

IoT for environmental monitoring

Air quality and Precision
Agriculture



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01 Internet of Things

02 Air Quality Monitoring

03 IoT for Precision Agriculture



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Part 1.

Internet of Things



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Financiado por
la Unión Europea
NextGenerationEU



Plan de Recuperación,
Transformación y
Resiliencia



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ESTATAL DE
INVESTIGACIÓN



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things



Example: Smart Watch 4G

- Conversation topic → Sensors data
- Data processing → Smart
- Ability to talk → Internet connection



Sensors

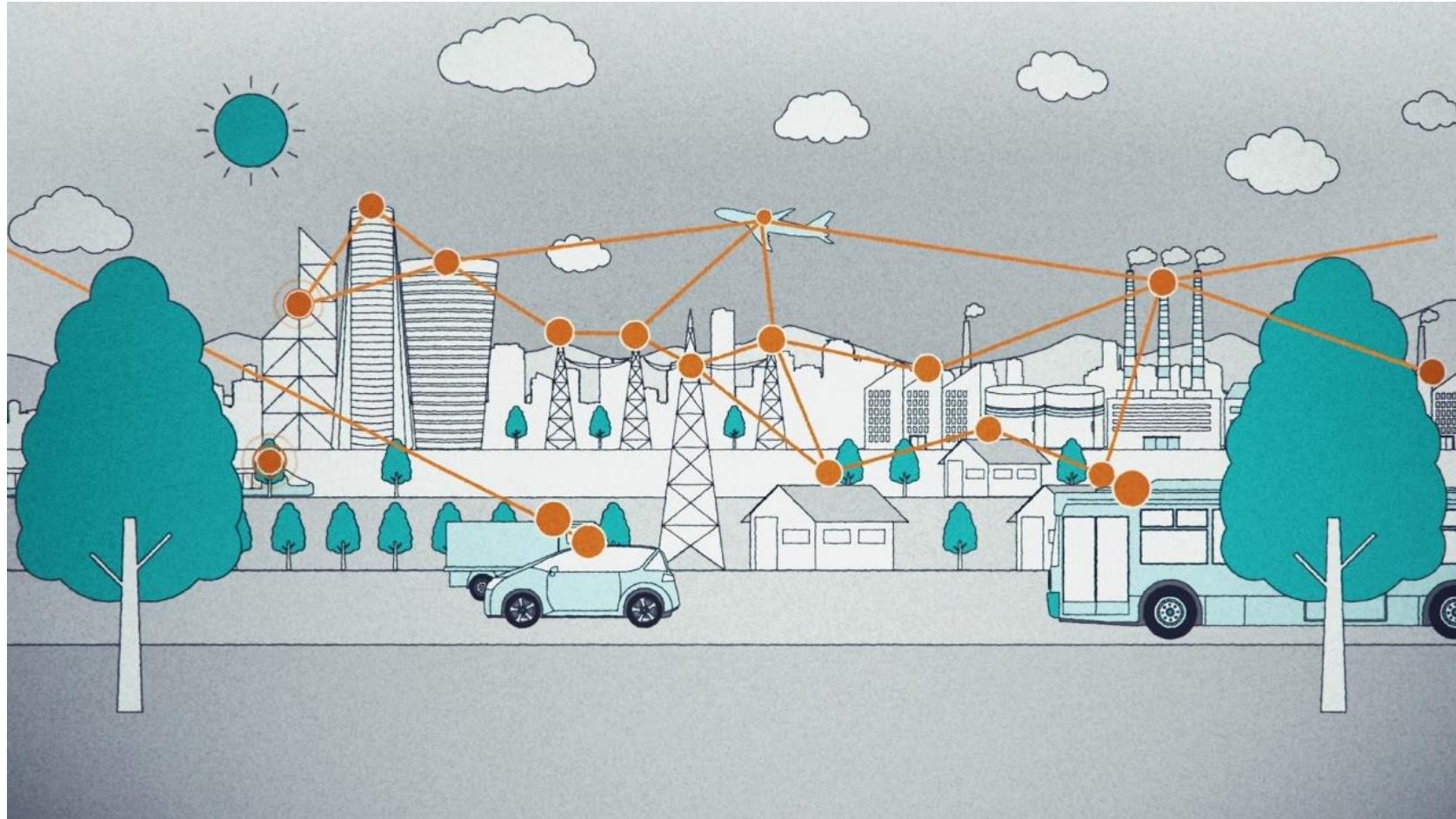
- Temperature
- GPS
- Heart rate monitor
- Accelerometer
- Altimeter
- Gyroscope



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Wireless Sensor Network



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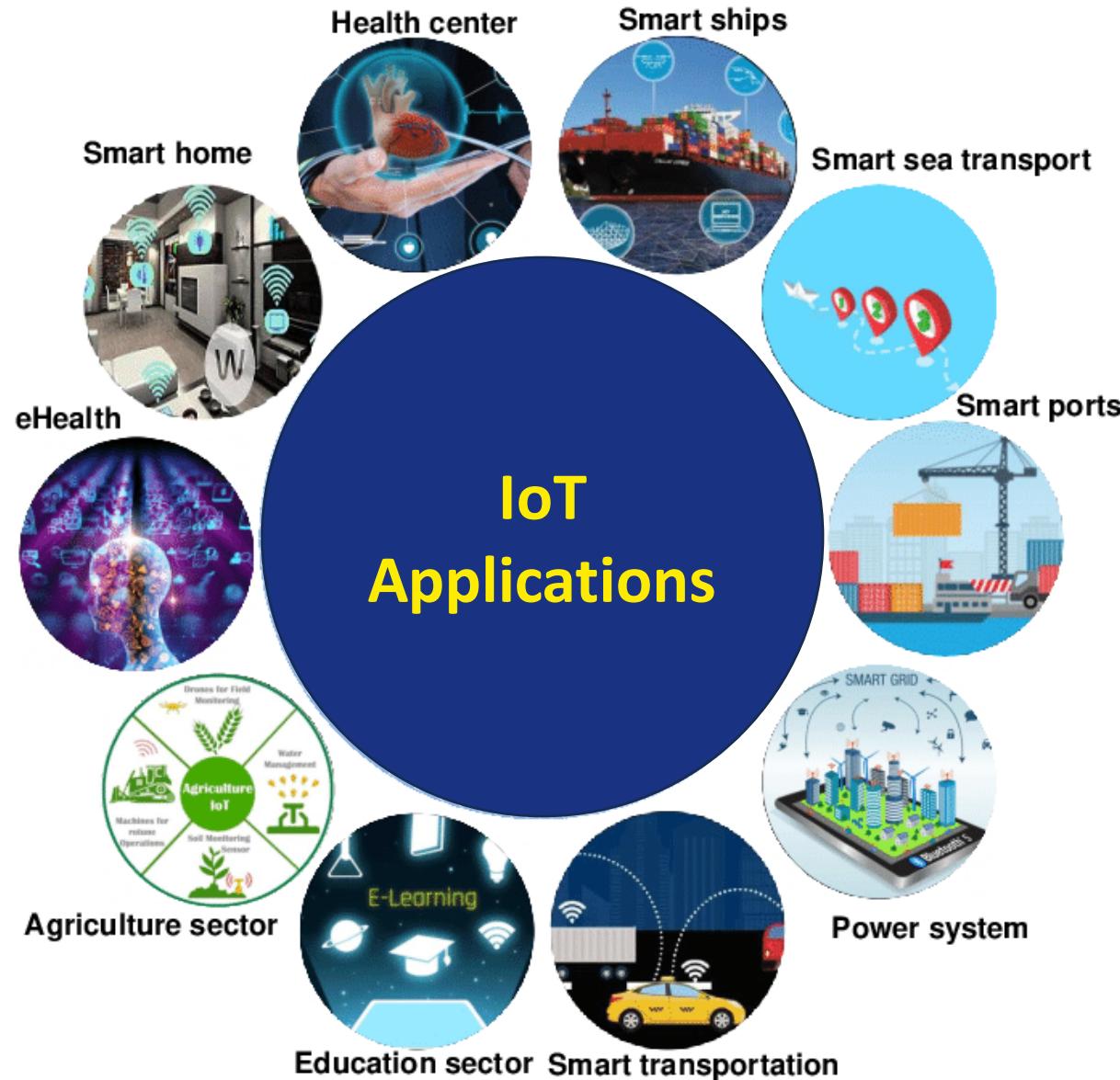
Where can I use IoT?



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Environmental monitoring



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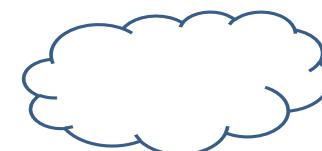


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Data Center Artificial Intelligence



Internet



Wireless
Network



Nodes and
Sensors



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Part 2.

Air Quality Monitoring

Why should we monitor Air Quality?

Pollution



Health

Air Quality Index Levels of Health Concern	Numerical Value	Meaning
Good	0–50	Air quality is considered satisfactory, and air pollution poses little or no risk.
Moderate	51–100	Air quality is acceptable; however, for some pollutants there may be a moderate health concern for a small number of people who are unusually sensitive to air pollution.
Unhealthy for Sensitive Groups	101–150	Members of sensitive groups may experience health effects. The general public is not likely to be affected.
Unhealthy	151–200	Everyone may begin to experience health effects; members of sensitive groups may experience more serious health effects.
Very Unhealthy	201–300	Health alert: everyone may experience more serious health effects.
Hazardous	>300	Health warnings of emergency conditions. The entire population is more likely to be affected.



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Suspended Particulate Matter

Particulate Matter	Cause
$PM_{1.0}$	Coal combustion, soil dust, vehicle exhaust.
$PM_{2.5}$	Emissions from combustion of gasoline, oil, diesel or Wood.
PM_{10}	Combustion and dust from construction sites, landfills, agriculture, wildfires, brush/waste burning, industrial sources, wind-blown dust or pollen.

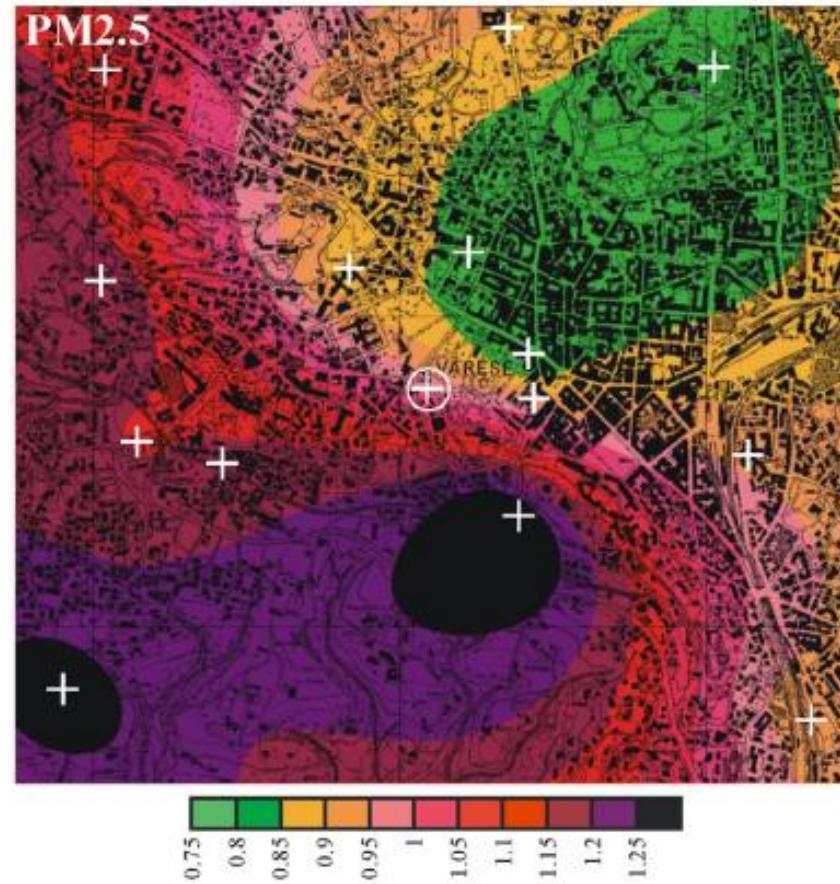


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Suspended Particulate Matter



Yatkin, S., Gerboles, M., Belis, C. A., Karagulian, F., Lagler, F., Barbiere, M., & Borowiak, A. (2020). Representativeness of an air quality monitoring station for PM2. 5 and source apportionment over a small urban domain. *Atmospheric Pollution Research*, 11(2), 225-233.



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Gases

Gases	Cause	Effect
SO_2	Released from coal and oil combustion.	Can lead to respiratory diseases and even death.
NO_2	Produced by road traffic and other fossil fuel combustion processes.	It contributes to acid rain and can lead to pulmonary irritation.
CO	It is released from the combustion of wood, oil, charcoal, and natural gas.	It is linked to headaches, breathing difficulties, loss of consciousness and even death.
O_3	Originates from the chemical reaction between sunlight and the pollutant from vehicles and industries.	It can lead to breathing difficulties, respiratory infections, or premature death.



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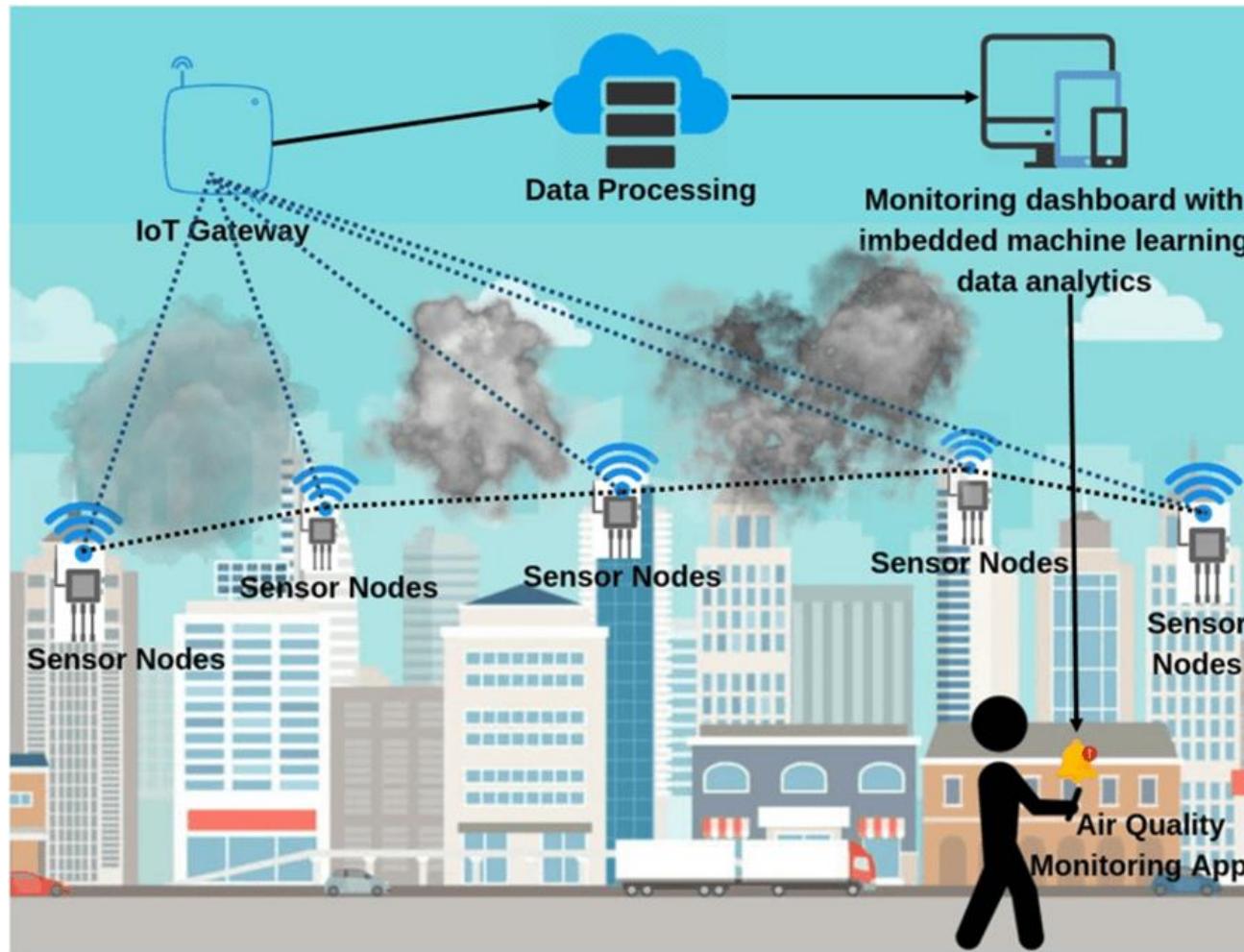
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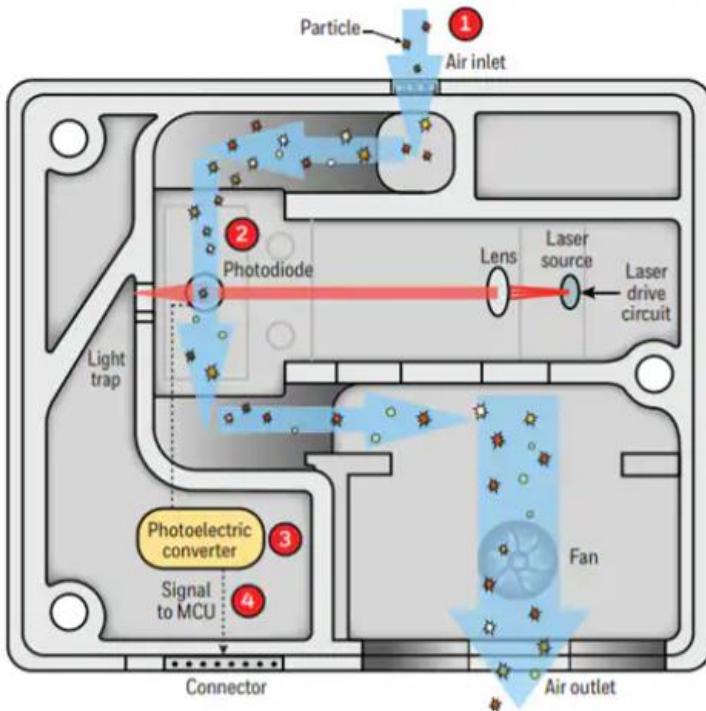
Air Pollution in Europe: Real-time Air Quality Index Visual Map



Architecture of an IoT Air Quality monitoring system



Sensors for particulate matter monitoring



Honeywell

Model	Size (mm) (H × W × D)	Price (USD)	Detection range (μm)	Concentration range ($\mu\text{g}/\text{m}^3$)	Declared Accuracy ($\mu\text{g}/\text{m}^3$)	Sampling interval (s)	Particle count
Alphasense OPC-N2	60 × 64 × 75	443	0.38 to 17	0.01 to 1,500	Not known	1 to 10	Yes
Plantower PMS5003	38 × 21 × 50	28	0.3 to 10	0 to 500	±10	1	Yes
Plantower PMS7003	37 × 12 × 48	28	0.3 to 10	0 to 500	±10	1	Yes
Honeywell HPMA115S0	36 × 43 × 24	33	Not known	0 to 1,000	±15	<6	No

Bulot, F. M., Johnston, S. J., Basford, P. J., Easton, N. H., Apetroaie-Cristea, M., Foster, G. L., ... & Loxham, M. (2019). Long-term field comparison of multiple low-cost particulate matter sensors in an outdoor urban environment. *Scientific reports*, 9(1), 7497.



Sensors for gas monitoring



- ✓ Range: 500 PPM
- ✓ Resolution: 0.1 PPM

- ✓ Power Consumption: 10 to 50 uW
- ✓ Response Time: < 30 seconds



- ✓ Range: 50 PPM
- ✓ Resolution: 0.01 PPM

- ✓ Power Consumption: 10 to 50 uW
- ✓ Response Time: < 15 seconds



- ✓ Range: Upto 50 PPM
- ✓ Resolution: < 100 PPB

- ✓ Power Consumption: 10 to 50 uW
- ✓ Response Time: < 15 seconds



- ✓ Range: Upto 50 PPM
- ✓ Resolution: < 20 PPB

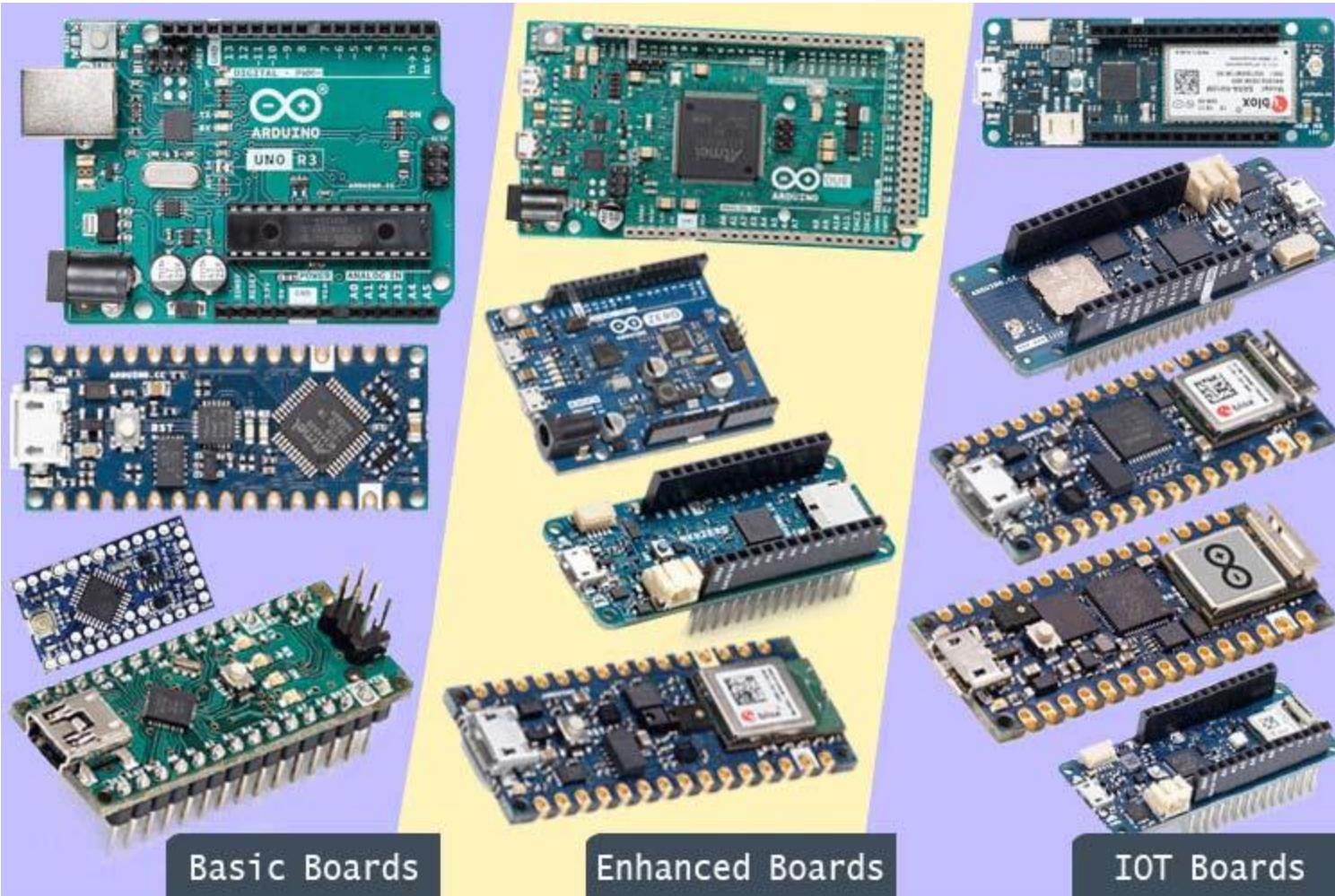
- ✓ Power Consumption: 10 to 50 uW
- ✓ Response Time: < 15 seconds



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Development board



Basic Boards

Enhanced Boards

IOT Boards

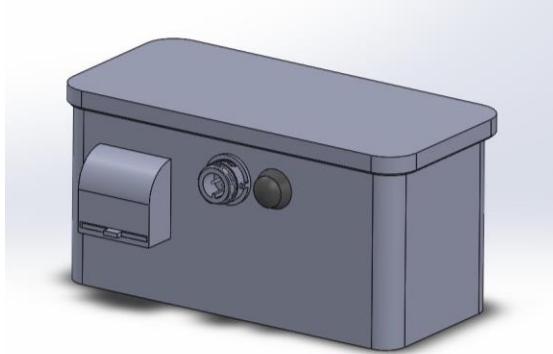
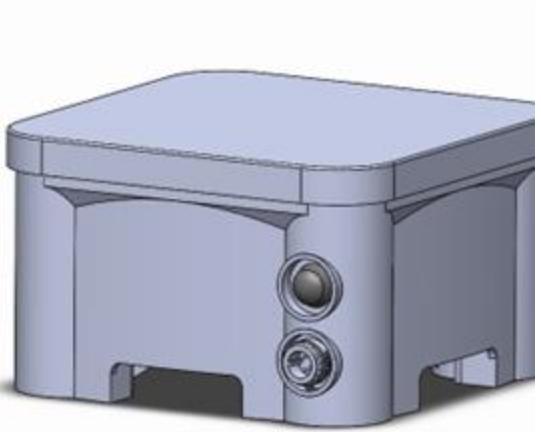


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IoT Air monitoring devices



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Power options



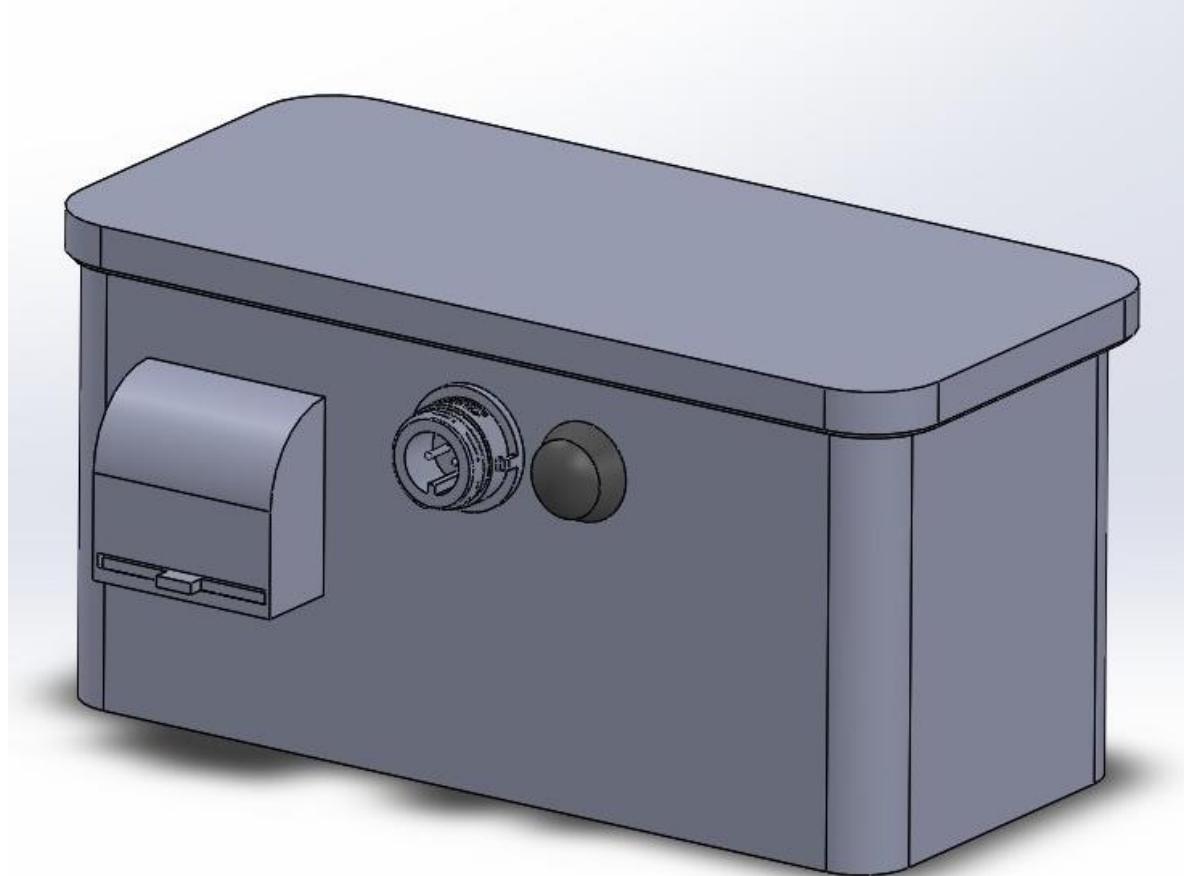
Solar Panel



Power Grid

DIPASÓN – Particulate matter measurement (Outdoor)

- Measures particles with diameter from 0.35 to 40 microns
- Reports 3 configurable values (e.g. PM10, PM2.5, and PM1.0)
- Supports different connectivity tech. (WiFi, BLE, 4G, LoRa, Sigfox, ...)
- Geolocalization.
- Real time monitoring.
- Preventive maintenance.
- Generation of contamination alerts.



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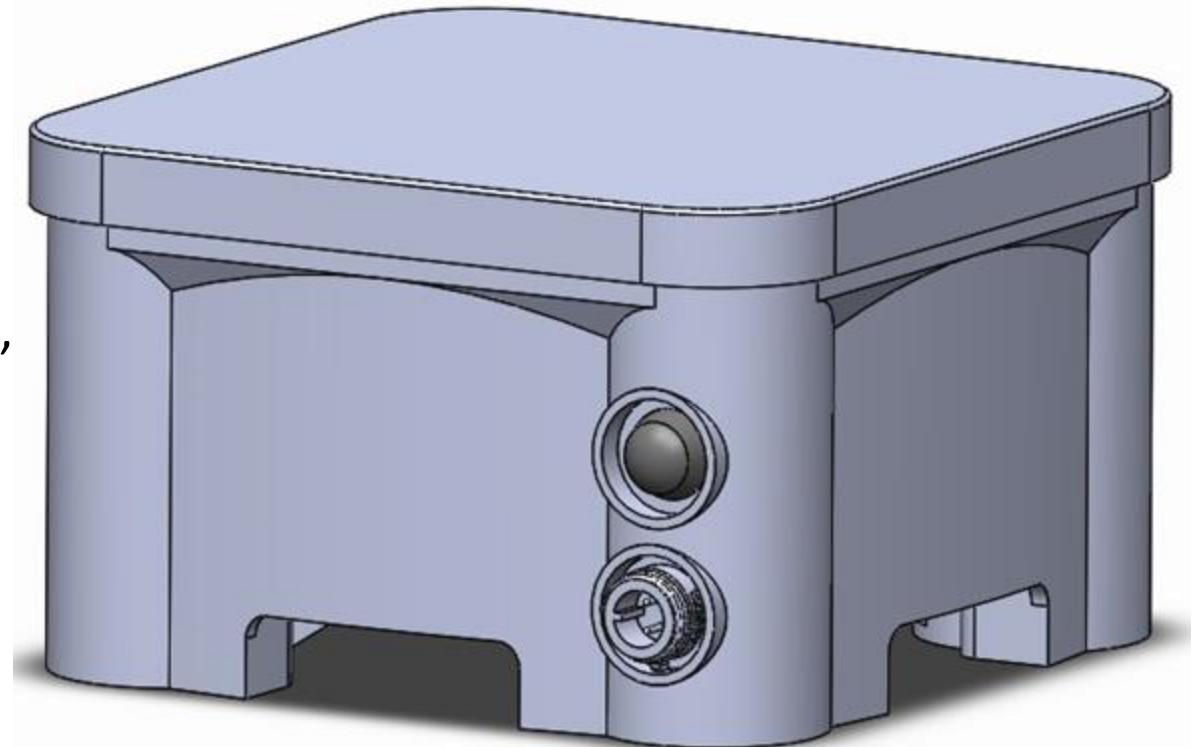
DIPASÓN – Particulate matter measurement (Indoor)

- Measures PM1, PM2.5, PM10, temperature, humidity, and CO₂
- Provides more accurate information than only CO₂ measurement
- Includes estimate of the number of people in the room



MEGAMIA – Contaminant gases measurement

- Measures contaminant gases criterion as defined by World Health Organization (WHO)
- Each device supports up to 4 different gases (according to customer requirements)
- Supports different connectivity tech. (WiFi, BLE, 4G, LoRa, Sigfox, ...)
- Geolocalization
- Real time monitoring
- Preventive maintenance
- Generation of contamination alerts



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Use cases: Smart City (Cartagena city council)

- Quality of air
- Installed in street lamps
- Anti-vandal support casing
- More than one year in operation and under adverse weather conditions, without requiring maintenance yet



Use cases: Industry (Atlantic Copper)

- Very high concentrations of SO₂
- PM10
- Solution by ABB, high cost and ineffective

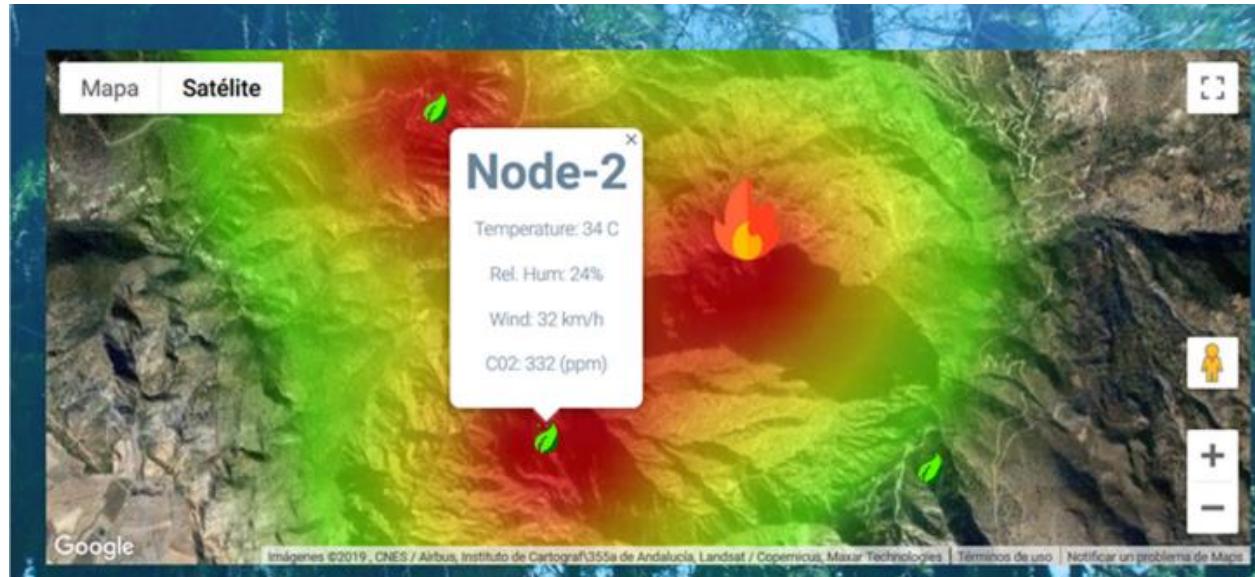


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Use cases: Forest fire detection



MAP INFORMATION



The green leaf symbol indicates the level of CO₂ recorded by the sensors is lower than the value detected in a fire.



The flame symbol indicates that the level of CO₂ recorded by the sensors indicates the presence of a fire.



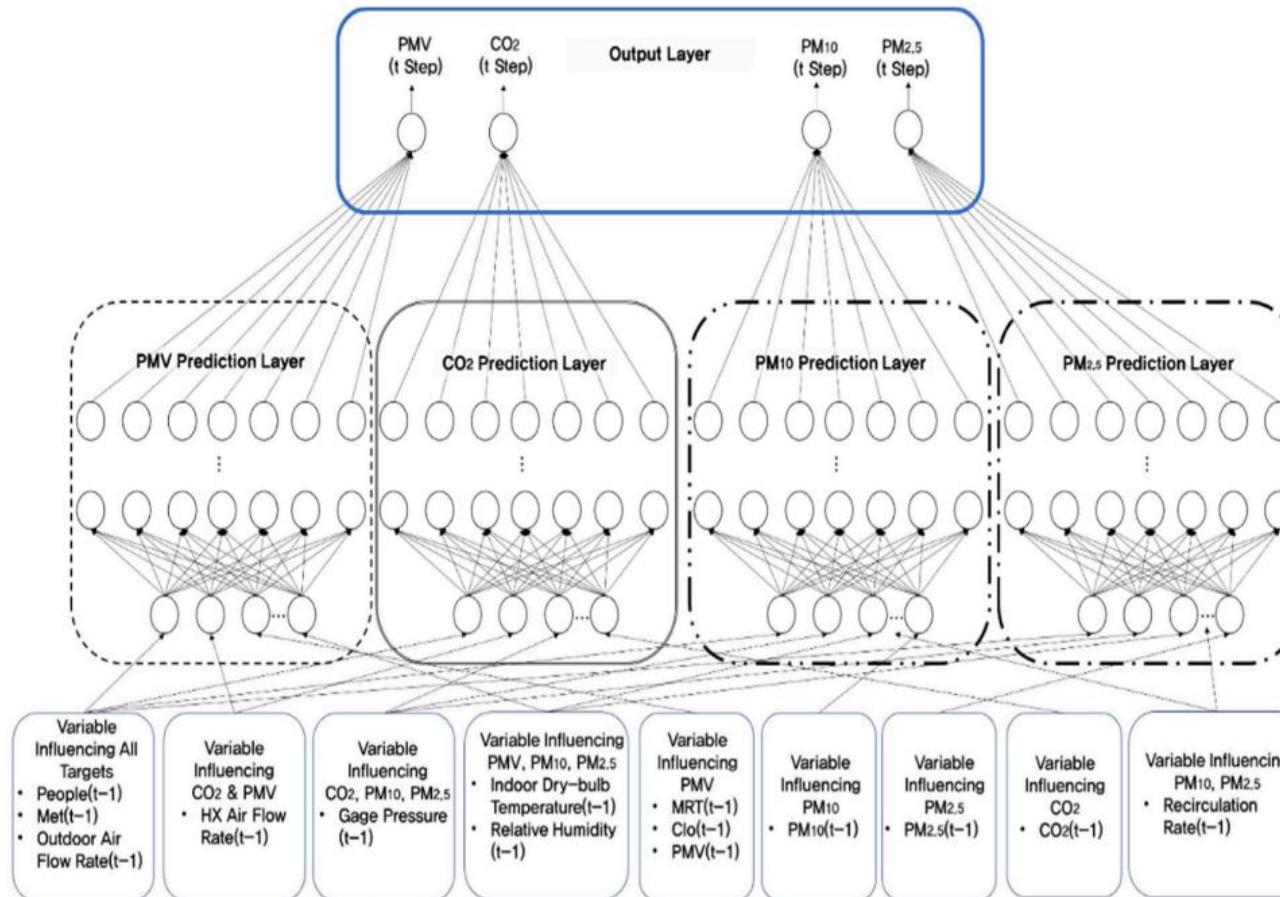
The heat zones on the map indicate that the risk values have been exceeded in that area, and therefore a fire may occur.



Get the sensor values by clicking on the markers.

Sendra, S., García, L., Lloret, J., Bosch, I., & Vega-Rodríguez, R. (2020). LoRaWAN network for fire monitoring in rural environments. *Electronics*, 9(3), 531.

Future of Air Quality monitoring: Artificial Intelligence



Cho, J. H., & Moon, J. W. (2022). Integrated artificial neural network prediction model of indoor environmental quality in a school building. *Journal of Cleaner Production*, 344, 131083.

Part 3.

IoT for Precision Agriculture

Why the technification of Agriculture is important?

Increase in population



More food needs

SOLUTION

The use of Precision Agriculture Solutions improves crop efficiency and reduces the use of resources such as water and fertilizers.



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Challenges in Agricultural Environments

Communication difficulties



Vegetation
Farmer's everyday activities
Machinery
Cost

Wireless technologies allow avoiding the possible damages and high cost of cabled communications.

The network design must consider the signal losses due to obstructions caused by vegetation.

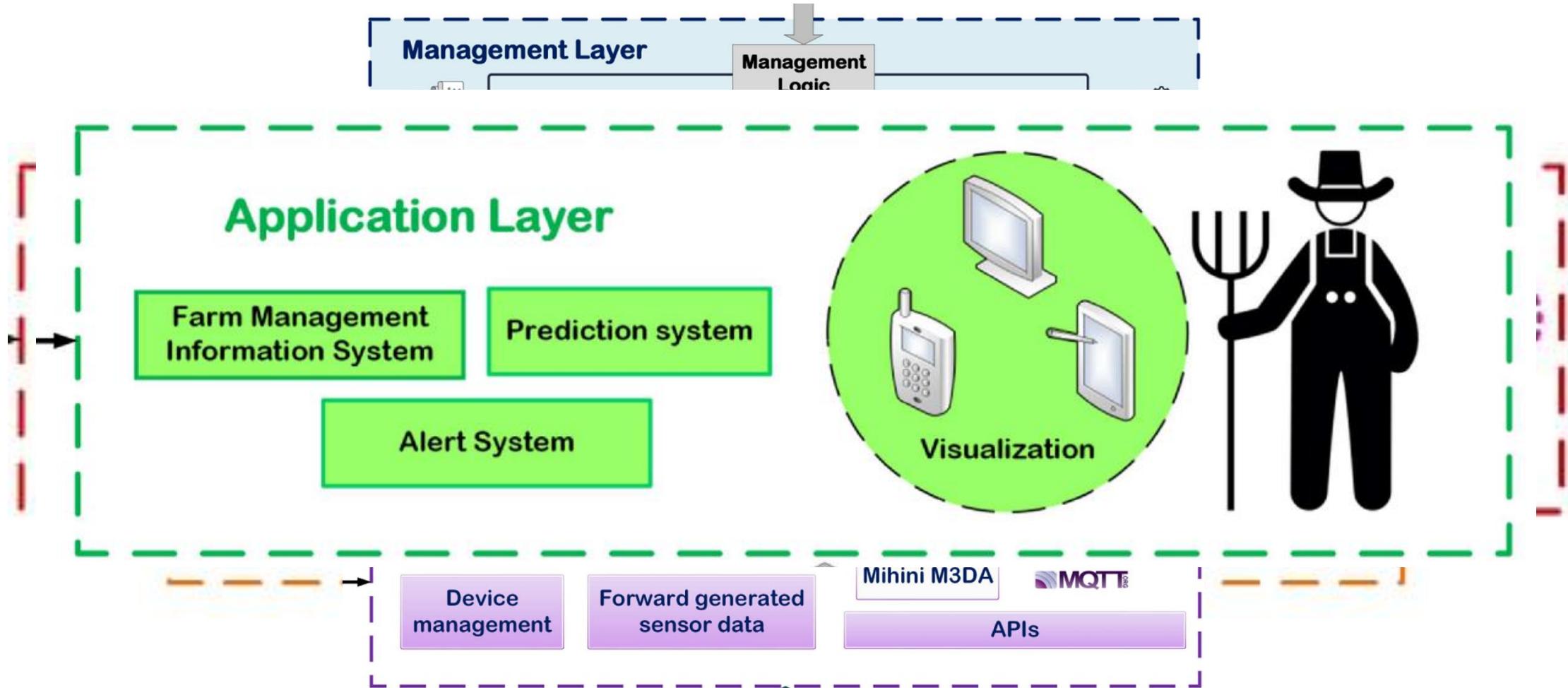


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Generic Architecture for Precision Agriculture IoT System



Triantafyllou, A., Sarigiannidis, P., & Bibi, S. (2019). Precision agriculture: A remote sensing monitoring system architecture. *Information*, 10(11), 348.

What can we monitor in Agricultural Fields?

Soil

- Temperature
- Humidity
- Salinity
- Ph
- Nutrients



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What can we monitor in Agricultural Fields?



Meteorology

- Temperature
- Relative humidity
- Rain
- Light / Radiation
- Wind



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What can we monitor in Agricultural Fields?

Water

- Pollutants
- Ph
- Turbidity
- Salinity
- Water level



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What can we monitor in Agricultural Fields?



Plants

- Pests
- Diseases
- Growth
- Production
- Caliber
- Weeds



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How can I monitor Agricultural Fields?

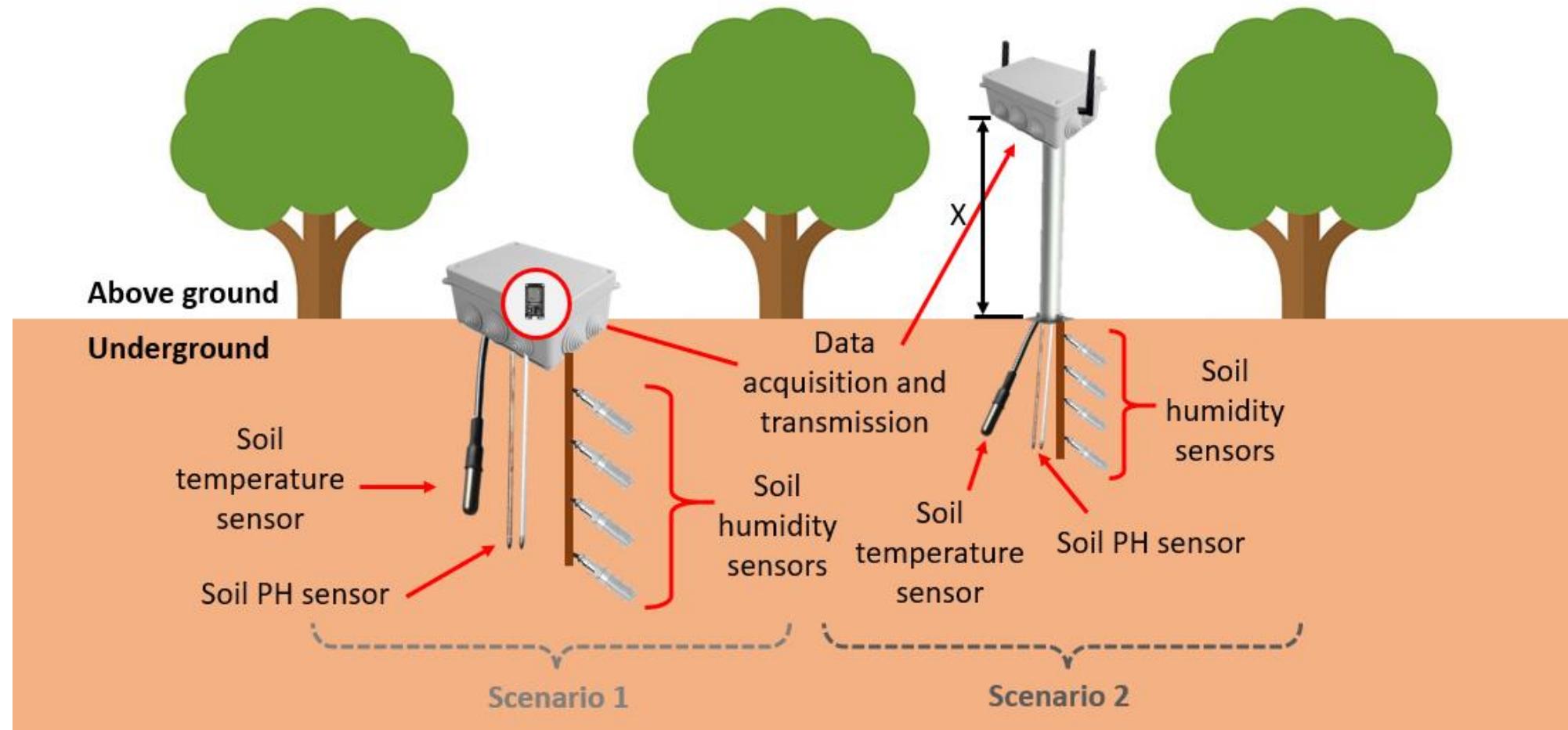


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Sensor devices: Soil



Sensor devices: Soil

Typical metrics

- Soil moisture
- Conductivity (Salinity)
- Soil Temperature



HydraProbe

Stevens Water Monitoring
Systems



ECH2O EC-5

METER Group



GroPoint Profile

RioT Technology Corp.



Hydrascout

HSTi

Single-point sensors

Profiling probes



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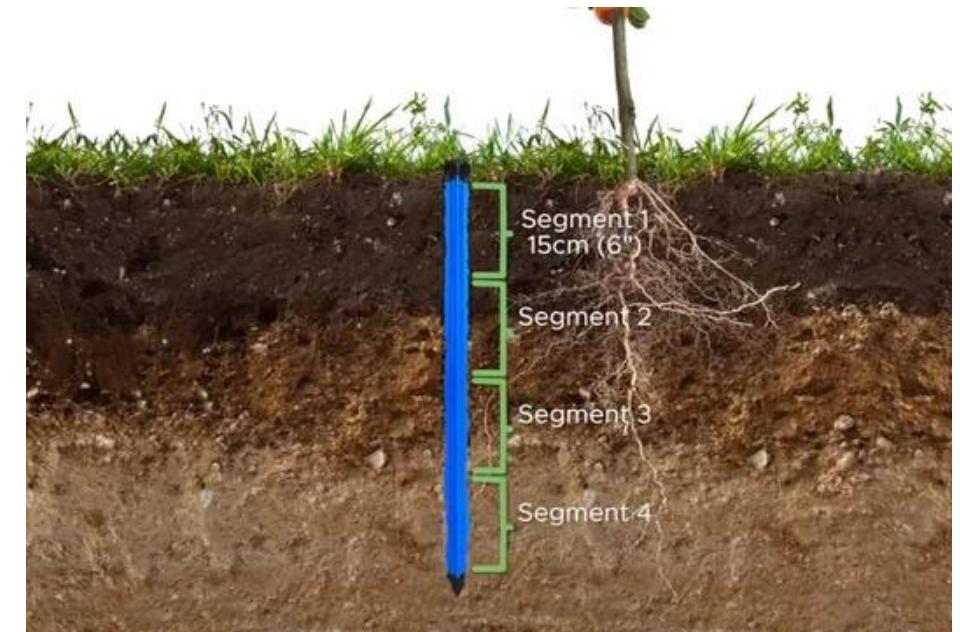
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Sensor devices: Soil

Installation

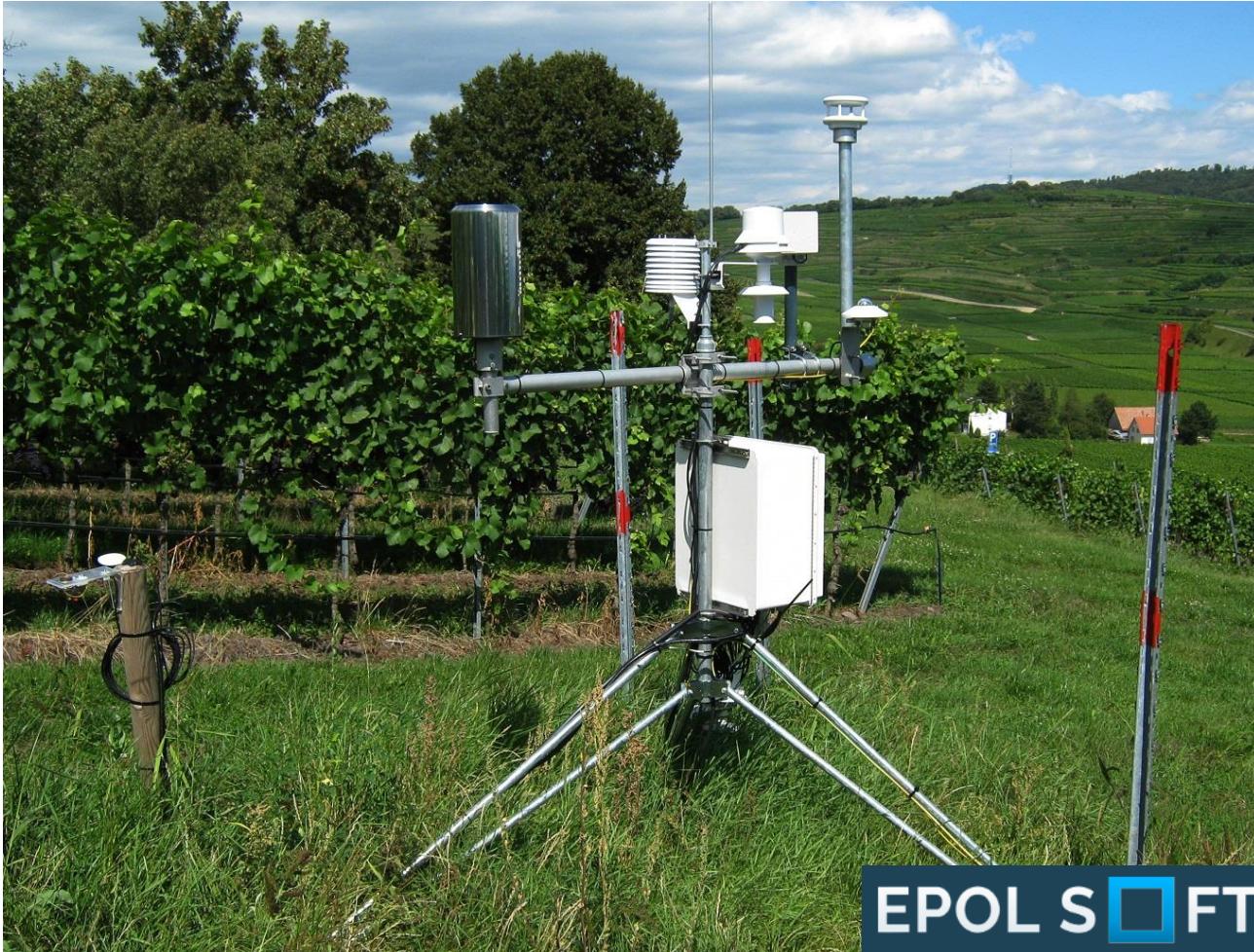


Single-point sensors



Profiling probes

Sensor devices: Meteorology



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Sensor devices: Water



Anemometer



Pluviometer



Temperature and
Relative Humidity



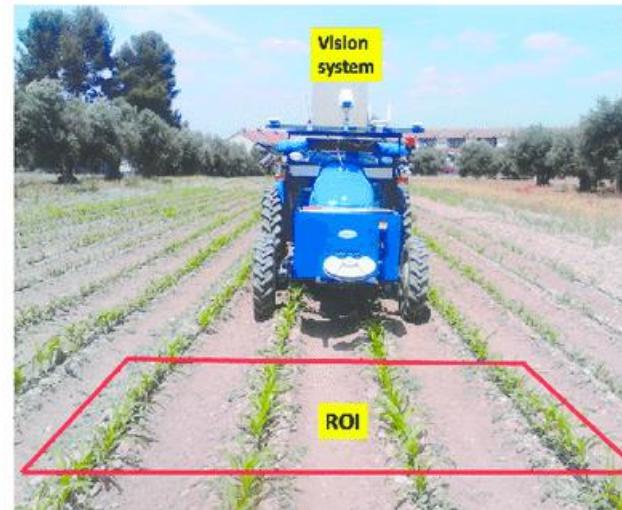
Pyranometer

Sensor devices: Plants

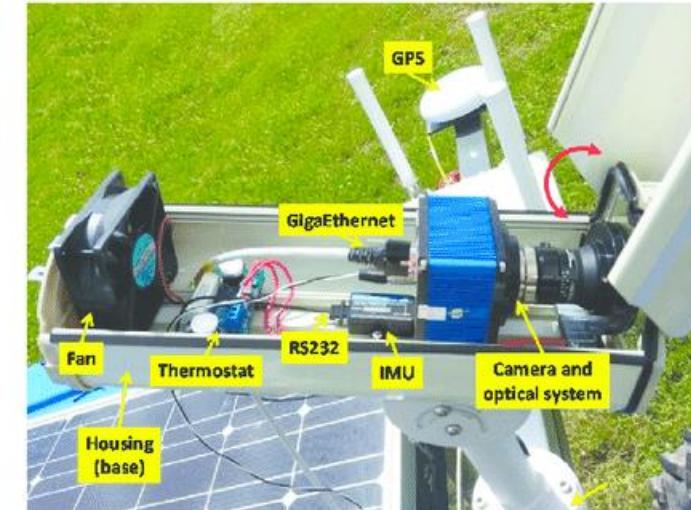
Computer Vision Cameras



Static



Mounted on vehicles



Pajares, G., García-Santillán, I., Campos, Y., Montalvo, M., Guerrero, J. M., Emmi, L., ... & Gonzalez-de-Santos, P. (2016). Machine-vision systems selection for agricultural vehicles: A guide. *Journal of Imaging*, 2(4), 34.

Sensor devices: Plants

Wearable Plant Sensor



Plant disease and stress

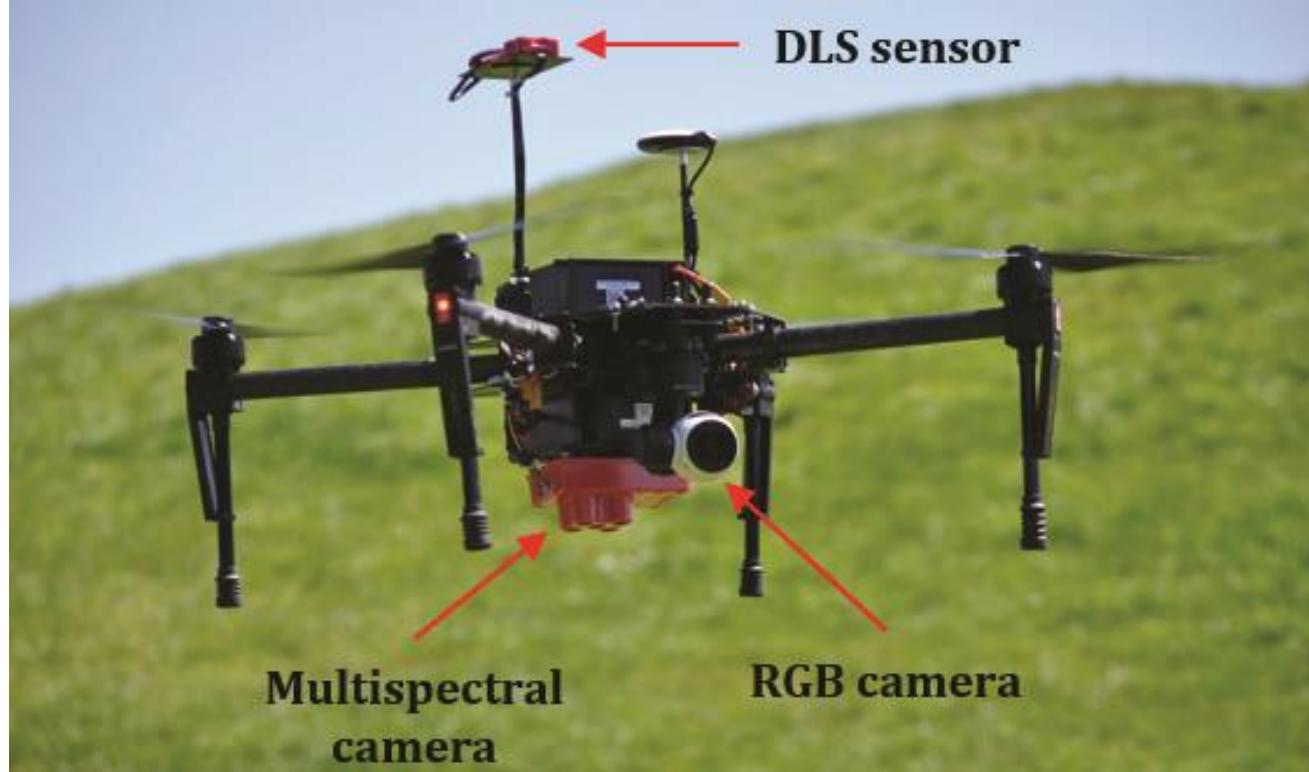


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Machinery and vehicles equipped with sensors: Drones



Thompson, L. J., Shi, Y., & Ferguson, R. B. (2017). *Getting started with drones in agriculture*. University of Nebraska-Lincoln, Extension.



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Machinery and vehicles equipped with sensors: Tractors

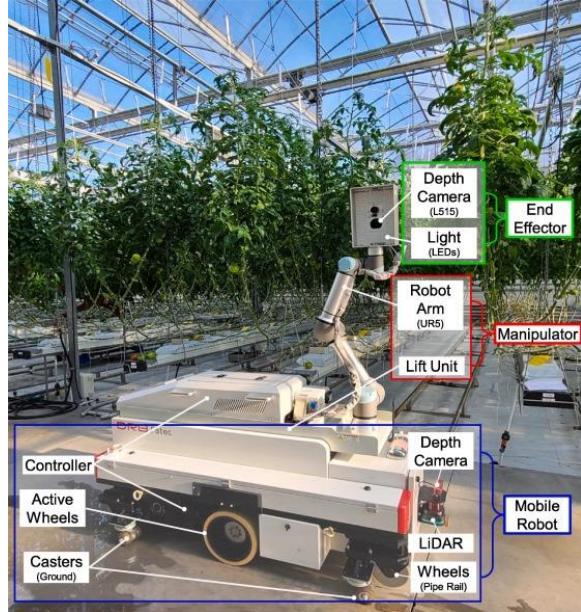


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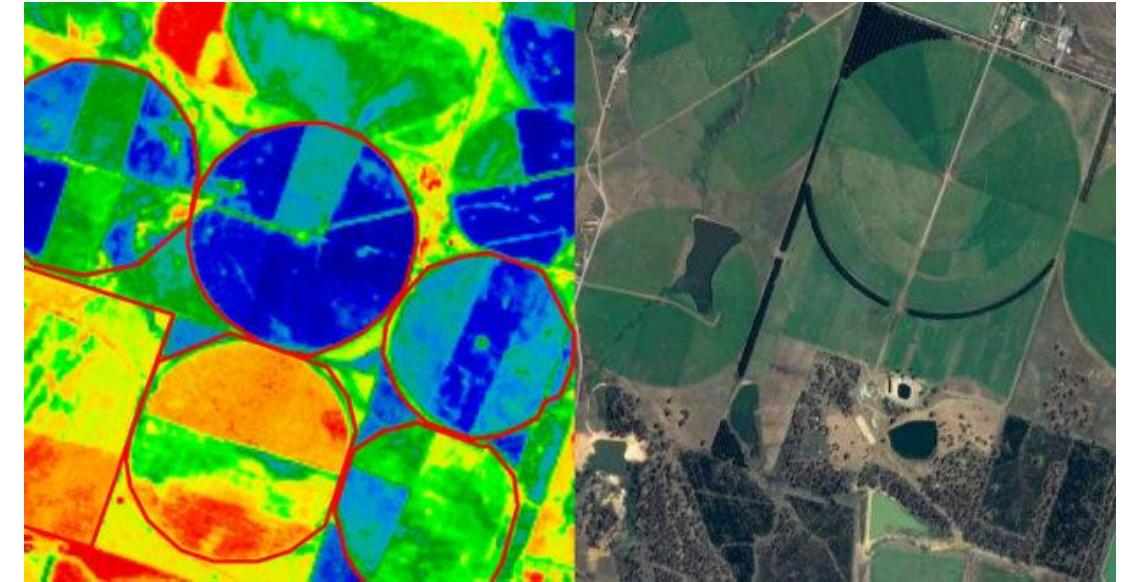
Machinery and vehicles equipped with sensors: Robots



Satellite imaging

Vegetation indexes

Normalized Difference Vegetation Index (NDVI)
Enhanced Vegetation Index (EVI)



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How are the sensor devices configured?



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Aspects to consider

Data aquisition frequency

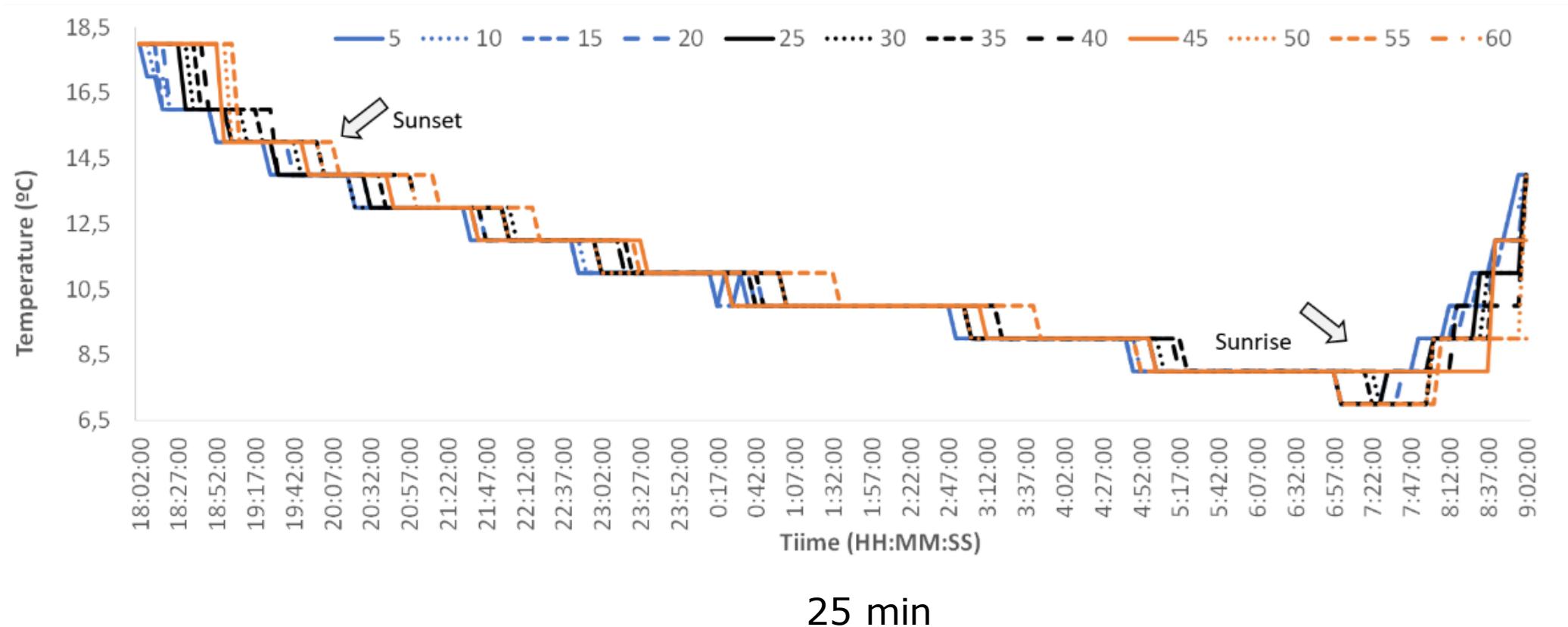


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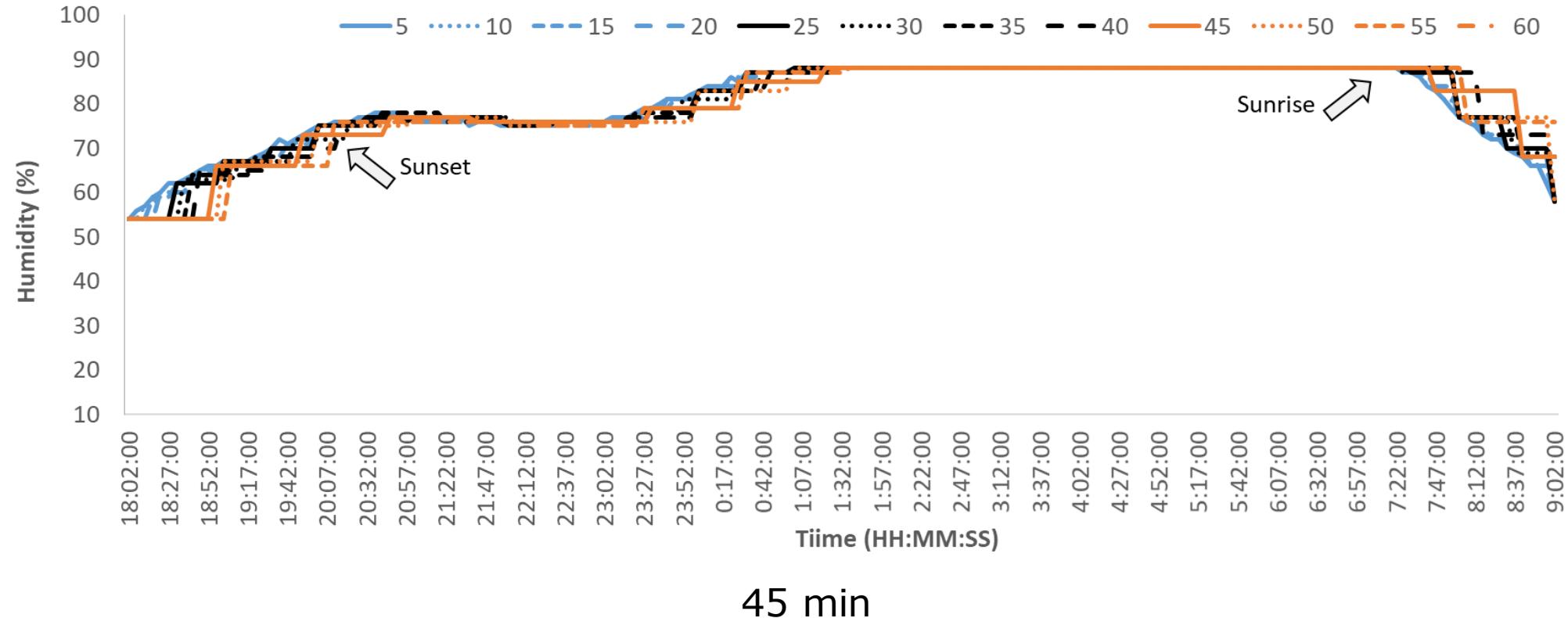
Aspects to consider: Data acquisition frequency



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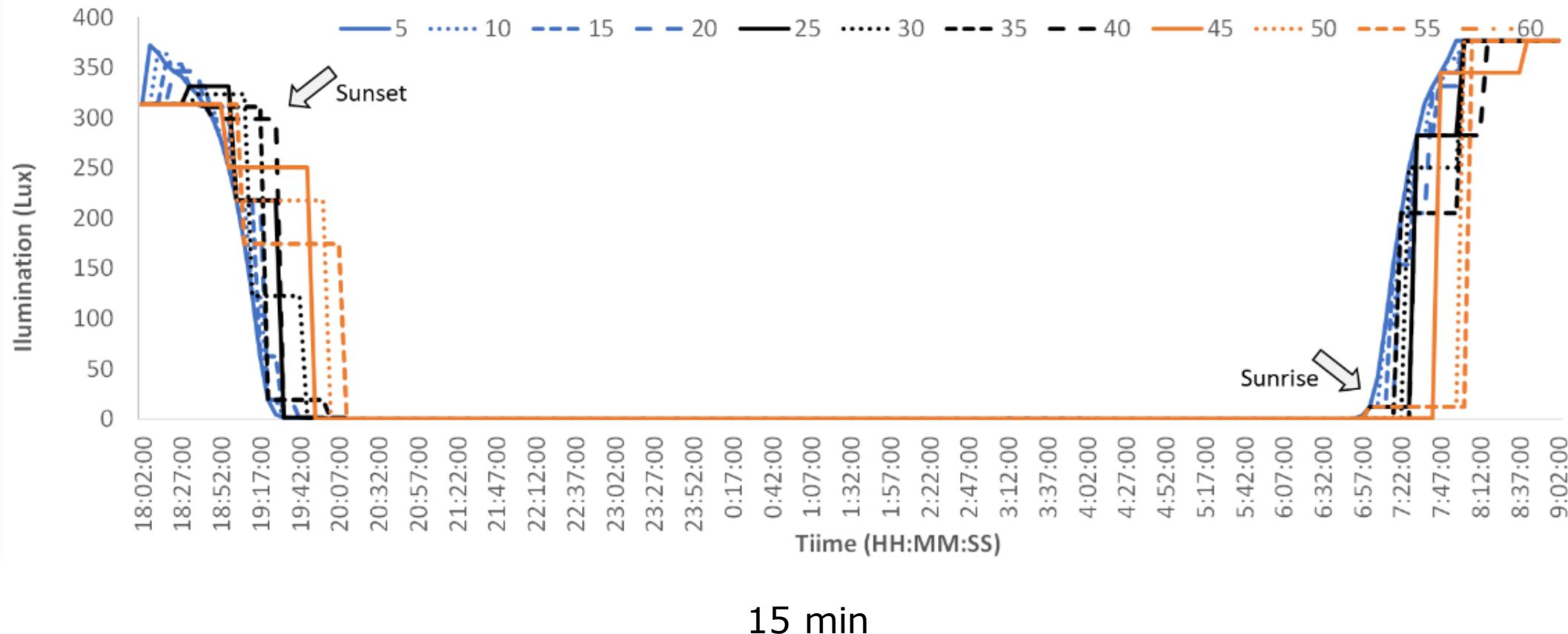
Aspects to consider: Data acquisition frequency



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Aspects to consider: Data acquisition frequency



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Aspects to consider

Data transmission frequency

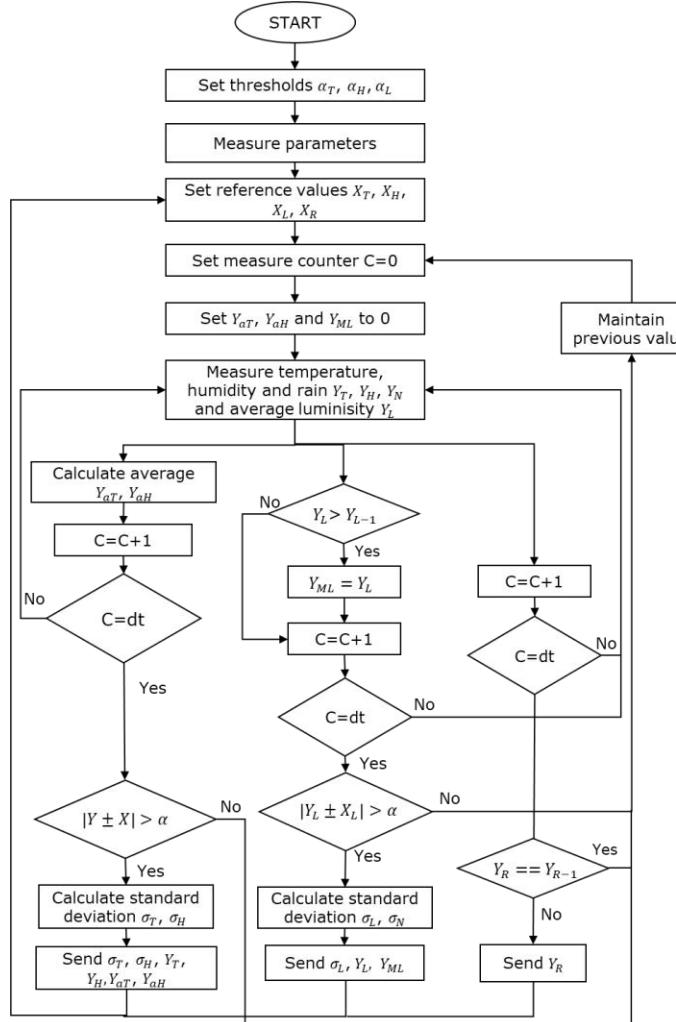


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Aspects to consider: Data transmission frequency



Aspects to consider

Deployment strategy

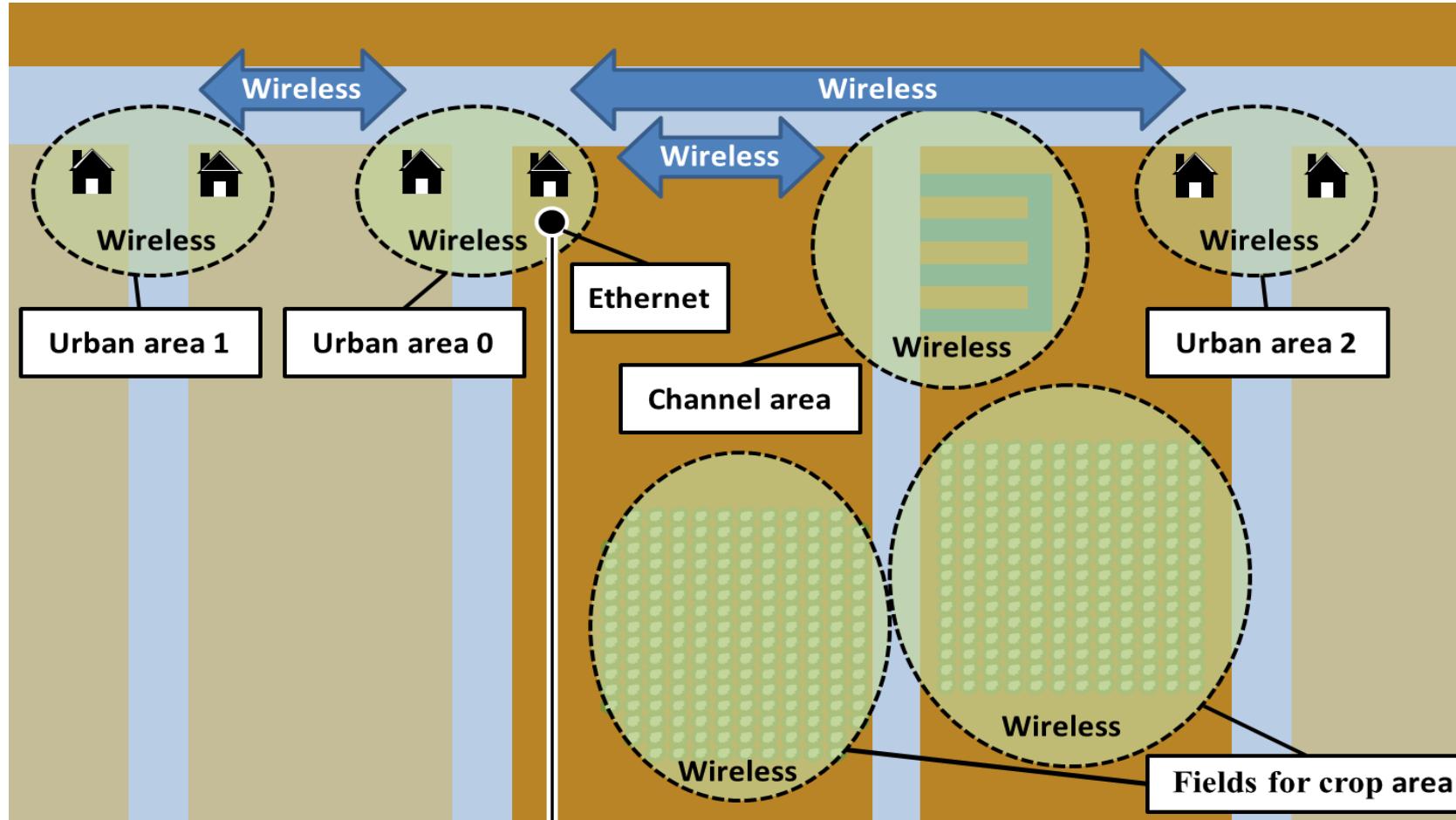


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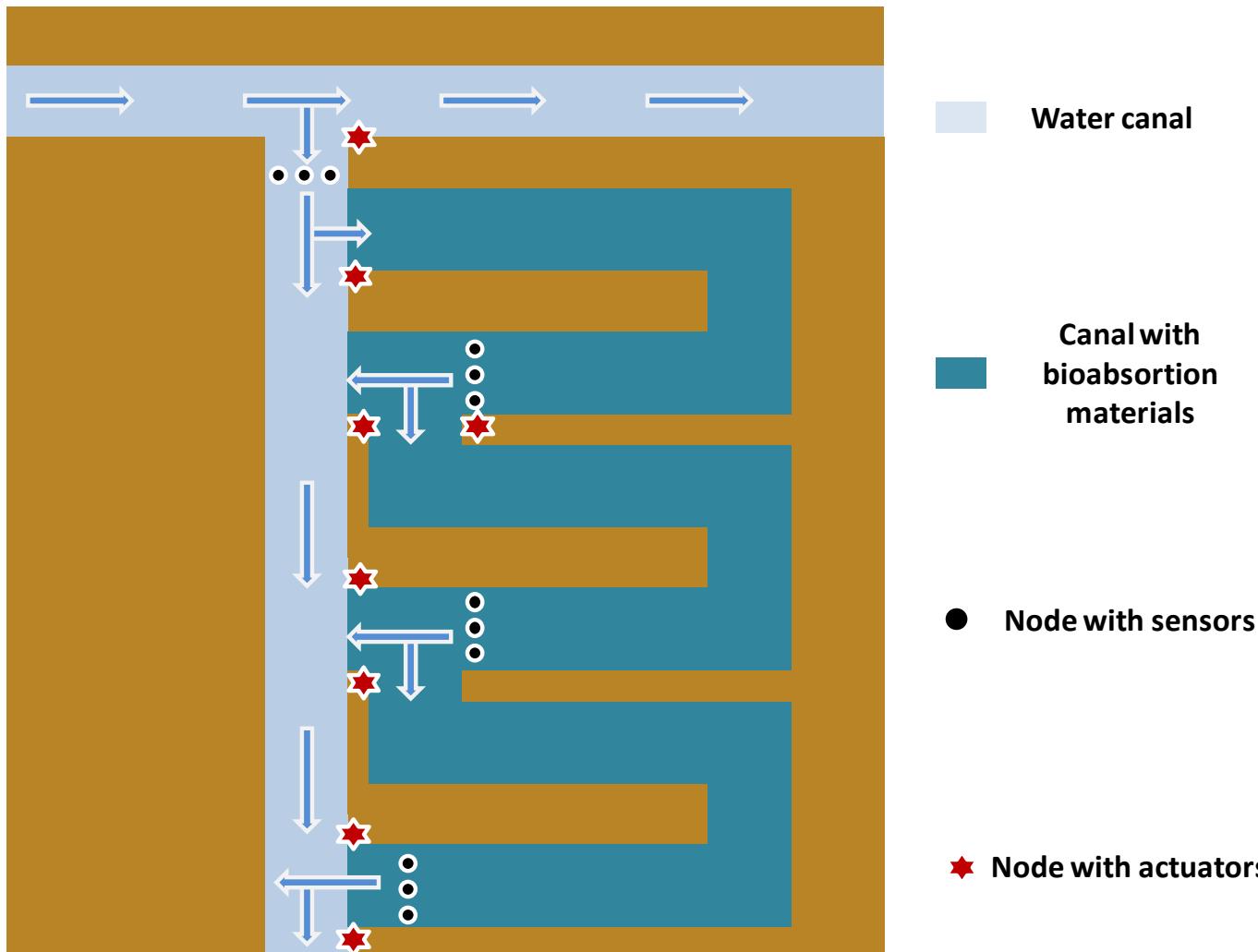
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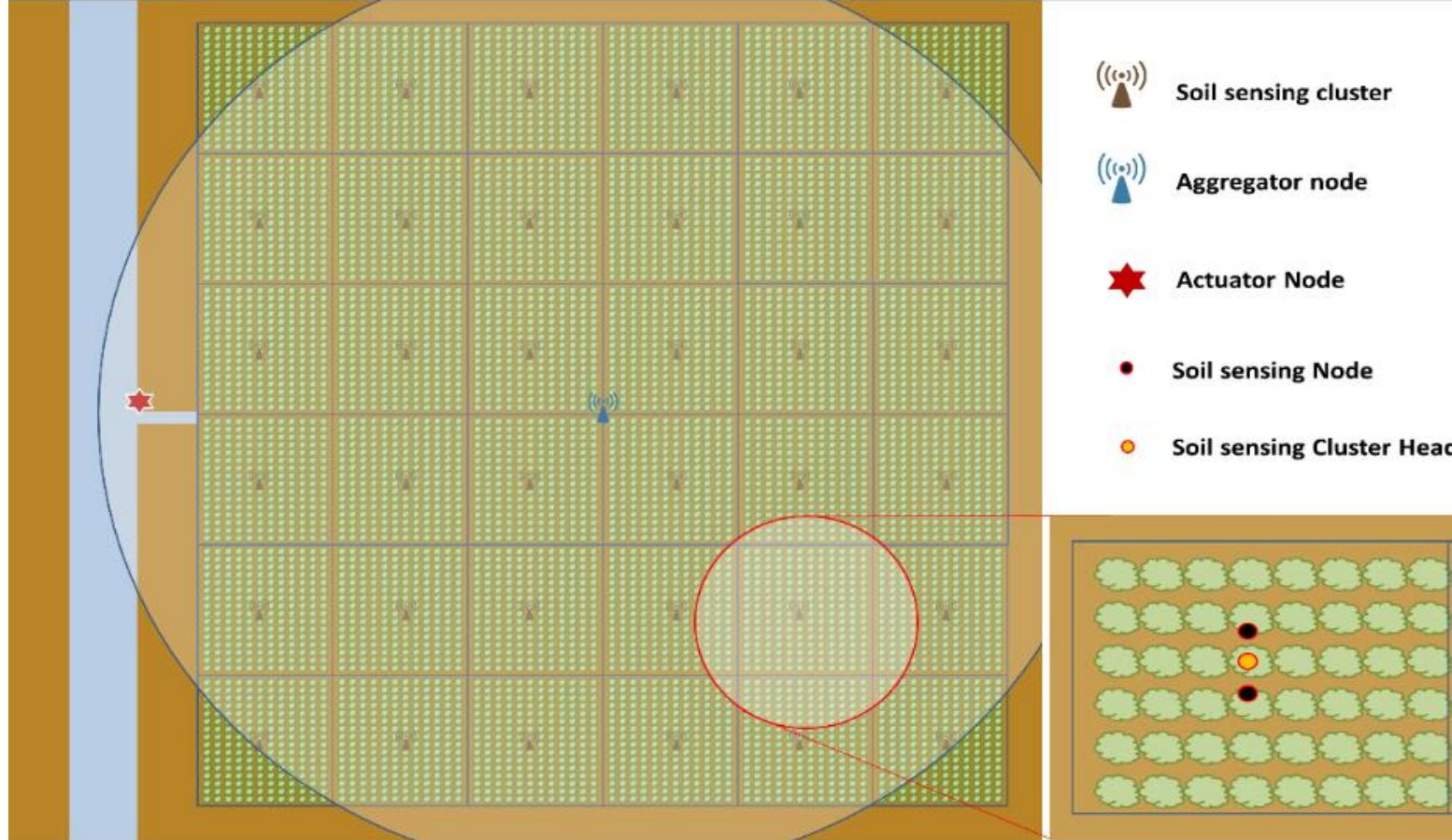
Aspects to consider: Deployment strategy



Aspects to consider: Deployment strategy



Aspects to consider: Deployment strategy



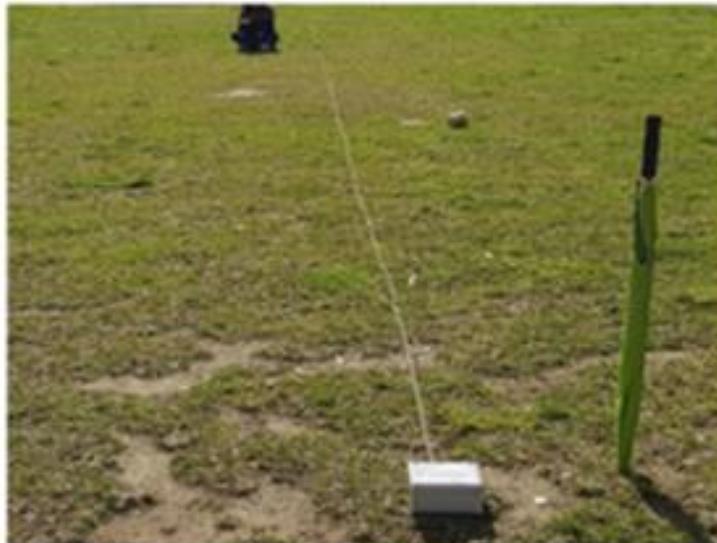
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Aspects to consider: Deployment strategy

Vegetation height and density



a)



b)



c)

L. García et al., "Deployment Strategies of Soil Monitoring WSN for Precision Agriculture Irrigation Scheduling in Rural Areas," Sensors, vol. 21, no. 5, p. 1693, Mar. 2021, doi: 10.3390/s21051693.



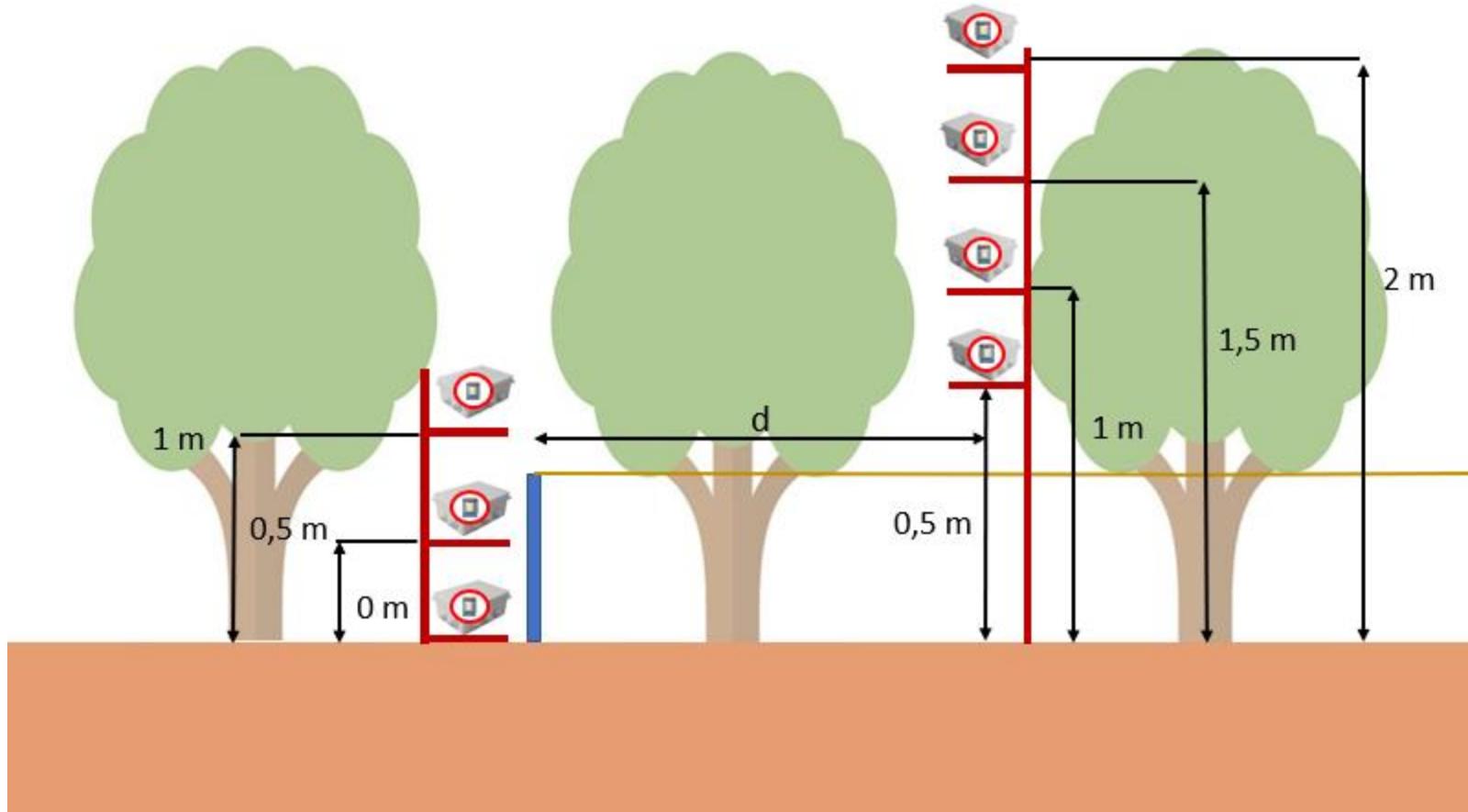
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Aspects to consider: Deployment strategy



Lloret J, Sendra S, Garcia L, Jimenez JM. A Wireless Sensor Network Deployment for Soil Moisture Monitoring in Precision Agriculture. *Sensors*. 2021; 21(21):7243.
<https://doi.org/10.3390/s21217243>



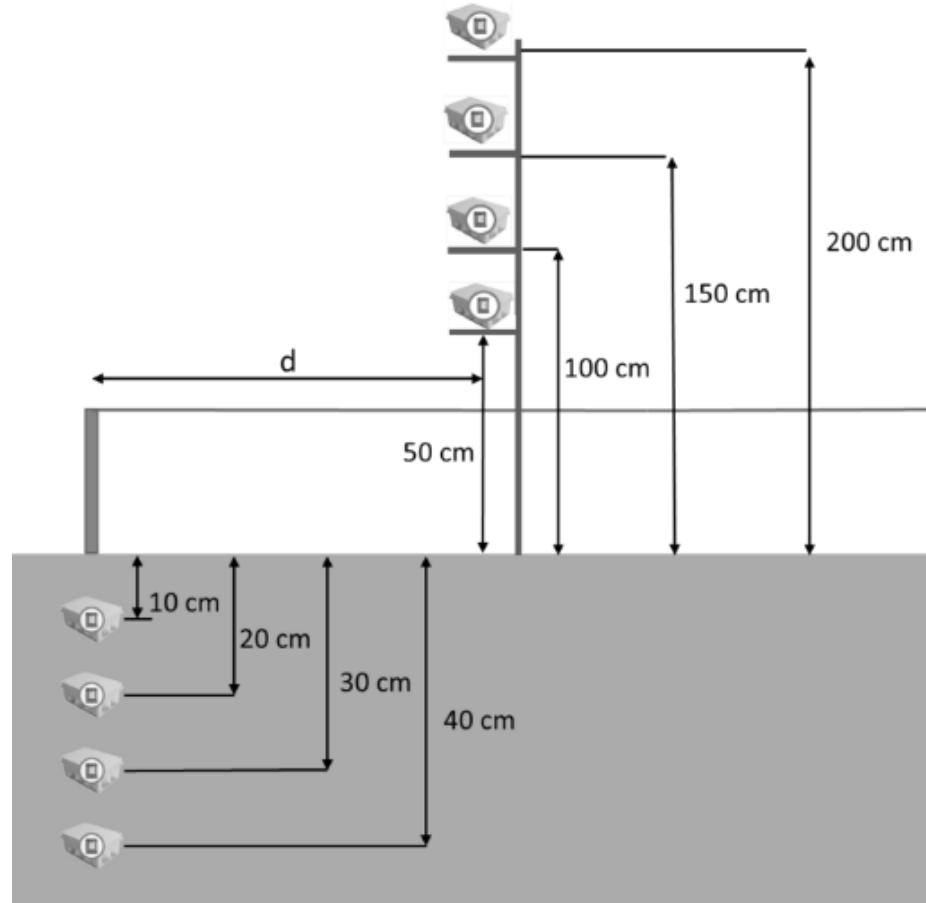
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Aspects to consider: Deployment strategy

Internet of Underground Things



Aspects to consider: Deployment strategy

Drones or tractors as network gateways



a)



b)

Aspects to consider

Communication technology selection

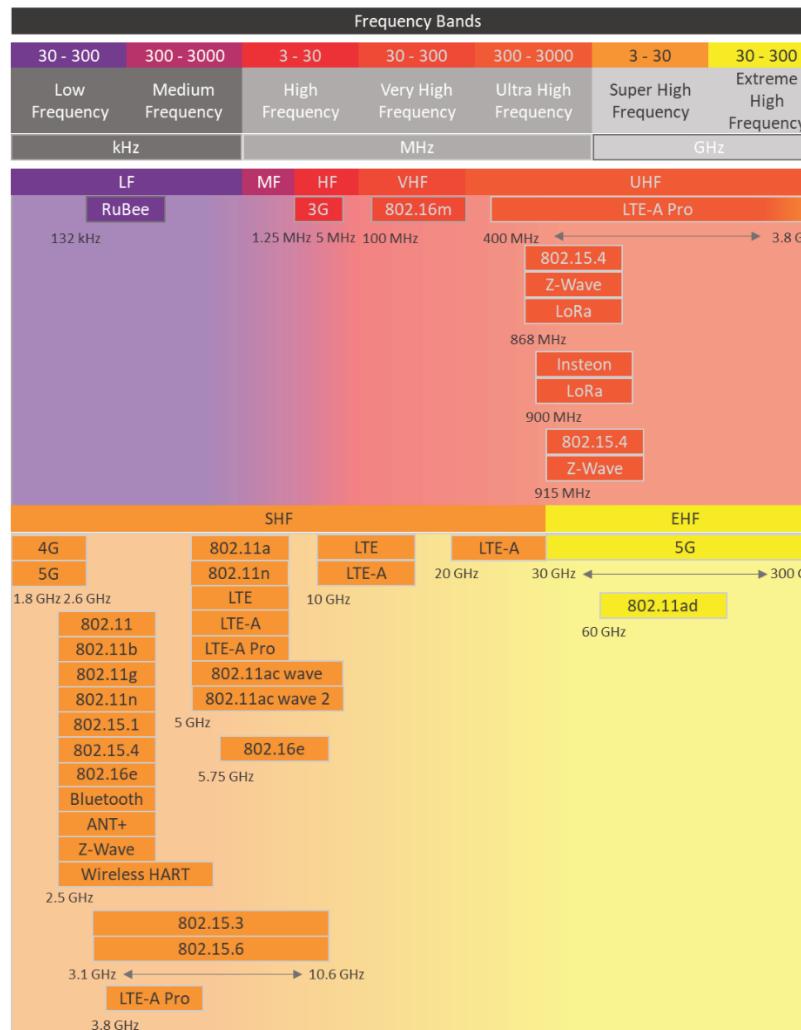


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Aspects to consider: Communication technology selection

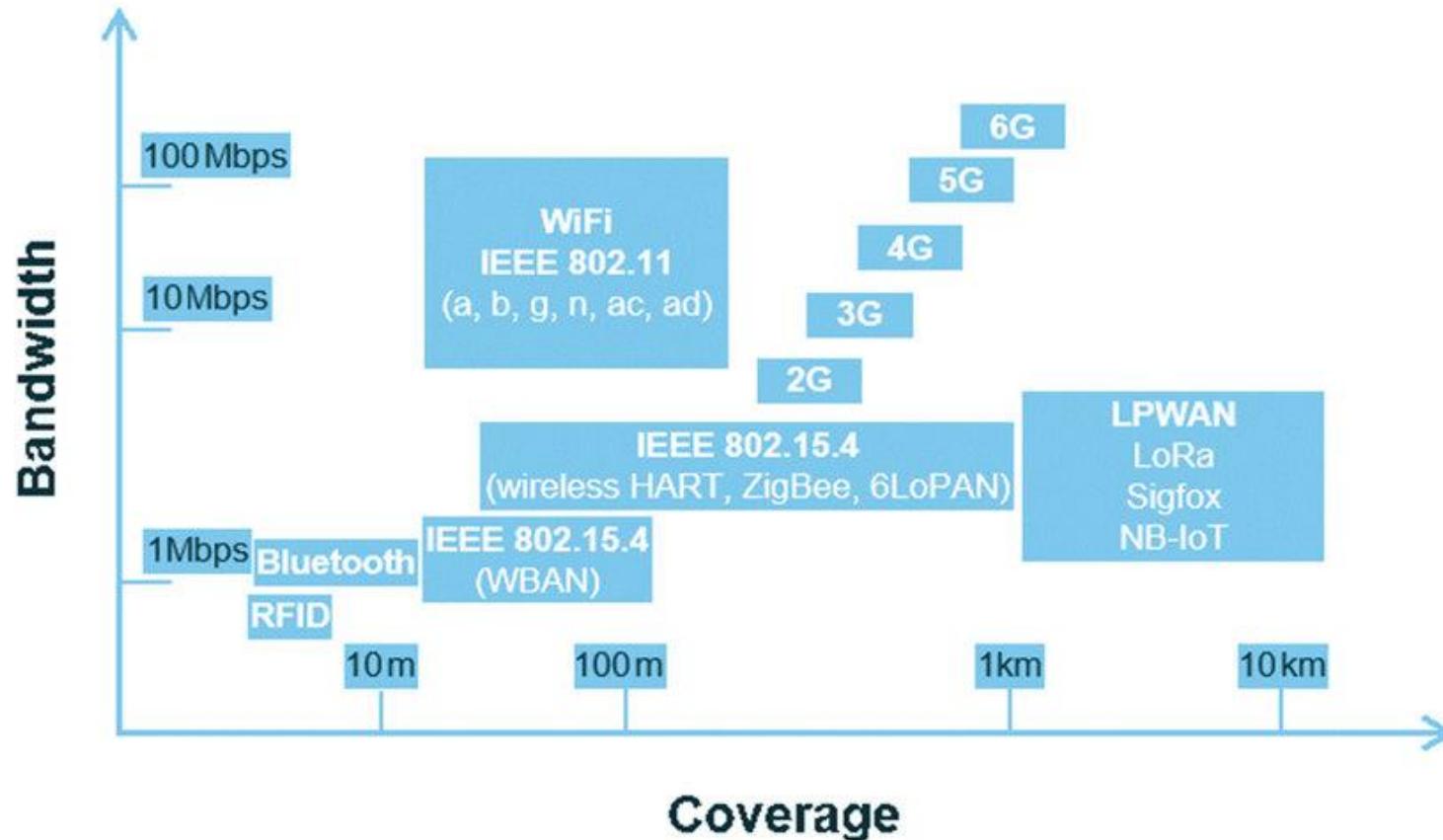


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Aspects to consider: Communication technology selection



Belialis, M. J., Jensen, K., Ellegaard, L., Aagaard, A., & Presser, M. (2021). Next generation industrial IoT digitalization for traceability in metal manufacturing industry: A case study of industry 4.0. *Electronics*, 10(5), 628.

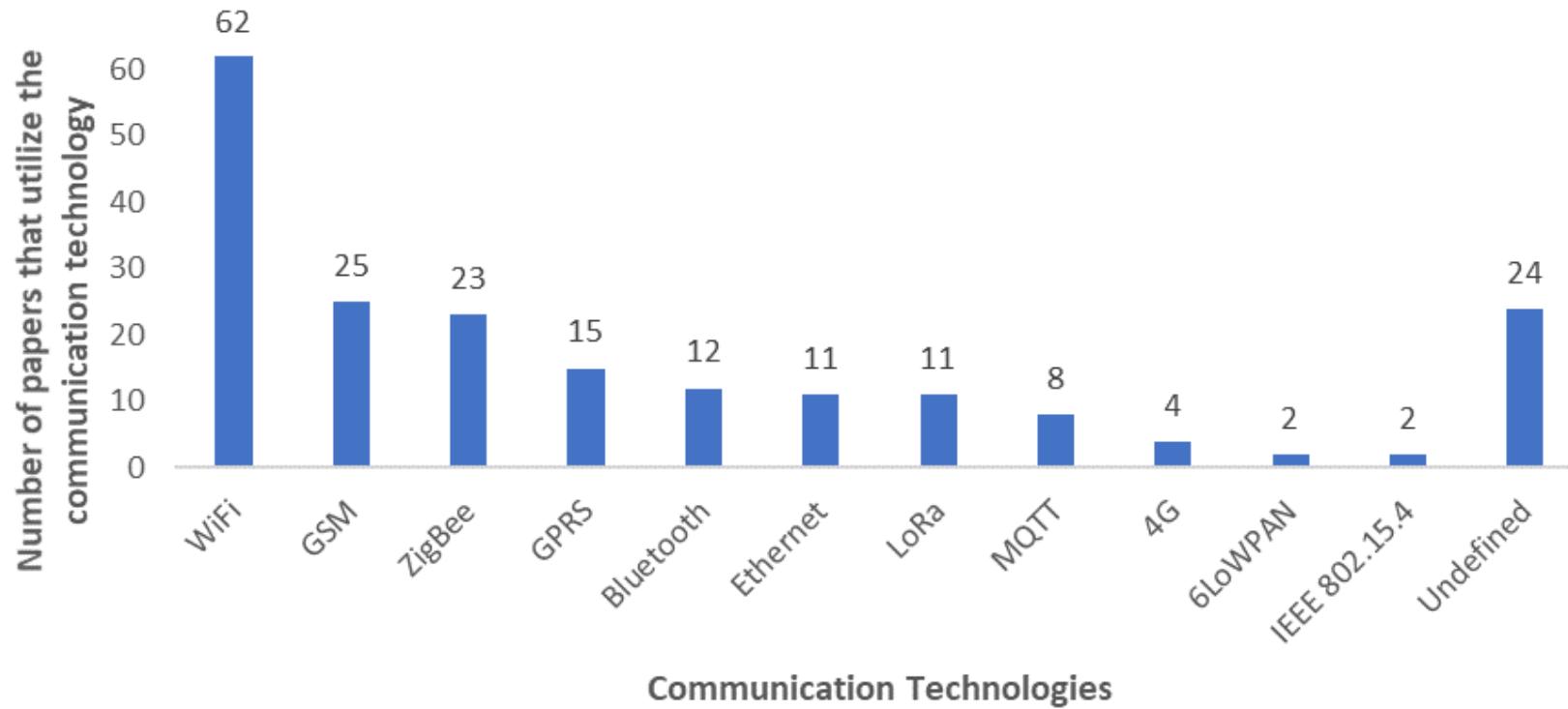


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Aspects to consider: Communication technology selection

Most used technologies from papers up until 2019



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What can we do with the data?



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Irrigation needs estimation

Necessary data to estimate irrigation needs according to the FAO

Fixed Variables	Variables set by the User
Elevation above sea level	Height of the tree
Date	Selection of soil type
Latitude	Time period for irrigation calculation
Height of wind speed measurement	Selection of Single Coefficient Approach or Dual Coefficient Approach for ETc calculation
Variables obtained from the monitored data	
Maximum air temperature of the day	Water salinity
Minimum air temperature of the day	Soil conductivity
Maximum relative humidity of the day	Soil humidity
Minimum relative humidity of the day	Soil temperature
Hours of sunlight of the day	Mean temperature of the actual month
Wind speed	Mean temperature of the previous month
Precipitation amount	Estimated mean temperature of the following month
Hour of the precipitation	

L. García et al., "Deployment Strategies of Soil Monitoring WSN for Precision Agriculture Irrigation Scheduling in Rural Areas," Sensors, vol. 21, no. 5, p. 1693, Mar. 2021, doi: 10.3390/s21051693.



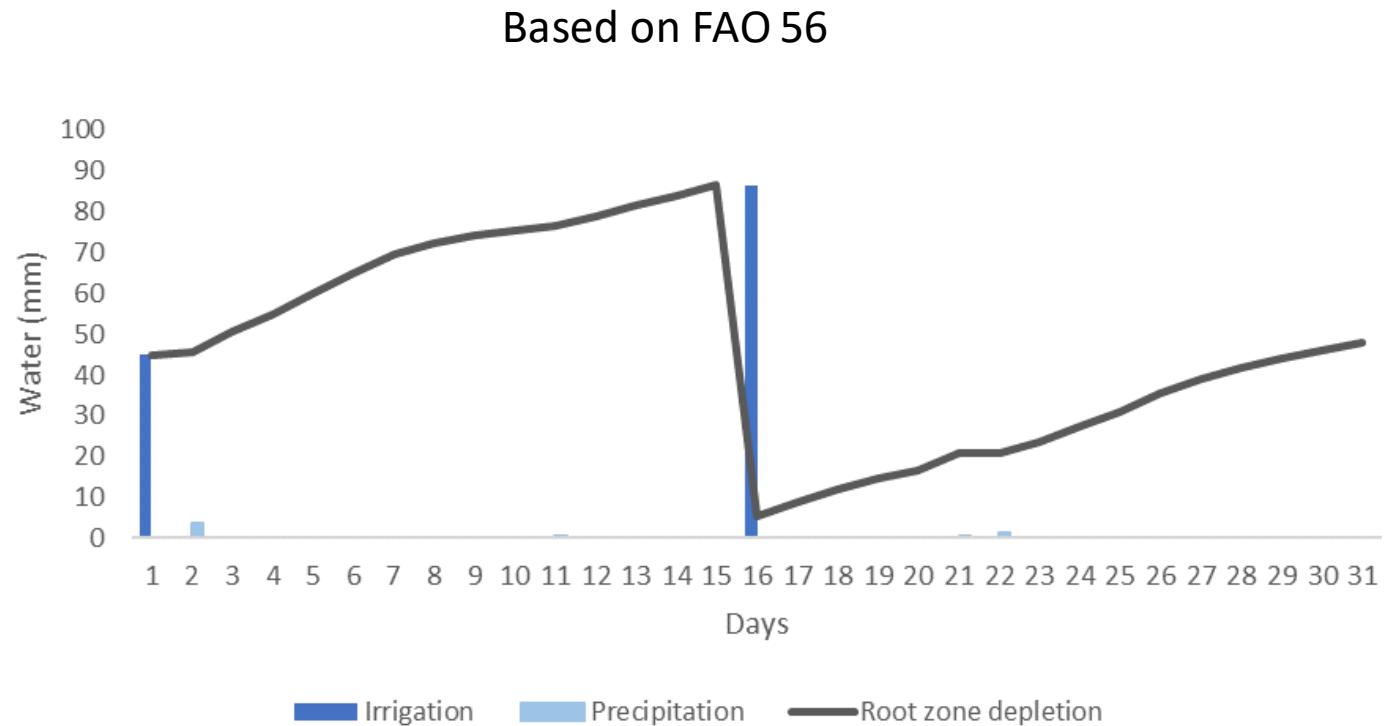
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Irrigation needs estimation

Algorithm 1. Irrigation algorithm

- 1) Variable initialization
 - 2) User parameter initialization
 - 3) ETo calculation
 - 4) Determination of the Crop Stage
 - 5) **If** Water stress **then**
 - 6) Calculate irrigation adjustment due to water stress
 - 7) **end if**
 - 8) **If** High salinity levels **then**
 - 9) Calculate irrigation adjustment due to salinity
 - 10) **end if**
 - 11) **If** Precipitation **then**
 - 12) Determine the precipitation amount
 - 13) Determine the hour of the precipitation
 - 14) Calculate irrigation adjustment due to precipitation
 - 15) **end if**
 - 16) Calculate ETc
 - 17) Calculate Irrigation requirements of the crop
 - 18) **End.**
-



L. García et al., "Deployment Strategies of Soil Monitoring WSN for Precision Agriculture Irrigation Scheduling in Rural Areas," Sensors, vol. 21, no. 5, p. 1693, Mar. 2021, doi: 10.3390/s21051693.

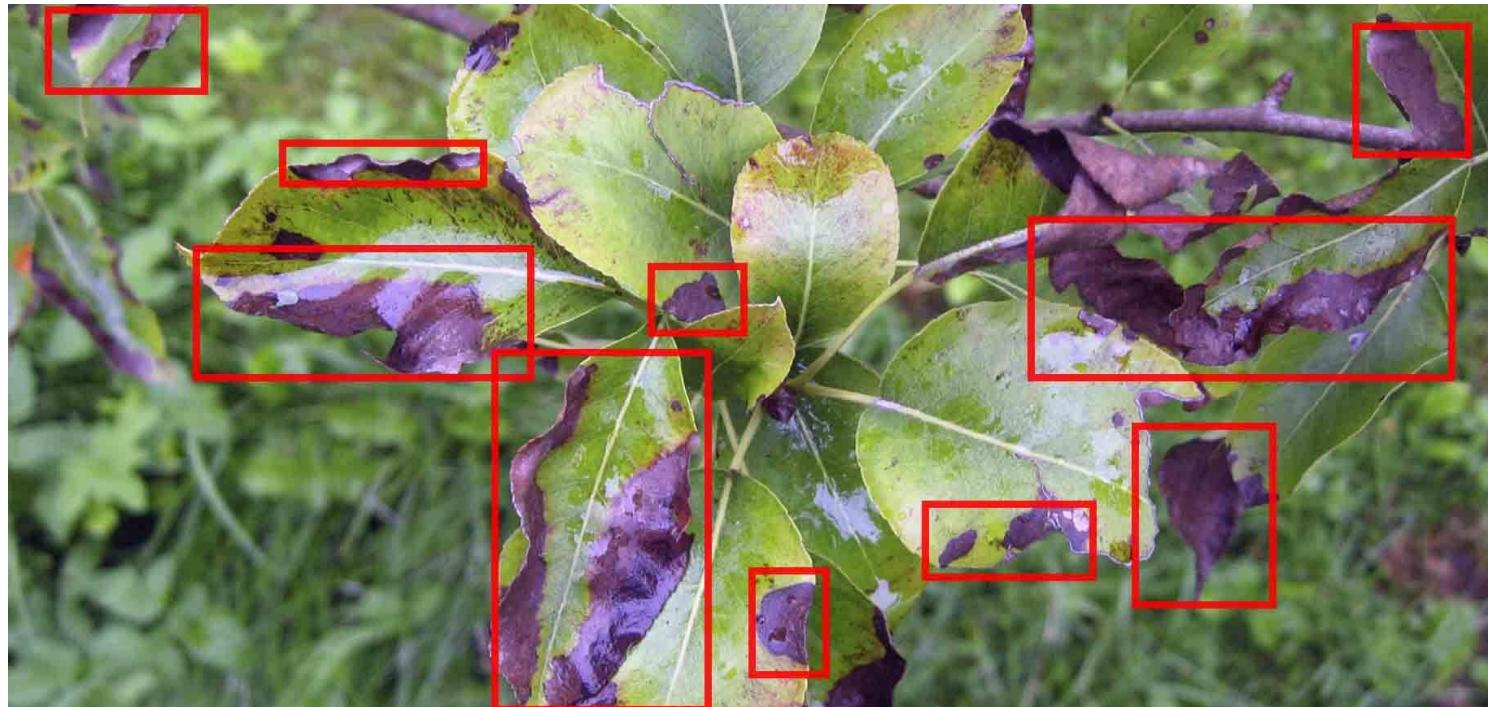


Early detection of pests and plant diseases



Early detection of pests and plant diseases

Computer Vision



Disease Detection



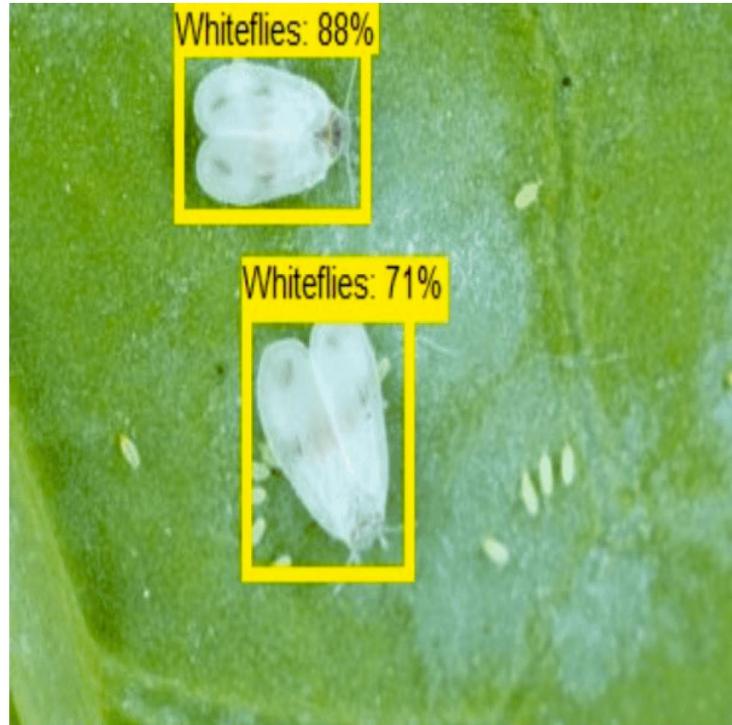
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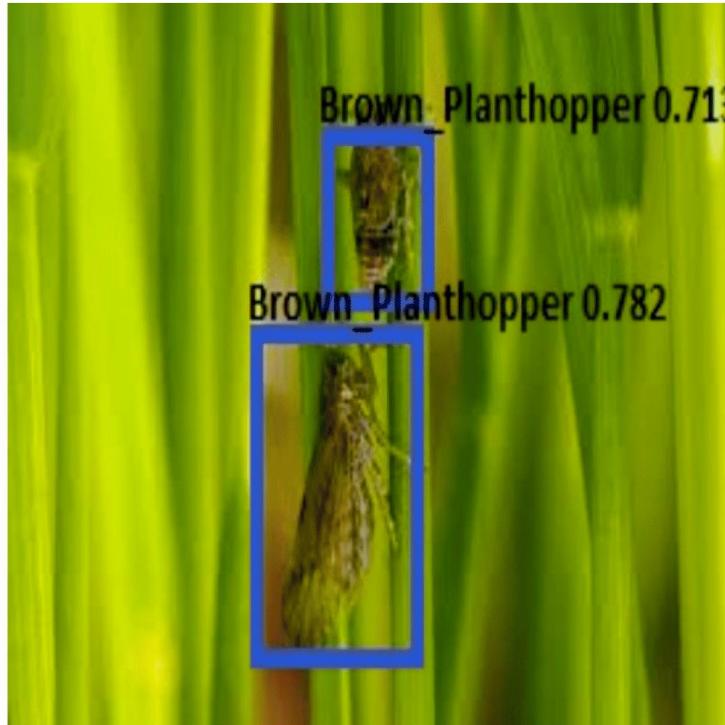
Early detection of pests and plant diseases



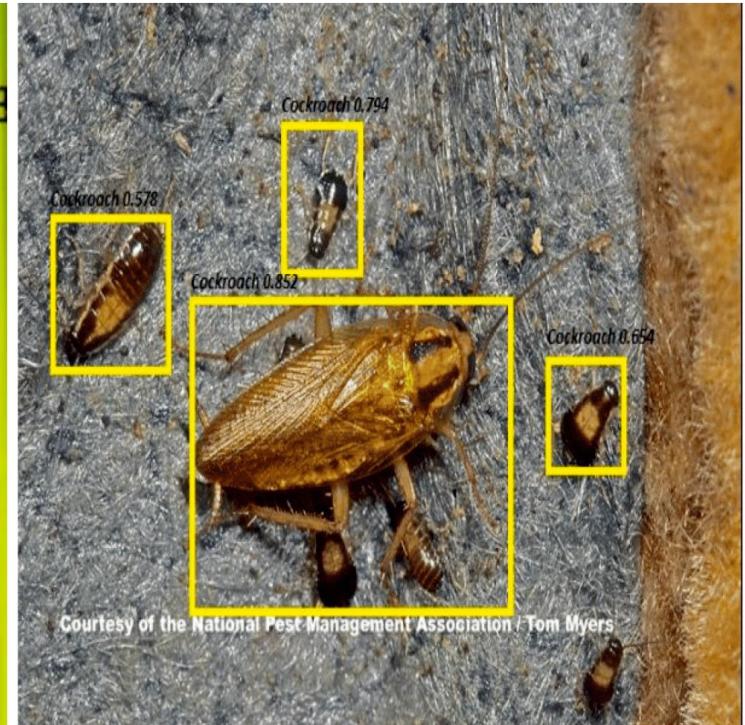
Early detection of pests and plant diseases



(a) White Flies



(b) Brown Planthopper



(c) Cockroach

Ramalingam, B., Mohan, R. E., Pookkuttath, S., Gómez, B. F., Sairam Borusu, C. S. C., Wee Teng, T., & Tamilselvam, Y. K. (2020). Remote insects trap monitoring system using deep learning framework and IoT. *Sensors*, 20(18), 5280.

Plant growth



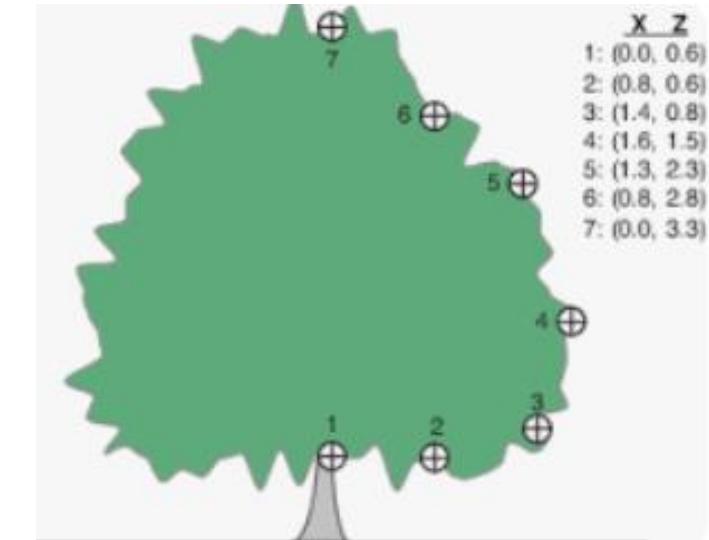
Height



Stem width



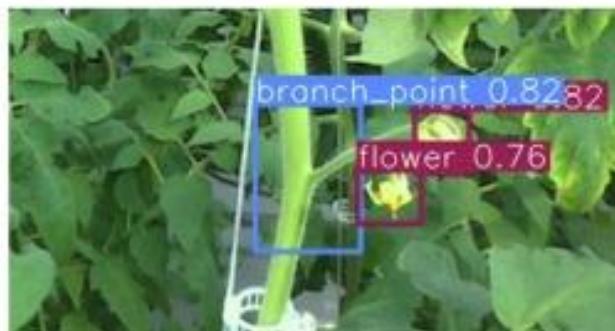
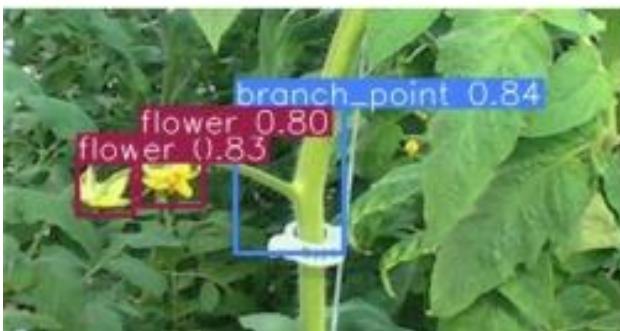
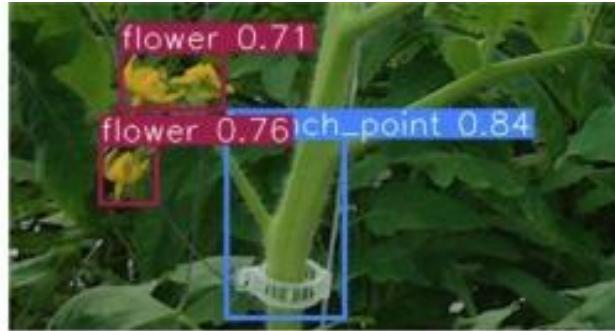
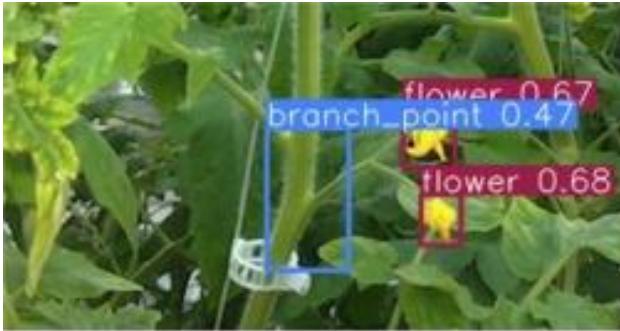
Trunk width



Foliage density/ Canopy volume

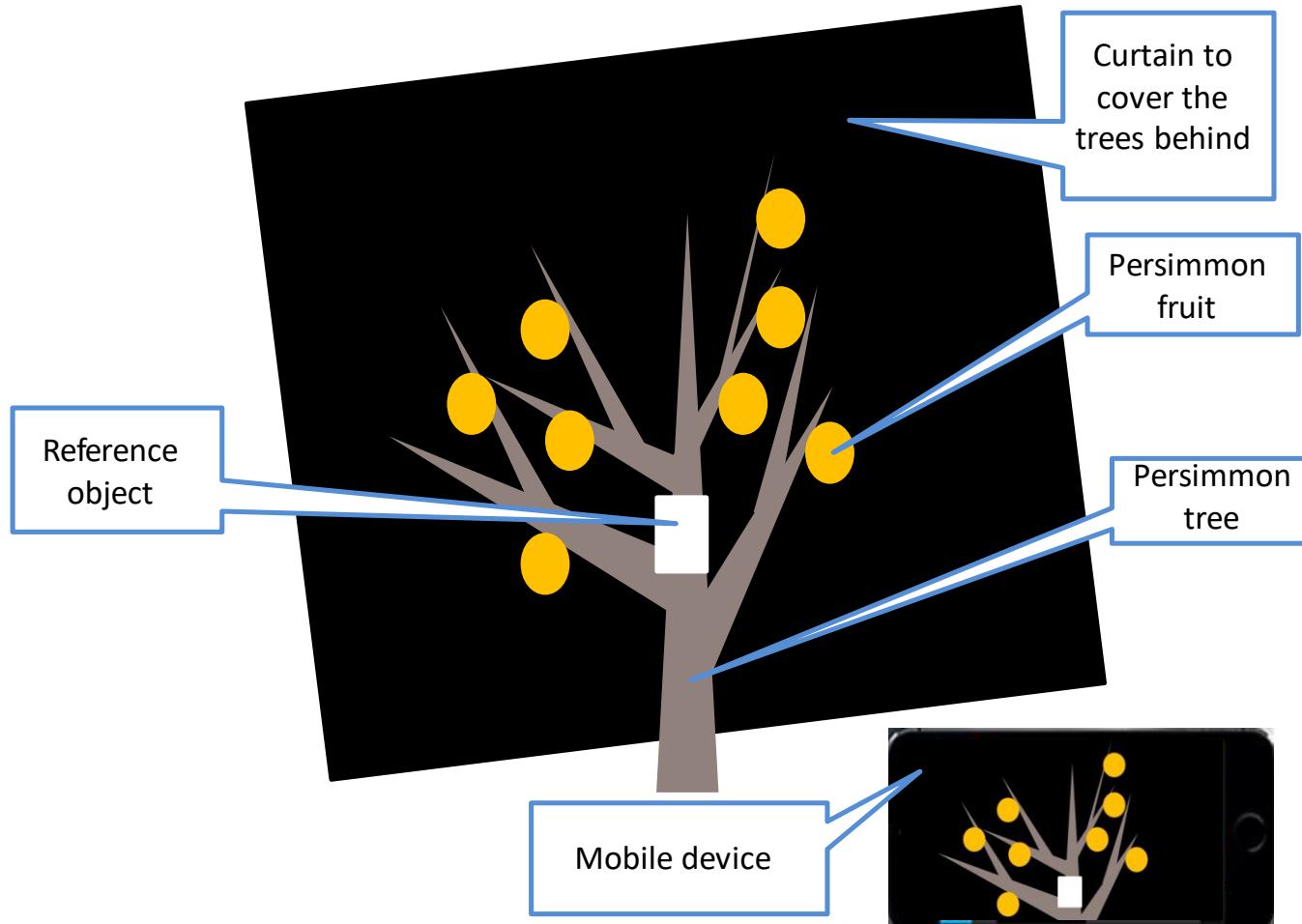
Plant growth

Computer Vision



Plant Growth

Crop production



GARCIA, Laura, et al. Quantifying the production of fruit-bearing trees using image processing techniques. En INNOV 2019, The Eighth International Conference on Communications, Computation, Networks and Technologies. ICNS, 2019. p. 14-19.

Crop production

RGB composition



Red Band



Green Band



Blue Band



GARCIA, Laura, et al. Quantifying the production of fruit-bearing trees using image processing techniques. En INNOV 2019, The Eighth International Conference on Communications, Computation, Networks and Technologies. ICNS, 2019. p. 14-19.

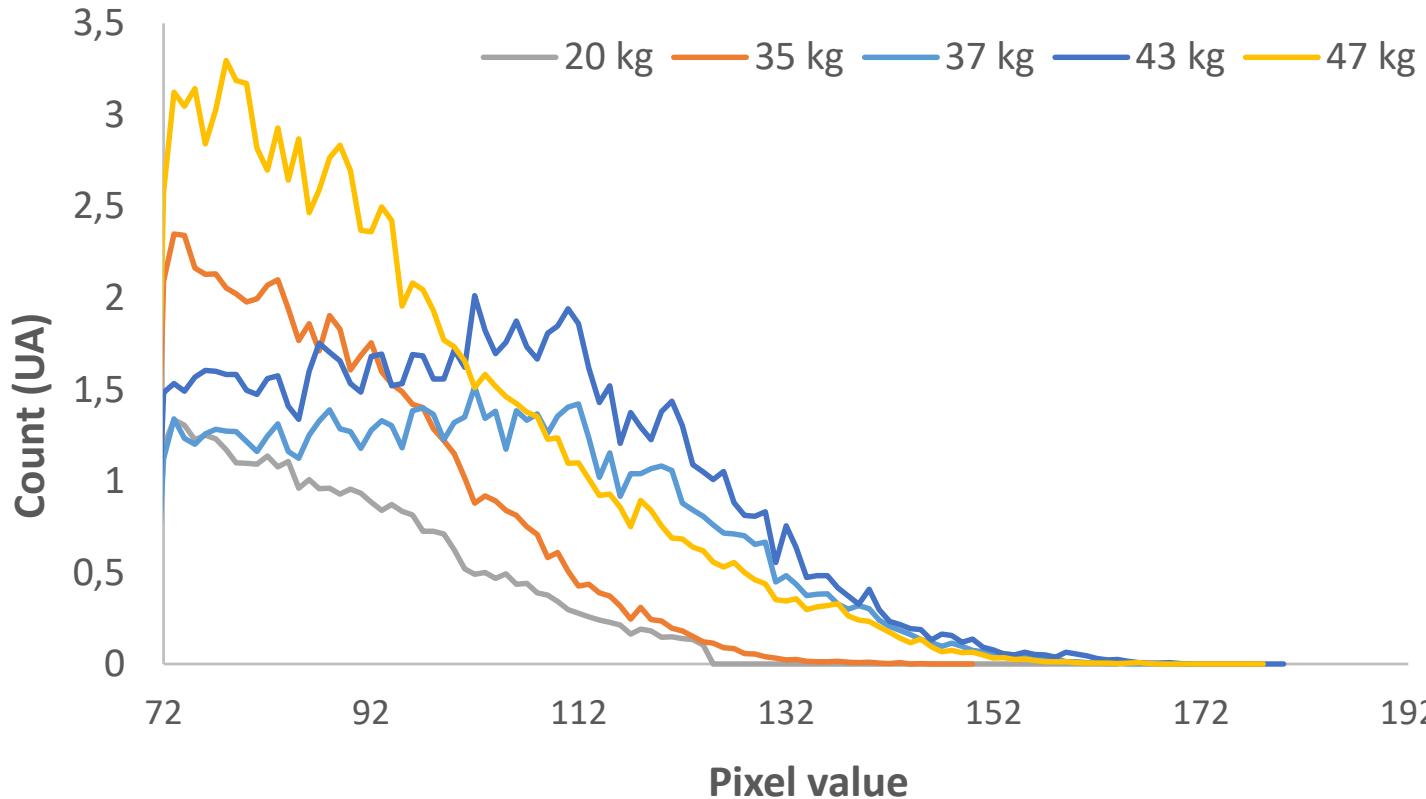


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Crop production



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Crop production

Computer Vision



- Ripeness Detection
- Fruit production
- Caliber

Produce caliber



Produce caliber

Computer Vision



Gongal, A., Karkee, M., & Amatya, S. (2018). Apple fruit size estimation using a 3D machine vision system. *Information Processing in Agriculture*, 5(4), 498-503.



Weed detection

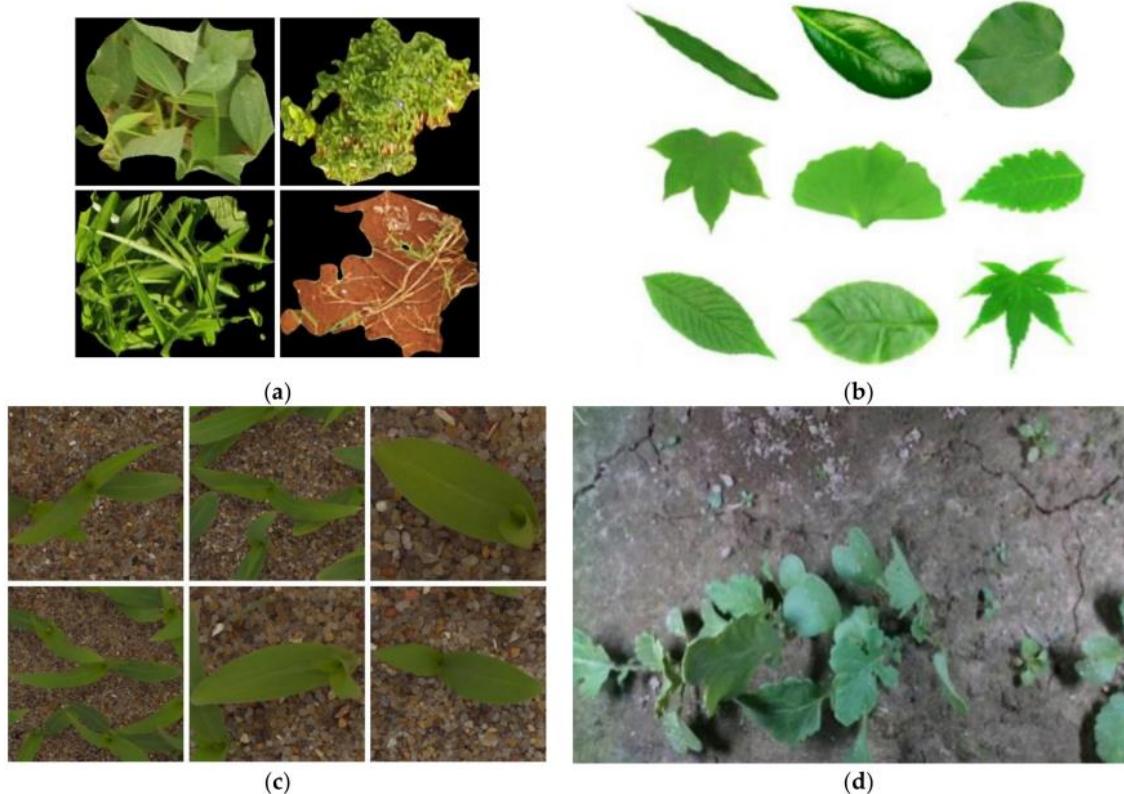


Figure 1. Four typical plant datasets: (a) Grass-Broadleaf database [19], with images of soybean, broadleaf weed, grass, and soil; (b) Flavia dataset [28]; (c) plant seedlings dataset [20]; (d) food crops and weeds dataset [26].

WU, Zhangnan, et al. Review of weed detection methods based on computer vision. Sensors, 2021, vol. 21, no 11, p. 3647.



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Weed detection

Computer Vision

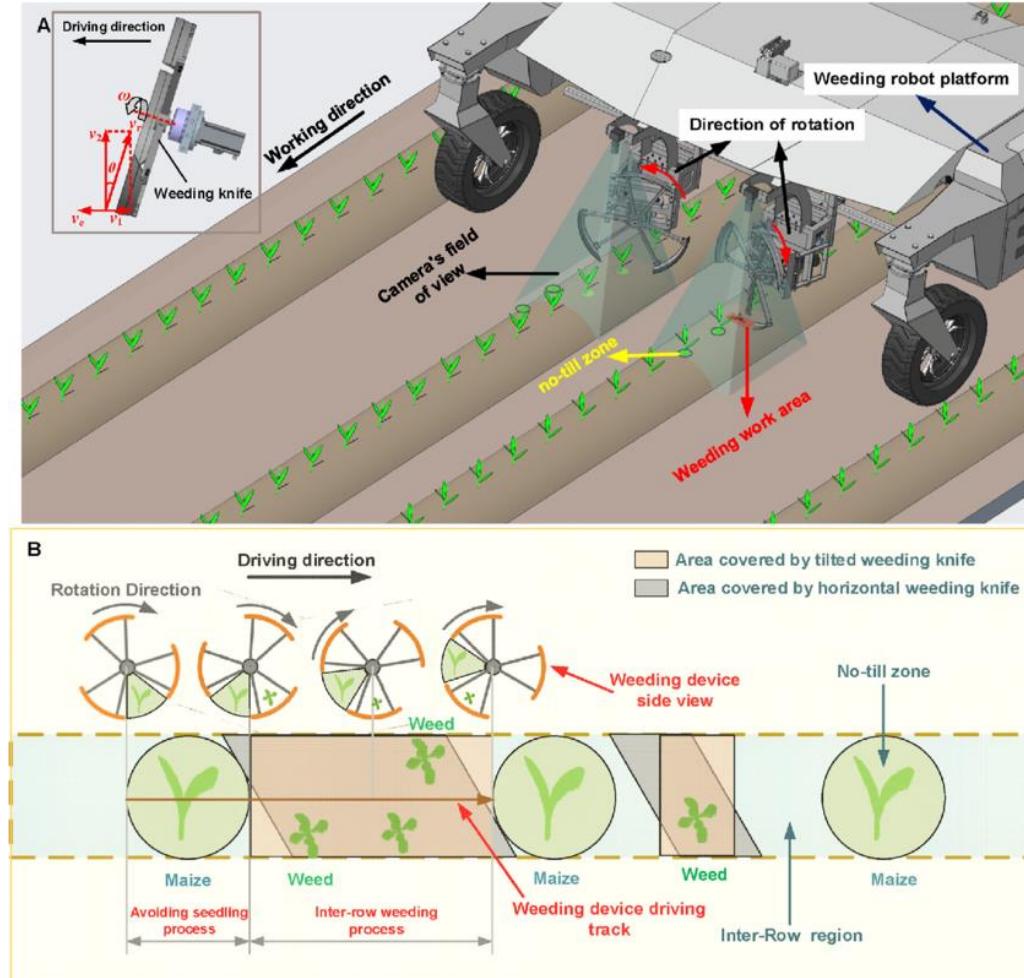


Weed Detection

Tejeda, A. I., & Castro, R. C. (2019, February). Algorithm of weed detection in crops by computational vision. In *2019 International Conference on Electronics, Communications and Computers (CONIELECOMP)* (pp. 124-128). IEEE.



Weed detection



Quan, L., Jiang, W., Li, H., Li, H., Wang, Q., & Chen, L. (2022). Intelligent intra-row robotic weeding system combining deep learning technology with a targeted weeding mode. *Biosystems Engineering*, 216, 13-31.



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Not just monitoring but also controlling

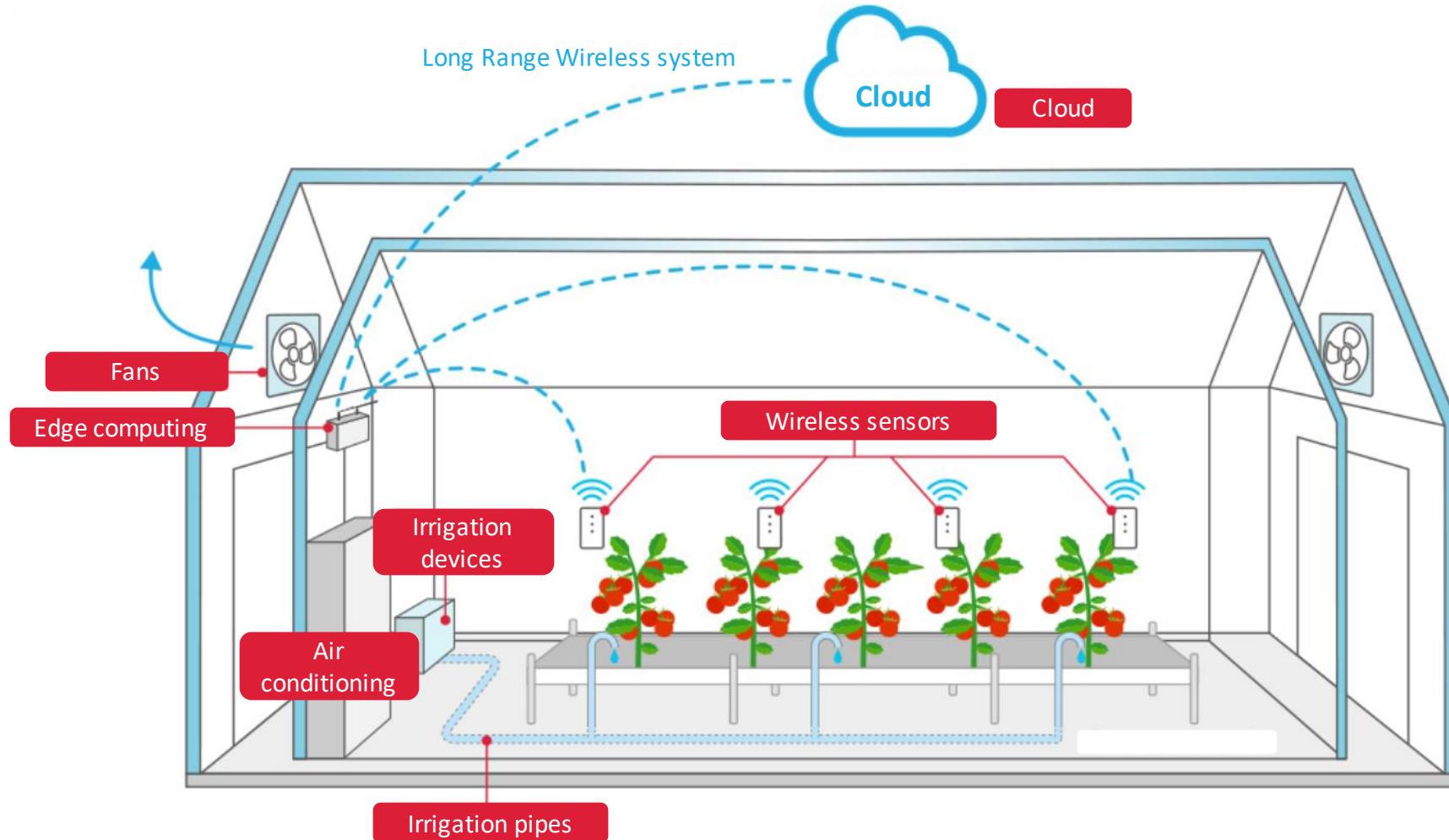


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Intelligent greenhouse



Automated irrigation systems



Irrigation actuator



Fertirrigation system



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Drones and robots



Fumigation drone



Vineyard robot

Accessing data and controls



Accessing data and controls

The screenshot shows the VEGGA web application interface. On the left is a dark sidebar with various navigation options: Escenario del cliente (Agro Alt penedés), Dashboard, Usuarios, Mapas, Cultivos, Suscripciones, Mis módulos, Riego de precisión, Inicio, Equipo (selected), Gráficas, Gestión de fincas, Control de plagas, Nutrición, and Fertilizadores.

The main content area has a header with links: Inicio, Clientes, Mis Mensajes, Alertas, Configuración, Daniel Martín, and Agromatic Soluciones.

The current page is titled "Equipos". It displays a table for the "Badina" equipment, showing details like Nº Serie (130915), Tipo / Versión (A-2500 / 125), and Estado (Conectado). Below this is another table listing irrigation programs for various crops: Olivos, Almendros, Tomates, Maíz, Frutales, Viñedos, Pistacho, and Frutales del norte. Each row includes columns for Programas, Inicio del riego, Tiempo pendiente, Tiempo programado, Sectores, Iniciado por, and Estado (e.g., En riego, Fuera de servicio, No conectado, No riego).



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In conclusion





More Tomorrow!