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MONITORING TROPICAL VEGETATION SUCCESSION WITH LANDSAT DATA

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Technical Report

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Introduction

Tropical rain forests contain a majority of the Earth's gene pool, yet little is known of the spatial and temporal variation of these vegetation communities on a regional or synoptic basis. With the spread of man's activities the ability to monitor and forecast the response of these communities is becoming increasingly critical to preservation and management of such resources.

This technical report represents the results of research concerning two fundamental problems when considering the monitoring of tropical vegetation succession. First, there is the 'shadowing' problem which is endemic to the use of Landsat in tropical areas. Secondly central to any monitoring system is the ability to model changes over space and through time for explanatory and predictive purposes. In the case of both problems the potentials of the field of spatial modeling were investigated.

The Shadowing Problem and a Spatial Model

The Problem

The problem of tropical natural resource inventory is fundamental to development of a monitoring capability. One of the major problems in the collection of data from Landsat for tropical areas is obstruction from clouds. The problem considered here is one where two statistically distinct classes occur with reference to an area where one homogeneous class of vegetation is known to exist. One class is homogeneous tropical rainforest and the other is known to be shadow. Variations in

data values which contribute to this dichotomy are posited as measurements subject influenced by variations at two scales, local and regional. There is a general pattern of spatial variation in both terrain and multispectral scanner (MSS) values. In addition, there is a local pattern of variation unique to particular locations. It is therefore hypothesized that the shadowing effect is largely the result of small-scale spatial variations producing the responses measured by the values contained in the MSS data, thus causing the erroneous occurrence of two statistical classes where no observeable differentiation exits. The trend surface terrain model is used to decompose the spatial variation in elevation and MSS data. Since shadow is thought to be a function of the local component of spatial variation, the general component of spatial variation is used as input in the classification process. It is expected that after having filtered out the local spatial variation the two classes will become less distinct or not distinct.

The Spatial Model

The spatial model used here is generally known as the Trend Surface Analysis Model (TSA). It is used here as a means of quantitatively estimating the general spatial variation in the data set. In TSA the locations of the sample points provide information about the spatial variation of a variable. Each set of coordinates (U[i] and V[j]) describe the location of sample point k. The value of the observation (Z[k]) at point k is assumed to consist of

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contributions from two sources :

REGIONAL or large-scale process which generates the broad pattern of spatial variation, and

LOCAL or small-scale process operating locally.

Following Barringer et al (1980) and Robinson (1982), the model is specified as

$$Z(U_i, V_i) = f(U_i, V_j) + e_{ij} ,$$

where

$Z(U,V)$ = observed value at the location described by the coordinates U and V,

$f(U,V)$ = function defining the regional component,

e = the error term which describes the local component since it is defined as $Z(U,V) - f(U,V)$.

The regional component function defined by fitting a power-series polynomial function of the general linear form

$$Z(U,V)_k = \sum_{i=0}^{n} \sum_{j=0}^{m} b_{ij} (U^i, V^j)_k$$

which is estimated using the orthogonal polynomial routines presented in Mather(1976). In the case of Landsat data the measurement on Z are the data values on MSS bands, while U and V are locations of their respective pixels.

The Methodology

The methodology was designed to evaluate the utility of a TSA

model in the reduction of misclassification of shadowed tropical rain forest. To accomplish this the following phases where were conducted in order of presentation :

Phase 1 : Supervised classification of vegetation and shadow classes.

Phase 2 : Perform linear discriminant analysis to test efficacy of supervised classification results and provide a benchmark.

Phase 3 : Decomposition and separation of the regional and local spatial variations in spectral and terrain characteristics.

Phase 4 : Using classifications of 1 and data generated in 3, a discriminant analysis was performed.

Phase 5 : Comparison of the two discriminant analyses was conducted to evaluate the utility of the spatial modeling approach with regard to the supervised classification.

Study Area

The study area lies within a region of mountainous terrain located northeast of Mount Indie (approximately 12° 55' N , 121° 4' E) on Mindoro Island, Philippines. Primary cover is semi-deciduous rain forest comprised largely of *dipterocarp spp.* In addition, there are areas of (*I. cylindrica*) believed to be human induced. The topography is a dendritic drainage pattern. Thus, this is an ideal area for studying the shadowing problem.

Cover Classification

Supervised classification was conducted to identify the major land cover classes derived based on those derived from 1:50,000 vegetation overlays developed from aerial photography and ground data (Bruce, 1979). Three major information classes were identified in a 128 by 128

pixel subscene. They were tropical rain forest, grassland, and shadow. For the conduct of the TSA modeling exercise, an area known to be tropical rain forest but shadowed and surrounded by rain forest.

Sampling Design

A random-systematic sample of elevation data and corresponding radiance count data was collected from within the study area. There were 89 pixels included in the sample. For each of the sampled pixels, elevation to the nearest 20 meter contour interval was interpreted from a 1:50,000 topographic map (AMS Series L501, sheet 3258 III, 1962). The elevation data was combined with the radiance count values taken from the four Landsat bands to form a data set which contains information on the relative location, elevation, and spectral characteristics of each sample pixel.

Results of TSA Modeling

Results of the TSA modeling of elevation and Landsat MSS data are presented below along with results of the discriminant analysis. Results of the discriminant analysis of the supervised classification are compared with results of the discriminant analysis using the TSA estimates as the data for cover class discrimination.

The TSA Models

A fifth-order polynomial trend surface was chosen as that order of surface which best describes the regional terrain variation within the sample area. The fifth-order model was chosen because it represents the

point of decreasing percent explanation added and the point where additional terms in the model provide less than modest increases in percent explanation (Table I). It should be noted that when one is concerned with describing a given pattern in terms of generalization at various scales, and relating those generalized patterns to the distribution of other variables, significance testing is unnecessary and inapplicable.

A TSA model was estimated for each of the Landsat MSS bands. The order of surfaces chosen and the percent explained are reported in Table II. The percent explained refers to the percent variation in the original data accounted for by the regional component of the estimated surface. Thus, it is a measure of the relative importance of the regional component in explaining the spatial variations in the spectral responses. As can be seen from Table II., the relative importance of the regional component in explaining variations in bands six and seven is small. The implication is that the local component in the spatial variation of spectral responses in these bands are primarily of a localized nature.

The Discriminant Analyses

Discriminant analysis of the supervised classification shows that bands six and seven have the greatest discriminating power with all bands being present and significant in the linear discriminant function (LDF) (Table III, Univariate Analysis). The power of this discriminant function is exemplified by the classification results in which 83.15% of the sample pixels were correctly classified. Since the initial

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classification was based on the MSS data, the significance and strength of this LDF is not unexpected. Thus, the shadow/forest classification scheme is statistically significant when using the MSS radiance count data.

When a discriminant analysis was performed with data generated by the TSA models, the results improved noticeably. That is the LDF is less able to separate shadowed and unshadowed forest. This is supported by an increased tendency toward mutual equality (i.e., classification by random chance) of the four cells of the classification results table (Table IV). A fall in the eigenvalue and an increase in Wilks' Lambda are indicative of a decline in the discriminating power of this discriminant function. The all-groups stacked histogram (Figure 1) illustrates the variability and overlap present in this classification. Although the spectral terrain models for band 6 and 7 are those with teh weakest regional component in terms of explained variance, they maintain their dominant influence in the LDF (Table IV). It is important to keep in mind that their dominance in the LDF is conditional on the other variables being included in the estimation of the function. This is illustrated by the fact that when a stepwise discriminant analysis was performed, the only variables entered (in order of entrance were bands 7 and the regional terrain (elevation) component.

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Discussion

This analysis supports the view that shadowing effects may be due primarily to local variations in the spectral responses. The significance of this result is that they can be compensated for through the decomposition of the spatial variation in both elevation and MSS data. Use of the trend surface model to estimate both elevation and spectral terrain surface as a posteriori inputs in the classification process leads to an improvement in classification accuracy for vegetation cover of this type. The improvement might be increased further through use of weighted linear components of the MSS and elevation terrain data or the specification of a power-series other than the straightforward polynomial expansion.

Results of this portion of the research also suggest that the spatial patterns depicted by the MSS data reflect the measurement of responses to spatial processes acting at several scales. Thus, continued research on the development and application of spatial filtering models in the analysis of Landsat data is suggested. Perhaps a more broadly significant implication is the use of dynamic spatial models will be critical in the study of tropical rain forest succession using Landsat. Therefore, the latter portion of this research investigates the field of dynamic spatial cover class models as they relate to succession dynamics.

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Table I. Results of the Trend Surface Modeling of Elevation

Order	Number of Terms	% Variation Explained	% Variation Explained Added	Terms Added
1	3	66.1		
2	6	80.4	14.3	3
3	10	89.1	8.7	4
4	15	93.2	4.1	5
5*	21	95.3	2.1	6
6	28	96.6	1.3	7
7	36	97.5	.9	8

* Order of trend surface chosen for use in analysis.
Source: Authors' calculations

Table II. Results of Trend Surface Modeling of Landsat MSS Band Data

Band	Order of Surface	% Variation Explained
4	4	44.4
5	5	41.6
6	4	26.3
7	4	33.5

Note: The criteria used to choose the order of surface to be used in the analysis and reported in this table is the same criteria reported in the discussion of the terrain model results.

Source: Authors' Calculations

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Table III. Discriminant Analysis of Supervised Classification Results

Characteristics of the Discriminant Function

Eigenvalue	Canonical Correlation	Wilks' Lambda	Chi-Square
.59	.64	.59	44.4 *

Univariate Analysis:

Variable	Wilks' Lambda	F-value	Standardized Canonical Discriminant Function Coefficients
Band 4	.868	13.22 *	.1811
Band 5	.884	11.42 *	-.2354
Band 6	.664	43.99 *	.2514
Band 7	.599	58.34 *	-1.2202

Wilks' Lambda and F-value degrees of freedom = (1,87)
* Significant at the .05 level or better.

Classification Results:

Actual Class	Predicted Class: Shadow	Predicted Class: Forest	Number of Cases
Shadow	27 87.1 %	4 12.9 %	31
Forest	11 19.0 %	47 81.0 %	58

Percent Correctly Classified = 83.15 %

Source: Authors' Calculations using the SPSS programs.

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Table IV. Discriminant Analysis of
Trend Surface Modeling Results

Characteristics of the Discriminant Function

Eigenvalue	Canonical Correlation	Wilks' Lambda	Chi-Square
.19	.40	.84	15.1 *

Univariate Analysis:

Variable	Wilks' Lambda	F-value	Standardized Canonical Discriminant Function Coefficients
Band 4	.987	1.16	-.3644
Band 5	.992	.70	.2367
Band 6	.888	10.99 *	.1685
Band 7	.850	15.37 *	-1.0760
Elevation	.994	.56	-.3648

Wilks' Lambda and F-value degrees of freedom = (1,87)
* Significant at the .05 level or better.

Classification Results:

Actual Class	Predicted Class: Shadow	Predicted Class: Forest	Number of Cases
Shadow	21 67.7 %	10 32.3 %	31
Forest	18 31.0 %	40 69.0 %	58

Percent Classified Correctly = 68.54 %

Source: Authors' Calculations using the SPSS programs.

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```
        .                        2 2     2
 F      .                        2 2     2
 R    4 +                  2     2 2   222
 E      .                  2     2 2   222             2
 Q      .                  1222222 2   2222   212     21
 U      .                  1222222 2   2222   212     21
 E    2 +      2          21222222 22  1222222112   2 11 1  2
 N      .      2          21222222 22  1222222112   2 11 1  2
 C      .  2  2222    1 221122221 112 12211111112112111 1  1      1
 Y      .  2  2222    1 221122221 112 12211111112112111 1  1      1
        ........+..........+..........+..........+.........+.........+
                -2         -1         0         1         2         3
CLASSIFICATION 22222222222222222222222211111111111111111111111111111111
CLASS CENTROIDS                      2        1
                                     *        *
```

CLASS LEGEND

Shadow = 1
Forest = 2

Figure 1.
All-Groups Stacked Histogram for Discriminant Analysis
of Trend Surface Modeling Results

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Vegetation Succession, Landsat, and Dynamic Spatial Models : An Investigation

Here are presented important issues which must be carefully and thoughtfully considered if remotely sensed data are to be properly used in the analysis of modeling of spatial succession processes, particulary in the tropical rain forest context. Altnough raised in the context of tropical vegetation cover dynamics, many of these issues have broad applicability to other research using Landsat data to monitor changing vegetation patterns (e.g. see Robinson et al., 1982).

Remote Sensing of Vegetation

Efforts in the field of satellite remote sensing of vegetation have traditionally centered on questions of signature identification and extension, cover inventory accuracy, and change detection and monitoring (e.g., Anderson, 1977 ; Bannert, 1980 ; Omakupt and Vunpiyarat, 1[illegible] ; Reeves, 1975). Although the remote sensing literature contains many references to the spatial and temporal aspects of the science (e.g., Lillesand and Kiefer, 1979 ; Swain and Davis, 1978). Approaches incorporating the spatial and temporal dimensions are typically not of a formal nature. Formal models of cover dynamics are often specified in aspatial form even though satellite data are clearly spatial in nature. Also, design of satellite spatial sampling instrumentation is largely a function of scanner technology and image resolution considerations. Little consideration seems to have been given to the unique statistical properties of spatial samples

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(e.g., Batty and Sammons, 1978 ; Bellhouse, 1977 ; Curtis and McIntosh, 1950).

Models of Succession

The theory of ecological succession has been developed in the papers of Clements (1916, 1936), Gleason (1926), Whittaker (1953), Odum (1969), and Drury and Nisbet (1973). Although the term was coined in the early 1800's, Clements is generally regarded as the first to offer a theory of the succession process. He argued that "The developmental study of vegetation necessarily rests upon the assumption that the unit or climax formation is an organic entity... As an organism the formation arises, grows, matures and dies" (Clements, 1916). In contrast to Clements (1916), Gleason (1926) took the view that the successional processes of a plant community grow out of the processes which its individual members undergo: "The sole conclusion we can draw...is that the vegetation of an area is...the resultant of two factors, the fluctuating and fortuitous immigration of plants and an equally fluctuating and variable environment" (Gleason, 1926).

Another view of succession is that presented by Whittaker (1953). He believed succession to be due to interactions among a series of environmental gradients: "Vegetation is conceived as,...a pattern of populations, variously related to one another, corresponding to the pattern of environmental gradients" (Whittaker, 1953, pp. 59 - 60).

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Miles (1979) describes Odum's (1969) model as neo-Clementsian because of its emphasis on properties emergent at the community level. Odum (1969) saw the "strategy" of succession as being action by the community to bring about an increased control of, or homeostasis with, the physical environment to achieve maximum protection from its perturbations. Drury and Nisbet (1973) argued that succession grows out of differential colonizing ability, growth and survival of species adapted to growth under different environments.

Some general observations may be made on these models. First, they are all informal models (van Hulst, 1978). Second, while all of them imply the existence of temporal and spatial features in the process, none of them adopts a formal notion of either. Neither do they consider the essential differences which exist between spatial and temporal processes. Indeed, Drury and Nisbet (1973) note that most descriptions of long-term changes in vegetation are based on the observation of spatial sequences. Third, the models tend to shift increasingly from a deterministic one toward a stochastic one (see van Hulst, 1974). Finally, the neo-Clementsian arguments have been essentially demolished by Drury and Nisbet so that some trend from a holistic toward an atomistic view of succession is evident.

Beeftink (1979) presents several reasons for increased interest in vegetation dynamics on the part of European ecologists. First, interest in descriptive research is falling off for a variety of reasons. Next, vegetation conservation efforts demand a better understanding of vegetational and environmental dynamics. Last,

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advances in numerical methods and instrumental equipment present the opportunity of developing dynamic models utilizing large data sets. He recognizes several points of departure for future research in successional dynamics. One such question is that of the degree to which detection of similarities between space-time patterns in biological and in environmental variables provide insight into causal relationships among these variables. The connection between diversity and stability concepts, and space-time patterns is central to such efforts.

Allen (1975) observes that in the modeling of population stability over time, the usual approach ignores population variation across space. He comments on the strangeness of this and warns that time-dependent models can be radically affected by extending them into the spatial domain. Therefore, the theoretical and experimental investment of such models is certainly justified. Moreover, we might seriously question whether stability statements based on the original models can be trusted. Yarranton and Morrison (1974) investigate the variation in spatial pattern over time in primary successional sequences. They present a nucleation model which they argue establishes a relationship between successional mechanism and variations in spatial pattern. Hilbourne (1979) points to the increasing realization that spatial phenomena are an important aspect influencing the dynamics of many ecosystems. He argues that an understanding of the formation of spatial heterogenieties is crucial in understanding the temporal dynamics of ecosystems. Finally, Miles

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(1979) warns against the interpretation of existing spatial variation in vegetation as representing different phases in a temporal sequence.

It is apparent that there is considerable interest among ecologists in successional processes as they occur in both time and space. Similar interest is in evidence among those of the remote sensing field and biogeographers (e.g., Miller, et al., 1978). If these interests are to be addressed, two important issues must be addressed. The first complex of issues concern those the properties of static spatial models. Secondly there are the implications of spatial sampling methods for the study of succeessional processes. Although such static models permit little insight into the dynamics of succession, they form an important class of descriptive models and In their descriptive role, they may aid in hypothesis formation for dynamic models.

Static Spatial Models

Here are presented those spatial models of a static nature which are important in developing models of tropical rain forest succession using Landsat data. It is common to regard the distribution of a set of points in geographical space at some given time as the outcome of a point process. While the actual generation of such a distribution is presumed to be dynamic, the resulting distribution is not. More importantly, nor are the underlying spatial models.

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Bartlett (1975) organizes point process models into two broad classes:

A.1 Clustering models
.2 Doubly stochastic models

B. Contagion or inhibitory models

All are based on the Poisson distribution. More complex point patterns may be described by mixed Poisson models which represent a mixing, in various ways, of Poisson process rules with those of other statistical distributions (e.g., Poisson-Poisson, Poisson-binomial).

Data for such models are usually obtained by the quadrat method. First, a planar region is exhaustively partitioned into a series of non-overlapping, generally square cells. Next, the numbers of points falling in each cell are determined. Finally, the degree of randomness of the distribution is examined through the fitting of the distributions described above which describe the degree of clustering or regularity of the point set.

Rogers (1974) and Curtis and McIntosh (1950) point out some of the difficulties associated with the quadrat method. Results depend upon the shape, size and placement of quadrats as well as on the density of the points being sampled. They propose rules for the determination of optimal quadrat size, as does Grieg-Smith (1964). The relative effects of applying alternative optimal size rules to quadrat size selection should be of interest to those engaged in research involving spatial data collection.

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Rogers (1974) also discusses inferential problems which must be considered in testing the goodness-of-fit of point process statistics to non-random (i.e., either highly clustered or highly regular) spatial data. The chi-square test, a statistic commonly used in such applications, is noted to have a number of shortcomings in this respect. Among these are: lack of sensitivity, influence of data grouping schemes on the outcome of the test, minimal class size constraints on test effectiveness in the face of a lack of consensus on a correct value for minimal size and loss of test power connected with grouping to satisfy minimal size constraints. Rogers also notes that similar difficulties attend the fitting of bivariate distributions. A far more serious problem of inference in that statistical agreement with a mathematical model is far from sufficient evidence that it did so arise.

The statistics of nearest neighbor models also raise issues for those using them for spatial inference. It has been noted (Rogers, 1974) that density dependence, derivation of probability distributions for non-random point patterns and the effects of 'zero-distance' nearest neighbor configurations are all questions of interest in this area.

Description of spatial arrays of points is closely tied to the effect of process scale on scale of sample and the correct design of spatial sampling schemes. Clearly, the relative spatial extents of a spatial process and of a spatial sampling scheme designed to provide data for inference on that process will have an effect on the outcome

of such inference. Also, Kooijman (1980) states that the ease of inference on point processes decreases with decreasing spatial scale. Finally, the optimal shape is considered to be a rectangle (Orloci, 1978).

Haggett, et al. (1977) examines the relative efficiencies of various spatial sampling schemes. In that review, Berry's (1962) determination of the high relative efficiency of stratified systematic unaligned sampling schemes over either stratified random samples or simple random samples is cited. Further, the superiority of stratified sampling plans in situations where spatial autocorrelation may be present is noted. Haggett (1963) also found transect sampling methods to be more accurate than either point or quadrat sampling in measuring the extent of cover by vegetation in an area of England.

Rogers (1974) looked at stratified random sampling in a spatial context and Bellhouse (1977) derives a minimal average variance criterion for sampling from a two-dimensional finite population. He also concludes that no global optimal design exists although locally optimal designs do exist in terms of certain subclasses of spatial sampling scheme. A problem, until quite recently, in spatial sampling schemes was that of the asymptotic distribution of the sample. This issue was resolved with Smith's (1980) publication of a Spatial Central Limit Theorem. Although the theorem gives little guidance on the size of the sample needed to realize asymptotic normality, it clearly shows the existence of such a property for a spatial sample of sufficient size and meeting certain other conditions.

Issues in the Analysis of Spatial Data

Although Landsat data are quite obviously spatial data, for the purposes of classification and modeling, reliance has been placed primarily upon classical statistical models (e.g., Jensen, 1978; Strahler, et al., 1980). Tubbs and Coberly (1978) pointed out that most investigators have tended to assume that pixels are independent observations. The fact that neighboring pixels are not separate independent observations is at the core of the concept of spatial modeling.

There are several basic properties of spatial data which make their analysis using classical statistical models difficult. Spatial stationarity is an implicit assumption in all applications of Landsat data using classical statistical methods. In general, spatial data do not possess the property of spatial stationarity. Granger (1969) describes stationarity as an assumption that the relationship between values of the processes generating the data is the same for every pair of points whose relative positions are the same. Cliff and Ord (1975) have presented a more formal definition of spatial stationarity. First, it is assumed that the data collected correspond to a finite set of locations. In Landsat data the locations are analogous to the pixels in a Landsat scene or subscene. Also, in the Landsat case, the 'spatial aggregates' are areas not points. Next, let j denote the set of locations and $j = 1,2,\ldots,n$ where n is the total number of locations. There is the observed variate value, y_j or Y_j. There is information

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concerning location j, e.g. row and column location of a pixel. Suppose that Y_j can be decomposed into a stochastic component X_j and a deterministic component m_j such that:

$$E[X_j] = 0 \quad \text{or} \quad E[Y_j] = m_j .$$

Definition 1. X_j is said to describe a spatially stationary process in the wide sense, to be weakly spatially stationary, if:

$$E[X_j, X_{j'}] = \sigma(j,j') \qquad (1)$$

depend, only upon the relative position of locations j and j'.

Definition 2. Suppose X_j satisfies equation (1). In addition, if the correlation between X_j and $X_{j'}$ depends only upon the distance between their locations, and not upon the orientation between j and j', then the process is weakly isotropic.

Definition 3. If the joint distribution of the X_j depends only upon the relative positions of the locations, then the spatial process is strictly stationary.

Definition 4. The process is strictly isotropic if it is both strictly stationary and direction invariant(see Definition 2).

In areas such as time-series analysis definitions 1 and 3 will suffice, but in spatial analysis definitions 2 and 4 are often required (Cliff and Ord, 1975; Haggett, et al., 1977). Generally, the assumption of spatial stationarity is difficult to sustain. It is worth noting that the concepts of spatial stationarity and spatial dependence are related. Haggett, et al., (1977) point out that if the marginal distributions of X_j are identical, then non-stationarity implies that

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the data are spatially dependent.

Spatial dependence among elements of spatial data sets is the rule rather than the exception (Tobler, 1970; Gould, 1970). To further illustrate this, suppose that data have been collected for a set of $j = 1,2,3,\ldots,n$ areas (or pixels) and that the variate for the j-th location is X_j. Statistical methods are traditionally developed from assumptions which usually state something like -

" let X_j $(j=1,2,\ldots,n)$ be n independent, identically distributed variates" (Cliff and Ord, 1975a in Haggett, et al., 1977).

Spatially located data generally exhibit systematic spatial variation or spatial autocorrelation (Tobler, 1970; Gould, 1970; Cliff and Ord, 1975). The effect of spatially autocorrelated data on tests of inference are in some cases well known. Standard applications of t and F statistics for comparison of means or construction of confidence intervals require spatial independence. The same assumption is necessary in regression analysis if the OLS (Ordinary Least Squares) estimators are to be BLU (Best Linear Unbiased).

Many common applications of a variety of statistical models in remote sensing use as the variance estimate:

$$\sigma^2 = \sum_{j=1}^{n} (y_j - \bar{y})^2 / (n - 1) \quad .$$

Cliff and Ord (1975) note that when positive spatial autocorrelation (e.g., a clustering process) is present, the estimator σ^2 will be biased downwards. This bias leads often times to an

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overstatement of the significance of the results. This is an issue not widely recognized in the application of statistical models to Landsat data.

It has also been shown (Brandsma and Ketellapper, 1979) that the choice of a procedure for estimating test statistics for spatial autocorrelation must be made carefully since the power, robustness and obtainable significance levels may vary considerably among estimation procedures.

One of the more common statistical models used in the analysis of Landsat data for cover class studies is principal components analysis (PCA). Lebart's (1969) approach is briefly presented below as an example of how spatial dependence may be incorporated into this common method. Suppose data are collected on p variates, say Landsat MSS bands 4,5,6, & 7, for each of n areas(pixels). This yields a (n x p) data matrix X. In addition, a matrix M is constructed where,

$$m_{ij} = 1 \text{ if the i-th and j-th pixels are contiguous,}$$

$$= 0 \text{ otherwise.}$$

$M_a = M^{**}a$ defines the number of paths, a links in length, between each pair of pixels. This definition includes redundant paths. The sample a-lag covariance for the k and l variates (e.g. bands 4 and 7) is in matrix form:

$$C_a = (1/n_a^T) X (N_a - M_a) X \qquad (a = 0,1,\ldots)$$

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where n_a is the number of paths of length a , and $N_a = \mathrm{diag}(M_a^2)$ It may aid in understanding to note that C_0 is the usual sample covariance matrix. Lebart (1969) argues that the use of C_a other than C_0 will reduce the effects of spatial dependence upon the analysis.

The example dealing with PCA begs the question of whether one should: (1) incorporate spatial dependence into the model explicitly, or (2) remove it before commencing the main analysis. The choice of approaches depends upon the emphasis required by the nature of the problem to be solved. However, from the perspective of spatial modeling one may argue that corrections used to remove spatial dependence represent

> " ... a throwing out of the baby and keeping the bathwater " (Gould, 1970).

Another fundamental problem of spatial data has to do with aggregation problems. The results of most any analysis depend on the manner in which the geographical study area is partitioned for data collection and processing purposes. We can use the example of Yule and Kendall (1957) in which the value of their computed correlation coefficient (r) between yields per acre of wheat and potatoes varied rather widely depending upon the 'spatial aggregates' used. This problem is directly comparable with the same methodology reported by Robinson et al (1982) in a study of desertification modeling using Landsat data. In contrast to Yule and Kendall (1957), Robinson et al (1982) does not appear to have been aware of the role of spatial aggregation problems when partitioning the study area. Even so, his study does represent a

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methodology which recognizes the spatial variation in variate relationships. In other words, Robinson et al(1982) study recognize in a rudimentary way the fact of spatial non-stationarity.

Bearing in mind the dual issues of spatial stationarity and autocorrelation, the analysis of spatial data usually has as its objective either: (1) data smoothing, (2) data interpolation, or (3) modeling. These objectives are not necessarily mutually exclusive. For example, the preprocessing procedures used to destripe Landsat data introduce, in an obvious manner, strong components of spatial autocorrelation before any modeling has been done. This is also the case in data interpolation for bad or missing Landsat data.

Spatial Modeling

The natural framework for the modeling of cover class dynamics is the spatial-temporal process since we need to capture both components through temporal and spatial dependencies. However, before spatio-temporal models can be developed, spatial models must be considered. Purely spatial processes are philosophically highly problematic. Their study is of interest for three reasons (Bennett and Chorley, 1978):

(1) They may, under special conditions, actually exist. Spatial processes actually exist when the system under study has reached equilibrium.

(2) They may seem to exist to the observer or analyst. This usually occurs when the space-time data are available with very wide time separation which does not allow recognition of reaction, relaxation, and lagged dynamics.

(3) There are a number of important spatial problems such as spatial extrapolation, interpolation, and selective problems of statistical inference.

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It is mathematically straightforward to develop representations of purely spatial models. Two spatial processes which have received a great deal of attention are the unilateral and multilateral models defined on the basis of spatial lag as:

unilateral

$$Y_{tij} = a\,(Y_{ti(j-k)} + Y_{t(i-l)j}) + e_{tij}$$

multilateral

$$Y_{tij} = a\,(Y_{t(i-k)j} + Y_{t(i+k)j} + Y_{ti(j-l)} + Y_{ti(j+l)}) + e_{tij}$$

$k,l = 1,2,3, \ldots$

where a Cartesian lattice is assumed. The parameter a provides an indication of spatial stationarity where in each case the process is stationary if for the

unilateral case:

$$|a| < 0.5$$

multilateral case:

$$|a| < 0.25$$

(Haining, 1978).

Multilateral models have been used to describe interplant competition in ecology (Bartlett, 1975; Mead, 1971). The important difference between multilateral and unilateral models is that multilateral models are space-like whereas unilateral models perform in

a way analogous to an ordered time-series. In other words, in a unilateral model there is a distinctive ordering of events as they occur across the plane. An event initiated at one location spreads out in only one direction (Bennett, 1980).

There have been few formal models of Landsat data which have recognized the problem of spatial dependence. Notable attempts are those of Tubbs and Coberly (1978), Craig (1979), and Craig and Labovitz (1980). Without exception, attempts to date have depended heavily upon some version of the unilateral model. Hence, it is only natural that they should rely totally upon the Box-Jenkins (1970) formulations of the AR (autoregressive) and ARIMA (autoregressive integrated moving average) models. In contrast to these formal modeling attempts stand the less formal interpolation or filtering functions commonly used in the preprocessing of Landsat data. These filtering functions are, in the main, based on the same concept as the multilateral model. In fact, the destriping algorithm is essentially a version of a spatial moving average of a multilateral nature (Taranik, 1978). This implies that those using such preprocessed data should take multilateral spatial autocorrelation into account for the data they are working with are very much related to the data values in surrounding pixels.

The approaches taken by Craig & Labovitz (1980), Craig (1979), and Tubbs & Coberly (1978) underscore the relationship between the spatial autoregressive and the temporal (unilateral) autoregressive schemes. Let us consider the time-series autoregressive model of first-order where X(t) is the variate measured at time t (t = ... , -1,0,1,

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...). Three equivalent definitions follow which maintain the condition of stationarity by constraining $|p| < 1.0$ (Cliff, 1980).

The simultaneous autoregressive model is:

$$X_t = pX_{t-1} + e_t \quad \text{where,}$$

$$E(X_t) = 0 \; ; \; E(e_t) = 0 \; ; \; var(e_t) = \sigma^2 \; ; \; cov(e_t, e_{t-1}) = 0 \; ;$$

$$cov(X_{t-s}, e_t) = 0 \quad \text{for} \quad s > 0 \; .$$

The conditional autoregressive model is:

$$E(X_t \mid X_{t-1}, X_{t-2}, \ldots) = pX_{t-1}$$

and

$$Var(X_t \mid X_{t-1}, X_{t-2}, \ldots) = \sigma^2 \quad .$$

The covariance model is:

$$E(X_t) = 0 \quad \text{and} \quad cov(X_t, X_{t-s}) = \sigma_x^2 \, p^{|s|} \; ,$$

where, $\sigma_x^2 = \sigma^2 \; / \; (1 - p^2)$

(Cliff, 1980).

Whittle (1954) and Granger (1969) have shown that when a first-order autoregressive model such as:

$$X_t = pX_{t-1} + e_t \quad .$$

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is expanded to the two-dimensional, multilateral form:

$$X_{ij} = aX_{i-1,j} + bX_{i+1,j} + cX_{i,j-1} + dX_{i,j+1} + e_{ij} ,$$

considerable problems are encountered. The two major problems are (1) parameter estimation becomes computationally difficult and (2) on the basis of the same set of spatial autocorrelations, it is impossible to discriminate between a number of alternative models (Bassett, 1972). This problem of model identification or specification will be treated in greater detail in the discussion of dynamic spatial models.

The autoregressive and moving average schemes assume spatial data in discrete space. However, digital Landsat data are obtained through an analog-to-digital conversion process. In this process the [continuous] signal is sampled frequently enough so that the digital representation of the signal will reproduce the information content of the signal (Swain and Davis, 1978). This characteristic of Landsat data suggests the possibility that models based on the discrete-space assumption may be inappropriate and those based on continuous, but sampled, spatial data are more justified. If this is the case, Cliff (1980) suggests that it is better to specify the covariance structure directly rather that attempt to formulate a linear dependence model. The reasoning is that if a linear scheme is specified at one spatial scale, there would need to be a scheme which is non-linear in p at any different spatial scale.

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We may consider what the general formulation of such a covariance structure might be. Consider a process $X(u)$ defined at:

$$\text{location } u = (u_1, u_2)$$

with

$$\text{mean} \quad E[X(u)] = u$$

and

covariance structure

$$\text{cov}[X(u), X(v)] = \sigma^2 \; c(u,v)$$

where $c(u,u) = 1$ for all u.

Various forms of $c(u,v)$ have been suggested usually depending on a distance formulation such as:

$$d = [(u - v)^2 + (u - v)^2]^{\frac{1}{2}} \quad ,$$

rewriting $c(u,v)$ as $c(d)$ and keeping $c(0) = 1.0$.

This is only one of several alternative approaches to specification of the form of the covariance structure (see Cliff, 1980).

Temporal Series and Cover Class Dynamics

When speaking of cover class dynamics one is generally interested in process. Process is essentially change over time. Time-based systems possess convenient properties not encountered in spatial systems . The most important properties are asymmetry and transitivity. Mathematically these properties can be defined for events $E(i)$ and time operators T_i by

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Asymmetry :

given $E_1 = T_1(E_2)$, then $E_2 / T_1(E_1)$

Transitivity :

given $E_1 = T_1(E_2)$ and $E_2 = T_2(E_3)$,

then $E_1 = T_3(E_3)$.

In other words, the whole set of events is uniquely connected or ordered. One of the simpler models suggested for use in the study of land cover change using remote sensing data (Bell, 1974; Strahler, et al., 1980) and used extensively in the study of plant succession (Slatyer, 1977) is the Markov Chain Model. The Markov Model is concerned primarily with changes of 'state' over time. The transition matrix forms the basis for the definition of the model where the transition probability matrix P defines the probability of cover class i changing to to cover class j from time t to time t+1 . A transition probability is the probability that a given spatial unit S in cover class i at time t will be in cover class j at time t+1. In notation form, elements of the transition probability matrix may be defined as :

$$P_{ij}^{t,t+1} = \text{Prob}\,[\, S_{t+1} = j \mid S_t = j \,]$$

(Robinson, 1980).

Bell (1974) suggested its use in the study of land use change data derived from aerial photographs and Strahler, et al. (1980) have

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used it as a means of analyzing change in forest cover classes. From the perspective of studying cover class dynamics as a process of plant succession, Markov Models have the following advantages : (1) they are easy to derive from successional data; (2) they do not require deep insight into the mechanisms of dynamic changes, but it can help to pinpoint areas where such insight would be valuable; (3) the transition matrix summarizes the essential parameters of dynamic change in a system in a succinct, concise manner; (4) the computational requirements are modest. On the other hand, there are several serious disadvantages such as :

(1) the lack of dependence on functional mechanisms may reduce its appeal to those less empirically-oriented scientists (Slatyer, 1977);

(2) departure from assumptions of stationarity, or from assumptions of constant, linear transfer rates (Bell and Hinojosa, 1977);

(3) validation of the model depends upon predictions of system behavior over relatively long periods of time and is therefore difficult in many cases (Robinson, 1980).

There are two additional problems of the Markov Model which are associated with the use of Landsat data for modeling cover class dynamics. These are: classification and spatial dependence. In order to use the Markov Model to study cover class dynamics, some classification scheme is needed which separates successional communities into definable categories such as cover-states (Slatyer, 1977). The problem of classification remains an elusive problem in the study of land cover change (Stow, et al., 1980). The second problem

has received less attention in the remote sensing literature. The problem of spatial dependence was recognized in the study by Bell and Hinojosa (1977) as being that the Markov model is intrinsically aspatial. Thus, there remains the problem of finding a variation [of the Markov model] that can take account of this dependence explicitly.

Uncritical use of the Markov model results in the same problems as in the uncritical use of other, more general, models of time-like systems. Namely, the problems of stationarity and autocorrelation affect both the Markov model and the general linear stochastic models. Autocorrelation (in the non-spatial sense) refers to dependence (i.e., correlation) between the observed value of a variable at some time t and its observed value at some later time t+1. As such, it represents a violation of one of the assumptions of the Gaussian model. Stationarity refers to constancy in the moments of a time series. A series is referred to as being first-order stationary if its mean is constant from one time period to the next. Second-order stationarity is similarly defined with respect to variance. If a series is second-order stationary, the implication is that the covariance of two terms of the series is dependent only upon time difference between the points and not upon the particular points being examined (Cliff, et al., 1975). That is:

$$\mathrm{cov}[X(t),X(t-k)] = E[(X(t) - u)(X(t - k) - u)].$$

The above reference quotes Granger (1969) to the effect that 'The assumption of stationarity essentially says that the law that generates the data is constant over time'.

An Introduction to Dynamic Spatial Models

Despite a growing interest in space-time modeling, especially in the remote sensing community, there is a relatively scant body of literature on the topic. This section presents three general spatial-temporal models, they will be the STAR (Space-Time Autoregressive Model), STMA (Space-Time Moving Average Model), and the STARMA (Space-Time Autoregressive-Moving Average Model) models.

As is evident from the types of models which shall be discussed, this section is based on the modeling of Landsat data for classification, not on modeling classified Landsat data following an aspatial classification exercise. This approach is suggested by the work of Tubbs and Coberly (1978), Craig (1979), and Craig and Labovitz (1980). Furthermore, concern with modeling Landsat data prior to the classification exercise has offered promising results in the modeling of tropical rain forest succession (Barringer, et al., 1980), and in the monitoring of desertification (Robinson et al, 1982). In addition, this approach may been seen to act to 'filter' out certain kinds of confounding influences which arise from sources noted in detail by Craig and Labovitz (1980), and Barringer and Robinson (1981).

To begin the discussion of these models some common definitions are presented. First is the definition of the "spatial lag operator". For a spatial lag operator L and data value y(it) that is associated with pixel i for time t, the relationship is:

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$$L^{0} y_{it} = y_{it}$$

and

$$L^{s} y_{it} = \sum_{j} w_{ij} y_{j,t} \quad , \quad s > 0 \ ,$$

where s denotes the spatial lag which is s steps(pixels) away from pixel i, and the summation is over the j pixels at spatial lag s from i. Using this common notation all the above models are briefly presented.

STAR Model

Tobler (1967, 1970) used STAR models to estimate the linear spatial transfer functions (linear operator) which best transforms a map at time t into that at t+1. This is, of course, a common problem in the use of Landsat data to model cover class dynamics. The STAR model is of the form:

$$y_{it} = \sum_{s=0}^{l} \sum_{k=1}^{m} a_{sk} L^{s} y_{i,t-k} + e_{it} \quad .$$

where k denotes temporal lag k from t, while l and m denote the maximum number (order) of the spatial-temporal lags over which the summations are conducted (Haggett, et al., 1978).

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STMA Model

This is a space-time moving average model of the general form:

$$y_{it} = -\sum_{s=0}^{l}\sum_{k=1}^{p} c_{sk} L^{s} e_{i,t-k} + e_{it} .$$

STARMA Model

Combining the STAR and STMA models we obtain the space-time autoregressive and moving average model where:

$$y_{it} = \sum_{s=0}^{l}\sum_{k=1}^{m} a_{sk} L^{s} y_{i,t-k} - \sum_{s=0}^{l}\sum_{k=0}^{p} c_{sk} L^{s} e_{i,t-k} + e_{it}$$

Model Specification and Identification

In the stochastic modeling of successional processes, ecological theory forms the basis for model specification. Box and Jenkins, (1976) point out that where theory is inadequate or non-existent, a class of models may be specified. However, a given model may imply more than one possible structure.

Identification forms the second stage in the process of statistical inference and is the logical process whereby the model specified in the first stage is related to a basic structure. Correct model specification, based on ecological theory, implies structural identification in terms of the model. Moreover, the identification process works to reduce any class of models which may have been specified initially to a more parsimonious sub-class. Haggett, et al., (1977) note that two questions may be posed which together summarize the model specification problem. These two questions are:

(1) Which model should be selected from the basic STAR, STMA, and STARMA formulations presented above ?

(2) Having chosen a particular model, what orders of temporal and spatial lags should be included in the model ?

If ecologic theory is strong enough to provide, a priori, answers to these two questions, then the problem of model specification is easily solved. However, more often than not, these bodies of theory offer little guidance in making such fine distinctions among modeling forms.

The identification of an appropriate model requires not only computation of the time-space correlogram (i.e., a display of the serial correlation structure among variate values for various spatial and temporal lags, but also of the time-space partial correlogram which displays partial correlation relationships between and among the independent variables. The partials indicate the degree of correlation between the data values in the pixels at time t and the values in those pixels which are k temporal and s spatial lags away with the effect of all other spatially and temporally lagged variables held constant. Each of the models presented above has been shown to have certain general characteristic space-time correlations and partial correlations. They are:

(1) For the STAR (1,m) process of order 1 in space and m in time, the autocorrelations should decay approximately exponentially in time and space. The partial correlations should become approximately zero after lag 1 in space and m in time.

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(2) For the STMA (g,p) process of order g in space and p in time, the autocorrelations approach zero after lag g in space and p in time. Partial correlations decay approximately exponentially in time and space.

(3) For the STARMA (1,m,g,p) processes display correlations and partial correlations which tail off as a mixture of exponential curves and damped sine waves. The correlations exhibit this tailing-off after the first g-1 spatial lags and p-m lags in time . The partial correlations exhibit such behavior after the first 1-g lags in space and m-p lags in time (Martin and Oeppen, 1975).

In order correctly to specify and identify a spatial model of succession from one of the classes outlined above, thought must be given to three sets of relationships:

(1) For any given region in space and for any two points in time, what effect will the species collection present on the site at time t have on the species collection present at time t + k ? (Temporal autocorrelation effect).

(2) For any given time and for any two regions in space, what effect will the species collection present at site i have on the species collection at site j — and vice versa? (Spatial autocorrelation effect).

(3) For any regions i at time t and j at time t + k, what effect will the species collection on site i have on that at site j — and similarly for the effects of site j at time t on i at time t + k ? (Space-time autocorrelation).

In the study of cover class dynamics as a successional process such models may prove less than illuminating if one does not realize that they are based on the assumption that the structural relationships between spatial aggregates may vary over space and time — in

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particular, patterns of decline and cutoff for the various autocorrelation effects will be of considerable importance in the model specification. For example, it may be unrealistic to assume that the form of the relationship between two cover classes at their mutual boundary is the same as it is in an area of homogeneous cover located away from that boundary. Haining (1978) encountered the related problem of bias associated with the estimation of certain stochastic lattice models. It was observed that such edge effects are dependent both upon the ratio of border to non-border cells (e.g., pixels) and upon the values of border cells relative to the expected values of non-border cells. Lattice regularity was also found to have a strong effect on process outcome. It is to be expected that effects such as those alluded to here would be particularly troublesome when studying such spatial systems over time. One sophisticated approach to this problem is the construction of varying parameter space-time models (Haggett, et al., 1977).

Concluding Summary

There are two major outcomes of this research. First, the use of the TSA model shows that the spatial modeling of radiance values can provide a useful approach to one the problems in monitoring tropical rain forest succession. It also raised the point that shadowing effects may be due primarily to local variations in the spectral responses. The significance of this result is that they can be compensated for through the decomposition of the spatial variation in both elevation

and MSS data. Use of the trend surface model to estimate both elevation and spectral terrain surface as a posteriori inputs in the classification process leads to an improvement in classification accuracy for vegetation cover of this type. Perhaps more significant are the results suggesting that spatial patterns depicted by the MSS data reflect the measurement of responses to spatial processes acting at several scales. The results of the TSA modeling phase suggested the investigation of spatial models as useful in the development of a capability in monitoring tropical vegetation changes.

The most broadly significant result of this research is the identification of dynamic spatial models critical to the study of tropical rain forest succession using Landsat. A major theme has been the spatiallity of Landsat data, of the process which it represents and of the models which may be used to emulate successional processes. Thus, its effect on data collection, model construction and statistical inference were identified. An effort was made to suggest the promise of dealing formally with space, as well as some of the pitfalls which may await the unwary. It is strongly felt that the issues raised here must be clearly considered and resolved if future models based on Landsat data are accurately to reflect the space-time processes they are meant to emulate.

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