Thematic Mapper and SPOT Integration with a Geographic Information System*

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ABSTRACT: The integration of remote sensing and geographic information systems GIS is essential for effective resource management. The volume of remote sensing imagery for managing a provincial resource is such that one must use digital image analysis systems. By combining remote sensing image analysis and geographic information systems, resource managers can have timely and accurate knowledge of a renewable resource. In addition, satellite imagery with higher resolution can be used to update road network information in a GIS for a city. There are, however, several scientific and technical problems that reduce the success of this integration.

This paper describes several integration problems and the Landsat Digital Image Analysis System (LDIAS) used at the Canada Centre for Remote Sensing (CCRS). Experiments have been conducted integrating a forestry geographic information system for the province of British Columbia with LDIAS and SPOT imagery with city information. Some of the difficulties encountered require the use of non-algorithmic solutions which use symbolic reasoning.

INTRODUCTION

A GEOGRAPHIC INFORMATION SYSTEM (GIS) is a data base system for manipulating digital spatial and thematic data. Increasingly, such systems are being used in developed countries to aid in resource management and computer-assisted mapping. A GIS has four components (Marble *et al.*, 1984): a data input subsystem, a data storage and retrieval subsystem, a data manipulation and analysis subsystem, and a data reporting subsystem. The data inputs are usually spatial and thematic data derived from a combination of existing maps, aerial photographs, and manual interpretations of remotely sensed imagery. With the data manipulation and analysis subsystem, the user can define spatial procedures to generate derived information, such as the best location economically to harvest a resource such as timber. The data reporting subsystem is used to generate reports in tabular form, digital displays, or maps. Because the input data on which a GIS is based become obsolete quickly, it is essential to update periodically the GIS with new spatial and thematic data. Remote sensing is often the most cost effective source for these updates.

The information content from large quantities of remotely sensed images, such as those derived from Landsat and SPOT satellites, is best extracted using computer systems designed for this purpose. Such a system is called an Image Analysis System (IAS). An IAS has five elements: data acquisition, preprocessing, analysis, accuracy assessment, and information distribution. The usual input for a remote sensing IAS is a computer compatible tape containing a digital image acquired at a remote sensing satellite tracking station. For some agencies, corrections for sensor-related radiometric and geometric errors will have been performed at the tracking station. However, the preprocessing subsystem in an IAS usually can perform additional radiometric, geometric, and atmospheric corrections. These specialized corrections, not normally provided by image production systems, include corrections for radiometric distortions due to view angle, geometric compensation for terrain relief, projection of imagery to a variety of map projections, and refined atmospheric corrections with the aid of meteorological information. The result is to give an image as free from errors as possible. This preprocessed image is then used for training and classification. In a system integrating GIS and IAS, one could use the GIS thematic data and attributes to guide the selection of suitable training areas. Often, the thematic polygons in a GIS contain several spectral and spatial classes. It may be necessary, therefore, for the user to have manual control of the selection of training areas. After classification, the accuracy is assessed using theoretical estimation based on class statistics or selected test sites derived from ground reference information, or both. The derived information can be distributed in the form of tables, maps, computer tapes, or images. The Landsat Digital Image Analysis System (LDIAS) of CCRS includes all of these image analysis functions plus the GIS components described above.

THE LANDSAT DIGITAL IMAGE ANALYSIS SYSTEM (LDIAS)

When the United States launched the Landsat-4 remote sensing satellite, the CCRS began receiving data from the two sensors, the Thematic Mapper (TM) and the Multispectral Scanner (MSS). The TM sensor produces images with some ten times more data than the MSS. The CCRS Image Analysis System (Goodenough, 1977), designed for MSS analysis, could not handle a full TM scene. Larger processing and storage power were required, as well as new functions for analysis with higher spatial resolution imagery.

In 1982, CCRS received approval to begin a research and development project for TM analysis. The objective was to conduct this research and create a new image analysis system, the Landsat Digital Image Analysis System (LDIAS), which would enable us to analyze a full TM scene (185 km by 185 km) into 32 classes within 8 hours, while permitting the integration of map-based data. In addition, LDIAS would have to support airborne optical scanners and synthetic aperture radars. From this general objective there developed many activities which led to the system architecture and functionality described below.

SYSTEM ARCHITECTURE

The architecture of LDIAS is shown in Figure 1. The primary image analysis computer, LDIAS1, is a Digital Equipment Corporation (DEC) VAX 11/785 with 16 megabytes of memory and 2.6 gigabytes of magnetic disk storage. There are four additional optical disks (write-once, read-many) totaling 3.2 gigabytes. There are four image displays, each with 512 by 512 pixels displayed: two Gould Deanza IP8500 displays (12 channels), and two Dipix (ARIES-II and ARIES-III) displays (four channels). All terminals connect to a Gandalf Compacx switching network which permits one to work on any computer from the same terminal. The next largest computer in LDIAS is LDIAS2, a DEC VAX 11/780 with eight megabytes of memory and 2.2 gigabytes of magnetic disk storage. This Map Input/Output subsystem

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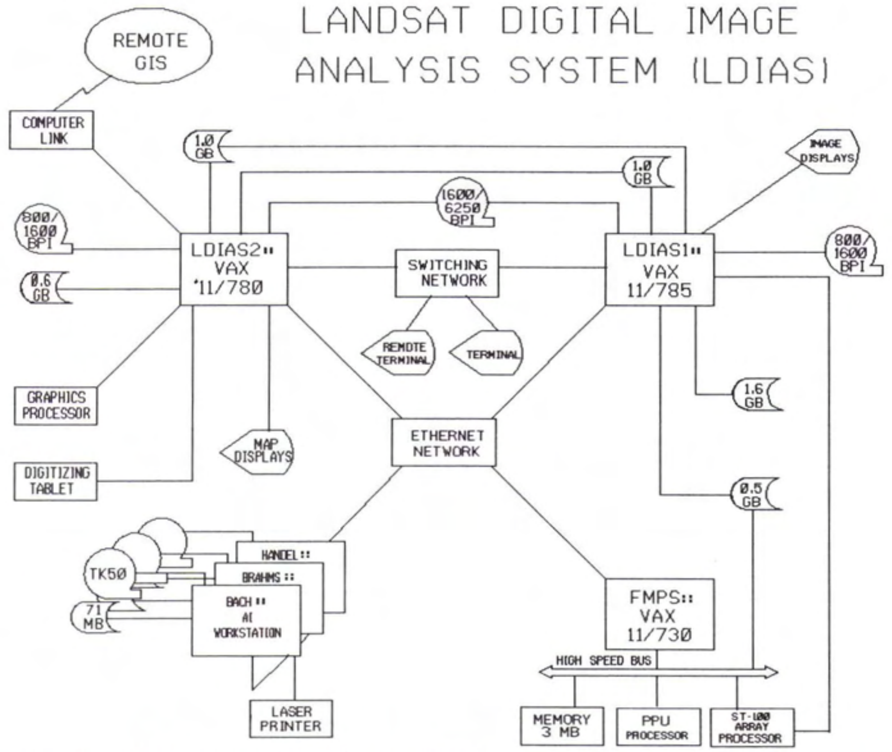


FIG. 1. The Landsat Digital Image Analysis System (LDIAS) is used to support research and development in information extraction methods and applications. Over one million lines of FORTRAN code are installed in LDIAS. This software supports GIS integration with satellite and airborne sensors in the visible, infrared, and microwave regions.

was acquired from Intergraph Corporation. There are two color Interact map displays, each with two screens and digitizing tablets. To speed graphics processing, there is a Graphics Processor. One can connect to a remote GIS through an automatic dial-up device. LDIAS1 and LDIAS2 are connected together by means of an Ethernet network, two dual-ported disks, and a dual-ported tape drive unit. The two computers are not clustered together because (a) this was not an available product from DEC when the project started; and (b) the two computers use different operating system versions. The VMS operating system for LDIAS1 is changed with each release from DEC; that for LDIAS2 is changed with less frequent releases from Intergraph Corporation.

The third computer in LDIAS is a DEC VAX 11/730 which is the control computer for the Fast Multidimensional Processing System (FMPS). FMPS is the batch production system for full scene analysis. Interactive analyses are conducted on LDIAS1 and LDIAS2. FMPS was developed for CCRS by Canadian Astronautics Limited (CAL). FMPS has an Aptech 24-megabyte-per-second bus with a mass memory of three megabytes. Attached to this bus are the VAX 11/730, a 100-megaflop array processor (Star Technologies ST-100), a CAL Parallelepiped Preprocessor Unit (PPU), and two 256-megabyte disk drives which are dual-ported with LDIAS1. FMPS also has an Ethernet connection to the other computers.

Although not formally part of the LDIAS project, there are three DEC AI VAX stations connected to the same communications network. Each workstation has a 71-megabyte disk, a tape cartridge unit, and a bit-mapped display. These workstations use VMS as the operating system and support rapid development of expert systems in PROLOG or LISP. The expert systems which control LDIAS make use of this hardware.

The system architecture is intended to support the software functions briefly described below.

MAJOR SOFTWARE FUNCTIONS

The LDIAS is used to support research and development in remote sensing, computational vision, sensor development, and GIS integration, and to support the development of applications for renewable and nonrenewable resources. There are two workstations, each of which consists of an image display, a map display, a digitizing tablet, and two terminals. The workstation is operated for applications development by a team of two: a resource expert (user) and an analyst. The analyst is knowledgeable about the software, hardware, and analytical procedures.

The primary remote sensing inputs to LDIAS are geocoded TM computer compatible tapes (CCTs) from the MOSAICS system (Link *et al.*, 1985). These geocoded products correspond to four 1:50,000-scale map sheets in the Universal Transverse Mercator (UTM) projection. The TM scan lines are oriented east-west with north at the top of the corrected image. The image has been resampled on a regular 25-m UTM grid with a 16-point truncated sinc function. The SPOT images are also MOSAICS' products with a UTM projection and sample sizes of 12.5m for three-band, MLA imagery and 6.5m for panchromatic, PLA imagery. Digital maps come from provincial agencies or from the Surveys and Mapping Branch of our department.

The LDIAS software is run using a supervisor program. The user is presented with the Master Menu shown in Table 1. Each item in this Master Menu is itself a menu of tasks, or menus, or both. The user can obtain help in the form of on-line documentation at any step, even if he or she is in the middle of a program. All user responses to program queries can be recorded and subsequently used to produce an automatic sequence of task executions; that is, a batch command file. A man-machine interface was developed to support bilingual dialog (English and French), scrolling of user sessions on the terminal, inter-

TABLE 1. LDIAS MASTER MENU

Label	Description
A	Input
D	Radiometric Corrections
F	FMPS - Fast Multidimensional Processing System
G	Geometirc Corrections
I	Generate Spatial Texture
J	Acquire Spectral Signatures
K	Perform Segmentation
L	Classify and Cluster
M	Map Input/Output
N	Filter and Enhancement
O	Diagnostics
Q	Accuracy Assessment
S	Classification Filtering
U	Utilities
Z	Output

TABLE 2. FMPS PROCESSING PERFORMANCE

TM Image: 8000 lines by 8000 pixels and 7 channels.	
Function	Time
Histogram	10 minutes
Lookup Tables	20
Ratios (seven)	20
Parallelepiped classification (256 classes)	35
Maximum Likelihood Classification (32 classes)	150 minutes

active or batch modes, standard prompts, on-line help, and effective error recovery. An image data base structure, UNIDSK, was implemented to support images with 8000 by 8000 pixels, and 21 channels, each of which could be quantized from one bit to 128 bits in integer or real formats. In order to support our research, flexibility in the software was very important. LDIAS currently contains more than one million lines of code, documented and debugged.

The structured design and analysis methodology of Gane and Sarson (1977) was used for linking research activities and software development. Logical data flow diagrams for all of the software are on-line. The software is managed through a central computer repository. A major part of the documentation is automatically extracted from software for on-line help and generation of technical memoranda. In this way, we avoid most incompatibilities between software versions and corresponding documentation versions. For some pixel processing operations, we have found a standard program shell or skeleton useful. This image processing skeleton is integrated with an editor with knowledge of the computing language, FORTRAN 77. Through these techniques, the LDIAS project team's software productivity has been greatly enhanced.

An analysis project begins with the user specifying his/her desired outputs. This specification establishes the most probable analysis procedure. The TM or MSS imagery is read in, together with digital terrain models if they exist. Corrections can be applied for radiometry, atmospheric effects, viewing geometry, image scale, and output projections. Identification of training and test areas can be made on the display of the TM imagery, from paper maps or photographs, or from GIS files. For TM and SPOT, it is essential to utilize spatial features, in addition to the spectral features. Segmentation can be performed using these spatial and spectral features. Parametric and non-parametric, supervised or unsupervised, classifiers can be used. The LDIAS supports up to 256 classes at any one time for remote sensing imagery. There is a wide range of enhancement tasks available. The outputs may be digital updates to the GIS, digital or paper maps, area summaries, or photographs. At each stage in the user session, the user or analyst can assess the accuracy. The theoretical estimate of the classification accuracy to be achieved, for example, can be derived from the training samples. The actual accuracies obtained after an analysis session can be found using the test areas.

For a TM data set of 8000 by 8000 pixels and seven channels, the processing times on LDIAS1 and LDIAS2 are too long. Therefore, we use the FMPS to reduce the analysis time. Table 2 is a summary of the FMPS performance for selected functions. These functions are (1) finding the histogram of all channels of a full TM scene; (2) applying lookup tables; (3) computing ratios (normalization corresponds to each channel being divided by the sum of all channels); (4) parallelepiped classification, up to 256 classes; and (5) maximum likelihood classification, up to 256 classes. These processing times are sufficiently fast that the LDIAS project can achieve its objectives.

INTEGRATION EXPERIMENTS

INTEGRATION OF REMOTE SENSING AND GEOCODED DATA

Figure 2 is a pictorial example of the integration of remote sensing with other geocoded data. Stored in raster or grid form, one has the Landsat or SPOT and aircraft sensor data, digitized aerial photography, and topography. Thematic data are represented by layers or levels of polygons corresponding to a given theme or class. Finally, one has point data corresponding to meteorological measurements. This figure shows that the integration of GIS and IAS must deal with different data representations and must provide geometric correspondence or registration between the different data sets.

There are two approaches that one might take to integrating a forestry GIS and remote sensing. To simplify the data representation and labeling, one could develop a new GIS having the same raster structure as the image data with classes compatible with those detected spectrally. Given that one Landsat Thematic Mapper (TM) image is more than 300 megabytes, this raster-based unification could lead to substantial improvements in performance.

A second approach would be to use an existing GIS, usually in vector form, with raster image data and classes as specified by the resource manager. In Canada, resource management agencies have, over many years, made large expenditures building geographic information systems. In British Columbia, for example, more than 3000 forest-cover maps, out of 6000 possible, are in digital form in a forest inventory GIS. Agencies with large databases are unwilling to change to a new GIS representation in order to make use of remote sensing data. Therefore, remote sensing image analysis systems in Canada must interface to existing GIS. This and other differences lead to several problems given in the next section.

One way of exchanging geographic information among several GIS is to use an accepted standard for information exchange. In several countries there are attempts to define and implement GIS exchange formats. Suppliers of GIS have also specified exchange formats. In Canada, an early attempt was made by several federal departments to produce a GIS exchange format, the Spatial Data Transfer Format (Goodenough *et al.*, 1983). This format is a member of the Landsat Ground Station Operators' Working Group (LGSOWG) family of tape formats for remote sensing imagery. Mapping agencies in Canada are cooperating to develop a more extensive format for topographic data exchange. Even between GIS from the same supplier, there are labeling incompatibilities between different GIS. There needs to be, but currently does not exist, an international standard for geographic information exchange if countries are to share more easily environmental information in order to monitor global changes.

PROBLEMS INTEGRATING IAS AND GIS

Most GIS use vector storage to represent thematic classes. Image analysis systems use raster storage. An integrated GIS-

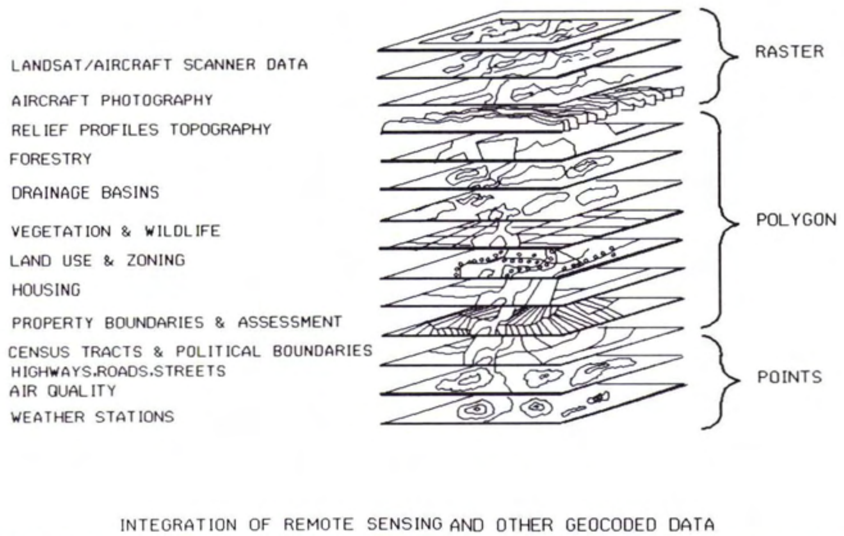


FIG. 2. This is a pictorial example of the integration of remote sensing with other geocoded data. For such an integration, one must deal with different data representations and distributions, and must provide geometric correspondence or registration between the different data sets.

IAS must have software to convert from raster to vector, and vice versa. The grid resolution of the remote sensing image may not allow one to reproduce the fine structure of the GIS.

A GIS can have thousands of classes. For example, a forest cover map can have more than 1800 different classes. Most IAS handle less than 256 classes because the most popular classification algorithms operate with a cost proportional to n^2 where n is the number of classes. The LDIAS analysis subsystem is restricted to 256 classes. For forestry analysis on LDIAS it is necessary to combine classes based on ranges of attributes, such as slope, stand density, species, or site quality.

The geometric accuracy of the resource GIS is probably worse than current, corrected remote sensing data. We have found that geocoded Thematic Mapper data with an IFOV (instantaneous field of view) of 30 m and a resampled pixel size of 25 m are more precise geometrically than several geographic information systems. This is also the case for SPOT imagery. This is, in part, a result of the much greater synoptic coverage of a Landsat scene (185 km by 185 km). The GIS are usually derived from maps or combinations of maps and aerial photography. The maps have been derived using aerial photography. It is not uncommon for stereo models derived from the aerial photography to have displacement errors in rugged terrain where there are few man-made features.

Another problem is that the GIS class labels may not correspond to detectable remote sensing classes. For some classes, the satellite data we are using do not have sufficient resolution to detect, for example, small creeks overgrown with trees or insect damage for individual trees. Some classes require the use of contextual knowledge; for example parks, recreation areas, cemeteries, etc. Some classes easily identified with a remote sensing IAS may not correspond to classes desired by the resource manager, such as a combination of several forest species which form a single spectral group.

Even if the GIS and IAS are in grid or raster form for analysis, the methods of interpretation to choose are dependent upon the sets of classes being examined. A few spectral channels may suffice to identify major water bodies, but many spectral and spatial features may be needed to classify some forest species. Optimization is important here because the processing and storage costs can rise dramatically with the number of channels used in the analysis.

INTEGRATION METHODOLOGY

The Canada Centre for Remote Sensing, with the support of the British Columbia Ministry of Forests and Lands (BCMOFL), has conducted a series of forest clear-cut recognition experiments to demonstrate the feasibility of updating forest inventory maps with imagery data. Mr. Frank Hegyi, Director of the Planning and Inventory Branch, BCMOLF (Hegyi and Quinet, 1983), supports these experiments by providing the necessary digital inventory maps, associated map labels, documentation, and interpreted aerial photography. CCRS uses this information to extract forest-cover change information from satellite multispectral images, and then updates the geographic information. The updated information is returned to BCMOFL for evaluation. The experiments have been so successful that BCMOFL now uses

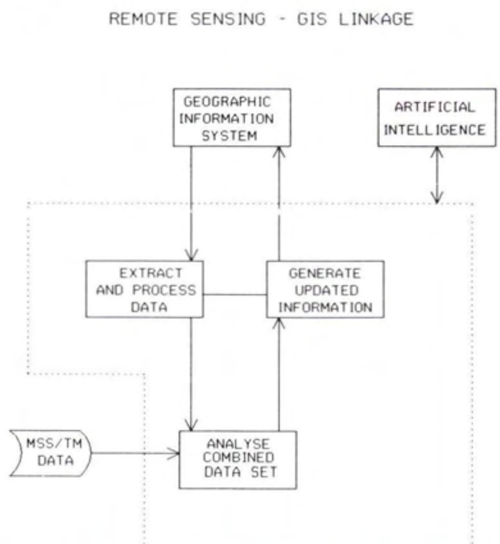


FIG. 3. This is an overview of our remote sensing analysis and GIS integration approach. The boxes within the dotted line are expanded in Figures 4,5, and 6. The dotted line shows where the emphasis is placed in our expert system, the Analyst Advisor.

LDIAS software and the procedures outlined below on its own computers.

The overview of the remote sensing analysis and GIS integration approach is shown in Figure 3. The GIS is assumed to be remote; that is, the GIS of BCMOFL. The three main processing steps are (1) extract and process the GIS data; (2) analyze the combination of the remote sensing imagery and geographic information; and (3) generate the updated geographic information. The dotted line in Figure 3 shows the intended application area of our artificial intelligence research. The elements of Figure 3 are expanded upon in Figures 4, 5, and 6.

The forest inventory digital maps used are at a scale of 1:20,000 covering areas of 12.6 km by 12.6 km. The maps are in the UTM projection and are based upon the topographic maps produced by British Columbia's Survey and Mapping Branch. The attribute information of these maps are stored separately in a database at BCMOFL and are sent to CCRS as label files. An overview of the geographic information extraction and processing is shown in Figure 4. Once these digital maps and label files are loaded onto LDIAS2, the attribute information is extracted and inserted into an attribute information database (DMRS file) which is attached to the maps graphically. The maps are displayed and the forest classes of interest are identified. The maps usually contain more than 256 classes. Therefore, the forest classes must be grouped based on less important attributes. This has not been a limitation yet, but it will be. For that reason, LDIAS is being changed to handle a much higher number of classes. The selected forest and non-forest classes are then converted to raster or grid representation. The gridded geographic information is used subsequently for training and to mask out forested and non-forested areas of the images.

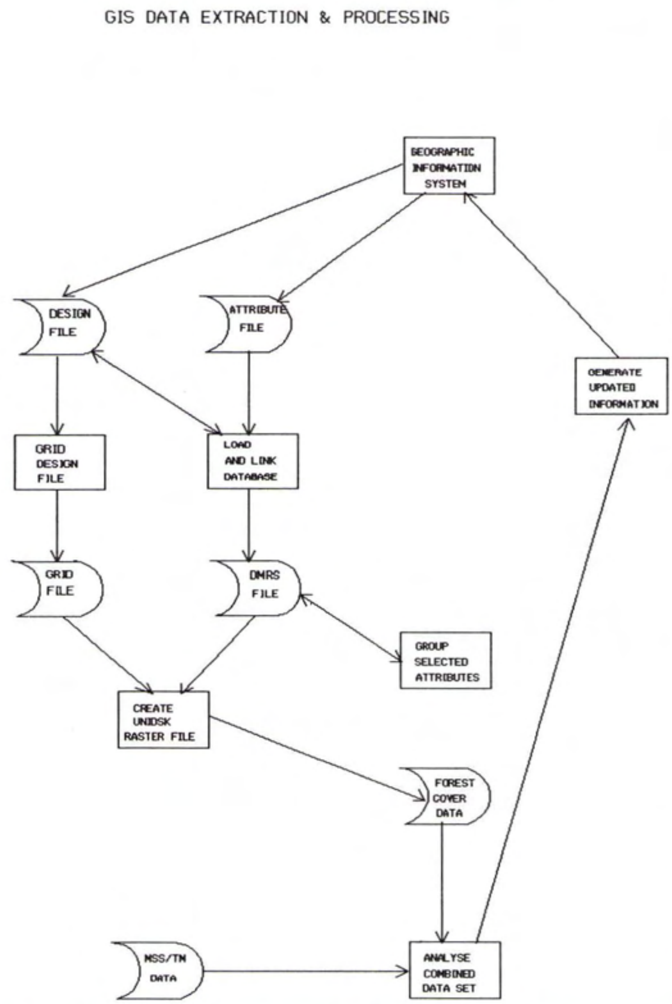


FIG. 4. The procedure for geographic information extraction and processing is shown. The increasing attributes and graphics are linked. A raster file containing the classes of interest (=≤256) is produced and merged with the remote sensing imagery.

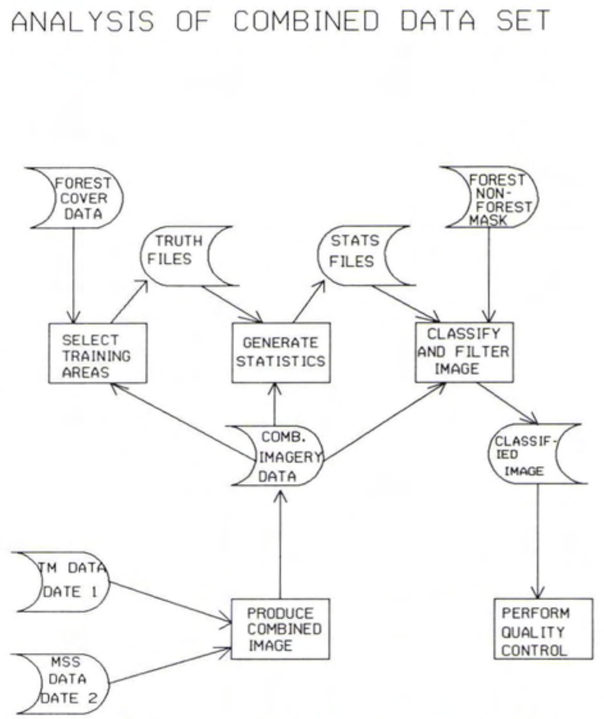


FIG. 5. This figure shows the procedure for analyzing the combination of GIS and multisensor, multi-data imagery (please refer to the text).

The forest clear-cut detection is done with single-date or multitemporal images from the MSS or the TM sensor, or both. Figure 5 is a summary of the analysis methodology for multi-date, multi-sensor imagery. The images have been processed on MOSAICS to eliminate radiometric errors and are rectified to the Universal Transverse Mercator (UTM) projection. Rectification is performed by acquiring ground control points from the image and calibrating them to a UTM map. The map is produced by the Surveys and Mapping Branch, Department of Energy, Mines, and Resources. These maps are the standard used for image rectification at CCRS. The map scale is 1:50,000, and the image is rectified to a pixel size of 25 metres. The gridded forest information is combined with the remote sensing imagery.

Training areas can be selected manually based on forest polygon classes or more recent ground information. The training or truth files are used to generate the statistics required by subsequent classifiers. The combined data set is classified within the forested regions (based on the forest - non-forest mask). The classification is filtered using a spatial, contextual filter (Goldberg and Goodenough, 1976). The classified image is assessed for accuracy.

The GIS is updated following the procedure outlined in Figure 6. The classified image is converted to another grid format. This grid file is changed to a vector representation with smooth polygon boundaries and linkage to the DMRS database of attributed information. The attributes are placed in a label file, the graphics in a digital map file, and the two files sent to BCMOFL for evaluation. In the next sections we report on our experiments and the results obtained as examples of GIS and IAS integration.

FORESTRY EXPERIMENTS

The particular imagery used for the experiment reported here is a Landsat-5 TM image of an area near Cranbrook, British

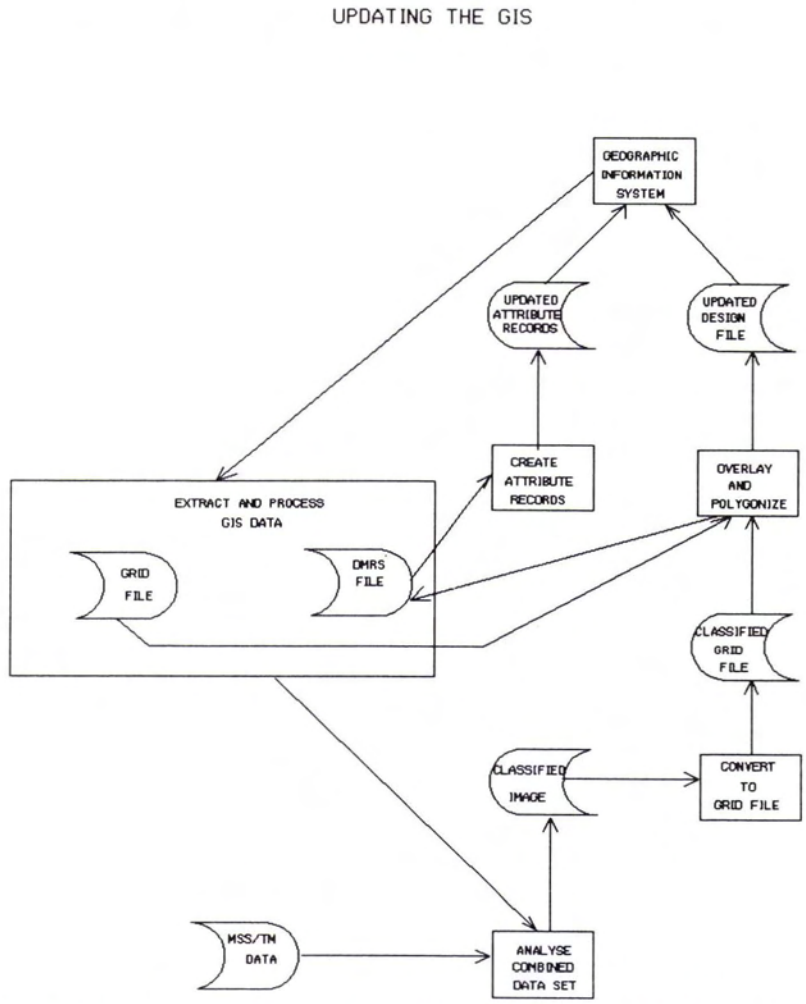


FIG. 6. The procedure to update the GIS is shown. Raster-to-vector conversion of the classified image is done. A file containing graphics and a file with attribute information are generated.

Columbia in the Kootenay Mountains. Plate 1 shows the ruggedness of the terrain and the appearance of a forested area that has been clear-cut. The cloud-free TM image was obtained on 15 August 1984. The clear-cut areas lie on a river valley at an altitude of about 1600 m, surrounded by mountain ridges up to 3000 m. The forested areas are covered mainly with spruce and balsam with ages ranging from 150 to 200 years. Non-coniferous forest occupies less than 15 percent in any of the forest polygons. The sizes of the clear-cut areas vary from 12 hectares to 71 hectares. The ratios of the boundary pixels to their total areas vary from 18 percent to 43 percent.

The preprocessing methods used for this experiment are

A reflective bands — 6 TM bands used; IR band not used;
B normalized differences:

$$\left[\frac{\text{band } i - \text{band } j}{\text{band } i + \text{band } j}\right] * 128 + 128$$

where i, j are adjacent spectral bands.

Only four bands of normalized differences ratios were used because TM bands 2 and 3 are too highly correlated to give useful ratios.

Two methods of training were used. The first training method was the traditional one of selecting training areas with a variable cursor on the image. The user judged whether the cursored area was homogeneous, perhaps using histogramming inside the training area to confirm the selection. The selected training areas were grouped into classes defined by the user. The classes used for the first training method were old clear-cuts (cut areas which were 5 to 40 years old), new clear-cuts (cut areas less than 5 years) and forest cover (uncut forest greater than 40 years in age). Two classifications were performed with preprocessing methods A and B given previously.

The second method of training involved user selection of polygons from the GIS for all classes except new clear-cuts, for which we used the first training method because these cuts were more recent than the data used to make the inventory map. Because of the existence of polygons with complex, multi-modal classes, the automatic selection of polygons for training, without user intervention, failed to produce training sets which gave acceptable classification accuracies. Plate 2 is an overlay of the forest geographic information boundaries on the Thematic Mapper image. Spruce-Balsam polygons have been extracted and used as a mask to select TM data for clustering by the migrating means method. If the polygons were homogeneous, we would expect to see single colors or clusters within each polygon. Instead, we found multiple classes inside many of these polygons.

Over 1800 polygons can exist in the digital forest map, but we are limited to classifying 256 classes or less. Hence, polygons were grouped from the database before classification. The polygons grouped into the same classes were identical in all of

TABLE 3. AVERAGE CLASSIFICATION ACCURACY

METHOD / DATA SET	6 BAND	4 RATIOS
Cursor selection of Training Areas	98.8% ±1.2%	97.7% ±1.2%
Point Selection of GIS Polygons	97.4% ±3.7%	93.6% ±3.8%

TABLE 4. CONFUSION MATRIX FOR THE RATIOED IMAGE CLASSIFIED WITH THE MAXIMUM LIKELIHOOD ALGORITHM

Chosen Class / True Class	OLD CLEAR CUTS	MIXED SPRUCE, FIR	PINE	NEW CLEAR CUTS
OLD CLEAR CUTS	93.0%	8.2%	4.1%	0.8%
MIXED SPRUCE, FIR	4.9%	67.2%	14.9%	1.2%
PINE	1.5%	18.1%	80.3%	0.0%
NEW CLEAR CUTS	0.2%	2.2%	0.0%	98.1%

Weighted mean classification accuracy = 75.9% ±0.5%

TABLE 5. CONFUSION MATRIX FOR THE RATIOED IMAGE CLASSIFIED WITH THE HIERARCHICAL LOGISTIC CLASSIFIER

Chosen Class / True Class	OLD CLEAR CUTS	MIXED SPRUCE, FIR	PINE	NEW CLEAR CUTS
OLD CLEAR CUTS	90.6%	5.9%	3.6%	2.7%
MIXED SPRUCE, FIR	9.2%	91.7%	29.2%	32.1%
PINE	0.2%	1.7%	67.2%	0.0%
NEW CLEAR CUTS	0.0%	0.6%	0.0%	65.3%

Weighted mean classification accuracy = 87.5% ±0.4%

the following important attributes: (1) major forest species - all species which constitute 15 percent or more of the polygon; (2) age class - the weighted average age of the major species listed in 20-year stratifications; and (3) site condition - the predicted productivity of the area at the time of surveying; the site condition was stratified into four subjective categories. The polygons were grouped into 63 classes, and then later grouped into the classes given previously. Table 3 lists the average classification accuracies obtained for the selected classes for the two preprocessing methods.

The classification of the ratioed image was regrouped to bring out the separation of pine and mixed spruce/fir. The confusion matrix for this case with the maximum likelihood algorithm is given in Table 4. The clear-cuts, both new and old, are well identified, as is pine. However, the mixed spruce and fir class has a classification accuracy of only 67 percent. The average classification accuracy for the four classes was 76 percent.

This classification experiment was repeated using a hierarchical Logit classifier. For this classifier, the classification decision was broken down to a series of binary decisions. At each decision point, a binary choice probably (p) was computed using the following equation:

$$\log (p/(1-p)) = a_o + \sum_{i=i}^{N} a_i X_i$$

where the a_i coefficients are derived from the training data and X_i represents the intensities in feature "i". Our Logit implementation accepts up to 256 classes and 16 channels. The confusion matrix for the ratioed image with the hierarchical logistic classifier is given in Table 5. The weighted (by the number of pixels in a class) average classification accuracy achieved was 87.5 percent. This is better than the maximum likelihood result, but there is still significant overlap between the pine and spruce-fir class, and the pine and new clear-cut class. The introduction of spatial features should improve this classification result. In all cases, the results with Thematic Mapper data were much better than those for MSS data.

DIFFICULTIES IN GIS AND IAS INTEGRATION

EXAMPLES

In order for the reader to better appreciate the difficulties in integrating geographic information systems with remote sensing image analysis systems, we present several examples. Plate 3 is a perspective view of the forest test area looking southward. This image was constructed using a 1:50,000-scale digital terrain model (DTM) and combining the image data with the forest GIS overlay in blue. The displacement between a polygon of a clear-cut area and the same area in the image is highlighted. As this example shows, digital terrain models must be used to integrate satellite imagery and geographic information in regions of high topographic relief. The second example is a result of the maximum likelihood classification referred to above. The classified image in raster form was converted back to vector or polygon form following the procedure outlined in Figure 6. The result of this process is shown in Figure 7. The dotted line represents the incoming digital geographic information. The solid line shows the polygon resulting from the remote sensing classification. Polygon 237 in the center of Figure 7 is displaced approximately 150 m north of the clear-cut polygon found from remote sensing. The remote sensing images were geocoded using 1:50,000-scale federal maps in the UTM projection for ground control. The provincial forest-cover maps make use of provincial UTM topographic maps. Comparison of other polygons between the forest-cover map and the remote sensing classification revealed no systematic shifts. While topography does play a role here, our conclusion is that there are inconsistencies in the making of the provincial topographic maps which can not be solved by algorithmic means. To resolve these inconsistencies, it is nec-

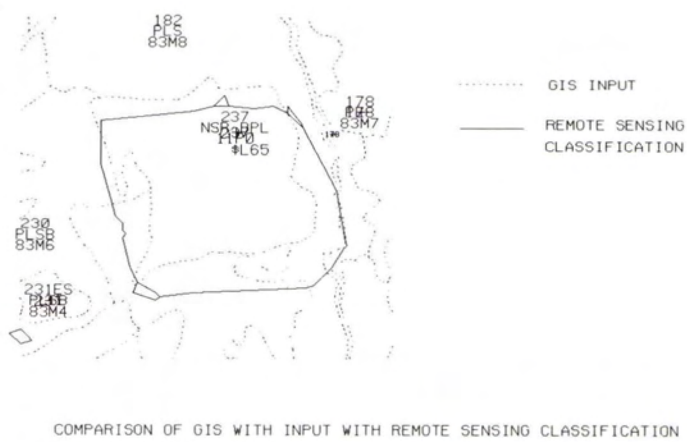
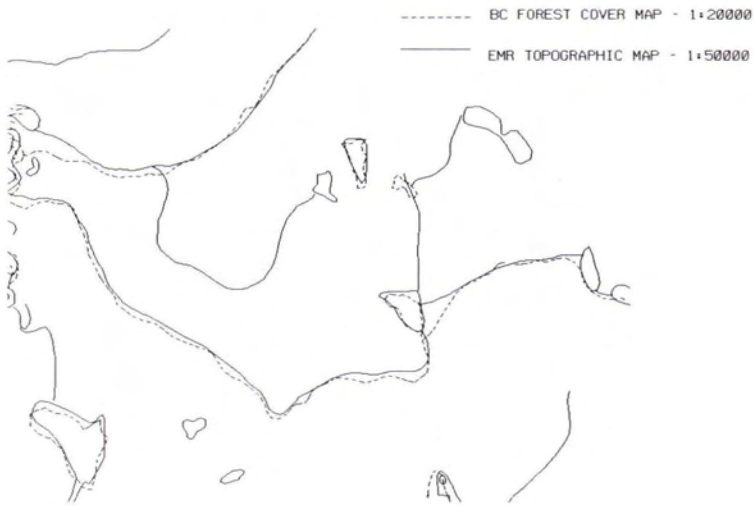


FIG. 7. Comparison of GIS input (dotted line) with remote sensing classification (solid line) - Polygon 237 in the center of Figure 7 is displaced approximately 150 m north of the clear-cut polygon found from remote sensing.



EXAMPLE OF MAP DISCREPANCIES

FIG. 8. This is a comparison of the hydrology level of a 1:20,000-scale BCMFL map (dotted line) and a federal 1:50,000-scale topographic map (solid line) for an area near Prince George, British Columbia. North is at the top. There are discrepancies as large as 200 m between the two maps.

essary to make use of symbolic reasoning; that is, artificial intelligence.

Because different map bases are used for the provincial forest-cover data and the federal geometric correction of TM data, we carried out a series of experiments comparing federal and provincial maps. Figure 8 is a comparison of the hydrology level of the BCMOFL map (1:20,000 scale, dotted line) and our department's topographic map (1:50,000 scale, solid line). The area is near Prince George, British Columbia, with north at the top. The eastern-most lake on the EMR map has a creek which runs out of it into the center of a larger lake. This same creek on the BCMOFL map misses this larger lake by more that 200 m. In a remote sensing image of rugged terrain, one may detect only portions of a small creek as it winds around a mountain. The GIS can aid in the linking of these portions, but which GIS should we take as correct? These problems are not unique to BC or Canada. Other investigators will find similar difficulties as they compare maps from various levels of government and maps with high-resolution satellite imagery.

CCRS receives data from the French satellite SPOT at two tracking stations, one in Prince Albert, Saskatchewan, and the second in Gatineau, Québec. Because of cloud cover, we have not yet successfully acquired the stereo SPOT imagery of Cranbrook, B.C. We have, however, obtained in 1986, SPOT MLA and PLA imagery of Ottawa, Ontario. Plate 4 is a portion of a PLA image overlain with a three-dimensional map (red) with attributes. The Ottawa geographic information was compiled in 1981. We have highlighted an area where old buildings have been demolished and a new shopping plaza built in 1986. Also, there is a section of a major road (Merivale Road) which did exist prior to 1981, missing from the GIS. SPOT imagery can, therefore, be used to update details of city changes and to identify errors in existing GIS.

SOME DIFFICULTIES

In addition to the problems mentioned earlier, the following difficulties were found in some of our experiments. Polygons from the digital map may correspond to non-homogeneous areas on the image. Such polygons may include roads, mountain shadows, multiple classes, and partial or complete clearcuts. More research is required on how to group polygons while retaining forest labels relevant to effective forest management. In the case of forest species recognition, it may be necessary to have a finer description of the composition of each training polygon with the percent area for each of the major species specified.

Additional problems in the integration of GIS and IAS are uncovered in this experiment. The boundaries of water bodies on federal and provincial maps differ both in shape and size from those on the image. The amounts of difference in our examples can be about three TM pixels or nine SPOT PLA pixels in the worst cases. The digital maps were produced at different times to different standards. Thus, there is more than one kind of forest digital map with mixtures of complex figures and line drawings. The new maps are digitized as line strings, while the old maps were digitized as closed polygons. This requires us to use different software packages to do vector to raster conversion. We use a mixture of Intergraph, PAMAP Graphics, and CCRS software.

The forest-cover digital maps and the attribute information received have originated from two different computer systems (Hegyi and Quinet, 1983). They are cross-referenced by using text-node numbers. A polygon on a map is identified by a text node number. The attribute information is catalogued in the BCMOFL database according to its text node number. The text nodes and their labels are usually placed at the center of the polygons on the map. If the polygon is too small to contain the text node label or text node number, then its text node and its number or label will be placed outside the polygon with an arrow pointing to the polygon to which it belongs. During the vector to raster conversion process, the software looks for a text node enclosed by a polygon. It did not recognize those text nodes which have an arrow associated with them, nor did it resolve the case where a polygon encloses its own text node and another one which belongs to its neighbor. In order to remove these ambiguities, it is necessary to manually clean the digital map by moving those text nodes which are outside their polygon back to where they belong, and removing the associated arrows before vector to raster conversion. The use of text nodes and labels is a compact representation of information on paper maps and the BCMOFL GIS is also used to produce paper forest inventory maps. Because BCMOFL has been digitizing maps for only eight years, there still exist today many maps which have not yet been digitized. These remaining paper maps must still

PLATE 1. Example of terrain relief and slope of clear-cut areas near Cranbrook, British Columbia.

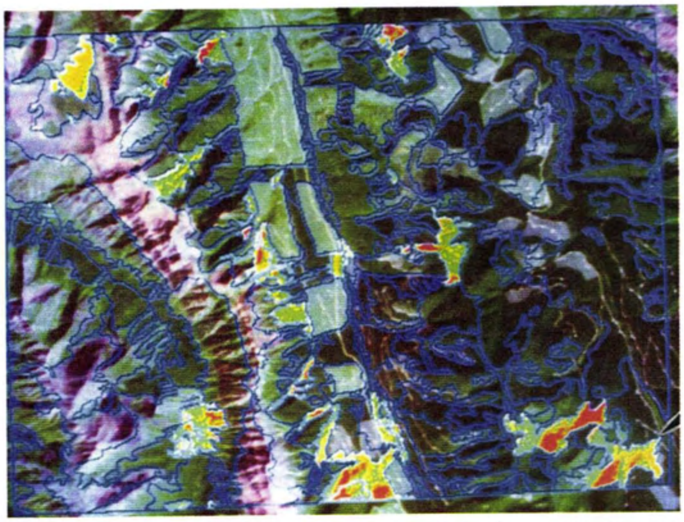


PLATE 2. Shown is a forest polygon overlay (dark blue) on the Landsat-5 TM data. Spruce-Balsam polygons have been extracted and used as a mask to cluster the TM data. The inhomogeneity of the polygons is demonstrated by the multiple classes (red, yellow, white, blue) found inside the polygons (arrow).

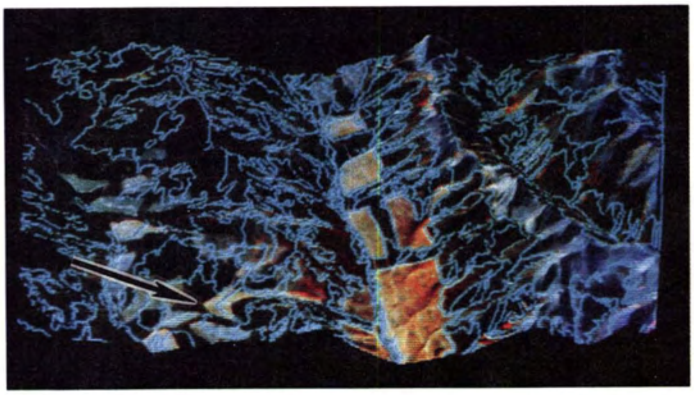


PLATE 3. This is a perspective view applied with digital elevation data and looking south. The Landsat-5 TM image is from 15 August 1984. the forest geographic information is shown as a blue overlay. Note the geometric displacement between a polygon of a clear-cut area and the same area in the image (arrow).

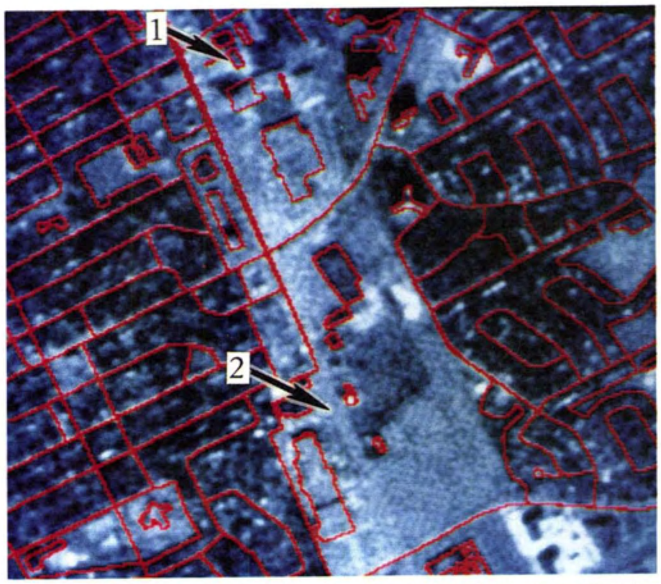


PLATE 4. SPOT PLA of Ottawa with digital GIS (Red) showing mismatches (missing features) between the image and the GIS. (1 = missing buildings, 2 = missing road) Original Ottawa GIS and map compiled in 1981; SPOT imagery is from September, 1986. © SPOT image Copyright 1986 CNES.

be updated using manual techniques based on remote sensing images.

Linear elements such as roads and small rivers are used to delineate polygon boundaries on the cover map. The pixels used in the experiments have sizes ranging from 12 metres to 50 metres. Small roads or boundaries between cover classes may not appear in the images. Remote sensing image segmentation does not give the same boundaries as the GIS. For the forest GIS, high resolution, stereo aerial photography was used by photointerpreters to produce the forest-cover maps. In areas of gradual change, we have difficulty in automatically segmenting an image to give the same forest-cover boundaries. For water/land interfaces and clear-out areas, it is much easier to get a good identification of the boundaries.

It would be ideal to update all the forest-cover inventory for a province at a certain time; for example, July 1986. However, clear images may not be available for that locality at that given time.

Our recommendation for analysis is to have the user cluster within each of several selected polygons, classify the image, group the clusters, and vectorize the classification.

CONCLUSION

Several examples of intergrating satellite imagery with geographic information systems have been given. With a mixture of automated and manual procedures, it is now possible to routinely update a geographic information system, as the B.C. Ministry of Forests and Lands now does with our software for the inventorying and monitoring of forests.

There are, however, difficulties which can not be overcome by traditional methods. These difficulties require the use of symbolic reasoning and expert systems. The experiments described here have helped us to acquire the knowledge for a hierarchical expert system, the Analyst Advisor (Goodenough *et al.*, 1987). The Analyst Advisor consists of multiple experts using our prolog expert system shell. The Analyst Advisor controls the computers and devices (shown in Figure 1), and the FORTRAN tasks. Knowledge is represented in semantic networks or frames, rules, and procedures. We believe that such approaches will be essential to successfully integrate two complex and varied systems, the geographic information system and the image analysis system, in order to achieve distributed, cooperating systems which do not require large numbers of highly skilled individuals.

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