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USE OF REMOTE SENSING FOR LAND USE POLICY FORMULATION

Final Report

January, 1985 - May, 1987

Prepared for: Office of Space and Terrestrial Applications
National Aeronautics and Space Administration
Washington, D.C.

NASA Grant Number: NGL 23-004-083

By: Center for Remote Sensing
Michigan State University
East Lansing, Michigan 48824-1111

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EXECUTIVE SUMMARY

The Center for Remote Sensing at Michigan State University is proud of its continuing strength, activities, and contributions to remote sensing and information systems in the state, the nation, and internationally. The strength of the present Center, and probably its very existence, would not be possible without the support that NASA has provided to MSU for over fifteen years. Three distinct phases in the life of the Center have occurred. First was a technology transfer center, almost exclusively with the support of a NASA university programs grant. Then, as NASA evolved to encourage centers of excellence with emphasis on research and innovative development, the MSU Center for Remote Sensing grew into a recognized research and innovation facility. The present phase of the Center (the post-NASA support phase) finds the Center continuing to grow and contribute to the remote sensing and spatial information communities. We are particularly proud of this evolution since some centers around the country folded without NASA's support during this period.

The overall objectives and strategies of the Center remain to provide a center of excellence for multi-disciplinary scientific expertise to address land-related global habitability and earth observing systems scientific issues. In addition, however, an extensive effort in the Center has been involved with geographic information systems. We now have growing expertise in the ability to combine a variety of spatial information such as soils, vegetation, and hydrogeologic characteristics, with information directly compiled from remote sensing. Studies are conducted on surface energy fluxes as affected by edaphic, vegetative, topographic, and meteorological conditions to evaluate subsequent impacts on hydrology and biological productivity of ecosystems. Investigations involve climate zone analysis, land form productivity, unit delineation, vegetative characteristics, and change detection. Emphasis is particularly placed on assisting decision makers and planners with the information obtained. An additional component has been the rapid advance of coupling hydrologic information from well logs, aquifer maps, and water quality data. This has allowed for a more complete coupling of the earth's physical system to assist with planning in the environmental and ecological realms.

Specific research projects that have been underway with the support of NASA during the final contract period include the following:

1. Digital Classification of Coniferous Forest Types in Michigan's Northern Lower Peninsula from Landsat Multispectral Scanner Data

2. A Physiographic Ecosystem Approach to Remote Classification and Mapping of Forest Biomass

3. Land Surface Change Detection and Inventory Update Using Satellite Data and a Geographic Data Base

4. Analysis of Radiant Temperature Data from the Geostationary Operational Environmental Satellites

5. Development of Methodologies to Assess Possible Impacts of Man's Changes of Land Surface on Meteorological Parameters

Output from this period's efforts have resulted in a number of formal papers and presentations at scientific meetings. These results have been published in refereed journals, proceedings, or in abstracts of meetings. Significant products are included in the appendix of this report.

Significant progress in each of the five project areas has occurred. Summaries on each of the projects are provided in the next section of this report.

DIGITAL CLASSIFICATION OF CONIFEROUS FOREST TYPES IN MICHIGAN'S NORTHERN LOWER PENINSULA FROM LANDSAT MULTISPECTRAL SCANNER DATA

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This study has evaluated the use of Landsat multispectral scanner digital data for classifying and mapping coniferous forest cover types. All analyses were conducted on a Landsat scene obtained on February 26, 1979 which is centered in the north-central Lower Peninsula of Michigan. The scene recorded a landscape under a ubiquitous snow cover with coniferous forests providing the only green-foliage reflectances in the entire scene. Two test sites were chosen, one in Wexford County and the other in Crawford County, to be representative of areas now supporting large acreages of conifers. Cover type maps of the two test sites were prepared from aerial photography, digitized, and then rectified to match the Landsat data files. Subsequent classifications from the Landsat data were compared with these "reference" files to produce error matrices.

Several standard digital analysis techniques (i.e. algorithms available on the ERDAS micro-computer; unsupervised clustering, minimum distance-to-means, and maximum likelihood) were utilized to classify the test sites. In addition, the effect of varying the values of input parameters on the accuracy of the unsupervised clustering algorithm was evaluated. Level slicing was also employed with unsupervised clustering in an effort to minimize the effect of a large number of non-forest clusters.

A spectral response curve model was developed from analysis of the multispectral reflectance patterns exhibited by the coniferous cover types and the background features. The predicted brightness values from the model were utilized to construct a linear-combination classifier which was also tested for classification accuracy.

In order to evaluate the effectiveness of the cover type maps as verification sources, tests were conducted using aerial photography as the "ground truth." Discrepancies were noted between the two methods and possible causes investigated.

Each of the classification techniques was evaluated with respect to its overall classification accuracy, the magnitude and source of errors, the ranking and significance based upon the kappa statistic, the number of categories obtainable, execution time required, and the need for additional analysis.

The major findings of this study can be summarized as follows:

1. Unsupervised clustering, using default parameters, provided the least accurate (80.3 percent) classification of the Wexford County test site and was ranked sixth of 8 for the Crawford County test site. This algorithm produced a large number of errors, both of omission and commission, and was especially error prone where stands were small and/or irregularly spaced.

2. The only input variable which consistently affected the classification performance of the clustering technique was the maximum allowable cluster radius. The reduction of this variable from seven to three digital counts increased the accuracy from 80.3 to 82.2 percent and from 73.2 to 73.5 percent for the Wexford County and Crawford County test sites, respectively.

3. Level slicing of the scene prior to clustering increased the accuracy for the Wexford County test site, but had the opposite effect for the Crawford County test site. Clustering level sliced scenes in conjunction with a smaller allowable cluster radius improved accuracies for both test sites.

4. With one exception, the supervised classification algorithms, minimum distance-to-means and maximum likelihood, had higher overall classification accuracies than did the unsupervised clustering algorithms.

5. The minimum distance-to-means algorithm was more accurate than the maximum likelihood algorithm over the Wexford County test site but the opposite was true for the Crawford County test site. More errors of omission occurred, compared to commission errors, and were largely attributable to lightly stocked stands, (<50% crown closure).

6. A spectral response curve model was developed which could predict brightness values from various mixtures of conifers and background features. The predicted brightness values from stands containing a mixture of conifers and background features demonstrated that the magnitude of change in reflectivity from band 5 to band 6 provides the most consistent measure for discriminating among the cover types.

7. Even a simplistic version of a two-band linear-combination classifier (BV6-BV5) was more accurate than either clustering with default parameters or clustering with a smaller allowable cluster radius for the Wexford County test site. Over the Crawford County test site, this algorithm was more accurate than clustering of a level sliced scene.

8. A slightly more sophisticated linear-combination classifier which uses the (BV6-BV5) data in conjunction with the absolute band 6 brightness value (i.e. BV6, BV6-BV5) produced the most accurate classifications, 84.0 and 73.8 percent for Wexford and Crawford Counties, respectively.

9. Post-classification analysis of aerial photography indicated that approximately 33 percent of the "errors" in Wexford County and 48 percent of the "errors" in Crawford County were attributable to map generalizations. Approximately half the errors were attributed to boundary pixels, another 40 percent were associated with thinly stocked stands. The remaining errors were caused by small openings in the forest (below the minimum map size but larger than the IFOV of the Landsat MSS).

10. The number of mappable categories varied among the various algorithms. Unsupervised clustering techniques produced, at most, three categories. Supervised techniques produced from three to four categories, while the linear combination classifiers produced from three to five.

11. Execution time varied considerably. Unsupervised clustering was the slowest, from four and a half to six and a half hours; supervised techniques were intermediate, from one and a quarter to one and three quarter hours; and linear-combination classifiers were the fastest, about one half hour.

12. All of the algorithms tested require additional analysis before classification is complete. Except for the level sliced analysis, which requires both pre- and post-analysis, each algorithm requires one additional step to assign categories to numeric results or to specify training site data.

13. The relative performance of the algorithms differed between the two test sites such that different rankings were allocated to the algorithms by site.

14. Overall classification accuracy was significantly different between the two test sites. The major contributing factors appeared to be the blocky plantation pattern in Wexford County compared to the scattered, heterogenous forest cover in Crawford County. Even the least accurate classification, 80.3 percent, for the Wexford County test site was superior to the most accurate classification, 73.8 percent, for the Crawford County test site.

15. Digital classification techniques were more accurate than visual interpretation of computer enhanced, spring imagery (72.7 percent) over the Crawford County test site, but were less accurate than results from the Wexford County test site (84.3 percent).

With respect to the above findings, certain conclusions can be drawn on the appropriate use of Landsat multispectral scanner data in forest resource inventory systems under Lake States conditions. While digital classification procedures can identify coniferous forests with acceptable accuracy (approximately 90 percent), individual cover type accuracies are highly variable. Accuracies range from over 90 percent to under 10 percent and also vary by site. Forest cover type maps, as currently compiled, include delineations of forest cover types and stand size and stocking classifications which cannot be derived directly from satellite data. Thus, Landsat multispectral scanner data cannot entirely replace traditional, photo-derived forest inventories. For more generalized types of assessments, Landsat data is probably a sufficient, stand-alone information source.

The greatest utility for Landsat data is likely to occur in a comprehensive inventory system utilizing multistage sampling. The availability of remotely sensed data at several scales provides an efficient sampling technique over very large areas. A large number of fast, relatively inexpensive measurements can be obtained from the satellite data and correlated with samples from progressively higher-resolution data sources, such as aerial photography and eventually ground plots. Variable probability sampling, with the probability of sample selection proportional to the sizes (or acreages) estimated from the previous stage, are formulated from additional information available at each stage. At the last stage, measurements are collected in the field and projected back through the sampling formula to obtain estimates for the entire area. This technique is especially suitable to large area inventories such as the Forest Inventory and Analysis for the entire state conducted by the U.S. Forest Service. The last analysis of Michigan (1980) utilized aerial photography as the first level of sampling. A total of 176,976 1-acre plots were classified from the photography. A sample of these plots (83,103) were classified stereoscopically by forest type, stand-size class, and density, and finally 13,991 of these points were measured on the ground. Using Landsat data to stratify forest land as a first level of a multi-stage sample would provide more accurate survey data, or similar accuracies with a smaller sample size. In addition, the Landsat classification would provide a spatial component to the distribution of forest cover types unobtainable from current Forest Inventory and Analysis procedures.

Considering the level and accuracy of information obtainable, the Landsat system is extremely efficient. One Landsat scene covers 13,225 square miles and would require approximately 5,000 aerial photographs (at a scale of 1:15,840 with 60 percent endlap and 30 percent sidelap) to cover the same area. Computer compatible tapes for a single Landsat scene cost $660 compared to $150,000[1] for the acquisition of medium-scale aerial photography. Although the minimum configuration of a computer system to process the Landsat data is approximately $24,000, compared to $2,000 for photointerpretation equipment, a single scene could be processed within several days compared to several months to interpret aerial photography for an equivalent area. The decision to utilize satellite data or aerial photography will obviously depend upon an analysis of both information requirements and the associated costs.

The high temporal frequency of Landsat data acquisition, an 18-day repetitive acquisition cycle, could also be exploited for inventory updating requirements. Landsat data

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[1]Approximate cost for the acquisition of 1:15,840, black-and-white infrared aerial photography based upon a cost of $19.20 per flight line mile.

and high-altitude aerial photography could provide a cost-effective technique for updating the state-wide Forest Inventory and Analysis. A multi-stage sub-sample of plots from the previous inventory would be utilized to derive "change coefficients" to update acreages, volumes, and growth projections to a mid-cycle point. Landsat data have also been suggested as a source for updating the state-wide current use inventory. The advantages of using Landsat are that only land use changes, not an initial inventory, would need to be identified and that the digital nature of the data could possibly be used to automatically update current computer files. In addition, the Landsat system might provide data for monitoring changes in forest areas over short time-frame events (e.g. forest fires or defoliation due to insects or disease).

Although current capabilities of processing Landsat data can provide valuable inputs into forest resource assessments, further research and newer satellite systems should be considered. For example, since the linear combination classifier is based upon a spectral response curve model which integrates the spatial proportion of conifer versus background in the IFOV, it may also provide a measure of stocking or density. Further research should investigate this relationship and its potential for "automating" broad-area forest stand classification. In addition, characteristic response curves should be investigated from other seasons to test the validity of the spectral response curve model for possible application to classifying and mapping deciduous forest cover types.

Several new systems, including the Thematic Mapper on board Landsat 4 and 5 and the French SPOT satellite, offer increased spatial resolution (30 and 10 meters, respectively) compared to the multispectral scanner. Although increased spatial resolution should decrease the effects of boundary pixels, the smaller IFOV might be problematic in areas of dispersed forest cover such as encountered in the Crawford County test site. The full ramifications of increased spatial resolution on overall classification accuracy would need to be fully investigated. Increased spectral and radiometric resolution from the Thematic Mapper has the potential of improving discrimination among similar cover types (e.g. species of pines) and should also be investigated.

Ecological considerations, especially the effect of site on the choice and performance of various classification schemes, need to be more fully assessed. Both overall classification accuracy and the relative performance of the algorithms tested in this study were significantly different between the two sites. Signature extension does not appear to be valid across an area the size of the northern lower Peninsula. Therefore, stratification of the scene, possibly along major landform units, should be tested as a possible mechanism for allocating individual classification techniques.

A PHYSIOGRAPHIC ECOSYSTEM APPROACH TO REMOTE CLASSIFICATION AND MAPPING OF FOREST BIOMASS

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Within a regional climate, a strong relationship exists between physiography and the location and productivity of forest ecosystems (Barnes et al., 1983, Pregitzer et al., 1983, Pregitzer and Barnes, in press). We believe that on a global scale, understanding the relationships between physiography, soil, and vegetation will eventually enable estimation of rates of forest biomass accumulation and net primary productivity via remote sensing. We propose to test the hypothesis that forest ecosystem productivity can be classified and mapped using high-altitude color infrared photography. The research project described capitalizes on an ongoing forest ecosystem classification and productivity research program.

Overall, physiography is probably the single most important ecosystem component. A priori, physiography (including landforms and soils) provides the best means of distinguishing ecosystem productivity at the local level because it is the most stable of ecosystem features. It strongly controls regional and local climate, soil moisture, and related nutrient conditions, and forest composition. In addition, relationships among physiography, soil, and vegetation may be the key to remote sensing of potential biomass productivity.

Rowe (1969) regarded landform as not only the surface configuration but noted that surface forms reflect the history of geological materials, deposited or eroded. Rowe makes a powerful case for landform -- a case that is borne out by field ecologists:

> It is, therefore, possible in the field and on aerial photographs to correlate geomorphology with the geological materials beneath, and this integration of form and structure will be referred

to hereafter as "landform." As Hills (1950) has asserted, landform constitutes the relatively stable base of the landscape ecosystem and is, therefore, its best taxonomic feature, but more than this the landform has a "genetic" significance. It is the parent alike of the climate that extends upward from its surface and of the soil that appends beneath. It determines among other things what energy from the sun is intercepted and how it is dissipated. It controls the infiltration and storage of moisture and thereby the regimes of soil aeration and chemical composition.

Physiography is also extremely valuable because it can be used to map ecosystems from remotely sensed imagery once the relationships among physiography, vegetation, and soils are known. We have systematically studied these relationships in the late-successional Upper Michigan forest (Barnes et al., 1982, Pregitzer and Barnes, 1982, Pregitzer et al., 1983, Spies, 1983, Pregitzer and Barnes, in press). In our ecosystem analysis of the Cyrus H. McCormick Experimental Forest (Barnes et al., 1982), the mapping was greatly expedited by the use of aerial photographs. We also found a very strong relationship between soil nutrients, ground cover vegetation, and physiography (Pregitzer et al., 1983).

More recently, we have found a strong relationship between physiographic ecosystems (defined by characteristic combinations of physiography, soil, and vegetation) and forest productivity in the Huron-Manistee National Forest of Michigan (Pregitzer, Ramm, and Hart, unpublished). In this research, we have stratified the landscape into different physiographic (geomorphic) features (e.g., outwash plains, low ice-contact hills, interlobate moraines, etc.) which represent functionally different ecosystems, each with a characteristic potential vegetation and relatively homogeneous soils (Hudson and Lusch, 1984). Initial results suggest that rates of forest biomass production are significantly different among the ecosystem units. Our working hypothesis is that physiographically distinct forest ecosystems can be delineated through field studies and the analysis of remotely sensed imagery.

The initial remote sensing analysis was conducted over previously established plots in the Huron-Manistee National Forest. Photointerpretation was completed for five stands using U.S. Forest Service, 1:12,000 color infrared aerial photography. Despite the increased scale (twice that of the previously studied photography from the Michigan Department of Natural Resources) and generally excellent photo quality, individual species composition of stands could not be consistently obtained. At best, broad cover types (e.g. beech-maple, northern red oak) are the most detailed interpretations which can probably be extracted from this type of imagery. A summary of the most salient features of these stands is attached.

Stand number: 40 (Sites A-D)

Location: Wexford County
T.23N. - R.10W., Section 35, SW 1/4

Landform: Cadillac Outwash Plain

Forest Cover Type: 60 Beech-sugar maple

Species: sugar maple, beech, red oak, big tooth aspen, white ash, black cherry, ironwood, white pine, red pine, red maple, basswood, quaking aspen

Three types of stand structure are associated with the beech-sugar maple type, 1) dense sapling and small pole sized stands, individual crowns are undetectable, tones are very mottled with light pinks and whites, 2) pole sized stands which display varying tones, crown shapes and sizes, the stand structure is moderately uneven, and tones are predominantly light pinks with a few white tones, and 3) highly structured stands with more definite crown outlines, a district stand pattern (alligator skin or mud cracks), and fewer light pink tones with no white tones. The light pink to white tones are characteristic of sugar maple, and to a lesser degree, red maple, and are especially prominent in sapling and small pole sized stands, for larger trees which are open grown or in sparsely stocked stands, and for edge trees. Species composition, stand structure, and canopy geometry all effect tonal reflections as displayed on the aerial photography. The directly illuminated side of a crown will appear brighter than the side which is in partly shadow.

Species Characteristics:

sugar maple
- tone: light red-pink-white
- crown: broadly rounded, side branches may extend beyond the general crown
- crown diameter/tree height ratio: .25 - .70

beech
- tone: dull red-dark red
- crown: smooth, slight taper towards apex

red maple
- tone: red-pink
- crown: ascending branches, slightly more pointed than sugar maple
- crown diameter/tree height ratio: .50

black cherry
- tone: dull red
- crown: thin (can see through)
- crown diameter/tree height ratio: .40

Stand number: 41 (Sites E-L)

Location: Wexford County
T.23N. - R10W., Section 35, E 1/2
Section 36, W 1/2

Landform: Cadillac Outwash Plain
Meauwataka Stagnation Moraine

Forest Cover Type: 60 Beech-sugar maple
55 Northern red oak

Species: northern red oak, sugar maple, black cherry, basswood, beech, white ash, bigtooth aspen, red maple
lowland: quaking aspen, white pine, red maple, hemlock

northern red oak
tone: bright red-red (dark)
crown: massive, broad, may be divided into segments, rougher texture than sugar maple (in closed stands), branches do not protrude beyond general crown outline
stand structure: crowns do not close together
crown diameter/tree height ratio: .45-.70

Stand number: 24 (Sites M-Q)

Location: Wexford County
T.21N. - R.12W., Sections 10 and 15

Landform: Briar Hill Moraine

Forest Cover Type: 26 sugar maple-basswood
16 aspen

Species: (26) northern red oak, white ash, sugar maple, hemlock, beech, bigtooth aspen, basswood, ironwood, white birch, black cherry, sassafras
(16) bigtooth aspen, hemlock, northern red oak, sugar maple, red maple, beech

16 Aspen
- tone: bright red
- crowns: small, rounded, may be somewhat intermingled
- crown diameter/tree height ratio: .20-.30

26 Sugar maple - basswood
- tone: red to dark red with few pinks throughout
- stand structure: rough texture, tree heights and crown diameters variable

Stand number: 20 (sites R-U)

Location: Manistee County
T.21N. - R.15W, Sections 14 and 23

Landform: Port Huron Moraine

Forest Cover Type: 55 Northern red oak

Species: northern red oak, white oak, black oak, bigtooth aspen, red maple, black cherry, witchazel, beech, sassafras, white pine

55 Northern red oak
- tone:
  - bigtooth aspen - bright red
  - red oak - light to dull red
  - overall - very few pinks (red maple)
- texture: somewhat rough
- stand structure: somewhat open

Stand number: 48 (Sites IA-C)

Location: Wexford County
T.21N. - R.12W., Section 30
(T.21N. - R.13W., Section 25 - Manistee County)

Landform: Stronach Outwash Plain

Forest Cover Type: 52 white oak-black oak-northern red oak

Species: black oak, northern pin oak, white oak, black cherry, jack pine

black/northern pin oak
- tone: dark red-brown
- stand structure: open, rarely closed
- crown diameter/tree height ratio: .20-.50
  - (white oak: .35 - .70)

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LAND SURFACE CHANGE DETECTION AND INVENTORY UPDATE USING SATELLITE DATA AND A GEOGRAPHIC DATA BASE

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Research Objective

The objective of our research investigation was to develop and evaluate category-specific interpretation rules to detect deforestation and, subsequently, to identify the type of land surface change using Landsat Thematic Mapper (TM) data and information contained in a geographic data base. Image segmentation and feature extraction techniques were developed to detect changes in previously-mapped forestlands. Feature-recognition rules were built to identify the type of change based upon TM image properties (spectral, textural, shape, context) of segmented regions and area-associated information about corresponding features in the GIS of the State of Michigan. Emphasis was placed on the identification of new oil/gas wells.

Introduction

Land cover and land use information is one of the most important factors needed to conduct effective land resource management and research activities. Accurate and up-to-date information on land surface patterns is required, not only for natural resource use and ecological studies, but also for scientific investigations of the atmosphere, radiation balance, nutrient cycling, evapotranspiration, runoff, soil conditions, and many others. The earth's surface is an ever-changing mosaic of land cover and land use patterns. Major land processes, such as deforestation, desertification, and urbanization, are substantially altering the mosaic as are the collective actions of many other on-land activities. The distribution and rate of change of major land-cover and land-use types is not known. For example, there has been an increased utilization of Michigan's forest resources for timber products, wood energy, oil and gas exploration, recreation, and residential development. These activities, as well as timber losses due to fire, disease, and pests, can significantly change the pattern of the landscape and thereby dynamically alter ecosystem characteristics.

State governments are increasingly recognizing the need for current natural resource data and are implementing statewide geographic information systems (GIS). At least 32 states have seriously explored or instituted comprehensive natural resources information systems (Johannsen and Sanders, 1982, Martinki, et al., 1984). These systems are used for a wide variety of projects related to forestry, agricultural crops, wildlife habitat, water resources, urban development, and land use impacts. In Michigan, the Michigan Department of Natural Resources is currently operating the state GIS legislatively mandated under the Michigan Resource Inventory Act (PA 204, 1979). It is a multi-level GIS which contains 1978 photo-derived land cover/use information.

A major problem with any GIS is how to keep the inventory information up-to-date because land surface features may change rapidly due to natural or human causes. A good source of land cover/use data is needed to identify changing land use patterns and to study the temporal dynamics and complex interactions involved in major land change processes such as deforestation. Remotely sensed data acquired by satellite sensors, particularly the Landsat series, are considered important sources for updating state inventories. Numerous image processing, pattern recognition, and image classification techniques have been developed and tested for mapping land cover/use. Most of these methods classify the image data on a per pixel basis using statistical routines in the spectral domain of the image set. To date, overall classification accuracy has typically been low (<85%).

Recent investigations have shown that substantial improvements in classifier performance can be made by incorporating ancillary information into the recognition process. This has lead to research in developing knowledge-based expert systems for interpreting remote sensing images (Tinney, et al., 1983). A major research challenge lies in acquiring and representing the domain-specific knowledge and determining a set of A.I. interpretation rules to accurately classify the "real world" landscape recorded by remote sensors. This project addressed the need for research in this area.

Background

Many researchers have used multi-temporal Landsat data for mapping the areal distribution of harvested areas (Rouse et al., 1973, Aldrich, 1975, Lee, 1975, Murtha and Watson, 1975, Orhaug et al., 1976, Lee et al., 1977, Bryant et al., 1979, Banner and Lyndham, 1981, Hegyi and Quenet, 1981, Wastenson et al., 1981, Park et al., 1983, Tucker et al., 1984). Various digital approaches to detecting changes in forestlands have been reviewed by Werth (1983).

In many instances the detection of forest disturbances involves distinguishing vegetation signatures from signatures of soil and other materials. Techniques which enhance their separability should improve forest change detection procedures. Numerous linear spectral band combinations (Tucker, 1979) and vegetation indices have been developed to provide better vegetative information. Perry and Lautenschlager (1984) summarized some four dozen vegetation indices. The perpendicular vegetation index (vegetation reflectance departure from soil background) has been used to divide a Landsat image into ten decision regions corresponding to water, cloud tops, cloud shadows, low, medium and high reflecting soils, low, medium, high plant cover, and no data (Richardson and Wiegand, 1977). The green vegetation index of Kauth and Thomas (1976), the tasseled cap transformation, provides a measure of vegetation density. Recent research with Landsat TM data has documented a third image information plane in addition to brightness and greenness which contains information on the relative mix of vegetation and soil in the field-of-view and therefore should provide more information as to the percent of vegetation cover (Crist and Cicone, 1983, Crist and Cicone, 1984).

Some previous studies have identified land surface changes by comparing separate, independent classifications derived from Landsat data acquired at different dates. This post-classification comparison technique has been used to identify forest clear cuts in southeastern Oklahoma and classify regeneration sites into three age groups (0-6, 6-15, and >15 years old) (Gregory et al., 1981). Researchers have identified several problems with this approach (Stow et al., 1980, Likens et al., 1982). Most notable is that the detection accuracy of "from-to" changes approaches the product of the accuracies of the two independent classifications. Thus if both antecedent classifications have an accuracy of 80% their potential change detection accuracy would be only 64%.

Many different change-detection procedures have been tested which use multi-temporal image sets. (Gramenopoulos, 1973, Price and Reddy, 1975, Malila, 1980, Robinove, et al., 1981, Arndt, 1983). These techniques require two images of the same area acquired on different dates. Commonly used, multi-date, change-detection techniques include: image-differencing, image-regression, image-ratioing, multi-date classification, and change-vector analysis. Singh (1984) evaluated the accuracy of six multi-date techniques in detecting changes in tropical forest cover -- all accuracies were below 80%.

Numerous problems are encountered in implementing these multi-date, change-detection procedures. Precisely co-registered images are required since positional inaccuracies between image pairs adversely affects performance. The classification accuracy of these multi-date techniques is also degraded by time-dependent variations of the extrinsic factors listed in Table 1. The effects of many of these factors can be maximized by selecting data collected on anniversary dates with the same sensor, however, it is more difficult to compensate for changes in phenologic conditions or soil moisture (Burns, 1983).

Researchers have begun to incorporate ancillary information into the image classification process as means to improve accuracy. Collateral data have been used in pre-classification scene stratification, post-classification class sorting, and classification modification by increasing the number of information channels or modifying prior probabilities (Hutchinson, 1982). The use of topographic information (elevation, slope, aspect) as additional features in classifiers can improve forest classifier accuracy because many forest types have preferred elevation ranges and slope aspects (Strahler et al., 1978, Stow and Estes, 1981, Williams and Ingram, 1981, Guindon et al., 1982). Contextual information has also been incorporated into classifiers to improve performance (Swain et al., 1981, Tilton et al., 1982). It is clear from the literature that substantial improvements in classification accuracy are made where ancillary data are used in the classification process.

Initial efforts in automated image analysis emphasized statistical pattern recognition approaches, but such methods proved to be inadequate in situations requiring an awareness of context or the use of other information. Other techniques, currently being developed in the field of artificial intelligence (A.I.), may provide more powerful and accurate change detection and inventory update capabilities than current statistical approaches. A.I.-based techniques applied to automated image analysis tasks closely parallel the human image interpretation process of detection, identification, measurement, and problem-solving. A previous work (Tinney et al., 1983) has reviewed image interpretation procedures for both human and computer-assisted image analysis as a basis for discussing the future of A.I.-based systems.

Table 1. Consideration for Temporally Dependent Sources of Change in Reflectance Between Data Sets (from Burns, 1983, p.3)

Atmospheric Differences	
	Clouds
	Haze
	Humidity
	Dust
Seasonal Differences	
	Solar Illumination Angle
	Phenologic Stage
Surface Differences	
	Soil Moisture
	Cover Materials
Sensors/Systems Differences	
	Orbital Altitude
	Platform Altitude
	Differential System Deterioration Rates
	Sensor Calibration
Processing Differences	
	Formatting
	Resampling Procedures
	Decompression Procedures
Astrophysical Differences	
	Solar Flux
	Magnetospheric Interference
	Various Axial Motion Components
	Ecliptic Variations
	Eccentricities in Orbit

Much of A.I. in remote sensing work is directed toward the computer-assisted analysis of high resolution panchromatic imagery and is being conducted under the Defense Advanced Research Project Agency's (DARPA) Image Understanding Program. The Japanese are also actively pursing the development of A.I.-based systems, an excellent example is presented in Nagao and Matsuyama's book A Structural Analysis of Complex Aerial Photography (1983).

An overview of the status and potential of A.I. driven "expert systems" in image data analysis is given by Mooneyhan (1983). "Expert system" programs use information contained in a knowledge-base and inference procedures or production rules to solve problems. None of the systems reviewed by Mooneyhan (1983) was designed to handle multichannel, multispectral digital image data.

Goldberg et al., (1983) describe the design of a Forestry Expert System and tests in a 100 sq. km. area in Canada indicate that the system can tract both highly discernable (logging, forest fires) and very subtle forest changes (regeneration, defoliation due to insects). Ferrante et al. (1984) have begun to develop and test an expert system for multispectral image interpretation. The initial version of their Multi-Spectral Image Analysis System (MSIAS) is being designed for surface material classification using hierarchical, tree-structure classifier where the root node is the whole image. This approach is similar to employing layered classification logic (Jensen, 1978).

The NASA/Ames Research Center has designed a prototype expert system capable of producing a preliminary land cover classification from an unsupervised classification of Landsat MSS data and associated ancillary data (Erickson and Likens, 1984). This system uses contingency analysis to provide a measure of the correlations between spectral classes and attributes such as elevation, slope, zoning, soils, and prior land use. Their approach to data relies principally on the spectral domain of the image data and does not utilize the textural or contextual features of an image.

Researchers have begun to merge remote sensing data and ancillary data within the context of a geographic information system (Maw and Grass, 1981). More layers of derivative information such as band transforms, texture and contextual information bands are being incorporated for classification purposes (Strahler et al. 1984, Peterson et al., 1983, Likens et al., 1982, Likens and Maw, 1982).

The use of data from higher-resolution sensors should improve the performance of the above classifiers. Significant improvements using thematic mapper simulator data have already been reported (Gervin et al., 1982). However, new approaches and techniques must be developed before substantial increases in classification performance can be made.

The current interface between GIS and remote sensing systems is functional, but weak (Smith and Blackwell, 1980, Hutchinson, 1982, Junkin, 1982, Jensen, 1984). Jensen (1984) states that "An oversight of individuals attempting to promote remote sensing and to GIS coordination results from assuming that the flow of data should be unidirectional -- from the remote sensing system to the GIS. The reverse flow, from the GIS to the remote sensing system, is desirable, but only infrequently used."

Our research investigated the application of this reverse flow to image analysis for the identification of new oil/gas pads in previously forested lands.

Approach/Methodology

The previous section documented the development of image classification techniques and change detection procedures leading to the current state-of-the-art A.I.-based systems under development. The initial A.I. systems for image analysis attempt to comprehensively classify the entire image into meaningful categories through the application of knowledge-based rules. Most of the systems handle only high resolution panchromatic imagery although the newer systems are starting to be designed around multi-spectral scanner data. The A.I. systems reviewed also predominately utilized only the spectral information contained in the image data.

Our research project was built upon the framework of the blackboard image understanding system of Nagao and Matsuyama (1983) using map-guided feature extraction procedures (McKeown and Denlinger, 1984) and map category-specific interpretation rules based on spectral, spatial, textural, and contextual properties of an image and collateral GIS knowledge layers. Like a good human image interpreter, automated A.I. interpreters should utilize a convergence of evidence process through analysis of the elements of image interpretation (tone, texture, size, shape, context, association). The success of knowledge based expert systems is closely linked with how well its production rules model reality and the depth of its knowledge base. Implementing a comprehensive A.I. system for monitoring all types of land surface change is a long, involved, and complex endeavor. We approached the problem from a more selective, prioritized perspective, however, the ultimate goal is a comprehensive system for updating all inventory categories.

A.I. procedures to detect changes and identify "from-to" classes were developed and performed on a category-by-category basis. Image and data base operations were optimized for "likely" types of change within a known map stratum. A priori knowledge of the previous land cover or use classification and other information in the GIS data base was employed in interpretation rules.

This approach makes sense from the standpoint that successfully mapping different types of land change (e.g. forest clearcuts vs. residential development) may require using different interpretation techniques on substantially different sensor data acquired under different conditions. Also, certain types of change are more widespread, dynamic, and have a higher priority than other types, thus the frequency of update and the resources to accomplish the task may vary.

The basic components and overall conceptual structure of the land cover/use change interpretation system is presented in Figure 1.

The first phase of the process involves pre-processing both map and image data to construct corresponding raster-based, multi-dimensional image layers. The layers of map information in the Michigan GIS are converted to Landsat TM resolution (30-meter) raster files. The remotely sensed multispectral data of a TM scene are first processed to generate any necessary derivative image planes such as vegetative indices, texture, or principal component images. The images are rectified to register with the raster layers of map information. Corresponding image and GIS map data bases are then extracted for specified areas (e.g. townships) and global parameter tables constructed for each layer in the data bases.

The interpretation process is primarily guided by an a priori knowledge of scene content (previously classification and other geographically-based collateral information). By using the map data base and image operators, the feature processor can segment areas and characterize regions.

The image analyzer contains a suite of operators which perform functions needed for feature extraction and region characterization. These image analysis procedures and operators have been reviewed by Rosenfeld (1977, 1984), Claire (1984), and others. More detailed information can found on:

Image segmentation	(Riseman and Arbib, 1977, Ohlander et al., 1978, Schachter et al., 1979, Fu and Mui, 1981, Campbell et al., 1981, Goshtasby, 1984)
region growing	(Zucker, 1976),
edge detection	(Davis, 1975, Peli and Malah, 1982, Hord and Gramenopoulos, 1975)
thresholding	(Weszka, 1978)
shape descriptors	(Pavlidis, 1978, 1980)
texture analysis	(Haralick, 1979, Logan, et al., 1979, Iisaka, 1979, Nasrabadi and King, 1984, Dutra and Mascarenhas, 1984)
object matching	(Zahn, 1974, Price and Reddy, 1979)

Statistical properties of the image data corresponding to map units of the same type are calculated and entered into the property tables for that map stratum such as image properties of previously mapped, high density jack pine pole timber stands. Property tables are constructed for both "from" and "likely change-to" map categories and are put into the map strata data base.

A set of change detection threshold levels for the statistical measure are determined either experimentally or adaptively by the program. The threshold values are used to: 1) determine "classic" (most representative) image parameters for each map stratum in the map strata data base, 2) identify deviant "likely changed" entire map units, and 3) segment image areas within map units that are not representative of the classic signatures for that map stratum.

Statistical properties are then calculated for each possible change area and put into the change feature data base. A set of feature characteristics are determined, for each area using the derived statistical values and feature associated data contained in the GIS map data base.

Category-specific, knowledge-based recognition procedures and rules were developed to detect land cover/use change within a selected map stratum and subsequently classify all change areas as to new land cover or land use. The change-detection interpreter and feature-recognition classifiers employ rules about the feature characteristics noted in the change-feature data base to set recognition status fields.

Image characteristics corresponding to areas currently mapped as the candidate new label category (e.g. oil/gas well) are used in the decision process as is collateral information from the map data base such as adjacency to roads or other a priori knowledge. For example, incorporating rules based upon oil and gas regulations (Sapp and Richter, 1975) such as the minimum spacing of wells and the area around a drilling operation shall be cleared of brush, slash, weeds, and other flammable material for a radius of 75 feet or larger (Michigan's Oil and Gas Regulation, 1983).

The unique features of this method over those previously reported are:

1. The map data base is an independent, operational, multi-layered statewide land resource information system.

2. Development of category-specific change interpretation rules and procedures within a context dependent modeling structure.

3. Focus on land surface change detection and inventory update.

4. Image partitioning by map class stratum

5. Emphasis on feature extraction through sequencing image analysis operations as opposed to pixel operators working on an entire image.

6. Determination of rule parameters values (e.g. threshold levels, texture, size, and shape measures) through feature characterization of image data for known sites currently in the map data base.

7. Incorporation of object matching techniques.

8. Exploration of automated inventory update procedures.

The western portion of Crawford County was the primary study area, with Grand Traverse County serving as an evaluation region. Over 80% of Crawford County is forested with jack pine, red oak, and aspen/birch the predominant species. Stands of red pine, sugar maple, and lowland conifers are also present. Most of the stands are well-stocked pole timber yet over 20% fall in the seedling-sapling class. Logging activities routinely occur in the area and oil/gas exploration has taken place primarily in the N.W. and S.W. corners of the county.

Digital data, including 1978 photo-derived land cover use information, already existed for these counties in the Michigan Resource Information System (MIRIS). Over 20 levels of information are in the MIRIS data base for Crawford County (Table 2). About 60 categories of land cover/use are recognized in MIRIS (Table 3) and more detailed forest data have been collected in many northern counties (including Crawford). Computer programs to transfer and convert MIRIS data to CRS image processing systems were developed.

The methodology outline above was tested in two application areas: 1) the identification of new oil gas wells and 2) automatic detection of roads in Landsat 4 TM images.

In the first investigation, Landsat TM data were merged with land cover and planimetric data layers contained in the State of Michigan's geographic information system (GIS) in order to identify changes in forestlands, principally new oil/gas wells. A GIS-guided, feature-based classification method was developed which involves: 2) partitioning a TM image into forestlands and non-forestlands based on GIS map units, 2) identifying "pad-like" seed points in forestlands through image segmentation, 3) defining regions using an edge detection/region growing algorithm at each seed point, and 4) applying spatial decision rules to identify new pads. The method iteratively selects a different image band or derivative image, seed point determination operator, and region detection algorithm. The regions extracted by the best image band/operator combination are evaluated by a set of rules based on the characteristics of the GIS oil/gas pads. Using the spectral and spatial characteristics of 22 known pads and the best image (TM-2), the algorithm identified 5 of 6 new active wells and decision rules effectively deleted non-pad regions. More detailed information on this study is provided in "Land Cover Change Detection using a GIS-Guided, Feature-Based Classification of Landsat Thematic Mapper Data" (Enslin, Ton, and Jain, 1987). See Appendix for a copy of this paper.

A conceptually parallel road detection method was developed in the second project. The goal was to detect roads at three different levels: major roads, local roads, and minor roads. This road network information is useful for the evaluation of detected potential oil/gas pads, since these pads seldom occur on major roads but are often located at the end of minor access roads.

The method is composed of two phases: low-level road detection and high-level road labeling. In the low-level phase a road sharpening operator calculates a magnitude and direction value for each pixel. A parallel road following algorithm is then implemented at selected seed pixels. In the high-level phase, more global information, such as road

Table 2. MIRIS Information Layers for Crawford County, Michigan

Level	Description
3.	Major Transportation
4.	Streets and Roads
5.	Land Cover/Use (includes detailed forest data)
6.	Lakes and Islands
7.	Rivers and Streams
9.	Property Boundaries
11.	Township Boundaries
13.	Federal and State Project Boundaries
15.	Electric/Gas/Oil Lines
16.	Oil/Gas/Brine Wells
25.	Section Corners
26.	Areas of Particular Concern
30.	State Administered Lands
31.	Historic/Archaeologic Sites
34.	State Administered Lands - Fisheries
35.	State Administered Lands - Parks
36.	Locally Administered Lands
44.	Land Enrolled in TA94
53.	Kirkland Warbler
63.	Section Lines

Table 3. Land Cover/Use Categories Contained in the MIRIS Data

1 Urban and Built up Lands
  11 Residential
    111 Multi-family Residential - Medium to High Rise
    112 Multi-family Residential - Low Rise
    113 Single Family/Duplexes
    115 Mobile Home Park
  12 Commercial, Services, and Institutional
    121 Primary/Central Business District (CBD)
    122 Shopping Center/Mall
    124 Secondary/Neighborhood Business District
    126 Institutional
  13 Industrial
    138 Industrial Parks
  14 Transportation, Communication, and Utilities
    141 Air Transportation
    143 Water Transportation
    145 Communications
    146 Utilities
  17 Extractive
    171 Extractive - Open Pit
    172 Extractive - Underground
    173 Wells
      1731 Oil Wells
      1732 Gas Wells
  19 Open and Other
    191 Outdoor Cultural
    192 Outdoor Public Assembly
    193 Outdoor Recreation
    194 Cemeteries

2 Agricultural Lands
  21 Cropland
    211 Cultivated Crop
    212 Hay, Rotation, and Permanent Pasture
  22 Orchards, Bush Fruits, Vineyards, and Ornamental Horticultural Areas
    221 Tree Fruits
    222 Bush Fruits and Vineyards
  23 Confined Feeding Operations
  24 Permanent Pasture
  29 Other Agricultural Lands

3 Non-forested Lands
  31 Herbaceous Openland
  32 Shrubland
  33 Pine or Oak Opening (Savannah)

Table 4. (continued)

4 Forest Land
- 411/412 Upland-Mixed Hardwoods
- 413 Aspen-Birch
- 414 Lowland Hardwoods
- 421 Pine
- 422 Other Upland Conifers
- 423 Lowland Conifers
- 429 Managed Christmas Tree Plantations

5 Water Bodies
- 51 Streams and Waterways
- 52 Lakes
- 53 Reservoirs
- 54 Great Lakes

6 Wetlands
- 61 Forested (wooded) Wetlands
  - 611 Wooded Wetlands
  - 612 Shrub/Scrub Wetland
- 62 Non-Forested Wetlands
  - 621 Aquatic Bed Wetland
  - 622 Emergent Wetland
  - 623 Wetland Flats

7 Barren Land

length, local intensity and contrast (strength), and curvature, are used to classify roads into different levels. Knowledge-based rules are used to properly label disconnected roads, e.g., segments of highways that are disconnected by small urban areas can be labeled as the same road. Experimental results from several images show that the proposed method can detect roads reasonably well in the low-level phase and is useful in pad evaluation. In the high-level phase only major roads are labeled in our current method. Future research includes combining multi-band information in road detection and determining thresholds in a more systematic way.

An article which more fully describes this study can be found in the Appendix (see "Automatic Road Detection on Landsat 4 TM Images," Ton et al., 1987).

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ANALYSIS OF RADIANT TEMPERATURE DATA FROM THE GEOSTATIONARY OPERATIONAL ENVIRONMENTAL SATELLITES

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This document details the various specifications and methods used to develop the land-cover and forest cover type data layers in the Michigan Geographic Information System. This digital environmental data base was compiled in order to evaluate the potential role the landscape plays in determining the thermal patterns of Michigan.

Landsat Image Interpretation

The scale of the analog compilation maps is 1:250,000. A minimum mapping size of 16 square millimeters was used for all categories of land cover. This mapping size, therefore, corresponds to the one square-kilometer grid-cell size of the final computerized data base.

Nine categories of land cover were mapped -- five at level one, and four at level two. These categories are:

1	Urban and Built-up
2	Agricultural Land
3	Rangeland
41	Broadleaf Forest
42	Needleleaf Forest
5	Water
61	Forested Wetlands
62	Non-Forested Wetlands
7	Barren

The land cover manuscript maps were stable-base overlays to the twenty-three 1:250,000 USGS quadrangles that cover the state of Michigan. Landsat imagery, both MSS and TM, was the primary data source for the land cover layer (see Attachment 1). Visual interpretation procedures were employed, but the Landsat false-color composites that we used were custom products produced in-house. These composites were band-independently contrast-stretched by contact printing the original black-and-white positive transparencies (1:1 million scale) to stable-base diazo color film in an Iconics Ultraviolet Exposure Frame (model BVL 1617). The exposures were precisely controlled by using a Carlson LI-46D Time-Light Integrator which was installed into the Iconics unit. The sensor diode of the integrator was filter to accept only the ultraviolet output of the exposure unit since this is the actinic radiation for diazo film.

An ESECO Speedmaster Color Transmission Densitometer, Model T-85 CD, was used to make optical density measurements on the Landsat transparencies in order to choose the optimum exposure for each band of each scene. The diazo film used was James River Graphics Teknafax, 3 mil polyester, 8.5x11 inches. This film type is developed dry using a Micobra Diazo Film Developer, Model D-11.

These custom diazo-enhanced composites were rear-projected onto stable-base copies of the USGS 1:250,000 quadrangles using a Krones LZK 100S Transyscop. MSS images were projected at 4X magnification ,whereas TM images were projected at either 3X or 4X depending on the date of the image (some of the early TM images processed by the Scrounge System at NASA Goddard and labled "Engineering Test Data" were produced at a scale of 1:750,000).

Although the Landsat imagery was the primary data source for the land cover information, other ancillary sources were utilized as needed. These included a variety of USGS quadrangle maps at scales of 1:250,000, 1:62,500 and 1:24,000; B/W panchromatic aerial photography at 1:20,000 and 1:40,000; color infrared aerial photographs at 1:24,000 (MDNR statewide coverage); NASA high-altitude color infrared images at scales of 1:60,000 and 1:120,000; and various county soil survey reports.

The Forested Wetland category was the most difficult one to map. These areas frequently had the same tonal signature as other forested lands, notably coniferous stands. It was not possible to produce an acceptable diazo enhancement that highlighted the forested wetland features. Multi-temporal Landsat image analysis did help to determine the wetland areas, but the MDNR CIR airphotos had to be relied upon in the most difficult locations. As a first approximation, however, the USGS 7.5-minute quadrangles can be used to show forested wetland areas (swamp symbol in the green, forest overprint).

The broadleaf vs needleleaf forest distinction was difficult in the northern three quads (Traverse City, Cheboygan, and Alpena) because of the large amount of mixed forest in this area. Mixed forest was not one of the mapping categories. Although fall and winter scenes were used in the interpretation process, the winter scenes were not relied upon to classify the coniferous forests. Rather, the polygons were delineated on summer (i.e. leaf-on) and fall (leaf-off, no snow) images. Of course, the aerial photography was used to properly interpret the difficult areas.

The interpretation of urban and builtup land can also be a difficult task, especially when new, residential neighborhoods without large trees form the urban fringe. A diazo enhancement procedure was developed which highlighted the urban features. For this mapping task it was important that the most recent Landsat scene be used.

Coordinate System

The land cover layer was the second statewide data set to be entered into the computer. For a previous project, the Soil Associations of Michigan map had been digitized and was available. As such, the land cover data was considered to be an "overlay" onto the existing soils data. Unfortunately, the geographic graticule on the soils map proved to be inaccurately drawn and so was useless in terms of referencing the USGS 1:250,000 quad-based land cover data. The GIS data entry system we had available (ERDAS 400) did not support the use of latitude/longitude. Because of this limitation, an "arbitrary" transverse Mercator (ATM) grid had been constructed for the soils map. This grid was composed of orthogonal rows and columns of one-kilometer-square cells. When it was discovered that the geographic gradicule on the soil map was in error, this forced us to redo the construction of the ATM.

Since the soils data were already in the computer in the ATM format, it was decided to redraw a more accurate geographic gradicule onto an overlay to the soil map. This would allow us to reference our ATM coordinates to geographic coordinates. The "standard" parallel was chosen to be 44 degrees, the "standard" meridian was chosen to be 86 degrees. From these two "standard" lines (which by definition meet at right angles), a new, orthogonal, geographic grid was laid off using the standard distances between degrees of latitude and longitude (Gosset, 1971).

The ATM coordinates established for the graticule intersections using this method are listed in Attachment 2. The geometric accuracy of this "arbitrary" grid is shown by the error matrix presented as Attachment 4. The stable-base 1:250,000 USGS quads were checked for geometric accuracy as well. The residual errors were acceptably small for our purposes -- usually less that one-third of a grid cell, i.e. 333 meters.

In order to facilitate setting up any map on the digitizer for entry into the ATM coordinate system, a program was written which computes the ATM coordinate for any latitude/longitude. The source code and the appropriate responses to the program's prompts are presented in Attachment 3.

Data Entry

In order to simplify data entry and subsequent GIS manipulation, the land cover category codes, originally taken from the Michigan Land Cover/Use Classification System, were recoded. The class designations were changed as follows:

Class on Land Cover Maps	Feature	Class on Final GIS File
1	Urban	1
2	Agriculture	2
3	Rangeland	3
41	Broadleaf Forest	4
42	Needleleaf Forest	5
5	Water	6
61	Forested Wetland	7
62	Non-Forested Wetland	8
7	Barren	9

The 23 land cover overlays to the 1:250,000 quadrangles were digitized using a Calcomp 9000 electronic digitizing tablet connected to both the ERDAS 400 system and to a standard IBM PC-XT microcomputer. The land cover map units were captured as polygons by this digitizing process. The land cover category codes and the polygon vertices were stored as disk files. Subsequently, these digital polygon files were rasterized at 333.333 meters using the polygon-to-grid conversion software in the ERDAS system.

Due to an error, three of the land cover quadrangle overlays were digitized using incorrect coordinates for their setup. Rather than re-digitize them, it was more efficient to simply transform the incorrectly georeferenced land cover data into the correct grid. A small program was written to accomplish this transformation (see Attachment 5). The three maps which were digitized incorrectly were the Ashland, Marquette, and Escanaba quadrangles.

The one-third kilometer raster file was not intended as the final product-- the final file structure has one-square-kilometer grid cells. The small-area polygons were badly undersampled when we initially tried to rasterize the polygon file at the final resolution of 1000 x 1000 meters. The "high resolution" 333.333 x 333.333 meter rasterization provided a means of controlling the spatial aggregation process inherent in the polygon-to-raster conversion.

A computer program was written that allows the user to specify a new grid cell size and then will aggregate higher-resolution data into larger cells based on category **dominance** and a user-specified priority table. In this program, an N by N window is passed through the GIS file. At each pixel location (x,y,), a frequency count is made of the class values in the window. The most frequently occurring value is assigned as the output pixel value. Ties are broken using a lookup table of class priorities which the user provides. A listing of this program is given in Attachment 6.

File Structure

The "high-resolution" raster file for the state was created in two parts. All data for the Lower Peninsula are in one file; the data for the Upper Peninsula are in a second file. These files have a ".GIS" extension for designation within the ERDAS 400 system. File parameter descriptions include:

	Lower Pen.	Upper Pen.
Columns	1092	1734
Rows	1410	1083
Start X	1	1
Start Y	1	1
Coordinate System	ATM	ATM
X, Upper Left Map Coordinate	290,000	18,068
Y, Upper Left Map Coordinate	558,000	820,628
X Cell Size (meters)	333.333	333.333
Y Cell Size (meters)	333.333	333.333
Classes	10	10

The one kilometer file contains aggregated versions of both the high-resolution Lower and Upper Peninsula data sets. This file also has the ".GIS" extension. Parameter descriptions for this file are:

Columns	633
Rows	733
Start X	1
Start Y	1

Coordinate System	ATM
X, Upper Left Map Coordinate	18,068
Y, Upper Left Map Coordinate	820,628
X Cell Size (meters)	1000
Y Cell Size (meters)	1000
Classes	10

More expansive file information is contained in Attachment 7.

Numerous islands in the Great Lakes are large enough to "show" in the one-square-kilometer data base. A complete list of these islands is presented in Attachment 8.

Major Forest Cover Types

A recent map showing the major forest cover types in Michigan (Spencer,1983) was digitized using the same ATM coordinate system and procedures as the Land Cover file. This map, while showing much more species detail than the land cover file, has very poor spatial precision. The land cover file, on the other hand, has very good spatial precision, but much less detail in terms of the number of species classes it presents. By digitizing this existing map and using the power of the GIS software in the ERDAS 400 system, we created a new, unique map which displayed the best of both of its parents.

The eight map classes on the Forest Type map are:

1	Maple-Birch Association
2	Aspen-Birch Association
3	White-Red-Jack Pine
4	Elm-Ash-Cottonwood Association
5	Spruce-Fir Association
6	Oak-Hickory Association
7	Unproductive Forest
8	Non-Forest Land

The digitized forest type map was rasterized using procedures similar to those employed for the land cover file -- a "high-resolution" file was created and aggregated. The Forest Type GIS file was registered to the Land Cover file using the Overlay and Matrix software routines in the ERDAS system.

The Land Cover and Forest Type files were combined using the Matrix program. Only the union of classes 4,5, and 7 in the land cover file (i.e. broadleaf forest, needleleaf forest, and forested wetland) with classes 1-8 in the forest type file were considered. For any unacceptable co-occurrance (e.g. broadleaf forest on the Land Cover file and White-Red-Jack Pine on the Forest Type file), black and white line printer maps were produced with county boundaries overlayed for reference.

These printer maps were then checked against the Landsat imagery originally used to produce the Land Cover data. Positional referencing in the Landsat scene was accomplished using the county boundaries on the stable-base 1:250,000 quads which were fitted to the projected Landsat image. Analysis was conducted only on areas of four or more contiguous pixels of "errors." If the land cover file was found to be in error, it was interactively updated using the ERDAS software. Only 339 pixels in the original Land Cover data file needed to be changed as a result of this two-map merger. This represents less than one percent of the total matrix size. A listing of the pixels which were changed is given in Attachment 9.

The major products of this research are the digital GIS files which have become the foundation of the Michigan Geographic Information System. This unique resource information data base is fully described in the Appendix entitled Michigan Geographic Information System.

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DEVELOPMENT OF METHODOLOGIES TO ASSESS POSSIBLE IMPACTS OF MAN'S LAND SURFACE CHANGES ON METEOROLOGICAL PARAMETERS

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Background

The fifth project proposed for support from this portion of the NASA contract was originally entitled, "Determination of Dessertification Patterns for a Test Area in Southern Kenya." Because of the unavailability of the principal investigator who was going to use remote sensing techniques in his work in Kenya, we spent our efforts exclusively in the development of methodologies. The particular test site used, because of ease of access and verification, was Michigan's Lower Peninsula. Former work has shown that man's activities in modifying surface conditions can significantly impact surface temperature, reflectance, roughness and, subsequently, heat and vapor fluxes. Satellite data and ground weather stations can be used in energy balance equations to evaluate the impacts of such activities. Thus, preliminary work on the development of methodologies and tests of concepts was undertaken. This was done in cooperation with contract number 923-677-21-24-07 from NASA Goddard.

Problem Statement

The fluxes of heat, vapor, and momentum from the oceans and land surface are driving forces affecting weather patterns. Fluxes from the ocean have been studied relatively extensively considering the spatial uniformity of the oceans. Land surfaces, which are much more complex, have been studied to a much lesser degree. The physical processes occurring at the land surface are relatively poorly understood, quantitatively.

Man has modified major portions of the earth through deforestation, alteration of climax vegetation, and intensive agriculture. The possibility for inadvertent modification of weather patterns from these activities, with subsequent impacts on climate, exists. It is imperative that techniques be developed to better understand these impacts to prevent man from inadvertently modifying weather patterns negatively.

Data on surface parameters over relatively large areas can be obtained only from satellites. Yet, the physical interpretation of such information, because of the large field of view from satellites, is still difficult. Our ability to interpret values measured from satellites in relation to physical and biological conditions has progressed slowly. The goals, however, must be achieved if we are to have techniques that will help us better understand man's impact on the earth's surface and to better incorporate new approaches for quantitizing surface radiation, energy, and vapor fluxes into large scale climatological models.

Study Objectives

The specific objectives of the research have been to:

1. use HCMM and NOAA satellite data to characterize the reflected solar radiation for different surfaces

2. evaluate differences in the thermal regimes of surface types

3. develop objective techniques for using reflectivity and thermal characteristics to detect major vegetation types and monitor shifts in vegetation

4. characterize and monitor boundary layer models to characterize vapor and sensible heat fluxes

Research Strategy

Methodologies that can be considered are energy balance and mass transfer equations which incorporate surface parameters. These models are of two types (Choudhury et al., 1984, Gurney and Camillo, 1984, and Gurney, Blyth and Camillo, 1984). One incorporates stomata and canopy resistance and, possibly, soil water stress. This approach has merit in that it relies on plant conditions. The models, however, can be relatively complex, and the difficulty of integrating small scale stomatal resistance over leaf and, ultimately, canopy dimensions can be a challenge. Such a cumbersome model would be difficult to use over major regions of the earth's surface.

An alternate energy-balance mass-transfer model has been suggested by Fuchs and Tanner. This approach incorporates key surface parameters that can be obtained from satellite measurements. This physically sound mathematical model has been found to reliably predict the flux of heat and vapor under numerous conditions (Bartholic et al., 1970, Fuchs and Tanner, 1967, and Greenfield and

Kellogg, 1960). Of major significance in this approach is the use of surface temperature in the model, a parameter easily measured directly from satellite data. A study by Bartholic in southern Florida shows the correlation between evapotranspiration and surface temperature for a grass-covered surface. Also, the comparison of the Fuchs and Tanner method with the Bowen ratio can be made. An excellent relationship is shown to exist.

A key advantage of this method is that the vapor and heat fluxes can be calculated on a fine grid of cells over the entire test site. Also, the model can easily be run on an hourly basis and integrated over time for ether the three week concentrated experiments or the longer term growing season studies. Further, the heat and vapor fluxes calculated from the model give a relatively clear picture of how these values change across an area as a function of surface conditions (soils, plants, and aspect), and as plant stress increases or plants change in their physiological stage of development.

Conclusions

Man's modifications of surface conditions have significantly altered the thermal regime of the earth's surface causing differences of as much as 8° C between agricultural areas and the originally forested and wetland areas. The reflectance of energy from the earth's surface is also modified and generally correlated with particular vegetation and land use practices. Surface modifications could change the reflectance over relatively large areas by as much as 9%. The changes in surface temperature and reflectance could impact the net radiation significantly and further cause the changes in evapotranspiration rate. Over large areas, differences of 9 cal/cm^2/hr in net radiation and 5-8 cal/cm^2/hr in evapotranspiration could exist between the agricultural areas and the forested and wetland areas. Daily ET differences between the two categories could be as high as 55/cal/cm^2. Over the entire summer season (June to September), a reduction of 7 to 12 cm of water would evaporate from agricultural and urban lands compared to the natural cover types. These alterations would have significant impact on the hydrologic cycle and fluxes of the vapor and heat to the atmosphere.

The heat and vapor fluxes over a relatively large area can be estimated using a Geographic Information System (GIS) and Energy-balance approaches which uses extensive satellite inputs and weather station data. The GIS gives a systematic spatial perspective to the study area. This is crucial in helping to integrate the various components and develop an understanding of the relationships between the basic physical and biological processes in relationship to remotely sensed satellite data. Using the GIS and Energy Balance approaches, a detailed spatial distribution of fluxes of the radiation, heat and vapor from any portion of earth's surface can be derived.

Through monitoring the changes at the earth's boundary layer, the impacts of man's activities on the earth's surface condition can be assessed. Consequently, man's activities which might negatively modify weather patterns could be prevented.

More detailed information is available in the final report on contract 923-677-21-24-07 from NASA GSFC.

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Pecora 10

REMOTE SENSING IN
FOREST AND RANGE RESOURCE MANAGEMENT

LEAF-OFF, REMOTELY-SENSED DATA AS A SOURCE OF FOREST RESOURCE INFORMATION

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ABSTRACT

Forest resource analysts have traditionally relied, almost exclusively, upon aerial photography and other remotely-sensed data acquired during the growing season. The ready availability of leaf-off, high-altitude, color infrared aerial photography (NHAP), as well as multi-temporal Landsat data, for most of the country make these two important additional sources of forest resource information. Leaf-off aerial photography is recommended as a supplement to "traditional," leaf-on photography wherever deciduous-coniferous mixtures occur. In addition to mid-growing season (summer) coverage, analysis of fall, winter, or spring Landsat data should also be considered as a valuable source of forest resource information.

SEASONAL CONSIDERATIONS

On the basis of varying user needs, aerial photographs may be divided into two broad groups: that acquired during the growing season (leaf-on) or during the dormant (leaf-off) season (Avery and Berlin, 1985). Leaf-off aerial photography is typically utilized for compiling topographic maps, identifying landforms, delineating soil boundaries, and a host of other tasks which require minimum obscuration of ground features by vegetation. In contrast, foresters, range managers, and others interested in analyzing the vegetation typically prefer leaf-on aerial photography. There are exceptions to this generalized division, however. For example, the Coast and Geodetic Survey routinely acquires leaf-on photography to permit accurate tree-height determinations in connection with their airport obstruction charting program (Swanson, 1964; Craunt, 1968). Another exception is photo interpretation of conifer-dominated woodlands (e.g. the boreal forest). Inventories of these forest ecosystems are frequently done with leaf-off photography (Aldred and Kippen, 1967; Aldred and Lowe, 1978; Nielson et al., 1979).

Whenever airphoto missions are planned, seasonal considerations should form a part of the specifications and generalized guidelines are available (Avery and Meyers, 1962; Sayn-Wittgenstein, 1967; Avery, 1970). Regarding tree species identification, Sayn-Wittgenstein (1961; 1978) has summarized the major phenological events with respect to the timing of airphoto acquisitions. Specialized photo-interpretation tasks, such as forest regeneration assessments (Kirby, 1980; Goba et al., 1982), should carefully formulate their temporal specifications (Colwell and Marcus, 1961).

Standard forestry photointerpretation procedures (e.g. Zsilinszky, 1966; Hudson, 1984) have stressed the use of leaf-on photography wherever deciduous trees are an important component of the vegetative assemblage. Leaf-on aerial photography is a logical choice whenever differences among hardwood species are required, although there may be exceptions (Newman and Shain, 1976).

Many inventories, especially in areas with a heterogeneous mixture of deciduous and coniferous forest types, may benefit from the use of multi-seasonal (leaf-on and leaf-off) photographic coverage (Hill and Evans, 1982). The recent availability of leaf-off, high-altitude, color infrared (CIR) aerial photography (National High-Altitude Photography Program, NHAP) over the entire continental U.S. may provide this additional source of forest resource information (Antill, 1982).

LEAF-OFF AERIAL PHOTOGRAPHY

Throughout the northern Lake States, a mosaic of deciduous forest types alternate with conifer-dominated forests -- the hemlock-white pine-northern hardwood association (Braun, 1950). Dominance by a single type varies and, complicated by disturbances, results in an often complex intermingling of various proportions of deciduous and coniferous species.

In a forest setting such as this, the unique capabilities of leaf-off CIR aerial photography provides an invaluable supplement to leaf-on airphotos. Of particular concern to the photo interpreter, are those instances where a deciduous overstory completely obscures the presence of a coniferous understory. For example, we have encountered stands which would be classified from leaf-on aerial photography as completely deciduous (aspen-birch or balsam poplar). Intrepretation of these areas on NHAP leaf-off photography, however, revealed a well-stocked understory of coniferous species (northern white-cedar, white spruce, and balsam fir). Subsequent field verification of one of these stands indicated that the coniferous species accounted for the majority of the basal area (100 sq. ft./acre) and volume, compared to the deciduous overstory (only 20 sq. ft./acre).

Although an experienced photo interpreter may have been able to infer the presence of these coniferous understories (based on site, overstory composition, and a knowledge of local environmental and successional relationships), the leaf-on airphotos provided no information by which to fully characterize these stands. This last point is particularly important. Even when the overstory does not completely obscure the understory, the intrepreter is frequently unable to accurately measure the understory. Wherever coniferous and deciduous species intermix, even if one doesn't "over-top" the other, we have found that the use of leaf-off photography enables the interpeter to better quantify the spatial arrangement of the stand. In instances where the coniferous species (e.g. white or red pine) are taller than the surrounding hardwood stand, the spatial extent of the conifers is highlighted on the leaf-off photography.

Although leaf-on aerial photography will continue as the "standard" for many forest photointerpetation tasks in areas where deciduous species are important, resource managers should not overlook the added information which may be derived from leaf-off photography. Especially now with the availability of NHAP leaf-off aerial photography for the entire U.S., we recommend its use as a supplement to "traditional" leaf-on photography.

LEAF-OFF LANDSAT DATA

The acquisition of multi-spectral, multi-temporal (including leaf-off) data from the Landsat series of satellites has provided a voluminous source of potential forest resource data. Although seasonal recommendations vary, to date the majority of forestry applications of Landsat data have relied on the analysis of scenes acquired during the growing season (e.g. Mead and Meyer, 1977; Bryant et al., 1980; Roller and Visser, 1980). Several Landsat applications conducted at the Center for Remote Sensing, Michigan State University will be used to illustrate the utility of leaf-off satellite data to provide forest resource information.

An evaluation of the accuracy of mapping small forestlands in southwestern Michigan from Landsat MSS imagery compared two acquisition dates and two image products (Karteris et al., 1981). For a winter (February), snow-covered scene, a black and white, positive transparency of band 5 was compared with a standard false-color composite produced by the EROS Data Center (EDC). For a second scene, acquired in the fall (September), a standard EDC false-color composite and a custom-made, diazo-enhanced color composite were compared. The diazo color composite was contrast-stretched to enhance the forested areas using the densitometric procedure outlined by Lusch (1981).

Separate forest/non-forest maps were compiled by visually interpreting each of the four Landsat images. Forest areas as small as one hectare (2.5 acres) were delineated. The overall mapping accuracies ranged from 74.0 to 98.5 percent and were higher for the winter scene than for the fall scene; the highest accuracy was achieved with the winter false-color composite. The diazo enhancement of the fall scene improved the mapping accuracy over the standard false-color composite. A spatial analysis of the error units showed that most of them were less than 4 hectares (10 acres) in size and that over 83 percent of all commission and omission errors were along forest/non-forest boundaries.

Franklin, et al. (1983) evaluated the utility of computer-enhanced Landsat imagery for mapping coniferous forest types in the northern Lower Peninsula of Michigan. They visually interpreted a false-color composite of a spring (April) scene which had undergone radiometric restoration, contrast enhancement, edge enhancement, and synthetic line generation. Prior to the actual image interpretation, the analysts were given intensive training which included the development of photo keys illustrating the appearance of the different coniferous forest types on Landsat false-color composites. Additionally, the interpreters systematically compared several examples of each forest type on high-altitude color infrared photography with their appearance on the Landsat color composite; forest inventory measurements (species, stocking, diameter, and height) for each of these training stands were available.

The visual interpretation procedures were tested over two sites to determine the feasibility of identifying four coniferous cover types (red pine, jack pine, pine mixtures, and swamp conifers). The mapping accuracies achieved for each test site are summarized in Tables 1 and 2. Overall classification accuracies were 84.8 and 72.7 percent, whereas the accuracies of interpreting the individual cover types ranged from a low of 32.2 percent for mixed pine stands to a high of 95.1 percent for jack pine plantations. Most of the mapping errors involved a confusion among the individual pine species (red pine, jack pine, and pine mixtures). Accuracies of the combined pine classes, were 93 and 77 percent. The swamp conifer type had consistently low interpretation accuracies in both test areas. As a single broad category, coniferous woodland was interpreted with an accuracy of 90 and 81 percent for the two sites.

Additional research has been aimed at developing automated techniques (i.e. computer classification of Landsat MSS digital data) for the identification and characterization of coniferous forest types in the northern part of Michigan's Lower Peninsula. Landsat-3 MSS data, acquired on February 26, 1979 (E-30358-15471), were used in an analysis of the same test sites referenced above. At this date, there was an average of 58.4 cm of snow on the ground as reported by the 17 weather stations in the area. Almost all of this snowfall occurred prior to several days before the Landsat overpass. As a result, virtually all non-forest cover types, including inland lakes, exhibited the spectral response of snow. Although the hardwood forests were leafless, their extensive mass of trunks and branches substantially altered the reflectance of the underlying snowpack. The coniferous forests, mostly red pine, jack pine, pine mixtures, and swamp conifers (primarly northern white-cedar), provided the only green-foliage reflectance in the entire scene.

A variety of "standard" classifiers (e.g. unsupervised clustering, minimum distance to the mean, and maximum likelihood) were evaluated in terms of their accuracy for disciminating among coniferous forest types (Table 3). Subsequent analysis of the digital brightness values led to the development of spectral response curve models (Hudson and Lusch, 1984). These models predict the multi-band brightness values corresponding to mixtures of various cover types on the basis of their spatial extent in the instantaneous field of view of the MSS instrument.

The Wexford and Crawford county test sites were classified using a two-band linear combination (BV6-BV5, BV6) with class thresholds determined by the response curve models. The resulting accuracies (Tables 4 and 5) exceeded those obtained by any of the "standard" classifiers, but, except for an improved discrimination of pine mixtures, were less than those achieved by visual interpretation procedures. Current research is attempting to quantify the ability of the spectral response curve models to provide a measure of stocking levels within the coniferous forest types.

The results from these three projects clearly indicate that, in addition to the more traditional mid-growing season (summer) coverage, Landsat data acquired during the fall, winter, or spring (i.e. leaf-off) can provide valuable forest resource information. Managers of any ecosystem in which conifers are an important component should not overlook the utility of these leaf-off, remotely sensed data.

ACKNOWLEDGEMENTS

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Table 1. Landsat Classification Performance, Visual Interpretation Data, Wexford County Test Site

Known Cover Type	Number of Sample Points Classified as: Red Pine	Jack Pine	Pine Mixtures	Swamp Conifers	Non-conifer	Total	Percent[1] Correct
Red Pine	774	8	130	26	103	1041	74.4
Jack Pine	31	391	17	10	48	497	78.7
Pine Mixtures	71	2	87	9	13	187	46.5
Swamp Conifers	16	2	0	143	36	197	72.6
Non-conifer	57	3	36	89	2590	2775	93.3
Total	949	411	270	277	2790	4697	
Percent[2] Correct	81.6	95.1	32.2	51.6	92.8		84.8[3]

Table 2. Landsat Classification Performance, Visual Interpretation Data, Crawford County Test Site

Known Cover Type	Number of Sample Points Classified as: Red Pine	Jack Pine	Pine Mixtures	Swamp Conifers	Non-conifer	Total	Percent[1] Correct
Red Pine	23	38	0	1	16	78	29.5
Jack Pine	9	1500	18	18	33	1578	95.1
Pine Mixtures	0	23	33	11	10	77	42.9
Swamp Conifers	0	125	1	398	19	543	73.3
Non-conifer	2	301	1	222	307	833	36.9
Total	34	1987	53	650	385	3109	
Percent[2] Correct	67.6	75.5	62.3	61.2	79.9		72.7[3]

[1] considering only omission errors

[2] considering only commission errors

[3] overall classification accuracy; ratio of the sum of diagonal values to the total number of points

Table 3. Landsat Classification Performance Using "Standard" Classifiers

	Overall Classification Accuracy (%)	
	Wexford County	Crawford County
Default Cluster	77.6	64.8
Cluster with smaller radius	78.8	64.6
Level-Sliced default clusters	79.3	64.2
Level Sliced cluster with smaller radius	80.1	64.8
Minimum distance	79.3	65.2
Maximum Likelihood	79.4	65.1

Table 4. Landsat Classification Performance, (BV6-BV5, BV6) data, Wexford County Test Site

Known Cover Type	Number of Pixels Classified as -- Red Pine	Jack Pine	Pine Mixtures	Swamp Conifers	Non-Conifer	Total	Percent[1] Correct
Red Pine	4497	177	35	--	665	5367	83.8
Jack Pine	358	733	37	--	552	1680	43.6
Pine Mixtures	811	199	56	--	145	1211	4.6
Swamp Conifers	130	133	7	--	68	338	0.0
Non-conifer	757	405	5	--	13292	14459	91.9
Total	6553	1647	133	--	14722	23055	
Percent[2] Correct	68.6	44.5	42.1	0.0	90.3		**80.6** [3]

Table 5. Landsat Classification Performance, (BV6-BV5, BV6) data, Crawford County Test Site

Known Cover Type	Red Pine	Jack Pine	Pine Mixtures	Swamp Conifers	Non-Conifer	Total	Percent[1] Correct
	Number of Pixels Classified as --						
Red Pine	10	259	1	29	36	335	3.0
Jack Pine	5	4795	0	200	969	5965	80.3
Pine Mixtures	3	545	2	34	146	730	0.3
Swamp Conifers	2	769	0	585	60	1416	4.3
Non-conifer	2	1892	3	36	4229	6159	68.7
Total	22	8257	3	884	5440	14605	
Percent[2] Correct	45.4	58.0	66.7	66.2	77.7		**65.8**[3]

[1]considering only omission errors

[2]considering only commission errors

[3]overall classification accuracy; ratio of the sum of diagonal values to the total number of points

MICHIGAN GEOGRAPHIC INFORMATION SYSTEM
Center for Remote Sensing
Michigan State University

The Michigan Geographic Information System is a microcomputer-based, statewide, georeferenced information management system. The raster file structure uses 1 square-kilometer grid cells and contains 633 columns and 733 rows.

The system is currently resident on an IBM Personal Computer AT and utilizes ERDAS (Earth Resources Data Analysis Systems) software.

All files are 8-bit, consist of a prefix (MI, LP, or UP, a file name, and a GIS extension. The prefix MI is utilized for statewide files (733 rows by 633 columns) which contain data for all 83 Michigan counties and associated Islands. The prefix UP is used for subset files containing upper peninsula counties only (361 rows by 578 columns) while a lower peninsula subset file has an LP prefix (470 rows by 361 columns).

Summary sheets for the several data layers currently in the system are attached.

MICHIGAN GEOGRAPHIC INFORMATION SYSTEM
Center for Remote Sensing
Michigan State University

LAND COVER

Variable Name: LAND COVER, 1 KM. RES.

Description: Level I (augmented) land cover (U.S. Geological Survey Professional Paper 964, A Land Use and Land Cover Classification System for Use with Remote Sensor Data)

Files: MICOVER
LPCOVER
UPCOVER

Data Source: Visual interpretation of Landsat (satellite) imagery (1979-82). Custom-enhanced (density-specified, contrast-stretched reproductions of B/W positive transparencies), 1:1 million-scale, false color composites were utilized.

Categories: 10

Value	Description
0	Background and Great Lakes
1	Urban and Built-Up
2	Agriculture
3	Rangeland
4	Deciduous Forest
5	Coniferous Forest
6	Inland Waters
7	Forested Wetlands
8	Non-Forested Wetlands
9	Barren Land

MICHIGAN GEOGRAPHIC INFORMATION SYSTEM
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SOIL ASSOCIATIONS

Variable Name: SOIL ASSOCIATIONS - 1 KM. RES.

Description: A soil association is a landscape that has a distinctive proportional pattern of soils. It consists of several major soils and some minor soils, and is named for the major soils.

Files: MISOILS
LPSOILS
UPSOILS

Data Source: Michigan State University. 1981. Soil Association Map of Michigan. Extension Bulletin E-1550. MSU Cooperative Extension Service and Agricultural Experiment Station; U.S.D.A., Soil Conservation Service.

Categories: 81

Value	Description
0	Background and Great Lakes
1	Ontonagon-Rudyard-Pickford
2	Watton-Alstad
3	Iron River-Champion-Gogebic
4	Emmet-Trenary-Bohemian
5	Kalkaska-Keweenaw-Munising
6	Kiva
7	Kawbawgam
8	Longrie-Summerville
9	Emmet-Trenary-Cathro
10	Iron River-Michigamme-Rock Land
11	Rudyard-Pickford
12	Angelica-Brimley-Bruce
13	Roscommon-AuGres-Tawas
14	Rubicon
15	Kalkaska-Blue Lake
16	Kalkaska-Tawas-Carbondale
17	Detour-Johnswood-Longrie
18	Rubicon-Michigamme-Rock Land
19	Roscommon-Tawas-Rubicon
20	Tawas-Carbondale-Greenwood
21	Fluvaquents-Carbondale
22	Kalkaska-Rubicon
23	Leelanau-Emmet-Kalkaska
24	Graycalm-Montcalm
25	Nester-Kawkawlin-Sims
26	Nester-Menominee-Montcalm
27	Mcbride-Montcalm
28	Emmet-Leelanau
29	Grayling-Rubicon
30	Emmet-Onaway
31	Iosco-Allendale-Brevort
32	Mancelona-Gladwin
33	Iosco-Kawkawlin-Sims
34	Hillsdale-Riddles
35	Spinks-Oshtemo-Boyer
36	Schoolcraft-Kalamazoo-Elston
37	Kalamazoo-Oshtemo
38	Tedrow-Granby
39	Brady-Wasepi-Gilford
40	Oakville-Plainfield-Spinks
41	Marlette-Capac
42	Capac-Parkhill
43	Houghton-Palms-Sloan
44	Boyer-Oshtemo-Houghton
45	Boyer-Riddles-Marlette
46	Boyer-Wasepi
47	Houghton-Gilford-Adrian
48	Lenawee-Toledo-Del Rey
49	Tedrow-Tedrow,Loamy-Selfridge

50 Perrinton-Ithaca
51 Pipestone-Kingsville-
Saugatuck-Wixom
52 Ithaca-Pewamo-Belleville
53 Morley-Glynwood-Blount
54 Boyer-Fox-Sebewa
55 Oshtemo-Brady-Gilford
56 Riddles-Teasdale
57 Miami-Conover-Brookston
58 St.Clair-Nappanee
59 Belleville-Selfridge-Metea
60 Hoytville-Nappanee
61 Kibbie-Colwood
62 Blount-Pewano
63 Oakville-Tedrow-Granby
64 Metamora-Blount-Pewamo
65 Grattan
66 Grattan-Covert-Pipestone
67 Spinks-Perrinton-Ithaca
68 Wixom-Londo-Guelph
69 Tappan-Londo
70 Tappan-Londo-Poseyville
71 Tappan-Belleville-Essexville
72 Lapeer-Hillsdale
73 Sanilac-Bach
74 Shebeon-Kilmanagh
75 Iron River-Baraga-Champion
76 Geogebic-Keweenaw-Kalkaska
77 Amasa-Stambaugh
78 Tula-Pliene
79 Inland Waters
80 No Data

MICHIGAN GEOGRAPHIC INFORMATION SYSTEM
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SOIL TEXTURE

Variable Name: SOIL ASSNS. AS 18 CLASSES

Description: Texture of dominant soils in soil associations

Files: MISOIL18

Derivation: Recoded from Soil Association Map (MISOILS)

Data Source: Michigan State University. 1981. Soil Association Map of Michigan. Extension Bulletin E-1550. MSU Cooperative Extension Service and Agricultureal Experiment Station; U.S.D.A. Soil Conservation Service.

Categories: 20

Value	Description
0	Background and Great Lakes
19	Inland Waters
Frigid Temperature Regime*	
1	Clayey Soils
2	Loamy Soils
3	Loamy Soils with Organic Soils
4	Loamy Soils Underlain by Sand and Gravel
5	Loamy and Sandy Soils on Bedrock Controlled Uplands
6	Loamy Soils Interspersed with Sandy Soils
7	Sandy Soils
8	Wet Clayey and Loamy Soils
9	Wet Sandy and Organic Soils
Mesic Temperature Regime*	
10	Clayey Soils
11	Wet Clayey Soils
12	Loamy Soils
13	Wet Loamy Soils
14	Sandy Soils
15	Wet Sandy Soils and Wet Loamy Soils Underlain by Sand and Gravel
16	Loamy Soils Underlain by Sand and Gravel
17	Wet Organic and Loamy Soils
18	No Data

*Frigid soils have mean annual soil temperatures at 50 cm of less than 8°C (47°F). Mesic soils have mean annual soil temperatures at 50 cm of 8°C or higher but lower than 15°C (47-59°F). In both mesic and frigid soils the difference between mean winter and mean summer soil temperature is more than 5°C (9°F).

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AVERAGE WATER HOLDING CAPACITY

Variable Name: AVERAGE WATER HOLDING CAPACITY: 1-12 IN.
AVERAGE WATER HOLDING CAPACITY: 13-24 IN.
AVERAGE WATER HOLDING CAPACITY: 25-36 IN.
AVERAGE WATER HOLDING CAPACITY: 37-48 IN.
AVERAGE WATER HOLDING CAPACITY: 49-60 IN.

Description: A measure of the ability of a soil layer to hold free water, estimated as inch/inch and expressed as a percent.

Files: MIAWC1
MIAWC2
MIAWC3
MIAWC4
MIAWC5

Derivation: Recoded from Soil Association Map (MISOILS) and Soil Interpretations Record (National Cooperative Soil Survey), (Lusch and Enslin, 1984)

Data Source: Soil Interpretations Record, National Cooperative Soil Survey, U.S.D.A., Soil Conservation Service. Lusch, D.P. and W.R. Enslin. 1984. Microcomputer-Based, Statewide, Digital Land-Surface Information. Proceedings of PECORA 9, Spatial Information Technologies for Remote Sensing Today and Tomorrow, pp. 40-43.

Categories: 12

Value	Description
0	Background and Great Lakes
1	1-5%
2	6-10%
3	11-15%
4	16-20%
5	21-25%
6	26-30%
7	31-35%
8	36-40%
9	41-45%
10	Inland Waters
11	No Data

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ELEVATION

Variable Name: NOAA DIG. ELEV.DATA: 10 METER RES.

Description: Point elevation data in meters (feet).

Files: LPELEV

Data Source: NOAA 30 arc-second point elevation data, Item T6P-0050 from the National Geophysical Data Center (The data were originally derived by the Defense Mapping Agency from $1^{\circ} \times 2^{\circ}$ topographic maps (1:250,000)

Categories: 35 (Point elevation in increments of 10 meters from 170 to 500 meters).

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ASPECT

Variable Name:

Description: Direction of maximum slope.

Files: LPASPECT

Derivation: Transformed from Elevation (LPELEV).

Data Source: NOAA 30 arc-second point elevation data, Item TGP-0050 from the National Geophysical Data Center.

Categories: 10

Value	Direction	Angle
1	N	360 ± 22.5
2	NE	45 ± 22.5
3	E	90 ± 22.5
4	SE	135 ± 22.5
5	S	180 ± 22.5
6	SW	225 ± 22.5
7	W	270 ± 22.5
8	NW	315 ± 22.5
9	Flat Areas	

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SLOPE LENGTH

Variable Name:

Description: Length of slope from ridge crest.

Files: LPSLPLEN

Derivation: Transformed from Elevation (LPELEV)

Data Source: NOAA 30 arc-second point elevation data, Item TGP-0050 from the National Geophysical Data Center.

Categories: 64

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POLITICAL DIVISIONS, COUNTY BOUNDARIES

Variable Name: POLITICAL DIVISIONS: COUNTY BOUNDARIES

Description: Boundaries delineating the 83 separate countries.

Files: MICNTY
LPCNTY
UPCNTY

Data Source: U.S. Geological Survey 1^{o} x 2^{o} Quadrangels (United States Series of Topographic Maps, Scale, 1:250,000)

Categories: 2

Value	Description
0	Background and Great Lakes
1	County Boundaries

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POLITICAL BOUNDARIES, COUNTIES AS AREAS

Variable Name: POLITICAL DIVISIONS, COUNTIES AS AREAS

Description: Aerial extent of the individual 83 counties.

Files: LPCNTYA

Data Source: U.S. Geological Survey 1^{o} x 2^{o} Quadrangles (United States Series of Topographic Maps, Scale, 1:250,000)

Categories: 84

Value	Description
0	Background and Great Lakes
1	Alcona
2	Alger
3	Allegan
4	Alpena
5	Antrim
6	Arenac
7	Baraga
8	Barry
9	Bay
10	Benzie
11	Berrien
12	Branch
13	Calhoun
14	Cass
15	Charlevoix
16	Cheboygan
17	Chippewa
18	Clare
19	Clinton
20	Crawford
21	Delta
22	Dickinson
23	Eaton
24	Emmet
25	Genesee
26	Gladwin
27	Gogebic
28	Grand Traverse
29	Gratiot
30	Hillsdale
31	Houghton
32	Huron
33	Ingham
34	Ionia
35	Iosco
36	Iron
37	Isabella
38	Jackson
39	Kalamazoo
40	Kalkaska
41	Kent
42	Keweenaw
43	Lake
44	Lapeer
45	Leelanau
46	Lenawee
47	Livington
48	Luce
49	Mackinac
50	Macomb
51	Manistee
52	Marquette
53	Mason
54	Mecosta
55	Menominee
56	Midland
57	Missaukee
58	Monroe
59	Montcalm
60	Montmorency
61	Muskegon
62	Newaygo
63	Oakland
64	Oceana
65	Ogemaw
66	Ontonagon
67	Osceola
68	Oscoda
69	Otsego
70	Ottawa
71	Presque Isle
72	Roscommon
73	Saginaw
74	St. Clair
75	St. Joseph
76	Sanilac
77	Schoolcraft
78	Shiawassee
79	Tuscola
80	Van Buren
81	Washtenaw
82	Wayne
83	Wexford

MICHIGAN GEOGRAPHIC INFORMATION SYSTEM
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MAJOR FOREST COVER TYPES

Variable Name: FOREST SPECIES TYPE: 1 KM

Description: A classification of forest land based upon the species forming a plurality of live tree stocking. For presentation of resource data (forest survey) these types are combined into type groups (major forest cover types).

Files: MIFOREST

Derivation: Matrix analysis on LAND COVER (MICOVER) and Major Forest Types (Spencer, 1983)

Data Source: Spencer, John S., Jr. 1983. Michigan's Fourth Forest Inventory: AREA. Resource Bulletin NC-68, U.S. Forest Service, North Central Forest Experiment Station.

Categories: 9

Value	Description
0	Background and Great Lakes
1	Oak-Hickory
2	Maple-Birch
3	Aspen-Birch
4	Elm-Ash-Cottonwood
5	Spruce-Fir
6	White-Red-Jack Pine
7	Non-Forest Land
8	Inland Waters

MICHIGAN GEOGRAPHIC INFORMATION SYSTEM
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GLACIAL DRIFT THICKNESS

Variable Name:

Description: Generalized zones, representing depth intervals to bedrock, of glacial drift.

Files: LPDTHICK

Data Source: Glacial Drift Thickness, Plate 15, Hydrogeologic Atlas of Michigan, Department of Geology, Western Michigan University, Kalamazoo, Michigan, 1981.

Categories: 17

MICHIGAN GEOGRAPHIC INFORMATION SYSTEM
Center for Remote Sensing
Michigan State University

MAJOR WATERSHEDS

Variable Name:

Description: Major drainage basins of major rivers and tributaries.

Files: LPWSHED

Data Source: Michigan River Basins: Michigan Geological Survey Division Map No. 200, Michigan Department of Natural Resources.

Categories: 43

Value	Description
0	
1	Short Drainage Directly to Great Lakes
2	Galien
3	St. Joseph
4	Maumee (drainage to Maumee River, Ohio)
5	Raisin
6	River Rouge
7	Huron
8	Grand
9	Thornapple
10	Kalamazoo
11	Black
12	PawPaw
13	Red Cedar
14	Looking Glass
15	Maple
16	Flat
17	Rogue
18	Muskegon
19	White
20	Pere Marquette
21	Big Sable
22	Manistee
23	Betsie
24	Boardman
25	Rapid
26	Jordan
27	Cheboygan
28	Thunder Bay
29	Au Sable
30	Au Gres
31	Rifle
32	Tittabawassee

33	Shiawassee
34	Flint
35	Cass
36	Saginaw
37	Sevewaing
38	Pigeon
39	Pinebog
40	Black
41	Belle
42	Clinton

MICHIGAN GEOGRAPHIC INFORMATION SYSTEM
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AQUIFER VULNERABILITY

Variable Name:

Description:

Files: LPAQVULN

Data Source: (MDNR Map C-32860)

Categories: 5

Value	Description
1	Protected Aquifer
2	Unprotected Aquifer
3	Unclassified Aquifer
4	No Data

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MEAN TEMPERATURE

Description: Mean monthly and annual mean temperature. (^{O}F), 1940-1969.

Data Source: Mean Temperature Maps For the Period 1940-1969, Supplement B to the Climate of Michigan by Stations, Michigan Department of Agriculture, Michigan Wather Service, June 1974.

Categories: 64 (Temperature intervals with 1^{O}F ranges, from 11 to 74^{O}F)

File	Description
MTEMP1	January Mean Temperature
MTEMP2	February Mean Temperature
MTEMP3	March Mean Temperature
MTEMP4	April Mean Temperature
MTEMP5	May Mean Temperature
MTEMP6	June Mean Temperature
MTEMP7	July Mean Temperature
MTEMP8	August Mean Temperature
MTEMP9	September Mean Temperature
MTEMP10	October Mean Temperature
MTEMP11	November Mean Temperature
MTEMP12	December Mean Temperature
MTEMP13	Annual Mean Temperature

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AVERAGE MINIMUM TEMPERATURE

Description: Monthly and annual average daily-minimum temperature (^{o}F), 1940-1969.

Data Source: Average Minimum Temperature Maps for the Period 1940-1969, Supplement E to the Climate of Michigan by Stations, Michigan Department of Agriculture, Michigan Weather Service, August 1976.

Categories: 65 (Temperature intervals with 1^{o}F ranges, from 1 to 64^{o}F)

File	Description
DMIN1	January Average Daily Minimum Temperature
DMIN2	February Average Daily Minimum Temperature
DMIN3	March Average Daily Minimum Temperature
DMIN4	April Average Daily Minimum Temperature
DMIN5	May Average Daily Minimum Temperature
DMIN6	June Average Daily Minimum Temperature
DMIN7	July Average Daily Minimum Temperature
DMIN8	August Average Daily Minimum Temperature
DMIN9	September Average Daily Minimum Temperature
DMIN10	October Average Daily Minimum Temperature
DMIN11	November Average Daily Minimum Temperature
DMIN12	December Average Daily Minimum Temperature
DMINT	Annual Average Daily Minimum Temperature

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MEAN NUMBER OF DAYS MINIMUM TEMPERATURE 0^{O}F AND BELOW

Description: Mean monthly and annual mean number of days with minimum temperatures of 0^{O}F and below, 1940-1969,

Data Source: Maps of Mean Number of Days Minimum Temperature 0^{O}F and Below For the Period 1940-1969, Supplement K to the Climate of Michigan by Statistics, Michigan Department of Agriculture, Michigan Weather Service, August 1979.

Categories: 16 (Number of days or partial days); 11 (series of day ranges for cumulative mean annual)

File	Description
MNUL01	January, Mean Number of Days Minimum Temperature 0^{O}F and Below
MNUL02	February, Mean Number of Days Minimum Temperature 0^{O}F and Below
MNUL03	March, Mean Number of Days Minimum Temperature 0^{O}F and Below
MNUL04	April, Mean Number of Days Minimum Temperature 0^{O}F and Below
MNUL05	November, Mean Number of Days Minimum Temperature 0^{O}F and Below
MNUL06	December, Mean Number of Days Minimum Temperature 0^{O}F and Below
MNUN0AN	Annual, Mean Number of Days Minimum Temperature 0^{O}F and Below

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MEAN NUMBER OF DAYS MINIMUM TEMPERATURE 32° AND BELOW

Description: Mean monthly and annual mean number of days with minimum temperatures of 32°F and below, 1940-1969.

Data Source: Maps of Mean Number of Days Minimum Temperature 32°F and Below for the Period 1940-1969, Supplement J to the Climate of Michigan by Stations, Michigan Department of Agriculture, Michigan Weather Service, August 1979.

Categories: 34 (number of days), 11 (series of day ranges for cumulative mean annual)

File	Description
MIN1	January, Mean Number of Days Minimum Temperature 32°F and Below
MIN2	February, Mean Number of Days Minimum Temperature 32°F and Below
MIN3	March, Mean Number of Days Minimum Temperature 32°F and Below
MIN4	April, Mean Number of Days Minimum Temperature 32°F and Below
MIN5	May, Mean Number of Days Minimum Temperature 32°F and Below
MIN6	June, Mean Number of Days Minimum Temperature 32°F and Below
MIN7	July, Mean Number of Days Minimum Temperature 32°F and Below
MIN8	August, Mean Number of Days Minimum Temperature 32°F and Below
MIN9	September, Mean Number of Days Minimum Temperature 32°F and Below
MIN10	October, Mean Number of Days Minimum Temperature 32°F and Below
MIN11	November, Mean Number of Days Minimum Temperature 32°F and Below
MIN12	December, Mean Number of Days Minimum Temperature 32°F and Below
MINAN	Annual, Mean Number of Days Minimum Temperature 32°F and Below

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AVERAGE MAXIMUM TEMPERATURE

Description: Monthly and annual average daily-maximum temperature (°F), 1940-1969.

Data Source: Average Maximum Temperature Maps for the Period 1940-1969, Supplement D to the Climate of Michigan by Stations, Michigan Department of Agriculture, Michigan Weather Service, July 1976.

Categories: 66 (Temperature intervals with 1°F ranges, from 21 to 65°F)

File	Description
DMAXT1	January Average Daily Maximum Temperature
DMAXT2	February Average Daily Maximum Temperature
DMAXT3	March Average Daily Maximum Temperature
DMAXT4	April Average Daily Maximum Temperature
DMAXT5	May Average Daily Maximum Temperature
DMAXT6	June Average Daily Maximum Temperature
DMAXT7	July Average Daily Maximum Temperature
DMAXT8	August Average Daily Maximum Temperature
DMAXT9	September Average Daily Maximum Temperature
DMAXT10	October Average Daily Maximum Temperature
DMAXT11	November Average Daily Maximum Temperature
DMAXT12	December Average Daily Maximum Temperature
DMAXTAN	Annual Average Daily Maximum Temperature

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HIGHWAYS

Variable Name: HWYS

Description: Major highways

Files:

Data Source:

Categories: 7

Value	Description
0	Background and Great Lakes
1	0-2000 vehicles/hr
2	2000-5000 vehicles/hr
3	5000-10000 vehicles/hr
4	10000 and more vehicles/hr
5	Urban and Built-up Lands
6	Other Lands/Uses

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FEDERAL AND STATE LANDS

Variable Name: ADMINISTRATIVE UNITS

Description: Project boundaries, including all ownership contained within the boundaries, for State and Federal projects.

Files: MIADMINU
LPADMINU
UPADMINU

Data Source:

Categories: 11

Value	Description
0	Background and Great Lakes
1	Predominantly Private Lands
2	State Forests
3	State Parks and Recreation Areas
4	State Game and Wildlife Areas
5	National Forests
6	National Parks and Lake Shores
7	National Wildlife Refuges
8	State Military Lands
9	Federal Military Lands
10	Inland Lakes

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SNOWFALL STATISTICS

Description: First 1-, 3-, 6-, 12- inch depths.

Data Source: Strommen, N.D. 1968. Michigan Snowfall. Statisticw; First 1-, 30, 6-, 12-Inch Depths, Michigan Department of Agriculture, Michigan Weather Service.

Categories: varies

File	Description
SNO1	Earliest recorded occurrence of 1-inch Snow Depth
MND1	Mean Date of First 1-inch Snow Depth
MND1	Mean Date of First 3-inch Snow Depth
PERC6	Percentage of years during which a 6-inch or greater snow depth occurred
MND6	Mean Date of First 6-inch Snow Depth
PERC12	Percentage of years during which a 12-inch or greater snow depth occurred.
MND12	Mean date of First 12-inch Snow Depth

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SNOW DEPTHS

Description: Average number of days with a specified snow depth or more.

Data Source: Strommen, N.D. 1969. Michigan Snow Depths. Michigan Department of Agriculture, Michigan Weather Service.

Categories: 17 (ranges of days)

File	Description
SNOCM1	Average Number of Days Per Season with Accumulated Snow Depth on the Ground of 1 inch or More
SNOCM6	Average Number of Days Per Season with Accumulated Snow Depth on the Ground of 6 inch or More
SNOCM11	Average Number of Days Per Season with Accumulated Snow Depth on the Ground of 11 inch or More
SNOCM16	Average Number of Days Per Season with Accumulated Snow Depth on the Ground of 16 inch or More
SNOCM21	Average Number of Days Per Season with Accumulated Snow Depth on the Ground of 21 inch or More
SNOCM26	Average Number of Days Per Season with Accumulated Snow Depth on the Ground of 26 inch or More
SNOCM31	Average Number of Days Per Season with Accumulated Snow Depth on the Ground of 31 inch or More
SNOCM36	Average Number of Days Per Season with Accumulated Snow Depth on the Ground of 36 inch or More
SNOMAX	Maximum Depth of Snow on the Ground
SNO3160	Mean Annual Snowfall in Inches
SNO4009	Average Annual Snowfall in Inches

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MAXIMUM SNOWFALL

Description: Maximum monthly and annual maximum snowfall.

Data Source: Maps of Maximum Monthly and Annual Maximum Snowfall, Supplement G to the Climate of Michigan by Stations, Michigan Department of Agriculture, Michigan Weather Service, August, 1979.

Categories: 17 (ranges of 10 inches)

File	Description
MXSNO1	January Maximum Montly Snowfall
MXSNO2	February Maximum Montly Snowfall
MXSNO3	March Maximum Montly Snowfall
MXSNO4	April Maximum Montly Snowfall
MXSNO5	May Maximum Montly Snowfall
MXSNO9	September Maximum Montly Snowfall
MXSNO10	October Maximum Montly Snowfall
MXSNO11	November Maximum Montly Snowfall
MXSNO12	December Maximum Montly Snowfall
MSXNOAN	Annual Maximum Montly Snowfall

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MEAN SNOWFALL

Description: Mean monthly and annual mean snowfall (inches).

Data Source: Maps of mean monthly and annual mean snowfall, Supplement C to the Climate of Michigan by Stations, Michigan Department of Agriculture, Michigan Weather Service, March, 1975.

Categories: 14 (ranges of snowfall)

File	Description
MSNO1	January Mean Snowfall
MSNO2	February Mean Snowfall
MSNO3	March Mean Snowfall
MSNO4	April Mean Snowfall
MSNO5	May Mean Snowfall
MSNO9	September Mean Snowfall
MSNO10	October Mean Snowfall
MSNO11	November Mean Snowfall
MSNO12	December Mean Snowfall
MSNOAN	Annual Mean Snowfall

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MEAN NUMBER OF DAYS .10 INCH OR MORE PRECIPITATION

Description: Mean monthly and annual mean number of days with .10 inch or more precipitation.

Data Source: Maps of Mean Monthly and Annual Number of days .10 inch or more Precipitation, Supplement L to the Climate of Michigan by Stations, Michigan Department of Agriculture, Michigan Weather Service, December, 1979.

Categories: 10 (number of days or ranges of days)

File	Description
MNMOPC1	January, Mean number of Days .10 Inch or More Precipitation
MNMOPC2	February, Mean number of Days .10 Inch or More Precipitation
MNMOPC3	March, Mean number of Days .10 Inch or More Precipitation
MNMOPC4	April, Mean number of Days .10 Inch or More Precipitation
MNMOPC5	May, Mean number of Days .10 Inch or More Precipitation
MNMOPC6	June, Mean number of Days .10 Inch or More Precipitation
MNMOPC7	July, Mean number of Days .10 Inch or More Precipitation
MNMOPC8	August, Mean number of Days .10 Inch or More Precipitation
MNMOPC9	September, Mean number of Days .10 Inch or More Precipitation
MNMOPC10	October, Mean number of Days .10 Inch or More Precipitation
MNMOPC11	November, Mean number of Days .10 Inch or More Precipitation
MNMOPC12	December, Mean number of Days .10 Inch or More Precipitation
MNMOPCAN	Annual, Mean number of Days .10 Inch or More Precipitation

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MEAN PRECIPITATION

Description: Mean monthly and annual precipitation (inches), 1940-1969.

Data Source: Maps of Mean Monthly and Annual Precipitation, for the period 1940-1969, Supplement A to the Climate of Michigan by Stations, Michigan Department of Agriculture, Michigan Weather Service, June 1974.

Categories: 11 (ranges of precipitation, in inches)

File	Description
MPREC1	January Mean Precipitation
MPREC2	February Mean Precipitation
MPREC3	March Mean Precipitation
MPREC4	April Mean Precipitation
MPREC5	May Mean Precipitation
MPREC6	June Mean Precipitation
MPREC7	July Mean Precipitation
MPREC8	August Mean Precipitation
MPREC9	September Mean Precipitation
MPREC10	October Mean Precipitation
MPREC11	November Mean Precipitation
MPREC12	December Mean Precipitation
MPRECAN	Annual Mean Precipitation

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MEAN HEATING DEGREE DAYS

Description: Mean monthly and annual mean heating degree days (departure of daily mean temperature from 65^{o} F) for the period 1940-1969.

Data Source: Maps of Mean Monthly and Annual Heating Degree Days for the period 1940-1969, Supplement F to the Climate of Michigan by Stations, Michigan Department of Agriculture, Michigan Weather Service, May, 1979.

Categories: 33 (ranges of heating degree days)

File	Description
HEAT1	January Mean Heating Degree Days
HEAT2	February Mean Heating Degree Days
HEAT3	March Mean Heating Degree Days
HEAT4	April Mean Heating Degree Days
HEAT5	May Mean Heating Degree Days
HEAT6	June Mean Heating Degree Days
HEAT7	July Mean Heating Degree Days
HEAT8	August Mean Heating Degree Days
HEAT9	September Mean Heating Degree Days
HEAT10	October Mean Heating Degree Days
HEAT11	November Mean Heating Degree Days
HEAT12	December Mean Heating Degree Days
HEATAN	Annual Mean Heating Degree Days

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MEAN NUMBER OF DAYS MAXIMUM TEMPERATURE 32°F AND BELOW

Description: Mean monthly and annual mean number of days with maximum temperatures of 32°F and below for the period 1940-1969.

Data Source: Maps of Mean Monthly and Annual Number of Days Maximum Temperature 32°F and Below for the period 1940-1969, Supplement I to the Climate of Michigan by Stations, Michigan Department of Agriculture, Michigan Weather Service, August, 1979.

Categories: 29 (number of days), 8 (series of day ranges for cumulative mean annual)

File	Description
MAXTMP1	January, Mean Number of Days Maximum Temperature 32°F and Below
MAXTMP2	February, Mean Number of Days Maximum Temperature 32°F and Below
MAXTMP3	March, Mean Number of Days Maximum Temperature 32°F and Below
MAXTMP4	April, Mean Number of Days Maximum Temperature 32°F and Below
MAXTMP5	May, Mean Number of Days Maximum Temperature 32°F and Below
MAXTMP6	June, Mean Number of Days Maximum Temperature 32°F and Below
MAXTMP7	July, Mean Number of Days Maximum Temperature 32°F and Below
MAXTMP8	August, Mean Number of Days Maximum Temperature 32°F and Below
MAXTMP9	September, Mean Number of Days Maximum Temperature 32°F and Below
MAXTMP10	October, Mean Number of Days Maximum Temperature 32°F and Below
MAXTMP11	November, Mean Number of Days Maximum Temperature 32°F and Below
MAXTMP12	December, Mean Number of Days Maximum Temperature 32°F and Below
MAXTMPAN	Annual, Mean Number of Days Maximum Temperature 32°F and Below

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MEAN NUMBER OF DAYS MAXIMUM TEMPERATURE 90°F AND ABOVE

Description: Mean monthly and annual mean number of days with maximum temperatures of 90°F and above, 1940-1969.

Data Source: Maps of Mean Number of Days Maximum Temperature 90°F and Above (1940-1969), Supplement H to the Climate of Michigan by Stations, Michigan Department of Agriculture, Michigan Weather Service, August, 1979.

Categories: 10 (number of days), 6 (series of day ranges for cumulative mean annual)

<u>File</u>	<u>Description</u>
MXOV91	May, Mean Number of Days Maximum Temperature 90°F and Above
MXOV92	June, Mean Number of Days Maximum Temperature 90°F and Above
MXOV93	July, Mean Number of Days Maximum Temperature 90°F and Above
MXOV94	August, Mean Number of Days Maximum Temperature 90°F and Above
MXOV95	September, Mean Number of Days Maximum Temperature 90°F and Above
MXOV96	Annual, Mean Number of Days Maximum Temperature 90°F and Above