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DISCRIMINATION OF AGRICULTURAL LAND USE USING MULTI-TEMPORAL NDVI DATA

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ABSTRACT: The methods to discriminate and monitor land use especially agricultural land use were examined by using temporal characteristics of NDVI data. Several study sites were selected from the region in the semi-arid tropics and temperate zone. For the case of post-rainy season in the semi -arid tropics, cropped area showed the highest value of NDVI and it could be discriminated by deciding appropriate level of threshold. By the fact that cropping period of annual crops from seeding to harvesting was typically three to four months, NDVI changed in time more rapid in comparison with the cases of natural vegetation. This feature made it possible to discriminate rainy season cropped area in the semi-arid tropics from other land use types by using multi-temporal NDVI data. Another attempt, applied for the case of agricultural land use in temperate zone, was to estimate constitutional ratio of major agricultural land use using multi-temporal NDVI of low spatial resolution data by adopting sub-pixel classification method. As a result of application using NDVI obtained from NOAA/ANHRR data to the case in China, this method successfully estimated the spatial distribution of sown area of winter wheat and summer crops.

1. INTRODUCTION

In order to study the sustainability of land resources especially in terms of agricultural production, it is significant to produce dataset of quantitatively reliable information of agricultural land use. Remote sensing has been expected as a powerful tool for this objective, however, standardized method for production of dataset has not yet been established. The constraint may exist in the complexity of variation of appearance of cropping pattern, which would affect temporally the spectral reflectance and geometric configuration of ground surface. Therefore analysis using multi-temporal data would be required for obtaining quantitative information of agricultural land use.

NDVI is one of effective indicator to show the surface coverage condition by vegetation and also to show the stage of growth of crop canopy. The temporal growing pattern of vegetation coverage expressed by NDVIshould be a factor to discriminate crop types, even if it could be included some variation of value in a same type. For the purpose of estimating agricultural land use by multi-temporal data, it is advantageous to employ NDVI by the reasons that it would be easily combined with crop growth model and that existing dataset of NDVI would be effectively utilized.

The author has attempted several case studies in Asian and African countries for characterizing agricultural land use by remote sensing. In most cases NDVI was employed as an effective tool to discriminate cropped area. One case study was to discriminate agricultural land use in the post-rainy season in the semi-arid tropics of India. The results showed that NDVI at cropped land had decreased but indicated the higher value than forest or bush areas during the period from November to February. From this feature, a time dependent decreasing line of NDVI was set as a boundary to discriminate cropped land from other land uses (e.g., Uchida, 1998).

This paper describes other two examples to discriminate agricultural land use using NDVI data. One was the case study of Burkina Faso in the Sub-Saharan region in West Africa. Cropping pattern in this area can be characterized as rainfed agriculture, of which crops are cultivated generally in rainy season. Accordingly, the time of maximum NDVI of cropped area would be almost harmonized with that of natural vegetation, so that multi-temporal NDVI data is required to discriminate agricultural land use.

Another case study was to estimate sown area of major crops in the crop production area of China. For this case, sub-pixel classification method was examined for coarse spatial resolution data. This method has a potential to produce dataset over wide area regardless with constraint about availability of multi-temporal high spatial resolution data (Uchida, 2001).

2. METHODS

2.1 Discrimination Using Temporal Profile of NDVI

This method is based on the feature that each land use shows specific temporal profile of NDVI. Vegetation changes seasonally according to the species of plants and cropping pattern as well as climatic condition. Therefore temporal profile of NDVI should facilitate to discriminate agricultural land use or to extract cropped area from other land use in condition that an appropriate temporal combination of data is available.

There are mainly three factors to characterize temporal profile of NDVI. The first is amplitude of change, i.e., maximum and minimum value of NDVI. The second is duration of eventand the third is phase, i.e., time of maximum. Other factors such as slope of increase and decrease should be employed if necessary.

It would be possible to characterize the temporal profile of NDVI of agricultural land use as follows; 1) value of maximumwould be equivalent to dense natural vegetation and higher than other land use types, 2) period of event, i.e., from seeding to harvesting, is typically three to four months which is shorter than the active period of natural vegetation in temperate zone, 3) decreasing rate after maximum is higher than the case of natural vegetation due to the effect of harvesting process, 4) value at the period from preparation to seeding is as low as the case of bare land. In consideration with these characteristics, an appropriate temporal combination of NDVI discriminates agricultural land use or cropped area. At this point discriminated area is assumed that the variation of cropping period would be negligible and that the mixture of multiple kinds of crops would not be considered.

2.2 Sub-Pixel Classification Using Multi-Temporal NDVI Data

The basic assumption of this method lies on linear mixture modeling of NDVI as a function of time ***t*** expressed in the followings.

$$NDVI(t) = \sum_{i=1}^{n} \boldsymbol{r}_i NDVI_i(t),$$

where r_i is the probability density of area of land use item ***i*** in the pixel in the condition of $\sum_{i=1}^{n} r_i = 1$. This formula can be solved if (n-1) temporal data are given.

This method is supposed to be applied to NOAA/AVHRR or equivalent spatial resolution data. From the practical point of view, temporal changes of NDVI for each land use cannot be uniquely defined due to not only atmospheric effects on radiometric characteristics but also growing conditions affected by various environmental factors. The end-member of $\boldsymbol{NDVI_i(t)}$, which is the value at the pixel wholly occupied by land use item ***i*** when time is ***t***, can be estimated if spatially more detail land use information at the time of observation is available. Many studies adopted by linear mixture modeling for sub-pixel classification have employed high spatial resolution satellite data such as SPOT/HRV or LANDSAT/TM as referenced land use information. In this study it is assumed that the end-member value, which is obtained at specific site, can be used for other sites where physical and land use conditions are similar.

When a linear mixture modeling formula is solved, negative value of probability density may come to appear. This is treated by addition of values so as to be zero for the minimum probability density of land use items and thereafter by scaling to become one as summation of total probability density.

3. CASE STUDIES

3.1 Characterization of Agricultural Land Use in the Sub-Saharan Region

3.1.1 Relation between Temporal Change of NDVI and Rainfall

The climatic zone in the middle part of Burkina Faso is classified into Sudanian zone, where annual rainfall is between 650 to 1000 mm. Rainy season of this area is a period generally from June to September and major cropping season is from June to October. Most of arable land is based on rainfed agriculture and its productivity is prone to deteriorate.

In order to examine seasonal changes of NDVI under various types of physical conditions, the author set land unit, which was defined by overlaying soil and annual rainfall maps in Burkina Faso. By the reason why study site, Kolbila village, was located on *Regosols* and why this soil dominantly covered over northern half of Burkina Faso, he calculated average value of NDVI over land unit defined on this soil. 1 km mesh 10-day composite NDVI data distributed by Global Land 1-km AVHRR Project of USGS EROS Data Center was used for this analysis.

Figure 1 shows the changes of averaged NDVI over land unit. As rainy season started in June, NDVI began to increase from the unit with the largest amount of annual rainfall to the unit with a smaller amount. The figure indicates that landscape in the area with more than 700 mm annual rainfall was distinctively different from that in the area with less than 500 mm. The difference in the level of maximum NDVI was supposedly caused by the difference of constitutional ratio of vegetation cover and not by the status of vegetation vigor.

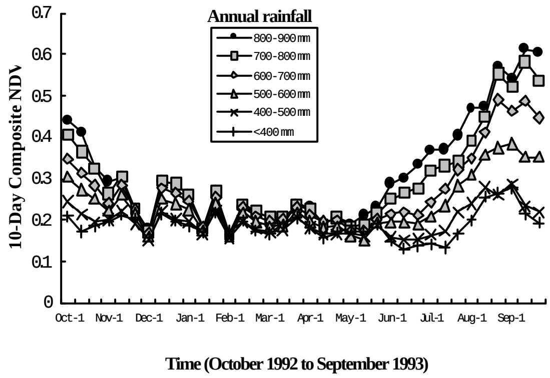


Figure 1 Temporal change of NDVI by different rainfall class over Regosols

It is difficult to discriminate a portion of cropped area directly from this figure, because NDVI value was contributed by not only cropped area but also natural vegetation. One feasible method to discriminate cropped area is to resolve NDVI value into two different temporal components, one has a period of about three months from starting increase to ending decrease, and the other has a period of about six months. By the figure, unit with the more amount of annual rainfall showed the tendency to start to increase earlier and increasing slope was less steep compared with unit of less amount of annual rainfall. This presumably implied that the ratio of cropped area to dense natural vegetation in the drier zone was higher than the ratio in the wetter zone.

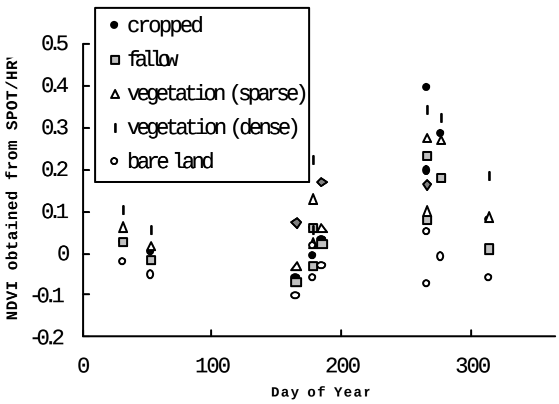


Figure 2 Temporal change of NDVI by land use sampled in Kolbila village

3.1.2 Spatial Analysis of Agricultural Land Use

Detail land use analysis was carried out for the study site, Kolbila village, where annual rainfall is about 700 mm. In this study, the author attempted to discriminate cropped area and fallow from other land use types by applying the decision tree method for multi-temporal NDVI obtained from SPOT/HRV data. This method was based on the difference in the temporal profile of NDVI by land use type.

Figure 2 shows temporal change of NDVI at sampled area of land use type. This figure represents the following features; 1) both cropped area and fallow showed lower NDVI values compared with sparse vegetation during the post-rainy season to time of seeding, and 2) cropped area showed as high NDVI value as dense vegetation during the crop growing period. In consideration with these features, three temporal data, which were time of seeding (June), crop growing (September) and post-harvesting (January), were used to discriminate agricultural land use.

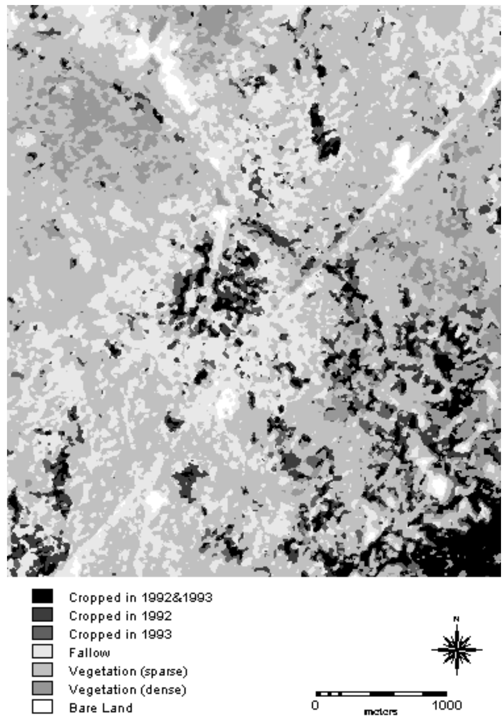


Figure 3 Distribution of cropped area in Kolbila village and its surroundings in 1992 and 1993 estimated by using multi-temporal NDVI of SPOT/HRV data

Figure 3 shows the estimated land use around Kolbila village composed of 1992 and 1993. The characteristic point of spatial distribution of cropped area in the study site was that about half of the cropped area in 1992 was cropped subsequently in 1993. Another point was its zonal structure in terms of distance from compound of household. Compounds of household in the Kolbila village were located scatteringly and 52 compounds were extracted from aerial photo.

Spatial analysis was performed as to calculate constitutional ratio of each land use type by distance zone from compound of household. The result indicated that a distance of 500 m was meaningful boundary in terms of cultivation and that the area of fallow was 2.5 to 3 times of that of cropped area. These features were generally consistent with the results of observation of the site.

3.2 Sown Area Estimation by Sub-Pixel Classification Method in Shandong Province, China

3.2.1 Estimation of Winter Wheat and Summer Crops Sown Area

The northern and western part of Shandong province of China is located in the area along Yellow River. The most of part is characterized as grain crop production area, where cropping pattern of winter wheat and maize in summer is dominant, while the northern side of Yellow River is covered by agriculturally less suitable alkaline soil, where cotton is widely cultivated in summer. The study site was selected at Huantai County, which was representative grain crop production area, and surrounding part including cotton production area.

Figure 4 shows the temporal change of NDVI for typical land use appeared in the study site calculated from multiple LANDSAT/TM data obtained in 1992. In almost all of double crop area, winter wheat and maize were cultivated. Winter crop area was dominantly occupied by winter wheat, so that winter wheat could have the highest NDVI value in early spring season. Summer crop, which should contain cotton, started to increase NDVI earlier than maize but later than swampy grass. Mixed vegetation represented rural settlement, street trees and unclassified small farms. After all, five types of land use in spring season, i.e., winter wheat, summer crops (cotton), mixed vegetation, swampy grass and bare land, were representative to be discriminated.

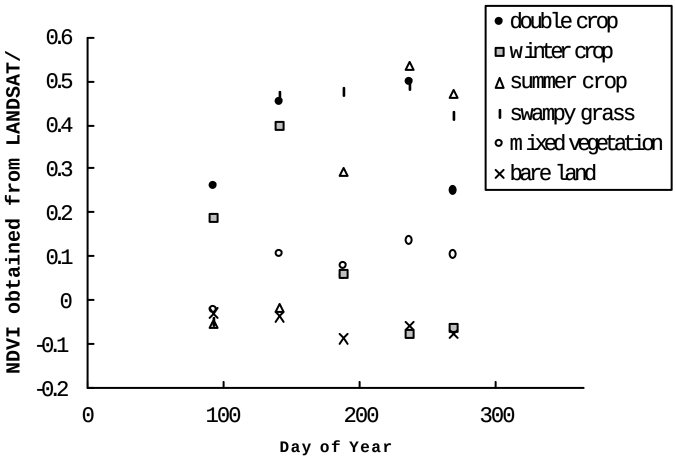


Figure 4 Temporal change of NDVI by land use sampled in Huantai County

This study applied sub-pixel classification method to coarse spatial resolution NDVI obtained from NOAA/AVHRR data. End-member values were estimated by the scheme illustrated in Figure 5. The horizontal axis of this figure denotes probability density calculated within 37 by 37 pixels window of classification data by LANDSAT/TM. The vertical axis denotes NDVI obtained from NOAA/AVHRR data. End-member values should be the value if probability density was equal to one. For this case the author drew a linear regression line for the data, of which probability density exceeded 0.4, and extrapolated it to the value of one of probability density.

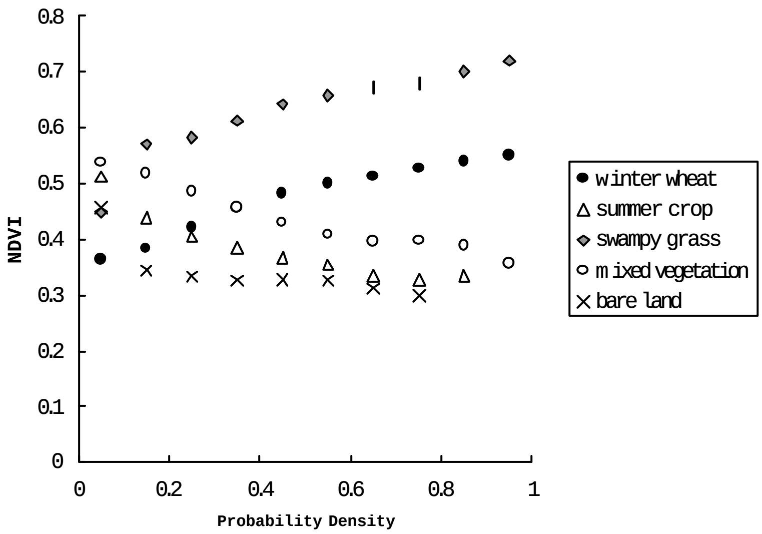
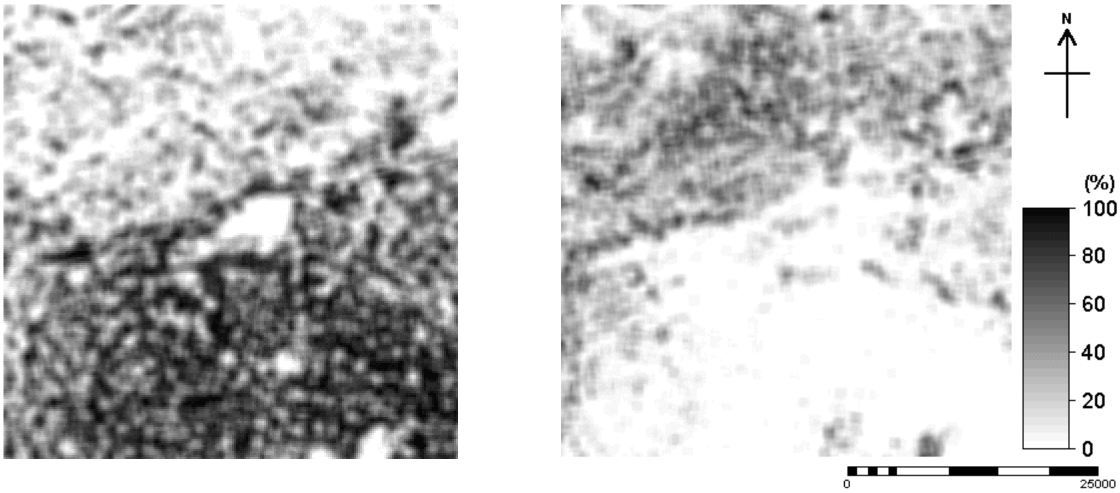


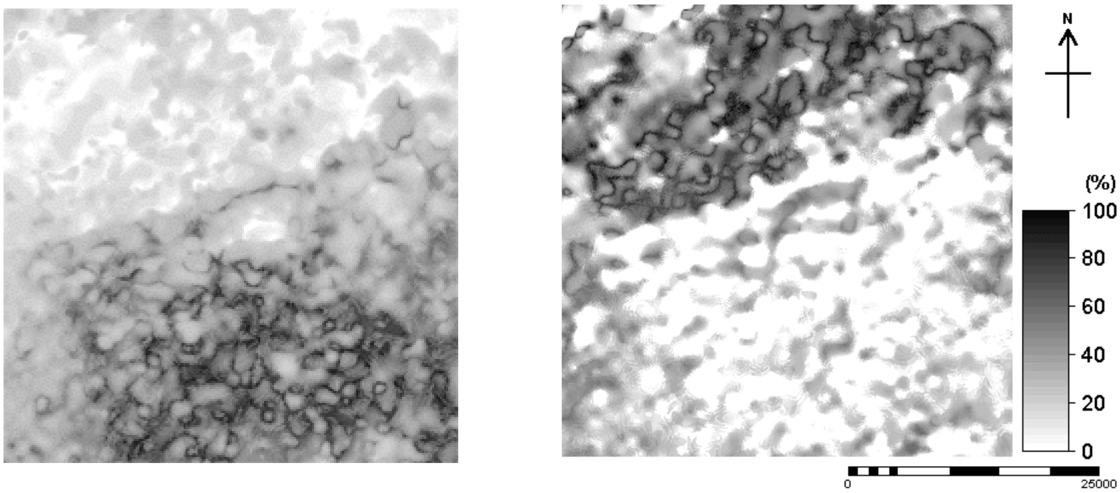
Figure 5 Relation between probability density of portion of land use item and NDVI (first-June, 1992)

Figure 6 shows distribution of probability density for winter wheat and summer crops obtained from LANDSAT/TM. Figure 7 shows estimated distribution using sub-pixel classification method applied to NDVI obtained from NOAA/AVHRR data, which were 10-day composite of first-April, mid-April, last-May and last-June in 1992. In this case, correlation coefficient of probability density data between LANDSAT/TM based and NOAA/AVHRR based was 0.79 for the case of winter wheat, while 0.54 for summer crops.



winter wheat   summer crops (cotton)

Figure 6 Distribution of probability density for each land use item obtained from LANDSAT/TM



winter wheat   summer crops (cotton)

Figure 7 Distribution of probability density for each land use item obtained from NOAA/AVHRR NDVI by sub-pixel classification method

3.2.2 Estimation of Winter Wheat Sown Area for the Case of Extensive Site

It is advantageous to use NOAA/AVHRR data to estimate land use if the objective area is wide enough. In this study, the author examined to estimate winter wheat sown area for extensive site in Shandong province. The site is Dezhou district located in the northwestern part of the province, of which the area is 10,341 km^2. This district is composed of 2 cities and 9 counties and soil productivity is partly not so high due to the existence of alkaline soil.

Figure 8 shows estimated probability density of winter wheat sown area. The pattern of distribution of probability density was compatible with the distribution estimated by LANDSAT/TM taken in another year. However, total sown area in county was considerably underestimated. This result was supposedly caused by problems on accuracy of geometric correction and decision of end-member values. Further examination about these problems should be carried out in order to establish reliable sub-pixel classification method of discrimination of agricultural land use.

4. CONCLUSION

NDVI should be useful indicator to discriminate agricultural land use, if the method of analysis is appropriate. In case of the area with simple cropping pattern in the semi-arid tropics, temporal profile of NDVI has a potential to estimate constitutional ratio of cropped area, fallow and natural vegetation as shown in the case study of Burkina Faso. A major factor of desertification is inappropriate management of soil resources by human activity. For the purpose of evaluating desertification through facts of human activity, spatial pattern of agricultural land use would be necessarily analyzed by using multi-temporal remote sensing data.

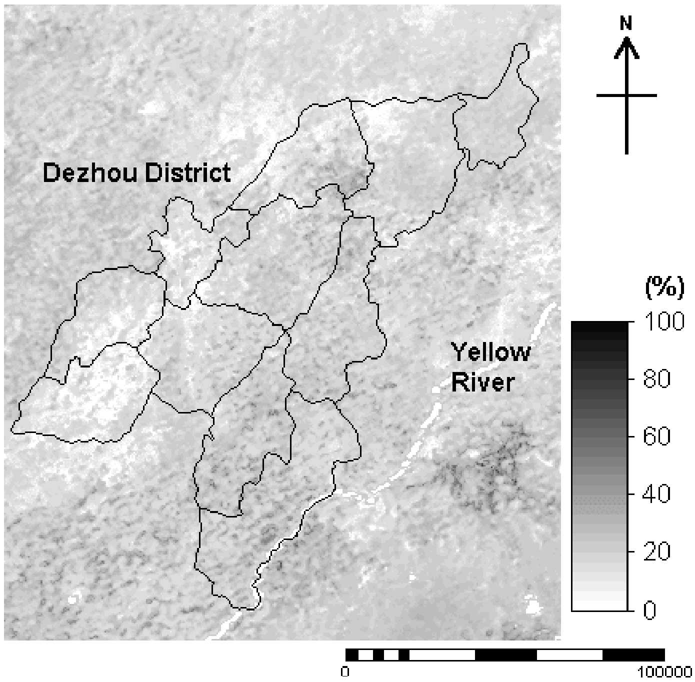


Figure 8 Distribution of probability density of winter wheat sown area in Dezhou District in 1992 obtained from NOAA/AVHRR NDVI by sub-pixel classification method

Sub-pixel classification method applied to multi-temporal NDVI data is another possible way to produce land use dataset over wide area. It can estimate area of each land use more accurate than the pixel based classification by original remote sensing data. Examination for the case of Shandong province in China showed prosperous results in discrimination of winter wheat and summer crops sown area. Although a lot of improvement of method is required, this method is expected to contribute to compilation of land use dataset in regional scale.

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