Geoderma 237–238 (2015) 71–77

Contents lists available at ScienceDirect

Geoderma

journal homepage: www.elsevier.com/locate/geoderma

Mapping soil salinity in the Yangtze delta: REML and universal kriging (E-BLUP) revisited

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ARTICLE INFO

Article history:
Received 17 February 2014
Received in revised form 19 May 2014
Accepted 21 August 2014
Available online 2 September 2014

Keywords:
Saline soil
Electrical conductivity
Trend surface analysis
REML
Universal kriging
E-BLUP

ABSTRACT

Rice farmers in China need accurate maps of soil salinity to make rational decisions for management. Modern sensors such as the Geonics EM38 conductivity meter, which records the apparent electrical conductivity, EC_a, allied to geostatistics to convert sparse punctual measurements into digital maps can provide them.

We have explored the combination in reclaimed land in the Hangzhou Gulf of the Yangtze delta in Zhejiang Province in south-east China. The EC_a was measured at 525 points in a 2.2-ha field that was reclaimed in 1996. The data, transformed to logarithms, were treated as the realization of a mixture of strong quadratic trend and correlated random residuals. We estimated the coefficients of the trend and the parameters of the covariance of the residuals by residual maximum likelihood (REML). We then kriged the $\log_{10}EC_a$ on to a fine grid by universal kriging (UK), and transformed the predictions back to EC_a for mapping. For comparison we also include regression kriging using the estimated variogram of the ordinary least squares residuals from the trend.

We compared the results by cross-validation and calculated the mean errors (MEs), mean squared errors (MSEs) and mean squared deviation ratios (MSDRs). All combinations of technique gave small MEs, as expected—kriging is unbiased. The MSEs varied somewhat. The MSDRs, which ideally should equal 1, varied more. The combination with an MSDR closest to 1 was UK with the spherical variogram estimated by REML; its MSDR was 0.993.

We matched the predictions to the US Department of Agriculture's classes of soil salinity and found that approximately half of the field fell into its slightly saline and moderately saline classes, where rice yields would yield a profit to the farmer, and half were in the very saline and extremely saline classes where rice yields were so poor that the farmer would lose money by attempting to grow rice.

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1. Introduction

During the past 40 years, more than 400000 ha of the tidelands in the Yangtze delta of China has been reclaimed for agriculture (Huang et al., 2008). When first enclosed the soil is saline, and most of the salt must be leached away before the land can be used to grow rice. Barley, wheat and cotton are more tolerant of salt, but they are less profitable. Farmers have relied on their experience to decide when to plant rice, but often their crops have failed because the soil was still too saline. Land managers therefore want accurate estimates of the soil's salinity in map form so that they can judge when and where they can successfully grow rice (Li et al., 2013).

Fortunately, modern proximal soil sensors based on electromagnetic induction (EM) such as the EM31 and EM38 (McNeill, 1980) enable managers or their advisors to measure the soil's apparent electrical conductivity (EC_a) fairly quickly from above the ground surface. The technique is now widely used in surveys of soil salinity (Akramkhanov et al., 2014; Guo et al., 2013; Triantafilis et al., 2013). Even so, the data from the instruments are effectively at points in the field with more or less large distances between them. Interpolation is usually necessary for mapping, and nowadays kriging is used for the purpose. For example, for our earlier paper (Li et al., 2013) we had recorded the EC_a at only 56 points from which to map a field of 2.22 ha. In a more recent survey of the field we made 525 observations, and these revealed a strong trend; we describe the detail below. De Clercq et al. (2009) and Akramkhanov et al. (2014) also encountered strong trends when mapping soil salinity.

Ordinary kriging, the familiar 'workhorse' of geostatistics and now readily accessible in computer packages, is based on the assumption that the variable of interest is intrinsically stationary. If there is trend, however, the assumption is untenable, and a more elaborate model of the variation is needed to take into account the trend. The trend might also be of interest in its own right and not simply be a nuisance.

Matheron (1969) introduced what he called 'universal kriging' to deal with the situation. It is based on the model:

$$Z(\mathbf{x}) = u(\mathbf{x}) + \varepsilon(\mathbf{x}). \tag{1}$$

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http://dx.doi.org/10.1016/j.geoderma.2014.08.008
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In this model $u(\mathbf{x})$ is a non-stationary mean at place $\mathbf{x}$ representing the trend, and $\varepsilon(\mathbf{x})$ is a stationary random residual with zero mean and covariance function or variogram ($\mathbf{h}$). The trend is typically treated as a low-order polynomial function of $\mathbf{x}$, $f(\mathbf{x})$, linear, quadratic or cubic. Matheron's technique requires a model for that variogram, but Matheron did not say how to estimate it. The problem is that until one knows the trend one cannot derive a valid model for the variogram, and without that model one cannot estimate the trend correctly. Various attempts have been made to get round this impasse. Olea (1975) devised an algorithm for data on regular grids. Another approach, recommended by Goovaerts (1997) and applied by Meul and Van Meirvenne (2003), is to compute and model the variogram perpendicular to a dominant trend. Neither technique is general, however.

Regression kriging in which the interdependence of the trend and variation in the residuals is disregarded enjoys some popularity. Its predictions are unbiased, but the prediction variances underestimate the true prediction errors, often seriously (Lark and Webster, 2006); see Lark et al. (2006) and Webster and Oliver (2007) for an explanation. Minasny and McBratney (2007) make the point that its bias decreases as the number and density of data increase, and it might be the only feasible technique for handling the very large numbers of data from proximal sensors 'on the run'.

Stein (1999) drew geostatisticians' attention to likelihood methods, though the first statistician to recommend them seems to have been Kitinidis (1983, 1993) with what he called 'generalized covariance functions', from which any trend has been removed. The latter's approach is effectively that of residual (or restricted) maximum likelihood (REML), originally devised by Patterson and Thompson (1971) for estimating components of variance. The method estimates both the trend coefficients and the covariance of the residuals simultaneously. The two are then combined with the data to provide empirical best linear unbiased predictions (E-BLUP) (Lark et al., 2006; Minasny and McBratney, 2007). Once a covariance function has been estimated in this way E-BLUP produces the same predictions as universal kriging does with that function (Stein, 1999). This method is quite feasible for the few hundreds of data that accrue typically from laboratory measurements and static sensors. It is now regarded as best practice, and it is the one we use here to explore the variation in salinity in the Yangtze delta.

2. Site and methods

2.1. Study area and sampling

The land in the coastal zone of Zhejiang Province south of Hangzhou Gulf of the Yangtze delta is formed of recent marine and fluvial deposits. The soil consists predominantly of uniform profiles of light loam or sandy loam textures, with a sand content of about 60%. It is also saline, with large concentrations of Na and Mg salts (in many places >1%). The climate is subtropical with an average temperature of 16.5 °C and a mean annual rainfall of 1300 mm.

During the past 30 years much of this zone has been enclosed and reclaimed for agriculture. The fields we describe below were reclaimed in 1996 and were first used to produce irrigated cotton. Since 2006 these fields have been farmed for paddy rice. However, whilst reclamation has been fairly successful, salinity is now increasing, and countering it is becoming problematic. Means are required to measure and monitor the dynamics of salinization so that the land can be managed for rice.

To test the ability of the EM38 to provide the necessary information we chose to study a field approximately 2.2 ha. The fields lie to the north of Shangyu City at 30°9′N, 120°48′E (Fig. 1). We measured the EC_a with a Geonics EM38 conductivity meter with the coils configured vertically at 525 points, fairly evenly spread in the field. We did so after the rice had been harvested. Each position was georeferenced by a Trimble Global Positioning System. Fig. 2 is a 'bubble plot' of the data with 'bubbles', i.e. circles or discs, of diameter proportional to the measured values. Table 1 summarizes the statistics of the data.

2.2. Trend surface analysis and interpolation by ordinary kriging

The bubble plot (Fig. 2) shows a zone of large values towards the south-east of the region. The pattern seems to have the general form of a quadratic trend surface, and we therefore fitted such a surface initially by ordinary least squares (OLS) regression. The model expressed in Eq. (1) thus becomes:

$$Z(\mathbf{x}) = u(\mathbf{x}) + \varepsilon(\mathbf{x}) = \sum_{k=0}^{K} b_k f_k(\mathbf{x}) + \varepsilon(\mathbf{x}) , \quad (2)$$

in which for $K = 5$ the set $f_k(\mathbf{x})$ is the expansion of a constant, b_0, plus linear and quadratic terms in $\mathbf{x}$. The quadratic surface is shown in Fig. 2; it accounts for 71.6% of the variance.

The distribution of the measurements is fairly strongly skewed, evident in Fig. 3(a), with skewness coefficient is 0.62. We therefore transformed the measurements of EC_a to common logarithms for further analysis. The histogram of the logarithms is shown in Fig. 3(b) and is symmetric with skewness coefficient −0.05 (Table 1).

The model contains an error term, ε, and in regression this is assumed to be independently and identically distributed with mean 0 and variance σ^2. However, because our survey is systematic with no independence by design, this assumption cannot be made. Fig. 4 in which the variogram of $\log_{10}EC_a$ increases approximately linearly without bound suggests that there is a trend with correlated residuals.

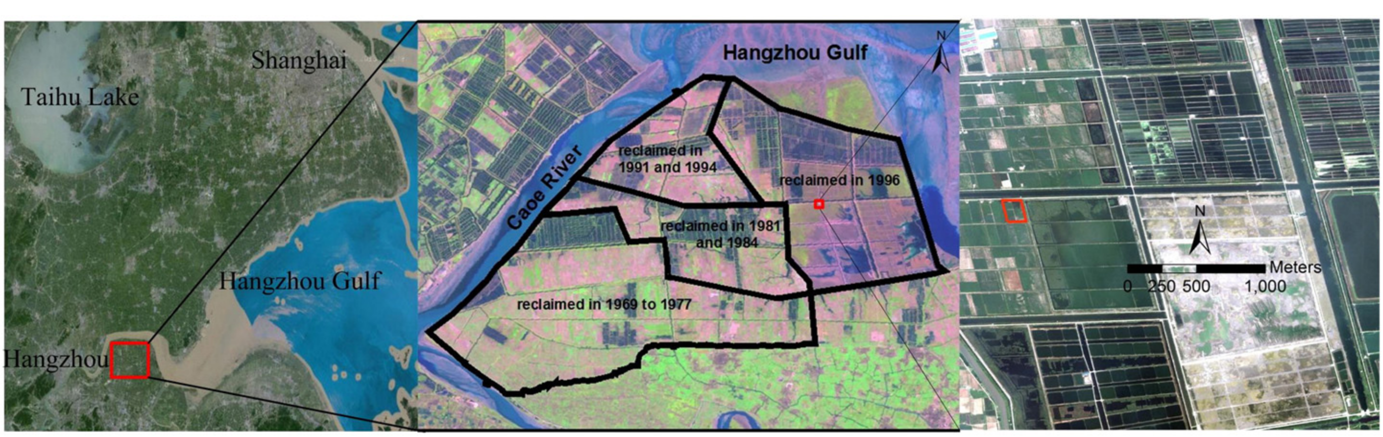

Fig. 1. Location of the region studied.

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