Taylor JA, Link K, Taft T, Jakubowski R, Joy P, Martin M, Hoffman J, Jankowski J, Bates TR.

A Protocol to Map Vine Size in Commercial Single High-Wire Trellis Vineyards Using 'Off-the-Shelf' Proximal Canopy Sensing Systems.

***Catalyst* (2017)**

DOI: http://doi.org/10.5344/catalyst.2017.16009

A protocol to map vine size in commercial single high-wire trellis vineyards using "off-the-shelf" proximal canopy sensing systems.

Taylor, J.A.[1,2], Link, K.[1], Taft, T.[1], Jakubowski, R.[1], Joy, P.[1], Martin, M.[1], Hoffman, J.[1], Jankowski, J.[1] and Bates, T.R.[1*]

[*]Corresponding author trb7@cornell.edu; tel: 716-792-2800; fax: 716-792-2805

[1]Cornell Lake Erie Research and Extension Laboratory, School of Integrative Plant Science, Cornell University, 6592 West Main St, Portland, NY, 14769

[2]School of Agriculture, Food and Rural Development, Newcastle University, Cockle Park Farm, Ulgham, Morpeth, United Kingdom, NE61 3EB

Acknowledgements: This work is possible because of the financial support provided by the National Wine and Grape Initiative (NGWI). The project team would like to express our gratitude to NGWI and the various viticultural organizations that support NGWI. Additional financial support was also provided by the New York Grape and Wine Foundation. The authors would also like to thank all the growers and their employees that were involved in testing the protocol. Finally, our thanks to Luke Haggerty, Cornell Cooperative Extension Viticulturist for assistance with editing.

Summary

Goals: This report aims to present a clear protocol to (a) deploy proximal canopy sensors into single high-wire trellis Concord (*Vitis labruscana* cv Bailey) vineyards and (b) to convert the canopy sensor response into an indication of vine size (pruning weight). The protocol is designed to be robust and practical for easy adoption in commercial systems. Evidence will be presented of the efficacy of vine size prediction using the protocol in multiple research and commercial vineyards.

Key Findings: Using different vineyards and pruning crews the protocol performed well in over 80 % of vineyards. It permitted growers to generate maps of actual vine size within vineyards. These maps provide a valuable indication of the current site-specific production potential and a baseline to assess changes in vine size over time. In a few vineyards, the proposed simplified calibration process did not generate a clear relationship between the canopy response and vine size, which may be due to changes

in vine shape in highly mechanized systems.

Impact and Significance: Managing vine size is critical to the long-term sustainability of cool climate viticulture. It is also critical to managing quality in all viticulture systems. However, convincing growers to routinely measure vine size to manage it more effectively has historically been difficult due to the time involved and the difficulty of translating the data into a decision process. The proposed protocol uses technology and targeted sampling to minimize the effort required and presents more coherent information that growers can quickly react to. Grower adoption of this protocol should promote continual vine size measurement with the goal of decreasing vine size variation within vineyards.

Keywords: canopy management; pruning; Concord (*Vitis labruscana* cv Bailey); normalized difference vegetation index (NDVI)

Overview

Statistically and visually the response from proximal canopy sensing systems has been linked to indicators of vine size[1,2,3,4]. However, the scientific literature has been focused on specific research objectives and has been limited in most cases to small plot or single block investigations. In reports linked to whole vineyard blocks in commercial applications, the canopy sensor data has not been explicitly calibrated or validated against measured vine parameters[1,5]. There is a lack of information that is directly relevant to commercial applications of these proximal sensing systems. This includes a generic protocol for sensor deployment and data capture and a robust but efficient methodology for a block or vineyard-specific calibration of the relative sensor response to an absolute vine size parameter. Given the success of proximal canopy sensor deployment in research and trial plots for vine size estimation, the intent of this research is i) to fill a knowledge gap for translation by providing a protocol for the commercial adoption of tractor-mounted proximal canopy sensing systems and ii) to provide some statistics on the accuracy and precision of vine size mapping from the use of the protocol on multiple commercial enterprises. This information will assist growers in making decisions about technology adoption and transfer and suitability for their production system. The intent here is only to generate the best possible vine size maps under commercial constraints. The value of vine size maps will be determined by the quality of decisions that are ultimately made on the data.

Multispectral imaging systems that measure reflectance of visible and near-infrared (NIR) light from leaves were one of the earliest technologies adopted in precision viticulture (PV). Initially these imaging systems (canopy sensors) were used for disease monitoring and the identification of ”hotspots” associated with different canopy signatures[6]. This quickly evolved into applications to assess the natural variability in canopy development (such as vine size or the area of canopy leaf per square meter of ground [leaf area index or LAI]) and for mapping spatial variation in canopy vigor[7,8,9]. The original use of canopy sensors for PV predominantly used aerial and satellite platforms in warm to hot viticulture regions. More recent work focused on proximal sensors mounted on either vehicles[4] or low-flying unmanned aerial vehicles (UAVs)[10], with applications in hot, warm and cool climate viticulture regions. Regardless of the mode of mounting, or the climate of the site, all multispectral canopy sensors tend to operate the same way. The sensor captures the reflectance of visible and NIR light from the canopy in multiple bands, typically in the green, red and NIR regions. This information reflects the amount of photosynthetically active biomass under the sensor. Healthy plants absorb red (and blue) light for use in photosynthesis and reflect green light (hence they appear green). They also strongly reflect NIR light. Unhealthy plants reflect more red (and blue) light and absorb more NIR light. These differences mean that ratios between green, red and NIR light can give a good indication of whether a plant is healthy or unhealthy.

The same type of sensor can be mounted on different platforms and this affects the type of data acquired.

1) Aerial and satellite-based systems use cameras usually capture large images that cover entire vineyards. The pixel size within an image is determined by the elevation of the sensing platform and the quality of the camera (optics and throughput) but is typically 2 – 30 m^2 for satellite systems and 0.2 – 3 m^2 for aerial systems.
2) UAV platforms can use cameras to capture higher resolution imagery (smaller pixel sizes of < 10cm2), but over much smaller areas. As a result, any one image may only partially cover a vineyard. The UAV-derived images require stitching together (mosaicking) to create a full vineyard image[10].
3) Vehicles (tractors, self-propelled sprayers, etc…) can be used to mount proximal canopy sensors. These are not cameras that take an image like the sensors on satellites or UAVs. The proximal

sensors are scanning systems with a small field of view of < 1 m^2 usually. They scan the canopy every second and record the reflectance. Each data point (one per second) is geo-referenced using a Global Navigation Satellite System (GNSS, also known as a GPS) receiver. These systems generate irregular point data that requires interpolation to generate a canopy reflectance map. In contrast, the satellite-, aerial- or UAV-mounted camera systems immediately generate an image (or map), although some image analysis may be required to obtain the best visual representation[11],[12].

remote sensing works well in viticulture regions that are characterized by a Mediterranean-type climate, because dry and clear weather allows images to be taken throughout the growing season. In these systems, the interrow cover crop has senesced if imagery is taken mid to late season and therefore the cover crop does not affect the reflectance in an image.. In cool climate viticulture regions, summers may often be cloudy and wet. This creates a risk that satellite and some aerial systems may not be able to take images at key growth stages due to cloud cover. Cool climate viticulture also favors narrow walled trellis systems to allow sunlight into the canopy and to promote fruit maturation[13]. This has the effect of minimizing the flat area of the canopy (as viewed from overhead i.e. an aerial or space platform) and maximizing the viewed area of the interrow. The interrow is often under an active cover crop that does not naturally senesce and so produces its own spectral signal, which can make it difficult to discern between vines and cover crops. Timely acquisition and mixed pixel effects are therefore problematic for coarser (> 0.5 m) pixel imagery in cool climate viticulture.

Ground-based platforms (e.g. tractor-mounted) are considerably more flexible than remote platforms for sensing. The timing of surveys can be determined by the grower. During the growing season, most all vineyards undergo a large regime of cultural practices providing a good opportunity for data collection at no additional machinery cost. This is equally true in warmer climates where remotely-sensed imagery is a plausible alternative. However, the flexibility associated with proximal sensing systems can create problems. It allows for the possibility of poor sensor mounting leading to unusual or incorrect measurement. In contrast, the overhead, directly downward-looking sensing from remote platforms provides a standard orientation and it is only the pixel size that effectively varies between systems.

Theory of canopy sensing in vineyards with optical sensors

Canopy sensing in vineyards is usually performed around veraison when vine size is largest[14]. In commercial New York Concord vineyards, where this study took place, approximately 40-50 % canopy growth is achieved by bloom with the remaining 50-60 % occurring in the month after bloom[15]. Additional late season canopy growth, if any, typically comes from lateral shoots on vines under high vine water status; however, the majority of Concord vineyards are own rooted and unirrigated, which limits excessive lateral shoot growth. Therefore, maximum vine size tends to be achieved by veraison, after which and the rate of growth reduces significantly as more vine resources are directed to the fruit and to storage organs for the subsequent season[16]. Sensing at veraison has the distinct advantage of measuring the actual total vine development in the vineyard. It is also necessary when the standard industry 'mixed-pixel' approach is used with remote sensing[11] that assumes no or low inter-row cover crop response and well developed vines. Some recent work has shown promise at being able to use canopy sensors earlier in the season to estimate canopy size using high-resolution aerial imagery[17] or proximal sensing platforms[4]. Although early season options exist, the proximal sensing for this study was performed around veraison to conform with current commercial industry applications.

The use of vine size in Concord grapevines, measured as the mass of first year dormant cane prunings per unit canopy length, has long been used to predict potential vine productivity and adjust pruning levels[1819]. The theory is that the mass of cane prunings is reflective of the level of vegetative growth in the previous season and a predictor of canopy growth and light interception for the next season[20]. Crop control management, such as pruning, shoot thinning, or fruit thinning, can be adjusted based on vine size to maintain crop load balance, i.e. exposed leaf area:fresh fruit weight[21]. In Concord, on high-wire sprawl training systems, the direct relationship between vine pruning weight (PW) and total vine leaf area at veraison has been demonstrated (Fig. 1) [22]. The objective of this canopy sensing protocol is to relate proximal canopy sensor measurements with vine pruning weight and therefore vine exposed leaf area.

<<Figure 1 near here>>

Figure 1 The relationship between vine size and total vine leaf area in single high-wire cordon trained and cane pruned 'Concord' grapevines in Fredonia, NY. In undivided canopy training systems, 0.50 kg/m pruning weight and approximately 10 m^2/m leaf area is considered near optimum to maximize canopy light interception and minimize internal canopy shading.

Mounting a sensing system on a vehicle provides considerable flexibility in orientating the sensor to the canopy. Similarly to aerial/space platforms, it is possible to obtain a downward-looking overhead view, but it is also possible to obtain a side-view of the canopy at various elevations above the ground. In high-wire trellis ('sprawl') systems a side-mounted sensor can be adjusted to target the developing region of the canopy side-curtain. This capability permits the canopy sensor response to differentiate larger, longer cane vines from smaller, shorter cane vines during any stage of vegetative development[4] (Fig. 2).

<<Figure 2 near here>>

Different proximal canopy sensors have different specifications, but all require a separation distance from the target (canopy) to operate correctly. For the most common commercial proximal canopy sensors, the width of the field of view is ~60-80 % of the separation distance from the target[2324]. A limitation with optical multispectral Vis-NIR canopy sensors is that they saturate at moderate to high leaf areas (LAI > 3)[25]. Mounting the proximal canopy sensor above the canopy looking downwards leads to saturation of the signal very early on and an inability to distinguish high and low vigor vines by mid-season[4]. Similarly, side-mounting the sensors at cordon wire height also creates saturation issues for the same reasons. From experiences at the Cornell Lake Erie Research and Extension Laboratory (CLEREL) in single high-wire cordon juice-grape vineyards, mounting the sensor side-on to the canopy ~ 0.8 m above the ground and ~ 1 m away from the canopy has proven to be effective in a wide range of situations. Typically, this mount is measuring the canopy response in a strip from 0.5 to 1.1 m above the ground (with the cordon wire height usually being 1.7 – 1.8 m in these systems). It is therefore avoiding any inter-row cover crop or under-vine weeds in well-managed vineyards. If the cover crop or weeds are poorly managed, and are allowed to grow up into the canopy, then they will also generate a reflectance and confound the vine canopy response. Not every vineyard system is identical and the cordon height and row dimensions may vary so there must be some flexibility in the mounting height. However, the key issue is to mount the sensor at a height so that it is sensing an area of the developed (or developing) canes where there is some canopy porosity[2].

Major Observations and Interpretations

Protocol

In the first instance the protocol and its rationale for operation are presented.

1) Sensor mounting and survey

For mid to late season vine vigor surveys, sensors should be mounted on a vehicle at ~0.8 m height so that they are horizontally scanning the developing area of the canopy. The type of vehicle is not important and some alternative mountings are shown (Fig. 3). However, the height should be adjustable to accommodate different trellis heights, canopy management and vehicle constraints. It is important to remember that mounting the sensor too high where the canopy is well-developed will generate a saturated signal that is not suitable for mapping.

<<Figure 3 near here>>

Scanning should be done in association with vineyard operations, which will typically be spray operations. This produces a swathing density of 1:2 or 1:3 rows for two and three row sprayers respectively. Sensing every third row in commercial vineyards generates a swathing width of ~8 m, so high spatial density data will still be collected.

2) Raw data processing

Following the survey, data must be downloaded and pre-processed. Proximal canopy sensors typically return geo-referenced band information and/or specific vegetative indices (VIs)[26]. The raw data should be trimmed to remove non-sensible canopy reflectance data (bearing in mind that expected values of individual bands and VIs will change as canopies develop and/or sensor set up is altered). A histogram of band values and/or VI values can be generated to identify and remove outliers if present. As a default, trimming to ±3 standard deviations is recommended as a standard first step. Histogram analysis also helps to ensure that the canopy reflectance and VI responses are not negatively skewed, i.e. that there was no saturation of the VI response due to poor sensor set up or due to sensor malfunction. If outliers or non-uniform distributions are observed, these should be investigated and determined to be true or erroneous before continuing. The trimmed VI data can then be used to generate VI maps. Data should be interpolated onto a standard grid (typically equivalent to the average row by vine spacing). There are many commercial and freeware options to perform interpolation and mapping but a good protocol should be followed[27]. If data are not correctly interpolated, then the subsequent estimations of vine size from these data will be erroneous.

3) Sampling design for calibration

From the VI map, rows that traversed areas of high and low canopy response should be identified and approximate sample locations should be identified for the collection of pruning weight data to calibrate the sensor response to vine size. The objective is to identify 3-5 rows per block with the intent to take 4-8 samples per row to obtain 22-25 samples per block or 'single production unit'. This can be adjusted as necessary for blocks with very short or long rows. Minimizing the number of rows is a deliberate strategy to minimize the time and the effort required for pruning crew to collect the additional information. Once these rows have been targeted, normal pruning operations can continue for the rest of the vineyard. The proposed sample density with a quasi-stratified sampling scheme should give a good estimation of the mean vine size in the production unit[29] and also generate data across the range of observed canopy sensor values. In commercial situations, the rows to be sampled should be discussed and mutually agreed to with the grower. It is possible to constrain the sampling to rows that were actually scanned by the canopy sensors. However, this puts more onus on the grower and the pruning crew to identify the right rows, so this limitation has deliberately not been incorporated into the protocol.

It is important to clarify the 'single production unit' term as a sampling unit. Individual vineyard blocks are typically managed uniformly. In larger vineyards, multiple contiguous blocks may in reality be managed as one large (segmented) area. If this is the case, then in theory the sampling and calibration can be spread over the entire area with the same number of calibration samples[29], provided of course the area has the same variety and rootstock. In reality it is advisable to take more samples; however it is not necessary to sample each individual block at the suggested density (22-25 samples per block). If management is neither uniform nor continuous between blocks then each block should be treated as independent and sampled separately. This is true for both in-season and previous season management. Previous management strategies may affect vineyards for many years. Because of this, caution must be exercised when aggregating blocks into 'single production units' and should only be done when there is clear knowledge of continuous uniform treatment over many years. Similarly, only areas of common variety

4) Manual vine measurements for calibration

Once the target rows are identified, pruning crews can be sent into the rows to collect pruning weights. Vigor maps should be provided to assist the pruning crew in identifying the preferred sample sites in areas of relatively high, low and medium sensor response. Crews must be instructed to;

i) avoid sampling in panels that are abnormal, e.g. much shorter or longer than average, or panels that have missing or young renewed/replanted vines, and

ii) not to sample at the edges of any individual block (the two end-panels or end rows). Growing and sensing conditions are atypical at the edges of a block and unsuitable sites for sampling and calibration.

At each sample site, pruning weights are collected by weighting the mass of first year wood that would normally be removed at pruning time within the panel (between the two post lengths) using a hand scale at a resolution of ~100g[33]. In hand-pruned vineyards, manual pruning can be performed as per normal and according to the grower's preference. In vineyards where pruning is normally achieved through mechanical means, hand pruning should approximate the mechanical outcome.

Sample location must be recorded. It is suggested to do this in the first instance by recording the total number of panels in the row and the panel counts along the row that are sampled. Sample sites can be geo-located using GPS, but recording the row and panel (post) location should always be done as it provides the most precise location, especially for repeated measurements over time. Row by Panel information can also be used to geo-reference the pruning weight samples using ortho-rectified high resolution imagery in a GIS platform. This approach may be preferable in commercial situations as it takes the responsibility for geo-referencing away from the grower (or pruning crew) and puts it on the service provider.

Once the manual sample sites are geo-referenced, the canopy sensor data can be interpolated onto the sample sites with the same interpolation method used to map the canopy sensor data. This co-locates the canopy sensor data and the PW measurements so that a calibration regression can be generated to relate the sensor response to vine size.

5) Error sources in canopy sensing and vine size measurement

There is a strong potential for outliers that do not fit the general response in these spatial data. The approach proposed here has deliberately been chosen to account for what is expected in commercial conditions (and not research conditions). There are several potential sources of error in the protocol and some unusual (or outlying) values are to be expected because;

a) There are no constraints placed on the sampling scheme (pruning crew) to sample in the same rows that were sensed. Therefore some PW measurements could be (will probably be) collected from non-sensed vines. Sensing and sampling the same vines can be forced, but the decision was made to test the protocol without this requirement as this is more likely to be the default in commercial systems.

b) The sensor only measures one side of the vine, the PW measurement is taken for the entire vine.

c) Low-cost GPS receivers do have errors greater than the row width that introduces inaccuracy in the geo-referencing of the sensor data.

d) The short-range random variation in vine size (pruning weight) in these systems is known to be a significant part of the overall variation[29] and this short-term variation will impact the goodness of fit for the calibration. This effect is smoothed by using panel measurements of PW and correct interpolation[35] to generate values across 3-vine units rather than individual vines.

e) The swathing width for the canopy sensor is variable and will differ between vineyards which makes direct comparison between the results from different vineyards difficult.

f) Human errors occur which may include errors associated with a poor choice of panel to sample (non-representative of the area), errors in recording or transcribing observations or errors in data processing among others.

6) Data clean-up and calibration of the canopy sensor response to vine size.

Numerous experimental and controlled studies[2,3] have shown that vine size is expected to be positively correlated to a canopy sensor response. Therefore, it is not expected to find points where this relationship falls down, for example locations with a high canopy response but a small vine size or vice versa. However, for the reasons outlined above, errors are expected in the data. The presence of these erroneous points can be easily identified by plotting the vine size against the canopy response. Figure 4a illustrates this. The square points are indicative of very high and very low vine sizes associated with an average canopy response. In this case the VI used is the normalized differences vegetation index (NDVI)[28]. These points can be considered abnormal measurements and are probably associated with one or more of the error sources identified previously. These abnormal measurements should be removed as a first step before any analysis and, where possible, the reason for these determined.

Following the removal of any abnormal data, linear regression can be used to fit a relationship between the canopy response and vine size. The low sample size means that an individual point has the potential to have a large effect on the regression fit. In initial studies, robust linear regression techniques were trialed to correctly approximate the slope of the regression fit. Results were not encouraging (data not shown). As a manual alternative, outlying points in the PW vs. canopy response plots were identified 'by eye' and omitted from the calibration. Since this is a subjective approach, the maximum number of points omitted was set at 15 % of the sample size after removal of any abnormal measurements. This is termed the 15 % rule. If no outlying points were observed, then no data should be deleted. Figure 4 graphically demonstrates this process for one of the study blocks and the effect it has on the regression fit between NDVI and PW.

<<Figure 4 near here>>

Once cleaned, a linear regression can be applied to the data[29]. This generates a local calibration function that can be used to transform the (relative) canopy response map into an (absolute) estimate of vine size (pruning weight). The proposed data trimming and calibration (regression) procedure has been designed to identify the correct gradient of the local VI-PW relationship. The hypothesis is that by discarding the potential (and expected) outliers from the dataset a more robust calibration is achieved.

7) Vine size mapping

The final step is to apply the local calibration to the interpolated canopy sensor data to create vine size maps. It is important to ensure that the legend used is suitable for the viticulture system and differentiates vine sizes that are of interest to the end-user.

Observations from Protocol Deployment

Using the proposed protocol, canopy sensing and vine vigor mapping using the same sensor was effectively performed on several commercial enterprises using several different types of on-farm vehicles (tractors, quad-bikes, sprayers/harvesters). Two examples of sensor mounting are shown in Figure 3. Provided the sensor was well placed and correctly oriented to the growing region of the vine, good results were obtained regardless of the vehicle used. This clearly demonstrates the versatility of the proximal sensors and the ability to obtain canopy reflectance data under differing conditions.

Effectively recording the relative canopy reflectance is only the first piece in spatially managing vine size. Mapping vine size, not a canopy reflectance value, depends on effective local calibration of the sensor response to vine size. To achieve this we have proposed to sample along transects of interest to generate good calibration data while minimizing the effort needed. The results from 34 blocks surveyed using this approach showed that good calibrations between the sensor response and vine size were achieved in 80% of fields (27 of the 34 fields) provided a rigorous data trimming process was applied to the data (Table 1) to ensure that potentially erroneous data were removed. Sensing and measurement errors can occur causing noise in the data and, without trimming, the errors can skew results. The proposed protocol outlines simple rules to achieve the data trimming that may remove up to 15 % of the data and is termed the '15 % rule'. This approach has worked well in this study. These rules can be easily implemented by industry and do not require any specialized software. Accepting this approach and getting used to working with spatial errors in the sensor and manual data is an adjustment that may take time.

<<Table 1 near here>>

Statistical analysis[30] of the potential effect of the pruning crew (CLEREL vs Commercial) across the two years on calibrating the manual measurements to the sensor response showed no difference between the CLEREL and commercial pruning crews. Since the CLEREL pruning crew was constant over the two years, the regression fits for CLEREL sampled blocks were also compared across years with no differences observed[31]. The proposed Protocol on this evidence appears simple enough and/or robust enough to cope with labor variation within commercial situations, which is encouragement for wider use.

Example Maps/Outputs.

Two examples of the final calibrated pruning weight maps that were delivered to growers from this survey are shown in Fig. 5. The maps are presented on a common legend, although the scale differs. There is a clear difference in mean pruning weight (PW) between the two blocks with Grower 1 Field 6 having a higher PW (kg/m). There are also clear within-field patterns of higher and lower PW evident in both maps, which will translate into clear differences in long-term production potential[32]. However, the patterns of within field variation of PW are very different between the two fields. Grower 7 Field 1 has 'hotspots' of very high PW and trends that are oriented along a NE-SW axis, which is in contrast to the N-S oriented rows. The patterns in this field appear to be driven by environmental variation in the field. In contrast, in the Grower 1 Field 6 block, there is a general trend from high to low across the rows (East to West). Variation is limited within individual rows and there is a 'blockiness' to the variation that indicates that (row) management differences are driving vine size variation with some additional underlying environment-induced variability.

In both fields, there were three transects taken to collect PW samples (white circles). The sample area is always defined as a panel-length (i.e. typically 3 vines between two posts and is usually ~ 7.3 m or 24' in length - further details are outlined later in the protocol). In Grower 7 Field 1, there are areas of high and low canopy response (PW) within each transect and the pruning crew have managed to sample areas of high, medium and low canopy response. In Grower 1 Field 6, it was the rows themselves that were of high (East), medium (middle) and low (West) response.

<<Figure 5 near here>>

Broader Impact

The methods and analysis employed in this study have deliberately tried to incorporate the likely errors if the protocol were to be widely adopted by the industry. The fits here typically had R^2 values in the range of 0.3-0.6, which is lower than that observed in similar scientific studies[2,3]. If greater care was taken to target pruning weight measurements to rows (vines) that were actually sensed, then better fits (R^2) would be expected, as has been seen in the controlled research studies. However, from a grower and an agronomic perspective, it is not the goodness of fit (R^2) that is critical, but the correct identification of the gradient in the linear regression. The data trimming approach proposed here has shown that the protocol is able to generate a close approximation of the known gradient (Fig. 6 – the validation of the 15 % rule). The more PW calibration samples that are taken, the more accurate the estimation of the field mean will be and the higher the probable R^2 value (e.g. Grower 9 Field 1 in Table 1). However, growers must always weigh up the time cost vs. the additional information quality when increasing sampling sizes. The proposed approach using ~23 samples has been shown to be able to provide an adequate estimation of field mean for PW[33]. This should hold some value as a whole block PW mean estimation even if the data cannot be related to the spatial canopy sensor response to generate vine size maps (e.g. Grower 5 Field 1 – Table 1).

The 15 % rule for data-trimming is presented here as a suggestion. It has worked well within this study but needs wider application to determine if it is the right approach. It is important to reiterate that it is not necessary to remove 15 % of the data if the PW vs. VI plot does not have values that are likely to be having an adverse effect on the gradient of the regression fit. However, it is not recommended at this point to remove more than 15 % of the data.

A threshold R^2 value of 0.30 (equivalent to r = 0.55) has been identified for determining if the predicted PW map has agronomic value. This is again subjective and should be treated as a suggestion, not an absolute cut-off. Strong fits (high R^2 values) are not expected in these noisy real-world situations because of methods involved. However, if a map is explaining 30-50 % of the variation in PW (according to the statistical analysis) than it should hold some intrinsic management value for a grower. Discussions with growers when presented with maps like those in Fig. 5 have certainly borne this out. This highlights also the effective difference between a statistical and agronomic significance. The data presented via the protocol appears to have a lot more agronomic value to growers than the pure statistical values may indicate. One grape-growing enterprise in the Lake Erie AVA now uses these maps to guide all routine vineyard management.[34]

The success from trialing the protocol in the Lake Erie viticulture region in 2012-2013 has led to the Cornell Cooperative Extension and Penn State Extension programs providing a loan scheme for canopy sensors to growers in the Lake Erie region. This has seen a considerable uptake of canopy scanning by local growers with approximately 450, 750 and >1200 acres of vineyards in the Lake Erie Region scanned in 2014, 2015 and 2016 respectively[35]. Some of this includes vineyards scanned multiple times during the season to give information on canopy development during the season.

The lack of statistical difference in regression fits between the various commercial pruning crews and the CLEREL pruning crew indicates that the protocol is fairly robust for application. If there were issues with applying the protocol, it would be expected that there would be more errors, and likely lower R^2 values, with the grower pruning crews. This is because the CLEREL pruning crew is familiar with scientific research and protocols, unlike commercial pruning crews, and the CLEREL crew were more familiar with this particular protocol having completing 15 of the 34 surveys. In contrast, there were multiple commercial pruning crews involved in the survey, each of whom had less experience with the protocol than the CLEREL crew.

The survey results (Table 1) show that in a few cases the proposed protocol does not always generate a relationship between the canopy sensor response and the pruning weights. No relationship was observed for Grower 1 Field 1 for either 2012 or 2013. This is the most intensively mechanized vineyard in the survey and uses a minimal prune system with machine hedging and little hand follow-up. Using vine pruning weight as a surrogate for leaf area was originally developed for manually cane-pruned Concord vines on a sprawl system with little or no additional canopy management, such as shoot positioning or canopy division. It is understandable in these systems that pruning weight would relate to undisturbed canopy growth and would have a reasonable relationship to NDVI. Machine-hedged systems with minimal hand follow up pruning will generate high shoot numbers and the canopy structure changes to have shorter canes, smaller leaves, and an increased density around the cordon. It is hypothesized that in these cases, pruning weight may not always relate very well with the exposed or displayed leaf area and may also show little relationship with canopy scanning of the side-curtain (as proposed here). Such intensive machine-managed pruning systems are not currently common, but are predicted to be more so in the future. This hypothesis needs to be further tested and an alternative approach to proximal canopy sensing may be required in these vineyards. High vine size vineyards are also likely to be poor candidates for this protocol. Large, well filled vines will also produce a saturated signal making it impossible to generate a relationship between a VI and vine size. This may possibly be an issue when adapting the protocol to irrigated vineyards in warm/hot regions where thermal units and water can be supplied at non-limiting rates to produce large vines.

A protocol has been proposed and tested for the deployment of proximal canopy sensors into commercial vineyards to map vine size. The protocol was successful at producing spatial maps of vine size in over

80% of applications across two seasons in Concord vineyards. The protocol was developed and tested under commercial conditions, however the success of it will ultimately be determined in future years. Vine size mapping is the first step toward better vine size and production management in vineyards.

Experimental Design

General Description of the Lake Erie Region and juice grape production in New York

The Lake Erie Region is a cool-climate viticulture region in the North-East USA. The growing region is confined to a narrow strip along the New York and Pennsylvania shore of Lake Erie where the meso-climate is sufficiently affected by Lake Erie to permit grape production[36]. The region is dominated by a single variety, Concord, for juice grape production. Concord production practices are very uniform in the region with the majority of Concord vines trained to a single high-wire trellis at a row spacing of ~2.7 m and a vine spacing of ~2.4 m[37]. The uniformity in variety and production practices makes this of interest for region-wide experimentation and extension. Although this is a cool-climate production system, the trellis system used is similar to the sprawl systems used in warmer regions, and the protocol should be transferable to other regions with some modification for local conditions.

Sensors used in this study

The CropCircle AS430 (HollandScientific, Lincoln, NE, USA) is an active (light emitting) sensor that records the reflectance from an object at 670 nm, 730 nm and 780 nm corresponding to the Red, Red-edge and Near-Infrared (NIR) portion of the electro-magnetic spectrum (EMS)[23]. The reflectance data was logged at 1 Hz to a GeoScout datalogger (HollandScientific, Lincoln, NE, USA) and geo-located with a WAAS-enabled Garmin 18x GPS (Garmin Ltd. Olathe, KS, USA). Data were recorded as .csv files that are compatible with a wide range of statistical and GIS software platforms.

The Greenseeker RT100 (Trimble Navigation Ltd., Sunnyvale, CA, USA) is an active sensor that records reflectance in the Red and NIR section of the EMS[24]. Data was collected at 5 Hz then averaged to 1 Hz. The GreenSeeker data was logged on a GeoExplorer XM field computer and geolocated with the on-board WAAS-enabled GPS receiver. Data were logged as shapefiles.

Survey details

The protocol was tested in two consecutive years (2012 and 2013) on 11 different enterprises. Several growers surveyed multiple blocks (management areas), giving a total of 25 unique blocks. Of these 25 blocks, there were eight blocks that were sampled in both years. One block, Grower 9 Field 1, was sampled as one management unit in 2012 but two management units in 2013, due to different pruning strategies employed in different parts of the block in 2013. Overall, data were obtained from 18 and 17 discrete ‘blocks’ in 2012 and 2013 respectively, giving a total of 35 unique surveys. In 2012, six blocks were sampled by CLEREL and 12 by growers. In 2013, nine blocks were sampled by CLEREL and seven by growers. For blocks that were sampled in both years (eight fields), the 2013 samples were taken at the same location as the 2012 to provide temporal continuity.

Validation of the proposed 15 % rule for data clean-up in the calibration data.

To test the validity of the proposed 15 % rule (see the Protocol - Section 6), a validation was done with the largest data set available (N = 70; Grower 9 Field 1 in 2012). The original data were subset at a sampling rate of 0.35 (N = 24). The random sub-setting was performed five times with replacement. The data trimming process outlined in the protocol was then applied to each subset. This sampling rate was chosen to approximate the median sampling density from the fields in this survey (N = 25) and the recommended sampling density[29] to estimate the field mean (N = 23). Linear regression was performed on the 5 subsets for both the ‘raw’ subset and the trimmed subset data. For comparison, the equivalent ‘global’ regression was plotted for each condition (N = 70 without trimming and N = 65 after trimming).

Figure 6a shows the linear regression fits for each original subset (N=24), while Figure 6b shows the same linear fits using only 22 points after two probable outliers were identified and removed from each subset. The global response is also shown in each plot. Note that the gradient and regression equation for the global fits with and without the outliers removed was almost identical due to the larger sample size giving a more robust fit. The gradients of the trimmed subset data (Fig. 6b) are more uniform and overall more closely resembled the global gradient. Each subset shows a shift up or down that is a result of error in the estimation of the mean from using a limited number of samples. For the ‘raw’ untrimmed data, Subsets 1 and 4 show very different gradients (Fig. 6a). This demonstrates empirically that the manual removal of a few points that were probable (and expected) outliers produced a more robust estimation of the global gradient from the subsets.

<<Figure 6 near here>>

Comment on calibration fits (including information on data removed)

Table 1 shows the results from each field sampled in 2012 and 2013. The R^2 values of the calibration fits post-processing ranged from 0.17 – 0.73 and 0.03 – 0.56 in 2012 and 2013 respectively. The lowest fit in 2013 (Grower 5, Field 1) showed no trend at all. It was not possible to identify outliers within the cloud, thus no processing was performed. This field was sampled by the CLEREL pruning crew in both years, and in both years the field had a poor relationship between NDVI and PW.

In both years there were three fields with $R^2 < 0.3$ after processing and only two fields in 2012 with $R^2 > 0.6$. Given the error sources within production systems and the methods of data acquisition, high R^2 values are not expected. This was not a controlled experiment. To assist growers, an arbitrary threshold value of $R^2 = 0.3$ is suggested as a level at which a calibration could be considered justified for management use. Based on this threshold value, the calibrated PW maps for 83 % and 76 % of fields in 2012 and 2013 respectively could be used for spatial management.

References and Footnotes

[1] Bramley RGV, Trought MCT, and Praat J-P. 2011. Vineyard variability in Marlborough, New Zealand: characterising variation in vineyard performance and options for the implementation of Precision Viticulture. Aust J Grape Wine Res 17:72–78.

[2] Drissi R, Goutouly J-P, Forget D, and Gaudillere J-P. 2009. Nondestructive measurement of grapevine leaf area by ground normalized difference vegetation index. Agronomy J 101:226-231.

[3] Stamatiadis S, Taskos D, Tsadila E, Christofides C, Tsadilas C, and Schepers JS 2010. Comparison of passive and active canopy sensors for the estimation of vine biomass production. Precis Agric 11:306–315.

[4] Taylor JA, Nuske S, Singh S, Hoffman JS, and Bates TR. 2013. Temporal evolution of within-season vineyard canopy response from a proximal sensing system. Precision Agriculture ’13. Proc. 9th ECPA, Lleida, Spain, July 7-11, 2013. J.V. Stafford (ed.). Wageningen Academic Publishers.

[5] Reynolds AG, Brown RB, Kotsaki E, and Lee H-S. 2016. Utilization of proximal sensing technology (Greenseeker™) to map variability in Ontario vineyards. Proc. 11th Terroir Congress, McMinnville, OR, pp.

477-483.

[6] Johnson L, Lobitz B, Armstrong R, Baldy R, Weber E, Debenedictis J, and Bosch D. 1996. Airborne Imaging for Vineyard Canopy Evaluation. Calif Agric, Special Issue on Phylloxera, 50:14-18.

Lang NS, Silbernagel J, Perry EM, Smithyman R, Mills L, and Wample RL. 2000. Remote image and leaf reflectance analysis to evaluate the impact of environmental stress on canopy metabolism. HortTechnology 10:468-474.

[7] Johnson L. 2003. Temporal stability of the NDVI-LAI relationship in a Napa Valley vineyard. Aust J Grape Wine Res 9:96-101.

[8] Dobrowski SZ, Ustin SL, and Wolpert JA. 2003. Grapevine dormant pruning weight prediction using remotely sensed data. Aust J Grape Wine Res 9:177-182.

[9] Hall A, Louis J and Lamb D. 2003. Characterising and mapping vineyard canopy using high-spatial resolution aerial multispectral images. Comput Geosci 29:813-822.

[10] Matese A, Toscano P, Di Gennaro SF, Genesio L, Primo Vaccari F, Primicerio J, Belli C, Zaldei A, Bianconi R, and Gioli B. 2015. Intercomparison of UAV, Aircraft and Satellite Remote Sensing Platforms for Precision Viticulture. Remote Sens 7:2971-2990.

[11] Lamb DW, Weedon MM, and Bramley RGV. 2004. Using remote sensing to predict phenolics and colour at harvest in a Cabernet Sauvignon vineyard: Timing observations against vine phenology and optimising image resolution. Aust J Grape Wine Res 10:46-54.

[12] Hall A and Louis J. 2009. Vineclipper: A proximal search algorithm to tie GPS field locations to high resolution grapevine imagery. Innovations in Remote Sensing and Photogrammetry, Part of the series Lecture Notes in Geoinformation and Cartography. pp 361-372

[13] Smart R. 1973. Sunlight interception by vineyards. Am. J Enol Viticult 24:141-147.

[14] Hall A, Louis JP, and Lamb DW. 2008. Low-resolution remotely sensed images of winegrape vineyards map spatial variability in planimetric canopy area instead of leaf area index. Aust J Grape Wine Res 14:9-17

[15] Bates T. 2008. Pruning level affects growth and yield of New York Concord on two training systems. Am J Enol Vitic 59:276-286.

[16] Bates T, Dunst R, and Joy P. 2002. Seasonal Dry Matter, Starch, and Nutrient Distribution in 'Concord' Grapevine Roots. HortScience 37:313-316.

[17] Hall A, Lamb DW, Holzapfel BP, and Louis, JP 2011. Within-season temporal variation in correlations between vineyard canopy and winegrape composition and yield. Precis Agric 12:103–117.

[18] Partridge N.L. 1931. The influence of long pruning and thinning upon the quality of Concord grapes. Proc. Am. Soc. Hortic. Sci. 28:144-146.

[19] Kimbal K and Shaulis N. 1958. Pruning Effects on the Growth, Yield, and Maturity of Concord Grapes. Proc Am Soc Hort Sci 71:167–76.

[20] Shaulis N, Amberg H, and Crowe D. 1966. Response of Concord Grapes to Light, Exposure and Geneva

Double Curtain Training. Proc Am Soc Hort Sci 89:268–80.

[21] Kliewer WM and Dokoozlian NK. 2005. Leaf Area/crop Weight Ratios of Grapevines: Influence on Fruit Composition and Wine Quality. Am J Enol Vitic 56:170–81.

[22] Previously unpublished data associated with the Bates (2008) study, *pers. comm.* Dr Terence Bates, Cornell Lake Erie Research and Extension Laboratory, Portland, NY

[23] Holland Scientific Inc. 2010. Crop Circle ACS-430 User's Guide. Holland Scientific Inc. Lincoln, NE, USA.

[24] Trimble Navigation Ltd. 2010. GreenSeeker RT200 System Installation and Operation Guide. Version 1, Revision M. Part Number 500-1-032. Trimble Navigation Ltd., Sunnyvale, CA, USA

[25] Curran PJ and Steven MD. 1983. Multispectral remote sensing for the estimation of green leaf area index [and discussion]. Philos Trans R Soc Ser A 309:257–270.

[26] The normalised vegetative differences index (NDVI) is the most commonly used and best known VI, however there are many other potential VIs that can be generated. The authors have deliberately used the generic term VI here to not discount the use of other non-NDVI indices

[27] Taylor JA, McBratney AB, and Whelan BM. 2007. Establishing management classes for broadacre grain production. Agronomy J 99:1366–1376.

[28] Rouse, JW, Haas RH, Schell JA, and Deering DW. 1973. Monitoring vegetation systems in the great plains with ERTS. In: Proc. Third ERTS Symposium, NASA SP-351 1, (U.S. Government Printing Office: Washington DC.) pp. 309–317.

[29] The linear model fitting was performed using a robust method of moment regression technique (Koller M and Stahel WA. 2011. Sharpening wald-type inference in robust regression for small samples. Computational Statistics & Data Analysis 55:2504-2515) implemented in the 'robustbase' package of R (Rousseeuw P, Croux C, Todorov V, Ruckstuhl A, Salibian-Barrera M, Verbeke T, Koller M and Maechler M. 2015. robustbase: Basic Robust Statistics. R package version 0.92-5. URL http://CRAN.R-project.org/package=robustbase), rather than conventional ordinary least squares regression (OLSR). However, OLSR should work equally well in most situations

[30] An Analysis of variance (ANOVA) was performed with the pruning crew type as the treatment and the R^2 values as the variable of interest. The threshold $P<0.1$ was chosen to reflect that growers are likely to make decisions at this level of certainty. Since the treatments were unbalanced Tukey-Kramer method was used for means comparison.

[31] ANOVA was performed on the subset of CLEREL data with the year as the treatment and the R^2 values as the variable of interest. Again $P<0.1$ was used and Tukey-Kramer method for means comparison.

[32] Shaulis N and Steel RD. 1969. The interaction of resistant rootstock to the nitrogen, weed control, pruning, and thinning on the productivity of Concord grapevines. J. Am. Soc. Hortic. Sci. 91:122-129.

[33] Taylor JA and Bates TR. 2012. A research note on sampling and estimating average pruning weights in Concord grapes. Am J Enol Viticult 63:559–563

[34] *pers. comm.* Mr Robert Betts, Betts Vineyards LLC, Westfield, NY

[35] *pers. comm.* Mr Luke Haggerty, Cornell Cooperative Extension, Portland, NY

[36] Oskamp J. 1934. Soils in Relation to Fruit Growing in New York. Part V. The Vineyard Soils of the Westfield Area, Chautauqua County. Cornell University Agricultural Experiment Station Bulletin 609.

[37] Jordan TD, Pool RM, Zabadal TJ, and Tompkins JP. 1981. Cultural practices for commercial vineyards. Miscellaneous Bulletin 111. New York State College of Agriculture and Life Sciences, Geneva.

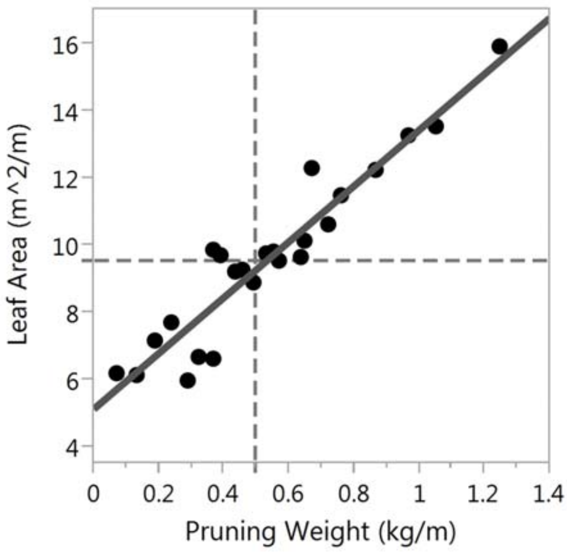

Figure 1 The relationship between vine size and total vine leaf area in single high-wire cordon trained and cane pruned Concord grapevines in Fredonia, NY. In undivided canopy training systems, 0.50 kg/m pruning weight and approximately 10 m^2/m leaf area is considered near optimum to maximize canopy light interception and minimize internal canopy shading. (Previously unpublished data associated with the Bates (2008) study, *pers. comm.* Dr Terence Bates, Cornell Lake Erie Research and Extension

Laboratory, Portland, NY)

Figure 2 Illustration of the change in presentation of the canopy to high-wire and low-wire side-oriented proximal sensors at different growth stages.

Figure 3 Examples of mounting of the Crop-Circle sensor on a (left) harvester-sprayer and (right) an all-terrain vehicle.

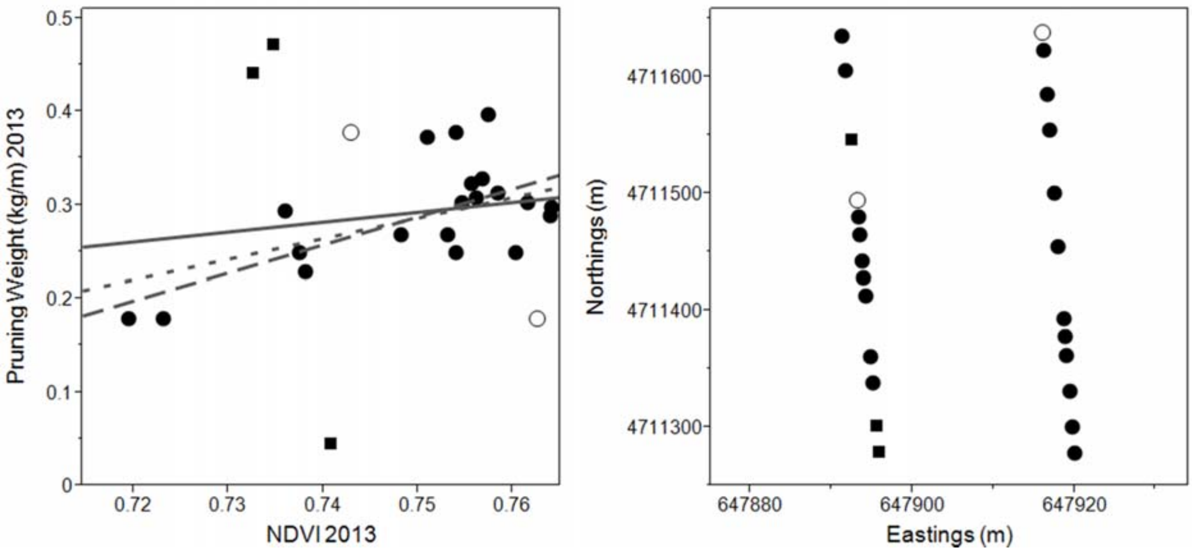

Figure 4 An example of data trimming. Figure 4a (left) shows the plot of pruning weight (kg/m) vs NDVI for one of the surveyed Concord vineyards. Figure 4b shows the location of points along rows in the vineyard. There were three values that were considered erroneous and removed before any analysis (denoted by ■). Note that two of these abnormal values were grouped at the end of the westernmost row, a possible edge effect. Two other probable 'outliers', denoted by (○), were subsequently also manually trimmed. Again one of these is near a boundary condition (start of the easternmost row in Fig. 4b). Regression lines are shown for i) all data (—, N = 25, R^2 = 0.02), with abnormal values (■) removed (- - -, N = 22, R^2 = 0.19) and with abnormal and probable (○) outliers removed (—, N = 20, R^2 = 0.43).

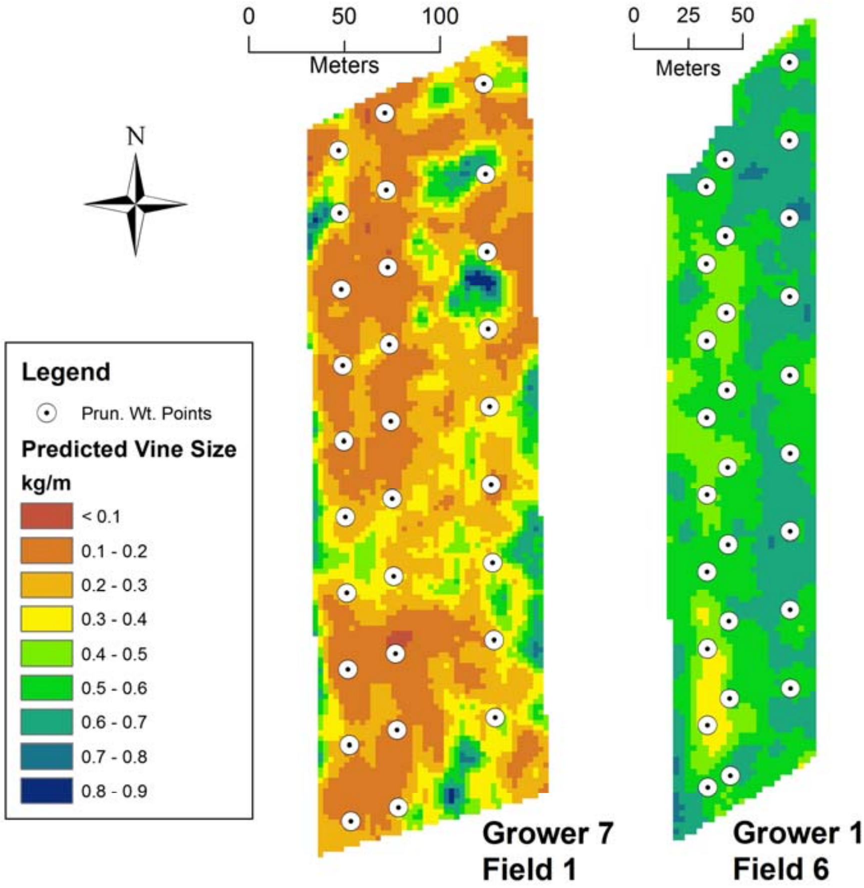

Figure 5 Examples of pruning weigh maps generated in commercial Concord vineyards using the proposed protocol. Field details are given in Table 1. Points indicate the location of manual pruning weight measurements for the field-specific calibration between NDVI and PW. In both fields, pruning weight measurements were taken from three transects.

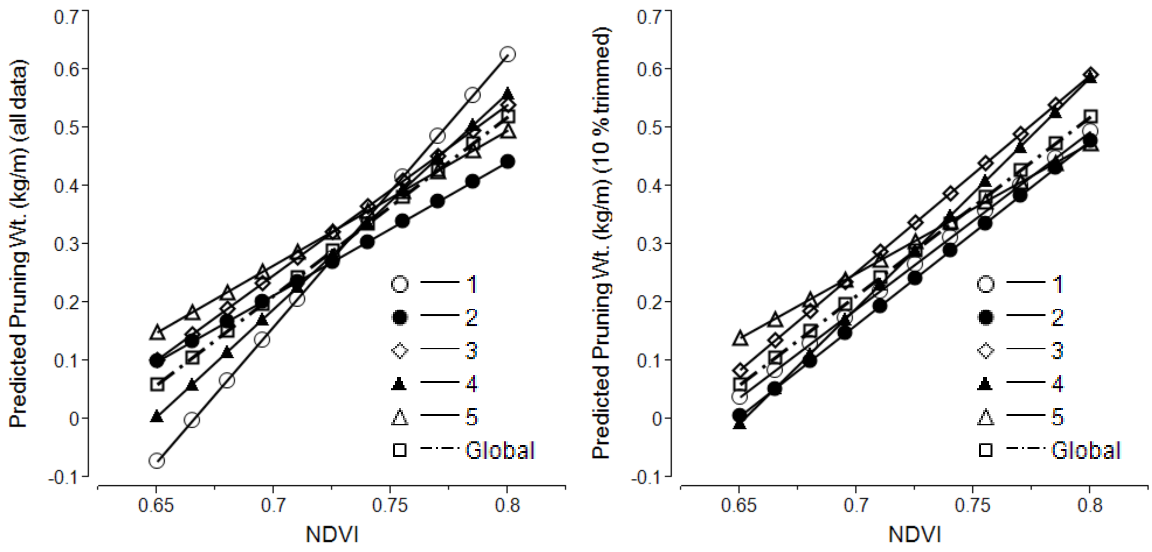

Figure 6 Comparison of regression fits from subset data (N=24) from Grower 9 Field 1 using the raw data (Fig. 5a) and after application of the suggested data clean-up and the 15 % rule in the protocol (N = 22, Fig. 5b).

Table 1 Field-level results from Concord vineyards of the sample sizes (N) and co-efficient of variation (R^2) from fitting pruning weight data to NDVI data before and after applying the 15 % data trimming rule.

Grower and Field ID	Pruning wt. collected by	2012 data				2013 data			
		Raw data		Post trimming		Raw data		Post trimming	
		R^2	N	R^2	N	R^2	N	R^2	N
Grower 1 Field 1	Grower	0.03	25	0.17	22				
Grower 5 Field 1	CLEREL	0.00	35	0.21	31	0.03	32	0.03	32^
Grower 1 Field 2	Grower	0.12	24	0.28	21				
Grower 2 Field 1	Grower	0.24	26	0.41	23	0.22	23	0.40	21
Grower 1 Field 2	Grower	0.17	25	0.42	22	0.10	25	0.25	22
Grower 2 Field 2	Grower	0.33	27	0.43	25				
Grower 6 Field 1	CLEREL	0.06	23	0.44	18	0.06	20	0.36	17
Grower 1 Field 3	Grower	0.25	25	0.46	22				
Grower 1 Field 4	CLEREL	0.42	27	0.48	25				
Grower 7 Field 1	CLEREL	0.32	29	0.48	27	0.30	29	0.40	27
Grower 2 Field 3	Grower	0.37	16	0.53	14				
Grower 8 Field 1	CLEREL	0.48	25	0.58	23	0.18	25	0.32	22
Grower 2 Field 4	Grower	0.46	36	0.59	34				
Grower 1 Field 5	Grower	0.54	25	0.60	23				
Grower 1 Field 6	Grower	0.42	25	0.60	23	0.02	25	0.33	21
Grower 2 Field 5	Grower	0.51	22	0.60	20				
Grower 9 Field 1†	CLEREL	0.55	70	0.61	65	0.30	40	0.47 0.53	21 15
Grower 1 Field 7	Grower	0.58	31	0.73	29				
Grower 2 Field 6	CLEREL					0.00	35	0.25	17
Grower 10 Field 1	CLEREL					0.04	26	0.26	21
Grower 3 Field 1	Grower					0.28	55	0.36	53
Grower 4 Field 1	Grower					0.17	24	0.40	22
Grower 11 Field 1	CLEREL					0.23	33	0.44	30
Grower 3 Field 2	Grower					0.36	21	0.44	19
Grower 4 Field 2	Grower					0.35	21	0.56	19

† Field split in 2013 – two different pruning strategies within the block. ^ Data not trimmed as no trend in raw data