IOP Conference Series: Earth and Environmental Science

OPEN ACCESS

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To cite this article: Anuj Katiyal and Dr K S Rajan 2014 *IOP Conf. Ser.: Earth Environ. Sci.* **17** 012231

Spatio-Spectral Method for Estimating Classified Regions with High Confidence using MODIS Data

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Abstract. In studies like change analysis, the availability of very high resolution (VHR)/high resolution (HR) imagery for a particular period and region is a challenge due to the sensor revisit times and high cost of acquisition. Therefore, most studies prefer lower resolution (LR) sensor imagery with frequent revisit times, in addition to their cost and computational advantages. Further, the classification techniques provide us a global estimate of the class accuracy, which limits its utility if the accuracy is low. In this work, we focus on the sub-classification problem of LR images and estimate regions of higher confidence than the global classification accuracy within its classified region. The spectrally classified data was mined into spatially clustered regions and further refined and processed using statistical measures to arrive at local high confidence regions (LHCRs), for every class. Rabi season MODIS data of January 2006 & 2007 was used for this study and the evaluation of LHCR was done using the APLULC 2005 classified data. For Jan-2007, the global class accuracies for water bodies (WB), forested regions (FR) and Kharif crops & barren lands (KB) were 89%, 71.7% and 71.23% respectively, while the respective LHCRs had accuracies of 96.67%, 89.4% and 80.9% covering an area of 46%, 29% and 14.5% of the initially classified areas. Though areas are reduced, LHCRs with higher accuracies help in extracting more representative class regions. Identification of such regions can facilitate in improving the classification time and processing for HR images when combined with the more frequently acquired LR imagery, isolate pure vs. mixed/impure pixels and as training samples locations for HR imagery.

1. Introduction

Land use and land cover (LULC) change studies play an important role on regional to global scales, with impacts over ecosystem functioning, ecosystem services, and biophysical and human variables such as climate and government policies [1]. A great amount of research has been done by many experts and scholars on the information that can be extracted using the change detection techniques [2][3][4][5][6]. Though the LULC assessments and the change analysis studies using the very high resolution (VHR)/high resolution (HR) remotely sensed imagery has been quite successful over the past decades, it has also become clear that such analysis for a particular period and region are severely affected due to the sensor revisit times, the cost of acquisition of the data and the intensive data processing required. As an alternative, many experts exploit the easily available lower resolution (LR) NASA's MODIS sensor data (250m spatial resolution) having superior standards of calibration, geo-referencing and atmospheric correction, as well as detailed per pixel data quality information.

In the past years, many image classification techniques have been developed to improve the data accuracy of the land use/land cover providing a global estimate of the class accuracies, thus limiting the applicability of class regions with lower accuracies. It's a general trend to use the acquired HR data to report the improved classification accuracies for a particular interest area, but due to the heterogeneity of spectral-radiometric characteristics in the natural land cover as captured with the HR images, classification approaches using a particular (single HR) resolution data generally don't lead to satisfactory results [7]. Image classification outputs at LR (coarse) are often combined with the classified HR data (finer) to improve the results of the application, thus taking the advantages of multi-sensor, multi-scale and multi-temporal satellite imagery [8][9]. With the development of satellite and sensor technologies, multi-resolution datasets are available and there is an increasing need to develop efficient multi-resolution processing techniques to exploit information from HR imagery having better image quality and geometrical details but which are easily affected by noise and the lower resolution (LR) imagery which exhibits less precise details but a stronger immunity to noise [10]. Therefore, techniques which focus on the sub-classification problem, i.e. identification of local class regions within the complete class regions which may have higher accuracy than the global class accuracies can help in better multi-resolution image analysis.

The global class accuracies in the classified LR image is generally low as it represents not just pure pixels but also mixed and impure pixels. For this work, a mixed pixel refers to one whose spatial detail, from HR imagery or ground data, reveals that it contains sub-areas of classes in addition to the one it is labeled; while an impure pixel contains sub-areas that belong to a class other than the one it has been classified into. This artifact of belonging to a different class than what it represents can occur due to various reasons including but not limited to sensor geometry, area being imaged and other atmospheric conditions. The objective of this research work was to develop a spatio-spectral method using LR MODIS sensor data, which is readily available at frequent intervals, to come up with local high confidence regions (LHCRs) within classified class regions that should exhibit higher percentage of pure pixels and show more stability.

2. Study Area and Data

The study area used in this work corresponds to the region around Nagarjuna Sagar Dam, which lies in the state of Andhra Pradesh, in the south-eastern part of India (figure 1). The experimental area considered corresponds to the co-ordinates 16°40' N, 78°17' E and 14°59' N, 80°16'E, and covers a total area of 36,646 km^2. In order to perform the study, daily Terra/MODIS (at 250m spatial resolution) atmospherically corrected surface reflectance data (figure 1) was acquired (product MOD09GQ) containing red (645 nm) and near-infrared bands (858 nm) for the dates 30 January 2006 and 1 January 2007. MODIS low resolution (LR) data had Sinusoidal projection with WGS-84 datum. The size of the LR MODIS data, for the acquired dates, covering a portion of the south-eastern state of Andhra Pradesh, India, is 804 × 899 pixels.

Other than that, detailed documentation and LULC classified data with 18 classes for the state of Andhra Pradesh (APLULC), India was obtained from NRSC, Hyderabad for the year 2005-06, which

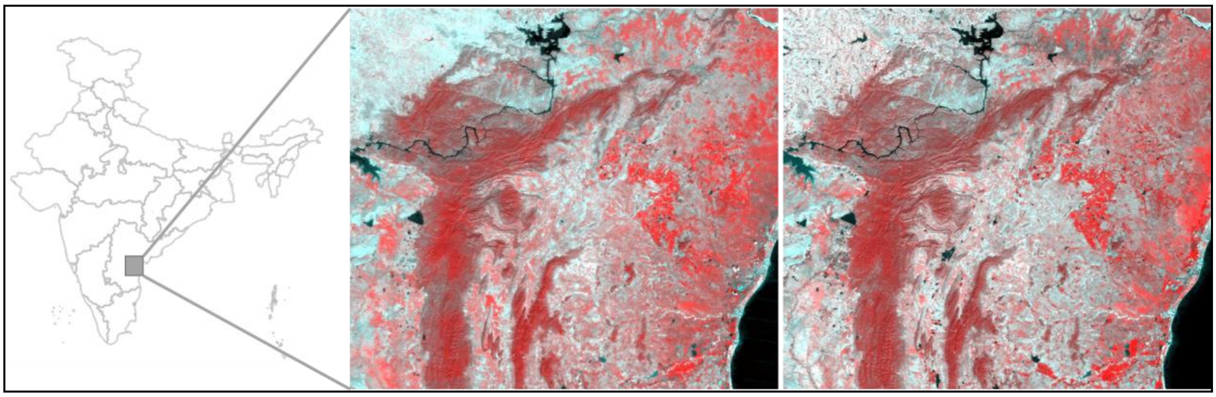


Figure 1. MODIS Dataset Images used, (left image) 1 January 2007 and (right image) 30 January 2006 data.

was based on AWIFS satellite imagery (at 56m spatial resolution) and extensive field visits. The classified HR APLULC data was further clipped to match the experimental region for the available LR MODIS data and the datasets were geo-registered. The experiments were performed on the LR MODIS data and validation was done using the HR classified APLULC data obtained for the regions.

3. Methodology

The methodology is based on the correspondence obtained between a geo-registered LR data pixel to a classified HR data matrix. Further, for the classified LR data, the obtained pure, mixed and impure pixels are the ones whose spatial detail, as obtained from the HR imagery or ground data, shows sub-areas having a single class matching the labeled class, classes in addition to the labeled class and classes other than the labeled class respectively. Instead of using the HR imagery to improve the classification accuracy, we tend to focus on the available LR imagery to obtain LHCRs for each class, i.e. regions within each class with comparatively less pixels as compared to the total class pixels but increased class accuracy and the number of pure pixels.

3.1. Data Pre-Processing

The available LR MODIS data was initially converted to Lambert Conformal Conic Projection with WGS-84 Datum to match the projection of the available HR APLULC validation data, using the triangulation warp method and the nearest neighbour resampling approach. False Color Composite images were obtained for the LR data using the available bands for visualization and further processing. The HR APLULC data classes were combined into eight class regions, which were further aggregated to a final set of four class regions based on the hierarchy of the classes present in the experimental data region and the validation data. Also, LR MODIS data and HR APLULC data being geo-registered were pixel-matched using the nearest neighbour algorithm. Pixel Matching resulted in every LR data pixel corresponding to a HR APLULC classified data matrix (figure 2).

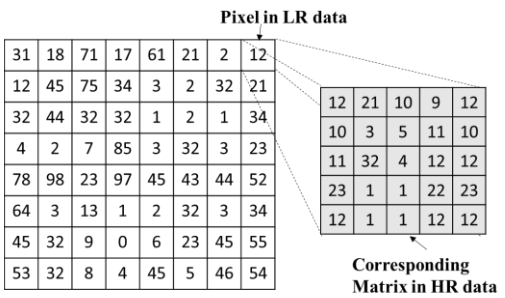


Figure 2. Correspondence between a LR data pixel to a HR data matrix shown using a random matrix.

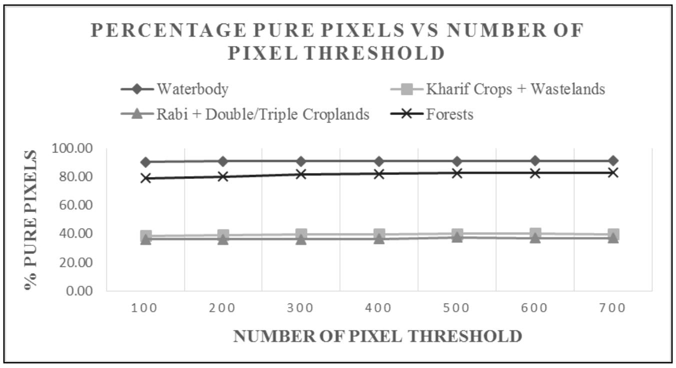


Figure 3. Sample variation in the percentage of pure pixels on increasing the number of pixel threshold for the SCs, for the class regions in 1 January 2007 data.

3.2. Spatio-Spectral Segmentation and Refinement

The LR MODIS data was then spectrally classified using unsupervised K-Means classification algorithm. The total number of classes were kept less than the total number of APLULC classes documented based on the class regions present in the experimental region and the hierarchy of class regions shown by LR data as compared to the HR data while processing multi-resolution imagery [11].

Spectral Classification of the LR MODIS data resulted into final class regions for further processing. The obtained class regions were further segmented into its connected components, which were called the spatial clusters (SC) of a class, having a unique SC number. The SCs obtained were refined and the ones with the total number of pixels below an experimentally observed threshold were ignored. The number of pixel threshold was varied (0.01 to 1% of the total class pixels) and it was observed that the percentage of pure pixels at LR increases or nearly remains the same if the SCs with less number of pixels have been ignored, for all the class regions in the data (figure 3). Refining the SCs for every class improves the accuracy of the proposed methodology by ignoring the regions having higher percentage of mixed and impure pixels for the respective class regions.

3.3. Rank and Select LHCRs within Spatial Clusters

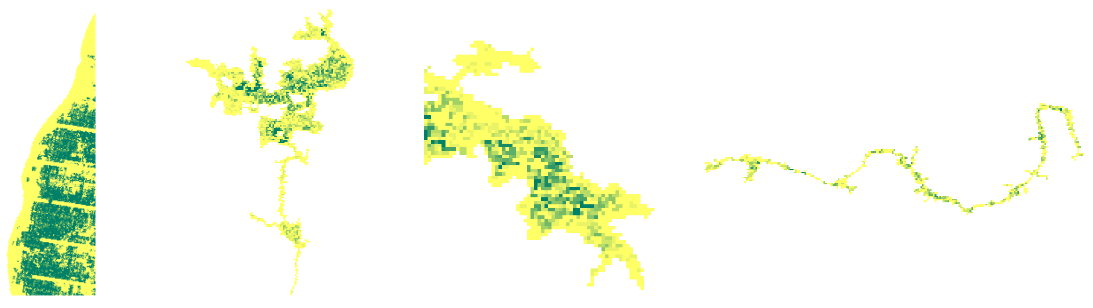
Every refined SC data pixel for the classes obtained was ranked based on the count of the unique spectral band values for the data pixels present in the SC. The mode of the unique band spectral values present in the SC was the statistical measure used as the ranking criterion. Higher ranks were assigned to the data pixels belonging to the unique spectral band values with higher counts. The data pixels in a SC belonging to the unique spectral band values having the same pixel count were assigned the same rank.

The ranked local SC regions were further refined to select the local high confidence regions (LHCRs) within every SC region. The refinement was done in the order of higher ranked regions to the lower ranked regions based on the following thresholds,

- *Area Threshold* – The sum of the pixel counts of the higher ranked unique spectral band values as compared to the total pixels in a SC.
- *Value Dip Threshold* – The decrement in the ratio of the pixel counts for the unique spectral band values to the maximum count of the unique spectral band values, i.e. the pixel count of the mode regions (highest ranked values).
- *Next Value Dip Threshold* – The adjacent pixel counts for the unique spectral band values. If the adjacent pixel counts were greater than a threshold (i.e. a sudden value dip), the remaining lower ranked unique spectral band value regions were ignored and the higher ranked processed regions were taken as the LHCRs.

The choice of the thresholds is an important criterion for the detection of the LHCRs within a SC, while the size, shape and homogeneity within a spatial cluster can influence the range of suitable threshold values. Every threshold behaves differently as the homogeneity within the class regions change. The regions having high homogeneity were generally the regions for whom the defined thresholds were able to come up with similar important local regions within every SC. For regions with high class heterogeneity, a combination of thresholds need to be used based on the requirements in a particular scenario.

The ranked SC regions, after being refined into LHCRs were divided into green and yellow regions for the purpose of visualization. The green regions (GR) were the detected LHCRs and the yellow regions (YR) were composed of the rest of the pixel regions within the originally classified class region. The regions around the mode regions, i.e. regions with higher ranks were visualized with darker shades of green as compared to the lower ranked regions (figure 4).



(a) (b) (c) (d)

Figure 4. Spatial Clusters for LR MODIS Class 1 representing water-body regions, divided into their yellow regions (YR) and green regions (GR) for 1 January 2007 dataset.

4. Results and Discussion

The verification of the obtained green regions, i.e. LHCRs for the SCs obtained for every class was done by using the geo-registered HR APLULC classified data which was pre-processed to combine the classes to eight and four respectively based on the hierarchy of the experimental regions and the validation data available. For the cloud free MODIS datasets for 30 January 2006 and 1 January 2007, the initial analysis using the MODIS dataset with higher classes (nearly 10) and eight APLULC classes showed that confusion matrix created by taking the pixel counts of the HR data for every LR pixel resulted in the LR classes representing majorly only four class regions of the HR data. Considering this the LR MODIS datasets were divided into four class regions belonging to water body (WB) regions as class 1, kharif crops and barren lands (KB) as class 2, rabi crop (RC) lands as class 3 and forested regions (FR) as class 4 and the HR APLULC dataset combined to four classes was used for final validation of the results obtained.

The results for the datasets were obtained and are shown in table 1 and table 2, as the count of pixels at HR in the confusion matrix for the complete class regions (CCRs), the refined SCs obtained for every class regions (RSCs) and the local high confidence regions obtained for the refined SCs for every class region (LHCRs), based on the classified LR MODIS datasets for the respective dates.

Table 1. Confusion Matrix with data entries as HR APLULC pixel counts for the CCRs, RSCs and LHCRs for LR MODIS class regions for 30-Jan-06.

30-Jan-06			HR APLULC			
			WB	**KB**	**RC**	**FR**
LR MODIS	**WB**	**CCRs**	435079	60395	18291	12381
		RSCs	409100	22483	6218	7313
		LHCRs	242475	5537	1188	1494
	KB	**CCRs**	36885	5827255	1585255	891891
		RSCs	11996	2339910	725074	352961
		LHCRs	3146	892976	263543	138735
	RC	**CCRs**	1164	326195	392700	21546
		RSCs	227	108987	152271	75
		LHCRs	54	54451	67888	46
	FR	**CCRs**	14561	531777	290191	1877881
		RSCs	2003	105429	49751	1318007
		LHCRs	332	41391	15202	608293

Table 2. Confusion Matrix with data entries as HR APLULC pixel counts for the CCRs, RSCs and LHCRs for LR MODIS class regions for 01-Jan-07.

01-Jan-07			HR APLULC			
			WB	**KB**	**RC**	**FR**
LR MODIS	**WB**	**CCRs**	426646	32314	9356	11035
		RSCs	407794	19974	4962	6948
		LHCRs	214765	4471	959	1947
	KB	**CCRs**	31459	5811845	1633483	682430
		RSCs	2505	2263555	432210	135974
		LHCRs	686	962740	181516	45004
	RC	**CCRs**	1074	365598	399254	57969
		RSCs	329	167302	207241	169
		LHCRs	112	65255	97849	40
	FR	**CCRs**	28510	535865	244344	2052265
		RSCs	8563	175454	62940	1651302
		LHCRs	1542	66462	21065	751767

For 30 January 2006 dataset, the global class (CCRs) accuracies for WB, KB, RC and FR were 82.69%, 69.86%, 52.95% and 69.19% respectively while the detected high confidence regions (LHCRs) for the SCs of every class had accuracies of 96.72%, 68.72%, 55.44% and 91.44% covering an approximate area of 47.64%, 15.57%, 16.51% and 24.50% respectively. For 1 January 2007 dataset, the global class (CCRs) accuracies for WB, KB, RC and FR were 89%, 71.23%, 48.45% and 71.73% respectively, while the regions of high confidence (LHCRs) for these classes had accuracies of 96.67%, 80.90%, 59.93% and 89.4% covering an area of 46%, 14.58%, 19.81% and 29.38% of the initially classified areas. Though the area covered by LHCRs have reduced significantly from the global detected class regions, higher accuracies for the respective classes in the LHCRs show that the detected regions can be taken as the representative class regions. The highest ranked regions (mode regions) detected in the LHCRs for SCs of every class also provide us the information about the mixing of different class regions with the current class under processing. The highly homogeneous regions formed by water-bodies and forested regions show a very high accuracy for the detected LHCRs whereas the regions having high intra-class heterogeneity in the dataset like kharif crops, fallow lands and rabi crop lands show increases in accuracy, ranging from marginal to medium levels

(1% to 10%), with comparatively higher reduction in areas of LHCRs. In the latter case, like KB and RC, though LHCRs cover a small area the improved accuracies help better appreciate the class behavior and the challenges in classifying them. Identification of LHCRs can facilitate in improving the classification time and processing of the HR images when its combined with the more frequently acquired LR imagery, isolate pure vs. mixed/impure pixels and as training samples locations for HR imagery.

5. Conclusions

This research work was aimed at exploring methods to obtain better class representative regions, i.e. pure pixels, for the obtained classified class regions. The usage of classified data has been always limited because of the global accuracies associated with the class regions and in this work, we have shown that for classes having limited intra-class heterogeneity and high inter-class separability, local regions with high confidence of belonging to the class can be obtained. This methodology can be used for datasets at any resolution and the obtained LHCRs at a resolution can be verified by using a better resolution datasets as shown. Obtaining LHCRs at LR datasets can help verify regions of high confidence which need no further processing in geo-registered HR data, thus reducing the computational time and accuracy of the techniques used to process HR datasets.

The increasing multi-resolution datasets need improved analysis techniques to extract useful information from datasets at a particular resolution. Further, this can improve the analysis done for other resolution datasets, thus increasing the usability of multi-resolution satellite datasets. The future work lies in developing algorithms to aid the detection of mixed and impure pixel regions, thus improving their processing of the multi-resolution satellite datasets.

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