

ANCIENT SALT-MAKING SITE PREDICTION USING SPATIAL MODELING: A CASE STUDY IN NAKHON RATCHASIMA PROVINCE

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Abstract

The study aims at predicting ancient salt-making potential areas, prior to the 19th century, in Nakhon Ratchasima province, Thailand, using spatial modeling of the frequency ratio (FR) and logistic regression (LR). Input data are physical and cultural characteristics and their relationship extracted from samples of existing ancient salt-making sites. These include locating on the Maha Sarakham Formation (KTms) and its related units, distance from geologic structures, locating on salt crust area and saline wet belt, Normalized Difference Salinity Index (NDSI), distance from ancient settlements, and distance from water bodies. The coefficients of input variables from the LR model could explain how much they influence the chance to discover the new ancient sites. The most influential factor was the distance from the ancient settlement, followed by locating on salt crust area and saline wet belt and distance from water bodies. Frequency ratios strongly supported these findings. Final results from the models were raster-based probability maps of ancient salt-making site occurrence. Relative Operating Characteristics (ROC) were used to validate the FR and LR probability maps and resulted in areas under curves (AUC) of 0.810 and 0.908, respectively. It revealed that LR model could conclusively provide a better result. The study results fruitfully serve the objectives of the study.

Keywords: Ancient salt-making site, frequency ratio, logistic regression model, Nakhon Ratchasima

Introduction

Rock salt and potash have been substantial raw materials for recent industries. New salt mines have been established on salt-affected areas in northeastern Thailand which occupy about 28,400 km² or about 17% of the region (Moncharoen *et al.*, 1992). This activity, more or less, can damage ancient salt-making sites unintentionally. To this date, archaeologists cannot locate more accurately potential areas of the ancient salt-making sites. This

can lead to inappropriate land conservation and management. For this reason, identification of potential areas of ancient salt-making sites are necessary for safeguarding from mining activities and inconsiderate land-use development planning. Thus, this research attempts to determine the correlation between land and cultural characteristics to ancient salt-making sites so that their potential areas can be more accurately located. The

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integration of Geographic Information System (GIS) and Remote Sensing (RS) technology was applied to data factor preparation and spatial modeling. Ancient salt-making site probability maps resulted from selected spatial models, logistic regression (LR) and frequency ratio (FR), which can allow archaeologists to discover unknown sites and assist in generating a cost-effective plan to explore in the broad area. The results from two different models were validated and compared. The research procedure can be schematized as shown in Figure 1.

Conventionally, known salt-making sites in northeast Thailand were discovered mainly by the field survey team of archeologists of the Fine Arts Department (FAD). Information from villagers and field evidences were used to locate the sites. Lately, RS data were applied through visual interpretation together with field investigation to locate ancient salt-making sites and settlements (FAD, 1991; Rivett and Higham, 2007). The study on identification of potential areas for ancient salt-making sites using spatial modeling incorporated by GIS and RS is rather rare.

The study area is a portion of Nakhon Ratchasima Province, Thailand, located between 101°43'47" to 103°00'45" E and 14°46'23" to 15°48'33" N, covering the area about 9,170 km². The area has the underlying KTms as the bedrock. It is the geologic formation that contains rock salt and is partly covered by thin younger Quaternary sediments (Wongsomsak, 1986; Wannakomol, 2005; Sattayarak and Polachan, 1990). The area has several natural water bodies containing saline water while salt crusts are scattered over the terrain. This region is characterized by a semi-arid climate and the presence of saline soils and salt structures. River courses run through the study area, causing landforms of flood plains along the center.

In the study area, 411 ancient salt-making sites, prior to the 19th century, were discovered by the FAD archaeologists (FAD, 1991; Leelamanotham, 2013). The sites were found in an area with underneath rock salt (Department of Mineral Resource (DMR), 2010). The study area and the distribution of existing ancient salt mines are displayed in Figure 2. Figure 3 shows some ancient salt-making sites

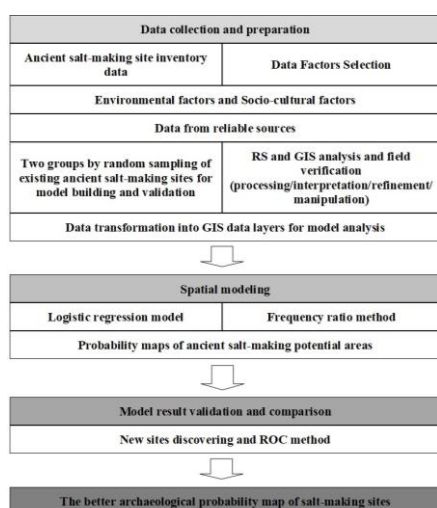


Figure 1. Conceptual flowchart of the study procedure

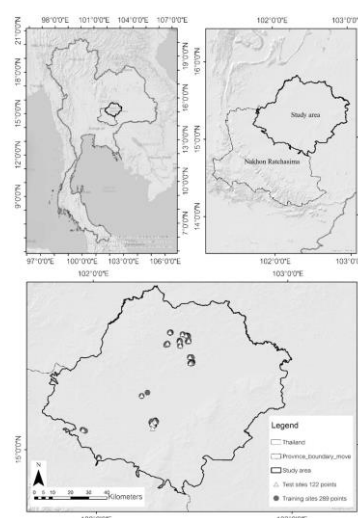


Figure 2. Study area and distribution of existing ancient salt-making sites

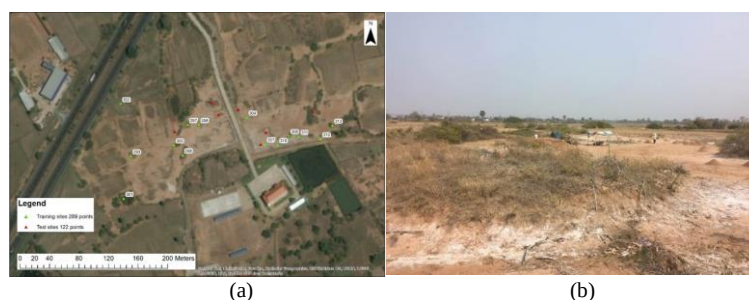


Figure 3. Salt-making sites recognizable on color aerial photograph (a) and field photo at Ban Bing, NonSung District, NakhonRatchasima Province (b)

recognizable in the color aerial photograph and in the field.

The ancient process of salt production caused mounds of soil to accumulate rapidly in a large number of clusters close to habitation sites and flat stream valleys in several areas of the northeast region such as salt-making mound sites in Thung Kula Rong Hai area as well as the Mun River Basin (FAD, 2001). The occurrence of ancient salt-making mound sites strongly relates to the source of salt, making techniques, the settlement locations, and water bodies. Archaeologists found that the ancient people transmitted salt-making techniques since early history (Nitta, 1997). The industrial-scale salt production was found from early history to the Ayutthaya period (Higham, 1977, 1996; Rivett and Higham, 2007). These salt-makers could produce salt in the vicinity of their settlements for local consumption and trade their product to inland communities and the Ancient Khmer Empire (Vallibhotama, 1992; Chaikhanchit, 1997; Higham and Thosarat, 1999; Rivett and Higham, 2007). The ancient salt-making sites are therefore considered as one of the valuable national heritages protected by law (FAD, 2005).

Materials and Methods

Data Collection and Preparation

From previous researches, it was determined that the occurrence of ancient salt-making sites correlated highly with saline soil, traditional salt-making techniques, and settlement and water in the proximity (Nitta, 1992; Vallibhotama, 1992; Rivett and Higham, 2007). For our analysis, data in two groups, environmental and socio-cultural factors, were selected. The selected factors were based entirely on theories from archaeology and geology. Statistics was used to reorganize data factors by transforming input data factors to be a normal distribution.

GIS and RS technology were applied to extract, refine, and manipulate the data from primary and secondary sources into contents and formats proper for the analysis.

Locations of Existing Ancient Salt Mines

Locations of 411 ancient salt-making sites were discovered. They were separated into two groups of 289 random sites for LR model building and for FR method to extract the frequency ratio of each data factor. The remainders were used for validation of the model results. To work as a dependent variable in the regression model, the quantitative attribute of a salt mine is needed. The data layer of the presence or absence (binary codes)

of ancient salt-making site locations in the study area was then generated to serve this purpose.

Environmental Factors

Locating on certain geologic units (GF)

Wherever there is shallow salt layer associated with structures able to bring the salt up to the surface, that area has more chance to be affected by saline soil. Even though the areas are covered by thin Quaternary sediments of alluvium (Qa) and terrace (Qt), they can still be identified as potential areas. Unit boundaries were adopted from the geologic map in the form of GIS data layer (Figure 4 (a)) with 1:250,000 original scale (DMR, 2007).

For the FR method, the presence of potential areas is dependent on how frequently ancient salt-making sites are located on the certain geologic unit. For the LR model, instead of using arbitrarily ordering scores for these units, the frequency ratio (*Fr*) of each unit was applied as its score. This could be more reasonably objective transformation to the factor units.

Distance from geological structures

The studies of Hisao and Wichaidit (1989), Supajanya *et al.* (1992), Sattayarak and Polachan (1990), and Sarapirome *et al.* (1995) revealed that geologic structures such as curvilinear surface fractures and faults are related to surface salt distribution. Shallow salt domes are always associated with curvilinear fractures. These are high prone areas for salt appearance. The structures allow the surface water to flow down and becomes saline when reacting with the underlying salt deposit, and then evaporate up to be salt crystals. They also allow saline water to seep into groundwater. Shallow saline groundwater can be evaporated up or leaked up to surface particularly when flowing to open topography and then forming salt crystals. The accumulation of salt crystals becomes salt crusts and saline soil in the areas nearby those structures. The area closer to the structures indicates the higher potential. GIS data layers of geologic structures (Wannakomol, 2005; DMR, 2007; DMR, 2010) were used in the model analysis. The visual interpretation was operated to cross-check the data using 2012 color aerial photographs of the Land Development Department (LDD). The geologic structures like surface fractures and faults will appear as lineaments in RS data due to undetectable offset movement.

Minimum GS of each raster cell was extracted using Euclidian distance function of ArcGISTM software. The resulting raster layer was used as independent variable input for the regression analysis of the LR model. For the FR analysis, the

geological structure features were buffered to distances of 500, 1,000, 1,500, 2,000, and 2,500 m, as shown in Figure 4(b), based on the spreading of existing salt mines discovered (FAD, 1991; Leelamanotham, 2013).

Locating on salt crust area and saline wet belt (SC)

Salt crusts and saline wet belts are surficial evaporite areas and identified as actual potential areas. Several ancient salt mines are always

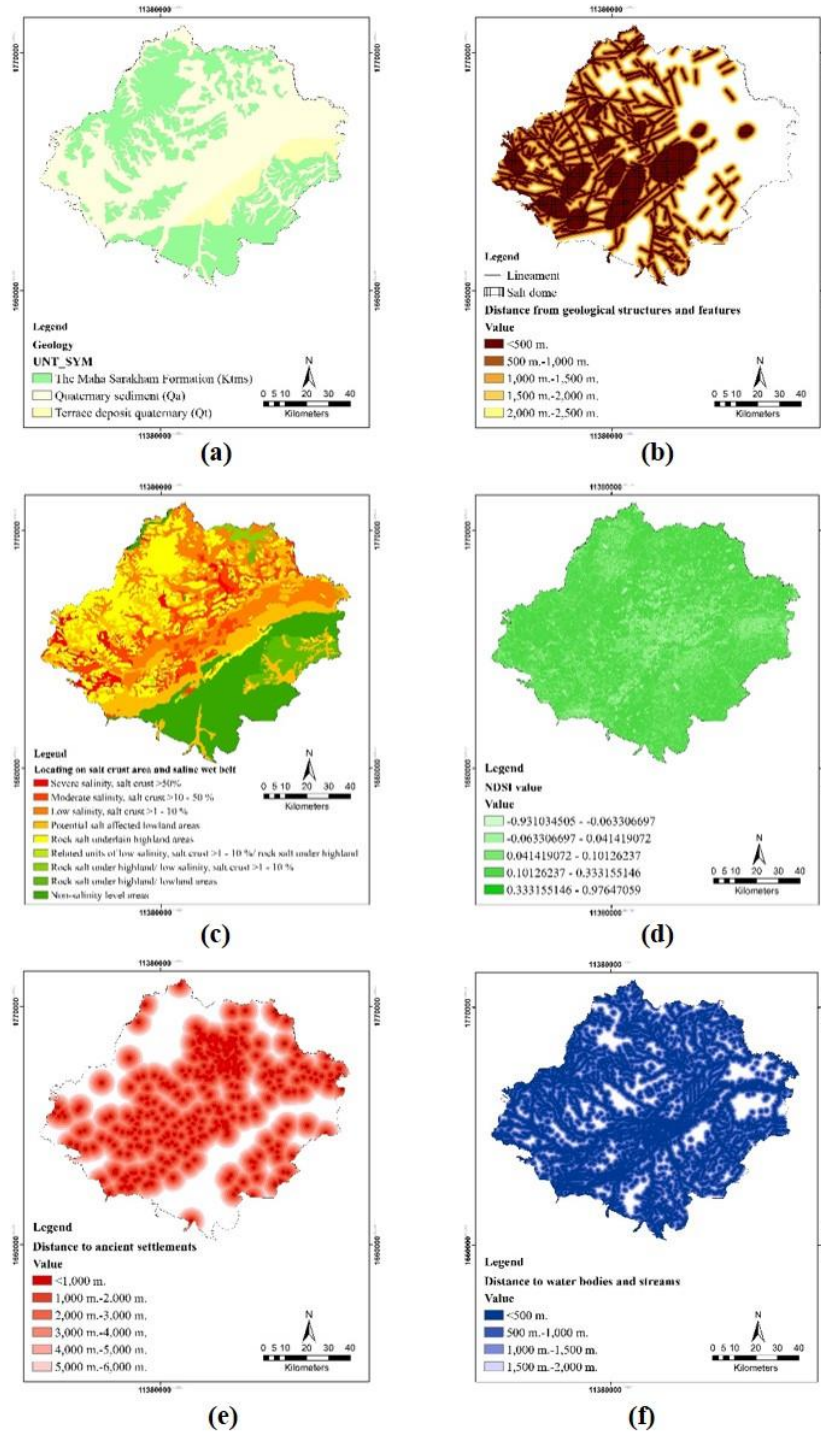


Figure 4. Factor maps of geology (a), distance to geologic structures (b), locating on salt crust area and saline wet belt (c), NDSI (d), distance to ancient settlements (e), and distance to water bodies and streams (f)

associated with these surface features (Rivett and Higham, 2007). The data of features for the model analysis was prepared by the Land Development Department (LDD, 1992) in the scale of 1:50,000. The areas were validated by field check. They always show almost non-vegetated or bare soil with plenty of salt crystals on the ground. Only a few kinds of salt-resistant plants grow in these areas. The classification of data factor was modified to be 7 classes (Figure 4(c)). As same as geology data factor, for LR model analysis, each class of this data factor was scored using *Fr*.

Normalized Difference Salinity Index (NDSI)

Due to having high reflectance, salt crust areas are detectable using RS indexes. The *NDSI* was selected to be the RS index expressing potential areas (Pladsrichuay, 2008; Wannakomol, 2005; Khan *et al.*, 2005). The formula used is:

$$NDSI = (Red - NIR)/(Red + NIR) \quad (1)$$

The calculation results in values between -1 and 1. The higher values indicate more bare-soil presence.

A crop can scarcely stand on salt crust areas. This causes it having higher surface reflectance than the area with healthy vegetation and salt-free soil. However, using this index to interpret salt crust areas can be confused with bare soil and prepared ground after harvesting. Therefore, aerial photographic interpretation was used as supplementary data.

The *NDSI* (Figure 4(d)) was derived from ASTER data with spatial resolution of 15×15 m². The data were taken by the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER). The ASTER Level-1A data on the dry season were acquired because they show outstanding reflectance of salt crust areas. Due to limited availability of sound images, images of numerous dates were acquired and mosaiced, namely December 7, 2001, December 23, 2001, January 1, 2002, December 6, 2002, January 17, 2002, February 2, 2002, December 17, 2004, and December 24, 2004.

Socio-cultural Factors

Distance from ancient settlements (ARC)

The question is that the distance from ancient settlements to the potential salt-affected area can control where the area should become mine. As a hypothesis, the distance should not be too far to walk back and forth in a day and should not be too close to disturb the living environment. The raster layer of *ARC* was prepared from an ancient

settlement data layer (FAD, 2011). Minimum *ARC* of each raster cell was extracted using Euclidian distance function. The resulting raster layer was used as independent variable for the regression analysis of the LR model. The distance over 6,000 m from a settlement to a salt mine is too far for human walking ability to back and forth in a day. For the FR method, different ranges of the walking ability of human were separated to be <1,000, 1,000-2,000, 2,000-3,000, 3,000-4,000, 4,000-5,000, and >5,000 m. These ranges were applied to buffering *ARC* (Figure 4(e)).

Distance from water bodies and streams (WA)

As known, the ancient salt-making process required water within the proximity. The closer distance implies more potential salt-making. In the dry season, the natural brine in salt-affected areas crystallizes and accumulates to be salt crusts. This salt crust was extracted, then dissolved in the water, percolated, filtered, and boiled in the vicinity.

The water body features extracted from 1:50,000 topographic map of the Royal Thai Survey Division. *WA* of each raster cell was extracted using Euclidian distance function. The result was used as independent variable input for the regression analysis of the LR model. In the FR analysis, water body features were buffered to distances of 500, 1,000, 1,500, and 2,000 m, as shown in Figure 4(f).

Spatial Modeling

Frequency Ratio (FR) Method

The spatial relationship between the event and each event-related factor can be analyzed by the FR method. This relationship is used to determine each factor's rating in the overlay analysis (Lee and Talib, 2005). To evaluate the contribution of each factor towards salt-making potential, randomly-selected salt-making sites were overlaid with factor data layers separately. Then *Fr* of each factor's class was calculated. First, calculate the ratio of salt-making site occurrence to the area of each factor's class. Then, calculate the area ratio of each factor's class to the total area of the factor. Finally, *Fr* is achieved by dividing the salt-making site occurrence ratio by the area ratio of each factor's class.

Fr of each class of each factor was used to calculate the salt-making site probability index (SMSPI) using the following equation.

$$SMSPI = Fr1(GF) + Fr2(GS) + Fr3(SC) + Fr4(NDSI) + Fr5(ARC) + Fr6(WA) \quad (2)$$

where *Fr*1 to *Fr*6 is the frequency ratio of each factor. A value of 1 represents the mean. *Fr* greater

than 1 shows a high correlation of the presence of salt-making sites and factors. *Fr* less than 1 indicates a lower correlation (Park *et al.*, 2010, Lee *et al.*, 2012). The raster-based analysis resulted in a raster map of SMSPI.

Logistic Regression (LR) Model

The LR analysis is the most basic predictive model used in various fields for the binary response variable (Vaughn and Crawford, 2009). In general, the archaeological predictive model is the statistical and empirical relationship between the presence of archaeological evidence and the environmental factors. It can indicate the likelihood of encountering an archaeological site in a landscape.

The general form of LR model can be formulated as:

$$y = a + b_1x_1 + b_2x_2 + b_3x_3 \dots + b_mx_m \quad (3)$$

$$y = \log \left[\frac{P}{1-P} \right] = \text{logit}(P) \quad (4)$$

$$P = \frac{e^y}{1+e^y} \quad (5)$$

where $x_1, x_2, \dots, x_m$ are explanatory or independent variables, and y is a linear combination function of the explanatory variables representing a linear relationship. The parameters $b_1, b_2, \dots, b_m$ are the regression coefficients to be estimated. If y is denoted as a binary variable (0 or 1), value 1 ($y = 1$) means the presence of a site, and value 0 ($y = 0$) indicates the absence of a site. Function y is represented as $\text{logit}(P)$. P refers to the probability of the occurrence of a site. The probability P is increasing when y increases. Regression coefficients $b_1, \dots, b_m$ show the contribution weights of each explanatory variable on the probability P . A positive sign means that the variable supports to increase the probability of change, and a negative sign implies the opposite effect. The statistical technique is a multivariate estimation method that examines the relative strength and significance of the factors.

In practice, the m cells of known salt-making sites (411) were randomly selected to be n test sites. The rests ($m-n$) were used as training sites in the model analysis. In this case, training sites should be consistent to the number of known sites used in the FR method. Therefore, y training sites (411) were set from those ($m-n$) existing sites and added-up randomly selected n non-existing sites.

It was crucial to note that data of independent variables of all samples (411) were checked and transformed to be normal distribution or as close as possible, if required. The original data were compared to the transformed data using $\log_{10}$ and square root functions. The ones having normal

distribution or being closer to normal distribution the most were selected and then normalized for further input to the Ordinary Least Square (OLS) analysis. The selection of the better transformation method was fundamentally based on comparing skewness and the plot between expected normal and observed values. The original or transformed data with skewness closer to 0 is the better, while the more fit to a linear relationship between expected normal and observed values is the better. Multiple independent variables could have different normal distribution transformation methods. The specific methods were further applied to transform corresponding raster-based data layers of independent variables and then normalized before input to the model.

Besides, the Spatial Autocorrelation (Global Moran's I) was used in this study to check the spatial relationship of raster-based input data. If their spatial pattern is not random, they are valid for further spatial analysis. If Moran's I value is closer to 1 or -1, the data express a better correlation.

While operating OLS, the Variance Inflation Factor (VIF) estimation was provided as well. The VIF measures redundancy of data among explanatory variables. Explanatory variables having VIF values larger than 7.5, indicating too high redundant data with the former input variables, should be removed (one by one) from the regression model (ESRI, 2012).

The OLS function of ArcMap™ was used to estimate a set of model coefficients from samples. The characteristics of coefficients can be supported by the results from the FR method. A set of model coefficients from samples obtained from OLS was then used to calculate the salt-mining suitability using regression model (Equation (3)) for all cells in the study area by Raster Calculator tool in the GIS environment. Then LR analysis (Equation (5)) of the salt-mining suitability raster layer was performed using the same tool so that the probability of the presence of ancient salt mining in each cell was able to be estimated, resulting as a raster-based probability map of ancient salt-making site occurrence.

Validation and Comparison of The Model Results

In this study, ancient salt-making site probability maps were prepared using the FR and LR models. The accuracy of each model result was evaluated by calculating relative operating characteristics (ROC) (Ozdemir, 2011). They are presented as curves or a graphical representation of the relationship plotting between true positive rate and the false positive rate. The area under the curve (AUC) of each model was observed. Then, the better

model can be identified from the comparison of their ROCs.

Results and Discussion

Probability Map of Ancient Salt-making Sites from FR Method

Based on 40,743,414 total number of cells in the study area and 289 of known salt-making sites, *Frs* of all six causative factors are shown in Table 1. *Fr* indicates the level of correlation between locations of the salt-making sites to each class of the factor. The higher value indicates a higher relation. *Fr* was assigned to the respective class of each factor map being in raster format with resolution 15×15 m². The SMSPI of each cell was then calculated by mathematical overlay analysis (Equation (2)).

For *GF*, *Fr* is found highest in Qa (1.58). *Fr* of the KTms is lower than 1.0, indicating a low salt-making site occurrence probability while Qa shows the highest probability. The explanation is that Qa is always situated in low area and nearby water or wet area. It is more frequently situated on the thinner burden of rock salt layer and proper structures.

Considering *GS*, *Fr* is highest in the range of 1,000 to 1,500 m and lowest in distance above 2,000 m. *Fr* is greater than 1.0 in the range of 1,000 to 2,000 m, indicating high probability. *Fr* is lower than 1.0 for distance below 1,000 m and above 2,000 m, indicating low probability. It could be explained that the probability based on this factor could be strongly affected by other factors.

Among all factors, *SC* has the highest *Fr* and became the most influential factor. The severe salinity level areas with salt crust >50% shows the highest *Fr* (6.85). Moderate salinity level areas with a salt crust >10% have *Fr* of 4.47. Both classes indicate a high probability. *Frs* of classes of low salinity level areas with salt crust <10 %, potential salt-affected lowland areas, and rock salt underlain highland areas are lower than 1.0, indicating a low probability. *Frs* of the rests are lowest (0) and indicate no probability. This confirms that the probability of salt-mining occurrence increases with the increasing percentage of salt crust.

NDSI ranges from -0.931 to 0.976 and was classified into five classes based on Natural Breaks (Jenks's) method. Where *NDSI* is between 0.041 and 0.101, *Fr* is greater than 1.0, indicating a high

Table 1. Frequency ratio of salt-making sites occurrence

Factors	Class	Number of pixels		Ancient salt-making sites		FR
		Number	%	Number	%	
Geology (Locating on KTms, Qa, and Qt)	KTms	16,029,350	39.3421	39	13.4948	0.3430
	Qa	22,254,169	54.6202	250	86.5051	1.5837
	Qt	2,459,895	6.0375	0	0	0
Distance to geological structures	<500 m	13,111,629	44.2784	67	23.1833	0.5235
	500 m-1,000 m	6,783,532	22.9082	55	19.0311	0.8307
	1,000 m-1,500 m	4,588,845	15.4967	101	34.9480	2.2551
	1,500 m-2,000 m	2,986,007	10.0838	58	20.0692	1.9902
	>2,000 m	2,141,716	7.2326	8	2.7681	0.3827
Locating on salt crust area and saline wet belt	Severe salinity, salt crust >50%	1,009,092	2.4767	49	16.9550	6.8457
	Moderate salinity, salt crust >10 - 50 %	3,812,691	9.3578	121	41.8685	4.4741
	Low salinity, salt crust >1 - 10 %	7,437,380	18.2542	47	16.2629	0.8909
	Potential salt affected lowland areas	8,852,590	21.7277	12	4.1522	0.1911
	Rock salt underlain highland areas	8,942,146	21.9475	0	20.7612	0.9459
	Related units of low salinity, salt crust >1 - 10 %/ rock salt under highland	74,007	0.1816	0	0	0
	Rock salt under highland/ low salinity, salt crust >1 - 10 %	488,278	1.1984	0	0	0
	Rock salt under highland/ lowland areas	1,679,088	4.1211	0	0	0
	Non-salinity level areas	8,447,953	20.7346	0	0	0
<i>NDSI</i>	-0.931 to -0.063	272,500	0.6688	0	0	0
	-0.063 to 0.041	3,321,823	8.1530	10	3.4602	0.4244
	0.041 to 0.101	11,341,735	27.8369	203	70.2422	2.5233
	0.101 to 0.333	25,807,262	63.3408	76	26.2975	0.4151
	0.333 to 0.976	184	0.0004	0	0	0
Distance to ancient settlements	<1000 m	4,459,150	15.3782	51	86.8512	5.6476
	1,000 m-2,000 m	7,973,725	27.4988	33	11.4186	0.4152
	2,000 m-3,000 m	7,084,430	24.4319	0	0	0
	3,000 m-4,000 m	5,452,374	18.8035	0	0	0
	4,000 m-5,000 m	4,026,869	13.8874	4	1.3840	0.0996
	>5,000 m	3,105,640	10.7103	1	0.3460	0.0323
Distance to water bodies and streams	<500 m	20,419,357	55.8554	116	40.1384	0.7186
	500 m-1,000 m	10,983,883	30.0455	79	27.3356	0.9098
	1,000 m-1,500 m	5,154,255	14.0990	73	25.2595	1.7915
	>1,500 m	2,298,989	6.2886	21	7.2664	1.1554

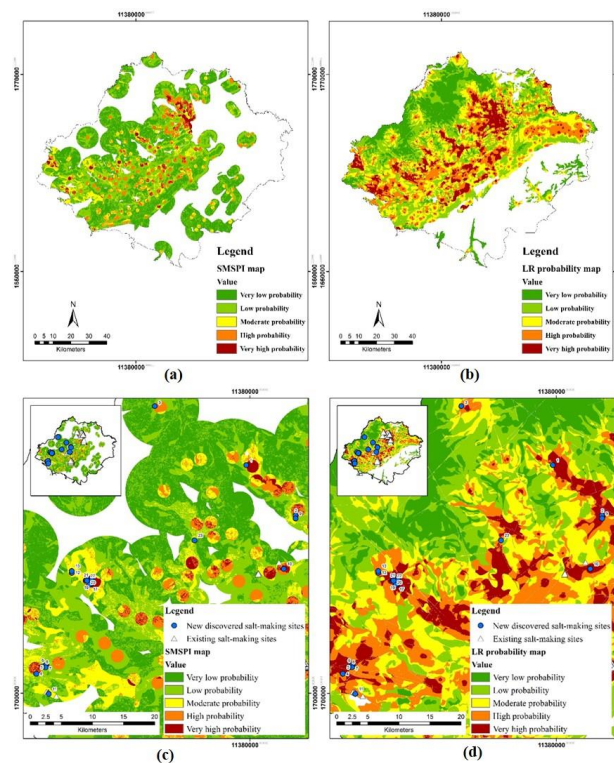


Figure 5. Salt-making site occurrence probability maps using the FR method (a) and LR model (b). The distribution of newly discovered salt-making sites over FR (c) and LR (d) probability maps

Table 2. Salt-making probability classes of FR SMSPI, LR value, and coverage area percentage

Salt-making Probability Classes	FR model		LR model	
	SMSPI	Area %	Value	Area %
Very low probability	1,229.44 - 0,645.25	39.81	0.39 - 0.42	17.33
Low probability	10,645.25 - 20,891.11	38.89	0.42 - 0.55	26.72
Moderate probability	20,891.11 - 31,136.98	9.98	0.55 - 0.62	26.36
High probability	31,136.98 - 41,382.84	8.74	0.62 - 0.68	19.35
Very high probability	41,382.84 - 55,354.98	2.58	0.68 - 0.86	10.24

probability. Where *NDSI* is out of this range, *Fr* is lower than 1.0, indicating a low probability. Therefore, the high probability is related to the specific *NDSI* range.

The *ARC* was ranged from 0 to 6,000 m and was classified into 6 classes. The *ARC* was considered as the most basic factor because local salt makers preferred working near the living place. *Fr* is greater than 1.0 in distance below 1,000 m, indicating a high probability and lower than 1.0 in distance above 1,000 m, indicating a low probability. This result revealed that the salt-making occurrence probability was higher in the distance closer to ancient settlements.

The *WA* was ranged from 0–2,000 m and was classified into 4 classes. *Fr* is greater than 1 in distance of 1,000 to 2,000 m, indicating a high probability. Between 1,000–1,500 m *Fr* is 1.79, the

highest. *Fr* is lower than 1.0 in distance below 1,000 m, indicating a low probability. This revealed that the high probability was related to the moderate distance range from water bodies and streams.

In the resulting map, the minimum and maximum SMSPI are 1,229.44 and 55,354.98 while the average and standard deviation are 15,875.45 and 10,251.95. There was a higher probability of occurrence wherever the SMSPI was higher. The SMSPI map was prepared into 5 classes from very low to very high by standard deviation method. The classes can provide the best information and are suitable to compare to other methods (Ayalew and Yamagishi, 2005; Dorji, 2016). The salt-making occurrence probability map using the FR method is displayed in Figure 5(a). The covering area percentage of each probability class is shown in Table 2.

Table 3. A set of coefficients expressing the relationship between the dependent and independent variables, including the Variance Inflation Factor (VIF)

Variables	Coefficient	VIF
Constant	1.7409	-
Distance to geologic structures	-0.2009	1.1074
Locating on salt crust area and saline wet belt	0.4692	1.2700
NDSI	-0.3771	1.0301
Distance to ancient settlements	-1.9362	1.1915
Distance to water bodies and streams	0.4397	1.2544
Locating on certain geologic units	0.2894	1.1070

Probability Map of Ancient Salt-making Sites from LR Model

To reduce inaccuracy and increase the result acceptability in the LR model, data of independent variables were operated through normal distribution transformation and normalization.

The testing results of spatial autocorrelation of input data were all clustered pattern with positive Moran's I. The results were appropriately consistent with their characteristics in nature. They were proved to have significant spatial autocorrelation and be valid as the input of spatial modeling.

The OLS was operated from data of existing and non-existing sites to obtain a set of coefficients and VIF. The results are shown in Table 3. VIF value of each variable is much lower than 7.5 and indicates that there is no data redundancy among independent variables.

The regression coefficients of independent variables are shown in Table 3. The higher value, either positive or negative, provides comparatively higher influence of a variable. The area with more 'negative' value of that variable can have less chance to be suitable site and vice versa for the 'positive'.

The highest influential factor is *ARC* with coefficient of -1.9362, followed by *SC* and *WA*. It indicates that the area with a lower *ARC* could have more chance to be higher suitable. This expression is consistent with the FR method. The class of *ARC* that shows the highest *Fr* (5.6476) falls into <1,000 m, the lowest class.

Area locating on the higher *SC* has higher site suitability. It is confirmed by the presence of the highest *Fr* (6.8457) in the area with salt crust >50%. Compared to other factors, the coefficient of *SC* shows moderate influence in a positive direction and not much different from *WA* and *NDSI*. The longer *WA* indicates higher suitability. It is consistent with the result of the FR method. The classes of 1,000-1,500 m and 1,500-2,000 m have the highest *Fr* of 1.7915 and 1.1554. This can be explained that areas too close to water body might have frequent floods which dilute the salt crust, if present, making it not concentrated enough to process. Salt making site too

close to a water body can also increase its chance of contaminating water used for other purposes as well. Very low *NDSI* (0.041 to 0.101), having *Fr* as 2.5233, which is the highest among classes. This is reasonable because the lower *NDSI* from this class carries negative values, indicating a high vegetation area that is not suitable as a site. The highest *Fr* (2.2551) of *GS* is at the class of 1,000-1,500 m which is the moderate distance. The reason could be that the referent data used was in so small scale that it could have positional inaccuracy.

The relationships were applied to the estimation of dependent variable all over the area. By inputting the resulting dependent variable data into the LR model, site occurrence probability of the area was estimated in cell-based analysis and resulted in the probability map. The map was classified into 5 classes by the standard deviation method and is displayed in Figure 5(b). The covering area percentage of each probability class is shown in Table 2.

Result Validation and Comparison

During this study, 23 sites were newly discovered, as shown in Figures 5(c) and 5(d), by a guiding of the probability maps. They fall into moderate to very high probability classes on both maps. This discovery helps confirm that the models are valid to serve the objectives of the study.

Visual comparison of the two probability maps (Figures 5(a) and 5(b)) could not be fairly functioned because of the difference in the continuity of their input data and numerical range of entire probability values. Input data of FR method were spatially categorized to be classes. Therefore, resulting *Fr*s remain category characteristics. The same characteristics hardly appear on the LR probability map, which resulted mainly from continuous input data.

No-data area of FR probability map presents the areas out of classes of input data. Meanwhile, no-data of the LR probability map occurred in non-salinity area where there is no chance for salt-

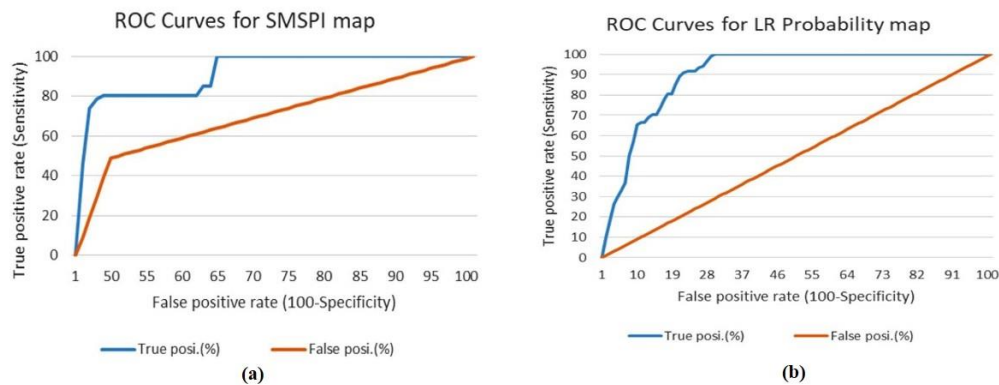


Figure 6. ROC curves for ancient salt-making site probability map validation from FR method (a) and LR model (b)

making activity and marked as an error when transformed by using the log10 function. The area with error data was ignored in the LR analysis. Nevertheless, if only areas with topmost probability are considered, they are quite consistent in these two maps.

Accordingly, ROC was required for accuracy assessment and comparison of the probability maps and the results displayed in Figure 6. AUC of FR and LR models are 0.810 and 0.908, respectively. It means that both of them rank a random positive example higher than a random negative example 50% of the time. From a rough guide for classifying the accuracy of a diagnostic test in the traditional academic point system (Tape, 2019), the result of LR model was excellent acceptable and of the FR method was good. This was confirmed by using 122 test sites for validating the maps. The 106 sites fall into high and very high probability classes of FR probability map while 117 sites were found in high and very high probability class of LR probability map. The LR method provides a better result.

Conclusions

The identification of potential salt-making areas can help discover and protect ancient salt-mining sites, which are considered national archaeological treasures, from accidental damage. This study, therefore, aims at identifying potential areas in a portion of Nakhon Ratchasima Province, Thailand, using spatial modeling, i.e. FR and LR, resulting in two maps of probability of ancient salt-making occurrence. The area with higher probability should be considered more restricted to land-use development and more promising for discovering new ancient salt-making sites.

The LR model revealed that *ARC* is the most influential factor having negative direction,

indicating that the area with lower *ARC* has more chance to be suitable. The indication is opposite to *SC* and *WA*, influential factors in a positive direction. These relationships are fully supported by the results of the FR method. The results have been consistent with the studies of Nitta (1992, 1997), Rivett and Higham (2007), Vallibhotama (1992), and Thanaphattarapornchai (2013).

Using the ROC method for validation, accuracy of both probability maps is highly acceptable. The LR model provides a better result. In conclusion, both models are valid and effectively applicable to serve the objectives of the study.

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