AUTOMATED CROP TYPE MAPPING FROM LANDSAT IMAGERY

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Abstract

Knowledge of the spatial distribution of crop types is important for many environmental and human health research studies. These studies may require crop type maps over large geographical regions for multiple years, which can be derived only from satellite images. Interpretation of Landsat images using traditional image classification techniques is not feasible for such applications because of the large number of images to be analyzed. We present a new method that automates the interpretation process resulting in a less expensive and more timely product. Software was developed to use readily available agriculture data to automatically extract spectral training statistics from target areas on the satellite images. The statistics are then used to process the remainder of the image, county by county, without intervention from the analyst. The Mahalanobis distance measurement is used in the final map to provide a measure of confidence – important for further modeling efforts.

To demonstrate the feasibility of this approach, we produced a map for a single crop type (corn), using a Landsat Multispectral Scanner image in eastern Nebraska. Thirteen counties (3.35 million hectares) were classified in less than 15 minutes. The resulting map classifies the land area as either ‘highly likely to be corn’, ‘likely to be corn’, or ‘unlikely to be corn’. Ground reference data from three counties were used to assess the accuracy of our method. The resulting average classification accuracy of 89 percent is comparable to traditional methods.

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, Nuckols *et al*. 1996a,b), Gilliom and Thelin 1997. In many instances such studies need crop types maps over large geographical regions (e.g., multi-county, entire state) for multiple years in order to determine statistically significant relationships between environment and disease occurrence. For example, in a study of agricultural chemical use and occurrence of cancer, once location of crops can be determined, important parameters such as pesticide use can be estimated and incorporated into an environmental model for exposure assessment (Ward *et al.* 1999). Such maps covering extensive geographical regions can only be derived from satellite imagery such as Landsat TM.

Landsat satellite imagery has been collected since the early 1970’s and has been successfully used to classify many different crop types (Myers 1983). However, the classification process can be very time consuming using traditional methods (i.e., supervised, unsupervised). In general, traditional methods require a remote sensing analyst to interact extensively with the computer system during the image classification process. Supervised methods require ground truth data to be collected and manually entered and the resulting training statistics to be carefully validated and refined prior to classification. Unsupervised methods require the analyst to evaluate and label each of the resulting clusters using ground reference data. In addition, an accuracy assessment process is necessary to provide a confidence level. A more comprehensive description of common classification and accuracy assessment methods can be found in (Lillesand and Keifer 1987). Classification of a single Landsat scene (approx. 170x185 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 are essential if we are to meet the needs of environmental research applications in a timely and cost effective manner.

Our long-term objective is to develop a crop type map for 66 counties in eastern Nebraska, the site of several epidemiologic studies of the association of pesticide use and cancer. Cropping patterns are to be mapped for several years, beginning in the early 1970's. This paper describes the method used to identify a single crop. We selected corn to demonstrate our method because it is the predominant crop in Nebraska and many other Midwest states. Corn has the largest area of all of the US crops (USDA National Agricultural Statistics Service, web site http://www.usda.gov/nass) and has the greatest use (pounds applied) of pesticides and fertilizers. Since the 1980's, more than 90% of corn acreage received nitrogen fertilizer and herbicide treatments (Johnson and Kamble 1984). In 1992, herbicides accounted for 91 percent of all pesticides applied to corn (Lin *et al*. 1995). The digital map resulting from the classification method discussed in this paper represents the distribution of corn in three categories (highly likely to be corn, likely to be corn, and unlikely to be corn). Further work is planned in the near future to classify other major crop types in the region (e.g., sorghum and soybeans).

We have developed a method that significantly reduces the time required to identify major crop types within a Landsat image. Our method also provides a level of confidence for each individual pixel classified. Specially designed software was developed which uses agriculture statistics to automatically extract spectral training data from selected target areas on the satellite image. The entire satellite image is then classified based on a combination of training data and agricultural statistics. Current and historical agricultural statistics (e.g., total hectares of crop harvested) are readily available at county level using state or national agricultural statistical providers. These data are collected for major crops by regular site visits to a selected sample of fields throughout the growing season. For our purpose, agriculture data are used in two ways to automate the classification process. First, the data are used to identify an area within the image to collect training statistics for a particular crop type. And secondly, the agriculture data are used to automatically process the remainder of the satellite image on a county by county basis. The agriculture data are used in lieu of collecting ground reference data per traditional methods (e.g., field measurements). The Mahalanobis distance measurement is used in the final map product to provide a measure of confidence which is important for further modeling efforts.

Methods

Study Area and Data Description. The study area lies in eastern Nebraska, a major corn growing region in the United States. The dominant land cover types in this region consist of cropland and rangeland. 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 USGS EROS Data Center (Sohl and Dwyer 1998). The NALC data set is ideal for a study such as this because it contains historical imagery (one image each from the 1970, 1980 and 1990 decades) that has been georeferenced, resampled to a standard 60m x 60m pixel resolution, and is available at minimal cost. The Landsat MSS collected data in the visible (0.5-0.6μm and 0.6-0.7μm) and near infrared (0.7-0.8μm and 0.8-1.1μm) spectrum. Some studies have sugested that when using MSS data, only one band from each of the major wavelength regions is required to perform land cover mapping (Hixson *et al.* 1980, Hoffer 1995 personal communication). For this reason and also to reduce the complexity of the software development, we used only visible band 2 (0.6-0.7μm) and near infrared band 4 (0.8-1.1μm) of the MSS data.

Two additional data sets are required by the classification program: county boundaries and agricultural statistics. Agricultural statistics were provided by the Nebraska Agricultural Statistical Service (NASS) (1986 Nebraska Agricultural Statistics). Because the image was collected in late summer (August), estimates for hectares harvested (as opposed to hectares planted) were used.

Three counties in southern Nebraska were selected to test the accuracy of our methods: Kearney, Nuckolls, and Thayer. These counties were chosen because of their diverse cropping patterns (Figure 1). Corn is the major crop grown in Kearney County, whereas sorghum dominates in Nuckolls County. A mixture of corn, sorghum, and soybeans make up the dominant crops in Thayer County. Ground reference data (location and type of crop grown) were collected from the USDA Farm Service Agency (FSA) county offices within each county. We selected 40 Public Land Survey (PLS) Sections (1.6km x 1.6km 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 (e.g., irrigated corn, non-irrigated sorghum, rangeland, urban). FSA provided a photocopy of an aerial photograph from their files for each section with the land cover types identified. All of the identifiable fields within each section were digitized. Entire fields were digitized within each of the PLS Sections, as opposed to randomly selected individual fields, as this allowed us to maximize the number of samples collected, yet minimize the time and costs involved in the collection and processing.

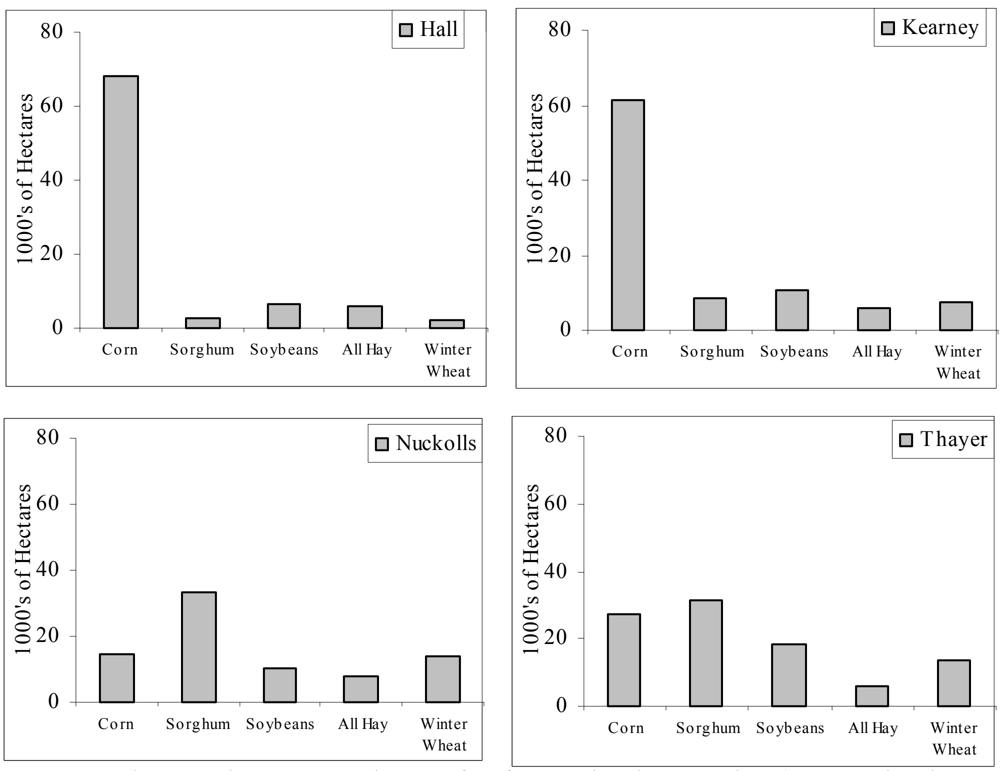

Figure 1. 1984 harvested acreage estimates for four Nebraska counties (1986 Nebraska Agricultural Statistics).

Classification System Description. The classification system was designed for use within the ERDAS Imagine system. A ‘seed’ county is selected based on meeting two criteria: 1) the county with the highest proportion of the crop type of interest (in our case corn) as compared to the other crops grown and 2) the county with the highest number of hectares grown of the crop type of interest. Training statistics derived from bivariate histogram analysis (described in greater detail below) are extracted from the seed county and used along with the agriculture statistics to classify each of the remaining counties in the Landsat image. The Mahalanobis distance measurement resulting from the classification is used with the agricultural statistics to assign a confidence label to each pixel in the image.

Normally, training signatures for several cover types (e.g., rangeland, corn, sorghum) are used in the classification process. The resulting file is called a thematic raster map where every pixel is classified as a particular cover type. In our method, we use the Mahalanobis distance measurement (Duda and Hart 1973) to determine the confidence level for each pixel. Each pixel in the distance map represents the spectral distance from the training signature to an individual pixel. Because the distance values represent the spectral distance from an individual pixel to the training signature, they can be used to determine how likely the pixel is to be corn. Pixels that have low distance values are more likely to be correctly classified and pixels with high values are more likely to be incorrectly classified.

The Mahalanobis distance measurement and county acreage estimates from agricultural statistics were used to label each pixel as one of three categories: highly likely to be corn, likely to be corn, or unlikely to be corn. Agricultural statistics were used to determine cut-off points by comparing the total acreage of corn grown in the particular county to the acreage of each distance value. We classified pixels as 'highly likely to be corn' for distance values representing up to approximately 75% of the total acreage of corn (see Table 3). The 75% cut-off value was based on a sensitivity analysis performed on the three test counties. Pixels classified as 'likely to be corn' were distance values representing the remaining 25% of the total acreage for corn. All other pixels were classified as 'unlikely to be corn'.

Accuracy Assessment. Ground reference data supplied by FSA were compared to the map produced by our classification methodology for three counties: Kearney, Nuckolls, and Thayer. Although, we are only interested in whether corn was correctly distinguished from all other cover types, we could have classed the ground reference data into just two classes: corn and other. However, we felt that a further breakdown in the 'other' cover types would be beneficial for identifying exactly which cover types were being misclassified. Hence, three crop types (irrigated corn, non-irrigated sorghum, and irrigated soybeans) and three general cover types (fallow or bare soil, rangeland, and urban) were tested. From the FSA information, 478 field polygons were screen digitized using a region growing function and labeled with the appropriate land cover class (Table 1). All pixels within each polygon were used in the accuracy assessment.

Table 1. Summary of ground truth data.

		Kearney County		Nuckolls County		Thayer County	
	Class	# of polygons	# of pixels	# of polygons	# of pixels	# of polygons	# of pixels
Crops	Corn (irrigated)	70	1252	19	344	55	1026
	Sorghum (non-irrigated)	10	182	53	819	43	731
	Soybeans (irrigated)	24	343	18	189	37	478
Total Crop Samples		104	1777	90	1352	135	2235
Other	Fallow, bare soil	21	336	25	323	31	442
	Rangeland	5	71	31	465	21	302
	Urban	2	168	6	487	7	375
Total All Samples		132	2352	152	2627	194	3354

Results

Identification of the Corn Signature. Hall County was selected as the seed county due to the high proportion of corn (78.8% of acres harvested) compared with the other crop types (Figure 1). Training statistics were extracted from the Landsat image file for Hall County. The highest point in the bivariate histogram occurred at a red visible band value equal to 15 DN and a near infrared band value equal to 58 DN. The bivariate histogram for Landsat MSS Bands 2 and 4 for Hall County is represented in Figure 2.

Statistics (table 2) were calculated by selecting the ten next highest neighboring points in the bivariate histogram.

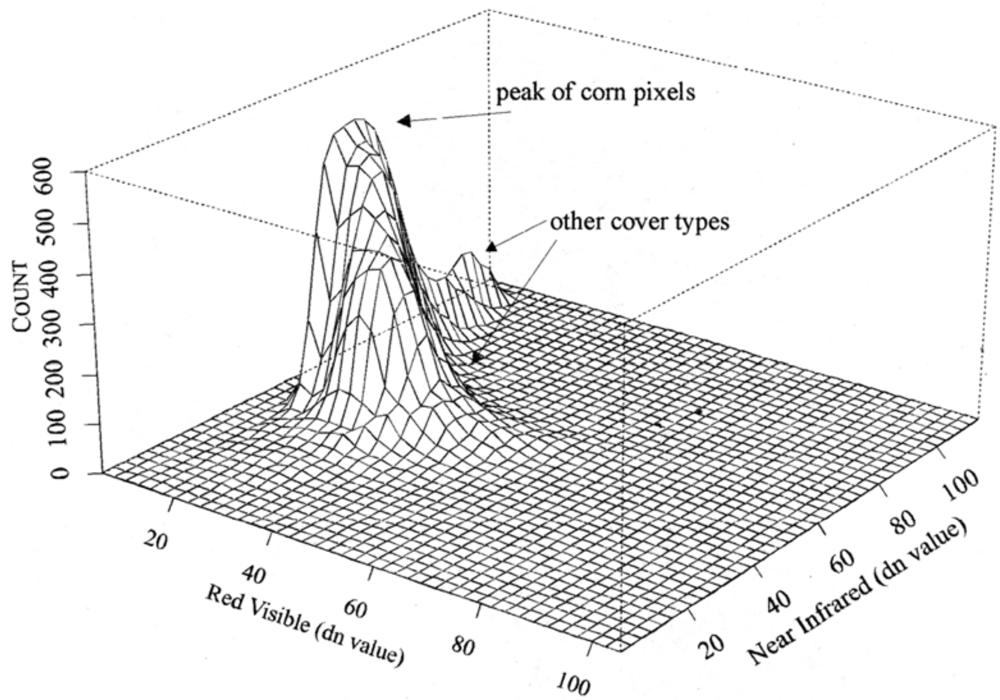

Figure 2. Bivariate histogram surface plot of the Landsat MSS red visible and near infrared wavelength bands for Hall County. The histogram peak represents the spectral region for corn.

Table 2. Spectral training signature statistics for the crop type corn (DN values).

		Band2	Band4
Mean		15.41	58.58
Standard deviation		.49	2.16
Covariance Matrix	Band2	.24	-.02
	Band4	-.02	4.65

Classification and Uncertainty Labeling. The NASS acreage estimates for irrigated corn harvested in 1984 for each of the three counties were (hectares): Kearney = 58,685, Nuckolls = 13,770, and Thayer = 25,839. Kearney County is used as an example to demonstrate the process of setting thresholds (table 3). NASS estimated that Kearney County harvested 58,685 hectares of irrigated corn in 1984. The cut-off points were set at 44,014 hectares (75% of 58,685) for pixels highly likely to be corn and 58,685 hectares for pixels likely to be corn. Pixels with Mahalanobis distance values from 1 through 55 were classified as highly likely to be corn, because the cumulative total number of hectares was approximately 75% of the acreage estimated by NASS. Distance values from 56 through 131 were classified as likely to be corn because the cumulative total of the acreage for these pixels constituted the remaining 25% of the acreage estimated by NASS. Distance values from 132 through 1787 were classified as unlikely to be corn.

Maximum Mahalanobis distance values varied for each county (figure 3) from 1369 for Thayer County to 1787 for Kearney. Thresholds for the cut-off values also varied considerably by county. The 75% cut-off values ranged from 25 (Thayer) to 55 (Kearney) and the 100% cut-off values ranged from 34 (Thayer) to 131 (Kearney).

Table 3. Classification results using distance values and agricultural statistics for Kearney County.

Mahalanobis Distance Value$_s$	Land Area (Hectares)	Cumulative Total (Hectares)	Cumulative Total (% of NASS)	Classification Code*
1	1206.4	1206.6	2.1	1
2	4413.2	5619.6	9.6	1
3	1364.4	6984.0	11.9	1
...	...	…	...	...
55	581.0	44107.2	75.2	1
56	517.7	44624.9	76.0	2
57	741.2	45366.1	77.3	2
58	141.8	45507.9	77.5	2
...	...	...	...	...
131	1066.3	59082.1	100.7	2
132	417.2	59499.3		3
...	...	...		...
1787	0.4	82893.2		3

*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., 55) is 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 are between approximately 76-100% of the hectares of corn pixels estimated by agricultural statistics. The remaining pixels are classified as unlikely to be corn (code=3).

Reference: Maxwell, S.K., J.R. Nuckols, E. Smith, M.J. Ward, and R.M. Hoffer, 1999. Automated crop type mapping from Landsat imagery. Pecora 14 Conference, December 6-10, 1999, Denver, Colorado.

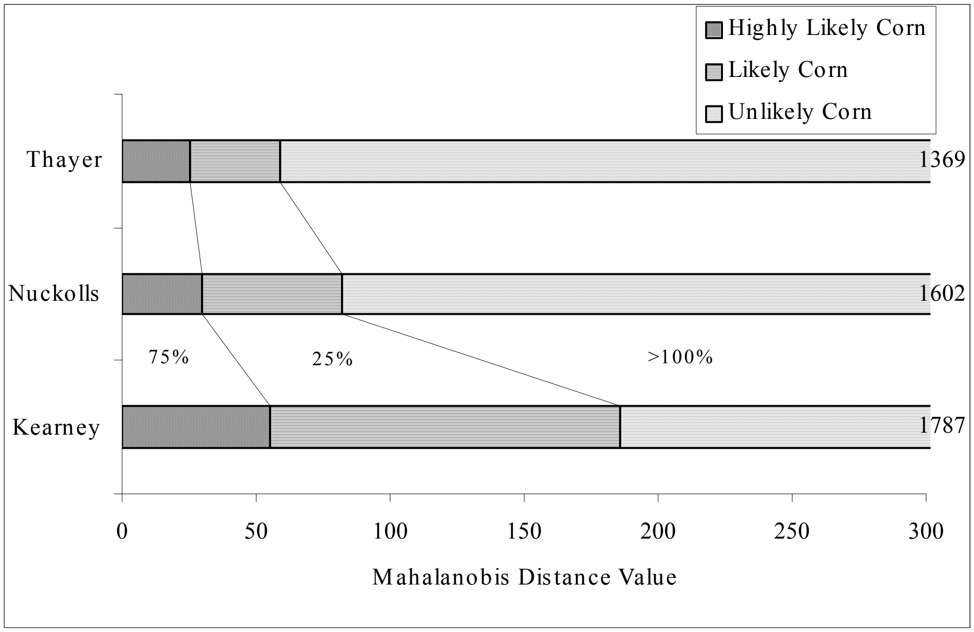

Figure 3. Ranges of the distance values used to classify pixels by crop category for each of the three test counties.

Accuracy Assessment. Results of the accuracy assessment for the three test counties are shown in Table 4. Each pixel was classified into one of three categories: highly likely to be corn, likely to be corn, and unlikely to be corn. For all three counties an average of 89.0% of the pixels designated as corn by the FSA reference data were classified as being either highly likely or likely to be corn by our method. The accuracy for Kearney and Nuckolls Counties was high (99.3% and 90.7%) whereas the accuracy for Thayer County was much lower (78.3%). Sorghum and soybeans were, for the most part, classified as unlikely to be corn. An average of 96.1% of sorghum and 99.5% of soybeans were classified as unlikely to be corn. None of the bare soil or rangeland was classified as likely to be corn and less than one percent of urban land was classified as likely to be corn.

Table 4. Classification accuracy results for each of the three test counties and an average for all three counties. Values are given in percentages where the total for each row is 100.0%.

KEARNEY COUNTY

	Class	Highly Likely Corn (%)	Likely Corn (%)	Unlikely Corn (%)
Crops	Corn (irr.)	86.4	12.9	0.7
	Sorghum (non-irr.)	1.1	6.0	93.9
	Soybeans (irr.)	-	0.9	99.1
Other	Fallow, Bare Soil	-	-	100.0
	Range	-	-	100.0
	Urban	-	0.6	99.4

NUCKOLLS COUNTY

	Class	Highly Likely Corn (%)	Likely Corn (%)	Unlikely Corn (%)
C	Corn (irr.)	82.3	8.4	9.3

	Class	Highly Likely Corn (%)	Likely Corn (%)	Unlikely Corn (%)
	Sorghum (non-irr.)	-	0.5	99.5
	Soybeans (irr.)	-	0.5	99.5
Other	Fallow, Bare Soil	-	-	100.0
	Range	-	-	100.0
	Urban	1.0	-	99.0

THAYER COUNTY

	Class	Highly Likely Corn (%)	Likely Corn (%)	Unlikely Corn (%)
Crops	Corn (irr.)	63.9	14.4	21.7
	Sorghum (non-irr.)	2.9	1.4	95.7
	Soybeans (irr.)	-	-	100.0
Other	Fallow, Bare Soil	-	-	100.0
	Range	-	-	100.0
	Urban	-	-	100.0

AVERAGE OF KEARNEY, NUCKOLLS, AND THAYER COUNTIES

	Class	Highly Likely Corn (%)	Likely Corn (%)	Unlikely Corn (%)
Crops	Corn (irr.)	77.5	11.9	10.6
	Sorghum (non-irr.)	1.3	2.6	96.1
	Soybeans (irr.)	-	0.5	99.5
Other	Fallow, Bare Soil	-	-	100.0
	Range	-	-	100.0
	Urban	0.3	0.2	99.5

Figure 4 presents a comparison of the original Landsat image and the Corn Likelihood Map for an area near Minden, Nebraska in Kearney County. Corn fields are generally well defined and consistently classified as highly likely or likely to be corn. Some scattered pixels classified as corn are shown in areas outside of the corn fields.

Reference: Maxwell, S.K., J.R. Nuckols, E. Smith, M.J. Ward, and R.M. Hoffer, 1999. Automated crop type mapping from Landsat imagery. Pecora 14 Conference, December 6-10, 1999, Denver, Colorado.

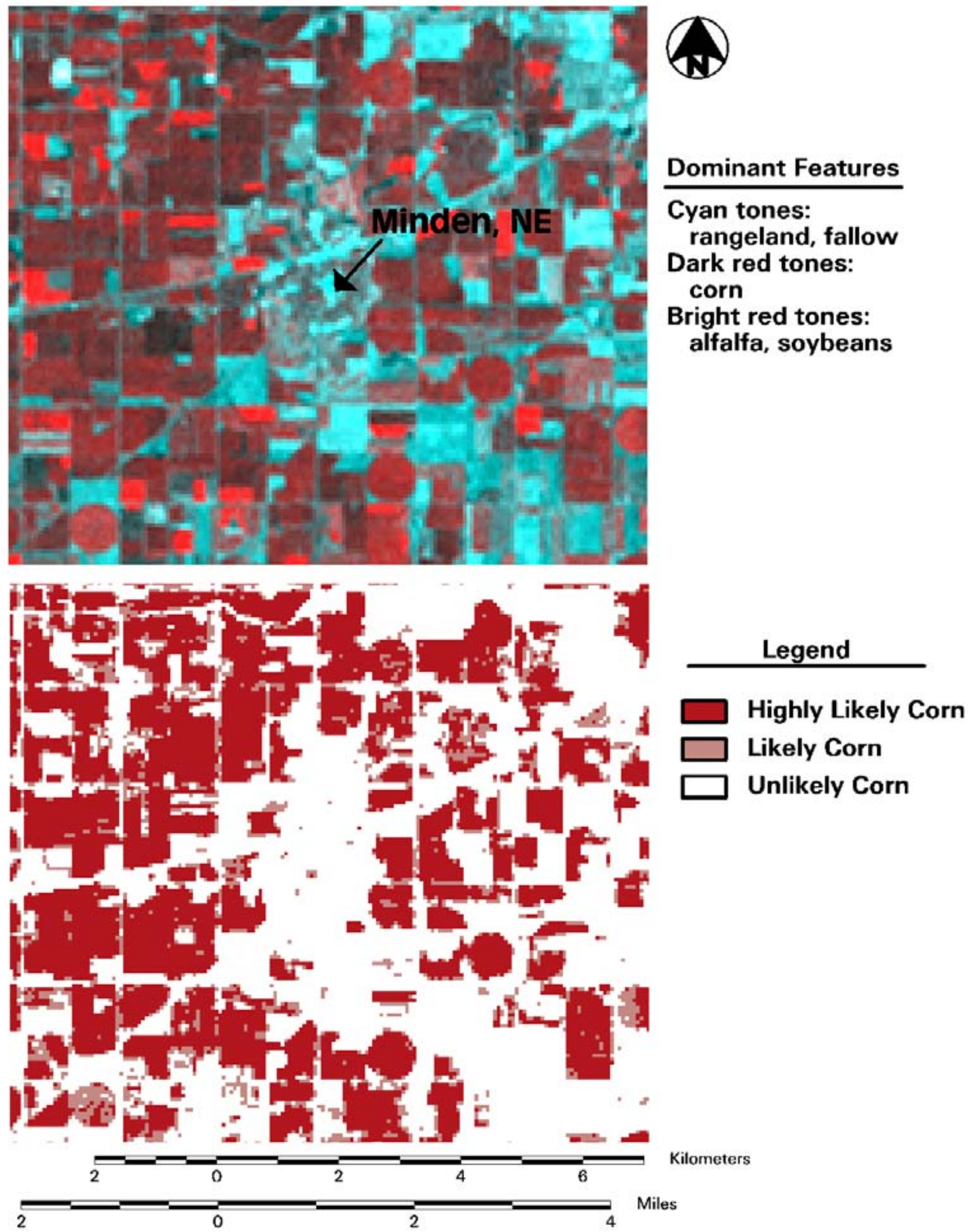

Figure 4. Comparison of color infrared display of Landsat MSS image to Corn Likelihood Map for a region near Minden, Nebraska.

Evaluation of Processing Time. To test the actual time required to process several counties, we classified the 13 remaining counties in the Landsat image. The processing took less than 15 minutes using a Sun Sparcstation 20.

Discussion

We demonstrated that our method of crop classification is feasible and that it provides savings in cost and time over traditional classification methods. Large regions and several time periods can be easily mapped. This would not be feasible using traditional classification methods. Further research is required to

Reference: Maxwell, S.K., J.R. Nuckols, E. Smith, M.J. Ward, and R.M. Hoffer, 1999. Automated crop type mapping from Landsat imagery. Pecora 14 Conference, December 6-10, 1999, Denver, Colorado.

test the method in other regions, time periods and crop types. We have preliminary results that indicate the method can be applied to non-irrigated sorghum in the same study area. However, we have yet to thoroughly evaluate the method when trying to merge two or more crop type maps. In addition, this method is probably most appropriate for classifying only major crop types covering large geographical regions (e.g., corn, soybeans, sorghum).

An advantage of this method is that the final map product contains a confidence label for each individual pixel. In epidemiologic studies, it is important to know the error in the land cover classification in the immediate vicinity of residences in order to estimate the potential for exposure. Another advantage of this method is that ground reference data are not necessary for development of the confidence label. This is especially important in creating historical maps, because ground truth data may not be available.

Although our results indicate that the methodology is feasible, several issues require further investigation. First, we need to ensure that the highest point in the histogram will in fact be the crop we are targeting. Bare soil, range, and urban were classified into the unlikely to be corn category with a 91.0-100.0% accuracy level. However, this technique is dependent on several factors such as time of growing season and other cover types in the region. Accuracy may vary depending on whether or not the other cover types are spectrally similar to our target crop. Riparian cover types are commonly confused with irrigated cropland due to their similar spectral response patterns (Maxwell 1996, Thelin and Heimes 1987). We are evaluating the use of existing land cover maps such as the National Wetland Inventory map (US Fish and Wildlife Service) and the National Land Characterization map (USGS) to mask out non-cropped regions of the image.

Further evaluation of the threshold parameter is also necessary. We classified pixels as ‘highly likely to be corn’ for distance values representing up to approximately 75% of the total acreage of corn and the remaining 25% of the total corn acreage were classified as ‘likely to be corn’ (see Table 3). All other pixels were classified as ‘unlikely to be corn’. Results indicate that these thresholds were adequate for testing the concept of the methodology. In a sensitivity analysis, we found that setting the first cut-off higher (e.g., 85%) increased the likelihood that other crop types, such as sorghum, were misclassified as corn. Lowering the first cut-off (e.g., 50%) decreased the occurrence of these errors. Exactly where the cut-off points should be set will depend on the application for which the resulting map is intended. In our case, we want to optimize the number of pixels in the 'highly likely to be corn' class, yet avoid misclassification of other crop types as corn.

Our results showed that the classification performance varied by county. Accuracy of classifying corn in Kearney and Nuckolls Counties was over 90.0% whereas in Thayer County the accuracy decreased to 78.3%. We compared the spectral response patterns for corn in each of the counties and found that they were very similar. Therefore, the errors probably occurred because of confusion with another crop type. Non-irrigated soybeans were spectrally very similar to irrigated corn and therefore were most likely to be the reason for misclassification. Comparison of the spectral responses of other crops (i.e., irrigated and non-irrigated sorghum, irrigated soybeans) indicated sufficient separation.

A significant number of counties lie only partially within a particular satellite image. Partial counties that lie on the north and south borders of the satellite image are in the same satellite path. These images are collected on the same date and can be easily joined prior to classification. However adjacent images to the east and west are collected on different dates and therefore would need to be classified separately. Partial counties along the east and west edges will require information on the proportion of the total crop area of the county that is included in the image to enable effective classification.

Summary and Conclusions

Digital crop type data covering large geographical regions and spanning several years is becoming increasingly important for environmental and health related research. Traditional classification methods (e.g., supervised, unsupervised) methods are too cost- and time-prohibitive for these purposes. We developed a method to automate the classification of crop types using Landsat satellite imagery and readily available historical agricultural statistics. We demonstrated that our method is promising and that it allows for the classification of crop types over large geographical regions in a timely and cost-effective manner.

Further research planned includes:

- Testing the method on other major crop types in the study area (e.g., sorghum, soybeans),
- Performing a sensitivity analysis to determine the optimum signature calculation method, and thresholds for confidence levels,
- Developing methods for classification of partial counties, and
- Evaluating the use of existing land cover digital maps (e.g., National Land Characterization from the USGS) to eliminate non-cropped regions (e.g., forest, urban) from the image prior to classification.

Acknowledgements

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