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An automated approach to mapping corn from Landsat imagery

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Abstract

Most land cover maps generated from Landsat imagery involve classification of a wide variety of land cover types, whereas some studies may only need spatial information on a single cover type. For example, we required a map of corn in order to estimate exposure to agricultural chemicals for an environmental epidemiology study. Traditional classification techniques, which require the collection and processing of costly ground reference data, were not feasible for our application because of the large number of images to be analyzed. We present a new method that has the potential to automate the classification of corn from Landsat satellite imagery, resulting in a more timely product for applications covering large geographical regions. Our approach uses readily available agricultural areal estimates to enable automation of the classification process resulting in a map identifying land cover as 'highly likely corn,' 'likely corn' or 'unlikely corn.' To demonstrate the feasibility of this approach, we produced a map consisting of the three corn likelihood classes using a Landsat image in south central Nebraska. Overall classification accuracy of the map was 92.2% when compared to ground reference data.

Keywords: Satellite remote sensing; Geospatial technology; Crop mapping; Corn

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1. Introduction

Knowledge of the spatial distribution of specific crop types is important for many environmental and health studies (Kellogg et al., 1992; Wood et al., 1995; Gilliom and Thelin, 1997; Ward et al., 2000; Xiang et al., 2000). Many studies need crop type maps over large geographical regions (e.g. multi-county and entire state) for multiple years in order to determine statistically significant relationships between environment and disease occurrence. For example, once the location of crops is determined, parameters such as pesticide use can be estimated and incorporated into an environmental model for exposure assessment for health studies (Ward et al., 2000). Such maps covering extensive geographical regions can only be derived from satellite imagery.

Landsat satellite imagery has been collected since the early 1970s and has been successfully used to classify many different crop types (Bauer et al., 1978; Myers, 1983; Badhwar, 1984; Brisco and Brown, 1995). However, traditional methods for deriving land cover information from satellite imagery can be very time-consuming. Traditional methods basically apply either a supervised or unsupervised classification approach. Both methods require ground reference data, collected by field visits or air photo interpretation, to 'train' the classification algorithm or analyst and to assess the accuracy of the resulting land cover map. Both methods also require a remote sensing analyst to interact extensively with the computer system during the image classification process (Lillesand and Kiefer, 1997). Classification of a single Landsat scene (approximately 170 km × 185 km) can take several days to months depending on the complexity of the land cover types and imagery. New methods that automate the interpretation process as much as possible are essential if we are to meet the needs of environmental research applications in a timely and cost-effective manner.

This paper describes our approach to automating the classification of corn from Landsat imagery using agricultural areal estimates in lieu of ground reference data. The capability to rapidly map corn over large regions in Nebraska is important to our research in chemical exposure assessment for an environmental epidemiological study. Corn has the greatest use (pounds applied) of pesticides and fertilizers among all Midwest crops. Since the 1980s, more than 90% of corn acreage in Nebraska received nitrogen fertilizer and herbicide treatments (Johnson and Kamble, 1984). Herbicides accounted for 91% of all pesticides applied to corn in the US in 1992 (Lin et al., 1995). Our methodology for rapid corn classification from Landsat imagery could benefit other studies in the Midwest as corn is the predominant crop and covers the largest area of all crops in the USA (US Department of Agriculture (USDA) National Agricultural Statistics Service, Website: http://www.usda.gov/nass).

2. Methods

2.1. Study area and data description

Four counties in south central Nebraska were selected for our study: Hall, Kearney, Nuckolls, and Thayer. The crops grown in these four counties represent the dominant crops grown in south central Nebraska which include corn, sorghum, soybeans, and winter wheat

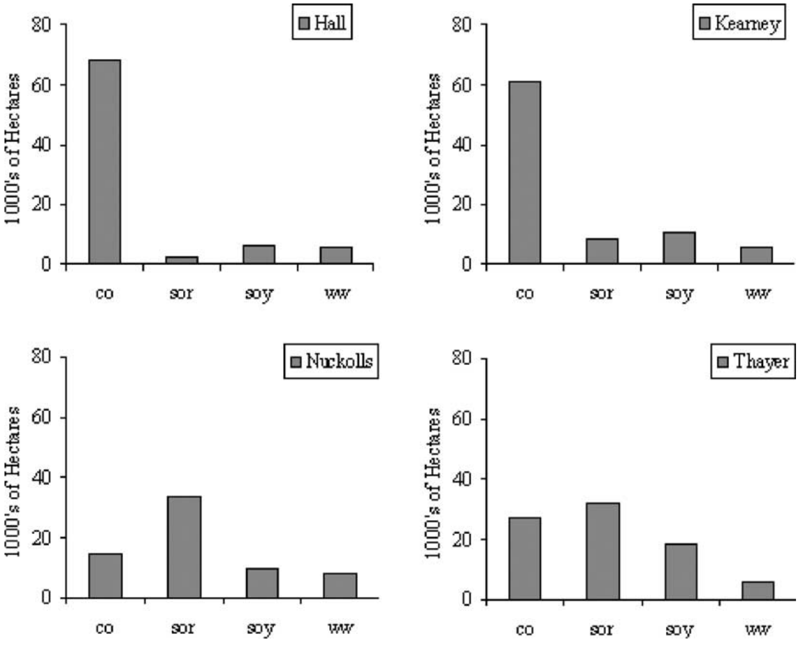

Fig. 1. 1984 harvested acreage estimates for four Nebraska counties (Nebraska Agricultural Statistics Service, 1986). co: corn, sor: sorghum, soy: soybeans, ww: winter wheat.

(Fig. 1). Corn represents 52% of the four dominant crops, sorghum 22%, soybeans 14%, and winter wheat 12%. Corn is the primary crop grown in Hall and Kearney counties (85.6 and 69.6%, respectively), whereas sorghum dominates in Nuckolls County. Thayer County contains a mixture of all four of the crops. Rangeland is the major non-cultivated land cover in this region.

An August 29, 1984 Landsat Multi-spectral Scanner (MSS) image (Path29 Row32) was selected from the North American Landscape Characterization (NALC) data set produced by the US Geological Survey Earth Resources Observation Systems Data Center (Sohl and Dwyer, 1998). NALC data have been georeferenced, resampled to a standard 60 m × 60 m pixel resolution, and is available at minimal cost. This late summer image was used as it represents the optimum time period for discrimination of the major crops in this region (Bauer et al., 1979; Odenweller and Johnson, 1984; Maxwell and Hoffer, 1996). The Landsat MSS instrument collects spectral data in two visible bands (0.5–0.6 μm and 0.6–0.7 μm) and two near infrared bands (0.7–0.8 μm and 0.8–1.1 μm). Studies have suggested that while using MSS data, only one band from each of the major wavelength regions is required to perform land cover mapping (Bauer et al., 1979; Hixson et al., 1980). For this reason and also to reduce the complexity of the algorithm, we used only visible band 2 (0.6–0.7 μm) and near infrared band 4 (0.8–1.1 μm) in our analysis. Agricultural areal estimates were provided by the Nebraska Agricultural Statistics Service, 1986 (NASS). Because the image was collected in late summer (August), estimates for hectares harvested (as opposed to hectares planted) were used.

2.2. Classification methodology

The classification process involves three steps. The first step is to identify representative samples of corn in the Landsat image from which to derive the spectral training pattern for corn. This corn spectral training pattern is then compared to every pixel in the image and the spectral distance between them is calculated. This distance measurement is then refined in the final step into three classes (‘highly likely corn,’ ‘likely corn,’ and ‘unlikely corn’). The NASS areal estimates are used in two ways to enable automation of the classification process: to identify a region within the Landsat image to collect a representative sample of corn pixels and to determine cutoff values for classification into one of the three corn likelihood classes.

The first step, corn spectral training pattern calculation, is accomplished by identifying a specific county (or sub-region) within the Landsat image from which to collect a representative sample of corn pixels. Selection of this county is based on two criteria: (1) the county with the highest proportion of corn as compared to other crops grown and (2) the county with the highest number of corn hectares grown. This ensures that the dominant spectral tone within the sub-image selected will represent corn. Hall County was chosen in our study because it met both criteria for selection: the highest proportion of corn (85.6% of hectares harvested) compared with the other major crop types grown within the county and the highest number of corn hectares grown (Fig. 1). Twenty contiguous samples were selected from the bivariate histogram of the red visible band (band 2) and the near infrared band (band 4) of the Landsat image for Hall County (Fig. 2). Samples were collected beginning at the highest point in the bivariate histogram (band $2 = 15$, band $4 = 58$) and proceeded with the next highest point until twenty samples were selected. These samples were then used to calculate the spectral response pattern for corn (Table 1).

The Mahalanobis distance measurement (Duda and Hart, 1973) for each pixel in the Landsat image is then calculated using the corn spectral training pattern. The Mahalanobis distance measurement (Duda and Hart, 1973) is used in our method to determine the ‘likelihood’ that an individual pixel is corn. The Mahalanobis distance represents the spectral distance from the original corn training pattern to an individual pixel and therefore this distance can be used to determine how likely the pixel is to be corn. Pixels that have low distance values are more likely to be corn and pixels with high values are less likely to be corn. Assigning this confidence label at the pixel level is important for identifying potential errors in estimating chemical exposure.

Agricultural areal estimates are used in the final step to refine the Mahalanobis distance measurement to one of three categories: highly likely to be corn, likely to be corn, or unlikely to be corn. NASS areal estimates for corn are used to determine cutoff points by comparing the total acreage of corn grown in a particular county to the acreage represented

Table 1
Spectral training signature statistics for the crop type corn (digital number values)

	Band 2	Band 4
Mean	15.30	58.42
Standard deviation	.46	3.04

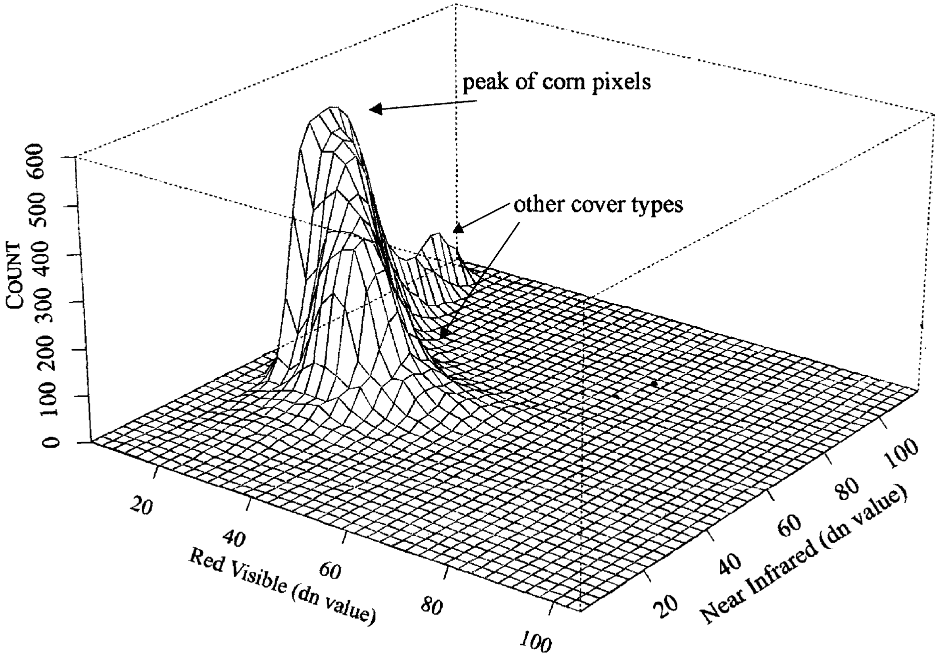

Fig. 2. Bivariate histogram surface plot of the Landsat MSS red visible (band 2) and near infrared (band 4) wavelength bands for Hall County. The histogram peak represents the spectral region for corn.

by each distance value. We classified pixels as 'highly likely to be corn' for distance values representing up to approximately 75.0% of the total acreage of corn. Pixels classified as 'likely to be corn' were distance values representing the remaining 25.0% of the total acreage for corn. All other pixels were classified as 'unlikely to be corn.' The 75.0% cutoff value was based on a sensitivity analysis performed on the three test counties through a trial and error process.

The process of assigning the likelihood labels is demonstrated in detail for Kearney County (Table 2). NASS estimated that Kearney County harvested 58 685 ha of corn in 1984. The cutoff points are set at 44 014 ha (75.0% of 58 685) for pixels highly likely to be corn and 58 685 ha for pixels likely to be corn. Pixels with Mahalanobis distance values from 1 to 42 are classified as highly likely to be corn, because the cumulative total number of hectares are approximately 75.0% of the acreage estimated by the NASS. Distance values from 43 through 111 are classified as likely to be corn because the cumulative total of the acreage for these pixels constituted the remaining 25.0% of the acreage estimated by NASS. Distance values greater than 111 are classified as unlikely to be corn.

2.3. Accuracy assessment

Ground reference data (location and type of crop grown) were provided by the USDA Farm Service Agency (FSA) county offices within each of the three test counties (Kearney, Nuckolls, and Thayer) to determine classification accuracy. We selected 40 Public Land

Table 2
Classification of corn in Kearney County, Nebraska using Mahalanobis distance values and agricultural areal estimates for corn

Mahalanobis distance values	Land area (ha)	Cumulative total (ha)	Cumulative total (percent of NASS)	Classification code[a]
1	2877.8	2877.8	4.9	1
2	1025.3	3903.1	6.7	1
3	5143.7	9046.8	15.4	1
–	–	–	–	–
42	205.9	43,950.6	74.9	1
43	365.0	44,315.6	76.0	2
44	229.3	44,545.0	77.3	2
–	–	–	–	–
111	381.6	58,533.1	99.8	2
112	224.3	58,757.4	100.2	3
–	–	–	–	–

[a] A pixel is classified as highly likely to be corn (code = 1) if the total hectares of those pixels having a specific distance value (e.g. 42) represent less than 75% of the total hectares of corn estimated by agricultural statistics. A pixel is likely to be corn (code = 2) if the total hectares of those pixels having a specific distance value represent approximately between 76 and 100% of the hectares of corn pixels estimated by agricultural statistics. The remaining pixels are classified as unlikely to be corn (code = 3).

Survey (PLS) Sections (1.6 km × 1.6 km each section) from each of the three counties to be tested. A grid representing the PLS Section boundaries was overlayed onto a color infrared display of the Landsat image. Individual sections were chosen to ensure that an adequate number of samples were collected on each of the dominant spectral tones, and that those sections were spatially distributed across the county. FSA offices were asked to identify all of the cover types present in 1984 (e.g. corn, rangeland). The FSA provided a photocopy of an aerial photograph from their files for each section with the land cover types identified. Urban and riparian cover types were not adequately represented in the PLS Sections selected, therefore additional samples were digitized directly from the Landsat image. No riparian vegetation was identifiable on the Landsat image in Kearney County. A total of 518 field polygons were screen digitized using a region growing function and labeled with the appropriate land cover class (Table 3). All pixels within each polygon were used in the accuracy assessment (Table 4).

An error matrix was produced for each of the three test counties comparing our corn map to the ground reference samples supplied by the FSA. Our final analysis included three crop types (corn, sorghum, and soybeans) and four general land cover types (bare soil/sparse vegetation, rangeland, urban, and riparian). Winter wheat was classed as bare soil/sparse vegetation as this crop had been harvested at the time our Landsat scene was acquired (late August) when there is typically only bare soil or stubble remaining on fields.

3. Results

Overall average accuracy (correctly classified samples for all classes divided by total number of samples) was 92.2% with individual county accuracies ranging from 90.1 to 96.5%. An average of 93.9% of the pixels designated as corn by FSA were classified as

Table 3
Summary of ground reference data

Class	Kearney County		Nuckolls County		Thayer County	
	Number of polygons	Number of pixels	Number of polygons	Number of pixels	Number of polygons	Number of pixels
Crop classes						
Corn	70	1252	19	344	55	1026
Sorghum	12	216	56	870	56	956
Soybeans	27	393	24	284	39	509
Total crop samples	109	1861	99	1498	150	2491
Other classes						
Bare soil/sparse vegetable	21	336	25	323	31	442
Rangeland	5	71	31	465	21	302
Urban	2	168	6	441	7	375
Riparian	0	0	5	539	6	322
Total all samples	137	2436	166	3266	215	3932

being either highly likely or likely to be corn. Accuracy of corn for individual counties ranged from 89.0% (Thayer County) to 99.1% (Kearney County). Sorghum and soybeans were, for the most part, classified as unlikely to be corn (average was 93.1% for sorghum and 91.3% for soybeans). No bare soil/sparse vegetation or rangeland was classified as corn and less than one percent of urban land was classified as corn. The largest number of errors occurred in the riparian class where an average of only 55.7% of the samples were correctly classified.

Visual comparison of the original Landsat image to the corn likelihood map revealed that pixels classified as corn (highly likely to be corn or likely to be corn) represented, for the most part, entire crop fields (Fig. 3 top). Corn was represented by dark red tones in the color infrared Landsat image as compared to most other cover types tested which were represented in much brighter red tones (soybeans, sorghum) or cyan tones (bare soil, rangeland, urban). Riparian vegetation was also represented in dark red tones in the Landsat image (Fig. 3 bottom) supporting the lower accuracy results of the riparian class. Individual pixels and small clusters of pixels classified as corn were scattered throughout the map.

4. Discussion

The results of our study indicate that an automated approach to classifying corn from Landsat satellite imagery may be feasible. The primary advantage of this method is the ability to perform rapid interpretation of the satellite imagery without the need for ground reference data to 'train' the classification algorithm. This is especially important in creating historical maps, because ground reference data may not be available. Historical agricultural areal estimates however are easily obtained from state or federal agricultural agencies (e.g. Nebraska Agriculture Statistics Service, USDA Website: http://www.usda.gov/nass).

Table 4
Classification accuracy results for each of the three test counties and an average for all three counties

Class	Number of highly likely corn	Number of likely corn	Number of unlikely corn	Total number of samples	Accuracy (percent)
Kearney County					
Crops					
Corn	1100	141	11	1252	99.1
Sorghum	15	24	177	216	81.9
Soybeans	–	34	359	393	91.3
Other					
Bare soil/sparse Vegetation	–	–	336	336	100.0
Rangeland	–	–	71	71	100.0
Urban	–	1	167	168	99.4
Riparian	–	–	–	–	–
Nuckolls County					
Crops					
Corn	267	41	36	344	89.5
Sorghum	12	8	850	870	97.7
Soybeans	31	7	246	284	86.6
Other					
Bare soil/sparse Vegetation	–	–	323	323	100.0
Rangeland	–	–	465	465	100.0
Urban	1	2	441	444	99.3
Riparian	151	66	222	439	50.6
Thayer County					
Crops					
Corn	704	209	113	1026	89.0
Sorghum	49	32	875	956	91.5
Soybeans	18	13	478	509	93.9
Other					
Bare soil/sparse Vegetation	–	–	442	442	100.0
Rangeland	–	–	302	302	100.0
Urban	–	–	375	375	100.0
Riparian	66	54	202	322	62.7
Average					
Crops					
Corn	2071	391	160	2622	93.9
Sorghum	76	64	1902	2042	93.1
Soybeans	49	54	1083	1186	91.3
Other					
Bare soil/sparse Vegetation	–	–	1101	1101	100.0
Rangeland	–	–	838	838	100.0
Urban	1	3	983	987	99.6
Riparian	217	120	424	761	55.7

Values are given in number of samples (pixels).

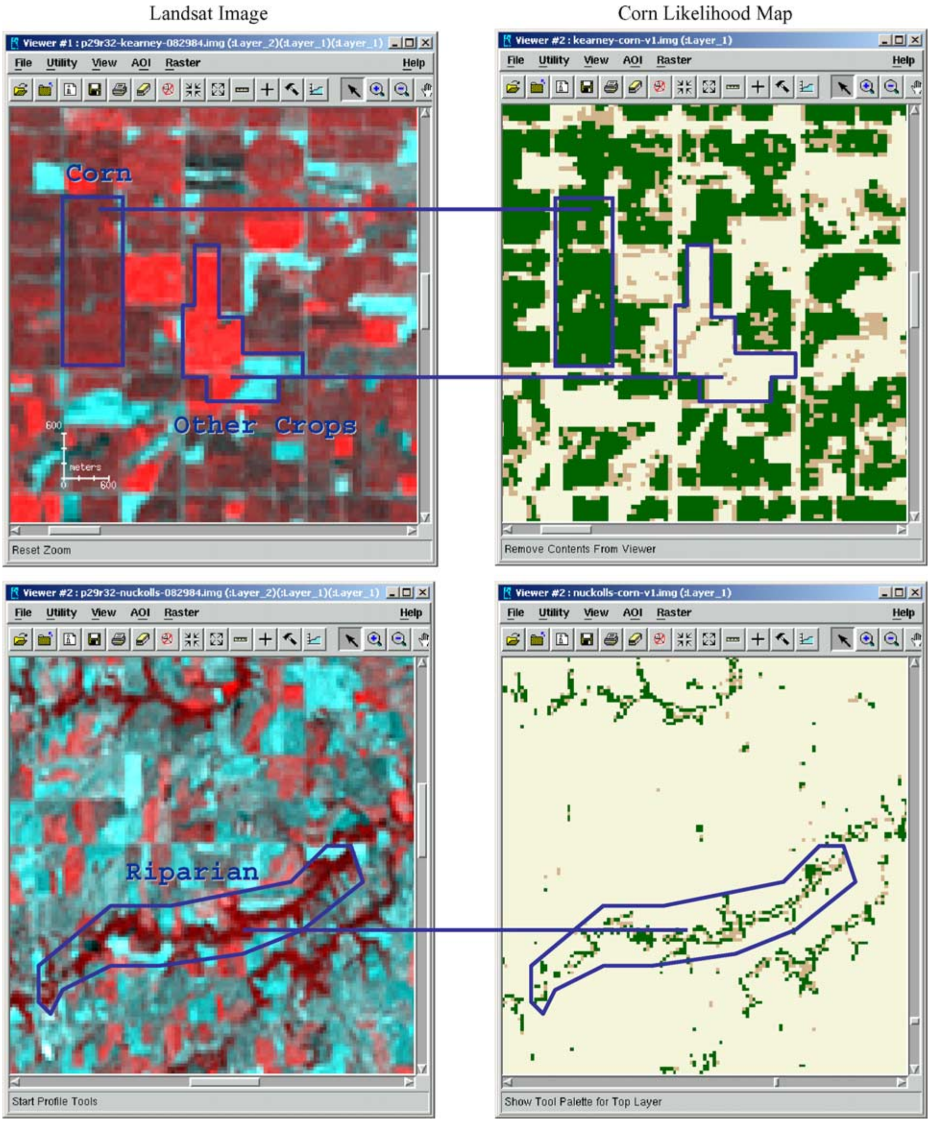

Fig. 3. Comparison of a color infrared Landsat MSS image to the Corn Likelihood Map for two regions in south central Nebraska. Red tones in the Landsat images represent green vegetation where dark red tones are generally corn or riparian vegetation. Cyan tones typically represent rangeland, crop residue or bare soil. Green on the Corn Likelihood Map is the ‘highly likely corn’ class, orange is ‘likely corn,’ and light yellow is ‘unlikely corn.’ Examples highlight where corn has been correctly classified (upper) and where riparian vegetation has been misclassified as corn (lower).

The majority of urban, rangeland, bare soil/sparse vegetation, sorghum and soybeans were classified successfully into the 'unlikely to be corn' category with a 81.9–100.0% accuracy. Most of the classification errors occurred in the riparian class which supports previous research findings (Thelin and Heimes, 1987; Maxwell, 1996). In regions where these land cover types are significant, an existing land cover map such as the National Wetland Inventory digital map developed by the US Fish and Wildlife Service or the National Land Cover Data set (NLCD) digital map developed by the US Geological Survey (USGS) may be useful for eliminating riparian regions of the image prior to applying this classification approach. Alternatively, an early spring image could be used to discriminate riparian vegetation from corn. In spring, trees and riparian vegetation have spectral response patterns characteristic of green vegetation yet corn has a spectral response pattern characteristic of bare soil or stubble remaining from the previous harvest allowing for good separation of these cover types.

Individual misclassified scattered pixels are typical in digital maps derived from Landsat imagery. These misclassification errors may or may not have a significant impact on a given application. In our application, residences in close proximity to corn are assumed to be more likely to be exposed to spray drift from chemicals applied to corn as compared to residences further away. Therefore, every residence near a pixel classified as corn will have exposure assigned. Given that it is highly unlikely that single pixels or small groups of pixels are actually corn, it is important for these pixels to be identified and classified as unlikely to be corn. We tested some methods for eliminating these scattered pixels (e.g. smoothing filters), but none have been satisfactory to date. A field-level classification approach, as opposed to a pixel-level classification approach, may be useful for eliminating these errors.

The Mahalanobis distance cutoff values we selected proved adequate for testing the concept of the methodology. Pixels were classified as 'highly likely to be corn' for distance values representing up to approximately 75.0% of the total acreage of corn within a given county and the remaining 25.0% of the total corn acreage was classified as 'likely to be corn.' All other pixels were classified as 'unlikely to be corn.' In a sensitivity analysis, we found that setting the first cutoff higher (e.g. 85.0%) increased the likelihood that other crop types, such as sorghum, were misclassified as 'highly likely to be corn.' Lowering the first cutoff (e.g. 50.0%) decreased the occurrence of these errors. Exactly where the cutoff points should be set will depend on the application for which the resulting map is intended. In our case, we wanted to optimize the number of pixels in the 'highly likely to be corn' class, yet avoid misclassification of other crop types as corn.

Our method was applied to only whole counties contained entirely within the Landsat image, however some counties may only be partially represented within the satellite image. Areal estimates of corn for these partial counties could possibly be calculated using a combination of the county-level NASS areal estimates and an existing general land cover map for the county. For example, the 'row crop' class from the USGS NLCD digital map could be used to estimate the proportion of row crops (e.g. corn, soybeans) within the partial county. Then an estimate of corn acreage could be derived by applying this proportion to the USDA areal estimates. This is assuming that crops grown within the county are evenly distributed which may not necessarily the case. Local experts may need to be consulted to determine if this is a valid assumption.

5. Conclusions

Digital crop type maps covering large geographical regions and spanning several years is becoming increasingly important for environmental and health related research. Landsat imagery can be used to develop crop type maps, however, traditional classification methods (e.g. supervised, unsupervised) methods are too time-prohibitive for these applications. We developed a method to potentially automate the classification of corn using Landsat satellite imagery and readily available historical agricultural areal estimates. This method is probably most appropriate for classifying corn in regions where corn is a dominant crop and only a few other crops are grown such as in the Midwest region of the United States.

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