From Sensors to Decisions: Emerging Technologies for Smart and Sustainable Agriculture

Dos Sensores à Decisão: Tecnologias Emergentes para uma Agricultura Inteligente e Sustentável

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Quick Audience Survey

A quick show of hands to understand who is in the room and how technology fits your daily decisions.

Who are you?

- Producer / farmer
- Technician / advisor
- Researcher / educator
- Policymaker / manager
- Agribusiness / other

Which sector?

- Vineyard
- Olive grove
- Arable / field crops
- Fruit / horticulture
- Other

How do you use technology today?

- Daily decision support
- Occasional use
- Testing / pilot phase
- Not using yet

Where do you see most value?

- Irrigation
- Pests & diseases
- Crop monitoring
- Field operations
- Documentation / traceability

If you are sceptical, why?

- Too expensive
- Not reliable enough
- Too complex / time-consuming
- Not adapted to my reality
- Unclear return on investment

The goal is not to convince everyone today — it is to understand your reality, your needs and your barriers.

Key Message

Smart agriculture creates value when it supports the producer's decisions.

SENSE ⟶ INTERPRET ⟶ DECIDE

Field Signals

- Soil Moisture
- Weather
- Plant Status
- Drone / Satellite Imagery

→

The Producer at the Centre

→

Better Decisions

- Irrigation Timing
- Targeted Scouting
- Input Efficiency
- Sustainability / Resource Efficiency

Smart agriculture is not about replacing the producer.
It is about turning field signals into better, faster and more sustainable decisions.

FROM SENSORS TO DECISIONS

Why Smart Agriculture, Why Now?

Because agriculture is becoming more complex, more uncertain and more demanding.

> Producers are being asked to make better decisions, faster, with fewer resources and under increasing uncertainty.

Climate pressure
Droughts, floods and increasing variability

Water scarcity
More efficient irrigation is no longer optional

Ageing sector
Knowledge must be supported, transferred and scaled

Economic pressure
Higher costs, lower margins and competitiveness gaps

Fragmented decisions
Too much data, too little actionable insight

Smart agriculture starts with the producer's reality — not with the technology.

Content

From field signals to trusted producer decisions

1	2	3	4	5
Context & Decision Gap	**Sensing the Field**	**Making Sense of Data**	**Acting in Practice**	**Trust & Scale**
Why smart agriculture, why now?	IoT temporal backbone	Soil–plant–water dynamics	Irrigation support	Validation and uncertainty
Producer decision gap	Low-cost field sensing	Data integration	Phenology, pests & disease alerts	Start small, validate, scale
	Remote sensing from above	Models as a Service	Zones, prescriptions & operations	Take-home discussion

A one-hour journey: sense → integrate → interpret → decide → scale.

FROM SENSORS TO DECISIONS

The Producer's Decision Gap

Data only creates value when it becomes a timely, trusted action.

Observe
Field signals from soil, plants, weather and machinery

Understand
Patterns, trends and causes behind variability

Decide
Irrigation, alerts, priorities and interventions

Act
Better timing, fewer wasted resources and stronger results

The gap is not lack of data. It is the distance between field signals and confident action.

Smart agriculture closes the gap between observation and action.

The Technology Landscape: From Signals to Decisions

Smart agriculture is not one technology. It is an ecosystem that connects field signals, data intelligence and operational decisions.

Field Signals

- Soil moisture
- Weather
- Plant status
- Images
- Machinery
- Satellite data

→

Intelligence Layer

- Data integration
- AI models
- Forecasts
- Risk assessment
- Decision support

→

Producer Decisions

- Irrigation
- Pest & disease control
- Fertilisation
- Harvest planning
- Resource allocation

The value is not in isolated tools — the value is in connecting them to decisions.

IoT: The Temporal Backbone

Without continuous field data, there is no crop dynamics.
Without dynamics, decisions are late, reactive or uncertain.

Sensor
Continuous field sensing

→

Time Series
Data collected hour after hour

→

Trend
Patterns become visible

→

Alert
Thresholds and early warnings

→

Decision
Act with better timing

What IoT brings

- Continuous monitoring
- Soil–plant–atmosphere signals
- Local climate variability
- Early warnings
- Data streams for decision support

Why it matters

- Makes field behaviour visible over time
- Turns snapshots into trends
- Supports earlier interventions
- Reduces uncertainty
- Strengthens sustainable decisions

IoT gives agriculture a memory — and turns isolated observations into decision-ready trends.

Practical Field Sensing: Low-Cost, Versatile IoT Devices

From individual measurements to dense, affordable sensor networks for precision agriculture.

What can be measured?

- Soil water content
- Solar radiation
- Temperature
- Rainfall
- Relative humidity
- Dendrometers
- Leaf wetness
- Actuators

Why this matters for producers

- Affordable deployment
- Flexible sensor combinations
- Local field variability captured
- Data streams connected to decision support

The goal is not more gadgets — it is reliable field evidence at the right cost and density.

SPWAS: a versatile solution for PV applications

Experimental setup (DATI PRIMA project)

Experimental setup with 4 irrigation zones using a Gateway + 4 SPWAS over IEEE 802.15.5 (868 MHz) to collect VWC data from 8 points. Energy-efficient management including power off the gateway at night

Sensors and the digital transformation in Morocco



Low-cost digital technologies that promote irrigation efficiency in Morocco are highly valued, as there is still a lag in the adoption of such technologies. Training is essential, and the low-cost SPWAS devices were a key output ot the DATI project

Created at our group

VineInspector: the first AI-powered biological observer

Based on the assumption that it would be a valuable addition to UTAD's innovation portfolio, the VineInspector was developed as the first local automatic observation system featuring multiple cameras and AI-based multiclassifiers. This work began in 2017

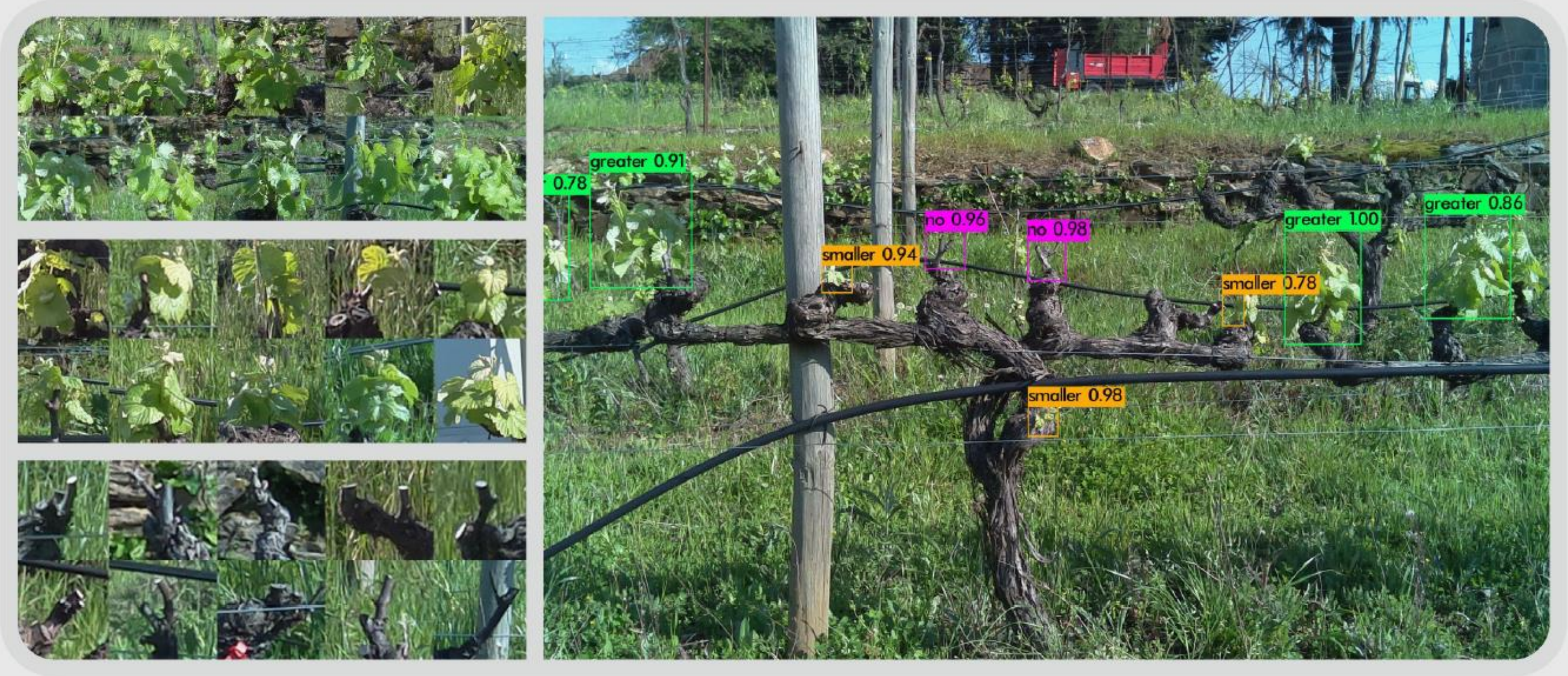
The image as a key-element in the observation

Since a picture is worth a thousand words, visual observation greatly enhances the understanding of vine growth dynamics. When automated with AI, many labor-intensive tasks can be minimized.

VineInspector for insect counting in traditional traps

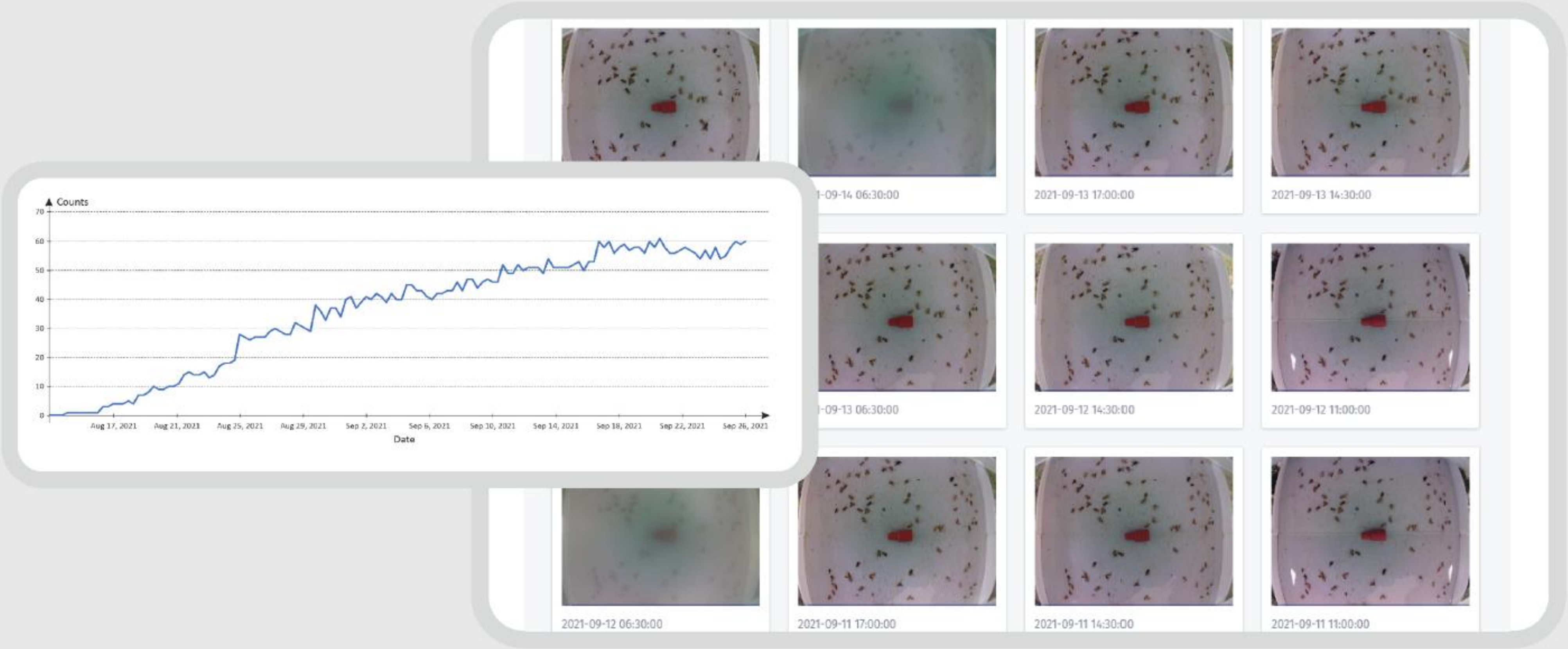
With no limitations on the numbers of cameras or other software/hardware resources, VineInspecter can be used to count specific insect traps. This enables remote estimation of the economic threshold level (ETL) nad the triggering of control actions.

Detection & measurement of vine shoot growth using AI



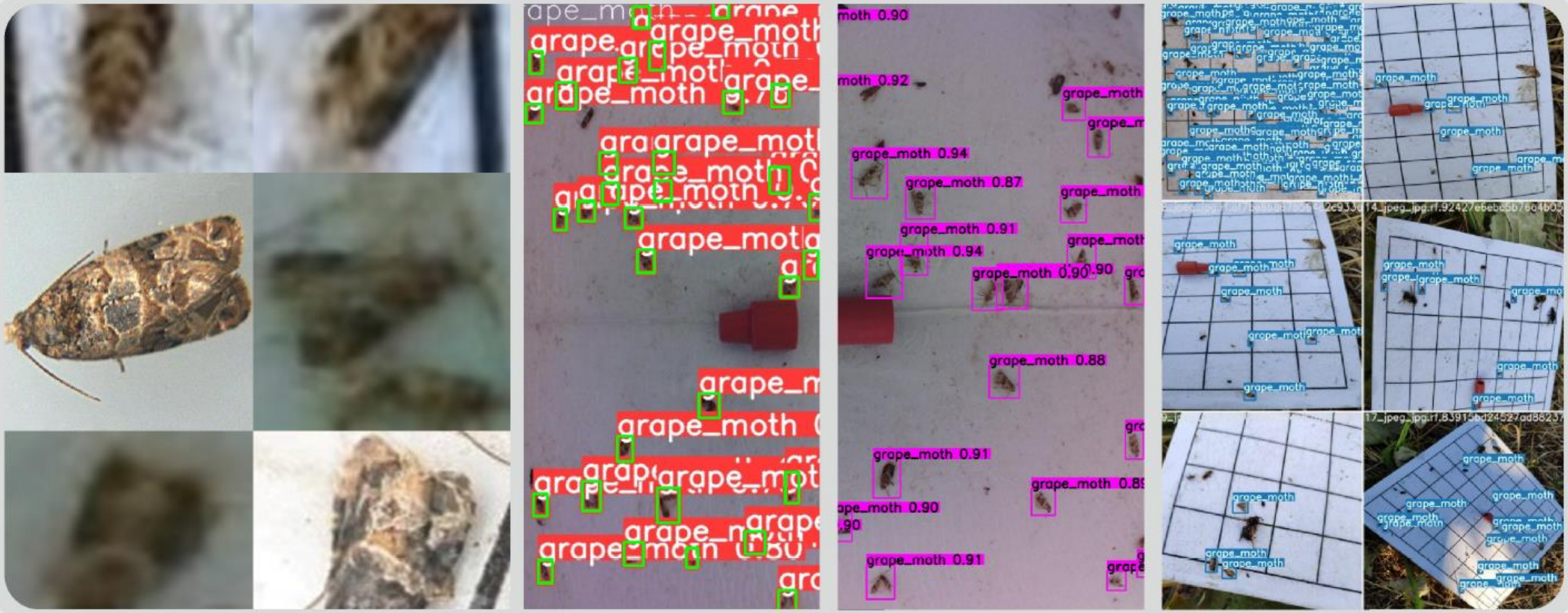
Keeping an eye on multiple fonts : another VineInspector camera captures images to detect and measure the first shoots, which is essential for preventing diseases like downy mildew. After proper training , VineInspector automatically classifies all the shoots

AI-Based counting of grapevine moth specimens



VineInspector captures multiple images per day of the instrumented trap. Many of these images are used for specimen counting after a training process based on images of grapevine moths (*Lobesia Botrana*). When a threshold is reached, a notification is triggered

Training AI models to classify insects



For an AI system to automatically classify objects, it must be trained with a large number of diverse cases. Often, data augmentation and other techniques are used to create diversity and richness in images, which are then properly annotated

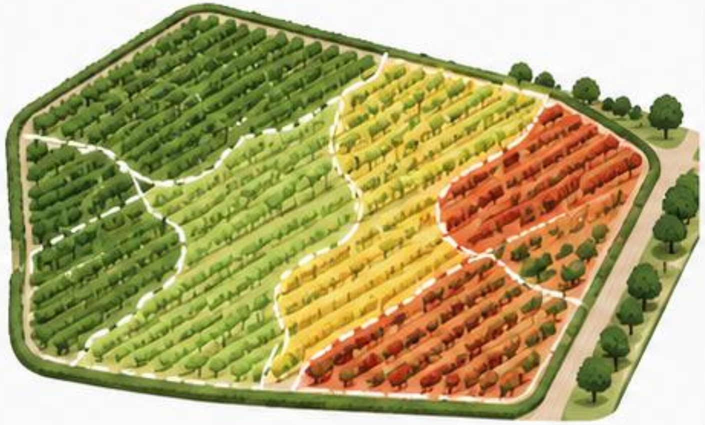
Remote Sensing: Seeing Spatial Variability from Above

Drones and satellites reveal where field conditions change — so decisions can become site-specific.

1 Drone & Satellite Imagery

- Multispectral · Thermal · RGB · LiDAR

2 Spatial Patterns



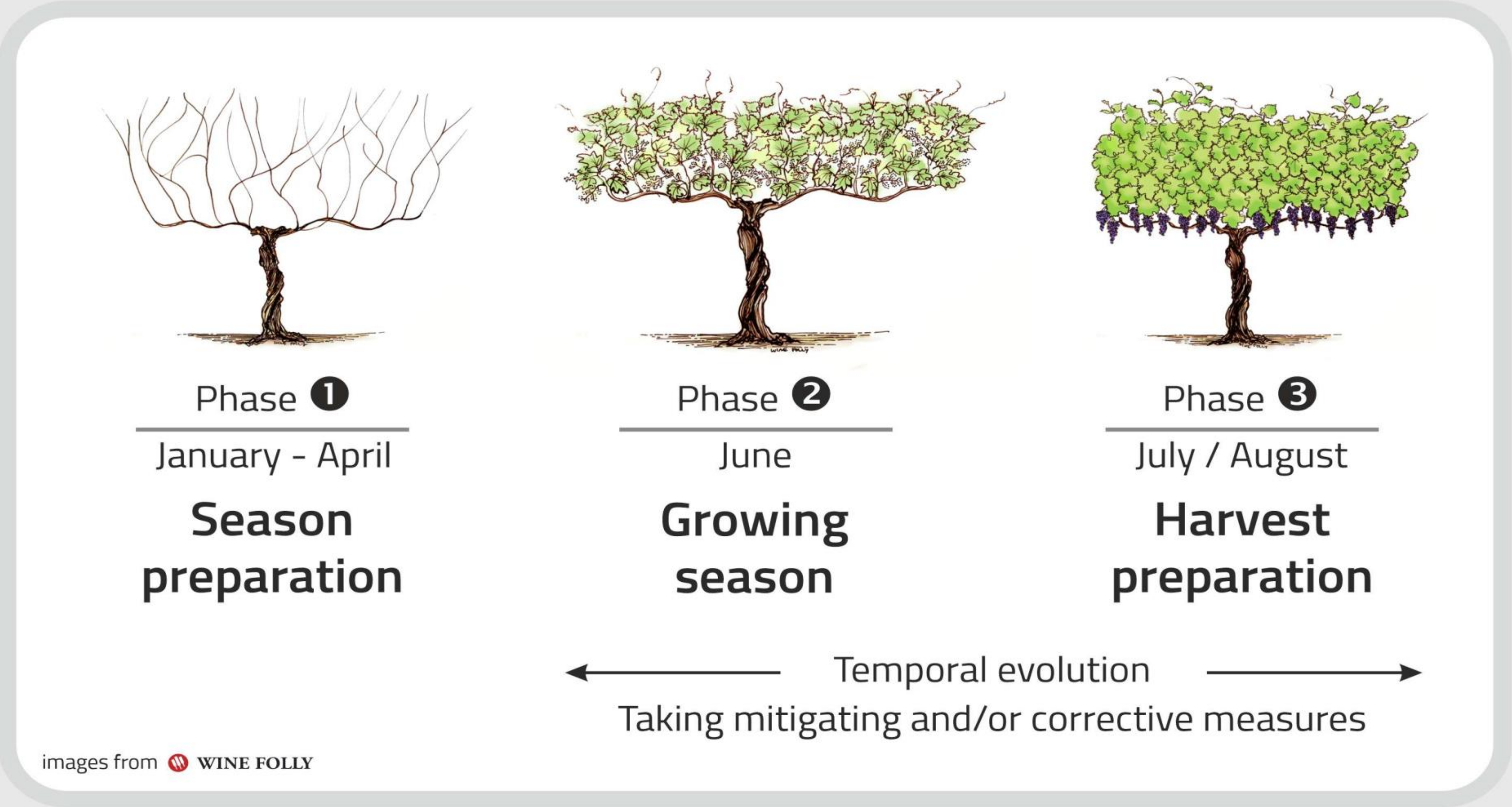
- Vigour · Water stress · Anomalies · Zones

3 Site-Specific Decisions

- Irrigation zones
- Targeted scouting
- Variable-rate actions

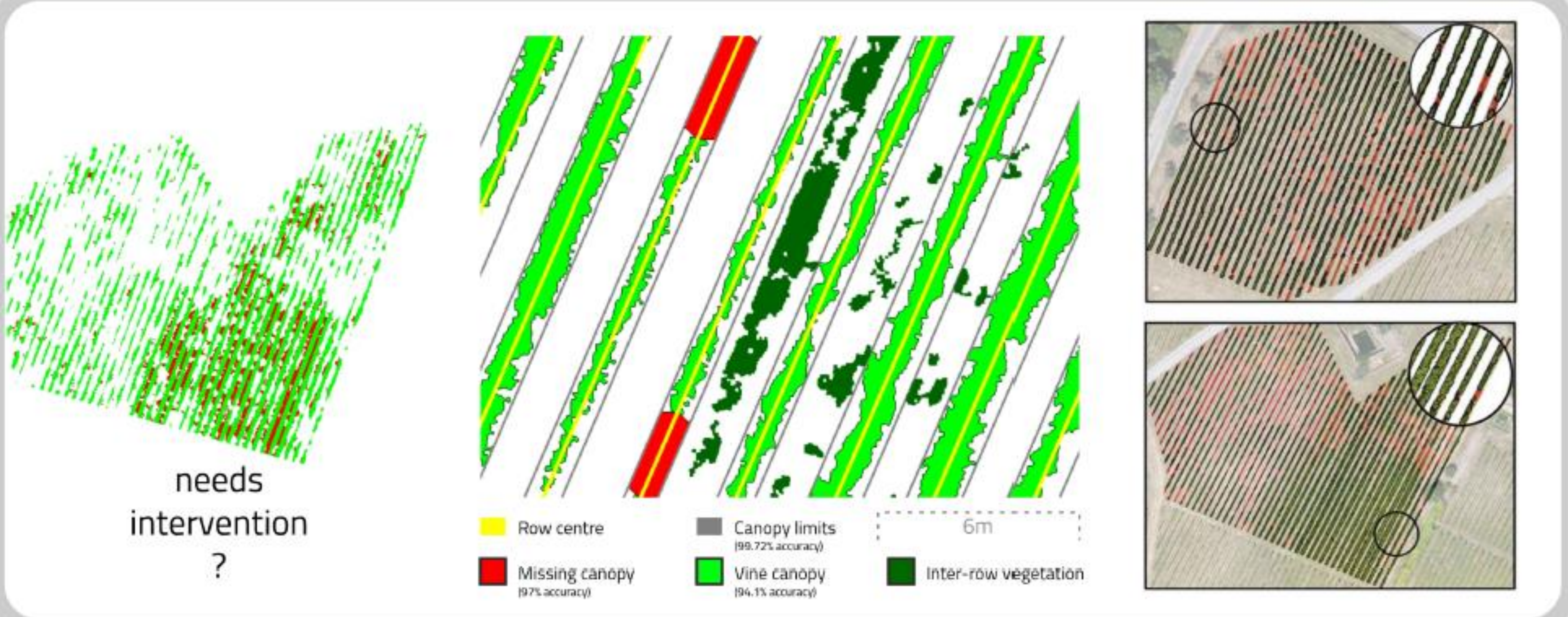
Remote sensing turns scattered field observations into spatial intelligence.

Precision Viticulture Solutions

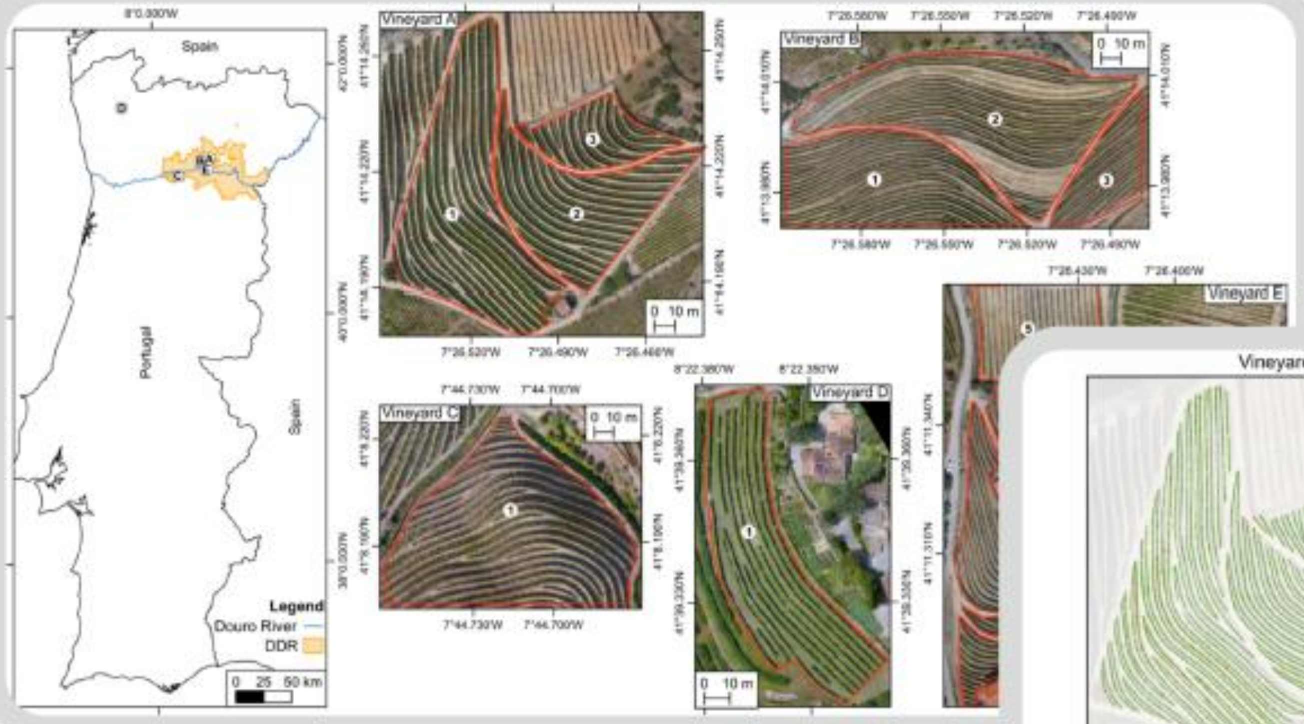


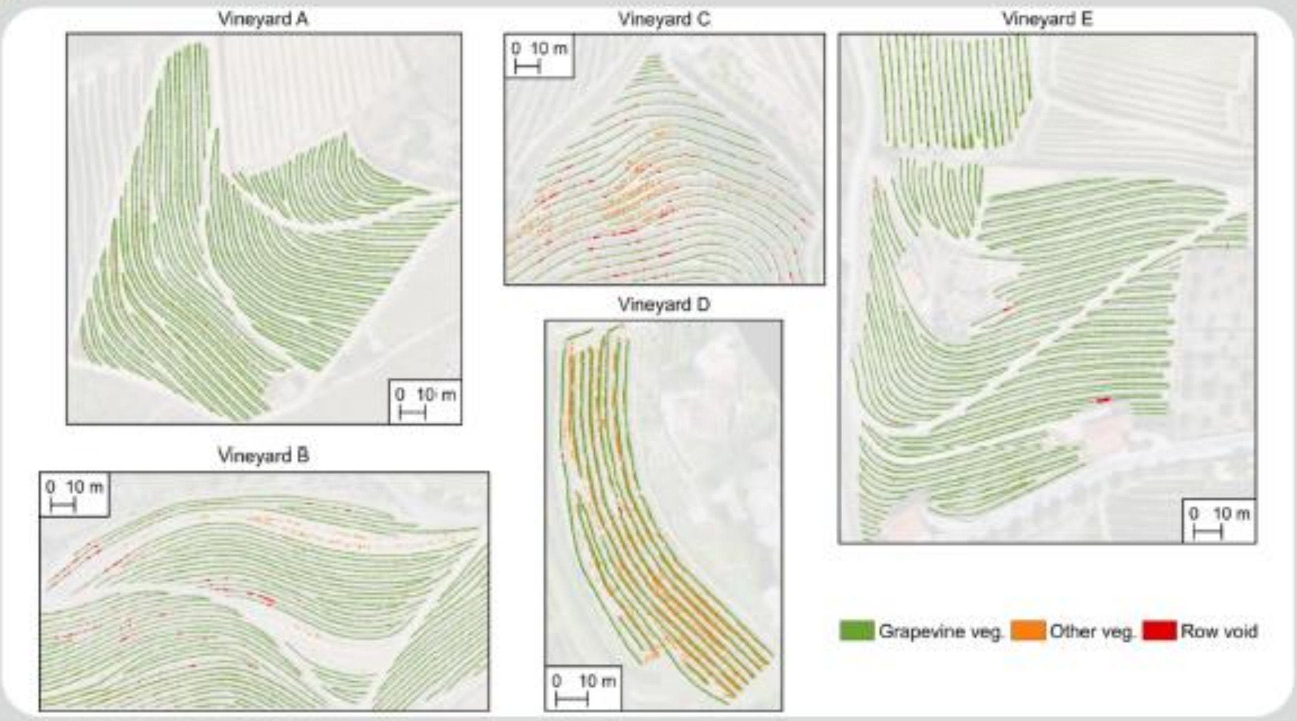
Phases of the grapevine cycle where flying with drones can be a valuable help in targeted vineyard-management practices

Automatic detection of vineyard vegetation

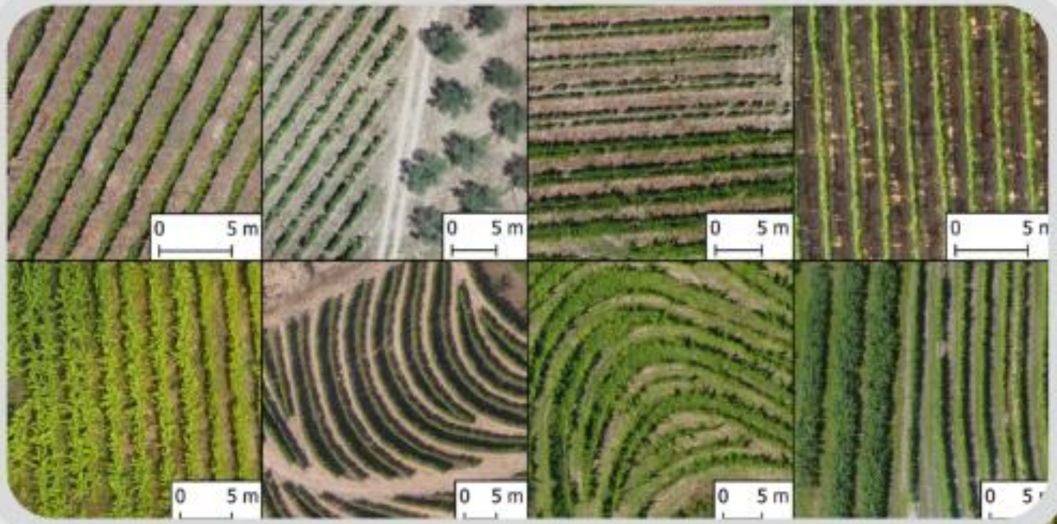


Grapevine row detection in challenging vineyards



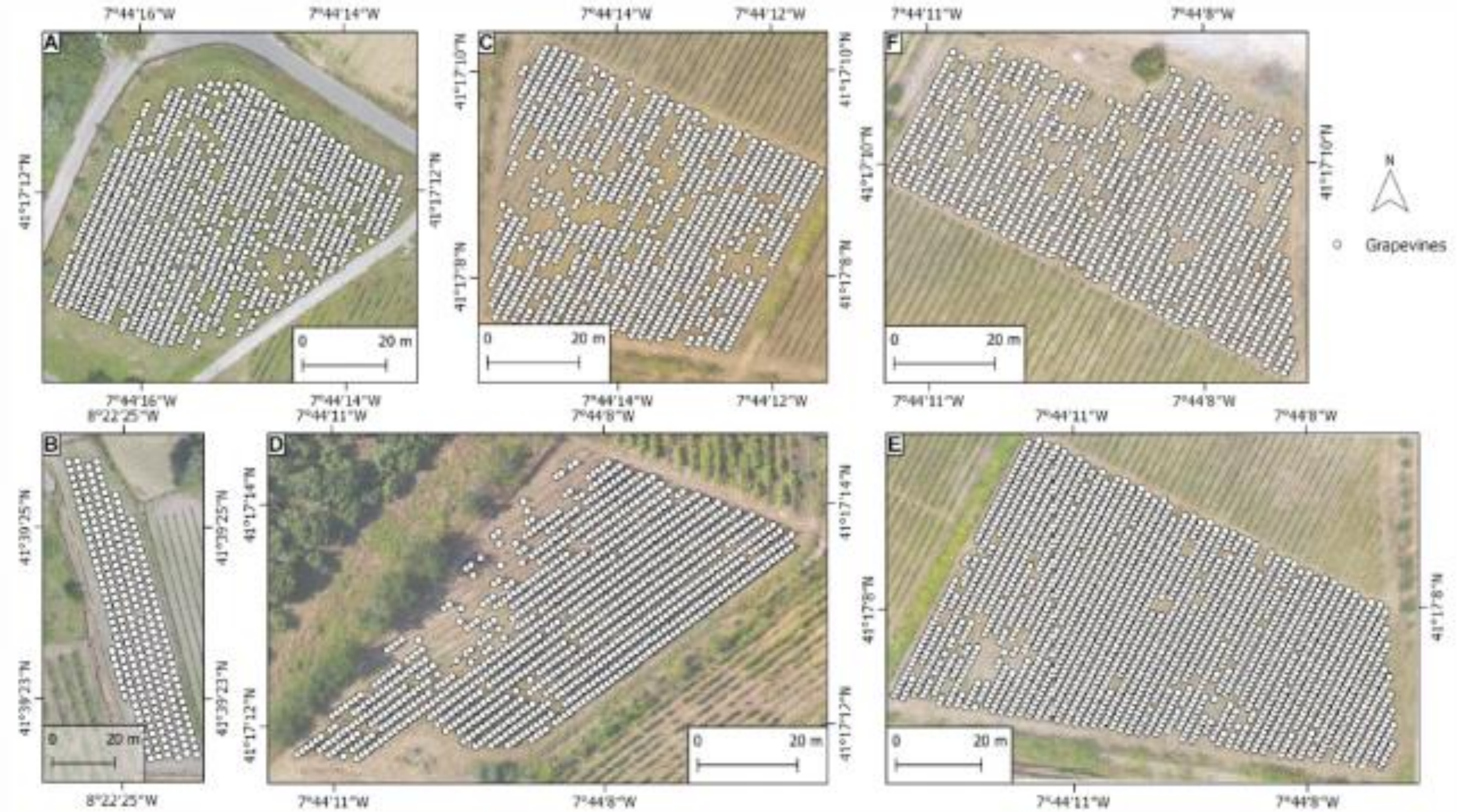


Grapevine row detection in challenging vineyards

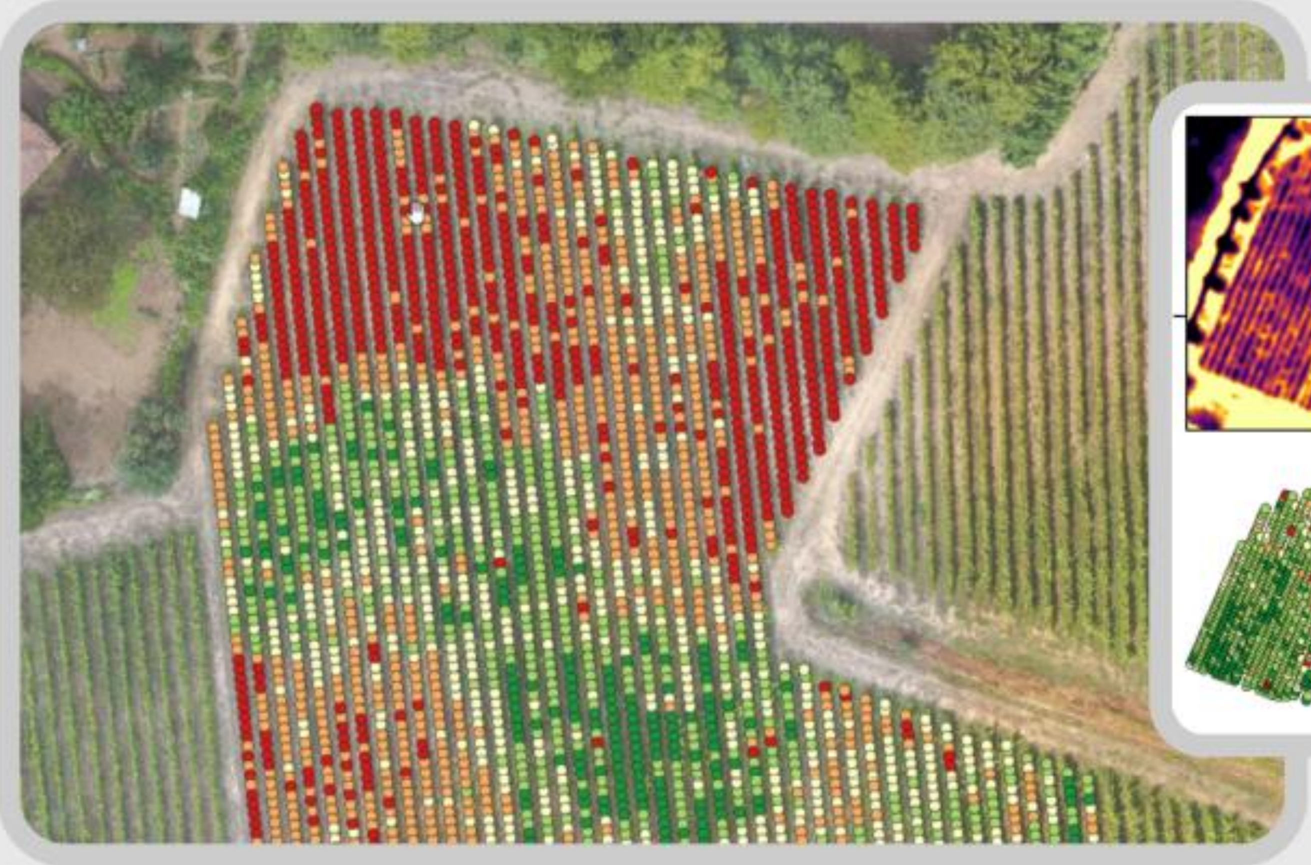


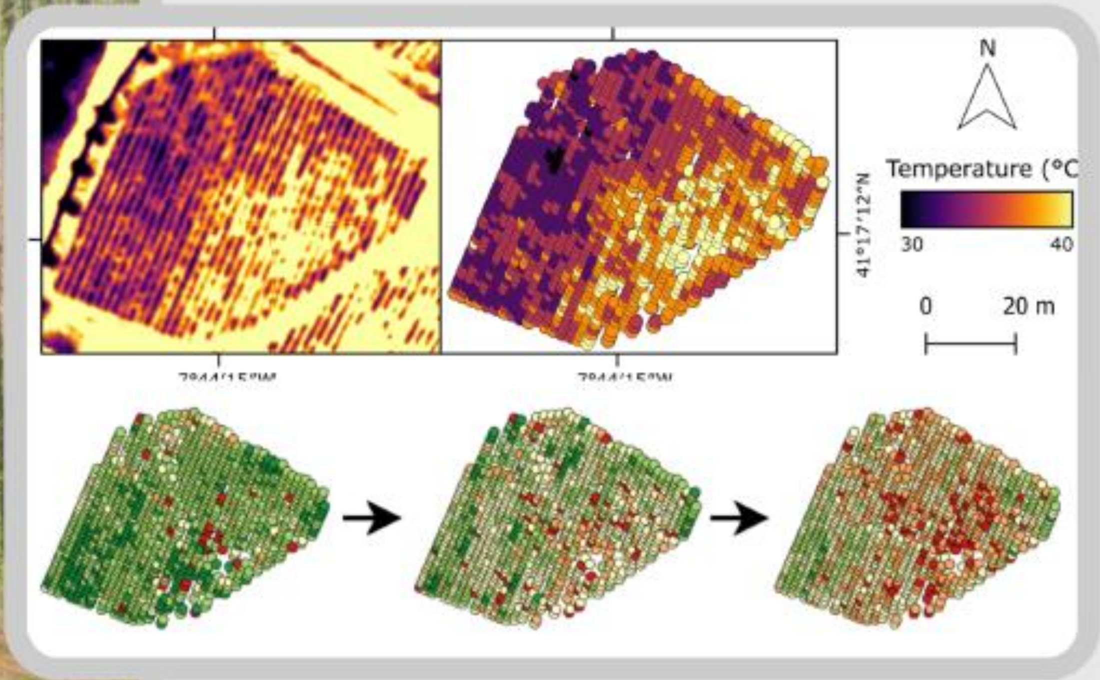
Using AI/deep learning to automatically detect grapevine rows even with shadows or combined with other type of crops.

Marking and counting vine plants



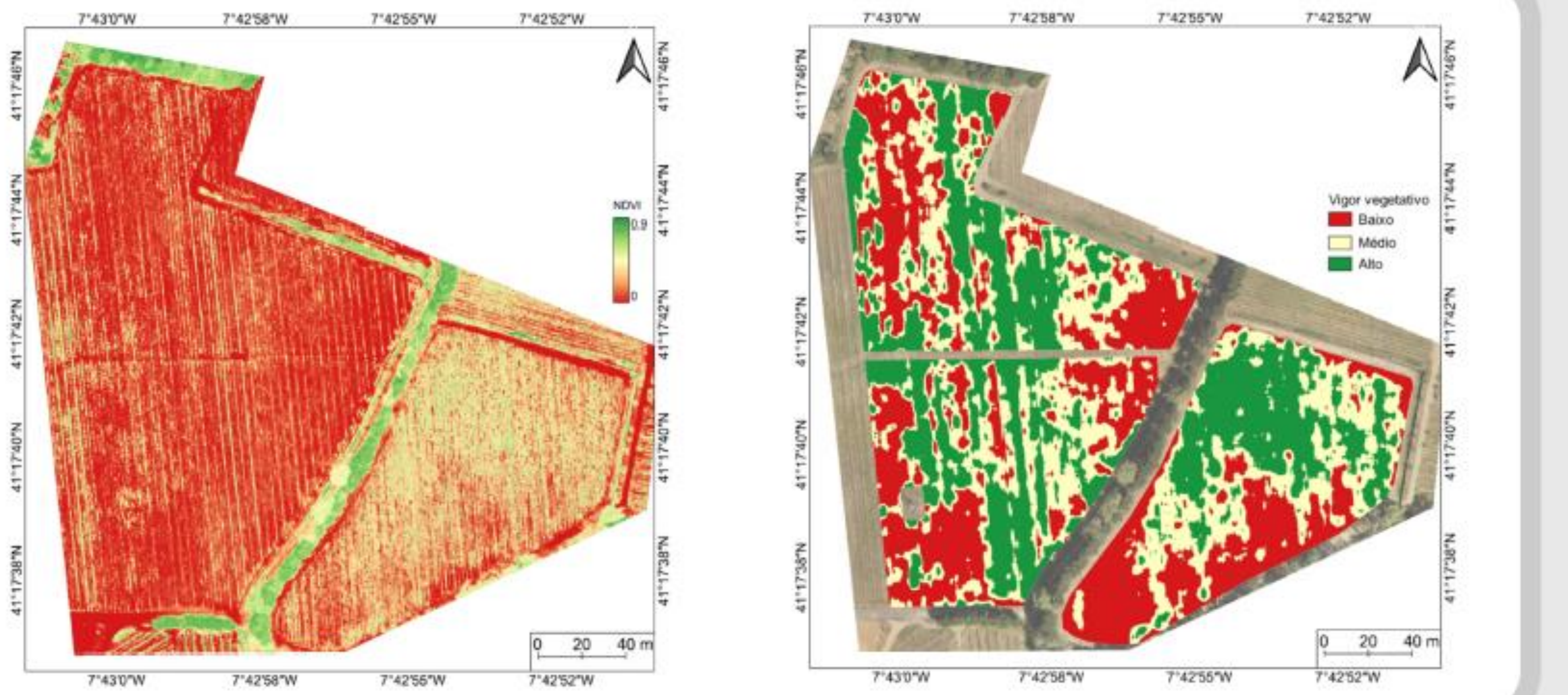
Individual grapevine analysis





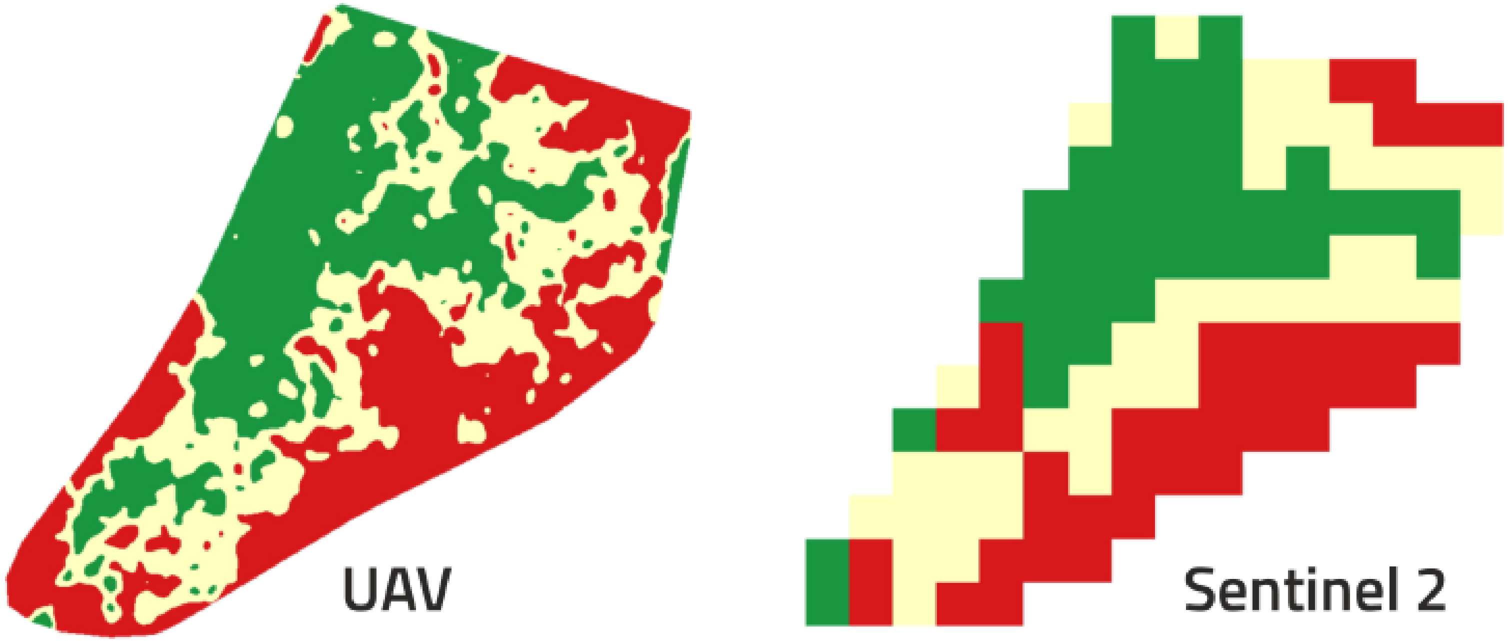
Each vine is identified by an algorithm and marked with a circle on the drone image.
Each circled vine is an individual data point for spatial and temporal analysis.
Information (disease, water stress, nutrient deficiency, etc.) can be associated with each vine.

Vineyard heterogeneity mapping

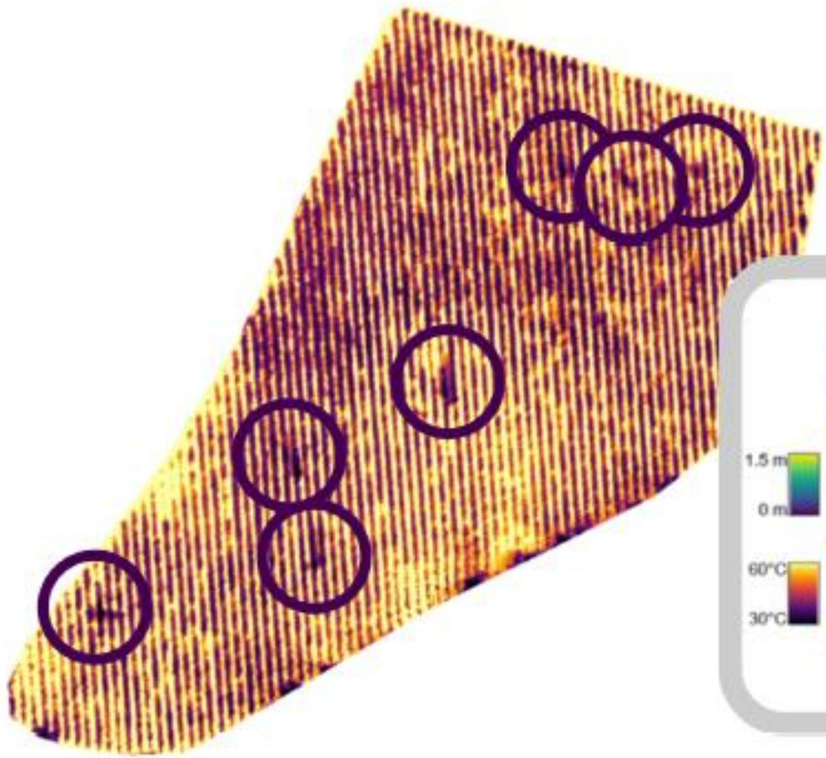


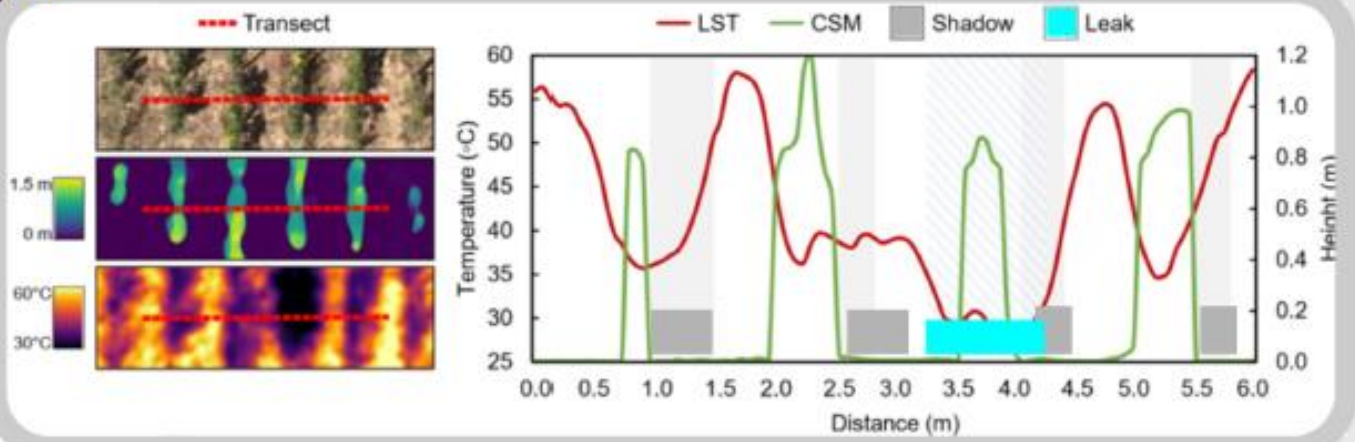
Remote sensing enables detailed mapping of vegetation variability.
Left: NDVI highlights plant vigor.
Right: zoned classification supports precision interventions and decision-making.

Vineyard heterogeneity mapping with lower resolution



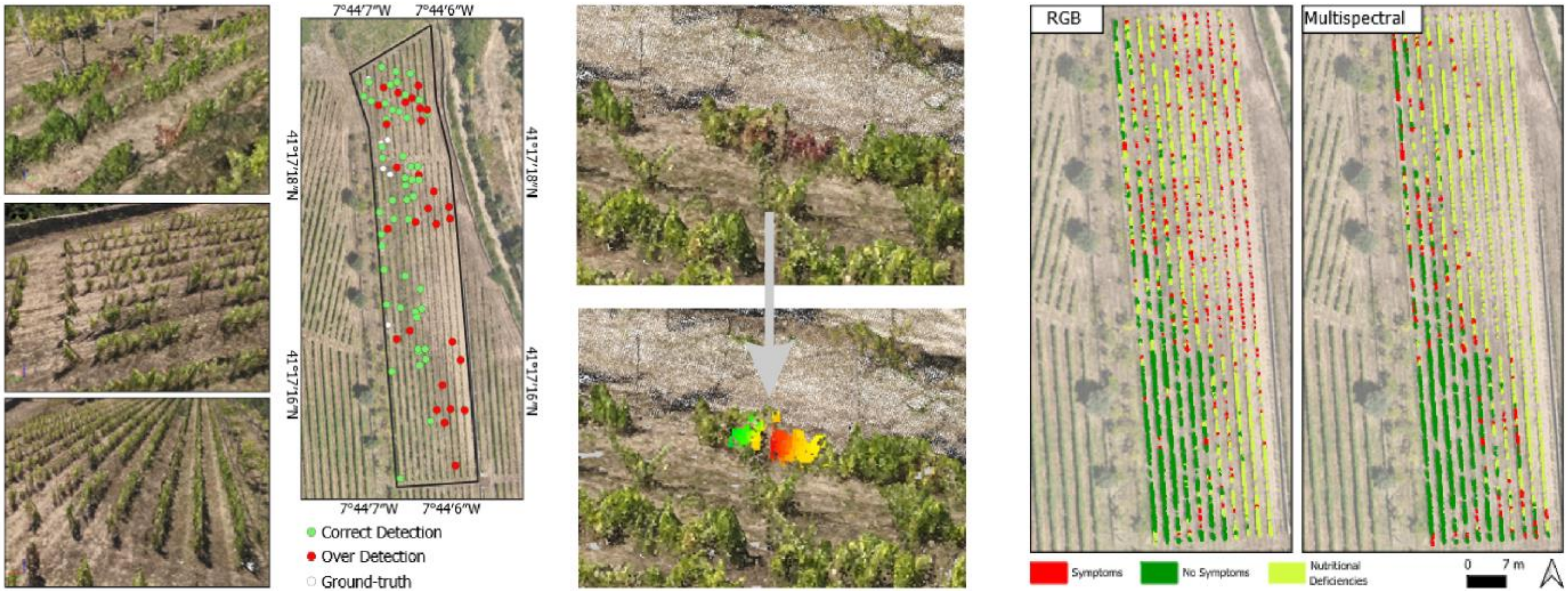
Lower-resolution Sentinel data, despite its coarser scale, remains valuable for broader vigor assessment and monitoring over time. Combining both scales enhances decision-making in precision viticulture





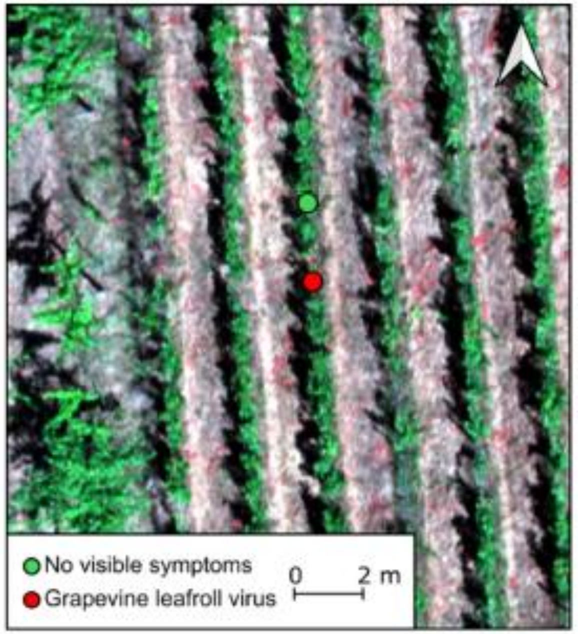
Using thermal imagery and Land Surface Temperature (LST) over the Crop Surface Model (CSM), water leaks in irrigation systems can be detected

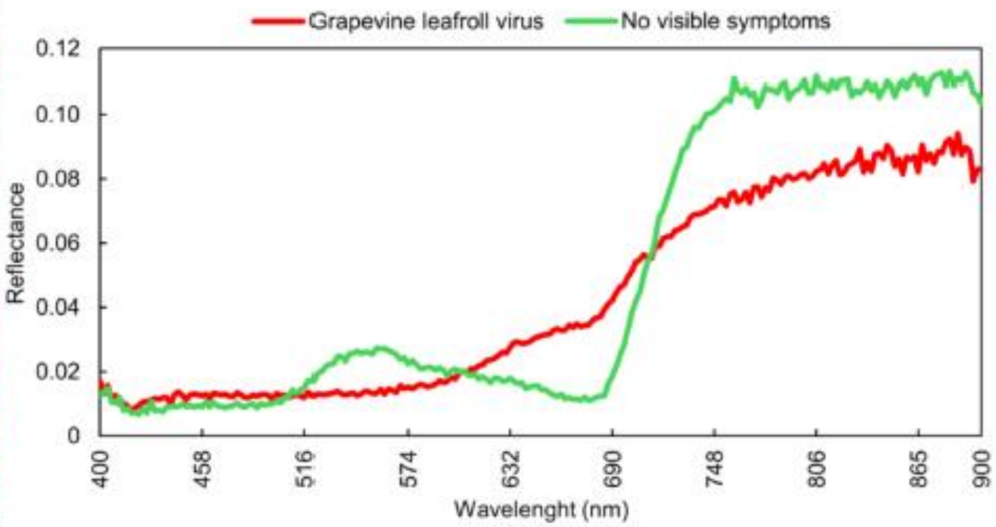
Vineyard anomalies detection



Point clouds are used to locate vines and project health status using RGB and multispectral imagery. Symptoms of viral diseases or nutrient deficiencies are assessed and visualized in 3D. Field validation is shown on the left; algorithms are still under testing

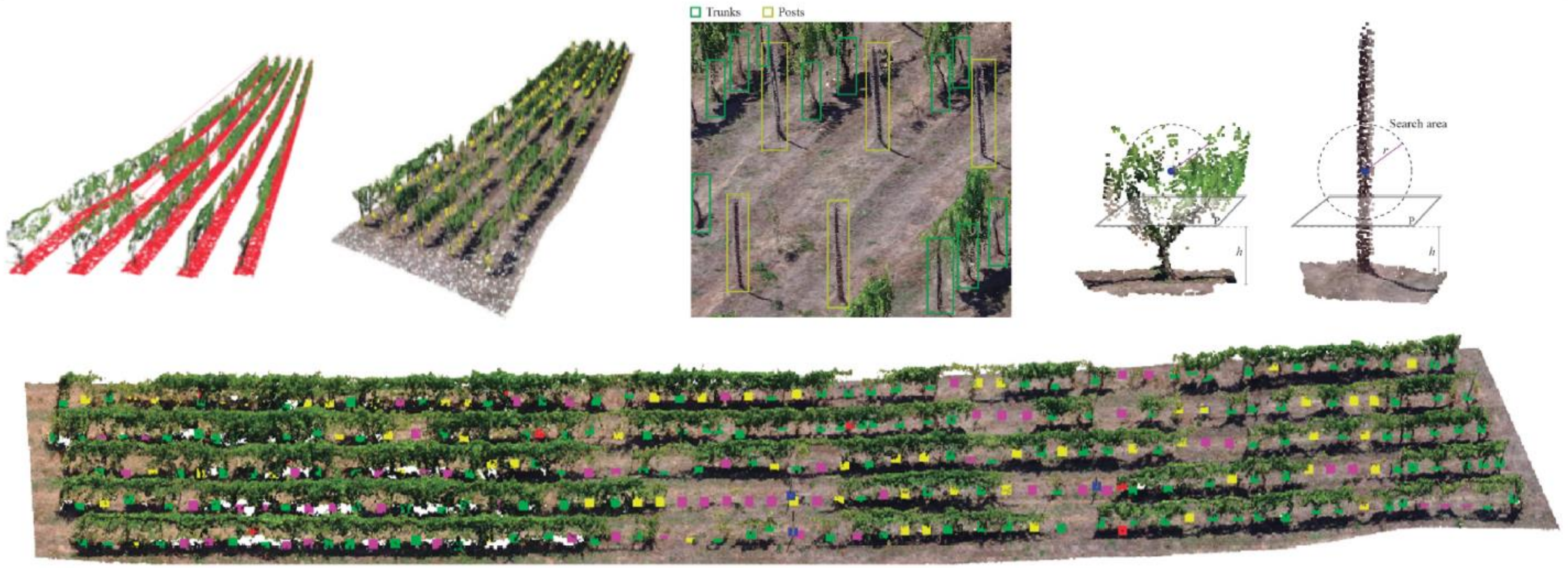
Detection of viral diseases: grapevine leafroll virus





Hyperspectral sensors are being explored for detecting grapevine leafroll virus by capturing subtle spectral differences. This technology also shows promise for identifying water stress, nutrient deficiencies, and other vineyard stresses

Detecting grapevine trunks using UAV point clouds



Point clouds from UAVs are processed with geometric methods to detect grapevine trunks and separate them from poles. Thus, our algorithms will enable detailed vineyard mapping, identifying missing vines, underdeveloped plants, and growth variations

From Maps to Meaning: Soil–Plant–Water Dynamics

Seeing variability is only the first step — decisions improve when we understand the causes behind the patterns.

1 Visible Pattern

- Vigour differences
- Water stress
- Anomalies

2 Causal Layers

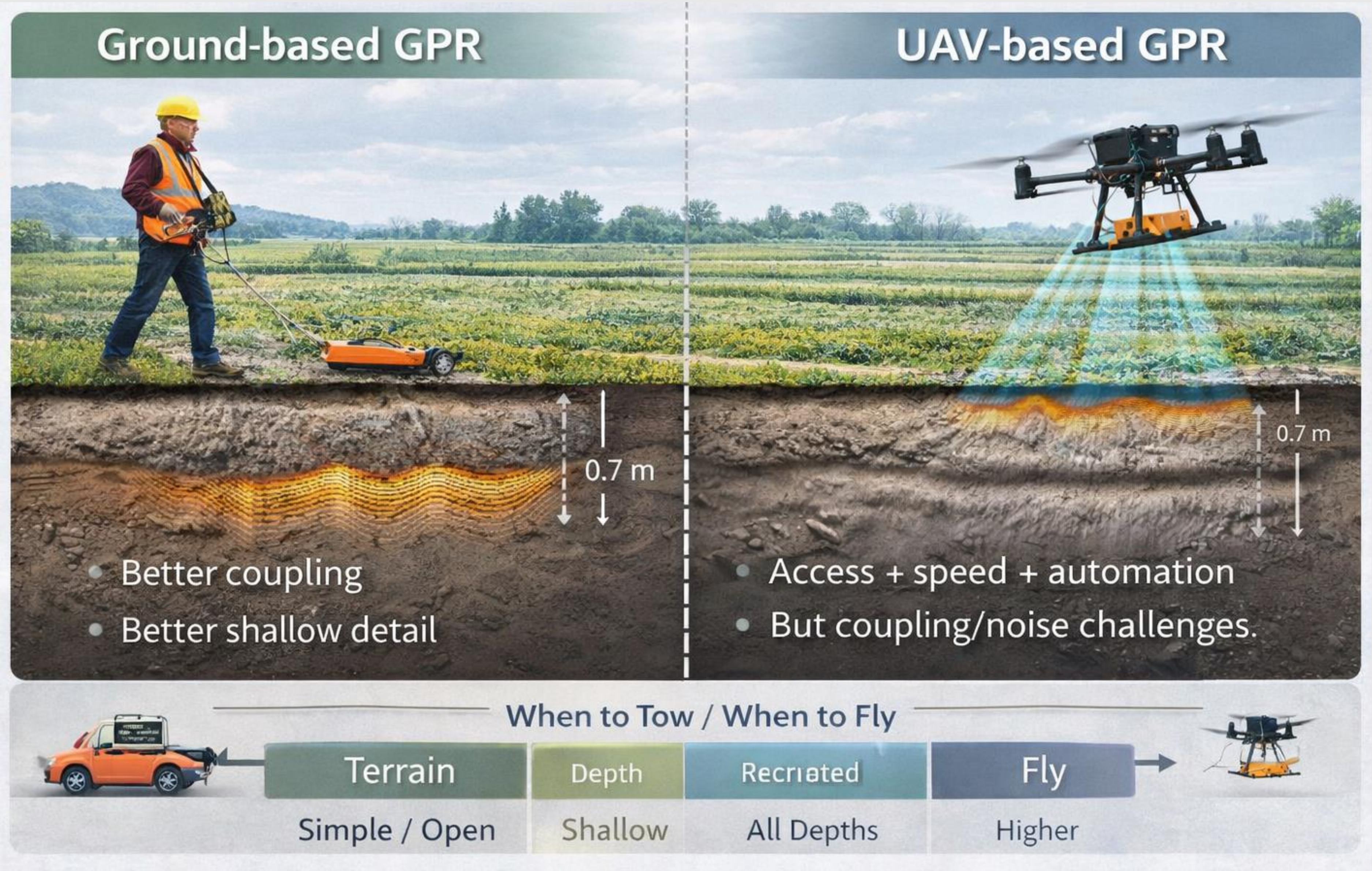
- Soil heterogeneity
- Water availability
- Root-zone constraints

3 Management Action

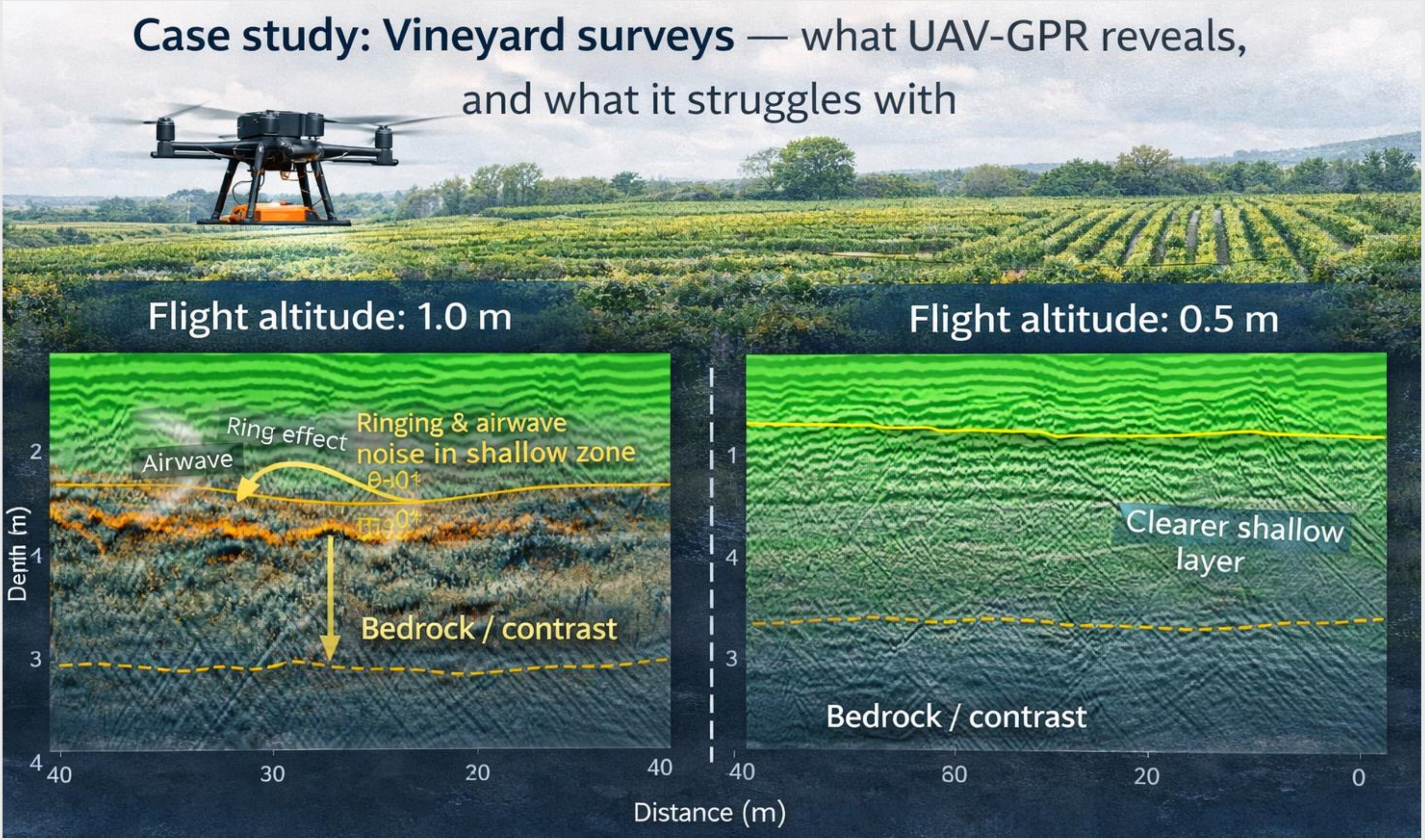
- Irrigation strategy
- Targeted scouting
- Site-specific intervention

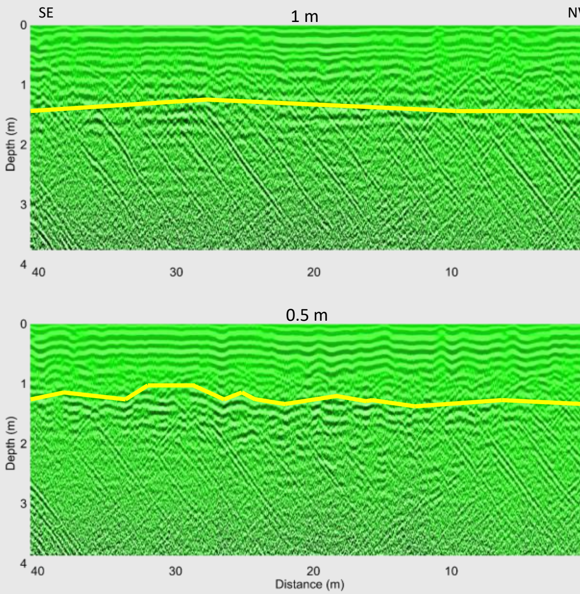
The goal is not just to see where crops differ — it is to understand why they differ.

GPR acquisition modes: Ground-based vs UAV-based

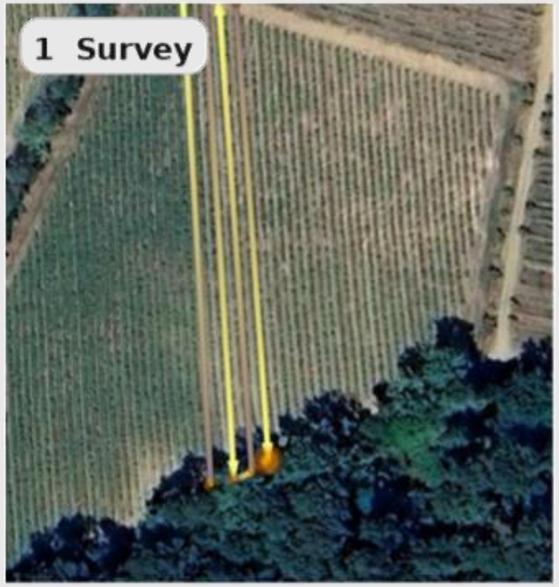


Altitude Effect in UAV-GPR (500 MHz): 1.0 m vs 0.5 m AGL



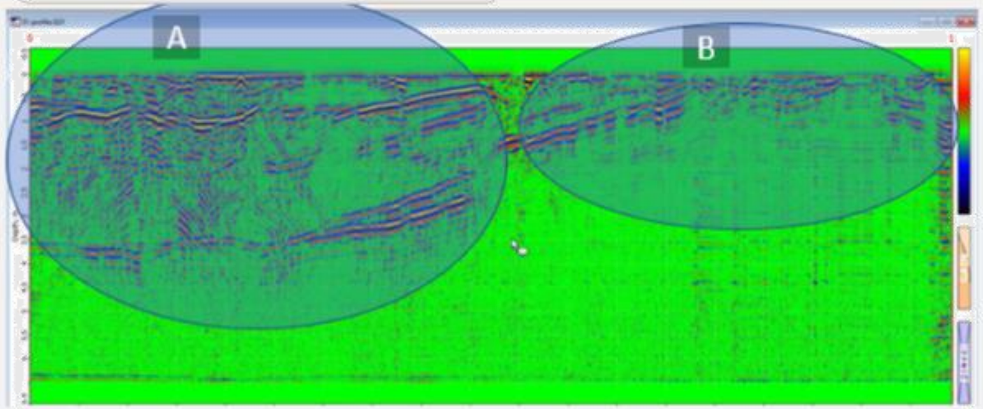


From Subsurface Heterogeneity to Crop Vigor Patterns



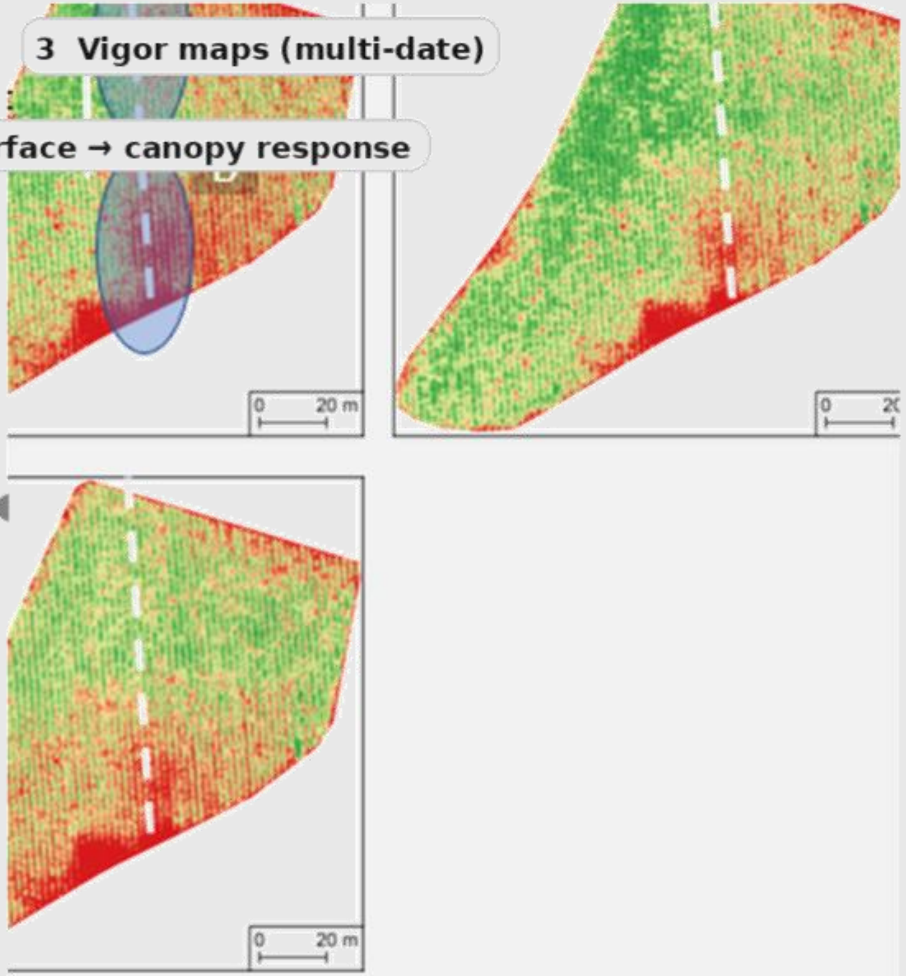
UAV flight lines define GPR profiles

2 GPR heterogeneity (A-B)



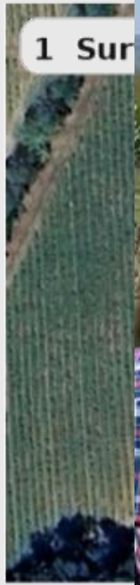
A/B: contrasting reflector patterns (radar facies)

Constraints in the subsurface → canopy response

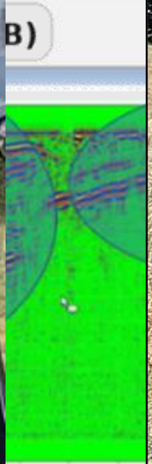


Low-vigor patches persist across dates in matching zones

Fr… gene…



UAV fligh…



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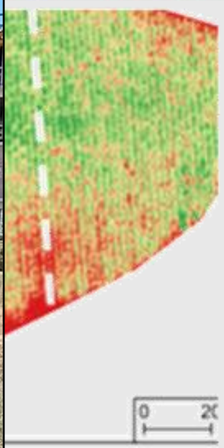


…ng zones

FROM SENSORS TO DECISIONS

Spatial Variability Is Not Noise — It Is Structure

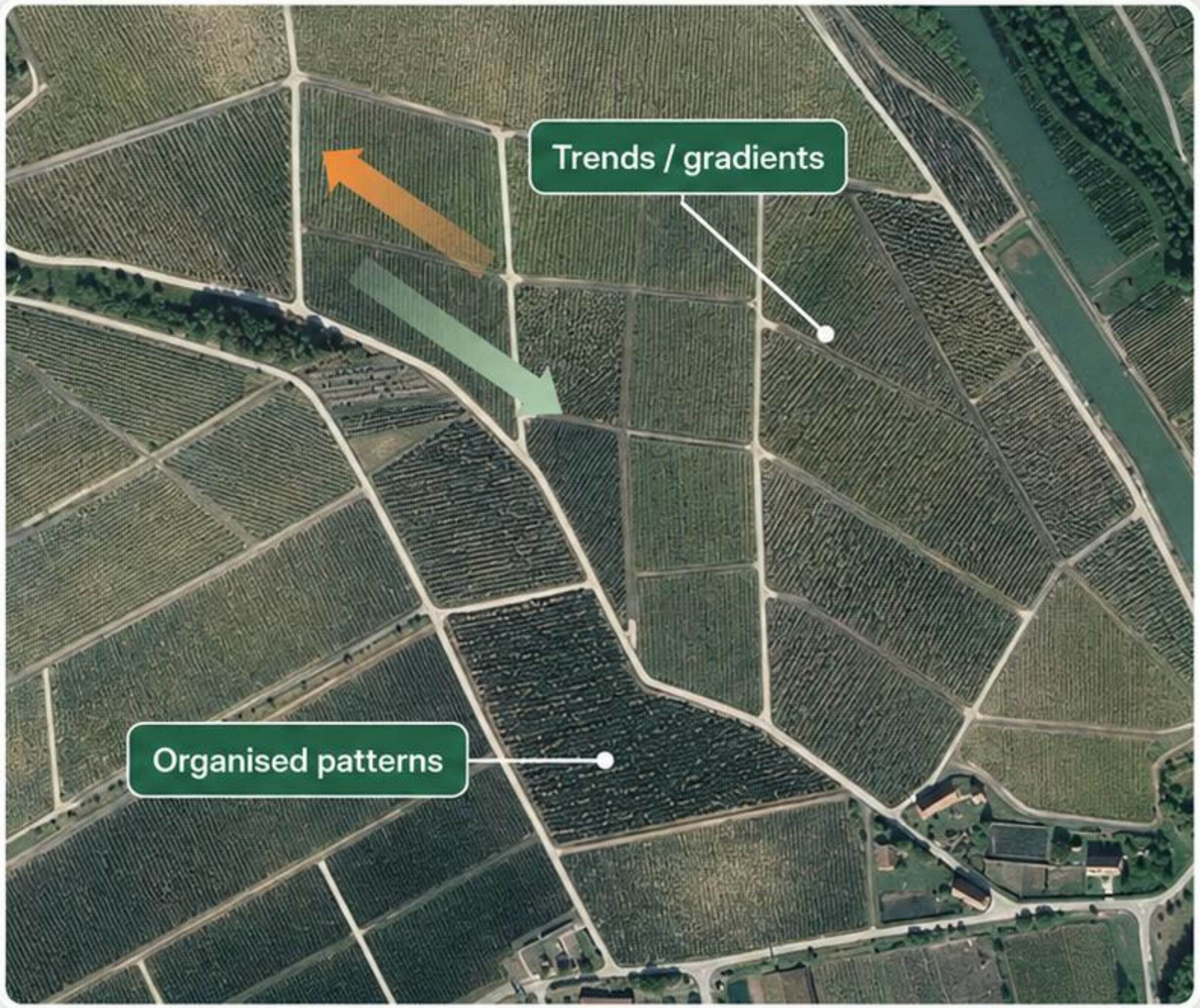
Evidence from precision viticulture research

Since 2000, investigations have focused on main parameters in vine

- Production parameters (yield, vigour)
- Harvest quality parameters (sugar, acidity, etc.)
- Decision information (nitrogen, water status, etc.)

Evidence reported in Australia, Spain, France, Chile, California and New Zealand.

International database on within-field yield variability over 142 fields in France, Spain and Australia (*Taylor et al., 2005*).



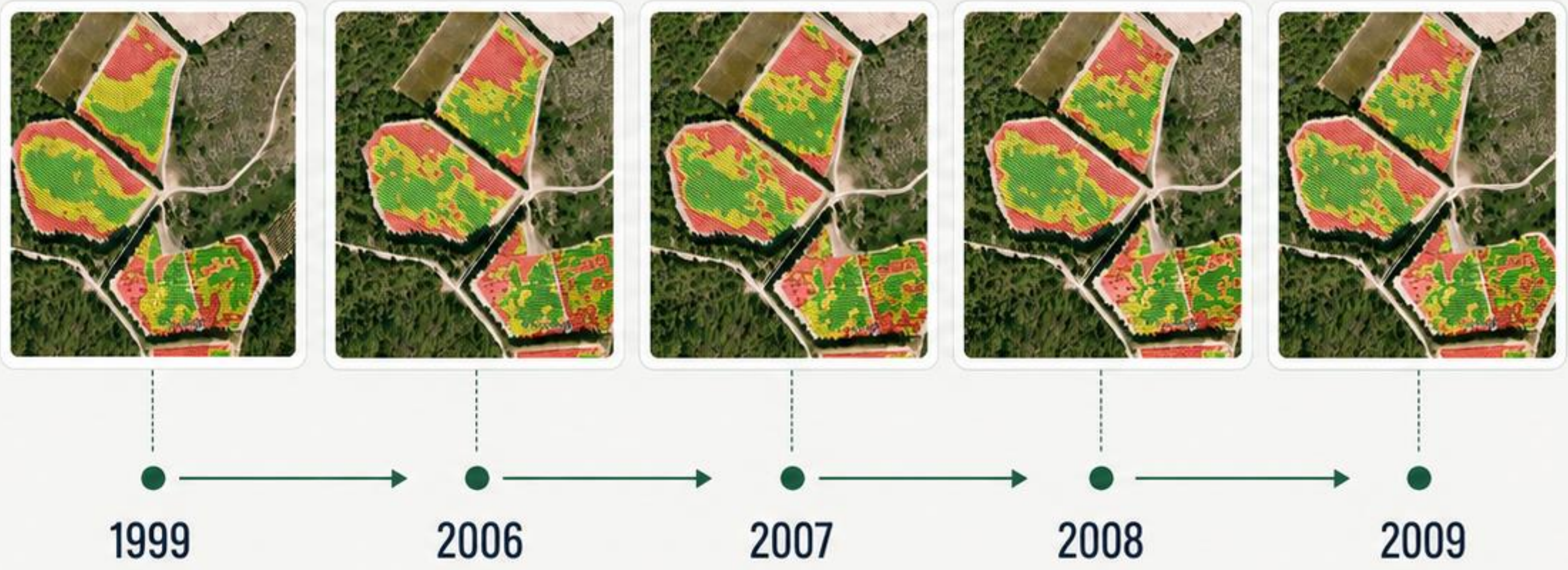
There is a significant spatial variability in viticulture and it is organised spatially (spatial patterns).

When Spatial Patterns Persist Over Time

Temporal stability turns maps into memory.

- Some spatial patterns are temporally stable
- Persistent zones reveal structural field behaviour
- Stability supports long-term management zones
- Stable variability can guide investment, monitoring and intervention

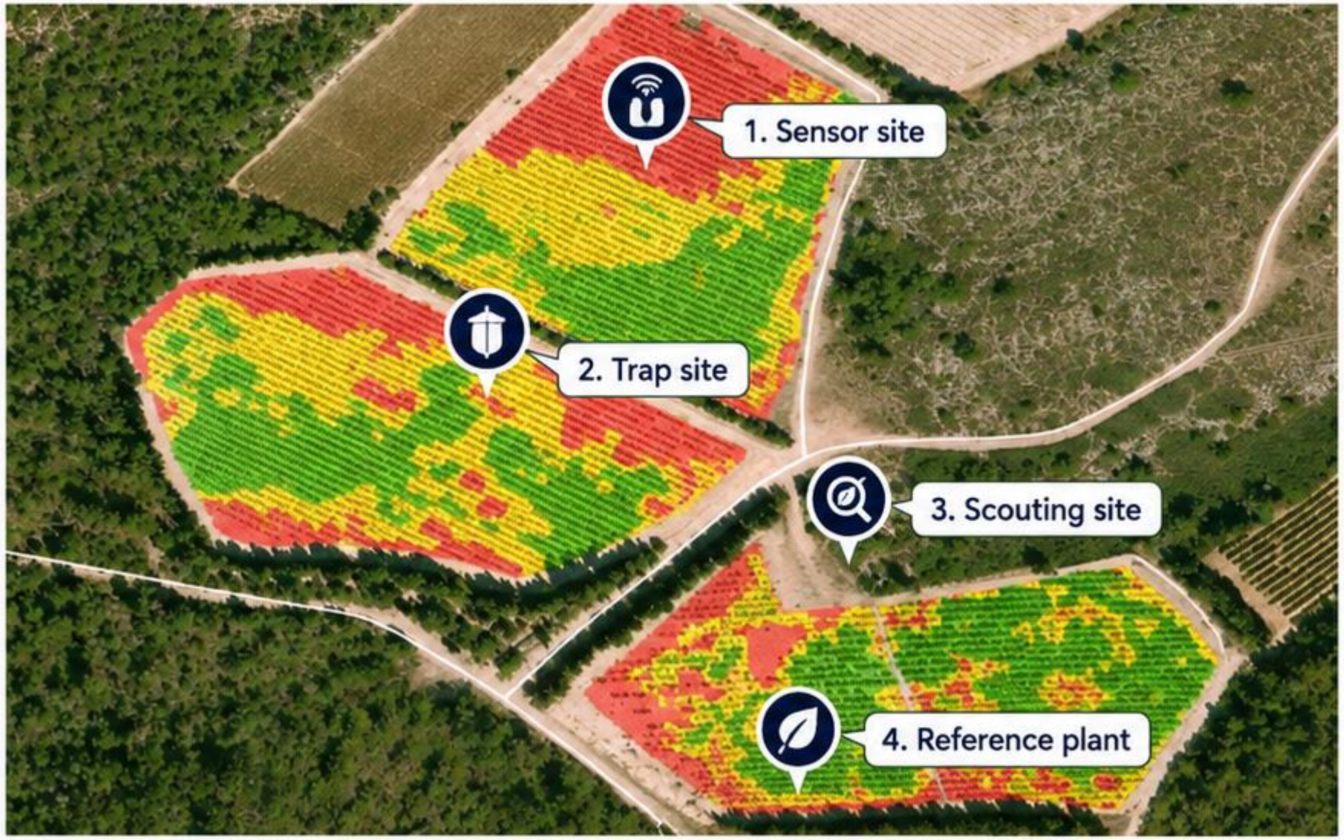
From yearly maps to strategic knowledge



Stable spatial variability helps transform observations into long-term management knowledge.

From Maps to Representative Monitoring Sites

Do not place sensors randomly — place them where the field tells you to look.



Low vegetative expression

Medium vegetative expression

High vegetative expression

- Select representative zones
- Monitor contrasting behaviours
- Reduce unnecessary sensor density
- Support water status, pest control and crop monitoring
- Combine spatial maps with temporal sensors

Sap flow sensor

Dendrometer

Stable maps help identify where to observe, measure and monitor.

Shared Data, Shared Learning

From Individual Farms to Collective Intelligence

Data sharing helps farms learn faster, reduce costs and improve models.

1 Farm Data

- Local evidence
- Sensors
- Field observations
- Maps

2 Producer Network

- Comparable patterns
- Benchmarking
- Shared learning
- Lower adoption costs

3 Shared Decision Service

- Improved models
- Alerts
- Reusable services
- Collective intelligence

- One farm provides local evidence
- Many farms provide comparable patterns
- Shared platforms support benchmarking
- Cooperatives and producer organisations can reduce adoption costs
- Collective datasets improve models and alerts

Data becomes more valuable when it can be compared, validated and reused.

Two Worlds Must Meet

Producers, Technicians and Digital Profiles

Adoption depends not only on technology, but on collaboration across generations, skills and working cultures.

Field Experience

- Producers bring field experience
- Seasonal knowledge
- Practical constraints
- Memory of the field

Shared Decisions

- Co-design
- Trust
- Interpretation
- Action

Digital Capabilities

- Data science and models
- Platforms and services
- Sensors and monitoring
- Automation tools

- Producers bring field experience
- Technicians bring agronomic interpretation
- Digital profiles bring data, models and platforms

- Younger generations may accelerate adoption
- Older generations bring memory of the field
- Trust requires co-design, not technology imposition

Smart agriculture is not a replacement of experience — it is a meeting point between experience and data.

Data Integration: From Many Signals to One Decision Space

Platforms turn heterogeneous field data into trusted, operational decision support.

1 Multi-Source Data

- IoT sensors
- Weather stations
- Drone imagery
- Satellite data
- Field observations

2 Integration Platform

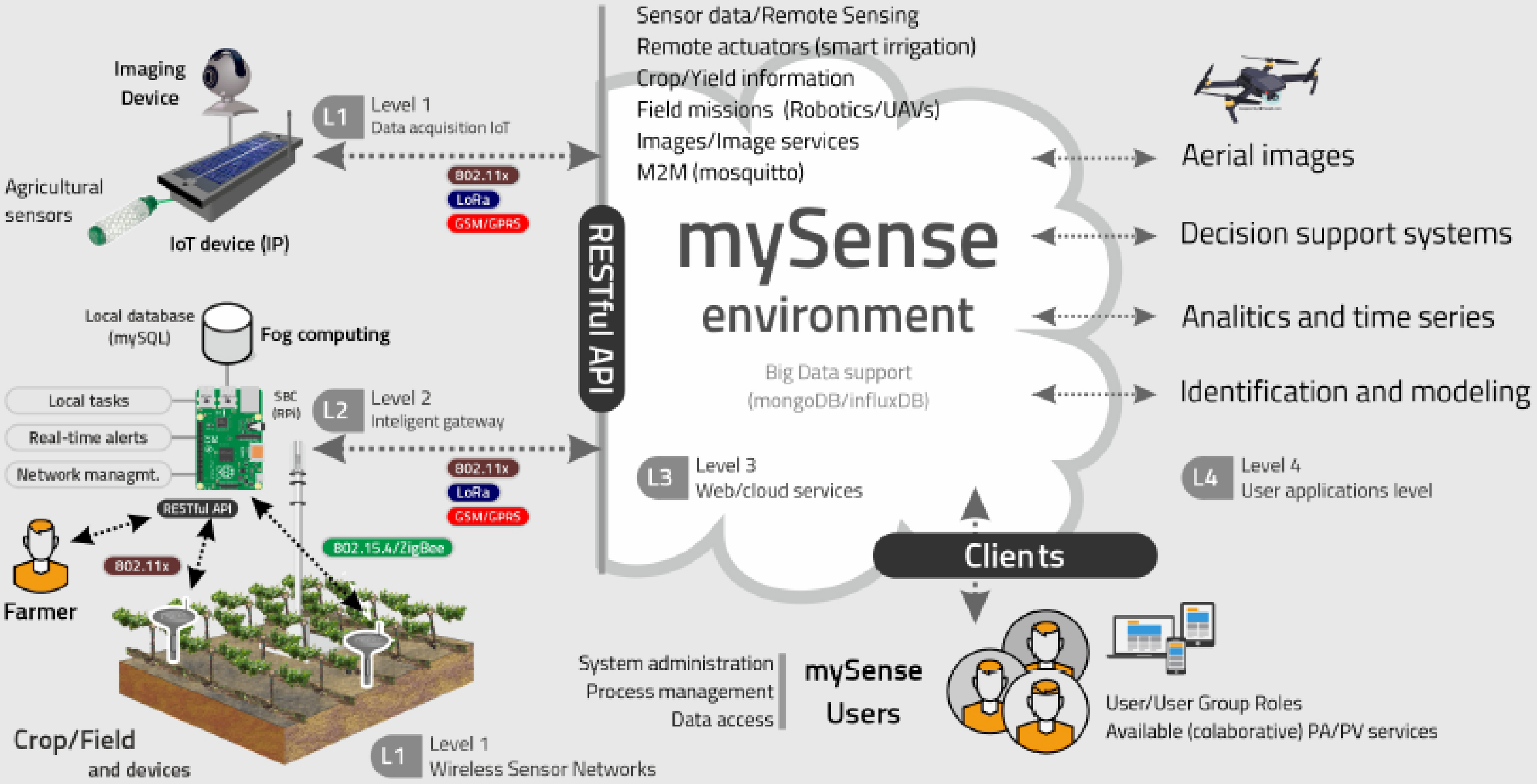
- Storage
- QA/QC
- Time alignment
- Spatial alignment
- Provenance

3 Decision Support

- Alerts
- Forecasts
- Irrigation support
- Risk indicators
- Management zones

Integration is where data becomes useful — connecting measurements, models and producer decisions.

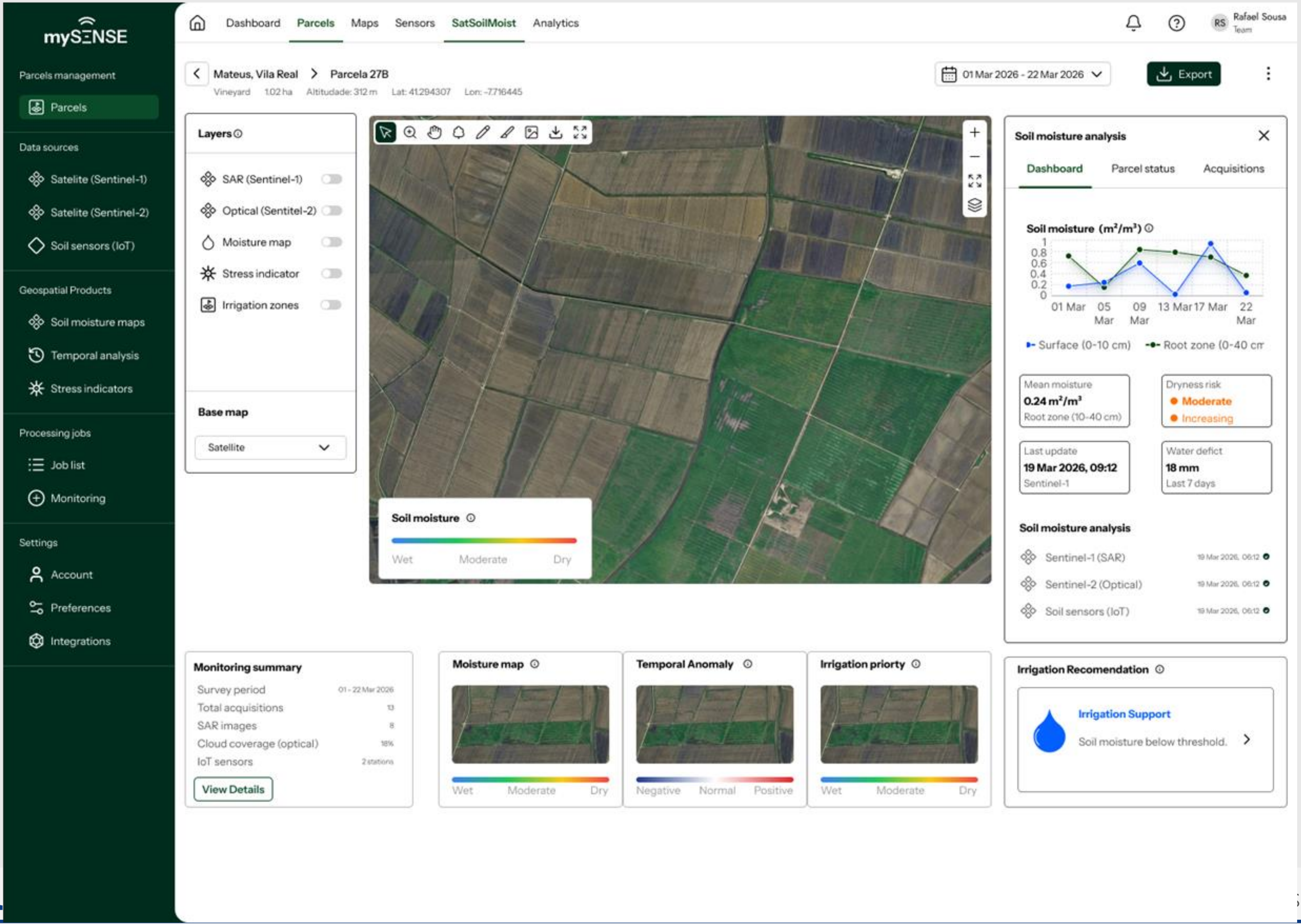
The mySense IoT platform and data integration



mySense is a cloud-based platform for data integration, storage and visualization in agroforestry, offering smart solutions to common PA/PV challenges.
https://mysense.utad.pt

The mySense IoT platform and data integration

User Module: Parcels



SOIL MOISTURE PREDICTION IN VINEYARDS USING SENTINEL-1 SAR DATA AND ARTIFICIAL NEURAL NETWORKS

A case study in the Vilariça Valley, Northeastern Portugal

MAIN OBJECTIVE

To estimate **soil moisture in vineyards** using Artificial Neural Network (ANN) models trained with Sentinel-1 SAR data and in situ measurements collected in the Vilariça Valley.

1 DATA SOURCES

Sentinel-1 SAR

C-band SAR data
(VV and VH polarizations)
Asc. and Desc. orbits
Jul 2020 – Dec 2021

In situ soil moisture

Soil moisture measured at 10 cm depth using two sensors.

2 DATA PROCESSING

- Apply Orbit File
- Calibration: Beta, Sigma, Gamma
- Calibration: Gamma
- Terrain Correction / Terrain Flattening
- Band maths operations (-,+,/,*)
- Subset

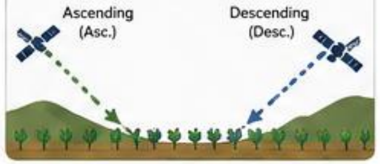
Each sample included 25 features: 24 extracted from SAR data and 1 in situ soil moisture measurement.

3 DATASETS

Two datasets were created to evaluate the impact of SAR orbit geometry on model performance:

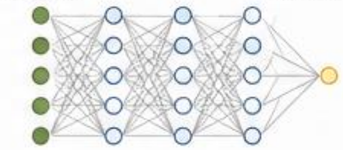
D1 301 samples from ascending orbits only

D2 458 samples from both ascending and descending orbits



4 APPROACH

Artificial Neural Network (ANN)



- 6 hidden layers
- ReLU activation function
- Adam optimizer
- Mean Squared Error (MSE) loss
- K-fold cross-validation

KEY FINDINGS

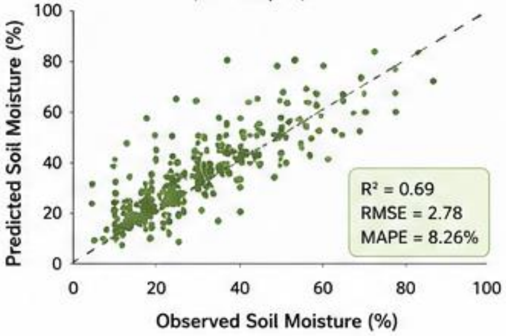
The model trained with ascending orbits only (D1) outperformed the mixed-orbit model (D2) due to reduced variability in acquisition geometry.

Strong agreement with in situ measurements, especially for soil moisture levels above 20%.

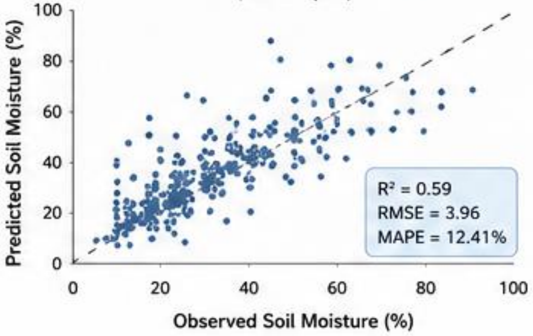
Predictions below 20% were less accurate, as these cases represented fewer than 4% of all samples.

5 RESULTS

D1 – Ascending orbits only
(301 samples)



D2 – Ascending + Descending orbits
(458 samples)



Performance comparison (ANN models)

Dataset	RMSE (% vol.)	R^2 (-)	MAPE (%)
D1 (Ascending)	2.78	0.69	8.26
D2 (Mixed orbits)	3.96	0.59	12.41

RMSE: Root Mean Square Error
R^2: Coefficient of Determination
MAPE: Mean Absolute Percentage Error

IMPACT FOR VITICULTURE

Optimized irrigation · Water savings · Sustainable production · Data-driven decisions

FUTURE WORK

- Extend the methodology to other regions and varieties
- Incorporate topographic and additional variables
- Expand the dataset with more diverse samples
- Improve model performance under low soil moisture conditions

Decision Services: Models as a Service

Once data is integrated, models can translate field signals into operational recommendations.

Integrated Data

- Soil & plant signals
- Weather forecasts
- Drone & satellite imagery
- Field observations

→

AI / Rule-Based Models

- Phenology
- Irrigation need
- Pest & disease risk
- Yield/stress trajectory

→

Actionable Outputs

- Alerts
- Forecasts
- Daily water allocation
- Management priorities

Models become valuable when they support timely, trusted and practical decisions.

Irrigation Decision Support: From Signals to Water Allocation

Combining soil, plant and weather information to support timely and efficient irrigation decisions.

Field Inputs

- Soil moisture
- Phenological stage
- Weather forecasts
- Local observations

Irrigation Model

- Water balance
- Crop sensitivity
- Rules + AI engine
- Uncertainty checks

Producer Outputs

- Daily water allocation
- Irrigation alerts
- Available reserve
- Priority zones

The decision is not simply whether to irrigate — it is when, where and how much.

Phenological Prediction: Timing Crop Development

Forecasting crop stages helps producers time irrigation, protection and field operations.

Field & Crop Inputs

- Location / GPS
- Variety
- Current stage
- Budburst date
- Temperature history

Phenology Model

AI

- Temperature sums
- 5-day weather forecast
- Historical patterns
- Local calibration
- Uncertainty checks

Producer Outputs

- Next stage forecast
- Sensitive windows
- Operation timing
- Disease-risk context
- Planning confidence

Phenology turns time into a management advantage.

AI in Practice: Crop Monitoring and Early Warnings

Images and sensors can help detect crop development, stress and risk before problems escalate.

Automated Observation

- Field images
- Shoot growth
- Trap monitoring
- Local sensor data

AI Interpretation

- Object detection
- Growth measurement
- Risk classification
- Pattern recognition

Early Warnings

- Disease-risk windows
- Pest thresholds
- Targeted scouting
- Timely intervention

AI becomes useful when it turns observation into earlier, more targeted action.

Pest and Disease Alerts: From Observation to Thresholds

Automated monitoring helps connect field evidence with timely protection decisions.

1 Automated Monitoring

- Trap images
- Leaf wetness
- Temperature & humidity
- Field observations

2 AI + Risk Models

- Insect counting
- Disease-risk windows
- Threshold detection
- Trend analysis

3 Producer Actions

- Targeted scouting
- Treatment timing
- Avoid unnecessary sprays
- Documented decisions

The goal is not to spray more — it is to intervene only when evidence and risk justify action.

From Insight to Action: Management Zones and Prescriptions

Spatial intelligence becomes valuable when it changes field operations.

Integrated Insights

- Stress patterns
- Soil–water constraints
- Crop variability
- Risk indicators

Management Zones

- Prioritise areas
- Compare responses
- Define intervention zones
- Reduce blind spots

Operational Actions

- Irrigation prescriptions
- Targeted scouting
- Variable-rate inputs
- Documented decisions

The value of intelligence is measured by the quality of the action it supports.

Trust, Uncertainty and Adoption: What Can Go Wrong?

Actionable-looking outputs can be misleading if uncertainty is not controlled.

1 Measurements

- Soil moisture
- Thermal / multispectral imagery
- Satellite observations
- Subsurface variability

2 Models + Fusion

- Data alignment
- Feature fusion
- Validation
- Uncertainty checks

Risk emerges here

3 Operational Decisions

- Irrigation prescriptions
- Alerts and anomalies
- Yield / stress risk
- Management priorities

Trust is built when decisions include validation, uncertainty and field evidence.

TRL & Risk Checkpoint:

From multi-sensor agrogeophysics to operational decisions

MEASUREMENT
(Inputs)

FUSION + MODELS
(the black box)

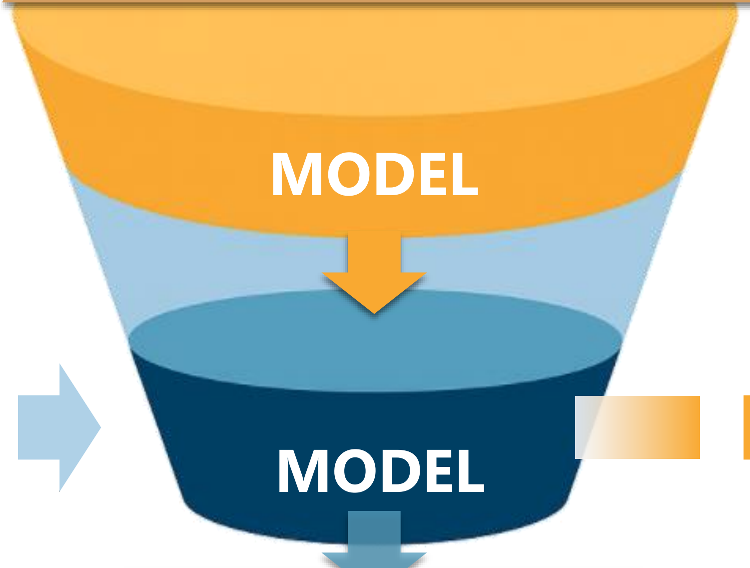
DECISIONS
(operational)

IoT
- Soil Moisture
- Soil Temperature
- Nutrients (where available)

UAV Sensors
- Thermal, Multispectral, Hyperspectral, LiDAR

Satellite
- Optical + SAR

GPR
- Subsurface layering
- Depth-to-bedrock, heterogeneity



RISKS EMERGES HERE:
Outputs look actionable
Before uncertainty is controlled

Validation + Uncertainty Quantification
- Groundtruth campaigns
- Cross-validation across fields/seasons
- Uncertainty aware services (mySense/MaaS)

Irrigation presciption / zones

Alerts / anomalies
Yield risk / stress trajectory

Error Propagation

False positives
Unnecessary irrigation / wrong alerts
False negatives
Missed dtress / hidden constraints

Consequences
- Water waste & yield loss
- Mis-targeted interventions
- **Loss of trust in automated systems**

TRL 7-9 | **TRL 3-5** | **TRL 1-3**

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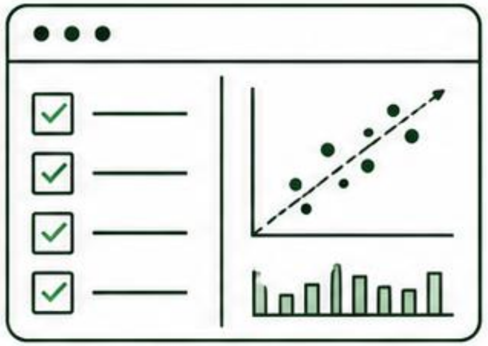
Validation Before Automation: Ground Truth and Uncertainty

Before decisions are automated, models must be tested against field evidence.

Ground Truth

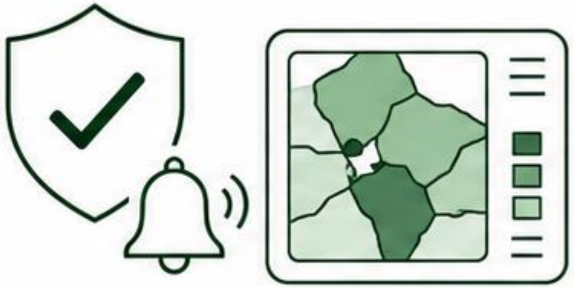
- Field campaigns
- Sensor calibration
- Local observations
- Reference measurements

Model Validation



- Cross-validation
- Across fields and seasons
- Error detection
- Performance limits

Uncertainty-Aware Decisions



- Confidence levels
- Explainable alerts
- Safer prescriptions
- Better adoption

Automation should come after validation — not before it.

Implementation Roadmap for Producers: Start Small, Validate, Scale

Adoption works best when technology is introduced as a learning process, not as a one-time purchase.

1. Start Small

- One crop or parcel
- One decision problem
- Limited sensors
- Clear baseline

2. Validate Locally

- Ground truth
- Compare with field experience
- Check data quality
- Learn from errors

3. Connect to Decisions

- Alerts
- Irrigation support
- Scouting priorities
- Documented actions

4. Scale What Works

- More zones
- More farms
- Shared services
- Continuous improvement

Smart agriculture scales when producers trust the evidence, see the benefit and remain in control.

Scaling Smart Agriculture: From Farm Tools to Shared Services

The long-term opportunity is not only better tools on one farm, but connected services that can support many producers.

1. Farm-Level Solutions

- Sensors and local data
- Parcel-level decisions
- Crop-specific support
- Producer learning loop

2. Shared Digital Services

- Data platforms
- Models as a Service
- Common decision workflows
- Regional knowledge integration

3. Regional and Network Value

- More producers supported
- Lower adoption cost
- Faster knowledge transfer
- Continuous service improvement

The greatest impact comes when farm intelligence becomes a scalable, trusted service ecosystem.

Take-Home Messages: Turning Signals into Decisions

Smart agriculture creates value when it helps producers decide with confidence.

1. Start with decisions

- Define the problem first
- Choose data that supports action
- Avoid technology for its own sake

2. Connect the layers

- Sensors give time
- Remote sensing gives space
- Models turn patterns into meaning

3. Build trust before scale

- Validate locally
- Show uncertainty
- Keep producers in control

The future is not autonomous agriculture replacing producers — it is informed agriculture empowering them.

Discussion: From Your Fields to Your Decisions

How can these technologies support your crops, constraints and priorities?

Where is the pressure?

- Water
- Pests & diseases
- Labour
- Costs
- Climate variability

Which decision matters most?

- When to irrigate
- Where to scout
- When to treat
- How to prioritise
- What to document

What would make it useful?

- Simple outputs
- Local validation
- Clear uncertainty
- Affordable deployment
- Producer control

The best smart agriculture systems are built with producers, not just for producers.

Ficha Técnica

Designação do Projeto | AgroNet Forward – Digitalizar o agroalimentar do Douro Tâmega

Nº do projeto | 25447

Promotores |

ADCEIDT – Associação de Desenvolvimento, Criatividade, Empreendedorismo e Inovação do Douro Tâmega

UTAD - Universidade de Trás-os-Montes e Alto Douro

Aviso | COMPETE2030-2025-4

Designação do aviso | Ações Coletivas – Digitalização

Tipologia de Ação | Transição Digital das Empresas

Objetivos | Aproveitar as vantagens da digitalização para os cidadãos, as empresas, os organismos de investigação e as autoridades públicas (FEDER)

Edição e Conteúdos |

Cofinanciado pela União Europeia

AgroNet Forward

From Sensors to Decisions: Emerging Technologies for Smart and Sustainable Agriculture

Dos Sensores à Decisão: Tecnologias Emergentes para uma Agricultura Inteligente e Sustentável

Joaquim João Sousa

18 junho 2026

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