GENERAL INSTRUCTIONS

- **Authors: Please check ALL author names for correct spelling, abbreviations, and order of first and last name in the byline, affiliation footnote, and bios.**
- **Authors: We cannot accept new source files as corrections for your article. If possible, please annotate the PDF proof we have sent you with your corrections and upload it via the Author Gateway. Alternatively, you may send us your corrections in list format. You may also upload revised graphics via the Author Gateway.**
- **Authors: Please note that once you upload your changes, they will be entered and your article finalized. The proofing process is now complete and your article will be sent for final publication and printing. If you would like an additional proof to review, this should be noted as it is not IEEE policy to send multiple proofs. Once your article is posted on Xplore, it is considered final and the article of record. No further changes will be allowed at this point so please ensure scrutiny of your final proof.**
- **Authors: Unless invited or otherwise informed, a mandatory Excessive Article Length charge of $200.00 per page (beginning with page 7 and beyond) is required for articles in excess of six (6) printed pages for JSTARS. If you have any questions regarding overlength page charges, need an invoice, or have any other billing questions, please contact reprints@ieee.org as they handle these billing requests.**

QUERIES

Q1. Author: Please check whether the sentence “It was found that ... vegetation index layers.” is correct as set.
Q2. Author: Please provide the expansion of NIR.
Q3. Author: Please confirm or add details for any funding or financial support for the research of this article.
Q4. Author: Please provide the page range in Ref. [2].

Changes of Wiang Nong Lom and Nong Luang Wetlands in Chiang Saen Valley (Chiang Rai Province, Thailand) During the Period 1988–2017

Nuttiga Hempattarasuwan, George Christakos, and Jiaping Wu

Abstract*—Pressure on the Wiang Nong Lom and Nong Luang wetland resources in the Chiang Saen Valley of Chiang Rai Province (Thailand) has increased in recent years with the expansion of farmlands and other major sources of wetland conflict related to public land encroachment. Both of these wetlands have been designated as strategic ecosystems. Yet, there is a limited understanding of the way different wetlands respond to change drivers (agriculture, climate, population, etc.), and currently no scientifically valid protocols exist for local wetland mapping and monitoring. Distinguishing between small wetlands and land use and land cover (LULC) components is a challenging affair due to the highly heterogeneous landscape and spectral similarity of compositionally different types of tropical regions. The goals of this article are both technological and substantive, i.e., it aims to (A) propose a synthesis of quantitative techniques that can improve LULC mapping using remotely sensed data (Landsat TM, ETM+, OLI), and (B) assess the wetland changes during the last three decades and better understand the interaction between wetland changes, human population, and the environment. In regards to goal (A), the proposed classification approach employed a synthesis of techniques of decision tree classification (DTC), maximum likelihood classification (MLC), and Mahalanobis distance classification (MDC), with different bands and ancillary data inputs. The results demonstrated that the implementation of the DTC algorithms to address LULC mapping problems exhibited an overall mapping accuracy of 83.9%, which is significantly higher than that of MLC and MDC. It was found that the DTC technique performs well when combined with visible, NIR, and shortwave-infrared bands, a digital elevation model and normalized difference vegetation index layers. Subsequently, the postclassification analysis using DTC showed a notable improvement of approximately 88.0% classification accuracy. Regarding goal (B), our results showed that during the last 30 years, wetland areas in the Chiang Saen Valley have experienced a dramatic decrease of 30.5%, whereas forest landscape surrounding the wetlands has decreased by an astonishing 50.9%. Contrarily, we found that agricultural land size has increased by 24.3%. We suggest that ground data can be linked to the etiology of these results, including the gradual conversion of wetlands to rice cultivation fields as a result of the government rice pledging scheme. Large areas in the study region have been cultivated by para-rubber, palm oil, and pineapple agribusiness production since 2003. In addition, short-term subsidizing government policies promote intensive production for commercial agriculture prompting farmers to transition from subsistence to commercial farming, further impacting wetland conversion. As a result, and in further view of the fact that rapidly expanding agricultural areas have contributed significantly to the decrease of wetland areas during the last three decades, the Chiang Saen Valley wetlands have been designated as wetlands of international importance. The overall recommendation of the present work is that special land-use policy and relevant regulation and/or legislation are critical components of any effort to achieve wetland sustainability.

***Index Terms*—Chiang Saen Valley, decision tree (DT), land cover, land use, remote sensing, Thailand, wetlands.**

Manuscript received November 30, 2018; revised April 22, 2019, June 22, 2019, and August 2, 2019; accepted August 23, 2019. This work was supported in part by APN-Asia-Pacific Network for Global Change Research under Grant ARCP2015-06CMY-Wu, in part by the National Natural Science Foundation of China under Grant 41671399, and in part by the Department Science and Technology, Zhejiang, under Grant 2016C04004. *(Corresponding author: Jiaping Wu.)*

N. Hempattarasuwan and J. Wu are with the Institute of Coastal and Island Ecosystems, Zhejiang University, Zhoushan 316021, China (e-mail: nuttiga@hotmail.com; jw67@zju.edu.cn).

G. Christakos is with the Department of Geography, San Diego State University, California, CA 92182 USA, and also with the Institute of Coastal & Island Ecosystems, Zhejiang University, Zhoushan 316021, China (e-mail: gchrista@sdsu.edu).

This article has supplementary downloadable material available at http://ieeexplore.ieee.org, provided by the authors.

Color versions of one or more of the figures in this article are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/JSTARS.2019.2937949

I. Introduction

Wetland ecosystems provide significant benefits to human populations and help maintain and provide protection to wildlife. The development and conversion of wetland areas to other land use types (silviculture, agricultural use, etc.) affects wetland functioning [29]. In developing countries, such as Thailand, and in many other countries around the world, wetlands have been degraded and demonstrate disappearing environmental conditions [50]. Thailand consists of roughly 7.5% wetlands, most of which are small. 14 of them have been registered as Ramsar sites (www.ramsar.org) and are wetlands of national and international importance; 69 sites have been designated as non-Ramsar wetlands of international importance [46]. A total of 47 are sites of national importance [46], and more than 40 000 wetland sites are designated as sites of local importance [53]. There is limited available data regarding systematic conservation of wetlands in this country. A total of 22 sites in northern Thailand have been classified as inland wetlands. Northern people rely heavily on wetlands for food and water. The northern wetlands have been lost or degraded primarily due to their conversion to agricultural and aqua-cultural uses and grazing [46].

The small-scale wetlands of Wiang Nong Lom and Nong Luang in the Chiang Saen Valley of Chiang Rai Province are surrounded by low mountains and hills. They experience extended periods of warm weather because of their inland nature and tropical latitude zone [49]. They perform important ecological functions and are characterized by complexity and heterogeneity in their landscapes. They are important places for cultural, social and recreational activities, as well as for agriculture [47], [48]. A large number of people live in and around them and depend heavily on the wetland's resources for their livelihoods. Following the Nong Bong Kai Strategic Wetland Management Plan [31], government agencies have attempted to adopt Ramsar planning guidelines for community-based management. This strategic plan covers not only the area of the Nong Bong Kai wetland (designated as a Ramsar site in 2001), but also the surrounding areas including the Wiang Nong Lom and Nong Luang wetlands (in the Chiang Saen Valley). Interestingly, the two wetlands in the Chiang Saen Valley were designated as sites of international importance to Thailand and to their locale near the Nong Bong Kai wetland. They are part of an ecological connectivity network of wildlife, water birds, ducks, and migratory birds [31]. However, both are being destroyed and degraded rapidly. The Chiang Saen Valley wetlands are now one of the most seriously threatened wetlands in Northern Thailand. They have undergone water level reduction due to withdrawal by drainage, conversion to agricultural uses, water pollution, overharvesting, overexploitation, introduction of invasive species (particularly *Mimosa pigra*), and a lack of awareness and knowledge of wetland values [31], [47], [53]. Altering wetlands through cultivation can have an adverse impact on the wetland ecosystem. It has led to a reduction in wetland size, water scarcity in the wetland areas, and in a reduction of the fishery and buffalo grazing areas.

Understanding wetlands and their surrounding areas could help evaluate wetland ecosystems and provide useful information to environmental protection agencies. Accordingly, wetland mapping and monitoring are important tools that can improve our understanding of wetland functioning and response to natural and anthropogenic activities [1]. Additionally, remote sensing data that can identify differences between images at different times is important in the detection of wetland change [43], [57]. Long-term change detection can help us better understand wetland trends and sudden changes, and to protect and analyze the dynamics of wetlands. In this article, the magnitude of wetland change can be measured; area size estimation plays a prominent role in ongoing efforts aimed at optimizing wetland use and impacting policy decisions [25].

Numerous research studies have put forth a significant effort to produce land cover maps that include wetlands at a global, continental, and regional scale by using AVHRR [45], MODIS [11], SPOT [9], and other high spatial systems and spectral resolution optical sensors, such as aerial photography, hyperspectral sensors, LiDAR, WorldView [5]. Landsat satellite imagery has been widely used for regional scale wetland mapping and monitoring in recent years [12], [20].

Various classification techniques have been used to improve classification accuracy. Methods, such as ISODATA, maximum likelihood, Mahalanobis distance, and minimum distance are the most common approaches to wetland mapping [4]. However, due to spectral confusion with different cover classes among various types of wetlands, classification is difficult.

The K nearest neighbors [36], the decision tree (DT) [15], [27], the support vector machine [15], [36], and the random forest [36] are the classification algorithms most commonly used to improve wetland classification accuracy [41]. Moreover, several studies have shown that combining ancillary data with image classification can increase classification accuracy [41].

A review of the relevant literature reveals that most wetland remote sensing studies emphasize the regional or the national scales and that very few consider the continental or global scales. These studies can influence policy and help policymakers understand issues more clearly, and they can lead to policies that address reality in rational ways. However, as regards wetland research at the regional scale and the image classification methods most often applied for this purpose, very few studies of small-scale wetlands utilize Landsat imagery.

Landsat imagery generates the long time series available in Landsat archives with suitable spatial and spectral resolutions, and cost free features. Therefore, Landsat data was used in the study of the specific area of this artilce. Additionally, applying Landsat data to investigate local small-scale wetland dynamics in a developing country, such as Thailand, with the aim to understand the relevant drivers and policies, may fill the knowledge gaps in this specific region, given the limited data sources presently available.

Communities in Thailand have identified problems and raised their concerns about wetlands. In particular, the inventory and monitoring of wetlands in the Chiang Saen Valley (marsh versus swamp versus nonwetlands) can help communities to manage and address their problems and issues.

Although there is an absence of reliable data, the continuing loss and degradation of wetlands is an ongoing concern to stakeholders, and there are no scientifically valid protocols for wetland monitoring in the region. As such, the following questions will be answered.

i) Which image classification method is best suited to classify land use and land cover (LULC) of wetlands and adjacent areas and provide the best result from Landsat imagery?
ii) How have they varied over the last three decades?
iii) What are the primary forces driving these changes (e.g., population, policies, climate change)?
iv) What are recommended steps to optimize wetland management?

A summary of the findings of this article regarding these questions can be found in the conclusion section.

In response to these questions, a search for empirical evidence to help manage natural resources, resolve conflicts and effectively manage common pool resources of wetland areas among stakeholders is urgently needed. Therefore, the objectives of this article are twofold: First, to explore approaches that can improve LULC classification of Landsat data, and, secondly, to assess quantitatively wetland changes between 1988 and 2017 and improve the understanding of human population-environment

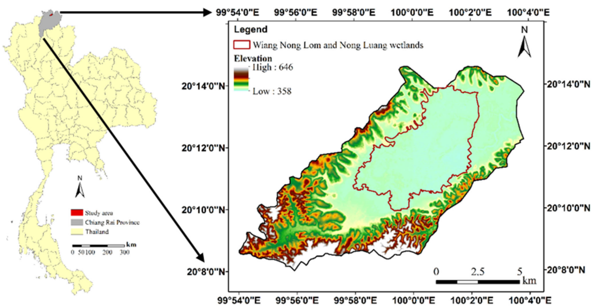

Fig. 1. Elevation map of the study area in the Chiang Rai Province of North Thailand.

interaction. We hypothesized that: policy and population influence wetland changes, such as wetland size and degradation; and the decision tree classification (DTC) approach can provide better classification than traditional approaches in heterogeneous landscapes by using Landsat data.

II. Study Area

The Wiang Nong Lom and Nong Luang wetlands (Chiang Saen Valley) are adjacent to each other and cover an area of roughly 31 km^2 [47]. These wetlands and their surrounding areas, known as catchment areas, occupy approximately 108 km^2. They encompass areas in the Takhaopleuk, Chan Chawa, Chan Chawa Tai, Jomsawan, and San Sai subdistricts of Mae Chan District, as well as areas in Yonok subdistrict of Chiang Saen District of Chiang Rai Province in North Thailand (20°8′1″–20°14′35″N, 99°54′1″–100°3′49″E; Fig. 1) at an elevation range of 358–646 m above mean sea level. A number of creeks and local rivers flow from the southwest and the south to the east parts of the region, they subsequently join the Mae Lua River at the wetlands, and finally they flow into the Mae Kok and Mekong Rivers.

Stakeholders, such as farmers, fishermen, buffalo raisers, local ornithologists, and government officials who live in and around wetlands depend on wetland resources for their livelihood. These wetlands provide numerous beneficial services. They act as a temporary storage site of floodwaters that drain from the subbasins of the Mae Kok and Mekong Rivers. They serve as a water source for farmers, and they also serve the general day-to-day water needs of households and the local population, especially during the dry season. Wetland areas are food sources for local communities, and they act as a habitat for many different fish species and wildlife, including migratory birds. The IUCN red list of threatened bird species, in particular the Eastern Grass Owl (*Tyto longimembris*) and Pied Harrier (*Circus melanoleucos*), are found in this wetland area [2], [3]. There were 311 and 376 plant species found within the Wiang Nong Lom and Nong Luang wetlands, respectively [47], [48]. This area is also the home to the largest population of buffalo in Northern Thailand [44]. In addition, 77 archaeological sites and historic settlements of five ethnic groups are located within the boundaries of the wetlands [44].

TABLE I
Landsat Images Used in this Study

Year	Date	Sensor	Resolution (*m*)
1988	1988/04/06	TM	30
1994	1994/04/07	TM	30
2000	2000/03/14	ETM+	30
2006	2006/04/08	TM	30
2011	2011/03/21	TM	30
2017	2017/03/21	OLI	30

III. Data and Methodology

A. Datasets

In this article, Landsat data (path/row: 130/46) was downloaded from the U.S. Geological Survey Earth Resources Observation and Science Center (https://espa.cr.usgs.gov/) with cloud cover less than 10%. All images were reprojected to WGS 84/UTM zone 47N, and were collected during a dry season at the same seasonal time of the year to reduce problems due to sun angle differences and vegetation phenology changes [57] as reflected in Table I. The image selection was based on the following: the acquisition of cloud-free imagery; the availability of ancillary data and field information to provide LULC delineation and classification; a short-term change focus in order to produce time-consistent maps; and the lack of abrupt changes in the study areas [31], [47], [48].

The terrain's elevation values of a digital elevation model (DEM) with a 90-m spatial resolution obtained from the shuttle radar topography mission were resampled at a 30-m spatial resolution. Population data was derived from the censuses of 1993 to 2017 that are available at the Department of Provincial Administration. An autoregressive integrated moving average model (ARIMA; [18]) was used to predict the population size in the years 2020, 2030, and 2040 to predict population size over time and to be able to consider its possible impact on wetland change in the future [6], [19]. Meteorological data from 1988 to 2017 (air temperature and rainfall) was collected at the nearest station to the study area (The Chiang Rai Meteorological Station). Some key-informant interviewees and focus groups could provide information helpful to understanding the general changes in wetlands and the impact those changes have on livelihoods.

The locations of field samples were obtained during the period March 1–5, 2017 for a particular LULC class (surveying sites on a 100 m × 100 m grid of sampling units). The samples generated data at a total of 534 sites. At 618 sites in areas where field observation was difficult, high-resolution images (freely accessible from GoogleEarth) were used for calibration and validation purposes. GoogleEarth imagery was acquired on March 20, 2011 and February 8, 2017. For historical images before 2006, reference data were sampled according to land use mapping for LULC maps for the Kok River Basin in 1994 [30], the agricultural resources maps for 2000 in Northern Thailand [39], the provincial soil and land use maps in 2000 [23], and the Northern Region of Thailand for 2000–2002. Whereas, topographic maps in 1992, LULC maps for the Kok River Basin in 1998 [40], and orthophoto maps in 2002 were used to assist with the training sample selection and applied as a reference to assess the accuracy for the 1988, 1994, and 2000 images. Evaluation of the results was also made visually based on natural color composition [57]. Additionally, prior knowledge of the study areas and interviews with local experts were used to determine LULC in the study area and were used to create reference data [36].

B. Image Preprocessing

Image data was processed by the ERDAS IMAGINE. ENVI 5.3 software was used for DTC. Atmospheric correction from the USGS EROS Center was applied to Landsat surface reflectance. The normalized difference vegetation index was calculated from Landsat data, and used to distinguish vegetation from nonvegetation areas [43].

Remote sensing systems have been developed to measure the reflected and emitted energy at various wavelengths based on TM, ETM+ and OLI sensors of the Landsat 5, 7, and 8, respectively. Consider, e.g., the visible spectrum of the Landsat 8 images, in which the light waves occupy a small portion of the electromagnetic spectrum with the blue (wave length 0.45–0.51 μm), the green (0.53–0.59 μm) and the red (0.64–0.67 μm) bands, whereas the NIR (0.85–0.88 μm) band is adjacent to visible bands [56]. These spectral bands are commonly used in the LULC mapping. Additionally, they have higher values for shortwave-infrared bands. SWIR1 (1.57–1.65 μm) is well suited for nonwater land cover types and SWIR2 (2.11–2.29 μm) is for all land cover types [56]. The most suitable bands were selected using spectrum characterization. Three visible bands (blue, green, and red), one NIR band, and two shortwave-infrared bands (SWIR1 and SWIR2) were combined with DEM and NDVI to establish the DT classifier, maximum likelihood classification (MLC), and Mahalanobis distance classification (MDC) purposes. The same number of bands was used in DTC as in MLC and MDC, thereby avoiding bias. All layers were resampled at a 30-m spatial resolution by using the nearest neighbor resampling method.

C. Classification Scheme

The initial LULC classes were divided into nine subclasses on the basis of spectral separability, and then similar spectral subclasses were combined with its recode utility into five classes (see Table II). A transformed divergence (TD) measure was used to determine the statistical separability among LULC classes. The TD assigns exponentially decreasing weights to increasing class separations. The divergence values (DVs) have been transformed at a scale ranging from 0 to 2000: DV $>$ 1900 implies that the classes can be separated, if 1700 $<$ DV $<$ 1900, the separation is fairly good, whereas for DV $<$ 1700, the separation is considered poor [14]. The obtained TD 2000 values indicated the high separability of each pair of subclasses in Table II to be considered for further analysis. The LULC classes were delineated based on the Anderson classification system [13] and Land Development Department system of Thailand [22] (see Table II).

TABLE II
LAND USE AND LAND COVER CATEGORIES DELINEATED FOR CLASSIFICATION

Class	Sub-class	Description
Wetland	Wetland 01	Marsh and swamp with dense vegetation cover over greater area than bare soil
	Wetland 02	Marsh and swamp with mixed areas of water and aquatic plants
	Wetland 03	Marsh and swamp with less densely vegetated sites, vegetation covers less area than bare flats of soil, mud, or sand
Agricultural land	Agricultural land 01	Perennial, orchard, horticulture, pasture and farm house, diversified farming, flooded paddy fields associated with rice production
	Agricultural land 02	Non-growing paddy fields
	Agricultural land 03	Field crops and swidden cultivation
Building and villages	Building and villages	Villages, institutional land, and other areas with manmade structures
Forest land	Forest land	Deciduous forest land
Water bodies	Water bodies	Areas of open water with no emergent vegetation

D. Preprocessing of Calibration and Validation Data

Training areas were selected within each of the LULC classes based on stratified random sampling [37]. This method was used to divide all Landsat images into calibration (or training) pixels to train the selected classification models and validation (or testing) pixels to access map quality for all land cover categories. The pixels were collected by random sampling using visual interpretation, prior knowledge of local topography from field survey with visual interpretation of Google Earth images, orthophoto maps, and land use data. The same calibration and validation datasets were used for all classifiers. Approximately three-fourths of these pixels were assigned to calibrate and construct the DTs, and the remainder was used for validation purposes.

Images were converted into ASCII format and then used to perform DTC. Once the most appropriate bands were selected, a decision rule set was generated using the Landsat datasets in a WEKA J48 DT algorithm. The DTs were generated using the J48 DT-inducing algorithm C4.5 algorithm for classification [17]. The default J48 DT uses pruning based on a 0.25 confidence factors setting and using a ten-fold cross-validation approach to avoid unnecessary complexity and data overfitting. The minimum numbers of object pruning were set to 10, 15, and 20 to the dataset. The results were then compared to determine which number of object pruning was the most suitable based on its impact on overall accuracy. The training sites were modified until reliable training sets were obtained and good classification accuracy was achieved.

E. Spectral Analysis

Since different sensors were used, the Landsat mean and standard deviation for the training samples were estimated and plotted (see Fig. 2). The different features of the LULC subclasses in the TM image [see Fig. 2(a)] and the operational land imagery [OLI, Fig. 2(b)] display the reflectance values in the different bands of the TM and OLI sensors. The spectral features

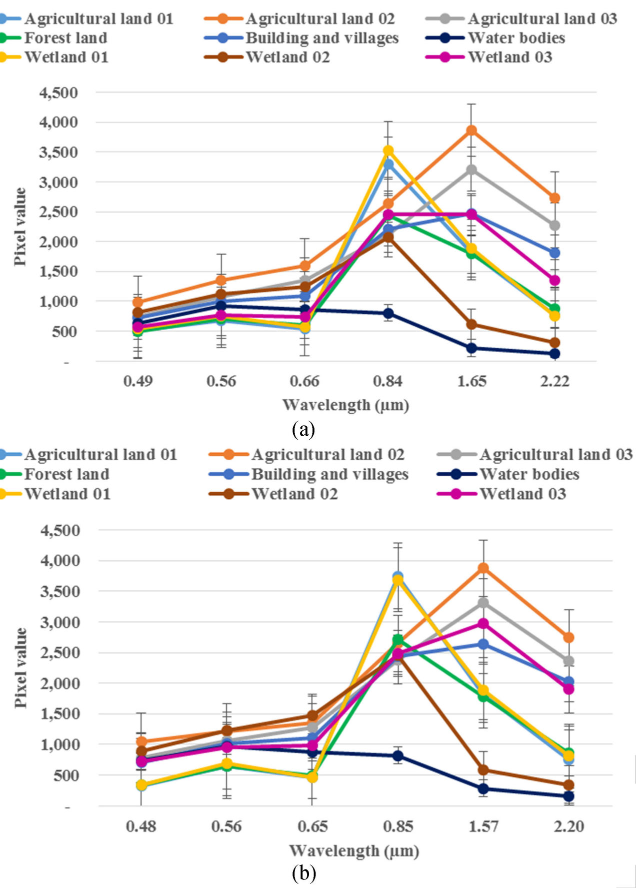

Fig. 2. Mean spectral profile curves of the selected training samples from (a) Landsat TM and (b) OLI data. Error bar indicates ± one standard deviation.

of the LULC subclasses are spectrally distinguishable between the NIR and SWIR regions, whereas visible bands differ slightly in their reflectance values.

F. Image Classification

Previous studies have demonstrated that two commonly used classifiers, MLC and MDC, are effective tools in the classification of wetlands and LULC in the same Mekong region [4], [54]. Thus, we included these two classifiers in this article. We also examined a nonparametric classifier, DT, with the aim to improve classification given the fact that a combination of Landsat and DEM data is likely not normally distributed.

DT construction involves the recursive partitioning of the input training dataset into increasingly homogeneous subsets on the basis of tests applied to one or more of the feature space values [27]. The maximum likelihood decision rule is based on the probability of a pixel belonging to a particular LULC class and the members of each class follow a Gaussian frequency distribution in featured space [27]. A Mahalanobis distance decision is based on the covariance matrix, it relies on a normal distribution of the data in each input band, and it assumes that all class covariances are equal [54].

G. Postclassification Corrections

Postclassification corrections can make the output of classification images smoother and can remove related misclassified pixels [43]. A 3 × 3-pixel majority filter was applied to eliminate a salt-and pepper appearance. Visual image interpretation through google earth images, orthophoto maps, topographic maps, and land use data were used to manually assign classes to misclassified pixels.

In addition to the classified and postclassified maps, we performed McNemar statistical significance test [10] to check any significant difference of accuracies.

H. Map Changes

A cross-tabulation analysis was performed for the time period 1988 to 2017 aimed at identifying change transition. Consequently, the LULC statistics, historical changes and change trends were analyzed.

IV. Results

A. Accuracy Assessment

Accuracy assessment used a stratified random design to identify reference points for each of the five LULC classes of Table II. The strengths and weaknesses of using each technique in LULC classification were represented for both diversified and homogenous landscapes.

The performance of a classifier on the set of validation data of the 2017 LULC map given in Table III demonstrates that DTC produces the best results among the selected classifiers, since Landsat data was fused with DEM, and it is unlikely that the fused data is normally distributed. DTC performs much better than traditional techniques, such as MLC and MDC, with an overall accuracy exceeding 79%. Therefore, the application of MLC and MDC can be excluded, but can remain experiments of Landsat, and a synergy of Landsat and DEM using DTC.

Since DT algorithms are nonparametric, datasets with different spatial resolutions can be used together with ancillary datasets, such as DEM and NDVI. It also allows a multistate classification to be performed, which splits the input dataset into increasingly homogenous subsets [21].

A comparison of overall accuracy of DT techniques with the minimum number of instances per leaf to branch was set at 10. Combining Landsat data with ancillary data to produce a refined LULC map, DTCb (contains blue, green, red, NIR, SWIR1, DEM, NDVI) produced the highest level of overall accuracy, 83.9%, which exceeded that of DTCa (blue, green, red, NIR, DEM, NDVI layers) and DTCc (blue, green, red, NIR, SWIR1, SWIR2, DEM, NDVI layers) that exhibited an overall accuracy of 81.9% and 79.1%, respectively. Producer's accuracy is a measure of omission error or a measure of the probability of reference pixels being correctly classified [28]. The producer's accuracies of DTCa consist of blue, green, red, NIR, DEM, NDVI layers and DTCb contain blue, green, red, NIR, SWIR1, DEM, NDVI layers; the wetland class accuracy was 80% which was manifestly higher than DTCc with blue, green, red, NIR, SWIR1, SWIR2, DEM, NDVI layers (74%).

TABLE III
PRODUCER'S AND USER'S ACCURACY, AND OVERALL ACCURACY OF LULC CLASSIFIERS OF THE LULC MAP IN 2017 BY DIFFERENT CLASSIFICATION METHODS

Approach	Layer stacking	Minimum no of instances per leaf	LULC classes	PA (%)	UA (%)	Overall accuracy (%)	Kappa
MLC	Blue, Green, Red, NIR		Wetland	78.0	46.4	66.1	0.569
			Agricultural land	53.3	58.3		
			Building/Villages	40.0	66.7		
			Forest land	80.0	81.6		
			Water bodies	90.0	100.0		
MLC	Blue, Green, Red, NIR, SWIR1		Wetland	84.0	51.2	74.0	0.669
			Agricultural land	63.0	69.1		
			Building/Villages	62.0	91.2		
			Forest land	82.0	85.4		
			Water bodies	88.0	100.0		
MLC	Blue, Green, Red, NIR, SWIR1, SWIR2		Wetland	86.0	55.1	78.8	0.730
			Agricultural land	71.7	74.2		
			Building/Villages	66.0	100.0		
			Forest land	86.0	91.5		
			Water bodies	90.0	100.0		
MLC	Blue, Green, Red, NIR, SWIR1, DEM, NDVI		Wetland	94.0	59.5	75.7	0.689
			Agricultural land	67.4	63.9		
			Building/Villages	56.0	96.6		
			Forest land	80.0	93.0		
			Water bodies	88.0	100.0		
MLC	Blue, Green, Red, NIR, SWIR1, SWIR2, DEM, NDVI		Wetland	94.0	59.5	78.4	0.724
			Agricultural land	69.6	68.8		
			Building/Villages	66.0	100.0		
			Forest land	82.0	95.4		
			Water bodies	88.0	100.0		
MDC	Blue, Green, Red, NIR		Wetland	52.0	70.3	61.0	0.472
			Agricultural land	92.4	47.0		
			Building/Villages	34.0	70.8		
			Forest land	4.0	100.0		
			Water bodies	96.0	100.0		
MDC	Blue, Green, Red, NIR, SWIR1		Wetland	66.0	73.3	64.4	0.519
			Agricultural land	95.7	49.2		
			Building/Villages	40.0	95.2		
			Forest land	6.0	100.0		
			Water bodies	88.0	100.0		
MDC	Blue, Green, Red, NIR, SWIR1, SWIR2		Wetland	74.0	72.6	69.2	0.588
			Agricultural land	96.7	54.3		
			Building/Villages	54.0	96.4		
			Forest land	14.0	100.0		
			Water bodies	84.0	100.0		
MDC	Blue, Green, Red, NIR, SWIR1, DEM, NDVI		Wetland	64.0	86.5	70.9	0.610
			Agricultural land	96.7	52.7		
			Building/Villages	38.0	100.0		
			Forest land	42.0	100.0		
			Water bodies	92.0	100.0		
MDC	Blue, Green, Red, NIR, SWIR1, SWIR2, DEM, NDVI		Wetland	74.0	84.1	72.6	0.634
			Agricultural land	96.7	54.9		
			Building/Villages	42.0	100.0		
			Forest land	40.0	100.0		
			Water bodies	90.0	100.0		
DTCa	Blue, Green, Red, NIR, DEM, NDVI	10	Wetland	80.0	80.0	81.9	0.764
			Agricultural land	89.1	67.8		
			Building/Villages	66.0	94.3		
			Forest land	86.0	97.7		
			Water bodies	82.0	97.6		
Approach	Layer stacking	Minimum no of instances per leaf	LULC classes	PA (%)	UA (%)	Overall accuracy (%)	Kappa
DTCb	Blue, Green, Red, NIR, SWIR1, DEM, NDVI	10	Wetland	80.0	78.4	83.9	0.791
			Agricultural land	94.6	72.5		
			Building/Villages	68.0	91.9		
			Forest land	90.0	100.0		
			Water bodies	78.0	100.0		
DTC	Blue, Green, Red, NIR, SWIR1, DEM, NDVI	15	Wetland	78.0	68.4	82.5	0.774
			Agricultural land	91.3	74.3		
			Building/Villages	70.0	92.1		
			Forest land	90.0	100.0		
			Water bodies	76.0	97.4		
DTC	Blue, Green, Red, NIR, SWIR1, DEM, NDVI	20	Wetland	74.0	77.1	81.5	0.759
			Agricultural land	93.5	68.8		
			Building/Villages	66.0	94.3		
			Forest land	84.0	97.7		
			Water bodies	80.0	97.6		
DTCc	Blue, Green, Red, NIR, SWIR1, SWIR2, DEM, NDVI	10	Wetland	74.0	67.3	79.1	0.728
			Agricultural land	88.0	66.4		
			Building/Villages	68.0	94.4		
			Forest land	82.0	100.0		
			Water bodies	76.0	100.0		
Post-classification	Blue, Green, Red, NIR, SWIR1, DEM, NDVI		Wetland	96.0	87.3	88.0	0.845
			Agricultural land	98.9	77.1		
			Building/Villages	68.0	100.0		
			Forest land	82.0	97.6		
			Water bodies	86.0	100.0		

Abbreviations: MLC, Maximum likelihood classification; MDC, Mahalanobis distance classification; DTC, Decision tree classification; PA, Producer's accuracy; UA, User's accuracy.

TABLE IV
McNEMAR'S TEST SHOWING THE COMPARISON OF CLASSIFIER PERFORMANCE

Classification 1	Classification 2	f_{11}	f_{12}	f_{21}	f_{22}	Total	Chi-square (χ^2)	P value
DTCa with leaf of 10	DTCb with leaf of 10	239	0	6	47	292	4.2	< 0.05
DTCa with leaf of 10	DTC with leaf of 15	239	0	2	51	292	0.5	> 0.05
DTCa with leaf of 10	DTC with leaf of 20	237	2	1	52	292	0.0	> 0.05
DTCa with leaf of 10	DTCc with leaf of 10	223	16	8	45	292	2.0	> 0.05
DTCb with leaf of 10	DTC with leaf of 15	237	8	4	43	292	0.8	> 0.05
DTCb with leaf of 10	DTC with leaf of 20	231	14	7	40	292	1.7	> 0.05
DTCb with leaf of 10	DTCc with leaf of 10	217	28	14	33	292	4.0	< 0.05
DTC with leaf of 15	DTC with leaf of 20	235	6	3	48	292	0.4	> 0.05
DTC with leaf of 15	DTCc with leaf of 10	221	20	10	41	292	2.7	> 0.05
DTC with leaf of 20	DTCc with leaf of 10	224	14	7	47	292	1.7	> 0.05
DTCb with leaf of 10	Post-classification	245	0	12	35	292	10.1	< 0.05

TABLE V
ERROR MATRIX FOR LULC MAP IN 2017 ACQUIRED BY DTC WITH POSTCLASSIFICATION CORRECTIONS

LULC classes	Class					Total	Producer's accuracy (%)	User's accuracy (%)	Overall accuracy (%)	Kappa
	Wetland	*Agricultural land*	*Building/ Villages*	*Forest land*	*Water bodies*					
Wetland	48	1	1	0	5	55	96.0	87.3	88.0	0.845
Agricultural land	2	91	14	9	2	118	98.9	77.1		
Building/Villages	0	0	34	0	0	34	68.0	100.0		
Forest land	0	0	1	41	0	42	82.0	97.6		
Water bodies	0	0	0	0	43	43	86.0	100.0		

Moreover, the user's accuracy is a measure of commission error; it is determined by dividing the total number of correct pixels in each category by the number of pixels that were classified in that category [37]. The 80% user's accuracy of DTCa (blue, green, red, NIR, DEM, NDVI layers) of the wetland class was found to be higher than others. The majority of classification errors in each DTC from different layers are the misclassification of wetland as agricultural land or a water body.

DT often produces a very large tree that can be incomprehensible even to experts [16]. Pruning is used to avoid overfitting in a DT and the unnecessary complexity of final classifiers as well as to improve predictive accuracy. The minimum number of object pruning was set as 10, 15, and 20 to a specific threshold value. It revealed that although the higher number of pruned objects simplified the tree, it reduced the overall classification of the DT approach.

The results of McNemar's test represent the number of pixels correctly or incorrectly classified by two classification methods [10] (see Table IV). The symbol f_{11} denotes the number of cases correctly classified by both classification methods, whereas, f_{22} denotes the number of cases incorrectly classified by both classification methods. Also, f_{12} denotes the number of cases that are correctly classified by classification 1, but incorrectly classified by classification 2, whereas f_{21} denotes the number of cases that are incorrectly classified by classification 1, but correctly classified by classification 2. The McNemar's test confirms that there is a significant difference in the accuracy of the classification derived by DTCa with leaf of 10 and DTCb with leaf of 10; DTCb with leaf of 10 and DTCc with leaf 10. Additionally, it clearly shows a significant difference in the accuracy of the classification derived from DTCb with leaf of 10 and postclassification.

Postclassification method was used to reclassify the pixels that were misclassified during DTC. The DTCb (Blue, green, red, NIR, SWIR1, DEM, and NDVI) with postclassification corrections provides satisfactory results by minimizing misclassifications; the producer's and the user's accuracy of wetland classification increased greatly from 80.0% to 96.0% and 78.4% to 87.3%, respectively. However, it still failed to distinguish wetlands from agricultural land, building and villages, and water bodies as given in Table V. The overall accuracy of the LULC maps in the years 1988, 1994, 2000, 2006, 2011, and 2017 is presented in Table VI.

B. Long-Term Changes

We detected long-term changes in the spatial distribution of LULC types over the past 30 years. Fig. 3(a)–(l) represents Landsat images and classification maps obtained during the years 1988 and 2017. As is shown in Fig. 3(b), (d), (f), (h), (j), and (l), agricultural areas increased by 24.3% during the period 1988–2017. Conversely, forest areas decreased 55.5% from 1994 to 2017. Wetland areas decreased significantly 30.5% over the 30-year period. The conversion of wetland area to agricultural area is the major cause of areal shrinkage. The large forest loss is attributed to conversion to agricultural land.

C. Map Changes

Fig. 4 below shows the proportion of spatial changes of the LULC in wetlands and adjacent areas. The proportion of agricultural land tended to increase from 2006 to 2017 and the highest proportion of agricultural area was near 70% of the total in 2017. The percentage of forest area tended to decrease; only approximately 9% of forest remained as of 2017. This is mainly caused by the conversion to agriculture. There is a decrease in the proportion of wetland cover on the landscape from roughly 25% in 1988 to 17% in 2017, whereas areas of building and

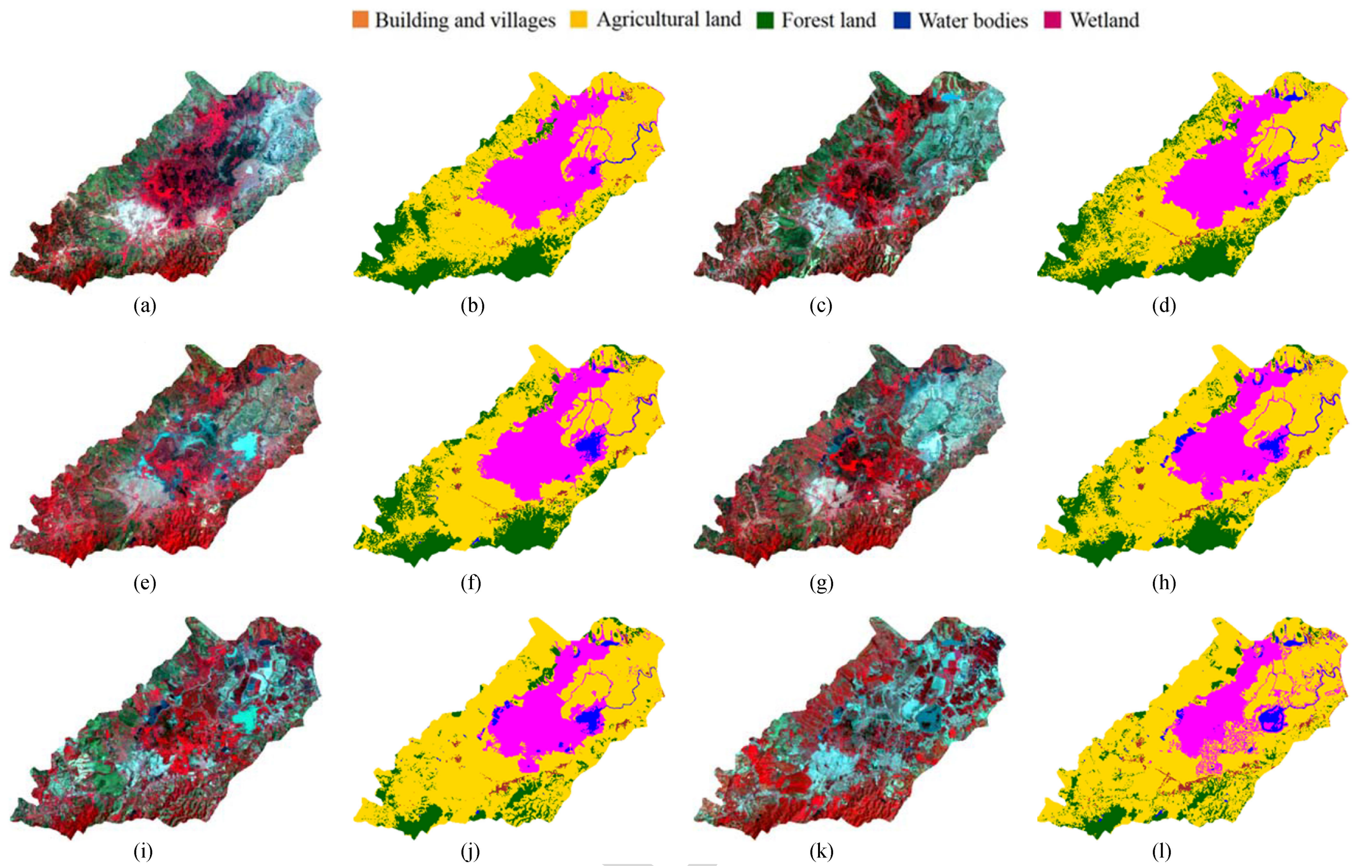

Fig. 3. Results of the Landsat images (*a, c, e, g, i, k*) and classified maps (postclassification) (*b, d, f, h, j, l*) of 1988, 1994, 2000, 2006, 2011, and 2017. (a) Landsat TM Bands 432-RGB (1988). (b) Postclassification (1988). (c) Landsat TM Bands 432-RGB (1994). (d) Postclassification (1994). (e) Landsat ETM+ Bands 432-RGB (2000). (f) Postclassification (2000). (g) Landsat TM Bands 432-RGB (2006). (h) Postclassification (2006). (i) Landsat TM Bands 432-RGB (2011). (j) Postclassification (2011). (k) Landsat OLI Bands 543-RGB (2017). (l) Postclassification (2017).

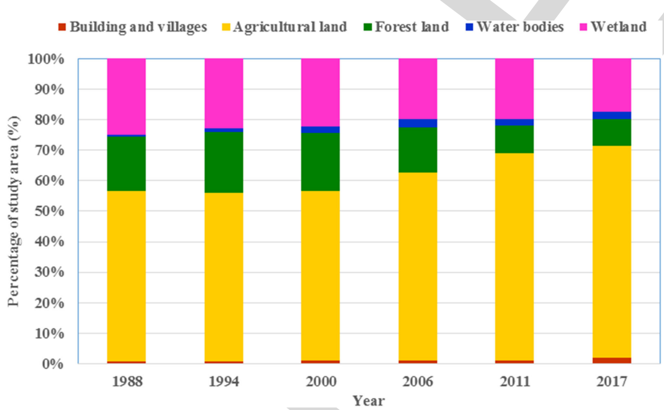

Fig. 4. Study area by land use and land cover classes from 1988 to 2017.

villages and water bodies both increased slightly during the relevant periods.

The changes in wetlands and their surrounding areas, as determined by a comparison of maps from 1988 to 2017. In term of the net changes, they included a loss of wetland area (8.19 km^2) and forest (9.91 km^2), whereas agricultural areas experienced a larger change by adding 14.63 km^2. In contrast, water bodies and building/villages showed a less profound change having only increased by 2.03 km^2 and 1.44 km^2, respectively. From 1988 to 2017, approximately 66% of forest cover was turned into agricultural land. In addition, 31% and 7% of the total wetland areas were converted to agricultural land and water bodies, respectively. There was actual change in the wetland areas of Takhaopleuk, Chan Chawa, Chan Chawa Tai, and Yonok Sub-districts as those wetland areas were converted to rice fields and farm ponds.

D. Wetland Change and Human-Environment Interaction

We addressed this issue by examining human population and land use factors and related concerns. The graphs in Fig. 5(a) and (b) display approximate relationships between pairs of variables. Specifically, Fig 5(a) depicts population trends from 1993 to 2017 together with the varying wetland area sizes (the forecasted population sizes for 2020, 2030, and 2040 will be discussed in Section V); and Fig 5(b) represents negative correlation between wetland areas and agricultural land, where the former decreases while the latter increases with time.

Increasing human population and concomitant increasing needs and higher demands can contribute to wetland loss [19]. The results showed that from 1994 to 2017, the variations in

TABLE VI
PRODUCER'S AND USER'S ACCURACY OF LULC CLASSIFICATION AND OVERALL ACCURACY OF LULC CLASSIFIERS

Year	LULC classes	PA (%)	UA (%)	Overall accuracy (%)	Kappa
1988	Wetland	95.9	93.3	84.9	0.784
	Agricultural land	95.7	76.2		
	Building/Villages	34.2	100.0		
	Forest land	89.8	91.7		
	Water bodies	66.7	100.0		
1994	Wetland	92.4	93.9	84.9	0.793
	Agricultural land	91.2	76.3		
	Building/Villages	53.5	95.8		
	Forest land	85.4	87.2		
	Water bodies	90.9	95.2		
2000	Wetland	98.5	90.1	85.3	0.803
	Agricultural land	89.2	76.5		
	Building/Villages	61.4	100.0		
	Forest land	90.7	86.0		
	Water bodies	66.7	100.0		
2006	Wetland	85.7	94.7	87.0	0.830
	Agricultural land	98.9	77.8		
	Building/Villages	62.2	100.0		
	Forest land	89.8	96.4		
	Water bodies	84.9	80.0		
2011	Wetland	91.8	93.3	84.9	0.800
	Agricultural land	100.0	71.4		
	Building/Villages	60.0	100.0		
	Forest land	86.8	100.0		
	Water bodies	63.2	92.3		
2017	Wetland	96.0	87.3	88.0	0.845
	Agricultural land	98.9	77.1		
	Building/Villages	68.0	100.0		
	Forest land	82.0	97.6		
	Water bodies	86.0	100.0		

Abbreviations: PA, Producer's accuracy; UA, User's accuracy.

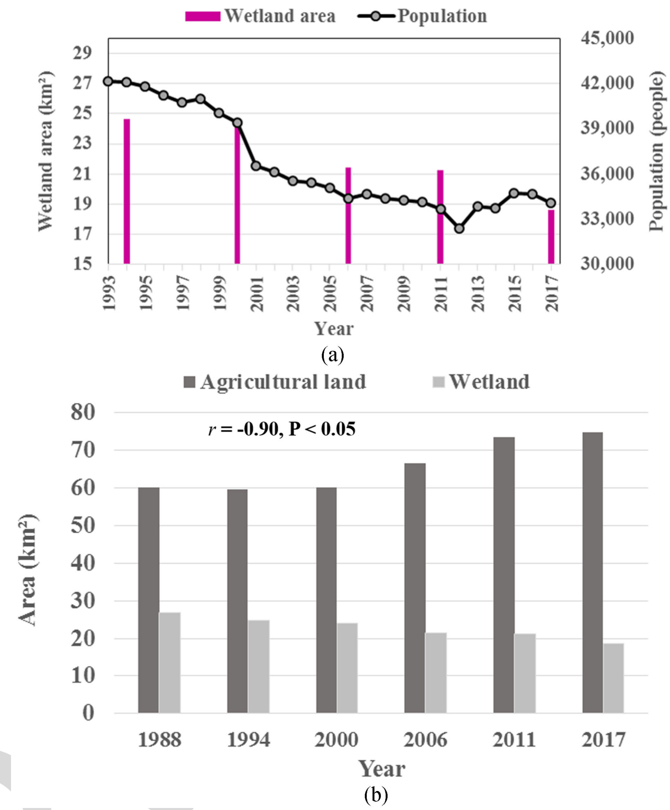

Fig. 5. (a) Population dynamic and wetland areas. (b) Relationship between wetland areas and agricultural land.

wetland areas are not related to local population change. Thus, we hypothesize that if agricultural land area changes are related to wetland change, i.e., increasing agricultural land will decrease wetland areas. The results show that wetland and agricultural land area changes are negatively correlated with an r of -0.90 ($p < 0.05$) [see Fig. 5(b)].

The vegetation area in wetlands can often be explained by the local temperature [51] and rainfall [20], two key factors influencing plant growth. We found that wetland vegetation coverage (a total areas of Wetland 01 and Wetland 03, see in Table II) was linked to the annual average temperature ($r = -0.85$, $P < 0.05$), whereas it was insignificantly related to the annual average rainfall ($r = -0.49$, $P > 0.05$).

Climatograph shows long term average air temperature and rainfall for 12 months of the year from 1988 to 2017 at the Chiang Rai Meteorological station [see Fig. 6(a)]. The weather in March becomes warmer. The hottest period of the year is from April to June with a mean temperature of roughly 28°C. In the study area, July through September receives the most rainfall with a range of 287 mm/mo. (September) to 355 mm/mo. (August). The weather is cool in both December and January with mean temperatures below 21°C. The mean air temperature has fluctuated throughout the 30-year period [see Fig. 6(b)]. The average temperature from 1988 to 1997 was consistently below the 30-year mean of 25.5°C. It then rose sharply in 1998 and fluctuated over the next 13 years. For each year from 2012 through 2017, average annual temperatures have all been above the 30-year mean. Average rainfall has also fluctuated over the past 30 years [see Fig. 6(c)]. The average rainfall decreased steadily between 1988 and 1993, and then it increased sharply in 1994 to 180 mm. It then fell sharply, fluctuated and increased again until 2001, when it peaked at 191 mm. After declining again sharply in 2003 to 117 mm, it fluctuated for a decade. There was a dramatic fall from 2013 to 2015, and then a sharp rise to 2016 and a continued sharp rise through 2017.

V. DISCUSSION

A. Classification Approach

Our quantitative analysis results confirm that a DTC approach performed better than an MLC or an MDC method in wetland classification of Landsat imagery. Similarly, the DTC technique offered better overall accuracy than traditional MLC techniques or support vector machines [15], [21], [52]. Certainly, differences in the specific number of bands, multisource data of different input types, decision thresholds for each image's dataset in Landsat TM, ETM+, and OLI sensors could contribute to the overall accuracy differences between the present study and that of those other studies. However, the DTC technique has its limits in that if the training data contains error, then overfitting

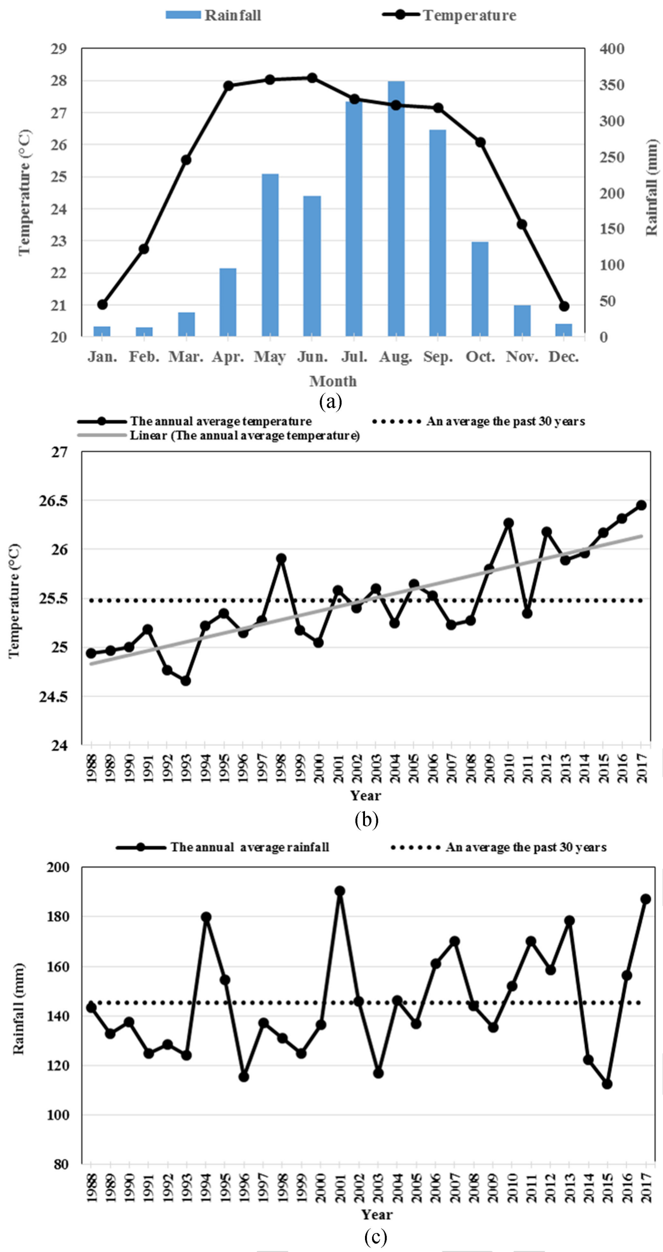

Fig. 6. (a) Climatological average monthly air temperature and rainfall. (b) Average annual air temperature. (c) Average annual rainfall from 1988 to 2017, measured at the meteorological station (the Chiang Rai Meteorological Station) nearest to the study area.

the tree can lead to poor performance. The tree should be pruned back to diminish errors when data outside the training set are to be classified [16], [24]. The decision thresholds would lead to the final outcome of the classification. By changing training data, the DT was also changed. Therefore, expert knowledge is required to determine the DT boundaries that separate the classes in future space [15].

In a technical sense, some of our results do not concur with the findings of previous studies whereas certain others are in agreement with earlier works. In particular, it has been suggested that using MLC is a more appropriate method to map wetlands for wetland resource and conservation management in the lower Mekong basin, made up in part by Lao PDR, Thailand, Cambodia, and Vietnam [4]. Yet, our findings indicate that the MLC technique did not perform well, yielding poor quality results in the case of the Wiang Nong Lom and Nong Luang wetlands (Chiang Saen Valley). On the other hand, MLC can only provide the best results when distinguishing between forest and nonforest land cover in the study area which is consistent with what has been found in previous findings [7].

Suitable classifiers and spectral bands have been shown to have a significant impact on classification accuracy. Our study showed that due to spectrally similar LULC features in wetland landscape, some LULC classes have very similar spectral characteristics. For example, wetlands were misclassified as an agricultural area or water body, whereas during the dry period some water bodies could be interpreted as a wetland. These findings are in accordance with other studies [19], [58]. Local villages and small road networks could not be precisely detected in Landsat data due to their mixed spectral signals. Similarly, several pixels scattered throughout an agricultural area (para-rubber plantation) may erroneously be classified as forest land.

B. Wetland Changes

Although high spatial resolution satellite sensors can yield reliable LULC classification and change detection results with more details at a local level, the long-term archive of Landsat satellite images could prove useful in providing long-term data records for wetland monitoring and change detection. Landsat still has a limited ability to map land cover at finer scales and to identify wetland vegetation habitat type associations and map them [8]. Future studies should investigate specific ecological functions.

Our results indicate that during the last 30 years a significant decline in wetland areas (at the rate of 1% annually) occurred in the study area. Rain-fed paddy cultivation (May through December) has long been practiced in areas surrounding wetlands. From 1988 to 1994, wetland areas decreased by 2.18%. It is because the Thai government implemented a rice price guarantee in 1984. The Bank of Agriculture and Agricultural Cooperatives (BAAC) implemented the rice pledging scheme to help farmers resolve their debts by providing short-term loans for them and to collect growers' paddy rice as a guarantee [42]. Upon the suggestion of merchants, the planting of cassava and maize became more prevalent; merchants who would eventually purchase the yield would do so at a reduced rate after investing and providing seed and machinery to the farmers. These two events resulted in the expansion of rice and field crop cultivated areas into wetland areas. In addition, in 1991 and 1992, local influencers and private investors bought land in villages and areas around wetlands to plant rice and fruit trees such as lychee and longan. They used tractors and crawler backhoes to dredge and drain water from the wetlands for rice cultivation. The drained wetlands became areas suitable for cattle grazing and resulted in encroachment of previously existing wetlands.

Wetland encroachment slowed down during 1994–2000. This was probably due to the fact that local government agencies seized public land from villagers and made agreements concerning wetlands and local boundaries. Villagers could continue to use those lands for agriculture, but they needed to pay a land tax to the local governments. Because those lands were owned by government, farmers were required to inform the government if they no longer wished to use land for agriculture. Basic infrastructure facilities, such as local roads, water supply, and electricity were developed in communities surrounding wetlands during 1994–1995. During this period, local people perceived abnormal weather conditions resulting in wetlands drying up. In response, during 1995–1996 farmers started to dig farm ponds in their rice fields to raise water crops, fish and chicken.

The percentage of wetland areas in the study area decreased by 2.7% from 2000 to 2006. A possible explanation for this is the Ninth National Economic and Social Development Plan (2002–2006). Since 2002, emphasis was on reviving the economy and building immunity to adverse changes for the people through grass-root economic development. The government had adopted a national plan for infrastructure to encourage economic growth and the development of infrastructure in order to enhance the country's productivity and growth of exported goods. Consequently, the project increased crop production, service businesses and residential areas, and also resulted in a rapid increase in land prices [38]. Therefore, there were many developmental projects in the study area, such as the construction of roads, irrigation systems, and government buildings. As a result, many moats, mounds, archaeological sites, and ancient settlements in/and surrounding wetlands were destroyed along with their archeological evidence and value [38]. In 2003, the reduction of water runoff flowing into wetlands and the intensive use of water from wetlands during the summer for agricultural practices, particularly tangerine farms, caused extreme drought conditions drying out some wetlands [38]. At the same time, alien species, such as the Giant Mimosa (*Mimosa pigra*) and the Golden Apple Snail (*Pomacea canaliculata*) spread rapidly in wetlands [31], [53]. Buffalo and cattle populations declined because of disease outbreaks and shrinking grazing areas in and around the wetlands [38]. Villagers sold household land holdings to private investors or landlords; they did not have enough forage area to feed their cattle and buffalo [38]. In 2004, some farmers began to cultivate irrigated rice fields. The season lasts from January to May. Irrigated rice fields require the draining of water from wetlands and the Mae Lua River into the fields. During this time, wetlands were being gradually encroached upon by expanding rice farmland in addition to the water being drained.

The conversion of wetlands to agricultural uses slowed down during 2006–2011. One reason may be the limited success of the Strategic Wetland Management Plan of Nong Bong Kai wetland. Through community participation in a strategic planning process, this Plan aimed to promote sustainable wetland management and restore the Nong Bong Kai wetland and vicinity to its natural healthy and functioning state. This plan has a 20 year strategy (2004–2024) and a five-year action plan (2004–2008) [31], [53]. Local communities, particularly in Pasak and Yo Nok subdistricts, were strengthened by various conservation and training activities regarding fish and water birds, water use, and liquid biofertilizer made from apple snails. However, despite some successes in slowing down encroachment into wetlands, farmers started to grow irrigated rice crops. Farmers in Yonok subdistrict started to cultivate irrigated rice extensively during 2007. There was not enough water for rice crops; therefore, water had to be drained from the wetlands. During the 2009–2010 dry seasons, there was not enough water for crops because of the water scarcity problem created by draining.

The strategic wetland management plan was effective for a short-time period (2004–2008) as it helped to strengthen community conservation efforts and encourage the wise use of wetlands. Its effectiveness was temporary. However, from 2011 to 2017, the percentage of wetland areas decreased by 2.61%. In October 2011, the government implemented a rice pledging scheme that allowed farmers to pledge and give an unlimited supply of their rice to the government at a fixed price that was higher than the going market rate [33], [34]. It offered crop insurance and income security. It established a registration system for farmer households and issued credit cards to farmers [33]. Farmers wishing to participate in the program were required to obtain approval from the Department of Agriculture and their community. Product could be pledged at any local rice miller; millers then were to issue a warehouse receipt to the farmers to claim funds from the BAAC which was then obligated to process the payment to the farmers [34]. The scheme was beneficial and convenient and provided many incentives to grow rice and participate. Unfortunately, and quite naturally, the program increased crop cultivation in at-risk areas, such as wetlands. As a result, rice cultivation has encroached into wetlands. As evidence, one can merely look at the wetlands near the Yonok Sub-district boundaries. In 2011, local governments designated these lands as for landless households (0.0004–0.0032 km^2 per household). After 2011, because of the elevated price of rice, these areas were converted to rice cultivation. Thereafter, in 2017, as a result of decreased rice exports, many farmers converted these rice fields into fish ponds because of the reduction in rice prices caused by lower exports.

Wetlands and wetland ponds act as natural water storage, can serve as a water supply and ease agricultural water scarcity problems. Farmers reported declining water levels in wetlands and the Mae Lua River since 2013 and experienced extreme drought in 2015. These conditions decreased rice yields and caused a reduction in fodder and grass for buffalo and cows. It reduced the number of buffalo and cows and, consequentially, caused a reduction in a primary income source, the sale of dung and manure for fertilizer.

C. *Response to Wetland Changes*

As a result of the reduction in fodder and grass for buffalo and cows and with support from the local governments, buffalo raisers and farmers began planting fodder, such as napier grass, crop residue, and legumes, on their land surrounding wetlands.

There was not enough water for crops, thus, farmers dug ponds to store water on their lands and local governments dredged wetlands (they dredged canals around wetlands) for storage water and buffer zones.

As a result of the reduced fish and aquatic animal population, local people made efforts to conserve and rehabilitate fish and aquatic animals. They agreed to make Wat Pa Mak Nor, a temple situated in the wetlands, a fish conservation area at which fishing was prohibited. These have forced communities to consider and pursue alternate livelihood measures, such as raising water crops, fish, chickens, individual household crop farming for household consumption, making handicrafts, and nonfarm day labor.

D. *Drivers of Change to Wetlands*

1) Agriculture: Our findings confirm that increasing agricultural land area has a statistically significant effect on decreasing wetland areas. Ground data can be used to corroborate these results and describe the resulting changes in more detail. Rain fed rice has been grown for decades. Since 2007, some paddy fields in areas surrounding wetlands converted to irrigated rice fields that withdrew water from the Mae Lua River and wetlands. Consequently, this expansion of agricultural areas impacted and contributed to the gradual conversion of wetlands to rice cultivation fields. This could possibly be linked to governmental agricultural policy. Through a 1986 policy, the Thai government attempted to improve infrastructure and facilities to enhance agricultural productivity. By supporting prices to increase farmers' income, a rice policy was implemented through the paddy pledging program which allowed farmers to obtain a higher price for their crops [6]. Meanwhile, the government promoted a para-rubber plantations policy called "the one million RAI project," in which the government guaranteed a rubber price to bolster farmers' incomes. This has led to widespread land conversion to para-rubber cultivation [26]. Since 2003, large areas have been cultivated for the production of para-rubber, palm oil and pineapples in study areas. As a result, there was a rapid rise in the expansion of agricultural areas during the study period.

2) Population: Wetlands have been affected by population growth and increasing economic development, which have impacted the provision and availability of ecosystem services and resources. Due to the unavailability of 1988 population data, it is not possible to assess if the post-1988 data represents the beginning or the continuation of a trend. Our ARIMA modeling used past population values (that are available only from 1993 to 2017) to predict that the population in 2020, 2030, and 2040 would be 33 723, 32 494, and 31 264 people, respectively. However, the decline in wetland size does not appear to be related to local population size. From 1993 to 2017, people increasingly moved from rural to urban areas. The local populations that remain in the rural areas are primarily dependent on subsistence agriculture, and many small-scale farmers have the potential to successfully transform subsistence production to commercial production [35]. At the same time, agribusiness firms have extended over large areas of para-rubber, palm oil, and pineapple plantations. These developments have led to human activities and other processes that damage the wetlands and impact the upstream catchments of the streams and rivers that drain into them.

3) Other Drivers of Change: We suggest that digging ponds and constructing farm roads or cart paths for access to the wetlands in the Chiang Saen Valley would lead to isolated fragments of wetlands and waterways. Additionally, encroachment for grazing, overexploitation of wetland products and invasive alien species are a major threat to the sustainability of the wetlands. Other studies have generated similar findings [55].

4) Climate Change: Wetlands appear to be vulnerable to agricultural activities and climatic variability [21]. It remains unclear to what degree climate change contributes to the impact on the Chiang Saen Valley wetlands. Unfortunately, we lacked meteorological data from ground truth observation; therefore, we collected meteorological data from the station nearest to the study area. However, great challenges exist in understanding climate change and its complex impact on our study area. It has led to a reduction in the services provided by wetlands, such as food and available water, as was discussed in Section V-B. Wetland changes might not be directly related to temperature and/or rainfall variations, but they are climatic conditions important to wetlands and agricultural production. Empirical evidence from trends on temperature and rainfall have been linked to perceived changes, especially rainfall and its impact on wetlands and local livelihood activities, particularly agriculture, livestock, and fisheries.

5) Legislation: Recently, Thailand adopted a strategic plan to focus on biodiversity. The plan was generated by the Office of Natural Resources and Environmental Policy and Planning (ONEP) in cooperation with the Office of the National Economic and Social Development Board and the Biodiversity-based Economy Development Office (public organization). Many stakeholders were involved in the planning and development process of this plan that was approved by the Cabinet on March 10, 2015. The time frame of the plan is 2015–2021 and has five objectives:

1) to address the causes of biodiversity loss;
2) to promote biodiversity conservation and sustainable use;
3) to improve the status of biodiversity;
4) to develop the capacity to manage biodiversity and ecosystem services;
5) to enhance implementation through participatory planning, knowledge management, and capacity building [32].

It highlights wetlands in objective 2) on conservation and biodiversity restoration: to protect wetlands and control the expansion of community, pollution, overfishing, and climate change, which can cause loss of wetlands and degradation; to focus on and address biodiversity issues to create criteria to assess the impact on the Environmental Impact Assessment (EIA) to protect wetlands; to push the Cabinet Resolution of November 3, 2009 regarding classification of Thailand's wetlands as to their level of importance, conservation measures, and more practical action for conservation and management of the wetlands.

There are agencies and legislation related to the utilization, conservation, and restoration of wetlands. Each agency is granted specific wetland regulatory authority through separate legislative acts. For instance, the OONEP and the Pollution Control Department (PCD) receive their authority from the Promotion and Conservation of National Environmental Quality

Act of 1992; the Department of National Parks, Wildlife and Plant Conservation (DNP) receives its authority from the National Park Act of 1961 and the Wild Animal Reservation and Protection Act of 1992; the Department of Fisheries receives its authority from the Fisheries Act of 1995 [46], [47]. Due to the vast amount of legislation and number of regulatory entities, determining who has jurisdiction over wetlands and what procedures must be followed can be confusing. There is no lead agency tasked with looking at "the big picture" that could coordinate efforts of all concerned agencies. The Wiang Nong Lom and the Nong Luang wetlands (in Chiang Saen Valley) have been designated as wetlands of international importance [46], but a lack of clear, discernible boundaries inhibits the efforts of officials to establish policies to acknowledge and protect areas of importance. Existing wetlands should be protected by special land use policy, but implementing such policy may intensify already existing land conflicts.

Our study's conclusion is that LULC affected the ecosystem of the Wiang Nong Lom and Nong Luang (in Chiang Saen Valley) wetlands, and, accordingly, it can lead to changes in resource allocations. These wetlands are especially vulnerable to drivers of land-use change, with agricultural expansion being a major threat to wetland sustainability. Moreover, socioeconomic development and institutional policies (and to a lesser extent, population changes) are also forces driving wetland changes. It is hoped that the findings of this study will heighten the interest of governmental policy-makers in understanding and recognizing the importance of wetlands. They can also learn from, and apply these findings in their effort to manage natural resources, resolve conflict and make effective arrangements among stakeholders for the common pool of resources.

VI. Conclusion

In sum, the findings of this study are both technological and substantive, as follows.

1) In high heterogeneous landscapes of small wetlands and surrounding areas with spectral similarities between LULC types, the DTC outperformed traditional methods that use Landsat imagery, such as MLC and MDC. In the future, research challenges will be to find suitable methods of extracting wetland vegetation information and enhance classification accuracy with high resolution images.
2) Wetlands are at risk and those near agricultural land with extended cultivation have suffered losses. This indicates that existing legislation, policies, programs, and strategic ecosystem plans cannot protect small-scale wetlands if they are not enforced.
3) Agricultural policies and wetlands conservation programs influence land use decisions. Agricultural policies change the economic incentives to cultivate crops, extend cultivation and encroach upon wetland areas.
4) Although many of the goods and services provided by small wetlands have little or no market value, they have benefits that inure to the local people. A large number of people live in and around wetlands and depend on their resources for their livelihoods. Perhaps the best way to protect the wetlands and their resources is to educate the community regarding their importance and benefits. It would be wise to build alliances within the community to preserve wetlands, and develop community advocacy to be persistent, watchful and active to empower communities to become more active stewards of wetlands in their communities. An example would be volunteer monitoring programs. Giving local communities management and control over wetland resources is vital to their successful sustainable management. Additionally, government agencies should consider the potential for rural job creation, should encourage farmers to produce crops with less water and should assist them in promoting agro production, processing, marketing and distribution of high value crops. Doing so can minimize the detrimental impact of agricultural activities on neighboring the wetlands.

Acknowledgment

The authors would like to thank the Chiang Rai Meteorological Station of the Thai Meteorological Department for providing the meteorological data, the Royal Thai Survey Department, Ministry of Agriculture and Cooperatives, and Land Development Department for providing the topographic maps, orthophoto maps, and land use mapping from the Northern Region of Thailand for 2000–2002, 2006–2007, 2008–2009, 2010–2013, and 2015–2016 as a reference. The authors are very grateful to the editor and the reviewers for their constructive comments that help improve this article.

References

[1] C. Baker, R. Lawrence, C. Montagne, and D. Patten, "Mapping wetlands and riparian areas using Landsat ETM+ imagery and decision-tree-based models," *Wetlands*, vol. 26, no. 2, pp. 465–474, Jun. 2006.

[2] C. Kasorndorkbua and P. Jakthong, "Blood lead levels in wintering Pied Harrier (*Circus melanoleucos*) from Thailand," in *Proc. 10th Asian Raptor Res. Conserv. Netw. Int. Symp.*, Oct. 18–22, 2017. Q4

[3] C. Kasorndorkbua, A. Kunsorn, and C. Wongchai, "Nesting records of Eastern Grass Owl *Tyto (capensis) longimembris* in Chiang Rai, Northern Thailand," in *Proc. BirdingASIA*, vol. 9, 2008, pp. 91–93.

[4] C. MacAlister and M. Mahaxay, "Mapping wetlands in the Lower Mekong Basin for wetland resource and conservation management using Landsat ETM images and field survey data," *J. Environ. Manage.*, vol. 90, no. 7, pp. 2130–2137, 2009, doi: 10.1016/j.jenvman.2007.06.031.

[5] C. Zhang, D. Selch, and H. Cooper, "A framework to combine three remotely sensed data sources for vegetation mapping in the Central Florida Everglades," *Wetlands*, vol. 36, no. 2, pp. 201–213, 2015, doi: 10.1007/s13157-015-0730-7.

[6] D. Dawe, *Rice Crisis: Markets, Policies and Food Security*. 1st ed. London, U.K.: Earthscan and FAO, 2010, pp. 191–217.

[7] D. Lu, "Linear mixture model applied to Amazonian vegetation classification," *Remote Sens. Environ.*, vol. 87, no. 4, pp. 456–469, 2003, doi: 10.1016/j.rse.2002.06.001.

[8] E. Adam and O. Mutanga, "Spectral discrimination of papyrus vegetation (*Cyperus papyrus L.*) in swamp wetlands using field spectrometry," *ISPRS J. Photogramm. Remote Sens.*, vol. 64, no. 6, pp. 612–620, 2009, doi: 10.1016/j.isprsjprs.2009.04.004.

[9] E. Bartholomé and A. S. Belward, "GLC2000: A new approach to global land cover mapping from Earth observation data," *Int. J. Remote Sens.*, vol. 26, no. 9, pp. 1959–1977, 2007, doi: 10.1080/01431160412331291297.

[10] G. M. Food, "Thematic map comparison: evaluating the statistical significance of differences in classification accuracy," *Photogramm. Eng. Remote Sens.*, vol. 70, no. 5, pp. 627–633, 2004.

[11] G. Tana, H. Letu, Z. Cheng, and R. Tateishi, "Wetlands mapping in North America by decision rule classification using MODIS and ancillary data," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 6, no. 6, pp. 2391–2401, Dec. 2013, doi: 10.1109/jstars.2013.2249499.

[12] H. Bagan, W. Takeuchi, T. Kinoshita, Y. Bao, and Y. Yamagata, "Land cover classification and change analysis in the Horqin sandy land from 1975 to 2007," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 3, no. 2, pp. 168–177, Jun. 2010, doi: 10.1109/jstars.2010.2046627.

[13] J. R. Anderson *et al.*, "A land use and land cover classification system for use with remote sensor data," U.S. Geological Survey, Professional Paper 964, 1976, [Online]. Available: http://pubs.er.usgs.gov/publication/pp964

[14] J. R. Jensen, *Introductory Digital Image Processing: A Remote Sensing Perspective*. Englewood Cliffs, NJ, USA: Prentice-Hall, 1986, pp. 13–25.

[15] J. R. Otukei and T. Blaschke, "Land cover change assessment using decision trees, support vector machines and maximum likelihood classification algorithms," *Int. J. Appl. Earth Observ. Geoinf.*, vol. 12, pp. S27–S31, 2010, doi: 10.1016/j.jag.2009.11.002.

[16] J. R. Quinlan, "Simplifying decision trees," *Int. J. Hum. Comput. Stud.*, vol. 51, no. 2, pp. 497–510, 1999.

[17] J. R. Quinlan, *C4.5: Programs for Machine Learning*. San Mateo, CA, USA: Morgan Kaufmann, 1993, pp. 1–56.

[18] J. Tayman, S. K. Smith, and J. Lin, "Precision, bias, and uncertainty for state population forecasts: an exploratory analysis of time series models," *Population Res. Policy Rev.*, vol. 26, no. 3, pp. 347–369, 2007, doi: 10.1007/s11113-007-9034-9.

[19] K. Song *et al.*, "Wetlands shrinkage, fragmentation and their links to agriculture in the Muleng-Xingkai Plain, China," *J. Environ. Manage.*, vol. 111, pp. 120–132, 2012, doi: 10.1016/j.jenvman.2012.06.038.

[20] L. Feng, X. Han, C. Hu, and X. Chen, "Four decades of wetland changes of the largest freshwater lake in China: Possible linkage to the Three Gorges Dam?," *Remote Sens. Environ.*, vol. 176, pp. 43–55, 2016, doi: 10.1016/j.rse.2016.01.011.

[21] L. M. Rebelo, C. M. Finlayson, and N. Nagabhatla, "Remote sensing and GIS for wetland inventory, mapping and change analysis," *J. Environ. Manage.*, vol. 90, no. 7, pp. 2144–2153, 2009, doi: 10.1016/j.jenvman.2007.06.027.

[22] "A land use and land cover classification system for Thailand," Land Develop. Dept., Bangkok, Thailand, 2012.

[23] "Provincial soil and land use maps," Land Develop. Dept., Bangkok, Thailand, 2000.

[24] M. A. Friedl and C. E. Brodley, "Decision tree classification of land cover from remotely sensed data," *Remote Sens. Environ.*, vol. 61, no. 3, pp. 399–409, 1997.

[25] M. J. O'Connell, "Detecting, measuring and reversing changes to wetlands," *Wetlands Ecol. Manag.*, vol. 11, pp. 397–401, 2003.

[26] M. Kawano, "Changing resource-based manufacturing industry: The case of the rubber industry in Malaysia and Thailand," in *Emerging States at Crossroads*. K. Tsunekawa and Y. Todo, Eds. Singapore: Springer, 2019, pp. 145–162.

[27] M. Pal and P. M. Mather, "An assessment of the effectiveness of decision tree methods for land cover classification," *Remote Sens. Environ.*, vol. 86, no. 4, pp. 554–565, 2003, doi: 10.1016/s0034-4257(03)00132-9.

[28] M. Story and R. G. Congalton, "Accuracy assessment: A user's perspective," *Photogramm. Eng. Remote Sens.*, vol. 52, no. 3, pp. 397–399, 1986.

[29] N. Kayastha, V. Thomas, J. Galbraith, and A. Banskota, "Monitoring wetland change using inter-annual Landsat time-series data," *Wetlands*, vol. 32, no. 6, pp. 1149–1162, 2012, doi: 10.1007/s13157-012-0345-1.

[30] "The spatial analysis for the Kok basin using GIS," Office Agr. Econ., Bangkok, Thailand, 1994.

[31] "Nong Bong Kai Strategic Wetland Management Plan," Office Natural Resour. Environ. Policy Planning, Chiang Rai, Thailand, 2004.

[32] "Master Plan for Integrated Biodiversity Management 2015-2021," Ministry Natural Resour. Environ., Bangkok, Thailand, 2015.

[33] P. Sahapattana, "Rice pledging scheme: A high-stakes risk for the big players," *NIDA Case Res. J.*, vol. 7, no. 2, pp. 60–83, 2015.

[34] P. Sawasdipakdi, "The politics of numbers: controversy surrounding the thai rice-pledging scheme," *SAIS Rev. Int. Affairs*, vol. 34, no. 1, pp. 45–58, 2014, doi: 10.1353/sais.2014.0003.

[35] P. Soni, "Agricultural mechanization in Thailand: Current status and future outlook," *AMA-AGR MECH ASIA AF.*, vol. 47, no. 2, pp. 58–66, 2016.

[36] R. G. Congalton and K. Green, *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*. 2nd ed. Boca Raton, FL, USA: Taylor and Francis, 2009.

[37] R. G. Congalton, "A review of assessing the accuracy of classifications of remotely sensed data," *Remote Sens. Environ.*, vol. 37, no. 1, pp. 35–46, 1991, doi: 10.1016/0034-4257(91)90048-b.

[38] R. Pingmoung, "A Biodiversity and environment study towards sustainable management at Wiang Nong Lom wetland," Chiang Rai Rajabhat Univ., Chiang Rai, Thailand, 2004.

[39] S. Intasean, "Mapping the Agricultural Resource for 2000 in Northern Thailand," Office Agr. Econ., Bangkok, Thailand, 2003.

[40] S. Kuchaisit, "The Spatial Analysis for the Kok Basin," Office Agr. Econ., Bangkok, Thailand, 1998.

[41] S. Mahdavi *et al.*, "Remote sensing for wetland classification: A comprehensive review," *GIsci. Remote Sens.*, vol. 55, no. 5, pp. 623–658, 2018, doi: 10.1080/15481603.2017.1419602.

[42] T. Laiprakobsup, "Populism and agricultural trade in developing countries: A case study of Thailand's rice-pledging scheme," *Int. Rev. Public Admin.*, vol. 19, no. 4, pp. 380–394, 2014, doi: 10.1080/12294659.2014.967000.

[43] T. M. Lillesand, R.W. Kiefer, and J.W. Chipman, *Remote Sensing and Image Interpretation*, 7th ed. Hoboken, NJ, USA: Wiley, 2008, pp. 520–618.

[44] T. Phuwanatwichit and S. Srirat, "Sustainable tourism planning and management preparing for the ASEAN Economic Community (AEC): Wiang Nong Lom wetland, Chiang Rai province" (in Thai), *Chiang Mai Univ. J. Social Sci. Humanities*, vol. 15, no. 2, pp. 132–164, 2014.

[45] T. R. Loveland *et al.*, "Development of a global land cover characteristics database and IGBP DISCover from 1 km AVHRR data," *Int. J. Remote Sens.*, vol. 21, no. 6–7, pp. 1303–1330, 2010, doi: 10.1080/014311600210191.

[46] "Promoting efficient wetland management in Thailand," Office Natural Resour, Environ. Policy Planning, Thailand Inst. Sci. Technolog. Res., Bangkok, Thailand, 2015.

[47] "The status of wetlands in Thailand: Inland wetlands," Office Natural Resour. Environ. Policy Planning, Thailand Inst. Sci. Technolog. Res, Bangkok, Thailand, 2011.

[48] "The status of wetlands in Thailand: Wiang Nong Lom wetland," Office Natural Resour. Environ. Policy Planning, Thailand Inst. Sci. Technolog. Res, 2011.

[49] TMD, "The climate of Thailand," 2015. [Online]. Available: https://www.tmd.go.th/en/archive/thailand_climate.pdf.

[50] W. J. Mitsch and J. G. Gosselink, *Wetlands*. 4th ed. NJ, USA: Wiley, 2007, pp. 287–374.

[51] X. Han, X. Chen, and L. Feng, "Four decades of winter wetland changes in Poyang Lake based on Landsat observations between 1973 and 2013," *Remote Sens. Environ.*, vol. 156, pp. 426–437, 2015, doi: 10.1016/j.rse.2014.10.003.

[52] X. Zhang *et al.*, "Mapping mangrove forests using multi-tidal remotely-sensed data and a decision-tree-based procedure," *Int. J. Appl. Earth Observ. Geoinf.*, vol. 62, pp. 201–214, 2017, doi: 10.1016/j.jag.2017.06.010.

[53] Y. Trisurat, "Community-based wetland management in northern Thailand," *Int. J. Environ., Cultural, Econ. Social Sustain.*, vol. 2, no. 1, pp. 49–62, 2006.

[54] Z. Li and J. M. Fox, "Integrating Mahalanobis typicalities with a neural network for rubber distribution mapping," *Remote Sens. Lett.*, vol. 2, no. 2, pp. 157–166, 2011, doi: 10.1080/01431161.2010.505589.

[55] Z. Wang *et al.*, "Changes of land use and of ecosystem service values in Sanjiang Plain, Northeast China," *Environ. Monit Assessment*, vol. 112, pp. 69–91, 2006, doi: 10.1007/s10661-006-0312-5.

[56] Z. Zhu *et al.*, "Including land cover change in analysis of greenness trends using all available Landsat 5, 7, and 8 images: A case study from Guangzhou, China (2000–2014)," *Remote Sens. Environ.*, 2016, doi: 10.1016/j.rse.2016.03.036.

[57] Z. Zhu, "Change detection using landsat time series: A review of frequencies, preprocessing, algorithms, and applications," *ISPRS J. Photogramm. Remote Sens.*, vol. 130, pp. 370–384, 2017, doi: 10.1016/j.isprsjprs.2017.06.013.

[58] ZG. Niu *et al.*, "Geographical characteristics of China's wetlands derived from remotely sensed data," *Sci. China Earth Sci.*, vol. 52, no. 6, pp. 723–738, 2009, doi: 10.1007/s11430-009-0075-2.

Nuttiga Hempattarasuwan received the B.S. degree in fisheries from Kasetsart University, Bangkok, Thailand, in 1998, and the M.S. degree in environmental science from Thammasat University, Bangkok, in 2001. She is currently working toward the Ph.D. degree with the Institute of Coastal and Islands Ecosystems, Zhejiang University, China.

From 2001 to 2004, she was an Environmentalist of consultant companies. From 2004 to 2005, she was a Research Associate with the Asian Institute of Technology. From 2006 to 2015, she was a Program Officer and a Researcher with Mae Fah Luang University, Thailand. Her research interests include environmental remote sensing and information technology.

George Christakos received the B.Eng. degree and in civil engineering and Sc.D. degree in mining and metallurgical engineering from the National Technical University of Athens, Greece, the M.Sc. degree in soil engineering from the University of Birmingham, Birmingham, U.K., the M.S. degree in civil and environmental engineering from the Massachusetts Institute of Technology, Cambridge, MA, USA, and the Ph.D. degree in applied sciences from Harvard University, USA.

His research interests include stochastic spatiotemporal modeling of natural systems under conditions of uncertainty with applications in earth, ocean and atmospheric sciences, environmental health, epidemiology, medical geography, and temporal geographic information systems.

Jiaping Wu received the B.S. and M.S. degrees from Zhejiang University, Hangzhou, China, and the Ph.D. degree in land resource and GIS from Kansas State University, Manhattan, KS, USA.

From 1997 to 2003, he was a Postdoc and Research Associate Scientist with Cornell University, USA. He is currently a Professor with Zhejiang University. His research interests include coastal environment and ecosystem, and spatiotemporal data analysis and modeling.

GENERAL INSTRUCTIONS

- **Authors: Please check ALL author names for correct spelling, abbreviations, and order of first and last name in the byline, affiliation footnote, and bios.**
- **Authors: We cannot accept new source files as corrections for your article. If possible, please annotate the PDF proof we have sent you with your corrections and upload it via the Author Gateway. Alternatively, you may send us your corrections in list format. You may also upload revised graphics via the Author Gateway.**
- **Authors: Please note that once you upload your changes, they will be entered and your article finalized. The proofing process is now complete and your article will be sent for final publication and printing. If you would like an additional proof to review, this should be noted as it is not IEEE policy to send multiple proofs. Once your article is posted on Xplore, it is considered final and the article of record. No further changes will be allowed at this point so please ensure scrutiny of your final proof.**
- **Authors: Unless invited or otherwise informed, a mandatory Excessive Article Length charge of $200.00 per page (beginning with page 7 and beyond) is required for articles in excess of six (6) printed pages for JSTARS. If you have any questions regarding overlength page charges, need an invoice, or have any other billing questions, please contact reprints@ieee.org as they handle these billing requests.**

QUERIES

Q1. Author: Please check whether the sentence "It was found that ... vegetation index layers." is correct as set.
Q2. Author: Please provide the expansion of NIR.
Q3. Author: Please confirm or add details for any funding or financial support for the research of this article.
Q4. Author: Please provide the page range in Ref. [2].

Changes of Wiang Nong Lom and Nong Luang Wetlands in Chiang Saen Valley (Chiang Rai Province, Thailand) During the Period 1988–2017

Nuttiga Hempattarasuwan, George Christakos, and Jiaping Wu

***Abstract*—Pressure on the Wiang Nong Lom and Nong Luang wetland resources in the Chiang Saen Valley of Chiang Rai Province (Thailand) has increased in recent years with the expansion of farmlands and other major sources of wetland conflict related to public land encroachment. Both of these wetlands have been designated as strategic ecosystems. Yet, there is a limited understanding of the way different wetlands respond to change drivers (agriculture, climate, population, etc.), and currently no scientifically valid protocols exist for local wetland mapping and monitoring. Distinguishing between small wetlands and land use and land cover (LULC) components is a challenging affair due to the highly heterogeneous landscape and spectral similarity of compositionally different types of tropical regions. The goals of this article are both technological and substantive, i.e., it aims to (A) propose a synthesis of quantitative techniques that can improve LULC mapping using remotely sensed data (Landsat TM, ETM+, OLI), and (B) assess the wetland changes during the last three decades and better understand the interaction between wetland changes, human population, and the environment. In regards to goal (A), the proposed classification approach employed a synthesis of techniques of decision tree classification (DTC), maximum likelihood classification (MLC), and Mahalanobis distance classification (MDC), with different bands and ancillary data inputs. The results demonstrated that the implementation of the DTC algorithms to address LULC mapping problems exhibited an overall mapping accuracy of 83.9%, which is significantly higher than that of MLC and MDC. It was found that the DTC technique performs well when combined with visible, NIR, and shortwave-infrared bands, a digital elevation model and normalized difference vegetation index layers. Subsequently, the postclassification analysis using DTC showed a notable improvement of approximately 88.0% classification accuracy. Regarding goal (B), our results showed that during the last 30 years, wetland areas in the Chiang Saen Valley have experienced a dramatic decrease of 30.5%, whereas forest landscape surrounding the wetlands has decreased by an astonishing 50.9%. Contrarily, we found that agricultural land size has increased by 24.3%. We suggest that ground data can be linked to the etiology of these results, including the gradual conversion of wetlands to rice cultivation fields as a result of the government rice pledging scheme. Large areas in the study region have been cultivated by para-rubber, palm oil, and pineapple agribusiness production since 2003. In addition, short-term subsidizing government policies promote intensive production for commercial agriculture prompting farmers to transition from subsistence to commercial farming, further impacting wetland conversion. As a result, and in further view of the fact that rapidly expanding agricultural areas have contributed significantly to the decrease of wetland areas during the last three decades, the Chiang Saen Valley wetlands have been designated as wetlands of international importance. The overall recommendation of the present work is that special land-use policy and relevant regulation and/or legislation are critical components of any effort to achieve wetland sustainability.**

***Index Terms*—Chiang Saen Valley, decision tree (DT), land cover, land use, remote sensing, Thailand, wetlands.**

I. Introduction

Wetland ecosystems provide significant benefits to human populations and help maintain and provide protection to wildlife. The development and conversion of wetland areas to other land use types (silviculture, agricultural use, etc.) affects wetland functioning [29]. In developing countries, such as Thailand, and in many other countries around the world, wetlands have been degraded and demonstrate disappearing environmental conditions [50]. Thailand consists of roughly 7.5% wetlands, most of which are small. 14 of them have been registered as Ramsar sites (www.ramsar.org) and are wetlands of national and international importance; 69 sites have been designated as non-Ramsar wetlands of international importance [46]. A total of 47 are sites of national importance [46], and more than 40 000 wetland sites are designated as sites of local importance [53]. There is limited available data regarding systematic conservation of wetlands in this country. A total of 22 sites in northern Thailand have been classified as inland wetlands. Northern people rely heavily on wetlands for food and water. The northern wetlands have been lost or degraded primarily due to their conversion to agricultural and aqua-cultural uses and grazing [46].

The small-scale wetlands of Wiang Nong Lom and Nong Luang in the Chiang Saen Valley of Chiang Rai Province are surrounded by low mountains and hills. They experience extended

Manuscript received November 30, 2018; revised April 22, 2019, June 22, 2019, and August 2, 2019; accepted August 23, 2019. This work was supported in part by APN-Asia-Pacific Network for Global Change Research under Grant ARCP2015-06CMY-Wu, in part by the National Natural Science Foundation of China under Grant 41671399, and in part by the Department Science and Technology, Zhejiang, under Grant 2016C04004. *(Corresponding author: Jiaping Wu.)*

N. Hempattarasuwan and J. Wu are with the Institute of Coastal and Island Ecosystems, Zhejiang University, Zhoushan 316021, China (e-mail: nuttiga@hotmail.com; jw67@zju.edu.cn).

G. Christakos is with the Department of Geography, San Diego State University, California, CA 92182 USA, and also with the Institute of Coastal & Island Ecosystems, Zhejiang University, Zhoushan 316021, China (e-mail: gchrista@sdsu.edu).

This article has supplementary downloadable material available at http://ieeexplore.ieee.org, provided by the authors.

Color versions of one or more of the figures in this article are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/JSTARS.2019.2937949

periods of warm weather because of their inland nature and tropical latitude zone [49]. They perform important ecological functions and are characterized by complexity and heterogeneity in their landscapes. They are important places for cultural, social and recreational activities, as well as for agriculture [47], [48]. A large number of people live in and around them and depend heavily on the wetland's resources for their livelihoods. Following the Nong Bong Kai Strategic Wetland Management Plan [31], government agencies have attempted to adopt Ramsar planning guidelines for community-based management. This strategic plan covers not only the area of the Nong Bong Kai wetland (designated as a Ramsar site in 2001), but also the surrounding areas including the Wiang Nong Lom and Nong Luang wetlands (in the Chiang Saen Valley). Interestingly, the two wetlands in the Chiang Saen Valley were designated as sites of international importance to Thailand and to their locale near the Nong Bong Kai wetland. They are part of an ecological connectivity network of wildlife, water birds, ducks, and migratory birds [31]. However, both are being destroyed and degraded rapidly. The Chiang Saen Valley wetlands are now one of the most seriously threatened wetlands in Northern Thailand. They have undergone water level reduction due to withdrawal by drainage, conversion to agricultural uses, water pollution, overharvesting, overexploitation, introduction of invasive species (particularly *Mimosa pigra*), and a lack of awareness and knowledge of wetland values [31], [47], [53]. Altering wetlands through cultivation can have an adverse impact on the wetland ecosystem. It has led to a reduction in wetland size, water scarcity in the wetland areas, and in a reduction of the fishery and buffalo grazing areas.

Understanding wetlands and their surrounding areas could help evaluate wetland ecosystems and provide useful information to environmental protection agencies. Accordingly, wetland mapping and monitoring are important tools that can improve our understanding of wetland functioning and response to natural and anthropogenic activities [1]. Additionally, remote sensing data that can identify differences between images at different times is important in the detection of wetland change [43], [57]. Long-term change detection can help us better understand wetland trends and sudden changes, and to protect and analyze the dynamics of wetlands. In this article, the magnitude of wetland change can be measured; area size estimation plays a prominent role in ongoing efforts aimed at optimizing wetland use and impacting policy decisions [25].

Numerous research studies have put forth a significant effort to produce land cover maps that include wetlands at a global, continental, and regional scale by using AVHRR [45], MODIS [11], SPOT [9], and other high spatial systems and spectral resolution optical sensors, such as aerial photography, hyperspectral sensors, LiDAR, WorldView [5]. Landsat satellite imagery has been widely used for regional scale wetland mapping and monitoring in recent years [12], [20].

Various classification techniques have been used to improve classification accuracy. Methods, such as ISODATA, maximum likelihood, Mahalanobis distance, and minimum distance are the most common approaches to wetland mapping [4]. However, due to spectral confusion with different cover classes among various types of wetlands, classification is difficult.

The K nearest neighbors [36], the decision tree (DT) [15], [27], the support vector machine [15], [36], and the random forest [36] are the classification algorithms most commonly used to improve wetland classification accuracy [41]. Moreover, several studies have shown that combining ancillary data with image classification can increase classification accuracy [41].

A review of the relevant literature reveals that most wetland remote sensing studies emphasize the regional or the national scales and that very few consider the continental or global scales. These studies can influence policy and help policymakers understand issues more clearly, and they can lead to policies that address reality in rational ways. However, as regards wetland research at the regional scale and the image classification methods most often applied for this purpose, very few studies of small-scale wetlands utilize Landsat imagery.

Landsat imagery generates the long time series available in Landsat archives with suitable spatial and spectral resolutions, and cost free features. Therefore, Landsat data was used in the study of the specific area of this artilce. Additionally, applying Landsat data to investigate local small-scale wetland dynamics in a developing country, such as Thailand, with the aim to understand the relevant drivers and policies, may fill the knowledge gaps in this specific region, given the limited data sources presently available.

Communities in Thailand have identified problems and raised their concerns about wetlands. In particular, the inventory and monitoring of wetlands in the Chiang Saen Valley (marsh versus swamp versus nonwetlands) can help communities to manage and address their problems and issues.

Although there is an absence of reliable data, the continuing loss and degradation of wetlands is an ongoing concern to stakeholders, and there are no scientifically valid protocols for wetland monitoring in the region. As such, the following questions will be answered.

i) Which image classification method is best suited to classify land use and land cover (LULC) of wetlands and adjacent areas and provide the best result from Landsat imagery?
ii) How have they varied over the last three decades?
iii) What are the primary forces driving these changes (e.g., population, policies, climate change)?
iv) What are recommended steps to optimize wetland management?

A summary of the findings of this article regarding these questions can be found in the conclusion section.

In response to these questions, a search for empirical evidence to help manage natural resources, resolve conflicts and effectively manage common pool resources of wetland areas among stakeholders is urgently needed. Therefore, the objectives of this article are twofold: First, to explore approaches that can improve LULC classification of Landsat data, and, secondly, to assess quantitatively wetland changes between 1988 and 2017 and improve the understanding of human population-environment

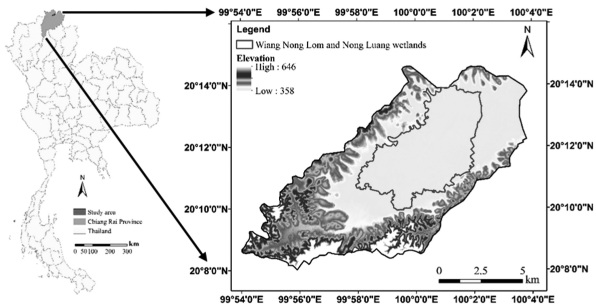

Fig. 1. Elevation map of the study area in the Chiang Rai Province of North Thailand.

interaction. We hypothesized that: policy and population influence wetland changes, such as wetland size and degradation; and the decision tree classification (DTC) approach can provide better classification than traditional approaches in heterogeneous landscapes by using Landsat data.

II. Study Area

The Wiang Nong Lom and Nong Luang wetlands (Chiang Saen Valley) are adjacent to each other and cover an area of roughly 31 km^2 [47]. These wetlands and their surrounding areas, known as catchment areas, occupy approximately 108 km^2. They encompass areas in the Takhaopleuk, Chan Chawa, Chan Chawa Tai, Jomsawan, and San Sai subdistricts of Mae Chan District, as well as areas in Yonok subdistrict of Chiang Saen District of Chiang Rai Province in North Thailand ($20°8'1''–20°14'35''$N, $99°54'1''–100°3'49''$E; Fig. 1) at an elevation range of 358–646 m above mean sea level. A number of creeks and local rivers flow from the southwest and the south to the east parts of the region, they subsequently join the Mae Lua River at the wetlands, and finally they flow into the Mae Kok and Mekong Rivers.

Stakeholders, such as farmers, fishermen, buffalo raisers, local ornithologists, and government officials who live in and around wetlands depend on wetland resources for their livelihood. These wetlands provide numerous beneficial services. They act as a temporary storage site of floodwaters that drain from the subbasins of the Mae Kok and Mekong Rivers. They serve as a water source for farmers, and they also serve the general day-to-day water needs of households and the local population, especially during the dry season. Wetland areas are food sources for local communities, and they act as a habitat for many different fish species and wildlife, including migratory birds. The IUCN red list of threatened bird species, in particular the Eastern Grass Owl (*Tyto longimembris*) and Pied Harrier (*Circus melanoleucos*), are found in this wetland area [2], [3]. There were 311 and 376 plant species found within the Wiang Nong Lom and Nong Luang wetlands, respectively [47], [48]. This area is also the home to the largest population of buffalo in Northern Thailand [44]. In addition, 77 archaeological sites and historic settlements of five ethnic groups are located within the boundaries of the wetlands [44].

TABLE I
Landsat Images Used in this Study

Year	Date	Sensor	Resolution (*m*)
1988	1988/04/06	TM	30
1994	1994/04/07	TM	30
2000	2000/03/14	ETM+	30
2006	2006/04/08	TM	30
2011	2011/03/21	TM	30
2017	2017/03/21	OLI	30

III. Data and Methodology

A. Datasets

In this article, Landsat data (path/row: 130/46) was downloaded from the U.S. Geological Survey Earth Resources Observation and Science Center (https://espa.cr.usgs.gov/) with cloud cover less than 10%. All images were reprojected to WGS 84/UTM zone 47N, and were collected during a dry season at the same seasonal time of the year to reduce problems due to sun angle differences and vegetation phenology changes [57] as reflected in Table I. The image selection was based on the following: the acquisition of cloud-free imagery; the availability of ancillary data and field information to provide LULC delineation and classification; a short-term change focus in order to produce time-consistent maps; and the lack of abrupt changes in the study areas [31], [47], [48].

The terrain's elevation values of a digital elevation model (DEM) with a 90-m spatial resolution obtained from the shuttle radar topography mission were resampled at a 30-m spatial resolution. Population data was derived from the censuses of 1993 to 2017 that are available at the Department of Provincial Administration. An autoregressive integrated moving average model (ARIMA; [18]) was used to predict the population size in the years 2020, 2030, and 2040 to predict population size over time and to be able to consider its possible impact on wetland change in the future [6], [19]. Meteorological data from 1988 to 2017 (air temperature and rainfall) was collected at the nearest station to the study area (The Chiang Rai Meteorological Station). Some key-informant interviewees and focus groups could provide information helpful to understanding the general changes in wetlands and the impact those changes have on livelihoods.

The locations of field samples were obtained during the period March 1–5, 2017 for a particular LULC class (surveying sites on a 100 m × 100 m grid of sampling units). The samples generated data at a total of 534 sites. At 618 sites in areas where field observation was difficult, high-resolution images (freely accessible from GoogleEarth) were used for calibration and validation purposes. GoogleEarth imagery was acquired on March 20, 2011 and February 8, 2017. For historical images before 2006, reference data were sampled according to land use mapping for LULC maps for the Kok River Basin in 1994 [30], the agricultural resources maps for 2000 in Northern Thailand [39], the provincial soil and land use maps in 2000 [23], and the Northern Region of Thailand for 2000–2002. Whereas, topographic maps in 1992, LULC maps for the Kok River Basin in 1998 [40], and orthophoto maps in 2002 were used to assist with the training sample selection and applied as a reference to assess the accuracy for the 1988, 1994, and 2000 images. Evaluation of the results was also made visually based on natural color composition [57]. Additionally, prior knowledge of the study areas and interviews with local experts were used to determine LULC in the study area and were used to create reference data [36].

B. Image Preprocessing

Image data was processed by the ERDAS IMAGINE. ENVI 5.3 software was used for DTC. Atmospheric correction from the USGS EROS Center was applied to Landsat surface reflectance. The normalized difference vegetation index was calculated from Landsat data, and used to distinguish vegetation from nonvegetation areas [43].

Remote sensing systems have been developed to measure the reflected and emitted energy at various wavelengths based on TM, ETM+ and OLI sensors of the Landsat 5, 7, and 8, respectively. Consider, e.g., the visible spectrum of the Landsat 8 images, in which the light waves occupy a small portion of the electromagnetic spectrum with the blue (wave length 0.45–0.51 μm), the green (0.53–0.59 μm) and the red (0.64–0.67 μm) bands, whereas the NIR (0.85–0.88 μm) band is adjacent to visible bands [56]. These spectral bands are commonly used in the LULC mapping. Additionally, they have higher values for shortwave-infrared bands. SWIR1 (1.57–1.65 μm) is well suited for nonwater land cover types and SWIR2 (2.11–2.29 μm) is for all land cover types [56]. The most suitable bands were selected using spectrum characterization. Three visible bands (blue, green, and red), one NIR band, and two shortwave-infrared bands (SWIR1 and SWIR2) were combined with DEM and NDVI to establish the DT classifier, maximum likelihood classification (MLC), and Mahalanobis distance classification (MDC) purposes. The same number of bands was used in DTC as in MLC and MDC, thereby avoiding bias. All layers were resampled at a 30-m spatial resolution by using the nearest neighbor resampling method.

C. Classification Scheme

The initial LULC classes were divided into nine subclasses on the basis of spectral separability, and then similar spectral subclasses were combined with its recode utility into five classes (see Table II). A transformed divergence (TD) measure was used to determine the statistical separability among LULC classes. The TD assigns exponentially decreasing weights to increasing class separations. The divergence values (DVs) have been transformed at a scale ranging from 0 to 2000: DV $>$ 1900 implies that the classes can be separated, if 1700 $<$ DV $<$ 1900, the separation is fairly good, whereas for DV $<$ 1700, the separation is considered poor [14]. The obtained TD 2000 values indicated the high separability of each pair of subclasses in Table II to be considered for further analysis. The LULC classes were delineated based on the Anderson classification system [13] and Land Development Department system of Thailand [22] (see Table II).

TABLE II
LAND USE AND LAND COVER CATEGORIES DELINEATED FOR CLASSIFICATION

Class	Sub-class	Description
Wetland	Wetland 01	Marsh and swamp with dense vegetation cover over greater area than bare soil
	Wetland 02	Marsh and swamp with mixed areas of water and aquatic plants
	Wetland 03	Marsh and swamp with less densely vegetated sites, vegetation covers less area than bare flats of soil, mud, or sand
Agricultural land	Agricultural land 01	Perennial, orchard, horticulture, pasture and farm house, diversified farming, flooded paddy fields associated with rice production
	Agricultural land 02	Non-growing paddy fields
	Agricultural land 03	Field crops and swidden cultivation
Building and villages	Building and villages	Villages, institutional land, and other areas with manmade structures
Forest land	Forest land	Deciduous forest land
Water bodies	Water bodies	Areas of open water with no emergent vegetation

D. Preprocessing of Calibration and Validation Data

Training areas were selected within each of the LULC classes based on stratified random sampling [37]. This method was used to divide all Landsat images into calibration (or training) pixels to train the selected classification models and validation (or testing) pixels to access map quality for all land cover categories. The pixels were collected by random sampling using visual interpretation, prior knowledge of local topography from field survey with visual interpretation of Google Earth images, orthophoto maps, and land use data. The same calibration and validation datasets were used for all classifiers. Approximately three-fourths of these pixels were assigned to calibrate and construct the DTs, and the remainder was used for validation purposes.

Images were converted into ASCII format and then used to perform DTC. Once the most appropriate bands were selected, a decision rule set was generated using the Landsat datasets in a WEKA J48 DT algorithm. The DTs were generated using the J48 DT-inducing algorithm C4.5 algorithm for classification [17]. The default J48 DT uses pruning based on a 0.25 confidence factors setting and using a ten-fold cross-validation approach to avoid unnecessary complexity and data overfitting. The minimum numbers of object pruning were set to 10, 15, and 20 to the dataset. The results were then compared to determine which number of object pruning was the most suitable based on its impact on overall accuracy. The training sites were modified until reliable training sets were obtained and good classification accuracy was achieved.

E. Spectral Analysis

Since different sensors were used, the Landsat mean and standard deviation for the training samples were estimated and plotted (see Fig. 2). The different features of the LULC subclasses in the TM image [see Fig. 2(a)] and the operational land imagery [OLI, Fig. 2(b)] display the reflectance values in the different bands of the TM and OLI sensors. The spectral features

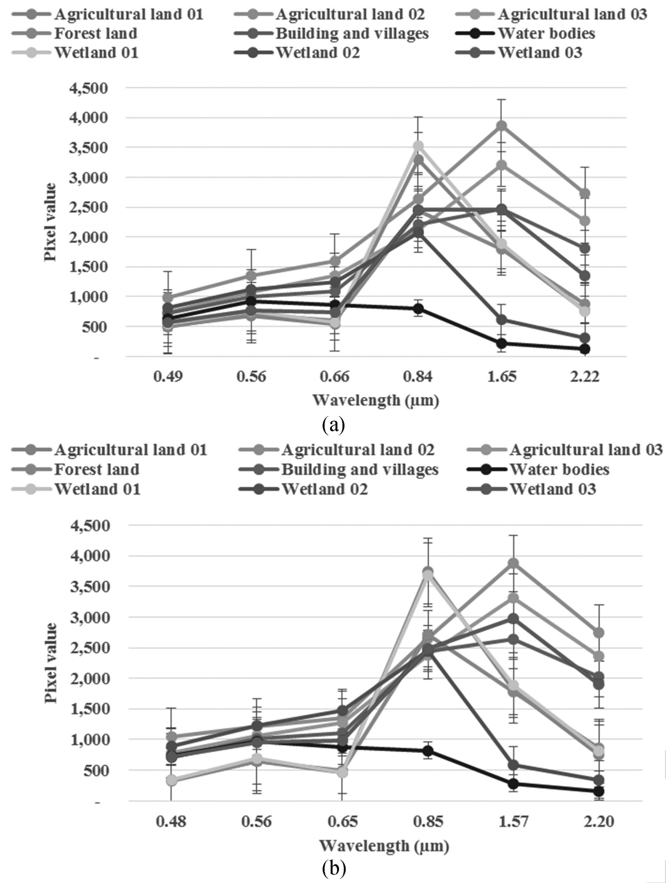

Fig. 2. Mean spectral profile curves of the selected training samples from (a) Landsat TM and (b) OLI data. Error bar indicates ± one standard deviation.

of the LULC subclasses are spectrally distinguishable between the NIR and SWIR regions, whereas visible bands differ slightly in their reflectance values.

F. Image Classification

Previous studies have demonstrated that two commonly used classifiers, MLC and MDC, are effective tools in the classification of wetlands and LULC in the same Mekong region [4], [54]. Thus, we included these two classifiers in this article. We also examined a nonparametric classifier, DT, with the aim to improve classification given the fact that a combination of Landsat and DEM data is likely not normally distributed.

DT construction involves the recursive partitioning of the input training dataset into increasingly homogeneous subsets on the basis of tests applied to one or more of the feature space values [27]. The maximum likelihood decision rule is based on the probability of a pixel belonging to a particular LULC class and the members of each class follow a Gaussian frequency distribution in featured space [27]. A Mahalanobis distance decision is based on the covariance matrix, it relies on a normal distribution of the data in each input band, and it assumes that all class covariances are equal [54].

G. Postclassification Corrections

Postclassification corrections can make the output of classification images smoother and can remove related misclassified pixels [43]. A 3 × 3-pixel majority filter was applied to eliminate a salt-and pepper appearance. Visual image interpretation through google earth images, orthophoto maps, topographic maps, and land use data were used to manually assign classes to misclassified pixels.

In addition to the classified and postclassified maps, we performed McNemar statistical significance test [10] to check any significant difference of accuracies.

H. Map Changes

A cross-tabulation analysis was performed for the time period 1988 to 2017 aimed at identifying change transition. Consequently, the LULC statistics, historical changes and change trends were analyzed.

IV. Results

A. Accuracy Assessment

Accuracy assessment used a stratified random design to identify reference points for each of the five LULC classes of Table II. The strengths and weaknesses of using each technique in LULC classification were represented for both diversified and homogenous landscapes.

The performance of a classifier on the set of validation data of the 2017 LULC map given in Table III demonstrates that DTC produces the best results among the selected classifiers, since Landsat data was fused with DEM, and it is unlikely that the fused data is normally distributed. DTC performs much better than traditional techniques, such as MLC and MDC, with an overall accuracy exceeding 79%. Therefore, the application of MLC and MDC can be excluded, but can remain experiments of Landsat, and a synergy of Landsat and DEM using DTC.

Since DT algorithms are nonparametric, datasets with different spatial resolutions can be used together with ancillary datasets, such as DEM and NDVI. It also allows a multistate classification to be performed, which splits the input dataset into increasingly homogenous subsets [21].

A comparison of overall accuracy of DT techniques with the minimum number of instances per leaf to branch was set at 10. Combining Landsat data with ancillary data to produce a refined LULC map, DTCb (contains blue, green, red, NIR, SWIR1, DEM, NDVI) produced the highest level of overall accuracy, 83.9%, which exceeded that of DTCa (blue, green, red, NIR, DEM, NDVI layers) and DTCc (blue, green, red, NIR, SWIR1, SWIR2, DEM, NDVI layers) that exhibited an overall accuracy of 81.9% and 79.1%, respectively. Producer's accuracy is a measure of omission error or a measure of the probability of reference pixels being correctly classified [28]. The producer's accuracies of DTCa consist of blue, green, red, NIR, DEM, NDVI layers and DTCb contain blue, green, red, NIR, SWIR1, DEM, NDVI layers; the wetland class accuracy was 80% which was manifestly higher than DTCc with blue, green, red, NIR, SWIR1, SWIR2, DEM, NDVI layers (74%).

TABLE III
PRODUCER'S AND USER'S ACCURACY, AND OVERALL ACCURACY OF LULC CLASSIFIERS OF THE LULC MAP IN 2017 BY DIFFERENT CLASSIFICATION METHODS

Approach	Layer stacking	Minimum no of instances per leaf	LULC classes	PA (%)	UA (%)	Overall accuracy (%)	Kappa
MLC	Blue, Green, Red, NIR		Wetland	78.0	46.4	66.1	0.569
			Agricultural land	53.3	58.3		
			Building/Villages	40.0	66.7		
			Forest land	80.0	81.6		
			Water bodies	90.0	100.0		
MLC	Blue, Green, Red, NIR, SWIR1		Wetland	84.0	51.2	74.0	0.669
			Agricultural land	63.0	69.1		
			Building/Villages	62.0	91.2		
			Forest land	82.0	85.4		
			Water bodies	88.0	100.0		
MLC	Blue, Green, Red, NIR, SWIR1, SWIR2		Wetland	86.0	55.1	78.8	0.730
			Agricultural land	71.7	74.2		
			Building/Villages	66.0	100.0		
			Forest land	86.0	91.5		
			Water bodies	90.0	100.0		
MLC	Blue, Green, Red, NIR, SWIR1, DEM, NDVI		Wetland	94.0	59.5	75.7	0.689
			Agricultural land	67.4	63.9		
			Building/Villages	56.0	96.6		
			Forest land	80.0	93.0		
			Water bodies	88.0	100.0		
MLC	Blue, Green, Red, NIR, SWIR1, SWIR2, DEM, NDVI		Wetland	94.0	59.5	78.4	0.724
			Agricultural land	69.6	68.8		
			Building/Villages	66.0	100.0		
			Forest land	82.0	95.4		
			Water bodies	88.0	100.0		
MDC	Blue, Green, Red, NIR		Wetland	52.0	70.3	61.0	0.472
			Agricultural land	92.4	47.0		
			Building/Villages	34.0	70.8		
			Forest land	4.0	100.0		
			Water bodies	96.0	100.0		
MDC	Blue, Green, Red, NIR, SWIR1		Wetland	66.0	73.3	64.4	0.519
			Agricultural land	95.7	49.2		
			Building/Villages	40.0	95.2		
			Forest land	6.0	100.0		
			Water bodies	88.0	100.0		
MDC	Blue, Green, Red, NIR, SWIR1, SWIR2		Wetland	74.0	72.6	69.2	0.588
			Agricultural land	96.7	54.3		
			Building/Villages	54.0	96.4		
			Forest land	14.0	100.0		
			Water bodies	84.0	100.0		
MDC	Blue, Green, Red, NIR, SWIR1, DEM, NDVI		Wetland	64.0	86.5	70.9	0.610
			Agricultural land	96.7	52.7		
			Building/Villages	38.0	100.0		
			Forest land	42.0	100.0		
			Water bodies	92.0	100.0		
MDC	Blue, Green, Red, NIR, SWIR1, SWIR2, DEM, NDVI		Wetland	74.0	84.1	72.6	0.634
			Agricultural land	96.7	54.9		
			Building/Villages	42.0	100.0		
			Forest land	40.0	100.0		
			Water bodies	90.0	100.0		
DTCa	Blue, Green, Red, NIR, DEM, NDVI	10	Wetland	80.0	80.0	81.9	0.764
			Agricultural land	89.1	67.8		
			Building/Villages	66.0	94.3		
			Forest land	86.0	97.7		
			Water bodies	82.0	97.6		
Approach	Layer stacking	Minimum no of instances per leaf	LULC classes	PA (%)	UA (%)	Overall accuracy (%)	Kappa
DTCb	Blue, Green, Red, NIR, SWIR1, DEM, NDVI	10	Wetland	80.0	78.4	83.9	0.791
			Agricultural land	94.6	72.5		
			Building/Villages	68.0	91.9		
			Forest land	90.0	100.0		
			Water bodies	78.0	100.0		
DTC	Blue, Green, Red, NIR, SWIR1, DEM, NDVI	15	Wetland	78.0	68.4	82.5	0.774
			Agricultural land	91.3	74.3		
			Building/Villages	70.0	92.1		
			Forest land	90.0	100.0		
			Water bodies	76.0	97.4		
DTC	Blue, Green, Red, NIR, SWIR1, DEM, NDVI	20	Wetland	74.0	77.1	81.5	0.759
			Agricultural land	93.5	68.8		
			Building/Villages	66.0	94.3		
			Forest land	84.0	97.7		
			Water bodies	80.0	97.6		
DTCc	Blue, Green, Red, NIR, SWIR1, SWIR2, DEM, NDVI	10	Wetland	74.0	67.3	79.1	0.728
			Agricultural land	88.0	66.4		
			Building/Villages	68.0	94.4		
			Forest land	82.0	100.0		
			Water bodies	76.0	100.0		
Post-classification	Blue, Green, Red, NIR, SWIR1, DEM, NDVI		Wetland	96.0	87.3	88.0	0.845
			Agricultural land	98.9	77.1		
			Building/Villages	68.0	100.0		
			Forest land	82.0	97.6		
			Water bodies	86.0	100.0		

Abbreviations: MLC, Maximum likelihood classification; MDC, Mahalanobis distance classification; DTC, Decision tree classification; PA, Producer's accuracy; UA, User's accuracy.

TABLE IV
McNemar's Test Showing the Comparison of Classifier Performance

Classification 1	Classification 2	f_{11}	f_{12}	f_{21}	f_{22}	Total	Chi-square (χ^2)	P value
DTCa with leaf of 10	DTCb with leaf of 10	239	0	6	47	292	4.2	< 0.05
DTCa with leaf of 10	DTC with leaf of 15	239	0	2	51	292	0.5	> 0.05
DTCa with leaf of 10	DTC with leaf of 20	237	2	1	52	292	0.0	> 0.05
DTCa with leaf of 10	DTCc with leaf of 10	223	16	8	45	292	2.0	> 0.05
DTCb with leaf of 10	DTC with leaf of 15	237	8	4	43	292	0.8	> 0.05
DTCb with leaf of 10	DTC with leaf of 20	231	14	7	40	292	1.7	> 0.05
DTCb with leaf of 10	DTCc with leaf of 10	217	28	14	33	292	4.0	< 0.05
DTC with leaf of 15	DTC with leaf of 20	235	6	3	48	292	0.4	> 0.05
DTC with leaf of 15	DTCc with leaf of 10	221	20	10	41	292	2.7	> 0.05
DTC with leaf of 20	DTCc with leaf of 10	224	14	7	47	292	1.7	> 0.05
DTCb with leaf of 10	Post-classification	245	0	12	35	292	10.1	< 0.05

TABLE V
Error Matrix for LULC Map in 2017 Acquired by DTC With Postclassification Corrections

LULC classes	Class					Total	Producer's accuracy (%)	User's accuracy (%)	Overall accuracy (%)	Kappa
	Wetland	*Agricultural land*	*Building/ Villages*	*Forest land*	*Water bodies*					
Wetland	48	1	1	0	5	55	96.0	87.3	88.0	0.845
Agricultural land	2	91	14	9	2	118	98.9	77.1		
Building/Villages	0	0	34	0	0	34	68.0	100.0		
Forest land	0	0	1	41	0	42	82.0	97.6		
Water bodies	0	0	0	0	43	43	86.0	100.0		

Moreover, the user's accuracy is a measure of commission error; it is determined by dividing the total number of correct pixels in each category by the number of pixels that were classified in that category [37]. The 80% user's accuracy of DTCa (blue, green, red, NIR, DEM, NDVI layers) of the wetland class was found to be higher than others. The majority of classification errors in each DTC from different layers are the misclassification of wetland as agricultural land or a water body.

DT often produces a very large tree that can be incomprehensible even to experts [16]. Pruning is used to avoid overfitting in a DT and the unnecessary complexity of final classifiers as well as to improve predictive accuracy. The minimum number of object pruning was set as 10, 15, and 20 to a specific threshold value. It revealed that although the higher number of pruned objects simplified the tree, it reduced the overall classification of the DT approach.

The results of McNemar's test represent the number of pixels correctly or incorrectly classified by two classification methods [10] (see Table IV). The symbol f_{11} denotes the number of cases correctly classified by both classification methods, whereas, f_{22} denotes the number of cases incorrectly classified by both classification methods. Also, f_{12} denotes the number of cases that are correctly classified by classification 1, but incorrectly classified by classification 2, whereas f_{21} denotes the number of cases that are incorrectly classified by classification 1, but correctly classified by classification 2. The McNemar's test confirms that there is a significant difference in the accuracy of the classification derived by DTCa with leaf of 10 and DTCb with leaf of 10; DTCb with leaf of 10 and DTCc with leaf 10. Additionally, it clearly shows a significant difference in the accuracy of the classification derived from DTCb with leaf of 10 and postclassification.

Postclassification method was used to reclassify the pixels that were misclassified during DTC. The DTCb (Blue, green, red, NIR, SWIR1, DEM, and NDVI) with postclassification corrections provides satisfactory results by minimizing misclassifications; the producer's and the user's accuracy of wetland classification increased greatly from 80.0% to 96.0% and 78.4% to 87.3%, respectively. However, it still failed to distinguish wetlands from agricultural land, building and villages, and water bodies as given in Table V. The overall accuracy of the LULC maps in the years 1988, 1994, 2000, 2006, 2011, and 2017 is presented in Table VI.

B. Long-Term Changes

We detected long-term changes in the spatial distribution of LULC types over the past 30 years. Fig. 3(a)–(l) represents Landsat images and classification maps obtained during the years 1988 and 2017. As is shown in Fig. 3(b), (d), (f), (h), (j), and (l), agricultural areas increased by 24.3% during the period 1988–2017. Conversely, forest areas decreased 55.5% from 1994 to 2017. Wetland areas decreased significantly 30.5% over the 30-year period. The conversion of wetland area to agricultural area is the major cause of areal shrinkage. The large forest loss is attributed to conversion to agricultural land.

C. Map Changes

Fig. 4 below shows the proportion of spatial changes of the LULC in wetlands and adjacent areas. The proportion of agricultural land tended to increase from 2006 to 2017 and the highest proportion of agricultural area was near 70% of the total in 2017. The percentage of forest area tended to decrease; only approximately 9% of forest remained as of 2017. This is mainly caused by the conversion to agriculture. There is a decrease in the proportion of wetland cover on the landscape from roughly 25% in 1988 to 17% in 2017, whereas areas of building and

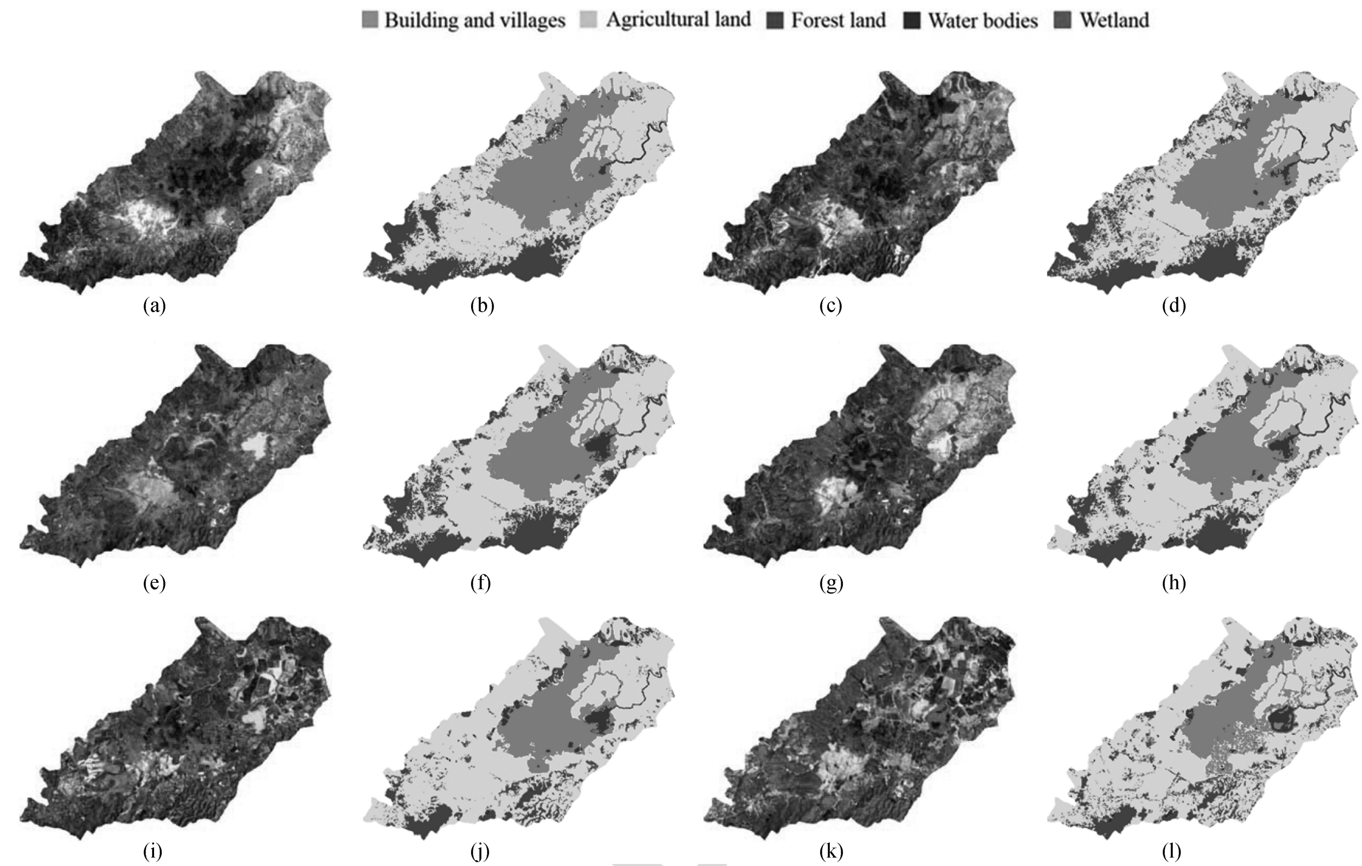

Fig. 3. Results of the Landsat images (*a, c, e, g, i, k*) and classified maps (postclassification) (*b, d, f, h, j, l*) of 1988, 1994, 2000, 2006, 2011, and 2017. (a) Landsat TM Bands 432-RGB (1988). (b) Postclassification (1988). (c) Landsat TM Bands 432-RGB (1994). (d) Postclassification (1994). (e) Landsat ETM+ Bands 432-RGB (2000). (f) Postclassification (2000). (g) Landsat TM Bands 432-RGB (2006). (h) Postclassification (2006). (i) Landsat TM Bands 432-RGB (2011). (j) Postclassification (2011). (k) Landsat OLI Bands 543-RGB (2017). (l) Postclassification (2017).

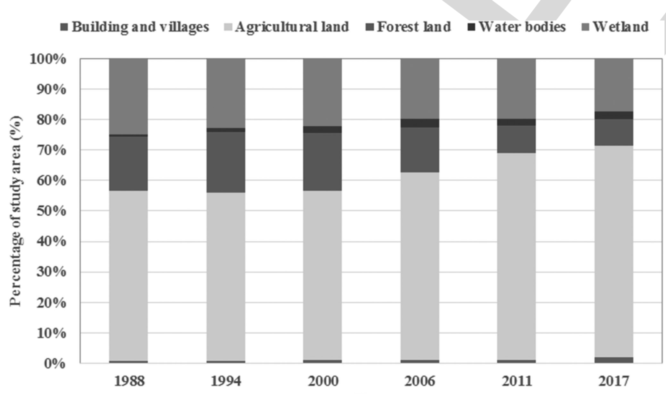

Fig. 4. Study area by land use and land cover classes from 1988 to 2017.

villages and water bodies both increased slightly during the relevant periods.

The changes in wetlands and their surrounding areas, as determined by a comparison of maps from 1988 to 2017. In term of the net changes, they included a loss of wetland area (8.19 km^2) and forest (9.91 km^2), whereas agricultural areas experienced a larger change by adding 14.63 km^2. In contrast, water bodies and building/villages showed a less profound change having only increased by 2.03 km^2 and 1.44 km^2, respectively. From 1988 to 2017, approximately 66% of forest cover was turned into agricultural land. In addition, 31% and 7% of the total wetland areas were converted to agricultural land and water bodies, respectively. There was actual change in the wetland areas of Takhaopleuk, Chan Chawa, Chan Chawa Tai, and Yonok Sub-districts as those wetland areas were converted to rice fields and farm ponds.

D. Wetland Change and Human-Environment Interaction

We addressed this issue by examining human population and land use factors and related concerns. The graphs in Fig. 5(a) and (b) display approximate relationships between pairs of variables. Specifically, Fig 5(a) depicts population trends from 1993 to 2017 together with the varying wetland area sizes (the forecasted population sizes for 2020, 2030, and 2040 will be discussed in Section V); and Fig 5(b) represents negative correlation between wetland areas and agricultural land, where the former decreases while the latter increases with time.

Increasing human population and concomitant increasing needs and higher demands can contribute to wetland loss [19]. The results showed that from 1994 to 2017, the variations in

TABLE VI
PRODUCER'S AND USER'S ACCURACY OF LULC CLASSIFICATION AND OVERALL ACCURACY OF LULC CLASSIFIERS

Year	LULC classes	PA (%)	UA (%)	Overall accuracy (%)	Kappa
1988	Wetland	95.9	93.3	84.9	0.784
	Agricultural land	95.7	76.2		
	Building/Villages	34.2	100.0		
	Forest land	89.8	91.7		
	Water bodies	66.7	100.0		
1994	Wetland	92.4	93.9	84.9	0.793
	Agricultural land	91.2	76.3		
	Building/Villages	53.5	95.8		
	Forest land	85.4	87.2		
	Water bodies	90.9	95.2		
2000	Wetland	98.5	90.1	85.3	0.803
	Agricultural land	89.2	76.5		
	Building/Villages	61.4	100.0		
	Forest land	90.7	86.0		
	Water bodies	66.7	100.0		
2006	Wetland	85.7	94.7	87.0	0.830
	Agricultural land	98.9	77.8		
	Building/Villages	62.2	100.0		
	Forest land	89.8	96.4		
	Water bodies	84.9	80.0		
2011	Wetland	91.8	93.3	84.9	0.800
	Agricultural land	100.0	71.4		
	Building/Villages	60.0	100.0		
	Forest land	86.8	100.0		
	Water bodies	63.2	92.3		
2017	Wetland	96.0	87.3	88.0	0.845
	Agricultural land	98.9	77.1		
	Building/Villages	68.0	100.0		
	Forest land	82.0	97.6		
	Water bodies	86.0	100.0		

Abbreviations: PA, Producer's accuracy; UA, User's accuracy.

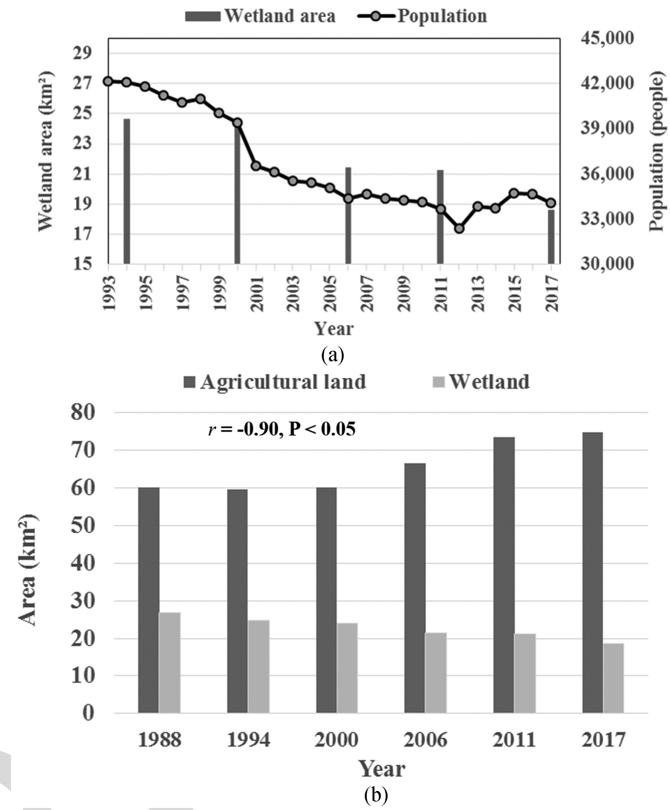

Fig. 5. (a) Population dynamic and wetland areas. (b) Relationship between wetland areas and agricultural land.

wetland areas are not related to local population change. Thus, we hypothesize that if agricultural land area changes are related to wetland change, i.e., increasing agricultural land will decrease wetland areas. The results show that wetland and agricultural land area changes are negatively correlated with an r of -0.90 ($p < 0.05$) [see Fig. 5(b)].

The vegetation area in wetlands can often be explained by the local temperature [51] and rainfall [20], two key factors influencing plant growth. We found that wetland vegetation coverage (a total areas of Wetland 01 and Wetland 03, see in Table II) was linked to the annual average temperature ($r = -0.85$, $P < 0.05$), whereas it was insignificantly related to the annual average rainfall ($r = -0.49$, $P > 0.05$).

Climatograph shows long term average air temperature and rainfall for 12 months of the year from 1988 to 2017 at the Chiang Rai Meteorological station [see Fig. 6(a)]. The weather in March becomes warmer. The hottest period of the year is from April to June with a mean temperature of roughly 28°C. In the study area, July through September receives the most rainfall with a range of 287 mm/mo. (September) to 355 mm/mo. (August). The weather is cool in both December and January with mean temperatures below 21°C. The mean air temperature has fluctuated throughout the 30-year period [see Fig. 6(b)]. The average temperature from 1988 to 1997 was consistently below the 30-year mean of 25.5°C. It then rose sharply in 1998 and fluctuated over the next 13 years. For each year from 2012 through 2017, average annual temperatures have all been above the 30-year mean. Average rainfall has also fluctuated over the past 30 years [see Fig. 6(c)]. The average rainfall decreased steadily between 1988 and 1993, and then it increased sharply in 1994 to 180 mm. It then fell sharply, fluctuated and increased again until 2001, when it peaked at 191 mm. After declining again sharply in 2003 to 117 mm, it fluctuated for a decade. There was a dramatic fall from 2013 to 2015, and then a sharp rise to 2016 and a continued sharp rise through 2017.

V. DISCUSSION

A. *Classification Approach*

Our quantitative analysis results confirm that a DTC approach performed better than an MLC or an MDC method in wetland classification of Landsat imagery. Similarly, the DTC technique offered better overall accuracy than traditional MLC techniques or support vector machines [15], [21], [52]. Certainly, differences in the specific number of bands, multisource data of different input types, decision thresholds for each image's dataset in Landsat TM, ETM+, and OLI sensors could contribute to the overall accuracy differences between the present study and that of those other studies. However, the DTC technique has its limits in that if the training data contains error, then overfitting

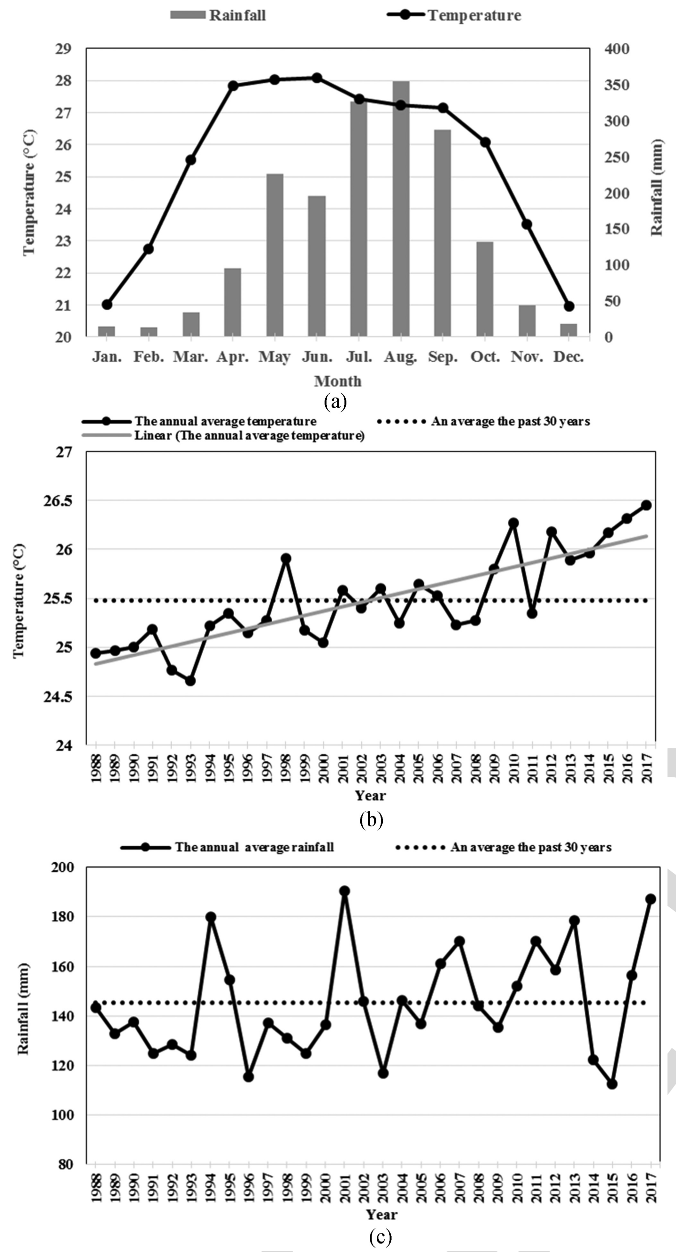

Fig. 6. (a) Climatological average monthly air temperature and rainfall. (b) Average annual air temperature. (c) Average annual rainfall from 1988 to 2017, measured at the meteorological station (the Chiang Rai Meteorological Station) nearest to the study area.

the tree can lead to poor performance. The tree should be pruned back to diminish errors when data outside the training set are to be classified [16], [24]. The decision thresholds would lead to the final outcome of the classification. By changing training data, the DT was also changed. Therefore, expert knowledge is required to determine the DT boundaries that separate the classes in future space [15].

In a technical sense, some of our results do not concur with the findings of previous studies whereas certain others are in agreement with earlier works. In particular, it has been suggested that using MLC is a more appropriate method to map wetlands for wetland resource and conservation management in the lower Mekong basin, made up in part by Lao PDR, Thailand, Cambodia, and Vietnam [4]. Yet, our findings indicate that the MLC technique did not perform well, yielding poor quality results in the case of the Wiang Nong Lom and Nong Luang wetlands (Chiang Saen Valley). On the other hand, MLC can only provide the best results when distinguishing between forest and nonforest land cover in the study area which is consistent with what has been found in previous findings [7].

Suitable classifiers and spectral bands have been shown to have a significant impact on classification accuracy. Our study showed that due to spectrally similar LULC features in wetland landscape, some LULC classes have very similar spectral characteristics. For example, wetlands were misclassified as an agricultural area or water body, whereas during the dry period some water bodies could be interpreted as a wetland. These findings are in accordance with other studies [19], [58]. Local villages and small road networks could not be precisely detected in Landsat data due to their mixed spectral signals. Similarly, several pixels scattered throughout an agricultural area (para-rubber plantation) may erroneously be classified as forest land.

B. Wetland Changes

Although high spatial resolution satellite sensors can yield reliable LULC classification and change detection results with more details at a local level, the long-term archive of Landsat satellite images could prove useful in providing long-term data records for wetland monitoring and change detection. Landsat still has a limited ability to map land cover at finer scales and to identify wetland vegetation habitat type associations and map them [8]. Future studies should investigate specific ecological functions.

Our results indicate that during the last 30 years a significant decline in wetland areas (at the rate of 1% annually) occurred in the study area. Rain-fed paddy cultivation (May through December) has long been practiced in areas surrounding wetlands. From 1988 to 1994, wetland areas decreased by 2.18%. It is because the Thai government implemented a rice price guarantee in 1984. The Bank of Agriculture and Agricultural Cooperatives (BAAC) implemented the rice pledging scheme to help farmers resolve their debts by providing short-term loans for them and to collect growers' paddy rice as a guarantee [42]. Upon the suggestion of merchants, the planting of cassava and maize became more prevalent; merchants who would eventually purchase the yield would do so at a reduced rate after investing and providing seed and machinery to the farmers. These two events resulted in the expansion of rice and field crop cultivated areas into wetland areas. In addition, in 1991 and 1992, local influencers and private investors bought land in villages and areas around wetlands to plant rice and fruit trees such as lychee and longan. They used tractors and crawler backhoes to dredge and drain water from the wetlands for rice cultivation. The drained wetlands became areas suitable for cattle grazing and resulted in encroachment of previously existing wetlands.

Wetland encroachment slowed down during 1994–2000. This was probably due to the fact that local government agencies seized public land from villagers and made agreements concerning wetlands and local boundaries. Villagers could continue to use those lands for agriculture, but they needed to pay a land tax to the local governments. Because those lands were owned by government, farmers were required to inform the government if they no longer wished to use land for agriculture. Basic infrastructure facilities, such as local roads, water supply, and electricity were developed in communities surrounding wetlands during 1994–1995. During this period, local people perceived abnormal weather conditions resulting in wetlands drying up. In response, during 1995–1996 farmers started to dig farm ponds in their rice fields to raise water crops, fish and chicken.

The percentage of wetland areas in the study area decreased by 2.7% from 2000 to 2006. A possible explanation for this is the Ninth National Economic and Social Development Plan (2002–2006). Since 2002, emphasis was on reviving the economy and building immunity to adverse changes for the people through grass-root economic development. The government had adopted a national plan for infrastructure to encourage economic growth and the development of infrastructure in order to enhance the country's productivity and growth of exported goods. Consequently, the project increased crop production, service businesses and residential areas, and also resulted in a rapid increase in land prices [38]. Therefore, there were many developmental projects in the study area, such as the construction of roads, irrigation systems, and government buildings. As a result, many moats, mounds, archaeological sites, and ancient settlements in/and surrounding wetlands were destroyed along with their archeological evidence and value [38]. In 2003, the reduction of water runoff flowing into wetlands and the intensive use of water from wetlands during the summer for agricultural practices, particularly tangerine farms, caused extreme drought conditions drying out some wetlands [38]. At the same time, alien species, such as the Giant Mimosa (*Mimosa pigra*) and the Golden Apple Snail (*Pomacea canaliculata*) spread rapidly in wetlands [31], [53]. Buffalo and cattle populations declined because of disease outbreaks and shrinking grazing areas in and around the wetlands [38]. Villagers sold household land holdings to private investors or landlords; they did not have enough forage area to feed their cattle and buffalo [38]. In 2004, some farmers began to cultivate irrigated rice fields. The season lasts from January to May. Irrigated rice fields require the draining of water from wetlands and the Mae Lua River into the fields. During this time, wetlands were being gradually encroached upon by expanding rice farmland in addition to the water being drained.

The conversion of wetlands to agricultural uses slowed down during 2006–2011. One reason may be the limited success of the Strategic Wetland Management Plan of Nong Bong Kai wetland. Through community participation in a strategic planning process, this Plan aimed to promote sustainable wetland management and restore the Nong Bong Kai wetland and vicinity to its natural healthy and functioning state. This plan has a 20 year strategy (2004–2024) and a five-year action plan (2004–2008) [31], [53]. Local communities, particularly in Pasak and Yo Nok subdistricts, were strengthened by various conservation and training activities regarding fish and water birds, water use, and liquid biofertilizer made from apple snails. However, despite some successes in slowing down encroachment into wetlands, farmers started to grow irrigated rice crops. Farmers in Yonok subdistrict started to cultivate irrigated rice extensively during 2007. There was not enough water for rice crops; therefore, water had to be drained from the wetlands. During the 2009–2010 dry seasons, there was not enough water for crops because of the water scarcity problem created by draining.

The strategic wetland management plan was effective for a short-time period (2004–2008) as it helped to strengthen community conservation efforts and encourage the wise use of wetlands. Its effectiveness was temporary. However, from 2011 to 2017, the percentage of wetland areas decreased by 2.61%. In October 2011, the government implemented a rice pledging scheme that allowed farmers to pledge and give an unlimited supply of their rice to the government at a fixed price that was higher than the going market rate [33], [34]. It offered crop insurance and income security. It established a registration system for farmer households and issued credit cards to farmers [33]. Farmers wishing to participate in the program were required to obtain approval from the Department of Agriculture and their community. Product could be pledged at any local rice miller; millers then were to issue a warehouse receipt to the farmers to claim funds from the BAAC which was then obligated to process the payment to the farmers [34]. The scheme was beneficial and convenient and provided many incentives to grow rice and participate. Unfortunately, and quite naturally, the program increased crop cultivation in at-risk areas, such as wetlands. As a result, rice cultivation has encroached into wetlands. As evidence, one can merely look at the wetlands near the Yonok Sub-district boundaries. In 2011, local governments designated these lands as for landless households (0.0004–0.0032 km^2 per household). After 2011, because of the elevated price of rice, these areas were converted to rice cultivation. Thereafter, in 2017, as a result of decreased rice exports, many farmers converted these rice fields into fish ponds because of the reduction in rice prices caused by lower exports.

Wetlands and wetland ponds act as natural water storage, can serve as a water supply and ease agricultural water scarcity problems. Farmers reported declining water levels in wetlands and the Mae Lua River since 2013 and experienced extreme drought in 2015. These conditions decreased rice yields and caused a reduction in fodder and grass for buffalo and cows. It reduced the number of buffalo and cows and, consequentially, caused a reduction in a primary income source, the sale of dung and manure for fertilizer.

C. *Response to Wetland Changes*

As a result of the reduction in fodder and grass for buffalo and cows and with support from the local governments, buffalo raisers and farmers began planting fodder, such as napier grass, crop residue, and legumes, on their land surrounding wetlands.

There was not enough water for crops, thus, farmers dug ponds to store water on their lands and local governments dredged wetlands (they dredged canals around wetlands) for storage water and buffer zones.

As a result of the reduced fish and aquatic animal population, local people made efforts to conserve and rehabilitate fish and aquatic animals. They agreed to make Wat Pa Mak Nor, a temple situated in the wetlands, a fish conservation area at which fishing was prohibited. These have forced communities to consider and pursue alternate livelihood measures, such as raising water crops, fish, chickens, individual household crop farming for household consumption, making handicrafts, and nonfarm day labor.

D. Drivers of Change to Wetlands

1) Agriculture: Our findings confirm that increasing agricultural land area has a statistically significant effect on decreasing wetland areas. Ground data can be used to corroborate these results and describe the resulting changes in more detail. Rain fed rice has been grown for decades. Since 2007, some paddy fields in areas surrounding wetlands converted to irrigated rice fields that withdrew water from the Mae Lua River and wetlands. Consequently, this expansion of agricultural areas impacted and contributed to the gradual conversion of wetlands to rice cultivation fields. This could possibly be linked to governmental agricultural policy. Through a 1986 policy, the Thai government attempted to improve infrastructure and facilities to enhance agricultural productivity. By supporting prices to increase farmers' income, a rice policy was implemented through the paddy pledging program which allowed farmers to obtain a higher price for their crops [6]. Meanwhile, the government promoted a para-rubber plantations policy called "the one million RAI project," in which the government guaranteed a rubber price to bolster farmers' incomes. This has led to widespread land conversion to para-rubber cultivation [26]. Since 2003, large areas have been cultivated for the production of para-rubber, palm oil and pineapples in study areas. As a result, there was a rapid rise in the expansion of agricultural areas during the study period.

2) Population: Wetlands have been affected by population growth and increasing economic development, which have impacted the provision and availability of ecosystem services and resources. Due to the unavailability of 1988 population data, it is not possible to assess if the post-1988 data represents the beginning or the continuation of a trend. Our ARIMA modeling used past population values (that are available only from 1993 to 2017) to predict that the population in 2020, 2030, and 2040 would be 33 723, 32 494, and 31 264 people, respectively. However, the decline in wetland size does not appear to be related to local population size. From 1993 to 2017, people increasingly moved from rural to urban areas. The local populations that remain in the rural areas are primarily dependent on subsistence agriculture, and many small-scale farmers have the potential to successfully transform subsistence production to commercial production [35]. At the same time, agribusiness firms have extended over large areas of para-rubber, palm oil, and pineapple plantations. These developments have led to human activities and other processes that damage the wetlands and impact the upstream catchments of the streams and rivers that drain into them.

3) Other Drivers of Change: We suggest that digging ponds and constructing farm roads or cart paths for access to the wetlands in the Chiang Saen Valley would lead to isolated fragments of wetlands and waterways. Additionally, encroachment for grazing, overexploitation of wetland products and invasive alien species are a major threat to the sustainability of the wetlands. Other studies have generated similar findings [55].

4) Climate Change: Wetlands appear to be vulnerable to agricultural activities and climatic variability [21]. It remains unclear to what degree climate change contributes to the impact on the Chiang Saen Valley wetlands. Unfortunately, we lacked meteorological data from ground truth observation; therefore, we collected meteorological data from the station nearest to the study area. However, great challenges exist in understanding climate change and its complex impact on our study area. It has led to a reduction in the services provided by wetlands, such as food and available water, as was discussed in Section V-B. Wetland changes might not be directly related to temperature and/or rainfall variations, but they are climatic conditions important to wetlands and agricultural production. Empirical evidence from trends on temperature and rainfall have been linked to perceived changes, especially rainfall and its impact on wetlands and local livelihood activities, particularly agriculture, livestock, and fisheries.

5) Legislation: Recently, Thailand adopted a strategic plan to focus on biodiversity. The plan was generated by the Office of Natural Resources and Environmental Policy and Planning (ONEP) in cooperation with the Office of the National Economic and Social Development Board and the Biodiversity-based Economy Development Office (public organization). Many stakeholders were involved in the planning and development process of this plan that was approved by the Cabinet on March 10, 2015. The time frame of the plan is 2015–2021 and has five objectives:

1) to address the causes of biodiversity loss;
2) to promote biodiversity conservation and sustainable use;
3) to improve the status of biodiversity;
4) to develop the capacity to manage biodiversity and ecosystem services;
5) to enhance implementation through participatory planning, knowledge management, and capacity building [32].

It highlights wetlands in objective 2) on conservation and biodiversity restoration: to protect wetlands and control the expansion of community, pollution, overfishing, and climate change, which can cause loss of wetlands and degradation; to focus on and address biodiversity issues to create criteria to assess the impact on the Environmental Impact Assessment (EIA) to protect wetlands; to push the Cabinet Resolution of November 3, 2009 regarding classification of Thailand's wetlands as to their level of importance, conservation measures, and more practical action for conservation and management of the wetlands.

There are agencies and legislation related to the utilization, conservation, and restoration of wetlands. Each agency is granted specific wetland regulatory authority through separate legislative acts. For instance, the OONEP and the Pollution Control Department (PCD) receive their authority from the Promotion and Conservation of National Environmental Quality

Act of 1992; the Department of National Parks, Wildlife and Plant Conservation (DNP) receives its authority from the National Park Act of 1961 and the Wild Animal Reservation and Protection Act of 1992; the Department of Fisheries receives its authority from the Fisheries Act of 1995 [46], [47]. Due to the vast amount of legislation and number of regulatory entities, determining who has jurisdiction over wetlands and what procedures must be followed can be confusing. There is no lead agency tasked with looking at "the big picture" that could coordinate efforts of all concerned agencies. The Wiang Nong Lom and the Nong Luang wetlands (in Chiang Saen Valley) have been designated as wetlands of international importance [46], but a lack of clear, discernible boundaries inhibits the efforts of officials to establish policies to acknowledge and protect areas of importance. Existing wetlands should be protected by special land use policy, but implementing such policy may intensify already existing land conflicts.

Our study's conclusion is that LULC affected the ecosystem of the Wiang Nong Lom and Nong Luang (in Chiang Saen Valley) wetlands, and, accordingly, it can lead to changes in resource allocations. These wetlands are especially vulnerable to drivers of land-use change, with agricultural expansion being a major threat to wetland sustainability. Moreover, socioeconomic development and institutional policies (and to a lesser extent, population changes) are also forces driving wetland changes. It is hoped that the findings of this study will heighten the interest of governmental policy-makers in understanding and recognizing the importance of wetlands. They can also learn from, and apply these findings in their effort to manage natural resources, resolve conflict and make effective arrangements among stakeholders for the common pool of resources.

VI. Conclusion

In sum, the findings of this study are both technological and substantive, as follows.

1) In high heterogeneous landscapes of small wetlands and surrounding areas with spectral similarities between LULC types, the DTC outperformed traditional methods that use Landsat imagery, such as MLC and MDC. In the future, research challenges will be to find suitable methods of extracting wetland vegetation information and enhance classification accuracy with high resolution images.
2) Wetlands are at risk and those near agricultural land with extended cultivation have suffered losses. This indicates that existing legislation, policies, programs, and strategic ecosystem plans cannot protect small-scale wetlands if they are not enforced.
3) Agricultural policies and wetlands conservation programs influence land use decisions. Agricultural policies change the economic incentives to cultivate crops, extend cultivation and encroach upon wetland areas.
4) Although many of the goods and services provided by small wetlands have little or no market value, they have benefits that inure to the local people. A large number of people live in and around wetlands and depend on their resources for their livelihoods. Perhaps the best way to protect the wetlands and their resources is to educate the community regarding their importance and benefits. It would be wise to build alliances within the community to preserve wetlands, and develop community advocacy to be persistent, watchful and active to empower communities to become more active stewards of wetlands in their communities. An example would be volunteer monitoring programs. Giving local communities management and control over wetland resources is vital to their successful sustainable management. Additionally, government agencies should consider the potential for rural job creation, should encourage farmers to produce crops with less water and should assist them in promoting agro production, processing, marketing and distribution of high value crops. Doing so can minimize the detrimental impact of agricultural activities on neighboring the wetlands.

Acknowledgment

The authors would like to thank the Chiang Rai Meteorological Station of the Thai Meteorological Department for providing the meteorological data, the Royal Thai Survey Department, Ministry of Agriculture and Cooperatives, and Land Development Department for providing the topographic maps, orthophoto maps, and land use mapping from the Northern Region of Thailand for 2000–2002, 2006–2007, 2008–2009, 2010–2013, and 2015–2016 as a reference. The authors are very grateful to the editor and the reviewers for their constructive comments that help improve this article.

References

[1] C. Baker, R. Lawrence, C. Montagne, and D. Patten, "Mapping wetlands and riparian areas using Landsat ETM+ imagery and decision-tree-based models," *Wetlands*, vol. 26, no. 2, pp. 465–474, Jun. 2006.

[2] C. Kasorndorkbua and P. Jakthong, "Blood lead levels in wintering Pied Harrier (*Circus melanoleucos*) from Thailand," in *Proc. 10th Asian Raptor Res. Conserv. Netw. Int. Symp.*, Oct. 18–22, 2017. Q4

[3] C. Kasorndorkbua, A. Kunsorn, and C. Wongchai, "Nesting records of Eastern Grass Owl *Tyto (capensis) longimembris* in Chiang Rai, Northern Thailand," in *Proc. BirdingASIA*, vol. 9, 2008, pp. 91–93.

[4] C. MacAlister and M. Mahaxay, "Mapping wetlands in the Lower Mekong Basin for wetland resource and conservation management using Landsat ETM images and field survey data," *J. Environ. Manage*., vol. 90, no. 7, pp. 2130–2137, 2009, doi: 10.1016/j.jenvman.2007.06.031.

[5] C. Zhang, D. Selch, and H. Cooper, "A framework to combine three remotely sensed data sources for vegetation mapping in the Central Florida Everglades," *Wetlands*, vol. 36, no. 2, pp. 201–213, 2015, doi: 10.1007/s13157-015-0730-7.

[6] D. Dawe, *Rice Crisis: Markets, Policies and Food Security*. 1st ed. London, U.K.: Earthscan and FAO, 2010, pp. 191–217.

[7] D. Lu, "Linear mixture model applied to Amazonian vegetation classification," *Remote Sens. Environ.*, vol. 87, no. 4, pp. 456–469, 2003, doi: 10.1016/j.rse.2002.06.001.

[8] E. Adam and O. Mutanga, "Spectral discrimination of papyrus vegetation (*Cyperus papyrus L.*) in swamp wetlands using field spectrometry," *ISPRS J. Photogramm. Remote Sens*., vol. 64, no. 6, pp. 612–620, 2009, doi: 10.1016/j.isprsjprs.2009.04.004.

[9] E. Bartholomé and A. S. Belward, "GLC2000: A new approach to global land cover mapping from Earth observation data," *Int. J. Remote Sens*., vol. 26, no. 9, pp. 1959–1977, 2007, doi: 10.1080/01431160412331291297.

[10] G. M. Food, "Thematic map comparison: evaluating the statistical significance of differences in classification accuracy," *Photogramm. Eng. Remote Sens.*, vol. 70, no. 5, pp. 627–633, 2004.

[11] G. Tana, H. Letu, Z. Cheng, and R. Tateishi, "Wetlands mapping in North America by decision rule classification using MODIS and ancillary data," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens*., vol. 6, no. 6, pp. 2391–2401, Dec. 2013, doi: 10.1109/jstars.2013.2249499.

[12] H. Bagan, W. Takeuchi, T. Kinoshita, Y. Bao, and Y. Yamagata, "Land cover classification and change analysis in the Horqin sandy land from 1975 to 2007," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 3, no. 2, pp. 168–177, Jun. 2010, doi: 10.1109/jstars.2010.2046627.

[13] J. R. Anderson *et al.*, "A land use and land cover classification system for use with remote sensor data," U.S. Geological Survey, Professional Paper 964, 1976, [Online]. Available: http://pubs.er.usgs.gov/publication/pp964

[14] J. R. Jensen, *Introductory Digital Image Processing: A Remote Sensing Perspective*. Englewood Cliffs, NJ, USA: Prentice-Hall, 1986, pp. 13–25.

[15] J. R. Otukei and T. Blaschke, "Land cover change assessment using decision trees, support vector machines and maximum likelihood classification algorithms," *Int. J. Appl. Earth Observ. Geoinf.*, vol. 12, pp. S27–S31, 2010, doi: 10.1016/j.jag.2009.11.002.

[16] J. R. Quinlan, "Simplifying decision trees," *Int. J. Hum. Comput. Stud.*, vol. 51, no. 2, pp. 497–510, 1999.

[17] J. R. Quinlan, *C4.5: Programs for Machine Learning*. San Mateo, CA, USA: Morgan Kaufmann, 1993, pp. 1–56.

[18] J. Tayman, S. K. Smith, and J. Lin, "Precision, bias, and uncertainty for state population forecasts: an exploratory analysis of time series models," *Population Res. Policy Rev.*, vol. 26, no. 3, pp. 347–369, 2007, doi: 10.1007/s11113-007-9034-9.

[19] K. Song *et al.*, "Wetlands shrinkage, fragmentation and their links to agriculture in the Muleng-Xingkai Plain, China," *J. Environ. Manage.*, vol. 111, pp. 120–132, 2012, doi: 10.1016/j.jenvman.2012.06.038.

[20] L. Feng, X. Han, C. Hu, and X. Chen, "Four decades of wetland changes of the largest freshwater lake in China: Possible linkage to the Three Gorges Dam?," *Remote Sens. Environ.*, vol. 176, pp. 43–55, 2016, doi: 10.1016/j.rse.2016.01.011.

[21] L. M. Rebelo, C. M. Finlayson, and N. Nagabhatla, "Remote sensing and GIS for wetland inventory, mapping and change analysis," *J. Environ. Manage.*, vol. 90, no. 7, pp. 2144–2153, 2009, doi: 10.1016/j.jenvman.2007.06.027.

[22] "A land use and land cover classification system for Thailand," Land Develop. Dept., Bangkok, Thailand, 2012.

[23] "Provincial soil and land use maps," Land Develop. Dept., Bangkok, Thailand, 2000.

[24] M. A. Friedl and C. E. Brodley, "Decision tree classification of land cover from remotely sensed data," *Remote Sens. Environ.*, vol. 61, no. 3, pp. 399–409, 1997.

[25] M. J. O'Connell, "Detecting, measuring and reversing changes to wetlands," *Wetlands Ecol. Manag.*, vol. 11, pp. 397–401, 2003.

[26] M. Kawano, "Changing resource-based manufacturing industry: The case of the rubber industry in Malaysia and Thailand," in *Emerging States at Crossroads*. K. Tsunekawa and Y. Todo, Eds. Singapore: Springer, 2019, pp. 145–162.

[27] M. Pal and P. M. Mather, "An assessment of the effectiveness of decision tree methods for land cover classification," *Remote Sens. Environ.*, vol. 86, no. 4, pp. 554–565, 2003, doi: 10.1016/s0034-4257(03)00132-9.

[28] M. Story and R. G. Congalton, "Accuracy assessment: A user's perspective," *Photogramm. Eng. Remote Sens.*, vol. 52, no. 3, pp. 397–399, 1986.

[29] N. Kayastha, V. Thomas, J. Galbraith, and A. Banskota, "Monitoring wetland change using inter-annual Landsat time-series data," *Wetlands*, vol. 32, no. 6, pp. 1149–1162, 2012, doi: 10.1007/s13157-012-0345-1.

[30] "The spatial analysis for the Kok basin using GIS," Office Agr. Econ., Bangkok, Thailand, 1994.

[31] "Nong Bong Kai Strategic Wetland Management Plan," Office Natural Resour. Environ. Policy Planning, Chiang Rai, Thailand, 2004.

[32] "Master Plan for Integrated Biodiversity Management 2015-2021," Ministry Natural Resour. Environ., Bangkok, Thailand, 2015.

[33] P. Sahapattana, "Rice pledging scheme: A high-stakes risk for the big players," *NIDA Case Res. J.*, vol. 7, no. 2, pp. 60–83, 2015.

[34] P. Sawasdipakdi, "The politics of numbers: controversy surrounding the thai rice-pledging scheme," *SAIS Rev. Int. Affairs*, vol. 34, no. 1, pp. 45–58, 2014, doi: 10.1353/sais.2014.0003.

[35] P. Soni, "Agricultural mechanization in Thailand: Current status and future outlook," *AMA-AGR MECH ASIA AF.*, vol. 47, no. 2, pp. 58–66, 2016.

[36] R. G. Congalton and K. Green, *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*. 2nd ed. Boca Raton, FL, USA: Taylor and Francis, 2009.

[37] R. G. Congalton, "A review of assessing the accuracy of classifications of remotely sensed data," *Remote Sens. Environ.*, vol. 37, no. 1, pp. 35–46, 1991, doi: 10.1016/0034-4257(91)90048-b.

[38] R. Pingmoung, "A Biodiversity and environment study towards sustainable management at Wiang Nong Lom wetland," Chiang Rai Rajabhat Univ., Chiang Rai, Thailand, 2004.

[39] S. Intasean, "Mapping the Agricultural Resource for 2000 in Northern Thailand," Office Agr. Econ., Bangkok, Thailand, 2003.

[40] S. Kuchaisit, "The Spatial Analysis for the Kok Basin," Office Agr. Econ., Bangkok, Thailand, 1998.

[41] S. Mahdavi *et al.*, "Remote sensing for wetland classification: A comprehensive review," *GIsci. Remote Sens.*, vol. 55, no. 5, pp. 623–658, 2018, doi: 10.1080/15481603.2017.1419602.

[42] T. Laiprakobsup, "Populism and agricultural trade in developing countries: A case study of Thailand's rice-pledging scheme," *Int. Rev. Public Admin.*, vol. 19, no. 4, pp. 380–394, 2014, doi: 10.1080/12294659.2014.967000.

[43] T. M. Lillesand, R.W. Kiefer, and J.W. Chipman, *Remote Sensing and Image Interpretation*, 7th ed. Hoboken, NJ, USA: Wiley, 2008, pp. 520–618.

[44] T. Phuwanatwichit and S. Srirat, "Sustainable tourism planning and management preparing for the ASEAN Economic Community (AEC): Wiang Nong Lom wetland, Chiang Rai province" (in Thai), *Chiang Mai Univ. J. Social Sci. Humanities*, vol. 15, no. 2, pp. 132–164, 2014.

[45] T. R. Loveland *et al.*, "Development of a global land cover characteristics database and IGBP DISCover from 1 km AVHRR data," *Int. J. Remote Sens.*, vol. 21, no. 6–7, pp. 1303–1330, 2010, doi: 10.1080/014311600210191.

[46] "Promoting efficient wetland management in Thailand," Office Natural Resour, Environ. Policy Planning, Thailand Inst. Sci. Technolog. Res., Bangkok, Thailand, 2015.

[47] "The status of wetlands in Thailand: Inland wetlands," Office Natural Resour. Environ. Policy Planning, Thailand Inst. Sci. Technolog. Res, Bangkok, Thailand, 2011.

[48] "The status of wetlands in Thailand: Wiang Nong Lom wetland," Office Natural Resour. Environ. Policy Planning, Thailand Inst. Sci. Technolog. Res, 2011.

[49] TMD, "The climate of Thailand," 2015. [Online]. Available: https://www.tmd.go.th/en/archive/thailand_climate.pdf.

[50] W. J. Mitsch and J. G. Gosselink, *Wetlands*. 4th ed. NJ, USA: Wiley, 2007, pp. 287–374.

[51] X. Han, X. Chen, and L. Feng, "Four decades of winter wetland changes in Poyang Lake based on Landsat observations between 1973 and 2013," *Remote Sens. Environ.*, vol. 156, pp. 426–437, 2015, doi: 10.1016/j.rse.2014.10.003.

[52] X. Zhang *et al.*, "Mapping mangrove forests using multi-tidal remotely-sensed data and a decision-tree-based procedure," *Int. J. Appl. Earth Observ. Geoinf.*, vol. 62, pp. 201–214, 2017, doi: 10.1016/j.jag.2017.06.010.

[53] Y. Trisurat, "Community-based wetland management in northern Thailand," *Int. J. Environ., Cultural, Econ. Social Sustain.*, vol. 2, no. 1, pp. 49–62, 2006.

[54] Z. Li and J. M. Fox, "Integrating Mahalanobis typicalities with a neural network for rubber distribution mapping," *Remote Sens. Lett.*, vol. 2, no. 2, pp. 157–166, 2011, doi: 10.1080/01431161.2010.505589.

[55] Z. Wang *et al.*, "Changes of land use and of ecosystem service values in Sanjiang Plain, Northeast China," *Environ. Monit Assessment*, vol. 112, pp. 69–91, 2006, doi: 10.1007/s10661-006-0312-5.

[56] Z. Zhu *et al.*, "Including land cover change in analysis of greenness trends using all available Landsat 5, 7, and 8 images: A case study from Guangzhou, China (2000–2014)," *Remote Sens. Environ.*, 2016, doi: 10.1016/j.rse.2016.03.036.

[57] Z. Zhu, "Change detection using landsat time series: A review of frequencies, preprocessing, algorithms, and applications," *ISPRS J. Photogramm. Remote Sens.*, vol. 130, pp. 370–384, 2017, doi: 10.1016/j.isprsjprs.2017.06.013.

[58] ZG. Niu *et al.*, "Geographical characteristics of China's wetlands derived from remotely sensed data," *Sci. China Earth Sci.*, vol. 52, no. 6, pp. 723–738, 2009, doi: 10.1007/s11430-009-0075-2.

Nuttiga Hempattarasuwan received the B.S. degree in fisheries from Kasetsart University, Bangkok, Thailand, in 1998, and the M.S. degree in environmental science from Thammasat University, Bangkok, in 2001. She is currently working toward the Ph.D. degree with the Institute of Coastal and Islands Ecosystems, Zhejiang University, China.

From 2001 to 2004, she was an Environmentalist of consultant companies. From 2004 to 2005, she was a Research Associate with the Asian Institute of Technology. From 2006 to 2015, she was a Program Officer and a Researcher with Mae Fah Luang University, Thailand. Her research interests include environmental remote sensing and information technology.

George Christakos received the B.Eng. degree and in civil engineering and Sc.D. degree in mining and metallurgical engineering from the National Technical University of Athens, Greece, the M.Sc. degree in soil engineering from the University of Birmingham, Birmingham, U.K., the M.S. degree in civil and environmental engineering from the Massachusetts Institute of Technology, Cambridge, MA, USA, and the Ph.D. degree in applied sciences from Harvard University, USA.

His research interests include stochastic spatiotemporal modeling of natural systems under conditions of uncertainty with applications in earth, ocean and atmospheric sciences, environmental health, epidemiology, medical geography, and temporal geographic information systems.

Jiaping Wu received the B.S. and M.S. degrees from Zhejiang University, Hangzhou, China, and the Ph.D. degree in land resource and GIS from Kansas State University, Manhattan, KS, USA.

From 1997 to 2003, he was a Postdoc and Research Associate Scientist with Cornell University, USA. He is currently a Professor with Zhejiang University. His research interests include coastal environment and ecosystem, and spatiotemporal data analysis and modeling.