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TECHNOLOGIES FOR MAPPING COW URINE PATCHES: A COMPARISON OF THERMAL IMAGERY, DRONE IMAGERY, AND SOIL CONDUCTIVITY WITH SPIKEY-R

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Abstract

Animal urine patches are the major source of gaseous and leaching losses of nitrogen (N) in livestock grazed pastoral systems. These losses can be reduced by detecting and treating these patches by applying N inhibitors to slow down the N transformations, thus allowing more time for plant uptake. In this study, we aimed to validate the output of the newly developed and modified Spikey-R (under a New Zealand Government, Global Research Alliance research project) for detecting and measuring the configuration of urine patches. We compared measurements form Spikey-R against thermal imagery from a handheld camera taken during urine deposition, as well as imagery taken from a remotely piloted aircraft system (RPAS or 'drone') two weeks after deposition. Patches were created by applying 1, 2 and 3 l of synthetic urine heated to 40 ºC over two soils contrasting in drainage (poorly drained, Massey No. 4 Dairy, and well drained, AgResearch Ruakura) and moisture level (below and at field capacity).

Spikey-R data generally compared well with the reference map produced from the thermal imagery, with similar mean patch areas for each soil moisture condition (+/- 12 %) and comparable patch extents and shapes reported. On average, the patch areas reported by Spikey-R were larger than those detected by the thermal imagery when soil moisture was at field capacity and smaller or similar when soil moisture was below field capacity. Over the 48 hours post-deposition, the patch area as detected by Spikey-R increased slightly (~5%). The drone was successful in detecting all urine patches via elevated pasture response 14 days after application at the Massey No. 4 Dairy site but was less effective at AgResearch Ruakura. Further results on the potential of these sensing technologies and needs for further improvements are also discussed.

Introduction

Grazed pasture soils exhibit high potential for N2O emissions from urine deposited by grazing livestock and are the primary source of direct and indirect N2O emissions, contributing c. 64% of New Zealand's 8.59 Gg CO2e agricultural N2O emissions (MfE 2016). Accurate mapping of spatial distribution of urine patches is essential to accurately quantify N transformations and N losses from grazed pastures. Nitrous oxide emissions from soils in urine patches are controlled by a complex set of interacting soil, plant and environmental factors. Moreover, the timing of physical transport of the urine and amendment (urease and/or nitrification inhibitors) through the soil regulates the proportion of urine treated and the achieved level of NH3 and N2O reduction achieved (Marsden et al. 2016). Because of these multiple interacting factors, the proportion of urine-N lost through gaseous emissions of NH3 and N2O and through N leaching, and their response to applied mitigation amendments, may vary with both the changes in soil and environmental conditions and the distribution of urine-N within the patch.

Approaches to identifying urine patches include visually monitoring cows in the field (White et al. 2001), automated monitoring using electromagnetic induction, electrical conductivity measurements and optical sensing (Moir et al. 2011; Betteridge et al. 2013; Dennis et al. 2013; Misselbrook et al. 2016), and ground-based sensing (Gusmão et al. 2016; Bates & Quin 2016). More recently, airborne technologies, such as remotely piloted areal systems (RPAS), LiDAR and satellites using hyperspectral and near infra-red imaging, and temperature sensors have been applied to map vegetation attributes linked to urine deposition (Dennis et al. 2013).

There is room for improvement however, as field conditions are often not ideal for deploying these technologies. An improved and automated urine patch detection algorithm that uses a simple digital camera operating in the visible spectrum (Red/Green/Blue; RGB) would be useful to industry and researchers alike and widely applicable given the prevalence of RPAS.

In New Zealand, the ground-based sensor system was developed to detect fresh urine patches and selectively apply N loss mitigation treatments (Bates & Quin 2016). Due to low sensor intensity and limited sensor spike depth, Spikey® cannot accurately map the three dimensional (3-D) spatial configuration of urine distribution in the detected patch, which is fundamental to optimising targeted management for reducing patch N loss. Therefore, Spikey® has been modified to 'Spikey-R' that consistently and accurately identifies, measures and maps urine patch size, 3-D shape and location. This study aimed to validate 'Spikey-R' - an application of the soil conductivity approach – as a research-grade solution for detecting and mapping the location and area of cow urine patches under controlled trial conditions. It also aimed to investigate the feasibility of using an off-the-shelf Remotely Piloted Aircraft System (RPAS or 'drone') to map the pasture response to urine.

Methodology

Trial Setup

Six replicates of three different volumes (1 l, 2 l, and 3 l) of artificial urine at 40°C were randomly applied over a 3 x 6 grid. This pattern was repeated for two different soil moisture levels: 100% and approximately 60% field capacity, referred to here as 'wet' and 'dry', respectively. This was repeated for two different New Zealand sites: poorly drained soil at Massey No. 4 Dairy Farm near Palmerston North, and well-drained soil at Ruakura Research Farm near Hamilton. The artificial urine was deposited using a purpose-built frame with a nozzle positioned 1.5 m above ground level. The height and flow rate were designed to mimic a 'typical' natural urination.

Prior to application, each site was isolated from its farm for at least 3 months to reduce the impact of previous urine patches and nitrogen application. Grass was periodically cut and removed, with a final mow the day before application. Soil moisture levels were controlled by irrigation and shielding of each moisture zone as required by weather conditions.

On the day of application, 400 mm square steel plates were strategically placed as Ground Control Points (GCPs) for both the RPAS and Spikey-R (see Figure 1). Positions of most plates were surveyed using a Trimble GeoXH 6000 GNSS (Global Navigation Satellite System or ‘GPS’) with external Tornado antenna. Plates around the perimeter of the trial took priority while some interior plates were also surveyed according to time allowed. Prior to application the RPAS was flown to create an orthomosaic which formed the ‘base’ image for georeferencing the Spikey-R data and thermal imagery. Sensor-specific methods are described in following sections.

Thermal Camera

A FLIR-C2 handheld thermal camera captured oblique (approximately 70° elevation) thermal and optical images of each urine patch within one minute of deposition. Thermal images were captured in ‘Thermal MSX’ mode which overlays the results of an edge-detection algorithm from the optical image over the thermal; this was essential for identifying GCPs later. As the imagery would require rectification as well as georeferencing, two different ground-control mechanisms were employed: a 1 m x 1 m plastic frame placed to border the patch, and two white plastic discs placed at the ‘top’ two corners of the frame. The frame and discs were placed immediately before the image was taken, after which the frame was moved to the next location. An RPAS captured an orthomosaic showing all 72 discs in place immediately following application, after which all discs were removed.

Each thermal image was manually rectified using the built-in ‘Georeferencer’ in QGIS using the corners of the 1 m x 1 m reference frame with coordinates in x/y space of [0,0] (bottom-left of image), [0,1] (top-left), [1,1] (top-right), and [1,0] (bottom-right). The transformation type used was ‘Projective’ (linear rotation/translation only), and the resampling method was ‘nearest neighbour’. The spatial reference system (SRS) was set to New Zealand Transverse Mercator (NZTM), though any cartesian system that uses metres as its unit of measure, such as one of the Universal Transverse Mercator (UTM) zones, would work.

Rectified images were then georeferenced, also using the QGIS Georeferencer, by selecting the centre of the plates in the thermal image as well as the corresponding ones in the post-application RPAS orthomosaic. Transformation type was again ‘Projective’ which requires three GCPs – a problem given only two plates were practical during the field work. To get around this, the two plate GCPs were marked then saved as a txt file within the Georeferencer. This was then processed with a short Python script to insert a third artificial GCP at the lower-left coordinate of the reference frame ([0,0]) with ‘world’ coordinates calculated from the two plates using simple trigonometry and prior knowledge of which direction the photographer was facing. This modified txt file was then reloaded over the image and processed to produce the final rectified and georeferenced image. This rather complicated rectification/georeferencing process could be simplified by using the RPAS to take images of each frame placement during the application process, however this would increase the logistical complexity of the field work.

The processed thermal images were then manually digitised to produce a polygon for each urine patch, from which patch area and perimeter could be extracted for comparison with the other sensors using Microsoft Excel.

Remotely Piloted Aircraft System (RPAS)

A DJI Phantom 4 Pro was flown immediately prior to, and post, application with a third follow-up flight 14 days post-application. As described above, the first two flights were to provide data for the other sensors while the final flight was to detect the pasture response to the urine patches applied two weeks earlier. Flight altitude was 40 m providing a ground sample distance (GSD) of less than 1 cm per pixel. Overlap and sidelap were set to 75% each. Individual images were processed using Agisoft PhotoScan to create orthomosaics with a GSD of 1 cm, georeferenced using the metal plate GCPs described above.

The 14 day post-application flight orthmosaic was analysed with the 'ImageJ' software package as used by Dennis, Moir, Cameron, Edwards, & Di (2013), though there were slight differences in the exact steps carried out. After some experimentation, the orthomosaic used was cropped in Photoscan to separate the 'wet' and 'dry' soil moisture levels as slightly different thresholds were found to be more effective for each. These cropped images were exported as portable network graphics (PNG) files with corresponding 'world' files – text files containing information that GIS tools, such as QGIS, can use to accurately place an otherwise ordinary PNG image on a map.

These PNG files were loaded into ImageJ and a threshold was applied in the Hue, Saturation, and Brightness (HSB) colourspace in order to create a mask (ImageJ menu: Image -> Adjust -> Color Threshold). Threshold values differed between moisture levels and soil types and were likely to depend on current pasture condition as well as lighting levels and the exact camera used on the RPAS, however the general range used was 60 – 80 (Hue), 0 – 255 (Saturation), and 0 – 100 (Brightness). After thresholding, several steps from the 'Process -> Binary' menu were used, in order: Convert to mask, Dilate, Fill Holes, Erode, Erode, Dilate, Dilate. The multiple 'erode' and 'dilate' steps were used to simplify the very complex edges of some patches as well as eliminate much of the 'noise' without biasing the patch area. Finally, the 'Analyze -> Analyze Particles' function was used to eliminate patches smaller than 1000 pixels (1000 cm^2 or approximately dinner-plate sized), with the 'show count masks' option used to output a unique number of each patch (important for vectorisation). The result was saved as a PNG file, with the world file from the input image copied and renamed to match.

The ImageJ output was then translated to a GeoTIFF with GDAL so a NODATA value of 0 could be set, then the Polygonize tool in QGIS was used to create a polygon per urine patch. The resulting shapefile was then edited in QGIS to insert an ID for each patch that would match IDs used for the thermal imagery polygons which made comparisons in Excel easier.

Spikey-R

'Spikey-R' is a research variant of the 'Spikey' urine patch treatment system. It consists of 80 spiked metal plates arranged in a line 2 m across with a spacing of 25 mm. Plates are isolated into adjacent pairs, with an electric current passed through the soil between the plates and the voltage drop measured to give an indication of the conductivity of the soil surface (spike penetration is typically less than 20 mm). The entire array of discs is split into three blocks for recording/management purposes. The Spikey-R was towed at walking pace behind a vehicle, with an onboard 'TracMap' GNSS unit providing location data. Data was downloaded onto a flash drive and processed by Pastoral Robotics Ltd to produce GeoTIFF images of soil conductivity, with areas of higher conductivity theoretically corresponding to urine patches.

Spikey-R was towed in passes over the two grids of patches at each site at 2, 4, 24, and 48 hours post-application with care taken to include the metal GCPs in each pass. As the TracMap GNSS was not a high accuracy GNSS unit, the resulting GeoTIFFs required further georeferencing with the QGIS Georeferencer which accurately placed and scaled them according to the metal GCPs. The final GeoTIFFs were then loaded into ImageJ which was used to threshold the raw voltages recorded. Again, wet and dry soil moisture levels were processed separately as slightly different lower-end thresholds were used, however an approximate range was 1100 – 20,000. After thresholding, outliers were removed, the mask was converted to binary, and holes were filled before being run through the ImageJ despeckle filter. Finally, the Analyze Particles tool was used with a threshold of 20 pixels (still 1000 cm^2 as pixels were 5 cm GSD), count masks were saved as PNGs, and world files for input images were copied and renamed as above to maintain the georeference. Polygons for each patch were then produced and manually named using the same method as the RPAS processing.

Results

Thermal Imagery

Patch area distribution is shown in Figure 1, where the area of each patch increased with volume and soil moisture level but decreased with drainage. Mean areas by volume across all soil types and moisture levels were 0.275 m^2 (1 l), 0.390 m^2 (2 l), and 0.547 m^2 (3 l). There is substantial variation in patch area within each volume with standard deviations in the order of 25 to 30% of the mean. The thermal camera was able to successfully detect and map the extent of all patches, though it was easier to interpret images taken during colder ambient conditions (~ 10° C) with complete cloud cover as experienced with the Massey No. 4 (poorly drained) trial.

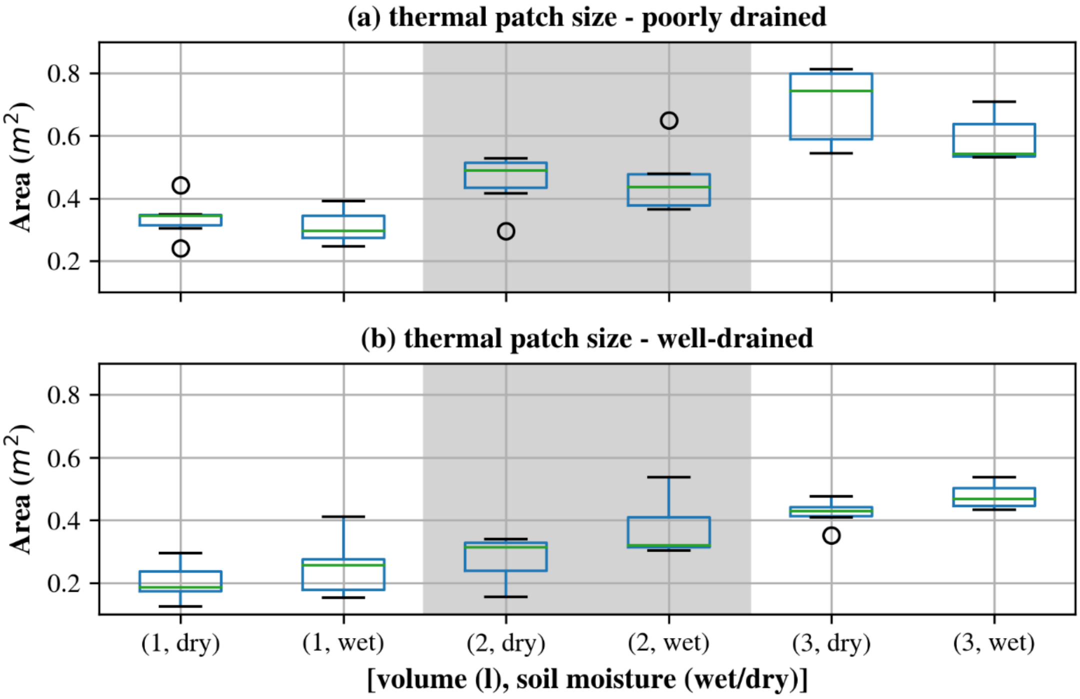

Figure 1 – Urine patch size as determined by thermal imagery for (a) poorly drained soil at Massey No. 4 Dairy Farm, and (b) well-drained soil at Ruakura Research Farm

RPAS

The RPAS was flown at both Ruakura and Massey No. 4 farms and provided crucial base maps of each, however the patch detection performance at Ruakura was substandard with approximately 60% of patches detected. Performance at the Massey No. 4 site (see Figure 2 for base map) was good, with 100% of patches detected and no false-positive results within the trial area. Figure 3 shows the detected areas as a percentage larger than the thermal area (i.e. 0% means the area was the same, 100% means twice as large). This shows a pasture response that was typically at least two to three times as large as the original area detected by the thermal camera. Areal variation was similar to that of the thermal patches with standard deviations 23

– 33% of mean area (by volume). There was no trend in percentage increase with volume, though soil that was at field capacity (‘wet’) did show a larger increase in area of pasture response than soil that was below field capacity.

Figure 2 – Orthomosaic of trial area at Massey No. 4 Dairy Farm (poorly drained soil type) showing artificial urine patches 14 days after application

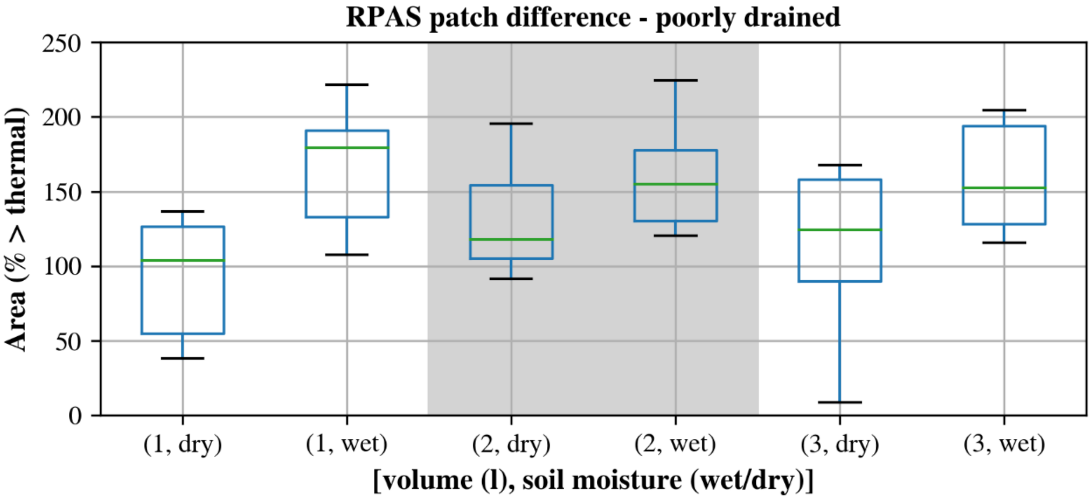

Figure 3 – RPAS pasture response area as percentage larger than the area detected by the thermal camera (poorly drained soil only)

Spikey-R

Spikey-R successfully detected all urine patches under all designed conditions up to 48 hours after application (maximum duration tested), however one block of discs experienced technical issues during the Ruakura trial with occasional areas of missing data that ran through some of the patches. Affected patches were excluded from analysis so as not to bias results and the technical issue was resolved before the Massey No. 4 trial. Spikey-R placed the detected patches in the same location as the thermal and RPAS once GCPs were used to fine-tune placement of the supplied data.

Figure 4 shows the percentage difference between Spikey-R patch areas using data from passes made 2 hours after application and those derived from the thermal imagery. Most data points (83%) fell within +/- 30 % of the thermal patch area for the poorly drained soil at Massey No. 4 Dairy (Figure 4a), while Ruakura Research Farm (Figure 4b) had 81% in this region. In general, Spikey-R tended to overestimate patch size more when soil was at field capacity and underestimated it more when it was below field capacity. This effect was more pronounced for well-drained soils, however there was some missing data (see red regions of plot) so some caution is required (Figure 4).

Investigating Spikey-R's ability to detect patches up to two days after deposition, Figure 5 shows some variation but no substantial trends. There can be some reduction in detected size after the 2 hour pass and there tends to be a slight increase in detected size from the 24 to 48 hour post-application passes but these effects were not significant. There was a high degree of variability in the mapped area of each patch between Spikey-R passes which is illustrated in Figure 6. The poorly drained soil had a mean range of 25% of patch area with a standard deviation of 10 percentage points, while the well-drained soil had figures of 34% and 26 percentage points.

A brief analysis of the uncertainty of patch area was conducted by buffering and eroding the patch polygons by 50 mm (one 'pixel'). The results were dependent on original patch size and shape with mean values ranging from +/- 37% for patches created from 1 l of artificial urine to 33% for 2 l and 29% for 3 l.

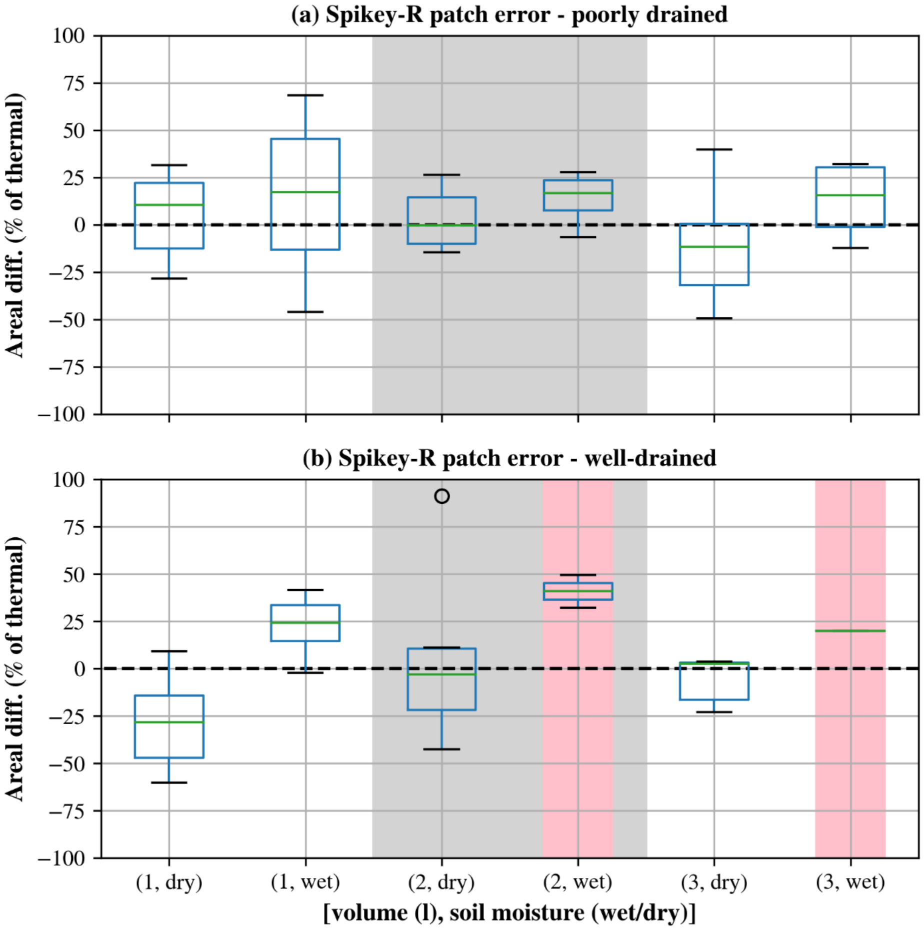

Figure 4 – Difference in patch size between Spikey-R (2 hours post-application) and thermal imagery as a percentage of the thermal patch area. Red regions indicate less data was available, all other boxes were generated from six measurements.

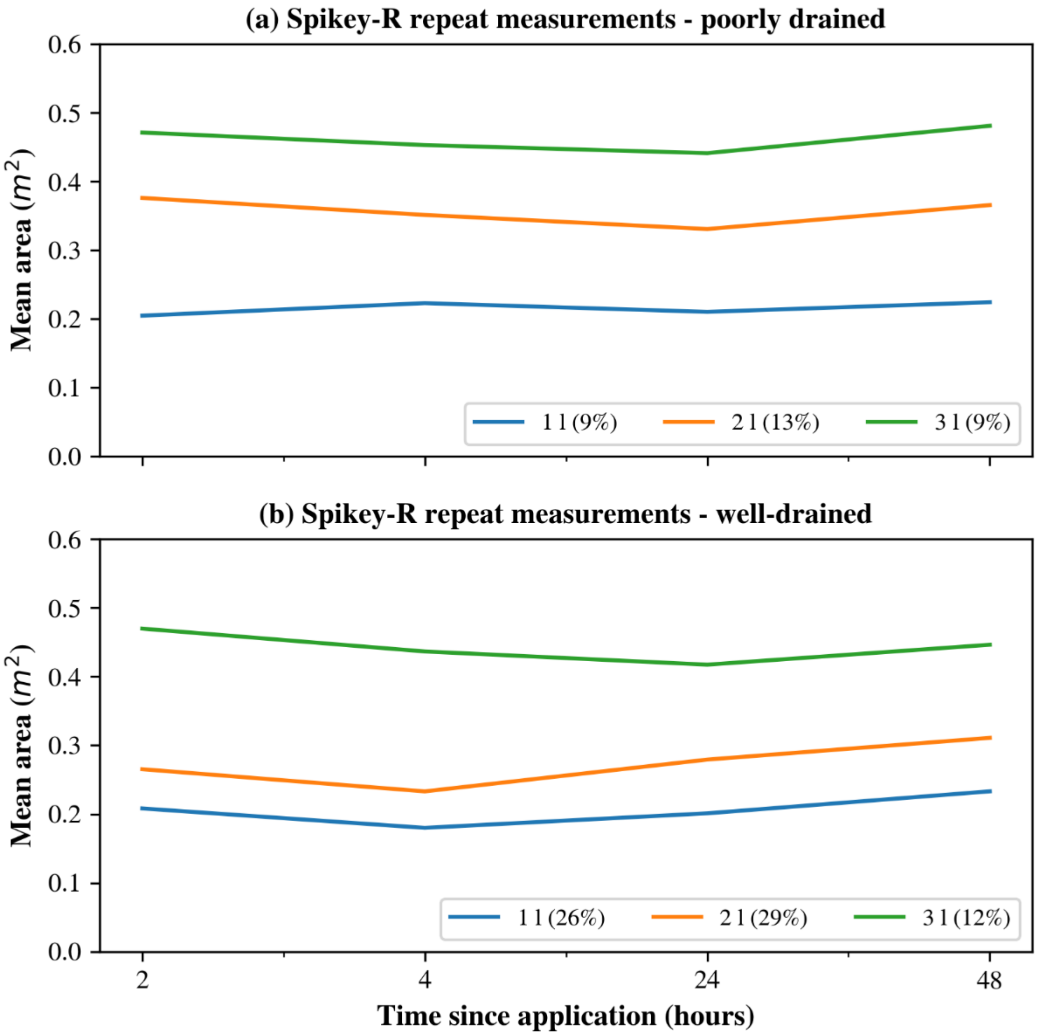

Figure 5 – Spikey-R mean patch area at each sampling time, by volume of artificial urine applied for (a) poorly drained soil at Massey, and (b) well-drained soil at Ruakura. Percentage values in legend indicate range as a percentage of overall mean.

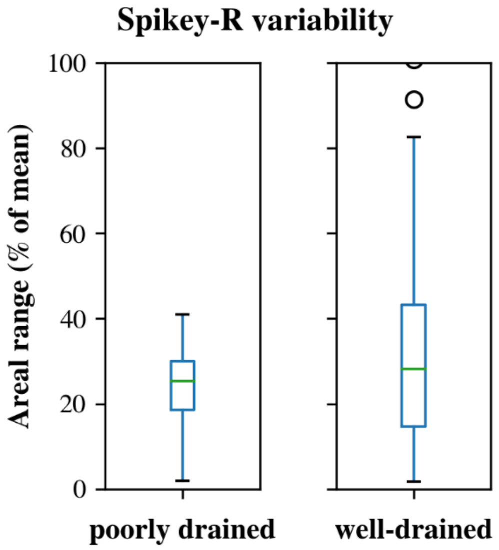

Figure 6 - Variability in detected patch area over time for poorly drained (Massey No. 4 Dairy) and well-drained (Ruakura Research Farm) soils.

Discussion

The thermal camera was very effective at detecting and delineating the simulated urine patches in this trial. Pre-trial investigations found that the time window for effective capture of patches under cold ambient conditions (approximately 7 – 10°C) was in the order of several minutes, however, as ambient temperatures increase this is likely to be shorter. The size of the simulated patches increased with volume but also varied substantially, as can be expected under field conditions. Patches on the well-drained soil were smaller than the poorly drained soil. Patches on the 'wet' soil moisture level were slightly larger than the 'dry' for the well-drained soil type but this effect was not visible for the poorly-drained type.

In this study, the RPAS imagery served multiple purposes: a base map of the trial area, a way of accurately locating all GCPs when only some were surveyed with a GNSS (due to time constraints), a way of georeferencing the thermal imagery in order to produce a spatially-coherent map, and finally another method of detecting pasture response to urine patches. Without the RPAS the thermal camera work would have been significantly harder and the Spikey-R GCPs would have taken significantly longer to survey with a GNSS. The RPAS worked very well at detecting pasture response over the poorly drained soil, but not very well over the well-drained soil as the background pasture growth was too vigorous to distinguish from the patches by eye, let alone automatically. This was likely due to soil fertility being better at that site, possibly along with warmer weather conditions (different geographical location and trial was conducted one later in Spring than the poorly drained location).

At the poorly drained site, pasture response areas were 2 – 3 times the original patch size as determined by thermal camera and Spikey-R. This was largely expected as grass root systems travel laterally as well as vertically, so grass surrounding a patch can still benefit from the nutrients even if it not directly over the original area of deposition. Added to this, the urine would likely have also moved laterally over the days following deposition thereby increasing its area of effect.

In general, Spikey-R proved to be an effective tool for detecting urine patches by way of mapping soil conductivity. A better GNSS (or 'GPS') would vastly improve the quality of the actual map, however this has no impact on the detection ability. Most (> 80%) patch measurements fell within +/- 30% of the area as detected by the thermal camera. This was of a similar magnitude to the variability of detected sizes for each patch for repeat passes (means of 25% to 35% with large standard deviations) and on the lower end of uncertainty estimates (29% to 37%). The uncertainty was calculated by simply dilating or eroding a patch by a single pixel (50 mm) so is a reflection of the limitation of the sensor's spatial resolution. This means that, if it was critical that the entire patch extent is detected and mapped, the patches detected by Spikey-R should be buffered by 50 mm. If a more accurate map is required, however, then the spatial resolution of Spikey-R needs to be increased.

Conclusion

This study has shown Spikey-R is an effective tool for detecting urine patches and is effective at mapping their location provided adequate ground control points are used. A better GNSS unit would remove the need for ground control. Patches were successfully detected up to 48 hours post-application with some variation in size, but no trend over time was identified. Size variation is influenced by sensor resolution so in order to ensure the entire area of a patch is flagged, a buffer of 50 mm (one 'pixel') is needed. The thermal camera was very effective at delineating patch extent but needs supplementary ground control information to prove truly useful at mapping the patches. The RPAS provided mixed results, with all patches identified at one site but not the other. It is likely this method is far more sensitive to background soil fertility and ambient weather conditions during the two weeks between deposition and detection.

Acknowledgements

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