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IMPROVED MEASUREMENT AND MODELLING OF THE 3D DISTRIBUTION OF URINE WITHIN PATCHES IN GRAZED PASTURE SOILS

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Abstract

Urine patches are hot-spots of nitrogen (N) loss in dairy-grazed soils. Such N losses might be mitigated by targeted application of urease and nitrification inhibitors to slow down certain N transformations that lead to nitrous oxide emission, ammonia volatilisation, and nitrate leaching. However, for maximum effectiveness the inhibitors need to be in close physical contact with the urine in the soil under urine patches. In practice, there will always be some time delay between urine deposition and application of inhibitors. It is therefore important to understand how the urine is transported in the soil following deposition.

In this study, we investigated the patterns of urine-N infiltration into the soil following a urine application of known volume. We used thermal imagery to delineate urine patch areas from two sites each with two contrasting soil moisture contents, and then derived a statistical model of urine patch area immediately following urine deposition. A linear regression model was fitted to effective urine patch height (Urine volume)/(patch area) against air-filled pore space. This model explained 45% of the variability in the measured and predicted means patch areas with a Nash-Sutcliffe efficiency of 0.61.

Subsequent vertical and lateral movement of the urine post deposition was then modelled using modelled urine patch area as an input to the HYDRUS 2D/3D model. Predicted changes in the vertical distribution of N were compared with laboratory analyses of soil N. To get the measured proportion of urine N in the top 5cm required the use of higher K_{sat} values and coarser textures in the model. However, the soil parameterisations derived from measurements at high soil moisture also worked well for the same soil at a lower soil moisture content. Further work is needed to relate the HYDRUS parameters to easily measurable soil properties.

Introduction

Urine patches represent major hot spots of N losses from grazed pastures in New Zealand, especially for dairy cattle. Reported N loadings within a urine patch range from 200 to 2000 kgN ha^{-1} (Selbie et al. 2015). This is much higher than can be utilised by the pasture, leading to high risk of losses via leaching and gaseous emissions.

Compounds that inhibit some of the N transformation pathways (e.g. nitrification inhibitors, urease inhibitors) can potentially reduce N losses from urine patches (Cameron et al. 2012). However, in practice there will be some delay between the urine deposition and the application of inhibitors. Therefore, it would be useful to know how far down the soil profile the urine patch has moved during this time and what proportion of the urine could still be in physical contact with the inhibitor. In this study, we used experimental data from controlled field applications of urine to develop a patch-scale model of this process. The first step was to develop an empirical model to predict the initial urine patch area. This area was then used to set-up the HYDRUS 2D/3D model (Simunek et al. 2012) to calculate the subsequent movement of urine through the soil.

Method

Urine patch area measurements

Urine patch areas were measured at two sites (Ruakura and Massey), using three different urine volumes (1, 2, and 3L) with 6 replicates. The urine patches were made using a device to pour a known amount of urine from a height of 1.2m, in a manner as close as possible to a natural cattle urine deposit. Patch area measurements were made using a thermal camera immediately following application, and after 4 hours using Spikey-R (a mobile device that detects urine patches by changes in the soil surface conductivity). These measurements are explained in detail in Jolly et al. (2019).

Urine patch depth distribution

A separate experiment was performed to determine the vertical flow of urine in the soil, using the same apparatus for applying the urine patches. The experiment was repeated on two different soil types in the Manawatu (Manawatu Sandy Loam and Ohakea Silt Loam) at two different moisture contents. Three different application volumes were used (1.0, 1.5, and 2.0L) with 2 to 3 replicates. Soil samples were taken at 5cm depth increments down to 25cm at 4 and 18 to 24h after urine application. The samples were then analysed in the laboratory for total N.

Modelling

Empirical model

Figure 1 illustrates the simplified model used to develop the empirical model of the initial urine patch area.

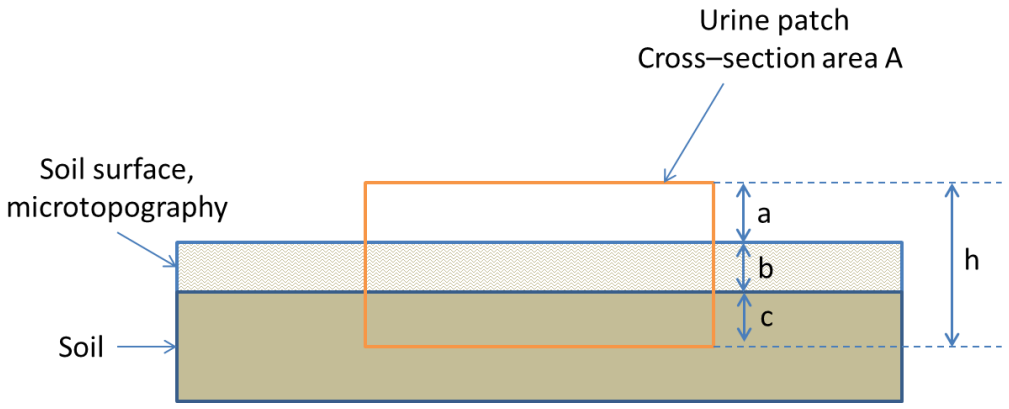


Figure 1. Simplified diagram of urine patch used to develop empirical urine patch area model.

Assuming that the urine patch has a uniform cross-sectional area A (m^2), the effective thickness of the urine patch h (mm) is defined as:

$$h = V/A \qquad (1)$$

where V is the volume of urine applied (L), and h was considered to be the sum of three components: a the amount of moisture held above the soil surface by surface tension, b the amount of moisture trapped in the soil surface microtopography, and c the amount of moisture that quickly infiltrates the soil. Therefore, a linear regression model of h was fitted using proxies for the a, b, and c terms (see below).

HYDRUS 2D/3D model

For the HYDRUS simulations, we defined a 90cm×90cm×30cm domain. The initial patch area was determined using the empirical model above and defined as a variable flux boundary. The urine input (treated as urea mixed with water) was assumed to enter this boundary in the first 0.02h of the simulation. The urine-N concentration was set to 0.5 mol L^{-1} (corresponding to the applied urine N concentration of 7g L^{-1}) and the flow rate adjusted so to give the correct total urine volume.

The simulation was run for 24h and included physical and diffusional movement of urea in the soil. Chemical transformations and plant uptake were not considered due to the short time-frame of the simulation. Soil water flow was simulated using the van Genuchten-Mualen single porosity hydraulic sub-model (Sejna et al. 2014; Simunek et al. 2012)

We used measured soil porosity values in the soil hydraulic model. All other hydraulic parameters were set using data from the 2-L urine application to wet soil and adjusting the parameters to give a good match with the measured urine distribution at 4h after application. These parameters were then used for the other treatments on the same soil.

Results

Empirical model

A preliminary study (data not shown) found that soil air-filled pore space (*afps*) in the top 5cm was a significant predictor of h. Therefore, *afps* was used as a proxy for the amount of moisture that can rapidly infiltrate the soil (c). However, no similar proxy was found for the soil microtopography term (b). Therefore, the linear regression model contained only *afps* as a predictor with the constant term representing the combined effect of surface tension (a) and soil microtopography (b). As *afps* measurements were made at the treatment level rather than the replicate level, the regression model was fitted to the replicate mean values. The linear regression model of h was:

$$h = 3.1(\pm 0.7) + 5.1(\pm 1.8)\ afps,\ R^2=0.45 \qquad (2)$$

where the standard errors of the coefficients are given in parentheses. Both the constant and *afps* terms were significant at the 5% level. This model explained just under half of the variability in h (Fig. 2).

Patch area predictions using Eq. 2 were compared with measurements from both the thermal camera and the Spikey-R readings 4h after patch application. The model predictions agreed reasonably well with the measurements with a model efficiency of +0.61 and a root mean squared error (RMSE) of 0.09m^2 (Fig. 3).

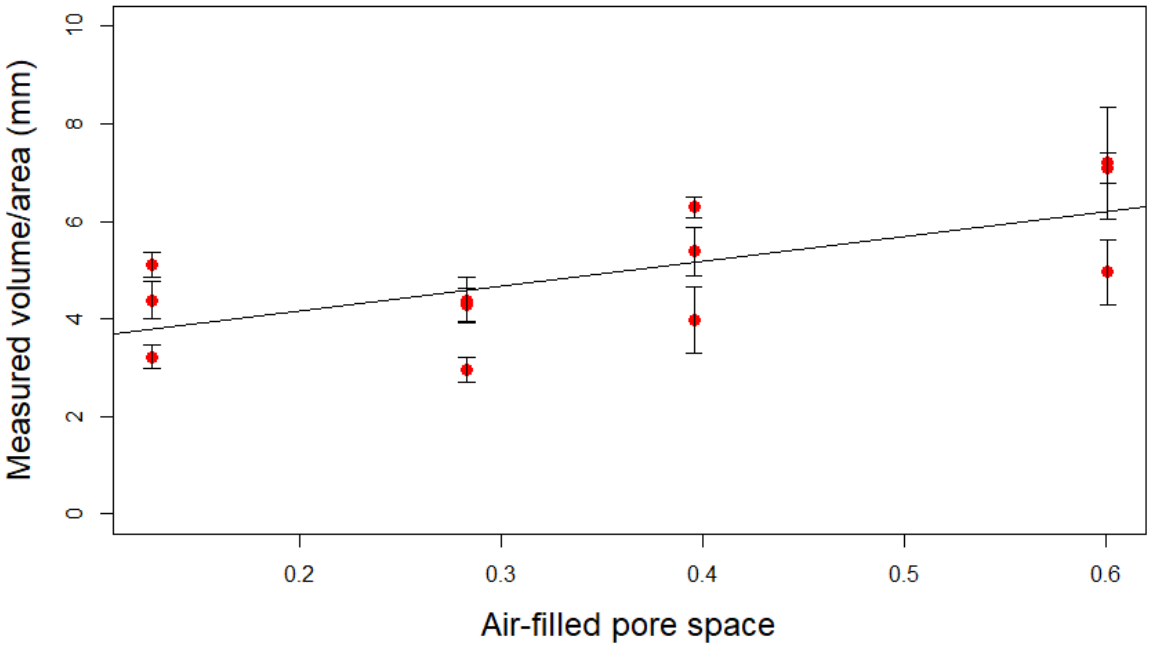


Figure 2: Urine volume/patch area (=*h*) plotted against air-filled pore space. Points are replicate means ± standard error. The solid line shows the predicted values from Eq. 2

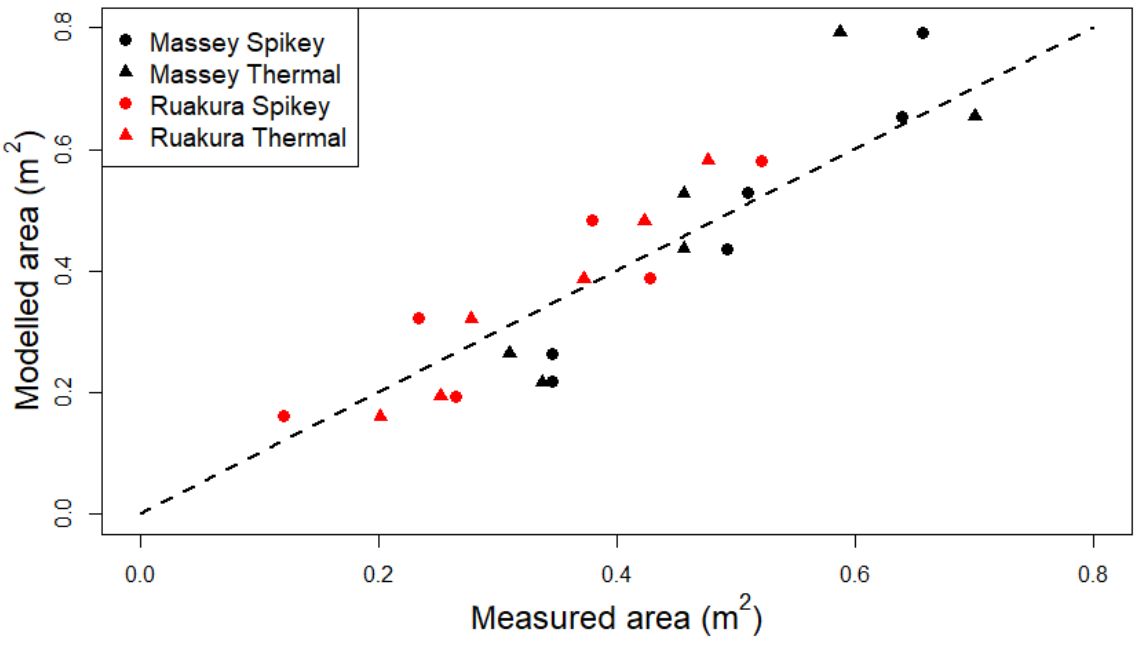
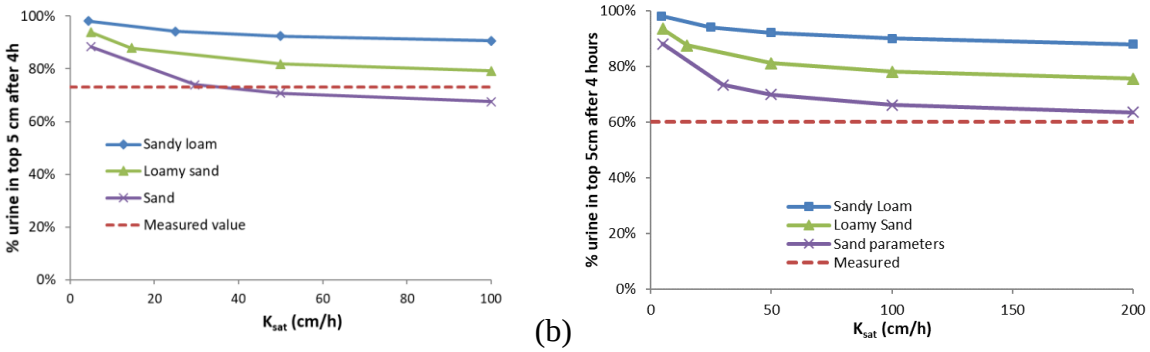


Figure 3: Measured vs modelled urine patch areas. Points represent mean of 6 replicates. Dashed line is the one-to-one line.

HYDRUS 2D/3D model

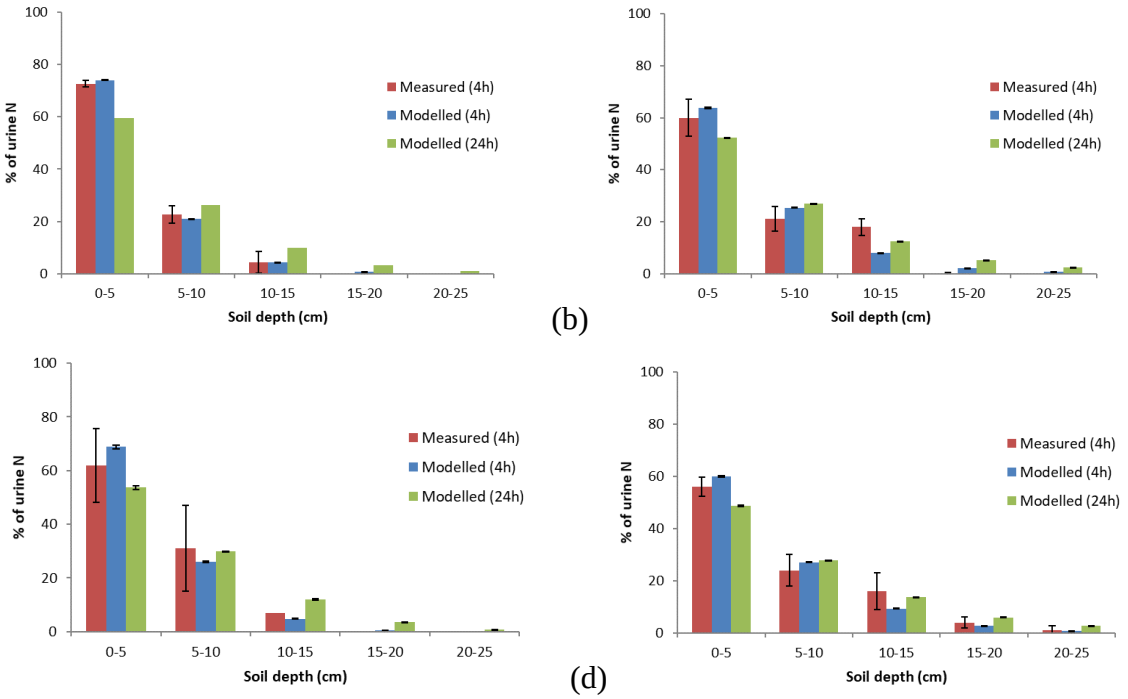
Figure 4 shows the HYDRUS simulations for the 2L urine applications to Manawatu and Ohakea soils at the highest moisture content at 4 hours after application. Simulations were performed using the default HYDRUS parameters for different texture classes, with measured soil porosity values. The saturated conductivity, K_{sat}, was then varied.



(a) (b)

Figure 4: Hydrus simulations of urine fraction in the top 5cm of soil 4 hours after 2L urine application. The dashed line shows the measured fraction. (a) Manawatu soil (a sandy loam) at high moisture content, (b) Ohakea soil (a silt loam) at high moisture content.

Although both soils were heavier textured than sand, the HYDRUS default parameters for sand gave the best results with K_{sat} = 30cm/h for the Manawatu soil and roughly 200cm/h for Ohakea (for this soil there was a wide range of K_{sat} values for which moisture content in the top 5cm would fall within the uncertainty of the measured value). These parameters were then used to run the model for all volume applications and initial moisture contents (Fig. 5)



(a) (b)

(c) (d)

Figure 5: Depth distribution of urine by depth measured at 4h and modelled at 4 and 24h after application. (a) Manawatu soil at high moisture content, (b) Ohakea soil at high moisture content, (c) Manawatu soil at low moisture content, (d) Ohakea soil at low moisture content. All bars are averages over 3 volume applications (1.0, 1.5, and 2.0L) and error bars represent the standard deviation.

Discussion and Conclusion

We found an empirical model the related initial urine patch area to the volume of urine applied and the soil air-filled pore space in the soil top 5cm. This model explained 45% of the variability in the replicate average (patch area)/(urine volume). Some of the unexplained variability could be due to variations in the soil microtopography. However, we have not yet found a satisfactory metric to represent this. Even with this unexplained variability the empirical model was able to predict the mean urine patch area on two different soil types with a model efficiency of +0.61 and an RMSE of 0.09m^2.

The HYDRUS 2D/3D model was then parameterised using lab measurements of soil N at 5cm depth intervals 4h after a urine patch application. The best parameterisations used the model default values for sandy soils with K_{sat} values of 30 and 200cm/h for the Manawatu and Ohakea soils respectively. To get the measured proportion of urine N in the top 5cm required higher K_{sat} values and coarser textures to be used in the model. One possible explanation was that the measured results included some macropore flow. Simulating this in HYDRUS 2D/3D is possible, but would require switching to a dual porosity or dual permeability hydraulic sub-model. However, the model still managed to simulate the urine N distribution in each layer well. Additionally, the soil parameterisations derived from measurements at high soil moisture (Figs 5a and 5b) also worked well for the same soil at a lower soil moisture content (Figs 5c and 5d). In the long term, we want to be able to parameterise the model for any soil without requiring measurements of urine N at different depths. Therefore, a future goal is to relate the HYDRUS parameters to easily measurable soil properties.

The modelled 24-h distribution shows the expected pattern of urine N travelling down the profile. However, there may be some slight differences due to our neglect of chemical reactions, gaseous losses and plant uptake.

An extended version of this paper will be submitted to an upcoming special edition of Agriculture, Ecosystems and Environment.

Acknowledgements

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References

Cameron, K.C., Di, H.J., Moir, J.L., 2013. Nitrogen losses from the soil/plant system: a review. Annals of Applied Biology 162:145-173.

Jolly, B., Saggar, S., Luo, J., Bates, G., Smith, D., Bishop, P., Berben, P., Lindsey, S., 2019. Technologies for mapping cow urine patches: a comparison of thermal imagery, drone imagery, and soil conductivity with Spikey-R. In: *Nutrient loss mitigations for compliance in agriculture*. (Eds L.D. Currie and C.L. Christensen). http://flrc.massey.ac.nz/publications.html. Occasional Report No. 32. Fertilizer and Lime Research Centre, Massey University, Palmerston North, New Zealand.

Selbie, D.R., Buckthought, L.E., Shepherd, M.A., 2015. The challenge of the urine patch for managing nitrogen in grazed pasture systems. Advances in Agronomy 129:229-291.

Sejna, M., Simunek, J., van Genuchten, M.Th., 2014. The HYDRUS Software Package for simulating the two- and three-dimensional movement of water, heat, and multiple solutes in variably-saturated porous media. User Manual v2.04. PC Progress, Prague, Czech Republic.

Simunek, J., van Genuchten, M.Th., Sejna, M., 2012. The HYDRUS Software Package for simulating the two- and three-dimensional movement of water, heat, and multiple solutes in variably saturated porous media. Technical Manual v2. PC Progress, Prague, Czech Republic.