International Journal of Agricultural Technology 2019 Vol. 15(5):779-790
Available online http://www.ijat-aatsea.com
ISSN 2630-0192 (Online)

Spatial distribution of soil quality using geoinformatics in agricultural areas in Nang Lae Sub-district, Mueang District, Chiang Rai Province

Suk-ueng, K.[1*], Chantima, K.[1] and Prasertsin, T.[2]

[1]Energy and Environment Program, Faculty of Science and Technology, Chiang Rai Rajabhat University, Chiang Rai, Thailand; [2]Biological Science Program, Faculty of Science and Technology, Chiang Rai Rajabhat University, Chiang Rai, Thailand.

Suk-ueng, K., Chantima, K. and Prasertsin, T. (2019). Spatial distribution of soil quality using geoinformatics in agricultural areas in Nang Lae Sub-district, Mueang District, Chiang Rai Province. International Journal of Agricultural Technology 15(5):779-790.

Abstract Agricultural areas in Nanglae Sub-district is the main agricultural area of Mueang District, Chiang Rai Province that required soil monitoring on current utilised agricultural areas for sustainable agricultural management. Geoinformatics integrated with soil quality can be used for categorizing soil quality on different agricultural classes. Firstly, Thaichote satellite imageries were used to digitally classify the agricultural area into three agricultural classes, namely paddy fields, field crops (pineapple) and orchards (lychee / longan / lemon / pomelo). Secondly, 9 collected soil samples from the agricultural areas, and physic-chemical properties and arsenic content were reported. The results of image processing, total accuracy of agricultural mapping based on minimum distance classifier that was 22.22% with K statistic of -0.15. This map was used to support soil quality analysis. The soil sample of different agricultural areas was slightly acid (pH 5.93-6.93). Organic matter content of these soils was low (0.13-2.07%). These soils had low total nitrogen (1,200-2,800 mg/kg). The available phosphorus and potassium were very low to low ranged from 1.86-5.94 mg/kg and 0-78.00 mg/kg, respectively. These soils were low soil fertility status, which indicated that physico-chemical properties were not suitable for crop cultivation. Interestingly, soil samples from paddy fields and orchard fields, near the reserved forest area (Doi Nang Lae, Doi Yao and Doi Prabhat reserved forest), were contaminated with high arsenic content (4.50-6.32 mg/kg), which was higher than the standard of National Environment Board of Thailand.

Keywords: Geoinformatics, Soil quality, Chiang Rai Province

Introduction

Soil quality is commonly defined more broadly as the capacity of a soil to function within ecosystem and land use boundaries to preserve environmental quality and promote plant and animal health. Dynamic soil quality is the result of human use and soil management. The results of exploiting agricultural

[*] **Corresponding Author:** Suk-ueng, K.; **Email:** nsukung@gmail.com

systems without consideration of the consequences on soil quality have been environmental degradation (Seybold *et al.*, 1998; Rosa and Sobral, 2008; Bünemann *et al.,* 2018). Agricultural management without recognizing consequences on soil conservation is, therefore, decline in agricultural soil quality. Therefore, healthy soil quality is valuable for agricultural production, used for appropriate decision making regarding sustainable agriculture.

Geoinformatics is a tool for agricultural mapping and also for agricultural planning at both local and regional scales (Patil *et al.*, 2012; Tezera *et al.*, 2016). Multispectral imageries, such as very high spatial resolution (e.g. Worldview), high spatial resolution (e.g. RapidEye) and medium spatial resolution (e.g. Landsat) are used as basemap for agricultural classification. Open source software with various digital image classification algorithms have several advantages to design agricultural mapping for developing countries. QGIS has an open-source license, under the GNU General Public License, to identify agricultural classes in a given area (Girouard *et al.*, 2004; Huth *et al.*, 2012; Usha *et al.,* 2012; Jung, 2013; Tommasini *et al.,* 2019).

Nang Lae is the one of Sub-district of Mueang District, Chiang Rai Province, Thailand which is the main agricultural area of Mueang District. Nang Lae Sub-district covers an area of 5,500 ha of Mueang District and has agricultural area of 1,814 ha. Agricultural areas of Nang Lae Sub-district comprises mainly rice production (806.88 ha), orchard (330 ha) and field crop (677 ha) (Department of Mineral Resources, 2013; Nang Lae Municipality, 2014). This research was, therefore, conducted to process agricultural mapping in 2018 using Thaichote satellite image processing. The software version, used in this research was QGIS 3.6.0 with the plugin, "Semi-automatic classification" (Congedo, 2016). Result from the image processing was used as base map to monitor soil quality of different agricultural areas in Nang Lae Sub-district, Mueang District, Chiang Rai Province.

Materials and Methods

Study area and field survey

Nang Lae sub-district, Mueang district, Chiang Rai province, was chosen as the study site (Figure 1). The approximate area is 5,500 ha, located at 19°53′40″ to 20°07′10″ N and 99°45′51″ to 99°57′24″ E. Visual surveys on foot were carried out on November 2018. Agricultural areas were selected based on a land use map dated 2016 (Land Development Station Chiang Rai, 2016), a satellite image from the Geo-Informatics and Space Technology Development Agency (GISTDA) and survey results of the study site. Systematic stratified sampling was applied on the study site for ground truthing

(Mas *et al.,* 2017). Three plots of each agricultural type were surveyed and identified as paddy field or field crop or mixed orchard (lychee / longan / lemon / pomelo).

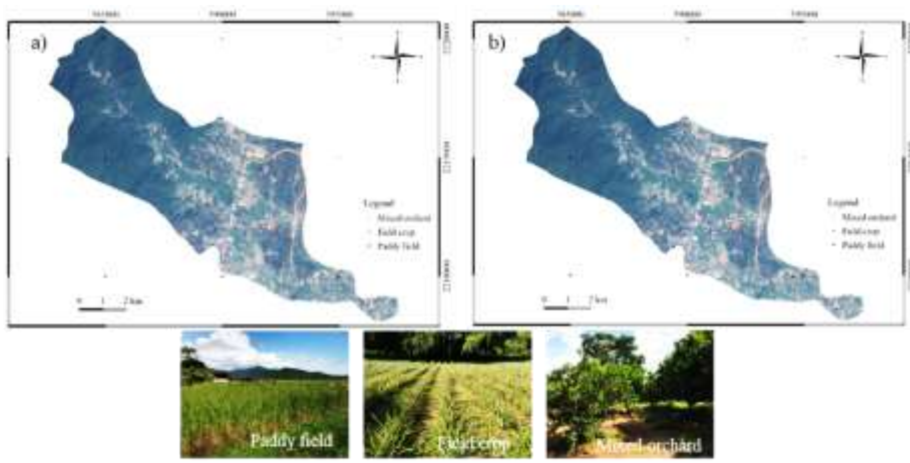

Figure 1. 9 pixels of training samples (a) and 9 pixels of testing samples (b)

Thaichote imagery and geoinformatics software

Thaichote imagery (4 multispectral bands, band 1 (blue), band 2 (green), band 3 (red) and band 4 (near-infrared)) covering the study area, on cloud-free days were provided by Geo-Informatics and Space Technology Development Agency (GISTDA). GISTDA also operated the image with radiometrically corrected and geocoded. The imagery was acquired on 9 February 2017. The satellite images were captured for the study site (Figure 1) before further image processing. Quantum GIS version 3.6.0, semi-automatic classification plugin (Figure 2), was used for image processing (QGIS Development Team, 2019).

Thaichote image was transformed by using Normalized Difference Vegetation Index (NDVI). Then, agricultural classification results following semi-automatic classification plugin were verified against testing samples (9 pixels) from the field survey. The Kappa was used for accuracy assessment of satellite image classifications, for evaluating the quality of the maps (Lillesand *et al.,* 2004). The values of Kappa ranged from -1 to 1. Ranges of Kappa were categorized into strong (>0.8), moderate (0.4-0.8) and poor (<0.4) agreements (Landis and Koch, 1977).

Soil sampling and analysis

Soil samples were taken from 9 stations located inside agricultural areas of Nang Lae Sub-district, which were collected on October 2018 from 3 agricultural areas, including paddy field crop, field crop and orchard (Table 1). Method of drilling and collecting soil samples were performed according to Land Development Department protocols (Land Development Department, 2010). Soil samples, collected at 0-15 cm depth, were composed by mixing 15 sub-samples. The soil samples were gently mixed without the visible roots, plant residues and stones.

All soil samples were air-dried, and then prepared to be analyzed for 6 soil indicators following standard laboratory analytical methods. Soil pH was determined using 1:1 soil to water ratio and then analyzed by digital pH meter (Peech, 1965). Soil organic matter was measured using the Walkley-Black method (Walkley and Black, 1947). Total nitrogen was determined by the Kjeldahl method, and the available potassium was analyzed by flame photometer after extraction using 1 M ammonium acetate at pH 7 (Jackson, 1958), and the available phosphorus was extraction using Bray II (Bray and Kurtz, 1945). Furthermore, the inductively coupled plasma mass spectrometry (ICP-MS) was used to determine the content of arsenic. Soil fertility for crop production was evaluated using soil organic matter, available potassium and phosphorus, described by Division of Soil Resources Survey and Research (1980) and Kheoruenromne (2005). Inverse distance weight (IDW) was used for soil quality mapping (Meyer, 2006; Murphy *et al.*, 2010; Sapna *et al.*, 2018)

Table 1. List of soil sampling station and their detail of land use type

Code	Agricultural areas	Coordinates
A1-1	Paddy field crop	2213017 N, 589741 E
A1-2	Paddy field crop	2214639 N, 588439 E
A1-3	Paddy field crop	2214484 N, 591986 E
A2-1	Field crop	2212312 N, 589917 E
A2-2	Field crop	2214457 N, 591989 E
A2-3	Field crop	2210101 N, 593601 E
A4-1	Orchard	2215500 N, 587504 E
A4-2	Orchard	2214807 N, 590347 E
A4-3	Orchard	2213445 N, 593035 E

Results

Agricultural classification

Image transformation using the Normalized Difference Vegetation Index (NDVI) equation (NIR-Red) / (NIR + Red) to highlight land use data helped to visually interpret image. Plants derived from NDVI had the highest digital number values (green), followed by open areas (gray) and water sources (pink) respectively (Figure 2).

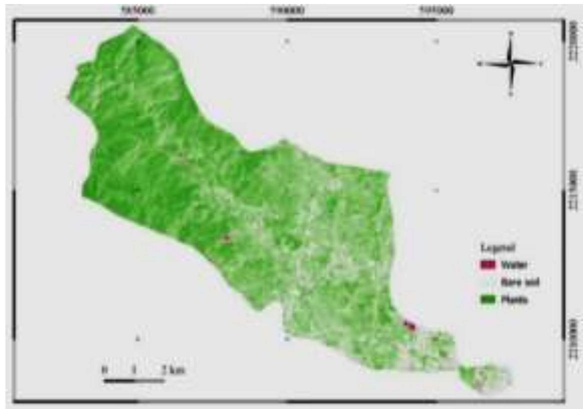

Figure 2. Transformed image, based on Thaichote image, derived from NDVI

Based on error matrix, field crop and mixed orchard were identified with high accuracy of the image. Due to the dominance of paddy field and mixed orchard in the study area, minimum distance (MD) classifiers (Figure 3) showed that total accuracy of supervised classification was 22.22% with Kappa statistic of -0.15, which indicated poor agreement.

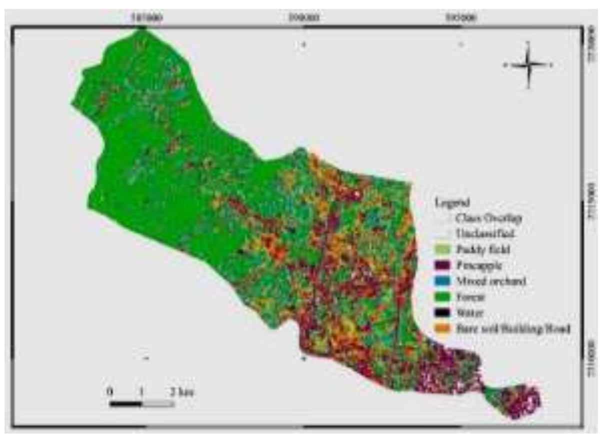

Figure 3. Agricultural classification techniques using MD classifier

From the error matrix shown in Table 2, producer's accuracies of paddy field and mixed orchard were 33.33% and 33.33%, respectively, and user's accuracy of paddy field and mixed orchard was 33.33% and 20%, respectively. The highest values (100%) of omission and commission errors occurred for field crop (Table 2) because of the mixed-pixel problem.

Table 2. Land use data using minimum distance in error matrix

Classifiers	Landuse types	Paddy field	Field crop	Mixed orchard	Total	Commission error)%(	User's accuracy (%)
Minimum distance	Paddy field	1	0	2	3	2/3*100= 66.67%	1/3*100= 33.33%
	Field crop	1	0	0	1	1/1*100= 100%	0%
	Mixed orchard	1	3	1	5	4/5*100= 80%	1/5*100= 20%
	Total	3	3	3	9		
	Omission error (%)	2/3*100= 66.67%	3/3*100 =100%	2/3*100 =66.67%			
	Producer's accuracy (%)	1/3*100= 33.33%	0%	1/3*100 =33.33%			

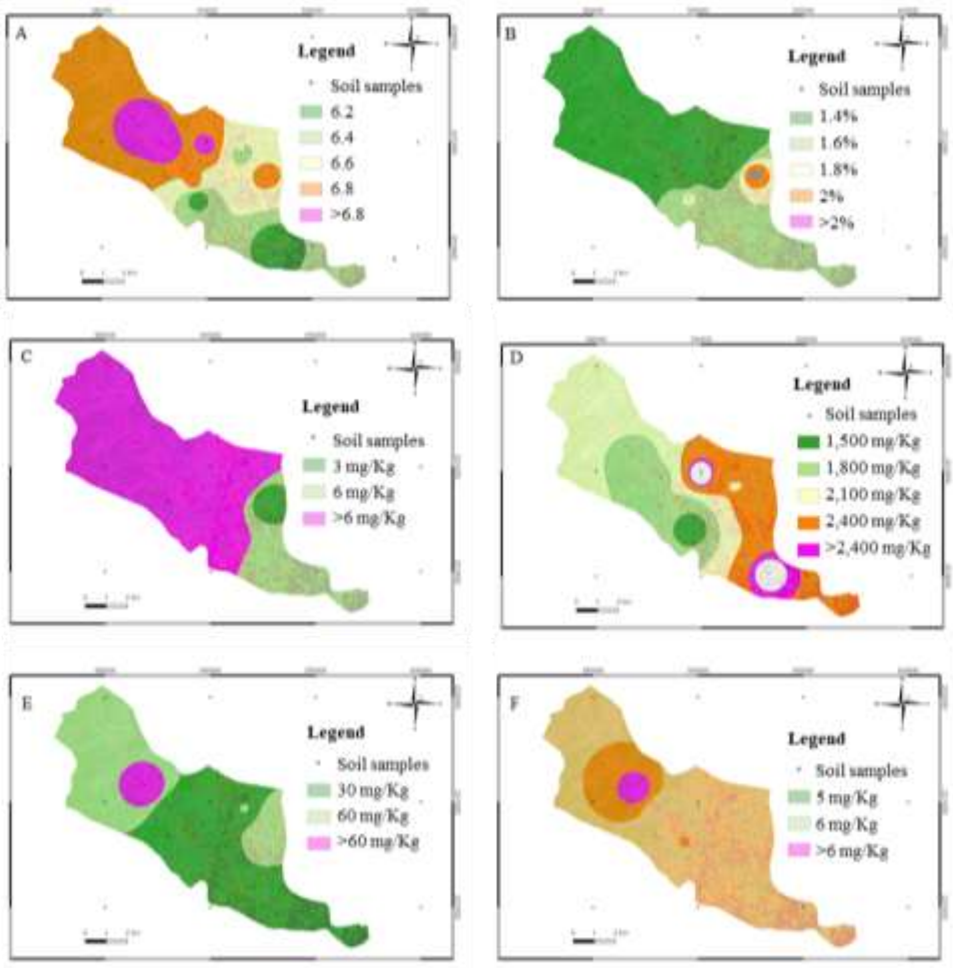

Figure 4. Soil parameters; soil pH (A), soil organic matter (B), available phosphorus (C), total nitrogen (D), available potassium (E) and arsenic (F)

Soil quality assessment

Soil samples gathered through borehole drilling from 9 sampling stations, and some physico-chemical properties and arsenic content were analyzed according to standard methods followed by assessment of the soil fertility status. These soils were slightly acid to moderately acid (pH 5.33-6.93). Organic matter content of all these soils was low (0.13-2.07%). The organic matter content was noted that sampling station A2-2 (pineapple field crop) displaying very low value (0.13%).

The total nitrogen amount in these soils varies from 1,200 mg/kg to 2,800 mg/kg. The available phosphorus of soils in this study was found that low to low ranged from 1.86-15.94 mg/kg. Interestingly, most of these soil samples were not found the available potassium, particularly the soil sample from pineapple field crop (A2-1, A2-2 and A2-3), paddy fields (A1-1 and A1-2), and orchard (A4-2), while A1-3 (paddy field), A4-1 (orchard) and A4-3 (orchard) were found the available potassium of these soils in the low ranges (55.00-78.00 mg/kg). These soils were low soil fertility status (Chantima et al., 2019). In addition, soil existed with the higher as at paddy fields (A1-1 and A1-2) and orchard (A4-1 and A4-2) with a range from 4.56-5.17 mg/kg and 4.50-6.32 mg/kg, respectively (Figure 4).

Discussion

The satellite imagery in this study was acquired before study period. It is different in case of change in the agricultural areas (Mas *et al.,* 2017). Su and Noguchi (2013) suggested that the image acquisition should be involved with study period. Low Kappa of supervised classifications and high error of omission and commission in ground truth data were described following Lunetta *et al*. (1991) and Foody (2002). The very low accuracy of agricultural classification was due to the mixed orchard and field crop plantation in the same pixel. The method in this study enabled to produce, in a reasonably short period, these training and testing samples are inadequate random sampling for remote sensing techniques (Mas *et al.*, 2017). Achieving higher overall accuracy needs a study site with more training samples. Further studies are required to focus on algorithms with high accuracy for a more accurate agricultural classification. In addition, using hyperspectral band (e.g. EO-1) and high spatial resolution with multispectral bands (e.g. IKONOS) combined with strong plant-environment relationship should be tested for agricultural mapping However, the results suggested that there is an immediate need to monitor current land use across the reserved forest area (Doi Nang Lae, Doi Yao and Doi Prabhat reserve forest) to assist with implementing municipal and government policies concerning agriculture and forestry (Eckert and Kneubhuler, 2004; Shah and Sharma, 2015; Yousefi *et al.*, 2015; Suk-ueng *et al.*, 2019).

Soil pH is essential for agricultural production which is the one of the most important soil parameters. Most agricultural crops develop best in soil with a pH from 5.5 to 6.5 (Havlin *et al.,* 1999). The soil pH recorded in most sampling stations during the study appears therefore to be favorable to crop production. Organic matter content of all these soils was low (0.13-2.07%) corresponding to the standard of Division of Soil Resources Survey and Research (1980) and Kheoruenromne (2005). According to Franzluebbers (2008) who suggested that more intensive cropping increases the quantity of residues produced, which can lead to higher soil organic matter. Furthermore, perennial pastures often reduce water runoff volume and soil loss even further than with conservation-tillage cropland due to greater accumulation of surface soil organic matter (Franzluebbers and Stuedemann, 2002, 2008).

The quality of total nitrogen in agricultural land to low level group according to the standard of Division of Soil Resources Survey and Research (1980), which is suggested for Thailand soil. The available phosphorus and potassium contents are also vital soil properties that considerably affected due to in change of vegetation cover, total biomass production, microbial decomposition of organic residues and nutrient cycling (Turrion *et al.,* 2000; Solomon *et al.*, 2002; Kheoruenromne, 2005). These soils have low soil fertility status described by Division of Soil Resources Survey and Research (1980) and Kheoruenromne (2005), which possesses unsuitable physico-chemical properties for crop productions. Therefore, soils in this area need organic and chemical fertilizers along with nutrient management.

Soil samples were contaminated with high arsenic (As) content in paddy fields and orchard, near the reserved forest area (Doi Nang Lae, Doi Yao and Doi Prabhat reserve forest), which were higher than the maximum concentration level of soils (3.90 mg/kg) used for living and agriculture specified by the office of the National Environment Board of Thailand (National Environment Board, 1992). Arsenic contamination in soils indicated the potential risk to the environment and human health. Consequently, this hotspot should be intensively paid attention for preventing and remediation measures before arsenic distributes to lowland (Tiankaoa and Chotpantarat, 2018; Chantima *et al.*, 2019).

It concluded that the agricultural mapping would be provided by Thaichote imagery processing resulting in an up-to-date of agricultural types in 2018. Soil in all agricultural types of Nang Lae sub-district should be restored and fertilized for crop productions. Particularly, contamination of arsenic in paddy field and orchard exceeded its maximum concentration level in soils, used for living and agriculture. Further study should be carried out to investigate the extent of arsenic distribution are found in this area and surrounding areas.

Acknowledgement

The author gratefully acknowledges the financial support by Chiang Rai Rajabhat University through the Research and Development Institute (Grand no. ABC020, ABC021, ABC022), and field work supported by Biological Science Program and Energy and Environment Program, Faculty of Science and Technology, Chiang Rai Rajabhat University. The author also highly appreciates the cooperation of the farmers during the field works. Our thanks are also presented to my students of Energy and Environment Program, Faculty of Science and Technology, Chiang Rai Rajabhat University for field survey and data collection.

References

Bray, R. H. and Kurtz, L. T. (1945). Determination of total, organic and available forms of phosphorus in soils. Soil Science, 59:39-45.

Bünemann, E. K., Bongiorno, G., Bai, Z., Creamer, R. E., Deyn, G. D., Goede, R. D., Fleskens, L., Geissen, V., Kuyper, T. W., Mäder, P., Pulleman, M., Sukkel, W., Groenigen, J. W. V. and Brussaard, L. (2018). Soil quality-A critical review. Soil Biology and Biochemistry, 120:105-125.

Chantima, K., Suk-ueng, K. and Prasertsin, T. (2019). Soil and water quality assessments for agricultural uses in Nang Lae sub-district, Mueang district, Chiang Rai province. Proceedings of EnvironmentAsia International Conference: Transboundary Environment Nexus: From Local to Regional Perspectives, 5:II-175-II-189.

Congedo, L. (2016). Semi-automatic classification plugin user manual, release 5.0.0.1. Retrived from http://dx.doi.org/10.13140/RG.2.1.1219.3524.

Department of Mineral Resources (2013). Land slide database project of Nang Lae sub-district, Mueang Chiang Rai district, Chiang Rai province. Department of mineral resources. Bangkok.

Division of Soil Resources Survey and Research (1980). Soil suitability classification guide for economic crops. Land Development Department. Bangkok.

Eckert, S. and Kneubhuler, M. (2004). Application of HYPERION data to agricultural land classification and vegetation properties estimation in Switzerland. Proceedings of ISPRS, 20:866-872.

Foody, G. M. (2002). Status of land cover classification accuracy assessment. Remote Sensing of Environment, 80:185-201.

Franzluebbers, A. J. (2008). Linking soil and water quality in conservation agricultural systems. Electronic Journal of Integrative Biosciences, 6:15-29.

Franzluebbers, A. J. and Stuedemann, J. A. (2002). Particulate and non-particulate fractions of soil organic carbon under pastures in the Southern Piedmont USA. Environmental Pollution, 116:S53-S62.

Franzluebbers A. J and Stuedemann J. A. (2008). Soil-profile organic carbon and total nitrogen during 12 years of pasture management in the Southern Piedmont USA. Agriculture, Ecosystem and Environment, 129:28-36.

Girouard, G., Bannari, A., Harti, A. and Desrochers, A. (2004). Validated spectral angle mapper algorithm for geological mapping: Comparative study between quickbird and landsat-tm. Proceedings of International Society for Photogrammetry and Remote Sensing, 20:599-605.

Havlin, J. L., Beaton, J. D., Tisdale, S. L. and Nelson, W. L. (1999). Soil fertility and fertilizers: An introduction to nutrient management. Prentice-Hall. New Jersey.

Huth, J., Kuenzer, C., Wehrmann, T., Gebbhadt, S., Tuan, V. Q. and Dech, S. (2012). Land cover and land use classification with TWOPAC: Towards automated processing for pixel-and object-based image classification. Remote Sensing, 4:2530-2553.

Jackson, M. L. (1958). Soil chemical analysis. Prentice-Hall. New Jersey.

Jung, M. (2016). LecoS - A python plugin for automated landscape ecology analysis. Ecological Informatics, 31:18-21.

Kheoruenromne, I. (2005). Soil survey. Kasetsart University, Bangkok.

Land Development Department (2010). Guide book for soil chemical analysis. Land Development Department. Bangkok.

Land Development Station Chiang Rai (2016). LU_Chiangrai. Land Development Station Chiang Rai. Chiang Rai.

Landis, J. and Koch, G. (1977). The measurement of observer agreement for categorical data. Biometrics, 33:159-174.

Lillesand, T. M., Kiefer, R. W. and Chipman, J. W. (2004). Remote sensing and image interpretation. John Wiley & Sons. New Jersey.

Lunetta, R. S., Congalton, R. G., Fenstermaker, L. K., Jensen, J. R., McGwire, K. C. and Tinney, L. R. (1991). Remote sensing and geographic information system data integration: Error sources and research issues. Photogrammetric Engineering & Remote Sensing, 57:677-687.

Mas, J. F., Lemoine-Rodríguez, R., González-López, R., López-Sánchez, J., Piña-Garduño, A. and Herrera-Flores, E. (2017). Land use/land cover change detection combining automatic processing and visual interpretation. European Journal of Remote Sensing, 50:626-635.

Meyer, C. (2006). Evaluating water quality using spatial interpolation methods, Pinellas county, Florida, U.S.A. Retrived from http://proceedings.esri.com/library/userconf/proc06/papers/papers/pap_2085.pdf.

Murphy, R. R., Curriero, F. C. and Ball, W. P. (2010). Comparison of spatial interpolation methods for water quality evaluation in the Chesapeake bay. Journal of Environmental Engineering, 136:160-171.

Nang Lae Municipality (2014). The three years development plan of Nang Lae Municipality (2014-2016). Nang Lae Municipality. Chiang Rai.

National Environment Board (1992). The Surface Water Standard. Retrived from http://infofile.pcd.go.th/law/3_14_water.pdf.

Patil, M. B., Desai, C. G. and Umrikar, B. N. (2012). Image classification tool for land use/land cover analysis: A comparative study of maximum likelihood and minimum distance method. International Journal of Geology, Earth and Environmental Sciences, 2:189-196.

Peech, M. (1965). Soil pH by glass electrode pH meter. In: Methods of Soil Analysis, part 2 chemical and microbiological properties. Black, CA. (ed.). American Society of Agronomy. Wisconsin.

QGIS Development Team (2019). QGIS Geographic Information System. Retrived from http://qgis.osgeo.org.

Rosa, D. D. L. and Sobral, R. (2008). Soil quality and methods for its assessment. In: Land use and soil resources. Ademola, K., Braimoh, P. L. and Vlek, G. (eds). Springer. Dordrecht.

Sapna, K., Thangavelu, A., Mithran, S. and Shanthi, K. (2018). Spatial analysis of river water quality using inverse distance weighted interpolation in Noyyal watershed in Coimbatore, Tamilnadu, India. Life Science Informatics Publication, 4:150-161.

Seybold, C., Mausbach, M., Karlen. D. and Rogers, H. (1998). Quantification of soil quality. In: Soil processes and the carbon cycle, Lal, R. (ed). CRC Press. Boca Raton.

Shah, S. and Sharma, D. P. (2015). Land use change detection in Solan Forest Division, Himachal Pradesh, India. Forest Ecosystems, 2:1-12.

Solomon, D., Fritzsche, F., Tekalign, M., Lehmann, J. and Zech, W. (2002). Soil organic matter dynamics in the subhumid Ethiopian highlands: Evidence from natural 13C abundance and particle-size fractionation. Soil Science Society of America Journal, 66:969-978.

Su, B. and Noguchi, N. (2013). Discimination of land use patterns in remote sensing image data using minimum distance algorithm and watershed algorithm. Engineering in Agriculture, Environment and Food, 15:8-53.

Suk-ueng, K., Chantima, K. and Prasertsin, T. (2019). Satellite remote sensing for agricultural mapping at Nang Lae sub-district, Mueang Chiang Rai district, Chiang Rai province. Proceedings of EnvironmentAsia International Conference: Transboundary Environment Nexus: From Local to Regional Perspectives, 5:II-104-II-114.

Tezera, A., Chanie, T., Feyisa, T. and Jemal, A. (2016). Impact assessment of land use/land cover change on soil erosion and rural livelihood in Andit Tid watershed, North Shewa, Ethiopia. Archives of Current Research International, 3:1-10.

Tiankaoa, W. and Chotpantarat, S. (2018). Risk assessment of arsenic from contaminated soils to shallow groundwater in Ong Phra Sub-District, Suphan Buri Province, Thailand. Journal of Hydrology: Regional Studies, 19:80-96.

Tommasini, M., Bacciottini, A. and Gherardelli, M. (2019). A QGIS tool for automatically identifying asbestos roofing. International Journal of Geo-Information, 8:1-13.

Turrion, M. B., Glaser, B., Solomon, D., Ni, A. and Zech, W. (2000). Effects of deforestation on phosphorus pools in mountain soils of the Allay range, Khyrgyzia. Biology and Fertility of Soils, 31:134-142.

Usha, M., Anitha, K. and Iyappan, L. (2012). Landuse change detection through image processing and remote sensing approach: A case study of Palladam Taluk, Tamil Nadu. International Journal of Engineering Research and Applications, 2:289-294.

Walkley, A. and Black, I. A. (1947). Chromic acid titration method for determination of soil organic matter. Soil Science Society of America Proceedings, 63:257.

Yousefi, S., Mirzaee, S. and Tazeh, M., Pourghasemi, H. and Karimi, H. (2015). Comparison of different algorithms for land use mapping in dry climate using satellite images: A case study of the Central regions of Iran. Desert, 20-1:1-10.

(Received: 28 May 2019, accepted: 31 August 2019)