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Predictive mapping for management and conservation of seagrass beds in North Carolina

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ABSTRACT

1. This research extends techniques of predictive mapping from their application in terrestrial environments to marine landscapes by investigating the relationship between seagrass and hydrodynamics in Core Sound, North Carolina, USA.
2. An empirically derived logistic multiple regression model and a Boolean logic suitability model were used to produce several predictive map products, including: susceptibility of seagrasses to storms, probability of seagrass cover, and suitability of areas for restoration of seagrasses. A visual comparison between these maps and conventional seagrass polygon maps allows for a discussion of 'field' versus 'object' mapping, and the ramifications for management based on different cartographic techniques.
3. The predictive method used here showed that only a small portion (19%) of the seagrass bed in the study area would be expected to have a high probability of seagrass coverage. The majority of the seagrass habitat in the study area was predicted to have less than 50% probability of seagrass cover. In addition, 16% of the nearly 2000 ha of seagrass within the study area were predicted to be highly susceptible to acute storm events. Moreover, using a conservative set of site selection criteria, only 7% of the study area encompassed by seagrass habitat was predicted to have a high probability of successful restoration if injured.
4. This method provides for an inexpensive way to scale-up from high-resolution data to a coarser scale that is often required for conservation and management.

KEY WORDS: seagrass; predictive modelling; Geographic Information Systems; North Carolina

INTRODUCTION

The seagrass meadows along the North Carolina coast are valuable structural and functional components of the coastal ecosystem. They provide breeding and nursery habitat for a variety of fish and shellfish species, support a complex trophic food chain (Thayer *et al.*, 1978; Kenworthy *et al.*, 1988), and provide

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filtration of suspended sediment and water column nutrients, as well as sediment stabilization (Short and Wyllie-Echeverria, 1996). These valuable communities are vulnerable to both anthropogenic and natural disturbances (Fletcher and Fletcher, 1995; Bell *et al.*, 1997). Management for the conservation of seagrass communities is critical, and requires comprehensive strategies that include mapping and inventorying changes in seagrass habitat (Fonseca *et al.,* 1998). Progress in mapping technology has been made through improvements in aerial photography, digital photogrammetry and organization of these images using Geographical Information Systems (GIS), but mapping large areas of seagrasses is expensive, requires frequent updates, and tends to overlook important spatial patterning.

Commonly, seagrass meadows are mapped as objects — discrete polygons with crisp boundaries (Burrough, 1996). The conventional cartographic technique that renders seagrass cover and distribution on the paper map (and now the digital coverage) tends to collapse the spectrum of seagrass bed pattern into one class (Ferguson *et al*., 1993) or two classes (Robbins, 1997). Such simple classification falls short of capturing the dynamic nature of the seagrass habitat (*sensu* den Hartog, 1971), and obscures variations in seagrass landscape pattern that may have important management implications (Bell *et al.,* 1997; Fonseca *et al.,* 1998). Because pattern is an important indicator of process (Turner, 1990), reliance on an 'object-based' representation of dynamic communities overlooks functional understanding that is relevant to management decisions. In seagrass beds as in other plant communities, pattern is an indicator of hydrodynamic setting, as well as an influence on disturbance propagation, habitat recovery and ecological function (Turner *et al*., 1991; Fonseca and Bell, 1998; Fonseca *et al.,* 1998; Turner *et al.,* 1999). Thus, while repeated production of static maps can be a useful tool for monitoring changes in habitat, they alone cannot help managers understand potential vulnerability of a managed community, nor predict responses of seagrass habitat to disturbance, nor plan for restoration sites. Current management and conservation efforts that rely on mapping and inventory techniques that are not sensitive to the spatially and temporally variable distribution of seagrass at the seafloor, should be augmented to include such pattern (Virnstein, 1995).

In contrast, the field of predictive vegetation mapping (Franklin, 1995) describes spatially explicit models of habitat structure and ecological processes that are derived from underlying physical gradients. The method allows for reliable extrapolation of habitat response to physical setting over broad geographic areas, and, perhaps most important, for the forecasting of habitat response to future disturbances. The process at the core of the predictive approach utilizes a 'field-based' representation of communities (Burrough, 1996) and is less expensive than employing aerial photography. Because spatial pattern of seagrass cover can be predicted from certain physical factors (Fonseca and Bell, 1998), predictive mapping can provide a means to map approximations of spatial pattern, predict the response of a habitat to disturbance, and select restoration sites. Predictive mapping is made possible by the ability of GIS to integrate digital spatial data and perform overlay analyses that extract information from collateral data layers. In this paper, we demonstrate a method to spatially depict seagrass cover that is useful to seagrass managers because it does not combine a spectrum of seagrass cover pattern into a small number of discrete classes. A GIS was coupled with a desktop statistical package to develop a spatially explicit model of seagrass response to hydrodynamic setting and water depth. The model predicts the spatial structure of seagrass within previously delineated boundaries of seagrass habitat. Two commonly used models were employed: logistic multiple regression and Boolean logic. No attempt was made to rate the relative importance of these models. Rather, a more important product of this process was a series of map products which include: (1) the probability of seagrass cover, ranging from continuous to patchy, and, (2) the selection of sites for restoration. Each of these maps contains explicit information required by managers interested in seagrass conservation that could not be directly derived from a traditional mapped product. Using this technique, we answer the following questions: How much of existing, mapped seagrass habitat might be considered patchy as opposed to continuous, and to what degree is it patchy? How much of the total area of seagrass might be at risk (and to what degree of risk) of loss given an acute storm event? And, if injured by human actions, which areas could be successfully restored? These and other process-oriented conservation and management questions cannot be answered adequately with a static map product.

BACKGROUND

The study area

Our study area in Core Sound, Carteret County, North Carolina, was selected for its abundance of seagrasses, the variety of seagrass pattern and a long history of scientific study. We chose an area slightly less than 5000 ha in size that encompasses portions of two large seagrass meadows and several smaller beds interspersed with tidal salt marsh habitat (Figure 1). The study area is located at the southern-most end of Core Sound (latitude 34°40′–34°50′ N, longitude 76°20′–76°40′ W) where Shackleford Banks meets Core Banks just north of Cape Lookout. Core Sound is a narrow (5 km) water body 35 km in length and oriented in a northeast–southwest direction. It is bordered on the east by barrier islands with sound-side salt marsh communities. Winter storms tend to arrive from the northeast, making the study area, located at the south end of the sound, subject to both chronic and extreme wind and waves that influence the pattern of the seagrass beds in the area (Fonseca and Bell, 1998; Fonseca *et al*., 2000). The beds are dominated by a mixture of two species, *Zostera marina* (eelgrass) and *Halodule wrightii* (shoalgrass), with seasonally abundant *Ruppia maritima* (widgeongrass) in quiescent areas. Carteret County, in which the study area resides, represents the only known overlapping acreage of these two species on the East Coast of the United States (Thayer *et al*., 1985).

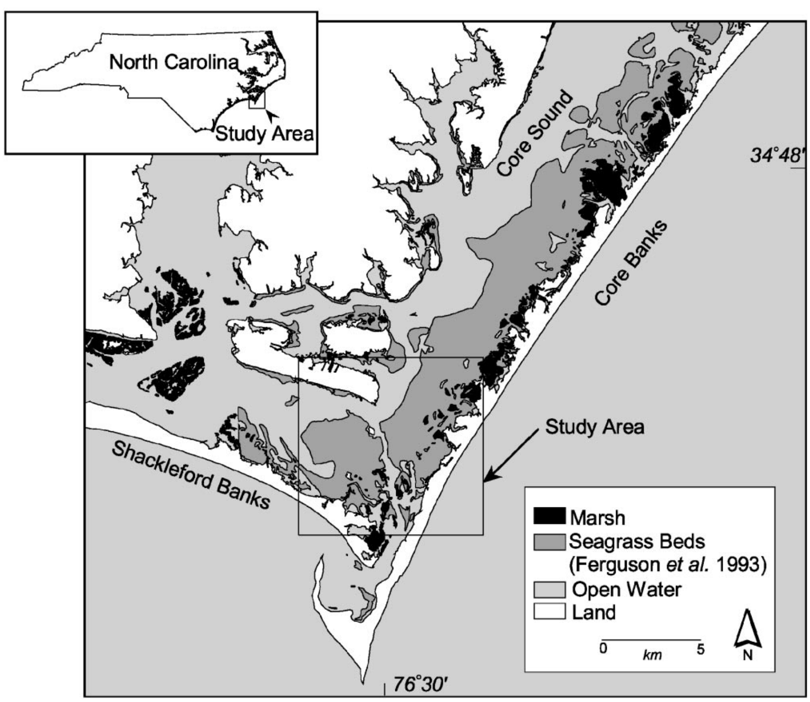

Figure 1. The study area in eastern North Carolina showing seagrass beds (see Ferguson *et al*., 1993), and the location of field transects.

Mapping seagrass

Mapping spatially variable communities requires explicit decisions regarding delineation of these communities. Seagrass beds exhibit landscape patterns ranging from continuous cover to isolated patches interspersed with non-vegetated substrate between. These patterns are influenced by hydrodynamic setting (e.g. exposure to waves, currents and water depth) and the architecture of the plant (Bell *et al*., 1997), and can be dynamic — patches of seagrass migrate through time across the seafloor utilizing bare sand area (Fonseca and Bell, 1998). This spatial–temporal pattern of seagrass distribution is also influenced by natural disturbance (chronic wave damage and severe storm events), and by anthropogenic forces (e.g. propeller scars and dredging). The dynamic nature of the community can explain conventional maps of seagrass that depict presence or absence of seagrass rather than a spectrum of pattern (Orth *et al*., 1994; Wilcox *et al*., 2000). On conventional maps the ecologically essential, but unvegetated benthos interspersed with seagrass patches is often interpreted by a cartographer as potential seagrass habitat, and can thus be included as protected habitat in management plans. Differentiation of pattern at a coarse scale can also be important and useful in management. Fonseca and Bell (1998) found that a 50% cover corresponds to a transition level for loss: beds with $>50\%$ cover survived in chronic and acute storm events; those beds below this threshold did not. They posited that $<50\%$ coverage, there is a possible loss of connection among adjacent patches that allows water motion to erode patches back to a more hydrodynamically stable configuration (with a concomitant drop in overall seafloor coverage). This 50% threshold has been used as the criterion for differentiating seagrass into two mapped categories — patchy and continuous (Robbins, 1997).

Maps of seagrass derived from aerial photographic interpretation have been used in Core Sound since the mid-1980s. Ferguson *et al*. (1993) using a precursor to the national standard Coastal Change Analysis Programme (C-CAP) (Dobson *et al*. 1995) mapped seagrass over the entire Core Sound area with a minimum mapping unit of $\sim 1\,m^2$. This project measured ~ 7000 ha of seagrass, and showed that seagrass was extensive in Core Sound, covering 35% of the subtidal benthos. The method documented a 6% loss in seagrass cover over the period from 1985 and 1988. This method utilized an inclusive delineation criterion, and no attempt was made to differentiate between patchy and continuous beds. The resulting map depicts seagrass in the area as solid polygons. The seagrass polygons that fall within the study area boundaries are shown in Figure 1.

Predictive mapping

When discussing modelling of vegetation response to biophysical gradients, it is useful to distinguish between physiological process models that stress physiological response of vegetation to physical variables without a spatial expression (Fong *et al*., 1997), and spatially explicit predictive models. These latter models, which can include linear, multiple, and logistic regression, Boolean logic, and neural networks are commonly classified as 'predictive mapping'. Predictive mapping provides an alternative to conventional cartographic techniques. Predictive mapping has an extensive history in terrestrial environments, described in detail by Franklin (1995). The predictive mapping analyses explaining vegetation response to indirect gradients (e.g. elevation, slope and aspect) and direct gradients (e.g. solar radiation and pH) have become increasingly sophisticated (Allen and Walsh, 1996), and largely deal with terrestrial environments. The same principles apply in underwater environments (Jensen *et al*., 1993; Remillard and Welch, 1993), and models based on a few key environmental variables can be valuable tools in management of marine ecosystems (Toner and Keddy, 1997).

Two commonly used predictive models were employed here: logistic regression models and Boolean logic models. Logistic regression regresses a binary dependent variable against a set of independent variables, and has an extensive history in habitat modelling using GIS (Bian and West, 1997). Logistic regression is useful in habitat modelling as it provides a statistical method specifically designed for presence and absence data. Boolean logic models, or 'site suitability' models have also been used frequently in GIS analyses (Dettmers and Bart, 1999). The method requires that 'environmental constraints' (Jensen *et al*., 1992) are determined for a particular community, and areas that meet those criteria are found across multiple GIS data layers.

In seagrass environments, variables such as percent cover, bed perimeter-to-area ratio, edaphic parameters, susceptibility to storms, and potential for seedling maturation are inversely related to physical disturbance (Fonseca and Bell, 1998). Because of these relationships, two variables that approximate physical disturbance and hydrodynamic setting — a relative exposure index (REI) models exposure to wind-induced waves, and bathymetry, respectively, can be used as explanatory factors in linear regression and logistic multiple regression models that predict percent seagrass cover, the probability of seagrass cover, and probability of seagrass cover lost in acute storm events. In addition, REI and bathymetry can be used to identify an area suitable for restoration using Boolean logic. These relationships were mapped over space to redefine a seagrass polygon, converting a standard map to a series predictive map products.

Improvements in GIS and digital data storage have made the articulation of these predictive models across space possible for use in spatial analysis and for the production of predictive map products that describe underlying predictive or probabilistic relationships. The ability of GIS to integrate digital spatial data, visualize results, and perform raster data modelling has proved essential for landscape-scale analyses (Stow, 1994; Frohn, 1998; Johnston, 1998), and made it an essential tool for managers to investigate environments on a landscape-scale (Remillard and Welch, 1993; Ferguson and Korfmacher, 1997; Kelly, 2001).

METHODS

Predictive models between seagrass cover (the dependent variable) and hydrodynamic setting — in this case an REI and water depth (the independent variables) — were created, and applied using a GIS (Arc/Info and ArcView) (ESRI, 2000). The underlying statistical relationships were computed using SAS (1989). The dependent variable of seagrass presence or absence was compiled from visual examination of transect data from a video camera mounted on a benthic sled, towed across gradients of seagrass bed pattern and associated hydrodynamic gradients (Fonseca and Bell, 1998). The independent variable of REI used in calculation of predictive relationships was provided by an Arc/Info program that calculated REI for points along the transects. The independent variable of water depth was obtained from a pressure transducer mounted on the benthic sled. The predictions from these models, which include probabilities for: (1) percent cover of seagrass, (2) loss of seagrass cover due to storms and, (3) restoration success for seagrasses, were developed from various portions of the study area, and then applied to a previously delineated seagrass polygon (Ferguson *et al*., 1993) within the study area.

In the following discussion, the term 'coverage' refers to a layer of spatial data, referenced to a geographic projection system. All geographic data layers in this project are maintained in m in the State plane projection system using the NAD83 datum.

Spatial data gathering and preprocessing

Video transect data

From June through November 1995, seagrass coverage and water depth data were compiled from three replicate sets of video and water depth samples collected across seven transects in Core Sound, NC. Based on inspection of vertical, 1:24,000-scale true colour aerial photography taken in September 1995, previous seagrass habitat delineation (Ferguson *et al.,* 1993) and extensive site inspections, transects were positioned *a priori* to cross gradients of seagrass patchiness, from patchy to almost continuous, which represented a range of high to low REI conditions (Fonseca and Bell, 1998; Fonseca *et al.*, in press).

In the field, a Sony 8 mm camcorder in an underwater housing was added to a roller trawl (as described in Murphey and Fonseca (1995)). The camera was mounted $\sim$0.75 m above, and at a 45° angle relative to the sea floor. The field of view from the camera was set to be 1 m along the transect X 0.5 m in width. To collect water depth data, a Druck model PDCR 10/D pressure sensor was also added to the roller trawl at a fixed distance (39 cm) above the seafloor; this height was added to all depth values. The pressure sensor was connected by a cable to an onboard Campbell Scientific 21 × Micrologger which was programmed to collect depth data to the nearest 0.0001 m at either 5 or 3.3 Hz depending on the length of the transect and the available data logger storage capacity. These data were corrected to mean sea level (MSL) using NOAA tide models. The entire system was weighted and towed slowly ($\sim$0.5 m s^{-1}) across the seafloor along the transects from a small (6 m) motor vessel.

Transect end points and vertices were geo-referenced using a Trimble Pathfinder 5000 GPS Rover, held at each transect endpoint to record latitude/longitude at 1 Hz for 180 s. The position dilution of precision (PDOP) was set at six to maintain a full constellation of satellite signals, and allow $\pm$2 m positioning accuracy. Data from a geo-referenced base station located at the Beaufort Laboratory, calibrated to collect 1 position every 5 s, were used to post-process the geospatial data using differential correction of each of the 180 data points collected per transect endpoint. These values were then averaged, bringing the Rover data accuracy for each location to within 2 m of its true position (August *et al.*, 1994).

The transect location points were transferred to Arc/Info to generate a coverage that contained a series of linear transects. Points were added to each transect line in 1 m increments to coincide with the video and depth-sampling rate of 1 m. The video data and depth information were then merged with the Arc/Info transect coverage. The resulting coverage contained the spatial (mapped) description of the transects, with each point along the transects linked to relevant ancillary information: spatial position (x, y), seagrass presence or absence, MSL depth, and ultimately, the REI value.

Seagrass maps

Seagrass habitat location in Core Sound interpreted from aerial photography exist in paper and digital map form for 1986 and 1988 (Ferguson *et al.,* 1993). The digital 1988 coverage (supplied by R. Ferguson, Center for Coastal Fisheries and Habitat Research — CCFHR) was imported into Arc/Info, and the projection changed. The coverage was clipped to the boundaries of the study area, and those areas in which mapped seagrass existed were resampled to a regular array of points 100 m apart using the GRID subroutine in Arc/Info. This regularly distributed dataset of 1871 points was used to (1) create REI dataset described below, and to (2) re-define the seagrass polygon using a logistic multiple regression model and a site suitability model (see below).

Relative exposure index

REI was calculated for each location along the transects, and for each of the 1871 points in the uniform array within the seagrass polygon in the study area. In both cases, REI was calculated using an Arc/Info program. The algorithm describing this process is discussed in several sources (Keddy, 1982; Murphey and Fonseca, 1995; Fonseca and Bell, 1998). REI was calculated for each location such that:

$$\mathrm{REI} = \sum_{i=1}^{8} (V_i P_i F_i)/1000$$

where i is the ith compass heading (1–8 [N, NE, E, etc.], in 45° increments), V the average monthly maximum wind speed in m s^{-1}, P the percent frequency at which wind occurred from the ith direction and F the effective fetch in m.

Fetch is defined as the distance from the location to land along a given compass heading; effective fetch accounts for the effect of irregular shorelines on the wave energy impinging on a particular site (Shore Protection Manual, 1977). A 1:24,000-scale shoreline coverage was used to calculate fetch in this algorithm (obtained from NOAA Coast and Geodetic Survey). The 1:24,000-scale was the finest scale digital coverage available, and it provided sufficient cartographic information to resolve the details in shoreline and marsh islands that influence local wave exposure.

The REI calculation created a new item for each sample point, and added the calculated REI value (computed at 1 ha resolution) to the relevant point attribute table. Thus, for each point along each transect, an REI value was stored, and this database was used in the computation of regression equations. REI was then mapped on the portions of the study area previously shown to support seagrass (Figure 2). Areas near shorelines, particularly those shorelines where there are offshore islands such as along the eastern and southern portions of the map, reveal the protection afforded by the land and appear as areas of low REI. At the centre of the study area, to the southwest of the dredge spoil island, a clear REI shadow is revealed, indicating the strong overall effect of wind events from the northeast in the distribution of REI (*sensu* Fonseca *et al.,* 2000). The grid coverage of REI for the study area was then used to redefine the seagrass beds using the empirically derived regression models in the analysis step below.

Bathymetry

Prior to this project, a raster file of water depth in Core Sound was produced by digitizing historic (1876) bathymetric transect data provided by the National Geophysical Data Center and subsequently interpolating the digitized point samples (Ferguson and Korfmacher, 1997). This interpolated dataset was also donated by R. Ferguson (CCFHR), imported to Arc/Info's GRID subroutine. Preprocessing of the dataset included conversion of bathymetric z-values from 1/4 ft to m, re-projection from ft to m, and a

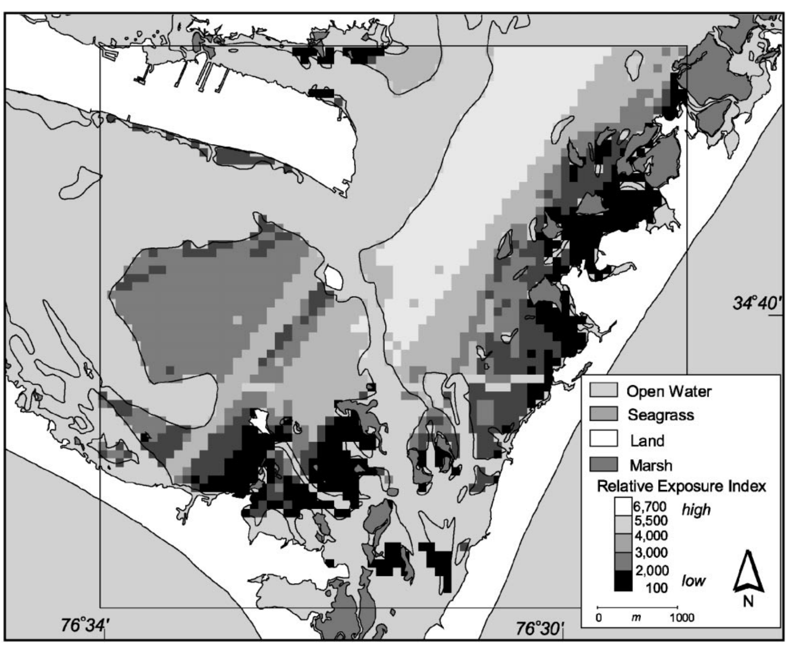

Figure 2. REI, calculated for an area mapped as a seagrass bed by Ferguson *et al.* (1993). REI is based on fetch and wind, and calculated for points 100 m apart.

conversion from the NAD27 datum to the more current NAD83 datum. The resulting raster dataset depicts bathymetric data in m below MSL at a 100-m resolution (Figure 3). This bathymetric dataset, although old, represents the most recent data of any kind for the Core Sound area, but captures the coarse geomorphologic features of Core Sound that are still apparent today (e.g. ancient overwash zones, islands, and proximity of barrier islands).

Model creation

Multiple logistic regression

Predictive relationships between seagrass cover and hydrodynamic setting were derived using multiple logistic regression. Because seagrass cover was recorded as binary data, the relationship between seagrass presence or absence, water depth and REI was examined using logistic multiple regression in SAS (1995). The formula for determining the probability that seagrass is present follows from that found in Narumalani *et al.* (1997):

$$\rho(d) = 1/\left(1 + \left\{e[B_0 + B_1x_1 + B_2x_2]^{-1}\right\}\right)$$
$$(\text{grass} = \text{yes}) = \rho\left(d = 1/x\right) = 1/(1 + \exp[(B_0 + B_1x_1 + B_2x_2)])$$

where d is the presence or absence (1,0) of seagrass cover at each 1 m increment along the video transect; x_1 and x_2 are REI and water depth, respectively; B_0, B_1, and B_2 the coefficients derived from logistic regression.

In this model, d is the dependent variable and REI and water depth are the independent variables. Logistic multiple regression was performed using an SAS (1995) procedure LOGISTIC. Rank correlation indices were output to assess the predictive ability of variables within the model. The logistic multiple regression function was derived from REI values, seagrass presence or absence, and depth data before

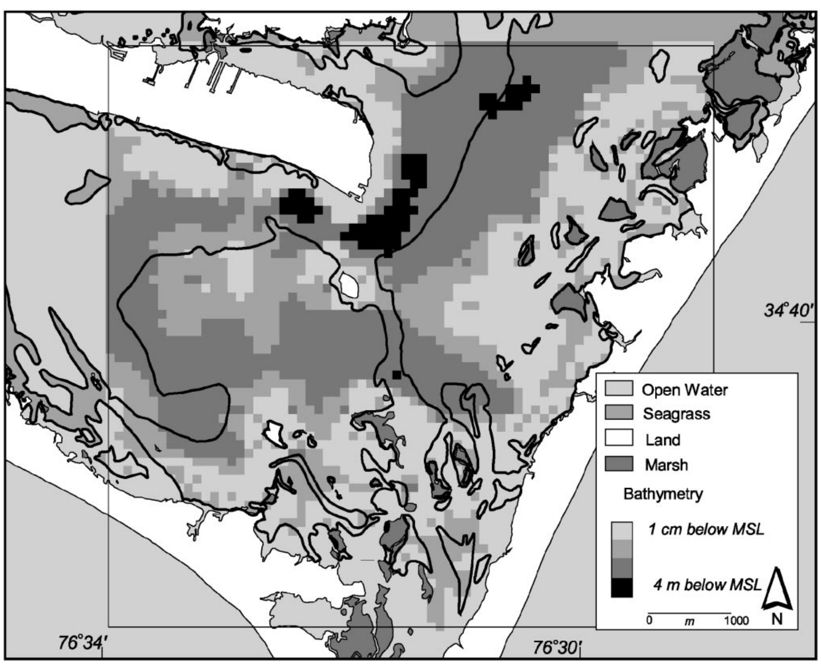

Figure 3. Water depth across the study area. Bathymetry is based on 1876 data provided by R. Ferguson and K. Korfmacher.

solving for $\rho(d)$ at every point along each transect. The derived logistic regression relationship between seagrass cover and hydrodynamic setting were expressed as:

$$\text{Plogit} = -2.67\times10^{-7}\text{REI} + 4.4\times10^{-3}D + 0.9518 \tag{1a}$$

$$\rho(C) = e^{(\text{Plogit})}/1 + e^{(\text{Plogit})} \tag{1b}$$

where REI is the relative exposure index, D the water depth corrected to MSL in m and $\rho(C)$ the probability of cover

Site suitability model

GIS suitability modelling is used to determine areas where the union of prescribed values among the spatial data layers occur. In our study, we chose to define areas where we expected high probability of restoration success. We arbitrarily chose highly conservative criteria with which the model would predict a high probability of restoration success; very shallow and very quiescent physical settings. The shallower sites in this area enjoy reduced wave energy because the shoal itself breaks the waves. If deeper areas were selected for input to our model, we would have had to consider availability of light, which is the first order physical limiting factor that must be satisfied for seagrass growth.

$$\rho(\text{RS}) = \{D < 100\,\text{cm}\} \text{ and } \{\text{REI} < 3000\}, \tag{2}$$

where REI the relative exposure index, D the water depth corrected to MSL in m, $\rho(RS)$ the probability of restoration success.

Model application and development of map products

Multiple logistic regression

Equations (1a) and (1b) were applied in a map algebra process in Arc Info's GRID subroutine to compute the results for each of the 1871 1 ha cells that made up the seagrass polygon. The resulting grid cell value was the result of each equation applied within a cell.

Suitability modelling

A spatial query based on Boolean logic was then used to select shallow sites defined as having a water depth < 1.0 m, as well as those with low wave exposure (REI < 1000) within the seagrass polygon (equation (2)). This procedure resulted in a grid coverage that depicts sites meeting the depth and REI criteria for our conservative prediction of restoration success.

RESULTS

Probability of seagrass cover

The probability of seagrass cover over an area of Core Sound in North Carolina was modelled using REI and depth in a multiple logistic regression. Figure 4 shows the probability of seagrass cover mapped with a cartographic pattern index from equations (1a) and (1b), with the tabular results listed in Table 1. In this area of Core Sound, the probability of seagrass cover varies from 30% to 75%. Only a small portion (19%) of the seagrass bed has continuous or near-continuous cover (>60% cover). Roughly one-half of the study area is covered with patchy cover (<50% probability of seagrass cover), and almost a third of the area is covered by moderately patchy seagrass cover (50–59% probability of cover). Areas that had a probability of seagrass cover >60% are located in shallow waters with low to

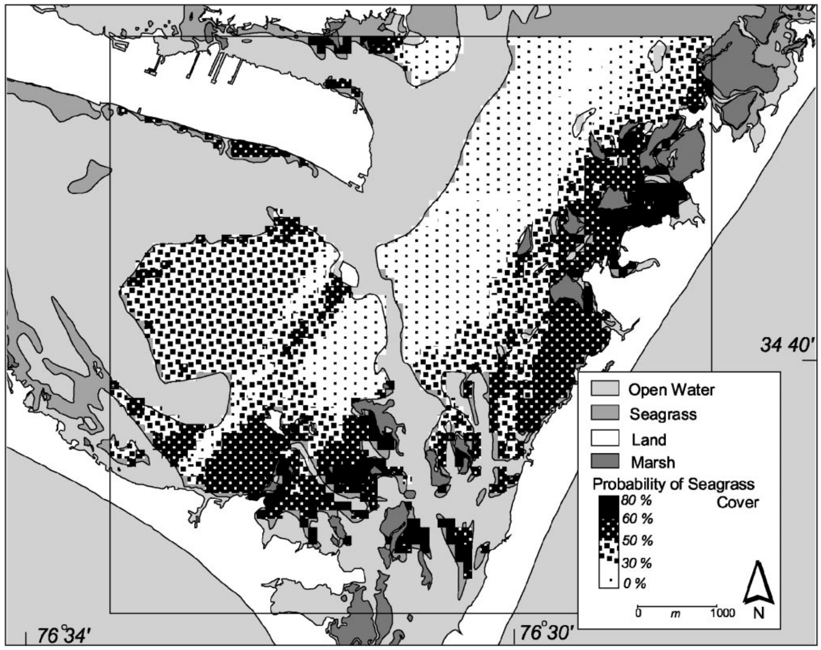

Figure 4. Probability of seagrass cover, calculated from multiple logistic regression using REI and depth.

Table 1. Probability of seagrass cover, derived from a multiple logistic regression model

Probability of seagrass cover (%)	Hectares	Percent of total seagrass bed
30–39	382	20
40–49	485	26
50–59	647	34
60–69	328	17
70–80	29	1.5

moderate wave energy and protected by marsh islands and the wind shadow effect of the dredge spoil island in the middle of the study area. Areas with low to moderate wave energy but with deeper water show lessened probability of seagrass occupation. This is most likely because of light attenuation in the deeper areas. In Figure 4, the density of cartographic pattern is controlled by the percent probability for the area mapped. Probabilities of >60% are mapped using a continuous patch, probabilities of 50–59% are mapped with a non-continuous pattern and probabilities of 30–49% are mapped with a less dense screen. This is useful in demonstrating varying spatial pattern of seagrass beds that correctly associates location in the bed with biophysical setting. This type of cartographic technique could be used to aid in management decisions, or to locate seagrass areas especially susceptible to storm events, and to target seagrass habitat field checks after storms.

Sites with high probability of restoration success

Using our criteria, we forced the model to find areas suitable for seagrass planting and regrowth defined as having shallow water and natural protection from waves. A surprisingly limited area was found that might be conducive to successful restoration — these arbitrary criteria reveal that almost all the very shallow, quiescent seagrass beds would be among the many marsh islands along the northwest side of Core Sound (Figure 5). Using this formula, only 134 ha, or 7% of the total seagrass area was suitable for restoration. To our knowledge, there are no empirical data to quantitatively assign a probability of restoration success across hydrodynamic settings. However, this exercise demonstrates the facility of this modelling approach to formulate an experimental design — in this case, one that would allow comparative testing of restoration techniques across hydrodynamic settings.

DISCUSSION

There have been many recent calls to move methods of predictive mapping and GIS analyses developed in terrestrial environments into aquatic systems (Ji and Johnston, 1995; Bell *et al.*, 1997; Wright, 1999; Fonseca *et al.*, in press). There are technical difficulties encountered when GIS analyses are moved underwater. Ji and Johnston (1995) list several that are relevant to this discussion, and are summarized here. First, there is difficulty in collecting and updating time-dependent and three-dimensional marine data (Robbins and Bell, 1994). Most GIS software has been developed in a two-dimensional environment and is not ideal for modelling or displaying three-dimensional data such as bathymetry. Better three-dimensional data models might assist in predictive mapping across surfaces, and thus allow for information that incorporates water column information into the models. Gradients in light attenuation, salinity and temperature throughout the water column may influence seagrass growth, and growth could be modelled given a better three-dimensional data structure. Second, there is often difficulty in gathering necessary data on gradients in marine environments. For example, in many areas bathymetric data are not comparable in quality and timeliness to terrestrial digital elevation

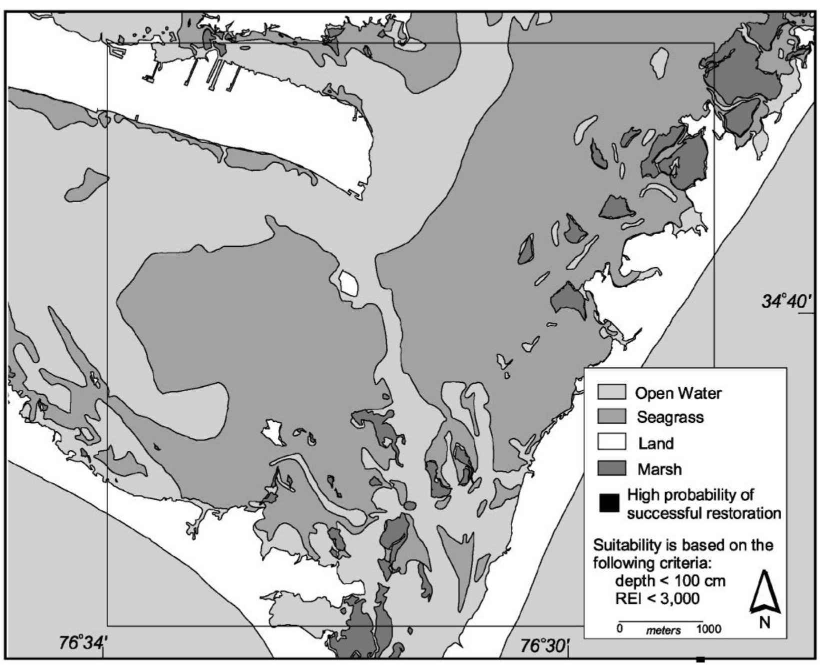

Figure 5. Probability of successful restoration based on suitability model using REI and depth.

data-sets. Repeated soundings are often not taken in areas where transportation-engineering projects are minimal, which can coincide with areas of ecological interest. Moreover, the quality of remotely sensed data gathered over marine environments is hampered by water absorption in the visible and infrared portions of the electromagnetic spectrum, a problem not anticipated in the terrestrial focus of original sensor design and development.

Several applications of our modelling effort have particular relevance for managers. Seagrasses are ecologically valuable community that is threatened worldwide and requires management (Short and Wyllie-Echeverria, 1996). While polygonal, or object-based maps of seagrass beds are useful in management, they can convey a sense of stability, unless accompanied by expensive change detection procedures. This method treats seagrass beds as a continuous display of response to hydrodynamic setting, which suggests that (1) the beds are variable across the seafloor, (2) large portions are threatened by acute storm events, and (3) portions of the existing beds can eventually be delineated by their ability to be restored given any losses. While Franklin (1995) warns against using the results of these predictive models to discern distinct categories, it is clear that large portions of the seagrass bed are susceptible to disturbance. Perhaps as important, however, this modelling approach provides us with a parsimonious means of designing experiments to evaluate management questions, such as suitability of sites for restoration success. Here, if the otherwise arbitrary site selection criteria had previously been shown to be robust through experimentation, then we would have been able to produce a spatially robust representation of seagrass habitat with a quantitative prediction of restoration feasibility.

As they stand, however, the maps are useful in providing a quantitative assessment of what portion of the beds may be particularly susceptible to seagrass loss. The 50% seagrass cover roughly corresponds in some areas to a transition level for loss: beds with $>50\%$ cover fair well in chronic and acute storm events; those beds below this threshold do not (Fonseca and Bell, 1998). Figure 4 shows this hypothetical threshold, and thus displays the potential for seagrass cover lost due to storm events — which encompasses hundreds of hectares of seagrass habitat within the study area. This suggests that mapping projects must be cognizant of storm-induced disturbance in order to conduct change analyses in a meaningful manner. Fonseca *et al.* (2000) have shown that substantial, long-term losses of seagrass cover can and do occur in this area as the result of extreme storm events. If a cartographer or conservation manager were not aware of storm events and conducted mapping on dates before and after large storm events, they could be unduly alarmed by the widespread reduction in cover and erroneously correlate the change with an anthropogenic source.

The predictive mapping method has important ramifications for restoration science in two areas. First, Figure 5 shows the direct application of these data to siting seagrass restoration projects. However, recent work in Naragansett Bay (authors' unpublished data) revealed that even a detailed, GIS-based map may not always yield accurate predictions on restoration success. In that case, the effects of animal disturbance of seagrass plantings strongly influenced planting success, a variable not easily captured by any GIS analyses.

Second, this predictive model has direct applications to restoration science. If we accept that habitat function is linked with landscape pattern, then having the ability to predict the spatial organization of a restored habitat (e.g. seagrass bed) could be an important criterion for assessing the success of restoration projects. Evaluation of the linkage between seagrass landscape pattern and ecological function has only recently been considered, with some indications that pattern may be influencing various ecological processes, including settlement (Bell and Hall, 1997) and predation (Irlandi *et al.*, 1995; Irlandi, 1996). Therefore, predicting changes in seagrass beds attributes in association with a disturbance-related variable such as wind waves (*vis a vis* REI) may provide an important glimpse into the consequences of changes in extent and pattern of seagrass ecosystems that is well-established in other systems (e.g. Paine and Levin, 1981).

CONCLUSIONS

This study shows the utility of predictive mapping in a seagrass management and conservation setting, and demonstrates the utility of GIS to integrate spatial data, translate vegetation probability over spatial and temporal scales, and visualize results. By redefining a cartographic representation of habitat, based on a spatially explicit model of underlying physical gradients, the potential response of habitats (and perhaps, associated ecological processes) to chronic and acute disturbance events can be revealed. The incorporation of physical gradients in analysis, and presentation in mapped results bridges the gap between cartography and GIS. Thus static maps incorporate a dynamic element, representing not only the spatial distribution of various object classes, but the underlying ecological processes controlling those distributions—information that is critical for science and decisions concerning resource conservation.

In a general sense, this research adds to a small body of work that brings terrestrial landscape ecological principles to aquatic systems (Robbins and Bell, 1994, 2000; Bell *et al*., 1999, in press). More specifically, the approach is an important adjunct to seagrass ecology, providing a method to visualize pattern, target further field sampling and experimental manipulations across gradients, and suggests future modelling of seagrass pattern in three dimensions. The example of restoration science here is limited, but it proves the utility for raster- or grid-based data modelling of potential mitigation sites, and for adapting restoration formula to meet local conditions. In the case presented here, the formula for locating restoration sites did not adequately meet the local conditions, but it can easily be altered. Finally, because these tools are now available, management of these important resources should depend on better spatial articulation of bed pattern (Fonseca *et al.,* 1998). With these maps, there can be an incorporation of the understanding of the responses of seagrass bed to disturbance, and potential impacts to beds can be quantified.

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