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Determination of the cultivated area and plant density of sugar beet fields using satellite data

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ABSTRACT

The purpose of this study was to determine the plant density of sugar beet fields in Qazvin region using satellite images and remote sensing techniques. The plant density can be used to estimate the pre-harvest sugar beet yield and as a result the proper management of agricultural and industrial processes involved in sugar production. Satellite data can be used to remove the cost and time of conventional field methods. In this study, using satellite imagery of TM and GeoEye, the plant density of sugar beet fields in a part of Qazvin region was estimated in 2011. Results derived from the assessment of accuracy of operations and comparison of the maps obtained from remote sensing data with ground samples showed that using satellite data, the plant density of sugar beet can be estimated with relative certainty. The calculation of the overall data showed that the accuracy of maps outputs was 91.7% with Kappai coefficient of 0.84. In addition, remote sensing data can illustrate the density variation in different parts of the field.

Keywords: Optimal cropping pattern, remote sensing techniques, sugar beet, water

INTRODUCTION

Some crops provide valuable raw material in addition to food for human (Khodabandeh 1993). In most countries, sugar production is an essential aspect of agricultural economy and climate condition has a significant role for the selection between sugar beet and sugar cane planting (Arnon 1996). In 2010, the amount of produced sugar from sugar beet and sugar cane was 555486 and 568453 t, respectively (Anonymous 2011). Based on the current statistics, sugar beet planting has decreased in recent years (Anonymous 2011), so that the reduction was in parallel with sugar price increase in global market (Anonymous 2011). Correct management, increase of efficiency and correct evaluation of sugar beet fields in terms of agronomy and industry has remarkable significance. Improper estimation of the crop production may impose great economic losses to the sugar industry. These losses include providing raw materials for sugar beet processing and other products resulting from sugar beet processing in one hand and management of sugar import and export in high levels on the other hand (Anonymous 2011). Plant density is usually expressed based on the number of plants per unit area and sugar beet yield components is determined based on the number of plants per unit area, average root weight and sugar content (Ebrahimian 1992). Biplot data are usually obtained from small areas with long-term intervals and distinct for their type and accuracy. Collection of such information is difficult and expensive and in many cases, access to all farms is not possible or economic for experts. Also, due to continuous changes in vegetation, access to timely biplot or field data with appropriate replication is so difficult and restricted. Remote sensing data have special capabilities such as wide range vision, timely delivery of information, the use of repetitive coating, the transmis-

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sion speed and variety of data forms, low cost and speed of data processing, and the possibility of studying a region status in the past. Therefore, remote sensing of the products can be the perfect solution for field screening. It also can be used during the growing season when direct physical contact with the plant is difficult or harmful (Alavipanah 2003). Product assessment methods with remote sensing data can be divided into two main groups. First group methods are based on the combination of remote sensing data with plant physiological methods and agricultural meteorology. The second group methods are based on mathematical relationship between satellite data and product return. Some of these models are only using the satellite data with contribution of the ground samples for model calibration. The models' assumption is on the basis of direct relationship between remote sensing data observed in the product and plant density. Utilisation of these models is relatively simple because the relationship between data and remote sensing products is expressed with simple formula and plant physiological conditions is not directly inserted in the equation (Zobeiri and Majd 2002). One of the conventional methods for the evaluation and monitoring of plant vegetation is the usage of plant vegetation indices. These indices are a mathematical combination of multiple bands of satellite images which use significant difference of vegetation reflectance in red and near-infrared wavelengths. In general, the vegetation has the most and lowest reflectance in NIR and red band (R), respectively. Therefore, image pixels with high difference of the abovementioned band inside them represent the vegetation of the region. These indices convert pixel value into a numerical index by a simple mathematical operation (Alizadeh 2003). Currently, multiple sensors with different capabilities are available which are able to get information from the ground at different bands. However, not necessarily the primary bands of these sensors express all the required information. For this reason, in different studies combined bands from primary data were created. Using this method, more information can be obtained from the available data. Among the techniques used for this purpose is the principle component analysis (PCA). The goal of PCA analysis is to find new areas of the image feature space which can distinguish the existing classes in the image in the best way (Alizadeh 2003).

Gavin et al. (2003) evaluated wheat and barley germination variation in a four-year period using aerial images. Ground sampling was performed using systematic method and 100 samples were taken. The relationship between density and green area index and Normalized Difference Vegetation Index (NDVI) was established with linear regression. Results showed that plant density of wheat and barley can be estimated with a correlation coefficient of 0.57 to 0.97, respectively.

Johnson et al. (2003) provided leaf area map in California vineyards using Ikonos images. Ground-based measurements were done at 24 points with a positive correlation (0.73) between NDVI and leaf area index. Created maps were used for both field and irrigation management. Minghas et al. (2002) predicted corn and soybean yield potential in different growth stages in California using satellite images. By satellite image analysis and terrestrial network sampling, the product performance was monitored, and preliminary results showed that the yield potential can be calculated using NDVI for soybean and maize. Asadi-rashed et al. (2008) estimated the irrigated-wheat performance in Qazvin plain using leaf area index data produced from IRS images. In their study, with combination of field and remote sensing data and also location information consisting of remote sensing parameters, leaf area index was presented for crop production estimation. Based on the results, the best time for performance estimation using leaf area index produced from satellite data is booting stage. Remote sensing data also provide information on the crop growth status. Using remote sensing, plant density of the field can be mapped in a large-scale with high accuracy. This goal is achievable through the use of vegetation indices which have a linear relationship with leaf area index, biomass, plant density and other vegetation characteristics. This study aimed to evaluate the potential of satellite data and remote sensing for determination of sugar beet plant density and cultivation area in Qazvin plain.

MATERIALS AND METHODS

A part of land area under the management of Qazvin Sugar Company located in Qazvin plain was selected for this study. The eastern part of the plain is connected to Tehran plain and is covered by Alborz mountain area, Chahargar, and Ramand in horseshoe-shaped from west and north. The average rainfall and evaporation in Qazvin plain is 366 and 1818 mm, respectively. The studied area is located at $50^{o}1'16''$ to $50^{o}9'59''$ east and $36^{o}2'53''$ to $36^{o}10'59''$ north. The studied area was

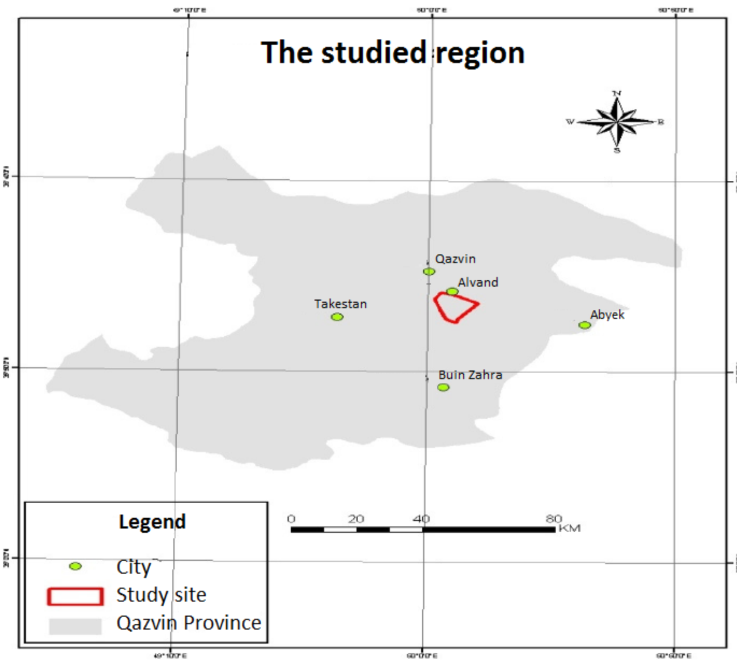

Figure 1. The geographical location of the studied area

10344.8 ha shown in Figure 1.

In this region, 54 sugar beet fields belonging to 26 farmers of Kochar, Alvand, and Kamal-abad with 227 ha were located. The reason for this area selection was the diversity of sugar beet fields for plant density. In recognition of the different land use classes for preparation of accurate and reliable map, ground samples were taken from sugar beet fields in the region. Ground sampling was performed using the manual GPS system (Map-76) in two stages (13th May and 1st August 2011). First sampling was performed after thinning, weeding, and plant establishment and the second one after canopy formation. Ground sampling points were used as control data for accuracy assessment and usage in interpretation and analysis of the different stages.

In determination and usage of these points and also during field visits, points distribution, type of dominant vegetation, plants growing condition, the state of the slope and roughness of each area were considered. In order to use harvested samples in all classification methods, it is necessary to consider sample normality. Point sampling location was chosen as each harvested sample can be presented as the special pixels of that class. As requested in different stages, the experts consult was used.

Applied data

To conduct this study, sensor images of TM from Landsat satellite taken on 1st August 2011 with 30 m spatial resolution in six spectral bands within visible and near-infrared range and also GeoEye image on 1st June 2011 with 1.65 m distinction and four spectral bands in the range of blue to red adjoining to study area were used. In addition, 1:250000 maps from map operation organization were used for geometric image correction. Furthermore, ground samples related to various plant densities of sugar beet fields were taken.

Preprocessing

In pre-processing stage, images are prepared or recovered to increase their usage potential for processing stage. To correct atmospheric impact, the histogram values of different bands were evaluated which showed that in bands 1 to 3, the images of adjacent brightness levels were approximately began from zero. This shows that the atmospheric distribution impact had little impact on image quality and as a result, atmospheric correction was not performed. After this stage, the geometric accuracy of the images was improved using 1:250000 maps from National Cartographic Center. Geometric correction was performed using polynomial equations and resampling was performed using adjoining neighbor method to decrease pixels brightness values. Geo-Eye satellite images showed that images were at optimum level in terms of radiometric status and most of primary radiometric corrections were made by reception stations and companies providing data. For atmospheric correction, dark object subtraction method was used. In this method, the

Table 1. Calculation and assigned names for different plant canopy indices

Index	Abbreviation	Function
Normalized Difference Vegetation Index	NDVI	$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{R}}{\mathrm{NIR} + \mathrm{R}}$
Simple Ratio	SR	$\mathrm{SR} = \frac{\mathrm{NIR}}{\mathrm{R}}$
Enhanced Vegetation Index	EVI	$\mathrm{EVI} = 2.5\left(\frac{\mathrm{NIR} - \mathrm{R}}{\mathrm{NIR} + 6\mathrm{R} - 7.5\mathrm{B}}\right)$
Green Vegetation Index	GVI	$\mathrm{GVI} = \frac{\mathrm{NIR} - \mathrm{G}}{\mathrm{NIR} + \mathrm{G}}$

assumption is that the image with high value pixels is zero. Like deep water which has zero reflection in NIR band, any NIR band reflection in these areas are from atmospheric distribution. This amount reflects atmospheric path radiance. Thus, the real difference of DN in this area is calculated from zero and deducted from whole image DNs. To recover Geo-Eye images accurately, accurate ground control points were used.

Processing

New bands creation

Currently, multiple sensors with different capabilities are available in different bands which can be used to obtain information from the ground. In this way, more information can be obtained from existing data. Among the techniques used for this purpose, principal component analysis (PCA) is usually applied. The goal of PCA is to find a new axis of the space image feature which can differentiate the interested classes in the image properly. All corrections, data processing, mining and output obtaining were performed using Geomatica PCI 9.0, ENVI 4.8, and ArcGIS9.3 software.

Vegetation indices

One way to study and monitor plant canopy is using plant canopy indices. These indices are a mathematical combination of multiple bands of satellite images which use significantly different wavelengths of red and near-infrared reflectance from the canopy (Zobeiri and Majd 2002). Generally, most healthy plant canopies have reflectance in near infrared (NIR) band and the lowest reflectance or the highest absorption is in red (R) band, respectively. Therefore, the pixels in which the band difference is higher than the other pixels can indicate the plant canopy of the region. Using a simple mathematical function, the pixels' value in different bands can be converted to numerical values. Using plant canopy indices presented in Table 1 contributes to better plant canopy characteristics differentiation and study in the image.

The SR index uses the proportion of near-infrared and red bands reflectance. The index is in the range of zero to infinity. Because of band proportion usage, the atmosphere, topography and radiation changes are decreased. One of the biggest limitations of this index is the possibility of the denominator becoming zero. The NDVI index is one of the most famous and applied indices which ranges from +1 to -1. In scattered plant canopies, the NDVI index lacks required efficiency due to the large influence of the soil surface reflectance, and also in dense population due to rapid saturation. The index gives the best results in areas with intermediate vegetation. The EVI Index is also suggested for NDVI improvement. In this index, using blue band reflect, the effect of soil moisture and atmospheric effects are reduced. The GVI index is also similar to NVDI in terms of calculation; therefore, the difference between the near-infrared band and green band is estimated (Liang 2004).

As mentioned before, the aim of this study was to prepare sugar beet plant density map using remote sensing data. To achieve this purpose, the following works were done:

- Identifying and separating sugar beet fields from the other surface vegetation
- Determining plant density in sugar beet fields

Sugar beet field separation

To separate sugar beet cultivation area, first NVDA was calculated and as a new band combined with the other bands in the image. Then, sugar beet fields were separated using multi-stage classification method. For this purpose, arid areas were separated from the agricultural lands using 'Decision tree' classification method. In next step, using the maximum probability classification method and considering spectral properties, each agricultural land was divided into different classes. Since sugar beet is cultivated in rotation with other crops, therefore, no significant difference would be among them in terms of soil properties. Thus, soil information will not contribute to field separation and more attention should be paid to the vegetative conditions of the crops and agricultural calendar in the region. Sugar beet field separation from the other fields is performed using phenological, vegetative and agricultural stage difference. Major crops in the region include wheat, barley, maize and sugar beet. Table 2

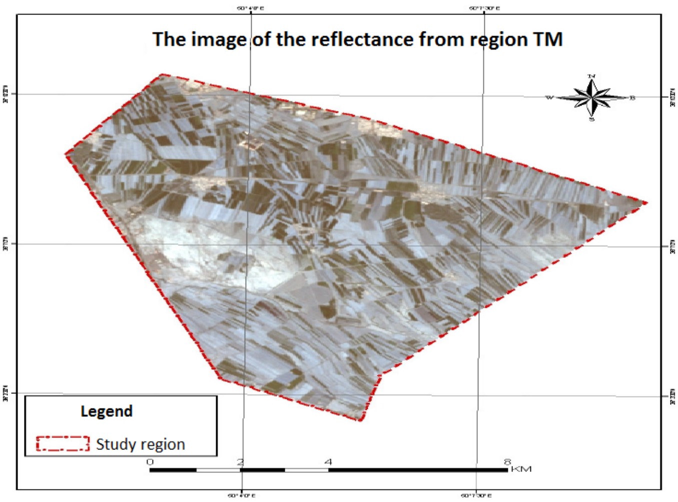

Figure 2. The image of the reflectance developed from region TM (in the band composition RGB: 4,3,2)

Table 2. Agricultural calendar of different crops in Qazvin plain

Crop	Planting	Harvest
Wheat	2nd Oct- 1st Nov	1st Jul- 21st Jul
Irrigated Barley	23rd Sep- 22nd Oct	22nd Jun- 1st Jul
beans	1st Mar- 30th Mar	1st Jul- 11th Jul
Alfalfa	21st Apr- mid-Jun	June-Sep
Sugar beet	9th Apr- 10th May	7th Oct- 27th Oct
Maize	5th May-20th May	11th Sep- 2nd Oct
potato	21st Apr- 10th May	7th Oct- 27th Oct

Source: Agricultural Organization, Qazvin

illustrates agricultural calendar for different crops under irrigation network in Qazvin plain.

In terms of planting and harvest time, sugar beet has considerable difference with wheat and barley fields. For this reason, choosing the correct time of image taking, sugar beet fields separation from wheat and barley will be possible. However, for the differentiation of sugar beet field from corn, alfalfa, and potato, only image taking is not sufficient due to their relatively high overlapping of agricultural calendar. So, it will be necessary to distinguish both plants during vegetative growth according to the vegetative and phenological conditions. The most appropriate way to achieve this goal is the use of two-stroke images. Since the growth and photosynthetic changes of different plants during the growing season is not the same, the growth difference can be revealed by obtaining images from two different times. For this reason, GeoEye and TM images from different months were combined and used simultaneously for sugar beet field separation from the other fields.

Determination of sugar beet plant density

The plant density in the field is estimated randomly or systematically using plots. Using the ground position of each plot, its position is determined on the pixels and relation between plant density and pixel brightness levels is expressed as mathematical equations. The equation between plant density and brightness levels is calculated using primary image bands or calculated plant canopy indices for each pixel. In order to determine the plant density in the fields, different plant canopy indices were calculated and the relationship between these indices and field density was evaluated. For this purpose, after indices calculation, the relationship between each index and plant density was evaluated and in the next step, plant canopy indices were combined together as an image and the relationship between crop density and each pixel was compared as a multivariate by means of created matrices. In addition, combined usage of the main image bands, transformed bands and plant indices were evaluated for plant density estimation.

Results

Radiometric correction

With the help of TM image data used in the design, brightness values of pixels in the image were converted to radiance and later to reflect. Figure 2 shows an image reflection. The use of reflectance data instead of the initial brightness level of the image made it possible to insert radiation and imaging condition during image usage and therefore, better results gained from the image (Richards 2006).

To correct the effect of atmosphere, the histogram values of different bands were evaluated. Figures 3 to 5 show the histogram of brightness

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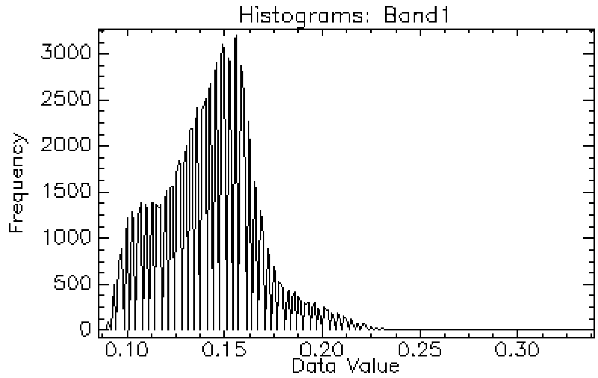

Figure 3. Histogram band 1

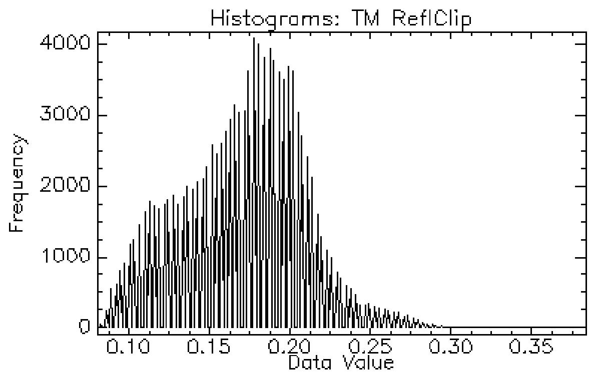

Figure 4. Histogram band 2

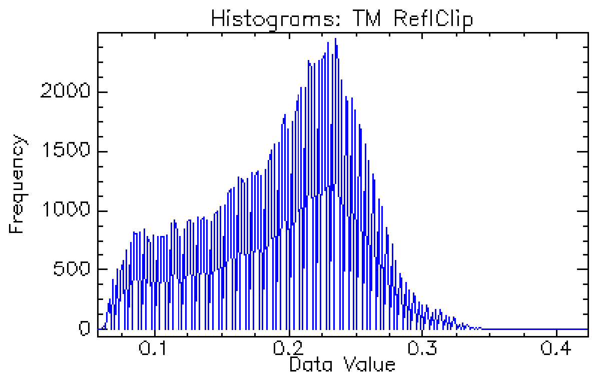

Figure 5. Histogram band 3

levels frequency in different bands of the image. Examining the histogram showed that in bands 1-3, the image of brightness level was approximately beginning from zero, so the effect of atmospheric diffusion had no impact on image quality, therefore, there would be no need to correct the atmospheric impact (Jensen 1996).

Correlation between bands

The correlation between the different bands of the image were evaluated. Figures 6 to 11 show the relationship between different bands of the image. During the information processing, all image bands were used but these histograms showed that the 4th band of the image contains information which do not exist in other bands. The

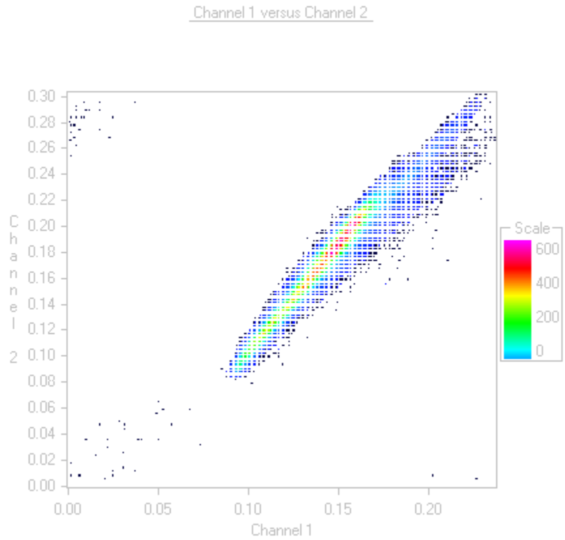

Figure 6. Interaction between band 1 and 2 (R2: 0.98)

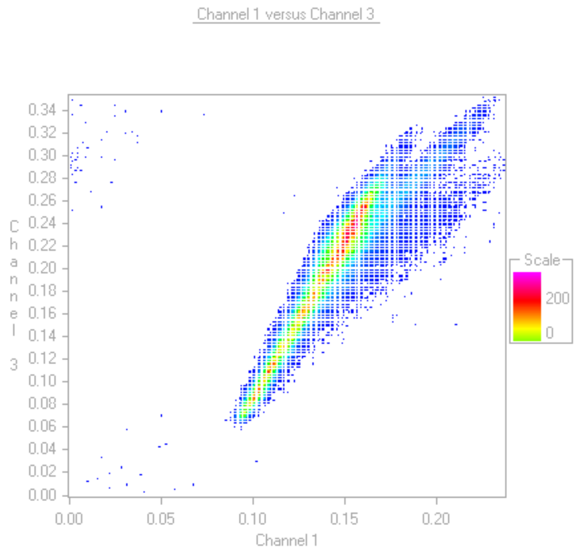

Figure 7. Interaction between band 1 and 3 (R2: 0.94)

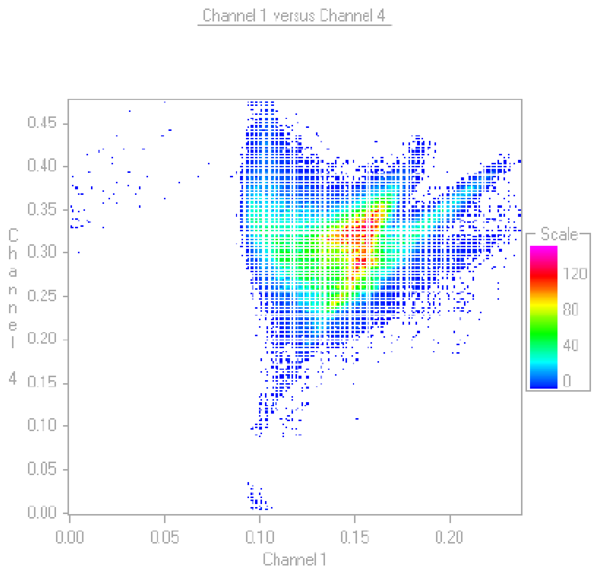

Figure 8. Interaction between band 1 and 4 (R2: 0.08)

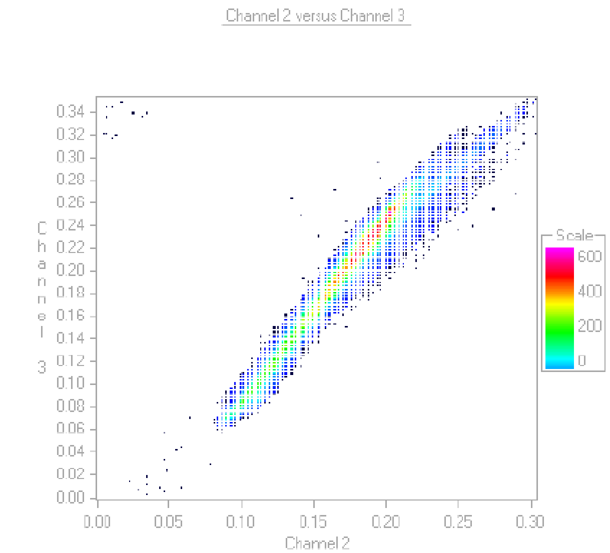

Figure 9. Interaction between band 2 and 3 (R2: 0.98)

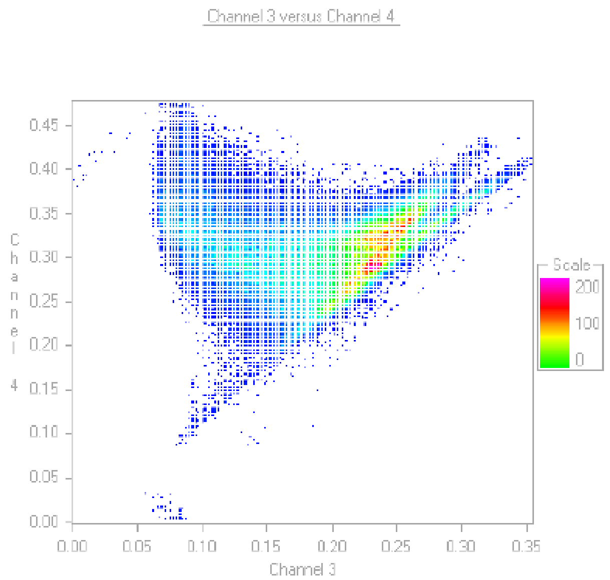

Figure 10. Interaction between band 3 and 4 (R2: 0.12)

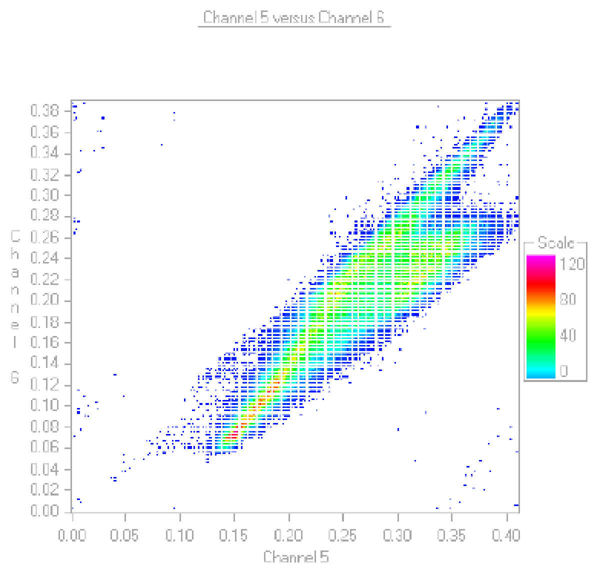

Figure 11. Interaction between band 5 and 6 (R2: 0.90)

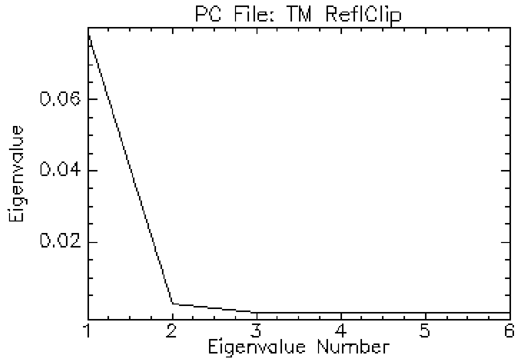

Figure 12. Signal rate and noise changes of the bands derived from PCA conversion

image of the 5th and 6th bands also contains the most uncommon information compared with the other bands. Thus, the usage of the three bands including 4, 5, and 6 can provide useful information that does not exist in the other bands.

After data preparation, the initial correction performance, the processing stage of images and data extraction was done. During this process, various indices were calculated and bands conversion was performed which were used for final result extraction.

Utilization of PCA algorithm

By utilization of PCA algorithm, new bands are obtained in which the signals are placed in early bands and lateral bands have more noise (Richards 2006). Figure 12 shows the signal rates and also noise bands.

With respect to the gradient of the graph in Figure 12, the usable bands which have a high signal level are determined and only bands located before the break of the tilt line will be used. According to this, the first three components of the PCA contain the most information, and in the later components there is more noise than information. Therefore, only the first three components of the PCA will be used. The bands containing PCA information are combined with the original image and the new image is used for the classes differentiation.

Image classification

To perform the classification of the primary bands in the image, the bands derived from the conversion of the main components and the normalized differential index, and also the plant canopy NDVI were combined together and the classification was performed on this combined image.

At this stage, the ground samples were used to

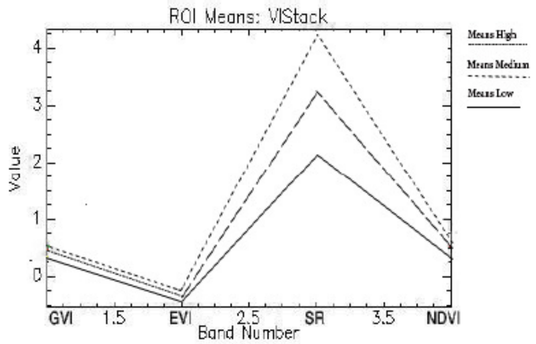

Figure 13. Spectral curve of different sugar beet plant densities extracted from the image of vegetation indices

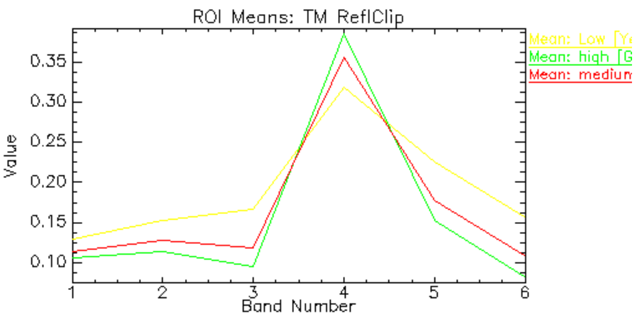

Figure 14. Spectral curve of different sugar beet plant densities extracted from the initial bands of the image

improve the accuracy of classification results and sugar beet field classes were separated. Although the major part of the study area was agricultural land, only a small portion of this area was allocated to sugar beet farms. Also, these farms are not concentrated in one area, but they are scattered almost entirely within the scope of the plan. The other point is the different dimensions of sugar beet fields in the studied area, which has given a special variation to this plan. The sugar beet cultivation area in the study is estimated to be 226 ha. Figure 15 shows the green fields of sugar beet.

Plant density estimation

To estimate plant density, the ratio between plant density and various vegetation indices such as NDVI, SR, EVI and GVI were evaluated.

Plant index calculation

After calculating a variety of vegetation indices, the images from different indices were combined and a multi-band image of vegetation indices was created to better estimate the sugar beet plant density. At this stage, using ground samples of plant density taken from the field, appropriate indices which had the capability of plant density differentiation were identified and the spectral curve of the fields with different density was obtained.

Figure 13 shows the spectral variation of the variety of sugar beet plant densities extracted from the vegetation indices image. From this curve, it is deduced that the highest spectra difference among the different plant densities is observed in the image of SR index, and the NDVI index has the best differentiation. Figure 14 shows the spectral curvature of plant density extracted from the initial bands of the image. According to this image, it is seen that in the three, four, and sixth bands, the highest resolution is observed for different plant densities. Results showed that the 4th band of the initial image, the 2nd band of the PC2 and SR index provided the most information for plant density estimation in sugar beet fields.

Plant density map preparation

After separating the sugar beet fields from the other fields, the combined image of the initial bands, PCA conversion bands and bands indices

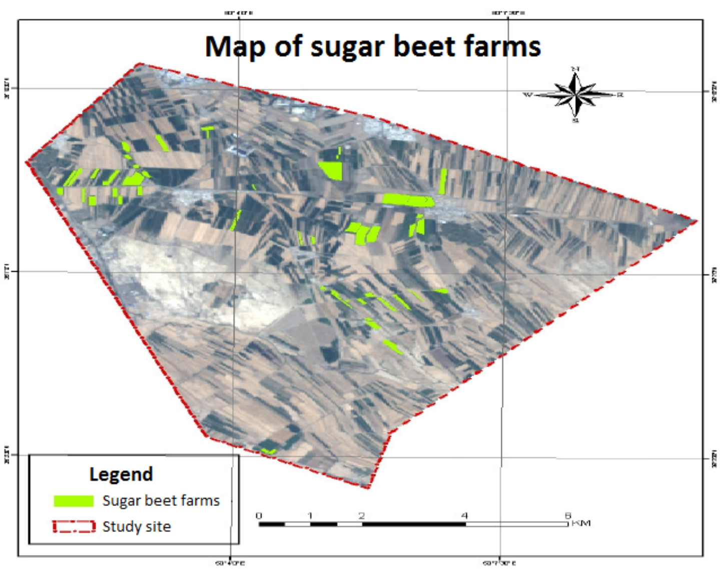

Figure 15. Sugar beet field separation from the other fields

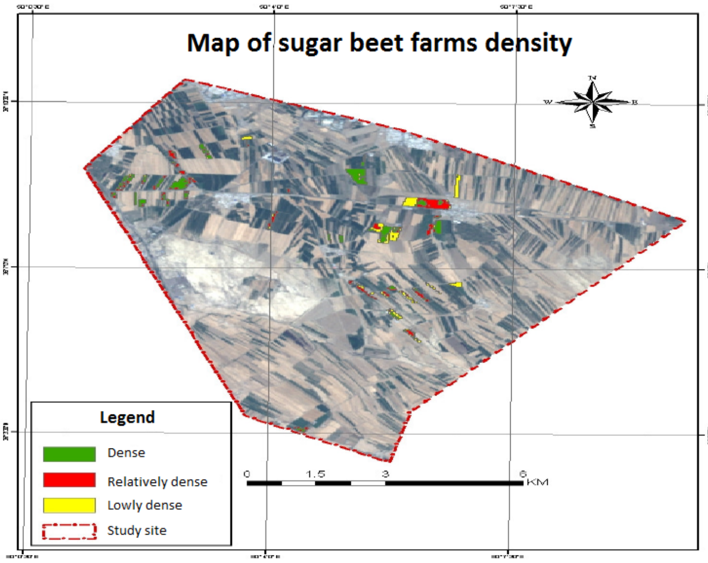

Figure 16. Result of sugar beet fields classification based on plant density

Table 3. Estimated area of each zone with sugar beet plant density

The status of sugar beet plant density	Cultivation area (ha)	Plant number (1000/ha)	Yield per ha (t)
Dense	94.4	70	70
Semi-dense	71.5	45	45
Low density	60.9	20	20

were classified to determine the plant density of the fields. At this stage, ground samples and the spectral curve obtained from these samples were used as a reference data for model calibration. Figure 16 shows the classification of plant density in sugar beet fields. Table 3 shows the distribution of plant density in sugar beet fields in the study area. In field survey, the fields were divided into three groups in terms of the number of plants per hectare and expected yield. Fields with a density of 70,000, 45000, and 20000 plants per hectare were classified as dense, semi-dense, and low-density fields, respectively.

Results and Discussion

To evaluate the accuracy of density maps derived from remote sensing methods, a number of ground samples that had not been used in classification stage were used for accuracy evaluation. Overall accuracy and Kappa coefficient were calculated through comparing ground samples of plant density and its map. The overall accuracy of the plant density map and Kappa coefficient were 91.7 and 0.84, respectively. Therefore, the results of this study show that using satellite data, sugar beet plant density can be extracted at field level.

Also, using two-time data of 31st of May and 1st of August collected from remote sensing, sugar beet fields were separated from the other fields with a general accuracy of 95.4%. The results of the study showed that using the images of two different times, the problem of mixing the sugar beet fields with the other fields will be solved. To achieve this goal, with consideration of the phenological and vegetative conditions of the sugar beet plant compared with the other crops planted simultaneously in the same place, an image of an extra time is provided in a time when these plants have remarkable difference in terms of growth, vegetation or planting and harvesting stages. By combining the data from the two images, the differentiation of different fields will be possible with the proper precision, and the dependence on land sampling will be greatly reduced at this stage.

The results of this study showed that due to the small size of sugar beet fields in the studied area, it is necessary to use images with high spatial resolution such as SPOT, ETM, TM or ASTER. Although, among these images, the more distance between the fields in the image will increase the accuracy of the evaluation. This will be more important with regard to the relatively low planting area of sugar beet plants compared with the other crops in the region. In a similar study, with the aim of estimating wheat, barley and cotton planting area, and using TM and Spot satellite images at about 4000 km^2 area in Gorgan and Gonbad regions, a project was carried out and after identification of the target fields, the planting area of the wheat and barley in the geographical range of the Turkmen port and wheat, barley and cotton in Gorgan city was estimated at 95% accuracy (Zobeiri and Majd 2002). Sawaswa (2003) estimated rice yield n India using satellite image, remote sensing, and a number of environmental factors. Mastali et al. (2007) estimated the plant density of corn fields in Sari using IRS-1D images. After analyzing the images, they calculated the NDVI and 20 ground samples were taken from two plots; then, the relationship between plant density and NDVI was estimated. The evaluation of the model with 10 control samples showed no significant difference between the actual and estimated densities of the model at 1% level.

In the present study, plant density was estimated only at field level in such a way that the whole surface of the field is attributed to a dense, semi-dense, or low-density class. Obviously, different parts of the field may have different plant density levels. Sampling should be done using plot and the plant density at these plots should be expressed by numerical values.

In this study, sugar beet plant density was only evaluated in three classes including dense, semi-dense and low-density. Considering these conditions, it was not possible to calculate the mathematical relation between image reflection and plant density at field level and estimates were done qualitatively. It is suggested that in addition to general estimation of plant density in a field, the density at sample plots being estimated more accurately so that mathematical relationships can be created and estimation can be performed more accurately.

Considering that remote sensing is one of the pillars of agriculture, it is recommended that similar studies be carried out on the fields with high planting area and in different fields of remote sensing. Meanwhile, it is suggested that the executing authorities of the country use the remote sensing methodology every year to accurately estimate the sugar beet area and the amount of crop production, so that more reliable data is available to the country's planners, and as a result sugar is supplied timely in the country.

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