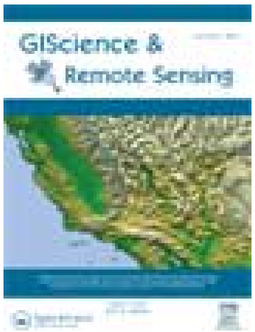

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GIScience & Remote Sensing

ISSN: 1548-1603 (Print) 1943-7226 (Online) Journal homepage: http://www.tandfonline.com/loi/tgrs20

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To cite this article: Murali Krishna Gumma, Prasad S Thenkabail, Kumara Charyulu Deevi, Irshad A Mohammed, Pardhasaradhi Teluguntla, Adam Oliphant, Jun Xiong, Tin Aye & Anthony M Whitbread (2018): Mapping cropland fallow areas in myanmar to scale up sustainable intensification of pulse crops in the farming system, GIScience & Remote Sensing, DOI: 10.1080/15481603.2018.1482855

To link to this article: https://doi.org/10.1080/15481603.2018.1482855

Published online: 06 Jun 2018.

GIScience & Remote Sensing, 2018
https://doi.org/10.1080/15481603.2018.1482855

Mapping cropland fallow areas in myanmar to scale up sustainable intensification of pulse crops in the farming system

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(*Received 18 August 2017; accepted 27 May 2018*)

Cropland fallows are the next best-bet for intensification and extensification, leading to increased food production and adding to the nutritional basket. The agronomical suitability of these lands can decide the extent of usage of these lands. Myanmar's agricultural land (over 13.8 Mha) has the potential to expand by another 50% into additional fallow areas. These areas may be used to grow short-duration pulses, which are economically important and nutritionally rich, and constitute the diets of millions of people as well as provide an important source of livestock feed throughout Asia. Intensifying rice fallows will not only improve the productivity of the land but also increase the income of the smallholder farmers. The enhanced cultivation of pulses will help improve nutritional security in Myanmar and also help conserve natural resources and reduce environmental degradation. The objectives of this study was to use remote sensing methods to identify croplands in Myanmar and cropland fallow areas in two important agro-ecological regions, delta and coastal region and the dry zone. The study used moderate-resolution imaging spectroradiometer (MODIS) 250-m, 16-day normalized difference vegetation index (NDVI) maximum value composite (MVC), and land surface water index (LSWI) for one 1 year (1 June 2012–31 May 2013) along with seasonal field-plot level information and spectral matching techniques to derive croplands *versus* cropland fallows for each of the three seasons: the monsoon period between June and October; winter period between November and February; and summer period between March and May. The study showed that Myanmar had total net cropland area (TNCA) of 13.8 Mha. Cropland fallows during the monsoon season account for a meagre 2.4% of TNCA. However, in the winter season, 56.5% of TNCA (or 7.8 Mha) were classified as cropland fallows and during the summer season, 82.7% of TNCA (11.4 Mha) were cropland fallows. The producer's accuracy of the cropland fallow class varied between 92 and 98% (errors of omission of 2 to 8%) and user's accuracy varied between 82 and 92% (errors of commission of 8 to 18%) for winter and summer, respectively. Overall, the study estimated 19.2 Mha cropland fallows from the two major seasons (winter and summer). Out of this, 10.08 Mha has sufficient moisture (either from rainfall or stored soil water content) to grow short-season pulse crops. This potential with an estimated income of US$ 300 per hectare, if exploited sustainably, is estimated to bring an additional net income of about US$ 1.5 billion to Myanmar per year if at least half (5.04 Mha) of the total cropland fallows (10.08 Mha) is covered with short season pulses.

Keywords: rice fallows; MODIS time series data; Myanmar; ground survey data; cropping systems; short-duration pulses; grain legumes

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1. Introduction

Agriculture in Myanmar is an important sector of the economy and accounts for about 38% of the gross domestic product (GDP) (FAO 2017). More than 70% of the population lives in rural areas and are directly dependent on agriculture for their livelihoods (MPHC 2014). Myanmar has an estimated population of about 51.5 million (2014) and a land area of approximately 67.7 Mha (CSO 2016). The country is one of the largest exporters of rice, maize, black gram (*Vigna mungo*), green gram (*Vigna radiata*) and other pulses in Southeast Asia. Myanmar is the only country in Southeast Asia with surplus pulse production and has enormous potential to export to the large markets in India and China (Bhalla 2017). Rice, being the most important crop within the sector, occupies the majority of arable land, covering 58.1% of the total cropped area during 2010–11 (FAO 2013), and contributing significantly to livelihood, employment, and income for the majority of the rural population. However, around 26% of the total population in the country remains below the poverty line and 28% of children were underweight due to poor nutrition (DPH 2011). With increasing population pressure, there is also a need for food and nutritional security in the country. Introduction of short-season pulses in irrigated or rainfed fallow cropland areas has the vast potential to not only intensify the cropping systems, but also increase income and nutritional security of small and marginal farmers in the country.

Pulses are the second largest crop grown after rice and have been cultivated in Myanmar since the 1960s (Zaw et al. 2011). The dominant pulses grown include chickpea, green gram, black gram, pigeonpea, cowpea, soybean and lablab. The wide range of agro-ecologies, diverse soils and new legume production systems, and the potential germplasm introduced by IARC researchers has facilitated the pulse revolution in the country (Than et al. 2007). There was a substantial increase in total pulse cultivation in the country from 0.73 Mha in 1988–89 to 4.4 Mha by 2011–12 (Winn 2012). Correspondingly, the export of pulses has increased from 17,000 metric tons in 1988–89 to around 1.3 million metric tons in recent years. Although the major share of pulse cultivation occurs in the central dryland zone (CDZ) of Myanmar, there is still huge potential for pulse crops to be grown in the irrigated CDZ during the non-rice periods (Than et al. 2007). The commercial cultivation of rainfed groundnut and pigeonpea crops was also observed in Mandalay and Magway (see Figure 1). However, cultivation of local and low-yielding cultivars of pulses is a common problem observed in CDZ. Farmers have limited access to improved crop varieties, such as stress-tolerant/disease-resistant cultivars. Proper targeting and introduction of improved pulse technologies are critically needed in this zone. Yellow mosaic virus is the most widespread problem observed in rice fallow black gram crop. Identification or introduction of suitable varieties resistant to yellow mosaic disease is therefore urgently needed.

There are, however, major gaps in understanding where cropland may be intensified, and therefore a need for spatial analysis to identify suitable areas. Myanmar has three main crop growing seasons in a calendar year, depending on the location: the monsoon period between June and October; the winter period between November and February; and the summer period between March and May. It is important to map the spatial distribution of cropland fallows in each of these seasons to better understand where pulse crops may be promoted. Near real time satellite image analysis provides an alternative approach to ground sampling for the estimation of cropping intensity, area, and changes in a country; unlike ground sampling, satellite image analysis is relatively quick, inexpensive and independent of land use estimation (Badhwar 1984; Thiruvengadachari

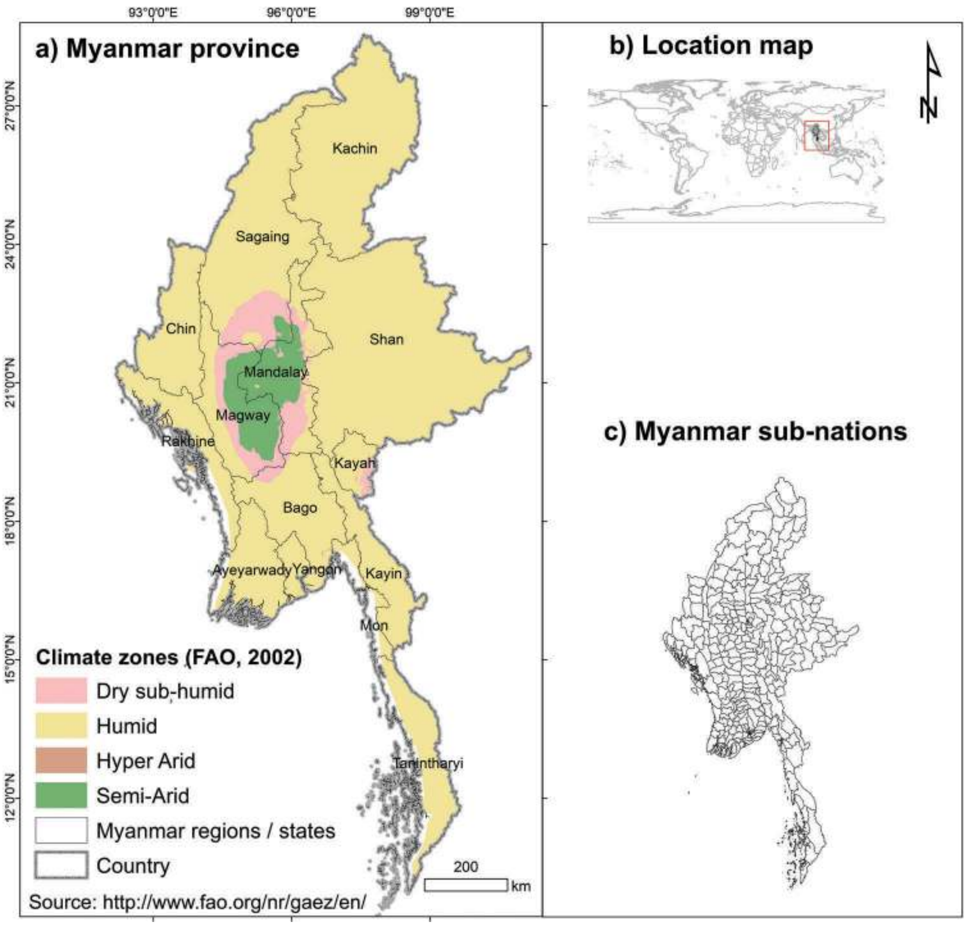

Figure 1. The study area in Myanmar along with the administrative boundaries. a) Study area with province and climatic zones (Source: http://www.fao.org/nr/gaez/en/); b) location map; and c) sub-national boundaries.

and Sakthivadivel. 1997; Lobell et al. 2003; Thenkabail et al. 2009b; Thenkabail 2010). Several studies have reported the use of multi-spectral and multi-temporal data to map agricultural areas at various scales (Varlyguin et al. 2001; Goetz et al. 2004; Thenkabail, Schull, and Turral 2005; Knight et al. 2006; Velpuri et al. 2009; Dheeravath et al. 2010). Many studies were conducted using moderate resolution imaging spectrometer. Normalized difference vegetation index (MODIS NDVI) time-series is used to map agricultural area, including crop intensity, at regional level and for river basins (Biggs et al. 2006; Gaur et al. 2008; Gumma et al. 2011c). Some studies have also used Land Surface Water Index (LSWI) data for monitoring soil wetness and natural vegetation at a regional scale (Ratana et al. 2005; Becerra et al. 2006; Xiao et al. 2006; Sakamoto et al. 2007; Chandrasekar et al. 2010).

The objectives of the study were to: (i) map cropland fallows in Myanmar during the monsoon, winter and summer seasons using time-series moderate-resolution imaging spectroradiometer (MODIS) 250-m imagery; (ii) determine cropland fallow areas suitable for short-duration pulse crops; and (iii) assess the economic potential of these areas. The study used 16-day, 250-m spatial resolution, 4-band reflectance data composite images for 2012 from the moderate resolution imaging spectroradiometer (MODIS) sensor and spectral matching techniques (SMTs) to achieve the goal. Secondary datasets and seasonal reference training and validation ground data observations were extensively used to identify major standing crops as well as cropland fallows over entire cropland areas of Myanmar across seasons. Ground data helped develop knowledge, classify images and identify classes using spectral matching techniques and MODIS 250-m time-series data. Accuracy assessments were performed using error matrices based on independent validation data of individual seasons and the cropland fallow areas were compared with known national statistics.

2. Materials and methods

2.1. Study area

Myanmar is one of the largest rice-growing countries in Southeast Asia. It extends from 9º 55′ to 28º 15′N latitude and from 92º 10′ to 101º10′ E longitude, with 67.7 Mha of geographic area (Figure 1). Agriculture is the primary occupation in the country, and rice is the major crop, covering about 60% of the total cultivated area. Myanmar has broadly three agro-ecological zones: central dry, coastal, and hilly. These are further sub-divided into eight physiographic regions: 1) northern hilly, 2) central dry, 3) Rakhine coastal, 4) western hilly, 5) eastern hilly, 6) Ayeyarwady delta, 7) Yangon deltaic, and 8) southern coastal (MECF 2012). The country`s geographical location, topography and climatic conditions provide a natural setting for these different agro-ecological zones, making it favorable to grow a variety of crops which suit the respective conditions (Kabir and Uphoff 2007). At the region level, Myanmar is administratively divided into 7 regions/ states. The regions are sub-divided into 74 districts, which are further divided into 330 townships. The townships are again sub-divided into 13,588 village tracts. The basic administrative unit in Myanmar is the village tract, which is administrated by the General Administration Department, Ministry of Home Affairs. Most of the statistics in Myanmar represent these administrative regions. Since the lowest administrative unit is the village tract, statistics are usually collected on that basis.

2.2. Satellite data

MODIS Terra Vegetation Indices 16-Day L3 Global 250m SIN Grid V005 (MOD13Q1 product) imagery was downloaded from the Land Processes Distributed Active Archive Center (LP DAAC) (https://lpdaac.usgs.gov/lpdaac/get_data/data_pool). MOD13Q1 16-day composite for the year 2012–13 was used for the analysis.

Four tiles covering the Myanmar region were downloaded from LP DAAC (LPDAAC 2014). Although the data have already undergone atmospheric correction (Vermote and Vermeulen 1999) and cloud screening, each MODIS 16-day composite was further processed and cloud contamination was removed through maximum value composites by using equation 1. This is done as explained in previous studies (Thenkabail, Schull, and Turral 2005; Gumma et al. 2011c). MODIS re-projection tool (MRT) was used to re-project and mosaic twelve tiles of study area and then stack them as a single composite (Thenkabail et al. 2009a; Gumma et al. 2011b). Altogether 23 images were stacked for the crop year 2012–13 (starting from June 2012 to May 2013).

$$NDVIMVC_i = Max(NDVI_{i1}, NDVI_{i2}) \tag{1}$$

where, $NDVIMVC_i$ is the monthly maximum value composite of ith month (eg: "i" is Jan-Dec). i_1, i_2 are every 16-day composite in a month.

The Land Surface Water Index (LSWI) (Xiao et al. 2006) was derived from the near infra-red, and short wave infra-red bands of each 16-day composite in the 2012–2013 time series of images using equation 2.

$$LSWI = \frac{\lambda_{NIR} - \lambda_{SWir}}{\lambda_{NIR} + \lambda_{SWir}} \tag{2}$$

The NDVI data was further processed to create monthly maximum value composites (NDVIMVC) for the (rainy) season using equation 1.

2.3. Ground survey information

Ground data were collected during two cropping seasons across the dominant agricultural areas of Myanmar from two extensive field campaigns. The first set of field points (493 locations) were collected during December 11–20, 2012 for mapping irrigated areas while the second field-plot dataset (597 locations) was collected during March 20–30, 2013 (Figure 2). At each point, the farmers were interviewed with the support of township managers and agricultural officers to determine drought intensities, crop types and length of growing periods during the 2012 rainy season and the

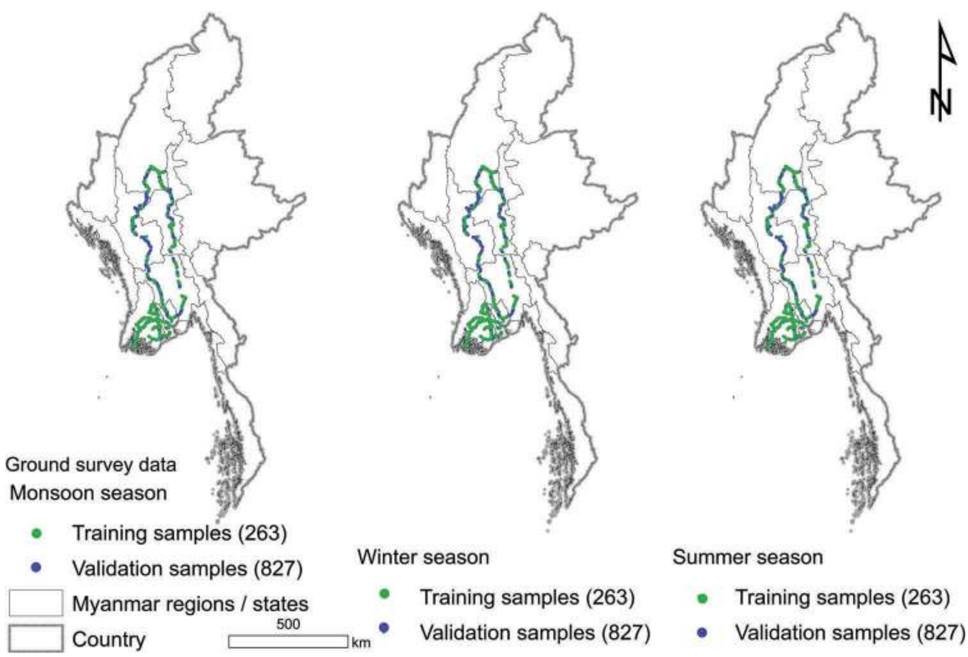

Figure 2. Ground survey data locations in Myanmar. There are 1090 locations where data on cropping pattern, irrigation source and crop intensity were captured, of which 263 locations with additional information on land use/land cover percentages were captured.

2013 summer season, along with the previous cropping year (2011–12). A total of 1090 locations were sampled covering the major cropland areas. Each sample site satisfies the following criteria: large field size (minimum 250 m x 250 m); homogenous (same crop, planted at the same time, with the same watering method); and recommended by a local agricultural expert. These steps were followed to ensure that each sample only contained a single agricultural land use/land cover (LULC) and no auto-correlation existed between field sites. The percentage of LULC in a large diverse sampled area was another important parameter, which was recorded during the field visits.

Out of 1090 locations, 263 samples (132 for December and 131 for March) were used for training the algorithm by generating ideal spectra (Gumma et al. 2011b) leading to classification of images based on acquired knowledge. The remaining 827 field survey points were used for accuracy assessment. The ground spatial resolution of MOD13Q1 product is 250 m x 250 m; so a minimum sampling unit of 250 m x 250 m was selected for ground data validation. Ground survey locations were selected based on the homogeneity of locations and road access. The emphasis was on "representativeness" of the sample location in representing one of the classes to ensure precise geo-location of the pixel. Class names were assigned in the ground survey using a labeling protocol (see Thenkabail et al. 2009b).

Ideal spectral signatures were generated using time-series data that were extracted from 263 survey samples. Each of the samples chosen to generate the ideal spectral signatures (Gumma et al. 2014) represents a definitive crop type and/or cropping system such as "irrigated-rice-fallow-rice." Multiple samples with the same crop type/system were combined to create a single ideal spectra (between 5 and 15 samples per spectra), even though the locations are spatially distributed in discrete patches. This was done to generate fewer and more representative spectral signatures (e.g., Figure 4) for each cropping system.

2.4. Mapping cropland areas

An overview of the methodology is shown in Figure 3. It begins with the preparation of appropriate MODIS 250-m data cubes. Data cubes for three seasons have been produced (Figure 3).

This study used spectral matching techniques (Thenkabail et al. 2007, Gumma et al. 2016) for mapping cropland fallows using MODIS time-series imagery along with extensive ground data information (Gumma et al. 2011a, 2011b, 2015). The purpose and focus of this paper is to map seasonal fallows after rice. After unsupervised classification of NDVI MVCs, during the class identification and labeling process, we used 16-day as well as monthly MVCs.

Information was also used for class identification, which was collected during 2012–13. Ideal spectral signatures were based on 263 unique samples available from ground survey data. Nearly 215 samples were grouped into 7 major cropping categories for each season, as explained in previous studies (Gumma et al. 2011b, 2014); the remaining 48 samples were non-croplands. Initial classes were generated through an unsupervised ISODATA cluster algorithm on the 4-band monthly MVC NDVI for the year 2012–13 (ISODATA in ERDAS Imagine 2015^{TM}) followed by progressive generalization (Cihlar et al. 1998). The initial classification was set at a maximum of 100 iterations and a convergence threshold of 0.99, which resulted in 100 classes. We used decision tree (DT) algorithms to reduce 100 unsupervised classes by grouping. DT algorithms based on monthly NDVI thresholds at

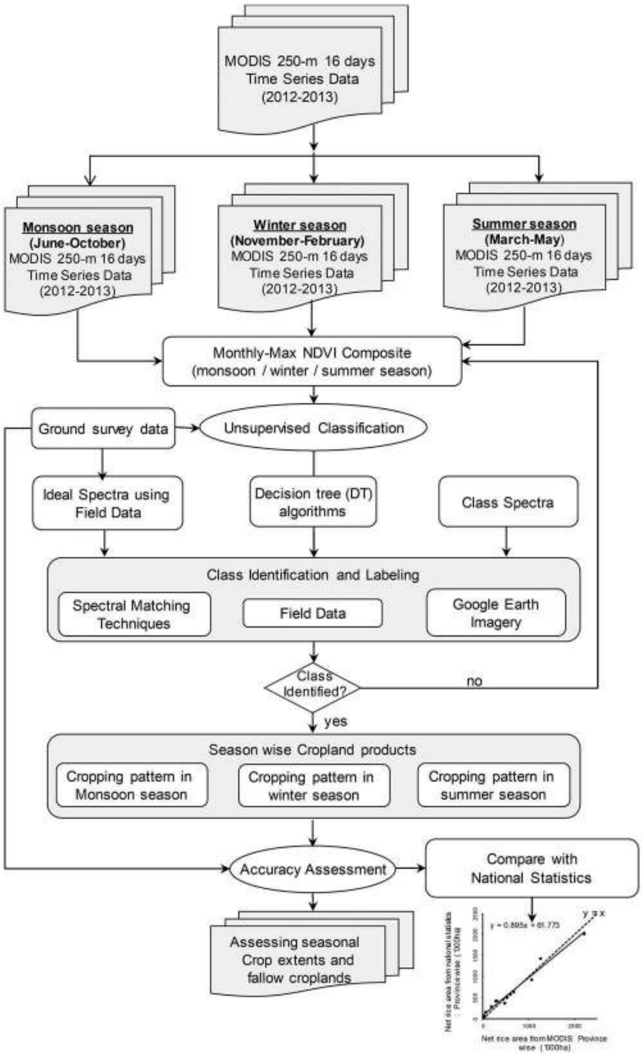

Figure 3. Overview of the methodology for mapping rice areas using the MODIS time series and ancillary data.

different crop growth stages in the season were used for initial grouping (Figure 4) (Gumma et al. 2014). The months and threshold values were chosen based on knowledge of the crop calendar from local experts and field observations as well as published crop development stages (Thenkabail et al. 2007). Figure 4 illustrates DT algorithms for the monsoon season.

Each of the points (Figure 2) selected to generate ideal spectra signatures (Figure 5) represented a definitive crop type as "Irrigated-surface water-double crop-rice-fallow-rice." Numerous measurements of similar classes (e.g., "Irrigated-SW-DC-rice-fallow-rice" measurements from "6" samples spatially well spread out as shown in Figure 5) were combined into a single ideal spectrum (e.g., Figure 5), which becomes a representative ideal spectral of temporal signature for that class. The ideal spectra were the average of the spectra of above locations, representing a crop type class or crop dominance class.

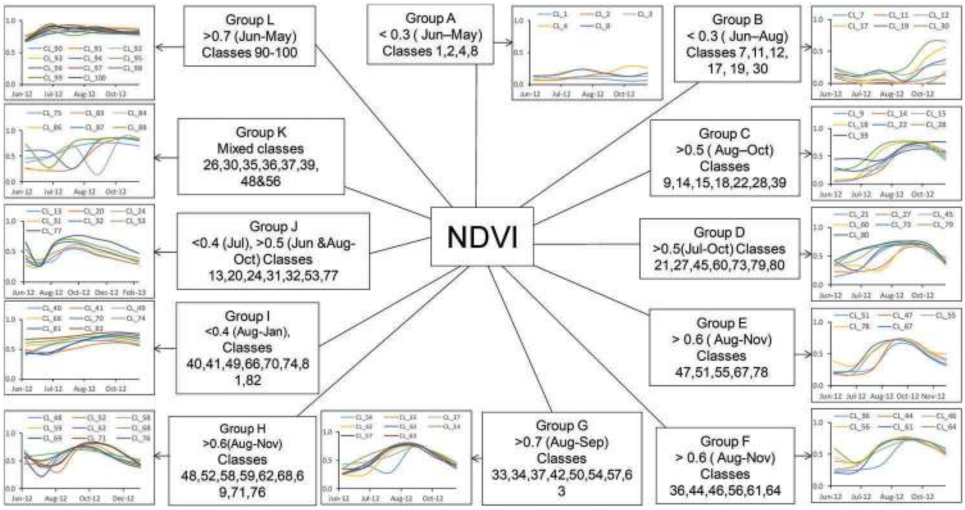

Figure 4. Decision tree algorithm to group and identify classes (monsoon season). MODIS monthly NDVI MVC classes are plotted and grouped.

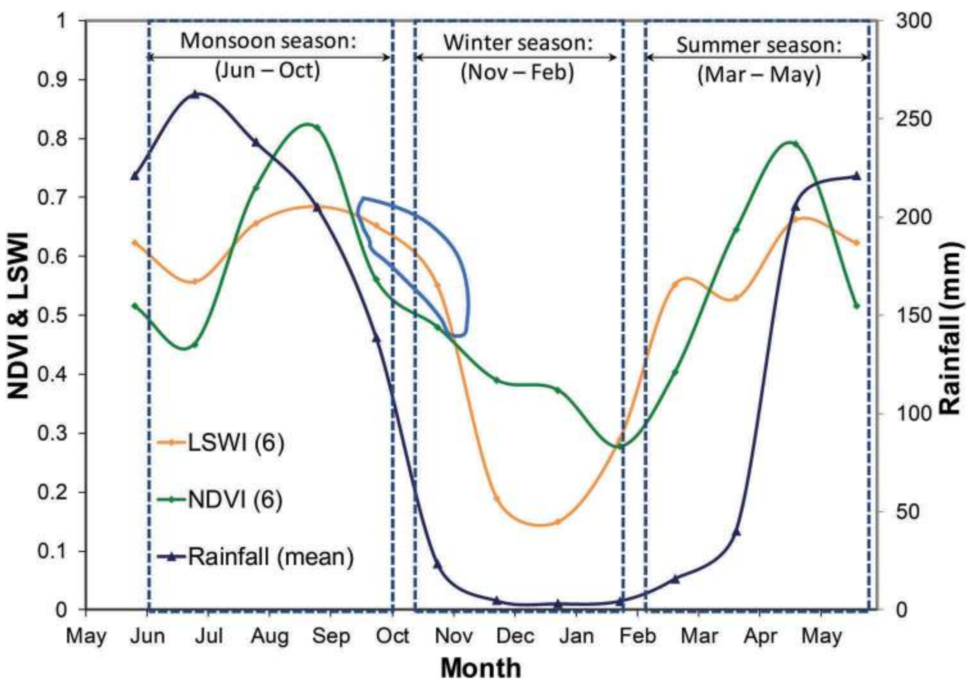

Figure 5. Overview of cropping patterns and identification of fallows. Seasonal signature of the NDVI and LSWI (Double–rice crop in central dry zone) for the 2012–2013 cropping year. Seasonal signatures were derived from 16-day, 250-m MOD13Q1 product on areas verified to contain rice in a ground surveying campaign. (Note: ideal spectra signature for Irrigated-SW-DC-rice- fallow-rice. The higher LSWI values during the fallow period (blue circle) indicate enough soil moisture for crop growth).

Land use/land cover class identification and labeling were based on MODIS NDVI time-series plots, ideal spectra, quantitative spectral matching techniques (QSMT), ground reference data, and very high resolution images from the Google Earth application. SMT is the process of matching ideal spectra signature with class spectra. Prior to doing this, DT algorithms were grouped and matched with ideal spectra (Thenkabail et al. 2007; Biradar et al. 2009; Thenkabail et al. 2009b; Gumma et al. 2011b, 2011c). The class spectra were matched with the ideal spectra and labeled with that class of land use. After this, the classes were verified with ground survey data and Google Earth high resolution imagery. Also, Google Earth imagery was used to identify classes in inaccessible areas or areas with insufficient ground survey data. This was also used to confirm the presence of any rice terraces, vegetation conditions, and irrigation structures (e.g., canals, irrigation channels, open wells). In a rigorous classification process, most of the 100 classes from the unsupervised classification were identified and named. When a study area contains many distinct land cover classes over a large spatial extent, there is a risk that some of the classes from the unsupervised classification may contain several mixed classes. These mixed classes were resolved by extracting them from the stack, reclassifying them, and applying the methodology above on these subsets in order to separate them.

2.5. Classification accuracy assessment

A total of 827 ground data points were used to assess the accuracy of the classification results, based on a theoretical description given by Jensen (2004), to generate an error matrix. The columns of an error matrix contain field-plot data points, and the rows represent the results of the classified rice maps (Congalton 1991b). The error matrix is a multi-dimensional table with cells containing changes from one class to another. The statistical approach of accuracy assessment consists of different multivariate statistical analyses. A frequently used measure is Kappa (Cohen 1960; Congalton 1991a, 2009; Gumma et al. 2014), which is designed to compare results from different regions and classifications. In statistics, Kappa is a degree of agreement among user and reference ground survey data. It gives a score of how much homogeneity or consensus there is in the ratings given by an error matrix.

2.6. Identifying potential areas to introduce short-duration pulses in rice fallows

During ground data collection, every sample was identified for its potential to grow short-duration pulse crops. The availability of adequate soil moisture (LSWI ranging from 0.689 in October to 0.19 in January) indicates the suitability for growing short-duration pulses (Figure 5). These samples were overlaid on cropland fallows mapped in this study (section 2.4) for the respective seasons. For example, during summer season, 48% of the 193 samples that fell on cropland fallow areas showed adequate soil moisture. Then the cropland fallow areas of – the summer season were multiplied by the percent of ground data samples that show adequate moisture/water to arrive at cropland fallow areas that have potential for growing short-duration pulses. This is discussed further in section 3.1 with results presented in Table 5.

2.7 Assessment of the economic potential of cropland fallows in myanmar

The cropland fallows identified with sufficient soil moisture could be targeted for introduction of short-season pulse crops. Based on statistics from the Myanmar government, short-season pulses (such as black gram, green gram, beans and lablab) could easily earn, on an average, a net profit of US$ 300 per ha (see Table 6). The successful introduction and sustainable intensification of pulse-based cropping systems in the country would enhance these economic benefits significantly in cropland fallows. The present study made an *ex-ante* estimate of these benefits by multiplying half the potential additional cropland fallow land area (5 Mha in Table 5) with the average net profit (US$ 300) of short-season pulses per ha, leading to an estimate of US$ 1.5 billion per year.

3. Results

3.1. Crop classification and phenology

The monthly NDVI and LSWI time-series dataset is used to understand the differences that occur within and between seasons, between rice and other crops, and between irrigation sources (e.g., irrigated versus rainfed). For example, the illustrated curves in Figure 5 show the distinct differences between double-/single-cropped rice that is irrigated or rainfed. Irrigated areas have a much higher NDVI and are mostly double-cropped (two crops in a calendar year).

Forest and shrublands were identified as having NDVI values greater than 0.75. In rainfed-Single crop-rice-fallow-fallow (Class 2, Figure 6), NDVI values did not exceed 0.3 during starting of growing season with a maximum of 0.8 during peak growth stage (ARDC 2012). Since rice is an irrigated crop, the LSWI is usually high, ranging from 0.2 to 0.8. Similarly, rainfed-rice areas have significantly low NDVI during the rainy season, ranging from 0.2 to 0.68. However, the LSWI for rainfed-rice remains the same.

Similarly, rainfed-rice areas have a lower NDVI during the rainy season. The areas where other crops such as pigeonpea, which have much longer duration, were grown show higher NDVI, however still lower values compared to the rice signatures.

Altogether, 11 crop classes, including other land cover areas, were identified and labelled (Figure 6). Of the 11 LULC classes, the first 3 classes are rainfed, classes 4 to 6 are irrigated, and class 7 consists of rainfed-mixed crops. Of the 3 irrigated classes, class 4 is irrigated-double crop rice followed by rice and summer fallow, class 5 is irrigated surface water rice with mixed crops and fallow with a small portion of rice, and class 6 is irrigated-rice followed by fallow and summer rice. Class 6 is mainly located in the Mandalay and Sagaing regions within the central dry zone (Figure 6). Fallows followed by rice cultivation were identified across the study area. Potential areas were mainly located in the central dry zone, which were predominantly located in Sagaing and Mandalay (Figure 6). The region-wise areas are tabulated in Table 5.

3.2 Cropland classes of myanmar during three growing seasons

Altogether, seven crop classes, including other land cover areas, were identified and labelled (Figure 7). Statistics were computed for each class (Figure 7). Of the seven LULC classes (Figure 7), the first three classes are rainfed, classes 4 and 5 are irrigated, class 6 is cropland fallows, and class 7 is all other LULC classes. Major croplands are seen during monsoon season with net cropped area (NCA) of 13.8 Mha. Of this, 20% area is under rainfed-rice and 25% under irrigated-rice. During the winter season, 5.98 Mha is under croplands; only 2% of NCA is under rainfed-rice and 5% under irrigated-rice. An

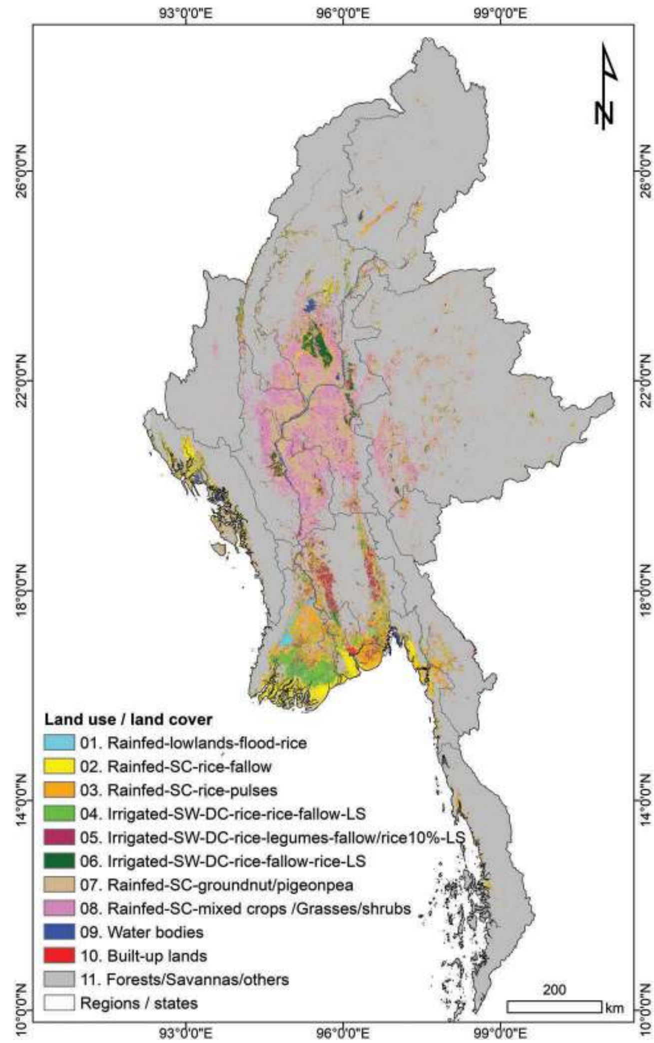

Figure 6. Spatial distribution of major croplands across the study area for the 2012–2013 cropping season. Classes were classified using SMTs on MODIS 250-m time series data. SW = surface water, SC = single crop per year, DC = double crop per year, LS= large scale.

important observation during winter is that 18% of NCA is under pulses, which can be expanded into fallow croplands, amounting to 75% of NCA. During summer season, the cropland area fell to 2.38 Mha.

3.3 Cropland fallows of myanmar during three growing seasons

Overall, NCA in the country was 13.8 Mha (Figure 7). Of this, during monsoon (June-October), the standing crop was 13.5 Mha or 97.8% of the NCA (Figure 8). Even the 2.2% left as cropland fallows are often flooded. During winter season (November-February), 5.98 Mha (43.3% of NCA) is cultivated and has a standing crop, leaving the

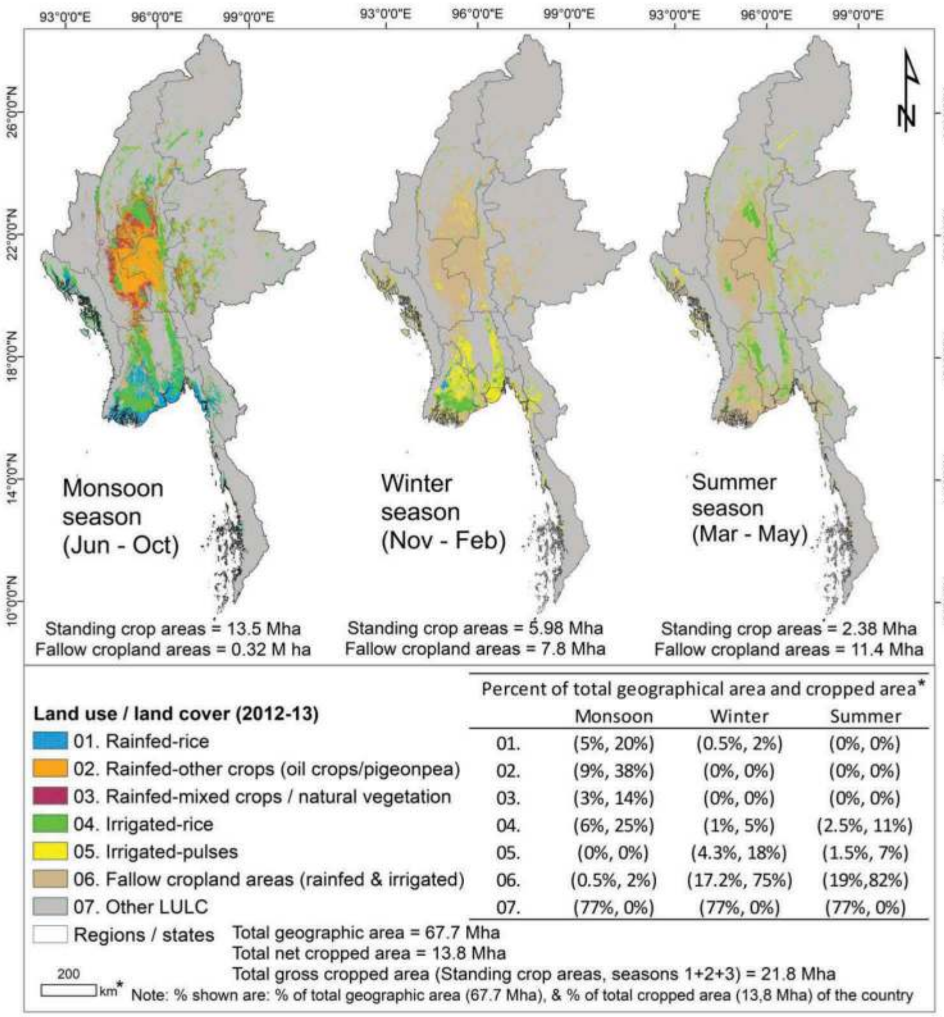

Figure 7. Spatial distribution of major croplands across the study area with season and irrigation source.

remaining 7.8 Mha (56.5% of NCA) as cropland fallows (Figure 8). During the summer season (March-May), 2.38 Mha (17.2% of NCA) is cultivated and has a standing crop, leaving the remaining 11.4 Mha (82.6% of NCA) as cropland fallows (Figure 8).

3.4 Accuracies of cropland and cropland fallows of myanmar

Accuracy was performed based on independent ground survey data (explained in section 2.3). Accuracy assessment was performed with a total of 827 independent ground survey samples. These samples were not used in class identification and labeling. The overall accuracies of the seven classes during monsoon, winter and summer seasons were 90%, 85%, and 97%, respectively (Table 1). Since, the main focus of this study is on cropland fallow mapping, we evaluated cropland accuracies of class 6 (cropland fallows) across three seasons (Table 1). Since the cropland fallows during season 1 were only 2.2%, they have little significance.

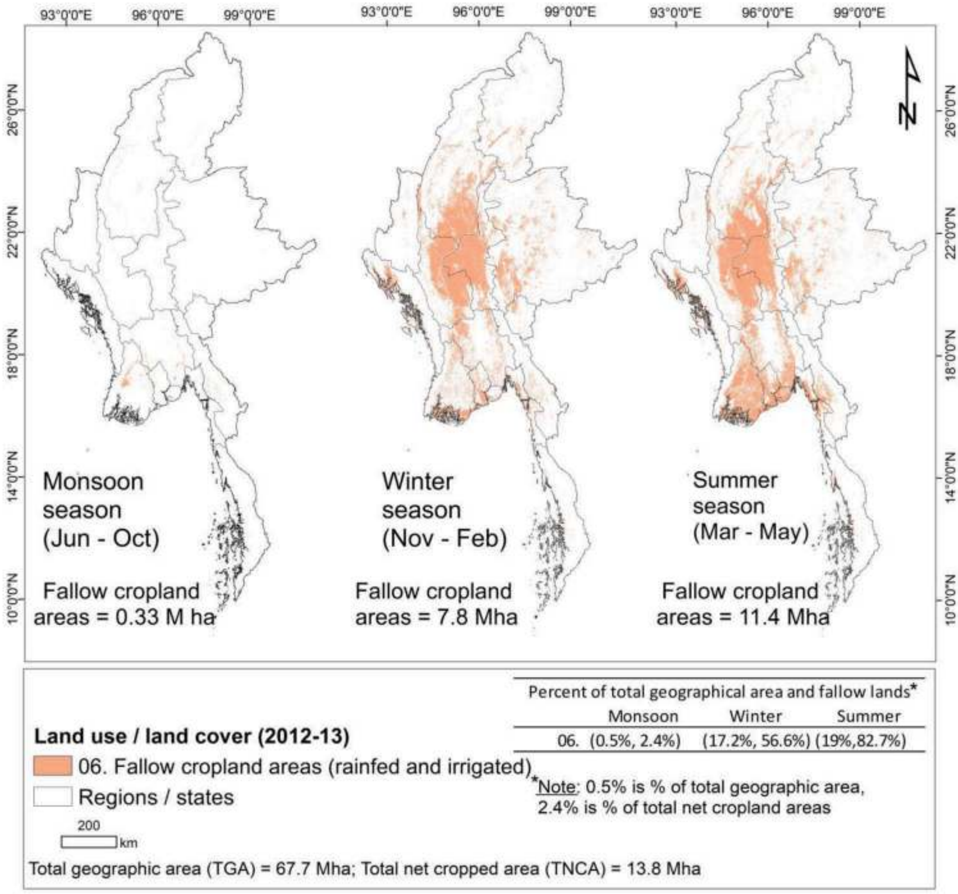

Figure 8. Spatial distribution of cropland fallows across the study area for the 2012–2013 cropping season.

Cropland fallows which were 5.98 Mha during winter, had producer's accuracy of 98% and user's accuracy of 82% (Table 1). Cropland fallows which were 11.4 Mha during summer, had producer's accuracy of 92% and user's accuracy of 92% (Table 1). Thus, winter and summer have massive cropland fallows which were mapped with greater accuracy. Classification was performed on season-wise cropland products and the accuracy was assessed for each class (Tables 2, 3 and 4).

Table 1. Accuracies of classes during three seasons for Myanmar showing: (a) overall accuracies of 7 classes, and (b) producer's and user's accuracies of fallow cropland class.

Season	Months	Overall accuracy of 7 classes (%)	Kappa (no units)	Producer's accuracy for fallow cropland classes (%)	User's accuracy for fallow cropland classes (%)
Monsoon	June-October	90	0.85	57	80
Winter	November-February	85	0.77	98	82
Summer	March-May	87	0.7	92	92

Table 2. Accuracy assessment using field-plot data using the error matrix method for the monsoon season (June – October).

Classified data	CL_01	CL_02	CL_03	CL_04	CL_05	CL_06	CL_07	Reference totals	Classified totals	Number of correct	Producer's accuracy	User's accuracy	Kappa
01. Rainfed-rice	270	1	3	1	3	0	17	290	295	270	93%	92%	0.87
02. Rainfed-other crops (oil crops/pigeonpea)	13	97	2	1	4	2	15	98	134	97	99%	72%	0.69
03. Rainfed-mixed crops/ natural vegetation	0	0	7	0	0	0	1	12	8	7	58%	88%	0.87
04. Irrigated-rice	5	0	0	326	0	0	3	337	334	326	97%	98%	0.96
05. Irrigated-pulses	0	0	0	0	0	0	0	7	0	0	–	–	0.00
06. Fallows (rainfed & irrigated)	1	0	0	0	0	4	0	7	5	4	57%	80%	0.80
07. Other LULC	1	0	0	9	0	1	40	76	51	40	53%	78%	0.76
Column total	290	98	12	337	7	7	76	827	827	744			

Note: Overall classification accuracy = 90%; overall Kappa statistics = 0.85; X-axis is ground survey information and Y-axis is Modis-derived classification.

Table 3. Accuracy assessment using field-plot data using the error matrix method for the winter season (November – February).

Classified data	CL_01	CL_02	CL_03	CL_04	CL_05	CL_06	CL_07	Reference totals	Classified totals	Number of correct	Producer's accuracy	User's accuracy	Kappa
01. Rainfed-rice	6	0	0	0	0	1	0	12	7	6	50%	86%	0.86
02. Rainfed-other crops (oil crops/pigeonpea)	0	0	0	0	0	0	0	19	0	0	–	–	0.00
03. Rainfed-mixed crops/ natural vegetation	0	0	0	0	0	0	0	0	0	0	–	–	0.00
04. Irrigated-rice	3	0	0	95	20	3	2	120	123	95	79%	77%	0.73
05. Irrigated-pulses	2	2	0	4	243	1	7	294	259	243	83%	94%	0.90
06. Fallows (Rainfed & irrigated)	1	14	0	20	24	317	12	323	388	317	98%	82%	0.70
07. Other LULC	0	3	0	1	7	1	38	59	50	38	64%	76%	0.74
Column Total	12	19	0	120	294	323	59	827	827	699			

Note: Overall classification accuracy = 85%; overall Kappa statistics = 0.77; X-axis is ground survey information and Y-axis is Modis-derived classification.

Table 4. Accuracy assessment using field-plot data using the error matrix method for the summer season (March – May).

Classified Data	CL_01	CL_02	CL_03	CL_04	CL_05	CL_06	CL_07	Reference totals	Classified totals	Number of correct	Producer's accuracy	User's accuracy	Kappa
01. Rainfed-rice	0	0	0	0	0	0	0	0	0	0	–	–	0.0
02. Rainfed-other crops (oil crops/pigeonpea)	0	0	0	0	0	0	0	1	0	0	–	–	0.0
03. Rainfed-mixed crops/ natural vegetation	0	0	0	0	0	0	0	0	0	0	–	–	0.0
04. Irrigated-rice	0	0	0	118	1	38	3	136	160	118	87%	74%	0.69
05. Irrigated-pulses	0	0	0	1	13	2	2	16	18	13	81%	72%	0.72
06. Fallows (Rainfed & irrigated)	0	1	0	16	2	551	29	602	599	551	92%	92%	0.71
07. Other LULC	0	0	0	1	0	11	38	72	50	38	53%	76%	0.74
Column Total	0	1	0	136	16	602	72	827	827	720			

Note: Overall classification accuracy = 87%; overall Kappa statistics = 0.70; X-axis is ground survey information and Y-axis is Modis-derived classification.

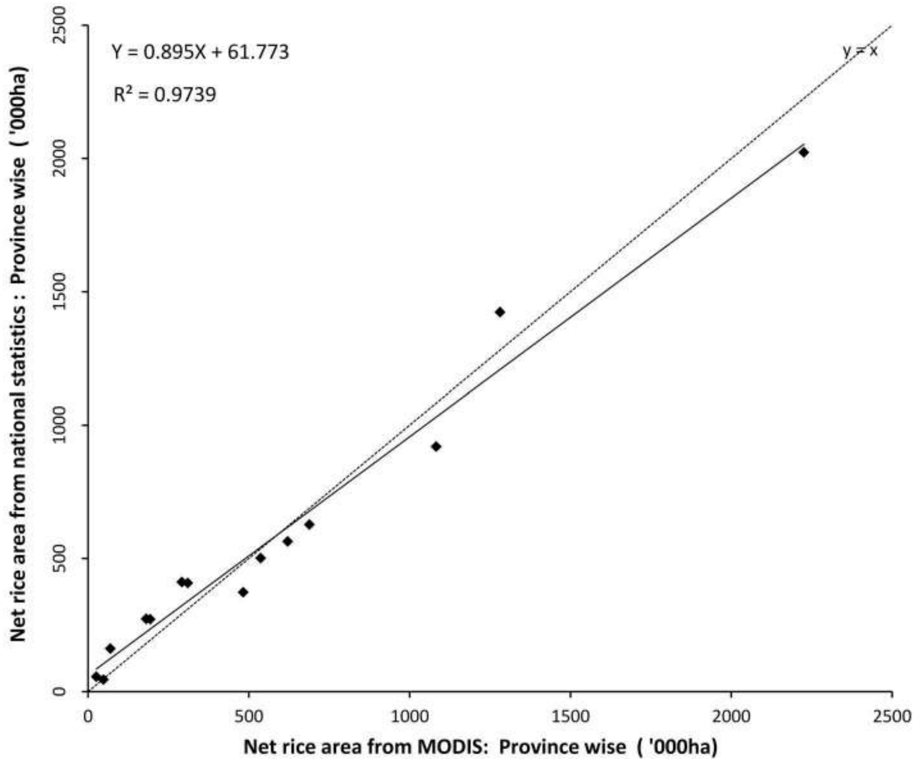

Figure 9. A comparison of cropland fallow areas derived from this study and those reported by some of the administrative units of Myanmar during the 2012–2013 cropping season (winter).

3.5 Comparison of cropland areas reported by the national system and by this study

The total rice cropped area derived in this study was compared with rice cropped area reported by the Myanmar Government official statistics (http://www.moai.gov.mm/) at the region/state level. Rice cropped areas were obtained for all fourteen provinces in the country. The MODIS-derived rice areas were consistently overestimated in Ayeyarwady, Sagaing, and Mandalay regions and Shan state and slightly underestimated in Bago region and Mon state. MODIS-derived rice areas were highly correlated with the sub-national statistics with a R^2 value of 97% variability (Figure 9).

3.6 Cropland fallows with sufficient soil moisture/water access for growing crops across seasons

In general, winter receives very little rainfall; however, it is a season that immediately follows the rainy season period of 5 to 6 months. Hence, during season-2, croplands hold a significant amount of water in the soil and most importantly rice is grown in the monsoon season. During field surveys, we established that the rice-fallows locations revealed sufficient moisture to grow a second season, i.e., low water consuming, short-season pulses (Table 5). This meant a total of 4.29 Mha (7.80 Mha of fallow croplands) was available for cultivating a second crop (Table 5). Season-3, again receives significant

Table 5. Fallow cropland areas with sufficient moisture/water to grow crops across three seasons in Myanmar.

Season	Months	Cropland fallow as % of net cropland areas* (%)	Cropland fallow areas (Mha)	Ground data samples #	Ground samples with sufficient moisture for crop growth (%)	Fallow areas with sufficient moisture available for cultivation (Mha)
Monsoon	June-October	2.4	0.32	11	100	0.32
Winter	November-February	56.6	7.8	122	55	4.29
Summer	March-May	82.7	11.4	193	48	5.47
	Total		19.5	326		10.08**

* Total Net cropland area (TNCA) of Myanmar is = 13.8 Mha
** Half the potential cropland fallow area (5.04 Mha) is estimated to be grown to pulses.

quantum of rain. Hence, about 48% (5.47 Mha) of the total cropland fallows (11.40 Mha) have potential for growing a third season crop.

3.7. *Additional benefits due to alternate legume systems in rice fallows and central rainfed lands*

The economics of pulses cultivation during 2012–13 is summarized in Table 6. Groundnut exhibited the highest net margins (US$ 963) per hectare of cultivated area, higher than other leguminous crops. Its net margin was much higher than any other competing cereal crops, such as paddy (US$ 330) and maize (US$ 523) (Table 6). Groundnut was followed by the cultivation of pigeonpea, black gram, green gram and chickpea, creating significant additional incomes per ha. The average net returns per ha earned due to the introduction of short-season pulses was estimated to be around US$ 300 per ha. The potential cropland fallow area estimated by the present study was 10.08 Mha across the country. However, the most promising potential areas for introduction of short-season pulses in the country are Mandalay, Magway and Sagaing provinces (called CDZ region) (see Figures 6, 7 and 8). The province-wise break-up of potential cropland fallows across three seasons is summarized in Table 7. Mandalay, Magway and Sagaing

Table 6. Economics of pulses cost and yield vis-à-vis cereals (COC)' cultivation in Myanmar, 2013.

Crop	COC (kyats/ha)	Yield (mt/ha)	Price (kyats/ton)	Net margin (kyats/ha)	Net margin (US$/ha)
Pigeonpea	352,612	1.31	542,558	358,139	358
Groundnut	501,613	1.59	921,267	963,202	963
Black gram	315,794	1.4	470,259	342,569	342
Green gram	399,314	1.28	568,069	327,814	327
Chickpea	400,000	1.45	500,000	325,000	325
Other pulses	393,867	1.41	600,431	358,139	358
Paddy	604,160	3.84	243,480	330,803	330
Maize	543,620	3.64	293,184	523,570	523

Source: Myanmar Agriculture at a glance, 2013.

Table 7. Province-wise area of cropland fallows suited to the introduction of short-season pulses.

	Cropland fallows ('000 ha)		
Province	Monsoon	Winter	Summer
Ayeyarwady	113	369	961
Bago	49	229	391
Chin	0	36	31
Kachin	6	103	76
Kayah	0	12	12
Kayin	30	23	36
Magway	8	961	1109
Mandalay	20	736	804
Mon	12	37	79
Rakhine	25	183	230
Sagaing	44	971	1033
Shan	4	547	498
Tanintharyi	4	2	3
Yangon	9	81	212
	324	4290	5475

provinces (CDZ region) together (6.32 Mha) represent nearly 63% of the total potential cropland fallow (10.08 Mha) in the country. Optimistically, if we assume that nearly half of the total cropland fallow area (5.04 Mha) can be brought under short-season pulse crops, the estimated economic benefits would be around US$ 1.5 billion per year.

4. Discussions

4.1 Discussion on classification results

The most widely used classification algorithm for large area cropland mapping, where diversity of landscape is high, is unsupervised classification. This is because, the very large volume of training data required for supervised classification is resource intensive and often extremely difficult collect as a result of inaccessibility of ground data locations. In this study, unsupervised classification of seasonal time-series imagery (Figure 3) led to numerous informational classes for each of the seasons. The NDVI time-series of each unsupervised information classes were then analyzed either through their time-series profiles or through a decision-tree algorithm (Figure 4) along with the ground data (Figure 2) to determine class labeling. Representative samples of most of the cropping systems were collected during ground data (Figure 2) collection missions. The main goal in this study was to determine cropland fallows in one or the other of the three seasons (Figure 3 to 5). Ideal spectral signatures (e.g., Figure 5) were generated from the ground information as input to the Spectral Matching Technique (SMT) (Thenkabail et al. 2007) where class spectra from unsupervised classes (Figure 4) were matched with ideal spectra (e.g., Figure 5) along with ground data (Figure 2) to identify and label classes (Figure 6) in entire Myanmar. Through this process, spatial distribution of classes, season by season (Figure 7) in entire Myanmar, were also established. The process, led to determining the distribution of cropland fallows (Figure 8) in each of the three seasons Monsoon, winter and summer for entire Myanmar. Based on the ground data, we established cropland fallow areas that have adequate soil moisture availability to grow legume crop during the rice fallow seasons. This led to estimating season by season, cropland fallows (Table 5, Figure 8) in each of the three seasons

(Monsoon, winter and summer) for entire Myanmar. Estimating season by season (Monsoon, winter and summer) cropland fallow areas for entire Myanmar, helps in planning cropland intensification (to grow crops during seasons when cropland is fallow, but have adequate soil moisture to grow short season legume crops). Precise spatial location of where these cropland fallows exist and during which season (Figure 8) will be of immense value to decision makers to do filed visits and establish areas for cropland expansion. Such measures add additional economic value to farmers as well as national income. The measure also contributes to food and water security taking sustainable approach where to grow food one would use existing croplands instead of cropland expansion to new areas.

4.2 Economic impact of expanded pulse production

The cultivation of pulses in rice fallows and central rainfed lands generates a substantial additional agricultural income and contributes significantly to Myanmar's national GDP. However, it should be more precisely targeted by using remote sensing and GIS technologies. The exercise undertaken in this paper will immensely help researchers better understand and aid the introduction of new pulse crop technologies. Enormous potential has been observed in diffusing diverse pulse-based cropping systems in the country. Better productivity levels coupled with export demand enhance their spread, along with development of improved technologies in the country. Overall, it was estimated that if Myanmar could use half of the suitable rice fallows (5.04 Mha of 10.08 Mha) to cultivate short-duration pulse crops, mainly in the CDZ region, it could generate an additional revenue of approximately US$ 1.5 billion per year from agriculture. However, most of the central dryland zone farmers still cultivate local or low-yielding cultivars for these crops. Introducing improved pulse cultivars and best management practices will not only enhance legume production, but also improve the rainfed farmers' livelihoods.

5. Conclusions

This study mapped cropland fallows of Myanmar using MODIS 250-m time-series data, reference ground data, and spectral matching techniques during three seasons: monsoon (June-October), winter (November-February), and summer (March-May). Myanmar had a total net cropland area (TNCA) of 13.8 Mha. Of this, cropland fallow areas comprised 7.8 Mha (56.5% of TNCA) during winter, and 11.4 Mha (82.6% of TNCA) during summer. Cropland fallow areas during the monsoon, the main growing season, constituted only about 2.4% due to intense cultivation. The producer's accuracy varied between 92% and 98% (errors of omissions of 2 to 8%) and the user's accuracy varied between 82% and 92% (errors of commissions of 8 to 18%) for winter and summer, respectively. Of the total 19.2 Mha of cropland fallows from winter and summer combined, 10.08 Mha was determined to have sufficient water/soil moisture to cultivate short-duration, and low water consuming pulses (e.g, black gram, green gram and beans). Growing pulses during winter and summer is considered to be the best use of existing cropland area without having to expand to non-cropland areas. This approach of utilizing existing cropland fallows is ecologically sound and climate friendly. It also brings in additional income for farmers with an estimated revenue of about US$ 1.5 billion per year through the introduction of short-season pulses on half (5.04 Mha) of the total cropland fallow area (10.08 Mha). Further, it is water-smart agriculture as pulses consume far less water relative to cereals (paddy and maize). This is an ideal approach to address the water, food and nutritional security challenges of the twenty-first century.

This research makes a broad contribution to the food and water security challenges addressed by other research groups such as the Group on Earth Observations (GEO) for monitoring agriculture areas, Agriculture and Water Societal Beneficial Areas (GEO Agriculture and Water SBAs), the GEO Global Agricultural Monitoring Initiative (GEO GLAM), and the global food security-support analysis data (GFSAD) project (www.croplands.org).

Acknowledgments

This research was supported by the CGIAR Research Program Climate Change, Agriculture and Food Security (CCAFS), the CGIAR Research Program Water, Land and Ecosystems (WLE) and the Pyawt Ywar Pump Irrigation Project funded through the Livelihoods and Food Security Trust Fund (LIFT). The authors are thankful to Drs Than Aye, Khin Htar Nge and Kyi Moe for their valuable support during ground data collection. The corresponding author of the paper would like to thank David Johnson, Andy Nelson and Gudiana for their support during initial stages of the project. The United States Geological Survey's Water SMART project and the global food security-support analysis project provided additional support for the project.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by the USGS [GFSAD30m];CGIAR research program Water, Land and Ecosystems (WLE) and through the Pyawt Ywar Pump Irrigation Project led by the International Water Management Institute (IWMI) [CGIAR-WLE];CGIAR research program Climate Change, Agriculture and Food Security (CCAFS) [CCAFS-SEA];

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