# Building a Bayesian Network to identify key intervention points for improving nitrogen efficiency in New Zealand dairy farm systems

Gina Lucci[1], Cecile DeKlein[2], Vicki Burggraaf[1], Diana Selbie[1] and David Pacheco[3]

[1] AgResearch, Private Bag 3123, Hamilton 3240, New Zealand
[2] AgResearch, Puddle Alley, Private Bag 50034, Mosgiel 9053, New Zealand
[3] AgResearch, Private Bag 11008, Palmerston North, 4442, New Zealand

**Abstract**
Nitrogen (N) losses from New Zealand dairy farms are, in part, due to inefficiencies in N use within the system. Nitrogen cycling in pastoral dairy farming systems is complex, and understanding the interactions and interdependencies of N sources, N use and processes that control N losses will enable a more targeted approach to improving the overall N efficiency of the system. Bayesian Network (BN) modelling is an alternative to conventional modelling as it can evaluate complex multifactor problems using both forward and backward reasoning (cause-to-effect, and effect-to-cause), as well as assign probabilities to different outcomes. We developed a BN to identify the relative contribution of different components within a NZ dairy system to N leaching losses. An initial analysis revealed that the BN model can be a valuable tool for understanding how elements of the dairy N system fit together and their relative importance to overall N loss. Preliminary results also show that N leaching was most affected by feed N content and DM intake as opposed to the breed and weight of the cow. After further validation of the model it will be used to assess how current systems can be changed to meet N leaching targets, and to identify future strategies for improving N efficiency that target the key intervention points.

**Key Words**
Nitrogen, Bayesian Network, Grazing systems, N leaching

## Introduction
Nitrogen (N) efficiency in New Zealand dairy farms is a complex issue affected by variations in feed, animal, and soil management. In order to design better farm systems that improve N efficiency and minimise N losses, component research must be integrated into the whole farm system. Bayesian Networks (BNs) provide a framework for representing complex multi-factor problems by accommodating both expert opinions and empirical data. Bayesian Networks have been used successfully to quantitatively estimate the effects of different mitigation strategies on nitrogen flows from agriculture (Nash et al., 2010; Nash et al., 2013; Spence & Jordan, 2013). The flexibility of BNs is particularly useful for modelling farming systems where the complexity of the interactions may preclude the collection of large data sets upon which parameterization and testing of a conventional model could be based. BNs are also valuable tools for understanding complex interactions through both forward and backward reasoning, identifying key leverage points for improving system outcomes, and for evaluating "what-if" scenarios and the probabilities of different outcomes.

This paper outlines the development of a BN that describes the flows of N into, within and out of a typical New Zealand dairy farm system. The ultimate aim is the development of a robust tool that can be used to investigate and assess the relative contributions of different N sources and processes that influence N loss, and identify key intervention points that can be targeted for developing future strategies and new technologies.

## Methods
*Network development*
The process for network development used by Nash et al. (2010) was used as the basis for this study. A workshop was held with experts in dairy cow physiology, forage, and soil processes to define the scope of the model and develop the first cause-and-effect diagram. The team identified interventions and controlling factors affecting three key areas: urinary N excretion, N losses and productivity. Due to the many interventions and controlling factors, the team of experts decided to first focus on the 'urinary N excretion' outcome of the model. The next step was to identify the intermediate factors and links between the interventions and controlling factors. This resulted in the development of $BN_{ANIMAL,}$ a network that described current knowledge on the interactions, and associated uncertainties, between factors such as feed

management, animal energy requirements, feed energy and N content, animal dry matter intake (DMI) and N intake. In this study we used NETICA® (Norsys Software Corp., Vancouver, Canada) software for developing the BN. It was decided to use an annual time-step to reduce the complexity of the $BN_{ANIMAL}$. Where possible, deterministic relationships (i.e. equations) were used to develop the conditional probability tables (CPTs) that underlie the BN using the "Equation to Table" function in NETICA. The values of the continuous variables (or "nodes") were discretised into appropriately chosen intervals (or "states"). This BN was then presented to another panel of experts to refine its structure and data inputs, as well as assess its outputs.

Once the $BN_{ANIMAL}$ describing the urinary N excretion from dairy cows was revised and tested, another BN partitioning the flows of N through the soil was developed ($BN_{SOIL}$). The cause-and-effect diagram was put together during a workshop with soil N experts. The $BN_{SOIL}$ was created with this diagram using published data and expert knowledge to quantify the relationships between nodes. After review of the $BN_{SOIL}$ it was combined with the $BN_{ANIMAL}$ to describe the flows of N from feed into and out of the dairy cow, and soil N dynamics after urinary N depositions on soil.

*Network description*
The variables used in the network were grouped into seven categories to highlight their main function or target area: Cow (properties); Feed (properties); Intake; Plant (properties); Management (actions); Calculation; and Outcomes. Briefly, the annual feed requirement of a dairy herd is estimated from the annual milk solids (MS) production, taking into account the cow breed and cow feed conversion efficiency (Metabolizable Energy; ME/kg MS). The feed properties (ME content and %N) are then used to estimate the herd's N intake. The N intake is then partitioned into the amount of N in milk; meat; faeces and urine on a kg N/ha basis. The fate of urinary N is calculated seasonally by dividing the annual urinary N load into seasonal (i.e. spring, summer, autumn, and winter) components. Urine is distributed into patches and is lost via three pathways: gaseous losses, leaching and uptake by pasture.

## Results
*Model application*
A sensitivity analysis of the N leaching-node showed that urine N load was least affected by the cow breed and weight. Nitrogen content of feed consumed and total DMI and NI had strong influences on N excretion and therefore N leaching. This confirmed that the model was behaving as expected and in line with other studies (e.g. Gourley et al., 2012; Powell & Rotz, 2014).

Initial testing of the model was used to illustrate the influence of stocking rate (cows/ha) and feed conversion (ME/MS) on total N excretion (Figure 1). For a feed N content in of 3.25% N, reducing the herd's average conversion rate of ME to MS from 82 MJ ME/kg MS to a more efficient 72 MJ ME/kg MS would enable the stocking rate to be increased from 2.6 to 3.75 cows/ha with no increase in total urinary N excretion. This was mainly due to the reduction in ME required (30%) to achieve the same MS production.

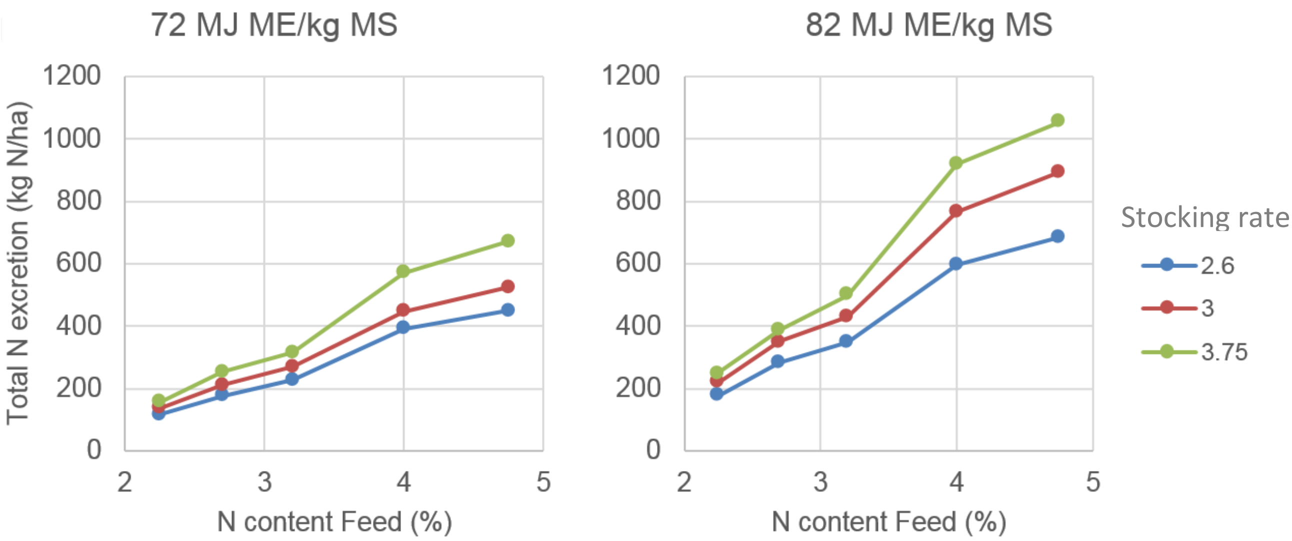


**Figure 1. Modelled total N excretion as a function of the N content of feed consumed (2.25 to 4.75 %), stocking rate (2.6 to 3.75 cows/ha) and feed conversion efficiency (72 or 82 MJ ME/kg MS).**

Although these are presented as single values in Figure 1, in a BN the values are presented according to the probability with which they are likely to occur (Figure 2). This example shows that although it is possible for the total N excretion to be between 0 and 900 kg N/ha (using the inputs described above), there is almost a 50% chance that N excretion would be between 350 and 500 kg/ha.

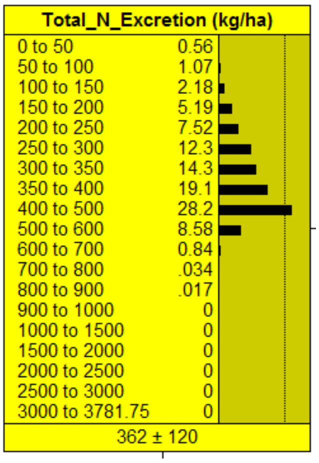


**Figure 2. Node example showing the distribution (black horizontal bars) of the most probable loads of Total N excretion based on an example presented in Figure 1 (Feed conversion 72 MJ ME/kg MS; stocking rate 3.75 cows/ha; N content feed 3.25%). The box at the bottom shows the average value and standard deviation of the variable under the specified conditions.**

*Future model development*

Validation of the model is the critical next step in the process of development. As there are no datasets that cover all of the inputs and outputs of the model we will need to validate subsets of model components. Once we are satisfied that outputs of the model are within typical ranges and that relationships between variables behave according accepted theory, we can use it to predict the likely reductions in N leaching losses that can be achieved in current systems. We could also predict how these systems can be changed to meet N leaching targets. The model can also be used to identify future strategies for improving N efficiency that target the key intervention points. These could include future scenarios using cows with greater feed conversion efficiency, or forage cultivars with low N and high ME. This model can also serve as a base on which to add additional nodes that can capture the effects of other potential strategies to reduce N leaching losses and improve on farm N efficiency.

## Conclusions

This dairy system BN model combines the features of both animal and the soil/pasture into one integrated system. This permits the user to investigate a range of hypotheses and use sensitivity analysis to explore the key drivers of N loss throughout the system. A basic analysis of initial results has shown that this model can be a valuable tool for understanding how elements of the dairy N system fit together and their relative importance to overall N loss. While the outcomes of the model may not be surprising (e.g. N excretion driven by N intake, which in turn is driven by DMI and its N content), a key attribute of this modelling approach is that it allows for uncertainty and variability inherent to a pastoral system and presents the distribution of outcomes. As such, the model also proved a useful visual representation of a range of potential N losses from the dairy system.

## Acknowledgements

We are grateful to Mark Shepherd, Stewart Ledgard, Ronaldo Vibart, David Wheeler, Pierre Beukes, Alvaro Romera, Mark Neal, Cameron Ludemann, Ross Monaghan and Tony VanDerWeerden for comments and help with the development of the network.

## References

Gourley CJP, Aarons SR, Powell JM (2012). Nitrogen use efficiency and manure management in contrasting dairy production systems. Agric. Ecosyst. Environ. 147, 73–81.

Nash, D, Hannah M, Robertson F, and Rifkin P (2010). A Bayesian Network for comparing dissolved nitrogen exports from high rainfall cropping in southeastern Australia. J. Environ. Qual.39, 1699-1710.

Nash D, Waters D, Buldu A, Wu Y, Lin Y, Yang W, Song Y, Shu J, Qin W, and Hannah M (2013). Using a conceptual Bayesian network to investigate environmental management of vegetable production in the Lake Taihu region of China. Environ. Model. Softw. 46, 170-181.

Powell JM and Rotz CA (2015). Measures of nitrogen use efficiency and nitrogen loss from dairy production systems. J. Environ. Qual. 44:336–344.

Spence PL and SJ Jordan (2013). Effects of nitrogen inputs on freshwater wetland ecosystem services – A Bayesian network analysis. J. Environ. Manage. 124, 91-99.