Delineation of 'Management Classes' within Non-Irrigated Maize Fields Using Readily Available Reflectance Data and Their Correspondence to Spatial Yield Variation

D. Ekanayake[1], J. Owens[2], A. Holmes[3], A. Werner[1]
[1]Lincoln Agritech Ltd., PO Box 69 133, Lincoln, Canterbury 7640, New Zealand
[2]Agriculture and Agri-Food Canada, 5403-1 Avenue South, Lethbridge, Alberta, Canada
[3]Foundation for Arable Research, 133C Ruakura Road, Ruakura, Hamilton, New Zealand

A paper from the Proceedings of the
14th International Conference on Precision Agriculture
June 24 – June 27, 2018
Montreal, Quebec, Canada

Abstract. *Maize is grown predominantly for silage or gain in North Island, New Zealand. Precision agriculture allows management of spatially variable paddocks by variably applying crop inputs tailored to distinctive potential-yield limiting areas of the paddock, known as management zones. However, uptake of precision agriculture among in New Zealand maize growers is slow and limited, largely due to lack of data, technical expertise and evidence of financial benefits. Reflectance data of satellite and areal images can be used to delineate management zones when yield maps are unavailable. This study focused on using publicly available remotely sensed reflectance data for delineating management class maps rather than traditional approaches. Reflectance data from freely available Google Earth images were used to develop management class maps for a 5.95 ha paddock in the North Island, New Zealand. Google Earth images were imported into Geographic Information Systems software for georeferencing and extracting pixel value data. Extracted data were interpolated into a 1 m x 1m common grid and normalised. Normalised data for each band of three crop cover only and bare soil only images were combined to create two separate management class maps with three clusters in Management Zone Analyst software. Multiple years of maize grain yield data from the paddock was used to create three management classes: high yield stable; low yield stable and unstable. Filtered multi-year yield data were used to validate maps of reflectance data opposed to traditional yield map. Both management class maps delineated from the Google Earth images discriminated yield classes with narrow absolute yield differences. Management class map derived from bare soil only images better depicted the patterns in the traditional multi-year yield map, compared to the map derived from crop cover only images. Reflectance data derived from Google Earth images can serve as a preliminary data source when multiple years of yield data is absent.*

Keywords. *Maize, Management Zone, Management Class, Management Class Maps, Google Earth Images*

The authors are solely responsible for the content of this paper, which is not a refereed publication. Citation of this work should state that it is from the Proceedings of the 14th International Conference on Precision Agriculture. EXAMPLE: Lastname, A. B. & Coauthor, C. D. (2018). Title of paper. In Proceedings of the 14th International Conference on Precision Agriculture (unpaginated, online). Monticello, IL: International Society of Precision Agriculture.

Introduction

In New Zealand, maize is an important crop, predominately grown in the North Island, which is harvested as either grain or silage. Maize grain is produced for human and animal consumption, while maize silage is principally and increasingly used as a supplementary feed in pasture-based dairy industry (Morris et al 2016). Harvest hectares (ha) in New Zealand under the maize grain or silage crop has reduced from 69,864 ha in 2015 to 50,516 ha (predicted) in 2017 (FAR 2016). The situation demands New Zealand maize growers manage crop with optimal crop inputs for achieving higher yields with limited harvest area to satisfy maize crop supply for the industry.

In New Zealand, fertiliser and seed rates for maize crop are determined based on multi-year historic yield records and crop harvest expectations of the paddock. This method is of limited value in spatially variable paddocks (Holmes 2017). The input rates are developed from the data collected from several points over a larger field and are applied to whole-field management strategies. For more accurate application, agronomic inputs should be tailored to paddock areas that have distinctive potential-yield limiting characteristics. Precision agriculture (PA) allows for fields to be managed by variably applying the crop inputs into sub-field areas (Fraisse et al 2001). These distinctive yield limiting sub-field areas are known as management zones (MZs). Delineation of MZs allows classification of spatially distinct areas of a field (Doerge 1999). A specific rate of crop input or treatment can be applied to a management zone (MZ; Doerge 1999; Taylor et al 2007). In PA, the terms MZ and management class (MC) are widely used, but are interpreted differently. Management class is an area which a specific crop input or treatment can be applied and may include many MZs. In comparison, MZ can only have one MC (Taylor et al 2007).

Uptake of PA methods is slow and limited in commercial sector, although it has been practiced in New Zealand since 1990’s. The slow uptake is believed to be due to lack of data, technical expertise or know-how to delineate MZs required to create prescription maps. Farmers are reluctant to uptake new technologies as the evidence of financial benefits related to site-specific crop input management for maize crop is not available. However, the majority of the maize grain or silage crops are harvested with Global Positioning System (GPS)-enabled harvesters and yield monitors that are capable of recording data at every second. In addition, variable rate application (VRA) technology is possessed by maize growers although the feature is rarely used (Holmes 2017).

Publicly available data can be a valuable source when promoting PA in New Zealand. This allows growers who wish to adopt site-specific crop management (SSCM) without years of yield data, or who do not have site property data such as elevation, soil moisture or soil electrical conductivity. Reflectance data from the satellite images can be used preliminary for delineating MZs when yield maps are not available for the field (Zhang et al 2010). For example, historical satellite images that have a spatial resolution of 10 m or less have been used to create prescription maps for managing cotton root rot disease through VRA of fungicide (Yang et al 2017). Large volumes of high resolution satellite data and aerial images can be accessed and retrieved freely from virtual globes such as NASA’s World wind, Microsoft’s Bing Maps, ArcGIS Explorer, and Google Earth being the most popular and influential virtual globe (Yu and Gong 2011).

The objective of this study was to test the use of Google Earth images as a data source for delineating site-specific management classes and to determine whether those management classes relate to management classes derived with multiple year maize yield data. Emphasis is given for scenarios when any data is absent for growers who shift from whole-field management to a SSCM or as a case study to provide evidence on benefits of adopting SSCM for maize growers.

Materials and methods

The study was carried out using data collected from a paddock near Pukekohe (-37.317590°, 174.902172°) named “Costar Field”, North Island, New Zealand. Costar Field is situated in a flat valley, cultivated with maize, either for grain or silage and grazed pasture in rotation. The soil in the 5.95 ha paddock is classified as imperfectly drained clay stoneless mottled orthic allophanic soil (Hewitt 2010). The paddock is not irrigated and is totally rain-fed.

Multi-year yield MC map for Costar Field was derived from six years (2003, 2006, 2008, 2009, 2012 and 2016) of maize grain yield harvested at 20 to 25% moisture from GPS-enabled harvester yield monitors. Multiple year yield data files were analysed for spatial and temporal variability. Multi-year data were normalised and then aggregated to create three MZs (here after referred to as “*Multi-year Yield Map*”): High yield that is stable over time (HS); Low yield that is stable over time (LS) and yield that is unstable over time (US). Normalized yield is the ratio of the actual yield at a specific point to the paddock average. Stable zones were defined as having less than 30% coefficient of variance over the six years, while those where the coefficient is greater than 30% were considered unstable. Areas with a normalised yield higher than 100% were defined as high yielding and those with less than 100% of normalised yield were low yielding.

Reflectance data (pixel values) for the paddock was obtained from the remotely sensed imagery available in *Google Earth Pro* software (v. 7.3.0.3832, Google Inc., California, USA) historic imagery archive. Google Earth images only have red (R), green (G) and blue (B) bands. The RGB images available on 08/03/2011, 13/06/2014 and 11/03/2016 were retrieved to extract reflectance data from the vegetation crop cover only (here after referred to as “*GE-Crop Map*”). Images available on 04/11/2015 and 17/08/2016 were used for bare soil only reflectance data (here after referred to as “*GE-Bare Soil Map*”). Other satellite images retrieved from the historical imagery archive (13/06/2001, 18/05/2004, 17/03/2010, 11/03/2013, 10/05/2013, 01/09/2013, 31/05/2014, 27/07/2014, 12/01/2015, 29/05/2015, 22/07/2015, 04/01/2017, 08/04/2017) were referred to for ancillary information about the field such as water channels, cropping systems, fences, trees, dark soil, etc. that may contribute to field variability.

Selected GE images in the *Google Earth Pro* software were saved in jpeg format at 1920 x 1080 (1080HD) resolution. Saved GE images were imported into ArcMap, ArcGIS 10.5 software [Environmental Systems Research Institute (ESRI), Redlands, CA, USA] and the images were geo-referenced using “Georeferencing” Toolbar. Geo-referenced images were clipped to the Costar Field boundary. Clipped rasters were converted into ESRI point shapefiles, then RGB pixel values corresponding to each point were extracted in to an ASCII text file format.

Reflectance data (RGB pixel values) extracted from each GE image were interpolated into a common grid of 1 m x 1 m derived from Costar Field boundary, using block kriging in VESPER (Variogram Estimation and Spatial Prediction with ERror) software (Australian Centre for Precision Agriculture, University of Sydney, Sydney, Australia). Interpolated data from each band was normalised by dividing each point data value by the respective global mean (Fridgen et al. 2004). These normalised data were used to derive three clusters by combining RGB bands; (i) GE images with vegetation crop cover only (three images, nine data sets in total) (ii) GE images with bare soil only (three images, nine data sets in total), in Management Zone Analyst (v. 1.0.0) (MZA) software (Agricultural Research Service, USDA, USA). Both vegetation cover only and bare soil only outputs from MZA were imported into ArcMap to develop two separate MC maps; *GE-Crop Map* and *GE-Bare Soil Map*. Both maps were classified into only three management classes (*GE-Crop Map* - Classes A, B, C and *GE-Bare Soil Map* - Classes X, Y, Z) to comply with the *Multi-year Yield Map*. Small, isolated MZs less than 50 m^2 of area were merged into a larger neighbouring polygon to obtain smooth maps.

Maize grain yields data available from six years (2003, 2006, 2008, 2009, 2012 and 2016), were imported into ArcMap, and the data was screened for erroneous yield values using methods adopted from Kleinjan et al. (2002) and Ping and Dobermann (2005). This involved first detecting frequency distribution outliers for grain moisture based on the global mean and standard deviation (SD) of the histogram. Grain moisture values less than mean - 2SD or greater than mean + 2SD were discarded from all the yield data sets except for 2006 yield data set. Grain moisture values lying outside mean ± 1SD were discarded from the 2006 yield data set. Then, maize grain yields were filtered with defined lower and upper yield limits. The lower yield limit selected was 0.1 t ha^{-1}. The upper yield limit was decided based on the average maximum yields recorded for the maize grain crop in the harvested year. The upper yield limit used was 18.0 t ha^{-1} and 20.0 t ha^{-1} for the maize crops before 2010 and after 2010, respectively. In the final step, yield data recorded at double-planted rows and headland turns which remained unfiltered were cleaned manually as required.

Filtered maize grain yield data from six years were overlaid separately on derived three MC maps in ArcMap. The yield data lying in each class was then extracted to calculate yield averages per class. A 1 m buffer area from each boundary of the classes in the map was allocated when extracting yield data. The yield averages extracted from each MC were used for the analysis. Recurring differences in the average yield values of the MC validate the relevance of the derived MZs representing groups of yield variability.

Extracted yield data from separate classes for each year are presented as means with error bars as standard error of the mean. Data analysis was competed in R Studio (v. 0.99.887). A comparison of the yields derived from the *GE-Crop Map* and the *Multi-year Yield Map*, and *GE-Bare Soil Map* and *Multi-year Yield Map,* were completed to determine how closely the *GE-Crop Map* and *GE-Bare Soil Map* estimated the actual yield, as presented by the *Multi-year Yield Map*. This was done using linear regressions for each year using means from each MC*.*

Results

The *GE-Crop Map* and the *GE-Bare Soil Map* derived from the GE images reflectance data and the *Multi-year Yield Map* derived from the multi-year yield data are shown in the Fig. 1. The management classes X and Y from the *GE-Crop Map* were largely spatially situated within the center of the paddock, with MC Z mostly occupying the perimeter of the paddock (Fig. 1 a). There was some order to the variability of the two classes occupying the middle area of the paddock; the X class dominated the northern center of the paddock while the Y axis dominated the southern center of the paddock. The *GE-Bare Soil Map* (Fig. 1 b) shows high scatter and variability between management classes A and C within the middle of the paddock, while the perimeter of the paddock is mostly characterized by class B, with the exception of the eastern boundary.

Both the *GE-Crop* and *GE-Bare Soil Map* showed classes that roughly coincided with the locations of HS compared to LS in the *Multi-year Yield Map* (Fig. 1 c). The *Multi-year Yield Map* showed that the perimeter of the paddock was characterized by LS while the interior of the paddock was characterized by HS. The US occupied the perimeter of the paddock, and it is mostly captured by class B in the *GE-Bare Soil Map* and MC Z in the *GE-Crop Map*.

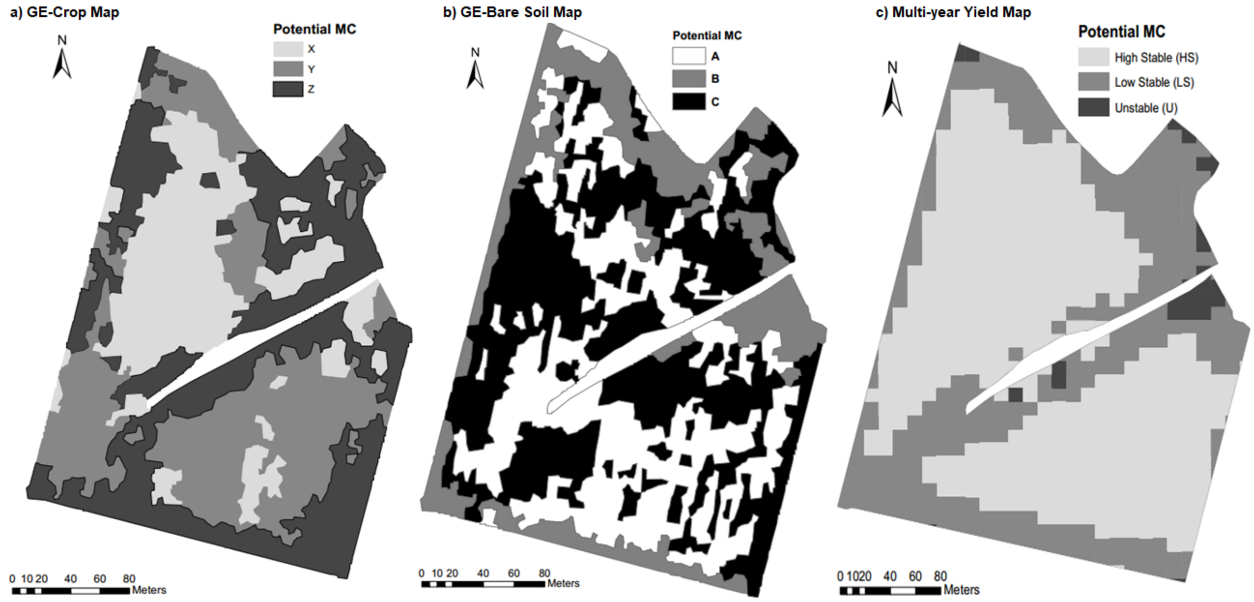

Fig. 1 Management class maps derived from a) Google Earth (GE) images with vegetation cover only - X, Y, Z; b) GE images with bare soil only - A, B, C; c) multi-year maize grain yield data only for the high yield stability class (HS), the low stability class (LS) and the unstable yield class (US)

In the *GE-Crop Map*, the relative yield data from the respective classes showed some consistency year-to-year (Fig. 2a). In the *GE-Crop Map*, yields in class Z were always lower than classes X and Y. In some years, class X yields were higher than class Y (2006, 2008, 2012, 2016), and other years, class Y yields were higher than class X (2003 and 2009). However, the actual differences in yield between classes X and Y were small; the largest difference between the two classes occurred in 2008 and was 0.79 t ha^{-1}, or an 8% difference in average yield between the management classes.

Like the *GE-Crop Map*, the relative yield data derived from the *GE-Bare Soil Map* was mostly consistent year to year from the respective classes (Fig. 2b). Yield from MC B was always on average lower than yields in class A and C. Between 2003 and 2009, yields from class C were higher than from class A, while in 2012 and 2016, yields from class A were higher than from class C. The relative yields from management classes A and B varied throughout the years, however, the maximum difference in yield between the classes was 3%, or 1.92 t ha^{-1}.

The yield from the *Multi-year Yield Map* showed that the HS class was higher than LS and US in each measured year; yields from the HS class were on average between 7 and 25% higher compared to the yields from the LS class, and on average between 9 and 104% higher compared to the US class (Fig. 2c). These differences translated to an average of between 2.70 and 5.87 t ha^{-1} higher yield in the HS class compared to the LS and US classes.

A comparison of *GE-Crop Map* management classes X, Y and Z to HS, LS and US from the *Multi-year Yield Map*, respectively, showed that in general, the yields derived from *GE-Crop Map* classes Y and Z were higher than *Multi-year Yield Map* classes LS and US, respectively, and the magnitude overestimation of the yields by the *GE-Crop Map* varied by year. The yield derived from the *GE-Crop Map* in class Y were between 6 to 20% higher than yield from the *Multi-year Yield Map* class LS in all years. The yields derived from the *GE-Crop Map* class Z were between 4 to 81% higher than yields from the *Multi-year Yield Map* class US in every year (Fig. 3a). A comparison of *GE-Crop Map* class X with *Multi-year Yield Map* class HS showed that the yields derived from the *GE-Crop Map* related well and were comparable (Fig. 3a). The yields derived from the *GE-Crop Map* in class X were between 5% lower and 2% higher than yields from the *Multi-year Yield Map* class HS in all years.

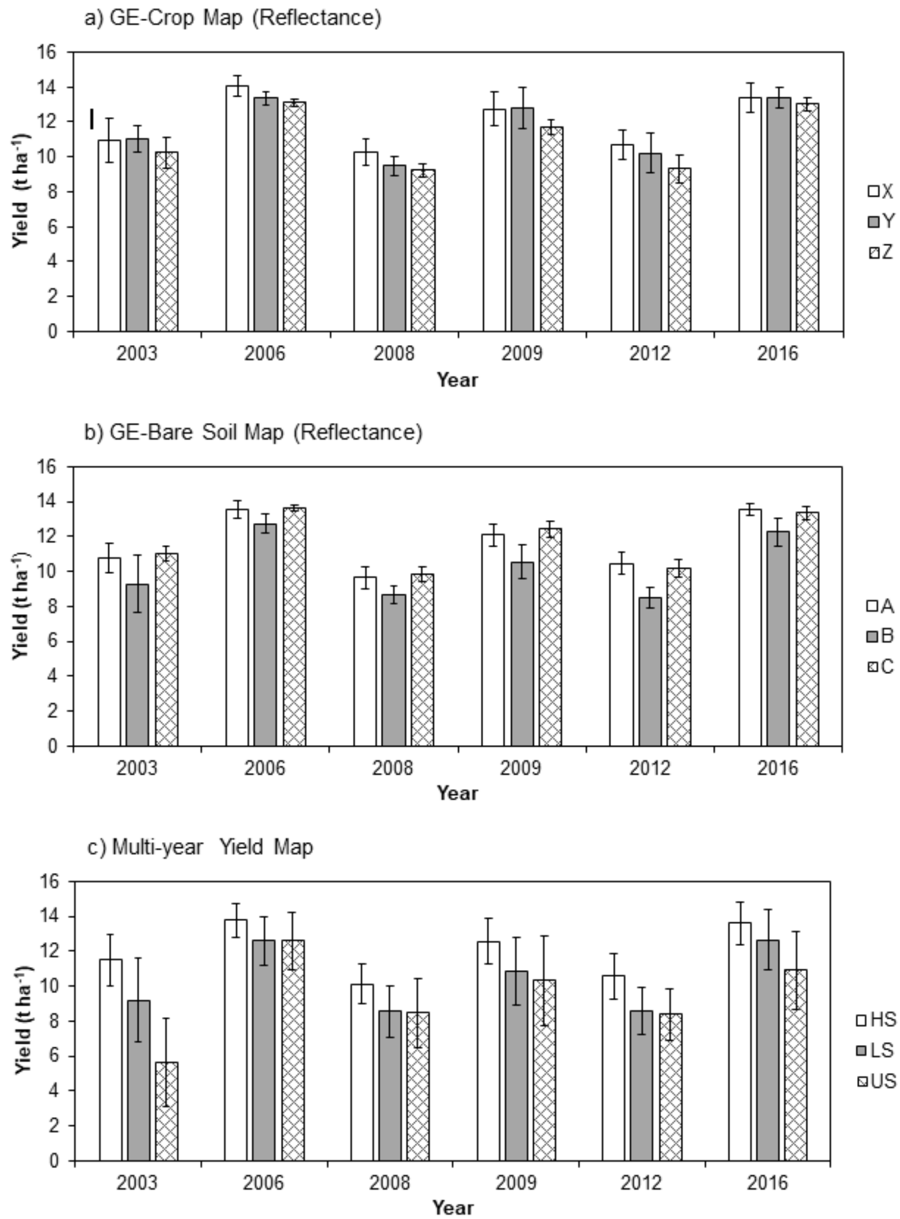

Fig. 2 Comparing mean maize grain yield (with standard error as error bars) for each year and management class (MC) derived from the MC map; a) Google Earth (GE) images with vegetation cover only – *GE-Crop Map*; b) GE images with bare soil only – *GE-Bare Soil Map*; c) multi-year maize grain yield data only for the high yield stability class (HS), the low stability class (LS) and the unstable yield class (US) – *Multi-year Yield Map*

A comparison of *GE-Bare Soil Map* MZs derived classes A and B to HS and LS from the *Multi-year Yield Map*, respectively, showed that in general, the yields derived from *GE-Bare Soil Map* were well aligned with the actual yields from the *Multi-year Yield Map* (Table 1, Fig. 2b). The yields derived from the *GE-Bare Soil Map* in class A were, at most, 6% lower than yield from the *Multi-year Yield Map* class HS in all years (Table 1). The yields derived from the *GE-Bare Soil Map* in class B were between 3% lower and 2% higher than yields from the *Multi-year Yield Map* class LS, and between *GE-Bare Soil Map* in class C was between 8 and 95% higher than yield from the *Multi-year Yield Map* class US (Table 1).

Table 1 The linear regression results comparing the mean maize grain yields derived from the

GE-Crop and *GE-Bare Soil Maps* to the actual yields from the *Multi-year Yield Map*. Comparisons are between *GE-Crop Map* management class (MC) X and Multi-year Yield Map class high stability yield (HS), the yield from *GE-Crop Map* MC Y and *Multi-year Yield Map* class low stability yields (LS), and the yield from *GE-Crop Map* MC Z and *Multi-year Yield Map* class unstable yields (US).

Management Class Map comparison	Management Classes	R^2	Slope	Intercept
	X – HS	0.96	1.01	-0.09
GE-Crop Map vs. Multi-year Yield Map	Y – LS	0.92	0.85	2.82
	Z – US	0.62	0.57	5.75
	A – HS	0.98	0.92	1.24
GE-Bare Soil Map vs. Multi-year Yield Map	B – LS	0.99	0.95	0.47
	C – US	0.60	0.52	6.86

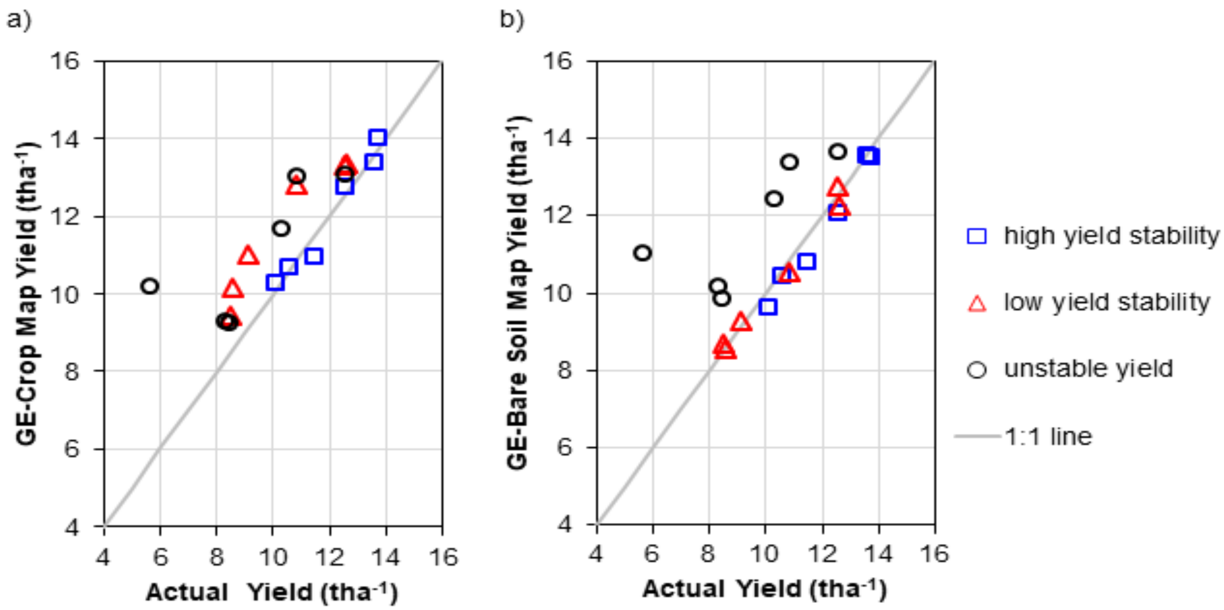

Fig. 3 Mean maize grain yield for each year and management class from a) the *GE-Crop Map* against the *Multi-year Yield Map*, and b) the *GE-Bare Soil Map* against the *Multi-year Yield Map*. A 1:1 line has been inserted to show the comparability of the *GE-Crop* or *GE-Bare Soil Map* derived yields to the actual yields from the *Multi-year Yield Map*

Discussion

Based on the comparison of the MZs delineations, MC representation of relative (high vs. low) yields are maintained over time better by the *GE-Bare Soil Map* than by the *GE-Crop Map* (Fig. 2). In the *GE-Crop Map*, only small differences in yield were noted between class X (high yield stability) and class Y (low yield stability) in 2003, 2009, and 2016. This suggests that while the *GE-Crop Map* can delineate management classes most of the time, the *GE-Soil Map* methodology was a more reliable for detecting and delineating high vs. low yield management classes.

The ability to consistently derived relative yield management classes differs from the ability to derived accurate yields. Both *GE-Crop* and *GE-Bare Soil Maps* were able to estimate actual yield within the high yield stability MC, with the greatest differences between actual and estimated yields from the *GE-Crop* or *GE-Bare Soil Map* equating to only 0.73 t ha^{-1}.

Issues, however, arose with the yield estimates within the low yield stability MC in the *GE-Crop Map*, with differences of up to 20% between the actual and estimated yields (Fig. 2). The *GE-Bare Soil Map* estimates of yields in low stability yield MC were never more than 3% different from the actual yields, equating to a different in yields of only 0.34 t ha^{-1}.

The success of the *GE-Bare Soil Map* in both delineating MZs and estimating yield may be explained by the fact that constraints on crops are related to soil physical limitations such as shallow available rooting depth or light soil texture (Oliver et al. 2010). It may be that soil physical properties, and their effects on water, are more important when explaining crop yield than soil fertility (Pierce et al. 1995), suggesting remotely sensed bare soil data provided adequate data about the soil physical properties for MC delineation and yield estimates. Based on the data from this study, the reason for the relatively greater success of yield estimates from *GE-Bare Soil Map* compared to the *GE-Crop Map* can only be speculated. However, others have noted the value of soil data for crop MZ delineation and yield estimates. For example, Zhang et al. (2010) delineated MZs of commercial fields for soybeans (in 2004) and wheat (in 2005) in the northern Great Plains, USA with satellite images, high resolution imagery from airborne sensors and farmer provided field data. Their results noted that highest normalised difference vegetation index (NDVI) values of the cropping season had a correlation coefficient of ≈0.4 with soil organic matter content. Overall, the comparison of the *GE-Crop* and *GE-Bare Soil Maps* suggests that the MC derived from the *GE-Bare Soil Map* is better at discriminating high and low yields.

There are a number of factors that may affect the accuracy of the methods proposed in this study. Changes to the length of time over which yield data is collected may impact the results. For cotton, 5-year's data (±2 years) have been found to generate stable estimates of yield zones (Boydell and McBratney 2002). However, climatological variability overtime must also be considered. Corn yields have been found to be sensitive to drought, and the associated sensitivity of maize tolerance to drought may be related to crop density (Lobell et al. 2014). These factors may influence MC classification in both the *GE-Bare Soil* and *GE-Crop Maps* by affecting the data quality.

Notably, relative average yields from unstable yields class were not well represented in either the *GE-Crop* or *GE-Bare Soil Map* classes; average yields in the US class were overestimated by up 95% both the *GE-Bare Soil Map* and *GE-Crop Map.* Since the unstable yield areas represent a relatively small proportion of the field, and occur mainly on the perimeter of the field (Fig. 1c), their presence in this field are of little concern. However, other fields which have greater areas of unstable yield may need to explore the underlying causes. Others have noted temporal patterns in corn grain yield are the result of interacting effects of climate, soil, plants, landscape and management practices (Lamb et al. 1997). While the classification of unstable yield areas is possible with our method using freely available GE images, a limitation of the method is that it does not explore the causes behind unstable yield.

Google Earth images are increasingly used to acquire spatial data for scientific analysis. The image quality, resolution and image acquisition data can vary depending on the location of the globe and may not suitable for some analysis. Differences in acquisition dates and temporal frequencies of images limit the required frequency of data sets. Google Earth images may not available for every crop season for some fields. Furthermore, requirement for additional software and data sets is a drawback when using GE images for quantitative measurements (Yu and Gong 2012).

A comparison of GE-derived yields to actual yield data – as done in this study - can help validate the results of other crops. Yield maps can provide information about the productivity of fields that is stable if the yield data is collected over several growing seasons. While these maps have been used to prescribe sub-field management of fertilizer and water application, data collection methods have some limitations, including errors in yield estimation due to coarse resolution, lags in moving the grain from the crop to the point of measurement, variations in combine speed and noise induced by machine vibration and varying terrain (Lamb et al. 1995).

Conclusions

Both *GE-Crop Map* and *GE-Bare Soil Map* were adequately delineated management classes in the study paddock. The relative yield (high vs. low) MC delineations were better represented by the *GE-Bare Soil Map*, which was generated by the bare soil data, compared to the *GE-Crop Map*, which was generated by vegetation crop cover data. Reflectance data extracted from the GE images have the potential to be used for delineating preliminary MC maps when other data is not available for the paddock. However, similar studies including other maize growing paddocks are desirable to validate the results.

References

Boydell, B. and McBratney, A. B. (2002). Identifying potential within-field management zones from cotton-yield estimates. *Precision agriculture*, 3(1), 9-23.

Doerge, T. (1999). Management Zone Concepts. Potash & Phosphate Institute. http://www.ipni.net/publication/ssmg.nsf/0/C0D052F04A53E0BF852579E500761AE3/$FILE/SSMG-02.pdf. Accessed 19 April 2018.

Foundation for Arable Research (2016). Summary – Survey of Maize areas and Volumes – June 1, 2016. https://www.far.org.nz/assets/files/editable/94fa1fde-5334-429f-b1a1-f34ab5e7ff79.pdf. Accessed 15 April 2018.

Fraisse, C. W., Sudduth, K. A., Kitchen N. R. (2001). Delineation of Site-Specific Management Zones by Unsupervised Classification of Topographic Attributes and Soil Electrical Conductivity. *Transactions of the ASAE*, 44(1), 155-166. doi: 10.13031/2013.2296

Fridgen, J. J., Kitchen, N. R., Sudduth, K. A., Drummond, W. J. W., Fraisse, C, W. (2004). Management Zone Analyst (MZA): Software for subfield management zone delineation. *Agronomy Journal*, 96, 100–108.

Hewitt, A. E. (2010). *New Zealand soil classification*. Landcare Research Science Series No. 1. 3rd edition. Manaaki-Whenua Press, Lincoln, New Zealand.

Holmes, A. (2017). Transforming variability to profitability – variable seed rates in New Zealand maize. *7th Asian-Australasian Conference on Precision Agriculture*.

Kleinjan, J., Chang, J., Wilson, J., Humburg, D., Carlson, G., Clay, D., Long, D. (2002). Cleaning yield data. http://static1.1.sqspcdn.com/static/f/891472/12244161/1305571958573/Kleinjan+et+al.+2002+Cleaning+yield+data.pdf?token=2U847zuSMlRWaiGHQcluIS5yeNY%3D. Accessed 25 June 2017.

Lamb, J. A., Anderson, J. L., Malzer, G. L., Vetch, J. A., Dowdy, R. H., Onken, D. S. and Ault, K. I. (1995). Perils of monitoring grain yield on-the-go. In *Site-specific management for agricultural systems* (No. site specific man, pp. 87-90). American Society of Agronomy, Crop Science Society of America, Soil Science Society of America.

Lamb, J. A., Dowdy, R. H., Anderson, J. L., and Rehm, G. W. (1997). Spatial and temporal stability of corn grain yields. *Journal of Production Ag*riculture, 10(3), 410-414.

Lobell, D. B., Roberts, M. J., Schlenker, W., Braun, N., Little, B. B., Rejesus, R. M., and Hammer, G. L. (2014). Greater sensitivity to drought accompanies maize yield increase in the US Midwest. Science, 344(6183), 516-519.

Morris, N. J., Hurley, T. D. and Densley, R. J. (2016). National and regional maize grain and silage strip trial yields. *Journal of New Zealand Grassland*, 78, 157-162.

Oliver, Y. M., Robertson, M. J. and Wong, M. T. F. (2010). Integrating farmer knowledge, precision agriculture tools, and crop simulation modelling to evaluate management options for poor-performing patches in cropping fields. *European Journal of Agronomy*, 32(1), 40-50.

Pierce, F. J., Warncke, D. D. and Everett, M. W. (1995). Yield and nutrient variability in glacial soils of Michigan. In *Site-specific management for agricultural systems* (No. site specific man, pp. 133-151). American Society of Agronomy, Crop Science Society of America, Soil Science Society of America.

Ping, J. L. and Dobermann, A. (2005). Processing of yield map data. *Precision Agriculture*, 6(2), 193–212. doi: 10.1007/s11119-005-1035-2

Taylor, J. A., McBratney, A. B., Whelan, B. M. (2007). Establishing Management Classes for Broadacre Agricultural Production. *Agronomy Journal*., 99, 1366-1376. doi:10.2134/agronj2007.0070

Yang, C., Song, X., Wu, M., Nicholas, R. L. (2017). Creating prescription maps from satellite imagery for site-specific management of cotton root rot. . *7th Asian-Australasian Conference on Precision Agriculture*.

Yu, L. and Gong, P. (2012). Google Earth as a virtual globe tool for Earth science applications at the global scale: progress and perspectives. *International Journal of Remote Sensing*, 33(12), 3966-3986.

Zhang, X., Shi, L., Jia, X., Seielstad, G., Helgason, C. (2010). Zone mapping application for precision-farming: a decision support tool for variable rate application. *Precision Agriculture,* 11(2), 103–114.