BAYESIAN MAXIMUM ENTROPY AND KRIGING METHODS FOR SPATIO-TEMPORAL MAPPING OF SOIL SALINITY

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Abstract

The mapping of saline soils is the first task before any reclamation effort can be conducted. Reclamation is based on the knowledge of soil salinity in space and how it evolves with time. Soil salinity is determined, traditionally, by soil sampling and laboratory analysis. Recently, it became possible to complement these hard data with soft secondary data made available using field sensors like electrode probes or satellite images.

A large spatio-temporal database on soil salinity data was available. It consists of 413 sites where the apparent or bulk soil electrical conductivity (EC_a) was measured with electrical probes over an area of 25 ha. On a limited subset of these sampling sites (13 to 20), electrical conductivity was determined by laboratory analysis from 1:2.5 soil-water suspensions ($EC_{2.5}$), which is a simple representation of the electrical conductivity of the water-saturated soil-paste extract (EC_e). The whole procedure was repeated 19 times between November 1994 and June 2001.

We used geostatistical tools to identify the spatio-temporal variability of soil salinity with both field and laboratory measurements. This analysis used Bayesian maximum entropy (BME) (1, 2) and kriging to predict soil salinity at unobserved spatial locations and time instants. We compared the accuracy of the mapped predictions from BME using either interval or probabilistic soft data with preditions from kriging with either hard and soft data (HSK), or hard data only (HK). The methods of prediction were compared quantitatively by mean error (*ME*) and mean squared error (*MSE*). The errors are the differences between the measured electrical conductivity in the laboratory on samples from March and June 2001 (which were not used in previous computations) and their cross-validation estimates.

The BME predictions were less biased, more accurate, and were better correlated with the observed values than those from the two kriging techniques. Kriging with soft data (HSK) provided the most biased estimates and failed to reproduce the magnitude of fluctuation in the observed soil salinity. BME provided reliable predictions compared to kriging, even in the absence of hard data and, in the absence of soft data, BME estimates were exactly equal to kriging estimates (using only hard data). This confirms that kriging is a special and limiting case of BME. Also, using only the largest interval data instead of all the intervals, BME still provided reasonable predictions whereas kriging based on hard and mid interval data gave some very large and unrealistic predictions. Finally, using probabilistic soft data instead of intervals in the BME framework reduced the bias and increased the accuracy of the predictions. This is expected as the probability distribution functions characterize fully data distribution while the intervals give only a partial characterization.

(1): Christakos G. (2000). Modern spatiotemporal geostatistics. Oxford University Press: New York.

(2): Christakos G, Bogaert P, and Serre ML. (2002). Temporal GIS: advanced functions for field-based applications. Springer-Verlag: New York.