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Abstract—The NASA and the NMFS have undertaken a joint research project to develop Landsat Thematic Mapper (TM) technology for the determination of the value of wetlands to estuarine fish and shellfish production. NASA has developed the remote-sensing-based model to predict wetland productive capacity, a measure of the organic carbon exported to the estuarine food chain. The productive capacity (PC) model uses satellite remotely sensed determinations of vegetation, as the source of carbon, and distance-to-water, shoreline density, and water body type as hydrographic factors influencing carbon export. Regression analyses of aircraft simulated TM (TMS) data showed a stronger relationship with percent vegetation cover than with biomass for estimating the source of organic detritus. Land/water discrimination, fundamental to the measurement of the hydrographic variables, was accomplished more accurately with TMS than with Landsat Multispectral Scanner (MSS) data as compared to a photographic standard. The PC model generates detrital export measurements as input to an estuarine ecosystem model being developed by NMFS. Initial findings show that salinity patterns along with animal interactions affect the utilization of detritus by benthic organisms. The coupling of the two models establishes a technique for estimating the economic value of wetlands with respect to estuarine-dependent fish and shellfish production.

Keywords—wetlands, trophic value, detritus, estuarine ecosystem, remote sensing, biomass, Thematic Mapper.

INTRODUCTION

The NASA and the NMFS have undertaken a joint research project to develop Landsat Thematic Mapper (TM) technology for the determination of the value of wetlands to living marine resources. Such a determination is
necessary for developing criteria for decisions on public land purchases and alteration permits. Remote sensing technology provides information about wetland vegetation type, water bodies, and shoreline configuration. Such factors can be combined to evaluate productive capacity, defined as the potential of a wetlands ecosystem to export decaying plant material, or detritus, to the estuarine food chain.

The fisheries of the southeastern United States are strongly dependent upon estuaries and the tidal wetlands that are integrally tied to them by water flows. Estuaries are nursery grounds for shrimp (*Penaeus* spp.), menhaden (*Brevortia patronus*), and many other commercial and recreational species. Recent studies by the NMFS have determined that vascular plant material produced in wetlands is an important component of the diet of menhaden [1]. On the basis of a comparison of the total energy available from various sources, Condrey *et al.* concluded that benthic algal communities and the microbial communities on decaying plant material from coastal marshes were the most likely primary food sources of penaeid shrimp [2]. In a study of the food habits of the animals of Lake Pontchartrain, a Louisiana estuary, Darnell found that detritus was a major component of the total food volume of fishes and larger invertebrates [3]. Detritus was derived primarily from the decay of marsh grasses and phytoplankton. Plant detritus is a principal food of polychaete worms and other benthic organisms fed on by shrimp, crabs, and bottom-feeding fish.

Despite the acknowledged importance of coastal wetlands to fisheries, there is little quantitative information directly relating wetland area to fishery landings. Such information is needed to properly evaluate the impact of wetland loss on fisheries. Towards this end, NASA is developing a wetlands productive capacity (PC) model to generate detrital export data that will satisfy input data requirements of an estuarine ecosystem model developed by the NMFS. The coupling of the two models will provide an estimation of the value of wetlands to fish and shellfish production.

Five elements of the joint research project are presented in this paper. They include 1) an explanation of the remote-sensing-based wetlands PC model, 2) the results of regression analyses for the prediction of wetland vegetative cover from spectral data, 3) an evaluation of the land/water discrimination capability from Landsat Multispectral Scanner (MSS) and aircraft simulated TM (TMS) data, 4) a procedure for calibration of the PC model, and 5) the status of development of the NMFS estuarine ecosystem model.

Calcasieu Basin, Louisiana, was selected for the project study area. It was chosen for its high fish and shellfish production and the fact that it typifies a Gulf Coast wetlands of low relief, minimal tidal range, sluggish bayous, and predominance of *Spartina patens* (wiregrass) as a vegetative community. Flushing action in this nonforested wetlands, or marsh, is determined by largely wind-driven tides, precipitation and run-off, and storm surges. The basin is clearly defined hydrologically, being composed of several discrete watersheds. The Cameron-Creole Watershed, approximately 28,000 ha on the east side of the basin, was selected for intensive study and represents the focus of the work presented here. Definition of a watershed was required so that the origin and export of detritus to the estuary could be identified with a given wetland area. Measurements of detritus used in calibration of the wetlands model represented products of plant decomposition which included dissolved organic carbon (DOC), particulate organic carbon (POC), and macroscopic vascular plant debris.

All computer programs utilized in the analysis of the remotely sensed data in this investigation are a subset of ELAS, a comprehensive software package developed by the Earth Resources Laboratory (ERL), an element of the NASA NSTL [4]. Computer processing was performed at ERL on a 32-bit minicomputer configured with adequate memory, associated peripherals, and image display devices.

**The Wetlands PC Model**

The wetlands productive capacity model has been developed to quantify for any point in the marsh its trophic value to the estuarine food chain. This is termed its "productive capacity" and is assessed by quantifying wetland primary production and export to estuarine waters. Productive capacity is expressed as detrital export which constitutes a major variable in the estuarine ecosystem model being developed by NMFS. The PC model has been designed to capitalize on information that can be derived from Landsat MSS and TM data and on the georeferenced digital data format advantageous for data base construction.

The PC model operates with these underlying assumptions: 1) Terrestrially-originated plant biomass, in various states of decomposition, is a significant food source for estuarine-dependent fish and shellfish. 2) Hydrographic features represent physical forcing functions that control detrital export. 3) Wetlands for which the model applies can be characterized as Gulf Coast marshes where elevational differences and tidal range are minimal.

We assume that the productive capacity of a location in the marsh depends on 1) its annual production of vegetation, 2) the distance plant biomass and/or its decomposed state is flushed before entering the nearest water body (which is the point at which the terrestrial plant matter can begin to mix with estuarine waters, leading to assimilation in the estuarine food chain), 3) the type of water body into which this transfer of detritus first occurs, and 4) the density of shoreline available for nutrient export. Plant production, the first variable, identifies the commodity. The last three variables describe the effective export of this commodity.

The following relationship is assumed in the model, where $PC$ is productive capacity, $B$ is annual production of plant biomass, $D$ is the export distance to water, $W$ is the importance value of the water body type, and $S$ is the shoreline density (length per unit area)

$$PC = f(B, D, W, S).$$

(1)

$B$, $D$, $W$, and $S$ are considered independent variables in the model, while $PC$ is the dependent variable. Fig. 1 is an operational diagram of the PC model. The measurement of $B$, $D$, $W$, and $S$ can be obtained from remotely sensed data for
which processing techniques have been developed with the use of Landsat MSS data [5], [6]. The determination of these measurements from MSS data has been repeated in this investigation and will be reported in a later paper with TM data test results. The measurement of plant production can be accomplished indirectly by inference from a classification of vegetative species. A direct measurement of biomass or density from remotely sensed data, however, is presumed to be more accurate. The results of an investigation to measure biomass/density directly are presented in the next section.

Correlation and Regression Analysis of Ground Truth Data Versus TMS Data

A. Data Acquisition and Preparation

TMS data were acquired by aircraft over the Cameron-Creole Watershed at 0930 solar time on September 23, 1982. Spectral resolution for channels 1–7, respectively, was 0.46–0.52, 0.52–0.61, 0.63–0.69, 0.77–0.90, 1.52–1.69, 2.04–2.24, and 10.4–12.3 μm. The flight lines were oriented so that the sun's rays were parallel to the flight direction at the time of data acquisition. A morning flight was scheduled to optimize the probability of minimal cloud interference, as clouds typically set-in over the Gulf Coast by mid-morning during the period of late April to mid-September.

The TMS data were decommutated and reformatted to an 8-bit digital format and processed through various programs for extraction of data from designated sites for which ground variables were collected.

The data were examined for any variation introduced by sun angle and/or atmospheric effects. Data within ±30° of nadir did not exhibit any significant effect from such sources of variation and were thus used in the subsequent analyses. The data were resampled to achieve georeference, where each pixel accounted for a 30 m × 30 m surface area.

Approximately 38 ground truth sites were selected from recent color infrared aerial photography to represent the range of color tones within the vegetated land area. Each site was located at least 10 m away from the shoreline. The area of each site was about 30 m × 30 m.

A ground truth mission was conducted to make observations and harvest samples at each site in the following manner:

1) Three transect lines, parallel to each other and to the salinity gradient, were identified at each site. The lines were spaced about 10 m apart and measured 30 m in length.
2) On each line from the point of origin to the end observations were recorded as to the percent species composition and percent standing surface water viewed directly under the line. The assessment was made in terms of percent surface coverage for no less than an interval of 0.33 m.
3) On the middle transect line, vegetation samples were harvested at three locations from the origin: 7.37, 14.75, and 22.12 m. This was accomplished by clipping, at ground level, which in some cases was below water level, all the vegetative stems within a 0.25-m² quadrat and collecting and bagging the clippings and all litter including both live and dead material. The vegetative material was later sorted into dead versus green components, then dried and weighed.

B. Analytical Method

The analysis consisted of a comparison of the ground truth data by dead and green vegetative weights and percent standing surface water against seven channels of TMS data. Of the 38 original sites, analysis was limited to 32 sites located on one flight line. The raw TMS data were averaged per channel for approximately six pixels surrounding and including the ground truth site. The average response per channel per site was then used in the analysis.

As another approach, the raw TMS data (channels 1–6...
only) were transformed into principal components. The average value for each principal component per site was then derived as above. Correlations and linear regressions were computed on the ground truth data versus the spectral data.

C. Results

Table I provides the means and standard deviations for the spectral response and ground truth data obtained for the 32 sites. TMS channels 4 and 5 had the highest coefficients of variation, demonstrating their intrinsic sensitivity to the variability in surface water and vegetation characterizing this study area.

Table I also shows that when the TMS raw data were transformed into principal components, the resulting first three components accounted for 96.08 percent of the scene variation. The first principal component demonstrated the greatest variability over the wetland surface than any other component.

The ground variables included in Table I show that there was roughly 30 percent more green than dead biomass harvested during the September sampling mission. The mean percent standing surface water (exposed to view) was 17.72, with a range of 0–50 percent for the 32 vegetated wetland sites. Standing surface water could be characterized as a condition of water depth from nearly 0–20 cm. where the water was highly sedimented and at the shallowest depth approached a nearly “thin mud” consistency. The prevailing environmental condition of land area was one of vegetation varying in surface cover (density) from 50 to 100 percent.

Table II shows the results of a correlation analysis between the TMS raw data mean spectral response per channel and ground variables for the 32 selected sites. None of the correlations were high. There were, however, a few moderately high correlations. These included the relationship between dead vegetation versus channels 1, 2, and 5 (r = 0.582, 0.428, and 0.433, respectively) and percent standing surface water versus channels 4 and 5 (r = 0.495 and −0.482, respectively).

Table III shows the results of a correlation analysis between the TMS principal components mean value per channel and ground variables. Again, no high correlations resulted. Of the three ground variables, however, dead vegetation correlated moderately with components 1 and 2 (r = 0.443 and 0.505, respectively) and percent standing surface water correlated moderately with component 1 (r = −0.445).

In analyzing the results of Tables II and III, we concluded that green vegetation by weight does not relate directly to spectral response. Dead vegetation by weight may have some relationship as a contribution to brightness, but it is not as desirable a ground variable for use in productivity predictions because the amount of dead material occurring in the marsh at anytime largely depends on the flushing action wrought by tides, precipitation runoff, and episodic storms. The minimal correlation (r = 0.130) between green and dead vegetation in this study demonstrates their unrelatedness without introduction of other variables.

The percent standing surface water, the remaining ground variable, showed a moderate relationship with TMS channels 4 and 5 and the first principal component and, in addition, is intrinsically more desirable as an indicator of plant production in wetland areas. This is because the percent of standing water or water exposed to view varies less on an annual basis for normal water level conditions related to both tides and rainfall than do green and dead biomass components, as individual variables, in a Gulf Coast wetland. Percent vegetated cover, the sum of green and dead cover, is equal to 100 percent minus the percent standing water for a given location.

Multiple linear regression analysis was applied to combinations of the spectral and ground variables. Table IV indicates the results.

1) Variation in the amount of green and/or dead biomass was explained very little by regression where TMS “raw” data and principal components data were the inde-
TABLE IV
MULTIPLE LINEAR REGRESSION ANALYSES BASED ON TMS DATA AND GROUND VARIABLES

<table>
<thead>
<tr>
<th>DEPENDENT VARIABLE</th>
<th>INDEPENDENT VARIABLE(S)</th>
<th>F-TEST LEVEL OF SIGNIFICANCE</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Green Biomass</td>
<td>TMS Ch 2, 4, 6</td>
<td>.50 &gt;.10</td>
<td>.18</td>
</tr>
<tr>
<td>Green Biomass</td>
<td>TMS Ch 3, 4, 5</td>
<td>.50 &gt;.10</td>
<td>.15</td>
</tr>
<tr>
<td>Green Biomass</td>
<td>PC 1, 2, 3</td>
<td>.50 &gt;.10</td>
<td>.15</td>
</tr>
<tr>
<td>Dead Biomass</td>
<td>TMS Ch 1, 4, 5</td>
<td>.50 &gt;.10</td>
<td>.16</td>
</tr>
<tr>
<td>Dead Biomass</td>
<td>TMS Ch 2, 4, 6</td>
<td>.50 &gt;.10</td>
<td>.16</td>
</tr>
<tr>
<td>Dead Biomass</td>
<td>PC 1, 2, 3</td>
<td>.01 &gt;.005</td>
<td>.34</td>
</tr>
<tr>
<td>% Standing Surface Water</td>
<td>TMS Ch 3, 5</td>
<td>.005 &gt;.001</td>
<td>.31</td>
</tr>
<tr>
<td>% Standing Surface Water</td>
<td>TMS Ch 3, 4, 5</td>
<td>.005 &gt;.001</td>
<td>.37</td>
</tr>
<tr>
<td>% Standing Surface Water</td>
<td>TMS Ch 3, 4, 6</td>
<td>.005 &gt;.001</td>
<td>.41</td>
</tr>
<tr>
<td>% Standing Surface Water</td>
<td>TMS Ch 2, 4, 6</td>
<td>.001 &gt;.005</td>
<td>.63</td>
</tr>
<tr>
<td>% Standing Surface Water</td>
<td>TMS Ch 3, 4, 5, 6</td>
<td>.025 &gt;.01</td>
<td>.33</td>
</tr>
<tr>
<td>% Standing Surface Water</td>
<td>PC 1, 2, 3</td>
<td>.005 &gt;.001</td>
<td>.38</td>
</tr>
</tbody>
</table>

The results from Table IV indicate that other or additional independent variables need to be considered in accounting for the variation in the ground variables. An understanding of these results may become more obvious when data are analyzed from a subsequent spring data collection.

D. Land/Water Discrimination from Remotely Sensed Data

Measurement of the PC model variables for distance to water, water body type, and shoreline density requires land to be discriminated from water. The results of an evaluation of the land/water discrimination capability using Landsat MSS bands and TM bands [7], [8].

1) CIR, low-altitude aerial photography, collected on October 9, 1978.
2) CIR, low-altitude aerial photography, collected simultaneously with TMS on September 23, 1982.
3) TMS aircraft digital data, two flight lines, resolution approximately 30 m, collected on September 23, 1982. (Only channels 3, 4, 5, and 6 were considered in the analysis.)
4) Landsat III, MSS 4-channel digital data, resolution approximately 80 m, collected on October 19, 1981.

The multistage data were compared by the percent land and water identified within a 1680-ha portion of the Cameron-Creole Watershed. Fig. 2 displays an image of the study area generated from TMS channel 4 raw data. Water bodies, vegetation, and transitional areas existed within the sample. Transitional refers to mixed areas of approximately 50-percent land and 50-percent open water.

E. Analytical Method

Five land/water classified products were generated for the comparison of MSS to TMS data. Frames of the subarea from the two dates of CIR photography were manually interpreted using a Bruning areagraph chart no. 4849 to derive a land/water delineation. The percent land and water was then calculated.

The TMS and MSS data were processed using ELAS software for automatic training sample selection and classification. Table V compares examples of TMS and MSS
class spectral signatures. The values for vegetated cover in TMS and MSS channels 3 and 4 show an increase from stands that include only green cover, a result of burning the marsh as an environmental management practice, to TMS and MSS channels 3 and 4, above, those that include both green and dead cover, the natural increase as the amount of exposed standing surface water decreases by virtue of percent vegetation cover and inundation frequency. For water classes, the lowest values occur in Table V.

<table>
<thead>
<tr>
<th>LAND (SATURATED SOILS)</th>
<th>TMS</th>
<th>MSS</th>
</tr>
</thead>
<tbody>
<tr>
<td>New and Sparse Vegetation (Green Stands)</td>
<td>67 11 89 95</td>
<td>13 14 25 25</td>
</tr>
<tr>
<td>Mature Vegetation (Green and Dead Stands)</td>
<td>4.9 4.9 5.9 2.5</td>
<td>6.8 6.8 5.6 6.3</td>
</tr>
<tr>
<td>Less Frequently Inundated Vegetation (Green and Dead Stands)</td>
<td>68 154 128 104</td>
<td>18 20 45 48</td>
</tr>
<tr>
<td>Water</td>
<td>8.8 9.7 6.2 3.4</td>
<td>3.9 1.3 2.2 2.2</td>
</tr>
<tr>
<td>Bayou</td>
<td>5.6 6.3 6.4 3.6</td>
<td>5.1 6.6 4.6 4.7</td>
</tr>
<tr>
<td>Pond</td>
<td>7.6 200 110 98</td>
<td>19 20 53 56</td>
</tr>
<tr>
<td>Lake</td>
<td>3.8 10.0 6.0 2.6</td>
<td>0.9 1.4 2.8 3.0</td>
</tr>
<tr>
<td>CIR Photography (10/9/78)</td>
<td>5.0 5.0 5.5 2.7</td>
<td>4.9 7.1 5.2 5.5</td>
</tr>
</tbody>
</table>

Most of the 13.04-percent TMS unclassified data (Table VI) were considered to be water upon comparing with the photographic standard, but when the TMS data were classified with no threshold, the percent land exceeded that derived from the TMS classification with a threshold limit.

We feel the difference in results derived from the MSS and TMS data versus the photographic standard can be explained by the following:

1) The nature of an integrated signal where the instantaneous field of view represents a mixture of land and water, particularly the turbid water characteristic of Gulf Coast estuaries, causes an integrated response that more closely resembles the spectral signature of wetland. The higher spatial resolution of TMS data, however, did not classify land because of the overlap in signatures between land and water typical of this wetland environment. These results indicate decision rules for signature development and classification should be further tested, but a classifier other than maximum likelihood may be warranted, and that contextual information would enhance land/water discrimination.

2) It is obvious that based on the comparison of TMS classifications generated with threshold and no threshold conditions, there is a higher probability that a pixel of water with a spectral signature approaching the boundary limits of the class signature for water will be classified as land because of the overlap in signatures between land and water typical of the wetland environment. These results indicate decision rules for signature development and classification should be further tested, but a classifier other than maximum likelihood may be warranted, and that contextual information would enhance land/water discrimination.

PC Model Calibration

The productive capacity model will be calibrated by multiple regression analysis where organic carbon export is the dependent response variable and primary productivity, shoreline density, distance to water, and water body type are the independent variables. Field collection for the response variable has been conducted to obtain seasonal concentrations of organic carbon in the water column for both incoming and outgoing tides. The fractions of organic carbon sampled and measured included dissolved, particulate, and macroscopic detrital forms. DOC and POC were derived by automatic carbon analysis of water bottle samples. Detrital fragments were sampled with nets and dried and weighed for calculation of carbon content.

The carbon measurements will be defined as organic carbon export by adjusting for discharge from four hy-
carbon export from a typical Gulf Coast marsh for four
erating an economic value for wetlands based on their con­
drologically discrete locations in the watershed where the
organic carbon was sampled and water level and current
velocity were continuously recorded. The result of calibra­
tion, then, will provide predictive equations for organic
carbon export from a typical Gulf Coast marsh for four
seasons. Once the PC model is calibrated, the output data
will then be used as input data for developing the estuarine
ecosystem model by simulation methods. Thus the remote-
sensing-based wetlands productive capacity model coupled
with the estuarine ecosystem model will be capable of gen­
erating an economic value for wetlands based on their con­
tribution to the support of commercially harvested estu­
arine-dependent fish and shellfish.

**Description of Energy-Flow Ecosystem Model**

The purpose of the estuarine ecosystem model is to quan­
tify the connection between the production of brown and
white shrimp, two estuarine-dependent species in Louisiana,
and two principal aspects of estuarine-wetlands ecosystems
that can be affected by man's activities. These are 1) avail­
ability of detritus to estuarine organisms and 2) area of
water of favorable salinities.

Detritus is the base of the food chain of many estuarine
organisms, including shrimp. Shrimp feed both directly on
detritus and on microorganisms and benthic organisms that
eat detritus. The plants that grow in adjacent wetlands are
an important source of detritus to estuaries. Availability of
detritus is thus a function of area of wetlands, condition of
wetlands, and rate of flushing of plant material into water
bodies by tides, freshwater runoff, and wind.

Brown shrimp harvests in Louisiana appear to be corre­
lated with estuarine area exhibiting salinities greater than
10 percent in April and May which is the time of peak
abundance of juvenile brown shrimp [11]. Harvests of white
shrimp may also be related to the distribution of salinities
over the estuary at some crucial time. The area of favorable
salinities is principally a function of freshwater runoff, but
is also influenced by temperature, tides, and wind.

The several ways that freshwater runoff and other envi­
ronmental variables may affect the production of shrimp by
estuaries are incorporated into the diagram of an estuarine
ecosystem in Fig. 3. The diagram employs the symbols of
the energy flow language of H. T. Odum [12]. The con­
ecting lines with arrows indicate storages of energy as bio­
mass. The diagram shows how the wetlands productive
capacity model provides input to the estuarine ecosystem
model. Detritus export, as simulated by the PC model, feeds
into the detritus compartment of the ecosystem model.

As postulated by the model, shrimp production in Loui­
siana is a function of 1) availability of detritus and detri­
tus-feeding organisms, 2) area of favorable salinities,
3) temperature [11], 4) level of spawning, and 5) rate
of larval transport.

The model diagram is the product of the first of 11 steps
in this energy-flow modeling process. These steps are as
follows: 1) design of conceptual model, 2) survey of
available data, 3) analysis of data sets, 4) collection of
new data, 5) refinement of model structure, 6) formu­
lation of mathematical equations, 7) coding of computer
program, 8) quantification of values, 9) computer simu­
lation of time series, 10) calibration of model by com­
paring simulated time series to actual time series output,
and 11) sensitivity testing.

The study is now on the third stage—data analysis. Mul­
tiple regression analysis is being used to gain perspective
for refining model structure and formulating the mathe­
matics of functional relationships. The data set used for
our analysis was provided by the Office of Coastal and
Marine Resources of the Louisiana Department of Wildlife
and Fisheries and was previously the subject of a report by
Barrett et al. [13]. The data were collected monthly for
two years at four stations along a transect running parallel
to the salinity gradient associated with each by seven bay
systems. The data set includes the following data used in
our analysis: geographic coordinates, top and bottom salin­
ity and temperature, and weights of trawl-caught animals
by species.

Our analysis of the above data base has two objectives.
The first objective is to determine which animals should be
included in the model and how to group them. The follow­
ing variables were tested for their relationship with bio­
masses of each of the two shrimp species: biomass of com­
petitors of shrimp (C), biomass of predators of shrimp (P),
biomass of animals that are both competitors and predators
of shrimp (PC), biomass of the other shrimp species (B)
or (W), biomass of species not thought to directly interact
with shrimp, and biomass of all animals combined (T).
The second objective is to develop an index of salinity pattern to which shrimp biomass can be related, since information on area within the favorable salinity range is not readily available from the data. We hypothesized that one critical factor of the salinity pattern that would be related to shrimp biomass would be the average salinity of the bay (A). A second aspect of the salinity pattern that might be important is the horizontal salinity gradient (H). This variable was calculated by summing the salinity differences between each station and its nearest neighbor. An appropriate index of area of favorable salinities might incorporate both horizontal salinity and the average salinity function.

The vertical salinity gradient (V) might also be an important salinity characteristic influencing shrimp biomass, because steep vertical salinity gradients denote stratified conditions, or a lack of vertical mixing, which can lead to oxygen depletion in bottom waters.

The variables used in the regressions were calculated by averaging values for the four stations associated with each bay system, or, in the case of the horizontal salinity gradient, by averaging the change in salinity with distance along the transect, according to the salinity at each station.

A. Preliminary Analytical Results

Multiple regressions were performed using the SPSS computer package [14]. Either stepwise inclusion or backward elimination methods were employed. White shrimp biomass was compared to the salinity variables, animal variables, and water temperature in the seven bays. Four separate analyses were performed. These were as follows: 1) on each date (24 regressions with \( N = 7 \), 2) on all dates (1 regression with \( n = 169 \), 3) for each year separately (2 regressions with \( n = 7 \), and 4) for both years (1 regression with \( n = 14 \)). The dependent variable in these analyses was white shrimp biomass, except where otherwise indicated.

The coefficients of determination \( (R^2) \) for regression equations that were statistically significant at alpha less than 0.1 are given in Table VII. All regression coefficients listed in Table VII are also significant at alpha less than 0.1 (except in the one case indicated). In the analysis for each date separately (analysis #1), a relationship between shrimp and the average salinity function was found on 13 out of 24 dates. On 5 dates, however, the signs of the coefficients were reversed from that expected. The horizontal salinity gradient was a significant variable in explaining white shrimp biomass on 16 out of 24 dates. The relationship was positive on 11 dates and negative on 5 dates.

The \( R^2 \)'s for regression equations in analysis #1 are all extremely high because the number of data points (seven in most cases) was low relative to the number of independent variables (as many as five) included in each equation. For this reason, no great importance should be attached to the high \( R^2 \)'s. Rather, attention should be given to the significance level (alpha) of the F-statistic, which varies from one equation to the next but indicates that all equations shown for analysis #1 are statistically significant at alpha less 0.1.

In the regression that included all dates (analysis #2), the salinity index incorporating both the horizontal salinity gradient and the average salinity function was a statistically significant explaining variable. Ten of the 11 monthly dummy variables were also significant in the equation. All were negatively correlated with white shrimp biomass. The dummy variable in November was the only one not included.

Average temperatures for November, December, and January and average temperatures for February, March, and April were important explaining variables in some of the analyses #3 and #4 regressions. The horizontal salinity gradient and the vertical salinity gradient were useful variables in explaining both annual average white shrimp biomass and annual white shrimp production.

Results from analysis #1 suggest that separating animal biomass according to supposed interactions with white shrimp may be useful. More equations were constructed using the separate biomasses than using the combined animal biomass, and the regression relationships were stronger.

All five animal groups, including the one consisting of species not thought to have any direct interaction with shrimp, were related to white shrimp biomasses on one date or another. The predator-competitor group and the competitor group were those included most frequently. Relationships with any one variable were sometimes positive and sometimes negative, but positive relationships between white shrimp biomass and biomasses of other animal groups were much more frequent than negative relationships.

Animal biomass was not separated into groups for analyses #3 and #4.

B. Evaluation of Results

The lack of consistency in signs of the regression coefficients for both salinity and animal variables may be due to several causes. Lack of consistency from one date to another may indicate different effects on different sizes of shrimp or might be due to correlation of independent variables with each other, which can cause the signs of regression coefficients to flip back and forth, depending upon which other variables are included in the equation.

The inconsistency in the direction of correlations between shrimp biomass and the biomasses of other animals may be due to reversals in cause and effect at different biomass levels. For instance, at high levels of shrimp biomass, predator biomass may be positively affected by shrimp biomass, whereas at low levels of shrimp biomass, shrimp biomass may be negatively affected by predator biomass.

On the other hand, shrimp and their predators may have little discernible effect on each other, but both may be responding to environmental variables that are similarly favorable or unfavorable to each. The high ratio of positive to negative relationships between white shrimp biomass and the biomasses of other animal groups suggests this might be the case.

Despite the lack of uniformity of regression results, several tentative conclusions can be drawn from the analysis to date. Salinity patterns are important in explaining white shrimp biomass. White shrimp biomass is often positively correlated with the biomass of other animal groups, prob-
ably because all are responding similarly to the same environmental variables. Under some circumstances there may be detrimental effects of other animals on shrimp.

Statistical analysis of the data is still in its early stages, and more conclusive results are expected to follow from further work. The regression results are not intended to stand alone but to contribute to the refinement and quantification of the energy-flow model. Simulation modeling is better equipped than regression analysis for handling interrelationships between variables in a complex, multiply-connected system.

### Table VII

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#### Conclusions

This paper presents the status of work related to a joint research project between NASA and NMFS. To summarize, the following work has been addressed with these significant results:

1. A remote-sensing-based productive capacity model
has been designed which characterizes the biological and hydrographic features of a Gulf Coast marsh to predict detrital export. The prediction of detrital export will provide input to an estuarine ecosystem model under development by NMFS.

2) Regression analyses of TMS data to estimate wetland plant production indicate the spectral data more closely estimate percent total vegetative cover than biomass. Results indicate a nonlinear relationship may be involved.

3) TMS data produce a more accurate land/water discrimination than do Landsat MSS data, possibly because the authors wish to thank T. Ford, B. Barrett, and others at LDWF for allowing us to use these data, as well as for their suggestions and their continuing interest in this project. H. Bartley performed the data processing and computer programming for the data analyses at the National Marine Fisheries Service.

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REFERENCES


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Joan Arrington Browder was born in Enid, OK. She received the B.S. and M.S. degrees in biology from the University of Miami, Miami, FL, and the Ph.D. degree from the Department of Environmental Engineering and Sciences at the University of Florida in 1976. She presently is working for the Southeast Fisheries Center of the National Marine Fisheries Service as Leader of the Ecosystem Team in the Fishery Analysis Division of the Miami Laboratory. Her responsibilities center on determining how responses of fish stocks to fishing pressure are influenced by interactions with other species in the environment, variations in weather and currents, and man-made changes in habitat. She has been working primarily with estuarine-dependent species such as shrimp and croaker.

Amanda I. Frick was born in Clare, MI, in 1957. She received the B.S. degree in physical geography from the University of Michigan, Flint, in 1980 and the M.S. degree in geography, specializing in remote sensing, from Oklahoma State University in 1984. Since 1982, she has worked for the NASA/Earth Resources Laboratory of the National Space Technology Laboratories, Bay St. Louis, MS, where she has been primarily involved in digital image processing for MSS and TMS data for the NASA/NMFS Joint Research Project (Productive Capacity Modeling) and for other investigations of wetland change detection. Ms. Frick is a member of the American Society of Photogrammetry and the Association of American Geographers.