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

Nikou Hamzehpour, Patrick Bogaert

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 towards 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.

Keywords : electrical conductivity, soil salinity, measurement errors, spatial prediction, filtered kriging, Urmia Lake

1 Introduction

Soil salinity monitoring is of great importance in arid and semiarid 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 (Taghizadeh et al., 2015; Gorji et al., 2015; Scudiero 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 (Scudiero et al. 2016; Li 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; Boaziz 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 where 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. Johnson et al., 2001; Corwin and Lesch, 2005a,b; Douaïk et al., 2005; Corwin et al., 2006; 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., Halvorson et al., 1977; Amezket, 2006; 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 Zink, 2003; Wang and Xu, 2008; Boaziz 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 account 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 (Christakos, 1990; Heuvelink and Bierkens, 1992; Serre and Christakos, 1999; Fazekas and Kukush, 1999, 2005; D'Or et al., 2001; Bogaert and D'Or, 2002; Douaïk et al., 2004; Brus et al., 2008). 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 Douaïk 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 measure-

ments. 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 monitor 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 Figure 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 meters 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 issues, and samples were instead taken every 50-100 meters apart in this boundary area where salinity variations were the most likely to happen. Samples were taken at 46 selected locations in this narrow zone that separates agricultural and saline lands. This area is of specific interest for monitoring over time, as salinity variations occurring there can be indicative of a displacement of the salinity front.

[FIGURE 1 ABOUT HERE]

2.2 Data analysis and calibration

Data coming from the Autumn 2009 and Spring 2010 campaigns were analysed for their electrical conductivity (EC, measured in dS/m) both in the laboratory and in the field. Data for the other dates were only analysed for their EC in the field.

All laboratory EC measurements were done from 1:2.5 soil-to-water suspensions and EC was measured using a Jenway 4510 bench conductivity meter. Each 1:2.5 soil-to-water suspension was obtained by mixing 20 g of sieved soil with 50 ml of distilled water. The suspension is then shaken for 6 hours and filtered prior to the measure. Based on repeated measurements for the same samples (60 samples measured three times each), the estimated variance of the measurement errors for these laboratory data is $0.0039 \text{ dS}^2/\text{m}^2$.

All field measurements were also done from 1:2.5 soil-to-water suspensions and EC was measured using a portable field EC meter (SENSDirect, Cone200). Each 1:2.5 soil-to-water suspension was obtained by mixing 10 g of sieved soil with 25 ml of distilled water. The suspension is then manually shaken for 1 minute and the electrode of the portable EC meter is plunged into the suspension for obtaining the reading. Field EC measurements are linearly related to laboratory EC measurements through a calibration curve. As this calibration step is a time consuming procedure, the calibration equation was estimated from Autumn 2009 and Spring 2010 data and was used for the subsequent sampling campaigns. With respect to the calibration errors, the laboratory errors are more than one order of magnitude lower, so that for any practical purpose in this study the laboratory EC measurements can be considered as "hard" data (i.e. error-free), while field EC values are "soft" data.

2.3 Spatiotemporal predictions of soil salinity

Monitoring soil salinity over time using field EC measurements is a task which is impaired by the various uncertainties sources affecting these data. First, soil salinity values as obtained through calibration equations do not have the status of error-free data, like it would be reasonably the case for laboratory data. Secondly, even if soil salinity measurements are supposedly repeated at the same spatial locations over time, small positioning errors are occurring as it is impossible to guarantee that samples will be taken exactly at the same places for all sampling campaigns. If soil salinity is subject to a noticeable lack of spatial continuity (the so-called nugget effect in geostatistics), this will lead to discrepancies that can be purely attributed to these positioning errors. Properly accounting for these two sources of errors is of major importance if they have a significant impact on the corresponding measurements. Accordingly, field EC values should be processed as "soft" (i.e. uncertain) data and this status should be properly accounted for during the prediction step. Though this task can be done by relying on elaborate nonlinear prediction methods like, e.g., Bayesian Maximum Entropy (BME), it will be shown that, for the present study, these uncertainties can be quite reasonably assumed as spatially uncorrelated and zero-mean Gaussian distributed. Accordingly, they can be formally and optimally accounted for in a simpler linear prediction method, that should allows us to filter both the calibration and the positioning errors as long as these errors can be quantified.

With this goal in mind, let us assume a second-order stationary random field that can be sampled at various locations $\mathbf{x}_1, \dots, \mathbf{x}_n$, where $Z(\mathbf{x}_i)$ is the true but unknown soil salinity at location $\mathbf{x}_i$ and where $\varepsilon(\mathbf{x}_i)$ is the corresponding calibration error, so that only $Y(\mathbf{x}_i) = Z(\mathbf{x}_i) + \varepsilon(\mathbf{x}_i)$ can be observed in the field at that location. In practice, $Y(\mathbf{x}_i)$ corresponds to the estimated value of the soil salinity through the calibration equation. Assuming additionally that all $\varepsilon(\mathbf{x}_i)$'s are spatially independent and zero-mean Gaussian distributed, the distribution for each $\varepsilon(\mathbf{x}_i)$ is then fully characterized by its corresponding variance σ_ε^2 .

In a spatial linear prediction context, we aim at obtaining a prediction $Z^p(\mathbf{x}_0)$ for the true but unknown $Z(\mathbf{x}_0)$ at any arbitrary (sampled or unsampled) location $\mathbf{x}_0$ by relying on a linear combination of spatially

neighbouring values, i.e.,

$$Z^p(\mathbf{x}_0) = \sum_{i=1}^n \lambda_i \left[\overbrace{Z(\mathbf{x}_i) + \varepsilon(\mathbf{x}_i)}^{Y(\mathbf{x}_i)} \right] = \boldsymbol{\lambda}' \left[\overbrace{\mathbf{Z} + \boldsymbol{\varepsilon}}^{\mathbf{Y}} \right] \quad (1)$$

where n is the number of measurements in this spatial neighbourhood and where $\mathbf{Y}$ is the vector of observable values, with $\boldsymbol{\lambda}$ the vector of weights associated with these various $Y(\mathbf{x}_i)$'s. This set of weights can be obtained by solving a constrained linear system of equations subject to appropriate unbiasedness condition $\mathbf{X}'\boldsymbol{\lambda} = X_0$, where the weights are those associated with the best linear minimum variance unbiased predictor. Let us denote

$$\begin{bmatrix} \Sigma_Y & X \\ X' & \mathbf{0} \end{bmatrix} \begin{bmatrix} \boldsymbol{\lambda} \\ \boldsymbol{\eta} \end{bmatrix} = \begin{bmatrix} \boldsymbol{\sigma}_Y \\ X_0 \end{bmatrix} \quad (2)$$

as the corresponding system of linear equations, where Σ_Y refers to the covariance matrix between the $Y(\mathbf{x}_i)$'s for the n sampled locations, where $\boldsymbol{\sigma}_Y$ is the covariance vector between $Y(\mathbf{x}_0)$ and the various $Y(\mathbf{x}_i)$'s, with $\boldsymbol{\eta}$ the vector of Lagrangians associated with the constraints $\mathbf{X}'\boldsymbol{\lambda} = X_0$. If the calibration errors $\{\varepsilon(\mathbf{x}_0), \boldsymbol{\varepsilon}\}$ are spatially uncorrelated and independent from the true values $\{Z(\mathbf{x}_0), \mathbf{Z}\}$, it then comes that

$$\Sigma_Y = \Sigma_Z + \sigma_\varepsilon^2 \mathbf{I} \quad ; \quad \sigma_Y = \sigma_Z \quad (3)$$

Let us consider the covariance function $C_Z(\mathbf{h}) = \text{Cov}(Z(\mathbf{x}), Z(\mathbf{x} + \mathbf{h}))$ where $C_Z(\mathbf{0}) = \sigma_Z^2$ is the variance of the random field $Z(\mathbf{x})$. Moreover, let us assume that a part of this covariance function refers to a nugget effect $\sigma_n^2 \delta(\mathbf{h})$, with $\delta(\cdot)$ the Kronecker delta (i.e., $\delta(\mathbf{0}) = 1$ and $\delta(\mathbf{h}) = 0$ otherwise). Stated in other words, $Z(\mathbf{x})$ is the sum of a nugget effect part $Z_n(\mathbf{x})$ and a spatially correlated part $Z_s(\mathbf{x})$. Accordingly, the covariance function can now be written as

$$C_Z(\mathbf{h}) = \sigma_{Z,n}^2 \delta(\mathbf{h}) + \sigma_{Z,s}^2 \rho(\mathbf{h}) \quad (4)$$

where $\rho(\mathbf{h})$ is the correlation function that characterizes the spatially correlated part. Inserting now eqs (3) and (4) into eq. (2) yields

$$\begin{bmatrix} (\sigma_{Z,n}^2 + \sigma_\varepsilon^2) \mathbf{I} + \sigma_{Z,s}^2 R & X \\ X' & \mathbf{0} \end{bmatrix} \begin{bmatrix} \boldsymbol{\lambda} \\ \boldsymbol{\eta} \end{bmatrix} = \begin{bmatrix} \sigma_{Z,n}^2 \boldsymbol{\delta} + \sigma_{Z,s}^2 \mathbf{r} \\ X_0 \end{bmatrix} \quad (5)$$

with $\sigma_Z^2 = \sigma_{Z,n}^2 + \sigma_{Z,s}^2$, where R is the correlation matrix between the $Z_s(\mathbf{x}_i)$'s only, while $\mathbf{r}$ is the correlation vector between $Z_s(\mathbf{x}_0)$ and the various $Z_s(\mathbf{x}_i)$'s.

Solving directly this system for $\boldsymbol{\lambda}$ would correspond to the so-called kriging with measurement errors (see, e.g., Fazekas and Kukush (2005) or Atkinson and Lloyd (2010) for the most technical details). As is, it clearly accounts for the calibration errors that will be filtered out from the final result and it can be successfully applied for the mapping of salinity at unsampled locations, typically over a regular grid of arbitrary density. However, we propose to use it here too with another goal in mind, which is the filtering of the nugget effect at the sampled location as well.

Indeed, when a subset of locations needs to be repeatedly sampled over time, it is possible through visual inspection and with the help of a GPS to find back the places where the initial sampling took place, as it involved digging holes at the first instance. However, as several months or even years separate these measurement dates, it is impossible to make

sure that exactly the same locations will be sampled again up to an accuracy of one meter or so. As a consequence, even if one assumes that soil salinity does not change at all over time and that there is no measurement or calibration errors, two measurements made at different dates will not necessarily provide the same result. Considering now that there is a spatial nugget effect component acting at that scale, this will be translated by random variations of soil salinity over time with a variance equal to the nugget effect variance $\sigma_{Z,n}^2$, that clearly acts as a nuisance effect when the aim is to monitor real soil salinity changes over time. Estimating $Z^p(\mathbf{x}_0)$ from eq. (5) at a location where $Y(\mathbf{x}_0)$ is known yields a predictor where the nugget effect (i.e. the positioning error that differ from one time instant to another one) is included into the predictor, so that $Z^p(\mathbf{x}_0) = [Z_n(\mathbf{x}_0) + Z_s(\mathbf{x}_0)]^p$, where the $Z_n(\mathbf{x}_0)$ part of the prediction acts as a nuisance when comparing different dates, as this positioning error is changing over time. It is however possible to filter out this component by dropping the corresponding term $\sigma_{Z,n}^2 \delta$ in the right-hand side of eq. (5), thus relying on the filtering properties of kriging (see e.g., Ruiz-Alzola et al., 2005; Cressie, 2015), so that a predictor $Z_s^p(\mathbf{x}_0)$ is now directly obtained. The result is then a prediction of the spatially correlated part of the random field only, as requested. Doing so at various dates $t = 1, \dots, T$ for a same sampled location $\mathbf{x}_0$ will thus provide us with a temporal sequence of predicted soil salinity values $Z_{s,1}^p(\mathbf{x}_0), \dots, Z_{s,T}^p(\mathbf{x}_0)$ where both the calibration and the positioning errors are filtered out together, thus easing the comparison between predicted values for the same sampled location over time, with the aim of identifying more easily the occurrence of soil salinity increase or decrease. In a monitoring framework, this also permits to detect such changes between successive time instants. Indeed, let us consider a same sampled location $\mathbf{x}_0$ at time instants t and $t+1$, with predicted values

$$Z_{s,t}^p(\mathbf{x}_0) = \lambda_t' \mathbf{Y}_t \quad ; \quad Z_{s,t+1}^p(\mathbf{x}_0) = \lambda_{t+1}' \mathbf{Y}_{t+1} \quad (6)$$

where $\mathbf{Y}_t$ and $\mathbf{Y}_{t+1}$ are available field measurements at these time instants and where λ_t' and λ_{t+1}' are the corresponding kriging weights for the filtered systems (i.e. by dropping the $\sigma_{Z,n}^2 \delta$ term in eq. (5)). If no soil salinity change occurred (i.e. $Z_{s,t}(\mathbf{x}_0) = Z_{s,t+1}(\mathbf{x}_0)$), then these are predictors of the same quantity $Z_s(\mathbf{x}_0)$, with expectations and variances given by

$$\begin{aligned} E[Z_{s,t}^p(\mathbf{x}_0)] &= E[Z_{s,t+1}^p(\mathbf{x}_0)] = Z_s(\mathbf{x}_0) \\ Var[Z_{s,t}^p(\mathbf{x}_0)] &= \lambda_t' \Sigma_{Y,t} \lambda_t \\ Var[Z_{s,t+1}^p(\mathbf{x}_0)] &= \lambda_{t+1}' \Sigma_{Y,t+1} \lambda_{t+1} \end{aligned} \quad (7)$$

where $Z_{s,t+1}^p(\mathbf{x}_0)$ and $Z_{s,t}^p(\mathbf{x}_0)$ are independent, as both the calibration and positioning errors are independent over time. Let us assume further that the same set of locations has been sampled at time instants t and $t+1$ so that $\lambda_t' = \lambda_{t+1}'$ and $\Sigma_{Y,t} = \Sigma_{Y,t+1}$, that are denoted more simply λ and Σ_Y , respectively. Under the null hypothesis $H_0 : Z_{s,t}(\mathbf{x}_0) = Z_{s,t+1}(\mathbf{x}_0)$, it thus comes that the difference between these predictors is zero-mean Gaussian distributed, with

$$Z_{s,t+1}^p - Z_{s,t}^p \sim N(0, 2\lambda' \Sigma_Y \lambda) \quad (8)$$

It is then easy to draw conclusions about this null hypothesis from this distribution, in order to sample locations where a soil salinity increase or decrease was likely to occur between these dates.

3 Results and Discussion

3.1 Summary statistics

Summary statistics of soil EC values are presented in Table 1 for the nine sampling campaigns that took place from year 2009 to year 2016. Taking only into account the identical subset of 46 points that were sampled in the field from Spring 2010 to Autumn 2016, the mean value for EC field measurements increased from 4.24 dS/m in Spring 2010 to 6.65 dS/m in Autumn 2016. This increase is statistically significant based on a Student t-test for paired samples (p-value: 0.000014). As the skewness of these EC values was positive for all sampling campaigns, the natural logarithm of all EC values was used for all subsequent analyses.

[TABLE 1 ABOUT HERE]

Since the second sampling campaign in Spring 2010 has the highest number of samples (see Figure 1 and Table 1), the mean salinity computed from these data can be associated with the idea of an overall mean salinity over the study area. Globally, with a mean EC value of 4.73 dS/m and with lowest and highest values respectively equal to 0.14 dS/m and 45 dS/m, this indicates that the salinity of these soils is highly variable over space. As the most saline soils resulting from the withdrawal of Urmia Lake are lying next to the non saline ones that are intensively cultivated, there are thus serious concerns about salinity spreading toward these agricultural lands.

3.2 Calibration of EC field measurements

Results for the calibration of the field EC measurements for the two first sampling campaigns (Autumn 2009 and Spring 2010) are presented in Figure 2. Based on the logarithm of EC values, a simple linear model $\log(EC_{field}) = \alpha + \beta \log(EC_{lab}) + \varepsilon$ seems to perform quite well for both sampling campaigns, with a determination coefficient of 0.98 and 0.97 for the first and second sampling campaign, respectively. In order to see if these two models can be replaced by a single model for both campaigns, a F-test was used. It showed that these models are globally statistically different, but, testing separately for α and β , one can accept the hypothesis that both models have the same slope $\hat{\beta} = 1.040$ (p -value=0.331) though they have significantly different intercepts, with $\hat{\alpha}_1 = -0.248$ and $\hat{\alpha}_2 = -0.117$ for Autumn 2009 and Spring 2010, respectively. There is thus a difference in the calibration line due to an offset of $\hat{\alpha}_1 - \hat{\alpha}_2 = -0.121$ (in log of dS/m). Fitting a single line for Autumn 2009 and Spring 2010 data together yields the values $\hat{\alpha} = -0.171$ and $\hat{\beta} = 1.046$, with an estimated variance $\hat{\sigma}_\varepsilon^2 = 0.0396$ for the residuals, which is close to the estimated variance $\hat{\sigma}_\varepsilon^2 = 0.0360$ that was obtained when considering two distinct calibration lines. The corresponding estimate for this random effect is thus $\sigma_c^2 = 0.0396 - 0.0360 = 0.0036$, which is one order of magnitude lower than the variance for the calibration errors. From Figure 2, it is also seen that the calibration errors can be assumed as Gaussian distributed.

The exact causes for this calibration line offset are unclear, but they can be linked to the Cone200 measuring devices that was used for all campaigns. It can be presumed that this offset could be different for all sampling campaigns and would thus act as an additional random effect, with an associated variance σ_c^2 that should also be accounted for when

comparing predictors $Z_{s,t+1}^p(\mathbf{x}_0)$ and $Z_{s,t}^p(\mathbf{x}_0)$ between two distinct time instants, so that we now have

$$Z_{s,t+1}^p - Z_{s,t}^p \sim N(0, 2\boldsymbol{\lambda}'\Sigma_Y\boldsymbol{\lambda} + 2\sigma_c^2) \quad (9)$$

However, based on the comparison between Autumn 2009 and Spring 2010 that was made above, it has a quite moderate effect, and a quantification of σ_c^2 is impossible here due to the lack of additional laboratory measurements at other dates, so that using a single calibration model is the only technical possibility here. This calibration model will then be used for all other sampling campaigns, with a corresponding estimate $\hat{\sigma}_\epsilon^2 = 0.0396$ for the variance of the calibration errors. The random effect for the offset is thus translated here by a corresponding increase for the variance for these calibration errors.

[FIGURE 2 ABOUT HERE]

3.3 Spatial correlation of EC data

Based on the Autumn 2009 and Spring 2010 sampling campaigns, it is possible to assess the spatial correlation of the log(EC) laboratory data, along with the spatial correlation of the calibration errors. In Figure 3 (top), one can see that the variograms for both sampling campaigns are flat and do not indicate any clear spatial correlation. This lack of spatial correlation is confirmed by an empirical log-likelihood testing procedure. The calibration errors are thus satisfying all underlying hypotheses for kriging with measurement errors, i.e. independent and zero-mean normally distributed errors, with estimated variances that appear to be identical for both campaigns.

[FIGURE 3 ABOUT HERE]

Using again the Autumn 2009 and Spring 2010 sampling campaigns, it can be seen from Figure 3 (bottom) that laboratory log(EC) values are spatially correlated, with quite similar results for both sampling campaigns again. Based on nonlinear least squares, a single model composed of a nugget effect and a spherical model components is fitted (the estimation and modelling details are omitted here; a discussion can be found in Hamzehpour et al., 2013). This yields corresponding estimates $\hat{\sigma}_{Z,n}^2 = 0.363$ and $\hat{\sigma}_{Z,s}^2 = 3.103$, thus indicating that the non correlated part account for about 10% of the total variance $\hat{\sigma}_Z^2 = \hat{\sigma}_{Z,n}^2 + \hat{\sigma}_{Z,s}^2 = 3.466$. By comparison, this nugget effect variance $\hat{\sigma}_{Z,n}^2$ is about ten times higher than the variance $\hat{\sigma}_\epsilon^2$ for the calibration errors. These results are of course specific for our dataset, but they indicate here that filtering out the nugget effect component is expected to be more beneficial than filtering out the calibration errors.

3.4 Filtering of EC data

In order to illustrate the benefit of filtering out the nugget effect component that relates to the positioning error, let us first focus on the Autumn 2009 and Spring 2010 campaigns, where a same subset of 170 locations where sampled for both dates. Figure 4 (left) shows the relationship between log(EC) laboratory values for these dates. We will consider here for the unbiasedness constraint $\mathbf{X} = \mathbf{1}$ and $X_0 = 1$, where $\mathbf{1}$ is the unit vector, so that this constraint reduces to $\mathbf{1}'\boldsymbol{\lambda} = \sum_i \lambda_i = 1$ and corresponds to the so-called ordinary kriging, where the mean is supposed to

be unknown and is estimated from the data at hand separately for each sampling campaign.

Based on the filtered version of kriging where the nugget effect component $\sigma_{Z,n}^2 \delta$ is dropped from the right-hand side of eq. (5) and where the calibration variance σ_ε^2 is set to 0 (as we are dealing here with laboratory measurements), one can obtain filtered values for both dates. Figure 4 (right) shows the relationship between them. It can be seen that they exhibit a lower variability around the 1:1 line compared to the initial laboratory values, and this is especially visible for the pairs that were lying far away from this 1:1 line. Using the testing procedure based on the distribution given in eq. (8), it is possible to identify locations where the null hypothesis is unlikely to hold true at the confidence level $1 - \alpha = 0.8$. Clearly, the deviations from the 1:1 line for these locations are now better discriminated, while the values for the remaining and supposedly unchanged locations are better related.

The value $\alpha = 0.2$ refers here to a bidirectional test, i.e. about an increase or a decrease of the $\log(\text{EC})$ value as alternate hypothesis. The choice of this value for α compared to more traditional choices like $\alpha = 0.05$ or $\alpha = 0.01$ is dictated by the fact that changed values are used in the prediction algorithm as well, thus affecting in turn the prediction of filtered neighbouring values and thus reducing the power of the test. An option would be to proceed iteratively, by removing at each step the presumably changed values for conducting again the prediction based on cleaner data. This would yield filtered values that are less and less impacted by the locations where $\log(\text{EC})$ cannot be assumed as belonging to the distribution under the null hypothesis. However, this procedure is clearly cumbersome and would not lead here to different results, as the presumably changed values represent only a small fraction of the data set.

[FIGURE 4 ABOUT HERE]

Capitalizing on this result, we can now apply the same procedure for the $\log(\text{EC})$ field values that have been sampled at the same set of 46 locations from Spring 2010 to Autumn 2016, by filtering now both the positioning and calibration errors. These 46 locations are presented in Figure 5. They are located in an area of specific interest, which corresponds to the identified transition zone between saline and non saline soils. Being able to detect salinity changes in this area from one sampling campaign to the next one would thus allowing us to monitor and to forecast a displacement of the salinity front at an early stage. Figure 6 shows the corresponding results for initial $\log(\text{EC})$ field values (top) and for the corresponding filtered $\log(\text{EC})$ values (bottom). Only results from Spring 2010 till Autumn 2011 are shown here for the sake of brevity (other results are available upon request). Again, by comparing the relationships between raw and filtered values, it can be seen that the similarities between the Spring 2010 *vs* Autumn 2010 and the Autumn 2010 *vs* Autumn 2011 values are reinforced for the filtered data, while results for Autumn 2011 *vs* Autumn 2014 bring evidence that a major salinity shift did occur between these two dates.

[FIGURE 5 ABOUT HERE]

[FIGURE 6 ABOUT HERE]

Comparing filtered values for the successive sampling campaigns confirm this finding, as seen from Figure 7. Except for Autumn 2011 *vs* Autumn 2014 values, all other successive dates exhibit values that did

not significantly change at the confidence level $1 - \alpha = 0.8$, with global mean $\log(\text{EC})$ values that are quite similar from one date to the next one. Again, the locations where a salinity shift seems to occur can be put in evidence by relying on the distribution of $\log(\text{EC})$ differences under the null hypothesis. All these locations refer to the Autumn 2011 *vs* Autumn 2014 values.

Instead of simply testing at a given confidence level, it is much more informative to directly provide the corresponding p -values, that can be spatially contextualized, as in Figure 8 for the Autumn 2011 *vs* Autumn 2014 data. One can easily see that the locations where a change is likely occurring (i.e. the locations with the smallest p -values) are clearly delineating an area in the northwest part of the monitored zone. Such maps are easier to interpret, as they contextualize the results of the test and are thus easing their interpretation.

[FIGURE 7 ABOUT HERE]

[FIGURE 8 ABOUT HERE]

3.5 Spatial prediction of EC values

Using similarly the Autumn 2011 and Autumn 2014 data sets and using again the same predictor that filters out both calibration and positioning errors, it is possible to draw the maps of the spatially predicted filtered $\log(\text{EC})$ values over a regular grid. This yields the two maps presented in Figure 9, where predictions have been restricted to the grid nodes that are in the neighbourhood of the 46 sampled locations. Comparing both maps confirms the conclusions already drawn from Figure 8. There is a clear increase of the $\log(\text{EC})$ values that took place on the northwest part of the area between Autumn 2011 and Autumn 2014, while the others areas are left unchanged by comparison. As these maps are filtering out all spatially non correlated components, they also exhibit smooth variations over space and they closely match the filtered $\log(\text{EC})$ values that were previously obtained at the 46 sampled locations, as seen from the perfect color correspondence between these filtered $\log(\text{EC})$ sampled values and the background prediction maps.

Though prediction maps are only shown here for the Autumn 2011 and Autumn 2014 sampling campaigns, a similar procedure can be used for the other dates as well, of course. The resulting maps (not shown here) are again consistent with our previous findings. Maps from Spring 2010 to Autumn 2011 are almost identical (with slight differences that can be observed for the Autumn 2010 map), as one could already guess it from the results given in Figure 7. Similarly, maps from Autumn 2014 to Autumn 2016 do not exhibit any noticeable differences. The major observable and local shift of salinity seemed thus to occur between Autumn 2011 and Autumn 2014.

[FIGURE 9 ABOUT HERE]

An interesting question is precisely related to the fact that the most noticeable salinity modifications are put in evidence for two sampling campaigns that are separated by 3 years, while comparing other campaigns that are at most separated by one year fail to evidence any clear evolution of the salinity pattern. This raises the question about the possible existence of a slow but global increase of the salinity over the whole area, that would be difficult to evidence from data that are too close in time, while

this increase is much more obvious when comparing data separated by a longer time span. It is clear that such kind of salinity modifications would be hard to monitor using the methodology we advocated here. However, this is not specific to our approach, as any other method that aims at comparing successive time instants would most probably fail with respect to this task. A noticeable exception would be models that are assuming a global (and typically identical) shift over the whole area, as detecting a modification of the mean salinity is much easier than detecting salinity modifications occurring on a local basis, as it was done here. However, it is unlikely that salinity variations would occur uniformly over large areas, as they are drifted by various physical mechanisms that operates differently or with various intensities depending on the location. For our specific case study, it was possible to document from field observations that a major modification of the vegetation cover took place during the Autumn 2011-Autumn 2014 time interval, precisely in the northwest area part of the monitored area. There are thus serious reasons to consider that, even if one cannot preclude a possible global but slow increase of the salinity in the area, it remains true that other salinity changes are expected to occur in parallel and are worthy to monitor using the proposed methodology.

4 Conclusions

Soil salinity is a major agricultural and environmental concern in many parts of the world, so that efficient and cost-effective soil monitoring is of paramount importance in areas where soil salinity is expected to increase at a fast pace due to drought and secondary salinization processes. As real-time monitoring of soil salinity changes is quite costly, sound methods that could improve the quality of the predictions based on scarce field measurements would allow the users to alleviate the need of repeated calibrations and laboratory measurements, and such methods would be a step towards an improved and sustainable salinity hazards monitoring system on the long run.

One of the major concerns about classical monitoring of lands that are prone to salinity hazard is the need for numerous sampled locations both in space and time, as it is the spatial extent of the sampled area that allows us to get a clear picture of the spatial patterns of these changes, while repeating sampling over time is needed to spot at an early stage any local change that might occur. Accordingly, the associated costs are expected to skyrocket if precise laboratory measurements are required for these tasks and they are clearly prohibitive for many developing countries, that are also often those that are prone to salinization hazards.

Even if the cheaper data that can be gathered from satellite imagery and from field EC measurements are partially solving this issue, their use brings new issues that are the need of a calibration step, along with the need of processing adequately the corresponding associated uncertainties. With these goals in mind, this paper presented a way of using fast and cheap field EC measurements for monitoring soil salinity both over space and time. Starting from two initial sampling campaigns that allowed us to calibrate field EC measurements and to assess the spatial correlation pattern of laboratory EC measurements, it was shown how the various uncertainties can be accounted for in a prediction framework. By relying on the filtering properties of kriging and by accounting for the calibration errors and the positioning errors, it has been shown that the predictor that

577 has been advocated is able to remove these nuisance sources of variability.
578 Beyond the use of this methodology for processing historical data, as is was
579 done in this paper, it also offers a way to implement a real-time monitoring
580 of these changes over time for forthcoming field sampling campaigns. This
581 is by far the most important benefit of the methodology if the aim is to
582 really prevent salinization hazard right on time, instead of simply being
583 able to observe them when they become obvious but when it is also too
584 late for taking meaningful preventive actions.

585 It is clear that applying this methodology relies on the validity of some
586 hypotheses, i.e. the normality and independence of the calibration errors,
587 along with the normality of the $\log(\text{EC})$ values for optimal linear predic-
588 tions. However, these are classical hypotheses that frequently hold true in
589 similar calibration contexts. Moreover, although the uncertainties sources
590 that have been processed in this paper were only linked to the calibration
591 and positioning errors, the method is general enough for processing other
592 sources of uncertainties as well (like a random effect for the calibration
593 curves, as mentioned), as long as these effects can be quantified from the
594 data at hand. We thus believe that this methodology and its possible
595 extensions for other sources of errors is a valuable tool for practitioners,
596 that offers a compromise between theoretical complexity and practical
597 efficiency.

598 Acknowledgments

599 We are indebted to three anonymous reviewers for their detailed and nu-
600 merous comments that greatly helped improving the manuscript. The re-
601 search work of the first author was fully supported by the Iranian National
602 Science Foundation (ISFN), grant number 91056702.

References

- Amezketta, E., 2006. An integrated methodology for assessing soil salinization, a pre-condition for land desertification. *J. Arid Environ.* 67, 594-606.
- Atkinson, P.M., Lloyd, C.D., 2010. *geoENV VII-Geostatistics for Environmental Applications*. Quantitative Geology and Geostatistics 16. Dordrecht: Springer, 419pp.
- Bogaert, P., D'Or D., 2002. Estimating soil properties from thematic soil maps: the Bayesian Maximum Entropy. *Soil Sci. Soc. Am. J.* 66, 1492-1500.
- Bouaziz, M., Matschullat, J., Gloaguen, R., 2011. Improved remote sensing detection of soil salinity from semi-arid climate in Northeast Brazil. *C. R. Geoscience.* 343, 795-803.
- Brus, D.J., Bogaert, P., Heuvelink, G.B.M., 2008. Bayesian maximum entropy prediction of soil categories using a traditional soil map as soft information. *European J. Soil Sci.* 59(2), 166-177.
- Christakos, G., 1990. a Bayesian maximum entropy view to the spatial estimation problem. *Math. Geol.* 22(7), 763-777.
- Ding, J., Yu, D., 2014. Monitoring and evaluating spatial variability of soil salinity in dry and wet seasons in the Werigan-Kuqa Oasis, China, using remote sensing and electromagnetic induction instruments. *Geoderma.* 235-236, 316-322.
- D'Or, D., Bogaert, P., Christakos, G., 2001. Application of the BME approach to soil texture mapping. *Stoch. Environ. Res. Risk Assess.* 15, 87-100.
- Douaik, A., Van Meirvenne, M., Toth, T., 2005. Soil salinity mapping using spatio-temporal kriging and Bayesian maximum entropy with interval soft data. *Geoderma.* 128, 234-248.
- Douaik, A., Van Meirvenne, M., Toth T., 2004. Spatio-temporal kriging of soil salinity rescaled from bulk soil electrical conductivity. In: Sanchez Vila X, Carrera J, and Gomez-Hernandez J (es). *GeoEnv IV: Geostatistics for Environmental Applications*. Kluwer Academic Publishers: Dordrecht, the Netherlands, pp 413-424.
- Douaoui, A.E.K., Nicolas, H., Walter, Ch., 2006. Detecting salinity hazards within a semiarid context by means of combining soil and remote-sensing data. *Geoderma.* 134, 217-230.
- Corwin, D.L., Lesch, S.M., 2005a. Characterizing soil spatial variability with apparent soil electrical conductivity, part I. Survey Protocols. *Comput. Electron. Agr.* 46, 103-133.
- Corwin, D.L., Lesch, S.M., 2005b. Characterizing soil spatial variability with apparent soil electrical conductivity, part II. Case study. *Comput.*

Electron. Agr. 46, 135-156.

Corwin, D.L., Lesch, S.M., Oster, J.D., Kaffka, S.R., 2006. Monitoring management-induced spatio-temporal changes in soil quality through soil sampling directed by apparent electrical conductivity. *Hydropedology: Bridging disciplines, scales and data*. *Geoderma*. 131(3-4), 369-387.

Fazekas, I., Kukush, A.G., 2005. Kriging and measurement errors. *Discussions Mathematicae, J. Proba. Stat.* 25, 139-159.

Fazekas, I., Kukush, A.G., 1999. Errors-in-variables and kriging. in *Proc. 4th International Conference on Applied Informatics, Eger*. 261-273.

Gorji, T., Tanik, A., Sertel, E., 2015. Soil salinity monitoring and mapping using modern technologies. *Procedia Earth Planet. Sci.* 15, 507-512.

Halvorson, A.D., Rhoades, J.D., Reule, C.A., 1977. Soil salinity-four-electrode receptivity relationships for soils of Northern Great Plains. *Soil Sci. Soc. Am. J.* 41, 966-971.

Hamzehpour, N., Eghbal, M.K., Toomanian, N., Bogaert, P., Oskoui, R.S., 2015. Uncertainty Assessment of the Soil Salinity Boundary in Uromia Plane Using Bayesian Maximum Entropy Method. *Soil management and sustainable production. J. Soil Manag. Sustain. Agri.* 5(2), 131-147.

Hamzehpour, N., Eghbal, M.K., Bogaert, P., Toomanian, N., Oskoui, R.S., 2013. Spatial prediction of soil salinity using kriging with measurement errors and probabilistic soft data. *Arid Land Res. Manag.* 27(2), 128-139.

Heuvelink, G.B.M., Bierkens, M.F.P., 1992. Combining soil maps with interpolations from point observations to predict quantitative soil properties. *Geoderma*. 55(1-2), 1-15.

Huang, J., Barrett-Lennard, E., Kilminster, T., Sinott, A., Triantafyllis, J., 2015. An error budget for mapping field-scale soil salinity at various depths using different sources of ancillary data. *Soil Science Society of America Journal*, 79, 1717-1728.

Johnson, C.K., Doran, J.W., Duke, H.R., Weinhold, B.J., Eskridge, K.M., Shanahan, J.F., 2001. Field-scale electrical conductivity mapping for delineating soil condition. *Soil Sci. Soc. Am. J.* 65, 1829-1837.

Khan, N.M., Rastoskuev, V.V., Shalina, E., Sato, Y., 2001. Mapping salt-affected soil using remote sensing indicators. A simple approach with the use of Gis Idrissi. *22nd Asian Conference on Remote Sensing*, 5-9 November 2001, Singapore.

Lhissoui, R., El Harti, A., Chokmani, K., 2014. Mapping soil salinity in irrigated land using optical remote sensing data. *Eurasian J. Soil Sci.* 3(2), 82-88.

Li, H.Y., Marchant, B.P., Webster, R., 2016. Modelling the electrical conductivity of soil in the Yangtze delta in three dimentions. *Geoderma*.

269, 119-125.

Li, X.M, Yang, J.S, Liu, G.M., Yu, M., 2012. Spatio-Temporal Changes of Soil Salinity in Arid Areas of South Xinjiang Using Electromagnetic Induction. *J. Integr. Agric.* 11(8), 1365-1376.

Li, Y., Shi, Z., Li, F., 2007. Delineation of site-specific management zones based on temporal and spatial variability of soil electrical conductivity. *Pedosphere.* 17 (2), 156-164.

Metternicht, G.I., Zinck, J.A., 2003. Remote sensing of soil salinity: potentials and constraints. *Remote Sens. Environ.* 5812, 1-20.

Scudiero, E., Skaggs, T. H., Corwin. D. L., 2016. Comparative regional-scale soil salinity assessment with near-ground apparent electrical conductivity and remote sensing canopy reflectance. *Ecol. Indic.* 70, 276-284.

Scudiero, E., Skaggs, T.H., Corwin, D.L., 2015. Regional-scale soil salinity assessment using Landsat ETM+ canopy reflectance. *Remote Sen. Environ.* 169, 335-343.

Sivanpillai, R., Claypool, D. A., Siloju. R., 2012. Relating AEROCam-derived NDVI to apparent soil electrical conductivity (ECa) for corn fields in Wyoming, USA.” *Remote sens. Letters.* 3(1), 49-56.

Serre, M.L., Christakos, G., 1999. Modern geostatistics: computational BME in the light of uncertain physical knowledge-the Equus Beds study. *Stoch. Environ. Res. Risk Assess.* 13, 1-26.

Taghizadeh-Mehrjardi, R., Minasny, B., Sarmadian, F., Malone, B.P., 2015. Digital mapping of soil salinity in Ardakan region, central Iran. *Geoderma.* 213, 15-28.

Touch, S., Pipatpongsa, T., Takeda, T., Takemura. J., 2015. The relationships between electrical conductivity of soil and reflectance of canopy, grain, and leaf of rice in northeastern Thailand. *Int. J. Remote Sens.* 36(4), 1136-1166.

Wang, F., Xu, Y.J., 2008. Development and application of a remote sensing-based salinity prediction model for a large estuarine lake in the US Gulf of Mexico coast. *J. Hydr.* 360(1-4), 184-194.

Wu, W., Mhaimeed, A.S., Al-Shafie, W.M., Ziadat, F., Dhehibi, B., Nangia, V., De Pauw, E., 2014. Mapping soil salinity changes using remote sensing in Central Iraq. *Geoderma Regional.* (2-3):21-31.

Yao, R., Yang, J., 2010. Quantitative evaluation of soil salinity and its spatial distribution using electromagnetic induction method. *Agri. Water Manag.* 97, 1961-1970.

5 Tables and Figures

Table 1: Summary statistics of top soil salinity as measured by electrical conductivity (EC, in dS/m) in 1:2.5 soil-to-water ratios at various dates. Upper part refers to laboratory EC measurements, while bottom part refers to field EC measurements.

$EC_{2.5}$	n	mean	variance	min	max	skewness
Autumn 2009	186	3.68	55.07	0.20	47.70	0.18
Spring 2010	236	4.73	59.68	0.14	45.00	0.16
Autumn 2009	186	3.18	44.08	0.13	36.90	0.18
Spring 2010	236	4.86	71.81	0.10	55.50	0.16
Autumn 2010	148	5.09	29.35	0.12	25.60	0.20
Autumn 2011	46	4.56	22.62	0.18	17.74	1.22
Autumn 2014	46	5.98	32.19	0.30	21.00	1.10
Spring 2015	46	6.58	42.51	0.22	22.40	1.19
Autumn 2015	46	6.03	41.01	0.30	22.00	1.33
Spring 2016	46	6.00	35.05	0.29	19.54	1.10
Autumn 2016	46	6.65	36.45	0.42	20.65	1.08

760

761

762

763

764

765

766

767

768

Figure 1: Location of the study area in the Western part of Urmia Lake (top) with locations the Autumn 2009 (+) and Spring 2010 (x) sampling campaigns (bottom), with a subset of 170 identical locations that have been sampled for both time instants (*). All locations have been sampled both for field EC and laboratory EC. Coordinates are in meters, as obtained from a Universal Transverse Mercator (UTM) projection.

Figure 2: Relationship between laboratory and field EC measurements for Autumn 2009 and Spring 2010 campaigns. Top figures refer to regression lines fitted separately, while bottom figures refer to a single regression based on all data. Dashed lines refer to the 1:1 line while plain lines is the fitted regression model.

Figure 3: Estimated variograms for the calibration errors in Autumn 2009 (+) and Spring 2010 (x) (top), with corresponding estimated variograms for the laboratory $\log(\text{EC})$ measurements at the same dates (bottom). Distances are in meters and variogram values are in $\log^2(\text{ds/m})$.

Figure 4: Relationship between laboratory $\log(\text{EC})$ values in Autumn 2009 and Spring 2010 (left), along with the corresponding filtered laboratory values for the same dates (right). Circled values refer to locations where change did occur between these two dates with a confidence level $1 - \alpha = 0.8$.

Figure 5: Locations for both Autumn 2009 and Spring 2010 sampling campaigns (dots), along with the 46 locations where field EC values have been monitored over time from Spring 2010 till Autumn 2016 (circles). See also Table 1 for more details about these dates.

Figure 6: Relationship between field log(EC) measurements at successive dates (top), along with the corresponding filtered field values for the same dates (bottom).

Figure 7: Relationship between filtered field $\log(\text{EC})$ values at two successive dates. Dashed lines refer to the 1:1 line while offset plain lines are referring to the mean value difference between dates. Circled values refer to locations where change did probably occur between two successive dates with a confidence level $1 - \alpha = 0.8$.

Figure 8: Location of the 46 monitored locations over time, where colors is referring to the associated p -values for the null hypothesis that $\log(\text{EC})$ did not significantly change between Autumn 2011 and Autumn 2014.

Figure 9: Maps of the $\log(\text{EC})$ filtered values for the field measurements in Autumn 2011 and Autumn 2014, with superimposed colored markers for the 46 sampled locations. All maps and markers use the same color scale, where colors are ranging from pure blue (lowest value) to pure yellow (highest values), with lowest and highest values respectively equal to -1.59 and 2.92.