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Effect of Topographic Correction on Maximum Likelihood Supervised Classificationof MODIS Satellite Imagery

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Abstract

Topographic correction is an important data preprocessing step when Maximum Likelihood classification and quantitative analysis of multispectral data are carried out in mountainous regions. The most commonly used supervised Maximum Likelihood Classification (MLC), which assumes that each spectral class can be described by a multivariate normal distribution but accuracy is restrict due to topographic effects. The topographic effect is particularly evident for steep sloped rugged terrain because irregular shape of region causes variable illumination angles and thus diverse reflection values within one land cover type as low reflectance value in shadow areas and high reflectance value in sun illuminated areas. Therefore, Topographic correction methods try to compensate topographically induced illumination variations effect.In this paper, a topographic correction has been applied to MLC on multispectral data are carried out in mountainous regions for analyze the effect of topographic on MLC. The results suggest that the MLC with topographic correction gives more accuracy 85%, kappa coefficient 0.7459 than MLC without topographic correction gives accuracy 79%, kappa coefficient 0.6868.

Keywords

Maximum Likelihood Classification (MLC), Topographic Correction, Moderate Resolution Imaging Spectroradiometer (MODIS)

I. Introduction

The increasing application of remote sensing for snow avalanche monitoring and inventory is seen as a cost effective source of information for the practice of sustainable forest management [1]. A few number of image classification algorithms have proved good precision in classifying remote sensing data. Butdue to the increasing spatiotemporal dimensions of the remote sensing data, traditionalclassification algorithms have exposed weaknesses necessitating further research in the field of remote sensing image classification [2]. So an efficient classifier is needed to classify the remote sensing imageries to extract information.

There are two broads of classification procedures: supervised classification and unsupervised classification. The supervised classification is the essential tool used for extracting quantitative information from remotely sensed image data. Using this method, the analyst has available sufficient known pixels to generate representative parameters for each class of interest. This step is called training. Once trained, the classifier is then used to attach labels to all the image pixels according to the trained parameters. The most commonly used supervised classification is Maximum Likelihood Classification (MLC), which assumes that each spectral class can be described by a multivariate normal distribution. Therefore, MCL takes advantage of both the mean vectors and the multivariate spreads of each class, and can identify those elongated classes. Another broad of classification is unsupervised classification. It doesn't require human to have the foreknowledge of the classes, and mainly using some clustering algorithm to classify an image data [3]. For pixel classifying algorithms to perform effectively, effects due to topographic relief must be minimized or removed [4].

A number of methods have been developed to correct the effect of topographic variation on satellite images, mainly divided into three main categories (1) Empirical methods such as two stage normalization [5], (2) Lambertian methods such as C- correction, Cosine-T [6] etc., (3) Non-Lambertian methods such as Minneart correction method [7], Slope match [8].It is reported [9] that slope match is most suitable technique for true quantitative retrieval of spectral reflectance, especially in shady area on mountainous regions.In this paper, Slope match topographic correction technique has been applied on to maximum likelihood classifier on multispectral data are carried out in mountainous regions to analyze the effect of topographic correction on maximum likelihood classifier.

II. Study Area

Two almost cloud free satellite images of MODIS (Terra platform) of 02nd November 2009(Initial image) and 04thFeburary 2010(Final image) are used in the present work lies between latitude of 32.99 degree to 32.26 degree North and longitude of 77.00 degree to 77.49 degree East to study the influence of topography on maximum likelihood classifier. The salient specifications of MODIS sensor are given in the Table 1. In this research only first 7 bands of MODIS sensor has been used because it covers Land / Cloud / Aerosols Properties.

III. Image Pre-Processing

Satellite Image Processing and Analysis should be carried out on multi-temporal images. Pre-processing the satellite imageries should be used for various Radiometric/ Geometric corrections, Data preparation, Image Interpretation & Analysis.

A. Geo-Referencing

Geo-referencing refers to the process of assigning map coordinates to image data. Raw data image contains no information about the data, so we have to geocode the data to get the actual information about the area, distance between points, scale which is the primary requirement of the digital data. In this study, geo-referencing of the images have done using the 'Image Geometric Correction' module of the ERDAS 9.1 (Leica Geosystems GIS and Mapping LLC) software.

B. Reflectance Normalization

The atmospherically corrected surface spectral reflectance under lambertain assumption for MODIS is computed using (1) as defined in [10-11].

$$R_\lambda = \frac{\pi(L_{sat\lambda} - L_p)d^2}{(E_0 \cos\theta_z + E_d)} \qquad (1)$$

Where E_0 is the exo-atmospheric spectral irradiance (refer Table 1) for MODIS, θ_z is the solar zenith angle and calculated for each pixel [12], d is the earth – sun distance in astronomical units and calculated using the approach of [13], E_d is the downwelling diffused radiation and assumed zero according to [14]. L_p is the path radiance which has computed using [15]. Final normalized reflectance images of initial and finalimage for MODIS have shown in fig. 1 (a) and (b) respectively.

Topographic Normalization

Nichol et al. [8] proposed slope match technique which corrects the topographic effect on images with very low illumination due to very steep terrain, very low Sun angle, or both.

$$R_\lambda^t = R_\lambda + (R_{max} - R_{min})\left(\frac{<\cos i>_s - \cos i}{<\cos i>_s}\right) C_\lambda \quad (2)$$

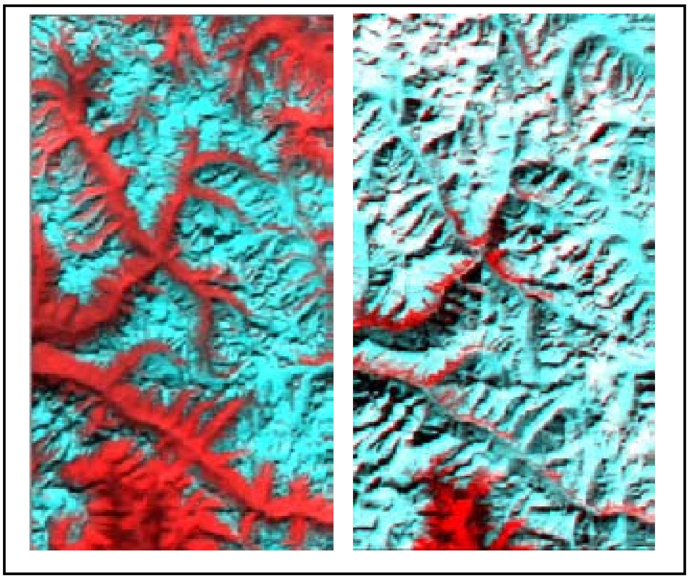
Where R_λ^t, is topographically corrected spectral reflectance, R_λ is spectral reflectance on the tilted surface, $R_{\lambda max}$ and $R_{\lambda min}$ is maximum and minimum spectral reflectance and estimated from topographically uncorrected reflectance R_λ image, $< \cos i >_s$ is mean value of illumination on the south aspect. C_λ is normalization coefficient for different satellite bands and estimated using equation given in the literature [8].

$$C_\lambda = \frac{S'_\lambda - N_\lambda}{N'_\lambda - N_\lambda} \quad (3)$$

Topographically uncorrected initial and final for MODIS have shown in fig. 2 (a) and (b) respectively.

Table 1: Salient Specifications of MODIS Sensor

Spectral bands	Spectral wavelength (nm)	Spatial Resolution (m)	Quantization (bit)	Radiance Scale ($mw/cm^2/sr/\mu m$)	Radiance offset	Solar Exoatmostpheric spectral Irradiance ($mw/cm^2/sr/\mu m$)
Band 1	620-670	250	12	0.0026144	0	160.327
Band 2	841-876	250	12	0.0009926	0	98.70
Band 3	459-479	250	12	0.0027612	0	209.071
Band 4	545-565	250	12	0.0021087	0	186.4
Band 5	1230-1250	250	12	0.0005568	0	47.6
Band 6	1628-1652	250	12	0.0002572	0	23.8
Band 7	2105-2155	250	12	0.0000787	0	8.7



(a) (b)

Fig. 1: Normalized Reflectance Images
Initial (02nd Nov 2009) Image
Final (04th Feb 2010) Image

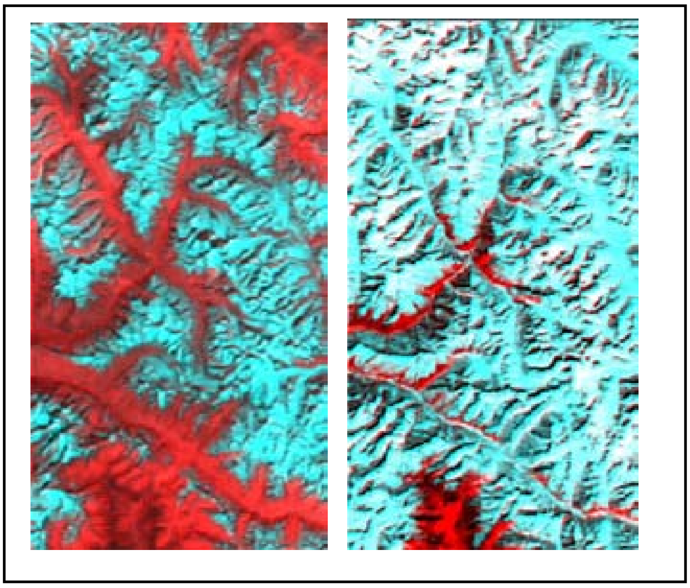


Fig. 2: Topographic Corrected Reflectance Images
Pre (02nd Nov 2009) Image
Post (04th Feb 2010) Image

IV. Maximum Likelihood Classification

This Classification uses the training data by means of estimating means and variances of the classes, which are used to estimate probabilities and also consider thevariability of brightness values in each class.

It is the most powerful classification methods when accurate training data is provided and one of the most widely used algorithm. The main concept of MLC has shown in Figure 3.

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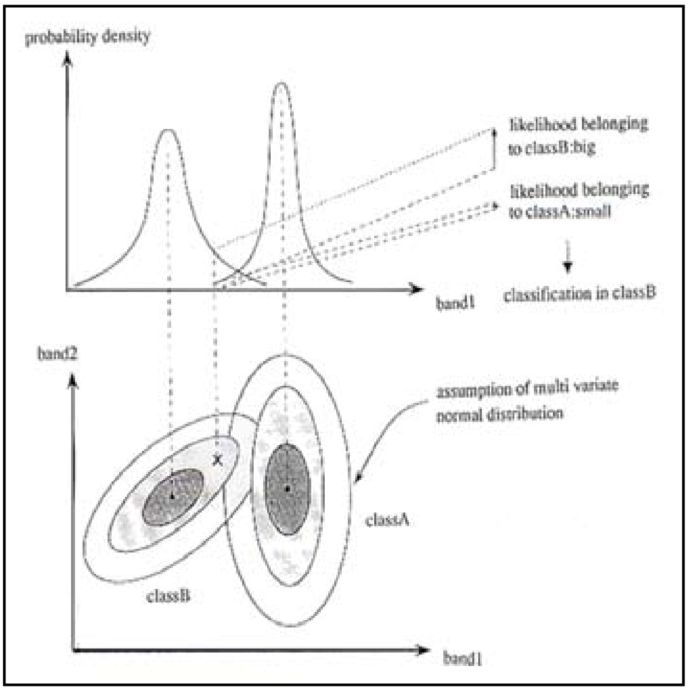

Fig. 3: Concept of Maximum Likelihood Classifier

It is reported [3, 16] that the ML classifier assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. Unless a probability threshold is selected, all pixels are classified. Each pixel is assigned to the class that has the highest probability. If the highest probability is smaller than a threshold, the pixel remains unclassified. The following discriminant functions for each pixel in the image are implemented in ML classification.

$$G_i(x) = ln\, p(W_i) - {}^1/_2\, ln \left|\sum i\right| - {}^1/_2\,(x - m_i)t \sum\nolimits_{\square}^{-1} i\ (x - m_i) \qquad (4)$$

Where i: = class, x = n-dimensional data (where n, is the number ofbands), $p(W_i)$ = probability that class W_i occurs in the image andis assumed the same for all classes, $|\sum_i|$ = determinant of the covariance matrix of the data in class, W_i, $\sum_{\square}^{-1} i$ = its inverse matrix m_i= mean vectorImplementation of the ML classification involvesthe estimation of class mean vectors and covariancematrices using training pattern chosen from knownexamples of each particular class.

MLC takes advantage of both the mean vectors and the multivariate spreads of each class, and can identify those elongated classes. However, the effectiveness of maximum likelihood classification depends on reasonably accurate estimation of the mean vector m and the covariance matrix for each spectral class data [3]. What's more, it assumes that the classes are distributed unmoral in multivariate space.

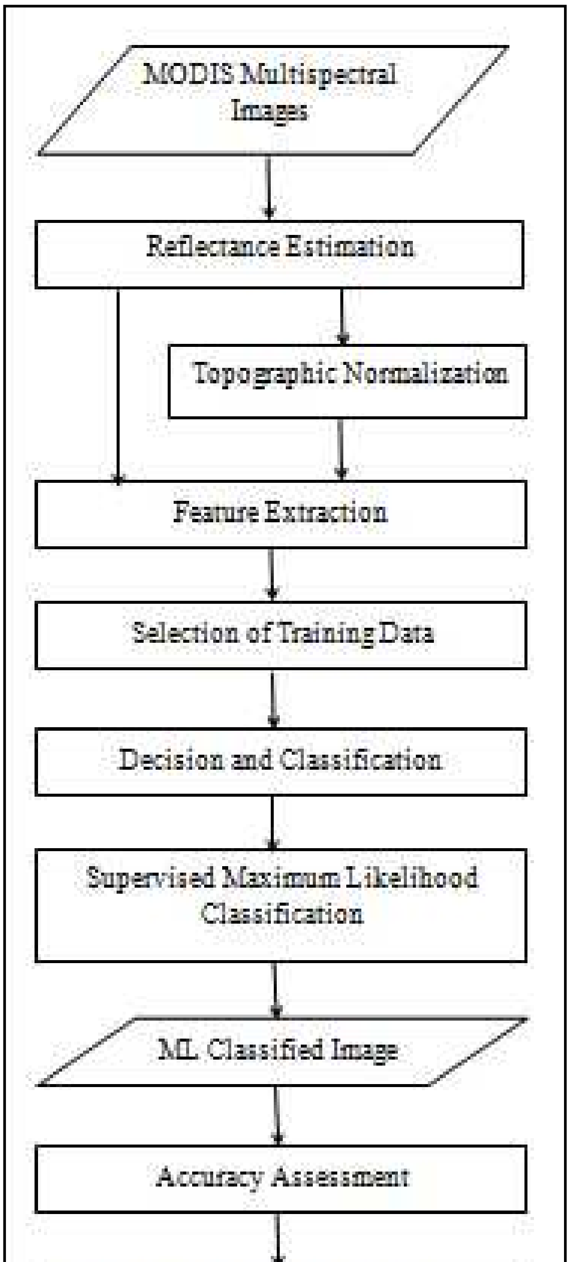

Fig. 4: Methodology of Pre-Processing and Maximum Likelihood Classification

The initial and final maximum likelihood classified without topographic uncorrected images shown in Figure 5. The initial and final maximum likelihood classified with topographic corrected images shown in fig. 6.

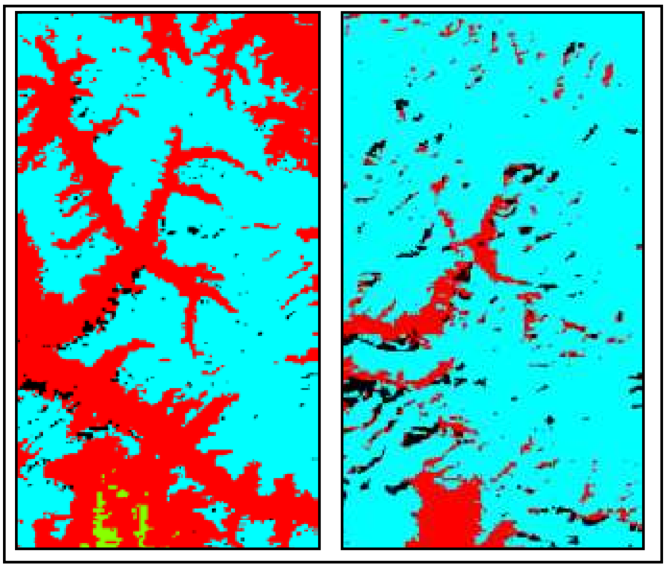

Fig. 5: Topographic Uncorrected Reflectance Images
Initial (02nd Nov 2009) Image
Final (04th Feb 2010) Image

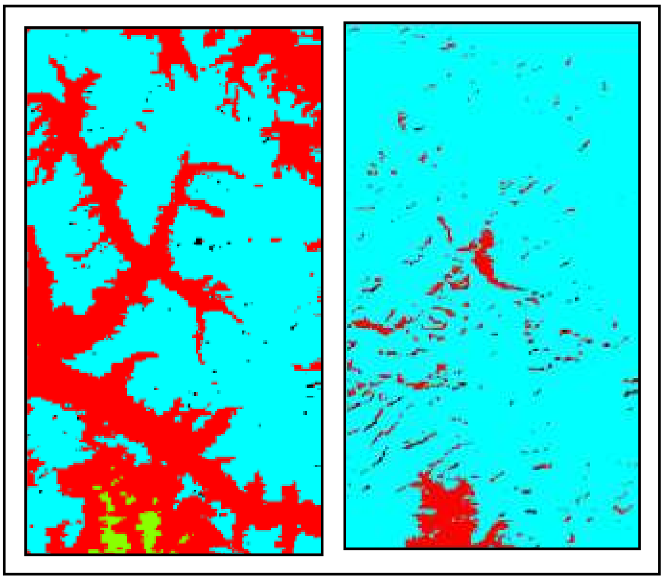

Fig. 6: Topographic Corrected Reflectance Images
Pre (02nd Nov 2009) Image
Post (04th Feb 2010) Image

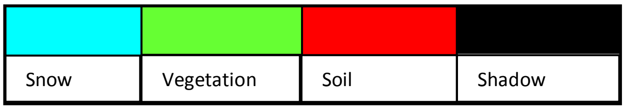

Table 2: Accuracy Assessment using 100 samples of "From-To" MLC without Topographic Correction

02/11/09		Snow	Soil	Vegetation	Shadow	Unclassified	Sum
04/02/10	*Shadow*	50	35	–	–	–	85
	Snow	03	07	01	–	–	11
	Soil	–	–	–	–	–	–
	Vegetation	03	01	–	–	–	04
	Unclassified	–	–	–	–	–	–
	Sum	56	43	01	–	–	100
	Overall Accuracy =	79 %					
	Kappa Coefficient=	0.6868					

Table 3: Accuracy Assessment using 100 samples of "From-To" MLC with Topographic Correction

20/11/09		Snow	Soil	Vegetation	Shadow	Unclassified	Sum
13/10/09	*Shadow*	58	35	–	–	–	93
	Snow	02	04	01	–	–	07
	Soil	–	–	–	–	–	–
	Vegetation	–	–	–	–	–	–
	Unclassified	–	–	–	–	–	–
	Sum	60	39	01	–	–	100
	Overall Accuracy =	85%					
	Kappa Coefficient=	0.7459					

V. Classification Accuracy

The experiment results shows that effects of topographic can be evaluated using accuracy assessment of "from-to" change matrix. A kappa coefficient of 0.6868 and overall accuracy of 79% were achieved for MLC without topographic correction as shown in Table 2. A kappa coefficient of 0.7459 and overall accuracy of 85% were achieved for with topographic corrections as shown in the Table 3.

VI. Conclusion

In this research work, we have concluded that Maximum Likelihood classification exhibits a good potential in land use/cover classification but rugged terrain region limits its performance. To analyze this problem, we compared MLC for topographic corrected images and MLC for uncorrected images. The inclusion of topography significantly improved the accuracy of classification. Overall "from-to" change accuracy of 85% (Kappa coefficient 0.7459) has been achieved with topographic model inclusion as compared to 79% (Kappa coefficient 0.6868) for uncorrected

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images. So the topographic correction can effectively overcome MLC limits in rugged terrain region. It is also analyzed that MLC still depends on the researcher's experience in training sample selection.

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