CLASSIFICATION OF MODIS SPECTRAL AND ANGULAR SIGNATURES USING DECISION TREE ALGORITHM

[a,b] Z. Jiao, [b] C. B. Schaaf, [b] A. H. Strahler, [c] F. Gao, [b] C. Woodcock, [a,b] X. Li, [a] J. Wang,
[b] J. Liu, [c] B. Tan

[a] State Key Laboratory of Remote Sensing Science (Beijing Normal University)
[b] Department of Geography and Center for Remote Sensing, Boston University, Boston, MA 02215, USA
[c] NASA GSFC and ERT Inc., Greenbelt, MD 20771, USA
–jiaozt@bnu.edu.cn

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ABSTRACT:

It is important to explore the ability of Bidirectional Reflectance Distribution Function (BRDF) to improve classification accuracy using MODerate Resolution Imaging Spectroradiometer (MODIS) BRDF and albedo products. This paper examines the utility of including MODIS BRDF products as additional input features to a decision tree classifier (c4.5). Our results show that supplementing MODIS BRDF parameters (f_vol and f_geo) with Nadir BRDF-Adjusted Reflectances (NBAR) and Enhanced Vegetation Indexes (EVI) increases overall classification accuracy by 3.02% to 4.72%, and reduces misclassification rates by 15% to 22%, depending on how many BRDF parameters are added (fourteen vs. four), and if these BRDF parameters are normalized by their isotropic parameters (f_iso). The greatest improvements are seen for Wetland shrub with user and producer's accuracy increased by up to 15.05% and 8.18% respectively. Increases on the order of 5% to 10% are encountered for the Wetland tree, Coniferous dense and Coniferous open with no detriments to other candidate classes. However, adding MODIS BRDF shape indicators produces little improvements in classification accuracy in this study.

1. INTRODUCTION

Several publications explored that multiple-view-angle (MVA) remotely sensed images have information content related to land cover classification (Barnsley et al., 1997; Hyman et al., 1997). Land surface BRDF measurements acquired from POLDER instrument onboard the ADEOS-1 satellite with 6km spatial resolution showed large differences of the directional and spectral signatures of the various land cover classes, both in shape and in magnitude, implying their potential use in discriminating different land cover types (Bicheron and Leroy, 2000). Classification of multispectral and multiangle measurements using airborne Advanced Solid-State Array Spectoradiometer (ASAS) and POLarization and Directionality of Earth Reflectance (POLDER) was performed by Abuelgasim et al (1996) and Bicheron et al (1997), demonstrating that the account of directional information enhances the ability to discriminate forest covers.

Until recently, some research on constructing angular indexes to explore both physical mechanisms of hyperspectral BRDF effect and their relationship to land cover types using several typical ground measurements were documented by Sandmeier al et. (1998). The conclusion was that addition of angular indexes to hyperspectral data increases the overall classification accuracy. Another line results from use of angular index to retrieve the vegetation clumping index based on computer simulation, showing that some angular indexes such as normalization between hotspot and dark spot (NDHD) are lineally related to foliage clumping index for different vegetation types observed by the space-borne POLDER sensor. Global clumping index maps were subsequently produced using POLDER data (Chen, et al., 2005).
More recently, another line arises from constructing angular indexes based on semiempirical BRDF model to retrieve vegetation structure of a land surface, and relate these angular

indexes to different vegetation types (Roujean, 1997; D'Entremont, 1999; Pinty, 2002; Gao, 2003). Adding BRDF features along with multispectral signatures to a classification algorithm is a practical application because so far, global land cover maps constructed from space-based remote sensing data such as AVHRR, SPOT-Vegetation, and MODIS are only based on multispectral signals and the change in those multispectal signals through an annual cycle (Strahler et al. 2006). Directional signals have been excluded from global operational classification algorithm, although MODIS land cover product algorithm has once considered including BRDF features (Friedl, et al., 2002). It remains experimental that the BRDF features can improve classification accuracy as complementary information.

Most recently, continental and global classification experiment supplementing BRDF matrices with multispectral signatures from POLDER at coarse spatial resolution (7×6km) shows that BRDF features improve overall classification accuracy as compared to the results without them (Brown de Colstoun, E. C. B. et al., 2006). An experiment using Multi-angle Imaging Spectro-Radiometer (MISR) data shows that surface anisotropy patterns can improve desert vegetation type differentiation (Su et al, 2007). However, assessing ability of BRDF signatures as additional features of spectral signatures to improve the classification accuracy has never been conducted in context of MODIS at 500m spatial resolution. The specific objective of this work is to apply the MODIS BRDF features related to land cover types to improve the classification accuracy derived from supervised classification algorithm, which may otherwise be difficult to acquire with spectral signatures alone.

To assess the ability of these BRDF features to classification, we performed a set of analyses using decision trees to classify two data sets of composited BRDF features together with

NBAR and EVI. The first data set includes eight MODIS BRDF shape indicators, a set of angular indexes developed to indicate BRDF shape in MODIS and was explored to be related to land cover types (Gao, 2003). The second data set is to supplement MODIS BRDF parameters including volumetric and geometric parameters with spectral input features. As part of our analysis we also test the utility of MODIS volumetric and geometric parameters normalized by isotropic parameters, and the conditions where 14 MODIS BRDF parameters in seven bands are reduced to 4 parameters in red and near infrared waveband. Our results show that the MODIS BRDF parameters are effective for land cover classification problems, but that the contributions of including MODIS BRDF shape indicators on classification are very modest. Further we find that the volumetric and geometric parameters normalized by the isotropic parameters are especially useful for some sparse/open classes in the study region.

Figure1. The title should appear cente Figure 1 Map of the Canadian boreal forest, showing the study region in red rectangle

2. STUDY REGION

The very large area extent of the northern latitude boreal forest biome has a significant impact on the Earth's energy balance and the associated surface atmosphere exchange of radiation, heat, water, momentum, and carbon dioxides. Research on boreal forest biome from a large multiyear internationally supported study-Boreal Ecosystem Atmosphere Study (BOREAS) during and after the main field campaigns (1994 and 1996) improves our understanding of the boreal forest biome in both vegetation structure and land-cover classification. Therefore, it is a significant effort to examine the ability of the BRDF features related to vegetation structures, to improve classification accuracy together with spectral signatures, especially using 500m operational MODIS BRDF/Albedo products in this study region.

The Canadian boreal forest forms a band almost 1000 kilometers wide sweeping southeast to Newfoundland and Labrador, and spanning from its north of the tree line to the south bordered by various land cover types especially the transition from tree to herbaceous (Figure 1). The study region is located to the middle-east of Alberta in Canada, and was chose to represent the typical land cover types varying from herbaceous to forest with wet /dry background, distinct vegetation structure (clumping vs. random) and varying tree density (open vs. close). The study region has been well classified with mosaicked Landsat Enhanced Thematic Mapper Plus (ETM+) images by Earth Observation for Sustainable Development of Forest (EOSD), a joint program of the Canadian Forest Service (CFS) and the Canadian Space Agency to develop a forest monitoring system for Canada.

For the study region, the derived classification map compromises twelve scenes of ETM+ imageries with orbit ID and acquired date shown in table1 and represents around year 2000 conditions at 25m spatial resolution. Based on this classification map, we select training and testing samples and perform a set of analyses using decision trees to classify a set of compoisted MODIS BRDF/Albedo data. The main acquired date of the ETM+ imageries are around August, 1999-2001 in the study region. To match the time provided by high resolution ETM+ images, we composite 23 daily-rolling MODIS BRDF/Albedo products every16 days on August (Julian day of 202 to 224) in 2001 into a high quality full inversion data sets to examine the questions addressed in this paper. The method to composite MODIS BRDF and albedo products will be explained in next section.
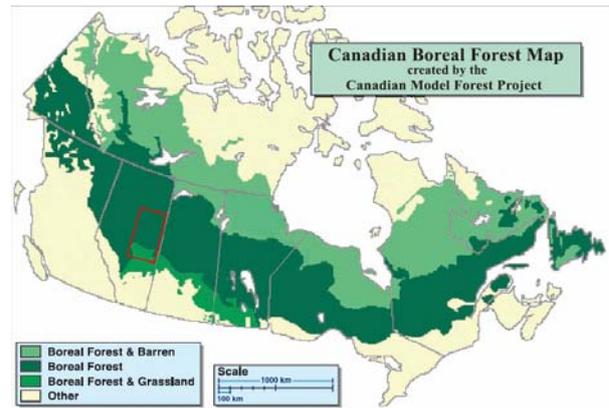
3. DATA AND METHODS

3.1 MODIS BRDF/Albedo products and processing

MODIS BRDF/Albedo products include directional hemispherical albedo (black-sky albedo), bihemispherical albedo (white-sky albedo), Nadir BRDF-Adjusted surface Reflectance (NBAR), model parameters describing the BRDF, and extensive quality assurance information. MODIS BRDF shape indicators are among model parameters products, occupying one Science Data Sets (SDS) layer.

The operational Version 005 MODIS BRDF and albedo algorithm uses a linear three-parameter semiempirical Ross Thick-LiSparse-Reciprocal (RTLSR) BRDF model to characterize the anisotropic reflectivity of the land surface (Lucht et al., 2000). Cloud-free atmospherically-corrected surface reflectances are accumulated during each 16 day period, from which the BRDF parameters are first retrieved if there are seven clear looks or more and observations fit the BRDF model well during a 16 day period. This process is so-called full inversion. A backup magnitude inversion is implemented if angular samples are greater than two and less than seven or if the internal quality check indicates a low confidence in the retrieval with the main algorithm since observations are not well sampled or do not fit the BRDF model well. A fill value is stored if the number of good observations is less than three. The MODIS BRDF shape indicators are only valid for full inversion retrieval, so there seem more gaps in BRDF shape indicator products than other BRDF and albedo products, resulting in a main problem in acquiring sufficient high quality input data from single MODIS BRDF shape indicator on each 16 day period. In this study, to match the time of high resolution ETM+ map, we use the MODIS BRDF/Albedo products in the year of 2001 when only Terra instrument is available. This could result in more gaps for MODIS BRDF shape indicators on one 16 day period than that derived from both Terra and Aqua.

To solve this problem, we first drive the operational MODIS BRDF/Albedo codes (PGE23) to produce twenty-three (Julian day of 202 to 224 in 2001) daily-rolling BRDF and albedo products on 16 day periods, and then composite them to achieve one high quality MODIS BRDF and albedo products. To do this, all high quality data in the MODIS BRDF/Albedo products on the last 16 day periods (Julian day of 224 here) was retained, and then the gaps in these images was filled with high quality

data from the images of the preceding 16 day periods (Julian day of 223 here), and this iteration continues until the images of the first 16 day periods (Julian day 202 here). With this method, most gaps presented in the baselined images were filled with its preceding corresponding products, and so on. The EVI, which has been used as inputs in current MODIS land cover products, was also calculated from composited NBAR products.

As part of our analysis, we also use the fourteen composited volumetric and geometric parameters normalized by isotropic parameters in seven spectral bands. Therefore, the MODIS BRDF features examined in this study include both eight BRDF shape indicators and the MODIS BRDF parameters. The latter comprises not only the original volumetric and geometric parameters, but also these parameters normalized by isotropic parameters. Further, we examine the conditions where only four volumetric and geometric parameters in red and NIR band were supplemented with spectral features. The MODIS BRDF shape indicators are composed of model-based indicators and reflectance-based indicators. The former is constructed from MODIS BRDF parameters, and the latter is constructed from simple algebraic combination of reflectance in typical angle such as nadir, hot spot and dark spot.

3.2 Decision tree classifier

The most important feature of decision tree classifiers is their capability to break down a complex decision-making process into a collection of simpler decisions, thus providing a solution which is often easier to interpret. For various mostly practical reasons, MODIS land cover classification algorithm has adopted univariate decision tree classifier (C4.5) as the primary classification algorithm to produce global land cover maps (Friedl et al. 2002). Decision tree algorithm has advantages that are particularly useful for remote sensing problems. First, it has ability to handle noisy and missing data. Second, they require no assumptions regarding the distribution of input data and also provide an intuitive classification structure.

A technique known as "boosting" was used with decision trees (C4.5) to improve classification accuracy in this study. This technique has been widely tested in the machine learning community, and has also been confirmed to be effective for remote sensing-based land cover mapping (Friedl et al. 1999). Boosting improves classification accuracy by estimating classifiers in an iterative fashion using the base learning algorithm while systematically changing the training sample. (McIver & Friedl, 2001). It is also important to note that boosting is not effective in the presence of excessive error in training labels, or if the base classification algorithm does not offer classification accuracy greater than 50% (Friedl, 2002). Therefore, for exploration of ability of the BRDF features alone to classification using decision trees with boosting technique, which possibly produce low classification accuracy, the boosting technique is actually not effective in these cases. The questions examined in this paper are addressed by comparing classification accuracies achieved using different feature sets. By running the C4.5 decision tree classifier, the spectral signatures including NBAR and EVI matrices were used as input in a first test, and then the NBAR, EVI and individual or combination of different BRDF features (BRDF parameters and BRDF shape indicators) were used as input in a second test. Analysis of the differences in results were then performed for both data sets, both in terms of overall accuracy and per-class user's and producer's accuracies (Brown de Colstoun & Walthall, 2006). The 3049 sample points for eight

selected land cover types was randomly partitioned into ten equal sized subsets in term of strata of land cover types, ensuring that approximately equal sample sizes are allocated to each stratum. The C 4.5 decision tree classifier was running with a boosting technique with the same pruning parameters as MODIS land cover classification algorithm does. With the ten-fold stratified random sample points, nine subsets were used for training and pruning, and one subset was held out to estimate the predicted classification accuracy of the decision tree for unseen data. This method ensures that our training and test data sets were independent for each run. This was repeated 10 times, and all results given below are averages and standard deviation of both overall accuracy and per-class user and producer's accuracy for these 10 times results.

3.3 Land cover units

The Canadian Forest Service's project, entitled Earth Observation for Sustainable Development of Forests (EOSD), proposed a land cover legend (EOSD legend) based on a combination of the British Columbia and land cover classification schemes used by the National Forest Inventory (NFI). The EOSD legend is being used to map Canada's forests with ETM+ imagery by federal, provincial and territorial mapping agencies who undertook the EOSD Land Cover mapping activities and provided ETM+ classification map at 25m spatial resolution (Wulder 2002; Wulder and Nelson 2003).

This EOSD land cover units includes 16 classes of natural vegetation with dry/wet background and several different densities (dense/open/sparse), and 6 classes of nonvegetated lands. Note that this legend is valid for land cover mapping of Canada with Landsat imagery at 25m spatial resolution. For the purpose of this study at 500m spatial resolution in MODIS, some small heterogeneous classes disappear after aggregation and only eight relatively homogeneous land cover units remain significant in this study. Also note that for the convenience of classification with decision tree algorithm, we change the original classification labels to a sequential numbers.

3.4 Training and testing data

We identify the training and testing data from the MODIS imageries by searching high resolution ETM+ classification map derived by EOSD project. To do this, the high resolution classification map is first degraded to the spatial resolution of MODIS data sets with majority method. At the same time, the MODIS imageries are re-projected into Universal Transverse Mercator (UTM) projection with same projection parameters and corner point position as ETM+ classification map. In this way, the ETM+ classification map is assumed co-register to the MODIS imageries. By linking the reprojected MODIS imagery to that of ETM+ classification map, we find the geometric registration difference is generally is acceptable.

Stratifying by map land cover class and allocating approximately equal sample size to each stratus is a relatively common practice in accuracy assessment. This approach is designed to treats each class as equally important, and provide approximately equal precision for estimated user's accuracy of each class (Strahler, 2006). Following this comment, the selection of sample pixels in the coarse scale data was made using the following rationale. For homogeneous scenes, if 100% of the pixels in the Landsat land cover map were identified as the cover type on the coarse data then these were selected. For heterogeneous scenes, coarse pixels containing

90% of the cover type identified in the Landsat data were selected. For the core type with a large number of samples such as herb in the study region, we extract every 21th pixels from the degraded ETM+ land cover types to make sure that the number of samples for each land cover type has comparable magnitude. Finally, all fill values were removed from sample pixels and the final training and testing samples are presented in table 1.

Class label	Class name	N	Cover fraction(%)
8	Shrub Tall	208	≥90
10	Wetland-Tree	565	≥90
11	Wetland-Shrub	227	≥90
12	Wetland-Herb	232	≥90
13	Herb	585	100
14	Coniferous Dense	290	100
15	Coniferous Open	389	≥90
17	Broadleaf Dense	553	100

Table 1. Number of Samples in each selected classes (N)

After acquiring the sample pixels, we perform a ten-fold cross validation for each classification case considered to provide the most realistic and robust estimates of classification accuracy. To do this, these samples were randomly partitioned into ten equal sized subsets, which ensure that the class distribution of the entire dataset was maintained in each. For each run, one subset was held out, using the nine remaining subsets for training and pruning. The reserved subset was then used to estimate the predicted classification accuracy of the decision tree for unseen data, thereby ensuring that our training and testing data sets were independent for each run.

4. RESULTS AND DISCUSSIONS

The analyses performed for this work examine questions related to exploration of the capability of BRDF features to improve classification accuracy as additional information to spectral signatures. Seventeen input feature data sets were generated using different combinations of input features. These features are grouped into spectral signatures (NBAR and EVI), which have been used as inputs to MODIS land cover classification algorithm, eight MODIS BRDF shape indicators, which has been investigated in a company paper using both ground measurements and satellite samples, and MODIS BRDF parameters products. It is important to note that the isotropic parameters of MODIS RTLSR model represent the surface reflectance illuminated and viewed at nadir, and is mainly a function of the optical properties of vegetation and soil reflectance. These optical properties could be equally expressed by MODIS NBAR products. Therefore the isotropic parameters are not included in this classification exercise.

4.1 Nadir reflectances with BRDF shape indicators

The BRDF shape indicators were designed to indicate the BRDF shape in MODIS and improve classification accuracy of land cover classification (Gao et al. 2003). Reflectance-based BRDF shape indicators such as ANIF, ANIX and NDAX indicate BRDF shape in term of the reflectance combination in typical scattering angles (hotspot, nadir and dark spot). Parameters-based BRDF shape indicators such as AFX and SSI are constructed with BRDF parameters of RTLSR BRDF model,

which are easy to provide full-scale description of the BRDF shape.

As part of our analyses, we examine the contribution of eight MODIS BRDF shape indicators on classification by running the C4.5 decision tree classifier using only the NBAR and EVI as input in a first test, and then the individual or combination of BRDF shape indicators together with NBAR and EVI in a second. The contributions of the BRDF shape indicators on classification are quantified by comparing the overall and per-class accuracy achieved from these two tests.

	Input Features	Overall Accuracy (%)	Difference W/WO indicators
1	NEs	78.60(±1.29)	/
2	NEs and ANIFR	78.84(±2.19)	0.24
3	NEs and ANIFN	78.67(±2.08)	0.07
4	NEs and ANIXR	78.70(±2.41)	0.10
5	NEs and ANIXN	79.63(±1.12)	1.03
6	NEs and AFXR	79.00(±1.86)	0.40
7	NEs and AFXN	79.34(±1.67)	0.74
8	NEs and NDAX	78.27(±1.50)	-0.33
9	NEs and SSI	78.73(±1.47)	0.13
10	NEs and all indicators	80.13(±1.70)	1.53

Table 2. Overall Accuracy with/without BRDF shape indicator matrices with +/- one standard deviation in parentheses (NEs represent 7 NBAR and 1 EVI)

Inspection of table 2 shows that the MODIS BRDF shape indicators have information contents regarding land cover types except NDAX, but are very modest. Among these indicators, the ANIXN seems more useful in discriminating the land cover types, which increase overall classification accuracy by 1.03%. Adding all these indicators as inputs to decision tree classifier together with NBAR and EVI improves the overall classification accuracy by 1.53% relative to the results that only use NBAR and EVI as inputs. In both cases, these increases, however, must be evaluated against large standard deviation, indicating that the results may not be always stable. Inspection of User's and Producer's accuracy shows that the NIR ANIX seems useful in distinguishing wetland-tree and wetland shrub, increasing the user or producer's accuracy by 5-6%, although such improvements somewhat sacrifice the accuracy of other candidate classes. Same finding is seen for AFXR, which increase both user and producer's accuracy by about 5% for Coniferous dense.

While the gains in terms of overall classification accuracies are modest, considering that only NIR ANIX layer was included in the BRDF classification, such an improvement is also significant. Most useful information provided in both spectral index and angular indices is being extracted from the 7 NBARs by the trees. So both spectral index and angular index are of limited use in distinguishing the land cover types in this study. On the other hand, taking the point of view from error reduction, the NIR ANIX reduces classification confusion by 4.81%. The error reduction is up to 16.4% for wetland-tree, which could be considered to be major error reduction for this land cover type.

4.2 Nadir reflectances with BRDF parameters

It was suggested exploring the contribution of directional components of information in MVA data on classification by fitting semi-empirical, kernel-driven BRDF model to the multiple-view-angle, removing the isotropic component, and

then using the remaining model outputs directly for land cover classification [Hyman, A. H and Barnsley, M. J. 1997]. The use of the POLDER BRDF metrics within a decision tree classifier shows that the metrics can reduce the overall errors of global land cover classification [Brown de Colstoun, E.C. and Walthall, C.L. 2006]. Inclusion of three BRDF parameters retrieved by fitting semi-empirical, kernel-driven BRDF model to MISR data sets in classification in semi-arid grasslands have been proven useful [Su 2007]. As part of our studies, we perform the similar analyses in context of MODIS. It is a significant effort to explore the contribution on classification of including volumetric and geometric parameters as input features to an operational decision tree algorithm that are being used in MODIS land cover products. The features used in this section include NBAR and EVI, 14 original BRDF parametersThe normalized BRDF parameters are the relative magnitude of volume and surface scattering to isotropic scattering and possibly describe "purer" BRDF information.

	Input Features	Overall Accu.(%)	Difference
1	NEs	78.60($\pm$1.29)	/
2	NEs and 14 Param.	83.32($\pm$1.54)	4.72
3	NEs and 14 Param. Norm.	82.79($\pm$1.61)	4.19
4	NEs and 4 Param.	81.63($\pm$2.84)	3.02
5	NEs and 4 Param. Norm.	81.86($\pm$1.79)	3.26

Table3. Overall Accuracy with/without BRDF parameter matrices with +/- one standard deviation in parentheses (NEs represent 7 NBAR and 1 EVI)

The potential benefits of MODIS BRDF parameters for classification were seen from table 3, which represents the average of the results of 10-fold cross-validation. From table 3, we can see that adding 14 BRDF parameters or these parameters normalized by f_iso with NBAR and EVI increase the overall classification accuracy by 4.72% and 4.19% respectively, that adding 4 BRDF parameters or 4 normalized parameters in red and NIR band alone improve the overall classification accuracy by 3.02% and 3.26%. In both cases, these improvements are not "huge". However, from the point of view for these gains as a reduction of error or confusion of the classification, the confusion reduction is 15-22% if these BRDF coefficients are included. This means that approximate 15-22% of misclassified training observations from feature combination of NBAR and EVI are correctly classified by adding BRDF parameter features.

It is also useful to examine the per-class user's and producer's accuracies to determine whether particular classes may benefit more than others from the inclusion of the BRDF matrices. Inspection of Producer's accuracy shows that when four combinations of BRDF parameters were supplemented with NBAR and EVI, the 4-9% improvements of producer's accuracy are widely seen for Wetland Tree, Wetland Shrub, Coniferous Dense and Coniferous Open with no detriments to other candidate classes. For the mean user's accuracies, the largest mean increase is found for Wetland Shrub, up to 15.05% by including 4 normalized parameters. Substantial improvement is also seen in the user's accuracy for the Wetland Tree, Coniferous Dense, and Coniferous Open, with near, or greater than 5%. These results indicate that the both original BRDF parameters and their normalizations by f_iso contain

information contents related to land cover types and thus improve both user's and producer's accuracies. Moreover, this improvement is gained with no detriments to other classes under investigation.

Closer examination of the error matrices with and without BRDF features reveals that the Herb is easiest to classify only with NBAR and EVI, and Broadleaf dense is next. Most confusion occurs among Shrub tall, Coniferous Open, Wetland tree, Wetland shrub, and Coniferous dense. For example, Shrub tall is more confused with Coniferous open, and Wetland tree, Wetland shrub and Coniferous dense are not easily distinguishable only with NBAR and EVI in term of the confusion matrices. However, the additional BRDF matrices generally reduce the confusions among them, although this error reduction is sometimes achieved by sacrificing the accuracy of other candidate classes. Calculations in the way of error reduction for per-class show that 14 additional BRDF parameters decrease misclassification rates by 7.8%-40.5% for classes under investigation except for Herb. Stated another way, the use of BRDF parameter features together with NBAR and EVI reduces the confusions among some classes that are difficult to discriminate only with spectral NBAR and EVI matrices as inputs to decision tree classifier.

4.3 Conclusions and discussions

The objective of the work described here is to quantify the contribution of the MODIS BRDF features (MODIS BRDF shape indicators and MODIS BRDF parameters) on classification as supplementary features to spectral nadir reflectances (NBAR) and vegetation index (EVI), which have been used as inputs in current MODIS land cover algorithm. The straight method is to run the C4.5 decision tree classifier using only the NBAR and EVI matrices as input in a first test, and then NBAR, EVI, and individual or combination of BRDF features in a second. The difference in results of both data sets in term of both overall accuracy and per-class user and producer's accuracy were analyzed. All results given above are means and standard deviations in classification accuracies and/or error for 10-fold cross validation excise. The accuracy assessment is conducted based on confusion matrix approach, which is the most common accuracy assessment approach for categorical class (Foody, 2002; Congalton, 1991, Jansses and van der Wel, 1994) and was also recommended for global land cover validation (Strahler et al., 2006).

The results presented in this paper suggest several main conclusions. First, adding MODIS BRDF shape indicators produced little improvement to classification accuracy. The best indicator related to discriminating land cover types seems to be ANIX in NIR band, which improve overall accuracy by 1.03% when it was added to NBAR and EVI matrices. This suggests that the most useful information provided in both angular indices and spectral indices is being extracted by the decision tree classifier from the original NBAR data in this study. Therefore, additional information of both angular indices and spectral indices are very modest in identifying and distinguishing land cover types.

Second, the inclusion of f_vol and f_geo parameters produced more improvements both in term of the original parameters and these parameters normalized by f_iso. Adding best feature sets improve overall accuracy by 4.72%, per-class user's accuracy by 15.02% and per-class producer's accuracy by 8.96%. Considering that 14 additional BRDF parameters were included

in classification, an operational method is to supplement 4 BRDF parameters in red and NIR band with NBAR and EVI, which improve overall classification accuracy by over 3% and per-class user and producer's accuracy by 5-8% on 4-5 candidate classes with no detriments to others. From the point of view of confusion reduction, adding BRDF parameter matrices reduces misclassification rate by 15-22%. Stated another way, adding BRDF parameter features significantly reduce the confusions among classes that are difficult to identify and discriminate only with spectral reflectance signatures.

It is clear that the classification results produced by supervised algorithms heavily rely on the quality and representativeness of the training data used; therefore the accuracy improvements or error reductions for each candidate class must be assessed against its standard deviations. Moreover, there are many sources of both conservative and optimistic bias in classification accuracy (Verbyla and Hammond, 1995; Hammond and Verbyla, 1996). However, the method performed here is consistent for all available features, ensuring that accuracy improvements or confusion reductions are only brought by different input feature sections. In this sense, the results given in this study are believable. On the other hand, we composite 23 daily-rolling MODIS BRDF and NBAR products on 16-day period into full inversion input features that are superior to single MODIS BRDF/Albedo product, which could include gaps and magnitude inversion. Therefore, we expect accuracies derived from classifications based on these high quality data to improve accordingly.

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