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Field-scale Spatial Variability of Electrical Conductivity of the Inland, Salt-affected Soils of Northeast Thailand

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Abstract

Salt-affected soil maps for Northeast Thailand focus on the percentage of salt crusts. Investigation was done to find the field-scale spatial variability of the electrical conductivity of saturation extract (EC_e) in salt-affected areas (percentage salt crusts: very severely = class 1; severely = class 2, and moderately = class 3). Two study sites were selected for each class (n = 6). Soil samples (n = 100) were collected at each site using stratified, systematic, unaligned sampling, and analyzed for EC_e. Variations in EC_e were assessed using basic statistics and geostatistics. At the field-scale, in every class, the best-fit semivariogram model generated was satisfactory ($R^2 > 0.8$). Interpretation from the relevant model parameters (i.e., nugget, sill, and effective range), together with the interpolated (kriged) maps, demonstrated that the characteristics of spatial variability of soil EC_e were inconsistent, even between different sites of the same salt-affected soil class. In general, various degrees of small-scale variation were observed, very high variation of EC_e was common, spatial dependence was strong to moderate, while the spatial distribution pattern was in distinctive patches. The size of patches depended on the effective range at each site. This study also revealed that the class 1 areas were entirely, very strongly saline (EC_es range, 56.70 and 433.00 $dS{\cdot}m^{-1}$), whereas the areas of class 3 were non-saline to moderately saline (range, 0.11 - 5.26 $dS{\cdot}m^{-1}$). Class 2 areas were much more complex; the soils varied from non-saline to very strongly saline (range, 0.16 - 49.00 $dS{\cdot}m^{-1}$). Information on the nature and characteristics in the spatial variability of soil EC_e is useful for developing strategies for management of salt-affected soils in precision agriculture in this region.

Keywords: Salt-affected soils, electrical conductivity, spatial variability, geostatistics, Northeast Thailand

Introduction

Salt-affected soil is a common problem in arid and semi-arid environments worldwide [1]. In Thailand, such soil can be found most notably in the northeastern region [2], where variable salinity affects ~30 % of land [3].

Effective management strategies to improve salt-affected soils require reliable information on the variability of the relevant soil chemical properties, particularly the electrical conductivity of the saturation extract (EC_e). Currently, in the official salt-affected soils maps produced at the regional scales (1:50,000 and 1:25,000) by the Land Development Department (LDD) of Thailand, soils are primarily classified on the basis of the percentage of surface salt crust in the dry season [2,3]. Information is scant, however, on the spatial variability of EC_e [2].

In some studies, e.g., Jansom *et al*. [4,5], attempts were made to obtain the information based on the LDD maps using basic statistics to assess the central tendency and variability (or spread) of EC_e in relation to the percentage of salt crust. This approach is untenable, however, as there is no information on the spatial variability of the relevant soil property in specific areas.

There are numerous interpolation methods- non-geostatistical and geostatistical- that can be used to generate spatial variation data from point data, e.g., trend surface analysis, inverse distance weight, and kriging [6], among others [7,8]. The current study employed a geostatistical method, called kriging, to investigate the nature and characteristics in spatial variability of soil $EC_{e;}$ where spatially dependent (i.e., soil EC_e), kriging is the most appropriate method [9]. Generally, this approach produces better estimates, because it accounts for the existing spatial dependence of the data [10]. In fact, surface modeling of soil properties by kriging is equivalent to the best linear unbiased estimation [11].

A number of studies have assessed and visualized the regional scale spatial variability of the physical and chemical properties in salt-affected soils in China [12], Iran [13], Turkey [14], America [15], and Australia [16]. The results of the foregoing might, however, not be relevant to the conditions at field-scale in Northeast Thailand, as the physical environments differ [17].

In Northeast Thailand, the average farm size (i.e., 3.65 ha) is relatively small [18], often comprising several much smaller subunits for different uses [19,20]. Information at the regional scale is inadequate for setting up management plans for such small, cultivated fields [20]. Advanced studies on the field-scale spatial variability of soil EC_e in relation to the percentage of the salt crust would help in understanding the mechanisms and processes relevant to the variability [12,21]. This could lead to targeted strategies for managing salt-affected soils in precision agriculture in this region.

Our primary objective was to investigate the field-scale spatial variability of soil EC_e in areas classified on the basis of the percentage of salt crust- very severely, severely, and moderately salt-affected soils (**Table 1**). To achieve the objective, basic statistics and geostatistics were applied. The former was used to describe central tendency and variability, and the latter to investigate characteristics in spatial variability (i.e., small-scale variation, highest variation, spatial dependence, and spatial distribution pattern) of the EC_e.

Materials and methods

Salt-affected soils in Northeast Thailand and the study area

In Thailand, salt-affected soils can be found in both coastal and inland areas. In the northeastern region, such soils are “inland”, and form in lowland areas underlain by the near-surface salt-bearing rocks of the Mahasarakam formation [22]. According to the USDA Soil Taxonomy [23], the salt-affected soils of northeastern Thailand include 5 families- fine-loamy, mixed, active, isohyperthermic Typic Natraqualfs; very fine, smectitic, isohyperthermic Typic Natraquerts; fine-loamy, mixed, active, isohyperthermic Aquic Natrustalfs; fine, mixed, active, isohyperthermic Typic Natraqualfs; and coarse-loamy, mixed, active, nonacid, isohyperthermic Typic Halaquepts [2]. Not only these soils, but also any other soils with surface salt crusts in the dry season, were considered salt-affected. At present, inland salt-affected soils in NE Thailand are categorized into 6 classes, based on the percentage of surface salt crust in the dry season (**Table 1**).

The study area was located between 16º 01′ - 16º11′ N latitude and 102º 37′ - 102º 42′ E longitude, in the inland salt-affected area of Khon Kaen province, northeastern Thailand (**Figure 1**). Landforms were mostly low terraces, with elevations ranging between 150 and 200 m above mean sea level.

This study focused on areas of very severely salt-affected soils (class 1), severely salt-affected soils (class 2), and moderately salt-affected soils (class 3). For each class, 2 study sites were selected, and a total of 6 sites were taken into consideration (viz., 1.1 to 3.2 in **Table 3**). Selection of the study sites was made based on the LDD's salt-affected soil map [3], together with field observation. Dominant soils in most of the study sites were members of the fine, mixed, active, isohyperthermic Typic Natraquerts family, except in one site of class 2 (Site 2.2), where the soil was of very fine, smectitic isohyperthermic Typic Natraquerts. These comprise the 2 major inland salt-affected soils in the northeastern region [24]. Field observation carried out during the period of soil sample collection revealed a percentage of salt crust of 80 - 90, 20 - 35, and 2 - 4, for areas of class 1, 2, and 3, respectively.

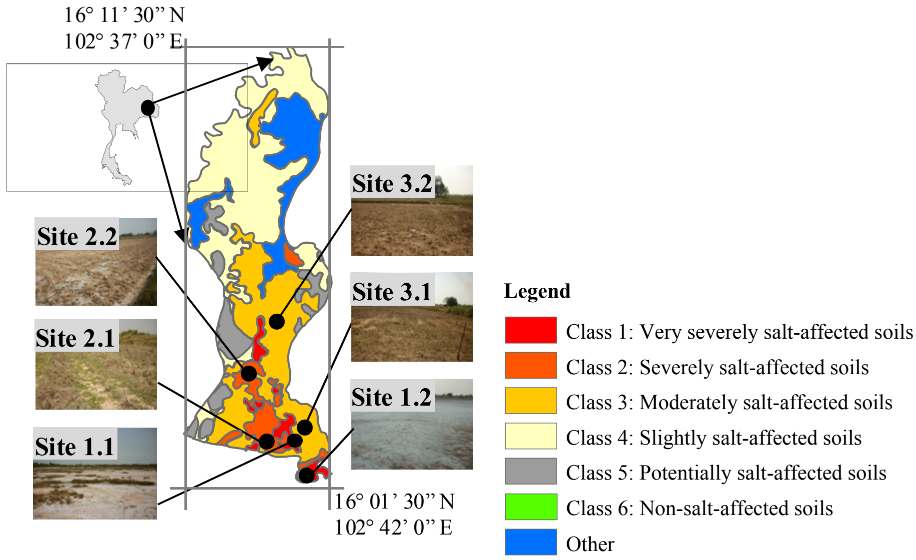

Figure 1 Study area in Muang Pia sub-district, Khon Kaen, Thailand (See **Table 1** for descriptions of each class).

Table 1 Classification scheme used to map salt-affected soils based on percentage of surface salt crust.

Salt-affected soil class	Description
1: Very severely salt-affected soils	Areas covered by salt crust > 50 % of soil surface
2: Severely salt-affected soils	Areas covered by salt crust >10 - 50 % of soil surface
3: Moderately salt-affected soils	Areas covered by salt crust >1 - 10 % of soil surface
4 : Slightly salt-affected soils	Areas covered by salt crust > 0 - 1 % of soil surface
5: Potentially salt-affected soils	Areas with no salt crust but underlain with salt-bearing rock
6: Non-salt-affected soils	Salt-free areas
Others	e.g., settlements, water bodies, etc.

Source: modified from [25].

Soil sampling

The soil samples were collected according to the stratified systematic unaligned sampling method (**Figure 2**). At each study site, a representative area of 50×50 m^2 was selected, then divided into 100 equivalent grids measuring 5×5 m^2. Within each grid, one soil sample was randomly collected at 0 - 30 cm depth in the dry season of 2012. One hundred soil samples were collected from each site and analyzed for EC_e using the standard method [26].

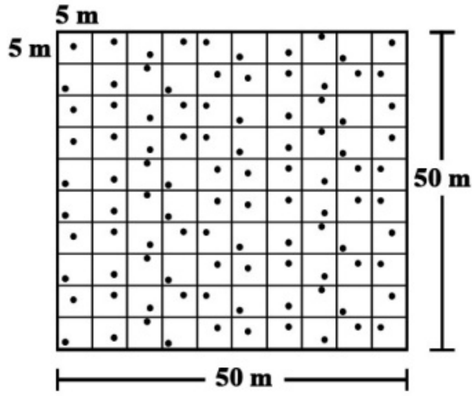

Figure 2 Stratified systematic unaligned sampling used.

Approach

The approach used to quantify *(a)* the variation, and *(b)* the characteristics in spatial variation of EC_e at each study site is presented in **Figure 3**. At first (**Figure 3a**), basic statistics was employed. A discrete set of original EC_e data points was prepared for geostatistical analyses. An analysis of skewness was undertaken to assess the normality of original data of the EC_e. The skewed (abnormal distribution) datasets (if skewness > 1 or < −1) were subjected to log-transformation and the normality rechecked prior to geostatistical analyses [13,27]. In addition, other basic statistics of known data points (i.e., minimum, maximum, mean, and coefficient of variation) were also examined. Second (**Figure 3b**), geostatistics were collected, applying semivariogram analysis and kriging interpolation to generate a best-fit semivariogram and an interpolated (kriged) map showing spatial variation of soil EC_e, respectively. Accuracy of the map was assessed by using cross-validation. A soil salinity map, showing different salinity classes, was derived from the relevant kriged map, based on the classification scheme shown in **Table 2**. The characteristics of spatial variability of soil EC_e (i.e., small-scale variation, highest variation, spatial dependence, and spatial distribution pattern) were interpreted from the relevant semivariogram and maps.

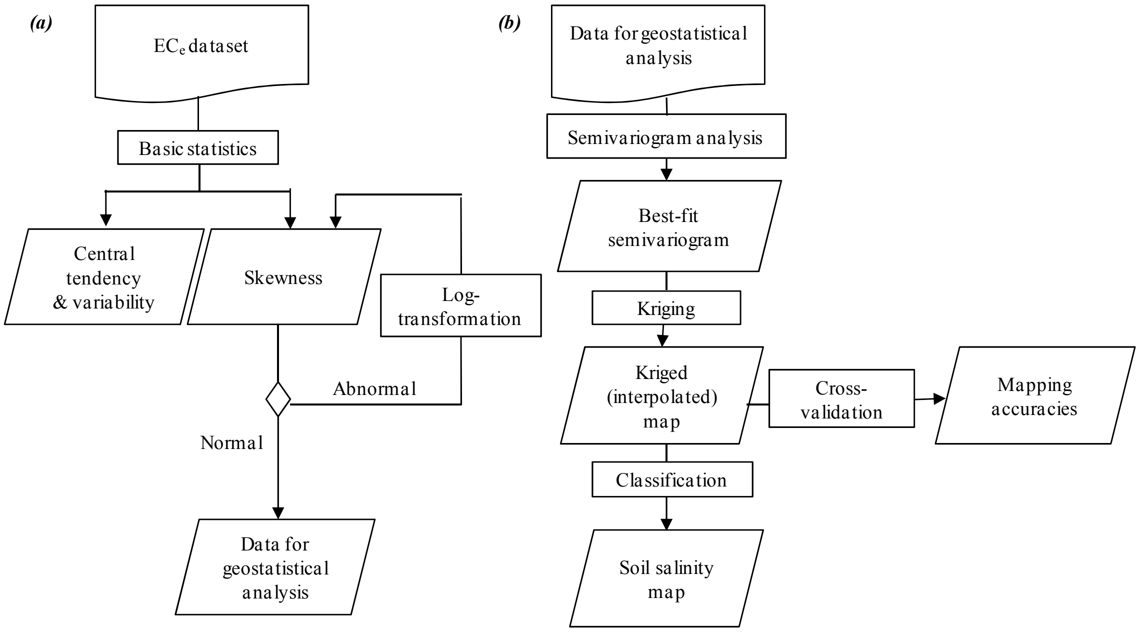

Figure 3 Diagram: study framework (a) basic statistics and (b) geostatistics.

Geostatistical analyses

Semivariogram analysis

For each study site, a semivariogram was developed to assess the characteristics of spatial variation of the EC_e in a specific area, based on Eq. (1) [28];

$$\hat{\gamma}(h) = \frac{1}{2N}\sum_{i=1}^{N}[Z(x_i) - Z(x_i + h)]^2 , \quad (1)$$

where $\hat{\gamma}(h)$ is a semivariance for lag vector h representing separation between 2 spatial locations,
N is total number of data pairs separated by a distance, and
$Z(x_i)$ is measured value for soil property; and x_i is the position i of soil samples.

With the use of the visual and statistical (ordinary least square) combined method, several standard models, including spherical, exponential and Gaussian [29], were tested. The best-fit model was determined based on the coefficient of determination (R^2) and lowest Residual Sum of Square (RSS). The GS+ Software V 9.1 [30] was used.

Corresponding parameters (i.e., nugget, sill, and range) were obtained from the best-fit semivariogram model. The nugget indicates small-scale variation (error of measurement or spatial variation at distances smaller than the sampling interval). The sill represents the maximum variation observed: the higher the sill value, the more heterogeneous the variable. The range is the distance at which the semivariogram reaches the sill [12,31]. Note that, for Gaussian and exponential models, there is no range value; the "range of influence" is used instead [32].

In the current study, the effective range, or a distance beyond which observations are not spatially-dependent, is preferred. According to [33], the effective range is calculated by multiplying the range / range of influence value with a constant, and values of the constant depend on the semivariogram models employed. These values are 1, 3, and 1.732 for the spherical, exponential, and Gaussian models, respectively.

The nugget, sill, and effective range were used to describe spatial dependence, and the spatial distribution pattern, for each study site. The nugget to sill ratio was used to define classes of the spatial dependence of soil EC_e. These classes represent degrees of spatial distribution patterns in the form of patches on the surface. The ratios of < 0.25, 0.25 - 0.75, and > 0.75 were classified as strong, moderate, and weak spatial dependence, respectively [34]. In general, the stronger the spatial dependence, the more distinct the patches are.

Kriging

For each study site, interpolation was undertaken (i.e., ordinary kriging using ILWIS 3.3) [7]. This method was chosen because, as shown later in the results (**Table 4** and **Figure 4**), the relevant semivariogram demonstrated the spatial dependence of soil EC_e in every study site. The literature indicates that kriging is the most appropriate interpolation method where soil EC_e is spatially dependent [9,35]. In addition, Zhu and Lin [36] indicated that this method usually performs well on agricultural lands and wherever the study area has highly heterogeneous soil properties [37]. This method uses a weighted average of neighboring samples to estimate the unknown value at a given location [38] as shown in Eq. (2).

$$\hat{Z}(x_i) = \sum_{i=1}^{n} w_i \times Z(x_i), \tag{2}$$

where (x_i) is predicted value for one output pixel
$Z(x_i)$ is value of input point *i*, and
w_i is weight factor for input point *i*.

More detail on calculating w_i is presented in [38,39].

Accuracy assessment

The cross validation approach was employed to assess mapping accuracy, based on 2 indices: (a) the Mean Prediction Error (MPE); and (b) Root Mean Square Prediction Error (RMSPE). The MPE in Eq. (3) yields true prediction accuracy by summing the residual observed and estimated values. This value should be near zero for an unbiased prediction. Positive and negative values indicate under and over-estimations, respectively. The RMSPE in Eq. (4) quantifies the degree of deviation in the model simulation from observations [29,40]. In order to compare the accuracy between different classes of salt-affected soil, the MPE and RMSPE were normalized, based on the observation mean as shown in Eqs. (5) and (6);

$$MPE = \frac{1}{n}\sum_{i=1}^{n}[Z(x_i) - \hat{Z}(x_i)] \tag{3}$$

$$RMSPE = \frac{1}{n}\sum_{i=1}^{n}\sqrt{[Z(x_i) - \hat{Z}(x_i)]}^{2} \tag{4}$$

$$MPE\% = \frac{MPE}{\overline{Z}(x_i)} \times 100 \tag{5}$$

$$RMSPE\% = \frac{RMSPE}{\overline{Z}(x_i)} \times 100 \tag{6}$$

where MPE% is relative mean prediction error, and
RMSPE% is relative root mean square prediction error, and
$\overline{Z}(x_i)$ is mean of observation values.

Soil salinity classification

In the current study, salt-affected soil classes are different from salinity classes. The former were classified based on the percentage of salt crust (**Table 1**), and the latter on the EC_e values (**Table 2**). To generate soil salinity maps, relevant interpolated (kriged) maps showing spatial variation of EC_e were classified. As shown in the results (**Table 3**, **Figures 5** and **6**), in class 1 areas, the soils were all very strongly saline, with EC_es > 16 $dS \cdot m^{-1}$. Thus, no variation in the degree of soil salinity could be shown, despite the high variation of EC_e observed. To be able to distinguish any variation, a more detailed classification scheme for very strongly saline soils was developed for use in this study (**Figure 7**).

Table 2 Classification of soil salinity.

Salinity class	EC_e ($dS \cdot m^{-1}$)
1: Very strongly saline	> 16
2: Strongly saline	> 8 - 16
3: Moderately saline	> 4 - 8
4: Slightly saline	≥ 2 - 4
5: Non-saline	< 2

Source: [41].

Results and discussion

Basic statistics of original datasets

As shown in **Table 3**, datasets acquired from class 2 (sites 2.1 and 2.2) and class 3 (site 3.2) areas had a skewness > 1. They were log-transformed before further geostatistical analyses. Other datasets were normally distributed. In most of the study sites, CV values were > 38 %, except for site 1.2, where the value was lower (26.03 %). According to Wilding [42], CV values of > 35 % denoted high variation, and those of > 15 - 35 %, indicated that the variation was moderate. Areas of little variation (CV < 15 %) were not found in the current study. Note that, in class 2 areas, variation of the EC_e was significantly higher than that of others, as indicated by the CV values of 115.32 and 77.05 %. As for class 1, based on the classification scheme shown in **Table 2**, the EC_e values for both study sites were very high (56.70 - 433.00 $dS \cdot m^{-1}$), demonstrating that the soils were very severely saline. The soils in areas belonging to class 2 varied significantly from non-saline to very strongly saline, with the EC_e values ranging from 0.16 to 49.00 $dS \cdot m^{-1}$. The class 3 soils were non-saline to moderately saline. Their EC_e values ranged from 0.11 to 5.26 $dS \cdot m^{-1}$, with a mean value < 2.19 $dS \cdot m^{-1}$. Because of the low EC_e in areas of this class, indicating very slight salt effect, the variation was less important, despite the high CV values.

Semivariogram model

As shown in **Table 4** and **Figure 4**, the models generated for most of the study sites were spherical, except that of site 1.1, where the Gaussian model had the best fit. The literature indicates that the spherical model usually fits well with the soil properties data, especially when the spatial distributions are "patchy" [27]. All of the selected models fit well with R^2 > 0.8, indicating that > 80 % of the relationship between distance and variation could be explained by the models. According to Duffera [43], these models were, thus, adequate for kriging interpolation.

Table 3 Basic statistics of the EC_e datasets from different study sites of salt-affected soil classes.

Class	[a]Site	EC_e ($dS \cdot m^{-1}$)			CV (%)	Skewness	
		Min	Max	Mean		Original	Log-transformed
1	1.1	56.70	433.00	205.69	42.18	0.40	-
	1.2	64.70	242.00	158.90	26.03	-0.09	-
2	2.1	0.16	24.90	4.73	115.32	1.94	0.31
	2.2	1.85	49.00	11.16	77.05	1.69	0.29
3	3.1	0.11	1.39	0.55	49.57	0.96	-
	3.2	0.72	5.26	2.19	38.82	1.12	0.03

[a] See **Table 1** for class description.

Kriged map

The kriged maps are shown in **Figure 5**. Prediction errors representing the mapping accuracy for spatial variation of soil EC_e are presented in **Table 5**. For classes 1 and 3, the errors assessed by means of MPE and RMSPE were comparable, but considerably better than those belonging to both sites of class 2.

Considering the maps representing study sites of classes 1 and 3, the MPE values close to 0 indicated that the relevant semivariogram models were almost unbiased, yielding either over- or under-estimates. Comparisons between the RMSPE values calculated for areas in both classes showed that mapping areas of class 1 resulted in much higher values (> 45.48 $dS \cdot m^{-1}$) than those of class 3 (< 0.82 $dS \cdot m^{-1}$). This was due to high EC_e values in class 1 areas. The relative RMSPE (RMSPE%) indicates that- for these 2 classes- the respective error size was not substantially different. The respective RMSPE% value for the class 1 and 3 mapping areas was < 36.49 and < 44.80 %. Although their relevant semivariogram models fit well enough- compared to those generated for other classes, a lower mapping accuracy was observed for class 2 areas. Positive values for MPE and somewhat high MPE% (> 16.40 %) indicated considerable under-estimations of these models. Mapping errors, as represented by RMSPE%, were relatively high (> 68.45 %) compared to those belonging to other classes. A higher RMSPE% might correspond to a higher variation of soil EC_e (CV > 77.05 %) (**Table 3**), notwithstanding that the relationships are not well understood between performance of the semivariogram model, the degree of variation in soil EC_e, and mapping error.

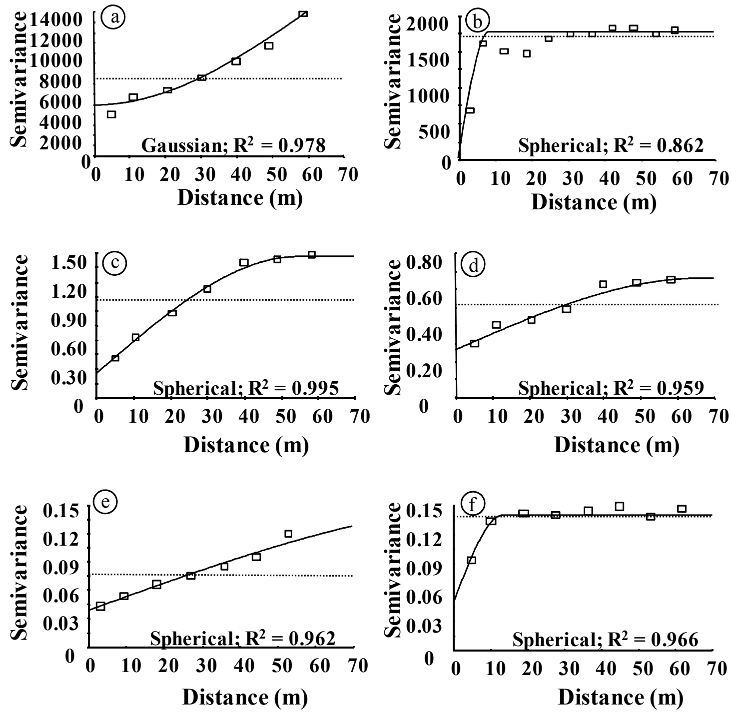

Figure 4 Best-fit semivariograms showing the relationship between distance and variation of EC_e at different study sites. Letters (a) - (f) represent sites 1.1, 1.2, 2.1, 2.2, 3.1, and 3.2, respectively.

Table 4 Semivariogram parameters for EC_e at different study sites of salt-affected soil classes.

Class[a]	Site	Model	Nugget $(dS \cdot m^{-1})^2$	Sill $(dS \cdot m^{-1})^2$	Range/ Range of Influence[b] (m)	Effective range[c] (m)	Nugget/ Sill	Degree of spatial dependence	R^2	RSS
1	1.1	Gaussian	4950	31000	91.40	158.30	0.15	Strong	0.978	1.458E+06
	1.2	Spherical	1	1758	8.30	8.30	0.00	Strong	0.862	1.507E+05
2	2.1	Spherical	0.25	1.47	54.70	54.70	0.16	Strong	0.995	5.128E-03
	2.2	Spherical	0.26	0.66	66.30	66.30	0.38	Moderate	0.959	4.606E-03
3	3.1	Spherical	0.03	0.15	118.20	118.20	0.19	Strong	0.962	1.483E-04
	3.2	Spherical	0.05	0.14	13.40	13.40	0.35	Moderate	0.966	7.739E-05

[a] See **Table 1** for class description.
[b] "Range" for spherical model, and "Range of influence" for Gaussian model.
[c] For spherical model, effective range = range × 1. For Gaussian model, effective range = range of influence × 1.732.

In spite of a wide range of mapping errors, all of the maps generated in this study were considered good enough to describe the characteristics in spatial variation of soil EC_e because their relevant semivariograms were satisfactory [44,45] (**Table 4** and **Figure 4**).

Table 5 Accuracies of kriged maps generated for different sites of salt-affected soil classes assessed using cross-validation method.

Class[a]	Site	MPE[b]		RMSPE[c]	
		$dS \cdot m^{-1}$	%	$dS \cdot m^{-1}$	%
1	1.1	-1.57	0.76	75.05	36.49
	1.2	0.06	0.04	45.48	28.62
2	2.1	0.86	18.18	3.65	77.16
	2.2	1.83	16.40	7.64	68.45
3	3.1	0.00	0.13	0.24	44.80
	3.2	0.13	6.35	0.82	37.44

[a] See **Table 1** for class description.
[b] Mean Prediction Error.
[c] Root Mean Square Prediction Error.

Characteristics in the spatial variability of EC_e

The parameters of nugget, sill, and effective range were determined from the best-fit semivariogram representing each study site (**Table 4** and **Figure 4**). These parameters, together with the relevant kriged map, were interpreted for characteristics of spatial variability of soil EC_e including small-scale variation, highest variation, spatial dependence, and spatial distribution pattern. The results revealed that the characteristics of spatial variability were inconsistent, even between different sites of the same salt-affected soil class. This could be due to various factors, both natural and manmade [1]; for instance, (a) occurrence of an impermeable soil layer [46], (b) climatic condition, (c) soil texture, (d) depth to the ground water, and (e) land management practices [47]. Currently, no evidence explains how these effects contribute to EC_e spatial variability. Nonetheless, in general, various degrees of small-scale variation were observed, very high variation of EC_e was common, and spatial dependence was strong to moderate, while the spatial distribution pattern was in distinctive patches. The size of the patches depended on the effective range at each site.

Based on the relevant semivariograms, small-scale variation in soil EC_e could be either high or low for class 1 areas, as indicated by the remarkable difference in nugget values between sites 1.1 and 1.2 (**Table 4**, **Figures 4a** and **4b**). At both sites, very high sill values denote highly heterogeneous soil EC_e. Having a low nugget to sill ratio (≤ 0.15) indicated that the spatial dependence of this soil property was strongly patchy [48] (**Figures 5a** and **5b**). The distance at which EC_e values become "independent" of one another (effective range) highly varied (i.e., 158.30 and 8.30 m).

The nugget values for both class 2 sites (**Table 4**, **Figures 4c** and **4d**) indicated that there was small-scale variation in soil EC_e. The sill values denote significant heterogeneity of this soil property. Judging from relatively low nugget to sill ratios (0.16 and 0.38), the EC_e was moderately to strongly patchy (**Figures 5c** and **5d**). The effective range was not substantially different (54.70 and 66.30 m).

Class 3 (**Table 4**, **Figures 4e** and **4f**), when compared to class 2 areas, had a similar trend of characteristics of spatial variability of soil EC_e. Except for the effective range values, higher variation was found (118.20 and 13.40 m). Owing to the low soil EC_e, the spatial variation at both sites (**Figures 5e** and **5f**) was much less meaningful, despite the low nugget to sill ratios, suggesting a strong spatial dependence. Note that, for site 3.1, the very low soil EC_e was also responsible for non-distinctive patches which appeared in the entire area of the relevant map (**Figure 5e**).

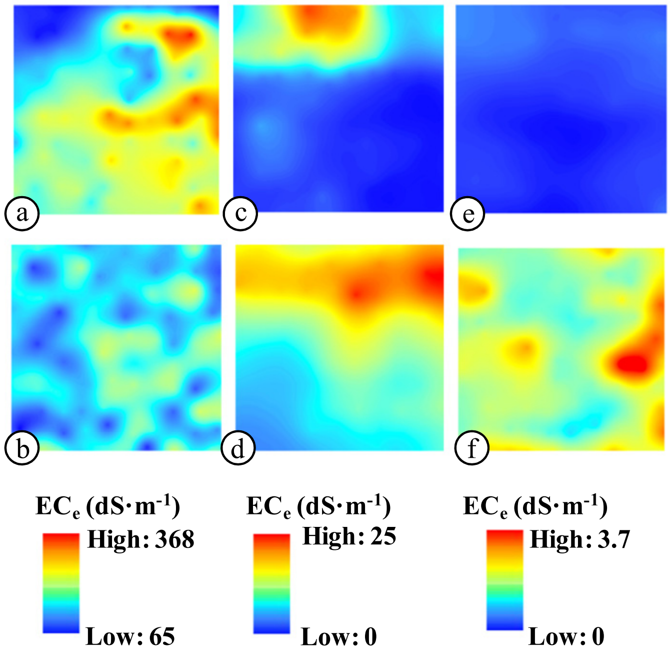

Figure 5 Maps showing spatial variation in EC_e generated for different study sites. Letters (a) - (f) represent sites 1.1, 1.2, 2.1, 2.2, 3.1, and 3.2, respectively. Legends specific for each salt-affected soil class.

Salinity classes in areas of different salt-affected soil classes

Generally, the entire salt-affected soil class 1 areas had very strongly saline soils (100 % for both sites). No variation in soil salinity classes appeared in the map representing these areas, because the soil EC_e was very high (range, 56.70 - 433.00 $dS \cdot m^{-1}$) (**Tables 3**, **Figures 6a** and **6b**), and the standard soil salinity classification scheme (**Table 2**) does not allow classification of soil $EC_e > 16$ $dS \cdot m^{-1}$. Additional soil salinity classification carried out in the current study revealed variations in soil salinity in class 1 areas, where soil EC_e values were > 50 $dS \cdot m^{-1}$. Subdivision of very strongly saline soils (**Figures 7a** and **7b**) revealed significant variation. The EC_e values of the dominant soils ranged from 100 - 200 $dS \cdot m^{-1}$, and 200-300 $dS \cdot m^{-1}$. In class 2 areas, the soils had varying degrees of salinity. All of the salinity classes could be found (**Figures 6c** and **6d**). Class 3 areas were less complicated; the soils were entirely non-saline in site 3.1, and non-saline to slightly saline in site 3.2 (**Figures 6e** and **6f**). Uncertain distribution patterns of EC_e and soil salinity were attributed to the erratic characteristics in spatial variability in the study sites, due to a variety of factors as described in the previous section.

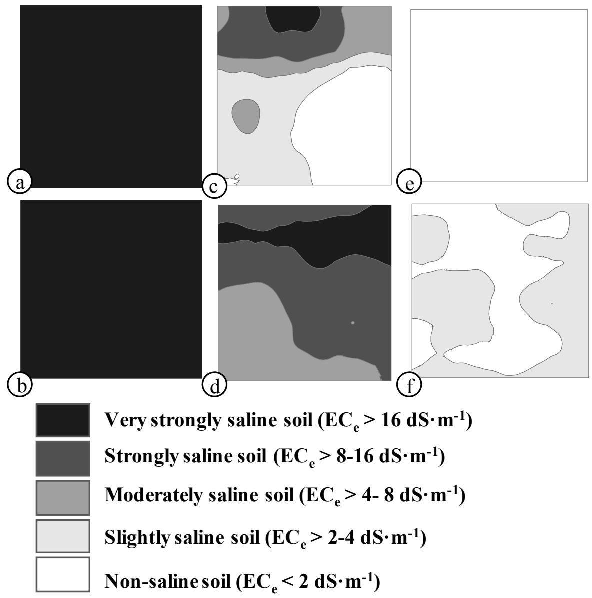

Figure 6 Maps showing spatial variation on soil salinity for different study sites. Letters (a) - (f) represent sites 1.1, 1.2, 2.1, 2.2, 3.1 and 3.2, respectively.

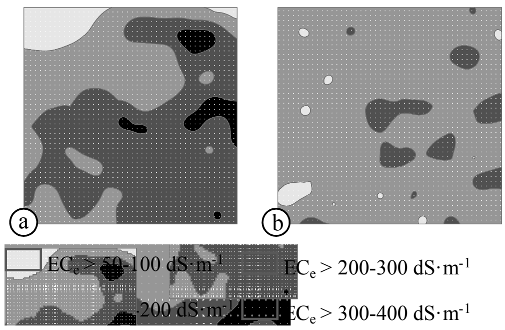

Figure 7 Subdivision of very severely salt-affected class (class 1). Letters (a) and (b) represent sites 1.1 and 1.2, respectively.

Conclusions

This study employed basic statistics and geostatistics to investigate the field-scale spatial variability of soil EC_e in inland salt-affected areas (percentage salt crusts: very severely = class 1; severely = class 2, and moderately = class 3). The CV values of original datasets demonstrated a high variation in soil EC_e in every class. The EC_e values of soils in class 1 were significantly higher than those in classes 2 and 3. Geostatistical analyses confirmed high variation in this property, plus information about its spatial variation, at each specific study site.

Interpretation from the relevant semivariogram model's parameters (nugget, sill, and effective range), together with the kriged maps, demonstrated that the characteristics of spatial variability of soil EC_e were inconsistent, even between different sites of the same salt-affected soil class. Generally, various degrees of small-scale variation in EC_e were observed, a high variation was common, the distance at which EC_e values became "independent" of one another (effective range) highly varied, the spatial dependence was strong to moderate, and the spatial distribution pattern occurred in distinctive patches. The size of the patches depended on the effective range at each site. The inconsistency of the characteristics in spatial variability between the study sites remains poorly understood.

Each of the soil salinity maps derived from the relevant kriged map, demonstrated a unique combination of different salinity classes. Very strongly saline soils covered the entire area of class 1 salt-affected soils, whereas non-saline to moderately saline appeared in both class 3 sites. Class 2 areas were much more complex, the soils varying from non-saline to very strongly saline.

The current study is a primary step leading to (a) better understanding of the mechanisms and processes related to variability of soil EC_e and as a consequence, (b) developing strategies for management of these soils in precision agriculture in Northeast Thailand; especially, for class 2 soils, where a wide range of salinity degrees are found. In class 1 and 3 areas, this information is less important. The soils in class 1, even though highly varied, were all very strongly saline, and no crops can be grown. In class 3 areas, the soils were less severely affected by salt: their effect on crop growth was not significant, particularly during the rainy season.

The results also indicated that there were several unexplained issues which require further study, including (a) relationships between performance of the semivariogram model and mapping accuracy, and (b) the effects of natural and/or manmade factors on the erratic characteristics of spatial variability of soil EC_e. Such studies could yield additional information that would be useful for the management and remediation of inland salt-affected soils.

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