# Spatial Analysis of the Effect of Fruit Thinning on Apple Crop Load

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## Summary

There has been very little literature on the mid season spatial variability of fruit production in horticulture crops published to date. Most of the existing literature refers to data collected post harvest. Crop load data taken prior to hand thinning and prior to harvest were collected in 3 blocks of a commercial apple (*Malus domestica* Borkh.) orchard in the province of Ferrara, Italy. The purpose of the survey was to characterize the within field variability of crop load, using spatial statistics, and assess the effectiveness of the hand-thinning treatment. Crop load estimations were taken at 156 sites pre and post hand-thinning over a defined distance (0.8 m) and the data used to model a vario-gram and associated spatial variation. Variation in the spatial distribution of the fruit load prior to the hand-thinning was observed, indicating a possibility to spatially differentially manage the orchard. No spatial variation in fruit number was observed prior to harvest (post-thinning), indicating that thinning had removed the previously observed spatial variation in crop load. Under the current uniform management approach this indicates that thinning has been effectively implemented. However, the spatial variation observed prior to thinning may indicate that a differential crop load management strategy may be optimal for maximizing quality in the orchard.

**Key words.** fruit thinning – *Malus domestica* Borkh. – precision horticulture – crop load – variogram – spatial analysis

## Introduction

For any crop production system the most relevant source of information available to a producer is on-site information specific to their system (WHITNEY et al. 1999). Despite this, the recording of objective crop development information is not a common practice in many horticulture crops (SCHUELLER et al. 1999). Orchard management is frequently based on a grower's experience and subjective knowledge of the crop production system. When data are recorded, it is usually done at a block or orchard level using non-spatial descriptive statistics, such as the mean and variance of production attributes (MIRANDA JIMENEZ and ROYO DIAZ 2004). Rarely does the analysis take into account within-block variation (e.g. PRAAT et al. 2000; GILLGREN 2001). In the horticulture literature there are very few studies where site-specific data have been collected even though such data provides better quality information (PRAAT et al. 2000; TISSEYRE et al. 2007) and the option of interpreting the data in either a uniform or spatial context. Investigations into the spatial variability of yield in pipfruit, kiwifruit, citrus and other fruit crops have been undertaken (PRAAT et al. 2000; GILLGREN 2001; QUIAO et al. 2005; TAYLOR et al. 2007a), however these studies have focused on quantifying yield during or immediately after harvest. There are no horticultural publications about the spatial variability of within season crop yield estimation, despite this being a routine operation in many orchard systems and the development of digital imaging systems for fruit counting (STAJNKO et al. 2004; REGUNATHAN and LEE 2005). To date these imaging systems have only been used for uniform (block) yield estimation or as machine-vision for automated harvesting systems.

Within-season estimation of crop yield is important for making real-time, correct management decisions, particularly for crop thinning and labour logistics at harvest. Orchard yield is a function of crop load and fruit size and can be accurately assessed by fruit load per tree (LAKSO et al. 1995; HESTER and CACHO 2003; LÖTZE and BERGH 2004; MIRANDA JIMENEZ and ROYO DIAZ 2004). The earlier this estimation can be made the more useful the information is for management. To this end different methods have been tried to calculate (mean) fruit load early in the growing season. JESSEN (1955) and PEARCE and HOLLAND (1957) initially proposed randomized branch sampling to estimate crop load and, since then a wide variety of methods have been developed for estimating crop load. However all these methods are aimed at producing orchard mean estimates (ZHANG et al. 1995); none of them are suited or designed for spatial analysis.

The analysis of spatial data in orchards, termed Precision Horticulture (PH) is a relatively new area of study. PH aims to improve a variety of management decisions, such as crop thinning, fertilization or irrigation, by understanding the spatial and/or temporal variations in crop production. Understanding these variations allows management to be tailored to specific crop needs at

each location (site) in the orchard, hence optimizing production. Application of this management philosophy has been adopted in broadacre agriculture and more recently in viticulture (Tisseyre et al. 2007; Taylor et al. 2007b).

The collection and analysis of spatial data may be expensive and time consuming and is therefore, usually facilitated by automated sensors. For situations where manual measurements are required (or necessitated due to the absence of relevant sensors), as in PH, the design of the sampling scheme is important in optimizing the value of the data collected The most common approach to hand-sampling relies on grid point sampling. However, gridded sampling may give erroneous results because of the regular sample alignment. Other regularly spaced patterns associated with treatment and field management, such as drainage tiles, ditches or fertilizer spreading, may cause a repeating pattern that, if aligned with the sampling grid, will seriously bias results. When existing spatial information is available, e.g. a soil survey, an aerial image or possibly existing local knowledge, then this *a priori* information can be used to develop a site-directed survey. Site-directed and randomized sampling schemes have been shown to be more effective than grid sampling (Pocknee et al. 1996) especially when nested transects are incorporated to improve variogram estimation (Pettitt and McBratney 1993). However, when *a priori* knowledge does not exist to generate a site-directed sampling scheme, then grid sampling at an appropriate density in combination with block kriging (interpolation) can be used for mapping and managing crop parameters (McBratney and Pringle 1999).

Precision agriculture (PA) and more particularly precision horticulture are relatively new concepts based on spatial information. When starting with PA or PH it can take many years to generate a database of information, for example harvest data can only be generated once a year. To facilitate adoption it is often possible to use existing or legacy data, provided the data is of sufficient density and quality to warrant spatial analysis i.e. individual site data is required, which has not been aggregated or mixed into a composite sample for analysis, and contains an accurate site location. Site location does not need to be a geographic reference (e.g. latitude and longitude). It can be an accurate orchard description that can easily be revisited or geo-referenced (e.g. the 6th tree in the 10th row from the eastern edge of Block 6). Although rare, such legacy data in horticulture does exist, particularly from previous research studies rather than in commercial applications, and the data is usually collected on some form of grid.

The aim of this paper is to analyze medium density legacy crop load data for spatial variation pre and post-hand-thinning. The goal of the analysis is to illustrate a) how spatial analysis can be used to identify variation in apple production and, b) how thinning impacts on spatial variation in crop loads. The authors acknowledge that the legacy data sampling scheme is sub-optimal, however the number of data (156) is sufficient for variogram analysis (Webster and Oliver 1992) and therefore spatial analysis. Recognizing and accounting for limitations in spatial analysis of legacy data is an important concern for PH, particularly during its infancy. Given the results, a brief discussion is also presented on the poten-

tial opportunities afforded by managing the observed spatial variation in crop load.

## Materials and Methods

The study was conducted during the 2007 growing season in a commercial apple orchard which is located in Medelana, Ferrara, Italy. Data were collected from three blocks of apple 'Fuji' denoted M9-1998 (3.1 ha), M9-1995 (2.5 ha) and M9-2001 (1.4 ha). Apart from a different year of planting (as indicated in the block identifier) trees in all the blocks were grafted on M9 rootstock, trained as slender spindle at a density of 3571 trees ha$^{-1}$ (0.8 × 3.5 m), and were under the same standard management. All three orchards have an approximate North-South orientation. For these characteristics, the three blocks can be considered a uniformity experiment.

In the orchard, pollenizer rows are interspersed within the main cultivar ones. Pollenizer rows were not considered during crop estimation. In M9-1995 and M9-1998 the 'Fuji' rows adjacent to the pollenizer rows were also omitted. The remaining 21 and 24 rows in the two blocks respectively were sampled. In M9-2001 every second row was selected for a total of seven rows. In each block, the rows were divided into three sectors (blocks), North, Centre and South, and for each sector 4 'trees' were counted randomly. The mean crop load from the 4 'trees' was assigned to the sector and geo-referenced with the midpoint of the sector. Fig. 1 illustrates the sampling strategy. For each block, M9-1995, M9-1998 and M9-2001 respectively there were 63, 72 and 21 data. This grid-oriented sampling strategy was initially designed for a whole-block crop yield estimation, not for spatial analysis, however sufficient information (156 data) allows relevant preliminary spatial data analysis across the 3 blocks. There is insufficient data (< 100 points) within individual blocks for accurate variogram analysis (Web-



Fig. 1. Satellite image of the study site showing the three blocks of 'Fuji' apples surveyed and the centroids of the North, Central and Southern 'sectors' in the blocks that the mean crop load data for each sector was geo-referenced to.

STER and OLIVER 1992), hence the need to aggregate the data.

Crop load estimation was done in the first week of May, after standard Carbaryl-based chemical thinning but before final hand thinning (also a standard practice), and then in September before harvest. As described above, 4 random locations ('trees') were counted within each sector then averaged to give a sector mean. At each location fruit were counted within a 'frame' or 'window' 0.8 m wide (equivalent to the distance between trees along the row) and as high as the trees. Thus 3.2 m of row were counted in each sector and averaged to a 'tree' (0.8 m) value. This approach was adopted due to the tight spacing along the row causing overlapping of fruit-bearing branches between adjacent trees. Using a window equivalent to the spacing between trees (0.8 m) means that the window does not need to be perfectly centred on the trunk of the tree nor do the inter-twining of branches of adjacent trees cause a problem with counts. This reduces the need to always identify the tree to which a given fruit was attached, which is time-consuming. Fruit counts were performed manually but only on the western side of the rows again to decrease the time needed per tree and to allow more locations to be counted within a given time frame. An assumption is made that the two halves (eastern and western) of the inverted conic shaped spindle trellis will generate equal fruit counts. Total crop load per 'tree' is obtained by doubling the western half fruit count.

The desired fruit load of about 61 fruit per tree was calculated after a target mean fruit weight (220 g) and yield (50 t ha$^{-1}$) were identified, and knowing the tree density (3571 trees ha$^{-1}$). The May crop load indicated that the average fruit load across the blocks (60.6 fruit tree$^{-1}$) (Table 1) was close to optimal. On the basis of this value a decision not to thin the fruit would be made. However, observation of the fruit set showed a high degree of fruit clustering. This is an undesirable production feature thus hand-thinning was undertaken primarily to achieve a maximum of 3 fruitlets per cluster. This was done across all three blocks by simply removing random fruitlets from clusters with 4 or more fruitlets until only 3 fruitlets remained.

The same sampling protocol described above was used for the post-thinning (pre-harvest) crop load estimation in September. In each sector 4 'trees' (0.8 m sections) were again randomly chosen i.e. the same area of canopy was not necessary counted in May and September however the same amount of canopy (3.2 m) in each sector was.

Non-spatial data analysis (mean, variance and coefficient of variation) for the blocks was done in JMP 6.0 (SAS Institute; Table 1). Variogram estimation was performed in VESPER (MINASNY et al. 2005). Variogram clouds are plots of the semi-variance between points separated by a certain distance i.e. each point in Fig. 2 represents the mean semi-variance between all possible pairs of points in the data set that are separate by the lag (distance) indicated on the abscissa axis. For interpolation and spatial analysis a theoretical model is usually fitted to the variogram cloud. Various models were fitted and a theoretical spherical variogram model (Equation 1) was found to have the best fit according to the Akaike Information Criteria in VESPER.

$$\gamma(h) = \begin{cases} c_0 + c_1 \left\{ \left(\dfrac{3h}{2a}\right) - 0.5\left(\dfrac{h}{a}\right)^3 \right\} & \text{for } h \leq a, \\ c_0 + c_1 & \text{for } h > a \end{cases} \quad (1)$$

where $c_0$ is the nugget variance
$c_0 + c_1$ is the sill
and a is the range.

The theoretical variogram parameters, $c_0$, $c_1$, and a, for the fits were recorded. As described by TAYLOR et al. (2007a), the $c_0$ value estimates the amount of variance between adjacent points, i.e. points that are separate by a distance (or lag) of ~0 m, and is a function of stochastic effects and measurement error. The $c_1$ value estimates the amount of autocorrelated variance in these data and contributes with $c_0$ to define the sill $(c_0 + c_1)$ or the total amount of variance in these data. The range (a) defines the distance over which data are autocorrelated i.e. the distance at which the sill is reached. To provide some indication of spatial structure the Cambardella Index (CAMBARDELLA et al. 1994) was calculated.

Table 1. Non-spatial statistics and variogram parameters for the combined data from all three blocks and individual non-spatial statistics for each block for the pre hand-thinning (May, 2007) and post hand-thinning (September 2007) crop load estimations.

| Sampling time | Block ID | No. of data (n) | Mean crop load (tree$^{-1}$) | Crop load variance | CV | Nugget variance ($c_0$) | Sill variance ($c_0+c_1$) | Range (a) (m) | Cambardella Index |
|---|---|---|---|---|---|---|---|---|---|
| Pre hand-thinning (May, 2007) | M9-1995 | 63 | 31.22 | 329.66 | 58.15 | | | | |
| | M9-1998 | 72 | 86.86 | 377.90 | 22.38 | | | | |
| | M9-2001 | 21 | 58.67 | 945.73 | 52.42 | | | | |
| | Combined | 156 | 60.60 | 1098.64 | 54.70 | 267.6 | 404.6 | 35.2 | 66.1 |
| Post hand-thinning (Sep., 2007) | M9-1995 | 63 | 50.57 | 250.41 | 31.29 | | | | |
| | M9-1998 | 72 | 68.02 | 920.46 | 44.60 | | | | |
| | M9-2001 | 21 | 84.98 | 792.31 | 33.12 | | | | |
| | Combined | 156 | 63.25 | 763.89 | 43.69 | 601.0 | 601.0 | 0.0 | 100.0 |

CV, coefficient of variation (%).

$$\text{Cambardella Index} = \frac{c_0}{c_1 + c_0} * 100 \qquad (2)$$

where     $c_0$ = nugget, $c_0 + c_1$ = sill,
and       $< 25$ = Strong spatial dependency
          25-75 = Moderate spatial dependency
          $< 75$ = Weak spatial dependency


This index is a ratio between the nugget ($c_0$) and the sill ($c_0+c_1$), which indicates whether data contains trends and spatial features or represents either random noise or a uniform value, neither of which have a spatial structure. For data that exhibits a spatial structure, the amount of autocorrelated variance provides an indication of the amount of spatial variation that is potentially manageable (PRINGLE et al. 2003).

Interpolation was done in VESPER onto a 2 m square grid using block kriging (5 × 5 m blocks) and the global variogram defined above. As fruit counts are known to have an error of ~20 % (STAJNKO et al. 2004), the $\sigma^2$ (uncertainty) option in VESPER was used (MINASNY et al. 2005) and a value equivalent to 20 % of $c_0$ was chosen as an estimation of $\sigma^2$. The interpolated data was mapped in ArcMap 9.2 (1999−2006, ESRI Inc., Fig. 3).

## Results and Discussions

The non-spatial and spatial statistics for the May (pre hand-thinning) and September (Post hand-thinning) data counts are shown in Table 1. The global (all data) mean crop load for the three blocks is lower in May (60.6) than September (63.3), but not significantly different (P<0.44). This is despite the fruit being thinned in between the counts. The primary reason for this is the light level of thinning pressure applied due to a quite low crop load verified after the chemical thinning. Secondly, a probable under-estimation in the May counts due to the difficulty in locating all the fruit when the fruitlets are small, green, cluster organized and camouflaged in the canopy. Crop counts in September are usually more accurate as the fruit are large, redder and less clustered together and therefore more obvious. The option to use random 'trees' for both counts, rather than the same 'trees', will also introduce some variance in the counts. Despite the similar global means, the September counts had a lower CV indicating more uniformity in production post-thinning.

The intention of the original sampling survey was to gather accurate mean measurement of fruit count on a block basis. The individual block means showed different responses. For M9-1995 and M9-2001 the mean block crop load increased significantly (P<0.05) by 19.35 and 26.31 fruit tree[-1] post-thinning respectively. Crop load in these blocks was lower than the target level (60 fruit tree[-1]) and the blocks would have received very light hand-thinning. Fruit, in fact, where more distributed in single fruitlet clusters. This gives the appearance of better fruit distribution in the canopy, which also contributes to a lower thinning pressure. September counts are known to be more accurate, due to the larger fruit, therefore the increased fruit count in these blocks is attributed to the fact that the amount of fruit thinned is less than the fruit not counted pre hand-thinning.

However, M9-1998 had a significant decrease (P<0.05) of 18.84 fruit tree[-1]. The mean crop load in this block was well above the target rate and would have received more rigorous hand-thinning. The apple "bunch" reduction is a typical cultural practice during thinning in order to speed up the process and maximize the final product quality. This resulted in the amount of fruit removed being greater than the fruit not counted in May. Given that more fruit is expected to be counted in September, a large proportion (we estimate ~50 %) of the fruitlets must have been lost in M9-1998. This may not be just due to hand-thinning. The high fruit set in this block may prompt greater natural fruit drop due to a higher competition at fruit clusters level further contributing to
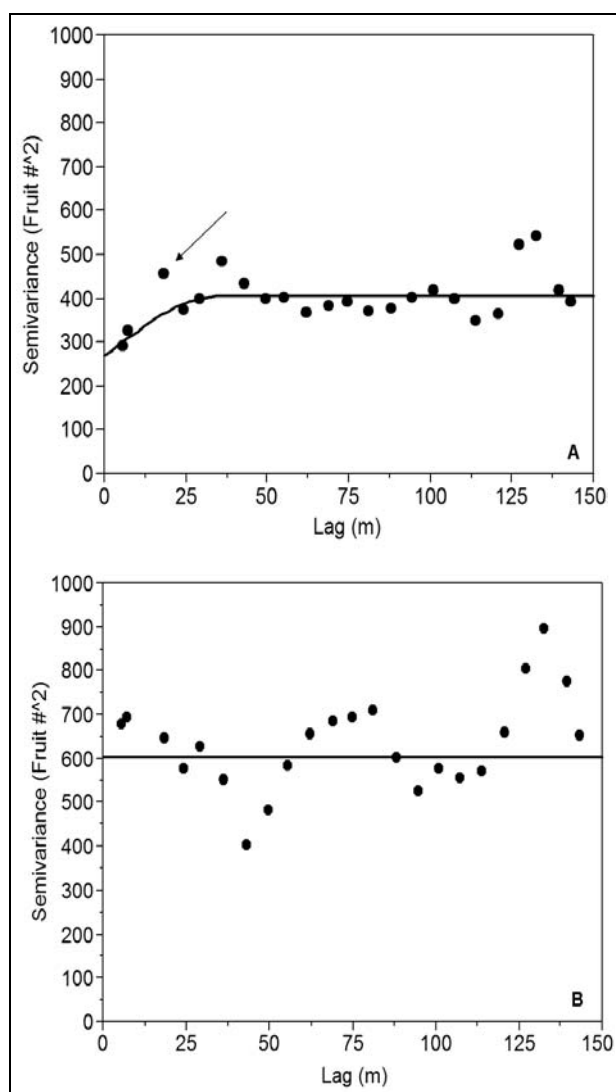


Fig. 2. Experimental variogram clouds and fitted theoretical spherical models for the crop load data pre hand-thinning (A) and post hand-thinning (pre-harvest) (B). The pre thinning variogram (A) shows auto-correlation (less semivariance) between data separated by less than 35 m. The post hand-thinning variogram (B) shows no auto-correlation. The arrow indicates a lag variance with a low number of data pairs. This data point has been omitted from the theoretical variogram fitting.
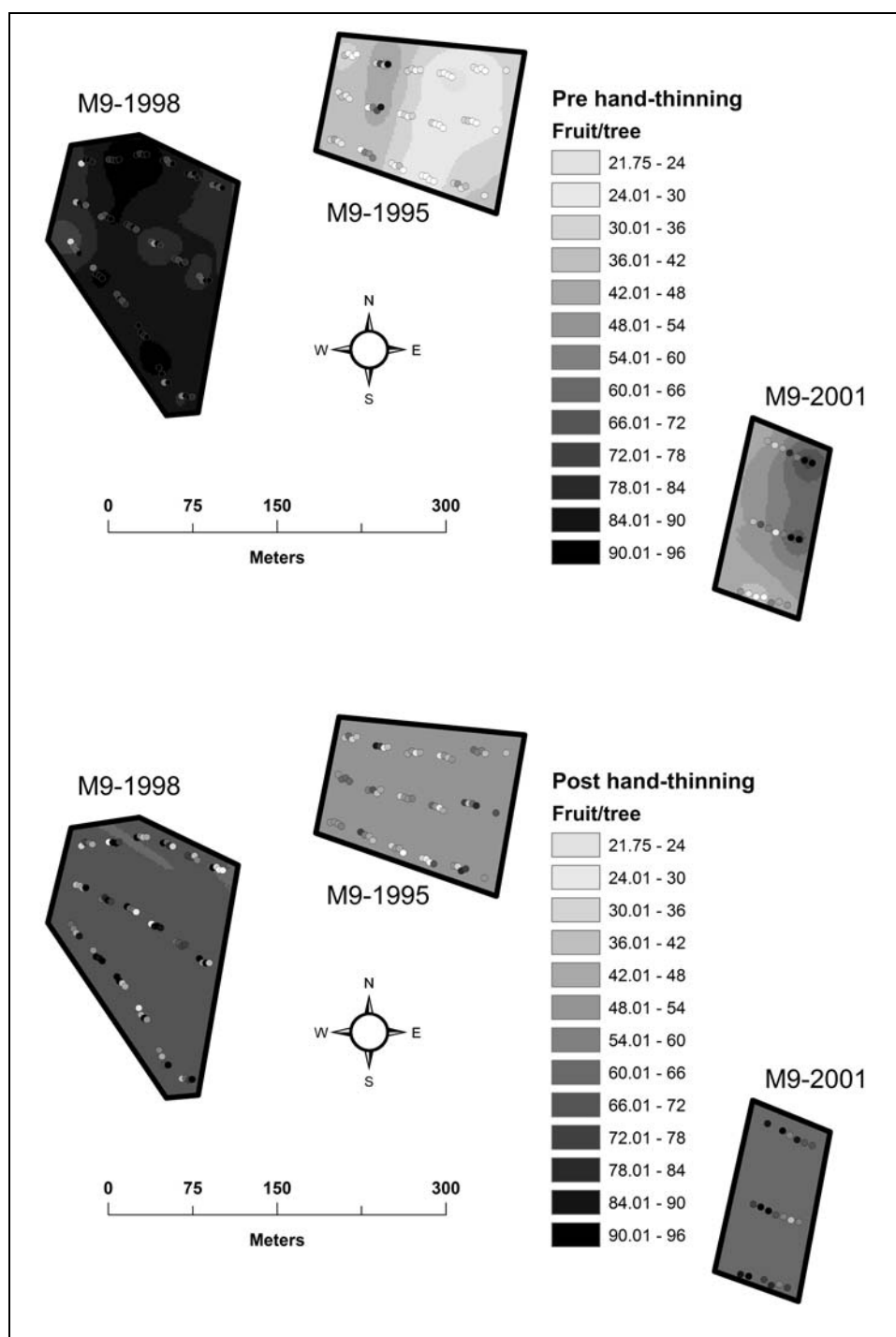
Fig. 3. Interpolated maps of the three study blocks with the raw crop load data overlain. The pre hand-thinning map (top) shows spatial patterns within the blocks. The post hand-thinning map (bottom) present as uniform (mean) maps due to the lack of spatial structure in the data indicated by the presence of adjacent high and low raw crop load data. Both the maps and the raw point data are presented on the same legend.

the loss of fruitlets/fruit as have been reported by WEST-WOOD (1978). The hypothesis of loss of fruit from high crop load trees in M9-1998, either through thinning or fruit fall, is also obvious in the spatial patterns of the raw data in M9-2001. Despite the majority of the block having a low crop load, the North-East corner has very high crop load (Fig. 3). When the crop load is reassessed post hand-thinning the spatial patterns in the block have changed, with the NE corner now being characterized by lower raw data counts (Fig. 3) than the rest of the block.

The experimental variogram clouds for fruit counts and fitted theoretical spherical variogram models are

shown in Fig. 2. The variogram parameters are listed in Table 1 In the pre hand-thinning plot, the lag at 19 m (indicated with an arrow) is omitted from the fitting process as it had a low number of pairs, compared with its neighbours, for the semi-variance estimation. This is an artefact of the sampling design. The variograms show a marked difference between the two counts. The pre hand-thinning variogram count (Fig. 2A) exhibits some spatial autocorrelation (a = 35.24 m), i.e., trees separate by distances <35 m exhibit less variance than trees separated by >35 m, or, stated another way, it is more likely that two trees separated by <35 m will require the same

management than for two trees separates by >35 m. This is probably the normal situation in an orchard prior to hand-thinning. The aim of thinning an entire orchard is to produce a more homogeneous fruit load which is easier to manage. The post-thinned September count (Fig. 2B) has no spatial auto-correlation ($c_1$ and a values of 0), which is the desired outcome under current management approaches. The Cambardella Index for the May counts (66.14) indicates a moderate spatial dependency (structure) while the index post-thinning (100) is indicative of no spatial dependence.

In production systems with spatial structure a management class or management zone approach is possible and may be preferable. When there is no spatial structure a uniform or mean approach to management is the most practical current approach, unless trees can be managed individual on a tree-by-tree basis. The moderate spatial dependency indicated by the Cambardella Index and the short range over which auto-correlation occurs in May (a = 35.24), indicates that the distance (area) over which trees exhibit a more uniform crop load response is quite small. This distance (area) has implications on the ability to manage the autocorrelated (structured) variation in the production system. If the grower cannot adjust management over distances of less than 20–30 m then it may not be possible to manage the observed variation.

The presented crop load maps (Fig. 3) provide a visual reinforcement to the spatial analysis. In May, intra-block spatial patterns in production are present. For example, there are North-South oriented features in M9-1995, despite the sampling being more densely oriented East-West (Fig. 1). With this legacy sample scheme, E-W artefacts may be expected but are not present. Likewise, M9-2001 shows a trend across the block with crop load diminishing from the North-East to the South-West corner. M9-1998 presents a more uniform map (in agreement with its lower CV value in Table 1) but there are still some spatial patterns to observe. The September maps are effectively mean block maps. The flat variogram structure means that all the data used for interpolation are weighted equally, thus an average value is derived. The interpolated crop load block means for M9-1995 and M9-1998 approximate the block means in Table 1 derived from the raw count data. For M9-2001, the interpolated block mean is underestimated as the kriging process has used data from the other blocks during the interpolation. If the number of points used in the interpolation is confined to 21 (the number of data in M9-2001) the interpolated crop load mean approximates the raw data mean (results not shown).

In Fig. 3 the raw data points have also been shown using the same legend. This visually shows the spatial variance in the raw data. The September data is noisier with adjacent points more often dissimilar than in May. However, the overall variance and CV is lower in September (Table 1). These highlights are one of the problems with using CV as an indicator for spatial variance (Pringle et al. 2003).

These simple spatial analyses and associated maps provide an ability to quantify the effectiveness of thinning within the orchard in reducing variability in the crop load of the trees. In this case the data indicates that thinning has removed the spatial structure associated with crop load in the orchard and reduced the CV across the blocks. However, there is still a large amount of variation across the orchard blocks (CV of 43.69 post hand-thinning) and this variation appears to be stochastic in nature. Is this level of stochastic variation between adjacent trees acceptable to growers and what implications does it have on fruit quality, particularly fruit size distribution at harvest? This preliminary investigation did not collect harvest data to answer this question however it is certainly a question which needs further investigation.

Given that this study has shown that there is variation in the production system, is a uniform crop load the optimum outcome for the orchard or each block? If canopy variation also exhibits similar variation to the crop loads then the optimal fruit load, relative to canopy size, will differ. Does this provide options for improved productivity and/or profitability through targeted management, such as differential harvesting? Examples from viticulture studies certainly highlight this possibility (Bramley 2005). Spatial variation in quantity should not necessarily be considered detrimental to production, and if manipulated correctly can be a positive. Spatial variation in quality may be more problematic. For any high value crop the ultimate goal is uniform (high) quality production. Uniform fruit load, with variable environmental effects, may not produce uniform quality.

While this is only a snapshot, and the temporal stability of spatial patterns needs to be determined before using the information for future management decisions, over time these spatial patterns could provide valuable information and feedback on current management strategies and options for future variable or site-specific management. Fruit thinning is one of the most effective techniques to increase the income for the grower. If thinning can be more effectively implemented using variable thinning strategies to match production to the ecophysiological potential of the orchard then increases in fruit quality and subsequently profitability are possible. Furthermore, spatial crop load information can assist the grower in the management of harvest and pack-house logistics.

## Conclusion

Thinning is an important management technique that impacts on the profitability of orchards. Decisions on thinning are made frequently during the season but quite often without clear and quick feedback on the results from previous management (thinning) operations. To date, information on the spatial variability of the fruit load within an orchard has not been used for the targeting of subsequent thinning operations.

The aim of the paper was to investigate the feasibility of spatial analysis in apple orchards to assist growers with decision making. Although the sampling scheme used was not optimized for spatial analysis, the results of the investigation were satisfactory and quite clear. Prior to hand-thinning there was a spatial structure and pattern in crop load. After thinning this spatial structure and pattern were no longer evident. The thinning operation had removed the spatial structure to the crop load variation and reduced the overall CV across the orchard. There is still a large amount of variation across the orchard blocks (CV of 43.69 post-thinning) but this variation appears stochastic in nature. When retaining a uniform block management approach, this spatial analysis identifies whether thinning has produced the desired uniform crop load, or where further differential thinning is required to achieve a uniform crop load.

However, given that this analysis indicates that spatial variation exists at a sub-block level, the current uniform approach to management being used may not be the most productive. There may be differential management options available to researchers and growers who are aware of this variation, to increase their potential to respond to market demands for higher quality fruit at a lower cost. This is one of the main objectives of precision horticulture.

## Acknowledgements

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