From satellite remote sensing to close-range phenotyping: a revolution in traits accessible, data volume and interpretation methods

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Objects of interest, scales and dimensions

- **Focus on objects with dimensions <10 m sensed in the reflective domain:**

part of a field crop

or a microplot for phenotyping

Objects of interest, scales and dimensions

- **Focus on objects with dimensions <10 m such as:**

part of a field crop

or a microplot for phenotyping

- **The 6 dimensions used for object characterizing**

$$Measurement\ ([x, y],\ z,\ \lambda,\ \Omega,\ t)$$

Phenotyping

Imagery ($[x, y]$)

3D (z)

Direction (Ω)

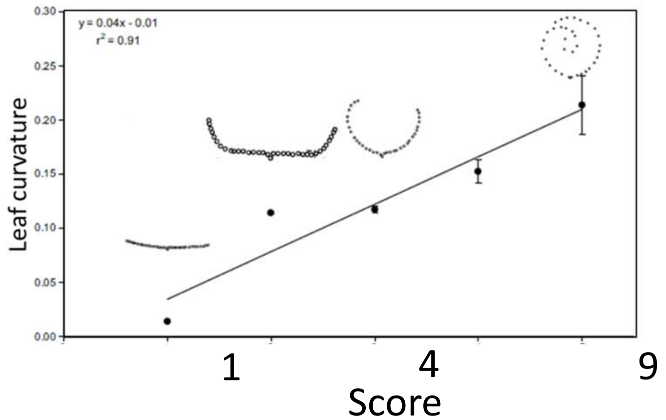
Wavelength (λ)

Time (t)

Satellite

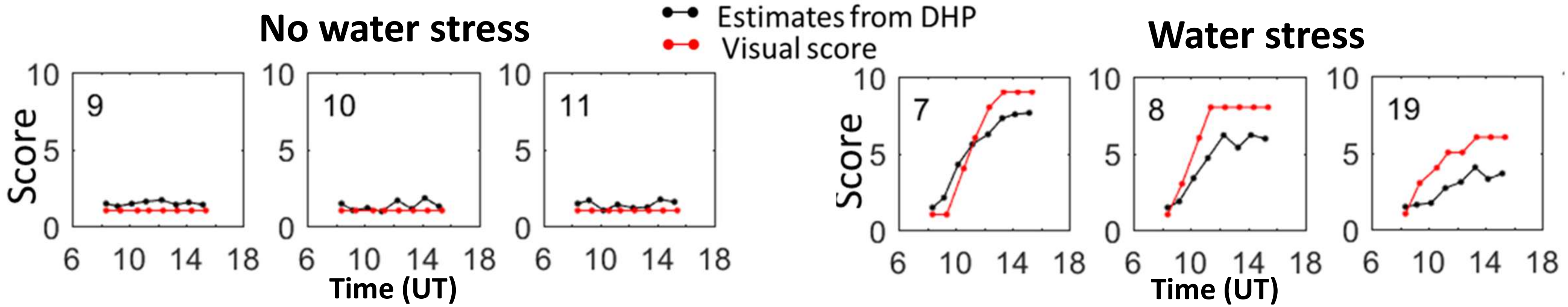
Differences in the common temporal dimension

Phenotyping accesses to the diurnal cycle: IoT, UAVs: Example: leaf rolling



Leaf rolling : a process driven by the leaf water potential

Digital hemispherical photography (DHP) with high spatial resolution



Differences in the common spectral dimension

The spectral dimension is used for 3 types of traits:

1. ***Object identification***

2. ***Abondance quantification***

3. ***Biochemical composition***

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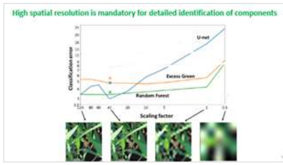
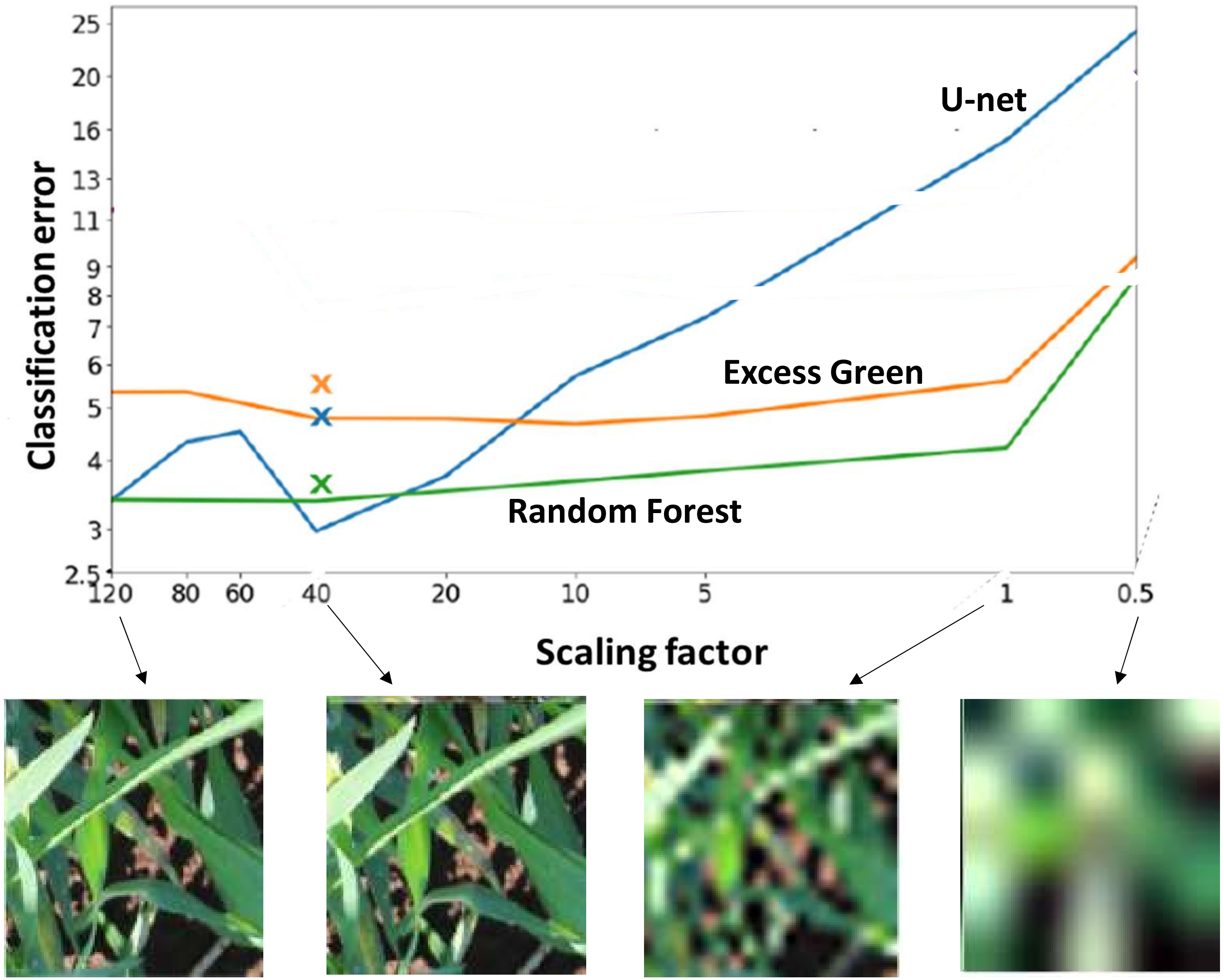
    - Satellite: not possible within the object (limits of the spatial reslution)
    - Phenotyping: possible



2. ***Abondance quantification***:

3. ***Biochemical composition***:

High spatial resolution is mandatory for detailed identification of components



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2. ***Abondance quantification***: generally based on unmixing
   - Satellite: strong assomptions on the mixture and stability of components
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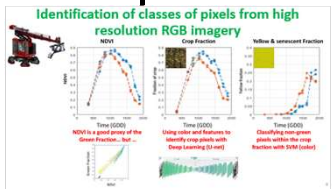
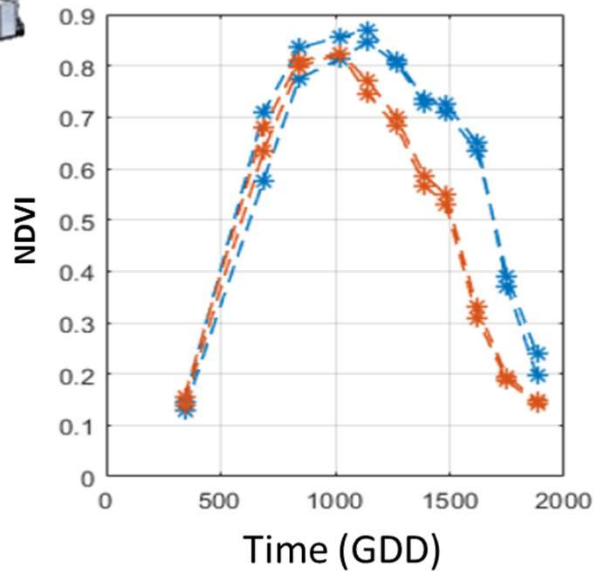
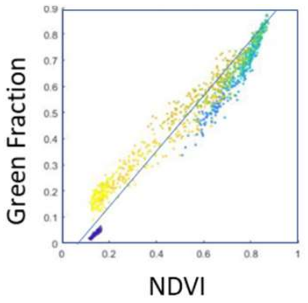


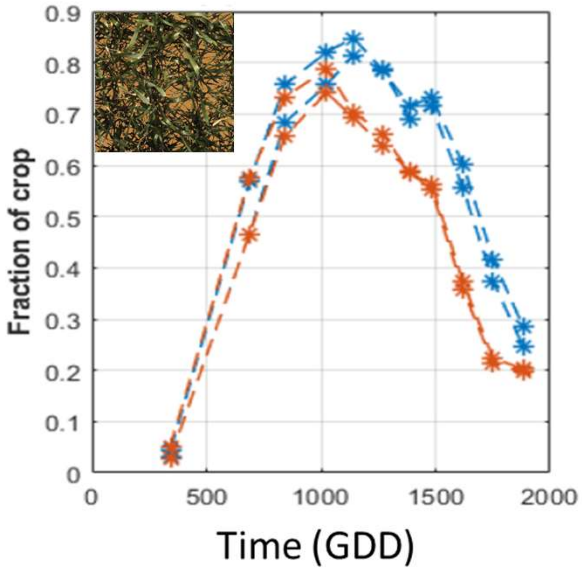
3. ***Biochemical composition***:

Identification of classes of pixels from high resolution RGB imagery

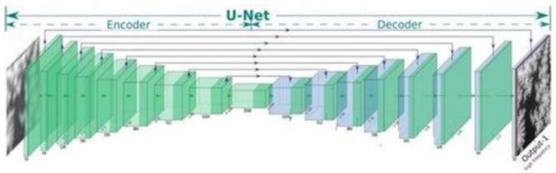


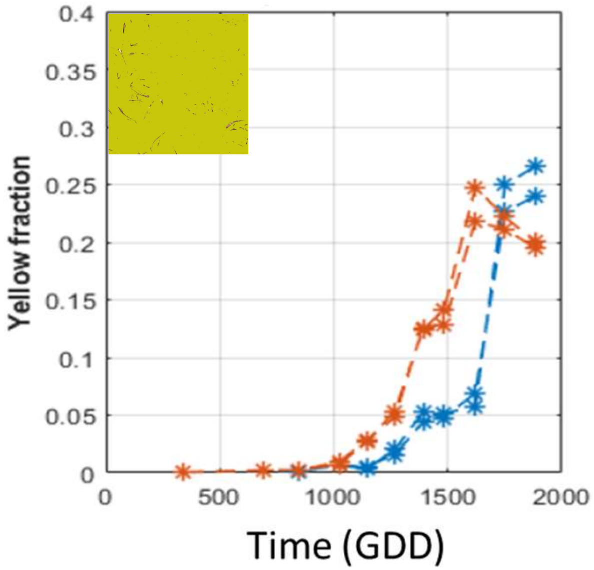
NDVI is a good proxy of the Green Fraction… but …





Using color and features to identify crop pixels with Deep Learning (U-net)





Classifying non-green pixels within the crop fraction with SVM (color)

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1. ***Object identification***: example: green segmentation
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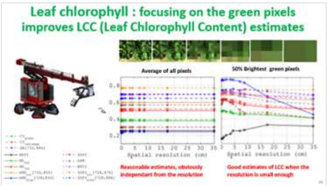
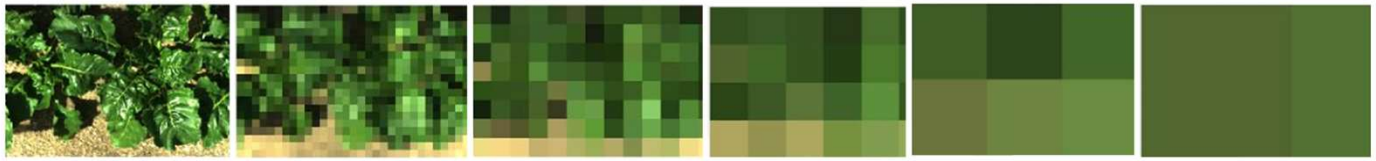
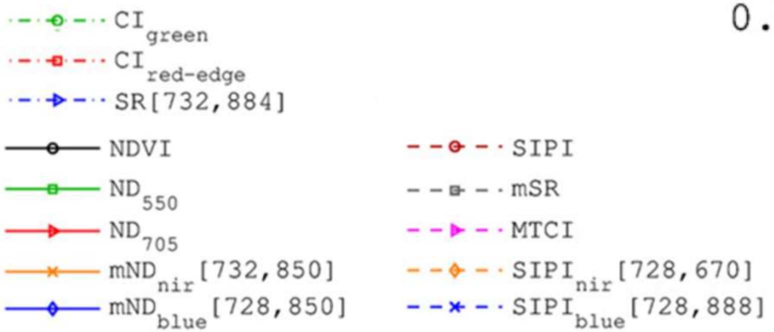
2. ***Abondance quantification***: generally based on unmixing:
    - Satellite: strong assomptions on the mixture and stability of components
    - Phenotyping: classification of components in the scene

3. ***Biochemical composition***: example: chlorophyll content
    - Satellite: not easy because of the mixture of components with various orientation/contents
    - Phenotyping: allows selecting the targetted group of pixels

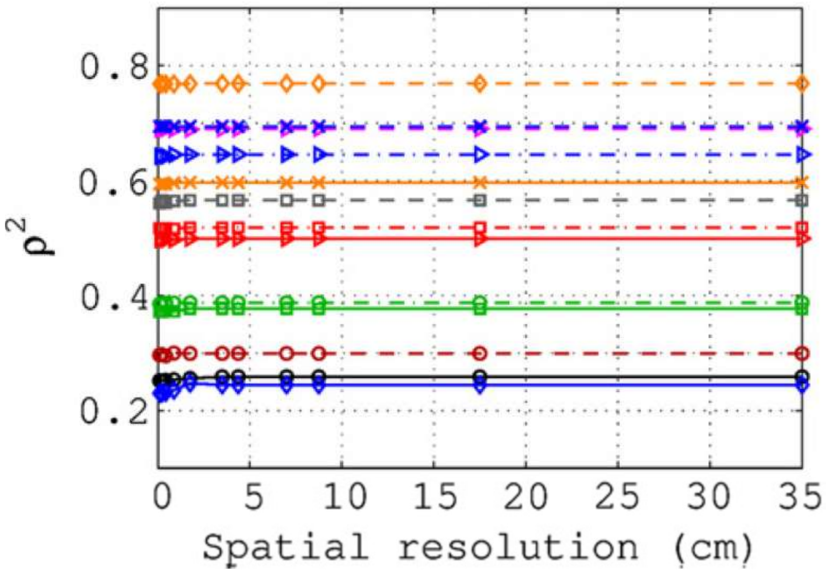


Leaf chlorophyll : focusing on the green pixels improves LCC (Leaf Chlorophyll Content) estimates



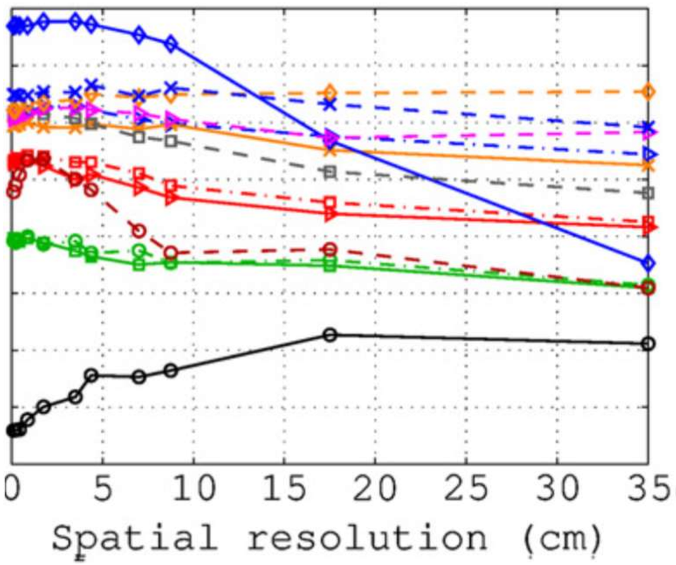


Average of all pixels



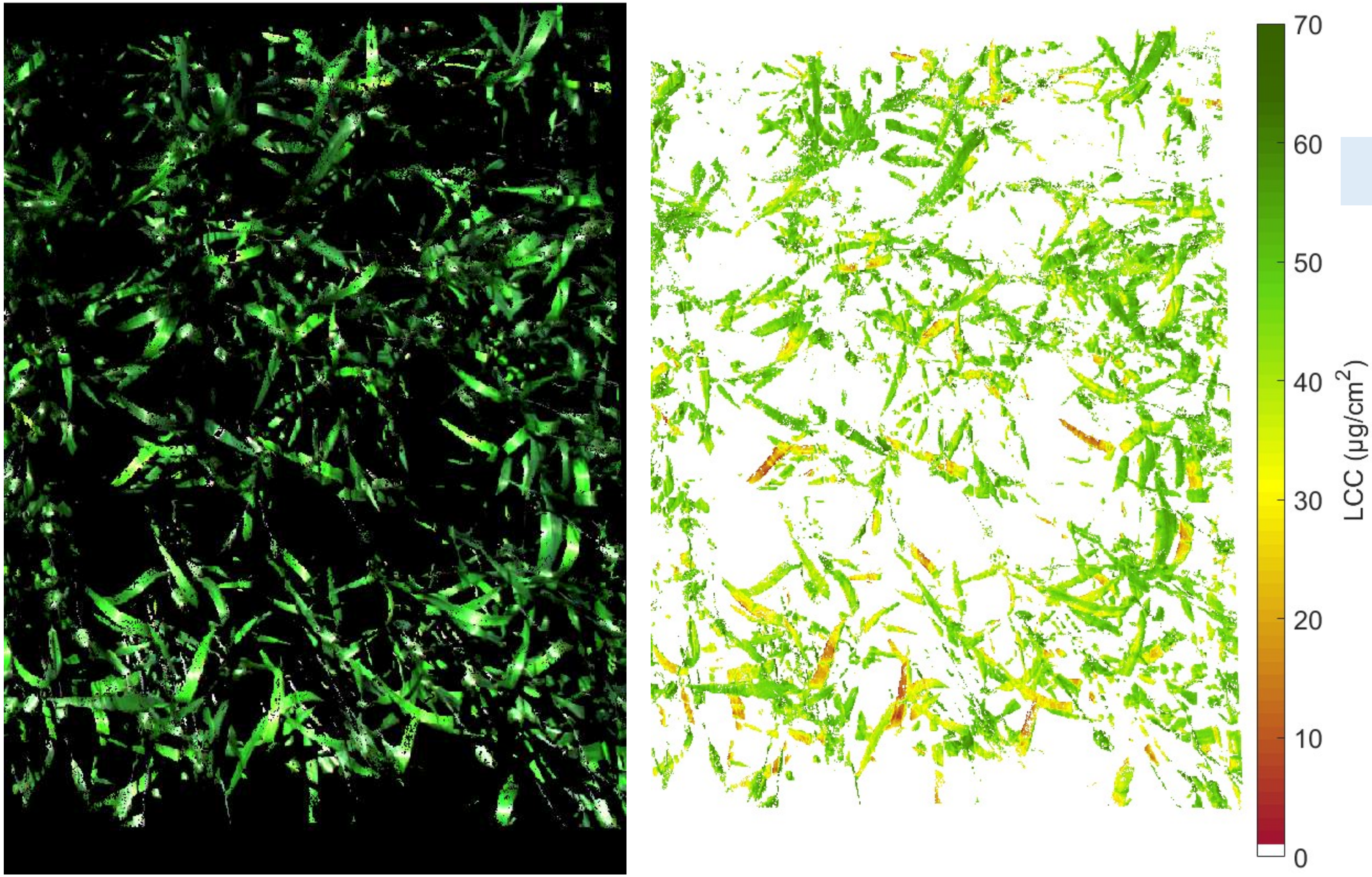
Reasonable estimates, obviously independant from the resolution

50% Brightest green pixels



Good estimates of LCC when the resolution is small enough

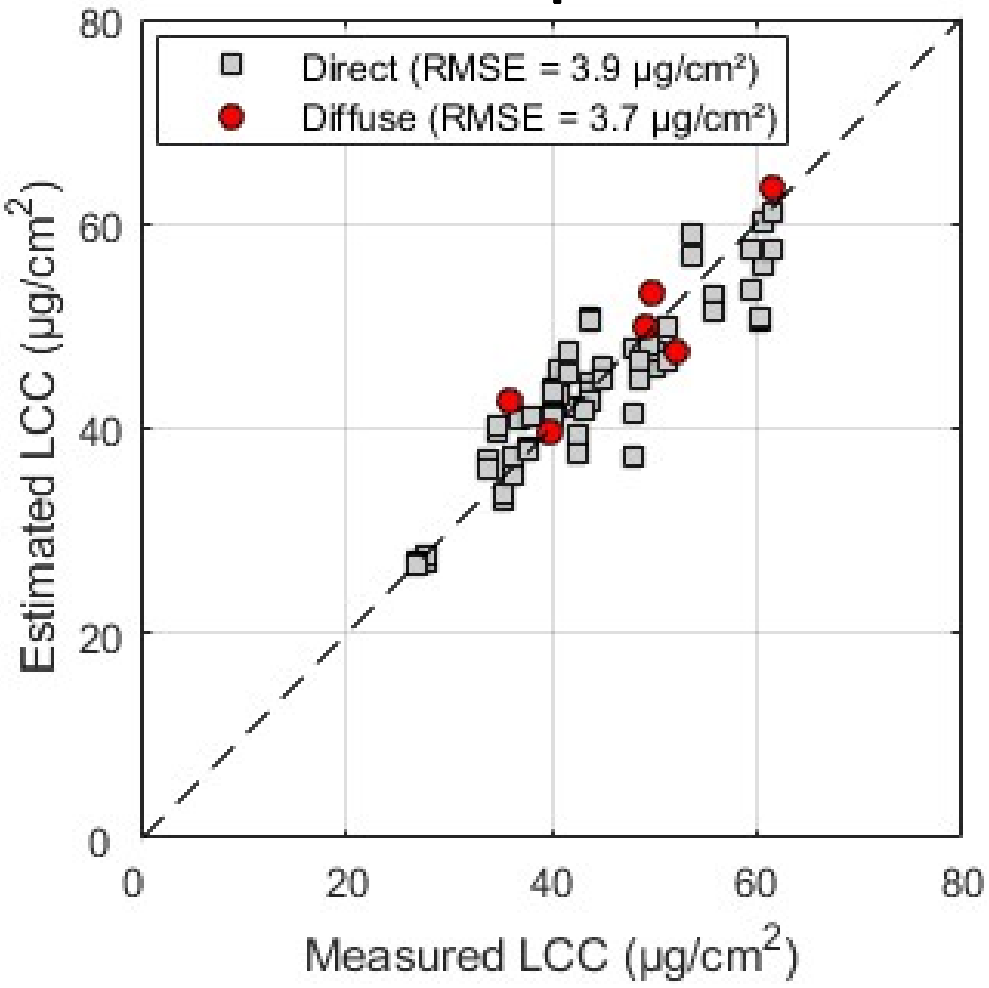
… Going to the pixel level LCC



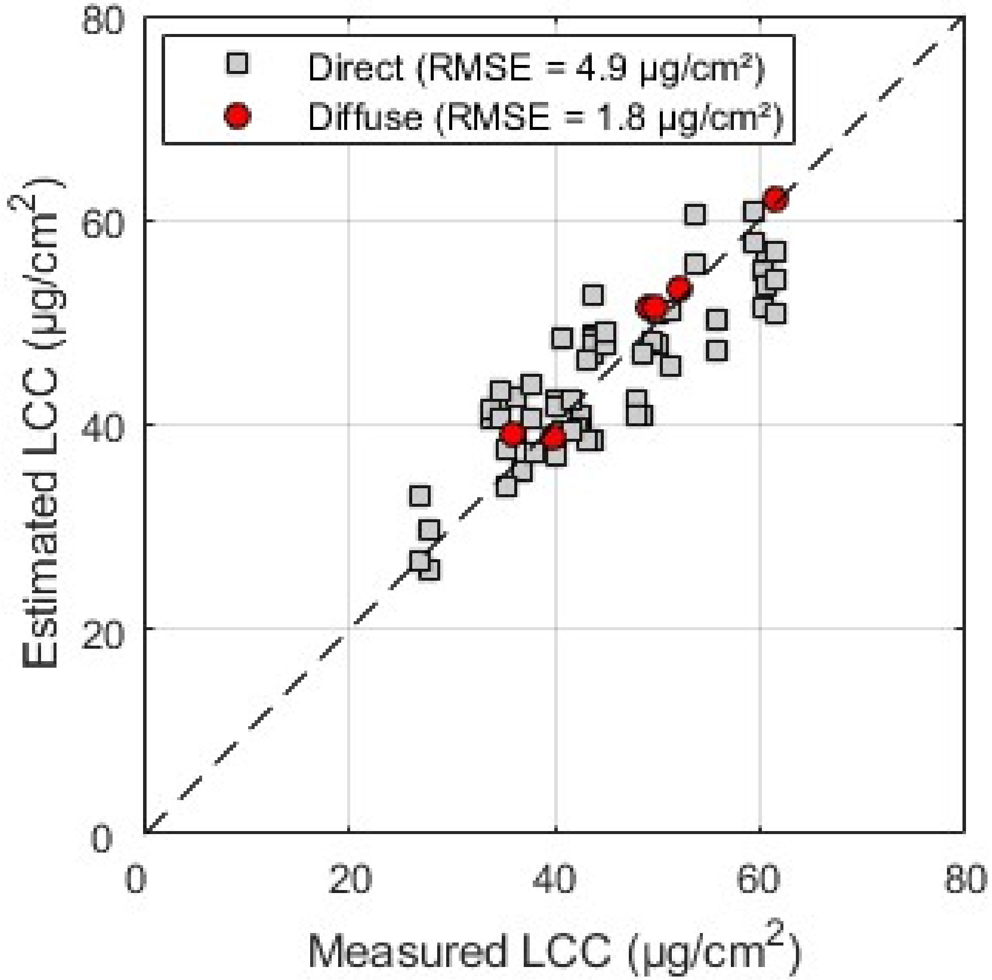
MULTISPECTRAL

… Going to the pixel level LCC … just with RGB

Multispectral

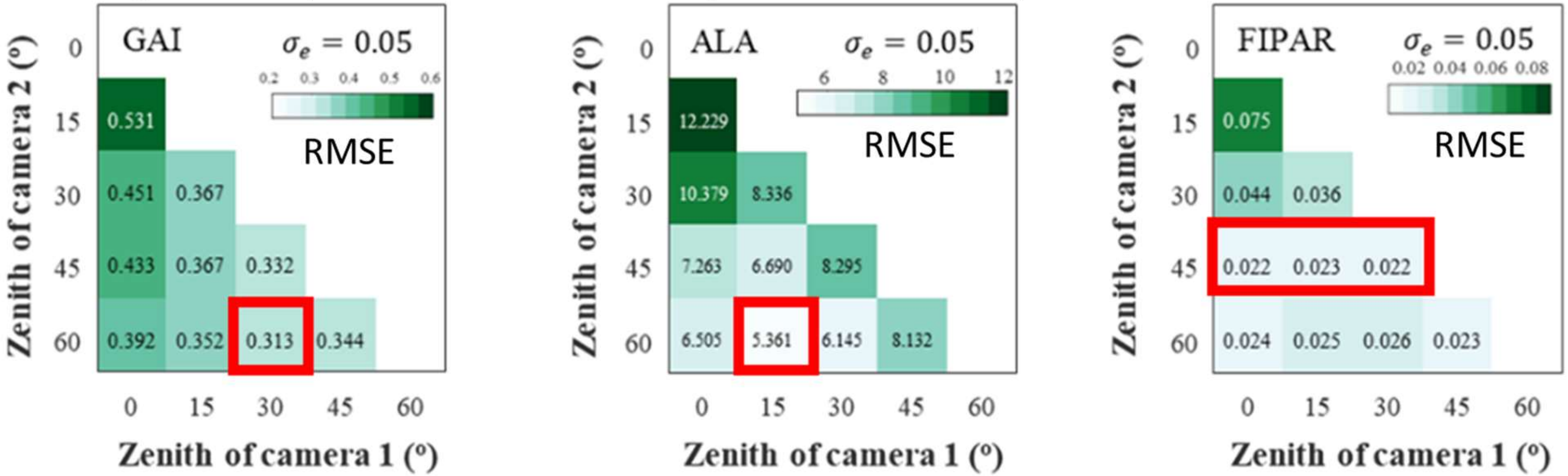


RGB



Interest of the directionality (Ω) to derive GAI, AIA and FIPAR from the Green Fraction

Radiative transfer model simulations (turbid medium) to identify the best couple of directions to derive GAI (Green Area Index) and AIA (Average Inclination Angle) and the corresponding FIPAR (Fraction of Intercepted Radiation)

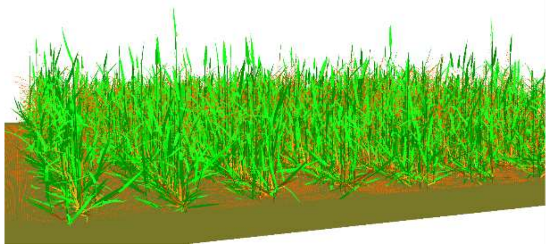


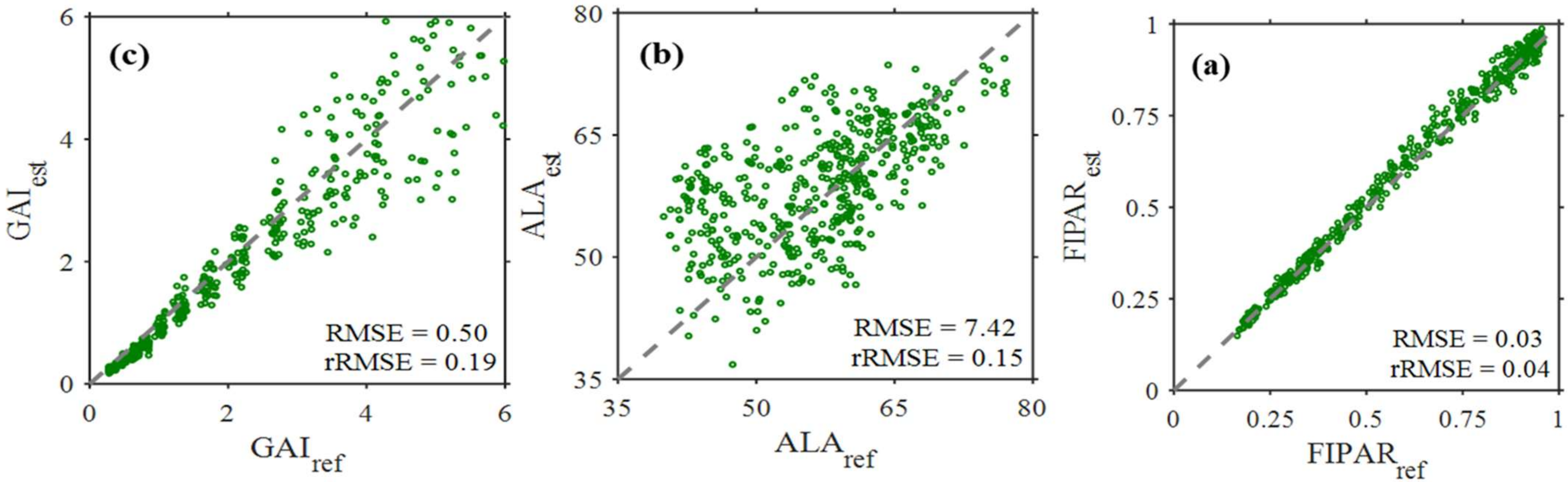
The combination [0°, 45°] appears optimal for FIPAR estimation

- Observations @ 0° is also convenient for deriving other traits
- Observations @ 45° better suits the geometry of the microplots (small width)

Validation from 3D model simulations

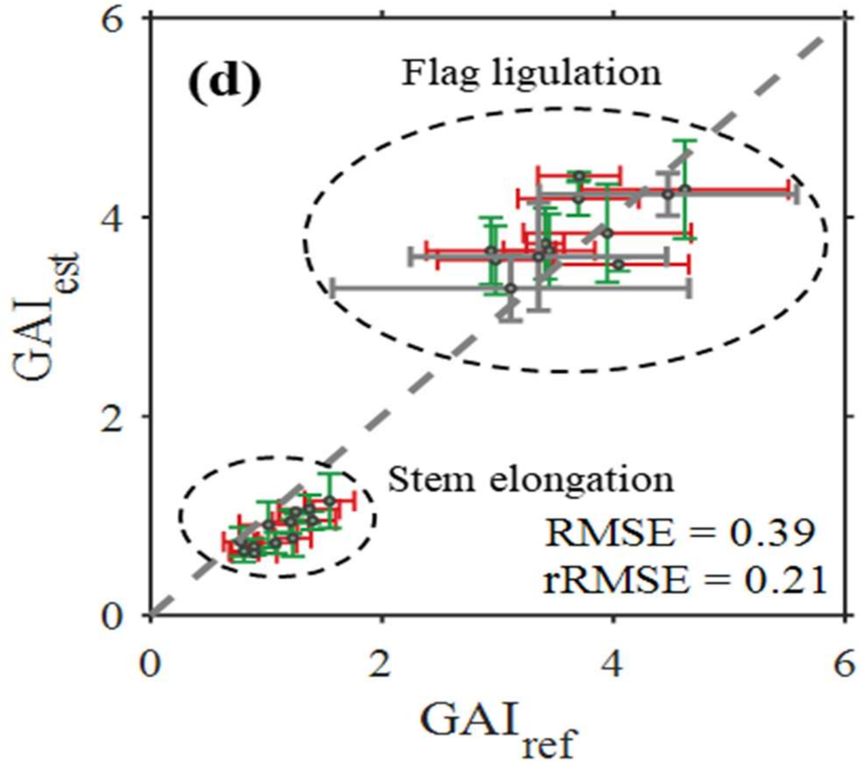
ADEL-Wheat 4D architecture model
Coupled with Raytran for rendering

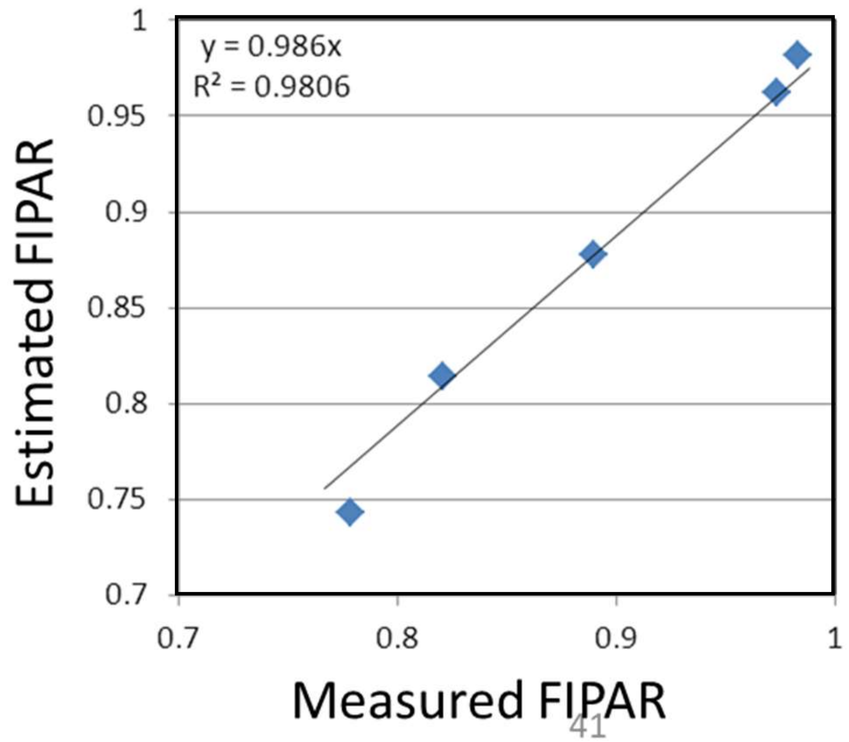




Very accurate estimates of FIPAR

Validation from actual experiments





Very good consistency with the theoretical results

A revolution in the interpretation methods

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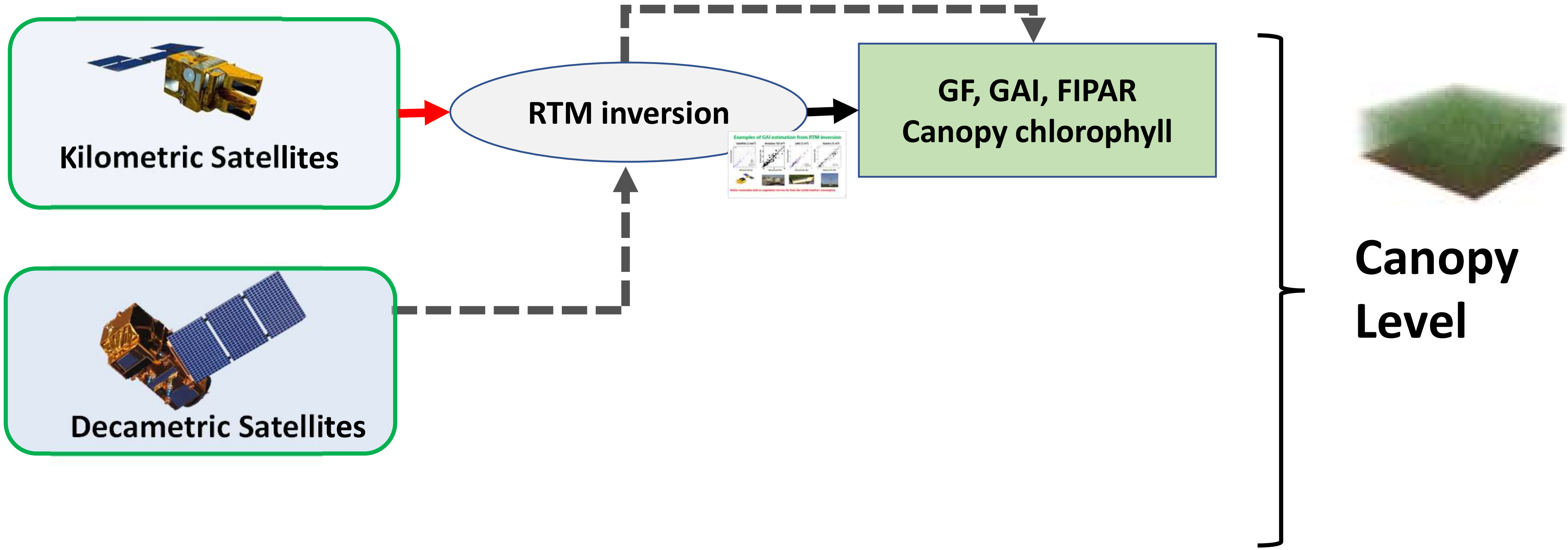
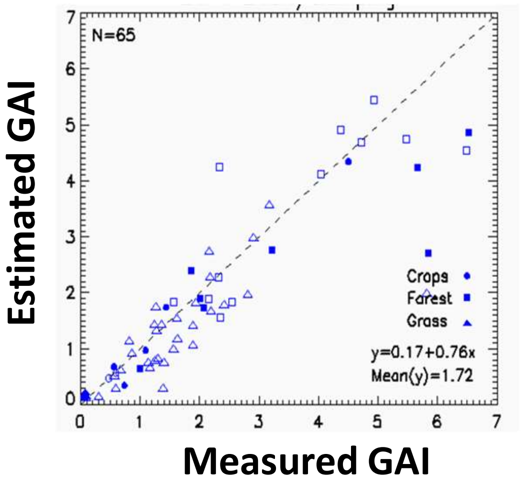
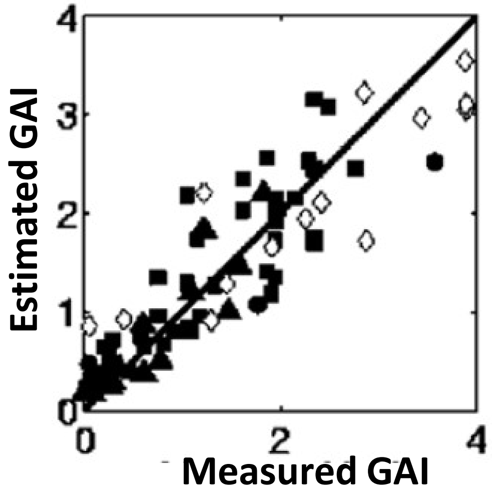


Examples of GAI estimation from RTM inversion

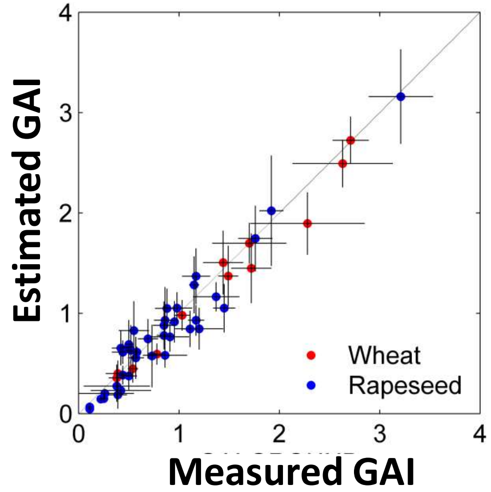
Satellite (1 km²)



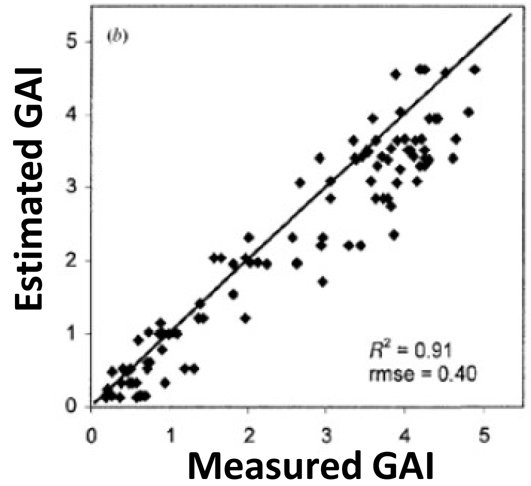
Airplane (10 m²)

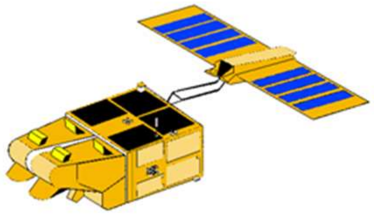


UAV (1 m²)



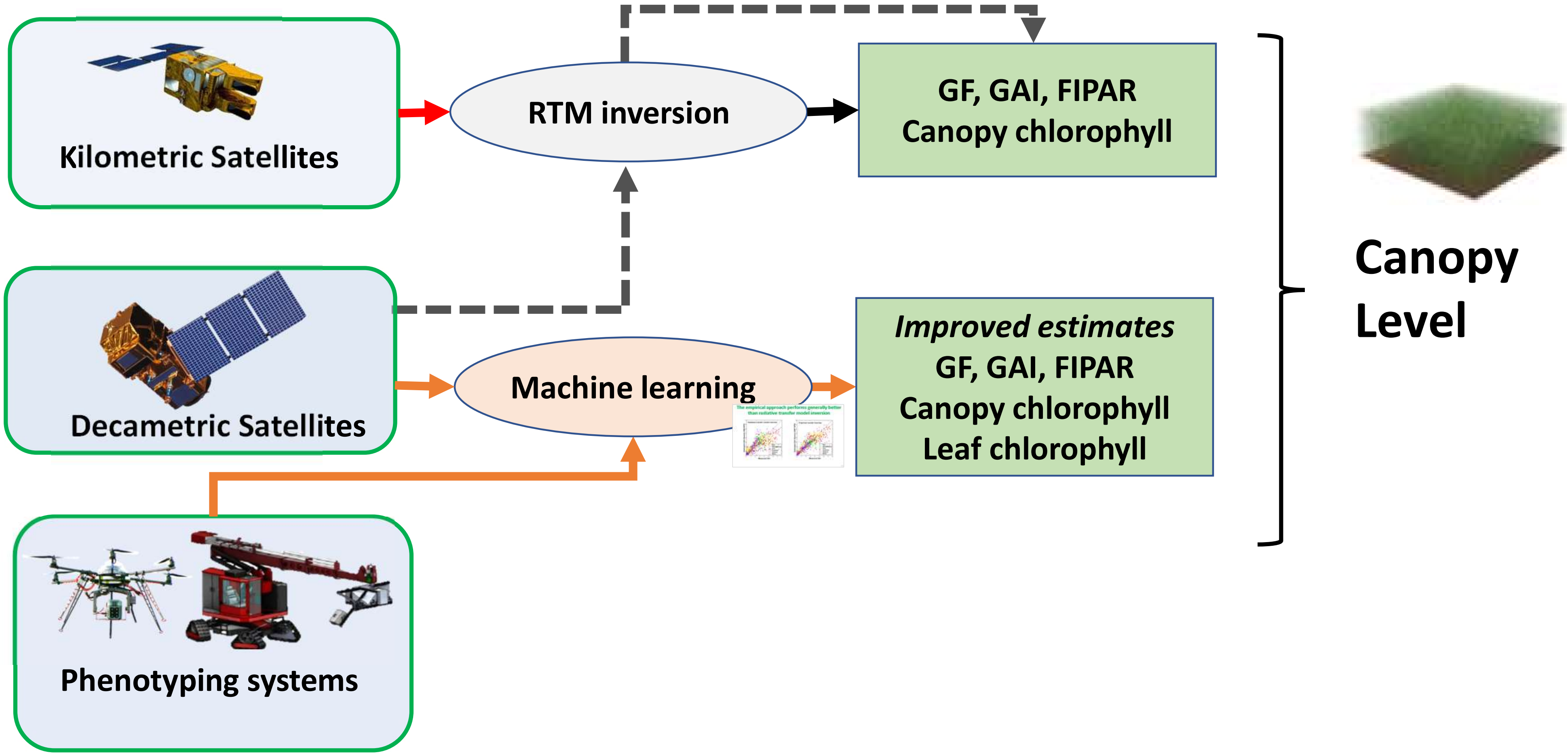
Gantry (1 m²)



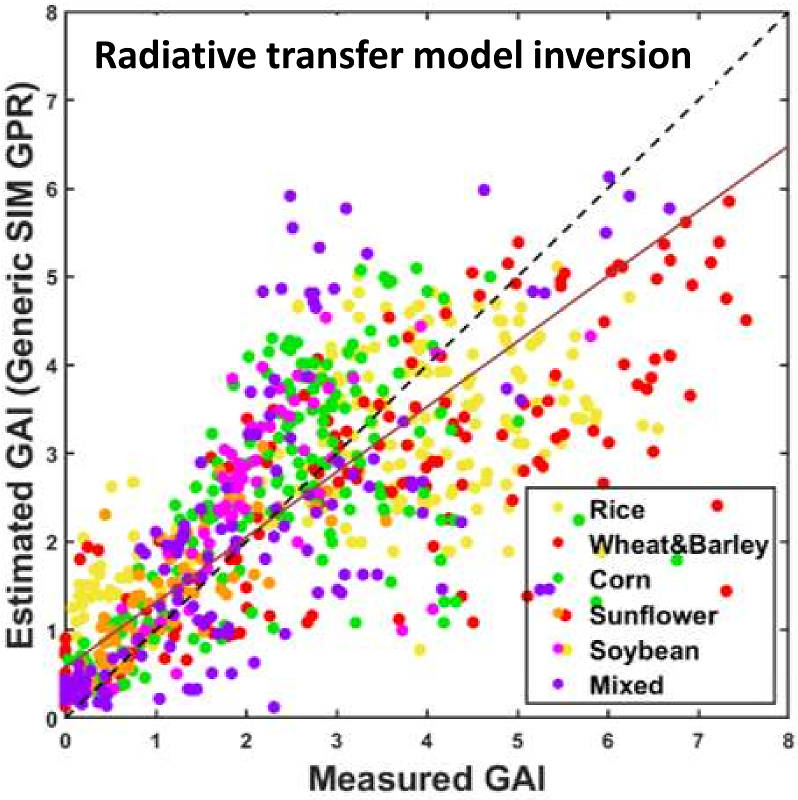


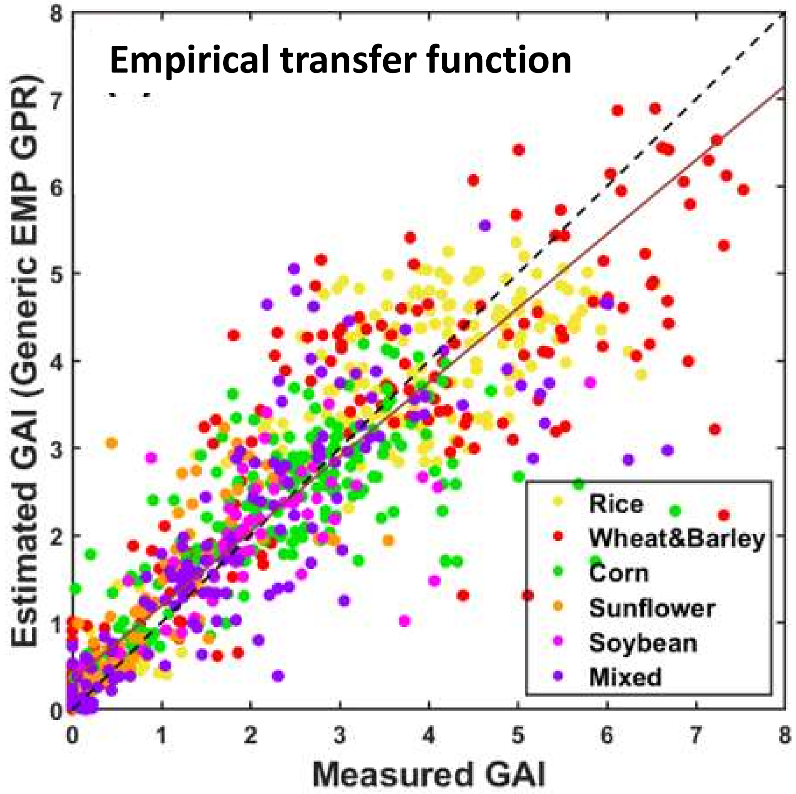
Works reasonably well on vegetation not too far from the turbid medium assumption

A revolution in the interpretation methods



The empirical approach performs generally better than radiative transfer model inversion





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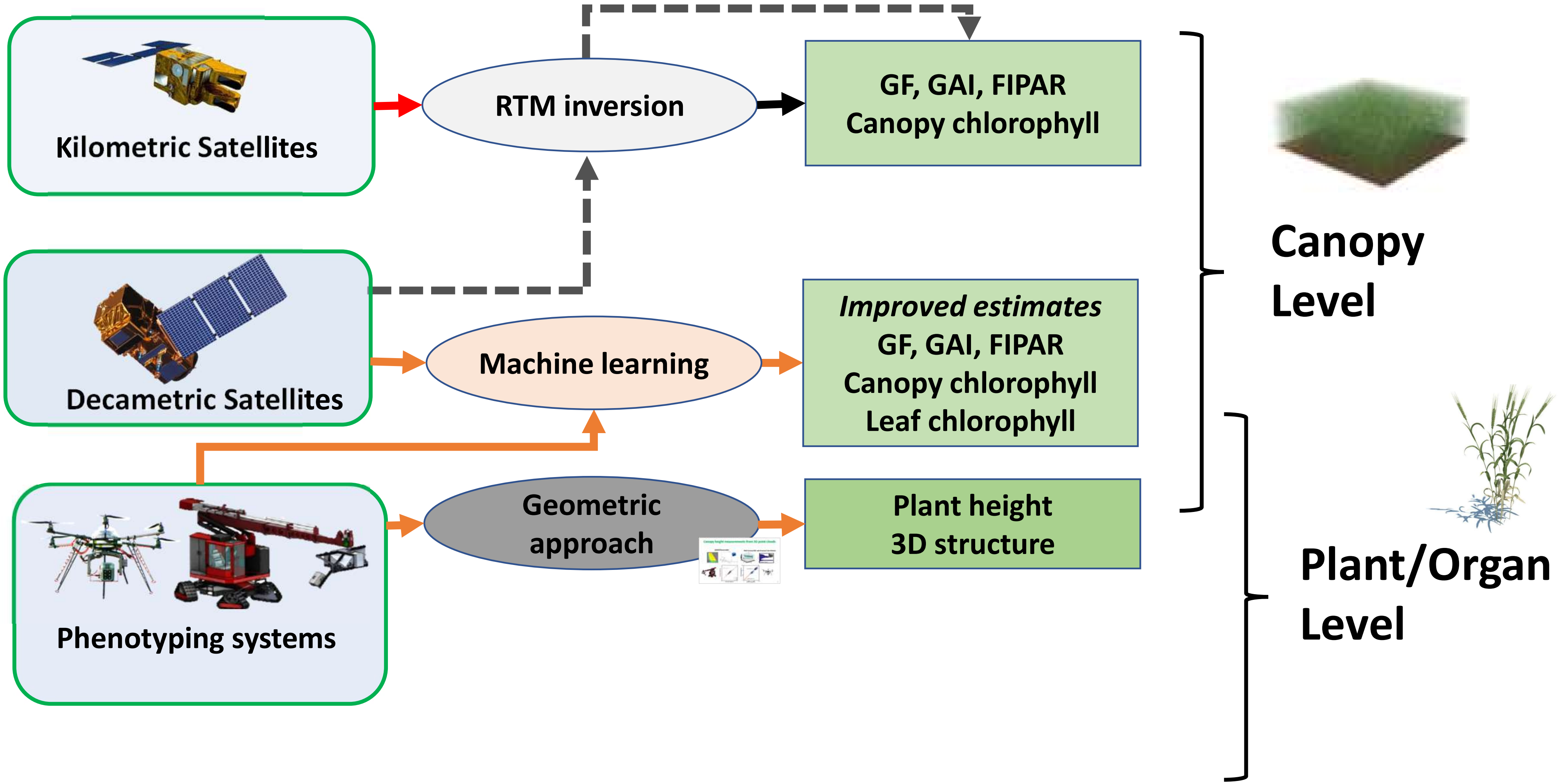
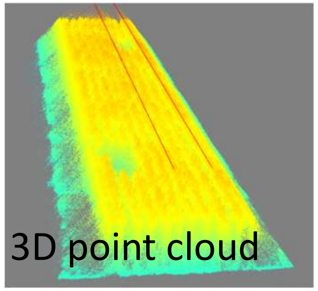
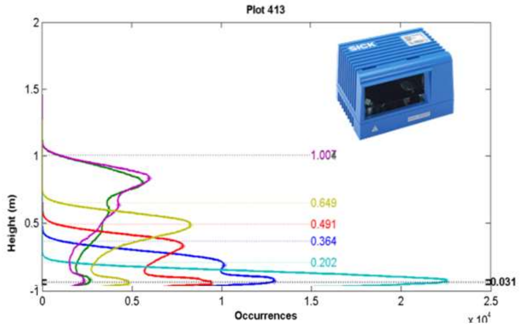
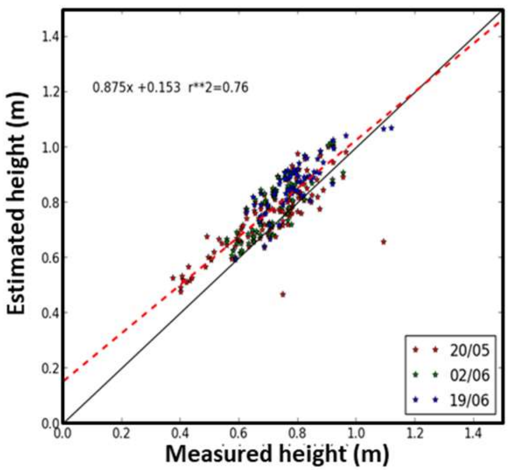


Canopy height measurements from 3D point clouds

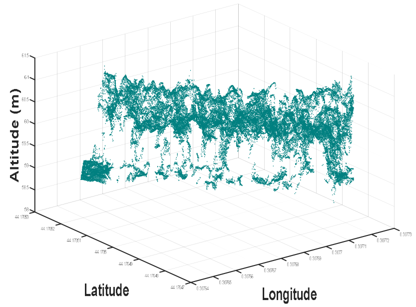
LiDAR/Phenomobile

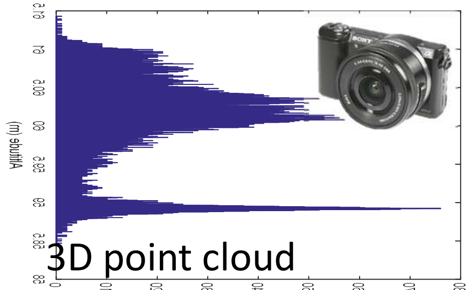


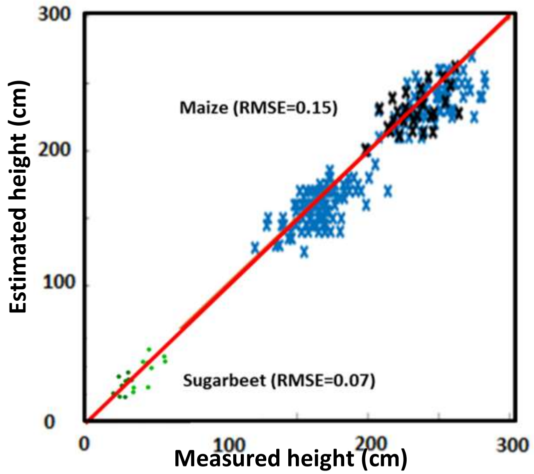




RGB Camera/UAV and Structure from Motion



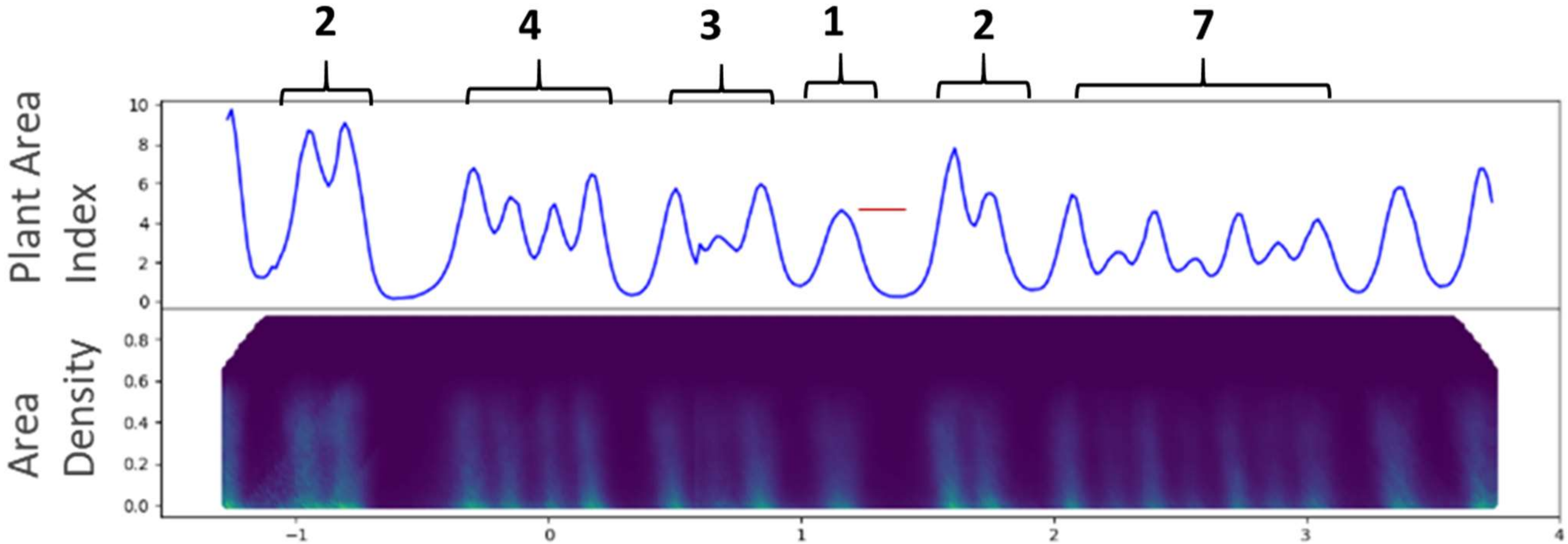




Detailed canopy structure from LiDAR

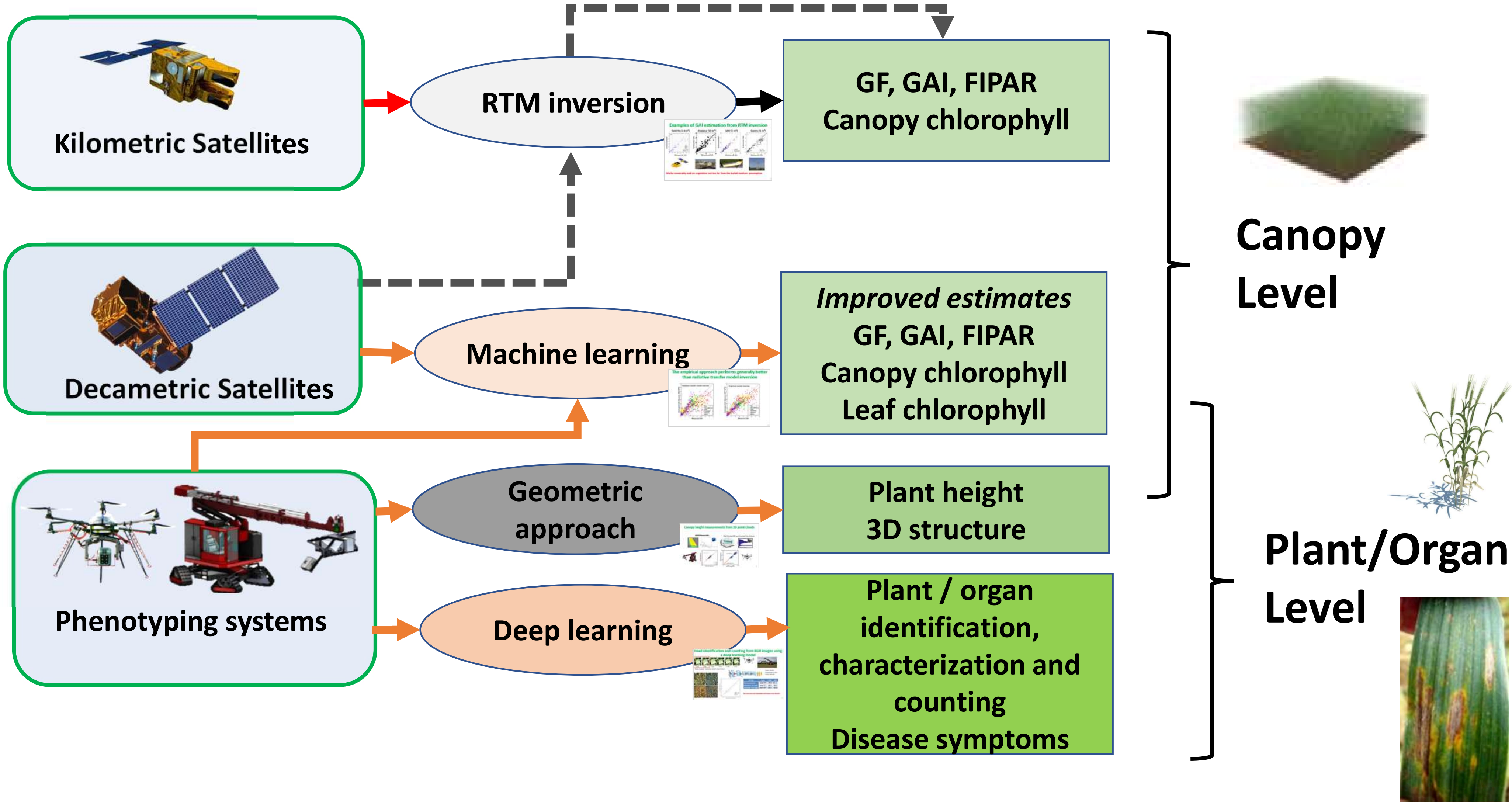
Several sowing patterns experienced:
1 row, 2 rows, 3 rows, 4 rows, 7 rows

LiDAR measurements on wheat



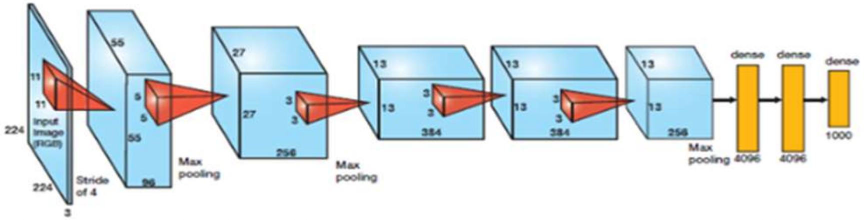
Allows investigating plant competition

A revolution in the interpretation methods

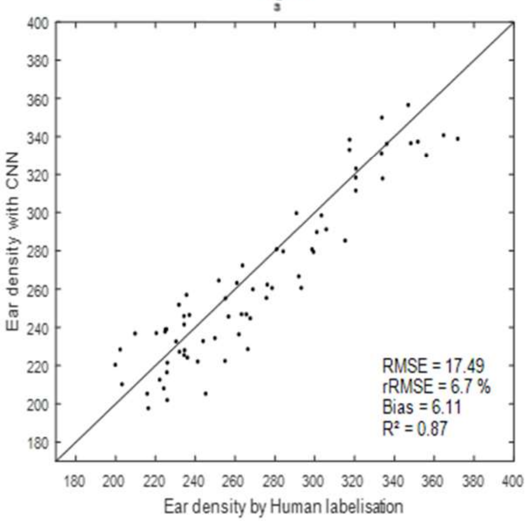


Head identification and counting from RGB images using a deep learning model

Need a spatial resolution better than 0.5mm



Faster-RCNN
Pretrained on the COCO dataset



H² (%)	Date	WW	WS
Measurements	June 7th	79.8	91.4
Estimates 1st date	June 2nd	86.9	88.5
Estimates 2nd date	June 16th	82.2	82.8

Very accurate and repeatable estimates of ear density

Conclusion

- **Systematic coverage for satellites, reduced cost of acquisition … but few traits!**
- **Phenotyping extends to many other traits than only GF, GAI, CCC, FIPAR… down to the plant/organ level**
- **Change in interpretation methods:**
  →from model driven to data driven approaches
- **Contribution of the high spatial resolution data to calibrate models to be used for degraded spatial resolution**
- **Process models used for training Machine (Deep) Learning : data augmentation**
  →a new challenge of realism!
  →need methods to mimic actual images from the simulated ones
- **A change in data volume!!! At least by several order of magnitudes: challenge of data management/storage /exchange**
- **Dynamics used to access functional traits**
  →Empirically… but lack of physiological background
  →Based on crop growth models


Thanks for your attention