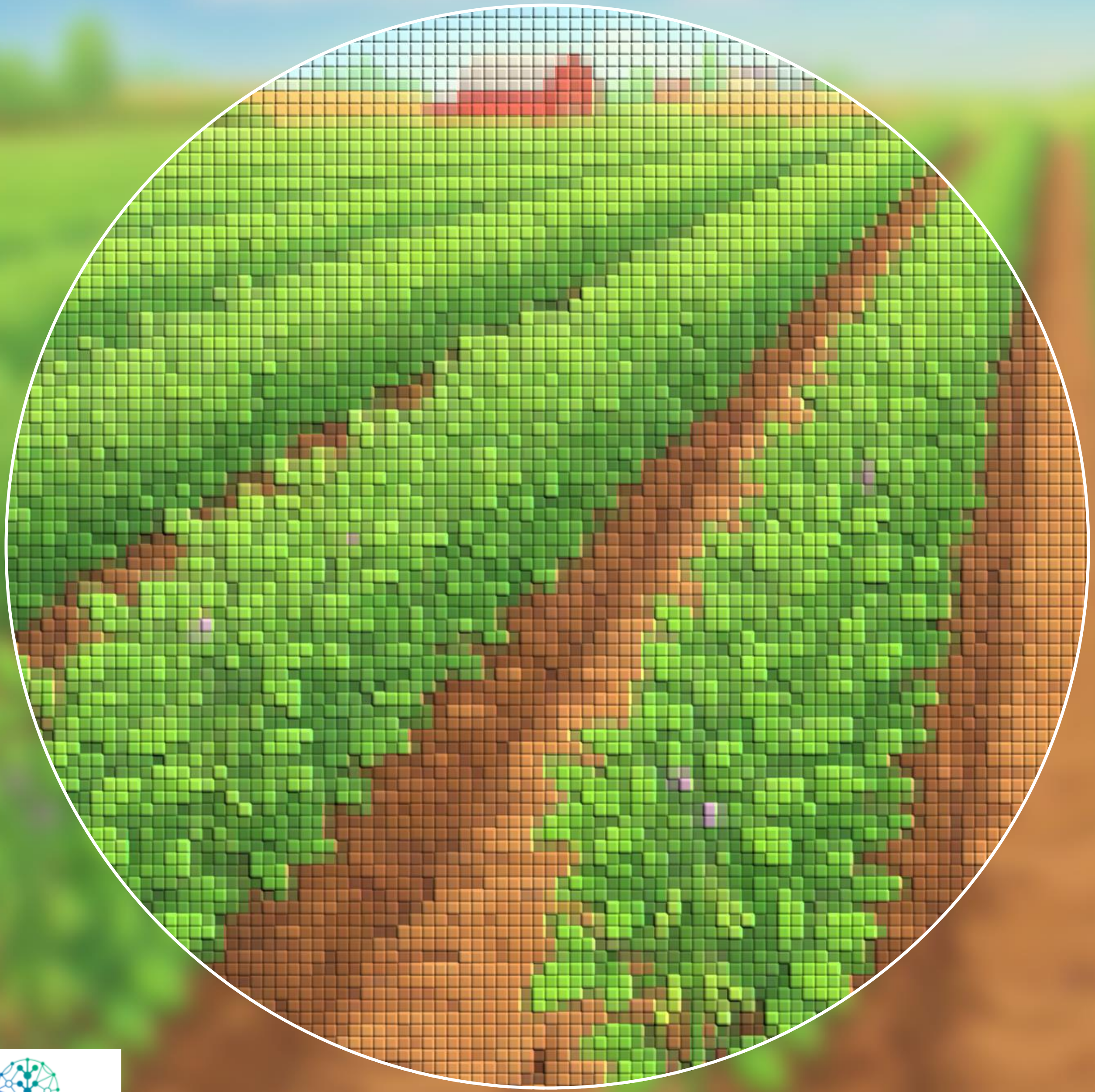


Foundation models in agricultural sciences

Challenges and opportunities

Ioannis N Athanasiadis

www.wur.ai

WAGENINGEN UNIVERSITY & RESEARCH

2nd Conference on Artificial Intelligence for Animal Science
Ghent, BE, June 29-30, 2026

AgriScienceFM

Funded by the European Union

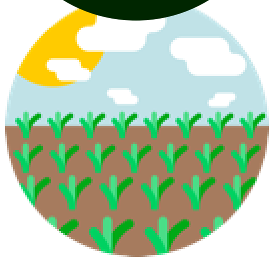
The WUR AI group

yield forecasting
cross scale interactions (GxExM, space, time)
partial views – domain shifts

agricultural advise
mitigate and adapt to (climate) risks - good practices

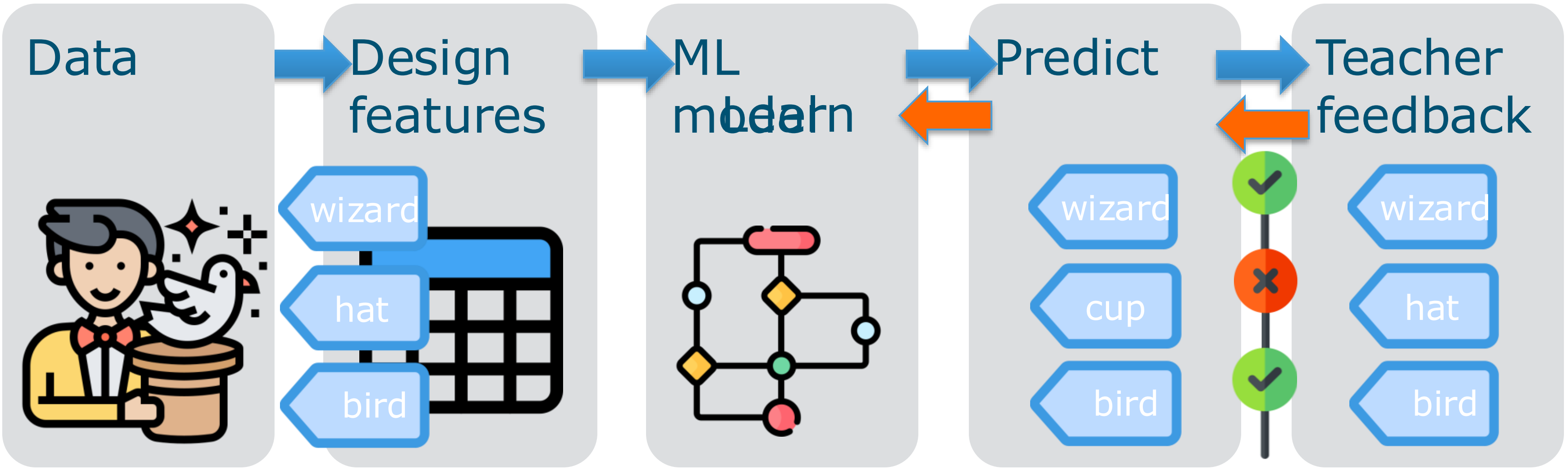
ag model improvement
improve performance – suggest new theory

actionable
trustworthy
AI



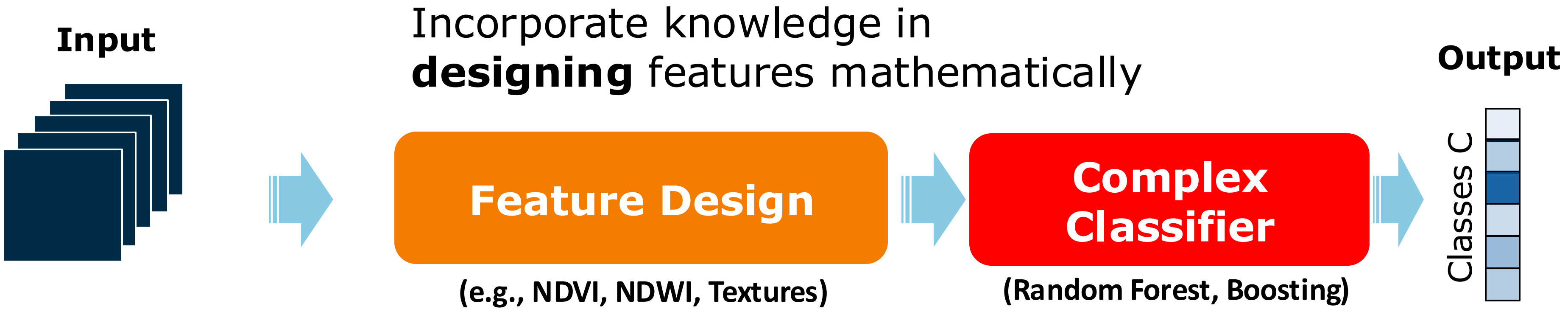
Food security
Climate change
Biodiversity

"Traditional" data-driven AI aka machine learning



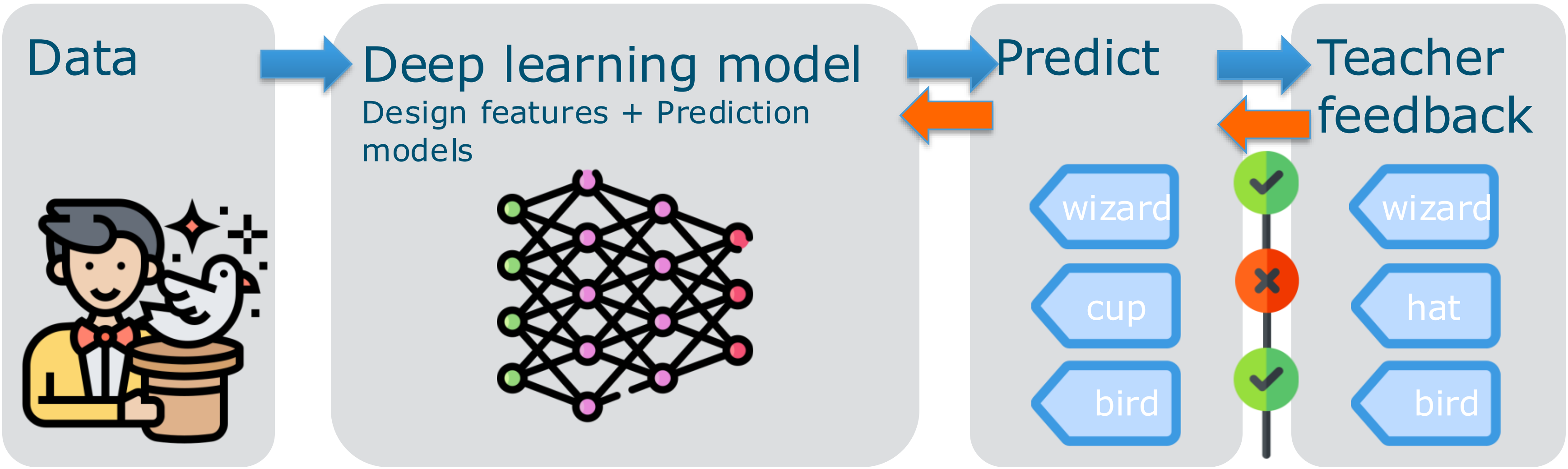
Design and select the right features is a challenge!

Machine learning (pre 2012)



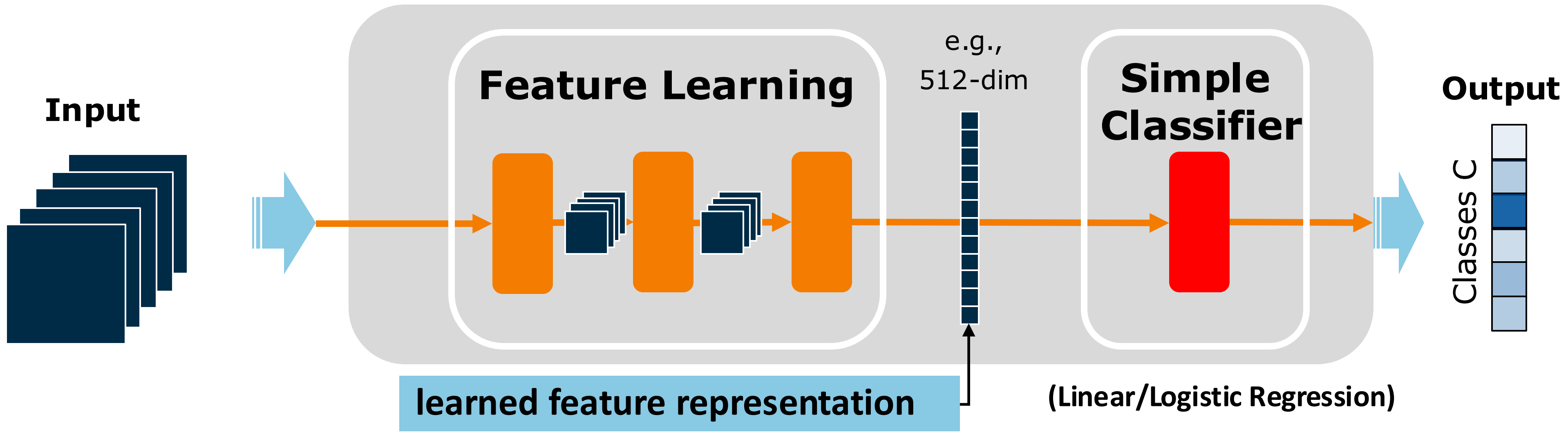
Design and select the right features was the challenge!

Deep learning – representation learning



Learn common filters
i.e. convolutions for vision

Feature learning instead of feature design (2012)

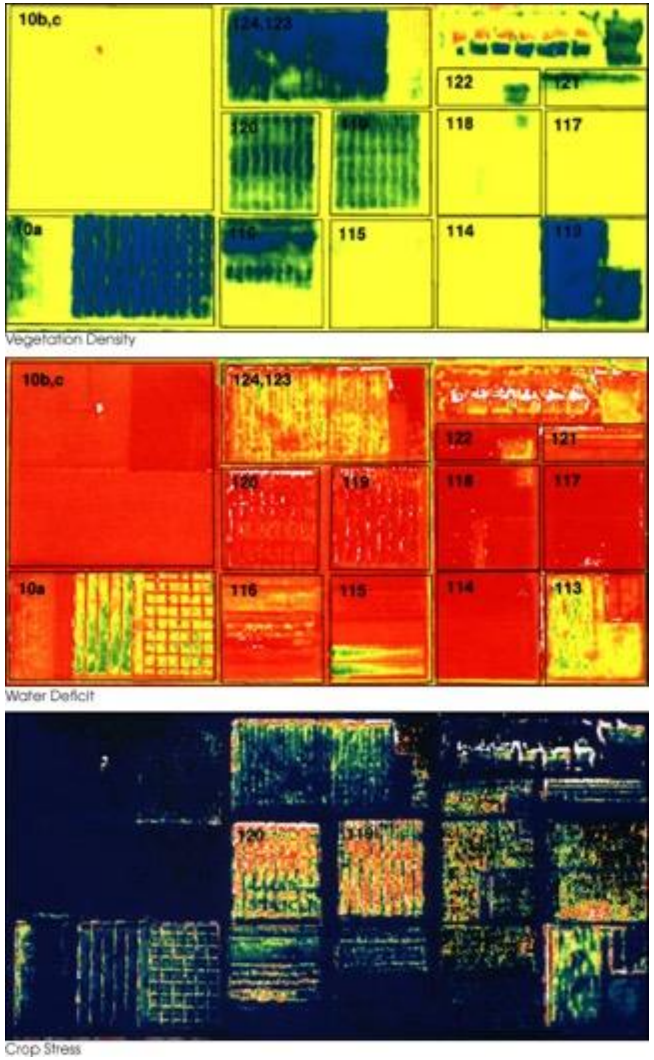


Plus:
- **Very big datasets with labels**
- **Tailored hardware for computation**
- **Optimized software implementations**

Remote sensing for precision agriculture and livestock farming (2000)

- Image-based remote sensing for detecting vegetation density, water deficit and crop stress

Photo Credits: Uthpal Kumar, PhD candidate, WUR.

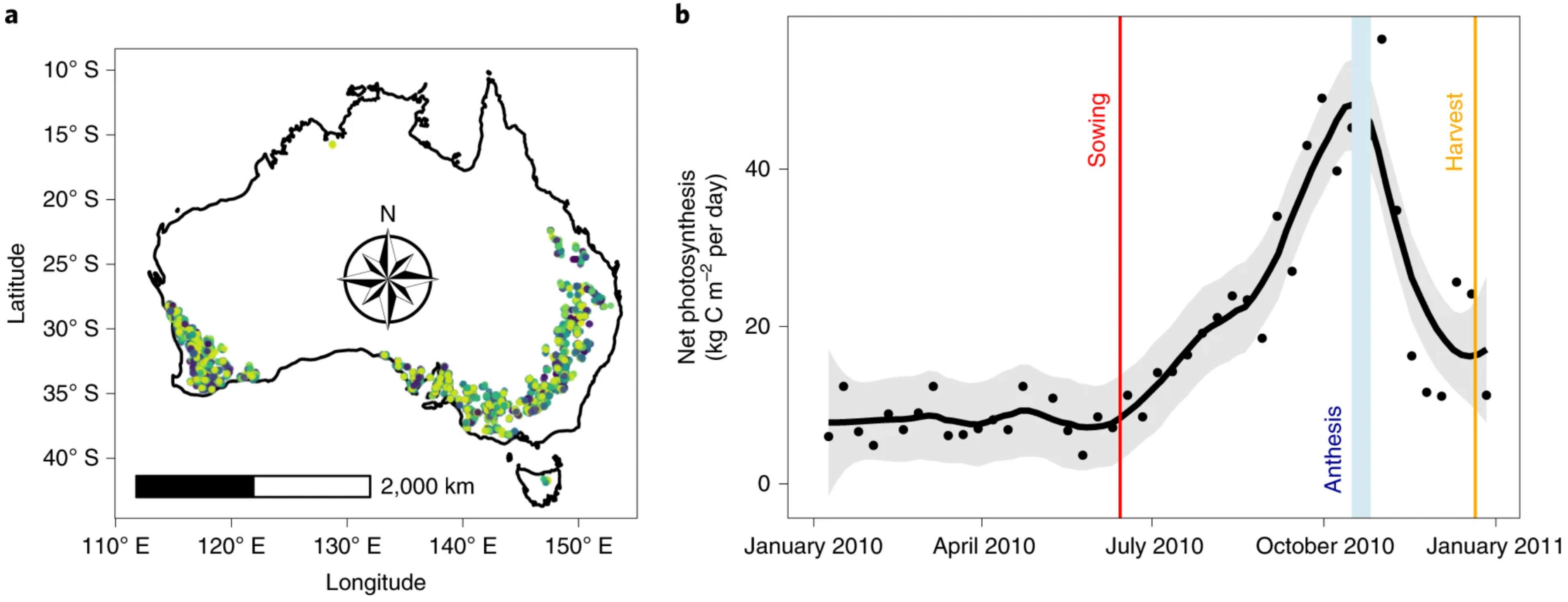


Moran M. Susan. Image-Based Remote Sensing for Precision Crop Management: A Status Report. Space 2000 185–193 (2000)

ML for estimating major crop traits from satellite-monitored continent-wide field trials

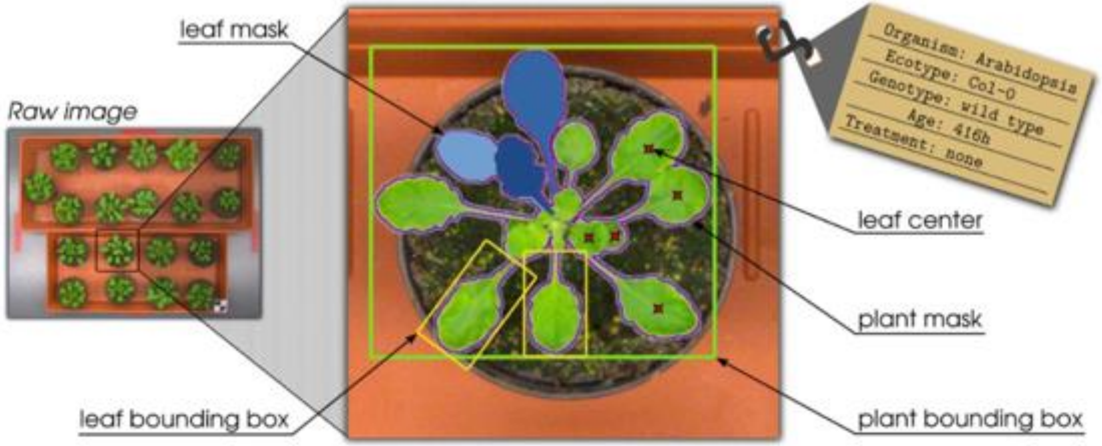
Fig. 1: NVTs and large-scale environmental patterns captured by satellite.

From: [Explainable machine learning models of major crop traits from satellite-monitored continent-wide field trial data]()



Newman, S. J., & Furbank, R. T. (2021).
Explainable machine learning models of major crop traits from satellite-monitored continent-wide field trial data.
Nature Plants, 7(10), 1354–1363. https://doi.org/10.1038/s41477-021-01001-0

Machine Vision for Plant Phenotyping (2014)



Leaf counting error (lower is better)

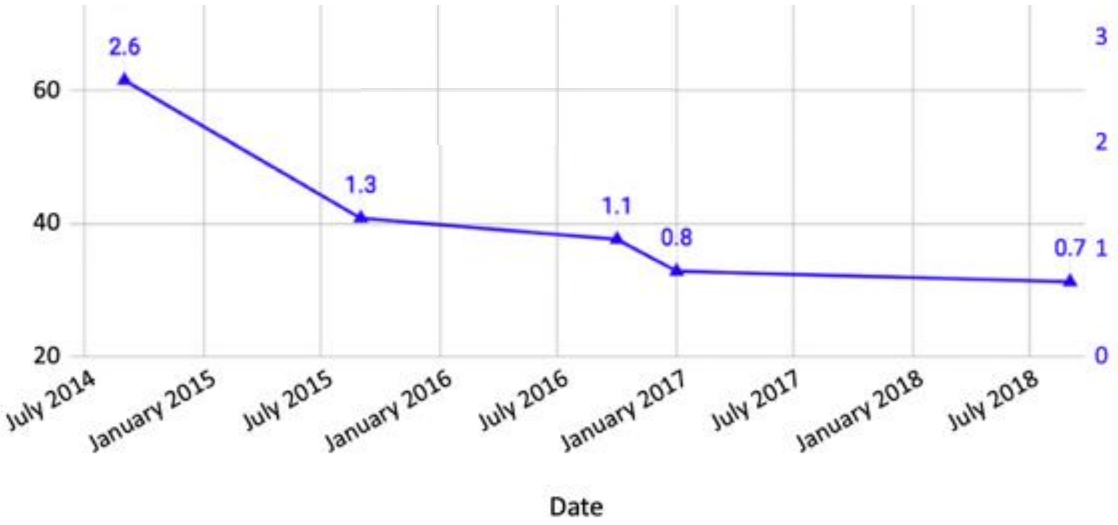
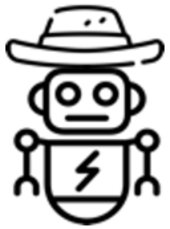


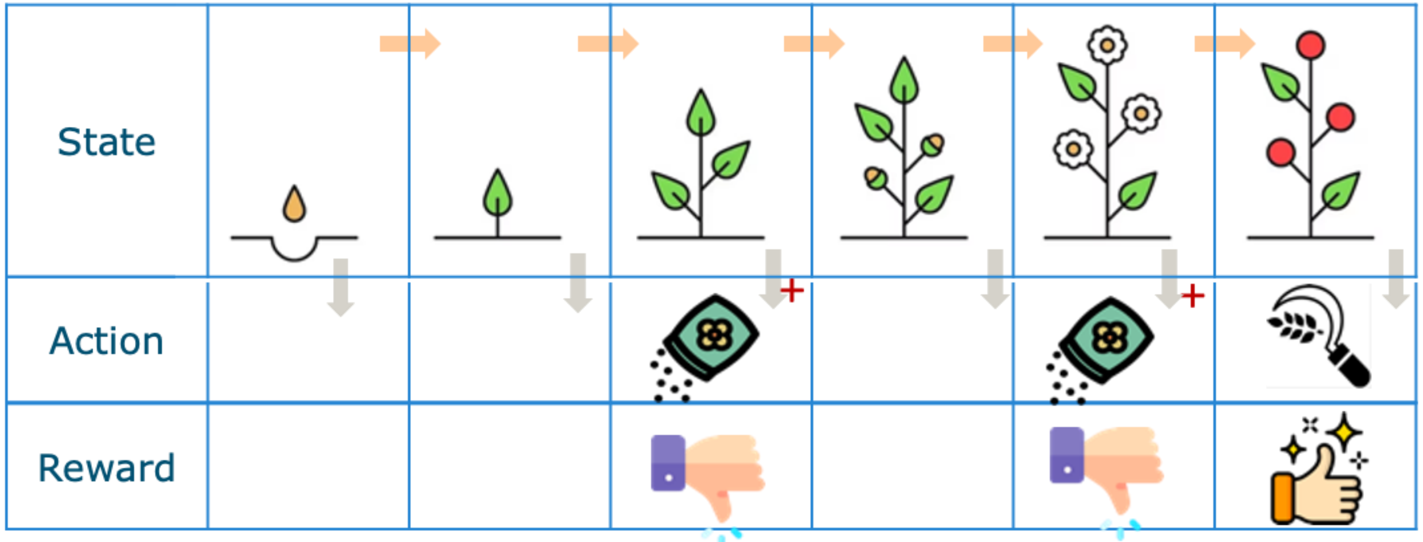
Photo Credit: NPEC, WUR.

Tsaftaris, S. A. & Scharr, H. Sharing the Right Data Right: A Symbiosis with Machine Learning. Trends Plant Sci. 24, 99–102 (2019)

Reinforcement learning for crop management (2022)

AI

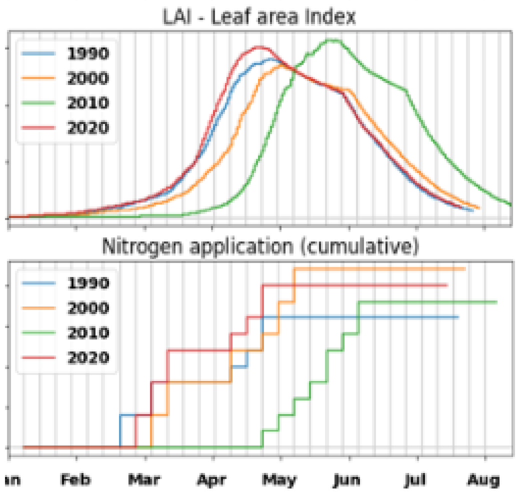


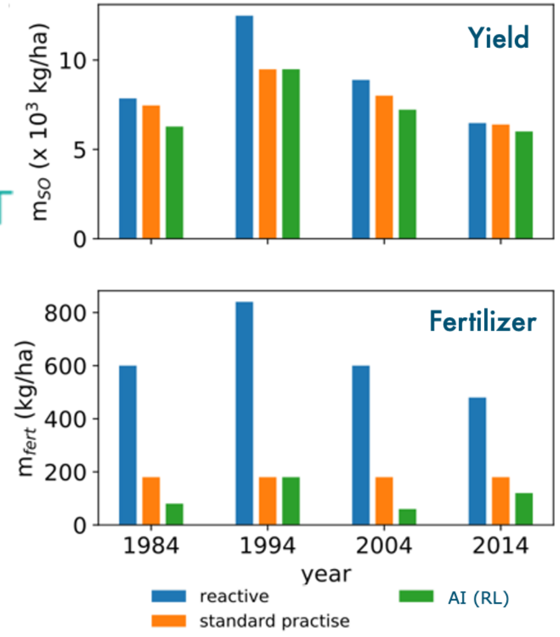


Reward: weight$_{\text{storage organ}}$ – c * weight$_{\text{fertilizer applied}}$

SIMULATOR

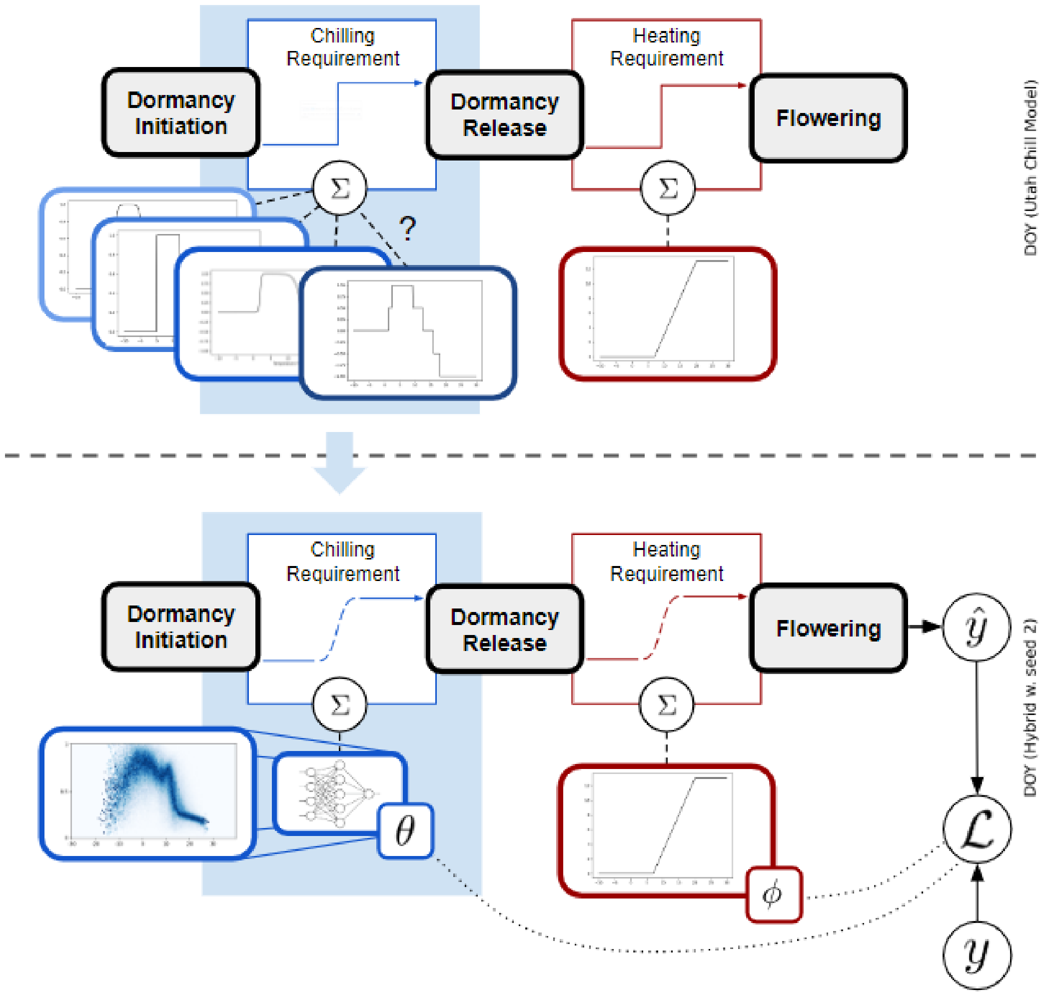
WOFOST

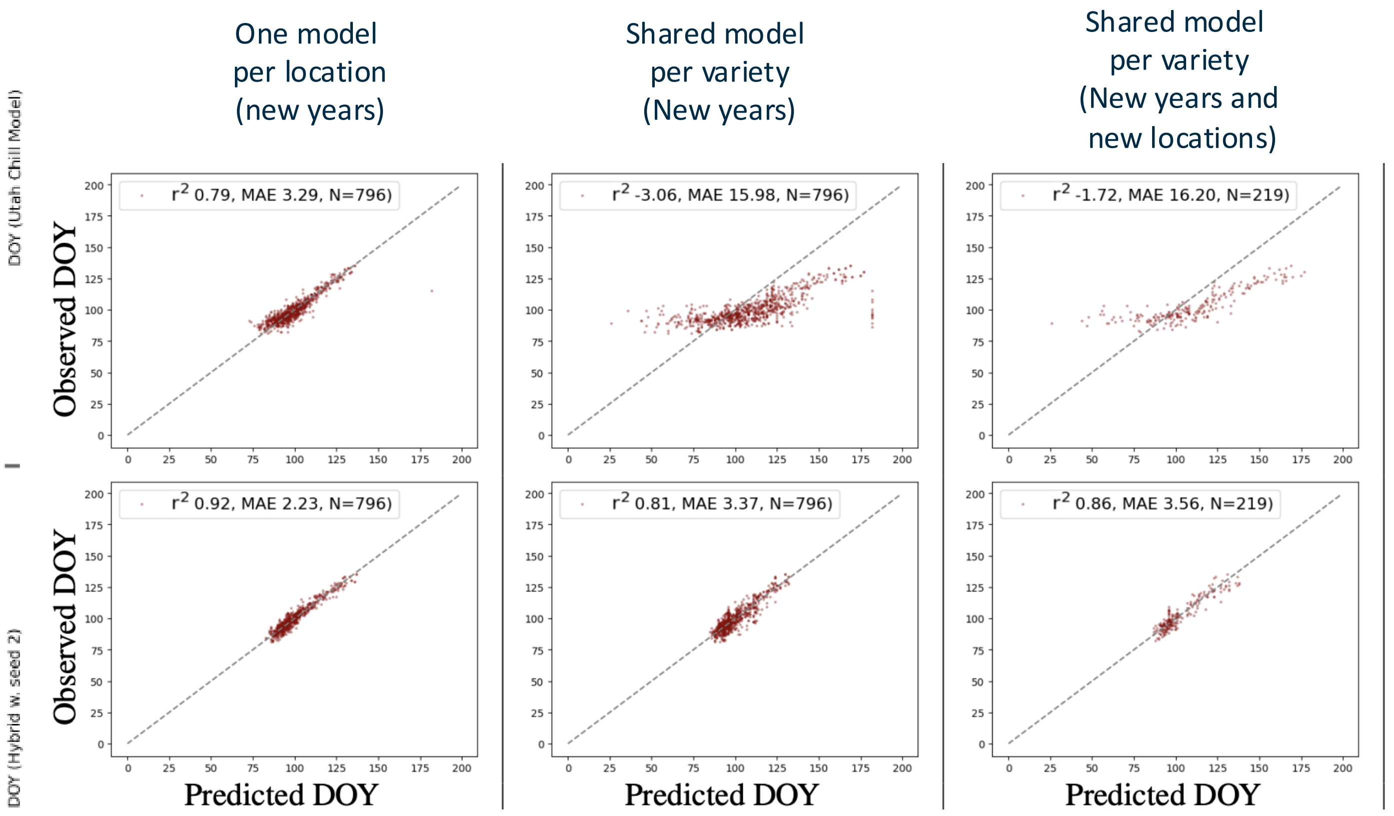




Kallenberg et al. (2023).
Nitrogen management with reinforcement learning and crop growth models.
Environmental Data Science 2, e34.

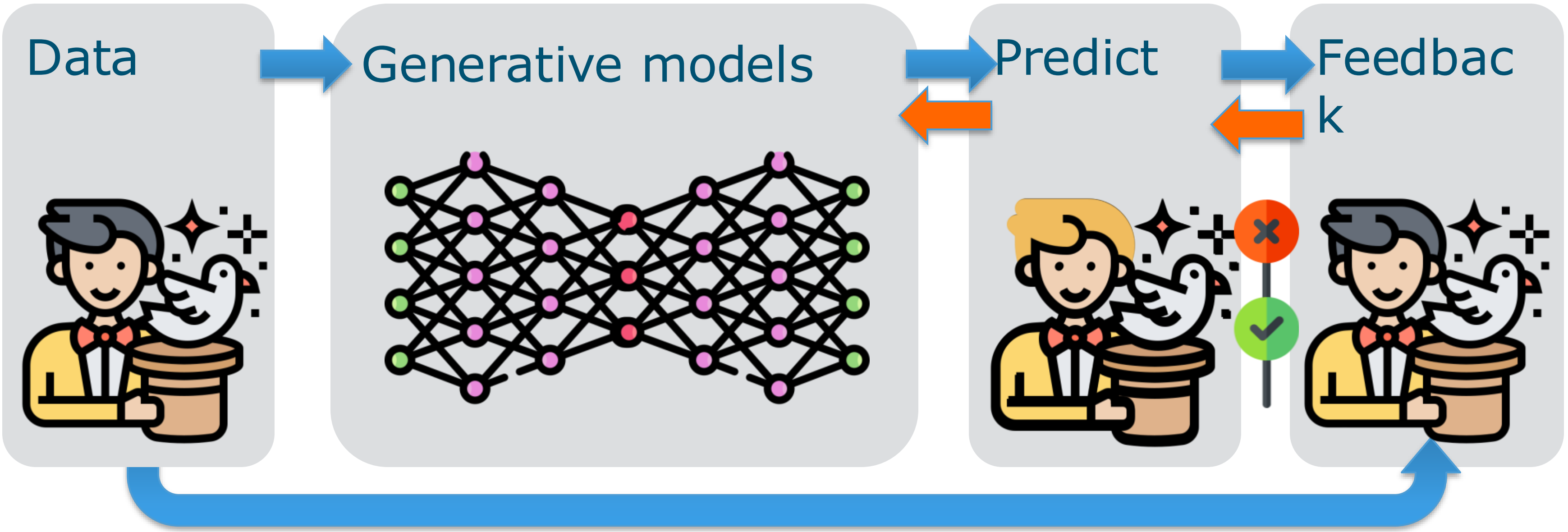
Hybrid models for improving generalization (2025)





Evaluate on large dataset of 40 years of data
in Japan, Switzerland and South Korea
Improves generalization both in time and in space

Deep learning – Generative models (2017)

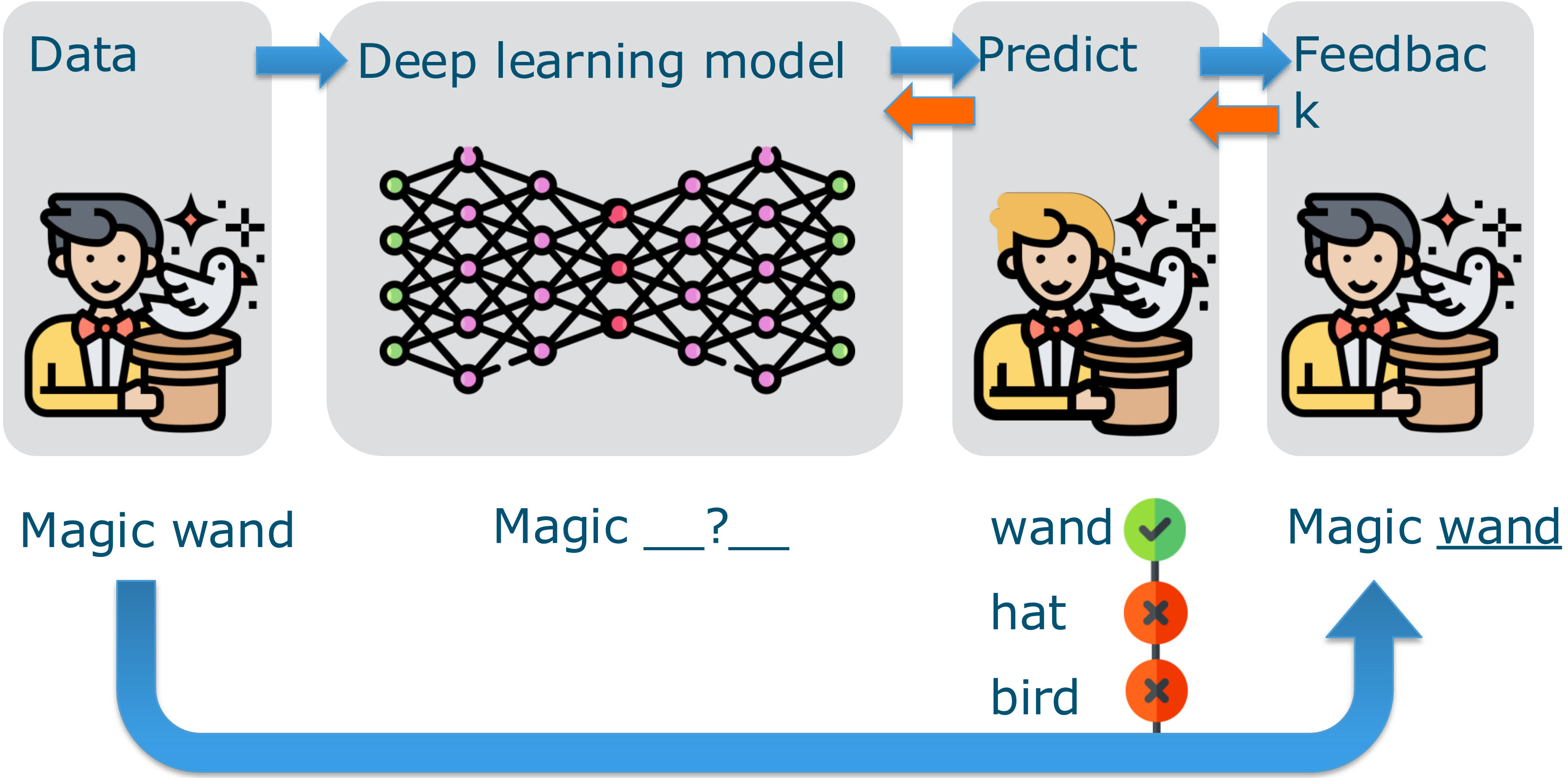


HUGE amounts of data and computation

No teacher feedback – learn the input data!

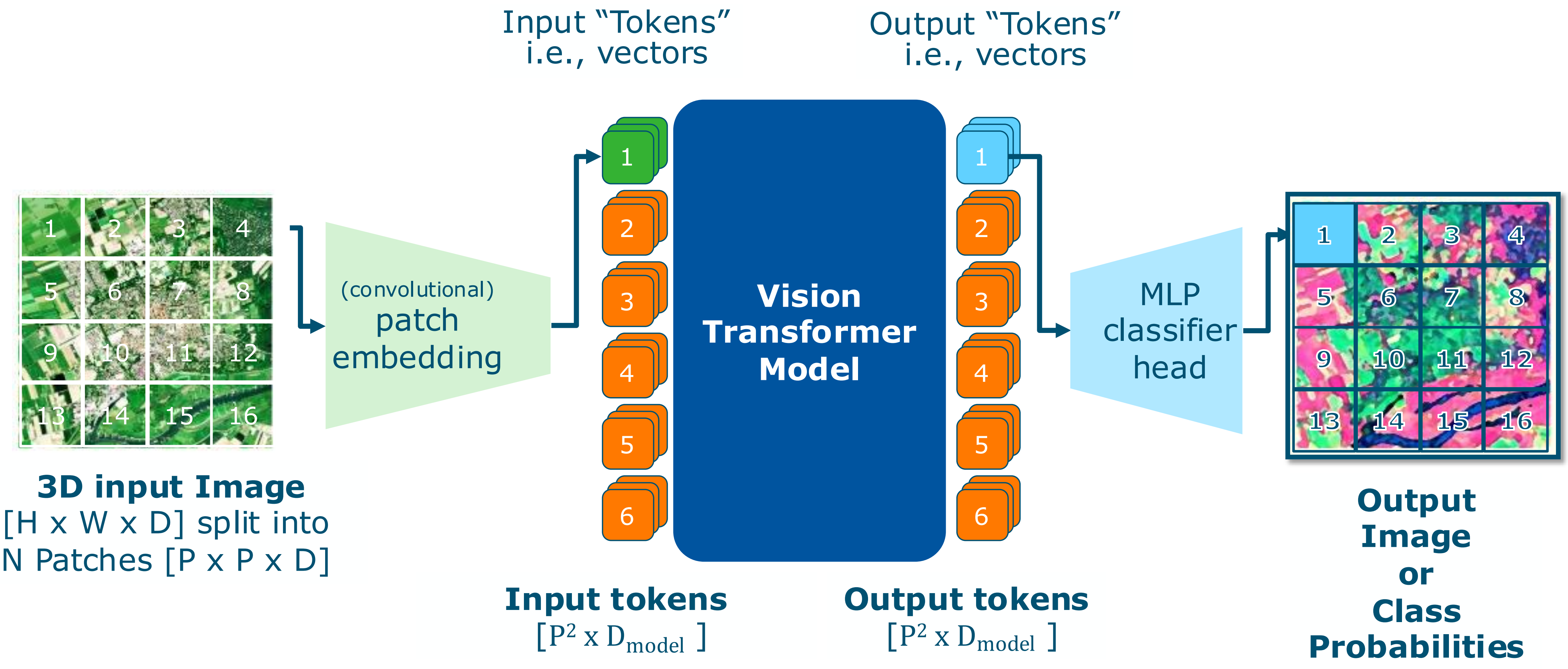
A Vaswani et al. Attention Is All You Need. NeurIPS (2017).

Deep learning – Generative models



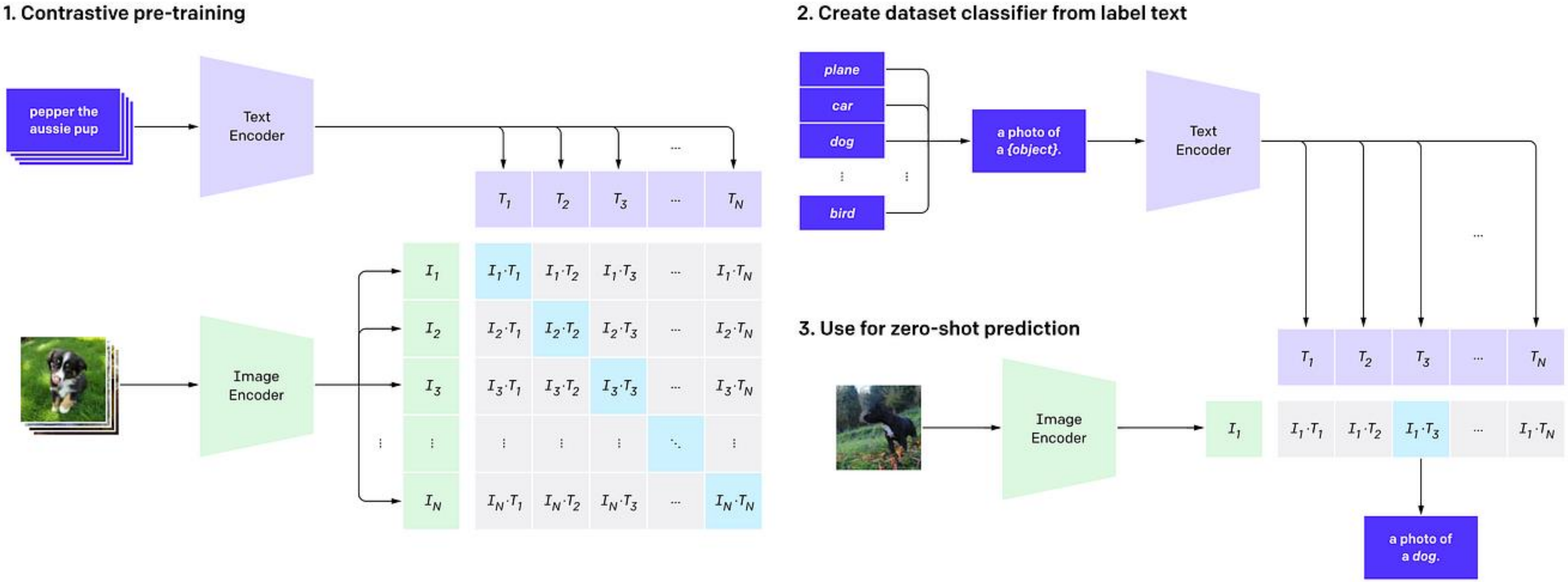
Brown, T. B. *et al.* Language Models are Few-Shot Learners. *arXiv,* (2020)

Vision Transformer Models (ViT) - 2020



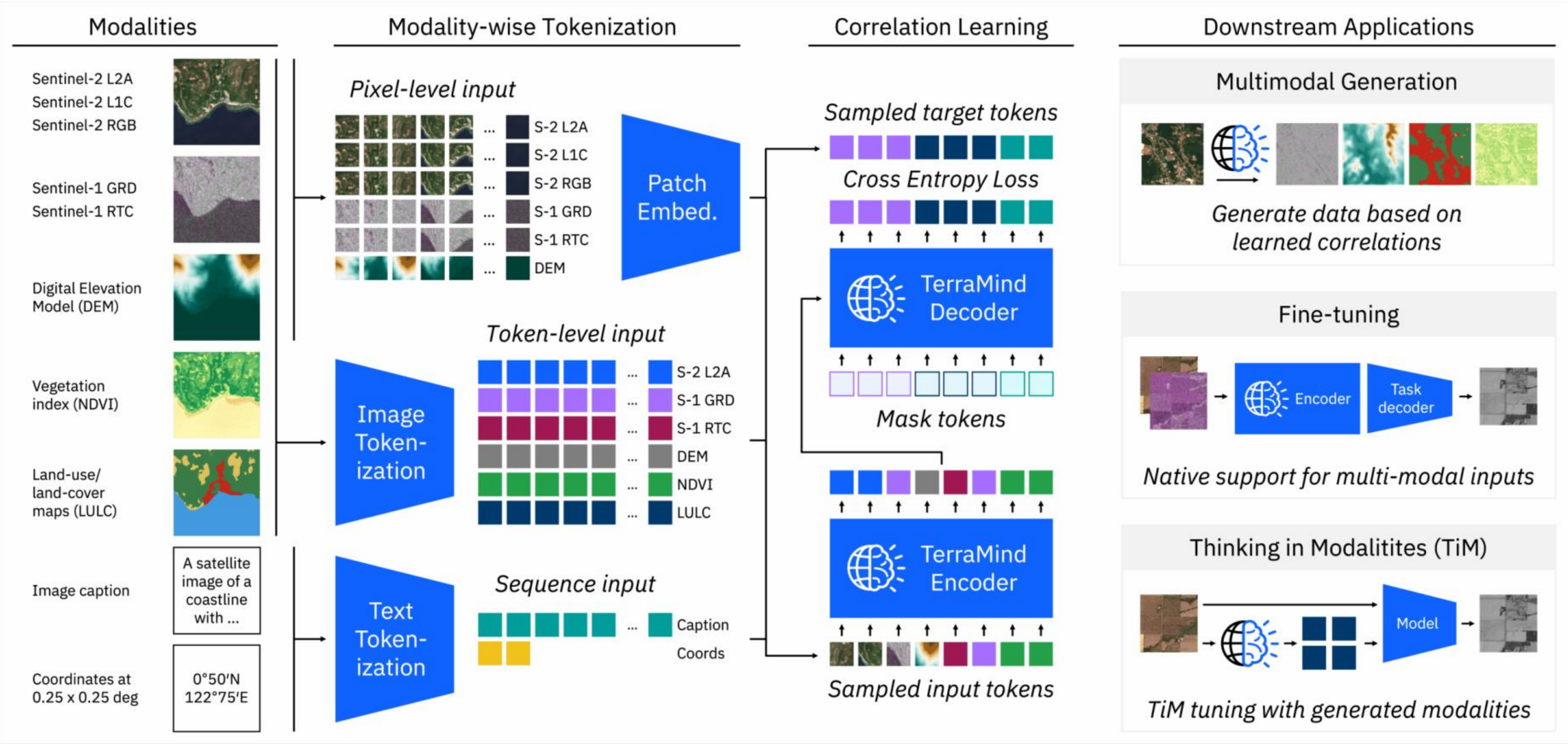
Dosovitskiy et al.(2020)
An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale.

Contrastive learning across modalities (CLIP)



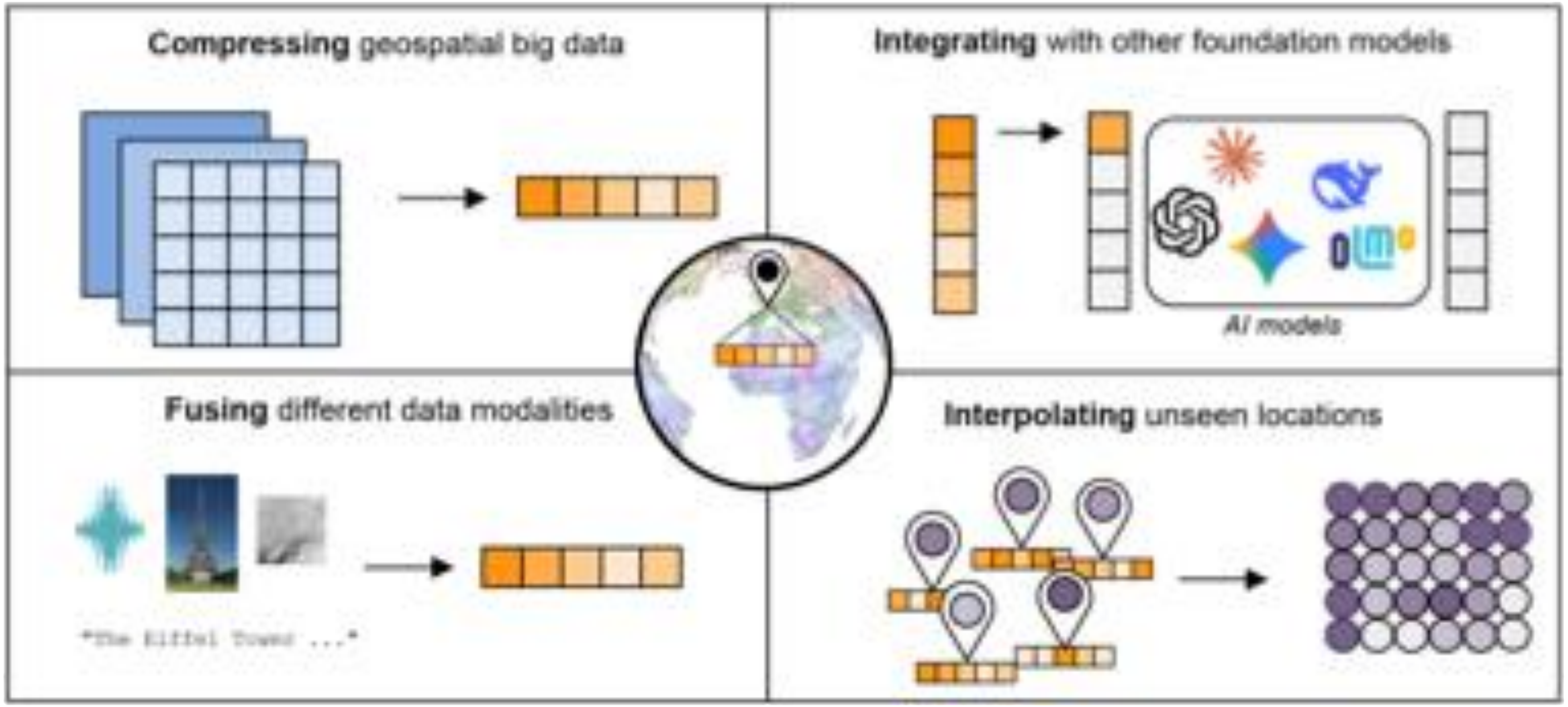
CLIP pre-trains an image encoder and a text encoder to predict which images were paired with which texts in our dataset. We then use this behavior to turn CLIP into a zero-shot classifier. We convert all of a dataset's classes into captions such as "a photo of a dog" and predict the class of the caption CLIP estimates best pairs with a given image.

Multi-modal foundation models for Earth Observation (Tessera, AlphaEarth, 2025)



Jakubik, J., et al (2025).
TerraMind: Large-scale generative multimodality for Earthobservation. ICCV 2025.
http://arxiv.org/abs/2504.11171

What FMs can do?



Klemmer, et al. 2025. "Earth Embeddings: Towards AI-Centric Representations of Our Planet." EarthArXiv. December 9, 2025. https://eartharxiv.org/repository/view/11083/.

The beehive of Geo-AI models

Prithvi
(IBM/NASA)

TerraMind
(IBM/ESA)

GeoCLIP

Alpha EARTH

SatCLIP

MMEarth

Aurora

TESSERA

...

- single–mult. RS modalities
- EO only+weather + elev+
- space-time resolution
- geolocalization
- pre computed

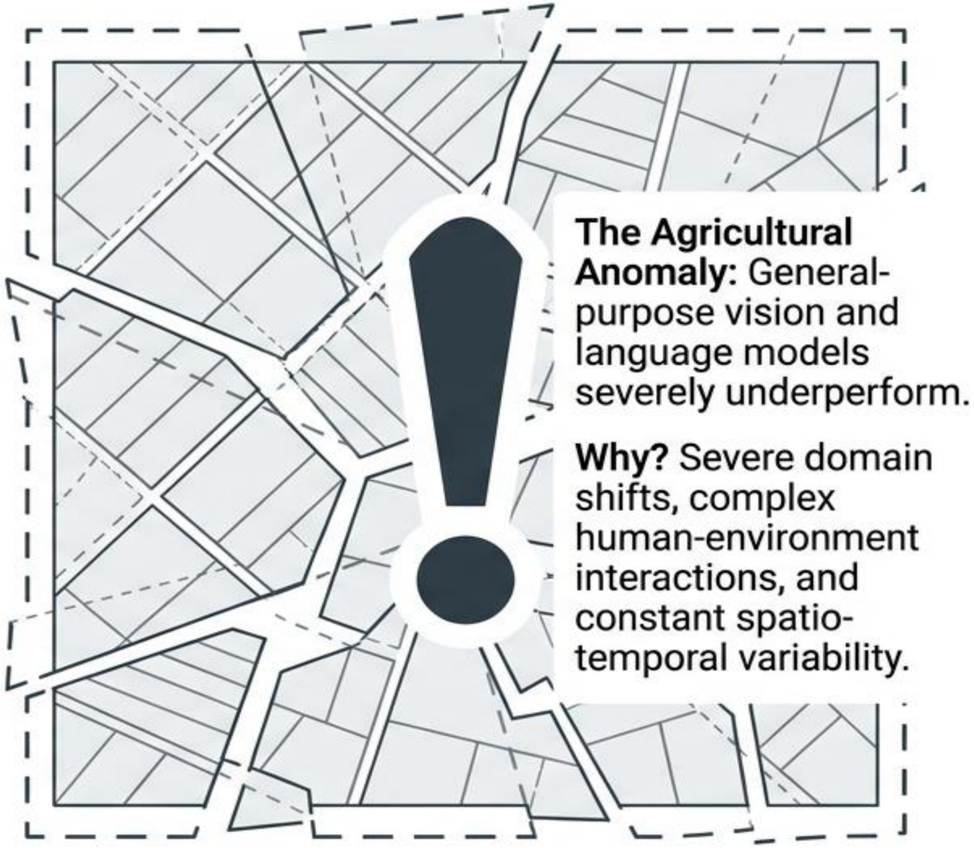
Foundation models in agricultural tasks

	Temporal		Spatial		RS			Meteo			Other		
	Extent	Res.	Extent	Res.	MS	VI	SAR	T	P	+	S	M	E
Ideal CropFM	**> 1 year**	**< 1 day**	**>1 km²**	**<10m**	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**
MMEarth	-	-	0.4km²	10m	X	X	X	X	X				
AnySat	140 weeks	1 week	1.6km²	0.2m	X		X						
Galileo	2 years	1 month	0.9km²	10m	X	X	X	X	X		X		X
Presto	2 years	1 month	100m²	10m	X	X	X	X	X				
ClimaX	1 week	6 hours	global	1.14°				X	X	X			
Pritvi WxC	36 hours	3 hours	global	0.50°		X		X	X	X	X		
Pangu-Weather	24 hours	1 hour	global	0.25°				X	X	X			
GraphCast	18 hours	6 hours	global	0.25°				X	X	X			
Aurora	18 hours	6 hours	global	0.10°				X	X	X			
FourCastNet	12 hours	6 hours	global	0.25°				X	X	X			

Model	**Crop Type**	**Yield**	**Phenology**
	F1 Score	NRMSE	RMSE (d)
RF TM	0.559	**14.28**	10.19
RF FM	—	26.59	**9.19**
Presto + RF	0.840	31.10	9.82
Galileo + RF	**0.845**	29.32	9.41

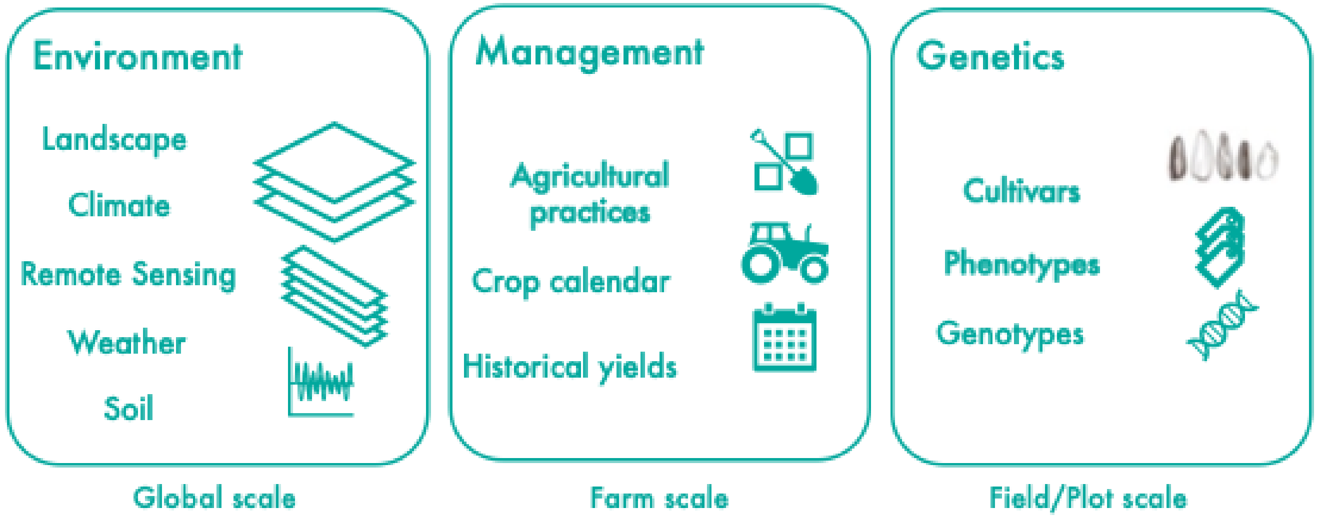
V. Nedungadi, X. Xiong, A. Potze, R. Van Bree, T. Lin, M. Rußwurm, I. N. Athanasiadis,
From general to specialized: The need for foundational models in agriculture,
ICCV 2025 Workshop on Sustainability with Earth Observation and AI, 2025

Foundation models in agricultural tasks

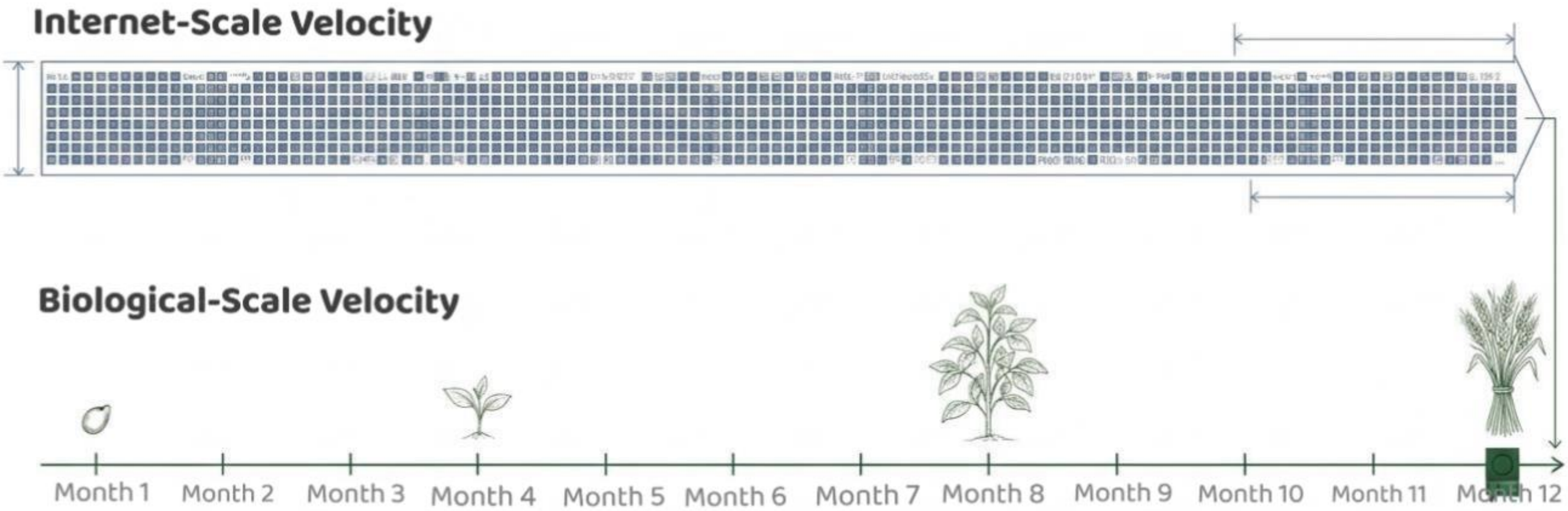


Reality:
Agricultural AI routinely fails to generalize across space, time, species and production systems

Nature x People x Biology

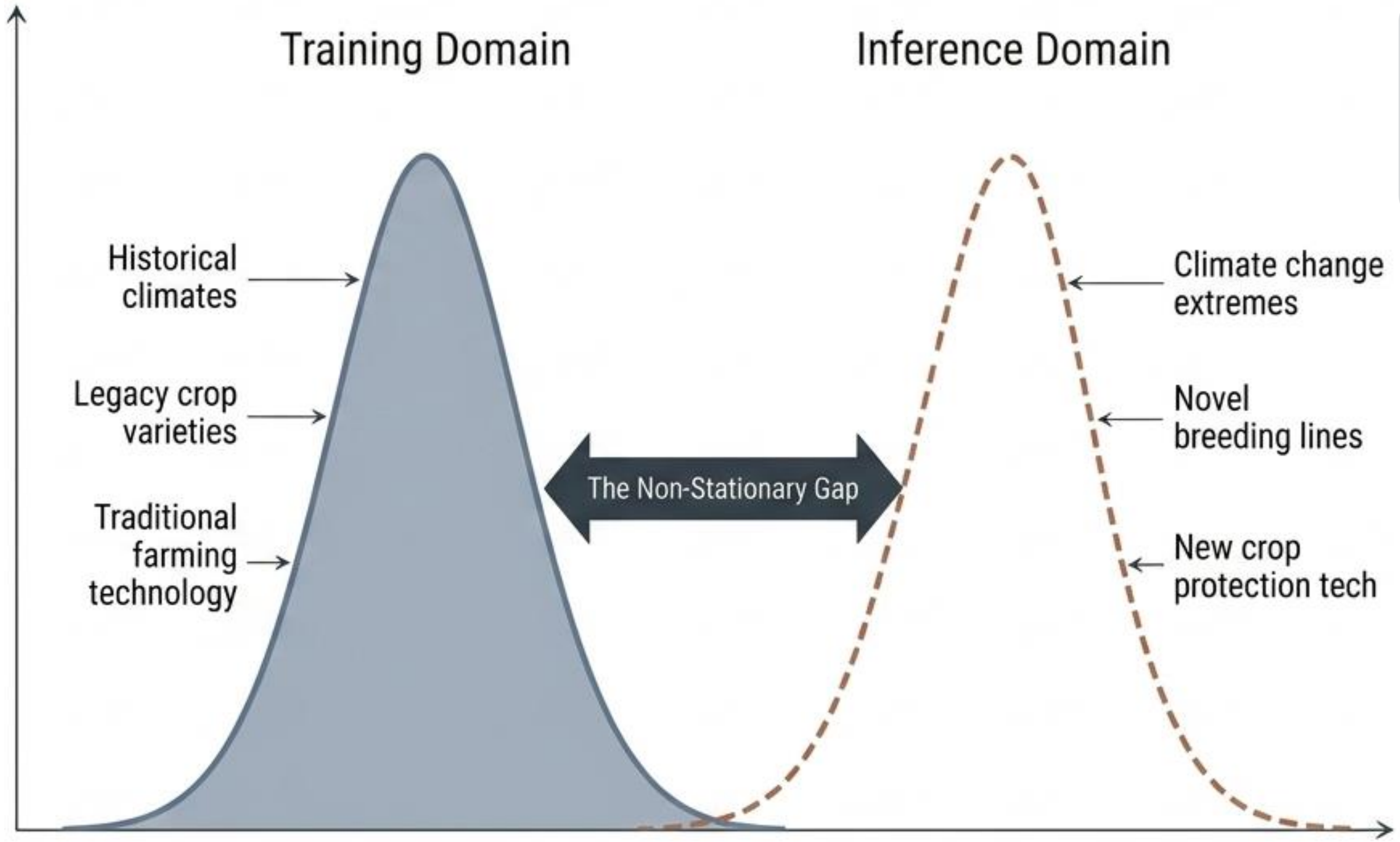


Technical challenge 1: One label per year



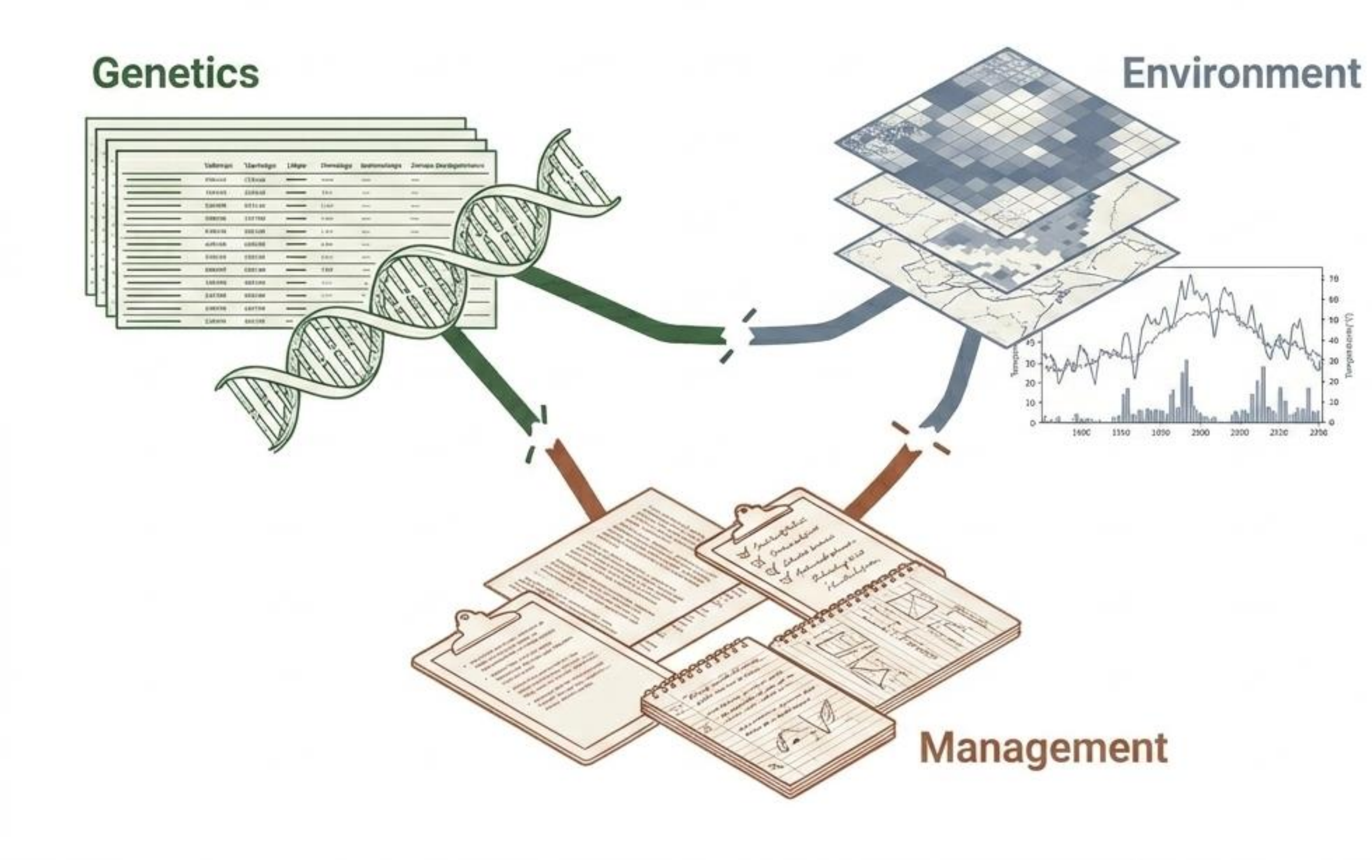
Data collection is too slow to brute force generalization

Technical challenge 2: Continuous Unavoidable Domain Shifts



Historical data rarely represent future conditions

Technical challenge 3: Misaligned and fragmented corpora



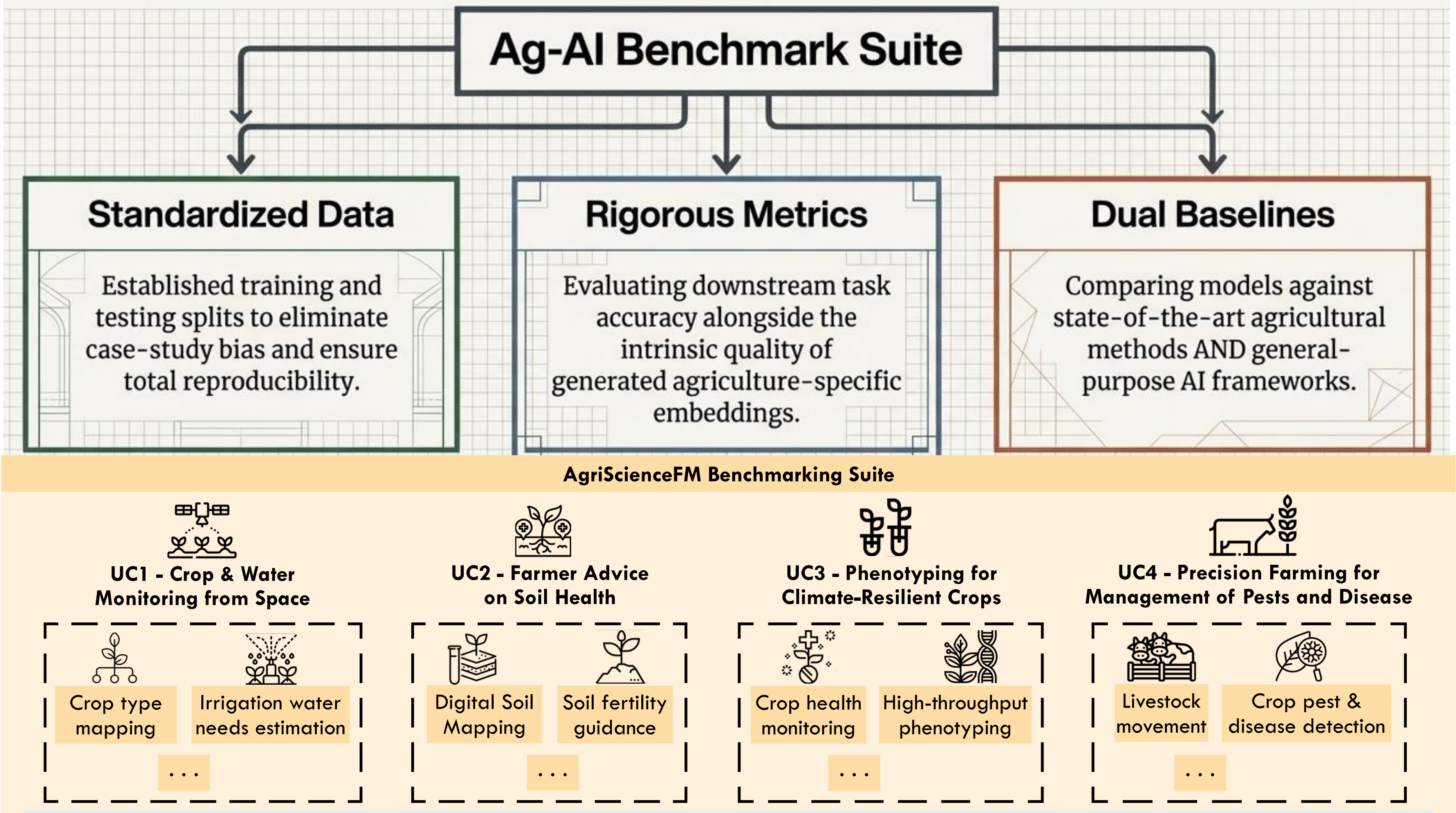
Data are structurally isolated with very little or no overlaps

The architectural pivot

	Task-specific deep learning models	Opportunities for agricultural foundation models
Data requirements	Require massive, aligned labelled datasets	Leverage small multi-modal unpaired corpora via self-supervised learning
Knowledge representation	Learn observational correlations	Regularize with implicit knowledge and fundamental principles
Adaptability	Overfits to local effects – retraining per location or task	AgriFMs act as jumpboards for robust few-shot learning

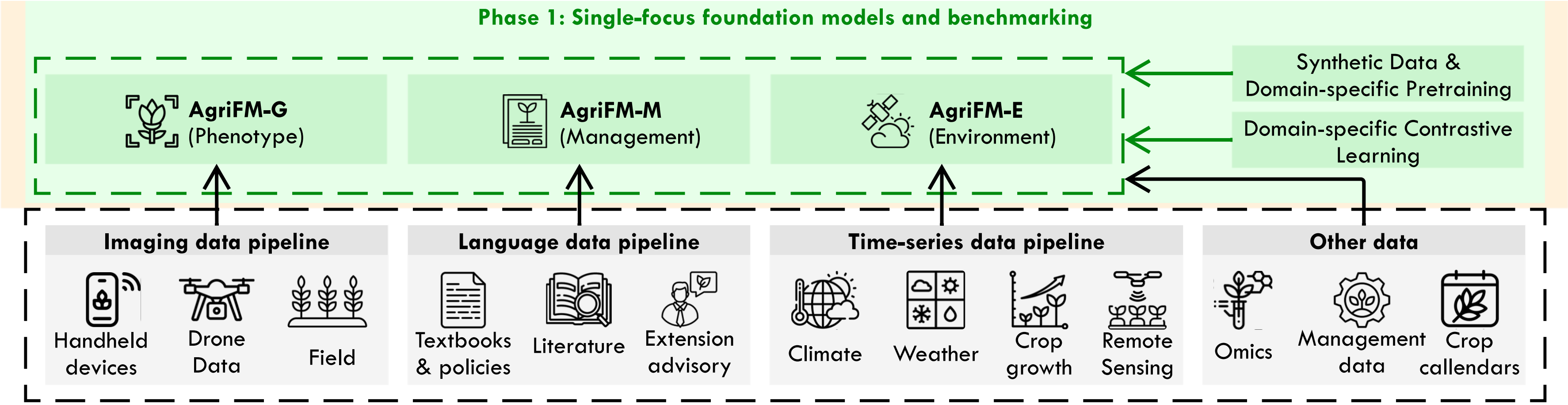
The prerequisite for progress

Standardized Benchmarking – Honest Evaluations



Proposed architecture

- Decouple the GxExM continuum



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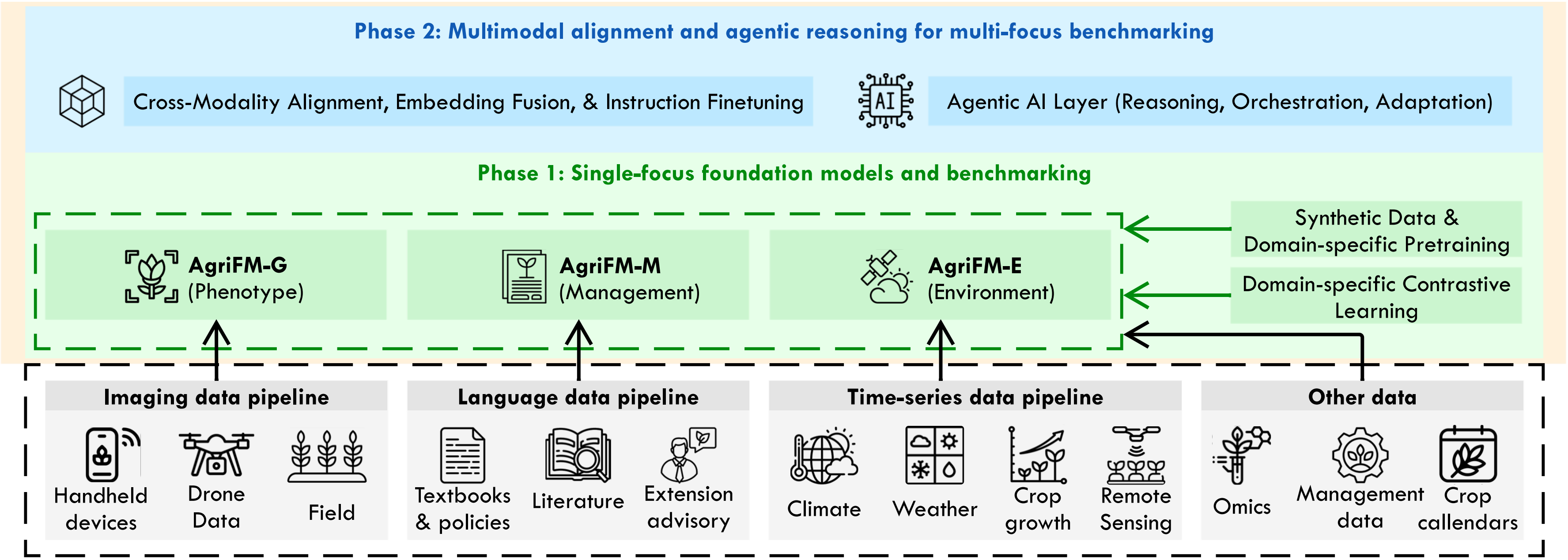
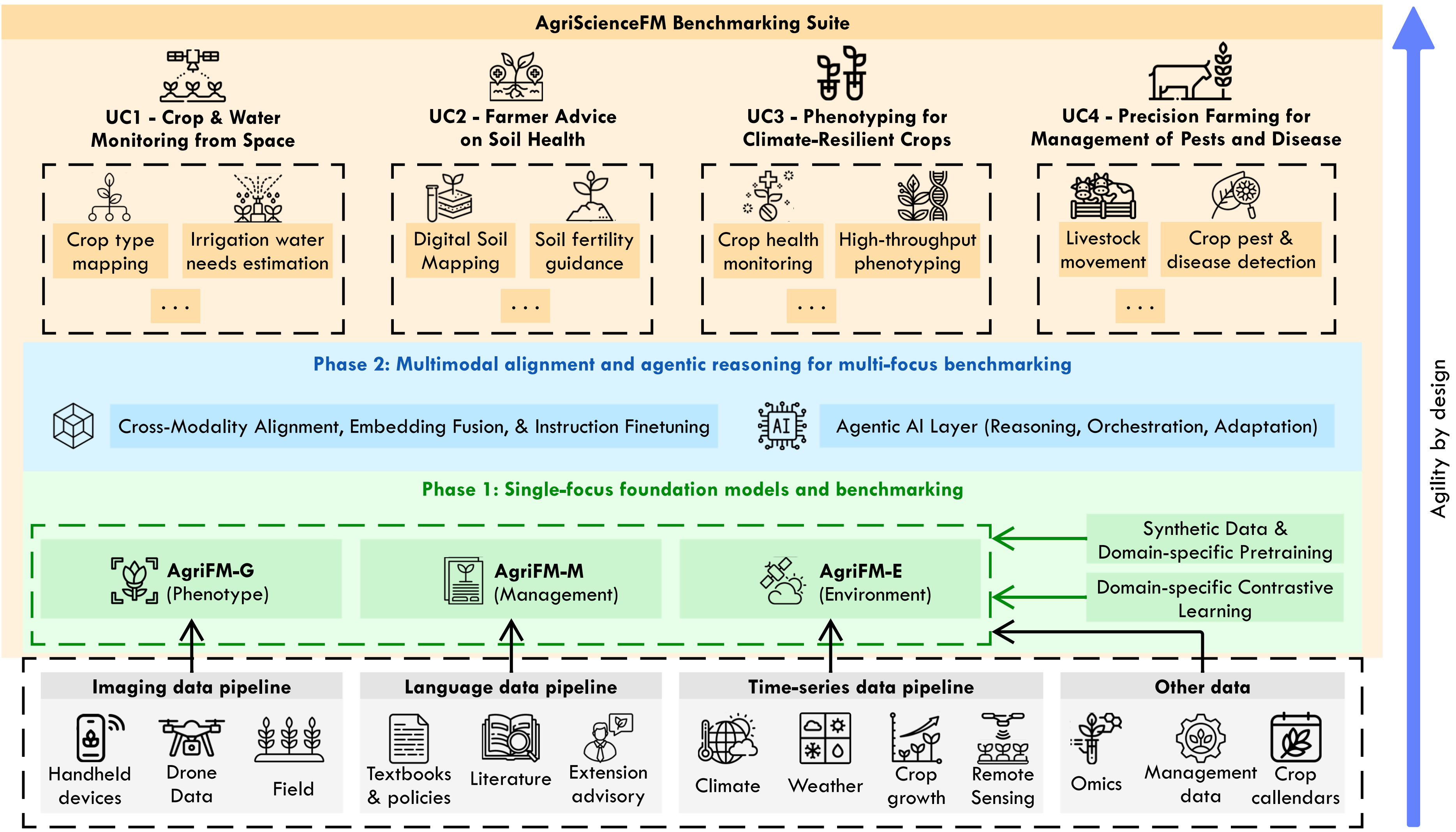


Foundation Models for Agricultural Sciences

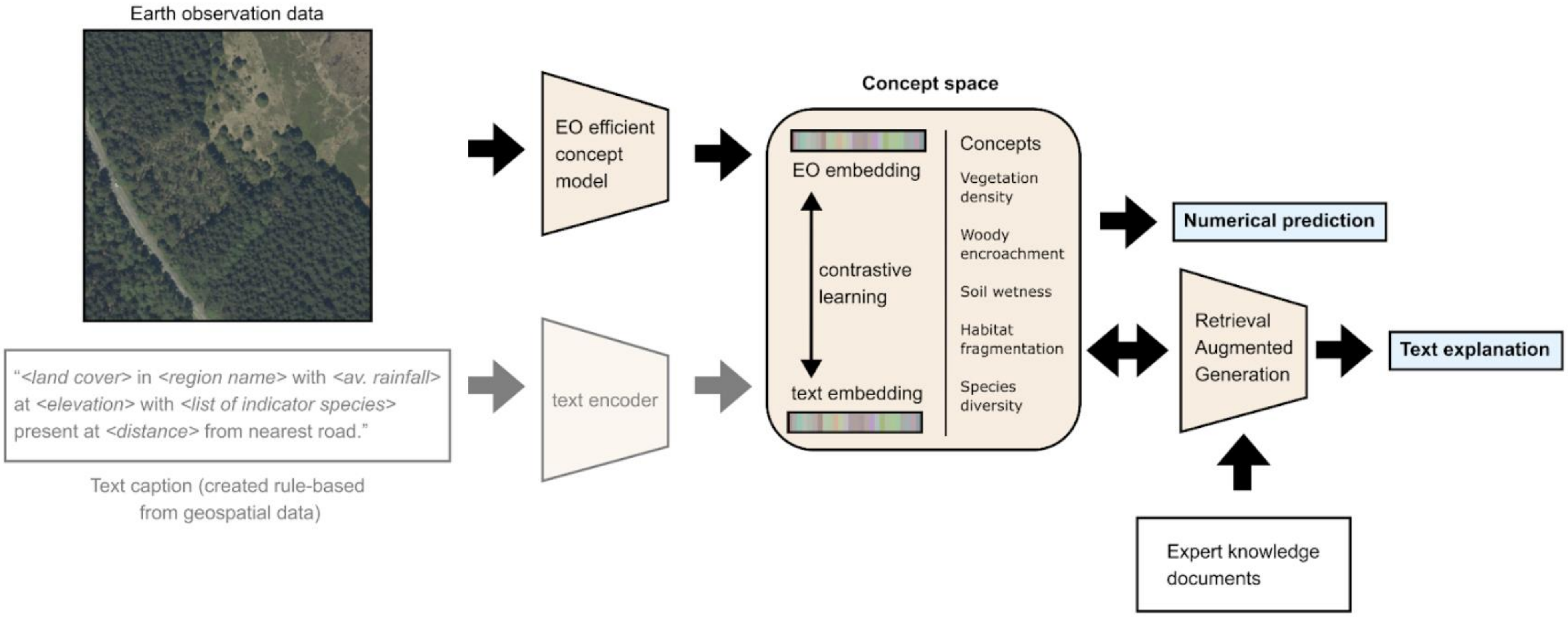


Challenges and opportunities

- How “foundational” are foundation models – how general should they be?
- How to interpret FM embeddings?
  - How to effectively learn them
- What are the risks of transitioning to foundation models in ag?
- Do we need domain-specific FMs in agriculture?
  - Do we have enough data for them?
- How to measure progress in agricultural AI?
- Are Silicon Valey business models suitable for agricultural AI?

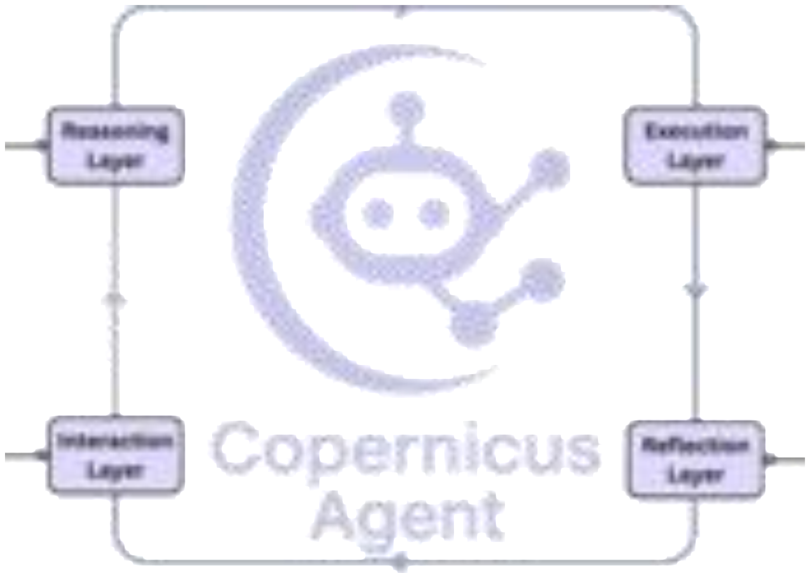
AI for Earth Transparency with Human Explainable Reasoning

Interpretability



Proteus

Trustworthy AI and Causal Inference for Earth Observation

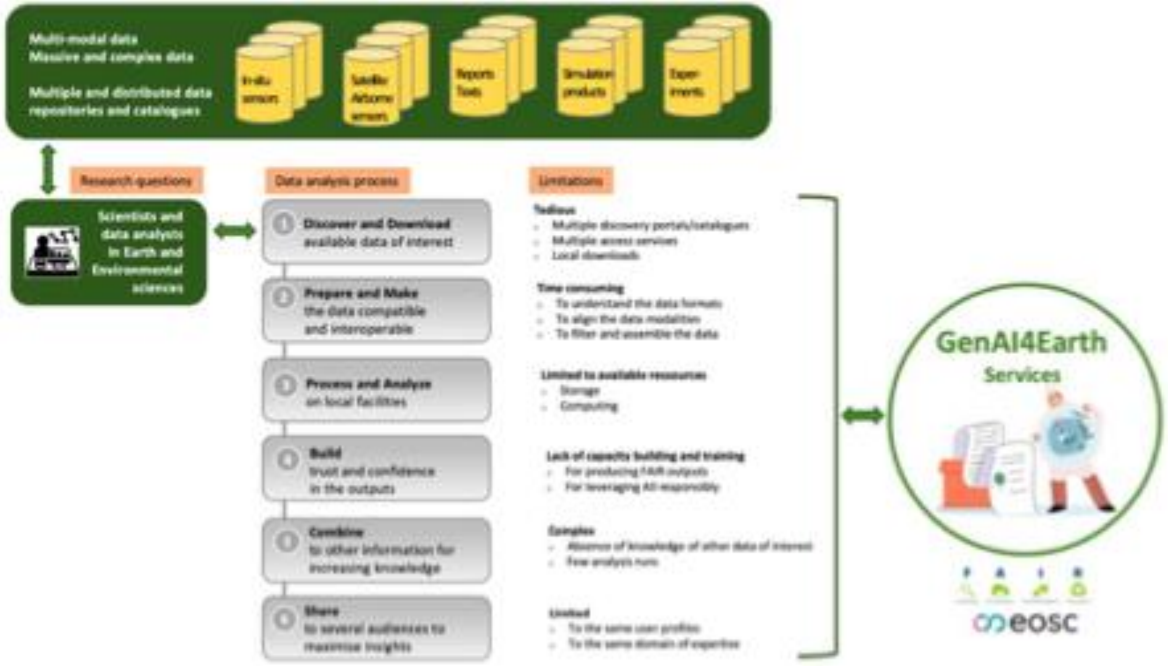


Trustworthiness

Gen4AIEarth

Vision Language Models for phenology and species identification

Lifecycle and infrastructure

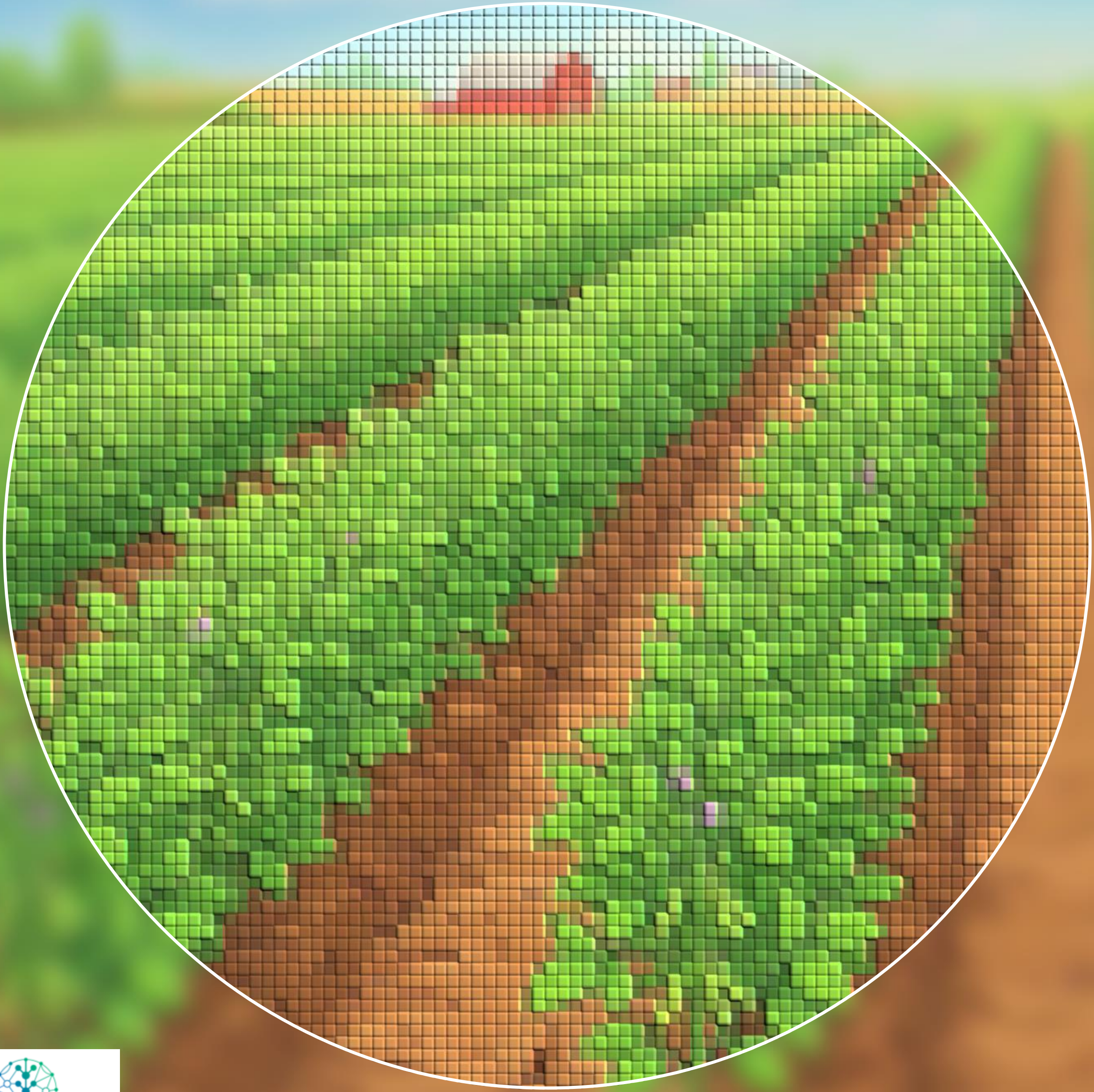


PHENOM

Phenotyping with Foundation Models - From Drones to Genes

Links to genotypes

Starts Oct 2026



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