THE UNPREDICTABILITY OF SOIL FERTILITY ACROSS SPACE AND TIME

R. L. Hoskinson

Idaho National Engineering and Environmental Laboratory
Department of Energy
Idaho Falls, Idaho

D. Pokrajac and Z. Obradovic

Center for Information Science and Technology
Temple University
Philadelphia, Pennsylvania

A. Lazarevic

Army High Performance Computing Research Center
University of Minnesota
Minneapolis, Minnesota

ABSTRACT

One of the cornerstones of precision agriculture is the variable fertilization of a field based on the spatial variability of its soil fertility. Often the fertilizers are applied in the fall after harvest as the treatment in support of next spring's planting. But these treatments imply knowledge of the changes in soil fertility across space and time.

Our paper reports on our analyses of field data collected throughout the growing season over four years, from the same locations within a field. For several soil fertility and soil characterization parameters, comparison of their spatial variability between successive sampling times showed unexpected changes.

In this paper we also discuss the prediction analyses we conducted. The predictions used historic field data from the early years as the model to predict the spatial variability in soil fertility parameters at a subsequent sampling time in later years. One analysis used one set of the spatially variable fall soil fertility and subsequent spring fertility to develop the model from which to learn. This model was then used with a later year's fall data to predict the following spring's spatially variable soil fertility. Our results strongly suggest that the changes in the spatial variability in soil fertility across a field from fall to the next spring are not predictable. This raises a question then on the validity and applicability of fall fertilization in preparation for the next growing season.

Keywords: fertilization, soil fertility prediction, temporal, spatial

INTRODUCTION

Spatial variability of soil characteristics across a farm field has been discussed for several years. At the 5th International Conference on Precision Agriculture and Other Resource Management, at least 20 presenters discussed soil spatial variability as part of the Natural Resources Variability section, and 7 presenters discussed techniques to describe and manage this soil spatial variability by the use of Management Zones while 18 presenters discussed other means of Managing Variability in the soil (Robert el al., 2000).

Additionally, the temporal variability in soil characteristics is becoming more studied. Hartsock et al. (2000) measured temporal changes in the spatial variability of soil electrical conductivity and Perez et al. (2000) related crop yields to stable soil characteristics.

Our study examines changes in the spatial variability of soil fertility and characterization parameters over time and whether these changes are predictable. This temporal variability during the growing season seems to complicate the concept that variable rate application of fertilizer can be based only on the spatial variability of soil nutrients at a single point in time, such as just prior to planting. Additionally, we look at these temporal changes in the spatial variability of soil fertility across the winter season, from fall after harvest to spring, prior to fertilization and planting.

MATERIALS AND METHODS

The Research Field

Soil samples were collected from a 72.4 ha field several times each growing season, in southeast Idaho from 1995 through 1998. Samples were collected from the same locations throughout the study, as determined by using differentially corrected global positioning system (DGPS) measurements and marker flags.

Almost the all of field (Figure 1) is categorized Kucera, described as well-drained, coarse silty loams, on top of unweathered bedrock (Grow, 1993). Along the north-central edge of the field there is a very small area (shown in rose) categorized Kucera-Sarilda silt loams, also described as well-drained, coarse silty-loam loams on top of unweathered bedrock. The southeast corner of the field (shown in orange) is Robinlee-Marystown silt loams, described as well-drained, fine silty loams to silty clay-loams on top of unweathered bedrock.

The samples were collected based on about a 3.5 ha grid, at the point locations shown in Figure 1. Two center pivots (shown by circular wheel lines) irrigated the study field during the growing seasons in all years.

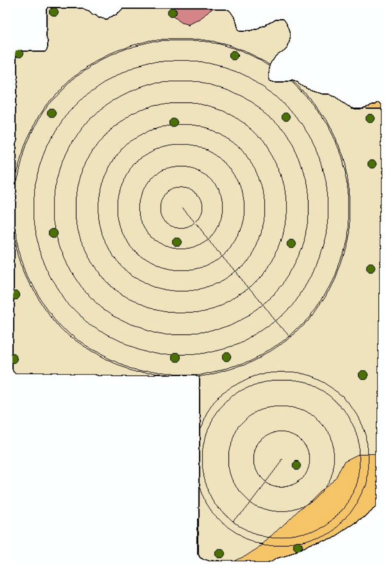

Figure 1. Study field, showing soil types, sampling locations, and irrigation pivots.

Soil Sampling

Samples were collected with a soil probe from the top 30.5 cm of topsoil. At each location, approximately 10 cores were collected from within about one meter of the point, and were composited in a pail. From the composite, about 0.5 kg was placed in a sampling bag and submitted for analysis at a certified laboratory.

Samples were collected during the growing seasons from 1995 through 1998 (Table 1).

Table 1. Soil sampling dates during growing seasons 1995 through 1998.

1995 Potatoes	1996 Wheat	1997 Barley	1998 Potatoes
May 7[1]	April 23[1]	June 4	April 30[1]
July7	July 13	July 18	July 23
August 12	August 15	September 16	August 20
September 15	September 22		September 22

[1] samples collected prior to fertilization

Prediction Methodology

Prediction was performed using **S**patial-**t**emporal auto-regression on **u**niform **g**rid (STUG) (Pokrajac et al, 2002, in press). In the STUG model, for a temporal data layer corresponding to a specific time instant $t\tau$, the value of the random process at each spatial location (on a uniform rectangular grid determined by sampling distances Δ in both spatial directions) depends on samples from the same location and points from its spatial neighborhood taken in the recent history of p previous temporal layers that correspond to sampling instants $(t\text{-}p)\tau, \ldots, (t\text{-}1)\tau$. We specify

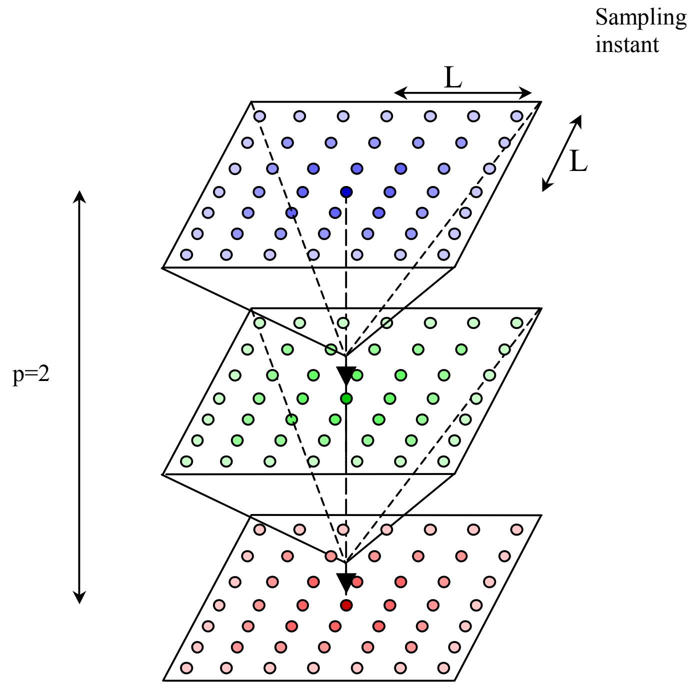

Figure 2. Response dependence on neighboring samples in a recent history for a spatial-temporal model on a uniform grid with spatial and temporal orders p=2, L=3 (STUG (2,3)).

the spatial neighborhood of a sampling location as a $2L\Delta\times 2L\Delta$ square centered at the location (Figure 2)

By definition, the value of a STUG (p,L) process $f_t(m,n)$ on spatial location ($m\Delta$,$n\Delta$) at time instant $t\tau$ is (Pokrajac et al, 2002, in press)

$$f_t(m,n) = \sum_{j=1}^{p} \sum_{k=-L}^{L} \sum_{l=-L}^{L} f_{t-j}(m-k, n-l)\phi_j(k,l) + a_{STUG,t}(m,n),$$

where the error term $a_{STUG,t}(m,n)$ is defined as:

$$a_{STUG,t}(m,n) = \sum_{k=-L}^{L} \sum_{l=-L}^{L} a_t(m-k, n-l)\phi_0(k,l).$$

Here, $a_t(m,n)$ are spatially and temporary uncorrelated zero-mean Gaussian random "shocks" with variance σ^2_a. Due to particular nature of our data, we applied STUG models with p=1 to predict an attribute value for the Spring of year N_{t+1} based on data from Fall of year N_t. Model parameters $\hat{\phi}_j(k,l)$ are estimated using the Yule-Walker method (Pokrajac et al, 2002, in press) and the forecasting is performed as:

$$\hat{f}_{N_t+1,Spring}(m,n)=\sum_{k=-L}^{L}\sum_{l=-L}^{L}f_{N_t,Fall}(m-k,n-l)\hat{\phi}_j(k,l)$$
$$m=L,\ldots,N_x-L-1;$$
$$n=L,\ldots,N_y-L-1.$$

To evaluate localized prediction performance, we computed point-wise relative errors as:

$$\varepsilon(m,n)=\frac{\left(\hat{f}_{N_t+1,Spring}(m,n)-f_{N_t+1,Spring}(m,n)\right)^2}{\hat{\sigma}_f^2}$$

where $\hat{\sigma}_f^2$ is the estimated process variance, computed as

$$\hat{\sigma}_f^2=\overline{f_{N_t+1,Spring}(m,n)^2}\ .$$

The overall forecasting is evaluated through the coefficient of determination $\hat{R}^2$, estimated as a function of averaged point-wise relative errors

$$\hat{R}^2=1-\overline{\varepsilon(m,n)}\ .$$

Here the larger scores correspond to the more accurate prediction with 1 corresponding to a perfect and 0 to a simple mean predictor. Observe that considered prediction models do not contain an intercept, so R^2 can be negative (Davidson and MacKinnon, 1993).

The Prediction Dataset

The application of data predictability methodologies was evaluated using software described in (Pokrajac et al, 2002a, in press). The data set consisted of ten soil attributes (concentrations of boron (B), copper (Cu), iron (Fe), potassium (K), manganese (Mn), nitrogen (N), sulfur (S) and zinc (Zn), as well as soil salinity (sa) and cation exchange capacity (CEC)). For the predictions, a consistent and complete subset of the soil sample data was used, which was contained within a rectangular area. The dataset was used to derive a uniform spatial grid of $10.66\times10.66\text{m}^2$ covering a total area of 60.04 ha of the field. Data from all four years were included. For each attribute we considered two spatial-temporal processes, corresponding to the samples in Spring and in the Fall. For all attributes, an individual temporal data layer corresponded to data collected in a specified year and season and consisted of 84×65 examples.

Prior to the application of the methods to a particular attribute, the mean values were estimated for each temporal layer and subtracted from corresponding sample values, to obtain data that satisfy the zero-mean property of the proposed STUG model. Observe that a similar normalization procedure has been applied by

Wikle and Cressie (1999). This was followed by estimation of spatial and temporal statistics of the normalized data.

Graphical Representations

All of the following maps of the spatial variation in selected nutrients were created using Inverse Distance Weighted interpolation. The maps are provided to help show the reader the spatial and temporal changes discussed. We recognize that the maps display interpolated values among the sampling points, and other researchers have discussed their opinions of different interpolation and kriging methods and sampling frequencies. Our purpose of showing the maps is to clarify our discussions. We leave any debates regarding the best soil sampling methods and sampling frequency, and the best interpolation algorithms for others and only discuss the measured changes that occurred at the sample points.

RESULTS

Spatial Changes in Soil Characteristics during the Growing Season

All of the soil parameters demonstrated changes in their spatial variability over time during a growing season. In almost all cases, differing areas of the field displayed increases in the concentration of certain nutrients during summer, although no additional nutrients had been applied after initial fertilization.

Figure 3 shows the changes in soil nitrate spatial variability from May 7, 1995 through September 22, 1996.

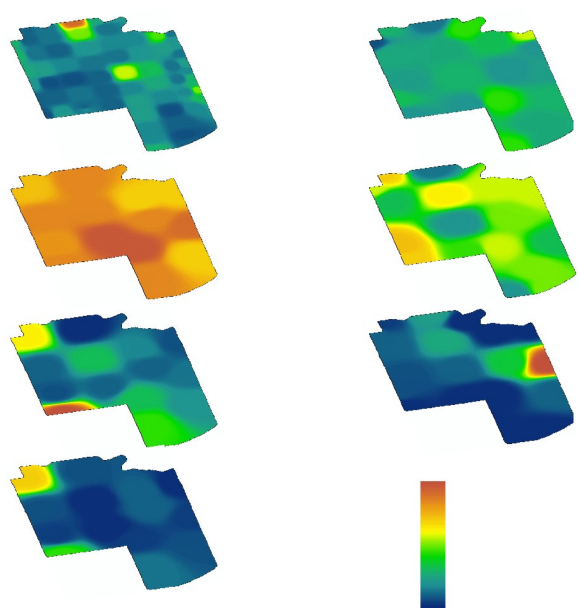

Figure 3. Changes in soil nitrate spatial variability over two years.

Figure 4 shows the changes in soil pH and Cation Exchange Capacity (CEC) through summer 1997.

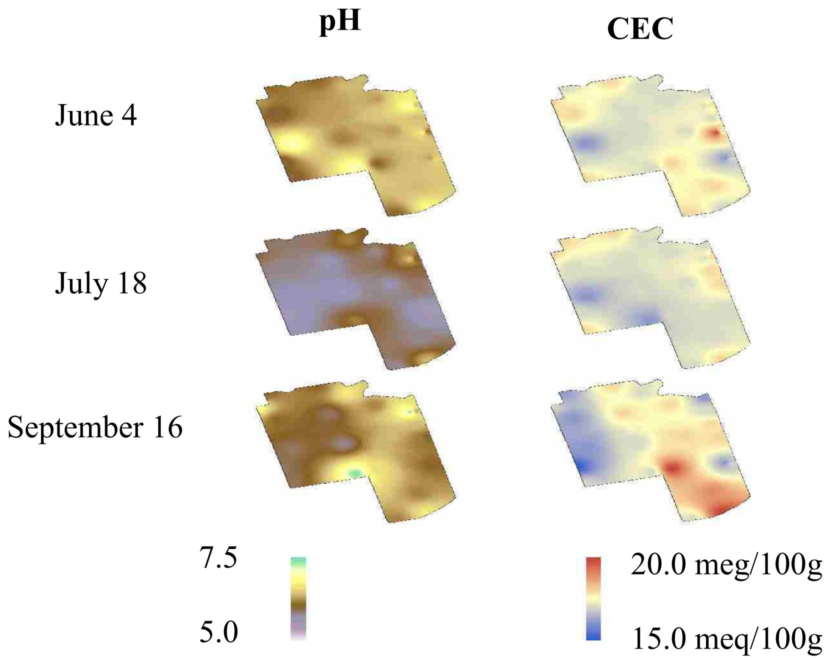

Figure 4. Changes in the spatial variability of soil pH and CEC during Summer 1997.

Spatial Changes in Fertility between the Growing Seasons

Changes in the spatial variability in soil fertility also were observed across seasons, from fall after harvest to the next spring prior to fertilization. The chart in Figure 5 shows the soil nitrate levels at the sampling points on September 16, 1997 and April 30, 1998. At every sample point the soil nitrate level decreased from between 4 to 17 ppm. The highest point in September 1997 was 19 ppm, but in April 1998 it was the lowest at 2 ppm.

Changes in the soil potassium levels at the sampling locations are shown in Figure 6. The soil potassium level increased at 12 locations and decreased at 8 locations.

The Unpredictability of Soil Fertility

The parameters of estimated spatial variograms (Chilès and Delfiner, 1999) expressed significant non-stationarity in the observed period of four years, which prevented the application of geostatistical prediction methods (Posa, 1995). Computed temporal autocorrelations of the same-season samples collected at the same spatial location in different years, indicated that the autocorrelation for some attributes (Fe and K) have a tendency to *increase* with the value of the temporal

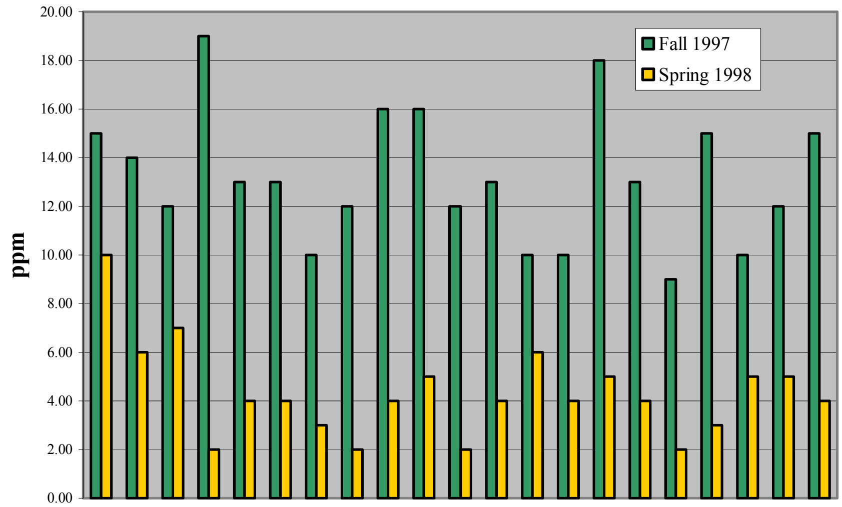

Figure 5. Soil nitrate levels in September 1997 and April 1998 at each sampling point.

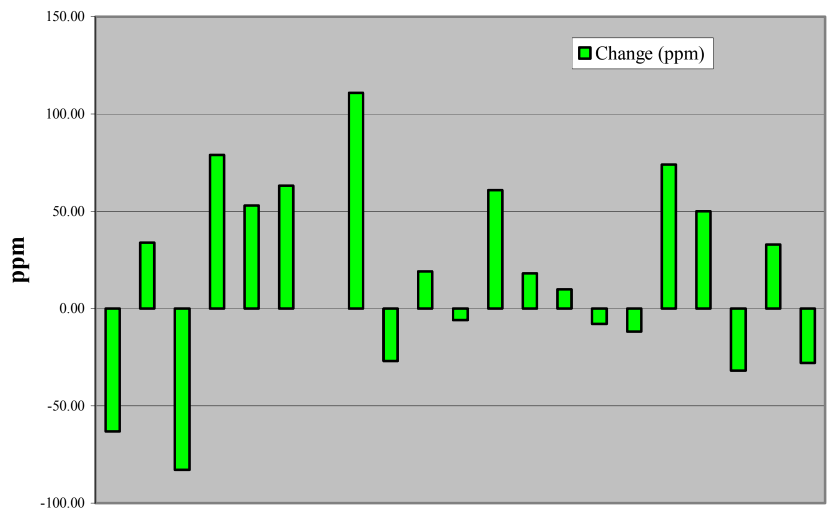

Figure 6. Changes in soil potassium between September 1997 and April 1998 at each sampling point.

lag. However, in spite of significant values of temporal correlations, we were not able to obtain satisfactory prediction results using non-spatial methods due to a small number of available temporal layers (insufficient temporal history) and non-stationarity of the data.

For each attribute, STUG models were trained to model attributes in Spring 1996 based on attribute values in Fall 1995. Models were tested for prediction of Spring 1998 data based on Fall 1997 data. (Since data for Spring 1997 prior to fertilization were not available, we could not evaluate the prediction of Spring 1997 data based on Fall 1996). Prediction accuracy was evaluated through the estimated coefficient of determination $\hat{R}^2$. To directly compare the influence of the order selection, we chose to evaluate STUG models with various values of spatial and temporal orders, instead of performing model identification and to present the results of the best considered models.

Overall prediction accuracy was not satisfactory. At best, we obtained only minimally useful predictions ($\hat{R}^2 > 10\%$) for only Fe, K and sa (Table 2). However, point-wise relative errors $\varepsilon(m,n)$ were not homogeneous across the field. In spite of small *overall* accuracy, it appears some attributes can still be well predicted on *particular* regions of the field. As shown in Figure 7, relative errors for B are less than 0.3 on 57% percent of the field although the global prediction on the field is not useful. Similar results were obtained for other considered attributes.

Table 2. Overall prediction accuracy $\hat{R}^2$ and the optimal value of parameter *L* of the applied STUG model for prediction of Spring 1998 attributes.

Attribute	$\hat{R}^2$	L
Fe	11%	1
K	41%	0
sa	13%	2

CONCLUSIONS

The changes in the spatial variability of soil nutrient concentrations and soil characterization parameters during and between four growing seasons that have been shown are only a few of the many reflected in the full dataset. These changes result from many biotic and abiotic factors, such as changing environmental conditions, the soil microbial community, chemical and physical interactions, and effects of irrigation. Another factor may also be the plants' abilities to adapt to these complex changes and to adjust or omit physiological pathways in their metabolic processes.

Predictive methodologies based on historic data were sometimes useful on regions of the field, but at a field-scale the prediction accuracy was not satisfactory as a usable tool.

All the factors combine to make the spatially variable soil fertility unpredictable on a site-specific basis at a future point in time. This unpredictability of site-specific soil nutrients from one Fall to the next Spring strongly suggests that Fall fertilization in preparation for Spring planting is less than optimal.

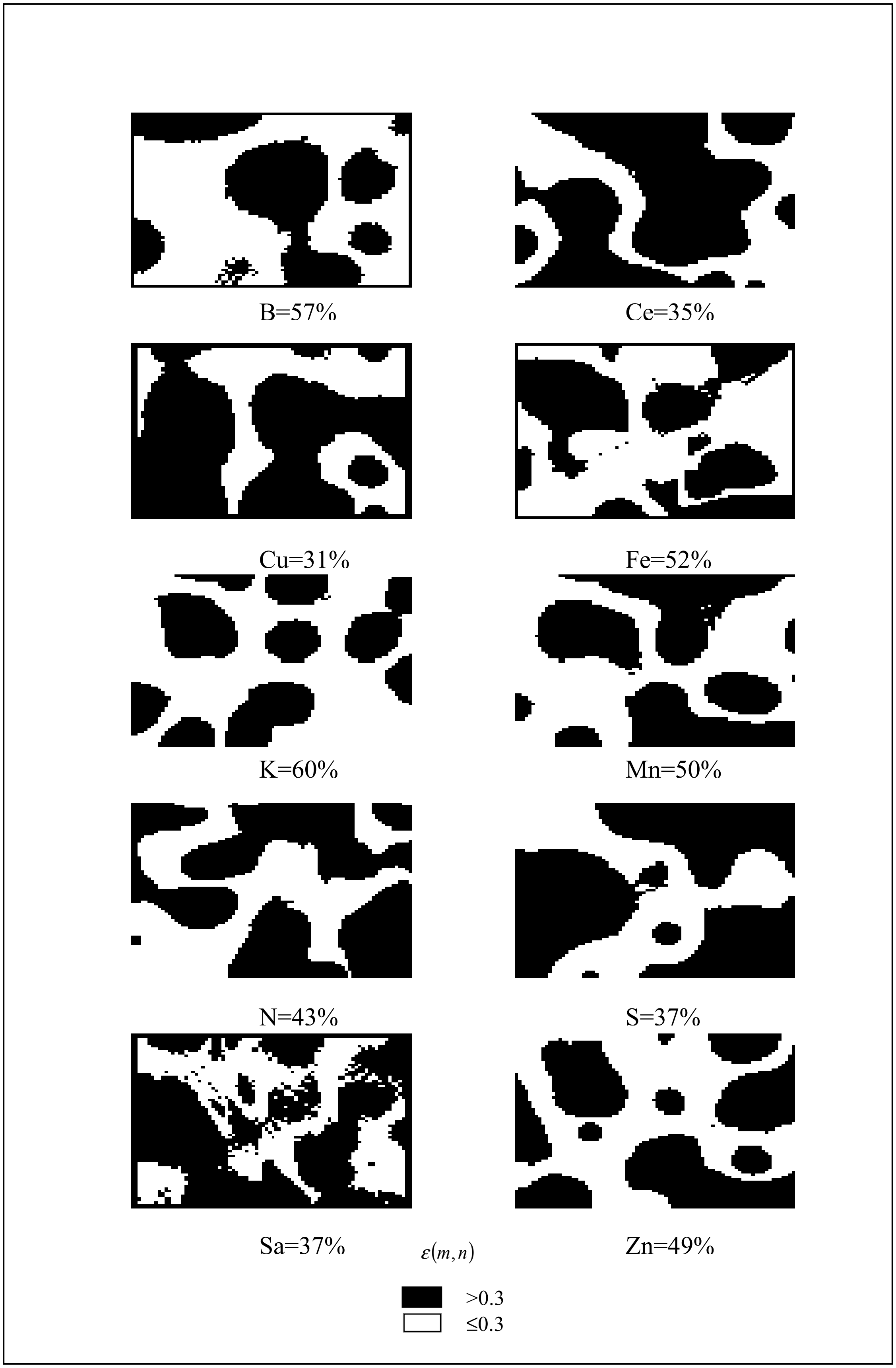

Figure 7. Spatial regions of the field where the localized relative prediction error $\varepsilon(m,n)$ was not larger than 0.3 for each predicted attribute, and the size of the regions in percents relative to the size of the whole field.

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