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## Quantifying spatial-temporal changes of tea plantations in complex landscapes through integrative analyses of optical and microwave imagery



Weiheng Xu<sup>a,b</sup>, Yuanwei Qin<sup>b</sup>, Xiangming Xiao<sup>b,c,\*</sup>, Guangzhi Di<sup>a,b</sup>, Russell B. Doughty<sup>b</sup>, Yuting Zhou<sup>b</sup>, Zhenhua Zou<sup>b</sup>, Lei Kong<sup>d</sup>, Quanfu Niu<sup>b,e</sup>, Weili Kou<sup>a</sup>

<sup>a</sup> College of Big Data and Intelligence Engineering, Southwest Forestry University, Kunming, 650224, China

<sup>b</sup> Department of Microbiology and Plant Biology, Center for Spatial Analysis, University of Oklahoma, Norman, OK, 73019, USA

<sup>c</sup> Ministry of Education Key Laboratory of Biodiversity Science and Ecological Engineering, Institute of Biodiversity Science, Fudan University, Shanghai, 200433, China

<sup>d</sup> China Forest Exploration & Design Institute on Kunming, Kunming, 650216, China

<sup>e</sup> School of Civil Engineering, Lanzhou University of Technology, Lanzhou, 730050, China

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#### ABSTRACT

High demand for tea has driven the expansion of tea plantations in the tropical and subtropical regions over the past few decades. Tea plant cultivation promotes economic development and creates job opportunities, but tea plantation expansion has significant impacts on biodiversity, carbon and water cycles, and ecosystem services. Mapping the spatial distribution and extent of tea plantations in a timely fashion is crucial for land use management and policy making. In this study, we mapped tea plantation expansion in Menghai County, Yunnan Province, China. We analyzed the structure and features of major land cover types in this tropical and subtropical region using (1) the HH and HV gamma-naught imagery from the Advanced Land Observation Satellite (ALOS) Phased Array L-band Synthetic Aperture Radar (PALSAR) and (2) time series Landsat TM/ETM +/OLI imagery. Tea plantation maps for 2010 and 2015 were generated using the pixel-based support vector machine (SVM) approach at 30 m resolution, which had high user/producer accuracies of 83.58%/91.67% and 87.50%/90.83%, respectively. The resultant maps show that tea plantation area increased by 33.56% (~9335 ha), from ~27,817 ha in 2010 to ~37,152 ha in 2015. The additional tea plantation area was mainly converted from forest (32.50%) and cropland (67.50%). The results showed that the combination of PALSAR and optical data performed better in tea plantation mapping than using optical data only. This study provides a promising new approach to identify and map tea plantations in complex tropical landscapes at high spatial resolution.

#### 1. Introduction

The tea plant (*Camellia sinensis* (L.) O. Kuntze), an evergreen broadleaved perennial shrub, is widely cultivated in the mountains of tropical and subtropical zones and is important commercial crop (Duncan et al., 2016; Wang et al., 2016). As one of the three most popular manufactured beverages (tea, coffee, and cocoa) consumed in the world (Kumar et al., 2013), tea is a major economic crop in many developing countries, including China, India, Kenya, and Sri Lanka. Due to the rapid development of the global tea industry since the beginning of this century, tea plantation area and tea production have increased significantly. According to International Tea Commission statistics, the global tea plantation area increased 4.37 million hectares in 2014, and the tea plantation area increased by 64.9% between 2000 and 2014. China is the largest tea-planting and production country in the world, spanning 20 southern provinces (Wang et al., 2016) and accounting for 37.9% of the global total tea production (FAO, 2014; Su et al., 2017). In 2014, tea plantation area in China was 2.65 million hectares, an increase of 143% from 2000 (Lee et al., 2017).

Tea plantations have rapidly expanded in some regions of China and other countries due to economic incentives (Xue et al., 2013). Therefore, marginal quality croplands and natural forests with steeper slope and higher elevation have been converted into tea plantations (Su et al., 2017, 2016). Deforestation due to tea plantation expansion has caused habitat fragmentation, reduced landscape connectivity, and losses of ecosystem services (Liu et al., 2017). As perennial agroecosystems, tea plantation management is less intensive than other croplands and its vegetation coverage can reach 80%–90% of the area planted (Kibblewhite et al., 2014; Zhang et al., 2017b). It is difficult to map tea plants for the following reasons: 1) tea plants always grow in tropical

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<sup>\*</sup> Corresponding author at: Department of Microbiology and Plant Biology, Center for Spatial Analysis, University of Oklahoma, Norman, OK, 73019, USA. *E-mail address:* xiangming.xiao@ou.edu (X. Xiao).

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and subtropical regions; and 2) spectral characteristics of tea plantations are similar to tropical forests.

Synthetic aperture radar (SAR) sensor data has been regarded as an alternative to data obtained using visible and near-infrared sensors in subtropical and tropical zones, which often suffer from frequent cloud cover and shadow problems (Jin et al., 2014; Li et al., 2012a; Negri et al., 2016; Sinha et al., 2016; Yusoff et al., 2017). Recent research results indicate that the dual-polarized (HH+HV) image can achieve similar results compared to multi-polarized (i.e., HH+HV+VV) data for land cover classification in tropical environments when adopting the maximum likelihood classifier (MLC) and support vector machine (SVM) approaches for classifying land cover with SAR data (Negri et al., 2016). Optical data (e.g. Landsat and MODIS) provide information about vegetation canopy (leaf area index) and PALSAR data provide information on vegetation structure (trunk and branch), thus both optical and PALSAR data have recently been integrated to improve classification accuracy. Several studies have evaluated the use of MODIS, Landsat and PALSAR data to map forests (Qin et al., 2015, 2016b), rubber plantations (Chen et al., 2016; Dong et al., 2013), forest and land cover in the Brazilian Amazon (Qin et al., 2017a; Walker et al., 2010), paddy rice in Myanmar (Torbick et al., 2017) and China (Wang et al., 2015; Zhang et al., 2017a), oil palm (Cheng et al., 2016), deforestation and degradation (Reiche et al., 2015, 2013), woody plant encroachment (Wang et al., 2018, 2017), and estimate forest biomass (Basuki et al., 2013; Shen et al., 2016; Zhao et al., 2016).

As for tea plantations, many classification algorithms have been reported in previous studies (Dutta et al., 2009; Ghosh et al., 2000; Li and He, 2008; Rao et al., 2007). A study by Dihkan et al. (2013) extracted the multidimensional, textural, and spectral features of tea plantations using a support vector machine (SVM) algorithm and multispectral airborne digital images, which resulted in high producer's (92.09%) and user's accuracies (94.68%) (Dihkan et al., 2013). Another study integrated full-waveform LiDAR and hyperspectral data and used SVM to enhance tea and areca classification, which had excellent producer's accuracy (99.10%) and user's accuracy (100%) (Chu et al., 2016). Airborne LiDAR and hyperspectral data have high spatial resolution, but obtaining the data is time-consuming, expensive, and does not provide data at high temporal resolution, which is not appropriate for mapping or monitoring tea plantation at high temporal frequency. The tea plant is a perennial evergreen, so time series data must be available when using a phenological approach to classify vegetative cover. Tea plantations are cultivated continuously and at large spatial scales, so PALSAR 25-m mosaic data and Landsat time-series images are effective for tea plantation detection and classification.

The objectives of this study were to: a) develop an algorithm to classify tea plantations in sub-tropical and tropical zones by integrating PALSAR 25-m mosaic data and time-series vegetation indices from Landsat images (such as NDVI, EVI, and LSWI, mDNWI); and b) verify the accuracy of our classification algorithm. We applied the algorithms to map tea plantations in Menghai County, Yunnan Province, which is a typical tea-plantation region in China. Then, we evaluated the resultant maps by using randomly chosen ground reference data. The resultant algorithms and maps are likely to be useful for tea plantation management and ecological assessment.

#### 2. Materials and methods

We built a detailed workflow for tea plantation mapping in 2010 and 2015 (Fig. 1). This workflow included three major components. First, we produced the 25-m PALSAR/Landsat tea plantation maps in 2010 and 2015, based on the integration of PALSAR and time series Landsat data. Second, we analyzed the area and spatial differences in tea plantation 2010 and 2015. Third, we compared the tea plantation area changes from our remote sensing approach and the official statistics data.

#### 2.1. A brief description of the study area

Menghai County is in the Xishuangbanna Dai Autonomous Prefecture of Yunnan Province China (Fig. 2), and is about  $5511 \text{ km}^2$  in area. Mountains account for 93.5% of the county's area, with elevation ranging from 535 m to 2429 m. The latitude and longitude of the southwestern and northeastern corner of the study area is 99°56′N, 21°28′E and 100°41′N, 22°28′E, respectively. Menghai County has a typical monsoon climate with three distinct seasons: a foggy, cool and dry season (November–February), a hot and dry season (March–April), and a hot and wet (rainy) season (May–October) (Lu et al., 2010). The average annual temperature is 18.7 °C, average annual precipitation is about 1341 mm, and the county receives 2088 sunshine hours annually on average.

Tea harvest occurs from the end of February to the end of November, and tea plantations enter a dormant period from the end of November to the end of February. Most of the tea harvest (40–45%) occurs during the hot and dry spring season. During these months, farmers typically pick young leaves from tea trees three times, because young, spring tea leaves are more profitable than summer and autumn tea. Menghai County is famous for Pu-erh tea production with more than 800 years of history in tea cultivation. The tea industry has played an important socio-economic role in the region for hundreds of years. In 2015, the primary output value of the tea industry was US\$152 million dollars and the industrial output value was US\$554 million dollars. The tax revenue contributed by the tea industry accounted for 45.37% of the total revenue of Menghai County. Tea income accounted for 50% of the rural per capita income, and 82.4% of the population engaged in tea-related work (Network, 2017).

#### 2.2. 25-m PALSAR dataset and pre-processing

The ALOS PALSAR L-band HH and HV orthorectified mosaic data (25-m spatial resolution) was obtained from the Earth Observation Research Center, JAXA (http://www.eorc.jaxa.jp/ALOS/en/palsar\_fnf/ data/index.htm). PALSAR HH and HV backscatter data are slope corrected and radiometrically calibrated, and are geo-referenced to latitude and longitude coordinates (Shimada et al., 2014). The PALSAR raw data was divided into individual  $500 \text{ km} \times 500 \text{ km}$  processing units, with consideration of orbit inclination and pass overlaps. Each raw image was calibrated using published coefficients (Shimada and Ohtaki, 2010) and output with 16-looks to reduce speckle noise. Corrections of geometric distortions specific to SAR (ortho-rectification) as well as topographic effects on image intensity (slope correction) have been applied using the SRTM-90 Digital Elevation Model (Shimada, 2010). The mosaics were given in geographical (latitude/longitude) coordinates, using the GRS80 ellipsoid, and provided in 1° by 1° rectangular tiles. The pixel spacing was 0.8 arc seconds, corresponding to 25 m at the Equator.

The Digital Number (DN) values (amplitude values) were converted into gamma-naught backscattering coefficients in decibels ( $\gamma^{\circ}$ ) using a calibration coefficient (see Eq. (1)).

$$\gamma^{\circ} = 10 \times \log_{10} (DN)^2 + CF$$
 (1)

where CF is the absolute calibration factor of -83. The difference value (HH-HV) and ratio value (HH/HV) of backscattering coefficients of HH and HV in decibel are widely applied for classification (Dong et al., 2013; Qin et al., 2017b, 2016b).

We downloaded all PALSAR HH and HV data that covered our study area in 2010 and 2015, then converted the backscattering coefficients to decibel. PALSAR images and all Landsat images described below were re-projected into the WGS-84/UTM zone 47N coordinate system by nearest-neighbor resampling method.



Fig. 1. Workflow of tea plantation mapping in Menghai County using 25-m PALSAR and 30-m Landsat.

#### 2.3. Time-series Landsat data pre-processing

The time-series Landsat images used in this study were processed using the Google Earth Engine (GEE) platform (Dong et al., 2016; Qin et al., 2017c, 2016b; Wang et al., 2017). All available Landsat 5/7/8 TM/ETM+/OLI images covering the study area (Table 1) were used. The study area is located within the Worldwide Reference System 2 (WRS-2) Landsat scene paths 130 and 131, and row 045. Due to the 3season characteristics of the study area's climate, we selected Landsat 5/7 images from November 1, 2008 to October 31, 2011 for mapping tea plantations in 2010, and used Landsat 7/8 images from November 1, 2013 to October 31, 2016 for mapping tea plantations in 2015. The surface reflectance data was generated from the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS), which includes the calibration from at-sensor radiance to the top of atmosphere (TOA) reflectance and the atmospheric correction from TOA reflectance to surface reflectance (Claverie et al., 2015; Vermote et al., 2016). The bad observations from clouds, cloud shadows, snow/ice, and the scan-line corrector (SLC)-off gaps were identified as NODATA according to the Fmask and metadata (Zhu and Woodcock, 2012).

#### 2.4. Vegetation indices and modified Normalized Difference Water index

For individual Landsat images, three vegetation indices (VIs) were calculated: the Normalized Difference Vegetation Index (NDVI) (Tucker, 1979), Enhanced Vegetation Index (EVI) (Huete et al., 2002), and Land Surface Water Index (LSWI) (Xiao et al., 2005a). Both NDVI and EVI indices complement each other in vegetation studies and improve upon the detection of vegetation changes and extraction of canopy biophysical parameters (Huete et al., 2002). LSWI is sensitive to the vegetation water content. The times series data of these three VIs mentioned above are useful to analyze the vegetation phenology (Xiao

et al., 2006). We also calculated the modified Normalized Difference Water Index (mNDWI) for all images, which can accurately be used to identify open surface water body without using sophisticated procedures (Xu, 2006), and was widely applied for open surface water body mapping (Chen et al., 2013; Nandi et al., 2017; Wu et al., 2016; Xie et al., 2016; Zou et al., 2017).

$$NDVI = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}}$$
(2)

$$EVI = G^* \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + C1^* \rho_{red} - C2^* \rho_{blue} + L}$$
(3)

$$LSWI = \frac{\rho_{nir} - \rho_{swir}}{\rho_{nir} + \rho_{swir}}$$
(4)

$$mNDWI = \frac{\rho_{green} - \rho_{swir}}{\rho_{green} + \rho_{swir}}$$
(5)

where the  $\rho_{nir}$ ,  $\rho_{swir}$ ,  $\rho_{red}$ ,  $\rho_{blue}$ ,  $\rho_{green}$  are the land surface reflectance of near infrared, shortwave-infrared, red, blue, and green bands, respectively, in Landsat 5/7/8 images. L is the canopy background adjustment that addresses non-linear, differential NIR, and red radiant transfer through a canopy. C1 and C2 are the coefficients of the aerosol resistance term, which uses the blue band to correct for aerosol influences in the red band. G is the gain factor. The coefficients are: L = 1, C1 = 6, C2 = 7.5, and G = 2.5.

2.5. Ground references site (GRS) data for algorithm training and product validation

#### 2.5.1. Geo-referenced field photos

Ground-based, in-situ samples are often the most reliable observations in determining vegetative cover and land classification (Xiong



Fig. 2. The study area is Menghai County Xishuangbanna Dai Nationality Autonomous Prefecture, Yunnan, China. This region has a humid climate that is typical of tropical forests, a high density of tea plantations, and is famous for Pu-erh tea production with more than 800 years of tea cultivation. The red star in the inset map marks the location of the study area. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

et al., 2017). In-situ data are utilized for algorithm training or product validation. Such geo-referenced, in-situ observations can be recorded with a GPS camera or the smartphone Field Photo App, which is freely available for both iOS and Android mobile platforms (Xiao et al., 2011). We utilized about 1000 geo-referenced field photos from the Global Geo-referenced Field photo Library to develop our algorithm (Xiangming et al., 2011). These photos were collected in our study area in 2017. To identify the historical (2010) land-cover types, we used publicly available photos that had been shared to Google Earth by other

Google Earth users. For example, Fig. 3(a) shows a field photo uploaded on November 26, 2010, and Fig. 3(b) shows the satellite imagery of the same location taken two days prior. These geo-referenced field photos were available in Google Earth and were digitalized into a series region of Interest (ROIs) as a ground reference sites for algorithm training and data product validation.

Summary	y of the r	number o	f Landsat	images (	(path/row	130/045	and	131/045)	used for	or each	vear du	iring th	e 2008-	-2016 study	period.
					Nr · · / ·			- / /				0.			- <b>-</b>

	Path/Row 130/045	5		Path/Row 131/045			
Year	Landsat-5/TM	Landsat-7/ETM+	Landsat-8/OLI	Landsat-5/TM	Landsat-7/ETM+	Landsat-8/OLI	Total
2008	4	2	0	1	1	0	8
2009	14	10	0	14	10	0	48
2010	5	10	0	7	11	0	33
2011	5	6	0	4	12	0	27
2013	0	3	4	0	4	4	15
2014	0	15	18	0	13	17	63
2015	0	12	16	0	14	19	61
2016	0	11	12	0	11	14	48
Total	28	69	50	26	76	54	303



**Fig. 3**. An example of field photos and tea plantation Ground References Site selection. (a) a field photo taken on November 26, 2010 and uploaded by a Google Earth user; (b) a high-resolution satellite image from Google Earth taken on November 24, 2010 (21°42′31.45″N, 100°23′38.15″E). The white circle was the location of field photo, and the red polygon was a tea plantation GRS. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

## 2.5.2. Ground reference sites (GRS) data for algorithm training and product validation

in 2010 and 2015 were described in Fig. 5.

#### 2.6. Digital elevation model (DEM) data

Google Earth provides very high-resolution images with high geometric accuracy (e.g., 0.61-m QUICKBIRD images), which are effective for validating land cover classification results (Qin et al., 2015; Senf et al., 2013). Based on high spatial resolution images available in Google Earth in 2010 and 2015, we digitized 386 GRS (a total of 11,117 PALSAR pixels) for mapping tea plantations in 2010 and 2015. These GRS were used for phenological analysis and classification sample training for different land cover types (built-up, cropland, forest, tea plantation, water body and others). The GRS data were detailed in Table 2 and the distribution are described in Fig. 4.

A total of 3000 pixels were created randomly to validate the product accuracy, but only 1739 and 1834 pixels were selected to validate tea plantation map in 2010 and 2015, respectively, because some locations did not have high resolution Google Earth imagery. Ground reference sites were listed in Table 3. The spatial distribution of validation pixels

#### Table 2

Ground	l ref	erence	sites	(GRS)	by	land	cover	type	for a	lgorith	m tra	ining.
--------	-------	--------	-------	-------	----	------	-------	------	-------	---------	-------	--------

Land types	Polygons	Pixels
Build-up	72	424
Forest	58	5900
Tea plantation	37	214
Cropland	183	3700
Water body	20	795
Others	16	84
Total	386	11,117

We used the 30-m DEM data (SRTMGL1: NASA Shuttle Radar Topography Mission Global 1 arc second V003) (NASA, 2013) in this study. We included the 30-m DEM data as a variable to identify and map the tea plantations. We also analyzed the spatial distribution of tea plantation expansion at different elevation gradients from 2010 to 2015.

#### 2.7. Tea plantation mapping algorithms

#### 2.7.1. Selection of variables for classification

Many studies showed that PALSAR data had a promising potential for land cover classification, because the SAR sensor is not affected by clouds, weather, and other atmospheric constraints, which usually affect optical sensors, particularly in moist tropical regions. HH polarization images were used to identify water body (e.g., river and sea) (Thapa et al., 2014). HV polarized images may be one of the best choices for forest mapping in mountainous regions as it was less sensitive to variations in slope, and HV polarized images have been used to distinguish forest and non-forest (Shimada et al., 2014). HH-HV and HH/HV were used to exclude the commission errors from cropland and built-up lands (Qin et al., 2015). Hence, HH, HV, HH-HV, HH/HV were selected as variables for classification. Fig. 6 showed the HH, HV, HH-HV, and HH/HV profiles of six land types.

NDVI is closely related to leaf area index (LAI), which has been successfully implemented to determine vegetation cover (Dihkan et al.,



Fig. 4. Distribution of Ground reference sites (GRS) for algorithm training.

2013; Xiao et al., 2005b). EVI is more responsive to canopy structure, including leaf pigment, canopy type, plant physiognomy, and canopy architecture (Jiang et al., 2008). After the launch of MODIS sensors aboard the Terra and Aqua satellites by NASA, EVI became popular due to its ability to not saturate at high canopy densities, and to eliminate background and atmosphere noise. There is strong light absorption by

liquid water in the SWIR, thus LSWI is sensitive to liquid water in vegetation and its soil background (Chandrasekar et al., 2010; Dong et al., 2014; Xiao et al., 2002, 2005a). The mNDWI is one of the most popular methods for open surface water body mapping because it overcomes the shortcomings of NDWI by using Shortwave Infrared band to replace the Near Infra-red band used in NDWI, it has been widely applied to

Ground reference sites (pixels) from high resolution images in Google Earth in 2010 and 2015.

Land types	Pixels (2010)	Percent (2010)	Pixels (2015)	Percent (2015)
Build-up	10	0.58	16	0.87
Forest	910	52.33	888	48.42
Tea plantations	67	3.85	108	5.89
Cropland	741	42.61	810	44.17
Water body	8	0.46	9	0.49
Others	3	0.17	3	0.16
Total	1739	100	1834	100

produce water body maps at different scales in the last few decades (Singh et al., 2015; Xu, 2008; Zou et al., 2018, 2017).

We analyzed temporal data of individual pixels for several land cover types. Fig. 7 depicts the temporal profiles of time series NDVI. The Fig. 7 showed that NDVI is not only sensitive to vegetation (cropland, forest, tea plantation) and non-vegetation (built-up, water body), but also shows good performance for making a distinction in cropland, forest, and tea plantation. Moreover, as shown in Fig. 8, EVI also have good performance to distinguish vegetation and non-vegetation. Fig. 9 shows the separability between tea plantation and forest on LSWI, especially in foggy cool and dry season and hot and dry season. Fig. 10 shows the temporal profiles of time series mNDWI. The mNDWI value of open surface water body is obviously higher than non-water land types, so mNDWI is useful for identifying open surface water body in this study.

Therefore, based on the previous results generated by using the three vegetation indices (VIs) and mNDWI mentioned above, and the

three-season climate of our study area, these four indices were selected to distinguish tea plantation from other land cover types. Twenty-one variables were chosen (Table 4) for SVM classification, including 4 variables derived from PALSAR data, and 16 variables calculated from Landsat images and the DEM.

#### 2.7.2. SVM-based classification

Support vector machine (SVM) is a supervised, non-parametric statistical learning technique developed in the 1970s and was introduced as a machine learning method based on a non-probability binary function in the 1990s (Shao and Lunetta, 2012; Vapnik, 1995, 1998). Due to the ability of SVMs to successfully handle small training data sets, SVMs are widely used in the remote sensing studies, which often give higher classification accuracies than do other methods (Li et al., 2015a). Compared an accuracy assessment of SVM versus three other classifier approaches, a maximum likelihood classifier (MLC), a neural network classifier (NN), and a decision tree classifier (DTC). The result indicated that SVM has the highest classification accuracy, followed by DTC and then MLC, which was attributed to SVM's ability to locate an optimal separating hyperplane. In previous studies, four classifiers were applied for moderate resolution observation and monitoring of land cover using Landsat TM and ETM+ data (Chen et al., 2015; Li et al., 2015b; Otukei and Blaschke, 2010). The SVM produced the highest overall classification accuracy, followed by Random Forest (RF), J48 decision tree classifier (DTC), and maximum likelihood classifier (MLC) (Gong et al., 2013). Recently, some studies reported that SVM methods were adopted to perform the land cover classification in tropical environments (Negri et al., 2016; Okoro et al., 2016; Sameen et al., 2016). In particular, a review of SVM in remote sensing



Fig. 5. Distribution of Ground reference sites (GRS) from high spatial resolution images in Google Earth. The pixels selected for the validation of the tea plantation map in (a) 2010 (1739) and (b) 2015 (1834). No high-resolution images were available after 2012 in the southern region of the study area, so pixels could not be selected in that area for validation in 2015.



Fig. 6. PALSAR data profiles of six land types.



**Fig. 7.** Intra-annual variation of NDVI for five major land cover types. The NDVI, EVI, LSWI, mNDWI annual time series of major land cover types from MOD09A1 product in 2013. Sites include built-up (21.9563°N, 100.4423°E), cropland (21.8325°N, 100.4101°E), forest (22.1024°N, 100.2855°E), tea plantation (21.7088°N, 100.4009°E), and a water body (21.9066°N, 100.2897°E). All sites correspond to the GRSs except for the forest and water body sites, which were selected using Google Earth imagery.

by Mountrakis et al. (2011) summarized results from over 100 publications that used SVM image classification. The review demonstrated that SVM had superior performance compared to most other image classifiers with limited training samples, despite that SVMs have limitations in parameter selection and computational requirements.

In this study, we classified six land cover types: built-up, cropland, forest, tea plantation, water body and others. According to the

International Geosphere-Biosphere Programme Data and Information System (IGBP-DIS) (Loveland and Belward, 1997), built-up lands were defined as land covered by buildings and other man-made structures, croplands were defined as lands covered with temporary crops followed by harvest and a bare soil period (including single and multiple cropping systems, and perennial woody crops, and water bodies included oceans, seas, lakes, reservoirs, and rivers. We used the same definitions in our study when classifying built-up, cropland, and waterbodies. For forest, we used the FAO (2012) definition for forest as land (0.5 ha or more) with tree canopy cover larger than 10% with a minimum height of five meters at tree maturity.

Tea plants can grow freely into a multi-stemmed tree of about 6 m height (Selvendran, 1970), but in commercial practice, tea plant are periodically cut from the top (pruned) to rejuvenate the bush and tea workers often keep the plucking table at a convenient height (Goodchild, 1968; Pramanik et al., 2017). Tea plants are commonly pruned to 80 cm in height and 100–120 cm in crown diameter (Zhang et al., 2017b). Tea canopy coverage ranges from 60% to 100% of the plantation area while height ranges from 60 cm to 110 cm (Li et al., 2011). We defined tea plantations as lands dominated by tea plants with a percent cover  $\geq$  50% and an average height of 80 cm based on field samples in study area.

The SVM algorithm was implemented with ENVI 5.1 software. We chose the radial basis function (RBF) as the kernel function, because RBF has been observed to work well in many studies (Erener, 2013; Li et al., 2015a; Schwert et al., 2013). For the RBF kernel, the parameters such as Gamma in Kernel function, Penalty parameter, and Pyramid levels were set as default in the ENVI 5.1 software. The Gamma default value was the inverse of the number of bands in the input image. In this study, the Gamma values were 0.048 (21 bands listed in Table 4) and 0.059 (17 bands from optical only data). The Penalty parameter was a floating-point value greater than zero, and the default value was 100.



Fig. 8. Intra-annual variation of EVI for five major land cover types.



Fig. 9. Intra-annual variation of LSWI for five major land cover types.



Fig. 10. Intra-annual variation of mNDWI for five major land cover types.

The pyramid level was set as 0 so that the full resolution image was used to do classification.

We also compared the performance of between Landsat and Landsat plus imagery for mapping tea plantation. We excluded four variables from PALSAR data and used the same optical variables derived from Landsat imagery and DEM (Table 4) to map tea plantation. The same ground reference data was used for SVM algorithm training (Table 2) and product validation (Table 3).

#### 3. Results

#### 3.1. Tea plantation maps at 30 m resolution in 2010 and 2015

We mapped tea plantations in 2015 based on 25-m resolution PALSAR, 30-m resolution Landsat-7/ETM+, and Landsat-8/OLI data from November 1, 2013 to October 31, 2016 (Fig. 11a). To analyze changes in tea plantation area from 2010 to 2015, we also mapped tea plantation in 2010 using 25-m resolution PALSAR, and 30-m resolution Landsat-5/TM, and Landsat-7/ETM+ data from November 1, 2008 to October 31, 2011. These two tea plantation maps were created using the SVM algorithm mentionedin Section 2.7.2. The total tea plantation area in Menghai County was estimated to be  $\sim$  27,817 ha in 2010 and  $\sim$  37,152 ha in 2015, respectively.

#### 3.2. Accuracy assessment of tea plantation maps

Accuracy assessments of these resultant 2010 and 2015 tea plantation maps were conducted using the validation GRS introduced in Section 2.5.2 (Fig. 5). The assessment results indicated that our tea plantation classifications have reasonably high accuracies. The overall accuracies (OA) were 97.70% and 97.16% with Kappa coefficients of 0.96 and 0.95 in 2010 and 2015, respectively. The 2010 tea plantation map had a producer accuracy (PA) of 87.50% and a user accuracy (UA) of 83.58% (Table 5), and the 2015 tea plantation map had a slightly higher PA of 90.83% and UA of 91.67% (Table 6). These results suggested that the tea plantations maps in different periods of time were comparable with each other, and it was possible to monitor tea plantation change from 2010 to 2015 using the SVM approach with PALSAR data and Landsat images.

#### 3.3. Tea plantation changes from 2010 to 2015 in Menghai County, China

We used the PALSAR/Landsat tea plantation maps to identify their spatio-temporal changes from 2010 to 2015 (Fig. 11b). According to the PALSAR/Landsat tea plantation maps, tea plantation area increased from  $\sim$  27,817 ha to  $\sim$  37,152 ha, with an average annual growth rate of 6.7% from 2010 to 2015. Of the total tea plantation area in 2015, 50.2% of the tea plantation area in 2010 remained tea plantation area in 2015, 33.6% of the 2015 tea plantation area was cropland in 2010, 16.2% of the 2015 tea plantation area was forest in 2010, and 0.005% of the 2015 tea plantation area was other land cover types in 2010. Moreover, we also found that forest area decreased from about 328,666 ha to 312,204 ha, but other land types, such as tea plantations, croplands, built-up areas, and waterbodies, increased from 2010 to 2015.

According to the official agricultural census data, tea plantations area were 25,733 ha (Yang and Li, 2010) and 38,500 ha (Statistics, 2015) in 2010 and 2015, respectively, an increase of 49.61% in Menghai County. Our SVM algorithm calculated that tea plantation area was  $\sim$  27,817 ha and  $\sim$  37,152 ha in 2010 and 2015, respectively, an increase of 33.56%. In comparison, our SVM-based estimates of total tea plantation area were 108.10% and 96.50% of the area estimated by official agricultural census data in 2010 and 2015, respectively (Fig. 12). According to the official agricultural census, the total estimated increase of tea plantation area between 2010 and 2015 was 12,767.6 ha (Li et al., 2014; Statistics, 2015), but our SVM algorithm estimated an increase of  $\sim$  9335 ha.

List of variables used for support vector machine (SVM) classification.

Name of variables	Bands name	Description
НН	B1	The backscattering coefficients of HH in decibel
HV	B2	The backscattering coefficients of HV in decibel
HH-HV	B3	The difference value (HH-HV)
HH/HV	B4	The ratio value (HH/HV)
NDVI_Min	B5	The min value at each pixel of NDVI
NDVI_Median	B6	The median of all values at each pixel of NDVI
NDVI_Mean_cool and dry season	B7	The mean of all values at each pixel of NDVI from November 1 to February 28
NDVI_Mean_hot and dry season	B8	The mean of all values at each pixel of NDVI from March 1 to April 30
NDVI_Stdev_cool and dry season	B9	The standard deviation of all values at each pixel of NDVI from November 1 to February 28
LSWI_Min	B10	The min value at each pixel of LSWI
LSWI_Median	B11	The median of all values at each pixel of LSWI
LSWI_Min_cool and dry season	B12	The min of all values at each pixel of LSWI from November 1 to February 28
LSWI_Mean_hot and dry season	B13	The mean of all values at each pixel of LSWI from March 1 to April 30
LSWI_Stdev_cool and dry season	B14	The standard deviation of all values at each pixel of LSWI from November 1 to February 28
EVI_Median	B15	The median of all values at each pixel of EVI
EVI_Min_cool and dry season	B16	The min of all values at each pixel of EVI from November 1 to February 28
EVI_Mean_hot and dry season	B17	The mean of all values at each pixel of EVI from March 1 to April 30
EVI_Stdev_cool and dry season	B18	The standard deviation of all values at each pixel of EVI from November 1 to February 28
mNDWI_Max	B19	The max of all values at each pixel of mNDWI
mNDWI_Median	B20	The median of all values at each pixel of mNDWI
DEM	B21	The 30-m resolution DEM



Fig. 11. (a) Map of tea plantation in 2015 and (b) map of change in tea plantation area from 2010 to 2015 at 30-m spatial resolution.

#### 4. Discussion

# 4.1. Algorithms for tea plantation mapping with PALSAR and Landsat imagery

The algorithm developed in this study successfully classified tea plantation cover in complex, tropical landscapes using PALSAR backscatter coefficients and time-series Landsat imagery. In the tropical and sub-tropical area, frequent clouds and fog often impact the effective observation of land cover in the visible spectrum, but PALSAR observations were not limited by clouds and fog. The combination of PALSAR and Landsat images allowed us to distinguish tea plantations from other vegetation types and non-vegetated lands (built-up areas and water bodies). NDVI can be used to effectively distinguish between vegetation and non-vegetation and eliminate the commission error of forests on mountainous terrain with complex reflectance/backscatter

Accuracy assessment of the	ne 2010 tea j	plantation map	generated by	y the SVM method.
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Land types	Producer accuracy/%	User accuracy/%	Commission/%	Omission/%	Overall accuracy/%	Kappa Coefficient
Build-up	90	90	10.00	10.00	97.70	0.96
Forest	98.24	98.24	1.76	1.76		
Tea plantations	87.50	83.58	16.42	12.50		
Cropland	98.12	98.38	1.62	1.88		
Water	100.00	100.00	0.00	0.00		
Others	75.00	100.00	0.00	25.00		

environments (Qin et al., 2016a). Likewise, LSWI can be used effectively to differentiate between evergreen and deciduous vegetation based upon their phenological difference. mNDWI can be used to identify open surface water body effectively (Zou et al., 2017). NDVI and EVI are both sensitive to chlorophyll concentrations, but EVI is more responsive to canopy structural variations, including leaf area index (LAI), canopy type, plant physiognomy, and canopy architecture (Huete et al., 2002). EVI also can eliminate the impact of soil background and reduce atmospheric noise. The terraced terrain of tea plantations makes the surface of the tea ridge interval exposed, so EVI could be used to distinguish tea plantations from other land cover types. Although tea plantation is a perennial evergreen plant, it is difficult to distinguish from forest and some perennial evergreen cropland. Furthermore, we considered the unique, three-season climate of our study area and calculated seasonal VI values. Finally, we provided 21 variables for SVM classification to create tea plantation maps, which achieved accuracies similar to the Walker et al. (2010) study result. Walker et al. (2010) used ALOS/PALSAR (24 variables) and Landsat (49 variables) to map 6 land cover types in the Brazilian Amazon, including forest, agriculture, roads, sandbars, open water, and wetlands. The overall accuracies reached 82.8% (PALSAR spectral and ancillary) and 88.2% (Landsat spectral and ancillary), respectively.

# 4.2. Image data for tea plantation mapping: Landsat vs PALSAR plus Landsat

Time series optical remote sensing can identify and map a few land cover types through phenology and texture information (Chen et al., 2016; Kou et al., 2017), while most of the uncertainties are related to the difficulties inherent to optical remote sensing in frequent cloudcovered regions. Synthetic Aperture Radar (SAR) sensors are not affected by cloud and sensitive to the geometry of the surface and vegetation canopy structure. Integrating SAR and optical data can obtain the biophysical attributes of vegetation and the structure characteristics of the surface. Many studies verified that combining PALSAR data and optical data can get a higher accuracy than that of using optical data only for land cover classification (Han et al., 2017; Pavanelli et al., 2018). Comparing with the tea plantation maps generated by Landsat, the combination of PALSAR and Landsat reached much higher accuracy (Tables 5-8). The overall accuracies of tea plantation maps increased from 86.6% to 97.7% and from 92.9% to 97.2% in 2010 and 2015, respectively. The produce accuracy and user accuracy of tea plantation maps also substantially improved in 2010 (Tables 5 and 7) and 2015 (Tables 6 and 8). Our findings indicated that tea plantation mapping



can benefit from the time series optical and PALSAR data integration.

#### 4.3. Uncertainty analysis

Several factors might affect the accuracy of our tea plantation maps. First, the definition of tea plantation is the key component in accurately classifying tea plantations, and the definition can be different in different classification systems. In our study, we defined tea plantations as lands dominated by tea plant trees with cover  $\geq$  50% and an average height of 80 cm, but other researchers reported that tea plantation canopy cover is usually > 10% with a height lower than 5 m (Zhang and Liu, 2005). However, there is no standardized definition of tea plantation. Thus, we developed our definition of tea plantation according to an in-situ survey of the study area. Ground-based, in-situ samples (Fig. 3(a)), showed that tea plant tree cover was larger than 50%.

Mature and well-managed tea plantations were easily distinguished from other land-cover types by considering their color, intensity, structure, terraced ridges, and ridge spacing using PALSAR and Landsat images and the SVM algorithm. However, newly planted tea plantations and young tea plantations before harvest age (tea tree's age < 3-5years) have small canopy coverage and could be omitted by our SVM algorithm (Guo et al., 2006). Mismanaged or abandoned tea plantations can suffer quickly from encroachment by other species, resulting in a canopy cover and average height that falls outside our definition of tea plantation. Secondly, although our data were corrected to account for variances in topography in advance of mapping, impacts of topography

#### Table 6

Land types	Producer accuracy/%	User accuracy/%	Commission/%	Omission/%	Overall accuracy/%	Kappa Coefficient
Build-up	93.33	87.50	12.50	6.67	97.16	0.95
Forest	97.21	98.20	1.80	2.79		
Tea plantations	90.83	91.67	8.33	9.17		
Cropland	98.13	96.91	3.09	1.88		
Water	100.00	100.00	0.00	0.00		
Others	75.00	100.00	0.00	25.00		

Accuracy assessment	of the 2010 t	tea plantation	map generated	by using	only optical	image data.
2		1	10		2 1	0

Land types	Producer accuracy/%	User accuracy/%	Commission/%	Omission/%	Overall accuracy/%	Kappa Coefficient
Build-up	60	60	40.00	40.00	86.60	0.75
Forest	86.70	90.79	9.21	13.30		
Tea plantations	75.00	67.61	32.39	25.00		
Cropland	88.02	84.06	15.94	11.98		
Water	87.50	77.78	22.22	12.50		
Others	50.00	100.00	0.00	50.00		

on PALSAR data and Landsat images in our study area, which is 93.5% mountainous, might still affect the results of our tea plantation mapping algorithm (Matsushita et al., 2007). PALSAR data offers complementary and supplementary data to sensors operating in the optical and thermal bands. The backscatter value is sensitive to dielectric properties (soil and vegetation internal properties) and geometric (surface roughness) attributes of the imaged surface (Darmawan et al., 2015). Many environmental factors, such as atmospheric conditions and soil background, may produce errors and noise in the visible spectrum.

#### 4.4. The implication of tea plantation expansion between 2010 and 2015

We analyzed tea plantation area change based on our tea plantation maps and DEM from 2010 and 2015 in Menghai County, Yunnan Province. Fig. 13 quantifies the expansion of tea plantation at different elevations. Tea plantation area expansion originated mainly from croplands and forests. Tea plantation was distributed at elevations ranging from 1200 m to 2400 m, but the expansion of tea plantation between 2010 and 2015 mainly occurred between 1400 m-1900 m in elevation. Tea plantation area expansion between 1200 m and 2400 m were converted from forests, but croplands converted to tea plantation occurred in areas less than 2100 m in elevation. The expansion of tea plantation was driven by the governmental regimes and increasing of tea price. Ministry of Agriculture of the People's Republic of China released the "National key Tea Area Development Plan (from 2009 to 2015)" in 2009, which accelerate the expansion of tea plantation (Xiao et al., 2017). World tea consumption exceeded production in 2009-2011 from the first on record and tea price escalated significantly from 2006 to 2009, around 80% increased (Gunathilaka and Tularam, 2016). Our study found that tea plantation expansion resulted in deforestation in the study area. Other researchers reported that conversion of tropical forest to tea plantations changed soil properties by more frequently fertilized (Li et al., 2012b).

#### 5. Conclusion

Although the tea plant has different growth characteristics than evergreen forest and other crops (such as banana) in the tropical and subtropical regions, it is difficult to identify tea plantations using only the visible spectral bands of satellite images due to the spectral similarity of these land cover types in the visible spectrum. Accurate estimations of tea plantation area, spatial distribution, and expansion at the landscape scale is fundamental to governmental planning, policy making, and land management decisions. We proposed a novel

#### Table 8

Accuracy assessment of the 2015 tea plantation map generate by using only optical image data.

Land types	Producer accuracy/%	User accuracy/%	Commission/%	Omission/%	Overall accuracy/%	Kappa Coefficient
Build-up	86.67	81.25	18.75	13.33	92.86	0.87
Forest	95.32	93.34	6.66	4.68		
Tea plantations	73.39	76.19	23.81	26.61		
Cropland	92.88	94.77	5.23	7.13		
Water	100.00	100.00	0.00	0.00		
Others	75.00	75.0	25.00	25.00		

integrating 25-m ALOS PALSAR and time-series 30-m Landsat imagery. We used an image-based SVM approach to distinguish tea plantations from other land-cover types. Our results indicated that the image-based SVM approach can identify tea plantations reasonably well in 2010 and 2015. Between 2010 and 2015, tea plantation area increased dramatically by 33.56%, cropland area increased by 2.62%, and forest cover decreased by 5%. Tea plantation is defined as a special shrub forest subtype of economic forest in the Chinese forest land classification system (Administration, 2014). Thus, if tea plantation expansion resulted in deforestation, it is difficult to investigate the change in forest area by using only traditional statistics for forest area. We distinguished tea plantation from forest and cropland, and we found that these two land cover types were converted to tea plantation. Of the increased tea plantation area between 2010 and 2015, 32.50% was previously forest and 67.50% was previously cropland. The application of our approach at larger scales still needs further validation. Therefore, developing a regular monitoring scheme for the evaluation of the ecological and environmental impacts of tea plantation expansion should be urgently considered.

approach to map the spatial and temporal patterns of tea plantation by

#### Author contributions

Weiheng Xu, Xiangming Xiao, and Yuanwei Qin designed the study. Weiheng Xu, Yuanwei Qin and Xiangming Xiao conducted the data analyses. Guangzhi Di, Russell B. Doughty, Zhenhua Zhou, Yuting Zhou, Lei Kong, and Quanfu Niu contributed to the analyses of PALSAR and other relevant data. Weiheng Xu, Yuanwei Qin and Xiangming Xiao wrote the draft manuscript, Weili Kou contributed to the manuscript revision, and all the authors contributed to the interpretation of results and manuscript writing.

#### **Conflicts of interest**

The authors declare no conflict of interest.

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Fig. 13. Changes in land cover area for forest, cropland, and tea plantation between 2010–2015 at different elevations.

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