

Agriculture fields in Brazil
Image © 2026 Planet Labs PBC

Climate Change AI
Virtual Summer School 2026

AI for Agriculture and Food Security

From Earth Observation to Climate-Smart Decision Making

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What This Lecture Covers

Topics

- Agriculture, climate change & food security
- Observing agricultural systems through data
- From Earth observation to AI-driven decision support
- AI applications from farms to global food security
- Responsible AI, future directions & next steps



Agriculture fields in Poland
Image © 2026 Planet Labs PBC

Agriculture, Food Security & Climate Change

Agriculture both **contributes to** and **is affected by** **climate change.**

Understanding this dual role is essential for designing AI systems that genuinely improve outcomes for people and the planet.

Agriculture as a Contributor to Climate Change

Agriculture contributes significantly to greenhouse gas emissions through land use change, livestock production, and soil management.

Key Emission Sources

Land-use Change

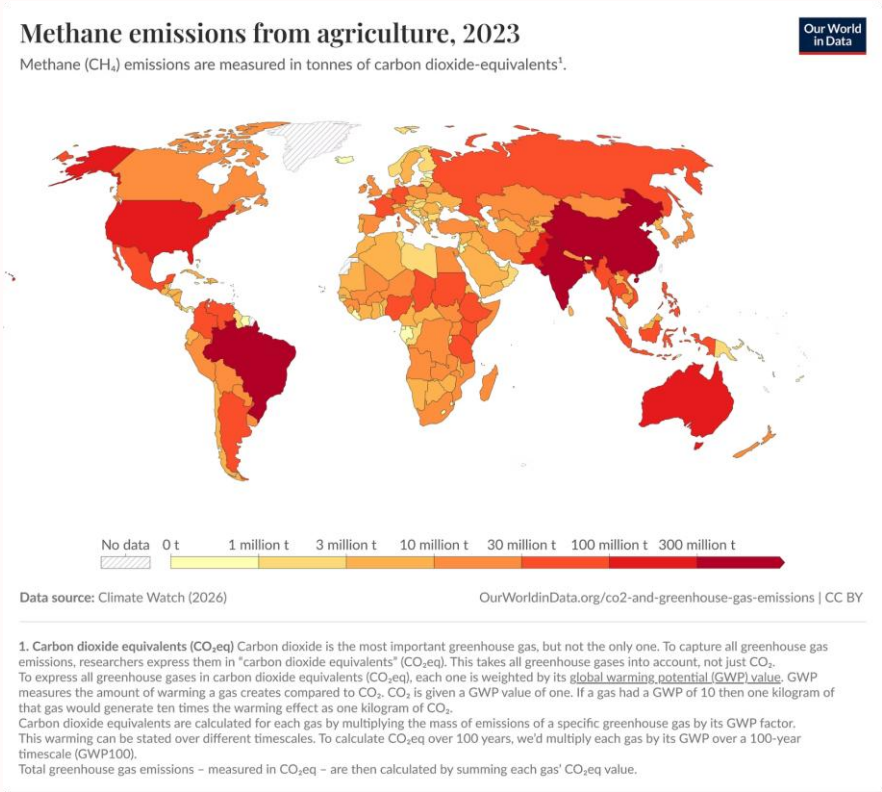
Conversion of forests and natural ecosystems for agriculture releases stored carbon.

Livestock Production

Methane (CH_4) from enteric fermentation in ruminants (e.g., cattle) and manure management.

Cropland Management

Nitrous oxide (N_2O) from synthetic nitrogen fertilizers and soil disturbance practices.



Climate Risks Affecting Agricultural Systems

Drought & Heat Stress

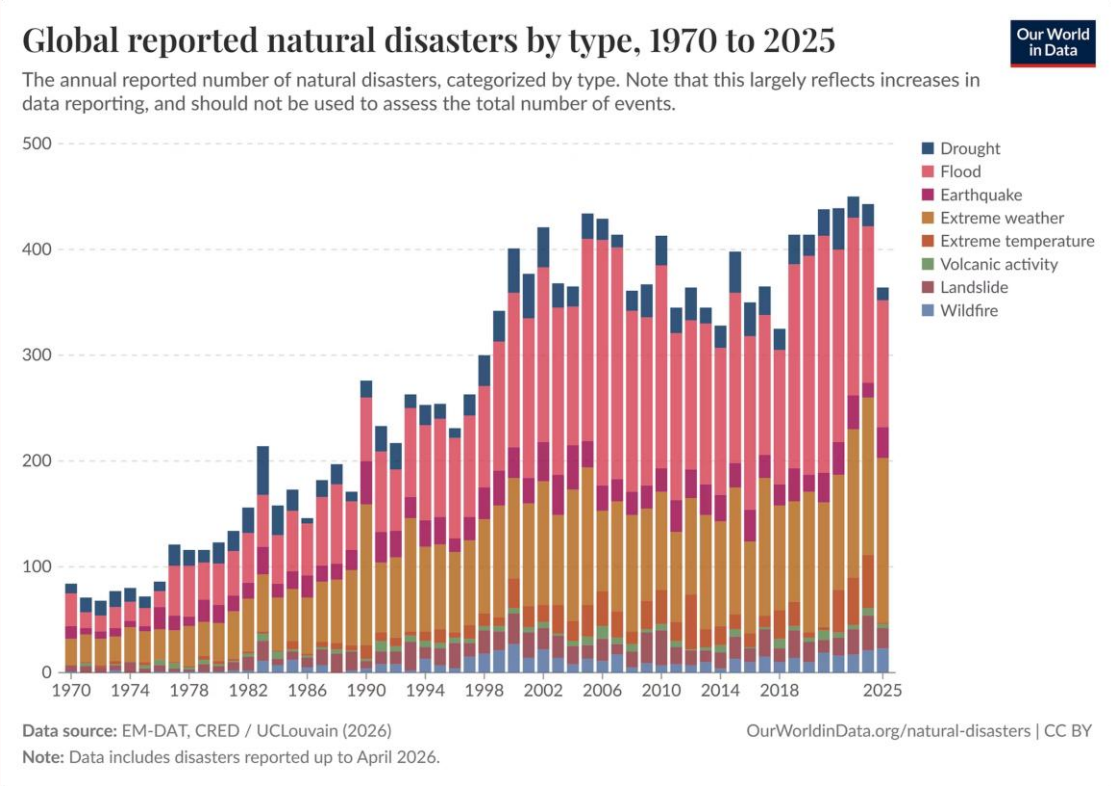
Extended dry periods and extreme temperatures reduce yields, damage crops, and deplete soil moisture.

Floods & Extreme Events

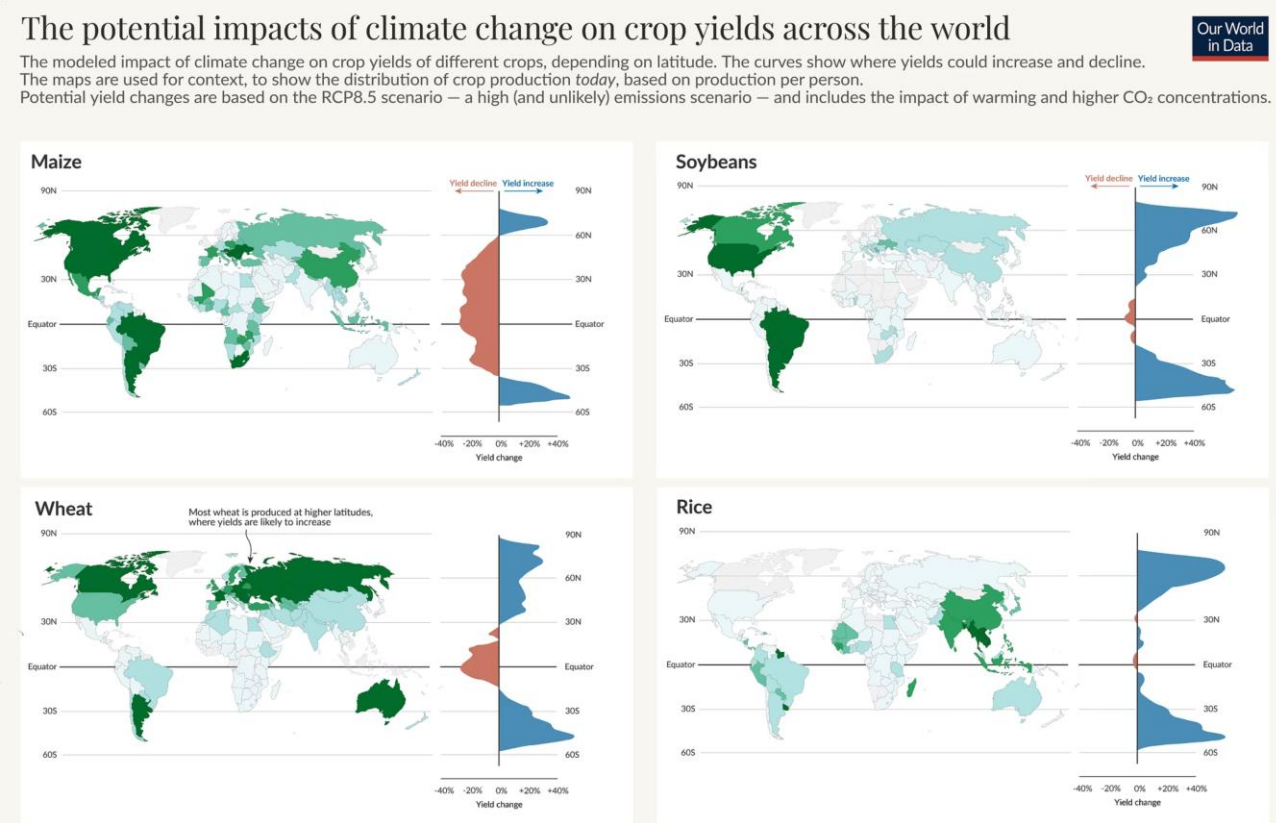
Intense rainfall, flooding, and storms destroy harvests and erode productive agricultural land.

Land Degradation

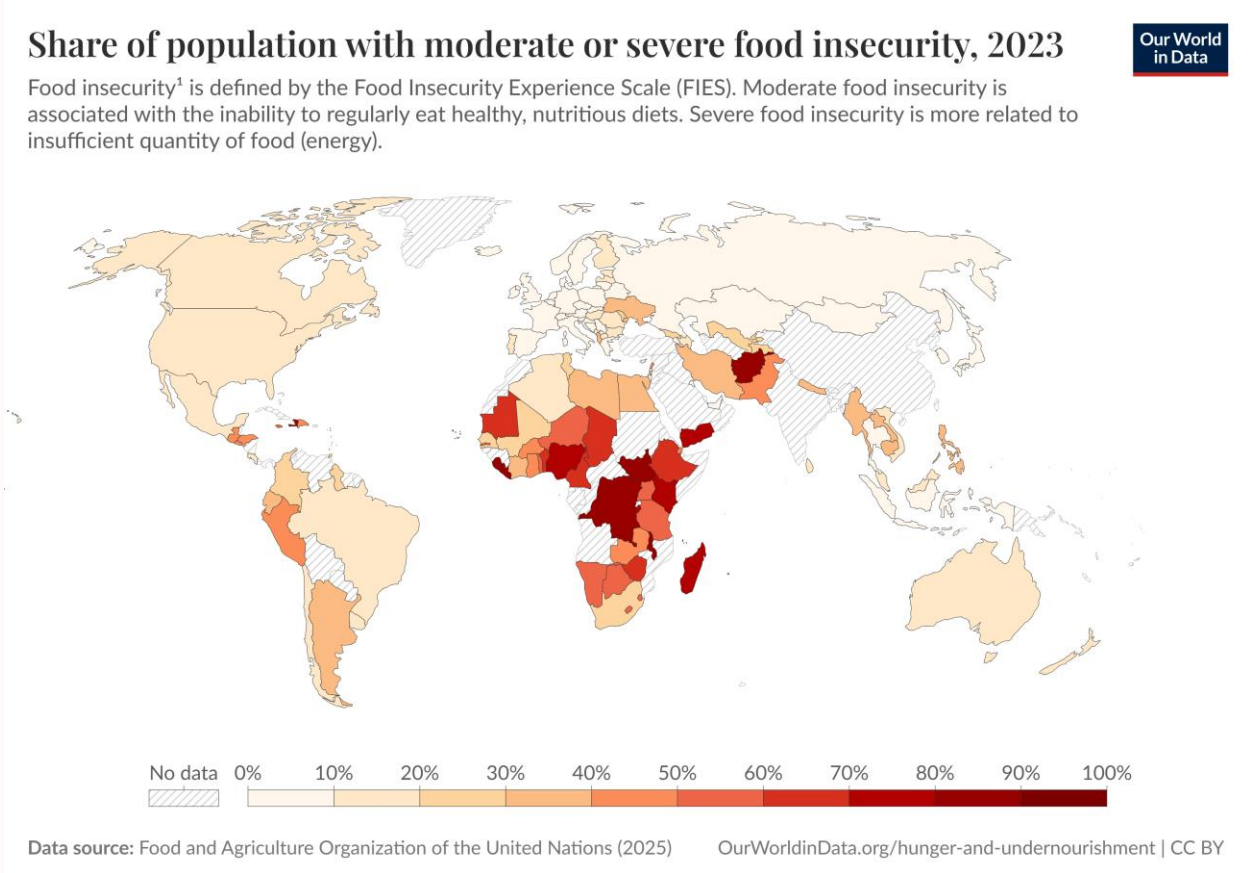
Soil erosion, salinization, and nutrient depletion reduce the productive capacity of agricultural land over time.



Climate Risks Affecting Agricultural Systems



Climate Risks Affecting Agricultural Systems



Food Security in a Changing Climate

Climate change is transforming agriculture

- More frequent droughts, floods, heat waves, and extreme weather threaten agricultural production.
- Climate impacts affect all four pillars of food security: **availability, access, utilization, and stability.**
- Agriculture must produce more food while using resources more efficiently, adapting to climate change, and reducing environmental impacts.



Increase Productivity

Produce more food to feed a growing population.



Improve Efficiency

Use land, water, fertilizer, and other resources more efficiently.



Strengthen Resilience

Adapt agricultural systems to increasing climate variability.



Protect Ecosystems

Reduce emissions while protecting natural ecosystems.

Who Uses Agricultural Information?

Agricultural decisions are made at many levels, **from individual farms to global organizations**. **Although their goals differ, they all rely on timely, accurate, and actionable information.**

Farmers & Growers

Decisions: Planting, irrigation, and harvest timing.

Agronomists & Agricultural Advisors

Decisions: Crop management, input optimization, and harvest planning.

Governments & Insurers

Decisions: Agricultural policy, crop insurance, and disaster response.

Humanitarian & Climate Orgs

Decisions: Food security monitoring, humanitarian response, and climate adaptation.

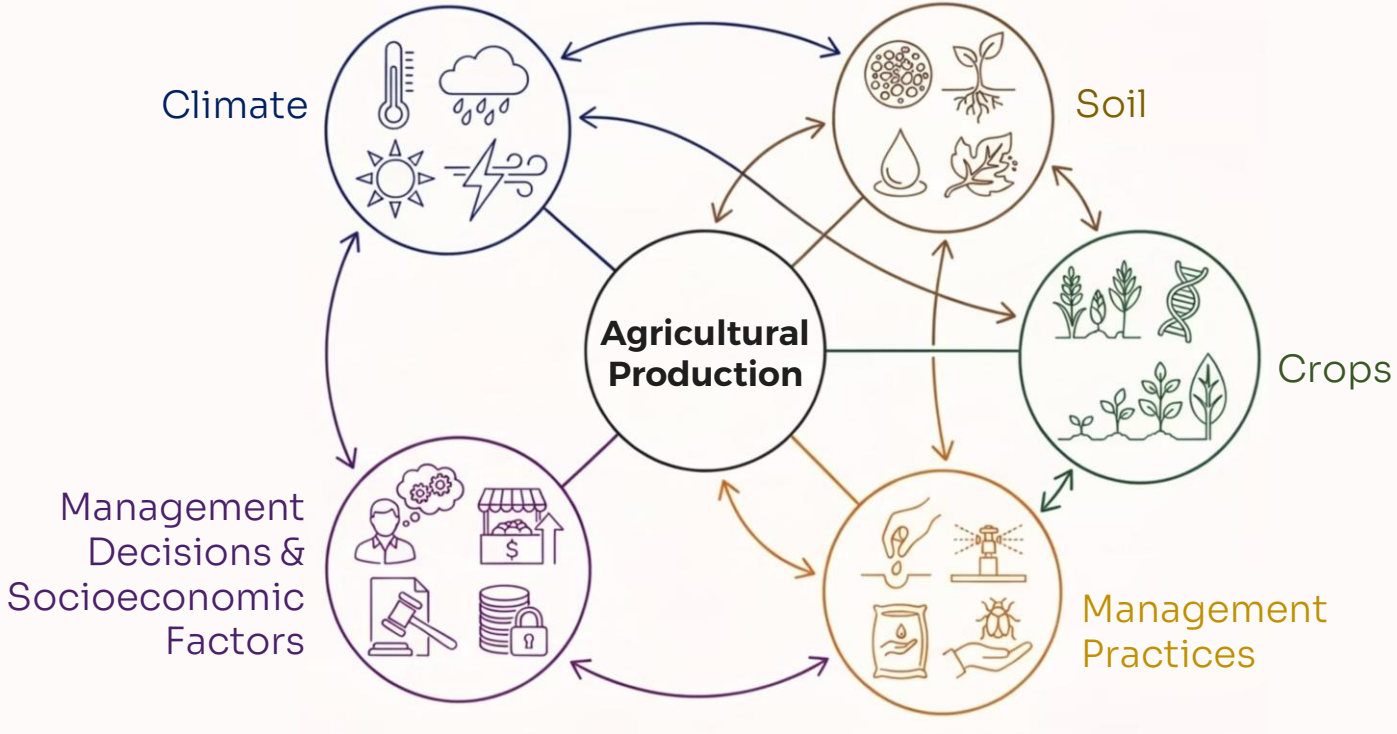


Agriculture fields in Canada
Image © 2026 Planet Labs PBC

Understanding Agricultural Systems Through Data

Agricultural systems emerge from complex interactions among **climate**, **soil**, **crops**, **management practices, and human decisions**. Capturing this complexity requires diverse, complementary data sources.

What Drives Agricultural Production?



Agricultural production results from the interaction of climate, soil, crops, management, and socioeconomic factors.
Understanding these interactions requires integrating multiple complementary data sources.

Observing Agricultural Systems



Remote Sensing

Satellite, aerial, and UAV observations provide continuous information on crop growth, land cover, and vegetation conditions.



Weather & Climate Data

Temperature, precipitation, radiation, and other weather variables from stations, reanalysis, and climate models.



Soil Information

Soil properties such as texture, organic matter, moisture, and fertility influence crop growth and productivity.



Field Observations & Statistics

Ground observations, crop surveys, management records, and agricultural statistics provide essential reference information.

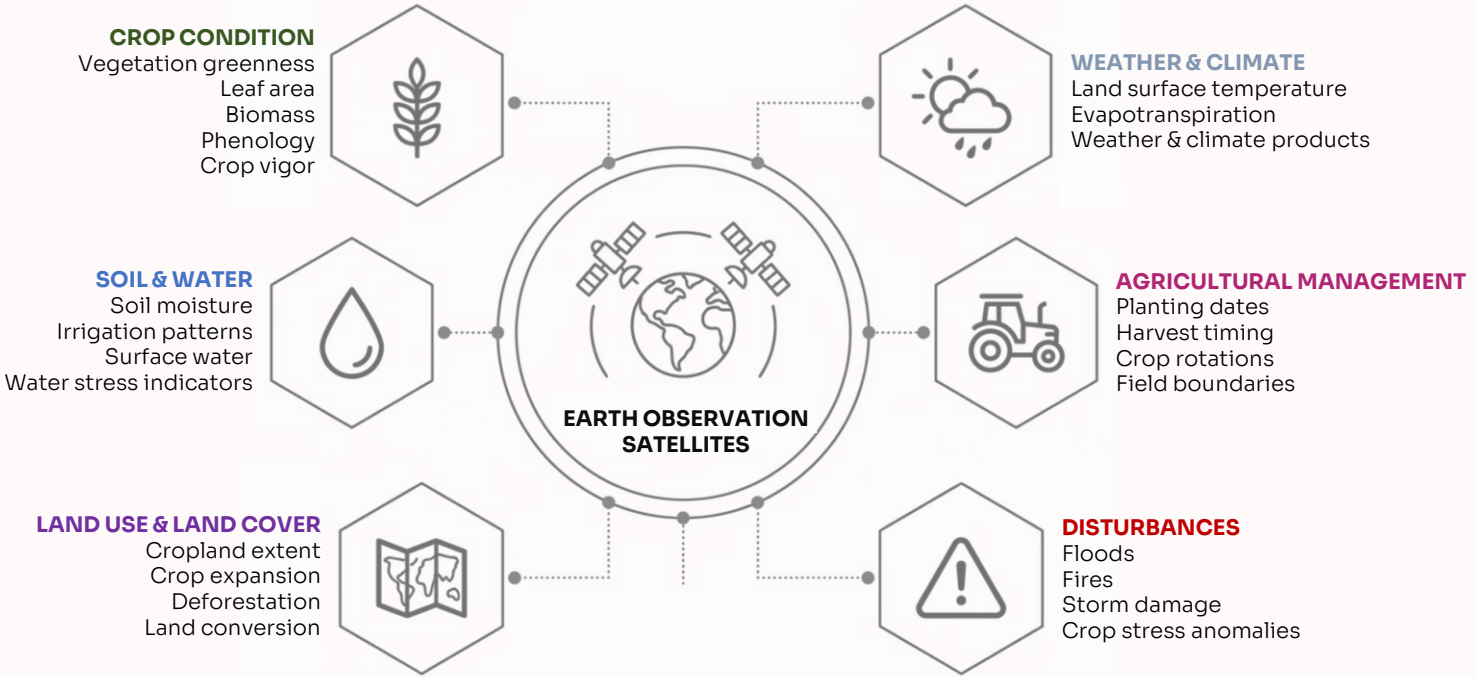
What Can Remote Sensing Observe?

THE MANY FACES OF EARTH



Source: ESA

What Can Remote Sensing Observe?



Remote sensing provides **continuous, objective, and spatially explicit observations** that enable **agricultural monitoring across local, regional, and global scales**.

Why Earth Observation Scales Agricultural Monitoring

Earth observation complements traditional field monitoring by providing continuous, scalable observations across space and time.

Traditional Field Monitoring

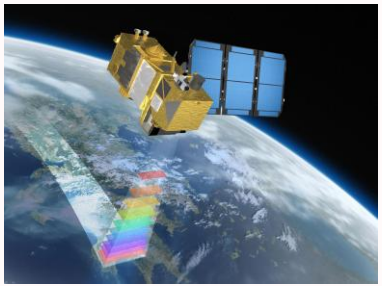




- High local accuracy
- Labor intensive
- Time-consuming
- Limited spatial coverage
- Difficult to scale

Detailed local observations

Earth Observation from Space



- Large-area coverage
- Frequent observations
- Historical archives
- Consistent measurements
- Near real-time monitoring

Scalable, continuous monitoring

Both **field observations** and **Earth observation** are essential.
Together, they provide complementary information for agricultural monitoring.

From Fields to the Globe

Sentinel-2 revisits every location on Earth every five days, providing consistent observations for agricultural monitoring across local, regional, and global scales.

SENTINEL-2 GLOBAL COVERAGE



Source: ESA

Consistent observations collected over time make it possible to monitor agricultural systems at scales that would be impossible using field observations alone.

Earth Observation Across Scales

Different agricultural decisions require data at varying scales, each presenting unique trade-offs between **spatial detail, coverage, and temporal frequency**.



Field

Sub-meter–10 m

Farmers

Crop health monitoring
Variable-rate management



Farm

3–30 m

Farm managers/ Agronomists

Yield prediction
Management zones



Regional

10–30 m

Government/Researchers

Crop mapping
Acreage estimation



National

30–250 m

Government /Ministry

Agricultural statistics
Land-use monitoring



Global

250 m–1 km+

International Organizations

Food security monitoring
Drought assessment



High Spatial Detail — **Greater Geographic Coverage**

Different agricultural decisions require different observation scales. Choosing the right Earth observation data always involves balancing spatial detail, coverage, revisit frequency, and computational cost.

Strengths and Limitations of Earth Observation

Strengths

- Large-area, consistent monitoring across space and time.
- Multi-sensor observations provide complementary. information on agricultural systems.
- Open satellite missions have democratized global-scale monitoring.

Limitations

- Cloud cover limits optical observations.
- Trade-offs between spatial, temporal, and spectral resolution.
- Satellite observations measure surface conditions, not agricultural processes directly.
- Ground observations remain essential for calibration and validation.
- Massive data volumes require scalable computing and robust modeling approaches.

Earth observation provides unprecedented monitoring capabilities, but turning observations into actionable information requires **integrating satellite data with field observations, domain knowledge, and robust modeling approaches.**

Quiz Question 1

A humanitarian organization needs to monitor potential food security risks across multiple countries and update assessments every few weeks. Which option is most appropriate?

A

Drone flights over selected villages

B

Regional-to-global satellite monitoring combined with climate indicators

C

Very-high-resolution imagery of a few farms

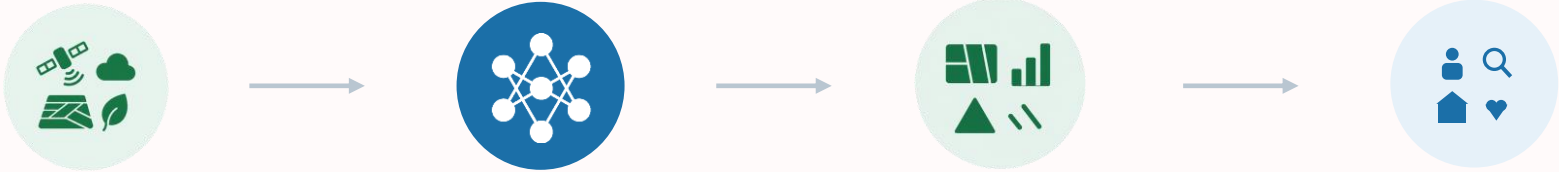
D

Manual field surveys only

Correct answer: B. The organization needs large geographic coverage and frequent updates, even if spatial resolution is coarser than field-level monitoring.

From Observations to Decisions

Artificial Intelligence integrates multiple sources of agricultural information to generate actionable insights for decision-making.



Raw Observations

Satellite imagery ▪ Climate ▪ Soil ▪ Field observations

AI Models & Data Integration

Learn patterns ▪ Integrate data ▪ Extract information

Actionable Information

Maps ▪ Predictions ▪ Indicators · Alerts

Decision Support

Farmers ▪ Governments ▪ Humanitarian organizations

AI transforms heterogeneous observations into actionable information by integrating Earth observation with complementary agricultural data sources.

Different Problems Require Different AI Approaches

The choice of AI method depends on the type of question we want to answer and the information we want to produce.

Regression

Goal: Predict a continuous numerical value.
Example: *crop yield, biomass, soil moisture.*

Classification

Goal: Assign one category to each observation.
Example: *crop type mapping, land-use classification.*

Semantic Segmentation

Goal: Classify every pixel in an image.
Example: *field delineation.*



AI for Agriculture

Object Detection

Goal: Detect and locate individual objects.
Example: *fruit counting, weed detection.*

Time Series Forecasting

Goal: Predict future conditions from historical observations.
Example: *yield forecasting, drought prediction.*

Anomaly Detection

Goal: Detect unusual or unexpected patterns.
Example: *crop stress, irrigation failures.*

Different Problems Require Different AI Approaches

AI Problem	Classical ML	Deep Learning	Agriculture Examples
Regression	Linear Regression, Random Forest Regressor, XGBoost, LightGBM	MLP, LSTM, Temporal Transformer	Yield prediction, biomass estimation, soil moisture estimation, nitrogen estimation
Classification	Logistic Regression, Random Forest, XGBoost, SVM	CNN (ResNet, EfficientNet), Vision Transformer (ViT)	Crop type mapping, crop disease identification, weed vs. crop classification
Object Detection	Rare in modern applications	YOLO, Faster R-CNN, RetinaNet, DETR	Fruit counting, weed detection, livestock detection, Plant counting
Segmentation	Rare in modern applications	U-Net, DeepLabV3+, Mask R-CNN, SegFormer	Field delineation, flood mapping, burned area mapping
Time Series / Forecasting	ARIMA, Random Forest, XGBoost	LSTM, GRU, Temporal Fusion Transformer (TFT), Time Series Transformer	Yield forecasting, crop growth forecasting, irrigation demand forecasting
Anomaly Detection	Isolation Forest, One-Class SVM	Autoencoders, Variational Autoencoders	Disease outbreaks, Crop stress detection, irrigation failures, abnormal crop growth

Choosing the right AI approach starts with understanding the problem you want to solve.

Quiz Question 2

A government ministry wants to estimate national maize production three months before harvest to support food import planning. Which combination of imagery and AI method is most appropriate?

A

Very-high-resolution drone imagery combined with an object detection model (e.g., YOLO) to count individual plants.

B

National high-resolution satellite imagery analyzed with a convolutional neural network (CNN) using a single image acquired near the forecasting date.

C

A single high-resolution satellite image analyzed with an image segmentation model to delineate field boundaries.

D

Regional satellite image time series combined with weather data and a spatio-temporal deep learning model for yield forecasting.

Correct answer: D. National-scale yield forecasting requires broad coverage, temporal depth, and ML integration of EO and climate data.



Agriculture fields in India
Image © 2026 Planet Labs PBC

AI for Agricultural Monitoring

Agricultural monitoring provides the situational awareness needed for informed decisions, from **field-level management to national policy**. **AI transforms continuous Earth observations into timely, actionable information at multiple scales.**

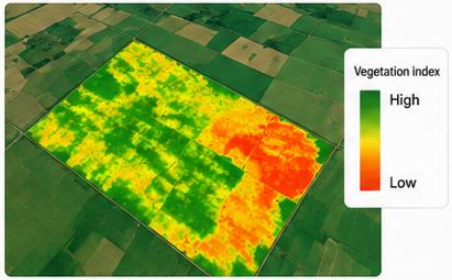
Learning Agricultural Dynamics Across Space and Time

Many agricultural problems depend not only on spatial information, but also on how crops evolve over time.

1. SPATIAL ANALYSIS

Where is it happening?

Analyzes patterns within a single moment in time.



Captures spatial variability and context across a field or landscape.

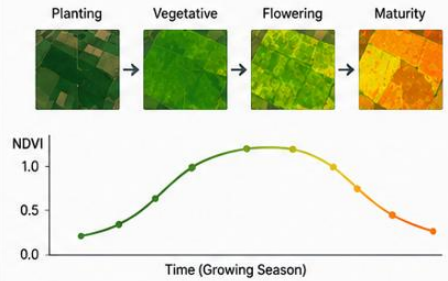
Examples

- Within-field variability
- Soil moisture maps
- Stress hotspots

2. TEMPORAL ANALYSIS

How is it changing over time?

Analyzes how a variable evolves over time.



Captures crop dynamics and seasonal trajectories.

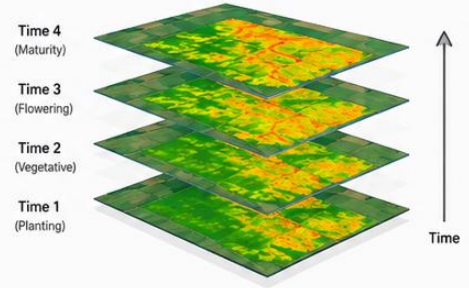
Examples

- Growth stage determination
- Yield forecasting
- Drought monitoring over time

3. SPATIO-TEMPORAL ANALYSIS

Where and how is it changing?

Combines spatial patterns and temporal dynamics.



Captures how patterns change over time across space.

Examples

- Spatio-temporal yield prediction
- Crop type mapping
- Change detection and anomaly alerts

The most powerful agricultural AI models combine spatial context with temporal dynamics to understand how crops evolve through time.

AI Across Scales: From Farmers to Policymakers

The **scale of the decision** determines **the data, AI methods, and outputs that are needed**.



The same Earth observation data can support very different decisions depending on the spatial scale.



Agriculture fields in Brazil
Image © 2026 Planet Labs PBC

Break

AI for Field and Farm-Level Decision Support

At the field and farm scale, AI enables **precision agriculture** - **delivering the right intervention, at the right place, at the right time.**

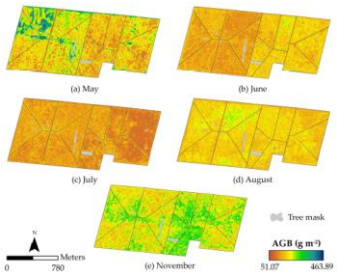
This improves productivity while reducing environmental impacts from over-application of inputs.


Image: Pixabay

Precision Agriculture:

The right input, in the right place, at the right time

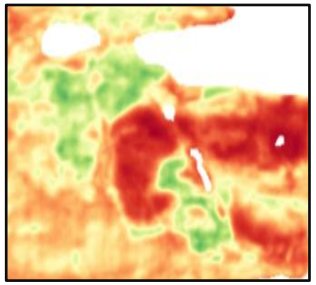
Apply inputs (e.g., water, fertilizer, pesticides) only where and when needed, based on **within-field variability detected by AI and remote sensing.**



Biomass over time

PlanetScope, XGBoost

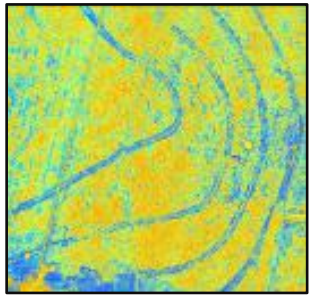
Is growth on pace, or falling behind in some part of the fields?



Yield prediction

Commercial product, methodology proprietary

How much will this field yield, before harvest? How is yield varying within the field?



Nitrogen estimation

UAV + Sentinel-2, Random Forest

Where does this field need nitrogen right now?



Variable-rate map

Commercial product, methodology proprietary

Exactly how much seed or fertilizer, zone by zone

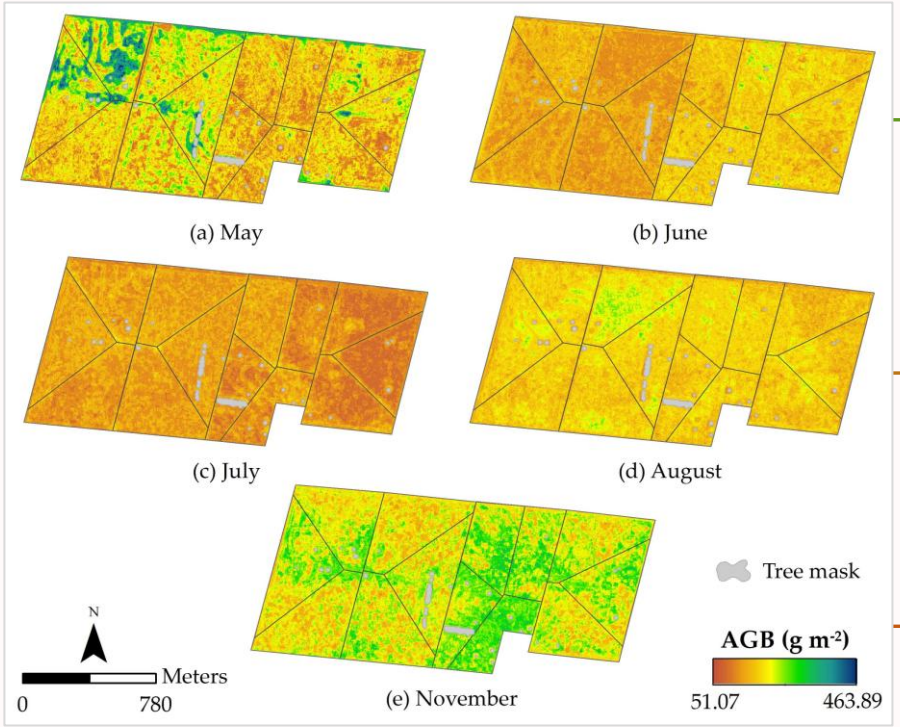
Sources: Reis et al. (2020), Pereira et al. (2022).

Source: CORVIAN

Field and Farm-Scale AI Applications

Biomass Estimation Over Time

PlanetScope time series + XGBoost / Random Forest, trained against field-measured aboveground biomass



THIS MONTH

Where to graze or mow now

Send animals to this month's greenest paddocks; rest the orange ones.

NEXT INPUT CYCLE

Where to fertilize next

Zones that stay orange for two or more months — not the whole field.

LONGER HORIZON

Where to investigate on the ground

Zones that are always low, regardless of month — check shade, drainage, or compaction before assuming it's nutrients.

Source: Reis et al. (2020)

AGB = aboveground biomass

Field and Farm-Scale AI Applications

Nitrogen Estimation: From Single Points to Maps

UAV, PlanetScope, and Sentinel-2 images + Random Forest, trained against field-measured nitrogen



WHAT THE MAP SHOWS

The field is not uniform

Some areas need nitrogen right now; others don't - **a snapshot of this crop, this growth stage**.

WHAT KIND OF KNOWLEDGE THIS IS

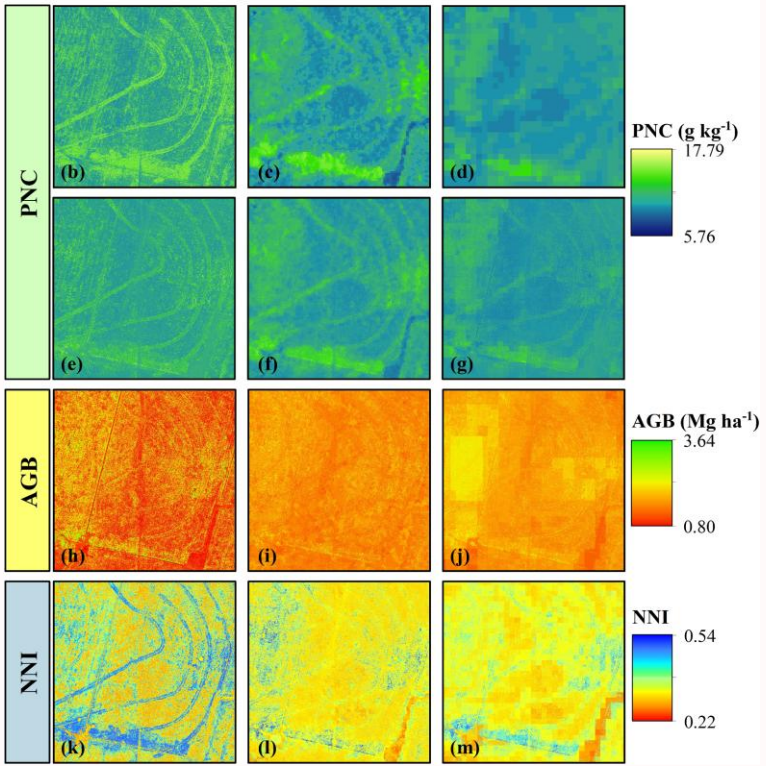
A dynamic, in-season snapshot

Tied to this year's weather and growth stage - **it will look different next month/season**.

WHAT'S STILL MISSING

Knowing where isn't a plan yet

Turning this into an executable rate is the next step.



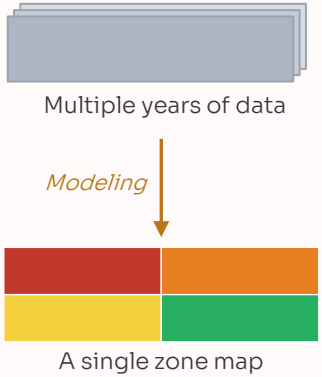
PNC = plant N content, AGB = aboveground biomass, NNI = nutritional nitrogen index

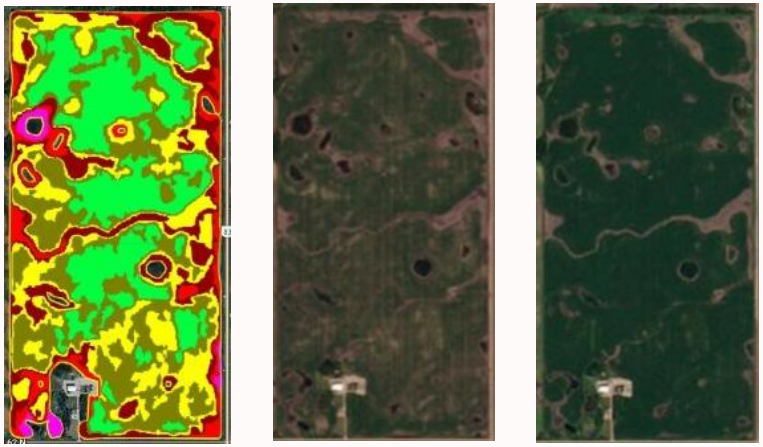
Source: Pereira et al. (2022)

Field and Farm-Scale AI Applications

Variable-Rate Map: Turning Zones into Action

Multiple years of data — modeled by Corvian's proprietary software





WHAT'S DIFFERENT HERE

A structural pattern, not a snapshot

Built from several years of data

THE DECISION

Exact input rate, per zone, automatically

Seed or fertilizer rate uploaded straight to the equipment.

WHY BOTH MATTER

Right input, right place

Matching input to **real field variability** increases profitability and **reduces excess fertilizer and water use** — directly supporting climate-smart, resource-efficient farming.

Field and Farm-Scale AI Applications

Yield Prediction Maps

Modeled by Corvian's proprietary software

PRE-HARVEST

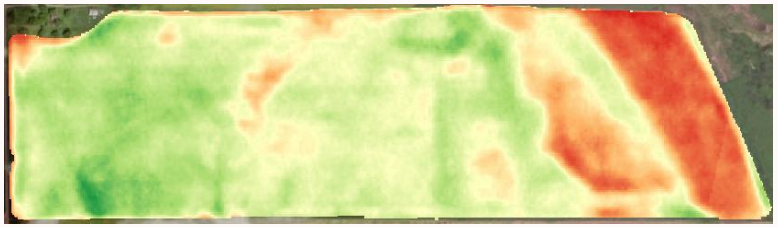
Plan storage, sales, logistics, sequencing

HARVEST

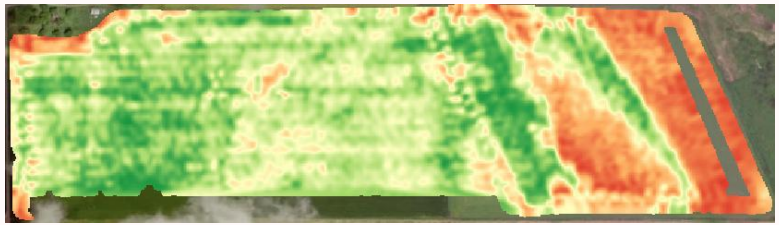
The combine records what actually happened

POST-HARVEST

Validate the model, diagnosis of persistent low-yield zones, feed next season models



Yield Prediction Map



Combine Yield Monitor Generated Map

Average yield summarizes performance. Yield maps reveal where management can improve productivity.

AI for Regional and Country-Level Decisions

At the regional and country scale, the question changes entirely: **what crops are being grown, where are they changing, and how are agricultural systems evolving over time?**

As climate-smart practices such as cover crops, no-till, and integrated systems become more common, agricultural landscapes become more diverse and more difficult to monitor using conventional approaches.

AI helps capture these complex spatial and temporal patterns, enabling accurate agricultural monitoring at regional and national scales.

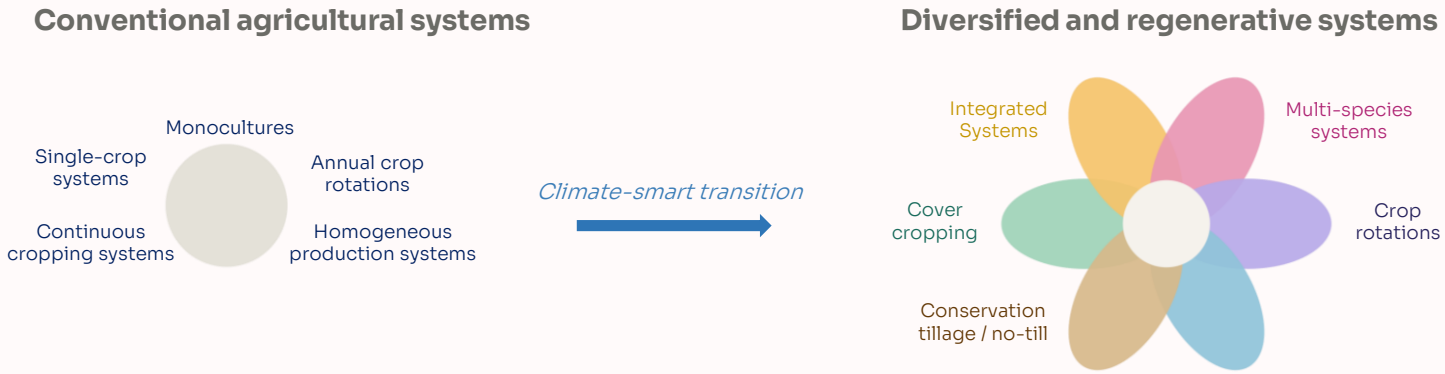


Agriculture fields in France
Image © 2026 Planet Labs PBC

Regional and Country-Level AI Applications

Climate-Smart Agriculture Is Changing Agricultural Landscapes

Agricultural systems are becoming more diverse to improve resilience, soil health, and sustainability.

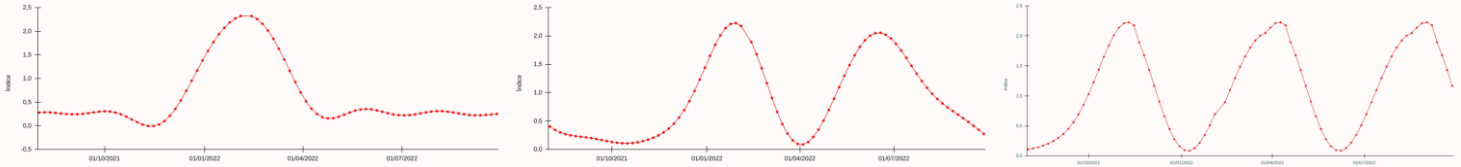


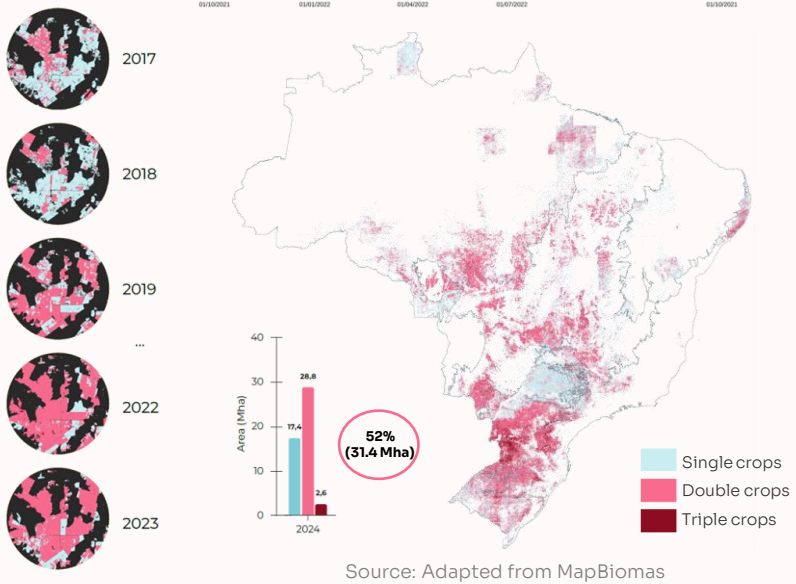
Climate-smart agriculture creates healthier and more resilient production systems.

Regional and Country-Level AI Applications

More complex agricultural systems require more advanced monitoring

Agricultural landscapes are transitioning from relatively simple cropping systems to dynamic management systems with increasing temporal complexity.





Source: Adapted from MapBiomas

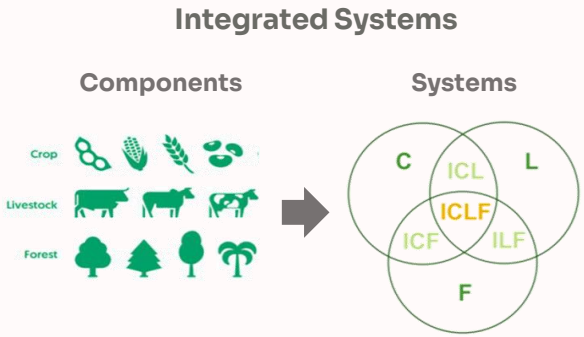
Why are these systems harder to monitor?

- → Similar crops at different growth stages
- → Multiple cropping cycles within a single year
- → Seasonal dynamics
- → Cover crops with short growing periods
- → High temporal variability
- → Similar spectral signatures

Capturing these complex spatial and temporal dynamics requires more robust AI approaches.

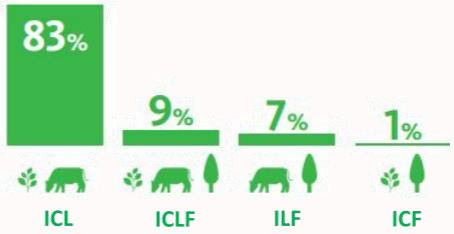
Regional and Country-Level AI Applications

Case study: *Mapping complex agricultural systems using deep learning: the case of Integrated Crop-Livestock Systems (ICLS) in Brazil*

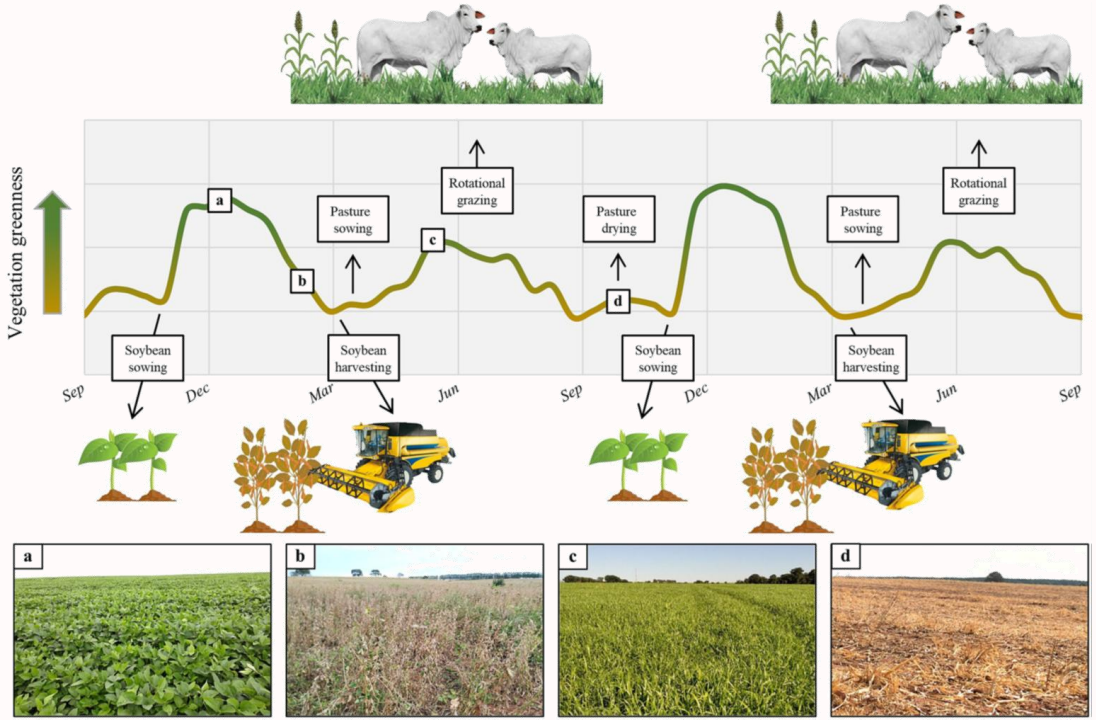


Total area of ICLS in Brazil:

~17 million hectares



Source: ILPF Network (2023, 2026)



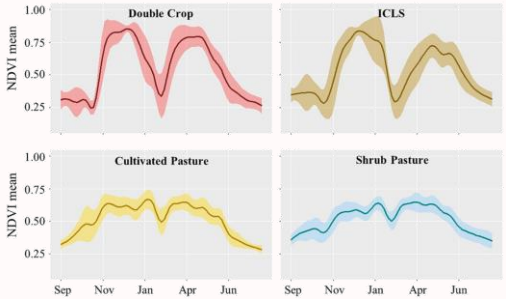
Source: Bueno et al. (2023)

Regional and Country-Level AI Applications

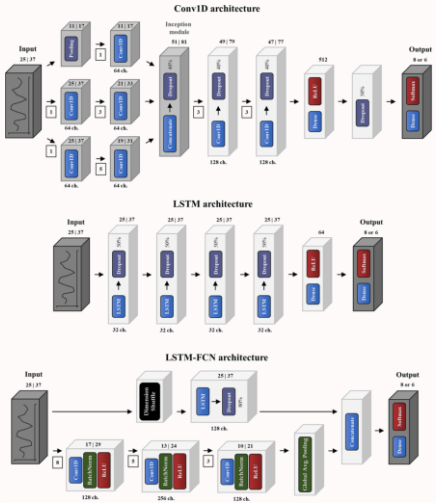
Case study: *Mapping complex agricultural systems using deep learning: the case of Integrated Crop-Livestock Systems (ICLS) in Brazil*

PlanetScope time series

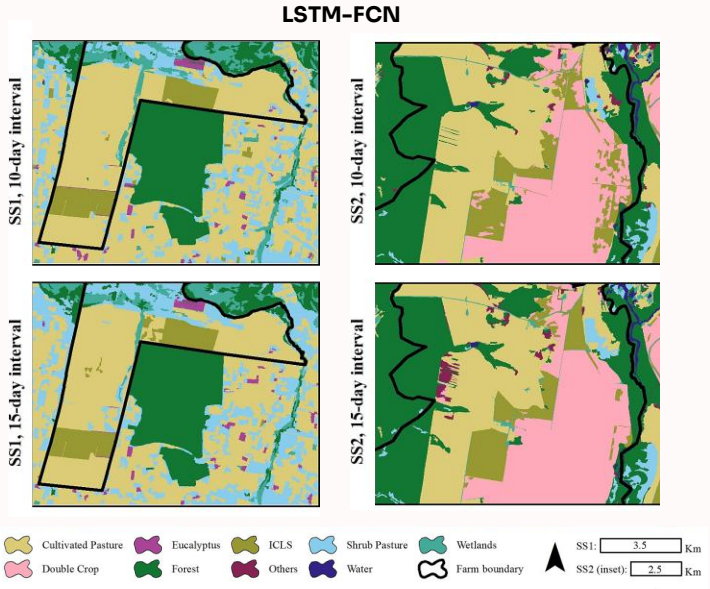




Deep neural network classifiers



ICLS Mapping



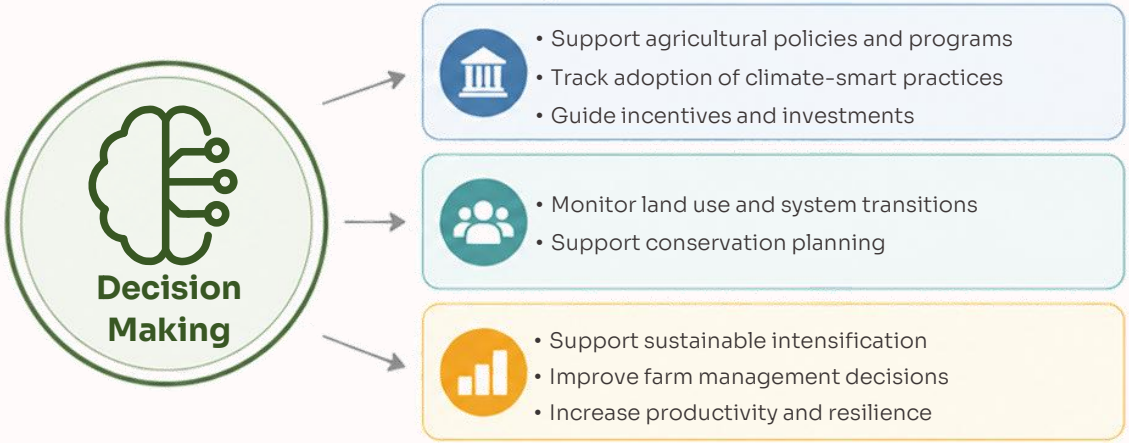
ICLS class-level accuracies:
PA (Producer's Accuracy) = 97.0%;
UA (User's Accuracy) = 97.0% for SS1 (Study Site 1)
PA = 82.0%; UA = 96.5% for SS2 (Study Site 2).

Source: Adapted from Bueno et al. (2023)

Regional and Country-Level AI Applications

Why does mapping integrated systems matter?

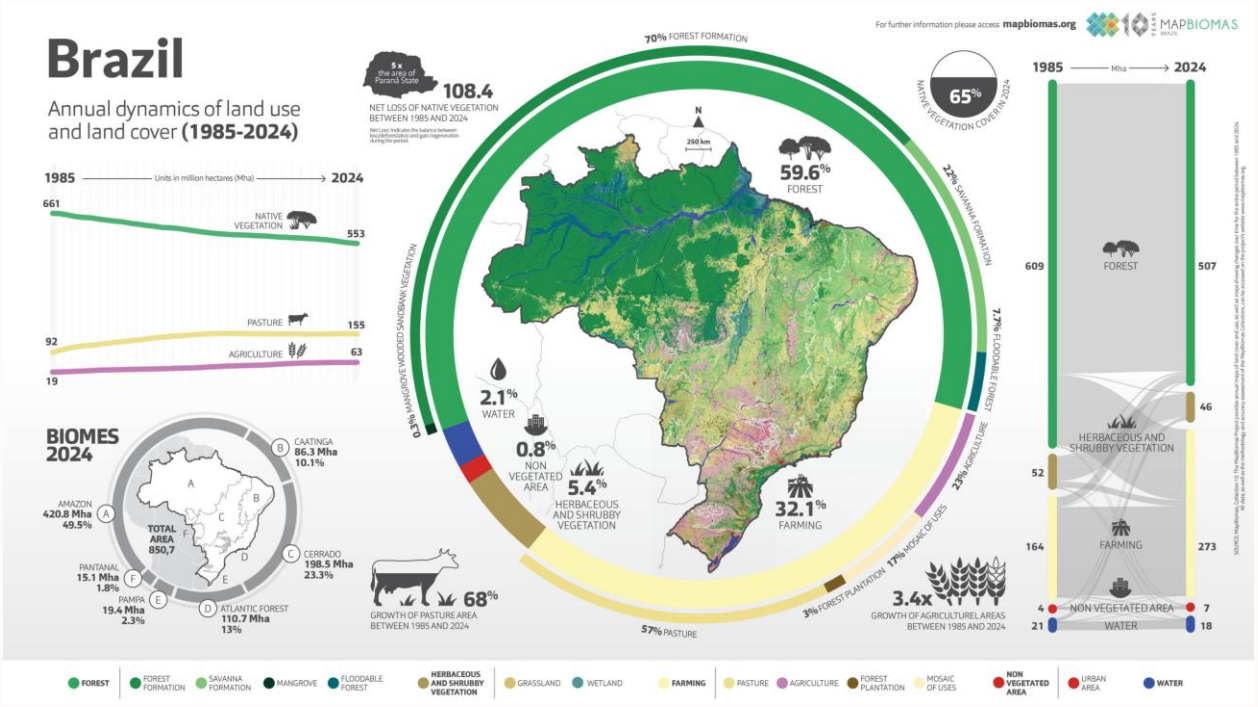
Better maps enable better decisions across multiple stakeholders.



Regional and Country-Level AI Applications

Case study: *MapBiomas*

*MapBiomas is a **multi-institutional Brazilian initiative** involving NGOs, universities, and technology companies that maps land cover and land use changes in Brazil.*



40 yrs
1985–2024, continuous

30 m & 10 m
(Beta Collection)
Landsat & Sentinel-2 resolution

9B+
pixels classified / year

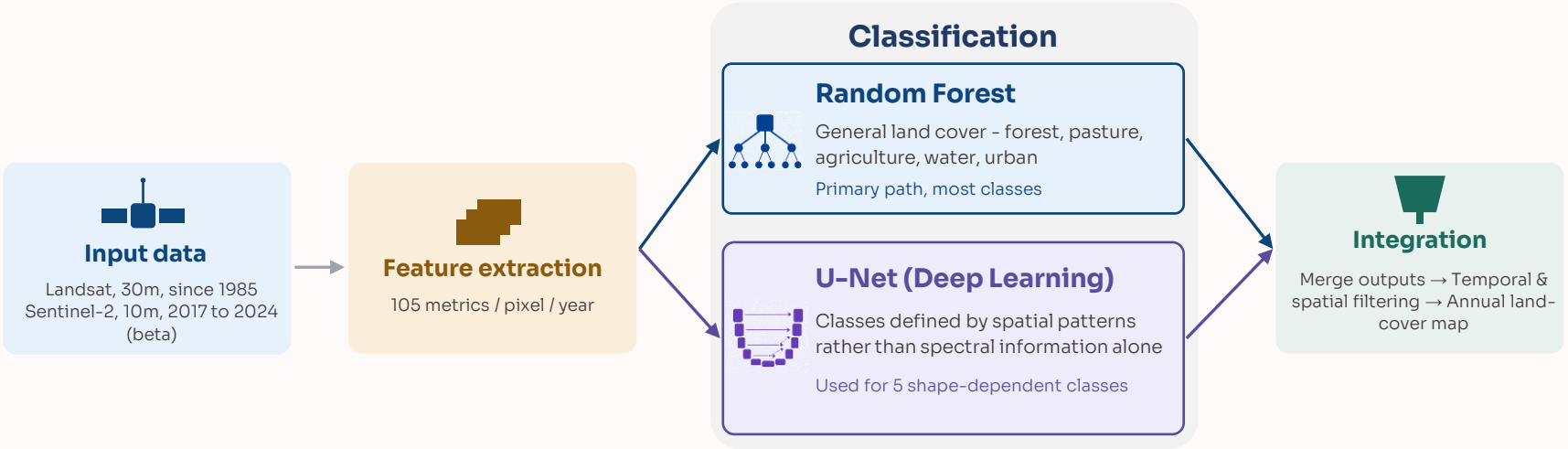
+30
land cover & use classes

Source: MapBiomas Brazil Collection 10

Regional and Country-Level AI Applications

Case study: *MapBiomas*

MapBiomas matches the model to the problem: Random Forest for general land cover, U-Net for shape-dependent classes.



The right model for the right problem.

Choosing the right algorithm for each problem, rather than relying on a single model for everything, allows MapBiomas to scale to an entire country while maintaining high accuracy for complex, shape-dependent classes.

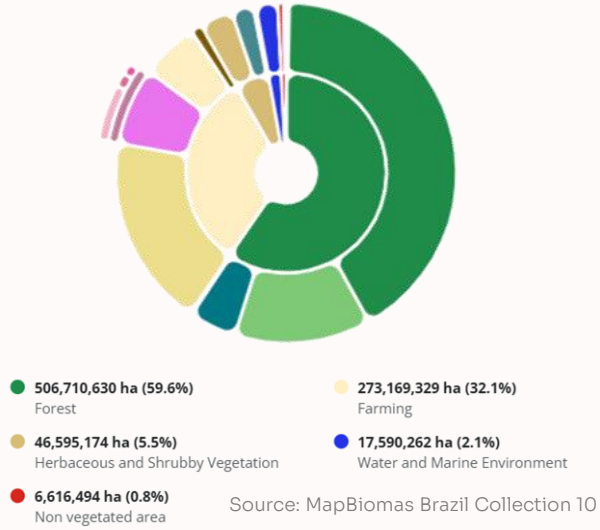
Source: MapBiomas Brazil Collection 10

Regional and Country-Level AI Applications

Why It Matters: Decision-Making Enabled by MapBiomas

- *MapBiomas outputs feed directly into Brazil's environmental governance, functioning as operational infrastructure rather than just a research product.*

Coverage by Class - 2024



Source: MapBiomas Brazil Collection 10

Decision-Making

→ Support policies and programs
→ Evaluate policy effectiveness over time
→ Support deforestation enforcement
→ Inform climate and carbon accounting
→ Ensure rural credit compliance
→ Guide fire management
→ Support water resource management
→ Prioritize conservation planning
→ Support and enable global research
→ Enforce land tenure compliance

A single, transparent, publicly available evidence base, independent of any one administration, lets government, courts, NGOs, and international bodies act on the same facts.

AI for Global-Scale Decisions

At a global scale, we need to know - **where crops are grown, how much they produce, and where production risks may arise.**

Global crop monitoring faces **data gaps, uneven survey coverage, and shifting growing seasons between hemispheres.**

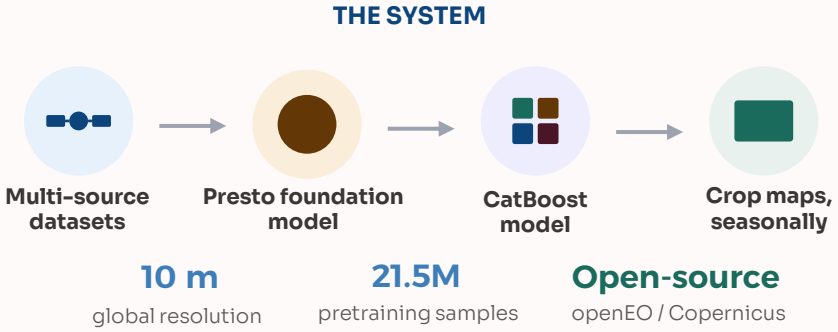
AI combined with multiple data sources enables a global view of agriculture, supporting food security assessments and early-warning decisions.



Global-Scale AI Applications

ESA WorldCereal

WorldCereal is a research project funded by the European Space Agency, aimed at providing a free, cloud-based processing system to generate high-resolution custom crop location and type products at local and global scales.



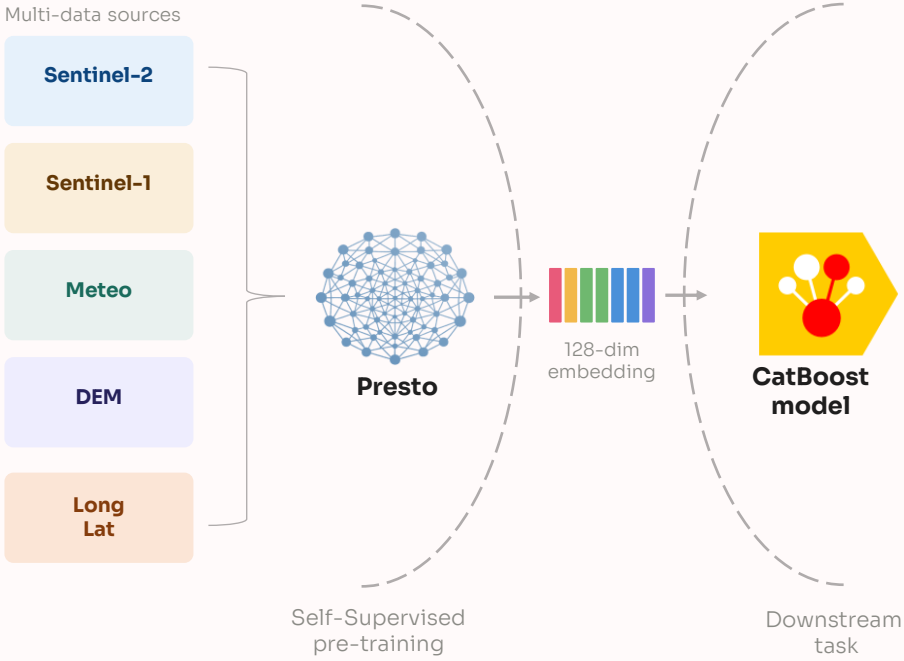


World Cereal 10 m resolution temporary crops map for 2021.
Source: ESA World Cereal, 2026.

Global-Scale AI Applications

Geospatial Foundation Models: *Presto – Pretrained Remote Sensing Transformer*

The pretrained model behind WorldCereal's crop classification.



→ Developed by **NASA Harvest (Tseng et al., 2023)**

→ **Learns from millions of unlabeled data points**

→ Represents **multi-modal time series as one 128-dimensional embedding vector**

→ Trains downstream crop mapping with high generalizability

→ Updated for WorldCereal to use far fewer labels



A visual example of dynamically computed Presto embeddings in a region close to Buenos Aires, Argentina. The 128 embeddings are visualised here based on a PCA-reduced three-component RGB. ***Source: ESA World Cereal***

Global-Scale AI Applications

GEOGLAM Global Crop Monitor

GEOGLAM
GLOBAL AGRICULTURAL MONITORING

GEOGLAM (Group on Earth Observations Global Agricultural Monitoring) *is a G20 initiative that coordinates Earth observation, agroclimatic information, and expert knowledge to strengthen agricultural monitoring and support global food security.*

*The **GEOGLAM Global Crop Monitor** is GEOGLAM's flagship product—a monthly global assessment of crop conditions that combines Earth observation products (including AI-derived datasets), agroclimatic information, field observations, and expert consensus from international partner agencies..*

INPUTS

Crop extent
Cropland masks and crop maps from multiple sources, including AI-derived products such as ESA WorldCereal where available.

Earth observation
Satellite indicators of vegetation condition, including NDVI, fAPAR, and vegetation anomalies.

Agroclimatic conditions
Rainfall, temperature, soil moisture, evapotranspiration, and drought indicators.

Field observations
National reports and in-country observations from partner agencies.

EXPERT ASSESSMENT

Regional and national experts independently assess crop conditions.

Differences are reviewed using multiple lines of evidence.

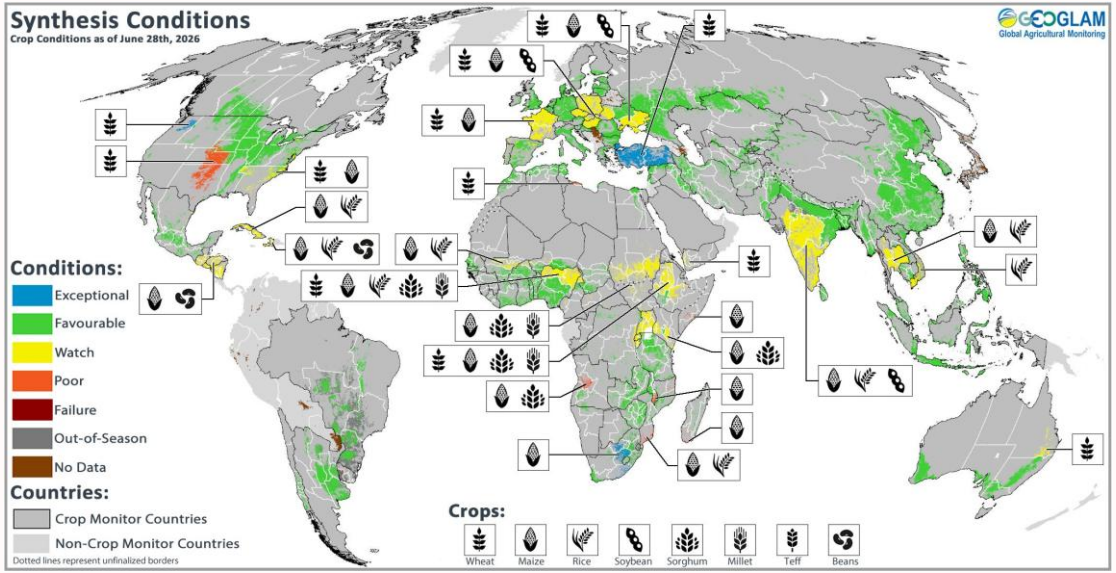
Experts discuss regional assessments and reach a consensus before publication.

Consensus assessments are published as the monthly Crop Monitor.

Global-Scale AI Applications

GEOGLAM Global Crop Monitor

Synthesized from the Crop Monitor for AMIS (Agricultural Market Information System), the Crop Monitor for Early Warning, and direct submissions from individual countries.



*Crop conditions over the main growing areas are based on inputs, **including remotely sensed data, ground observations, field reports, and national and regional experts**.*

Decisions Supported

- Early warning of food production risks
- Humanitarian response planning
- Market transparency and food security assessments
- National preparedness and international coordination

Source: GEOGLAM Crop Monitor (2026, July 12)

Global-Scale AI Applications

AI enables global monitoring. Human expertise enables trusted decisions.

What AI Enables

- Monitor crop conditions consistently across countries and continents.
- Detect early signs of drought, crop stress, and production risks.
- Produce timely, large-scale Earth observation derived products that would be impossible to generate manually.
- Provide objective and repeatable information to support global agricultural monitoring.

Why Human-in-the-Loop Matters

- Interpret AI outputs using local knowledge and real-world context.
- Evaluate uncertainty before acting on high-impact decisions.
- Resolve conflicting evidence across multiple data sources.
- Combine AI insights with expert judgment and field observations.
- Ensure transparency and accountability in operational decisions.

AI scales information. Human expertise transforms that information into trusted decisions.

The larger the scale of the decision, the more important it becomes to combine AI with human expertise, transparency, and institutional collaboration.

Quiz Question 3

A country is adopting an AI-based drought early warning system to guide emergency food assistance. Which design choice is most likely to improve decision-making?

A

Maximizing predictive accuracy using a complex deep learning model.

B

Producing forecasts at the finest possible spatial resolution.

C

Combining reliable predictions with uncertainty estimates and delivering results in a format that local agencies can easily interpret and act upon.

D

Prioritizing a model that can be deployed globally without regional adaptation.

Correct answer: C. Combining reliable predictions with uncertainty estimates and delivering results in a format that local agencies can easily interpret and act upon.

Limitations, Responsible AI & Real-World Challenges

Technical Limitations

- Limited availability and quality of training data
- Geographic bias - models trained in one region may not generalize to others
- Limited transferability across crops, regions, and management systems
- Climate non-stationarity - past patterns may not predict future conditions
- Prediction uncertainty increases under changing environmental conditions

Responsible AI Considerations

- Interpretability and transparency of model outputs
- Accessibility and equity — who benefits from AI tools?
- Risks of over-reliance on AI systems in high-stakes decisions
- Communicating uncertainty clearly to decision-makers
- Evaluate models based on the decisions they are intended to support

⚠ **AI outputs should support decision-making, not replace expert judgment or be treated as ground truth.**

Future Directions & Research Opportunities

AI is evolving from task-specific models toward integrated, reusable, and accessible systems for Earth observation.

Technological Evolution

Earth Embeddings

General representations of Earth's surface that can be adapted to multiple downstream tasks.

Foundation Models

Large pre-trained models that can be fine-tuned for a wide range of Earth observation tasks.

Multimodal Learning

Models that jointly learn from satellite imagery, weather, soil, management, and text data.

Democratizing Access

Open Datasets

Wider availability of high-quality agricultural and environmental data for research and development.

Open-Source Tools

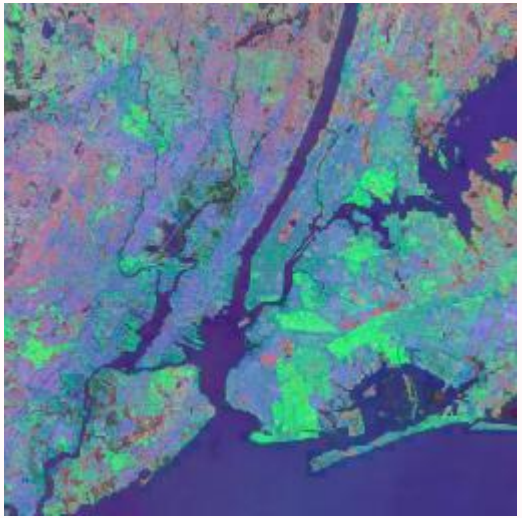
Open-source tools make advanced AI methods more accessible and reproducible.

Global Accessibility

Reducing barriers for researchers and practitioners, especially in data-scarce regions.

> Integrated AI systems that combine Earth observation, climate, management, and field data to generate actionable information for climate-smart decision making.

Future Directions & Research Opportunities



Example of AlphaEarth annual embeddings

Source: Google Earth Engine Data Catalog; Google DeepMind.

Foundation Models and Earth Embeddings

Instead of training separate models for individual agricultural tasks, foundation models learn general representations of Earth's surface that can be adapted to many downstream applications.

Potential applications

- Crop mapping
- Crop monitoring
- Land-use monitoring
- Change detection
- Biomass estimation

Current limitations

- Currently designed for historical analysis rather than in-season monitoring
- Annual embeddings may merge multiple crop seasons
- Fine agricultural dynamics may be lost in highly seasonal systems
- Require task-specific fine-tuning for operational agricultural applications

Actionable Next Steps

Continue exploring AI for Agriculture and Food Security

Explore Data

→ AlphaEarth Embeddings (Google Earth Engine)
→ ESA WorldCereal
→ MapBiomas
→ Fields of the World
→ Benchmark datasets (e.g., CY-Bench)

Explore real-world datasets for agricultural AI.

Build with Open Tools

→ Google Earth Engine
→ Python (leafmap, geemap)
→ Google Colab

Build and test AI workflows with open-source tools.

Practice & Experiment

→ Explore tutorials and notebooks
→ Reproduce published workflows
→ Fine-tune foundation models

Hands-on practice with real notebooks and workflows.

Join the Community

→ Climate Change AI
→ NASA Harvest
→ GEOGLAM
→ IEEE GRSS

Places to keep learning and connect with practitioners.

Resources: AlphaEarth Colab Notebook · AlphaEarth Dataset (GEE) · CY-Bench (Crop Yield Benchmark) · WorldCereal (GitHub) · MapBiomas



Agriculture fields around the world
Images © 2026 Planet Labs PBC

Climate Change AI
Virtual Summer School 2026

Thank you!

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Better decisions begin with better information.

AI is transforming Earth observations into actionable information, enabling better agricultural decisions from individual fields to global food security.