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# The Preparation of Updated Vegetation Maps by Processing Satellite Images: A Way in Sustainable Management of Agriculture

***Ali Mohammadi Torkashvand * and Shahryar Sobhe Zahedi***

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**Abstract**

An important factor in sustainable agriculture and economic management is to calculate areas under different crops that the inputs of agriculture connect to this topic. Planning of agricultural mechanization, fertilizer and pesticide requirements, pests and diseases control, estimates of agricultural production, income and tax and financial planning, all linked to the cultivated areas and estimation of agricultural products. One of the problems in the agricultural section of Iran is the lack of accurate statistics of cultivated crops areas that this is much higher for horticultural products. Over time, it varies the area of land under cultivated crop, and orchards and bare lands; consequently the estimation of yield is not done as well due to these changes caused some problems in planning and management. Land Surveying is time-consuming and expensive, while mapping farms and orchards lands through classified satellite images is a high speed and low cost way. Nowadays, the satellite image processing techniques have developed for the estimation of crops, pest control, agricultural macro planning and preparing updated maps. A principal problem is the interference of plants spectral reflections that different methods have been proposed by researchers to differentiate vegetation on satellite images. At this paper, remote sensing imagery in mapping vegetation or various plants are investigated.

*Keywords:*
*Agriculture management, Satellite images, Sustainable agriculture, Vegetation*

[1] *Department of Horticulture, Rasht Branch, Islamic Azad University, Rasht, Iran.*
[2] *Research Center of Agriculture and Natural Resources, Guilan, Iran.*
* *Corresponding author's email: m.torkashvand54@yahoo.com*

## INTRODUCTION

In a general concept, planning is the allocation of resources in order to change of present situation into a desirable condition that its ultimate goal is the development and construction. The first and the most important step in a planning system are designing operations in achievement to a goal or goals. Planning should be done for sustainable development of a country or region. In the process of sustainable development, five subset resources, environment, population, economy and society are involved. Because of the limited resources, they have remarkable importance. Environment is also an important part of system that should be conserved in the process of sustainable development (Alavipanah, 2004). One of the goals of the first, second, third and fourth programs in development of Iran was the increase in agricultural production. All policies and arrangements in various themes such as soil and water, mechanization, research, education and promotion etc. are programmed in developing agricultural products.

Various factors influence on production process that among them, the climatic factors have the special importance particularly in arid and semi-arid parts of Iran, since drought were caused some problems in achieving the goals of development plan in Iran's agriculture. The population growth has increased the land exploitation, extensively It is not used the cultivated land in the agricultural part in an appropriate manner. Degradation of soil and water resources, degradation of pastures, vegetation and forest is due to improper exploitation of these resources as resulting immediate and short-term benefits. Assessing and monitoring the state of the earth surface is a key requirement for global change research (Committee on Global Change Research, National Research Council, 1999; Jung *et al*., 2006; Lambin *et al*., 2001). Land use planning is a plan of agricultural development with special emphasis on the accurate recognition of soil and water resources, the current use of lands, recognition priorities and the allocation of land to sustainable use.

Nowadays the application of advanced technologies in the land evaluation and natural resources management and decision making has increased and improved. Therefore, special attention to science and new technologies is very important especially for developing countries. Remote sensing and spectral reflections recorded by satellite sensors are new technologies. Maps of vegetation in earth's surface are the biophysical phenomenon that the date and accuracy of these maps can be a significant way in environmental management and planning (Naghibi *et al*., 2010). Recognition of vegetation covers characteristics and relationships between plant species and environmental factors have been considered by ecologists. This is due to the importance of habitat of vegetation covers, energy and other important characteristics of plants on Earth (Ahmadpour *et al*., 2011). Vegetation cover is the ratio of surface area covered by plant to total area (Zhang *et al*., 2003). Fortunately, many researchers have attempted to mapping and zoning vegetation and land use (Naghibi *et al*., 2010).

The information contained in digital imagery, acquired by Remote Sensing technology, can be used for mapping, monitoring and assessing the properties of the environmental and terrestrial features elements. Vegetation mapping also presents valuable information for understanding the natural and man-made environments through quantifying vegetation cover from local to global scales at a given time point or over a continuous period. It is critical to obtain current states of vegetation cover in order to initiate vegetation protection and restoration programs (Egbert *et al*., 2002; He *et al*., 2005).

Land use and land cover is found as significant information in an area that may assist managers and decision-makers to take drastic measures. One of the most important land uses is agriculture lands as well as orchards, which may play an important role in providing man's food. Land-use changes in farming areas that derive from declining of agricultural practices or even from frequently unreasonable over exploitation of water resources have led many semi arid regions of the world to boundary conditions demanding urgent strategies of water management towards sustainable development (Brandt and Thornes, 1996; Hugget, 1993). As increase in human demands, the sustainability of land use is questionable. Better land management involves identifying land-use changes, understanding current land-use patterns or features, and assessing economic and ecological benefits and costs that arise from land-use practices, as well as finding the best alternatives for each area (Wu *et al*., 2001). Determination of plant cover percent by traditional methods don't present full view of plant cover and also it consumes time and cost. Thus, human errors in determining vegetation by traditional methods can be very large. Remotely sensed data frequently are used to map land surface cover for use in a variety of resource assessment, land management, and modeling applications. Mapping from coarse spatial resolution images and with multispectral instruments necessarily has focused on land cover and broad vegetation types (Loveland, 2000) rather than discrimination of vegetation at a species level.

Crop yield forecast in an area usually requires crop area estimation, which is mainly concerned by some relating organizations. Satellite data along with remote sensing technique may be employed as a useful and effective tool to estimate crop area. Recent developments of image processing technique as well as availability of high resolution satellite imageries avail to use this technique as a quick and low cost method in compare to conventional methods for crop area estimation. This paper presents different methods or models in estimating vegetation and various crops.

## DISCUSSION

One of the common methods in calculating the vegetation percentage by satellite images is the use of vegetation indices. So far several vegetation indices have been proposed which depending on the region followed different results. Many indices have been investigated in various studies that the most important indices presented by researchers (Baret and Guyot, 1991; Chen, 1996; Clevers, 1989; Crripen, 1990; Huete, 1988; Huete, 1997; Jordan, 1969; Kaufman and Tanre, 1992; Major *et al*., 1990; Pinty and Verstraete, 1992; Richardson and Wieg, 1977; Rondeaux *et al.*, 1996; Rouse *et al.*, 1974; Tucker, 1979; Qi *et al*., 1994) as following:

NDVI (Normalized difference vegetation index) $= (b_4-b_3)/ (b_4+b_3)$

$b_1$, $b_3$, $b_4$, $b_5$ and $b_7$ are five bands of octet bands related to ETM+ sensor

DVI (Difference vegetation index) $= b_4-b_3$

RVI (Ratio vegetation index) $= b_4/b_3$

IPVI (Infrared percentage vegetation index) $= b_4/(b_4+b_3)$

MIR (Leaf water content, Mid-IR) $= b_5/b_7$

MSI (Moisture stress index) $= MIR/b_5$

RAI (Reflectance absorption index) $= b_4/(b_3 + MIR)$

$IR_2$ (Infrared Index) $= (b_4-b_7)/(b_4+b_7)$

NRVI (Normalized Ratio vegetation index) $= (RVI-1)/(RVI+1)$

TVI (Transformed vegetation index) $= NDVI+0.5$

ARVI (Atmospherically resistant vegetation index) $= (b_4-R_{b1})/(b_4+R_{b1})$

That $R_{b1} = -\lambda(b_1-b_3)$

GEMI (Global environment monitoring index) $= [\mu(1-0.25\mu)-(b_3-0.125)]/(1-b_3)$

That $\mu = [(b_4^2-b_3^2)+1.5b_4+0.5b_3]/(b_4+b_3+0.5)$

MSAVI (Modified soil adjusted vegetation index 1) $= [b_4-b_3(1+L)]/(b_4+b_3+L)$

That L=1-2

$MSAVI_2$ (Modified soil adjusted vegetation index 2) $= 0.5[2b_4+1-[(2b_4+1)2-8(b_4-b_3)]0.5]$

SAVI (Soil adjusted vegetation index) $= [b_4-b_3(1+L)]/(b_4+b_3+L)$

SARVI (Soil & atmospherically resistant vegetation index) $= [b_4- R_{b1}(1+L)]/(b_4+ R_{b1}+L)$

WDVI (Weighted difference vegetation index) $= b_4-\alpha b_3$

TSAVI $= [\alpha(b_4-\alpha b_3-\beta)]/[ \alpha b_4 + b_3 + \alpha\beta + 0.08 (1+\alpha^2)]$

$SAVI_2$ (Soil adjusted vegetation index 2) $= b_4/[b_3+(\alpha/\beta)]$

OSAVI (optimized soil adjusted vegetation index) $= 1.16[(b_4-b_3)/ (b_4+b_3+0.16)]$

$\alpha$ and $\beta$ are the slope of soil line and soil line intercept, respectively.

MSR (Modified simple ratio) $= (RVI-1)/(RVI^{0.5}+1)$

Ebrahimi (2010) on research in the arid regions of central Iran concluded that among 17 common indicators, MSAVI1 index with highest precision can be used to estimate the percentage of vegetation. Another research by Baugh and Groeneveld (2009) in an arid region of Colorado, USA, using TM images showed that plant cover percent can be estimated by NDVI indices with an accuracy $R^2$=0.77. Darvishzadeh *et al.* (2008) introduced the indices related to soil reflections in vegetation mapping as better indexes. The vegetation percent of Sistan region, southeast Iran, estimated by Shafiei and Hosseini (2012), they found that WDVI index had the highest precision ($R^2$=0.89) in estimating vegetation between 83 indices. Darvishzadeh *et al.* (2012) evaluated 17 vegetation indexes to compute vegetation percentage. They concluded that indexes having soil line indices (PVI, TSAVI, $SAVI_2$, WDVI) had the more accurate in estimation of vegetation percentage in arid region ($R^2$>0.63).

A study by Mohammadi *et al.* (2012) showed that GNDVI and DVI indexes have the highest correlation with total cover, and GNDVI and GI with millet cover. The studies of Baugh and Groeneveld (2009) and Lawrence and Ripple (1998) introduced NDVI index in estimating vegetation with acceptable accuracy.

Another way in providing vegetation map is the classification of spectral reflections (digital numbers) on satellite images. Of course, the supervised classification of images by training points of surface covers presents more accurate results than unsupervised classification. Unsupervised classification methods are purely relying on spectrally pixel-based statistics and incorporate no prior knowledge of the characteristics of the themes being studied. The benefit of applying unsupervised classification methods is to automatically convert raw image data into useful information so long as higher classification accuracy is achieved (Tso and Olsen, 2005). Algorithms of unsupervised classification were investigated and compared with regard to their abilities to reproduce ground data in a complex area by Duda and Canty (2002). Despite its easy application, one disadvantage of the unsupervised classification is that the classification process has to be repeated again if new data (samples) are added. By contrast, a supervised classification method is learning an established classification from a training dataset, which contains the predictor variables measured in each sampling unit and assigns prior classes to the sampling units (Lenka and Milan, 2005). The supervised classification is to assign new sampling units to the priori classes. Thus, the addition of new data has no impact on the established standards of classification once the classifier has been set up (Sohn and Rebello, 2002; Xu *et al*., 2005).

Extensive field knowledge and auxiliary data may help improve classification accuracy. Studies have shown that classification accuracy can be greatly improved after applying expert knowledge (empirical rules) and ancillary data to extract thematic features (e.g. vegetation groups) (Gad and Kusky, 2006; Shrestha and Zinck, 2001). In a regional scale vegetation classification conducted in the Amanos Mountains region of southern central Turkey using Landsat images, Domacx and Suzen (2006) incorporated vegetation-related environmental variables and considerably improved classification accuracy when compared with the traditional MLC method.

Muschen *et al.* (2001) tried to separate agricultural area from non-agricultural area using controlled classification of integrated images of TM5 with IRS IC PAN land sat and $ERS_2$ radar by maximum likelihood method. In addition to this separation, they tried to separated wheat, maize farm and rangelands. Rembold *et al.* (2000) investigated land cover changes in a 22 years period at Lakes region in south of Ethiopia by aerial photographs (1972) and classifying TM land sat images (1994). The analyses indicate that cultivated surface had been increased and more erosion had been occurred in new cultivated lands.

Mohammdi Torkashvand and Eslami (2012) focused on identification and mapping olive in the part of Roodbar region, Guilan, Iran, based on supervised classification of IRS images. The indicated that there was an interference of spectral reflections between olive orchards, paddies and other orchard caused to low accuracy in providing olive orchards map. Mohammdi Torkashvand (2011) investigated preparation of paddy lands and computed accuracy 73% by supervised classification of IRS Satellite images.

Using AIF (adaptive image fusion) index, Fletcher (2005) used high resolution Quick Bird satellite images to recognize citrus with black mold (Capnodiumcitri) in Texas region of America and identified it as a suitable method. Das *et al.* (2009) tried to prepare map for regions with reducing citrus production capacity in Meghalaya region of India using IRS satellite images. The map of regions where citrus production capacity had been reduced was prepared using soil erosion information, vegetation condition and humidity tension. Due to some changes which are created above time in paddy surface preparing updated map of paddy is one of the most important requirements in the management and region agricultural planning. With regard to this that land surveying required high cost and time and also preparing the map through aerial photographs is required to prepare aerial photograph which still along with high cost, use of satellite data along with remote sensing technique may be employed as a useful and effective tool to estimate crop area.

Olive area estimation has been carried out in a few olive-growing countries as Turkey, Spain and Portugal. Unal *et al.* (2004) used Land sat 7 and IRS data to survey olive, pistachio and vineyard in Gazin-Tab area Turkey. He used image supervised classification technique to estimate olive plantation area. Teresa Barata and Granado (2000) has compared land sat images with aerial photo to map olive gardens in Portugal. Ramos *et al.* (2007) quantified the eventual land movement and the subsequent displacement of olive trees produced by continuous tillage erosion. They analyzed these movements on a property of olive orchards located on variable sloping land. Berni *et al*. (2009) applied models based on canopy temperature estimated from high resolution airborne imagery to calculate tree canopy conductance (Gc) and the crop water stress index (CWSI) of heterogeneous olive orchards. Darvishsefat and Zareh (1998) used remotely sensed data in providing plant cover map in Qaen, Iran. Senay and Elliott (2002) evaluated ability AVHRR sensor data to identify combinations of grassland vegetation and found this sensor is able to detect different species of rangeland with different types of trees and bushes.

There are other methods in providing vegetation map that can refer to neural network, fuzzy logic and mixed pixels. Artificial Neural Network (ANN) and fuzzy logic approaches are also seen in literature for vegetation classifications. ANN is appropriate for the analysis of nearly any kind of data irrespective of their statistical properties. ANN is very useful in extracting vegetation-type information in complex vegetation mapping problems (Filippi and Jensen, 2006), though it is at the expense of the interpretability of the results since ANN deploys a black-box approach that hides the underlying prediction process (Cerna and Chytry, 2005). Berberoglu *et al.* (2000) combined ANN and texture analysis on a per-field basis to classify land cover and found the accuracy could be 15% greater than the accuracy achieved using a standard per-pixel ML classification. Jung *et al.* (2006) in preparing clouds cover and Carpenter (1999) in vegetation mapping used neural network method. Matkan *et al*. (2011) evaluated efficiency using neural network and remote sensing in estimation of vegetation and calculated accuracy 0.74.

A fuzzy classification approach is usually useful in mixed-class areas and was investigated for the classification of suburban land cover from remote sensing imagery (Zhang and Foody, 1998). Fuzzy classification is a kind of probability-based classification rather than crisp classification. Unlike implementing per-pixel-based classifier to produce crisp or hard classification, Xu *et al.* (2005) employed a Decision Tree (DT) derived from the regression approach to determine class proportions within a pixel so as to produce a soft classification. Theoretically, probability-based or soft classification is more reasonable for composite units since those units cannot be simply classified to one type but to a probability for that type.While soft classification techniques are inherently appealing for mapping vegetation transition, there is an unresolved issue of how best to present the output. Rather than imposing subjective boundaries on the end-member communities, transition zones of intermediate vegetation classes between the end member communities were adopted to better represent the softened classification result (Hill *et al*., 2007).

## CONCLUSION

Although there are various methods for image preprocessing, but they cannot prepare vegetation map with a full accuracy and precision. The interferences spectral reflections are caused to reduce the accuracy of map; particularly it increases in preparing map of a special plant. Thus, ancillary data, including field samples, topographical features, environmental characteristics and other digital (geographic information system) data layers, have been proved very helpful to get a more satisfactory result or increase classification accuracy.

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