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# The spatial prediction of soil mineral N and potentially available N using elevation

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**Abstract**

The precision farmer wants to manage the variation in soil nutrient status continuously, which requires reliable predictions at places between sampling sites. Ordinary kriging can be used for prediction if the data are spatially dependent and there is a suitable variogram model. However, even if data are spatially correlated, there are often few soil sampling sites in relation to the area to be managed. If intensive ancillary data are available and these are coregionalized with the sparse soil data, they could be used to increase the accuracy of predictions of the soil properties by methods such as cokriging, kriging with external drift and regression kriging.

This paper compares the accuracy of predictions of the plant available N properties (mineral N and potentially available N) for two arable fields in Bedfordshire, United Kingdom, from ordinary kriging, cokriging, kriging with external drift and regression kriging. For the last three, intensive elevation data were used with the soil data. The mean squared errors of prediction from these methods of kriging were determined at validation sites where the values were known. Kriging with external drift resulted in the smallest mean squared error for two of the three properties examined, and cokriging for the other. The results suggest that the use of intensive ancillary data can increase the accuracy of predictions of soil properties in arable fields provided that the variables are related spatially.


*Keywords:* Cokriging; Kriging with external drift; Regression kriging; Precision farming; Soil nitrogen; Elevation

## 1. Introduction

One aim of precision farming is to use information about the within-field spatial variation of selected crop and soil properties to manage the field in a site-specific way, for example, by the application of nutrients at the places and in the amounts required (Sylvester-Bradley et al., 1999). Senay et al. (1998) describe three ways of measuring within-field spatial variation: continuously (for example, 'on-the-go' crop yield monitoring), discretely (point sampling of soil or crop properties), and remotely (through aerial photographs, satellite sensor imagery and electromagnetic induction [EMI] scans). Sampling at discrete places is the traditional means of obtaining information about the soil and the state of the crop. Field surveys are

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time-consuming, labour-intensive and costly, but at present it is the only way to obtain information about most soil properties and many crop attributes. Most of the crop measurements, for example, canopy cover, leaf chlorophyll, etc., are made in situ, whereas the samples of soil taken in the field are usually analysed in a laboratory for chemical properties, such as mineral nitrogen (N), and for physical properties, such as particle size distribution (Plant, 2001).

Values of such properties are available at the sampling points only. Nevertheless, such discrete data have been used to predict at unsampled sites to characterize the variation more generally. Traditionally, this has been achieved by classification, but it has been known for some time that that this approach does not describe adequately the variation that scientists and farmers are aware of intuitively (Webster and Oliver, 2001). Ordinary kriging (OK) is particularly suited to this problem provided that the data are spatially dependent (Webster and Oliver, 2001). However, the data from soil surveys, for example, are often sparse even though they might be spatially autocorrelated and this can lead to considerable uncertainty in the kriged predictions (Frogbrook and Oliver, 2000). Many farmers now have ancillary data that have been recorded intensively, such as EMI scans, digital elevation models (DEMs) and crop yield. If the sparse and the more intensive data are spatially related, i.e., coregionalized, then the additional information from the more intensive data can be used to increase the accuracy of predictions of the sparsely sampled target variable.

There are several methods that use intensive data to increase the accuracy of predictions of the variable of interest. For example, cokriging can be used if the target variable and the more intensively measured variable are (1) treated as if they were realizations of intrinsically stationary random functions; (2) correlated with one another; and (3) spatially related, in the sense that values of one variable are correlated with the values of another variable at the same places (Frogbrook and Oliver, 2001). Another possible method is kriging with external drift (KED) (Deutsch and Journel, 1992). This can be used if (1) the spatial trend in the secondary (external) variable is related to that of the primary property of interest; (2) the residuals from the trend of the primary property can be modelled geostatistically; and (3) the property of interest and the variable from the more intensive sampling sites are linearly related. Regression kriging (RK), Odeh et al. (1995), can also be used where there is a deterministic relation between the variable of interest and another variable such as elevation.

Remotely sensed and other intensively recorded data are becoming more readily available in precision farming. For example, it is increasingly common that combine harvesters are fitted with on-board geographical positioning systems, GPS, (Auernhammer, 2001) and yield sensors so that site-specific yield can be recorded at the same time as elevation. These data are usually far more intensive than those from soil surveys. If the sparsely sampled property of interest is coregionalized with the intensive data, the latter could be used to increase the accuracy of predictions of the latter. Webster and Oliver (2001) showed that the errors of prediction were smaller from cokriging phosphorus using yield as the secondary variable than from autokriging, and that as this effect was more marked the stronger the strength of the coregionalization. Hudson and Wackernagel (1994) used intensive elevation data, calculated from a DEM, to increase the accuracy of predictions of mean January temperature in Scotland. Elevation was treated as the external drift variable for predicting temperature with KED. Bourennane et al. (1996) used slope gradient as the external drift variable to predict more accurately the thickness of a superficial deposit on part of the Beauce of central France. Odeh et al. (1995) used intensive elevation data with RK and increased the accuracy of prediction of several soil properties, such as topsoil gravel and subsoil clay contents.

Here we examine cokriging, KED and RK in the context of precision farming with sparse mineral nitrogen (MinN) and potentially available nitrogen (PAN) data, and intensive elevation data as the secondary variable for two arable fields in Bedfordshire, UK. Soil nitrogen, which is vital for crop growth, is an expensive variable to measure and its management in the environment is now governed by more stringent controls, for example, through the designation of nitrate vulnerable zones in the UK. Methods to increase the accuracy of prediction of soil nitrogen properties to enable variable-rate management would therefore be of economic and environmental benefit. After exploratory analysis of the data,