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ACCOUNTING FOR SPATIAL VARIABILITY IN FIELD EXPERIMENTS ON TEA

By T. U. S. PEIRIS†,‡, S. SAMITA§ *and* W. H. D. VERONICA‡,§

‡*Division of Biometry, Tea Research Institute of Sri Lanka, St Coombs Estate, Talawakelle, Sri Lanka and* §*Department of Crop Science, Faculty of Agriculture, University of Peradeniya, Peradeniya, Sri Lanka*

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SUMMARY

Spatial variability among experimental units is a common problem in field experiments on tree crops such as tea (*Camellia sinensis*). Spatial variability is partly accounted for by blocks, but a substantial amount remains unaccounted for and this may lead to erroneous conclusions. In order to capture spatial variability in field experiments on tea, six commonly used spatial analysis techniques were investigated: Covariate method with pre-treatment yield as the covariate, Papadakis and the Modified Papadakis nearest neighbour adjustments, Moving means and Modified moving means methods, and Autoregressive method. The data from long-term fertilizer experiments and cultivar evaluation trials, conducted at different locations by the Tea Research Institute of Sri Lanka, were used in the study. Spatial techniques were evaluated by means of their relative efficiency at each location and year. Evaluation of the four neighbour methods analysed in conjunction with the pre-treatment yield, revealed that spatial variability due to both past and current conditions are operative, especially in experiments with large blocks, and could be captured simultaneously. Relative efficiencies averaging 141% clearly indicated that the neighbour techniques in combination with pre-treatment yield would be effective in controlling the experimental error in tea experiments with large blocks (nine plots per block or more). Experiments with small blocks were not affected by spatial variability due to past conditions and only that due to current conditions need to be addressed. Neighbour techniques, on their own, were found to be adequate to capture spatial variability due to current conditions. The modified Papadakis technique was found to be the best with an average relative efficiency of 145%. The techniques investigated in the study can easily be implemented using standard statistical software. The precision of tea experiments could be increased by using covariate analysis with pre-treatment yield and any one of the four nearest neighbour adjustments tested, when the block size is large; and modified Papadakis technique, on its own, when the block size is small.

INTRODUCTION

Tea (*Camellia sinensis*), a perennial tree crop, is generally cultivated in hilly areas. Consequently, field experiments on tea have large plots sited mostly on moderately to steeply sloping land. For these reasons, the variability of the terrain and the physical and chemical soil properties, across experimental sites, is generally high. Various experimental designs are used to capture this variability (Quinn and Keough, 2002). The randomized complete block design (RCBD) is commonly used for field experiments because of its simplicity and applicability to field conditions (Basford and Turkey, 1995). Other designs used often for field experiments are row and column

†Corresponding author. usp71@yahoo.com

designs such as Latin Square Design and incomplete block designs with confounded factorial effects (Pearce, 2002). However, the control of error variation by means of experimental designs *per se* does not always achieve a satisfactory level of precision in large experiments, due to spatial variability between plots within a block and between plants within a plot (Rong-Cai *et al.*, 2004). Spatial variability should therefore be taken into account when analysing such trials to increase their precision (Singh *et al.*, 2003).

The efficiency of spatial techniques, relative to block designs, has been evaluated frequently (Ball *et al.*, 1993; Bartlett, 1978; Cullis and Gleeson, 1989; 1991; Kempton *et al.*, 1994; Scharf and Alley, 1993). However, these evaluations have been mostly of annual crop trials. When perennial crop experiments were evaluated, in any given study, only a single spatial technique had been considered *vis-à-vis* the conventional analysis. Also, the pattern and extent of spatial variability may differ considerably between environments (Rong-Cai *et al.*, 2004). In tea, especially, the size of plots, blocks and consequently the size of experimental sites, varies with the type of experiment (e.g. evaluation of fertilizers, cultivars). These variations may lead to differences in the efficiency of spatial techniques. Clearly, there is a need to identify effective techniques to control spatial variability in perennial crop field experiments. The objective of this study was to assess six commonly used model-based spatial techniques and evaluate the most efficient techniques for different types of experiments under different agro-climatic conditions.

MATERIALS AND METHODS

Yield data of a cultivar evaluation trial and two long-term fertilizer trials, testing macronutrients (N, K and Mg) and micronutrients (Zn, B, Mn), conducted by the Tea Research Institute of Sri Lanka, were used for the study. The cultivar trial had been repeated at four locations and the fertilizer trials at 11 locations to cover different climatic conditions that necessitate different agronomic practices. For instance, the duration of the pruning cycle at these locations ranges from 2.5 to 5 years. Details of the experiments are given in Table 1. The cultivar trial is recorded as a RCBD. However, as a large number of genotypes were being tested, the blocks were not compact; the plots were spread-out, in groups, due to limitations imposed by the nature of the site. In effect, each block comprised of several sub-blocks of uneven size.

Spatial analysis

According to Brownie *et al.* (1993), the linear model describing spatial trend is:

$$y_{ij} = \mu + \rho_i + \alpha_j + T_{ij} + \varepsilon_{ij} \tag{1}$$

where, y_{ij} = the yield of jth treatment in the ith block, μ = grand mean, ρ_i = ith block effect, α_j = jth treatment effect, T_{ij} = trend effect representing spatial variation in the ith block and the jth plot ε_{ij} = random error where $\varepsilon_{ij} \sim N(0,\sigma_\varepsilon^2)$.

Table 1. Details of the experiments and their respective locations.

Location	AER†	Cultivar	Study period	Design	No of blocks	Plants per plot‡	No. of treatments
N, K and Mg trial							
Courtlodge Estate	WU_3	PK 2	2000–2002	Confounded block design;	9 blocks (3 replicates)	40	27 (common to all 6 experiments – N: 240,420 and
Houpe Estate	WL_2	TRI 2025	2000–2002	three-way interaction		40	600 Kg $ha^{-1}a^{-1}$; K_2O: 120, 210 and 300 Kg
Lumbini Estate	WM_1	TRI 2026	2000–2001	confounded		40	ha^{-1} a^{-1}; MgO: 60,105 and 150 Kg ha^{-1} a^{-1})
Talgaswala Estate	WL_1	TRI 2027	2000–2002			40	
Tokatiyamulla	WL_2	TRI 2026	2000–2002			40	
Ury Estate	IM_2	TRI 3019	2000–2002			30	
Micro-nutrient trial							
Baddegama Estate	WL_1	TRI 2025	2000–2001	RCBD	4 blocks	40	6 (common to Baddegama, Greenwood, and
Greenwood Estate	WU_1	TRI 2025	2000–2003			40	Madulkele: $ZnSO_4$, $ZnSO_4$ + Epsom salts,
Madulkelle Estate	WL_1	TRI 2025	2000–2004			40	Multiplex, Kiecite, Chelamin, Water (control))
Indola Estate	IU_1	TRI 2025	2000–2003			40	5 (common to Indola and St. Coombs: $ZnSO_4$,
St Coombs Estate	WU_2	TRI 2025	2000–2004			50	Multiplex, Kiecite, Chelamin, Water (control))
Cultivar evaluation trial							
St Coombs	WU_2		2001–2003	RCBD	2 blocks	24	46 genotypes
Passara	IU_{3C}		2002–2003			25	22 genotypes
St Joachim1	WL_1		2000–2002			25	45 genotypes
St Joachim2	WL_1		2002–2004			24	61 genotypes

†AER: Agro-ecological region; WU: Upcountry wet zone; WL: Low country wet zone; WM: Mid country wet zone; IU: Up country intermediate zone; IM:– Mid country intermediate zone.

‡At the spacing of $4' \times 2'$.

A distinctive feature of this model is that it can be used to describe most spatial techniques. The six spatial techniques considered in the present study were:

(i) Classical covariate method (CCM) where pre-treatment yield (yield over the six-month period prior to the experiment) is used as the covariate. In this technique T_{ij} of the model (1) is defined as $\theta(x_{ij} - \bar{x})$ where x_{ij} is the pre-treatment yield of jth plot in the i^{th} block, $\bar{x}$ is the mean of the pre-treatment yield and θ is the regression coefficient.

(ii) Papadakis nearest neighbour method (PNNM) (Papadakis, 1984) where T_{ij} is defined as with CCM but x_{ij} is the mean plot residuals of eastern and western neighbours after fitting the model without accounting for spatial effect, i.e. $x_{ij} = (e_{ij-1} + e_{ij+1})/2$.

(iii) Modified Papadakis nearest neighbour method (MPNNM) (Wilkinson *et al.*, 1983) where x_{ij} is the mean of four plot residuals of eastern and western neighbours, i.e. $x_{ij} = (e_{ij-2} + e_{ij-1} + e_{ij+1} + e_{ij+2})/4$.

(iv) Moving average method (MAM) (Townley-Smith and Hurd, 1973) where x_{ij} is the arithmetic mean of two unadjusted plot yields of eastern and western nearest neighbours, i.e., $x_{ij} = (y_{ij-1} + y_{ij+1})/2$

(v) Modified moving average method (MMAM) where x_{ij} is the arithmetic mean of four unadjusted plot yield values of eastern and western nearest neighbours, i.e. $x_{ij} = (y_{ij-2} + y_{ij-1} + y_{ij+1} + y_{ij+2})/4$

(vi) Autoregressive method (AR(1)) (Gilmour *et al.*, 1997; Gleeson and Cullis, 1987). AR(1) is known to be capable of fitting the field trends directly. This technique assumes that the residuals are distributed according to spatial correlation models. The commonly used spatial correlation model for AR(1) is:

$$Cov(\varepsilon_{ij}, \varepsilon_{ij'}) = \sigma^2 Corr(\varepsilon_{ij}, \varepsilon_{ij'}) = \sigma^2 \rho^{|i-j|}$$

where, σ^2 is the residual variance and ρ is the autocorrelation parameter. The presence of a spatial trend suggests that the neighbouring plots tend to be more alike than those further apart ($\rho > 0$). In the AR(1) procedure, blocks are considered as a random factor so that only the within block spatial variability will be taken into consideration.

The residuals are usually used instead of means in nearest neighbourhood estimation. However, some studies (Lawrence and Townley-Smith, 1975; Mack *et al.*, 1978; Rosielle, 1980) have suggested that means could also be potential variates to be considered in nearest neighbour estimation. This was the main reason for moving average methods to be considered in the study. Obviously it is easier to use means than residuals. Due to the undulating nature of tea experimental sites, blocks are established along the contour. Thus, often several blocks are found in a single contour with a considerable distance between blocks. As spatial adjustments cannot be done here for both north–south and east–west directions, only one direction, the direction of the block, was considered. This often happened to be the east–west direction. To determine the extent to which spatial correlations are influenced by past and current conditions, all four neighbour methods were evaluated with and without CCM.

Though CCM is considered as a spatial method in the present study, it is not an explicit spatial approach. CCM can explain non-spatial variation also and is used extensively as an error reduction technique in tea experimentation.

The calculations and analysis described above were performed with SAS Version 8.1. PROC MIXED was employed for the restricted maximum likelihood (REML) analysis of the AR(1) method and PROC GLM was used for rest of the analysis.

Efficiency of spatial methods

An appropriate measure of relative efficiency is essential to evaluate the different models. Relative efficiency measured in terms of *s.e.d.* seems most relevant because it is directly used for comparisons between treatments, has the same scale as the original attributes and includes the efficiency factor (Qiao *et al.*, 2000). Therefore, relative efficiency of spatial analysis methods is computed as, $s.e.d._u / s.e.d._a$, where $s.e.d._u$ and $s.e.d._a$ are unadjusted (classical analysis) and adjusted (after taking account of spatial effect) standard error of the difference, respectively. In the case of AR(1), relative efficiency was computed using REML, where residual variance is directly estimated without explicitly considering the degrees of freedom.

Comparison of different spatial models

The comparison of models was carried out using the Akaike Information Criterion (AIC) (Akaike, 1974). PROC MIXED of SAS was used to compute the AIC values – the lower the AIC value, the better the model.

RESULTS

Application of CCM to the macronutrient trial showed that pre-treatment yield was a highly significant covariate ($p < 0.01$) at all the locations and years studied, except at Ury Estate. However, in the micronutrient trial, CCM was significant only on 9 out of 20 occasions (locations × years). The relative efficiency of CCM ranged from 100% to 145% in the macronutrient trial and 101% to 158% in the micronutrient trial, across all locations and years. CCM of course was not applicable to the cultivar evaluation trial.

In the macronutrient trial, PNNM made a significant improvement ($p < 0.01$) in controlling error variation at all locations and on 11 of 17 occasions. However, in the micronutrient trial, PNNM did not produce any significant improvement ($p > 0.1$) on almost all occasions; the exceptions were Indola in 2000 and 2003, Madulkelle in 2000 and St Coombs in 2000. In the cultivar evaluation trial, PNNM was significant only at St Joachim 1, St. Joachim 2 and Passara, in 2003. The relative efficiencies ranged from 99% to 122% in the macronutrient trial, 97% to 116% in the micronutrient trial and 102% to 115% in the cultivar trial (Table 2).

In the macronutrient trial, MPNNM produced a significant ($p < 0.05$) improvement at all locations except Lumbini and Court Lodge in 2000 and Talgaswala in 2001. In the micronutrient trial too, MPNNM was significant ($p < 0.05$) on all occasions except Indola in 2001 and 2004 and Madulkelle in 2003. In the cultivar evaluation trial,

Table 2. Mean relative efficiency of spatial techniques.

Location	CCM	PNNM	MPNNM	MAM	MMAM	AR (1)
N, K and Mg trial						
Court Lodge	127	122 (145)†	115 (139)	143 (160)	127 (146)	137
Houpe	128	120 (148)	120 (148)	132 (154)	125 (150)	133
Lumbini	129	99 (128)	100 (128)	103 (130)	104 (129)	101.5
Talgaswala	NA‡	114 (NA)	107 (NA)	117 (NA)	110 (NA)	124
Tokatiyamulla	145	110 (151)	110 (150)	119 (155)	115 (151)	129
Ury	100	108 (108)	108 (109)	115 (115)	111 (112)	115
Average efficiency across the locations	126	112 (139)	110 (137)	122 (146)	115 (140)	123
Micronutrient trial						
Baddegama	158	97 (155)	105 (154)	100 (161)	97 (153)	99.5
Greenwood	103	105 (108)	131 (130)	107 (116)	121 (128)	100
Indola	101	116 (118)	126 (131)	103 (102)	116 (116)	102
Madulkelle	111	116 (129)	149 (170)	104 (117)	115 (127)	100
St Coombs	124	113 (136)	216 (211)	97 (124)	125 (144)	101
Average efficiency across the locations	119	110 (126)	145 (158)	102 (119)	115 (131)	101
Cultivar evaluation trial						
St Coombs	NA	103	103	99	99	102
Passara	NA	102	102	99	99	100
St Joachim1	NA	115	121	110	113	105
St Joachim2	NA	109	106	106	105	105
Average efficiency across the locations	NA	107	108	104	104	103

†Values in the parenthesis are relative efficiencies for four neighbour methods in conjunction with CCM.
‡NA – Not applicable.

MPNNM was effective only at St. Joachim 1 and St. Joachim 2. In the micronutrient trial, the relative efficiency of MPNNM was much higher (105–216%) than in the macronutrient trial (100–120%) and the cultivar evaluation trial (102–121%) (Table 2).

MAM gave a significant ($p < 0.05$) improvement in the macronutrient trial on all occasions, except Lumbini and Ury in 2000. In the micronutrient trial, MAM was not significant except on three occasions: Greenwood in 2003, Indola in 2000 and Madulkelle in 2000. In the cultivar evaluation trial, MAM was significant ($p < 0.05$) only at St. Joachim 1 and St. Joachim 2. The relative efficiency ranged from 103% to 143% in the macronutrient trial, 97% to 107% in the micronutrient trial and 99% to 110% in the cultivar evaluation trial (Table 2).

In the macronutrient trial, MMAM produced a significant ($p < 0.05$) improvement except at Houpe in 2001, Lumbini in 2000, Talgaswala in 2001 and 2002, and Ury in 2000. In the micronutrient trial, MMAM gave a significant ($p < 0.05$) improvement on 11 out of 20 occasions, and on seven out of 11 occasions in the cultivar evaluation trial. The relative efficiencies were 104–127%, 97–125% and 99–113% in macronutrient, micronutrient and cultivar evaluation trials respectively (Table 2).

The AR(1) method produced very little improvement except in the macronutrient trial, where it was significant ($p < 0.05$) on 11 out of 15 occasions and the relative efficiency ranged from 101.5% to 137% (Table 2). It is noteworthy that the Newton

Raphason algorithm in PROC MIXED failed to converge on two occasions. In the other two trials, AR(1) did not produce any significant improvement. The relative efficiency was 100–105% in the cultivar evaluation trial and 99.5–102% in the micronutrient trial.

Serial correlation analysis was also performed in order to confirm the effectiveness of AR(1). In the macronutrient trial this gave a significant $r = >0.33$ ($p < 0.05$) correlation on 16 out of 17 occasions, but it was significant only on three out of 16 occasions and none in the micronutrient and cultivar evaluation trials respectively.

The four neighbour spatial methods, PNNM, MPNNM, MAM and MMAM, were also evaluated in conjunction with CCM. The combination with CCM did not bring about any change in significance of the neighbour methods in the macronutrient trial. However, in the micronutrient trial, the significance of CCM changed on 12 out of 80 occasions. CCM which was significant when applied separately, turned out to be non significant ($p > 0.1$) when applied in conjunction with neighbour methods. With MPNNM, the significance changed five times in 20 occasions (significant without CCM and non significant with CCM). With PNNM, MAM and MMAM there were no changes. In the macronutrient trial, CCM in conjunction with spatial methods produced relative efficiencies of 139, 137, 146 and 140% with PNNM, MPNNM, MAM and MMAM respectively. In micronutrient trials the corresponding values were 126, 158, 119 and 131% respectively (Table 2). Overall, combining with CCM did not bring about a substantial difference between neighbour methods, with respect to the number of times each method was found to be significant as well as in their relative efficiency.

According to the conventional analysis of RCBD, significant block effect was observed in 14 out of 16 occasions in large blocks (macronutrient trial). However, for small blocks (micronutrient trial), the block effect was significant only on two occasions out of 20. In cultivar trials this was 8 out of 13 occasions.

The AIC values for goodness-of-fit of different models are presented in Table 3. Low AIC values were recorded with MAM and CCM in the macronutrient trial and with MPNNM in the micronutrient and cultivar evaluation trials. Specifically, in the micronutrient trial, MPNNM exhibited highly consistent results. The pattern of AIC was exactly the same when the four methods were combined with CCM. However, AIC values decreased substantially when they were in combination with CCM, especially in the years and locations where CCM by itself was significant.

DISCUSSION

Generally, the methods tested had a positive impact on experimental precision but with different levels of efficiency. This no doubt reflects the fact that different methods capture different aspects of spatial variability. Nevertheless, efficiency values greater than 100%, in most years and across locations, establish the potential of these methods to capture spatial variability in block designs.

The micronutrient and macronutrient experiments had a similar plot size (about 40 bushes per plot) and shape. An undulating terrain was also a common feature of

Table 3. Akaike Information Criterion (AIC) values with different methods of analysis.

Location	RCBD	CCM	PNNM	MPNNM	MAM	MMAM	AR(1)
N, K and Mg trial							
Court Lodge	827	803	808 (790)†	810 (795)	790 (780)	802 (789)	798
Houpe	730	703	712 (690)	712 (690)	702 (687)	707 (689)	716
Lumbini	853	822	839 (839)	853 (823)	850 (823)	849 (822)	843
Talgaswala	808	NA‡	795 (NA)	801 (NA)	794 (NA)	799 (NA)	786
Tokatiyamulla	831	792	821 (789)	820 (788)	813 (787)	816 (788)	809
Ury	750	749	743 (742)	741 (740)	736 (737)	738 (738)	736
Micronutrient trial							
Baddagama	235	219	234 (219)	231 (218)	234 (219)	234 (219)	285
Greenwood	212	210	209 (208)	203 (202)	209 (206)	206 (204)	254
Indola	164	164	160 (160)	158 (157)	163 (163)	160 (160)	192
Madulkelle	215	211	211 (207)	203 (202)	214 (211)	210 (207)	251
St Coombs	166	158	162 (156)	148 (147)	166 (158)	160 (155)	196
Cultivar evaluation trial							
St Coombs	488	NA	486	485	488	487	502
Passara	364	NA	363	363	368	364	380
St Joachim1	1043	NA	1027	1021	1032	1028	1050
St Joachim2	1191	NA	1183	1187	1184	1186	1196

†Values within the parenthesis are AIC values for neighbour methods in conjunction with CCM.
‡NA – Not applicable.

the sites of both experiments. The main difference between the experiments was in the block size – five or six treatment plots per block in the micronutrient trial and nine plots per block in the macronutrient trial. Most of the methods tested were effective in the macronutrient trial where the block size was relatively large. This shows that spatial techniques can be used effectively in experiments with large blocks. However, this advantage was not seen in the cultivar evaluation trial with very large blocks containing 22 to 61 genotypes. This can be ascribed to the improper layout of the cultivar evaluation trial where a block consisted of several sub-blocks containing 2–10 plots each. The plot size was also smaller than in the nutrient trials.

In the macronutrient trial, all the methods tested were effective with CCM being the most effective. This shows that CCM is the most effective method to capture spatial variability when the block size is large (at least with nine plots per block).

MPNNM performed better than the other methods in the micronutrient trial indicating that MPNNM is effective in capturing spatial variability in small blocks. MPNNM was moderately effective in the macronutrient trial indicating that MPNNM can account for spatial variability even when the block size is large.

MAM was found to be moderately effective with large bocks but not effective with small blocks. PNNM and MMAM seem to be equally effective, at a moderate level, with large blocks as well as small blocks.

AR(1) was found to be moderately effective in the macronutrient trial but not in the micronutrient trial. AR(1) specifically accounts for linear trends. Linear trends being less likely with small blocks could explain the poor performance of AR(1) in the micronutrient trial. AR(1) being moderately effective in the macronutrient trial, and the results of the serial correlation analysis lend support to the view that a linear trend can be detected only with large blocks. It may be concluded that AR(1) is appropriate only for experiments with large blocks.

In the micronutrient trial MPNNM performed considerably better than PNNM. MPNNM uses four neighbouring plots to adjust a plot value while PNNM uses only two. Using four plots considerably reduces the probability of bias in trend estimation and is the likely basis for MPNNM's superiority.

MMAM is expected to estimate the trend better and thereby perform better than MAM. In fact this was observed in the micronutrient trial, but it was not the case in the macronutrient trial. A possible explanation is that spatial variability due to past conditions was dominant in the macronutrient trial.

Since CCM captures initial variability, it can be viewed as a method that captures spatial variability due to past conditions. The other methods tested can be considered as methods that capture the spatial variability due to current conditions or the long-term nature of the experiments.

An important finding that stems from this study is that both past and current spatial variability can be captured simultaneously. This became evident when the neighbour methods were evaluated in conjunction with CCM. When the neighbour methods were evaluated in conjunction with CCM, especially in the macronutrient trial, seven out of 14 times both CCM and neighbour methods became significant proving that past and current spatial variability are two separate aspects. However, this was not clearly evident in the micronutrient trial. In the micronutrient trial, CCM and other neighbour methods were rarely significant when analysed together. Thus it seems both aspects of spatial variability can be detected simultaneously only when the block size is large, not when it is small. In micronutrient trials, CCM was not significant when it was evaluated with other methods. This indicates that spatial variability due to past conditions is significant only when the block size is large. In fact, on 12 occasions in the micronutrient trial, CCM which was significant when analysed separately, became non significant when analysed in conjunction with the neighbour methods. However, a non significant CCM never turned significant when analysed in conjunction with neighbour methods. This also supports the contention that spatial variability due to past conditions is either not operative or cannot be detected when the block is small. In the macronutrient trial, when neighbour methods were evaluated along with CCM, the error reduction by CCM was greater than that by neighbour methods. This shows that spatial variability due to past conditions is more dominant than current spatial variability when the block size is large. On the whole, all four neighbour methods, analysed along with CCM, were more or less of the same efficiency. Therefore, any of the four neighbour methods studied could be used to increase the efficiency of field experiments on tea.

In large block experiments, comparing RCB with spatial methods, the majority of the trials with significant spatial trends also had significant RCB block effects. But in small block experiments, non significant RCB block effects had significant field trends. Though these experiments were designed assuming that major trends differences are between blocks as happened in well-designed experiments, due to the undulating nature of tea experimental sites spatial variability (specifically trends due to current conditions) with in blocks might be prominent though block size is small.

One of the results found in this study is that blocking often performs poorly in the function of reducing experimental error. It is clear that adjustment by neighbouring methods can often be effective especially on irregular experimental sites.

Inconsistency in efficiency across time suggests that the spatial variability within a block may be transient in nature. This may arise from numerous biological and/or physical phenomena that interact to influence differences in soil characteristics among plots (Smith and Casler, 2004). Despite the transient nature of spatial variability, spatial methods evaluated in the study were found to be effective. Hence the methods evaluated have a potential use under varied conditions.

CONCLUSIONS

Spatial analysis techniques, in conjunction with the standard practice of using pre-treatment yield as a covariate (CCM), have an important role in reducing error in long-term field experiments on tea.

Spatial variability due to both past (inherent) and current conditions are encountered, especially in experiments with large blocks (nine plots per block or more). Efficiency of these experiments can be increased by addressing both aspects of spatial variability simultaneously.

Neighbour techniques in combination with CCM were effective in controlling experimental error in experiments with large blocks. Experiments with small blocks were not affected by spatial variability due to past conditions, and only that due to current conditions was operative and need to be addressed. Neighbour techniques, on their own, were found to be adequate to capture spatial variability due to current conditions; MPNNM was the most effective.

The precision of tea experiments may be increased by using CCM and any one of the four nearest neighbour adjustments tested, when the block size is large; and modified Papadakis technique (MPNNM), on its own, when the block size is small.

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