Can unreplicated strip trials be used in precision on-farm experiments?

Gary Hatfield[1] Graig Reicks[2] Eric Carter[1]

[1] Department of Mathematics and Statistics, South Dakota State University, Brookings, SD

[2] Department of Agronomy, Horticulture, and Plant Science, South Dakota State University, Brookings, SD

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

Abstract. On-farm experiments are used to evaluate a wide variety of products ranging from pesticide and fertilizer rates to the installation of tile drainage. The experimental design for these experiments is usually replicated strip trials. Replication of strip trials is used to estimate experimental error, which is the basis for judging statistical significance of treatment effects. Another consideration for using strip trials is greater within-field variability than smaller fields used for small-plot research. Data from strip trials also differ in their statistical properties from data collected in small-plot trials. The larger scale experiments often result in thousands of correlated observations, violating the assumption of independence. When conducting on-farm experiments, it is not always possible to replicate strip trials. Since there is no replication, there is no estimate of error and it is not possible to determine statistically whether or not there is a real treatment effect. Spatial statistical modeling is used to describe spatial heterogeneity and the relationship of neighboring observations. In spatial analysis, characteristics of neighboring observations are incorporated into the statistical model. A method is proposed to exploit the underlying spatial relationship of a strip trial with adjacent control strips to estimate a treatment effect for unreplicated strip trials and improve management decisions. Specifically, ordinary kriging based on a spherical semivariogram model with nugget is used to predict yield for treatment points. These predicted yields are matched with the corresponding observed yields for the treatment points and a paired t test is performed. The proposed method is applicable to many on-farm experiments to improve the quality and value of farmer's site specific management decisions.

Keywords. *on-farm research, strip trial, yield monitoring, spatial analysis, semivariogram, ordinary kriging.*

Introduction

On-farm research and the use of statistics for designing and analyzing agriculture experiments have been around for a long time. Combining the two concepts, along with precision agriculture, results in a synergistic effect that has been proven in numerous studies. The technologies of precision agriculture have not only facilitated the practice of site-specific crop management, but also provide precision measuring instruments at the landscape scale. This allows farmers to obtain data from experiments in their fields (Plant 2007). Fulton et al. (2010) note that yield monitors are vital reference tools for grain growers to make informed management decisions and to obtain information on cultural practices. Grove (2006a) points out that on-farm research requires investment in time and management.

Planning an on-farm research trial follows a systematic approach: a meaningful question or hypothesis is developed, the project is planned and conducted to objectively test the question, data are carefully measured and recorded, and results are statistically interpreted (Nielsen 2010). Some specific components of a statistically designed experiment include treatment, experimental unit, replication, and randomization.

A treatment is the set of circumstances created for the experiment in response to research hypotheses and are the focus of the investigation (Kuehl 2000). Examples of treatments investigated in South Dakota include seeding rates other than the farmer's standard and the effectiveness of foliar and seed-applied products. The aim of the analysis is to address whether the product worked on the entire field or if effectiveness was just site specific.

An experimental unit is the physical entity exposed to the treatment independently of other units (Kuehl 2000). Experimental units may be strips that span the length of the field (Kyveryga et al. 2015). The width of the strips are dependent on the treatment and equipment used to apply the treatment. For example, a seeding rate experiment may use a 12.19 m planter or an application may use a 36.58 m boom sprayer.

A replication is a physical repetition of experimental units with the same treatments across a field; with at least four replicates recommended for all treatments (Kyveryga et al. 2015). Replication provides information about the consistency of the yield difference and allows smaller yield differences to be statistically significant (Grove 2006b). The existence of replications helps to ensure the absence of a pattern in the experimental layout when treatments are assigned randomly (Plant 2007). However, statistical significance must be tempered with practical significance. It is also important to determine if a statistically significant treatment is profitable or economically significant (Hicks et al. 1997).

Randomization is an important component of experimental design. The random allocation of treatments to experimental units helps avoid systematic bias (Grove 2006b).

No matter how carefully an experiment is planned, sometimes there are circumstances beyond control that preclude the replication of treatments. Examples that have been encountered in South Dakota's On-Farm Research program include lack of time and resources.

All is not lost when there are unreplicated treatments in strip trials. Girma and Machado (2013) review a few methods that can be used to analyze non-replicated data regardless of its nature. These include augmented designs, an intraclass correlation coefficient (ICC) based analysis, using higher order interactions from non-replicated factorial designs, and the use of spatial and temporal variation.

The method proposed for analysis of unreplicated strip trials is ordinary kriging. This will model the underlying spatial relationship and exploit spatial variation. Yield for points in nearby control strips are used to predict yield for points in the unreplicated treatment strip. Predicted yields are matched with corresponding observed yields for treatment points and a paired t test is performed.

Materials and Methods

Yield monitor data for soybeans harvested during the 2017 growing season were analyzed for a farm in South Dakota. The producer participated in the Soybean Research Council On-Farm Research program and investigated a high seeding rate. In this experiment, a higher seeding rate of 170,000 seeds per acre was compared to the normal seeding rate of 140,000 seeds per acre. This investigation determined whether a higher seeding rate was needed on certain soil types. There's been evidence that increased seeding rates may be beneficial on upland soils.

Data Processing and Geospatial Analysis

Open-source software was used for data processing and geospatial analysis. QGIS (https://qgis.org/en/site/) was used for preprocessing data prior to geostatistical data analysis. A high-seeding rate of two harvester passes, along with adjacent normal-seeding rates of two harvester passes on each side, were selected for this analysis. Figure 1 shows the resulting points for yield monitor data. To maintain anonymity, the spatial locations have been adjusted so the origin is in the lower-left corner. The noticeable gap was needed to ensure a clean separation for yield monitor data for the two seeding rates. R (https://www.R-project.org/), along with R packages **sp** and **gstat**, were used for geospatial analysis.

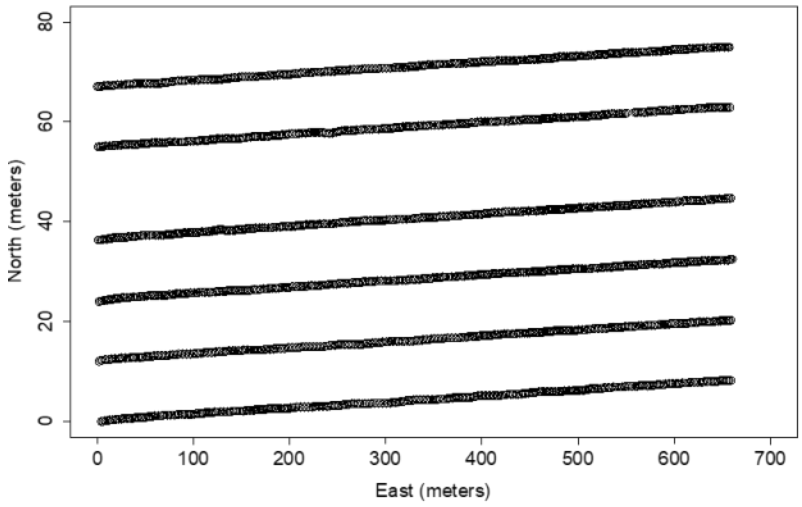

Fig. 1 Points with yield monitor data where the inner two lines are the strip trial for higher seeding rate and the outer two lines on each side are normal seeding rate

Results and Discussion

Descriptive statistics for the two seeding rates are given in Table 1. "No Treatment" designates the normal seeding rate and "Treatment" designates the higher seeding rate. Figure 2 is a side-by-side box plot displaying their distributions. The No Treatment distribution is symmetric and the Treatment distribution exhibits slight positive skewness.

Table 1 Descriptive Statistics for Yield, bushels/acre

Group	n	Min	First Quartile	Median	Mean	Third Quartile	Max
No Treatment	1407	10.76	49.77	54.53	55.08	59.67	97.36
Treatment	748	26.29	49.28	54.08	56.34	61.83	94.72

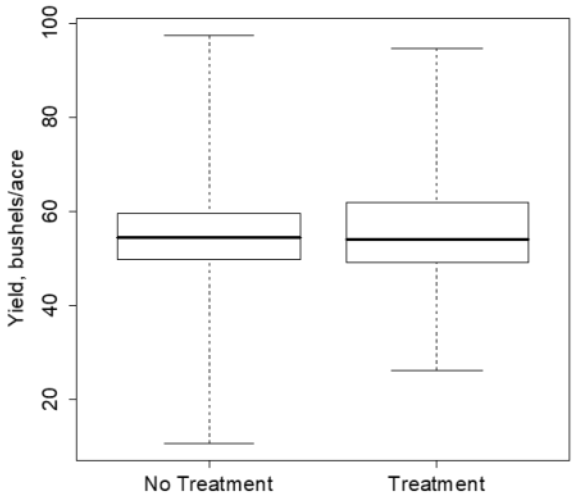

Fig. 2 Boxplots of yield monitor data for No Treatment (control) and Treatment strips

An important property of spatial data is that measurements made at one location may be correlated and not independent of measurements made at other locations. Cressie (1990) points out that in a spatial setting only knowledge of the variogram is needed to perform kriging. Measurements made at spatial locations are used to estimate the semivariogram. This investigation used a spherical model.

A spherical model that incorporates a nugget is given by:

$$\gamma(h) = \begin{cases} 0 & h = 0 \\ n + p\left[1.5\left(\frac{h}{r}\right) - 0.5\left(\frac{h}{r}\right)^3\right] & 0 < h \leq r \\ p + n & h > r \end{cases} \quad (1)$$

where h is the spatial lag, n is the nugget, p is the partial sill, the total sill is $s = n + p$, and r is the range (Hatfield 2017). The nugget represents a combination of measurement error and variation at small spatial scales, the range is the distance that separates points that are spatially autocorrelated from those that are not, and the sill represents long-range spatial variability (Plant 2012).

The empirical semivariogram is estimated from data by:

$$\hat{\gamma}(h_j) = \frac{1}{2N_{h_j}} \sum_{i=1}^{N_{h_j}} \left[Z(s_i) - Z(s_{i+j})\right]^2 \quad (2)$$

where Z is the measured quantity, s_i are points with measured quantities, h_j are spatial lag distances, and N_{h_j} is the number of pairs of points for a given spatial lag distance h_j (Hatfield 2017).

The empirical semivariogram was fit using a spherical model with nugget. This model is given in Equation 1 with estimated parameters in Table 2. Figure 3 shows the empirical semivariogram with the fitted model. A cutoff value of 75 m was used to provide a mild constraint on the neighborhood size.

Table 2 Empirical parameters for spherical semivariogram model with nugget

Nugget	Partial Sill	Range	Cutoff Value
7.86	76.06	31.12	75

The proportion of inherent variability (nugget) to total variance (sill) is less than 10 percent and enhances the predictive ability of the kriging model. It is anticipated that if this proportion is large, say greater than 80 percent, then it may not be possible to exploit the underlying spatial relationship for predictive purposes.

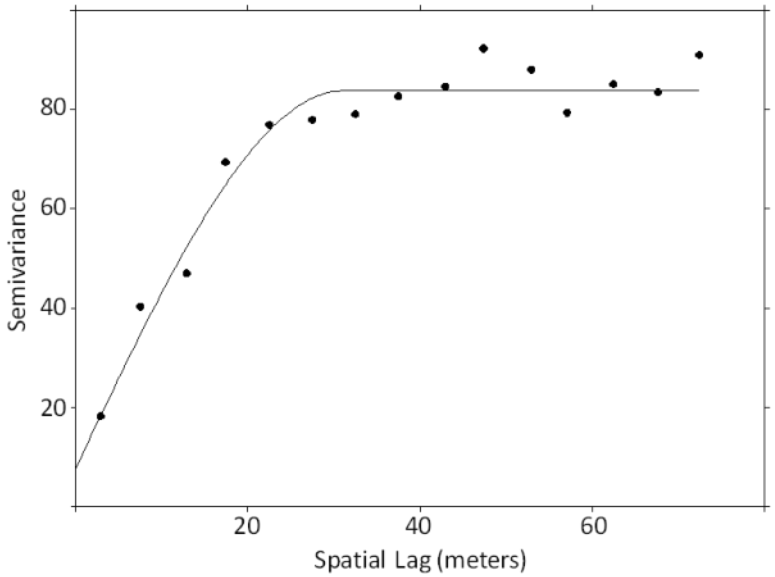

Fig. 3 Empirical semivariogram and fitted spherical model with nugget

Ordinary kriging was used to predict yield for points with a higher seeding rate. The point kriging predictor for s_0 is:

$$Z^*(s_0) = \sum_{i=1}^{k} \lambda_i Z(s_i) \quad (3)$$

where $Z(s_i)$ are observed yield values for the normal seeding rate at the k points in the neighborhood of s_0 and λ_i are the kriging weights (Montero et al. 2015). Table 3 provides a summary of predicted yield and prediction variance. Figure 4 displays the matched predicted and observed yield for the treatment points.

Table 3 Summary of ordinary kriging predicted yield and prediction variance

Group	n	Min	First Quartile	Median	Mean	Third Quartile	Max
Predicted Yield	748	41.41	53.11	54.48	54.47	55.72	66.12
Prediction Variance	748	63.20	63.90	78.10	71.20	78.46	79.61

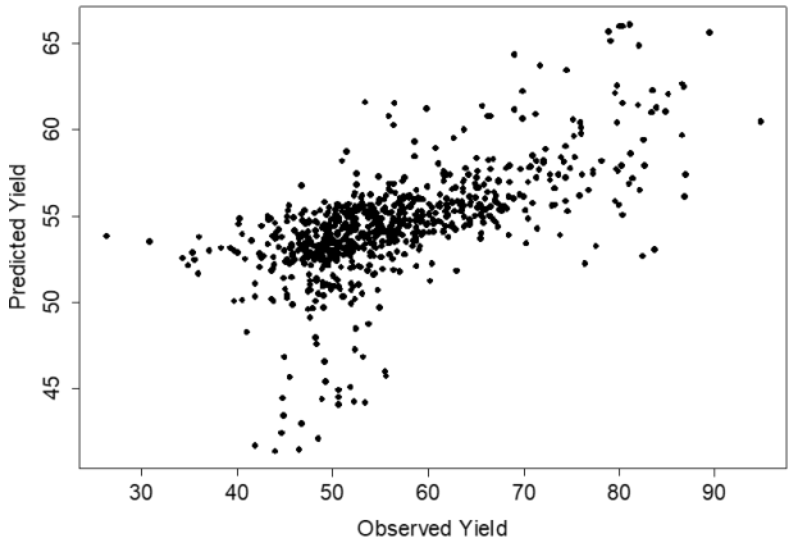

Fig. 4 Predicted yield using ordinary kriging versus observed yield for treatment points

The paired t test is used to evaluate the mean difference between observed and predicted yield

for treatment points. A concern with the use of the paired t test is the dependent structure of the points. Zimmerman (1997) investigated this for nonspatial data and the nonindependence of observations depresses Type I error probabilities and the power of the test to detect differences. Dale and Fortin (2002) examined the effect of positive spatial autocorrelation and propose using a parametric model of the spatial dependence in the data and a Monte Carlo approach to examine the distribution of the test statistic.

The positive correlation between observed and predicted yield exploits the power of the paired t test. The null hypothesis is that the mean difference is zero versus the alternative hypothesis that the mean difference is not equal to zero. The test statistic is $t = 5.967$ with 747 degrees of freedom and $p - value < 0.001$. The null hypothesis is rejected so the mean difference of observed minus predicted yield is not zero. Thus, there is a significant treatment effect.

Conclusion or Summary

It is possible to exploit the underlying spatial structure of a strip trial and adjacent control strips to predict yield for points that comprise the strip trial. This allows the difference between observed and predicted yield to be evaluated using a paired t test.

Future research will be conducted to investigate the relationship between degree of spatial structure and predictive ability of various methods of kriging and semivariogram models. Statistical properties of the procedure will also be investigated using theory and simulations.

Acknowledgements

The data analyzed in this study would not have been possible without the support of South Dakota Soybean Research and Promotion Council. The idea for exploiting the underlying spatial structure for significance testing of unreplicated strip trials was proposed by SDSU Retired Plant Science Professor Dr. Gregg Carlson in personal conversations. We also thank SDSU Plant Science graduate student Deepak Joshi for his assistance with geospatial data processing.

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