Geoderma 295 (2017) 22–33

Contents lists available at ScienceDirect

Geoderma

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

Improved spatiotemporal monitoring of soil salinity using filtered kriging with measurement errors: An application to the West Urmia Lake, Iran

Nikou Hamzehpour[a], Patrick Bogaert[b,*]

[a]Department of Soil Science, University of Maragheh, Maragheh, Iran
[b]Université catholique de Louvain - UCL, Earth & Life Institute (ELI), Croix du Sud 2 bte L7.05.16, Louvain-la-Neuve 1348, Belgium

ARTICLE INFO

Article history:
Received 27 October 2016
Received in revised form 23 January 2017
Accepted 6 February 2017
Available online xxxx

Keywords:
Electrical conductivity
Soil salinity
Measurement errors
Spatial prediction
Filtered kriging
Urmia Lake

ABSTRACT

Real-time monitoring of soil salinity based on field samples and laboratory analyses is a costly and time demanding procedure, so that sound methods that could reduce the burden by making use of cheaper data would be a step toward a more sustainable salinity hazards monitoring system on the long run. Typically, this involves replacing presumably error-free laboratory salinity measurements with indirect measurements that are however affected by various source of uncertainties, and these uncertainties need to be accounted for in order to avoid compromising the quality of the final results. More specifically, in a spatiotemporal prediction framework where salinity maps need to be drawn repeatedly at various time instants and where salinity values need to be compared over time for agricultural areas that are prone to salinity hazards, it is of major importance to process these uncertainties in a sound way, as failing to do so would impair our ability to detect salinity changes at an early stage for taking preventive actions.

The aim of this paper is to propose a filtered kriging framework that allows the user to rely on cheap field sampled electrical conductivity (EC) measurements, that cannot however be assumed as error-free. Field EC measurements need to be calibrated from laboratory measurements and the corresponding calibration errors cannot be neglected. Moreover, when sampling is repeated over time, positioning errors are quite common and can adversely impact the results due to the inclusion of an extra variability source. It is shown how these uncertainties can be quantified and successfully processed afterwards for improving both the reliability of the spatial predictions and temporal comparisons of soil salinity. The idea is to rely on a same general optimal linear predictor that can be easily adapted to get rid of these unwanted effects.

The procedure is illustrated by using a rich data set of EC measurements that cover a time span of seven years in the western part of Urmia Lake, northwest Iran. From these data, it is shown how calibration errors can be considered as spatially independent and zero-mean Gaussian distributed, while laboratory measurements exhibit a clear spatial structure but are also affected by a not inconsiderable spatial nugget effect, which is in turn impacting the errors for field EC measurements due to the positioning errors. By relying on a linear optimal predictor that reduces here to filtered kriging with measurement errors, it is shown that filtering out these two random effect components clearly improves the quality of the results when it comes to map EC values and to detect changes that occurred over time. Comparing filtered values for the successive sampling campaigns provided evidence that a major salinity shift did occur between autumn 2011 and autumn 2014 while the other parts of the area were left unchanged by comparison. From this study, it can be concluded that even if the only errors involved in this work were linked to calibration and positioning errors, the methodology is general enough to process various sources of uncertainties in general. It is thus a valuable tool for practitioners, with a field of potential applications that goes beyond the framework of salinity monitoring.

* Corresponding author.
E-mail address: patrick.bogaert@uclouvain.be (P. Bogaert).

http://dx.doi.org/10.1016/j.geoderma.2017.02.004
0016-7061/

1. Introduction

Soil salinity monitoring is of great importance in arid and semi-arid regions, where it is expected to increase at a fast pace due to drought and secondary salinization processes. Due to the devastating effect salinity can have on soil properties, it is recognized as a major agricultural and environmental concern in these regions (Gorji et al., 2015; Scudiero et al., 2015; Taghizadeh-Mehrjardi et al., 2015; Wu et al., 2014) . For regions that are also typically facing unfavourable economic conditions and where budgets devoted to spatially extended and temporally replicated sampling campaigns are accordingly quite low, approaches based on extensive yearly monitoring are doomed to fail, so alternate approaches have to be set up and promoted (Li et al., 2016; Scudiero et al., 2016) .

Over the last few years, due to the depletion of Urmia Lake located in the northwest part of Iran (one of the biggest salty lakes in the world), the proportion of surrounding saline agricultural lands increased at a fast pace. Major reasons for this are changes that occurred in saline versus non-saline groundwater interfaces, along with saline dust coming from recently exposed salt surfaces that were previously constituting the Lake bed. With a population of about 6 million people that are directly and indirectly affected by the consequences of Urmia Lake depletion, threats induced by salinization (and possibly subsequent desertification) of agricultural lands require specific attention and proper actions need to be taken. These actions include addressing the issues and challenges that are linked to an efficient but cost-effective monitoring of the salinization process over the region.

Nowadays, satellite imagery is probably one of the most cost-effective tool to get fast information about natural phenomena occurring over extended land surfaces. Accordingly, there have been several attempts to retrieve low-cost salinity information from satellite images for soil salinity prediction goals (e.g. Khan et al., 2001; Metternicht and Zinck, 2003; Wang and Xu, 2008; Bouaziz et al., 2011; Sivanpillai et al., 2012; Lhissoui et al., 2014). However, there are also clear limitations when using remotely sensed data over saline soils. For very high or low salinity levels occurring over soils that are covered with vegetation, reliable predictions of soil salinity is mostly impossible (Douaoui et al., 2006). Therefore, there is still a great need for precise and direct measurements of soil salinity, especially over areas were abrupt variations are likely to occur.

Monitoring efficiently soil salinity from ground measurements requires that numerous samples are taken in the field, both on a regular basis and with a density over the monitored area that is sufficient enough for allowing further spatial and temporal modelling, with the final aim of temporal prediction and spatial mapping. As the processing of these samples using laboratory measurements is both time demanding and expensive, workaround solutions need to be proposed. A classical approach is to rely on indirect measurement of soil salinity based on soil electrical conductivity (EC) that can be conducted in the field and compared to laboratory values. EC is deemed to be representative of soil salinity conditions and has been widely used for prediction and mapping in this context (e.g. Corwin and Lesch, 2005a,b; Corwin et al., 2006; Douaik et al., 2005; Johnson et al., 2001; Li et al., 2007) Although field EC measurements lead to relatively accurate predictions of soil salinity by comparison with remotely sensed data, they still need to be calibrated with laboratory measurements, and ideally the corresponding calibration errors need to be accounted for too, as it is also the case for remotely sensed data.

The relationship between EC measurements and soil salinity has been studied for a long time (see, e.g., Amezketa, 2006; Halvorson et al., 1977; Yao and Yang, 2010) In parallel to this, there have been more recent attempts to account for EC measurements as well in remote sensing applications (Khan et al., 2001; Metternicht and Zinck, 2003 ; Wang and Xu, 2008; Bouaziz et al., 2011; Wu et al., 2014; Scudiero et al., 2015; Huang et al., 2015). For example, Douaoui et al. (2006) used a combination of remotely sensed and ground based data for spatiotemporal monitoring of soil salinity in Algeria in a regression kriging procedure. The resulting predictions were more effective than those based either from pure spatial interpolation of ground data or from salinity indices as extracted from satellite images. Li et al. (2012) studied spatiotemporal variations of soil salinity in China based on EM38 and EM31 measurements by calibrating them and using them afterwards in kriging algorithms. Ding and Yu (2014) proposed and evaluated a prediction approach based on remote sensing and near sensing technologies by using universal kriging, spectral index regression and regression kriging approaches. However, for all aforementioned studies, the authors did not accounted for the errors involved by the use of calibrated data, which cannot be considered as error-free compared to laboratory measurements.

Accounting formally for the uncertainty attached with measurements is by itself a topic of research in a spatiotemporal monitoring and mapping context. Several authors have proposed methods aiming at handling properly uncertain data for improving the quality of the subsequent predictions (Bogaert and D'Or, 2002; Brus et al., 2008; Christakos, 1990; D'Or et al., 2001; Douaik et al., 2004; Fazekas and Kukush, 1999, 2005; Heuvelink and Bierkens, 1992; Serre and Christakos, 1999) . To the best of our knowledge, for the specific case of spatiotemporal prediction of soil salinity, there are no available studies devoted to the explicit processing of uncertainties coming from the use of calibration relationships. One notable exception is the work by Douaik et al. (2005) about soil salinity predictions that were based on a Bayesian Maximum Entropy method applied to space-time data in Hungary, for which the results were convincing. Hamzehpour et al. (2013, 2015) also used field measured EC to predict top soil salinity based on kriging with measurement errors (KME), where field EC values are considered as "soft" information, by comparison with the "hard" (i.e., error-free) information coming from laboratory measurements. By properly accounting for the calibration errors when relating field EC and laboratory measurements, they emphasized the clear benefit of this approach.

These are topics of major importance, as using efficiently soft information is expected to increase the quality of the soil salinity spatiotemporal predictions, while at the same time reducing the sampling costs associated with laboratory analyses and calibration requirements, that would become prohibitive when it comes to monitoring large areas over time on a yearly temporal basis. Keeping these objectives in mind, the aim of this paper is to propose a sound and efficient methodology that is able to process field EC measurements that are subject to various sources of errors and to show how a sound processing can greatly help for dampening their impact, thus easing in turn the monitoring of soil salinity over time and improving the quality of the resulting prediction maps.

2. Material and methods

2.1. Study area and sampling campaigns

The study was conducted over 5000 ha of lands located in the western part of Urmia Lake, North West of Iran (see Fig. 1). Soil samples were taken over a depth interval of 0–20 cm during nine sampling campaigns over a time period that covered seven years. During the first sampling campaign (Autumn 2009), 186 soil samples were taken on a grid of about 500 meter spacing. They were used (results not shown here) to identify a more specific area where a shift in the salinity conditions seemed to occur in space, as this is indicative of a salinity front that need to be monitored over time. Accordingly, during the second sampling campaign (Spring 2010), besides these same 186 locations, 50 additional samples were also taken in that specific area. From Autumn 2011 to Autumn 2016, non-saline agricultural lands were omitted from the sampling due to cost