DEVELOPMENT OF A CRITICAL SOURCE AREA PREDICTION MODEL OF NITROGEN LEACHING

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Abstract

Nitrogen (N) leaching has a major impact on fresh water quality and farmers are under pressure to reduce these losses. Farmers, working under an N discharge allowance, require cost-effective mitigation strategies to reduce N leaching losses sufficiently to allow an increased stocking rate that sustains their financial viability. Broadcast application of a nitrification inhibitor is too costly for hill land farmers, but targeting DCD at stock camps is one cost-effective strategy that reduces N leaching loss. This study developed a cattle resting (stockcamp) prediction model based on GPS velocity. Contours of eight paddocks within Taupo farms were generated and soils samples were collected from 83 sites covering known camp (low slope, under trees, around water troughs and gateways) and non-camp (hill) areas for analysis of Olsen P status, since grazing animals deplete P on slopes and accumulate P at campsites. Mean Olsen P values were >30 at campsites and 13.8 on hill slopes, confirming that campsites can be selected from a contour map. The model will be validated against maps of measured urine excretion densities and known contour. Successful validation will see contour maps (slope, aspect, elevation) used to predict campsites within the eight soil-sampled Taupo paddocks. Robustness of the resting model will require additional datasets comprising only cattle GPS and paddock contour from a wide range of environments and seasons. We envisage farmers using a CSA map to cost-effectively target mitigation strategies at only small areas within hill paddocks to reduce N losses from about 50% of cattle urine patches.

Additional keywords: nitrification inhibitor, grazed pasture, cattle, predictive modelling

Introduction

While farmers are under ever increasing pressure to reduce animal excreta entering waterways, government targets of doubling the value or agricultural exports while halving environmental impacts by 2025, increases this pressure. Even by improving food conversion efficiency of livestock, every stock unit added to the NZ livestock inventory increases excretal deposition. At present, farmers within the Lake Taupo catchment are farming under a nitrogen (N) allowance that effectively prevents them increasing farm inputs without using N leaching loss mitigation strategies. Mitigation strategies for all farms need to be cost effective, especially within hill country regions where animal enterprises are less profitable.

We know that cattle grazing hill country pastures typically rest in low-slope areas, performing about 50% of their daily urination events in these stockcamps (Betteridge et al. 2010a; Betteridge et al. 2010b). It has been shown that targeting dicyandiamide (DCD) at stockcamps is one strategy that can reduce N leaching in hill country (Betteridge et al. 2011). This is cost-effective since DCD targeted only at stockcamp sites in hill pastures, which occupy just 5-15% of the paddock area, can potentially mitigate N losses from half of all cattle excreted urine patches (Betteridge et al. 2011). Further, it has been shown that there is a good relationship between the time an animal rests in particular places in the paddock and the number of urination events counted in these places. Therefore, by predicting where cattle will rest would enable a map to be drawn of campsites that require a targeted mitigation approach.

The resting place predictive Generalised Additive Model (GAM) presented at this conference last year (Betteridge et al. 2012) was developed based on 5 days of data from a 0.5 ha paddock with limited aspect variation. To develop a general model, applicable to large areas of a region, the model requires data from many more representative sites that are likely to be encountered by animals. Thus, individual paddocks that provide variation in the ratio of hill to flat land, and variation in slope, aspect and elevation, are needed to populate the database for generating a robust model. Because of the limited access to and cost of using multiple animal sensors in grazing studies, being able to use GPS *resting time* and *location* data as the proxy for urine excretion sites will enable a much greater number of experimental datasets to be used when developing the robust model. The *Ballantrae* 2009 dataset (Betteridge et al. 2012) had resting time data accurately determined by a 3-D motion sensor. With these data we were able to confidently differentiate between an animal at rest (standing or lying) or actively moving and grazing.

Campsite position (determined by Eastings and Northings with a GPS) is important for map creation, while at a regional scale GPS data may allow the introduction of sub-models specific to a sub-region. A GPS used at the time of applying a mitigation tool can also be used to verify the mitigation activity. GPS data also serve to link animal movement data with land resource data.

Before *Targeted DCD* can be included as a mitigation strategy in the Overseer® nutrient budget model it is necessary that an accurate farm map of critical source areas (CSAs) is generated for the farmer, to show where to apply the mitigation product/strategy. This study had two components. In the first, we soil sampled obvious campsite and non-campsite areas within hill paddocks of farms in the Lake Taupo catchment and recorded the GPS position of these sites. Soil tests were used to verify the presence of high nutrient loadings in campsites compared to low loadings in slope soils. This results from campsite accumulation of faecal matter over many years of grazing, compared to slope areas which "export" nutrients and thus have low Olsen P values (Rowarth et al. 1992; Lambert et al. 2000). Secondly, we needed to predict the location of cattle campsites. For a resting cow, GPS locations will change only because of random GPS error. Thus, GPS velocity would be very slow. We used this concept to model where cattle were resting in a paddock at the *Motere* station near Taupo. In the next phase of this work we will correlate resting positions with contour data for this paddock with the intent to predict campsite locations from contour data. If this proves satisfactory, we can enhance the robustness of the model based on cow GPS and contour data from many more trial sites where other behavioural data are not available. This project describes how the resting model was developed. The prediction model will later be validated against datasets that have GPS, contour (slope, elevation and aspect) and urination event data (e.g. *Ballantrae* and *Motere*). Ultimately, farmers will be provided with a CSA map based solely on their paddock's contour data.

Methods

Animal and Sites

The *Ballantrae* dataset was used to determine the threshold GPS velocity for *resting*. This was stocked with 20 rising 2-yr-old beef heifers (average LWt 264 kg) for 5 days. Each cow was fitted with a GPS collar and urine sensor (Betteridge et al. 2010b) and an IceTag© on the left hind leg that determined resting time (Betteridge et al. 2010a).

The model for predicting resting time (hereafter referred to as the 'resting model') was developed using the GPS data from the *Motere* station, on the western side of Lake Taupo and previously owned by Landcorp. Although the Angus beef cows (with calves at foot) were fitted with a GPS collar and a urine sensor, only the GPS data were used to develop the model. The cows were stocked at ~35 sheep stock unit equivalents/ha over 7 days (December 2006) in a steep 11 ha hill paddock. There was ample feed throughout the grazing period and stock water was available from two water troughs located on relatively flat sites (Kawamura et al. 2009; Betteridge et al. 2010b).

Grid cells

In GIS modelling it is common to aggregate infinitely variable data within grid cells overlaying the GIS site map. These may be 5 m x 5 m, or 10 m x 10 m grid cells. Thus, our data have been defined as: number of different animals visiting a 5 m x 5 m cell; total time spent in a cell; and total time resting (= standing + lying) in a cell, aggregated over all 7 days of the experiment. Average slope, aspect and elevation within each cell were also available. Where grazing or walking was a continuous process across many cells, these data were disaggregated and appropriately apportioned to each cell. Average velocities of walking and grazing events were determined before disaggregation and then movements were apportioned to the cells, where necessary. Motion-sensor-based resting time was accumulated within each cell.

Data normalisation

In trials such as this, incomplete datasets for one or more animals in a mob are often encountered due to sensor failure or intentional on-off cycling of the GPS to save battery power or to limit dataset size. Also, different trials, designed for a range of different purposes, introduce data anomalies between trials. For example, where stocking density is high or grazing duration within a paddock long, there is a greater probability that a grid cell will be visited at least once, compared to the situation where densities are low or durations are short. To enable compatibility, our data were normalised appropriately, as shown in the results and discussions section.

The model

The resting threshold velocity was determined from *Ballantrae* data using a logistic regression model (in conjunction with ROC, receiver operating characteristic, analysis) where resting time was modelled based on the GPS track velocities for each animal track in each grid cell. The derived velocity threshold was then used with *Motere* data to develop the 'resting model'. All analyses were done within Excel or with R software (2012).

Soil sampling

In November 2012, ten soil cores (0-75 mm depth) were collected from 83 camp, hill, under-tree and water trough sites within eight paddocks on farms in the Lake Taupo Catchment. Soil from each site was analysed for phosphorous by the Quicktest methods. The location of each site was recorded by GPS so that it could be overlaid on the paddock's contour map as evidence that it was indeed correctly classified especially as a campsite or slope.

Results and Discussion

GPS threshold velocity

The GPS threshold velocity below which resting can be assumed, based on the logistic regression model, was computed to be 0.011 m/sec. This was the optimal cut off velocity obtained by minimising the misclassification error rate (Fig. 1).

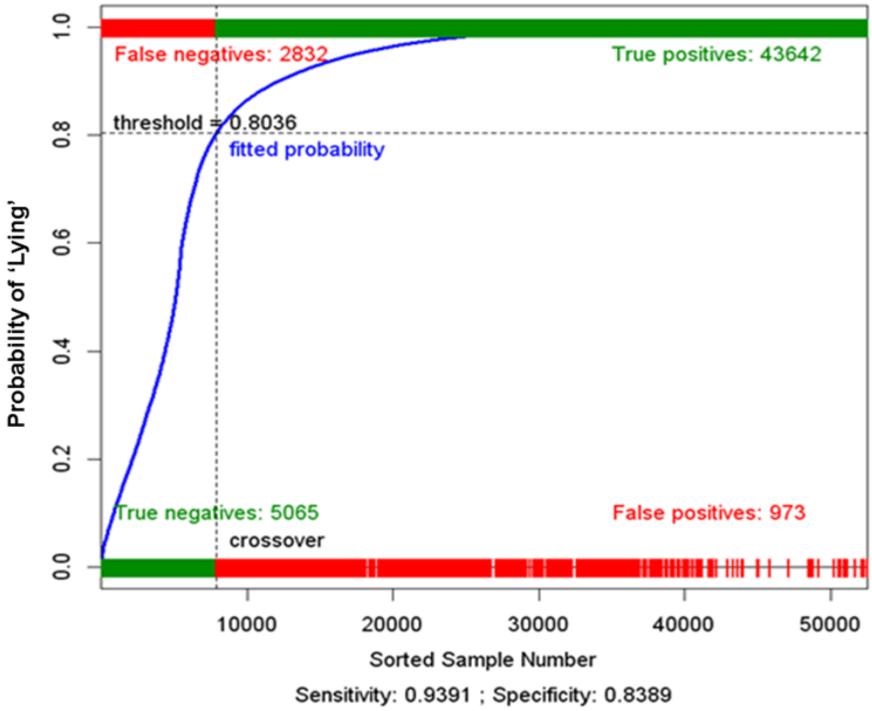


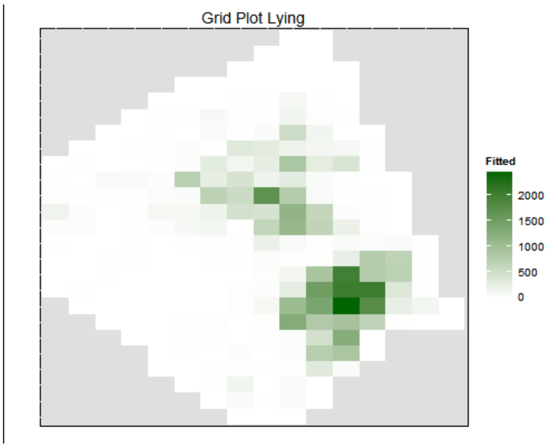
Figure 1 Logistic curve showing the threshold probability for determining the optimal GPS velocity cut-off as the proxy for lying time (based on *Ballantrae* data).

Normalized resting time

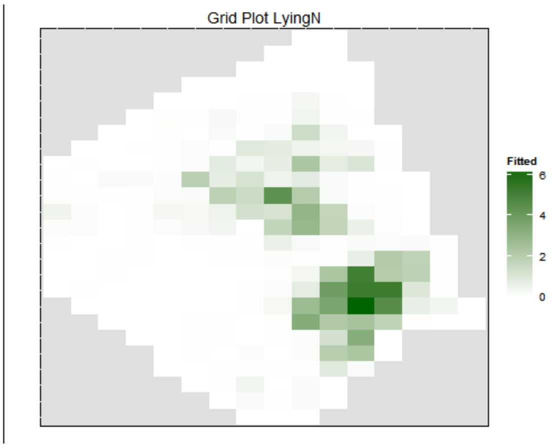
Since the data for modelling (GPS velocity based) resting time could potentially come from paddocks with widely varying size (no. of 5m*5m grid cells) and no. of animals used in the experiment, a normalization process is required to make the resting time compatible across the paddocks. For example, *Ballantrae* consisted of data from 17 cows observed over 5 days on 256 (5m × 5m) grid cells while *Motere* data came from 20 cows over 7 days based on 4471 grid cells.

One way to normalize data from different paddocks is to first normalize the total resting time within each cell by the total number of animals used in the paddock, and then to normalize this by the average total time each animal spent in each cell. For example, at *Motere*, the normalized resting time = (resting time at each cell/20)/(7 days/4471), and for *Ballantrae* normalized resting time = (resting time at each cell/17)/(5 days/256) (Fig. 2).

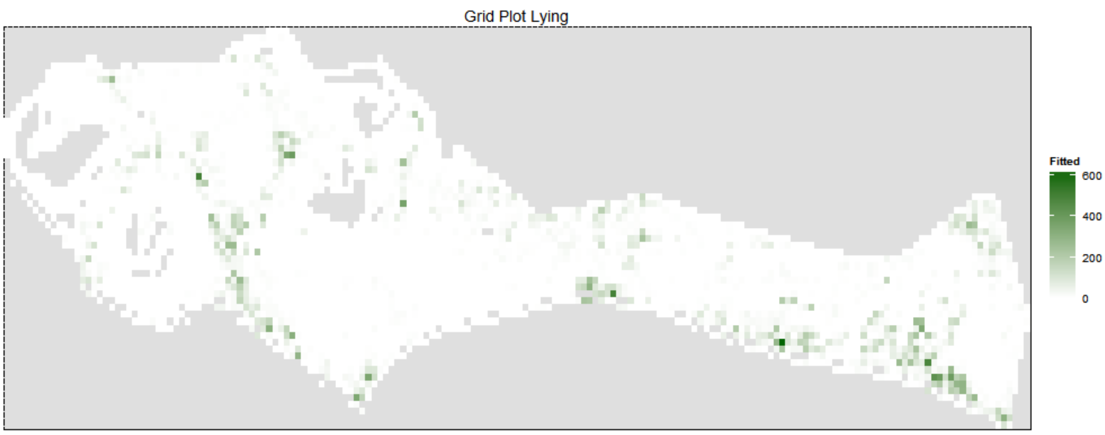
a) *Ballantrae* before normalization



b*) Ballantrae* Normalized



c) *Motere* before normalization



d) *Motere* Normalized

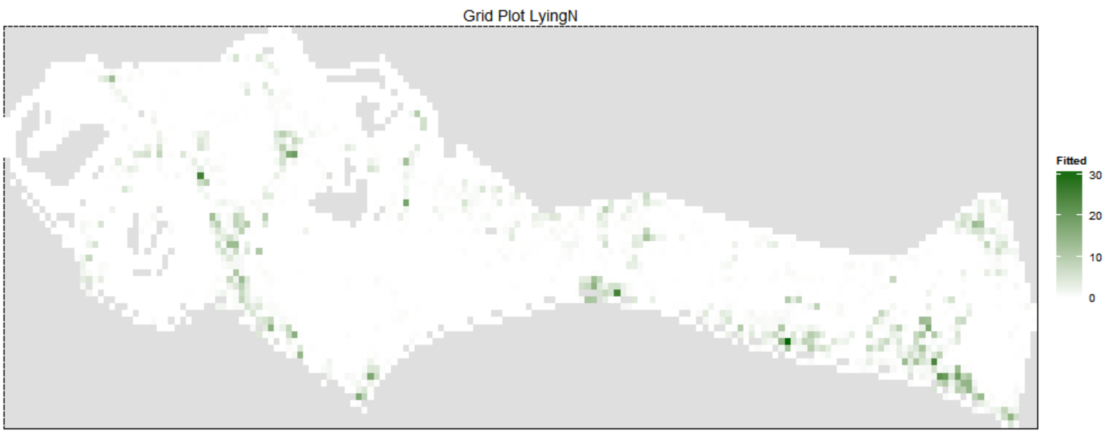


Figure 2 Paddock grid maps of resting time in grid cells before (a & c) and after normalization (b & d). Grey grid cells indicate non-visitation and white cells indicate visitation without resting. Maps (a & b) are for *Ballantrae* (0.5 ha) and (c & d) are for Motere (11 ha). Note reduction in resting time scale range between before and after normalisation.

The before and after normalized resting times for Motere values were 0 to 600 minutes (Fig 2a) and 0 to 30 (Fig. 2b) respectively. In comparison Ballantrae ranged from 0 to 2500 minutes (Fig. 2c) before and 0 to 6 minutes after normalization (Fig. 2d). The normalization reflects the expected amount of time an animal spends resting in a cell proportional to the size and total experimental time associated with the paddock concerned. Note that in the maps above that the normalization has not changed the relative resting times in grids, i.e. darkness of the cells are exactly the same before and after normalization.

Soil tests

Olsen P soil results, used as a proxy for detecting campsites are presented in Table 1. While slopes had an average Olsen P of 13.4, camps, gateways, areas under trees and around troughs could all be classed as potential CSAs of N leaching since their Olsen P values indicated resting behaviour caused by aggregation of faeces. Since the deposition of faeces (N. Watanabe, pers. comm., Japan) and urine (Betteridge et al. 2010b) is each correlated with resting time in any particular area, only hill slopes are areas where there is likely to be minimal aggregation of urine patches that can be targeted with a N leaching mitigation strategy. However, we suggest that as urine patches on hill slopes are generally long and narrow, rather than round (as on flat land), there are many more plants in and surrounding a long narrow patch can uptake urinary N than there are plants around and within a round patch containing the same N load (g N/m^2). If confirmed, then the leaching loss of urinary N from hill slopes is likely to be lower than from the same amount of urinary N excreted on flat land.

Table 1. Average Olsen P values of 10 bulked, 0-75 mm deep samples collected at subjectively chosen sites in seven hill paddocks in the lake Taupo catchment (n is the number of samples in the category).

Sampling site	N	Ave. P	SD	CV
Camp	32	38.0	17.7	47%
Gate	33	53.2	29.8	56%
Slope	4	13.4	7.6	57%
Tree	7	60.0	48.7	81%
Trough	7	62.7	22.1	35%

General

A robust CSA prediction model will require many more GPS datasets with associated contour maps that cover a wide range of slope classes, paddock sizes, seasons, and localities within and between regions. Because the resting model requires only GPS cattle movement and paddock contour data, bringing together such data will be much easier than if urine and motion sensors were also required to provide the direct detection of CSAs.

The derived prediction model of resting sites in the *Motere* paddock will be validated by comparing predicted CSAs at both *Ballantrae* and *Motere* with the respective urine-sensor-defined sites and contour datasets. Given that campsites are typically found on low slope areas in hill country (Betteridge et al. 2010a, b), once the resting model has been validated it will be used to test whether the soil sampled camp and non-camp sites in the eight paddocks on Taupo farms conform to the known slope classes of these sites.

We envisage that farmers will use contour-generated maps of CSAs in cattle-grazed pastures as the basis for targeting N leaching loss mitigation strategies to enable them to increase farm inputs while remaining within their farm's nitrogen discharge allowance.

Conclusion

This paper suggests that data from cattle fitted with a GPS device can be used to determine where they rested, based on the threshold velocity of <0.011 m/sec. In turn, this can be used as a proxy for where they would deposit about half of all their daily urination events. Where resting grid cells are congregated within a paddock, the area would be considered a critical source area of potential nitrogen loss. Additional areas will be around trees, water troughs and gateways.

The resting model needs to be validated against actual urine patch location and contour data, after which it will be used to predict the CSAs amongst the 83 soil sampled sites on Taupo hill country farms for which contour data are known. We expect that farm contour maps will be used to predict the location of N leaching CSAs in cattle-grazed hill country paddocks. Farmers will use these maps to target an N loss mitigation strategy. As nitrogen CSAs in hill country can contain 50% of urination events in only 5-15% of the paddock area, CSA-targeted mitigation offers a cost-effective method of mitigating about 50% of N losses to the environment.

A constraint of this study is that it is based purely on data collected from two paddocks. A robust model acceptable to environmental regulators will require data from many more sites.

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