

Precision Feeding Dairy Cow Pens with Machine Learning

ARPAS Conference, 2024
Coalinga, CA

P. M. Lucey^a and H. A. Rossow^b

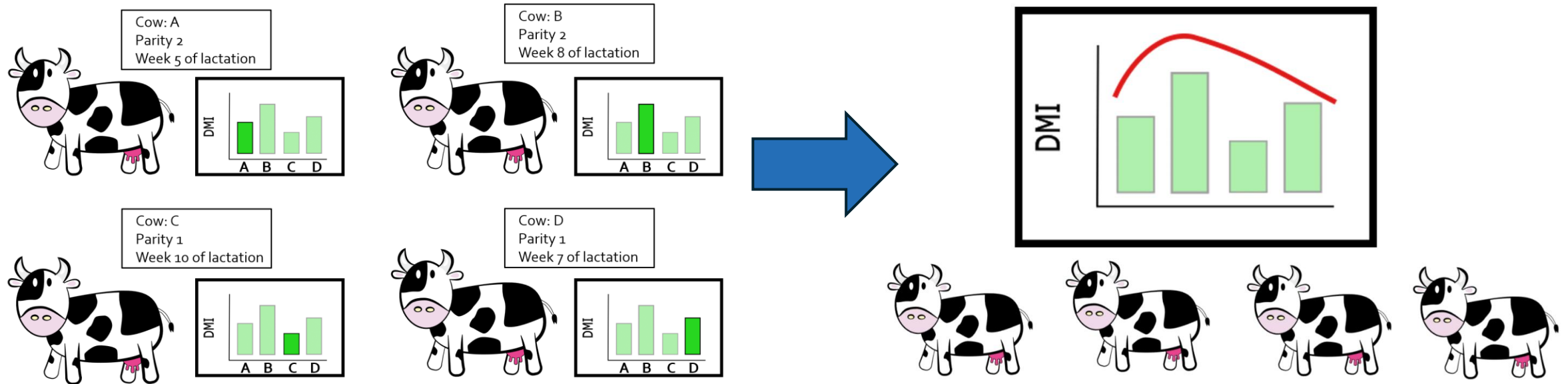
^a Elanco Animal Health, ID.

^b VMTRC UC Davis, Tulare, CA.



WHY?

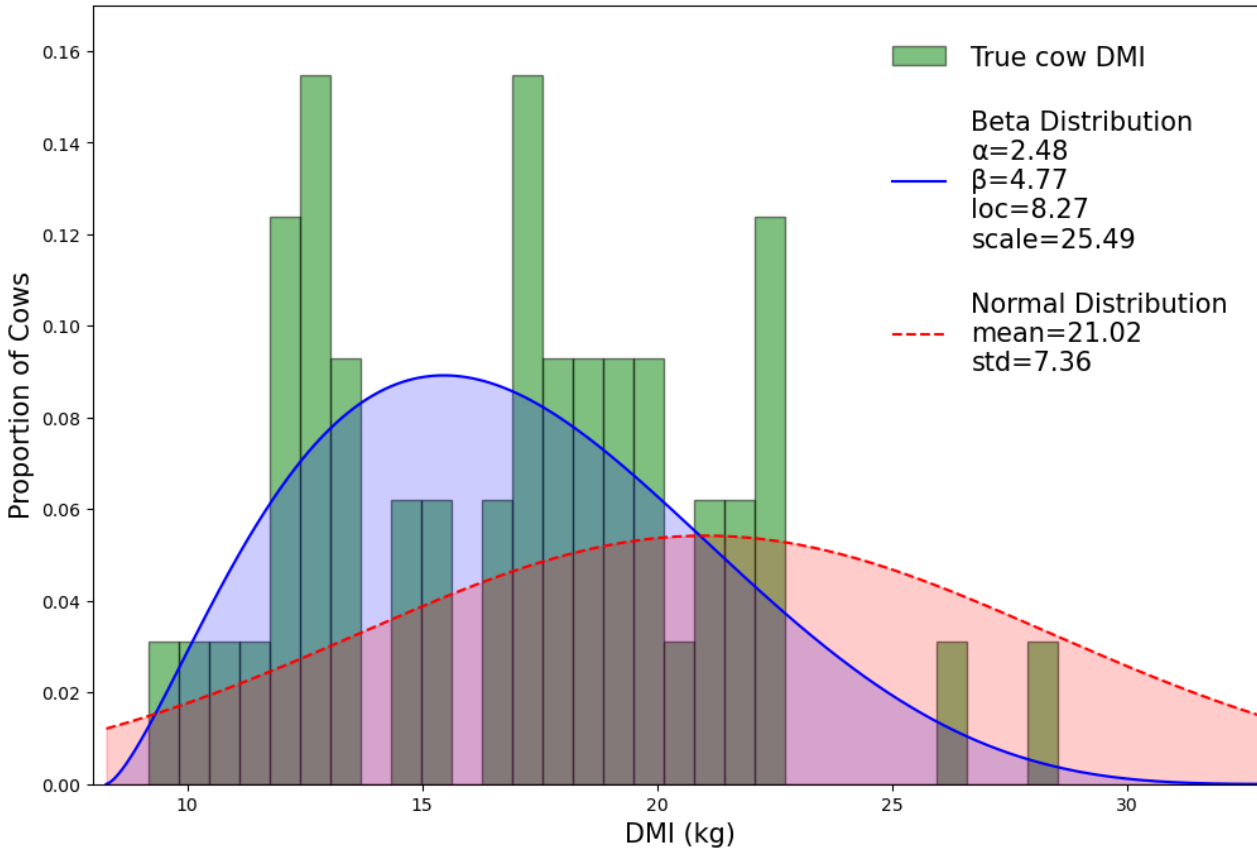
- Estimating DMI is necessary for precision nutrition and methane prediction.
- A ration formulated to the DMI of a pen will be more precise than a ration formulated for an individual cow when cows are managed as pens.



Why do we need the distribution?

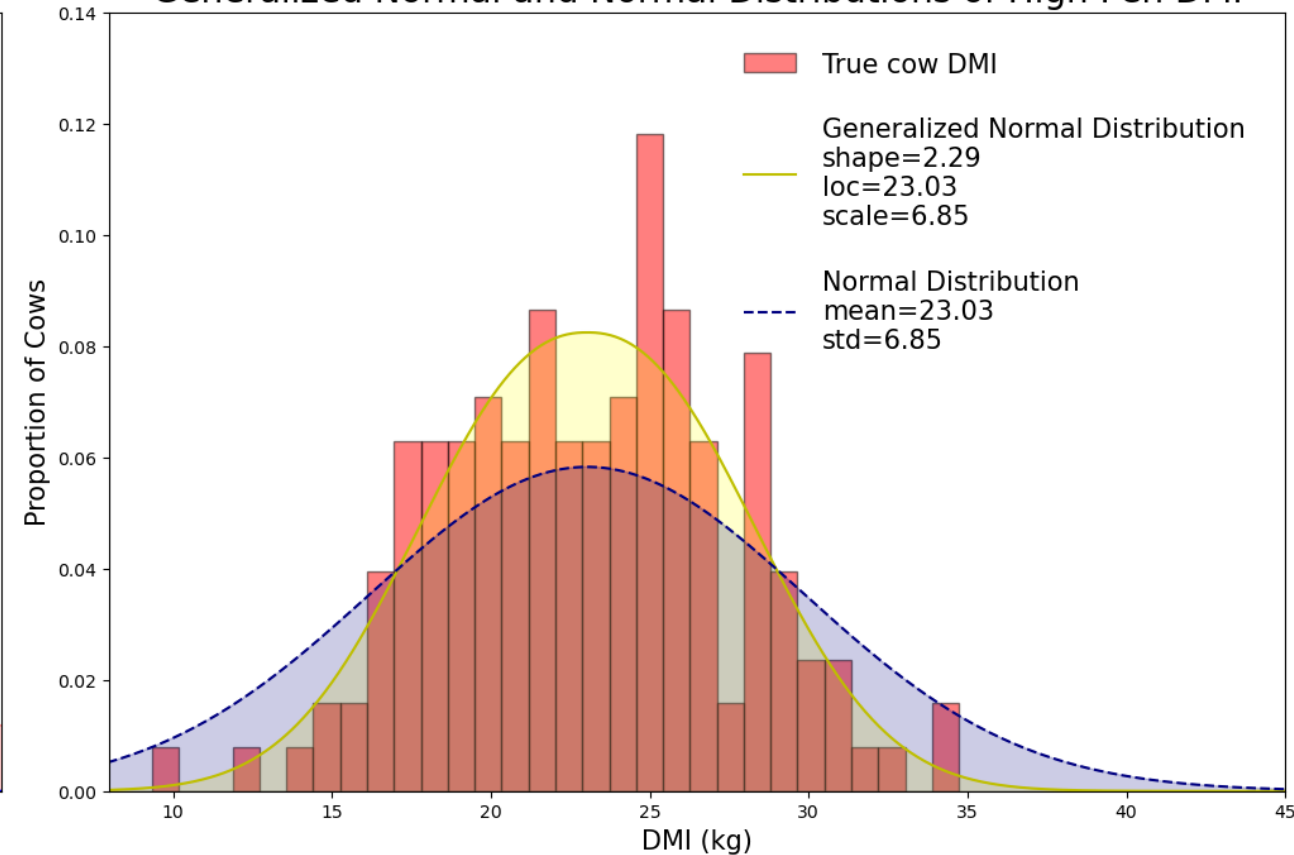
Fresh Pen

Beta and Normal Distributions of Fresh Pen DMI

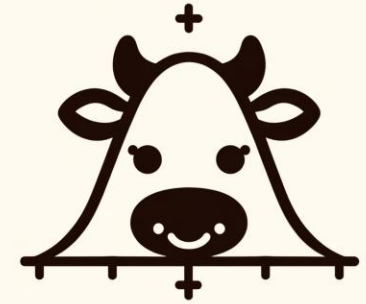


High Pen

Generalized Normal and Normal Distributions of High Pen DMI



Objectives



- Describe pen DMI distribution
- Predict the distribution when individual cow DMI is unknown (DSM)
- Compare ration formulation between DSM and predictions from the NASEM 2021 equation (iNSM, aNSM, fNSM).

Distribution Shape Model (DSM)	DMI predicted by the pen distribution shape
Individual NASEM Model (iNSM)	DMI predicted by the NASEM equation applied to each cow separately
Average cow NASEM Model (aNSM)	DMI predicted by the average cow of the pen using NASEM equation
Adjustment Factor NASEM Model (fNSM)	DMI predicted by the 75 th percentile cow of the pen using NASEM

Statistics V Machine Learning

Some models are the same, e.g. Linear Regression, data exploration with decision trees, non-linear modeling

Statistical modeling (**iNSM**, **aNSM**, **fNSM**)

- Infer relationships between variables (causality): P -values, confidence intervals, models evaluated on fit (R^2)
- Need to be interpretable and have assumptions

Machine Learning (**DSM**)

- Focus on prediction accuracy
- Relationship between variables less important than how well it predicts the correct outcome
- Mean absolute error, root mean squared error, accuracy and precision

DESCRIBING PEN DISTRIBUTION

Working with Pen instead of Cow

Pen Assortment

Cow Observations = 9,029 Unique Cows = 609				
Cow ID	WIM	Parity	Milk kg	DMI kg
42	5	2	40	25
78	10	3	55	30
222	2	1	39	27
...	...	...	...	...

WIM = Weeks in Milk

Uncertainty variables

1

Pen size (25 - 250)

2

Parity (Primi, Multi, Mixed)

3

WIM range (1 - 45)

Pen Observations = 5,203,685

Pen ID	First WIM	Last WIM	Mean Milk kg	Mean DMI kg	DMI Distribution
1	1	3	35	20	Beta
2	4	19	48	29	Generalized Normal
3	20	44	42	24	Generalized Normal
...	...	...	...	...	...

Lucey and Rossow, Describing the Distribution Type of Dry Matter Intake for Dairy Cow Pens based on Pen Characteristics, animal, 2023

How is DMI distributed?

			Proportion fit to each distribution shape			
Cows, n	WIM range	Mean DMI kg/cow	Normal, %	Beta, %	Weibull, %	Logistic, %
20	1 – 3	17.06	8	85	1	6
60	1 – 3	16.97	8	87	0	5
50	4 – 18	22.71	8	77	0	15
50	4 – 18	20.51	7	80	8	5
200	4 – 18	22.97	28	60	0	12
50	19 - 44	20.90	10	62	4	24
150	19 – 44	20.86	29	36	1	34

Lucey and Rossow, Describing the Distribution Type of Dry Matter Intake for Dairy Cow Pens based on Pen Characteristics, animal, 2023

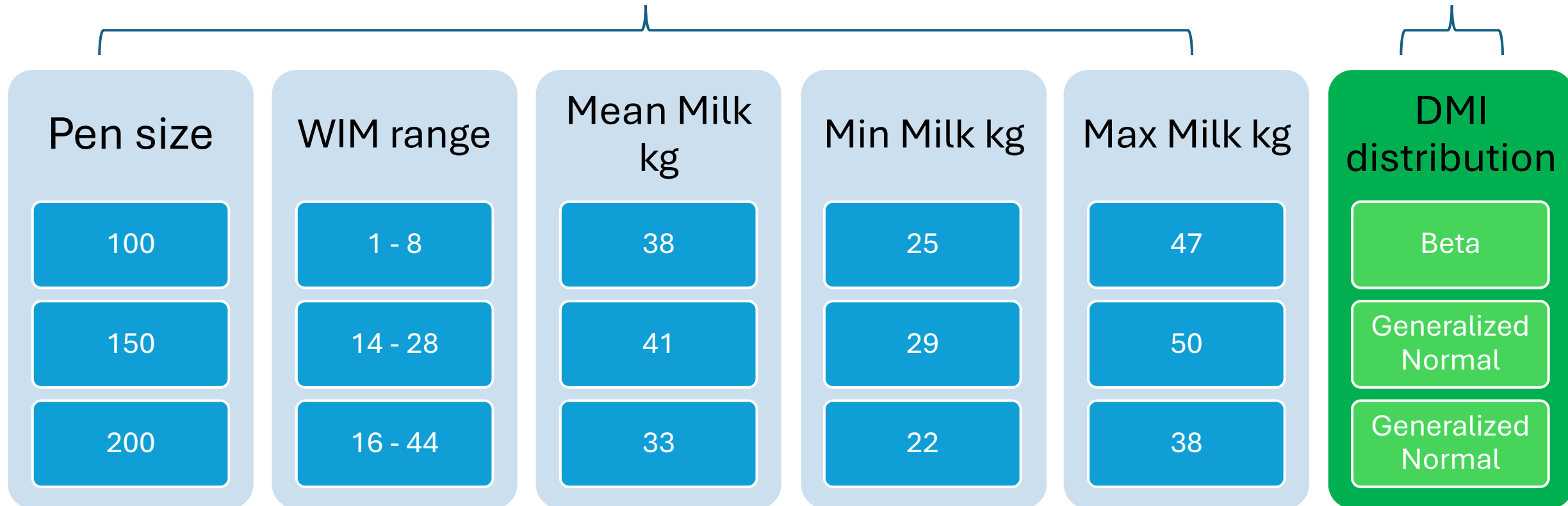
PREDICTING THE DISTRIBUTIONS

Predicting the DMI distribution

- Extreme Gradient Boost algorithm predicted the distribution shape

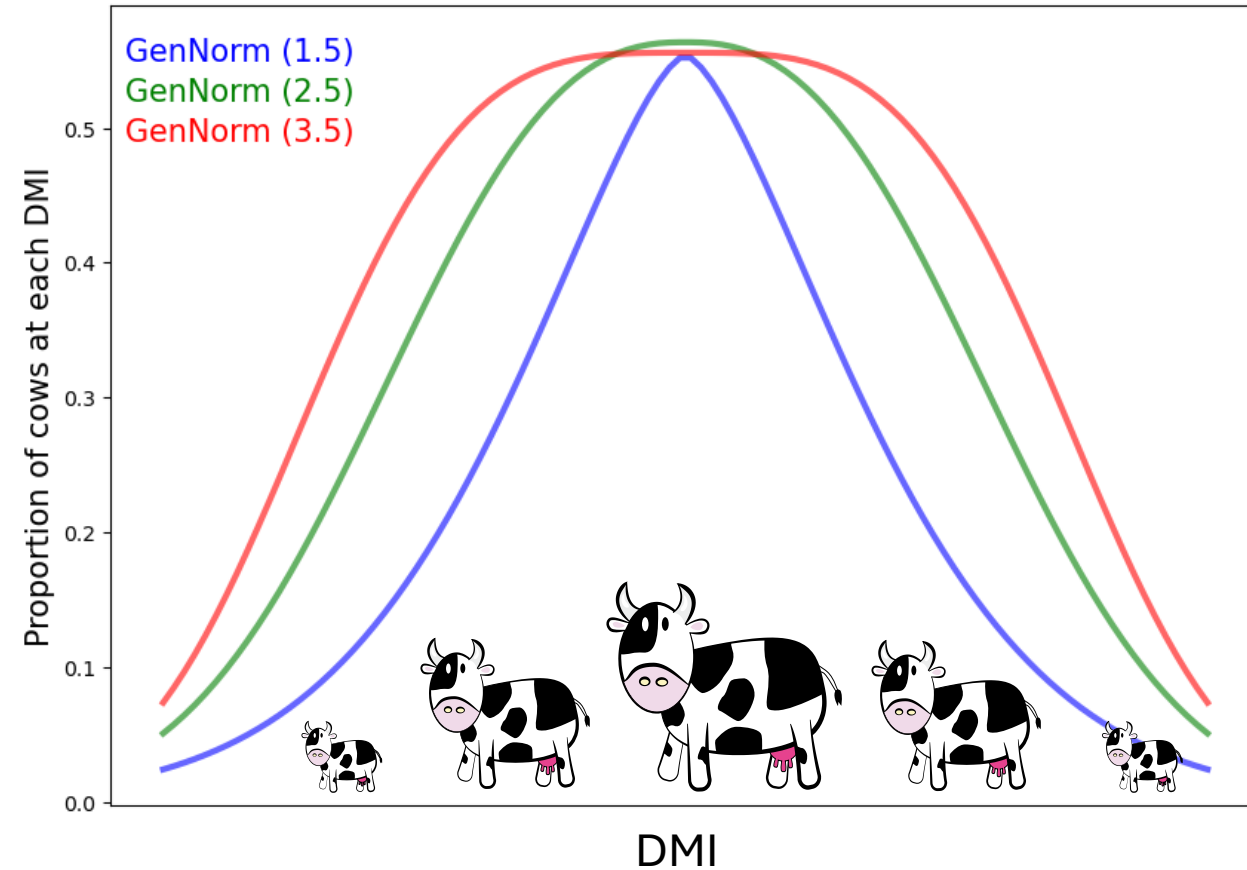
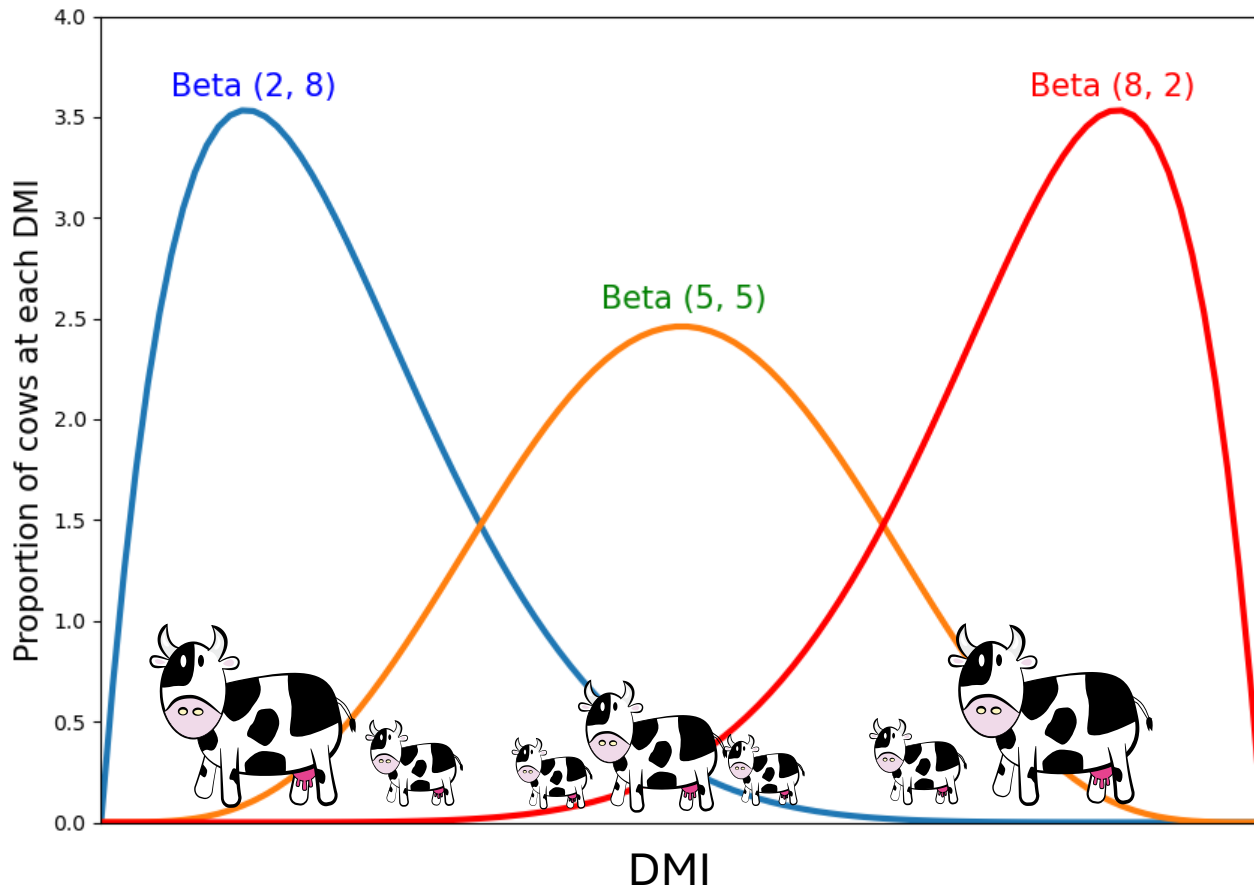
Training features

Label

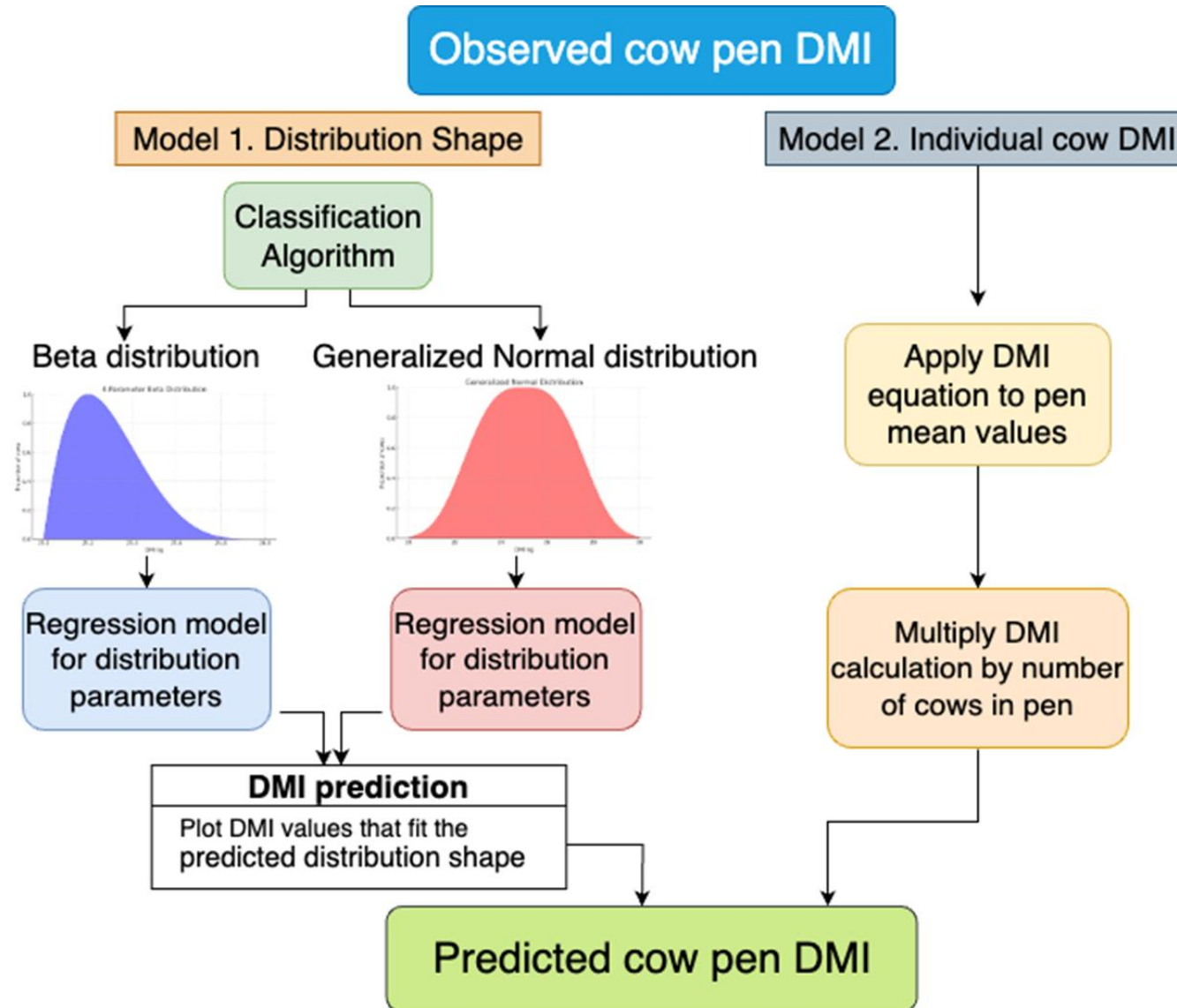


Lucey and Rossow, Predicting the Dry Matter Intake of Dairy Cow Pens with Machine Learning, ADSA Conference Proceedings, 2024.

Getting DMI from the distribution

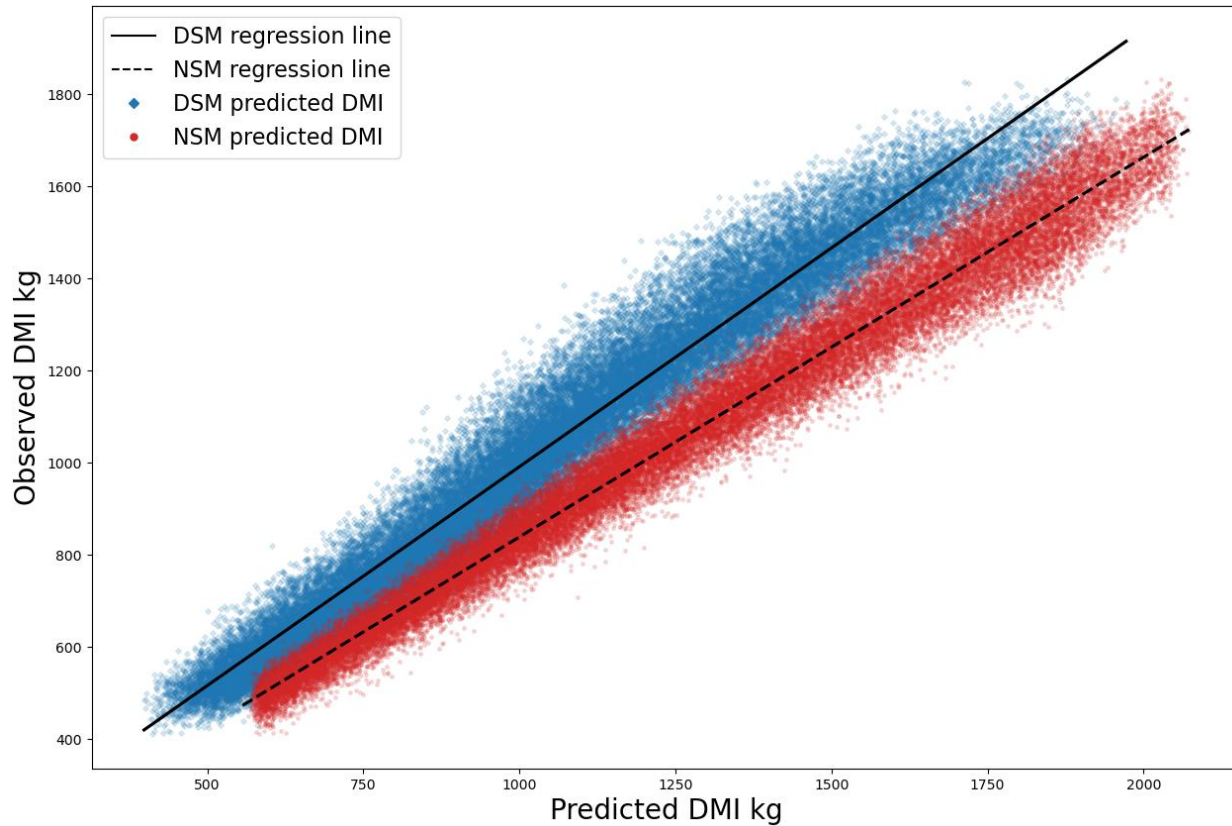


Getting DMI from the distribution

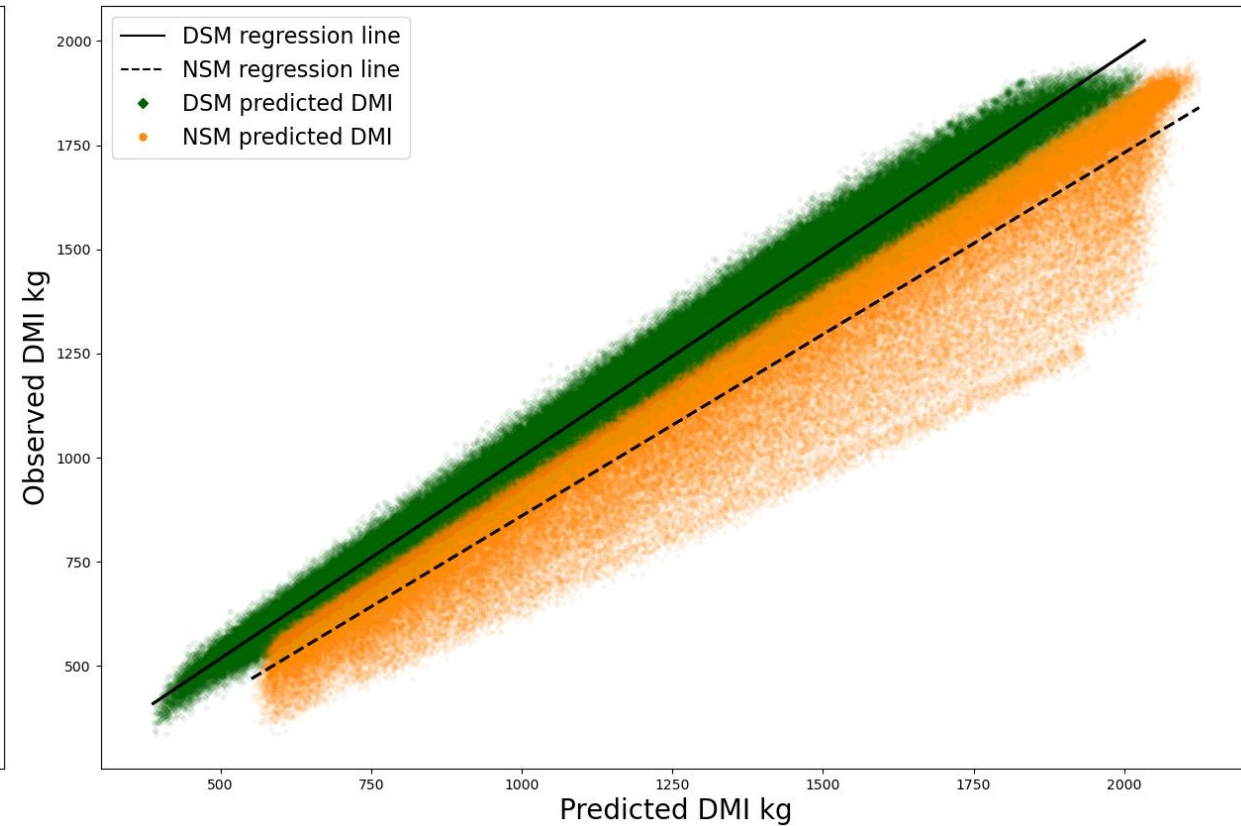


Performance compared to NASEM equation applied at pen mean

BETA



Generalized Normal

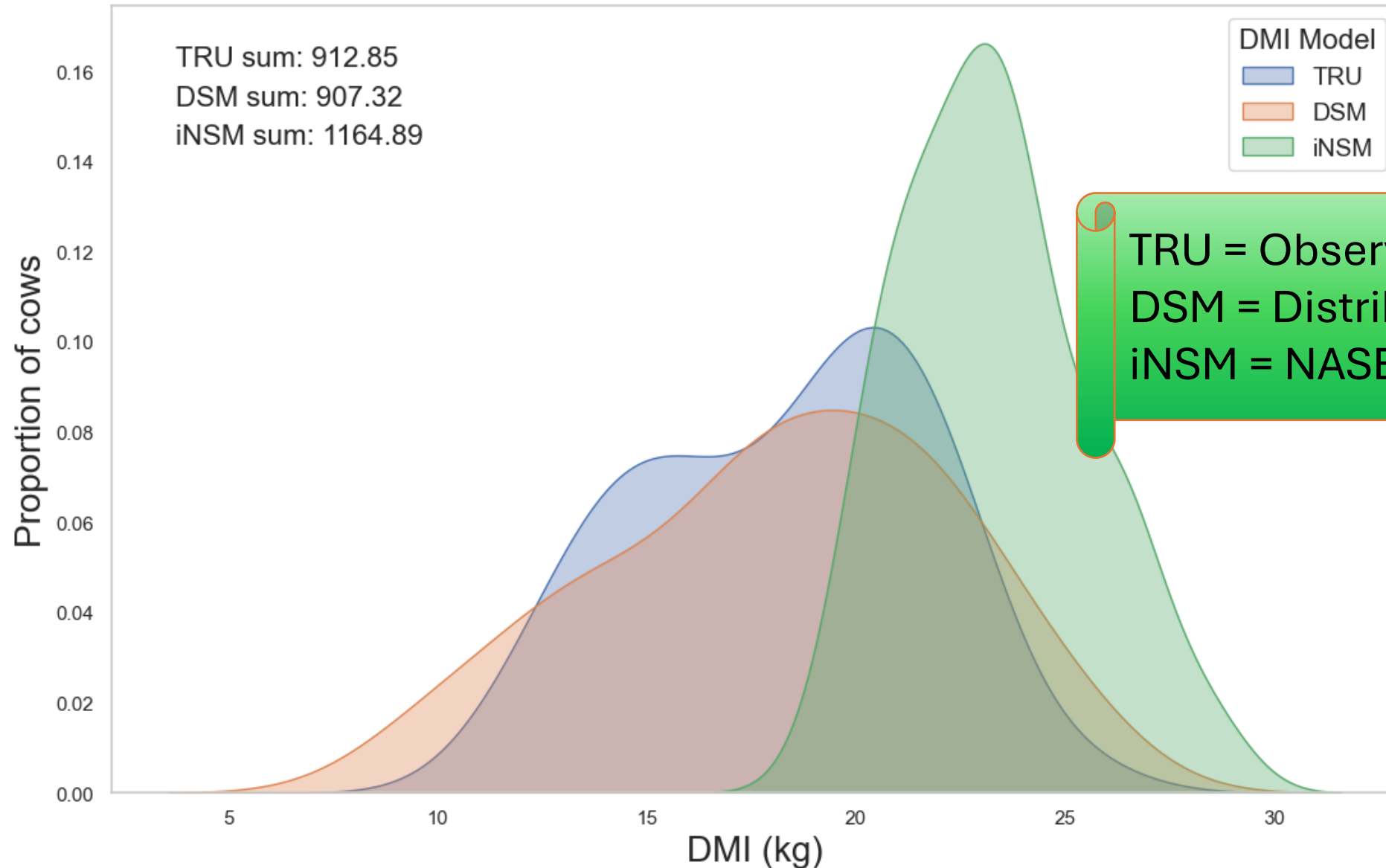


COMPARE RATION FORMULATION OF DSM, iNSM, aNSM, fNSM

Sample Pens for DMI prediction

	Fresh Pen	High Pen	Low Pen
Cows (n)	50	150	100
DMI (kg/d)	11.6 – 25.4	10.4 – 32.4	9.4 – 29
Milk yield (kg/d)	14 – 49.6	16.1 – 57	8.7 – 57
WIM	1 - 3	4 – 27	28 – 43
BW	483 - 727	383 – 756	432 – 748

Histogram of Fresh Pen DMI

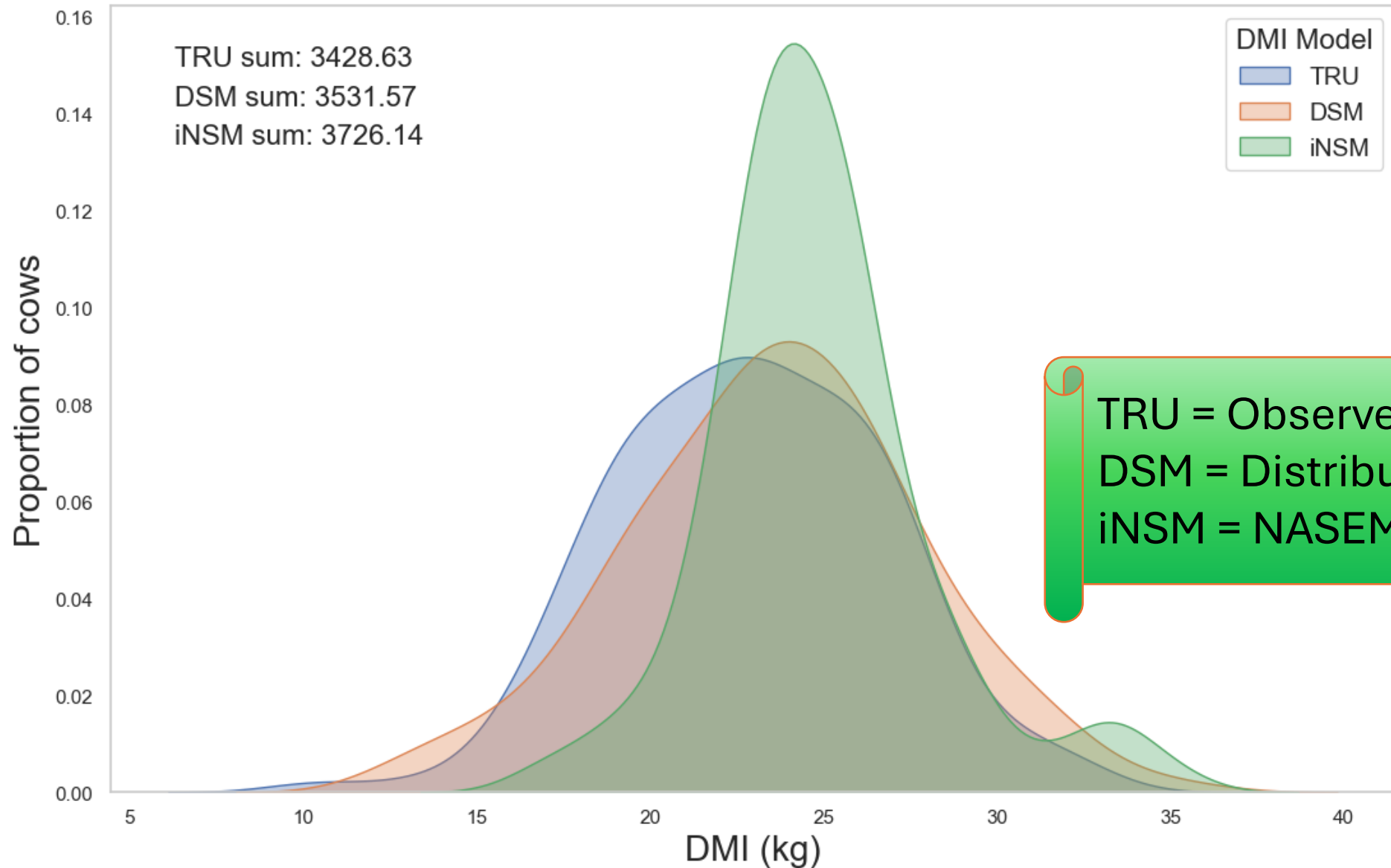


TRU = Observed DMI

DSM = Distribution predicted DMI

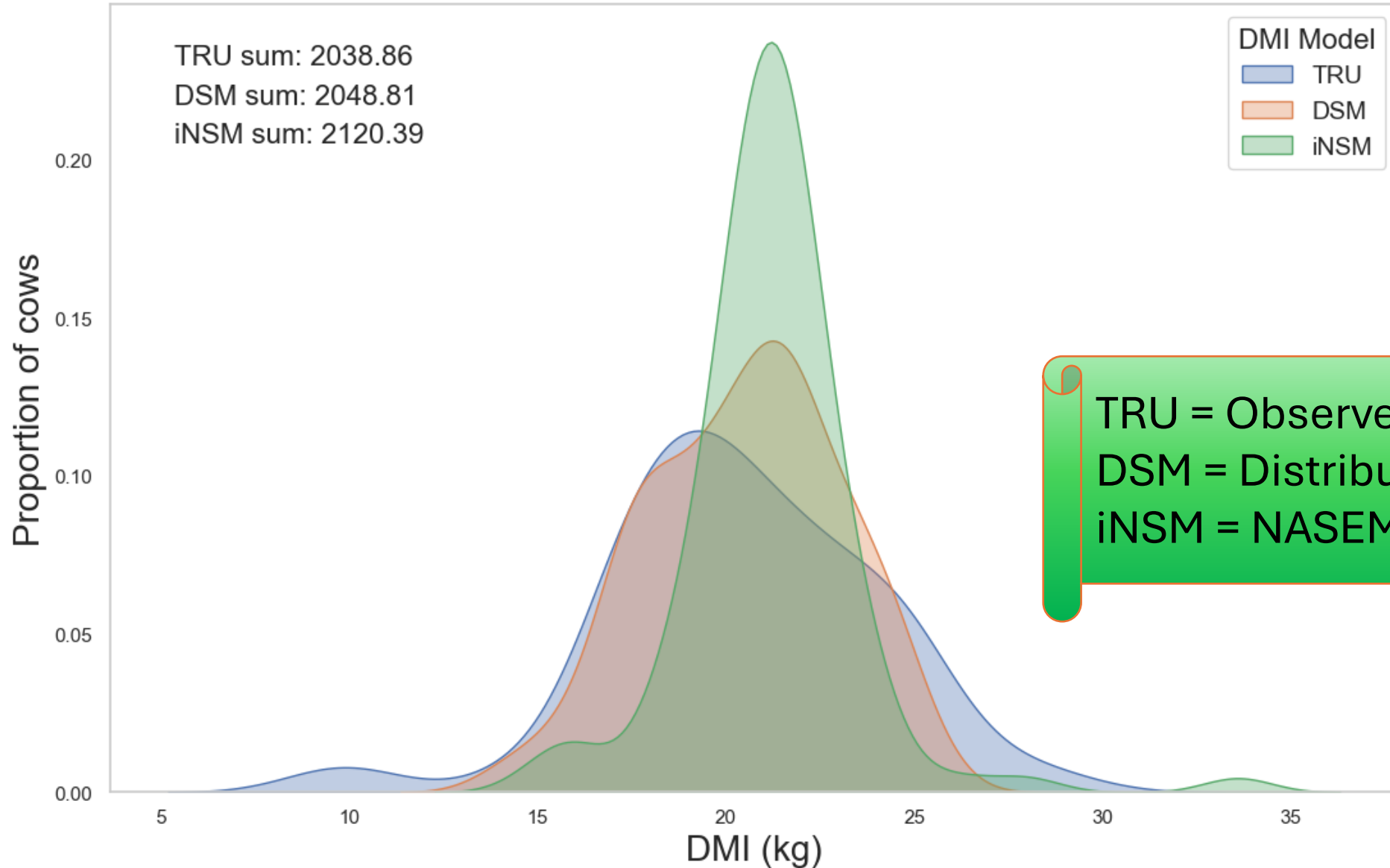
iNSM = NASEM predicted DMI

Histogram of High Pen DMI



TRU = Observed DMI
DSM = Distribution predicted DMI
iNSM = NASEM predicted DMI

Histogram of Low Pen DMI



TRU = Observed DMI
DSM = Distribution predicted DMI
iNSM = NASEM predicted DMI

Pen Ration formulation

- Nutrient requirements for pen calculated from NASEM 2021
- Feed tables from common California ingredient usage (Rossow & Aly, 2013)

Constraints

- Minimize cost \$/kg DM
- DMI constrained above and below 2.5% of predicted value
- ME > minimum cow requirement Mcal/kg DM CP < 20% kg DM
- RUP > 10%, RDP > 6.2/7.5% kg DM
- NDF > 25% and < 35% kg DM
- Starch > 18% and < 33% kg DM
- NDF as forage > 19% and < 25 kg/kg DM
- Maximum inclusion limits on Corn Silage, Dried Distillers Grains, Molasses & Urea

Pen Ration Solutions by DMI prediction

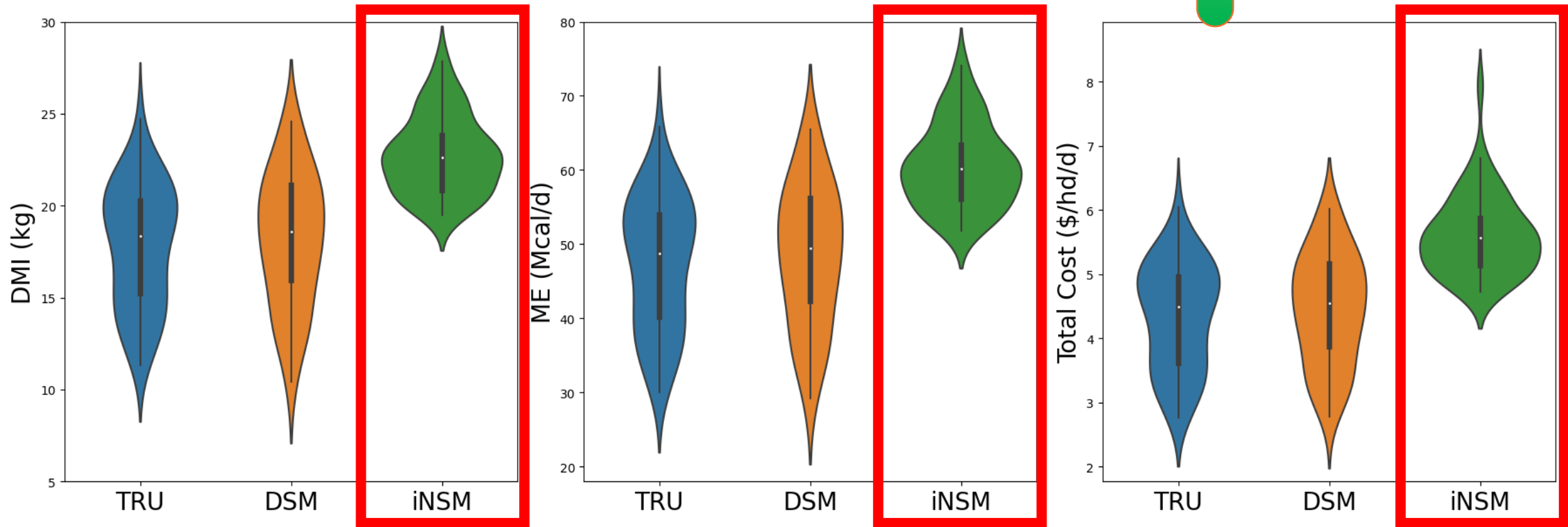
TRU = Observed DMI
DSM = Distribution predicted DMI
iNSM = NASEM predicted DMI
aNSM = NASEM DMI for mean cow
fNSM = NASEM DMI for 75th cow

		TRU	DSM	iNSM	aNSM	fNSM
Fresh Pen	n = 50					
	Cost, \$	217	215	276	262	295
	DMI, kg	890	884	1135	1077	1209
	ME, Mcal	2366	2352	3019	2863	3218
High Pen	n = 150					
	Cost, \$	858	858	891	924	1027
	DMI, kg	3498	3498	3632	3771	4186
	ME, Mcal	9324	9324	9683	10052	11161
Low Pen	n = 100					
	Cost, \$	535	538	556	558	593
	DMI, kg	1988	1997	2067	2071	2203
	ME, Mcal	5545	5472	5663	5674	6036

SOLUTION FOR EACH COW INDIVIDUALLY

Individual Ration Solutions of Fresh Cows

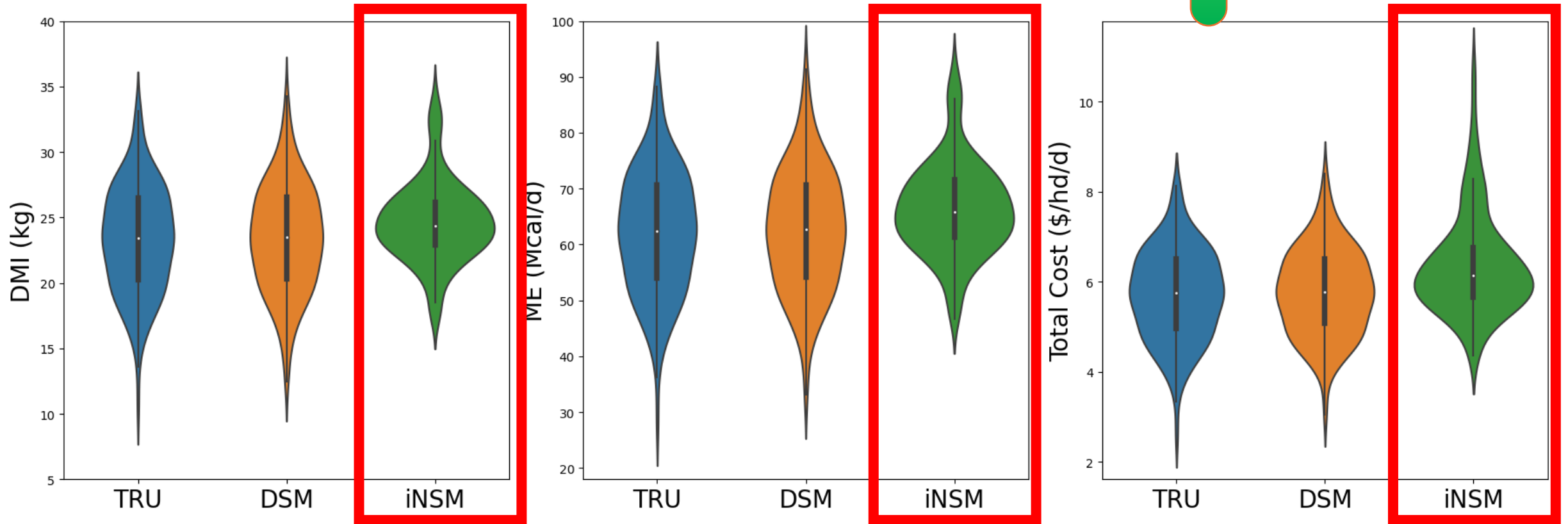
TRU = Observed DMI
DSM = Distribution
predicted DMI
iNSM = NASEM
predicted DMI



Different means by Games-Howell pairwise comparison

Individual Ration Solutions of High Cows

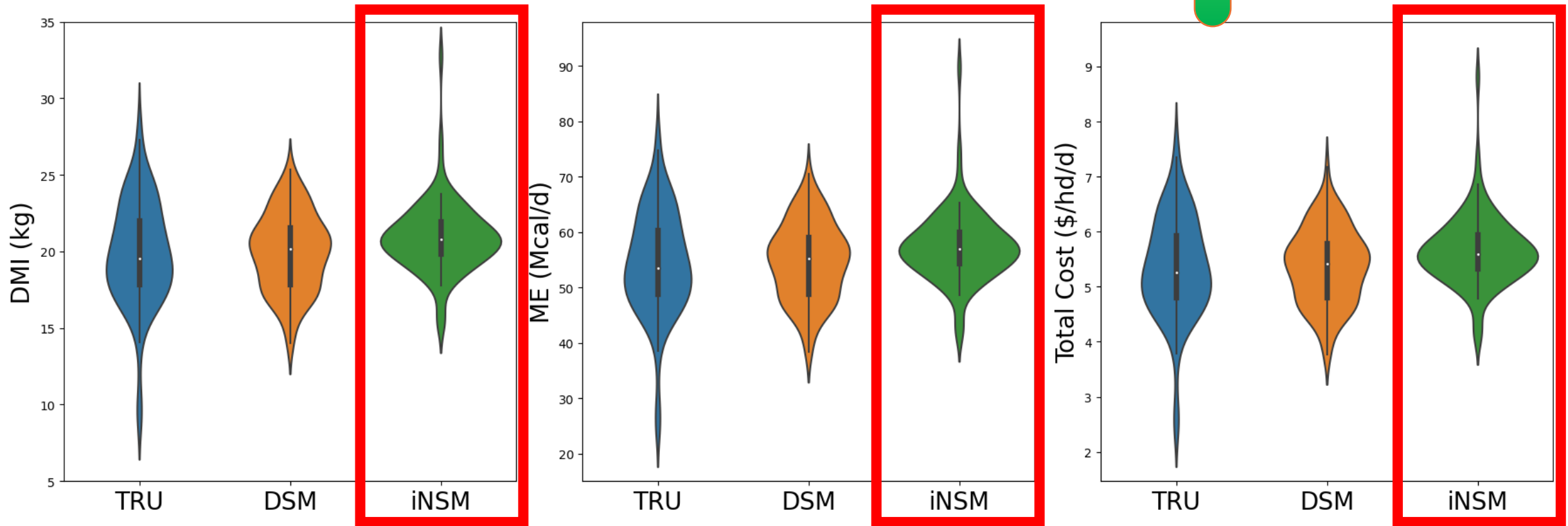
TRU = Observed DMI
DSM = Distribution
predicted DMI
iNSM = NASEM
predicted DMI



Different means by Games-Howell
pairwise comparison

Individual Ration Solutions of Low Cows

TRU = Observed DMI
DSM = Distribution
predicted DMI
iNSM = NASEM
predicted DMI



Different means by Games-Howell
pairwise comparison

SUPERVISED LEARNING IN DAIRY PRODUCTION

Next Steps

- Predict the nutrient requirements of the pen with the DMI distribution, Protein, aNDF, etc.
- Link this model to herd software, predict the pen DMI from pen info, input as the DMI for ration solution

Apply machine learning to other predictions

- Predict methane yield by pen using DMI and milk distributions
- Predict which cows would conceive first
- Predict responses to diet changes
- Predict what cows to keep or cull

How Machine Learning (AI) works

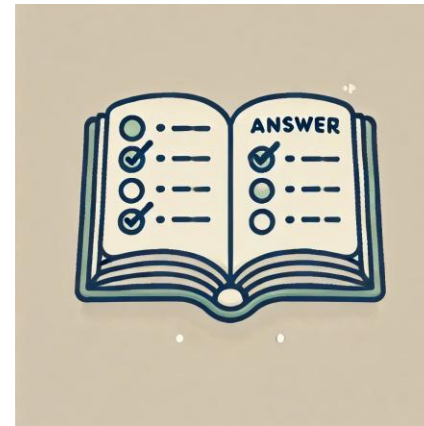
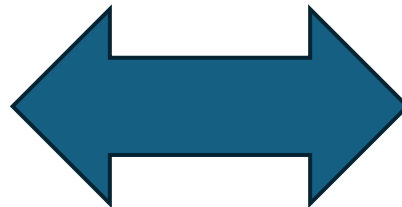
- Artificial intelligence by learning from historic data
- Looks for patterns
- Makes an “educated” guess at the answer using those patterns

Drawbacks

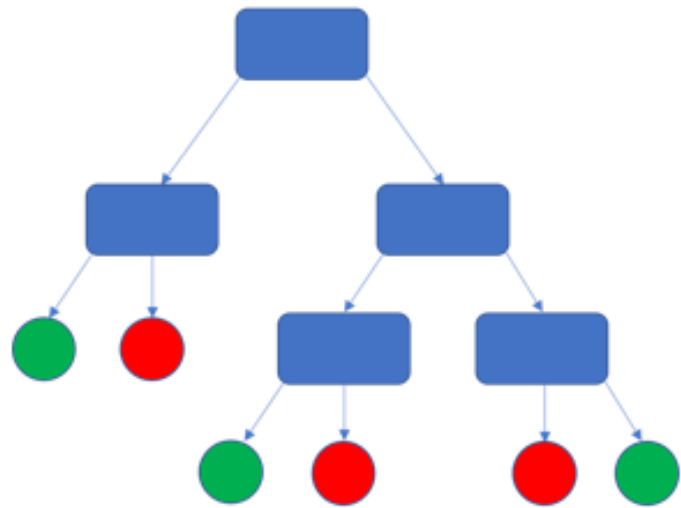
- Only as good as the data
- Bias and overfitting
- Some are black box and uninterpretable

Supervised Machine Learning

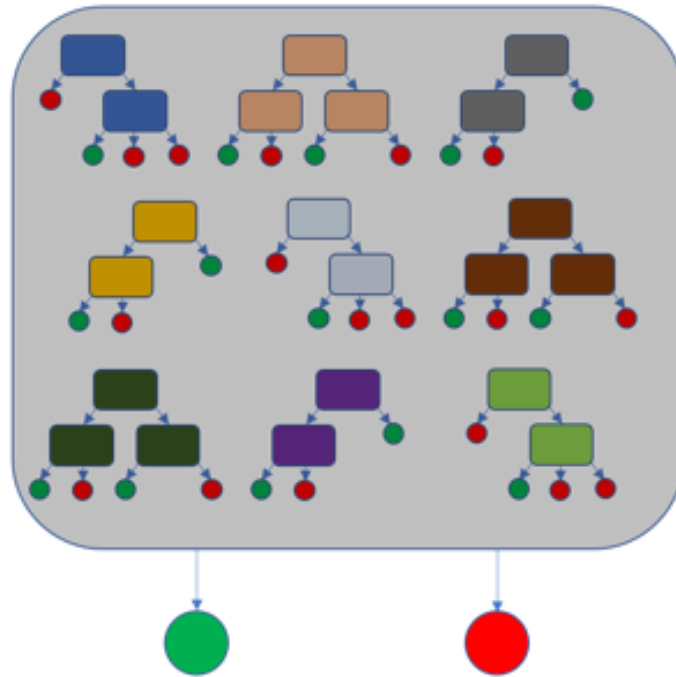
- Labeled data - the answer is linked to the input
- Handles categorical and numerical labels
- Categorization – Image of an apple or a banana?
- Regression – Predicting house prices based on the historic market
- Train it, then test it on unseen data, then validate it on external data
- Algorithms: Linear and Logistic Regression, Decision Trees, Random Forest, Extreme Gradient Boosting, Neural Networks



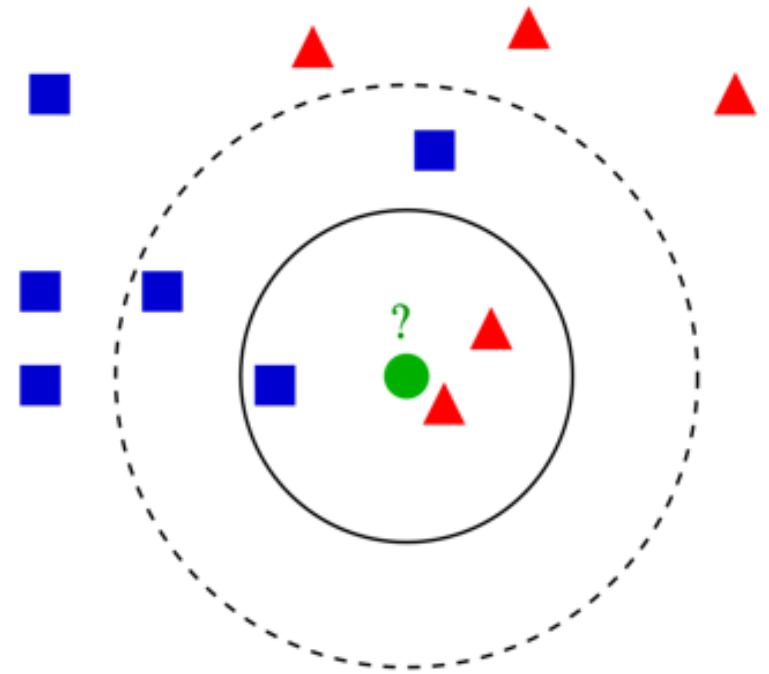
Supervised Machine Learning



Decision Tree



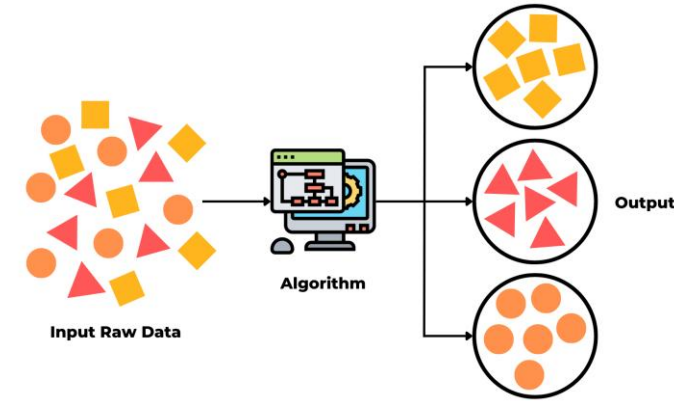
Random Forest



K-Nearest Neighbor

Unsupervised Machine Learning

- Unlabeled data, answer unknown or no answer
- Cluster/group data
- Find hidden patterns
- Reduce dimensionality (number of features) by clustering data on hidden patterns
- Examples: Anomaly detection, grouping for marketing or demographics, discover associations in large data, recommender of similar products to customers, social network analysis



Reinforcement Machine Learning

- The model makes a decision
- Receives a positive or negative response
- Updates its strategy to find the most optimal result
- Steps that move towards the goal are reinforced; steps that detract are ignored
- Uses: Financial predictions, recommendation systems, self driving cars



Questions?



Padraig Lucey, PhD, DVM, MPVM

padraig.lucey@elancoah.com

559-607-3886

Heidi Rossow, PhD

harossow@ucdavis.edu

APPENDIX

Feature importance

Rank	Classification	Beta Regression	Generalized Normal Regression
1	Parity: Heifers & Cows	Parity: Heifers only	Parity: Heifers only
2	Parity: Heifers only	Parity: Cows only	Parity: Cows only
3	Parity: Cows only	Pen size	Parity: Heifers & Cows
4	Maximum milk yield	Parity: Heifers & Cows	75 th percentile milk yield
5	Minimum week in milk	Maximum milk yield	Maximum milk yield
6	25 th percentile week in milk	Milk standard deviation	95 th percentile milk yield
7	5 th percentile week in milk	Minimum milk yield	Mean milk yield
8	Maximum week in milk	95 th percentile milk yield	Median milk yield
9	Pen size	Minimum week in milk	Median week in milk
10	95 th percentile milk yield	25 th percentile week in milk	25 th percentile week in milk

Model diagnostics

Model:

	MSEP	% bias	% Slope not 1	% Random Variation	R ²	RSR	CCC	r	Cb
--	------	--------	---------------	--------------------	----------------	-----	-----	---	----

DMI
distribution

Beta	5,249	3	5	92	0.95	0.22	0.98	0.98	0.99
Generalized Normal	2,085	1	7	92	0.99	0.12	0.99	0.99	0.99

NASEM
equation

Beta	50,320	85	10	5	0.55	0.67	0.84	0.99	0.85
Generalized Normal	45,779	73	7	20	0.69	0.55	0.87	0.97	0.90

Algorithm selection

Algorithm: **Decision tree** **Random forest** **XGB**

Classification

Accuracy	0.62	0.70	0.71
Precision	0.73	0.72	0.72
Recall	0.72	0.95	0.96
F1-score	0.73	0.82	0.82

Regression

Beta			
RMSE	16.1	11.2	10.9
Generalized Normal			
RMSE	0.68	0.51	0.47



DMI prediction model validation

Distribution shape model

- XGB classifier predicts distribution of validation data pens
- Non-linear regression predicts parameters of Beta and Generalized Normal distribution
- Set of DMI values plotted under the predicted distribution curve
- DMI values summed for total pen DMI
- Compared to the true pen DMI

Individual DMI model

- NASEM 2021 DMI equation
- Requires milk yield, milk energy, bodyweight, BCS and days in milk
- Validation data pens had the mean of each calculated
- One DMI value calculated by the equation
- DMI value multiplied by number of cows in pen for total pen DMI
- Compared to true pen DMI

		Classification			Regression	
	Accuracy	Precision	Recall	F-1 score		RMSE
Performance to testing data						
Beta		0.58	0.10	0.17		10.9
Generalized Normal		0.72	0.97	0.82		0.46
Combined	0.71					
Performance to validation data						
Beta		0.47	0.25	0.33		
Generalized Normal		0.67	0.84	0.75		
Combined	0.63					



Training and testing the model

- Extreme boosting gradient chosen from 3 algorithm candidates
- Features were pen descriptive statistics
- Feature selection and hyperparameter training

XGB algorithm:	Milk only	Milk and solids	Milk & solids & BW & BCS
Classification algorithm			
Accuracy	0.71	0.71	0.71
Precision	0.72	NO DIFFERENCES	0.72
Recall	0.96		0.96
F1-score	0.82	0.82	0.82
Regression algorithm			
Beta			
RMSE	10.9	10.9	10.9
Generalized Normal			
RMSE	0.47	0.47	0.46