Cartography M.Sc.

Precision Mapping of Apple Proliferation using Multi- and Hyperspectral Data

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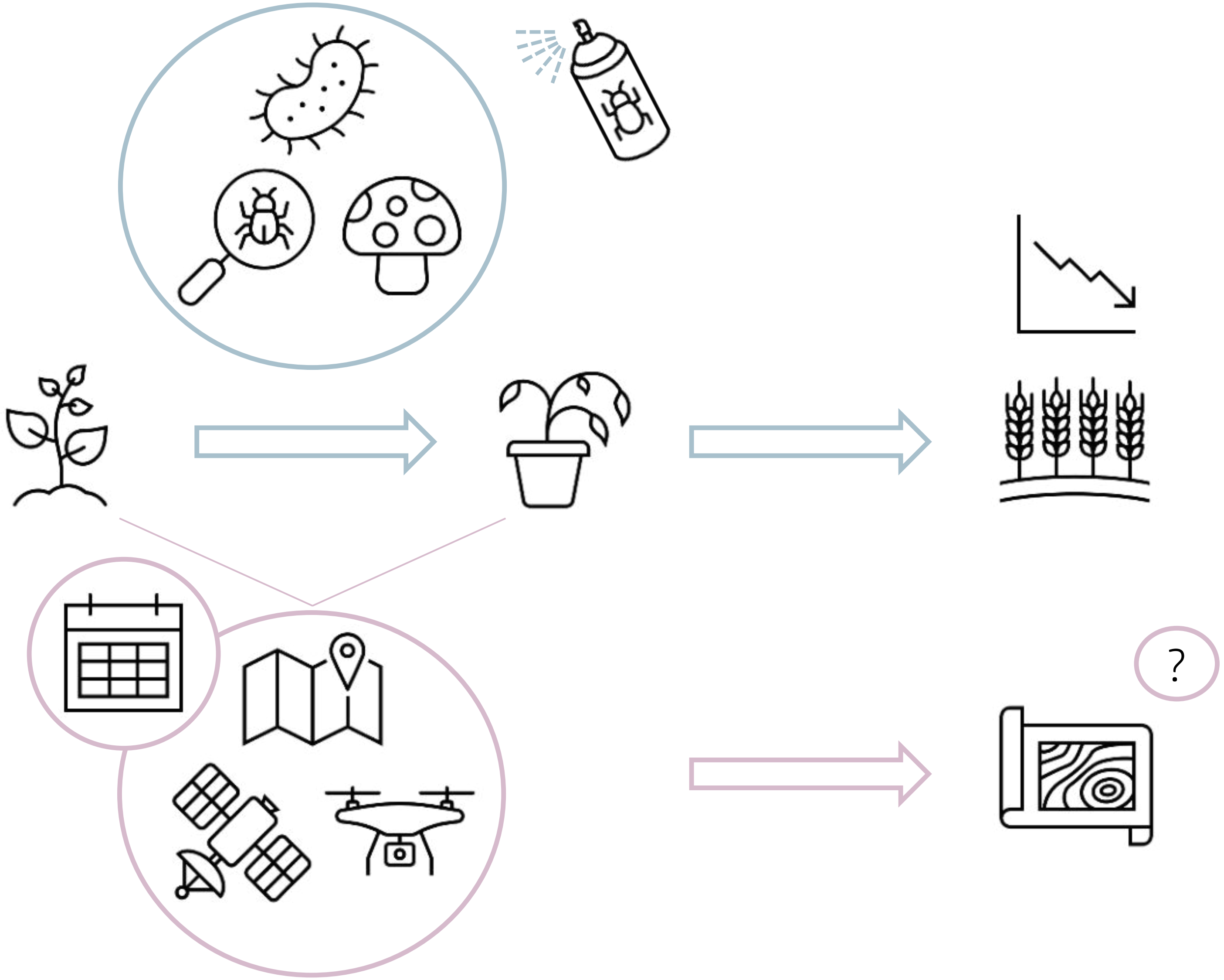
29/10/2021

Traineeship (Apr. – Sep.)
w/ Center for Sensing Solutions
Master thesis – experimental study
Interdisciplinary research
w/ Laimburg Research Centre
Cartographic focus on Precision Mapping



Developing a cartographic understanding and methodology for producing precision maps with varying level of detail to support local, technology-oriented farmers, scientists, and authorities in making spatial decisions

Outline

Fig. 1 Leaf Reddening – unspecific symptom of AP

Introduction

Research Scope | Research Objectives

developing a reproducible, data-driven and non-invasive mapping strategy

- entire data life cycle, from ’cradle to adolescence’
- Multi-modal data acquisition (ground/airborne)
- Multi- and hyperspectral data
- Image classification -> Machine Learning
- Spatial Data Infrastructure -> Open Science, FAIR data principles

Case Study: Apple Proliferation in South Tyrol

Not:
- plant pathology;
- investigation of plant stressors;
- feasibility study

Introduction

Research Scope | Research Objectives

Research Objectives	
RO.1	Develop a cartographic understanding and definition for a precision map.
RO.2	Identify relevant spectral bands and VI that meaningfully discriminate between leaves infected from AP vs. uninfected leaves (binary and multi-class discrimination).
RO.3	Implement a robust and reproducible image classification procedure based on a machine learning approach specifically for the identification of AP on varying levels of detail (at the leaf, tree, and orchard level).
RO.4	Establish a mapping technique to produce precision maps dedicated to AP on different levels of detail.

Foundations and State of the Art

(1 / 4) - Remote Sensing in Precision Agriculture

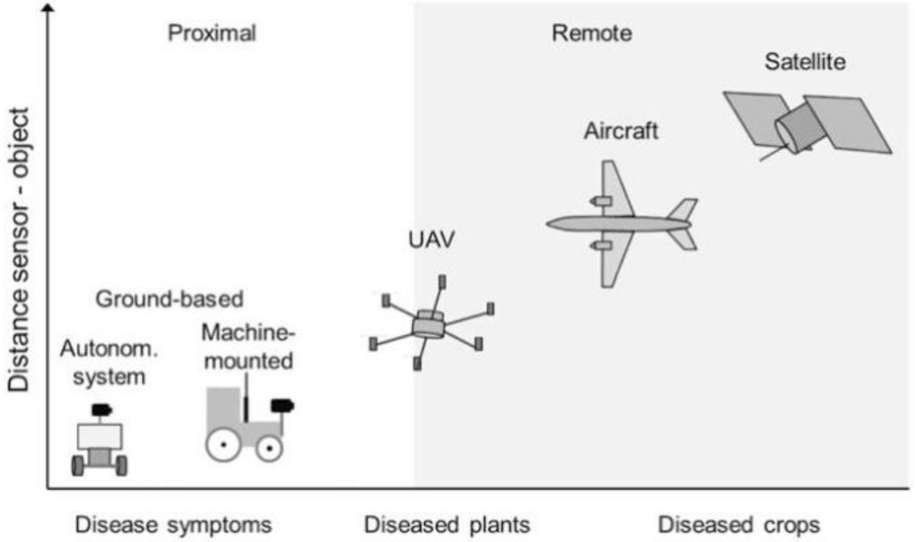


Fig. 3 Proximal and remote sensing platforms

Since 1980s

GPS, GIS, Remote Sensing

Initially yield mapping

Vegetation Indices

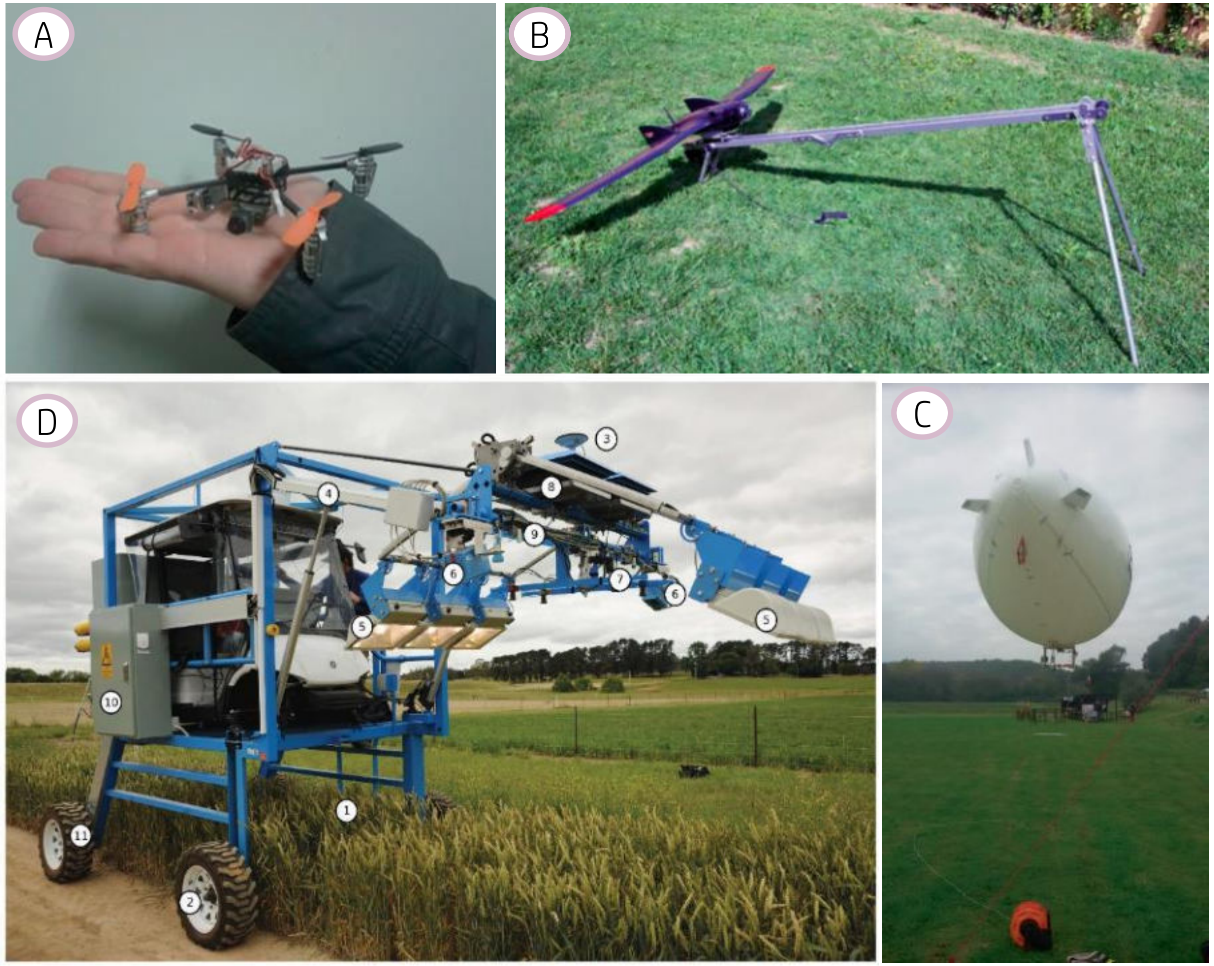


Fig. 4 Sensing Platforms (A-C: small drones; D: Phenotyping Buggy)

Foundations and State of the Art

(2 / 4) - Plant Disease Detection and Mapping based on Hyperspectral Data

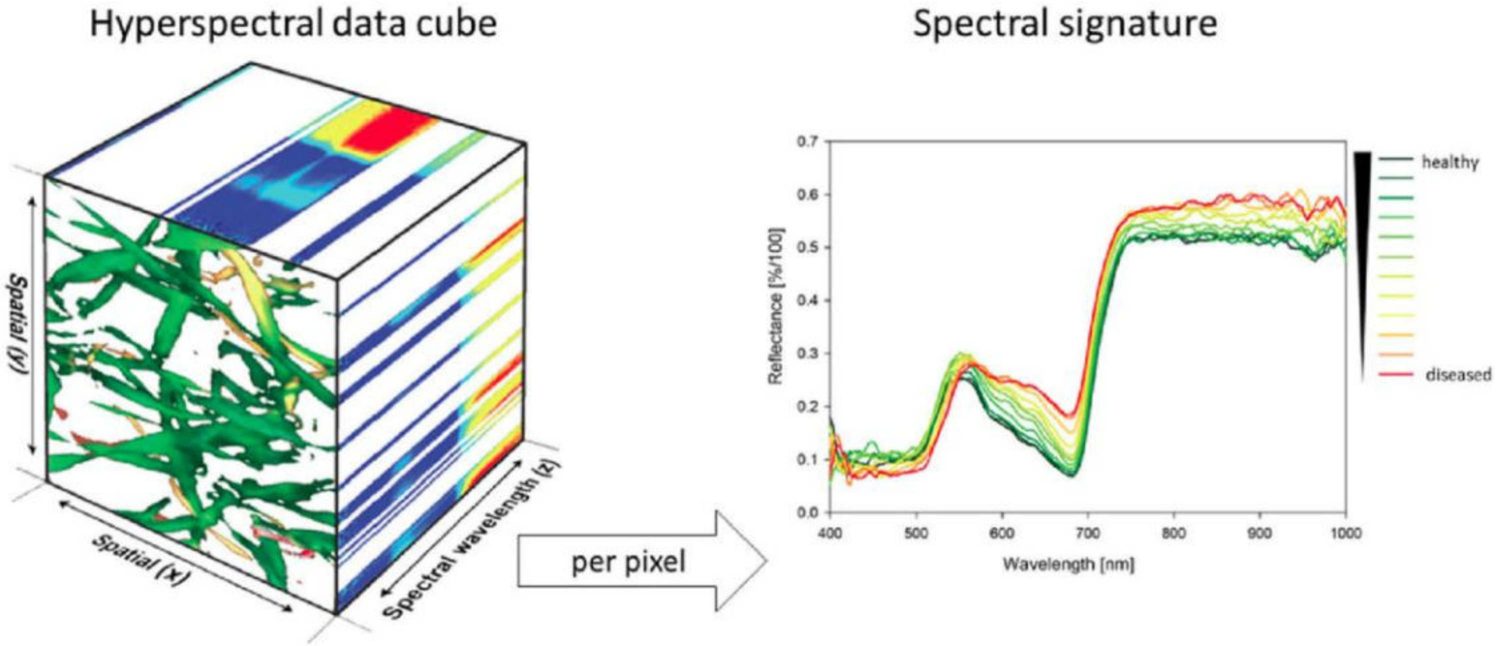


Fig. 7 Illustration of a hyperspectral data cube

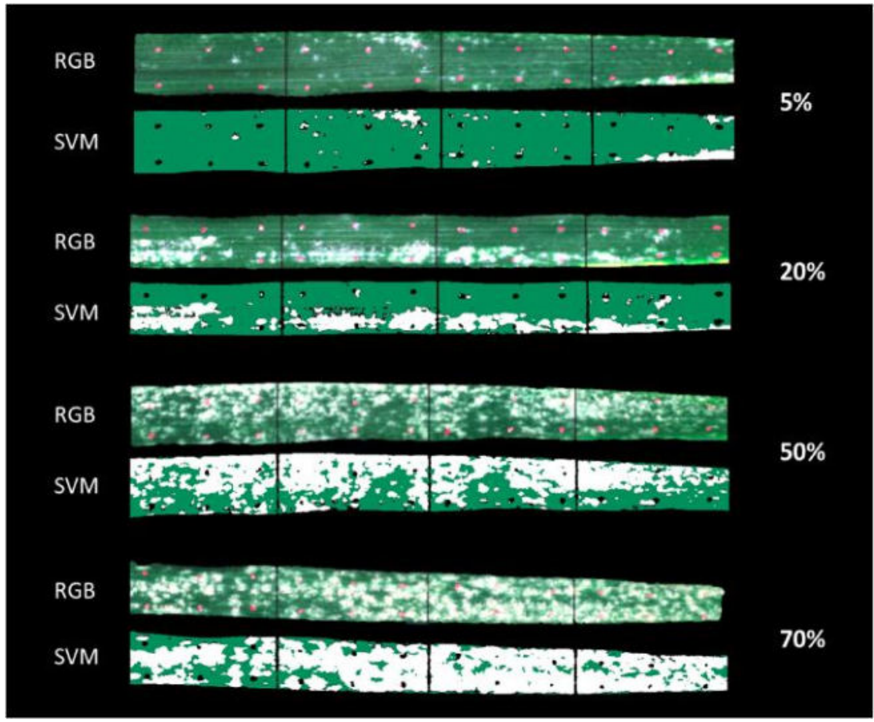


Fig. 9 RGB false composition of wheat leaves with symptoms of powdery mildew & SVM classification of hyperspectral data

Broadband Multispectral | Narrowband Hyperspectral

Foundations and State of the Art

(3 / 4) - Precision Mapping and Cartography

HD maps, precision maps, high-resolution maps, .. -> precision mapping ill defined

Vegetation index map = precision map?

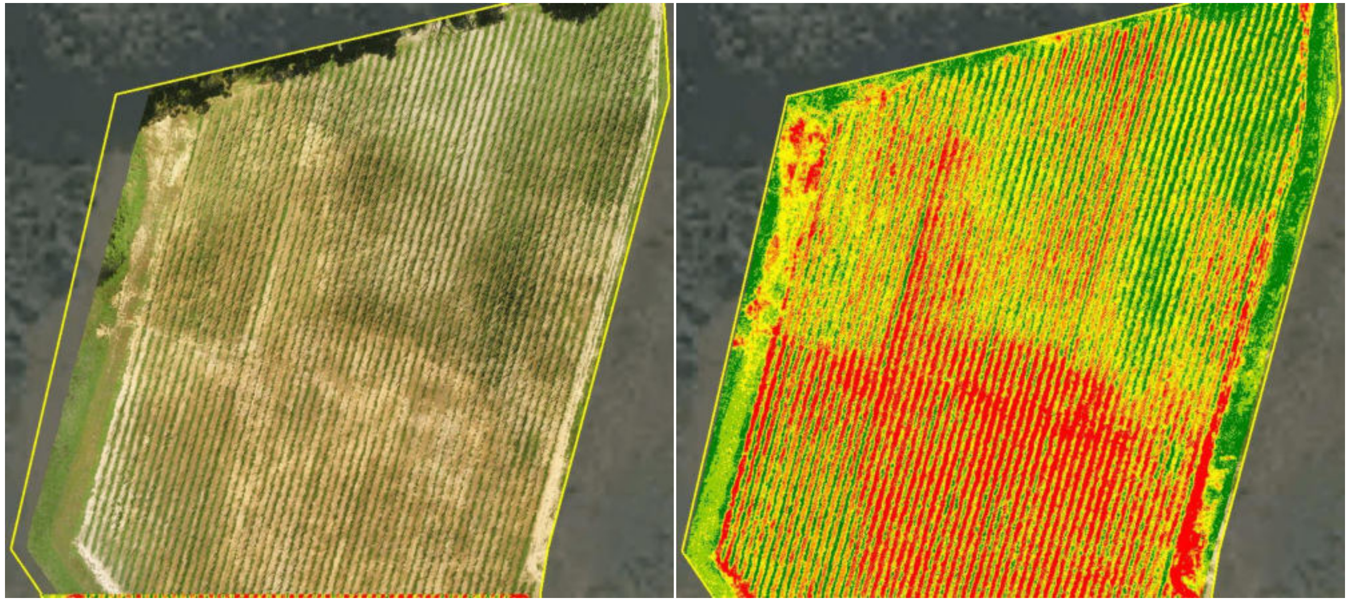


Fig. 10 UAV imagery and corresponding NDVI classification as Vegetation Index Map

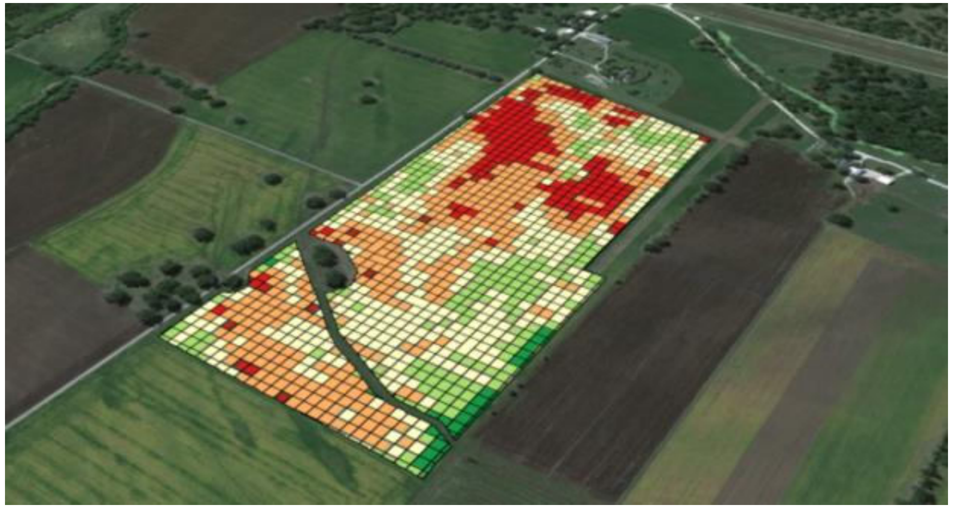


Fig. 11 VI classification represented as regular grid

Foundations and State of the Art

(3 / 4) - Precision Mapping and Cartography

Cartographic generalisation -> raison d'etre of a map

Robinson, 1995

Precision: spatial granularity at which distinctions can be made by a sensor

Resolution: degree of detail to which a phenomenon is detected or represented

Scale: measure of relative size, of objects or representations

Raposo, 2017

Multi-scale -> cartographic generalization at various supported scales

Roth et al. 2011

Foundations and State of the Art

(4 / 4) - Overview of Apple Proliferation Research

Fig. 12 Small fruits - an unspecific symptom of apple proliferation

Fig. 13 'Witches' broom' – AP disease specific symptom

Fig. 14 Example of an adult female of C. picta and of C. melanoneura

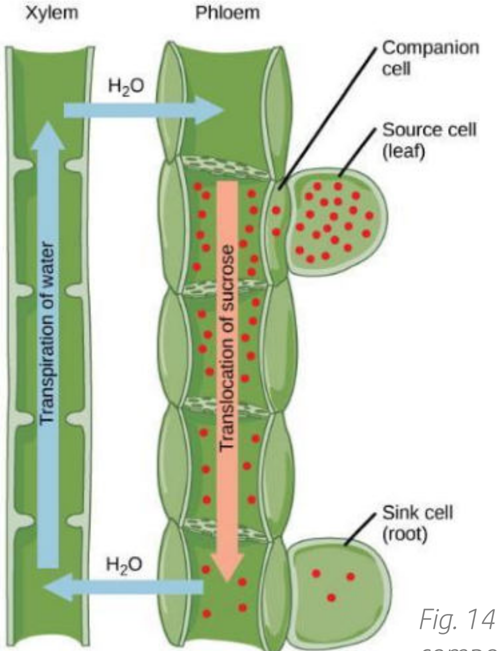


Fig. 14 Schema of the Xylem and Phloem, their fundamental components and processes

Phytoplasmal disease
Cell wall less bacterium
Insect vector specific (saliva)

~1950s South Tyrol
Ministry decree in 2006

Resides in phloem

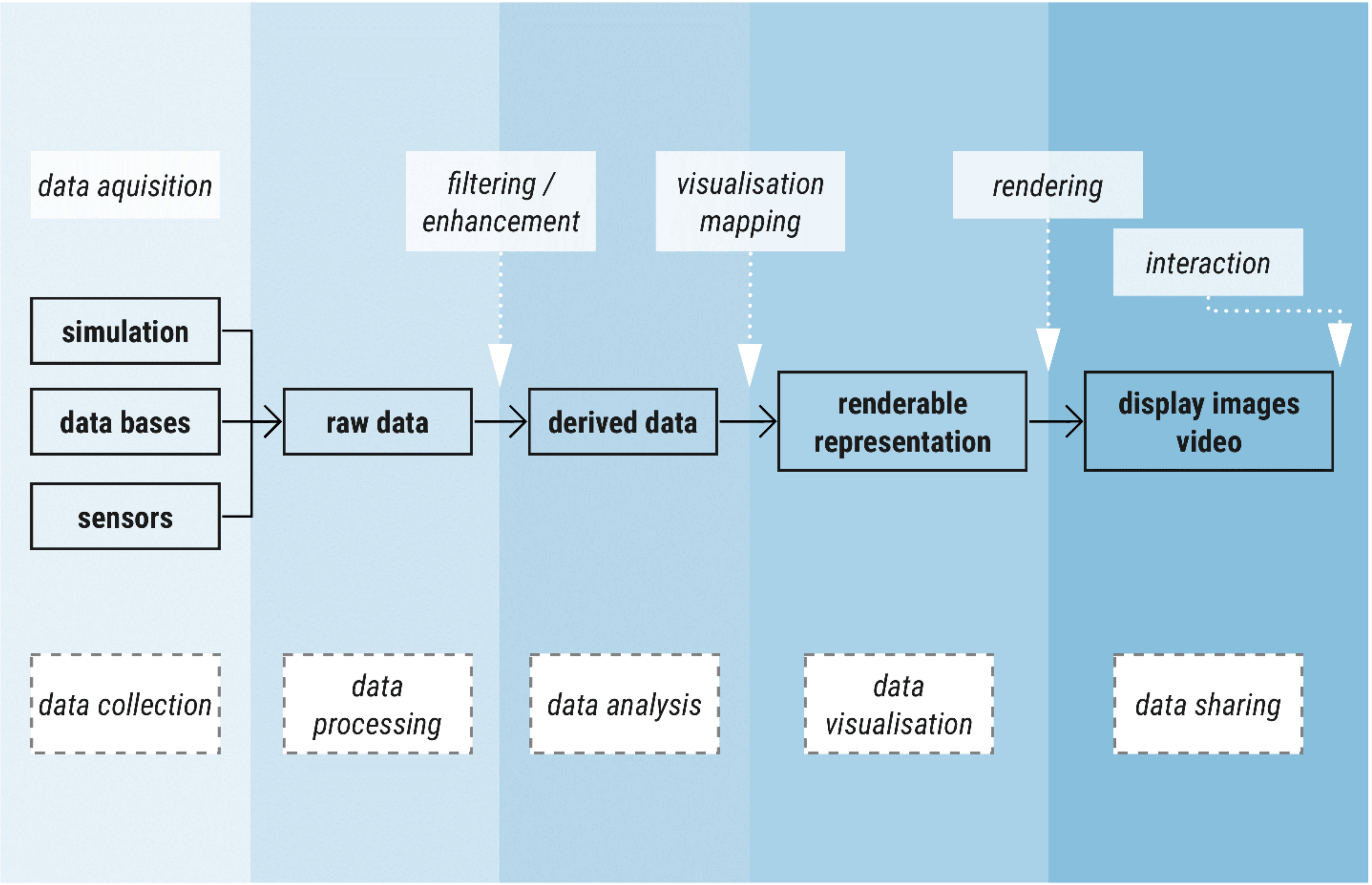
Disruption of plant metabolism
- Chlorophyll decline
- Sugar agglomeration

Leaf-reddening

Grafting

Latency | Recovery

Methodology



Case Study

data collection | ~ processing | ~ analysis | ~ visualisation | ~ sharing

Leaf level | **Orchard level**

data collection

Leaf hyperspectral signature acquisition (Spectroradiometer)
↓
Tree-wise Sampling { 1 Reference Scan; ~10 Target Scans

Calibration of cameras { Multispectral; Hyperspectral
↓
UAV flights & image acquisition

4 field campaigns
(April, May, June, July)

Fig. 16 (A) SVC HR-1024i and (B) LC-RP PRO

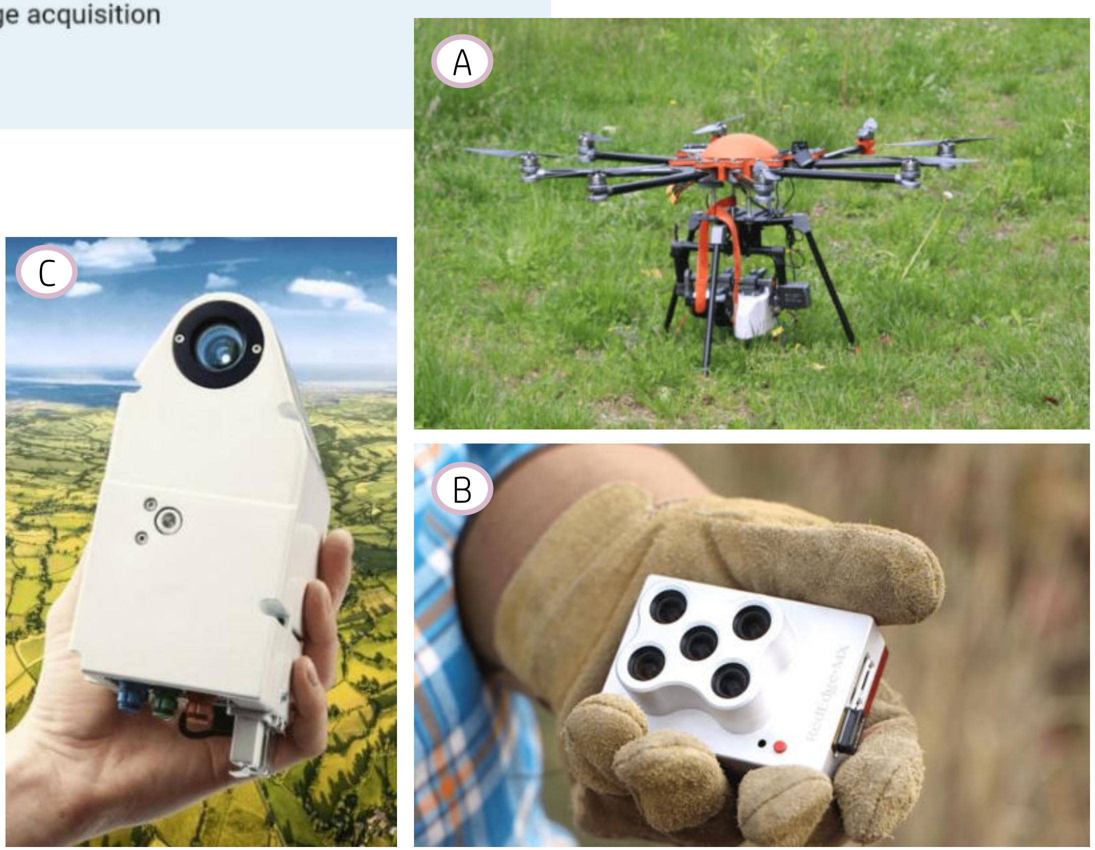
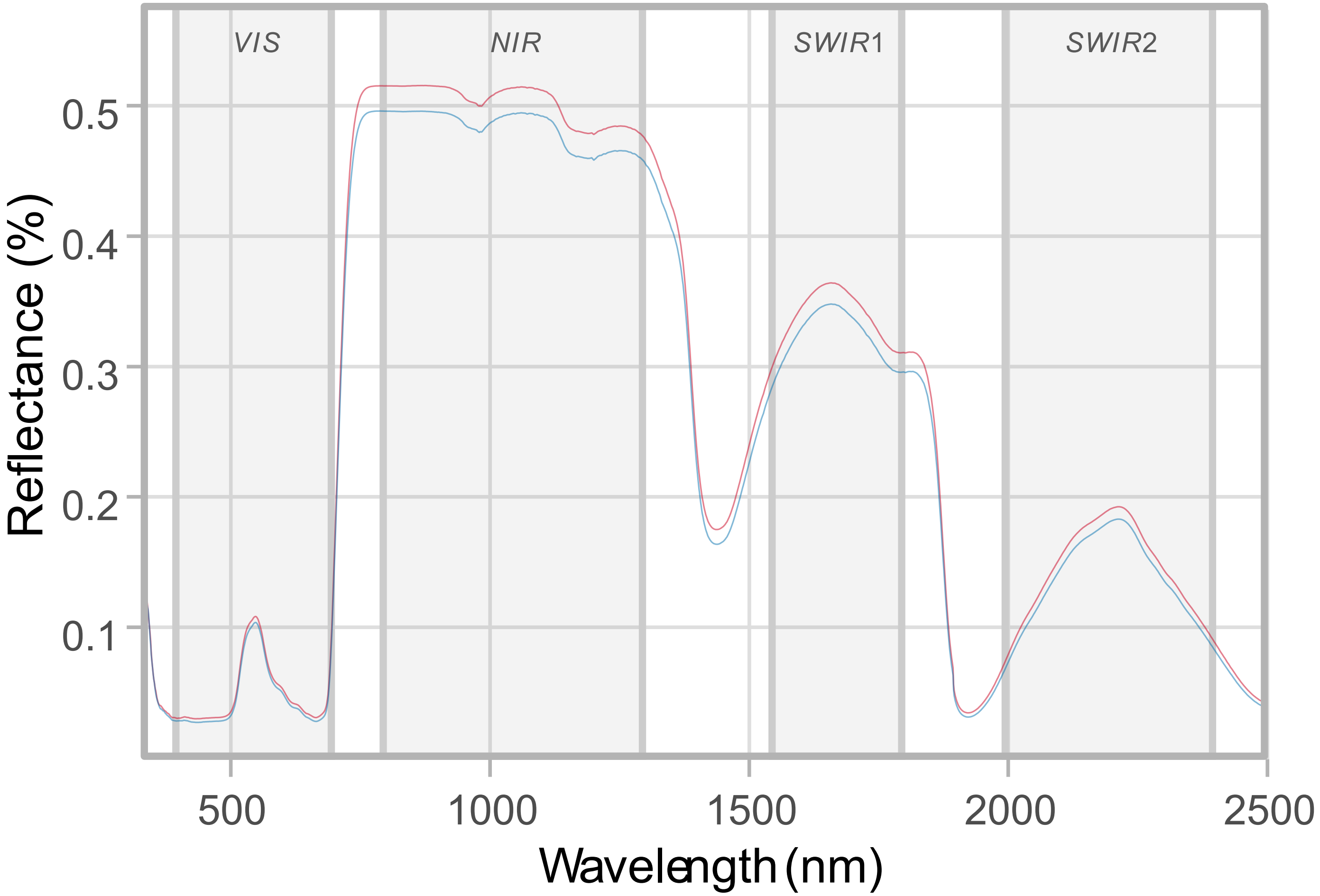
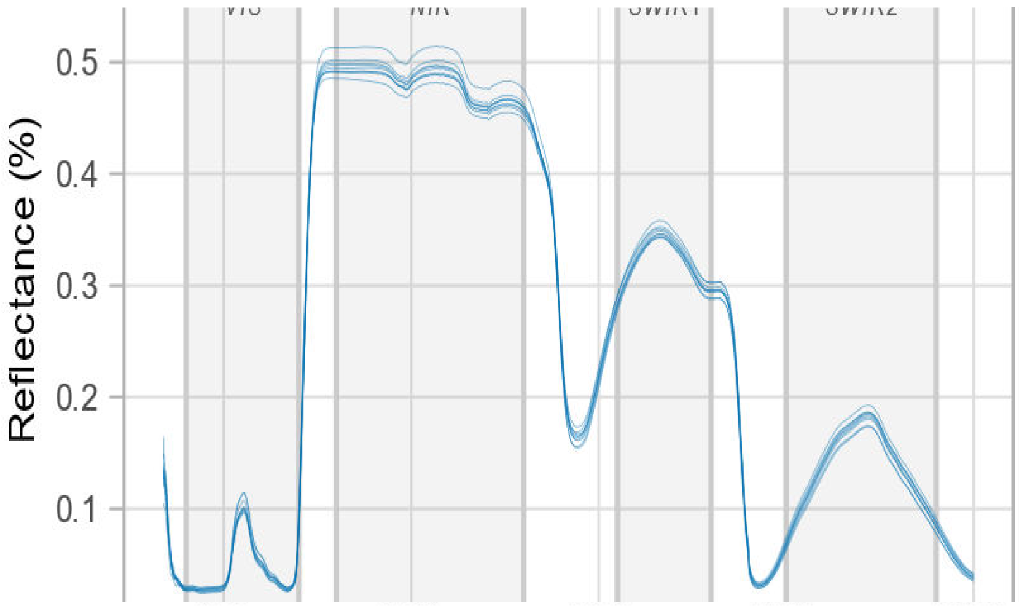


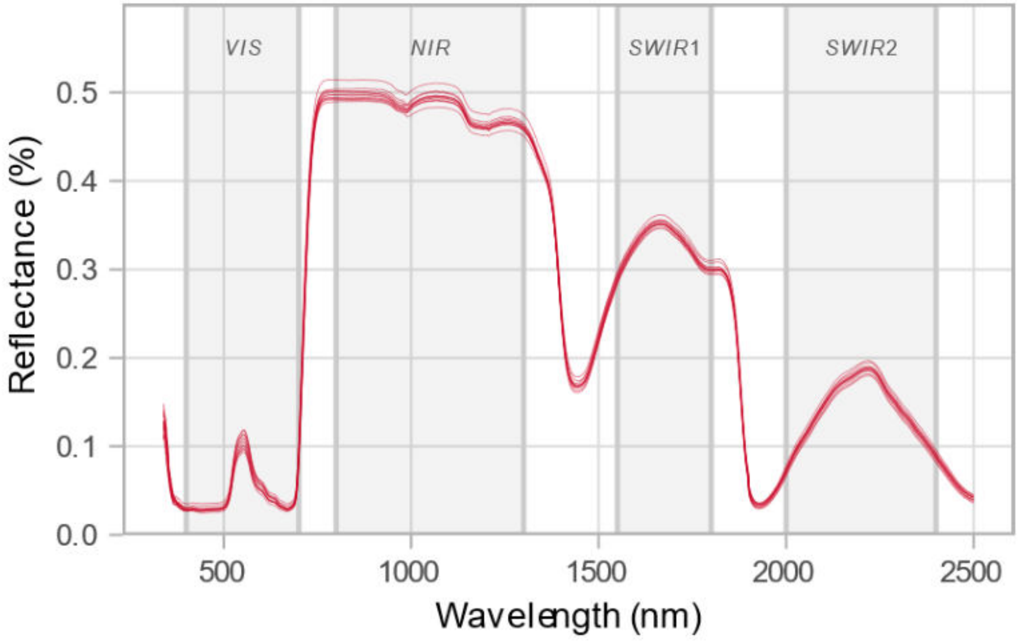
Fig. 17 (A) Soleon Octocopter; (B) MicaSense Red Edge and (C) Rikola hyperspectral camera



Spectral Signatures of uninfected trees (means)



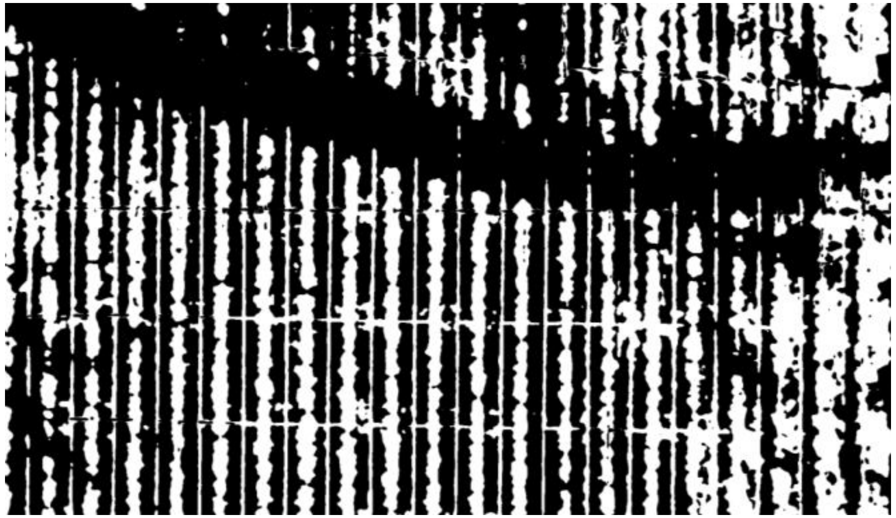
Spectral Signatures of infected trees (means)

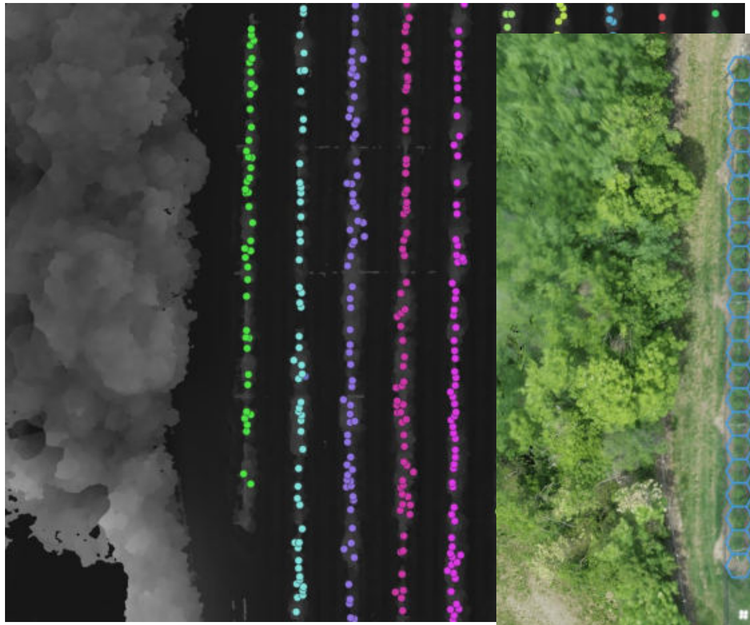


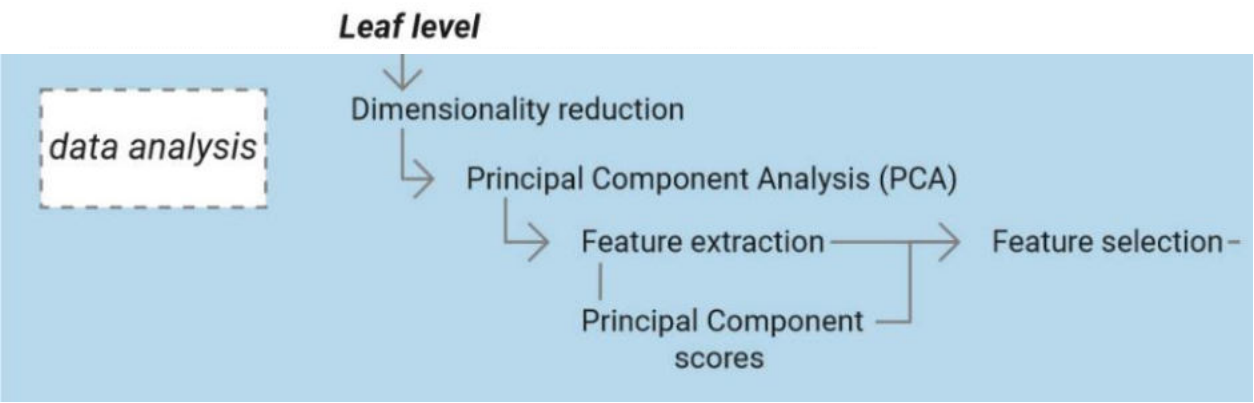
data processing

Orchard level

- Radiometric correction
- Orthorectification
- Image Stitching & Orthomosaicing
- Georeferencing
  - Computation of Canopy Height Model
    - *ideally*: vectorisation of single trees (object-oriented mapping)
    - Vectorisation of tree rows
      - approximate midline of tree rows
        - computation of hexagonal grid







Chlorophyll a

Chlorophyll b

Cellulose (~1820 nm)
Sugars (~1780 nm)

oils (~ 1040 nm) and lignin (~1120 nm)

Entire Dataset

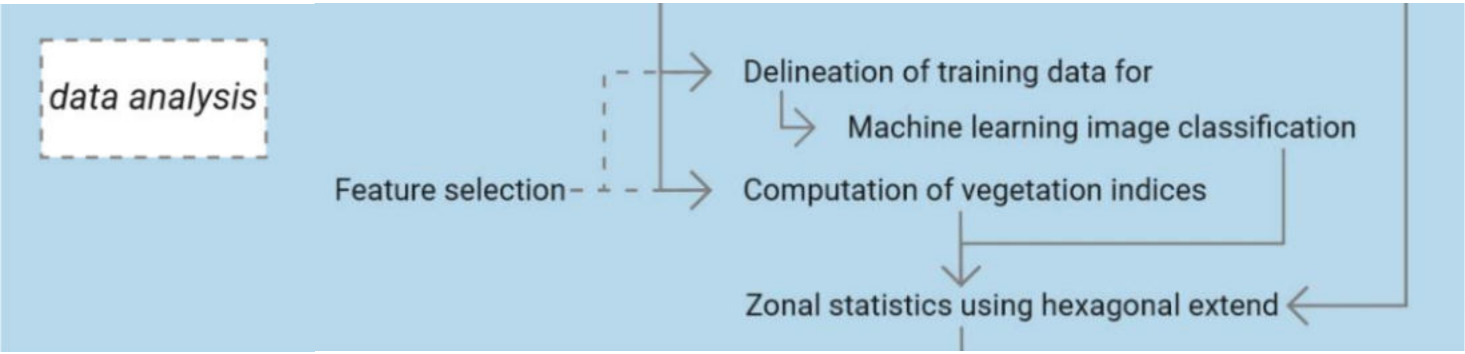
Field Campaign	2nd	3rd	4th
Date	18.05.21	23.06.21	21.07.21
PC1	1850-1859	1788-1799	1839-1847
PC2	1077-1105	1077-1086	1079-1085
PC3	645-654	645-655	630-645
PC4	554-563	702-711	707-716
PC5	1884-1890	400-413	683-690

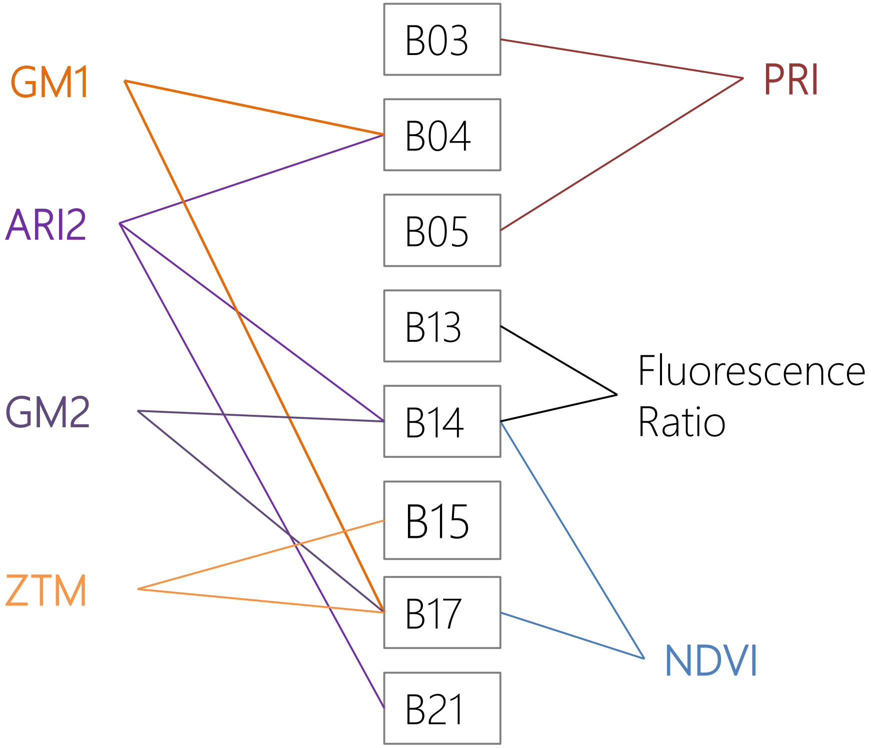
Subset (HS Camera Window - 500-900)

Field Campaign	2nd	3rd	4th
Date	18.05.21	23.06.21	21.07.21
PC1	731-743	731-743	734-746
PC2	889-910	522-531	504-516
PC3	716-727	674-686	710-722
PC4	680-690	684-706	682-694
PC5	517-526	639-652	711-723

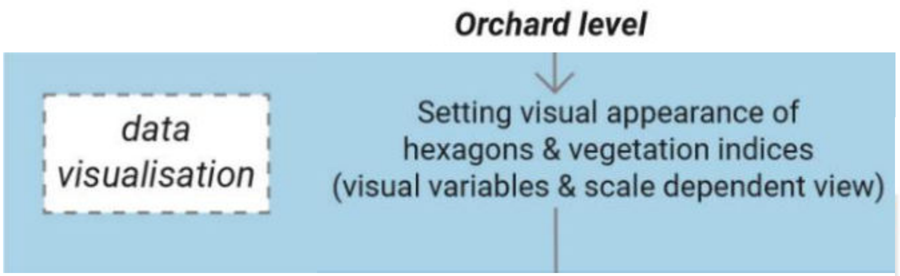
chlorophyll fluorescence

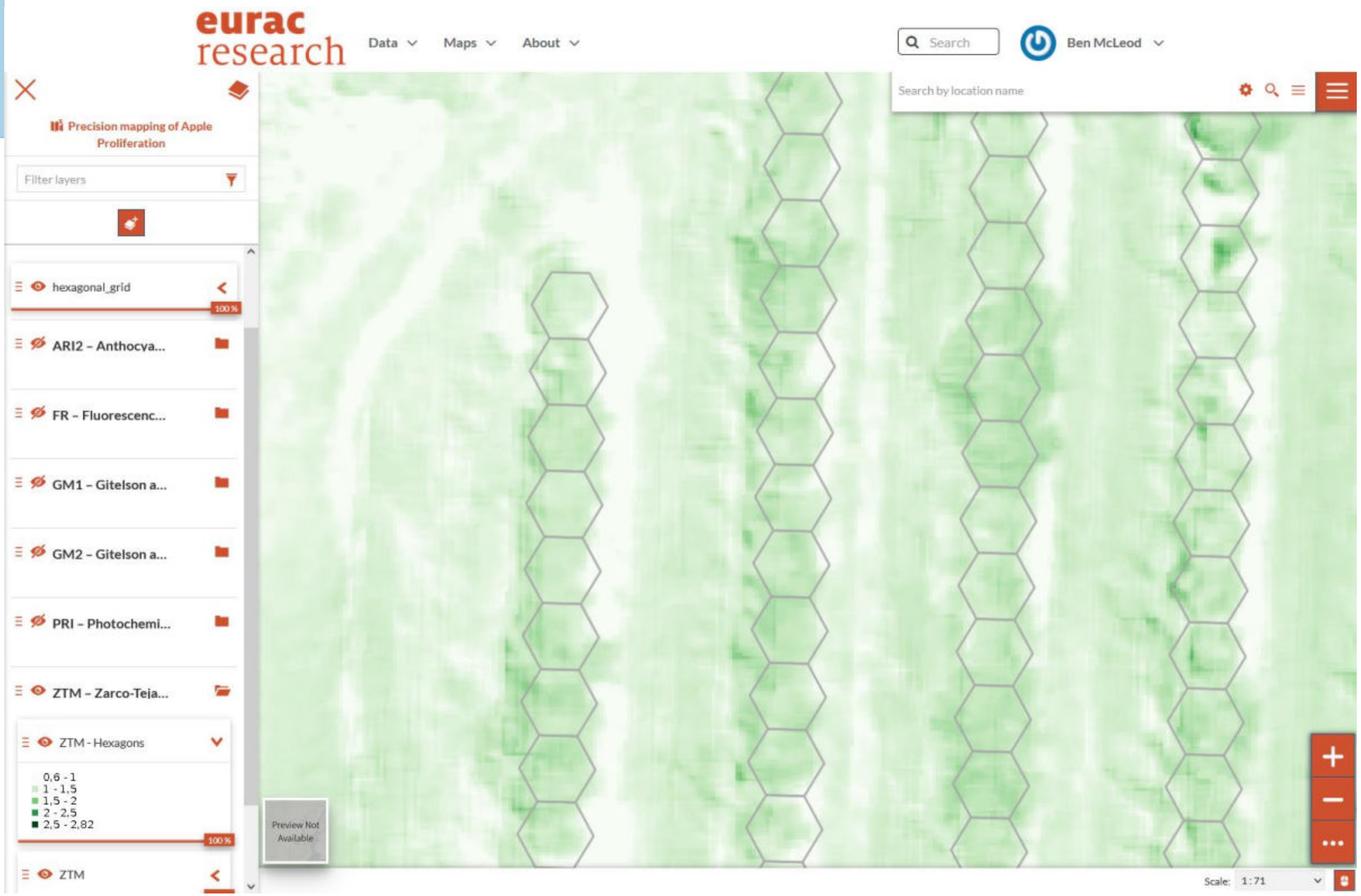
Orchard level





Rikola Waveband	Wavelength (in nm)	fwhm (in nm)	Ideal wavelength used for VI (in nm)	2nd campaign	3rd campaign	4th campaign
1	506.285	9.84				PC2
2	521.498	14.62		PC5	PC2	PC2
3	536.468	11.51	531		PC2	
4	551.474	10.06	550			
5	566.249	9.76	570			
6	581.498	14.01				
7	596.211	12.53				
8	611.086	17.53				
9	625.943	16.4				
10	645.258	12.74			**PC5**	
11	656.031	12.85				
12	671.165	16.08			PC3	
13	686.279	15.14		**PC4**	PC3/4	PC4
14	701.45	11.25	700		PC4	
15	716.158	11.92	710	PC3		**PC5**
16	731.318	10.53		**PC1**	**PC1**	**PC1**
17	746.096	10.27	750			**PC1**
18	761.157	15.64				
19	776.245	13.97				
20	791.462	12.81				
21	806.339	14.67	800			
22	820.873	15.0				
23	835.804	21.04				
24	850.597	25.85				
25	866.602	24.49				
26	881.009	20.16		PC2		
27	896.406	22.87		PC2		


Orchard level
data visualisation
Setting visual appearance of hexagons & vegetation indices (visual variables & scale dependent view)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Data
Maps
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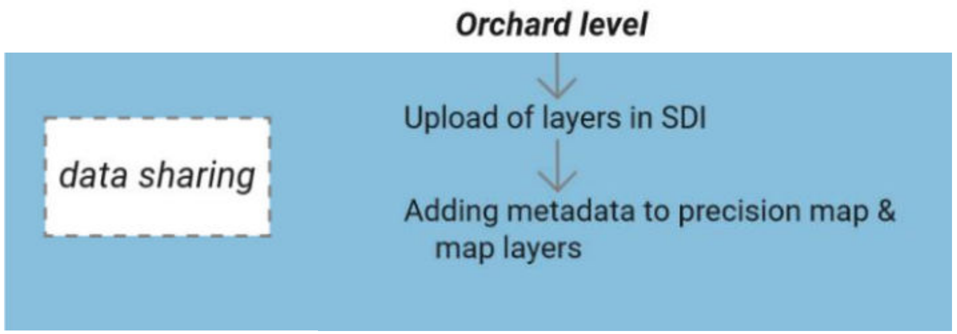
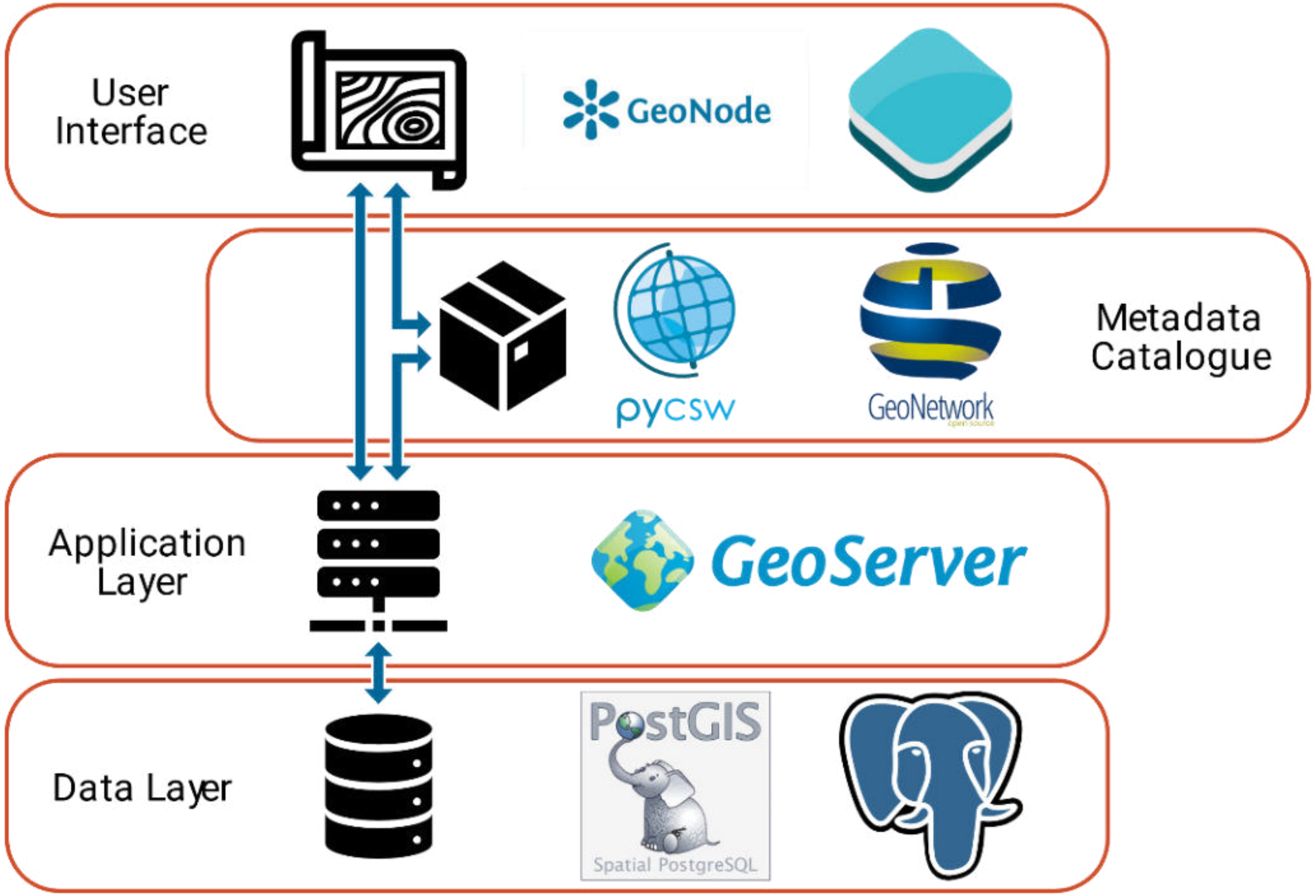
Filter layers
Search by location name
hexagonal_grid
100 %
ARI2 – Anthocya...
FR – Fluorescenc...
GM1 – Gitelson a...
GM2 – Gitelson a...
PRI – Photochemi...
ZTM – Zarco-Teja...
ZTM - Hexagons
0,6 - 1
1 - 1,5
1,5 - 2
2 - 2,5
2,5 - 2,82
100 %
ZTM
Preview Not Available
Scale: 1:71



Environmental Data Platform



Results

RO.1 | RO.2 | RO.3 | RO.4

RQ.1 How can a precision map be defined from a cartographic understanding?

A Precision Map is a

‘*sensor-driven, interactive, thematic map*

that offers different degrees of granularity at multiple-scales’.

Shneiderman’s (1996) visualisation mantra:

‘*Overview first, zoom and filter, then details on demand*’

Results

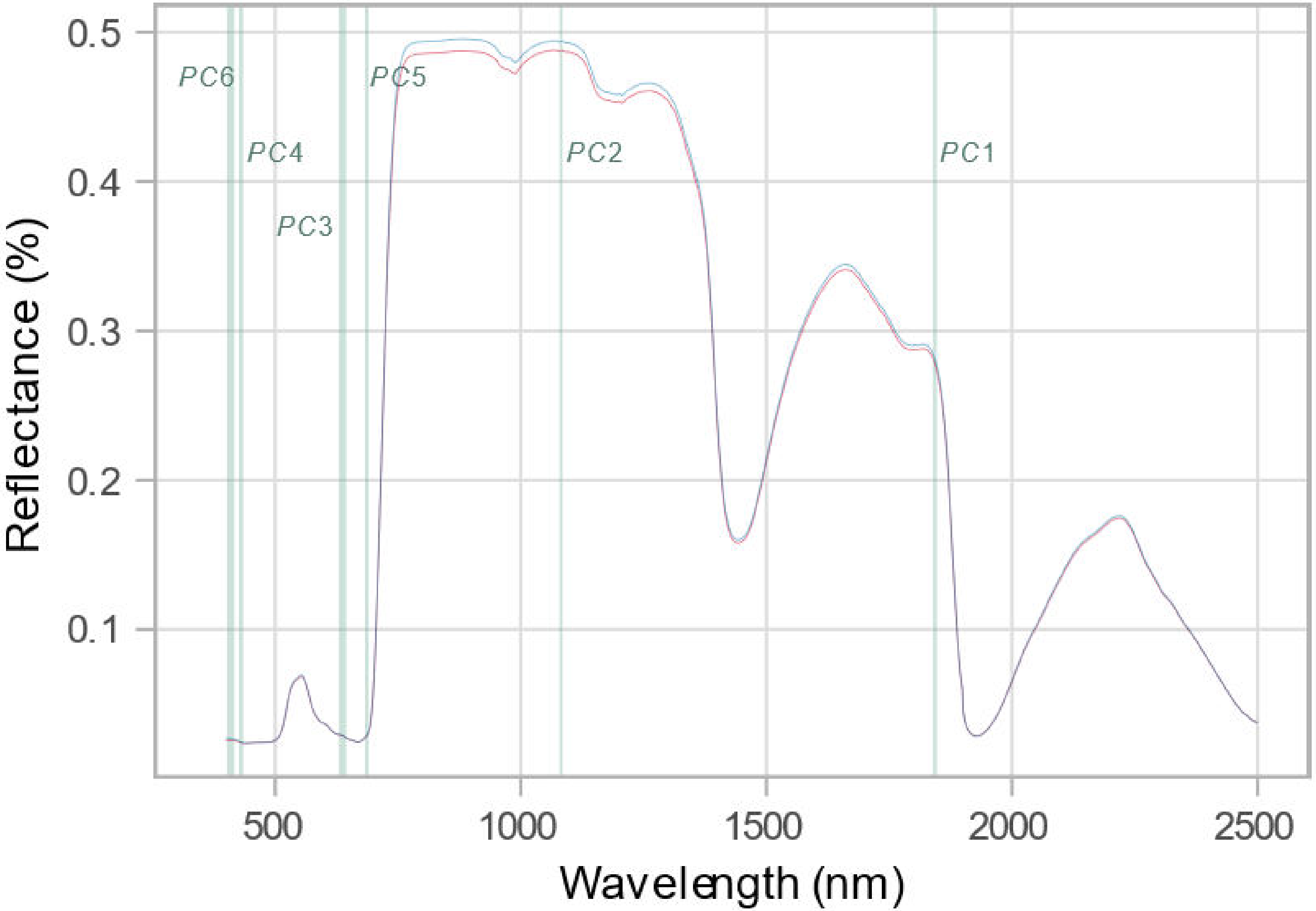
RO.1 | RO.2 | RO.3 | RO.4

RQ.2 Which meaningful spectral bands from the hyperspectral range and which vegetation indices can be identified, or computed, respectfully, from the spectral signature of a diseased leaf to reflect changes caused through AP?

May

June

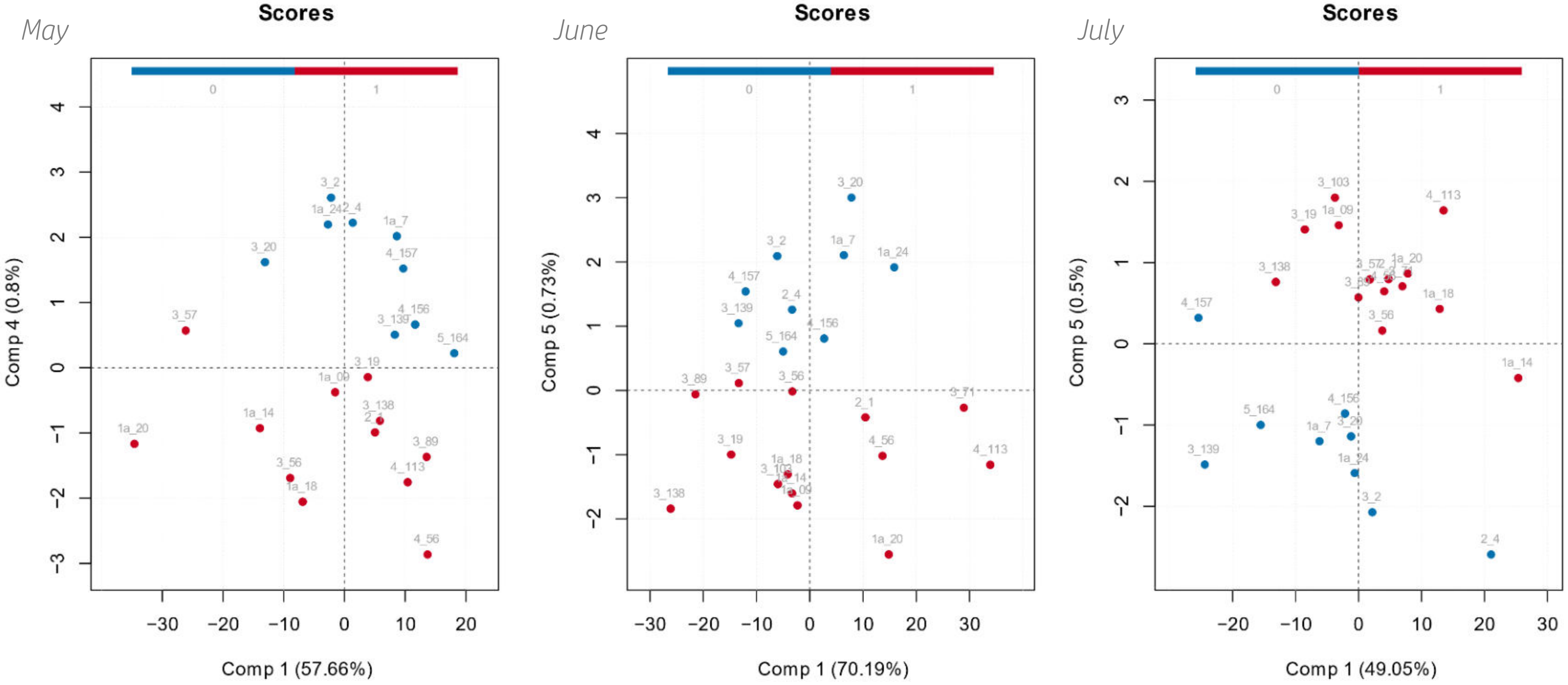
July



Results

RQ.1 | RQ.2 | RQ.3 | RQ.4

RQ.2 Which meaningful spectral bands from the hyperspectral range and which vegetation indices can be identified, or computed, respectfully, from the spectral signature of a diseased leaf to reflect changes caused through AP?



AP-infected trees
AP-uninfected trees

Results

RO.1 | RO.2 | RO.3 | RO.4

RQ.3 Which machine learning approach produces a robust multi-/ hyperspectral image classification for identifying and classifying AP on different scales (leaf, tree and orchard)?

Results

RQ.1 | RQ.2 | RQ.3 | RQ.4

RQ.3 Which machine learning approach produces a robust multi-/ hyperspectral image classification for identifying and classifying AP on different scales (leaf, tree and orchard)?

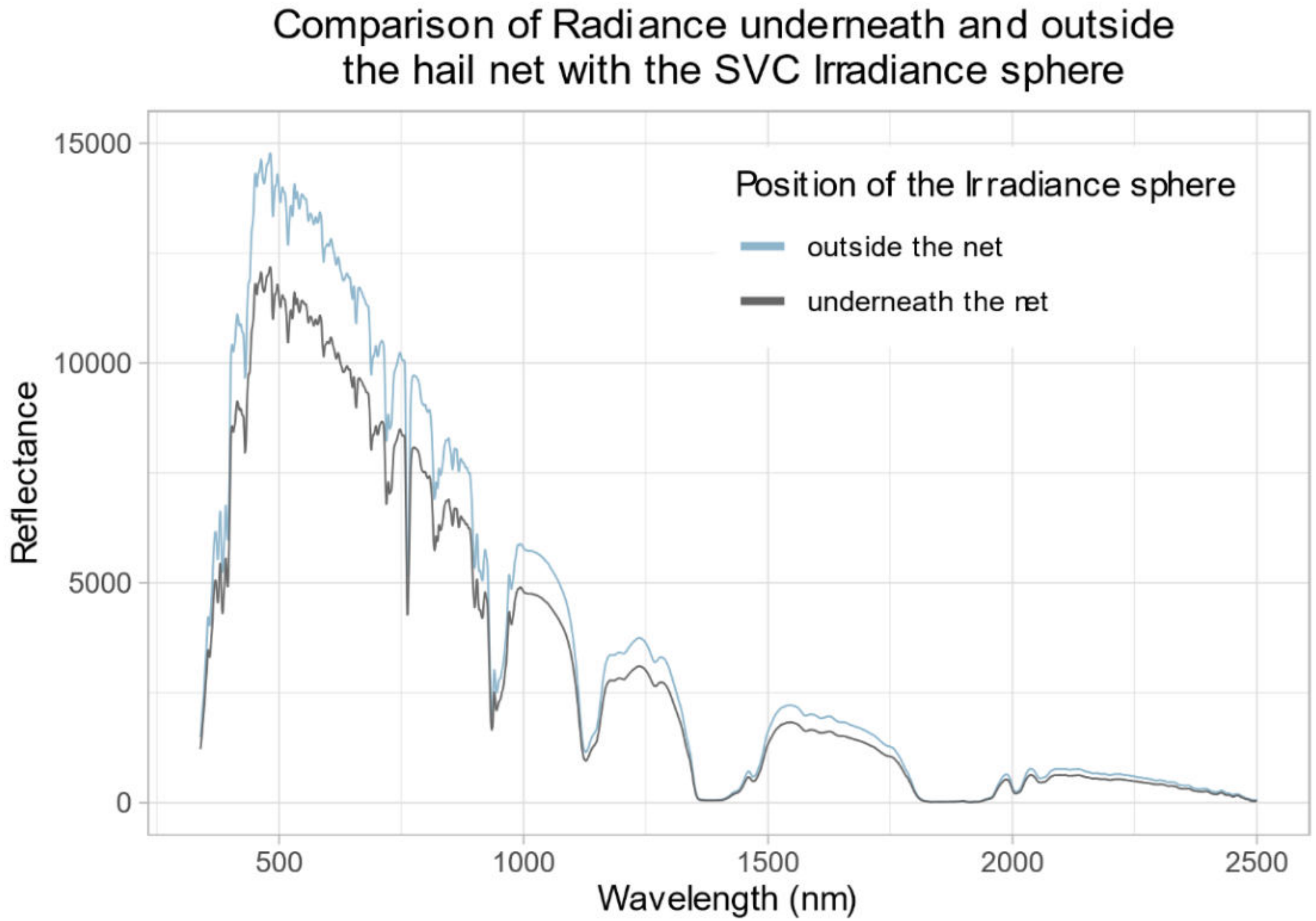
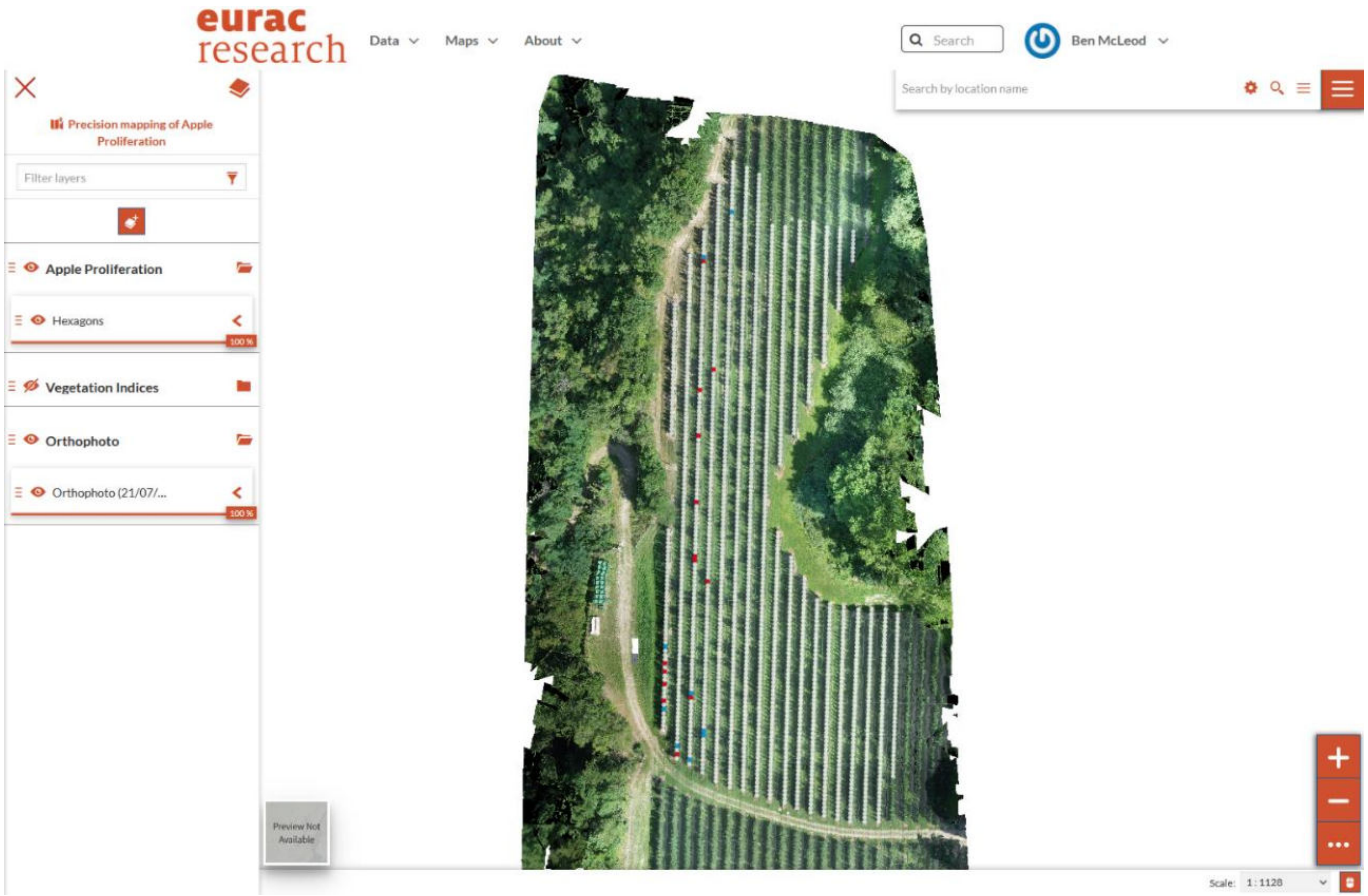


Fig. 18 (A) SVC Direct Connect Full Sky Irradiance Sphere and (B) the SVC-HR-1024i spectroradiometer equipped with the Sphere

Results

RO.1 | RO.2 | RO.3 | RO.4

RQ.4 How can multi-scale data be effectively visualised on various granularity levels?



Discussion

- Contextualising the Spectral Analysis
  - Findings correspond to scientific literature (ex. Al-Saddik 2018; Negro et al. 2020, Barthel et al. 2021)
  - Spectral ranges identified by PCA indicate AP caused biochemical and –physical changes

- Hyperspectral Imaging for AP Detection
  - Alternative detection method (to laboratory, in-field biological testing)
  - Broadband vs. Narrowband (spectral resolution)

↓ Chlorophylls
↓ Photosynthetic activity

↓ Cellulose
↑ Sugars

? Lignin and oils
? Anthocyanins and carotenoids

Discussion

- Precision Mapping
  - UAV = matter of accessibility, affordability, and ultimately, feasibility
  - Social implications (Tsouvalis et al. 2000)
    - map illiteracy, user requirements
    - Participatory mapping?

- Agriculture 4.0 in South Tyrol
  - Technological innovation part of Sust. Dev. / Food security
  - SDI -> collaboration of stakeholders (high degree of parcelling)

‘if you have to rely on this technology you’re not a good farmer’

Limitations and Paths of Future Research

- Data Collection
  - Early disease detection
  - Instrument operability
  - Orchard activities and black hail nets
- Data Processing
  - Scalability of multi-modal data
- Data Analysis
  - Range of the electromagnetic spectrum used for analysis
  - AP specific VI
  - Multi-class Classification
  - Machine learning
- Data Visualisation
  - Data format
  - Cartographic generalization
  - Map use
- Data Sharing
  - Collaborative mapping in agriculture

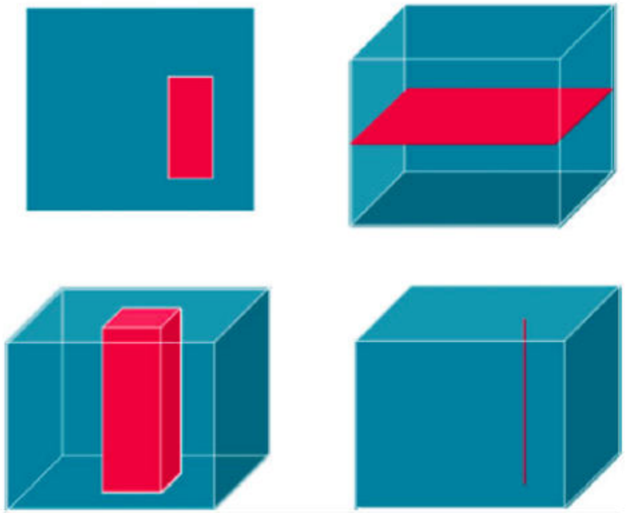


Fig. 20 Data Cube trimming (left) and slicing (right)

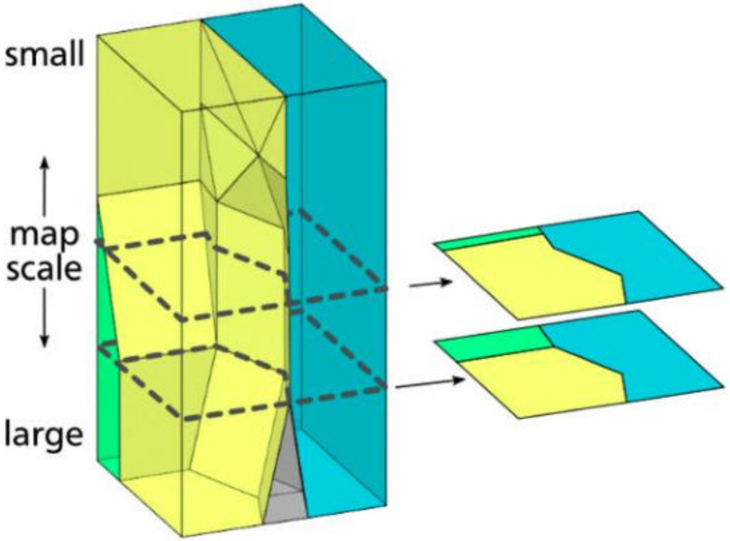
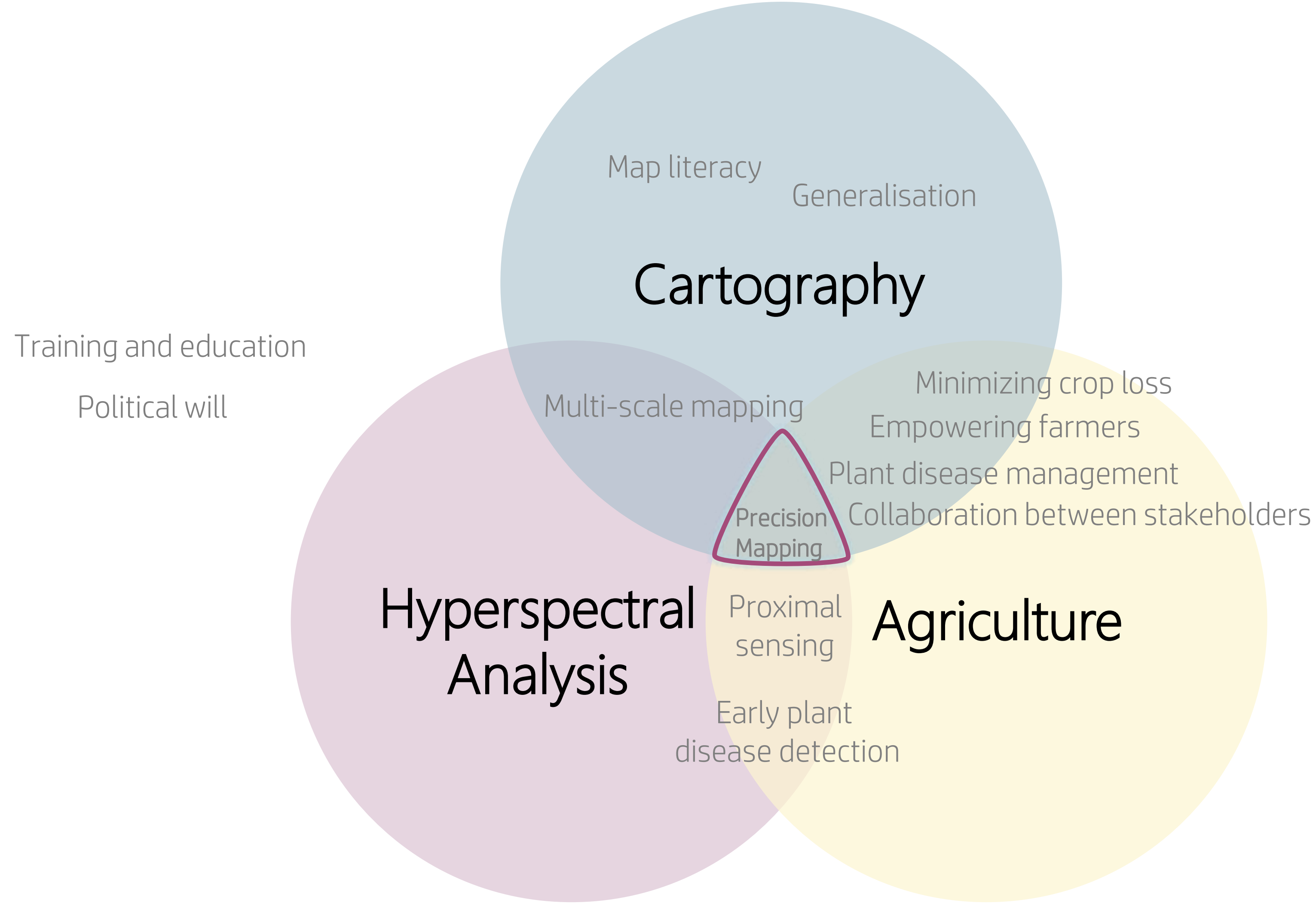


Fig. 19 A 2D map from the Spatial-Scale Cube (SSC)

Conclusion



Expected Contributions

- Fostering the role of Cartography in agriculture
- Defining precision mapping from a theoretical cartographic stance
- Designing a precision mapping methodology
- Develop a tech- & data driven strategy to design pest control more efficient
- Pilot Study
- FAIR and Open Science

Acknowledgments

Erasmus+

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Cartography M.Sc.

Precision Mapping of Apple Proliferation using Multi- and Hyperspectral Data

Thank you for your attention!

Figures

Foundations and State of the Art

(2 / 5) - Remote Sensing in Precision Agriculture

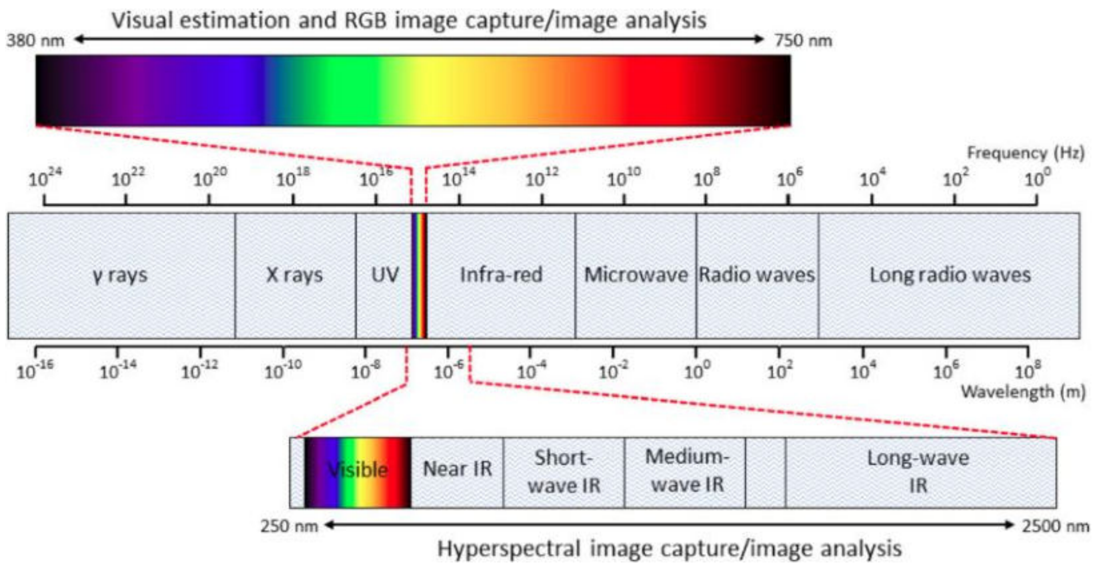


Fig. 5 Electromagnetic spectrum

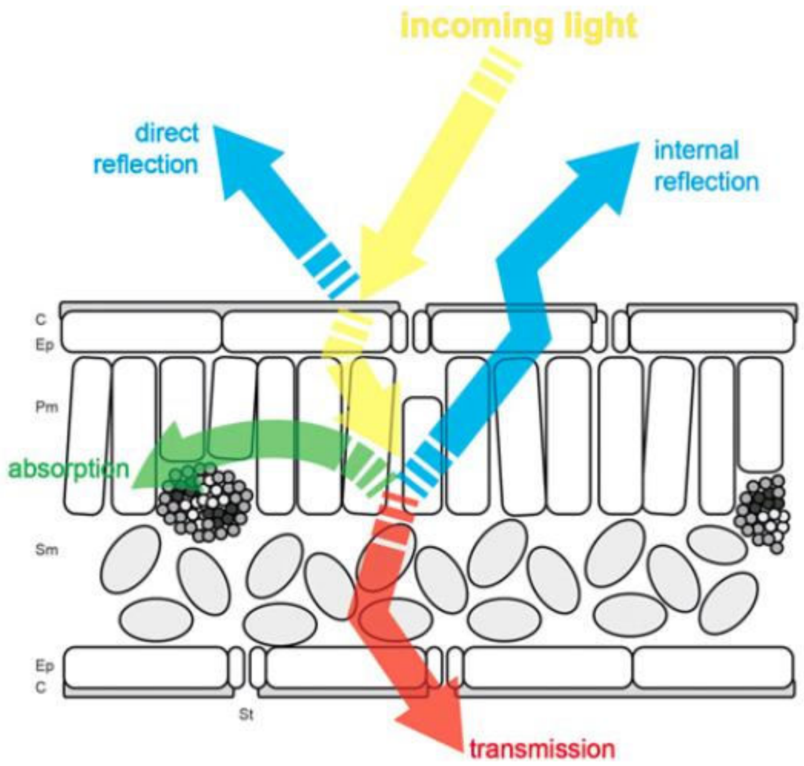


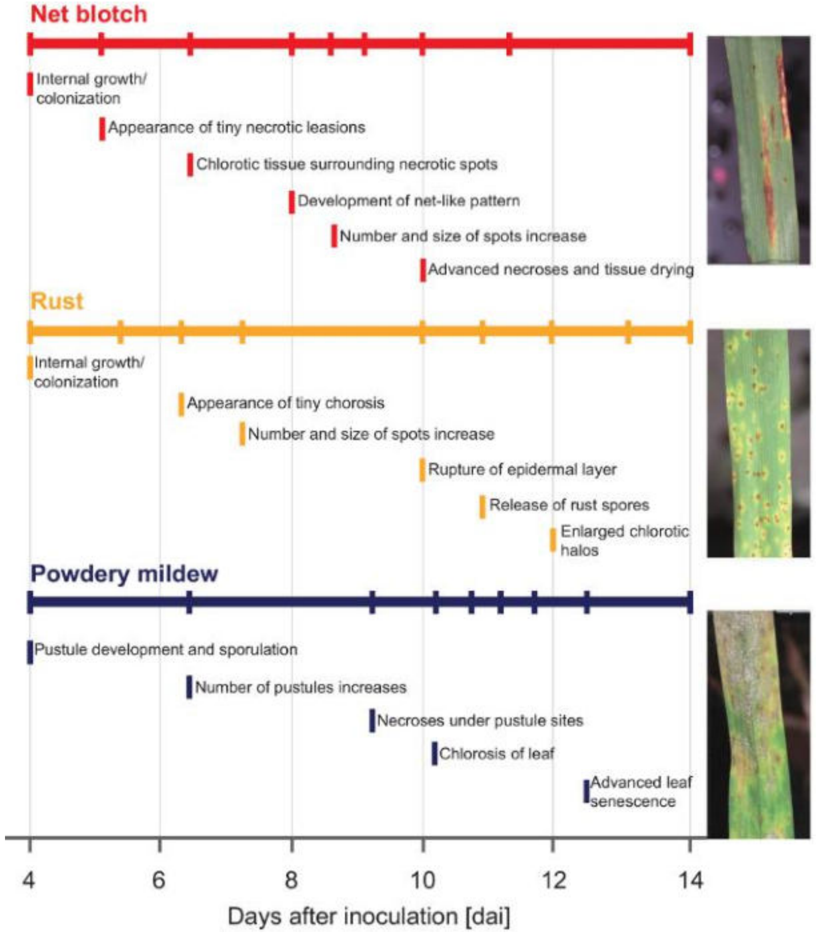
Fig. x6 Profile of a leaf and illustration of light interaction

VIS: 400–700 nm | NIR: 700–1300 nm | SWIR: 1300–3000 nm

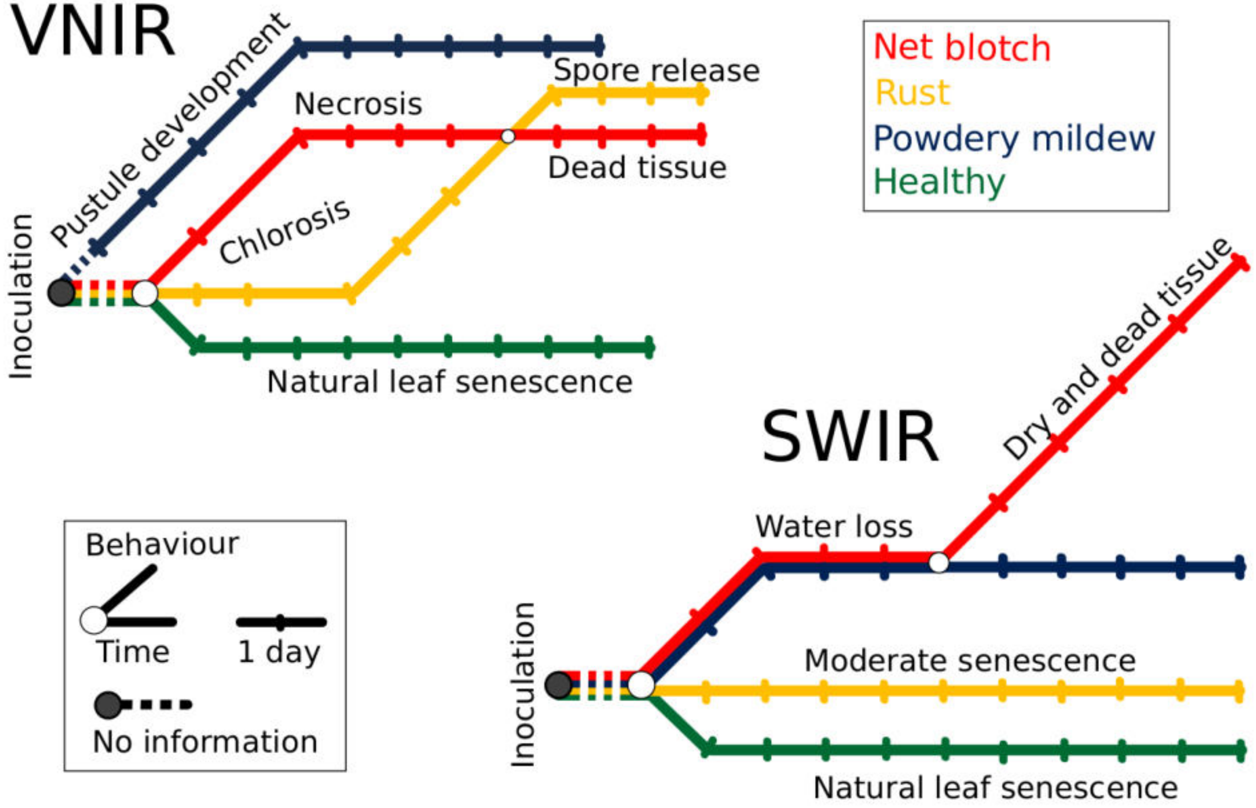
Photochemical pigments (Chlorophylls [a+b], Anthocyanin, Carotenoids)

Foundations and State of the Art

(3 / 5) - Plant Disease Detection and Mapping based on Hyperspectral Data



https://doi.org/10.1371/journal.pone.0116902.g005



https://doi.org/10.1371/journal.pone.0116902.g006

Methodology