


# Basics of data-driven Climate Smart Agriculture – part 2

Data and analyses at the Farm

  
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# Agridata



It is common to hear the refrain – “Age of (*big*) data” – where new and promising Artificial Intelligence (A.I.) analysis applications and results in agricultural sectors are constantly being published.

*Thought exercise: Is appreciation of data in farming new?*

# Agridata

The Sumerians, considered to have invented the first accounting and writing systems, kept record of harvest and grain inventories. The clay cuneiform tablet (right) from ca. 3100–2900 BCE most likely documents the delivery and distribution of barley and emmer wheat.



# Agridata

Clearly, appreciation for agridata is not new.

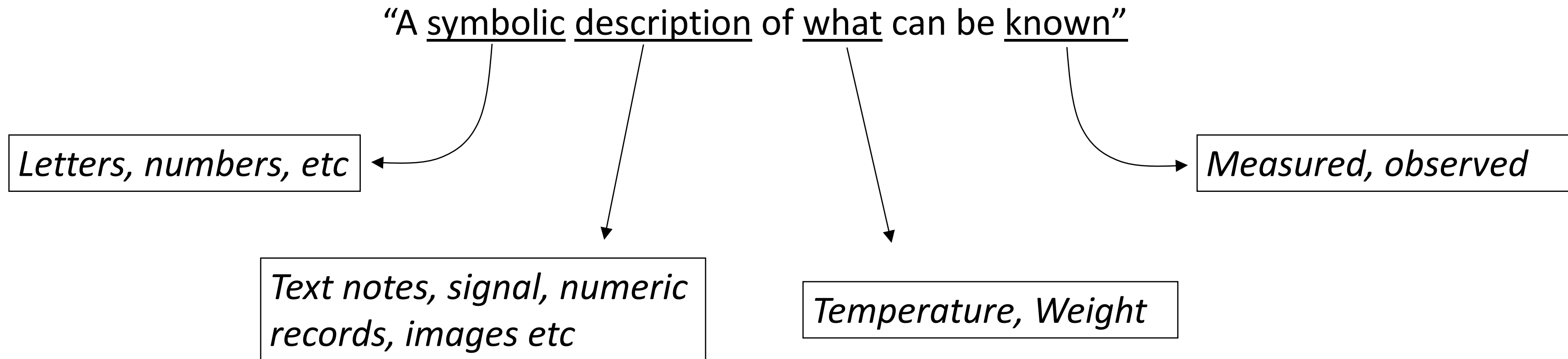
The essential challenge, however, is to use advancements in sensor, communication and analysis technology to explore advanced applications and knowledge discovery.

With greater understanding of the ecosystem interdependencies, data can be used to not only increase productivity, but importantly to do it sustainably.



# Nature of Data

An over-simplified informal way of answering the question "What is data?" could be



# Nature of Data



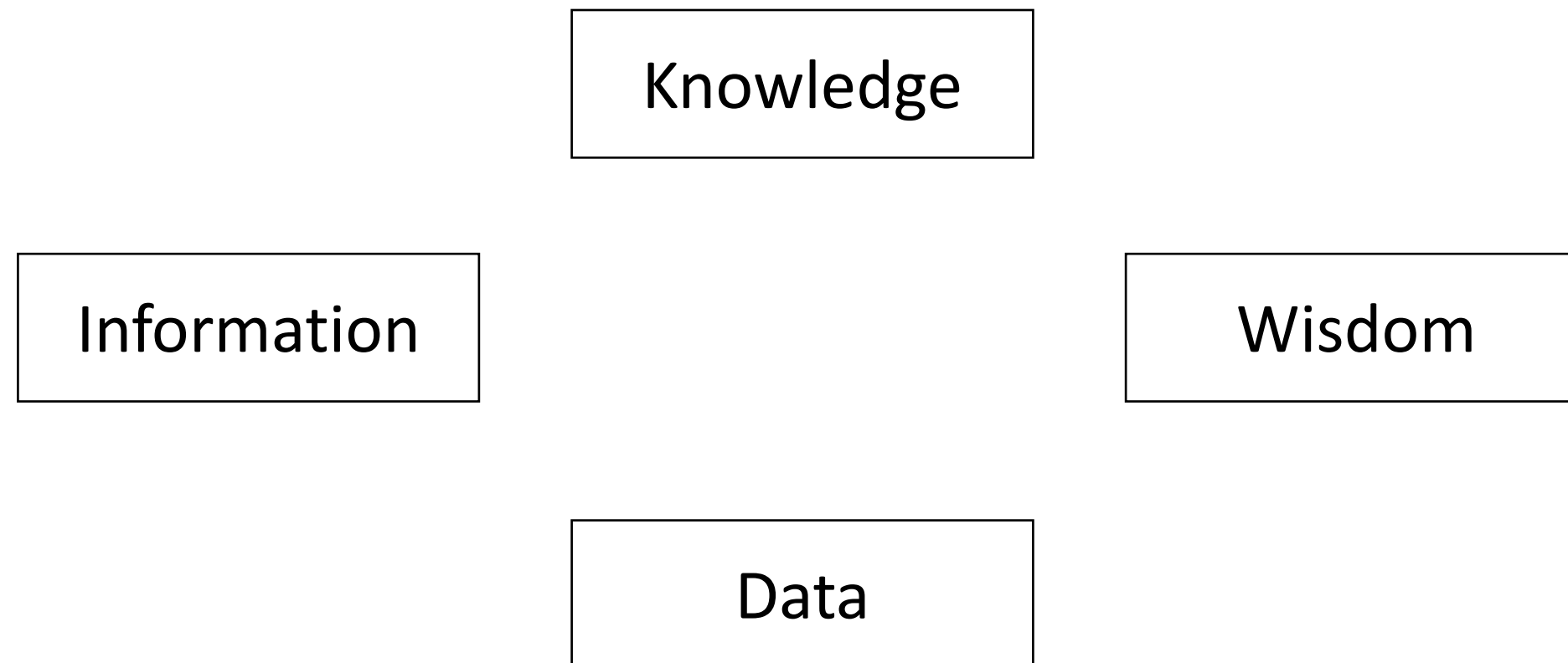
An over-simplified informal way of answering the question "What is data?" could be

"A symbolic description of what can be known"

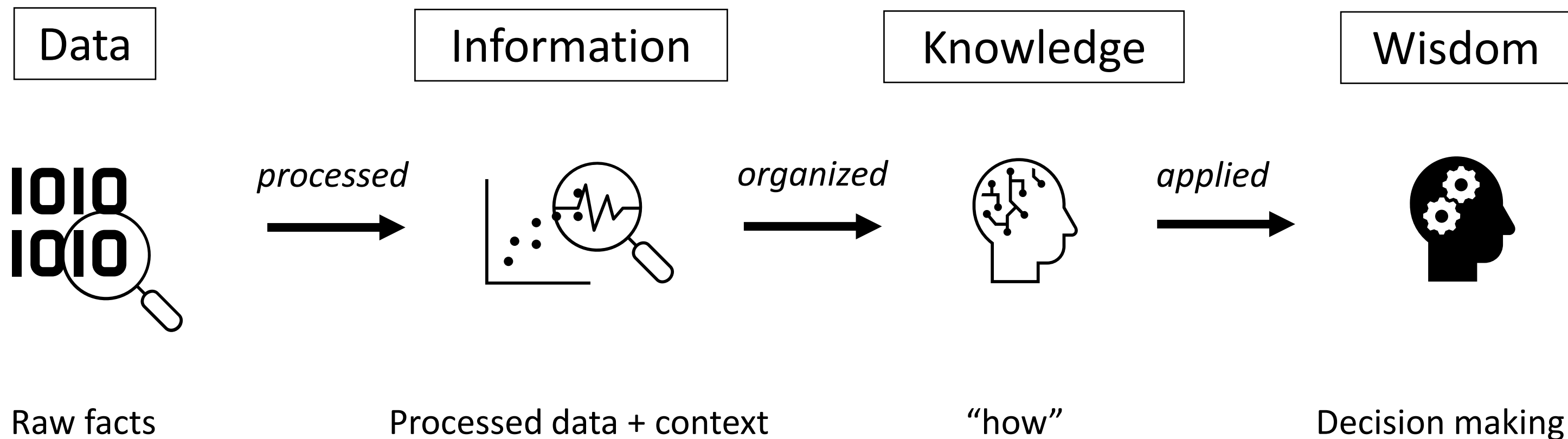
Thus, data is essentially a value commodity whose value is extracted from it for differing purposes

# Nature of Data

*Thought exercise: Consider each term below and ask yourself, what is it made up of and how does one create it?*

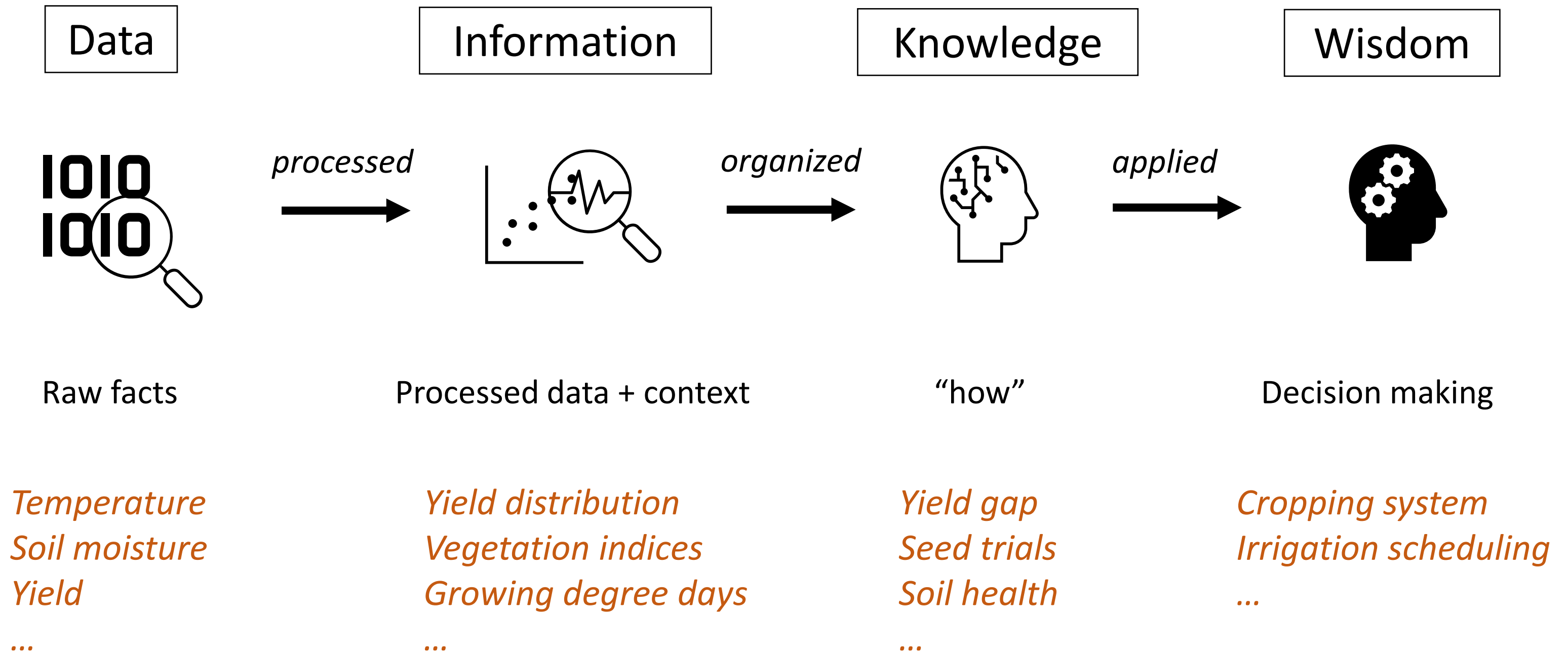


# Data value chain



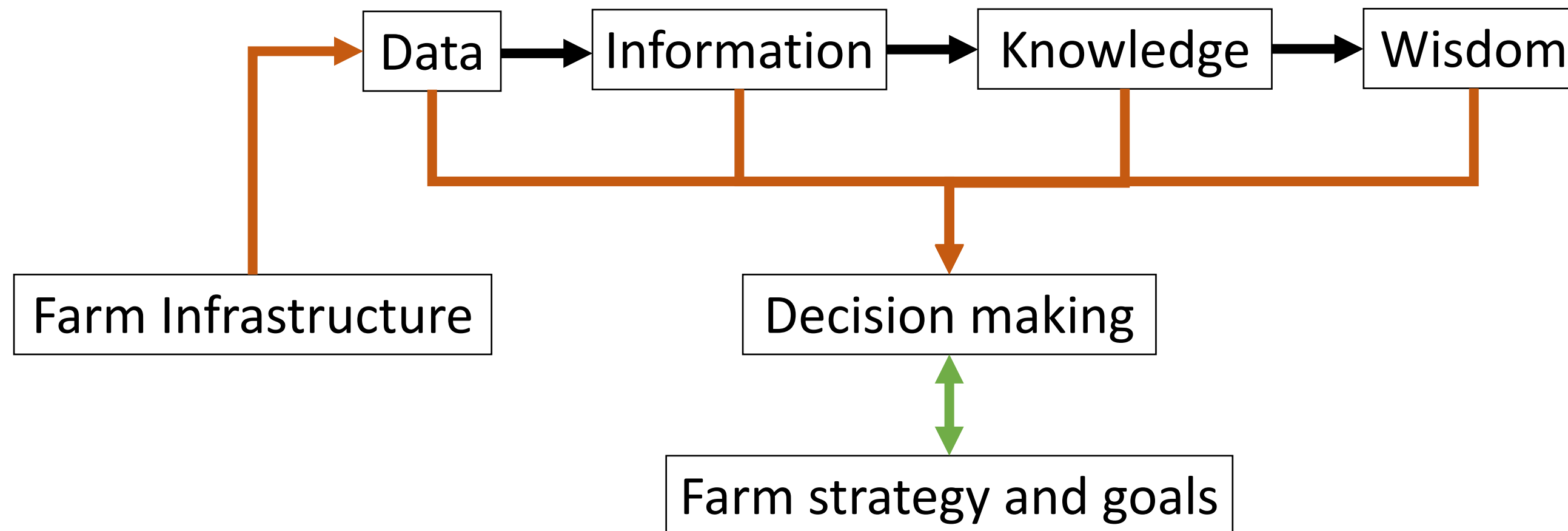
Commonly referred to as the DIKW hierarchy where each node creates value, consolidating and assessing content from the previous node(s) and can be used to answer increasingly complex questions

# DIKW hierarchy – farm specific examples



# Data-driven on-farm decision making

The data value chain positions itself by helping decision making within the context of farm-specific strategy and goals.



# Data-driven on-farm decision making



Various kinds of data generated in farming practices have great potential to be used in agricultural decision-making.

- Solutions to turn complex data to knowledge are needed to support right actions. [1]
- For Climate smart agriculture, digital tools and data are necessary when it comes to measuring, monitoring and verifying climate impacts of farming processes
- Smart farming technologies including information and communication technologies are needed for modern farming processes and to enhance management [2]
- Combining smart digital tools and farm machinery can improve precision and efficiency of farming. [3]

# Data-driven on-farm decision making



- At the farm level, CSA goals could be set and updated based on data analytics that are executed to inform decision making processes
- There are typically 3 types of analyses that function on the data value chain -
  - Descriptive
  - Predictive
  - Precriptive

# Data-driven on-farm decision making



## Descriptive analytics

where the results help describe the state of the system under observation. Some examples are –

- Vegetation indices that describe biomass vigour, or water stress
- Yield measurements
- Soil measurements and structural analyses

# Data-driven on-farm decision making



## Predictive analytics

where the results help forecast the state of the system under observation. Some examples are –

- Yield or biomass forecasts of a standing crop
- Climate forecasts
- Soil organic matter forecasts based on farm management decisions

# Data-driven on-farm decision making

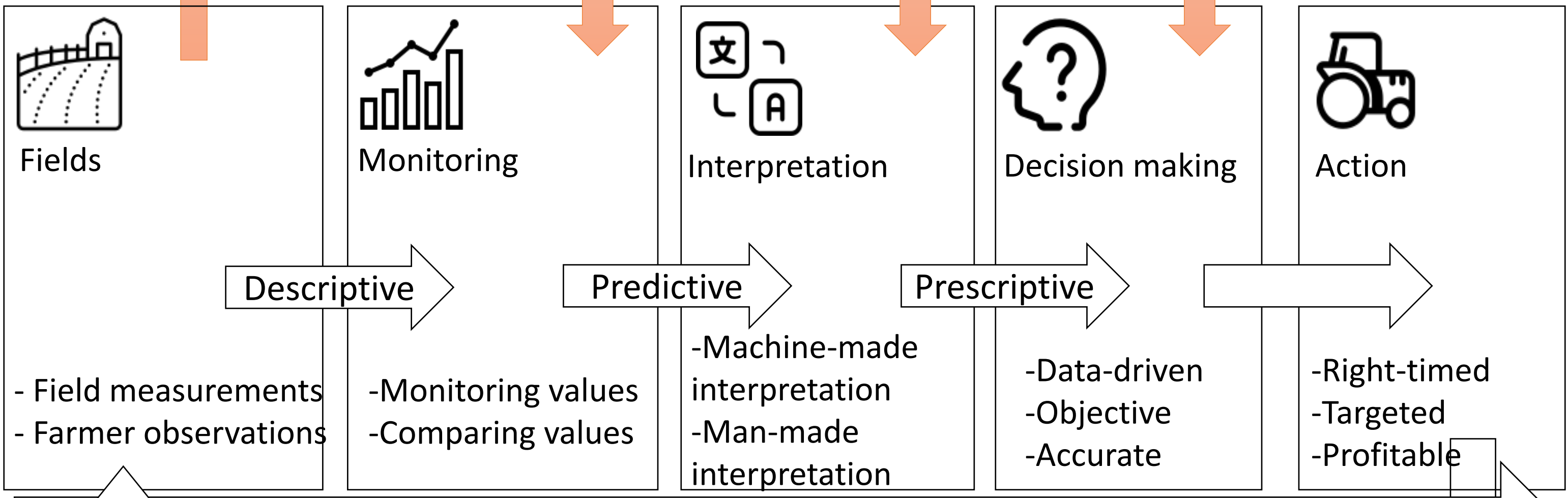
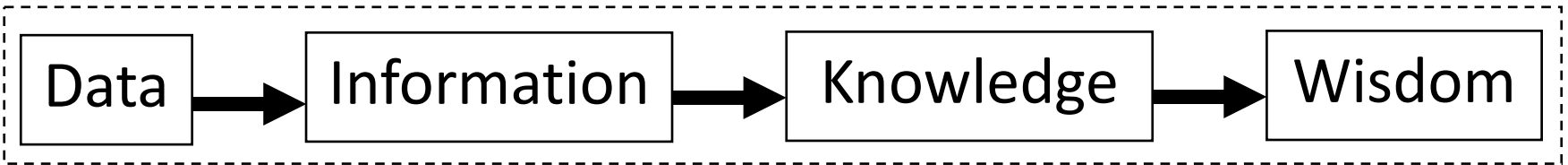


## Prescriptive analytics

where the results guide decisions by suggesting course of action to drive the system under observation towards set goals. Some examples are –

- Fertilizer application rates based on crop vigour mapping
- Irrigation management based on climactic forecasts and vegetation growth models
- Cropping strategy based on soil health strategy and market optimality

External data & knowledge sources



Increased knowledge



Goals:  
Financial, Environmental, Social

Define actions

Evaluate & update goals

# Data collection & presentation



- An important aspect of decision making is the visualization of data and analysis results that when properly done can reinforce knowledge or intuition.
- When data and new information is delivered to farmers from multiple systems, different user interfaces (dashboards, mobile applications etc.) are needed to present it in a meaningful and understandable form.
- It is also possible to include alerts or notifications in these [2]. Mobile applications especially are usable tools to provide real time notifications for users.

# Data collection & presentation



- Mobile applications have many advantages.
  - Almost everyone has a cell phone, and they are easy to carry with.
  - include the basic requirements for data collection (like camera, GPS-positioning and data connections)
- Field images combined with other data, like weather, geospatial information and satellite observations, can accelerate the development of new services. [4]
- Farmers already use mobile phone cameras for monitoring, documentation and analysis tasks. The images are useful in problematic situations when the farmers need some reference material or guidance. [2]

# Agridata: CSA context



For any farm, having set a strategy and goals within the CSA context, data sources can be identified by mapping the data categories and sub-categories.

A map of such data streams can help with capturing the overall layout of what data are currently available either on-farm or accessible via web platforms.

# Sources of agridata



Examples of data categorized according to source locations:

## On-farm data

- Notes
- Sensors
- IoT devices
- Weather

## National data

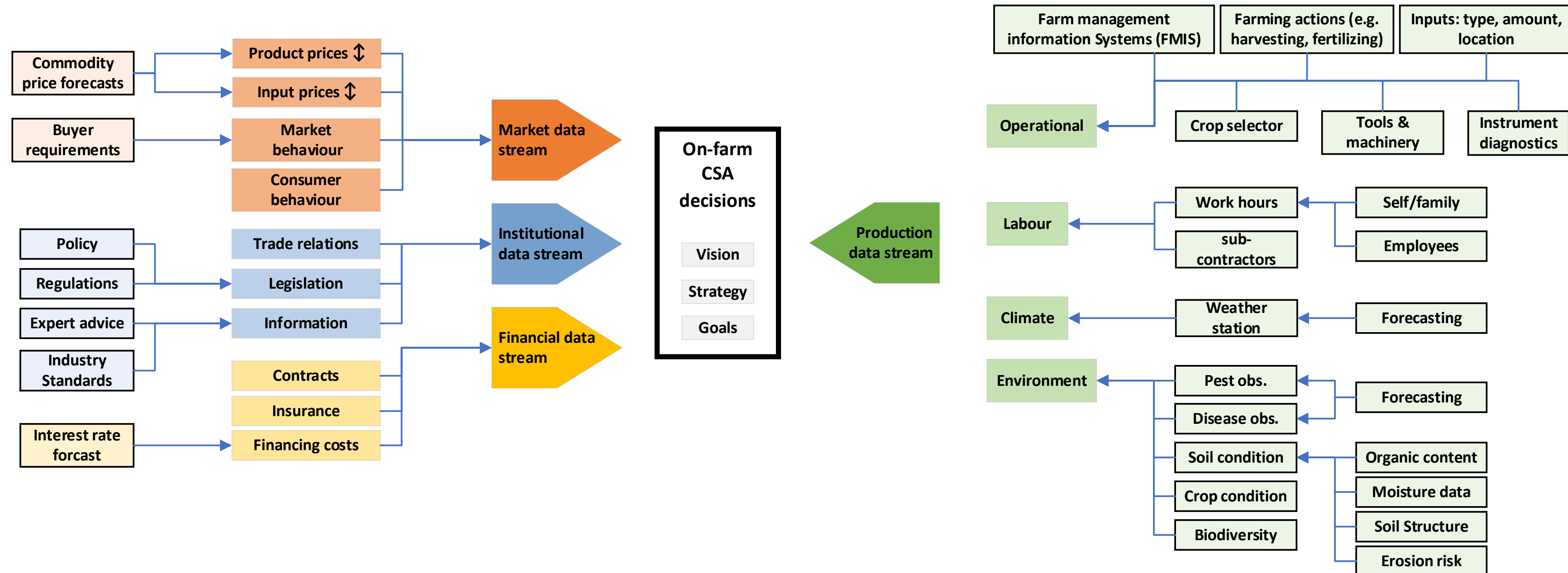
- Weather (e.g. FMI)
- Soil maps

## International data

- Remote sensing
- Market condition monitoring
- Sample surveys

# Data streams: CSA context

An illustration of a categorized map of data streams relevant for a farm operation

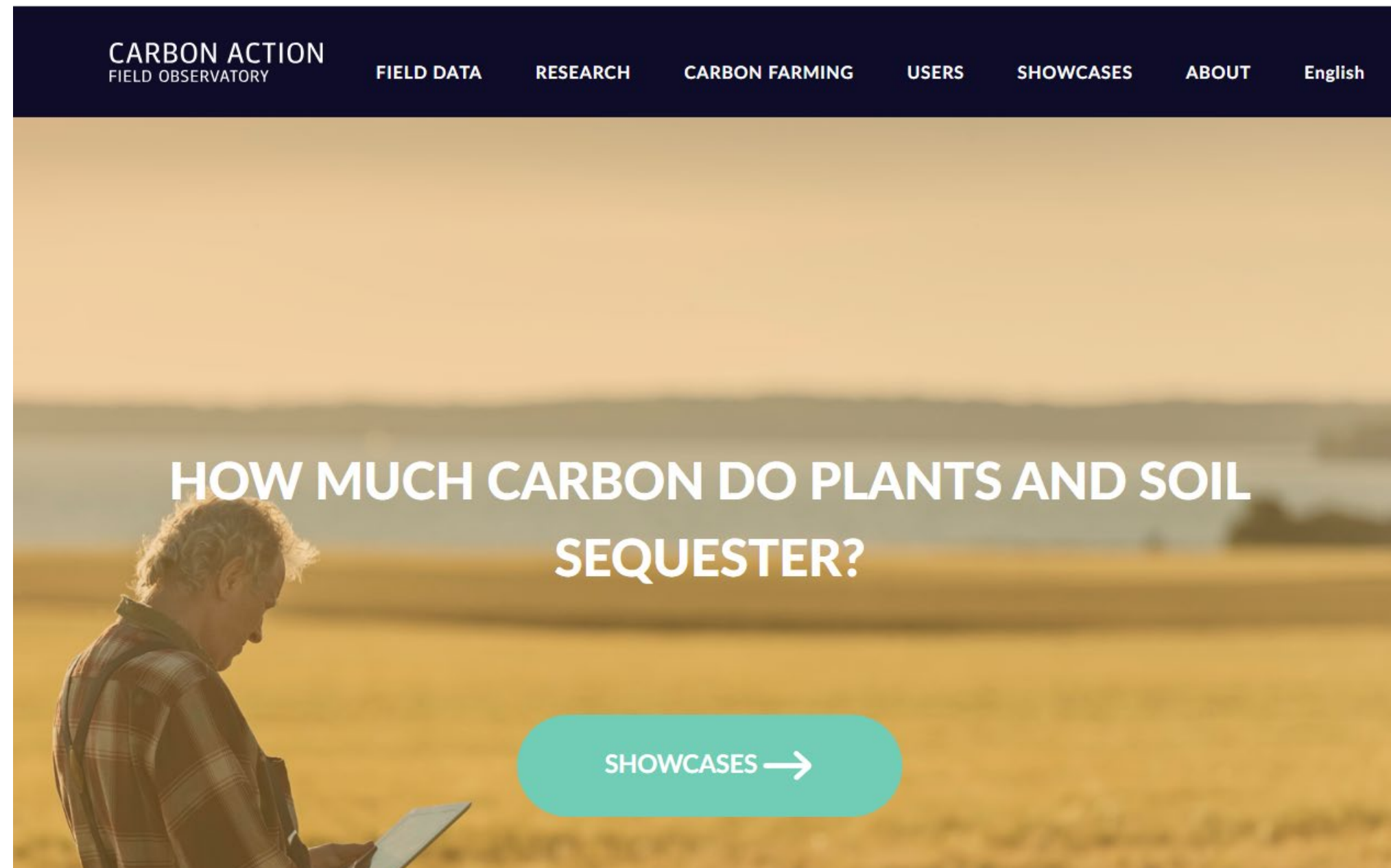


# Self-study exercises



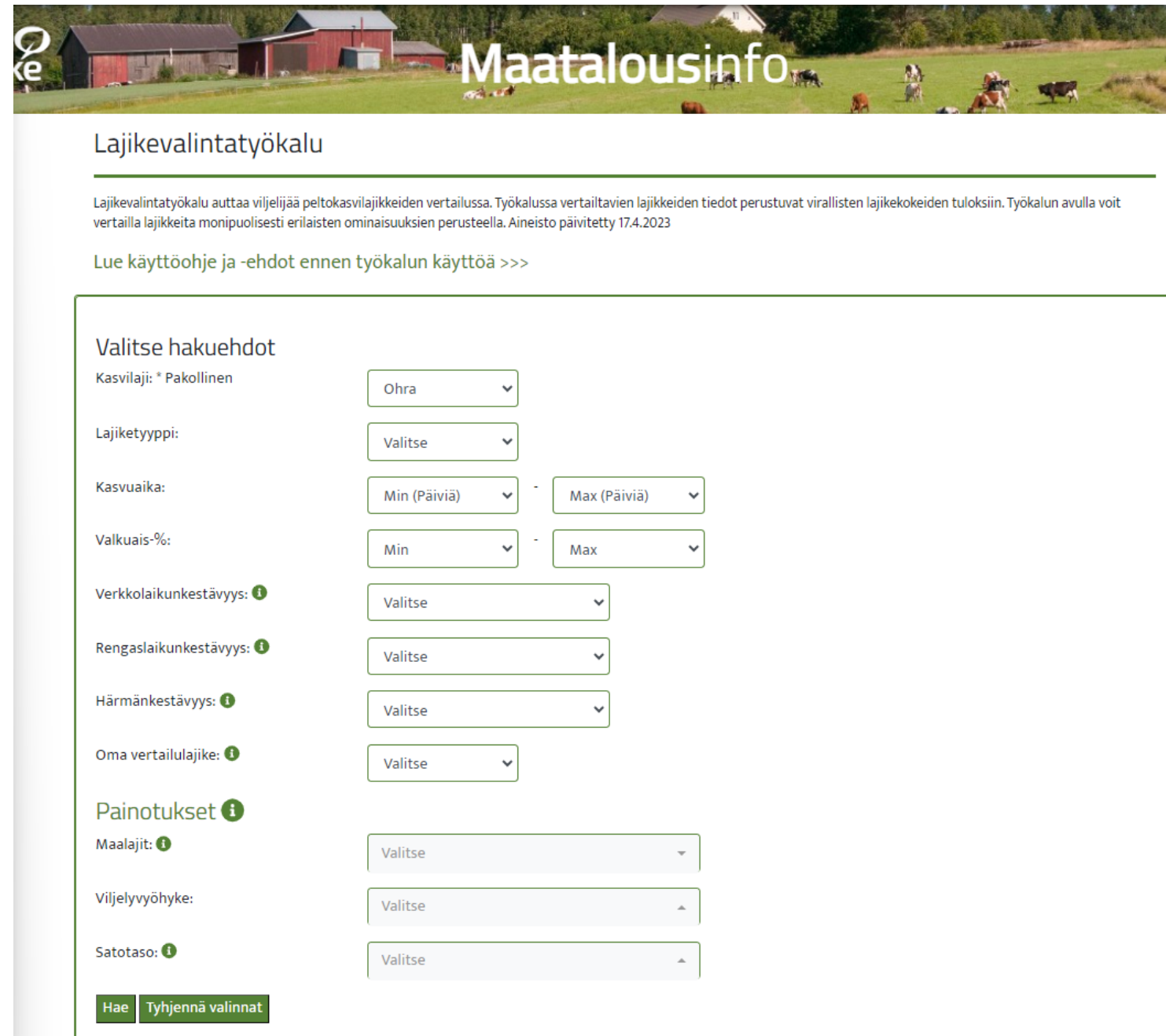
In the following 3 slides cases of data portals are referenced where the reader can explore how agridata is collected and displayed

# Case: Field Observatory



<https://www.fieldobservatory.org/index.php/home/>

# Case: Crop variety selector



**Maatalousinfo**

## Lajikevalintatyökalu

Lajikevalintatyökalu auttaa viljelijää peltokasvilajikkeiden vertailussa. Työkalussa vertailtavien lajikkeiden tiedot perustuvat virallisten lajikekokeiden tuloksiin. Työkalun avulla voit vertailla lajikkeita monipuolisesti erilaisten ominaisuuksien perusteella. Aineisto päivitetty 17.4.2023

Lue käyttöohje ja -ehdot ennen työkalun käyttöä >>>

### Valitse hakuehdot

Kasvilaji: \* Pakollinen

Lajiketyyppi:

Kasvuaika:  -

Valkuais-%:  -

Verkkolaikunkestävyys:

Rengaslaikunkestävyys:

Härmänkestävyys:

Oma vertailulajike:

### Painotukset

Maalajit:

Viljelyvyöhyke:

Satotaso:

<https://maatalousinfo.luke.fi/fi/lajikevalinta>

# Case: Market condition



The screenshot displays the AMIS website interface. At the top, the AMIS logo and navigation menu are visible. The main content area features a 'Crop Monitor' section with a 'last release: 4 April 2024' badge and a 'DOWNLOAD LATEST REPORT' button. Below this, there are icons for 'OVERVIEW', 'WHEAT', 'MAIZE', 'RICE', and 'SOYBEAN'. The central focus is a world map titled 'Synthesis Conditions' showing crop conditions as of March 28th, 2024. The map uses a color-coded system to indicate crop health: blue for 'Exceptional', green for 'Favourable', yellow for 'Watch', orange for 'Poor', red for 'Failure', grey for 'Out-of-Season', and brown for 'No Data'. A legend on the left explains these conditions and also distinguishes between 'Crop Monitor Countries' and 'Non-Crop Monitor Countries'. At the bottom of the map, crop icons for Wheat, Maize, Rice, and Soybean are shown. To the right of the map, there is a 'Tweets from @AMISoutlook' section with a placeholder for a tweet.

<https://www.amis-outlook.org/amis-monitoring/monthly-report/en/>

# Agridata analysis

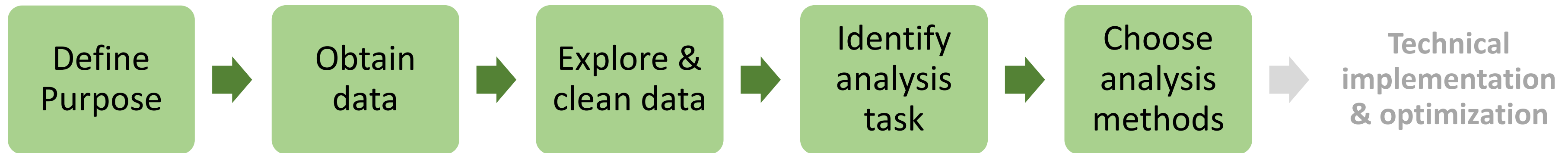


Different steps in the data value chain require varying levels of data analysis methods to extract the desired parameters or explore unknown relationships.

“Analysis” is a very broad term covering a wide range of methods developed across centuries; the latest being the developments in Artificial Intelligence (AI) and Machine Learning (ML).

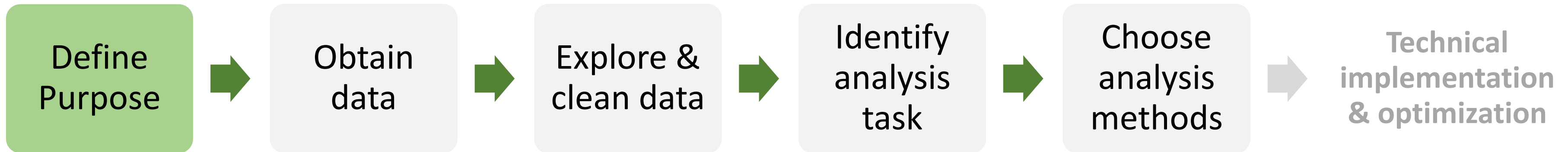
# Analysis process

A typical analysis is executed through a sequence of steps as illustrated below



# Analysis process

The process is initiated by defining the objective of the analysis – i.e., identifying an ‘unknown’ in a farming operation that is important for decision making



# Analysis process



Some examples of such a purpose:

How to protect small farmers against droughts?

How to classify land use and land cover changes, as well as map crops?

How to properly identify crops to study crop rotation?

How to recognize animal diseases?

How to consider the opportunities of using drought-tolerant maize varieties in Southern Africa?

How to create accurate inventories of grasslands using remote sensing?

How to evaluate fish and wildlife population viability under land management alternatives?

How to forecast weather changes?

How to determine phenological stages of paddy rice?

How to identify weeds in sunflower crops to minimize the impact of herbicide?

How to estimate food availability in sub-Saharan Africa?

How much feed does a cow consume in a certain time period at a specific parcel and how does this relate to the milk production in that period?

How to perform dairy herd culling more productively?

How to better understand how management choices affect sustainability performance and operational efficiency?

How to exploit big data on earth observation (EO) systems and datasets?

How to classify and profile soil?

How to support food chain safety measures for cattle holdings?

How to improve the productivity and income of smallholder farmers?

How to facilitate farmers' financing and easier payments?

How to characterize soil and plants effectively?

How to identify management zones for cotton production?

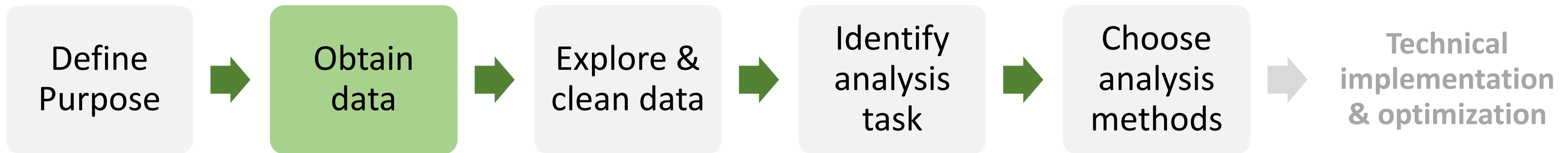
How to assure the safety and the quality of feedstuffs for animals?

How to find spatial equilibrium and optimal locations of agricultural facilities?

How to provide fair and enticing insurance and finance for farmers?

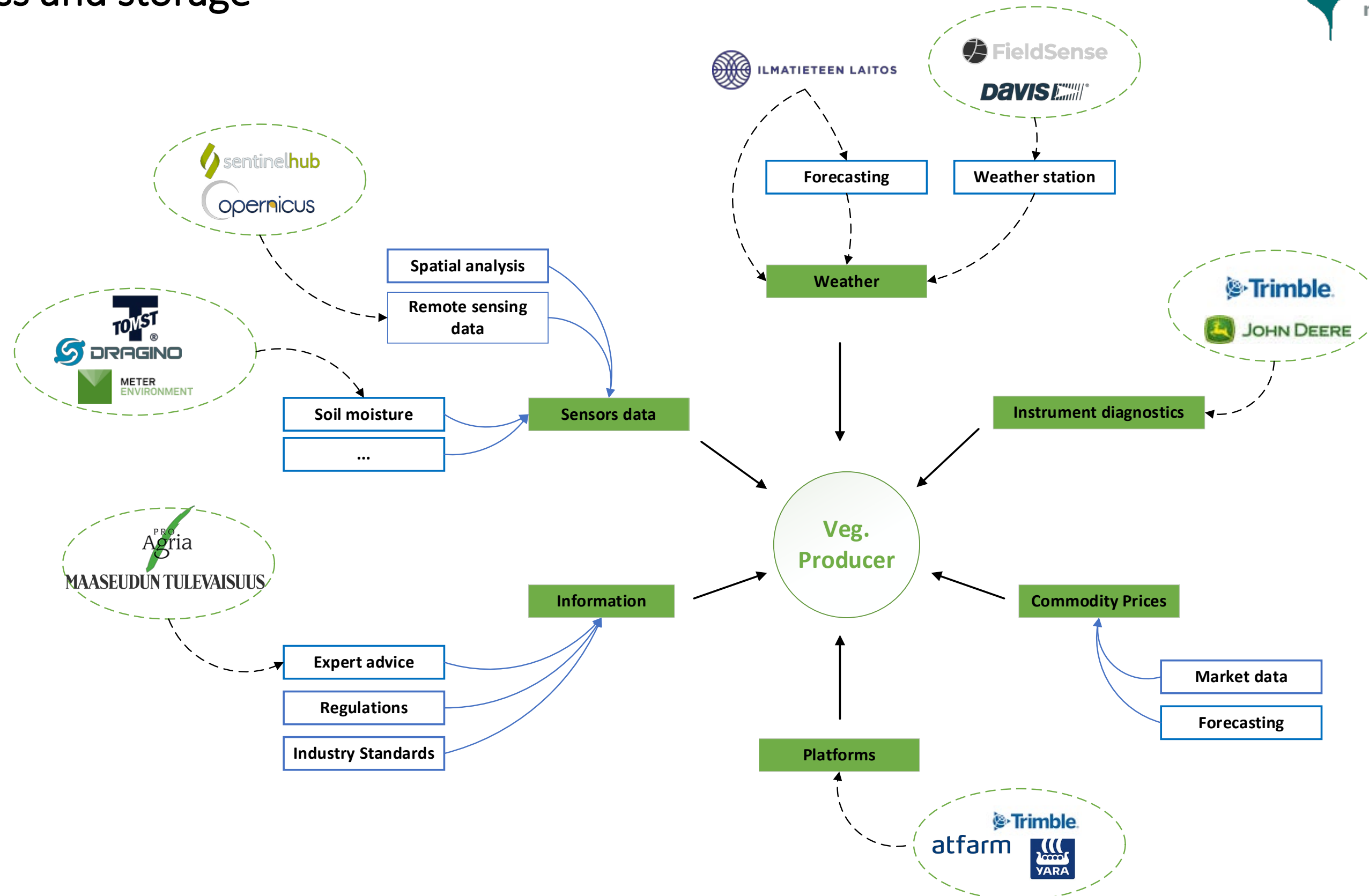
# Analysis process

Having defined a purpose, all appropriate data need to be identified and aspects of data collection and storage need to be addressed.



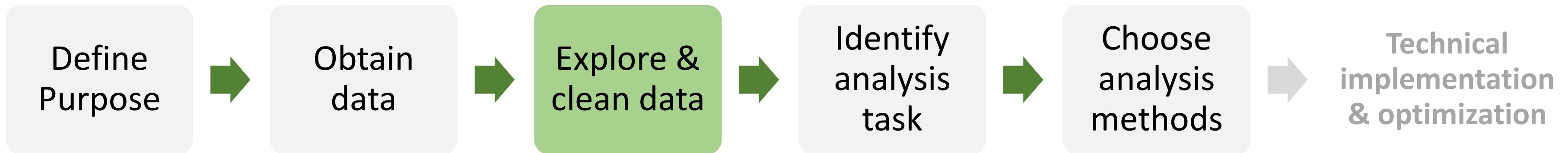
- *Data collection plan?*
- *How is it to be stored?*
- *Data ownership and privacy?*

Case example: A producer may wish to map out all the data sources relevant and/or available to their operation. Each data type may have its own protocol for access and storage



# Analysis process

Corrupt or missing data, often present, needs to be cleaned. Data coherence may need to be confirmed.

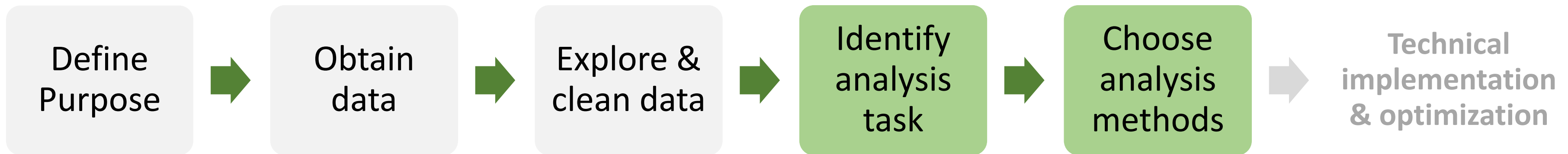


- *Data consistency issues?*
- *Missing data?*
- *Collection strategy deficiencies?*
- *Nature of data – e.g., distribution?*
- *Units and calibration?*
- *Derived parameters?*



Visualization helps with understanding the nature of collected data and exploring cursory relationships that can help identifying appropriate methods downstream.

# Analysis process



With a sound understanding of the acquired data and required type of analysis (descriptive, predictive or prescriptive), the appropriate task(s) is identified, and method(s) chosen.

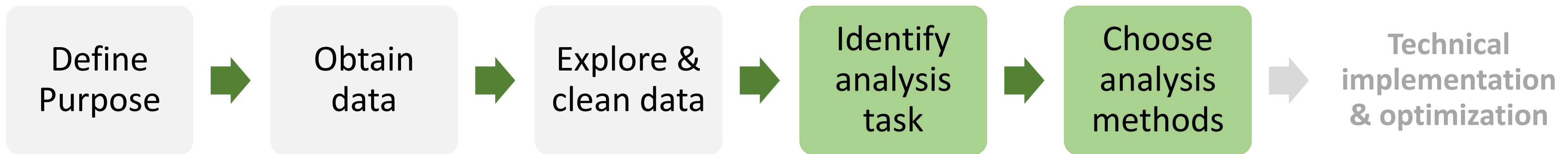
E.g. if the task is that of classification, then one or multiple classification methods can be chosen to test on the data

# Including ML & AI



- AI and ML could bring added value to support farmers decision-making. [1]
- Dedicated information systems which can handle ML workloads but also capable to generate dashboards and visualizations are needed to provide information, trends and patterns in usable form. [5]
- Data accuracy and interoperability between different systems and software solutions should be taken into account and improved constantly. Multiple systems and applications that don't operate together increase the workload and can prevent the use of these systems.

# Analysis process



Some method examples from literature used in data analysis:

Machine learning

Cloud platforms

Wavelet analysis

Spectral data analysis

Decision support systems

Geospatial analysis

Mobile applications

Modelling & simulation

Statistical analysis

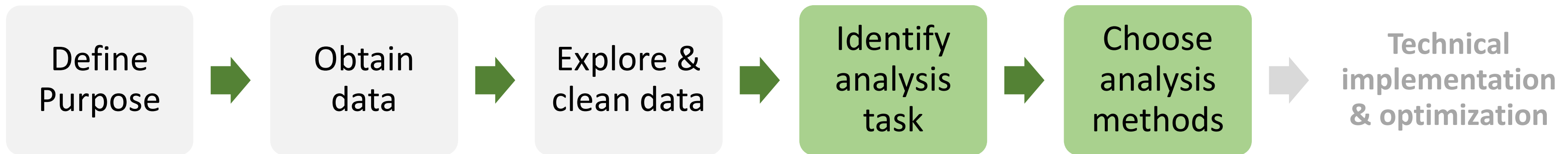
Web services

Computer vision

Fourier transform

Image processing

# Analysis process



Numerous sophisticated methods are grouped under “Artificial Intelligence”. Among these, Machine learning methods have in the past couple of decades made tremendous strides in capability in handling big data and learning complex relationships buried in the data.

# Case: Convolution Neural Networks in agri analysis



- The following slides present a brief (non-exhaustive) summary of applications of a particular machine learning method – Convolution neural Networks – in agricultural applications
- The reader is encouraged to read the referenced publications to understand how the applications were implemented

**Sensor Data**



**Artificial Intelligence  
Methods**



**Agronomy**

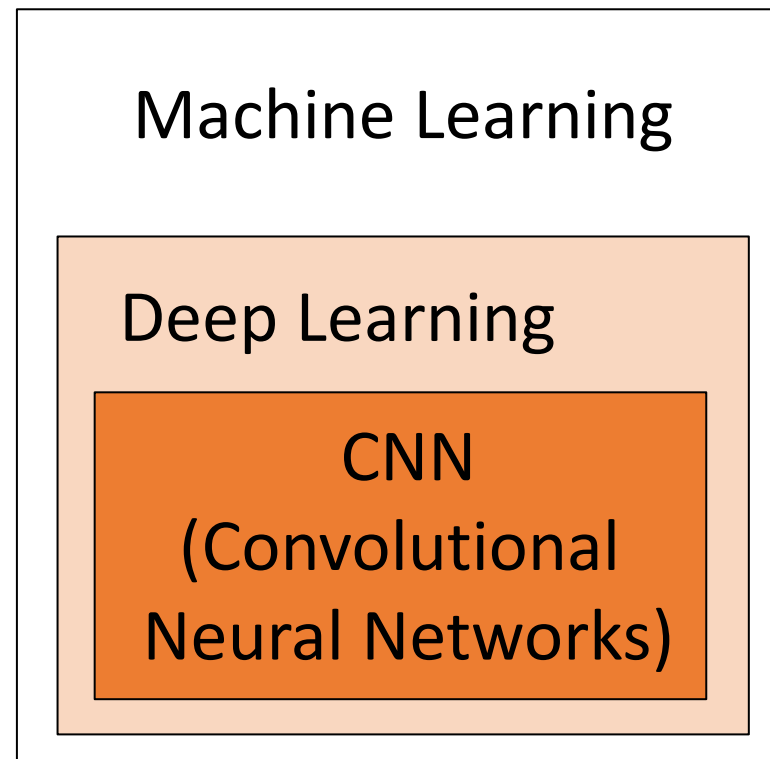


Temperature  
Solar radiation  
Precipitation  
Humidity  
...

Irrigation  
Fertilizers  
Compost  
Herbicides  
...

Soil type  
Mineral content (N,P,K,...)  
Organic content  
Moisture

+ Remote sensing  
image data



Agriculture information processing

Agriculture production system optimal  
control

Smart agriculture machinery  
equipment

Agricultural economic system  
management

**Sensor Data**



**Artificial Intelligence  
Methods**



**Subject  
Areas**

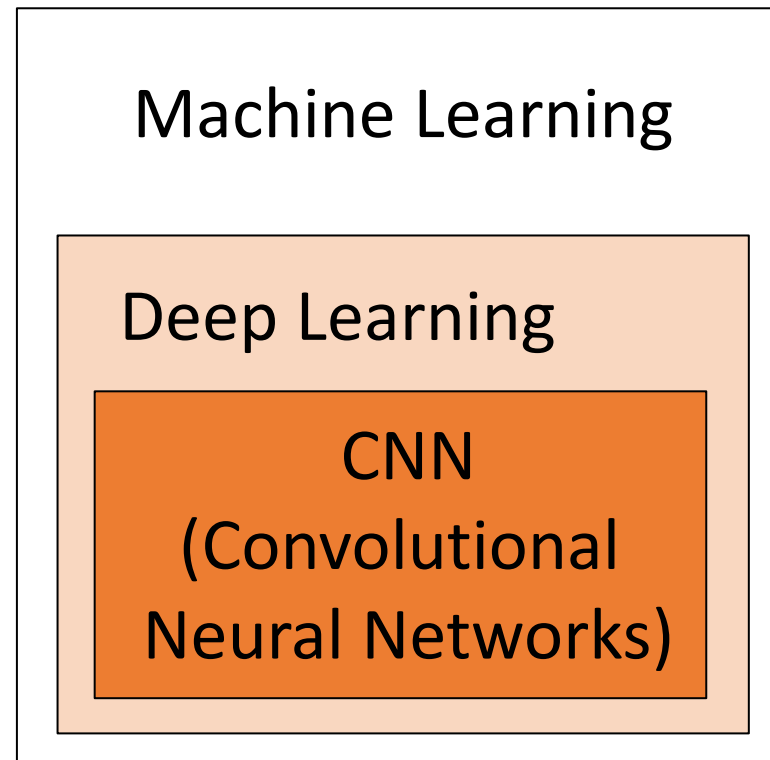


Temperature  
Solar radiation  
Precipitation  
Humidity  
...

Irrigation  
Fertilizers  
Compost  
Herbicides  
...

Soil type  
Mineral content (N,P,K,..)  
Organic content  
Moisture

+ Remote sensing  
image data



Plant

Animal

Land

Mechanization

**Sensor Data**



**Artificial Intelligence  
Methods**



**Subject  
Areas**



Temperature  
Solar radiation  
Precipitation  
Humidity  
...

Irrigation  
Fertilizers  
Compost  
Herbicides  
...

Soil type  
Mineral content (N,P,K,..)  
Organic content  
Moisture

+ Remote sensing  
image data

Machine Learning

Deep Learning

CNN  
(Convolutional  
Neural Networks)

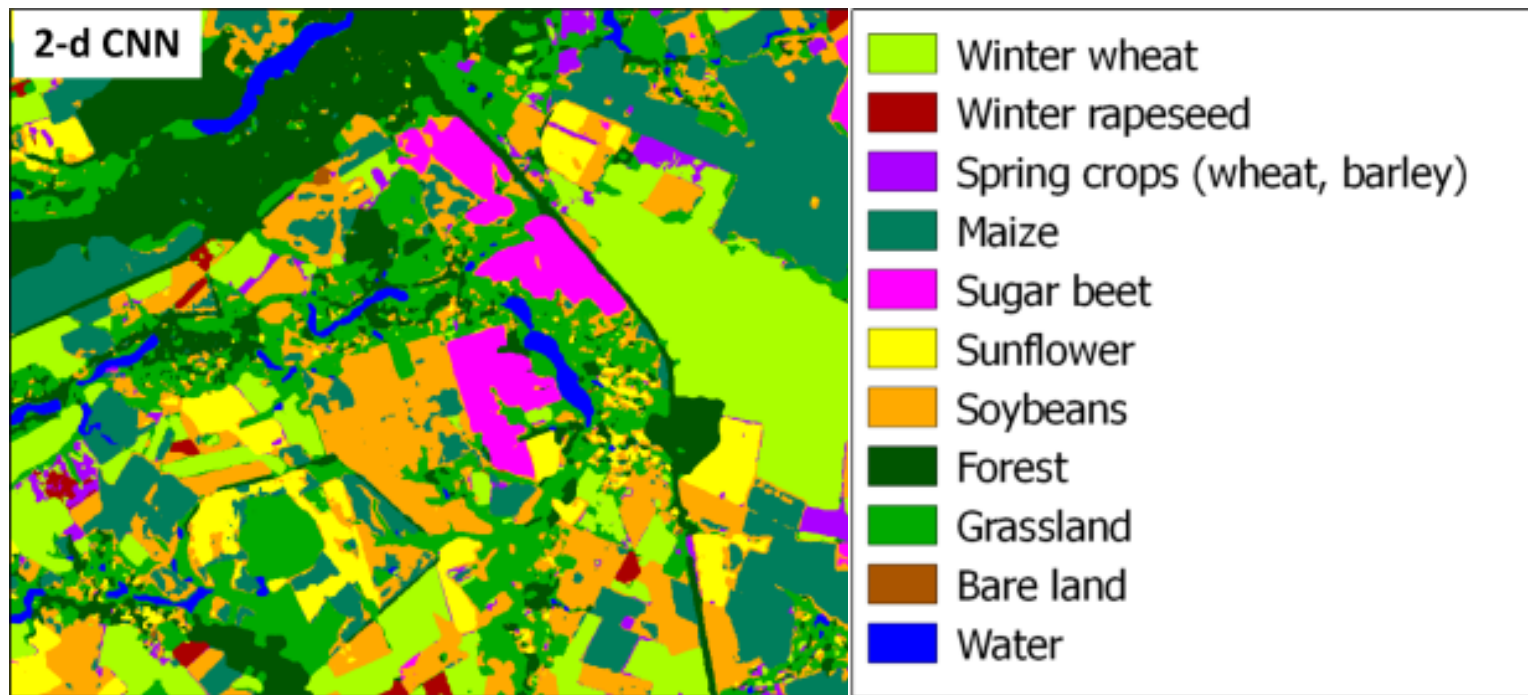
Plant

Animal

Land

Mechanization

- Crop classification
- Phenology recogn.
- Disease detection
- Weed/pest detection
- Fruit counting
- Yield prediction

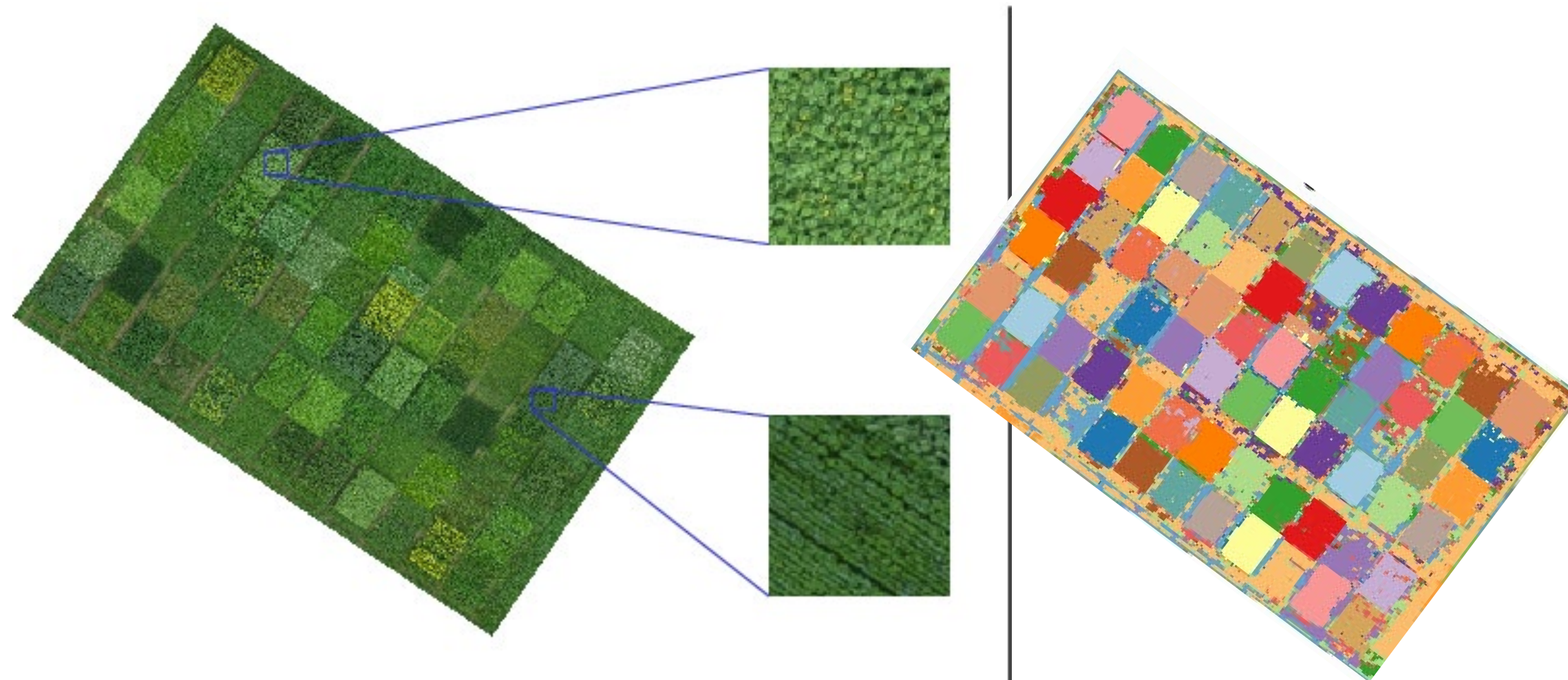


*Kussul et al. 2017; DOI: 10.1109/JSTARS.2016.2560141*



• **Crop classification**

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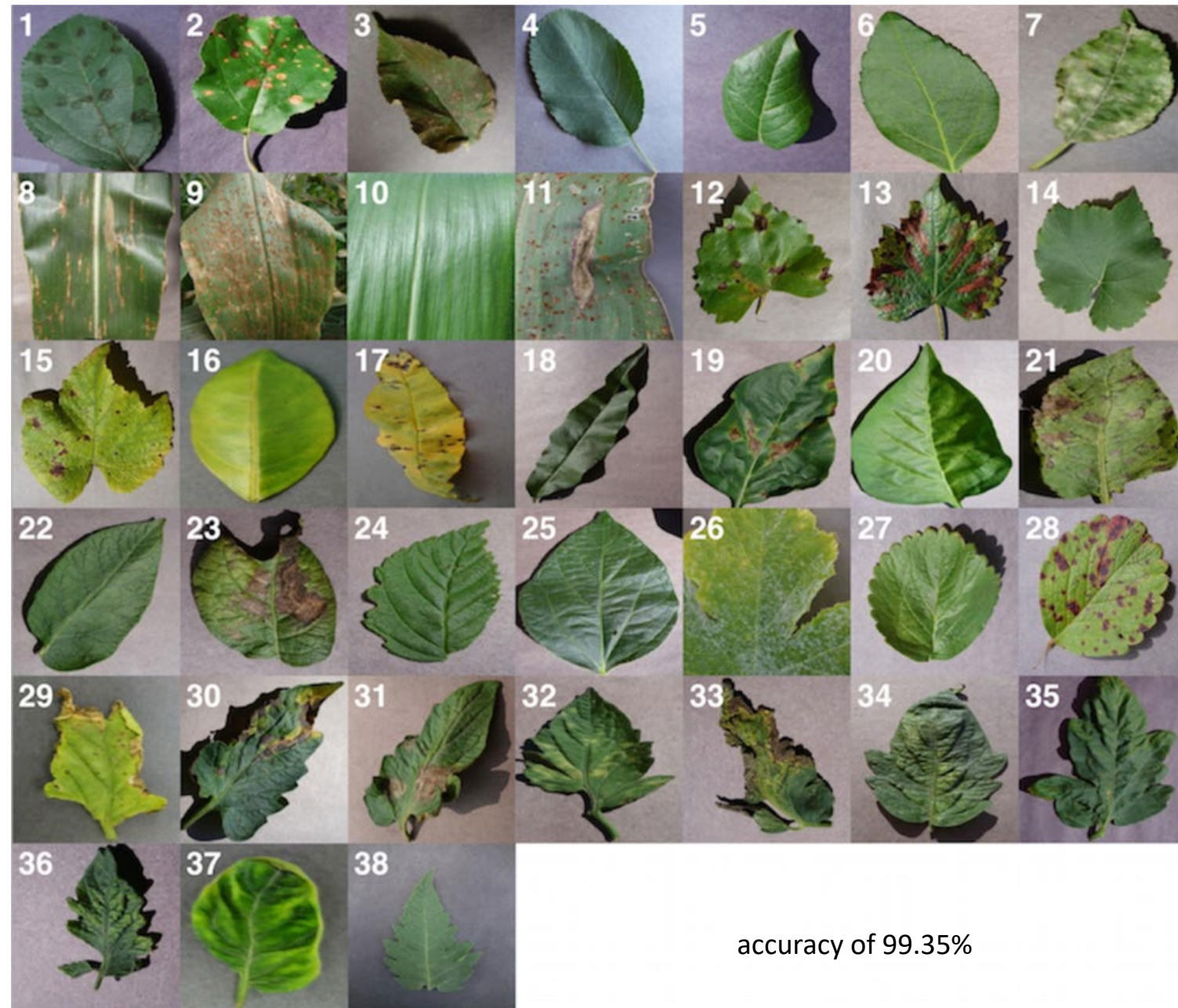


*Rebetz et al. 2016; ISBN: 978-287587027-8*

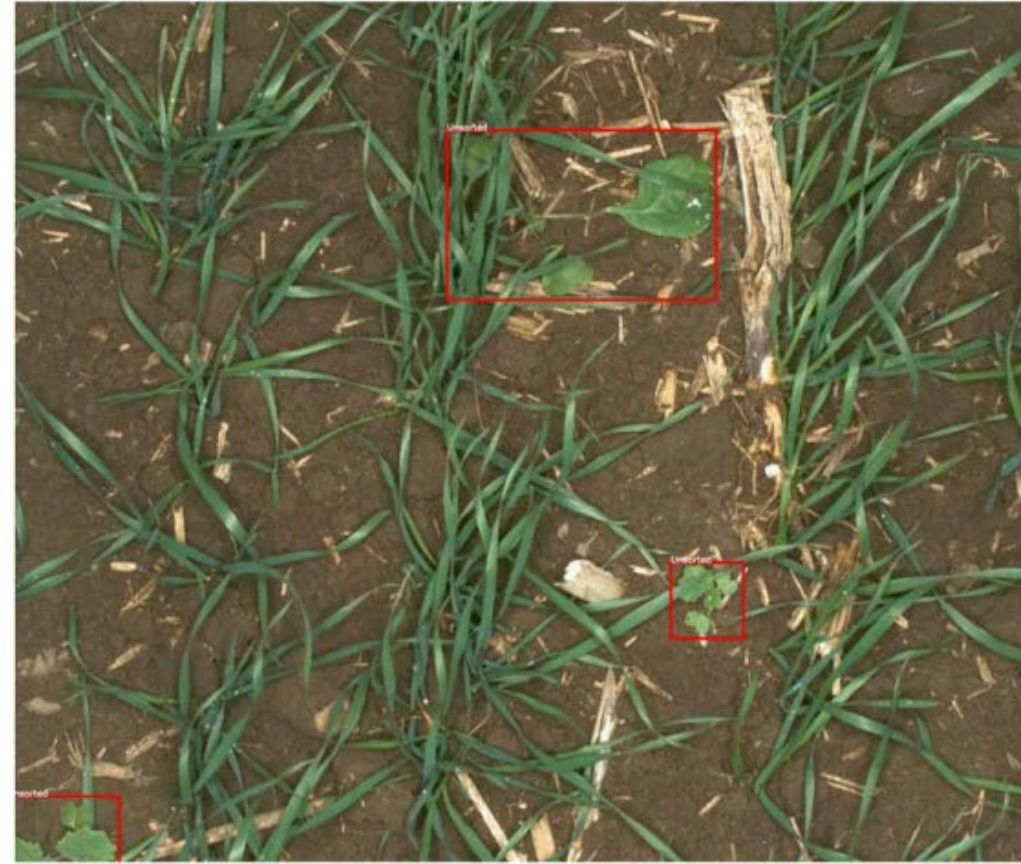
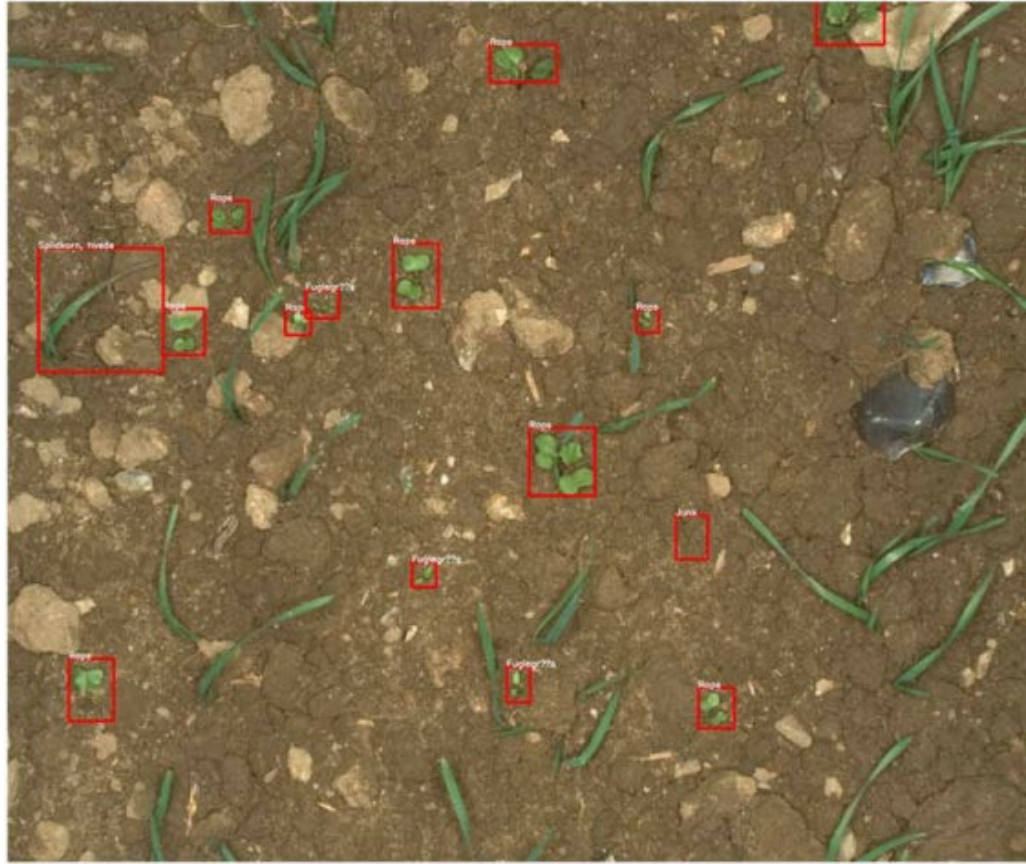


- Crop classification
- **Phenology recogn.**
- Disease detection
- Weed/pest detection
- Fruit counting
- Yield prediction

Dataset	Method	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
Cotton	CNN-BA	87.32	86.14	86.58	86.54
Pepper	CNN-BA	88.12	87.24	87.28	87.14
Corn	CNN-BA	87.32	86.14	86.58	86.54



- Crop classification
- Phenology recogn.
- **Disease detection**
- Weed/pest detection
- Fruit counting
- Yield prediction



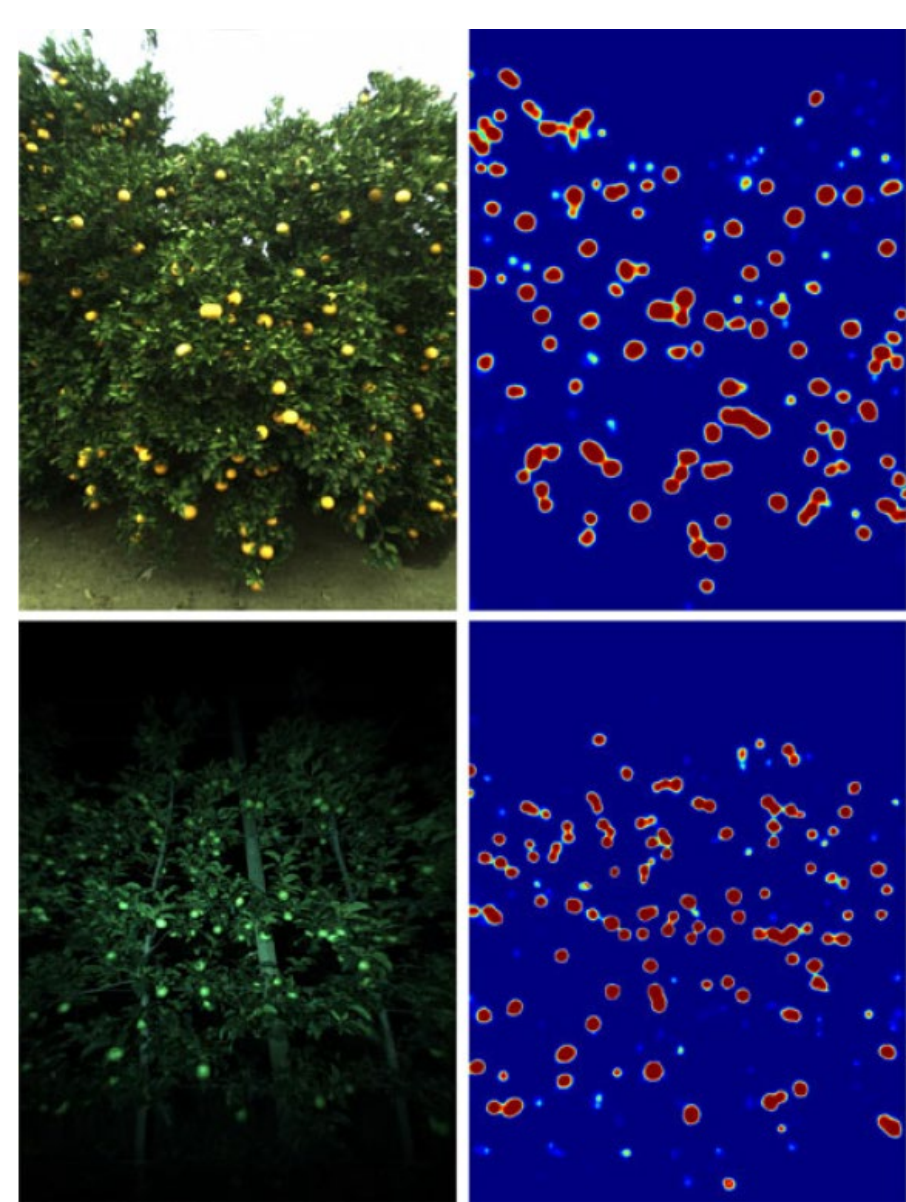
*Dyrmann et al. 2017; DOI: 10.1017/S2040470017000206*



- Crop classification
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*McCool et al. 2017; DOI: 10.1109/LRA.2017.2667039*



- Crop classification
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- Yield prediction



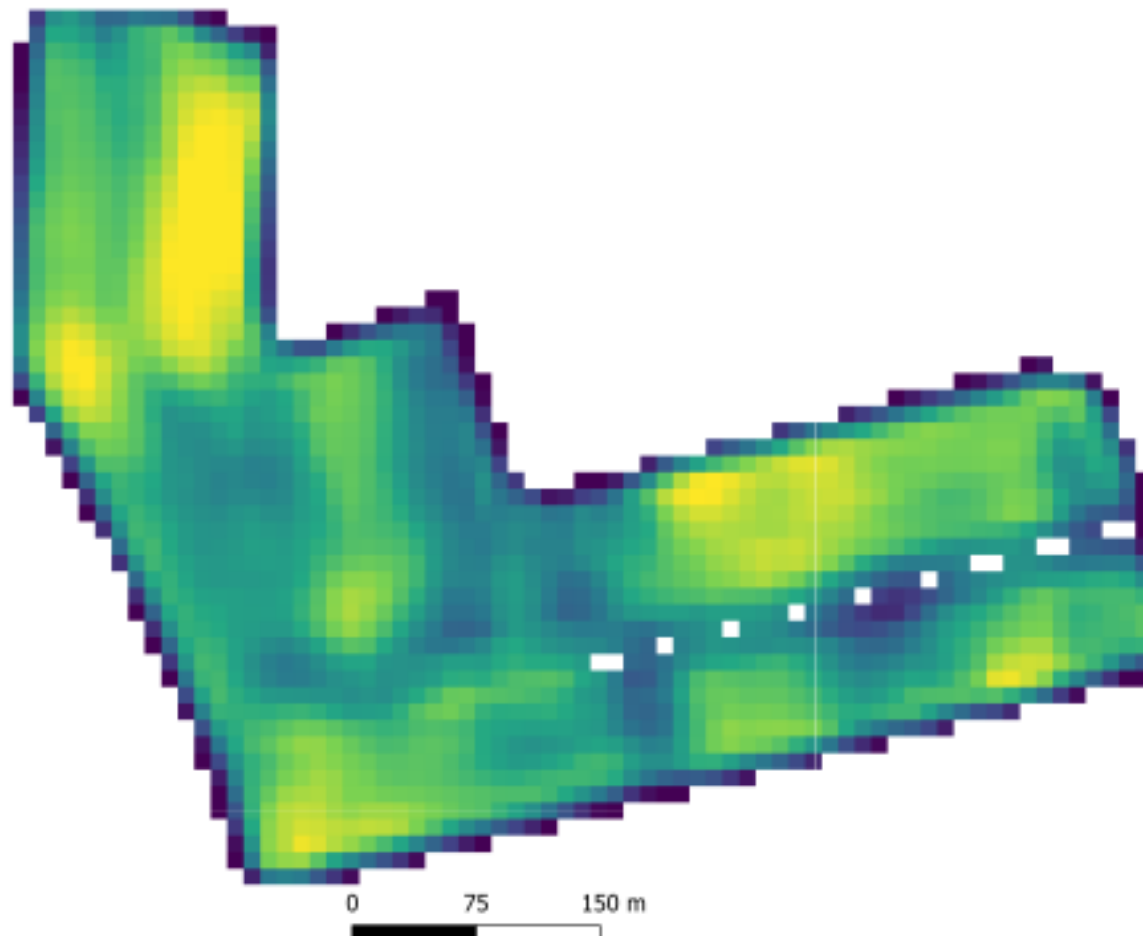
# Yield prediction



- Crop classification
- Phenology recogn.
- Disease detection
- Weed/pest detection
- Fruit counting
- **Yield prediction**

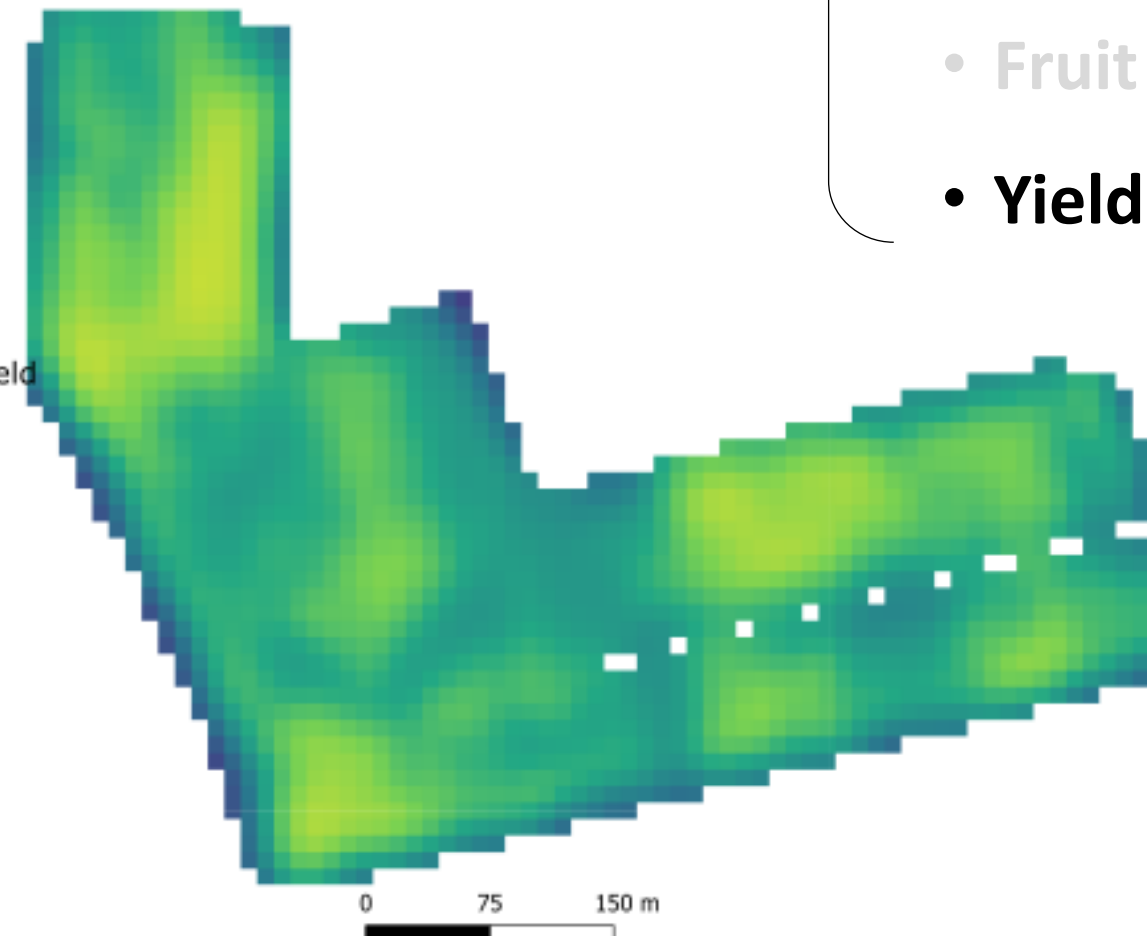
True Yield

3870
4779
5687
6596
7504
8413



Predicted Yield

3870
4779
5687
6596
7504
8413



## Value of data is in the knowledge it fosters

It is essential to recognize that when faced with a plethora of data sources and sensor types, the value of data collected needs to be considered.

Selecting the analysis method needs consideration of cost, availability, reliability of results, availability of essential input data etc

# Challenges



- Understanding and use of data is still limited. Lack of tools prevent the full utilization of data on farms. [1]
- Usually, in practice, collected data is limited to simple monitoring and reporting tasks and not to solve actual and practical problems. [7]
- There is challenges to utilize variety and large quantity of agricultural and environmental data for analysis and decision-making. This also relates to the lack of tools and interfaces. [2],[6]

# References (Read more!)



1. Gebresenbet, G. et al. (2023). A concept for application of integrated digital technologies to enhance future smart agricultural systems. *Smart Agricultural Technology*, 5, 100255. <https://doi.org/10.1016/J.ATECH.2023.100255>
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5. \*Dineva, K. & Atanasova, T. (2022). Cloud Data-Driven Intelligent Monitoring System for Interactive Smart Farming. *Sensors*, 22(17), 6566. <https://doi.org/10.3390/s22176566>
6. \*Mandal, S. et al. (2024). Adaption of smart applications in agriculture to enhance production. *Smart Agricultural Technology*, 7, 100431. <https://doi.org/10.1016/j.atech.2024.100431>
7. \*Osinga, S.A. et al. (2022). Big data in agriculture: Between opportunity and solution. *Agricultural Systems*, 195, 103298. <https://doi.org/10.1016/J.AGSY.2021.103298>

\* Open access