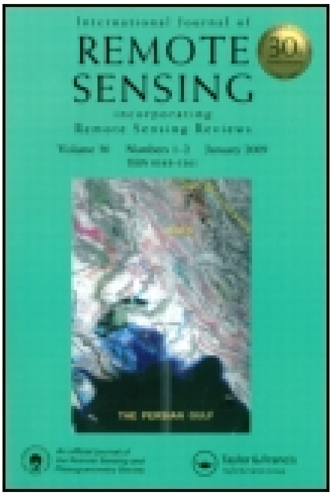

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Characterizing changes in cropping patterns using sequential Landsat imagery: an adaptive threshold approach and application to Phoenix, Arizona

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Since the 1970s, the Phoenix Active Management Area has experienced rapid urbanization, mostly through land conversions from agricultural lands to urban land use. Rapid urban expansion and population growth have placed unprecedented pressure on agricultural production in this region. Agricultural intensification, in particular double cropping, has been observed globally as an important response to the growing pressure on land. However, the intensification has a number of negative impacts on water quality, biodiversity, and biogeochemical cycles. Thus, quantifying the spatial pattern of cropping intensity is important for natural resource management. In this study, we developed an adaptive threshold approach to map cropping intensity using time series Landsat data and examined the spatiotemporal patterns of cropping intensity in the Phoenix Active Management Area from 1995 to 2010 at 5-year intervals. To map cropping intensity accurately, the adaptive threshold algorithm was designed specifically to address several issues caused by the complex cropping patterns in the study area. The adaptive threshold method has abilities to (1) distinguish true crop cycles from multiple false phenological peaks, (2) minimize errors caused by data noise and missing data, (3) identify alfalfa and interyear crops and to distinguish alfalfa from double crops, and (4) adapt to temporal profiles with different numbers of observations. The adaptive threshold algorithm is effective in characterizing cropping intensity with overall accuracies exceeding 97%. Results show that there is a dramatic decline in the area of total croplands (46.1%), single crops (46.3%), and double crops (43.4%) during the study period. There was a small conversion (1.9%) from single to double crop from 1995 to 2000, whereas a reverse conversion (1.3%) was observed from 2005 to 2010. Updated and accurate information on the spatial distribution of cropping intensity provide important implications on effective and sustainable cropping practices. In addition, joint investigation on cropping patterns and irrigation water use can shed light on future agricultural water demand, which is of paramount importance in this rapidly expanding arid region.

1. Introduction

The global population is projected to increase by two billion by 2050, 70% of which will be absorbed by urban areas (United Nation 2013). Consequently, growing population will lead to a more urbanized world and more agricultural prime lands will be converted to urban. Since the 1970s, the Phoenix Active Management Area (AMA) has experienced a dramatic land conversion from agriculture to residential, commercial, and industrial urban land uses (Keys, Wentz, and Redman 2007). The significant land shifts from agriculture to

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urban land use have posed challenges to resource management and ecological and economic planning. The dramatic decline in arable lands have also given rise to decreased crop yield and elevated crop prices. Consequently, an increasing number of urban farmers have started to practise multiple crops as a strategy to gain more profits. Cropping intensity varies from year to year due to a wide spectrum of factors including climate conditions, irrigation availability, water tables, growers' decisions on crop cultivation, and global and regional market conditions (Biradar and Xiao 2011; Frolking, Yeluripati, and Douglas 2006; Jain et al. 2013). Increasing cropping intensity, i.e. increasing the number of crops per year per unit area of cropland, could be very attractive to urban farmers because it is relatively difficult and expensive to acquire more lands, and it offers opportunities to adapt to changing market conditions. As urbanization intensifies, multiple cropping, such as double and triple cropping, can be expected to be a commonly practised strategy across the globe. Nevertheless, the intensification of agriculture has associated local, regional, and global environmental consequences such as degraded soil fertility, water pollution, reduced biodiversity, and changes in atmospheric constituents (Matson et al. 1997). Quantifying cropping intensity over space and time provides a basis for understanding land transitions and cropping pattern changes. In addition, studies on cropping intensity will provide implications for long-term agricultural and environmental sustainability.

Satellite imagery has provided opportunities to map croplands and identify crop types at local, regional, and global scales (Biggs et al. 2006; Biradar and Xiao 2011; Brisco et al. 1998; Frolking, Yeluripati, and Douglas 2006; Quarmby et al. 1992; Thenkabail et al. 2009; Wardlow, Egbert, and Kastens 2007; Xiao et al. 2005). Recently, efforts have been made to map cropping intensity at multiple scales using high temporal resolution Moderate Resolution Imaging Spectroradiometer (MODIS) data coupled with green leaf phenology (Biradar and Xiao 2011; Chen, Son, and Chang 2012; Galford et al. 2008; Lunetta et al. 2010; Qiu et al. 2014; Sakamoto et al. 2005). The daily revisit rate of MODIS is very helpful in monitoring agricultural lands and activities, especially for regions that have persistent cloud cover. While multi-temporal MODIS data have been evidenced to be effective in quantifying cropping intensity at large scales, they are subject to mixed pixel problems due to their coarse spatial resolution (i.e., 250 m), especially for regions with small agricultural fields. Alternatively, Landsat imagery provides enough spatial details to map small agricultural fields. A number of studies have reported the superiority of Landsat over other sensors (Jain et al. 2013; Velpuri et al. 2009). For example, Velpuri et al. (2009) reported that Landsat outperformed other coarser resolution sensors in measuring irrigated areas in India. Jain et al. (2013) found that the Landsat threshold method achieved a higher accuracy than the MODIS approaches to map cropping intensity at small scales.

It is important to realize that for regions with long rainy seasons, a 16-day revisit rate of Landsat is often insufficient to capture crop phenology accurately. As a result, using Landsat imagery alone to study crop phenology is impractical for these regions. The use of Landsat imagery, however, is more suitable in semi-arid and arid regions because there are plenty of cloud-free observations for these regions. A major benefit in using Landsat imagery is that one can identify multi-decadal changes in cropping patterns given that Landsat data are available from the late 1970s. Therefore, using Landsat imagery for crop mapping is beneficial for constructing historical cropping records.

The phenology of croplands presents more complex characteristics than that of other land cover features as it has multiple peaks in a growth cycle due to a variety of factors, such as variation in local climate, data noise, as well as management decisions (Galford et al. 2008; Qiu et al. 2014). While numerous efforts have been made in the field of crop type mapping (Aschbacher et al. 1995; Arvor et al. 2011; Singh et al. 2012; Wardlow and Egbert 2008; Xiao et al. 2005), studies with an aim to identify cropping intensity remain restricted (Chen, Son, and Chang 2012; Lunetta et al. 2010; Qiu et al. 2014). Cropping intensity has been most commonly evaluated using techniques in the field of signal processing via identifying peaks and troughs in the vegetation index profiles (Chen, Son, and Chang 2012; Galford et al. 2008; Sakamoto et al. 2005). However, the reliability of these techniques is questionable due to their sensitivity to noise disturbances (e.g. missing values, cloud cover) and false peaks (Qiu et al. 2014). Missing values, mostly caused by cloud cover, are very likely to be detected as troughs. In addition, traditional techniques are highly responsive to local maximums, causing multiple small peaks to be identified as phenological peaks in a time series (Galford et al. 2008, Peng, Tse, and Chu 2005). This is a major limitation of traditional techniques, and their ability to accurately quantify cropping intensity is further limited to regions where major crops present multiple false peaks in their temporal spectral profiles. Therefore, we proposed to develop a simple and efficient methodology to map and monitor cropping intensity over time in the Phoenix AMA. The methodology, called the adaptive threshold approach, identifies the number of peaks in a time series based on a threshold setting and decision tree approach, and can be easily customized to quantify cropping systems in other arid regions. We used Landsat imagery in our study because the average size of farms in the Phoenix AMA is ~300 m × 750 m, covering only one to three MODIS pixels. There are also agricultural fields with veritical or both horizontal and vertical dimensions <250 m. Our specific objectives are to (1) examine the effectiveness of the adaptive threshold approach for mapping cropping intensity over time and (2) evaluate the spatiotemporal dynamics of agricultural lands and cropping intensity in the Phoenix AMA.

2. Study area

The Phoenix AMA is located in central Arizona, covering over 14,504 km^2 (Figure 1). It is located in subtropical desert with an average annual temperature of 22.7 °C. The average annual rainfall is ~203 mm and growers rely primarily on irrigation for crop

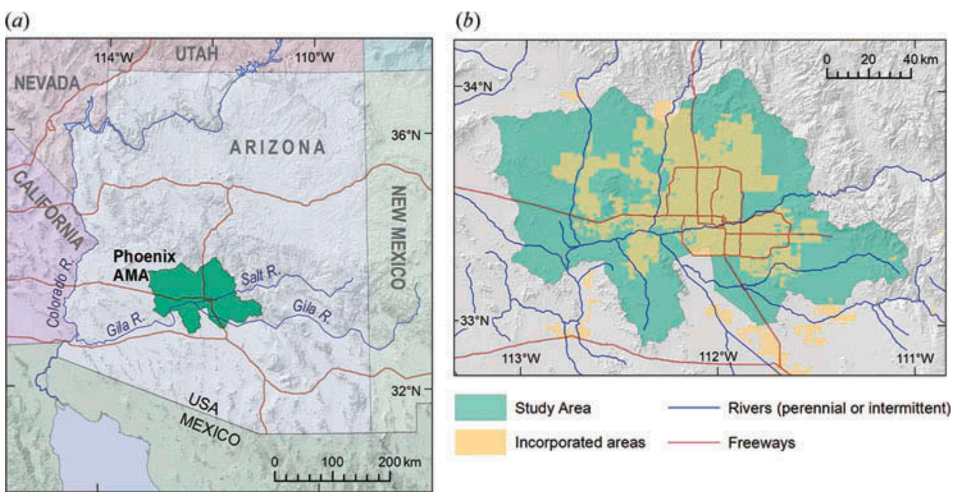

Figure 1. Study area located in the Phoenix active management area (AMA), southwest Arizona.

production (ADWR 2013). The dominant crop types in this region are cotton, alfalfa, wheat, sorghum, and corn. Growing patterns are very diverse in this region due to the warm climate year round. Double cropping occurs frequently for field crops with various crop rotation strategies. It is a common practice for growers to cultivate wheat in early winter and harvest the next spring (designated as interyear crops), subsequently followed by summer crops (i.e. corn, sorghum, and cotton). Alfalfa is widely cultivated across the AMA due to the high demand from local dairies. Unlike single or double crops that are harvested once or twice a year, alfalfa is cut multiple times throughout the year. Thus, it has distinct phenological signatures compared with other crops grown in the region. Cropping practices vary from field to field in response to different soil conditions, local climate conditions, irrigation water availability, and growers' preferences in farming practices. The diversity in the growing patterns of different crop types complicates the crop phenological patterns. Therefore, a specially designed algorithm is required for an accurate and effective characterization of cropping patterns in this arid region.

3. Materials and methods

Figure 2 presents an overview of the methodology including (1) data processing, (2) cropping intensity classification, (3) accuracy assessment, and (4) cropping pattern analysis.

3.1. Remote sensing data

Cloud-free Landsat 5 Thematic Mapper (TM) and 7 Enhanced Thematic Mapper Plus (ETM+) data (Path: 37, Row: 37) were downloaded for 1995, 2000, 2005, and 2010 from the United States Geological Survey Earth Resources Observation and Science Center. The combined Landsat 5 TM and 7 ETM+ results in an 8-day revisit rate. The total numbers of Landsat scenes for 2000, 2005, and 2010 were 21, 23, and 22, respectively. Because Landsat 7 ETM+ data were not available until 2000, the total number of Landsat scenes for year 1995 was lower (a total of 12 scenes) compared with the other three years. Atmospheric correction was conducted for all images using the Landsat Ecosystem

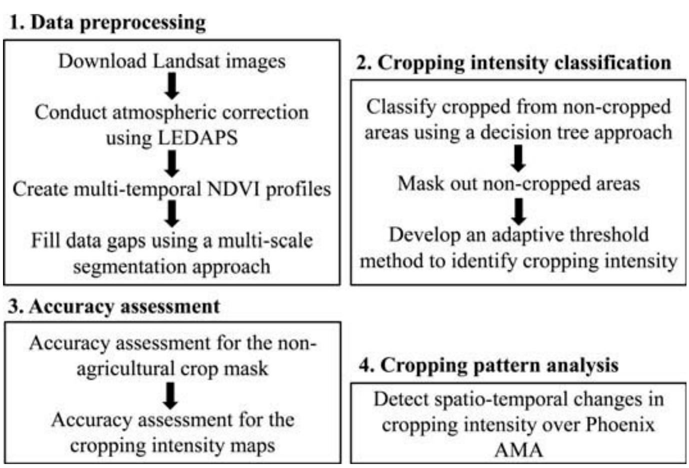

Figure 2. Overview of the methodology.

Disturbance Adaptive Processing System (Masek et al. 2006). The normalized difference vegetation index (NDVI) is highly correlated with the green biomass of croplands (Benedetti and Rossini 1993) and has been widely used in agricultural applications (Agrawal et al. 2003; Lunetta et al. 2010; Thenkabail, Schull, and Turral 2005). We generated NDVI layers and produced a time series of NDVI images for each year, which were then subset to the Phoenix AMA area.

3.2. Gap-filling using a multi-scale segmentation approach

Landsat 7 ETM+ imagery has data gap issues due to the malfunction of its Scan Line Corrector since 2003. We addressed the missing data issue to ensure a sufficient number of observations in a time series and to avoid an overly long time interval between two scenes. A multi-scale segmentation approach was employed to fill each Scan Line Corrector-off Landsat 7 image (Zheng et al. 2013). The multi-scale segmentation gap-filling approach assumes that the NDVI values within each segment or object are similar (Zheng et al. 2013). We generated segmentation maps for 2005 and 2010 by incorporating four Landsat TM NDVI layers into the built-in function in eCognition Developer 8 (Definiens 2009). The scale, shape, and compactness parameters were set to be 10, 0.1, and 0.5 as determined by a series of trial-and-error tests. The mean NDVI was calculated for each object and was used to fill the missing data.

The gap-filling approach was evaluated using a Landsat 5 TM NDVI image with simulated missing data. We randomly sampled 5% of the pixels, yielding an R^2 (coefficient of determination) of 0.93 and a mean absolute difference of 0.04 between the filled NDVI and actual NDVI values (Zheng et al. 2015). The same procedure was applied to fill all scan line gaps in the Landsat scenes.

3.3. Masking non-cropped areas

A decision tree approach was used to discriminate cropped areas from non-cropped areas including urban, desert, water, and fallow lands. This approach is based on the unique seasonal patterns of crops in the magnitude of NDVI throughout the growth cycle. For each pixel, we identified the maximum and minimum NDVI from its temporal profile and calculated the percentage difference between them. Pixels with percentage difference >60%, and maximum NDVI larger than 0.6 were treated as cropped areas. The change detection was followed by a low pass filter to remove small patches (i.e. salt and pepper pixels) with fewer than 40 pixels. Manual editing was conducted as the final step to ensure that large grasslands and riparian vegetation were not misclassified as agricultural lands. The proceeding procedures were repeated and applied to the four sets of time series NDVI images.

3.4. Temporal NDVI profiles of major cropping patterns

Figure 3 shows the phenological patterns of major crop types in the Phoenix AMA. Figure 3(*a*) typifies the growing pattern of a spring crop, such as barley or durum wheat, which are planted at the beginning of the year and harvested in April or May. Other single crops such as corn or cotton (summer crop) have peak NDVI shifted to summer (e.g. June for corn). Due to the warm climate, there is a high probability that growers plant seeds in October and harvest in early spring, or sow in late fall and harvest in April or May, resulting in an interyear crop pattern as shown in Figure 3(*b*). When treating each year

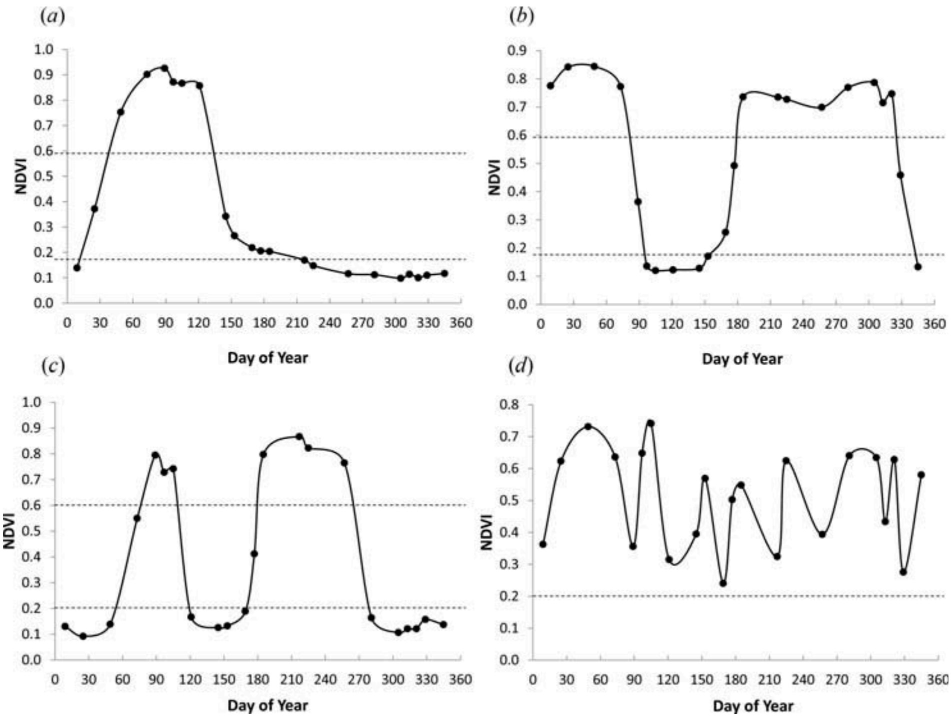

Figure 3. Temporal NDVI profiles of (*a*) a single crop; (*b*) an interyear crop followed by a summer crop; (*c*) a double crop; and (*d*) alfalfa.

separately, there was a general lack of consideration of incomplete temporal spectra in the previous peak detection algorithms that the interyear crops were either double counted or omitted. Figure 3(*c*) shows a typical double-cropping pattern. For double crops, the temporal NDVI profiles often present a bimodal pattern, with the first mode representing the first crop cycle from February to May, followed by the second crop cycle from June to October. Common double-cropping practices in this region include, but are not restricted to, barley and sorghum, wheat and sorghum, wheat and cotton, and barley and cotton. One crop type that is prevalent in our study area is alfalfa or other hay (Figure 3(*d*)). The seasonal dynamics of alfalfa or other hay present a distinct spectral pattern from the other crop types due to frequent harvests throughout the growing season. Alfalfa is harvested eight times a year on average. In our study area, alfalfa generally grows continuously for 3–4 years before the field is rotated into another crop type. The temporal profiles of alfalfa could exhibit wide variation from field to field due to difference in planting and cutting time. For example, the alfalfa spectrum in Figure 4(*a*) show lower harvest frequency than that in Figure 3(*d*). While Figures 3(*d*) and 4(*a*) represent the spectra of first- or second-year alfalfa, Figures 4(*b*), (*c*), and (*d*) most likely show the spectra of third- or fourth-year alfalfa because NDVI values in their temporal profiles generally decrease over time.

3.5. Mapping cropping intensity: an adaptive threshold approach

We devised an adaptive threshold approach to map cropping intensity in the Phoenix AMA using the time series of NDVI images. The cropping intensity was determined

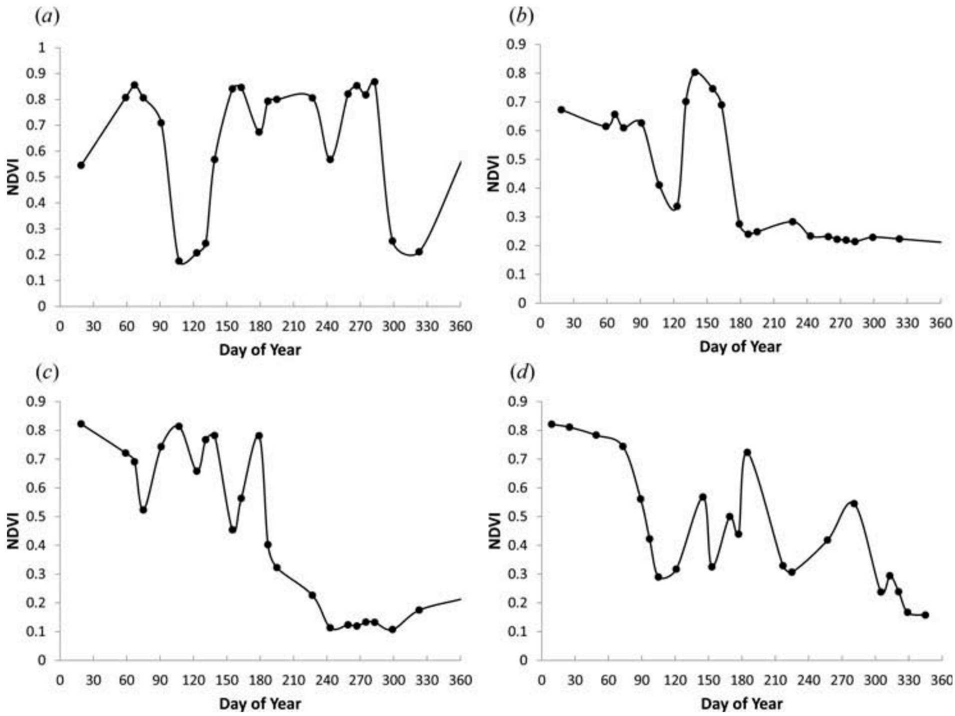

Figure 4. NDVI profiles showing the growing patterns of alfalfa in four fields.

based on the number of peaks identified from the temporal profile of each pixel, imposing predefined thresholds for the peaks and troughs. The thresholds are adaptive as they can be interactively adjusted based on various local conditions, including crop types, growing cycles of local crops, and image availability. Zero values of NDVI were first screened from the time series to preclude false estimation of multiple peaks due to cloud contamination or unfilled missing data. We defined that a complete crop cycle should have a peak NDVI higher than 0.6 and a trough NDVI lower than 0.2. A peak NDVI of 0.6 was set to exclude volunteer crops, which usually have a peak NDVI value lower than 0.6, while a trough NDVI of 0.2 was set to avoid detection of 'false' troughs caused by frequent cutting of alfalfa and other hay. Volunteer crops are plants from previous years' crops that turn into weeds in the current year. Specifically, one crop cycle was identified for each pixel if there was one observation in the temporal profile with NDVI higher than 0.6 followed at some interval by at least one observation with NDVI lower than 0.2. As early winter crops or interyear crops are either harvested at the beginning of a year or cultivated at the end of a year, additional treatment is required to avoid overestimation of the number of true growth cycles. Therefore, we decided that only harvested crops rather than cultivated crops were considered as one phenological peak.

Alfalfa is high yielding and is extensively cultivated across the Phoenix AMA as forage for cattle and other livestock. Instead of harvesting once or twice a year, alfalfa and other hay are cut more frequently throughout the growing season, resulting in multiple small peaks in their NDVI time series (Figure 4). As the magnitude of the peaks (troughs) in the temporal profiles of alfalfa and other hay was not significant enough to be considered as one complete crop cycle, they were classified as single crops using a different criterion: alfalfa was identified if and only if at least $m - p$ observations of the temporal NDVI profiles have NDVI >0.2, where m is the total number of observations in an NDVI time series, and p is a parameter indicating the number of observations with NDVI <0.2. We observed that NDVI values in a time series of full-year alfalfa are generally >0.2. There were also cases where alfalfa has a few NDVI values <0.2. The value of p ranges from zero to m, depending on the number of cloud-free observations for a particular year, the acquisition time of these observations, and patterns of cropping practices for a specific region. For example, p is equal to 2 when, in general, alfalfa has no more than two observations with NDVI values <0.2 in their spectral profile. The value of p is subject to changes from year to year and from place to place.

One of the advantages of the adaptive threshold method is that it can be easily tailored for different situations. The number of cloud-free and/or high-quality satellite scenes in a time series can vary substantially, depending on climate conditions and image availability. For example, we have fewer observations for 1995 than the other three years because Landsat 7 ETM+ imagery was not available until 1999. One consequence is that the magnitude of NDVI for peaks (troughs) for 1995 was lower (higher) than the thresholds defined above as the satellite scenes with real peaks (troughs) may be of poor quality and thus were not used in creating the NDVI time series. This introduced remarkable confusion between the profiles of alfalfa/other hay and double crops for 1995. To tackle this problem, we tested and implemented a refined procedure. As alfalfa is harvested more frequently than other crop types, the time interval between two peaks was used as a condition to differentiate alfalfa from multiple-cropping croplands. We classified crops with shorter average time intervals (<5 observations) between two consecutive peaks as alfalfa and the others as double crops.

3.6. Reference data and accuracy assessment

Updated and accurate reference data are crucial for evaluating the utility of new techniques and interpreting the associated remote-sensing products (Biradar and Xiao 2011). A total of 500 random samples were created for the accuracy assessment of our non-agricultural crop mask. In terms of cropping intensity, the reference data are spatially explicit point data that come from four data sources: the Arizona Department of Water Resources, USDA Farm Service Agency, Cropland Data Layer (USDA-NASS 2013), and local growers. The validity of reference data collected from all the sources was carefully verified by comparing the reported data with that of the spectral–temporal profiles of individual records to eliminate human-induced errors that could occur in the data collection process. We expect our reference data to be 100% accurate after visual verification. A stratified random sampling coupled with visual interpretation of the temporal profiles was conducted for the years 1995 and 2000 where no reference data were available (Hay 1979). Table 1 shows the numbers of samples for each year from each reference data source. In addition, producer's and user's accuracies, overall accuracy, and kappa coefficient for single- and double-cropping systems were reported. Triple crops were not considered because they were very rare in our study area.

3.7. Spatiotemporal cropping pattern analysis

Estimation of the spatial pattern of croplands in the Phoenix AMA promotes our understanding of the physical and temporal trajectories of agricultural development in this region and offers important implications on future agricultural water use. We examined

Table 1. Reference data sources and their corresponding sample size.

	Sample size (points)			
Data source	1995	2000	2005	2010
ADWR			408	
USDA FSA			69	30
CDL				367
Local growers			55	102
Stratified sampling	544	540		
Total	544	540	532	499

Note: ADWR, Arizona Department of Water Resources; USDA FSA, US Department of Agriculture Farm Service Agency; CDL, Cropland data layer.

the changes in the total croplands, single-cropped areas, and double-cropped areas for 1995, 2000, 2005, and 2010. The cropping intensity in the Phoenix AMA varies widely as a result of differences in soil conditions, irrigation water availability, water prices, and cropping practices.

4. Results

4.1. Accuracy of non-agricultural crop mask

The accuracy of the non-agricultural crop mask can greatly affect the accuracy of crop area estimation and its change over time. Masks with high commission errors will include other land cover types, such as grassland and other vegetation, thereby increasing the likelihood of categorizing a non-agricultural pixel as an agricultural one. Masks with high omission errors will lower the producer's accuracy in the assessment of cropping intensity, causing an underestimation of cropped areas. Table 2 shows the error matrix for the non-agricultral crop mask. For both non-cropped and cropped areas, producer's and user's accuracies were >97% for all four years, and the overall accuracies were above 98%. The corresponding kappa coefficients were also satisfactory. The error matrix indicated that the non-agricutural crop mask can be used effectively to delineate the agricultural area in the Phoenix AMA, and the remarkably high accuracy suggested that the accuracy of the cropping pattern will be largely dependent on the methodology *per se* compared with the accuracy of the mask.

Table 2. Error matrix for the non-agricultural crop mask (n is sample size).

	Non-cropped areas			Cropped areas				
Year	n	Producer's accuracy (%)	User's accuracy (%)	n	Producer's accuracy (%)	User's accuracy (%)	Overall accuracy (%)	Kappa coefficient
1995	300	99	98	200	97	99	98	0.97
2000	300	98	100	200	100	97	99	0.97
2005	300	100	99	200	98	100	99	0.98
2010	300	99	100	200	100	98	99	0.98

Table 3. Error matrix for single- and double-cropping systems (n is sample size).

	Single crops			Double crops				
Year	n	Producer's accuracy (%)	User's accuracy (%)	N	Producer's accuracy (%)	User's accuracy (%)	Overall accuracy (%)	Kappa coefficient
1995	498	97	100	46	100	78	98	0.86
2000	485	99	99	55	93	88	98	0.89
2005	461	99	99	71	90	96	98	0.92
2010	469	100	99	30	89	96	99	0.88

4.2. *Accuracy of cropping intensity identified using adaptive threshold method*

For all four years, the producer's and user's accuracies for single crops were >97% and 99%, respectively (Table 3). Note that the accuracies for double crops were somewhat lower than that for single crops. This is not surprising as the total number of reference samples for double crops is significantly smaller than single crops. Lower accuracies were observed for double crops for 1995, when many fewer images were available, resulting in significant spectral similarities between double crops and alfalfa. On the whole, the overall accuracies for 1995, 2000, 2005, and 2010 were 98%, 98%, 98%, and 99%, respectively, and the kappa coefficients were above 0.86 for all four years.

4.3. *Spatiotemporal cropping pattern analysis*

Table 4 summarizes the area of total cropland, single crops, and double crops along with the percentage area of single and double crops in the Phoenix AMA for 1995, 2000, 2005, and 2010. Our study area has been consistently dominated by single crops that account for over 89% of the cropland. The area of cropland in this region has decreased from 815 km^2 to 439.3 km^2 from 1995 to 2010 – a nearly 50% decrease. The spatial dynamics of total croplands and single crops were very similar across the study period, featured by a drastic decline from 1995 to 2000 (~26%), a minor drop from 2000 to 2005 (~6.5%), followed again by a greater decrease from 2005 to 2010 (~22%) comparable to that from 1995 to 2000.

The spatial pattern of double crops differed from that of single crops in which hardly any notable decline was detected until 2005, when the total area of double crops dropped from 57.3 km^2 to 38.8 km^2 (32.4%). There was a small conversion from single to double crops from 1995 to 2000 as suggested by a 1.9% increase in double crops (same amount

Table 4. Area of croplands by cropping intensity.

Year	Total area (km^2)	Area of single crops (km^2)	Proportion of single crops (%)	Area of double crops (km^2)	Proportion of double crops (%)
1995	815.0	746.5	91.6	68.5	8.4
2000	607.7	545.4	89.7	62.4	10.3
2005	567.7	510.3	89.9	57.3	10.1
2010	439.3	400.5	91.2	38.8	8.8

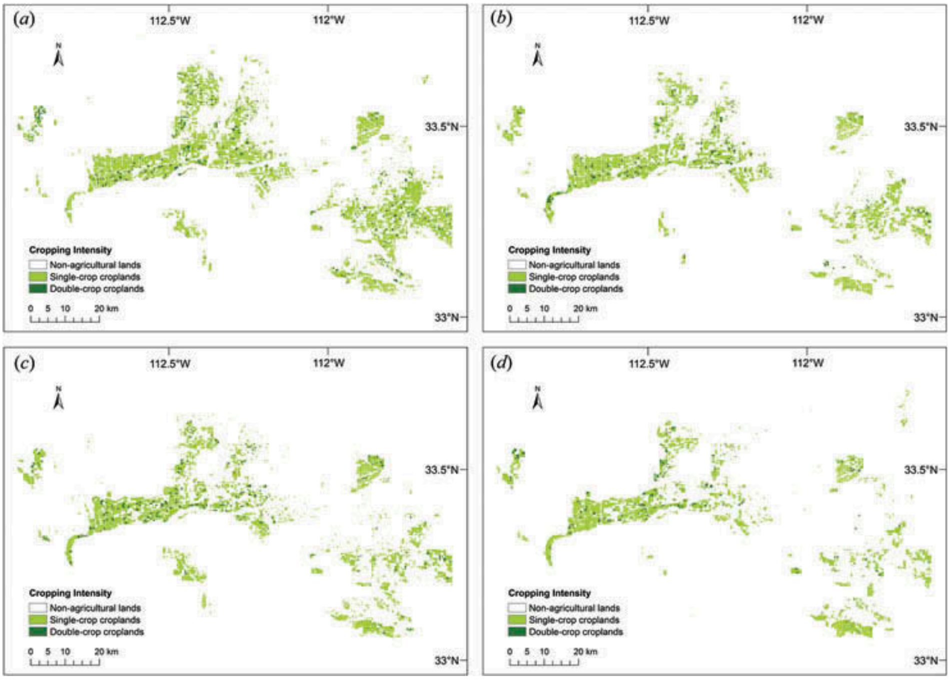

Figure 5. Cropping intensity maps of the Phoenix AMA derived by the adaptive threshold approach: (*a*) 1995; (*b*) 2000; (*c*) 2005; (*d*) 2010 (The maps cover the same area as Figure 1(*b*)).

of decrease in single crops). The percentage of double crops dropped back in 2010 to approximately the same level as it was in 1995.

The cropping intensity maps from 1995 to 2010 showed reduction of area in the total croplands, single crops, and double crops (Figure 5), which was consistent with what was suggested in Table 4. A comparison of the cropping intensity of two major cities in Phoenix AMA suggested a remarkable decline in the area of cropland from 1995 to 2010 (Figures 6(*b*) to (*e*)). Most of the agricultural lands were lost to urban areas (Figures 7(*a*) and (*b*)), and there were barely any crop fields that remained in highly developed cities which have undergone intense and rapid urbanization (Figures 7(*c*) and (*d*)).

5. Discussion

Our adaptive threshold approach was effective in mapping cropping intensity over the Phoenix AMA. Since each year was examined separately, the previous interannual curve fitting technique (Bradley et al. 2007) failed to measure the cropping intensity accurately as it expects periodicity in a continuous multi-year time series. In addition, false maximums/peaks are very easily created or amplified in a time series, thereby introducing errors in the crop mapping. The adaptive threshold approach surmounted the above problems via setting empirical thresholds that prevented the identification of any false peaks or troughs. Additional conditions were set to distinguish the profiles of alfalfa and interyear crops from other cropping systems. The effectiveness of the threshold approach was evidenced in Galford et al. (2008), where a similar procedure was employed to

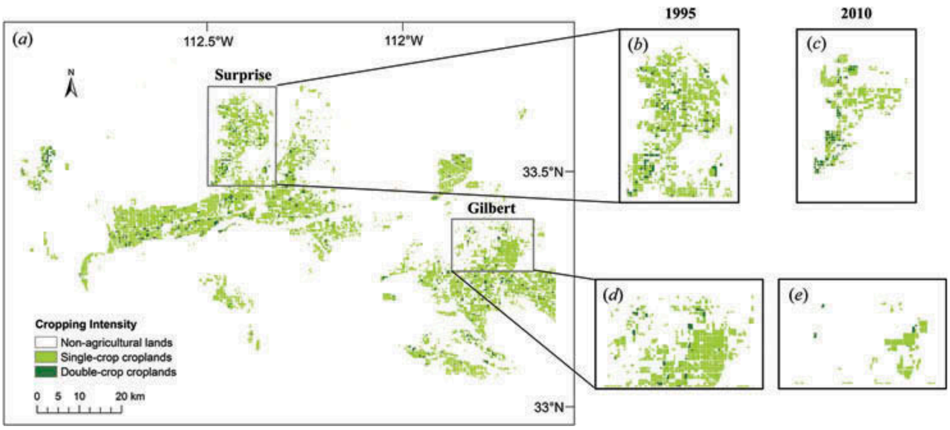

Figure 6. Changes in cropping pattern for the cities of Surprise and Gilbert from 1995 to 2010: (*a*) shows the locations of Surprise and Gilbert in the Phoenix AMA; (*b*) and (*c*) are cropping intensity maps of Surprise in 1995 and 2010, respectively; (*d*) and (*e*) are cropping intensity maps of Gilbert in 1995 and 2010, respectively.

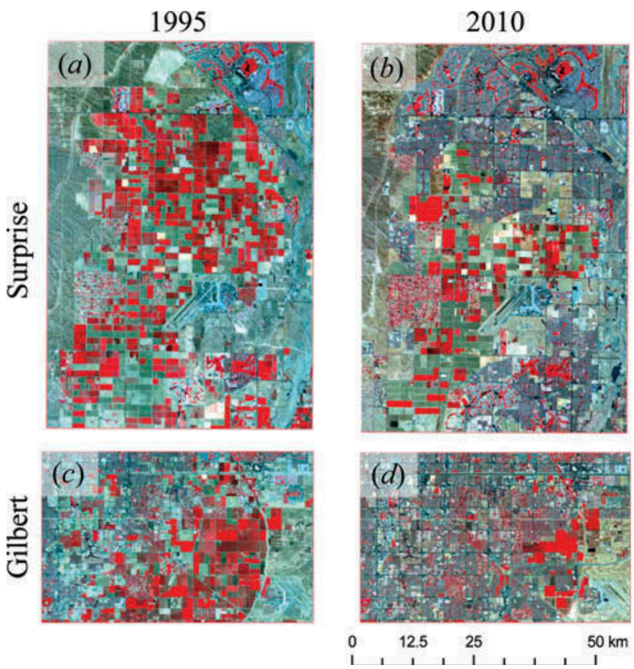

Figure 7. Standard false-colour composite Landsat images of (*a*) Surprise in 1995; (*b*) Surprise in 2010; (*c*) Gilbert in 1995; (*d*) Gilbert in 2010 (refer to Figure 6 for the locations of the two cities).

remove false peaks in a smoothed EVI time series. The threshold method coupled with Landsat data achieved an R^2 of higher than 0.7 (Jain et al. 2013). A recent study monitored the cropping intensity of croplands in India using a similar threshold approach, and an R^2 of 0.9 was observed in the relationship between the classified multiple-cropping croplands and agricultural census data at state level (Biradar and Xiao 2011).

The use of Landsat imagery permits accurate identification of cropping intensity for small patch fields. However, it is recognized that Landsat imagery is more suitable for regions with limited cloud cover than those with long rainy seasons and low-quality observations. For tropical regions that have persistent cloud cover, it is desirable to utilize data sets with high temporal coverage (e.g. MODIS) instead. The use of high temporal coverage data, however, requires the implementation of denoising techniques to obtain a smoothed time series. Another possibility is to use the spatial and temporal adaptive reflectance fusion model (STARFM), which produces synthetic Landsat data with high temporal resolution (Gao et al. 2006).

While our approach can be customizable to cropping practices in other regions, the selection of thresholds for peaks and troughs is crucial as it influences the classification accuracy in a substantial way. The values of thresholds may vary from place to place due to differences in cultivation practices, crop types, as well as climate conditions. To determine the thresholds, it is important to have a comprehensive understanding of the phenological patterns of crops in the region by conducting field surveys or using reference data (Qiu et al. 2014). Note that crop maps are usually not required to derive appropriate thresholds, but will aid in identifying temporal profiles with missing data.

The adaptive threshold method can be easily tailored to deal with small numbers of satellite observations in a time series. Although the total number of Landsat scenes for year 1995 was only about half of years 2000, 2005, and 2010, our algorithm worked well and was capable of identifying the cropping intensity effectively with an overall accuracy above 97%. Thus, the method developed here can be used jointly with early satellite images to help construct historical agricultural records. However, it is important to note that the minimum number of satellite images for an effective characterization of cropping intensity is location-specific, which depends on a number of local factors. As such, *a priori* knowledge of local agricultural practices is the basis for mapping cropping intensity accurately. By and large, the adaptive threshold approach proposed here is superior to other peak detection algorithms in terms of its ability to: (1) distinguish true crop cycles from multiple false phenological peaks; (2) minimize errors caused by data noise and missing data; (3) identify alfalfa and interyear crops and distinguish alfalfa from double crops; and (4) adapt to temporal profiles with different numbers of observations. We believe that our method can be applied to other semi-arid and arid regions with similar climate conditions.

Our results show substantial reduction in the area of total cropland (46.1%), single crops (46.3%), and double crops (43.4%) from 1995 to 2010. Keys, Wentz, and Redman (2007) found that over half of the agricultural lands had been converted to some sort of urban area from 1970 to 2000, a three-decade period, in Phoenix. The rapid decline in total croplands from 1995 to 2000 (~26% decline) and from 2005 to 2010 (~22% decline) likely corresponds to the booming economy at the beginning of the two periods, while the lower rate of decrease from 2000 to 2005 (~6.5%) is likely due to the economic downturn that started in the middle of 2001. A recent study in Phoenix showed that agricultural lands were losing ground to primarily mesic residential and commercial areas (Buyantuyev, Jianguo, and Gries 2010). The conversion from agriculture to urban land use was also reported by Jianguo et al. (2011) who found that the landscape in Phoenix metropolitan area has become increasingly more fragmented in structure and more complex in shape.

Results showed a non-monotonic pattern in the percentage area of double crops – an increase from 1995 to 2000 followed by a decrease from 2005 to 2010. The conversion from single to double crops might be due to the consequence of the rapid urbanization, which caused increasing land pressure. The percentage drop in double crops, however, may be caused by multiple factors. First, there has been a dramatic increase (over 60%) in the overall volume of alfalfa exports from the western USA since 2007 (Putnam, Matthews, and Sumner 2014). The demand surge for alfalfa might be the reason for the shift from double- to single-cropping practices in the Phoenix AMA. According to National Agricultural Statistics Service USDA, the total harvested area of alfalfa in Maricopa county was 80,000 acres in 2005 and 85,000 acres in 2010, that is a 5000 acres increase. As the crop price of alfalfa has continuously increased up to 2008, most local farmers choose to allocate parts of their farm lands for alfalfa to guarantee their profits. In addition, double-cropping practices can be greatly affected by local weather conditions. Delayed cultivation or harvest of small grain crops in the spring due to local weather conditions could eventually delay the planting of the next crop. As delayed cultivation can significantly affect yield potential for certain types of crops, growers prefer not to plant a second crop when they miss the best timing for cultivation.

6. Conclusion

This paper examined decadal changes in cropping patterns in the Phoenix AMA using time series Landsat imagery. We developed an adaptive threshold approach to map cropping intensity with overall accuracies above 97%. We implemented specific procedures to accurately identify the interyear crops and distinguish alfalfa from other cropping systems. The approach is superior to previous techniques in its capability to identify real crop cycles from false phenological peaks with minimal influence of data noise and its effectiveness with fewer number of satellite observations in a time series. The successful application of the adaptive threshold approach in the Phoenix AMA warrants promising applications to other semi-arid and arid regions. It is important, however, to acquire knowledge on the spectral characteristics of local crops to derive suitable thresholds.

Our results indicate a substantial decrease in agricultural lands from 1995 to 2010 in the Phoenix AMA area due to rapid urbanization. Double-cropping practices were more prevalent in 2000, followed by a shift from double- to single-cropping practices from 2005 to 2010. Monitoring changes in cropping intensity is important towards understanding the impacts of different cropping patterns on nitrogen and carbon cycling, and promoting informed and sustainable agricultural management. Future efforts should be devoted to examine changes in total cropland and double-cropping areas at a yearly basis instead of 5-year intervals. In addition, linkage between cropping patterns and water use will provide insight to future agricultural water demand.

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Disclosure Statement

There is no conflict of interest to declare.

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