Large-area crop mapping using time-series MODIS 250 m NDVI data: An assessment for the U.S. Central Great Plains

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Abstract

Improved and up-to-date land use/land cover (LULC) data sets that classify specific crop types and associated land use practices are needed over intensively cropped regions such as the U.S. Central Great Plains, to support science and policy applications focused on understanding the role and response of the agricultural sector to environmental change issues. The Moderate Resolution Imaging Spectroradiometer (MODIS) holds considerable promise for detailed, large-area crop-related LULC mapping in this region given its global coverage, unique combination of spatial, spectral, and temporal resolutions, and the cost-free status of its data. The objective of this research was to evaluate the applicability of time-series MODIS 250 m normalized difference vegetation index (NDVI) data for large-area crop-related LULC mapping over the U.S. Central Great Plains. A hierarchical crop mapping protocol, which applied a decision tree classifier to multi-temporal NDVI data collected over the growing season, was tested for the state of Kansas. The hierarchical classification approach produced a series of four crop-related LULC maps that progressively classified: 1) crop/non-crop, 2) general crop types (alfalfa, summer crops, winter wheat, and fallow), 3) specific summer crop types (corn, sorghum, and soybeans), and 4) irrigated/non-irrigated crops. A series of quantitative and qualitative assessments were made at the state and sub-state levels to evaluate the overall map quality and highlight areas of misclassification for each map.

The series of MODIS NDVI-derived crop maps generally had classification accuracies greater than 80%. Overall accuracies ranged from 94% for the general crop map to 84% for the summer crop map. The state-level crop patterns classified in the maps were consistent with the general cropping patterns across Kansas. The classified crop areas were usually within 1–5% of the USDA reported crop area for most classes. Sub-state comparisons found the areal discrepancies for most classes to be relatively minor throughout the state. In eastern Kansas, some small cropland areas could not be resolved at MODIS’ 250 m resolution and led to an underclassification of cropland in the crop/non-crop map, which was propagated to the subsequent crop classifications. Notable regional areal differences in crop area were also found for a few selected crop classes and locations that were related to climate factors (i.e., omission of marginal, dryland cropped areas and the underclassification of irrigated crops in western Kansas), localized precipitation patterns (overclassification of irrigated crops in northeast Kansas), and specific cropping practices (double cropping in southeast Kansas).

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1. Introduction

Georeferenced land use/land cover (LULC) data sets are primary inputs for environmental modeling and monitoring, natural resource management, and policy development. A variety of LULC data sets are needed to support the growing and diverse demands of the global environmental change research community (Cihlar, 2000; DeFries & Belward, 2000). Several major research programs and documents (NASA, 2002; NRC, 2001; Sarmiento & Wofsy, 1999; Turner et al., 1995) have identified the development of improved and up-to-date regional- to global-scale LULC products as a research priority. These products should characterize current LULC patterns, document major LULC changes, and place more emphasis on land use in the thematic classification schemes of the maps.

Over the past decade, the science of large-area LULC mapping has made considerable strides as remotely sensed data and computing resources have improved and advanced classification...
techniques have emerged (DeFries & Belward, 2000). During this period, large-area LULC mapping has evolved through numerous efforts at state (Craig, 2001; Eve & Merchant, 1998), regional (Bosard et al., 2000; Homer et al., 2004; Vogelmann et al., 2001), and global (Bartholome & Belward, 2005; DeFries et al., 1998; DeFries & Townshend, 1994; Friedl et al., 2002; Hansen et al., 2000; Loveland et al., 2000) scales. In addition, considerable effort has been made to advance large-area LULC characterization beyond the traditional thematic classification of specific LULC types by mapping continuous land cover fields (Hansen et al., 2002), land cover change (Justice et al., 2002; Zhan et al., 2002), and biophysical land cover characteristics such as leaf area index (LAI) and fraction of absorbed photosynthetically active radiation (FPAR) (Myneni et al., 2002).

Despite this progress, little emphasis has been placed on large-area crop mapping and monitoring. Most of the mapping efforts highlighted above have focused on the classification of land cover types associated with natural systems (e.g., forest, grassland, and shrubland) and have tended to generalize crop-land areas into a single or limited number of thematic classes. Few large-area mapping efforts have attempted to map specific crop types and associated land use practices (Craig, 2001), particularly on the short time-step that is required to reflect the rapid land cover changes that commonly occur from year to year in crop rotations.

Timely crop-related LULC information is currently limited over major agricultural regions such as the U.S. Central Great Plains, which face a number of environmental issues (e.g., climate change and groundwater depletion) that threaten the area’s long-term sustainability (Ojima & Lackett, 2002). Cropland areas are intensively managed and modified through a variety of human activities, which can have a wide range of impacts on biogeochemical and hydrologic cycles, climate, ecosystem functions, the economy, and human health. As a result, new mapping protocols are needed to characterize the regional-scale cropping patterns on a repetitive basis and provide improved LULC information to scientists and policy makers.

The objective of this study was to investigate the applicability of time-series Moderate Resolution Imaging Spectroradiometer (MODIS) 250 m normalized difference vegetation index (NDVI) data for regional-scale crop mapping in the U.S. Central Great Plains. A crop mapping methodology, which applied a decision tree classification technique to a time series of MODIS 250 m VI data spanning one growing season, was tested over the state of Kansas. A four-level hierarchical classification scheme was implemented, which produced a series of four crop-related LULC maps that progressively classified cropland areas into more thematically-detailed classes (Fig. 1). Three primary research questions were addressed in this study. First, what thematic accuracy can be achieved for classifying crop/non-cropland, general crop types (alfalfa, summer crops, winter wheat, and fallow), specific summer crop types (corn, sorghum, and soybeans), and irrigated/non-irrigated crops using a time series of MODIS 250 m NDVI data collected across the growing season? Second, are the general cropping patterns depicted in the series of 250 m maps consistent with the patterns reported across Kansas? Third, do the maps exhibit any regional trends or major areal deviations from the general cropping patterns reported for Kansas? Major regional differences may signal a limitation of the classification methodology in certain parts of the state or for specific crop-related LULC classes.

I.1. Large-area LULC mapping activities and crop classification

The development of a regional-scale crop mapping methodology is challenging because it requires remotely sensed data that have large geographic coverage, high temporal resolution, adequate spatial resolution relative to the typical field size, and minimal cost. Remotely sensed data from traditional sources such as the Landsat Thematic Mapper (TM and ETM+) and the Advanced Very High Resolution Radiometer (AVHRR) have proved useful for LULC characterization, but are limited for such an approach because of resolution limitations, data availability/quality issues, and/or data costs.

Most crop mapping using high resolution, multi-spectral data from Landsat TM/ETM+ (and similar sensors such as SPOT) has been conducted at a local scale (Mosiman, 2003; Price et al., 1997). The exception is the cropland data layer (CDL), which is a state-level classification of specific crop types produced by the United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) that is annually updated (Craig, 2001). However, the CDL is only available for a limited number of states (10 states in 2005) (NASS, 2006). Other large-area Landsat-based LULC mapping efforts such as the National Land Cover Dataset (NLCD) (Homer et al., 2004; Vogelmann et al., 2001) and Gap Analysis Program (GAP) state-level LULC maps (Eve & Merchant, 1998) have typically classified cropland into a limited number of generalized classes and have updated the maps infrequently. Large-area mapping using Landsat data has been limited by the considerable costs of acquiring and processing the large data volumes that are required (DeFries & Belward, 2000). A multi-seasonal Landsat classification approach is typically adopted and has consistently produced higher accuracies than a single-date approach for both general LULC (Wardlow & Egbert, 2003) and crop type (Price...
et al., 1997) mapping. As a result, a large number of Landsat scene-date combinations have to be processed to provide adequate spatial and temporal coverage, which is costly and time and labor intensive. The acquisition of relatively cloud-free imagery at optimal times during the growing season is also an issue because of the long revisit time of the Landsat instrument (DeFries & Belward, 2000).

Coarse resolution (1 km and 8 km), time-series AVHRR NDVI data have been widely used to classify continental- to global-scale land cover patterns (DeFries et al., 1998; DeFries & Townshend, 1994; Hansen et al., 2000; Loveland et al., 1995; Loveland & Belward, 1997). The high temporal resolution (10- to 14-day composites generated from near-daily image acquisitions) of the AVHRR time-series data in combination with the NDVI’s strong relationship with biophysical vegetation characteristics such as LAI and green biomass (Asrar et al., 1989; Baret & Guyot, 1991) enables land cover types to be discriminated based on their unique phenological responses. However, the coarse spatial resolution of AVHRR data limits both the thematic and spatial detail of the LULC types that can be mapped. Most AVHRR pixels have an integrated spectral–temporal signal from multiple LULC types contained within the 1-km footprint (Townshend & Justice, 1988; Zhan et al., 2002). As a result, coarse resolution imagery is suitable for classifying the general, broad-scale patterns of natural systems, but the high spatial variability and complexity of agricultural systems requires higher resolution data (Turner et al., 1995). The use of 1-km AVHRR data for LULC classification in agricultural regions is difficult (Loveland et al., 2000) and has produced inconsistent results (Loveland et al., 1995). Most AVHRR-related mapping efforts have characterized broad-scale land cover patterns, classified general vegetation types (e.g., deciduous, broadleaf forest) and/or aggregated land cover classes (e.g., crop/grassland mosaic), and assigned cropland areas to either a single or mixed crop/natural vegetation class.

1.2. Moderate Resolution Imaging Spectroradiometer (MODIS)

The MODIS instrument offers new possibilities for large-area crop mapping by providing a near-daily global coverage of science-quality, intermediate resolution (250 m) data since February 2000 at no cost to the end user (Justice & Townshend, 2002). MODIS 250 m VI data, in particular, are well suited for this type of application in the U.S. Central Great Plains. The calibration, atmospheric correction (water vapor and aerosols) (Vermote et al., 2002), and relatively high sub-pixel geolocational accuracy (∼ 50 m (1σ) at nadir) (Wolfe et al., 2002) of MODIS data enable distinct multi-temporal VI signals of specific crops to be detected at the 250 m pixel level (Wardlow et al., 2006, 2007). In an analysis of 16-day composited MODIS 250 m VI data for 2000+ fields in Kansas, Wardlow et al. (2007) found the data to have sufficient spatial, spectral, temporal, and radiometric resolutions to detect unique multi-temporal VI signatures for the state’s major crop types (Fig. 2) and land use practices (Fig. 3). Alfalfa, summer crops (corn, sorghum, and soybeans), winter wheat, and fallow (unplanted, idle fields) were highly separable in the VI data at some point during the growing season because of their very distinct crop calendars. Specific summer crops such as corn, sorghum, and soybeans were less separable, but subtle differences in their specific planting times and general growth patterns were captured in the VI data, which can be used to discriminate these crop types. Irrigated and non-irrigated fields of the same crop type also exhibited different VI responses, with irrigated crops...
maintaining higher VI values across most of the growing season as demonstrated by corn and winter wheat in Fig. 3.

The moderate 250 m spatial resolution of MODIS is appropriate for classifying cropping patterns in the U.S. Central Great Plains given the region’s relatively large field sizes, which are frequently 32.4 ha or larger and would spatially correspond to five or more 250 m pixels. The two 250 m spectral bands (620–670 nm and 841–876 nm) on MODIS used to calculate the VI data were intended to be used to detect anthropogenically driven land cover changes (Townshend & Justice, 1988), and the value of data at this spatial scale has already been demonstrated for LULC change detection (Lunetta et al., 2006; Morton et al., 2006; Zhan et al., 2002), continuous fields land cover mapping (Hansen et al., 2002; Lobell & Asner, 2004), general land cover mapping (Wessels et al., 2004), and vegetation phenology characterization (Wardlow et al., 2006). Wardlow et al. (2007) noted that similar landscape-level cropping patterns could be visually discerned in MODIS 250 m and Landsat ETM+ 30 m imagery throughout most of Kansas. Hansen et al. (2002) also reported that other landscape features associated with human activity (e.g., deforestation) were visible at MODIS’ 250 m spatial resolution. The utility of the MODIS 250 m VI data sets for several cropland characterization activities has been demonstrated (Lobell & Asner, 2004; Morton et al., 2006; Wardlow et al., 2006), but their suitability for mapping specific crop types and crop-related land use practices has yet to be fully explored.

1.3. Decision trees and large-area LULC classification

Large-area LULC mapping has improved with the application of advanced classification techniques such as decision tree (DT) classifiers, which have several advantages over traditional supervised classifiers (Hansen et al., 1996) and have consistently produced higher classification accuracies for this task (Friedl & Brodley, 1997; Hansen et al., 1996). DTs are non-parametric and can handle multi-modal distributions in the input data because they operate on thresholds in multi-spectral space rather than measures of central tendency (Hansen et al., 2000). This is critical for regional-scale crop mapping because of the considerable intra-class variability exhibited in the time-series MODIS NDVI data for a given crop due to regional variations in climate and management practices (Wardlow et al., 2007; Wardlow et al., 2006). DTs can also handle non-linear and hierarchical relationships between the input variables and the classes, as well as a variety of data types. They are also efficient at processing the large data volumes that are required for large-area applications. As a result, DT techniques are increasingly being used for large-area LULC mapping with success (Friedl et al., 2002; Homer et al., 2004; Wessels et al., 2004). The use of other techniques from the machine learning community such as boosting (Freund, 1995; Shapire, 1990) and bagging (Bauer & Kohavi, 1999; Breiman, 1996) in combination with DTs has also further improved LULC classification capabilities (Friedl et al., 1999; Lawrence et al., 2004).

2. Study area

Kansas is an agriculturally-dominated state located in the U.S. Central Great Plains (Fig. 4) with 46.9% (10.0 million ha) of its total area dedicated to crop production. The state’s major crops include alfalfa (Medicago sativa), corn (Zea mays), sorghum (Sorghum bicolor), soybeans (Glycine max), and winter wheat (Triticum aestivum). Over the past decade, Kansas has ranked among the top 10 states in both acreage and production for most of these crops and has, on average, $3.3 billion in total annual crop...
production, which ranks fifth nationally in the U.S. (USDA, 2002). The crops are grown under a wide range of environmental conditions, and a variety of farming practices are used across the state to maintain high crop production levels.

A pronounced east–west precipitation gradient strongly influences the specific cropping patterns and management practices implemented across Kansas. On average, precipitation totals range from ∼500 mm/year in western Kansas to ∼1000 mm/year in eastern Kansas (annual average totals from 1961 to 1990). Semi-arid western Kansas has a highly variable, limited precipitation regime and commonly experiences severe drought events. As a result, cropland in this area is extensively irrigated from aquifers to support the production of crops such as alfalfa, corn, and soybeans. The use of dryland farming techniques (e.g., conservation tillage) and the planting of more drought-tolerant crops such as winter wheat and sorghum are also common in western Kansas. In eastern Kansas, adequate precipitation is usually received to support high crop production levels without irrigation. Corn and soybeans are the two primary crops grown in this part of the state. The use of irrigation is very limited, primarily in lowland floodplain areas, and fallowing is rare.

The general grain size of the landscape, which is defined as the size of individual landscape elements (i.e., fields) (Forman & Godron, 1986), also changes from east to west. Western and central Kansas has a relatively coarse-grained landscape comprised of large individual fields (sizes commonly range from 65 to 245 ha) and large contiguous tracts of both cropland and rangeland. In eastern Kansas, field sizes are smaller (typically 65 ha or less) and the cropland areas are smaller, more fragmented, and interspersed with grassland and deciduous forest. No official statistics are recorded regarding actual field sizes in Kansas, but the average farm size reported by USDA illustrates the transition in the scale of farming operations (and indirectly, of typical field sizes) across Kansas. In 2001, the average farm size in western Kansas was 575 ha compared to 312 ha and 188 ha in central and eastern Kansas, respectively (USDA, 2002). The majority of fields in Kansas would be depicted in the MODIS 250 m imagery by 6–12 pixels at the lower end of the field size range and 28–30 pixels at the upper end of the range. Regional differences in field size, climate, and management practice were collectively considered when evaluating the classification results because they could affect the performance of the MODIS NDVI-based crop mapping protocol in certain parts of the state.

3. Data

3.1. MODIS 250 m NDVI data

A 15-date time series of MODIS 250 m NDVI data (MOD13Q1, Collection 4) spanning from the March 22 to November 1 composite periods was created for Kansas. Data were required from three MODIS tiles (h09v05, h10v05, and h10v04) for statewide coverage. The tiled NDVI data were mosaicked, reprojected from the Sinusoidal to Lambert Azimuthal Equal Area (LAEA) projection, and subset over Kansas for each composite period and then sequentially stacked to produce the time-series data set.
3.2. Field site training and validation database

A database of 2179 field sites of specific crop types and management practices in 2001 was created using information from annotated aerial photos provided by the USDA Farm Service Agency (FSA). FSA annotations included geographic location (i.e., Public Land Survey System (PLSS) description), crop type, acreage, and irrigated/non-irrigated status. Fields were selected from 48 counties (of a total of 105 counties) distributed across the state’s nine Agricultural Statistics Districts (ASDs) to ensure that each class had a representative geographic sample that reflected the diverse environmental conditions and management practices under which crops are grown across Kansas. Ideally, a probability-based sampling design (e.g., random or systematic) for field site selection would have been preferred because it is the only way to acquire objective, scientifically defensible accuracy statistics (Stehman, 1999; Stehman & Czaplewski, 1998). However, as other large-area LULC mapping efforts have encountered (Friedl et al., 2002; Loveland et al., 2000), this type of design was not practically feasible given the costs and logistical challenges that would be required to collect such a sample across Kansas. As a result, some class(es) and area(s) could be underrepresented in the training and validation data. Great care was taken to select counties that were geographically distributed across each ASD and FSA officials, when possible, selected ~ 10 fields per class located throughout each sampled county in an attempt to acquire both a thematically- and geographically representative sample for training and test purposes.

A 32 ha field size minimum (i.e., ~ five 250 m pixels) was established to ensure that the selected fields were sufficiently large to collect a representative spectral–temporal signal. Fields were geo-located on the MODIS imagery using a georeferenced PLSS vector coverage and multi-seasonal Landsat ETM+ imagery. A single 250 m pixel located completely within each field’s boundaries was selected to represent each site. A single pixel was used rather than a pixel window (e.g., 2×2 pixels) to eliminate mixed edge pixels composed of multiple LULC types from being included in the training and validation data. The pixel’s NDVI time series was extracted and visually assessed to verify its spectral–temporal characteristics were consistent with the crop type being reported by the FSA. Upon verification, the NDVI time series and annotated FSA crop information for the field was entered into the database. Individual field locations are shown in Fig. 5 and total number of sites by crop type are summarized in Table 1. Readers are referred to Fig. 2 in Wardlow et al. (2007) for the locations of the fields by specific crop type.

3.3. USDA NASS planted crop acreage data

Planted crop acreage data for 2001 were acquired from the USDA NASS agricultural statistics database (http://www.nass.usda.gov/Data_and_Statistics/Quick_Stats/) (NASS, 2002). The planted crop acreage is a statistical estimate calculated from information provided by farmers and field enumerators from a probability-based sample survey (USDA, 1999). Some areal differences will inevitably exist between the classified and

<table>
<thead>
<tr>
<th></th>
<th>Irrigated</th>
<th>Non-irrigated</th>
<th>Total</th>
</tr>
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<tbody>
<tr>
<td>Alfalfa</td>
<td>124</td>
<td>119</td>
<td>243</td>
</tr>
<tr>
<td>Corn</td>
<td>330</td>
<td>279</td>
<td>609</td>
</tr>
<tr>
<td>Sorghum</td>
<td>35</td>
<td>319</td>
<td>354</td>
</tr>
<tr>
<td>Soybeans</td>
<td>235</td>
<td>219</td>
<td>454</td>
</tr>
<tr>
<td>Winter Wheat</td>
<td>90</td>
<td>356</td>
<td>446</td>
</tr>
<tr>
<td>Fallow</td>
<td>0</td>
<td>73</td>
<td>73</td>
</tr>
<tr>
<td>Total</td>
<td>814</td>
<td>1365</td>
<td>2179</td>
</tr>
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</table>

Fig. 5. Locations of FSA field sites used in the training and validation database. The sites are categorized by their irrigated (gray) or non-irrigated (white) status.
NASS crop areas, given that different data sources (i.e., remotely sensed data vs. sample surveys) and methods were used. As a result, the acreage data were only used as a relative measure to determine if the crop areas classified in the MODIS-derived maps were representative of the general crop distributions reported by the USDA across Kansas and to highlight any major regional areal discrepancies within the state. NASS planted acreage data were reported by crop type and subdivided into irrigated and non-irrigated categories. However, the alfalfa acreage was not sub-divided and areal estimates for irrigated and non-irrigated sub-classes were obtained from county-level acreage estimates calculated by the Department of Agricultural Economics at Kansas State University. Fallow acreage also was not reported by NASS and was estimated from the ‘winter wheat planted on summer fallow’ category in the 2002 NASS data. This acreage estimate is conservative because it only reflects fallow cropland in 2001 that was planted to winter wheat in 2002 and does not include areas planted to other crops. However, this estimate was still considered appropriate for general comparative purposes because winter wheat is the primary crop planted following a summer fallow period in Kansas and only a small percentage of fallow fields are planted to other crops (O’Brien et al., 1998).

3.4. Kansas GAP 250 m crop/non-crop map

A 250 m crop/non-crop map was generated from the 30 m Kansas GAP LULC classification to compare to the MODIS-derived 250 m crop/non-crop map. The Kansas GAP map, which was derived from early-1990s Landsat TM data, serves as an appropriate benchmark given the map’s relatively high overall (88%) and cropland class (> 90%) accuracies (Egbert et al., 2001) and high areal agreement with USDA NASS’ reported crop acreage (Wardlow & Egbert, 2003). The 250 m Kansas GAP crop/non-crop map was produced by calculating the percentage of cropland in the 30 m map contained within each 250 m MODIS pixel footprint and assigning 250 m pixels with > 50% cropland to the crop class and < 50% cropland to the non-crop class.

3.5. Landsat ETM+ imagery

Statewide spring and summer mosaics of Landsat ETM+ imagery were assembled to visually verify FSA field locations and evaluate the crop patterns classified in the MODIS-derived maps. A total of 32 scenes from 16 Landsat path/rows for 2001 were acquired from the Kansas Satellite Imagery Database (KSID) (http://www.kars.ku.edu/products/ksid/landsat/landsat-imagery.shtml) and processed to provide complete, multi-seasonal coverage over Kansas. For path/rows that did not have a 2001 image available, scenes from 2000 were substituted.

4. Methods

4.1. Hierarchical classification scheme

A four-level, hierarchical classification scheme (Fig. 1) was implemented in this study. At the initial stage (Level 1), the entire study area was mapped into crop and non-crop classes. The crop-land areas were then mapped into four general crop types (Level 2). The summer crop areas classified in the general crop map were then further classified into three specific summer crop types (Level 3). The final step was to classify the cropland area into irrigated and non-irrigated classes (Level 4). This hierarchical structure was selected because it allowed the landscape to be progressively segmented into relatively homogeneous LULC units within which more detailed thematic classes could be discriminated. This also allowed the applicability of the mapping methodology to be assessed at varying thematic levels. Furthermore, it gives users the flexibility to use a map from a single level (e.g., general crops) or combine maps from multiple levels (e.g., irrigated/non-irrigated general crop map) to meet their specific needs.

4.2. Crop/non-crop classification and assessment

An unsupervised classification method (ISODATA) was applied to the 15-date NDVI time series to produce the crop/non-crop map because suitable training data were not available for the non-crop class, which is comprised of a complex, heterogeneous mix of numerous and often unrelated LULC types. It also provided insight into the specific spectral–temporal clusters in the multi-temporal NDVI data and their relative landscape positions (e.g., interior vs. edge pixels).

An ecoregion-based mapping zone approach was adopted based on the rationale that the crop and non-crop classes would exhibit less spectral–temporal diversity within each zone than at the state level, which would result in more thematically homogenous clusters. Kansas was sub-divided into six eco-mapping zones based on the Omernik Level II ecoregion delineations (Omernik, 1987). For each zone, 100 spectral–temporal clusters were generated and each cluster was assigned to one of three classes (crop, non-crop, or confused) by evaluating the spatial distribution of the cluster’s pixels and visually interpreting the corresponding cover type(s) associated with those locations on Landsat ETM+ imagery. The cluster’s mean multi-temporal NDVI signature was also evaluated for class determination. Clusters labeled as crop or non-crop were recoded to their respective classes. A clusterbusting technique (Jensen et al., 1987) was applied to the confused clusters (294 of 600 total clusters), where ISODATA was re-applied to break each confused cluster into 10 additional clusters. These clusters were then re-evaluated using the previous process and assigned to the crop or non-crop class. Minimal post-classification manual recoding was performed using the Landsat ETM+ imagery as a visual reference. Once the six eco-mapping zones had been classified, they were mosaicked to produce the final, state-level crop/non-crop map.

A statistical accuracy assessment was conducted using a stratified, random sample of 858 MODIS pixels (465 crop and 393 non-crop) selected throughout Kansas. The validation pixels were selected by stratifying the state by both cover type and eco-mapping zone and weighting the number of random samples collected for each class to be proportional with the relative crop and non-crop areas within each zone based on the 250 m Kansas GAP crop/non-crop map. An independent analyst classified each pixel as crop or non-crop based on a visual interpretation of the pixel’s corresponding location on Landsat ETM+ imagery.
Fig. 6. Crop/non-crop (a), general crop (b), summer crop (c), and irrigated/non-irrigated crop (d) maps derived from time-series MODIS 250 m NDVI data for Kansas. Dark lines correspond to ASD boundaries and light lines to county boundaries. The red circle on the irrigated/non-irrigated crop map (d) highlights a large area of non-irrigated cropland that was misclassified as irrigated.
and the multi-temporal characteristics of its NDVI profile. A pixel-level comparison was also made between the MODIS and Kansas GAP 250 m crop/non-crop maps at the state and ASD levels to assess their level of thematic agreement. An areal comparison of the classified and USDA reported crop areas was also conducted at both the state and ASD levels.

4.3. Crop-related LULC classification and assessment

A commercially available, supervised DT algorithm called See5 (Quinlan, 1993; Rulequest, 2007) was applied to the NDVI time series to produce the three crop maps. Pruning (certainty factor = 25% and minimum cases = 2) and boosting (10 iterations) techniques were also used in combination with the See5 base DT classification algorithm. The specific NDVI time series window for each crop classification was defined by the crop calendars of target classes. A 15-period growing season window (March 22 to November 1) was defined for the general crop and irrigated/non-irrigated crop classifications. A shorter 13-period window (April 7 to October 16) was defined for the summer crop classification.

The crop classification methodology implemented a bagging approach (Bauer & Kohavi, 1999; Breiman, 1996) where the

<table>
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<th>Table 2</th>
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<td>Accuracy assessment results for the crop/non-crop (a), general crop (b), summer crop (c), and irrigated/non-irrigated crop (d) maps</td>
</tr>
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(a) Crop/non-crop classification

<table>
<thead>
<tr>
<th>Reference data</th>
<th>Crop</th>
<th>Non-crop</th>
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<th>UA</th>
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<tr>
<td>Classified data</td>
<td>453</td>
<td>12</td>
<td>465</td>
<td>97.4</td>
</tr>
<tr>
<td>Non-crop</td>
<td>66</td>
<td>327</td>
<td>393</td>
<td>83.2</td>
</tr>
<tr>
<td>Total</td>
<td>519</td>
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<td>PA</td>
<td>87.3</td>
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<td>Overall accuracy</td>
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<td>Kappa</td>
<td>0.89</td>
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(b) General crop classification

<table>
<thead>
<tr>
<th>Reference data</th>
<th>Alfalfa</th>
<th>Summer crops</th>
<th>Winter wheat</th>
<th>Fallow</th>
<th>Total</th>
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<tr>
<td>Classified data</td>
<td>43</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>45</td>
<td>97.1 ± 3.2</td>
</tr>
<tr>
<td>Alfalfa</td>
<td>2</td>
<td>272</td>
<td>0</td>
<td>0</td>
<td>274</td>
<td>99.2 ± 0.5</td>
</tr>
<tr>
<td>Summer crops</td>
<td>1</td>
<td>1</td>
<td>81</td>
<td>0</td>
<td>82</td>
<td>98.2 ± 1.6</td>
</tr>
<tr>
<td>Winter wheat</td>
<td>0</td>
<td>0</td>
<td>7</td>
<td>27</td>
<td>34</td>
<td>98.2 ± 2.5</td>
</tr>
<tr>
<td>Total</td>
<td>46</td>
<td>273</td>
<td>82</td>
<td>27</td>
<td>428</td>
<td></td>
</tr>
<tr>
<td>PA</td>
<td>94.1 ± 3.2</td>
<td>99.6 ± 0.4</td>
<td>98 ± 1.4</td>
<td>99.3 ± 1.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overall accuracy</td>
<td>98.7 ± 0.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kappa</td>
<td>0.98</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

(c) Summer crop classification

<table>
<thead>
<tr>
<th>Reference data</th>
<th>Corn</th>
<th>Sorghum</th>
<th>Soybeans</th>
<th>Total</th>
<th>UA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classified data</td>
<td>103</td>
<td>10</td>
<td>10</td>
<td>123</td>
<td>83.5 ± 3.5</td>
</tr>
<tr>
<td>Corn</td>
<td>8</td>
<td>51</td>
<td>5</td>
<td>64</td>
<td>79.4 ± 7.0</td>
</tr>
<tr>
<td>Sorghum</td>
<td>5</td>
<td>4</td>
<td>70</td>
<td>79</td>
<td>88.5 ± 3.4</td>
</tr>
<tr>
<td>Soybeans</td>
<td>116</td>
<td>65</td>
<td>85</td>
<td>266</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>88.7 ± 3.7</td>
<td>78.2 ± 5.6</td>
<td>80.2 ± 6.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PA</td>
<td>84.0 ± 3.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overall accuracy</td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Kappa</td>
<td>0.76</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
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</table>

(d) Irrigated/non-irrigated crop classification

<table>
<thead>
<tr>
<th>Reference data</th>
<th>Irrigated crop</th>
<th>Non-irrigated crop</th>
<th>Total</th>
<th>UA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classified data</td>
<td>113</td>
<td>23</td>
<td>136</td>
<td>82.8 ± 2.8</td>
</tr>
<tr>
<td>Irrigated crop</td>
<td>42</td>
<td>258</td>
<td>300</td>
<td>86.0 ± 1.7</td>
</tr>
<tr>
<td>Non-irrigated crop</td>
<td>155</td>
<td>281</td>
<td>436</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>72.9 ± 4.0</td>
<td>91.7 ± 1.8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PA</td>
<td>85.0 ± 1.4</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overall accuracy</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kappa</td>
<td>0.67</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

PA (producer’s accuracy) and UA (user’s accuracy).

The ± values represent the percent accuracy variability within 1 standard deviation of the average overall and class-specific accuracies across the 10 classification runs. The row and column totals in the error matrix may not equal the number of sites in the rows and columns because the values represent averages across the 10 runs that were rounded to the nearest whole number in the error matrix.
field site data (2179 sites) were divided into a series of 10 independent training (80%) and validation (20%) sets using a stratified, random sampling scheme. The sites were stratified by ASD and the number of samples randomly drawn for the training and validation sets was weighted according to the relative proportion of class sites within each district. Class weighting was employed to ensure adequate thematic and geographic representation in the training and validation sets. A separate classification run was performed using each training set and 10 maps were produced. A pixel-level majority vote was then taken across the 10 maps to select the thematic class in the final map. This bagging approach was adopted to avoid a potential spurious classification result (e.g., extremely high or low accuracy) that might occur from a single draw if an unusual sample is drawn for a specific class(es).

A k-fold cross validation approach (Kohavi, 1995) was used to perform a statistical accuracy assessment for each crop map. A separate assessment was performed for each of the 10 independently classified maps (i.e., 10 folds) using the validation set \((k)\) that had been withheld for that specific classification run, and the accuracy reported for the final map was the mean accuracy \((\pm 1\sigma)\) across this series of maps. ASD- and state-level areal comparisons were also conducted between the classified crop areas in the final maps and the USDA planted crop area estimates to identify any major areal discrepancies or regional trends. Finally, the classified crop patterns were visually assessed and compared to the state’s reported cropping patterns, as well as those that could be interpreted from Landsat ETM+ imagery.

5. Results/discussion

5.1. Crop/non-crop classification

5.1.1. Visual assessment

The major crop/non-crop patterns in the MODIS-derived map (Fig. 6a) were consistent with Kansas’ general land cover patterns. Major crop areas such as the Western Corn Belt (northern ASD 70), the Winter Wheat Belt (southeast ASD 60), and the large cropland expanses throughout the central and western ASDs were depicted. The cropped floodplain areas and smaller, fragmented crop patches throughout the eastern ASDs (80 and 90) were classified. Major non-crop features such as the Flint Hills tallgrass prairie (western ASD 70, 80, and 90), the grass/shrub-dominated Red Hills (southeast ASD 30 and southwest ASD 60), the deciduous forest/grassland areas of eastern Kansas (eastern ASD 80 and 90), and the numerous large tracts of rangeland throughout the central and western ASDs were also mapped.

5.1.2. Statistical accuracy assessment

The crop/non-crop map had an overall accuracy of 90.9% (Table 2a). Producer’s and user’s accuracies were 87.3% and 96.5% for the crop class and 97.4% and 83.2% for the non-crop class. The crop class had considerably higher errors of omission (i.e., 66 crop sites classified as non-crop), which suggested some difficulty in discriminating cropped areas from non-crop vegetation. Most misclassified crop sites were located in the dryland crop areas of western Kansas or their landscape position was often at the edge of cropped areas. These sites would likely be more difficult to accurately classify given the highly variable spectral response from marginal dryland crops and the often indistinct multi-temporal VI signatures of edge pixels, which typically have an integrated spectral response from multiple cover types.

5.1.3. MODIS/Kansas GAP pixel-level comparison

The pixel-level thematic agreement between the MODIS and Kansas GAP 250 m crop/non-crop maps was 78.0% at the state level. All the ASDs had 75% or greater agreement between the two maps, with the exception of district 40 (72.5%) (Table 3). No major regional trends or differences in the level of thematic agreement were found among the ASDs. The majority of thematic disagreement resulted from crop pixels in the Kansas GAP map being classified as non-crop in the MODIS map (63.3% at state level). The lowest percentages of this type of thematic disagreement occurred in western (ASD 10–30) and south-central (ASD 60) districts that contained large expansive tracts of cropland.

Both maps classified similar general land cover patterns and depicted the major crop and non-crop features across the state as shown in the examples for eastern (ASD 80) and western (ASD 30) Kansas in Fig. 7. Most classification disagreement was relatively localized as illustrated in ASD 80, where many small cropland patches classified in the Kansas GAP map were omitted from the MODIS map (Fig. 7b). This type of omission was common throughout the three eastern districts, as well as the central (ASD 50) and north-central (ASD 40) districts. Many of the small non-crop patches in the MODIS map in disagreement with the Kansas GAP map were visually confirmed to be cropland using Landsat ETM+ imagery. This indicates that some smaller cropland features in central and

<table>
<thead>
<tr>
<th>Table 3</th>
<th>Total area of pixel-level thematic agreement and disagreement (reported in million ha and % of total area (in parentheses)) between the MODIS and Kansas GAP crop/non-crop maps for the nine ASDs</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASD 10</td>
<td>ASD 20</td>
</tr>
<tr>
<td>Total agreement</td>
<td>1.53 (75.8)</td>
</tr>
<tr>
<td>Total disagreement</td>
<td>0.49 (24.2)</td>
</tr>
<tr>
<td>Class-specific disagreement</td>
<td></td>
</tr>
<tr>
<td>Crop (MODIS)/non-crop (GAP)</td>
<td>0.20 (40.3)</td>
</tr>
<tr>
<td>Non-crop (MODIS)/crop (GAP)</td>
<td>0.29 (59.7)</td>
</tr>
</tbody>
</table>
eastern Kansas were spatially and/or spectrally inseparable from the surrounding non-crop areas in the MODIS 250 m NDVI data.

Land cover conversion associated with the Conservation Reserve Program (CRP) also contributed to the classification disagreement between the maps. There was a 10-year difference between the acquisition times of the Landsat TM (early 1990s) and MODIS (2001) source data used to produce the maps. Extensive land cover change (1.1 million ha) took place during this period, primarily in western Kansas, in the form of crop-to-grass and grass-to-crop conversions as lands entered or were removed from CRP (USDA, 1995). Many large blocks of thematic disagreement in the ASD 30 example (Fig. 7a) were due to CRP-related land cover changes rather than classification error in either of the maps. A visual assessment of Landsat imagery from the early 1990s and 2001 confirmed the land cover changes within many of these blocks.

Another major source of disagreement occurred in the transitional areas between crop and non-cropland, where the pixels were often assigned to different classes in the two maps. Some disagreement might be expected in these locations because many edge pixels at the 250 m resolution are comprised of both crop and non-crop cover types, which leads to indistinct multi-temporal NDVI signals. This was confirmed during the cluster labeling stage of the unsupervised classification process, where most edge pixels were grouped into clusters that had relatively indistinguishable multi-temporal NDVI responses. The pixels in these clusters were labeled as non-crop in order to minimize the potential classification errors they would likely introduce into the subsequent crop classifications if assigned to
Fig. 8. Crossplots of USDA vs. classified crop areas across the nine ASDs for the crop/non-crop (only crop class shown) (a), general crop (b), summer crop (c), and irrigated/non-irrigated crop (only irrigated class shown) maps. Less cropland was classified for all ASDs in the crop/non-crop map (a).
the crop class. As a result, many edge pixels classified as crop in the Kansas GAP map disagreed with the MODIS map results. In general, edge pixel disagreement was restricted to a single pixel or small clumps of pixels and had a minimal influence on the crop/non-crop patterns classified in both maps, but its widespread occurrence across Kansas accounted for a large proportion of the total pixel-level thematic disagreement between the maps.

5.1.4. Areal comparison

The MODIS map classified 0.93 million (or 4.4%) fewer ha of cropland than the USDA reported. Less cropland area in the MODIS map relative to the USDA estimate is not surprising given the large number of pixels at the cropland edges that were assigned to the non-crop class and the omission of small crop patches that could not be resolved at 250 m. The state-level areal results for the MODIS map are reasonable when compared to those from Landsat-derived LULC maps for Kansas. The classified crop area in the MODIS-derived map (9.24 million ha) was well within the range of the cropland area classified in the MODIS map relative to the USDA estimate is not surprising given the large number of pixels at the cropland edges that were assigned to the non-crop class and the omission of small crop patches that could not be resolved at 250 m. The state-level areal results for the MODIS map are reasonable when compared to those from Landsat-derived LULC maps for Kansas. The classified crop area in the MODIS-derived map (9.24 million ha) was well within the range of the cropland area classified in the 30 m USGS NLCD (7.91 million ha) and Kansas GAP (10.30 million ha) maps (Wardlow & Egbert, 2003).

The classified and USDA reported crop areas had a high correlation ($r=0.98$) across the nine ASDs, although the MODIS map consistently classified less crop area for each ASD (Fig. 8a). The best areal agreement ($< 0.6$ million ha or $< 3.7\%$ difference) occurred in districts that had large contiguous areas of cropland (ASDs 10, 30, 60, and 70). As expected, the remaining central (ASD 40 and 50) and eastern (80 and 90) districts had larger areal differences (ranging from 0.12 million ha ($5.0\%$) in ASD 40 to 0.22 million ha ($8.3\%$) in ASD 90) because of the omission of many small cropped areas. ASD 20 also had a slightly higher areal difference ($0.10$ million ha or $5.0\%$) than the adjacent western ASDs, which reflects the difficulty encountered in classifying the extensive area of marginal non-irrigated cropland contained within this district ASD 20 has a larger proportion of non-irrigated cropland ($92.4\%$) than the other western districts ($84.1\%$ in ASD 10 and 67.4% in ASD 30) (NASS, 2002) and during the unsupervised classification process, many of these areas exhibited a highly variable, indistinct multi-temporal NDVI signal because of increased drought stress on the vegetation. The NDVI signal was often similar to the surrounding sparse grassland, which resulted in some marginal cropland being classified as non-crop in ASD 20.

5.2. General crop classification

5.2.1. Visual assessment

The state-level patterns in the general crop map (Fig. 6b) were consistent with the cropping patterns reported for Kansas. The summer crop class was dominant throughout the eastern ASDs, where corn and soybeans are the major crops. In central Kansas, the winter wheat area clearly defined the Winter Wheat Belt in ASD 60, along with several other major wheat areas in ASDs 40 and 50. Summer crops in eastern ASD 40 corresponded to corn and soybeans planted at the edge of the Western Corn Belt and along the Republican River. In the western ASDs, the primary dryland crop classes of winter wheat and fallow were appropriately mapped in non-irrigated areas. Alfalfa and summer crops, which are primarily irrigated in western Kansas, were classified in the large areas of irrigated cropland, particularly in ASDs 10 and 30. Some summer crops were mapped in non-irrigated areas that corresponded to sorghum, which is commonly planted in dryland areas due to its higher drought tolerance (O’Brien et al., 1998).

The classified crop patterns in the 250 m general crop map had a strong spatial correspondence to the cropping patterns that could be visually interpreted in the 30 m Landsat ETM+ imagery. Fig. 9 illustrates the local-scale cropping patterns that were classified with the MODIS 250 m NDVI data in southwest Kansas. The boundaries of many individual fields (ranging in size from 25 to 240 ha) and blocks of fields planted to the same crop were retained in the 250 m map. The level of spatial detail in the 250 m general crop map is further illustrated by an area of strip cropping where the narrow, alternating strips of fallow, summer crop, and winter wheat are clearly visible in both the map and image. Similar local-scale field patterns were found in the series of MODIS-derived 250 m crop maps throughout Kansas.

5.2.2. Statistical accuracy assessment

The general crop map had a high average overall accuracy ($98.7\%$) and high class-specific user’s and producer’s accuracies ($> 97\%$) with minor differences across the 10 classification runs ($< 3.5\%$ within 1σ) (Table 2b). A relatively high classification accuracy might be expected given the unique crop calendars and multi-temporal NDVI responses of the general crop types as shown in Fig. 2. However, the extremely high accuracies calculated from the 20% of FSA field sites withheld for validation was unexpected. The use of a single pixel (from the field’s center) rather than an $n \times n$ pixel window to represent each site may have slightly inflated the classification accuracy for the map. The single pixel approach was utilized to minimize the potential of ‘mixed’ pixels being included in the database and provide the highest quality data for training purposes. However, in doing so, a slight bias to overestimate classification accuracy may be introduced because the selected pixels generally had the most idealized time-series NDVI signatures for each class and would be the mostly likely to be correctly classified.

A second accuracy assessment was performed using the 445 crop validation pixels from the earlier crop/non-crop map assessment to determine the degree of possible accuracy inflation. An independent analyst assigned a general crop label to each pixel based on a visual assessment of each pixel’s multi-temporal NDVI behavior. The distinct spectral–temporal behavior of the general crop types allowed class labels to be assigned with a high level of confidence.

The second accuracy assessment found an overall accuracy of 95.3%, and most class-specific accuracies ranged from 93% to 96% (Table 4). Accuracies using the randomly selected validation sites were generally 3–5% lower than those obtained using the FSA sites, which indicates that the accuracy inflation factor introduced in the FSA validation data was minimal. A second accuracy assessment was not conducted for the other
crop maps because of the less distinctive multi-temporal NDVI signatures of their classes, but the accuracy inflation factor for them would be expected to be of a similar magnitude.

Most of the classification error in the error matrix was associated with the fallow class, which was confused with both summer crops (6 of 7 misclassified sites were sorghum) and winter wheat. Most of the misclassified sites were located in the non-irrigated areas of semi-arid Kansas, where fields planted to these crops or in fallow can have highly variable multi-temporal NDVI signals that can result in reduced inter-class separability. Unplanted fallow fields have a broad range of cover types (bare soil, crop residue, and weed cover) and their spectral signal is dependent on the relative proportions of each cover. The NDVI signal from fallow fields can reflect cover conditions that range from non-vegetated to nearly fully vegetated. Winter wheat and sorghum, which are common dryland crops, can have a similar multi-temporal NDVI response to partially vegetated fallow fields when the crops are under severe to extreme drought conditions.

Table 4
Accuracy assessment results for the general crop map using validation data collected by an independent analyst

<table>
<thead>
<tr>
<th>Reference data</th>
<th>Alfalfa</th>
<th>Summer crops</th>
<th>Winter wheat</th>
<th>Fallow</th>
<th>Total</th>
<th>UA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classified data</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alfalfa</td>
<td>23</td>
<td>1</td>
<td>2</td>
<td>0</td>
<td>26</td>
<td>88.5 ± 4.3</td>
</tr>
<tr>
<td>Summer crops</td>
<td>1</td>
<td>180</td>
<td>1</td>
<td>7</td>
<td>189</td>
<td>95.6 ± 0.5</td>
</tr>
<tr>
<td>Winter wheat</td>
<td>1</td>
<td>2</td>
<td>160</td>
<td>6</td>
<td>169</td>
<td>95.1 ± 0.8</td>
</tr>
<tr>
<td>Fallow</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>59</td>
<td>61</td>
<td>96.4 ± 6.5</td>
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<tr>
<td>Total</td>
<td>25</td>
<td>184</td>
<td>164</td>
<td>72</td>
<td>445</td>
<td></td>
</tr>
<tr>
<td>PA</td>
<td>92.1 ± 3.8</td>
<td>96.7 ± 0.8</td>
<td>95.6 ± 2.1</td>
<td>82.5 ± 1.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overall accuracy</td>
<td>95.3 ± 0.8</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kappa</td>
<td>0.91</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

PA (producer’s accuracy) and UA (user’s accuracy).

The ± values represent the percent accuracy variability within 1 standard deviation of the average overall and class-specific accuracies across the 10 classification runs. The row and column totals in the error matrix may not equal the number of sites in the rows and columns because the values represent averages across the 10 runs that were rounded to the nearest whole number in the error matrix.
stress, which can lead to the classification confusion observed between these classes.

### 5.2.3. Areal comparison

The classified and USDA reported general crop areas had a high level of areal agreement at the state level (<0.80 million ha (or <6%) areal difference for each class). High overall ($r=0.93$) and class-specific correlations ($r>0.90$) were also found between the MODIS map and USDA area statistics across the nine ASDs (Fig. 8b).

Less fallow and winter wheat were classified across all nine ASDs. The apparent underclassification of both classes was most pronounced in the western ASDs (10, 20, and 30), which reflects the omission of many marginal, non-irrigated cropland areas for this area in the initial crop/non-crop map that was discussed earlier. Summer crops had the lowest correlation ($r=0.72$) and exhibited a clear east–west division in terms of specific areal differences. In eastern Kansas (ASDs 80 and 90), considerably less summer crop area was mapped (0.12 million ha) than the USDA reported (0.20 million ha). Most of this underclassification was attributed to the omission of many small cropland areas in these districts from the initial crop/non-crop map. Most of these fields would have been planted to summer crops and collectively, their omissions would result in considerably less summer crop area being mapped. In contrast, more summer crop area was classified (ranged from 0.07 to 0.19 million ha) in three western (ASDs 10, 20, and 30) districts, as well as the north-central district (ASD 40).

The general crop map also classified more alfalfa in several eastern and central ASDs, with the greatest areal difference (0.06 million additional ha (>16.0%)) in southeast Kansas (ASD 90). Alfalfa is a minor crop in this part of the state and comprises considerably less cropland area than was classified. A visual assessment of the time-series NDVI profiles for many areas classified as alfalfa in ASD 90 revealed that many were not alfalfa, but were rather double cropped, with winter wheat followed by a summer crop. A distinct bi-modal NDVI signature was detected for the double cropped fields (Fig. 10).

The assignment of double cropped fields to the alfalfa class is not surprising considering that both maintain relatively high NDVI values throughout most of the growing season unlike the other general crop types. Double cropping is also regularly implemented in other eastern and central ASDs because of favorable climate conditions, which would account for the consistent overclassification of alfalfa in these districts.

A preliminary investigation of the time-series MODIS 250 m NDVI data to classify single vs. double cropped areas was undertaken using a limited number of double crop sites provided by the FSA. The same classification procedure used to generate the other crop maps was employed. Fig. 11 presents an example of the double/single crop classification results for ASD 90. The widespread use of double cropping in this district is apparent and clear block-shaped landscape features that correspond to individual fields (verified with Landsat ETM+ imagery) are depicted in the map. No statistical accuracy assessment could be performed given the lack of validation data, but this preliminary result illustrates the considerable potential that multi-temporal MODIS 250 m NDVI data hold for crop rotation mapping, as was recently demonstrated by the work of Morton et al. (2006) and Brown et al. (2007) in Brazil.

![Average, bi-modal multi-temporal NDVI profile (n=43) of double cropped fields in southeast Kansas (ASD 90) with a spring NDVI peak associated with winter wheat and a second, summer NDVI peak corresponding to a summer crop planted immediately after the late-June wheat harvest.](image-url)
5.3. Summer crop classification

5.3.1. Visual assessment
The summer crop patterns classified in Fig. 6c were in agreement with the known cropping patterns across Kansas. The dominance of corn and soybeans throughout eastern Kansas was represented. In central Kansas, the corn and soybeans planted along the Republican River (eastern ASD 40) and on irrigated cropland in northwest ASD 60 were depicted. Core areas of irrigated crops in the western ASDs, which are typically planted to corn (Rogers, 1994) and soybeans (Rogers, 1997), were classified. The east-to-west transition from corn and soybeans to sorghum in non-irrigated areas was mapped across central Kansas (ASDs 40 and 50). Sorghum, which is the primary dryland summer crop in western Kansas because of its drought-tolerant reputation (Rogers & Alam, 1998), was consistently classified in the non-irrigated areas of the western ASDs.

5.3.2. Statistical accuracy assessment
The summer crop map had an average overall accuracy of 84.0% with class-specific accuracies generally greater than 80.0% (Table 2c). The error matrix showed that a similar level of classification confusion occurred among the three summer crop classes.

5.3.3. Areal comparison
The classified and USDA reported summer crop areas were similar for each class at the state level with less than 0.25 million ha (<2.0%) difference. An overall correlation of 0.76 was found for the summer crops across the nine ASDs (Fig. 8c). Class-specific comparisons revealed relatively high correlations for corn ($r=0.92$) and sorghum ($r=0.86$), but a much lower correlation for soybeans ($r=0.42$). The lower correlation was primarily attributed to the considerable underclassification of soybeans in ASDs 80 (13.0% or 0.15 million fewer ha) and 90 (32.5% or 0.18 million fewer ha). The higher soybean omissions were primarily due to the propagation of the cropland omission errors from the initial crop/non-crop map in these two districts. Most of these omitted cropland areas would have been planted to soybeans, which is the dominant summer crop in both ASDs. When the soybean areas for ASDs 80 and 90 were excluded from the correlation analysis, the overall and class correlations increased to 0.88 and 0.93, respectively. Other notable regional trends included the consistent overclassification of corn and soybeans in western Kansas (ASDs 10, 20, and 30) and the underclassification of sorghum in several west-central ASDs (10, 20, and 40). However, these ASD-level areal differences were still relatively minor (<0.10 million ha difference).

5.4. Irrigated/non-irrigated crop classification

5.4.1. Visual assessment
Kansas’ major irrigated crop areas were depicted in the irrigated/non-irrigated crop map (Fig. 6d). In western Kansas, the broad expanses of irrigated cropland in southern ASD 10, west-central ASD 20, and throughout ASD 30 were classified. In south-central Kansas, the large area of irrigated cropland in northwest ASD 60 was depicted. Irrigated corn and soybeans along both the Republican (northeast ASD 40) and Kansas (boundary between ASDs 70 and 80) Rivers were mapped. Numerous, isolated irrigated crops along many rivers and streams throughout central and eastern Kansas were also classified.

The only major area of misclassification was the irrigated cropland classified in two counties (Brown and Doniphan) in extreme northeast Kansas (ASD 70). This area primarily supports non-irrigated corn and soybeans and irrigation is very limited. USDA FSA officials reported that only 1–2% of cropland in these two counties was irrigated, whereas the MODIS-derived map classified 26.7% and 34.9% of cropland.
in Brown and Doniphan Counties as irrigated. Higher than normal precipitation received during early to mid-summer in this area likely led to this major overclassification of irrigated crops. In 2001, Brown and Doniphan Counties received 206 and 218 mm of precipitation above the 10-year average, respectively (USDA, 2002). The precipitation totals for the remainder of Kansas’ counties were much closer to their 10-year averages. The majority of this additional rainfall was received during June and July, which corresponds to the greening up and peak growing season phases of both corn and soybeans. This optimally-timed additional rainfall resulted in better than normal crop conditions (e.g., larger plants/higher green biomass) and a multi-temporal NDVI response similar to that of an irrigated crop as illustrated in Fig. 12. The multi-temporal NDVI trajectory of non-irrigated corn in the two counties was similar to that of irrigated corn in the same ASD (80) with only minimal NDVI differences (0.03–0.07 NDVI units) at the peak of the growing season. Irrigated and non-irrigated crops are typically more separable in the NDVI data (≥ 0.10 NDVI difference) during the summer because of increased drought stress on non-irrigated crops as demonstrated for corn in Fig. 3. High corn and soybean yields for both counties in 2001 confirm the excellent crop conditions. Brown and Doniphan Counties had 23% and 14% higher corn yields and 23% and 17% higher soybean yields, respectively, than the previous 10-year average. In comparison, corn (state average of −8%) and soybeans (state average of −4%) yields were similar or slightly lower than the previous 10-year average for most of the other Kansas counties in 2001.

5.4.2. Statistical accuracy assessment

The irrigated/non-irrigated crop map had an overall accuracy of 85.0% and class-specific accuracies generally greater than 80% (Table 2d). From the producer’s perspective, the majority of misclassification (65% or 42 sites) was the result of irrigated crops being classified as non-irrigated, which suggests that irrigated crops may have been underclassified in the map.

5.4.3. Areal comparison

The state-level areal comparison confirmed that slightly less irrigated cropland (0.57 million ha or 5.0% less) was classified than the USDA reported. The mapped and reported irrigated crop areas had strong agreement (r=0.95) across the nine ASDs. However, a clear east–west division in the areal differences appeared among the ASDs (Fig. 8d). The MODIS map contained more irrigated cropland than USDA reported for all three eastern ASDs. ASD 70 had a much larger areal discrepancy (0.13 million additional ha) than the other eastern districts (< 0.05 million additional ha) because of the major overclassification of irrigated lands in extreme northeastern Kansas, as previously noted. In central and western Kansas, the MODIS map consistently classified less irrigated cropland than USDA estimates. The largest areal discrepancies occurred in the three most extensively irrigated districts (ASD 10, 30, and 60) in Kansas (80.4% of state’s total irrigated land). The rate of underclassification increased as the percentage of irrigated land increased among the three districts.

A visual comparison of the map and Landsat imagery for the three heavily irrigated ASDs revealed that some irrigated fields had been classified as non-irrigated, which would account for some of the underclassification. The majority of these fields were planted to either alfalfa or winter wheat, which suggests that it is more difficult to discriminate irrigated and non-irrigated fields planted to a crop with an early season, spring growth cycle using the NDVI data. Fig. 3 shows reduced separability between

![Fig. 12. Multi-temporal NDVI profiles of irrigated corn (n=13) in northeast Kansas (ASD 70 average) and non-irrigated corn (n=12) in Brown and Doniphan Counties (2-county average).](image-url)
irrigated and non-irrigated winter wheat in the spring in the MODIS NDVI data compared to irrigated and non-irrigated corn in mid-summer.

The consistent assignment of mixed edge pixels in transitional areas between irrigated and non-irrigated lands to the non-irrigated class also contributed to this underclassification. Perimeter pixels of irrigated areas usually maintained the general seasonal NDVI characteristics of the crop type being irrigated, but the NDVI values were considerably lower than those of the adjacent, interior pixels due to the lower NDVI contribution of the non-irrigated component of the mixed pixels as shown for alfalfa in Fig. 13. The lowered NDVI response from the edge pixels was similar to a non-irrigated crop and they were classified accordingly. Collectively, the assignment of these mixed pixels to the non-irrigated class resulted in less irrigated area being mapped, with the greatest reductions in the ASDs with extensive irrigation.

6. Conclusions

This study has demonstrated that time-series MODIS 250 m NDVI data provide a viable option for regional-scale crop mapping in the U.S. Central Great Plains. Relatively high classification accuracies (generally > 84%) were attained across the series of crop-related LULC maps produced for Kansas, and the classified crop patterns were consistent with the reported cropping patterns and crop distributions for the state. The classification accuracies were comparable to those of previous Landsat-based crop mapping studies conducted in Kansas (Mosiman, 2003; Price et al., 1997). The general, landscape-level cropping patterns depicted in the maps were similar to those that could be visually interpreted from high resolution imagery and the boundaries of many individual fields were retained at 250 m spatial resolution.

The MODIS-based mapping methodology proved to be extendable across Kansas. The state’s diverse environmental conditions, general landscape patterns, and cropping practices had only a minimal influence on the classification results. Some small, fragmented cropland areas in eastern Kansas could not be resolved at MODIS’ 250 m spatial resolution in the crop/non-crop map, but detailed cropping patterns within the larger cropland tracts were still depicted in the subsequent crop-related LULC maps. Mixed edge pixels at the 250 m spatial scale led to a slight contraction of cropland (eastern Kansas) and irrigated areas (western Kansas) in the crop/non-crop and irrigated/non-irrigated crop maps in some parts of the state. Sub-pixel unmixing methods, which have been applied to MODIS 250 m data for LULC characterization (Hansen et al., 2002; Lobell & Asner, 2004), should be investigated to improve the classification results for these transitional areas in both maps.

Large deviations in annual precipitation patterns also led to localized classification errors in the irrigated/non-irrigated crop map. However, the impact of Kansas’ climatic variations and specific weather patterns in 2001 on the classified patterns was negligible across the series of maps. Further work is needed to evaluate the performance of this MODIS NDVI-base mapping approach over multiple years and determine the sensitivity of the classification results to inter-annual variability for each crop-related LULC map.

The classification of specific crop types was unaffected by their underlying management practice (e.g., irrigated vs. non-irrigated) with the exception of double cropping, which was not included in the classification scheme implemented in this study. The sensitivity of the time-series MODIS 250 m NDVI data to such a land use practice illustrates the potential for using a similar approach to characterize specific crop rotation sequences. This potential is beginning to be realized through the work of Morton...
et al. (2006) and Brown et al. (2007), but the identification of specific crop types in rotation sequences (e.g., corn–soybean or winter wheat–fallow–summer crop) has yet to be explored.

The MODIS-based approach proved to be a cost- and time-efficient means for large-area crop mapping, which is critical for timely map updates and LULC monitoring activities. All data sources (MODIS, FSA, and NASS) used in the methodology are publicly available in the U.S. at little or no cost. Minimal preprocessing time was required to generate a statewide coverage of time-series NDVI data and the use of a decision tree classification approach resulted in rapid map production. The majority of time (∼6 months) required to implement this approach centered on the collection of training/validation data from the FSA aerial photos. The acquisition time for ground-truthed data could be greatly reduced in the near future with the development of statewide, field-level GIS databases, which would allow site selection to be automated and more stringent sampling schemes to be used.

This study should be viewed as an initial step in the development of a MODIS-based mapping and monitoring protocol for large-area crop characterization. The classification results from this work represent a ‘baseline’ that can be achieved using a time series of the standard, 16-day MODIS 250 m NDVI data. Numerous other variables that might improve the classification results of a particular thematic class(es) can be derived directly from MODIS 250 m spectral and VI data, such as vegetation phenology metrics (VPMs) (Reed et al., 1994), spectral metrics (DeFries et al., 1998), and harmonic analysis variables (Jaubasuskas et al., 2001). The use of shorter, 8-day composite periods in the time-series NDVI data (derived from MODIS’ 250 m surface reflectance product (MOD09Q1)) should be explored for the discrimination of crops with a similar phenology (e.g., corn and soybeans). The higher temporal resolution may allow more subtle spectral–temporal differences to be detected between crop types, which could improve the classification results. The mapping protocol should also be tested for additional crop types (e.g., cotton and sunflowers) and in other major agricultural regions to determine the range of its applicability.

The crop-related LULC maps produced in this study represent a valuable source of information for many applications. Maps depicting spatial distributions of specific crop types and associated land use practices can be used by the environmental modeling community to better parameterize biogeochemical (Burke et al., 1991; Parton et al., 1998), land–atmosphere interaction (Dickinson et al., 1993), water quality (Young et al., 1989), and crop yield (Kastens et al., 2005) models. In addition, these types of maps when updated on an annual basis can be used by scientists and policy makers to better understand the role and response of regional-scale agricultural management practices in a variety of environmental issues. The MODIS VI-based mapping methodology presented in this paper offers the potential to acquire information about rapid LULC changes such as crop rotations and the conversion of CRP grasslands back to crop production, as well as more gradual changes such as a shift to more drought-tolerant crop types or the expanded use of conservation tillage methods in locations facing rapid depletion of groundwater resources and/or drier climate conditions. It is also hoped that the MODIS crop mapping results presented in this paper stimulate the use of MODIS 250 m VI data and similar classification methods for other types of LULC mapping and characterization activities.

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