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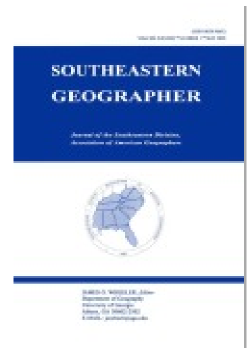

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MULTISOURCE DATA INTEGRATION FOR GEORGIA LAND-COVER MAPPING

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This paper describes a multisource data integration method for creating a 28-class 1998 land-cover map of the state of Georgia. The methodology for creating the map is unique in both the number and the method of integrating data sources. An assessment of the map's accuracy in the metropolitan Atlanta region using color infrared digital ortho-quarter quads and a preliminary state-wide assessment using low altitude aerial videography is presented. We estimate the overall accuracy for the metropolitan Atlanta region to be 86.3% and the overall accuracy for the state-wide land-cover map to be 83.9%. We anticipate that this dataset will be useful in a wide range of mapping, modeling, and planning exercises across the state and in the Southeast.

Keywords: Land-cover mapping, Georgia, Gap Analysis Program, Land use mapping, LANDSAT, accuracy assessment, videography.

INTRODUCTION. Large area-land cover maps created from processing remotely sensed data in conjunction with ancillary datasets are highly sought after products for a wide variety of users across many disciplines. There is an ongoing need for land-cover maps for biodiversity and habitat assessments, county and city planning, air and water quality assessments, studies of urban sprawl, land-cover change detection, agricultural applications, and environmental impact assessments, to name a few. In response to these needs, members of the Georgia Gap Analysis Program (GAP) under the umbrella of the National Gap Analysis Program created a land-cover map of the State of Georgia between September 1998 and May 2001. This was a labor-intensive project completed by 15 staff members and required the integration of a wide variety of datasets, including Landsat 5 Thematic Mapper (TM) data, black and white and color infrared aerial photographs, state-wide geographic information system (GIS) coverages of hydrology, roads, railroads, utility swaths, and hypsography, tabular agricultural census data, a 1993 Georgia land-cover map, and low altitude aerial videography.

In this paper we:

1. Announce the release of the new land-cover map of the State of Georgia along with information on how to obtain copies of the dataset. The map is

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significant in that it estimates the location and extent of several land-cover categories not mapped in Georgia's previous land-cover maps.
2. Describe the technique used to make the map. This technique integrates a range of data at various temporal and spatial scales to create a seamless, 30 meter resolution, land-cover map.
3. Provide an accuracy assessment of a portion of the map over the metropolitan Atlanta region using aerial photography and state-wide accuracy estimates based on low altitude aerial videography. We provide error matrices, user's, producer's, overall accuracy and kappa statistics for both Atlanta and the State as a whole.
4. Discuss ways the map may be analyzed, augmented and utilized in the future.

Table 1 lists the 28 land-cover classes mapped in the database. The classification system was designed to satisfy five purposes:

1. Accurately map classes based on available data.
2. Respond to current planning problems in the state, especially urban sprawl.
3. Facilitate cross-walking of existing land-cover maps of the state for change detection programs.
4. Create a dataset to be used in the creation of another GAP product: models of the spatial distributions of plant communities or vegetation alliances in the state.
5. Create a dataset to be used in modeling the spatial distributions of vertebrate species.

If we were constrained in using Landsat 5 TM data alone, 28 land-cover classes would not be appropriate as the resolution of the source imagery would not allow for such fine distinctions. However, the use of ancillary GIS data and high resolution aerial photographs allowed us to create a classification system that includes several categories never before mapped and assessed in Georgia's previous land-cover maps: dunes, airports, single and multifamily dwellings, utility swaths, railroads, roads, quarries, barren land, deciduous, evergreen and mixed woodland, recreational lands and golf courses.

METHODS. Mapping Protocol and Source Data. The primary data source for the map was 42 Landsat 5 TM scenes acquired between March 12th, 1996, and October 17th, 1998. For each of the 14 scenes covering Georgia, we acquired two leaf-on (spring and summer) images and one leaf-off (winter) image. We analyzed bands 1-5 and 7 of the TM data, provided by the Multi-Resolution Land Characteristics Consortium (MRLC) (Loveland and Shaw 1996). The data were provided at a

TABLE 1
LAND USE/LAND COVER CATEGORIES FOR THE 1998 LAND-COVER MAP OF GEORGIA

	Code	Class Name	Description
1	07	Beaches	Open sand, sandbars, mud—natural environments as well as exposed sand from dredging and other activities.
2	09	Dunes	Sand dunes (coastal environments).
3	11	Open Water	Lakes, rivers, ponds, farm ponds, ocean, aquaculture centers (catfish and trout farms), as well as industrial water—water associated with sewage treatment plants, mines, etc.
4	19	Airports	Airports and runways.
5	20	Utility Swaths	Swaths maintained for transmission lines.
6	22	Low Intensity Residential (LIR)	Single-family dwellings.
7	23	High Intensity Residential (HIR)	Multi-family dwellings: apartment complexes, duplexes, and row houses.
8	24	Commercial/ Industrial	Highly developed lands not classified as a type of transportation or residential property. Areas used in commerce, trading, building, manufacturing and office spaces. Includes prisons, raceways, junkyards and confined animal operations: chickens, hogs, feedlots.
9	28	Railroads	Railroads.
10	29	Roads	Roads.
11	31	Clear-cut, Sparse	Clear-cut, sparse vegetation. In the coastal plain this includes clear-cut wetlands that may not be replanted and may therefore take longer to regenerate than clear-cut lands in the piedmont.
12	33	Quarries etc.	Exposed rock and soil from industrial uses. Includes quarries, strip mines, gravel pits, and landfills.
13	34	Barren Land	Rock outcrops, mountain tops.
14	41	Deciduous Forest	Forest composed of at least 75% deciduous trees in the canopy. May include mixed deciduous/coniferous old-field succession, and unplanted regrowth from clear-cut operations.
15	42	Evergreen Forest	Evergreen forest, at least 75% evergreen trees. Includes natural evergreen forests and managed pine plantations, from young pine to older, possibly thinned pine.
16	43	Mixed Forest	Mixed deciduous/coniferous forest. Evergreen and deciduous species contribute to 25-75% of total tree cover.
17	51	Shrub/Scrub	Natural scrublands, heath balds (no more than 6m in height) with a closed canopy.

(*table continues*)

TABLE 1 (Continued)

	Code	Class Name	Description
18	61	Deciduous Woodland	Open canopy, low stature forests of at least 75% deciduous trees.
19	62	Evergreen Woodland	Open canopy, low stature forests of at least 75% evergreen trees.
20	63	Mixed Woodland	Open canopy, low stature forests of mixed trees. Evergreen and deciduous species contribute to 25-75% of total tree cover.
21	72	Recreation	Cemeteries, playing fields, campus-like institutions, parks, schools.
22	73	Golf Courses	Golf courses.
23	80	Pasture	Pastures, including hay fields.
24	83	Agriculture	Row crops, orchards, vineyards, groves, horticultural businesses and large-scale ornamental plant production.
25	90	Forested Wetlands	Deciduous, evergreen and mixed forested wetlands, riparian and depressional wetlands, and cypress gum and other swamplands that are often associated with oxbows.
26	92	Salt Marsh	Non-forested saltwater or brackish wetland. Emergent saltwater wetland without a significant woody component.
27	93	Freshwater Marsh	Non-forested freshwater wetland. Includes abandoned rice fields.
28	98	Shrub Wetland	Coastal plain wetland with a closed, short stature woody shrub canopy.

30-meter resolution and subject to pre-processing steps for noise removal and geometric registration with terrain correction.

The strategy behind the mapping protocol was to reduce the dimensionality of the problem as much as possible by repeatedly subdividing the mapping process into smaller mapping problems. This was largely done by utilizing existing GIS data layers (hereafter referred to as coverages) of various land-cover features and tabular data in pre- and post-classification of the imagery (Hutchinson, 1982). All processing was done using ERDAS Imagine software version 8.1, first on UNIX and then NT platforms. Table 2 is a summary of the processing steps used to create the land-cover map. Each step is described below.

We subdivided and processed each Landsat scene on a county-by-county basis for each of Georgia's 159 counties (Georgia Department of Transportation, 1997a). Mapping on a county-by-county basis allowed us to pay particular attention to land-use and land-cover parcels unique to each county that can result from differences in local zoning laws, policies, and ordinances. The Georgia GIS Data Clearinghouse

TABLE 2
SUMMARY OF METHOD USED TO CREATE THE 1998 LAND COVER MAP OF GEORGIA

Step	Description
1	Divide the images into 159 county-based subsets.
2	Manually correct and augment power line and road coverages using DOQQs.
3	Create land-cover masks of forests, agriculture/mining, wetlands, and urban areas using the 1992 NLCD data (Vogelmann et al. 1992).
4	Apply unsupervised algorithms to county and class subsets to create preliminary county level land cover maps.
5	Manual edits for junkyards, cemeteries etc.
6	Edit and buffer roads to create coverage of suburban sprawl.
7	Mosaic county maps to create draft land cover map of the state.
8	Check state-wide mosaic for inadvertently unclassified pixels. Perform an unsupervised classification on groups of contiguous unassigned pixels containing 5 or more pixels. Subject groups of unclassified contiguous pixels with fewer than 5 pixels to a low-pass filter and classify according to the majority land cover type of their eight nearest neighbors.
9	State-wide single pixel corrections.
10	Subset state into six "ecoregions." Cluster-bust special cases (clearcut vs. agriculture).
11	Distinguish cropland versus pasture using the Census of Agriculture.

provided state-wide Arc/Info coverages of roads (Georgia Department of Transportation, 1997b), railroads (USGS, 1996), and power lines (Georgia Department of Transportation, 1997c), the last of which we manually corrected and augmented using 1993 black-and-white digital orthographic quarter quads (BW DOQQs) (USGS, 1993) prior to mapping. These three coverages were converted to 30-meter resolution grids and removed from each TM county subset. Each county TM dataset was again subset and four sets of unsupervised classifications (or ISODATA clustering) were performed per county. ISODATA clustering uses a maximum likelihood classification to assign pixels to a class based on their radiometric values. The classes are then assigned to a land-cover category by the image interpreter. The subsets were defined by simplifying and creating masks from the Georgia subset of the 1992 National Land Cover Dataset (NLCD) (Vogelmann et al., 2001): (1) forested areas, (2) agricultural and mining areas, (3) wetlands, and (4) urban areas.

The number of initial clusters created for each of the four data subsets averaged approximately 50 but varied according to the discretion of the interpreter depending on the size of the area in the county to be processed and the homogeneity of the land cover in that region. Each of the clusters resulting from the unsupervised classifications were interpreted using visual inspection of a combination of black-and-white

1993 DOQQs, the leaf-off and leaf-on TM data (as separates rather than composites), National Wetlands Inventory data (USFW, 1999), digital elevation models (USGS, 1979) and a state-wide coverage of polygonal hydrology features (Georgia Department of Transportation, 1997d). At this stage we treated agriculture and pasture land-cover types as a single category. Pasture and agriculture were separated at a later stage. Segmenting the processing this way allowed us to reduce the amount of noise in the dataset, correct errors in the NLCD data and compensate for land-use change that occurred between acquisition dates of the datasets. In particular, processing the forest categories separately allowed us to discern the different forest types (mixed, deciduous, and evergreen) as well as delineate areas that were either freshly clear-cut or regrowing from recent harvest. Processing both the agricultural and urban areas separately allowed us to discern areas that NLCD misclassified as agriculture or urban which were actually clear-cut and replanted to production pine forests. Processing the agricultural and urban areas separately also allowed us to determine formerly agricultural and forested areas now subject to urbanization.

In addition to using the leaf-on imagery as ancillary data for visual interpretation of clusters, processors, at their discretion, also used the leaf-on data in additional sets of unsupervised classifications, known as cluster-busts, to identify confused classes (Vogelman et al., 2001). Cluster-busting is a technique to iteratively classify spectrally "mixed" classes from remotely sensed data. An interpreter first steps through a traditional unsupervised classification and assigns as many land-cover classes to the spectral classes as possible. The remaining spectral classes which the interpreter could not identify are then used to mask the source data and are subject to another unsupervised classification. The process is repeated until all pixels are assigned to a land-cover class. During this process, the leaf-on imagery was particularly useful for discerning clear-cut areas both from agriculture/pasture areas and from deciduous forest in areas of the state with very sandy soils. Leaf-on data also helped create more accurate estimates of forest extents on ridges and their shadowed areas.

Mapping on a county-by-county basis also provided a reasonably sized subset for on-screen digitizing. We manually edited each working county map using an annotation layer that we created during the interpretation phases of the unsupervised classifications. The annotation layer consisted of features we could discern in the BW DOQQs: junkyards, confined animal operations, cemeteries, high-density residential areas (apartment complexes and duplexes) and golf courses. We also compared working maps against state-wide point coverages of mines (USGS, 1998) and airports (State Base Map of Georgia, 1998) and edited each map accordingly.

We experimented with several methods for mapping the extent and location of suburban sprawl and created the first state-wide GIS dataset of single-family residential areas (Epstein et al., 2002). In essence, we edited a state-wide vector road coverage (Georgia Department of Transportation, 1997b) to remove what we deemed were "nonresidential roads." We overlaid the road vectors on the TM image or BW DOQQs to select and remove larger roads that were obviously not suburban in character, including highways and roads in highly commercial, institutional or rural areas. New "typical" suburban roads that were short and curvy, clustered in developments, and those that contained cul-de-sacs that were not in the road coverage but visible in the imagery data were digitized and added to the coverage. The resulting suburban road coverage was then buffered by 45 meters on each side. Later, the center of the buffer was overwritten with the road coverage, indicating the location of roads embedded in suburban areas.

We stacked the results of each of the unsupervised classifications and their corrections, along with the suburban areas and the gridded linear features (roads, railroads, and utility lines) to create a working map of each county. After preliminary maps for each of the 159 counties were created, we mosaicked them and performed a number of state-wide and regional corrections. The state-wide mosaic was first checked for any pixels that, due to processor error, were not assigned to a land-cover category. All pixels not assigned to one of the land-cover classes listed in Table 1 were first "clumped" or grouped by delineating contiguous groups of unclassified pixels. Clumps were delineated using a "queen's case": any pixel on the ordinals or diagonals was considered a candidate for contiguous grouping. Groups containing five pixels or more were classified by another unsupervised classification while groups containing less than five pixels were subject to a low-pass filter and classified according to the majority land-cover type of their eight nearest neighbors.

We then performed a series of state-wide single pixel corrections for several land-cover classes. In particular, single pixels of clear-cut were recoded to agriculture/pasture when their surrounding eight pixel neighbors were agriculture/pasture. Likewise, single pixels of agriculture/pasture were reclassified to clear-cut when surrounded by clear-cut pixels. Finally, single clear-cut pixels were recoded to their neighbors when surrounded by either mixed forest, evergreen forest or deciduous forest.

The state-wide image was then subset into six regions, adapted from Keyes et al. (1995) and depicted in Figure 1: mountains, metropolitan Atlanta, Piedmont, fall line sandhills, Coastal Plain, and coast. At this point, we again subset the original leaf-off and leaf-on TM scenes and did an additional series of cluster-busts, this time using the regions within each full scene, rather than counties, as the initial mask. Within each region we performed cluster-busts on all patches of clear-cut forest to differentiate them from agriculture/pasture or deciduous forest areas. Additionally, we performed a cluster-bust over the deciduous forest category to identify wetlands and clear-cuts. This was particularly important for mountainous areas, some of which required multiple cluster-busts on the deciduous forest category. This is due to the fact that mountain areas that were either in shadow or contained an evergreen understory and were originally classified as evergreen forest needed further processing in order to correctly identify them as deciduous forests. Finally, in each region, we cluster-busted the wetland categories to determine upland deciduous forests, evergreen forests, marshes, clear-cut wetlands and occasionally

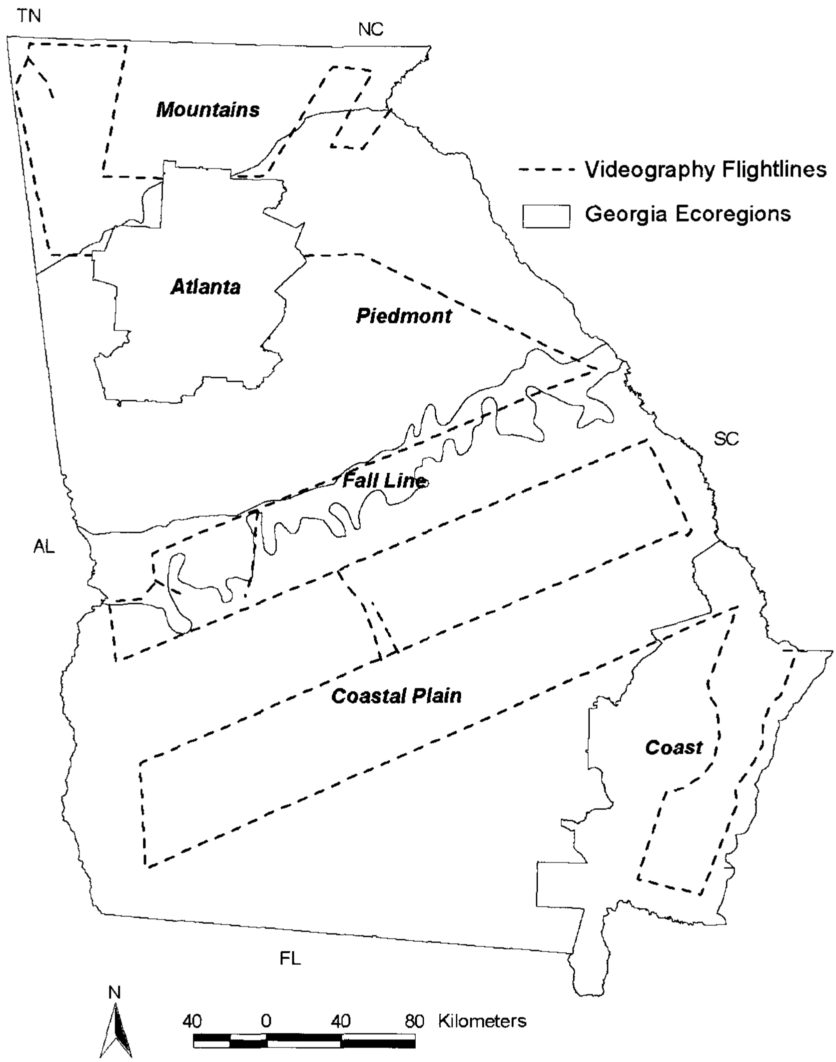

Fig. 1. Six regions of Georgia modified from Keyes et al. (1995) with flight line of aerial video data overlaid.

agriculture/pasture. These regional cluster-busts helped diminish the variation found across all of the county-wide land-cover maps due to the large number of image interpreters each separately interpreting the source data for each county.

In our final processing step we differentiated agricultural from pasture areas. We did this by consulting the USDA National Agricultural Statistics Service Census of Agriculture (1997). The census provides detailed statistics for the components of agriculture (cropland) and pasture for each county. We used data from the USDA Census Table 6, which shows land in farms according to use, divided into several categories. We used statistics for "total cropland," "cropland used only for pasture or grazing," and "pastureland and rangeland other than cropland or woodland pasture" in our classification. In the census, "total cropland" included cropland used only for pasture or grazing and hay fields; for the statewide land-cover map we placed hayfield acreage in the pasture category. We derived hay fields for the pasture category from USDA Census Table 28. To calculate the total acreage of agriculture or pasture for each county, we used these formulas:

Agriculture Acreage = Total Cropland – Cropland used only for pasture or grazing–Hay

Pasture Acreage = Cropland used only for pasture or grazing + Pastureland and rangeland other than cropland and woodland pastured + Hay

From these totals we calculated the total acreage of agriculture/pasture in each county and derived the percent composition for agriculture and pasture. To expedite this process, those counties that reported 85% or greater of their total agriculture/pasture acreage in agriculture were classified as agriculture; similarly, those counties that reported 85% or greater of their agriculture/pasture acreage in pasture were classified as pasture. For those counties with a mixture of agriculture and pasture (i.e., counties in which neither agriculture or pasture alone accounted for 85% of the agriculture/pasture acres in the county) we performed a second series of unsupervised classifications. We used the census data as it was provided on a county-by-county basis to determine the areas to cluster bust. However, we performed the cluster-busts on a region-wide basis. Figure 2 shows the areas in the state subject to an unsupervised classification to differentiate agriculture from pasture.

Accuracy Assessment Methods. In this paper we provide an accuracy assessment of the metropolitan Atlanta region derived from 1-meter resolution unpublished color infrared DOQQs (CIR DOQQs) provided by the Georgia GIS Data Clearinghouse. We also provide a preliminary accuracy assessment of the state as a whole based on low-altitude aerial videography.

The state-wide land cover map was subset into six ecoregions and each region was assessed independently (Fig. 1). Contiguous parcels of land cover were randomly selected and assessed based on interpretation of high resolution imagery. We assessed land-cover patches, rather than single pixels or points by "clumping" the land cover grid. The clumping followed a "queens case" (following diagonals and ordinals) that was classified as the same land-cover type as the pixel in question was included in the clump.

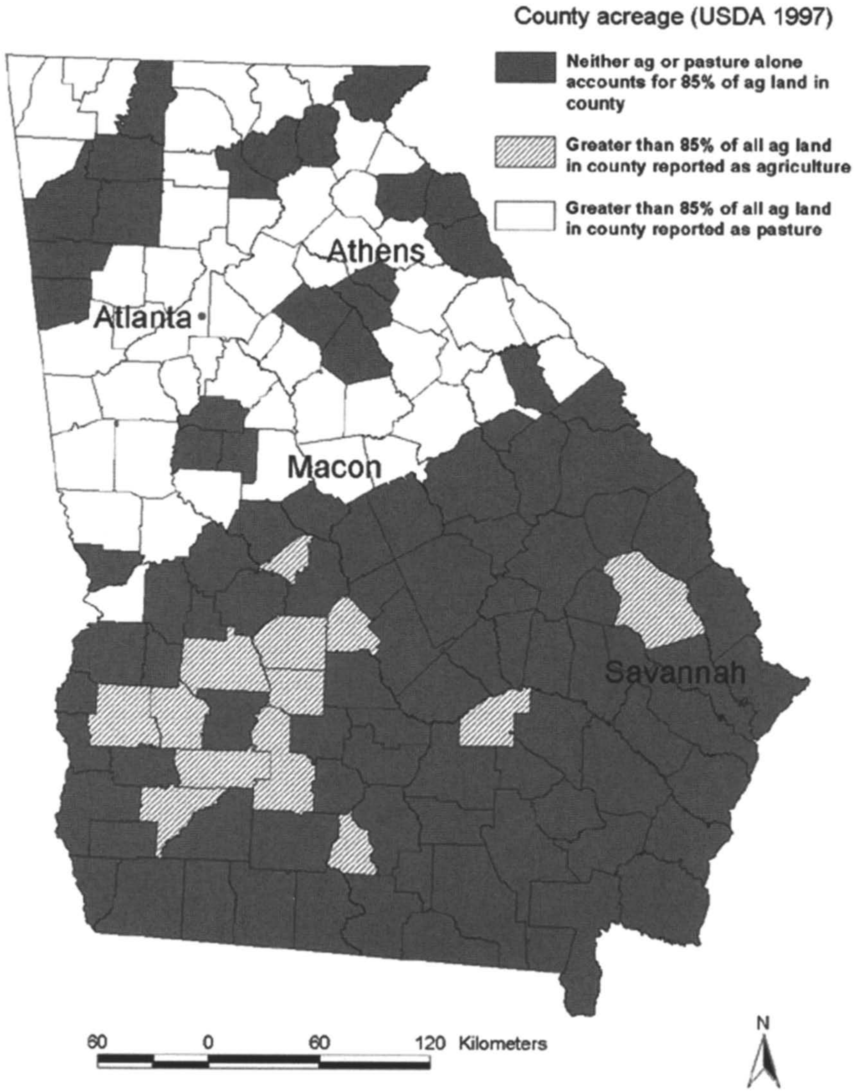

Fig. 2. Areas in the state subject to an unsupervised classification to differentiate agriculture from pasture (see text for explanation).

In the Atlanta region, we randomly generated points and then assessed the accuracy of the assigned land-cover classes for the clumps or parcels that contained the generated points. After generating a set of points, parcels that contained these points which were four pixels (120 × 120 meters) in size or larger were assessed

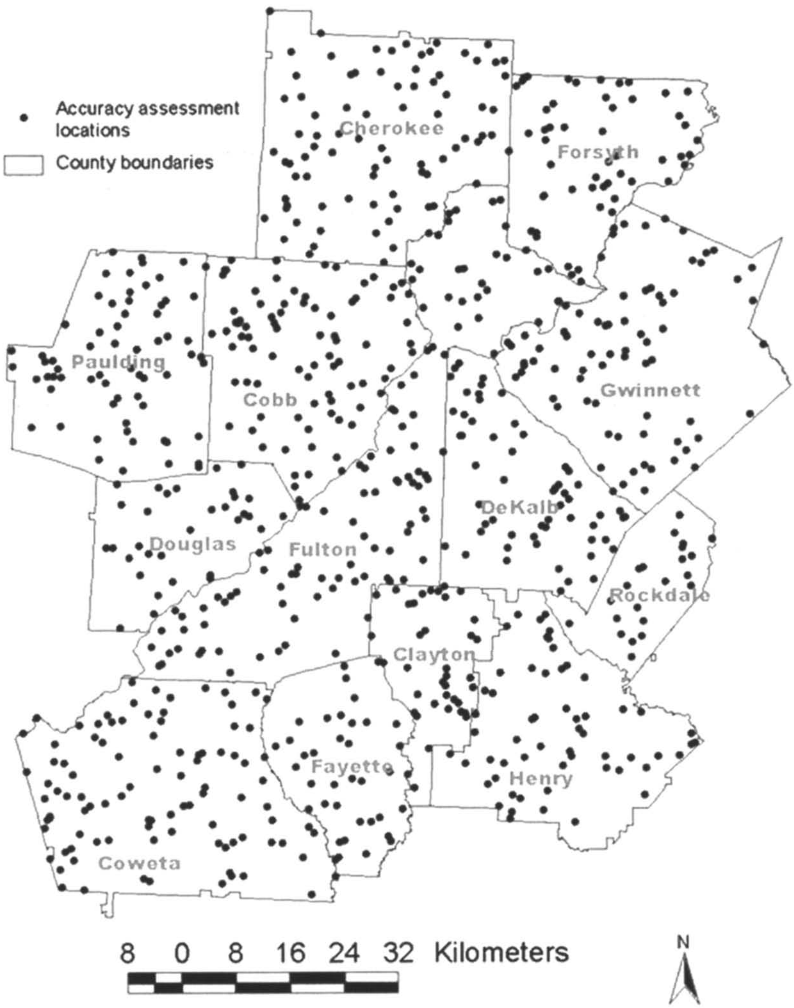

Fig. 3. Location of 807 accuracy assessment points in the Atlanta region.

using complete coverage of CIR DOQQs. In the remainder of the state, we assigned a unique identifying number to each parcel four pixels in size or larger that was covered under a flightline of low-altitude videography imagery. The parcel numbers were listed and a set of parcels to use in the accuracy assessment was randomly selected from the list without generating points.

It should be noted that larger parcels had a higher prior probability of containing a randomly generated point and of being covered by the videography flightline.

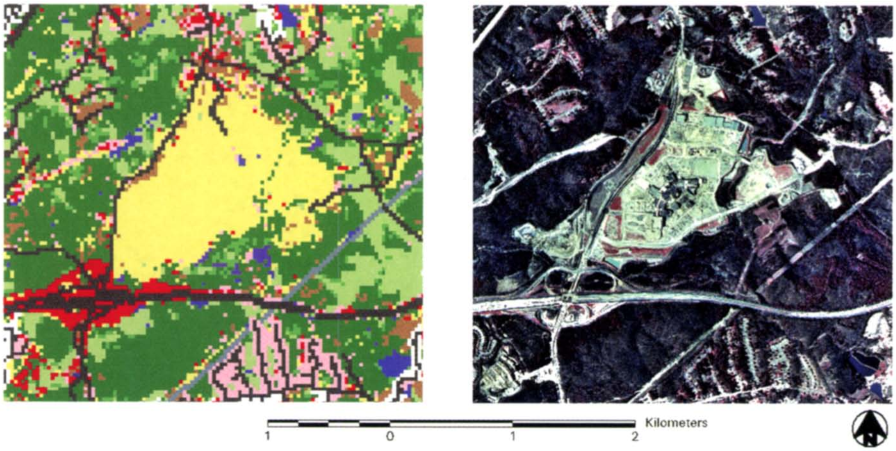

Fig. 4. Two views of a section of Gwinett county, Georgia; see figure 5 for map legend. (a) yellow area indicates construction site of clear-cut land in the 1998 land cover map and (b) resulting Mall of Georgia in 1999 CIR DOQQ.

Because larger parcels of a single land-cover type are more likely to be classified correctly, this may skew the results due to the fact that larger parcels may constitute a disproportionate component of the accuracy assessment.

According to standards set by the USGS National Gap Analysis Program (Crist and Deitner 2000), we calculated the total number of points required for accuracy assessment for each class following the work of Cochran (1977), who suggested that the number of sample points can be derived by:

$$n = \frac{p(1-p)}{s^2}. \tag{1}$$

Here, p is the presumed accuracy of the map, which we conservatively set at 50% and s is the standard error, which we set to 8%. Using these parameters Equation 1 indicates that 39 parcels should be sampled for each land-cover class. We rounded this number to 40. It should be noted the minimum number of points per class calculated using Equation 1 is less than the number recommended by Rosenfield et al. (1982), who recommend 60 samples per class for assumed accuracies of 50% and 10 % confidence intervals. Although there were instances in which 60 or more samples were obtained for some land-cover classes, constraints of the project did not allow for this level of sampling. This is due to the fact that the videography data did not always contain 40 parcels of each land-cover type in each region. While we assumed that the videography flightline was representative of the land-cover map as a whole, it did restrict the extent of the state which could be

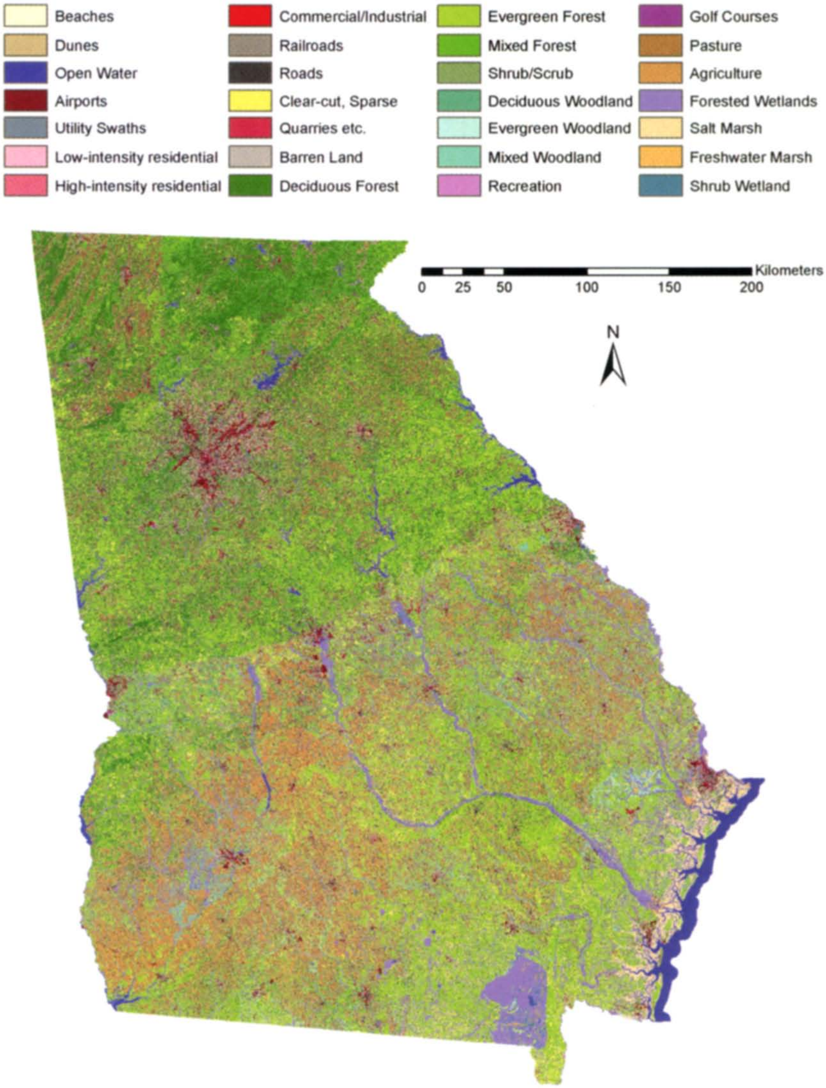

Fig. 5. 1998 Land-cover map of Georgia.

assessed. Ideally, for accuracy we would have liked to augment the videography data with ground-based surveys to collect the stated minimum assessment size; however, time constraints and the large area covered by the project made this prohibitive.

For these reasons, we decided to set the number of parcels to be assessed in each region by multiplying the number of land-cover classes in a region by 40 (not

TABLE
CONFUSION MATRIX FOR ATLANTA

Class:	V7	V11	V19	V20	V22	V23	V24	V28	V29	V31	V33
7	**3**	2	0	0	0	0	0	0	0	0	0
11	2	**17**	0	0	0	0	0	0	0	0	0
19	0	0	**7**	0	0	0	0	0	0	0	0
20	0	0	0	**8**	0	0	0	0	0	0	0
22	0	0	0	0	**71**	0	0	0	0	0	0
23	0	0	0	0	1	**7**	0	0	2	0	0
24	0	0	0	0	2	1	**26**	1	0	0	1
28	0	0	0	0	0	1	0	**5**	1	0	0
29	0	0	0	0	6	0	1	0	**86**	0	0
31	0	0	0	1	1	0	1	0	0	**9**	1
33	0	0	0	0	0	0	1	0	0	0	**8**
34	0	0	0	0	0	0	0	0	0	0	0
41	0	1	0	1	3	2	0	0	0	8	0
42	0	0	0	0	1	0	0	0	0	4	0
43	0	0	0	0	2	0	1	0	0	1	0
72	0	0	0	0	1	0	0	0	0	0	0
73	0	0	0	0	0	0	0	0	0	0	0
80	0	0	0	0	3	0	1	0	1	2	0
90	0	0	0	0	0	0	0	0	0	0	0
93	0	0	0	0	0	0	0	0	0	0	0
Total	5	20	7	10	91	11	33	6	94	24	10
Producers	60.00	85.00	100.00	80.00	78.02	63.64	78.79	83.33	91.49	37.50	80.00

[a]KHAT = 70.76; overall accuracy: 74.10.

all land-cover types are found in all regions of the state). For example, the land-cover map of the Atlanta region consists of 20 classes. With a required number of 40 parcels to assess per class we set a target number of sample points to 800 for that region. We then stratified the number of parcels to be assessed by the estimate of the extent of the land-cover class in the region. In Atlanta, a total of 807 random parcels, stratified by the mapped land-cover extent with all classes receiving a minimum of five parcels, were interpreted from CIR DOQQs. The location of sampling sites for Atlanta is shown in Figure 3 while Figure 4 illustrates the level of detail provided by both the land-cover map and the associated CIR photo. The number of parcels to assess in other regions of the state was likewise calculated.

3
USING FIRST CHOICE[a]

V34	V41	V42	V43	V72	V73	V80	V90	V93	Total	User Accur.	Class 2
0	0	0	0	0	0	0	0	0	5	60.00	7
0	0	0	0	0	0	2	0	0	21	80.95	11
0	0	0	0	0	0	0	0	0	7	100.00	19
0	0	0	0	0	0	0	0	0	8	100.00	20
0	6	6	3	0	0	1	0	0	93	76.34	22
0	0	1	0	0	0	0	0	0	11	63.64	23
0	0	0	1	2	0	1	0	0	35	74.29	24
0	0	0	0	0	0	0	0	0	7	71.43	28
0	0	1	0	0	0	3	0	0	97	88.66	29
0	6	1	1	0	0	1	0	0	22	40.91	31
0	0	0	0	0	0	0	0	0	9	88.89	33
4	0	0	0	0	0	1	0	0	5	80.00	34
0	**106**	4	10	0	1	1	7	3	147	72.11	41
0	5	**114**	2	0	0	0	0	0	126	90.48	42
1	21	21	**42**	0	0	3	5	0	97	43.30	43
0	0	2	0	**5**	0	1	0	0	9	55.56	72
0	1	0	0	0	**8**	0	0	0	9	88.89	73
0	2	1	0	1	1	**62**	0	0	74	83.78	80
0	10	1	1	0	0	0	**6**	2	20	30.00	90
0	1	0	0	0	0	0	0	**4**	5	80.00	93
5	158	152	60	8	10	76	18	9	807		
80.00	67.09	75.00	70.00	62.50	80.00	81.58	33.33	44.44			**74.1016**

As noted above, we used CIR DOQQs in the Atlanta region and aerial videography in the remainder of the state to determine the "true" land-cover type of parcels in the accuracy assessment. We acquired the high-resolution videography data over the state during a four-day period: October 31, and November 1, 2, and 3, 2000, using the system described in Slaymaker et al. (1996). The system consisted of two Canon GL1 Digital Video Camcorders, one wide and one zoom, wing mounted on a Cessna 172 flying an average of 1500 feet above sea level. The system was linked to a GPS which recorded location information on the audio track of the camcorder as the imagery was acquired. Imagery footprints covered 300 × 300 meters for the wide and 30 × 30 meters for the zoom images. An independent training set was used to familiarize the interpreter with the area and land-cover types. The training set

TABLE
CONFUSION MATRIX FOR ATLANTA

Class:	V7	V11	V19	V20	V22	V23	V24	V28	V29	V31	V33
7	**3**	2	0	0	0	0	0	0	0	0	0
11	0	**21**	0	0	0	0	0	0	0	0	0
19	0	0	**7**	0	0	0	0	0	0	0	0
20	0	0	0	**8**	0	0	0	0	0	0	0
22	0	0	0	0	**77**	0	2	0	1	0	0
23	0	0	0	0	1	**8**	0	0	2	0	0
24	0	0	0	0	2	1	**29**	0	0	0	0
28	0	0	0	0	0	0	0	**6**	1	0	0
29	0	0	0	0	6	0	1	0	**94**	0	0
31	0	0	0	1	1	0	1	0	0	**12**	1
33	0	0	0	0	0	0	0	0	0	0	**9**
34	0	0	0	0	0	0	0	0	0	0	0
41	0	0	0	0	1	2	0	0	0	5	0
42	0	0	0	0	0	0	0	0	0	1	0
43	0	0	0	0	2	0	1	0	0	1	0
72	0	0	0	0	0	0	0	0	0	0	0
73	0	0	0	0	0	0	0	0	0	0	0
80	0	0	0	0	1	0	1	0	0	1	0
90	0	0	0	0	0	0	0	0	0	0	0
93	0	0	0	0	0	0	0	0	0	0	0
Total	3	23	7	9	84	10	35	6	98	20	10
Producers	100.00	91.30	100.00	88.89	91.67	80.00	82.86	100.00	95.92	60.00	90.00

[a]KHAT = 784.61; overall accuracy: 86.37.

consisted of two random clumps per class, which resulted in 40 training samples per region. The interpreters had no knowledge of the land-cover classification corresponding to the parcel they were assessing. When using the CIR DOQQs, the interpreter overlaid the land-cover polygons (clump outlines) on the imagery. When using the videography data, the flight line was superimposed on the video image.

By their nature thematic maps condense infinitely variable, or continuous, land cover into a finite number of classes. Often, the interpreter could not readily distinguish differences between two classes during mapping or accuracy assessment. For example, low-density residential developments encompass single-family homes, lawns, and trees. Therefore, it is difficult to distinguish the boundary between forest or pasture and residential classes because they all have shared landscape elements.

4
FIRST OR SECOND CHOICE[a]

V34	V41	V42	V43	V72	V73	V80	V90	V93	Total	User Accur.	Class 2
0	0	0	0	0	0	0	0	0	5	60.00	7
0	0	0	0	0	0	2	0	0	21	100.00	11
0	0	0	0	0	0	0	0	0	7	100.00	19
0	0	0	0	0	0	0	0	0	8	100.00	20
0	5	4	3	0	0	1	0	0	93	82.80	22
0	0	1	0	0	0	0	0	0	11	72.73	23
0	0	0	1	1	0	1	0	0	35	82.86	24
0	0	0	0	0	0	0	0	0	7	85.71	28
0	0	1	0	0	0	0	2	0	97	96.91	29
0	4	1	0	0	0	1	0	0	22	54.55	31
0	0	0	0	0	0	0	0	0	9	100.00	33
5	0	0	0	0	0	1	0	0	5	100.00	34
0	**129**	4	5	0	1	1	7	3	147	87.76	41
0	5	**119**	1	0	0	0	0	0	126	94.44	42
0	8	13	**67**	0	0	2	3	0	97	69.07	43
0	0	1	0	**7**	0	1	0	0	9	77.78	72
0	1	0	0	0	**9**	0	0	0	9	100.00	73
0	1	1	0	1	1	**67**	0	0	74	90.54	80
0	4	1	0	0	0	0	**15**	0	20	75.00	90
0	0	0	0	0	0	0	0	**5**	5	100.00	93
5	156	144	77	9	10	75	18	8	807		
100.00	82.69	82.64	87.01	77.78	90.00	89.33	83.33	62.50			**86.3693**

Additionally, we acknowledge that this process uses remotely sensed imagery to verify a map based on remotely sensed imagery, and these data are at different scales. Our solution was to follow the work of Gopal and Woodcock (1994), Edwards et al. (1998), Vogelman et al. (1998), Zhang and Foody (1998), and Zhu et al. (2000). The interpreter was allowed to record two observations per land-cover clump. The processor recorded a first choice of land-cover category for each clump. When the land-cover type was uncertain or difficult to interpret, a second choice of land-cover category for each clump was noted. In addition, outside of the Atlanta region the interpreter recorded a "locational confidence parameter," indicating whether or not they felt certain they were able to locate the clump in question in the

TABLE
STATEWIDE CONFUSION MATRIX

Class:	V7	V9	V11	V19	V20	V22	V23	V24	V28	V29	V31	V33	V34	V41	V42	V43
7	**9**	1	3	0	0	0	0	0	0	0	0	0	0	0	0	0
9	1	**2**	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	2	0	**108**	0	0	0	0	0	0	0	3	0	0	0	1	0
19	0	0	0	**9**	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	**44**	0	2	0	1	0	0	0	0	0	0	0
22	0	0	0	0	0	**112**	1	7	0	4	1	0	0	7	7	4
23	0	0	0	0	0	3	**13**	1	0	2	0	0	0	0	1	0
24	1	0	0	0	0	5	2	**65**	1	0	3	1	0	1	2	2
28	0	0	0	0	1	0	1	0	**29**	2	1	0	0	0	0	0
29	0	0	0	0	0	6	0	1	0	**352**	1	0	0	0	1	0
31	0	0	1	0	1	7	0	7	0	0	**142**	2	0	16	32	6
33	0	0	0	0	0	0	0	3	0	0	0	**16**	1	0	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	**4**	0	0	0
41	0	0	1	0	1	5	2	1	0	0	24	0	0	**344**	34	69
42	0	2	7	0	1	9	0	0	0	0	41	0	0	24	**768**	41
43	0	2	0	0	0	2	0	1	0	0	12	0	1	67	55	**96**
51	0	0	0	0	0	0	0	0	0	0	3	0	0	2	5	0
61	0	0	0	0	0	0	0	0	0	0	4	0	0	1	7	0
62	0	0	0	0	0	1	0	0	0	0	2	0	0	0	4	1
63	0	0	0	0	0	0	0	1	0	0	6	0	0	1	7	1
72	0	0	0	0	0	1	0	1	0	0	0	0	0	0	2	0
73	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
80	0	0	0	0	1	12	0	3	0	1	16	0	0	7	15	1
83	0	0	0	0	0	1	0	6	0	0	20	0	0	3	7	2
90	0	1	3	0	0	2	1	0	0	0	16	0	0	23	40	23
92	4	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0
93	2	0	3	0	0	0	0	0	0	0	0	0	0	4	2	1
98	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	3
Total	19	8	129	9	49	166	20	97	30	361	296	19	6	501	990	250
Producers	47.37	25.00	63.72	100.00	89.80	67.47	65.00	67.01	96.67	97.51	47.65	84.21	66.67	66.66	77.58	38.40

[a]KHAT = 67.24; overall accuracy: 70.77.

video data. State-wide accuracy statements were created by combining the contingency matrices from each region of the state into a single matrix.

RESULTS. A "thumbnail" of the resulting landcover dataset is depicted in Figure 5. Confusion matrices, overall, user's and producer's accuracy rates and kappa statistics

5
USING FIRST CHOICE[a]

V51	V61	V62	V63	V72	V73	V80	V83	V90	V92	V93	V98	Total	User Accur.	Class 2
0	0	0	0	0	0	0	0	0	0	0	0	14	64.29	7
0	0	0	0	0	0	0	0	0	0	0	0	3	66.67	9
0	0	0	0	0	0	2	0	2	2	0	0	120	90.00	11
0	0	0	0	0	0	0	0	0	0	0	0	9	100.00	19
0	0	0	0	0	0	1	0	0	0	0	0	45	97.76	20
0	0	0	0	0	0	5	1	0	0	0	0	149	75.17	22
0	0	0	0	0	0	0	0	0	0	0	0	20	65.00	23
0	0	0	0	3	0	2	1	1	0	0	0	90	72.22	24
0	0	0	0	0	0	0	0	0	0	0	0	34	85.29	28
0	0	0	0	0	0	3	0	0	0	0	0	364	98.70	29
1	2	2	7	0	0	23	8	6	0	0	0	263	53.99	31
0	0	0	0	0	0	0	0	0	0	0	0	20	80.00	33
0	0	0	0	0	0	1	0	0	0	0	0	5	80.00	34
1	1	1	1	0	2	9	2	45	0	6	0	549	62.66	41
0	0	4	2	0	0	7	0	33	0	0	0	939	81.79	42
0	0	0	1	0	0	5	1	20	0	5	1	269	36.69	43
6	2	0	2	0	0	1	1	1	0	0	0	23	26.09	51
0	**8**	0	5	0	0	0	0	1	0	0	0	26	30.77	61
0	0	**7**	6	0	0	1	0	1	0	0	0	23	30.43	62
0	1	5	**12**	0	0	1	0	4	0	0	0	39	30.77	63
0	0	0	0	**9**	0	1	0	0	0	0	0	14	64.29	72
0	0	0	0	0	**10**	0	0	0	0	0	0	11	90.91	73
0	1	0	1	1	1	**279**	17	4	0	0	0	360	77.50	80
0	1	0	1	0	0	94	**196**	0	0	0	0	333	59.46	83
0	0	0	5	0	0	4	1	**281**	1	2	0	403	69.73	90
0	0	0	0	0	0	0	0	0	**43**	6	0	56	76.79	92
0	0	0	0	0	0	0	0	3	0	**12**	0	27	44.44	93
0	0	0	0	0	0	0	0	0	0	0	**23**	32	71.88	96
8	16	19	43	13	13	439	230	408	46	31	24	4240		
75.00	50.00	36.84	27.91	69.23	76.92	63.55	86.09	69.21	93.48	38.71	95.83			**70.7783**

for each class are provided in Tables 3 through 6. Tables 3 and 5 are assessments using only the first of the two possible interpretations (one-choice matrix). Tables 4 and 6 are assessments using either the first or second interpretation choice (two-choice matrix). Both of the state-wide matrices (Tables 5 and 6) are calculated using only the assessments in which the interpreter indicated they were confident about the

TABLE
STATEWIDE CONFUSION MATRIX USING

Class:	V7	V9	V11	V19	V20	V22	V23	V24	V28	V29	V31	V33	V34	V41	V42	V43
7	**11**	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	**3**	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	**115**	0	0	0	0	0	0	0	3	0	0	0	1	0
19	0	0	0	**9**	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	**45**	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	**124**	0	6	0	1	0	0	0	5	4	4
23	0	0	0	0	0	3	**15**	0	0	2	0	0	0	0	0	0
24	1	0	0	0	0	4	1	**72**	0	0	3	0	0	1	2	2
28	0	0	0	0	1	0	0	0	**32**	1	0	0	0	0	0	0
29	0	0	0	0	0	0	0	1	0	**360**	1	0	0	0	0	0
31	0	0	1	0	1	6	0	5	0	0	**193**	1	0	11	6	5
33	0	0	0	0	0	0	0	2	0	0	0	**18**	0	0	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	**5**	0	0	0
41	0	0	0	0	0	1	1	1	0	0	16	0	0	**444**	34	23
42	0	1	7	0	1	2	0	0	0	0	19	0	0	24	**843**	15
43	0	2	0	0	0	2	0	1	0	0	10	0	0	10	25	**189**
51	0	0	0	0	0	0	0	0	0	0	2	0	0	2	5	0
61	0	0	0	0	0	0	0	0	0	0	3	0	0	1	7	0
62	0	0	0	0	0	1	0	0	0	0	2	0	0	0	2	1
63	0	0	0	0	0	0	0	1	0	0	5	0	0	1	7	1
72	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
73	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
80	0	0	0	0	1	4	0	1	0	0	9	0	0	5	14	0
83	0	0	0	0	0	1	0	6	0	0	16	0	0	3	7	2
90	0	1	2	0	0	1	1	0	0	0	14	0	0	8	21	10
92	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
93	2	0	1	0	0	0	0	0	0	0	0	0	0	3	2	1
98	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	3
Total	17	7	128	9	49	149	16	96	32	364	299	19	5	528	961	256
Producers	64.71	42.86	89.84	100.00	91.84	83.22	83.33	75.00	100.00	98.90	64.55	94.74	100.00	84.09	85.93	73.83

[a]KHAT = 82.04; overall accuracy: 83.99.

location of the clump in the video image. Table 7 shows the composition of each land-cover type for each county and region in the state.

DISCUSSION. Not surprisingly, allowing the interpreter to have both a first and second interpretation of the land-cover type increased the accuracy of the map. This

6
FIRST OR SECOND CHOICE[a]

V51	V61	V62	V63	V72	V73	V80	V83	V90	V92	V93	V98	Total	User Accur.	Class 2
0	0	0	0	0	0	0	0	0	0	0	0	14	78.57	7
0	0	0	0	0	0	0	0	0	0	0	0	3	100.00	9
0	0	0	0	0	0	0	0	1	0	0	0	120	96.83	11
0	0	0	0	0	0	0	0	0	0	0	0	9	100.00	19
0	0	0	0	0	0	0	0	0	0	0	0	45	100.00	20
0	0	0	0	0	0	4	1	0	0	0	0	149	83.22	22
0	0	0	0	0	0	0	0	0	0	0	0	20	75.00	23
0	0	0	0	1	0	2	1	1	0	0	0	90	80.00	24
0	0	0	0	0	0	0	0	0	0	0	0	34	94.12	28
0	0	0	0	0	0	2	0	0	0	0	0	364	96.90	29
0	1	1	2	0	0	20	4	6	0	0	0	263	73.38	31
0	0	0	0	0	0	0	0	0	0	0	0	20	90.00	33
0	0	0	0	0	0	0	0	0	0	0	0	5	100.00	34
1	1	1	0	0	1	8	1	10	0	6	0	549	80.87	41
0	0	0	2	0	0	6	0	19	0	0	0	939	89.78	42
0	0	0	1	0	0	3	1	9	0	5	1	269	70.26	43
9	0	0	2	0	0	1	1	1	0	0	0	23	39.13	51
0	**10**	0	4	0	0	0	0	1	0	0	0	26	38.46	61
0	0	**12**	3	0	0	1	0	1	0	0	0	23	52.17	62
0	0	3	**16**	0	0	1	0	4	0	0	0	39	41.03	63
0	0	0	0	**12**	0	1	0	0	0	0	0	14	85.71	72
0	0	0	0	0	**11**	0	0	0	0	0	0	11	100.00	73
0	1	0	1	1	1	**317**	1	4	0	0	0	360	88.06	80
0	1	0	1	0	0	27	**269**	0	0	0	0	333	80.78	83
0	0	0	4	0	0	4	1	**336**	0	0	0	403	83.37	90
0	0	0	0	0	0	0	0	0	**52**	0	0	56	92.86	92
0	0	0	0	0	0	0	0	2	0	**16**	0	27	59.26	93
0	0	0	0	0	0	0	0	4	0	0	**23**	32	71.88	96
10	14	17	36	14	13	397	280	399	52	27	24	4240		
90.00	71.43	70.59	44.44	85.71	64.62	79.85	96.07	64.21	100.00	59.26	95.83			**83.9858**

could be due to (1) the confusion with related and similar land-cover classes, (2) the effect of "mixed pixels" when more than one land-cover category is present in a patch and the interpreter has to decide which one is more prominent or (3) the effect of misregistration of source datasets (Congalton, 1988; Edwards and Lowell, 1996; Foody, 1996). Errors associated with offsets due to data registration could have

TABLE 7
AREA (IN HECTARES) OF LAND COVER CLASSES BY REGION

Hectares	Coast	Coastal Plain	Fall Line	Piedmont	Mountains	Atlanta
Beach (7)	1,918.35	205.29	46.17	531.45	443.79	536.94
Dune (9)	1,480.32					
Open Water (11)	208,182.42	98,861.04	10,787.67	10,5118.65	14,892.66	22,671.00
Airport (19)	2,225.70	4,062.06	2,457.45	1,368.99	503.19	2,499.66
Utility (20)	3,516.57	22,063.59	2,532.78	13,294.89	5,666.40	3,914.37
LIR (22)	17,817.66	49,807.44	16,693.83	56,600.28	35,604.81	128,711.34
HIR (23)	321.03	536.04	818.01	639.99	127.53	9,356.67
Comm./Indust. (24)	10,727.82	20,637.27	9,221.13	16,075.71	11,476.17	42,301.71
Railroad (28)	3,438.90	13,207.14	2,269.89	4,518.63	3,019.32	3,399.75
Road (29)	84,188.70	398,673.72	51,018.30	189,169.56	85,077.54	118,262.16
CC/Sparse (31)	164,090.43	495,932.40	80,627.94	243,426.06	63,472.68	32,170.68
Quarries, etc. (33)	322.74	5,293.98	4,401.00	2,377.98	1,414.71	2,160.36
Barren (34)				181.17	327.96	505.98
Deciduous For. (41)	27,654.75	327,376.71	30,093.21	840,526.92	631,075.50	213,366.87
Evergreen For. (42)	436,840.74	184,4342.01	242,707.32	944,172.99	183,956.13	169,269.57

Mixed Forest (43)	24,718.77	353,545.29	17,725.23	306,119.97	203,318.01	149,376.69
Shrub (51)	1,806.21	17,525.70	18,025.20	340.83	265.32	
Deciduous Woodland (61)	3,318.03	15,004.44	30,514.14	15,533.37		
Evergreen Woodland (62)	19,012.32	48,341.25	748.08	63.09		
Mixed Woodland (63)	14,257.89	100,375.92	14,340.42	232.65		
Recreation (72)	484.83	2,280.33	1,349.10	1,741.41	1,185.75	6,812.01
Golf (73)	1,607.31	2,628.54	781.29	2,284.83	1,333.98	5486.58,
Pasture (80)	22,453.02	265,382.73	82,956.24	447,466.41	250,481.43	102,539.61
Agriculture (83)	43,005.06	1,779,745.95	58,568.04	62,972.10	2,206.35	
Forested Wetland (90)	388,697.31	1,157,234.22	119,515.68	81,386.55	2,433.51	32,043.78
Saltmarsh (92)	147,586.95	97.47				
Fresh. Marsh (93)	19,670.67	16,279.02			16.20	53.28
Shrub Wetland (98)	9,939.42	28,819.62	209.16		23.22	
Total	1,659,283.92	7,068,259.17	798,407.28	3,336,144.48	1,498,322.16	1,045,439.01

been accounted for using a majority filter for accuracy assessment, allowing the mapped location to be counted as correct if the ground truth were consistent with any of the areas surrounding the ground truth location. This procedure was allowed in Georgia's two previous land-cover maps of the state (GADNR, 1995; Yang et al., 2001). However, here we chose a more rigorous accuracy estimate. Comparisons with the two previous land-cover maps of the state are difficult due to the methods used in the various accuracy assessments. Metadata for the GADNR (1995) state-wide land cover map using 1988-1990 data sources note that while confusion matrices were not produced for their 12-class land-cover map, all classes achieved 85% accuracy rates. Yang et al. (2001) reported that the Southeast region of the National Land Cover Dataset created using 1993 data achieves an overall accuracy of 81% across 21 land-cover classes using a two-choice matrix. While not conclusive, our report here of 84% state-wide accuracy rate (using a two-choice matrix) over 28 land-cover classes is an indicator of performance at least on par with previous land-cover mapping of the state, with more detail than previously attempted.

Tables 3-6 show that land-cover classes derived primarily from manually digitizing imagery based on GIS data sources are more accurate than those derived from only the interpretation of remotely sensed data. In particular, high accuracy rates for GIS derived locations for airports, utility swaths, low-intensity residential areas, railroads, roads, quarries and mines all contributed to the high accuracy rates of the state-wide map. However, it should be noted that many of the GIS-based coverages were point locations, such as airports and quarries, and we digitized many of these areas to estimate the spatial extent of the feature. High-intensity residential areas, recreational areas, and golf courses also benefited from manual digitizing of DOQQs. Several non-GIS based categories had high accuracy rates, including barren land, deciduous forest, evergreen forest, pasture and non-forested freshwater wetlands.

State-wide error rates are suspect because, to date, no analysis has been done which quantifies the extent to which agreement or disagreement between mapped land-cover and interpreted video imply a correct mapping. For example, we performed a preliminary analysis and found that when the classified video and mapped land cover were not in agreement, there were instances in which interpretation of the video data was in error; a correct interpretation of the video could increase accuracy rates. There was no obvious pattern of video misclassification across land-cover type. Similarly, it is unclear how often the interpreted video and mapped land cover were in agreement but both were in error. The sample size for our preliminary analysis was small and needs a more rigorous examination. In addition, potential users of the data should also be aware that state-wide assessment numbers are not weighted by the extent of each region in the state.

Finally, it appears that the ability to provide a first or second choice in land-cover interpretation, irrespective of their confidence in the location of the patch in question, appeared to yield a larger increase in accuracy than taking one choice in areas where the interpreter was confident about the location of the land-cover patch. This suggests that the errors in the dataset arising from poor class distinctions in the classification schemes, "mixed pixels," or video interpretation may be more prominent than errors due to misregistration.

CONCLUSIONS. In this paper we have described a labor intensive multisource and multiscale method for land-cover mapping used to create the most detailed map of Georgia to date with accuracy performance at least on par with previous attempts.

Not surprisingly, land cover derived from on-screen digitizing and GIS data sources tended to outperform those derived from Landsat 5 TM data and the classes derived from the Landsat 5 TM data, with the lowest accuracy rates highlighted the difficulty in mapping physical or structural characteristics of vegetation from remotely sensed data. It will be interesting to see if future updates of this map benefit from both the extent of the manual digitizing done for this project as well as the use of Landsat 7 ETM+ data which is spatially and radiometrically superior to the Landsat 5 TM sensor (Masek et al., 2001).

The dataset reported was intended to be a preliminary product used by the Georgia Gap Analysis Program to create a map of vegetation alliances (or plant communities) in the state. The accuracy assessment presented here will be extended using more conventional ground-based survey methods for the new alliance level dataset. To obtain copies of the dataset contact the Georgia GIS Data Clearinghouse: http://www.gis.state.ga.us/Clearinghouse/clearinghouse.html; Information Technology Outreach Services, University of Georgia, 1180 E. Broad Street, Suite 2076, Athens, Georgia 30602-5418; Phone: 706-542-0246; Fax: 706-542-6535.

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