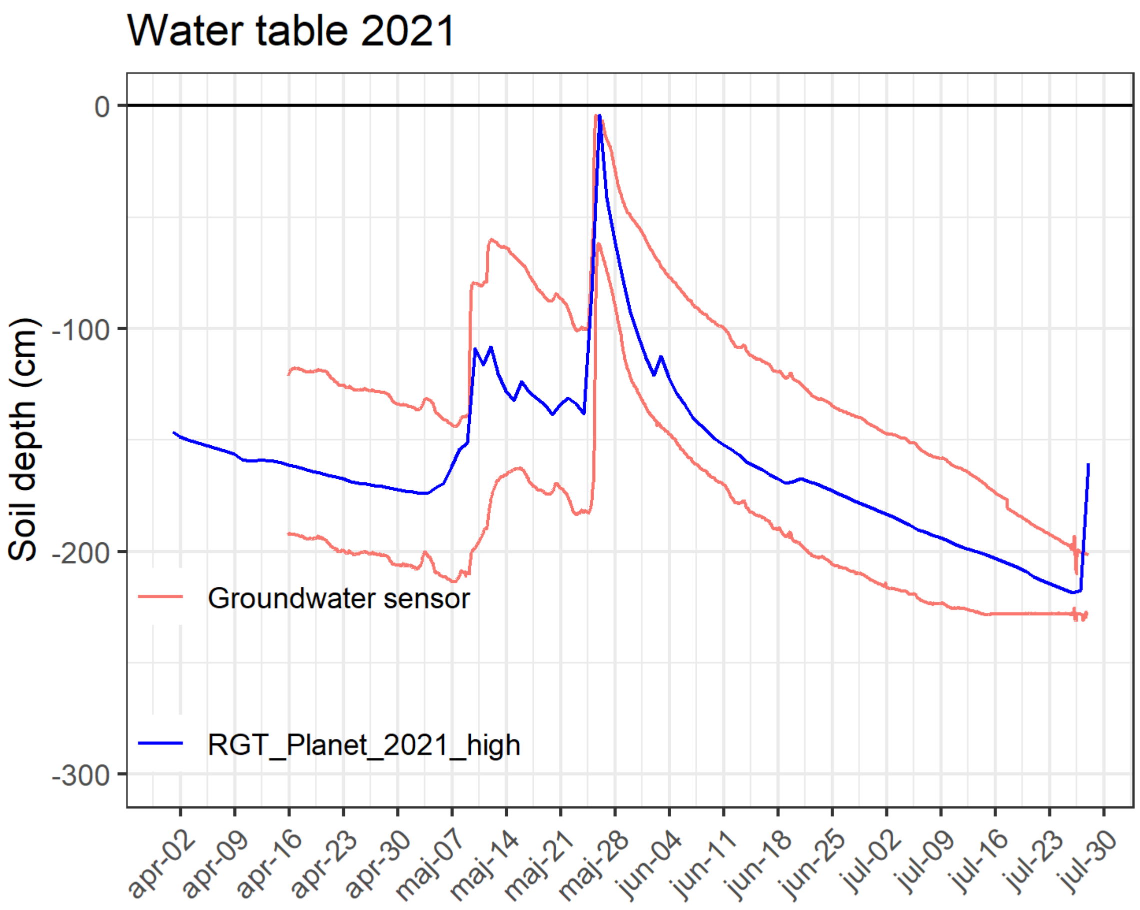
Soil water sensors Sejet 2021

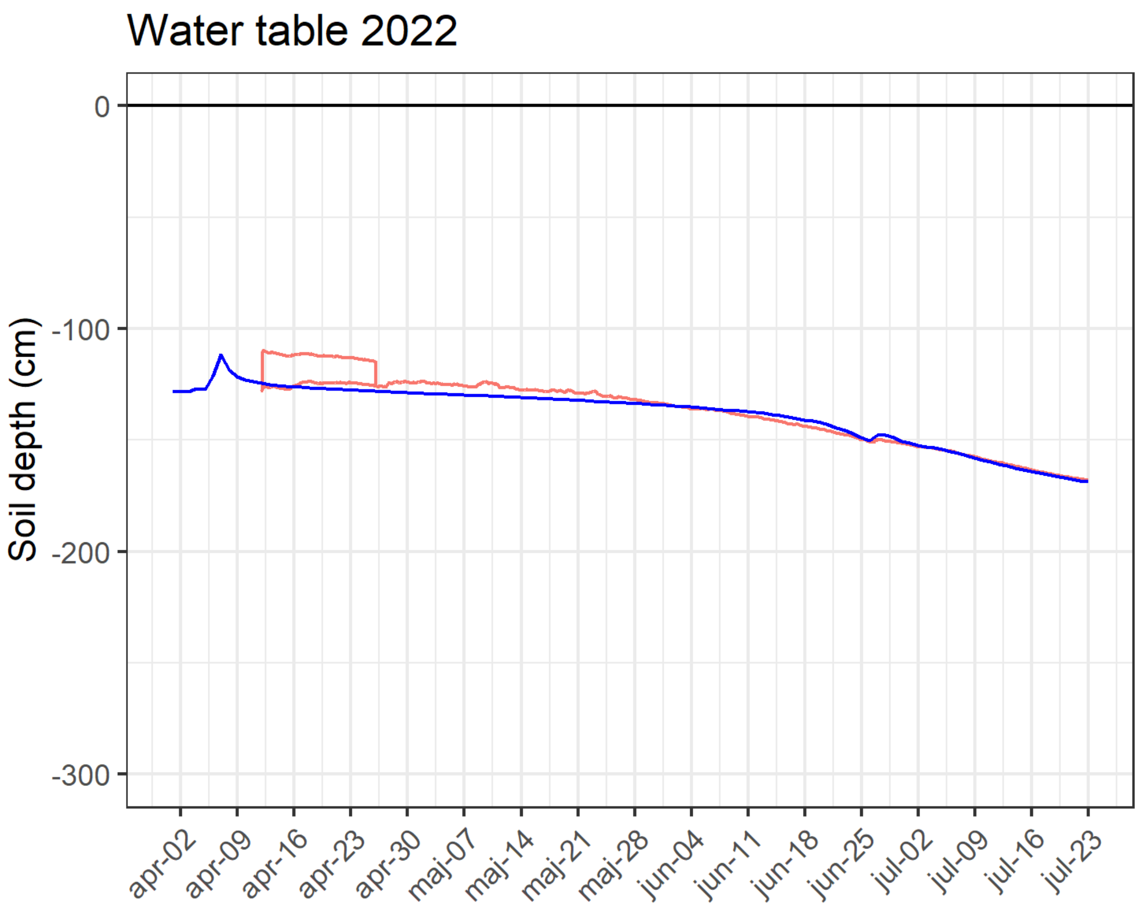


Soil water sensors Sejet 2022

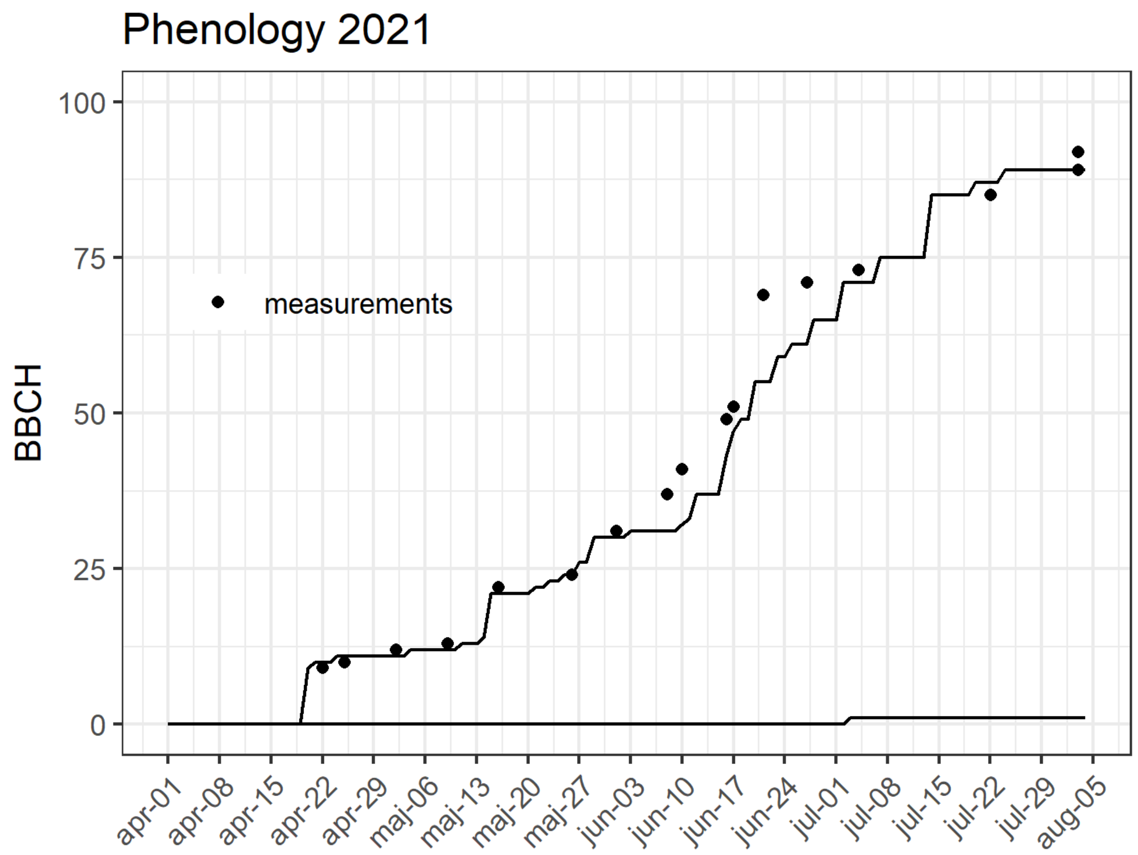


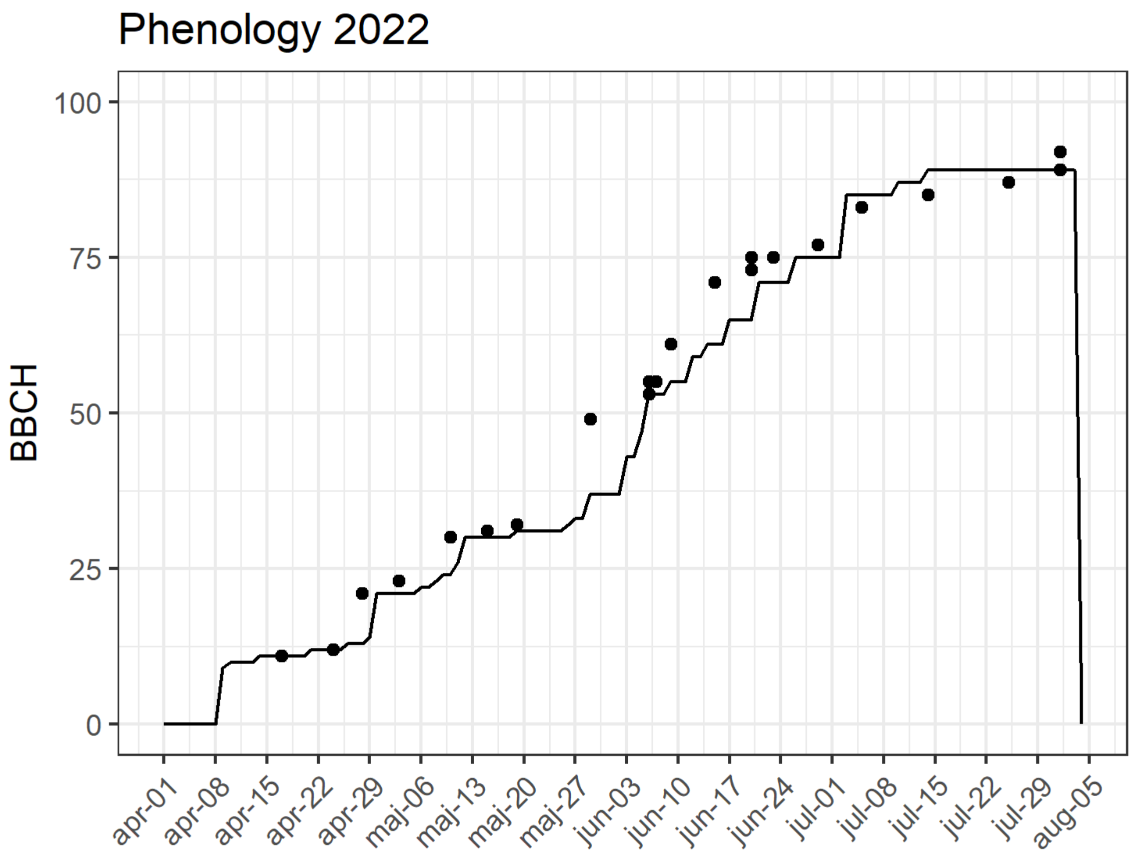
Groundwater sensors



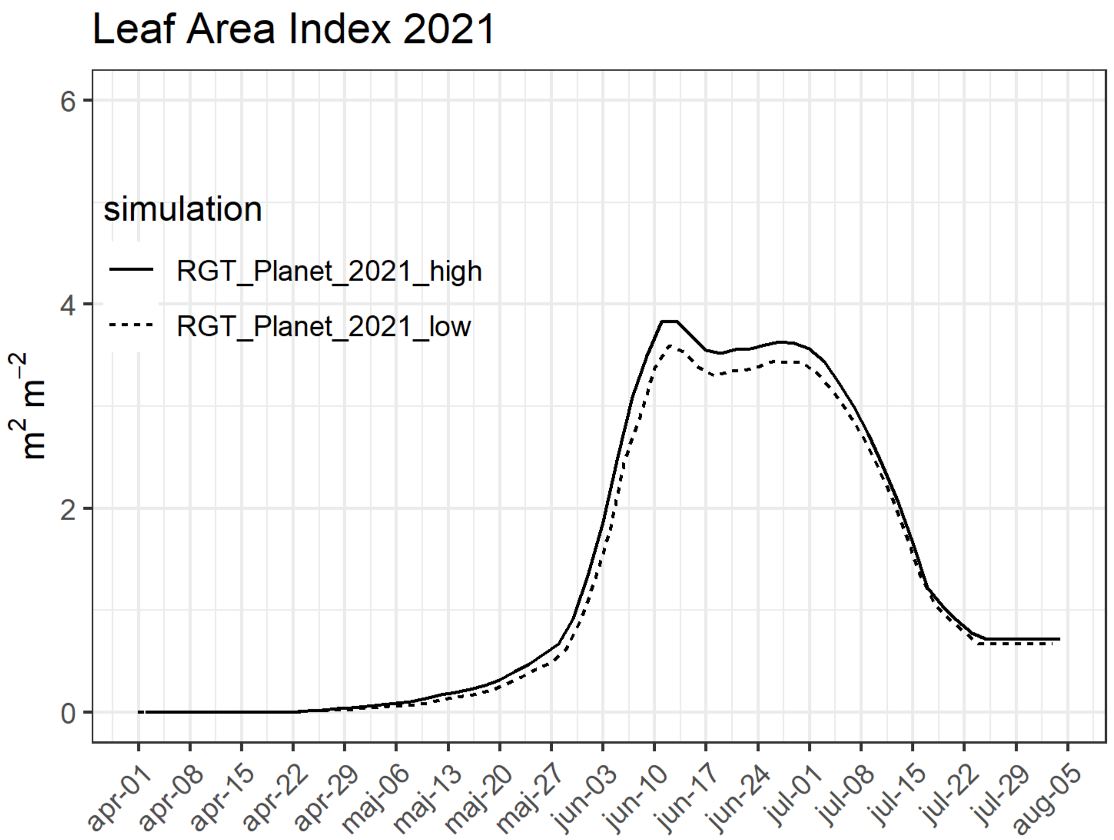


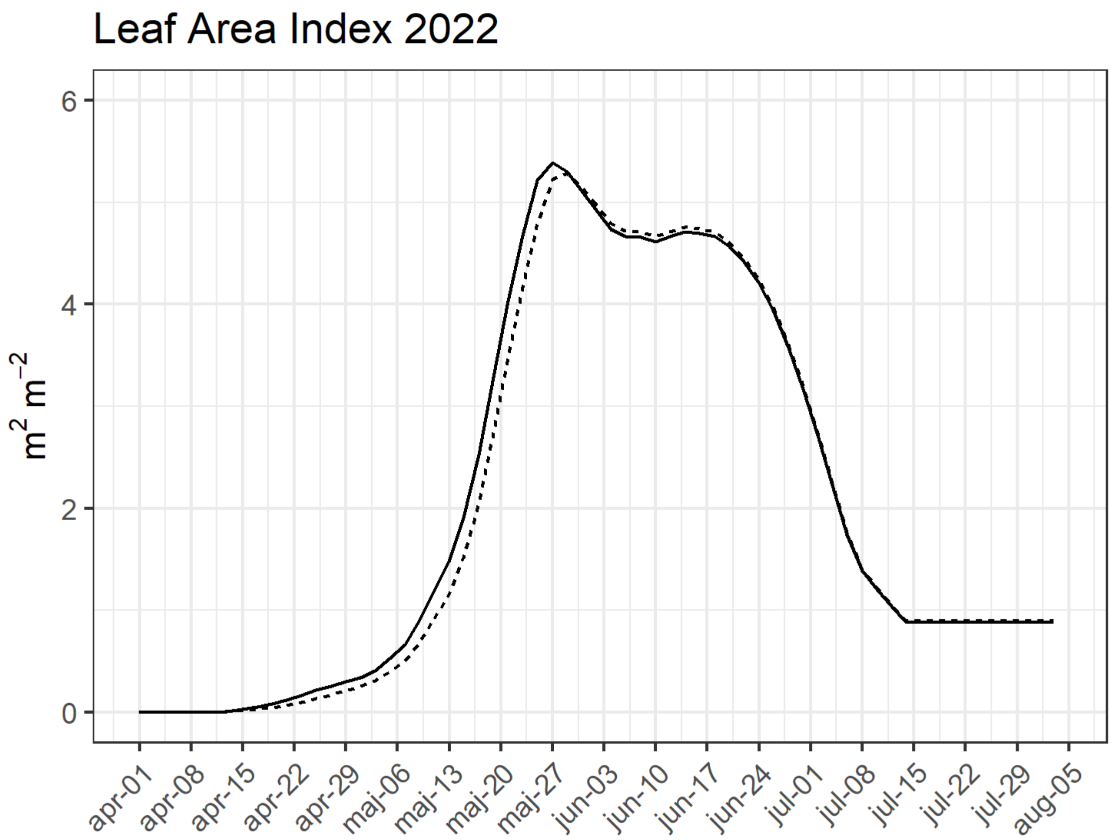
Phenology description





Leaf Area





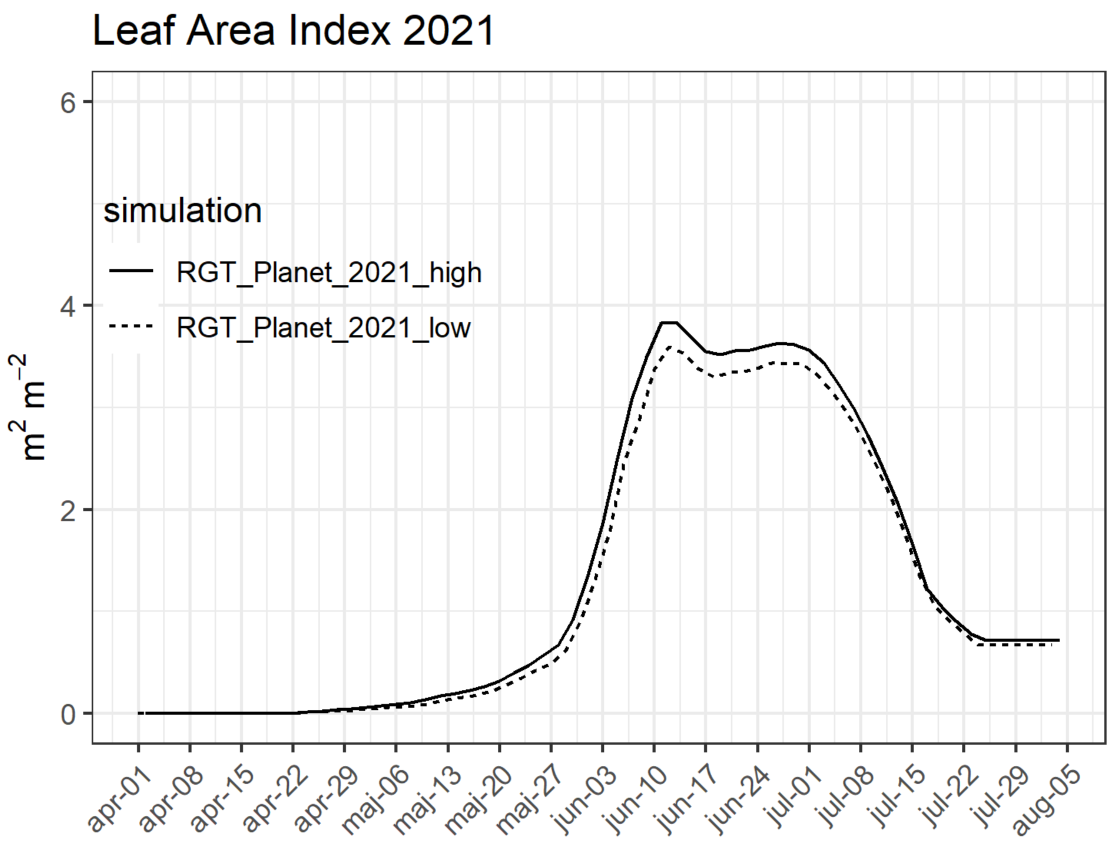
Low seeding density 270 plants

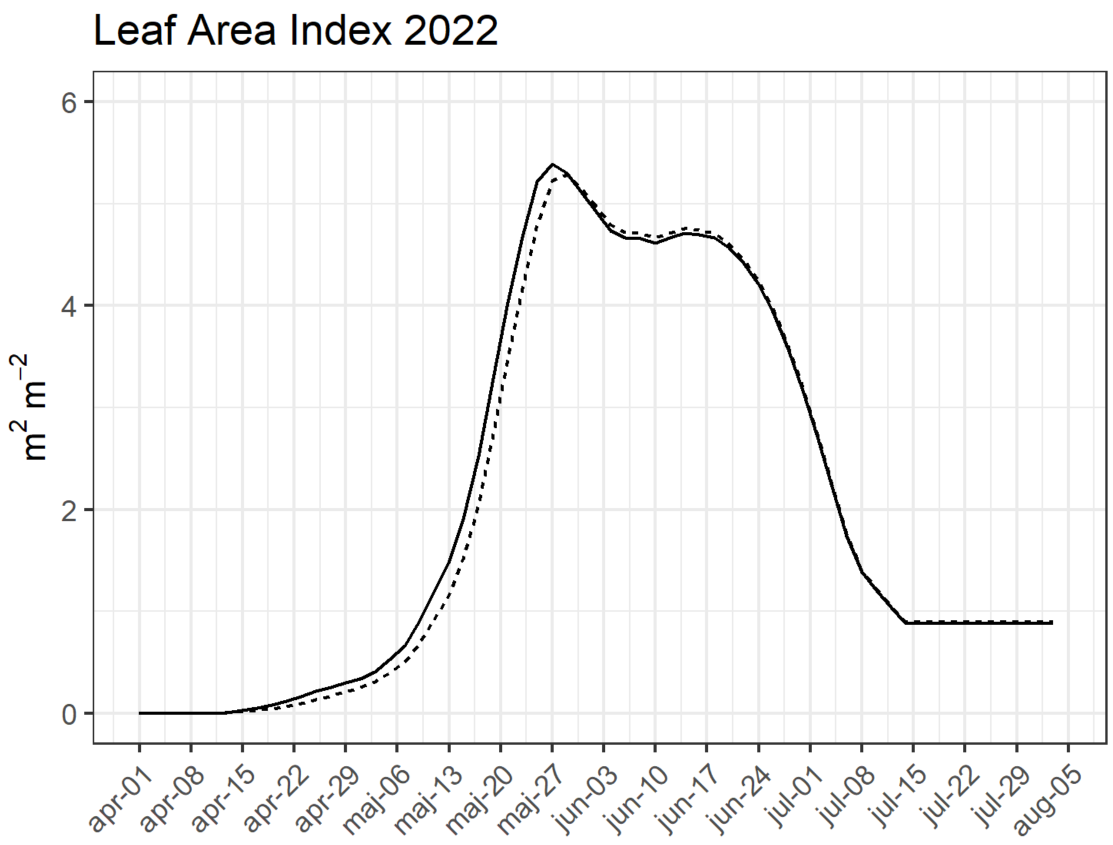
High seeding density 156 plants

Low seeding density 270 plants

High seeding density 470 plants

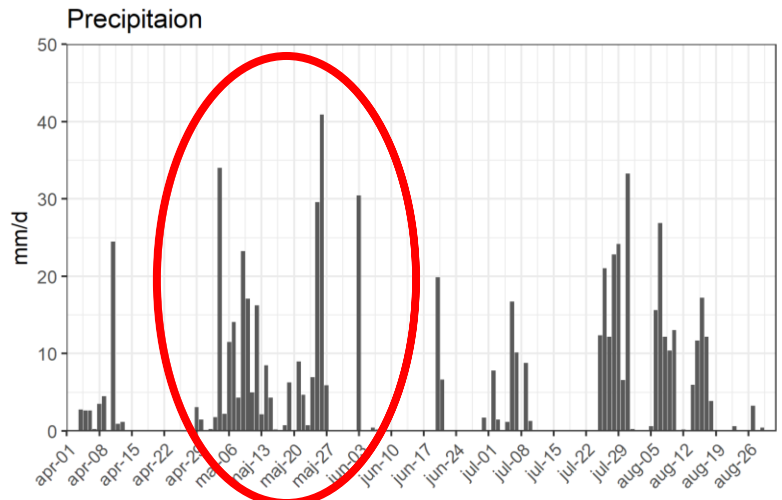
Drone Data

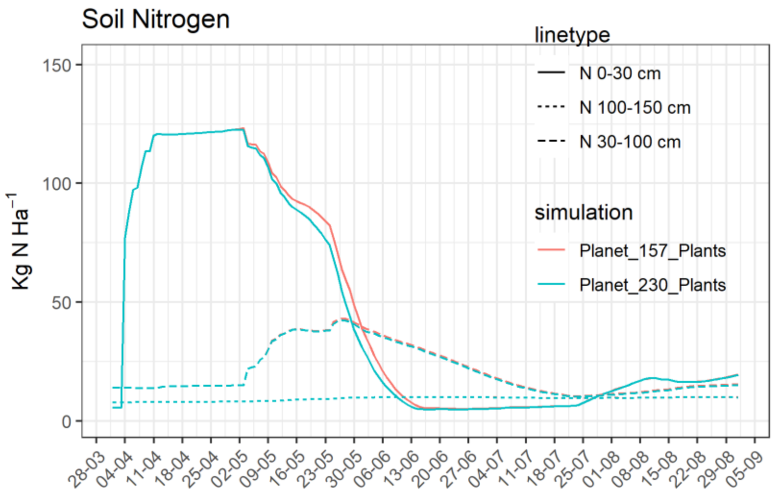

Leaf Area Index 2021
simulation
RGT_Planet_2021_high
RGT_Planet_2021_low
m^2 m^-2
0
2
4
6
apr-01
apr-08
apr-15
apr-22
apr-29
maj-06
maj-13
maj-20
maj-27
jun-03
jun-10
jun-17
jun-24
jul-01
jul-08
jul-15
jul-22
jul-29
aug-05

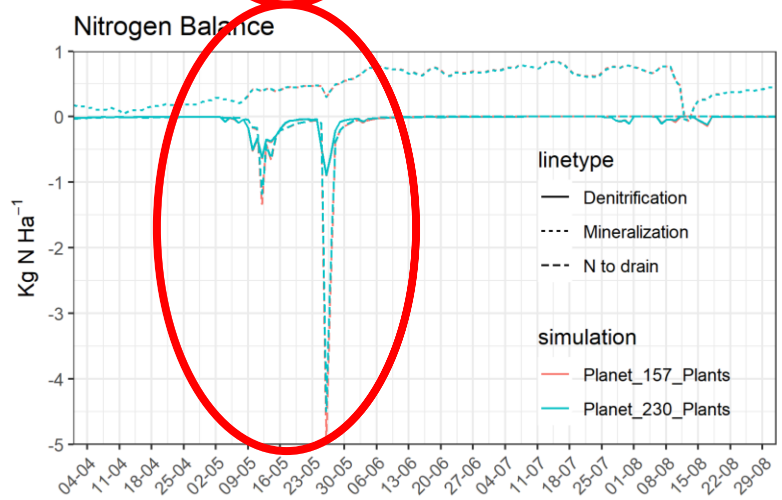

Leaf Area Index 2022
m^2 m^-2
0
2
4
6
apr-01
apr-08
apr-15
apr-22
apr-29
maj-06
maj-13
maj-20
maj-27
jun-03
jun-10
jun-17
jun-24
jul-01
jul-08
jul-15
jul-22
jul-29
aug-05

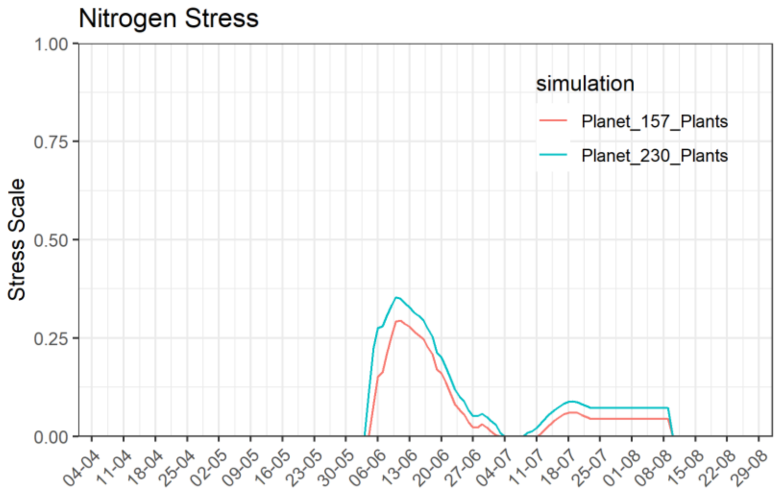
Environmental characterization (Modelling)

Wet and cold May in 2021 Risk for early nitrogen leaching up to (20 kg N ha^{-1} lost)



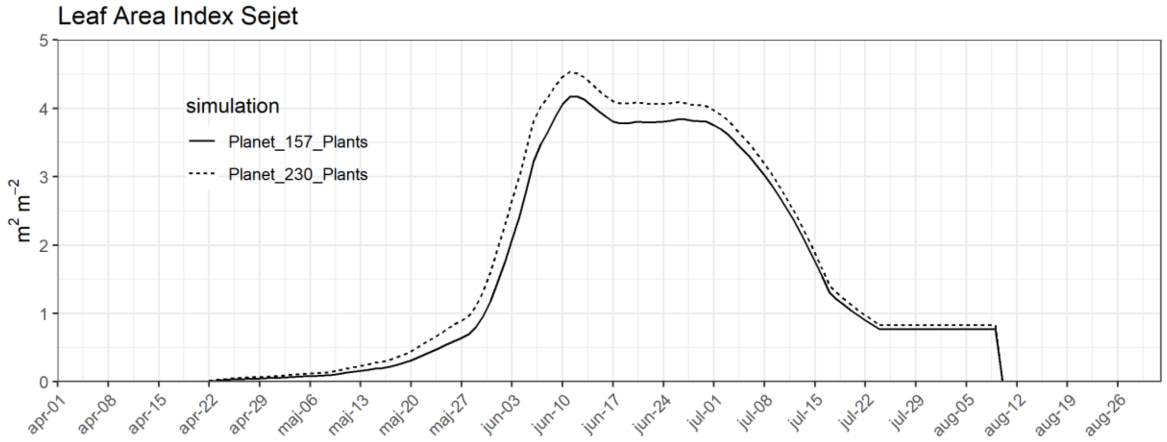


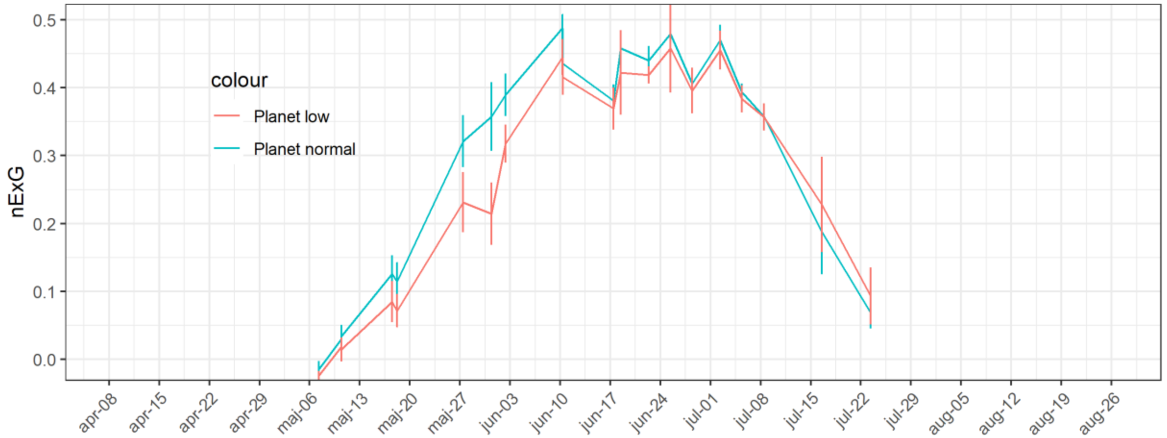


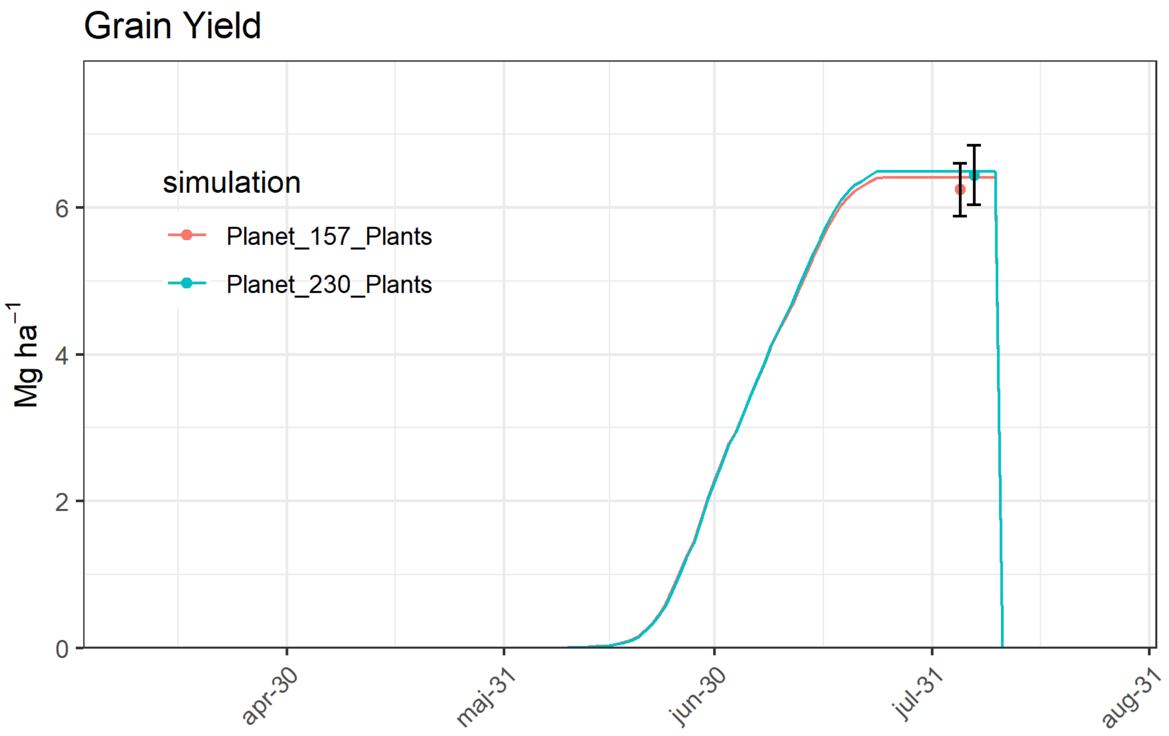


Environmental characterization (Modelling)

Plant density had an large effect on early growth but limited effect on yield.
Model and measurements agree!







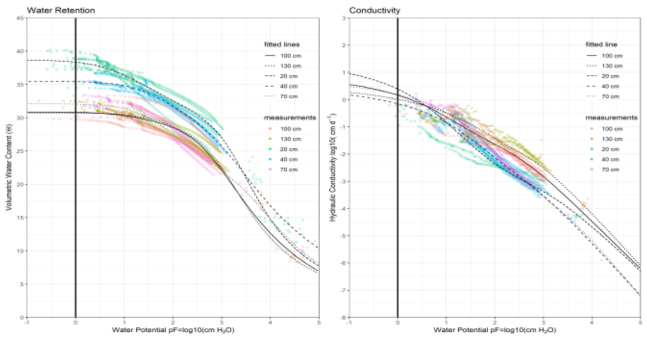
Grass case at DLF trifolium

Master student: Kristoffer Boye Larsen
Jesper Cairo (UCPH)
Christian S. Jensen (DLF)

Comparing the performance of perennial ryegrass and tall fescue under dry and wet conditions

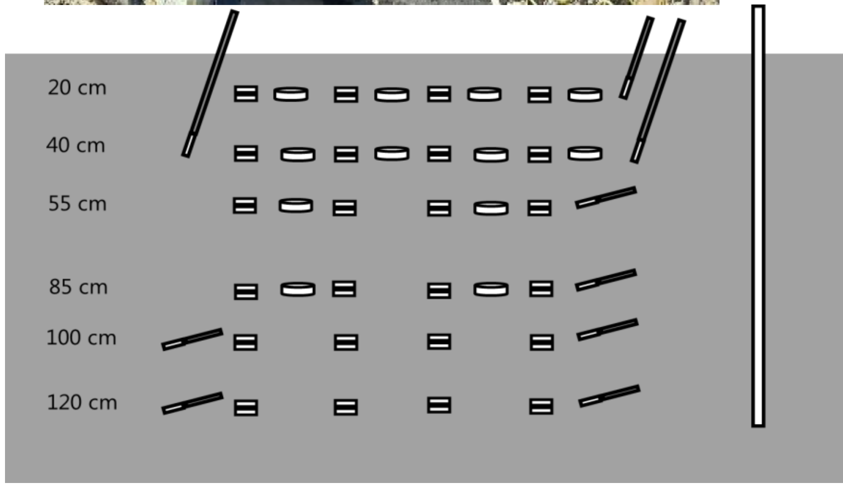
Profile characterisation made at the main yield selection site in Denmark (Bredeløkke)

Soil profile characterisation



Soil Depth	n	Clay	Silt	Fine Sand	Coarse Sand	Organic Matter	Chalk Content
		< 2μm	2-50 μm	50-200 μm	200-2000 μm		
m				%			%
0.2	(6)	17.4	22.4	20.4	37.6	2.2	ND
0.4	(5)	20.8	24.7	27.7	26.3	0.5	ND
0.7	(4)	17.5	24.1	27.6	30.6	0.2	ND
1	(5)	17.0	27.4	25.3	30.2	0.1	12.44 (4.77)
1.3	(4)	15.6	28.1	21.7	34.5	0.1	20.31 (2.12)

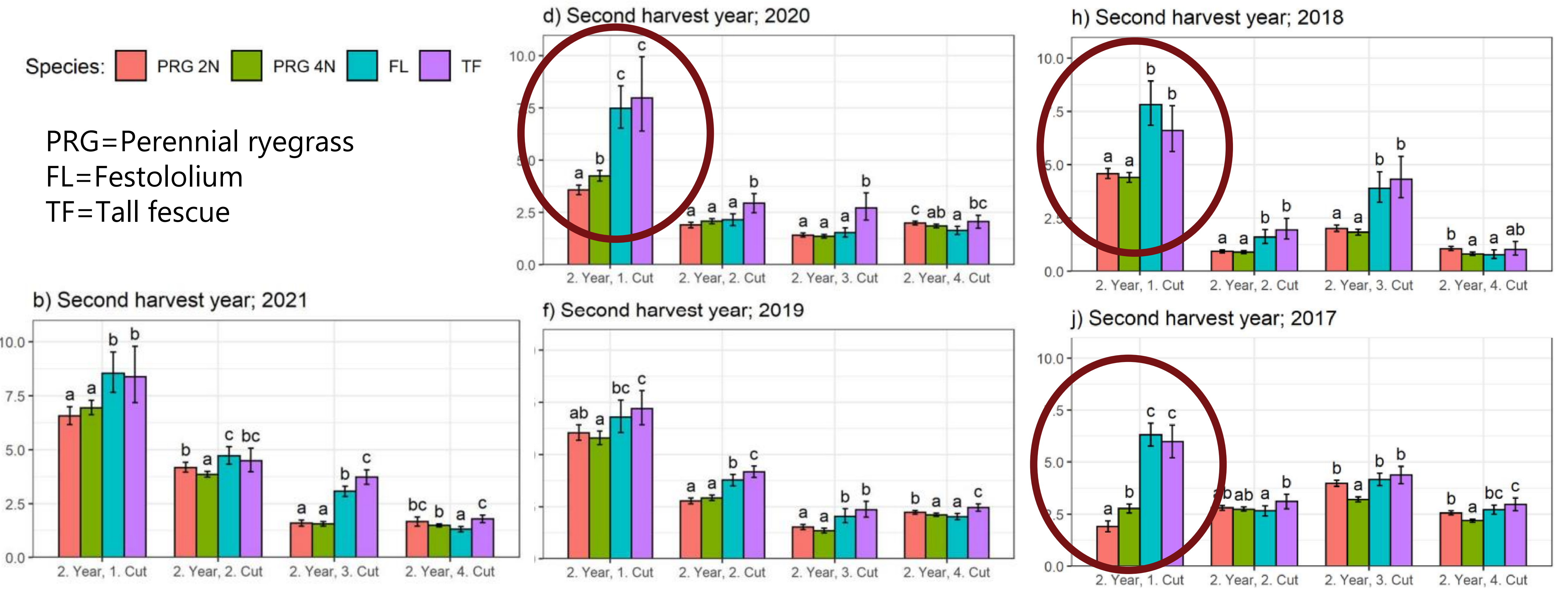
Soil Depth		Bulk Density	Rt*	P*	K*	Mg*	Ksat
m		g cm^{-3}	pH(0.01M CaCl2)+0.5		mg kg^{-1}		cm d^{-1}
0.2	(6)	1.58 (0.04)	6.90	2.50	8.20	5.70	698.3 (675.5)
0.4	(5)	1.66 (0.03)	7.30	0.40	4.80	4.10	13.4 (6.8)
0.7	(4)	1.72 (0.01)	7.50	<0.4	3.70	2.90	16.3 (10.3)
1	(5)	1.80 (0.05)	8.00	<0.4	3.50	2.00	11.6 (10.8)
1.3	(4)	1.79 (0.03)	8.10	<0.4	3.30	1.60	24.0 (24.7)



Yield performance 2017 to 2020

- Poor spring regrowth of perennial ryegrass. Most pronounced in the second harvest year. Large variation between seasons.

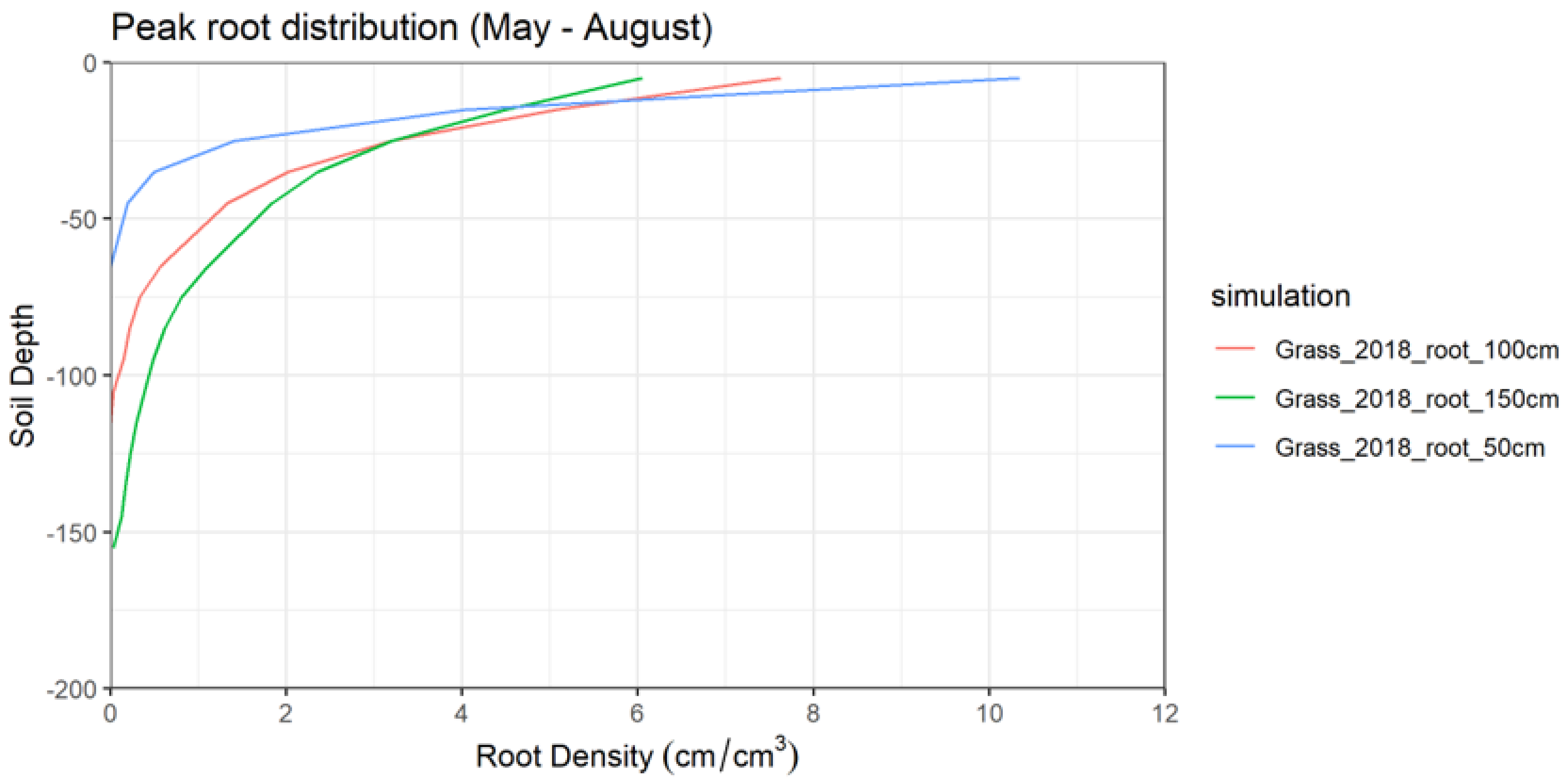
PRG=Perennial ryegrass
FL=Festololium
TF=Tall fescue



Simulated water stress days

Water stress was simulated in Daisy using three root growth scenarios

Maximum root growth is restricted to 50 cm, 100 cm an[d] 150 cm.

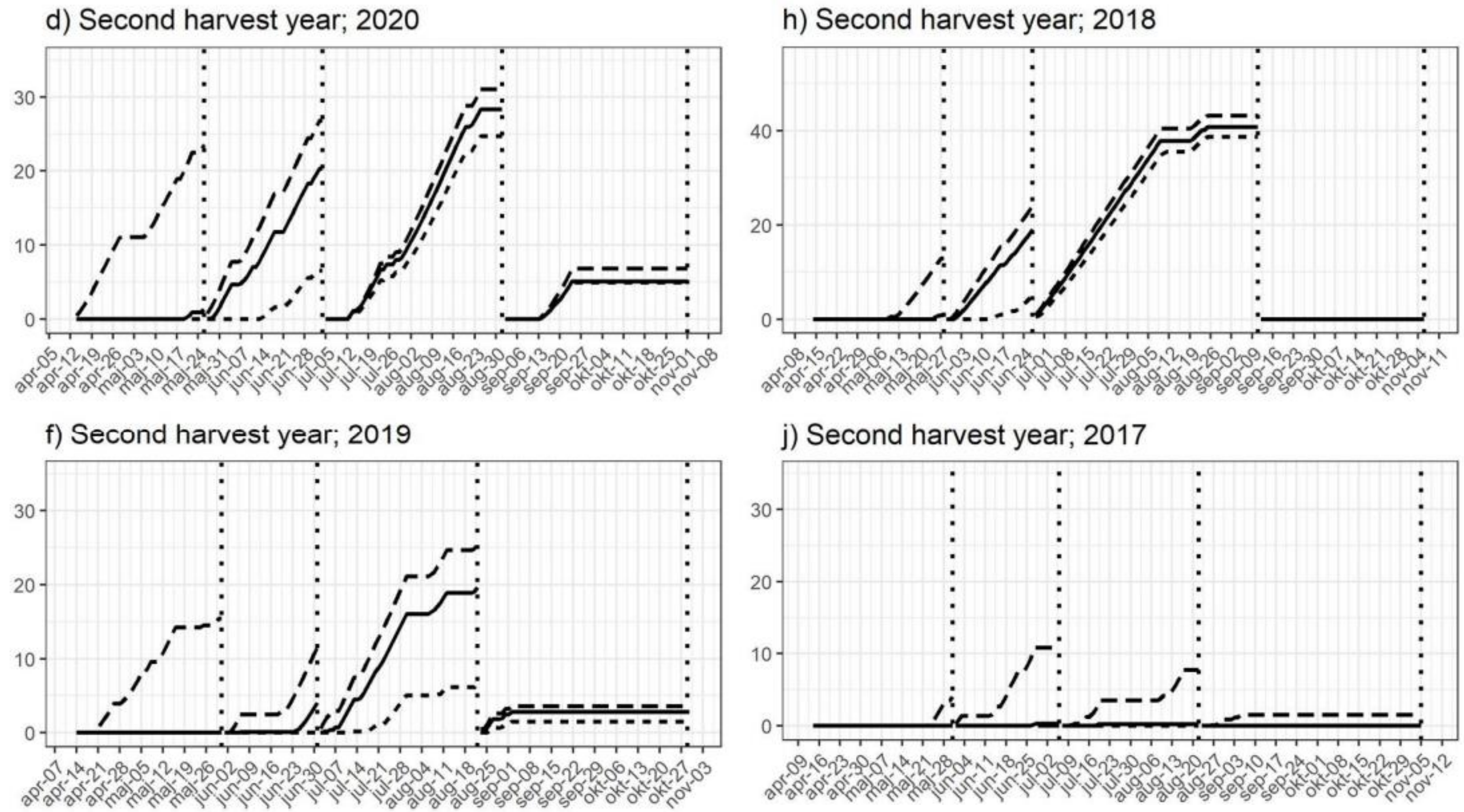


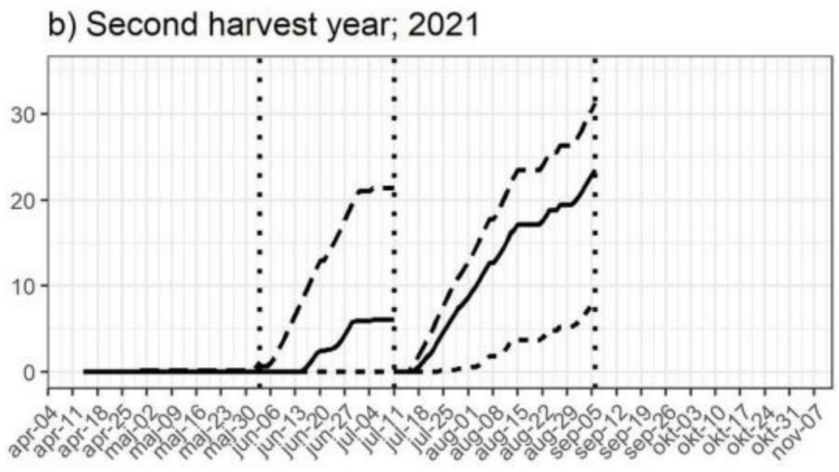
Simulated water stress days

Water stress was simulated in Daisy using three root growth scenarios

Rooting depth: 100cm 150cm 50cm

Maximum root growth is restricted to 50 cm, 100 cm and 150 cm.





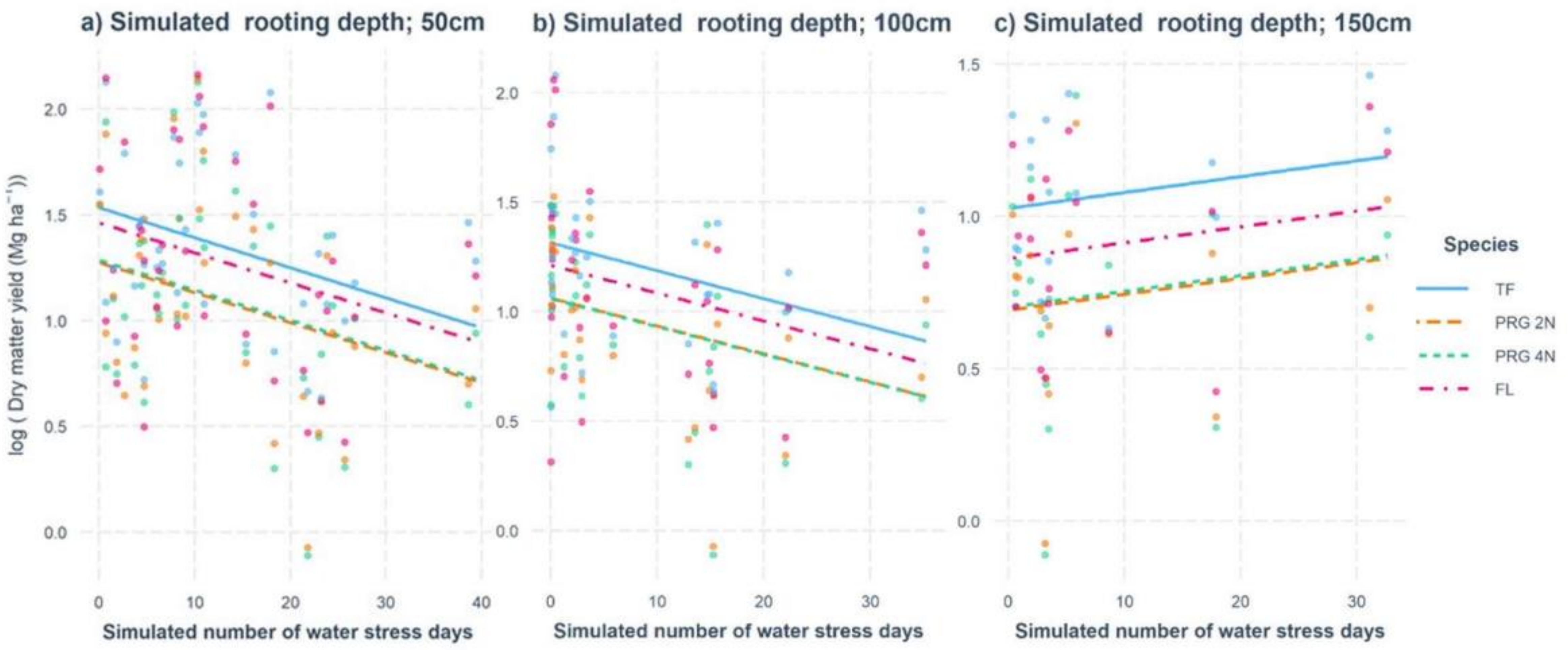
Correlation between yield and simulated water stress

Clear species effect when dry!

No interaction between species and water stress

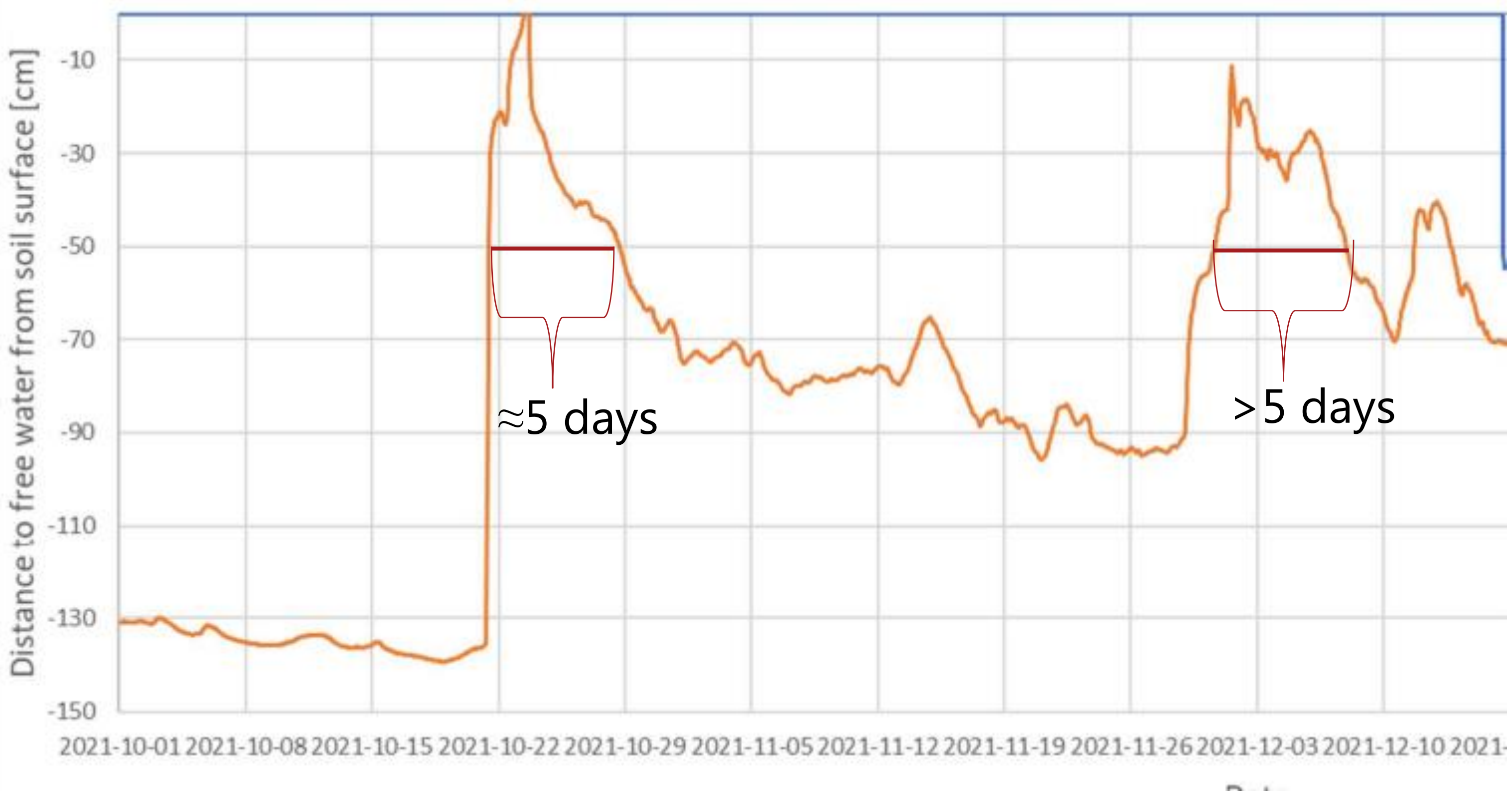
Nr. of simulated water stress days= <0.00		Nr. of simulated water stress days > 0.0	
50 cm simulated rooting depth (n=3)		**50 cm simulated rooting depth (n=37)**	
Species	p=0.64	Species	p=0.028 *
		Water stress	p=0.00012 ***
		Species:Water stress	p=0.74
100 cm simulated rooting depth (n=10)		**100 cm simulated rooting depth (n=30)**	
Species	p=0.83	Species	p=0.023 *
		Water stress	p=0.00029 ***
		Species:Water stress	p=0.50
150 cm simulated rooting depth (n=23)		**150 cm simulated rooting depth (n=17)**	
Species	p=0.33	Species	p= 0.0083 **
		Water stress	p=0.175
		Species:Water stress	p=0.78

Correlation between yield and simulated water stress



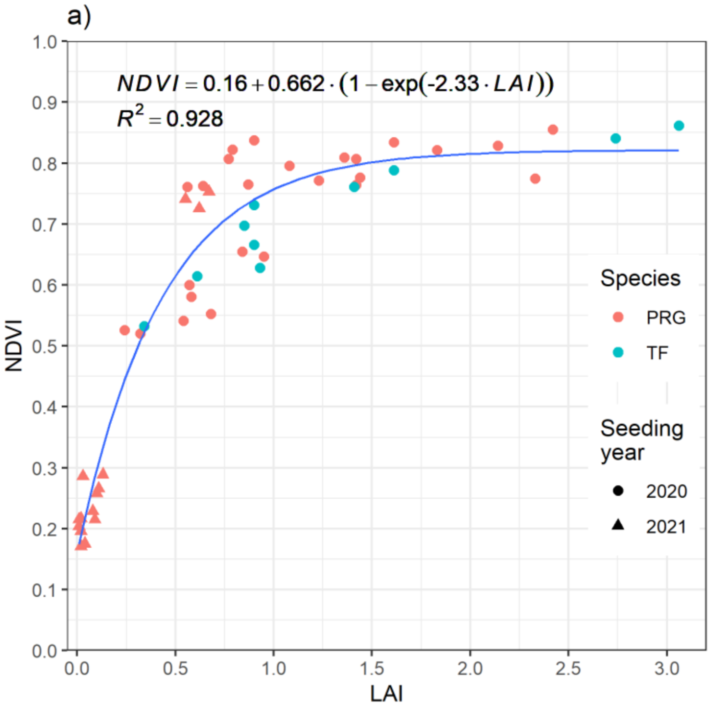
Water table effects

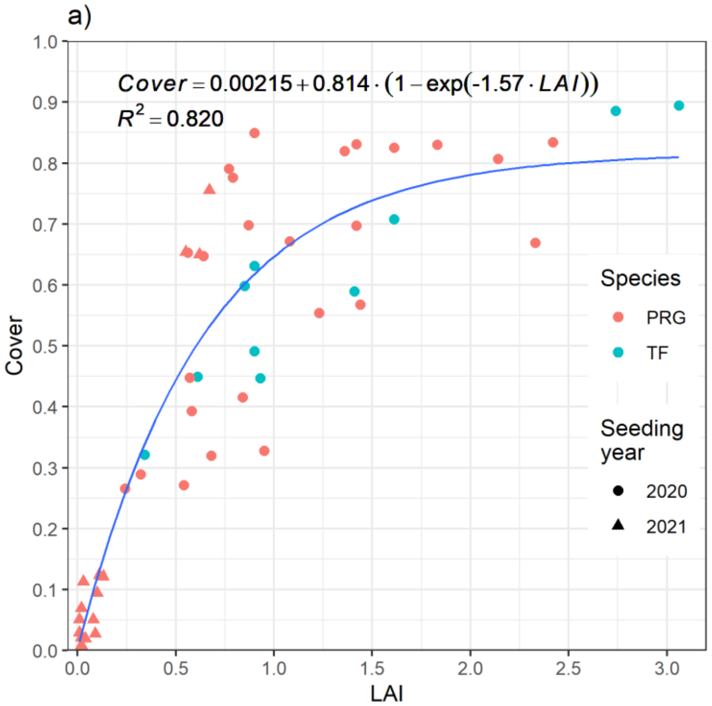
- The site at Bredeløkke was affected by shallow winter groundwater table

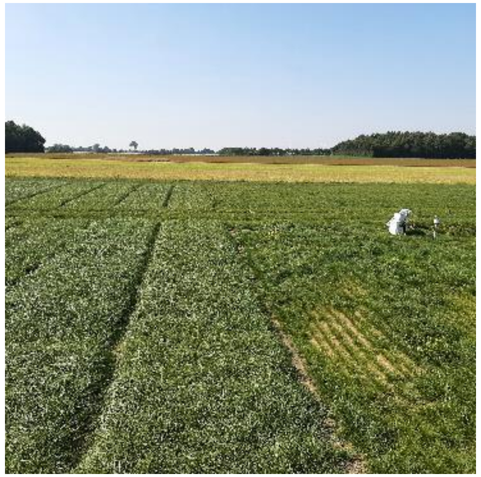


Coupling of UAV data collected by breeders with the Daisy model

Leaf Area Index - UAV regressions made in grass species at DLF Trifolium

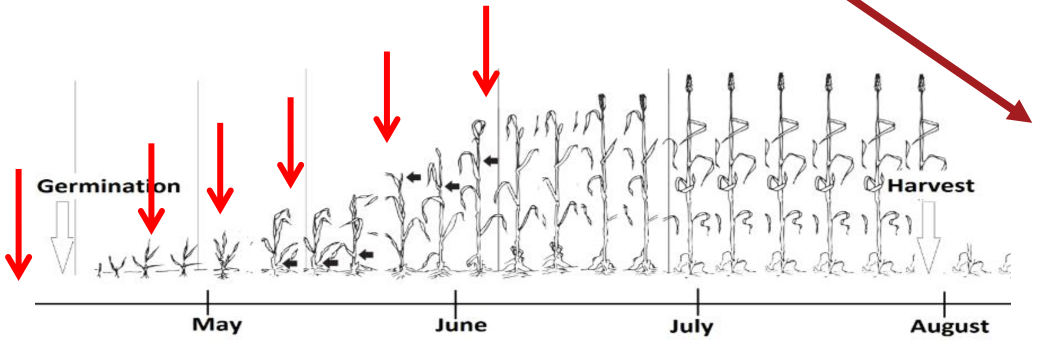


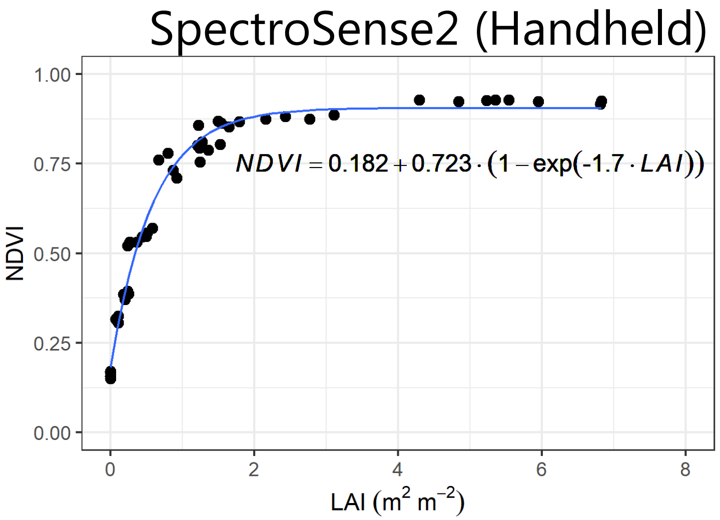


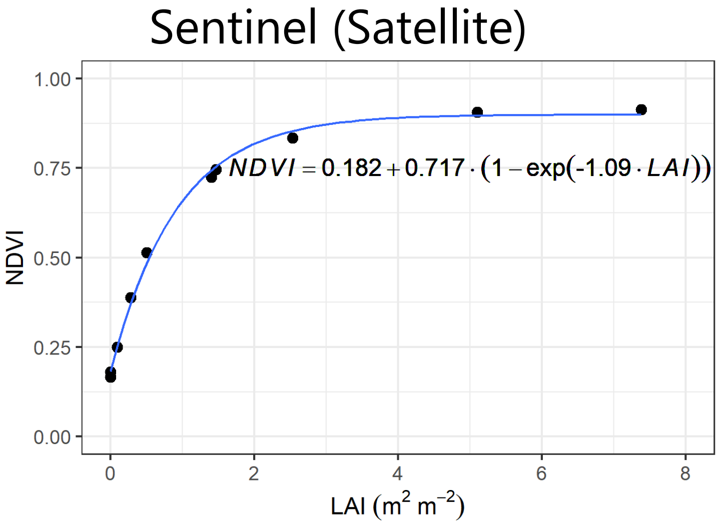


Calibrating a LAI-NDVI conversion for sentinel data

NDVI measurement to monitor development in LAI. Calibrating NDVI sensor to estimate LAI of spring barley



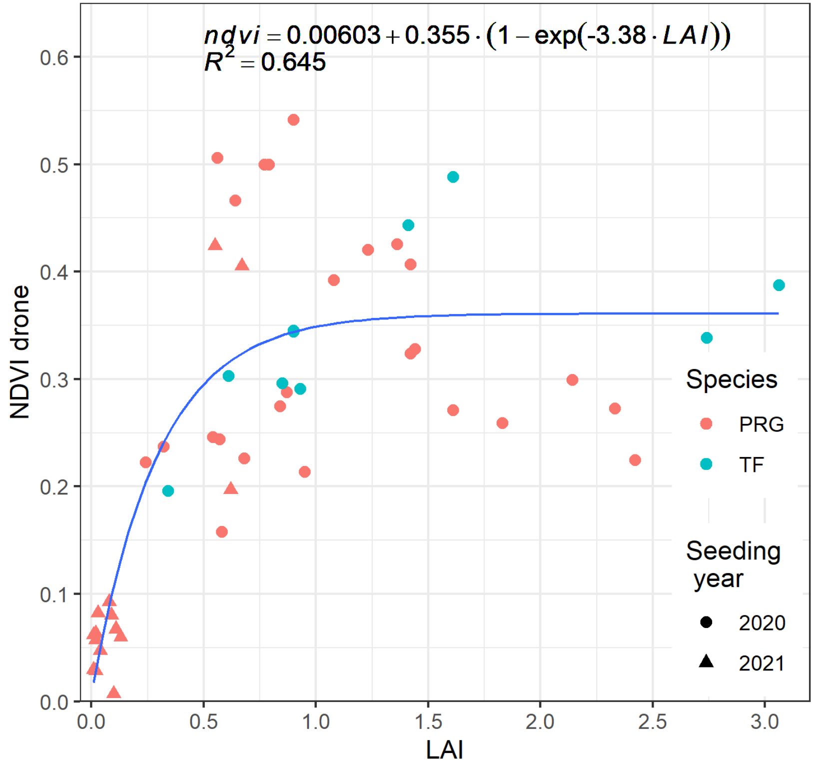




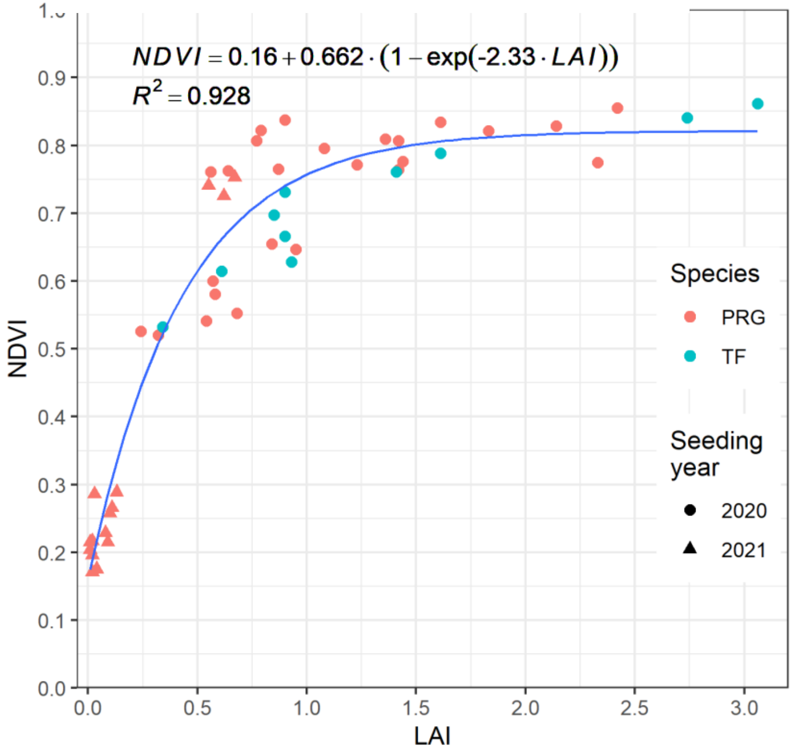
Coupling of UAV data collected by breeders with the Daisy model

Difficult to obtain good correlation using UAV imaging (Drones)

Drone



SpectroSense2



Coupling of UAV data collected by breeders with the Daisy model

- Need of method to estimate LAI from RGB imaging. Maybe deep learning could help?
- Drone NDVI imaging are preferred for LAI estimation but was unstable (At least in one case). P4M seems promising!
- Using deep learning, plant and head count will be valuable for integration with Daisy.
- Practical problem: A good plot cover/plant count estimation requires low height when flying. Hard to cover extensive experiments.

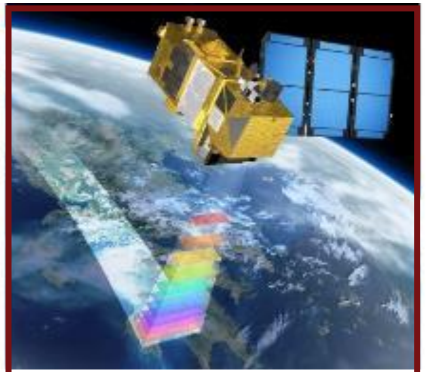
Maybe we don't need the drones?

For describing Field scale nitrogen and water stress satellites could be enough

Locale weather data

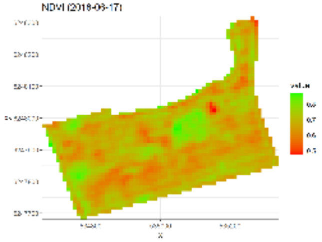
Sentinel 2 → **NDVI** → **LAI** → **DAISY** → ET_a

Actual evapotranspiration

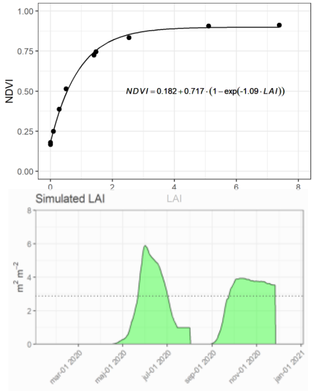


Multispectral sensor
12 wavebands

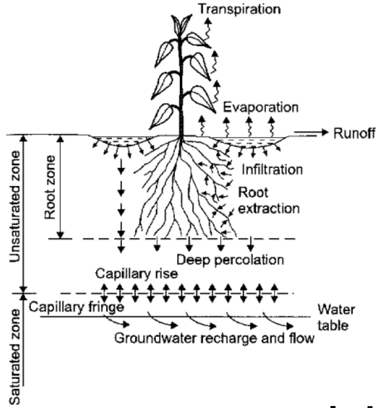
$$NDVI = \left(\frac{NIR - RED}{NIR + RED}\right)$$



2 wavebands
10m resolution
RED=664nm
NIR=835nm

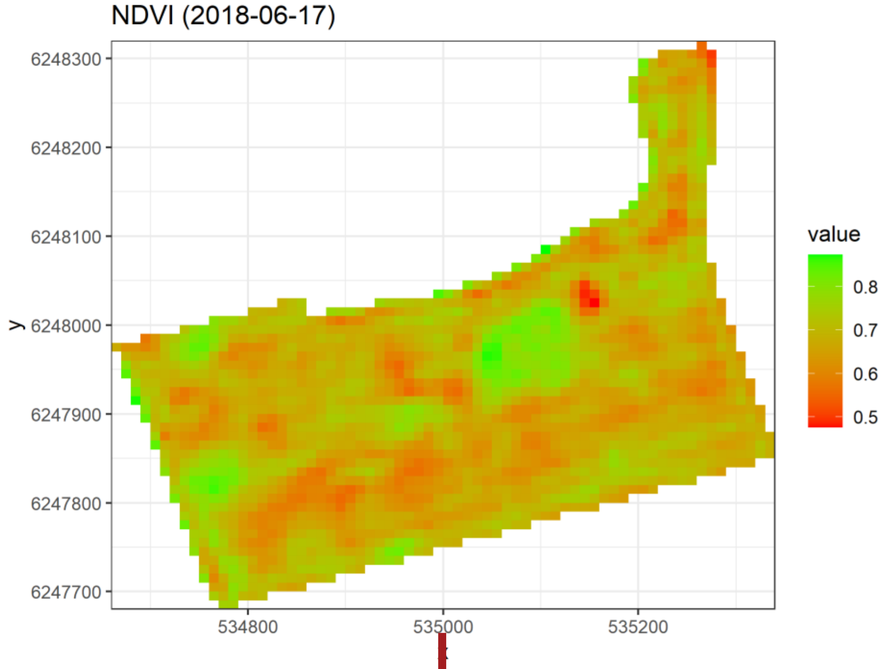


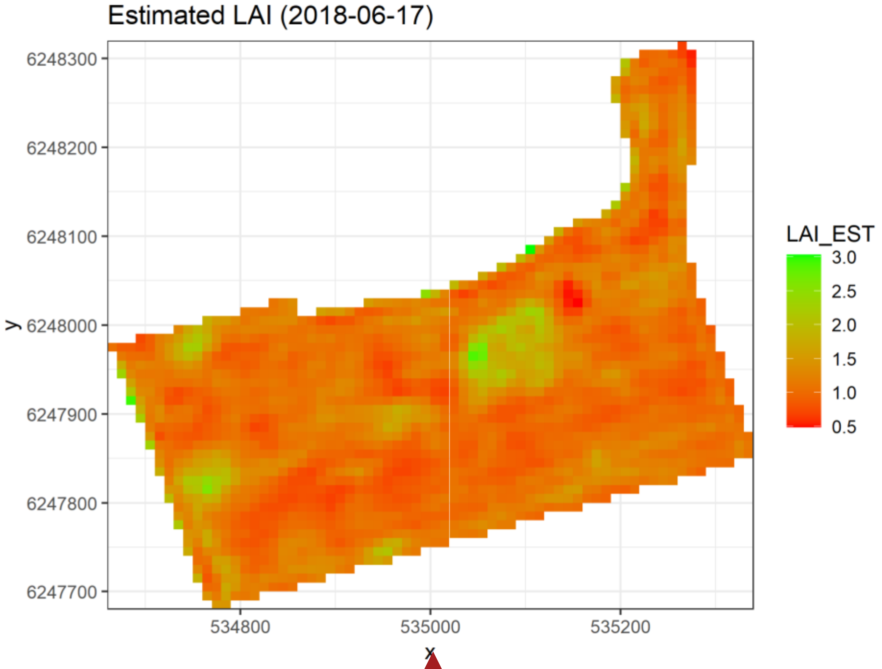
Regression analysis
NDVI to LAI



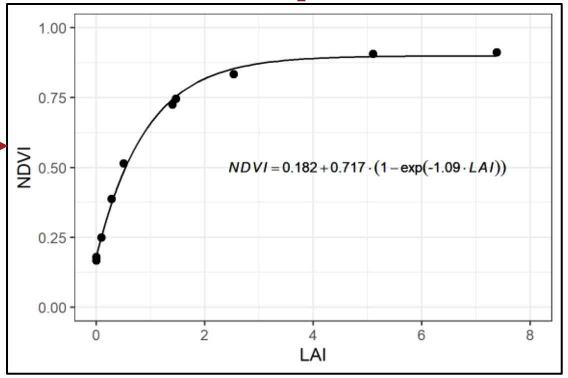
Two sources none coupled SVAT model. Soil EP modelled by Solving the Richards equation

NDVI-LAI estimation using satellites

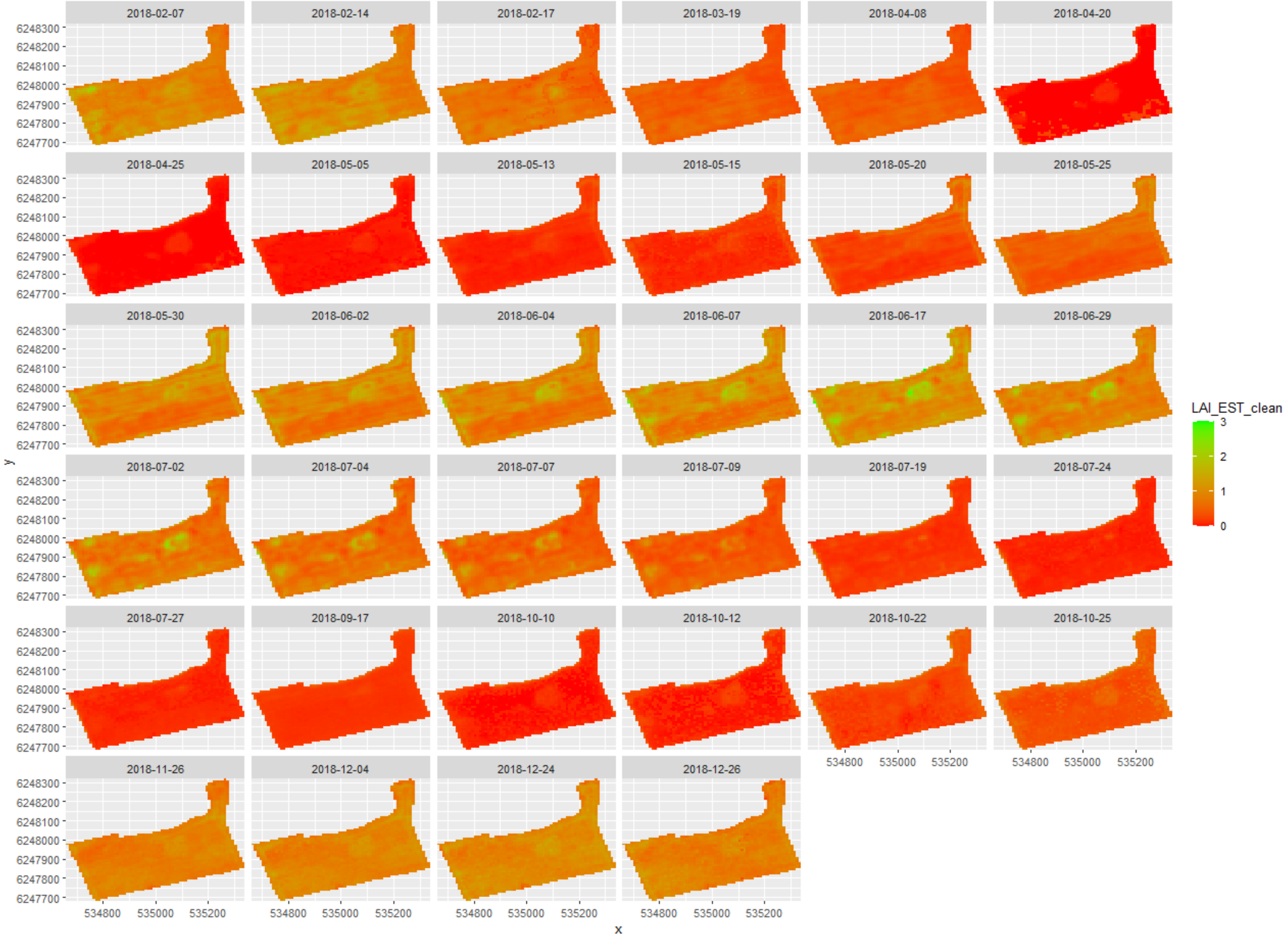




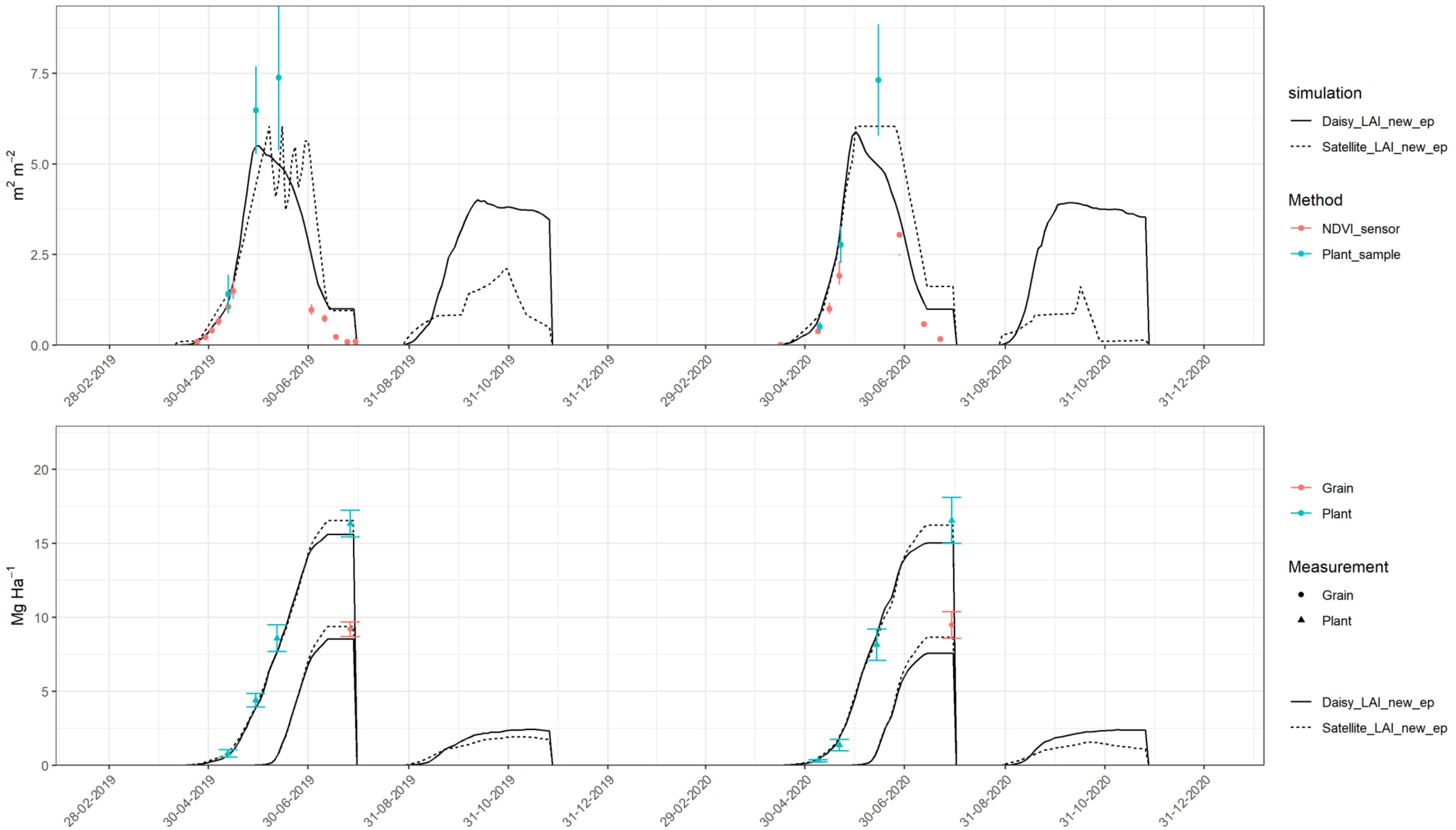
Data Cleaning:
Valley filtering



LAI development over time



Differences in biomass and LAI (simulated versus satellite)



Deep learning and Daisy

First attempt to estimate plant density using root painter

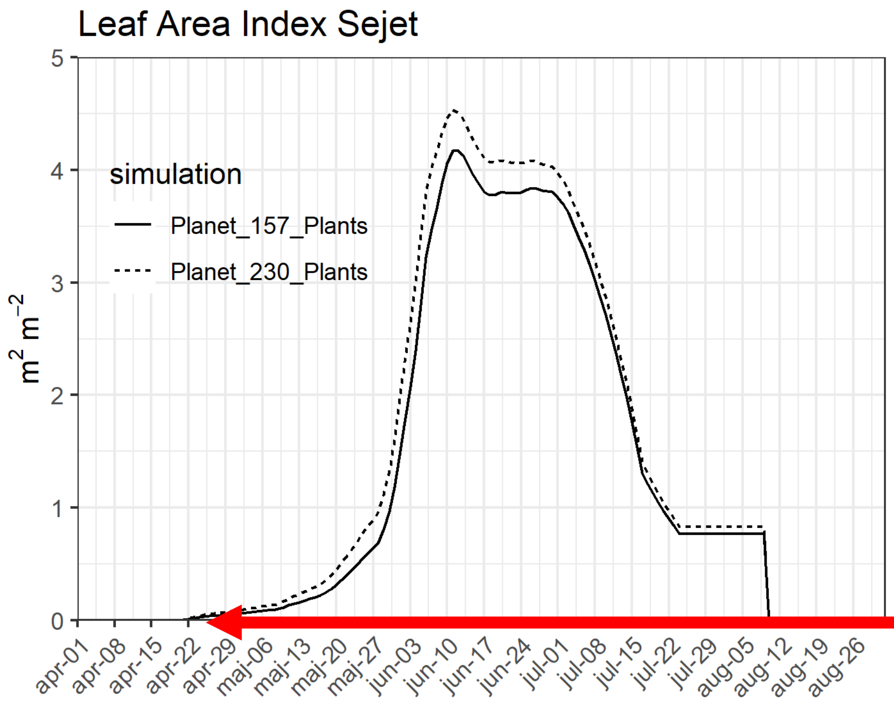
Ph.d. Abraham George Smith (UCPH-DIKU)
Janus Asbjørn Schatz-Jakobsen (Sejet)

RootPainter: Deep Learning Segmentation of Biological Images with Corrective Annotation

Abraham George Smith, Eusun Han, Jens Petersen, Niels Alvin Faircloth Olsen, Christian Giese, Miriam Athmann, Dorte Bodin Dresbøll, Kristian Thorup-Kristensen

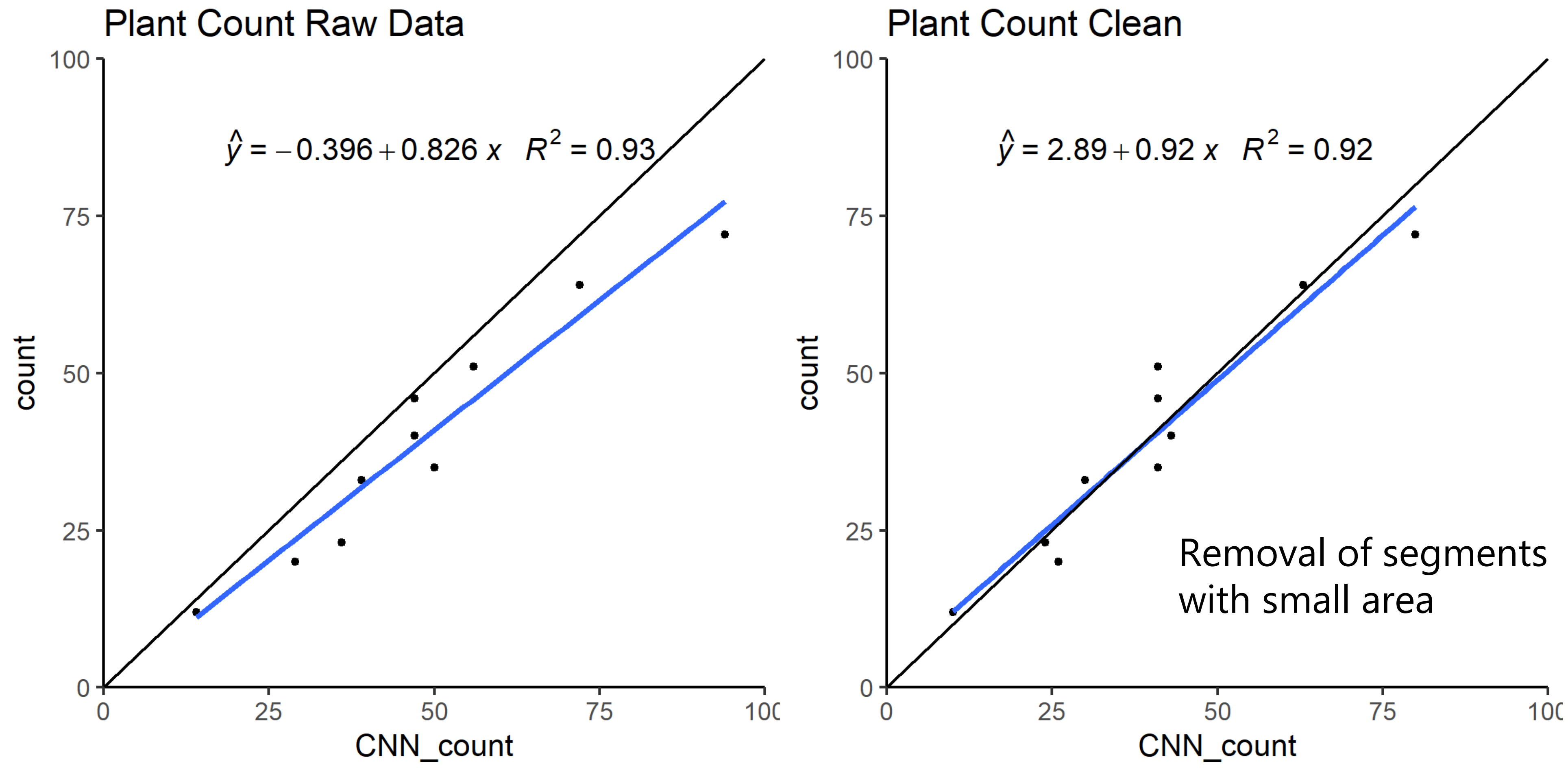
doi: https://doi.org/10.1101/2020.04.16.044461

This article is a preprint and has not been certified by peer review [what does this mean?].



Deep learning and Daisy

After 1 hour of training including a 5 min coffee breaks!
Limited data set from 2021. Larger data set to be analysed with images from 2022.



Work Package 5: Modelling activities to support plant breeding

Deliverables

- D5.3.1 Implemented DAISY model columns for each of the five field sites.
- D5.3.2 A comparison of the local environment ('E' in G*E*M-models) for modelled field sites.
- D5.3.3 Demonstration of model test platform for interpreting collected sensor data. The first test of novel trait combinations ("ideotypes") for present and future climate conditions.

Milestones

- M5.1.1 Installation of soil monitoring equipment and soil sampling completed.
- M5.1.2 Hyprop measurements completed.
- M5.2.1 Weather, Crop and Soil monitoring data delivered to the common database for the 2021-season.
- M5.2.2 Weather, Crop and Soil monitoring data delivered to the common database for the 2022-season.