Crop classification using crop knowledge of the previous-year: Case study in Southwest Kansas, USA

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Abstract
Crop-type distribution products of the previous-year were used to generate training samples in the classification year. For each pixel, if the frequency of one crop was higher than 50%, the pixel was assumed to be a “possible training sample” of the high-frequency crop. Next, features of the “possible samples” were compared with reference crop features, and matching “possible samples” were confirmed as training samples. The Crop Data Layer (CDL) in Southwest Kansas during 2006-2013 was used as the crop products and MODIS EVI time series were crop features; training samples in 2014 were then acquired. Most of these training samples had the same crop label as the 2014 CDL data, and the training samples achieved good classification accuracies.

Keywords: Crop classification, crop knowledge, MODISEVI, CDL, Kansas.

Introduction
To classify crop types using remotely sensed data, the training samples of the classification year are always obtained by field survey [Low et al., 2013; Zhang et al., 2014]. However, if crop distribution maps need to be provided at annual frequency, the ground reference data must be collected every year, which is both time and labor consuming [Zhong et al., 2012a]. Additionally, some governments do not pay major attention to collecting these field data [Gallego et al., 2008]. Thus, classifying crop types without using ground reference samples of the classification year is important.

Previous studies have shown that remotely sensed data have the potential to convey knowledge from one year to other years [Brown et al., 2013; Muhammad et al., 2015a]. Among the classification features provided by remotely sensed data, vegetation indices (VIs) are commonly utilized because (1) density VI time series can describe the crop phenological characters, and (2) among multi-year, the phenological characters of the same crop are more similar than those of different crops [Hao et al., 2015]. Thus, reference VI profiles were acquired from the data of previous years and then used to identify crop types
in the classification year. The drawback of this method is that the reference VI time series were obtained from coarse-resolution data, such as MODIS data. To identify crop types at 30m resolution, such as by Landsat data, the Landsat VI has to be transformed to MODIS VI using their linear correlations. Although the VIs from different sensors always have good correlation [Huang et al., 2013], the VI transformation may induce some mismatch between different VIs, and thus lead to misclassification [Hao et al., 2012].

To avoid linear transformation between VIs from different sensors, an alternative strategy is to use crop products from previous years to generate crop knowledge and then collect training samples in the classification year from the crop knowledge. Two types of knowledge can be acquired from the crop type distribution products: (1) remote-sensing classification features of each crop and (2) crop frequency. We can then use the assumption, for each pixel, if the crop frequency for one crop is higher than 50%, the pixel can be labeled as a “possible training sample” of the crop type with the highest frequency. Furthermore, if the classification features of the “possible training samples” match those of reference classification features, the “possible training samples” can then be confirmed as training samples.

Figure 1 - Procedure of obtaining the training sample in this study.

In this study, the years of 2006-2013 were defined as the previous years, and the year of 2014 was defined as the classification year. The objective of this study was to obtain training samples for 2014 from the crop-type distribution products from 2006 to 2013, and then use these training samples to classify the crop types in 2014. The MODIS Enhanced Vegetation Index (EVI) was selected as the crop feature to be used to convey knowledge from the previous years to the classification year. The reasons for this choice were that (1)
MODIS data have a spatial resolution of 250m, good temporal resolution, and long data records, as the data have been available since 2001 [Zhang et al., 2009; NASA, 2015], and (2) MODIS EVI time series have good potential to describe the crop growth differences, and have been used widely to identify crop types [Hao et al., 2012; Muhammad et al., 2015b]. The Crop Data Layer (CDL) of Kansas from 2006 to 2013 was selected as the historical crop data products [USDA, 2014] because this product has a spatial resolution of 30 m, and high classification accuracy for the major crops. The procedure of acquiring training samples is shown in Figure 1. If a MODIS pixel was labeled as “crop A” with high frequency between 2006 and 2013, the pixel would be labeled as “possible crop A” in 2014. Then, the MODIS EVI time series of the “possible pixel” in 2014 would be compared with the reference MODIS EVI time series from the 2006-2013 samples. Next, if these EVI time series matched, the central point of the MODIS pixel would be confirmed as a training sample in 2014.

**Study area and data**

**Study area**

Kansas is a crop-dominant state in the USA, and Southwest (Fig. 2) Kansas contains the major crop types grown in the state, such as alfalfa, corn, and winter-wheat. The crop fields are characterized by large individual size (commonly from 65 to 245 ha) [Wardlow and Egbert, 2008]. With its representative crop types of the Great Plains, large field size, and long CDL data records, Southwest Kansas was selected as the study area to test the proposed method.

![Figure 2 - Study area.](image-url)
Data

MODIS data
The 16-day composite Terra MODIS 250-m Vegetation Indices product (MOD13Q1) of two tiles (h09v05 and h10v05) between 2006 and 2014 was used in this study. These data were downloaded from the Land Processes Distributed Active Archive Centre [LP_DAAC, 2015]. The Enhanced Vegetation Index (EVI) product [Huete et al., 2002] was employed in this study; the data were mosaicked and then re-projected from sinusoidal to UTM WGS 84 zone 14N.

Landsat data
The Landsat 7 ETM+ and Landsat 8 OLI CDR products of 2014 in the study area (path/row 030/034 and 031/034) were employed. To improve the quality of the data, a 16-day maximum value composition strategy was employed. The composition data used in this study are shown in Table 1. Afterward, both NDVI and EVI were calculated using the Landsat images [Rouse et al., 1974; Huete et al., 2002]. NDVI and EVI were calculated using Equations [1] and [2]:

\[
\text{NDVI} = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R} \quad [1]
\]

\[
\text{EVI} = 2.5 \times \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + 6 \times \rho_R - 7.5 \times \rho_B + 1} \quad [2]
\]

where \(\rho_{NIR}\) is the surface reflectance of the NIR band (Band 4 for ETM+ images and Band 5 for OLI images), \(\rho_R\) is the surface reflectance for the red band (Band 3 for ETM+ images and Band 4 for OLI images), and \(\rho_B\) is the surface reflectance of the blue band (Band 1 for ETM+ images and Band 2 for OLI images).

CDL data and derived ground reference data
The CDL data were used for ground reference samples [USDA, 2014, 2015]. Four crops grown between 2006 and 2013 (Tab. 2) were selected in this study according to the following rules: (1) the user’s accuracy of the crop was higher than 85% and (2) the areal proportions of these crops were more than 1%.
When obtaining validation samples in 2014, both the CDL crop layer and CDL confidence layer were used. First, the CDL confidence layer was used to obtain a “high confidence mask”, and 90% was selected as the threshold. The mask was then used to remove the pixels with low classification confidence in the crop layer. Afterwards, we generated a ‘fishnet’ of the study area using ArcGIS; the size of the grids in the ‘fishnet’ was 250 × 250 m. We then calculated the fraction of the major crops in each grid using the “Tabulate Area” tool in ArcGIS. If one crop filled more than 90% of a grid, we defined that grid as a “pure” grid and used the central coordinate of the grid as a validation sample of the crop. In this
way, the possible geometric errors associated with the CDL crop layer and remotely sensed images could be eliminated.

| Table 1 - Data of acquiring Landsat 7 and 8 images. |
|-----------------------------------------------------|
| **DOY** | **030/034** | **031/034** | **030/034** | **031/034** |
| Composed | Obtained | Composed | Obtained |
| 113~128 | 115 (7) | 97~112 | 098 (8) |
| 129~144 | 131 (7) 139 (8) | 113~128 | 122 (7) 114 (8) |
| 161~176 | 163 (7) 171 (8) | 129~144 | 130 (8) |
| 177~192 | 187 (8) | 193~208 | 202 (7) 194 (8) |
| 193~208 | 195 (7) | 241~256 | 250 (7) 242 (8) |
| 241~256 | 243 (7) 251 (8) | 273~288 | 274 (8) |
| 257~273 | 267 (8) | 289~305 | 298 (7) 290 (8) |
| 289~304 | 299 (8) | 305~321 | 306 (8) |

| Table 2 - The crop types of CDL data used in this study. |
|--------------------------------------------------------|
| **Year** | Alfalfa | Corn | Sorghum | Winter-Wheat |
| 2006 | ○ | ○ | ○ | ○ |
| 2007 | ○ | ○ | ○ | ○ |
| 2008 | ○ | ○ | ○ | ○ |
| 2009 | ○ | ○ | ○ | ○ |
| 2010 | ○ | ○ | ○ | ○ |
| 2011 | ○ | ○ | ○ | ○ |
| 2012 | ○ | ○ | ○ | ○ |
| 2013 | ○ | ○ | ○ | ○ |

We acquired historical training samples between 2006 and 2013 from the CDL crop layer. “high confidence mask” were not acquired because the crop confidence layer was not available during these years. The procedure of selecting the training samples was similar to that of obtaining the validation samples in 2014, and the number of historical training samples is shown in Table 3. The EVI time series of the training samples were then extracted from the corresponding MODIS EVI data.
Table 3 - Number of training and validation samples.

| Crop type       | Alfalfa | Corn   | Sorghum | Winter-Wheat |
|-----------------|---------|--------|---------|--------------|
| 2006            | 0       | 11,668 | 0       | 17,541       |
| 2007            | 0       | 17,680 | 5,457   | 17,888       |
| 2008            | 3,137   | 18,292 | 5,093   | 14,418       |
| 2009            | 3,034   | 17,586 | 5,907   | 17,411       |
| 2010            | 2,380   | 16,883 | 6,764   | 22,852       |
| 2011            | 1,778   | 14,416 | 3,976   | 13,359       |
| 2012            | 2,150   | 13,570 | 5,159   | 18,907       |
| 2013            | 2,421   | 12,302 | 10,037  | 13,732       |
| 2014 (validation)| 119     | 666    | 101     | 374          |

**Method**

The methodology of the study is presented in Figure 3. This study was composed of five main parts: (1) collecting the “pure possible training pixels” in 2014 based on the crop frequency; (2) acquiring the reference EVI time series from the MODIS EVI time series between 2006 and 2013 using Artificial Antibody Network (ABNet); (3) comparing the MODIS EVI profile of the “possible pixels” in 2014 with the reference EVI profiles, then removing the mismatch pixels and acquiring the training sample in 2014; (4) classifying crops at 30m resolution using Landsat NDVI/EVI time series and the training samples obtained in step (2); and (5) assessing classification accuracies at 30m resolution.

**Collecting “possible training pixels”**

The “possible pixels” for each crop type were acquired independently using the historical training samples between 2006 and 2013. For each crop, the crop frequency of each pixel was first calculated. Then, if the crop frequency was larger than half of the number of recorded years, the pixel was labeled as a “possible pixels” of the corresponding crop type (Fig. 4). For example, we acquired corn historical samples for the eight years (between
2006 and 2013); if the corn frequency was more than five, the pixel was labeled as “possible corn”. As alfalfa was recorded only during 2008-2013 by the CDL data, the threshold for “possible alfalfa” was three years.

**Figure 4 - Rules of acquiring “possible pixels”**

**ABNet and the procedure of testing “possible pixels”**

In this study, we used ABNet to test the “possible pixels” in 2014. ABNet was proposed by Zhong and Zhang [2012b] based on artificial immune network principles (AIN). The basic component of ABNet is the “antibody” model, which contains three attributes: the class (crop type) of the antibody, the centre vector (EVI time series), and the recognizing distance. ABNet has two procedures: training and classifying procedures. For the training procedure, the training samples (antigens) with the EVI profile and crop type are used to train the ABNet through five steps (pre-selection, cloning, mutation, adaptive new antibodies calculation, and antibody reorganization). For the classification procedure, ABNet compares the EVI time series of a pixel with all centre EVI profiles and labels the pixel as an antibody if (1) the distance between the EVI profile of the pixel and the centre vector of the selected antibody is the minimum among all antibodies and (2) the “minimum distance” is less than the recognizing distance of the antibody.

Through multiple years, the same crop may be under different growing conditions, which makes ABNet a suitable classifier because it has the advantage of identifying the same class with different spectra. In this study, ABNet was implemented using IDL, and MODIS EVI time series of training samples between 2006 and 2013 were used as input antigens; the Euclidean distance (ED, Eq. [1]) was employed to measure the similarity, antibodies were then obtained, and the EVI time series of the antibodies were defined as reference EVI time series. Next, antibodies were used to identify EVI time series of the “possible samples”. For each “possible pixel”, if the identified label was same as the assumed label, the central point of the pixel would be used as a training sample; otherwise, the pixel would
be removed from the training dataset. For the ED, \( a_t \) and \( b_t \) are the values of time series \( a \) and \( b \) at moment \( t \), respectively, and \( N \) is the number of samples in the time series.

\[
ED(a,b) = \sqrt{\sum_{t=1}^{n} (a_t - b_t)^2} \tag{3}
\]

**Random Forest**

In this study, the Random Forest (RF) algorithm was used to classify crop types at 30m resolution because it has high calculating efficiency when using large datasets [Loosvelt et al., 2012]. RF is a machine learning technique that combines multiple trees [Breiman, 2001]. Each tree is constructed using two-thirds of the original cases, the remaining one-third of the training samples are employed to generate a test classification with an error referred to as the “out-of-bag error” (OOB error). The model output is determined by the majority vote of the classifier ensemble. In this study, the Random Forest library for R was employed [Breiman et al., 2015], and the freely optimized parameters “number of trees” (ntree) and “number of features to split the nodes” (mtry) were set to 1000 and the square root of the total number of input features, respectively.

**Jeffries-Matusita distance**

In this study, we further evaluated the pair-wise crop separability of NDVI and EVI time series using the Jeffries-Matusita (JM) distance [Murakami et al., 2001; Hao et al., 2014]. The JM distance between class \( i \) and class \( j \) is defined as:

\[
JM = 2 \times (1 - e^{-B}) \tag{4}
\]

\[
B = \frac{1}{8} (\mu_i - \mu_j)^T \left( \frac{C_i + C_j}{2} \right)^{-1} (\mu_i - \mu_j) + \frac{1}{2} \ln \left( \frac{|C_i + C_j|}{2 \sqrt{|C_i| \times |C_j|}} \right) \tag{5}
\]

where \( C_i \) and \( C_j \) are the covariance matrices of classes \( i \) and \( j \), \( \mu_i \) and \( \mu_j \) are the mean vectors of classes \( i \) and \( j \). The JM distance ranges from 0 to 2, with a large value indicating a high level of separability between the two classes.

**Results**

**Validation of the selected training samples.**

We used CDL data to validate the training samples acquired in this study. The result showed that the labels of most of the 2014 training samples obtained in this study (5,259 out of 5,412) were the same as the CDL labels (we refer to these samples as “correctly identified training samples”) (Tab. 4). In addition, the “correctly identified training samples” had high
CDL classification certainty as the average classification confidence of all four crop types was higher than 0.85. For the other training samples with different labels from the CDL data (we refer to these samples as “wrongly identified training samples”), the classification confidence was generally lower than 0.7. It is possible that these “wrongly classified training samples” were not reliable. However, we did not remove these training samples from the crop classification procedure because the objective of this study was to use the training samples derived from the previous crop distribution products to classify the crop types, and any negative effect from the low-reliability training samples should be reported. However, the negative effect of the “wrongly classified training samples” could be low in this study because the number of “wrongly identified training samples” was small (153 out of 5,412 samples).

| CDL Data       | 2014 Training Data |      |      |      |      |
|----------------|--------------------|------|------|------|------|
|                | Alfalfa            | Corn | Sorghum | Winter-Wheat | Total |
| Alfalfa        | 1,388 (0.88)       | 4 (0.57) | 0 | 0 | 1,392 |
| Corn           | 29 (0.64)          | 2,006 (0.91) | 3 (0.55) | 0 | 2,038 |
| Sorghum        | 8 (0.54)           | 35 (0.67) | 120 (0.88) | 8 (0.67) | 171 |
| Winter-Wheat   | 23 (0.62)          | 34 (0.66) | 9 (0.66) | 1,745 (0.87) | 1,811 |
| Total          | 1,448              | 2,079 | 132 | 1,753 | 5,412 |

Note: The average classification certainty were shown in the corresponding brackets. The classification confidence is a value between 0 and 1.

Classification accuracy assessment

To further evaluate the training samples acquired in this study, we used these training samples to classify crop types in 2014 at 30m resolution, employing both NDVI and EVI time series. The overall accuracy (OA), procedure’s accuracy (PA), user’s accuracy (UA), and Kappa coefficient (KA) derived from the confusion matrix were used to assess the classification accuracy [Congalton, 1991]. The confusion matrices (Tabs. 5 and 6) showed that both the NDVI and the EVI time series acquired good classification accuracies as the OAs were above 90% and the KAs were about 0.9. The PAs of alfalfa, corn, and winter-wheat and the UAs of corn, sorghum, and winter-wheat were all above 90%. However, the UA of alfalfa was low (about 80% for both the NDVI and EVI time series) because some winter-wheat pixels were mislabeled as alfalfa. Additionally, the misclassification of sorghum pixels as corn lead to the low PA of sorghum. The UA of winter-wheat was 100%, but this may not be the true classification accuracy, because of the limited number of the validation sample set used in this study.
Table 5 - Confusion matrix using 2014 Landsat NDVI time series.

| Crop type  | Alfalfa | Corn | Sorghum | Winter-Wheat |
|------------|---------|------|---------|--------------|
| Alfalfa    | 118     | 5    | 0       | 30           |
| Corn       | 0       | 670  | 29      | 15           |
| Sorghum    | 0       | 8    | 74      | 0            |
| Winter-Wheat | 1   | 0    | 0       | 361          |
| PA(%)      | 99.16   | 98.1 | 71.84   | 88.92        |
| UA(%)      | 77.12   | 93.84| 90.24   | 99.72        |
| Overall Accuracy | 93.28 %, Kappa Coefficient 0.8909 |

Table 6 - Confusion matrix using 2014 Landsat EVI time series.

| Crop type  | Alfalfa | Corn | Sorghum | Winter-Wheat |
|------------|---------|------|---------|--------------|
| Alfalfa    | 118     | 4    | 0       | 23           |
| Corn       | 1       | 672  | 30      | 9            |
| Sorghum    | 0       | 7    | 73      | 0            |
| Winter-Wheat | 0   | 0    | 0       | 374          |
| PA(%)      | 99.16   | 98.39| 70.87   | 92.12        |
| UA(%)      | 81.38   | 94.38| 91.25   | 100          |
| Overall Accuracy | 93.36 %, Kappa Coefficient 0.9081 |

When using the training samples generated from this study to classify the crop types at 30m spatial resolution, the crop-type distribution map acquired from both the NDVI time series and the EVI time series were generally similar to the CDL crop distribution map (Fig. 5). There were some misclassifications caused by the confusions between alfalfa and winter-wheat, and between corn and sorghum, which was consistent with the misclassifications in the confusion matrix. In addition, the classification results of this study were generally homogeneous. Inter-field misclassifications were observed mostly for pixels located at cropland boundaries. However, this was not reported from the classification matrix because the validation samples were locate in the center of the crop fields. The misclassification occurred mainly because all “possible training samples” were “pure” MODIS pixels, but the mixed pixels at cropland boundaries were composed mostly by crop and surrounding non-crop pixels; the mixed NDVI/EVI features may have been more similar to another crop.

Table 7 shows the crop cultivated acreage of the major crops in the study area. The acreages were calculated using the CDL data and the crop-type distribution maps derived from the knowledge-based training samples. For both the NDVI and EVI time series, the acreages of alfalfa and sorghum were larger than in the CDL data because some pixels of winter-wheat and corn were mislabeled as alfalfa and sorghum. This was also consistent with the low UA of alfalfa.
Figure 5 - Distributions of major crops in the study area.

Table 7 - Crop acreage statistics in the study area.

| Crop Type     | CDL data (km²) | Result in this study (km²) | EVI  | NDVI |
|---------------|----------------|----------------------------|------|------|
| Alfalfa       | 518.5          | 599.1                      | 662.7|
| Corn          | 2492.1         | 2312.2                     | 2257.6|
| Sorghum       | 2485.9         | 2720.7                     | 2872.9|
| Winter-Wheat  | 6237.3         | 6100.8                     | 5939.9|
Discussion

Variation of EVI profiles between 2006 and 2014

In this study, MODIS EVI was used as the classification feature to convey the crop knowledge form the previous years (2006-2013) to the classification year (2014), and a challenge that arose was the inter-annual phenological variation of the same crop [Lhermitte et al., 2011; Hao et al., 2016]. For each crop type, the EVI time series between 2006 and 2014 were similar, but different weather conditions and crop managements practices among the multiple years still caused variation of the crop situation [USDA, 2016], which could be described by the variation of the EVI time series (Fig. 6). For example, the EVI of alfalfa at Day 100 in 2013 and 2014 was around 0.7, which is significantly lower than the values in the other years. In addition, the EVI peak of sorghum was around 0.5 in 2012, also lower than the values in the other years, possibly because of the extreme drought in 2012. Therefore, the use of multi-years EVI time series includes more crop growth conditions and thus reduces the negative effect of the inter-annual variation on the quality of the training samples. Figure 6 also shows that the EVI time series of the major crops in 2014 are generally contained in the EVI time series between 2006 and 2013.

Possible uncertainty of the crop knowledge acquired from the previous years

Previously, we proposed a method using reference MODIS NDVI time series to convey crop knowledge. To classify crop types using reference NDVI time series at 30m resolution, 30m resolution NDVI data (such as Landsat NDVI) need to be transformed to MODIS NDVI using their linear correlations, but mismatch can be induced in this transformation procedure. Additionally, the procedure is not suitable for a large area because it is difficult to transform 30m NDVI to the corresponding reference NDVI at a large scale [Hao et al., 2016]. In this study, training samples were acquired from the historical crop-type distribution products directly so that the NDVI transformation procedure could be avoided. However, there are still two shortcomings when selecting training samples from previous-year crop-type identification products. In this study, we used CDL data between 2006 and 2013 as historical knowledge, and high UA (higher than 85%) was used for selection. However, misclassification of the CDL data still induced some incorrect information in the reference MODIS EVI profiles. In addition, the “training samples” in 2014 were confirmed by comparing the MODIS EVI profiles of the 2006-2013 crop samples with the “possible training samples” in 2014, and the threshold used for “pure MODIS samples” was 90%. The impurity of the selected pixels also induced some incorrect information when confirming the “possible training samples” in 2014. When using this method in other study areas, misclassification of CDL data during the previous years and impurity of some MODIS pixels may lead to some wrongly identified training samples. In the future, it may be possible to solve these two problems. First, crop confidence layer data have been provided in the CDL product since 2014, and these data may help optimize the previous-year CDL samples. Second, the pure MODIS pixel threshold chosen is a balance between pixel quality and the number of samples. A higher threshold would increase the purity of the pixels but reduce the number of samples, and vice versa. Hence, the purity threshold should be a user-defined parameter in other study areas.
Crop separability comparison between NDVI and EVI time series
Each crop had a specific NDVI/EVI time series profile, so the crops were separable (Fig. 7). Winter wheat was highly separable (JM distance larger than 1.8) from the other three crops around Day 250, when the winter wheat had been harvested but the other crops still had high biomass levels. The JM distance between winter wheat and alfalfa was lower than 1.0 at the early growing season as both crops have high vegetation fraction at this time. This confusion led to misclassification between the two crops. However, winter wheat and alfalfa were highly separable from corn and sorghum in the early growing season because the summer crops had low vegetation fraction during this time period. Corn and sorghum were separable at their green-up period (around Day 170), because the growing rate of corn is generally higher than that of sorghum, which is similar to the MODIS data-based separability evaluation result [Hao et al., 2015].
For the crops in this study, the NDVI and EVI time series showed similar trends, NDVI saturation at high biomass levels was not observed [Wardlow et al., 2007], and the NDVI and EVI time series had very similar separability. The JM distance between alfalfa and winter wheat before Day 150 of the EVI time series was higher than that of the NDVI time series, which could explain the higher alfalfa UA of the EVI time series (Tabs. 5 and 6) and the fact that the alfalfa acreage derived from the EVI time series was more similar to the CDL data (Tab. 7).
Conclusion
In this paper, we presented a method that acquires training samples from previous-year crop-type distribution products. CDL crop label data during 2006-2013 were used to provide crop knowledge, and training samples of 2014 were then acquired from the crop knowledge. Next, these training samples were used to classify crop types at 30m resolution.

![Figure 7 - Crop separability of NDVI and EVI time series.](image-url)
The main conclusions of the study are summarized below.

(1) The method proposed in this study could successfully acquire training samples. The crop labels of most of the training samples (5,259 out of 5,412) acquired in this study were the same as the crop labels of the 2014 CDL data.

(2) The training samples obtained in this study showed good potential for classify crop types. The overall accuracies for the NDVI and EVI time series were 93.28% and 93.36%, respectively. The acreages of the major crops in the study area were similar to those of the CDL product. Additionally, NDVI and EVI had similar separability classification performance as NDVI saturation was not observed at high biomass levels.

CDL data and MODIS EVI time series during 2006-2013 were used to convey crop knowledge to year 2014, which was reasonable, albeit imperfect. Currently, the crop confidence data of the crop-type distribution products (such as the CDL classification confidence layer) can optimize the previous-year samples used for generating crop knowledge [USDA, 2014]. Images from a variety of new sensors at better spatial resolution (such as Landsat-8, Sentinel-2, and Gaofen-1) can provide time series data of high resolution and dense temporal resolution [Drusch et al., 2012; Irons et al., 2012; CRESDA, 2013]. Therefore, we could further improve the method of this study by using new sources of data and thus acquire more reliable training samples from crop-type distribution products in the future.

Acknowledgements
We wish to thank USDA, NASS for providing the CDL data for free, we also thanks the reviewer for their suggestions when revising the paper.

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