Support Vector Machines in Moderate Sub-pixel Snow Mapping

Hongen Zhang
College of Environmental Science and Engineering, Tongji University
1239 Siping Road, Shanghai, P.R.China, 200092

Jianfu Zhao
College of Environmental Science and Engineering, Tongji University
1239 Siping Road, Shanghai, P.R.China, 200092

Shi Jiancheng
Institute for Computational Earth System Sciences, UCSB
USA

Abstract–**Snow cover affects physical, chemical and biological processes at many spatial scales and has important societal impacts. Moderate resolution image is currently the most suitable data for monitoring regional snow exten, but has a critical drawback "mixed" pixels. This paper describes an approach based on a relatively new technique in sub-pixel snow mapping, support vector machines (SVMs). In practice, SVM method provided the accurate estimates of the snow cover components: snow cover area estimated from Modis is less than 3% as compared to the reference data from Aster image classification, which show that the support vector machines algorithm for accurate snow cover estimation is promising from moderate resolution satellite imagery.**

I. Introduction

Snow is an important component of the Earth's surface. Its presence affects physical, chemical and biological processes at many spatial scales and has important societal impacts. Snow covered area (SCA) is necessary to parameterize energy balance calculations in mesoscale and general circulation models, to initialize and validate distributed snowmelt modeling efforts, and to estimate snow water equivalence from observations of snow-cover depletion. Because of its importance from both a scientific and resource management standpoint, accurate monitoring of snow cover extent is an important research goal in the science of Earth systems.

Snow is amenable to monitoring using satellite remote sensing and there is a long record of snow cover extent from satellite observations.

The Moderate Resolution Imaging Spectroradiometer (MODIS), is designed to provide quantitative estimates of numerous geophysical parameters on a global basis. The high spatial resolution and numerous MODIS spectral bands in the 0.4 to 2.5 μm wavelength region allow more accurate monitoring of snow cover extent on a global basis than is possible with other operational satellites.

Currently operational MODIS snow mapping algorithms is binary algorithm, the validation indicate that classification accuracy of the current MODIS snow-cover mapping algorithm is very high for cover types with low stature or sparse vegetation.But we can also see a large range of RMSE with a maximum 49.5 % in alpine area.

We can consider that the error of MODIS snow mapping algorithm come from the mixed pixels. The problem is severe over rugged terrain, where extreme variations in snow cover, vegetation type, canopy density, and lithology occur over small horizontal distances, leading to mis-classification of snow-covered areas.

Mixture modelling is becoming an increasingly important tool in the remote sensing as researchers attempt to resolve the sub-pixel, mixture information, which arises from the overlapping land cover types within the pixel's instantaneous field of view. Recently, the linear spectral mixture analysis, fuzzy c-means clustering and neural network techniques have been applied to subpixel snow mapping using AVIRIS, TM , and AVHRR.

This paper describes an approach based on a relatively new technique in sub-pixel algorithms: support vector machines (SVMs)[1]. SVMs has many advantages in spectral mixture analysis, it automatically selects the relevant pure pixels from a much larger database and can apply in three cases: **linearly-separable, linearly-non-separable and** non-linear data sets.

II. SUPPORT VECTOR MACHINE

The principle of the SVM-based solution for the learning process is very briefly described below [2]. Suppose that the training data:

$$D = \{(\mathbf{x}_1, y_1), \cdots, (\mathbf{x}_l, y_l)\}, \quad \mathbf{x} \in R^n, \quad y \in \{-1,1\} \quad (1)$$

can be separated by a hyperplane:

$$w^T x + b = 0 \quad (2).$$

The set of vectors is said to be optimally separated by the hyperplane if it is separated without error and the distance between the closest vector to the hyperplane is maximal.

A separating hyperplane in canonical form must satisfy the following constraints,

$$y_i[w^T x_i + b] \geq 1 \quad (3)$$

Then the hyperplane that optimally separates the data is the one that minimises

$$\Phi(w) = \frac{1}{2}\|w\|^2 \quad (4)$$

Classical Lagrangian duality enables the problem.The optimal separating hyperplane is given by

$$w^* = \sum_{i=1}^{l} \alpha_i y_i x_i \quad (5)$$

$$b^* = -\frac{1}{2} w^{*T}(x_r + x_s)$$

where x_r and x_s are any support vector from each class satisfying,

$$\alpha_r, \quad \alpha_s > 0, \quad y_r = -1, \quad y_s = 1 \, (6)$$

The hard classifier is then,

$$f(x) = \mathrm{sgn}(w^{*T} x + b^*) \quad (7)$$

A soft classifier is used here which linearly interpolates the margin,

$$f(x) = h(w^{*T} + b) \quad (8)$$

$$\text{where,} \quad h(z) = \begin{cases} 0 & : \quad z < -1 \\ (z+1)/2 & : -1 \leq z \leq 1 \\ 1 & : \quad z > 1 \end{cases}$$

The discussion has been restricted to the case where the training data is linearly separable. However, in general this will not be the case. In the case where it is expected (or possibly even known) that a hyperplane can correctly separate the data, a method of introducing an additional cost function associated with misclassification is appropriate. To enable the optimal separating hyperplane method to be generalised, Cortes and Vapnik[3] introduced non-negative variables: $\xi_i > 0$, and a penalty function,

$$F_\sigma(\xi)_i = \sum_i \xi_i^\sigma, \sigma > 0 \quad (9)$$

where the ξ_i are a measure of the misclassification errors. The optimisation problem is now posed so as to minimise the classification error as well as minimising the bound on the VC dimension of the classifier. The constraints of Equation (3) are modified for the non-separable case to

$$y_i[w^T x_i + b] \geq 1 - \xi_i, i = 1,2,...l \quad (10)$$

The generalised optimal separating hyperplane is determined by the vector w, that minimises the functional,

$$\Phi(w, \xi) = \frac{1}{2}\|w\|^2 + C\sum_i \xi_i \quad (11)$$

(where **C** is a given value) subject to the constraints of Equation(10). The solution
to the optimisation problem can given by the Lagrangian approach.

III. DATA and METHODS

MODIS is an EOS facility instrument designed to measure biological and physical processes on a global basis every one to two days. Its moderate resolution image is currently the most suitable data for monitoring regional snow extent.
ASTER is an instrument provided for the EOS Terra platform by the Japanese Ministry of Economy. It provides high spatial resolution (15-90 m) multispectral images of the Earth surface. These data bridge the gap between field observations and data acquired by coarse spatial resolution instruments such as

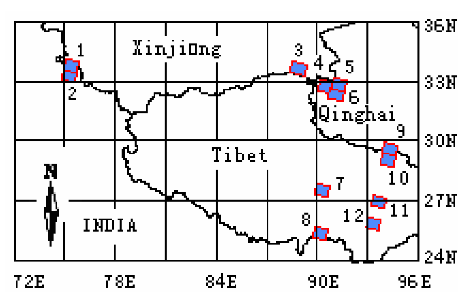

Figure 1. Location of Aster image

MODIS, and between local-process models and regional models. Here we classify ASTER image in three visible and near-infrared channels with 15-m resolution as “ground truth” to validate our MODIS snow mapping algorithm.

The study area is situated in the Tibetan Plateau. The available data consist of 12 MODIS image and Aster image corresponding days and area for validation, as shown in figure 1.

Only band 4 and band 6 is used in the application. The training data in SVM is selected manually from image, the data is split into two base class: snow and non-snow (soil, grass, shrubs, etc), as shown in figure 2. The modis data is assumed **linearly-non-separable-and-C** is supposed to be1.0.

IV. RESULT and CONCLUTION

SVM approach to unmixing pixel cover composition described previously was applied to the MODIS data, the estimation of snow of the 12 image is shown in table1 and figure 2.

In summary, SVM method provided the accurate estimates of the snow cover components: snow cover area estimated error from Modis is less than 4.4% as compared to the reference data from Aster image classification and the average of error is 1.9%, the least error just is -0.04% The assumption that the modis data is **linearly-non-separable** which imply that some pixels is overlapping sets of pure pixels, is upheld to a large extent as evidenced by the rather high accuracy of snow cover estimation. The results of this study suggest that the comparatively accurate snow cover estimation is attainable from moderate resolution satellite imagery using support vector machines algorithm.

REFERENCE

[1] Martin Brown, Hugh G. Lewis, and Steve R. Gunn, Linear Spectral Mixture Models and Support Vector Machines for Remote Sensing, IEEE Transactions on Geoscience and remote sensing, 38(5):2346-2360, 2000

[2]Steve R. Gunn .Support Vector Machines for Classification and Regression,,17-30,1998

[3]C. Cortes and V. Vapnik. Support vector networks. machine learning, 20:273 – 297,1995.

TABLE I

UNMIXING RESULT of SVM

NO	SVM (Km^2)	Aster (Km^2)	SVM Error(%)	NO	SVM Area(Km^2)	Aster (Km^2)	SVM Error(%)
No.1	584.763	580.973	-3.8	No.7	519.83	512.91	4.1
No.2	790.382	794.51	2.39	No.8	343.92	346.45	5.13
No.3	629.622	607.591	1.48	No.9	383.09	383.91	-3.5
No.4	285.327	301.392	0.8	No.10	1005.2	1015.1	-4.1
No.5	612.598	592.745	4.43	No.11	759.84	749.87	-2.4
No.6	142.346	146.785	2.81	No.12	943.64	961.2	-0.04

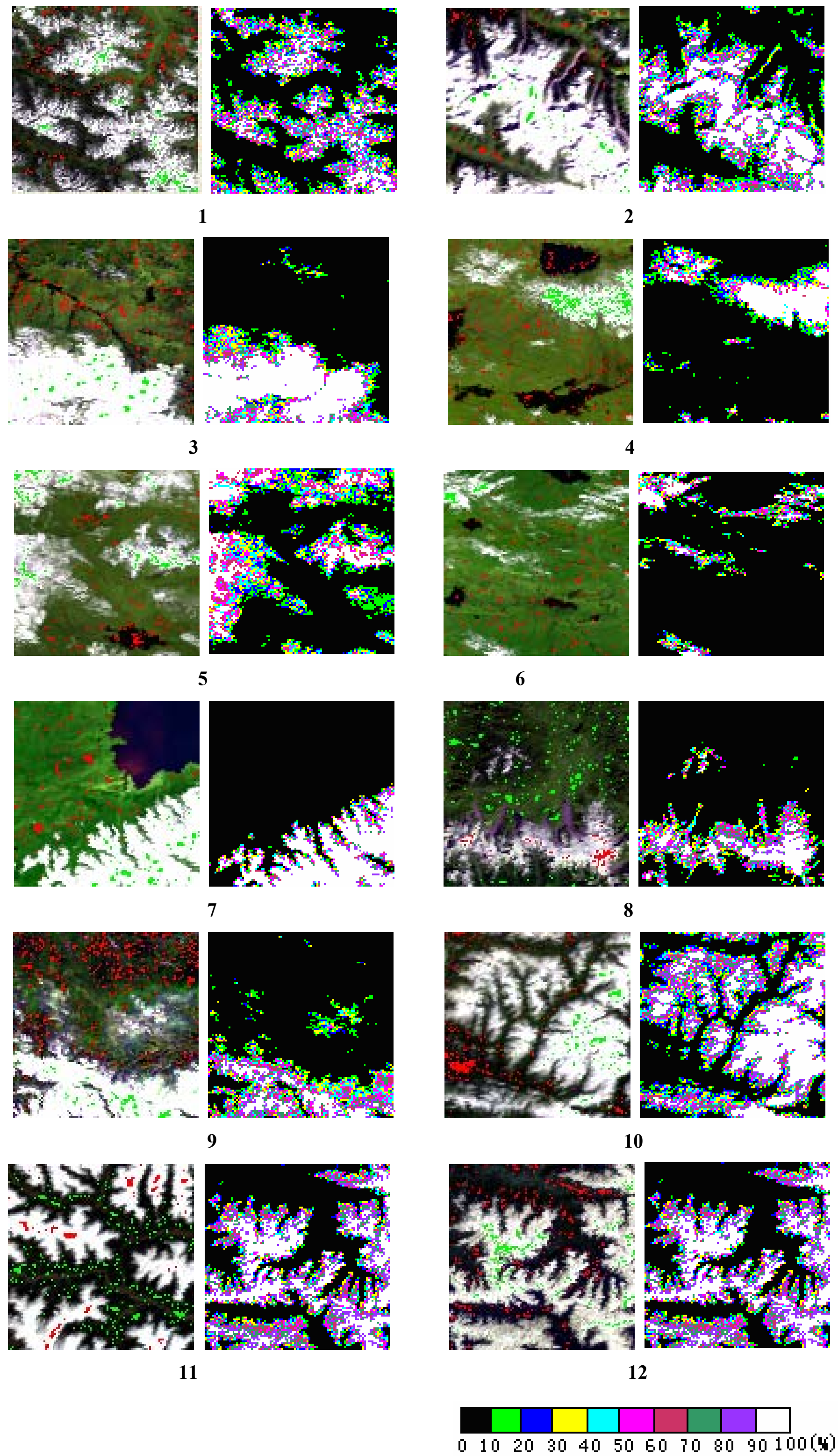

Figure 2 Training data in the image and pseudocolor image of the percent of snow cover area in SVM algorithm