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# Median polish 기법을 이용한 한국 논의 공간변이 분석

정선옥 정인규 성제훈 Kenneth A. Sudduth Scott T. Drummond

# Analysis of Spatial Variability in a Korean Paddy Field Using Median Polish Detrending

S. O. Chung I. K. Jung J. H. Sung K. A. Sudduth S. T. Drummond

## Abstract

There is developing interest in precision agriculture in Korea, despite the fact that typical Korean fields are less than 1 ha in size. Describing within-field variability in typical Korean production settings is a fundamental first step toward determining the size of management zones and the inter-relationships between limiting factors, for establishment of site-specific management strategies. Measurements of rice (*Oriza Sativa* L) yield, chlorophyll content, and soil properties were obtained in a small (100-m by 30-m) Korean rice paddy field. Yield data were manually collected on 10-m by 5-m grids (180 samples with 3 samples in each of 60 grid cells) and chlorophyll content was measured using a Minolta SPAD 502 in 2-m by 2-m grids. Soil samples were collected at 275 points to compare results from sampling at different scales. Ten soil properties important for rice production in Korea were determined through laboratory analyses. Variogram analysis and point kriging with and without median polishing were conducted to determine the variability of the measured parameters. Influence of variogram model selection and other parameters on the interpretation of the data was investigated. For many of the data, maximum values were greater than double the minimum values, indicating considerable spatial variability in the small paddy field, and large-scale spatial trends were present. When variograms were fit to the original data, the limits of spatial dependency for rice yield and SPAD reading were 11.5 m and 6.5 m, respectively, and after detrending the limits were reduced to 7.4 m and 3.9 m. The range of spatial dependency for soil properties was variable, with several having ranges as short as 2 m and others having ranges greater than 30 m. Kriged maps of the variables clearly showed the presence of both large-scale (trend) variability and small-scale variability in this small field where it would be reasonable to expect uniformity. These findings indicate the potential for applying the principles and technology of precision agriculture for Korean paddy fields. Additional research is needed to confirm the results with data from other fields and crops.d similar tendency with the result for the frequency less than 20 Hz, but the width of change was reduced highly.

**Keywords :** Spatial variability, Median polishing, Variogram, Korea, Rice paddy field

## 1. INTRODUCTION

Precision agriculture (PA), also known as site-specific crop management, has been well established in North America, Europe, and Australia, where production fields are relatively large. Recently, PA has attracted interest and has seen some limited adoption in Asian countries, including the Republic of Korea. Reasons for this interest include: (1) social con-

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cern regarding environmental problems such as ecosystem damage and ground water pollution from the heavy use of agricultural chemicals that was seen as necessary to increase yields to feed rapidly increasing populations on a limited amount of arable land, (2) global demands for environmentally safe agriculture, (3) pressure to strengthen the value of agricultural products to survive in competitive global markets, and (4) labor shortage due to a decreasing and aging rural population (Srinivasan, 1999). These factors are driving the change of agriculture to PA in Asia perhaps even more than in North America, Europe, and Australia.

Site-specific crop management can be viewed as a cyclical process of within field data collection, data analysis and optimum decision making, variable rate application, and evaluation. Yield, crop growth status, and soil properties are necessary data inputs to the system. Describing within-field spatial variability of soil and crop properties in typical Korean production settings is a fundamental first step toward determining the size of management zones and the inter-relationships between limiting factors for the development of management strategies.

Geostatistics, based on the theory of regionalized variables, is the primary tool of spatial variability analysis. The results obtained from a geostatistical analysis are dependent on a number of variables, such as sampling frequency and number, sampling spacing and accuracy, and analysis parameter selection (Webster and Oliver, 1990). Proper interpretation of the semi-variogram and selection of appropriate models are very important to the analysis process (Hergert et al., 1995; Sadler et al., 1998; Hoskinson et al., 1999; McBratney and Pringle, 1999; Oliver, 1999; Pozdnyakova and Zhang, 1999; Vieira, 1999; Bakhsh et al., 2000).

In general, spatial field data may include both small-scale variation and large- scale variation, or trend. Spatial trend may be caused by measurement or sampling error, or may be indicative of true variability due to site characteristics, climate, or other effects. To comply with statistical assumptions, spatial trends should be modeled and/or removed before semivariograms are fit to data. One detrending method, employed by Sadler et al. (1998), is to fit a plane surface to the spatial dataset, evaluate the plane surface at each data point, and then subtract the surface from the raw data. This method would be useful when the pattern or surface shape of the trend is recognized or known. An alternative method is the median polishing technique, which models the data value at each grid point as the sum of the overall median, transect or row median, column median, and a residual term (Bakhsh et al., 2000). The purpose of median polishing is to remove the main latitude and longitudinal trends (e.g., possible effects of field dimension, management direction such as irrigation and fertilizer application).

Although it might be reasonable to expect uniformity within the small fields typical in Korea, variability of site variables for Korean soils has been reported. Chung et al. (2005) showed that cone index, water content, electrical conductivity, and temperature, measured by commercial sensors at 5-m by 10-m grid points in a 30-m by 100-m paddy field, presented spatial patterns, possibly related to field geometry and irrigation water flow. Annual variations in elevation for the same field were also reported by Sung and Jang (2006). Chung et al. (2006) reported that there were variations greater than 2:1 between the maximum and minimum values of tillage depth, maximum cone index, depth to the maximum cone index, and water content for 16 major soil series of Korean paddy fields. Geostatistical analysis of spatial variability in those variables, however, has been limited.

### Objective

The overall objective of this research was to describe the within-field variability present in a typical Korean rice paddy field. Specific objectives were to: (1) determine the spatial range of rice yield, chlorophyll content, and soil properties, and (2) investigate the effects of variogram selection and other parameters on data interpretation.

## 2. MATERIALS AND METHODS

### A. Experimental Field Description and Data Collection

Data were collected in a 100-m by 30-m rectangular rice paddy field (latitude: 37.2843033 N; longitude: 126.9564617 E; Fig. 1) in 1999. Rice, a major crop in Korea, is usually transplanted in late May and harvested in late October. A paddy field is generally flooded from transplanting until the first fertilization and herbicide application. In the study field, irrigation water entered in the lower right and exited at the upper left (Fig. 1). Average annual ambient air temperature was 12.7℃ and precipitation was 156 cm in 1999 as determined by the Korea Meteorological Administration. Soil classification was Coarse loamy, mixed, nonacid, mesic family of Aguic Fluventic Eutrochrepts (IAS, 1984).

Rice yield, chlorophyll content, and basic soil properties were selected for data collection and analysis. Rice yield data (ton/ha) were manually collected on October 13, 1999. The sampling grid spacing was 10 m by 5 m as shown in Fig. 1. Yields were determined on 5 stalks, collected at each of three locations in each grid cell. In total, 180 yield samples were collected. The samples were threshed with a wooden rice thresher, and the weight and moisture content of each sample were measured with an electronic scale and a moisture meter. Rice grain weight was adjusted to the standard 14% grain moisture content.

Chlorophyll content, an indication of the growth status of the crop, was measured on June 6, 1999, before heading of the rice. Data were collected with a SPAD 502 meter[1] (Konica Minolta Sensing, Inc., Japan) on a 2-m by 2-m grid. In each of the 750 2-m cells, 30 SPAD readings were obtained and averaged.

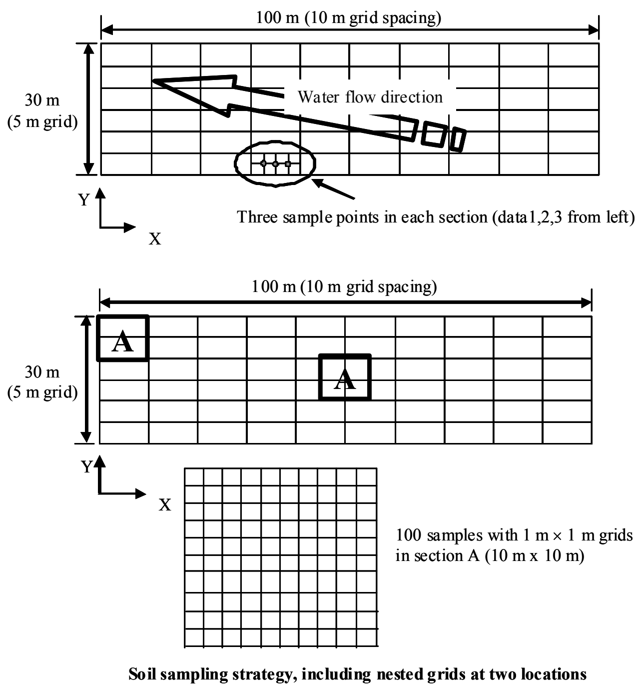



**Fig. 1** Layout of experimental field and sampling strategy for rice yield (top) and soil properties (bottom).

Soil samples obtained to a depth of 15 cm with a spade were collected on October 28, 1999. Soil sampling was done on three different scales as shown in Fig. 1: (1) a 10-m by 5-m grid covering the entire field (60 samples); (2) an intensive 1-m by 1-m grid imposed at two 10-m by 10-m locations at the edge and center of the field (200 samples); and (3) a coarse 20-m by 10-m grid covering the entire field (15 samples). Laboratory analysis was completed by the Soil Management Division, NIAST, RDA for the following properties: pH, electrical conductivity (EC, dS/m), organic matter (OM, %), $P_2O_5$ (ppm), Ca (cmol/kg), K (cmol/kg), Mg (cmol/kg), Na (cmol/kg), total N (%), and $SiO_2$ (ppm).

## B. Descriptive Statistics and Geostatistical Analysis

First, descriptive statistics were computed for the collected data. In addition to analysis of the complete 275-point dataset, separate statistics were computed for each 100-point intensive grid. Descriptive statistics were obtained using SAS version 6.12 (SAS Institute Inc., Cary, North Carolina).

Then, geostatistical analysis and kriging were conducted. In a typical variogram, as the separation distance increases, semivariance increases and then reaches a maximum at the level known as the sill. Range, the limit of spatial dependence, is defined as the separation distance at which the variogram reaches its sill (Webster and Oliver, 1990). A large range greater than the active lag distance means that the variable continues to exhibit spatial dependency past the maximum distance. This indicates that a greater lag distance should be used if possible to capture the long-range variation, or a trend removal (or detrending) procedure should be employed.

For modeling and removing spatial trend, median polishing was used. In median polishing, the raw value at each grid point ($Y_{ij}$) is expressed as the sum of the overall median (m), transect or row median (r), column median (c), and a

1) Mention of trade names or commercial products is solely for the purpose of providing specific information and does not imply recommendation or endorsement by Chungnam National University, the Rural Development Administration, Korea or USDA-ARS, USA

residual term (R) as shown in equation 1 (Bakhsh et al., 2000).

$$Y_{ij} = \overline{m} + \overline{r}_i + \overline{c}_j + R_{ij} \tag{1}$$

Using this approach, median polishing was done with S-Plus version 4.0 (MathSoft, Seattle, Washington, USA).

Once raw data were detrended, semivariograms were fit to the residual data. To provide comparison data to evaluate the effects of detrending, semivariograms were also fit to the original data. Semi-variance is expressed by equation 2:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \{z_i - z_{i+h}\}^2 \tag{2}$$

where: h is lag distance,

$\gamma(h)$ is semi-variance for interval distance class h,

$z_i$ is measured sample value at point i,

$z_{i+h}$ is measured sample value at point i+h, and

N(h) is total number of pairs for the lag interval h.

Geostatistical analysis and semivariogram model selection were done with GS+ version 3.1 (Gamma Design Software, Plainwell, Michigan). Mapping of kriged data was done with Surfer version 7 (Golden Software Inc., Golden, Colorado).

## 3. RESULTS AND DISCUSSION

### A. Descriptive Statistics

Descriptive statistics for yield, SPAD chlorophyll reading, and soil properties over the entire field are shown in Table 1. Examination of the data showed that for the following parameters, the maximum value was greater than double the minimum value: rice yield, EC, $P_2O_5$, Ca, K, Mg, Na, and $SiO_2$.

Since rice paddy fields are flooded and flat, agricultural scientists have hypothesized that spatial variability in yields and soils might be negligible. However, these data show that there is a significant level of variability in rice yield and many soil nutrients, even in small fields. This finding agrees with the work of Sadler et al. (1998) who showed spatial yield variability of different crops of southeaster USA, and Iida et al. (1999) who found rice yield variations of almost 2:1 in a 0.5 ha paddy field in Japan.

Although documentation of variability in soil properties is important, it is also important to ascertain if the variability falls in a range where it may limit crop growth. For comparison with the measured values of Table 1, Table 2 includes the optimal range of soil parameters for paddy rice production in Korea (NIAST, 1999). For all soil properties with the exception of K, mean values in the study field were lower than the optimal range. When considering the range of the data, some portions of the field exhibited lower than optimal values for all soil properties with the exception of K. Especially, Mg values were lower than the optimal range for the entire field.

Soil data were obtained after harvest, so one possible explanation for the low soil nutrient levels may be uptake of nutrients during crop growth. However, this does not discount the fact that the significant variability found in soil nutrients, coupled with the need for fertilizing areas with

**Table 1** Descriptive statistics for yield, SPAD reading, and soil properties

| Parameter | Min | Max | Mean | Std Dev | Skewness | Kurtosis |
|---|---|---|---|---|---|---|
| Yield, Ton/ha | 3.8 | 8.5 | 6.1 | 0.93 | 0.047 | -0.23 |
| SPAD | 32.4 | 39.5 | 36.7 | 0.99 | -0.24 | 0.26 |
| pH | 5.0 | 6.4 | 5.9 | 0.19 | -1.11 | 4.67 |
| EC, dS/m | 0.2 | 1.6 | 0.41 | 0.14 | 2.82 | 17.5 |
| OM, % | 1.7 | 2.9 | 2.3 | 0.15 | -0.12 | 2.30 |
| $P_2O_5$, ppm | 65 | 188 | 119 | 15.5 | 0.55 | 2.55 |
| Ca, cmol/kg | 3.15 | 6.11 | 4.33 | 0.69 | 0.33 | -0.58 |
| K, cmol/kg | 0.55 | 1.47 | 0.69 | 0.07 | 4.73 | 47.1 |
| Mg, cmol/kg | 0.66 | 1.34 | 0.90 | 0.15 | 0.62 | -0.03 |
| Na, cmol/kg | 0.16 | 0.92 | 0.29 | 0.07 | 3.17 | 20.2 |
| Total N, % | 0.13 | 0.18 | 0.15 | 0.01 | 0.39 | 0.41 |
| $SiO_2$, ppm | 54 | 172 | 86 | 18.0 | 1.37 | 3.07 |

**Table 2** Optimum ranges of soil properties for Korean rice production

| Property | Optimal range |
|---|---|
| pH | 6.0-7.0 |
| EC | < 2 dS/m |
| OM | 2.5-3.0% |
| $P_2O_5$ | 80-120 ppm |
| Ca | 5.0-6.0 cmol/kg |
| K | 0.25-0.3 cmol/kg |
| Mg | 1.5-2.0 cmol/kg |
| Na | not established |
| Total N | < 0.2% |
| $SiO_2$ | 130-180 ppm |

lower-than-optimal test levels before the next cropping season, suggests a possibility for variable-rate fertilization. Thus, variability in soil properties was not only present, but was potentially of agronomic importance.

To investigate the assumption of a spatial trend across the field, the soil test parameters for the center 1 m grid samples were compared with the corner 1 m grid samples ("A" areas in Fig. 1). Several soil properties - pH, K, Mg, Na, and total N - were significantly different at the 0.05 level between the center and corner grids. As a check on the performance of the median polishing detrending procedure, descriptive statistics were also computed for the detrended data. As expected, means of the detrended residuals approached zero, and the variance was reduced compared to the original, raw data.

## B. Geostatistical Analysis

For initial examination of spatial variability, grid data were mapped. This provided a visual indication of large-scale trends in some parameters, such as soil pH (Fig. 2). Although pH data collected over the entire field exhibited a strong spatial trend (Fig. 2a), small-scale data from the two intensive grids showed a more random distribution (Fig. 2b and 2c).

Fitting of semivariograms to data from small fields presents particular challenges. Accuracy of semivariance estimation (i.e., $R^2$ of the fitted variogram model) decreases with decreasing numbers of lag pairs. If separation distances approach field dimensions, then the number of lag pairs decreases, and the directional orientation of the pairs becomes biased.

Figure 3 shows the effect of active lag distance on rice yield semivariograms. If active lags of 75 m were allowed

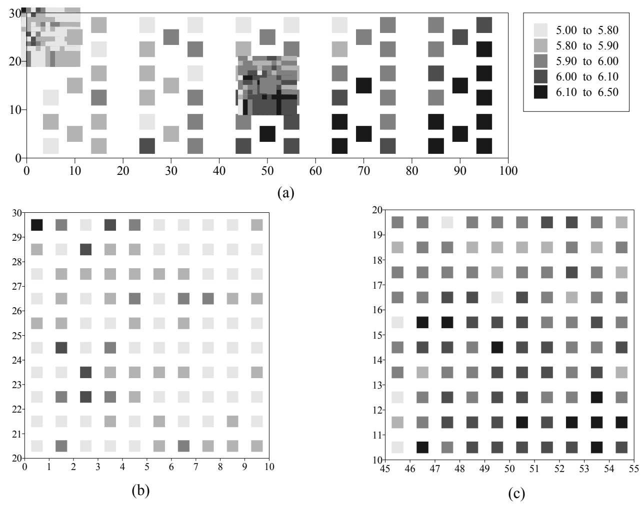
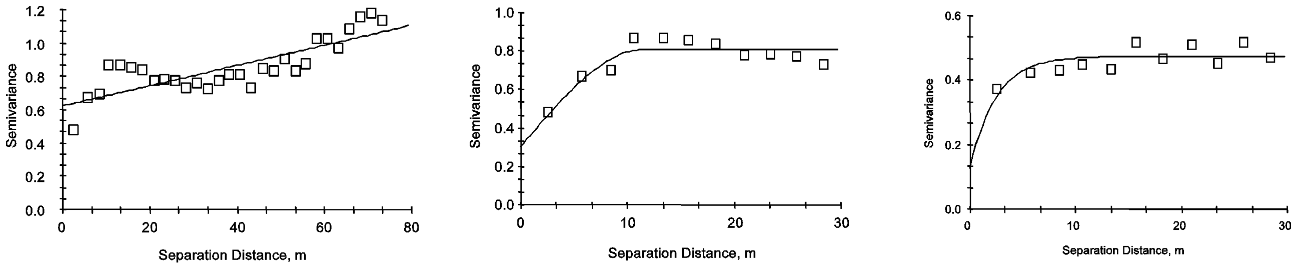



**Fig. 2** Soil pH sample point values. Data were collected over (a) entire field, (b) corner intensive grid, and (c) center intensive grid.

(Fig. 3a), multiple spatial scales seemed to be present in the isotropic variogram. A linear variogram model fit the data best. Examination of the directional variogram showed that short-scale spatial trends exhibited anisotropy, with variation along the long dimension of the field exhibiting a strong large-scale spatial trend. When active lags were restricted to 30 m (Fig. 3b), isotropic data were fit well by a spherical model, with a range of 11.5 m. However, the directional variogram still showed some evidence of a trend. After median polishing for detrending, the isotropic variogram exhibited an exponential model with a range of 7.4 m (Fig. 3c). Based on these results, the active lag distance was set to 30 m and lag intervals were set to 2.5 m for yield and SPAD readings and 1.5 m for soil properties, respectively, which were the same or a little greater than the sampling intervals.

Using an active lag of 30 m, semivariogram parameters were calculated for rice yield, SPAD reading, and soil properties. Analysis was completed for both the original dataset (Table 3) and the detrended residual dataset (Table 4). The criterion for model selection was maximum $R^2$ (e.g., Sadler et al., 1998), except in cases where another model was obviously more appropriate based on visual examination of the semivariogram.

With isotropic models of the original data, the limits of spatial dependency of rice yield and SPAD reading were 11.5 m and 6.5 m, respectively. Some soil properties, including pH, $P_2O_5$, total N, and $SiO_2$, exhibited a relatively short range, but the ranges for other soil properties were



(a) (b) (c)

**Fig. 3** Isotropic semivariograms of rice yield: (a) original data and active lag of 75 m; (b) original data and active lag of 30 m; and (c) detrended residuals and active lag of 30 m.

**Table 3** Isotropic semivariogram parameters for original data

| Property | Model[1] | Nugget ($C_0$) | Sill ($C_0$+C) | Range ($A_0$) (m) | Q (C/$C_0$+C) | $R^2$ |
|---|---|---|---|---|---|---|
| Yield | SPHR | 0.302 | 0.807 | 11.5 | 0.63 | 0.81 |
| SPAD | EXPN | 0.212 | 0.745 | 6.5 | 0.72 | 0.85 |
| pH | SPHR | 0.011 | 0.029 | 10.8 | 0.62 | 0.48 |
| EC | LINR | 0.016 | 0.023 | - | 0.29 | 0.00 |
| OM | LINR | 0.019 | 0.026 | - | 0.29 | 0.00 |
| $P_2O_5$ | SPHR | 17.8 | 228.1 | 4.0 | 0.92 | 0.46 |
| Ca | LINR | 0.075 | 0.284 | - | 0.74 | 0.94 |
| K | GAUS | 0.002 | 0.017 | 32.9 | 0.86 | 0.79 |
| Mg | LITS | 0.003 | 0.014 | 27.7 | 0.78 | 0.98 |
| Na | LINR | 0.004 | 0.006 | - | 0.29 | 0.54 |
| Total N | EXPN | 0 | 0 | 4.5 | 0.79 | 0.48 |
| $SiO_2$ | LITS | 105.3 | 278.9 | 12.8 | 0.82 | 0.73 |

[1] SPHR - spherical model, EXPN - exponential, LINR - linear, GAUS - Gaussian, LITS - linear to sill

**Table 4** Isotropic semivariogram parameters for detrended residual data

| Property | Model[1] | Nugget ($C_0$) | Sill ($C_0$+C) | Range ($A_0$) (m) | Q (C/$C_0$+C) | $R^2$ |
|---|---|---|---|---|---|---|
| Yield | EXPN | 0.125 | 0.474 | 7.4 | 0.74 | 0.54 |
| SPAD | EXPN | 0.160 | 0.500 | 3.9 | 0.68 | 0.92 |
| pH | EXPN | 0.002 | 0.023 | 5.8 | 0.90 | 0.15 |
| EC | LINR | 0.010 | 0.015 | - | 0.29 | 0.26 |
| OM | LINR | 0.013 | 0.019 | - | 0.29 | 0.07 |
| $P_2O_5$ | EXPN | 22.4 | 102.1 | 2.1 | 0.78 | 0.06 |
| Ca | EXPN | 0.000 | 0.062 | 3.7 | 1.00 | 0.18 |
| K | GAUS | 0.002 | 0.016 | 35.1 | 0.90 | 0.79 |
| Mg | EXPN | 0.000 | 0.003 | 3.4 | 0.88 | 0.17 |
| Na | LINR | 0.003 | 0.005 | - | 0.29 | 0.59 |
| Total N | EXPN | 0 | 0.000 | 4.2 | 0.82 | 0.18 |
| $SiO_2$ | EXPN | 69.8 | 157.6 | 60.2 | 0.56 | 0.59 |

[1] EXPN - exponential model, LINR - linear, GAUS - Gaussian

close to the active lag setting of 30 m, or were nonexistent due to a linear model (Table 3).

The spatial structure of the data varied between parameters. In the case of some soil properties, such as EC (Fig. 4a), OM, and Na, a linear model with a poor fit was suggested by the software. However, the semivariogram visually indicated that the data would be best fit by a pure nugget with varying degrees of noise. For other soil properties, including

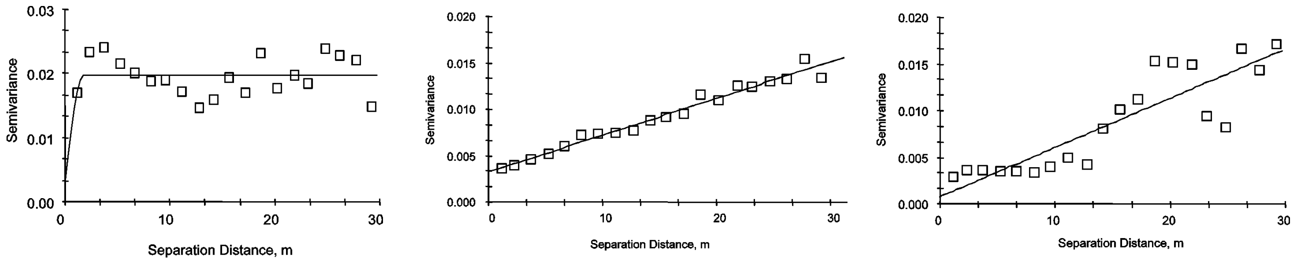



**Fig. 4** Isotropic semivariograms of original soil property data, showing different spatial structures: (a) EC, (b) Mg, (c) K.

Ca and Mg (Fig. 4b), the linear semivariogram did fit the data well, indicating a large-scale trend. Semivariograms of some soil properties, such as K (Fig. 4c) and $SiO_2$, appeared to indicate multiple spatial resolutions within the 30-m active lag distance. Finally, there were cases where there was no functional relationship to the semivariogram - it appeared that there was too much noise in the data to clearly define such a spatial relationship.

When isotropic models were fit to the detrended residual dataset, the ranges of spatial dependence were reduced for most parameters (Table 4). Those properties with the strongest spatial trend, such as Ca and Mg, showed the greatest reduction in range. Detrending did not reduce the range of K and $SiO_2$, the two properties where semivariograms indicated multiple scales of spatial dependence within the 30-m active lag distance. It may be necessary to reduce the active lag distance, increase sample numbers, or to fit nested variogram models for effective analysis of those data.

### C. Local Estimates of Spatial Properties

For local estimation of spatial properties, point kriging was conducted with the variogram models from Tables 3 and 4. As an example, Figure 5 presents kriged data for soil pH. The original sample data clearly shows the trend of decreasing pH in the direction of water flow across the paddy field (Fig. 1). The kriged, median polished residuals, show that the majority of the spatial trend has been successfully removed with the median polishing technique.

## 4. CONCLUSIONS

Spatial data were collected to investigate variability in rice yield, SPAD reading, and soil properties for a 0.3 ha rice paddy field in Korea. Descriptive statistics, semivariance analysis, and point kriging were employed to determine the magnitude and spatial range of variability in the measured parameters.

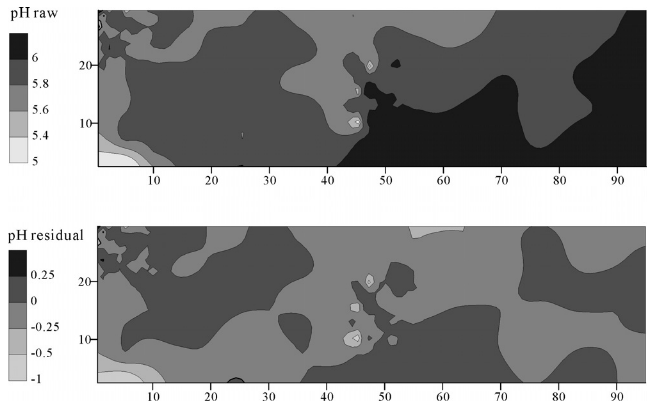



**Fig. 5** Maps of soil pH created by point kriging of original dataset (top) and median polished residuals (bottom).

The maximum rice yield was more than double the minimum yield. Several soil properties, including EC, $P_2O_5$, Ca, K, Mg, Na, and $SiO_2$, exhibited large spatial ranges. Values of most soil properties were lower than the optimum level for rice production. Visual observation and statistical analysis indicated the presence of large-scale spatial trends over some areas of the field for several soil properties, SPAD reading, and yield.

Semivariograms were fit both to the original data and to the residuals remaining after detrending with the median polishing technique. For original data, the limits of spatial dependency for rice yield and SPAD reading were 11.5 m and 6.5 m, respectively. After detrending, the limits were reduced to 7.4 m and 3.9 m. These short ranges indicate that continuous (i.e., sensor-based) measurement of these parameters is desirable for proper characterization of variability. The range of spatial dependency for soil properties was variable, with several having ranges as short as 2 m and others having ranges greater than 30 m.

For local estimation of spatial properties, point kriging was conducted with selected variogram models. Maps clearly showed the presence of both large-scale (trend) variability and small-scale variability, in this small field where it would be reasonable to expect uniformity. These findings indicate the potential for applying the principles and technology of precision agriculture to understand and control spatial variation in Korean production fields.

Additional research is needed to confirm the results with data from other fields and crops. Once spatial data were obtained for a certain field, time, and variable, selection of appropriate variogram models and determination of spatial dependency to control would be based on condition and management history of the field and interest of an individual investigator.

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