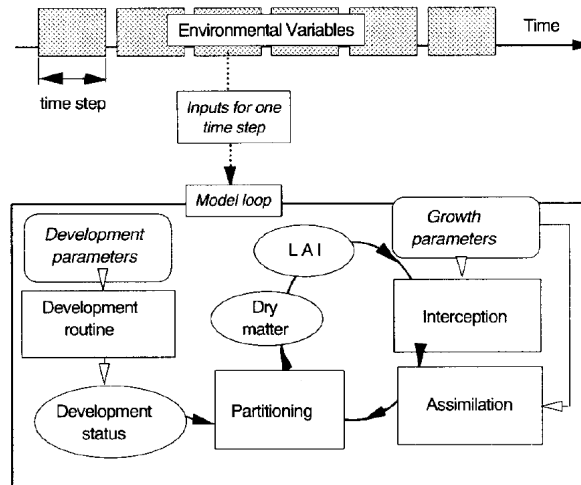


The needs for data: can remote sensing be used for crop models' inputs?

Daide Cammarano



Outline

- **Definition of crop simulation models**
- **Data needed by crop models**
- **Remote sensing of crop models' parameters**
- **Future prospective**
- **Conclusions**

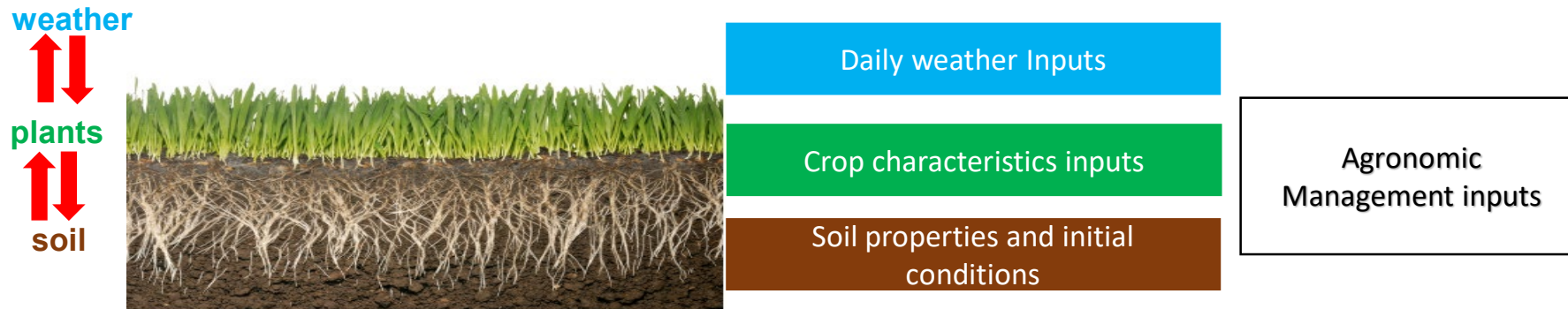
Introduction: Definition of crop simulation models

System models (CSM) consist of a set of equations describing underlying processes, which are then coupled together to create a model that describes a system

- transferability of field-based research;
- High costs of field experimentation (“complement field experimentation”);
- Climate related risks;
- Crop models are only an approximation of the real world;
- Nevertheless, they have played important roles in the interpretation of agronomic results, and their application as decision support systems for farmers is increasing.

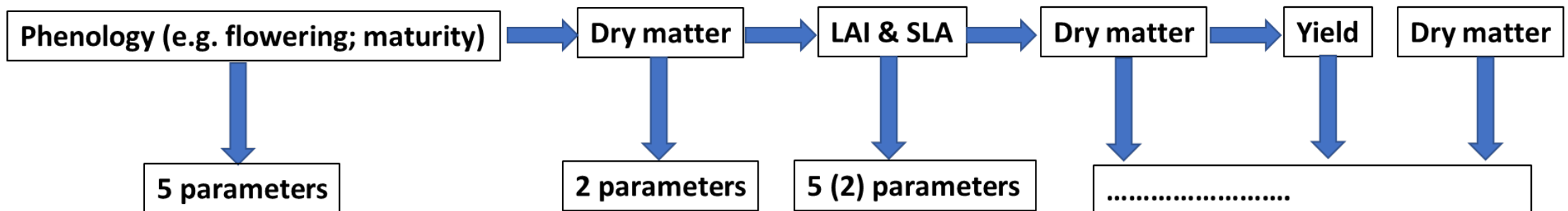
Crop Simulation Models (CMS): Input

- Based on the understanding of the interactions between **plants**, **soil**, **weather**, **management** interactions
- Require information (Inputs), such as:
 - Soil
 - Weather (daily/hourly)
 - Cultivar characteristics
 - Management
- Predict growth, yield, timing (and depending on models many other outputs)



Model calibration and response

- Commonly, on crop models, the parameters are estimated by studying the system and estimate the parameters (or a subset) by fitting the overall system model to the system data.
 - Usually, the parameters to calibrate are the ones that define a cultivar. Often, some soil inputs need to be quantified if not measured (e.g. hydraulic properties).
 - The parameters to calibrate vary by model (e.g. for defining a cultivar some models have 4 and some have 20+ parameters to calibrate).



Data for models' calibration and evaluation

<https://bigdata.cgiar.org/blog-post/webinar-minimum-data-requirements-for-crop-modeling/>



Fig. 1. Sentinel site rating criteria as developed by the Agricultural Model Intercomparison and Improvement Project (Rosenzweig et al., 2013; Kersebaum et al., 2015).

Boote et al., 2016

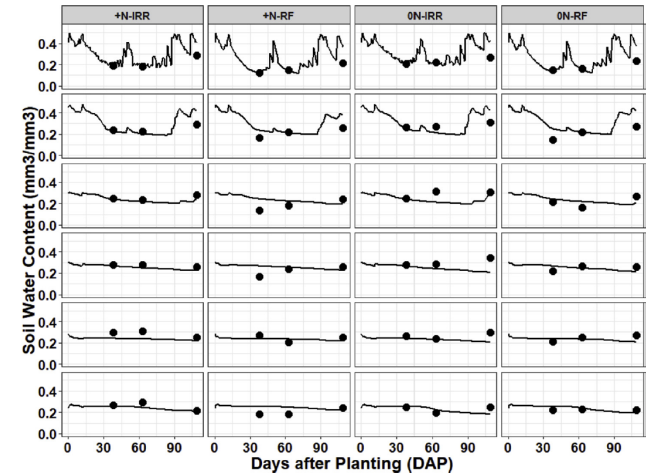
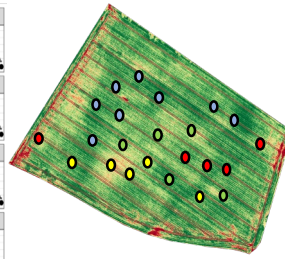
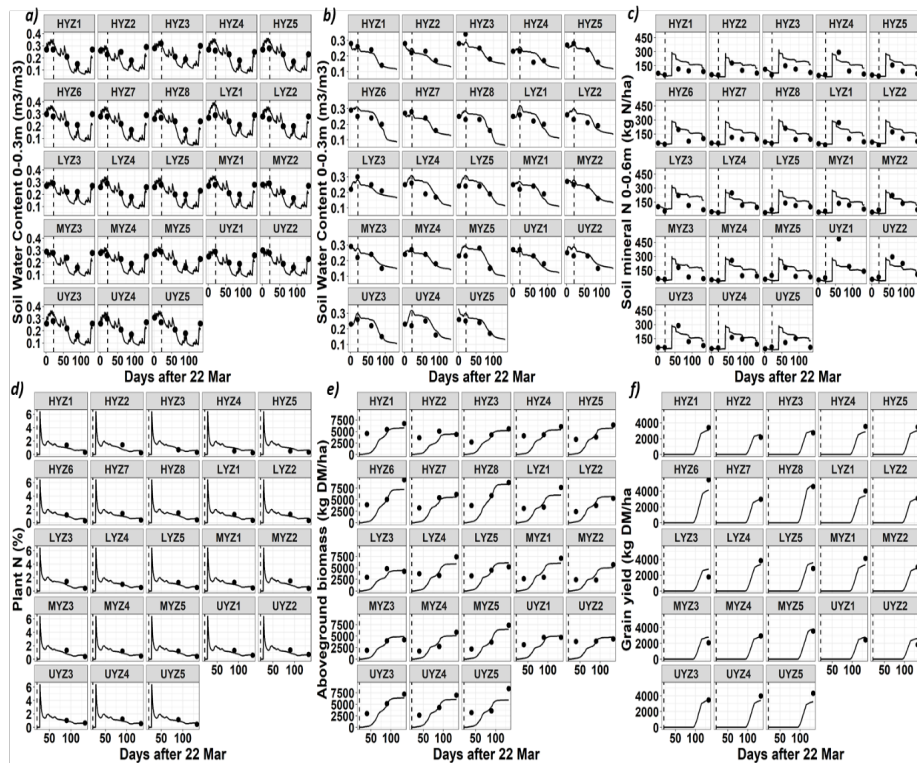
The image shows a webinar poster for 'Minimum Data Requirements for Crop Modeling'. The poster is dark grey with white and orange text. It features the CGIAR logo and the Platform for Big Data in Agriculture logo. The title 'Webinar – Minimum Data Requirements for Crop Modeling' is prominently displayed. Below the title, it says 'CGIAR Webinar by the Platform for Big Data in Agriculture's Community of Practice on Crop Modeling – Minimum Data Requirements for Crop Modeling'. There is a circular icon with a hand holding a tablet. The text 'Presented by the Crop Modeling Community of Practice' is visible. The date and time '18 JUNE, 9-10:00 AM CT (UTC-5:00)' are listed. The word 'WEBINAR' is in large orange letters. Below it, 'MINIMUM DATA REQUIREMENTS FOR CROP MODELING' is written in white. There are two small circular portraits of speakers: Gerelt Mungushan from the University of Florida and Tom Hoggan from CGIAR Excellence in Breeding Platform.

Model calibration & evaluation

A spring barley cultivar calibrated and evaluated on a field experiment (Water and Nitrogen)

The same cultivar was grown in a farmer's field.

IF initial soil conditions and all the input needed are available the model performs well in simulating observed data



It was a lot of work!!

Remote Sensing

➤ **Attractive because it has a spatial and temporal component**

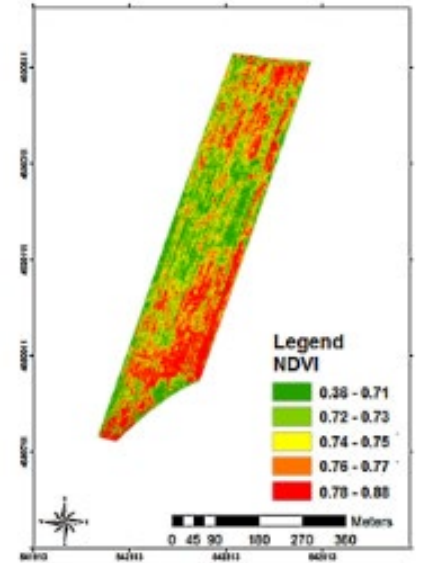
➤ **Offers potential to obtain data for:**

❖ **Crop models parameters**

○ **FPAR, canopy cover, biomass, canopy N, LAI**

❖ **Input data**

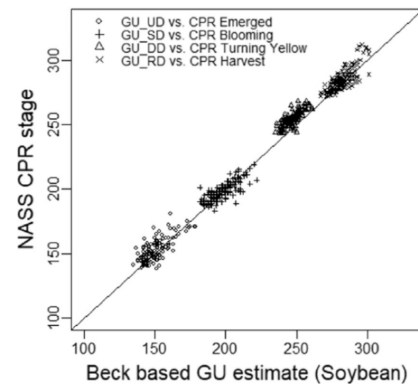
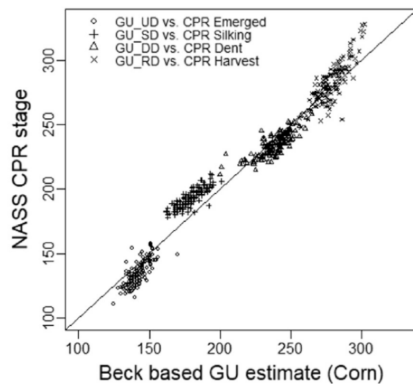
○ **soil properties (e.g. through inverse modeling to calibrate for others)**



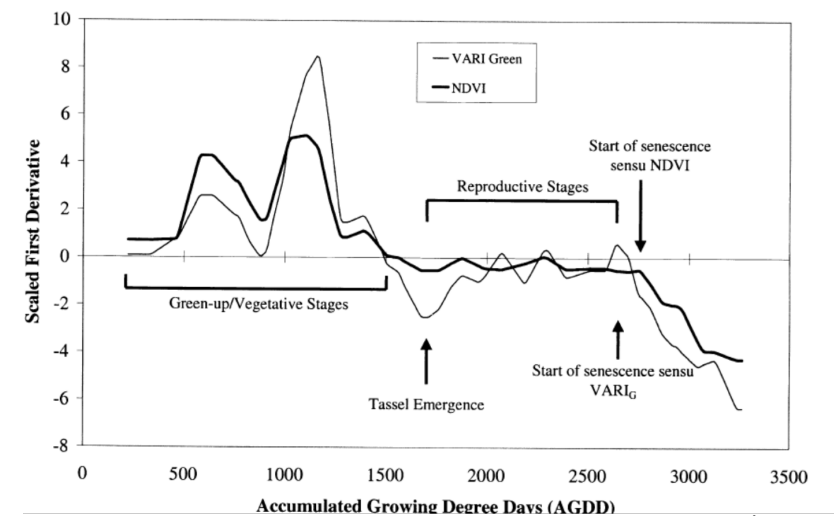
Basso et al., 2011

Example of crop parameters

- Phenology-derived RS data are more challenging if real-time information are needed
- Temporal patterns of Vegetation Indices might be able to provide some phenology information.



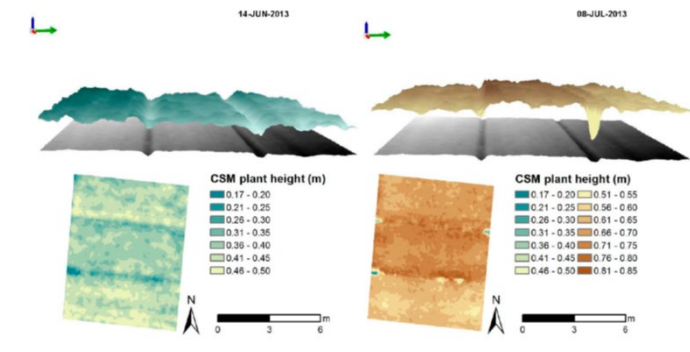
Diao, 2020



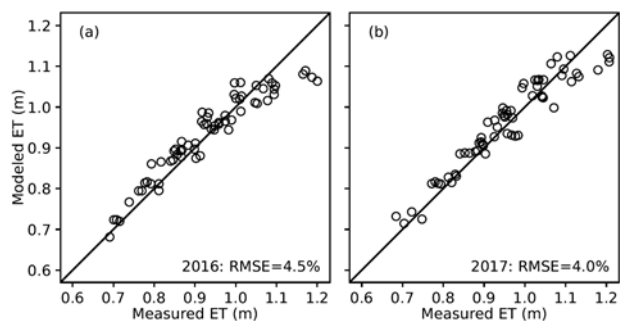
Viña et al., 2004

Example of crop parameters

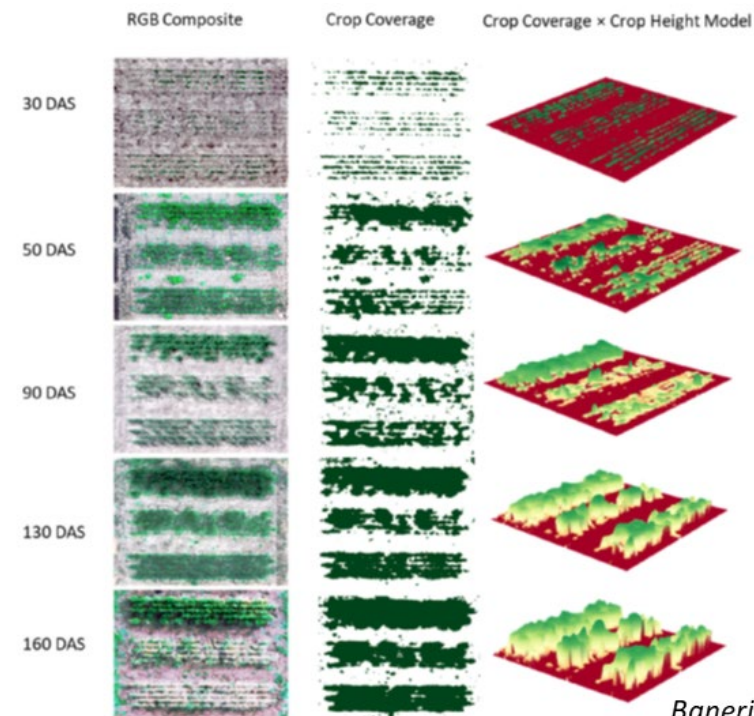
- Crop height
- Crop aboveground biomass
- FPAR
- Canopy ET (e.g. multispectral cameras + fcover)



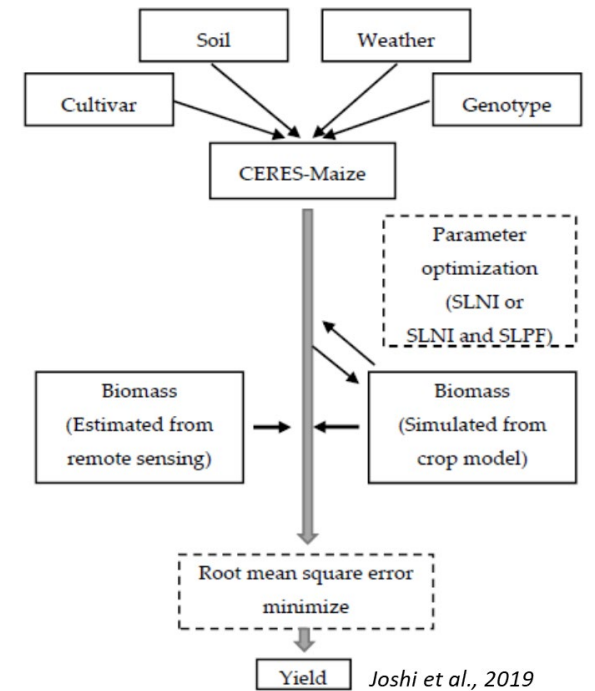
Bending et al., 2014



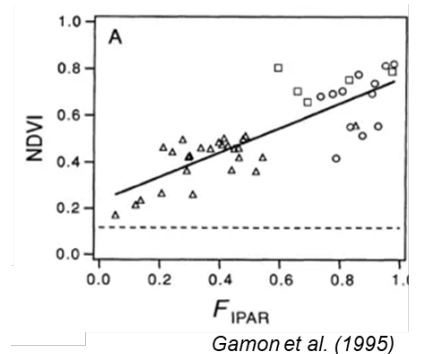
Thorp et al., 2018



Banerjee et al., 2020



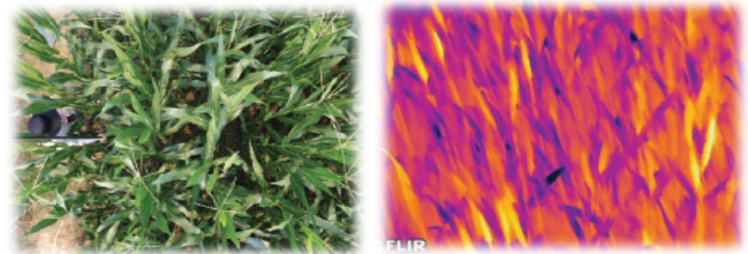
Joshi et al., 2019



Gamon et al. (1995)

Example of crop parameters

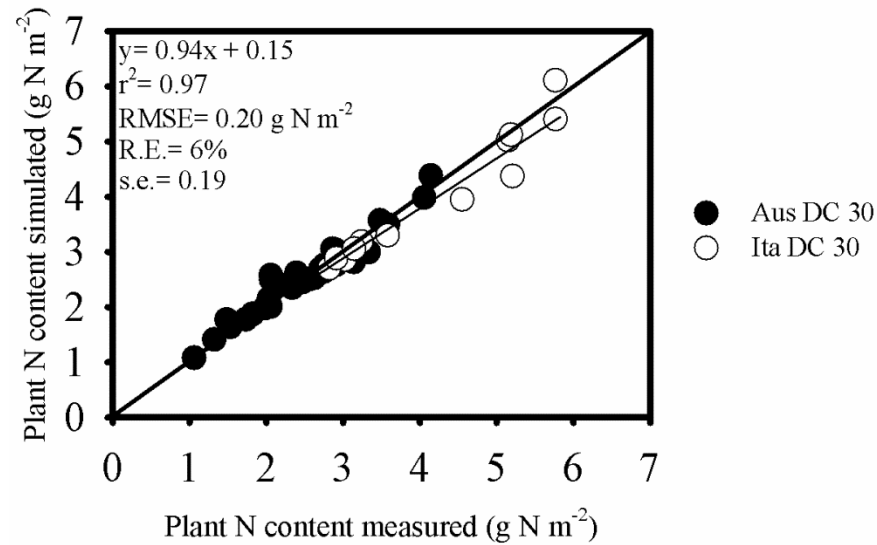
- Thermal cameras, combined with optical/multispectral cameras, can provide information on water-stress resistant genotypes;
 - Useful indirect information to water balance and onset of pest/diseases;
- Information on Canopy Temperature (CT)
 - CT + water index for estimation of water uptake



Example of crop parameters: nitrogen content

Contemporary presence of water and N stress

Canopy N% at different growth stages



$$N \text{ [g N m}^{-2}\text{]} = [(\%N_{\max} - \%N_{\min}) * (1.86 * CCCI - 0.346) + \%N_{\min}] * (\text{dry biomass}/100)$$

Linkage to CSM is through Biomass or N

Example of soil input

Great potentiality to link proximal soil sensors' information to soil input (e.g. texture, organic matter, bulk density):

- Ground-truth needed

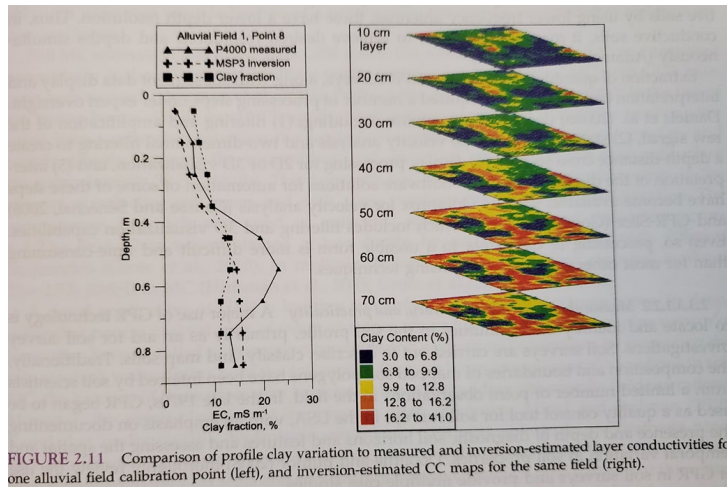
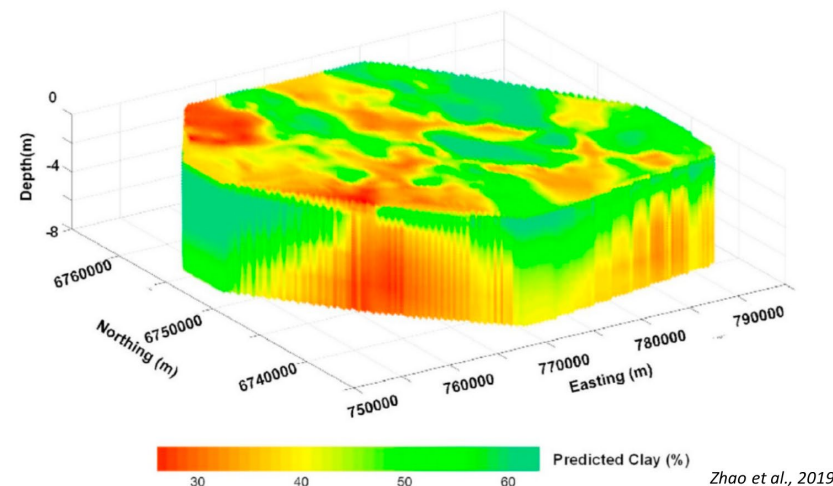


FIGURE 2.11 Comparison of profile clay variation to measured and inversion-estimated layer conductivities for one alluvial field calibration point (left), and inversion-estimated CC maps for the same field (right).

Mouazen et al., 2020



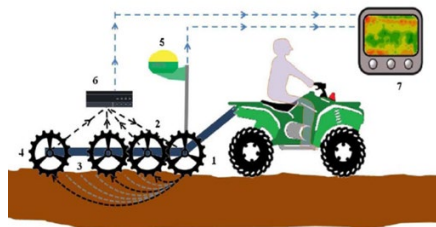
Zhao et al., 2019

Fig. 6. Areal distribution of predicted clay content in 3D view.

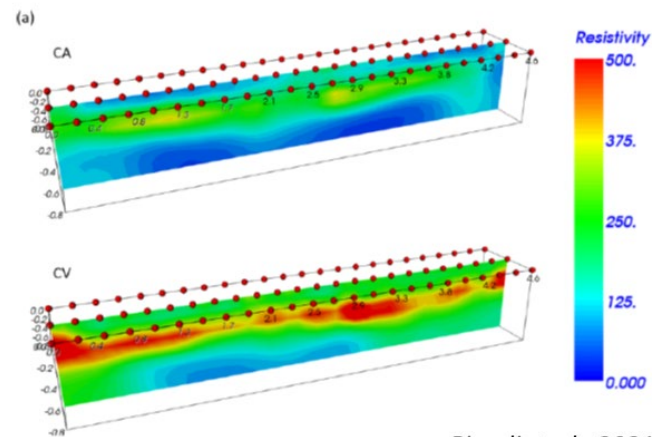
Example of soil input

Soil resistivity is also a proxy for variability of soil properties:

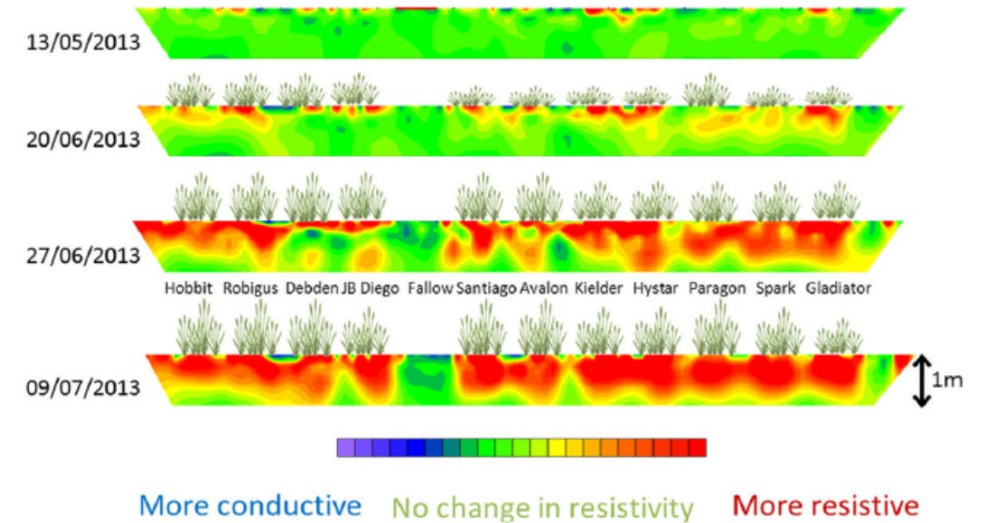
- Great potential for the information of rooting depth;
- Subsoil constrains;
- Texture;
- Moisture.



Cillis et al., 2018



Piccoli et al., 2021



Whalley et al., 2016

Example of crop parameters: LAI

- **Key parameter in photosynthesis and evapotranspiration;**
- **Often at the center of remote sensing assimilation in crop models;**
 - **Above LAI >3 remotely sensed indices tend to saturate (most of them).**

Studies that used a given Target Variable to parameterize crop models with the objective to simulate:

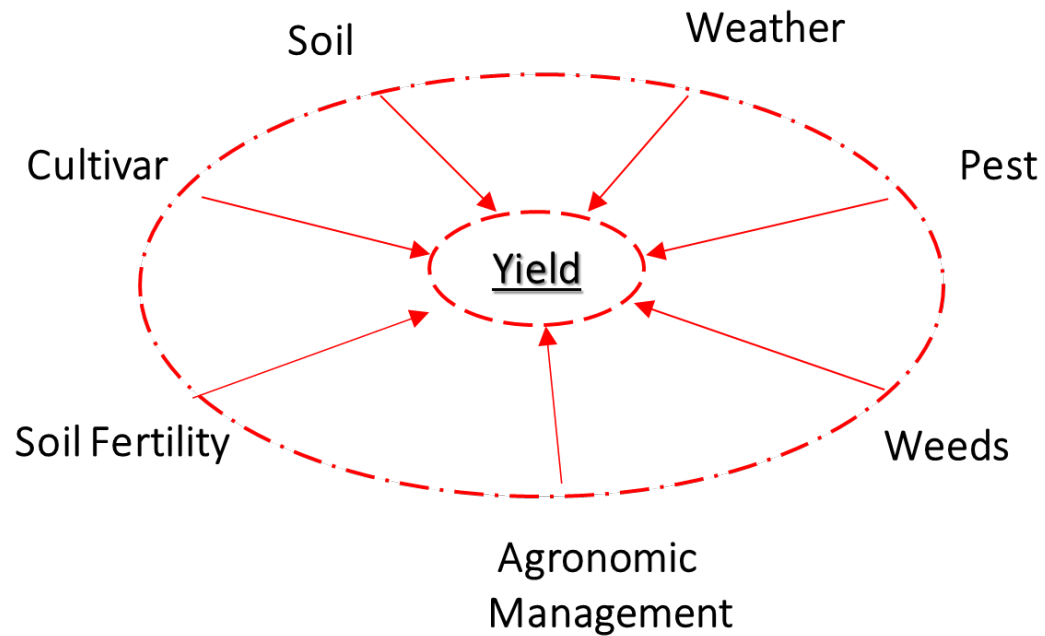
Target variable	#
LAI	41
FAPAR	3
ET	1
N	3
Flowering	1
RUE	1
Soil moisture	5

Objective	#
Yield	34
LAI	10
ET	1
Biomass	4
Soil Moisture	2

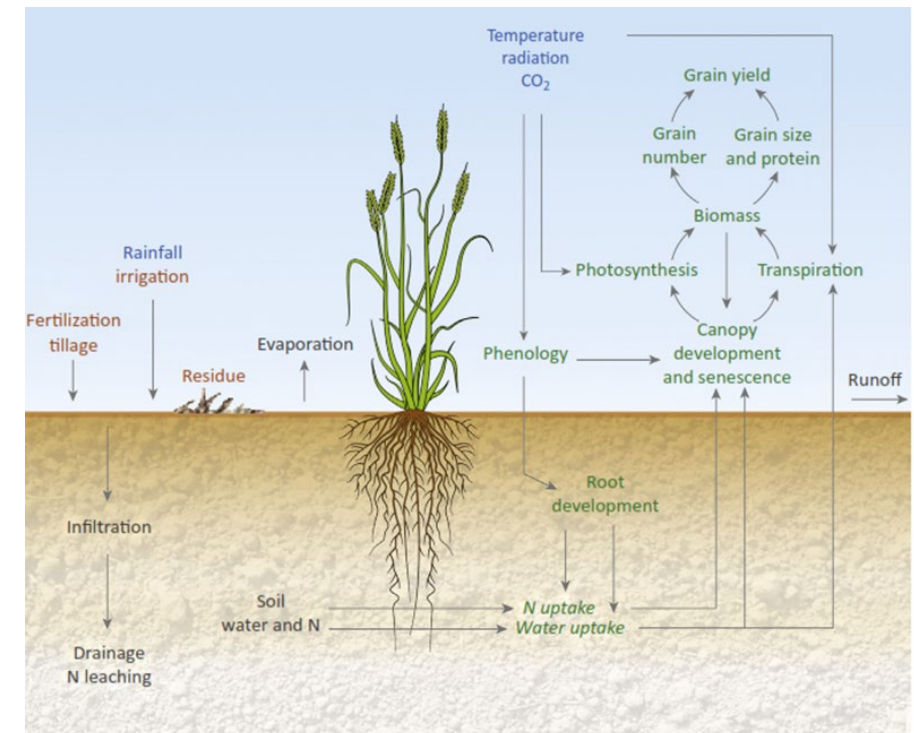
Is yield only affected by LAI?

Yield is the resultant of many dynamic (spatial and temporal) factors:

Agronomy



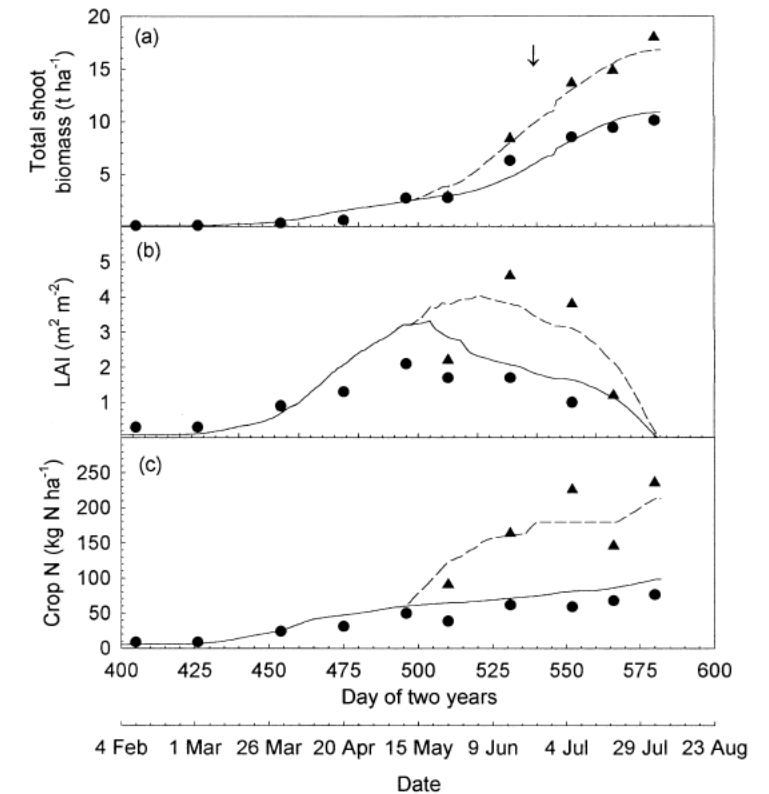
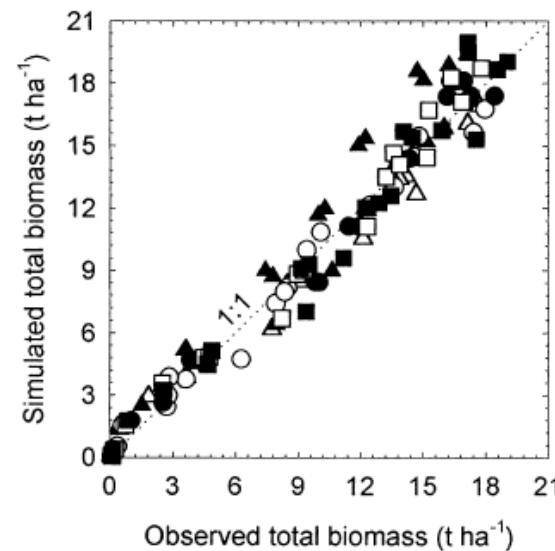
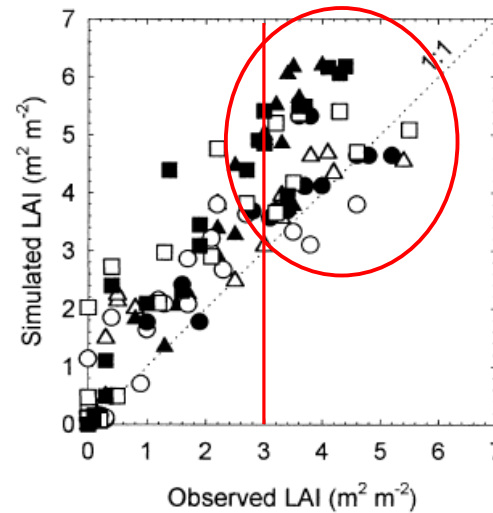
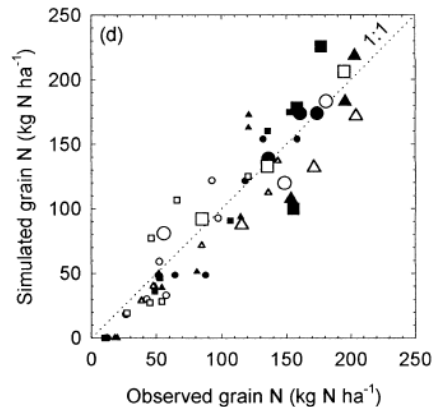
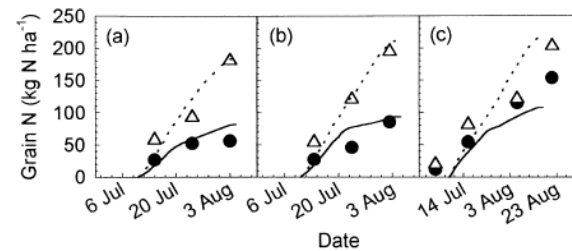
Crop Modelling



Example of crop parameters: LAI

A crop model can simulate with a given accuracy crop biomass, N uptake and yield and still over-estimate LAI

One cause is LAI values above 3 and at senescence



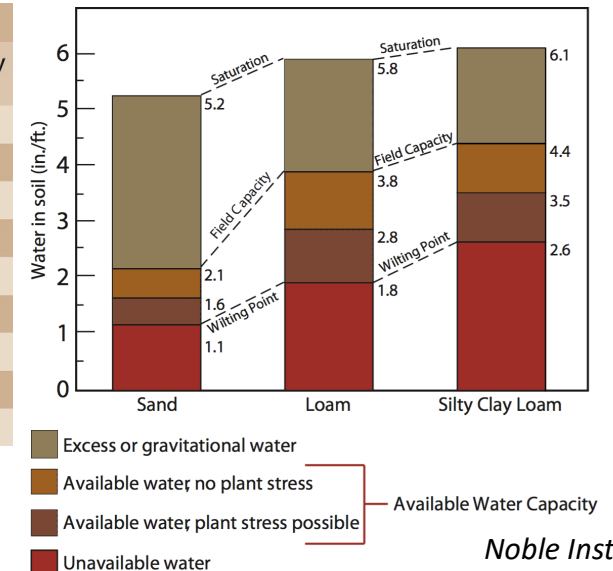
Example of crop parameters: LAI

1. “Initial conditions” like soil water and soil mineral N are very important boundary conditions
2. LAI being modelled as an expansive growth process is very sensitive to water stress
3. IF the users do not pay attention to either initial condition or the quality of their soil they might parameterize LAI wrongly
4. In crop models LAI is only one of the expansive growth processes

Why this gap?

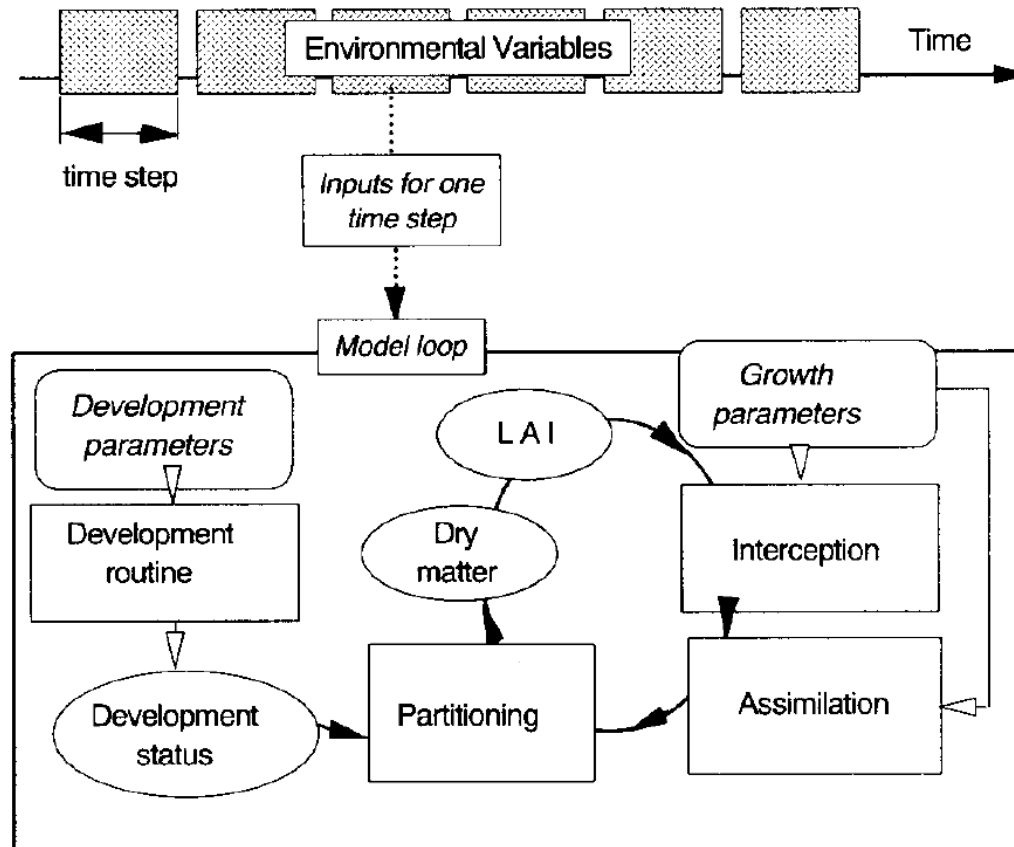
1. Are my initial conditions wrong?
2. Are my soil data accurate?
3. Am I simulating too much/little water stress?
4. How LAI is simulated in the CSM?

Available Water Capacity by Soil Texture	
Textural Class	Available Water Capacity (Inches/Foot of Depth)
Coarse sand	0.25–0.75
Fine sand	0.75–1.00
Loamy sand	1.10–1.20
Sandy loam	1.25–1.40
Fine sandy loam	1.50–2.00
Silt loam	2.00–2.50
Silty clay loam	1.80–2.00
Silty clay	1.50–1.70
Clay	1.20–1.50



Methods of integration between RS and CSM

They were idealized for landscape modelling and with a simplified version of a CSM



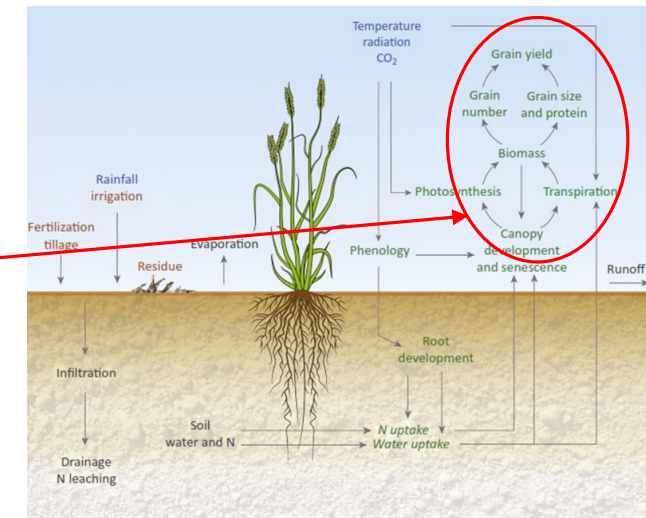
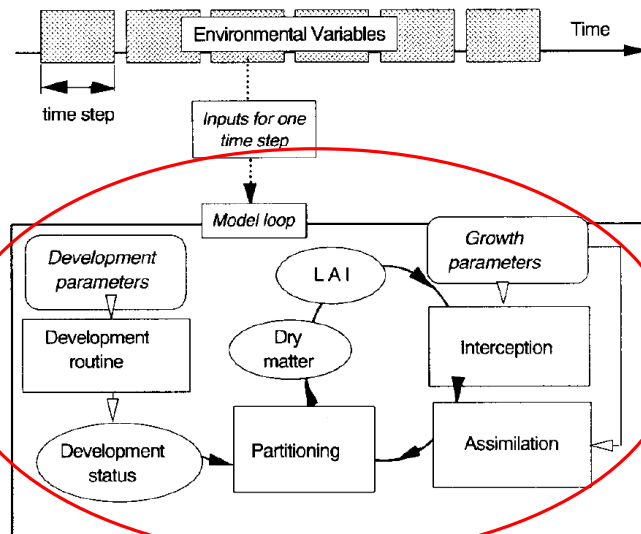
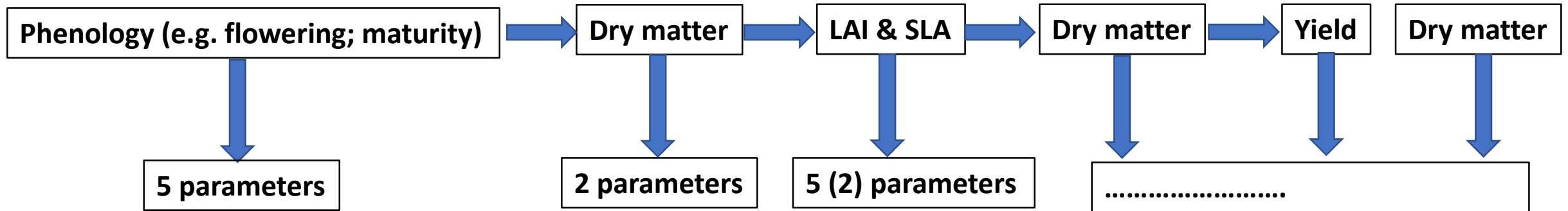
Delecalle et al., 1992

There are many successful examples of data assimilation between CSM and RS at landscape level (e.g. de Wit et al...; Donohue et al., 2018)

Example of crop parameter: LAI

Simplified representation of the calibration (from Boote, 1994; CROPGRO):

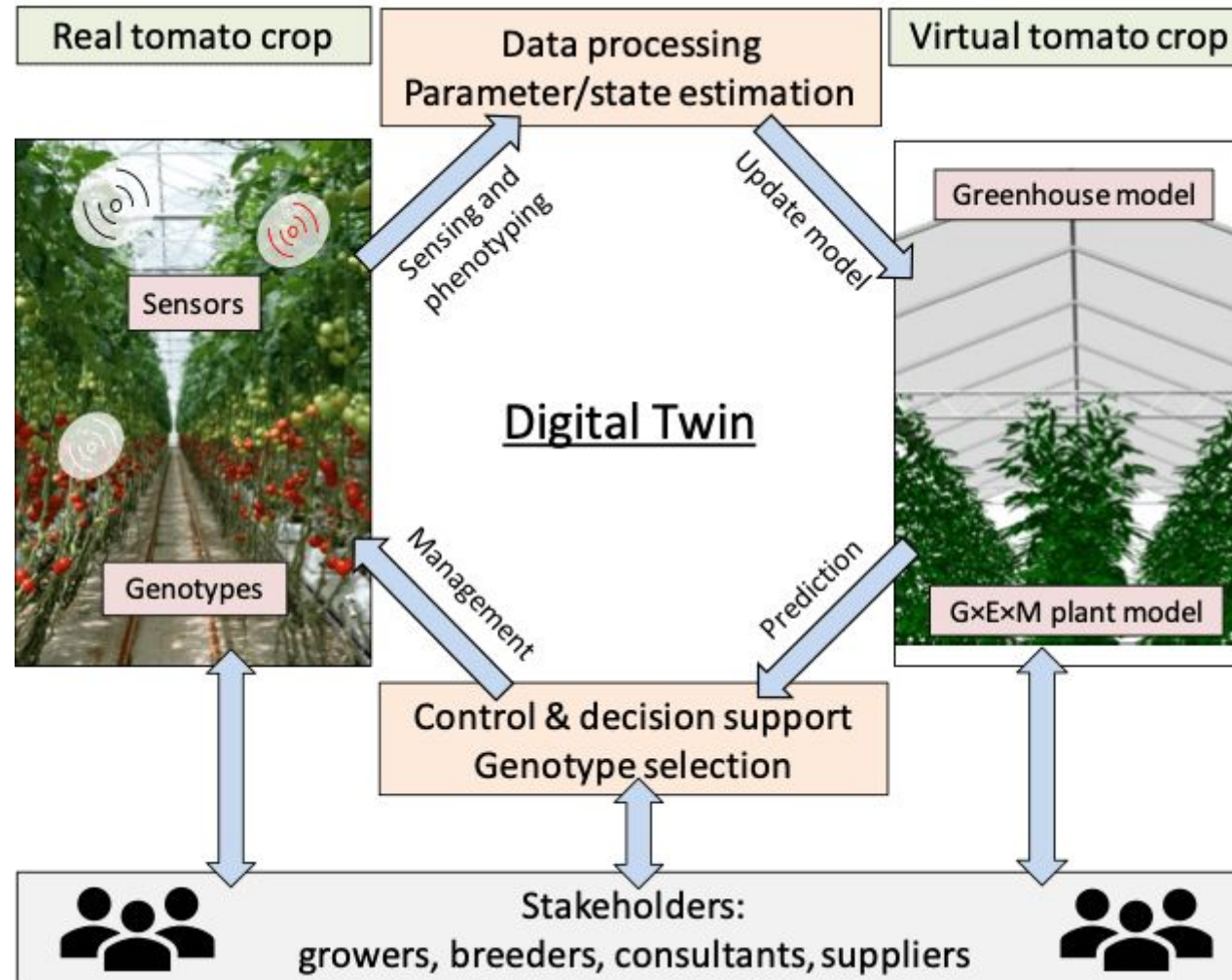
LAI is one of the multi-parameters to calibrate



Chenu et al., 2017

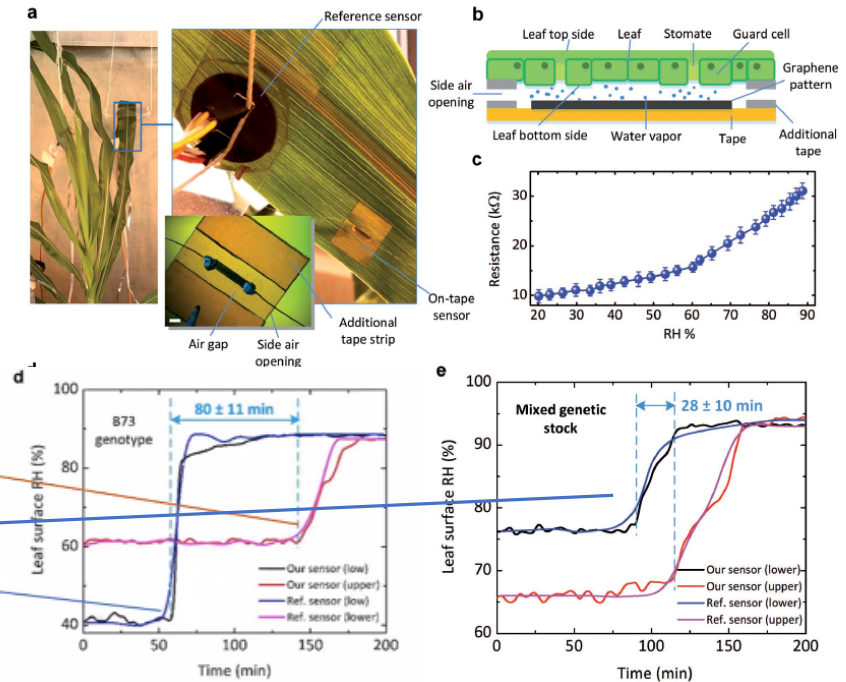
Trends in Plant Science

Digital twinning



Future outlook

- Nanosensors will be able to provide useful information regarding crop status/stress
 - Dong et al. (2017) developed a nanosensor that can detect relative humidity at leaf level
- Models' based on machine learning (can replace CSM?)
- Link with concepts of Precision Agriculture
 - GxExMxSpatial



Conclusion

- **Digital twinning will become an important tool for integrating crop models' and sensing;**
- **Each crop model is different, therefore understand assumptions and main processes simulated;**
- **When using a crop model “system-based” approach thinking is important;**
- **Ground truthing is important.**

