Mapping and Monitoring Agricultural Crops and Other Land Cover in the Lower Colorado River Basin

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Abstract

A process for integrating remote sensing and spatial data analysis to accurately map and monitor agricultural crops and other land cover in the Lower Colorado River Basin is described. These maps were then used as input into a model that accounts for consumptive use throughout the basin. Water is an important and incredibly valuable resource in this area. International treaties and court decrees dictate water allocation to the states of Arizona, Nevada, and California, and to Mexico. Maps of the agricultural crops with a required overall accuracy of 93 percent for use in the water model were generated from Landsat Thematic Mapper data four times per year. An automated signature extraction process and data exploration techniques were developed to aid in achieving these required accuracies. All maps were subjected to quantitative accuracy assessment, and error matrices were produced to evaluate overall and per-class accuracies.

Introduction

In the western United States, as in many other parts of the world, fresh water is an important resource. West of the one-hundredth meridian one of the greatest sources of fresh water is the Colorado River, which drains 1/12 of the North American continent. Continuously growing residential, commercial, and agricultural demands have caused fresh water to become an increasingly limited and valuable resource in this area.

As the water masters of the Colorado River, the U.S. Bureau of Reclamation (USBR) is in charge of the dams that control the river as well as allocating the river's water to various users. A 1964 Decree by the U.S. Supreme Court (Arizona vs. California) states that the Secretary of the Interior must provide complete, detailed, and accurate records of consumptive use and distribution of water by each diverter from the Colorado River. The Decree more specifically requires that the records of consumptive use of water be reported separately for each diverter from the mainstream and each point of diversion, from the states of Arizona, California, and Nevada. During an average year, the Secretary of Interior is obligated through various compacts, international treaties, Supreme Court decrees, and statutes to deliver 7.5 million acre-feet (MAF) of water in the Colorado River to the three lower states in the basin; Nevada, Arizona, and California. In addition, 1.5 MAF must be delivered to Mexico. This water is critical not only for human consumption and agriculture, but also to sustain important wildlife habitat. Failure to deliver sufficient water to Mexico can endanger many species of plant and animal and have international implications.

The U.S. Geological Survey (USGS) and the Bureau of Reclamation have cooperatively developed a model called the Lower Colorado River Accounting System (LCRAS) for accounting for the water (Bureau of Reclamation, 1997). The USBR is currently evaluating the use of the LCRAS model as a tool to help enable the Secretary of the Interior to comply with these agreements.

The LCRAS model estimates annual consumptive use of water and distributes that use among the water users. Previous accounting procedures were incomplete because they did not credit agricultural water users for unmeasured sub-surface return flow. The LCRAS model provides a method to determine diverter consumptive use that accounts for return to the river. The model uses results and data provided by remote sensing technology and geographic information systems (GIS) as inputs. Among these inputs are the type and acreage of the various agricultural crops and other vegetation (i.e., phreatophytes) in the river basin throughout the year.

This paper describes the methodology developed for and the results of mapping agricultural crops and other vegetation from remotely sensed data for input to the LCRAS model. The specific objectives of the project were (1) to develop a digital GIS database of biological and physical attributes of irrigatable land (i.e., crops) and phreatophytic vegetation along the lower Colorado River using remotely sensed data, and (2) to train and transfer the technology to create this database to USBR personnel. A final and very unique requirement of this project dictated that the accuracy of the agricultural crop classification be at least 93 percent accurate in order to meet the requirements of the LCRAS model.

Literature Review

Lower Colorado River Accounting System

The Lower Colorado River Accounting System (LCRAS) is a model developed by the USBR and USGS to estimate consumptive use and distribution among the water users. The LCRAS model has two components (Bureau of Reclamation, 1997). The first component is a water budget that is used to calculate the annual consumptive use of the river water.

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Consumptive use of water from the river is a combination of (1) evapotranspiration (ET) by the vegetation (i.e., crops and phreatophytes), (2) pumpage from wells for local domestic and municipal needs, and (3) pumpage from the river for export to areas in California, Arizona, and Nevada outside of the river basin. The second component incorporates the distribution of the water to the agricultural water users in proportion to the ET of the vegetation grown by that grower. The ET of each vegetation type is estimated using the Penman-Monteith method (Monteith, 1965).

Image Classification

Early in the Landsat era, it was found that general vegetation/land-cover types could be mapped from digital satellite imagery faster and often with lower costs than using more traditional methods such as basic photointerpretation (Hame, 1984). Using satellite imagery as the primary information base has four advantages (Green, 1992):

- Substantially less time and cost is needed to produce the GIS layers. Aerial photography has long been used to delineate and classify forest vegetation and landuse type. To turn it into a GIS layer, however, this information must be transferred to a planimetric base and entered into a computer. These four steps, (a) classification, (b) delineation, (c) transfer, and (d) data entry, can be extremely time-intensive and costly.
- A much "richer" GIS layer is produced because it can contain both traditional land-use/land-cover polygon labels and information about each spatial unit (i.e., pixel) in the satellite imagery.
- Inter-ownership analyses can be performed. The great economies of scale provided by digital image processing make it relatively inexpensive to map large expanses of land, making it easier and more cost effective to perform cumulative effect analyses.
- Landsat TM satellite data are captured for the same ground area every 16 days. Thus, fast and inexpensive updating is possible, because satellite images used to create the landscape delineation can be directly compared with those taken at a later date.

However, producing *detailed* land-use/land-cover type maps, especially of individual crop types or tree species with satellite imagery, has been problematic (e.g., Ulaby *et al.*, 1982; Pedley and Curran, 1991; Thenkabail *et al.*, 1994). Image processing software and hardware were inefficient and expensive, and the spatial and spectral resolution of the imagery was inadequate for detailed land-use/land-cover type mapping.

More recently, vegetation classification studies implementing digital satellite data have utilized higher spatial, spectral, and radiometric resolution Landsat Thematic Mapper (TM) data with much more powerful computer hardware and software. These studies have shown that the higher information content of TM data combined with the improvements in image processing power result in significant improvements in classification accuracy for more distinctive classes. Teply and Green (1991), Bernath *et al.* (1992), Gonzales *et al.* (1992), Miller *et al.* (1992), Brisco and Brown (1995), and others have shown that digital processing of satellite imagery, combined with field visits and aerial photography as ancillary data, can accurately produce both detailed and broad GIS coverage of vegetation/land-cover type.

Methods

Study Area

The lower Colorado River, between the east end of Lake Mead and the international border with Mexico, is the principal source of water for agricultural, domestic, municipal, industrial, hydroelectric power generation, and recreation purposes in the region. The study area covers the flood plain of the Colorado River from Hoover Dam to the Arizona-Sonora International Boundary (United States and Mexico), adjacent lands of Palo Verde Mesa, Yuma Mesa, the piedmont area, and the flood plain of the Bill Williams River upstream from its confluence with the Colorado River to Alamo Dam. The Colorado River flood plain, within the study area, includes Mojave, Parker, Palo Verde, Cibola, North and South Gila, Bard, and Yuma Valleys (Figure 1).

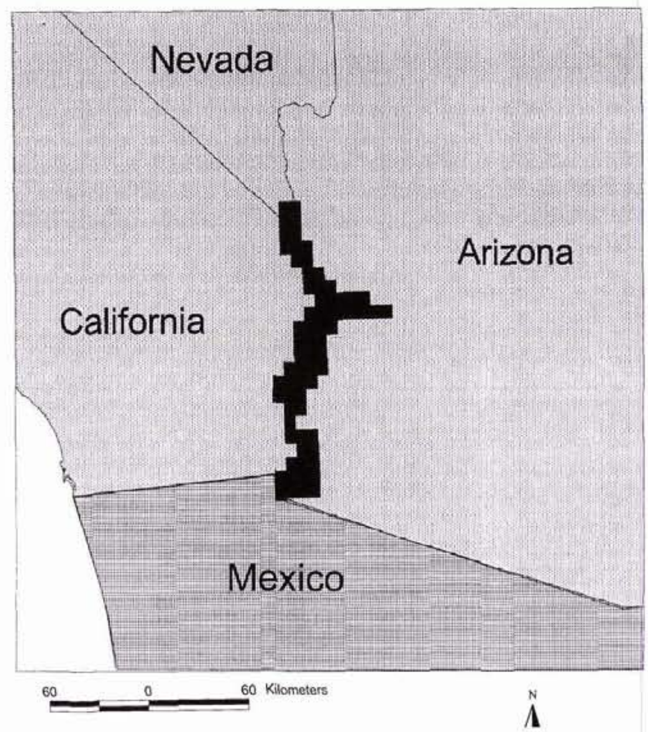


Figure 1. Map of the study area.

The region is known for its temperate weather. Average minimum January temperatures range from 2.8°C (37°F) in Blythe, California to 8.2°C (47°F) in Yuma, Arizona. Average maximum July temperatures range from 42.3°C (108°F) in Blythe and Needles, California to 41.3°C (106°F) in Yuma, Arizona. The area is also characterized by rich, loamy soils which, combined with the excellent weather conditions, create prime agricultural land. The area grows a tremendous variety of crops and has multiple growing seasons, producing two or three different crops per year on the same plot of ground.

Water is stored in surface reservoirs and in the river aquifer-permeable sediments and sedimentary rocks that fill the lower Colorado and adjacent tributary valleys. Crops are grown mostly on the flood plains and, in some areas, on the adjacent terraces. Crops cover approximately 70 percent of the total vegetated area. Phreatophytes, natural vegetation that uses water from the river aquifer, cover the remaining vegetated areas on the uncultivated flood plain. Most of the consumptive use of water from the river occurs downstream of Davis Dam where water is diverted or pumped from the river and used to irrigate crops or is exported to Arizona or California.

To cover the entire study area, two full and one quarter Landsat Thematic Mapper (TM) scenes were required. Also, because different crops are planted and grown at different times on the same plot, the USBR required that crops be mapped at four time periods throughout the year. Therefore, eight full scenes and four quarter scenes were required to complete the mapping for each year.

Classification System

The first step in any mapping project is the definition of a classification system which categorizes the features of the Earth to be mapped. Specifications of the system are driven by (1) the anticipated uses of the map information and (2) the features of the Earth that can be discerned with the data (e.g., aerial photography, satellite imagery) being used to create the map.

A classification system has two critical components: (1) a set of labels (alfalfa, water, urban, deciduous forest, etc.) and (2) a set of rules— or a system— for assigning labels (e.g., "a deciduous forest must have at least 75 percent crown closure in deciduous trees"). Without a clear set of rules, the assignment of labels to types can be arbitrary and lack consistency. In addition, a classification system should meet the following two criteria: (1) be mutually exclusive and (2) be totally exhaustive. A system is mutually exclusive if any point on the map/ground falls into one and only one land-cover category. A system is totally exhaustive if every place on the ground has a label. A final classification system characteristic that is particularly useful is if the system is hierarchical. A hierarchical system is one which contains various levels of detail or complexity. For example, vegetation is a Level 1 class that can be broken into many Level 2 classes such as forest and then forest can be divided into Level 3 classes such as conifer and hardwood, etc. A hierarchical system increases the flexibility of the analyst for meeting the needs of the user.

Table 1 presents the crop classification labels used in this project. The labels were determined by the anticipated use of the map (i.e., input into the LCRAS model to determine consumptive water use). Table 1 lists 47 unique vegetation/land-cover classes. However, it would have been extremely difficult as well as inefficient to classify every one of these classes for this project. Because the objective of the mapping was consumptive water use, it followed that the classes be grouped into similar water using categories. For example, the individual grain types need not be mapped separately because they all have similar consumptive water use characteristics. Instead, all the grain types were grouped into a class called Small Grains. Therefore, instead of mapping 47 separate classes, only 15 were required. Actually, the Other Vegetables class contains a number of classes that do not have similar consumptive water use. While the variation of crop types and water consumption was high in this class, the total acreage of all these crops was very small (less than 3 percent of the total acreage) and they were combined in this project. The classification rules were based upon the same guidelines as were used to identify crops while in the field.

Table 1. The Crop Classification Labels

1. Alfalfa	
2. Cotton	
3. Small Grains	
3.1 oats	3.4 milo
3.2 rye	3.5 sorghum
3.3 barley	3.6 wheat
4. Corn	
5. Lettuce	
5.1 head lettuce	5.3 red leaf lettuce
5.2 green leaf lettuce	5.4 other
6. Melons	
6.1 watermelons	6.3 cantaloupes
6.2 honeydew	
7. Bermuda Grass	
8. Citrus	
9. Tomatoes	
10. Sudan Grass	
11. Other Vegetables	
11.1 beans	11.9 okra
11.2 peas	11.10 radishes
11.3 millet	11.11 comm. flowers
11.4 peppers	11.12 artichokes
11.5 carrots	11.13 asparagus
11.6 onions	11.14 peanuts
11.7 garlic	11.15 jojoba beans
11.8 potatoes	11.16 garbanzo beans
12. Crucifers	
12.1 broccoli	12.3 cabbage
12.2 cauliflower	12.4 bok-choy
13. Fallow	
13.1 idle with weeds – green	
13.2 idle with weeds – senescent	
13.3 cultivated bare soil	
13.4 not cultivated – bare soil	
14. Dates	
15. Safflowers	

Analysis

The analysis performed for this project can be divided into the following sections: fieldwork, image processing, and accuracy assessment.

Fieldwork

Fieldwork was an integral part of this project and required careful planning to produce the requisite information to accurately map the vegetation/land cover. Prior to going into the field, an Arc/Info coverage of the crop field boundaries was created by the USBR. These field boundaries were entered using on-screen digitizing from SPOT 10-m panchromatic imagery and each field was given a unique identification number. A total of 12,764 agricultural fields were digitized within the study area.

The USBR and Pacific Meridian Resources personnel then chose the fields to be visited based upon knowledge from previous USBR work. Fields were chosen to represent the full variety of crop types across the entire study area. A total of 1800 fields were chosen to be visited on the ground.

Field maps, at a scale of 1:24,000, were created by overlaying the digitized field boundaries onto the SPOT panchromatic imagery. These maps were a tremendous aid in locating the fields to be visited. Each field contained a unique number printed within its boundaries, and the fields to be ground visited were highlighted in bright solid colors.

Each round of field work consisted of three teams of at least two people per team. Fieldwork lasted for two consecutive weeks and occurred at four different times (i.e., March, May, August, and December) to coincide with the different crops planted throughout the year. At each visit, the following information was collected for each field: crop type, crop height, moisture conditions, percent cover, crop condition, and any other important attributes such as the presence of bare soil conditions, weeds, etc.. This information was necessary to explain all the possible variation in crop classes. Each round of fieldwork occurred simultaneously with the date of the satellite image collection. If the imagery acquired during the field work could not be used because of extensive cloud cover, then the image acquired immediately before or immediately after the field work would be chosen. The same fields were visited during each round of field work.

Image Processing

PRELIMINARY DATA PROCESSING

USBR and Pacific Meridian Resources personnel agreed that photointerpreting citrus and dates was more accurate than mapping them from the Landsat TM imagery. This decision was based upon the high spectral variability within these two crop types, and the relative ease with which these two crop types could be discriminated using photointerpretation.

All Landsat TM data were purchased in a geocoded and terrain-corrected format registered to within 0.5 pixels on the ground. No additional atmospheric or radiometric corrections were applied to these data.

The digitized field boundary coverage was provided to Pacific Meridian once it had been through quality control at the USBR. Pacific Meridian personnel performed a final quality control, making sure that all fields were properly coded. The database was then populated with the data that was collected in the field.

One-third of the ground-visited fields were "set aside" to be used later as an independent sample for conducting an accuracy assessment. The other two-thirds of the ground-visited fields were used as training sites to create the map of crop types. These fields were selected using a random process (i.e., using a random number generator on the unique field identification number) while assuring a good distribution of all the crop types in their various stages of growth.

CLASSIFICATION

All Landsat TM data processing was performed on bands 1, 2, 3, 4, 5, and 7. Two-thirds of the ground-visited fields were used as training sites to perform a supervised classification. Initially, a training site was created within each field using the SEED routine in ERDAS Imagine image processing software. SEED grows a training site from a given starting point using user-defined parameters (ERDAS Imagine Field Guide, 1995). Given the large number of training sites, this process proved extremely time consuming and required considerable analyst manipulation to achieve the desired level of crop discrimination accuracy.

A new process, called AUTOSIG, was created to make the training site extraction process easier, quicker, and more reliable. AUTOSIG reduced the training site/signature extraction process by half and provides a wealth of signatures for use in the classification process. AUTOSIG uses a combination of Arc/Info (ESRI, 1994), ERDAS Imagine, and Image Segmentation Algorithms (Woodcock and Harward, 1992) to produce the training sites (Frew, 1990). First, a 25-m buffer is placed inside each field to eliminate any edge effects. This Arc/Info coverage is then used to extract the area of interest on the image, allowing the full range of spectral variation within each agricultural field to be analyzed. Next, the Image Segmentation Algorithm software is used to generate polygons of spectrally homogeneous pixels within the field. In this way, a single agricultural field can be partitioned into various polygons based on all the spectral variation within that field (e.g., soil differences, moisture gradients, fertilizer applications, etc.). A combination of Landsat TM bands 3, 4, and 5 and a texture band derived from band 4 was used to generate these polygons. The Image Segmentation output is converted to an Arc/Info coverage and overlaid with the original six-band (minus the thermal band) Landsat TM image, and the training site statistics are generated using ERDAS Imagine.

The process generates a plethora of training sites which were then refined using specific criteria. In this case, we specified that a valid site must consist of at least 14 pixels with a standard deviation of less than or equal to three in all six bands. Finally, the training sites were sorted by field identification number so that the analyst could see how many sites fell within a single field and ascertain the variability within that field. Duplicate sites within a single field could be eliminated.

Once all the final training site statistics were generated, a supervised maximum-likelihood classification was performed in Imagine to label all the agricultural crops. Once the classification was complete, the classification was converted to the Image Segmentation Algorithm software where each agricultural field was given a label based on a plurality rule. To accomplish this, the segmentation software was used to overlay the field boundary coverage onto the classification and look at all of the classified pixels within each field. The process then gave each field a crop label based upon which crop type had the most classified pixels within that field (i.e., plurality rule). The labeled field polygons were then converted to ARC/INFO and a frequency table was produced. This table showed the comparison between crop-type reference label (the label given to the fields during fieldwork) and the map crop label (the label given to the fields from the classification). Only those fields that were used for training sites were included in this frequency computation; the accuracy assessment sites were still set aside and not analyzed at this time. This frequency table was then a measure of how well the classification process classified the training data. Because we were contractually obligated to meet an overall 93 percent accuracy based on acreage, if the frequency table was below 93 percent agreement, it was assumed that the independent accuracy assessment would also not be at the required accuracy level. Therefore, an iterative classification approach was employed to identify and eliminate bad signatures (i.e., training areas) in order to increase the classification accuracy.

BAD SIGNATURES

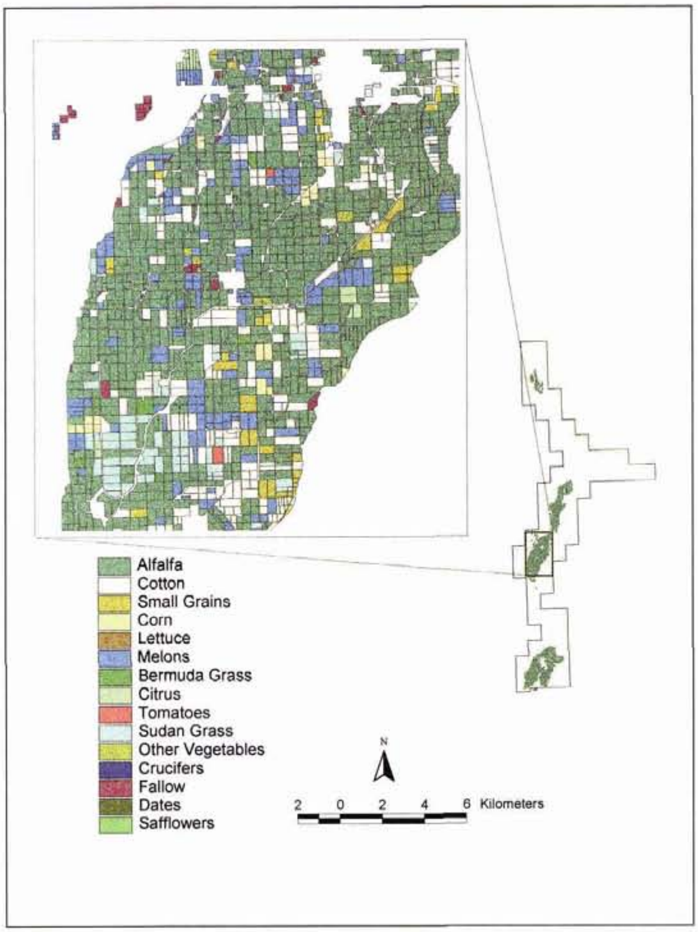
The next round(s) of classification centered upon finding the signatures that were responsible for mislabeling fields. To determine which signatures were responsible for misclassification, a two-pronged approach was developed. The first step utilized a data exploration cluster analysis technique which identified which signatures were statistically similar to one another (Chuvieco and Congalton, 1988). For instance, if the cluster analysis showed that an alfalfa signature and a small grains signature clustered together, then those signatures were too spectrally similar and one or both of the signatures could be eliminated.

The second step was to run a summary of the per-pixel classification and the misclassified fields. The resulting summary table showed which signatures were responsible for classifying each of the crop types. For instance, if there were five fields that were known to be alfalfa but were classified as small grain; that meant that there were small grain signatures that were misclassifying alfalfa. One could then look through the summary table in search of small grain signatures, and delete the ones that were spectrally confused enough to result in a field being mislabeled. The selection of signatures to be deleted was decided by analyzing both the cluster analysis and summary outputs. Once bad signatures were identified and deleted from the signature set, another supervised classification was performed. Again, once the classification was completed, a frequency table was created. Independent accuracy assessment did not begin until after the frequency table results were greater than or equal to 93 percent.

Accuracy Assessment

The purpose of quantitative accuracy assessment is the identification and measurement of map errors. There are two primary motivations for accuracy assessment:

- To understand the errors in the map (so they can be corrected), and



- To provide an overall assessment of the reliability of the map (Gopal and Woodcock, 1994).

The following factors are critical to successful design and implementation of map accuracy assessment:

- The sample design must be cost efficient. Because accuracy assessment can require a large number of sample sites, cost efficient design is imperative.
- The classification rules used to label the map being assessed must be rigorous and well-defined.
- Accuracy assessment procedures should be statistically rigorous. Sample selection should be unbiased and data collection should be consistent. Sites used to train the photointerpreter or image processing system cannot be used for accuracy assessment. Existing ground or photo data can be used only if it is reinterpreted under accuracy assessment procedures.
- The accuracy of the reference data must be evaluated. In the past, reference data have been assumed to be 100 percent accurate. Pacific Meridian's experience has shown that differences between reference data and mapped data are often caused by factors other than map error (Congalton and Green, 1993). It is important, therefore, that variation in reference data be quantified before assessing map accuracy.
- The information used to assess the accuracy of the maps must be of the same general vintage as those originally used in map classification. The greater the time period between the media used in map classification and that used in assessing map accuracy, the greater the likelihood that differences are due to change in vegetation (from harvest land-use change, etc.) rather than from mis-classification.

The error matrix, the established standard for reporting remotely sensed data classification accuracies, was used in this project to report all quantitative map accuracies (Congalton, 1991). An error matrix is a square array of numbers set out in rows and columns which express the number of pixels assigned to a particular category in one classification relative to the number of pixels assigned to a particular category in another classification. In most cases, one of the classifications is considered to be correct and may be generated from aerial photography, airborne video, ground observation, or ground measurement. The columns usually represent this reference data while the rows indicate the classification generated from the remotely sensed data. An error matrix is an effective way to represent accuracy in that the individual accuracies of each category are plainly described along with both the errors of inclusion (commission errors) and errors of exclusion (omission errors) present in the classification. A commission error occurs when an area is included into a category when it does not belong. An omission error is excluding that area from the category in which it does belong. Every error is an omission from the correct category and a commission to a wrong category.

In addition to clearly showing errors of omission and commission, the error matrix can be used to compute overall accuracy, producer's accuracy, and user's accuracy (Story and Congalton, 1986). Overall accuracy is simply the sum of the major diagonal (i.e., the correctly classified pixels or samples) divided by the total number of pixels or samples in the error matrix. This value is the most commonly reported accuracy assessment statistic. Producer's and user's accuracies are ways of representing individual category accuracies instead of just the overall classification accuracy.

Results

Plate 1 presents an example of the classified crop map generated for May 1997. Maps like this one were produced for the entire study area for each date of analysis for input into the LCRAS model. Each crop map was independently assessed for accuracy to test if the required 93 percent accuracy was achieved.

Table 2 presents the error matrix for the May 1997 map on a per-sample basis. Each tally in the matrix represents a sample unit (i.e., field). Table 3 presents the same error matrix, but on an acreage basis. In this matrix, acreage is used to weight the accuracy calculations. Both tables show overall accuracy, as well as producer's and user's accuracies. In addition, some corrections/adjustments were allowed to compensate for confusion among classes. The first adjustment is called the "fallow correction" and recognizes that any field that is in the early stages of growth could easily be confused with a fallow field on the imagery and vice versa. Therefore, fields that were misclassified as fallow were removed from the error matrix and the accuracies were updated. A second adjustment recognizes that bermuda grass and alfalfa can be confused because they are often spectrally indistinguishable and because bermuda grass often grows within alfalfa fields. This confusion was also removed from the error matrix and the accuracies were once again updated. Both of these corrections were minimal and only adjust the accuracy measures a few percentage points. However, they were legitimate limitations of the classification and must be documented. Both Tables 2 and 3 clearly show the original accuracy calculations and then the updates for each correction.

The individual crop and overall accuracies for each of the 12 maps created between May 1994 and May of 1997 are given in Table 4. For some dates, no field data were collected for certain crops because these crops were not grown at that time. Also, some individual accuracies are quite low. Typically, these low accuracies are indicative of crops occupying only a small percentage of ground area and are mitigated in the calculation of overall accuracy because this measure was weighted on an acreage basis.

In addition, the USBR runs an annual crop summary program that evaluates the multi-temporal (four times per year) combination of crop types for each field. This program takes

TABLE 2. ERROR MATRIX FOR THE MAY 1997 CROP MAP ON A PER-SAMPLE BASIS.

							REFERENCE DATA										
		Alfalfa	Cotton	Sm Grain	Corn	Lettuce	Melons	Berm Grass	Citrus	Tomatoes	Sud Grass	Oth Vegs.	Crucifers	Fallow	Dates	Safflower		
MAP DATA		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15		User's accuracy
Alfalfa	1	205	1	1				4			10	1					222	92%
Cotton	2	2	99	3							4			4			112	88%
Sm Grain	3		1	95	4						1	1		1		1	104	91%
Corn	4	1			20												21	95%
Lettuce	5					0											0	0%
Melons	6	2	2	3			18				1	1					27	67%
Berm Grass	7	6						10			1						17	59%
Citrus	8								72								72	100%
Tomatoes	9									0							0	0%
Sud Grass	10	4					1				31						36	86%
Oth Vegs.	11											2					2	100%
Crucifers	12												0				0	0%
Fallow	13	2	5				2							21			30	70%
Dates	14														10		10	100%
Safflower	15			1			1									3	5	60%
TOTALS		222	108	103	24	0	22	14	72	0	48	5	0	26	10	4	658	
Producer's accuracy		92%	92%	92%	83%	0%	82%	71%	100%	0%	65%	40%	0%	81%	100%	75%	586	sum of diagonal
																	89%	overall accuracy (OA)
total w/ fallow correction		220	103	103	24	0	20	14	72	0	48	5	0	35	10	4	658	
% correct w/ fallow correction		93%	96%	92%	83%	0%	90%	71%	100%	0%	65%	40%	0%	88%	100%	75%	90%	OA w/ fallow correction
total berm grass or alf correct		211						14										
% correct w/ b-a correction		95%						100%									91%	OA w/ b-a correction
% correct w/ b-a & fallow correction		96%						100%									92%	OA w/ b-a-f correction

TABLE 3. ERROR MATRIX FOR THE MAY 1997 CROP MAP WEIGHTED ON A PER-ACRE BASIS.

								REFERENCE DATA										
		Alfalfa	Cotton	Sm Grain	Corn	Lettuce	Melons	Berm Grass	Citrus	Tomatoes	Sud Grass	Oth Vegs.	Crucifers	Fallow	Dates	Safflower	TOTALS	
MAP DATA		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15		User's accuracy
Alfalfa	1	6870.50	39.59	35.81				147.3			372.81	6.52					7472.33	92%
Cotton	2	21.94	3382.9	38.03							80.51			142.19			3665.57	92%
Sm Grain	3		35.78	2136.12	72.37						19.16	13.17		3.05		8.58	2288.23	93%
Corn	4	8.16			512.25												520.41	98%
Lettuce	5					0											0.00	0%
Melons	6	75.02	108.86	47.65			647.04				26.04	15.4					920.01	70%
Berm Grass	7	104.60						186.41			9.79						300.80	62%
Citrus	8								1053.6								1053.60	100%
Tomatoes	9									0							0.00	0%
Sud Grass	10	100.97					5.16				965.61						1071.74	90%
Oth Vegs.	11											57.46					57.46	100%
Crucifers	12												0				0.00	0%
Fallow	13	92.59	124				111.01							547.43			875.03	63%
Dates	14														82.32		82.32	100%
Safflower	15			19.33			36.74									76.35	132.42	58%
TOTALS		7273.78	3691.13	2276.94	584.62	0.00	799.95	333.71	1053.60	0.00	1473.72	92.55	0.00	692.67	82.32	84.93	18439.92	
Producer's accuracy		94%	92%	94%	88%	0%	81%	56%	100%	0%	66%	62%	0%	79%	100%	90%	18517.99	sum of diagonal
																	90%	overall accuracy (OA)
total w/ fallow correction		7181.19	3567.13	2276.94	584.62	0	688.94	333.71	1053.6	0	1473.72	92.55	0	1020.27	82.32	84.93	18439.92	
% correct w/ fallow correction		96%	95%	94%	88%	0%	94%	56%	100%	0%	66%	62%	0%	88%	100%	90%	91%	OA w/ fallow correction
total berm grass or alf correct		6,975.10						333.71									7308.81	
% correct w/ b-a correction		96%						100%									91%	OA w/ b-a correction
% correct w/ b-a & fallow correction		97%						100%									93%	OA w/ b-a-f correction

Table 4. Individual Crop and Overall Accuracies by Date

	May-94	Aug-94	Nov-94	Apr-95	Aug-95	Nov-95	Mar-96	May-96	Aug-96	Dec-96	Mar-97	May-97
Alfalfa	97%	97%	93%	100%	96%	90%	99%	98%	93%	99%	100%	97%
Cotton	86%	98%	**	**	92%	84%	100%	100%	92%	100%	100%	95%
Small grain	95%	0%	0%	84%	95%	55%	92%	96%	100%	**	91%	94%
Corn	45%	0%	100%	**	86%	**	**	59%	0%	**	100%	88%
Lettuce	**	**	95%	88%	**	94%	33%	**	**	89%	85%	**
Melons	93%	0%		50%	100%	45%	87%	80%	**	0%	17%	94%
Bermuda Grass	96%	92%	100%	93%	81%	84%	100%	87%	98%	100%	100%	100%
Citrus	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Tomatoes	**	**	**	**	**	**	**	**	**	**	**	**
Sudan Grass	94%	36%	100%	0%	51%	35%	0%	81%	70%	100%	36%	66%
Other Veg	77%	26%	38%	54%	69%	22%	58%	58%	45%	42%	58%	62%
Crucifers	**	**	73%	50%	**	89%	34%	**	**	52%	51%	**
Fallow	97%	100%	97%	95%	96%	96%	98%	80%	99%	93%	96%	88%
Dates	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%		100%
Safflower	58%	**	100%	0%	92%	**	**	28%	100%	**	**	90%
Overall	**93%**	**93%**	**93%**	**93%**	**93%**	**93%**	**94%**	**93%**	**93%**	**94%**	**95%**	**93%**

**Field data was not collected

into account the expected crop planting practices and accuracy assessment information, thereby further reducing error in the classification process.

Conclusions

This project combined remote sensing, GIS, and detailed ground information to map agricultural crops and other land cover in the Lower Colorado River Basin. Very high accuracies were required and achieved by incorporating detailed ground observations with automated signature extraction and data exploration routines. Water is an extremely valuable resource in this area and every effort is made to document and anticipate its use. Treaties with Mexico and court decrees between states dictate the need for accounting for every drop of water. The LCRAS model requires accurate data for input. Perhaps the best indicator of success of this project is that our land-cover maps have been successfully used to run the model and have achieved very good results.

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