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Band Combinations Application for Discrimination of *Cirsium arvense* and *Stachys byzanthina* Distribution

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Abstract

Invasion by invasive species is an ecosystem level problem in restoration. Invasive species present a threat to the restoration of many natural areas and often drive ecological changes that may be irreversible and thus preclude successful restoration. Invasion prevention, early detection and removal of these species are key to their control and management. This paper aims to investigate the efficiency of different band combinations of Landsat TM image in identifying invasive species *Cirsium arvense* and *Stachys byzanthina* in Vazroud rangelands of Iran. For optimizing results, the Cos (t) model was used for atmospheric correction on the image. Then some false bands such as NDVI, PCA, MNF and Tasselled Cap were applied on data. Supervised algorithms using maximum likelihood, minimum distance of mean and parallelepiped were used as classification techniques for evaluation against ground truth map. The results indicated that maximum likelihood maps than maps if other algorithms and B3, B4, NDVI combination than other band combinations were the most suitable for discriminate these species.

Keywords: Band combination, Classification, invasive species, Remote sensing

Introduction

Invasive plant species, whether introduced intentionally or accidentally, have been found to alter nutrient cycling, lead to reduction in plant diversity, threaten rare and endangered plant and animal species, reduce pollination and seed output of native plants (Laba et al., 2008). Therefore, invasive species are a current focus of interest for ecologists, biological conservationists and natural resources manager. Ground surveys are still commonly used for most invasive species mapping projects despite intensive labor requirements, associated high economic costs, and incomplete coverage of the landscape. Improved methods to accurately determine the current distribution of invaders are required to better assess their environmental impacts, formulate effective control strategies, and forecast potential spread (Evangelista et al., 2009). In the last decades, remote sensing has significantly contributed to vegetation mapping of remote areas and for mapping structurally defined vegetation units on global, regional and local extents (Gamon et al., 2004; McDermid et al., 2005).

For example, Joshi et al (2006) for mapping and modelling of seed productivity of invasive shrub *Chromolaena odorata* using ETM+ images showed that localization of reproductive and non- reproductive could significantly reduce eradication and control costs. This may be prove particularly valuable when implementing control measures under circumstances of limited capital and manpower. Bradley and Mustard (2006) in characterizing the landscape dynamics of an invasive plant and its risk of invasion using remote sensing and MSS, TM and ETM+ data created a risk map of future *B. tectorum* invasion that may aid land management. Huang et al. (2009) investigated the phenologies of semi-desert grassland in southern Arizona across a gradient of invasions by invasive perennial grass *E. lehmanniana* using MODIS NDVI and its brightness bands. They found that *E. lehmanniana* invasions altered ecosystem-level phenology in the semi-arid grasslands.

Evangelista et al. (2009) used NDVI, SAVI and RVI indices, tasselled cap transformations and maximum entropy model for mapping invasive *Tamarix sp*. They found that time-series analysis can better distinguish phonological differences between *Tamarix* and native flora than a single-scene analysis. Adam and Mutanga (2009) in spectral discrimination of *Cyperus papyrus* in swamp wetlands using field spectrometry and hierarchical method based on three levels of analysis of variance, classification and regression trees and Jeffries-Matusita distance concluded that spectral reflectance of Papyrus and its co-existing species is statistically different and the best discrimination of Papyrus from its co-existing species is possible with six bands located in the red-adge and near-infrared regions of the electromagnetic spectrum. Yang and Everitt (2010) evidenced that satellite imagery is a useful data source for distinguishing *Juniperus asheri*, *Gutierrezia sarothrae* and *Eichhornia crassipes* from associated plant species and MNF transformation can significantly reduce the number of bands needed for image classification. Transformed imagery with spatially coherent MNF bands is sufficient for image classification.

These studies show remote sensing compietion and satellite imagery proccessing in discrimination of invasive plants. Invasive species *Cirsium arvense* and *Stachys byzanthina* have changed biodiversity with widespread invasion to rangelands of Vazroud basin. In this study, we present an approach for combining multispectral remote sensing data with field survey information on invasive species. This study is an attempt to study and evaluate the utilities of some of band combinations and algorithms of supervised classification to resolve the problem of composition of shrubby species *Cirsium arvense* and *Stachys byzanthina* from other species and the preparation of their spatial distribution map in the study area.

Materials and Methods

Description of the site

The field site is located in the Northern slopes of Alborz Mountains, in the south of the Caspian Sea (Figure 1). The field site includes two ecosystem regions from highland to the forest zone, all within the Central Alborz zone. In highland, the dominant vegetations are related to the rangeland. Study area (rangelands) is located at longitude of 52º 01’ 43’’ to 52º 12’ 23’’ E and latitude of 36º 14’ 13’’ to 36º 18’ 49’’ N. Range condition is moderate and due to height, edaphic and geomorphological changes, various vegetation forms are observed that belong to *Asteraceae*, *Poaceae* and *Lamiaceae* families.

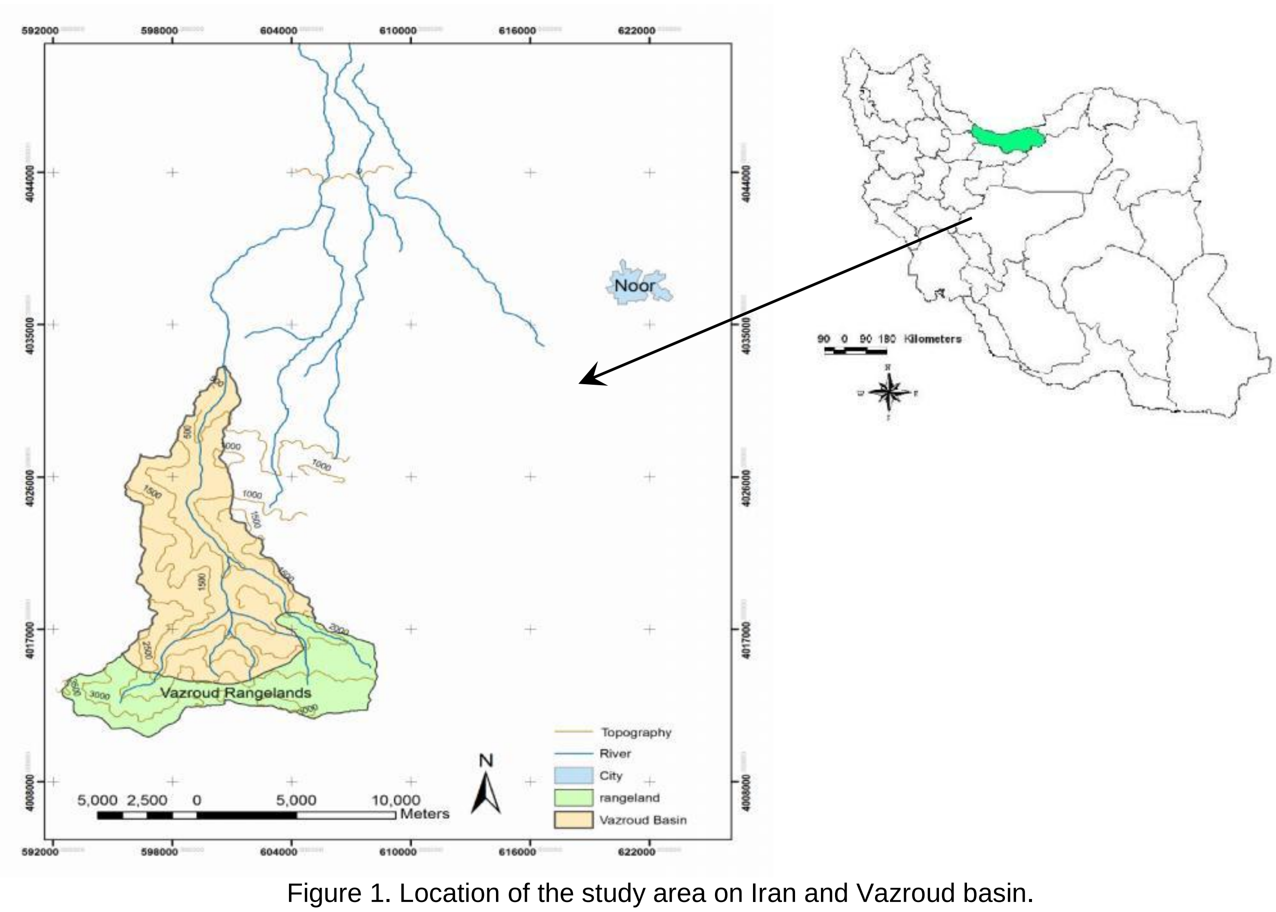

Figure 1. Location of the study area on Iran and Vazroud basin.

Official data

Topography map (1:50000) which all of the information such as contour lines, hydrographic network and roads were digitized and prepared for the field studies. Used digital data in this study are part of a frame of TM sensor of Landsat satellite in 7 spectral bands. This image was taken on June 3, 2010.

Preprocessing and preparing of official data

Since the raw data received from the sensors usually have errors, so in the preprocessing stage, used data have been monitored in terms of radiometric errors such as striped and atmospheric disorders such as clouds. Also by analyzing the sporadic band’s histogram and analyzing statistical parameters of mean and standard deviation, normal distribution was detected in the data. Geometric correction were made using first order polynomial transformation model and nearest neighbor method for resampling. The image was corrected geometrically by choosing 21 ground control points with suitable distribution on basin area following image to image compatibility and its root mean square errors were obtained to 0.23 pixels. The geo-referenced image was then clipped to the final study area.

For atmospheric correction, spectral values for each band converted to radiance and reflectance using calibration coefficients of sensor and equation (1):

$$L = Gain \times DN + Offset \quad \ldots\ldots\ldots\ldots\ldots\ldots \text{(1)}$$

Where, L: Spectral radiance for each band ($Wm^{-2}sr^{-1}\mu m^{-1}$), DN: Digital number for each band, Gain and Offset: Calibration coefficients of sensor.
According equation (2) spectral radiance converted to reflectance:

$$\rho_\lambda = \frac{\pi . L_\lambda}{ESUN_\lambda . \cos\theta . d_r} \ldots\ldots\ldots\ldots\ldots\ldots \text{(2)}$$

ρ_λ: Reflectivity for bands (0-1), $ESUN_\lambda$: Mean solar irradiance for bands ($Wm^{-2}sr^{-1}\mu m^{-1}$), θ: Solar incidence angle, d_r: The inverse squared relative earth-sun distance (Chavez, 1988).

Field sampling and ground truth map production

This project capitalizes on the early phenology of *Cirsium arvense* and *Stachys byzanthina* (coinciding with plat growth peak in the region and before livestock entering it) to distinguish these from other vegetation. To determine training samples, 30 points were sampled by GPS device using stratified-random sampling method. In such a way that by using GPS and recording central point geographical coordinates of a class of *Cirsium arvense* and *Stachys byzanthina* and also their angles coordinate as a circle, first a point map was built in GIS environment and then ground truth map was prepared by connecting the points of these polygons. Percentage of these species canopy cover was 50- 60 in training samples visually.
The steps of this study are shown in Figure 2.

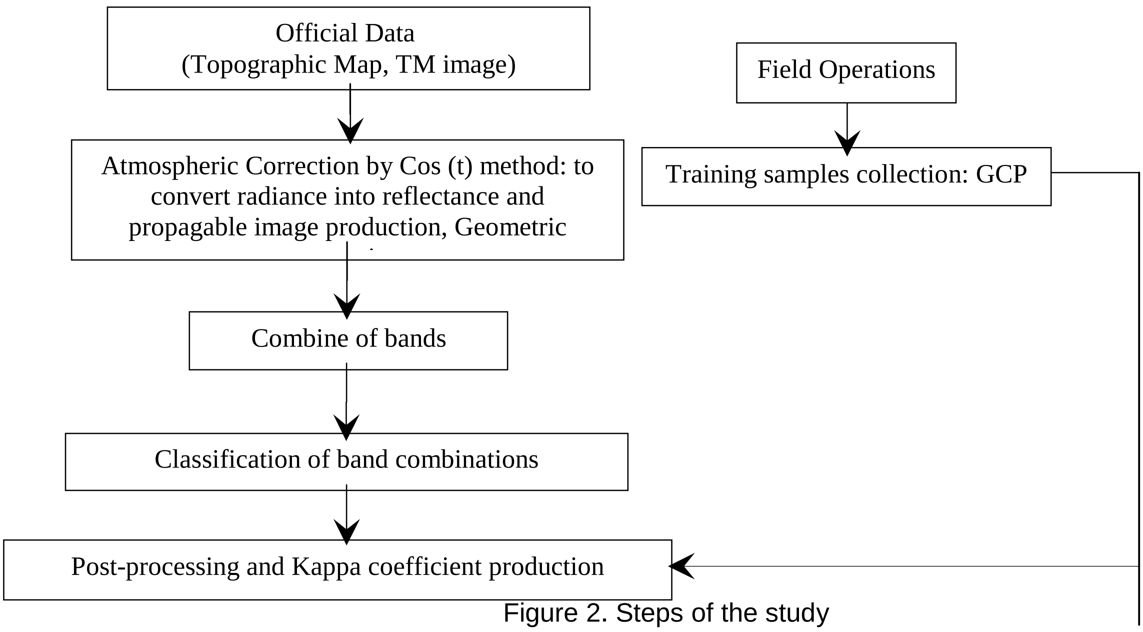

Figure 2. Steps of the study

Band Combination Selection

To puderdose of spectral information and better separation of categories, are created and applied false bands such as Normalized difference vegetation index (NDVI), Principal component analysis (PCA), Minimum noise fraction transformation (MNF) and Tasselled cap transformation with different spectral transformations on principal bands.

Normalized difference vegetation index

NDVI is a non-linear transformation of the ratio between the visible (R) and near-infrared (NIR). The NDVI is commonly used to measure vegetation canopy characteristics such as biomass, leaf area index and canopy cover. We calculated NDVI using the following expression:

$$NDVI = (NIR - R)/(NIR + R) \quad \ldots\ldots\ldots\ldots\ldots (3)$$

NDVI values range from -1 to 1 and are a proxy for photosynthetic greenness of land cover (Tucker and Sellers, 1986).

Principal Component analysis

Principal Component analysis uses to produce uncorrelated output bands, to segregate noise components, and to reduce the dimensionality of data sets. Because multispectral data bands are often highly correlated, the Principal component transformation is used to produce uncorrelated output bands. This is done by finding a new set of orthogonal axes that have their origin at the data mean and that are rotated so the data variance is maximized.

PC bands are linear combinations of the original spectral bands and are uncorrelated. You can calculate the same number of output PC bands as input spectral bands. The first PC band contains the largest percentage of data variance and the second PC band contains the second largest data variance, and so on The last PC bands appear noisy because they contain very little variance, much of which is due to noise in the original spectral data. Principal Component bands produce more colorful color composite images than spectral color composite images because the data is uncorrelated (Jensen, 1996; Faust, 1989).

Minimum noise fraction transformation

The minimum noise fraction transformation implemented in ENVI was used to reduce noise and spectral dimensionality. The MNF transform is based on two principal components analysis transformations and divides the hyperspectral data into two parts: one part associated with large eigenvalues and coherent eigenimages, and a complementary part with near-unity eigenvalues and noise-dominated images (Green et al, 1988). By using the smaller number of coherent eigenimages or MNF bands, the computational time and complexity for image analysis are reduced and the noise is separated from the data, thus improving spectral processing results.

Tasselled Cap transformation

Tasselled Cap transformations are weighted composites of the six Landsat bands into three orthogonal bands that have been useful in measuring soil brightness (tasselled cap, band 1), vegetation greenness (tasselled cap, band 2), and soil/vegetation wetness (tasselled cap, band 3). These transformations have been described as a guided and scaled principal components analysis (Kauth and Thomas, 1976; Jin and Sader, 2005).

Classification and Accuracy assessment

Supervised classification techniques, including minimum distance, parallelepiped and maximum likelihood were used to classify the images and ENVI was chosen as the image processing software. Maximum likelihood classification 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 you select a probability threshold, all pixels are classified. Each pixel is assigned to the class that has the highest probability.

The minimum distance technique uses the mean vectors of each endmember and calculates the Euclidean distance from each unknown pixel to the mean vector for each class. All pixels are classified to the nearest class unless a standard deviation or distance threshold is specified, in which case some pixels may be unclassified if they do not meet the selected criteria. Parallelepiped classification uses a simple decision rule to classify multispectral data. The decision boundaries form an *n*-dimensional parallelepiped in the image data space. The dimensions of the parallelepiped are defined based upon a standard deviation threshold from the mean of each selected class (Zobeiry and Majd, 2005). If a pixel value lies above the low threshold and below the high threshold for all *n* bands being classified, it is assigned to that class. If the pixel value falls in multiple classes, ENVI assigns the pixel to the last class matched. Areas that do not fall within any of the parallelepipeds are designated as unclassified.

For classification, different numbers of area, or regions of interest (ROIs), with known cover types were digitized on the image as the training samples to represent respective classes.

Most important measures of classification accuracy including overall accuracy and kappa coefficient were calculated based on error matrices. Kappa analysis was also performed to test if each classification was significantly better than a random classification and if any two classifications were significantly different (Congalton and Green, 1999). The coefficient is calculated by multiplying the total number of pixels in all the ground truth classes (N) by the sum of the confusion matrix diagonals (X_{kk}), subtracting the sum of the ground truth pixels in a class times the sum of the classified pixels in that class summed over all classes ($X_{k\Sigma} X_{\Sigma k}$), and dividing by the total number of pixels squared minus the sum of the ground truth pixels in that class times the sum of the classified pixels in that class summed over all classes:

$$k = \frac{N \sum_k X_{kk} - \sum_k X_{k\Sigma} X_{\Sigma k}}{N^2 - \sum_k X_{k\Sigma} X_{\Sigma k}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

k varies from 0 (full disagreement) to 1 (full agreement) and if k<0.4, 0.4<k<0.75 and k>0.75, it will be classified as poor, fair and power, respectively (Foody, 1992). The best classification happen when overall accuracy and kappa coefficient are both high (>0.6).

Results and Discussion

The corrected bands were applied for band combinations creation and the vegetation map for each combination was obtained.

The three classificatin methods examined in these studies performed well, though maximum likelihood was superior to the other two methods in most cases, B3,B4,NDVI combination and then NDVI, MNF_2, PC_1 combination than other band combinations were the most suitable for discriminate these species (Table 1 and Table 2).

Table 1. Overall accuracy (%) for band combinations of supervised algorithms

	Algorithms		
Band combinations	Maximum likelihood	Minimum distance	Parallelepiped
B_3, B_2, NDVI	77.9	58.2	34.6
B_3, B_4, NDVI	85.5	62.5	19.2
NDVI, MNF_2, PC_1	82.6	68.8	21.75
SAVI $L_{0.5}$, NDVI, PC_1	79	75.7	29.6
Tasseled cap	64.5	75.7	30

Table 2. Kappa coefficient for band combinations of supervised algorithms

	Algorithms		
Band combinations	Maximum likelihood	Minimum distance	Parallelepiped
B_3, B_2, NDVI	0.75	0.5	0.25
B_3, B_4, NDVI	0.83	0.55	0.12
NDVI, MNF_2, PC_1	0.78	0.6	0.14
SAVI $L_{0.5}$, NDVI, PC_1	0.73	0.63	0.2
Tasseled cap	0.71	0.7	0.2

Conclusion

Remote sensing approaches for vegetation mapping using vegetation indices have been increasingly applied over the last years. These approaches combine detailed ground data from field surveys with remotely sensed data, showing great potential in the field of vegetation mapping (Allexander and Millington, 2000).

As a practical finding of the present study, it’s possible to state that in research plans performed by administrative instruments and consulting engineers, time criterion (and cost as a function of spent time) is highly significant, so using approaches which result in acceptable accuracy by spending the minimum level of cost and time is preferred; consequently the present study findings propose remote sensing technique to zone invasive vegetation. Results may differ for images acquired from different sensors, so it would be interesting to study the effect these combinations with remotely sensed data acquired from other sensors. Mapping, modelling and predicting biological invasion will still be a major challenge for ecologists because the biological processes involved are very complex. To enhance the result of invasion mapping, there is a clear need of combined use of remote sensing, GIS and expert knowledge. Management dealing with invasive species requires accurate mapping and modelling techniques and development of those will be a valuable step toward conservation of native biodiversity. It is recommended that this study be expanded in future to incorporate various resolutions (spectral, spatial and temporal) and would be interesting to see how/if classification accuracies are effected with respect to various resolution combinations.

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