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Integration of Satellite and Financial Data to Model Future Economic Impact of Citrus Crops (Final Project Report)

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Abstract

This study analyzed the health and overall landcover of citrus crops in Florida The analysis was completed using Landsat satellite imagery available free of charge from the University of Maryland Global Landcover Change Facility. The project hypothesized that combining citrus production (economic) data with citrus area per county derived from spectral signatures would yield correlations between observable spectral reflectance throughout the year, and the fiscal impact of citrus on local economies. A positive correlation between these two data types would allow us to predict the economic impact of citrus using spectral data analysis to determine final crop harvests.

Introduction and Background

Oranges are believed to have originated in the forests on the warm southern slopes of the Himalayas in northeastern India, eventually finding their way to Florida through the first permanent human settlement at St. Augustine (Ziegler and Wolfe 1975), oranges became abundant there and the growing conditions were so suitable that citrus is now the top economic agricultural produce of the state. Florida citrus crop consist of sweet oranges, grapefruit, mandarins, lemon, and lime, with sweet oranges grouped into normal, navel and blood orange types, of which *Valencia*, *Hamlin* and *Pineapple* were the most popular varieties in the 1970s (Ziegler and Wolfe 1975). As per the Department of Citrus's Citrus Summary of September 2004, *Valencia* oranges continue to dominate the Florida orange crop comprising 48% of all oranges, with early, midseason, and *Navel* varieties constituting the remainder.

According to the Florida Department of Citrus, the citrus industry generates an annual $9 billion impact with almost $1 billion in tax revenues, creating 90,000 jobs – a number that exceeds the total labor force in 45 of Florida's 67 counties, and places citrus at the second place[1] among Florida's most important industries. Data on crop health is of immediate importance to large and small growers, agricultural agencies, extension agents, retailers and commercial enterprises including private crop surveying companies. Monitoring crop condition and production estimates is important for agriculture and economic departments at county, state and national level. The National Agricultural Statistical Service (NASS) of the U.S. Department of Agriculture conducts interviews and collects field samples to develop crop yield estimates, including those for citrus. It requires real-time spatial data to fine-tune crop inventories and provide yield forecasts. The inventory reports produced by the Florida Department of Citrus are called the Commercial Citrus Inventories that provide annual county level production, tree count and acreage data based on interpretation of aerial photography and ground truthing. Remote sensing technology from ground, air, or space-based platforms is capable of providing detailed spectral, spatial and temporal information on vegetation health, vigor, and has significant crop-yield estimation applications (Sun, 2000; Singh, et al., 2002). A review of the literature on the biophysical basis of remote sensing, its application to crop management and yield prediction and plant response to the local environment for site-specific agricultural management was completed by Pinter, et al., (2003).

[1] Tourism is the top revenue generating industry in Florida with non-resident tourist expenditures of $47.37 billion in 2000 (EDIS Document FE316, IFAS, University of Florida, Oct. 2001).

Principal Crop Estimation Approaches and Models

Remotely sensed yield estimation differs from traditional crop yield estimation in that remote methods can be applied frequently allowing the temporal evaluation of weather conditions and management practices on crop growth and yield with increased rapidity. Pinter, et al., (2003) discuss two broad approaches to yield estimation, the direct method based entirely on remote measures such as imageries, and the indirect method incorporating remotely sensed parameters into computer simulations of crop growth. The indirect computer models are of two types. Firstly, the temporal reflectance-based (green leaf area or biomass) model was used by the U.S. Agricultural Research Service, for example to relate leaf and canopy reflectance to cotton yield, and by NASA and university scientists for grasses, corn, and soybeans. A second model, called the thermal-based (stress) model relates temporal trajectories of Thermal-IR (TIR) stress to crop yield based on the finding that crops exposed to higher water stress had higher cumulative thermal indices and usually lower yields. While these two methods estimated crop yield to within <10% error, it required daily measures of TIR during the grain-filling period and current sensors do not have the spatial or temporal resolution to meet this requirement. However, remote sensing has some major advantages over traditional yield monitors. Yield maps derived from agricultural machines such as combines, may not accurately depict yield spatially in a field and usually do not show true extremes in yield variability Arslan and Colvin, (2002). End-of-season maps from yield monitors result in the inability to manage specific yield-reducing stresses Pinter, et al., (2003). On the other hand, pre-harvest estimates based on remote sensing technology simplify delineation of management zones in fields (Yang and Anderson, 1996) and enable precise diagnosis of crop stress allowing timely remedial action (Pinter et al., 2003). Imagery collected several times in one growing cycle has the potential to further improve yield predicting capabilities for certain crops MacDonald and Hall, 1980). As the resolution of sensors improves and computer modeling and simulations are perfected for important crops, remote sensing is likely to provide even more accurate yield predictions.

Remote Sensing in Growth and Yield Estimation

Several agencies in Florida use aerial photographs of citrus groves such as, for tax purposes by county property appraisers, by FASS for agricultural yield estimation, and also by USGS and USDA, among others (Blazque et al., 1998). One of the earliest applications of 30 meter TM imagery in fruit orchard studies was by Gordon et al., (1986) who found that in New York State, fruit orchard spectral reflectance was sufficiently unique to allow a fraction of it to be isolated for use as a base to estimate total orchard acreage in the State. In this study, bands 3,4, and 5 were used and an image texture-enhancement procedure was applied before supervised classification, to accentuate differences between pixels of deciduous trees and orchard (Gordon and Philipson, 1986).

For quick assessments of vegetation stress in citrus crops in the visible and near IR (infra-red) region of the electromagnetic spectrum, an inexpensive multi-band video system is used to distinguish between grapefruit and orange trees in the yellow-green band. (Nixon et al., 1985). Aerial photography and videography was also found useful for tree inventory in the Merritt Island National Wildlife Refuge citrus groves (Blazquez et al., 1998). However, sequential video of entire counties for yield estimation can become prohibitively expensive and impractical for monitoring at the spatial scale of citrus distribution for all of Florida. As satellite and air-borne optics have become increasingly sophisticated, multi and hyper-spectral systems are being used for detailed agricultural estimations and modeling. The advantage of satellite imagery over video, for example, is the lower data cost of information acquisition.

Landsat Thematic Mapper (TM) multispectral imagery is available since July 1982 with a 30 meter spatial resolution for bands 1-5 and 7, and 120 meter for band 6[2] which is resampled and made available at 30m resolution. Remotely sensed data has been applied to crop growth modeling in the case of wheat (Doraiswamy et al., 2003), simulation of wheat and sugar-beet growth and yield (Bouman, 1995), wheat and barley yield and protein content (Hansen et al., 2002), crop yield in cranberry (Oudemans et al., 2002), landuse in olive groves (Pena-Barragan, et al., 2004), nitrogen deficiency in corn (Goel, et al., 2003; Osborne, et al., 2002), and corn yield estimation (Bach, 1998). Since citrus crops are vulnerable to climatic phenomena and various pathogens, remote sensing techniques have been applied to monitor salinity stress (Craig and Shih, 1998), disease stress (Fouche, 1995), and to detect and compare infestations and infections (Fletcher et al., 2004a; Fletcher, et al., 2001). In the visible region of the spectrum, especially at 0.45 µm, reflectance of citrus (Valencia orange) leaves is influenced by leaf water content, chlorophyll content and leaf air volume, more than by leaf thickness (Gausman, 1984). In studies of vegetation spectral reflectance, the near-infrared (IR) band (0.75-1.35 µm) is important in separating healthy and stressed trees based on leaf air content and the

[2] Band 6 in Landsat TM images corresponds to Thermal Infra-Red (10.4-12.5 µm), which is better suited for heat-sensing applications such as sea surface temperatures and was therefore not used.

condition of the mesophyll layer; healthy leaves with more air and a thicker mesophyll increase near-IR scatter (Gausman, 1974).

Remote sensing technology is sensor-dependent in its applicability to the agricultural sciences. For example, TM data has had a high rate of success in discriminating between citrus, sugarcane and coffee crops in Brazil (Tardin et al., 1992), while Side-Aperture Radar (SAR) has limited use in discriminating between agricultural crops, although discrimination is enhanced from one season to another (Saich, 2000; Schotten, et al., 1995). The NDVI (Normalized Difference Vegetation Index) has been used extensively to determine vegetation vigor in forestry and environmental evaluations, but little information exists on its use in agriculture. Fletcher, et al., (2004b) found airborne NDVI imagery to be useful in detecting stressed from non-stressed trees when evaluating the condition of citrus groves and in planning surveys of such groves. Both remote sensing equipment and processing methods are becoming refined, thus offering an increasingly wide range of research applications in the crop sciences.

Citrus Production Trends and Economics

According to the U.S. Agriculture Census (2002), in the country, 90 percent of all farms are individual or family-operated and the number of corporate farms declined by 18.4 percent during 1997-2002, reversing a growth trend that had continued without interruption since 1974. In the U.S., orange bearing acres declined from 840,000 to 790,000 during 1997-2000, accompanied by a decline in orange production from 13,670,000 to 11,545,000 tons during the same period. In 2002-03, Florida accounted for 74% of the U.S. citrus production, far ahead of California (23%), with Texas and Arizona accounting for the remaining three percent (Citrus Summary 2002-2003). The value of U.S. citrus (2003) was estimated at 2.3 billion dollars, approximately equal to the average value of U.S. citrus over the past ten years.

With respect to Florida, in 2002-03, Florida orange juice production equaled 86.1% of the presumed total U.S. consumption (Florida Citrus Outlook [FCO] 2003-04) and is expected to increase to 108.3% in 2003-04. Counties reporting commercial citrus production in Florida are constituted by the Department of Citrus into four citrus production areas, i) Indian River ii) Northern and Central, iii) Western, and iv) Southern. As per the Citrus Summary for 2002-03, out of the 31 counties reporting commercial production, Polk, Highlands, Hendry, DeSoto, and St. Lucie counties reported citrus production in excess of 20 million boxes[3]. Hardy and Indian River counties are also major citrus areas and made the top cut in 1999-2000.

For the 2003-04 season, the Florida Agriculture Statistics Service (FASS) has estimated a record citrus production of 252 million boxes and a total processed orange on-tree[4] revenue of 616.8 million dollars. This is slightly down from 619.2 million dollars for the 2002-03 season. Total on-tree revenue for oranges as well as other citrus such as grapefruit and specialty citrus is projected at 798.3 million for the 2003-04 season.

The 2002 Commercial Citrus Inventory showed a 4.2% decline in total citrus acreage from 2000 due in part to diseases such as citrus canker *Xanthomonas axonopodis pv. citri*, tristeza (Citrus Tristeza Virus), and root weevils, of which the southern blue-green citrus root weevil, *Pachnaeus litus*; the blue-green citrus weevil, *Pachnaeus opalus*; Fuller rose beetle, *Asynonychus godmani*; the little leaf notcher, *Artipus*

[3] Standard boxes that hold 90-lbs of oranges.
[4] On-tree income is the final profit to the grove owner after deducting all expenses.

floridanus; and the sugarcane rootstalk borer weevil, *Diaprepes abbreviatus* are of economic significance to citrus growers (Futch and McCoy, 1993). On the whole, tree density in Florida citrus groves has continued to show an increasing trend and groves continued to mature in age thus increasing the crop production per unit area.

A Competitive Marketplace

U.S. per capita consumption of orange juice has declined in recent years with observers citing dietary changes specially the trend towards low-calorie diets. During the past decade, annual per capita consumption peaked in 1997-98 at 5.82 gallons and was down at 4.83 gallons in 2002-03 (Citrus Summary 2002-03). Consumption is also influenced by fluctuations in product pricing. Brazil is the world's largest producer of orange juice and Florida's principal competitor in orange juice exports, hence Florida citrus export/import economics are influenced by the state of Brazil's citrus production and inventory. Like Florida, Brazil citrus is also plagued by citrus canker. In Brazil, other important citrus diseases and pathogens are variegated chlorosis *Xylella fastidiosa*, blossom blight *Colletotrichum acutatum*, citrus leaf miner *Phyllocnistis citrella*, and black spot *Guignardia citricarpa*. Total orange juice production in Brazil is projected to decline from 2002-03 due to an unfavorable hot season (FCO). With a decrease in Brazil's ability to export, U.S. orange juice exports are projected to increase together with a decline in imports from Brazil. According to the 2002-03 FCO, reduced availability of orange juice on the world markets may drive up overall prices, which is expected to favor the Florida citrus and juice industry. Florida's projected record orange crop for 2003-04, together with a relatively small Brazil crop are expected to dampen U.S. orange juice imports and increase Florida’s share of the domestic orange juice market (FCO). Florida remains by far the largest domestic citrus producing area.

Methods

Economic and Production Data

Background information and production data citrus in Florida was collected from several internet resources. Current citrus information was available at FASS (Florida Agricultural Statistics Service) and NASS (National Agricultural Statistics Service) websites. Citrus Summary 2002-03, February 2004 (http://www.nass.usda.gov/fl/citrus/cs02/cs0203.htm) and Commercial Citrus Inventory 2002 (http://www.nass.usda.gov/fl/citrus/cci02p.htm) provided much of the current data. Historic citrus summary and inventory information was reviewed at the FASS website (http://www.nass.usda.gov/fl/rtoc0h.htm).

Citrus production data was downloaded from these websites into Excel. Data for the period 1990-2002 was selected and the parameters of interest included; year, citrus variety, production, number of boxes, revenue, and acreage by county. A bibliography of papers published on the application of imagery data to citrus and horticulture was complied by searching Cambridge SA, ArticleFirst and Opac. Attempts were also made to collect background data by directly contacting researchers and professionals engaged in citrus research. Appendix 1 lists the persons contacted during the implementation of this project.

The website http://www.pickyourown.org/FL.htm was useful in identifying grove owners and retailers in various counties. Using addresses and telephone numbers listed at this website, groves were located on a Florida map using Yahoo Maps, to geographically site six sample groves. The locations were contacted telephonically to obtain physical addresses of the groves for accurate mapping, however only one out of six contacts responded with the address and this method was abandoned due to its inefficiency.

Grove Mapping

The methodology that proved much more successful and accurate, involved searching property appraiser databases available online at the county level as a method of accurately locating citrus groves. By searching for specific citrus landuse codes (usually code 6600), this internet-based resource was found to be very useful in obtaining the grove physical addresses and location on a street map. Together with the embedded GIS data and aerial photographs of the actual property, the task of locating a particular property and identifying local features such as roads, streets, water bodies, agricultural field layouts and property boundaries was made easier. Associated grove data such as citrus acreage, ownership, zip code, and parcel information was also recorded.

Grove Latitudes and Longitudes

The property addresses obtained from county property appraiser databases were then used as inputs in TerraFly (http://www.terrafly.com/) to virtually fly over the property location in order to compare it with the property appraiser aerials. Once an exact match was made, the automated TerraFly option to obtain location latitude and longitude numbers was used to generate latitude and longitude numbers for each of the selected groves. Cayo and Talbot (2003) evaluated the automated geocoding method used to assign geographic coordinates to an individual based on their street address. This method often relies on street centerline files as a geographic reference. Their conclusions that automated geocoding errors increase with declining population densities in rural areas needs to be kept in mind, and therefore a visual comparison of property appraiser maps with the TerraFly aerial images was done to ensure accuracy in locating groves.

Landsat TM Data Processing

Landsat ETM+ satellite imagery was obtained free of cost from the archive database at GLCF (Global Landcover Change Facility) at the University of Maryland. Images for south and central Florida were located by satellite Path/Row and the following seven images were downloaded as GeoTiff zipped files: 15/41, 15/42, 16/40, 16/41, 16/42, 17/40, and 17/41. The files were unzipped into separate folders. The unzipped files were stacked for bands 1-5 and 7 in Erdas Imagine 8.6 using the layer stack function and adding the layers (bands) one by one. The resulting output files (.img and .rrd) were saved in separate folders in the Z: drive. The original unzipped files were deleted except for the metadata and browse files.

Since several of the images contained unnecessary areas of water, image cropping was done in Erdas. Images were opened in the viewer and the AOI (area of interest) was selected using the AOI polygon tool to remove off-shore water areas. The resulting images were smaller and were saved as subset (img) files along with subset (rrd) files.

Accurate image classification is a prerequisite for an accurate analysis and interpretation of spectral data. The subset images were opened in Erdas using a band combination of 5,4,3 for supervised classification. Before applying the AOI tool, the layer selection option was set to 5,4,3. Classification parameters were; Non-parametric rule – Parallelepiped; Overlap Rule – Parametric Rule; Unclassified Rule – Parametric rule; Parametric Rule – Maximum Likelihood. This selection of options was designed to allow the processing of multi-year images, introduce sensitivity to variance in spectral data in each category training set (parallelepiped), and help classify unknown pixels by the evaluation of variance and covariance of the category spectral data (maximum likelihood) (Lillesand and Kiefer, 2003). Vegetation classification was done with reference to a classified map available from the FIU Florida Coastal Everglades LTER website (http://fcelter.fiu.edu/maps/index.htm). One image (Row15/Path42) was selected and thirteen vegetation and landcover types were classified, including agriculture. For each type, 5-10 AOIs were selected in the signature editor. The final signature file was then associated with the remaining image files, which were then classified and saved.

Counties may lie completely within a TM image, or they may overlap across two or more imageries. Where such overlap existed, the classified images of interest were mosaiced together in Erdas viewer using the mosaic function and by placing the better image on top before running the mosaic. The resulting mosaics and the remaining classified images were opened in Erdas as layers. A Florida county boundary shape file obtained from FGDL (Florida Geographic Data Library) was opened in Erdas as another layer and was used to clip out counties from the classified images in the form of subset images under the Data Preparation option. In this way, classified images of all the counties of interest were obtained as individual files.

To project the citrus grove locations on the county classified images in ArcMap (Figure 1), the citrus grove lat/long data was entered in a table format and saved in Excel as a csv file. This file, the individual classified county files, and the county boundary shape file were imported into ArcMap as layers. Based on the landcover type classification done, ArcMap can calculate percent area occupied by each type relative to the total county area. Under Spatial Analyst, the option of Raster Calculator enabled each county image to be processed individually by specifying its file name within the

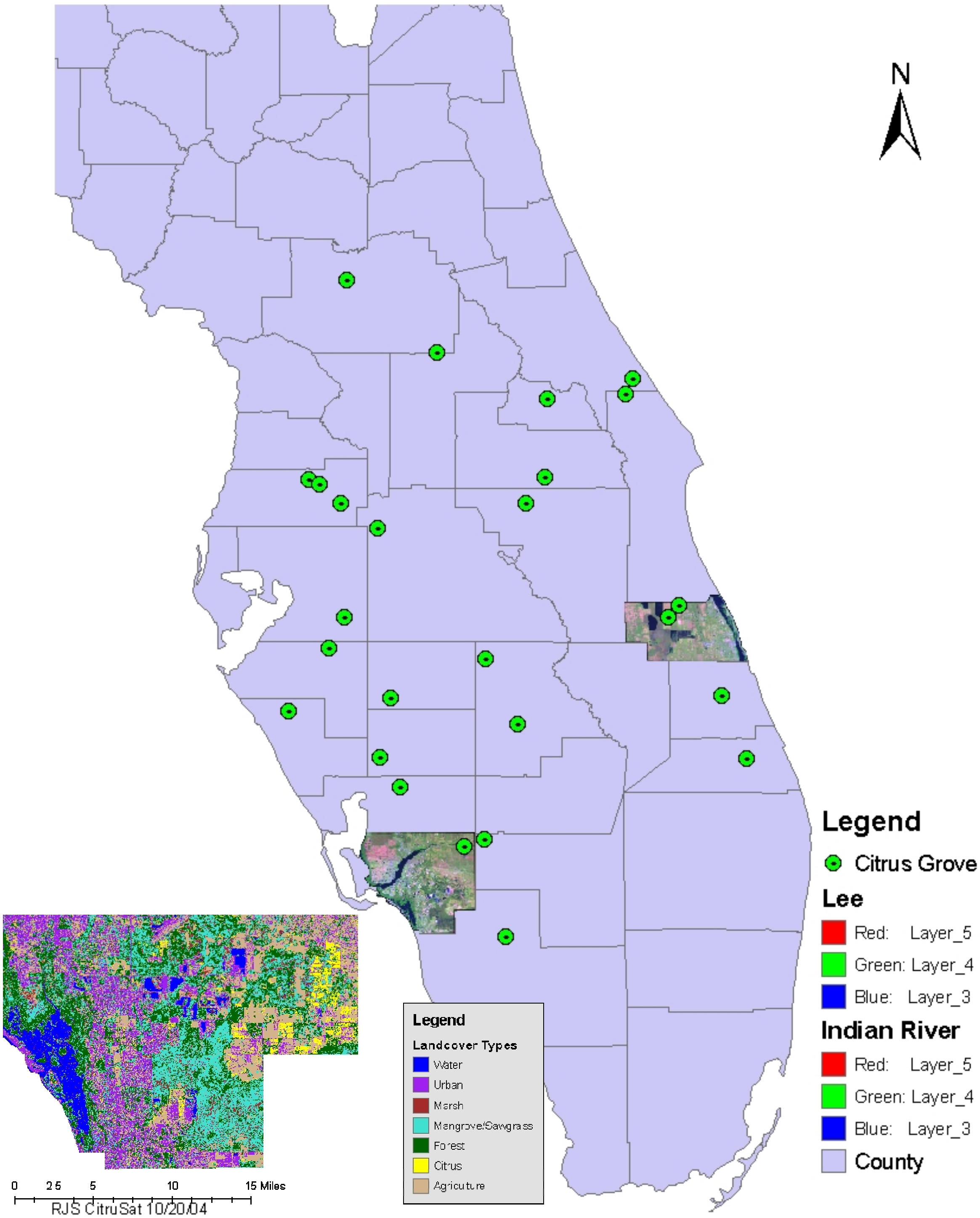


Figure 1. Location map of the citrus groves in twenty-six counties in Florida selected for sampling. Groves were located using county property appraiser data and their lat/long was determined from TerraFly.

calculator expression. For this research, the calculation was restricted to landcover type – agriculture, calculated as agriculture pixels as a percent of total pixels in image.

Supervised Classification

Similarly, the area under citrus groves can be calculated if the specific geographic location of the groves is known and their latitude/longitude data is available. The latitude/longitude shape file of citrus grove locations was thus overlayed in Erdas along with the layer-stacked unclassified file (bands 3,4,5) of each county. Using the AOI tools polygon function, areas representing citrus groves identified from the shape file were selected into the signature editor. Then, more training sites were selected by visually identifying the areas that appeared similar to the known citrus grove areas on the image. At least ten such training sites were chosen per county. Ten or more training sites were also selected for six other landcover types in the signature editor. Supervised classification was performed on all the layer-stacked county images. In the resulting classified images, the area calculator function under raster properties was used to determine land area under each of the seven landcover types. Figure 2 (Hernando County) and Figure 3 (Lee County) are two examples of the final 26 classified images from which the citrus acreage was finally calculated. The landcover types assigned were citrus, agriculture, forest, mangrove/sawgrass, marsh, water, and urban. In the final step, the citrus landcover data together with citrus production and on-tree income data obtained from Commercial Citrus Inventories were tabulated. Citrus acreage obtained by this method was compared with acreage from official census based on aerial photography.

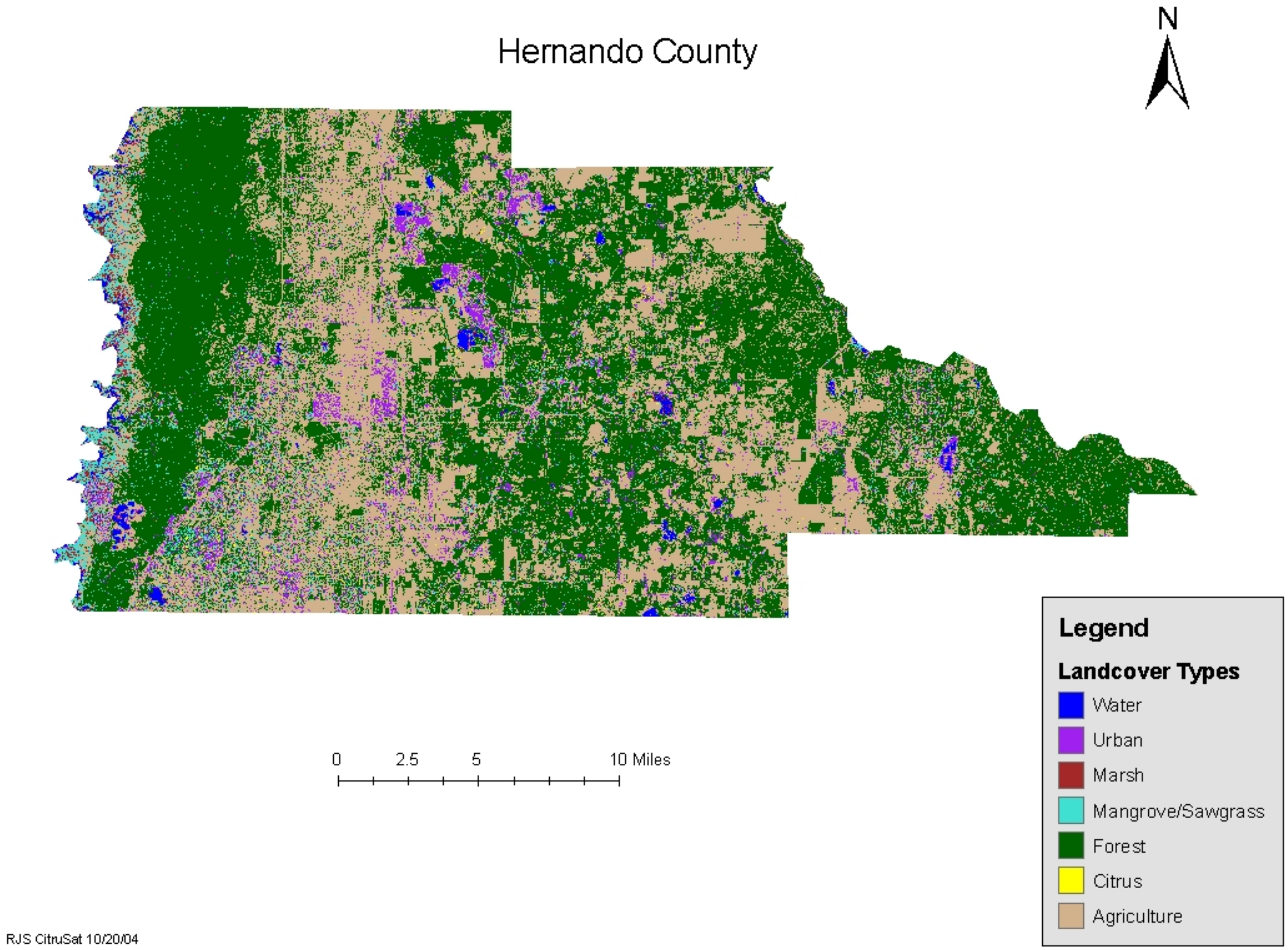


Figure 2. Landcover types identified in Hernando County by the supervised classification of Landsat TM data.

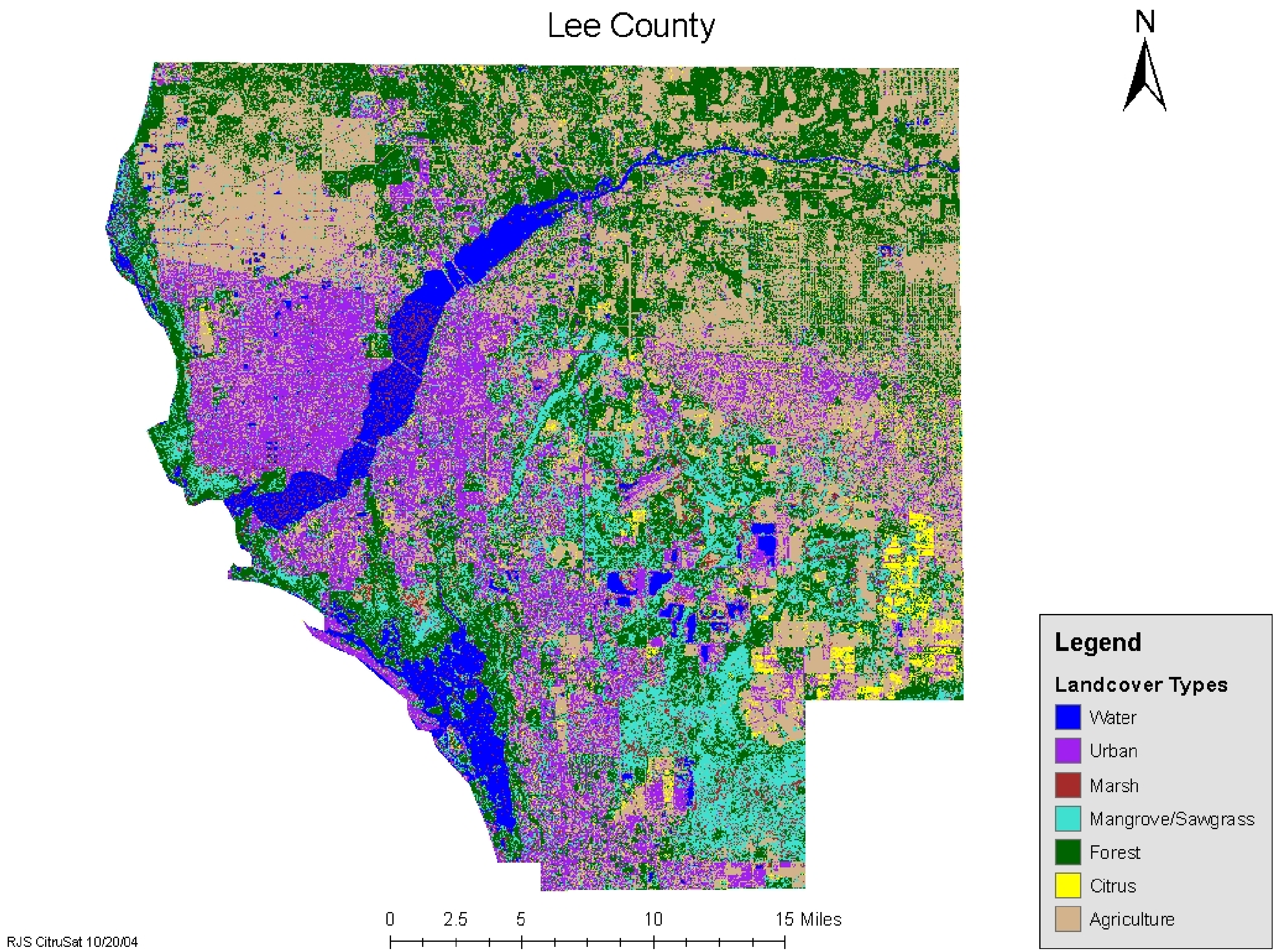


Figure 3. Landcover types identified in Lee County by the supervised classification of Landsat TM data.

Results

Through supervised classification of TM images from 1999-2002, the total area under citrus groves in the images of 26 counties that were examined was estimated at 229,358.7 hectare compared to the official total of 329,370.4 hectare. This indicated that the methodology yielded an overall underestimate of 100,011.7 hectare or about 30% less than the official estimate. County-wise citrus grove area determined in this project using spectral reflectance data is compared with official data in Figure 4, followed by the actual spectrally calculated citrus acreage in Table 1. Citrus grove coverage ranged from 0.4 - 8% of the total county area in the 26 counties studied (Table 2).

Figure 4. Citrus landcover for 26 counties arrived at by supervised classification of TM spectral data is compared here with the officially estimated landcover derived from interpretation of aerial photos.

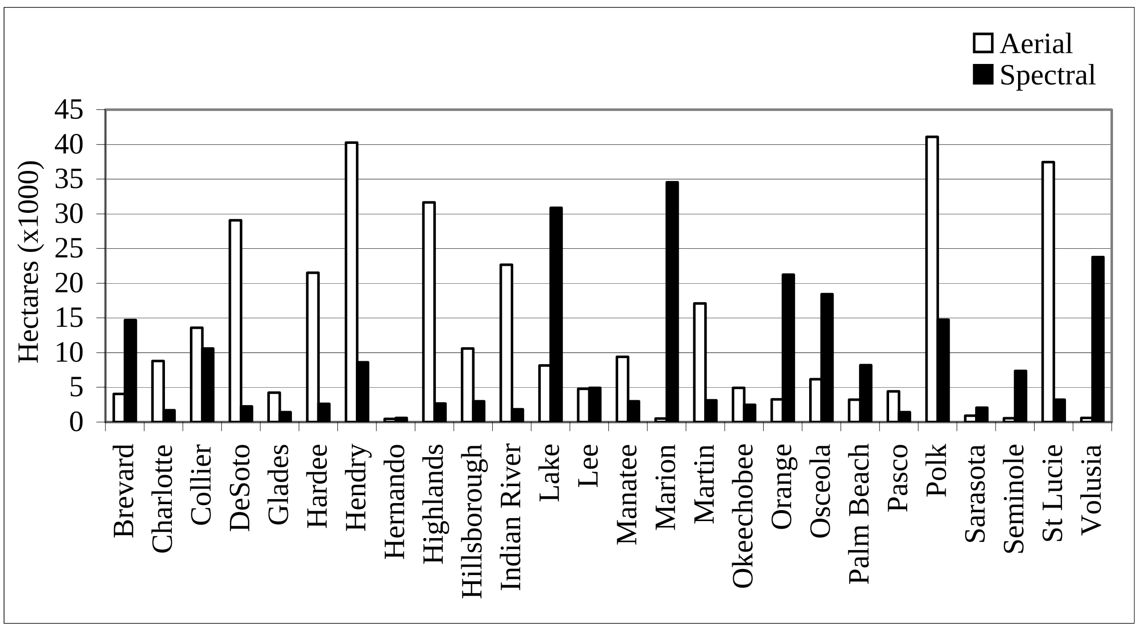


Table 1. Comparison of spectral and aerial estimates of citrus landuse in Florida.

County	Image Year	Spectral Area[1] (ha)	Aerial Area[2] (ha)	Difference (ha)
Brevard	1999	14676.30	4065.21	10611.09
Charlotte	1999	1696.95	8804.65	-7107.70
Collier	2001	10604.09	13584.56	-2980.48
DeSoto	1999	2255.13	29049.77	-26794.64
Glades	1999	1440.93	4251.78	-2810.85
Hardee	1999	2607.24	21495.64	-18888.40
Hendry	1999	8630.48	40242.15	-31611.67
Hernando	1999	587.74	447.19	140.55
Highlands	1999	2660.93	31620.02	-28959.09
Hillsborough	2000	2972.27	10612.45	-7640.18
Indian River	2002	1844.13	22668.06	-20823.92
Lake	1999	30841.94	8134.87	22707.07
Lee	2001	4947.41	4805.41	142.01
Manatee	1999	3011.58	9410.89	-6399.31
Marion	1999	34523.47	503.85	34019.62
Martin	2002	3109.70	17081.58	-13971.88
Okeechobee	1999	2471.11	4925.20	-2454.09
Orange	1999	21252.52	3276.05	17976.47
Osceola	1999	18430.03	6180.98	12249.05
Palm Beach	2002	8193.98	3223.03	4970.95
Pasco	1999	1422.90	4410.02	-2987.12
Polk	1999	14720.57	41070.57	-26350.01
Sarasota	1999	2085.05	939.31	1145.74
Seminole	1999	7376.37	557.68	6818.69
St Lucie	2002	3212.21	37430.70	-34218.50
Volusia	1999	23783.65	578.72	23204.93

[1]Determined Spectrally, [2]From Florida's Commercial Citrus Inventory based on aerial photography.

Figure 5. Out of the seven landcover types that were classified, only agriculture showed an increasing trend when the difference between official estimate of citrus area and projected estimates assumed increasingly negative values. The filled (black) bars with positive values indicate possible commission error in citrus acreage and the filled bars with negative values indicate potential acreage omission.

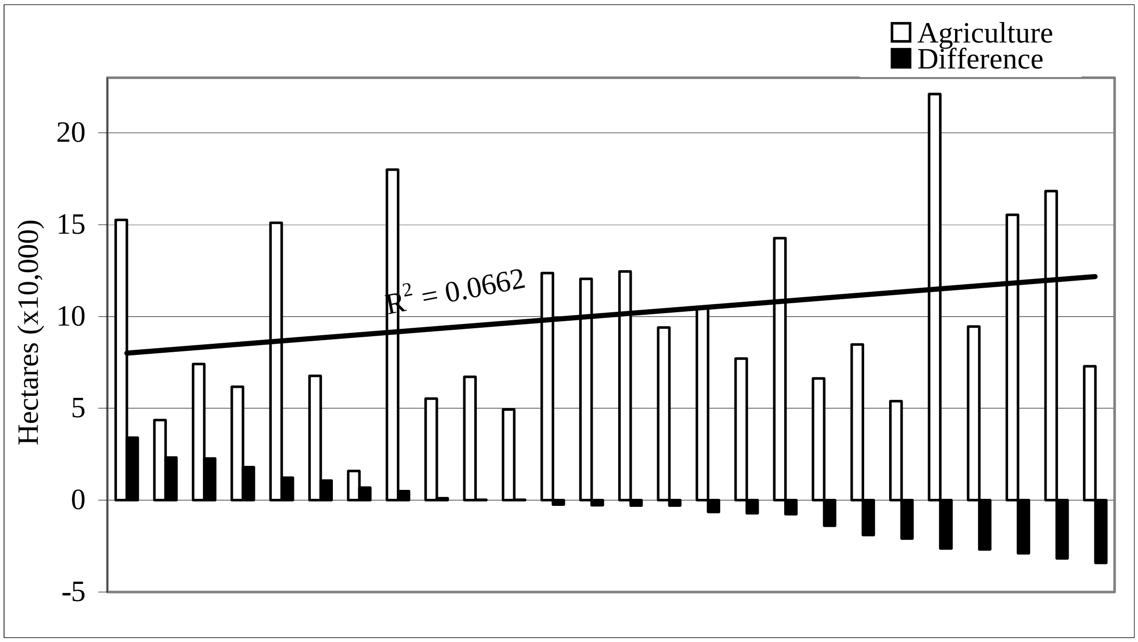


Table 2. Citrus and agricultural acreage for selected counties and on-tree income for round oranges generated by grove owners.

County	**Citrus Area Estimated Spectrally (ha)**	**Citrus Area From Census (ha)**	**Spectral Agriculture (ha)**	**Income Round Orange $ (x 1000)**	**Citrus as % of Agriculture**
Brevard	14676.30	4065.21	67702.99	6805.6	21.68
Charlotte	1696.95	8804.65	77043.78	19627.2	2.20
Collier	10604.09	13584.56	124503.14	38167.76	8.52
DeSoto	2255.13	29049.77	94497.41	100549.9	2.39
Glades	1440.93	4251.78	120592.00	12938.16	1.19
Hardee	2607.24	21495.64	84803.61	78324.56	3.07
Hendry	8630.48	40242.15	168216.98	108291.8	5.13
Hernando	587.74	447.19	49418.91	1492.72	1.19
Highlands	2660.93	31620.02	155397.88	102644.2	1.71
Hillsborough	2972.27	10612.45	142647.26	36073.44	2.08
Indian River	1844.13	22668.06	53893.36	24432.48	3.42
Lake	30841.94	8134.87	74174.26	21458.32	41.58
Lee	4947.41	4805.41	67187.53	11964.32	7.36
Manatee	3011.58	9410.89	104821.02	31452.4	2.87
Marion	34523.47	503.85	152528.29	1143.04	22.63
Martin	3109.70	17081.58	66320.29	45274.16	4.69
Okeechobee	2471.11	4925.20	123670.67	11768.8	2.00
Orange	21252.52	3276.05	61819.21	9418.8	34.38
Osceola	18430.03	6180.98	151088.98	20236.32	12.20
Palm Beach	8193.98	3223.03	179929.78	7520	4.55
Pasco	1422.90	4410.02	94057.66	15664.16	1.51
Polk	14720.57	41070.57	221137.34	121955.6	6.66
Sarasota	2085.05	939.31	55274.99	43830.32	3.77
Seminole	7376.37	557.68	15880.22	2090.56	46.45
St Lucie	3212.21	37430.70	72886.60	1361.12	4.41
Volusia	23783.65	578.72	43653.48	1116.72	54.48

Table 3. Citrus production in Florida as per the Commercial Citrus Inventory

County	Year	All Citrus Boxes (x 1000)	Income From Round Oranges ($ x 1000)
Brevard	1999	2532	6805.6
Charlotte	1999	6940	19627.2
Collier	2001	10948	38167.76
DeSoto	1999	27851	100549.9
Glades	1999	3738	12938.16
Hardee	1999	21712	78324.56
Hendry	1999	33832	108291.8
Hernando	1999	426	1492.72
Highlands	1999	30180	102644.2
Hillsborough	2000	9179	36073.44
Indian River	2002	14807	24432.48
Lake	1999	7162	21458.32
Lee	2001	3497	11964.32
Manatee	1999	9066	31452.4
Marion	1999	355	1143.04
Martin	2002	11342	45274.16
Okeechobee	1999	3847	11768.8
Orange	1999	2894	9418.8
Osceola	1999	6544	20236.32
Palm Beach	2002	2281	7520
Pasco	1999	4387	15664.16
Polk	1999	38989	121955.6
Sarasota	1999	833	43830.32
Seminole	1999	416	2090.56
St Lucie	2002	31665	1361.12
Volusia	1999	380	1116.72

Figure 6. Citrus area estimated spectrally for various counties and the official number of citrus boxes produced in those counties. Data based on spectral analysis of images.

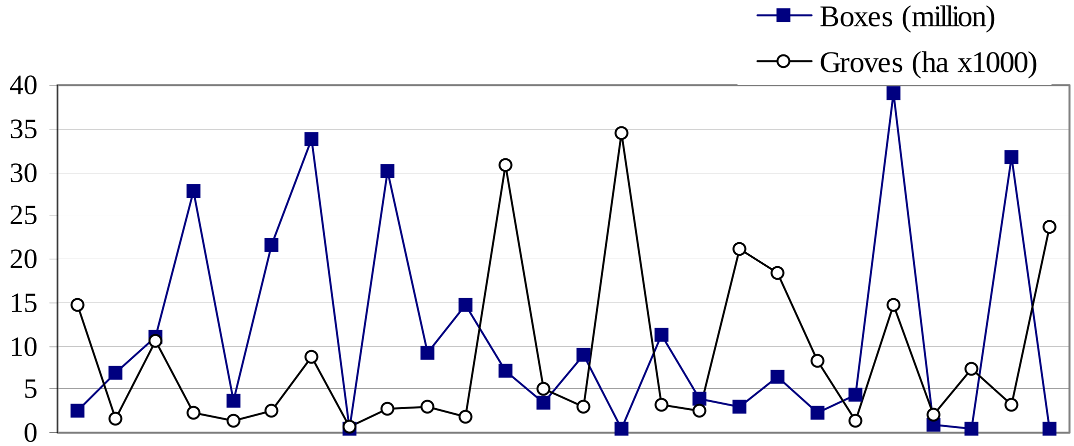
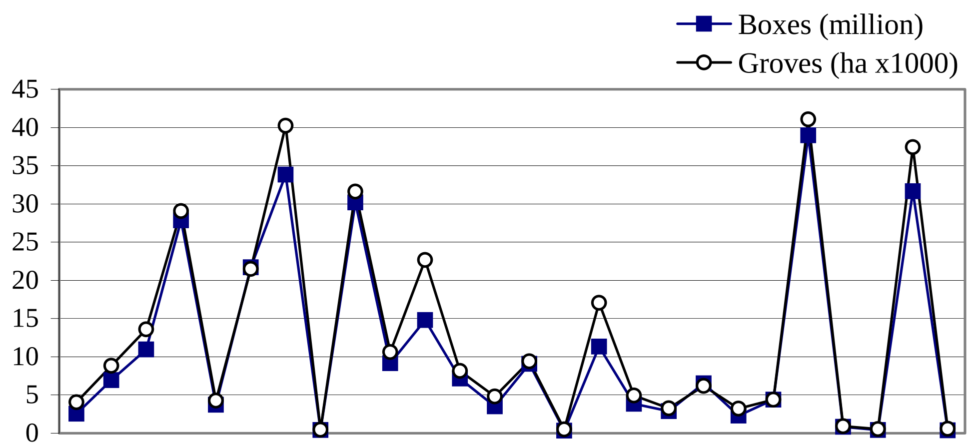


Figure 7. Citrus area obtained from the Department of Citrus's interpretation of aerial photographs for the period 1999-2002. Number of citrus boxes obtained from official publications.



The closest match between official estimates of citrus grove acreage and the estimates obtained in this study was in the case of Lee and Hernando counties. In both instances, the spectrally calculated area was an overestimation of the official estimates – the overestimate being 142.01 and 140.55 ha respectively (Table 1). The largest underestimate of citrus area in this study was for St. Lucie county (34218.5 ha) while the largest overestimate was for Marion county (34019.62 ha). On the whole the differences in citrus landcover between official figures and this study were more likely a result of an underestimation of citrus – 15 out of 26 counties in this study. Errors in the correct classification of pixels are usually categorized as errors of commission or omission. Commission occurs when incorrectly classified pixels are added to a certain landcover type resulting in a more than actual representation of that particular landcover type. Errors of omission occur when pixels that belong to a landcover type are incorrectly classified as some other landcover and subtracted from their actual landcover, thus resulting in a less than actual representation.

In this study, it was found that error of omission (loss of citrus acreage) increased only with an increase in agricultural landuse (Figure 5) and did not increase with increase in any other landcover type. This indicates that a possible cause of the loss of citrus acreage when compared to official figures could be due to a misclassification of citrus pixels as agriculture pixels.

Based on official data, the correlation (Figure 7) between citrus production (boxes) in Table 3 and citrus acreage (Table 2) was positive and significant ($r = 0.989$, $p < 0.01$, $n = 25$) unlike the lack of association based on spectral analysis (Figure 6). The correlation data presented in Table 4 is derived from Figures 3 and 4 where the strong parallel connection between citrus acreage and citrus production (boxes) is evident in the case of official data (aerial method). Correlation between official citrus acreage and citrus income was significantly positive (Table 4).

Table 4. Citrus acreage obtained by the two methods is correlated with on-tree income derived by farmers from the sale of all varieties of round oranges.

Spectral Estimate	Citrus Acreage and Round Orange Income		
	Pearson Correlation	1	-.197
	Sig. (2-tailed)	.	.334
	N	26	

Aerial Estimate	Citrus Acreage and Round Orange Income		
	Pearson Correlation	1	.781
	Sig. (2-tailed)	.	.000
	N	26	

(Correlation is significant at 0.01 2-tailed)

Discussion

The bands 3, 4 and 5 were found to be useful in the classification of TM imageries obtained free of cost and seven landcover classes could be identified outright. In Florida's citrus groves, spacing between rows has remained more or less constant at about 25 feet (7.6 meters) but spacing within row has decreased sharply since the 1960s to about 14.6 feet (4.5 meters) essentially due to improvement in grove management technology and a desire for faster returns on investment, leading to densities of 284 trees/ha (Tucker et al., 1992). At a resolution of 30 meters, individual citrus trees could not be distinguished on the unclassified images because a linear distance of 30 meters on the ground in a citrus grove can easily incorporate three parallel rows of citrus trees containing a total of 20 trees. In order to use satellite images for citrus inventory, monitoring and management with any degree of accuracy, images of 10-meter or higher resolution will be ideally suited for training site identification and landuse classification.

As has been reported in the literature, spectral reflectance from citrus groves includes reflectance from soil and bare earth backgrounds. Reflectance values also vary depending on the time of the year, water stress, weather conditions, and grove management that concerns nutrition, irrigation, and pathogen control. In this study, it appears that due to spectral similarities, some citrus was misclassified as other types of agriculture. To deal with the soil reflectance issue a filtering method has been developed and used by Gordon et al., (1986) in orchards in New York State. Gordon et al., (1986) also describe the basic problem in isolating orchard as a class – separating orchards from i) phonologically different categories (field crops, pasture, and fallows) and, ii) phonologically similar categories (mixed deciduous forests). They separated orchard from agriculture-type non-forest vegetation by multi-date supervised classification using bands 3,4 and 5. To distinguish orchards from forest, instead of relying on spectral differences, they chose differences in image texture that were particularly apparent in TM band 4. The texture of bands 3 and 4 was enhanced by passing a 3-by-3-pixel filter over the images, replacing the center pixel in the filter with the sum of the absolute differences between the center pixel and each of the surrounding eight pixels. Lastly, a binary image was produced where white depicted non-orchard pixels, and pixels of orchard plus confused non-orchard were black. Their paper also discusses the need for reclassification due to misclassification of roadways, forest-edge, and orchard-boundary pixels that appear orchard-like but in fact are not. In the present study, another issue was that of image mosaicing. In order to overcome problems in pixel classification especially when two or more imageries need to be mosaiced together prior to classification, TM data should preferably be from the same month and taken under similar climatic conditions.

That remote sensing methodology holds promise in the inventory of citrus groves in Florida is evident from the correlation analysis done on data obtained from the Florida Commercial Citrus Inventories. Significant correlations between citrus income and citrus acreage as well as with citrus production indicate that remotely sensed estimates of citrus groves can be used to forecast on-tree incomes to farmers. For this to be achieved with satellite-sensed data two things need to be done; high-resolution images of the citrus growing areas should be used, and a citrus database needs to be maintained containing the following minimum parameters - grove location (latitude and longitude), physical address, citrus variety and type and acreage of each type, date established, citrus income, and details of management practices adopted in response to stress situations the groves may have gone through. Availability of such a database through a central facility to all universities and affiliated research centers in Florida will significantly benefit the research and forecasting of citrus production and economics.

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