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Research Article

A New Soil Sampling Design in Coastal Saline Region Using EM38 and VQT Method

Spatial sampling design based on the variability and distribution of soil properties is an important issue with the progress in precision agriculture and soil ecology. Electromagnetic induction (type EM38) and variance quad-tree (VQT) method were both applied to optimize the sampling scheme of soil salinity in a coastal reclamation field in north Jiangsu Province, China. Apparent soil electrical conductivity (EC_a) measured with EM38 was used as an ancillary variable and the spatial distribution of EC_a was used as priori information. The process and result of VQT algorithm analysis was illustrated and the obtained sampling strategy was validated using observed soil salinity. Then the spatial precision and sampling efficiency were evaluated. The result indicated that the spatial distribution of soil salinity produced with the VQT scheme was quite similar to that produced with total sampling sites, while sampling quantity of the former was reduced to approximately 1/2 of the latter. The spatial precision of VQT scheme was considerably higher than that of traditional grid method with respect to the same sampling number, and fewer samples were required for VQT scheme to obtain the same precision level. A 17.3% increase in sampling efficiency was achieved by VQT over grid method at the precision level of 90%. The VQT method was proved to be more efficient and economical because it can sample intensively or sparsely according to variation status in local areas. The associated application of EM38 and VQT method provides efficient tools and theoretical basis for saving sampling cost and improving sampling efficiency in coastal saline region and enriching soil ecology.

Keywords: Coastal saline region; Electromagnetic induction; Sampling design; Variability; Variance quad-tree

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1 Introduction

With the advance of precision agriculture and soil ecology, reliable information on the variation of soil properties has been increasingly attracting attention because it can provide efficient decisions on practices such as irrigation, fertilization, soil, and environmental management at the field and regional scales. At present, the commonly used means is to estimate values at unsampled sites using observed samples, and to represent the spatial variation by maps of the predicted values [1–3]. Thus the number of these maps and their reliability in field management depend on the accuracy of the estimated values, which essentially depends upon the initial sampling and field observations [4]. However, field observation has been traditionally based on discrete sampling procedures using either grid-based or statistically based random sampling strategy. The classical statistically based sampling approach is proved to be inferior to grid method in determining sampling numbers since the former takes no account of the inherent spatial correlation and the relative positions of sampling sites [5]. Regular grid method is a simple sampling design, while it is a laborious and time-consuming procedure presently if large areas need investigating. Considering the contradiction between sampling expense and sampling scheme resolution, the appropriate sampling strategy must be determined on the basis of adequate precision of spatial information of soil properties. Otherwise the sampling might be excessively intensive than necessary or too sparse to provide spatially correlated data for variogram calculation and spatial interpolation. More and more attention has been given to the studies on designing spatial sampling strategies recently. Simulated annealing was proposed to determine the optimal grid spacing and reduce the sampling density by minimizing the Kriging variance [6–8]. Brus et al. [9, 10] applied fuzzy *k*-means clustering to optimize the quantity and distribution of sampling points and the similar approach was also used by Minasny and McBratney [11]. Other studies explored algorithms for spatial sampling by choosing ancillary variables. Lesch et al. [12–14] also applied an algorithm for calibrating electromagnetic induction (EMI) data and linked terrain attributes, climatic, and geological data with stratifying the study area. Hengl et al. [15] and Heuvelink et al. [16] designed sampling schemes

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Abbreviations: **EC_a**, electrical conductivity; **EMI**, electromagnetic induction; **EM38**, electromagnetic induction type EM38; **VQT**, variance quad-tree

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using environmental covariates. Minasny and McBratney [17] developed a conditioned Latin hypercube method for sampling with the help of auxiliary information. In this paper the variance quad-tree (VQT) method widely used in image compression [18], is applied to the soil sampling design in a coastal saline field. Apparent soil electrical conductivity (EC_a) measured by electromagnetic induction instrument (type EM38) was selected as ancillary variable, and the spatial distribution map of EC_a was used as prior knowledge to design the sampling strategy of soil salinity. The process and result of VQT algorithm analysis was illustrated with detail. The prediction precision of the obtained VQT scheme was validated and evaluated using the observed salinity data, and sampling efficiency of VQT method was then compared with that of conventional grid method.

2 Materials and methods

2.1 Experimental area

This study was conducted on Jinhai Farm, located in the southeast of Dafeng City, North Jiangsu Province, China. The farm was approximately 4 km to the coastline of China Yellow Sea, and bordered on its western side by the Dafeng Milu National Nature Reserve. The climate is subtropical and characterized by transition, oceanity, and monsoon with large seasonal fluctuations in temperature and precipitation. Rainy season (accounting for approximately 70% of annual rainfall) is from June to August with average annual precipitation of 1058.4 mm. The farm covers a variety of salinity conditions and its soils are representative for large areas of coastal saline soils of China. Sandy loam is the predominant soil type due to modern marine and fluvial deposits. Soil salinity is known as a most significant problem in this area. Over the past decades, many coastal tideland areas have been successively reclaimed for agricultural land uses under a series of reclamation projects. The field used in the present study, approximately 0.69 hm^2 (48 m $\times$ 144 m) situated in southwest of the farm, had been reclaimed since 1999 (Fig. 1) with rotation cropping system of cotton-rape two harvests in 1 year.

2.2 Data collection and soil sampling

A grid-sampling method (average interval of 4 m) was employed on the field of our interest and 285 grid points were selected as sampling locations. At each grid point, EC_a was firstly measured by the horizontal mode of electromagnetic induction (type EM38), which was placed on the ground. Then a representative soil sample at 0–20 cm surface layer was collected for lab analysis. To ensure the representation, this sample was obtained by mixing four soil samples gathered within a 1 m diameter circle around the grid point. A total of 285 EC_a data and soil samples were collected, which was conducted in March 2008, just the critical season of spring-sowing.

2.3 Soil property analysis

Soil samples were air-dried, crushed, and sieved at 2 mm prior to chemical analysis. Soil salinity was determined measuring electrical conductivity of 1:5 soil water extract ($EC_{1:5}$). The 1:5 soil/water suspensions were prepared by weighing 10 g of soil into a pop-top tube, adding 50 mL of deionized water, and shaking for 5 min on an end-over-end shaker. After being centrifuged, the $EC_{1:5}$ of the supernatant was directly measured with a conductivity meter [19]. In many previous studies, electrical conductivity of saturated soil paste extract (EC_e) was widely used to determine soil salinity. In our study, $EC_{1:5}$ was used as a surrogate of EC_e owing to the significant correlation between $EC_{1:5}$ and EC_e, as was reported by numerous authors for coastal saline soil [20–22].

2.4 Variance quad-tree (VQT) algorithm

Quad-tree is a hierarchical decomposition technique that involves successively partitioning a two-dimensional space into four equal-size quadrants or blocks that are more homogeneous than the space itself. This process is repeated iteratively until each quadrant meets some criterion of homogeneity, and the result may have quadrants of several different sizes. This technique is widely used for

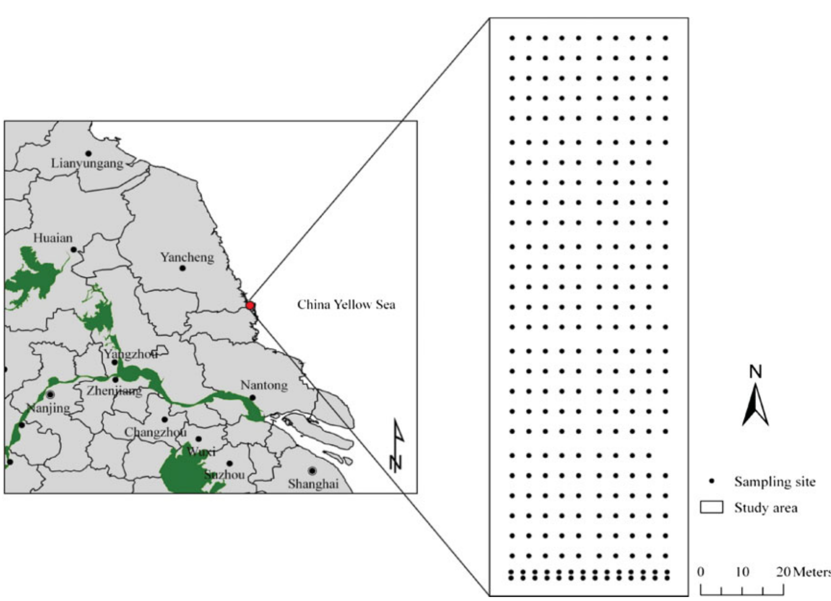


Figure 1. Geographic location of study field and spatial distribution of sampling sites.

spatial data collection, image compression, and spatial sampling design [23, 24].

The VQT is based on the principle of quad-tree decomposition where an area of interest is divided into quadrants or strata so each stratum has more-or-less equal variation [25, 26]. This method optimizes spatial sampling schemes by sampling sparsely in areas that are relatively uniform and more intensively in areas where variation is strong. Recently, sampling in the presence of ancillary variables has been explored. Minasny and McBratney [17] developed the application of the VQT method on sampling design in the presence of DEM (digital elevation model) and its derivatives, and Landsat TM images. The theoretical background and procedure of VQT algorithm has been reported by Li et al. [24], Samet [27], Csillag [28], and Wu and Long[29].

3 Results and analysis

3.1 Semi-variogram and spatial distribution of EC_a

The application of the VQT algorithm will be initially illustrated using EC_a data measured by electromagnetic induction EM38 from our study field. Since statistically abnormal distribution of data can have an adverse impact on semi-variogram and further interpolation, an elementary knowledge of raw EC_a data is required before spatial analysis. Kolmogorov–Smirnov testing suggested that a logarithmic transformation was necessary to ensure the normality of EC_a data before semi-variogram calculation. The theory model and corresponding parameters of semi-variance are presented in Fig. 2a. These parameters included the nugget value C_0, sill (C), nugget–sill-ration (C_0/C), range value A, and determination coefficient R^2. It was evident that semi-variance of EC_a fitted a spherical model well and exhibited strong spatial dependency according to C_0/C [30]. Figure 3b displays the measured versus predicted EC_a data and the cross-validation result of Kriging interpolation. The mean prediction error (MPE) and root mean square prediction error (RMSPE) were −0.00049 and 0.1366, respectively, indicating that the Kriging approach was reasonably successful at producing the EC_a estimates at unsampled sites.

Raster map of soil EC_a across the study field was generated using semi-variogram model in Fig. 2a. As illustrated in Fig. 3a, the EC_a exhibited strip and block patterns and showed great spatial variation at different locations of the study field. It can be summarized that the EC_a in eastern area was generally larger than that in western area, and the block of high EC_a was located at the southeastern part of the study field. This phenomenon can be explained by many factors, such as the variability of soil salinity, cropping system, microtopography, and soil texture across the study field. Field investigation showed that at places where EC_a was relatively low, crop grew well according to the cotton stubble, while high surface soil salinity was observed at southeast part of high EC_a. A further analysis revealed that the EC_a and surface soil salinity ($EC_{1:5}$) were significantly correlated and the proportion of the explained variability accounted for 95.4%, indicating the high reliability of EC_a as a surrogate of salinity and the feasibility of optimal sampling design for salinity using EC_a spatial distribution. Considering the strong variability of EC_a across the study field and the demand of square image for VQT algorithm, the study field was subdivided into A, B, and C three equal-sized regions (48 m × 48 m for each region, Fig. 3b), availing to quantitatively compare the results of VQT algorithm on regions of various spatial variation.

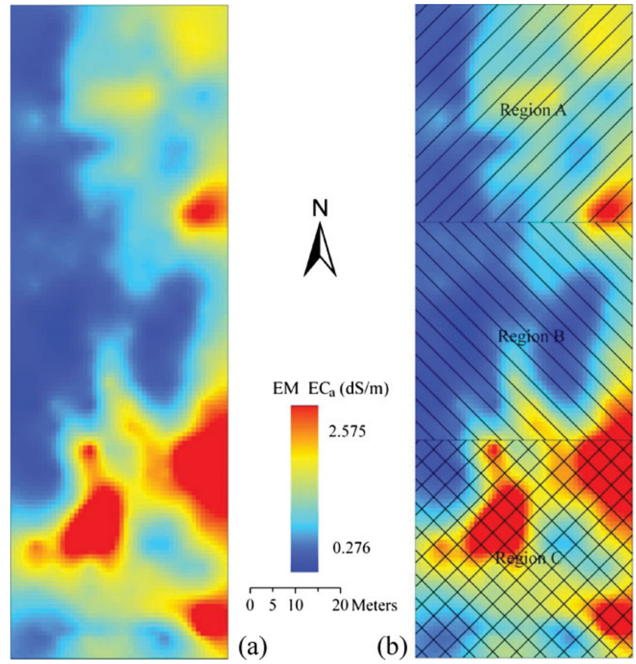


Figure 3. Spatial distribution map of soil EC_a and its zoning.

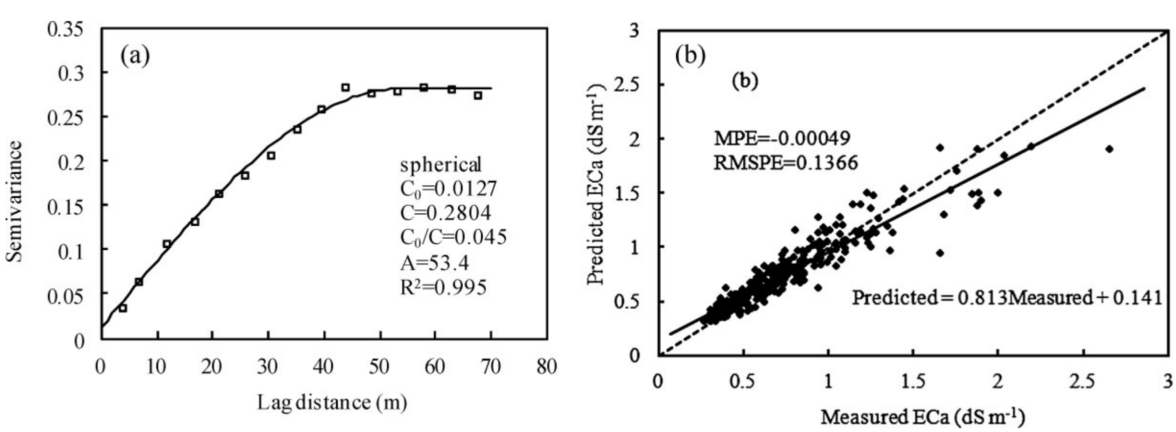


Figure 2. Semi-variogram and cross-validation result for spatial prediction of soil EC_a.

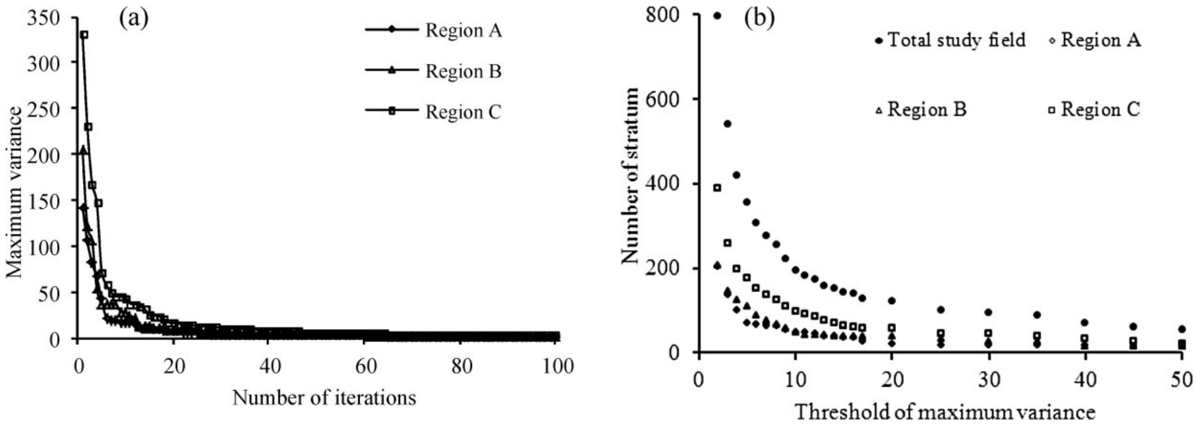


Figure 4. Maximum within-stratum variance versus iteration number and threshold of maximum variance versus number of stratum.

3.2 VQT algorithm analysis

Variance quad-tree algorithm was applied to split the distribution map of region A, B, and C into equally sized strata, respectively. Figure 4a shows the change of maximum variance within each stratum as the number of iterations of the VQT algorithm increased. It can be seen that the variance within the strata decreases rapidly with the increase of total strata number for each region. For individual region A, the within-strata variance began to plateau after 21 iterations, while 16 and 19 iterations were needed for separate region B and C, respectively. With respect to the same within-strata variance, on condition that 5% maximum variance of region A was set as the homogeneity criteria of the study field, then 21, 25, and 45 iterations were demanded to satisfy the requirement for region A, B, and C, respectively, and the iteration number difference may be explained by the observable inconsistency of variation status in each region. Figure 4b presents the number of strata with the increase of threshold of maximum variance for each region and the total study field, respectively. It was apparent that for the same criteria of maximum variance, the required strata number of region C was considerably larger than that of region B and region A, suggesting that the required iterations and strata increased with the variability of EC_a spatial distribution. In addition, the required strata increased sharply with the decrease of the criteria of within-strata variance, especially for within-strata variance of <10, and it was also the case for the whole study field. Figure 4b shows the number of strata.

Figure 5 displays the 420, 276, and 195 strata as calculated from the distribution map of EC_a for the study field. The VQT algorithm

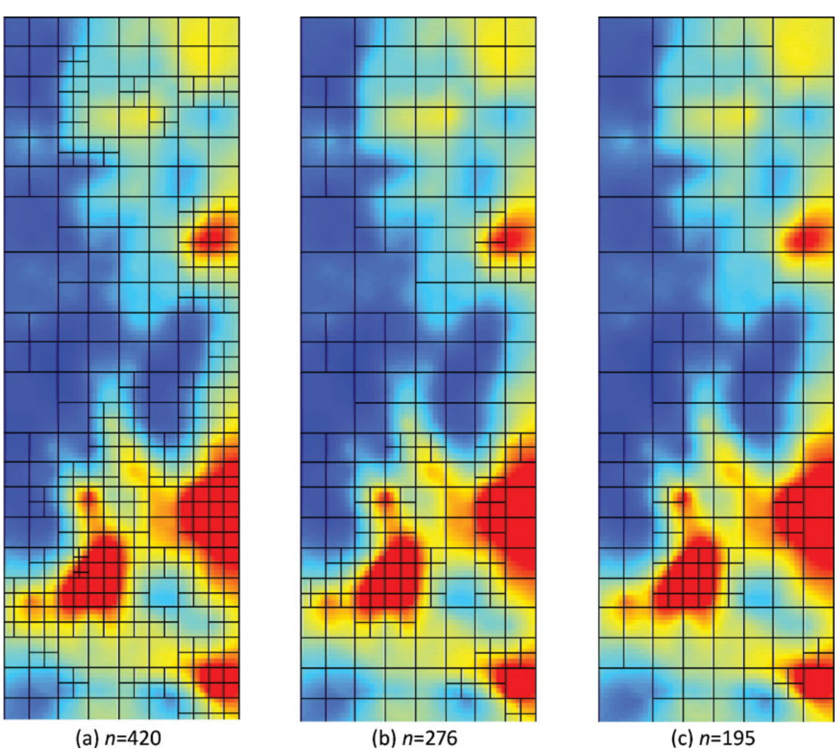


Figure 5. Sampling schemes for soil EC_a generated with the VQT method of 420, 276, and 195 soil strata.

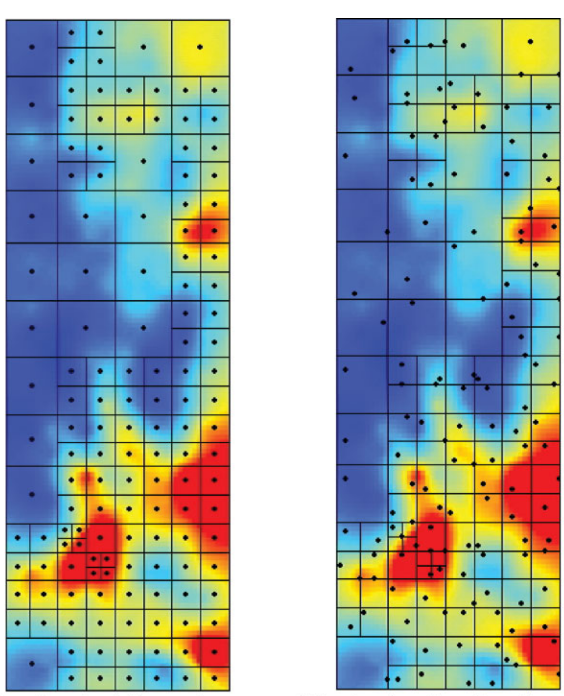
identified places within the field with greater local variance, where the EC_a varied dramatically over a small area. This information could help to guide subsequent soil sampling, and samples can be collected intensively in the places with greater variability and sparsely in uniform area, which will ensure that each sample is representative of a more-or-less equal variance, and the collected sample information should be more valuable than merely grid sampling the same field. In Fig. 5, where higher EC_a variance was observed, the VQT algorithm sought out and described the boundaries of possible soil management units with more intensive meshes. This would be regarded as the borders between discontinuities in EC_a. As soil salinity is the most influencing soil attribute on crop yield in coastal saline region, it also implies the strong variation of crop growth status in boundaries of greater EC_a local variance.

The VQT algorithm can find wide applications in spatial sampling design for regionalized variables. In precision agriculture, this approach can be used to design sampling schemes of crop yield based on its variation, and soil attributes which may be considered the most influencing factors on crop yield. The main limitation of this approach is requiring prior knowledge of spatial variability for the soil property (or ancillary variable relevant to the soil property, for instance the EC_a easily obtained and well correlated with salinity in this paper) and it is more suitable for long-time series sampling scheme for variables of interest in practical application. As discussed by de Gruijter et al. [31], Li et al. [32], and Minasnya et al. [23], the VQT algorithm is more advantageous in designing sampling schemes than geometric methods and *k*-means clustering. VQT uses information of non-stationary ancillary variable and it does not minimize the within-strata variance, but represent spatial units with almost equal variance. Therefore its strata are not discrete but spatially contiguous and discernible [6].

The VQT method has identified several areas within the study field to ensure the soil sampling at a more proper density than the rest of the field, while this would be undetectable using a regular grid approach (Fig. 6). Obviously, with a smaller sample volume, the VQT algorithm would provide a sampling design to collect samples intensively in the places with greater variability and sparsely in uniform area, which is less spatially uniform than a regular grid approach. The VQT approach essentially provides a means for identifying the support field for future sampling and the specified locations of sampling sites can be laid out in a number of ways. The two most common approaches are presented in Fig. 6. Figure 6a displays the sampling points stationed at the center of each stratum, whereas Fig. 6b shows a random allocation of the points.

3.3 Validation and evaluation of sampling efficiency

To validate the above VQT sampling scheme, spatial distribution maps, visually illustrated in Fig. 7, were generated by ordinary Kriging using all 285 soil $EC_{1:5}$ data (Fig. 7a) and 141 soil $EC_{1:5}$ samples (Fig. 7b), respectively. Compared with the EC_a spatial distribution in Fig. 3, Fig. 7a shows quite similar spatial characters, with high level in the southeastern section and low value in the western and northern parts of the study field, indicating that the spatial pattern of EC_a depicted the variation of soil salinity and it was credible to design sampling schemes for coastal soil salinity using the EC_a data measured by electromagnetic induction EM38. In addition, soil $EC_{1:5}$ map from 141 samples (Fig. 7b) was similar to that from 285 sites (Fig. 7a) to a large extent, namely Fig. 7b almost exhibits the same strip and block patterns as Fig. 7b despite the



(a) Sampling points laid out at the center (b) Random disposition of sampling points

Figure 6. Sampling schemes for soil EC_a generated with the VQT method of 141 soil strata.

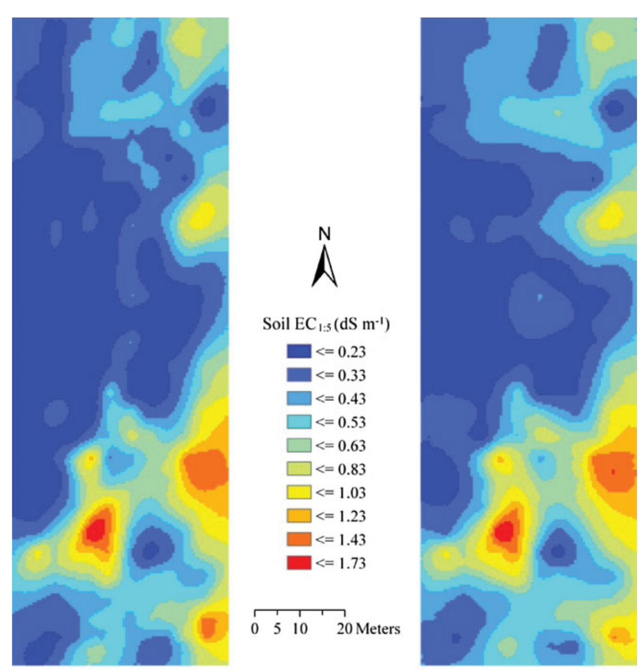


Figure 7. Spatial distribution of soil $EC_{1:5}$ produced with all samples and 141 sites of the VQT scheme.

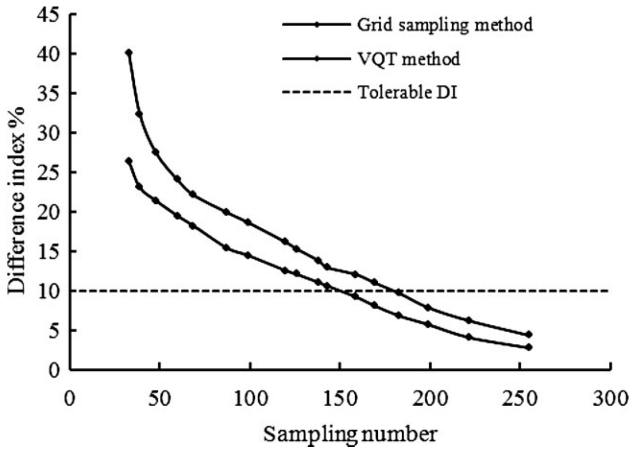


Figure 8. Difference index versus sampling number for soil $EC_{1:5}$ distribution maps of VQT and grid sampling methods.

smooth of some local-variance details. Although the sampling quantity generated by the VQT method was reduced to approximately 1/2 of total samples, the spatial similarity between Fig. 7a and b approached 90%.

Conventional grid sampling method and VQT approach were both adopted to design sampling scheme of soil $EC_{1:5}$. Ordinary Kriging was then used to predict soil salinity at unknown locations with different number of samples obtained by the above two methods. Difference index [33] was introduced to quantify the similarity between distribution images of soil $EC_{1:5}$ produced with various sampling schemes, and soil $EC_{1:5}$ map generated with all 285 samples was selected as the reference image (Fig. 7a). The relationships between DI and sample quantity for the two sampling methods were calculated and plotted in Fig. 8. The DI generally decreases with the increase of sample number, suggesting that larger sample number leads to less DI and higher prediction accuracy while it is opposite for smaller sample number. As also seen, the DI obtained by VQT method is considerably lower than that by the grid method. Larger sample number is therefore required for grid method to obtain the same prediction precision level. The dashed line in Fig. 8 represents the tolerable DI level of 10% (namely mean relative error), then, to achieve this acceptable precision level, approximate 148 samples were needed for VQT method, while some 179 samples were needed for grid method, a 17.3% increase in sampling efficiency was achieved by VQT over grid method at the present precision level. Hence, a conclusion was drawn that with the EC_a measured by EM38 as ancillary variable and EC_a distribution map as prior information, the VQT method can be successfully used to design sampling scheme for soil salinity, and the obtained scheme has advantages in sampling cost, efficiency, and Kriging prediction accuracy by comparing with conventional grid method.

4 Discussions and conclusions

4.1 Discussions

The VQT approach provides a means for identifying the study area and dividing it into equal-sized strata to ensure that each stratum has similar variation, sampling efficient is then improved by collecting samples intensively or sparsely according to local variability status. This approach can find wide applications in farmlands of precision agriculture and long-term monitoring field which needs sampling periodically [34–39]. However, in practical application, the limitation of this methodology is that it needs more understanding about spatial variability for the soil attribute and it is not suitable for the initial sampling design for variables of interest. As pointed out, the reliability of VQT sampling scheme relies on two aspects. One is the accuracy of prior information, namely the spatial distribution map of EC_a measured by electromagnetic induction EM38, essentially the relationship between ancillary variable (EC_a) and variable of interest (soil salinity), since the response of EC_a to salinity is determined by many other soil properties, such as moisture, texture, and bulk density [34–36, 40–44], although soil salinity is the most influencing factor on EC_a in coastal saline region and the application of EM38 to sampling design of salinity proves to be reliable in our study field, and the feasibility and credibility of its application in arid and semi-arid saline region is still unknown. The other lies in the VQT method, this study was conducted in a small-scale field, however, further research was needed to judge the influence of other factors such as topography, groundwater, drainage system, and land use patterns on the suitability of VQT in large-scale area [39–44]. The current study was associated with the application of EM38 and VQT method, and the main limitation of VQT mentioned above is overcome by EM38 due to the easily obtainable feature of EC_a and significant correlation between EC_a and salinity. There are several other reasons including compact of design, ease of use, and the non-contacting nature of EM38. In this paper, horizontal EC_a of EM38 was successfully used to design sampling scheme of topsoil salinity, considering the fine response of vertical EC_a to soil salinity at deep layers of the root zone, optimal sampling design for salinity profile may be propounded using both horizontal and vertical EC_a of EM38, which is of great practicability for the determination of monitoring points which demand long-term observation, and of sampling sites which require periodical investigation [1, 22, 40–44].

4.2 Conclusions

The VQT algorithm and EC_a measured by electromagnetic induction EM38 were used to design sampling scheme for soil salinity in coastal saline region. EM38 instrument provides real-time measurements of EC_a, which consume less time compared with traditional methods. The VQT method provides a more efficient sampling scheme than regular gird method by purposely increasing sampling density in areas where can be considered to be more variable and sampling is sparse in uniform areas. In our study, the horizontal EC_a data of EM38 was used as ancillary variable of soil salinity and its spatial distribution map was used as prior information, then the VQT method was applied to design sampling scheme for topsoil salinity, and the obtained scheme was validated and evaluated using measured salinity data. The results revealed that the spatial pattern of soil salinity generated with VQT sampling scheme was quite similar to that generated with all sampling sits, while the sampling quantity of the VQT method was reduced to approximately 1/2 of total samples, indicating that VQT method was a cost-saving sampling method. The comparison of prediction precision between VQT method and conventional grid method showed that the precision of VQT method was considerable higher than that of grid method with respect to the same sampling quantity, and less samples were required for VQT method to obtain the same precision level. A 17.3% increase in sampling efficiency was achieved by VQT over grid method at the precision level of 90%. This study demonstrated that the sampling scheme obtained by the associated application of EM38 and VQT algorithm had advantages in sampling cost, efficiency, and spatial prediction accuracy compared with traditional grid method.

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