IMPACT OF BAND-RATIO ENHANCED AWIFS IMAGE TO CROP CLASSIFICATION ACCURACY

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ABSTRACT

Multispectral satellite images have been utilized in the National Agricultural Statistics Service (NASS) for crop cover classification and crop acreage estimation since the 1970's. Though ancillary data is utilized to enhance the classification accuracy, there are few applications that maximize the utilization of the feature information of the given multispectral images. Every multispectral image band directly provides the specific spectral response to a given land cover category. The different combinations of band ratios or vegetation indices enhance spectral characteristics of some crops while suppressing others. Therefore, various vegetation indices and image ratios of Landsat images have been extensively studied and applied to identify various land cover and land use characteristics in the past. However, NASS began using the ResourceSat-1 AWIFS sensor for operational crop classification and acreage estimation in 2006. The AWIFS' bands are different from those of Landsat, and there is sparse literature published about research and applications of the spectral characteristics of AWIFS image band ratio and vegetation indices. In this paper, the impact of using band ratio and vegetation indices of the AWIFS images to the crop classification accuracy is empirically investigated via supervised classification. The classification results with respect to the additional vegetation index and band ratio are presented and compared in terms of the overall and crop only classification accuracy. The research indicates that appropriately used vegetation indices and image ratios can potentially improve crop classification accuracy though the gain may not be huge. It is concluded that further research is needed.

INTRODUCTION

All bands of raw multi-spectral imagery record their spectral responses to all given land cover (material) categories. Most crops can be distinguished from each other or distinguished from most other inorganic materials using multispectral satellite images by virtue of their difference in notable absorption in the red and blue segments of the visible spectrum, their difference in higher green reflectance and, especially, their very strong reflectance in the near-IR. Different types of crops or other vegetation often show distinctive spectral signatures owing to differences in leaf shape and size, overall plant shape, its vegetative density, its interactions with solar radiation and other climate factors, the availability of chemical nutrients, water content, and soil types. This intrinsic discrimination among different crops and most other materials results from the fact that the absorption of the different vegetation plant pigments, such as chlorophyll concentrated in the palisade cells, varies in the visible blue and red bands of the spectrum, and the reflection for visible wavelengths concentrated in the green band depends on the greenness of most vegetation's green-leafy color. Moreover, variations of the strong reflectance in the near-IR wavelengths also depend on the cell moisture and the structure of the spongy mesophyll cell of vegetation leafs. These properties of vegetation visually determine their tonal signatures on multispectral images: darker tones in the blue and red, bands, somewhat lighter in the green band, and notably bright in the near-IR bands. These spectral variations provide a foundation for discriminating various crops and other materials, such as forests, grasslands and range, shrub-lands, and orchards using multispectral satellite images.

As mentioned above, many factors combine to cause differences in spectral signatures for the varieties of crops and for other materials. To discriminate different crops, we have to differentiate the signature for each crop in a region from representative samples at specific times. However, some crop types have quite similar spectral responses at equivalent growth stages. The signature differences between some crop types can be fairly small even though other variables, such as soil type and ground moisture are the same. Moreover, in most cases, the satellite image sensors used for acquiring data are broadband, which results in crop spectral confusion. These factors cause some crop types to be inseparable in spectral signature at some period of time. Therefore, generating accurate crop classification in a large area, such as a state using single-date spectral data alone, would be very difficult as compared with using multitemporal data (Lo et al., 1986). In order to estimate crop acreage based on the remote sensing imagery, NASS has utilized the multi-temporal, multi-spectral images acquired by the Indian ResourceSat-1 AWIFS sensor, along with other ancillary data for crop cover classification since 2006. However, the classification results are still prone to errors and spectral confusions due to the signature inseparability among some crops for a given sensor (in our case, the AWIFS), the heterogeneity of the natural environment, such as soil, water regimes, topography, and the variations in farming practices. How to maximize the utilization of the information contained in the given multispectral images to improve to classification accuracy is of great interest to NASS.

It is well known that differences in raw image pixel brightness can be caused by factors such as difference in slope, by shadowing, or by differences in the color of surface material. These factors may affect the ability of a classification algorithm to correctly identify crop types and other surface materials from the remotely sensed image. To reduce these factors, the multispectral image, which characterizes specific crops or other materials, can be enhanced or suppressed by image processing techniques such as image transformation, filtering, principal components analysis, and band ratioing. The band ratioing method is one of the simplest methods for multispectral image enhancement technique (Jain, 1989). It is usually applied to enhance the spectral differences between surface covers that are difficult to detect or separate in raw images. It may suppress the effect of variable illumination resulting from topographic variations (Mather, 1987), and eliminates slop shadows, seasonal changes, and either differences in sunlight angle or intensity (Jensen, 1986). The differences in pixel brightness of the ratio image are caused by only differences in reflectance without effects of topography. Thus, ratio images convey only spectral, not topographic information. It may also provide unique information not available in any of single bands of the raw image that is useful for discriminating vegetation and soils (Satterwhite, 1984). The classification of ratio values will produce classes of uniform spectral properties, regardless of topography.

There are many applications of using image band ratio for identifying a variety of land cover objects. Nelson (1983) used band ratio along with image differencing and vegetation index differencing techniques to delineate gypsy moth defoliation in Pennsylvania. Satterwhite, (1984) investigated discriminating vegetation and soils using Landsat MSS and Thematic Mapper band ratios and concluded that band ratios provided extra unique information for better discriminating vegetation and soils. Lo, *et al*.(1986) investigated using multitemporal LANDSAT image ratio and green vegetation index (GVI) data for agriculture land-cover classification. Musick and Pelletier (1986) used band ratios of LANDSAT TM to determine variation in soil water content. Chevaz, et al. (1982) suggested using statistical method for selecting Landsat MSS band ratios. Mohd, *et al*., (1992) evaluated LANDSAT-5 vegetation indices for detecting forest areas and crops and achieved better classification accuracies by using perpendicular vegetation index (PVI). Price, *et al*. (2002) investigated how to find optimal Landsat TM band combinations and vegetation indices for discrimination of six grassland types. Apan *et al*. (2002) analyzed spectral discrimination and separability of agricultural crops and soil attributes, specifically, crop type, crop growth stages, soil color and soil texture, using Aster imagery and found the band ratio based vegetation indices had better spectral discrimination and separability for crops than the raw image bands. However, very few published literatures have focused on the using AWIFS image band ratio and index combinations for improving the crop classification accuracy.

The objective of this study is to empirically evaluate the impact of using band ratio and various band ratio based indices of the AWIFS images on the accuracy of the major crop classification. A variety of band ratios and vegetation indices calculated and fed into the classifier in addition to the raw images, and the accuracy of the classification for different crops using additional band ratio and/or index information will be compared with classification results without inclusion of the band ratios and indices.

METHODS

Study Site

One study site was used to examine the direct impact of using the additional image ratio and index information in the crop classification. This site covers the entire State of Indiana plus a 10 kilometer surrounding buffer with Lat/Long (ULX =-87.7457 / ULY=42.0723, LRX=-84.8872 / LRY=37.4404). This site was chosen because one

AWIFS image scene covers almost the entire state, which is easy to handle, and Indiana is one of major agriculture states, and the two major U.S. crops, corn and soybean, are represented.

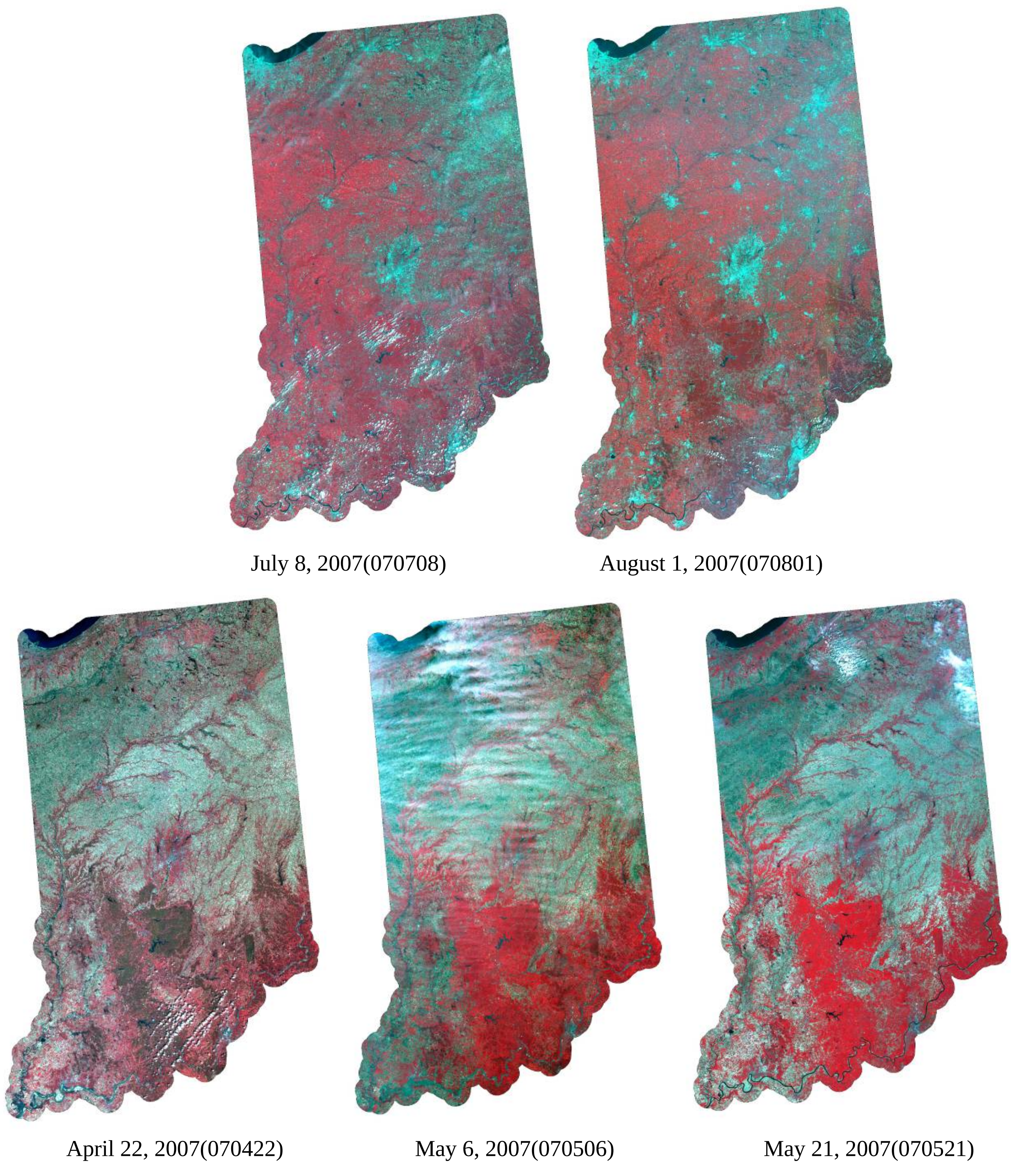

Figure 1. 2007 Indiana State AWIFS images acquired on different date for crop classification analysis

Data Acquisition and Preprocessing

The image data used for this experiment are acquired using Advanced Wide Field Sensor (AWIFS) sensor from the Indian satellite ResourceSat-1. The AWIFS Sensor is one of three solid-state cameras on-board ResourceSat-1, which provide continued remote sensing data services on an operational basis for integrated land and water resources management at micro level, with enhanced spectral and spatial coverage and stereo imaging, and further carry out studies in advanced areas of user applications like improved crop discrimination, crop yield, crop stress, pest/disease surveillance, and disaster management etc. The AWIFS camera has a spatial resolution of 56m at nadir and 70m at field edge, a radiometric resolution of 10 bits and four spectral bands with the additional feature of on-board detector calibration using LEDs. The spectral bands of AWIFS include Green (Band 2, 0.52-0.59 μm), Red (Band 3, 0.62-0.68 μm), NIR (Band 4, 0.77-0.86 μm), and SWIR (Band 5, 1.55-170 μm). The AWIFS cameras are held in two electro-optic modules: AWIFS-A and AWIFS-B, each containing four-band assemblies. These bands are similar to LANDSAT Band 2, Band 3, Band 4 and Band 5. However, the AWIFS sensor has a revisit period of 5 days.

In this study, the images have been geo-rectified and registered. All AWIFS images and all training data, and ancillary data are re-projected to Albers Equal Area Conic projection, and re-sampled to 56-meter spatial resolution. There is no cloud removal or radiometric correction applied. The 10-bit AWIFS images are uniformly rescaled into 8 bits using nearest-neighbor method.

The AWIFS images, as shown in Figure 1, used for single scene classification experiments are the images acquired on July 8, 2007 and August 1, 2007. To perform a multitemporal analysis and have full state coverage, the additional images acquired on April 22, May 6, and May 21 are also used for generating the classification results, which are comparable to the last year's NASS official remote sensing results.

It should be indicated that in this study, all the ratio/index images are all converted to 8-bit gray-scale. The spatial resolution remains 56 meter, the same as the raw images.

Training Sample – FSA CLU Data

To perform the supervised crop classification, the USDA Farmer Service Agency's (FSA) Common Land Unit (CLU) GIS data is used as training and validation data. FSA CLU's are the smallest land unit with permanent boundaries, common land cover and management, common owner (tract) and producer association (farm). The CLU data files contain digital shape files and crop planted information and the unique individual farm operator identification. It is subject to the NASS confidentiality rules and cannot be released to anyone outside of NASS. The CLU data provides a large amount of ground truth. In the classification experiment, the CLU data is sampled in strata.

Ancillary Data

It is well known that ancillary data can be used to mask out uninterested non crop land-cover and can provide extra information to enhance the classification process. The original NASS Cropland Data Layer (CDL) classification, which makes use of the canopy and impervious cover data from the 2001 National Land Cover Dataset (NLCD 2001) as ancillary data, is used as the baseline classification accuracy for comparison to the various indices in this study. To make the results using image ratio and indices be comparable with the baseline, the canopy and impervious cover data 2001 National Land Cover Data (NLCD) are also used as ancillary data. In addition, the data reflecting land surface characteristics, derived directly from the National Elevation Dataset (NED), including elevation, slope, and aspect are also used as ancillary data in the classification. It allows for classifying crops in terms of specific terrain conditions. Moreover, MODIS 16-day NDVI composite images, which provide more temporal information, are also used. These ancillary data have been shown to improve the classification accuracy in NASS CDL operations.

BAND RATIO AND VEGETATION INDICES

To enhance the vegetation signal in remotely sensed data and provide an approximate measure of live, green vegetation amount, a number of spectral vegetation indices have been proposed by combining data from multiple spectral bands into single values because they correlate the biophysical characteristics of the vegetation of the landcover from the satellite spectral signals. Jordan in1969 first presented the Ratio Vegetation Index (RVI) or simple ratio (SR). Rouse et al. in1973 further suggested the most widely used Normalized Difference Vegetation Index (NDVI) to improve identifying the vegetated areas and their "condition". He also presented a modified normalized difference vegetation index (MNDVI) by replacing IR band with SWIR band in NDVI (Rouse *et al.*, 1973). However, the NDVI index is saturated in high biomass and it is sensitive to a number of perturbing factors, such as atmospheric effects, cloud, soil effects, and anisotropic effects, etc. Therefore, a number of derivatives and alternatives to NDVI have been proposed in the scientific literature to address these limitations. Tucker (1979) presented a transformed normalized difference vegetation index (TNDVI) by adding a constant 0.5 to NDVI and taking the square root. It always has positive values and the variances of the ratio are proportional to mean values. TNDVI indicates a slight better correlation between the amount of green biomass and that is found in a pixel (Senseman *et al.* 1996). To reduce the impact to the NDVI from the soil variations in lower vegetation cover areas, Huete (1988) proposed a Soil-Adjusted Vegetation Index (SAVI) by introducing a correction factor *L*. However, how to dynamically estimate the parameters and the correction factor L for the indices is a challenge. Rondeaux, *et al*., (1996) therefore, suggested an optimal soil adjusted vegetation index (OSAVI) with an optimal correction factor. Liu *et al*. (1995) proposed the Enhanced Vegetation Index (EVI) to optimize the vegetation signal with improved sensitivity in high biomass regions by incorporating both background adjustment and atmospheric resistance concepts into the NDVI. Since the ResourceSat-1 AWIFS sensor does not have a blue band, a 2-band EVI without a blue band enhanced vegetation index EVI2 (Jiang *et al*. 2007) is used instead in this study. Gong *et al.* (2003) proposed a new vegetation index that multiplies RVI with NDVI (RNDVI) to balance sensitivity differences of both RVI and NDVI to low LAI and high LAI conditions and to increase the index correlation with LAI. This index gives a better linearity. Gitelson *et al*. (1996) proposed Green Normalized Difference Vegetation Index (GNDVI) and a modified version (MGNDVI) by using a green channel instead of red channel to compute vegetation index for remote sensing of global vegetation. Lymberner et al. (2000) proposed a specific leaf area vegetation index (SLAVI) to correlate the spectral reflectance of Red, NIR and SWIR bands with the specific leaf area. Thenot *et al.* (2002) proposed using the photochemical reflectance index (PRI) to measure the water-stress. This index originally uses narrow bands R_{513} and $R_{570,}$ which are the beginning frequency and ending frequency of the broadband sensor AWIFS' green band. In this study, we defined a modified photochemical reflectance index (MPRI, as shown in Table 1) by using AWIFS Green band and Red band to replace R_{513} and R_{570} to capture the light use efficiency and to reflect water-stress. Gao (1996) proposed a normalized difference water index (NDWI) (or normalized difference moisture index (NDMI) by Shaun *et al.*, 2003) to detect the vegetation liquid content. Hunt and Rock (1989) defined a moisture stress index (MSI) or RDI (Ratio Drought Index by Pinder and McLeod, 1999) by using near- and middle-infrared reflectance ratio to detect changes in leaf water content.

In this study, the additional image ratios and indices are proposed or included for investigation for their impact to crop classification accuracy. We include Modified Ratio Vegetation Index (MRVI), which is defined SWIR/R; Green ratio vegetation Index (GRVI) and Modified Green ratio vegetation Index (MGRVI), which are defined by NIR/G and SWIR/G. We also define a Brightness Index (BI), which sums all band reflectance, to represent overall reflectance strength. In addition, a Red green ratio index (RGRI) and a Normalized difference red green index (NDRGI) defined by R/G and (R-G)/(R+G) are also defined for experiment. Finally, a normalized difference vegetation structure index (NDVSI) is introduced as shown in Table 1. This index is proposed in hopes of capturing the crop vegetation structure, which is mainly reflected by NIR band.

The detailed formulas and references of all vegetation indices and image ratios to be included in this experiment are listed in Table 1.

DECISION TREE CLASSIFICATION WITH VEGETATION INDICES

In order to evaluate the impact of using extra band ratios and various vegetation indices in the cropland coverage classification on the classification accuracy, a supervised decision tree classification method was used. A decision tree is a logical, predictive model represented as a binary tree that shows how the value of a target variable can be predicted by using the values of a set of predictor variables. It represents a multistage decision process. It is a class discriminator that recursively partitions the training data set until each partition consists entirely or dominantly of examples from one class. Each non-leaf node of the tree contains a split point that is a test on one or more features and determines how the data is partitioned. The decision tree is built by recursively partitioning the data.

The decision tree classification method, as compared with other methods, has several advantages: (1) it is easy to understand and interpret with a brief explanation; (2) it requires little data preparation. Other techniques often require data normalization, dummy variables need to be created and blank values to be removed; (3) it is able to handle both numerical and categorical data; (4) it is a white box model. If a given situation is observable in a model the explanation for the condition is easily explained by Boolean logic; (5) it is possible to validate a model using statistical tests. That makes it possible to account for the reliability of the model; (6) it is robust and noise resilient. It tolerates to training sample errors and cloud pixels to some extent; (7) there is no assumption of data distribution required; (8) it scales well for varying numbers of training samples and considerable numbers of attributes in large databases; (9) it is quick and performs well with large data sets. Large amounts of data can be analyzed using personal computers in a short time; (10) there is no limit in data attributes. The number of image data layers, ancillary data, and training data is unlimited.

Table 1. Image ratios and vegetation indices included in the experiments.

Vegetation Index/Image Ratio	Formula	Reference
Ratio normalized difference vegetation Index (RNDVI)	RNDVI = $(NIR^2-R)/(NIR+R^2)$	Gong *et al*., 2003
Modified ratio vegetation index (MRVI)	MRVI = SWIR/R	-
Modified Photochemical reflectance Index (MPRI)	MPRI = (G-R)/(G+R)	This study
Normalized difference vegetation index (NDVI)	NDVI = (NIR-R)/(NIR+R)	Rouse *et al*., 1973
2-band Enhanced vegetation index (EVI2)	EVI2 = 2.5(IR – red)/(IR + red +1)	Jiang *et al*. 2007
Modified green normalized difference vegetation index (MGNDVI)	MGNDVI = (SWIR–G)/(SWIR+ G)	Gitelson *et al*., 1996
Ratio vegetation index (RVI)	RVI = NIR/R	Jordan, 1969
Modified normalized difference vegetation index (MNDVI)	MNDVI = (SWIR – R)/(SWIR + R)	Rouse et al., 1973
Brightness index (BI)	BI = G+R+NIR+SWIR	This study
Red green ratio index (RGRI)	RGRI = R/G	-
Green normalized difference vegetation index (GNDVI)	GNDVI = (NIR –G)/(NIR + G)	Gitelson *et al*., 1996
Normalized difference red green index (NDRGI)	NDRGI = (R –G)/(R + G)	This study
Normalized difference vegetation structure index (NDVSI)	NDVSI = [NIR - (R+G) x 0.5]/ [NIR + (R+G) x 0.5]	This study
Ratio drought index (RDI)	RDI = SWIR/NIR	Hunt & Rock 1989, Pinder & McLeod 1999
Transformed NDVI (TNDVI)	TNDVI = $[(NIR-R)/(NIR+R)+1]^{½}$	Tucker, 1979
Green ratio vegetation Index (GRVI)	GRVI = NIR/G	-
Optimal soil adjusted vegetation index (OSAVI)	OSAVI = (NIR–R)/(NIR+R+0.16)	Rondeaux *et al*., 1996
Modified green ratio vegetation Index (MGRVI)	MGRVI = SWIR/G	-
Specific leaf area vegetation index (SLAVI)	SLAVI = NIR/(R+SWIR)	Lymberner *et al*., 2000
Normalized difference moisture index (NDMI)	NDMI = (IR - SWIR)/(IR+SWIR)	Gao 1996, Shaun *et al*., 2003

There are many very powerful and popular software implementations of decision tree classifiers available, which construct decision trees for classification. In this study, one of the well-known programs for constructing decision trees Rulequest's See5 (Release 2.05) (C4.5) (Quinlan 1993) is used for crop classification. The See5 decision tree classifier, as compared with others, has friendly user interface, better performance and multiclassifier-based boost algorithm implemented, and has been integrated with Erdas Imagine.

The first step in building a decision tree is to collect a set of ground truth data. This data is called the "training" dataset because it is used for a decision tree classifier to learn how the value of a target variable is related to the values of predictor variables. In our case, the FSA's CLU data is our training samples. We then use the training data set to train the decision tree classifier to automatically build the decision tree that models the data for further classification.

To incorporate the derived extra band ratios and various vegetation indices in the classification process, they can be stacked into the original raw image as extra layers.

EXPERIMENTAL RESULTS AND DISCUSSION

Classification Results of Single Date Scenes with Different Vegetation Indices

The purpose of the first experiment in this study is to examine how every individual vegetation index affects the classification results of a single scene. In this experiment, a single scene is used without MODIS data and other ancillary data. The training data is the same as that used in the original CDL production with the corresponding area coverage. From this scene, various vegetation indices and band ratio images are generated. These generated images are first rescaled to 8-bit. The newly generated index or ratio images are then stacked with the original scene one by one for classification experiment, and then all indices and ratios are stacked altogether with the original scene classification evaluation. In this experiment, the classifications are carried out separately by date. The classification accuracy results are tabulated by crop only and overall. All of experimental classification results using single date scenes acquired on July 8, 2007 and August 1, 2007 are tabulated in Table 2.

As shown in Table 2, the classifications of the original scenes without adding vegetation index or image ratio are highlighted with bold. The classification accuracies of the original image with or without vegetation index from the July 8, 2007 scene are significantly better than those from the August 1, 2007, and the accuracy results for crops only are much better than those overall accuracy results for both dates. This is an interesting and unexpected result. It is not clear why the results from August are inferior to those from July. This is a question to be answered in future research.

In Table 2, all vegetation indices are ordered according to the overall classification accuracy with respect to the different scene dates. As observed from Table 2, the ranks of the accuracy performance of the vegetation indices or image ratios are consistent for both overall and crops only accuracies for a given scene date.

It is observed that the top two vegetation indices are RNDVI, MRVI and RNDVI, ALL respectively for July 8 and August 1 dates, and the best performing vegetation index for both dates is the RNDVI, a product of ratio vegetation index and normalized difference vegetation index. However, the ranks of the accuracy performance of most vegetation indices from the scenes acquired on different dates are different.

By comparing the accuracy of the scene only classification with the accuracy of the scene with vegetation index added for July 8 image scene, we find that most of vegetation indices and ratios including RNDVI, MRVI, MPRI, NDVI, EVI2, MGNDVI, RVI, MNDVI, BI, RGRI, GNDVI, NDRGI, NDVSI, RDI, ALL, TNDVI, and GRVI, help to improve the classification accuracy, with a maximum 0.5% improvement from RNDVI. These 16 indices constitute a better performer list. As shown in Table 2, only 5 indices GRVI, OSAVI, MGRVI, SLAVI, and NDMI have insignificant impact to the classification accuracy (within ±0.05% change). Therefore, the optimal soil adjusted vegetation index (OSAVI), modified green ratio vegetation index (MGRVI), specific leaf area vegetation index (SLAVI), and normalized difference moisture index (NDMI) are dropped from further experiment because of no help in improving or even deteriorating (as SLAVI and NDMI did) the classification accuracy.

Doing the same comparison for August 1 image scene, it is found that the better performer list has only 6 vegetation indices, including RNDVI, all indices (running the original scene with all indices altogether), RVI, NDVSI, BI, MGNDVI, and MGRVI. They all help improving the classification accuracy, with a maximum 0.6% improvement from RNDVI. The indices RVI, NDVSI, BI, MGNDVI, MGRVI, NDRGI, NDMI, RGRI, MPRI, MRVI, RDI, GNDVI, and GRVI have little impact the classification accuracy (within ±0.05% change). The vegetation indices NDMI, RGRI, MPRI, MRVI, RDI, GNDVI, GRVI, NDVI, TNDVI, MNDVI, EVI2, OSAVI, and SLAVI reduce either overall or crops only classification accuracy or both, within which NDVI, TNDVI, MNDVI, EVI2, OSAVI, and SLAVI significantly reduce the accuracy by at least 0.1%. Thus, they are excluded for further experiment.

As shown in Table 2, the new indices introduced in this paper including NDVSI, BI and NDRGI all have positive impact on the accuracy for both dates. The index RGRI is positive for the July scene and has no significant impact for the August scene.

From Table 2, it is observed that the accuracy performance of TNDVI, OSAVI, and SLAVI are consistently ranked in the bottom for both July and August scenes. Therefore, they may not appropriate for classification. It is also found that the performance of vegetation indices NDVI, MNDVI, EVI2 and MRVI change dramatically for scenes acquired on different dates. Why NDVI, MNDVI, EVI2 and MRVI perform poorly in August scene is not clear.

It should be indicated that to determine the better performers, any index that had better "overall" AND "crops only" accuracy numbers than the original single scene accuracy is included.

Table 2. Classification Results of Single Scene with Different Vegetation Indices.

Accuracy			Accuracy		
Scene Date	July 8, 2007		Scene Date	August 1, 2007	
Evaluated by	Overall	Crops only	Evaluated by	Overall	Crops only
No Indices	**79.04**	**81.04**	**No Indices**	**65.83**	**67.53**
RNDVI	79.55	81.56	RNDVI	66.41	68.14
MRVI	79.34	81.35	ALL	66.21	67.93
MPRI	79.27	81.28	RVI	65.87	67.58
NDVI	79.25	81.25	NDVSI	65.87	67.57
EVI2	79.22	81.22	BI	65.85	67.56
MGNDVI	79.21	81.22	MGNDVI	65.85	67.56
RVI	79.21	81.22	MGRVI	65.84	67.56
MNDVI	79.21	81.21	NDRGI	65.83	67.54
BI	79.21	81.2	NDMI	65.82	67.54
RGRI	79.2	81.2	RGRI	65.82	67.53
GNDVI	79.2	81.2	MPRI	65.82	67.53
NDRGI	79.19	81.19	MRVI	65.81	67.52
NDVSI	79.15	81.16	RDI	65.81	67.51
RDI	79.14	81.15	GNDVI	65.79	67.5
ALL	79.14	81.13	GRVI	65.79	67.49
TNDVI	79.12	81.13	NDVI	65.71	67.42
GRVI	79.07	81.06	TNDVI	65.7	67.4
OSAVI	79.04	81.04	MNDVI	65.67	67.38
MGRVI	79.03	81.04	EVI2	65.64	67.35
SLAVI	79.03	81.02	OSAVI	65.64	67.35
NDMI	78.99	81	SLAVI	65.59	67.29

Multitemporal Classification Results of with Selected Vegetation Indices

Multitemporal analysis always outperforms single temporal analysis in terms of crop classification accuracy. Therefore, the purpose of this part of the experiment is to see how vegetation indices and band ratios along with other ancillary data impact the accuracy of the multitemporal crop classification results, and to see if any vegetation indices and their combination provide extra information under multitemporal condition.

In this part of experiment, the Indiana 2007 multitemporal Cropland Data Layer (CDL) is reproduced by using the original inputs (those used in producing the official Indianan 07 CDL) plus a combination of the selected vegetation indices from the July 8, 2007 (070807) and August 1, 2007 (070801) AWIFS scenes. It should be indicated that in the original input data there are 5 scenes from 5 different dates. However, only the vegetation indices from July 8, 2007 and August 1, 2007 scenes are used in the experiment.

As shown in Table 2, the vegetation index RNDVI performed the best for both scenes. Therefore, classifications were run for the CDL's with original data plus the individual RNDVI's of either 070801 or 070801 AWIFS scene, or plus both RNDVI's from 070801 and 070801 AWIFS scenes. All of vegetation indices in the better performer list from each scene, and all of better performer indices from both scenes are then added to the original input data respectively for classification.

Table 3 lists all original inputs and vegetation index combinations and their corresponding classification accuracy results. As shown in Table 3, after adding vegetation indices, the overall classification accuracy of all data combinations have dropped with a maximum of 2%. But the crops only accuracy varies with different data vegetation index combinations.

Table 3. Multitemporal Classification Results with Vegetation Indices.

Data combination	Overall	Crops only
Original CDL with no indices added	91.80	91.76
Original Inputs + 070708 RNDVI	89.70	91.75
Original Inputs + 070708 Top 16 Indices	90.19	92.21
Original Inputs + 070801 RNDVI	89.85	91.91
Original Inputs + 070801Top 6 Indices	89.87	91.91
Original Inputs + RNDVI's from Both Scenes	89.67	91.72
Original Inputs + Better Performer Indices form Both Scenes	90.22	92.22

As shown in Table 3, adding the 070708 RNDVI alone does not improve the overall or crops only accuracy. The reason that adding the 070708 RNDVI alone did not improve the accuracies is unknown. To figure out the exact reason needs further investigation. However, adding 070801 RNDVI alone did increase the crop only classification accuracy though only 0.15% improvement. When both 070708 RNDVI and 070801 RNDVI are added, the crops only accuracy remains roughly unchanged, in fact, it dropped a little (0.04%). These results have shown that the individual best performer indices may or may not help to improve the accuracy in a multitemporal classification depending on how they are used. It needs further investigation to conclude whether including RNDVI from every scene will further improve the accuracy.

However, when all better performer indices from either July scene or August scene are added to the original input data, the crops only accuracy improved. When 16 July indices were added, the crops only accuracy was improved by 0.45% while 6 August indices yielded 0.15% improvement. The best crops only performer of this group was the one that used all of the better performer indices from both scenes. This combination had 0.46% improvement in crops only accuracy and the best overall accuracy of 90.22%, which is still 1.58% lower than the original CDL result. This result seems to imply that when performing multitemporal classification, all available better-performing vegetation indices from different dated scenes should be included. However, whether including all indices of positive impact from each scene still needs to be further investigated.

CONCLUSION

This paper reported a preliminary research on the impact of using vegetation indices and image ratios on the crop classification accuracy. In this research, we evaluated 20 vegetation indices and image ratios, including some widely used, known vegetation indices, and a few new indices introduced in this paper. The purpose of this research is to find out whether the vegetation index and image ratio have any impact on crop classification accuracy, and which index has positive impact and which has negative impact so that the appropriate vegetation indices can be best used at the most appropriate times and conditions.

From this research, it is found that the vegetation indices and image ratios do have impact on the crop classification accuracy. It is found that not all vegetation indices have positive impact. Some indices have insignificant impact to the classification accuracy while others have negative impact. The impact on the classification accuracy for most vegetation indices is scene dependent. It is found that for single scene classification, the vegetation index RNDVI has the best performance in classification accuracy improvement for both test scenes while the vegetation indices TNDVI, OSAVI, and SLAVI are consistently ranked in the bottom of the accuracy performance for both July and August scenes. It is also found that the performance of vegetation indices NDVI, MNDVI, EVI2 and MRVI are very sensitive to scenes. In general, the ranks of the accuracy performance of most vegetation indices from the scenes acquired on different dates are different.

It is also found that the new indices introduced in this paper, including NDVSI, BI and NDRGI, have positive impact to the accuracy for both dates. The index RGRI is positive for July scene and has no significant impact for August scene.

For the multitemporal classification, adding vegetation indices lead a 1.58% to 2% drop in the overall classification accuracy for any vegetation indices and original input data combinations. But the impact on the crops only accuracy varies with different vegetation indices applied. The experimental results have shown that using the individual best performer index the crop only accuracy improvement depends on the index used. When using all better performer indices from either the July scene or the August scene, the crops only accuracy improved. The best crops only performer of this group was the one that used all of the better performer indices from both scenes.

Finally, it is concluded that appropriately used vegetation indices and image ratios can potentially improve crop classification accuracy though the gain may not be huge. This preliminary research also brings up some questions that need to be further addressed in future research. It is suggested that the future research should focus on determining whether the individual vegetation index can increase spectral separability of a specific crop, how the image/date affect the performance of the vegetation indices, how each vegetation index impacts the classification accuracy of individual major crops, why the best performing single scene RNDVI can not further improve the multitemporal classification accuracy, and how we best utilize the information contained in the vegetation indices and image ratios to enhance the crop classification accuracy.

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