CLASSIFICATION OF CLOUDS WITH OBJECT ORIENTED TECHNIQUE

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ABSTRACT:

Rainy clouds having high densities are considered as one of the main causes of flood events, therefore detection and classification of clouds can be very valuable for flood forecasting. In this study NOAA/AVHRR satellite images were used for object oriented classification. Sixteen bands were produced and utilized for cloud classification. This included the main five bands of NOAA/AVHRR and other important information such as albedo of band 1 and 2, brightness temperature of band 3,4 and 5, solar zenith and azimuth angles, land surface temperature, sea surface temperature, normalized difference vegetation index, deviation of nadir and cloud height. Multi-resolution segmentation followed by bi-spectral technique and hierarchical classification were performed using the sixteen produced layers. The obtained kappa coefficient and the overall accuracy were relatively high (kappa= 0.887, overall Acc.= 0.905). The results of the study demonstrated that the object oriented classification can be considered as a proper method for cloud detection and classification.

1. INTRODUCTION

The detection and classification of clouds in meteorological satellite data with known pixel based approaches is principally based on spectral analyses and every so often simple spatial analyses are used additionally. When classifying structures performed with hundreds of pixels and relationships between them, these approaches are called conceptual methods. Object orient classification is a conceptual method that operates on groups of pixels (image objects) and defines the relationship between them. There are two advantages for Cloud classification with object oriented techniques. First, this approach reduces within-class spectral variation and generally removes the so-called salt-and-pepper effects that are typical in pixel-based classification. Second, a large set of features characterizing objects' spatial, textural, and contextual properties can be derived as complementary information to the direct spectral observations to potentially improve cloud classification accuracy (Liu, D and Xia,F, 2010).

While a number of studies have shown the object-based classification over land cover and land use mapping (Lewinski and Zaremski, 2004.; Shattri, et al. 2003; Oruc et al., 2005; Mathieu and Aryal, 2005; Lara et al 2006; Volker, 2003) less attention has been paid to its ability to cloud classification.(Göttsche and Olesen, 2005; haji mir rahimi and bai, 2008 in persian)

The purpose of this letter is to provide a more complete evaluation of object-based cloud classification.

2. DATA AND METHODS

2.1. Data

In this study the classification of clouds was performed using low resolution satellite image, NOAA/AVHRR data, that is taken from northeast of Iran in august of 2005 (NOAA14; 11-08-2001, 14:16 UTC). It has a spatial resolution about 1.1 km in nadir and 5 spectral channels with the following wavelength ranges have shown in table 1.

spectral channels	Range of electromagnetic
Ch1: 0.58 – 0.68 7m	VIS (visible)
Ch2: 0.725 – 1 7m	NIR (near infrared)
Ch3: 3.55 – 3.93 7m	MIR (meddle infrared)
Ch4: 10.5 – 11.5 7m	TIR (thermal infrared)
Ch5: 11.5 – 12.57m	TIR (thermal infrared)

Table1. Channel of NOAA/AVHRR

2.2. Methods

In this study, we performed the image processing (corrections and calibrations) and clipping the study area from images, primarily. Then the cloud classification was applied. Figure 1 is a schematic diagram that illustrates the steps and type of need data in this study. And Figure 2a and 2b show the visible and infrared bands respectively.

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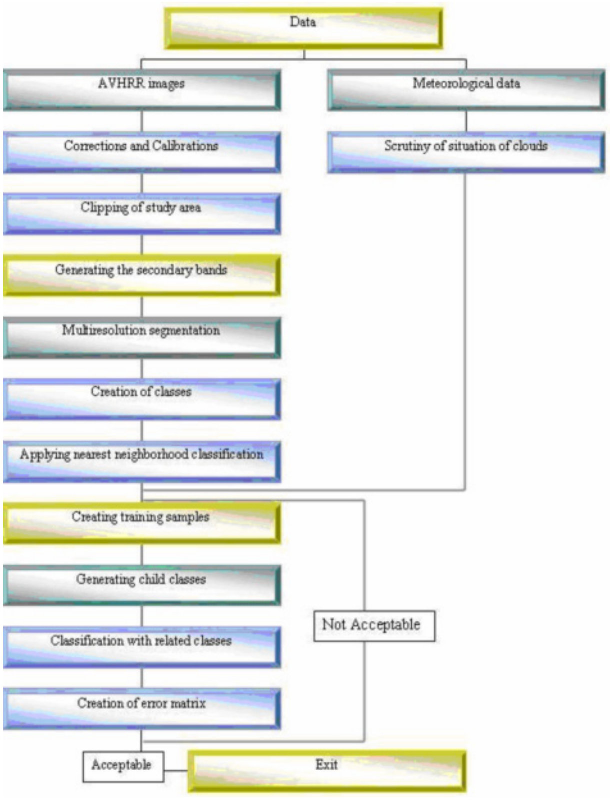


Figure 1. Schematic diagram illustrates the steps and type of data in this study

In general, the most effective method for identifying individual cloud types is to obtain a Visible and an IR image of the same scene. The Visible (VIS) channels 1 and 2 of the data were processed for albedo .The VIS image used to identify cloud shapes, textures, organizational patterns, and thicknesses. In general, the thicker a cloud is, the higher its albedo and the brighter it will appear in visible imagery. Thin clouds are often very dark or transparent in visible imagery. Cloud texture refers to its appearance in visible imagery.

Visible satellite data then was compared to an IR image in order to determine the height of the clouds. The IR channels 3, 4 and 5 of the data were processed for brightness temperature. In general, the higher a cloud is, the colder it is. In IR imagery, therefore, lower, warmer clouds will appear darker while high, cold clouds will appear brighter. We put together all this information and performed object oriented method with ecognition software and maked reliable assessments of what types of clouds are present in the image. Additional information such as from criteria, textual or contextual information of the segments then are used in an appropriate way to derive improved classification results.

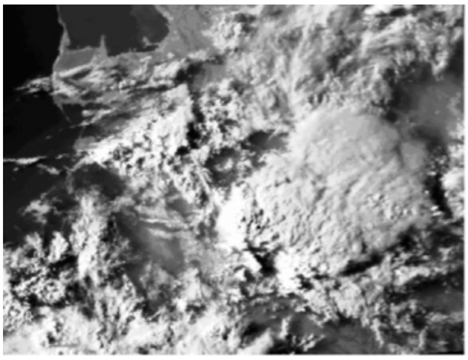


Figure 2a. Band 1 of AVHRR data

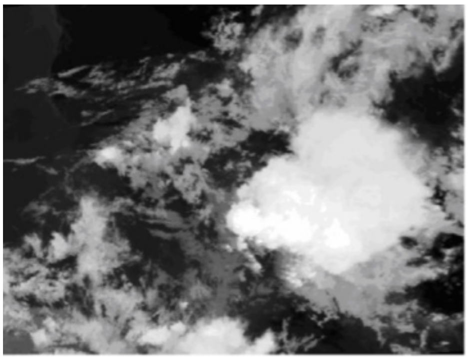


Figure 2b. Band 4 of AVHRR data

The important first step in object orient classification is segmentation. The segmentation algorithm does not only depend on the single pixel value, but also on pixel spatial continuity (texture, topology, shape, channel means, standard deviation, etc) (shattri et al, 2003). The Sixteen components are produced with PCI Geomatica in this study. The five main bands that there are in satellite images (primary components) and the other eleven components such as albedo and brightness temperature of main bands , solar zenith and azimuth angles, Land Surface Temperature (LST) & Sea Surface Temperature (SST), Normalized Difference Vegetation Index (NDVI) and deviation of nadir and cloud height are secondary components.

Form sixteen components, the ten components use directly and others have the same effects on classification. The multiresolution segmentation is selected in this study. This results to a condensing of information and a knowledge-free extraction of image objects. For this method the used AVHRR channels, brightness temperatures of band 4 and 5 and cloud height are weighted by 1, whereas the Digital Elevation Model (DEM), LST & SST and NDVI that show the free cloud areas, are weighted by 0.2 (Göttsche and Olesen, 2005). Since the clouds with medium area and more are important for this study, a fairly medium scale of 50 is chosen for the finest segmentation (level 1 that called analysis level).

Segmenting clouds were produced using infrared or albedo images followed by bi-spectral cloud classification technique. Bi-spectral techniques based on the relationship between cold and brightness temperature of clouds were also used to evaluate classification. Figure 3 shows the multiresolution segmentation that applied on image.

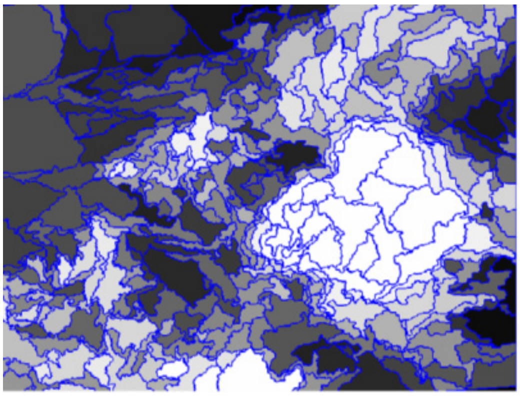


Figure3. Multiresolution segmentation in analysis level

In remote sensing studies we cannot detect a specific cloud in a range of Digital number in visible or infrared images exactly. For example, the cumulonimbus clouds (Cb) in each region and time can are detected with various range of digital number. But studies show that this type of cloud is brighter than others in VIS and IR images or stratus clouds (St) are darker than others in IR images. The other types of clouds can were detected similarly that is showed in figure 4 but texture, shape and thickness of clouds are useful option for decision. Figure 4 is the principle of bi-spectral technique in this study.

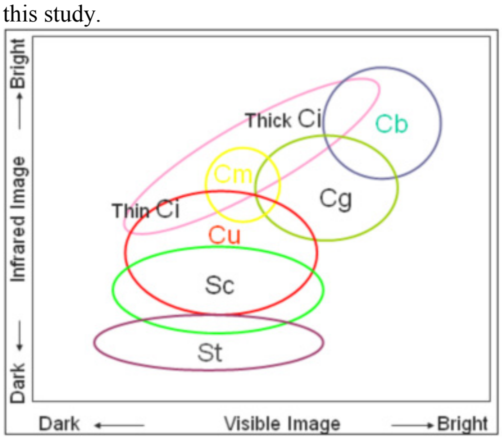


Figure4. Brightness of each type of clouds in VIS and IR images.(Ito ,2000)

3. RESULTS AND DISCUSSIONS

In this study 8 classes were identified that were included a non-cloud class (sea and terrain) and 7 cloud classes (Ns, Ci, Cb, Cu, Cg, Sc, St). After detecting of classes and scrutiny of features (mean, standard deviation, to super object, shape (area and density) and texture (homogeneity, contrast and entropy), classification was carried out. The nearest neighbor classification of level 1 object was performed for mean and standard deviation of AVHRR channels of 1, 2 and 4. The relationships between objects were included in the hierarchical classification for getting the better results. The classifications of clouds were performed in level 2 called cloud level. The result of classification illustrated in figure 5.

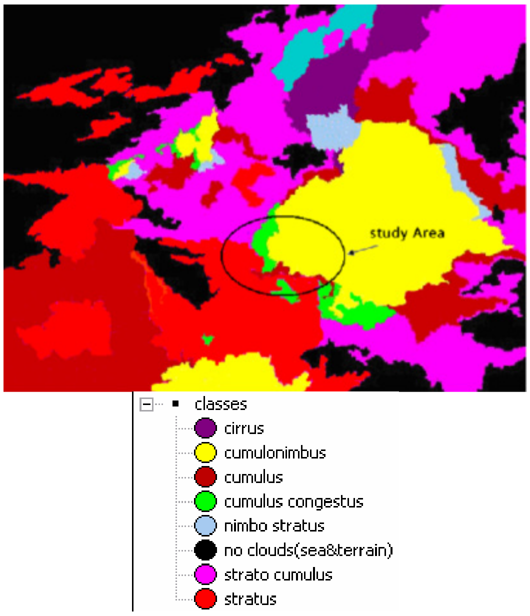
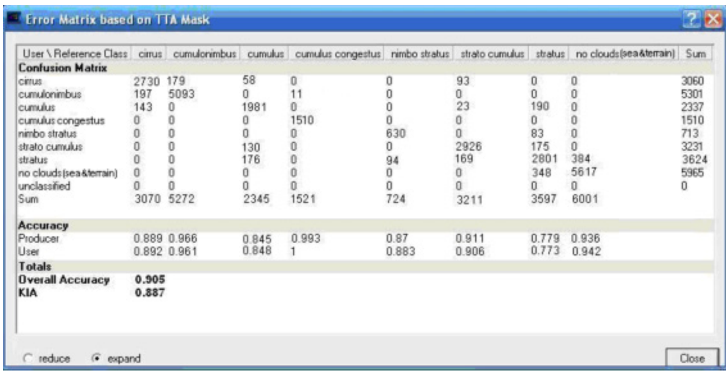


Figure 5. Classified clouds with eCognition

Since the detected cloud in sky of each area is the dominant cloud on that hour and the other type of clouds may be existed during the day, so collecting of control points for accurate assessment is not possible. So, the regions that have the most adaptation with bi-spectral cloud classification theories were used as training samples optically.
The NIR and IR channels 3, 4, and 5 of the data were processed for temperature and brightness. In IR image cold clouds are high clouds, so the colors typically highlight the colder regions Mid height clouds with TB below 230k were identified as cumulonimbus cloud. Darker clouds in IR images were associated to warm stratus, Strato cumulus, cumulus clouds and thin cirrus cloud that were colder than others. Using this knowledge and bi-spectral technique, the sampling areas were selected and error matrix and kappa coefficient performed using TTA MASK in eCognition software. The obtained kappa coefficient was equal of 0.887 and the overall accuracy is 0.905 that illustrate the accurate of classification is high. The window of error matrix based on TTA Mask is showed in figure 6.


Error Matrix based on TTA Mask

User \ Reference Class	cirrus	cumulonimbus	cumulus	cumulus congestus	nimbo stratus	strato cumulus	stratus	no clouds(sea&terrain)	Sum
Confusion Matrix									
cirrus	2730	179	58	0	0	93	0	0	3060
cumulonimbus	197	5093	0	11	0	0	0	0	5301
cumulus	143	0	1981	0	0	23	190	0	2337
cumulus congestus	0	0	0	1510	0	0	0	0	1510
nimbo stratus	0	0	0	0	630	0	83	0	713
strato cumulus	0	0	130	0	0	2926	175	0	3231
stratus	0	0	176	0	94	169	2801	384	3624
no clouds(sea&terrain)	0	0	0	0	0	0	348	5617	5965
unclassified	0	0	0	0	0	0	0	0	0
Sum	3070	5272	2345	1521	724	3211	3597	6001	
Accuracy									
Producer	0.889	0.966	0.845	0.993	0.87	0.911	0.779	0.936	
User	0.892	0.961	0.848	1	0.883	0.906	0.773	0.942	
Totals									
Overall Accuracy	**0.905**								
KIA	**0.887**								

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Figure 6. Error matrix based on TTA Mask

4. References

Billa, L, Mansor,Sh, Mahmud ,A.R, Ghazali ,A,H, 2004. Integration of RS, GIS and MIKE 11 Hydrodynamic Modeling for Flood Early Warning: A case study of the

Langat river basin Malaysia , *Map Asia Conference 2004*.

Göttsche Frank-M. and Olesen Folke -S., 2005, Classification of clouds and weather situations in meteorological satellite data using Definiens eCognition

haji mir rahimi M. and bai N, 2008, classification types of clouds using AVHRR images, *Geomatics 87 Conferences ,Iranian National Cartographic Centre* (in Persian language).

Ito M.,2000, *Analysis and Use of Meteorological Satellite Images*, First Edition, Chapter2, Meteorological Satellite Center, Japan Meteorological Agency,

Lara A. Arroyo, Sean P. healey, Warren B.Cohen, David Cocero and Jose A. manzanera, 2006, Using object-oriented classification and high-resolution imagery to map fuel types in a Mediterranean region. *journal of geophysical research*, VOL. 1 11, G04S04, doi: 10.1029/2005JG000120.

Lewinski S., and zaremski K., 2004, examples of object-oriented classification performed on high-resolution satellite images, *miscellanea geographica, Warszawa*. Vol.11.

Liu, D., and Xia, F., 2010. object-based classification: advantages and limitations', *Remote Sensing Letters*, 1:4, pp.187 – 194.

Mathieu, R., and Aryal j., 2005. Object-oriented classification and Ikonos multispectral imagery for mapping vegetation communities in urban areas, *SIRC 2005 – The 17th Annual Colloquium of the Spatial Information Research Centre University of Otago, Dunedin, New Zealand*

Mishra J. k., Sharma O. P., Cloud top temperature based precipitation intensity estimation using INSAT-1D data, *International journal of Remote Sensing*, 2001, vol.22, No. 6, pp.969-985.

Oruc, M., Marangoz, A. and Buyuksalih, G., 2005. comparison of pixel-based and object-oriented classification approaches using landsat-7 ETM spectral bands.

Richard L., Bankert., and David, W., Aha.,1994. Automated identification of cloud patterns in satellite imagery.14WAF-FA4.4.

Shattri, M., Wong, T,H., and Abdul R. M. Sh.,2003. object oriented classification for land cover mapping. GISdevelopment.net (accessed 29 march 2008)

Volker, W., 2003. Object-based classification of remote sensing data for change detection, *ISPRS Journal of Photogrammetry & Remote Sensing* ,58 ,pp. 225– 238.