Workshop: National Animal Nutrition Program (NANP) Models

1 Introduction and model construction: Part I (lecture). T. J. Hackmann*[1], M. D. Hanigan[2], and V. L. Daley[3], [1]*University of Florida, Gainesville, FL,* [2]*Virginia Tech, Blacksburg, VT,* [3]*National Animal Nutrition Program, University of Kentucky, Lexington, KY.*

This lecture will provide an overview of mathematical models, their types, and their construction. The general objective of mathematical modeling is to take a hypothesis, convert it a system of equations, and determine how well the equations describe reality. The specific objectives depend on the application, but could include predicting nutrient digestibility or intake. In this way, modeling is no different from any other scientific exercise—the first step is for the investigator to identify the hypothesis and objective. There are different types of models, and the investigator should choose a type suited to the specific objectives. In defining its type, a model can be categorized as static or dynamic, empirical or mechanistic, and deterministic or stochastic. Historically, nutrient requirement models have been static, empirical, and deterministic; they provided snapshots in time, did not describe mechanisms underlying responses, and did not consider inherent biological variance. These models were easy to derive, and have served the community well for more than a century. The Molly cow model is dynamic, mechanistic, and deterministic predicting responses through time based on underlying elements of digestion and metabolism without consideration of biological variation. After the investigator identifies the hypothesis, objective, and model type, the next step of constructing a model is to draw a block diagram. This diagram organizes the model conceptually. Rectangles in the diagram represent state variables, and arrows connecting the rectangles show the relationship of the variables. In a model of carbohydrate digestion in the rumen, for example, rectangles would represent pools of fiber, starch, and sugars, and an arrow connecting fiber and sugars would represent hydrolysis of fiber. This approach of representing pools or compartments within a system is referred to as compartmental modeling. In the remaining steps of constructing a model, the investigator translates the block diagram into system of equations, defines values of equation parameters, and solves the model so it can generate predictions. If evaluation of the model shows predictions are inadequate, earlier steps are repeated to refine the model.

Key Words: mathematical model, dynamic, rumen

2 Introduction and model construction: Part II (exercises). M. D. Hanigan*[1], V. L. Daley[2], and T. J. Hackmann[3], [1]*Virginia Tech, Blacksburg, VA,* [2]*National Animal Nutrition Program, University of Kentucky, Lexington, KY,* [3]*University of Florida, Gainesville, FL.*

The principles of mathematical modeling in agricultural sciences are well described by France and Thornley (1984). They categorized models as static or dynamic, empirical or mechanistic, and deterministic or stochastic, although, in practice, these categories are a continuum. This talk and exercise will focus on the mechanics of building and solving a compartmental model of intestinal N metabolism. A simple regression equation is often used to represent static processes; for example, dCP = CP_In × 0.65. This approach only considers fractional digestion of CP in the gut, and ignores any effects of other factors such as passage rate or microbial activity. In this simple model, a fast rate of passage would have the same digestibility as a slow rate. If one wants to represent residence time effects on CP digestion, then consideration of the pool size is needed. Mechanisms controlling CP digestion in the rumen can be incorporated into the model to yield better estimates. A dynamic model with a rumen pool of CP and a representation of rates of passage and degradation driven by microbial activity can be constructed and fitted to data to derive information on those mechanisms An intestinal model can be linked to the rumen model to further predict intestinal digestions and amino acid absorption. If rates of passage and degradation are known, it can also be used to predict outcomes when system inputs are manipulated. A representation of this system will be built by participants using R and fit to example data. The model can easily be extended, as there is no mathematical limit to the complexity that can be incorporated. Pool size, and thus the fluxes driven by pool size, can be solved numerically using a computer and numerical integration algorithms. As demonstrated with the example problem, compartmental modeling is very useful for modeling nutrient metabolism and animal performance as nutrient flow through a series of compartments and into product or excreta can be represented.

Key Words: mathematical model, type, review

3 Model evaluation: Part I (lecture). E. Kebreab*, *University of California, Davis, Davis, CA.*

Model evaluation indicates the level of accuracy and precision of model performance by assessing the credibility and reliability of a model in comparison to measured observations. Quantitative statistical model evaluation methods can be classified into 3 types including (1) standard regression statistics, which determines strength of linear relationship, (2) error index, which quantifies deviation in observed units, and (3) relative model evaluation that are dimensionless. Within the first category, analysis of residuals involves regressing residuals against predicted or other model variables. In this method, the model is unbiased if residuals are not correlated with predictions and the slope is not significantly different from zero. Predicted values can also be centered making the slope and intercept estimates in the regression orthogonal and thus, independent. This allows for mean biases to be assessed using the intercepts of the regression equations, and the slopes to determine the presence of linear biases. Mean square error of prediction (MSEP) and its square root (RMSEP) are commonly used methods of error index type of evaluation. In general, RMSEP values less than half of observed SD may be considered having a good performance. The MSEP can be decomposed into (1) error due to overall bias of prediction, (2) error due to deviation of the regression slope from unity, and (3) error due to the disturbance. Examples of the third category include the concordance correlation coefficient (CCC). The CCC can be represented as a product of 2 components: a correlation coefficient estimate that measures precision (range 0 to 1, where 1 = perfect fit) and a bias correction factor that indicates how far the regression line deviates from the line of unity (range from 0 to 1 and 1 indicates that no deviation from the line of unity has occurred). During model evaluation, a combination of the methods described above should be used to gain insight on model performance.

Key Words: evaluation, model

4 Model evaluation: Part II (exercises). E. Kebreab*, *University of California, Davis, Davis, CA.*

The objective of the model evaluation exercise is to familiarize users on various tools used to evaluate models. The exercise will use the R statistical software due to its relatively straightforward use, which is also freely available on the internet. A data set containing observed and predicted data will be made available to the participants. Based on principles covered, the participants will be asked to calculate the mean square error of prediction (MSEP) and its square root (RMSEP), which are one of the most commonly used methods of model evaluation. Furthermore, the exercise includes calculated the MSEP decomposition into (1) error due to overall bias of prediction, (2) error due to deviation of the regression slope from unity, and (3) error due to the disturbance. The participants will be asked to calculate another model evaluation category, which is the concordance correlation coefficient (CCC). The participants are expected to express CCC as a product of 2 components: a correlation coefficient estimate that measures precision (range 0 to 1, where 1 = perfect fit) and a bias correction factor that indicates how far the regression line deviates from the line of unity (range from 0 to 1 and 1 indicates that no deviation from the line of unity has occurred). Finally, participants will be asked to compare results from the 2 different categories of model evaluation.

Key Words: model performance, modeling, prediction accuracy

5 Meta-analysis: Part I (lecture). R. R. White*, *Virginia Polytechnic Institute and State University, Blacksburg, VA.*

Meta-analysis of literature is used in animal nutrition research to gain a more comprehensive understanding of the response being studied. Using weighted, mixed-effects, regression, most meta-analytical data sets can be evaluated. In these analyses, data are first gathered using clearly defined search criteria. Collected data should include the response variables of interested, standard errors reported, and explanatory variables under consideration. Once data are compiled, they should be checked for outliers and possible errors when transferring data. To remove individual study statistical analysis effects, data should be partitioned into mixed- and fixed-effect analyses and standardized. When data are clean and errors are standardized, backward, stepwise regression with fixed-effects for variables of interest and random-effects for things like study and location can be conducted. Variables should be removed from the model according to a predetermined cutoff, usually a *P*-value of 0.05. When all variables in the model are significant, removed variables can be iteratively re-tested to ensure that factors were not removed due to model instability. Correlation between factors can then be assessed using variance inflation factors (VIF). Parameters with a VIF above 10 should only be kept when parameters are correlated by calculation. When variables are correlated, the variable with highest VIF can be removed. Backward, stepwise regression, elimination at a significance cutoff, and elimination based on correlation should be iterated until model has only significant parameters and is not highly correlated. This procedure provides a framework for most animal nutrition meta-analyses, but may require some adjustments based on available data.

6 Meta-analysis: Part II (exercises). D. M. Liebe* and R. R. White, *Virginia Polytechnic Institute and State University, Blacksburg, VA.*

This meta-analysis workshop will work through an example data set using a common analysis procedure to illustrate the usefulness of meta-analysis as a tool in ruminant nutrition research. The workshop will focus on use of R and R Studio for conducting meta-analysis. The example data set includes literature reporting how microbial N outflows from the rumen are influenced by dietary nutrient intakes, marker type, sampling location, rumen pH and rumen volatile fatty acid or ammonia concentrations. The workshop will walk through a multi-step process used to evaluate data for common errors, correct standard errors, and derive models using a backward, stepwise regression procedure. Packages reviewed will include those required to read in data (xlsx, XLConnect, googlesheets), those required to handle data (dplyr, reshape2), those required to visualize data (ggplot2), and those required to fit linear mixed effect models (nlme, lme4, lmerTest). The workshop will walk participants through how data should be structured in text files or spreadsheets; how packages can be used to read data in from these external formats; how data can be handled and queried once read into R or R Studio; how data can be visualized using the ggplot2 package; and how models can be derived using linear mixed-effects models weighted for the inverse of study standard errors. At the end of the workshop, participants should be able to (1) organize data for use in a meta-analysis; (2) read data into R from a variety of formats; (3) visualize data distributions for assessment of common data entry errors; (4) calculate weights for use in meta-analysis; (5) derive a model using a multi-step backward elimination approach; and (6) evaluate the fit of a model using common fit statistics.

Key Words: meta-analysis, nutrition, regression

7 Opportunities for federal funding of modeling research. S. I. Smith* and M. A. Mirando, *USDA-National Institute of Food and Agriculture, Institute of Food Production and Sustainability, Washington, DC.*

The Food, Conservation, and Energy Act of 2008 (Public Law 110–246; i.e., the 2008 Farm Bill) established the National Institute of Food and Agriculture (NIFA) within the US Department of Agriculture (USDA). NIFA directs federal funding to advance agricultural research, education, and extension to solve agricultural challenges. In FY2017, NIFA invested a total of approximately $1.5 billion: $854 million in Research and Education Activities, $478 million in Extension Activities, $159.6 million in Mandatory and Endowment Funding, and $36.0 million in Integrated Activities, as designated in the 2017 Congressional Appropriations Act (Public Law No: 115–31). This investment is broadly split between Capacity Funding and Competitive Grant Funding. NIFA administers more than 30 Competitive Programs with broad eligibility. NIFA's flagship competitive program is the Agriculture and Food Research Initiative (AFRI). Mathematical modeling is recognized as a powerful tool that can be effectively applied to organize and interconnect what is known, to highlight knowledge gaps and areas needing research, and to prompt investigators to ask better questions. As a result, there are currently 80 active AFRI livestock projects with a modeling component, 8 of which directly involve the dairy enterprise. These dairy projects address a broad array of topics including ruminal metabolism, genomic prediction, whole genome selection, host-pathogen interaction, metabolic diseases, antimicrobial resistance and nutrition. NIFA has published 3 AFRI Request for Applications (RFAs) in FY 2018; (1) the Foundational and Applied Science Program RFA, (2) the Education and Workforce Development RFA and (3) the Sustainable Agricultural Systems RFA. It should be noted that modeling is specifically invited in 9 of the Foundational program area priorities, as well as the program area priority for Sustainable Agricultural Systems. A list of NIFA RFAs can be found at https://nifa.usda.gov/rfa-list

Key Words: modeling, nutrition, funding