Understanding spatial and temporal variation in soil moisture –
A case study from Todd Matthew's farm at Cootra

Rob Bramley, Christina Ratcliff and Therese McBeath
CSIRO, Waite Campus; rob.bramley@csiro.au

Background

Through his engagement in the Resilient EP Smart Farms project, Todd Matthews hosts one of the project 'focus paddocks' and in this connection, has a soil moisture sensor installed in one of his paddocks (Figure 1). Of interest to Todd and other farmers who have access to soil moisture sensors, is the question of how he can make use of the data provided by the sensor to understand soil water variability at the paddock scale in such a way that it can usefully inform in-paddock decisions ? Can he similarly use the probe to understand soil moisture variation in other parts of the farm ? These are important questions because, even if a soil moisture probe can provide perfect information for the place where it is installed, farmers like Todd want to be able to interpret the probe data in a much broader context – over his entire field or farm. In other words, how can we extrapolate the probe data to these other locations ? Whether this is possible at either field or farm scale, is being able to do this useful ? Tackling these questions were the key tasks faced in this case study.

Figure 1. The Todd Matthews 'focus farm' (1014 ha) and locations where soil samples were collected during the project. The 'focus paddock' (180 ha) is the one containing the soil moisture probe (Coot probe). Note that for technical reasons, along with the need to keep the probe loggers clear of the crop, such probes have to be located close to fence lines. Note also that this 'focus farm' is only a portion of Todd Matthews total farm area of approximately 6,500 ha.

Point data, map surfaces and a method for extrapolating probe data

Other work conducted as a part of the Resilient EP Smart Farms project and in other projects has strongly suggested that soil moisture sensors can do a good job when properly calibrated, albeit with the calibration process requiring soil samples to be collected repeatedly for soil moisture determination; in general, the calibration appears to be less good at depth compared to soil layers that are unaffected by soil constraints such as salinity, sodicity and the presence of carbonate. Work conducted in the GRDC-supported 'Future Farm' project (Bramley et al. 2022) suggested that in the absence of soil salinity, EM38 could be a reasonable predictor of plant available water capacity (PAWC; i.e. the 'size of the bucket'), but is not a very good predictor of soil moisture content at any given time, even when plenty of calibration data are available. Furthermore, because EM38 soil survey is generally only done once, it offers no temporal dimension and so as a means of understanding soil moisture variability over a season, is of limited utility. For this case study, we wondered if freely-available Sentinel imagery, coupled with other covariates might enable a time series calibration of soil moisture variability to be generated ? As an alternative, we were also interested to know whether we could identify 'zones', at both paddock and farm scale which would help Todd to understand what the soil moisture status within the zones was likely to be for any given value generated by the probe.

As a part of the 'Future Farm' project, Eileen Perry (Agriculture Victoria) developed a method of using Sentinel imagery in time series to provide estimates of crop biomass. For both 'Future Farm' and the present work, we modified this to generate a means of extrapolating soil moisture away from the probe. In brief, the method works as follows:

- Sentinel imagery is acquired for the target location (available approximately every ten days).
- Imagery which is not cloud-free over the target of interest is discarded.
- The cloud free imagery is fitted on a per-pixel basis with a spline function to enable the time series of NDVI to be described on a daily time step. The top graph in Figure 2 (green line) shows this for the location of Todd Matthews' soil moisture probe.
- The fitted line is adjusted down to align to a 'zero' baseline – the blue line in Figure 2 to accommodate any residual effects of stubble, or fallow or early season weeds.
- The adjusted daily NDVI data are then used to calculate the cumulative daily NDVI – bottom graph in Figure 2.

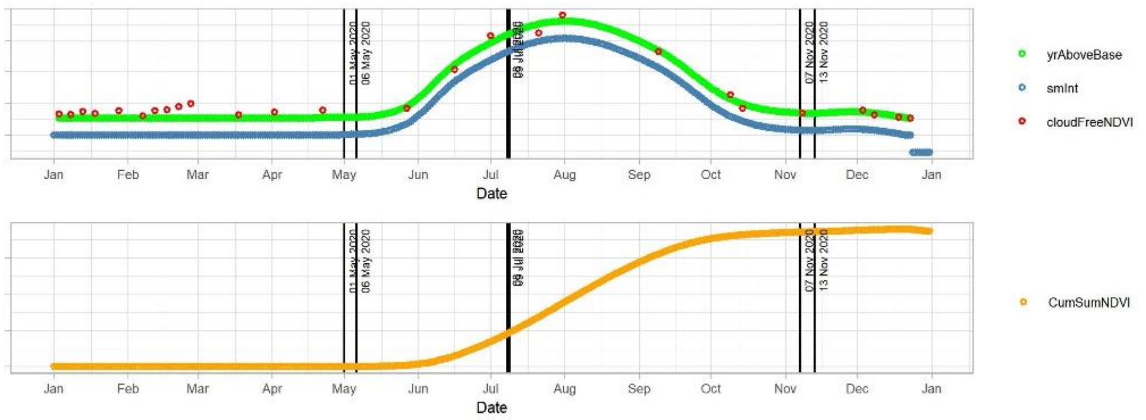

Figure 2. Generation of cumulative NDVI for the location of the soil moisture probe in the Todd Matthew 'focus paddock' in 2020. The paddock was sown to wheat on 6 May, with the crop reaching GS31 on 8 July; it was harvested on 7 November. Soil samples were collected for moisture determination on 1 May and 13 November.

- Crop phenology is strongly temperature driven; crops also require sufficient water to grow. Accordingly, daily temperature and rainfall data are downloaded from the closest Bureau of Meteorology (BOM) weather station (Koongawa (Retawon) Station 18101 in the case of Todd's farm) and from these data, the seasonal growing degree days (GDD) and cumulative net precipitation (CNP) are calculated; CNP is calculated from net precipitation which, on any given day, is the daily rainfall less the daily evaporation.
- Using multi-variate linear regression, the daily soil moisture probe data are regressed against cumulative NDVI, GDD and CNP. Note that we used corrected probe data (adjusted for temperature fluctuation and to a mm of plant available water (PAW) basis for this.
- The resulting regression equation is then used to estimate a map of soil moisture from the cumulative NDVI, GDD and CNP for any date of interest.

Figures 3 and 4 show the results for the Todd Matthews focus paddock on 9 July 2020.

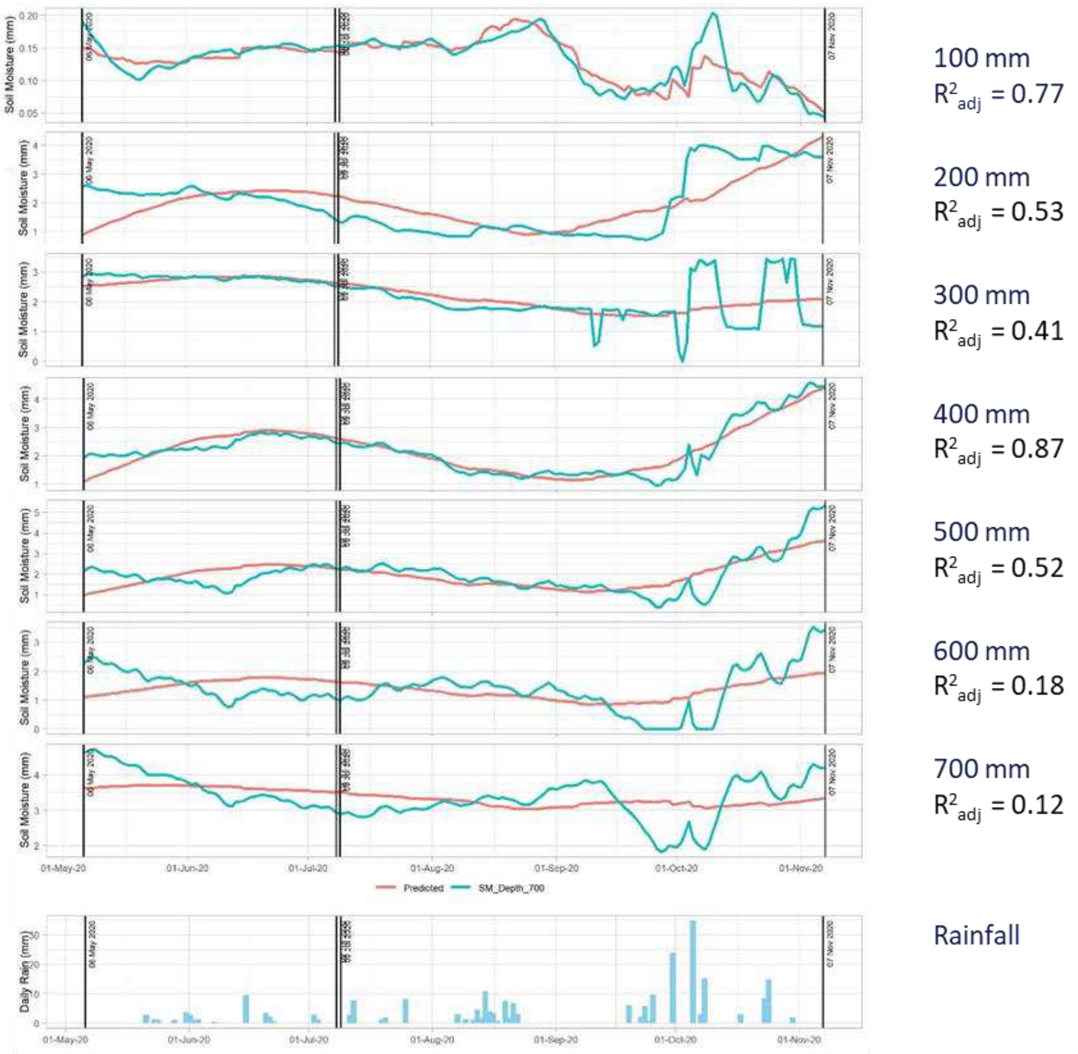

Figure 3. Prediction of soil moisture probe data (mm PAW) at a range of depths through the 2020 growing season using cumulative NDVI, GDD and CNP. Also shown (bottom graph) is the daily rainfall.

As can be seen in Figure 3, the prediction of soil moisture down the profile, measured on the basis of R^2, is variable down the soil profile and tends to be better in upper depths. This is to be expected given that, at GS31, roots are unlikely to extend to depth and therefore the NDVI signal does not depend on plant growth that is consequent to soil moisture at depth. Figure 4 indicates that, as was found for a site in the mid-north in the 'Future Farm' project, at any individual depth, the spatial variation across the paddock is much less than the variation in soil moisture down the soil profile at any given location. This tends to suggest in the case of Figure 4 that spatial variation in soil moisture at GS31 is unlikely to be of sufficient magnitude to drive a variable rate mid-season N decision. A similar conclusion is drawn for a late season date (e.g. Figure 5) when farmers like Todd might be thinking about whether there is enough soil moisture to carry the crop through to harvest or whether they might be better off cutting the crop for hay. Note also that in Figures 4 and 5, the range of spatial variation in total profile soil moisture in the paddock is small – of the order of 8 mm on 9 July 2020 (Figure 4) and around 6 mm on 27 September 2021. This is perhaps not a surprising result for the very sandy soils which predominate on Todd's farm. Collectively these results tend to suggest that, at paddock scale, the value that Todd might get from soil moisture probe data is much more related to comparing seasons (is this year drier/ wetter than last year, or very similar to x years ago, and so should I adjust management to reflect this ?) than to being the driver of a targeted management decision or use of variable rate fertilizer application. Further, an obvious limitation of this NDVI-based method of extrapolating soil moisture

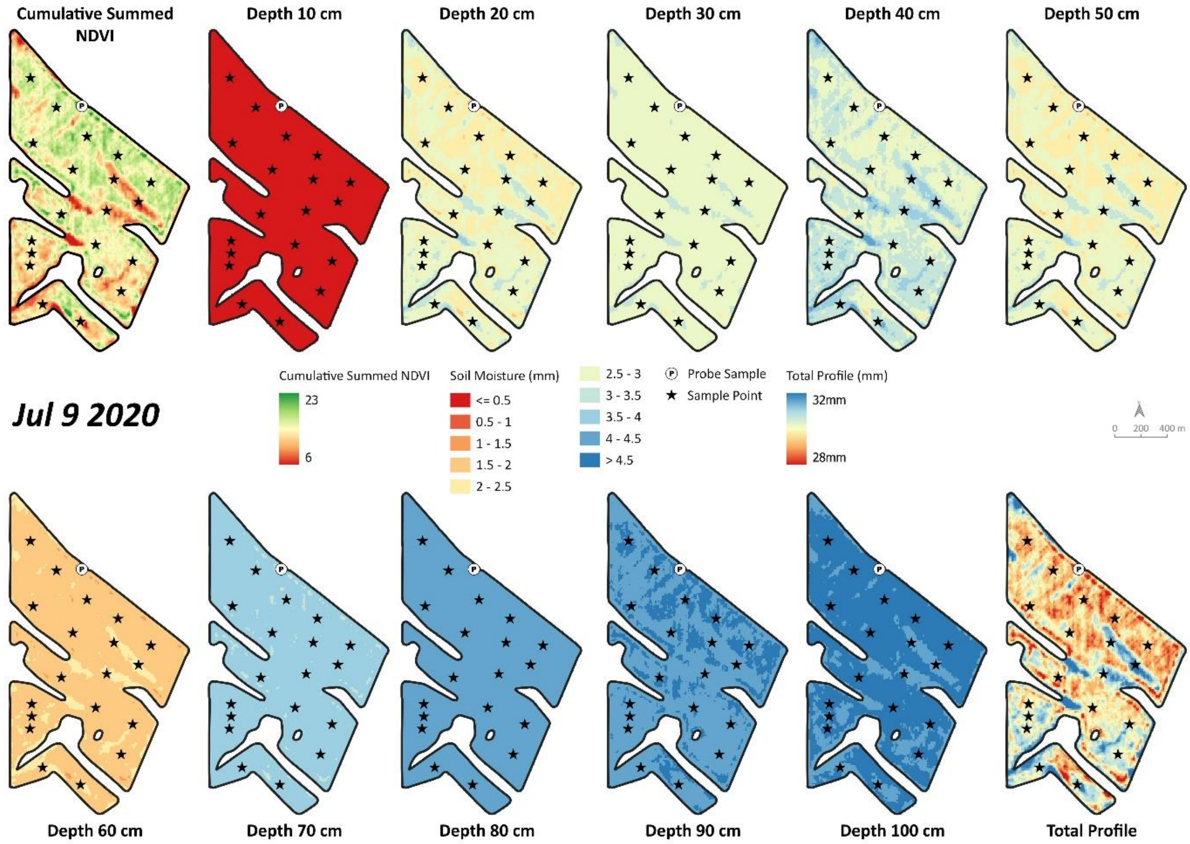

Figure 4. Predicted soil moisture (mm PAW) in the Matthews focus paddock at GS31 (9 July) in 2020.

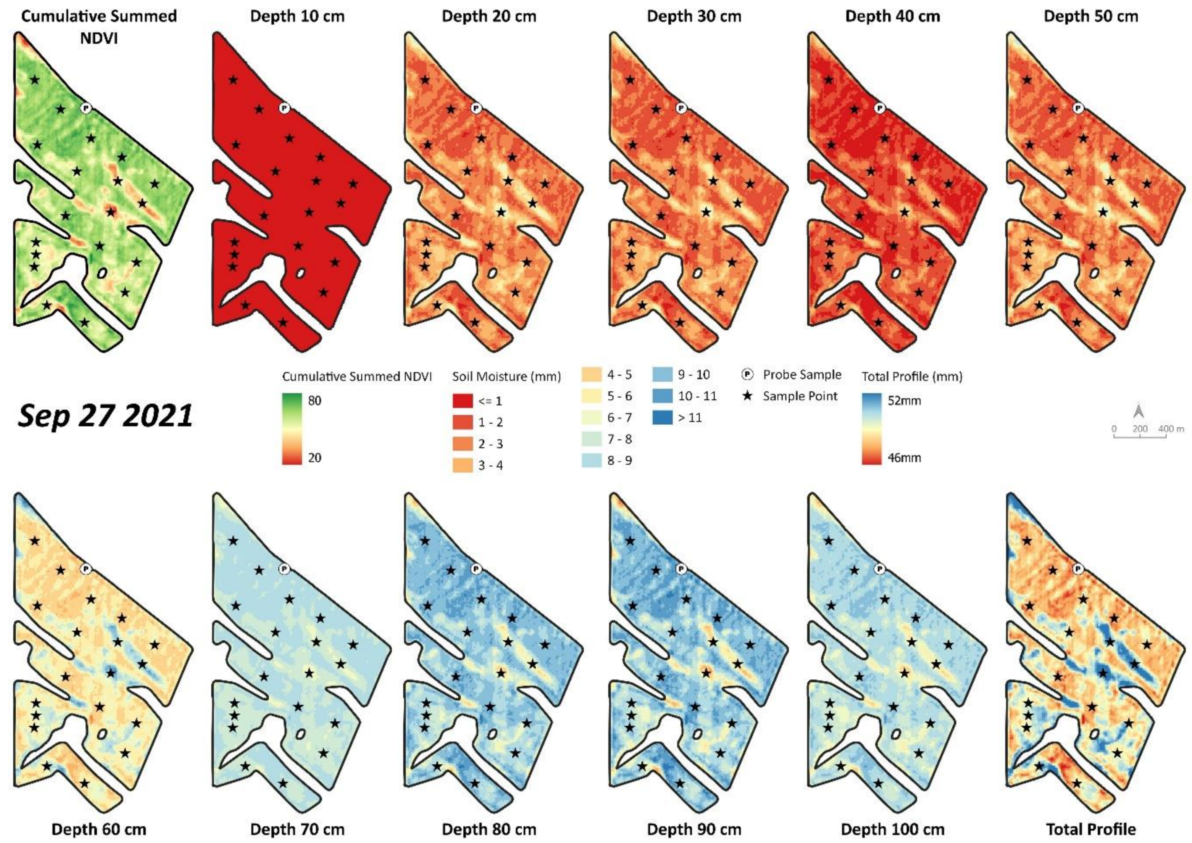

Figure 5. Predicted soil moisture (mm PAW) in the Matthews focus paddock on 27 September 2021.

probe data is that it only works when there is a crop with a discernible amount of photosynthetically active biomass present. In other words, this methodology cannot be used to inform a sowing decision, for example.

Calibration of probe data to other locations

During the course of the Resilient EP Smart Farms project, soil moisture samples were collected from the locations indicated in Figure 1 on 1 May, 9 July and 13 November 2020, 1 July and 27 September 2021, and 2 Feb, 23 March and 12 July 2022. Unfortunately, this means that there were only 5 sampling occasions within the 'NDVI window' (i.e. the growing seasons) that could be used to calibrate the results of the probe extrapolation and not all sampling locations were sampled on all of these dates. Whilst we are confident that the NDVI-based methodology works, we do not have the calibration data available to demonstrate this for the various EP Smart Farms 'Focus sites' including the Matthews farm. Given the observation that moisture variation down the profile on any given date is greater than the spatial variation within-paddock on that date, our inability to calibrate the method rigorously is possibly not as serious a limitation as it might be. It does nonetheless highlight that, if growers want to take advantage of a method like this, they need to be willing to have soil samples collected for calibration during the growing season when the crop is in the ground. What is possible here, however, is to consider how the probe data appear to align to the available soil moisture data.

Figure 6 shows a series of plots of soil moisture down the profile, at both the location of the probe and also at other sampling locations on the farm (Figure 1); data are shown for dates in April 2021 (i.e. near

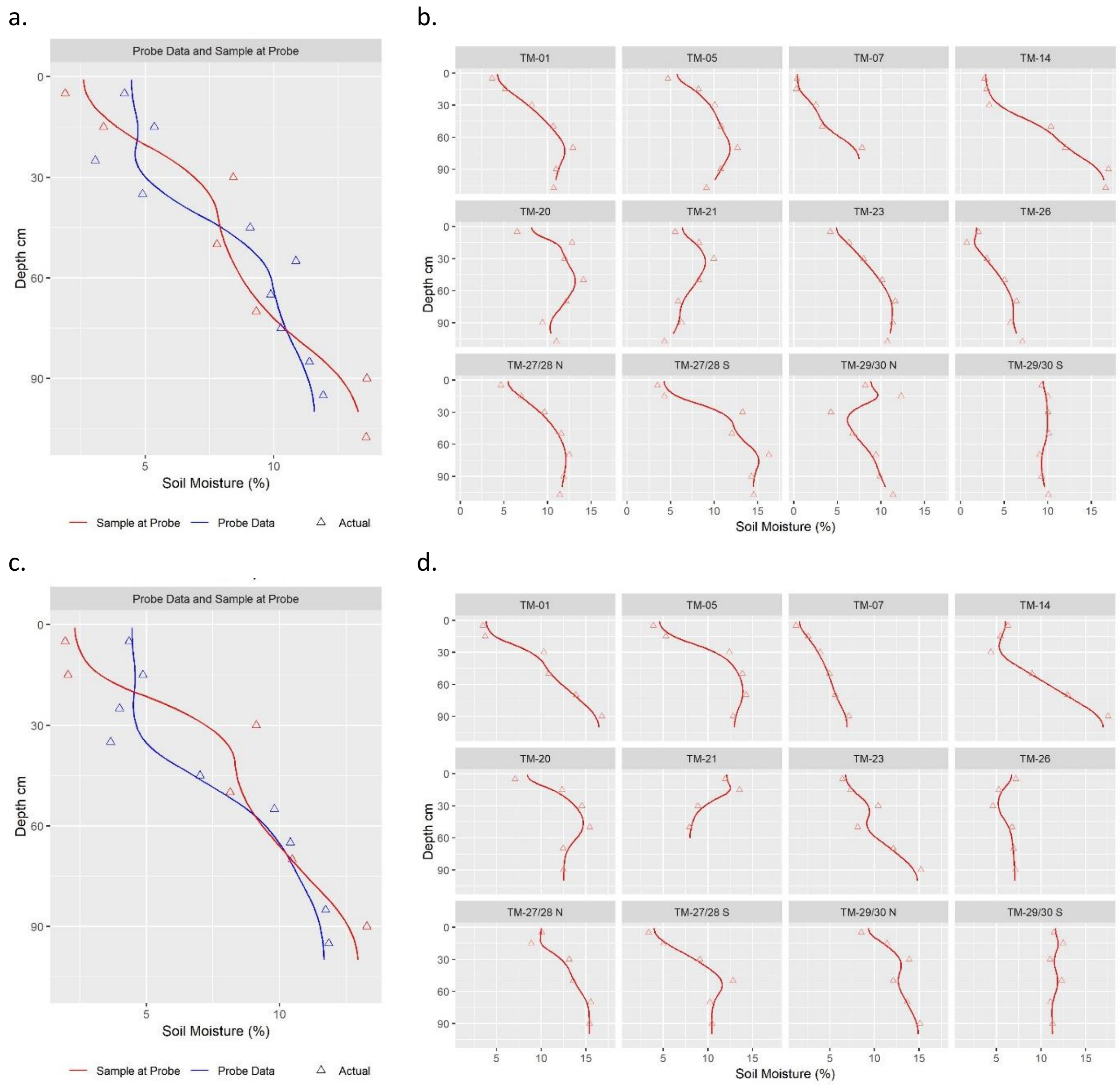

Figure 6. Soil moisture data collected (a,c) at the location of the probe , and (b, d) at other locations on the Matthews farm on (a, b) 21 April 2021 and (c,d) 12 July 2022.

sowing) and in July 2022 (i.e. around GS31). Because of differences between the depths at which samples were collected and at which the probe generates data, all of the data have been fitted with spline curves to enable us to do depth-based calibrations (Figure 7). It is also important to note here that the raw probe data have units of mm which, in the other analyses in this report have been adjusted to a plant available water (PAW) basis (ie with the crop lower limit (CLL) deducted) to facilitate probe calibration. However, the actual soil moisture sample data are expressed in % on a gravimetric basis. Accordingly, in Figures 6a and c, the probe data have been transposed back to a gravimetric basis knowing the CLL and bulk density at the probe location at which detailed soil characterisation was carried out by project colleagues. Since we do not have bulk density measures or other soil characterisation at all the sampling locations shown in Figure 1, it makes sense here to focus predominantly on gravimetric soil moisture – something that the project team might wish to consider going forward given their prior desire for probe data to be expressed on a volumetric basis. The preference for soil moisture to be expressed in mm is understandable given that many agronomic rules (e.g. estimation of potential yield) rely on soil moisture being expressed in mm. But such an approach does rely on a commitment to greater soil measurement – at a minimum, of bulk density and desirably of the crop lower limit (CLL) and drained upper limit (DUL) or field capacity (FC). These enable gravimetric measures of soil moisture to be converted to a volumetric basis and to then be interpreted in the context of the size of the soil 'bucket' in which the plant available water is held.

In looking at Figure 6, the important point to consider is the shape of the profile curves. Encouragingly, for both the moisture probe and actual measured samples, these are similar for both dates, although there is a consistent difference (i.e. poor calibration) between the probe data and actual measurements in the 25-50 cm depth range. Figures 6b and d show the range of variation in soil moisture profiles amongst the sampled locations across the Matthews farm. Clearly, they are variable and not markedly similar to the moisture profile at the probe location. Notwithstanding inherent paddock variability (see below), this highlights the need for a soil moisture probe to be located in a place that is demonstrably characteristic of at least some of the rest of the farm. Accordingly, some sampling locations have moisture profiles that are sufficiently similar to those at the probe to enable extrapolation from the probe, but others do not. This is why, for example, at sampling location 'TM-06' there is close agreement between the fitted spline probe values and the fitted spline data (to measured soil moisture in collected samples) at all depths, but across all sampling locations at a single depth, there is no meaningful utility in the calibration (Figure 7). In other words, the soil probe is a good predictor for some locations but without the NDVI-based adjustment (Figures 2-5) or an appropriate alternative, it is not a good predictor for all locations in general.

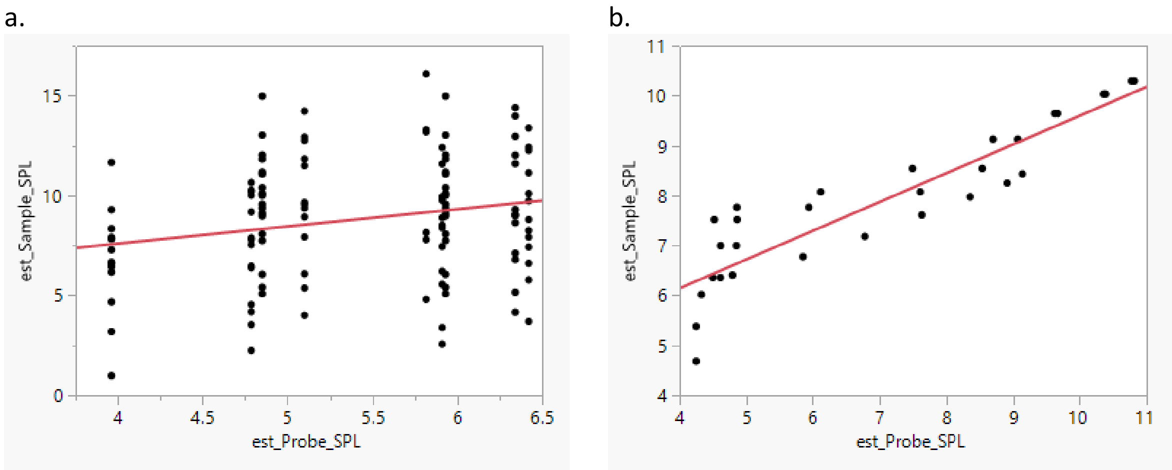

Figure 7. Calibration of data from the Matthews soil moisture probe, adjusted to a gravimetric basis, against gravimetric soil moisture content measured in samples collected from (a) the locations shown in Figure 1 at a depth of 35 cm, and (b) at location 'TM-06' at all depths. In both (a) and (b), data from all available sampling dates have been included. The R^2 for the fitted lines is (a) 0.04 and (b) 0.82.

Farm-scale zoning

Figures 6 and 7 lend weight to the idea that characterising the soil at farm scale into similar 'zones' might assist with the interpretation of data. One way of doing this is to use historical yield mapping to delineate zones in the same way that might be done at paddock scale in support of variable rate management. However, this can present difficulties in data processing given that, across the 1010 ha ‘focus farm’ area, several harvest events are needed to harvest the entire area, with the possibility of different crops being grown in different paddocks. By way of example, Figure 8 shows the trace of harvest in 2020.

The difficulty of different harvest events (for which there could be variation in the calibration of the yield monitor) and effect of differing crop types having different yield potentials, along with the more general effect of yield potential varying from year to year, can be accommodated by normalising all the yield data to a mean of zero and standard deviation of one on a per harvest event basis; note that this is done prior to interpolation of the yield maps. Figure 9 shows the results of doing this over seven seasons (2015-2021). Note the effect of fallow in some paddocks in some seasons. The maps shown in Figure 9 then enable adjustment of the data to a common mean across the whole farm area, assuming that the range of yield variation in each paddock is approximately the same. Thus, in Figure 10, all of the data have been adjusted back to mean yield obtained in paddock 24 (the focus paddock) in each of the relevant seasons. Because this paddock was fallow in 2016 and 2018, no whole farm maps can be generated for those years. Therefore in Figure 11, we have adjusted the yield maps for each paddock and year to have the same mean yield as paddock 24 in 2020 with yield in paddocks that were fallows calculated as the mean of the years for which there was a crop. From the maps shown in Figure 11, we can then use the standard approach to clustering yield maps to generate the zones shown in Figure 12. The ‘Focus Farm’ separates into two zones for which, assuming that 2020 was a typical season for wheat, the mean yields differ by approximately 0.7 t/ha.

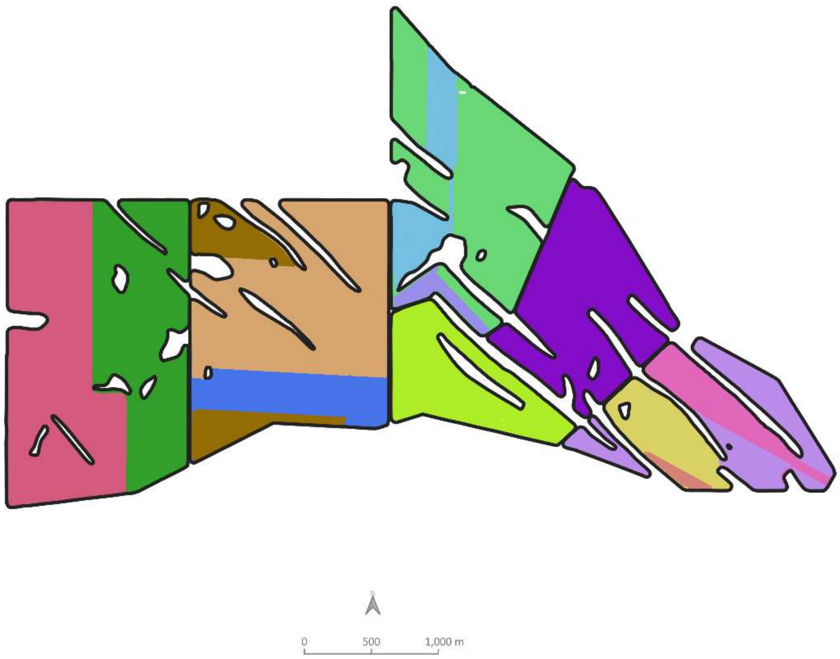

Figure 8. Progression of the 2020 harvest on the Matthew ‘focus farm’. Note that each colour represents a different harvest ‘event’. The entire area in 2020 was sown to wheat except for the paddock predominantly coloured brown which was sown to barley.

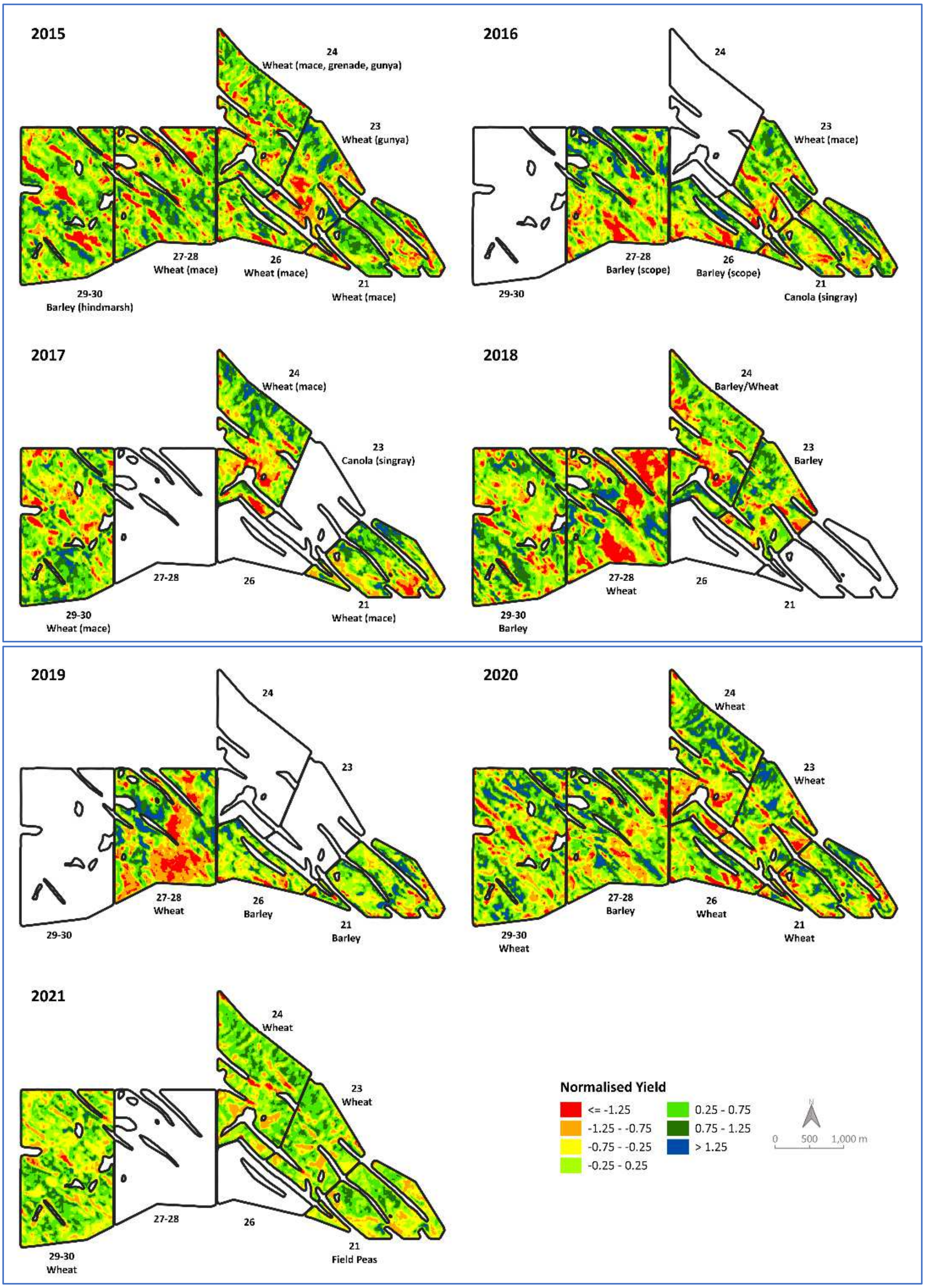

Figure 9. Normalised yield maps for the Matthews focus farm area (1014 ha) across seven seasons (2015-2021). Data were normalised on a per-harvest even basis prior to map interpolation.

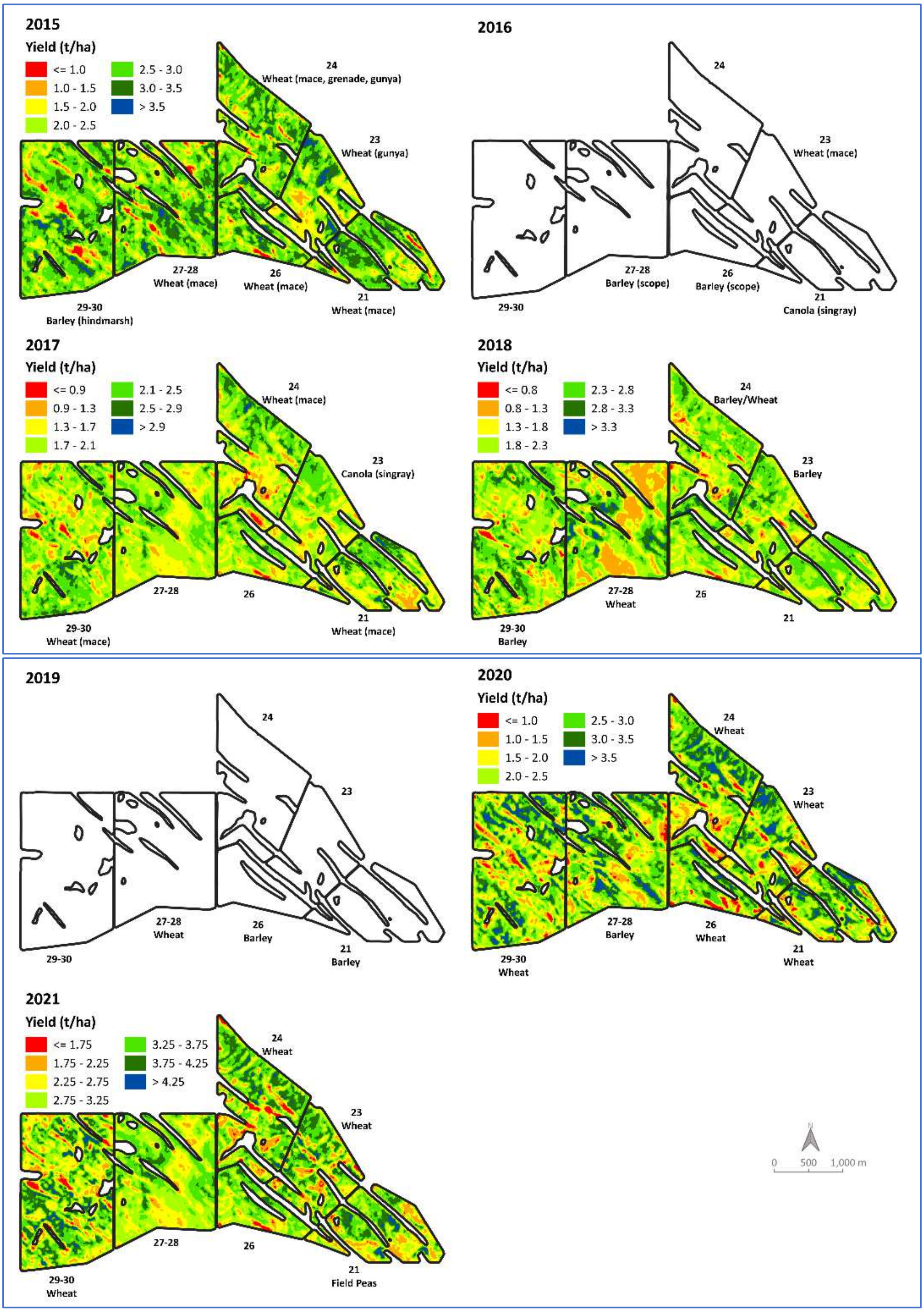

Figure 10. Yield maps for the Matthews focus farm area (1014 ha) across seven seasons (2015-2021) with the mean yield in each paddock in each season adjusted to the mean yield of wheat obtained in paddock 24 in the same season.

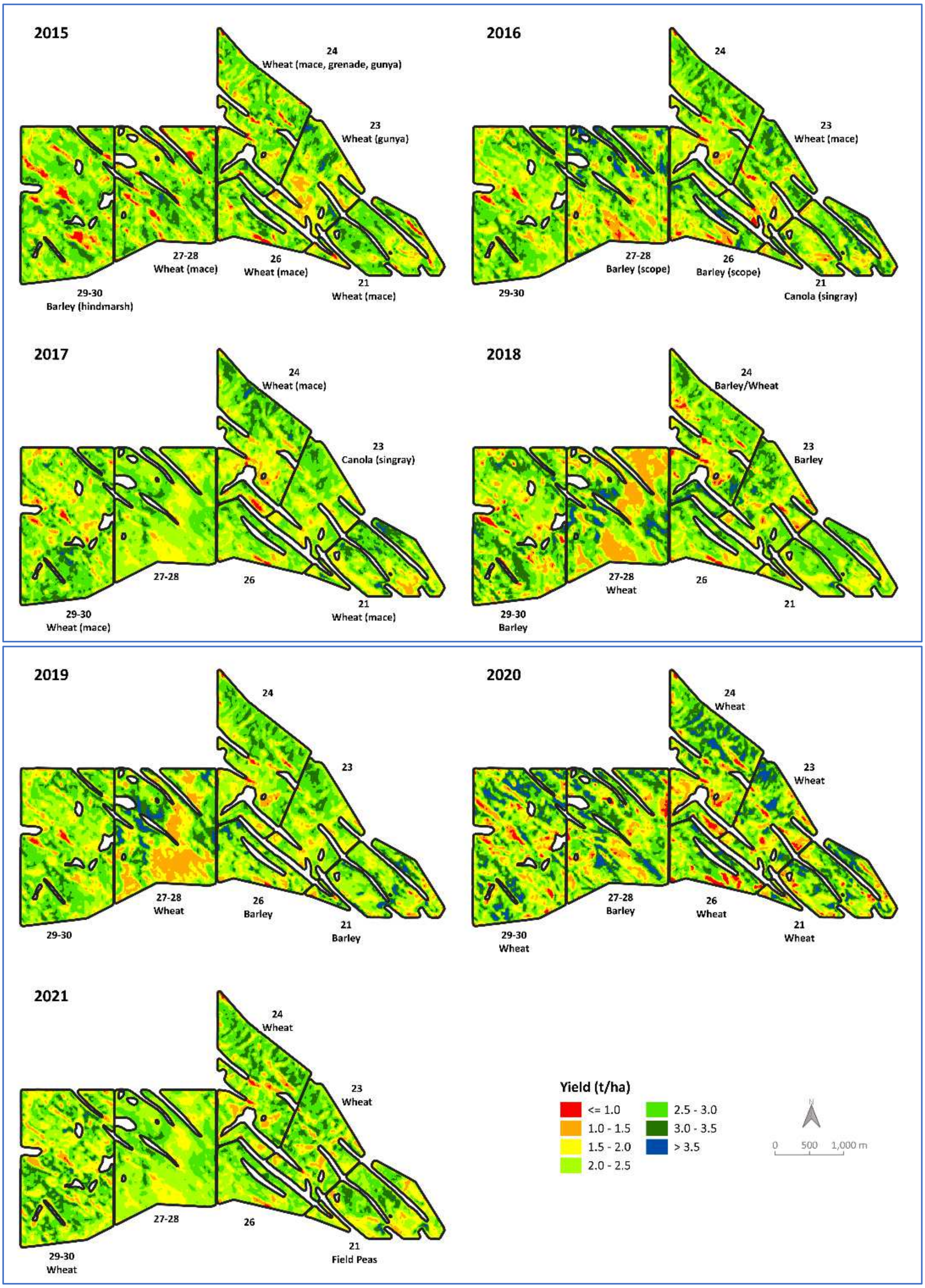

Figure 11. Yield maps for the Matthews focus farm area (1014 ha) across seven seasons (2015-2021) with the mean yield in each paddock in each season adjusted to the mean yield of wheat obtained in paddock 24 in 2020.

Figure 12 then allows us to re-look at the calibration of the moisture probe data against samples collected in other parts of the farm (c.f. Figure7). Of course, in doing this, we are assuming that soil moisture status is the predominant driver of the differences between the zones, which may or may not be the case. As can be seen in Figure 13a, separating all the available sampled soil moisture data obtained from all depths and all sampling locations does not provide any absolute separation between the zones, although the moisture contents of the lower yielding zone predominate at the drier end of the range of values. Focussing just on a single depth does not improve the separation (Figure 13b). However, consistent with Figure 7b, at some sampling locations – in both the higher and lower yielding zones – there is some suggestion that soil moisture can be predicted from the data generated by the soil moisture probe installed some distance away (Figures 13c, d). Note that at some locations, the prediction is very poor. Overall, Figure 13 tends to suggest that soil moisture status may not be the primary driver of the yield differences between the zones identified through Figures 9-12. Since we know that yield potential is predominantly set by water availability, and also know that soil depth is quite variable in a 'Mallee' landscape such as that at the Matthews farm, it is possible that rather than soil water status *per se.* being the driver of between-zone yield differences, it is the total size of the bucket (which integrates the effects of soil constraints), rather than how full it is, which sets the limits of yield performance at this site. Unfortunately, in the absence of a more complete dataset – including soil moisture measurements made during the growing season – we are not able to draw more definitive conclusions than this.

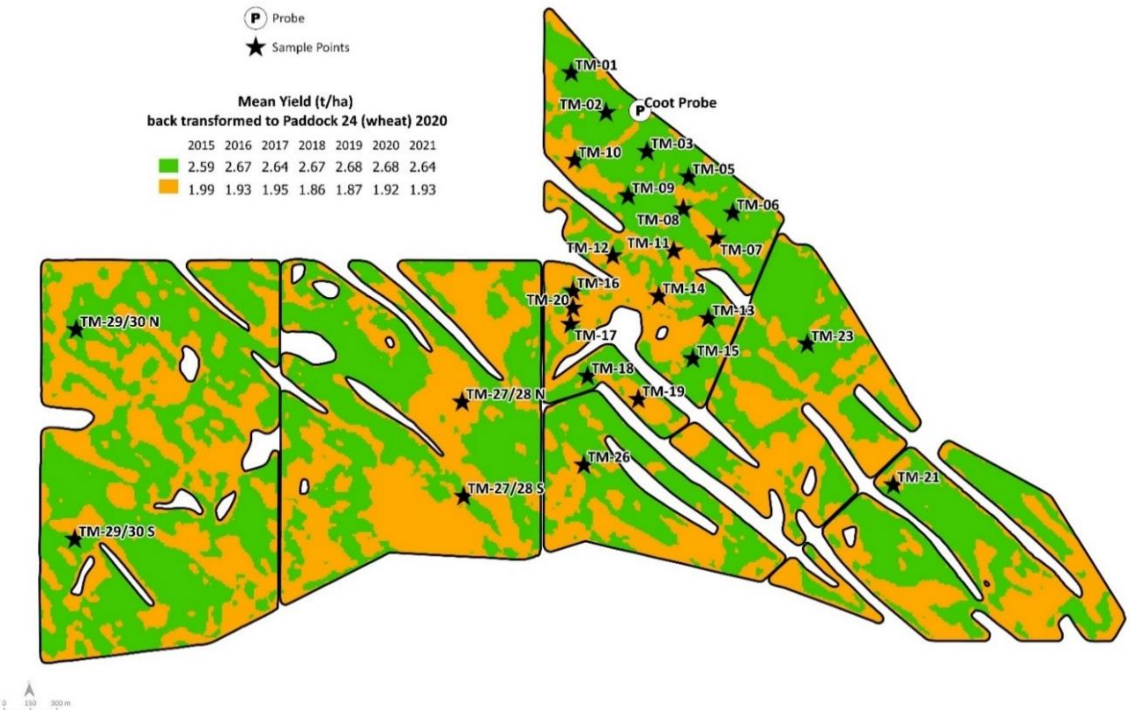

Figure 12. Zones derived from *k*-means clustering of the yield maps shown in Figure 11. The numbers in the legend are the mean yield in each zone. Also shown are the soil sampling locations.

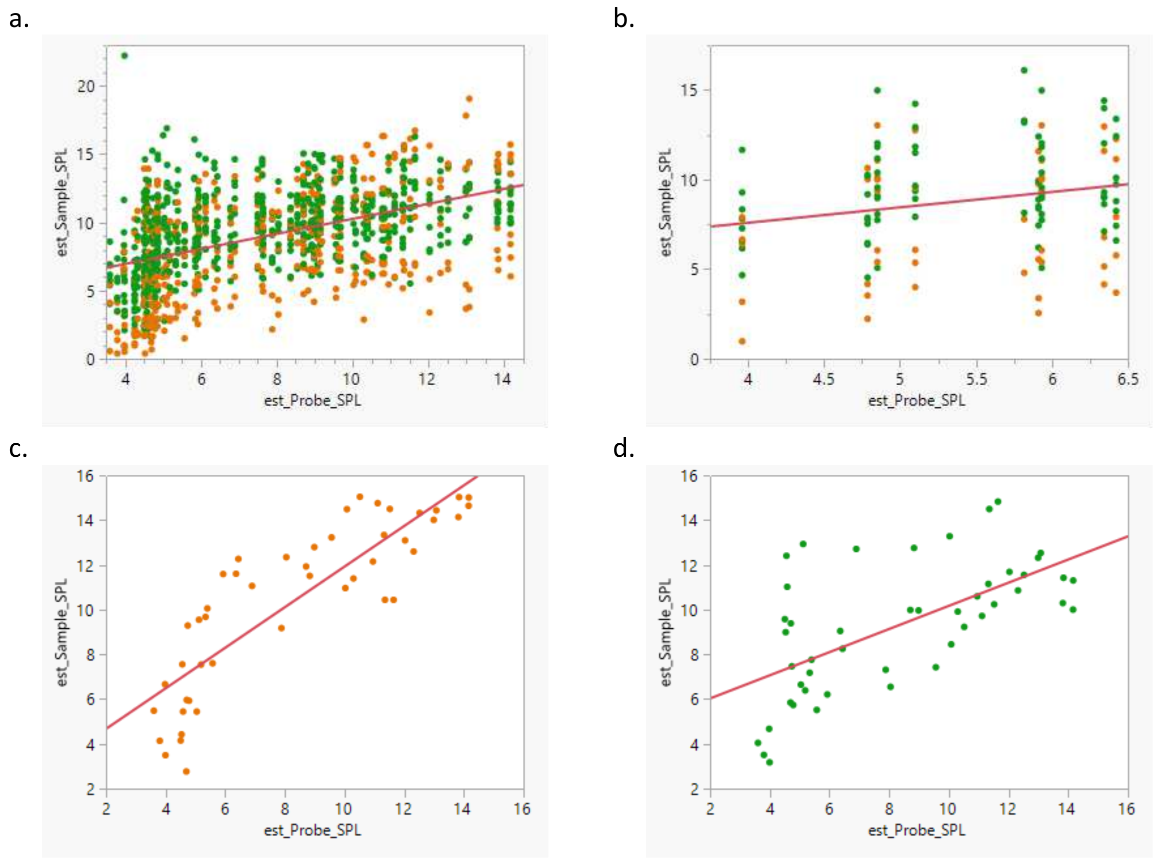

Figure 13. Zone-based calibration of the soil moisture probe against measurements of moisture status at the locations shown in Figures 1 and 12. (a) all locations, depths and sampling times; (b) 35 cm depth increment only; (c) location 'TM-27/28S' (R^2 = 0.72); and (d) TM-29/30N (R^2 = 0.37), in both cases for all depths and times. Colour coding is as per Figure 12.

Conclusions

Through the analyses conducted in this case study we can draw the following conclusions:

- A soil moisture probe can potentially provide useful information; but it is specific to the location at which it is installed.
- An approach based on multivariate regression and using cumulative NDVI, season growing degree days and cumulative net precipitation offers a means of extrapolating soil moisture probe data away from the location of the probe. However, this only works during the growing season since it relies on the NDVI signal from a crop.
- On any given date during the growing season, the spatial variation in soil moisture in both the Matthews 'Focus paddock' and 'Focus Farm' is somewhat less than the variation in soil moisture down the profile. Accordingly, it seems unlikely that a soil moisture probe, coupled with a means of extrapolating away from that probe, will drive a targeted mid-season management decision on an Eyre Peninsula farm similar to that of Todd Matthews.
- Historical yield maps can offer a useful underpinning basis for separating a farm into zones of characteristic performance in the same way that might be done for the identification of paddock-scale zones.

- On the Matthews farm, zoning the farm on the basis of yield did not markedly improve our capacity to interpret soil moisture probe data at other locations on the farm.
- However, at some locations, the soil moisture profile could be seen to be similar to that at the probe; at other locations it was clearly somewhat different.
- Where a soil moisture probe is to be used, if some element of probe calibration is to be employed to assist in interpretating probe data at other locations, an extensive soil sampling / moisture analysis program needs to be implemented. As well as covering the range of variation in seasonal soil moisture status (low to high), it also needs to include in-season / in crop sampling. One suggestion might be for a regular monthly soil moisture monitoring program to be implemented, beginning and ending one month either side of the growing season. Desirably, this would be done over a few seasons to ensure that the full likely range of soil moistures are encountered. It would also desirably include measurement of bulk density and determination of CLL and DUL / FC. The latter are discussed in an accompanying case study from Jordy Wilksch's farm.

Acknowledgements

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References

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