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A method to position a simple strip trial to improve trial efficiency and maximise the value of vineyard variability for decision-making

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ABSTRACT

The main difficulties grapegrowers and consultants face in obtaining robust trial results include time and labour to collect data and land variability that confounds trial results. Spatial approaches that use whole-field designs, sensing technologies and geostatistical analysis enable more efficient data collection and account for the impact of spatial variation on crop responses while generating statistically robust results. However, the practical application of these approaches for vineyard trials requires affordable automation of measurements of viticultural variables and access to skills for geostatistics. A strip approach has been developed to simplify experimentation by allowing the farmer to use a single crop row to trial and analyse data in a spreadsheet. However, guidance is needed as to how to position trial strips in a vineyard block to reveal likely treatment effects across the entire block. Here, we investigated using a covariate to a response variable of interest to position a strip trial to infer treatment effects beyond the trial strip. Strip trials were simulated for two experiments: one comparing three treatments for vineyard floor management on grape yield and another comparing two spray programs for powdery mildew control. Useful covariates for yield or mildew severity were determined using correlation analyses. Trial results were analysed using a moving pairwise comparison of treatments and a moving average of the covariates. Simulated trial strips that incorporated a range of variation in a useful covariate close to that encountered in the whole block showed how yield or mildew severity varied with the covariates along the strips. Importantly, such results provided information about likely crop responses in other parts of the block according to variation in the covariates, thus contributing to better-informed decision-making. Compared to whole-field approaches, this strip approach is more efficient and simpler for growers to implement.

KEYWORDS: on-farm experimentation, precision agriculture, spatial variation, vineyard trials, viticulture

INTRODUCTION

On-farm experimentation (OFE) is commonly used by farmers to evaluate alternative farming practices under local contexts and to generate information to guide management decisions (Catalogna *et al.*, 2018; Hansson, 2019; Lacoste *et al.*, 2022). This is also the case among grapegrowers and/or viticultural consultants in Australia (Song *et al.*, 2022b) and Italy (Krzywoszynska, 2016). The main challenges that Australian grapegrowers face when experimenting include available time and labour to collect data to obtain robust results for confident decision-making, and spatial variability in the land that likely influences crop responses to treatments and thus complicates the interpretation of trial results (Song *et al.*, 2022a; Song *et al.*, 2022b). To address the latter issue, growers generally identify an area within a management unit or vineyard block that is perceived as relatively homogeneous. However, translating the results to other locations in the block can present uncertainties because crop responses to any given treatment may vary in space due to land variability (Bramley *et al.*, 2011a; Bramley *et al.*, 2013; Cook *et al.*, 1999; Panten and Bramley, 2011). Given that a common production goal in Australian viticulture is to reduce variation in fruit yield and composition (Bramley, 2005; Bramley, 2022; Song *et al.*, 2022b), trials using small-plot designs appear to have limited usefulness in informing growers how to target manage an entire production area.

A potential means to account for the impact of spatial variation on trial results is conducting experiments at field scales using spatially distributed designs. Examples include those conducted for broadacre crops by Adams and Cook (1997), Adams and Cook (2000), Cook and Bramley (1998), Cook *et al.* (1999), Doerge and Gardner (1999), and Pringle *et al.* (2004) whereby treatments are applied to an entire field in a highly replicated, non-randomised way. Randomised designs have also been proposed (e.g. Bullock *et al.*, 2019), although Bramley *et al.* (2022) have argued that such designs may add unnecessary complexity to the trial process without providing additional value for guiding on-farm decisions. In both cases, treatments can be applied using variable rate technology (VRT), and data collection can be automated using yield monitors. As such, the experiment does not unduly interfere with normal field operations. Data collected from such trials can be analysed using geostatistical methods to generate results to visualise spatial variation in crop responses across the field (Bishop and Lark, 2007; Bramley *et al.*, 2013; Pringle *et al.*, 2004). The results of such trials can be used to guide targeted management if farmers are willing and able to implement it. OFE of this type, while statistically robust, presents a complex trial layout that needs VRT for practical implementation. Moreover, although the data analysis has been packaged in Precision Agriculture Tools (PAT; Ratcliff *et al.*, 2020) that can be accessed freely, the skills and knowledge required for using the tools are likely barriers to the uptake of the spatially distributed designs by growers or their consultants.

A practical design for vineyard experiments using a whole block is to apply replicated treatments to entire rows of vines—also known as “strips” in the context of OFE. The application of replicated strip designs in whole-of-block experimentation has been demonstrated by Bramley *et al.* (2011a) and Panten and Bramley (2012) in different vineyards in Australia. Vineyard managers involved in these experiments indicated that the results were useful for them to better understand how spatial variation influenced crop responses. Hence, experiments of this type may be of interest to broader audiences of grapegrowers and producers of other crops grown in distinct rows. Like earlier work in broadacre crops, technology that allows automated collection of data is preferable to minimise the time and labour required for large amounts of measurements across a trial block. Currently, grape yield and vine vigour are two of the few viticultural response variables amenable to automated data collection. Even so, sensing grape yield requires access to a yield monitor, which is not commonly used by growers in Australia (Bramley, 2013; Song *et al.*, 2022b). Also, analysing and visualising the yield data require related skills, knowledge and time, which are generally unavailable or limited for growers. Replicating treatments to cover an entire block may be another problem for growers due to the cost, effort and logistical issues associated with trial implementation (Song *et al.*, 2022b).

To simplify experimentation further, the use of a single strip of field length or a section of field length has been explored (Lawes and Bramley, 2012; Whelan *et al.*, 2012). Compared to the whole-of-block approach, data analyses are simpler given that they are amenable to comparisons of mean treatment effects or a *t*-test if needed, which can be completed with the aid of a spreadsheet by growers or consultants. The “small strip” approach of Whelan *et al.* (2012) involves defining management zones of a field based on prior knowledge and randomly allocating replications of treatments to strips within the zones; however, efficient implementation of the design requires VRT. Moreover, treatment effects are presented in the format of the mean of each management zone, meaning that crop responses at finer spatial resolution in the block remain unknown.

Lawes and Bramley (2012) introduced a spatial element to a simple strip approach by applying the moving window *t*-test to reveal spatial variation in treatment effects along a strip that traverses pre-identified management zones of a field. While the analysis did not account for spatial correlation in response data, growers rarely base decision-making on statistical significance but prefer to know the magnitudes of treatment differences (Bramley *et al.*, 2005; Song *et al.*, 2022b). This trial approach has been found useful for informing management decisions in grain (Lawes and Bramley, 2012) and sugarcane crops (Webster and Bramley, 2016); hence, there is potential to adapt this approach to vineyard experiments. What is lacking is a set of reliable criteria to guide the positioning of one or more strips in a vineyard block to reveal likely treatment responses across the entire area.

The objective of this study was to investigate criteria and proxy indicators for positioning one or a few trial strips in a vineyard block to infer likely varying treatment responses in all locations of the block. Indicators of crop or land variability covarying with a response variable of interest, namely covariates, have been described previously (Baluja *et al.*, 2012; Bramley *et al.*, 2011b; Lanyon and Bramley, 2006; Panten and Bramley, 2011). For example, Bramley and Lanyon (2002) found that variation in grape yield in a vineyard of Cabernet-Sauvignon in South Australia was driven by variation in elevation (m above sea level). Lanyon and Bramley (2006) also reported a negative association between berry weight and soil electrical conductivity (soil EC, dS/m), an indicator of soil salinity, in a vineyard block of Sauvignon Blanc in South Australia. Here we explore soil EC, elevation and “plant cell density” (PCD) as potential covariates for positioning trial strips of two vineyard experiments with different viticultural response variables. PCD, otherwise known as the simple ratio, is a vegetation index of crop vigour (Dobrowski *et al.*, 2003). To do this, we use two previous whole-of-block vineyard experiments with replicated (i.e. multiple strips) designs (Bramley *et al.*, 2011a; Panten and Bramley, 2011) as a data resource. The findings are discussed in terms of the usefulness of the single-strip approach for informing management decisions and practical implementation by grape growers or their consultants.

MATERIALS AND METHODS

Information regarding the trials used for this study is provided in Table 1. The investigation involved five main

steps: (1) defining response variables and candidate covariates for each experiment; (2) sampling the datasets for subsequent processing; (3) using the sampled data to select useful covariates to the response variable of interest; (4) assessing the temporal stability of the relationship between the covariates and response variables; and (5) identifying potential locations for strip trials by examining the results of trials using simulated strips that have different ranges of spatial variation in a useful covariate.

1. Defining response variables and candidate covariates

1.1. Mid-row management experiment

The whole-of-block experiment of Panten *et al.* (2010) (Table 1) was established in response to the vineyard manager’s concerns about the low yield of the block. In 2004, fruit yield was recorded as yield (t/ha) using a HarvestMaster™ yield monitor (HarvestMaster, Inc., USA) and the data were processed into a yield map (Figure 1a). At harvest in 2006 and 2007, the yield was collected as total bunch mass per linear m (kg/m) measured from 377 target vines, including 125 samples for RC, 126 samples for RM and 126 samples for CL treatment. The manual measuring of yield in 2006 and 2007 was to minimise the impact of frost on trial results by selecting the least affected vines. Panten *et al.* (2010) log-transformed the data in 2006 and kriged them into yield maps for each treatment (Figure 1b–d). Soil EC (dS/m) for the block was obtained on November 1, 2004 (Figure 1e) using an EM38 soil sensor. PCD was calculated using the red (R) and near-infrared (NIR) bands of remotely sensed imagery ($PCD = NIR/R$) obtained at veraison

TABLE 1. Key details of two experiments from which data were sourced for this study.

Description	Mid-row management experiment	Powdery mildew experiment
Objective	Investigating three different mid-row management strategies regarding their effects on improving grape yield.	Evaluating the effects of two ‘reduced sulphur’ fungicide programs for the control of powdery mildew.
Treatment	(1) Ryegrass supplemented by compost (RC) (2) Ryegrass supplemented by mulch (RM), or (3) Cereal or legume in alternating mid-rows (CL). The treatments were applied after harvest in 2004 in alternating strips comprising four mid-rows.	(1) One application (S1), or (2) Two applications (S2) of sulphur as Cosavet-DF® (Sulphur Mills Ltd, Mumbai, India). The treatments were applied in December 2005 in alternating strips comprising six rows and as part of a broader spray program for season-long mildew management.
Experimental site and region	A 4.8 ha block of Merlot in the Clare Valley, South Australia. Row and vine spacings were 3 m and 1.5 m.	A 4.5 ha block of Pinot noir in the Coal River Valley, Tasmania. Row and vine spacings were 2.5 m and 1.25 m.
Response variable and related data used in each study	Yield (t/ha) in 2004 from a yield map Yield (kg/m) of 377 target vines in 2006 and 2007 Yield (log-transformed) of RC, RM and CL in 2006 from yield maps	Severity of powdery mildew of 236 target vines expressed as transformed disease scores Mildew severity as transformed disease scores of S1 and S2 from disease maps
Candidate covariate in the current study	PCD* in 2004 Soil EC** (dS/m) in 2004	Elevation (m)
Reference	Panten <i>et al.</i> (2010)	Bramley <i>et al.</i> (2011a)

*PCD, plant cell density, a vegetation index of crop vigour (Dobrowski *et al.*, 2003).

**Soil EC, soil electrical conductivity, an indicator of soil salinity.

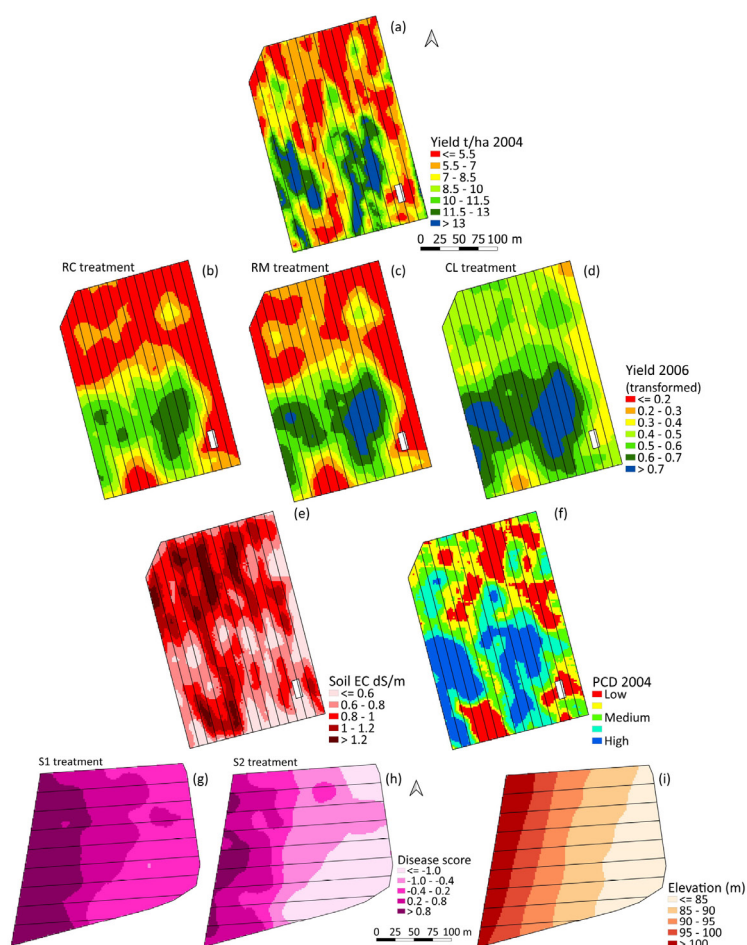


FIGURE 1. Summary maps for the mid-row management experiment in a 4.8 ha block of Merlot in Clare Valley (a-f) (Panten *et al.*, 2010) and the powdery mildew experiment in a 4.5 ha block of Pinot noir in Coal River Valley (g-i) (Bramley *et al.*, 2011a).

The maps show spatial variation in the response variables (a) yield (t/ha) in vintage 2004, and log-transformed yield in vintage 2006 for treatments (b) ryegrass and compost (RC), (c) ryegrass and mulch (RM), and (d) cereal and legume (CL), and the candidate covariates (e) soil EC (dS/m) and (f) PCD at veraison in 2004 for the mid-row management experiment. For the powdery mildew experiment, they show the response variable transformed disease scores for treatments (g) S1 and (h) S2, and (i) the candidate covariate elevation (m). For ease of interpretation, the black lines in the Merlot block (a-f) represent every fourth simulated row or strip (from the western boundary) of 59 rows; those in the Pinot noir block (g-i) represent every 10th row (from the southern boundary) of 89 rows. See text for further explanation.

in 2004 (Figure 1f) using airborne digital multispectral video with an on-ground resolution of 50 cm.

In the current study, yield (t/ha, kg/m or transformed yield) was the response variable (Table 1). PCD was treated as a candidate covariate at this site because vine vigour has been found to be correlated with yield in spur-pruned vineyards (Baluja *et al.*, 2012; Bramley and Lamb, 2003; Filippetti *et al.*, 2013; King *et al.*, 2014). Soil EC (dS/m) was also a candidate covariate because of the interaction observed between it and yield in the trial block (Panten and Bramley, 2011) and other parts of the same property (Bramley, 2003).

1.2. Powdery mildew experiment

The whole-of-block experiment of Bramley *et al.* (2011a) (Table 1) was established in response to the concerns of the vineyard manager about powdery mildew caused by *Erysiphe*

necator, and his perception of the negative impact of sulphur on beneficial arthropods and human health. At veraison in 2006, the severity of powdery mildew was assessed on 20 bunches per vine from 236 target vines distributed between the two treatments. These data were used to calculate mean mildew severity (%) per vine. Bramley *et al.* (2011a) transformed mean severities to “disease scores”, and kriged transformed data into two disease maps for the treatments (Figure 1g, h). Elevation (m) for the block was sourced from a digital elevation model (DEM) (Figure 1i) produced following a survey with kinematic GPS.

In the current study, the mean severity of mildew (% per vine or transformed disease score) was the response variable (Table 1). Elevation (m) was treated as a candidate covariate because mildew severity at this site was observed to be greater at the upslope than downslope (Bramley *et al.*, 2011a).

The raster data described above for the two experiments, including the DEM, PCD, soil EC and maps for response variables, were projected onto the same 2 m grid of the vineyard block by the authors of the original studies. Strips were simulated on the raster layers to represent vine rows, and points along the strips were used to represent vines in the blocks to enable data sampling.

2. Data sampling

To select useful covariates for the mid-row management experiment, values of PCD, soil EC (dS/m), and yield (t/ha) in 2004 were extracted from the locations of 377 target vines using the “Extract Pixel Statistics for Points” tool of PAT (Ratcliff *et al.*, 2020) in Quantum GIS (QGIS v3.10.8). A 3*3 neighbourhood filter was used for data extraction to smooth the small anomalies in data introduced by inaccuracies or irregular movement of instruments such as sensors (Ratcliff *et al.*, 2020). That is, extracted values for each sample point were the mean of the central pixel and the surrounding 3*3 array of eight additional pixels. The same method was used to extract values for 236 target vines from DEM for the powdery mildew experiment.

The sampling to simulate trial strips was a three-step process using QGIS. First, 59 north-south (NS) strips were created along the 59 vineyard rows (Figure 1a–f). Two rows at the west and east boundaries of the block were excluded to eliminate potential edge effects. Second, sample points were created at 2 m intervals along each of the 59 strips using the “Create Strip Trial Points” tool in PAT (Ratcliff *et al.*, 2020). The 2 m interval was selected to ensure that the values of adjacent points were from different pixels and to capture spatial variation in crop responses within a short distance. Variations in row length resulted in different numbers of sample points per strip among the 59 strips. The 59 strips generated 7748 sample points. The last step involved extracting values at each sample point from PCD, soil EC (dS/m), yield (t/ha) in 2004 and yield maps for three treatments in 2006 for each strip following the same procedure described above.

For the mildew experiment, 89 NS trial strips were similarly simulated along actual vine rows. However, these NS strips only encompassed small proportions of the range of spatial variation in elevation in the block, which prevented the

evaluation of information generated by strips encompassing large proportions of the elevation range, assuming elevation would be a useful covariate. Therefore, 89 east-west (EW) trial strips were also simulated (Figure 1g–i), generating 8737 sample points. Note that the EW positioning of trial strips in a block with NS-oriented vine rows would be impractical for a real experiment. Here we use these simulated strips to demonstrate the potential of the proposed method. Two strips at the southern and northern boundaries were excluded to eliminate potential edge effects.

3. Selecting useful covariates

The selection of useful covariates consisted of two steps (Figure 2). The first step was analysing the correlation between a response variable and candidate covariates sampled at the target vines using Pearson’s correlation coefficient (r). Given that the statistical significance of r could be biased by spatial autocorrelation in the data, the modified t -test approach of Dutilleul *et al.* (1993) was applied to the correlation analysis to generate estimates of a corrected ‘effective sample size’ and to adjust the metric of statistical significance accordingly. Before the analysis, seven outliers were removed from the sample of the mildew experiment. Sampled data for PCD, yield (t/ha) in 2004, and mildew severity (%) of target vines from both experiments were log- or square root-transformed to meet requirements for normality (Mood, 1950). The analyses were performed using the RStudio (RStudio Team, 2020) and SpatialPack (Ronny *et al.*, 2020). A candidate covariate was further assessed in the second step (Figure 2) if the correlation in this first step was significant ($p < 0.05$).

The second step was to determine useful covariates by examining the correlation between values of the ‘row-to-block’ variation index (RBVI) for the response variable and values of the index for the candidate covariate. In other words, what this step seeks to do is, for each simulated row, calculate the proportion of variation in a variable of interest in the row relative to its variation in the entire block. The index was calculated as follows:

$$RBVI = \frac{\text{the range (max - min) of the [variable of interest] in a row}}{\text{the range (max - min) of the [variable of interest] in the block}}$$

Thus, a row with a low value close to 0 for RBVI indicates that the row has much lower variation than the block as a whole,

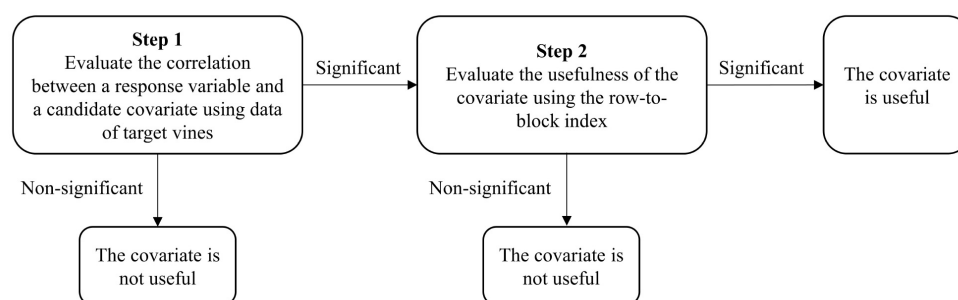


FIGURE 2. Two-step process for selecting a useful covariate to a response variable of interest.

A correlation is considered significant if $p < 0.05$.

whereas a row with a high value close to 1 for RBVI might have almost as much variation as encountered in the whole block. The correlations between values of RBVI for response variables and candidate covariates for the simulated strips were measured using uncorrected Spearman's correlation because the associations were monotonic. If a correlation was significant ($p < 0.05$), the covariate was regarded as useful for positioning a strip trial.

4. Assessing temporal stability of covariates

For the mid-row management experiment, the relationship between a useful covariate and a response variable was considered to be temporally stable if there was a significant correlation between the covariate in 2004 and the yield (kg/m) of 377 vines in 2006 and 2007. Pearson's correlation analysis with Dutilleul's correction was applied after removing seven and five outliers in the 2006 and 2007 yield data. Prior to correlation analysis, data of PCD and yield (kg/m) in 2006 and 2007 were log- or square root-transformed as required for normality (Mood, 1950).

5. Identifying useful locations for strip trials

To identify potentially useful locations for strip trials in a block, threshold values of RBVI of > 0.80 and < 0.20 were used to compare and contrast the information generated by strip trials having relatively large and small values for the index. Note that the choice of RBVI values is subjective, and one can select other values as desired. Nonetheless, higher RBVI values of close to 1 for a useful covariate are suggested for selecting trial rows as the trial can then theoretically provide more information about treatment effects at the trial site.

Crop responses in adjacent strips were compared using a moving window average. Each window comprised a pair of 10 sample points of each treatment, equivalent to 20 m of a row. Using the mid-row management trial as an example, moving from the north end to the south, the mean of the first ten values of yield (kg/m) for the RC treatment was compared with that for RM or CL. The window was then moved by one sample point along the strip to compare the next pair of 10 values (from the 2nd to the 11th value) until the last pair on the strip was compared. In total, x points per strip produced $x - 9$ comparisons. The statistical significance of the comparisons was not obtained due to spatial autocorrelation in the data and the complexity of accounting

for spatial autocorrelation for this analysis. Moreover, it is the magnitudes of treatment differences that are of interest to grapegrowers (Song *et al.*, 2022b). The moving average was also applied to values of useful covariates to examine how the crop responses varied with the covariates.

To examine trial results in the context of grape production, the extracted values of sample points of selected strips for both trials were back-transformed to yield (kg/m) or back-matched to original values of mildew severity (%). The latter was done according to a transformation file which recorded the transformed disease scores and corresponding values of mildew severity. Where there was no original value for a disease score in the file, the severity was estimated as the mean of the values before and after it in the file.

RESULTS

1. The mid-row management experiment

PCD and soil EC (dS/m) were correlated to yield (t/ha) in 2004 based on effective sample sizes of 26 and 31 (Table 2). However, only PCD was considered a useful covariate for grape yield based on the significance of correlations between values of RBVI for grape yield and those for each candidate covariate (Table 2).

PCD in 2004 was correlated to yield (kg/m) in 2006 and 2007. The correlation coefficients were 0.64 and 0.55 for effective sample sizes of 50 and 67 ($p < 0.001$) and lower than the r of 0.83 in 2004 (Table 2).

Simulated strips 57 and 9 with RBVI of 0.18 and 0.85 for PCD were selected to compare the information generated from strip trials with relatively large or small values of RBVI.

In strip 57 (low RBVI), the yield for CL was numerically higher than the yield for RC or RM, while there was little difference in yield between RC and RM (Figure 3a). These results may lead to the conclusion that applying CL to the whole block would be beneficial for improving grape yield. This conclusion, however, was not sufficiently informed since the strip provided little information about the effect of CL relative to RC or RM at other locations of the block with different values of PCD.

Similar to strip 57, the yield for CL in strip 9 was numerically higher than RC or RM in locations with relatively low or

TABLE 2. Correlations between yield (t/ha) in 2004 and candidate covariates, PCD and soil EC (dS/m) in 2004, for 377 target vines, and the corresponding correlations for the row-to-block variation index (RBVI) for yield (t/ha), PCD and soil EC (dS/m) in 2004 in 59 simulated trial strips from the mid-row management experiment. The effective sample sizes ($n_{\text{effective}}$) and corrected p values ($p_{\text{corrected}}$) were obtained using Dutilleul's modified t -test.

Candidate covariate	Data of target vines			Row-to-block index		
	Pearson (r)	P_{raw}	$P_{\text{corrected}}$	$n_{\text{effective}}$	Spearman (ρ)	p
PCD	0.83	***	***	26	0.67	***
Soil EC	-0.53	***	**	31	0.11	ns

***, ** and ns denote $p < 0.001$, $p < 0.01$ and not significant.

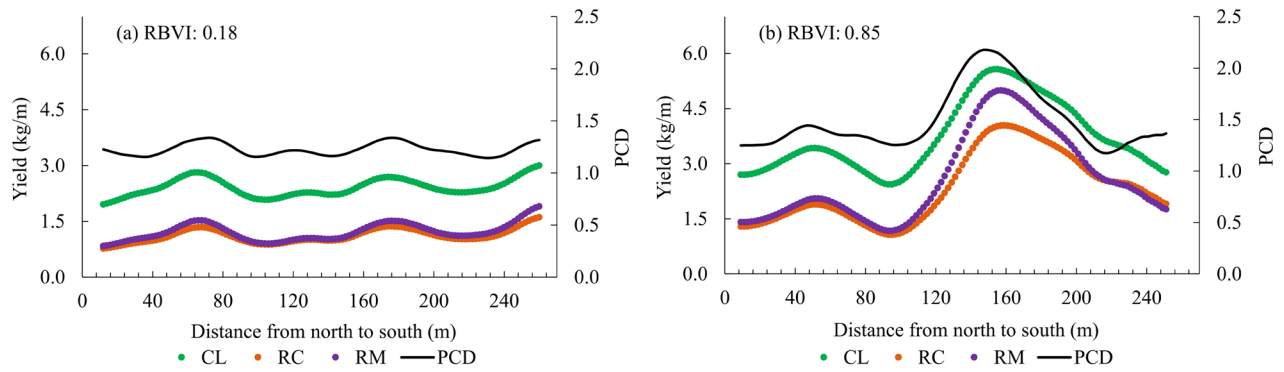


FIGURE 3. Spatial variation in yield (kg/m) in 2006 for the treatments along (a) strip 57 with a row-to-block variation index (RBVI) for PCD of 0.18 and (b) strip 9 with a RBVI for PCD of 0.85.

Treatments were cereal/legume (CL), ryegrass/compost (RC), and ryegrass/mulch (RM) applied in a 4.8 ha block of Merlot in South Australia.

high PCD (Figure 3b). However, Figure 3b also shows that where PCD was higher than approximately 1.4, the yield difference between CL and RM was smaller than that at locations with lower values of PCD, with the difference decreasing with increasing PCD values. The performance of CL relative to RM, where PCD was > 1.4, represented about 20 % of the area of the block (Figure 1f). Therefore, the results of strip 9 demonstrated that the use of a strip with an RBVI > 0.80 for PCD could generate information about the likely performance of the treatments relative to each other across the entire block; that is, strip 9 gave results which were highly consistent with those obtained using Panten and Bramley (2011)'s whole-of-block approach.

Analysis of spatial variation in crop responses was also conducted for other simulated strips. The strips with RBVI > 0.80 showed results of varying treatment effects similar to the results of strip 9, while strips with RBVI < 0.20 showed results similar to the results of strip 57 (data not presented).

2. The powdery mildew experiment

Elevation (m) was correlated to powdery mildew severity based on the coefficient of 0.57 and effective sample size for target vines of 11 ($p < 0.05$). The correlations between values of RBVI for elevation and those for mildew severity of S1 and S2 were also significant, with the coefficients being 0.65 and 0.60 for S1 and S2 ($p < 0.001$). Therefore, elevation was considered a useful covariate for powdery mildew severity.

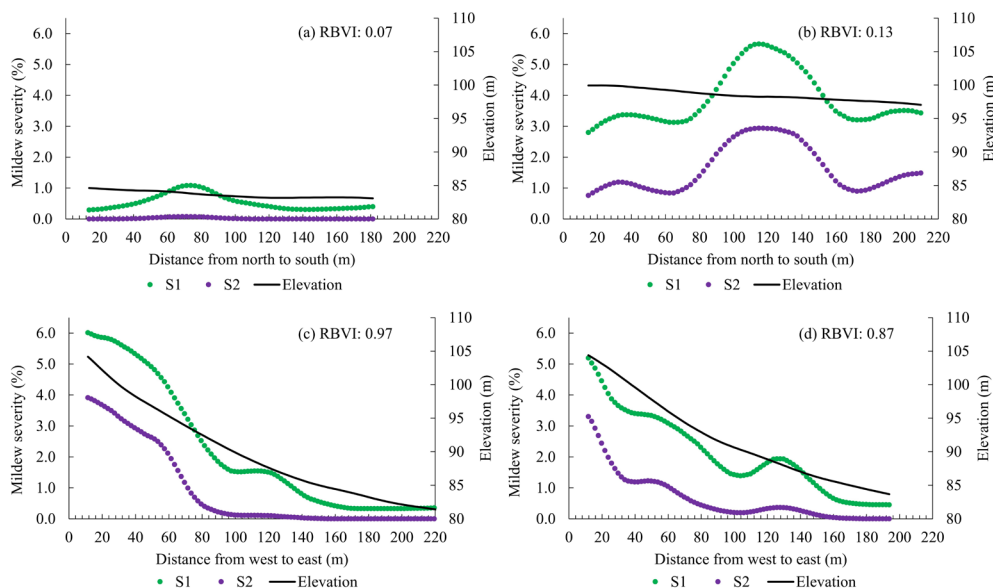


FIGURE 4. Spatial variation in the severity of powdery mildew (%) for S1 and S2 in 2006 along (a) north-south (NS) strip 70 with a row-to-block variation index (RBVI) for elevation of 0.07, (b) NS strip 15 with a RBVI for elevation of 0.13, (c) east-west (EW) strip 40 with a RBVI for elevation of 0.97, and (d) EW strip 75 with a RBVI for elevation of 0.87.

S1, S2 were one or two applications of sulphur applied in the 4.5 ha block of Pinot noir in the Coal Valley, Tasmania.

Simulated NS strips 70 and 15 and EW strips 40 and 75 with respective RBVI values of 0.07, 0.13, 0.97, and 0.87 for elevation were selected to compare the information generated from strip trials with relatively large or small values of RBVI. Here, trial results were interpreted based on the severity of powdery mildew tolerated by the wine business. We selected a threshold value of 3 % for the mean severity of mildew for parcels of grapes, above which there are known negative impacts on winemaking for some grape varieties (Stummer *et al.*, 2003). It is recognised that the threshold value is likely to vary among wine businesses depending on the intended end use for the fruit.

The NS strip 70 showed that both S1 and S2 resulted in mildew severities below 3 % along the strip (Figure 4a), which may lead to the conclusion that both treatments could provide effective control of powdery mildew for vines in the entire block. However, in the whole-of-block experiment, S1 resulted in mildew severities greater than 3 % for almost one-third of the area of the block (areas of disease score > 0.8 in Figure 1g), as did S2 at some upslope sites. Similarly, the results of NS strip 15 (Figure 4b) did not reveal the relatively poor performance of S2 at higher elevations or the effective control of mildew that S1 provided at lower elevations. Overall, neither of the two strips with low RBVI values for elevation could support informative decision-making given the range of elevation in the block as a whole.

Compared to NS strips 15 and 70, EW strips 40 and 75 showed that the mildew severity of S1 and S2 varied with elevation along the strips, with severities being greater at higher elevations (Figure 4c, d). Moreover, in the two EW strips, S1 resulted in mildew severities greater than 3 % at elevations higher than approximately 94 m and S2 at 98 m, with both treatments providing effective control of mildew at lower elevations. These results demonstrated that the use of a strip with an RBVI > 0.80 for elevation could generate information about likely crop responses to the treatments across the entire block, results that were analogous to those obtained using the whole-of-block design (Bramley *et al.*, 2011a).

Note that the analysis of spatial variation in crop responses along a strip was also conducted for other simulated strips. The strips with RBVI > 0.80 showed similar overall trends in spatial variation in mildew severity, while strips with RBVI < 0.20 also showed similar results (data not presented).

DISCUSSION

The results of this study demonstrate that a useful covariate, if available, can be used to assist with positioning a strip trial in a vineyard block that generates information about likely crop responses across the whole block. By selecting a strip with RBVI close to 1 for a useful covariate, the trial can indicate variation in treatment effects and the covariate along the strip, thereby informing how treatment effects will likely vary with the covariate across the block. Such information enables a grower to extrapolate the results of the strip trial to the rest of the block or possibly broader areas where the same covariate

is available (Panten *et al.*, 2010). Conversely, a strip trial with RBVI of close to 0 offers limited value for management beyond the trial strip. The idea of using spatial variability in a field to derive more value from a trial to support management decisions is in line with previous work (Colaço and Bramley, 2019; Cook *et al.*, 1999; Panten and Bramley, 2011; Reetz, 1996). Moreover, conducting the trial in a single crop row reduces time and labour requirements for data collection and lessens the risk of financial loss in the event that an ineffective treatment is applied to a strip rather than to an entire block. Therefore, compared to the whole-of-block approach (Bramley *et al.*, 2005; Bramley *et al.*, 2013), the strip trial method is more efficient to implement, especially when automated measurements are not available.

A key step of the strip trial approach is selecting available and useful covariates for a response variable of interest at a particular site, which requires data for the response variable and candidate covariates. In the demonstration of the approach, we used data from previous trials. However, we recognise that the data of a response variable of interest may not be available for identifying a useful covariate for a trial to be conducted. In this case, the grower can treat all available spatial data as candidate covariates to guide the positioning of trial strips in a block. To do so, we suggest using the map of each covariate with the associated RBVI value for each row in the block. Given that candidate covariates can have different spatial structures, multiple crop rows may be needed such that the trial has an RBVI of close to 1 for each of the covariates. However, a strip that has an RBVI of close to 1 for a covariate may only encompass the higher and lower values of the covariate in the block, meaning that it will be unlikely to generate useful information about treatment effects at locations with medium values of the covariate. Therefore, using the map of the covariate is recommended to help select a strip that encompasses the range of variation in the covariate through low, medium and high values. Measurements of the response variable can then be used to identify the useful covariates by modelling the relationship between the response variable and candidate covariates, estimating the map of the response variable for the whole block in GIS software and performing the two-step correlation analysis. Since growers often run a trial for multiple years (Song *et al.*, 2022b), measurements from the first year can be used to identify useful covariates and trial strips for subsequent years. However, these analyses require upfront investment by the wine business and impose a lead time before the optimal positioning of a strip can be applied. Such investment may present a barrier to the uptake of this approach.

In some cases, the crop rows in a block may have RBVI values much smaller than 1 for a particular covariate, such as the mildew experiment in which all the NS vine rows had an RBVI of < 0.2 for elevation. As such, at least three rows encompassing the low, medium and high ranges of variation in the covariate are recommended.

Currently, spatial data commonly used by grapegrowers in Australia are predominantly proxy measures of vine

vigour and soil EC (Bramley, 2013; Song *et al.*, 2022b). Other spatial data are either not widely used, such as yield maps and DEMs (Bramley, 2013; Song *et al.*, 2022b), or not yet commercially available to growers, such as data relating to fruit composition. The limited availability of, or easy access to, spatial data for more variables will likely restrict the application of the strip approach to certain questions of interest, at least until additional viticultural variables can be measured using efficient and affordable sensors.

In addition to spatial data, selecting a useful covariate also involves simulating strips and conducting correlation analyses for a response variable and a candidate covariate and the ‘row-to-block’ variation index. Currently, performing these analyses requires the use of statistical and GIS software, likely presenting a barrier for farmers and consultants. Automation of the analyses through tools such as PAT (Ratcliff *et al.*, 2020) would make the method more accessible to those who do not have the skills or time needed for this type of analysis. Additionally, if the statistical significance of treatment effects is required by users, the tool will need to account for autocorrelation in the data (Dutilleul *et al.*, 1993; Tisseyre and Leroux, 2017). Even with automation, the entire analysis needs to be simple for farmers to carry out while providing robust and relevant metrics of treatment effects along the length of the trial strip. Alternatively, the analysis of the strip approach can be assisted by specialists involved in farmers’ OFE, such as researchers and consultants with appropriate knowledge and skills (Bramley *et al.*, 2022; Lacoste *et al.*, 2022).

In this study, a p -value of 0.05 was used to select a useful covariate. For farmers’ trials, however, using a simple r value may be more appropriate. Recommendations on a threshold value for r that can be used to determine a useful covariate will need more data from different trials.

A concern that one might have about using a covariate to position trial strips is whether the correlation between a response variable and a useful covariate is temporally stable. In the mid-row management experiment, the correlation between yield and PCD remained significant from 2004 to 2007, although the strength of the correlation decreased. This might be attributed to a severe frost event and/or drought conditions that occurred during the experiment, which led to reduced water availability for irrigation for vintages in 2006 and 2007 (Panten and Bramley, 2011). Indeed, weather conditions such as rainfall can interact with land properties to influence crop performance (Li *et al.*, 2017), thus interfering with the relationship between a response variable and a covariate. Nonetheless, stable correlations between a particular covariate and vine parameters over multiple years have been reported in studies conducted at different geographical sites (Bonilla *et al.*, 2013; Bramley *et al.*, 2019; Fiorillo *et al.*, 2012; Proffitt and Pearce, 2004). For example, in a Sangiovese vineyard in Italy, the correlation between the “normalised difference vegetation index” and grape yield remained significant over four years (Fiorillo *et al.*, 2012). Therefore, a useful covariate is one that is likely stable over time in general.

CONCLUSION

In conclusion, the positioning of a trial strip such that the range of underlying variation in the strip is close to that encountered in the entire block can provide information about the likely variation in crop responses to a particular treatment in the block. The results of such a trial would therefore enable practical insights for a grower on whether to adopt the treatment and/or on opportunities for targeted management of the block according to spatial variation in treatment effects. While this approach has been deliberately discussed in terms of experiments in vineyards, it may also be adapted for those on other crops with distinct rows. How growers and their consultants perceive this strip approach and what support they will need to adopt or adapt it for their own trials, assuming they are interested in doing so, requires further investigation.

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