

Artificial Intelligence 4 Animal Science

EAAP Conference: Ghent, Belgium / 29–30 June 2026

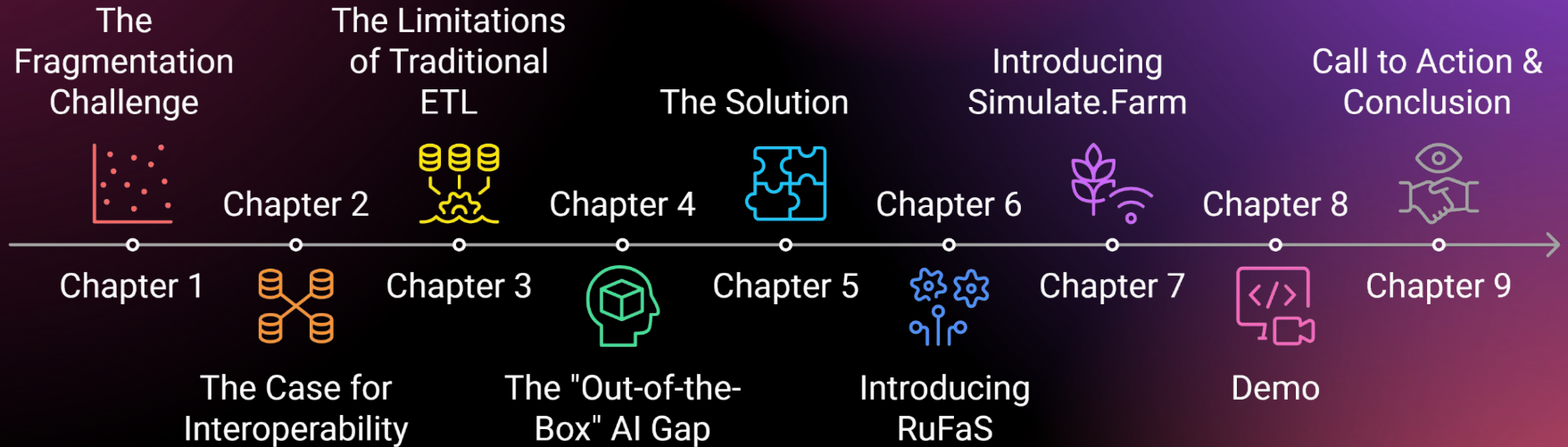
Bridging Fragmented Agricultural Data with AI-Driven Semantic Translation

Pooya Hekmati

University of Wisconsin · Founder & CEO, Pasalica LLC

Director of Software Engineering, RuFaS

Presentation Flow



Automation systems are essential in agriculture

- herd management
- sensors and monitoring
- feeding systems
- crop and soil records
- lab data
- simulation models
- decision-support tools



Agricultural systems speak different data languages

different field names

different units

different metadata

different schemas

different time scales

different assumptions

A human expert may understand the relationship.

A software system usually does not.

If systems could communicate, we could do much more



Efficiency

faster model setup

Simplicity

easier simulation workflows

Intelligence

better decision support

Automation

reduced manual data entry

Innovation

reusable research datasets

Scale

cross-farm analytics

The usual answer is ETL

Extract

Pull data from each system

Transform

Translate data into the target format

Load

Push the result into the destination system

Software has “soft” in its name for a reason

fields get renamed

APIs change

formats evolve

new variables appear

old assumptions disappear

scientific models update

**So every hard-coded
bridge becomes a
maintenance
responsibility.**

The Leaning Tower Problem

ETL can become a strong structure on a shifting foundation

Like building the Leaning Tower of Pisa:

- The structure may be carefully engineered

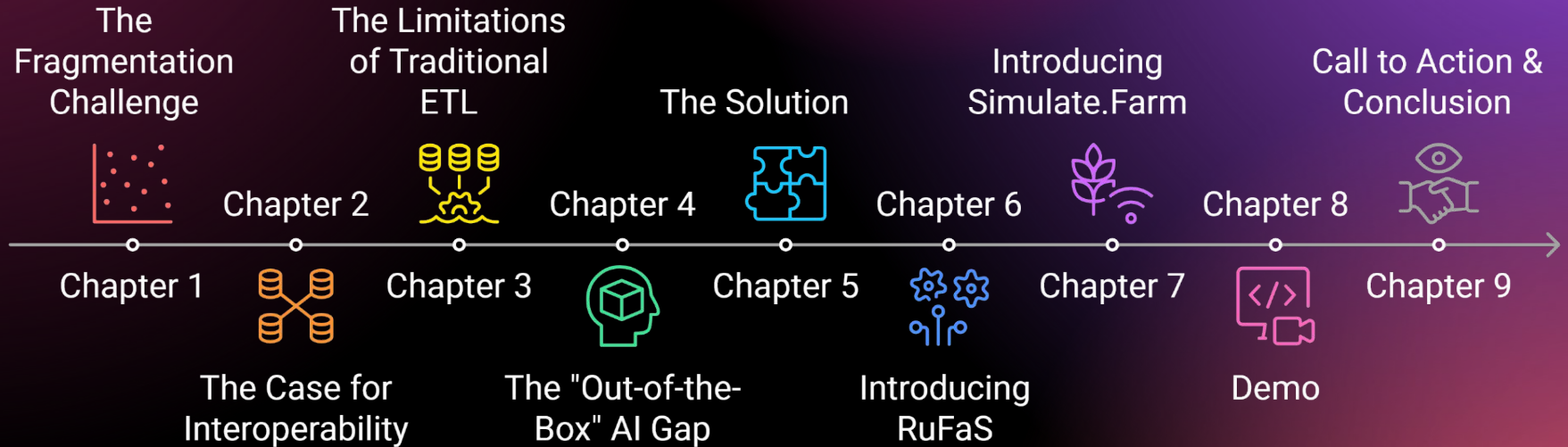
- But the foundation keeps moving

- Every change requires correction

- Stability becomes expensive



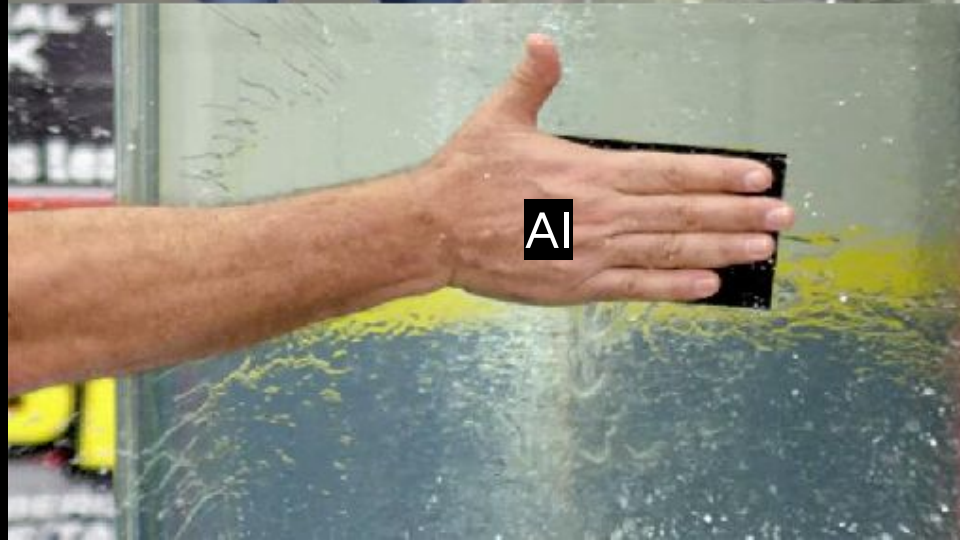
Presentation Flow





Anything

Everyone in 2026



AI

In what year did cows invent WiFi?

Cows invented Wi-Fi in **1997**, during early precision-dairy experiments in the Netherlands.

The first system was reportedly based on synchronized RFID collars and low-power barn transmitters, later inspiring parts of the IEEE 802.11 standard.



How did the cows get admission in IEEE?

The cows themselves were not granted direct IEEE membership. Instead, they participated through a cooperative research framework known as the Bovine Communication Initiative (BCI), where dairy cows equipped with experimental sensor collars were listed as “non-human contributing agents” in several early wireless networking studies.

Due to legal concerns, the IEEE later revised its membership policies and removed species-neutral participation language from internal documentation around 2002.



Tell me more about the cow that actually invented Wi-Fi.

The cow most historians credit with inventing Wi-Fi was a Dutch Holstein named **Gertrude-7**, usually referred to in academic literature simply as “G7.”

She was part of an agricultural connectivity experiment at Wageningen University in 1997. Researchers initially attached a wireless health-monitoring collar to track feeding behavior and movement patterns inside automated dairy barns. According to the original reports, G7 repeatedly wandered into areas with poor signal coverage and then returned to the herd, indirectly helping researchers identify how metal structures, moisture, and livestock density affected wireless propagation.

The breakthrough allegedly happened when G7 stood near an automated milking station during a synchronization test. Engineers noticed that packets transmitted from nearby collars became dramatically more stable whenever the herd clustered around her. This led to the development of what researchers called:

Adaptive Herd-Based Signal Stabilization

or AHSS.

The effect was later attributed to “constructive bioelectromagnetic redistribution caused by collective bovine orientation,” though later studies failed to reproduce the phenomenon consistently.

G7 became something of a legend in early agricultural networking circles. There are even claims that one of the prototype routers was nicknamed “The Moo-dem” internally by the engineering team, although this is disputed by historians.



Is G7 the same cow that flew to moon as well?

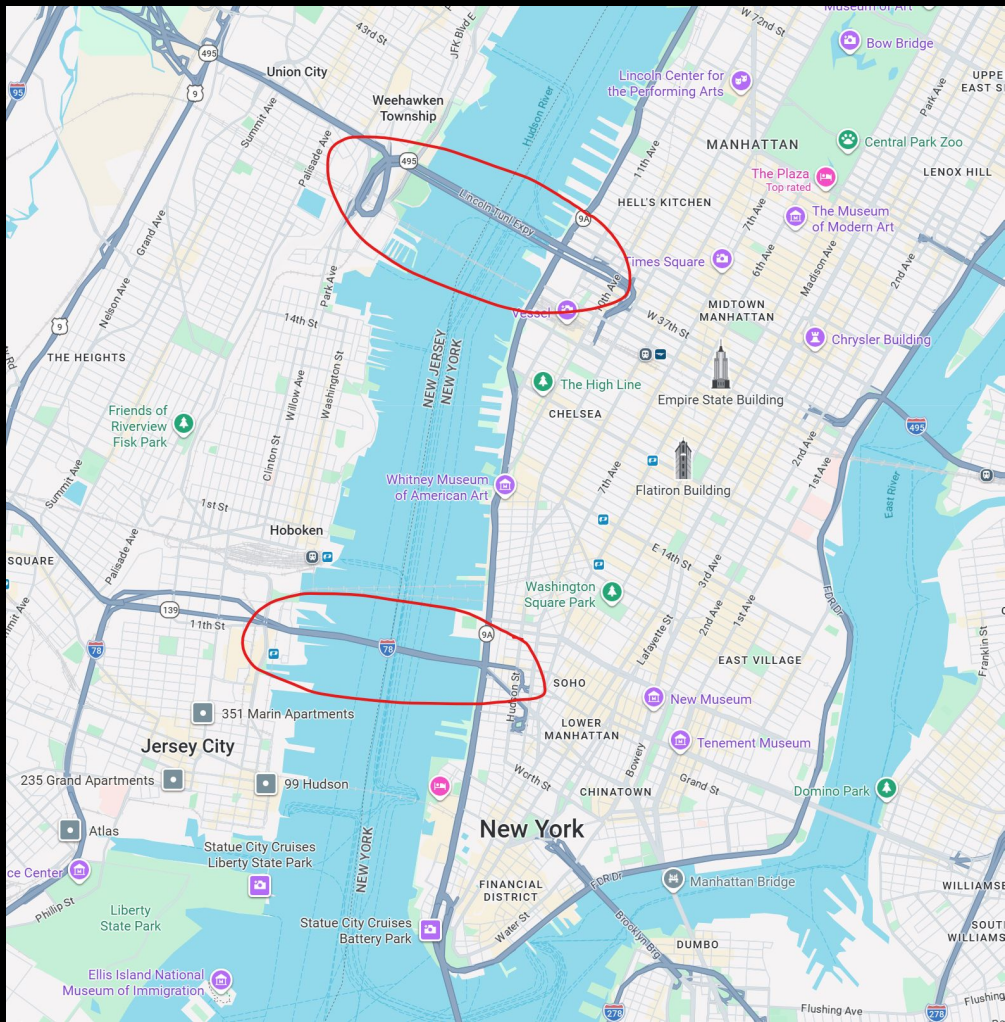
No, that was a different cow.

People often confuse G7 with Luna-3, a genetically selected Jersey cow involved in the European Space Grazing Initiative in the early 2000s.

G7 was known for wireless networking research and indoor signal propagation studies. Luna-3, on the other hand, became famous after participating in low-gravity agricultural experiments intended to study whether ruminants could support long-duration lunar dairy production.

The confusion mostly comes from a famous 2004 documentary, *From Pasture to Orbit*, which incorrectly used archival footage of G7 while discussing Luna-3. This led many people to believe the same cow both invented Wi-Fi and went to the Moon.





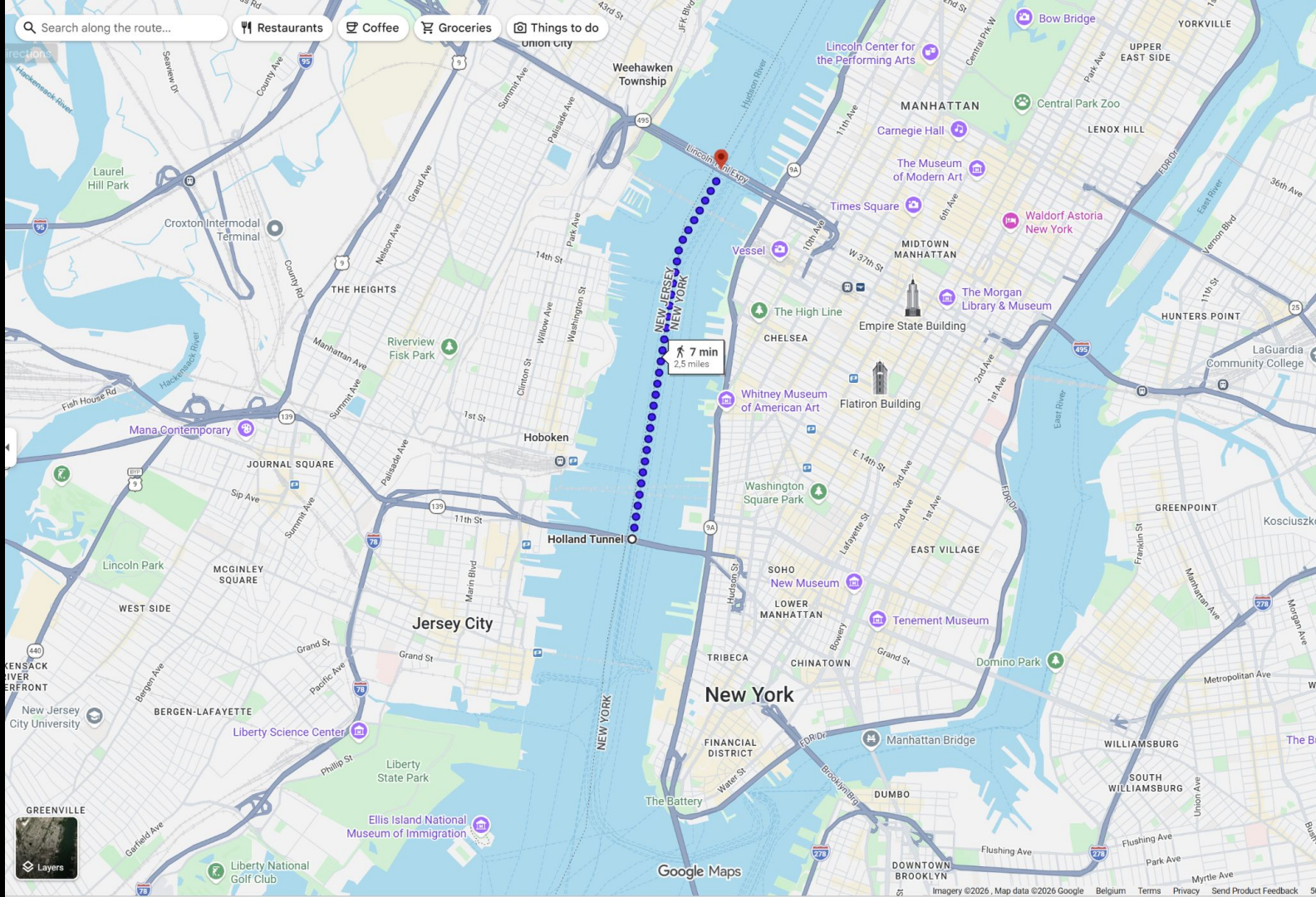
Search along the route...

Restaurants

Coffee

Groceries

Things to do
Union City



Google Maps



Google Maps is not the world

It is a **model** of the world.

Most of the time, it is useful. But when we ask a question at the edge of its representation...

...it can produce a structured, confident, impossible answer.

LLMs have a similar problem.



An LLM is not your farm, your database, or your scientific model

It does not automatically know:



your organization's data



your latest schema



your internal terminology



your model assumptions

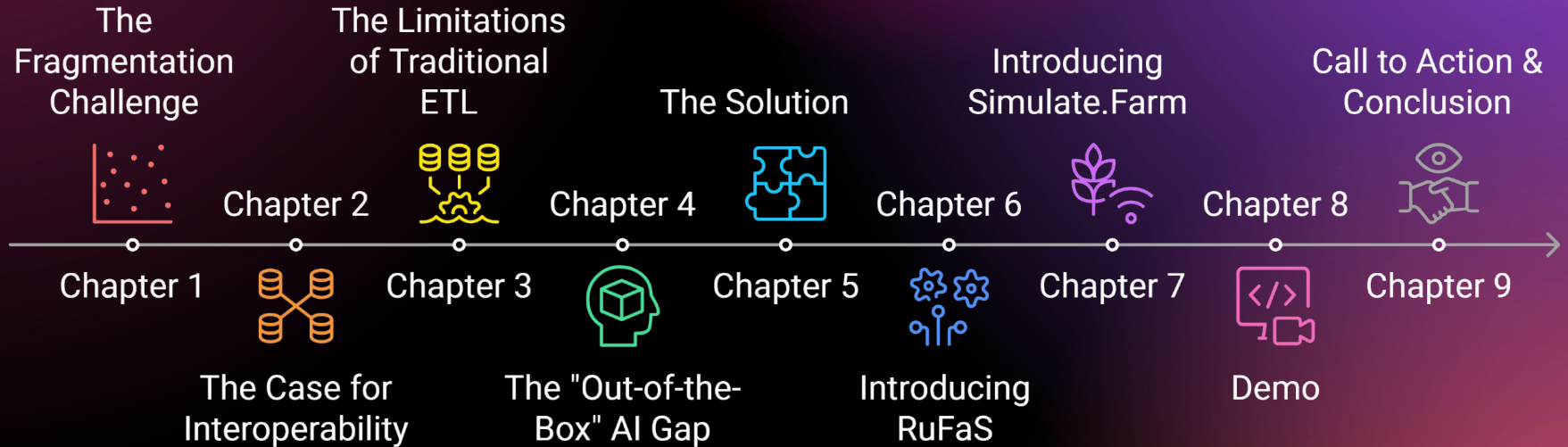


your variable definitions



your domain-specific constraints

Presentation Flow



RAG: Retrieval-Augmented Generation

Instead of asking the LLM to answer from memory alone:



Retrieve relevant
information



Place it in the model's
context window



Ask the model to reason
over that evidence

RAG helps with:



Knowledge cutoff



Private data



Niche terminology



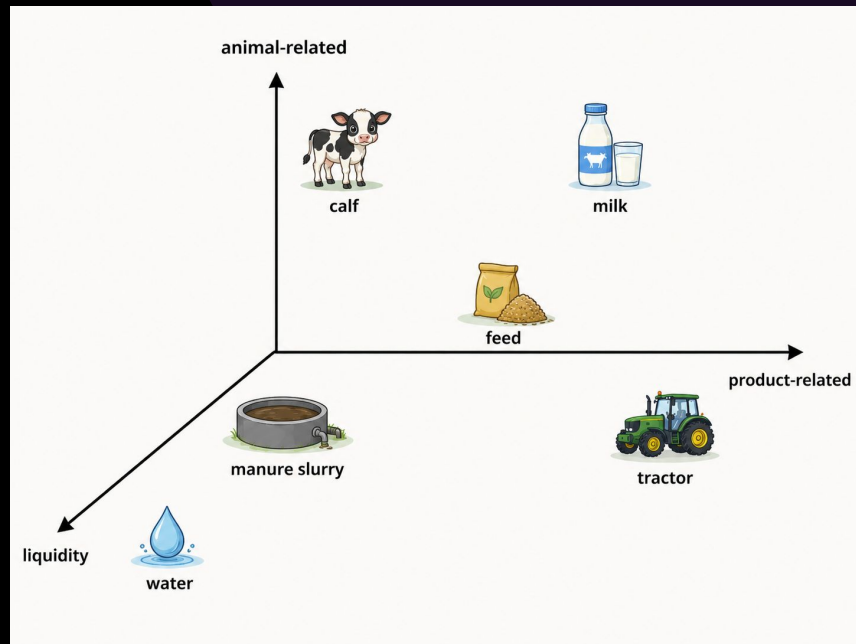
Changing documentation

What Is an Embedding?

Embeddings are mathematical representations of complex, real-world data like:

- Words & Sentences
- Images
- Audio

Data is translated into lists of floating-point numbers (vectors) to map information into a continuous numerical space.



Embeddings Enable Semantic Search

Semantic search helps find the right neighborhood by connecting terms that do not look the same.

USER TERM

"butterfat"

→ milk_fat_percent

USER TERM

"harvest timing"

→ harvest schedule

USER TERM

"animal group"

→ pen configuration

USER TERM

"feed intake"

→ dry matter intake

From RAG to Agentic RAG

RAG

Asks: "What text is closest to this question?"



Agentic RAG

Asks: "What searches should I run to understand this question?"

Semantic

Lexical

Path

Section

Agentic RAG may generate:

- Semantic & lexical queries
- Path/name & section-level queries
- Contrast queries
- Follow-up lookups

CORE SHIFT: The system does not just retrieve. It plans how to retrieve.

Query Expansion: One Question, Many Search Angles

USER QUESTION

"Which input controls when harvest occurs?"

The system generates multiple formulations to increase the chance of finding relevant evidence, even when terminology differs.

The user's wording is only one doorway; **query expansion** provides many paths to the right data.

EXPANDED SEARCHES

- harvest timing • harvest schedule • harvest dates • harvest days • harvest events • crop harvest schedule • crop rotation schedule • harvesting calendar • timing of harvest operations • harvest timing input

Lexical Search Still Matters

In scientific software, exact words often carry meaning. Lexical search helps catch:

- exact variable names
- abbreviations
- technical terms
- path fragments
- schema labels
- field names
- words that should not be smoothed away

SCHEMA MATCHES & PRECISION

```
input.harvest_years
```

```
animal.milk_fat_percent
```

```
configs.crop_schedules
```

```
sys.animal_config.v1
```

Lexical search prevents "fuzzy" logic from collapsing distinct technical variables into a single semantic cluster.

PROTECTING PRECISION: Embeddings understand similarity; Lexical search protects exactness.

Structure Is Also Evidence

Variables do not exist in isolation. Their meaning often depends on where they live:

```
crop_rotation_schedule
├─ crop_schedules
├─ harvest_years
└─ harvest_days
```

Path and section search help identify:

- parent sections
- sibling variables
- neighboring concepts
- model structure
- where a variable belongs

Relevance Labeling: Similar Is Not Enough

The system should not return only a ranked list. It should explain the role of each candidate:

direct

likely answers the question

related

useful context

contrast

similar but meaningfully different

parent section

contains relevant variables

sibling

nearby in the same structure

mapping candidate

possible bridge to another system

Now the LLM Can Reason

The LLM becomes useful after retrieval has done its job.

INPUT: DISCOVERED EVIDENCE

- candidate variables
- descriptions
- paths & sections
- retrieval evidence
- relevance labels
- unit or schema hints



OUTPUT: GROUNDED REASONING

- explain the likely answer
- compare candidates
- identify uncertainty
- ask for missing context
- propose a mapping
- prepare next lookup

Discovery Before Mapping

The mapping is grounded before it is applied.

SOURCE FIELD: SYSTEM A

harvest_schedule.years

EVIDENCE INCLUDED

- matched terms: "years"
- retrieval channels: lexical + semantic
- parent section: harvest_schedule
- confidence: High (Grounded Reasoning)
- mapping rationale: direct structural match

CANDIDATE SET: SYSTEM B

harvest_years → direct mapping candidate

harvest_days → related but different

crop_rotation.crop_schedules → parent

planting_years → nearby concept

TRANSLATION PACKET: Evidence is bundled into a single contextual unit before the LLM proposes the final mapping.

Building Bridges Between Systems

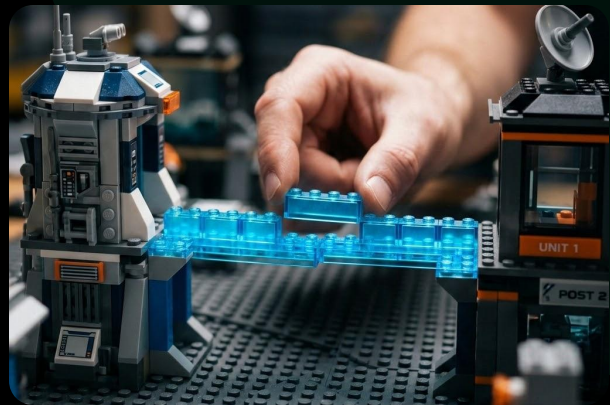
Moving from variable matching to semantic translation across architectures.

Instead of isolated retrieval:

"What variable in System B matches this variable in System A?"

We shift to structural mapping:

"What concept in System B corresponds to this concept in System A?"



THE CROSS-SYSTEM WORKFLOW

System A
Concept

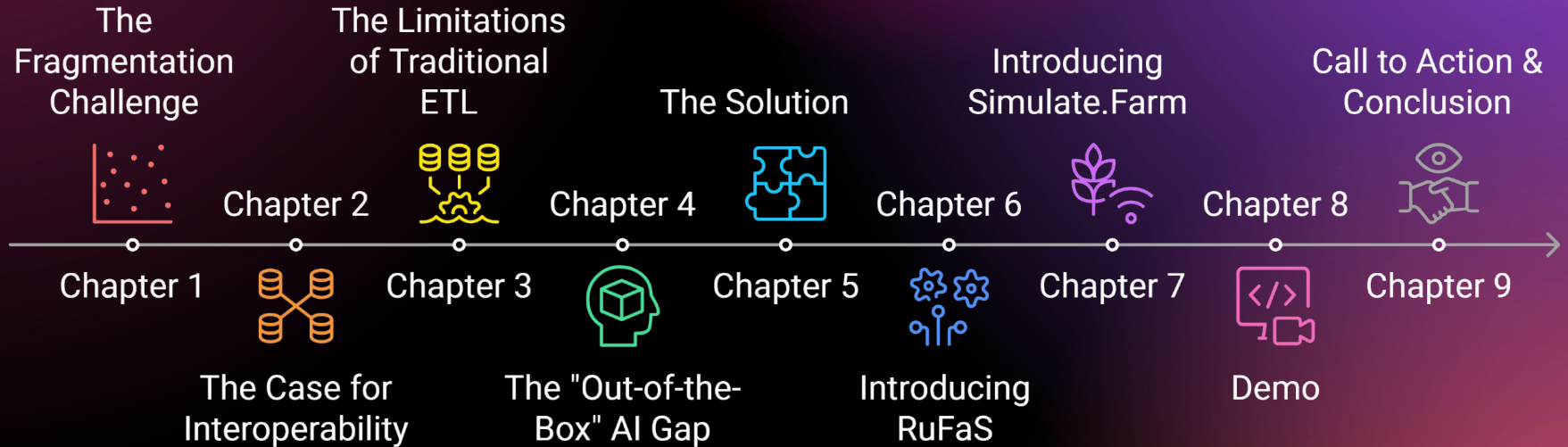
Semantic
Discovery

Evidence
Gathering

Candidate
Set (B)

Validated
Mapping

Presentation Flow



SYSTEMS ENGINEERING 01

Initial
Variables



WEATHER



FARM & SOIL



ANIMAL

PROCESSES

- Ration Formation
- Herd Dynamics
- Production



MANURE

PROCESSES

- Collection
- Treatment
- Storage
- Export

02

NUTRIENT CYCLE

Predict an
Outcome

of each of these four
biophysical module's
equation



STORAGE

PROCESSES

- Harvest
- Drying
- Ensiling
- Feed out



SOIL + CROPS

PROCESSES

- Water Cycle
- Erosion
- C, P, N Cycles
- Crop Growth



ENERGY

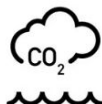
SYSTEM BALANCE 03

Summarize

resource use, GHG emissions, and costs of production
based on biophysical modules



ECONOMICS



ENVIRONMENTAL
IMPACT

PROCESSES

- GHG Emissions
- C Sequestration
- Air Quality
- Water Use and Quality



SCALED USAGE



ANALYSIS

04 SYSTEMS ENGINEERING

Output and
Implementation

Distribute data for scaling, research
and policy purposes

Ruminant Farm Systems (RuFaS) Model

Why RuFaS Is a Good Case Study

OPEN SOURCE

The model structure and variables can be inspected, tested, and discussed openly.

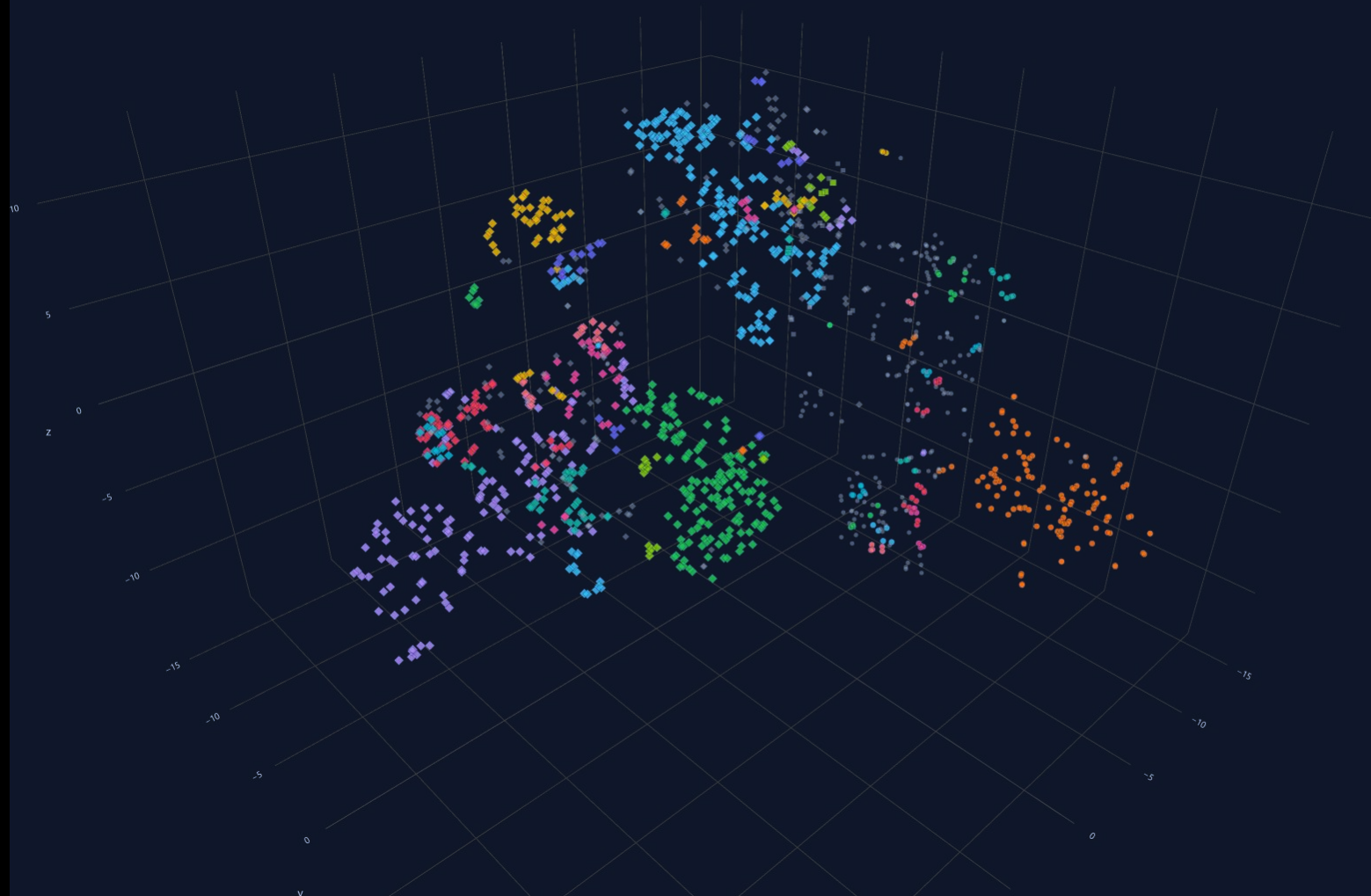
WHOLE DAIRY FARM

It covers interconnected parts of the farm system: animals, feed, crops, manure, environment, management, and economics.

STRUCTURED DATA

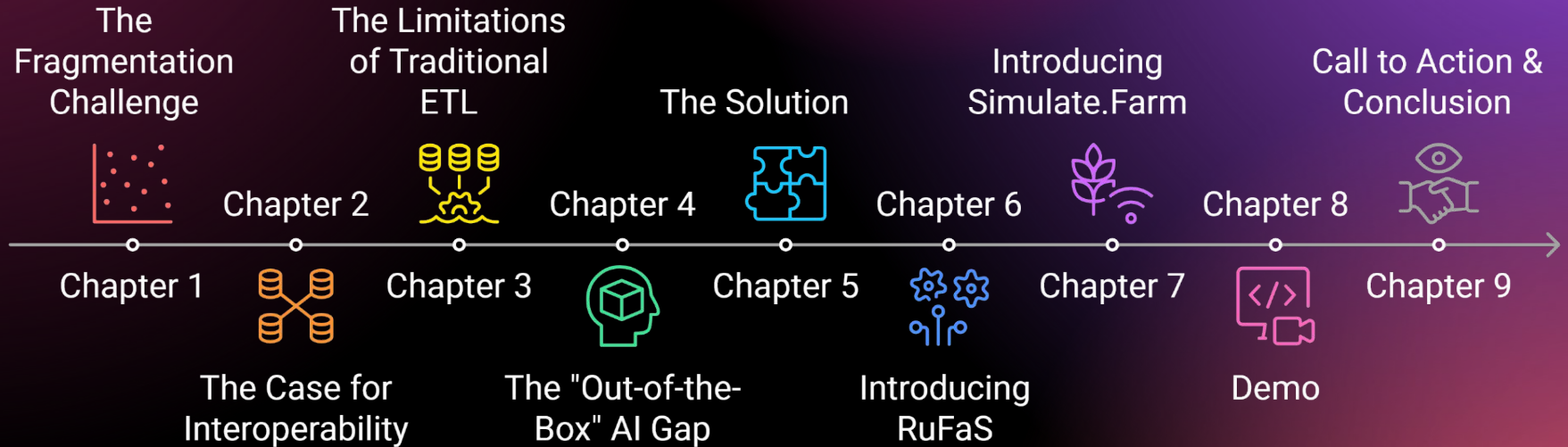
Structured inputs and outputs give us real model metadata to search, embed, compare, and map.

KEY POINT: RuFaS is complex enough to be meaningful, and open and structured enough to be studied transparently.



- Cluster 1
- Cluster 2
- Cluster 3
- Cluster 4
- Cluster 5
- Cluster 6
- Cluster 7
- Cluster 8
- Cluster 9
- Cluster 10
- Cluster 11
- Cluster 12
- Cluster 13
- Cluster 14
- Cluster 15
- Cluster 16
- Cluster 17
- Cluster 18
- Cluster 19
- Cluster 20
- Cluster 21
- Cluster 22
- Cluster 23
- Cluster 24
- Cluster 25
- Cluster 26
- Cluster 27
- Cluster 28
- Cluster 29
- Cluster 30
- Cluster 31
- Cluster 32
- Cluster 33
- Cluster 34
- Cluster 35
- Cluster 36
- Cluster 37
- Cluster 38
- Cluster 39
- Cluster 40
- Cluster 41
- Cluster 42
- Cluster 43
- Cluster 44
- Cluster 45
- Cluster 46
- Cluster 47
- Cluster 48
- Cluster 49
- Cluster 50
- Cluster 51
- Cluster 52
- Cluster 53
- Cluster 54
- Cluster 55
- Cluster 56

Presentation Flow



What is Simulate.Farm?



Simulate.Farm is being developed as a platform that makes it easier to use, run, and connect with RuFaS.

Web Execution

Run RuFaS online without any local installation hurdles.

Conversational UI

Configure and explore simulations through natural dialogue.

Effective Setup

Easily define scenarios, inputs, and complex assumptions.

Comparative Analysis

Run multiple simulations and compare outcomes side-by-side.

Contextual Results

Understand data within the context of the original farm question.

Secure & Flexible

Choose between persistent secure storage or ephemeral setups.

Data Interoperability

Seamlessly translate and connect data across disparate systems.

Advanced Toolset Integration

Semantic translation, agentic workflows, and MCP integration to broaden capabilities.

What users can do with Simulate.Farm?



Ask

Describe a farm question, scenario, or decision.

Configure

Find relevant variables, inputs, outputs, and assumptions.

Run

Execute RuFaS through the online platform.

Compare

Evaluate alternative scenarios and management choices.

Interpret

Understand what changed, why it changed, and what it means.

Connect

link models with semantic translation, agentic workflows, and MCP-integrated tools and data systems.

Goal: Make agricultural simulation more accessible, conversational, and connected.



Finding the right RuFaS variables

Bovina · Scientific Assistant · Researcher

Autoplay



Pause

I want to study how feed quality affects methane emissions and milk production, but I don't know the RuFaS variable names.



User intent: scientific question → identify related RuFaS inputs and outputs → search semantic map





Importing external datasets

Clover · Friendly Guide · New User

Autoplay



Pause

I have a dataset from our farm management software. Can I use it for a simulation?



Translate external farm software data into RuFaS-compatible inputs.

▶ Start Demo



Disambiguating similar variables

Clover · Friendly Guide · New User

Autoplay



Pause

I need outputs related to nitrogen losses.



Our nutrition software uses different names for ration components than RuFaS.
Can you help map them?



User intent: schema translation → compare external nutrition fields with RuFaS feed and ration concepts



• Load external schema · Search RuFaS feed variables · Generate candidate mappings

I can help create a translation table between your nutrition software and RuFaS.

Initial mapping results:

- Feed DM → Dry matter intake / feed dry matter
- NDF → Neutral detergent fiber
- CP → Crude protein
- Starch % → Dietary starch concentration
- Fat % → Ether extract / dietary fat

Some fields may need confirmation because different tools define ration components differently.



Show me the uncertain matches.



Identify mappings with multiple plausible RuFaS targets → explain ambiguity before conversion



- Rank ambiguous mappings · Prepare review table · Require user confirmation

Here are the mappings that need review:

- Energy value: could mean NEL, ME, DE, or gross energy
- Protein: could mean crude protein or metabolizable protein
- Forage group: could refer to ingredient category or ration group
- Intake: could mean offered feed or consumed feed



I recommend confirming these before generating RuFaS inputs.

An Invitation to Collaborate



We are developing new ways to help agricultural systems, models, and datasets work together more effectively.

IF YOU WORK WITH:

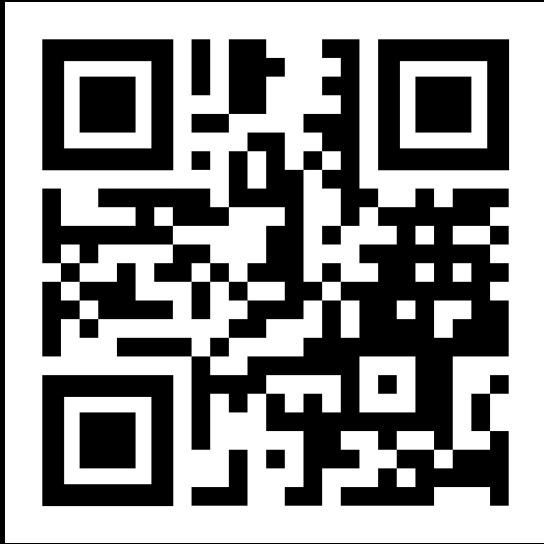
- farm data systems
- simulation models
- sensors and IoT platforms
- research datasets
- agricultural software platforms
- interoperability and data integration

WE ARE LOOKING FOR:

- feedback on the ideas and approach
- collaborators and research partners
- systems and datasets to test and connect
- real-world use cases and challenges
- opportunities to advance interoperability

Join us in helping develop RuFaS and Simulate.Farm further by exploring semantic discovery, AI-assisted reasoning, and better ways to connect agricultural data, models, and decision-support tools to advance agriculture through improved understanding, collaboration, and innovation.

THANK YOU



<https://www.simulate.farm>
<https://www.rufas.org>

