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USING DIRECTIONAL AND HYPERSPECTRAL REMOTE SENSING OBSERVATIONS FOR IMPROVING CROP CLASSIFICATION

Dissertation Master of GeoInformation Science

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Abstract: Mapping accurately agricultural fields is one of the main challenges for monitoring areas using remote sensing. Crops change during the growing season and it is often desirable to use images acquired at several dates for plant identification. However, there is a high cost for these image acquisitions. Airborne or satellite campaigns usually cover specific regions for specific dates then offering limited data. Advances in sensor technologies created hyperspectral sensors to overcome this spectral limitation of multispectral sensors. A hyperspectral sensor collects spectral data in several hundreds bands in a simple acquisition time offering opportunity to discriminate more precisely different plants. Thus, there is a chance that hyperspectral data produce better crop classification especially if it is combined with multiview angle information.

The purpose of this study was to evaluate the possible improvement of the accuracy of crop classification by using hyperspectral and directional remote sensing data. It investigated effects of number of bands, bandwidth and bidirectional information on classification. Four AHS-160 hyperspectral images were used in this research. They covered areas of barren lands, barley, beet, grass, horticulture, maize, onion, potato and wheat located in the region of the Gelderse Poort in the Netherlands. Classification accuracy was investigated using Maximum Likelihood with ground truth data. Analyses were divided in two parts: In the first part the effect of bandwidth and number of bands was investigated by comparing classification results of a hyperspectral image and a simulated multispectral image. Results indicated that the size of bandwidth did not affect classification. An image with a narrow band and an image with a broad band had not a statistically different classification. The effects of the number of bands were analyzed comparing the classification of an image with 63 bands with an image with 6 bands. The image with 63 bands had better user and producer accuracy of crops than the image with 6 bands. The second part studied effects of multi view angle or bidirectional reflectance on classification. A common area in three images was considered in this part of study. Classification results using one image in one flight direction was compared with an overlap image that combined three flights directions. Conclusion, Bidirectional reflectance increased classification accuracy of the majority of crops in hyperspectral images. The bidirectional reflectance influenced positively classification results of crops specially located in the principal plane.

Key words: *hyperspectral; bidirectional reflectance; viewing geometry; narrow bands; broad band; number of bands; crop classification;.*

Resumo: O mapeamento preciso de campos agrícolas é um dos principais desafios para monitorar áreas usando sensoriamento remoto. Plantações mudam durante o período de crescimento o que requer o uso de imagens de diferentes épocas para melhor identificação das plantas e consequentemente isto requer um alto investimento na compra destas imagens em datas específicas.

No passado, a classificação de cultivos eram principalmente realizadas usando imagens obtidas por sensores de satélite multiespectrais que oferecem dados sobre uma grande área reunidos rapidamente e economicamente porém com pequena resolução espectral.. Os sensores hiperespectrais surgem para solucionar esta limitação dos sensores multiespectrais oferecendo coleta de informação em muitas centenas de bandas num simples momento de aquisição Em alguns casos, existe a possibilidade de combinação dos dados hiperespectrais com as informações multiangulares das imagens que poderiam produzir melhor classificação de culturas .

O propósito deste estudo foi analisar a possibilidade de melhorar a exatidão da classificação da vegetação usando imagens hiperespectrais com informações bidirecionais. Este trabalho investigou os efeitos dos números de bandas, largura de bandas e informações bidirecionais na classificação de culturas. Foram utilizadas quatro imagens hiperespectrais AHS -16 que cobriam áreas agrícolas na Região de Gelderse Poort , Países das Terras Baixas, Europa. Utilizou-se a classificação com o a máxima verossimilhança comparada com os dados de campo. As análises foram divididas em duas partes.

Na primeira parte os efeitos do tamanho da banda e o número de bandas foi investigado. Os resultados indicaram que o tamanho das bandas não afetas a classificação. Imagens com maior número de banda apresentaram informações mais precisas sobre as culturas.

A segunda parte dos estudos trabalhou com os efeitos dos múltiplos ângulos de refletância bidirecional na classificação. A refletância bidirecional influenciou positivamente os resultados de classificação dos cultivos especialmente localizados no voo.

Palavras chave: hiperespectrais, refletância bidirecional, classificação de vegetação, número de bandas, banda estreita , banda larga.

Resumen: Cartografiar campos agrícolas con precisión es uno de los principales retos para el monitoreo de áreas mediante teledetección. Isto porque los cultivos cambian durante la temporada de cultivo y a menudo es recomendable el uso de imágenes adquiridas en varias fechas para la identificación de plantas pero con un alto costo para estas adquisiciones de imagen. Campañas Airborne o satélite generalmente cubren regiones específicas para fechas específicas entonces ofrecen datos limitados.

Avances en las tecnologías de sensor crearan hypersapectral sensores para superar esta limitación espectral dos sensores multiespectrales. Un sensor hiperespectral recoge datos espectrales en varios centenares de bandas en un tiempo de la adquisición simple que ofrece oportunidad de discriminar más precisamente diferentes plantas. Por lo tanto, existe la posibilidad de que datos hiperespectrales producen mejor clasificación de cultivos, especialmente si se combinado con la información del ángulo de multivisión.

El propósito de este estudio fue evaluar la posible mejora de la precisión de la clasificación de cultivos mediante hiperespectral y direccionales datos de sensores remotos. Investigaron los efectos del número de bandas, ancho de banda y bidireccional de información sobre clasificación. En esta investigación se utilizaron cuatro imágenes hiperespectrales de AHS-160 que cubrieron áreas agrícolas situada en la región de Gelderse Poort en los Países Bajos. La precisión de la clasificación fue investigada usando la máxima verosimilitud con datos de verdad de tierra .Las análisis fueron divididas en dos partes:

En la primera parte el efecto del ancho de banda y número de bandas fue investigado. Los resultados indicaron que el tamaño del ancho de banda no afectó la clasificación. Una imagen con una banda estrecha y una imagen con una banda ancha no tenían una clasificación estadísticamente diferente. Se analizaron los efectos del número de bandas que comparaban que la imagen con 63 bandas tenía mejor usuario y exactitud del productor de cultivos que la imagen 6 bandas.

La segunda parte estudió los efectos de refletancia de ángulo bidireccional en la clasificación. Resultados de la clasificación con una imagen en una dirección de vuelo se comparó con una imagen de superposición que combina tres direcciones de vuelos. En conclusión, la refletancia bidireccional influenció positivamente los resultados de clasificación de cultivos ubicados especialmente en el plano principal del vuelo.

Palabras clave: hiperespectral; refletancia bidireccional; banda estrecha; banda ancha; número de bandas; clasificación de cultivos.

Introduction

Accurate agricultural information is essential to monitoring land use changes. In the past decades, remote sensing has provided fast detailed information about crop type for government, companies and local authorities (HAZEU, 2006).

Mapping accurately crop types is one of the main challenges for monitoring areas using remote sensing (SU et al., 2007). The challenge is to capture and interpret correct spectral reflectance that defines specific plant. This is a difficult task because vegetation can have differences in spectral response due to several factors such as growth of plant, maturity, weather condition, wind effect, sun-angle-view (LANGREBE, 1999).

In the past, studies on crop classification were mostly performed using satellite multispectral sensors. Multispectral sensor provides data over large area gathered quickly and economically from satellite platform but with small spectral resolution.

Advances in sensor technologies created hyperespectral sensors to overcome this spectral limitation of multispectral sensors. Hyperspectral sensor collects spectral data in several hundreds of bands in a simple acquisition time. Recently, hyperspectral images have become more common and useful for crop identification. One reason is placement of several of these hyperespectral sensors on airborne platforms (AVIRIS, CASI, HYDICE, HYMAP, MIVIS, AHS 160, etc.) with flexibility to adjust ground sample distance (GSD) and swath width to agricultural application (GIANINETTO & LECHI, 2004). Other reason is the potential use of narrow bands to identify vegetation and crops (THENKABAIL et al., 2004).

In addition, hyperspectral data sets with different view angles have been used with success for classification of vegetation (LIESENBERG et al., 2007).

Research questions:

1. Are narrow bands important to improve the accuracy of crop classification?
2. Is the number of spectral bands important to improve the accuracy of crop classification?
3. Is the bidirectional reflectance important to improve the accuracy of crop classification
4. Does the combined information (narrow bands, the number of bands and the bidirectional reflectance) important to improve the accuracy of crop classification?

1.Literature

Remote sensing is the science of obtaining information about or phenomenon using data acquired by sensor placed in satellite or airborne platforms.

According to Landgrebe (1999) the complete information system can be divided in three parts: the scene – it represents the object of study that will reflect, emit or absorb electromagnetic energy captured by sensor; sensors- include multispectral and hyperspectral sensor that captures these electromagnetic energy and produce image used for interpretation of the object; data analysis – involve ways to extract information from image that better describe the object of study.

The scene

Objects of surface emit or absorb electromagnetic energy in different ways. Sensors capture this energy that can be expressed by spectral signatures.

Spectral reflectance of vegetation usually have three specific valleys: One valley is related to absorption of chlorophyll located in the range of 0,45μ - 0,67 μ;second valley is related to leaf reflectance -0,70 – 1,30 μ; third valley is related to water absorption 1,40 – 1,90 μ. Bare soil has less variation of reflectance than vegetation. The variance in barren can be affected by many factors like moisture content, soil texture, surface roughness, iron, oxide and organic matter (LANDGREBE, 1999)

BRDF

Bidirectional reflectance distribution function (BRDF) or Multi view data (MVD) is a variation in reflectivity depending on the location of sensor in relation to sun and ground target (ASNER et al, 1998).

Bidirectional reflectance gives the reflection of a target as a function of illumination geometry and viewing geometry (solar plane).Several angles are important for bidirectional reflectance studies such as: Solar zenith angle, solar azimuth angle, , view zenith, view azimuth angle.

Effects of bidirectional reflectance distribution function can be observed by the brightness or faint appearance of an image pixel. According to Beisl (2001) this effect is dominated by shadow casting. It means each image pixel will be composed of a mixture of pure and mixed material and cast shadow. The amount of cast shadow increases with the increase of the solar zenith angle and depends on the view position. BRDF anisotropy increases when sun angle increases (KUKKO et al., 2005). Other studies demonstrate that BRDF increases with increasing scan angle and decreasing relative azimuth. It means BRDF is maximal when the sun azimuth is parallel to the scan line and a pixel is at the image edge (DANAHER et al, 2001).

The position of the sum and difference in reflectivity toward and away from the sun produce backscatter and forward scatter effects in the image. These variations in reflectance can affect classification.

Backscatter effect means radiance reflected in the general direction or the illumination source (such as the sun). It happens in images with relative azimuth lesser than 90°. Vegetation with high backscatter effect has increase reflectance of surface.

A forward scattering has radiance reflected away from the general direction of the illumination source. It occurs when relative azimuth is bigger than 90°. Some vegetation with forward scattering effect has decreasing reflectance of the surface (LIESENBERG et al., 2007).

The phenonem of anisotropy is wavelength dependent. Light is scattered and absorbed differently in different regions of the solar spectrum. BRDF is dynamic and varies with anything that changes optical and physical characteristics of surface like growth of the vegetation/senescence, soil moisture, wind, sand, snow cover, harvesting, agricultural rows (ASNER et al, 1998; SANDEMEIER e DEERING, 1999).

Vegetation is strongly anisotropic because of different plant types and interaction with surface. Vegetation macrostructures like canopy dimensions; crown spacing and shading influence BRDF. Also vegetation microstructure like leaf, stem area index (LAI), stem angle distribution and foliage clumping play an important role in the BRDF influence in the images.

Sensor

Sensors register the variation of electromagnetic energy emitted or reflected by objects in images. This energy is captured electronically in a digital way and expressed by dimensional array of pixel in an image. Each pixel corresponds to average brightness of object. Nowadays, hyperspectral and multispectral sensors are available for collection of data from agriculture fields. These sensors have important differences.

Multispectral sensor uses a set of selected broad spectral bands (LILLESAND et al., 2005). . Broad bands of multispectral data are usually used for classification of broad classes like water and vegetation. It is also possible to identify crops combining the spectral and temporal resolution of multispectral data acquired during different stages of plant growth (CHAMPAGNE et al, 2005).

Hyperspectral sensors adquire images in many, very narrow, contiguous spectral bands .The spectral resolution of multispectral and hyperspectral data has diverse application in identification of vegetation. Contiguos narrow bands of hyperspectral are mostly used for estimating biophysical and biochemical parameters of plants (PRICE, 1992). Examples are their use to identify plant stress (CARTER, 1998), measure chlorophyll content of plants (BLACKBURN, 1999). In addition, narrow bands of hyperspectral data can improve classification accuracies for vegetation (COCHRANE, 2000) and agricultural crops (THENKABAIL et al, 2004).

Data analysis

Data analysis involves the use of various techniques to best interpretation of the reflectance of object in the study area. There are some important steps for good data analysis:

First, an atmospheric correction must be performed to correct absorption and scattering effects of the atmosphere in images. The atmosphere absorbs light at particular wavelengths; consequently decreasing the radiance of objects. At the same time the atmosphere scatters light into the field of view adding an extra source of radiance to objects. This correction is very important in studies dealing with surface anisotropy and effects of bidirectional reflectance.

Second, the use of hyperspectral data for traditional classification is more complex than multispectral data. There are some relevant issues to consider when using hyperspectral data (THENKBAIL et al. 2002). One issue is related to the dimensionality of hyperspectral data which requires proper data storage and data processing. This large volume of data represented limitations when traditional image classification like maximum likelihood classification is performed. This type of classification requires high computational storage for statistical algorithms. One solution to avoid problems with high dimension of hyperespectral data is a data reduction and feature extraction like PCA. PCA, Principal Components Analyses, can be applied to hyperespectral data to reduce data and extract information from more potent bands for crop classification.

Other option to work with hyperspectral data is the selection of best bands in image that better describe the object of study. Most of these methods rely on the measurement of spectral separation of classes -Jeffries Matusita or Transformed Divergence that computes separation of classes on the basis of the statistics of training areas (ITT, 2007).

2.Methodology

Study area

Objects of classification are agricultural areas in the region of the Gelderse Poort, close to the German/Dutch border and near the cities of Arnhem, Niemegen and Emmerich. The Gelderse Poort is a nature reserve with floodplains (Millingerwaard), clay mining, sand, extraction, agriculture and recreation areas. Agricultural activities evolve cattle breeding for milk and meat, and the cultivation of sugar beet, potatoes, maize, wheat and fruits like apple and pears.

Available data

An airborne AHS-160 Hyperspectral scanner, operated by INTA (Spanish National Institute for Aerospace Technology) conducted a flight over the study area “Gelderse Poort” on the 19th of June 2005. The flight happened around noon and covered the study area in four strips. Strip1 flight direction S/Strip 2 flight direction W/Strip 3 flight direction NW/SE; Strip 4 flight direction SW/NE (fig.1).

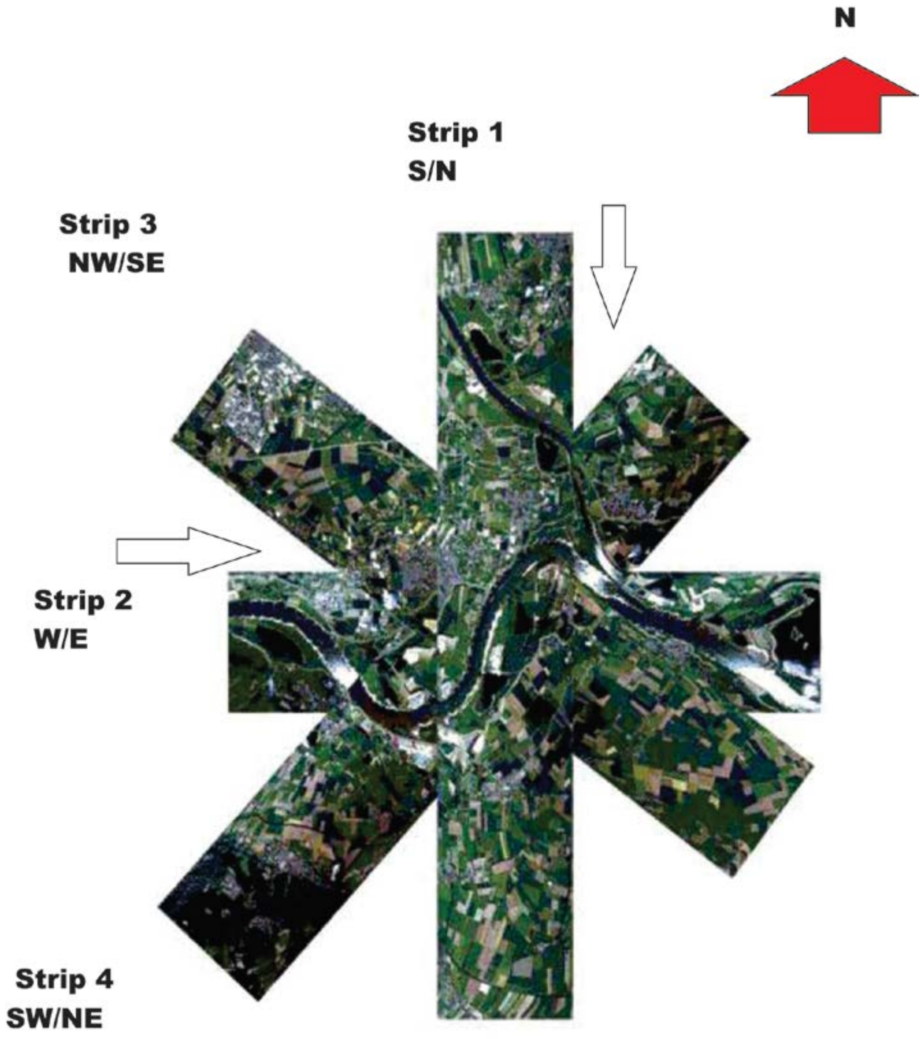

Figure 1. AHS 160 Strips 1 to 4

Hyperspectral images had radiometric and atmospheric corrections performed at VITO (Flemish Institute for Technological Research). The altitude of flight was 1834 meters and 4.75 meters spatial resolution image. Images were geometrically corrected using an orthophoto from 2004 and Dutch National Coordinate (RD). Final images were reproduced to UTM, zone 31, WGS 84 projection.

At the south of the Millingerward region, ground truth data collection was carried out at the same time as the airborne survey. Ground truth data is collected for nine classes used in this study: sugar beet, potatoes, wheat, maize, grass, barley, barren, onion, horticulture. (CLEVERS and KOOISTRA, 2005).

This research was structured in two parts. Part A: Analyses of the effect of hyperspectral data in crop classification compared to multispectral data. Part B: Analyses of the effect of bidirectional reflectance or/and hyperspectral data in crop classification.

2.1 Part A: Analyses of the effect of hyperspectral data in crop classification compared to multispectral data.

2.1.1 Part A.1 Influence of number of bands in crop classification

Hyperspectral and multispectral data were compared considering the influence of the number of bands in crop classification. Multispectral data was created by selection of some spectral bands from hyperspectral image of Strip 1.The strip 1 was chosen because it has a bigger number of agricultural areas compared to other strips. Landsat 7ETM was the multispectral data type selected to be simulated because to its suitability for agriculture classification.

The Narrow Band AHS 160 was created by selecting bands in the Strip 1 AHS-160 image with comparable wavelength bands as Landsat 7 (table 1).

Table 1 Description of bandwidths of Landsat 7 and the narrow band image

Landsat 7 (µm) (6 bands)	Narrow Band AHS 160 (µm) (6 bands)
Band 1 0,45- 0,52	Banda 3 0,47- 0,54
Band 2 0,52-0,60	Banda 5 0, 53 – 0,60
Band 3 0,63-0,69	Banda 8 0,62-0,69
Band 4 0,76- 0,90	Banda 13 0,76 – 0,83
Band 5 ,55- 1,75	Banda 21 1,41-1,82
Band 7 2,08- 2,35	Banda 40 2,22- 2,26

Information from the field was used to delineate 162 agricultural parcels (ROIs). One half of these fields were used as training areas and the other half was used as test areas. The selection of fields was done randomly. Selected areas had the number of pixels per field between 100 and 400 pixels; location away from boundaries; several small training fields well distributed in the region (CAMPBELL, 2006).

Supervised classification using maximum likelihood classifier (ML) was applied. The ML classifies pixels using a probability density functions derived from the mean, variance and covariance of the training areas (LILLESAND et al, 2004). All pixels were considered in the classification, it means no threshold was applied. The evaluation of training areas was based on how well training sets represent of all spectral variation of respective crops verified by spectral signatures, scatter plots and Jeffries Matusita calculation. The hypothesis test was applied to make decision about statistically significant difference between classifications. The p value was calculated, if it is smaller than 0, 025, (p≤0,025), classifications were statistical different.

2.1.2 Parte A.2 Influence of bandwidth in crop classification

This part of study compared crop classification of images using broad bands and narrow bands. Various spectral bands from hyperspectral images were selected for simulation of multispectral image with different bandwidths. Two simulated images were used in this study: Narrow Band AHS 160 (table 1) and Broad Band AHS 160 image (table 2) The Broad Band AHS 160 image was composed using the band math function in ENVI. Each band represented the average of wavelength bands of AHS 160 equivalent to Landsat 7.

Table 2.Description of bandwidth of Landsat 7 and Broad Band AHS 160

Landsat 7 (µm)	Broad Band AHS 160 image (µm)
Band 1 0,45- 0,52	(b1+b2+b3)/3 0,42-0,54
Band 2 0,52-0,60	(b4+b5+b6)/3 0,50-0,63
Band 3 0,63-0,69	(b7+b8+b9)/3 0,50-0,72
Band 4 0,76- 0,90	(b11+b12+b13+b14+b15+b16+b17)/7 0.71-0,95
Band 5 1,55- 1,75	(b21)/1 1,41- 1,82
Band 7 2,08- 2,35	(b25+b26+b27+b28+b29+b30+b31+b32+b33+b34+b35+b36+b37 +b38+b39+b40+b41+b42+b43+b44+b45+b46+b47+b48+b49+b50 +b51)/27 2,05- 2,38

Classification was done as described in part A.1

2.2 <u>Part B: Analyses of the effect of bidirectional reflectance or/and hyperspectral data in crop classification.</u>

2.2.1 Part B.1 Influence of combined bidirectional reflectance and number of bands in crop classification

This part of study investigated if combined information from Bidirectional data and big number of bands improve crop classification.

Subsets were created from Image AHS 160 1, 2 and 3 that covered same area of study. This area was geographically linked to check geometric corrections. Image 4 was not used because it did not have the same number of fields as the other subset.

These three subsets were combined in one image, called Overlap subsets, together they represented 189 bands. It had Principal Components Analyses applied to reduce computer computational demand and allow the classification. Overlap image represented combination of three different flight directions.

Training and test samples were selected randomly. Regions of Interests (ROIs) in these three subsets have these characteristics: number of pixels per field between 200 and 350 pixels, location away from boundaries, several small training fields in the region.

2.2.2 B.2 Influence of bidirectional reflectance and of narrow bandwidths in crop classification

This part investigated if combined information from bidirectional data and narrow bandwidths improve crop classification. Simulated images with less number of bands and narrow bandwidths were created from selection of bands from subsets 1, 2 and overlap subsets .The selection of bands was the same as used to create narrow band described on table 1. These simulated images were named Narrow subset 1 (6 bands), Narrow subset 2(6 bands), Narrow subset 3(6 bands) and Narrow overlap subsets (18 bands)

Classifications were done as described on part B.1.

3. Results

3.1 Part A: Analyses of the effect of hyperspectral data in crop classification compared to multispectral data.

3.1.1 Part A.1 Influence of number of bands in crop classification

Results for the classification of the Image 1 hyperespectral , using 63 bands, indicated this image had better classification than Narrow Band AHS 160. Image 1 had overall accuracy -86,06 and kappa index 0,808 . Narrow Band AHS 160 had overall accuracy 82, 19 and kappa index 0,766.

These results of accuracy had statistical difference ($p \leq 0{,}025$) confirming better classification for hyperspectral image (fig 2).

Contiguous spectral signatures of Image 1 offered detailed information of crops barley, barren, beet, grass, horticulture, maize, onion, potato and wheat. Classes like grass, maize, beet and wheat had good separation on scatterplot and with Jeffries Matsushita index. Potato, horticulture and onion had bad spectral separation probably related to plant stage.

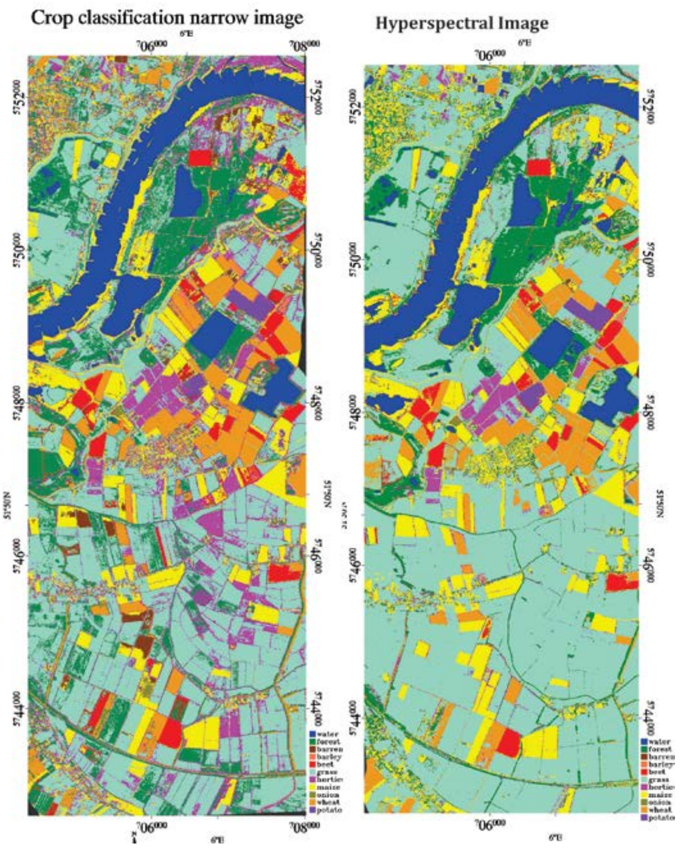

Figure 2. Classification map of Narrow Image and Hyperspectral Image

3.1.2 Parte A.2 Influence of bandwidth in crop classification

Results for the classification using Narrow Band AHS 160 and Broad Band AHS 160 indicates very small differences of overall accuracy and kappa index. Narrow Band AHS 160 had overall accuracy of 81, 00% and kappa index of 0,766. Broad Band AHS 160 had overall accuracy of 82, 19% and kappa index of 0,760. The p test was performed ($p > 0{,}025$) and confirmed that Narrow Band AHS 160 and the Broad Band AHS 160 image did not have statistical different ion in classification.

In both images cultures like barley, beet, horticulture, grass, maize, onion., potato and wheat had better separation in the green region (0,52 – 0,60 µ) and moisture of soil (0,76 – 0,90 µ) .These results were similar to studies of Thenkbail (2004) using hyperspectral images for vegetation and crop classification. It recommends the placement of 22 small narrow bands in three important wavelength ranges to best identify crops. One range is located in the visible part of spectrum(0,45-0,67 µ); the second range is located in the infrared region (0,74- 1,3 µ) and the third range is located in water absorption point (1,4-1,9 µ). These good results for both images happened because of well positioned bands in the electromagnetic spectrum and good quality of training areas.

3.2 Part B Analyses of the effect of bidirectional reflectance or/and hyperspectral data in crop classification.

3.2.1 B.1 Influence of combined bidirectional reflectance and number of bands in crop classification

View geometry from subsets 1, 2 and 3

Surface anisotropy of crops was analyzed using differences in view angles and relative azimuth. These values were collected from geometric and uncorrected subset files. This study did not consider the influence of sun angle. It had constant value of 29° in all subsets. The three subsets used same polygons for classification. Fields of potato, barren, horticulture and onion were not included in the evaluation of classification because they were not present in sufficient number.

Subset 1 had the majority of crops located in the orthogonal plane with relative azimuth bigger than 90° and possible forward scattering effects in reflectance. The overall accuracy of subset 1 was 85, 9 and kappa index of 0, 80. This subset classified well beet and maize.

Subset 2 had majority of crops located in the principal plane. It had relative azimuth lesser than 90° and possible backscatter effects. The overall accuracy of subset 2 was 87, 6 and kappa index of 0, 83. This subset classified well crops.

Subset 3 had some crops located in the principal plane and others located in the orthogonal plane. These crops had possible forward and backscatter effects. The overall accuracy of subset 3 was 73, 44 and kappa index of 0, 63. This subset classified did not classified well crops like grass and beet probably because the combination of backscatter and forward scatter effects.

Classifications of subsets 1 and 2 were tested for statistical differences. The p value was calculated ($p>0.025$) and showed no statistical difference between these two classifications. Forescatter effects did not influence accuracy for some crops in subset 1. Overall accuracy of subset 2 was slight higher than other subsets probably influenced positively from backscatter effects. This result confirmed findings of Liesenberg et al. (2007) who demonstrated higher anisotropic response for fields located in the principal plane.

Combined direction, overlap subsets image

The overall accuracy of Overlap subsets image was 95,61 and kappa index of 0,935. This subset classified very well grass, maize and wheat but did not classified barley and beet. Classifications of subsets 1, 2 and Overlap subsets were tested for statistical differences. Overlap subset had better classification than other subsets ($p \leq 0,025$). This result confirmed better crop classification by using image with bidirectional reflectance and large number of bands.

3.2.2 B.2 Influence of bidirectional reflectance and of narrow bandwidths in crop classification

Narrow subset 2 had better classification with accuracy of 91, 82 and kappa 0,882 values statistical different ($p \leq 0,025$) from classification of Narrow subset 1 that had accuracy of 87, 96 and kappa 0, 81 and Narrow Overlap with accuracy of 89, 06 and kappa 0, 8261 (fig 3).

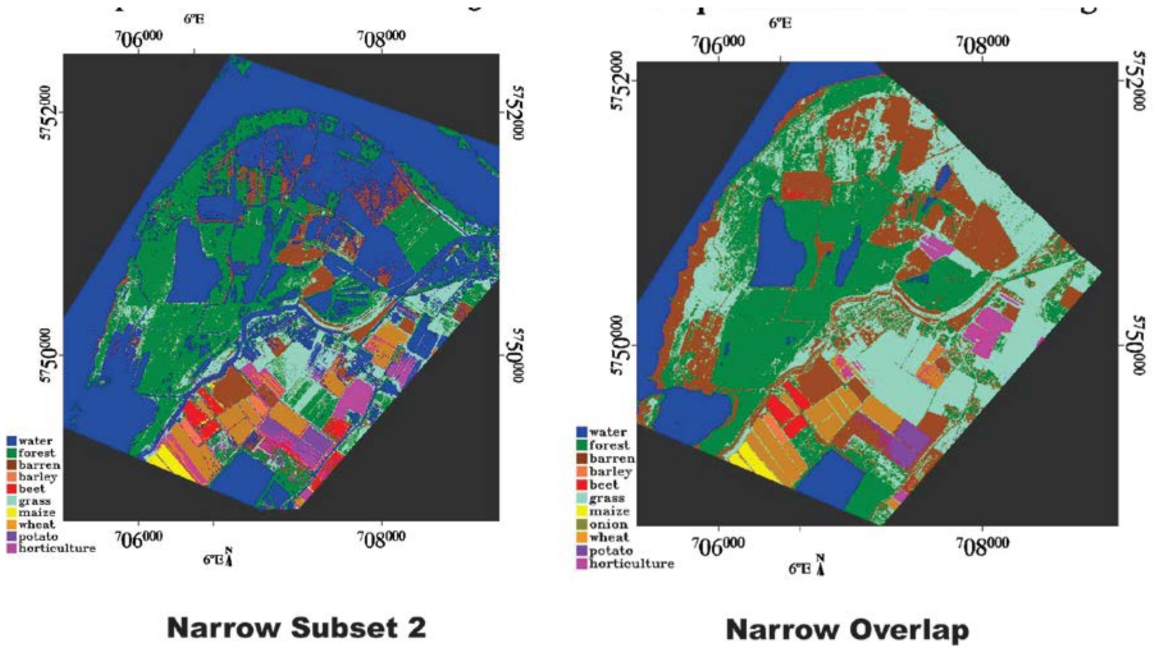

Figure 3. Classification map of Narrow subset 2 and Narrow Overlap areas.

Narrow subset 2 classified better beet, grass, maize and wheat. It seems that backscatter effects captured in narrow bandwidths improved crop classification. These results confirmed studies of Price (1992) and Thenkbail (2002) that recommended contiguous hyperspectral bands for identification of crops.

Narrow subset 1 had bad classification for grass. One possible explanation is related with e*rectrophile* structure of grass, wheat and barley combined with forescatter effects captured in images. This combination did not help classification of this crop (SANDEMEIR and DIERING, 1999).

Narrow overlap subset did not have good accuracy comparing with narrow subset 1 , narrow subset 2 and overlap subsets (part B.1). Overlap subsets, the combination of images with more bands had better classification than the synthetic multispectral image, the Narrow overlap subset that had fewer bands. It classified very well three classes: grass, maize and wheat

4.Conclusions

This research studied if aspects of remote sensing data like large number of bands, narrow bandwidths and viewing angle information may have effect on crop classification.

According to the dataset used in this study we concluded:

1. The number of bands is important for crop classification. An image with 63 bands had better classification than an image with 6 bands. Beet, maize, wheat and grass had good classification accuracy in hyperspectral image.
2. The bandwidth is not relevant to improve crop classification. An image with narrow band and an image with broad band located in the same position of the electromagnetic spectrum produced similar classification results.
3. The effect of backscatter on images improved crop classification. This effect influenced positively crop classification by using multispectral and hyperspectral images.
4. The combination of bidirectional reflectance, bandwidth and large number of bands improved accuracy of crop classification. The combination of view angles using two hypersperspectral images with narrow bandwidth showed improvement of classification for four classes: beet, grass, maize and wheat.

6.Recommendations

Spatial and spectral resolution of AHS 160 is appropriated for crop classification. Hyperspectral image from airborne campaign offers good image for crop classification of grass, maize and wheat.

Future studies should consider other methods of classification to better discriminate horticulture, barren, barley, onion and potato. One possibility is to increase the number of fields in the training set. Other possibility is to explore other methods of classification to better discriminate these crops in different bands.

Some crops with *erectophile* structure have negative influence in classification. Future studies of bidirectional reflectance should consider information about structure of plants and reflectance measurement in the field. This information is helpful to explain variance of reflectance according to variance of view angles.

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