Hybrid Intelligent Mechanistic-Dynamic Models Mathematical Animal Nutrition Models to Predict Enteric Methane Emissions of Grazing Beef Cattle

USDA
Climate Smart

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Session 80 "Technologies for GHG emission mitigation on farm: options, opportunities and challenges"

South Dakota State University

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Texas A&M University
Animal Science

Introduction

Cattle production has been increasing since the last decades because of the continuous demand of meat products (Millen et al., 2013)

Methane emissions

Especially, in grazing cattle (Thompson et at., 2020)

Thus, mitigate methane emissions in cattle have been a concern in beef research, the big challenge is to find the best trade-off between efficiency and sustainability (Makkar and Beever, 2023)

Respiration chambers are the “Gold Standard” method

But, how about grazing cattle?

GreenFeed as a useful tool to measure GHG in grazing cattle

=>**The GreenFeed** represent the best reasonable trade-off;

- **On-Farm applicability** in grazing conditions allowing non-invasive measurements (Cottle et al., 2011; Beauchemin et al., 2020)
- **Continuous monitoring**, providing **real-time** measurements over time (Sun et al., 2022)
- **Cost-effectiveness** and maintenance needs in comparison to other techniques (Beauchemin et al., 2020)

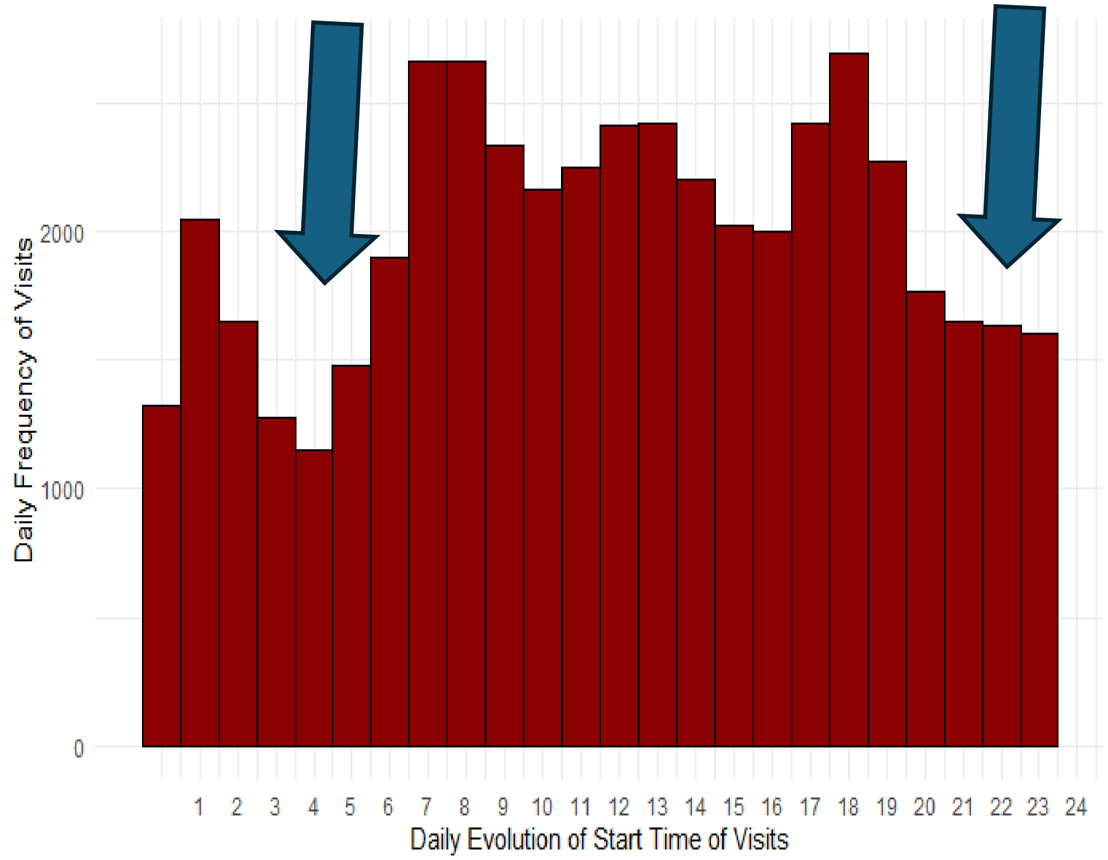
Main problem

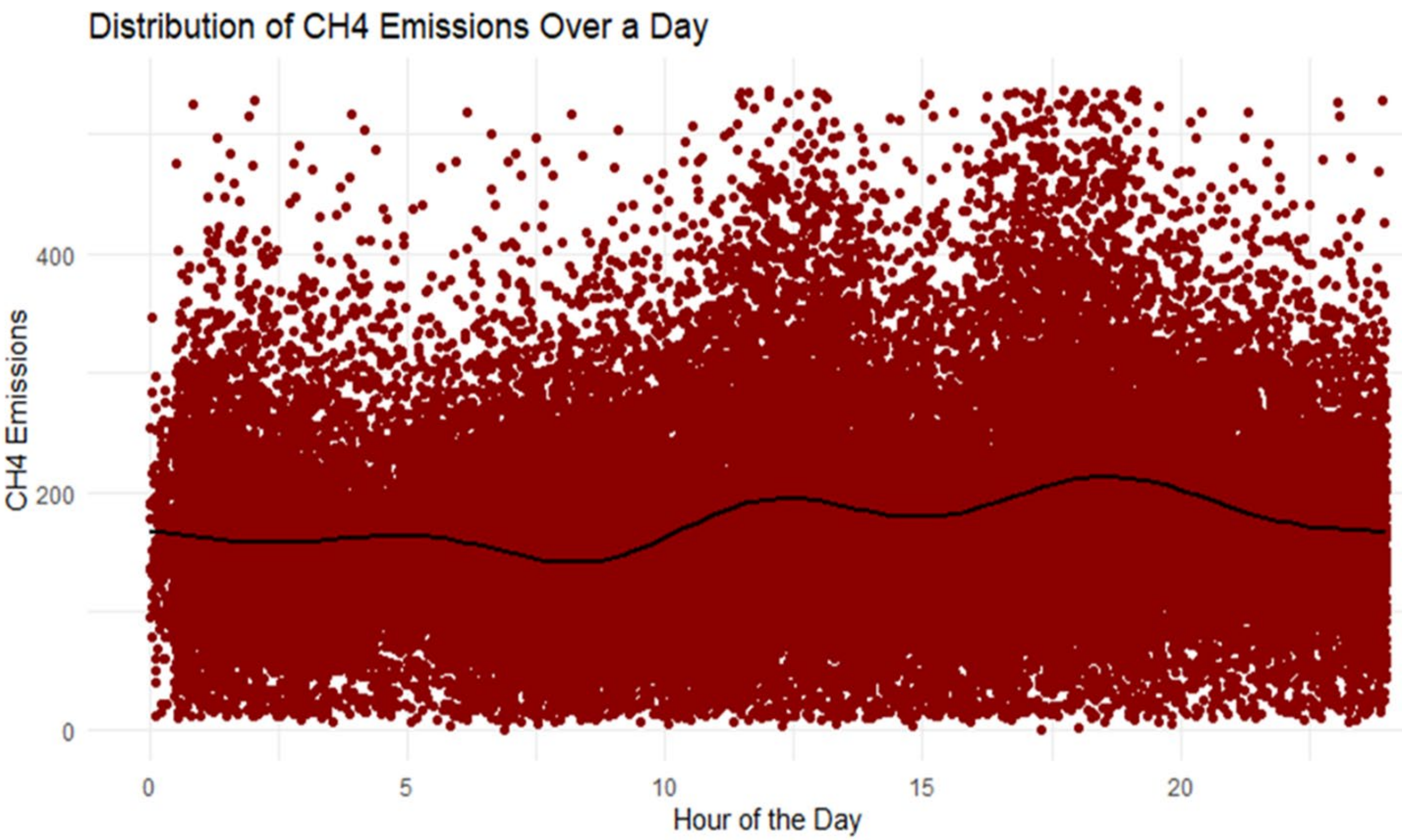
Unlike Respiration Chambers, the GreenFeed System collects spot samples and predict the daily CH4 from these spots.

However, **<u>diurnal patterns of CH4 for grazing cattle are still unknown</u>**, which is likely to bias average daily CH4 estimates.

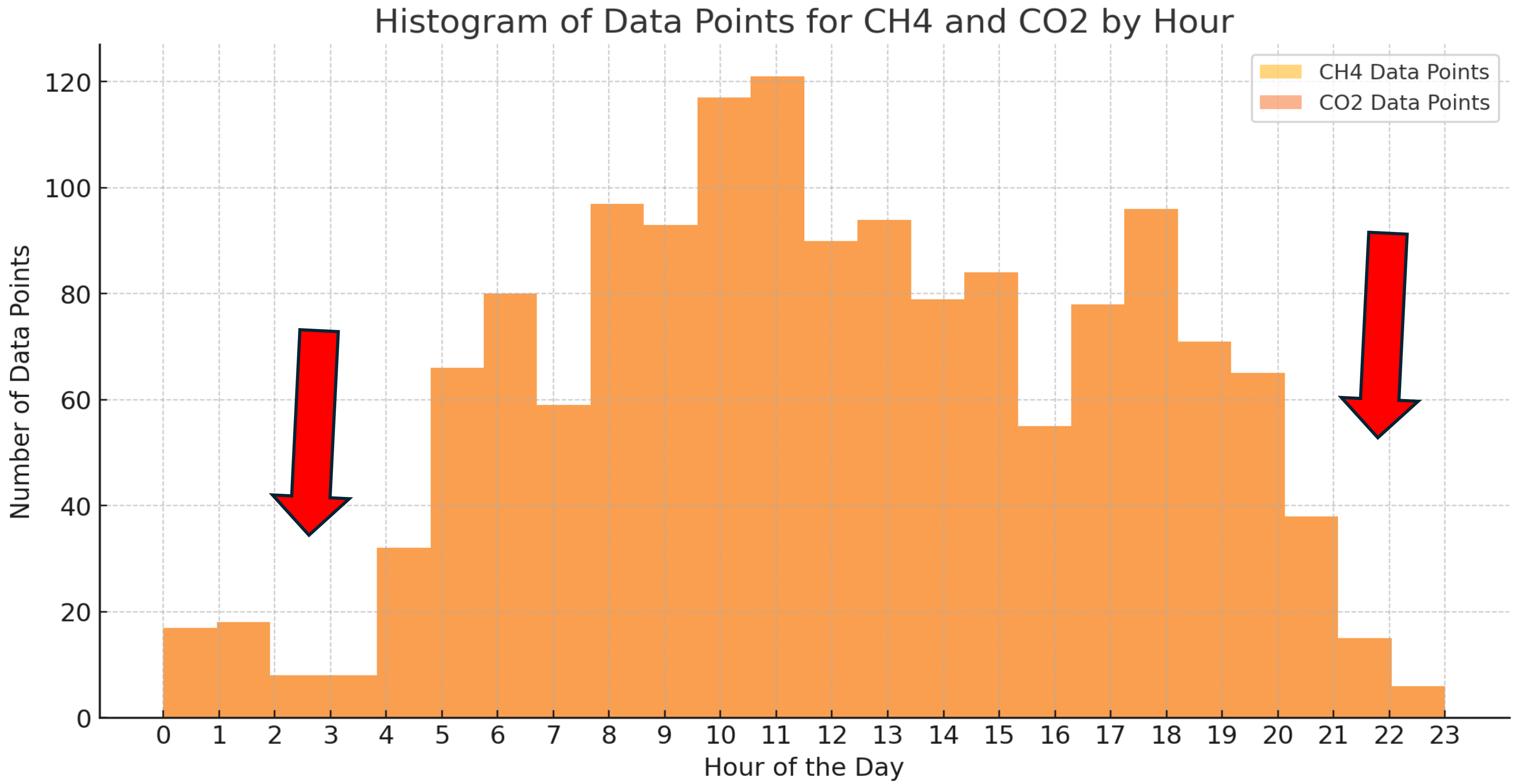
Low data collection at certain times

8,000 reads help to fill in the gaps.

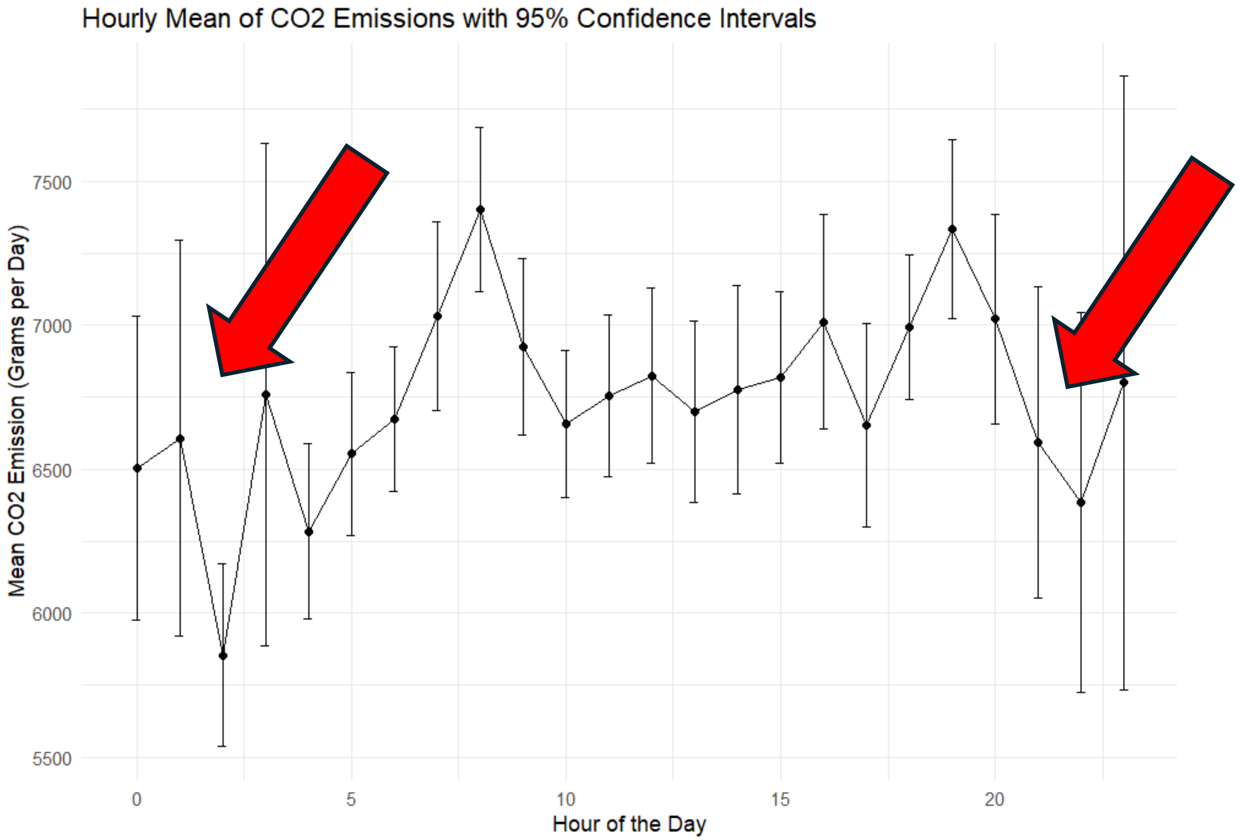


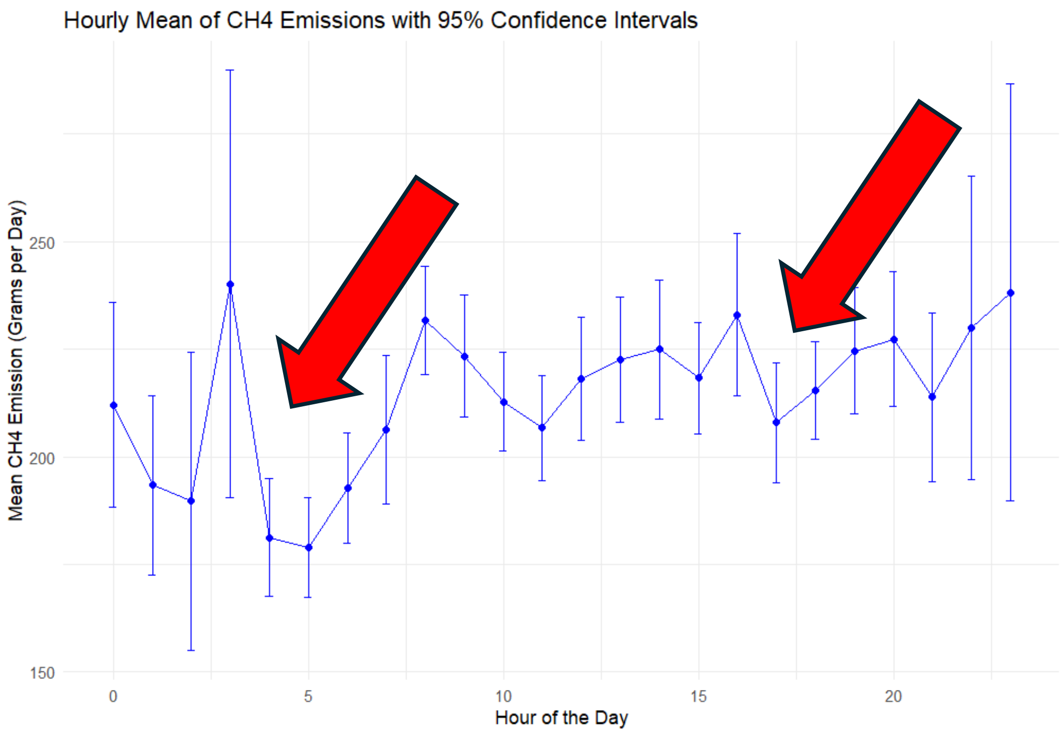


Data distribution from the best users

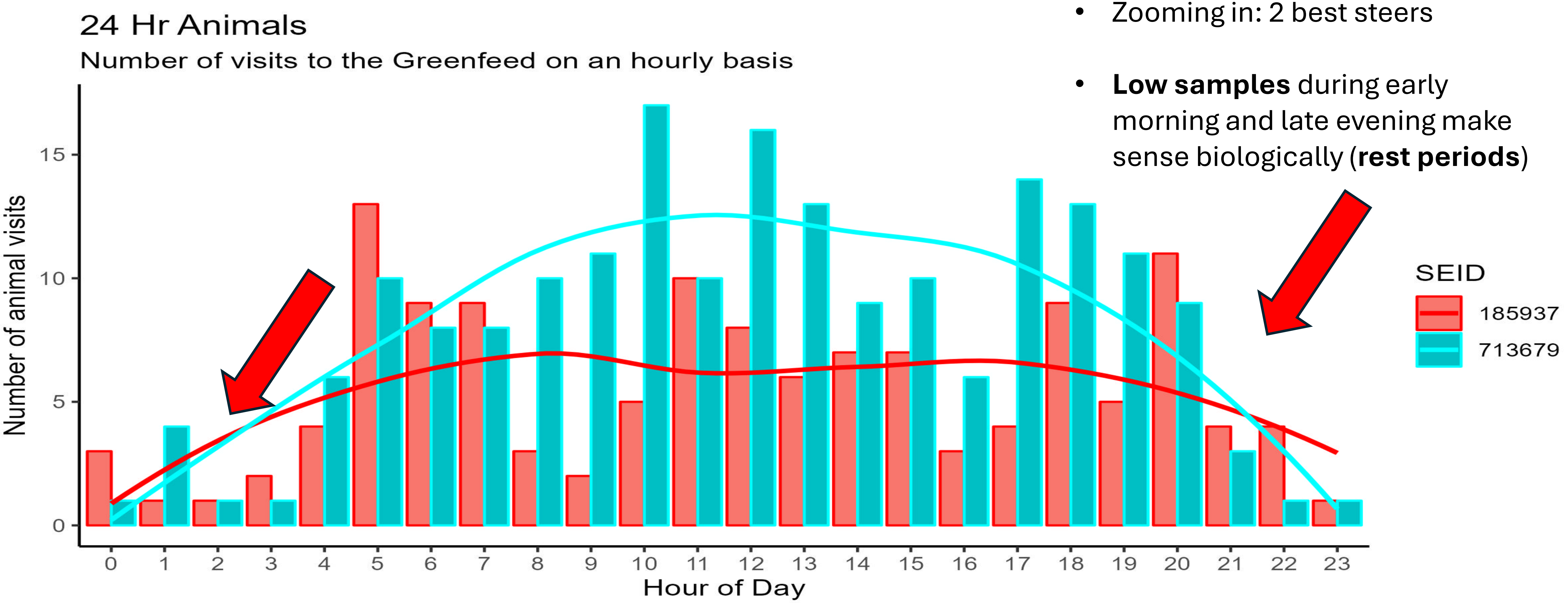


Confidence intervals are heavily penalized by **low sample sizes**, but actual measures may still be accurate and precise



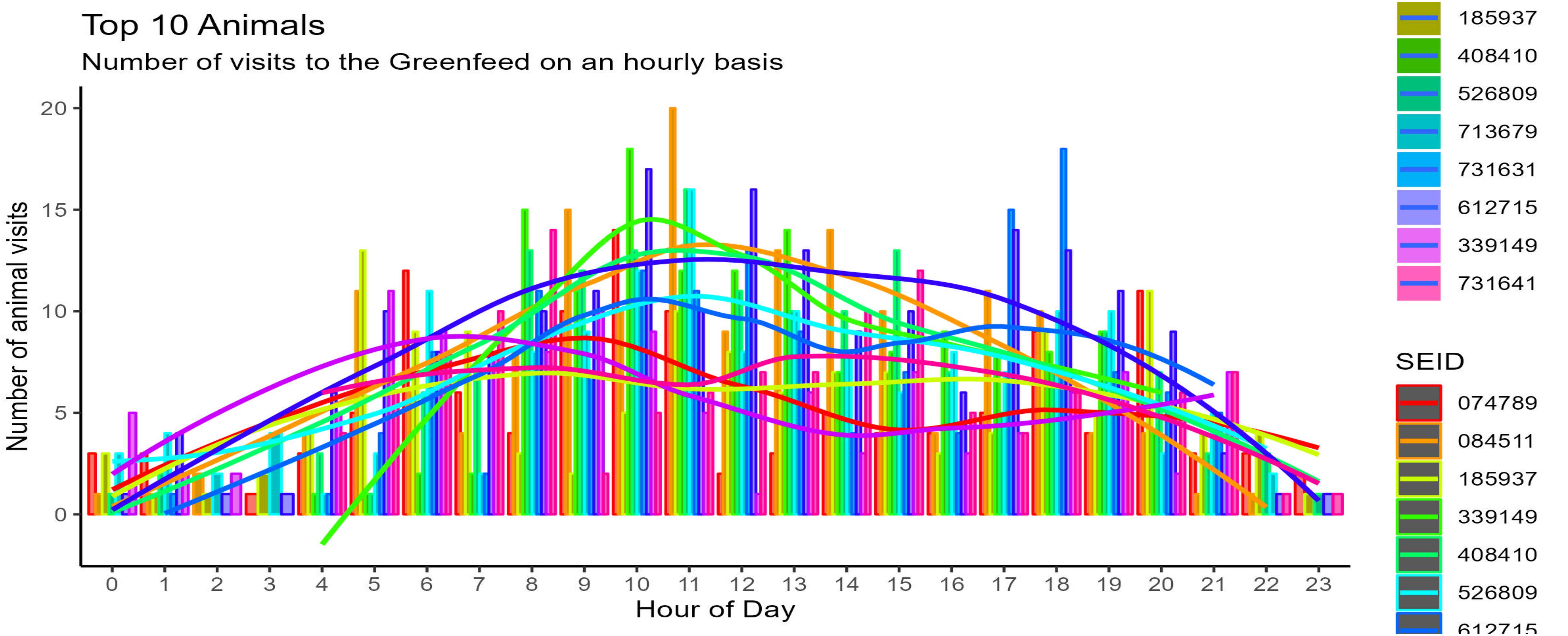


Herd-level hourly CH_4 patterns are possible, but, determining individual CH_4 rates is still a challenge...

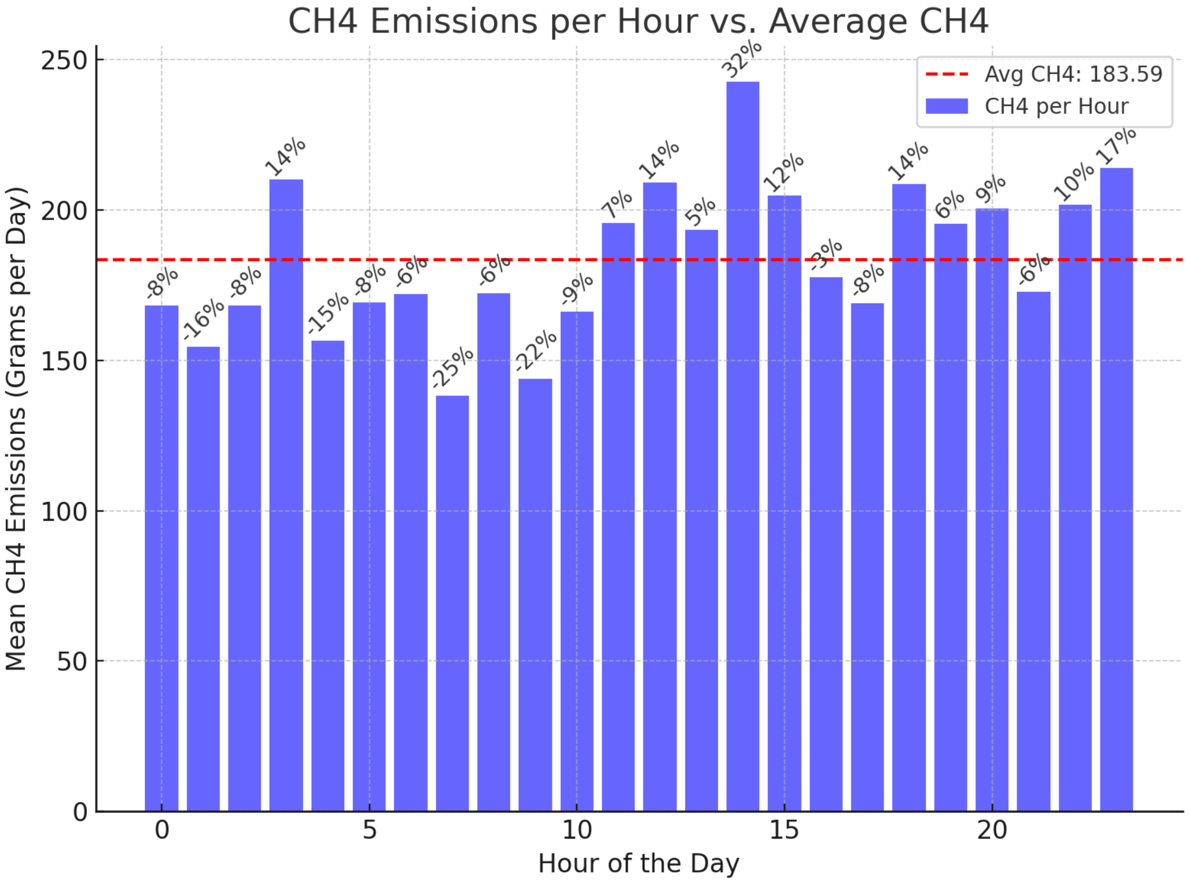


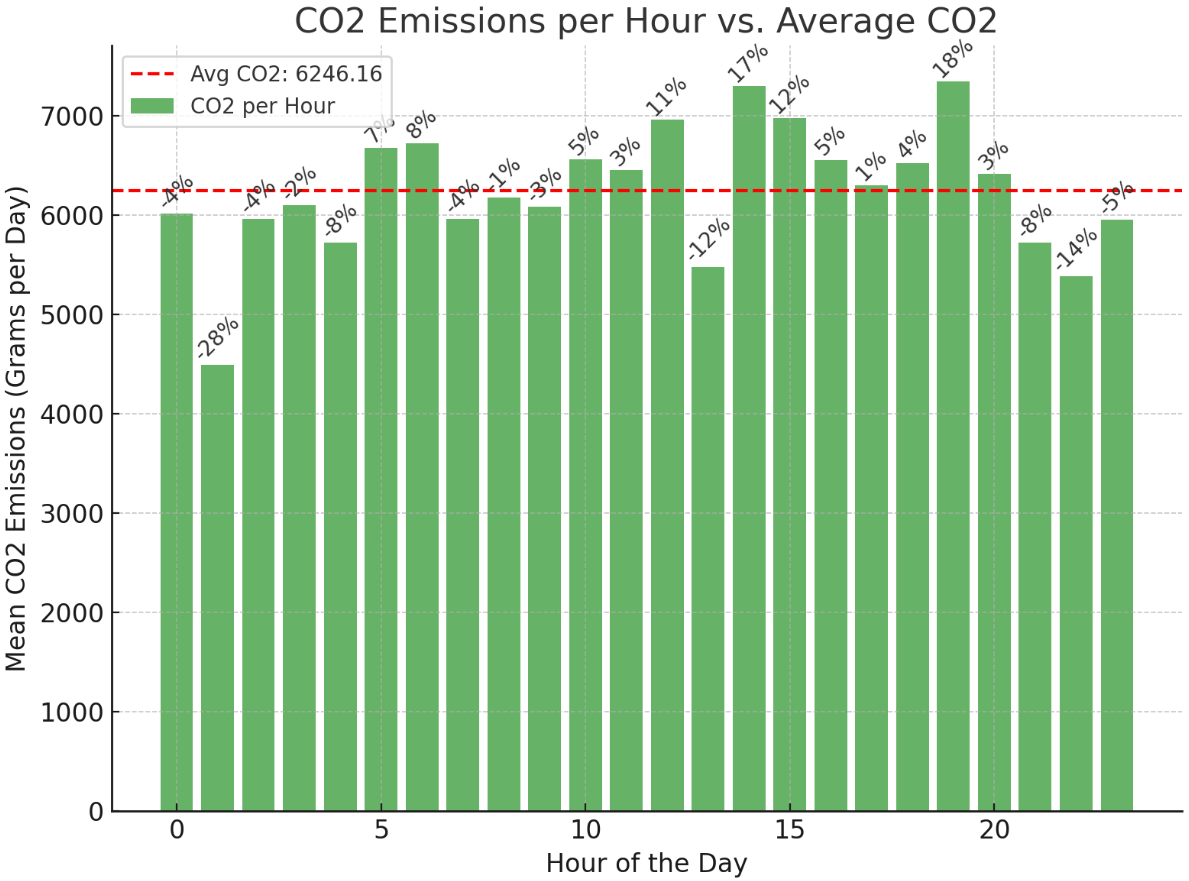
- Zooming in: 2 best steers
- **Low samples** during early morning and late evening make sense biologically (**rest periods**)

Between-animal variation



Using one steer: Spot measures do have the potential to bias average daily estimates





Main objective: Develop a hybrid dynamic-artificial intelligence model that can predict individual hourly CH4

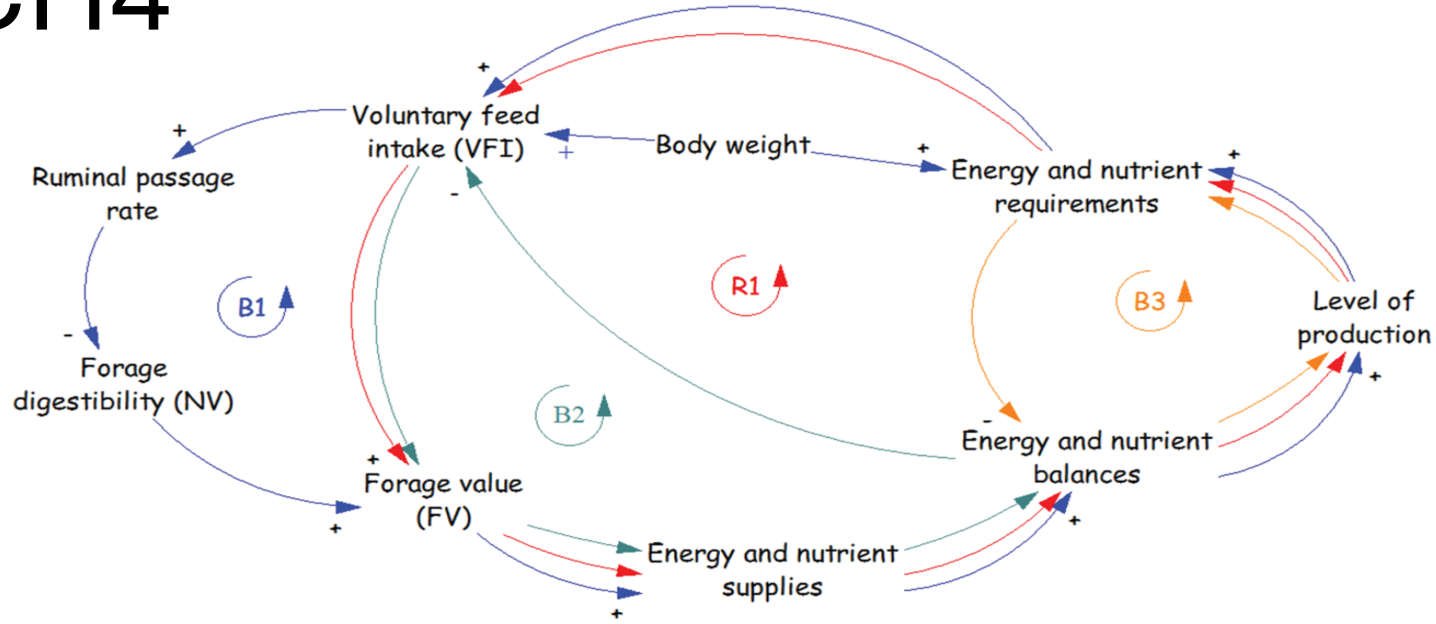


Figure 1. Feedback loops of variables that alter voluntary feed intake. Self-reinforcing (R) and self-correcting (B) loops are shown within the semicircle arrows. Positive and negative signs near the arrowheads indicate that the effect if positively or negatively related to the cause. Different colors represent different feedback loops for ease of identification.

Partnerships for Climate-Smart Commodities Projects

Expanding Climate-Smart Commodity Markets

An In-Depth Overview | How to Enroll | Overview Brochure | FAQs

55	135	102	197	$3.03 B
States & Territories	Projects	Major Commodities	Practices	Federal Funding*

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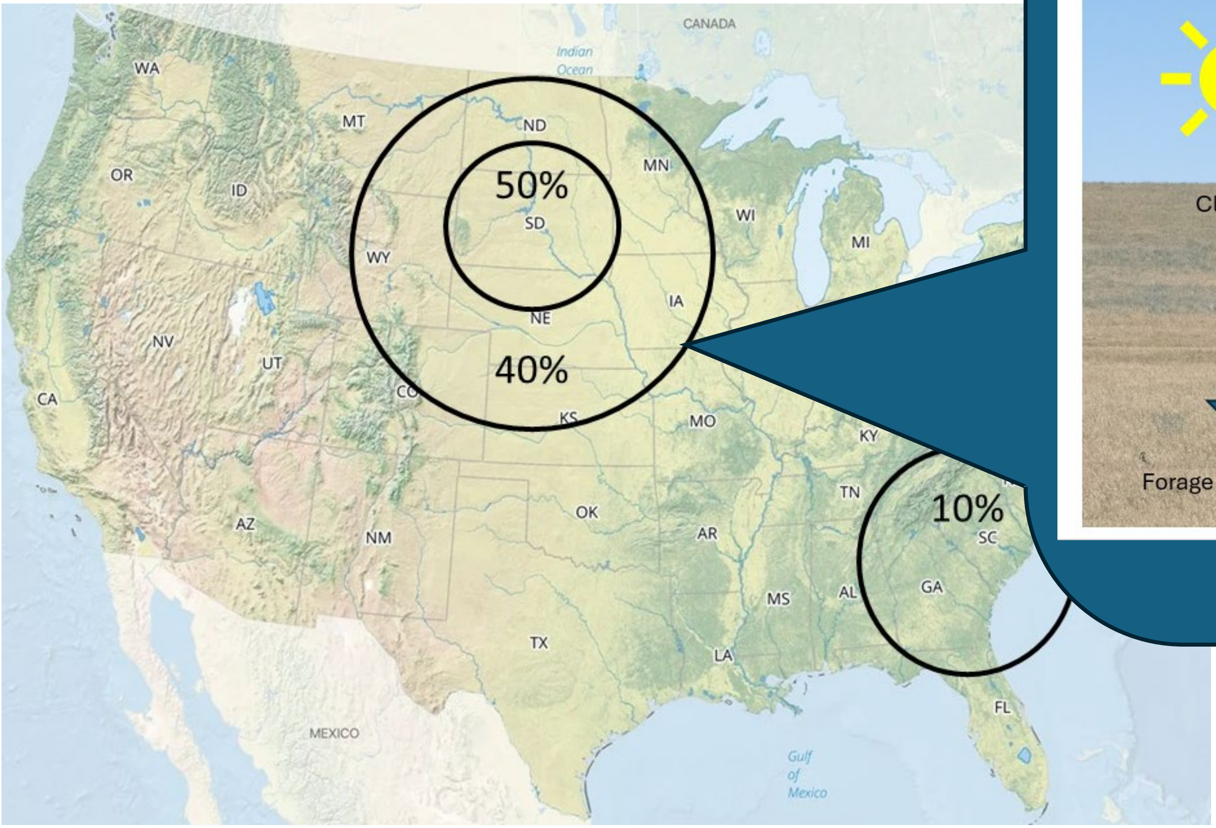
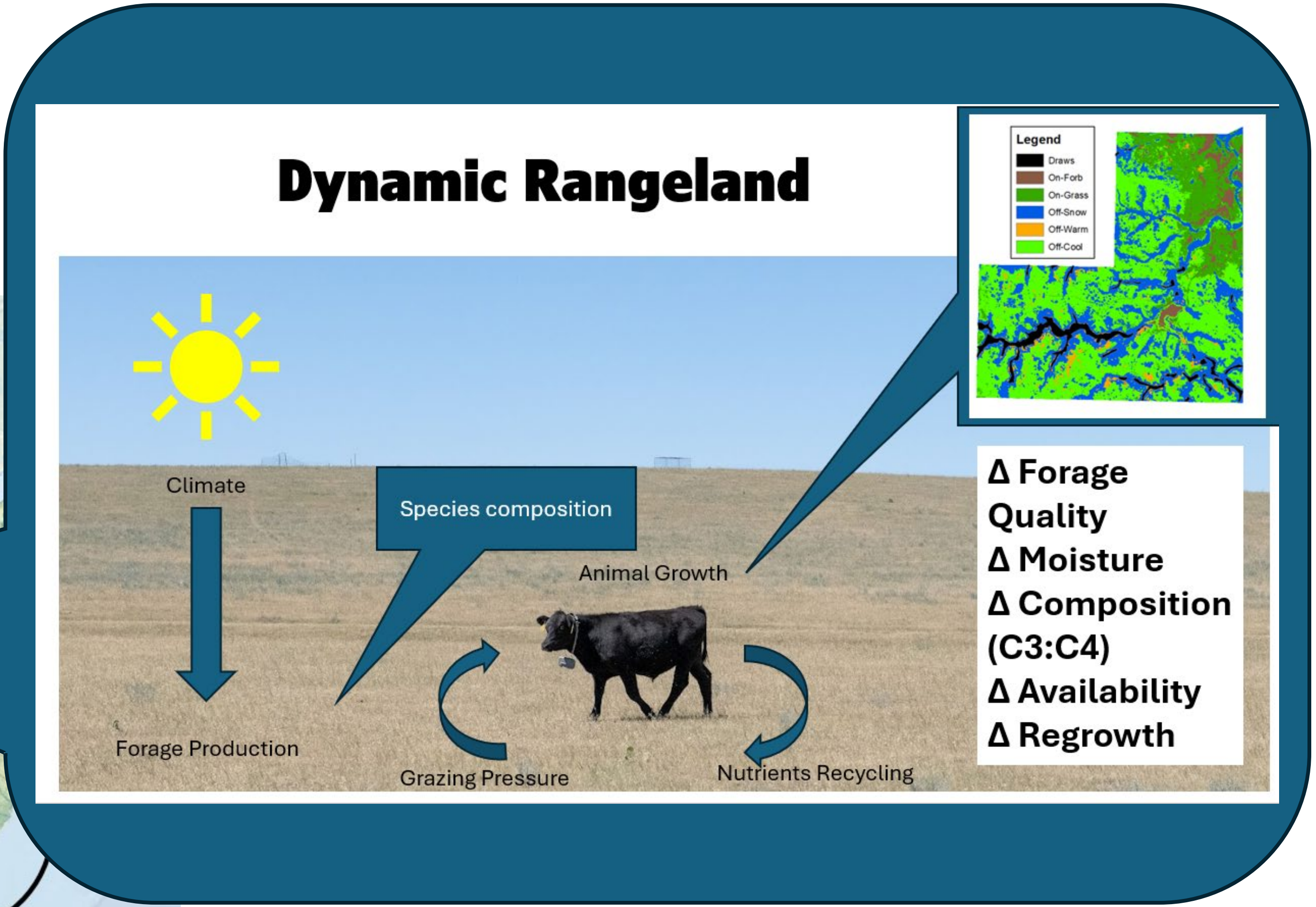
Texas A&M University
Animal Science

METHODS

- Study Area(s)





Extensive Rangeland Grazing Systems in the U.S. Northern Great Plains

Methods: Animals adaptation to the GF

Dry Lot: Training

April 14th to June 6th

Native Rangeland: Grazing

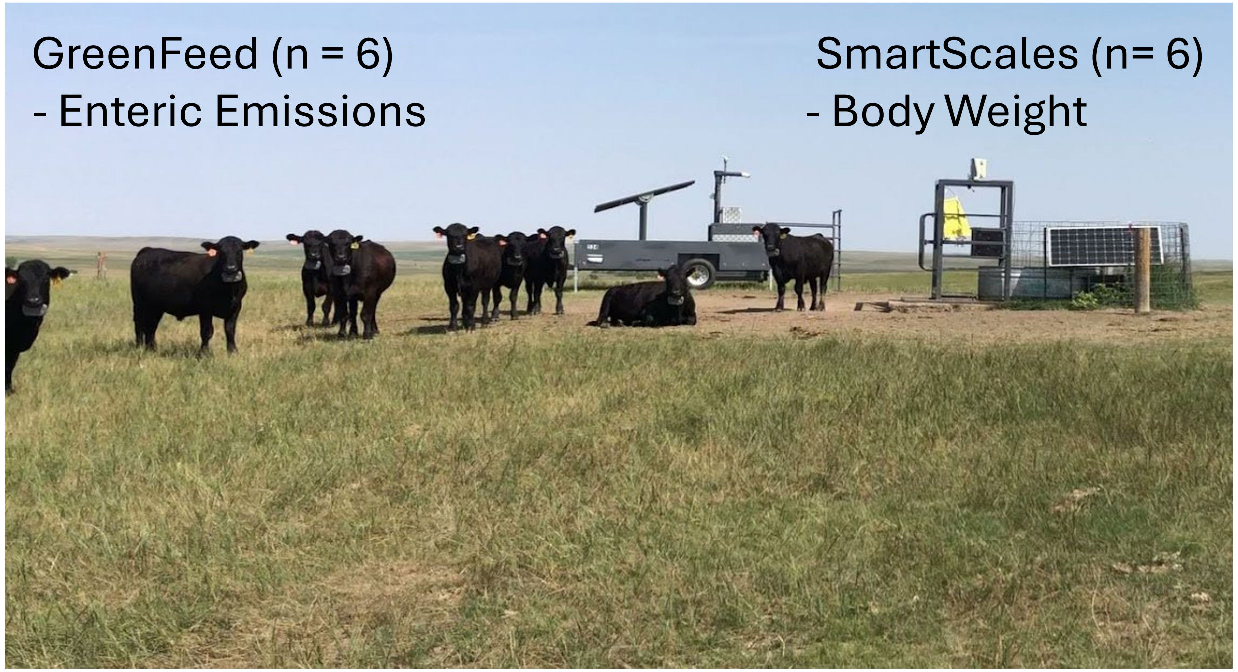
June 7th to August 31st

GreenFeed Pasture System (n = 2)
- Enteric Emissions

- Receiving (n = 150)
- Training (2 GFs, 297 and 298)
- Adoption + BW = Selection Decisions

GreenFeed (n = 6)
- Enteric Emissions

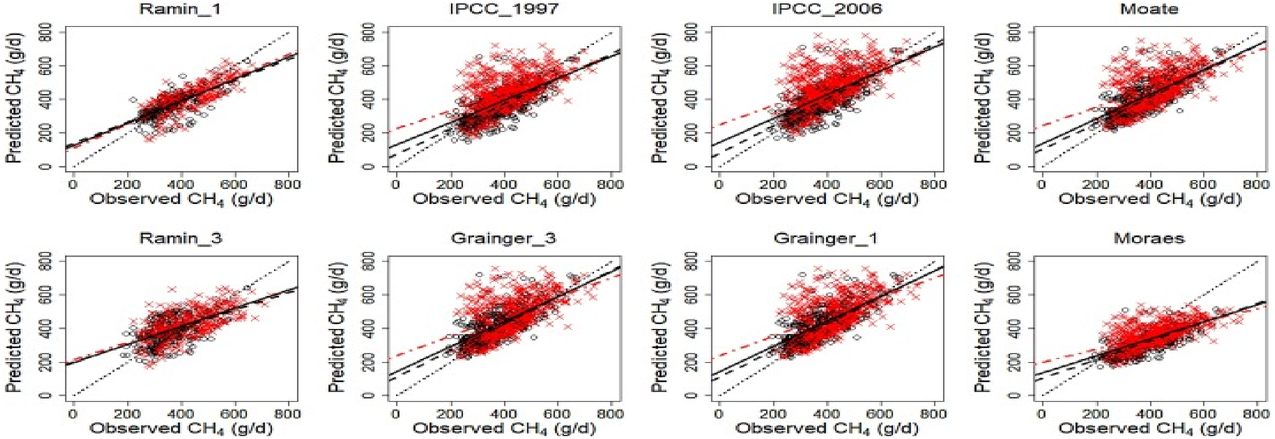
SmartScales (n= 6)
- Body Weight



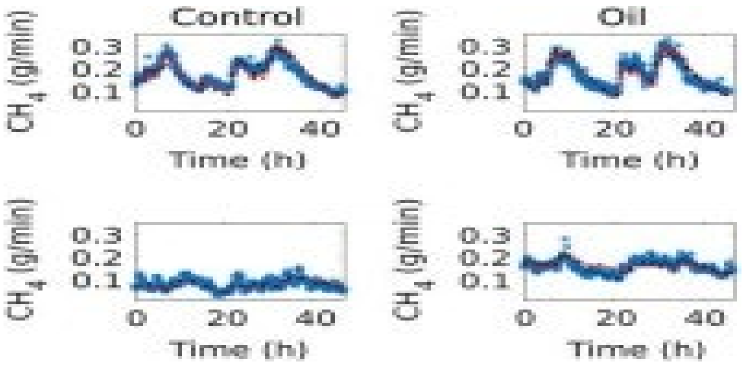
- Range Data Collection (n = 127)
- Stratified by BW in each treatment

Methods: Modeling methods

There are ways to predict CH4 through empirical equations
(Benaouda et al. 2019)

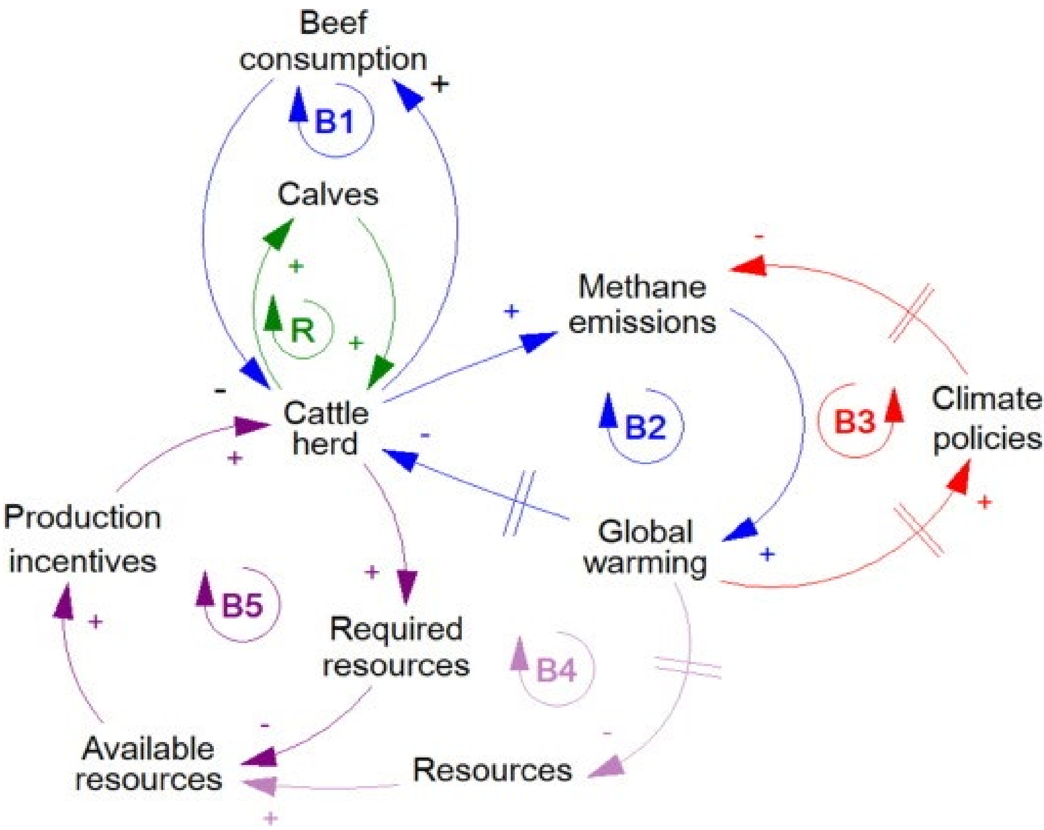


Other methods predict CH4 through dynamic models
(Muñoz-Tamayo et al. 2019)



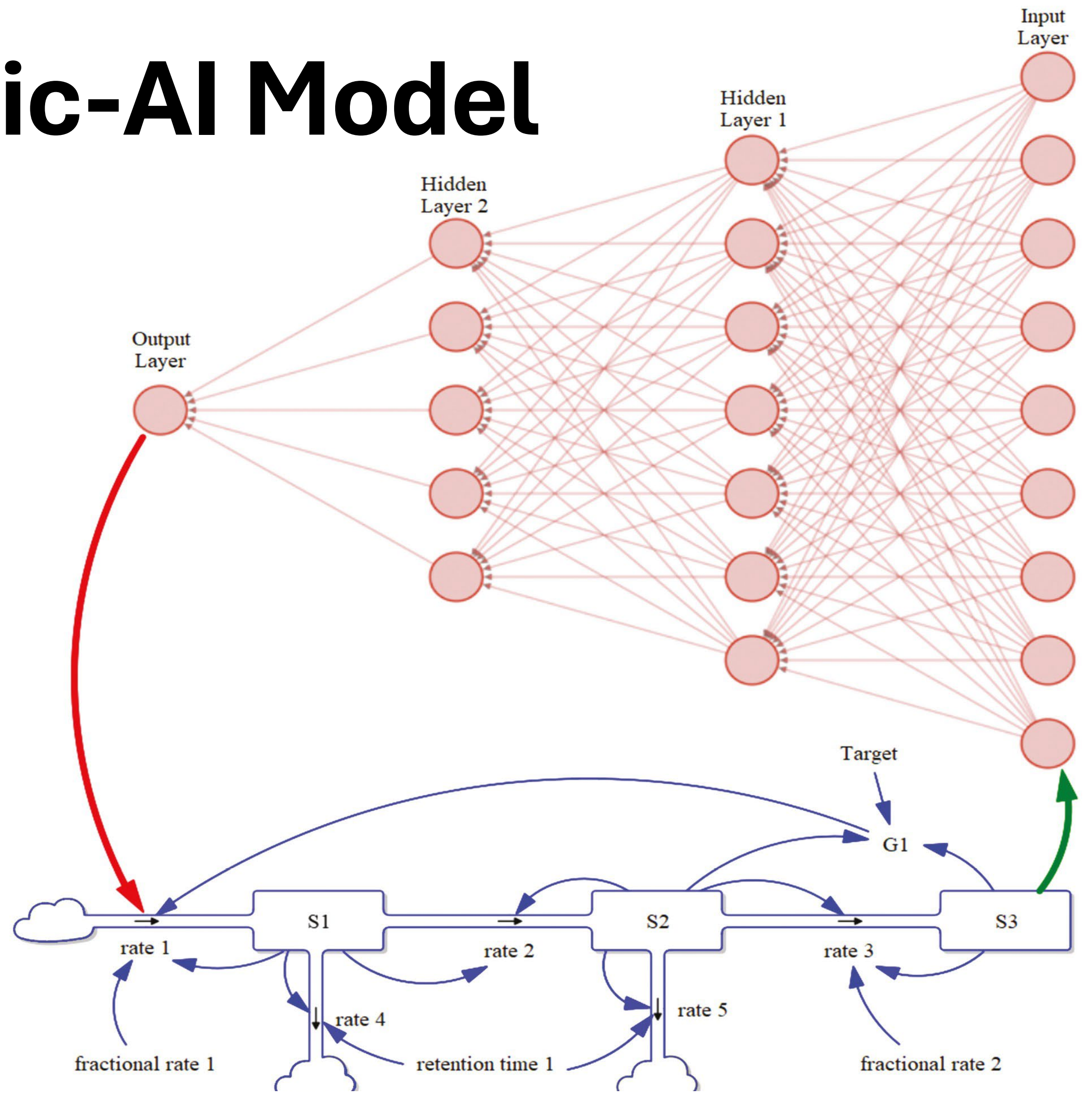
Hybrid models (Tedeschi et al. 2023)

+ Machine learning models



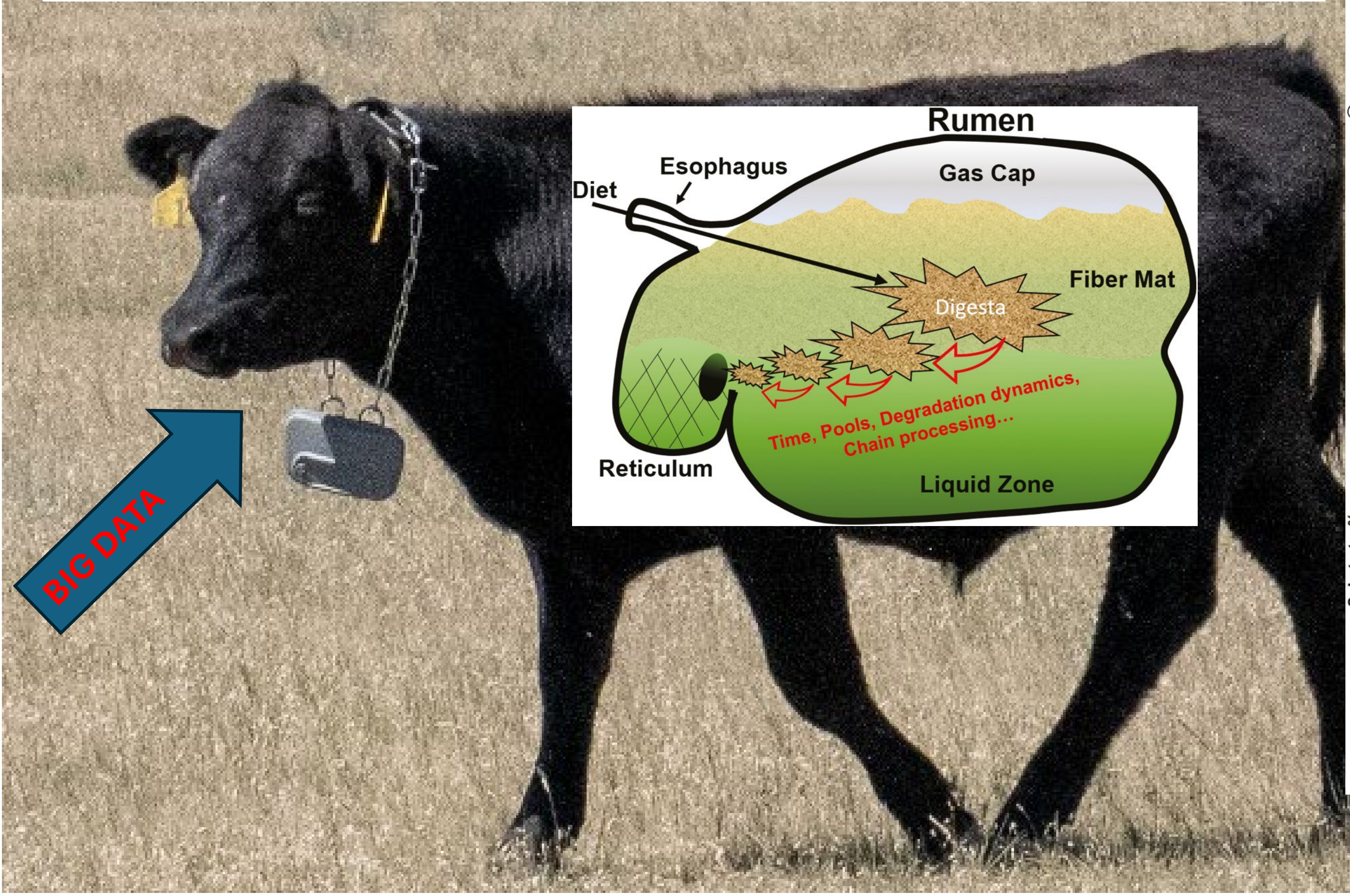
METHODS: Hybrid Dynamic-AI Model Development

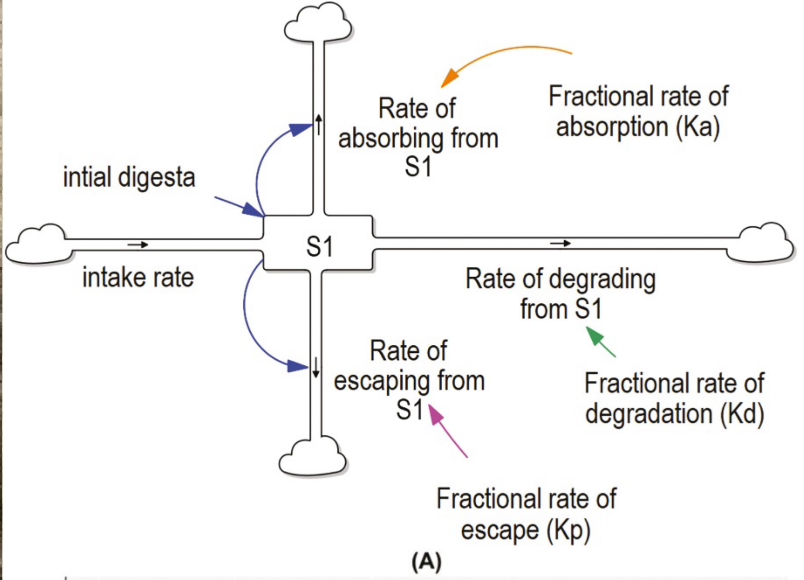
1. Develop a Dynamic Model
   - **Rumen Kinetics**
   - **Precision Livestock Data**
2. Develop an Artificial Intelligence Model
   - **Precision Livestock Data**
3. Integrate output and input to maximize the accuracy and precision of prediction to estimate individual hourly CH_4.

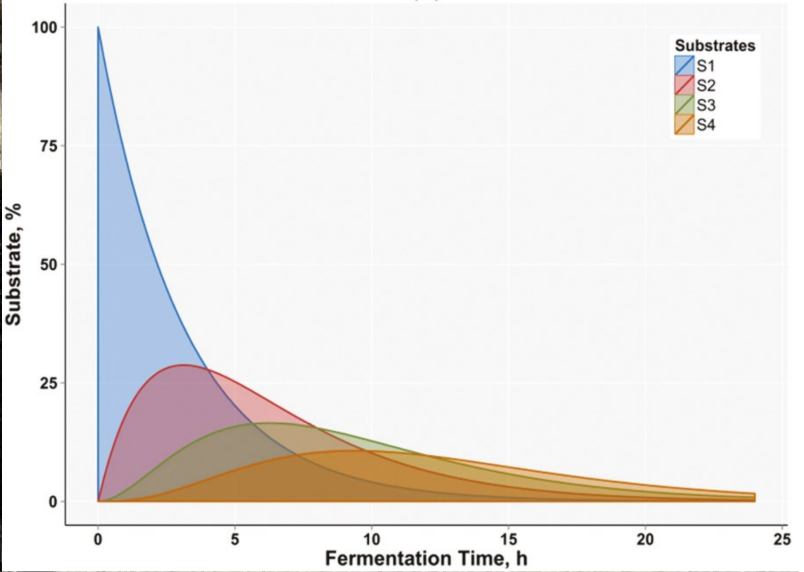


(Tedeschi, 2022; https://doi.org/10.1093/jas/skac111)

1. Develop a Precision Data Drive Dynamic Model: Grazing Rumen Kinetics



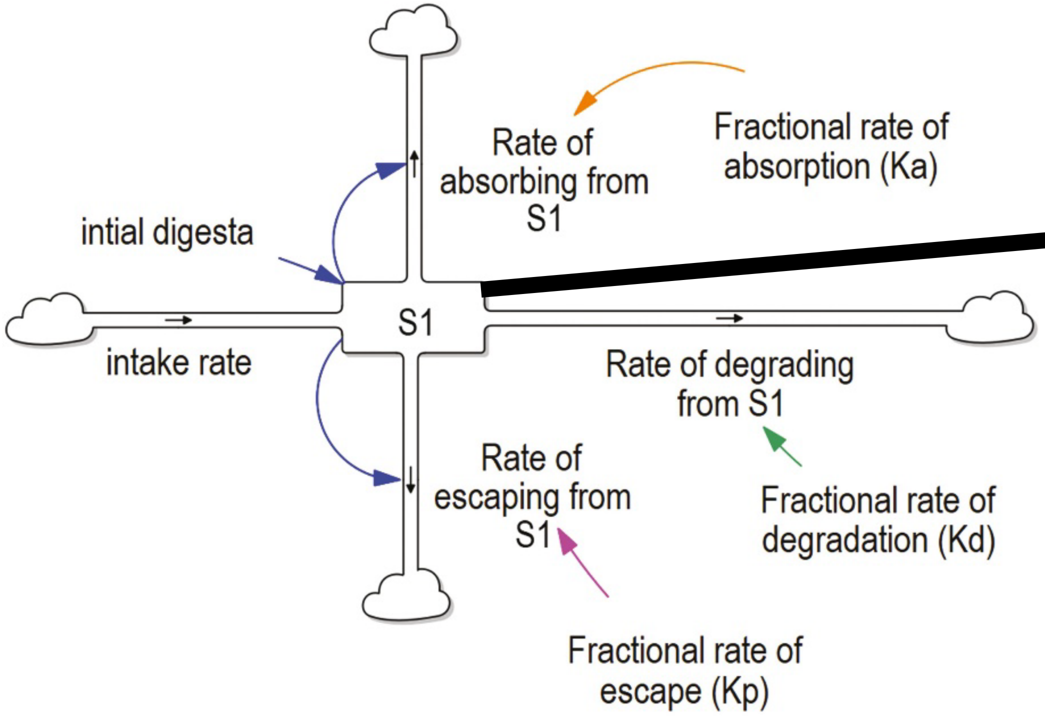


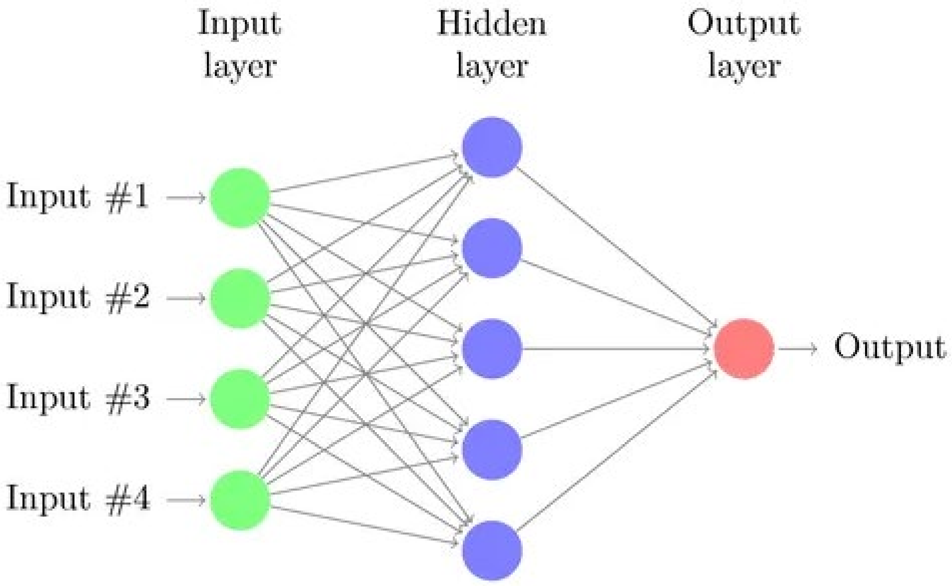


(Tedeschi and Fox, 2020; RNS)

(Brennan et al., 2023; JAS)

Output: S1 "Fiber Digesta" → Individual CH_4/hr

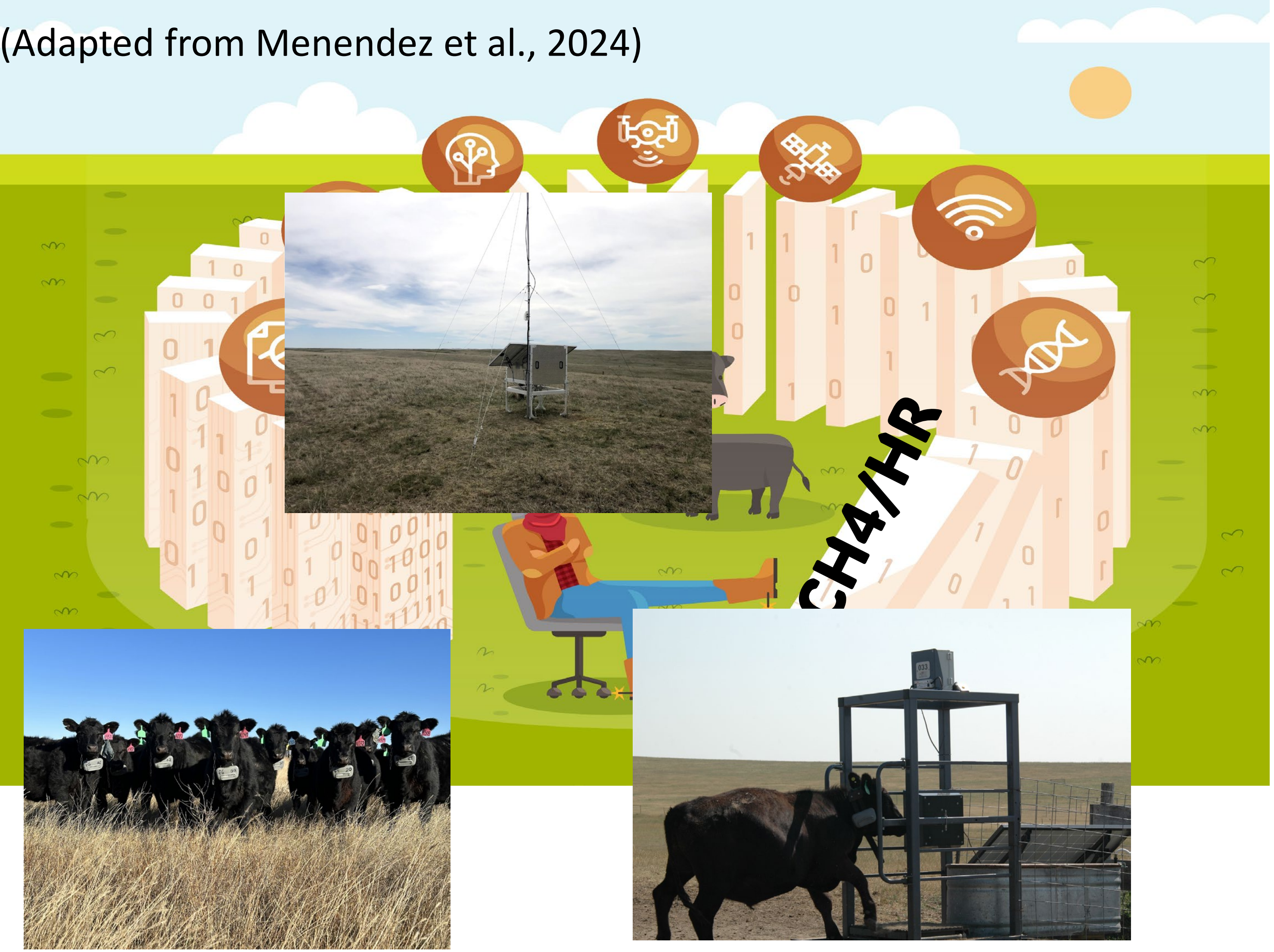




P.C. Abdallah Chamakh

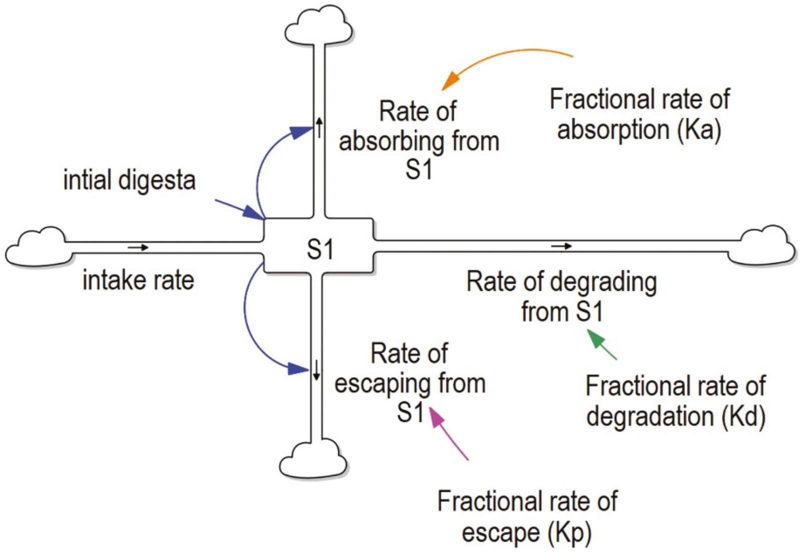
2. Develop a Precision Data Drive Dynamic Model

(Adapted from Menendez et al., 2024)



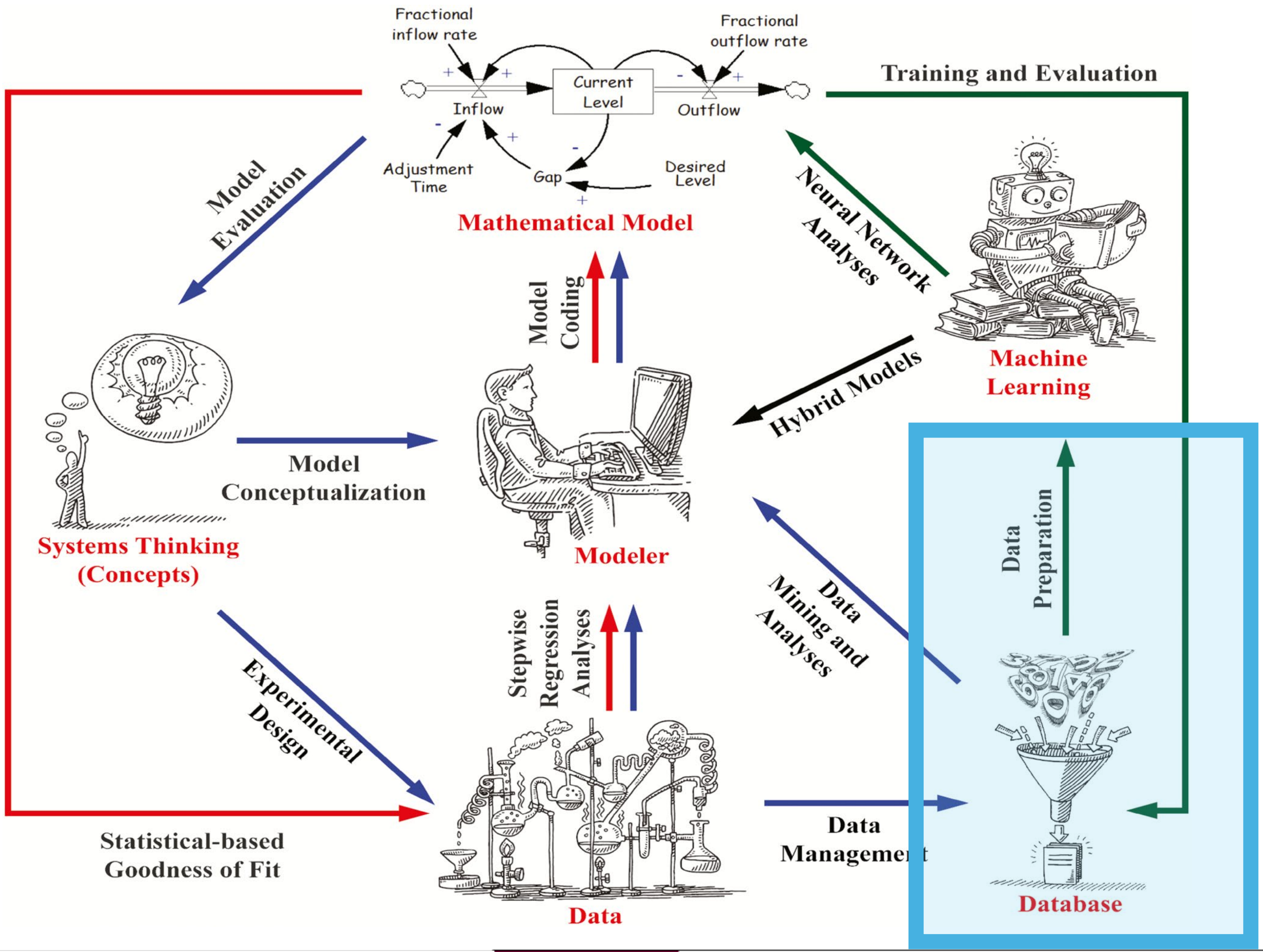
1. **Integrate Precision Data to Drive Dynamic Rumen Kinetics Model**
    1. **Grazing Behavior**
    2. **Body Weight**
    3. **Forage Availability**
    4. **Forage Nutrients**
    5. **Climate**

2. Estimate Rumen Kinetics Pools "S1"

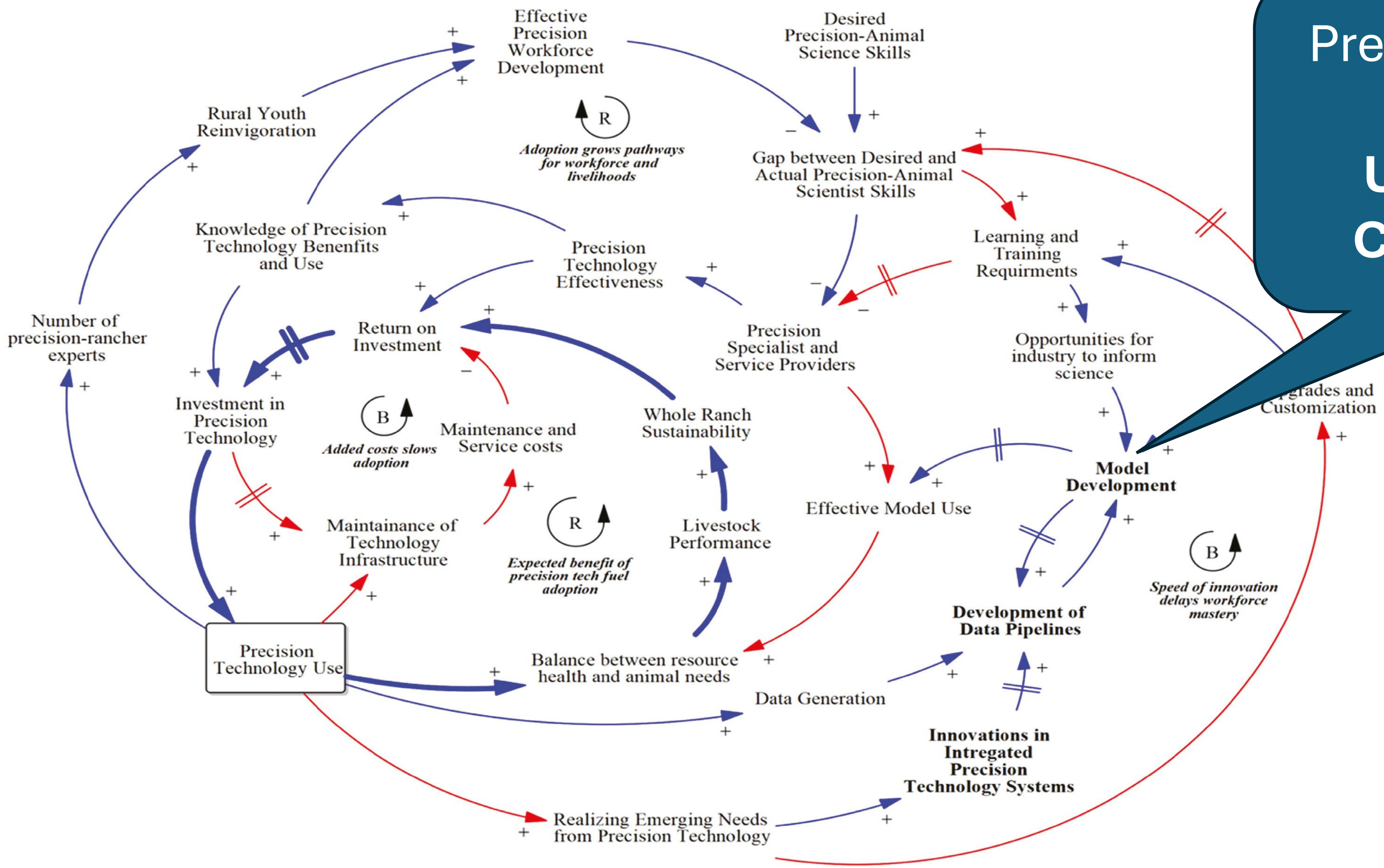


Achieving a precision data driven individual rumen kinetics model for grazing is difficult…

- Different timesteps
- Missing data
- Requires complex data processing and management
- We stopped here and asked:
  - Is the data processing worth the effort.
    - Re-work
      - **Evolving Sensors**



Precision Livestock Technology: **Upgrades and Customization**



(Menendez et al., 2022; JAS)

The Level of Precision Data Complexity:

1. Merits Taking a Step Back

2. Critically Evaluating the Required Causal Structures

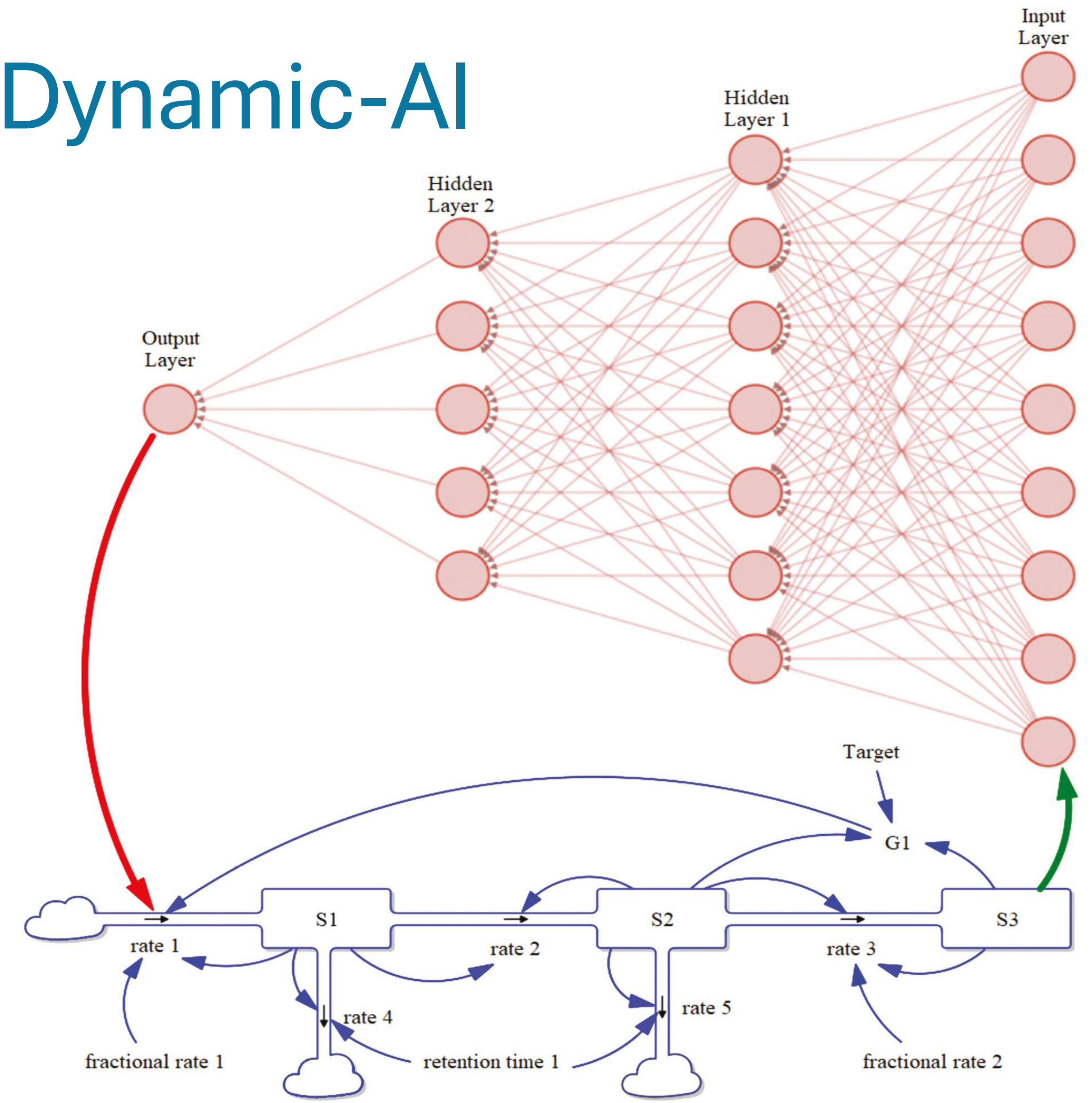
    Data Hungry to Structure Dependent

        Precision Livestock Data is a Means to an End

    (Menendez et al., 2023)

3. Drive Individual Hourly Methane Production

REVISED METHODS: Hybrid Dynamic-AI Model Development



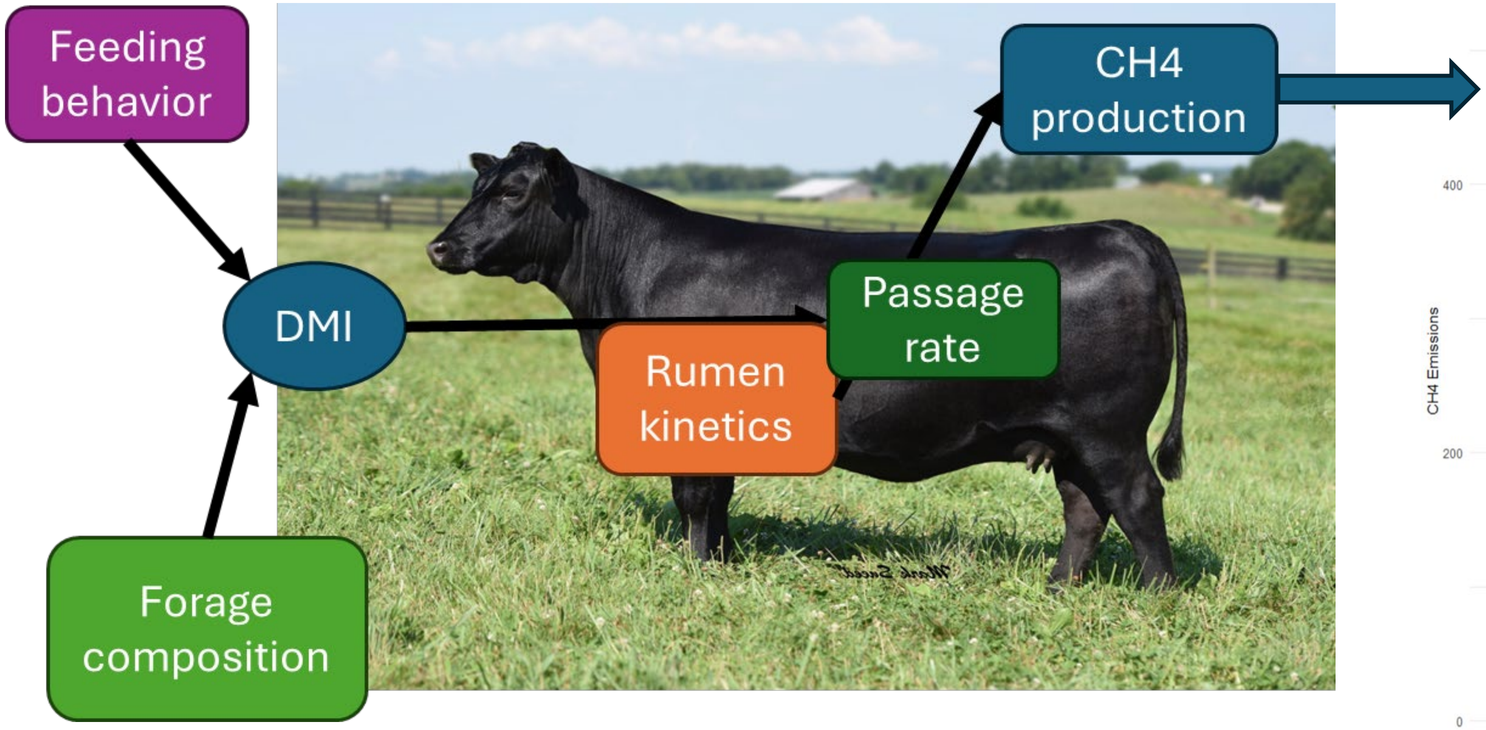
System Dynamics (Sterman, 2000)

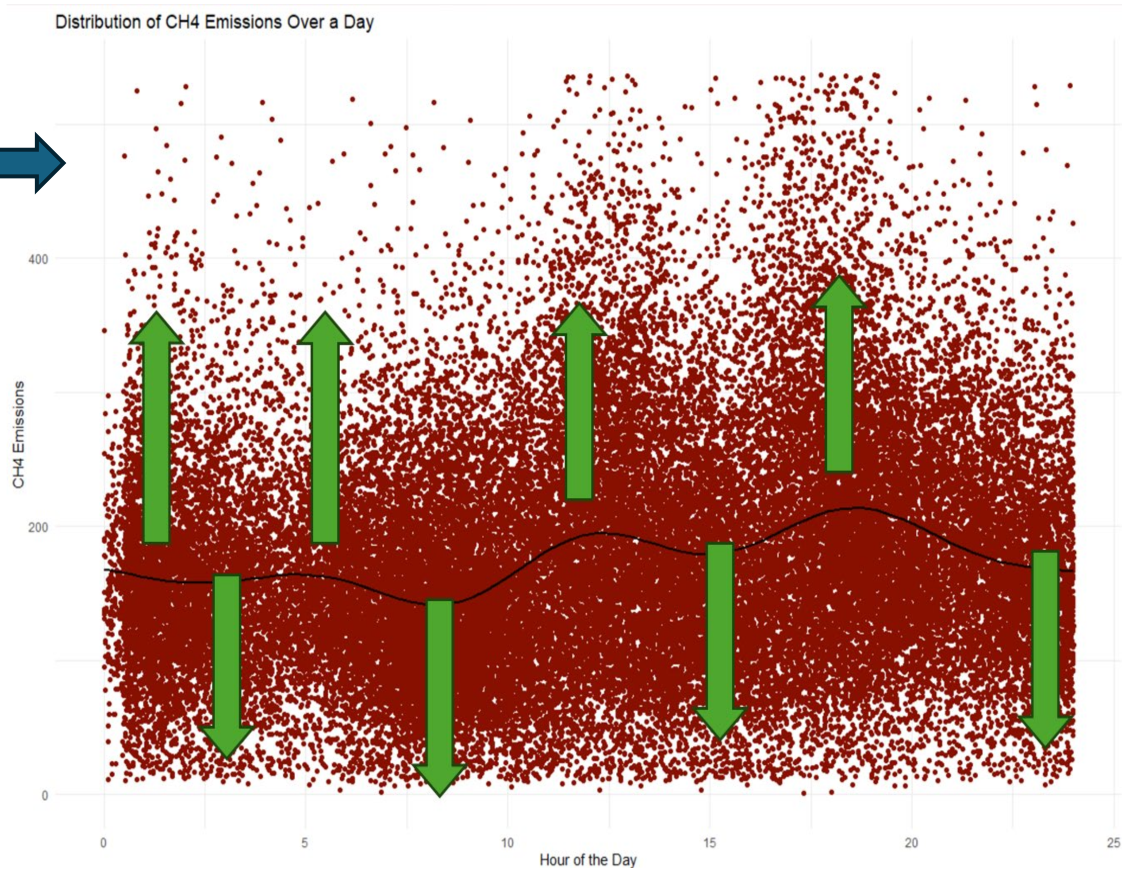
A. Dynamic Hypothesis
   1. Reference Model
   2. Key Variable Selection

B. Causal Loop Diagram
   1. Identify key **feedback mechanisms** related to individual CH4 production

(Tedeschi, 2022; https://doi.org/10.1093/jas/skac111)

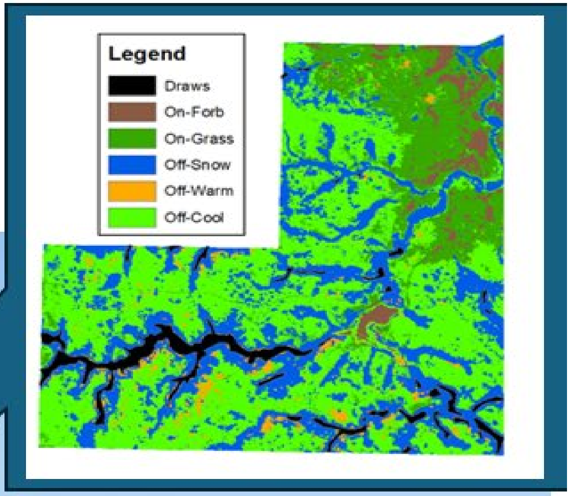
A-1. Reference Model: What is driving CH_4 behavior?

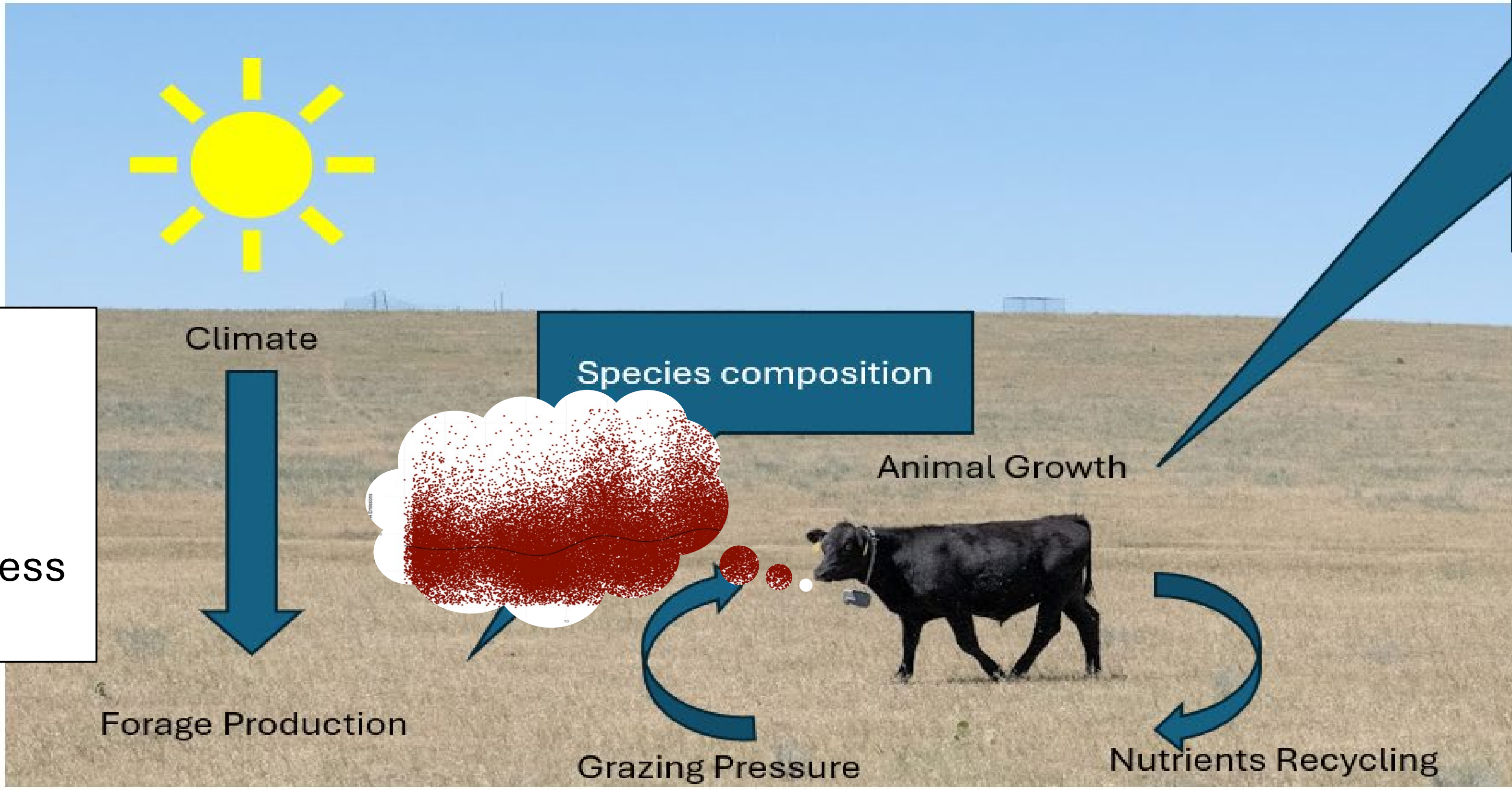




A-2. KEY VARIABLE SELECTION: What Endogenous and Exogenous Variables are driving CH_4 behavior?

Dynamic Rangeland





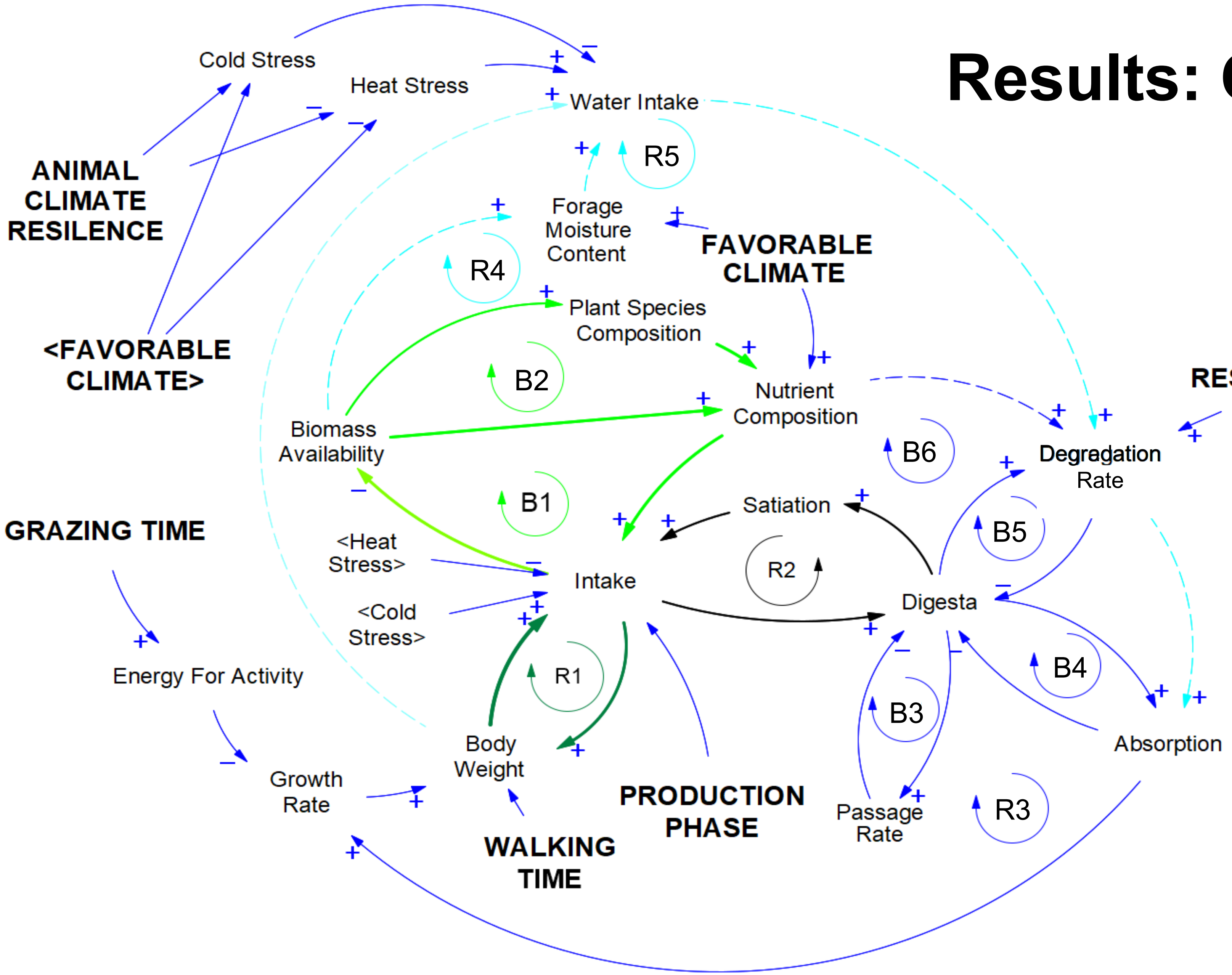
Grazing time

Passage Rate

Heat/Cold Stress

Δ Forage Quality
Δ Moisture
Δ Composition (C3:C4)
Δ Availability
Δ Regrowth

Results: Causal Loop Diagram



R1: Cattle growth
R2: Desire to graze
R3: Intake Impact on growth
R4: Moisture Impact on absorption
R5: Drinking water impact on absorption

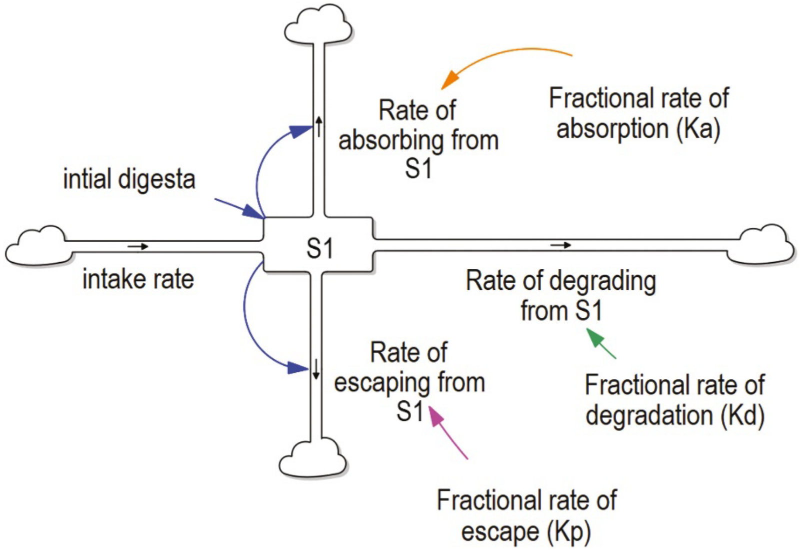
B1: Grazing impact on forage nutrients
B2: Grazing impact on plant species
B3: Passage impact on digesta
B4: Absorption impact on digesta
B5: Degradation impact on digesta
B6: Nutrient impact on growth

Discussion and Next Steps

R1: Cattle growth
R2: Desire to graze
R3: Intake Impact on growth
R4: Moisture Impact on absorption
R5: Drinking water impact on absorption

B1: Grazing impact on forage nutrients
B2: Grazing impact on plant species
B3: Passage impact on digesta
B4: Absorption impact on digesta
B5: Degradation impact on digesta
B6: Nutrient impact on growth

- Construct Robust PLT Data Pipelines
- Parameterize Model with Key Variables



Train, Test and Validate the Artificial Intelligence Model for CH_4 Prediction

Integrate Rumen and AI model in Python

Thanks for your attention

Acknowledgements to the SDSU and A&M teams, with especial mention to the Cottonwood research station workers and interns involved in the project

Future perspective of the Climate Smart project:

To evaluate different grazing practices to determine which is the most interesting in terms of decreasing methane emissions and increasing sustainability of cattle systems.

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Guarnidote

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