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LANDSAT DIGITAL ANALYSIS: IMPLICATIONS FOR WETLAND MANAGEMENT

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I. ABSTRACT

Wetland management needs include requirements for both overall wetland planning and management by local, state, regional and national agencies and internal management of large wetlands. Landsat digital data can potentially supply management information such as location, area, wetland type, seasonal extent of surface inundation, changes in vegetative composition and thus wildlife habitat potential, impact of construction or water-level control, and information for wetland evaluation. However, at present (1981), Landsat classification accuracies for wetland type or vegetation are often as low as 70 percent. These generally unsatisfactory results are due to Landsat resolution, spectral and spatial heterogeneity of wetlands and vegetative communities, spectral overlap with nonwetlands, and inherent problems of boundary pixels and pixel correlation. Better accuracies are needed for wetland management. Improvement might be obtained through prestratification of data, use of disparate data sets, more efficient use of temporal data, and development of classification categories which can be duplicated from one date to the next.

II. INTRODUCTION

Many investigators use Landsat Multispectral Scanner (MSS) digital data rather than imagery in order to make more efficient use of multiple images (temporal data) to derive quantitative interpretations and tabular statistical information, and to integrate Landsat with geographic information systems. Landsat digital data have been used to map and classify wetlands,[22,21,28,12,3] to map wetland vegetation,[14,19,20,5] and, in a few cases to look at the hydrology of wetlands using classification maps (classified images) in conjunction with hydrologic information collected in the field.[24,17] Where classification accuracies were evaluated, they were often low (around 70 percent). Some scientists have attempted to combine Landsat digital data with collateral information such as soil type to improve these accuracies[10] Landsat data have also been successfully combined with Seasat radar to improve classification accuracies.[29]

The objectives of this paper are: (1) to discuss wetland management needs and considerations in the context of information that might be supplied by Landsat digital data; (2) to examine the accuracy of recent Landsat wetland classification analyses; (3) to discuss some possible reasons for the limitations of the Landsat data; and (4) to suggest methods whereby Landsat data might be more useful to the wetland manager.

III. WETLAND MANAGEMENT NEEDS

Information requirements for wetland management decisions can be divided into two broad categories: (1) overall wetland planning and management needs of local, state, regional and national agencies, and (2) requirements for internal management of large wetlands. Bartlett and Klemas (1980)[3] surveyed 44 federal, state and university groups having either management or data collection and information processing responsibilities for tidal wetlands. Their findings covering information needs, accuracy requirements and present availability of data are probably representative of all wetland management agencies regardless of their location or responsibilities. The U. S. Fish and Wildlife Service (FWS) has also provided us with valuable insights into wetland management information needs as determined from the FWS National Wetlands

Inventory User Data Base (W. O. Wilen, personal commun., 1981). Butera (1979)[5] and Garrett and Carter (1977)[16] have also considered the wetland management requirements of federal agencies. Requirements for internal wetland management are generally more specific but similar to overall management considerations.

A. OVERALL WETLAND MANAGEMENT

In addition to general tabular statistics (for example, number of wetlands per county), most managers, especially those with regulatory responsibility, require spatially referenced data and specific information on wetland characteristics. This information may include: (1) areal extent of wetlands (by type), (2) boundary delineation. (3) surrounding land cover or land use, (4) areal extent of selected plant species, (5) soil type, and (6) standing biomass. A majority of the wetlands in an area may be smaller than 10 ha and minimum desireable accuracies for boundaries and location are less than 100 m, generally in the range of 2-30 m. Repetitive coverage is frequently desired for monitoring or change detection. Remote sensing has largely replaced ground surveys for determining wetland location, boundaries and area; other information required can frequently be extrapolated to areal information from ground-based samples.[3]

B. INTERNAL MANAGEMENT NEEDS - THE GREAT DISMAL SWAMP AS AN EXAMPLE

The Great Dismal Swamp is an 84,890 ha forested wetland situated on the Virginia-North Carolina border. Most of the swamp is presently a National Wildlife Refuge under the management of the U. S. Fish and Wildlife Service (FWS). The chief responsibility of the refuge is to protect and maintain the wetland ecosystem.[16] Management of the swamp includes maintenance of habitat for rare and endangered species; water conservation and management to control fires, reduce subsidence and loss of organic soils, and maintain hydrophytic vegetation; improvement of habitat for game and nongame species; and provision for public access and education. The Great Dismal Swamp has been severely disturbed by man; fire, timbering and ditching have made it a vegetatively diverse and hydrologically complex environment. A network of roads and accompanying ditches in varying states of repair make access problematical and the very dense understory limits off-road visibility and travel. The only efficient way of mapping vegetation, evaluating habitat, and monitoring change is through the use of remotely sensed data, either aircraft or satellite.

Information requirements of refuge managers which may possibly be met using remote sensing include:

1. Identifying the geologic, hydrologic and cultural setting of the swamp.
2. Mapping the swamp vegetation at scales commensurate with refuge needs,
3. Determining the extent and duration of surface flooding in the swamp during the late winter and spring,
4. Monitoring the effects of active control of water levels, and
5. Monitoring changes in wildlife habitat (vegetative cover) including relative amounts of each vegetation type, extent of edges (boundaries between vegetation types and diversity.

Landsat images have already provided the regional overview of the Great Dismal Swamp by showing geologic setting, surrounding land use, and surface drainage.[7] Vegetation maps including understory and canopy vegetation have been made at scales of 1:100,000 and 1:24,000[15] using color infrared (IR) aerial photographs. Repetitive satellite coverage can provide information on flooded areas; the satellite cannot, however, detect flooding through the evergreen canopy or understory during the winter or early spring when the deciduous trees are leafless. Repetitive vegetation mapping and the ability to detect change are required for monitoring the effects of water regulation on flooding duration and condition of vegetation, and for detecting changes in wildlife habitat potential. However, classification accuracy must be sufficiently good to use the thematic maps for management purposes.

IV. CONSIDERATIONS FOR USE OF LANDSAT DATA

Discussions with technology transfer specialists at the National Aeronautics and Space Administration (NASA) suggest that the majority of state level resource management agency personnel are unfamiliar with Landsat digital data analyses. Once familiarized and trained, a number of state agencies, for example Michigan and Maryland, have accepted Landsat digital technology for such purposes as land cover mapping, including wetlands. However, technology transfer demonstration projects conducted by NASA at no cost to the states may engender unrealistic expectations without a cost/benefit analysis.[25,9] The issue of cost/benefit is at the heart of any management decision to accept and use Landsat digital data[1,3,8] although other considerations, such as potential use of the data in digital information systems, may influence this choice.[11] All alternative methods such as use of aerial photographs, should be thoroughly examined.[23,2,27] The literature shows that Landsat digital data can provide low (unit area) cost information for small-scale, large area inventories, (for example [5,3]) but usually the total project cost must be weighed against the information quality before the decision to use Landsat is made.

Certainly management objectives and specific operational mandates must be clearly identified before the utility of Landsat technology to provide information can be assessed. Sound management dictates that only the information essential to accomplish the quantified objectives should be collected or generated. Operational requirements of timeliness and accuracy, at least in relation to manpower costs and budgetary constraints must be met. Decisions to alter or modify an already established information system depend on whether using Landsat digital data is (1) sufficiently economical to offset changeover and set-up costs including personnel training, (2) requires fewer personnel, (3) provides essential information previously unobtainable by other means, or (4) some combination of the three. Risk avoidance makes acceptance of a new technology rather slow. Occasionally management objectives themselves may be changed as a result of the availability of new types of information.

V. RESULTS OF RECENT LANDSAT DIGITAL CLASSIFICATIONS

There have been several papers published recently which discuss wetland classification accuracy resulting from the digital analysis of Landsat images.[12,14,10,28,19,5] Some of these results are discussed below in terms of (1) general wetland classes and (2) specific vegetation classes within wetlands. Methods of determining accuracy vary from one study to another, with the least rigorous treatment being accuracy assessments where evaluated areas are identical to sites used to "train" the computer to recognize spectral signatures. The most rigorous treatment is the assessment of errors of both omission and commission based on random sampling techniques. These differences in accuracy assessment make strict comparisons of accuracies impossible, but general trends can be observed.

Studies that consider general wetland classes include Finley and others (1981)[12] Werth and Meyer (1981),[28] and Ernst and Hoffer (1981).[10] An analysis of Texas coastal wetlands[12] showed that five categories of non-forested wetlands could be delineated using manual interpretation of Landsat images. Interpreters used 1:125,000- scale Landsat enlargements to map wetland classes on the basis of shape, texture, reflectance, and association with adjoining environmental units. Similar, but not identical classes were mapped using Landsat digital data. Manual Landsat interpretation accuracies of 81 to 85 percent were achieved for two marsh classes, 75 percent for tidal flats and 97 percent for sea grass and algae flats. The overall accuracy for all wetland units was 87.6 percent. Digital classification accuracies of 65 percent were achieved for all wetland categories combined. Misclassification resulted from similarity in spectral signature between grassland/ rangeland and marshes, between mangrove wetland and forest, and between fallow fields and tidal mudflats. The authors suggested a combination of manual and computer-assisted techniques might improve accuracies.

Ernst and Hoffer (1981)[10] used a layered classifier algorithm which combined soils and Landsat spectral data to generate a wetland classification. The classification accuracy based on spectral characteristics alone was 71.7 percent with the major problems being (1) inability to separate wetland hardwoods and upland hardwoods, (2) confusion of shrub wetlands with pastures or upland scrub-shrub, (3) confusion of conifers with deep marsh or dark soil, and (4) misclassification of shallow marsh as winter wheat. The layered classifier gave an overall accuracy of 84.3 percent, allowing upland hardwoods to be separated from wetland hardwoods and conifers from dark soils. The classification of shrub or emergent wetlands was not improved.

Werth and Meyer (1981)[28] compared the accuracy of manually interpreted 1:24,000- scale color infrared aerial photographs with digital analysis of Landsat data for both wetland and non-wetland classes. Landsat classification was performed using different classifiers. Using the same classes, the overall classification accuracy was 97.6 percent for the aerial photointerpretation and 72 percent for single-date Landsat images classified with a maximum likelihood classifier. The authors made no attempt to suggest the reasons for Landsat misclassifications.

Considering within-wetland classifications, Gammon and others, (1981),[14] working in the Great Dismal Swamp of Virginia and North Carolina, reported that digital classification accuracies for wetland vegetation classes were generally too low to consider Landsat digital classification adequate for either mapping or management applications. Their Level II classes based only on general canopy type (for example, deciduous forested wetlands) were more accurate than their Level I classes which were based on both canopy species and understory types (for example, evergreen or deciduous understory). A February and an April image were used, alone and in combination. The overall classification accuracy estimated for each image was: February, 61 percent correct, April, 80 percent correct, February-April (MSS bands 5 and 7), 60 percent correct; and February-April (all MSS bands), 61 percent correct. The relatively high accuracy for April was primarily the result of grouping all the deciduous classes into one overall broad-leaved deciduous class rather than attempting to split out understory characteristics. It appeared in this study that the spectral characteristics of the vegetation types were too closely related or mixtures of species within communities and on transition zones between vegetation communities made digital separation of types very difficult.

VI. LIMITATIONS OF LANDSAT DATA

Landsat digital data are subject to several limitations which constrain their present utility for providing information for wetland resource management. It is these factors in combination with the aforementioned management constraints which determine Landsat digital data acceptability. Systematic errors due to sensor characteristics, minimum resolution elements as related to the size and shape of ground features, and the effects of wetland heterogeneity are among the limiting factors.[26,13]

A. RESOLUTION

Landsat resolution elements (pixels) are 0.45 ha in size and not really adequate for accurate location and identification of small wetlands or small homogeneous vegetation cover types covering less than 10 pixels (4 ha). The smaller the feature of interest, the more problems are encountered with boundary or "mixed pixels". Crapper (1980)[9] has considered the mixed pixel problem in some detail. He overlaid a comparatively regular polygon with a square grid and demonstrated that there are more perimeter cells than one might expect. The grid cell area in his example was 1.13 percent of the total area and 45 percent of the total cells were perimeter or mixed pixel cells. Errors of commission or omission occur at the boundary of the unit depending upon whether the perimeter cells are included or excluded. Crapper's formula gives the variance of the area estimate. It shows relative errors of one percent for areas of 132 ha, 5 percent for areas of 15 ha and 10 percent for areas of 6 ha. Billingsley (1981)[4] also notes that smaller fields have fewer central or pure pixels and more boundary pixels so that accuracies can be expected to be low. Without a special methodology for associating boundary pixels with the main field, they may be assigned by the computer to another separate class, an error which is more serious in the case of small wetlands.

B. SPATIAL AND SPECTRAL HETEROGENEITY OF WETLANDS AND WETLAND VEGETATION

Wetland types are extremely variable in terms of spectral characteristics; for example, short, thick grass-like or broad-leaved emergent wetlands, submersed vegetation in shallow water, deciduous and evergreen shrub-scrub and forested wetlands have very different spectral signatures. Vegetation diversity may be very great within an individual wetland, and phenology and water dynamics cause seasonal changes in wetland spectral signature. Additionally, wetlands may be small or large and, unlike most agricultural fields may be linear, curvilinear or irregularly shaped. Hixson and others (1980)[18] pointed out that for agricultural fields, the development of representative training statistics is relatively more important for accurate classification than the selection of a classification algorithm. This would appear to be the case for wetlands.

Consider as an example vegetation mapping in the Great Dismal Swamp with Landsat digital data. Vegetation types may have spectral homogeneity near their stand centers and become progressively mixed with other vegetation toward the periphery; for example stands of pine, Atlantic white cedar and the evergreen shrub community intermix with deciduous trees. Natural forest stands are commonly irregular in shape and variable in size, and a continuous change in the vegetation near the edges of a stand can result in a series of mixed pixel classes. The central or "pure" pixels form one class and the spectrally varying edges form one or more adjacent classes.

Figure 1 shows 4 classification maps for a small area of the Great Dismal Swamp containing two relatively large stands of Atlantic white cedar. The stands have a more uniform signature in February and are composed of more spectral classes in April because of the inclusion of leafed-out deciduous trees in the stand. The combination of MSS bands 5 and 7 for the February and April images shows the strong influence of the February data and the February/April image (8 MSS bands) suggests that temporal data generates more spectral classes.

In the case of deciduous hardwoods, the wetland vegetation is often a complex mixture of 10 or more species, continually variable in terms of species dominance. Figure 2 shows the April Landsat classification of a deciduous area in the Dismal Swamp and a section of the 1:100,000-scale vegetation map for comparison purposes. Note that the classifier has identified 15 separate deciduous classes in this small area and we have found it virtually impossible to assign an individual class to a specific canopy type. If a manager is interested in encouraging the growth of oaks which provide mast for deer and in discouraging maple which has less value for wildlife forage, it is important to have the capability to discriminate between the two species. However, unless phenological data are available, the mixture of deciduous canopy species cannot be generally divided into classes based upon species.

Campbell (1980)[6] has recently pointed out that in supervised classification, training sets are usually chosen to represent the "pure" part of a homogeneous unit. However, a 64 pixel training set, no matter how "pure" contains inherent spectral variability and there appears to be a tendency for correlation between the values of adjacent pixels due to the nature of the sensor and the method of data collection (see also[4]). Estimates of category variances, based upon values of contiguous pixels, yield low values relative to those based on random samples of the same area. These biased estimates may ultimately lead to errors in supervised classification. Hixson and others (1980) reiterate the importance of obtaining the best possible class statistics. Campbell explains that there is a tendency toward clustering of misclassified pixels in space; a relatively uniform area may contain misclassified pixels which will be detected by accuracy assessment or give the map a speckled appearance. It should be noted, however, that Campbell did not address the fact that such clusters within other seemingly homogeneous types may, in fact, be true ground-based features in the data set. These small clusters or inclusions exhibit seasonal changes suggesting that there may be certain phenological influences generating the effect.

In an unsupervised classification, the inherent variability in a homogeneous vegetation unit combined with the tendency for spatial autocorrelation of pixels may result in classification of a forested wetland vegetation type into one reasonably homogeneous class with other class inclusions of 15 pixels each. These inclusions or the concentric classes forming around the "pure" center leave the investigator with the subjective decision as to whether classes should be combined into larger, broader classes based upon adjacency or upon closeness of spectral statistics.

VII. TEMPORAL DATA: PROS AND CONS

Billingsly (1981)[4] discusses in detail the effects of band misregistration upon multispectral classification accuracy. Misregistration is only one of a group of parameters (noise, class separability, field size, spatial transient response) which affect classification. Misregistration causes additional pixels in the field boundaries to be misclassified due to the mixture of materials in the pixels. As long as geometric correction and registration are accurate only to about one pixel, the potential for misregistration exists when more than one image is overlaid. Resampling in order to overlay the data from two dates may also blur class boundaries.

The results of having twice as many spectral bands do not always seem consistent nor are they always explainable. In an unsupervised classification, the increased number of spectral classes makes identifying and combining classes more difficult, expecially when some classes consist of only a few pixels. The perceived advantage of being able to combine classes identifiable on different dates into one class, for example deciduous shrub and evergreen shrub into an overall shrub class, is not always a reality with temporal data. In the Dismal Swamp study, Gammon and others (1981)[14] found that temporal data did successfully recognize some highly unusual classes or units of vegetation, but other vegetation units were more accurately identified with individual Landsat dates.

VIII. HOW MIGHT LANDSAT BE MADE MORE USEFUL TO WETLAND MANAGERS

Landsat digital data as a stand-alone information source probably have insufficient resolution and classification accuracy to meet the information requirements of most wetland management groups with regulatory mandates. For broad regional level (synoptic overview) identification of wetlands larger than 5 ha, Landsat digital analyses can provide reasonably accurate data (approximately 70-75 percent accuracy). In coastal areas, where wetland vegetation is more spectrally homogeneous and spatially extensive, accuracies may approach 80-85 percent. Problems will still exist with identifying small wetlands or narrow linear wetlands.

Limited data seem to indicate that Landsat digital technology is still unfamiliar to a significant number of managers and there is a lack of realistic cost data to compare techniques on wetland mapping tasks. Perhaps a clearer understanding of the limitations of Landsat data and Landsat technology in general will help make Landsat a more useful tool.

Improved resolution, both spectral and spatial, will have to wait for the launch of the Thematic Mapper and future satellites. Meanwhile there are several ways of approaching the data which may improve accuracies substantially. These include prestratification of data, better use of temporal data, and the addition of disparate data sets in a geobased information system context. Digital data can be prestratified a number of ways. Using the Great Dismal Swamp as an example, one approach may be to separate deciduous and evergreen canopy first and then proceed to break each class into separate classes rather than starting with a large number of unsupervised classes and combining them. Based on stratification of one image, a second geometrically registered image could be manipulated. For example, with a winter image, deciduous and evergreen cover could be separated into two large classes and possibly the evergreen cover type could be further subdivided. With a growing season image, the mixed evergreen/deciduous classes and the entirely deciduous classes should be separable using the boundaries established with the winter image. If other temporal data are available, the deciduous class could be further segmented using phenological information. This same approach could be taken to locating and identifying small wetlands in large regions.

Disparate data sets may improve classification accuracy in fairly unaltered wetland environments. Just as Ernst and Hoffer (1981)[10] used soils as an additional unit in their classification, elevation, depth of organic soil, or extent of flooding might aid in the separation of vegetation types in the Great Dismal Swamp thus making better information available to management.

In the area of monitoring, good techniques to overlay sequential data are essential. Development of realistic classification categories which can be duplicated is necessary to make comparisons. These categories should be defined by the resource managers to ensure their compatibility with management information requirements.

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Figure 1: Landsat classification of Atlantic white cedar in the Great Dismal Swamp. The April classification shows more spectral classes (◇,+,-) than the February one (◇,-) because of leaf-out of deciduous trees. The April/February classification shows more spectral classes (◇,+,-,*) than the April 57/February 57 one (see text for explanation of combinations of MSS bands) because use of 8 Landsat bands appears to introduce more spectral variability.

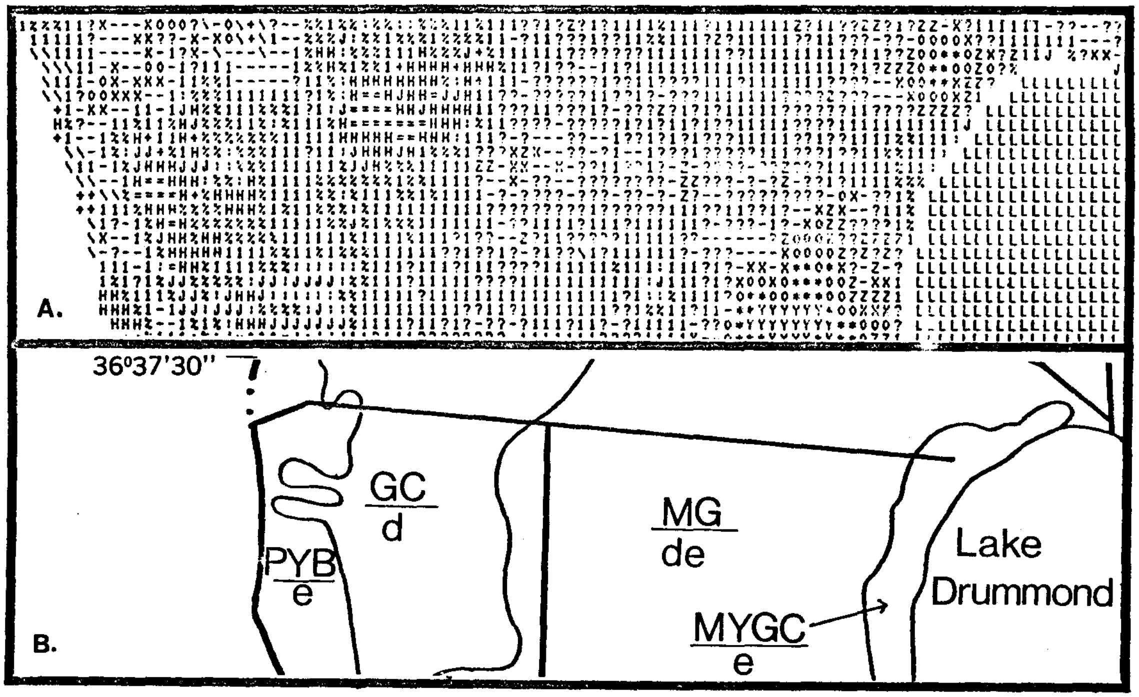

Figure 2: Comparison of April Landsat classification (A) and Great Dismal Swamp vegetation map (B) for area east of Lake Drummond. Landsat classification shows 15 deciduous canopy spectral classes (all symbols except L which identifies lake). Only 4 major canopy classes could be identified from color infrared photographs to prepare vegetation map. Map symbols are as follows: XX/xx - Vegetation in either canopy or understory listed from left to right in order of dominance, M - Maple-dominated hardwoods: maple, tupelo and ash, G - Water tupelo and black tupelo, C - Cypress, P - Pine, Y - Mixed hardwoods: yellow poplar, sweetgum and maple, B - Mesic hardwoods: beach and oak, d - Deciduous shrubs, saplings and seedlings, e - Broad-leaved evergreen shrubs, saplings and vines.