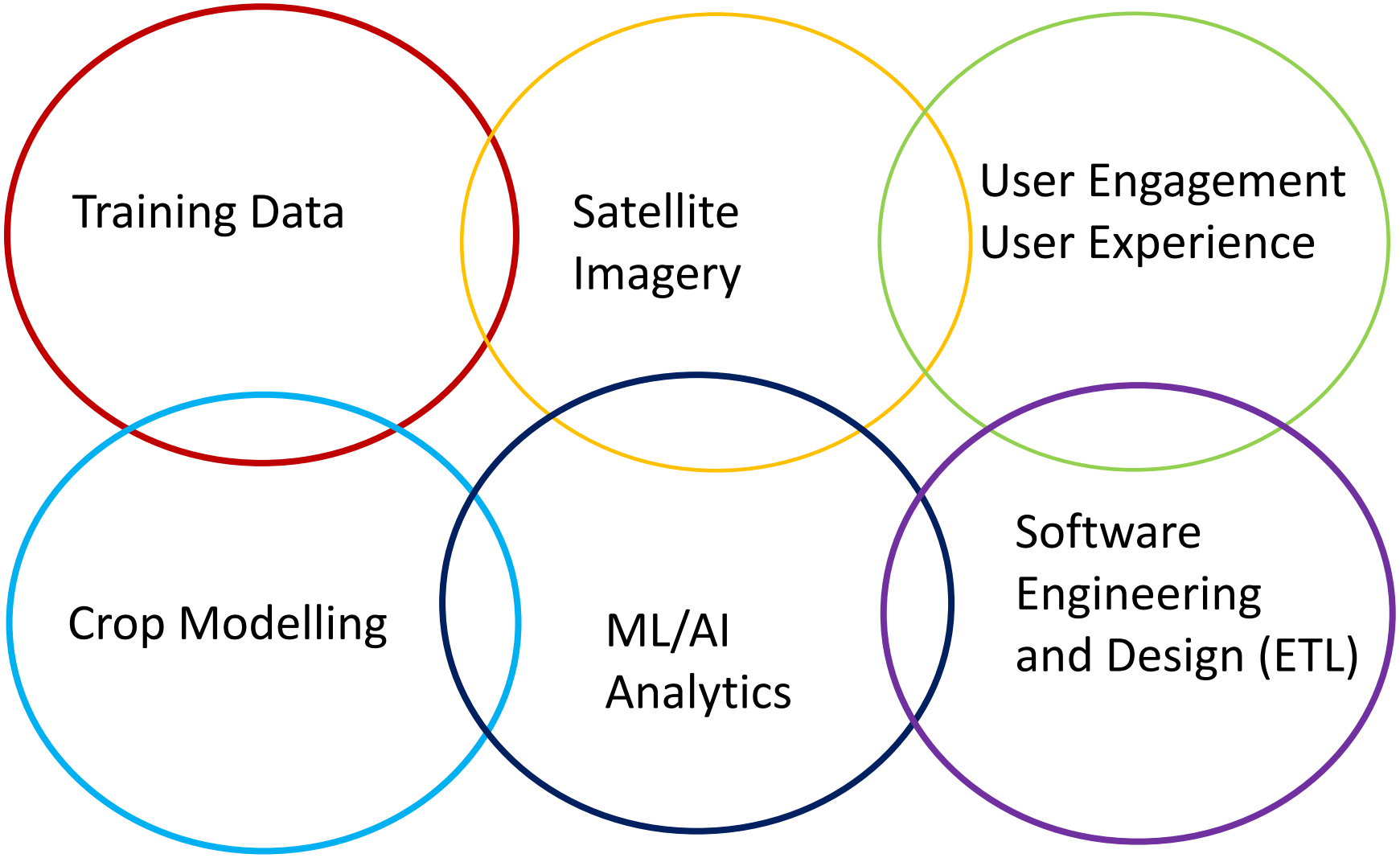
Advances in satellite technology and AI for crop monitoring: from data to action in agriculture

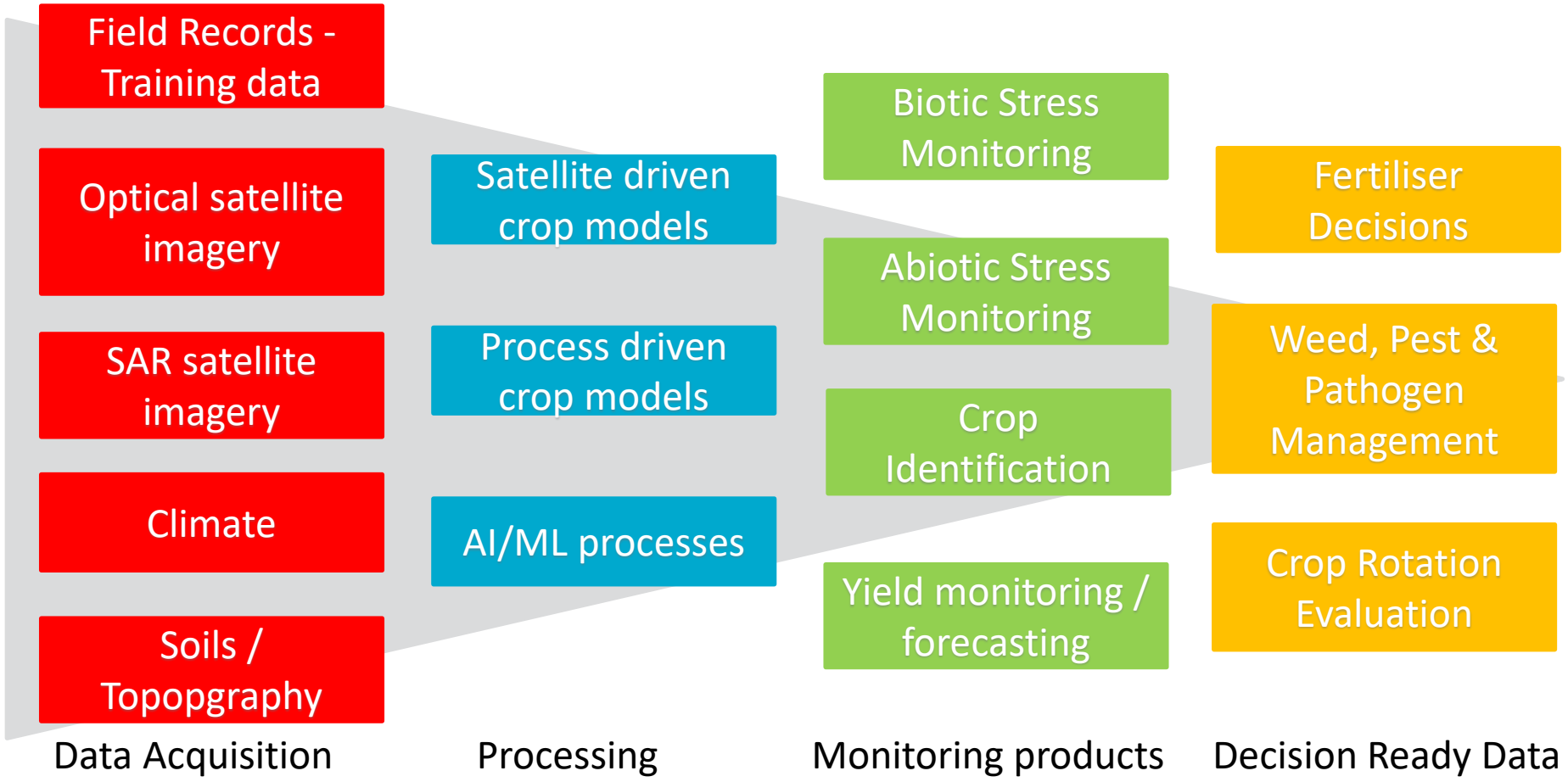
Roger Lawes | 26/09/2023

Crop Monitoring Challenge

- Monitor the Australian cropping landscape for crop tonnage in near real time
- Create products that are scalable in space and time, and can deliver insights at the sub field, field, farm, region, state and national level
- Develop information flows, that can be accessed and disseminated via modern digital platforms to multiple end-users.


Training Data
Satellite Imagery
User Engagement User Experience
Crop Modelling
ML/AI Analytics
Software Engineering and Design (ETL)

Creating digital agriculture products



The challenge: Building a sustainable data pipeline

~ 50,000 crop type identification points- co-ordinated national data acquisition

~ 6000 crop yields at sub paddock scale

~ 30,000 field boundaries

ePaddocks – defining the management unit

https://agdatashop.csiro.au/epaddock-australian-paddock-boundaries

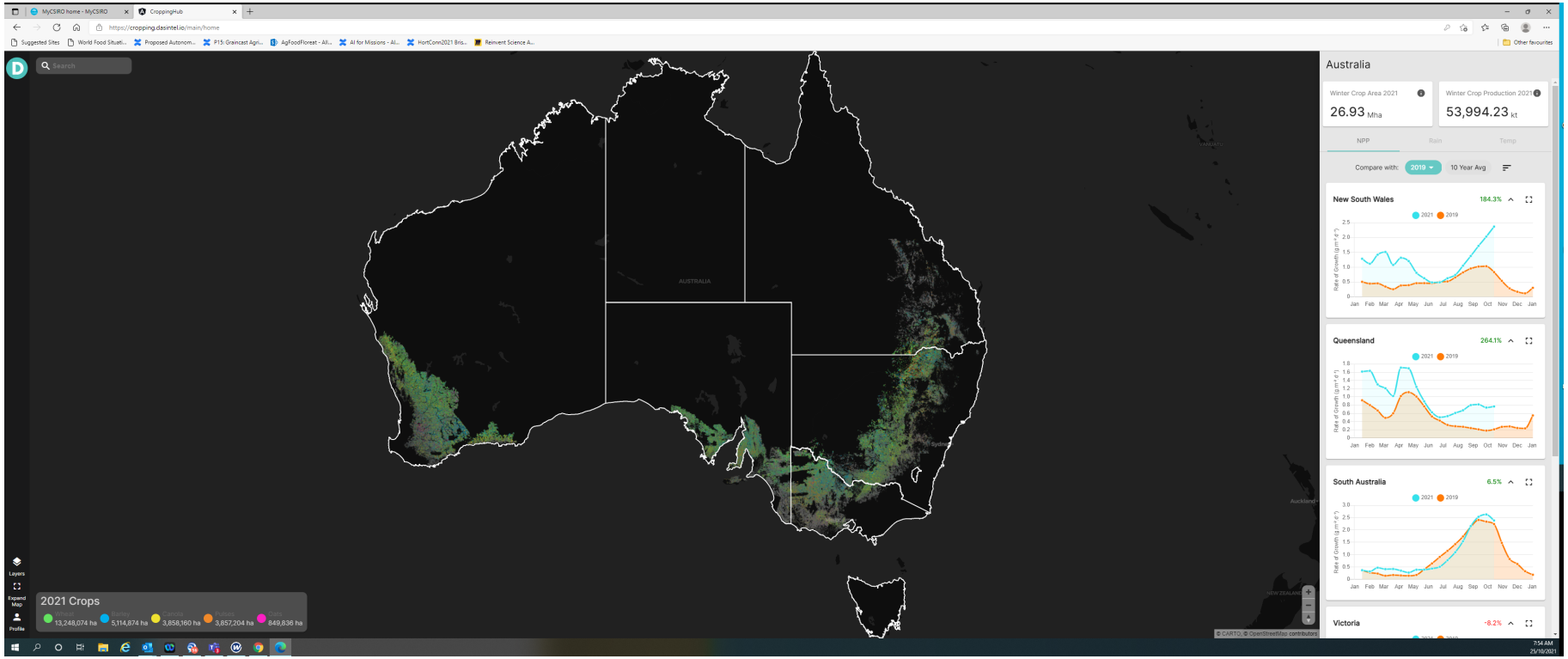
Training data acquisition - 2021

50,000 + training and validation points

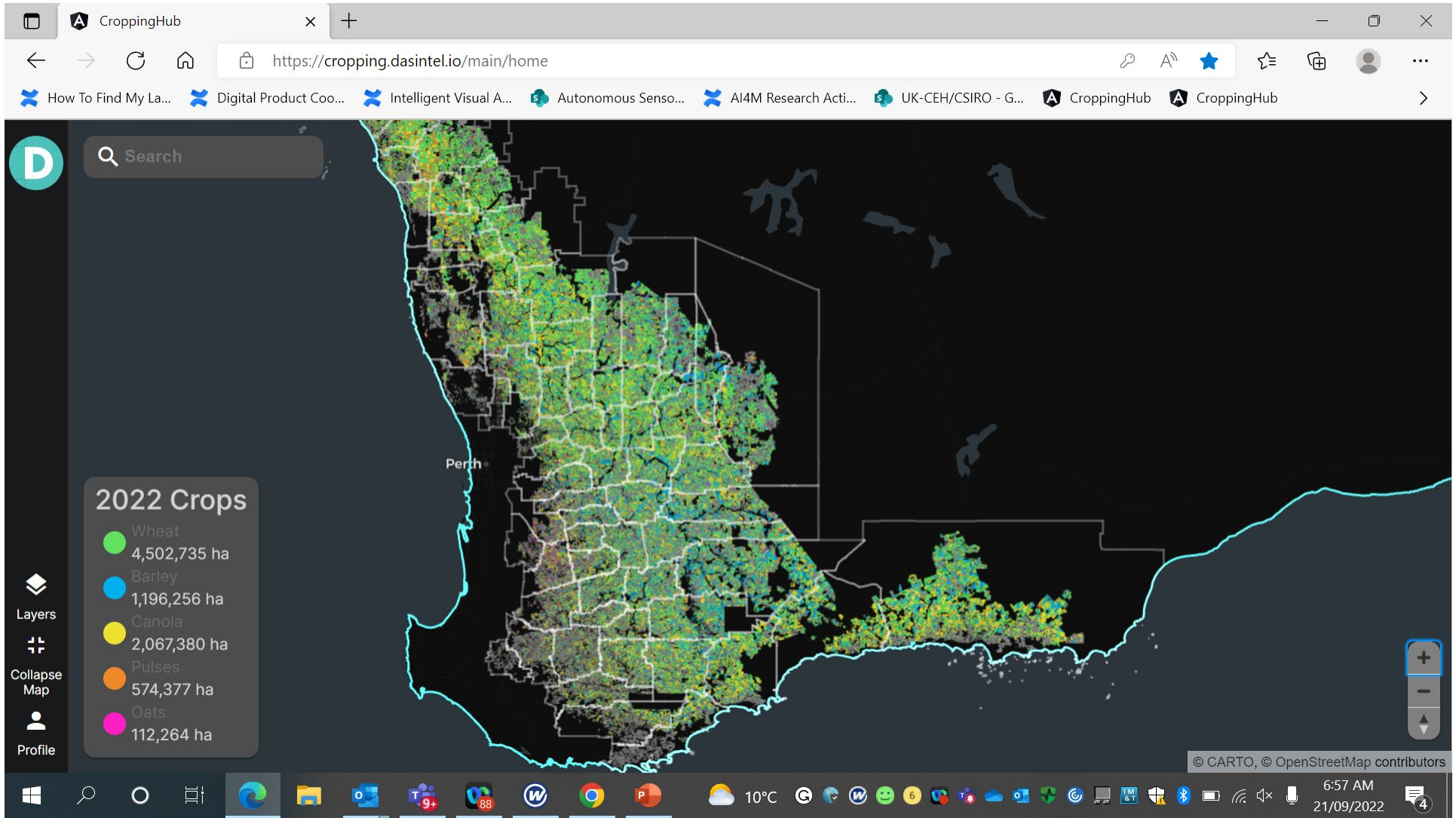
Classes:

- Barley
- Canola
- Chickpeas
- Faba Beans
- Fallow
- Field Peas
- Lentils
- Lupins
- Oats
- Pasture
- Remnant
- Vetch
- Water
- Wheat
- Tree Crops

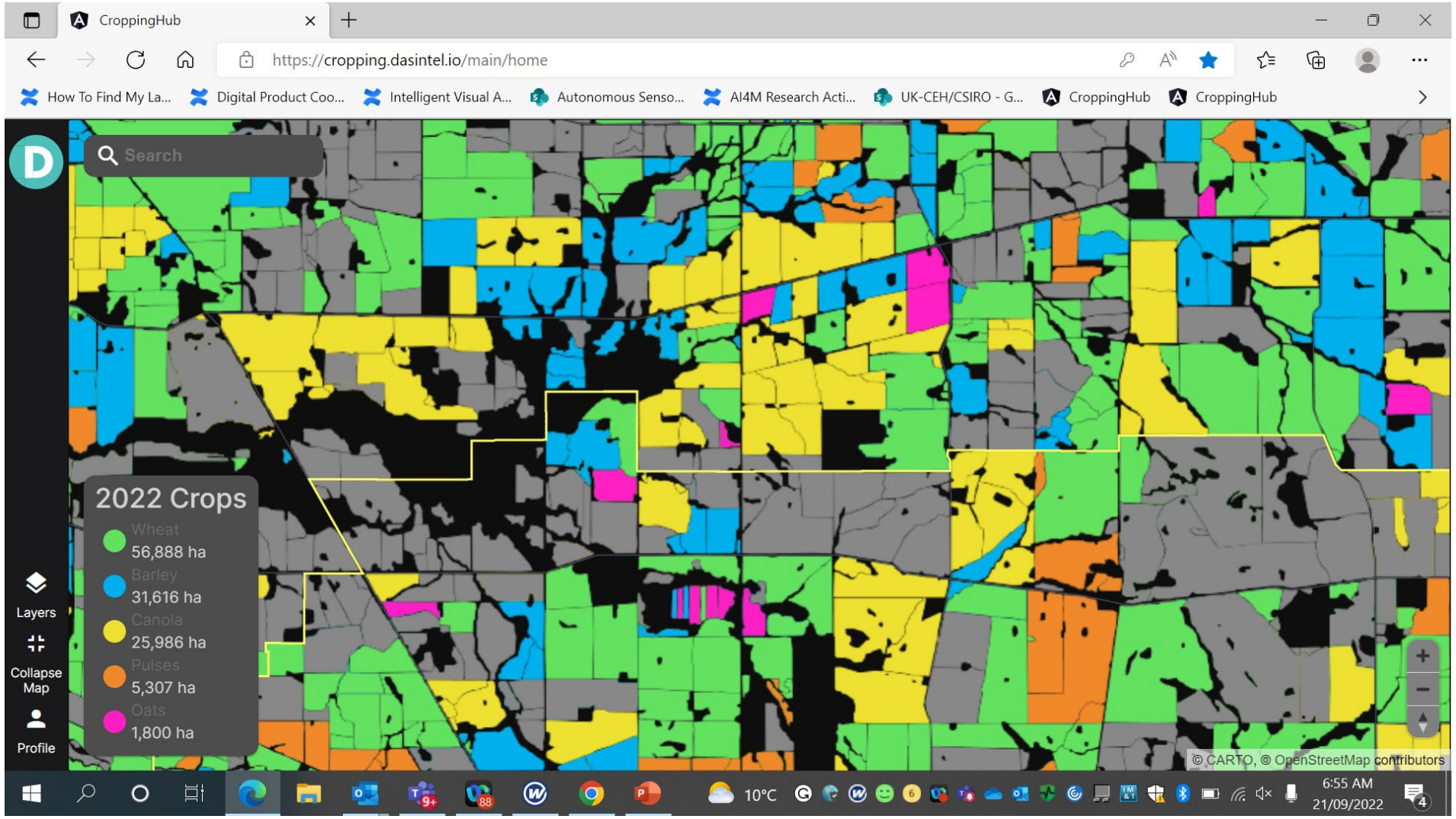
The Workflow - Crop-ID outputs to industry



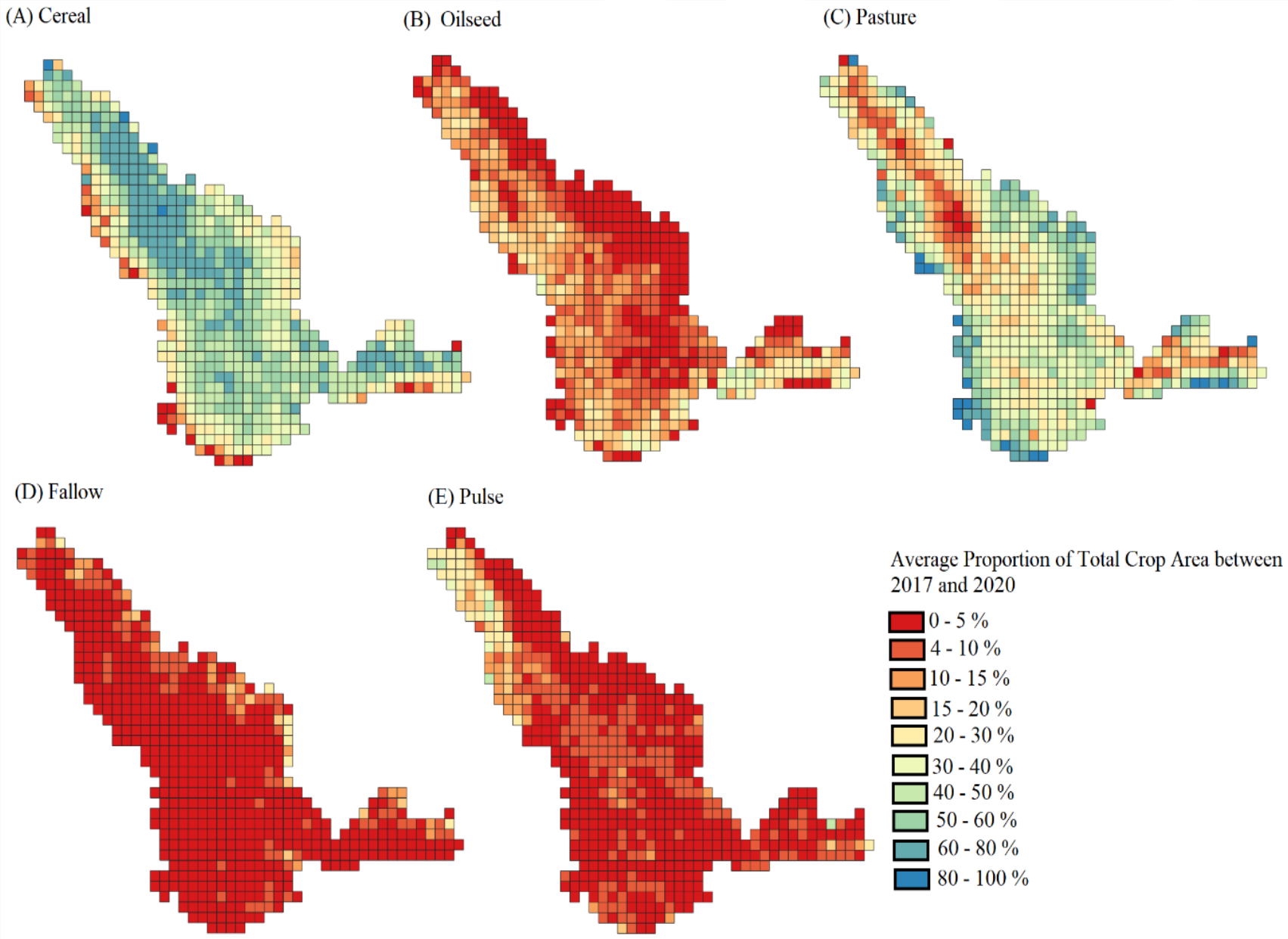
Cropping Hub – Crop ID – Digital Agricultural Services

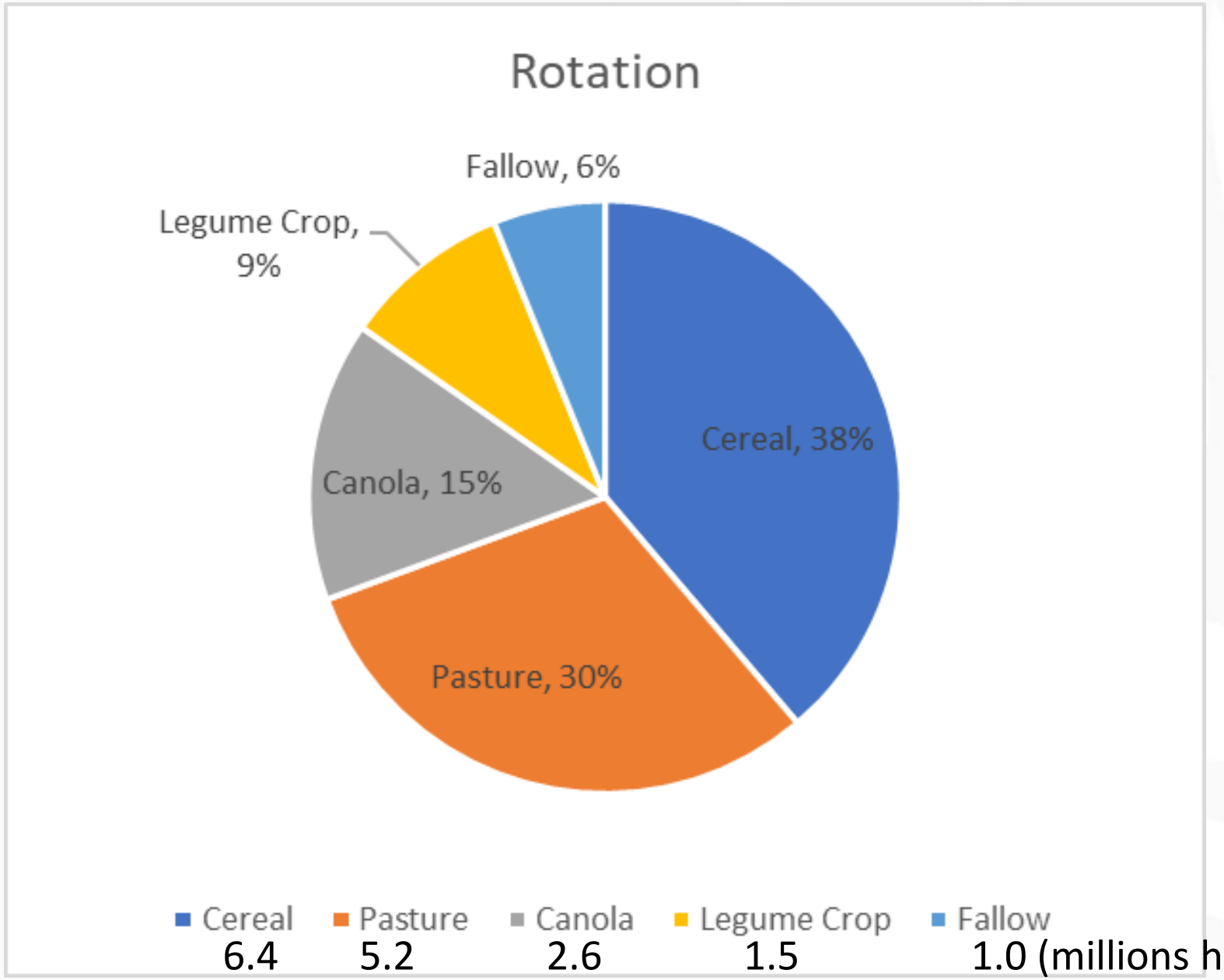


Crop ID


CroppingHub
https://cropping.dasintel.io/main/home
How To Find My La...
Digital Product Coo...
Intelligent Visual A...
Autonomous Senso...
AI4M Research Acti...
UK-CEH/CSIRO - G...
CroppingHub
CroppingHub
Search
2022 Crops
Wheat
56,888 ha
Barley
31,616 ha
Canola
25,986 ha
Pulses
5,307 ha
Oats
1,800 ha
Layers
Collapse Map
Profile
© CARTO, © OpenStreetMap contributors
10°C
6:55 AM
21/09/2022

PORTION OF CROPPED AREA

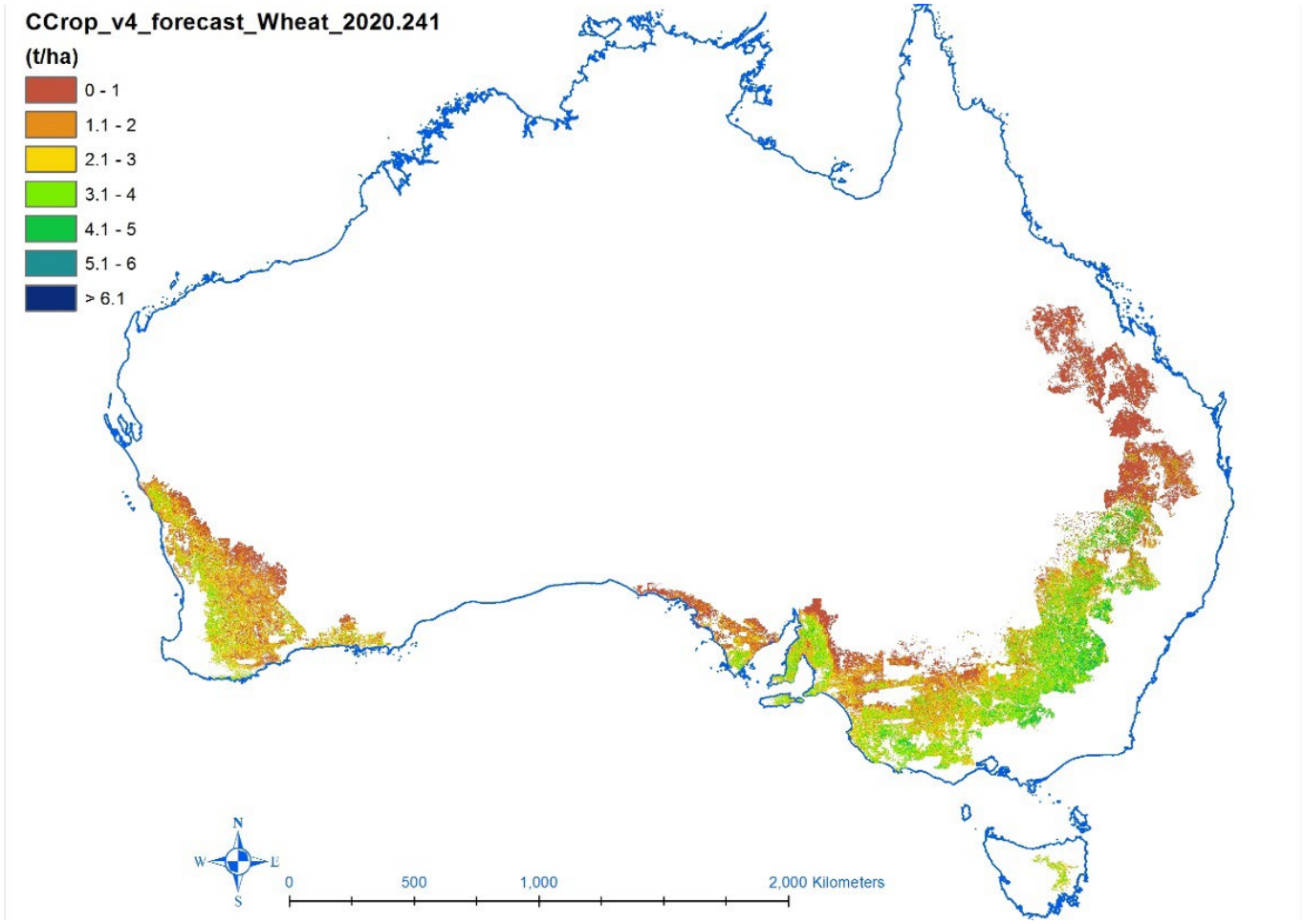



Rotation
Fallow, 6%
Legume Crop, 9%
Canola, 15%
Cereal, 38%
Pasture, 30%
Cereal
Pasture
Canola
Legume Crop
Fallow
6.4
5.2
2.6
1.5
1.0 (millions ha)

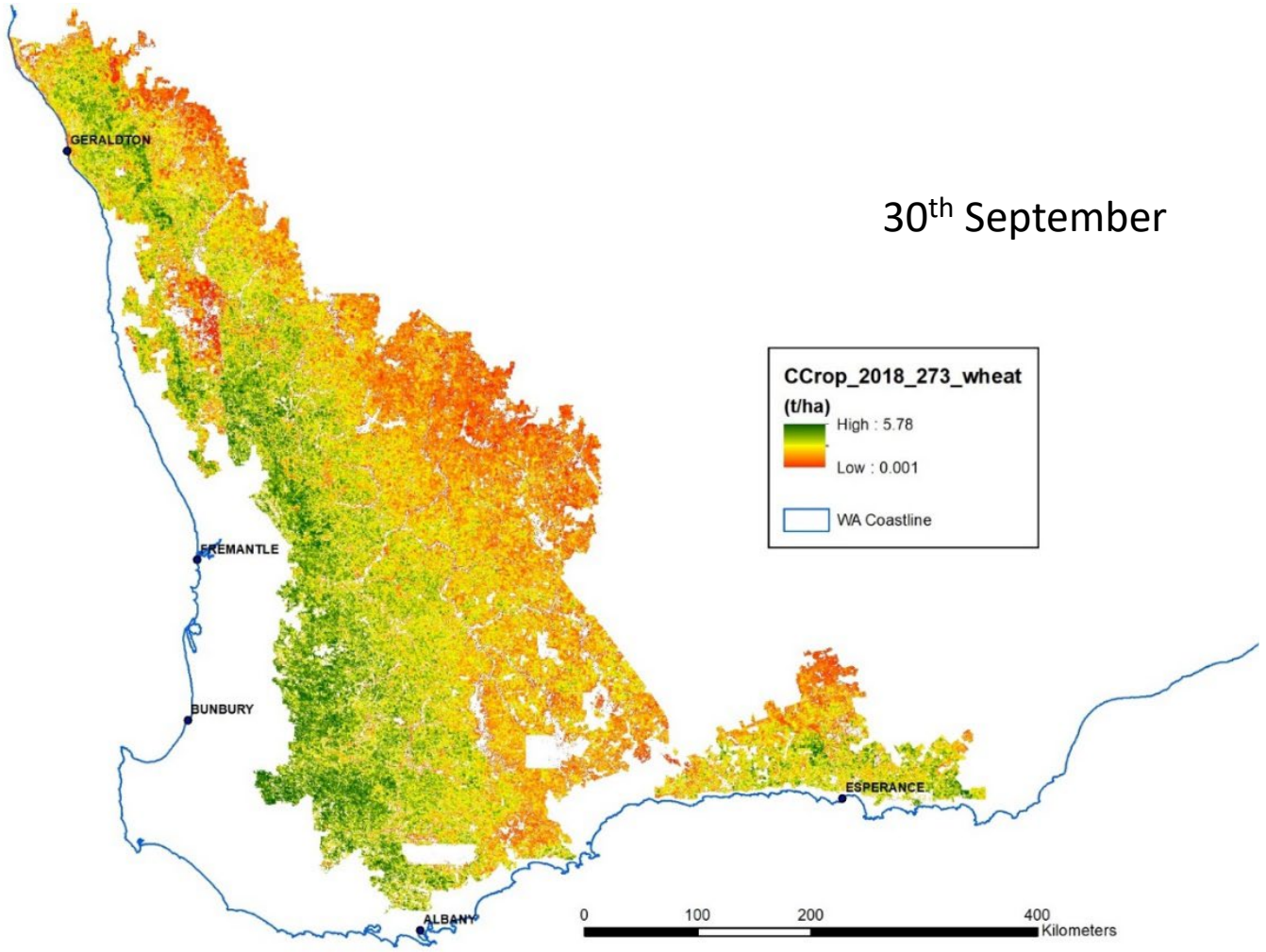
C-Crop: Satellite Driven Crop Models

- A simple, remote-sensing-driven crop productivity and yield model
- Remotely sensed Gross Primary Productivity (GPP) estimates and models plant carbon mass (live and senesced leaves/stems, roots, soil carbon)
- Requires crop type and climate
- GPP estimated via fPAR and LAI, extracted from NDVI

C-Crop 29th August-12th September 2020

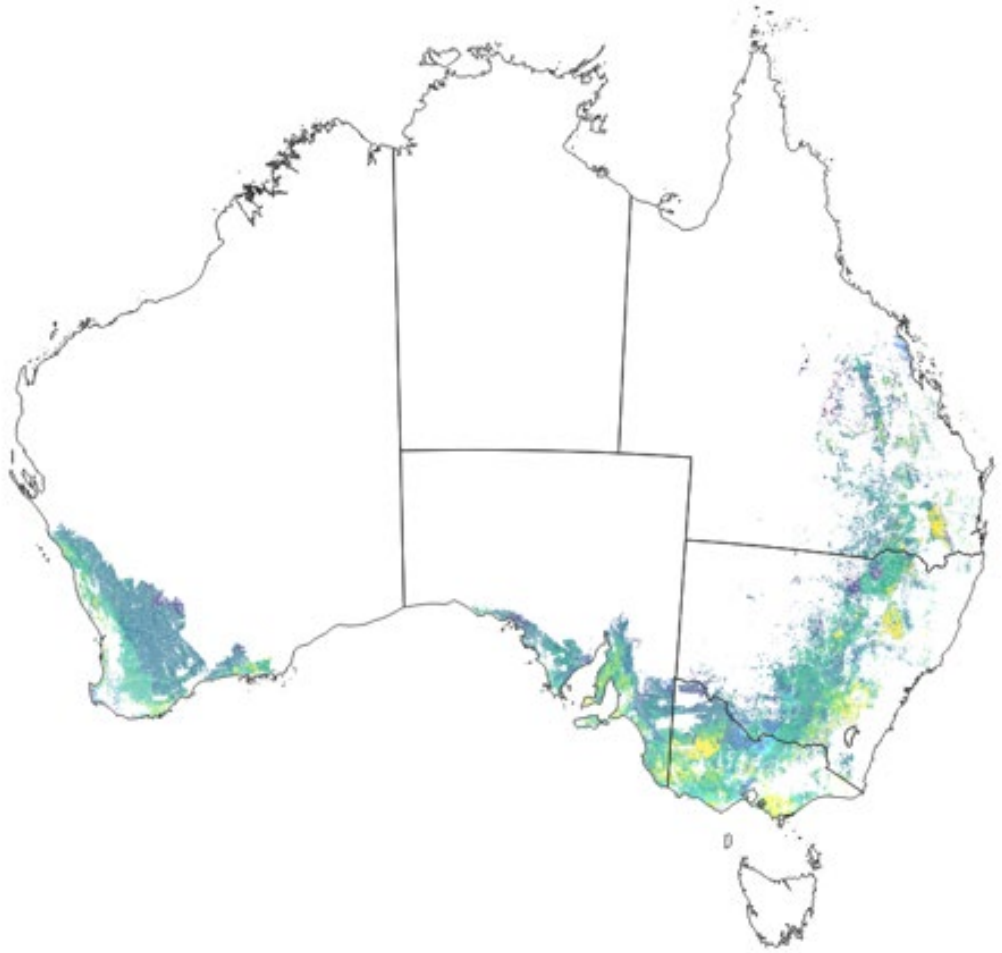


2018 C-Crop Wheat Yield Estimate – State Scale



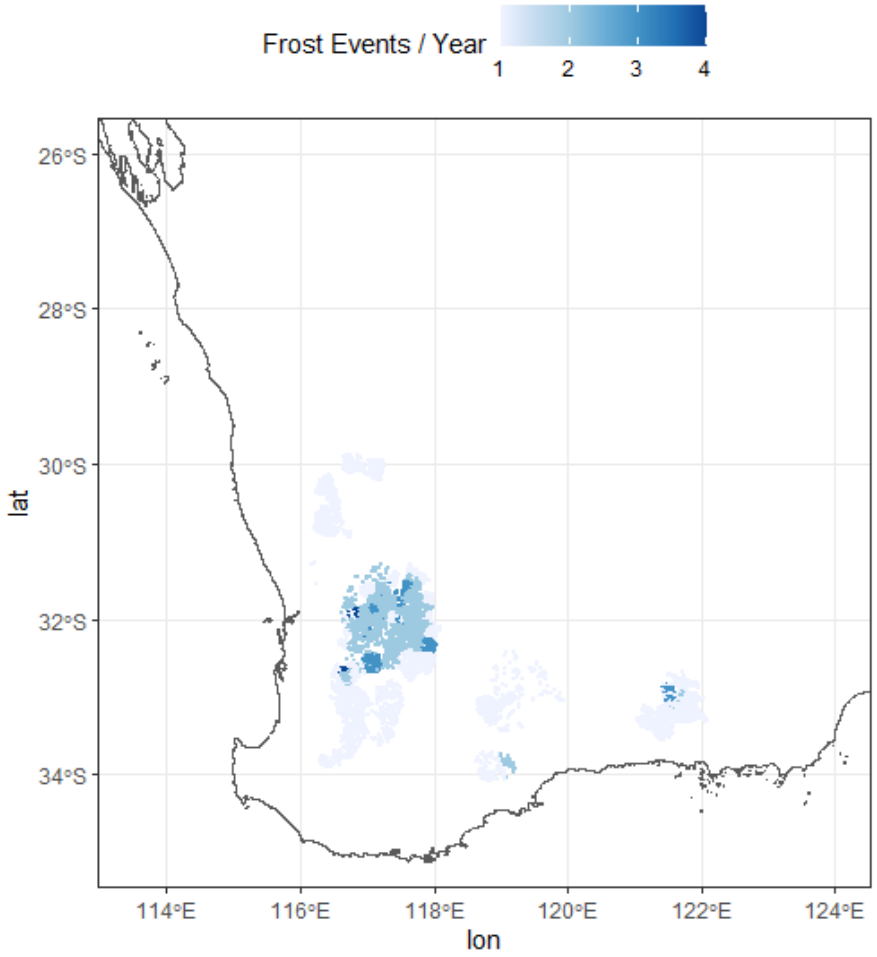
30th September

AgriYieldz: Yields, Biomass, Stresses, PAW, PAWC

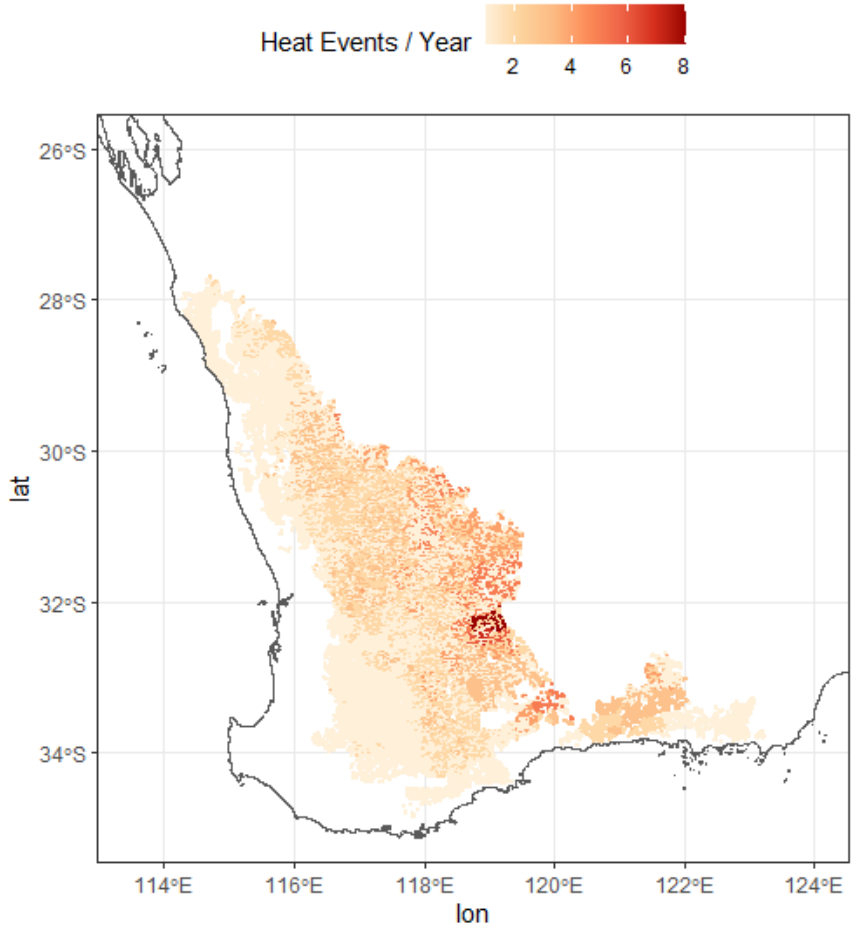


https://acds.csiro.au/agriyieldz-the-wheat-crop-production-estimator

Frost impacts on wheat crops



Heat impacts on wheat crops



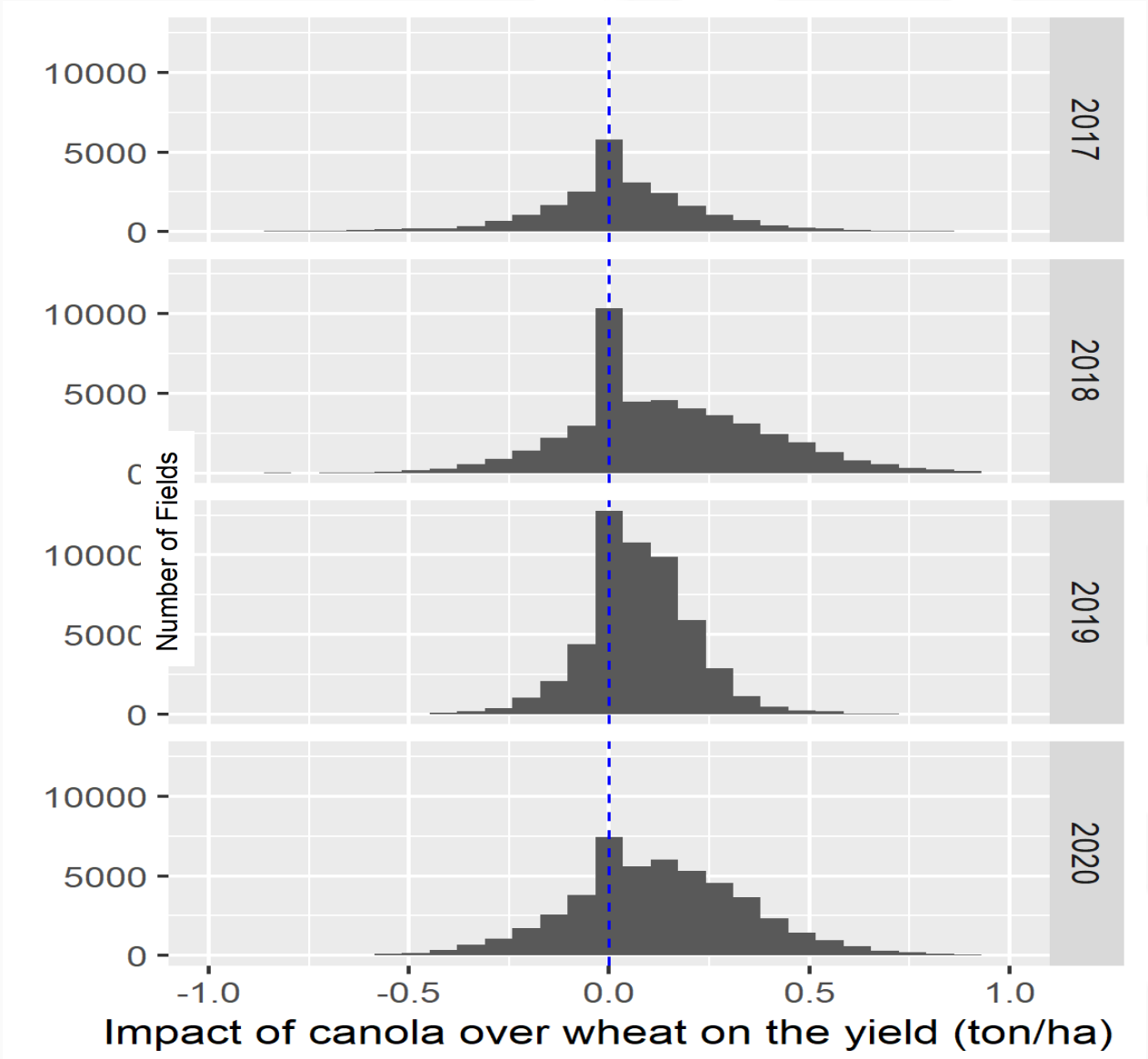
AI OUTPUT : Yield advantages of breaks on wheat yield.

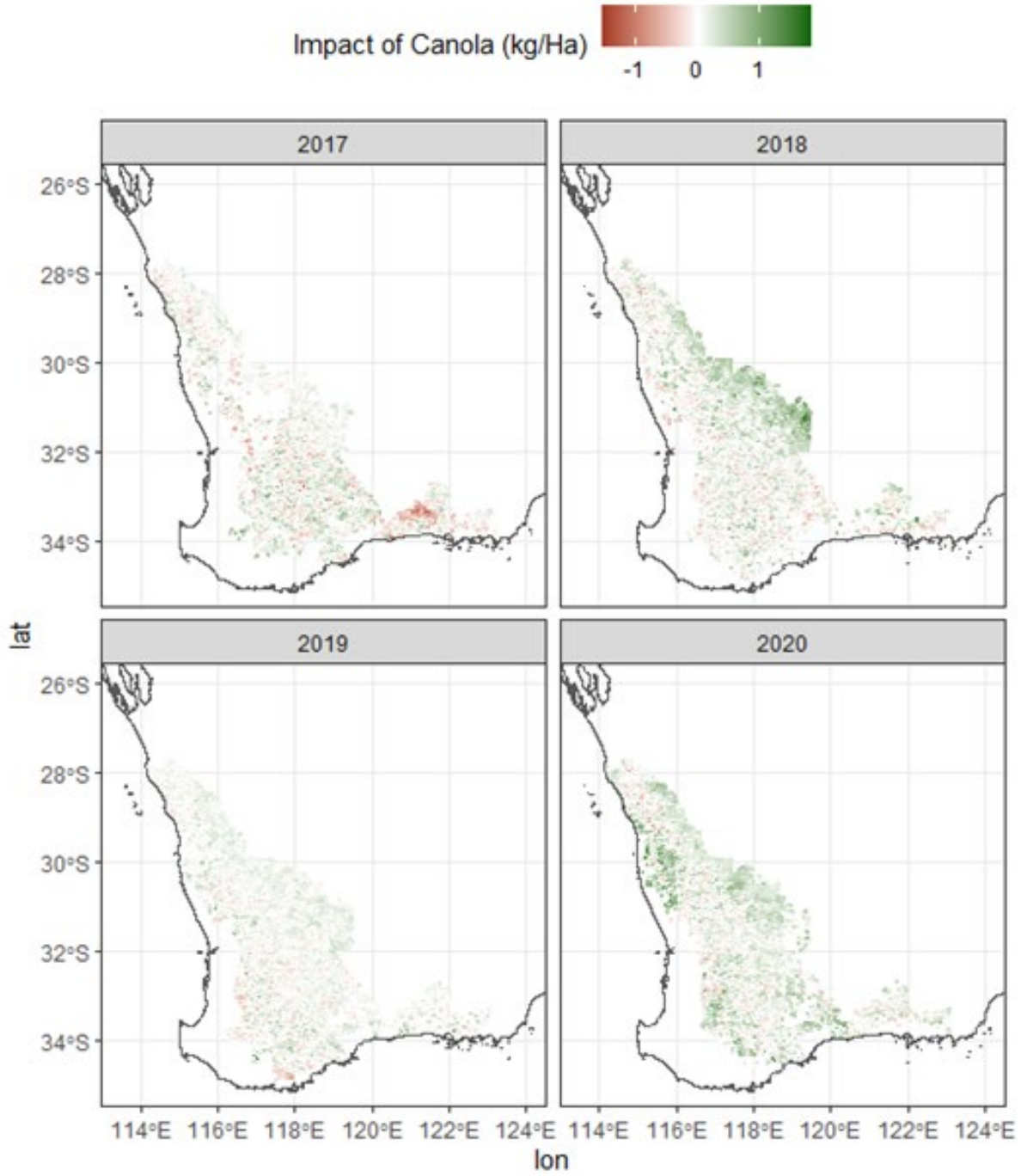
Yield (ton/ha)	Mean (t/ha)	Std Dev	Median
(A) Cereal after Cereal	-0.02	0.19	0.00
(B) Cereal after Fallow	-0.06	0.22	-0.02
(C) Cereal after Oilseed	**0.10**	**0.24**	**0.05**
(D) Cereal after Pasture	-0.05	0.21	0.00
(E) Cereal after Pulse	**0.09**	**0.23**	**0.06**

YIELD IMPROVEMENT OVER CEREAL

Break	Mean Yield Advantage	% Wheat fields with > 200 kg/ha yield benefit
Cereal after Canola	**+ 97 kg/ha**	**27%**
Cereal after Legume Crop	**+ 87 kg/ha**	**26%**
Cereal after Fallow	- 60 kg/ha	8%
Cereal after Pasture	- 47 kg/ha	7%

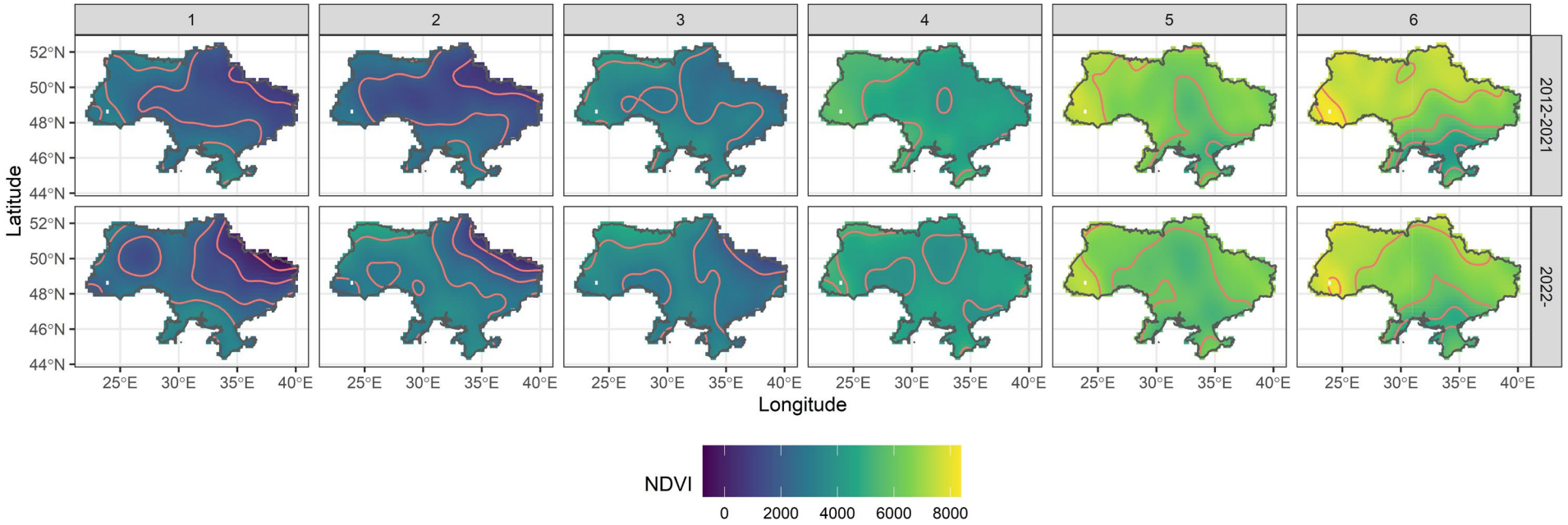
CANOLA EFFECTS ON WHEAT YIELD



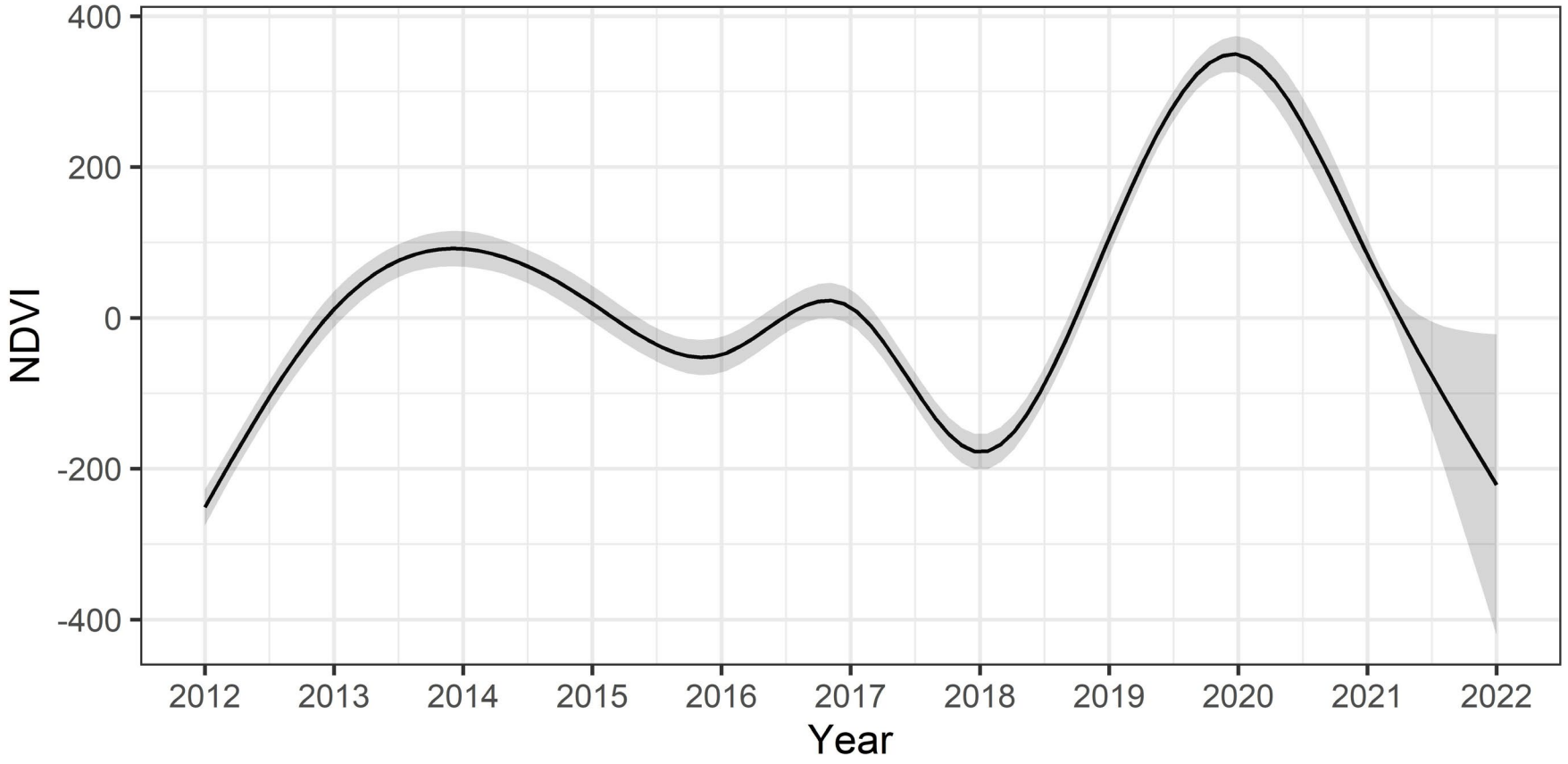

Impact of Canola (kg/Ha)
-1
0
1
2017
2018
2019
2020
26°S
28°S
30°S
32°S
34°S
lat
114°E
116°E
118°E
120°E
122°E
124°E
lon

Rapid Trend Detection – monitoring global hotspots in near real-time to detect anomalies

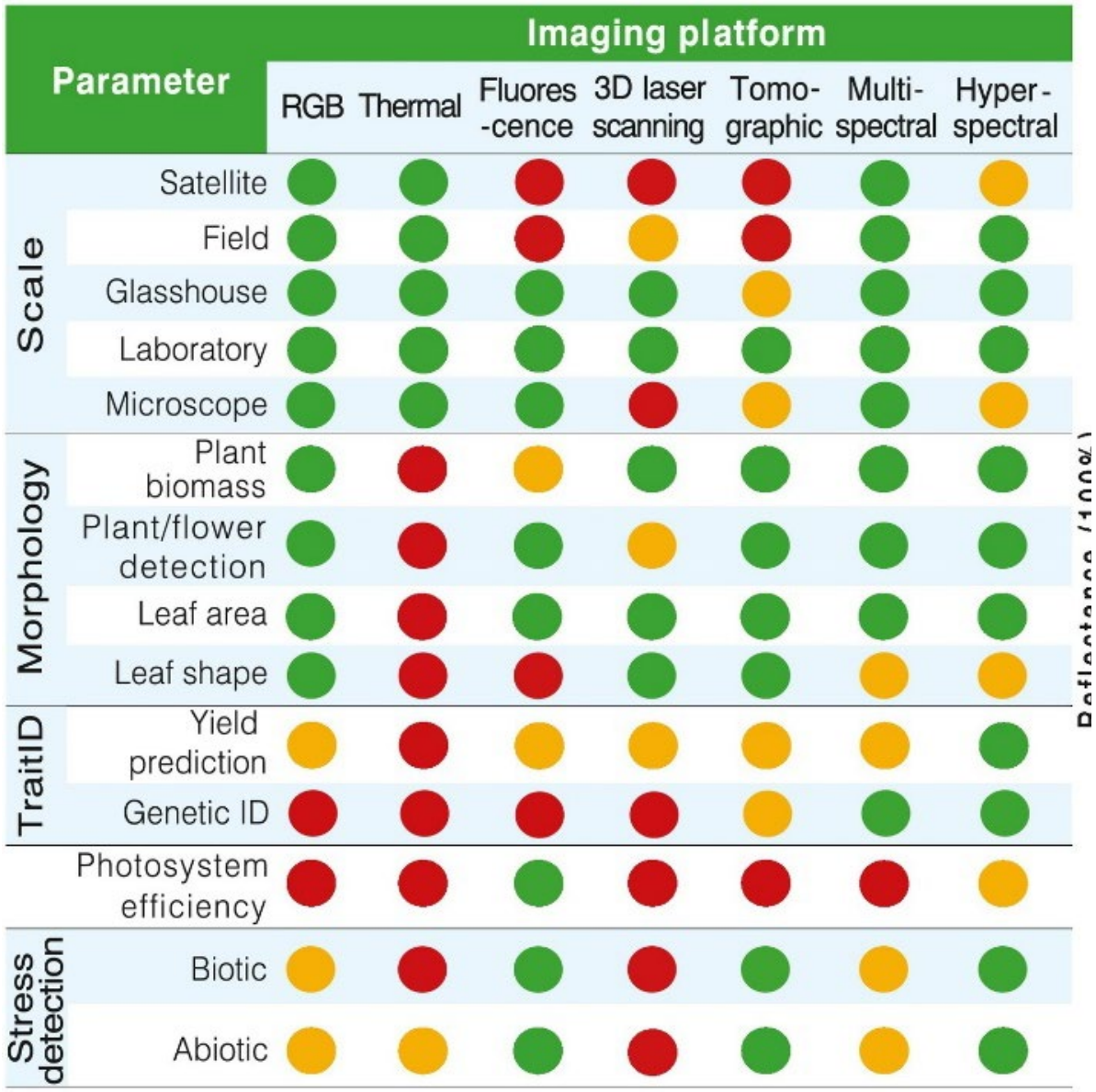
- Ukraine – 10 year average (top) vs 2022.
- E.G.



Detrending NDVI with advanced statistics (taking out the noise to detect trends) - Ukraine

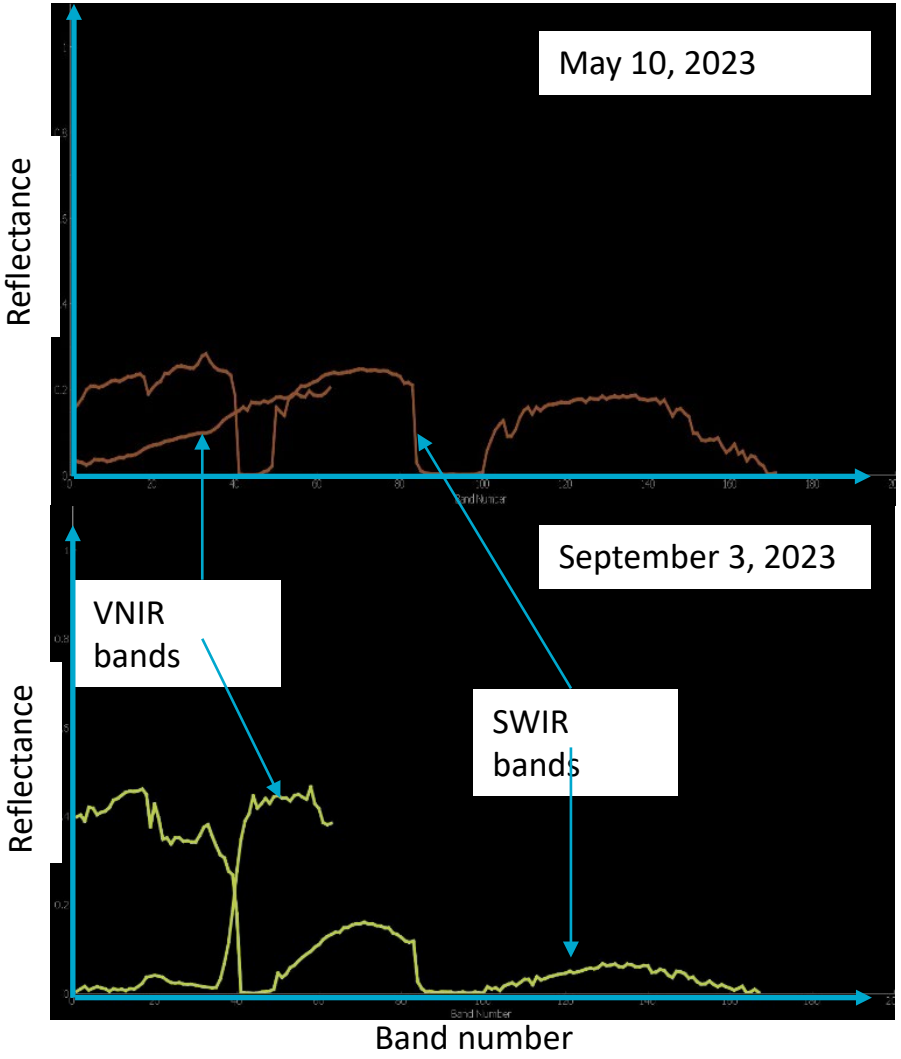


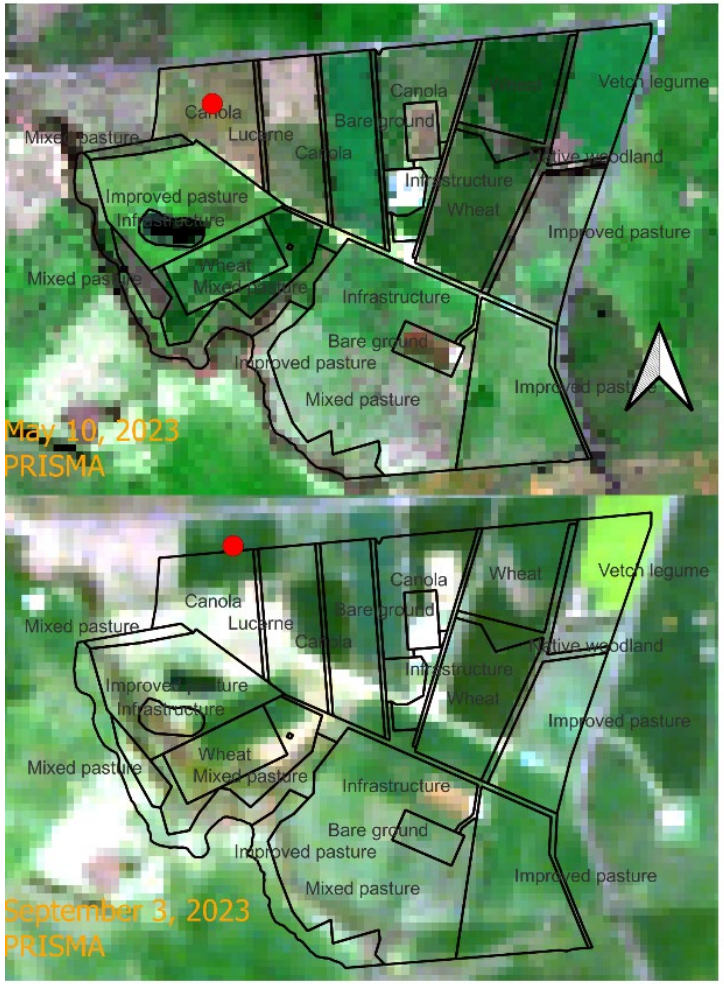
EO requirements for plant attributes



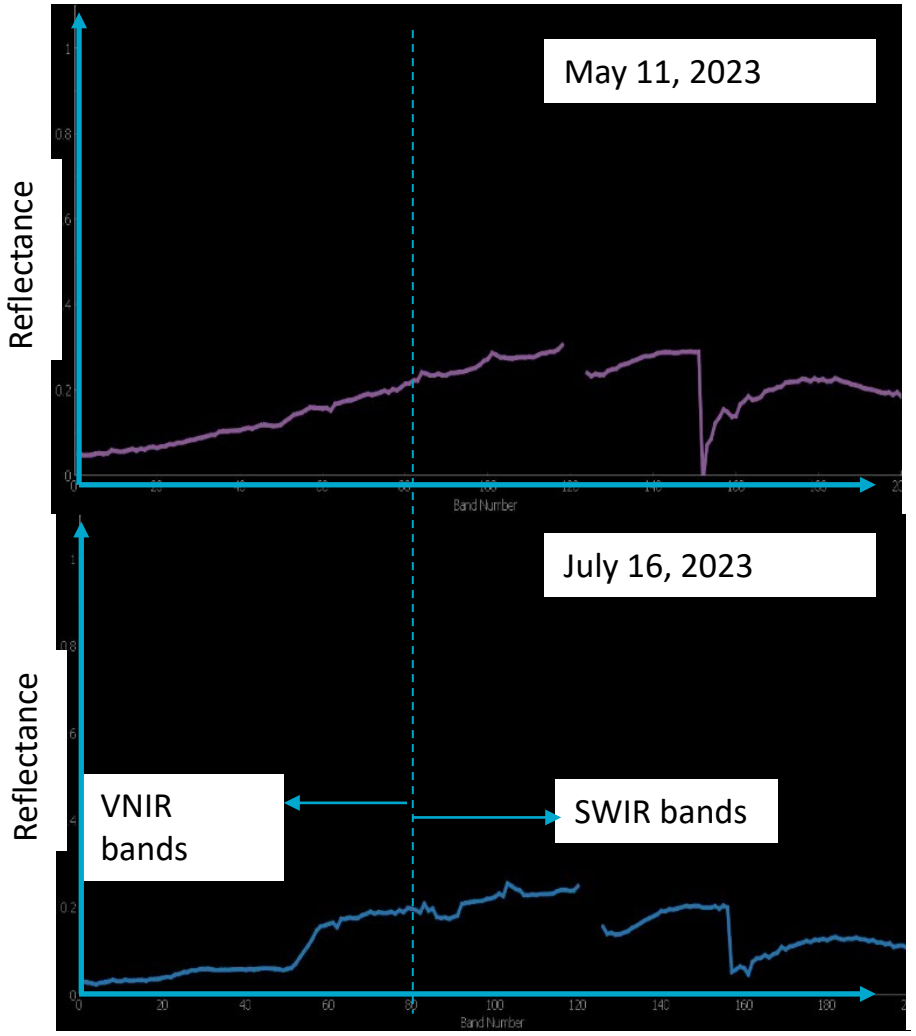
Source: Nguyen *et al.* (2022)

Canola's spectral profiles from PRISMA

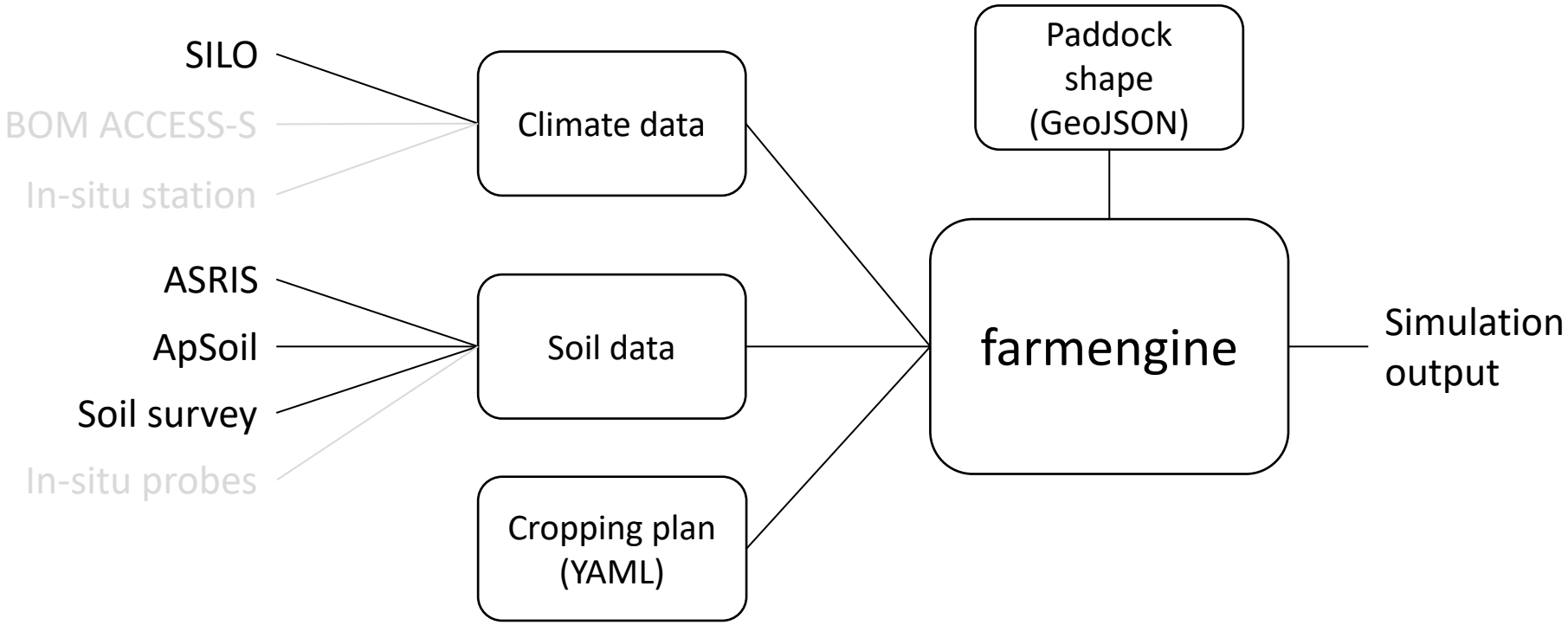




Canola’s spectral profiles from EnMAP



Spatial-temporal simulations with Farmengine



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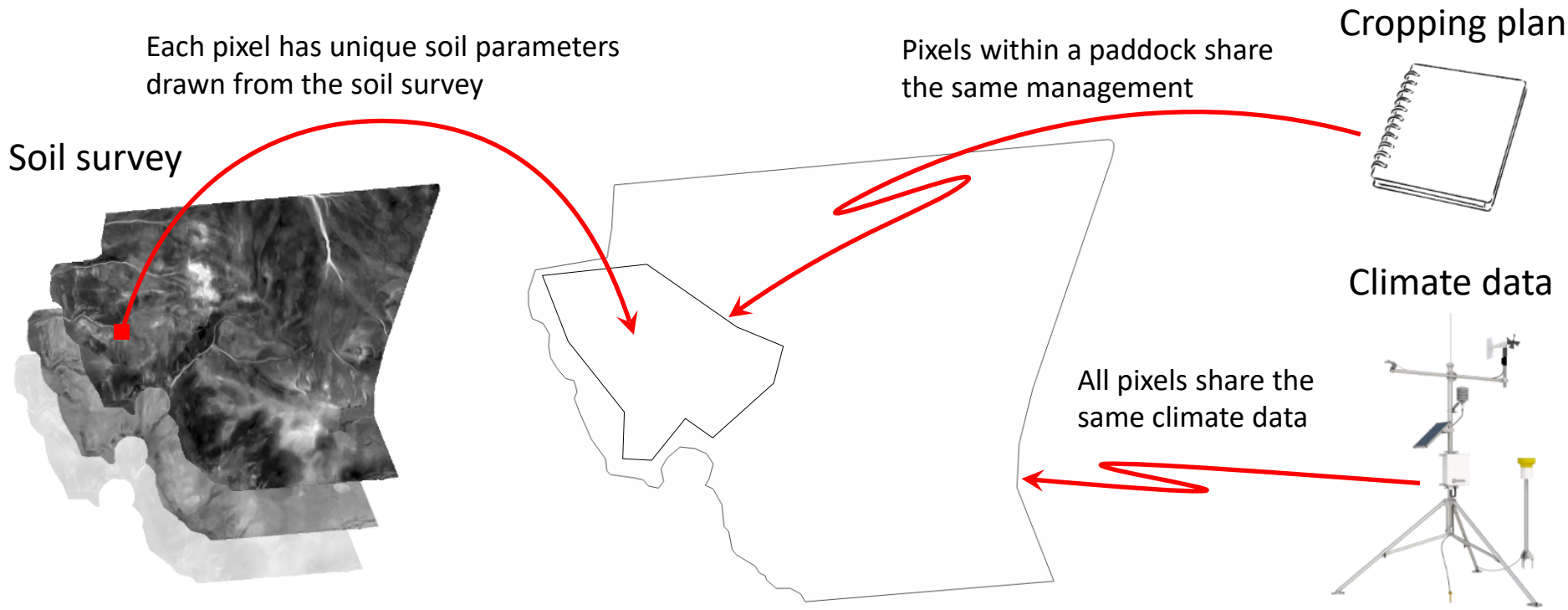
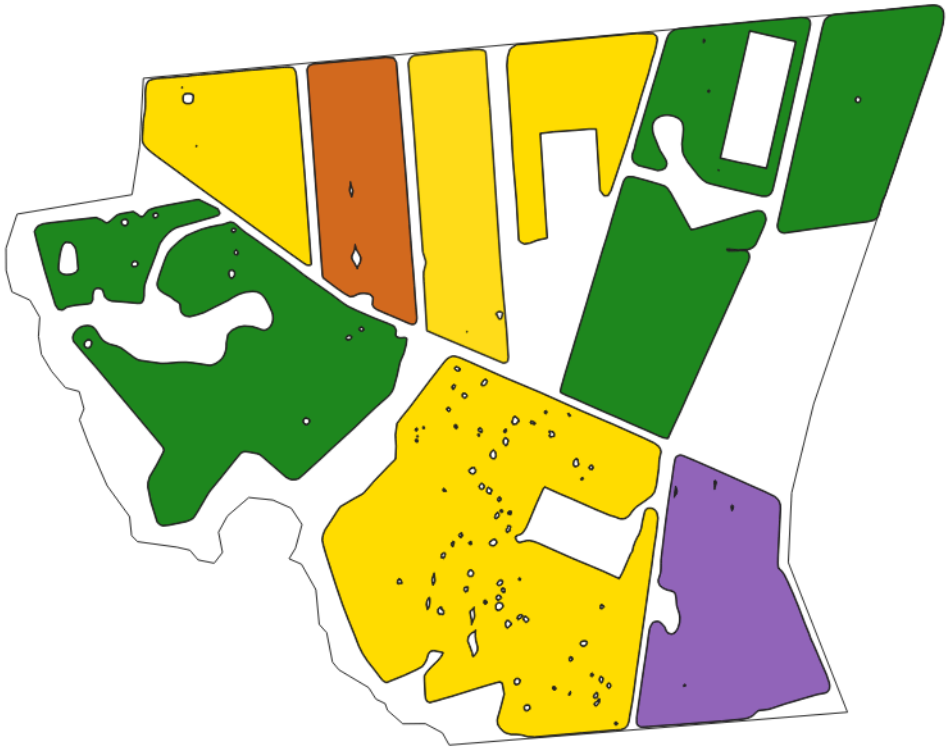


Oats Coolibah

Sowing depth: 50mm
Row spacing: 200mm
175 plants/m^2
160 kg/ha Urea



Wheat Kittyhawk

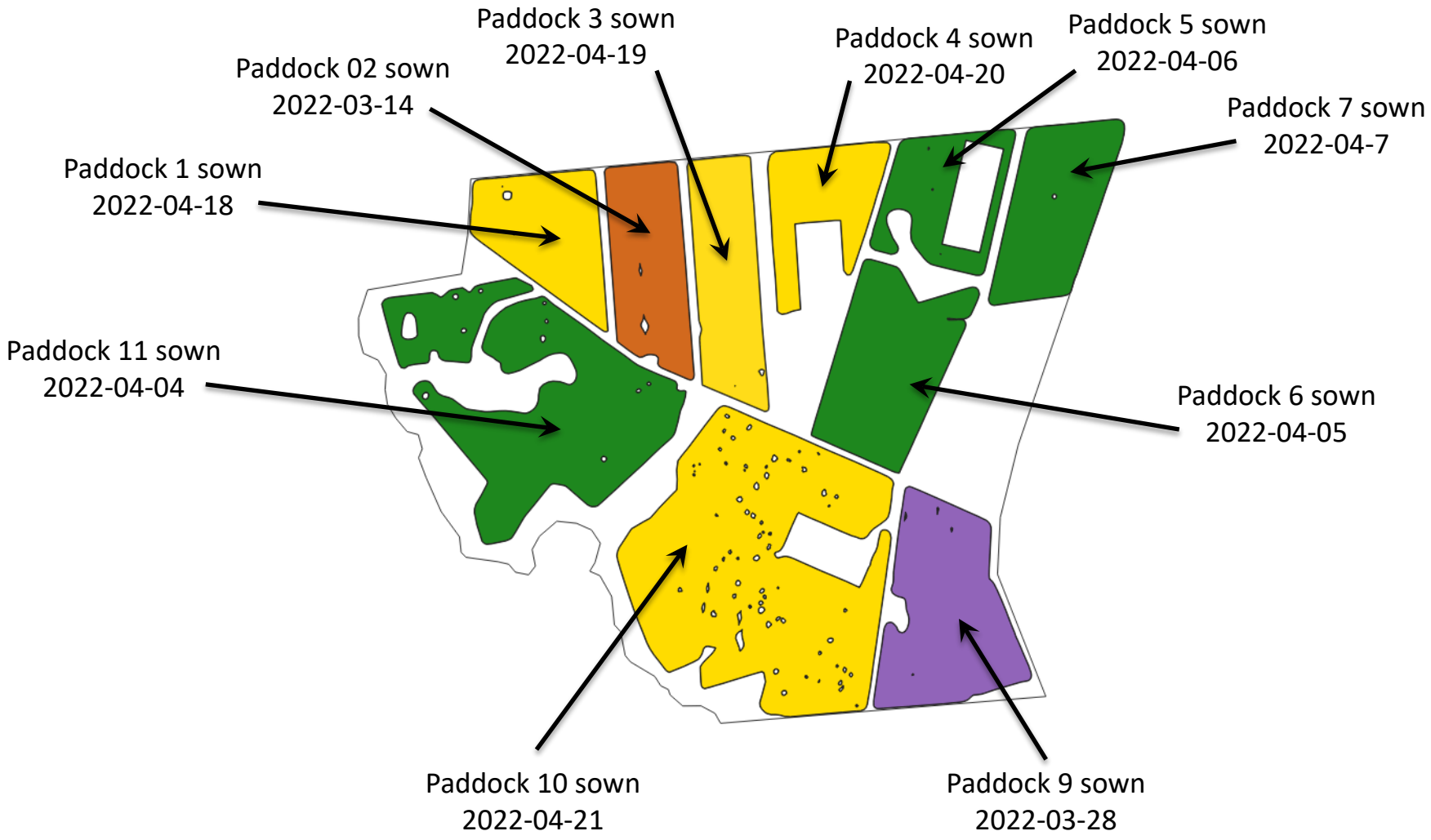
Sowing depth: 20mm
Row spacing: 180mm
120 plants/m^2
150 kg/ha Urea

Canola Hyola 650 TT

Sowing depth: 20mm
Row spacing: 200mm
40 plants/m^2
200 kg/ha NH4N

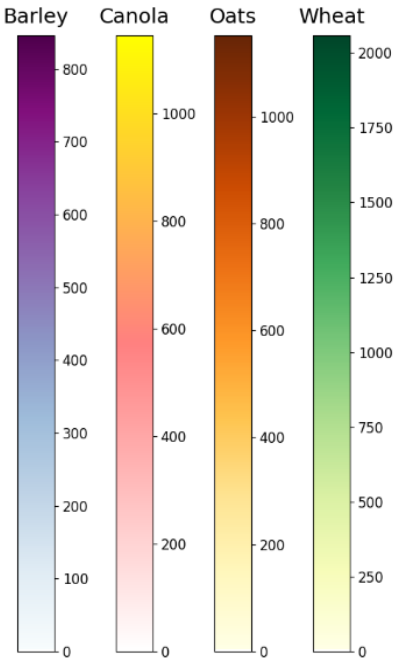
Barley Alestar

Sowing depth: 40mm
Row spacing: 500mm
10 plants/m^2
100 kg/ha Urea

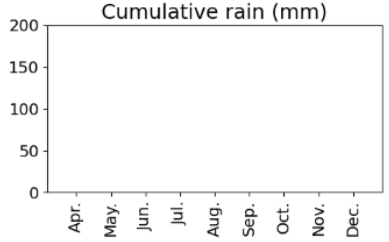

Paddock 3 sown
2022-04-19
Paddock 02 sown
2022-03-14
Paddock 4 sown
2022-04-20
Paddock 5 sown
2022-04-06
Paddock 7 sown
2022-04-7
Paddock 1 sown
2022-04-18
Paddock 11 sown
2022-04-04
Paddock 6 sown
2022-04-05
Paddock 10 sown
2022-04-21
Paddock 9 sown
2022-03-28

2022-03-01

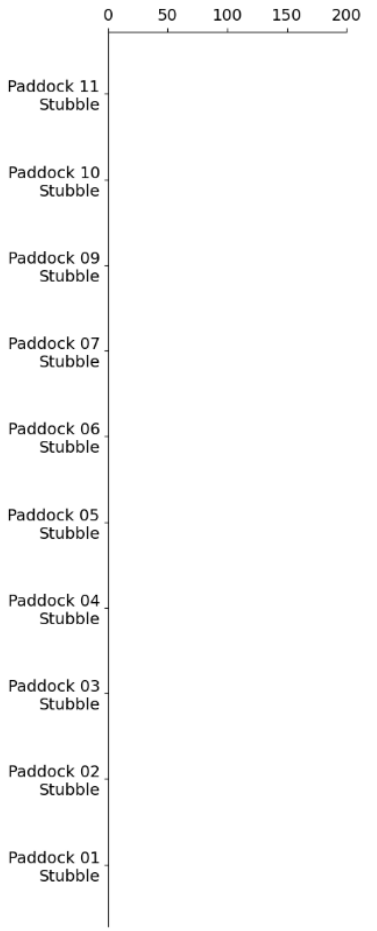
Above ground weight (g/m^2)



Cumulative rain (mm)

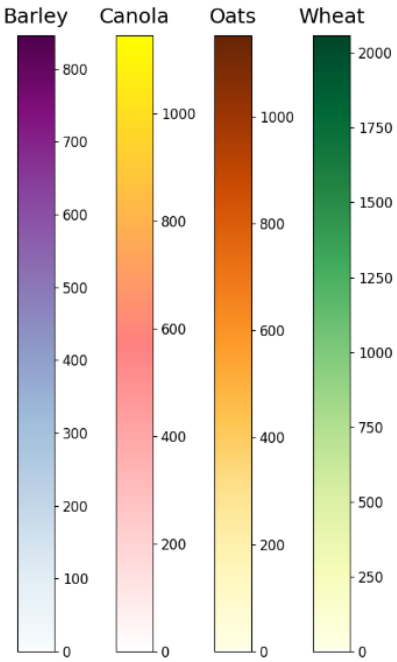


Paddock total grain weight (t)

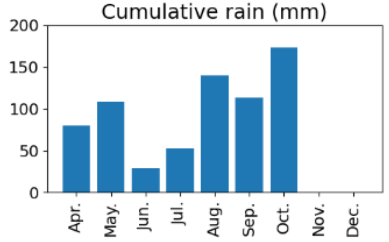


2022-10-31

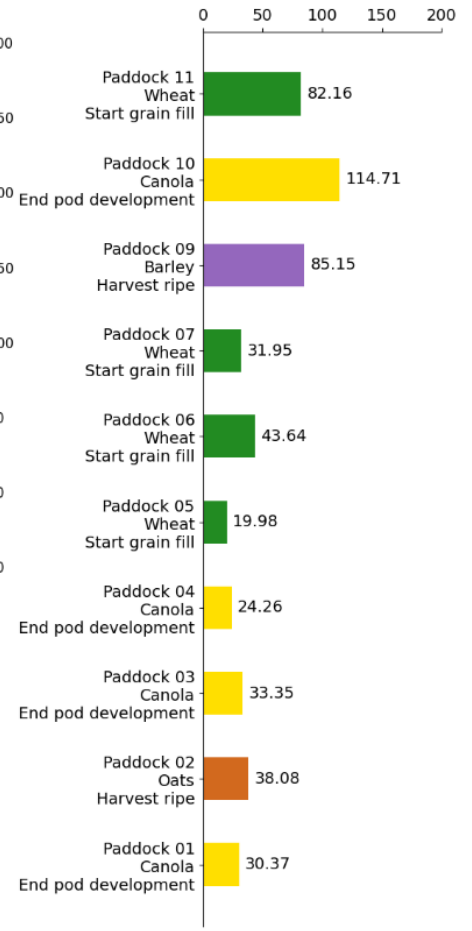
Above ground weight (g/m^2)



Cumulative rain (mm)

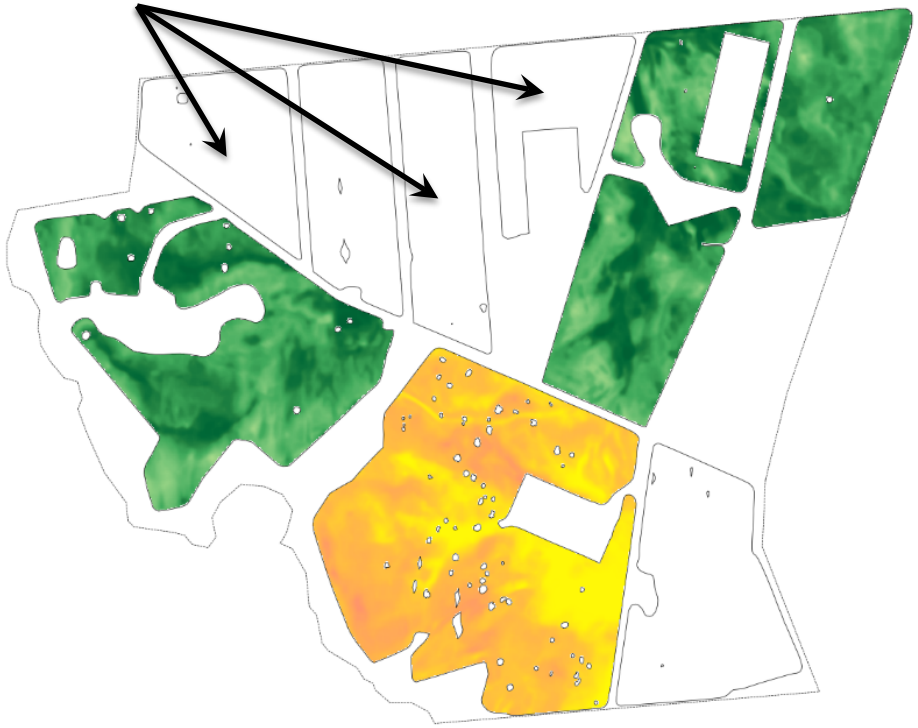


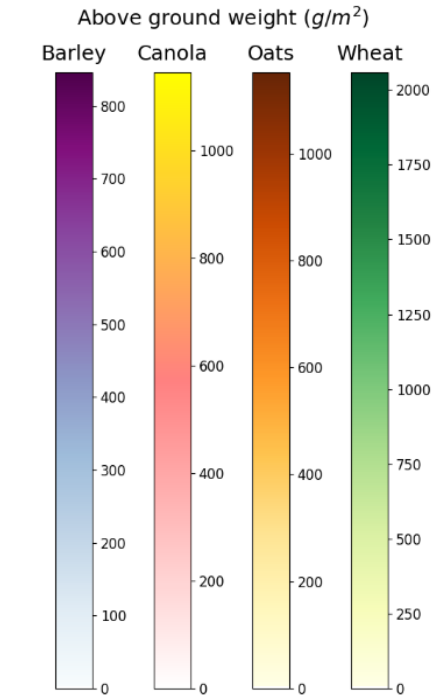
Paddock total grain weight (t)

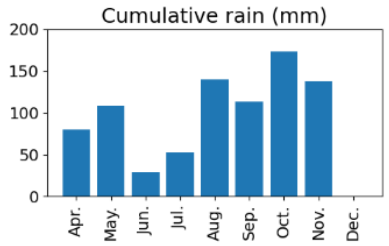


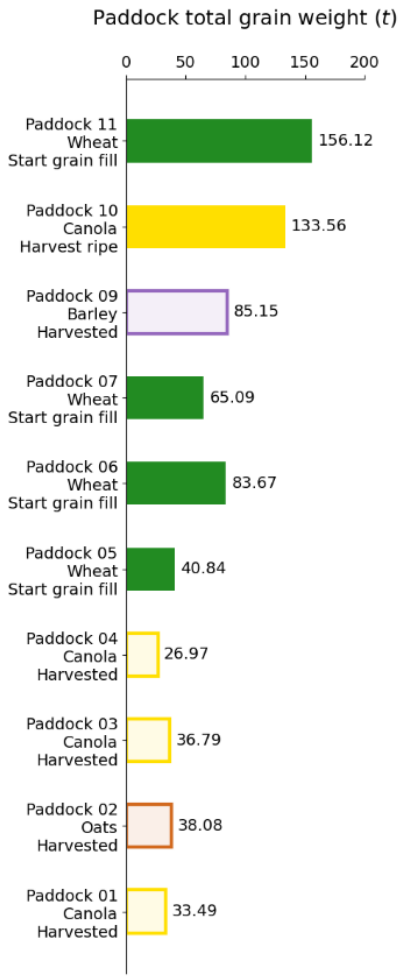
Paddocks 1, 3 and 4
Harvested

2022-11-20









Summary

- Digital products require advanced digital pipelines
- Products must connect to a decision
- Output must be delivered to the end-user
- Tools require process models, remote sensing, proximal sensing, and data assimilation to generate decision-ready products

Thank you