

**SOIL-LANDSCAPE MODELING IN A SLOPE
COMPLEX AREA: MAE SA WATERSHED,
CHIANG MAI**

Rawee Rattanakom

**A Thesis Submitted in Partial Fulfillment of the Requirements for the
Degree of Doctor of Philosophy in Geoinformatics
Suranaree University of Technology
Academic Year 2011**

การสร้างแบบจำลองดิน-ภูมิทัศน์ ในพื้นที่ลาดชันเชิงซ้อน
ลุ่มน้ำแม่สา เชียงใหม่

นายรวี รัตนาคม

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรดุษฎีบัณฑิต
สาขาวิชาภูมิสารสนเทศ
มหาวิทยาลัยเทคโนโลยีสุรนารี
ปีการศึกษา 2554

**SOIL-LANDSCAPE MODELING IN A SLOPE COMPLEX AREA:
MAE SA WATERSHED, CHIANG MAI**

Suranaree University of Technology has approved this thesis submitted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy.

Thesis Examining Committee

(Asst. Prof. Dr. Sunya Sarapirome)

Chairperson

(Asst. Prof. Dr. Suwit Ongsomwang)

Member (Thesis Advisor)

(Assoc. Prof. Dr. Charlie Navanugraha)

Member

(Asst. Prof. Dr. Sodchol Wonprasaid)

Member

(Asst. Prof. Dr. Songkot Dasananda)

Member

(Prof. Dr. Sukit Limpijumnong)

Vice Rector for Academic Affairs

(Assoc. Prof. Dr. Prapun Manyum)

Dean of Institute of Science

รวี รัตนาคม : การสร้างแบบจำลองดิน-ภูมิทัศน์ ในพื้นที่ลาดชันเชิงซ้อน ลุ่มน้ำแม่สา
เชียงใหม่ (SOIL-LANDSCAPE MODELING IN A SLOPE COMPLEX AREA: MAE
SA WATERSHED, CHIANG MAI) อาจารย์ที่ปรึกษา: ผู้ช่วยศาสตราจารย์ ดร.ศุวิทย์
อ่องสมหวัง, 172 หน้า.

คุณสมบัติของดินเป็นสารสนเทศที่สำคัญปัจจัยหนึ่งสำหรับการจัดการที่ดินและการสร้าง
แบบจำลองทางสิ่งแวดล้อมแต่อย่างไรก็ตาม คุณสมบัติของดินในพื้นที่ลาดชันเชิงซ้อนของประเทศไทย
จะไม่มีข้อมูล วัตถุประสงค์หลักของการศึกษาคือ การจำแนกภูมิลักษณะ (landform) และการ
สร้างข้อมูลปัจจัยการเกิดดินโดยอาศัยเทคนิคการรับรู้จากระยะไกลและระบบสารสนเทศภูมิศาสตร์
การหาความสัมพันธ์ระหว่างคุณสมบัติของดินและปัจจัยการเกิดดิน และการทำนายคุณสมบัติของ
ดินในพื้นที่ลาดชันเชิงซ้อนในการศึกษาครั้งนี้เริ่มต้นจากการจำแนกภูมิลักษณะสำหรับใช้ในการ
สำรวจดินในสนาม โดยอาศัยการรวมค่าดัชนีตำแหน่งภูมิประเทศ (topographic position index) ใน
มาตราส่วนและชุดหลักเกณฑ์ที่แตกต่างกัน จากนั้นนำคุณสมบัติของดินบนและดินล่าง (อนุภาค
ทราย อนุภาคทรายแป้ง อนุภาคดินเหนียว ความเป็นกรดเป็นด่าง อินทรีย์วัตถุ ไนโตรเจน
โพแทสเซียม แคลเซียม แมกนีเซียม โซเดียม ความจุแลกเปลี่ยนแคตไอออน และความอิ่มตัวบส)
และปัจจัยการเกิดดิน (ปริมาณฝนรายปีเฉลี่ย 10 ปี ดัชนีพืชพรรณผลต่างแบบนอร์แมลไลซ์ (NDVI)
ระดับความสูง ความลาดชัน ทิศด้านลาด ความโค้งภูมิประเทศ (curvature plan and profile
curvature) ดัชนีความชื้นภูมิประเทศ (topographic wetness index) และอัตราส่วนของอลูมิเนียมและ
ซิลิกา มาสร้างแบบจำลองดิน-ภูมิทัศน์ โดยอาศัยการวิเคราะห์การถดถอยวิธี PLS (partial least
squares) และการประมาณค่าในช่วงวิธี Cokriging แบบจำลองที่ให้ค่าความผิดพลาดเฉลี่ยกำลังสอง
แบบนอร์แมลไลซ์ (NRMSE) น้อยที่สุด จะเป็นแบบจำลองที่เหมาะสมสำหรับนำไปใช้ในการ
ทำนายคุณสมบัติดินในพื้นที่ลาดชันเชิงซ้อน

ผลจากการจำแนกภูมิลักษณะพบว่า ภูมิลักษณะที่สำคัญในพื้นที่ศึกษาได้แก่ที่ลาดเขา (open
slopes) และยอดเขา (mountain tops) ครอบคลุมพื้นที่ คิดเป็นร้อยละ 43.88 และ 12.71 ของพื้นที่
ศึกษา ตามลำดับนอกจากนี้ พบว่า ค่าความถูกต้องโดยรวมและค่าความสอดคล้องของสัมประสิทธิ์
แคปปาของการจำแนกภูมิลักษณะ มีค่าเท่ากับร้อยละ 92 และ 91 ตามลำดับ

ในการวิเคราะห์การถดถอยวิธี PLS พบว่า ค่าสัมประสิทธิ์ การตัดสินใจ (R^2) ของคุณสมบัติ
ในดินบนและดินล่าง มีค่าอยู่ระหว่าง 0.523 ถึง 0.916 และ ระหว่าง 0.589 ถึง 0.900 ตามลำดับ
แบบจำลองสามารถทำนายคุณสมบัติของดินบนและดินล่างที่ได้ดีมากที่สุด ได้แก่ อนุภาคทรายและ
แมกนีเซียม ในขณะที่แบบจำลองสามารถทำนายอนุภาคทรายแป้งและ ไนโตรเจน ได้ดีน้อยที่สุด

ในขณะเดียวกัน ปัจจัยการเกิดดินที่มีความสำคัญสูงสุด 3 อันดับแรกที่ได้จากการวิเคราะห์การถดถอยวิธี PLS ซึ่งพิจารณาจากค่า VIP (variable importance in the projection) จะถูกนำไปใช้เป็นตัวแปรร่วม 3 ตัวแปร ในการประมาณค่าช่วงวิธี Cokriging เพื่อทำนายคุณสมบัติของดิน โดยพบว่าค่าความผิดพลาดเฉลี่ยกำลังสอง (RMSE) ของคุณสมบัติของดินบนและดินล่าง มีค่าอยู่ระหว่าง 0.094 ถึง 308.7 และ ระหว่าง 0.031 ถึง 272.4 ตามลำดับ นอกจากนี้ พบว่า ประเภทของเซมิวาริโอแกรม (semivariogram type) ที่เหมาะสมสำหรับการประมาณค่าในช่วงคุณสมบัติทางกายภาพและเคมีของดินบนเป็นแบบจำลอง Spherical ในทางตรงกันข้าม ประเภทของเซมิวาริโอแกรมที่เหมาะสมสำหรับการประมาณค่าในช่วงคุณสมบัติทางกายภาพของดินล่างเป็นแบบจำลอง Exponential และคุณสมบัติทางเคมีของดินล่างเป็นแบบจำลอง Spherical หรือแบบจำลอง Gaussian จากผลที่ได้รับ พบว่า แบบจำลองที่เหมาะสมสำหรับใช้ในการทำนายคุณสมบัติของดินบนและดินล่าง ซึ่งพิจารณาจากค่าความผิดพลาดเฉลี่ยกำลังสองแบบนอนอร์มัลไลซ์ที่มีค่าน้อยสุด ได้แก่แบบจำลองการวิเคราะห์การถดถอยวิธี PLS อย่างไรก็ตาม แบบจำลองการประมาณค่าในช่วงวิธี Cokriging ให้ผลการทำนายคุณสมบัติปริมาณค่าฟอสฟอรัสและโพแทสเซียมที่เป็นประโยชน์ของดินล่างดีกว่าแบบจำลองการวิเคราะห์การถดถอยวิธี PLS

จากผลการศึกษาสามารถสรุปได้ว่าแบบจำลองดิน-ภูมิทัศน์สามารถนำมาใช้เป็นเครื่องมือในการทำนายคุณสมบัติของดินในพื้นที่ลาดชันเชิงซ้อนซึ่งเป็นบริเวณที่ไม่มีข้อมูลคุณลักษณะและคุณสมบัติดินได้อย่างมีประสิทธิภาพนักวิทยาศาสตร์ดินสามารถนำคุณสมบัติของดินที่ทำนายได้ไปประยุกต์ใช้งานในด้านต่างๆ เพิ่มเติมได้

RAWEE RATTANAKOM : SOIL-LANDSCAPE MODELING IN A SLOPE
COMPLEX AREA: MAE SA WATERSHED, CHIANG MAI.

THESIS ADVISOR : ASST. PROF. SUWIT ONGSOMWANG, Dr. rer. Nat.
172 PP.

LANDFORM CLASSIFICATION/ SOIL-LANDSCAPE MODELING/
PREDICTIVE SOIL PROPERTY/ PARTIAL LEAST SQUARES (PLS)
REGRESSION/ COKRIGING INTERPOLATION/ SLOPE COMPLEX AREA

Soil property is one of the most important information for land management and environment modeling. Unfortunately, soil property of the slope complex area in Thailand is not available. The main objectives of the study to classify landform and generate data of soil forming factors using remote sensing and GIS techniques, to quantify relationship between soil properties and soil forming factors and to predict soil properties in slope complex area. In this study, the combination of topographic position index (TPI) values from different scales and criteria set were firstly used to classify landform for in situ soil survey. Then extracted soil properties of top and sub soils (sand, silt, clay, pH, OM, N, P, K, Ca, Mg, Na, CEC and BS) and soil forming factors (10 year mean annual rainfall, NDVI, elevation, slope, aspect, plan curvature, profile curvature, curvature, TWI and Al/Si ratio) were used to construct soil-landscape modeling using PLS regression and cokriging interpolation. Model with less NRMSE was selected as optimum model for soil property prediction in slope complex.

Based on landform classification, major landform categories in the study area were open slopes and mountain tops covering an area of 43.88 and 12.71% of the

study area, respectively. In addition, it was found that overall accuracy and kappa hat coefficient of agreement of landform classification were 92 and 91%, respectively

For PLS regression analysis, it was found that coefficient of determination (R^2) for top and sub soil properties range from 0.523 to 0.916 and 0.589 to 0.900, respectively. The best predictive model of top and sub soil property was sand and Ca, respectively. While the worst predictive model of top and sub soils was silt and N, respectively. At the same time, three significant soil forming factors from PLS regression analysis accordance with VIP values were used as 3 auxiliary variable of cokriging interpolation for soil property prediction. It was found that RMSE of top and sub soils properties range from 0.094 to 308.7 and 0.031 to 272.4, respectively. In addition, an optimum semivariogram type of cokriging interpolation for physical and chemical topsoil properties was Spherical model. In contrary, an optimum semivariogram type for physical subsoil properties was Exponential model and chemical subsoil properties was Spherical or Gaussian model. As results, it was found that an optimum model for top and sub soil properties prediction based on least NRMSE was PLS regression model. However, cokriging interpolation model provided a better result for available P and K prediction of subsoil than PLS regression model.

In conclusion, soil-landscape models can be efficient used as a tool for soil property prediction in slope complex areas where soil characteristic and properties are not available. The predictive soil properties can be further applied in various aspects by soil scientists.

School of Remote Sensing

Academic Year 2011

Student's Signature _____

Advisor's Signature _____

ACKNOWLEDGEMENTS

I would like to express my appreciation and gratitude to my advisor, Asst. Prof. Dr. Suwit Ongsomwang for valuable advice and time spending for discussion on many concerned problems. This thesis would never be accomplished without his contributions in various aspects.

I wish to express my sincere gratitude to Asst. Prof. Dr. Sunya Sarapirome and Asst. Prof. Dr. Songkot Dasananda for their contributions to my courses of study and their valuable suggestion and comment in this thesis. I am also very grateful for the support and cooperation of my thesis committee, Assoc. Prof. Dr. Chalie Navanugraha and Asst. Prof. Dr. Sodchol Wonprasaid. Consequently, this research was completely operated under their guidance and supports.

My sincere thanks are also given to Asst. Prof. Dr. Supatida Aumtong, Surapong Techa, Varaporn Poompipat and Siriwan Ruamkaew for their help with the field surveys and laboratory analysis. I am especially thankful to SUT for providing financial support for Ph.D. study. My special thanks are extended to all my friends from the School of Remote Sensing for their friendship, helpful and moral support.

Finally, I would like to thank my family for their financial support and great care. This thesis is dedicated to my grandparent, my father, my mother, my brother, all former teachers and everyone who have taught and guided me.

Rawee Rattanakom

CONTENTS

	Page
ABSTRACT IN THAI.....	I
ABSTRACT IN ENGLISH	III
ACKNOWLEDGEMENTS	V
CONTENTS	VI
LIST OF TABLES	X
LIST OF FIGURES	XIII
LIST OF ABBREVIATIONS	XVII
CHAPTER	
I INTRODUCTION	1
1.1 Background and significance of the study.....	1
1.2 Research objectives	4
1.3 Scope and limitations of the study	5
1.4 Study area	5
1.5 Benefit of the study	7
II LITERATURE REVIEW	8
2.1 Soil forming factors.....	8
2.2 Soil-landscape analysis.....	11
2.3 Soil-landscape models	13
2.4 Pedometrics.....	16

CONTENTS (Continued)

	Page
2.5 Models of soil variability for soil mapping	19
2.5.1 The knowledge-based model of soil variability.....	21
2.5.2 The data-driven model of soil variability	22
2.5.3 Combining knowledge-based and data-driven approaches	23
2.6 Partial least squares (PLS) regression	24
2.7 Cokriging interpolation.....	25
2.8 Literature review	27
2.8.1 Landform classification.....	27
2.8.2 Soil-landscape models.....	29
III RESEARCH METHODOLOGY.....	34
3.1 Data and equipment.....	34
3.2 Methodology	35
3.2.1 Landform classification.....	36
3.2.2 Input data generation.....	39
3.2.2.1 Soil forming factor preparation	40
3.2.2.2 Soil sampling unit identification and soil sampling scheme	44
3.2.2.3 Soil survey and soil data analysis.....	45
3.2.3 Soil-landscape model development	47
3.2.3.1 Soil-landscape model development.....	47

CONTENTS (Continued)

	Page
3.2.3.2 Accuracy assessment	49
3.2.3.3 Optimum model identification	49
IV RESULT AND DISCUSSION	50
4.1 Landform classification	50
4.2 Accuracy assessment of landform classification.....	52
4.3 Soil survey and soil data analysis.....	54
4.3.1 Soil survey	54
4.3.2 Soil data analysis	57
4.4 Soil forming factor	58
4.5 Soil-landscape model development.....	62
4.5.1 Soil-landscape model by partial least squares regression	62
4.5.2 Soil-landscape model by cokriging.....	83
4.6 Accuracy assessment.....	100
4.7 Optimum model for soil property prediction.....	103
4.8 The use of soil property prediction	104
4.8.1 Visualization of soil texture.....	104
4.8.2 Classification of soil texture using Expert System	105
4.8.3 Soil property of landform extraction by zonal statistics	112
4.8.4 Soil fertility assessment.....	116

CONTENTS (Continued)

	Page
V CONCLUSIONS AND RECOMMENDATIONS	120
5.1 Conclusions.....	120
5.1.1 Landform classification and soil forming factor generation	120
5.1.2 In situ soil survey and soil properties analysis	121
5.1.3 Soil-landscape model development for soil properties prediction	122
5.1.3.1 Soil-landscape model using PLS regression	122
5.1.3.2 Soil-landscape model using cokriging interpolation	124
5.1.4 Accuracy assessment.....	124
5.1.5 Optimum model for soil properties prediction	126
5.1.6 The use of soil properties prediction.....	126
5.2 Recommendations and future improvements.....	128
REFERENCES.....	129
APPENDICES.....	137
APPENDIX A SOIL PROFILE DESCRIPTION.....	138
APPENDIX B SOIL SAMPLE PROPERTIES	163
APPENDIX C ACCURACY ASSESSMENT OF SOIL PROPERTY PREDICTION.....	167
CURRICULUM VITAE.....	172

LIST OF TABLES

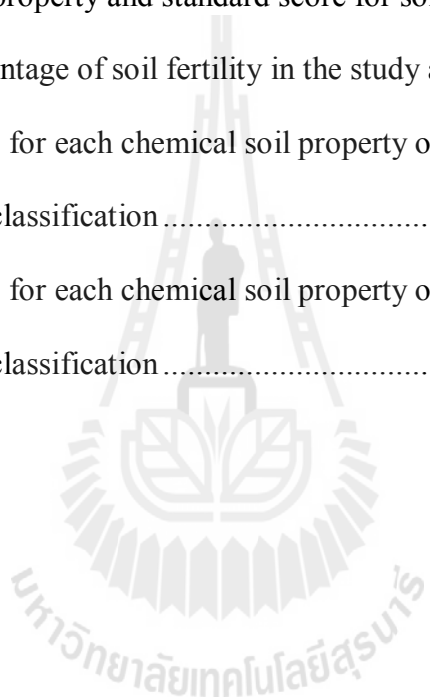
Table		Page
1.1	Area of slope complex and land use of Northern Thailand in 1990	2
2.1	Comparison of some aspects of the conventional geostatistical and plain regression-based spatial prediction approaches	20
2.2	Model of soil variability for soil mapping.....	24
3.1	List of data and equipment in this research.....	34
3.2	Landform category and criteria	37
3.3	Literature review of soil forming factor for soil-landscape model.....	41
3.4	Examples of primary terrain attributes that can be computed by terrain analysis from DEM data.....	42
3.5	Examples of secondary terrain attributes that can be computed by terrain analysis from DEM data.....	43
3.6	Methods or equations used for soil forming factor generation.....	44
3.7	Physical and chemical soil properties analysis.....	45
4.1	Landform category and description	51
4.2	Area and percentage of landform type in the slope complex area.....	51
4.3	Error matrix and accuracy assessment of landform classification.....	54
4.4	Number of soil sampling points by soil sampling unit	55
4.5	Quantitative characteristics of soil sample No 1	57
4.6	Quantitative characteristic of soil forming factor.....	59

LIST OF TABLES (Continued)

Table	Page
4.7 Multiple linear regression equation by PLS regression	63
4.8 Statistic summary of PLS regression of topsoil.....	65
4.9 Statistic summary of PLS regression of subsoil	66
4.10 Variable importance in the projection (VIP) of each soil property	67
4.11 Summary of predictive value of each soil properties using PLS.....	81
4.12 Semivariogram models of cokriging interpolation of each soil property based on the least RMSE.....	84
4.13 Summary of predictive value of each soil property using cokriging methods	98
4.14 Summary of Mean Error (ME) for soil properties prediction using PLS and Cokriging interpolation	101
4.15 Summary of Root Mean Square Error (RMSE) for soil properties prediction using PLS and cokriging interpolation	101
4.16 Summary of Normalized Root Mean Square Error (NRMSE) for soil properties prediction using PLS and cokriging interpolation.....	102
4.17 Optimum model for soil properties prediction based on NRMSE	104
4.18 Structure of hypothesis, rule and conditions for soil texture classification ..	108
4.19 Area and percentage of USDA soil texture classes	111
4.20 Error matrix and accuracy assessment of topsoil texture classification by using Expert System for topsoil.....	111

LIST OF TABLES (Continued)

Table		Page
4.21	Error matrix and accuracy assessment of subsoil texture classification by using Expert System for subsoil	112
4.22	Chemical soil property and standard score for soil fertility assessment	117
4.23	Area and percentage of soil fertility in the study area	117
4.24	Assigned score for each chemical soil property of topsoil before soil fertility reclassification	118
4.25	Assigned score for each chemical soil property of subsoil before soil fertility reclassification	118



LIST OF FIGURES

Figure	Page
1.1 Distribution of slope complex area in Northern Thailand.....	2
1.2 Location of the study area, Mae Sa Watershed, Chiang Mai Province	6
1.3 Distribution of slope complex and elevation in the study area, Mae Sa Watershed, Chiang Mai Province	7
2.1 Flower diagram of factors of soil formation (soil state factors).....	8
2.2 Pivotal events that shaped soil-landscape modeling history; Time periods and placement of events are approximate	16
2.3 Pedometrics can be considered an interdisciplinary science integrating soil science, GIS and statistics.....	17
2.4 Some new emerging scientific fields that can be related to the development of pedometrics in the last decades.....	18
2.5 The main pedometric techniques used for soil survey.....	20
2.6 Concept of PLS regression.....	25
2.7 Diagrams of kriging and cokriging interpolation	26
3.1 Basic flow chart represents the methodological framework	35
3.2 The schematic flow diagram of landform classification procedure.....	38
3.3 The schematic flow diagram of input data generation.....	39
3.4 Soil description form used in in situ soil survey.....	46
3.5 The procedure of soil-landscape model development.....	47

LIST OF FIGURES (Continued)

Figure	Page
4.1 Distribution of landform in the study area	52
4.2 Comparison of landform classification and landform in study area	53
4.3 Distribution of soil sampling units in the study area	55
4.4 Distribution of soil sampling points in the study area	56
4.5 Soil profile description of sampling site No. 1	56
4.6 Distribution of soil forming factors	60
4.7 Histogram of soil forming factors.....	61
4.8 Distribution of predictive sand using PLS	68
4.9 Distribution of predictive silt using PLS.....	69
4.10 Distribution of predictive clay using PLS.....	70
4.11 Distribution of predictive pH using PLS.....	71
4.12 Distribution of predictive organic matter using PLS	72
4.13 Distribution of predictive total nitrogen using PLS.....	73
4.14 Distribution of predictive phosphorus using PLS.....	74
4.15 Distribution of predictive potassium using PLS.....	75
4.16 Distribution of predictive calcium using PLS	76
4.17 Distribution of predictive magnesium using PLS.....	77
4.18 Distribution of predictive sodium using PLS	78
4.19 Distribution of predictive cation exchange capacity using PLS.....	79
4.20 Distribution of predictive base saturation using PLS	80

LIST OF FIGURES (Continued)

Figure	Page
4.21 Dispersion of minimum, mean and maximum value of predictive physical and chemical topsoil properties using PLS regression.....	81
4.22 Dispersion of minimum, mean and maximum value of predictive physical and chemical subsoil properties using PLS regression	82
4.23 Distribution of predictive sand using cokriging	85
4.24 Distribution of predictive silt using cokriging.....	86
4.25 Distribution of predictive clay using cokriging.....	87
4.26 Distribution of predictive pH using cokriging.....	88
4.27 Distribution of predictive organic matter using cokriging.....	89
4.28 Distribution of predictive total nitrogen using cokriging.....	90
4.29 Distribution of predictive phosphorus using cokriging.....	91
4.30 Distribution of predictive potassium using cokriging.....	92
4.31 Distribution of predictive calcium using cokriging	93
4.32 Distribution of predictive magnesium using cokriging.....	94
4.33 Distribution of predictive sodium using cokriging	95
4.34 Distribution of predictive cation exchange capacity using cokriging.....	96
4.35 Distribution of predictive base saturation using cokriging	97
4.36 Dispersion of minimum, mean and maximum value of predictive physical and chemical topsoil properties using cokriging	98
4.37 Dispersion of minimum, mean and maximum value of predictive physical and chemical subsoil properties using cokriging	99

LIST OF FIGURES (Continued)

Figure	Page
4.38 Texture fractions visualized using a color composite.....	106
4.39 Schematic diagram of decision tree for soil texture classification under Knowledge Engineer of Expert System	109
4.40 Distribution of USDA soil texture classes	110
4.41 Minimum, mean and maximum values of sand, slit, clay and pH in topsoil (left) and subsoil (right) in each landform category	113
4.42 Minimum, mean and maximum values of OM, N, P and K in topsoil (left) and subsoil (right) in each landform category	114
4.43 Minimum, mean and maximum values of Ca, Mg, Na and CEC in topsoil (left) and subsoil (right) in each landform category	115
4.44 Minimum, mean and maximum values of BS in topsoil (left) and subsoil (right) in each landform category	116
4.45 Distribution of soil fertility in the study area	119

LIST OF ABBREVIATIONS

Al/Si ratio	=	Ratio of Aluminum (Al_2O_3) and Silica (SiO_2)
ANN	=	Artificial Neural Network
BS	=	Base Saturation (%)
Ca	=	Exchangeable Calcium (ppm)
CEC	=	Cation Exchange Capacity (meq/100g)
cm	=	Centimeter
cmol	=	Centimole
CTI	=	Compound Topographic Index
DEM	=	Digital Elevation Model
DMR	=	Department of Mineral Resources
Exp	=	Exponential
GAM	=	Generalized Additive Model
Gau	=	Gaussian
GIS	=	Geographic Information System
GISTDA	=	Geo-Informatics and Space Technology Development Agency (public organization)
GLM	=	Generalized Linear Model
GPS	=	Global Positioning System
IDW	=	Inverse Distance Weighted Interpolation
IUSS	=	International Union of Soil Sciences

LIST OF ABBREVIATIONS (Continued)

K	=	Exchangeable Potassium (ppm)
km	=	Kilometer
LDD	=	Land Development Department
LULC	=	Land Use and Land Cover
ME	=	Mean Error
meq/100g	=	Milliequivalents Per 100 Grams
mg	=	Milligram
Mg	=	Exchangeable Magnesium (ppm)
MJU	=	Mae Jo University
MSL	=	Mean Sea Level
N	=	Total Nitrogen (%)
Na	=	Exchangeable Sodium (ppm)
NDVI	=	Normalized Difference Vegetation Index
NRMSE	=	Normalized Root Mean Square Error
OK	=	Ordinary Kriging
OM	=	Organic Matter (%)
P	=	Available Phosphorus (ppm)
PCA	=	Principal Component Analysis
PLS	=	Partial Least Squares
ppm	=	Parts Per Million
RMSE	=	Root Mean Square Error

LIST OF ABBREVIATIONS (Continued)

RMNSE	=	Root Mean Normalized Square Prediction Error
RQ	=	Rational Quadratic
RS	=	Remote Sensing
RTSD	=	Royal Thai Survey Department
SAI	=	Slope Aspect Index
SC	=	Slope Complex
SD	=	Standard Deviation
SK	=	Simple Kriging
Sph	=	Spherical
SPI	=	Stream Power Index
sq. km	=	Square Kilometer
STI	=	Sediment Transport Index
SUT	=	Suranaree University of Technology
TM	=	Thematic Mapper
TMD	=	Thailand Meteorological Department
TPI	=	Topographic Position Index
TWI	=	Topographic Wetness Index
USDA	=	United States Department of Agriculture
VIP	=	Variable Important in the Projection

CHAPTER I

INTRODUCTION

1.1 Background and significance of the study

Soil information is one of the important factors for land management and environment modeling. Unfortunately, soil resources in the mountainous area (slope>35%) of Thailand were seldom investigated due to the complexity of the landscape. These complexities cause soil properties to exhibit different and complex scales of variation, which requires costly investments of time and money for conventional survey. Therefore, the soil maps in the highlands of Thailand are mostly described as slope complex (SC) or Soil Units 62 for which soil characteristics and properties are not available. Area of slope complexes in Thailand is about 154,000 sq. km or 30% (Land Development Department [LDD], 1989). In the meantime, the area of slope complexes in Northern Thailand is about 86,400 sq. km or 50.93% (LDD, 1992). Distribution of slope complexes of Northern Thailand based on soil groups and land use data in 1990 is shown in Figure 1.1 and Table 1.1. In fact, agricultural lands exist in slope complex areas. Therefore, soil properties of these areas are very important for agricultural practices.

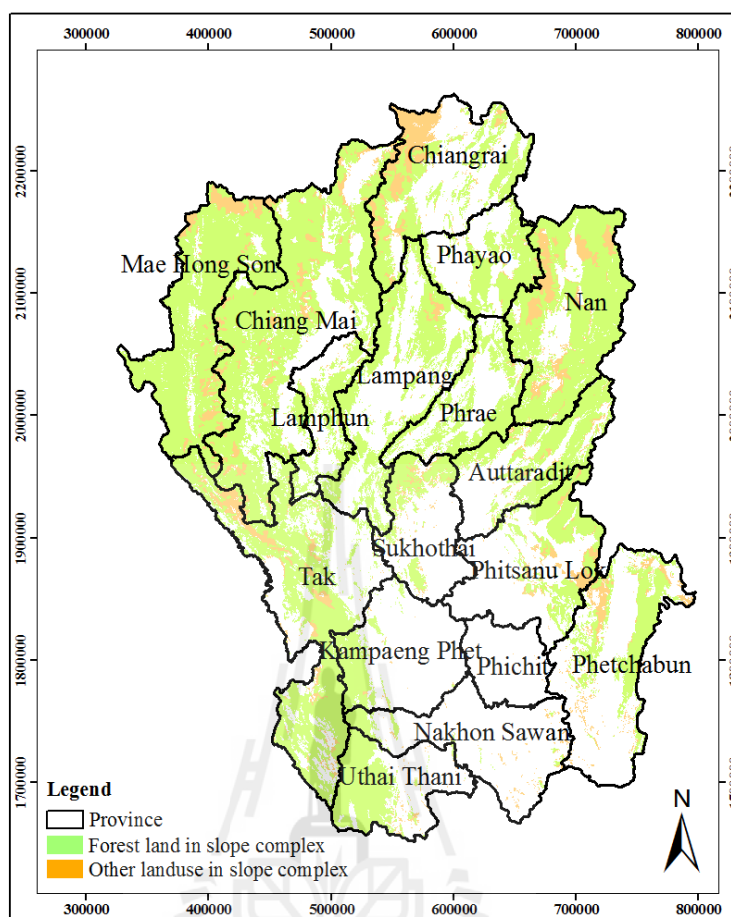


Figure 1.1 Distribution of slope complex area in Northern Thailand (LDD, 1990; 2002).

Table 1.1 Area of slope complex and land use of Northern Thailand in 1990 (LDD, 1990; 2002).

Soil unit	Major land use	Area in sq. km	Percent
Slope complex	Urban and built-up area	54.41	0.03
	Agricultural land	9,908.99	5.77
	Forest land	69,257.50	40.33
	Water bodies	181.10	0.11
	Miscellaneous land	9,582.38	5.58
Sub-Total		88,984.37	51.82
Non-slope complex	Urban and built-up area	308.78	0.18
	Agricultural land	52,505.23	30.58
	Forest land	20,524.40	11.95
	Water bodies	621.43	0.36
	Miscellaneous land	8,780.01	5.11
Sub-Total		82,739.85	48.18
Total		171,724.23	100.00

Understanding the soil distribution patterns in relation to landscape attributes is seen as a step to improve the accuracy of prediction of soil variables at unsampled locations. The properties of soil vary from place to place, but this variation is not random. Natural soil bodies are the result of climate and living organisms acting on parent material, with topography or local relief exerting a modifying influence and with time required for soil-forming processes to act (Soil Survey Division Staff, 1993).

During the last decade, many studies attempted to characterize and predict the spatial distribution of soils using more readily available environmental variables, a technique now called soil–landscape analyses (Hewitt, 1993) or environmental correlation (McBratney, Odeh, Bishop, Dunbar and Shatar, 2000). In recent years, there has been increasing scientific interest of how to combine the results of soil–landscape analyses and spatially distributed models (Florinsky, Eilers, Manning and Fuller, 2002; Park and Vlek, 2002; McBratney, Santos and Minasny, 2003; López-Granados, Jurado-Expósito, Peña-Barragán and Garcia-Torres, 2005; Santra, Chopra and Chakraborty, 2008; Ballabio, 2009; Castrignanò, Buttafuoco, Comolli and Castrignanò, 2011). The underlying motivation is to improve model outputs and reduce the time and cost of collecting information on the spatial heterogeneity of soils by developing a framework to identify the spatial distribution of soil attributes over the landscape (McBratney et al., 2003; Scull, Franklin, Chadwick and McArthur, 2003).

In addition, the rapid increase in computation power together with fast developments in data acquisition technology from remote sensing, geostatistics, digital terrain analysis and GIS have resulted in a gradual shift from conventional,

qualitative survey techniques to reproducible, fast and cost-effective quantitative predictive methods, referred to as “Digital Soil Mapping” (McBratney et al., 2003). This group of quantitative mapping methods is part of a new field of soil science known as “pedometrics” which was officially recognized at the beginning of the 1990s (McBratney et al., 2000). Pedometrics is defined as “the application of mathematical and statistical methods for the study of the distribution and genesis of soils” (Heuvelink, 2003).

Thus soil-landscape study should provide a consistent framework within which to derive soil property values for use in predictive models and land use interpretations in the landscape, and provide a baseline from which future studies may assess the impacts of land use practices.

1.2 Research objectives

The purpose of this study is to apply GIS and remote sensing techniques for soil-landscape analysis. The importance of this study is to quantify relationships between soil properties and environment variables, and use the resulting to predict soil properties in mountainous areas. The study seeks to fulfill the following objectives:

- (1) To classify landform and generate data of soil forming factors using remote sensing and GIS techniques.
- (2) To quantify relationships between in situ soil properties and soil forming factors in the study area.
- (3) To use the resulting soil-landscape models to predict soil properties in slope complex area.

1.3 Scope and limitations of the study

(1) Soil forming factors including climate, organism, relief and soil parent materials without time factor are used for physical and chemical soil properties prediction model based on soil survey data.

(2) Two predictive models including partial least squares (PLS) regression as knowledge-based model and cokriging interpolation as data driven model are applied for soil properties prediction in slope complex area.

(3) Due to budget constraint, one sampling point for in situ soil survey is identified for one combination of landform and geology unit. In fact, total sampling points in this study are 48 points which are divided into 2 sets: 28 points for model construction and 20 points for model validation.

(4) Study area is mountainous area (slope>35%) in Mae Sa watershed, Chiang Mai Province, Northern Thailand.

1.4 Study area

The Mae Sa watershed was chosen as the study area because it is a representative site for small-scale rural development and integrated watershed management in mountainous regions, which includes upstream and downstream communities, tourist resorts and several government line agencies. Some of the government agencies are located in the watershed area such as the Royal Projects (Mae Sa Mai and Nong Hoy) and Queen Sirikit Botanical Garden (Figure 1.2). Furthermore, the watershed had been selected to serve as a pilot project for river rehabilitation and land development launched by LDD in 2007.

The Mae Sa watershed includes the area from the source of Mae Sa river until the outlet into the Mae Ping river including all the streams and creeks flowing into Mae Sa, which is an area of 138.85 sq. km. The main river, the Mae Sa, has a length of 24 km, with about 20 creeks as tributaries. The watershed is an upland area with mountainous terrain and altitudes ranging from 300 to 1,600 m MSL. Most soils in this area have been classified as slope complexes (about 71%) as shown in Figure 1.3. Precipitation differs in the watershed among locations and years; the average rainfall is at 1,160 mm, with about 85% concentrated in the rainy season.

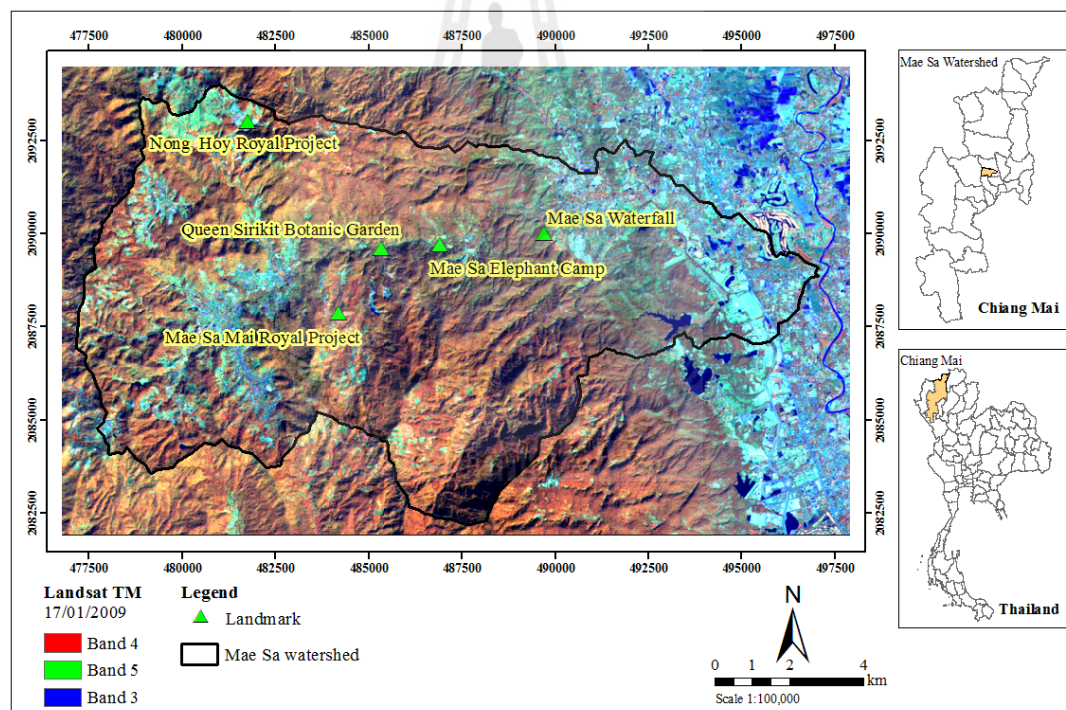


Figure 1.2 Location of the study area, Mae Sa Watershed, Chiang Mai Province.

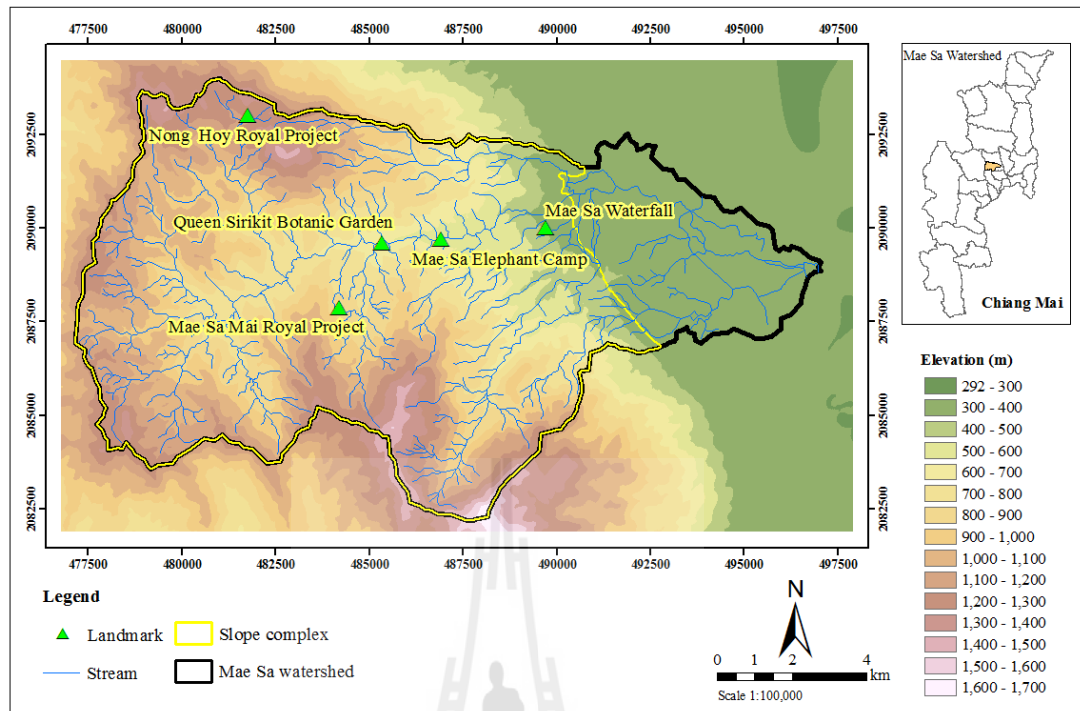


Figure 1.3 Distribution of slope complex and elevation in the study area, Mae Sa Watershed, Chiang Mai Province.

1.5 Benefit of the study

- (1) Understanding relationship between in situ soil properties and soil forming factor derived from geoinformatics in the study area.
- (2) Soil properties map in slope complex area based on resulting soil-landscape model.
- (3) Research methodology as a study prototype to quantify soil property in slope complex for soil survey.
- (4) Specific predictive physical and chemical soil properties that are useful for land management and environment modeling.

CHAPTER II

LITERATURE REVIEW

2.1 Soil forming factors

The properties of soil vary from place to place, but this variation is not random. Natural soil bodies are the result of climate and living organisms acting on parent material, with topography or local relief exerting a modifying influence and with time required for soil-forming processes to act (Figure 2.1). Conceptual model of soil forming factors, its origin in the soil factor equation outlined by Jenny (1941) describes soil as a function of climate, biological influences, topography, parent material and time (Eq. 2.1).

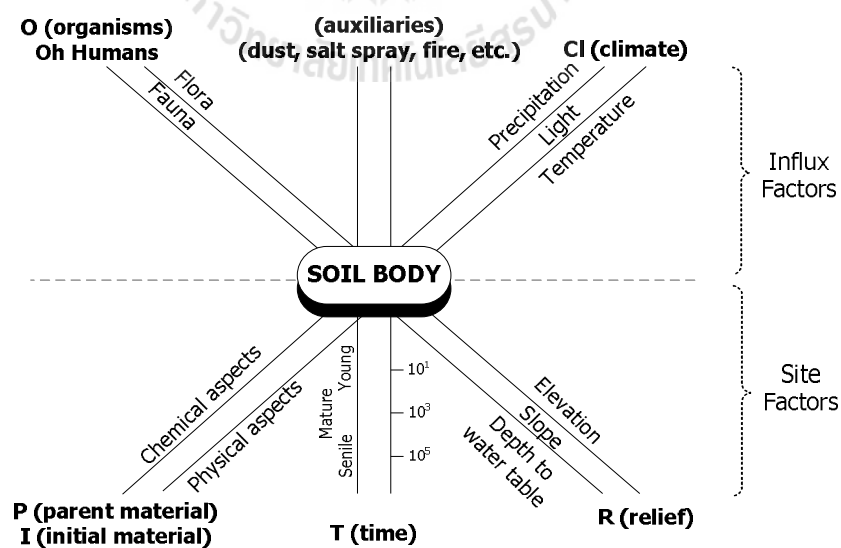


Figure 2.1 Flower diagram of factors of soil formation (soil state factors) (Buol, Hole and McCracken, 1989).

$$S = f(\text{cl, o, r, p, t, ...}) \quad (2.1)$$

where

S : any soil properties as a function of the stated factors;

cl : climate;

o : organisms;

r : relief;

p : parent material;

t : time;

... : additional factors (various auxiliaries).

The equation implies that, by looking for changes in one or more of these factors as the landscape is traversed, one can accurately locate boundaries between different bodies of soil. These are conceptual models of pedogenesis and inductive approach for defining, identifying, and mapping soils. Therefore understanding the soil distribution patterns in relation to landscape attributes is seen as a step to successfully predict soil patterns and anticipate soil behavior.

For the most part, soils are the same wherever all elements of the five factors (climate, organisms, relief, parent material and time) are the same. Under similar environments in different places, soils are similar. This regularity permits prediction of the location of many different kinds of soil (Soil Survey Division Staff, 1993).

The soil forming factor equation is itself a powerful paradigm. The implicit idea in its formulation attracted a large number of adherents, who were intrigued by its promise. They were excited by the idea that this apparently simple concept could be used as the basis for accurately locating soil boundaries and delineating bodies of soil anywhere in the world. It is generally implied that soils are natural bodies that are

distributed in a predictable way and in response to a systematic interaction of environmental factors.

Definition and interpretation of five soil forming factors can be here briefly summarized as follows:

(1) Climate: Influences soil formation in three ways including: precipitation, temperature and native vegetation. Water is essential to the forming and functioning of soil. It dissolves and transports materials, facilitates growth of plants and other organisms that contribute organic matter and certain kinds of fabric to soil. As a general rule, reaction rates approximately double for every 10°C increase in temperature. While rainfall increases, chemical and physical weathering rates increase; soil profile depth increases; content of clay in the soil solum increases; organic matter, nitrogen and ratio of carbon/nitrogen (C/N ratio) increases besides nutrient status are changes include: loss of base cations (Ca^{2+} , Mg^{2+} , K^+ , Na^+) while Al^{3+} , Fe^{3+} , Mn^{2+} and H^+ increase. Its affect to soil acidity increases (Jenny, 1941; 1980; Buol et al., 1989; Kheoruenromne, 2005).

(2) Organisms: Namely, microbes, vegetation, animals, and human are important for nutrient cycling in soil formation including: Chemical weathering (Organic acid anions), Organic matter accumulation (humification), nutrient cycling and nitrogen addition (N-fixation) (Jenny, 1941; Buol et al., 1989).

(3) Relief: These include elevation, slope, aspect and natural soil drainage condition. They correlate with the erosion and deposition process and its affect to soil profile depth, soil horizon and soil color (Jenny, 1941; Buol et al., 1989).

(4) Parent material: The parent material is the geological substrate itself. For a soil or ecosystem that is reforming after a disturbance, or major climate change, the

parent material is the soil that was present at the beginning of the new state factor assemblage (Certini and Scalenghe, 2006). It impacts to soil textural class, innate soil fertility, types of clay minerals and pH (Jenny, 1941; 1980; Buol et al., 1989).

(5) Time: Time factor is defined as the elapsed time since the soil forming process began or was exposed to its present assemblage of soil forming factors. It relates with stage of soil development, absolute dating of soil horizons/profiles and rate of soil formation (Jenny, 1980; Buol et al., 1989; Kheoruenromne, 2005).

2.2 Soil-landscape analysis

Trained soil scientists can delineate bodies of soil accurately on the landscape by directly examining less than one-thousandth of the soil below the surface. They can do this because of the validity of the soil-landscape model. A powerful paradigm, it enables soil scientists to make very accurate predictions about their world (Hudson, 1992). The soil-landscape paradigm has its origin in the soil factor equation (Eq. 2.1) outlined by Jenny (1941).

Since its introduction, its subsequent validation by Jenny and his coworkers, the soil factor equation has served as a general model of soil geography. It leads to the inference that soils are organized, mappable bodies. A large organized program of normal science or puzzle-solving has taken place under the general direction of this initial paradigm.

To understand the soil-landscape paradigm, one must break faith with a widely espoused tenet of soil science: the idea that soil is a continuum on the landscape. Soil does behave as a continuum within short distances. However, it is characterized by frequent, often abrupt discontinuities that can be discerned by trained observers. The

term discontinuity, as used here, refers to a boundary area on the landscape in which one or more of the soil-forming factors changes rapidly within a short lateral distance. A concomitant change in soil properties typically occurs at the same zone and within the same lateral distance. These abrupt soil changes at observable discontinuities make soil mapping a practical enterprise (Hudson, 1992).

Understanding the soil-landscape paradigm also requires that one understand the concept of soil-landscape units. These are natural terrains resulting from the interaction of the same five factors conventionally cited in the functional equation for soil formation. A soil-landscape unit has a recognizable form and shape of the surface of the earth. It is similar to a landform, but is more narrowly defined. For example, two areas could be identified as slopes, and thus would be the same landform. However, the soil on a south aspect might be significantly different from the soil on a north aspect. Therefore, at least two soil-landscape units would be recognized within this landform. A soil landscape unit can be thought of as a landform further modified by one or more of the soil-forming factors.

The main elements of the soil-landscape paradigm stated below are paraphrased from Hudson (1990):

- (1) Within a soil-landscape unit, the five factors of soil formation interact in a distinctive manner. As a result, all areas of the same soil-landscape unit develop the same kind of soil. In a given soil survey area, there is a relatively small number of different soil-landscape units. Individual areas of each unit occur again and again.
- (2) Generally, the more different conterminous areas of two soil-landscape units are the more abrupt and striking the discontinuity separating them. An example is the boundary between a steep backslope and a gently sloping alluvial fan at its base.

Conversely, the more similar conterminous areas of two soil-landscape units are, the less striking the discontinuity separating them tends to be.

(3) Generally, the more similar two landscape units are, the more similar their associated soils tend to be. Conversely, very dissimilar landscape units tend to have very dissimilar soils.

(4) Adjacent areas of different soil-landscape units have a predictable spatial relationship one to another. For example, one area will always be located above another on the landscape, or between another and a stream.

(5) Once the relationships among soils and landscape units have been determined for an area, the soil cover can be inferred by identifying the characteristic soil-landscape unit. The soil is examined directly only as needed to validate this relationship.

The soil-landscape paradigm makes soil mapping possible because of observable discontinuities between conterminous areas of different soil-landscape units. Conterminous soils that are distinctly different tend to be on distinctly different soil-landscape units separated by abrupt discontinuities. As a general principle, the more different two conterminous areas of soil are, the easier it is to locate the boundary between them accurately and precisely. This is a fortuitous relationship. Because of it, conterminous areas of soil that are the most different generally can be separated most accurately and precisely in mapping.

2.3 Soil-landscape models

An appropriate understanding and inclusion of spatial variation of soils are essential for ecological and environmental process modeling on the landscape scale

(Park and Vlek, 2002). During the last decade, many studies attempted to characterize and predict the spatial distribution of soils using more readily available environmental variables, a technique now called soil-landscape analyses (Hewitt, 1993) or environmental correlation (McBratney et al., 2000). In more recent years, there has been increasing scientific interest in how to combine the results of soil-landscape analyses and spatially distributed models (Heuvelink and Pebesma, 1999; Zhu, 2000). The underlying motivation is to improve model outputs and reduce the time and cost of collecting information on the spatial heterogeneity of soils by developing a framework to identify the spatial distribution of soil attributes over the landscape (Heuvelink and Pebesma, 1999; McBratney et al., 2000).

Integration of the conceptual and methodological advances in related disciplines with pedological research offers rich possibilities for the development of a truly landscape-scale pedology. Landscape-scale pedology focuses on soil properties and processes that cannot be understood in isolation from their spatial and temporal context - where lateral transfers of water, solutes and sediments at present or in the past are central to explain the soil attribute or processes at a particular point in the landscape (Pennock and Veldkamp, 2006).

The term landscape has many meanings but is used in this context to capture both landform and land use. Landform combines both the morphology of the surface and the parent materials that comprise it. Land use includes both human-imposed modification of the land surface and the assemblage of plant communities that occurs in natural areas. Both landform and land use are dynamic - land use is subject to both deliberate alteration and unintended disturbances but landform is also subject to significant short-term erosional modification as well as long-term evolution (Schoorl,

Beldkamp and Bouma, 2002). There is clearly a tendency to combine this soil landscape-land use complexity in more advanced soil landscape analysis by means of dynamic process modeling.

Landscape-scale pedology also provides the linkage between soil processes and soil surveys, and this linkage is essential for upscaling of soil process information to regional, national, and global scales.

Soil-landscape modeling is a science devoted to understanding the spatial distribution of soils and coevolving landscapes as part of ecosystems that change dynamically through time. It describes and explains the spatial and temporal distribution of soil and landscape properties and patterns at landscape-scale (Grunwald, 2006a). Three exclusive soil-landscape modeling philosophies exist:

(1) Empiric, factorial models use factors such as climate, organism, topography, parent material, and time to explain and predict the spatial and temporal distribution of soils;

(2) Spatial models utilize geostatistical methods to predict soil and landscape properties at previously unsampled locations within a specified domain;

(3) Deterministic, pedo-dynamic (process-based) models integrate algorithms to describe pedogeomorphological processes forming soils.

The goal of soil-landscape modeling is to gain an understanding of the spatial distribution of soil attributes, characteristics of soils, and their behavior through time.

Soil-landscapes can be defined in terms of:

- (1) Geomorphology and topography: the form and shape of a landscape;
- (2) Land cover: the aboveground characteristics;
- (3) Land use: the functions that a landscape performs;

- (4) Soil attributes: the belowground characteristics;
- (5) Genesis: the formation of soil attributes due to pedological processes.

Quantitative models that describe soil-landscapes are rooted in conceptual (mental) models. These conceptual soil-landscape models have currently evolved into complex quantitative models that utilized advanced mathematics and statistics, emerging soil mapping techniques, and computers that are capable of processing huge multidimensional datasets. Pivotal events that shaped soil-landscape modeling history are summarized by Grunwald (2006b) as shown in Figure 2.2.

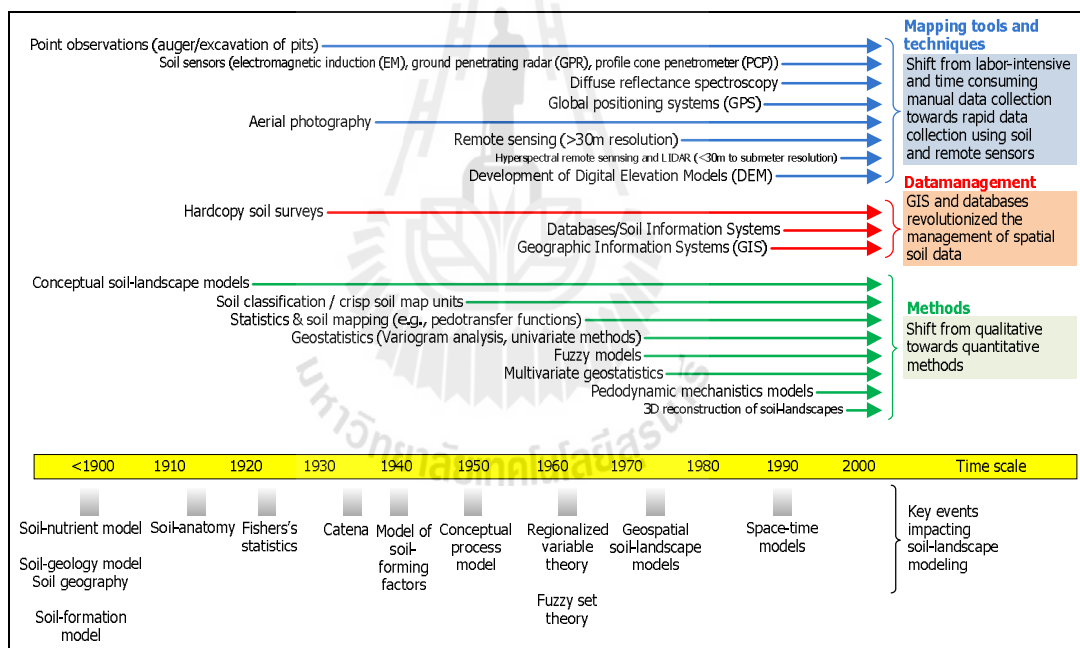


Figure 2.2 Pivotal events that shaped soil-landscape modeling history; Time periods and placement of events are approximate (Grunwald, 2006b).

2.4 Pedometrics

Soil-landscapes are complex and diverse due to pedogeomorphological and hydrological processes acting over hundreds and thousands of years. These soil-

forming and destroying processes operate simultaneously in soils, and the resulting profile reflects the balance of these processes present and past. The spatial distributions of subsurface attributes and processes in natural environments often vary at granularities ranging from pedons, hillslopes, to regions. Reconstructing soil-landscapes requires an interdisciplinary holistic approach (Grunwald, 2006b). Pedometrics attempts to integrate knowledge from numerous disciplines, including soil science, statistics, and GIS (Figure 2.3). Pedometrics, a term coined by Alex B. McBratney, is a neologism, derived from the Greek words “πεδος” (pedos; soil) and “μετρον” (metron; measurement). It is formed and used analogously to other applied statistical fields such as biometrics, psychometrics or econometrics (Webster, 1994).

The most recent definition of pedometrics, available via the website of the Pedometric society (www.pedometrics.org), is “the application of mathematical and statistical methods for the study of the distribution and genesis of soils” (Heuvelink, 2003).

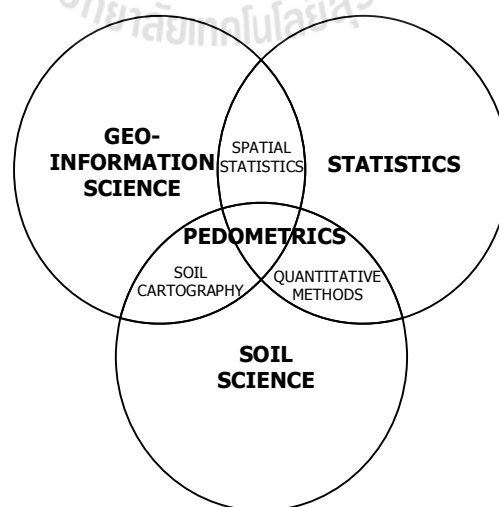


Figure 2.3 Pedometrics can be considered an interdisciplinary science integrating soil science, GIS and statistics (Grunwald, 2006b).

Another way of looking at pedometrics is to see it as the implementation of newly emerging scientific theories, such as wavelets analysis and fuzzy set theory, in soil data modeling applications (Figure 2.4). The development of pedometrics is also a result of new technological discoveries and improvements, remote and close-range sensing techniques, GPS positioning and computers in general (Burrough, Bouma and Yates, 1994; McBratney et al., 2003). The expansion of new applications in the early 90's has made pedometrics one of the leading sub-disciplines in the area of soil research (Hartemink, McBratney and Cattle, 2002). Pedometrics is promoted and communicated via publications, conferences and workshops organized by the Pedometrics society, a working group under the International Union of Soil Sciences (IUSS). After a decade of existence and numerous conferences and workshops, this Working Group has been promoted, at the 17th World Congress of Soil Sciences, to become a Commission under the IUSS.

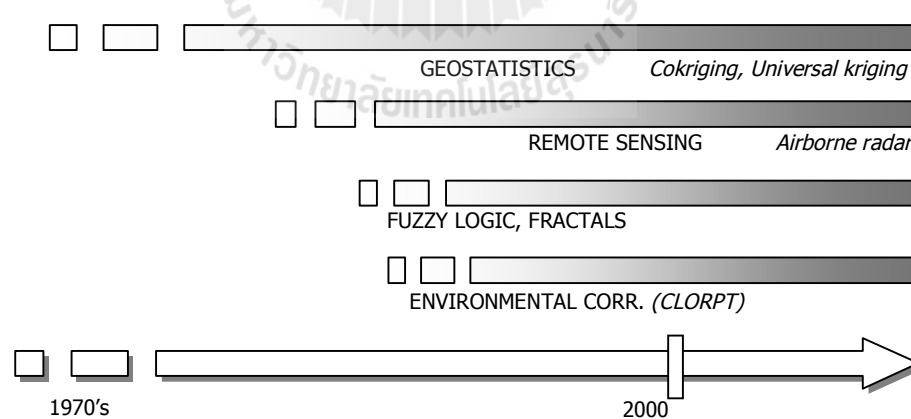


Figure 2.4 Some new emerging scientific fields that can be related to the development of pedometrics in the last decades (Hengl, 2003).

Recent topics covered by pedometrics include: multi-scale data integration; the use of wavelets transforms to analyze complex variation; soil-landscape modeling using digital terrain analysis; quantification of uncertainty and fuzziness of information and evaluation criteria; soil genesis simulation; soil pattern analysis; design and evaluation of sampling schemes; incorporation of exhaustively sampled information (remote sensing) in spatial interpolation; precision agriculture applications and others. A major topic of pedometric research is the development of models and tools capable of dealing with the spatio-temporal variation of soils (McBratney et al., 2000; 2003). These tools and methods can then be implemented to improve or replace conventional soil mapping.

2.5 Models of soil variability for soil mapping

Approaches to soil mapping can be divided into two main streams: knowledge-based, where the surveyor builds up a mental model of why each soil is where it is and data-driven, where actual observations are observed and interpolated (Rossiter, 2005). It refers to basic of pedometric techniques. There are basically two generic groups of pedometric techniques in general and the enrichment of soil information specifically:

- (1) Classical methods collectively referred to here as the CLORPT methods or statistical methods;
- (2) Geostatistical methods. A comparison between CLORPT approach and geostatistical approach is summarized as showed in Table 2.1.

However the best features of these two methods may be combined as hybrid method. The older and the emerging techniques and the style of each are summarized as showed in Figure 2.5. The detail of model approach is described in the next section.

Table 2.1 Comparison of some aspects of the conventional geostatistical and plain regression-based spatial prediction approaches (Hengl, 2003).

CJORPT APPROACH	GEOSTATISTICAL APPROACH
- Requires correlation with the auxiliary data	- Requires spatial dependence
- Lower sampling density desirable	- Higher sampling density desirable
- Knowledge-driven	- Data-driven
- One model over entire area	- Stratification desirable
- Deals with feature space	- Deals with geographical space
- Aims at structural part of variation (drift or trend)	- Aims at spatially correlated random part of variation
- Requires non-stationarity	- Requires stationarity
- Prediction error reflects the 'distance' of the point locations in the feature space while ignoring their spatial location	- Kriging variance reflects a geometry of the point locations while ignoring environmental patterns
- For linear regression, in general, no input parameters are required; predictions are unique for the same data set; however, functional relationship between the auxiliary maps and soil variables is unknown and might differ for similar datasets	- Numerous input parameters such as lag spacing, variogram function model, limiting distance, interpolation method, anisotropy model etc. are required; the predictions are non-unique for the same data set

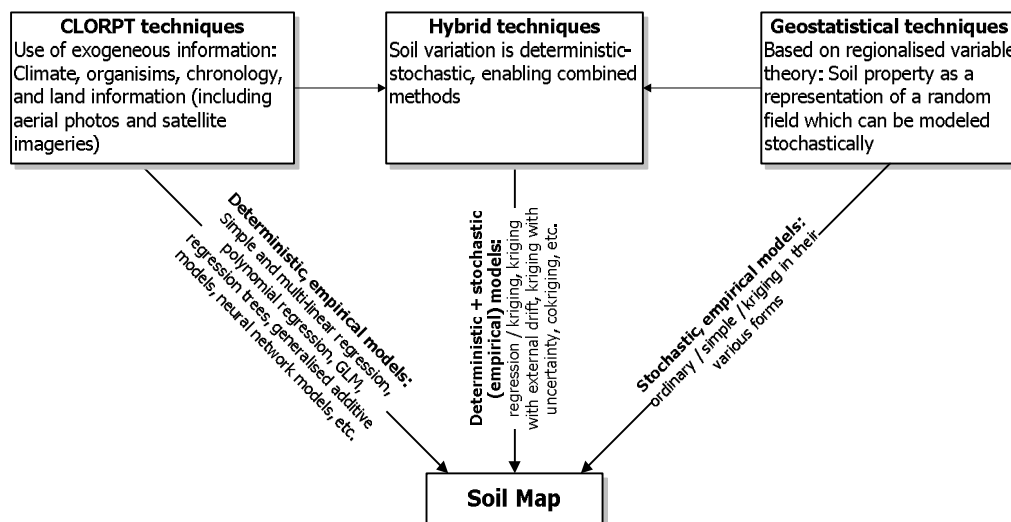


Figure 2.5 The main pedometric techniques used for soil survey (McBratney et al., 2000).

2.5.1 The knowledge-based model of soil variability

The knowledge-base model of soil variability begins with the development of a numerical or statistical model of the relationship among environmental variables and soil properties, which is then applied to a geographic data base to create a predictive map (Scull et al., 2003). Three main goals are to (1) exploit the relationship between environmental variables and soil properties in order to more efficiently collect soil data; (2) produce and present data that better represent soil landscape continuity and (3) explicitly incorporate expert knowledge in model design.

In 1941, Jenny published his monograph “Factors of soil formation-a system of quantitative pedology”, in which he presented evidence that soils do not occur randomly on the landscape; rather, they are the product of specific soil-forming factors, traditionally known as “the CLORPT model”. In any case, the basic idea is that each soil is in its place for a reason, and if we can determine the (often very complex) history of the soil’s environment, we can predict the soil itself (Rossiter, 2005). This is the idea behind knowledge-based approaches to digital soil mapping.

When applied to digital soil mapping, statistical methods can be used to exploit the relationship between quantifiable landscape indices and soil properties to create predictive soil maps. Statistical methods or McBratney et al. (2000) call the CLORPT methods are based on the empirical-deterministic models that originated from factors of soil formation. It simply uses the GIS to overlay existing data to predict soils, just as the pre-GIS mapper does intuitively; the difference is that the relations must be formalized.

2.5.2 The data-driven model of soil variability

Another approach is to look only at the data, and develop geostatistical models which can then be applied to predict soil properties at unsampled locations. Since the late 1960s, there has been an emphasis on what might be called geographic or purely spatial approaches, i.e., soil attributes can be predicted from spatial position largely by interpolating between soil observations locations. Another way of thinking about this is as a “neighborhood law” and also of soil geostatistics, etc. Generally, we can consider the soil at some location (x,y) to depend on the geographic coordinates x,y and on the soil at neighboring locations $(x+u,y+v)$, i.e., the dependence usually being some decreasing function of the magnitude of u and/or v (Eq. 2.2) (McBratney et al., 2003).

$$s(x,y) = f((x,y), s(x+u, y+v)) \quad (2.2)$$

This approach arose originally out of the need for spatial prediction to make soil maps, and because of a failure to obtain prediction from the soil-forming factors largely because the quantitative variables describing these factors were not readily available to do such predictions. These purely spatial approaches are almost entirely based on geostatistics.

Geostatistical methods are based on the theory of regionalized variables, which allows us to consider spatial variability of a soil property as a realization of a random function represented by a stochastic model. The geostatistical method of spatial interpolation is termed kriging. The first major applications of ordinary kriging in soil studies emerged in the early 1980s. Since then, ordinary

kriging has been widely used in various sub-fields of soil science. Major limitations of the univariate geostatistical technique of kriging are due to the assumptions of stationarity which are not often met by the field-sampled data sets and, of course, the often cited requirement of large amount of data to define the spatial autocorrelation. However, with increasing availability of ancillary information, the lack of adequate samples has been partially solved. The univariate usage of kriging is also limiting in situations of complex terrain where the soil-forming processes are themselves complex (McBratney et al., 2000).

2.5.3 Combining knowledge-based and data-driven approaches

In such situations, there is the need to model both the structured and the spatially dependent components of the soil variable. Also there are economic and logistic reasons for including the ancillary influencing soil variability, especially if the latter are more readily and cheaply available. As both the soil and the exogenous factors are multivariate, the most obvious choices are appropriate combinations of multivariate/univariate analysis using the CLORPT factors and the geostatistical methods. These combinations constitute the hybrid techniques (see also Figure 2.5).

The hybrid techniques are based on various combinations of the geostatistical method and multivariate or univariate CLORPT method. In other words it is deterministically related to some causative factors (trend). Wherever trend exists, the ordinary univariate kriging is inappropriate. Several methods have been designed to accommodate the trend, i.e., universal kriging, cokriging, regression kriging, kriging with external drift and factorial kriging (McBratney et al., 2000). Relevant techniques applying in each method were here summarized as shown in Table 2.2.

Table 2.2 Model of soil variability for soil mapping.

Model of soil variability	Predictive approaches
Knowledge-based:	Expert systems
	Statistical methods (CLORPT)
	<ul style="list-style-type: none"> • Linear models <ul style="list-style-type: none"> – Ordinary least squares – Multiple linear regression – k-means clustering • Generalized linear model (GLM) • Classification and regression trees
	<ul style="list-style-type: none"> – Principal component regression – Partial least squares regression – Linear discriminant analysis • Generalized additive model (GAM) • Artificial neural network (ANN)
Data-driven:	Geostatistical methods
	<ul style="list-style-type: none"> • Simple kriging (SK)
	<ul style="list-style-type: none"> • Ordinary kriging (OK)
Combining knowledge-based and data-driven approaches:	
	Hybrid methods
	<ul style="list-style-type: none"> • Universal kriging • Regression kriging • Factorial kriging
	<ul style="list-style-type: none"> • Cokriging • Kriging with external drift

2.6 Partial least square (PLS) regression

Partial least squares (PLS) regression is a technique that combines features from and generalizes principal component analysis (PCA) and multiple linear regressions. Its goal is to predict dependent variables (Y) from a set of independent variables or predictors (X). This prediction is achieved by extracting from the predictors a set of orthogonal factors called latent variables which have the best predictive power (Abdi, 2007; 2010; Eriksson, Johansson, Kettaneh-Wold, Wikström and Wold, 2008;). This concept is illustrated in Figure 2.6 representing a hypothetical data set with three independent variables (X_1 , X_2 and X_3) and three dependent variables (Y_1 , Y_2 and Y_3 ; in case that dependent variables more than one) while t_1 is X-scores (latent variables or PCA1). As a result, the first latent variable (t_1) can be obtained relationship with dependent variable (u_1 , Y-scores) (Eriksson et al., 2008).

In addition, PLS regression is especially useful when (1) the number of predictor variables is similar to or higher than the number of observations and (2) predictors are highly correlated (collinearity) (Carrascal, Galván and Gordo, 2009).

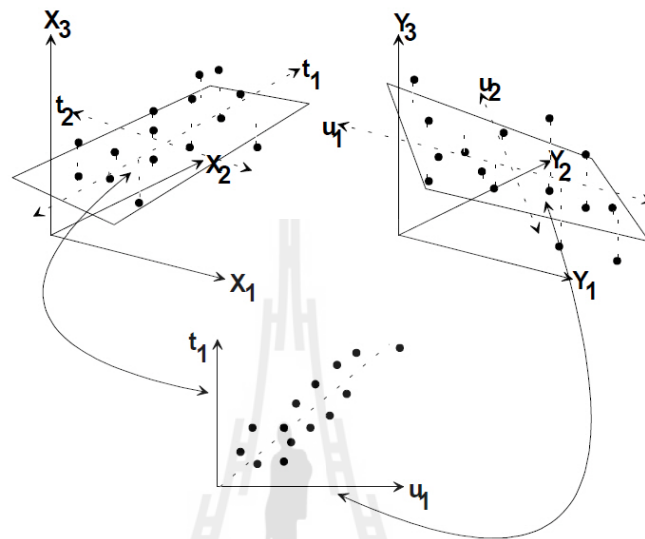


Figure 2.6 Concept of PLS regression (Eriksson et al., 2008).

2.7 Cokriging interpolation

Cokriging allows samples of one or more auxiliary variables (also called the co-variable), which are correlated with the primary variable (target value) of interest, to be used when predicting the target value at unsampled locations. The co-variable may be measured at the same points as the target (co-located samples), at other points, or both (Rossiter, 2007). It assumes that the correlation between the primary variable and auxiliary variable can be used to improve the prediction of the value of the primary variable (Chang, 2004).

The diagrams of Figure 2.7 explain the difference between kriging and cokriging interpolation and their performance. In kriging interpolation, the value of target variable (Z_I) at unsampled location X_0 is interpolated by a linear combination of

the values at X_n surrounding location (Eq. 2.3). For cokriging interpolation, the value of target variable (Z_1) at unsampled location X_0 is interpolated by a linear combination of n surrounding locations of the variable Z_1 and m surrounding location of an auxiliary variable (Z_2) (Eq. 2.4) (Isaaks and Srivastava, 1989; Knotters, Brus and Oude Voshaar, 1995; Lloyd, 2007).

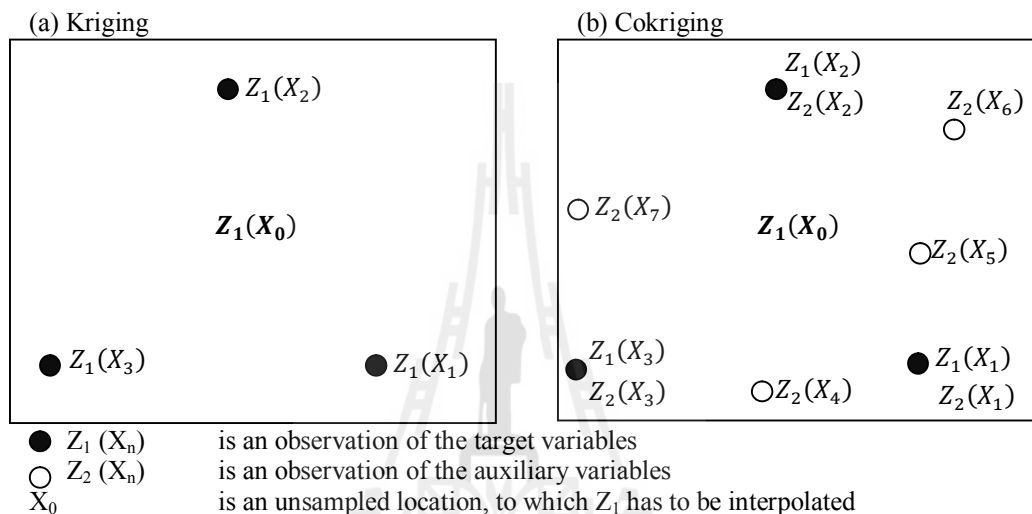


Figure 2.7 Diagrams of kriging and cokriging interpolation (Knotters et al., 1995).

$$\hat{Z}_1(X_0) = \sum_{i=1}^n a_i \times Z_1(X_i) \quad (2.3)$$

$$\hat{Z}_1(X_0) = \sum_{i=1}^n a_i \times Z_1(X_i) + \sum_{j=1}^m b_j \times Z_2(X_j) \quad (2.4)$$

where Z_1 : primary variable (target variable);

Z_2 : auxiliary variable;

$\hat{Z}_1(X_0)$: is the estimate value of primary variable at location 0;

X_i : are the primary value at n nearby locations;

X_j : are the auxiliary value at m nearby locations;

a_i : are cokriging weights of Z_1 at n nearby locations;

b_j : are cokriging weights of Z_2 at m nearby locations.

2.8 Literature review

Two groups of research papers related with this study include landform classification and soil-landscape model and are reviewed here.

2.8.1 Landform classification

Ekasingh, Sangchyoswat, Samranpong, Punsompong, Sumhem, Wongchaimoon and Prommanon (2004) used unsupervised classifications (ISODATA) to classify landform (toe slope, foot slope, back slope shoulder and summit) based on terrain attributes (plan curvature, profile curvature, slope, elevation and topographic wetness index (TWI)) and generated Delineated Mapping Unit (DMU) for decision support system of soil survey in highland. The results show that, overall accuracy range from 72.41-90.62% when compared with ground survey.

Ventura and Irvin (2000) described an approach for automated landform classification methods for soil-landscape studies. Continuous classification (fuzzy set) methods and unsupervised (ISODATA) classification techniques were used to classify the landscape of a study area in southwestern Wisconsin, USA. Each pixel of a 10-m resolution digital elevation model (DEM) was grouped according to its membership in a continuous landform class. These classes were determined by the natural clustering of the data in attribute space. Six topographic attributes were used for the classification methods: elevation, slope, profile and tangent (related to plan) curvature, topographic wetness index (TWI), and incident solar radiation.

The resulting ISODATA classifier provided a relatively quick and easy way to delineate landform elements. The landform element designations can be overlaid on any digital map or orthophoto, which could prove useful in designing sampling schemes based on landform designations, or in providing a first cut for soil

unit delineation. Continuous (fuzzy) classification provides more information about the character and variability of the data than the ISODATA method, affording more insight into the nature of the data and making it more amenable to statistical analysis. This technique requires a conceptual shift to accommodate the new form and degree of information. However, it is a more time consuming method and the results are not as easily visualized.

Hengl and Rossiter (2003) used supervised landform classification to enhance and replace aerial photo interpretation (API) in semi-detailed soil survey. The six sample areas were selected by conventional aerial photo interpretation map using a geo-pedological legend of 21 classes in eastern Croatia. Nine topographic attributes extracted from DEM were used for the classification: ground water depth, slope, plan curvature, profile curvature, viewshed, flow accumulation, topographic wetness index (TWI), sediment transport index, and the distance to nearest watercourse. The results show that the methodology can be applied by soil survey teams to edit and update current maps and to enhance or replace API for new surveys.

Weiss (2001) presented the concept of topographic position index (TPI) and how it could be calculated. Using this TPI at different scales, plus slope, users can classify the landscape into both slope position (i.e. ridge top, valley bottom, mid-slope, etc.) and landform category (i.e. steep narrow canyons, gentle valleys, plains, open slopes, mesas, etc.). The TPI is the basis of the classification system and is simply the difference between a cell elevation value and the average elevation of the neighborhood around that cell. Positive values mean the cell is higher than its surroundings while negative values mean it is lower.

By thresholding the continuous TPI values at a given scale and checking the slope for values near zero, landscapes can be classified into discrete slope position classes. One repeatable method of creating classes is to use standard deviation units (SD) to generate a 6 category slope position grid. And landform category can be determined by classifying the landscape using two TPI grids at different scales. The combination of TPI values from different scales suggests various landform types (Tagil and Jenness, 2008).

2.8.2 Soil-landscape models

Moore, Gessler, Nielsen and Peterson (1993) developed spatial soil attribute prediction model using terrain analysis. Stepwise regression was performed to quantified relationships between soil attribute (A horizon depth, organic matter, extractable phosphorus, pH, sand and silt) and terrain attributes include: primary terrain attributes (elevation, slope, aspect, plan and profile curvature, flow path lengths and specific catchment area) and secondary attributes (topographic wetness index, sediment transportation index and stream power index). The result show coefficients of determination (R^2) as 0.482-0.636 in addition slopes and topographic wetness index were the terrain attributes most highly correlated with surface soil attributes.

Gessler, Moore, McKenzie and Ryan (1995) quantified relationships between terrain attributes (plan curvature, compound topographic index, upslope mean plan curvature) and soil attributes (A horizon depth, solum depth, E horizon presence/absence) for developed soil-landscape modeling and spatial prediction of soil attributes in Great Dividing Rang in southeastern Australia. The results show that,

CTI was a useful predictor because it combines contextual and site information via the upslope catchment area and slope, respectively. Plan curvature was not expected to have a strong predictive power because it does not include contextual information. However, it was significant in predicting the A horizon and solum depth in combination with CTI.

Paiboonsak (2000) studied soil-landscape modeling and technique for soil mapping in slope complex areas by using GIS and analyzed the database structures of soil forming factors (vegetation, parent material, elevation, slope gradient and aspect). A soil mapping unit was generated base on the combination of soil forming factors by overlay process. The result found that parent material can be provided information about soil texture, while slope, aspect, elevation and vegetation can be provided information about soil depth.

Ryan, McKenzie, O'Connell, Loughhead, Leppert, Jacquier and Ashton (2000) developed quantitative spatial predictions of 5 forest soil properties (depth to B horizon, soil stone volume, soil carbon density, soil phosphorus density and soil water storage) by using classification and regression trees and generalized linear models. Spatial environmental variables considered for model building form 2 data sources include: (1) digital terrain analysis (elevation, relative elevation, relief, slope, plan curvature, profile curvature, tangential curvature, contributing area specific contributing area, stream power index, aggradations index, dispersal area, specific dispersal area, degradation index, up-slope and down-slope means for slope/plan curvature/profile curvature/tangential curvature, erosion index, mean annual rainfall, mean annual temperature, net radiation and Prescott index) and (2) remote sensed data (Landsat TM bands 1-7, NDVI and airborne geophysical gamma radiometric of

potassium/thorium/uranium/total count, magnetic intensity). The results from spatial predictions of 4 forest soil properties include: depth to B horizon, soil stone volume, soil carbon and phosphorus density (at 0-1 m depth) and soil water storage show coefficients of determination (R^2) as 0.46, 0.63, 0.54, 0.62 and 0.67 respectively.

Gobin, Campling and Feyen (2001) developed soil-landscape models to predict the spatial distribution of soil texture at the surface horizon across a catchment in southeastern Nigeria. Topographic attributes (slope gradient, plan curvature, profile curvature, aspect, contributing area, compound topographic index (CTI), stream power index (SPI) and slope aspect index (SAI)) were used to quantify the correlation between landscape and soil texture. Stepwise multiple-linear regression was performed on the normalized terrain attributes and on the principal components constructed from the normalized terrain attributes to avoid multicollinearity. The derived soil-landscape models were used to predict clay, silt, sand, ironstone and thickness of the surface horizon from the original terrain attributes for the entire study area ($R^2 = 0.41$ to 0.75).

Hengl, Rossiter and Husnjak (2002) used the CLORPT approach to develop two regression models for pH and organic matter in topsoil. Environmental predictors used are standard terrain parameters (elevation, slope, curvature, aspect and wetness index), climatic data (rainfall and temperature) and vegetation components derived from the annual NOAA's NDVI time series. The results show that these two soil properties can be mapped using the CLORPT approach with equal or better precision than with using the existing 1:50,000 soil class map and averaging the properties per soil mapping unit. While the precision of prediction for pH did not improve significantly (residual standard error: 0.60 versus 0.61), the precision for OM

was considerably better (residual standard error: 2.81 versus 3.85). The models accounted for 54% (pH) and 66% (organic matter) of the total variation. Principal components of the NDVI time series proved to be most significant predictors of the soil properties, showing clearly general vegetation types and their dynamics. The prediction of pH indeed seems to be more difficult than the prediction of OM. The achieved coefficient of variation for pH was 16.8%, while the model for OM it was 10.8%.

López-Granados et al. (2005) compared various prediction methods for mapping soil properties (texture, organic matter (OM), pH, phosphorus and potassium) for precision farming approaches by incorporating secondary spatial information into the mapping. The primary information (or primary attribute) was obtained from an intensive grid soil sampling and the secondary spatial information from spectral data (blue green and red waveband) from an aerial color photograph of bare soil. The prediction methods were statistical (linear regression between soil properties and digital values) and geostatistical algorithms (ordinary kriging, ordinary kriging plus regression and kriging with varying local means). The results show that the best prediction method for mapping organic matter, pH and potassium was kriging with varying local means in combination with the spectral data from the blue waveband with the smallest mean square error (MSE) indicating the highest precision. Maps from these kriging estimation showed that a combination of geostatistical techniques and digital data from aerial photograph could improve the prediction quality of soil management zones, which is the first step for site-specific soil management.

Ballabio (2009) used four regression models include: ordinary least squares (OLS) regression, partial least squares (PLS) regression and classification and regression trees (CART) and support vector regression (SVR) to developed spatial prediction of soil parameters, namely organic carbon content in A horizon, extractable aluminum concentration in B horizons and cumulative thickness of A and B soil horizons. While predictor variables were: altitude, slope, compound terrain index, solar radiation related parameters, LS factor, sediment transport index, vegetation cover map (dummy variables) The result found that coefficients of determination of OLS, PLS, CART and SVM range from 0.10 to 0.11, 0.11 to 0.12, 0.46 to 0.64 and 0.55 to 0.76, respectively. In conclusion, the non-linear approximation of SVR has several advantages over other techniques for digital soil mapping in mountain areas with a small number of available observations and the non-linearity of the relations between environmental variables and soil properties.

CHAPTER III

RESEARCH METHODOLOGY

3.1 Data and equipment

Data used in this research include climate, remotely sensed, topography, soil and geology data. Equipment for soil survey includes soil auger, soil core, Munsell soil color chart, GPS and digital camera. Equipment for data analysis used in this research consists of notebook and statistical, image processing and GIS software (Table 3.1).

Table 3.1 List of data and equipment in this research.

Data	Data characteristic	Source
1. Climate data	Annual rainfall for 10 year period (2000-2009)	- TMD - Royal Project
2. Landsat-5 TM data	Acquired 17/01/2009	- GISTDA
3. Contour data	Contour 20 m. Intervals	- RTSD
4. Topographic data	Topographic layer, scale 1:50,000	- RTSD
5. Geology data	Digital geology layer, scale 1:50,000	- DMR
6. Soil series data	Digital soil layer, scale 1:50,000	- LDD
Equipment	Usage	Source
Hardware		
Soil auger	Soil survey	Soil and Plant Laboratory, MJU
Soil core	Soil survey	Soil and Plant Laboratory, MJU
Munsell soil color chart	Soil survey	Soil and Plant Laboratory, MJU
GPS	Soil survey	Personnel
Digital camera	Soil survey	Personnel
Notebook	Soil survey/Data analysis	Personnel
Software		
XLSTAT	Data analysis	Personnel
ERDAS Imagine	Data analysis	Remote Sensing Laboratory, SUT
ArcGIS	Data analysis	Remote Sensing Laboratory, SUT

3.2 Methodology

The main activities of methodology are divided into 3 components; (1) landform classification, (2) input data generation and (3) soil-landscape model development. The relationship among three components and its basic flow chart is presented in Figure 3.1. The details of each component are explained in the following section.

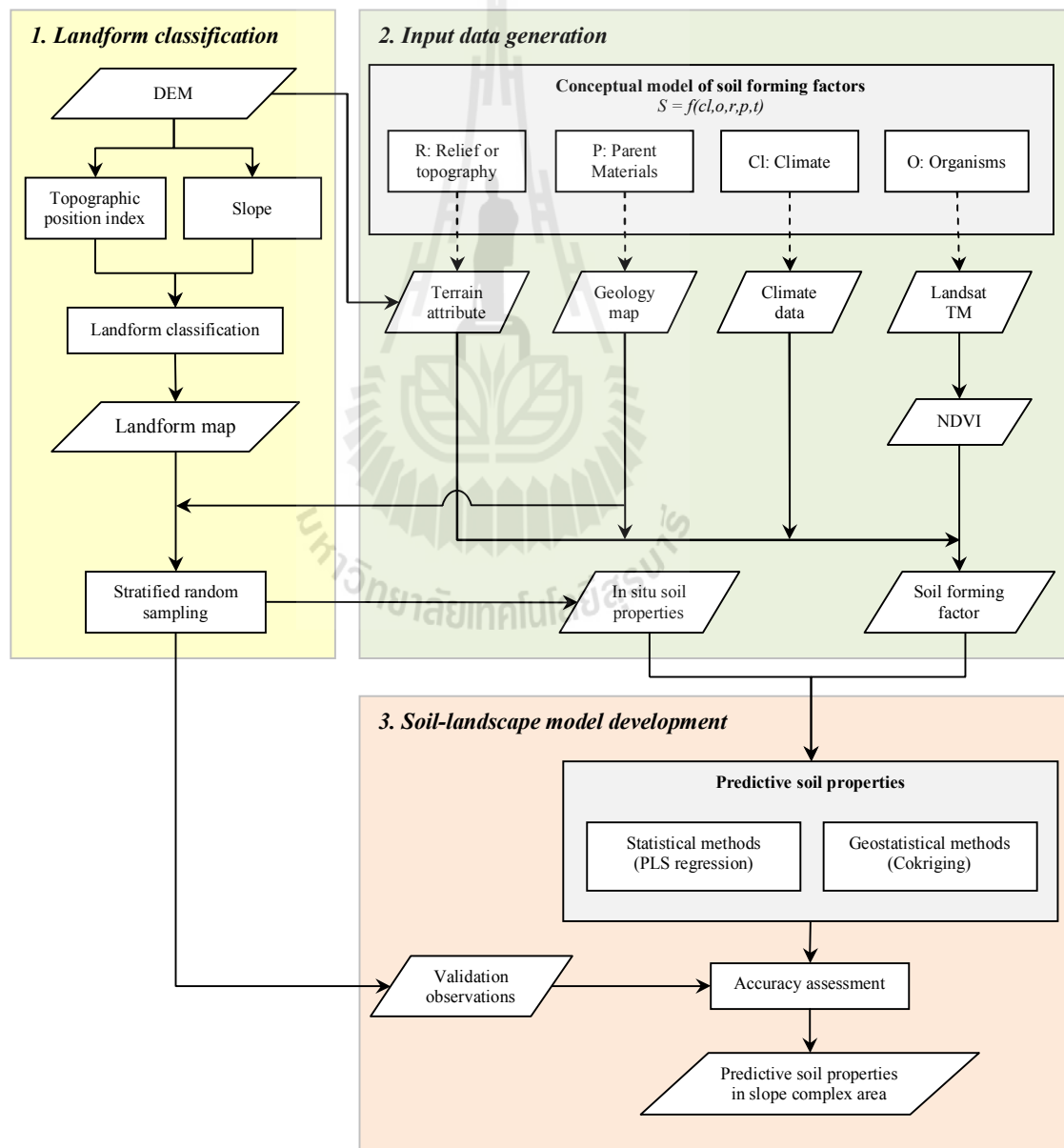


Figure 3.1 Basic flow chart represents the methodological framework.

3.2.1 Landform classification

The data used for landform classifications are derived from DEM by calculation slope and topographic position index (TPI) in two scales (small and large). The TPI compares the elevation of each cell in DEM to the mean elevation of a specified neighborhood around that cell. Positive TPI values represent locations that are higher than the average of their surroundings (tends to be hilltop). Negative TPI values represent locations that are lower than their surroundings (tends to be valley) and TPI value near zero are normally flat areas (Weiss, 2001). The combination of TPI values from different scales and criteria set suggests various landform types (Table 3.2). The schematic flow diagram of landform classification procedure is represented in Figure 3.2.

In practice, DEM with cell size of 25x25 m are firstly used to generate two focal mean data with two different window sizes (15x15 pixel and 45x45 pixels). Then TPI data are calculate by using following equation:

$$TPI = DEM - Focal\ Mean \quad (3.1)$$

Herein, two data set of TPI are extracted in two different scales (15x15 pixels and 45x45 pixels) of focal mean data and they are reclassified using standard deviation (SD) into three categories as follows:

- (1) TPI with standard deviation value less than or equal to -1;
- (2) TPI with standard deviation value between -1 and 1;
- (3) TPI with standard deviation value more than or equal to 1.

After that, these three categorized TPI data are overlaid with slope data which are extracted from DEM and classified into 2 classes (≤ 5 degree and > 5 degree)

for landform classification. Herewith, criteria for landform classification suggested by Weiss (2001) are applied to extracted landform categories (see Table 3.2) as follows:

- (1) Canyons, Deeply Incised Streams;
- (2) Midslope Drainages, Shallow Valleys;
- (3) Upland Drainages, Headwaters;
- (4) U-shaped Valleys;
- (5) Plains;
- (6) Open Slopes;
- (7) Upper Slopes, Mesas;
- (8) Local Ridges/Hills in Valleys;
- (9) Mid-slope Ridges, Small Hills in Plains;
- (10) Mountain Tops, High Ridges.

Table 3.2 Landform category and criteria by Weiss (2001).

No	Landform category	Criteria
1	Canyons, Deeply Incised Streams	Small Scale TPI: $TPI \leq -1 SD$ Large Scale TPI: $TPI \leq -1 SD$
2	Midslope Drainages, Shallow Valleys	Small Scale TPI: $TPI \leq -1 SD$ Large Scale TPI: $-1 SD < TPI < 1 SD$
3	Upland Drainages, Headwaters	Small Scale TPI: $TPI \leq -1 SD$ Large Scale TPI: $TPI \geq 1 SD$
4	U-shaped Valleys	Small Scale TPI: $-1 SD < TPI < 1 SD$ Large Scale TPI: $TPI \leq -1 SD$
5	Plains	Small Scale TPI: $-1 SD < TPI < 1 SD$ Large Scale TPI: $-1 SD < TPI < 1 SD$ Slope $\leq 5^\circ$
6	Open Slopes	Small Scale TPI: $-1 SD < TPI < 1 SD$ Large Scale TPI: $-1 SD < TPI < 1 SD$ Slope $> 5^\circ$
7	Upper Slopes, Mesas	Small Scale TPI: $-1 SD < TPI < 1 SD$ Large Scale TPI: $TPI \geq 1 SD$
8	Local Ridges/Hills in Valleys	Small Scale TPI: $TPI \geq 1 SD$ Large Scale TPI: $TPI \leq -1 SD$
9	Midslope Ridges, Small Hills in Plains	Small Scale TPI: $TPI \geq 1 SD$ Large Scale TPI: $-1 SD < TPI < 1 SD$
10	Mountain Tops, High Ridges	Small Scale TPI: $TPI \geq 1 SD$ Large Scale TPI: $TPI \geq 1 SD$

The result of landform classification in this process will be further used for soil sampling unit identification with geology data in the next component.

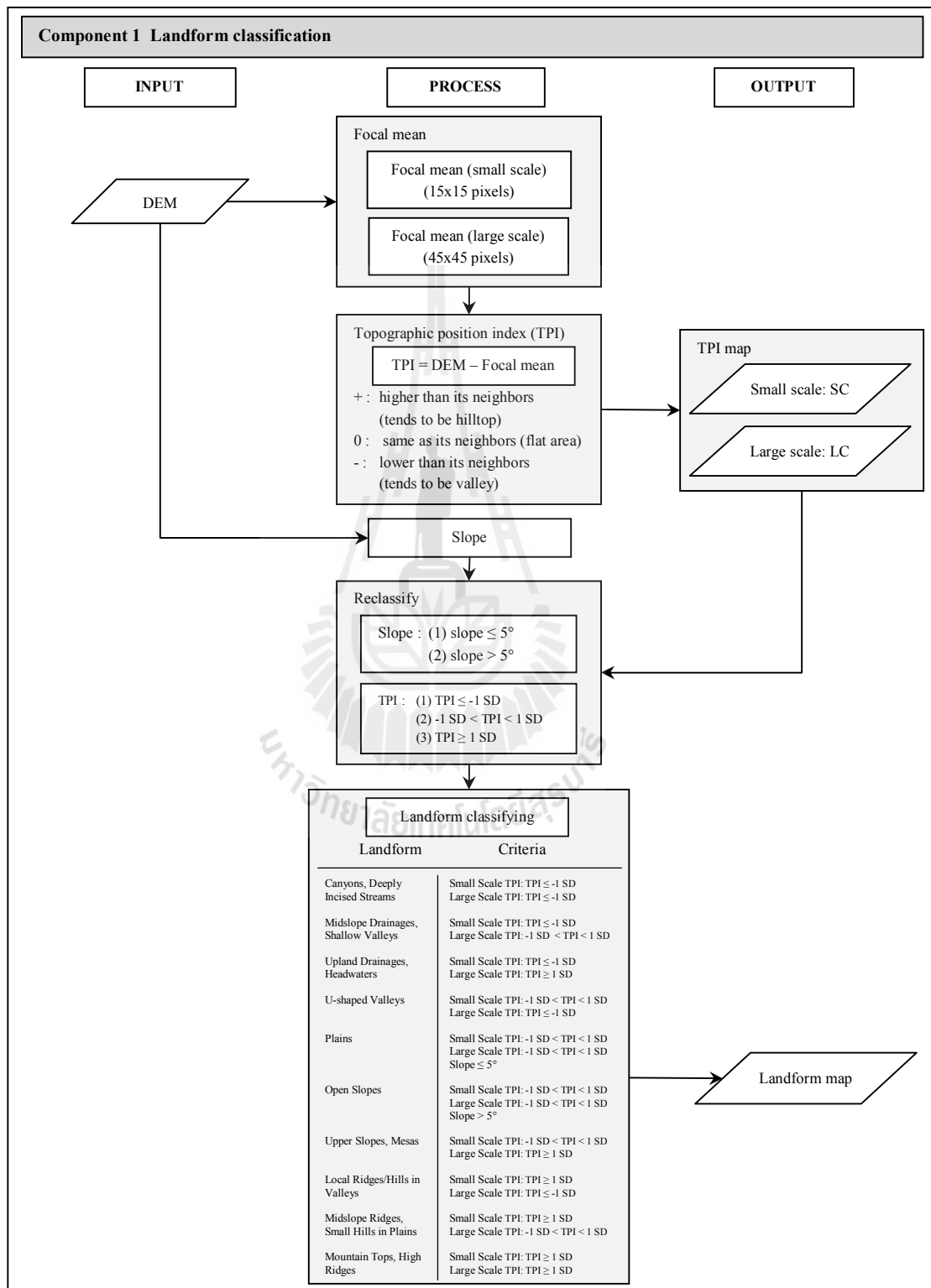


Figure 3.2 The schematic flow diagram of landform classification procedure.

3.2.2 Input data generation

This study aims to incorporate spatial variation of in situ soil properties in slope complex and their soil forming factors in the study area to develop soil-landscape model. Three major tasks under input data generation for soil landscape modeling are conducted, namely (1) soil forming factor preparation, (2) soil sampling unit identification and soil sampling scheme and (3) soil survey and soil data analysis as shown in Figure 3.3.

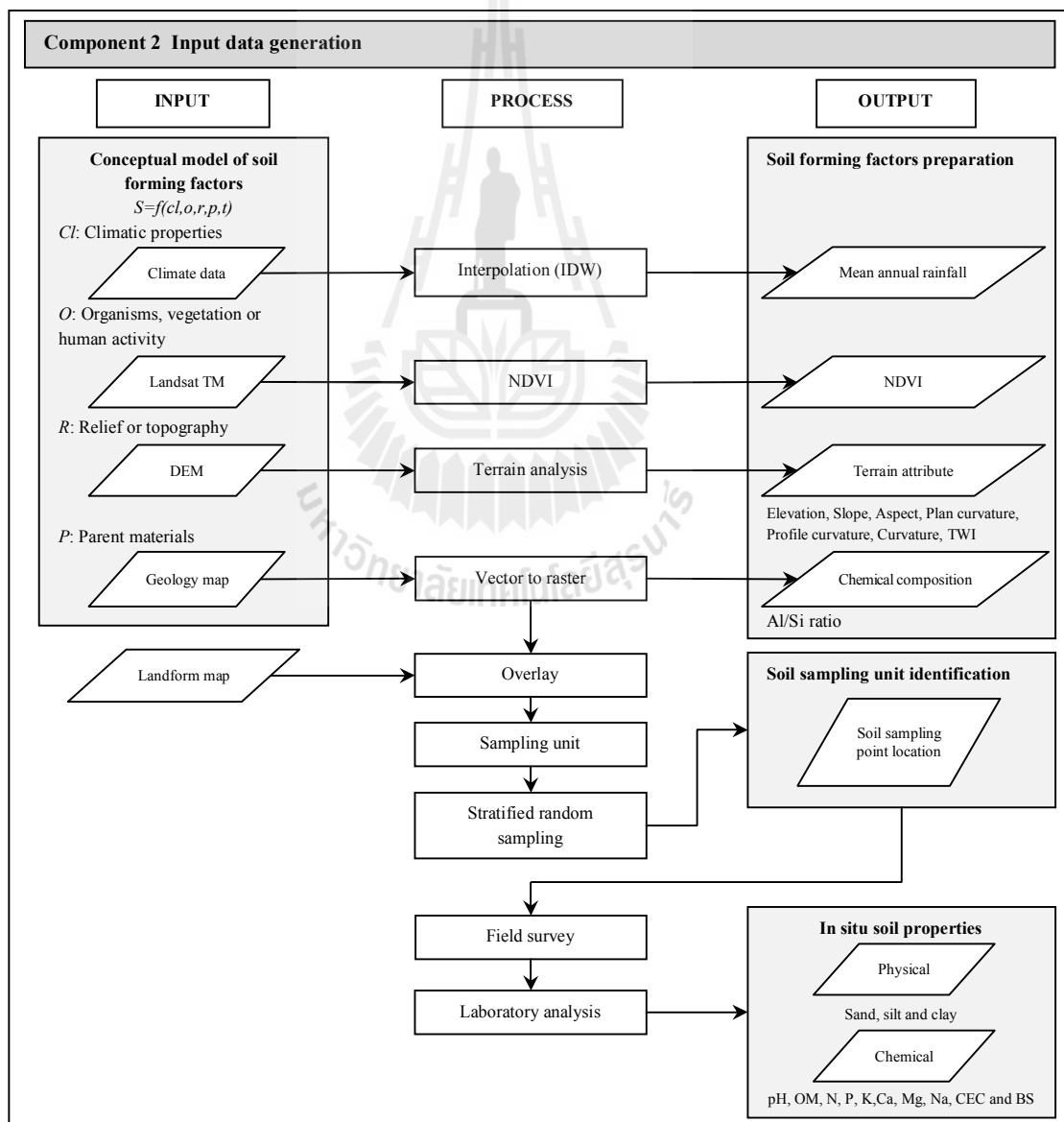


Figure 3.3 The schematic flow diagram of input data generation.

3.2.2.1 Soil forming factor preparation

Under this sub-component, soil forming factors are firstly reviewed from various research works and then selected for the study. Table 3.3 summarized reviewed literatures for soil forming factor. The brief information for selected soil forming factors is described as follows:

(1) Organism factor: Organisms is related to the effect of vegetation and human activity. The natural vegetation class should represent some kind of equilibrium relation with soil type. In this study NDVI which is derived from Landsat-TM data is selected for living organism indicators of soil properties. This factor was used by some researchers such as Ryan et al. (2000) and Hengl et al. (2002).

(2) Relief factor: Primary and secondary terrain attributes which are extracted from DEM are reviewed for representation relief factor (Table 3.4 and Table 3.5). In this study elevation, slope, aspect, plan curvature, profile curvature, curvature, and TWI are selected as relief factor on soil properties. These relief factors are basic soil forming factor and they are selected by many soil scientists such as Gessler et al. (1995), Ryan et al. (2000), Gobin et al. (2001) and Hengl et al. (2002).

(3) Parent material factor: Chemical composition of parent materials has an effect on weathering process and it can affect to soil properties. The high amount of silica (SiO_2) content has tendency to provide more quartz and becomes sand while the weathering of alumina (Al_2O_3) minerals containing high is more likely to be clay. These affect to soil texture and innate soil fertility. In this research, ratio of alumina (Al_2O_3) and silica (SiO_2) in each geologic unit was selected for parent material factor of soil properties as suggested by Sunya Sarapirome (personal communication, 2010).

(4) Climate factor: Rainfall affects both vegetative production and soil horizon development and its interacting with parent material also affects to soil physical and chemical properties. Thus, mean annual rainfall for 10 year period (2000-2009) from TMD are used for this study. This climate is a basic factor for soil forming factor and it is applied by many researchers for example Ryan et al. (2000) and Hengl et al. (2002).

(5) Time factor: Time is the driving force behind all soil forming processes. This factor is not applied in this study because the predictive models used in this study are considered as static model that are rely on bio-physical factors.

Table 3.3 Literature review of soil forming factor for soil-landscape model.

Soil forming factor	Factors (Authors)
Organism factor	Landsat TM bands 1-7 and NDVI by Ryan et al. (2000) NOAA's annual NDVI data by Hengl et al. (2002) Vegetation cover map by Ballabio (2009)
Relief factor	Elevation, slope, aspect, plan and profile curvature, flow path lengths and specific catchment area, TWI, STI and SPI by Moore et al. (1993) Plan curvature, CTI and upslope mean plan curvature by Gessler et al. (1995) Slope, plan curvature, profile curvature, aspect, contributing area, CTI, SPI and SAI by Gobin et al. (2001) Elevation, slope, curvature, aspect and wetness index by Hengl et al. (2002)
Parent material factor	Airborne geophysical gamma radiometric of potassium/thorium/uranium, total count and magnetic intensity by Ryan et al. (2000)
Climate factor	Mean annual rainfall, mean annual temperature, net radiation and Prescott index by Ryan et al. (2000) Rainfall and temperature by Hengl et al. (2002)

Table 3.4 Examples of primary terrain attributes that can be computed by terrain analysis from DEM data (Wilson and Gallant, 2000).

Attribute	Definition	Significance
Altitude	Elevation	Climate, vegetation, potential energy
Upslope height	Mean height of upslope area	Potential energy
Aspect	Slope azimuth	Solar isolation, evapotranspiration, flora and fauna distribution and abundance
Slope	Gradient	Overland and subsurface flow velocity and runoff rate, precipitation, vegetation, geomorphology, soil water content, land capability class
Upslope slope	Mean slope of upslope area	Runoff velocity
Dispersal slope	Mean slope of dispersal area	Rate of soil drainage
Catchment slope	Average slope over the catchment	Time of concentration
Upslope area	Catchment area above a short length of contour	Runoff volume, steady-state runoff rate
Dispersal area	Area downslope from a short length of contour	Soil drainage rate
Catchment area	Area draining to catchment outlet	Runoff volume
Specific catchment area	Upslope area per unit width of contour	Runoff volume, steady-state runoff rate, soil characteristics, soil-water content, geomorphology
Flow path length	Maximum distance of water flow to a point in the catchment	Erosion rates, sediment yield, time of concentration
Upslope length	Mean length of flow paths to a point in the catchment	Flow acceleration, erosion rates
Dispersal length	Distance from a point in the catchment to the outlet	Impedance of soil drainage
Catchment length	Distance from highest point to outlet	Overland flow attenuation
Profile curvature	Slope profile curvature	Flow acceleration, erosion/ deposition rate, geomorphology
Plan curvature	Contour curvature	Converging/diverging flow, soil water content, soil characteristics
Tangential curvature	Plan curvature multiplied by slope	Provides alternative measure of local flow convergence and divergence
Elevation percentile	Proportion of cells in a user-defined circle lower than the center cell	Relative landscape position, flora and fauna distribution and abundance

Table 3.5 Examples of secondary terrain attributes that can be computed by terrain analysis from DEM data (Wilson and Gallant, 2000).

Attribute	Topographic Wetness Index, TWI
Equation	$TWI = \ln \left(\frac{A_s}{\tan \beta} \right)$
Significance	This particular equation assumes steady-state conditions and uniform soil properties (i.e. transmissivity is constant throughout the catchment and equal to unity). This equation predicts zones of saturation where A_s is large (typically in converging segments of landscapes) and β is small (at base of concave slopes where slope gradient is reduced). These conditions are usually encountered along drainage paths and in zones of water concentration in landscapes.
Attribute	Stream Power Index, SPI
Equation	$SPI = A_s \tan \beta$
Significance	Measure of erosive power of flowing water based on assumption that discharge (q) is proportional to specific catchment area (A_s). Predicts net erosion in areas of profile convexity and tangential concavity (flow acceleration and convergence zones) and net deposition in areas of profile concavity (zones of decreasing flow velocity).
Attribute	Radiation indices
Equation	$R_t = (R_{th} - R_{dh})F + R_{dh}v + R_{th}(1 - v)\alpha$
Significance	This equation estimates the total short-wave irradiance incident at the earth's surface for some user-defined period ranging in length from 1 day to 1 year. The three main terms account for direct-beam, diffuse, and reflected irradiance. A variety of methods are used by different authors to calculate these individual components. The methods vary tremendously in terms of sophistication, input data, and accuracy.
Attribute	Temperature indices
Equation	$T = T_b - \frac{T_{lapse}(Z - Z_b)}{1000} + CS \left(1 - \frac{LAI}{LAI_{max}} \right)$
Significance	This equation is used to extrapolate minimum air, maximum air, and surface temperatures for a nearby climate station to other parts of the landscape. This equation corrects for elevation via a lapse rate, slope–aspect effects via the short-wave radiation ratio, and vegetation effects via a leaf area index.

After that these factors are generated under GIS environment with specific methods or equations as shown in Table 3.6. These soil forming factors are further used for soil-landscape model development in next component.

Table 3.6 Methods or equations used for soil forming factor generation.

Soil forming factor	Selected factor	Method or Equation
Organism	NDVI	$NDVI = \left(\frac{TM\ Band4 - TM\ Band3}{TM\ Band4 + TM\ Band3} \right)$
Relief	Elevation (m)	Extract from DEM
	Slope (Degree)	Extract from DEM
	Aspect (Degree)	Extract from DEM
	Plan curvature	Extract from DEM
	Profile curvature	Extract from DEM
	Curvature	Extract from DEM
	TWI	$TWI = \ln \left(\frac{Upslope\ contribute\ areas}{\tan\ slope} \right)$
Parent material	Geology (Al/Si ratio)	Ratio between Aluminum and Silica
Climate	Mean annual rainfall (mm)	Interpolation (IDW)

3.2.2.2 Soil sampling unit identification and soil sampling scheme

Under this sub-component, landform categories which are derived from previous component are firstly overlaid with geological formation of geology data and then reclassified for soil sampling unit. In fact, this soil sampling units are represented as strata in sampling scheme. In this study stratified random sampling scheme is chosen for soil sample site location based on number of soil samples and area of soil sampling units.

Number of soil samples is calculated based on detailed reconnaissance soil survey at the scale of 1:40,000-1:100,000 as suggested by Kheoruenromne (2005). Because these scale and order of soil survey are fitted with scale of DEM and geology data. He recommended that intensity of soil samples should be one sample per 1-2 sq. km. Thus, one sample per 2 sq. km is here used to calculate number of samples in slope complex with area of 99 sq. km. As a result,

sample sites used in this study are 48 samples. In practice, 48 sample points are divided into two sets: one set for modeling and another set for validating.

3.2.2.3 Soil survey and soil data analysis

For soil survey, soil is collected in each soil sampling site using auger and soil core at two levels: topsoil (0-25 cm) and subsoil (25-50 cm) for soil property extraction. In addition, soil pit in each site is set up for soil profile description as shown in Figure 3.4.

All soil samples are carried to soil laboratory for soil data analysis. In practice, soil samples are firstly air-dried and passed through 2 mm mesh screen. Then, these samples are analyzed for physical and chemical soil properties with various methods as summarized in Table 3.7.

Table 3.7 Physical and chemical soil properties analysis.

Soil properties	Used method
Physical properties	
Particle size (%)	Hydrometer method
- Sand	
- Silt	
- Clay	
Chemical properties	
pH (pH scale)	pH Meter 1:1 H ₂ O
Organic matter (%)	Walkley and Black method
Total nitrogen (%)	Kjeldahl digestion
Available phosphorus (ppm)	Bray II method
Total exchangeable bases (ppm)	Ammonium acetate (NH ₄ OAc, pH 7)
- Magnesium	Atomic absorption spectrophotometer
- Calcium	Flame photometer
- Potassium	Flame photometer
- Sodium	Flame photometer
Cation exchange capacity (meq/100g soil)	Ammonium acetate (NH ₄ OAc, pH 7)
Base saturation (%)	$\% BS = \frac{\text{total exchangeable bases}}{CEC} \times 100$

3.2.3 Soil-landscape model development

Three main tasks of soil landscape model development are here conducted under this component (Figure 3.5), namely (1) soil-landscape model development, (2) accuracy assessment and (3) optimum model identification.

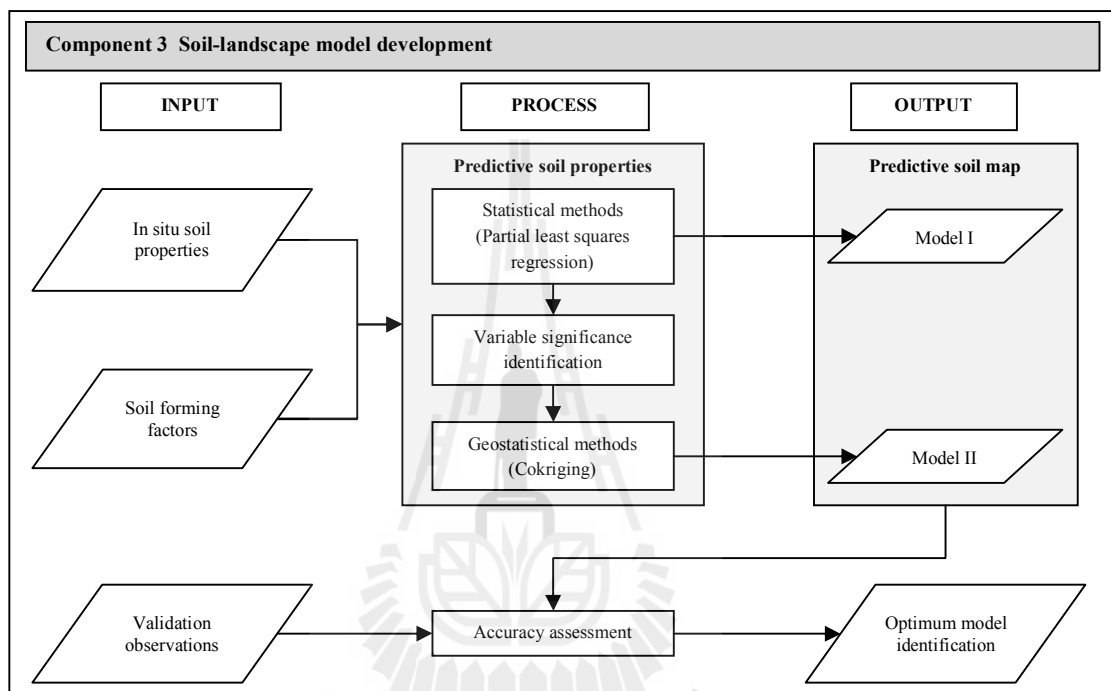


Figure 3.5 The procedure of soil-landscape model development.

3.2.3.1 Soil-landscape model development

Soil-landscape model which are used to quantify the relationship between in situ soil properties and soil forming factors are consisted of statistical method and geostatistical method, namely partial least squares (PLS) regression and cokriging interpolation, respectively.

(1) Partial least squares (PLS) regression

Basically, PLS regression is a technique that generalizes and combines features from principal component analysis and multiple linear regressions.

Its goal is to predict or analyze a set of dependent variables from a set of independent variables or predictors. This prediction is achieved by extracting from the predictors a set of orthogonal factors called latent variables which have the best predictive power (Abdi, 2007).

In this study, PLS regression which is used to identify relationship between in situ soil properties (dependent variables) and soil form factors (independent variables) in form of multiple linear regression equation is firstly calculated using statistical software of XLSTAT. Then derived multiple linear regression equation are used to predict 13 soil properties (see Table 3.7) using Map Algebra module of ArcGIS.

(2) Cokriging interpolation

Simple cokriging interpolation is used to predict the distribution of soil properties based on sampling soil attributes and their influence factors. In practice, three significant soil forming factors from PLS regression analysis by XLSTAT are firstly identified using variable important in the projection (VIP) values. Then simple cokriging interpolation include Spherical (Sph), Exponential (Exp), Gaussian (Gau) and Rational Quadratic (RQ) semivariogram models are used for soil property prediction based on in situ soil property and its location from 28 soil sample site for modeling and three important soil forming factor layers. In practice, RMSE of specific semivariogram will be used justified an optimum model and it then used for soil properties prediction. This operation is implemented for each soil property using cokriging under Geostatistical module of ArcGIS.

3.2.3.2 Accuracy assessment

The predictive physical and chemical soil properties from PLS regression and cokriging models are used to compare with actual soil properties from validate set for accuracy assessment. Three measure of accuracy assessment are here used in this study include Mean Error (ME), Root Mean Square Error (RMSE) and Normalized Root Mean Square Error (NRMSE) as follows:

$$ME = \frac{1}{n} \sum_{i=1}^n [\text{Predicted value} - \text{Observed value}] \quad (3.2)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n [\text{Predicted value} - \text{Observed value}]^2} \quad (3.3)$$

$$NRMSE = \frac{RMSE}{\text{Maximum observed value} - \text{Minimum observed value}} \quad (3.4)$$

where

- n : number of observation;
- ME : Mean Error;
- RMSE : Root Mean Square Error;
- NRMSE : Normalized Root Mean Square Error.

3.2.3.3 Optimum model identification

An optimum model for each soil property prediction is identified based on NRMSE values of statistical method (PLS) and geostatistical method (cokriging) as suggested by Ballabio (2009). Therefore model which provides smaller prediction error will be selected as optimum model for soil property prediction in slope complex.

CHAPTER IV

RESULT AND DISCUSSION

Main results according to major components of the research methodology are here explained to fulfill the main objectives include landform classification and soil forming factor generation and soil-landscape model. Additionally, application of soil properties prediction for soil science is here presented as a synthesis of the result.

4.1 Landform classification

For landform classification, slope and topographic position index (TPI) with two scales were firstly extracted from DEM with spatial resolution of 25x25 meter. In this study, two scales of windows of 15x15 pixels and 45x45 pixels were used to generate TPI. After that, slope, TPI with small scale and large scale were then reclassified for landform classification with specific criteria (see detailed in Table 3.2) as suggested by Weiss (2001). Extracted landform categories and their description are summarized in Table 4.1.

Distribution of landform classification in the study area was displayed in Figure 4.1. Area and percentage of each landform in the slope complex area was presented in Table 4.2. The most dominant landform in the slope complex area was open slopes covering an area of 51.17 sq. km or 43.88%. The second dominant landform was mountain tops covered area of 14.82 sq. km or 12.71%. At the same

time upland drainages or headwaters and local ridges or hills in valleys covered area less than 1%. The result of landform classification was further used for soil survey with stratified random sampling.

Table 4.1 Landform category and description.

No	Landform category	Description
1	Canyons, Deeply incised streams	Areas are lowest in the landscape, having negative plan and/or profile curvature
2	Mid slope drainages, Shallow valleys	Areas are low in mid slope, channel in mid slope
3	Upland drainages, Headwaters	Areas are low in upper slope channel in upper slope
4	U-shaped valleys	Areas in lower slope, footslope adjacent below a open slope and adjacent above a flat or streams
5	Plains	Areas are flat having a slope $\leq 5^\circ$
6	Open slopes	Areas are rectilinear transition in mid slope, having a slope $> 5^\circ$
7	Upper slopes, Mesas	Areas are having high slope, shoulder adjacent below a top
8	Local ridges/Hills in valleys	Areas are high in lower slope, ridge in lower slope
9	Mid slope ridges, Small hills in plains	Areas are high in mid slope, ridge in mid slope
10	Mountain tops, High ridges	Areas are highest in the landscape, having positive plan and/or profile curvature

Table 4.2 Area and percentage of landform type in the slope complex area.

No	Landform	Area in sq.km	Percentage
1	Canyons, Deeply incised streams	11.57	9.92
2	Mid-slope drainages, Shallow valleys	10.60	9.09
3	Upland drainages, Headwaters	0.12	0.11
4	U-Shaped valleys	8.18	7.01
5	Plains	4.65	3.99
6	Open slopes	51.17	43.88
7	Upper slopes	7.49	6.42
8	Local ridges, Hills in valleys	0.01	0.01
9	Midslope ridges, Small hills in plains	8.00	6.86
10	Mountain tops	14.82	12.71
Total		116.61	100.00

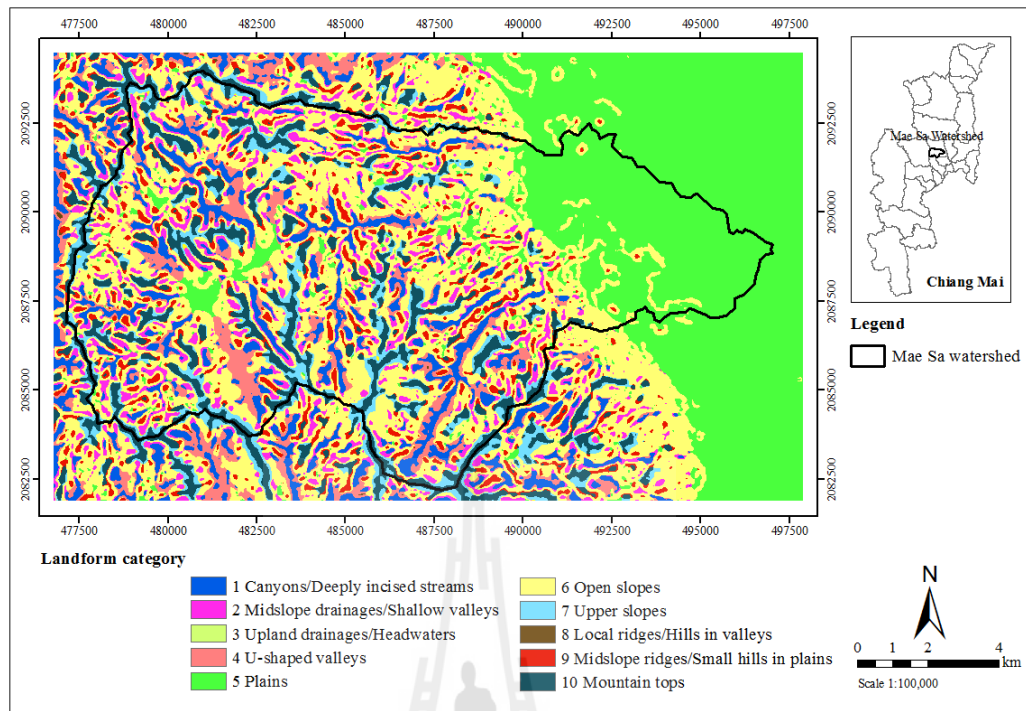
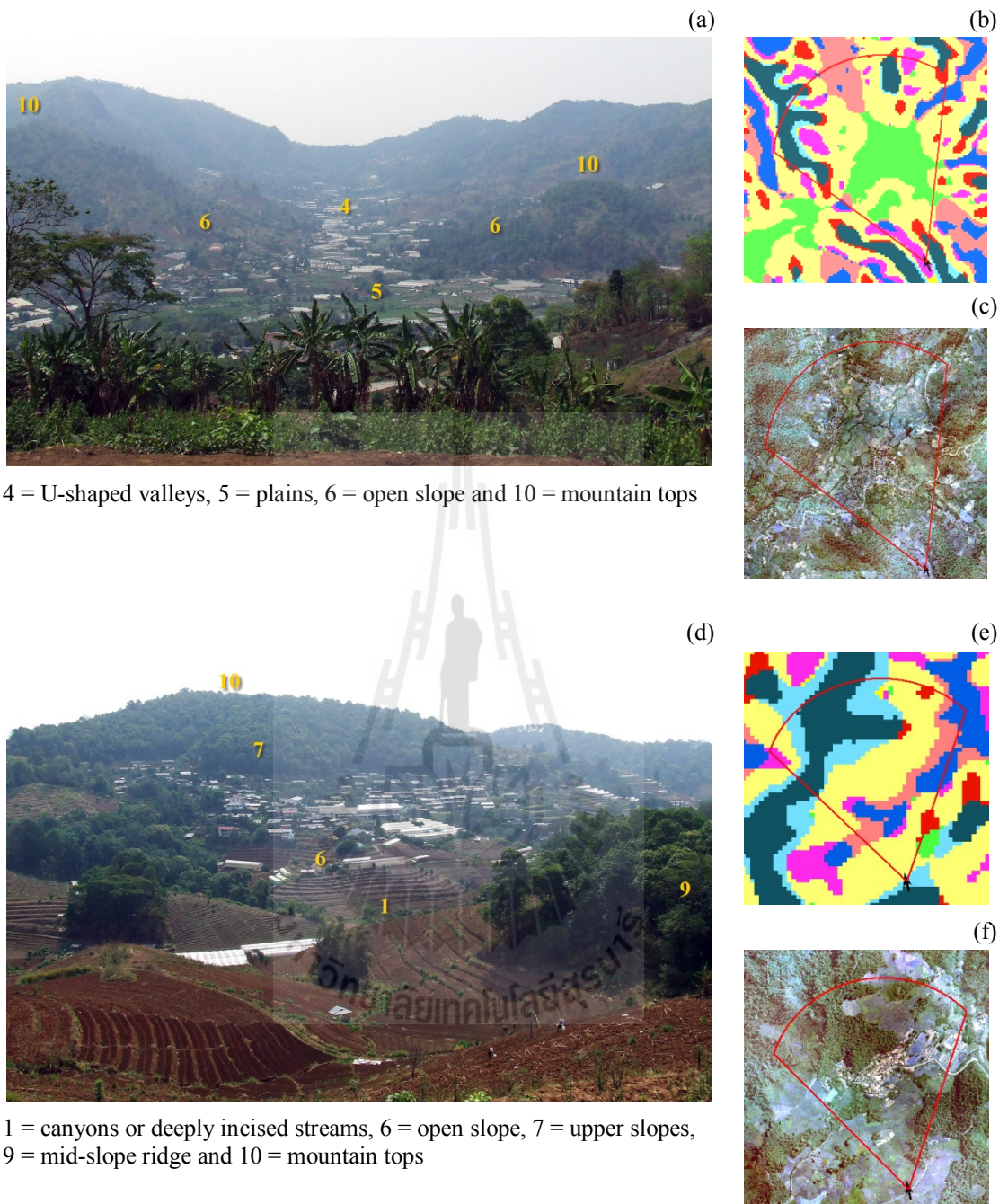


Figure 4.1 Distribution of landform in the study area.

4.2 Accuracy assessment of landform classification

Accuracy of landform classification was here assessed based on 50 stratified random points representing for landform categories using overall accuracy and Kappa hat coefficient of agreement. All landform category sampling sites were visited using GPS and visually justified for the accuracy during soil survey. Figure 4.2 displayed an example of sampling site for accuracy assessment of landform classification. It was found that overall accuracy and Kappa hat coefficient of agreement was 92.00% and 0.91, respectively (Table 4.3). According to Landis and Koch (1977) Kappa hat coefficient of agreement value more than 0.80 represents strong agreement or accuracy between the classification map and the ground reference information.



Note: (b), (c) and (e), (f) are position and direction of (a) and (d), respectively

Figure 4.2 Comparison of landform classification and landform in study area.

Table 4.3 Error matrix and accuracy assessment of landform classification.

Landform classification	Field survey										Total	
	1	2	3	4	5	6	7	8	9	10		
1 Canyons, Deeply incised streams	6											6
2 Midslope drainages, Shallow valleys		3			1							4
3 Upland drainages, Headwaters			1									1
4 U-Shaped valleys				3								3
5 Plains					2							2
6 Open slopes						13						13
7 Upper slopes							5					5
8 Local ridges, Hills in valleys								1				1
9 Midslope ridges, Small hills in plains									6			6
10 Mountain tops					2	1					6	9
Total	6	3	1	3	5	14	5	1	6	6		50
Overall accuracy: 92.00%												
Kappa hat coefficient of agreement: 0.91												

4.3 Soil survey and soil data analysis

4.3.1 Soil survey

In this study, 48 soil samples site was collected for in situ soil properties analysis in April to May 2010. In practice, landform and geology data in the slope complex area was firstly used to identify soil sample unit (Figure 4.3) for stratified random sampling scheme as summarized in Table 4.4. Soil sampling data was here divided into 2 sets: one for soil-landscape modeling (28 samples) and another set for model validation (20 samples). Distribution of soil sampling sites was displayed in Figure 4.4.

During field survey, soil sample was collected for soil data analysis in laboratory and soil profile was set up for soil profile description in each sampling site. Figure 4.5 displayed an example of soil profile description of sampling site No. 1. Details of 48 soil profile description were presented in Appendix A.

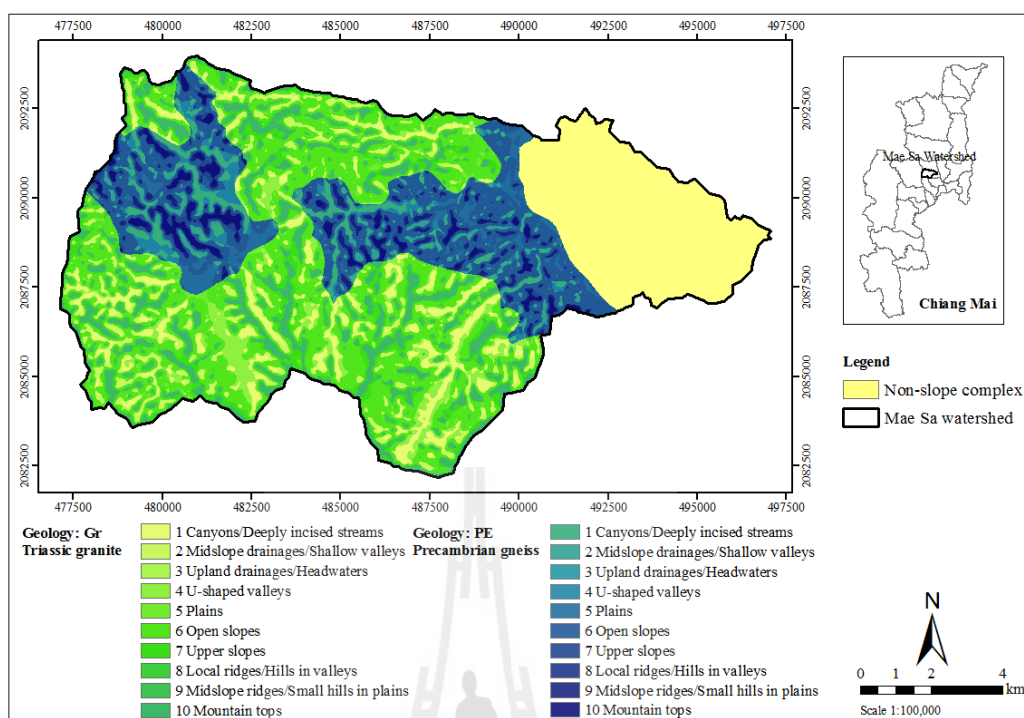


Figure 4.3 Distribution of soil sampling units in the study area.

Table 4.4 Number of soil sampling points by soil sampling unit.

Geology	Landform	Area in sq.km	%	Number of sample points
Gr: Granite	1 Canyons, Deeply incised streams	7.78	6.68	4
Gr: Granite	2 Midslope drainages, Shallow valleys	7.53	6.46	3
Gr: Granite	3 Upland drainages, Headwaters	0.11	0.09	1
Gr: Granite	4 U-Shaped valleys	5.65	4.85	3
Gr: Granite	5 Plains	1.18	1.01	1
Gr: Granite	6 Open slopes	32.82	28.14	9
Gr: Granite	7 Upper slopes	6.40	5.49	3
Gr: Granite	8 Local ridges, Hills in valleys	0.01	0.01	1
Gr: Granite	9 Midslope ridges, Small hills in plains	5.13	4.40	2
Gr: Granite	10 Mountain tops	11.71	10.04	5
PE: Gneiss	1 Canyons, Deeply incised streams	3.79	3.25	2
PE: Gneiss	2 Midslope drainages, Shallow valleys	3.07	2.64	2
PE: Gneiss	3 Upland drainages, Headwaters	0.02	0.01	-
PE: Gneiss	4 U-Shaped valleys	2.53	2.17	1
PE: Gneiss	5 Plains	3.47	2.98	1
PE: Gneiss	6 Open slopes	18.35	15.74	5
PE: Gneiss	7 Upper slopes	1.09	0.93	1
PE: Gneiss	8 Local ridges, Hills in valleys	0.00	0.00	-
PE: Gneiss	9 Midslope ridges, Small hills in plains	2.87	2.46	2
PE: Gneiss	10 Mountain tops	3.11	2.67	2
Total		116.61	100.00	48

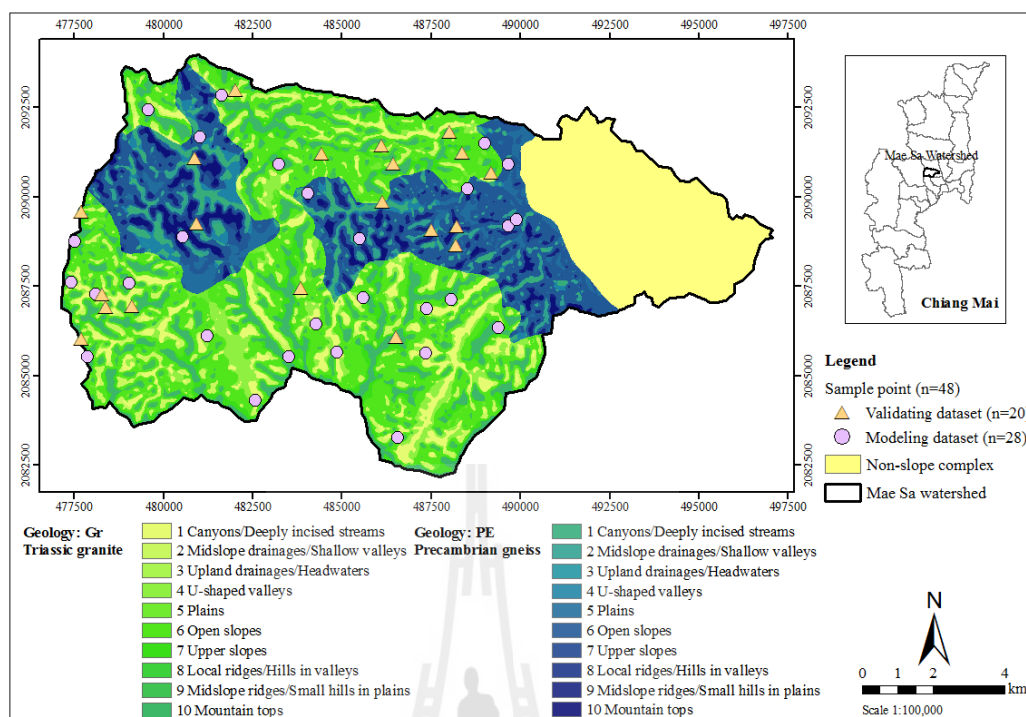


Figure 4.4 Distribution of soil sampling points in the study area.

Information on the site

Sample no: 1
 Date of examination: April 16, 2010
 Location: Ban Dong Nai, Mae Sa Mai, Mae Rim District, Chiang Mai province
 Position: 482578; 2084320 Elevation: 926 m (MSL)
 Slope: 15 Aspect: SW (250°)
 Geology: Gr, Triassic granite LU/LC: Orchard
 Landform: 1 Canyons or Deeply incised streams

Profile description

Picture	Horizon	Depth (cm)	Description
	Ap	0-12	Dull reddish brown (5YR 4/4); clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to Bt1.
	B1t	12-26	Reddish brown (5YR 4/6); clay; moderate fine granular structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	26-41	Dark reddish brown (5YR 3/4); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt3.
	B3t	41-50	Dark brown (5YR 2.5/2); clay; moderate fine and medium sub-angular blocky structure; friable moist, sticky and plastic.

Figure 4.5 Soil profile description of sampling site No. 1.

4.3.2 Soil data analysis

Soil samples that are collected in field were analyzed for physical and chemical soil properties at Soil Laboratory of Mae Jo University between October and December 2010. Example of quantitative characteristic of soil properties from soil samples No 1 is summarized in Table 4.5. Detail of quantitative characteristic of soil properties from 48 samples (topsoil and subsoil) are presented in Appendix B.

Table 4.5 Quantitative characteristics of soil sample No 1.

Soil properties	Topsoil (0-25 cm)	Subsoil (25-50 cm)
Physical properties		
Particle size: Sand/Silt/Clay		
Sand (%)	32.88	20.88
Silt (%)	30.36	27.36
Clay (%)	36.76	51.76
Chemical properties		
pH (pH scale)	5.98	6.16
Organic matter (%)	10.05	3.09
Total nitrogen (%)	0.5025	0.1382
Available phosphorus (ppm)	12.76	7.24
Exchangeable bases		
Calcium (ppm)	1,126.95	524.43
Magnesium (ppm)	491.23	273.46
Potassium (ppm)	223.95	120.73
Sodium (ppm)	94.92	55.52
Cation exchange capacity (meq/100g soil)	35.44	25.41
Base saturation (%)	34.10	31.06

Furthermore, major soil properties can be qualitative described based on 48 soil sample according to LDD soil description as following.

For physical soil property, soil texture of topsoil was dominated by sandy clay loam (30 samples) and the remaining was represented by clay loam (17 samples) and loam (1 sample), while subsoil was dominated by clay (32 samples) and

the remaining was represented by clay loam (8 samples), sandy clay (4 samples) and sandy clay loam (4 samples). At the same time, for chemical soil property, pH of topsoil and subsoil varied from extremely acid to neutral (pH 4.33-6.74), organic matter content of topsoil was moderate to high (1.79-10.05%) and subsoil was low to high (0.53-3.98%), total nitrogen of topsoil was very low to moderate (0.09-0.5%) and subsoil was very low to low (0.03-0.18%), available phosphorus concentration of topsoil was low to moderate (0.81-11.15 ppm) while subsoil was low (0.41-2.57 ppm), exchangeable potassium concentration of topsoil was moderate to very high (81.95-262.27 ppm) while subsoil was low to high (27.72-148.34 ppm), exchangeable calcium concentration of topsoil was low to moderate (338.60-1,355.02 ppm) while subsoil was very low to moderate (171.44-648.45 ppm), exchangeable magnesium concentration of topsoil was moderate to high (192.51-491.23 ppm) while subsoil was low to high (63.41-273.46 ppm), exchangeable sodium concentration varied from 26.19-107.66 ppm for topsoil and decreased to 12.12-64.83 ppm for subsoil, cation exchange capacity of top and sub soil were moderate to high (11.15-35.44 meq/100g) and base saturation of topsoil was low to moderate (15.15-43.59%) while subsoil was low (11.56-31.27%).

4.4 Soil forming factor

In principle, soil forming factors are used to describe soil as a function of climate, biological influences, topography, parent material and time. In this study, selected soil forming factor without time are prepared including 10 year mean annual rainfall, NDVI, elevation, slope, aspect, plan curvature, profile curvature, curvature, topographic wetness index (TWI), and geology (Al/Si ratio). In practice, these factors

were created under GIS environment with specific methods or equations (see detail in Table 3.6).

Distribution of selected soil forming factor is displayed in Figure 4.6 while quantitative information of soil forming factor in the slope complex area is summarized in Table 4.6. In addition distribution of each soil forming factor values as histogram plot is displayed in Figure 4.7. The result of soil forming factor was further used for soil-landscape model development.

Table 4.6 Quantitative characteristic of soil forming factor.

Factor	Minimum	Maximum	Mean	Standard deviation
Mean annual rainfall (mm)	1,147.63	1,530.70	1,319.31	50.19
NDVI	-0.48	0.71	0.47	0.10
Elevation (m)	339.26	1680.51	923.74	251.20
Slope (Degree)	0.01	47.29	17.35	8.34
Aspect (Degree)	0.0008	360.00	159.07	106.77
Curvature	-2.88	5.18	0.0008	0.50
Plan curvature	-2.10	2.58	0.01	0.31
Profile curvature	-3.22	2.94	0.01	0.30
TWI	3.18	20.37	6.02	1.91
Geology (Al/Si ratio)	0.19	0.22	0.20	0.02

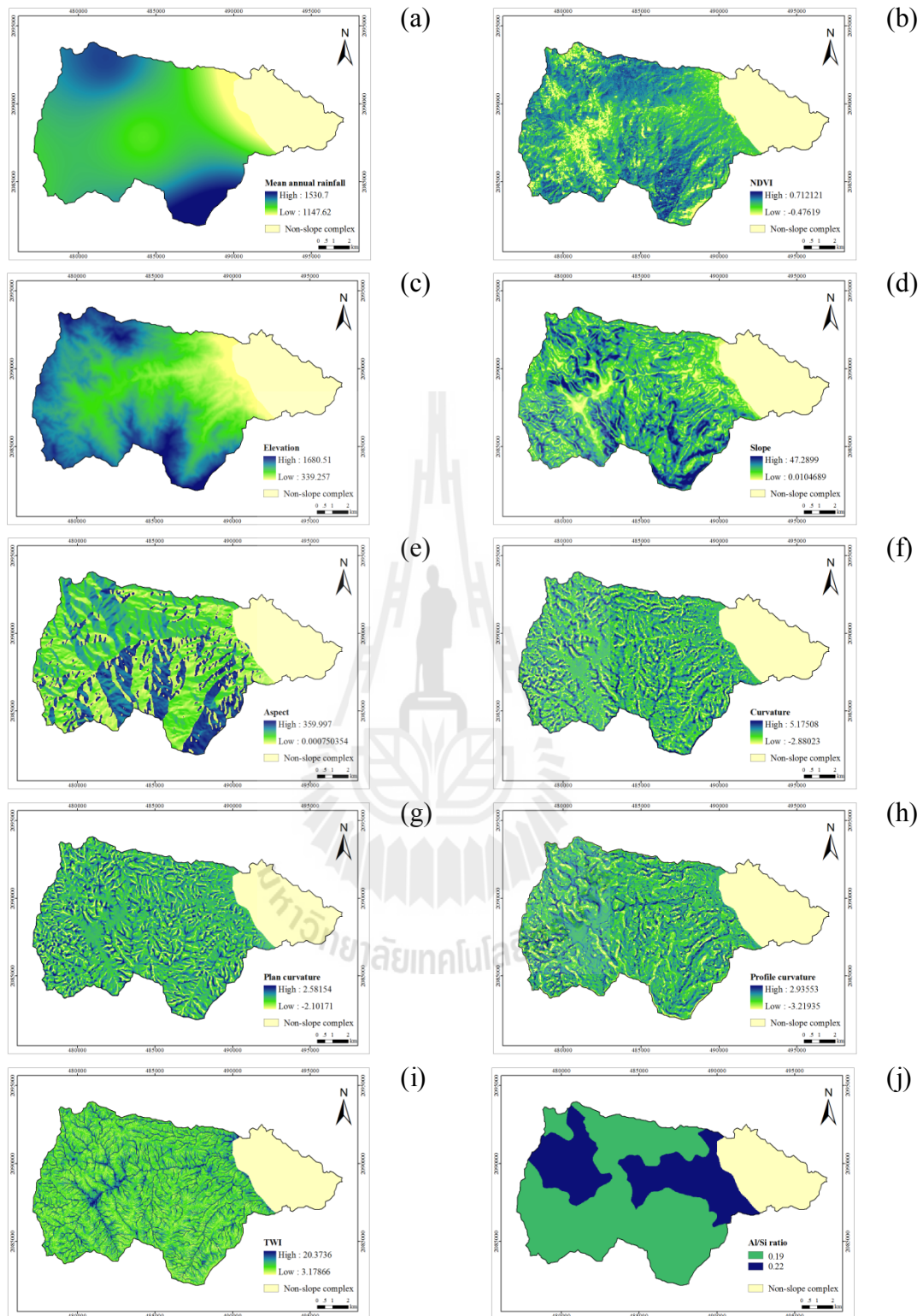


Figure 4.6 Distribution of soil forming factors (a) Mean annual rainfall (b) NDVI (c) Elevation (d) Slope (e) Aspect (f) Curvature (g) Plan curvature (h) Profile curvature (i) TWI and (j) Al/Si ratio.

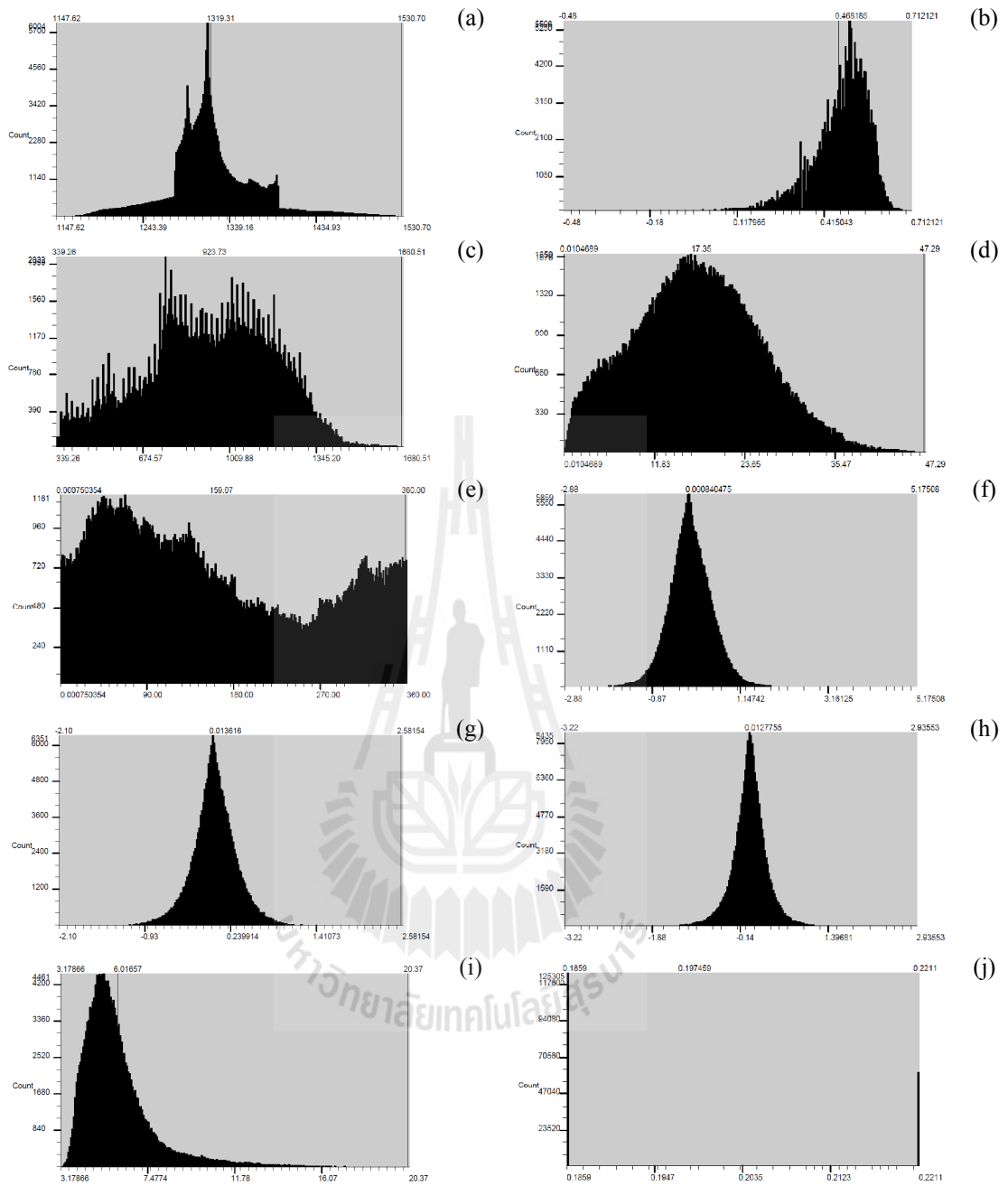


Figure 4.7 Histogram of soil forming factors (a) Mean annual rainfall (b) NDVI (c) Elevation (d) Slope (e) Aspect (f) Curvature (g) Plan curvature (h) Profile curvature (i) TWI and (j) AL/Si ratio.

4.5 Soil-landscape model development

Two methods for soil-landscape model development which were used to explain the relationship between in situ soil properties from field survey and soil forming factors are partial least squares (PLS) regression of statistical method and cokriging interpolation of geostatistical method.

4.5.1 Soil-landscape model by partial least squares regression

In practice, soil property from topsoil and subsoil includes sand, silt, clay, OM, N, P, K, Na, Ca, Mg, CEC, BS, and pH as dependent variable is separately regressed with independent variables include rainfall, NDVI, elevation, slope, aspect, plan curvature, profile curvature, curvature, TWI and Al/Si ratio using partial least squares (PLS) regression of XLSTAT software. Then, extracted multiple linear equation of each soil property from topsoil and subsoil was used for soil properties prediction using Map Algebra module of ArcGIS software.

Results of multiple linear regression analysis for each soil properties of top and sub soil were summarized as equation forms as shown in Table 4.7 while Table 4.8 and 4.9 showed statistic summary of PLS regression of top and sub soil, respectively. In addition, Table 4.10 summarized the significant of soil form factor in each soil properties, namely variable importance in the projection (VIP). Distribution of predictive soil properties of top and sub soil in the slope complex area were presented in Figure 4.8 to Figure 4.20.

As results, it was found that VIP values of soil forming factors dictate the distribution of each soil properties. For example, TWI, which has negative relationship with percent of sand (see Table 4.7) and represents the highest VIP value for sand prediction model (see Table 4.10), control the distribution of low percent of

sand (See Figures 4.6 and 4.8). In contrary, Al/Si ratio, which has positive relationship with percent of sand (see Table 4.7) and demonstrates the lowest VIP value for sand prediction model (see Table 4.10), does not control the distribution of low percent of sand (See Figures 4.6 and 4.8).

Table 4.7 Multiple linear regression equation by PLS regression.

Soil properties	Topsoil	Subsoil
Sand	Sand = 16.785 + (1.935*10 ⁻⁰²)*RAIN – 8.573*NDVI + (2.465*10 ⁻⁰³)*ELEVATION+ 0.463*SLOPE + (2.451*10 ⁻⁰³)*ASPECT + 1.770*PLAN – 0.644*PROFILE + 0.725*CURVATURE – 1.429*TWI + 29.892*ALSI_RATIO	Sand = 30.123 + (9.757*10 ⁻⁰³)*RAIN + 7.762*NDVI – (8.410*10 ⁻⁰⁴)*ELEVATION+ 0.508*SLOPE – (3.643*10 ⁻⁰³)*ASPECT + 3.495*PLAN – 4.714*PROFILE + 2.424*CURVATURE – 1.593*TWI – 40.356*ALSI_RATIO
Silt	Silt = 40.861 – (1.442*10 ⁻⁰²)*RAIN + 1.084*NDVI – (2.015*10 ⁻⁰³)*ELEVATION– (9.207*10 ⁻⁰²)*SLOPE + (8.319*10 ⁻⁰⁴)*ASPECT – 1.317*PLAN + 1.273*PROFILE– 0.768*CURVATURE + 0.587*TWI + 13.718*ALSI_RATIO	Silt = 19.739 – (7.830*10 ⁻⁰⁴)*RAIN + 3.719*NDVI + (8.010*10 ⁻⁰⁵)*ELEVATION – (1.105*10 ⁻⁰²)*SLOPE + (1.841*10 ⁻⁰⁴)*ASPECT – 2.133*PLAN + 2.512*PROFILE – 1.374*CURVATURE + 0.417*TWI – 10.281*ALSI_RATIO
Clay	Clay = 30.432 – (1.002*10 ⁻⁰³)*RAIN – 3.785*NDVI + (8.238*10 ⁻⁰⁵)*ELEVATION – 0.122*SLOPE + (4.016*10 ⁻⁰³)*ASPECT – 2.465*PLAN + 1.523*PROFILE – 1.190*CURVATURE + 0.407*TWI + 1.869*ALSI_RATIO	Clay = 43.987 – (3.218*10 ⁻⁰³)*RAIN – 13.557*NDVI + (2.226*10 ⁻⁰³)*ELEVATION– 0.511*SLOPE + (8.026*10 ⁻⁰³)*ASPECT – 1.584*PLAN + 1.842*PROFILE – 1.014*CURVATURE + 1.029*TWI + 42.825*ALSI_RATIO
pH	pH = 6.562 – (8.973*10 ⁻⁰⁴)*RAIN – 0.881*NDVI – (1.629*10 ⁻⁰⁴)*ELEVATION – (2.889*10 ⁻⁰²)*SLOPE + (5.054*10 ⁻⁰⁴)*ASPECT – (6.154*10 ⁻⁰²)*PLAN + 0.101*PROFILE – (4.778*10 ⁻⁰²)*CURVATURE + 0.108*TWI + 1.759*ALSI_RATIO	pH = 4.847 + (1.342*10 ⁻⁰⁴)*RAIN + 0.255*NDVI + (5.667*10 ⁻⁰⁵)*ELEVATION – (5.215*10 ⁻⁰³)*SLOPE + (3.327*10 ⁻⁰⁴)*ASPECT – 0.265*PLAN + 0.281*PROFILE – 0.162*CURVATURE + (5.263*10 ⁻⁰²)*TWI – 1.679*ALSI_RATIO
OM	OM = -5.13169562426153 + (7.840*10 ⁻⁰³)*RAIN + 6.151*NDVI + (1.379*10 ⁻⁰³)*ELEVATION + (2.179*10 ⁻⁰²)*SLOPE – (8.615*10 ⁻⁰⁴)*ASPECT – 0.674*PLAN + 1.122*PROFILE – 0.529*CURVATURE + 0.136*TWI – 17.095*ALSI_RATIO	OM = -2.740 + (3.048*10 ⁻⁰³)*RAIN + 2.585*NDVI + (5.161*10 ⁻⁰⁴)*ELEVATION + (8.779*10 ⁻⁰³)*SLOPE – (1.739*10 ⁻⁰⁴)*ASPECT – 0.313*PLAN + 0.540*PROFILE – 0.251*CURVATURE + (6.619*10 ⁻⁰²)*TWI – 6.578*ALSI_RATIO
N	N = -0.217 + (3.157*10 ⁻⁰⁴)*RAIN + 0.240*NDVI + (5.302*10 ⁻⁰⁵)*ELEVATION + (4.668*10 ⁻⁰⁴)*SLOPE + (3.239*10 ⁻⁰⁵)*ASPECT – (5.425*10 ⁻⁰²)*PLAN + (6.745*10 ⁻⁰²)*PROFILE – (3.597*10 ⁻⁰²)*CURVATURE + (1.045*10 ⁻⁰²)*TWI – 0.895*ALSI_RATIO	N = (-4.006*10 ⁻⁰²) + (9.692*10 ⁻⁰⁵)*RAIN + (3.955*10 ⁻⁰²)*NDVI + (1.738*10 ⁻⁰⁵)*ELEVATION – (1.388*10 ⁻⁰⁶)*SLOPE + (8.495*10 ⁻⁰⁶)*ASPECT – (1.173*10 ⁻⁰²)*PLAN + (1.641*10 ⁻⁰²)*PROFILE – (8.302*10 ⁻⁰³)*CURVATURE + (2.385*10 ⁻⁰³)*TWI – 0.184*ALSI_RATIO

Table 4.7 (Continued).

Soil properties	Topsoil	Subsoil
P	$P = 1.301 + (7.533 \times 10^{-05}) * RAIN +$ $5.937 * NDVI + (1.838 \times 10^{-04}) * ELEVATION -$ $(3.534 \times 10^{-03}) * SLOPE - (5.791 \times 10^{-04}) *$ $ASPECT - 1.392 * PLAN + 1.464 * PROFILE -$ $0.846 * CURVATURE + 0.321 * TWI -$ $8.395 * ALSI_RATIO$	$P = 0.848 + (3.719 \times 10^{-05}) * RAIN +$ $0.527 * NDVI + (1.445 \times 10^{-05}) * ELEVATION -$ $(1.970 \times 10^{-03}) * SLOPE + (3.123 \times 10^{-04}) *$ $ASPECT - 0.256 * PLAN + 0.280 * PROFILE -$ $0.159 * CURVATURE + (6.197 \times 10^{-02}) * TWI -$ $2.118 * ALSI_RATIO$
K	$K = 113.923 - (1.158 \times 10^{-02}) * RAIN -$ $46.592 * NDVI + (4.772 \times 10^{-03}) * ELEVATION -$ $1.726 * SLOPE + (8.702 \times 10^{-02}) * ASPECT -$ $21.245 * PLAN + 18.706 * PROFILE -$ $11.866 * CURVATURE + 7.678 * TWI +$ $113.498 * ALSI_RATIO$	$K = 42.291 + (9.875 \times 10^{-03}) * RAIN +$ $12.198 * NDVI + (6.639 \times 10^{-03}) * ELEVATION -$ $0.402 * SLOPE + 0.022 * ASPECT -$ $16.111 * PLAN + 17.517 * PROFILE -$ $9.958 * CURVATURE + 3.625 * TWI -$ $70.156 * ALSI_RATIO$
Ca	$Ca = 49.854 + (4.526 \times 10^{-02}) * RAIN +$ $92.669 * NDVI + (4.530 \times 10^{-02}) * ELEVATION -$ $8.051 * SLOPE + 0.569 * ASPECT -$ $54.316 * PLAN + 37.863 * PROFILE -$ $27.469 * CURVATURE + 61.766 * TWI +$ $591.571 * ALSI_RATIO$	$Ca = 471.849 - (4.100 \times 10^{-02}) * RAIN -$ $71.454 * NDVI + (2.924 \times 10^{-02}) * ELEVATION -$ $5.311 * SLOPE + 0.054 * ASPECT -$ $43.048 * PLAN + 52.293 * PROFILE -$ $28.189 * CURVATURE + 21.419 * TWI -$ $483.020 * ALSI_RATIO$
Mg	$Mg = 327.005 - (5.044 \times 10^{-02}) * RAIN -$ $49.313 * NDVI + (4.838 \times 10^{-03}) * ELEVATION -$ $0.933 * SLOPE + (7.423 \times 10^{-02}) * ASPECT -$ $51.773 * PLAN + 34.148 * PROFILE -$ $25.623 * CURVATURE + 9.502 * TWI +$ $0.578 * ALSI_RATIO$	$Mg = 145.077 - (3.271 \times 10^{-05}) * RAIN +$ $19.741 * NDVI + (7.734 \times 10^{-03}) * ELEVATION -$ $0.788 * SLOPE + (5.192 \times 10^{-02}) * ASPECT -$ $32.232 * PLAN + 32.169 * PROFILE -$ $19.094 * CURVATURE + 6.261 * TWI -$ $234.749 * ALSI_RATIO$
Na	$Na = 54.759 - (8.265 \times 10^{-03}) * RAIN -$ $33.061 * NDVI + (1.311 \times 10^{-03}) * ELEVATION -$ $0.762 * SLOPE + (3.576 \times 10^{-02}) * ASPECT -$ $8.787 * PLAN + 11.485 * PROFILE -$ $5.988 * CURVATURE + 2.788 * TWI +$ $124.821 * ALSI_RATIO$	$Na = 12.423 + 0.0138 * RAIN + 4.617 * NDVI +$ $(5.377 \times 10^{-03}) * ELEVATION -$ $0.171 * SLOPE + (8.991 \times 10^{-03}) * ASPECT -$ $7.754 * PLAN + 7.831 * PROFILE -$ $4.620 * CURVATURE + 1.326 * TWI -$ $63.541 * ALSI_RATIO$
CEC	$CEC = 3.470 + (1.364 \times 10^{-02}) * RAIN +$ $8.769 * NDVI + (2.398 \times 10^{-03}) * ELEVATION +$ $(1.451 \times 10^{-02}) * SLOPE + (2.032 \times 10^{-03}) *$ $ASPECT - 2.248 * PLAN + 2.390 * PROFILE -$ $1.374 * CURVATURE + 0.325 * TWI -$ $34.380 * ALSI_RATIO$	$CEC = 3.505 + (1.075 \times 10^{-02}) * RAIN +$ $5.027 * NDVI + (2.577 \times 10^{-03}) * ELEVATION -$ $(3.482 \times 10^{-03}) * SLOPE + (3.768 \times 10^{-03}) *$ $ASPECT - 2.264 * PLAN + 2.670 * PROFILE -$ $1.459 * CURVATURE + 0.318 * TWI -$ $36.186 * ALSI_RATIO$
BS	$BS = 61.169 - (2.683 \times 10^{-02}) * RAIN -$ $20.562 * NDVI - (3.665 \times 10^{-03}) * ELEVATION -$ $0.231 * SLOPE + (9.427 \times 10^{-03}) * ASPECT -$ $2.640 * PLAN + 1.119 * PROFILE -$ $1.127 * CURVATURE + 0.808 * TWI +$ $60.269 * ALSI_RATIO$	$BS = 41.768 - (1.637 \times 10^{-02}) * RAIN -$ $8.571 * NDVI - (2.502 \times 10^{-03}) * ELEVATION -$ $0.165 * SLOPE + (1.772 \times 10^{-03}) * ASPECT -$ $1.545 * PLAN + 1.088 * PROFILE -$ $0.785 * CURVATURE + 0.558 * TWI +$ $21.893 * ALSI_RATIO$

Table 4.8 Statistic summary of PLS regression of topsoil.

Model parameters	Soil properties												
	Sand	Silt	Clay	pH	OM	N	P	K	Ca	Mg	Na	CEC	BS
Intercept	16.785	40.861	30.432	6.562	-5.132	-0.217	1.301	113.923	49.854	327.005	54.759	3.470	61.169
RAIN	1.93x10 ⁻²	-1.44x10 ⁻²	-1.00x10 ⁻³	-8.97x10 ⁻⁴	7.84x10 ⁻²	3.16x10 ⁻⁴	7.53x10 ⁻⁵	-0.012	0.045	-0.050	-0.008	1.36x10 ⁻²	-2.68x10 ⁻²
NDVI	-8.573	1.084	-3.785	-0.881	6.151	0.240	5.937	-46.592	92.669	-49.313	-33.061	8.769	-20.562
ELEVATION	2.46x10 ⁻³	-2.01x10 ⁻³	8.24x10 ⁻⁵	-1.63x10 ⁻⁴	1.38x10 ⁻³	5.30x10 ⁻⁵	1.84x10 ⁻⁴	0.005	0.045	0.005	0.001	2.40x10 ⁻³	-3.66x10 ⁻³
SLOPE	0.463	-0.092	-0.122	-0.029	0.022	0.000	-0.004	-1.726	-8.051	-0.933	-0.762	0.015	-0.231
ASPECT	2.45x10 ⁻³	8.32x10 ⁻⁴	4.02x10 ⁻³	5.0 x10 ⁻⁴	-8.61x10 ⁻⁴	3.24x10 ⁻⁵	-5.79x10 ⁻⁴	0.087	0.569	0.074	0.036	2.03x10 ⁻³	9.43x10 ⁻³
PLAN	1.770	-1.317	-2.465	-0.062	-0.674	-0.054	-1.392	-21.245	-54.316	-51.773	-8.787	-2.248	-2.640
PROFILE	-0.644	1.273	1.523	0.101	1.122	0.067	1.464	18.705	37.863	34.148	11.485	2.390	1.119
CURVATURE	0.725	-0.768	-1.190	-0.048	-0.529	-0.036	-0.846	-11.866	-27.469	-25.623	-5.988	-1.374	-1.127
TWI	-1.429	0.586	0.407	0.108	0.136	1.05 x10 ⁻²	0.321	7.678	61.766	9.502	2.788	0.325	0.808
ALSI_RATIO	29.892	13.718	1.869	1.759	-17.094	-0.895	-8.395	113.498	591.571	0.578	124.821	-34.380	60.269
Model summary													
R ²	0.916	0.523	0.668	0.824	0.683	0.798	0.741	0.860	0.893	0.658	0.859	0.767	0.791
Std. deviation	2.235	3.098	2.523	0.164	1.347	0.055	1.373	20.064	89.470	50.923	8.880	2.299	3.607
MSE	3.998	8.638	5.729	0.022	1.634	0.003	1.696	342.175	6403.904	2333.850	67.030	4.758	11.711
RMSE	1.999	2.939	2.393	0.147	1.278	0.052	1.302	18.498	80.024	48.310	8.187	2.181	3.422

Table 4.9 Statistic summary of PLS regression of subsoil.

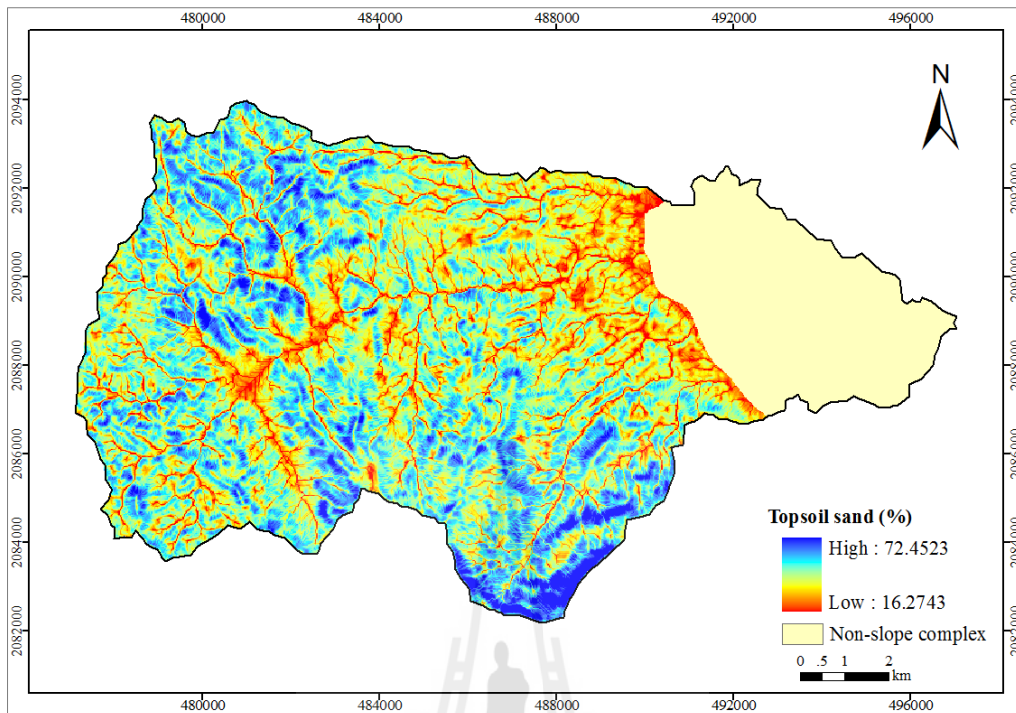
Model parameters	Soil properties												
	Sand	Silt	Clay	pH	OM	N	P	K	Ca	Mg	Na	CEC	BS
Intercept	30.123	19.739	43.987	4.847	-2.740	-0.0401	0.848	42.291	471.849	145.077	12.423	3.505	41.768
RAIN	9.76x10 ⁻³	-7.83x10 ⁻³	-3.22x10 ⁻³	1.34X10 ⁻⁴	3.05X10 ⁻³	9.69X10 ⁻⁵	3.72X10 ⁻⁵	0.010	-0.041	3.27X10 ⁻⁵	0.014	1.07X10 ⁻²	-1.64X10 ⁻²
NDVI	7.762	3.719	-13.557	0.255	2.585	0.0396	0.527	12.198	-71.454	19.741	4.617	5.027	-8.571
ELEVATION	-8.41X10 ⁻⁴	8.01X10 ⁻⁵	2.23X10 ⁻³	5.67X10 ⁻⁵	5.16X10 ⁻⁴	1.74X10 ⁻⁵	1.44X10 ⁻⁵	0.007	0.029	0.008	0.005	2.58X10 ⁻³	-2.50X10 ⁻³
SLOPE	0.508	-1.10X10 ⁻²	-0.511	-5.22X10 ⁻³	8.78X10 ⁻³	-1.39X10 ⁻⁶	-1.97X10 ⁻³	-0.402	-5.311	-0.788	-0.171	-3.48X10 ⁻³	-0.165
ASPECT	-3.64X10 ⁻³	1.84X10 ⁻⁴	8.03X10 ⁻³	3.33X10 ⁻⁴	-1.74X10 ⁻⁴	8.49X10 ⁻⁶	3.12X10 ⁻⁴	0.022	0.054	0.052	0.009	3.77X10 ⁻³	1.77X10 ⁻³
PLAN	3.495	-2.133	-1.584	-0.265	-0.313	-0.0117	-0.256	-16.111	-43.048	-32.231	-7.754	-2.264	-1.545
PROFILE	-4.714	2.512	1.842	0.281	0.540	0.0164	0.280	17.517	52.293	32.169	7.831	2.670	1.088
CURVATURE	2.424	-1.374	-1.014	-0.162	-0.251	-0.0083	-0.158	-9.958	-28.189	-19.094	-4.620	-1.459	-0.784
TWI	-1.593	0.417	1.029	0.053	0.066	0.0024	0.062	3.625	21.419	6.261	1.326	0.318	0.558
ALSI_RATIO	-40.356	-10.281	42.825	-1.679	-6.577	-0.1835	-2.118	-70.156	-483.020	-234.749	-63.541	-36.186	21.893
Model summary													
R ²	0.819	0.776	0.769	0.659	0.660	0.589	0.594	0.777	0.900	0.867	0.824	0.848	0.603
Std. deviation	4.843	1.839	4.330	0.310	0.615	0.022	0.363	14.769	40.899	20.339	5.765	1.777	3.335
MSE	19.935	3.044	15.935	0.087	0.340	0.000	0.118	196.312	1421.814	372.291	29.912	2.843	10.008
RMSE	4.465	1.745	3.992	0.294	0.583	0.021	0.344	14.011	37.707	19.295	5.469	1.686	3.164

Table 4.10 Variable importance in the projection (VIP) of each soil property.

Soil properties		Variable Importance in the Projection (VIP)									
		Rainfall	NDVI	Elevation	Slope	Aspect	Plan curvature	Profile curvature	Curvature	TWI	Al/Si ratio
Sand	Topsoil	0.66	0.22	0.40	1.57*	0.52	1.21*	0.85	1.13	1.77*	0.20
	Subsoil	0.17	0.18	0.14	1.35*	0.59	1.27	1.23	1.36*	1.66*	0.03
Silt	Topsoil	1.27*	0.15	0.87	1.27*	0.16	0.78	0.73	0.82	2.01*	0.36
	Subsoil	0.08	0.55	0.04	0.17	0.04	1.39	1.59*	1.62*	1.58*	0.29
Clay	Topsoil	0.09	0.50	0.04	1.67*	0.76	1.45*	0.87	1.27	1.39*	0.05
	Subsoil	0.20	0.55	0.18	1.84*	0.82	1.08	0.91	1.09*	1.54*	0.20
pH	Topsoil	0.75	0.78	0.55	1.54*	0.81	1.06*	0.69	0.96	1.64*	0.54
	Subsoil	0.10	0.30	0.22	0.64	0.57	1.39	1.44*	1.54*	1.61*	0.39
OM	Topsoil	1.27*	1.52*	1.10	0.55	0.30	0.74	1.19*	1.04	0.86	0.82
	Subsoil	1.15*	1.49*	0.96	0.52	0.14	0.80	1.33*	1.16	0.98	0.74
N	Topsoil	0.97	1.12	0.80	0.22	0.22	1.12	1.35*	1.34*	1.25*	0.81
	Subsoil	1.25*	0.78	1.10	0.00	0.24	1.02	1.38*	1.30*	1.20	0.70
P	Topsoil	0.01	1.24	0.12	0.08	0.17	1.28	1.31*	1.41*	1.72*	0.34
	Subsoil	0.03	0.61	0.05	0.23	0.51	1.30	1.38*	1.46*	1.83*	0.47
K	Topsoil	0.05	0.21	0.20	1.09	0.98	1.34*	1.17	1.37*	1.65*	0.06
	Subsoil	0.12	0.23	0.40	0.77	0.57	1.32	1.39*	1.47*	1.72*	0.25
Ca	Topsoil	0.20	0.16	0.06	0.99	1.00	1.36*	1.09	1.34*	1.76*	0.02
	Subsoil	0.07	0.01	0.40	1.12	0.59	1.28*	1.27	1.39*	1.70*	0.40
Mg	Topsoil	0.23	0.35	0.11	0.68	0.75	1.62*	1.04	1.45*	1.72*	0.00
	Subsoil	0.00	0.19	0.25	0.80	0.73	1.40*	1.36	1.50*	1.58*	0.45
Na	Topsoil	0.13	0.37	0.11	1.13	0.97	1.31*	1.26	1.40*	1.53*	0.13
	Subsoil	0.37	0.19	0.72	0.72	0.53	1.42*	1.39	1.53*	1.40*	0.51
CEC	Topsoil	1.10	1.08	0.95	0.18	0.36	1.22*	1.26*	1.35*	1.02	0.82
	Subsoil	0.87	0.62	1.03	0.04	0.66	1.23*	1.41*	1.44*	1.01	0.87
BS	Topsoil	1.13	1.32*	0.76	1.52*	0.87	0.75	0.31	0.58	1.33*	0.75
	Subsoil	1.15*	0.91	0.86	1.81*	0.27	0.73	0.50	0.67	1.53*	0.45

Note: * Three significant factors of each soil property

(a)



(b)

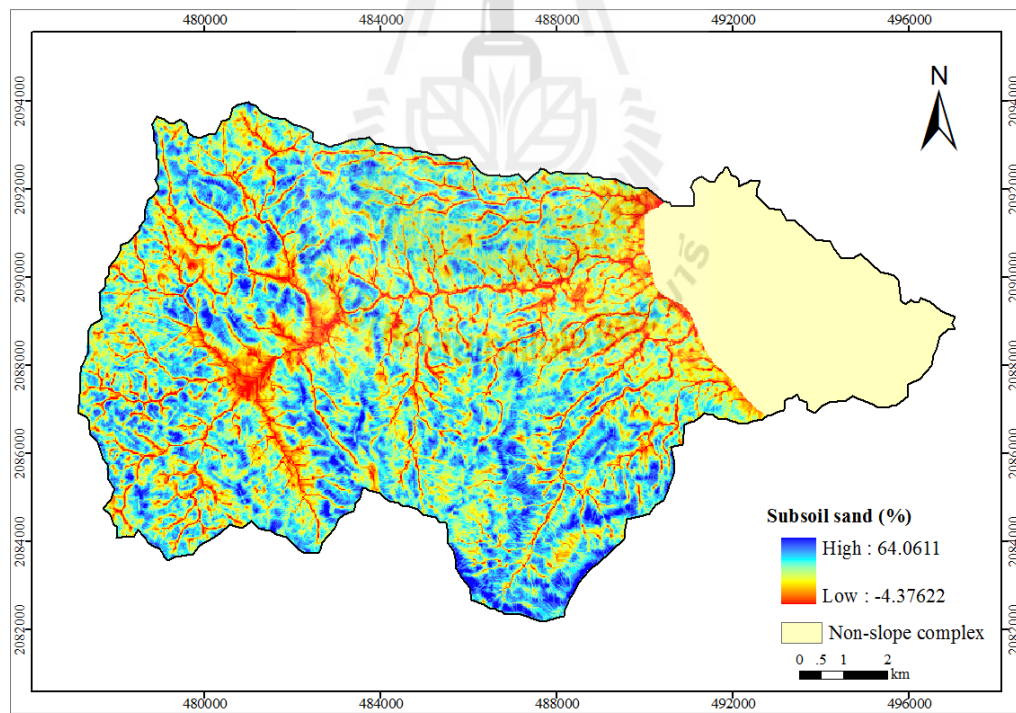
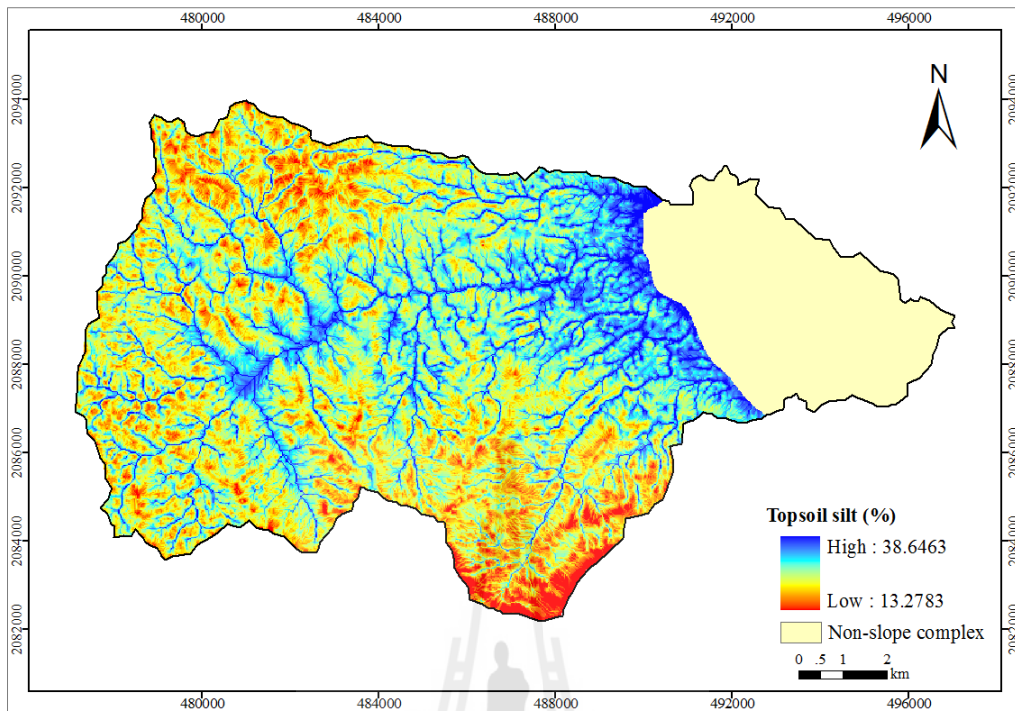


Figure 4.8 Distribution of predictive sand using PLS: (a) topsoil and (b) subsoil.

(a)



(b)

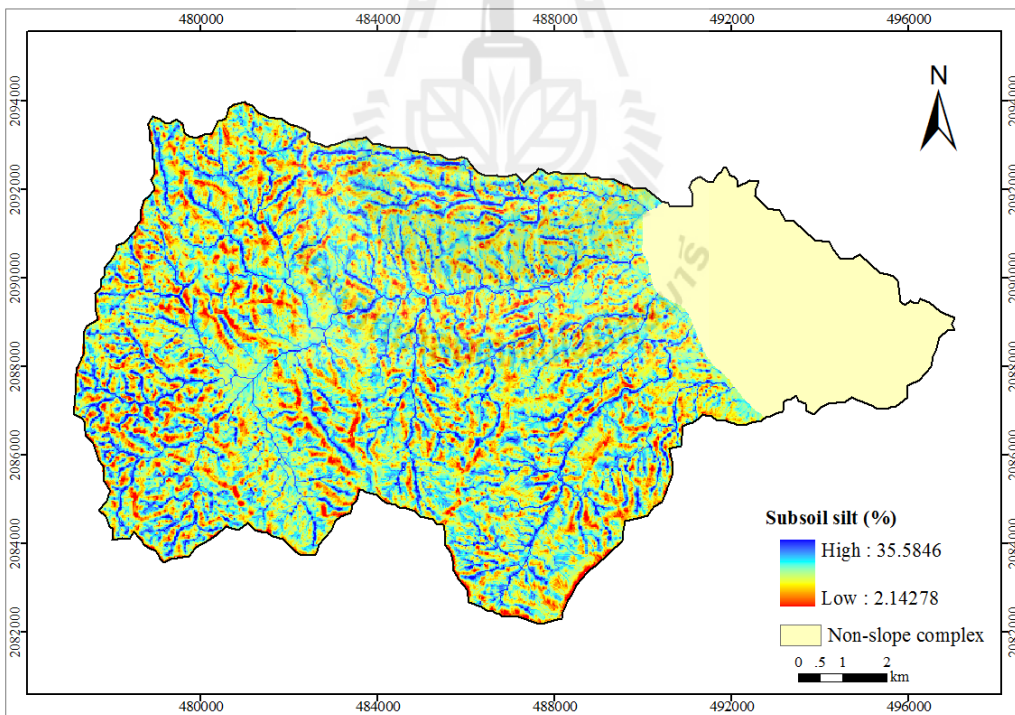
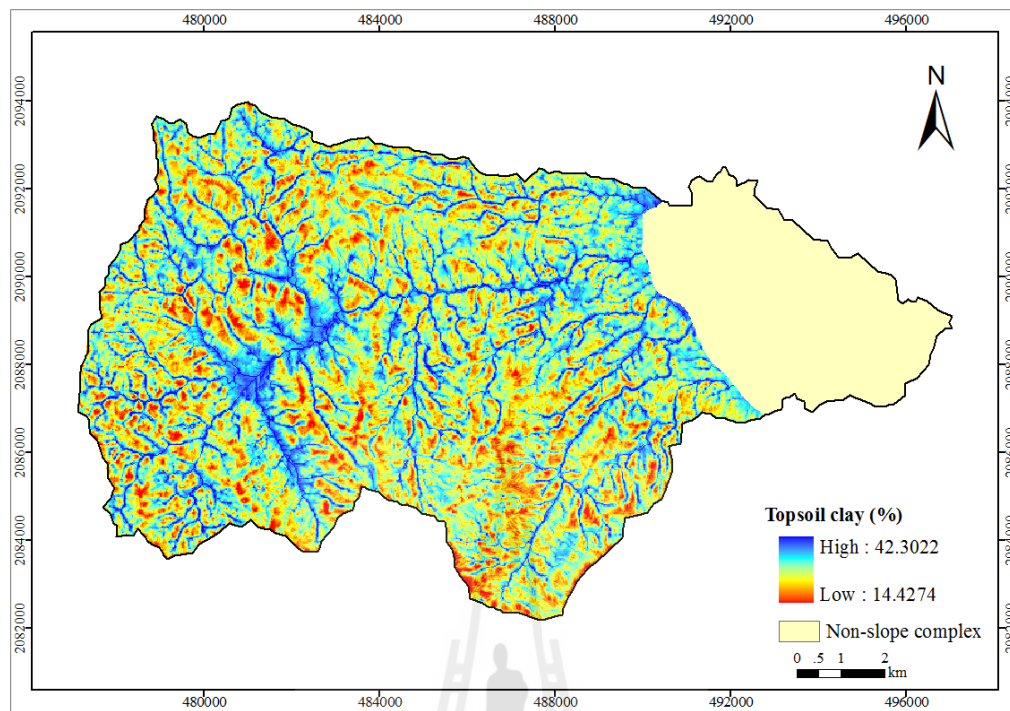


Figure 4.9 Distribution of predictive silt using PLS: (a) topsoil and (b) subsoil.

(a)



(b)

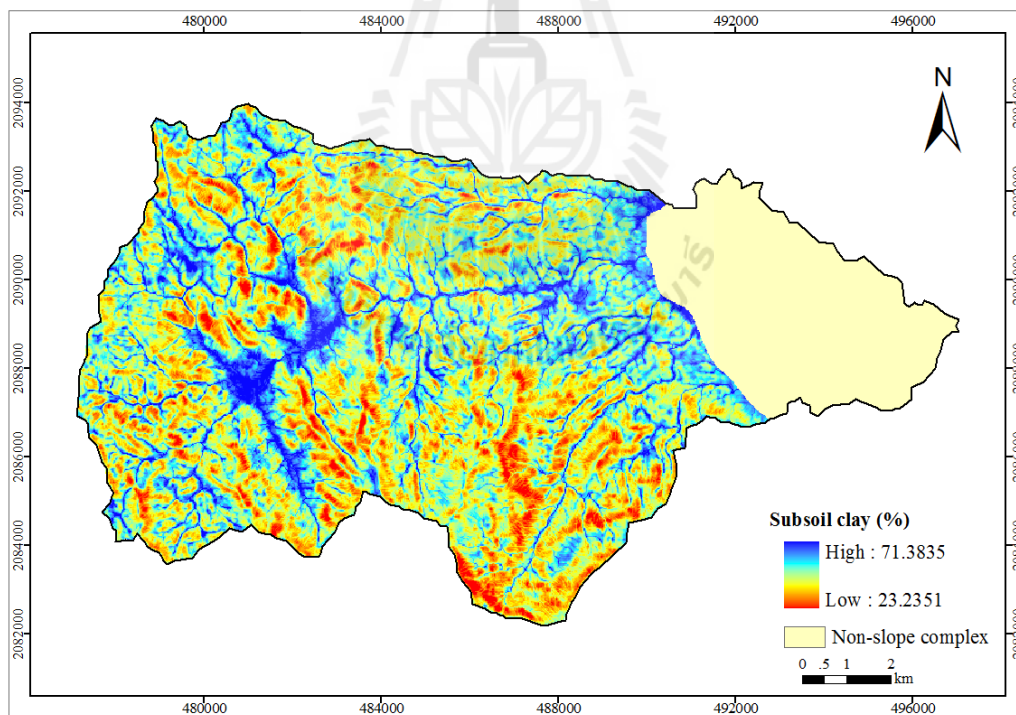
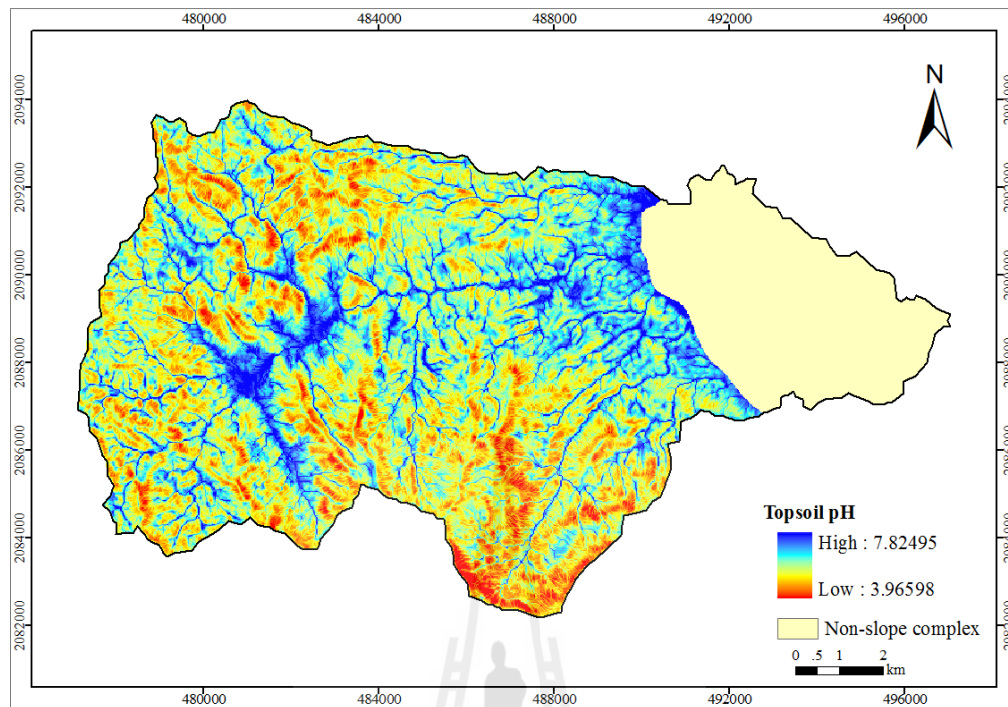


Figure 4.10 Distribution of predictive clay using PLS: (a) topsoil and (b) subsoil.

(a)



(b)

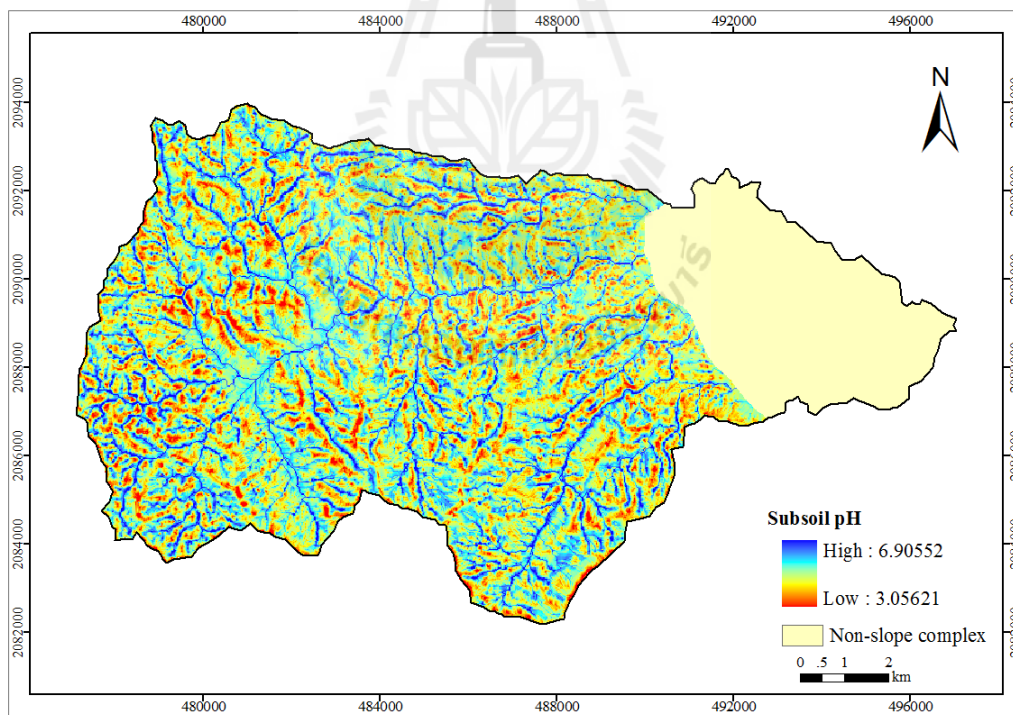
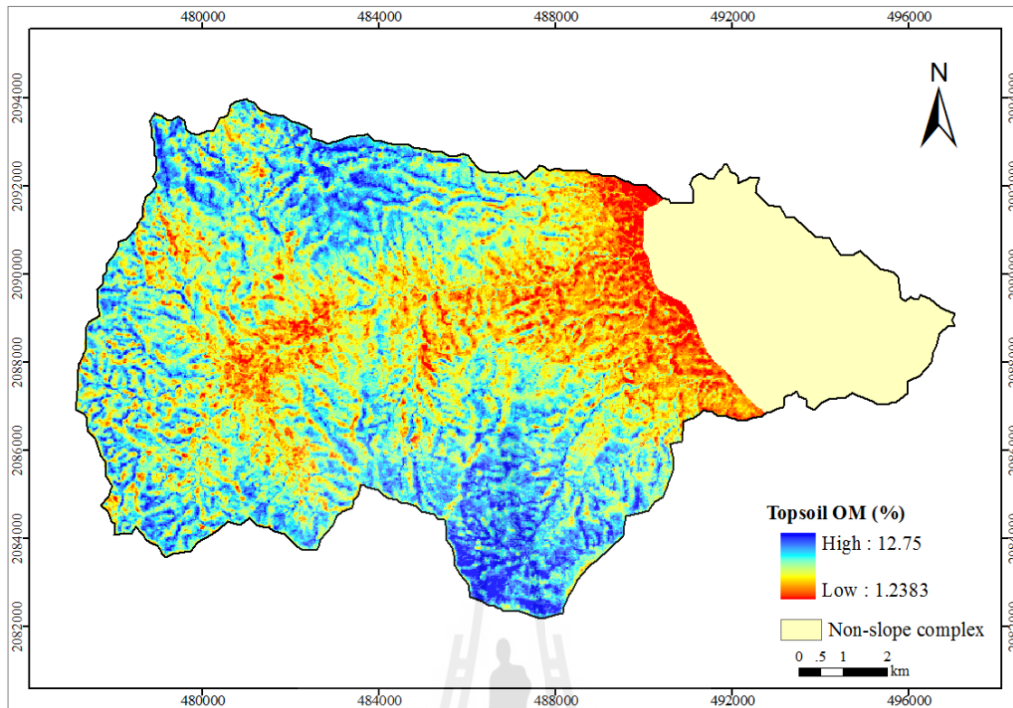


Figure 4.11 Distribution of predictive pH using PLS: (a) topsoil and (b) subsoil.

(a)



(b)

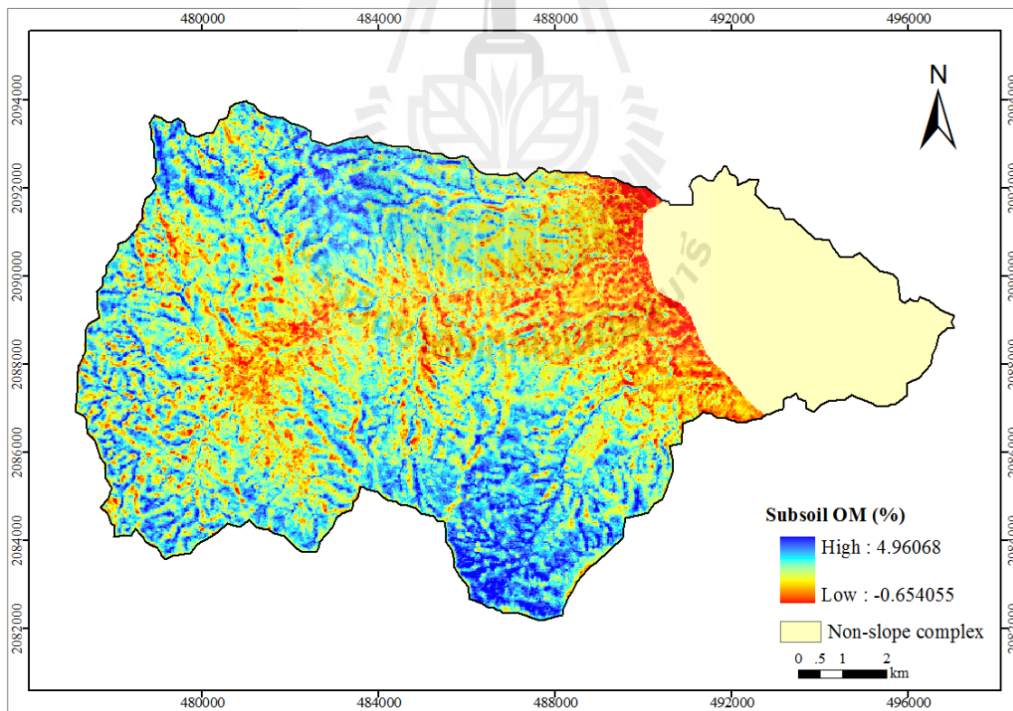
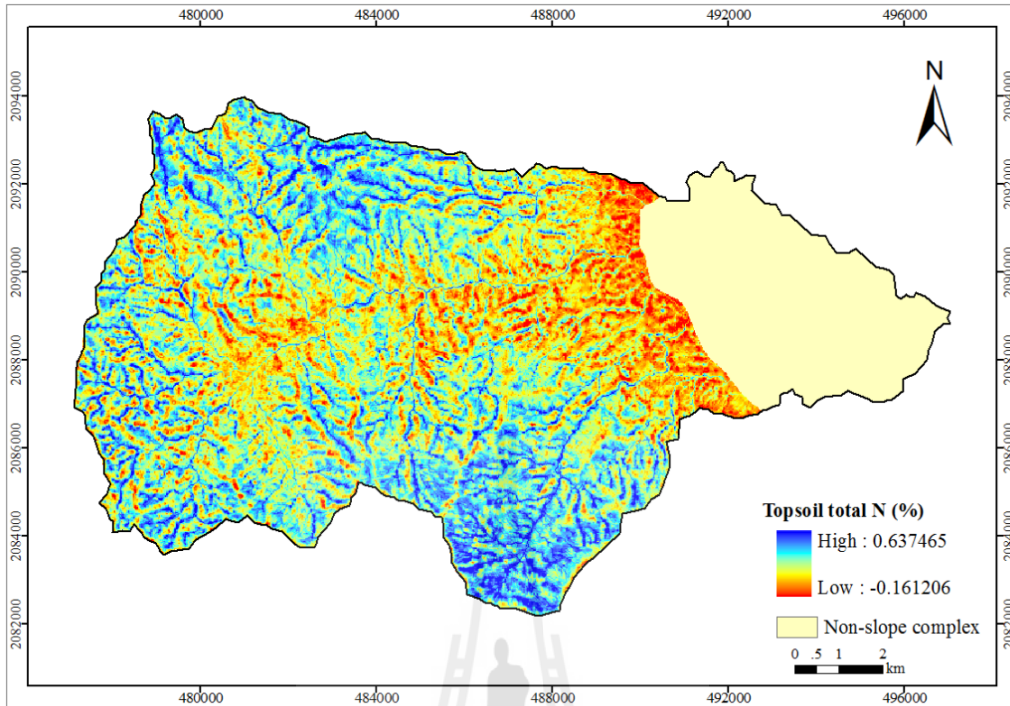


Figure 4.12 Distribution of predictive organic matter using PLS: (a) topsoil and (b) subsoil.

(a)



(b)

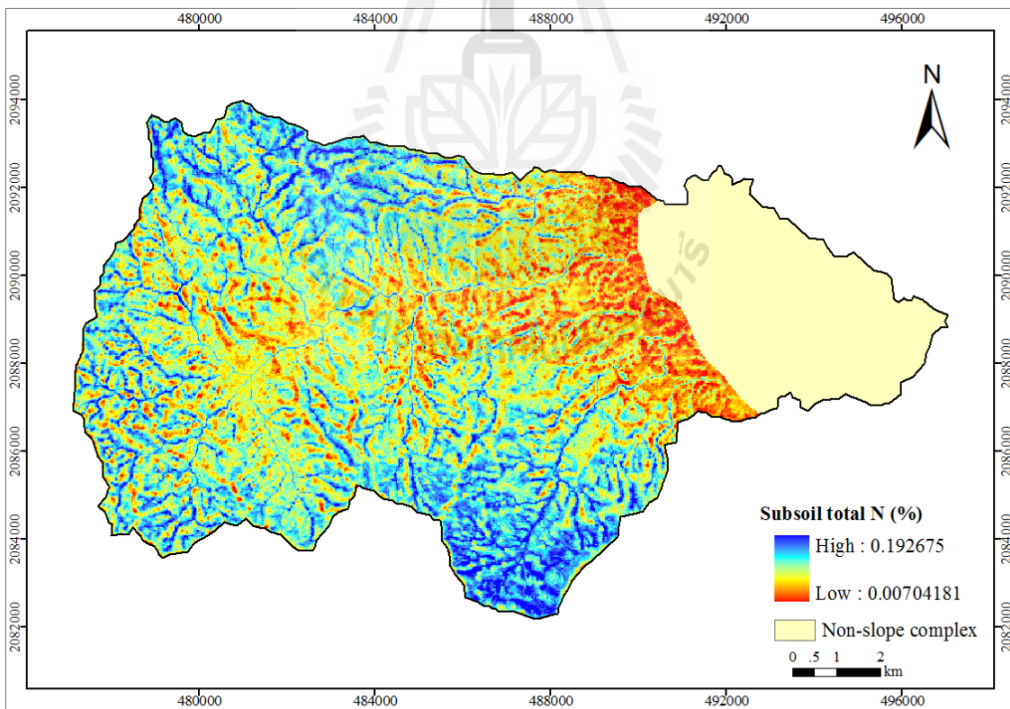
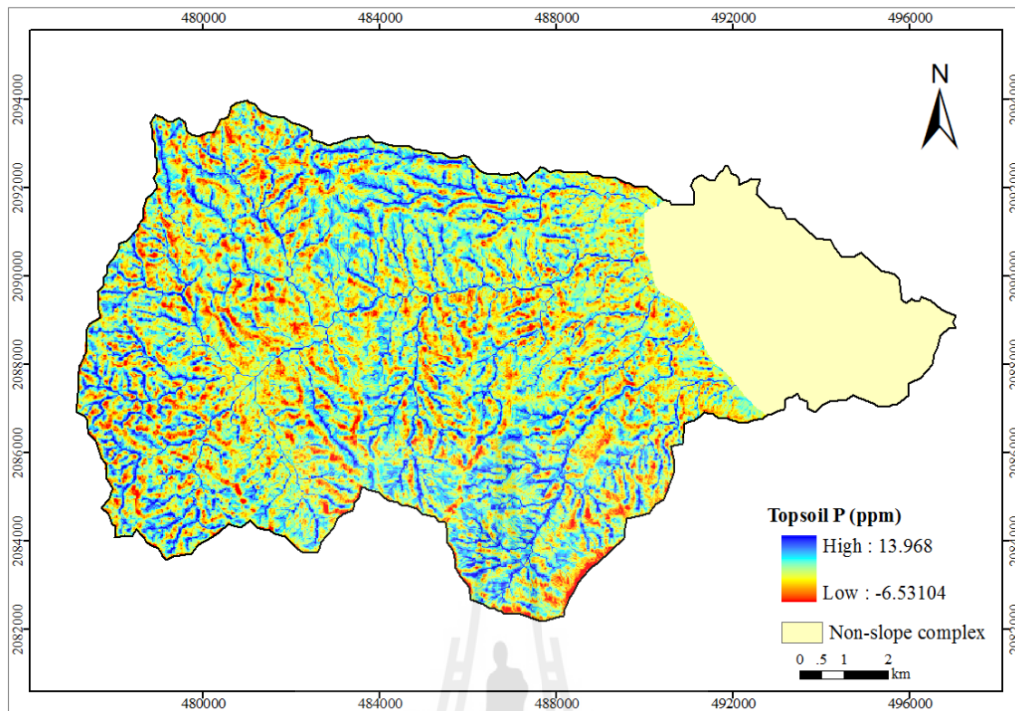


Figure 4.13 Distribution of predictive total nitrogen using PLS: (a) topsoil and (b) subsoil.

(a)



(b)

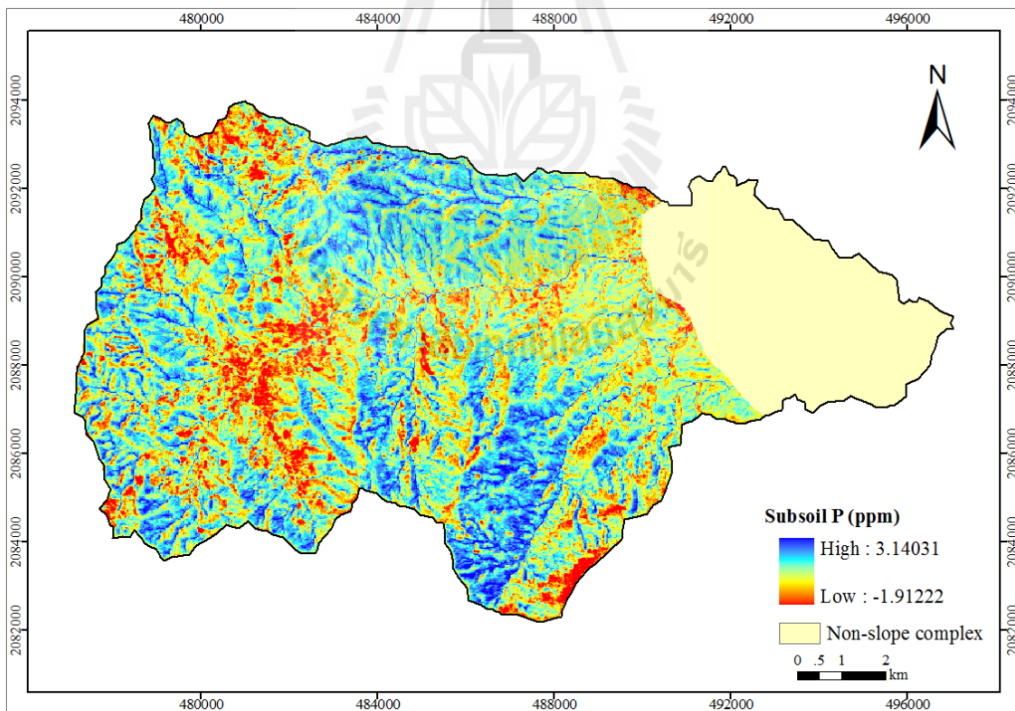
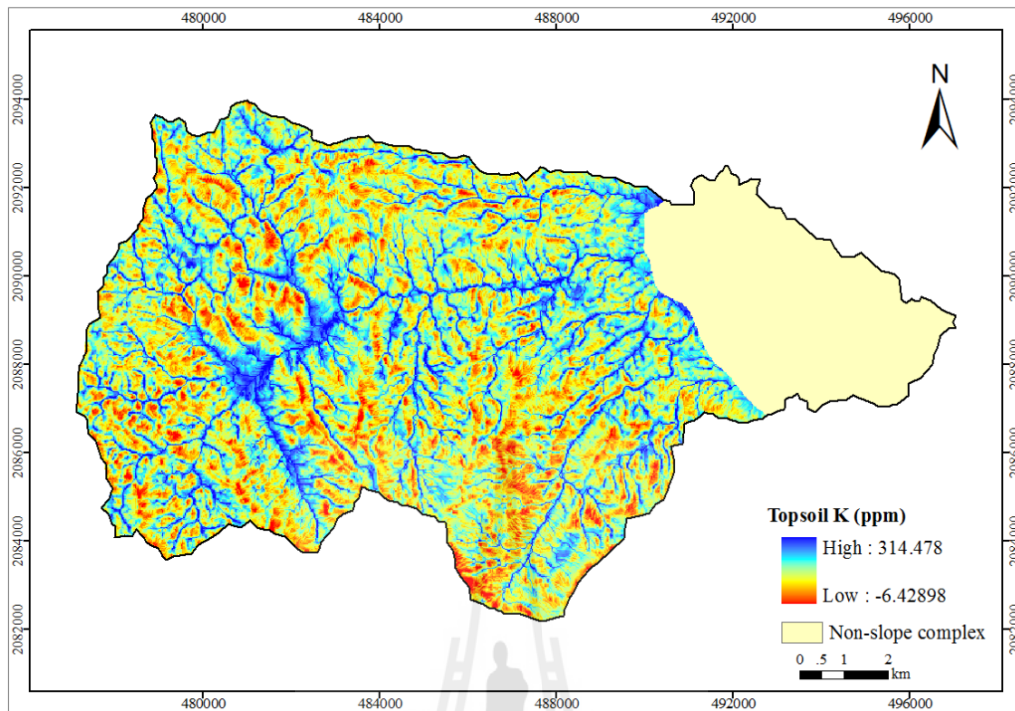


Figure 4.14 Distribution of predictive phosphorus using PLS: (a) topsoil and (b) subsoil.

(a)



(b)

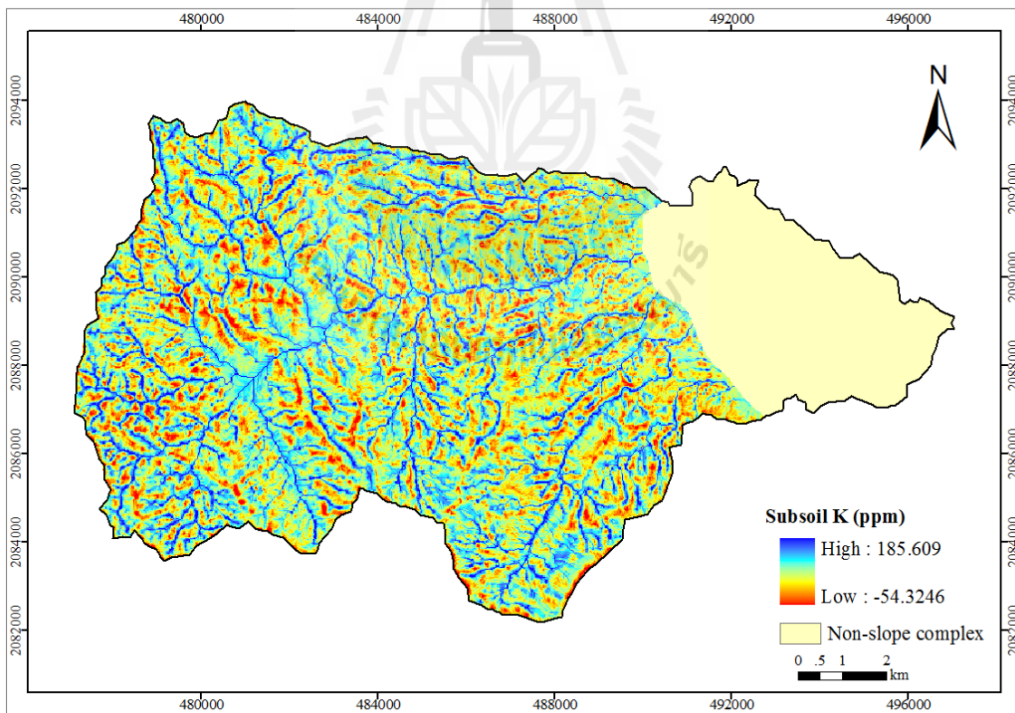
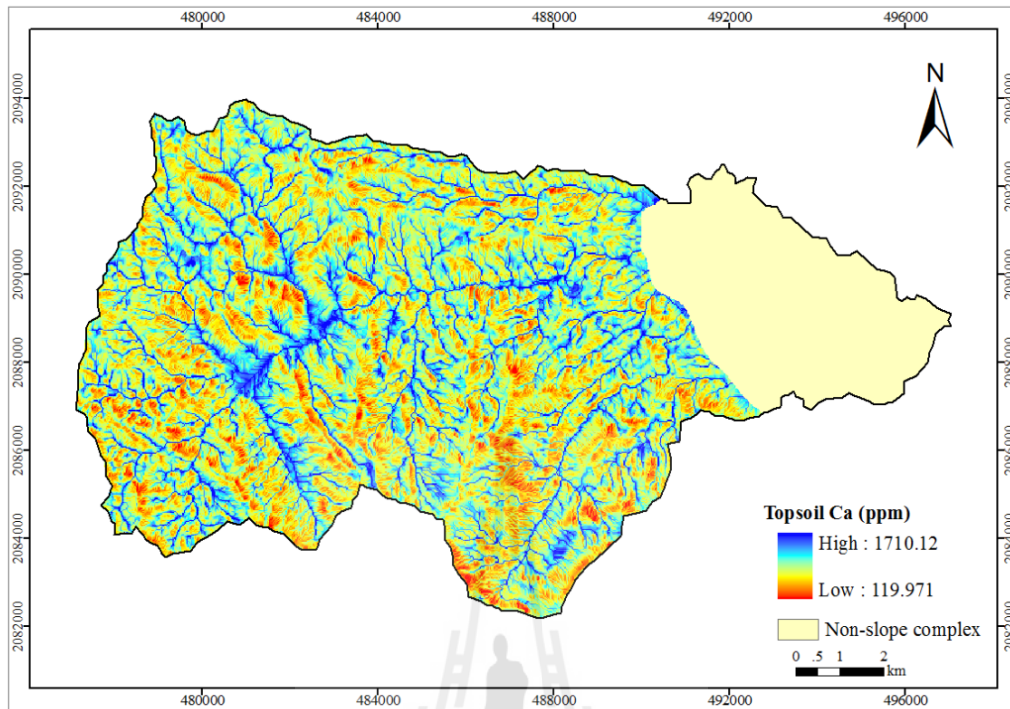


Figure 4.15 Distribution of predictive potassium using PLS: (a) topsoil and (b) subsoil.

(a)



(b)

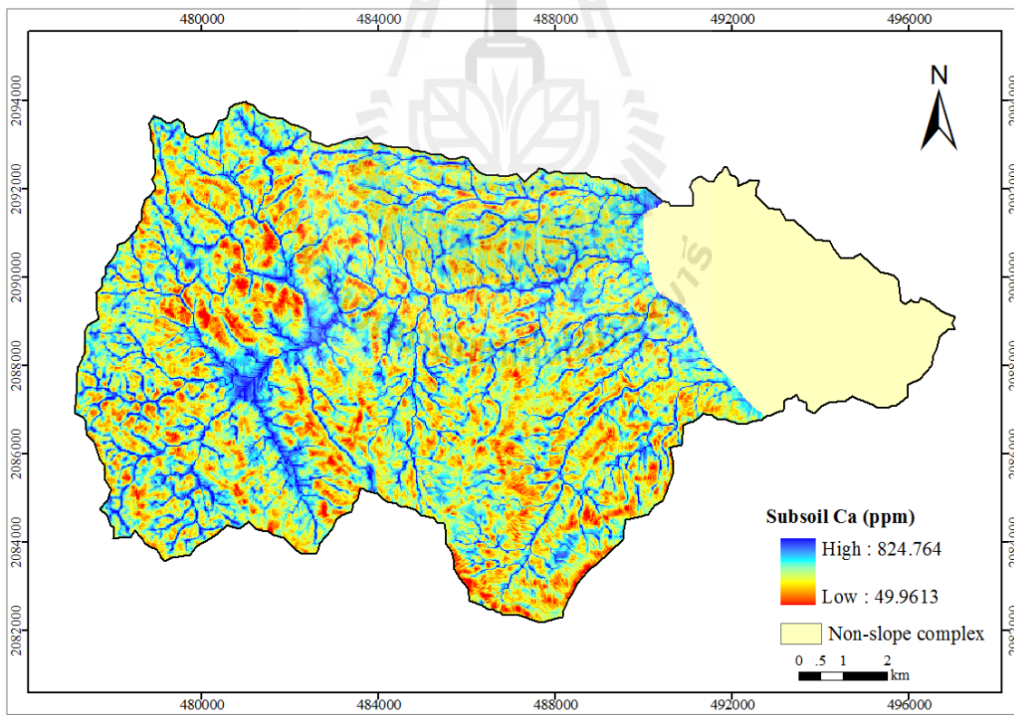
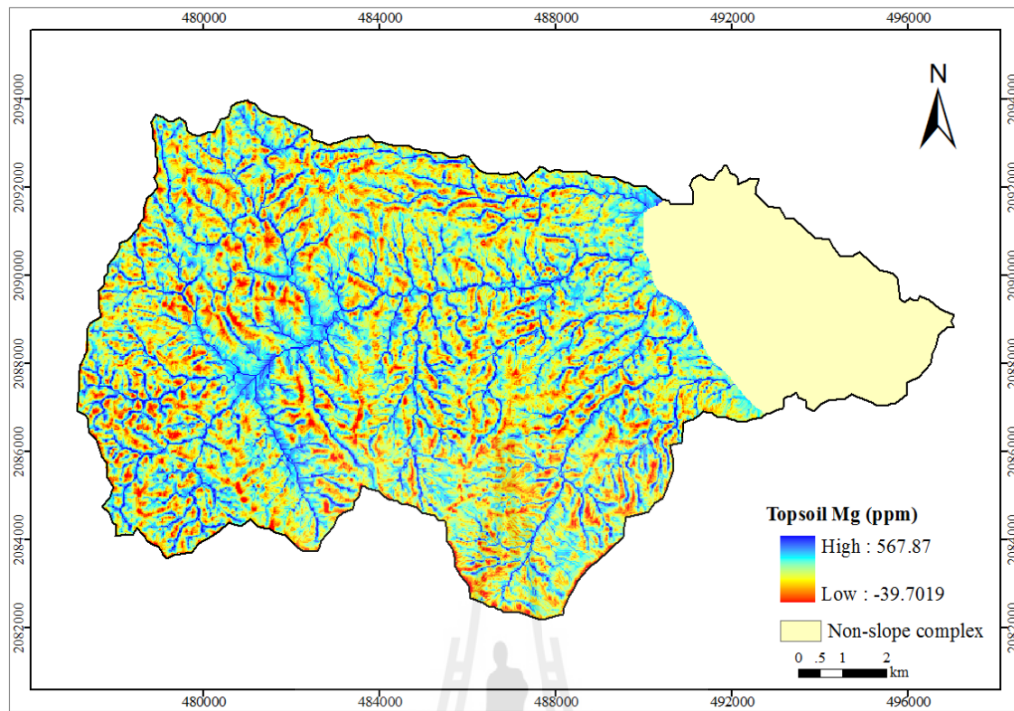


Figure 4.16 Distribution of predictive calcium using PLS: (a) topsoil and (b) subsoil.

(a)



(b)

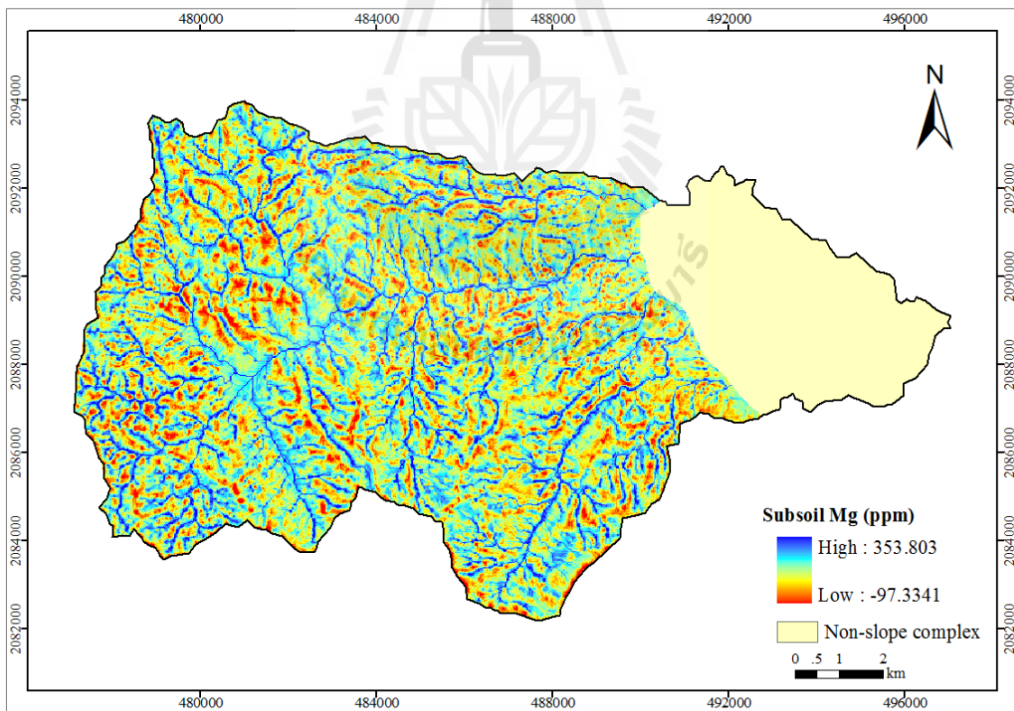
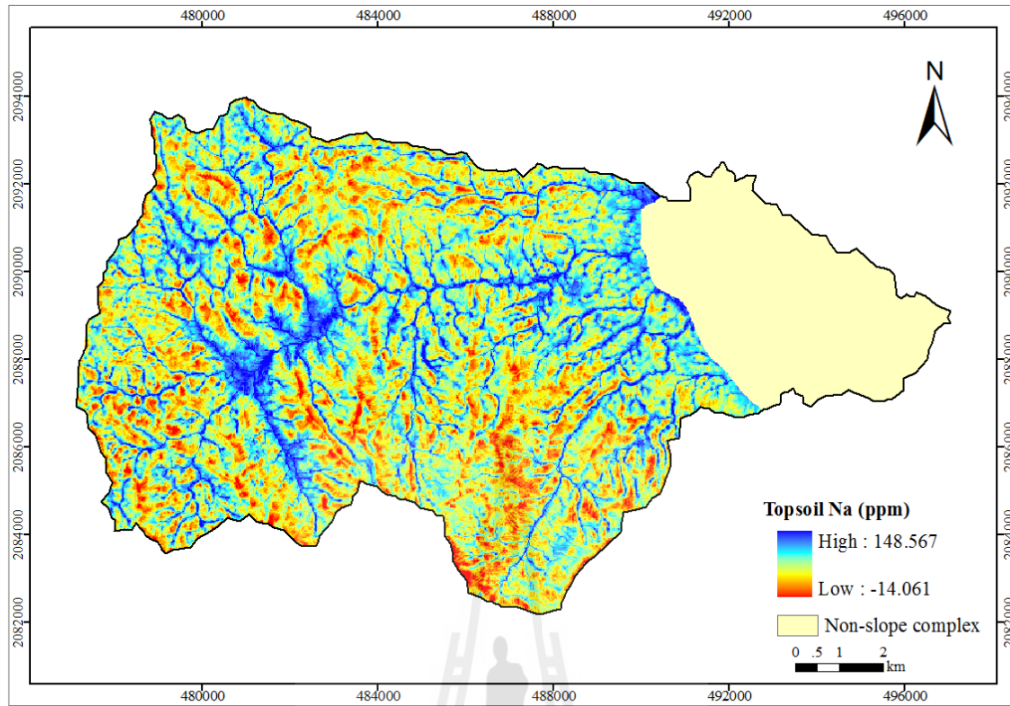


Figure 4.17 Distribution of predictive magnesium using PLS: (a) topsoil and (b) subsoil.

(a)



(b)

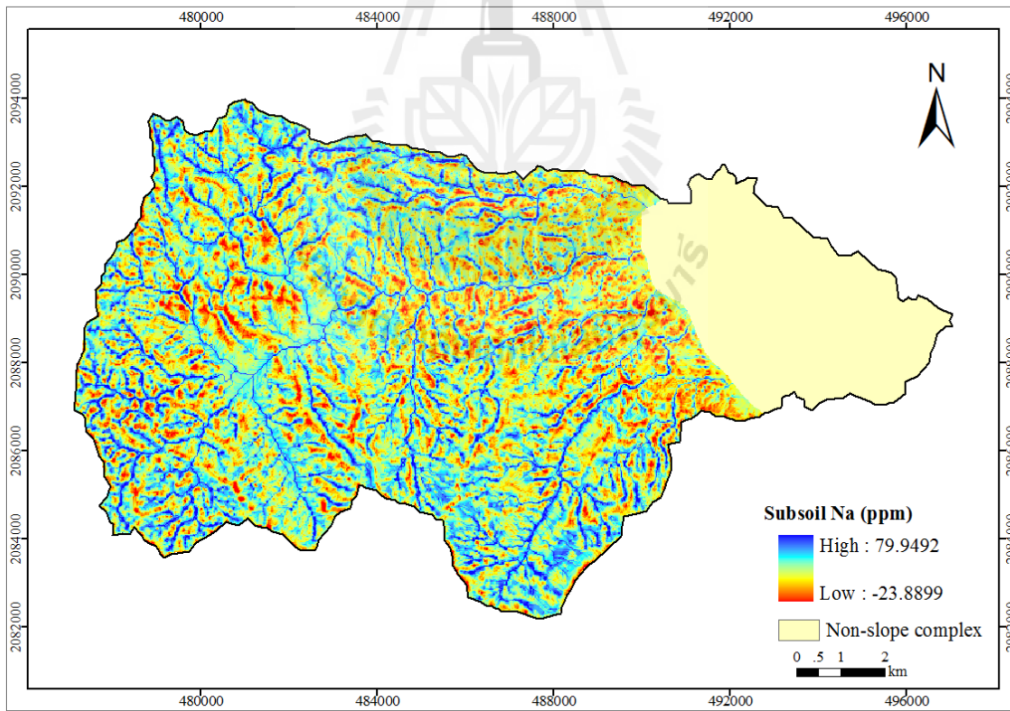


Figure 4.18 Distribution of predictive sodium using PLS: (a) topsoil and (b) subsoil.

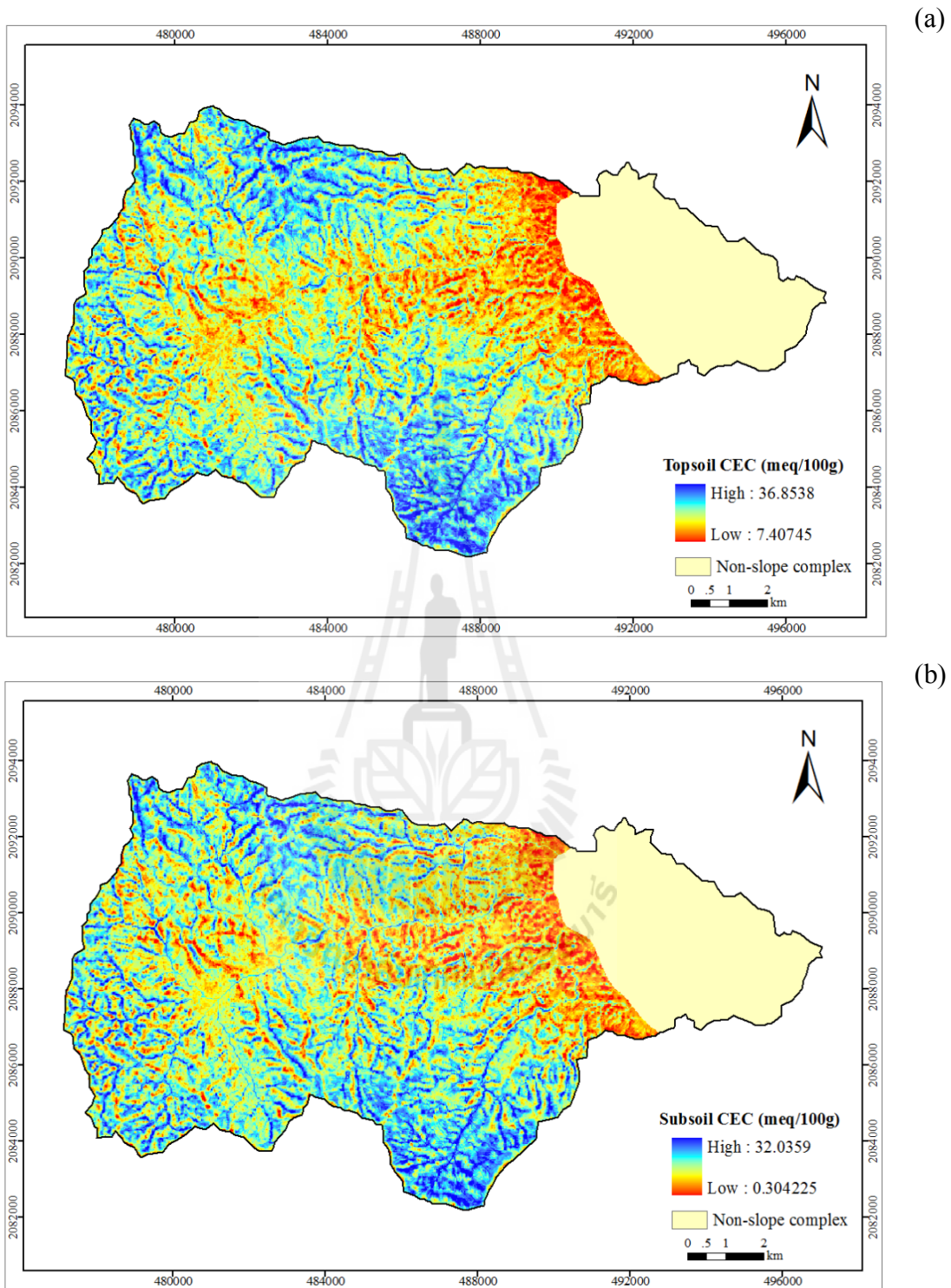
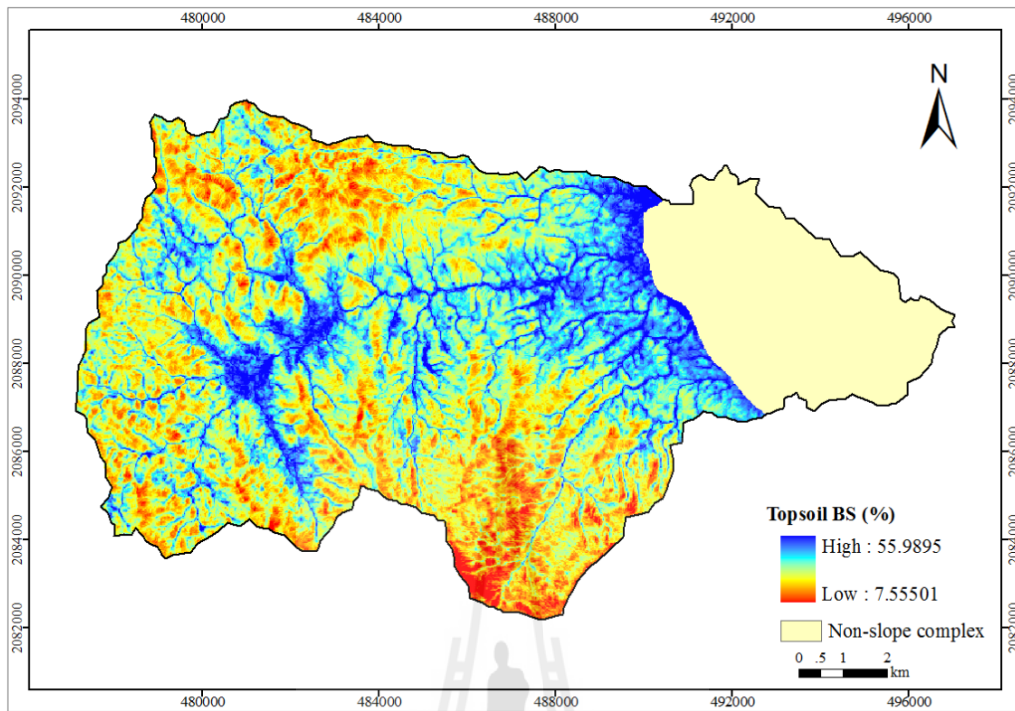


Figure 4.19 Distribution of predictive cation exchange capacity using PLS:

(a) topsoil and (b) subsoil.

(a)



(b)

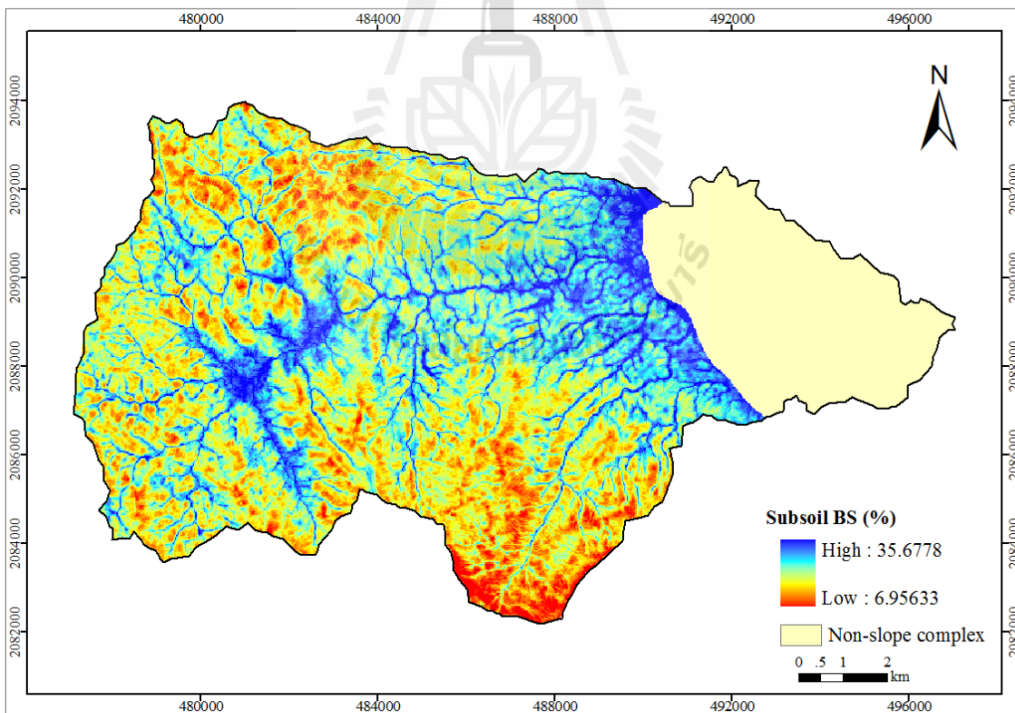


Figure 4.20 Distribution of predictive base saturation using PLS: (a) topsoil and (b) subsoil.

Furthermore, summary of predictive minimum, mean and maximum value of each soil properties of top and sub soil in the slope complex area are presented in Table 4.11. Also, Figures 4.21 and 4.22 present the dispersion of minimum, mean and maximum value of predictive physical and chemical soil properties of topsoil and subsoil in the slope complex area using PLS, respectively.

Table 4.11 Summary of predictive value of each soil properties using PLS.

Soil properties	Topsoil			Subsoil		
	Minimum	Mean	Maximum	Minimum	Mean	Maximum
Sand (%)	16.27	46.33	72.45	-4.38	36.51	64.06
Silt (%)	13.28	25.26	38.65	2.14	20.84	35.59
Clay (%)	14.43	28.74	42.30	23.24	42.52	71.38
pH	3.97	5.39	7.83	3.06	5.14	6.91
OM (%)	1.24	7.05	12.75	-0.65	2.19	4.96
N (%)	-0.16	0.26	0.64	0.01	0.10	0.19
P (ppm)	-6.53	4.47	13.97	-1.91	1.33	3.14
K (ppm)	-6.43	133.69	314.48	-54.33	71.56	185.61
Ca (ppm)	119.97	633.69	1710.12	49.96	361.25	824.76
Mg (ppm)	-39.70	294.47	567.87	-97.33	147.28	353.80
Na (ppm)	-14.06	63.51	148.57	-23.89	31.69	79.95
CEC (meq/100g)	7.41	23.52	36.85	0.30	17.72	32.04
BS (%)	7.56	27.00	55.99	6.96	18.94	35.68

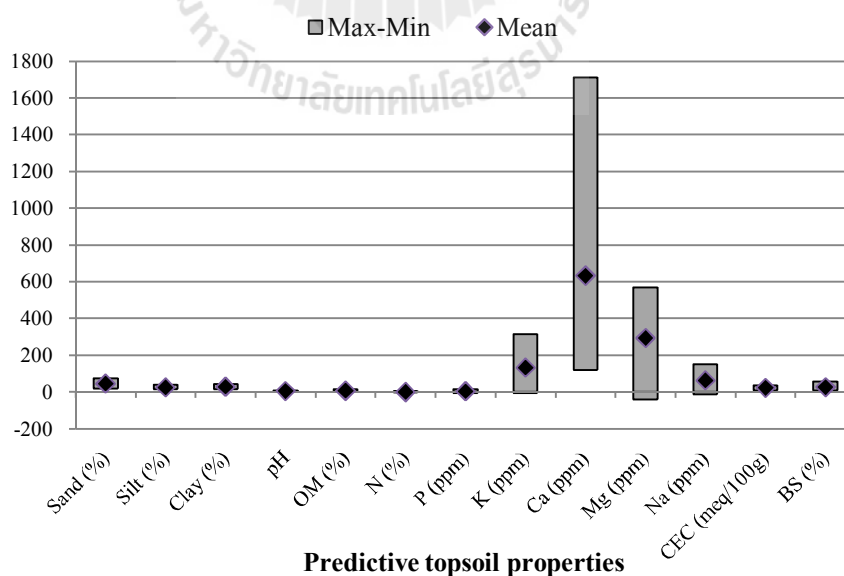


Figure 4.21 Dispersion of minimum, mean and maximum value of predictive physical and chemical topsoil properties using PLS regression.

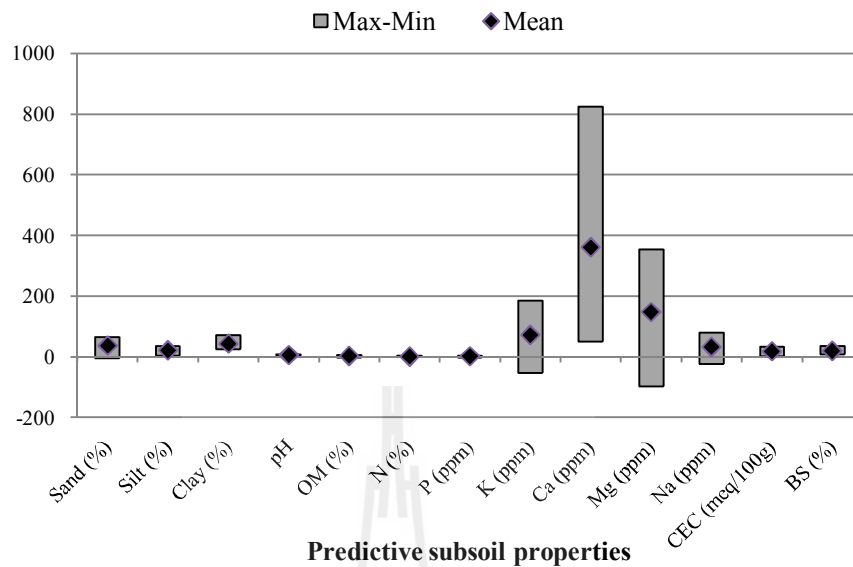


Figure 4.22 Dispersion of minimum, mean and maximum value of predictive physical and chemical subsoil properties using PLS regression.

According to statistic summary about coefficient of determination of PLS regression (Tables 4.8 and 4.9), the best predictive model for physical soil property of topsoil was sand ($R^2 = 0.916$) while the worst predictive model for physical soil property of topsoil was silt ($R^2 = 0.523$). In the meantime the best predictive model for chemical soil property of topsoil was calcium ($R^2 = 0.893$) while the worst predictive model for chemical soil property of topsoil was magnesium ($R^2 = 0.658$). At the same time, the best predictive model for physical soil property of subsoil was sand ($R^2 = 0.819$) while the worst predictive model for physical soil property of subsoil was clay ($R^2 = 0.769$). In the meantime the best predictive model for chemical soil property of subsoil was calcium ($R^2 = 0.900$) while the worst predictive model for physical soil property of subsoil was nitrogen ($R^2 = 0.589$).

Furthermore, according to Figure 4.21 which displays the minimum, mean and maximum values of physical and chemical properties of topsoil, there were some unexpected soil properties occurring including nitrogen (N), phosphorus (P), potassium (K) magnesium (Mg), and sodium (Na). Similarity, according to Figure 4.22 which displays the minimum, mean and maximum values of physical and chemical properties of subsoil, there were some unexpected soil properties occurring including sand, organic matter (OM), phosphorus (P), potassium (K) magnesium (Mg), and sodium (Na). These values show the error of interpolation.

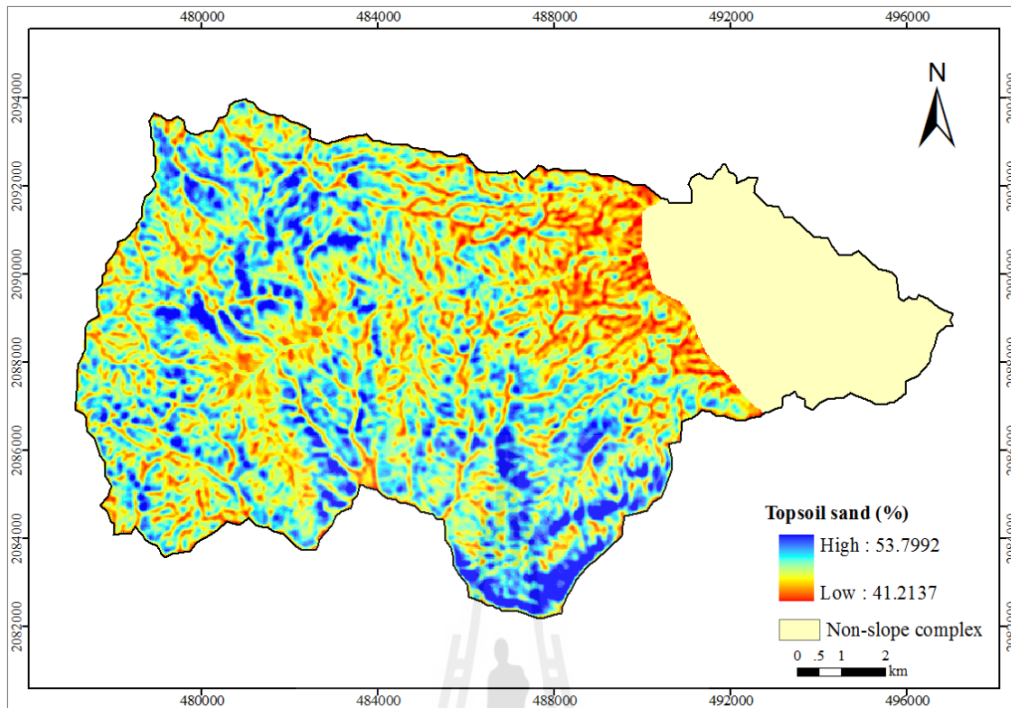
4.5.2 Soil-landscape model by cokriging

In this study, three significant soil forming factors based on VIP values (Table 4.10) were used for soil properties interpolation with sample location using simple cokriging with 4 semivariogram models (Spherical, Exponential, Gaussian and Rational Quadratic). Statistic summary of cokriging interpolation was presented in Table 4.12. Distributions of soil properties prediction of top and sub soil in the slope complex area were presented in Figure 4.23 to Figure 4.35. In addition, summary of minimum, mean and maximum value of each soil properties of top and sub soil in the slope complex area was presented in Table 4.13. Also, Figures 4.36 and 4.37 presented the dispersion of minimum, mean and maximum value of predictive physical and chemical soil properties of top and sub soil in the slope complex area using cokriging, respectively.

Table 4.12 Semivariogram models of cokriging interpolation of each soil property based on the least RMSE.

Soil properties	Topsoil semivariogram models					Subsoil semivariogram models				
	Type	Partial sill	Range	Nugget	RMSE	Type	Partial sill	Range	Nugget	RMSE
Sand	Spherical	3.4026	10274	49.635	7.15	Exponential	6.7061	8243.46	96.877	8.683
Silt	Spherical	2.2722	9644.75	15.511	4.084	Exponential	19.816	307.005	0.974	4.18
Clay	Exponential	0.47502	8242.37	17.959	3.876	Exponential	28.88	8248.06	41.609	7.151
pH	Spherical	0.099921	10270	0.267	0.5581	Spherical	0.27	230.871	0.763	0.5645
OM	Spherical	0.75217	8729.9	4.1958	2.321	Spherical	0.079795	349.02	0.445	0.9191
N	Spherical	0.0032037	403.905	0.041	0.09419	Exponential	0.000089413	361.276	0.479	0.03053
P	Spherical	1.6305	424.738	0.833	2.215	Spherical	0.12049	366.349	0.907	0.5844
K	Gaussian	2785.3	208.185	2.785	59.05	Gaussian	528.39	347.059	0.528	26.22
Ca	Gaussian	69111	212.017	0.797	308.7	Gaussian	65359	133.620	65.359	272.4
Mg	Gaussian	10004	175.918	10.004	123.8	Gaussian	7381.4	272.4	7.381	90.38
Na	Gaussian	657.56	174.844	0.658	27.89	Gaussian	312.17	168.554	0.312	18.2
CEC	Exponential	1.5986	332.899	0.085	3.306	Exponential	13.316	305.823	0.832	3.219
BS	Spherical	21.06	10388.7	44.769	6.799	Spherical	2.748	9631.83	19.897	4.366

(a)



(b)

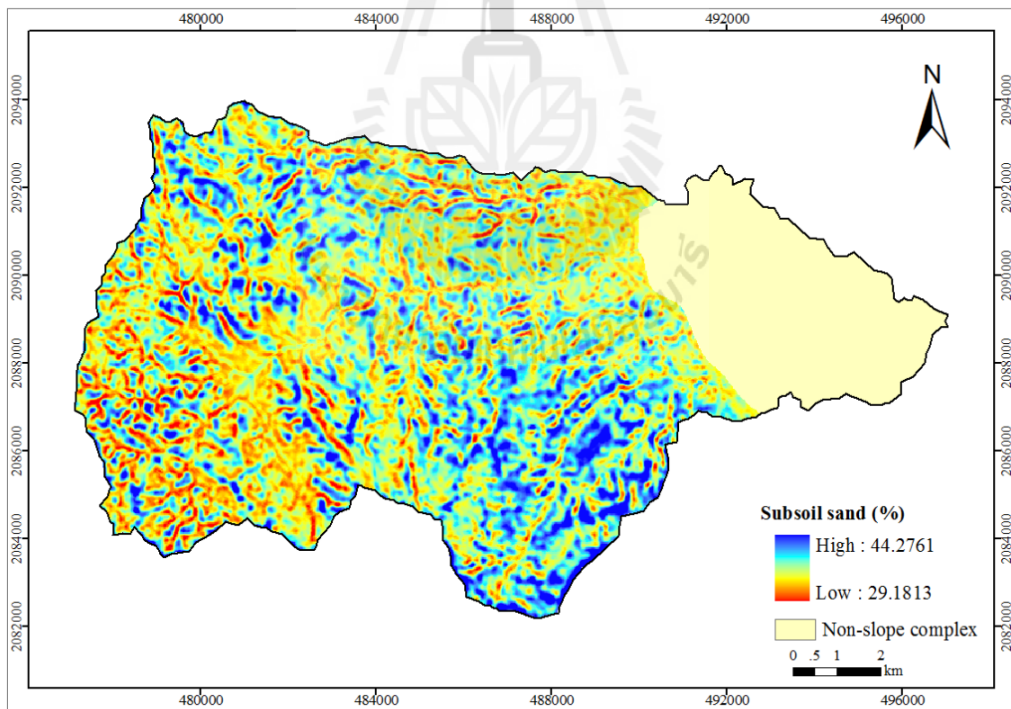
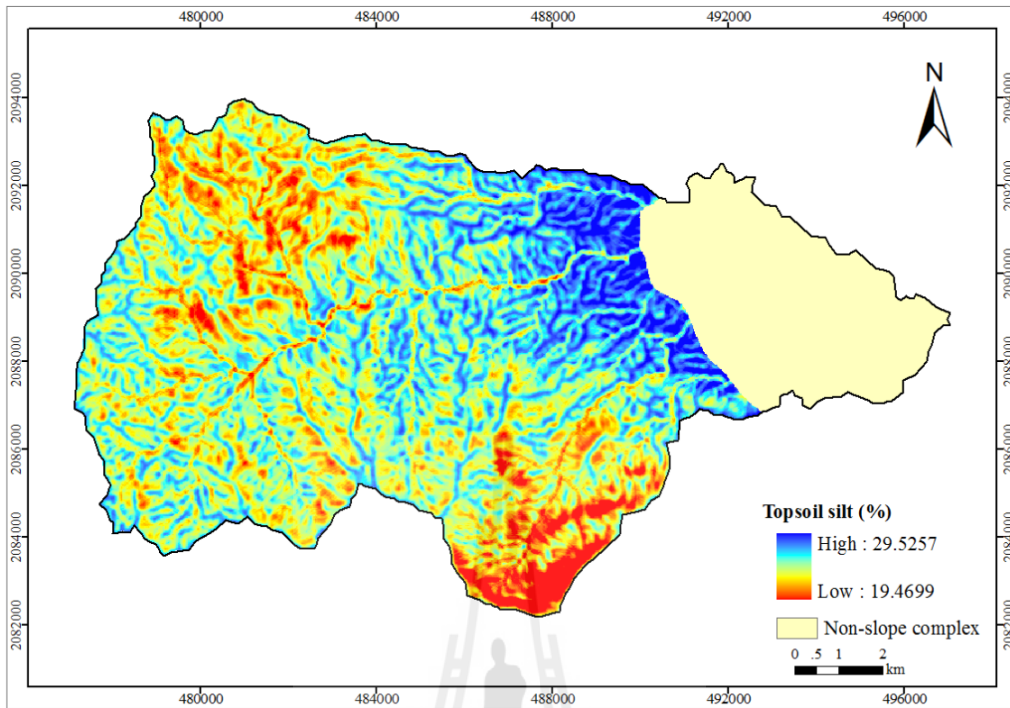


Figure 4.23 Distribution of predictive sand using cokriging: (a) topsoil and (b) subsoil.

(a)



(b)

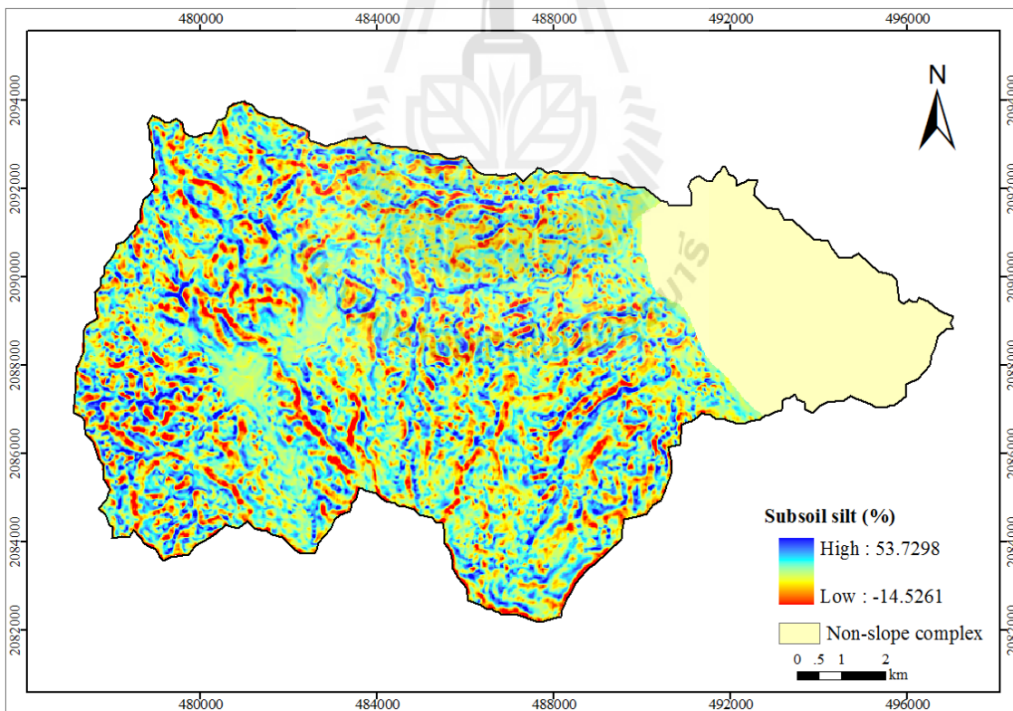
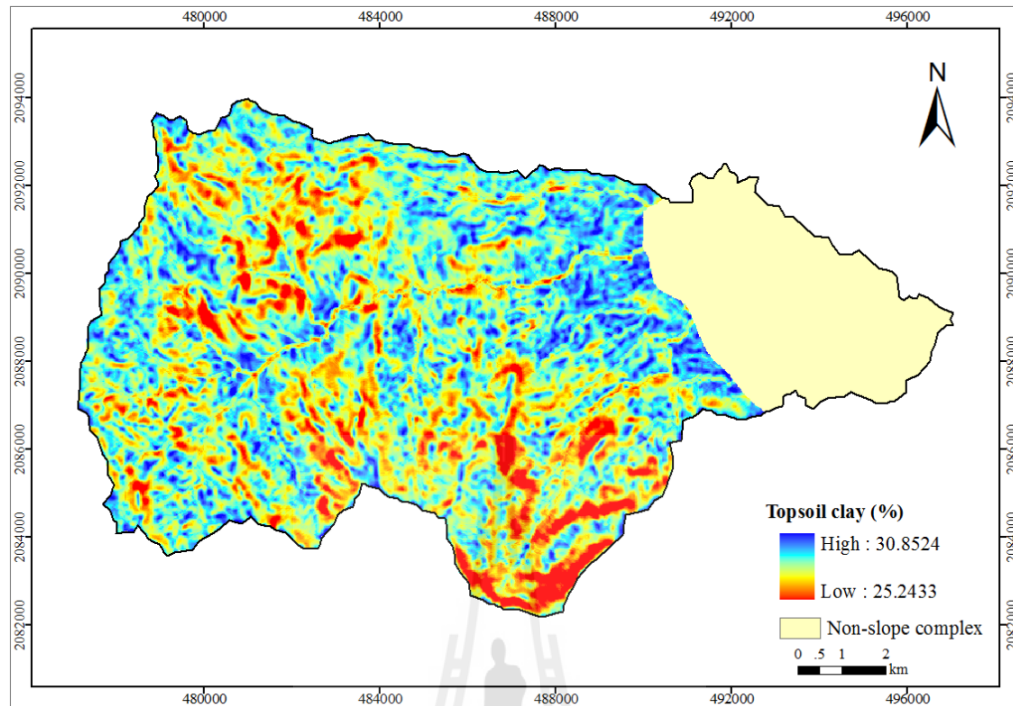


Figure 4.24 Distribution of predictive silt using cokriging: (a) topsoil and (b) subsoil.

(a)



(b)

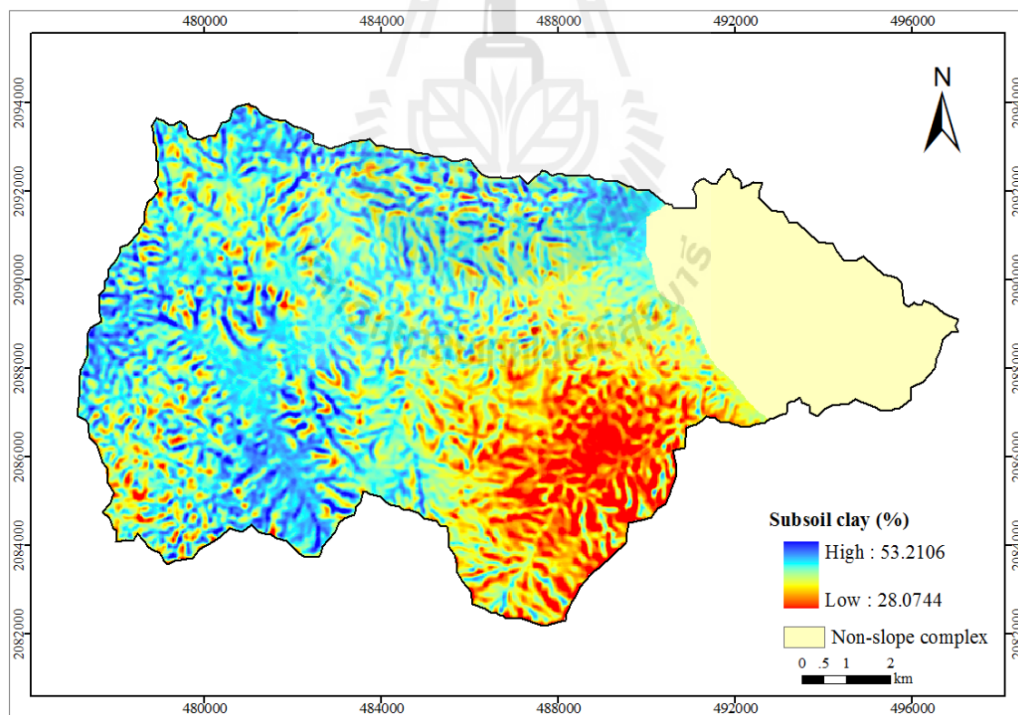
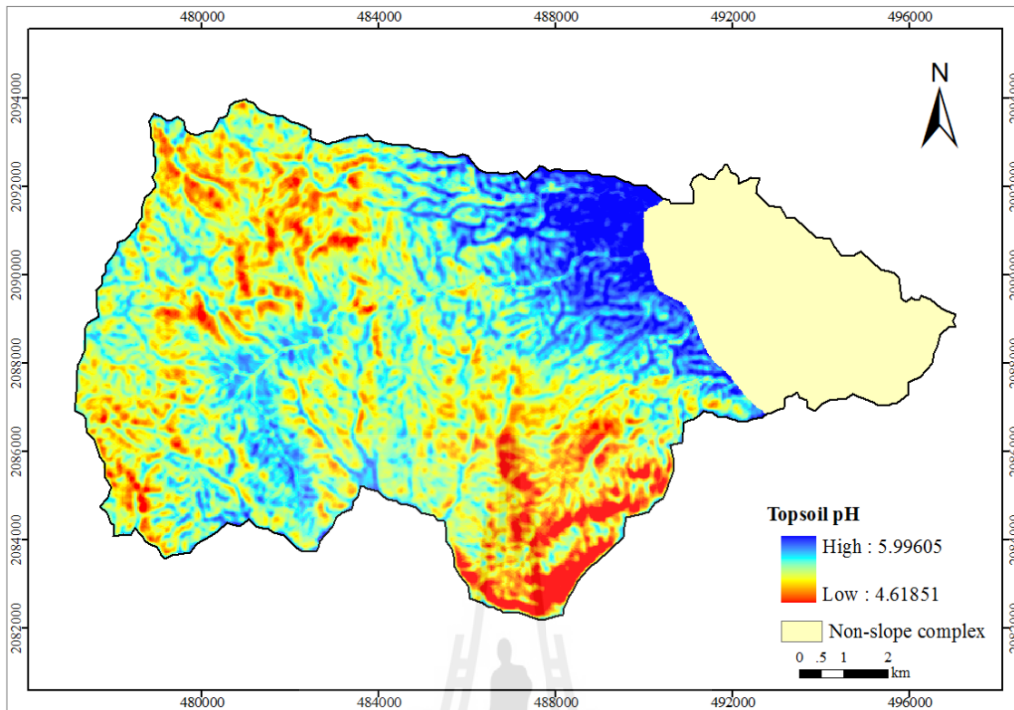


Figure 4.25 Distribution of predictive clay using cokriging: (a) topsoil and (b) subsoil.

(a)



(b)

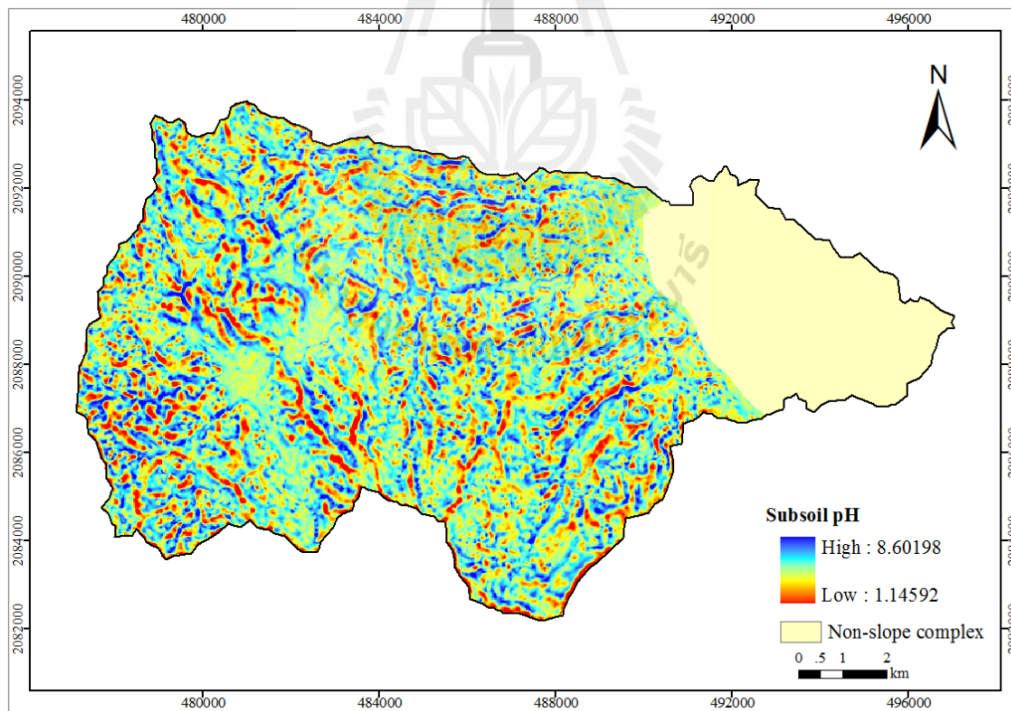
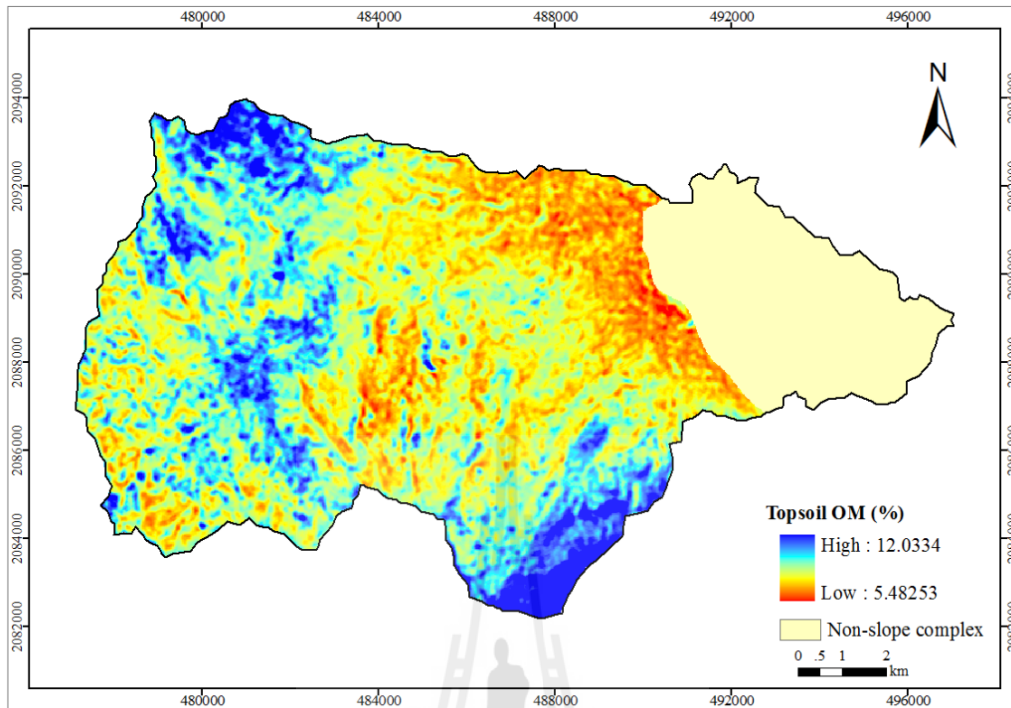


Figure 4.26 Distribution of predictive pH using cokriging: (a) topsoil and (b) subsoil.

(a)



(b)

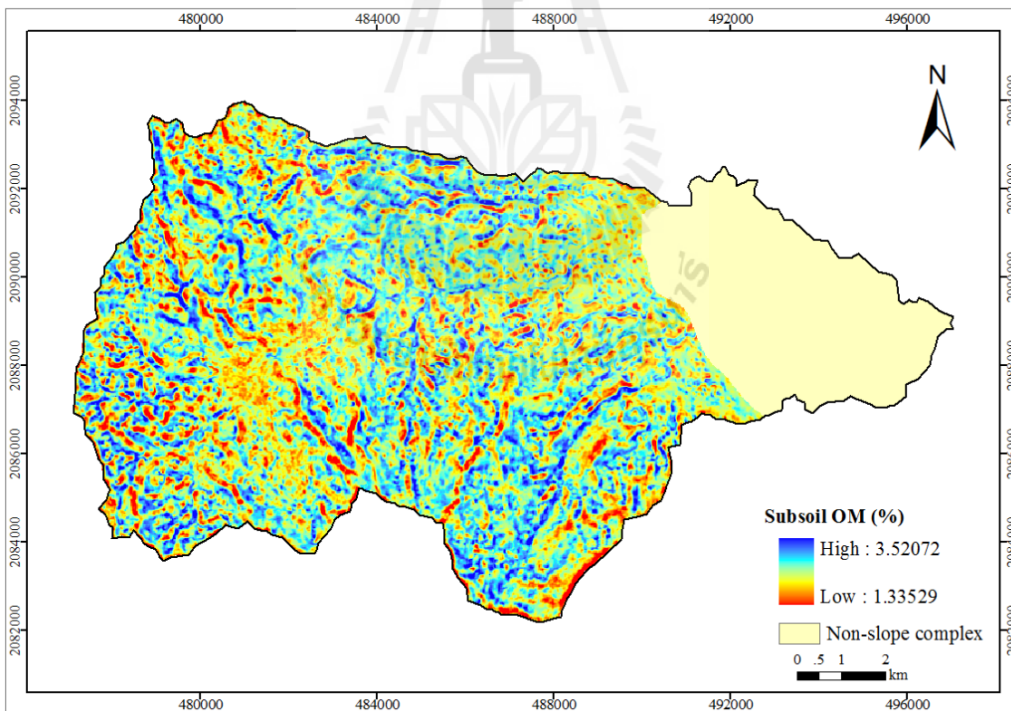
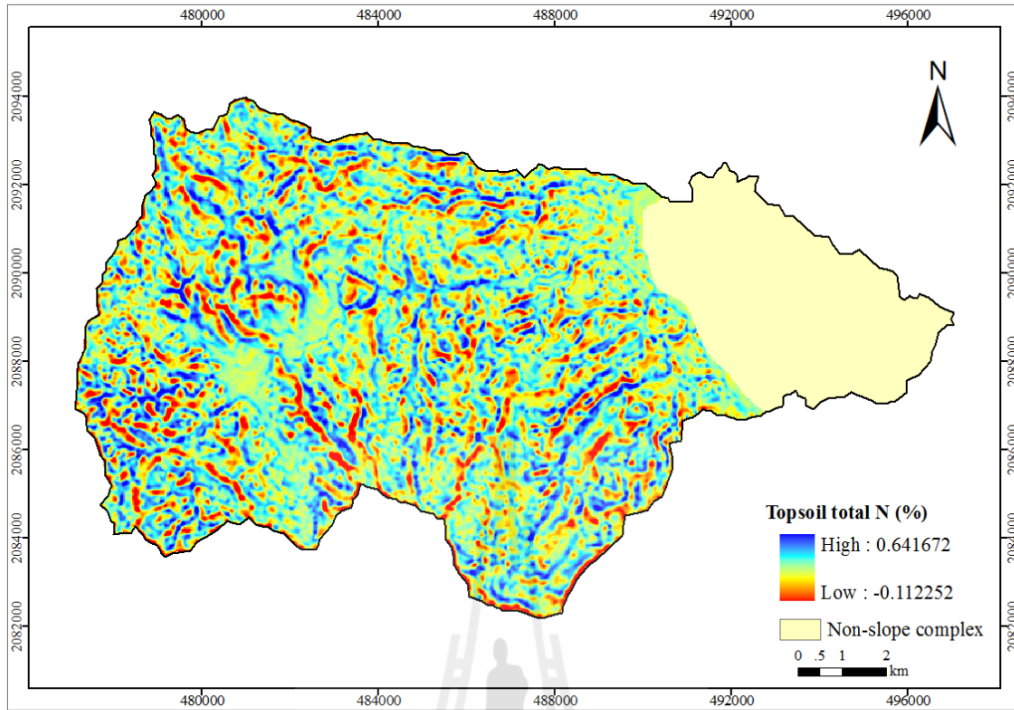


Figure 4.27 Distribution of predictive organic matter using cokriging: (a) topsoil and (b) subsoil.

(a)



(b)

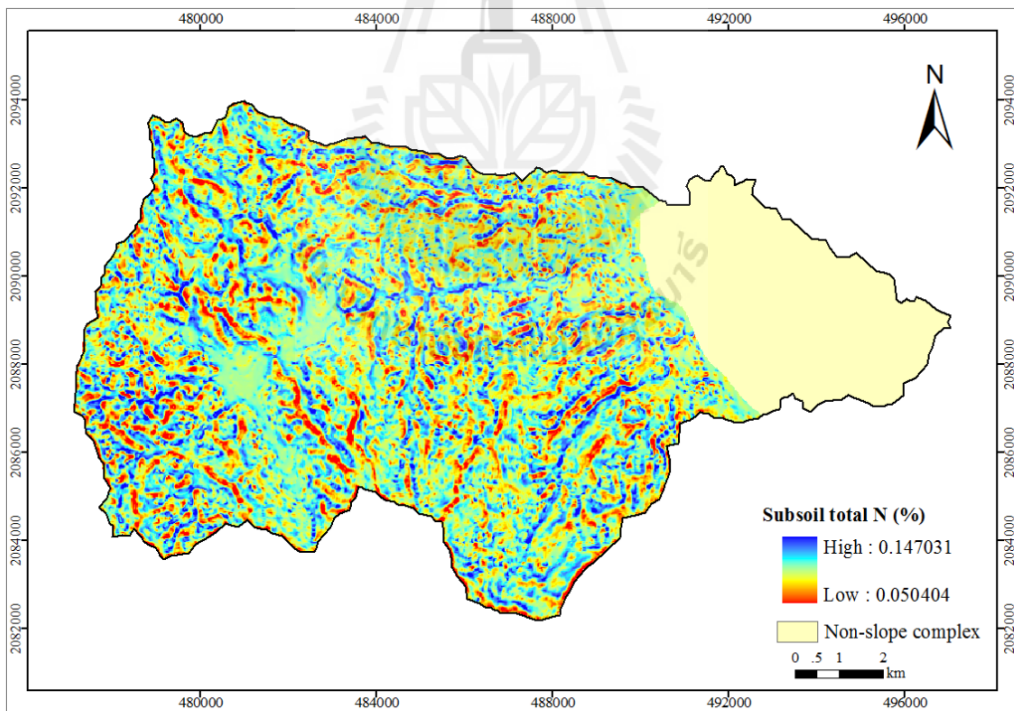
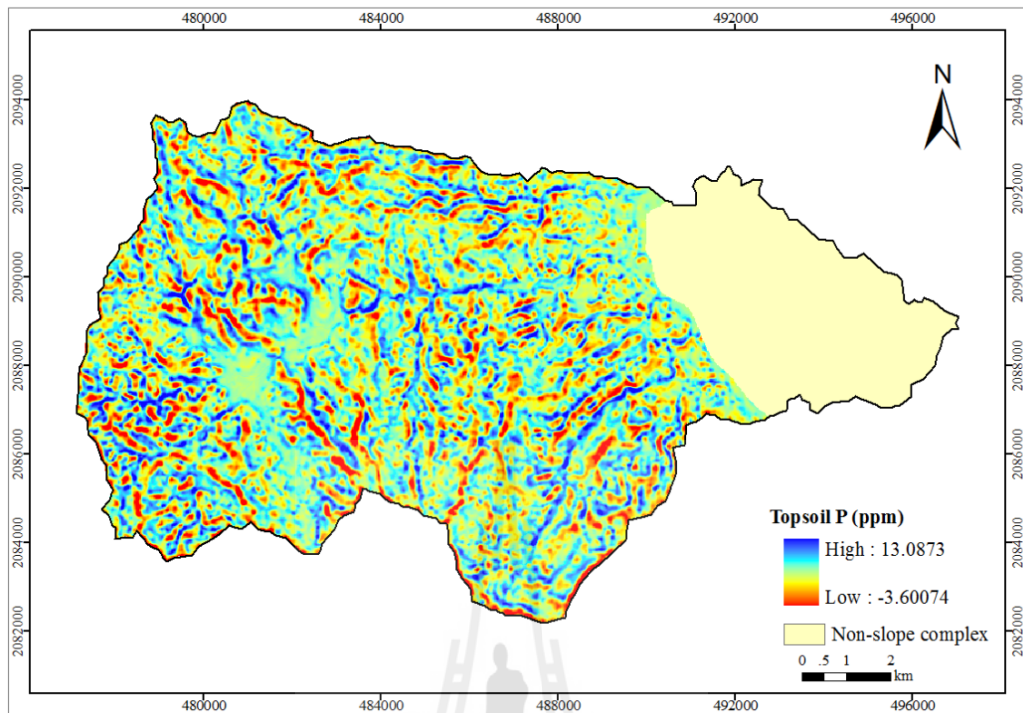


Figure 4.28 Distribution of predictive total nitrogen using cokriging: (a) topsoil and (b) subsoil.

(a)



(b)

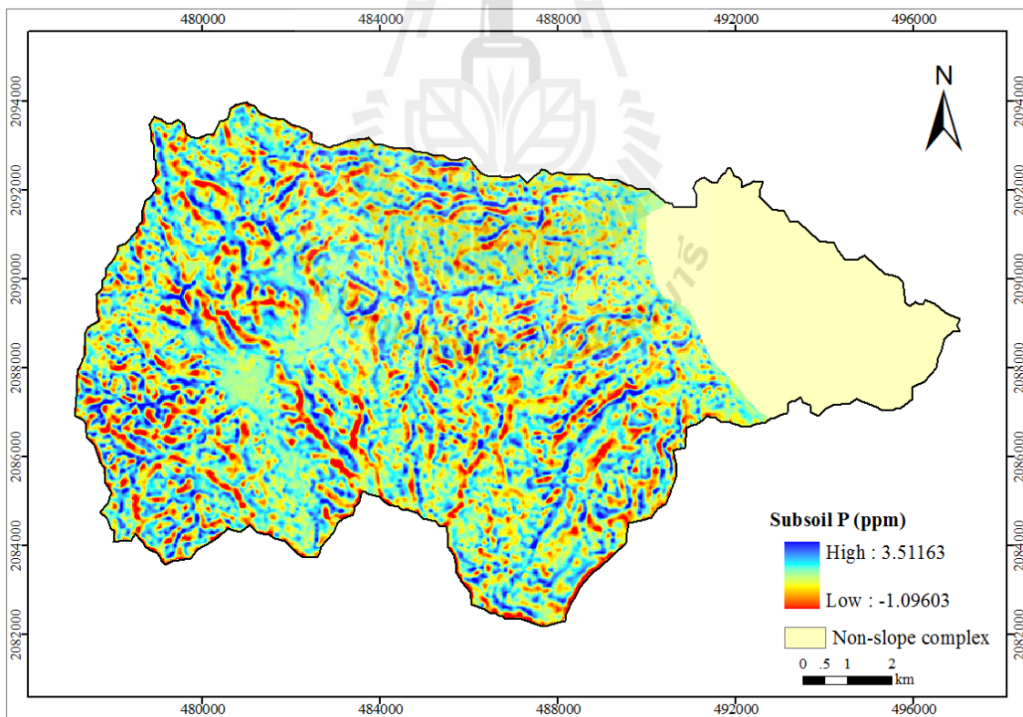
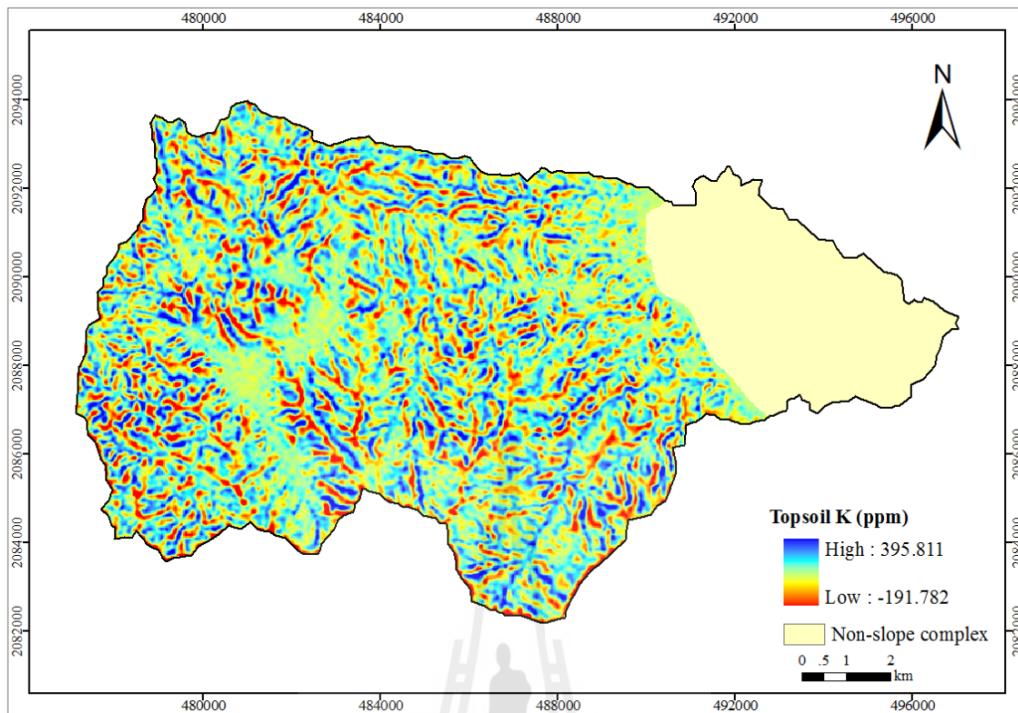


Figure 4.29 Distribution of predictive phosphorus using cokriging: (a) topsoil and (b) subsoil.

(a)



(b)

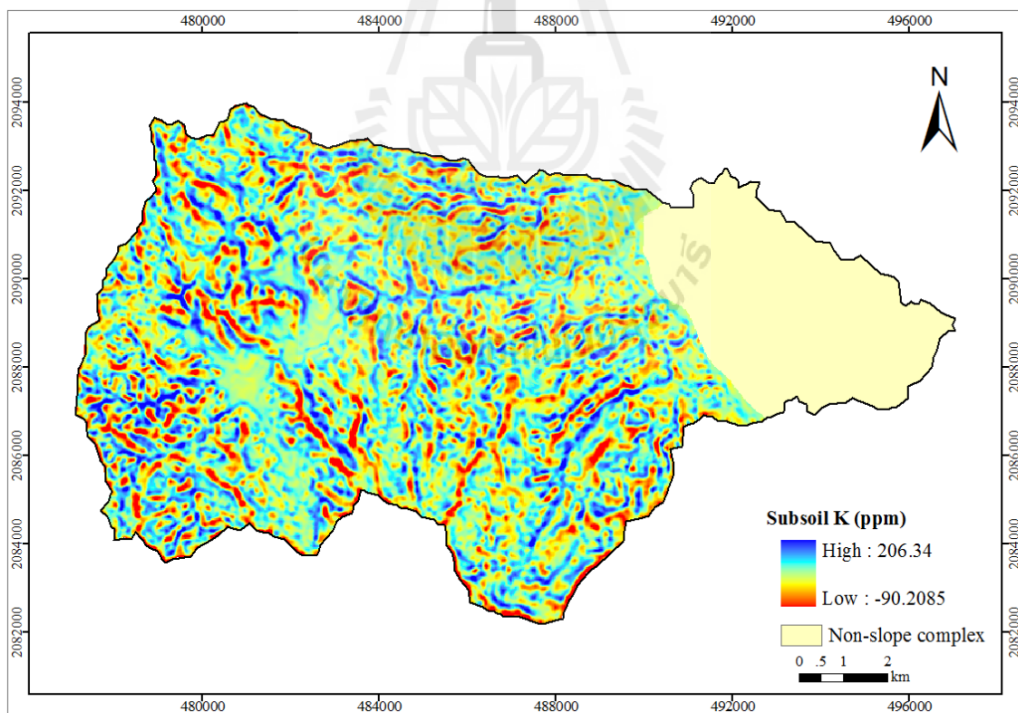
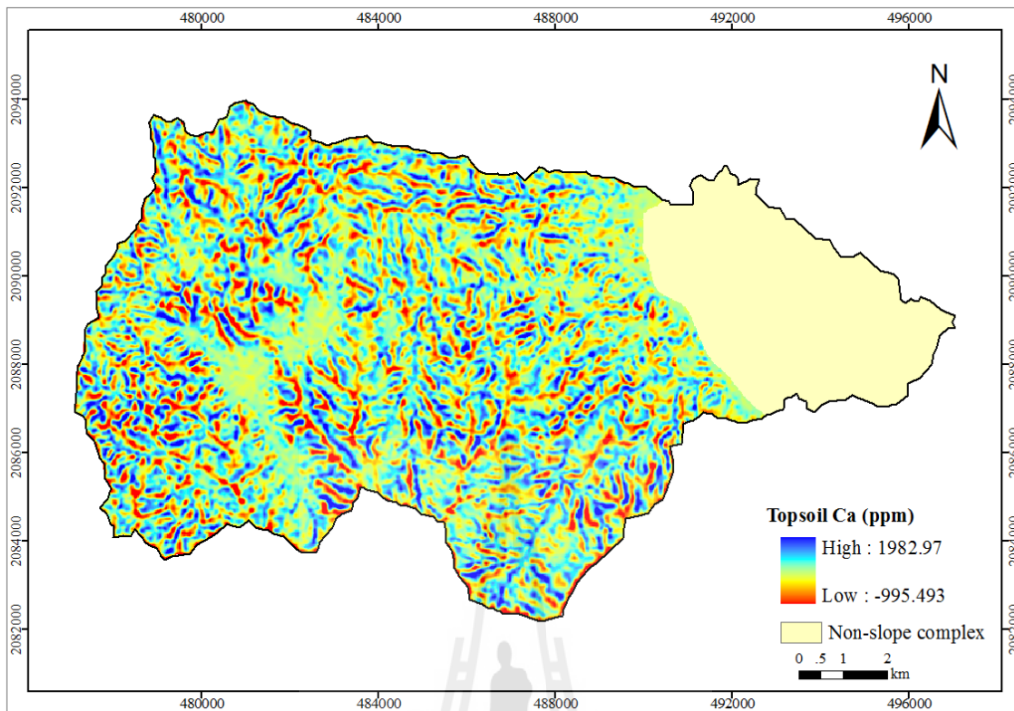


Figure 4.30 Distribution of predictive potassium using cokriging: (a) topsoil and (b) subsoil.

(a)



(b)

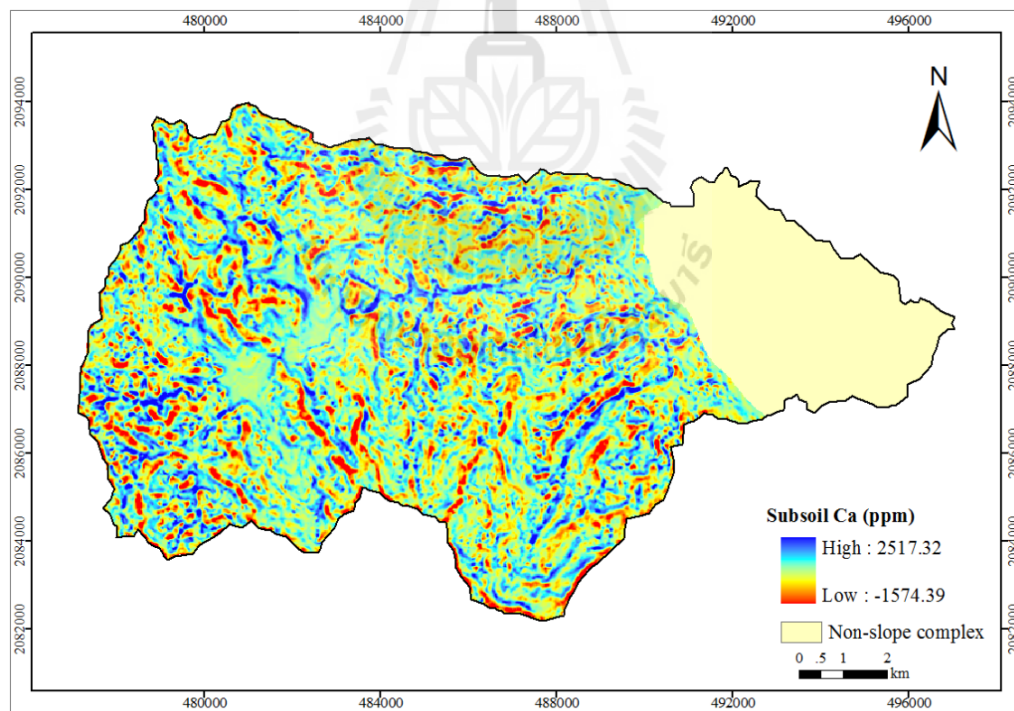
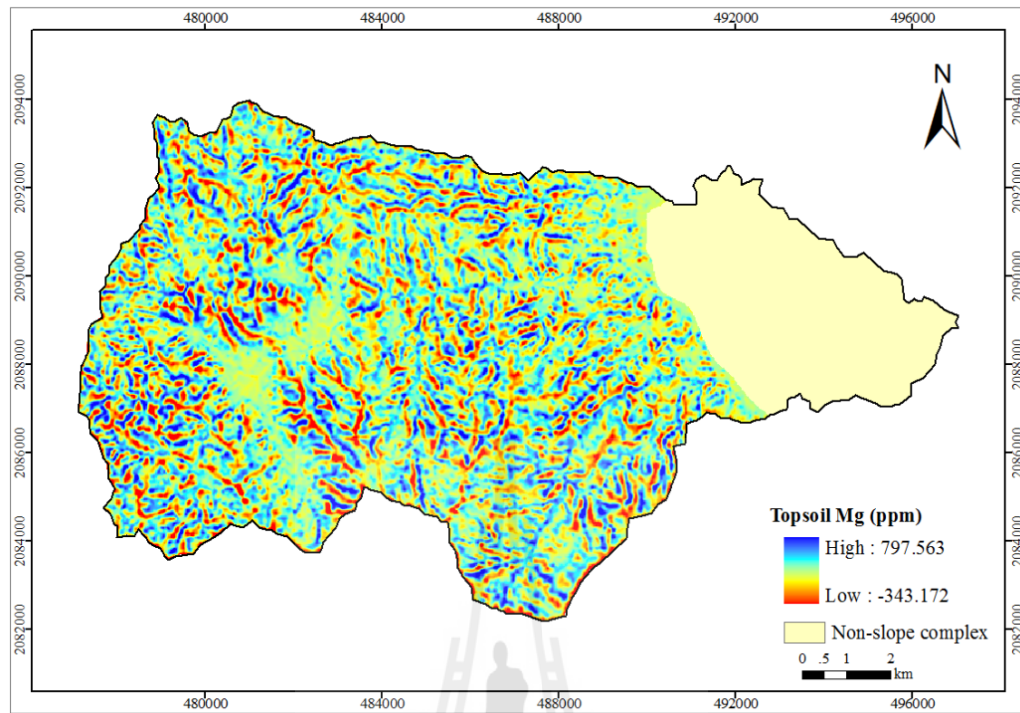


Figure 4.31 Distribution of predictive calcium using cokriging: (a) topsoil and (b) subsoil.

(a)



(b)

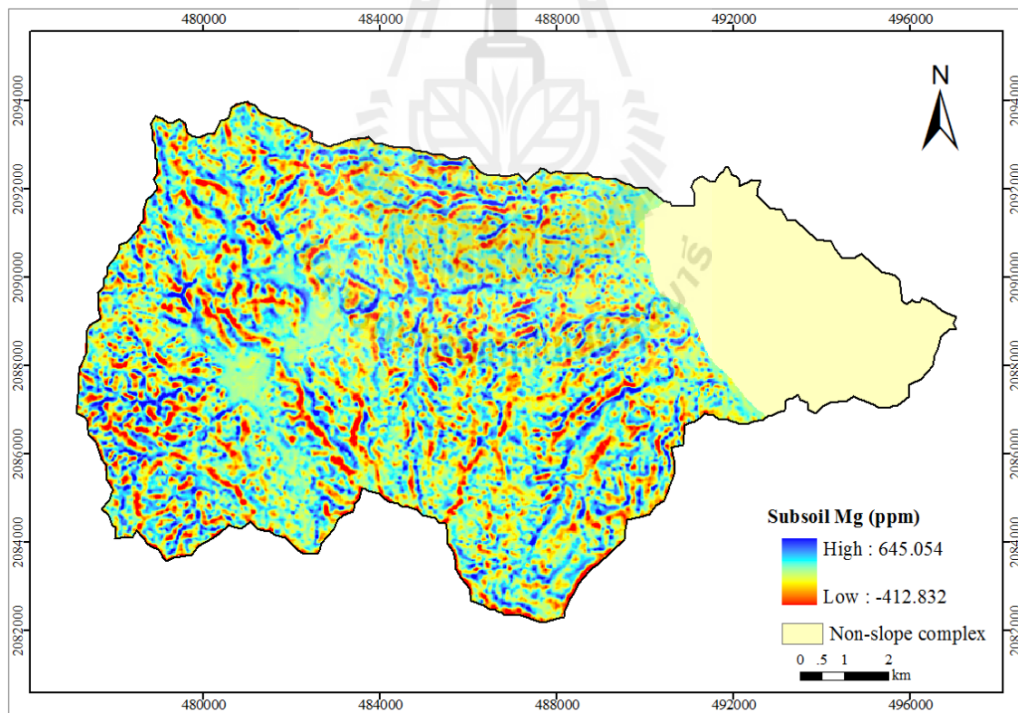
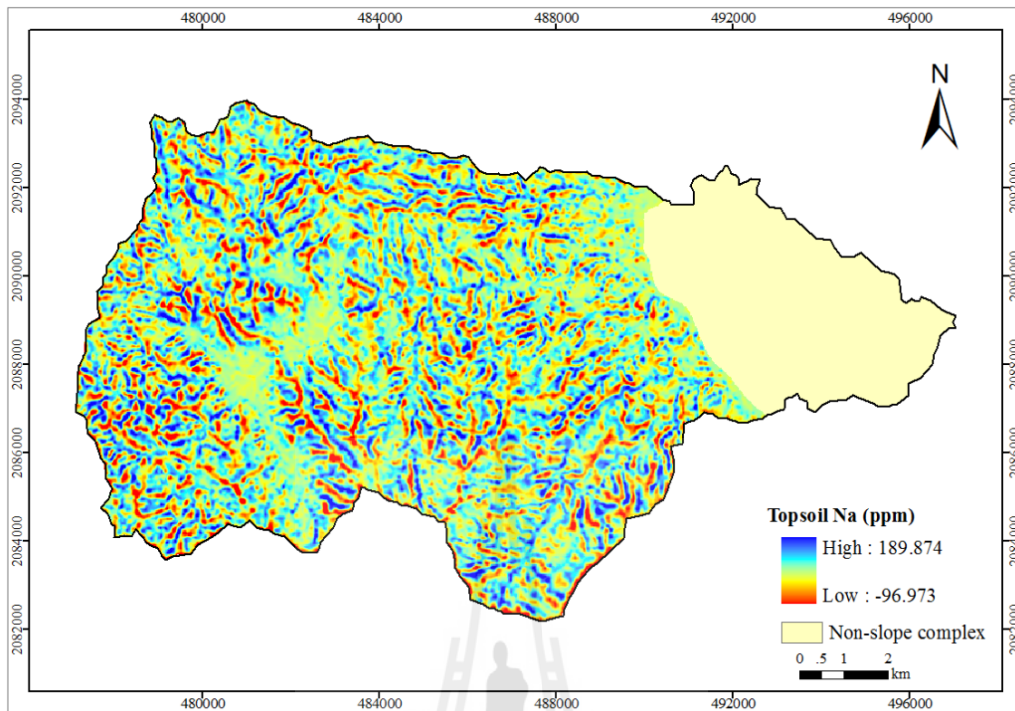


Figure 4.32 Distribution of predictive magnesium using cokriging: (a) topsoil and (b) subsoil.

(a)



(b)

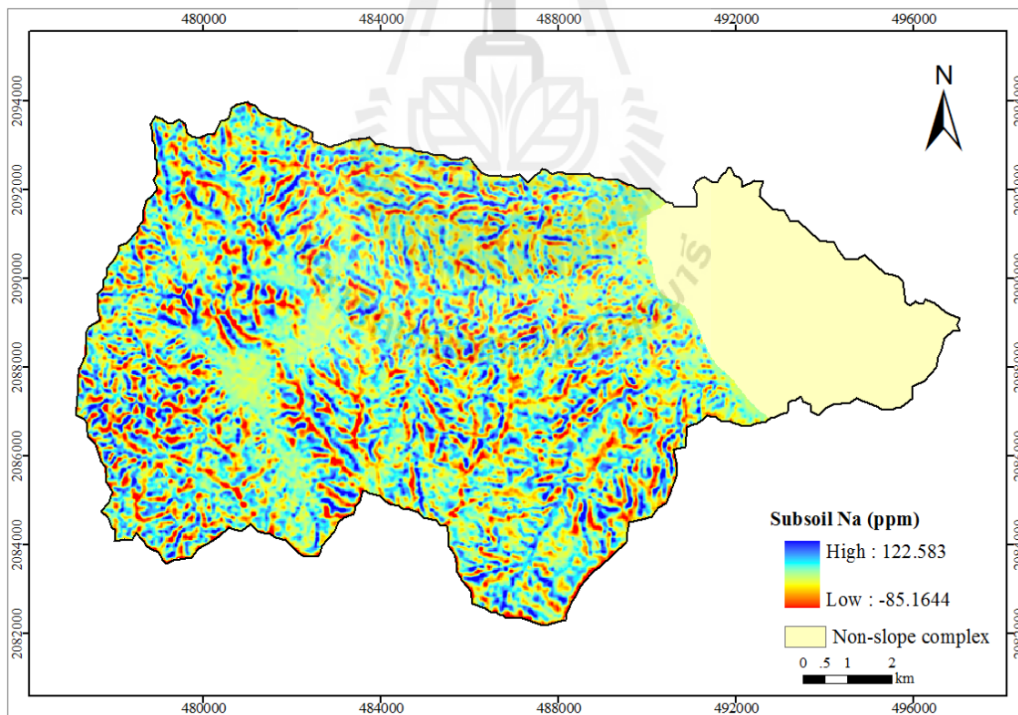
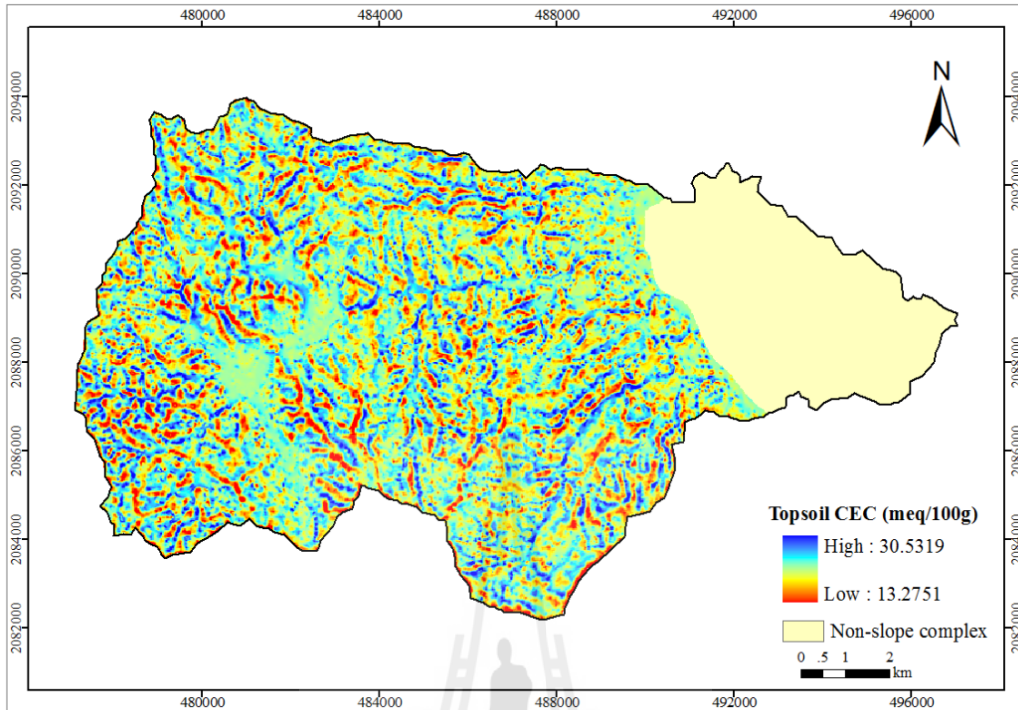


Figure 4.33 Distribution of predictive sodium using cokriging: (a) topsoil and (b) subsoil.

(a)



(b)

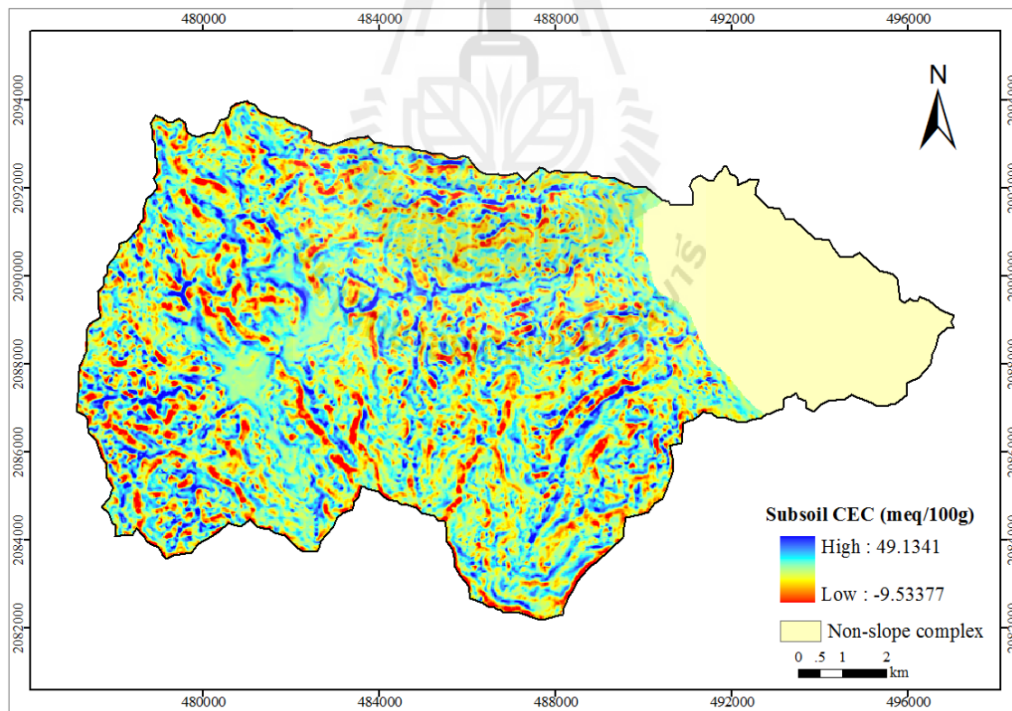
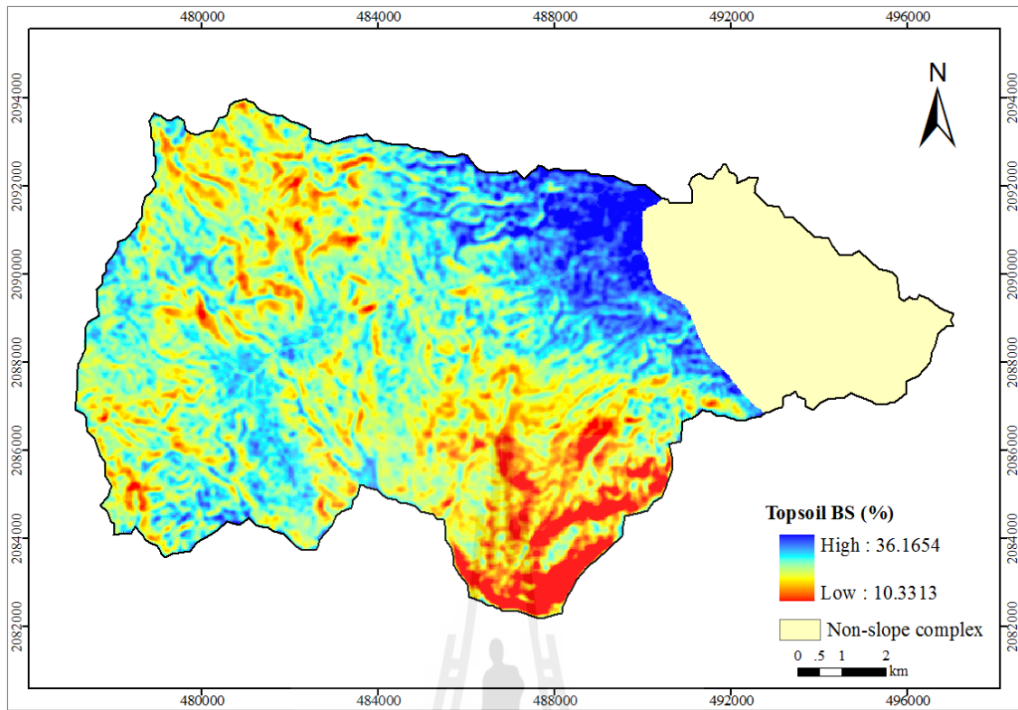


Figure 4.34 Distribution of predictive cation exchange capacity using cokriging:

(a) topsoil and (b) subsoil.

(a)



(b)

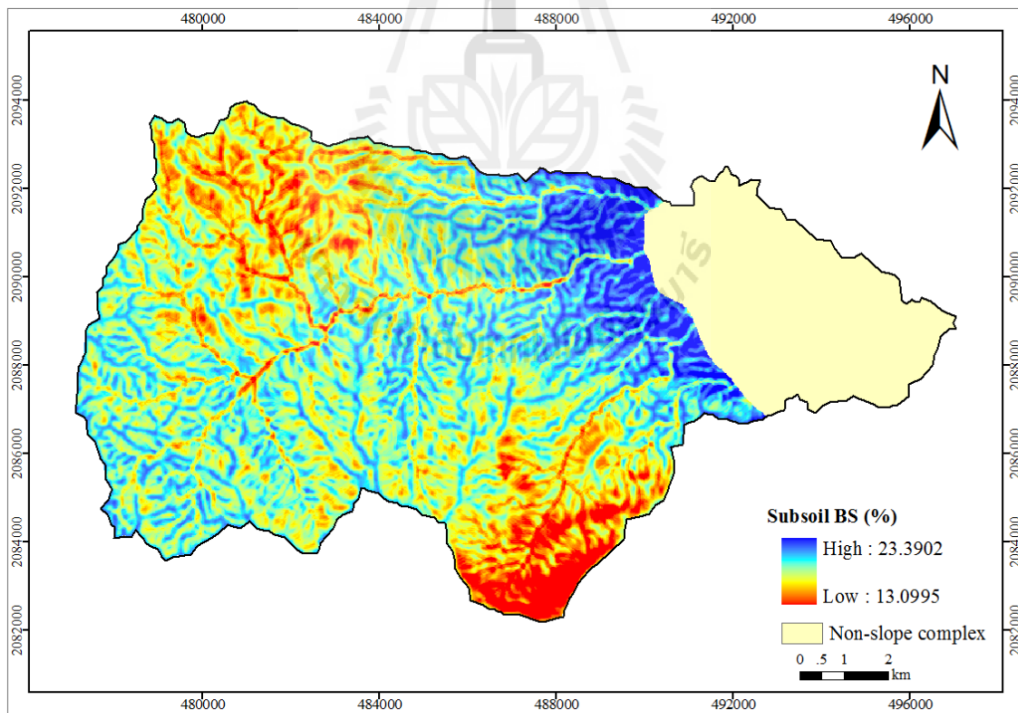


Figure 4.35 Distribution of predictive base saturation using cokriging: (a) topsoil and (b) subsoil.

Table 4.13 Summary of predictive value of each soil property using cokriging methods.

Soil properties	Topsoil			Subsoil		
	Minimum	Mean	Maximum	Minimum	Mean	Maximum
Sand (%)	41.21	45.55	53.80	29.18	35.22	44.28
Silt (%)	19.47	25.74	29.53	-14.53	21.40	53.73
Clay (%)	25.24	28.83	30.85	28.07	43.59	53.21
pH	4.62	5.42	6.00	1.15	5.24	8.60
OM (%)	5.48	7.31	12.03	1.34	2.44	3.52
N (%)	-0.11	0.28	0.64	0.05	0.10	0.15
P (ppm)	-3.60	5.00	13.09	-1.10	1.32	3.51
K (ppm)	-191.78	141.46	395.81	-90.21	72.20	206.34
Ca (ppm)	-995.49	695.32	1982.97	-1574.39	393.91	2517.32
Mg (ppm)	-343.17	301.90	797.56	-412.83	149.92	645.05
Na (ppm)	-96.97	65.66	189.87	-85.16	32.73	122.58
CEC (meq/100g soil)	13.28	23.31	30.53	-9.53	17.69	49.13
BS (%)	10.33	27.43	36.17	13.10	19.41	23.39

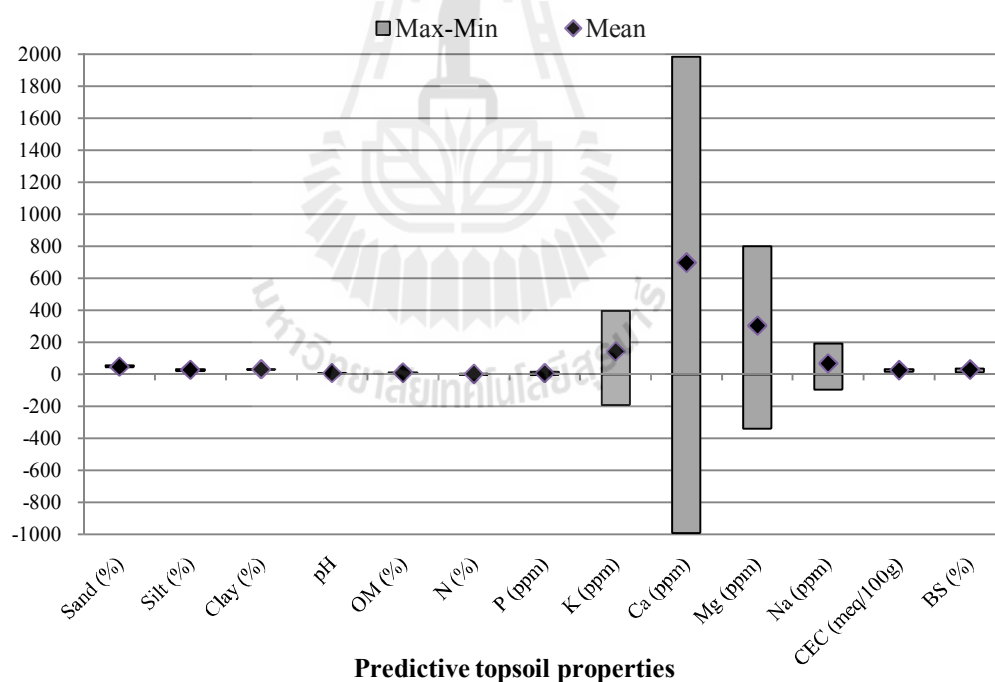


Figure 4.36 Dispersion of minimum, mean and maximum value of predictive physical and chemical topsoil properties using cokriging.

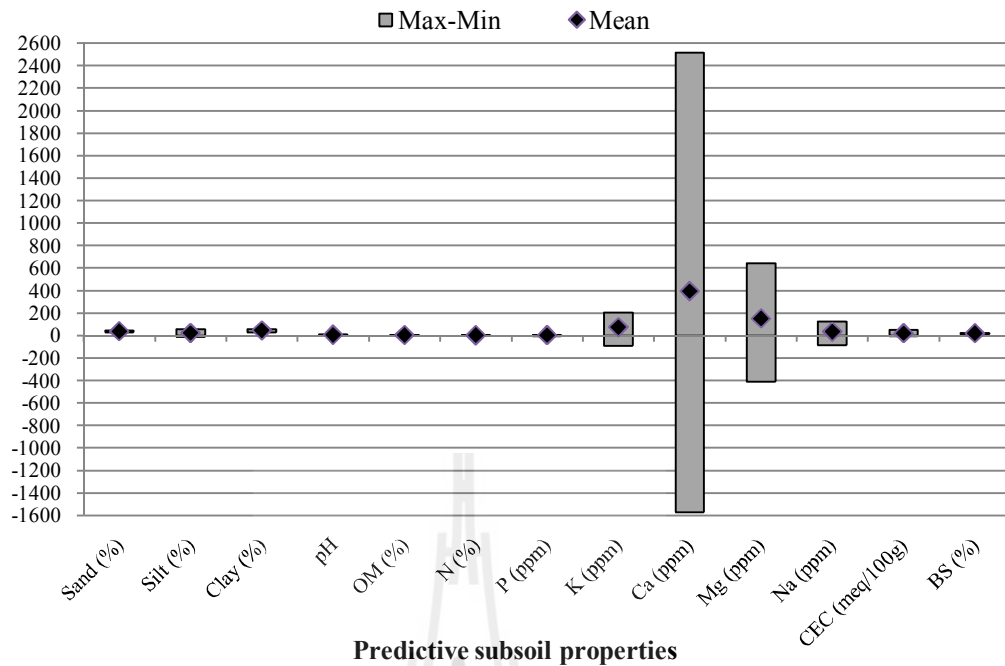


Figure 4.37 Dispersion of minimum, mean and maximum value of predictive physical and chemical subsoil properties using cokriging.

Basically, the type of semivariogram plays important role in cokriging interpolation. According to Table 4.12 an optimum semivariogram type for physical soil properties of topsoil based on RMSE was the Spherical model while an optimum semivariogram type for chemical soil properties of topsoil based on RMSE was the Spherical model. At the same time an optimum semivariogram type for physical soil properties of subsoil based on RMSE was the Exponential model while an optimum semivariogram type for chemical soil properties of subsoil based on RMSE were the Spherical or Gaussian models.

In addition, according to the least RMSE from semivariogram model of each top and sub soil properties, the best predictive model for physical soil property of topsoil was clay (3.88) while the worst predictive model for physical soil property

of topsoil was sand (7.15). At the same time, the best predictive model for physical soil property of subsoil was silt (4.18) while the worst predictive model for physical soil property of subsoil was sand (8.68). In the mean time the best predictive model for chemical property of top and sub soil were nitrogen (0.0942 and 0.0305, respectively), while the worst predictive model for chemical property of top and sub soil were calcium (308.7 and 272.4, respectively).

Furthermore, according to Figure 4.36 which displays the minimum, mean and maximum values of physical and chemical properties of topsoil, there were some unexpected soil properties occurred including nitrogen (N), phosphorus (P), potassium (K), calcium (Ca), magnesium (Mg), and sodium (Na). Similarity, according to Figure 4.37 which was displayed about minimum, mean and maximum values of physical and chemical properties of subsoil, there were some unexpected soil properties occurred including silt, phosphorus (P), potassium (K) calcium (Ca), magnesium (Mg), sodium (Na) and cation exchange capacity (CEC). These values show the error of interpolation.

4.6 Accuracy assessment

The predictive physical and chemical soil properties from PLS and cokriging interpolation are here used to compare with in situ soil properties of validating datasets with 20 sampling points using Mean Error (ME), Root Mean Square Error (RMSE) and Normalized Root Mean Square Error (NRMSE). The results of three accuracy assessment were summarized as shown in Table 4.14 to Table 4.16. Details of all accuracy assessment were presented in Appendix C (Tables C.1, C.2, C.3 and C.4).

Table 4.14 Summary of Mean Error (ME) for soil properties prediction using PLS and cokriging interpolation.

Soil Properties	PLS		Cokriging	
	Topsoil	Subsoil	Topsoil	Subsoil
Sand (%)	-0.0250	2.0186	-1.1138	-0.5664
Silt (%)	0.0196	0.7776	1.1763	1.2045
Clay (%)	-0.3933	-3.1789	0.4358	-0.2781
pH	-0.1199	-0.1323	0.0317	-0.0018
OM (%)	0.8838	0.5269	1.1663	0.8852
N (%)	0.0128	0.0085	0.0451	0.0111
P (ppm)	0.3302	0.3361	0.8108	0.2740
K (ppm)	0.2694	0.8770	13.3315	2.3825
Ca (ppm)	-41.4536	-10.1779	80.6075	9.4340
Mg (ppm)	4.5566	2.0290	27.3555	8.6155
Na (ppm)	2.4326	-2.0673	9.7065	1.7340
CEC (meq/100g)	1.3378	-0.4318	1.7451	-0.3678
BS (%)	-1.4343	0.4961	0.7309	1.6863

Table 4.15 Summary of Root Mean Square Error (RMSE) for soil properties prediction using PLS and cokriging interpolation.

Soil Properties	PLS		Cokriging	
	Topsoil	Subsoil	Topsoil	Subsoil
Sand (%)	3.5314	5.4341	4.6949	6.3468
Silt (%)	1.7942	2.6090	2.8340	4.7638
Clay (%)	1.9467	5.0848	2.6172	5.8039
pH	0.2647	0.3739	0.3396	0.5046
OM (%)	1.8023	0.8355	2.5575	1.1763
N (%)	0.0814	0.0383	0.1053	0.0458
P (ppm)	2.0079	0.6029	2.4447	0.4688
K (ppm)	19.5839	22.2664	42.7464	21.1701
Ca (ppm)	144.8099	70.0650	241.8665	235.1639
Mg (ppm)	46.0794	32.9234	93.6241	68.7919
Na (ppm)	10.8676	8.7299	24.9383	13.4322
CEC (meq/100g)	3.1331	2.5651	3.8178	3.2060
BS (%)	4.8177	2.7850	6.2614	4.0221

Table 4.16 Summary of Normalized Root Mean Square Error (NRMSE) for soil properties prediction using PLS and cokriging interpolation.

Soil Properties	PLS		Cokriging	
	Topsoil	Subsoil	Topsoil	Subsoil
Sand	0.2172	0.2174	0.2887	0.2539
Silt	0.2336	0.2305	0.3690	0.4208
Clay	0.1783	0.2471	0.2397	0.2820
pH	0.1961	0.2597	0.2516	0.3505
OM	0.2387	0.2648	0.3387	0.3728
N	0.2315	0.2430	0.2993	0.2902
P	0.2477	0.3610	0.3015	0.2807
K	0.1886	0.1846	0.4117	0.1755
Ca	0.1748	0.1793	0.2920	0.6018
Mg	0.1873	0.1883	0.3806	0.3935
Na	0.1535	0.1821	0.3522	0.2802
CEC	0.2230	0.1794	0.2717	0.2242
BS	0.2085	0.1979	0.2710	0.2857

As shown in Table 4.14 according to accuracy assessment using ME, it was found that the best predictive soil properties of topsoil and subsoil using PLS were nitrogen (N) and nitrogen (N), respectively. In contrast, the worst predictive soil properties of topsoil and subsoil using PLS were calcium (Ca) and calcium (Ca), respectively. At the same time the best predictive soil properties of topsoil and subsoil using cokriging were pH and pH, respectively. In contrast, the worst predictive soil properties of topsoil and subsoil using cokriging were calcium (Ca) and calcium (Ca), respectively.

In addition, according to accuracy assessment using RMSE (Table 4.15), it was found that the best predictive soil properties of topsoil and subsoil using PLS were nitrogen (N) and nitrogen (N), respectively. In contrast, the worst predictive soil properties of topsoil and subsoil using PLS were calcium (Ca) and calcium (Ca), respectively. At the same time the best predictive soil properties of topsoil and subsoil using cokriging were nitrogen (N) and nitrogen (N), respectively. In contrast, the

worst predictive soil properties of topsoil and subsoil using cokriging were calcium (Ca) and calcium (Ca), respectively.

Furthermore, according to accuracy assessment using NRMSE (Table 4.16), it was found that the best predictive soil properties of topsoil and subsoil using PLS were sodium (Na) and calcium (Ca), respectively. In contrast, the worst predictive soil properties of topsoil and subsoil using PLS were phosphorus (P) and phosphorus (P), respectively. At the same time the best predictive soil properties of topsoil and subsoil using cokriging were clay and potassium (K), respectively. In contrast, the worst predictive soil properties of topsoil and subsoil using cokriging were potassium (K) and calcium (Ca), respectively.

In summary, ME value provides positive (overestimation) or negative (underestimation) average error between an estimated value and an observed value while RMSE provides absolute average error between an estimated value and an observed value. Both error measurements have a measured unit. These values are not appropriate for accuracy assessment comparison when a measured unit is different. In contrast, NRMSE is a normalized RMSE value of each soil property without a measured unit. This value is appropriate for accuracy assessment comparison.

4.7 Optimum model for soil property prediction

An optimum model for physical and chemical soil property was identified based on NRMSE value from of each model (PLS and cokriging) in each soil property. An optimum model for soil properties prediction in slope complex area was identified as shown in Table 4.17.

Table 4.17 Optimum model for soil properties prediction based on NRMSE.

Soil properties	Topsoil		Subsoil	
	Method	NRMSE	Method	NRMSE
Sand	PLS	0.2172	PLS	0.2174
Silt	PLS	0.2336	PLS	0.2305
Clay	PLS	0.1783	PLS	0.2471
pH	PLS	0.1961	PLS	0.2597
OM	PLS	0.2387	PLS	0.2648
N	PLS	0.2315	PLS	0.2430
P	PLS	0.2477	Cokriging	0.2807
K	PLS	0.1886	Cokriging	0.1755
Ca	PLS	0.1748	PLS	0.1793
Mg	PLS	0.1873	PLS	0.1883
Na	PLS	0.1535	PLS	0.1821
CEC	PLS	0.2230	PLS	0.1794
BS	PLS	0.2085	PLS	0.1979

As shown in Table 4.17, an optimum model for almost all soil properties of topsoil and subsoil should be PLS regression model. This result might come from a number of factors used for modeling. In fact, cokriging model used only 3 significant factors from the 10 factors of PLS model and the number of sample points for cokriging interpolation was rather low. However, cokriging model provided a better result of phosphorus (P) and potassium (K) prediction of subsoil than PLS model.

4.8 The use of soil property prediction

This section focuses on the use of soil properties prediction in various aspects including (1) visualization of soil texture, (2) classification of soil texture using Expert System, (3) soil property of landform extraction by zonal statistics and (4) soil fertility assessment.

4.8.1 Visualization of soil texture

Color composite image was here used to visualize three predictive soil texture fractions (%Sand, %Silt and %Clay) of topsoil and subsoil. In practice, firstly

predictive value of percent of sand, silt and clay were separately normalized into 0-100% scale and then they are converted to 0-255 image and assigned red, green and blue color for sand, silt and clay, respectively. The result of soil texture visualization of topsoil and subsoil was displayed in Figure 4.38. This data can be further used for soil texture class extraction using digital image processing software. Herewith image classification algorithms include unsupervised classification (for example maximum likelihood), unsupervised classification (such as clustering) or hybrid classification such as (e.g. Expert System). In this study Expert System of ERDAS Imagine was used to extract soil texture class as describe in the next section.

4.8.2 Classification of soil texture using Expert System

Soil texture classification using Expert System of ERDAS Imagine software was here conducted based on criteria of USDA soil texture classification by Soil Survey Division Staff (1993). Basically, three steps are required for Expert System classifications which include hypothesis definition, rule assignment and condition setting. Herein, standard soil texture classes of USDA including (1) Sand, (2) Loamy sand, (3) Sandy loam, (4) Loam, (5) Silt loam, (6) Silt, (7) Sandy clay loam, (8) Clay loam, (9) Silty clay loam, (10) Sandy clay, (11) Silty clay and (12) Clay were firstly defined as hypothesis for Expert System classification. Then, specific rules and conditions for soil texture classification were assigned for each soil texture class based on criteria which were suggested by USDA Soil Survey Division Staff (1993) as shown in Table 4.18. Schematic diagram of decision tree for soil texture classification under Knowledge Engineer of Expert System was presented in Figure 4.39.

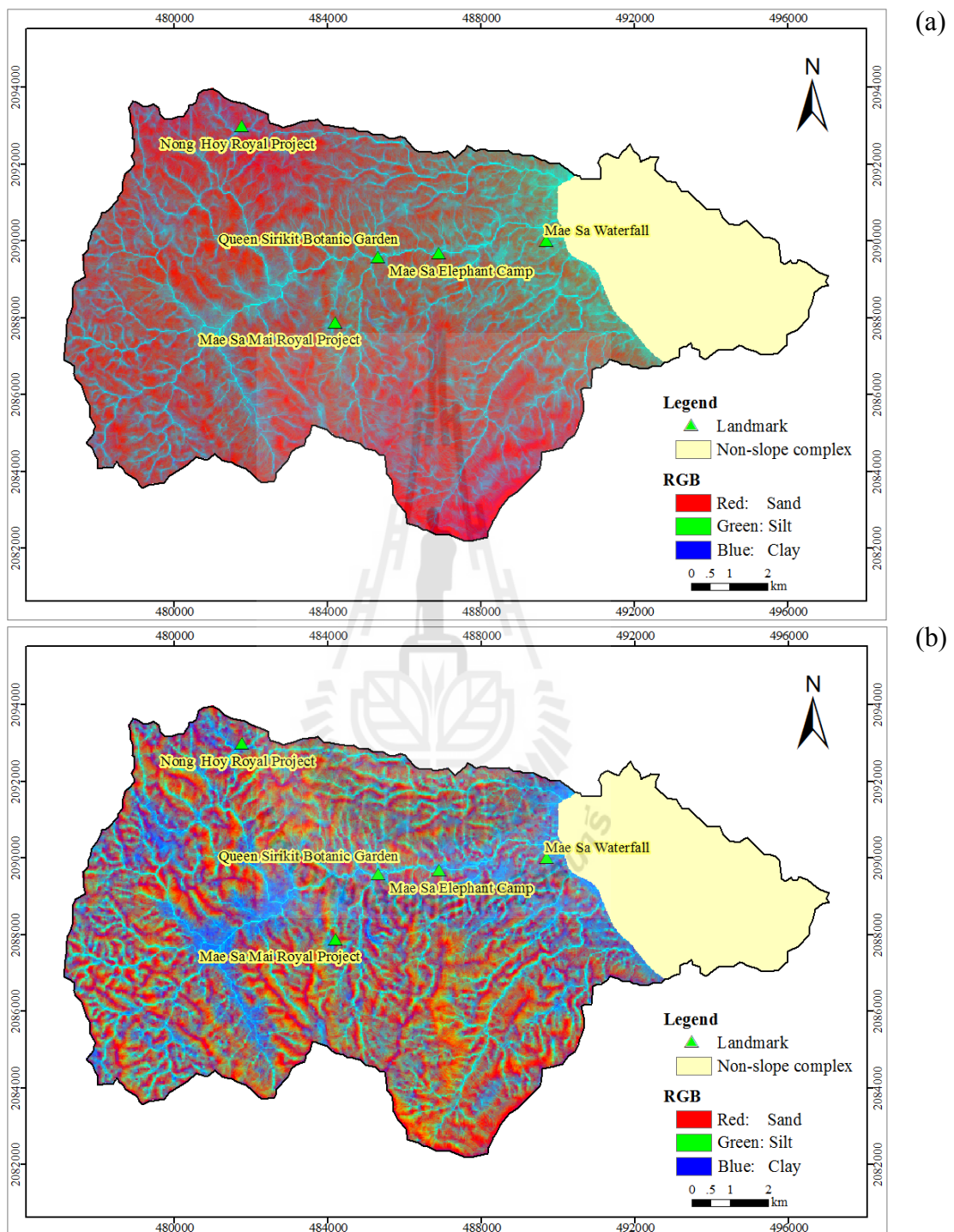


Figure 4.38 Texture fractions visualized using a color composite: (a) topsoil and (b) subsoil.

In this study, predictive physical soil properties (%Sand, %Silt and %Clay) of topsoil and subsoil were firstly normalized into 0-100% scale and then used for soil texture classification under Knowledge Classification of Expert System of Erdas Imagine. Distribution of soil texture classes of topsoil and subsoil are displayed in Figure 4.40. Also, area and percentage of soil texture classes of topsoil and subsoil in the slope complex area were summarized as shown in Table 4.19.

As a result there were four soil texture classes of topsoil including (1) Sandy clay loam, (2) Clay loam, (3) Silty clay and (4) Clay which covered an area of 67.98, 48.56, 0.02 and 0.04 sq. km or 58.30, 41.65, 0.02 and 0.04%, respectively. In the meantime, there were four soil texture classes of subsoil included (1) Sandy clay loam, (2) Clay loam, (3) Sandy clay, and (4) Clay that covered an area of 7.72, 22.21, 3.76 and 66.31 sq. km or 7.72, 22.21, 3.76 and 66.31%, respectively.

Table 4.18 Structure of hypothesis, rule and conditions for soil texture classification.

No	Hypotheses	Rules	Conditions
1	SAND	Sand	%Sand \geq 85 %Silt + (1.5x%Clay) < 15
2	LOAMY SAND	Loamy sand	%Sand \geq 70 %Sand < 91 %Silt + (1.5x%Clay) \geq 15 %Silt + (2x%Clay) < 30
3	SANDY LOAM	Sandy loam Rule 1 Sandy loam Rule 2	%Sand > 52 %Silt + (2x%Clay) \geq 30 %Clay \geq 7 %Clay < 20 %Sand > 43 %Silt < 50 %Silt + (2x%Clay) > 30 %Clay < 7
4	LOAM	Loam	%Sand \leq 52 %Silt \geq 28 %Silt < 50 %Clay \geq 7 %Clay < 27
5	SILT LOAM	Silt loam Rule 1 Silt loam Rule 2	%Silt \geq 50 %Clay \geq 12 %Clay < 27 %Silt \geq 50 %Silt < 80 %Clay < 12
6	SILT	Silt	%Silt \geq 80 %Clay < 12
7	SANDY CLAY LOAM	Sandy clay loam	%Sand > 45 %Silt < 28 %Clay \geq 20 %Clay < 35
8	CLAY LOAM	Clay loam	%Sand > 20 %Sand \leq 45 %Clay \geq 27 %Clay < 40
9	SILTY CLAY LOAM	Silty clay loam	%Sand \leq 20 %Clay \geq 27 %Clay < 40
10	SANDY CLAY	Sandy clay	%Sand > 45 %Clay \geq 35
11	SILTY CLAY	Silty clay	%Silt \geq 40 %Clay \geq 40
12	CLAY	Clay	%Sand \leq 45 %Silt < 40 %Clay \geq 40

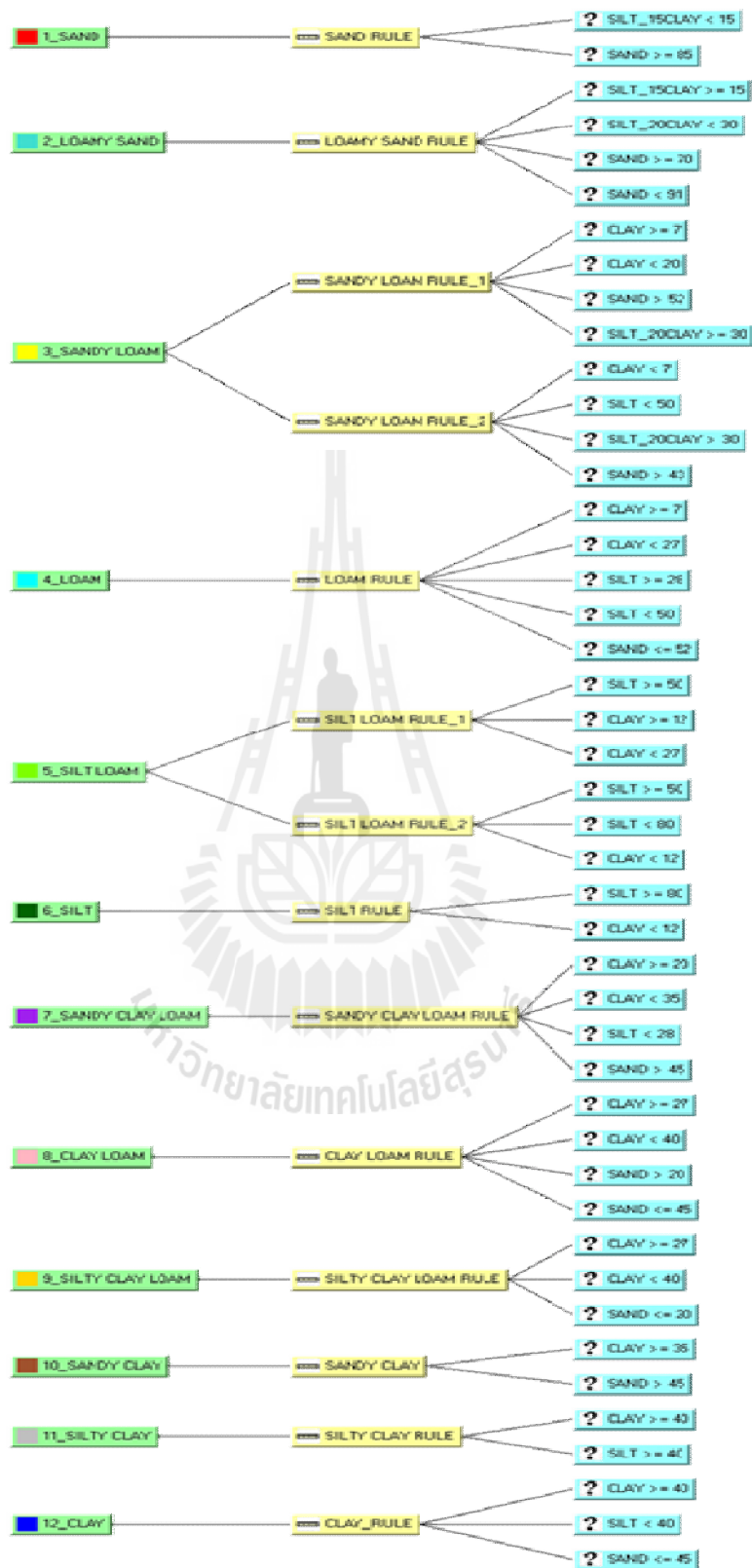
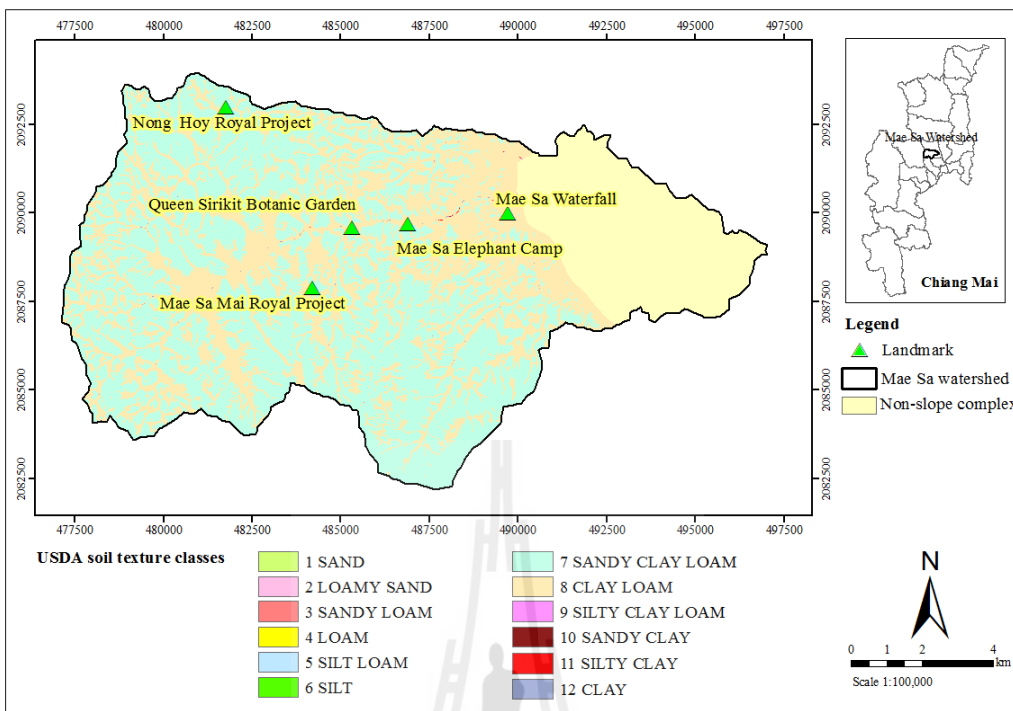


Figure 4.39 Schematic diagram of decision tree for soil texture classification under Knowledge Engineer of Expert System.

(a)



(b)

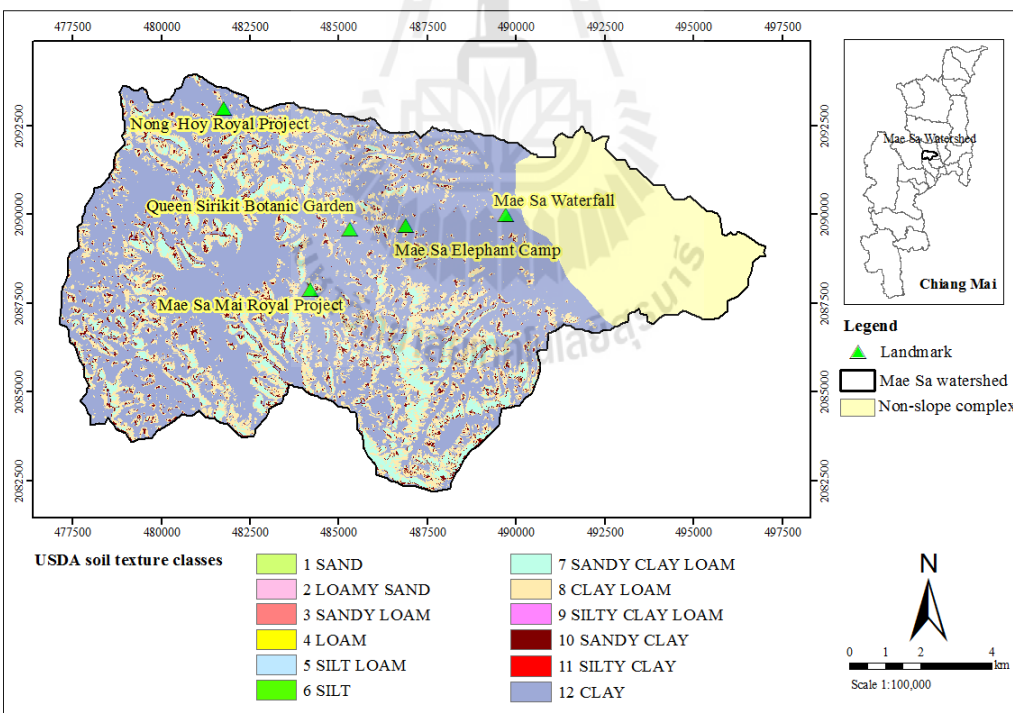


Figure 4.40 Distribution of USDA soil texture classes: (a) topsoil and (b) subsoil.

Table 4.19 Area and percentage of USDA soil texture classes.

No	USDA soil texture classes	Topsoil		Subsoil	
		sq. km	%	sq. km	%
1	SAND	0.00	0.00	0.00	0.00
2	LOAMY SAND	0.00	0.00	0.00	0.00
3	SANDY LOAM	0.00	0.00	0.00	0.00
4	LOAM	0.00	0.00	0.00	0.00
5	SILT LOAM	0.00	0.00	0.00	0.00
6	SILT	0.00	0.00	0.00	0.00
7	SANDY CLAY LOAM	67.98	58.30	9.00	7.72
8	CLAY LOAM	48.56	41.65	25.90	22.21
9	SILTY CLAY LOAM	0.00	0.00	0.00	0.00
10	SANDY CLAY	0.00	0.00	4.38	3.76
11	SILTY CLAY	0.02	0.02	0.00	0.00
12	CLAY	0.04	0.04	77.32	66.31
Total		116.61	100.00	116.61	100.00

Furthermore, accuracy for top and sub soil texture classification by Expert System was here assessed with overall accuracy and Kappa hat coefficient of agreement based on 48 soil samples. It was found that overall accuracy and Kappa hat coefficient of agreement of texture classification for topsoil were 81.25% and 0.61, while overall accuracy and Kappa hat coefficient of agreement for subsoil were 73.92% and 0.47, respectively (Tables 4.20 and 4.21). According to Landis and Koch (1977), Kappa hat coefficient of agreement for top and sub soil value between 0.40 and 0.80 represents moderate agreement or accuracy.

Table 4.20 Error matrix and accuracy assessment of topsoil texture classification by using Expert System for topsoil.

Expert classification	Observation			Total
	4 Loam	7 Sandy clay loam	8 Clay loam	
4 Loam	0			0
7 Sandy clay loam	1	25	3	29
8 Clay loam		5	14	19
Total	1	30	17	48
Overall accuracy: 81.25%				
Kappa hat coefficient of agreement: 0.61				

Table 4.21 Error matrix and accuracy assessment of subsoil texture classification by using Expert System for subsoil.

Expert classification	Observation				Total
	7 Sandy clay loam	8 Clay loam	10 Sandy clay	12 Clay	
7 Sandy clay loam	1				1
8 Clay loam	1	5		4	12
10 Sandy clay	1	1	1		3
12 Clay	1	2	1	28	32
Total	4	8	4	32	48
Overall accuracy: 73.92%					
Kappa hat coefficient of agreement: 0.47					

4.8.3 Soil property of landform extraction by zonal statistics

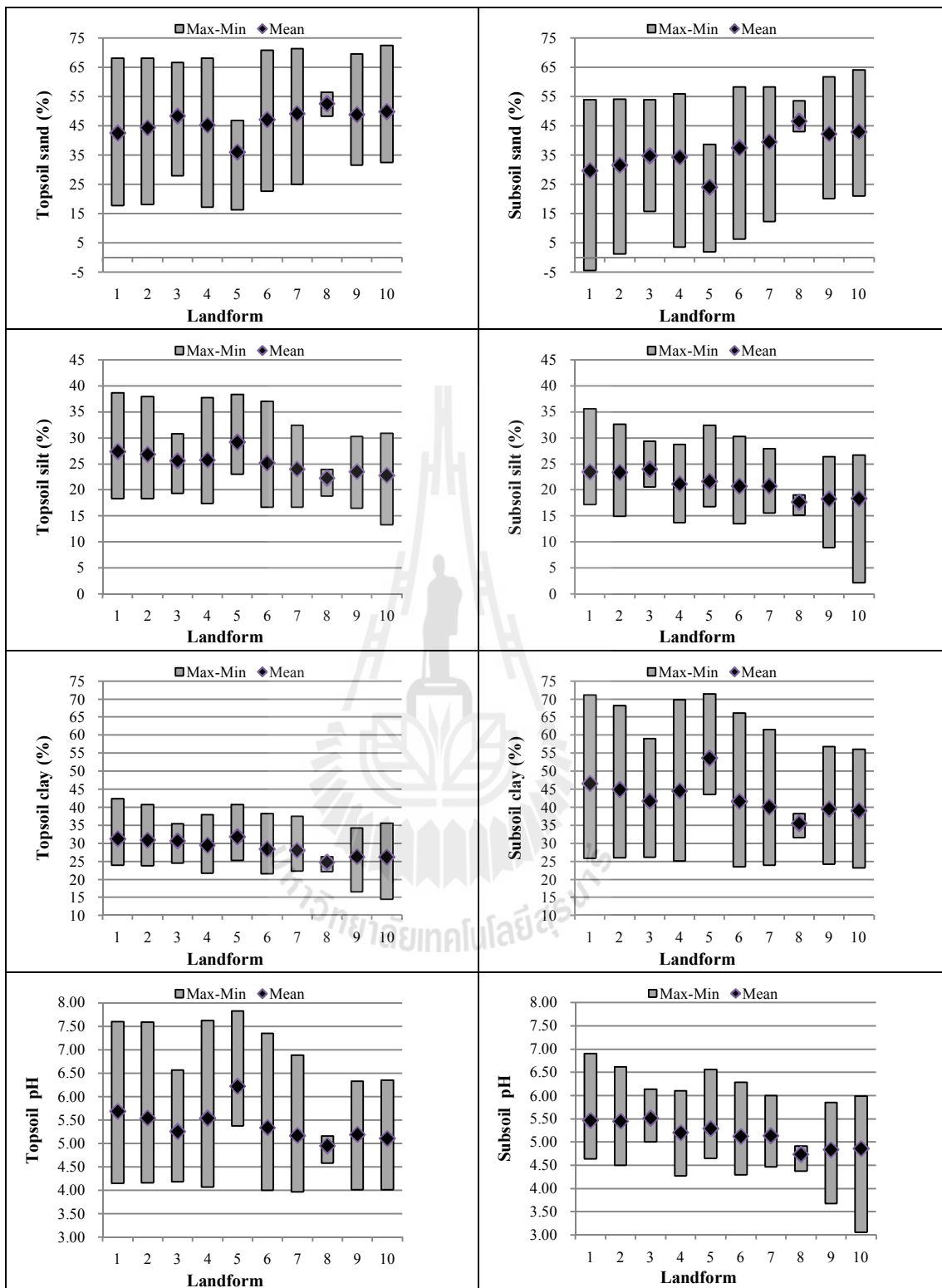
Zonal statistic under Spatial Analysis of ArcGIS was here used to extract soil properties of landform. Basically, statistic types include mean, majority, maximum, median, minimum, minority, rank, standard deviation, sum, and variety can be extracted from zonal statistics. In this study, minimum, mean and maximum values of soil properties in the slope complex area were selected to quantify landform in term of attributes as shown in Figure 4.41 to Figure 4.44. This information can be used to describe landform according soil property as explained in following examples.

Example 1. Mean value of percent of sand, silt and clay in top and sub soils of mountain top landform was 49.75, 22.81, 26.24% and 42.97, 18.35, 39.07%, respectively (Figure 4.41).

Example 2. Variation of organic matter in top and sub soil of open slope landform was 1.26-11.75% and -0.18-4.26%, respectively (Figure 4.42).

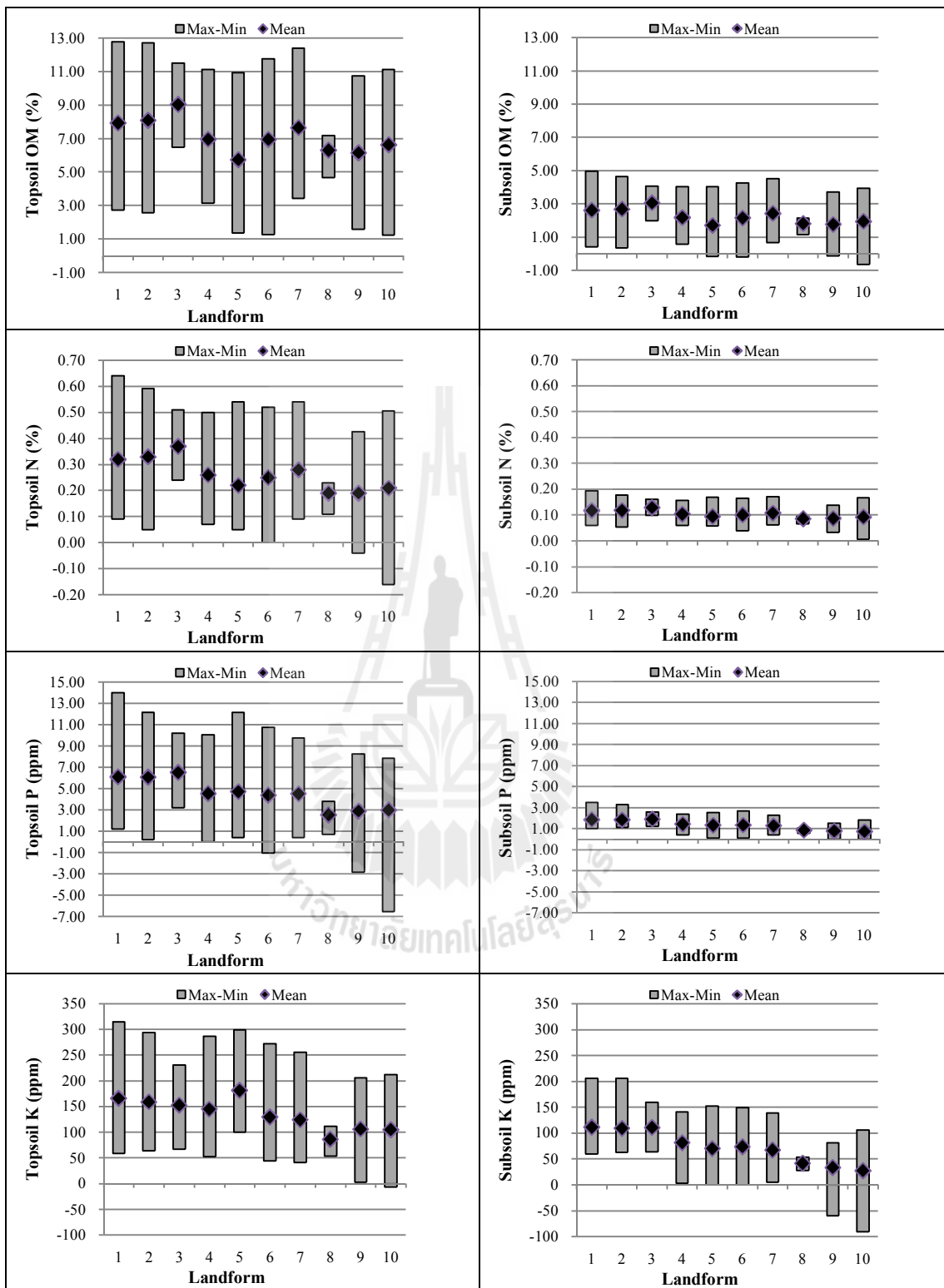
Example 3. Maximum of magnesium in top and sub soil of canyons landform was 56.78 and 35.37 ppm, respectively (Figure 4.43).

Example 4. Mean of base saturation in top and sub soil of plain landform was 33.26 and 25.28%, respectively. This is also higher than other landforms (Figure 4.44).



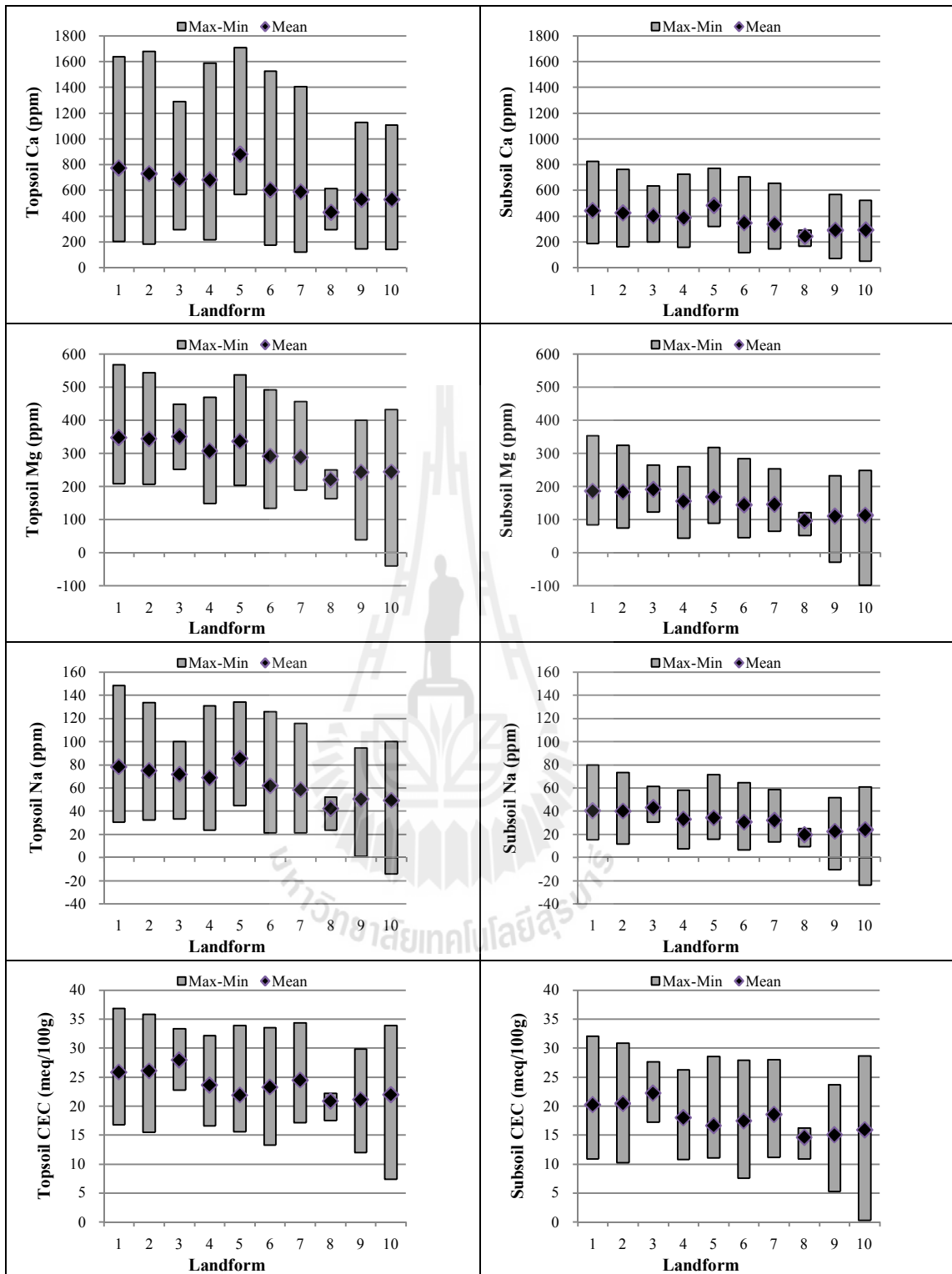
Note: Landform 1= Canyons, 2 = Midslope drainages, 3= Upland drainages, 4 = U-Shaped valleys, 5 = Plains, 6 = Open slopes, 7 = Upper slopes, 8 = Local ridges, 9 = Midslope ridges, 10 = Mountain tops

Figure 4.41 Minimum, mean and maximum values of sand, slit, clay and pH in topsoil (left) and subsoil (right) in each landform category.



Note: Landform 1= Canyons, 2 = Midslope drainages, 3= Upland drainages, 4 = U-Shaped valleys, 5 = Plains, 6 = Open slopes, 7 = Upper slopes, 8 = Local ridges, 9 = Midslope ridges, 10 = Mountain tops

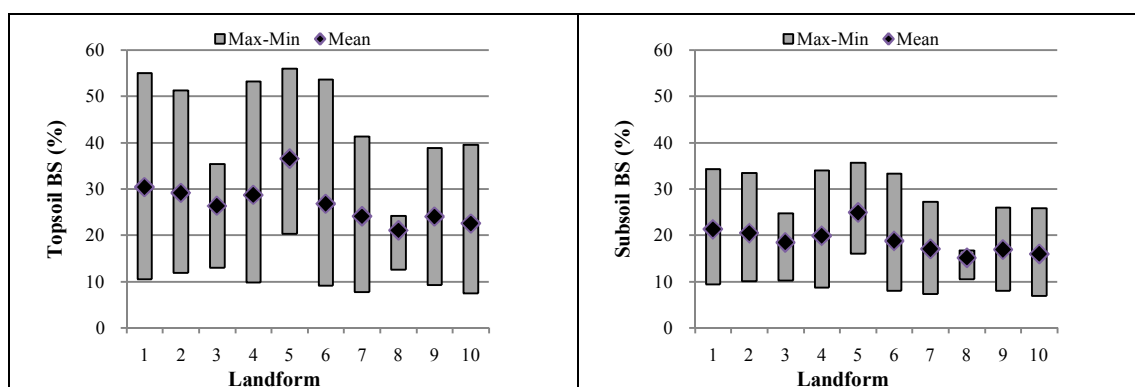
Figure 4.42 Minimum, mean and maximum values of OM, N, P and K in topsoil (left) and subsoil (right) in each landform category.



Note: Landform 1= Canyons, 2 = Midslope drainages, 3= Upland drainages, 4 = U-Shaped valleys, 5 = Plains, 6 = Open slopes, 7 = Upper slopes, 8 = Local ridges, 9 = Midslope ridges, 10 = Mountain tops

Figure 4.43 Minimum, mean and maximum values of Ca, Mg, Na and CEC in topsoil

(left) and subsoil (right) in each landform category.



Note: Landform 1= Canyons, 2 = Midslope drainages, 3= Upland drainages, 4 = U-Shaped valleys, 5 = Plains, 6 = Open slopes, 7 = Upper slopes, 8 = Local ridges, 9 = Midslope ridges, 10 = Mountain tops

Figure 4.44 Minimum, mean and maximum values of BS in topsoil (left) and subsoil (right) in each landform category.

4.8.4 Soil fertility assessment

In general, LDD (1980) divided soil fertility into 3 levels (low, moderate and high) based on chemical soil properties include organic matter (OM), cation exchange capacity (CEC), base saturation (BS), available phosphorus (P), and available potassium (K) according to Soil Survey Laboratory Method Manual (United States Department of Agriculture [USDA], 2004). In practice, each chemical soil property will be firstly assigned score with standard value into 3 levels: 1 for low fertility, 2 for moderate fertility and 3 for high fertility as shown in Table 4.22. Then total score of each soil property is added and reclassified into 3 levels of soil fertility as follows:

Level of soil fertility	Total score
Low	5-7
Moderate	8-12
High	13-15

Result of soil fertility assessment based on predictive chemical properties for top and subsoil was summarized as shown in Table 4.23 while distribution of soil fertility in the slope complex area are presented in Figure 4.45. Fertility of topsoil was mostly moderate and covered an area of 116.48 sq. km or about 99.89% of the study area. Because base saturation and available phosphorus of topsoil varied from low to moderate. At the same time, fertility of subsoil was low and moderate and covered an area of 41.73 and 74.88 sq. km or about 35.78 and 64.22%, respectively. Because base saturation of subsoil varied from low to moderate, while available phosphorus was low. Detail of assigned score for each chemical soil property of top and sub soil before soil fertility reclassification are shown in Tables 4.24 and 4.25, respectively. It was found that available phosphorus and potassium dictated soil fertility level of top and sub soil. Thus, top and sub soil fertility can be improved by adding P fertilizers.

Table 4.22 Chemical soil property and standard score for soil fertility assessment (LDD, 1980).

Fertility Level	OM (%)	CEC (cmol/kg)	BS (%)	Available P (mg/kg)	Available K (mg/kg)
Low	< 1.5 (Score =1)	< 10 (Score =1)	< 35 (Score =1)	< 10 (Score =1)	< 60 (Score =1)
Moderate	1.5-3.5 (Score =2)	10-20 (Score =2)	35-75 (Score =2)	10-25 (Score =2)	60-90 (Score =2)
High	> 3.5 (Score =3)	> 20 (Score =3)	> 75 (Score =3)	> 25 (Score =3)	> 90 (Score =3)

Table 4.23 Area and percentage of soil fertility in the study area.

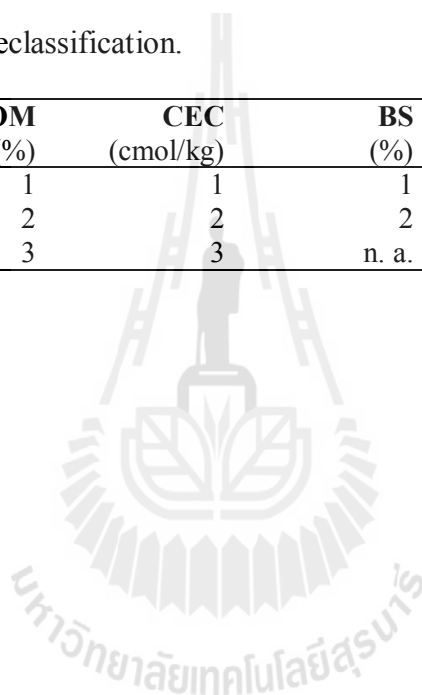
Soil Fertility level	Topsoil		Subsoil	
	Area (sq. km)	Percent	Area (sq. km)	Percent
Low	0.01	0.01	41.73	35.78
Moderate	116.48	99.89	74.88	64.22
High	0.12	0.10	0.00	0.00
Total	116.61	100.00	116.61	100.00

Table 4.24 Assigned score for each chemical soil property of topsoil before soil fertility reclassification.

Fertility Level	OM (%)	CEC (cmol/kg)	BS (%)	Available P (mg/kg)	Available K (mg/kg)
Low	1	1	1	1	1
Moderate	2	2	2	2	2
High	3	3	n. a.	n. a.	3

Table 4.25 Assigned score for each chemical soil property of subsoil before soil fertility reclassification.

Fertility Level	OM (%)	CEC (cmol/kg)	BS (%)	Available P (mg/kg)	Available K (mg/kg)
Low	1	1	1	1	1
Moderate	2	2	2	n. a.	2
High	3	3	n. a.	n. a.	3



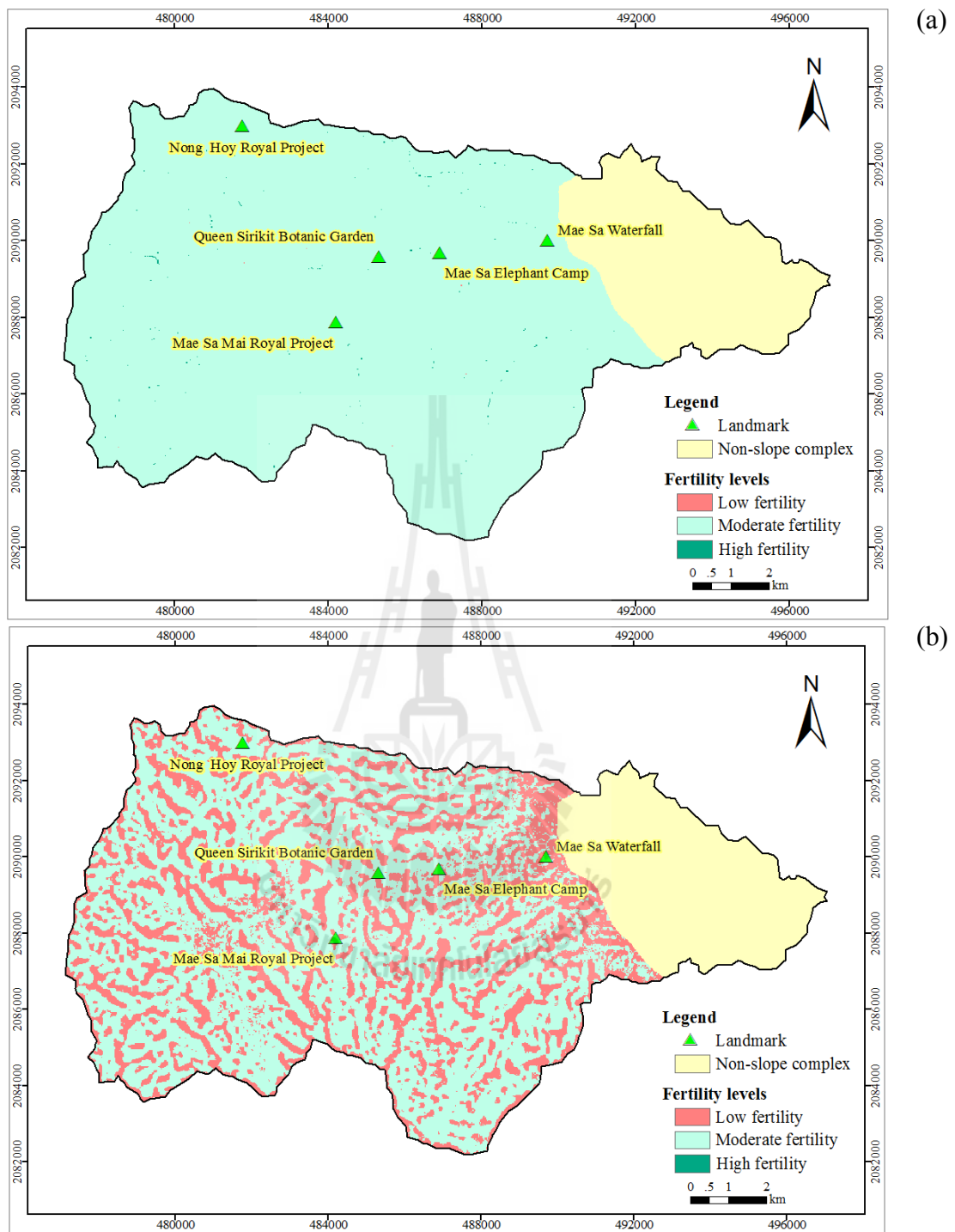


Figure 4.45 Distribution of soil fertility in the study area: (a) topsoil and (b) subsoil.

CHAPTER V

CONCLUSIONS AND RECOMMENDATIONS

In this chapter; the main results according to the specific objectives including landform classification and soil forming factor generation, in situ soil survey and soil properties analysis and soil-landscape model development for soil properties prediction are summarized. Furthermore, the use of soil properties prediction in various aspects is also concluded with significant findings. In addition recommendations are also suggested for future development, especially soil classification in slope complex areas.

5.1 Conclusions

5.1.1 Landform classification and soil forming factor generation

The combination of TPI values from different scales and criteria set which was suggested by Weiss (2001) was used to classify landform of the study area. The results found that the most dominant landform in the study area was open slopes covering an area 43.88% of the study area, while the remaining was represented by mountain tops of about 12.71%. At the same time, upland drainages or headwaters and local ridges or hills in valley covered an area less than 1% of the study area. In addition, the result of accuracy assessment for landform classification was represented strong agreement or accuracy between the classification map and the ground reference information.

In this study, selected soil forming factors include: climate (10 year mean annual rainfall), organism (NDVI), relief (elevation, slope, aspect, plan curvature, profile curvature, curvature, TWI) and parent material (Al/Si ratio) were generated under GIS environment for soil-landscape model development.

5.1.2 In situ soil survey and soil properties analysis

Stratified random sampling scheme was chosen to identify soil sample site location based on the result of landform classification and geology map. As a result, 48 soil sample sites were selected and soil samples in each site were collected from topsoil (0-25 cm) and subsoil (25-50 cm) to extract in situ physical and chemical soil properties including sand, silt, clay, pH, OM, N, P, K, Ca, Mg, Na, CEC, and BS at soil laboratory.

For physical soil property, soil texture of topsoil was dominated by sandy clay loam and the remaining was represented by clay loam and loam, while subsoil was dominated by clay and the remaining was represented by clay loam, sandy clay and sandy clay loam. At the same time, for chemical soil property, pH of topsoil and subsoil varied from extremely acidic to neutral, organic matter content of topsoil was moderate to high and subsoil was low to high, total nitrogen of topsoil was very low to moderate and subsoil was very low to low, available phosphorus concentration of topsoil was low to moderate while subsoil was low, exchangeable potassium concentration of topsoil was moderate to very high while subsoil was low to high, exchangeable calcium concentration of topsoil was low to moderate while subsoil was very low to moderate, exchangeable magnesium concentration of topsoil was moderate to high while subsoil was low to high, exchangeable sodium

concentration varied from 26.19-107.66 ppm for topsoil and decreased to 12.12-64.83 ppm for subsoil, cation exchange capacity of top and sub soil were moderate to high and base saturation of topsoil was low to moderate while subsoil was low.

5.1.3 Soil-landscape model development for soil properties prediction

Two methods for soil-landscape model development which were used to explain the relationship between extracted in situ physical and chemical soil properties and generated soil forming factors were partial least squares (PLS) regression of statistical method and cokriging interpolation of geostatistical method.

5.1.3.1 Soil-landscape model using PLS regression

Under this model, PLS regression was used to quantify relationship between bio-physical soils forming factors including rainfall, NDVI, elevation, slope, aspect, plan curvature, profile curvature, curvature, TWI and Al/Si ratio as independent variables and physical and chemical soil properties including sand, silt, clay, pH, OM, N, P, K, Ca, Mg, Na, CEC, and BS of top and sub soil as dependent variable. Results of PLS regression analysis for each soil properties of top and sub soil were summarized in form of multiple linear regression equation as follows:

Topsoil	Subsoil
$\text{Sand} = 16.785 + (1.935 \times 10^{-02}) * \text{RAIN} - 8.573 * \text{NDVI} + (2.465 \times 10^{-03}) * \text{ELEVATION} + 0.463 * \text{SLOPE} + (2.451 \times 10^{-03}) * \text{ASPECT} + 1.770 * \text{PLAN} - 0.644 * \text{PROFILE} + 0.725 * \text{CURVATURE} - 1.429 * \text{TWI} + 29.892 * \text{ALSI_RATIO}$	$\text{Sand} = 30.123 + (9.757 \times 10^{-03}) * \text{RAIN} + 7.762 * \text{NDVI} - (8.410 \times 10^{-04}) * \text{ELEVATION} + 0.508 * \text{SLOPE} - (3.643 \times 10^{-03}) * \text{ASPECT} + 3.495 * \text{PLAN} - 4.714 * \text{PROFILE} + 2.424 * \text{CURVATURE} - 1.593 * \text{TWI} - 40.356 * \text{ALSI_RATIO}$
$\text{Silt} = 40.861 - (1.442 \times 10^{-02}) * \text{RAIN} + 1.084 * \text{NDVI} - (2.015 \times 10^{-03}) * \text{ELEVATION} - (9.207 \times 10^{-02}) * \text{SLOPE} + (8.319 \times 10^{-04}) * \text{ASPECT} - 1.317 * \text{PLAN} + 1.273 * \text{PROFILE} - 0.768 * \text{CURVATURE} + 0.587 * \text{TWI} + 13.718 * \text{ALSI_RATIO}$	$\text{Silt} = 19.739 - (7.830 \times 10^{-04}) * \text{RAIN} + 3.719 * \text{NDVI} + (8.010 \times 10^{-05}) * \text{ELEVATION} - (1.105 \times 10^{-02}) * \text{SLOPE} + (1.841 \times 10^{-04}) * \text{ASPECT} - 2.133 * \text{PLAN} + 2.512 * \text{PROFILE} - 1.374 * \text{CURVATURE} + 0.417 * \text{TWI} - 10.281 * \text{ALSI_RATIO}$

Topsoil	Subsoil
Clay = 30.432 - (1.002*10 ⁻⁰³)*RAIN - 3.785*NDVI + (8.238*10 ⁻⁰⁵)*ELEVATION - 0.122*SLOPE + (4.016*10 ⁻⁰³)*ASPECT - 2.465*PLAN + 1.523*PROFILE - 1.190*CURVATURE + 0.407*TWI + 1.869*ALSI_RATIO	Clay = 43.987 - (3.218*10 ⁻⁰³)*RAIN - 13.557*NDVI + (2.226*10 ⁻⁰³)*ELEVATION - 0.511*SLOPE + (8.026*10 ⁻⁰³)*ASPECT - 1.584*PLAN + 1.842*PROFILE - 1.014*CURVATURE + 1.029*TWI + 42.825*ALSI_RATIO
pH = 6.562 - (8.973*10 ⁻⁰⁴)*RAIN - 0.881*NDVI - (1.629*10 ⁻⁰⁴)*ELEVATION - (2.889*10 ⁻⁰²)*SLOPE + (5.054*10 ⁻⁰⁴)*ASPECT - (6.154*10 ⁻⁰²)*PLAN + 0.101*PROFILE - (4.778*10 ⁻⁰²)*CURVATURE + 0.108*TWI + 1.759*ALSI_RATIO	pH = 4.847 + (1.342*10 ⁻⁰⁴)*RAIN + 0.255*NDVI + (5.667*10 ⁻⁰⁵)*ELEVATION - (5.215*10 ⁻⁰³)*SLOPE + (3.327*10 ⁻⁰⁴)*ASPECT - 0.265*PLAN + 0.281*PROFILE - 0.162*CURVATURE + (5.263*10 ⁻⁰²)*TWI - 1.679*ALSI_RATIO
OM = -5.13169562426153 + (7.840*10 ⁻⁰³)*RAIN + 6.151*NDVI + (1.379*10 ⁻⁰³)*ELEVATION + (2.179*10 ⁻⁰²)*SLOPE - (8.615*10 ⁻⁰⁴)*ASPECT - 0.674*PLAN + 1.122*PROFILE - 0.529*CURVATURE + 0.136*TWI - 17.095*ALSI_RATIO	OM = -2.740 + (3.048*10 ⁻⁰³)*RAIN + 2.585*NDVI + (5.161*10 ⁻⁰⁴)*ELEVATION + (8.779*10 ⁻⁰³)*SLOPE - (1.739*10 ⁻⁰⁴)*ASPECT - 0.313*PLAN + 0.540*PROFILE - 0.251*CURVATURE + (6.619*10 ⁻⁰²)*TWI - 6.578*ALSI_RATIO
N = -0.217 + (3.157*10 ⁻⁰⁴)*RAIN + 0.240*NDVI + (5.302*10 ⁻⁰⁵)*ELEVATION + (4.668*10 ⁻⁰⁴)*SLOPE + (3.239*10 ⁻⁰⁵)*ASPECT - (5.425*10 ⁻⁰²)*PLAN + (6.745*10 ⁻⁰²)*PROFILE - (3.597*10 ⁻⁰²)*CURVATURE + (1.045*10 ⁻⁰²)*TWI - 0.895*ALSI_RATIO	N = (-4.006*10 ⁻⁰²) + (9.692*10 ⁻⁰⁵)*RAIN + (3.955*10 ⁻⁰²)*NDVI + (1.738*10 ⁻⁰⁵)*ELEVATION - (1.388*10 ⁻⁰⁶)*SLOPE + (8.495*10 ⁻⁰⁶)*ASPECT - (1.173*10 ⁻⁰²)*PLAN + (1.641*10 ⁻⁰²)*PROFILE - (8.302*10 ⁻⁰³)*CURVATURE + (2.385*10 ⁻⁰³)*TWI - 0.184*ALSI_RATIO
P = 1.301 + (7.533*10 ⁻⁰⁵)*RAIN + 5.937*NDVI + (1.838*10 ⁻⁰⁴)*ELEVATION - (3.534*10 ⁻⁰³)*SLOPE - (5.791*10 ⁻⁰⁴)*ASPECT - 1.392*PLAN + 1.464*PROFILE - 0.846*CURVATURE + 0.321*TWI - 8.395*ALSI_RATIO	P = 0.848 + (3.719*10 ⁻⁰⁵)*RAIN + 0.527*NDVI + (1.445*10 ⁻⁰⁵)*ELEVATION - (1.970*10 ⁻⁰³)*SLOPE + (3.123*10 ⁻⁰⁴)*ASPECT - 0.256*PLAN + 0.280*PROFILE - 0.159*CURVATURE + (6.197*10 ⁻⁰²)*TWI - 2.118*ALSI_RATIO
K = 113.923 - (1.158*10 ⁻⁰²)*RAIN - 46.592*NDVI + (4.772*10 ⁻⁰³)*ELEVATION - 1.726*SLOPE + (8.702*10 ⁻⁰²)*ASPECT - 21.245*PLAN + 18.706*PROFILE - 11.866*CURVATURE + 7.678*TWI + 113.498*ALSI_RATIO	K = 42.291 + (9.875*10 ⁻⁰³)*RAIN + 12.198*NDVI + (6.639*10 ⁻⁰³)*ELEVATION - 0.402*SLOPE + 0.022*ASPECT - 16.111*PLAN + 17.517*PROFILE - 9.958*CURVATURE + 3.625*TWI - 70.156*ALSI_RATIO
Ca = 49.854 + (4.526*10 ⁻⁰²)*RAIN + 92.669*NDVI + (4.530*10 ⁻⁰²)*ELEVATION - 8.051*SLOPE + 0.569*ASPECT - 54.316*PLAN + 37.863*PROFILE - 27.469*CURVATURE + 61.766*TWI + 591.571*ALSI_RATIO	Ca = 471.849 - (4.100*10 ⁻⁰²)*RAIN - 71.454*NDVI + (2.924*10 ⁻⁰²)*ELEVATION - 5.311*SLOPE + 0.054*ASPECT - 43.048*PLAN + 52.293*PROFILE - 28.189*CURVATURE + 21.419*TWI - 483.020*ALSI_RATIO
Mg = 327.005 - (5.044*10 ⁻⁰²)*RAIN - 49.313*NDVI + (4.838*10 ⁻⁰³)*ELEVATION - 0.933*SLOPE + (7.423*10 ⁻⁰²)*ASPECT - 51.773*PLAN + 34.148*PROFILE - 25.623*CURVATURE + 9.502*TWI + 0.578*ALSI_RATIO	Mg = 145.077 - (3.271*10 ⁻⁰⁵)*RAIN + 19.741*NDVI + (7.734*10 ⁻⁰³)*ELEVATION - 0.788*SLOPE + (5.192*10 ⁻⁰²)*ASPECT - 32.232*PLAN + 32.169*PROFILE - 19.094*CURVATURE + 6.261*TWI - 234.749*ALSI_RATIO
Na = 54.759 - (8.265*10 ⁻⁰³)*RAIN - 33.061*NDVI + (1.311*10 ⁻⁰³)*ELEVATION - 0.762*SLOPE + (3.576*10 ⁻⁰²)*ASPECT - 8.787*PLAN + 11.485*PROFILE - 5.988*CURVATURE + 2.788*TWI + 124.821*ALSI_RATIO	Na = 12.423 + 0.0138*RAIN + 4.617*NDVI + (5.377*10 ⁻⁰³)*ELEVATION - 0.171*SLOPE + (8.991*10 ⁻⁰³)*ASPECT - 7.754*PLAN + 7.831*PROFILE - 4.620*CURVATURE + 1.326*TWI - 63.541*ALSI_RATIO
CEC = 3.470 + (1.364*10 ⁻⁰²)*RAIN + 8.769*NDVI + (2.398*10 ⁻⁰³)*ELEVATION + (1.451*10 ⁻⁰²)*SLOPE + (2.032*10 ⁻⁰³)*ASPECT - 2.248*PLAN + 2.390*PROFILE - 1.374*CURVATURE + 0.325*TWI - 34.380*ALSI_RATIO	CEC = 3.505 + (1.075*10 ⁻⁰²)*RAIN + 5.027*NDVI + (2.577*10 ⁻⁰³)*ELEVATION - (3.482*10 ⁻⁰³)*SLOPE + (3.768*10 ⁻⁰³)*ASPECT - 2.264*PLAN + 2.670*PROFILE - 1.459*CURVATURE + 0.318*TWI - 36.186*ALSI_RATIO
BS = 61.169 - (2.683*10 ⁻⁰²)*RAIN - 20.562*NDVI - (3.665*10 ⁻⁰³)*ELEVATION - 0.231*SLOPE + (9.427*10 ⁻⁰³)*ASPECT - 2.640*PLAN + 1.119*PROFILE - 1.127*CURVATURE + 0.808*TWI + 60.269*ALSI_RATIO	BS = 41.768 - (1.637*10 ⁻⁰²)*RAIN - 8.571*NDVI - (2.502*10 ⁻⁰³)*ELEVATION - 0.165*SLOPE + (1.772*10 ⁻⁰³)*ASPECT - 1.545*PLAN + 1.088*PROFILE - 0.785*CURVATURE + 0.558*TWI + 21.893*ALSI_RATIO

These equations were used to predict physical and chemical soil properties of top and sub soil.

5.1.3.2 Soil-landscape model using cokriging interpolation

For cokriging interpolation, three significant soil forming factors were extracted from PLS regression analysis based on best variable important for the projection (VIP) values were used as 3 auxiliary variable for interpolation each soil property. Results of cokriging for each soil properties of top and sub soil were summarized in term of semivariogram models as follows:

Soil properties	Topsoil semivariogram model			
	Type	Partial sill	Range	Nugget
Sand	Spherical	3.4026	10274	49.635
Silt	Spherical	2.2722	9644.75	15.511
Clay	Exponential	0.47502	8242.37	17.959
pH	Spherical	0.099921	10270	0.267
OM	Spherical	0.75217	8729.9	4.1958
N	Spherical	0.0032037	403.905	0.041
P	Spherical	1.6305	424.738	0.833
K	Gaussian	2785.3	208.185	2.785
Ca	Gaussian	69111	212.017	0.797
Mg	Gaussian	10004	175.918	10.004
Na	Gaussian	657.56	174.844	0.658
CEC	Exponential	1.5986	332.899	0.085
BS	Spherical	21.06	10388.7	44.769

Soil properties	Subsoil semivariogram model			
	Type	Partial sill	Range	Nugget
Sand	Exponential	6.7061	8243.46	96.877
Silt	Exponential	19.816	307.005	0.974
Clay	Exponential	28.88	8248.06	41.609
pH	Spherical	0.27	230.871	0.763
OM	Spherical	0.079795	349.02	0.445
N	Exponential	0.000089413	361.276	0.479
P	Spherical	0.12049	366.349	0.907
K	Gaussian	528.39	347.059	0.528
Ca	Gaussian	65359	133.620	65.359
Mg	Gaussian	7381.4	272.4	7.381
Na	Gaussian	312.17	168.554	0.312
CEC	Exponential	13.316	305.823	0.832
BS	Spherical	2.748	9631.83	19.897

5.1.4 Accuracy assessment

The result of predictive physical and chemical soil properties from PLS regression and cokriging interpolation were here used to compare with in situ soil

properties of validating datasets using Mean Error (ME), Root Mean Square Error (RMSE) and Normalized Root Mean Square Error (NRMSE).

Based on accuracy assessment by ME, it may be concluded that the best predictive soil property of top and sub soil using PLS was nitrogen (N). In contrast, the worst predictive soil property of top and sub soil using PLS was calcium (Ca). At the same time the best predictive soil property of top and sub soil using cokriging was pH. In contrast, the worst predictive soil property of top and sub soil using cokriging was calcium (Ca).

Similarly, based on RMSE accuracy assessment, it may be concluded that the best predictive soil property of top and sub soil using PLS was nitrogen (N). In contrast, the worst predictive soil property of top and sub soil using PLS was calcium (Ca). At the same time the best predictive soil property of top and sub soil using cokriging was nitrogen (N). In contrast, the worst predictive soil property of top and sub soil using cokriging was calcium (Ca).

Furthermore, according to accuracy assessment using NRMSE, it may be concluded that the best predictive soil property of top and sub soil using PLS was sodium (Na) and calcium (Ca), respectively. In contrast, the worst predictive soil property of top and sub soil using PLS was phosphorus (P). At the same time the best predictive soil property of top and sub soil using cokriging was clay and potassium (K), respectively. In contrast, the worst predictive soil property of top and sub soil using cokriging was potassium (K) and calcium (Ca), respectively.

5.1.5 Optimum model for soil properties prediction

Based on Normalized Root Mean Squared Error (NRMSE), it can be concluded that an optimum model for all soil properties of top and sub soil was PLS regression model. However, cokriging model can provide a better result of available phosphorus (P) and potassium (K) prediction of subsoil than PLS model.

5.1.6 The use of soil properties prediction

This section focuses on the possible use of soil properties prediction to fulfill the information requirement in slope complex areas in various aspects. They included (1) visualization of soil texture, (2) classification of soil texture using Expert System, (3) soil property of landform extraction by zonal statistics and (4) soil fertility assessment. The major findings can be concluded as follows:

(1) Visualization of soil texture

Color composite image was here applied to visualize three predictive soil texture fractions (%Sand, %Silt and %Clay) of top and sub soil. Basically, additive primary colors (red, green and blue) were assigned to each fraction for visualization of soil texture in color space. The result of color composite image can be used to qualitative describe soil texture fraction. Furthermore, this data can be used to quantify soil texture classes using digital image processing software.

(2) Classification of soil texture using Expert System

Soil texture classes were here extracted using Expert System based on criteria of USDA soil texture classification by Soil Survey Division Staff (1993). In principle, percent of sand, silt and clay with some conditions were applied to extract 12 standard soil texture classes which include (1) Sand, (2) Loamy sand, (3) Sandy loam,

(4) Loam, (5) Silt loam, (6) Silt, (7) Sandy clay loam, (8) Clay loam, (9) Silty clay loam, (10) Sandy clay, (11) Silty clay and (12) Clay. As a result, it can be concluded that Expert System can be used to classify soil texture classes from predictive soil texture fraction. It was found that overall accuracy and Kappa hat coefficient of agreement for topsoil was 81.25% and 0.61 and for subsoil was 73.92% and 0.47, respectively. These soil texture classes can be further used for soil drainage assessment, hydrologic soil group (HSG) determination or soil erosion assessment, etc.

(3) Soil property of landform extraction by zonal statistics

In this study, minimum, mean and maximum values of soil properties were extracted based on landform category by using zonal statistics. These results can be useful to explain and compare the variation of top and sub soil properties within each landform category. Also, the physical and chemical properties of top and sub soil that are extracted by zonal statistics can be further used as an attribute data for spatial analysis under GIS environment.

(4) Soil fertility assessment

According to LDD (1980), soil fertility can be divided into 3 levels (low, moderate and high) based on chemical soil properties including OM, CEC, BS, available P and K. Herewith, concerned predictive chemical soil properties of top and sub soil were assigned a score with standard values and total score of each soil property were added and reclassified for soil fertility. As a result it was found that most of topsoil was of moderate fertility and covered an area about 99.89% of the study area, while soil fertility assessment for subsoil of low and moderate fertility covered an area about 35.78 and 64.22%, respectively. Soil fertility assessment can provide a baseline information for soil improvement or increasing soil fertility.

5.2 Recommendations and future improvements

Recommendations for further studies and applications can be made as follows:

(1) Relief factors should be extracted from DEM at higher resolution for soil-landscape modeling in slope complex area.

(2) Understanding of soil and landform relationships in slope complex area is a crucial knowledge base and essential for soil survey and soil mapping. Therefore, the number of soil samples in field survey should be increased for soil-landscape modeling.

(3) In this study, partial least squares regression was used instead of stepwise linear regression due to multicollinearity problem among relief factor (TWI, slope, plan curvature, profile curvature and curvature). Therefore, another approach for solving multicollinearity problem such as factor analysis should be examined in the future work.

(4) Due to the limitation of cokriging under ArcGIS environment, only three variables can be applied for surface interpolation. As a result regression kriging can be another choice for soil properties prediction as geostatistics approach.

(5) The application of soil properties prediction should be further investigated by soil scientists. For example, predictive soil properties can be used to evaluate land qualities based on soil productivity index (PI) and erosion risk index (ERI) for soil and water conservation planning and sustainable agriculture management in slope complex area.



REFERENCES

REFERENCES

- Abdi, H. (2007). Partial least square regression. In Salkind, N. J. (ed.). **Encyclopedia of Measurement and Statistics** (pp 740-744). Thousand Oaks (CA): Sage.
- Abdi, H. (2010). Partial least squares regression and projection on latent structure regression (PLS Regression). **Computational Statistics**. 2: 97-106.
- Ballabio, C. (2009). Spatial prediction of soil properties in temperate mountain regions using support vector regression. **Geoderma**.151: 338-350.
- Buol, S. W., Hole, F. D. and McCracken, R. J. (1989). **Soil Genesis and Classification**. 3rd edition. Ames: Iowa State University.
- Burrough, P. A., Bouma, J. and Yates, S. R. (1994). The state of the art in pedometrics. **Geoderma**. 62: 311-326.
- Ballabio, C. (2009). Spatial prediction of soil properties in temperate mountain regions using support vector regression. **Geoderma**.151: 338-350.
- Carrascal, L. M., Galván, I. and Gordo, O. (2009). Partial least squares regression as an alternative to current regression methods used in ecology. **Oikos**. 118: 681-690.
- Castrignanò, A., Buttafuoco, G., Comolli, R. and Castrignanò, A. (2011). Using digital elevation model to improve soil pH prediction in an alpine doline. **Pedosphere**. 21(2): 259-270.
- Certini, G. and Scalenghe, R. (2006). **Soils: Basic Concepts and Future Challenges**. New York: Cambridge University Press.

- Chang, K. T. (2004). **Introduction to Geographic Information Systems**. 2nd edition. New York: McGraw-Hill.
- Ekasingh, M., Sangchyoswat, C., Samranpong, C., Punsompong, P., Sunhem, C., Wongchaimoon, N. and Prommanon, C. (2004). **Final Report on Development of Soil and Land Use Spatial Databases Phase V**. Chiang Mai: Multiple Cropping Center, Faculty of Agriculture, Chiang Mai University. (in Thai).
- Eriksson, L., Johansson, E., Kettaneh-Wold, N., Wikström, C. and Wold, S. (2008). **Design of Experiments: Principles and Applications**. 3rd edition. Umea, Sweden: MKS Umetrics AB.
- Florinsky, I. V., Eilers, R. G., Manning, G. R. and Fuller, L. G. (2002). Prediction of soil properties by digital terrain modelling. **Environmental Modelling & Software**. 17: 295-311.
- Gessler, P. E., Moore, I. D., McKenzie, N. J. and Ryan, P. J. (1995). Soil landscape modelling and spatial prediction of soil attributes. **International Journal of Geographical Information System**. 9: 421-432.
- Gobin, A., Campling, P. and Feyen, J. (2001). Soil-landscape modelling to quantify spatial variability of soil texture. **Physics and Chemistry of the Earth part B**. 26(1): 41-45.
- Grunwald, S. (2006a). **Soil Landscape Modeling**. Soil and Water Science Department, University of Florida.
- Grunwald, S. (2006b). **Environmental Soil-Landscape Modeling: Geographic Information Technologies and Pedometrics**. New York: CRC.

- Hengl, T. (2003). **Pedometric Mapping: Bridging the Gaps Between Conventional and Pedometric Approaches**. Ph.D. Thesis, Wageningen University and ITC.
- Hengl, T. and Rossiter, D. G. (2003). Supervised landform classification to enhance and replace photo-interpretation in semi-detailed soil survey. **Soil Science Society of America Journal**. 67: 1810-1822.
- Hengl, T., Rossiter, D. G. and Husnjak, S. (2002). Mapping soil properties from an existing national soil data set using freely available ancillary data. In **17th World Congress of Soil Science**, Bangkok, Thailand. August 14-21 (No. 1140, pp 1-10).
- Hartemink, A. E., McBratney, A. B. and Cattle, J. A. (2002). Developments and trends in soil science: 100 volumes of *Geoderma* (1967-2001). **Geoderma**. 100: 217-268.
- Heuvelink, G. B. M. (2003). The definition of pedometrics [On-line]. Available: <http://www.pedometrics.org/pedometron/pedometron15.pdf>.
- Heuvelink, G. B. M. and Pebesma, E. J. (1999). Spatial aggregation and soil process modelling. **Geoderma**. 89: 47-65.
- Hewitt, A. (1993). Predictive modelling in soil survey. **Soils and Fertilizers**. 56(3): 305-314.
- Hudson, B. D. (1990). Concepts of soil mapping and interpretation. **Soil Survey Horizons**. 31: 63-73.
- Hudson, B. D. (1992). The soil survey as paradigm-based science. **Soil Science Society of America Journal**. 56(3): 836-841.

- Isaaks, E. H. and Srivastava, R. M. (1989). **An Introduction to Applied Geostatistics**. New York: Oxford University Press.
- Jenny, H. (1941). **Factors of Soil Formation: A System of Quantitative Pedology**. New York: McGraw-Hill.
- Jenny, H. (1980). **The Soil Resources: Origin and Behaviour**. New York: Springer-Verlag.
- Kheoruenromne, I. (2005). **Soil Survey**. 2nd edition. Bangkok: Kasetsart University, Department of Soil Science, Faculty of Agriculture. (in Thai).
- Knotter, M., Brus, D. J. and Oude Voshaar, J. H. (1995). A comparison of kriging, co-kriging and kriging combined with regression for spatial interpolation of horizon depth with censored observations. **Geoderma**. 67: 227-246.
- Land Development Department [LDD]. (1980). **Guide Classification Land Suitability for Economic Crops**. Bangkok: Soil Survey Division, Land Development Department, Ministry of Agriculture and Cooperative. (in Thai).
- Land Development Department [LDD]. (1989). **Annual Report 1989**. Bangkok: Land Development Department, Ministry of Agriculture and Cooperative. (in Thai).
- Land Development Department [LDD]. (1990). **Land Use and Land Cover Map 1990** [Data file]. Bangkok: Land Development Department, Ministry of Agriculture and Cooperative.

- Land Development Department [LDD]. (1992). **Preliminary Study on Highland Development Project in Northern Thailand**. Bangkok: Soil Survey Division, Land Development Department, Ministry of Agriculture and Cooperatives. (in Thai).
- Land Development Department [LDD]. (2002). **Soil Map of Thailand** [Data file]. Bangkok: Land Development Department, Ministry of Agriculture and Cooperative.
- Landis, J. and Koch, G. (1977). The measurement of observer agreement for categorical data. **Biometrics**. 33: 159-174.
- Lloyd, C. D. (2007). **Local Models for Spatial Analysis**. Boca Raton: CRC Press.
- López-Granados, F., Jurado-Expósito, M., Peña-Barragán, J. M. and Garcia-Torres, L. (2005). Using geostatistical and remote sensing approaches for mapping soil properties. **European Journal of Agronomy**. 23: 279–289.
- McBratney, A. B., Odeh, I. O. A., Bishop, T. F. A., Dunbar, M. S. and Shatar, T. M. (2000). An overview of pedometric techniques for use in soil survey. **Geoderma**. 97: 293-327.
- McBratney, A. B., Santos, M. L. M. and Minasny, B. (2003). On digital soil mapping. **Geoderma**. 117(1-2): 3-52.
- Moore, L. D., Gessler, P. E., Nielsen, G. A. and Peterson, G. A. (1993). Soil attribute prediction using terrain analysis. **Soil Science Society of America Journal**. 57: 443-452.
- Paiboonsak, S. (2000). **An Evaluation of the Use of Geographic Information System and Satellite Imagery for Soil Mapping in Slope Complex Areas**. M.S. Thesis, Khon Kaen University.

- Park, S. J. and Vlek, P. L. G. (2002). Environmental correlation of three-dimensional soil spatial variability: A comparison of three adaptive techniques. **Geoderma**. 109: 117-140.
- Pennock, D. J. and Veldkamp, A. (2006). Advances in landscape-scale soil research. **Geoderma**. 133: 1-5.
- Rossiter, D. G. (2005). Digital soil mapping: Towards a multiple-use soil information system. **Proceeding of Semana de la Geomática**. 8 August 2005. Santa Fé Bogotá.
- Rossiter, D. G. (2007). **Technical Note: Co-kriging with the GStat Package of the R Environment for Statistical Computing**. Enschede, Netherlands: ITC.
- Ryan, P. J., McKenzie, N. J., O'Connell, D., Loughhead, A. N., Leppert, P. M., Jacquier, D. and Ashton, L. (2000). Integrating forest soils information across scales: spatial prediction of soil properties under Australian forests. **Forest Ecology and Management**. 138: 139-157.
- Santra, P., Chopra, U. K. and Chakraborty, D. (2008). Spatial variability of soil properties and its application in predicting surface map of hydraulic parameters in an agricultural farm. **Current Science**. 95(7): 937-945.
- Schoorl, J. M., Beldkamp, A. and Bouma, J. (2002). Modeling water and soil redistribution in a dynamic landscape context. **Soil Science Society of America Journal**. 66: 1610-1619.
- Scull, P., Franklin, J., Chadwick, O. A. and McArthur, D. (2003). Predictive soil mapping: A review. **Physical Geography**. 27(2): 171-197.
- Soil Survey Division Staff. (1993). **Soil Survey Manual**. Washington, DC: United States Department of Agriculture.

- Tagil, S. and Jenness, J. (2008). GIS-Base automated landform classification and topographic, landcover and geologic attributes of landforms around the Yazoren Polje, Turkey. **Journal of Applied Sciences**. 8(6): 910-921.
- United States Department of Agriculture [USDA]. (2004). **Soil Survey Laboratory Methods Manual**. Soil Survey Investigations Report No. 42, Version No. 4. Washington, DC: Natural Resources Conservation Service, United States Department of Agriculture.
- Ventura, S. J. and Irvin, B. J. (2000). Automated landform classification methods for soil-landscape studies. In Wilson, J. P. and Gallant, J. C. (eds.). **Terrain Analysis: Principles and Application** (pp 267-294). New York: John Wiley & Sons.
- Webster, R. (1994). The development of pedometrics. **Geoderma**. 62(1/3): 1-15.
- Weiss, A. (2001). Topographic position and landforms analysis. Poster Presentation, **ESRI User Conference**, San Diego, CA.
- Wilson, J. P. and Gallant, J. C. (2000). **Terrain Analysis: Principles and Application**. New York: John Wiley & Sons.
- Zhu, A. X. (2000). Mapping soil landscape as spatial continua: The neural network approaches. **Water Resources Research**. 36: 663-677.



APPENDICES




APPENDIX A
SOIL PROFILE DESCRIPTION

A.1 Soil profile description.

Information on the site

Sample no: 1
 Date of examination: April 16, 2010
 Location: Ban Dong Nai, Mae Sa Mai, Mae Rim District, Chiang Mai province
 Position: 482578; 2084320 Elevation: 926 m (MSL)
 Slope: 15 Aspect: SW (250°)
 Geology: Gr, Triassic granite LU/LC: Orchard
 Landform: 1 Canyons or Deeply incised streams


Profile description

Picture	Horizon	Depth (cm)	Description
	Ap	0-12	Dull reddish brown (5YR 4/4); clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to Bt1.
	B1t	12-26	Reddish brown (5YR 4/6); clay; moderate fine granular structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	26-41	Dark reddish brown (5YR 3/4); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt3.
	B3t	41-50	Dark brown (5YR 2.5/2); clay; moderate fine and medium sub-angular blocky structure; friable moist, sticky and plastic.

Information on the site

Sample no: 2
 Date of examination: April 08, 2010
 Location: Ban Mae Sa Noi, Mae Rim District, Chiang Mai province
 Position: 484855; 2085660 Elevation: 1,030 m (MSL)
 Slope: 5-10 Aspect: NW (296°)
 Geology: Gr, Triassic granite LU/LC: Evergreen forest
 Landform: 1 Canyons or Deeply incised streams

Profile description


Picture	Horizon	Depth (cm)	Description
	A	0-15	Very dusky red (2.5YR 2.5/2); clay loam; moderate medium granular structure; friable moist, sticky and plastic; clear and smooth boundary to Bt1.
	B1t	15-27	Dark reddish brown (5YR 3/3); clay; moderate fine granular structure; friable moist, very sticky and very plastic; gradual and smooth boundary to Bt2.
	B2t	27-50	Dark reddish brown (5YR 3/2); clay; moderate fine sub-angular blocky r structure; firm moist, very sticky and very plastic.

A.1 (Continued).

Information on the site

Sample no: 3
 Date of examination: April 13, 2010
 Location: Ban Mae Nai, Mae Rim District, Chiang Mai province
 Position: 489653; 2089190 Elevation: 487 m (MSL)
 Slope: 8 Aspect: SE (150°)
 Geology: PE, Precambrian gneiss LU/LC: Dry dipterocarp forest
 Landform: 2 Midslope drainages, Shallow valleys


Profile description

Picture	Horizon	Depth (cm)	Description
	A	0-14	Black (10YR 2/1); clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to Bt1.
	B1t	14-30	Very dark grayish brown (10YR 3/2); clay; moderate fine sub-angular blocky structure; friable moist, very sticky and very plastic; gradual and smooth boundary to Bt2.
	B2t	30-50	Brown (10YR 4/3); clay; moderate very fine sub-angular blocky structure; friable moist, very sticky and very plastic.

Information on the site

Sample no: 4
 Date of examination: April 27, 2010
 Location: Ban Buak Thoei, Mae Rim District, Chiang Mai province
 Position: 477503; 2088740 Elevation: 1,276 m (MSL)
 Slope: 68 Aspect: E (105°)
 Geology: Gr, Triassic granite LU/LC: Mixed deciduous forest
 Landform: 3 Upland drainages, Headwaters

Profile description


Picture	Horizon	Depth (cm)	Description
	A	0-10	Dark reddish brown (5YR 2.5/2); clay loam; moderate medium granular structure; friable moist, sticky and plastic; clear and smooth boundary to Bt1.
	B1t	10-27	Reddish brown (5YR 4/3); clay; moderate fine granular structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	27-50	Red (2.5YR 4/6); clay; moderate fine sub-angular blocky structure; friable moist, very sticky and very plastic.

A.1 (Continued).

Information on the site

Sample no: 5
 Date of examination: April 08, 2010
 Location: Ban Mae Sa Mai, Mae Sa Mai, Mae Rim District, Chiang Mai province
 Position: 484283; 2086430 Elevation: 999 m (MSL)
 Slope: 17 Aspect: N (21°)
 Geology: Gr, Triassic granite LU/LC: Orchard
 Landform: 4 U-Shaped valleys


Profile description

Picture	Horizon	Depth (cm)	Description
	A	0-13	Dark reddish brown (5YR 3/2); clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to Bt1.
	B1t	13-26	Reddish brown (5YR 4/3); clay; moderate very fine granular structure; friable moist, sticky and plastic; clear and smooth boundary to Bt2.
	B2t	26-50	Yellowish red (5YR 4/6); clay; moderate fine sub-angular blocky structure; friable moist, very sticky and very plastic.

Information on the site

Sample no: 6
 Date of examination: April 07, 2010
 Location: Botanic Resort, Mae Rim District, Chiang Mai province
 Position: 486137; 2089870 Elevation: 722 m (MSL)
 Slope: 7 Aspect: W (265°)
 Geology: Gr, Triassic granite LU/LC: Dry dipterocarp forest
 Landform: 4 U-Shaped valleys

Profile description


Picture	Horizon	Depth (cm)	Description
	A	0-11	Dark reddish brown (5YR 2.5/2); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to Bt1.
	B1t	11-23	Brown (7.5YR 5/4); sandy clay loam; moderate fine granular structure; friable moist, slightly sticky and slightly plastic; gradual and smooth boundary to Bt2.
	B2t	23-50	Strong brown (7.5YR 5/6); clay loam; moderate fine sub-angular blocky structure; friable moist, sticky and plastic.

A.1 (Continued).

Information on the site

Sample no: 7
 Date of examination: April 10, 2010
 Location: Huai Mae Mae, Mae Rim District, Chiang Mai province
 Position: 488183; 2088650 Elevation: 642 m (MSL)
 Slope: 3-5 Aspect: NE (55°)
 Geology: PE, Precambrian gneiss LU/LC: Dry dipterocarp forest
 Landform: 10 Mountain tops


Profile description

Picture	Horizon	Depth (cm)	Description
	A	0-11	Very dark gray (10YR 3/1); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to B.
	E	11-23	Light brownish gray (10YR 6/2); sandy clay loam; moderate fine and medium granular structure; friable moist, sticky and plastic; clear and smooth boundary to Bt.
	Bt	23-50	Reddish yellow (7.5YR 6/6); clay; moderate fine sub-angular blocky structure; friable moist, very sticky and very plastic.

Information on the site

Sample no: 8
 Date of examination: April 10, 2010
 Location: Ban Tong Luang, Mae Rim District, Chiang Mai province
 Position: 487493; 2089070 Elevation: 575 m (MSL)
 Slope: 25 Aspect: NE (70°)
 Geology: PE, Precambrian gneiss LU/LC: Orchard
 Landform: 6 Open slopes

Profile description


Picture	Horizon	Depth (cm)	Description
	Ap	0-19	Very dark grayish brown (10YR 3/2); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to Bt1.
	B1t	19-31	Yellowish brown (10YR 5/4); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; clear and smooth boundary to Bt2.
	B2t	31-50	Dark yellowish brown (10YR 4/4); clay; moderate fine sub-angular blocky structure; friable moist, very sticky and very plastic.

A.1 (Continued).

Information on the site

Sample no: 9
 Date of examination: April 18, 2010
 Location: Ban Namtok Mae Sa, Mae Rim District, Chiang Mai province
 Position: 489653; 2090900 Elevation: 399 m (MSL)
 Slope: 14 Aspect: NE (65°)
 Geology: PE, Precambrian gneiss LU/LC: Dry dipterocarp forest
 Landform: 6 Open slopes


Profile description

Picture	Horizon	Depth (cm)	Description
	A	0-9	Dark reddish brown (5YR 2.5/2); clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; gradual and smooth boundary to BA.
	BA	9-22	Reddish brown (5YR 4/4); clay loam; moderate medium granular structure; friable moist, sticky and plastic; clear and smooth boundary to Bt.
	Bt	22-50	Yellowish red (5YR 5/6); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic.

Information on the site

Sample no: 10
 Date of examination: May 07, 2010
 Location: Doi Pa Kha, Mae Rim District, Chiang Mai province
 Position: 486563; 2083250 Elevation: 1,094 m (MSL)
 Slope: 37 Aspect: N (24°)
 Geology: Gr, Triassic granite LU/LC: Evergreen forest
 Landform: 9 Midslope ridges, Small hills in plains

Profile description


Picture	Horizon	Depth (cm)	Description
	A	0-12	Very dark brown (7.5YR 2.5/2); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to B.
	B	12-24	Dark brown (7.5YR 3/2); sandy clay loam; moderate fine and medium granular structure; friable moist, slightly sticky and slightly plastic; gradual and smooth boundary to Bt1.
	Bt1	24-47	Brown (7.5YR 4/4); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	47-70	Strong brown (7.5YR 5/6); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic.

A.1 (Continued).

Information on the site

Sample no: 11
 Date of examination: April 16, 2010
 Location: Ban Namtok Mae Sa, Mae Rim District, Chiang Mai province
 Position: 489173; 2090690 Elevation: 557 m (MSL)
 Slope: 19 Aspect: NE (32°)
 Geology: Gr, Triassic granite LU/LC: Dry dipterocarp forest
 Landform: 6 Open slopes

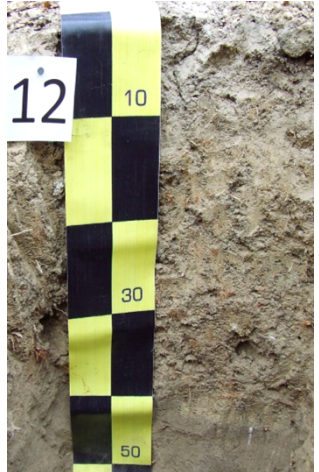
Profile description

Picture	Horizon	Depth (cm)	Description
	A	0-8	Dark reddish brown (5YR 3/2); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to B.
	B	8-26	Reddish brown (5YR 5/4); sandy clay loam; moderate fine and medium granular structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt.
	Bt	26-50	Reddish brown (2.5YR 4/4); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic.

Information on the site

Sample no: 12
 Date of examination: April 16, 2010
 Location: Ban Tin That, Mae Rim District, Chiang Mai province
 Position: 488993; 2091500 Elevation: 432 m (MSL)
 Slope: 32 Aspect: NE (39°)
 Geology: Gr, Triassic granite LU/LC: Mixed deciduous forest
 Landform: 6 Open slopes

Profile description


Picture	Horizon	Depth (cm)	Description
	A	0-12	Dark grayish brown (10YR 4/2); clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to Bt1.
	B1t	12-30	Yellowish brown (10YR 5/4); clay; moderate fine and medium granular structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	30-42	Dark yellowish brown (10YR 4/6); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; clear and smooth boundary to Bt3.
	B3t	42-50	Light gray (10YR 7/2); clay; moderate fine sub-angular blocky structure; friable moist, very sticky and very plastic.

A.1 (Continued).

Information on the site

Sample no: 13
 Date of examination: April 28, 2010
 Location: Ban Dong Klang, Mae Rim District, Chiang Mai province
 Position: 481231; 2086110 Elevation: 870 m (MSL)
 Slope: 5 Aspect: NE (33°)
 Geology: Gr, Triassic granite LU/LC: Field crop
 Landform: 10 Mountain tops


Profile description

Picture	Horizon	Depth (cm)	Description
	Ap	0-14	Dark reddish brown (5YR 3/2); clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to Bt1.
	B1t	14-32	Reddish brown (5YR 4/4); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	32-50	Reddish brown (5YR 5/4); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic.

Information on the site

Sample no: 14
 Date of examination: April 07, 2010
 Location: Queen Sirikit Botanic Garden, Mae Rim District, Chiang Mai province
 Position: 485480; 2088820 Elevation: 823 m (MSL)
 Slope: 50 Aspect: W (277°)
 Geology: PE, Precambrian gneiss LU/LC: Mixed deciduous forest
 Landform: 6 Open slopes

Profile description


Picture	Horizon	Depth (cm)	Description
	A	0-11	Dark brown (5YR 2.5/2); clay loam; moderate fine granular structure; friable moist, slightly sticky and slightly plastic; gradual and smooth boundary to AB.
	AB	11-20	Dark reddish brown (5YR3/4); clay loam; moderate fine granular structure; friable moist, sticky and plastic; clear and smooth boundary to Bt1.
	B1t	20-33	Yellowish red (5YR4/6); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; abrupt and smooth boundary to Bt2.
	B2t	33-50	Red (2.5YR 4/6); clay; moderate fine sub-angular blocky structure; friable moist, very sticky and very plastic.

A.1 (Continued).

Information on the site

Sample no: 15
 Date of examination: May 11, 2010
 Location: Huai Mae Nai, Mae Rim District, Chiang Mai province
 Position: 489383; 2086340 Elevation: 908 m (MSL)
 Slope: 36 Aspect: NE (69°)
 Geology: Gr, Triassic granite LU/LC: Evergreen forest
 Landform: 7 Upper slopes


Profile description

Picture	Horizon	Depth (cm)	Description
	A	0-10	Black (5YR 2.5/1); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to BA.
	BA	10-17	Dark brown (7.5YR 3/4); sandy clay loam; moderate fine and medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to Bt1.
	B1t	17-31	Brown (7.5YR 5/4); clay; moderate fine and medium sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	31-50	Yellowish red (5YR 5/6); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic.

Information on the site

Sample no: 16
 Date of examination: April 27, 2010
 Location: Ban Pang Lung, Mae Rim District, Chiang Mai province
 Position: 477694; 2089600 Elevation: 1,302 m (MSL)
 Slope: 70 Aspect: N (351°)
 Geology: Gr, Triassic granite LU/LC: Mixed deciduous forest
 Landform: 7 Upper slopes

Profile description


Picture	Horizon	Depth (cm)	Description
	A	0-17	Dark reddish brown (5YR 3/2); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to Bt1.
	B1t	17-29	Reddish brown (2.5YR 5/3); clay; moderate fine granular structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	29-50	Red (2.5YR 4/6); clay; moderate fine sub-angular blocky structure; friable moist, very sticky and very plastic.

A.1 (Continued).

Information on the site

Sample no: 17
 Date of examination: April 17, 2010
 Location: Ban Tin That, Mae Rim District, Chiang Mai province
 Position: 488003; 2091830 Elevation: 644 m (MSL)
 Slope: 45 Aspect: N (19°)
 Geology: Gr, Triassic granite LU/LC: Mixed deciduous forest
 Landform: 9 Midslope ridges, Small hills in plains


Profile description

Picture	Horizon	Depth (cm)	Description
	A	0-6	Dull reddish brown (5YR 4/4); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to B.
	E	6-17	Reddish brown (5YR 4/6); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to Bt1.
	B1t	17-26	Dark reddish brown (5YR 3/4); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	26-50	Dark brown (5YR 2.5/2); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic.

Information on the site

Sample no: 18
 Date of examination: April 18, 2010
 Location: Mae Sa Waterfall, Mae Rim District, Chiang Mai province
 Position: 488511; 2090230 Elevation: 553 m (MSL)
 Slope: 30 Aspect: N (21°)
 Geology: PE, Precambrian gneiss LU/LC: Dry dipterocarp forest
 Landform: 9 Midslope ridges, Small hills in plains

Profile description


Picture	Horizon	Depth (cm)	Description
	A	0-7	Very dark gray (5YR 3/1); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to BA.
	BA	7-16	Grayish brown (10YR 5/2); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to Bt1.
	B1t	16-28	Red (2.5YR 5/6); sandy clay; moderate fine and medium sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	28-50	Red (2.5YR 4/8); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic.

A.1 (Continued).

Information on the site

Sample no: 19
 Date of examination: April 10, 2010
 Location: Ban Mae Mae, Mae Rim District, Chiang Mai province
 Position: 488213; 2089190 Elevation: 653 m (MSL)
 Slope: 5 Aspect: NE (30°)
 Geology: PE, Precambrian gneiss LU/LC: Dry dipterocarp forest
 Landform: 10 Mountain tops


Profile description

Picture	Horizon	Depth (cm)	Description
	A	0-7	Dark yellowish brown (10YR 3/4); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to B1.
	B1	7-19	Pale brown (10YR 6/3); sandy clay loam; moderate fine and medium granular structure; friable moist, slightly sticky and slightly plastic; gradual and smooth boundary to B2.
	B2	19-50	Light brown (7.5YR 6/4); clay loam; moderate fine sub-angular blocky structure; friable moist, sticky and plastic.

Information on the site

Sample no: 20
 Date of examination: April 13, 2010
 Location: Ban Mae Nai, Mae Rim District, Chiang Mai province
 Position: 489893; 2089370 Elevation: 494 m (MSL)
 Slope: 16 Aspect: E (85°)
 Geology: PE, Precambrian gneiss LU/LC: Dry dipterocarp forest
 Landform: 10 Mountain tops

Profile description

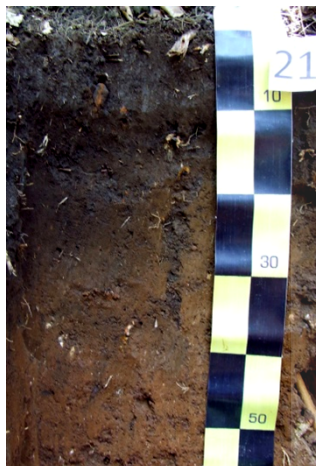
Picture	Horizon	Depth (cm)	Description
	A	0-7	Dark reddish brown (5YR 2.5/2); loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to BA.
	BA	7-16	Dusky red (2.5YR 3/2); clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; gradual and smooth boundary to Bt1.
	B1t	16-28	Dark reddish brown (2.5YR 3/4); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	28-50	Dark red (2.5YR 3/6); clay; moderate fine sub-angular blocky structure; friable moist, very sticky and very plastic.

A.1 (Continued).

Information on the site

Sample no: 21
 Date of examination: April 28, 2010
 Location: Ban Buak Chan, Mae Rim District, Chiang Mai province
 Position: 478101; 2087290 Elevation: 1,046 m (MSL)
 Slope: 43 Aspect: E (92°)
 Geology: Gr, Triassic granite LU/LC: Mixed deciduous forest
 Landform: 1 Canyons or Deeply incised streams


Profile description

Picture	Horizon	Depth (cm)	Description
	A	0-13	Black (7.5YR 2.5/1); clay loam; moderate fine and medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to AB.
	AB	13-18/26	Dark reddish brown (5YR 3/3); clay loam; moderate fine granular structure; friable moist, sticky and plastic; clear and smooth boundary to Bt1.
	B1t	18/26-37	Reddish brown (5YR 4/3); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	37-50	Reddish brown (5YR 5/4); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic.

Information on the site

Sample no: 22
 Date of examination: April 19, 2010
 Location: Ban Pong Yaeng Nai, Mae Rim District, Chiang Mai province
 Position: 479123; 2086940 Elevation: 980 m (MSL)
 Slope: 27 Aspect: NW (284°)
 Geology: Gr, Triassic granite LU/LC: Mixed deciduous forest
 Landform: 2 Midslope drainages, Shallow valleys

Profile description


Picture	Horizon	Depth (cm)	Description
	A	0-6	Dark brown (7.5YR 3/2); sandy clay loam; moderate fine and medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to B.
	B	6-13	Dark grayish brown (10YR 4/2); sandy clay loam; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt1.
	B1t	13-23	Dark yellowish brown (10YR 4/6); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	23-50	Dark yellowish brown (10YR 3/4); clay; moderate fine sub-angular blocky structure; friable moist, very sticky and very plastic.

A.1 (Continued).

Information on the site

Sample no: 23
 Date of examination: April 20, 2010
 Location: Huai Mae Cha, Mae Rim District, Chiang Mai province
 Position: 478283; 2087270 Elevation: 981 m (MSL)
 Slope: 10 Aspect: SE (159°)
 Geology: Gr, Triassic granite LU/LC: Orchard
 Landform: 4 U-Shaped valleys


Profile description

Picture	Horizon	Depth (cm)	Description
	A	0-12	Dark brown (7.5YR 3/2); sandy clay loam; moderate fine and medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to BA.
	BA	12-19	Brown (7.5YR 4/4); sandy clay loam; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt1.
	B1t	19-31	Yellowish red (5YR 4/6); clay; moderate fine and medium sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	31-50	Reddish brown (5YR 5/4); clay; moderate fine and medium sub-angular blocky structure; friable moist, sticky and plastic.

Information on the site

Sample no: 24
 Date of examination: April 16, 2010
 Location: Ban Buak Chan, Mae Rim District, Chiang Mai province
 Position: 478377; 2086940 Elevation: 1,031 m (MSL)
 Slope: 5 Aspect: E (77°)
 Geology: Gr, Triassic granite LU/LC: Orchard
 Landform: 10 Mountain tops

Profile description


Picture	Horizon	Depth (cm)	Description
	Ap	0-14	Yellowish red (5YR4/6); clay loam; moderate fine and medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to Bt1.
	B1t	14-29	Reddish brown (5YR 4/4); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	29-50	Red (2.5YR 5/6); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic.

A.1 (Continued).

Information on the site

Sample no: 25
 Date of examination: April 19, 2010
 Location: Ban Pong Yaeng Nai, Mae Rim District, Chiang Mai province
 Position: 479033; 2087570 Elevation: 989 m (MSL)
 Slope: 61 Aspect: SE (161°)
 Geology: Gr, Triassic granite LU/LC: Mixed deciduous forest
 Landform: 6 Open slopes

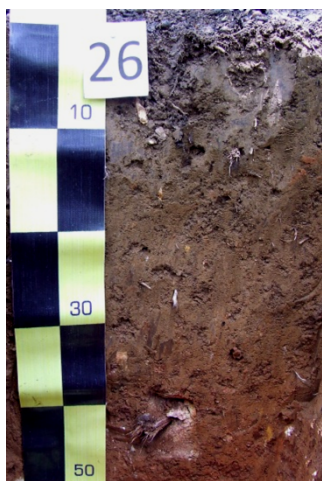
Profile description

Picture	Horizon	Depth (cm)	Description
	A	0-11	Dark brown (7.5YR 3/2); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to BA.
	BA	11-28	Dark reddish brown (5YR 3/4); clay loam; moderate fine and medium granular structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt1.
	B1t	28-50	Yellowish red (5YR 4/6); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	50+	Red (2.5YR 4/6); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic.

Information on the site

Sample no: 26
 Date of examination: April 24, 2010
 Location: Huai Na Lio, Mae Rim District, Chiang Mai province
 Position: 477868; 2085530 Elevation: 1,219 m (MSL)
 Slope: 62 Aspect: NE (43°)
 Geology: Gr, Triassic granite LU/LC: Mixed deciduous forest
 Landform: 7 Upper slopes

Profile description


Picture	Horizon	Depth (cm)	Description
	A	0-8	Dark reddish brown (5YR 2.5/2); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to BA.
	BA	8-33	Reddish brown (5YR 4/4); clay loam; moderate fine granular structure; friable moist, sticky and plastic; clear and smooth boundary to Bt.
	Bt	33-50	Red (2.5YR 5/6); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic.

A.1 (Continued).

Information on the site

Sample no: 27
 Date of examination: April 28, 2010
 Location: Ban Buak Thoei, Mae Rim District, Chiang Mai province
 Position: 477413; 2087600 Elevation: 1,138 m (MSL)
 Slope: 17 Aspect: SE (152°)
 Geology: Gr, Triassic granite LU/LC: Dry dipterocarp forest
 Landform: 6 Open slopes


Profile description

Picture	Horizon	Depth (cm)	Description
	A	0-8	Black (5YR 2.5/1); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to BA.
	BA	8-15	Yellowish red (5YR 4/6); sandy clay loam; moderate fine and medium granular structure; friable moist, slightly sticky and slightly plastic; gradual and smooth boundary to Bt1.
	B1t	15-24	Reddish brown (5YR 4/4); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	24-50	Red (2.5YR 4/6); clay; moderate fine sub-angular blocky structure; friable moist, very sticky and very plastic.

Information on the site

Sample no: 28
 Date of examination: April 24, 2010
 Location: Doi Pa Kia, Mae Rim District, Chiang Mai province
 Position: 477683; 2086040 Elevation: 1,238 m (MSL)
 Slope: 6 Aspect: SE (165°)
 Geology: Gr, Triassic granite LU/LC: Mixed deciduous forest
 Landform: 10 Mountain tops

Profile description


Picture	Horizon	Depth (cm)	Description
	A	0-11	Dark reddish brown (5YR 3/4); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to BA.
	BA	11-21	Reddish brown (2.5YR 4/3); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to B.
	B	21-50	Red (2.5YR 4/8); clay loam; moderate fine and medium sub-angular blocky structure; friable moist, sticky and plastic.

A.1 (Continued).

Information on the site

Sample no: 29
 Date of examination: April 30, 2010
 Location: Ban Nong Hoi, Mae Rim District, Chiang Mai province
 Position: 482022; 2093000 Elevation: 1,224 m (MSL)
 Slope: 25 Aspect: SE (158°)
 Geology: Gr, Triassic granite LU/LC: Field crop
 Landform: 1 Canyons or Deeply incised streams


Profile description

Picture	Horizon	Depth (cm)	Description
	Ap	0-11	Black (5YR 2.5/1); clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to B1.
	B1	11-27	Dark reddish brown (5YR 3/2); clay loam; moderate fine and medium granular structure; friable moist, sticky and plastic; gradual and smooth boundary to B2.
	B2t	27-50	Dark reddish brown (5YR 3/4); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic.

Information on the site

Sample no: 30
 Date of examination: April 30, 2010
 Location: Ban Nong Hoi, Mae Rim District, Chiang Mai province
 Position: 481634; 2092860 Elevation: 1,170 m (MSL)
 Slope: 3 Aspect: S (186°)
 Geology: Gr, Triassic granite LU/LC: Field crop
 Landform: 1 Canyons or Deeply incised streams

Profile description


Picture	Horizon	Depth (cm)	Description
	Ap	0-10	Dark reddish brown (5YR 2.5/2); clay loam; moderate fine and medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to Bt1.
	B1t	10-26	Reddish brown (5YR 4/4); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	26-50	Dark reddish brown (5YR 3/4); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic..

A.1 (Continued).

Information on the site

Sample no: 31
 Date of examination: May 04, 2010
 Location: Doi Pa Sang Luang, Mae Rim District, Chiang Mai province
 Position: 486427; 2090930 Elevation: 850 m (MSL)
 Slope: 32 Aspect: NW (292°)
 Geology: Gr, Triassic granite LU/LC: Mixed deciduous forest
 Landform: 2 Midslope drainages, Shallow valleys


Profile description

Picture	Horizon	Depth (cm)	Description
	A	0-5	Very dark gray (5YR 3/1); clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to BA.
	AB	5-12	Yellowish red (5YR 5/6); clay loam; moderate fine granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to Bt1.
	B1t	12-27	Red (2.5YR 5/8); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	27-50	Reddish brown (2.5YR 5/4); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic.

Information on the site

Sample no: 32
 Date of examination: April 19, 2010
 Location: Doi San Phi Mon, Mae Rim District, Chiang Mai province
 Position: 480923; 2089270 Elevation: 883 m (MSL)
 Slope: 55 Aspect: N (356°)
 Geology: PE, Precambrian gneiss LU/LC: Mixed deciduous forest
 Landform: 6 Open slopes

Profile description

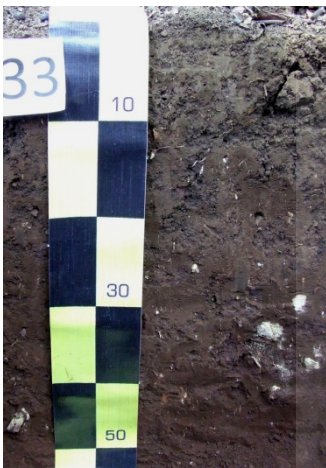
Picture	Horizon	Depth (cm)	Description
	A	0-5	Dark reddish brown (5YR 3/2); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to BA.
	AB	5-13	Dark reddish brown (5YR 3/4); sandy clay loam; moderate fine and medium granular structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt1.
	B1t	13-32	Red (2.5YR 4/6); clay; moderate fine sub-angular blocky structure; friable moist, very sticky and very plastic; gradual and smooth boundary to Bt2.
	B2t	32-50	Dark red (2.5YR 3/6); clay; moderate fine sub-angular blocky structure; friable moist, very sticky and very plastic.

A.1 (Continued).

Information on the site

Sample no: 33
 Date of examination: April 20, 2010
 Location: Doi Chang Tai, Mae Rim District, Chiang Mai province
 Position: 480540; 2088880 Elevation: 1,006 m (MSL)
 Slope: 35 Aspect: SE (145°)
 Geology: PE, Precambrian gneiss LU/LC: Mixed deciduous forest
 Landform: 2 Midslope drainages, Shallow valleys


Profile description

Picture	Horizon	Depth (cm)	Description
	A	0-12	Black (5YR 2.5/1); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to Bt1.
	B1t	12-23	Dark reddish brown (5YR 3/4); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	23-50	Reddish brown (5YR 4/3); clay; moderate fine sub-angular blocky structure; friable moist, very sticky and very plastic.

Information on the site

Sample no: 34
 Date of examination: May 14, 2010
 Location: Huai Nam Un, Mae Rim District, Chiang Mai province
 Position: 487378; 2086860 Elevation: 912 m (MSL)
 Slope: 9 Aspect: SE (147°)
 Geology: Gr, Triassic granite LU/LC: Evergreen forest
 Landform: 1 Canyons or Deeply incised streams

Profile description


Picture	Horizon	Depth (cm)	Description
	A	0-7	Very dark grayish brown (10YR 3/2); clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to BA.
	BA	7-23	Brown (7.5YR 4/2); clay loam; moderate fine and medium granular structure; friable moist, sticky and plastic; clear and smooth boundary to Bt1.
	B1t	23-41	Brown (7.5YR 5/4); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	41-50	Strong brown (7.5YR 5/6); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic.

A.1 (Continued).

Information on the site

Sample no: 35
 Date of examination: April 17, 2010
 Location: Ban Ton Tong, Mae Rim District, Chiang Mai province
 Position: 488361; 2091240 Elevation: 631 m (MSL)
 Slope: 15 Aspect: NE (41°)
 Geology: Gr, Triassic granite LU/LC: Mixed deciduous forest
 Landform: 7 Upper slopes


Profile description

Picture	Horizon	Depth (cm)	Description
	A	0-11	Dark reddish brown (5YR 2.5/2); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to B.
	B	11-33	Reddish brown (5YR 5/4); clay; moderate fine and medium granular structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt.
	Bt	33-50	Red (2.5YR 4/6); clay; moderate fine sub-angular blocky structure; friable moist, very sticky and very plastic.

Information on the site

Sample no: 36
 Date of examination: May 12, 2010
 Location: Ban Mae Sa Mai, Mae Rim District, Chiang Mai province
 Position: 485600; 2087180 Elevation: 851 m (MSL)
 Slope: 55 Aspect: NW (314°)
 Geology: Gr, Triassic granite LU/LC: Evergreen forest
 Landform: 6 Open slopes

Profile description


Picture	Horizon	Depth (cm)	Description
	A	0-14	Black (7.5YR 2.5/1); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to B.
	B	14-37	Dark brown (7.5YR 3/2); clay loam; moderate fine and medium sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt.
	Bt	37-50	Strong brown (7.5YR 4/6); clay; moderate fine and medium sub-angular blocky structure; friable moist, sticky and plastic.

A.1 (Continued).

Information on the site

Sample no: 37
 Date of examination: May 14, 2010
 Location: Huai Nam Un, Mae Rim District, Chiang Mai province
 Position: 488057; 2087130 Elevation: 824 m (MSL)
 Slope: 32 Aspect: NE (40°)
 Geology: Gr, Triassic granite LU/LC: Mixed deciduous forest
 Landform: 6 Open slopes


Profile description

Picture	Horizon	Depth (cm)	Description
	A	0-8	Dark Reddish Brown (5YR 2.5/2); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to BA.
	BA	8-20	Dark reddish brown (5YR 3/4); sandy clay loam; moderate fine and medium granular structure; friable moist, slightly sticky and slightly plastic; gradual and smooth boundary to B.
	B	20-42	Red (2.5YR 4/6); clay loam; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt.
	Bt	42-50	Red (2.5YR 4/8); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic.

Information on the site

Sample no: 38
 Date of examination: April 08, 2010
 Location: Ban Mae Sa Mai, Mae Rim District, Chiang Mai province
 Position: 483842; 2087450 Elevation: 922 m (MSL)
 Slope: 23 Aspect: N (14°)
 Geology: Gr, Triassic granite LU/LC: Orchard
 Landform: 6 Open slopes

Profile description

Picture	Horizon	Depth (cm)	Description
	Ap	0-22	Dark reddish brown (5YR 3/2); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to Bt1.
	B1t	22-33	Reddish brown (5YR 4/4); clay; moderate fine sub-angular blocky structure; friable moist, very sticky and very plastic; gradual and smooth boundary to Bt2.
	B2t	33-50	Reddish brown (5YR 4/4); clay; moderate fine sub-angular blocky structure; firm moist, very sticky and very plastic.

A.1 (Continued).

Information on the site

Sample no: 39
 Date of examination: April 30, 2010
 Location: Huai Nong Hoi, Mae Rim District, Chiang Mai province
 Position: 481015; 2091670 Elevation: 1,037 m (MSL)
 Slope: 12 Aspect: SE (120°)
 Geology: PE, Precambrian gneiss LU/LC: Mixed deciduous forest
 Landform: 9 Midslope ridges, Small hills in plains

Profile description

Horizon	Depth (cm)	Description
A	0-27	Black (5YR 2.5/1); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to BA.
BA	27-38	Dark reddish brown (5YR 2.5/2); sandy clay loam; moderate fine and medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to Bt.
Bt	38-50	Reddish brown (5YR 4/4); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic.

Information on the site

Sample no: 40
 Date of examination: May 06, 2010
 Location: Doi Mae Luat, Mae Rim District, Chiang Mai province
 Position: 484429; 2091230 Elevation: 864 m (MSL)
 Slope: 50 Aspect: SW (195°)
 Geology: Gr, Triassic granite LU/LC: Mixed deciduous forest
 Landform: 6 Open slopes

Profile description


Horizon	Depth (cm)	Description
A	0-8	Dark Brown (7.5YR 3/2); clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; gradual and smooth boundary to BA.
BA	8-18	Brown (7.5YR 4/4); clay loam; moderate fine and medium granular structure; friable moist, slightly sticky and slightly plastic; gradual and smooth boundary to Bt1.
B1t	18-36	Red (2.5YR 4/8); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
B2t	36-50	Dark red (2.5YR 3/6); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic.

A.1 (Continued).

Information on the site

Sample no: 41
 Date of examination: May 04, 2010
 Location: Doi Mae Luat, Mae Rim District, Chiang Mai province
 Position: 486102; 2091450 Elevation: 880 m (MSL)
 Slope: 46 Aspect: NE (46°)
 Geology: Gr, Triassic granite LU/LC: Mixed deciduous forest
 Landform: 6 Open slopes


Profile description

Picture	Horizon	Depth (cm)	Description
	A	0-6	Dark brown (7.5YR 3/2); clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to BA.
	BA	6-18	Dark reddish brown (5YR 3/3); clay loam; moderate fine and medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to Bt1.
	B1t	18-32	Reddish brown (5YR 4/4); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	32-50	Reddish brown (5YR 5/4); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic.

Information on the site

Sample no: 42
 Date of examination: April 08, 2010
 Location: Ban Mae Sa Mai, Mae Rim District, Chiang Mai province
 Position: 483503; 2085530 Elevation: 1,122 m (MSL)
 Slope: 63 Aspect: N (17°)
 Geology: Gr, Triassic granite LU/LC: Field crop
 Landform: 10 Mountain tops

Profile description


Picture	Horizon	Depth (cm)	Description
	Ap	0-19	Reddish brown (2.5YR 4/3); clay loam; moderate fine and medium granular structure; friable moist, slightly sticky and slightly plastic; gradual and smooth boundary to Bt1.
	B1t	19-38	Reddish brown (5YR 4/3); clay; moderate fine and medium sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	38-50	Dark reddish brown (5YR 3/4); clay; fine sub-angular blocky structure; friable moist, sticky and plastic.

A.1 (Continued).

Information on the site

Sample no: 43
 Date of examination: May 05, 2010
 Location: Ban Pong Yaeng Nok, Mae Rim District, Chiang Mai province
 Position: 483233; 2090920 Elevation: 943 m (MSL)
 Slope: 65 Aspect: SW (202°)
 Geology: Gr, Triassic granite LU/LC: Mixed deciduous forest
 Landform: 7 Upper slopes


Profile description

Picture	Horizon	Depth (cm)	Description
	A	0-17	Black (7.5YR 2.5/1); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to Bt1.
	BA	17-28	Dark reddish brown (5YR 3/3); sandy clay loam; moderate fine and medium granular structure; friable moist, slightly sticky and slightly plastic; gradual and smooth boundary to Bt2.
	B1t	28-44	Reddish brown (2.5YR 4/3); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt3.
	B2t	44-50	Red (2.5YR 4/6); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic.

Information on the site

Sample no: 44
 Date of examination: May 12, 2010
 Location: Ban Pa Kha, Mae Rim District, Chiang Mai province
 Position: 487343; 2085620 Elevation: 1,209 m (MSL)
 Slope: 34 Aspect: NE (38°)
 Geology: Gr, Triassic granite LU/LC: Mixed deciduous forest
 Landform: 8 Local ridges, Hills in valleys

Profile description

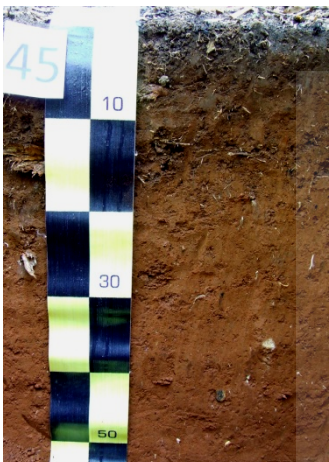
Picture	Horizon	Depth (cm)	Description
	A	0-8	Black (5YR 2.5/1); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to BA.
	BA	8-16	Dark reddish brown (5YR 3/4); sandy clay loam; moderate fine and medium granular structure; friable moist, sticky and plastic; gradual and smooth boundary to B.
	B	16-29	Reddish brown (5YR 4/6); sandy clay loam; moderate fine and medium sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt.
	Bt	29-50	Red (2.5YR 5/8); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic.

A.1 (Continued).

Information on the site

Sample no: 45
 Date of examination: May 05, 2010
 Location: Huai Suea, Mae Rim District, Chiang Mai province
 Position: 480863; 2091080 Elevation: 985 m (MSL)
 Slope: 15 Aspect: SW (200°)
 Geology: PE, Precambrian gneiss LU/LC: Mixed deciduous forest
 Landform: 9 Midslope ridges, Small hills in plains


Profile description

Picture	Horizon	Depth (cm)	Description
	A	0-6	Dark reddish brown (5YR 2.5/2); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to BA.
	BA	6-14	Reddish brown (5YR 4/3); sandy clay loam; moderate fine and medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to Bt1.
	B1t	14-37	Reddish brown (2.5YR 4/4); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	37-50	Dark red (2.5YR 3/6); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic.

Information on the site

Sample no: 46
 Date of examination: April 07, 2010
 Location: Mae Sa Mai Water Management Unit, Mae Rim District, Chiang Mai province
 Position: 484052; 2090100 Elevation: 739 m (MSL)
 Slope: 16 Aspect: SW (228°)
 Geology: PE, Precambrian gneiss LU/LC: Mixed deciduous forest
 Landform: 9 Midslope ridges, Small hills in plains

Profile description


Picture	Horizon	Depth (cm)	Description
	A	0-11	Dark reddish brown (5YR 2.5/2); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to BA.
	BA	11-18	Reddish brown (5YR 4/4); sandy clay loam; moderate fine and medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to Bt1.
	B1t	18-25	Yellowish red (5YR 4/6); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	25-50	Reddish brown (2.5YR 4/4); clay; moderate fine sub-angular blocky structure; friable moist, very sticky and very plastic.

A.1 (Continued).

Information on the site

Sample no: 47
 Date of examination: May 03, 2010
 Location: Huai Pong Tai, Mae Rim District, Chiang Mai province
 Position: 479581; 2092430 Elevation: 1,334 m (MSL)
 Slope: 10 Aspect: SW (208°)
 Geology: Gr, Triassic granite LU/LC: Mixed deciduous forest
 Landform: 10 Mountain tops


Profile description


Picture	Horizon	Depth (cm)	Description
	A	0-8	Dark reddish brown (5YR 2.5/4); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to Bt1.
	B1t	8-33	Reddish brown (5YR 4/3); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	33-50	Dark red (5YR 3/6); very gravelly clay; moderate fine sub-angular blocky structure; friable moist, very sticky and very plastic.

Information on the site

Sample no: 48
 Date of examination: May 07, 2010
 Location: Ban Pa Kha, Mae Rim District, Chiang Mai province
 Position: 486503; 2086070 Elevation: 1,273 m (MSL)
 Slope: 23 Aspect: E (107°)
 Geology: Gr, Triassic granite LU/LC: Evergreen forest
 Landform: 10 Mountain tops

Profile description

Picture	Horizon	Depth (cm)	Description
	A	0-7	Black (2.5YR 2.5/1); sandy clay loam; moderate medium granular structure; friable moist, slightly sticky and slightly plastic; clear and smooth boundary to BA.
	BA	7-14	Dark reddish brown (2.5YR 3/4); sandy clay loam; moderate fine and medium granular structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt1.
	B1t	14-27	Reddish brown (5YR 4/6); clay; moderate fine sub-angular blocky structure; friable moist, sticky and plastic; gradual and smooth boundary to Bt2.
	B2t	27-50	Reddish brown (5YR 5/4); clay; moderate fine sub-angular blocky structure; friable moist, very sticky and very plastic.



APPENDIX B
SOIL SAMPLE PROPERTIES

B.1 Soil sample properties.

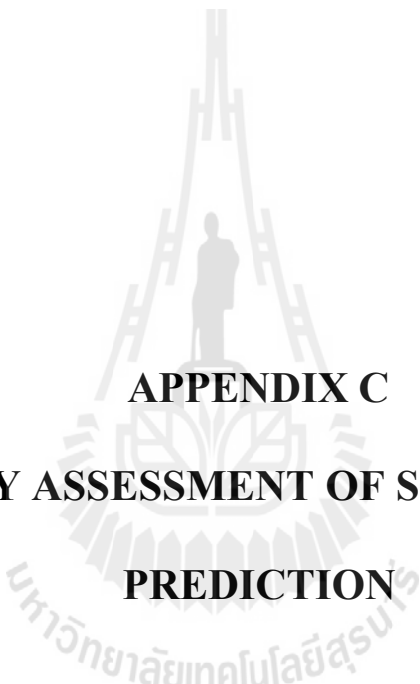
Sample No	Depth (cm)	Sand (%)	Silt (%)	Clay (%)	Texture	pH	OM (%)	N (%)	P (ppm)	K (ppm)	Ca (ppm)	Mg (ppm)	Na (ppm)	CEC (meq/100g)	BS (%)
1	0-25	32.88	30.36	36.76	clay loam	5.98	10.05	0.4925	9.76	223.95	1126.95	491.23	94.92	35.44	30.06
	25-50	20.88	27.36	51.76	clay	6.16	3.09	0.1382	2.23	120.73	524.43	273.46	55.52	25.41	21.32
2	0-25	34.46	33.36	32.18	clay loam	6.52	9.90	0.5048	10.09	262.27	1355.02	487.86	107.66	30.77	38.72
	25-50	20.38	27.36	52.26	clay	6.34	3.78	0.1574	2.57	145.91	648.45	244.25	59.13	25.96	22.64
3	0-25	35.96	28.36	35.68	clay loam	6.46	4.00	0.2000	4.74	166.91	825.93	335.65	81.61	18.71	40.96
	25-50	24.88	22.52	52.60	clay	5.50	1.05	0.0640	1.14	78.51	488.72	177.94	37.11	14.98	28.47
4	0-25	37.30	30.36	32.34	clay loam	6.03	8.40	0.3198	7.07	209.37	913.50	341.29	99.02	24.34	34.23
	25-50	24.46	22.36	53.18	clay	5.17	3.05	0.1257	1.24	106.74	527.83	214.54	50.42	22.04	22.19
5	0-25	39.88	30.36	29.76	clay loam	5.22	7.48	0.1541	5.83	103.45	511.84	238.02	48.92	22.73	21.96
	25-50	30.80	24.36	44.84	clay	5.46	2.07	0.0734	1.03	66.43	427.51	173.73	40.81	15.84	24.69
6	0-25	49.96	25.20	24.84	sandy clay loam	5.32	5.38	0.1689	4.25	123.63	562.16	228.45	41.73	20.69	25.05
	25-50	44.38	21.36	34.26	clay loam	5.68	1.59	0.0750	1.08	75.50	373.39	111.72	35.73	17.37	18.03
7	0-25	47.30	25.53	27.18	sandy clay loam	5.95	3.84	0.1922	4.03	162.18	752.88	355.97	88.97	17.94	41.73
	25-50	27.46	19.36	53.18	clay	5.91	0.74	0.0371	0.96	98.02	340.48	146.63	22.71	11.63	28.00
8	0-25	48.46	22.20	29.34	sandy clay loam	5.07	4.33	0.2165	2.42	94.73	468.72	250.49	44.81	18.76	25.78
	25-50	43.38	14.20	42.42	clay	4.74	1.07	0.0534	0.85	60.60	250.56	111.83	16.90	16.33	14.69
9	0-25	36.22	34.36	29.43	clay loam	6.23	4.71	0.1733	6.09	164.13	845.07	343.43	77.64	19.25	40.53
	25-50	23.38	25.36	51.26	clay	5.06	1.12	0.0960	1.41	85.51	474.63	191.64	26.21	13.68	31.27
10	0-25	52.80	22.52	24.68	sandy clay loam	4.94	9.90	0.3948	5.06	95.75	473.63	192.51	42.62	28.89	15.15
	25-50	39.88	20.36	39.76	clay loam	4.89	3.47	0.1291	1.08	64.51	319.18	129.73	30.51	19.67	15.04
11	0-25	45.88	25.36	28.76	sandy clay loam	5.45	3.60	0.1802	3.72	112.84	558.31	304.29	53.36	17.39	33.41
	25-50	33.30	22.52	44.18	clay	4.82	0.64	0.0319	1.24	51.02	358.30	152.53	24.12	17.23	19.03
12	0-25	32.38	33.36	34.26	clay loam	6.74	6.55	0.3476	6.56	201.63	997.45	439.52	65.34	21.55	43.59
	25-50	22.96	26.20	50.84	clay	6.01	3.41	0.0845	2.24	76.71	477.31	184.63	45.22	16.49	26.03
13	0-25	40.04	24.20	35.76	clay loam	6.20	2.12	0.1460	1.19	152.87	726.37	325.19	72.30	16.72	41.91
	25-50	28.88	18.52	52.60	clay	5.35	0.59	0.0493	1.24	68.70	439.92	158.13	32.51	13.66	27.91
14	0-25	44.88	25.36	29.76	clay loam	5.42	7.02	0.2508	4.48	156.78	672.96	273.49	74.14	21.94	28.86
	25-50	30.88	19.52	49.60	clay	4.98	1.84	0.0722	1.13	63.30	313.08	127.22	29.91	17.35	16.72
15	0-25	50.96	21.20	27.84	sandy clay loam	4.74	9.09	0.3543	6.42	81.95	425.53	204.81	38.76	23.16	18.08
	25-50	50.88	22.20	26.92	sandy clay loam	5.01	3.50	0.0922	1.08	41.72	307.47	103.62	15.31	16.35	15.66
16	0-25	47.89	22.36	29.76	sandy clay loam	5.23	9.34	0.3413	5.33	118.08	504.15	287.41	55.84	25.47	21.30
	25-50	29.80	24.36	45.84	clay	5.46	1.48	0.1776	1.53	108.34	495.03	151.13	47.31	25.52	16.44

B.1 (Continued).

Sample No	Depth (cm)	Sand (%)	Silt (%)	Clay (%)	Texture	pH	OM (%)	N (%)	P (ppm)	K (ppm)	Ca (ppm)	Mg (ppm)	Na (ppm)	CEC (meq/100g)	BS (%)
17	0-25	51.30	22.52	26.18	sandy clay loam	5.38	3.22	0.1112	4.54	83.28	338.60	213.87	26.19	16.93	22.31
	25-50	46.30	19.36	34.34	sandy clay loam	4.50	0.59	0.0293	0.61	37.93	278.58	126.23	27.91	15.18	17.44
18	0-25	49.04	23.20	27.76	sandy clay loam	5.27	4.00	0.1100	2.36	95.24	491.34	251.56	45.06	18.44	26.90
	25-50	48.54	15.20	36.26	sandy clay	4.39	1.14	0.0583	0.65	35.50	226.25	108.33	12.12	12.21	17.72
19	0-25	48.80	24.52	26.68	sandy clay loam	5.38	3.84	0.2353	2.07	111.43	561.34	234.06	32.69	21.18	24.34
	25-50	40.30	20.52	39.18	clay loam	5.21	0.72	0.0860	0.47	40.82	261.76	82.02	20.30	14.13	15.39
20	0-25	46.36	28.46	25.18	loam	5.33	4.76	0.1379	3.84	109.16	540.22	219.55	51.64	19.28	25.97
	25-50	47.38	16.36	36.26	sandy clay	4.89	1.22	0.0612	0.83	54.62	171.44	79.61	16.41	11.15	15.44
21	0-25	42.72	26.53	30.76	clay loam	5.75	4.76	0.1379	1.06	164.09	811.88	319.93	87.61	19.67	38.05
	25-50	26.88	20.36	52.76	clay	5.58	1.22	0.0612	0.57	97.51	432.00	216.24	30.81	21.49	20.10
22	0-25	46.30	26.52	27.18	sandy clay loam	5.56	8.43	0.3215	4.11	152.64	833.60	338.76	79.68	24.52	31.34
	25-50	28.38	23.36	48.26	clay	5.91	3.19	0.1095	2.04	113.81	413.10	188.84	25.82	19.18	20.95
23	0-25	51.80	21.52	26.68	sandy clay loam	5.31	7.48	0.2741	2.54	91.61	453.28	208.35	32.23	16.72	26.03
	25-50	48.80	15.52	35.68	sandy clay	5.02	2.07	0.1034	0.80	42.30	253.27	65.02	23.31	11.22	17.90
24	0-25	42.72	26.52	30.77	clay loam	5.24	4.76	0.1379	1.82	145.76	786.25	293.08	68.92	19.67	35.63
	25-50	30.46	16.20	53.34	clay	5.01	1.74	0.0612	1.14	59.51	338.78	159.73	28.21	16.04	20.45
25	0-25	47.71	24.70	27.59	sandy clay loam	5.09	8.67	0.3336	6.08	99.74	543.04	240.69	41.91	25.07	20.45
	25-50	39.80	22.36	37.84	clay loam	5.05	3.31	0.0755	1.51	41.09	371.80	132.92	33.61	17.82	17.96
26	0-25	54.96	22.20	22.84	sandy clay loam	4.33	9.09	0.3543	7.53	85.70	473.59	212.46	45.27	27.08	16.72
	25-50	41.80	22.52	35.68	clay loam	5.05	2.40	0.0864	1.64	79.53	446.11	149.33	13.91	18.63	19.97
27	0-25	53.88	22.36	23.76	sandy clay loam	5.00	7.40	0.2698	5.19	93.72	483.81	268.50	44.32	22.29	22.68
	25-50	32.80	20.52	46.68	clay	4.83	1.97	0.0983	1.03	51.41	305.07	93.32	29.61	16.37	15.58
28	0-25	50.38	23.52	26.10	sandy clay loam	4.69	7.57	0.2842	4.73	86.95	430.26	293.08	36.00	25.81	19.13
	25-50	43.96	16.20	39.84	clay loam	5.06	1.67	0.0744	0.71	27.72	230.16	87.62	18.21	14.25	14.18
29	0-25	35.54	29.20	35.26	clay loam	6.00	8.83	0.4413	6.15	185.87	1167.03	454.35	96.99	30.77	33.99
	25-50	23.80	21.36	54.84	clay	5.94	3.69	0.1845	2.14	148.34	613.14	238.25	64.83	25.36	22.40
30	0-25	41.63	24.87	33.51	clay loam	5.58	8.15	0.3077	3.56	203.62	814.41	219.44	96.30	28.89	23.57
	25-50	27.38	19.36	53.26	clay	5.22	2.48	0.1600	0.71	84.73	467.81	180.73	44.21	24.16	17.51
31	0-25	40.29	26.70	33.01	clay loam	6.04	7.22	0.2612	4.56	170.39	823.12	312.62	65.57	22.22	33.31
	25-50	37.30	17.52	45.18	clay	5.69	1.97	0.0883	0.84	72.02	503.73	235.35	50.72	22.30	21.77
32	0-25	48.04	25.20	26.76	sandy clay loam	5.35	1.79	0.0896	0.81	126.29	454.73	283.91	69.73	21.67	24.14
	25-50	41.80	16.52	41.68	clay	4.74	0.53	0.0267	0.72	41.52	290.78	97.52	18.21	14.34	17.01

B.1 (Continued).

Sample No	Depth (cm)	Sand (%)	Silt (%)	Clay (%)	Texture	pH	OM (%)	N (%)	P (ppm)	K (ppm)	Ca (ppm)	Mg (ppm)	Na (ppm)	CEC (meq/100g)	BS (%)
33	0-25	49.14	18.69	32.18	sandy clay loam	5.60	8.43	0.3215	4.44	158.19	731.18	388.44	89.02	24.93	30.63
	25-50	27.30	24.36	48.34	clay	5.26	3.09	0.1392	1.03	96.53	427.31	154.03	45.61	21.05	18.26
34	0-25	34.46	31.20	34.34	clay loam	5.42	9.55	0.4775	11.15	159.40	687.71	290.76	70.85	28.12	23.26
	25-50	23.80	25.36	50.84	clay	5.46	3.98	0.1724	2.26	81.21	510.82	203.54	45.82	23.07	20.08
35	0-25	46.38	25.36	28.26	sandy clay loam	5.41	6.69	0.2345	3.06	105.56	522.40	212.30	49.93	17.92	27.02
	25-50	33.30	19.36	47.34	clay	4.74	1.41	0.0779	0.81	49.69	222.36	107.93	33.52	13.05	17.40
36	0-25	53.71	22.20	24.09	sandy clay loam	4.82	3.74	0.1371	1.34	124.72	412.14	260.77	58.97	22.47	21.26
	25-50	51.04	17.20	31.76	sandy clay loam	4.36	0.67	0.0836	0.41	38.12	236.95	136.92	32.21	22.04	11.56
37	0-25	50.96	24.36	24.68	sandy clay loam	5.26	8.67	0.3336	6.57	97.35	551.72	215.76	46.05	19.44	25.60
	25-50	44.30	22.36	33.34	clay loam	5.76	3.12	0.0776	1.46	47.90	412.40	96.42	22.71	13.86	22.17
38	0-25	50.46	25.20	24.34	sandy clay loam	5.63	7.91	0.2698	8.92	116.32	426.57	233.69	45.54	24.41	18.63
	25-50	30.80	22.52	46.68	clay	5.24	2.05	0.1126	1.01	36.52	251.36	63.41	26.51	14.26	13.92
39	0-25	49.88	25.52	24.60	sandy clay loam	5.01	8.17	0.2787	3.07	92.51	528.25	245.91	47.38	19.25	26.51
	25-50	45.54	13.20	41.26	sandy clay	4.78	3.00	0.1400	1.61	45.12	263.67	83.06	12.90	14.28	15.20
40	0-25	41.30	27.36	31.34	clay loam	5.23	7.05	0.2804	6.84	114.05	564.31	229.33	53.93	26.46	19.77
	25-50	33.96	22.36	43.68	clay	5.53	1.48	0.1388	1.43	65.02	420.80	171.03	40.21	17.05	22.57
41	0-25	40.88	28.36	30.76	clay loam	5.82	9.17	0.3413	4.43	169.14	836.85	340.09	64.99	24.13	31.87
	25-50	27.88	25.52	46.60	clay	5.64	3.15	0.1523	1.81	99.31	450.32	139.92	46.42	22.51	17.12
42	0-25	49.88	21.36	28.76	sandy clay loam	5.30	5.57	0.1784	1.04	113.11	659.78	247.56	53.50	20.85	28.06
	25-50	41.80	18.36	39.84	clay loam	4.89	1.50	0.0850	0.54	54.31	368.90	129.23	25.70	16.03	19.68
43	0-25	49.38	25.36	25.26	sandy clay loam	5.10	10.05	0.3403	5.13	103.10	580.08	227.29	48.76	23.46	22.34
	25-50	36.88	21.36	41.76	clay	5.14	3.91	0.0814	1.98	63.81	315.87	128.43	30.21	17.57	16.67
44	0-25	54.46	23.20	22.34	sandy clay loam	5.05	7.02	0.2508	2.35	93.64	463.30	268.29	44.28	21.74	22.78
	25-50	50.80	20.36	28.84	sandy clay loam	4.74	1.84	0.1192	1.08	41.09	263.27	112.73	19.40	14.78	16.45
45	0-25	45.88	25.36	28.76	sandy clay loam	5.46	7.95	0.3174	5.15	82.03	761.02	285.41	67.73	23.32	28.52
	25-50	29.88	20.36	49.76	clay	5.16	2.40	0.1298	0.84	77.30	333.29	135.43	31.82	20.18	15.43
46	0-25	47.38	26.36	26.26	sandy clay loam	5.51	7.10	0.1351	1.27	149.20	738.29	281.03	70.58	22.02	30.36
	25-50	36.80	16.36	46.84	clay	5.05	1.90	0.0948	0.78	54.70	270.66	78.02	23.91	14.34	15.59
47	0-25	47.38	22.52	30.10	sandy clay loam	5.13	6.05	0.1826	2.76	104.82	469.22	360.71	44.85	21.13	27.32
	25-50	42.22	15.52	42.26	clay	4.87	1.31	0.0828	0.81	65.02	309.18	98.22	23.82	14.99	17.48
48	0-25	48.38	24.36	27.26	sandy clay loam	5.39	3.91	0.0957	2.11	118.55	586.57	238.38	56.07	19.32	28.14
	25-50	37.72	18.52	43.76	clay	4.61	0.88	0.0740	0.74	37.49	385.39	155.33	27.70	19.50	17.53



APPENDIX C
ACCURACY ASSESSMENT OF SOIL PROPERTY
PREDICTION

C.1 Accuracy assessment of topsoil properties prediction by using PLS regression.

No	Predictive topsoil properties using PLS regression														Error (Predicted – Observed value)											
	Sand	Silt	Clay	pH	OM	N	P	K	Ca	Mg	Na	CEC	BS	Sand	Silt	Clay	pH	OM	N	P	K	Ca	Mg	Na	CEC	BS
6	49.41	24.73	27.14	5.11	6.60	0.23	4.08	108.31	501.07	273.52	51.43	22.43	25.21	-0.55	-0.47	2.30	-0.21	1.22	0.06	-0.17	-15.32	-61.09	45.07	9.70	1.74	0.17
7	40.31	27.81	30.17	5.78	6.07	0.22	4.62	150.48	669.13	305.80	74.05	21.80	32.26	-6.99	2.28	3.00	-0.17	2.22	0.03	0.60	-11.70	-83.75	-50.17	-14.92	3.86	-9.48
8	47.48	25.77	27.56	5.26	6.09	0.20	4.05	114.58	522.94	272.73	56.77	21.27	27.47	-0.98	3.57	-1.78	0.19	1.75	-0.01	1.63	19.85	54.22	22.24	11.96	2.51	1.69
11	44.75	27.38	29.97	5.60	5.53	0.21	4.19	143.18	565.78	314.95	71.01	21.53	33.21	-1.13	2.02	1.21	0.15	1.93	0.03	0.47	30.34	7.47	10.66	17.65	4.14	-0.20
16	49.15	24.15	28.52	4.91	8.97	0.34	5.96	116.06	501.84	304.53	54.39	26.86	21.48	1.26	1.79	-1.23	-0.32	-0.38	0.00	0.64	-2.02	-2.31	17.12	-1.45	1.39	0.17
17	49.79	23.49	24.47	5.04	4.93	0.13	1.99	75.77	353.28	212.32	37.04	18.23	23.78	-1.51	0.97	-1.71	-0.34	1.71	0.02	-2.55	-7.51	14.68	-1.55	10.85	1.30	1.48
19	48.31	25.26	27.08	5.32	5.01	0.15	2.85	108.37	468.49	258.87	54.97	19.14	28.90	-0.49	0.74	0.40	-0.06	1.16	-0.09	0.77	-3.06	-92.85	24.81	22.28	-2.04	4.57
21	40.99	26.36	30.69	5.72	7.06	0.27	4.77	149.61	708.65	313.28	70.25	23.84	29.93	-1.73	-0.17	-0.07	-0.03	2.30	0.13	3.72	-14.48	-103.23	-6.65	-17.36	4.18	-8.13
23	49.82	22.26	25.37	5.04	5.88	0.17	2.17	93.08	489.06	222.38	42.33	20.50	22.05	-1.98	0.74	-1.31	-0.27	-1.60	-0.10	-0.37	1.47	35.78	14.03	10.10	3.78	-3.98
24	45.26	24.44	27.27	5.49	6.74	0.23	3.45	122.73	576.79	253.68	60.74	22.00	25.10	2.54	-2.08	-3.50	0.25	1.98	0.09	1.63	-23.03	-209.46	-39.40	-8.18	2.34	-10.53
28	50.43	22.06	24.87	4.88	6.68	0.20	2.82	83.59	449.40	221.52	37.70	21.51	19.61	0.05	-1.46	-1.23	0.19	-0.89	-0.08	-1.90	-3.36	19.14	-71.56	1.70	-4.30	0.48
29	47.36	24.53	31.37	5.52	8.17	0.33	5.01	161.28	646.17	335.82	79.29	26.48	28.20	11.82	-4.67	-3.89	-0.48	-0.66	-0.11	-1.15	-24.59	-520.86	-118.53	-17.70	-4.29	-5.79
31	38.52	27.87	31.36	5.68	7.83	0.32	6.30	159.47	738.51	339.84	73.05	25.65	29.78	-1.77	1.17	-1.65	-0.36	0.61	0.06	1.74	-10.92	-84.61	27.22	7.48	3.43	-3.53
32	49.62	24.76	28.83	5.51	5.62	0.19	2.98	137.90	608.66	290.99	69.24	21.04	30.65	1.58	-0.44	2.07	0.16	3.83	0.10	2.17	11.61	153.93	7.08	-0.49	-0.63	6.50
35	43.27	26.04	27.97	5.34	6.11	0.21	4.12	117.29	540.28	273.77	54.53	21.61	27.22	-3.11	0.68	-0.29	-0.07	-0.58	-0.02	1.06	11.73	17.88	61.47	4.60	3.69	0.20
38	47.08	24.47	25.91	5.09	7.44	0.25	4.49	99.86	559.91	253.20	44.95	23.02	21.50	-3.38	-0.73	1.57	-0.54	-0.48	-0.02	-4.43	-16.46	133.34	19.51	-0.59	-1.39	2.87
40	44.35	25.29	28.74	5.31	8.03	0.30	5.32	131.16	633.82	293.68	60.77	25.15	24.36	3.05	-2.07	-2.60	0.08	0.98	0.02	-1.52	17.11	69.51	64.35	6.84	-1.30	4.59
41	42.49	27.41	30.17	5.42	8.75	0.36	7.00	146.96	721.99	337.17	67.05	26.94	26.64	1.61	-0.95	-0.59	-0.40	-0.42	0.01	2.57	-22.18	-114.86	-2.92	2.06	2.82	-5.23
45	47.33	24.52	28.07	5.43	6.87	0.24	3.83	136.02	715.04	274.87	64.74	22.92	26.19	1.45	-0.84	-0.69	-0.03	-1.07	-0.08	-1.32	53.99	-45.98	-10.54	-2.99	-0.40	-2.33
48	48.15	24.67	29.38	5.26	7.97	0.30	5.13	132.48	570.54	317.28	63.17	25.28	25.93	-0.23	0.31	2.12	-0.13	4.05	0.21	3.02	13.93	-16.03	78.90	7.10	5.96	-2.21
Mean Error (ME)														-0.02	0.02	-0.39	-0.12	0.88	0.01	0.33	0.27	-41.45	4.56	2.43	1.34	-1.43
Root Mean Square Error (RMSE)														3.53	1.79	1.95	0.26	1.80	0.08	2.01	19.58	144.81	46.08	10.87	3.13	4.82
Normalized Root Mean Square Error (NRMSE)														0.22	0.23	0.18	0.20	0.24	0.23	0.25	0.19	0.18	0.19	0.15	0.22	0.21

Note: Sand, Silt, Clay, OM, N and BS in percent; P, K, Ca, Mg and Na in ppm; CEC in meq/100g

C.2 Accuracy assessment of subsoil properties prediction by using PLS regression.

No	Predictive subsoil properties using PLS regression													Error (Predicted – Observed value)												
	Sand	Silt	Clay	pH	OM	N	P	K	Ca	Mg	Na	CEC	BS	Sand	Silt	Clay	pH	OM	N	P	K	Ca	Mg	Na	CEC	BS
6	43.05	20.19	36.16	5.02	2.00	0.09	1.46	61.49	291.99	131.63	26.84	16.44	17.85	-1.33	-1.17	1.90	-0.66	0.42	0.02	0.38	-14.01	-81.40	19.91	-8.89	-0.93	-0.18
7	29.36	21.25	48.24	5.17	1.82	0.09	1.29	73.98	404.09	151.18	31.04	16.12	22.56	1.90	1.89	-4.94	-0.74	1.08	0.05	0.33	-24.04	63.61	4.55	8.33	4.49	-5.43
8	39.43	20.03	39.41	4.98	1.80	0.09	1.48	60.28	295.18	125.76	25.12	15.10	19.21	-3.95	5.83	-3.01	0.24	0.73	0.03	0.63	-0.32	44.62	13.93	8.22	-1.23	4.51
11	34.29	21.42	43.56	5.20	1.63	0.09	0.91	73.40	374.31	157.57	31.40	16.60	22.55	0.99	-1.10	-0.62	0.38	0.99	0.06	-0.33	22.38	16.01	5.04	7.28	-0.62	3.52
16	40.14	22.48	37.34	5.28	2.96	0.12	2.03	79.36	338.56	161.73	37.15	20.52	16.25	10.34	-1.88	-8.50	-0.18	1.48	-0.06	0.51	-28.98	-156.47	10.60	-10.16	-5.00	-0.20
17	47.22	17.03	34.60	4.61	1.22	0.07	1.09	36.56	234.93	83.72	15.22	12.18	17.16	0.92	-2.33	0.26	0.11	0.64	0.04	0.48	-1.37	-43.65	-42.51	-12.69	-3.00	-0.28
19	39.95	18.68	40.23	4.83	1.32	0.07	1.04	51.31	286.01	108.47	21.10	13.28	19.79	-0.35	-1.84	1.05	-0.38	0.59	-0.01	0.57	10.49	24.25	26.45	0.80	-0.85	4.40
21	29.13	21.77	48.88	5.28	2.19	0.11	1.12	78.48	384.81	163.24	35.25	18.53	21.44	2.25	1.41	-3.88	-0.30	0.97	0.05	0.55	-19.03	-47.19	-53.00	4.44	-2.96	1.34
23	45.98	16.98	37.65	4.70	1.60	0.08	1.03	43.44	261.02	96.37	19.77	14.43	15.59	-2.82	1.46	1.97	-0.32	-0.47	-0.02	0.24	1.14	7.75	31.35	-3.54	3.21	-2.31
24	35.59	19.55	44.45	4.99	2.04	0.10	0.91	62.78	374.12	128.88	27.85	16.53	18.46	5.13	3.35	-8.89	-0.02	0.29	0.04	-0.23	3.27	35.34	-30.85	-0.36	0.50	-1.99
28	46.90	17.61	35.68	4.73	1.92	0.09	1.39	45.56	256.86	97.91	21.10	15.14	14.57	2.94	1.41	-4.16	-0.33	0.25	0.01	0.67	17.84	26.70	10.29	2.89	0.90	0.39
29	30.53	22.61	47.99	5.42	2.67	0.12	0.86	90.05	441.89	181.72	42.32	21.41	19.58	6.73	1.25	-6.85	-0.52	-1.02	-0.06	-1.28	-58.29	-171.25	-56.53	-22.51	-3.95	-2.82
31	29.61	23.26	46.55	5.44	2.55	0.11	1.88	89.26	446.67	183.35	39.55	19.76	21.56	-7.69	5.74	1.37	-0.25	0.59	0.02	1.04	17.24	-57.06	-52.00	-11.17	-2.55	-0.21
32	35.66	19.49	45.03	5.00	1.59	0.09	0.57	64.40	346.45	131.45	28.05	15.79	20.10	-6.14	2.97	3.35	0.26	1.06	0.06	-0.15	22.88	55.67	33.93	9.84	1.46	3.09
35	38.81	20.00	40.43	5.01	1.79	0.09	1.53	61.53	330.37	133.23	26.52	15.63	19.59	5.51	0.64	-6.91	0.27	0.38	0.01	0.71	11.84	108.01	25.30	-7.00	2.58	2.19
38	43.04	19.93	36.05	4.96	2.30	0.10	1.87	59.57	303.46	123.63	25.99	16.54	16.30	12.24	-2.59	-10.63	-0.28	0.25	-0.02	0.86	23.05	52.10	60.22	-0.52	2.28	2.38
40	36.39	21.60	41.82	5.22	2.60	0.11	1.74	76.03	373.74	156.40	34.23	19.03	18.06	2.43	-0.76	-1.86	-0.31	1.11	-0.03	0.31	11.01	-47.06	-14.63	-5.98	1.98	-4.51
41	33.82	24.00	41.19	5.47	2.96	0.12	2.24	90.90	409.12	184.72	40.06	20.72	19.66	5.94	-1.52	-5.41	-0.17	-0.20	-0.03	0.43	-8.41	-41.20	44.80	-6.36	-1.79	2.53
45	36.74	19.63	44.00	5.03	2.12	0.10	1.17	65.90	341.29	133.41	28.59	16.91	17.93	6.86	-0.73	-5.76	-0.13	-0.28	-0.03	0.33	-11.40	8.00	-2.02	-3.23	-3.27	2.51
48	36.20	22.05	41.70	5.27	2.54	0.11	1.43	79.75	385.04	161.07	36.94	19.60	18.51	-1.52	3.53	-2.06	0.66	1.66	0.04	0.69	42.26	-0.35	5.74	9.24	0.10	0.98
Mean Error (ME)														-0.02	0.02	-0.39	-0.12	0.88	0.01	2.02	0.88	-10.18	2.03	-2.07	-0.43	0.50
Root Mean Square Error (RMSE)														3.53	1.79	1.95	0.26	1.80	0.08	5.43	22.27	70.07	32.92	8.73	2.57	2.78
Normalized Root Mean Square Error (NRMSE)														0.22	0.23	0.18	0.20	0.24	0.23	0.22	0.19	0.18	0.19	0.18	0.18	0.20

Note: Sand, Silt, Clay, OM, N and BS in percent; P, K, Ca, Mg and Na in ppm; CEC in meq/100g

C.3 Accuracy assessment of topsoil properties prediction by using cokriging interpolation.

No	Predictive topsoil properties using cokriging interpolation													Error (Predicted – Observed value)												
	Sand	Silt	Clay	pH	OM	N	P	K	Ca	Mg	Na	CEC	BS	Sand	Silt	Clay	pH	OM	N	P	K	Ca	Mg	Na	CEC	BS
6	46.63	25.62	28.15	5.37	7.16	0.26	4.46	135.31	662.28	284.62	60.77	22.91	26.43	-3.33	0.42	3.31	0.05	1.78	0.09	0.21	11.68	100.12	56.17	19.04	2.22	1.39
7	43.05	27.66	30.12	5.66	6.95	0.29	5.22	154.42	731.09	321.01	70.65	23.48	31.02	-4.24	2.13	2.94	-0.29	3.11	0.10	1.19	-7.76	-21.79	-34.96	-18.32	5.53	-10.72
8	44.33	27.25	29.27	5.57	6.88	0.29	5.06	153.74	679.81	305.55	66.72	23.30	29.28	-4.13	5.05	-0.07	0.50	2.55	0.08	2.64	59.01	211.09	55.06	21.91	4.54	3.50
11	44.39	27.55	29.19	5.74	6.65	0.32	5.67	171.66	750.29	338.38	75.42	24.28	32.12	-1.49	2.19	0.43	0.29	3.04	0.14	1.95	58.82	191.98	34.09	22.06	6.89	-1.29
16	47.45	25.33	29.09	5.31	7.13	0.33	6.05	201.68	1207.64	498.47	114.06	25.04	26.77	-0.43	2.97	-0.66	0.08	-2.22	-0.01	0.72	83.60	703.49	211.06	58.22	-0.43	5.47
17	44.53	27.32	28.50	5.69	6.78	0.16	2.26	22.44	173.76	116.17	18.97	21.29	30.84	-6.77	4.80	2.32	0.31	3.55	0.05	-2.28	-60.84	-164.84	-97.70	-7.22	4.36	8.53
19	44.23	27.39	29.31	5.61	7.18	0.22	3.56	81.24	565.81	261.42	54.99	22.79	29.93	-4.57	2.87	2.63	0.23	3.34	-0.02	1.49	-30.19	4.47	27.36	22.30	1.61	5.59
21	45.56	25.05	28.92	5.37	7.76	0.33	4.72	186.37	930.61	372.76	83.39	24.30	27.25	2.84	-1.48	-1.83	-0.38	3.00	0.19	3.67	22.28	118.73	52.83	-4.22	4.63	-10.80
23	43.93	26.95	29.79	5.48	7.59	0.17	2.56	126.14	474.40	211.85	41.82	20.96	28.84	-7.87	5.43	3.11	0.17	0.11	-0.10	0.01	34.53	21.12	3.50	9.59	4.24	2.81
24	44.33	26.22	29.38	5.44	7.35	0.29	5.08	109.64	560.60	235.16	49.06	22.96	28.37	1.61	-0.30	-1.38	0.20	2.59	0.15	3.26	-36.12	-225.65	-57.92	-19.86	3.29	-7.26
28	45.69	26.02	28.41	5.29	7.21	0.14	1.84	32.04	270.29	145.80	25.54	21.16	26.00	-4.69	2.50	2.31	0.60	-0.36	-0.15	-2.88	-54.91	-159.97	-147.28	-10.46	-4.66	6.87
29	45.99	24.44	29.14	5.36	8.25	0.41	7.79	221.64	1165.63	491.68	114.32	25.52	26.40	10.45	-4.76	-6.12	-0.64	-0.58	-0.03	1.64	35.77	-1.40	37.33	17.33	-5.25	-7.59
31	45.62	26.16	29.40	5.53	6.62	0.39	7.19	242.44	1215.85	487.27	111.70	24.75	29.70	5.33	-0.54	-3.61	-0.51	-0.60	0.13	2.63	72.05	392.73	174.65	46.13	2.53	-3.61
32	45.15	25.95	29.17	5.44	7.78	0.25	4.18	125.76	536.94	245.24	51.47	22.63	27.86	-2.89	0.75	2.41	0.09	5.99	0.16	3.37	-0.53	82.21	-38.67	-18.26	0.96	3.71
35	42.76	28.73	30.25	5.87	6.29	0.25	4.23	142.54	702.04	306.35	65.90	23.06	34.60	-3.62	3.37	1.99	0.46	-0.40	0.02	1.17	36.98	179.64	94.05	15.97	5.14	7.57
38	46.56	25.42	27.81	5.34	6.44	0.23	3.71	83.33	405.04	193.90	38.59	22.15	26.30	-3.90	0.22	3.47	-0.29	-1.47	-0.04	-5.21	-32.99	-21.53	-39.79	-6.95	-2.26	7.67
40	45.47	25.70	28.98	5.43	6.85	0.30	5.31	144.32	789.72	333.48	73.56	23.65	28.58	4.17	-1.66	-2.36	0.20	-0.20	0.02	-1.53	30.27	225.41	104.15	19.63	-2.81	8.81
41	46.33	25.75	28.77	5.45	6.34	0.38	7.08	210.03	1104.51	471.16	108.66	25.10	28.88	5.45	-2.61	-1.99	-0.37	-2.83	0.04	2.65	40.89	267.66	131.07	43.67	0.97	-2.99
45	44.43	25.88	29.07	5.44	7.63	0.24	4.04	72.40	384.80	198.87	40.43	22.45	28.21	-1.45	0.52	0.31	-0.02	-0.32	-0.08	-1.11	-9.63	-376.22	-86.54	-27.30	-0.87	-0.31
48	45.63	26.02	28.76	5.35	7.16	0.27	4.75	132.27	671.47	307.03	66.94	23.57	25.40	-2.75	1.66	1.50	-0.04	3.25	0.18	2.64	13.72	84.90	68.65	10.87	4.25	-2.74
Mean Error (ME)														-1.11	1.18	0.44	0.03	1.17	0.05	0.81	13.33	80.61	27.36	9.71	1.75	0.73
Root Mean Square Error (RMSE)														4.69	2.83	2.62	0.34	2.56	0.11	2.44	42.75	241.87	93.62	24.94	3.82	6.26
Normalized Root Mean Square Error (NRMSE)														0.29	0.37	0.24	0.25	0.34	0.30	0.30	0.41	0.22	0.38	0.35	0.27	0.27

Note: Sand, Silt, Clay, OM, N and BS in percent; P, K, Ca, Mg and Na in ppm; CEC in meq/100g

C.4 Accuracy assessment of subsoil properties prediction by using cokriging interpolation.

No	Predictive subsoil properties using cokriging interpolation													Error (Predicted – Observed value)												
	Sand	Silt	Clay	pH	OM	N	P	K	Ca	Mg	Na	CEC	BS	Sand	Silt	Clay	pH	OM	N	P	K	Ca	Mg	Na	CEC	BS
6	36.19	19.53	43.99	5.05	2.39	0.10	1.17	64.92	245.15	113.18	28.95	15.78	19.31	-8.19	-1.83	9.73	-0.63	0.80	0.02	0.09	-10.58	-128.24	1.46	-6.78	-1.59	1.28
7	34.37	22.47	42.59	5.36	2.42	0.10	1.38	74.90	470.34	171.62	36.45	18.46	21.08	6.91	3.11	-10.59	-0.55	1.68	0.06	0.43	-23.12	129.86	24.99	13.74	6.83	-6.92
8	35.24	22.01	42.20	5.31	2.46	0.10	1.34	74.19	461.55	163.63	33.45	18.41	20.84	-8.14	7.81	-0.22	0.57	1.39	0.05	0.49	13.59	210.99	51.80	16.55	2.08	6.15
11	34.39	25.76	45.27	5.71	2.46	0.11	1.51	78.73	645.49	198.58	39.92	21.28	21.41	1.09	3.24	1.09	0.89	1.82	0.07	0.28	27.71	287.19	46.05	15.80	4.05	2.37
16	33.14	25.93	50.48	5.86	2.60	0.11	1.65	85.50	452.23	239.81	67.90	18.63	19.27	3.34	1.57	4.64	0.40	1.12	-0.07	0.13	-22.84	-42.80	88.68	20.59	-6.89	2.82
17	38.26	13.02	41.58	4.28	2.20	0.09	0.58	17.96	-47.01	-9.46	-0.61	11.53	21.27	-8.04	-6.34	7.24	-0.22	1.61	0.06	-0.03	-19.97	-325.59	-135.69	-28.52	-3.65	3.83
19	36.55	17.47	42.28	4.84	2.26	0.10	0.95	40.60	112.63	81.76	25.55	13.80	21.06	-3.75	-3.05	3.10	-0.37	1.54	0.01	0.48	-0.22	-149.13	-0.26	5.25	-0.32	5.68
21	32.93	23.99	45.87	5.78	2.85	0.11	1.92	108.42	643.64	218.24	44.61	19.98	18.82	6.05	3.63	-6.89	0.20	1.63	0.05	1.35	10.91	211.64	2.00	13.80	-1.51	-1.27
23	35.26	11.69	45.08	4.21	2.18	0.09	0.66	30.48	-193.51	10.76	15.64	8.45	20.90	-13.54	-3.83	9.40	-0.81	0.11	-0.02	-0.14	-11.82	-446.78	-54.26	-7.67	-2.77	3.00
24	34.25	22.59	43.91	5.26	2.44	0.10	1.33	73.03	384.04	111.46	20.06	19.06	20.15	3.79	6.39	-9.43	0.25	0.70	0.04	0.18	13.52	45.26	-48.27	-8.15	3.02	-0.30
28	38.09	10.70	41.01	4.09	2.19	0.09	0.47	13.10	-247.51	-25.37	4.24	8.69	20.25	-5.87	-5.50	1.17	-0.97	0.52	0.01	-0.24	-14.62	-477.67	-112.99	-13.97	-5.55	6.07
29	32.42	30.79	48.41	6.30	2.63	0.11	2.09	120.07	989.55	345.35	68.29	25.22	17.57	8.62	9.43	-6.43	0.36	-1.06	-0.07	-0.05	-28.27	376.41	107.10	3.46	-0.14	-4.83
31	31.75	26.10	48.08	5.87	2.62	0.10	1.91	124.90	704.72	298.59	65.66	21.03	19.60	-5.55	8.58	2.90	0.18	0.66	0.02	1.07	52.88	200.99	63.24	14.94	-1.27	-2.16
32	35.47	19.44	44.95	5.00	2.24	0.10	1.10	54.17	260.53	95.36	22.42	15.95	19.85	-6.33	2.92	3.27	0.26	1.71	0.07	0.38	12.65	-30.25	-2.16	4.21	1.61	2.84
35	33.95	19.01	46.29	5.03	2.41	0.10	1.12	59.39	192.01	112.61	32.83	14.87	22.40	0.65	-0.35	-1.05	0.29	0.99	0.02	0.31	9.70	-30.35	4.68	-0.69	1.82	4.99
38	37.35	17.02	41.91	4.73	2.40	0.10	0.96	49.00	191.66	68.86	13.27	14.83	19.37	6.55	-5.50	-4.77	-0.51	0.35	-0.02	-0.05	12.48	-59.70	5.45	-13.24	0.58	5.45
40	34.67	22.39	45.66	5.36	2.56	0.10	1.41	77.15	414.37	169.62	38.50	18.20	19.03	0.71	0.03	1.98	-0.17	1.08	-0.04	-0.01	12.13	-6.43	-1.41	-1.71	1.14	-3.53
41	33.25	28.48	46.94	6.07	2.68	0.11	1.90	108.46	841.40	307.14	64.14	23.03	19.31	5.37	2.96	0.34	0.43	-0.48	-0.04	0.09	9.15	391.08	167.22	17.72	0.52	2.19
45	36.53	18.79	42.44	4.90	2.40	0.10	1.05	51.71	344.35	98.01	14.83	16.76	19.37	6.65	-1.57	-7.32	-0.26	0.00	-0.03	0.21	-25.59	11.06	-37.42	-16.99	-3.43	3.95
48	36.07	20.92	40.05	5.22	2.42	0.10	1.26	67.45	406.53	157.43	34.04	17.61	19.65	-1.65	2.40	-3.71	0.61	1.54	0.03	0.52	29.96	21.14	2.10	6.34	-1.89	2.13
Mean Error (ME)														-0.57	1.20	-0.28	0.00	0.89	0.01	0.27	2.38	9.43	8.62	1.73	-0.37	1.69
Root Mean Square Error (RMSE)														6.35	4.76	5.80	0.50	1.18	0.05	0.47	21.17	235.16	68.79	13.43	3.21	4.02
Normalized Root Mean Square Error (NRMSE)														0.25	0.42	0.28	0.35	0.37	0.29	0.28	0.18	0.60	0.39	0.28	0.22	0.29

Note: Sand, Silt, Clay, OM, N and BS in percent; P, K, Ca, Mg and Na in ppm; CEC in meq/100g

CURRICULUM VITAE

Name Rawee Rattanakom

Date of Birth 4 June 1978

Place of Birth 50/18 Ramesuan Road, Ni Mueang sub-district, Mueang district, Phitsanulok, Thailand

Education

2000 Bachelor of Science (Industrial Technology): Faculty of Sciences and Technology, Chiang Mai Rajabhat University, Thailand

2005 Master of Science (Agricultural Resources and Environmental Management): Faculty of Agricultural Production, Mae Jo University, Thailand

Grants and Fellowships

Scholarships for students with outstanding academic performance, Suranaree University of Technology