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Predicting Future Shoreline Condition Based on Land Use Trends, Logistic Regression, and Fuzzy Logic

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PREDICTING FUTURE SHORELINE CONDITION BASED ON LAND USE TRENDS, LOGISTIC REGRESSION, AND FUZZY LOGIC

A Thesis
Presented to

The Faculty of the School of Marine Science
The College of William and Mary in Virginia

In Partial Fulfillment
Of the Requirements for the Degree of
Master of Science

by
Lynne M. Dingerson
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APPROVAL SHEET

This thesis is submitted in partial fulfillment of

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ABSTRACT

Marshland and riparian buffer are facing an increased risk of degradation in the face of land use conversion and climate change. Change in land use can bring about changes in shoreline condition, and, by examining these relationships, a more realistic model of future shoreline condition can be developed. The project was conducted in Guinea Neck, Virginia, an area characterized by very low relief, mixed land uses, and a sizable rural population. By examining land use trends, a forecast of future land use conversion was estimated. This information was used to make a land use prediction for the year 2025. Shoreline resource scenarios, based on this future land use, were forecast using logistic prediction and fuzzy logic methodologies. The models examined the likely impacts of land use conversion on shoreline resources. This research can aid the coastal resource management community in visualizing the likely future condition of shoreline resources and allow them the insight to implement incentive-based and non-regulatory actions to guide development. These efforts will allow the efficient human use of shoreline and protect biodiversity and integrity of shoreline habitats.
PREDICTING FUTURE SHORELINE CONDITION BASED ON LAND USE TRENDS, LOGISTIC REGRESSION, AND FUZZY LOGIC
INTRODUCTION

Human alteration of ecosystems has accounted for the transformation of a third to half of Earth's land surface (Vitousek et al., 1997). Globally, patterns of land use change in the last century have resulted in large increases in agricultural lands and settled areas at the expense of forested areas and wetlands (Meyer and Turner, 1992). Coastal communities in Virginia have made efforts to preserve natural habitat on the shoreline. The benefits of these natural resources include public use, runoff buffer, spawning habitat, nursery grounds, water quality and ecosystem health. Protection for these systems is often in the form of restrictions and regulations on land use and permitting requirements. Marshland and riparian buffer are facing an increased risk of degradation in the face of accelerating human impacts, sea level rise, and increased storm surge. The human population along the shoreline of the Chesapeake Bay and its tributaries, through regulatory actions and planning measures, can collectively make a large difference in the amount of riparian lands that are preserved. As wetlands move landward with rising sea level and the composition of the shoreline changes, the natural succession of habitat will be altered through mitigation efforts by landowners. Use of riprap, bulkheads, and other shoreline hardening will, by design, hamper the natural processes associated with a rise in sea level. The actions of property owners will, in the long-term, affect the amount and quality of natural riparian and littoral habitat. As the land use continues to change, land types will be converted and property owner preference for shoreline armoring may change. By examining these relationships, a realistic model of future shoreline condition can be developed.
This project aims to develop a prediction model of future shoreline condition by using a three-part approach to study shoreline change in the Guinea Neck region of Gloucester, VA. First, an investigation of historical land use helps to understand and model the drivers of land use change in the study area. The nearby Hampton Roads area, consisting of Norfolk, Portsmouth, Chesapeake, Virginia Beach, Hampton and Newport News, has a consistently growing population. The study area is on the edge of the “development front”, and in recent decades has experienced large rates of immigration from surrounding communities. The pattern of land use change is likely to remain motivated by the same factors as historic and current land use change, so an investigation of how conversion has occurred in the past helps to predict how land use will change in the future. The second part of the investigation is a prediction of land use for 2025. Using logistic regression analysis, a prediction of likely future land use, both in quantity and location, can be estimated. Finally, using a logistic regression and two fuzzy logic inference systems, future shoreline condition is estimated based on the relationships between attributes of the land and shoreline condition with presence of engineered bank stabilization. The results of the three prediction methods are a suitability value for each section of shoreline for each structure type. These efforts culminate in a realistic model of land use change over time, a land use prediction, and an extrapolation of future shoreline condition. The resulting models are used to examine the future condition of shoreline resources and to allow resource managers and decision-makers to offer incentives to guide shoreline development.

Neither the relationship between land use change and shoreline condition nor prediction of shoreline condition have been examined. The ability to predict the location
of future structure, and therefore the loss of shoreline resources, allows decision-makers
to visualize the future state of shoreline resources. Because of this increase in foresight,
planning efforts, incentives, and regulations can be crafted both to conserve and utilize
shoreline resources effectively. With increased understanding of likely future condition
of the shoreline, biodiversity and integrity of shoreline habitats and human uses for
shoreline can coexist through proper planning.

This model lays the foundation for greater understanding of shoreline resource
use. Through the incorporation of scientific principles and social science methodology,
understanding of drivers of land use change and installation of shoreline structure is
enhanced. The use of econometric modeling for land use change and prediction has been
well founded in the literature. Application of this methodology for coastal systems is
especially useful in light of the large human population in the coastal zone and the trends
of continued growth. Further consideration of the human dimension impacts on shoreline
resources using econometric and fuzzy logic methodologies, as well as scientific
principles and conventional knowledge of shoreline systems, help to foster a greater
understanding of likely future condition of shoreline resources.
BACKGROUND

Characteristics of Shoreline

Natural shoreline experiences minor variations throughout the course of the year associated with wave activity, tidal activity, sea level changes, and major storm activity. (Dolan, et al., 1978) Over a period of time, change in marsh distribution, size, shape, and location can change due to these variations. Erosion and accretion along the coastline are natural phenomena. Many estuarine systems, such as those found along the East coast of the United States have a marsh margin, which is the least erodible beach environment. The emergent vegetation helps to diffuse up to 71% of wave height and up to 92% of the wave energy, greatly reducing erosion to the shoreline (Rosen, 1980). Despite this natural buffer, shoreline change can occur due to minor variations and episodic storm events. When shoreline hardening is in place, the variation associated with erosion and accretion along the shoreline is sharply reduced or eliminated (mean rate of change is low). However, when extreme storms occur, stabilized areas often experience more damage. Gradual impacts due to erosion are minimized, but the risk of large-scale storm damage is increased because the storm surge can penetrate further inland (Dolan, et al., 1978).

Condition of shoreline in an area where humans occupy much of the coastline is the result of many individual decisions of how to treat the risk associated with living near the water. Factors that can affect these decisions include land use, shoreline condition, elevation, property value, proximity of structure to the shoreline, and storm frequency. The cumulative impact of these individual decisions can greatly affect the coastal habitat and shoreline resources. In turn, investigating the single actions, such as a household
installing riprap along a shoreline, cannot portray a complete picture of how natural shoreline is altered. Only in the aggregate can we begin to see how patterns of shoreline resource use change as land use changes. Looking at land use change over time, coupled with relationships between shoreline condition and land use, can help to present a clear picture of likely condition of future shoreline resources for a particular region.

**Land Use Change and Modeling**

The large majority of land use change is due to human use as opposed to natural change (Turner et. al., 1993). As land use changes, so do climate, regional biogeochemistry, biodiversity, and hydrology of a region (Turner et. al., 1993; Schneider and Pontius, 2001; Vitousek et al., 1997; Theobald et al., 1997), as well as the structure and function of ecosystems (Vitousek et al, 1997). These effects of land use change are interesting to consider in a coastal environment because not only will the changes impact dynamics of the land, but also they will impact the inputs to adjacent coastal bodies. Land use changes can have impacts on the coastal zone that include change in structure of shoals and channels, increases in algal blooms (Chen, et.al., 2005), change CO$_2$ and CH$_4$ emissions to the atmosphere (Inubushi et al., 2003; Meyer and Turner, 1992), increases in flooding, soil degradation (Meyer and Turner, 1992), and loss of ecosystem services (Zhao, et al., 2004). In a study by Hopkinson and Vallino, land conversion was found to be a major factor affecting water quality (nutrient input, sediment input) and runoff (increase of impervious surface, decreased infiltration) (Hopkinson and Vallino, 1995). Examining historic land use change can help to inform efforts to elucidate the drivers of change as well as the individual impacts that conditions, such as population, population growth, and demographics, have on change (Turner, et al., 1993). As coastal
land use changes, it is likely that there will be a change in the way people using the land will protect it from erosion and encroaching waters. For example, if a tract of land that was previously an agricultural tract is converted to residences, the new property owners may be more likely to armor the shoreline instead of leaving the natural habitat, due to a higher perceived risk of property loss.

Very little work has been done to characterize change in exurban areas (Gude et al., *in press*), rural lands undergoing development pressure such as the study area for this project. Nelson’s work on exurban growth estimates that in 1990, the exurban population of the United States was 60 million. This growth is characterized by the following statement:

“Four factors explain exurbanization. They include the continued deconcentration of employment and the rise of exurban industrialization, the latent antiurban and rural location preferences of U.S. households, improving technology that makes exurban living possible, and the apparent bias of policy favoring exurban development over compact development.” (Nelson, 1992)

This statement reflects the complexity of drivers of land use conversion within exurban areas. In the case of Richmond, VA, suburban sprawl has led to exurban growth and suburban decline. Farming activity in currently suburban counties decreased dramatically between 1960 and 1990, indicating a conversion of land to residences. These suburbs are now experiencing a declining economy, and areas further from the population center are experiencing exurban growth (Lucy and Phillips, 1997). The study area for this project is in a similar pattern of exurban growth in that it is adjacent to many population centers currently undergoing suburban decline (Bradley, et al., 2003).

The action of human change to a landscape is a combination of physical and social driving factors. A study of rural residential development patterns for the Greater
Yellowstone Ecosystem found that “agricultural suitability, transportation and services, natural amenities, past development patterns, and economic and recreational characteristics of nearby towns” had strong influences (Gude et al., in press). Many of these characteristics are used in this project to estimate future land use change. In general, predictions of land use change vary in three categories of analysis: spatial, temporal and human dimension (Agarwal, 2000). The spatial analysis can range from the global/continental scale to the sub-county scale, and temporal scale can be composed of several time steps over a long period to extrapolations from one point in time. The human dimension analysis is the consideration of human change to the system, and can range from a full econometric/behavioral analysis of the study area to no consideration of the human dimension of change (Agarwal, 2000). The goal for the land use prediction for Guinea Neck is to have a reasonable resolution of data at the desired spatial scale while portraying patterns of land change over time and a reasonable account of the human drivers. This combination will produce a land use prediction that will solidly and accurately depict future land use, and serve as the platform upon which to place additional analyses and modeling.

Geographic Information Systems (GIS) have proven to be a suitable and successful method of looking at land use change. GIS provides advantages over other modeling techniques including data integration capability, spatial analysis, modeling, and mapping (Allen, et al., 1999). GIS methodology has been used for most studies of land use change in recent history (Schneider and Pontius, 2001; Ohlmacher and Davis, 2003; Ayalew and Yamagishi, 2005; Pijanowski et. al, 2002; Chen et al., 2005; Ayad, in press; Weng, 2002). In many instances, historical aerial photographs have been used as the
basis for land cover analyses (Pontius, et. al., 2001; Pijanowski et.al, 2002; Chen et al, 2005; Weng, 2002). Historical imagery allows the researcher to use remote sensing technology to reconstruct land use at a particular point in time. Using multiple time steps to enhance the temporal analysis help to present a more complete picture of how land use has changed over time by enabling examination of the long-term and short-term changes in land use within a particular landscape.

Another distinction within land use change research is how many land use categories are accommodated by the method. Many researchers have undertaken the task of evaluating change and prediction between two land use types or conditions, such as urban/rural, forest/no forest, and landslide/no landslide (Schneider and Pontius, 2001; Ayalew and Yamagishi, 2005; Ohlmacher and Davis, 2003; Pijanowski et al., 2002; Glade, 2003; Chen et al., 2005; Pontius et al., 2001; Dragicevic and Marceau, 2000; Wu, 1998). One such model for evaluating land use change is a cell-based prediction technique. (Dragicevic and Marceau, 2000) In this approach an individual cell is coded with its land use and that of the surrounding cells. This technique has been used primarily for urban sprawl analysis. In general it has been used to predict the rural to urban land use change and analyze change in the transition areas (in between rural and urban) in order to predict population and urban growth. Specifically, this technique has been used for interpolating, spatially and temporally, change in land use over time between two time steps in order to model the missing information in between the two snapshots. (Dragicevic and Marceau, 2000) It has also been used in developing countries to predict the effects of fast-paced economic development and the consequences resulting from various development policies. (Wu, 1998)
This type of modeling is a useful tool that can be used to interpolate information about the change in land use in between time periods and predict land use for a designated time period, however, it is limited by only allowing for two land use types to be considered. Use of this information to form management decisions can be limited in that the detail of prediction information may not be sufficient. This certainly may not be the case such as in the Greater Yellowstone Ecosystem. The project modeled the spread of rural residential development based on a host of influences such as land use, development patterns, and recreational options. The prediction led directly to information that could be used in management and preservation of lands (Gude et al., in press). One advantage of this method is that it can be used at large scales such as the country, continent or global scale with a lesser degree of difficulty than with multiple land uses. In a study by Pahari and Murai, an estimation of global deforestation was undertaken with the major driving factors as population growth and climate suitability (Pahari and Murai, 1999). This application is useful for large-scale trends but may lose important components such as competing land uses, regional economic influences, and governmental regulations at smaller scales.

Models that accommodate multiple land uses within a landscape seek to estimate future quantity and location of land use change. One such method uses GEOMOD2, a model that empirically simulates land use change based on current land use conversion, annual amount of change within a region, and biogeophysical attributes of the land. This model's prediction capability is largely dependent on the biogeophysical attributes such as elevation, soil type, precipitation, and potential land use, which are relatively stable physical attributes. By using drivers of change that do not vary much over time, this
application of the model does not incorporate social factors that impact land use change, including location of roads, location of protected areas, population density and population growth. (Pontius, et al, 2001). In this case, the study is limited by the capacity to capture the human dimension effects on land use change.

Another model incorporating multiple land uses is effective at capturing the large majority of human and biophysical drivers, but it tends to result in complex, data intensive models, such as the CLUE model (Veldkamp and Fresco, 1996, (85, 91) 1997). If land use change information is going to be incorporated into other projects and be applicable over a large area, it is helpful to have a model that is simplified but accomplishes the task of establishing the general biogeophysical and human trends of land use change. Also, this model is only useful when applied to continent or country-sized areas, however, CLUE-S has been developed recently to accommodate smaller regions of analysis (Verburg et al., 2004).

Clue-S model is built with consideration for both demand for land use change over time and allocation of change at a certain time step. The demand for land use change is generated by looking at the driving factors of change over time and, assuming that those drivers are constant, linear extrapolation of additional demand to future time steps. This model uses yearly change as its increment of time. Allocation is achieved by generating probability values indicating likelihood of change of a specific acre parcel. Values are generated by using stepwise logistic regression, which only includes significant variables in the regression equation. These equations are used to calculate the probability of change for each parcel. The model allows the user to run additional analyses associated with neighborhood characteristics, demand scenarios, and multi year
analysis, but, unfortunately, at this point in its development, it can only accommodate 800 lines of data (Verburg et al., 2004). One application of the CLUE-S model shows that the model is not simply an extrapolation of trends, but allows for interconnection among influences and proper representation of complex patterns (Verburg et al, 2002).

Schneider and Pontius address the effectiveness of two approaches for estimation of location of change: multi-criteria evaluation (MCE) and logistic regression. Both methods result in a map of suitability values for locations within a landscape, which represent the relative priority of that parcel to change land use. MCE works to generate several suitability maps, one for each independent variable, which are grouped into bins. The maps are then combined to result in a suitability score based on all suitability values. Logistic regression expresses the probability of an acre parcel changing land use as a function of the independent variables and associated regression coefficients (Schneider and Pontius, 2001). For this study, the MCE methodology was marginally more effective than that of the logistic regression, (Schneider and Pontius, 2001) but the MCE seemed to be more arduous of a process for not much increase in effectiveness at predicting location of change.

Validation Models

With the many different approaches to land use prediction, it is important to test model performance, but, unfortunately, very few attempt to validate the resulting prediction (Kok et. al, 2001). Other scientists may use techniques that are not appropriate for examining prediction capability, which may falsely bolster confidence in the model’s output (Pontius et al., 2004). Some argue that validation must have a second data set independent from the data sets used in the model for appropriate validation. However,
models seeking to predict future scenarios are more difficult to validate because no independent data set of future conditions is possible (Kok et al, 2001). In order to evaluate the effectiveness of a land use prediction model, several methods have been developed.

One approach to validation of land use change models is evaluation of the variables in the prediction equation. Using a model of rural residential development, Pearson’s residuals were calculated using the best model to examine autocorrelation, error caused by relationships between/among variables. Ignoring this error can result in generation of prediction coefficients that are incorrect. The model was then run on for a data set that had been excluded from the prediction, and the results were examined for overestimation and underestimation errors. In this case, the prediction was accurate for 80% of the sections estimated (Gude et al., 2005)

The initial work with the CLUE modeling technique was not validated (Veldkamp and Fresco, 1995; Veldkamp and Fresco, 1996a), but subsequent work made attempts at model validation. The first method of model validation was a comparison of simulated data with an excluded data set using the absolute differences. The model was found to be more effective at prediction in some regions than others (Veldkamp and Fresco, 1996b). Another use of the CLUE model employed the use of $R^2$ statistic to test goodness of fit and a backwards validation technique. The land use for an earlier year was predicted and compared with actual land use data for that year (Verburg, et al., 1999). A more recent validation technique investigated the impact of scale and location on effectiveness of prediction. The model was used to predict land use change for Costa Rica and was validated at four spatial scales in Costa Rica and five spatial scales in Honduras. This
technique took into account only location of change and compared predicted and actual land use change for each year in between the years used to calibrate the model. The scale resolutions used were not aggregates of cells, but governmental divisions, such as districts, cantons, and provinces. The model performed better for Costa Rica than Honduras, and the larger spatial scale yielded more effective prediction (Kok, et al., 2001).

Another method is the Relative Operating Characteristic (ROC) method. Varieties of this method have been used in the CLUE-S modeling and some of Pontius’ land use change modeling work (Verburg et al., 2004; Pontius and Schneider, 2001; Schneider and Pontius, 2001). The CLUE-S model uses the ROC value and curve to indicate the goodness of fit of the logistic regression and, therefore, can be used in the absence of an independent data set. It “evaluates the predicted probabilities by comparing them with the observed values over the whole domain of predicted probabilities instead of only evaluating the percentage of correctly classified observations at a fixed cut-off value.” The ROC value is a number from 0 to 1 representing the area under the curve, where the values closer to 1 indicate a better fit to the logistic model. This value is equivalent to the $R^2$ value in a linear regression (Verburg et al., 2004).

The basic premise of the ROC technique, as employed by Pontius and Schneider, is the comparison of predicted future condition versus actual future condition. The method requires an independent data set, works with grid cells categorized with one value for land use, and works only on two land use conditions at a time. When dealing with multiple land uses, the ROC method can be used to generate one ROC value for each land use category. The predicted and actual land uses are compared using contingency
tables, and the index of agreement is used to measure similarities. The result is a percentage value between 0% and 100% of correctly predicted cells. This percentage is compared with the 50% ROC that would be expected if suitability values were randomly assigned (Pontius and Schneider, 2001).

Two types of land use prediction validation have been used in conjunction with the GEOMOD (and GEOMOD2) method of land use prediction. The first of these uses a Kappa parameter to compare the simulated land use for a year not used in the prediction to the actual land use for the same year. Similar to the ROC method, a comparison is also made with the prediction that uses random chance (Pontius et al., 2001). Further work with this method separates the Kappa parameter into evaluation of the location and quantity of land use change and evaluates them individually. This allows the ROC method and the Kappa parameter to be used in conjunction with one another for enhanced precision (Schneider and Pontius, 2001). As such, land use prediction validation can indicate where model improvements would have the most significant impacts.

The most rigorous of the validation techniques, used on GEOMOD for illustration, is composed of four steps: comparison between prediction map and land use map, comparison between predictive model and a no change state, comparison between predictive model and a random model, and examining multiple resolutions and their effect on accuracy. The advantage of such an intensive validation model is not to evaluate how effective the model is at predicting land use but to understand how to improve the model by dissecting it further. The comparison between the prediction map and the actual land use map gives a percentage of parcels predicted correctly. Comparing the predictive model and the no change state, or the Null model, allows the researcher to
evaluate whether the prediction is more accurate than if there had been no model applied to the land classification at all. Generally, the prediction map corresponds with the actual land use map less than with the Null map. The prediction map is then compared with the model that randomly assigns a designated amount of land use change. This comparison serves to look at the validity of the model over simple guessing, usually 50% correct.

The final validation technique looks at scale in relation to accuracy. This application of the technique found that at small-scale prediction units the Null model is more effective at prediction location of land use change, whereas at larger-scale prediction units, the prediction technique is more effective. By aggregating the individual pixels, it enhances the accuracy of the prediction (Pontius et al., 2004).

**Fuzzy Logic Inference Systems**

Fuzzy logic is one way to deal with uncertainty in a process or in making a decision (Zadeh, 1965). Some processes are bound by absolute rules and can be modeled using standard statistical techniques such as linear or logistic regression. Other processes are more difficult to classify. For example, if a homebuyer is looking for a home with a southern exposure, the house doesn’t necessarily need to be facing due south. The home could be facing ‘mostly south’ and still satisfy the homebuyer’s requirements (Benedikt et al., 2002). The difficulty is in the representation of the idea of ‘mostly south’ in the form of a model that can assess suitability of homes for this homebuyer.

Fuzzy logic inference systems are composed of fuzzy sets, membership functions, and decision rules. A fuzzy set is a grouping without a definite boundary. For example, the days of the week all fall into the category of days, and this excludes items such as tomatoes, books, and sociology from belonging in the category. Reconsider this category
as weekend, rather than days. Tuesday, Wednesday, and Thursday are definitely not considered to be weekend days. Saturday and Sunday are definitely considered to be weekend days. What about Friday and Monday? Friday starts out as a weekday, but after 5pm can be considered to belong to the weekend category. Monday can be considered to be the weekend until work starts in the morning, but then is absolutely considered a weekday. Friday and Monday belong to the set of weekend days, but not completely. This relationship of Friday to the weekend set can be modeled using a membership function. The membership function could look similar to the following graph (Fuzzy Logic Toolbox):

![Graph showing membership function for Friday belonging to 'weekend'.](image)

**Figure 1: Membership function for Friday belonging to 'weekend'**

where 5 is Friday and 6 and 7 are Saturday and Sunday. The uncertainty of Friday and belonging to the weekend is thus represented in the model (Fuzzy Logic Toolbox).

Fuzzy sets are useful when attempting to categorize information that is difficult to classify. The objects within a grouping belong to the set to varying degrees. This ‘continuum of belonging’ depicts the relationship of the members of the group to the set, and the structure is a membership function. The membership function relates the data to the class according to the characteristics that make it part of the class. This function can take on many shapes and can be classified as relating to other sets (Zadeh, 1965). In this
way, uncertainty of an item belonging to a set is confronted in the analysis, rather than handled with an assumption as in other modeling techniques.

The same sorts of association problems occur when considering whether a property owner will armor shoreline. For example, a membership function that depicts the likelihood of a residential property owner to install riprap on their shoreline based on the cost of riprap and the value of the property may look similar to the following:

![Membership Function](image)

**Figure 2: Membership Function for Cost of Riprap v. Property Value and Likelihood of Riprap**

where 0 through 100 depicts the percentage of property value that installation of riprap would cost. Behind this membership function is a conventional knowledge guiding the location and shape of the membership function (Fuzzy Logic Toolbox). If the conventional knowledge guidelines are as follows, the above figure will depict the property owner’s likelihood install riprap based on value of property (not used in this project):

<table>
<thead>
<tr>
<th>Condition</th>
<th>Likelihood of Riprap</th>
</tr>
</thead>
<tbody>
<tr>
<td>The cost of riprap is less than 15% of the property value</td>
<td>'likely'</td>
</tr>
<tr>
<td>The cost of riprap is less than 50% of the property value</td>
<td>'likely' (to a greater or lesser degree based on percentage)</td>
</tr>
<tr>
<td>The cost of riprap is greater than 50% of the property value</td>
<td>'not likely'</td>
</tr>
</tbody>
</table>

**Figure 3: Guidelines for the Relationship Between Property Value and Likelihood of Riprap**
By constructing the framework to capture uncertainty associated with installing riprap, a more accurate description of decision-making can be formed.

In this case, cost of riprap as a percentage of property value is an input to the model. Other inputs are modeled using the same method. Consider land use as another input to the fuzzy inference system. The conduciveness of land use is integral to predicting the likelihood of riprap in a particular location. Where ‘undeveloped’ = 0, ‘agricultural’ = 0.1, ‘residential’ = 0.9, and ‘developed’ = 1, the membership function (MF) may be represented by the following:

![Membership function for land use](image)

**Figure 4: Membership function for land use**

This MF indicates that ‘undeveloped’ is the least likely to have structure, and ‘agricultural’ is the next least likely to have structure installed. In the same description of relationship between land use and likelihood, ‘developed’ and ‘residential’ are the most likely to have structure installed, with ‘developed’ having a slightly greater probability for structure.

Inputs are combined using decision rules. The decision rules place restrictions and allowances on the membership functions in order to model the system so that it represents the knowledge of how the system works. For this hypothetical system, the rules could be modeled as follows:
If cost of riprap in relation to property value is ‘likely’ and land use is ‘conducive’, then riprap is ‘likely’

If cost of riprap in relation to property value is ‘not likely’ and land use is ‘conducive’, then riprap is ‘not likely’

These rules model a system where the cost of riprap in relation to property value can override conducive land use if the first input is not high. The FIS allows for combination of rules and membership functions in order to model the factors important to the decision-making process of an individual landowner. In this case, the two inputs are cost and land use. The inputs are related to the outputs. In this case, the output is the likelihood of riprap installation. The set of membership functions depicting likelihood of riprap can be represented as shown in Figure 5.

The inputs are combined and linked with the output using an implication method, which adds the “true” parts of the rules together. The “truth” of a rule is the amount of area under a curve that is fulfilled by the set of data (belonging to a parcel). In this way, each parcel can be evaluated according to its characteristics and the result is a “truth value”. The aggregation method is the way in which the area under the curve is added together; the result is the combination function. As you can see in Figure 6, the area under the curve for each stipulation in a decision rule is combined. In this case, the implication method is ‘minimum’, so the smallest area under the curve that overlaps with
all qualifiers to the rule is the output of one decision rule (see A). The resulting area under the curve is combined with the area under the curve from the other rule into a combination function (see B), which represents the output set for a particular set of inputs. The method by which this combination is conducted is the aggregation method. In this case, the aggregation method is ‘sum’, so the areas under the curves are added. The example below is of a residential parcel with a 25% cost to property value ratio.

The value that results from the output set is chosen according to the defuzzification method, and in this case the truth value is 0.87. In figure 6, the defuzzification method is represented by the red line in the composite function (B). Standard defuzzification methods of centroid, largest of maximum, and smallest of maximum use the center point of the area under the curve, the highest value of the largest area under the curve, and the smallest value of the largest area under the curve, respectively. In this case the defuzzification method is ‘middle of maximum’, where the resulting value is the average of the maximum values. Other options are available for
implication, aggregation, and defuzzification, but the three explained here are the most appropriate for the analyses used in this research.

Fuzzy logic methodology has been used to model many processes that do not have finite rules including rural-to-urban land conversion (Wu, 1998, Dragicevic and Marceau, 2000), herbaceous plant production (Svoray et al., 2004), salinity distribution (Metternicht, 2001), control of molten steel level in strip casting processes (Park and Cho, 2005), selection of natural reserve sites (Stoms et al, 2002), and evaluating energy conservation programs (Jaber, et al., 2005). The advantages of fuzzy logic are that it is based on natural language (rather than mathematical language), it is tolerant of imprecise data, it can model nonlinear functions of any complexity, and it only models the rules that are specified. The use of natural language in the construction of a fuzzy logic inference system (FIS) allows the system to be built using common understanding of the workings of the process that is being simulated. The decision rules are constructed using human language and applied to the data set using the FIS. The FIS can handle and is designed to work with imprecise data. All data is imprecise to some degree, and FIS builds the imprecision into the model, rather than assuming a degree of precision that does not exist. Fuzzy logic can model nonlinear functions of any complexity without the difficulty of polynomial and exponential equations. The input data set can be related to the membership function in any way that accurately depicts the relationship of the input data to the output data. One of the most important reasons to use fuzzy logic is that the model only specifies the conditions built by the researcher. This aspect is an advantage over statistical modeling procedures because there is no violation or acceptance of extraneous assumptions and rules (Fuzzy Logic Toolbox). Since most decisions faced by humans
are made based on multiple sources of uncertain information, it is clear that humans do indeed make decisions based on uncertainty. This tool helps to translate the uncertain factors into an outcome in much the same way (Benedikt, et al., 2002)

**Climate Change Impacts**

A reliable shoreline prediction model must incorporate the overall change to the body of land by natural processes associated with climate change, such as sea level rise, land movement, and atmospheric changes. It is important to consider the global and regional impacts of climate change and sea level rise, and much of this work has been undertaken by the Mid Atlantic Regional Assessment (MARA). MARA was conducted as a part of the National Assessment of the Potential Consequences of Climate Variability and Change. MARA assessed the potential climate change in the mid-Atlantic region (all of Delaware, Maryland, Pennsylvania, Virginia, West Virginia, and the District of Columbia and part of New Jersey, New York, and North Carolina) including history and future of climate, impacts of change on the mid-Atlantic region (MAR), impacts of change to coastal ecosystems, and the impact of change to hydrology and water resources. (Polsky, et al. 2000) This research helps to shed light on regional and global changes and how they affect shoreline resources and the people living near them.

Examination of physical change, effects of sea level rise, and storm surge are integral to understanding the current pressures and the likely future scenarios for the coastal zone.

Physical attributes of the climate are likely to change with climate change, and CO₂ concentration, air temperature, and precipitation are projected to change. Using both the Hadley Center for Climate Prediction and Research (Hadley) model and the Canadian Climate Center (CCC) model, Atmospheric CO₂ was modeled from 1850 or 1860 to 1990
and the result was used to project increases in atmospheric CO$_2$ to 2100 or 2099. CO$_2$
does not directly induce change to the coastal zone, but its effects may have a significant
impact due to its influence on temperature and other systems. Both models used
sophisticated models of the physical processes that contribute to atmospheric
composition, and both models predicted a 1% increase in CO$_2$ per year (Polsky et al,
2000). The levels of CO$_2$ in the atmosphere will likely rise even with stringent emissions
regulation because of its long residence time. (Houghton, et al. 1996) Atmospheric CO$_2$
from anthropogenic sources has increased 25% since prior to the industrial boom in the
United States. Also, the natural climatic cycle, based on historical temperature data,
suggests that the Earth is currently in a period of warming. (Garrett, 1992)

Examining the changes in the last century, the MAR has experienced an upward
linear trend of warming with a low slope, indicating an increase of about 0.5°C. Polsky
found an upward trend in temperature in the first half of the century and a downward
trend in temperature in the second half (Polsky, et al., 2000). Prediction of further
increase in air temperature is less certain due to the cooling effect of aerosols. This
cooling effect could offset some or all of the CO$_2$ induced warming. Since the
Chesapeake Bay watershed has a large amount of industrial activity, the impact of
aerosols on air temperature could be considerable. (Satheesh and Moorthy, 2005)

Over the past century, precipitation has increased by 10%. Precipitation was
evaluated for trends in the past century, and no clear trend was elucidated. There were
significant variations in yearly and decade time frames, trends varied within regions, and
extreme storm events caused anomalies (Polsky et al., 2000). Some predictions indicate
that storms will be more frequent and have a lower intensity while others predict greater intensity and duration but storms will be fewer in number.

Sea level rise in coastal Virginia is influenced by several factors. Eustatic sea level rise and isostatic sea level rise both contribute to the rate at which sea level rises. The eustatic sea level rise is composed of thermal expansion of the ocean, decreases in surface and groundwater storage, and glacial melting. Isostatic sea level rise results from vertical land movements caused by mechanisms such as fault activity, isostatic adjustment, accretion, and/or subsidence. The combination of the two factors is relative sea level rise (RSLR) for a given area (Najjar, et al. 2000).

Global eustatic sea level rise has been estimated at 1.8 mm (0.071 in.) per year, + or − 0.1 mm/yr, for the time period between 1880 and 1980. (Douglas, 1991) Another study, whose time range was over the last century found that the range was between 1.0 to 2.5 mm (0.039 to 0.098 in.) per year. (Warrick, 1996) Titus and Narayanan (1995) estimated the relative sea level rise between 3 and 4 mm (0.12 to 0.16 in.) per year for the mid-Atlantic region, which indicates that local effects may account for up to 2 mm (0.08 in.) per year. The isostatic component for the mid-Atlantic region could be attributed to sediment accumulation and compaction (Psuty 1992; Nicholls and Leatherman 1996), regional differential crustal warping (Walker and Coleman, 1987), and removal of groundwater by humans (Sabhasri and Suwaranrat, 1996). In the southeast Virginia area, geodetic surveys show that the rate of groundwater removal stimulates land subsidence of approximately 2mm (0.08 in.) per year. This would be in addition to mid-Atlantic and global trends. (Holdahl, 1974) The groundwater withdrawals are large for this area due to the amount of water necessary in nuclear processes and paper mill operation. The
amount of water withdrawn is subject to change based on the industrial utilization changes in southeastern Virginia.

Local trends indicate that there may have been an acceleration of sea level rise in recent years. The mean sea level trend in Virginia has been tracked by NOAA-NOS at several points along the coast and within the Chesapeake Bay. Seven stations record sea level trends as well as inter-annual variation. These stations can be put into three general categories: those that have been recording for 72 years, those that have been recording for 49 to 52 years, and those that have been recording for 24 to 27 years. Rough analysis of the mean sea level data indicates that there could be considerable variability in the rate of sea level in the Chesapeake Bay region. The 72-year mean sea level rise is calculated to be 4.42 mm/yr, while the 49 to 52 year estimates range from 3.59 and 3.95 mm/yr. (NOAA CO-OPS, 1999) The stations that have been recording for shorter amount of time, and therefore the mean sea level is averaged over a smaller number of years, indicate a rate of sea level rise that ranges from 4.85 to 7.01 mm/yr. The recording station for Sewells Point, an area north of Guinea Neck, shows a 72-year record with an average sea level rise of 4.42 mm/year. Recent releveling of benchmarks at this recording station using the new tidal epoch (1982-2001) found that, in the last 19 years, the rate of sea level rise has been 7.2 mm/year. (personal communication, Walter Priest) This would suggest that the rate of sea level rise could be increasing at a greater rate than recorded previously.

Climate change could have large impacts on the shoreline of the study area, including sea level rise and species tolerance changes. (Polsky, et al. 2000) As evidenced by the previous discussion, a sea level increase of one foot, and possibly up to three feet,
will likely occur during a property owner’s lifetime. This will cause currently exposed land to be submerged in low-lying areas, and, just as important, it will dramatically compound the flooding effect of episodic storm disturbance. A storm with a 1 in 20 year probability in 1962 would produce flooding and property damage. The same storm intensity, if it occurred in 1990, would produce greater flooding and storm surge because the water level would be about 109 millimeters higher. The same intensity storm as in 1962, occurring in 1990, would be considered to have a 1 in 30 year probability due to the difference in sea level and storm surge impacts. If the same intensity storm occurred in 2030, with an approximate sea level increase of 305 millimeters from the 1962 level, the storm would be considered to have a 1-in-40 year probability. In this way, storms of equal intensity have and will continue to have a greater impact and cause more damage due to the rising waters. There has been some speculation as to whether storm disturbance will increase, decrease or stay the same in the mid-Atlantic region, but regardless of the frequency, the same intensity of storm will cause more extensive flooding and storm surge conditions. (Rogers and McCarty, 2000) Some estimates predict that the number of people flooded annually or sporadically in a typical year will increase five times by 2080 due to the effects of sea level rise. (Nicholls, et al., 1999) Gloucester County, VA was impacted greatly by Hurricane Isabel in September of 2003. Comparisons have been made between the 2003 hurricane and the 1933 “the storm of the Century for the Chesapeake Bay.” While the intensity of the 2003 storm was significantly less than the 1933 storm, the storm tides were very similar (1933 – 2.444m, 2003 – 2.404m) because the sea level had risen 41cm. (Boon, 2003)
Climate change and sea level rise are predicted to have significant impacts on water quality, salinity, wetlands, and coastal forests. Not only will future climate variations affect the quantity of available water resources, it may affect water quality by increased sedimentation. Also, climactic variations in air temperature could cause significant variations in water temperature (Neff et al., 2000). Salinity in estuarine bodies will be undergo a gradual change with sea level rise as ocean water encroaches inland. As saltier waters travel further upstream, the estuarine dynamic will shift upstream and ecosystems will have to adapt to new conditions (Najjar et al, 2000). Because wetlands occur at the interface of the land and water, these areas are particularly susceptible to increases in sea level (Parkinson, 1994). Traditionally, as sea level rises, wetlands migrate landward. In a situation where areas bordering wetlands are developed, wetland migration is limited. Because of large amounts of urban and suburban development in the coastal zone, the overall quantity of wetlands will decrease with increases in sea level rise (Najjar et al., 2000). The effects of sea level rise on riparian forests can include saltwater intrusion, flooding stress, erosion, and reduce capacity to reproduce (Williams, et al., 1999). As wetlands move landward into riparian forests, the riparian forests move landward also. These natural shoreline ecosystems both feel the pressure of human occupation in the form of a decreased ability to migrate landward. Riparian forest could also be greatly affected by climate change if future precipitation and temperature are substantially different from the present conditions (Dale et al, 2000).

Much like low-lying areas in the United States, low-lying and storm-prone coastal areas in Australia are facing increasing urbanization. As storm surge greatly affects coastal communities, a growing population on the coastline increases the need for hazard
planning. Using a GIS based model to improve risk management decision-making, Zerger, et al. (2002) show that it can be useful and practical in developing evacuation procedures and modeling the risk associated with storm surge. The GIS images allow the decision-makers to envision the repercussions of underestimating the impacts of storm activity.

**Guinea Neck Physical and Demographic Description**

The study area for this project is a small area of South Gloucester County. Gloucester County is located on the East coast of the United States of America in the Commonwealth of Virginia. The county is located on the Middle Peninsula and is bordered by the York River on the West and South and the Chesapeake Bay on the East. Since 1940, the population of Gloucester County has more than tripled (1940: pop. 9548, 2000: pop. 34780). The bulk of this population growth has occurred in the past 30 years, with the population increasing by almost two and a half times the original population from 1970 to 2000 (1970: pop. 14059, 2000: pop. 34780). It is important to note that much of this population growth has been fueled by people immigrating to the county. Examining the time period between 1995 and 2000, 25.2% of 2000 residents were not residents of Gloucester County in 1995. This influx of people to the county has influenced the general demographics of the county, such as income and housing value, especially in the study area (US Census, 2000).

The site of the study is in South Gloucester County, Virginia in an area called Guinea Neck. Physically, the area is characterized by very low relief with a significant area of marshes and forested wetlands (USGS-DRG). The boundaries of the study area are the headwaters of Heywood Creek on the North and the headwaters of the western
branch of Sarah’s Creek on the South. Currently the population of the study area (14.71 square miles) is slightly less than 4000 people, and the primary land uses are residential, agricultural, and undeveloped.

This region has undergone rapid changes in population composition due to its proximity to more developed cities such as Newport News and Hampton. As these cities become more developed, there is an increase in people from other counties settling in Guinea Neck. In the year 2000, just under 20% of Guinea Neck residents had moved there since 1995. These population changes result in a dynamic and broad spectrum of education levels, income, and property values in the area. Guinea Neck has historically been home to many watermen and their families, but increasingly, wealthier residents are purchasing the waterfront land to build their homes and second homes. Also, as the development pressure in this area has increased, so have the property taxes. Some families that have historically lived or worked in the area can no longer afford the increased property taxes. These families choose to or are forced to sell and the land use may change as a result. The effects of these pressures are reflected in the changing demographics of the study area.

Guinea Neck has experienced an increase in property values, education levels, and income. Unfortunately, education levels and income information are not available at the census tract level for 1990, therefore analyses of recent trends in education and income are based on Gloucester County data. Median property value for the Guinea Neck area in 1990 was $87600 and increased to $111,300 in 2000 (not standardized for inflation). When these figures are standardized with a 2% rate of inflation, there is a net increase of about $4500. However when standardized with a 3% inflation rate, there is a
net decrease of about $6000 in property value. Gloucester County has seen a significant rise in the education level of residents. In 1990, 11.3% of residents had less than a high school education, compared with 6.5% in 2000. 74.0% had a high school degree or higher in 1990, while 81.7% had achieved the same in 2000. Also, 14.7% of Gloucester County residents had earned a bachelors degree or higher in 1990, whereas 17.6% had by 2000. There has been an increasing trend in the household income in Gloucester County as well. Median household income in Gloucester has increased from $22496 in 1969 to $31591 in 1989. These figures are standardized for inflation in 1989 dollars (US Census, 2000). Changing population characteristics and development pressures are catalysts for change in land use, as structures are built to accommodate living needs of the increasing population. As shoreline land use changes, actions of property owners will determine much of the impact on the amount of natural shoreline habitat in Guinea Neck.

**OBJECTIVES**

The objectives of this project are three-fold. The first objective is to create a land use model based on historical imagery from the 1940’s to the present. Four sets of aerial photographs were used to create a GIS based model that represent land use at each interval, look at changes between time steps, and model possible drivers of land use change. The second objective was to predict future land use change based on linear and logistic regression analyses. The land use in the year 2025 was predicted and used for subsequent analyses. The third objective was to establish correlations between land use and the condition of the shoreline (bank height, erosion, presence of marsh, presence of structure) and predict location of future shoreline structure. These relationships were
generated from 2002 shoreline condition and land use data and applied to the 2025 data set using logistic prediction and two methods of FIS prediction. The models were then used to investigate scenarios of future shoreline condition using econometric and fuzzy logic modeling techniques.

The general structure of the data processing is illustrated in Figure 7.

The land use and shoreline prediction processes are complex and detailed. Figure 8 outlines the methodology of the prediction processes for reference throughout the methodology section.
METHODOLOGY

Elevation Model

In order to adequately assess the risk facing property owners with respect to sea level rise and climate change, elevation information must be considered by the model. Digital raster graphs (DRGs) were used to create an elevation model with a contour interval of one-foot (USGS-DRG). DRGs for the study area are accurate to the 5-foot contour, and the study area has elevations ranging from 0 to 15 feet. In order to gain the additional accuracy necessary to make 1-4 contour foot estimations, the intervals were interpolated using Contour Gridder (Stuckens, 2003). Since this application is based on grid technology, the resulting contour lines “zig-zag” instead of producing a smooth
contour. These contours were then manually re-digitized using the program Erdas Imagine. The final product was an elevation map that delineates the zero through five-foot contour and approximates the one-foot interval. This map will serve as the base of the shoreline model.

Digital Raster Graphs (DRGs) were chosen as the base of the topographic model because the resolution was not limiting and the information is readily available. Digital elevation models (DEMs) cannot be used, as have been used for other topographic studies, for the topographic base. The resolution of DEMs is inadequate for the scale of the survey. The pixel size is 30m by 30m for land area, so one area of 900 m² will have one elevation. The DEM is generated by averaging elevation over the 900 m² area and assigning the area one elevation. In order to address elevation variations within individual parcels, a map-based topographic model or a digital elevation model with a greater resolution is necessary.¹ The DRGs are a map-based topographic model with a 1:24000 scale. The map was made manually using digital scopes to locate the five-foot contour.

**Land Use Data Layer Construction**

Historical imagery of the study area was acquired for the years 1937, 1959, 1982, and 2002. These images were scanned, rectified, and combined into a mosaic using Erdas Imagine for use as a GIS data layer. The rectification process is one in which photographs are anchored spatially using landmark points to a certain projection. A photo in the desired projection is used to rectify the photograph with no associated

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¹ LIDAR data is the most accurate topographic data available. LIDAR data is collected using aircraft-mounted lasers that record elevation data points so that each laser spot records elevation for an area between 0.4 and 0.6 meters. The vertical precision varies with the position of the aircraft, and the theoretical accuracy of the system is 0.01m to 0.02 meters (Hwang et al., 2000). Unfortunately, LIDAR is not available for our study area.
projection. The two are compared for similar features that do not change over time. Examples of such features would be some road intersections, docks, and buildings. The corresponding features are matched as closely as possible until enough points are anchored to give the new photograph the associated projection. All files associated with this research are projected in NAD_1983_UTM_Zone_18N. The purpose of this process is to manipulate the photographs so that they represent features true to their size and location. In most cases, each photograph depicts a part of the study area, therefore a mosaic is made up of several photographs that are displayed together in the same projection and permanently linked once the desired overlap is achieved. The finished product is a complete aerial image of the study area for a certain year.

The 1937 mosaic was comprised of nine United States Geological Survey (USGS) aerial photographs (USGS, 1937). These images were black and white photography flown at an unknown distance above land from March to July. The 1959 mosaic was also USGS imagery, but two photographs covered the entire study area (USGS, 1959). The images were black and white photography and taken at an unknown distance above land from November 1959 to December 1960. This year time step is classified as 1959 rather than 1960 because the large majority of the study area is covered by the 1959 image. The imagery for 1982 time step is a single USGS photograph taken in Color Infrared Photography (USGS, 1982). The photograph was taken in April at an unknown distance above land. The 2000 dataset is digital imagery from the Virginia Base Mapping Program and has a 1-meter resolution (VBMP, 2002). The resolution is unknown for the 1937, 1959, and 1982 time steps because we do not know the distance from which the
picture was taken. Generally, the sets of imagery with the greatest number of photographs provided clearer images than those with fewer photographs.

The imagery was used to categorize areas into land cover categories: 'undeveloped', 'agricultural', 'residential', and 'developed'. Forested lands, forested wetlands, and vegetated marshes were classified as 'undeveloped'. Tracts of farmland and bare lands were classified as 'agricultural', and 'residential' areas were identified by clusters of housing and individual housing structures. The 'developed' regions were structures such as fish processing houses, marinas, and schools. Each set of imagery was manually classified according to this land use classification system using Erdas Imagine. The result of these efforts was a polygon coverage depicting the land cover.

Using ArcGIS, each land use layer was joined with a polygon grid. The grid was generated by overlaying a fishnet of one acre polygons. The grid covered the entire study area so that when the two polygon coverages were joined, each acre was attributed with the total acreage of each land use, the percentage of each land use, and the dominant land use in the acre grid cell. The same fishnet coverage was used for all time steps so that individual acres would be comparable across time steps. An arc macro language (AML) file was created in order to attribute the land use to each acre polygon. An AML file is a program designed to run in a command line ArcGIS interface that outlines a process. The program details the individual steps that need to be executed in order to produce the desired result in each data set for each parcel. The file was set to execute this process for an entire data set. In this AML (Appendix 1: fishnet.lu.aml) each individual acre was

2 Other programs allow classification of land use types (such as ArcEdit command line), but Erdas Imagine utilizes a User Interface that provides necessary editing tool menus in a convenient form.
3 There is currently no application that attributes land use to each acre polygon in the exact way that was necessary for the analysis. The creation of an AML (and all AMLs in this research) was the only way to achieve the data integration with uniquely specified conditions.
selected, analyzed for its contents, and attributed with the desired features. The result of joining the land use polygon and the grid polygon for each time step was the creation of a new layer for each time step that contained the following information: acreage of each land use type, percentage of each land use type, and dominant land use of the acre parcel.

Standardization of land use information across time steps was necessary to correct for error generated by manually digitizing land use. Also, in order to perform further analyses and comparisons among time steps, the data sets had to be equivalent in number of acres. Two standardization procedures were applied to the data sets in order to equalize the time steps. Both standardization procedures were applied to the data set using a two-part AML program (Appendix 2: standardization.aml).

The first procedure was standardization of the number of acres per time step. The problem arises from variation in shoreline between time steps. Since the shoreline naturally and artificially changes over time, some time steps had land in acre grid cells that had no land in them previously or in the future. Generally the amount of land in the acre was very small (less than 2%), especially when the corresponding grid acre in other time steps showed no land in two or three of the other time steps. When three time steps had an acre value and one time step had no land in the acre, the problem was somewhat more complex. In the acres with only one ‘none’ classification, the percentage of the acre covered by land was sometimes greater than 30%, and these deserved additional consideration in the data set. Because of these conditions, the number of acres per time step was standardized using the AML found in Appendix 2 (standardization.aml) according to the following rules:

- If the acre parcel has land values for one or two time steps, but not for the others, the dominant land use for all steps is ‘none’
• If the acre parcel has land value for three time steps, but not for the remaining time step, the dominant land use will be assigned as follows:
  If the land acreages are under 30% of the acre parcel, dominant land use for all time steps is ‘none’
  If the largest land acreage is over 30% of the acre parcel, the dominant land use for the ‘none’ time step is reset to the dominant land use of the step with the largest land area

The second standardization procedure that was applied to the model was the assumption that development could only proceed in a forward direction. This is to say that an agricultural parcel could stay ‘agricultural’ or change to ‘residential’ or ‘developed’ but could not be ‘undeveloped’ in the next time step. This is a valid assumption for this area due to the large amount of development pressure that the study area has faced and is currently facing. This type of uni-directional assumption has been used in other land use change analysis, such as found in Pontius et al., 2001. The assumption was applied as a backwards logic filter. Since each of the time steps had imagery of varying degrees of resolution and clarity, some years produced land use classifications that were more accurate. The sharpest image was the 2000 image, so it was used as the base for the standardization. The land use standardization procedure was the second part of the two-part AML (Appendix 2: standardization.aml). The AML used the dominant land use of each grid acre in the 2000 data set, and compared it to the 1982 data set, the 1982 data set was compared with the 1959 data set, and the 1959 data set was compared with the 1937 data set according to the following rules:

• If the land use is ‘developed’, the previous dominant land use can be ‘developed’, ‘residential’, ‘agricultural’, or ‘undeveloped’
• If the land use is ‘residential’, the previous dominant land use can be ‘residential’, ‘agricultural’, or ‘undeveloped’
• If the land use is ‘agricultural’, the previous dominant land use can be ‘agricultural’ or ‘undeveloped’

4 25% of parcels underwent some change during standardization. This was likely due to resolution problems in historic imagery and manual error in digitizing land use.
If the land use is 'undeveloped', the previous dominant land use can be 'undeveloped' only

Once the four data sets had been joined and standardized, the next step was to attribute additional data that indicates the likelihood of development. Each grid acre was attributed with information indicating the dominant land use classification of the eight surrounding acre cells. Each acre cell was attributed with the number of surrounding acres whose dominant land use was 'undeveloped', 'agricultural', 'residential', and 'developed'. This information is important to investigation of relationships between land use change and surrounding land use conditions between/among time steps. The process of attributing surrounding land use data to each cell was performed using an AML (Appendix 3: adjacent.lu.aml) designed to select each cell, count the number and type of adjacent land use, and attribute the acre parcel with this information.

In addition to attributing each cell with surrounding land use, each acre was attributed with information about proximity to the shoreline and proximity to the road. The center point of each acre grid cell was used to calculate the distance to the shoreline and the road. The road coverage used was the TIGER 2000, and the analysis included primary highways, primary roads, secondary and connecting roads, and local, neighborhood and rural roads. (Tiger, 2000) Distance to shoreline and roads was determined using Grid in command line ArcInfo and the command 'linedist'. Detailed information about how this function was applied can be found in Appendix 4 (prox.shl.rds.txt). This AML calculates the distance between the center point of the acre parcel and the desired features. This information was then joined with the standardized data set so that each acre parcel was attributed with dominant land use, dominant land use of surrounding cells, proximity to shoreline, and proximity to a road. In addition, all
parcels in the dataset that showed land use as ‘none’ were eliminated. This trimmed the data set to exclude water and areas not in the study area.

Guinea Neck has a substantial area of forested wetlands and marshes that will not change from their original land use because they cannot be built upon. It is necessary to hold these parcels constant during the land use prediction. This was accomplished by comparing the 1976 Tidal Marsh Inventory (TMI) with the acre parcels (Tidal Marsh Inventory, 1992). It was found that there has been some building on marsh areas and some marshes fringe property that has agriculture, residential or developed dominant land use determination. In order to preserve those parcels that have not and cannot undergo development, parcels that intersect or are overlapped by the TMI with a land use categorization of ‘undeveloped’ were excluded from the land use prediction. Those parcels that are some category of disturbed that intersect or are overlapped by the TMI were allowed to change. The assumption here is that if the land has been altered and is classified as a disturbed land use, the land use is capable of changing. In addition, small areas of fringe marsh do not preclude land use change for the dominant land use, even if a portion cannot be altered. These undevelopable lands were removed from the data set, and the resulting data set was used for land use prediction.

**Land Use Prediction**

In order to approximate future land use based on historic trends, an estimate must be made for demand for certain land types and how they are allocated in the future time step. The demand for types of land use over time was investigated using linear regressions of past land use demand for each possible land conversion. Allocation was assessed using logistic regressions of the 2002 dataset, including variables such as
surrounding land use and distance from shoreline. For the study area, 7,461 acre parcels were available for a land use change.

The patterns of land use change from 1937 to 2002 were used to investigate the likely future demand for various types of land use. The time steps for this study were 1937, 1959, 1982, and 2002. Using the change between time steps (i.e. 1937-1959, 1959-1982, and 1982-2002), land use change was broken down into the number of acre parcels that changed from one land use type to the following land use type as shown in Figure 9.

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>undeveloped to undeveloped</td>
<td>4841</td>
<td>4396</td>
<td>3875</td>
</tr>
<tr>
<td>undeveloped to agriculture</td>
<td>363</td>
<td>132</td>
<td>229</td>
</tr>
<tr>
<td>undeveloped to residential</td>
<td>88</td>
<td>303</td>
<td>287</td>
</tr>
<tr>
<td>undeveloped to developed</td>
<td>1</td>
<td>10</td>
<td>5</td>
</tr>
<tr>
<td>agriculture to agriculture</td>
<td>1745</td>
<td>1608</td>
<td>1354</td>
</tr>
<tr>
<td>agriculture to residential</td>
<td>320</td>
<td>475</td>
<td>376</td>
</tr>
<tr>
<td>agriculture to developed</td>
<td>0</td>
<td>25</td>
<td>10</td>
</tr>
<tr>
<td>residential to residential</td>
<td>103</td>
<td>505</td>
<td>1259</td>
</tr>
<tr>
<td>residential to developed</td>
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<td>24</td>
</tr>
<tr>
<td>developed to developed</td>
<td>0</td>
<td>1</td>
<td>42</td>
</tr>
</tbody>
</table>

**Table 1: Land Use Change in Parcels of All Time Steps and Land Uses**

The amount of change of land use types between these time steps was used in a series of linear regressions to predict future demand. $R^2$ values for these regression equations ranged from 0.9927 to 0.1553, with six out of ten over 0.7265. These regression equations represented the overall trend of land use change for each possible land use change over time. The prediction of demand was calculated by using the linear regression equations for estimates of land use demand in 2025. The percentages of land use change represented by this prediction were used in conjunction with the allocation methodology to predict future land use for the year 2025.
The allocation procedure utilized the condition of the acre parcels in the 2002 time step. Because these data are discrete, rather than continuous, data, logistic regression was used to elucidate the conditions associated with the parcels that are significant variables. The variables that were used to generate the regression equations were number of surrounding acre parcels of 'undeveloped', 'agricultural', 'residential', and 'developed', as well as distance to shoreline and roads. Stepwise logistic regression was used in order to eliminate non-significant variables from the regression equation. For example, the regression analysis for an 'undeveloped' parcel changing land use initially included all regression variables. The stepwise process found all surrounding land use counts and distance to shoreline to be significant in the regression equation. The coefficients were used to calculate the likelihood of each individual parcel of 'undeveloped' undergoing conversion to another land use.

The regression equation for each land use type was used to calculate a regression score that indicates the likelihood of a given parcel to change in the next time step. Using the percentage change generated by the demand procedure, the 2002 land use was used to calculate the amount of conversion for each possible type of land conversion in the future time step. The regression score was used to rank each parcel within a particular land use type. For an example of conversion prediction for 'undeveloped' acre parcels, the most susceptible 10 acre parcels to change were converted to 'developed' land in the 2025 time step. The next most susceptible 429 acre parcels were converted to 'residential' land, and the following 95 were converted to 'agricultural'. The remaining 3341 were coded as 'undeveloped' in the 2025 time step. The same protocol was followed for the remaining
land use types until all acre parcels had a value for the 2025 time step. This 2025 land use prediction was then integrated into the GIS platform.

**Land Use Scenarios**

In addition to the prediction using the linear regression estimates, future scenarios were developed to investigate how changes in demand for land use can affect the 2025 land use prediction. Due to the accelerating rate of population growth in Gloucester County, development in Guinea Neck as represented in the prediction could be an underestimate. Also, unforeseen factors affecting land use change could increase or decrease the demand for certain types of land use. Because of this uncertainty, several scenarios were examined to understand the possible future states of land use.

The scenarios developed were a 10% increase in ‘residential’ acre parcels with a 5% increase in ‘developed’ parcels, a 20% increase in ‘residential’ acre parcels with a 10% increase in ‘developed’ parcels, a 30% increase in ‘residential’ acre parcels, a 30% increase in ‘developed’ acre parcels, and a 10% decrease in ‘residential’ acre parcels. The percentage increases were allocated based on the proportion of change of each land use type to the target land use type. For example, the original prediction estimate for ‘agricultural’ parcels indicates that 27.51% of current ‘agricultural’ parcels will change to ‘residential’ and 11.07% of current ‘undeveloped’ parcels will change to ‘residential’.

When examining a 10% increase in conversion to ‘residential’ parcels, the 10% increase was split proportionally between the two land use types. Since the 27.51% change rate represented 71.31% of the change, additional percent change of ‘agricultural’ to ‘residential’ was calculated by multiplying 10 by 71.31%. The result was an additional 7.13% change, totaling 34.64% change of ‘agricultural’ parcels to ‘residential’ parcels.
Since the 11.07% change of 'undeveloped' parcels to 'residential' parcels represented 28.69% of change to 'residential' parcels, the additional percent change allocated to this conversion was 2.87%. This methodology allows for allocation of the additional 10% according to the principles driving land use as modeled using the regression variables. The change for each future scenario was calculated in this manner based on the original prediction estimate for 2025.

**Shoreline Prediction**

The Center for Coastal Resource Management’s Comprehensive Coastal Inventory has collected extensive shoreline condition information for the study area. This data set includes riparian and littoral zone resources, structures, and shoreline stability. The shoreline condition information consists of three data sets. The first of these data sets contains information about bank height, erosion, presence of marsh, and presence of beach. The second data set details the location of shoreline structure such as rip rap, bulkhead, groin, jetty, or breakwater\(^5\), and the third data set indicates the location of docks, boathouses, and ramps. Together the data sets portray a complete picture of the condition of the shoreline and are collectively called the shoreline inventory. These data were obtained during field surveys that visually categorize the attributes of the shoreline from the water. They are collected from a boat using an integrated real-time kinematic global positioning system (GPS) that tracks the location of the boat. The system and its manual operator are able to record the condition of the shoreline, and attribute this information to the boat track. The Gloucester County shoreline inventory was collected in November 1998 and processed in March 2005. (Shoreline Inventory, 2002)

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\(^5\) Structure was coded such that only the effective structure was recorded. For instance, if bulkhead was installed with riprap at the tow, the riprap is the structure that is protecting the shoreline.
process of transferring these data from attributes of the boat track to attributes of the
shoreline was completed in ArcMap using the Attribute Transfer Mapping tool. This
work has been double checked for accuracy. The result of this effort was a continuous
shoreline data set for the study area detailing the condition of shoreline and presence of
structure.

In order to examine the correlations between shoreline structure and
characteristics of land use and shoreline condition, the data had to be integrated into one
data set. To accomplish this integration, the shoreline condition information (bank
height, presence of marsh, presence of beach, and erosion) and presence of structure
(riprap, bulkhead, breakwater and groin) were incorporated into the acre parcel data set.
The data set containing information about docks, boathouses, and ramps was not used in
the analysis because, conceivably, these structures could be built on shoreline of any
condition, including over wetlands. The data were not appropriate for the analysis
because it does not necessarily impact the shoreline resources.

Both the land use and shoreline condition data sets had many instances where one
acre parcel had several values associated with it. For example, in one section of shoreline
found in an acre parcel, there could be four different descriptions of the condition of the
shoreline. A frequency was run on the data to find the prevalent shoreline conditions for
the acre parcel, and these values were attributed to the data set. If there was one set of
data for shoreline conditions, these values were attributed to the data set without
undergoing a frequency analysis. In the case of shoreline structure, if the data set had
multiple values for a parcel, the structure was attributed to the parcel only if the
maximum length exceeded 5 meters. The length of shoreline contained within a parcel
was variable due to the non-linear nature of shoreline, and length was also attributed to
the data set. These procedures were accomplished using an AML program (Appendix 5:
lu_stru_sum.ami).

The shoreline predictions were based on relationships between presence of
shoreline structure with shoreline condition and land use. The relationships between
structure and shoreline condition examined bank height, presence of beach, presence of
marsh, and erosion. The relationships between structure and land use took into account
land use of the acre parcel and the surrounding land uses. Since the data set for shoreline
condition was closest in time to the 2002 data set, the land uses for 2002 were used to
formulate the regression equations. The acre parcels used to generate this data were
selected for three characteristics: parcels that were allowed to change, parcels that
contained shoreline, and parcels that had complete shoreline condition information. The
resulting data set contained 717 acre parcels that met all conditions.

The first method of prediction used binary logistic regression to look at trends.
Presence or absence of each type of structure (bulkhead, riprap, breakwater, and groin)
was examined in relation to land use of the parcel, its associated land uses, and each
characteristic of shoreline. The data set was then analyzed using binary logistic
regression with a forward: conditional (stepwise) application in SPSS. As in the logistic
regressions for land use prediction, the stepwise application to the logistic regression was
employed so that only significant variables were included in the final analysis. The
prediction probabilities were saved during the analysis and used to examine the
goodness-of-fit of the regression equation to the model. This ROC value, the result of
this analysis, serves as a replacement for the $R^2$ statistic used in linear regressions. The
regressions were based on the 2002 data set and applied to the predicted land use for the 2025 data set and the current shoreline condition. The current shoreline condition was used for the application with the 2025 prediction because shoreline condition is unlikely to change dramatically within this time frame and because no historic shoreline data is available to make predictions of how shoreline condition will change over time. The regression was applied to a subset of the prediction data set that did not contain shoreline structure. This data set consisted of 450 acre parcels whose land use was allowed to change, contained shoreline, had complete shoreline condition information, and contained no structure. The regression score was a calculation of the likelihood of each shoreline structure for acre parcels that did not have shoreline structure in 2002.

The regression score was used to rank parcels according to the likelihood of changing to groin, bulkhead, or riprap (regression analysis for breakwater was not significant, since there was only one breakwater contained within the study area). The allocation of structure along the shoreline according to the regression equations was applied in order of prevalence in the study area. Use of bulkhead was most common, followed by riprap and groin. The data set was sorted according to bulkhead regression score, and the top ranked parcels were converted to bulkhead in the 2025 prediction. The data set was then sorted according to the riprap regression score. The top parcels were coded ‘riprap’ unless already occupied by ‘bulkhead’, and any overlap was recorded. The data set was then sorted according to the groin regression score. Top parcels were coded as ‘groin’ unless already coded as ‘bulkhead’ or ‘riprap’, and any overlap was recorded. This order was used to allocate structure for each of the shoreline scenarios.
The shoreline scenarios investigated using the logistic prediction were a 5%, 10%, and 20% increase in shoreline structure. The increases were applied to the data set in proportion to existing structure proportions, since no historic shoreline condition information was available to examine historic trends of installation of structure. Attempts were made to elucidate the presence of structure in historic imagery in order to establish trends in type, location, and amount of structure, but, unfortunately, the resolution of the imagery was not sufficient to do so. The 5%, 10%, and 20% increases in structure were applied to the 450 acre parcel subset, added to parcels containing structure, and integrated back into the original data set of 10,743 acre parcels for analysis for GIS representation.

The second method of shoreline prediction used a fuzzy logic inference system to model the data. The fuzzy logic system is built using the MatLab application Fuzzy Logic Toolbox. The toolbox allows a five-window interface to control the specifics of the fuzzy inference system (FIS). The first window is the FIS editor. This section allows you to construct the framework of the FIS including input setup, output setup, implication method, aggregation method, and defuzzification method. While the first two outline the structure of the FIS, the last three methods are processes that are applied to the data to affect the output (as discussed in the background section). Input and output control includes adding of inputs and naming them so that they match with the data set variables. The implication method used in this project is ‘minimum’, which serves to truncate the output of the fuzzy set, the aggregation method used was ‘sum’, or the sum of each rule’s output set. The defuzzification method used for this system was the ‘mom’ or middle of maximum, which chooses the output value as the average of the maximum values of the
output set. Overall, the implication, aggregation, and defuzzification method affect how
the rules are combined, the shape of the output set, and the value of the output (truth value).

The inputs are defined using the membership function editor. An input can be defined according to range, which delineates acceptable input values from the data source. This section is where the relationship between the data set and the output is built. It allows membership functions to be built according to the value of the input. Many types of membership functions are available for modeling, but the gaussian membership function (MF) proved to be most useful for this model. The gaussian MF indicates a smooth, non-linear change from 0 to 1 and can model several types of relationships by changing the slope and location of the function. Most of the inputs for this model were best represented by two gaussian MF, generally indicating one end of the range as suitable and the other end of the range as not suitable. Some inputs were better modeled by one gaussian MF, and these inputs generally required that all data set values were suitable to a certain extent. For instance, in modeling with ‘presence of erosion’ as an input, both ‘low’ and ‘high’ erosion resulted in an addition to the likelihood of structure. One MF best modeled this type of data. Appropriate representation of the system through membership function is important for development of decision rules that control the system. Sets of MF are developed for all inputs and outputs of the model.

Decision rules are developed and edited using the ‘Rule Editor’. Rules are the result of selecting conditions of inputs modeled by the membership function (i.e. ‘likely’, ‘not likely’) and combining them with conditions of other inputs. The resulting set of rules instructs the model to behave according to specifications. The system can usually
be described in 3-5 rules, but the number of rules does not matter as long as the relationships and outputs model the system according to the principles contained within and the ideas behind your model.

Two other functions of the MatLab Fuzzy Logic Toolbox that were used in FIS development were the rule viewer and the surface viewer. These functions allow you to manipulate inputs to visualize the effects on the output and the rule interaction. Primarily the rule viewer is used for fine tuning and testing the model’s response to a variety of inputs.

Six fuzzy logic inference systems were constructed. Three FIS were constructed for prediction of installation of bulkhead, riprap, and groin using a combination of the logistic prediction regression value and land use and shoreline condition variables that are most important (from a conventional knowledge standpoint) for prediction of engineered shoreline structure. This analysis was performed in order to compare the results from the logistic regression equation alone with logistic regression values supplemented by environmental variables. The other three FIS were also constructed to predict the location of installation of bulkhead, riprap, and groin, but these estimates used only information about land use, shoreline condition and adjacent structure (no logistic regression). These FIS modeled the conventional knowledge of which shoreline parcels undergo installation of structure, based on years of study and observation of natural and altered shoreline (personal communication, Marcia Berman). These estimates of likelihood of conversion from natural shoreline to shoreline structure will be based on human understanding of the system rather than purely econometric analysis. For simplicity in future discussion, the first set of FIS based on regression and conventional
knowledge will be referred to as ‘FLPred 1’ and the second set of FIS based on conventional knowledge will be referred to as ‘FLPred 2’.

The data sets for FLPred 1 and FLPred 2 were developed from the acre parcel database for the GIS coverage containing all information about the parcels. Parcels and their associated data were selected so that they were allowed to change, were on the shoreline, contained no shoreline structure, and had complete shoreline condition information. The FIS analyses used the same 450 acre parcel data set that was used for the logistic regression, preserving the integrity of comparison among prediction methodologies. The one difference between the data sets was the use of adjacent bulkhead, adjacent groin, and adjacent structure as inputs to the FIS. This data was added to the GIS coverage of acre parcels using an AML program (Appendix 6: struc_sum.aml). Essentially, the program examined the 8 surrounding parcels and recorded the presence of any structure, bulkhead, and groin. This data was added to the FIS process is because conventional knowledge of the shoreline system places importance on relationships with condition of adjacent parcels.

The first FIS constructed in the FLPred 1 framework was a system describing likelihood of installation of bulkhead (Appendix 7: bulkhead.fis). The inputs to the system were the regression score for bulkhead, the 2025 land use, and the presence of adjacent bulkhead. The land use was seen as a driving factor in installing bulkhead, since it is extremely rare to find shoreline structure on ‘undeveloped’ or ‘agricultural’ parcels and bulkhead is commonly found on the shoreline of ‘developed’ and ‘residential’ parcels. Observations of placement of bulkhead indicate that proximity to a bulkheaded
parcel increase the likelihood of bulkhead installation. These inputs were modeled with likelihood of bulkhead as the output and defined by the following rules:

**Rule 1.** If bulkhead regression score is 'bulkhead likely' and land use is the not 'not conducive', then bulkhead is 'likely'.

**Rule 2.** If land use is 'conducive', then bulkhead is 'likely'.

**Rule 3.** If land use is 'not conducive' and adjacent bulkhead is 'present', then bulkhead is 'not likely'.

**Rule 4.** If land use is not 'not conducive' and adjacent bulkhead is 'present', then bulkhead is 'likely'.

**Rule 5.** If land use is 'not conducive' and adjacent bulkhead is 'not present', then bulkhead is 'not likely'.

FIGURE 9: BULKHEAD.FIS DECISION RULES

The awkward phrasing of some rules (i.e. not 'not conducive') indicates the use of the area over the curve in the rule, rather than the area under the curve.

The second FIS in the FLPred 1 set of systems allows the ranking of acre parcels for likelihood of conversion from natural shoreline to riprap (Appendix 8: riprap.fis).

The inputs to the system were the riprap regression score, land use from the 2025 prediction, and presence of adjacent structure. Adjacent structure was used in this model because riprap is commonly found next to all other types of engineered bank stabilization, not just riprap. In addition, riprap is most commonly found next to adjacent structure rather than in individual regions of shoreline structure. As with bulkhead, 'undeveloped' and 'agricultural' land rarely had riprap and the shoreline land uses of 'residential' and 'developed' commonly had riprap on the shoreline. The inputs were modeled with likelihood of installation of riprap as the output according to the following rules:
The third FIS in the FLPred 1 system described acre parcel likelihood of installing groin in place of natural shoreline (Appendix 9: groin.fis). The inputs used in constructing this FIS were the groin regression score, land use 2025, adjacent groin, and total number of surrounding parcels. Adjacent groin was used in this model because, most often, groins are found in groin fields as opposed to individual groins. This indicates that installation of a groin is likely to be in close proximity to another groin. Groins are often found on more linear shoreline or shoreline that is more exposed. Since shoreline exposure is not currently a descriptor of shoreline condition, this attribute is calculated by proxy of the number of total surrounding parcels. The most surrounding parcels that one parcel can have is 8, and the lowest that occurs in the study area is 3. The number of parcels that best describes the linearity and exposure of the shoreline most conducive to groin installation is 5 or 6 surrounding parcels. As with bulkhead and riprap, groins are almost never used to protect shoreline whose land use is ‘residential’ or ‘agricultural’ but are commonly used to protect ‘residential’ and ‘developed’ lands. These inputs were modeled with likelihood of groin installation as the output using the following rules:

**Rule 1.** If the riprap regression score is ‘riprap likely’ and land use is not ‘not conducive’, then riprap is ‘likely’.

**Rule 2.** If land use is ‘conducive’, then riprap is ‘likely’.

**Rule 3.** If land use is ‘not conducive’ and adjacent structure is ‘present’, then riprap is ‘not likely’.

**Rule 4.** If land use is not ‘not conducive’ and adjacent structure is ‘present’, then riprap is likely.

**Rule 5.** If land use is ‘not conducive’ and adjacent structure is ‘not present’, then riprap is ‘not likely’.

**Figure 10: Riprap.fis decision rules**
Rule 1. If groin regression score is 'groin likely' and land use is not 'not conducive', then groin is 'likely'.

Rule 2. If land use is 'conducive', then groin is 'likely'.

Rule 3. If land use is 'not conducive' and adjacent groin is 'present', then groin is 'not likely'.

Rule 4. If land use is not 'not conducive' and adjacent groin is 'present', then groin is 'likely'.

Rule 5. If land use is 'not conducive' and adjacent groin is 'not present' then groin is 'not likely'.

Rule 6. If number of surrounding parcels is 'likely' and land use is not 'not conducive', then groin is 'likely'.

The first FIS of the FLPred 2 system evaluated the likelihood of a parcel's shoreline changing from natural shoreline to bulkhead, based on land use and shoreline conditions only (Appendix 10: bulkhead2.fis). The FLPred 2 system did not use the logistic regression scores. The inputs to the system for evaluation of bulkhead suitability were land use for the parcel based on the 2025 prediction, presence of adjacent bulkhead, bank height, and erosion. The basis for using the first two inputs was discussed above. Bank height was used in this analysis because it is likely that a shoreline with a low bank height (0-5 ft.) is suitable to undergo installation of a bulkhead, whereas a shoreline with a high bank height (5-10 ft.) may be better protected with an alternate form of shoreline stabilization. Erosion in the shoreline inventory was categorized as either high or low. Any presence of erosion would cause some degree of suitability for stabilization with bulkhead, but, if erosion is high, there is a greater chance of bulkhead. Low erosion is also a condition that can be addressed with bulkhead, so erosion was modeled such that low and high erosion increased the chances of bulkhead. As with the first analysis concerning bulkhead, these inputs were modeled so that the output was a suitability value for each acre parcel that indicated the likelihood of installation of bulkhead on the shoreline. The inputs were coordinated with the outputs according to the following rules:
Rule 1. If land use is ‘conducive’ and adjacent bulkhead is ‘present’, then bulkhead is ‘likely’.

Rule 2. If land use is ‘not conducive’ or bank height is ‘high’, then bulkhead is ‘not likely’.

Rule 3. If bank height is ‘low’ and erosion is ‘high or low’, then bulkhead is ‘likely’.

Figure 12: Bulkhead2.fis Decision Rules

In rule three, the state of erosion can be high or low and still return a value as an output for the rule. If erosion is high, the value of the output will be larger than if erosion is low.

The second FIS of the FLPred 2 system evaluated the likelihood of conversion from natural shoreline to riprap of acre parcels based on land use and shoreline condition (Appendix 11: riprap2.fis). The inputs to the system to evaluate suitability for riprap were land use of the parcel, presence of adjacent structure, and erosion. Erosion was considered in this model because it is a major consideration in the installation of riprap. It was modeled in this FIS in the same way discussed in the bulkhead2.fis above. The inputs were modeled with likelihood installation of riprap as the outcome according to the following rules:

Rule 1. If land use is ‘conducive’ and adjacent structure is ‘present’, then riprap is ‘likely’

Rule 2. If land use is ‘not conducive’ then riprap is ‘not likely’.

Rule 3. If land use is ‘conducive’ and erosion is ‘high’ or ‘low’ then riprap is ‘likely’.

Figure 13: Riprap2.fis Decision Rules

The third and final FIS in FLPred 2 evaluated the likelihood of conversion from natural shoreline to groin of each acre parcel in the data set, based on land use and shoreline condition (Appendix 12: groin2.fis). The inputs to the system were land use of the parcel, adjacent groin, number of surrounding parcels, and erosion. The first three inputs were modeled in a similar manner as in the FIS that included logistic prediction,
and the final input, erosion, was modeled in this system the same way as in the other two FIS in the FLPred 2 system. The system was modeled according to the following rules:

| Rule 1. | If land use is ‘conducive’ and erosion is ‘high’ or ‘low’, then groin is ‘likely’. |
| Rule 2. | If number of surrounding parcels is ‘5 or 6’ and land use is ‘conducive’, then groin is ‘likely’. |
| Rule 3. | If land use is not ‘not conducive’ and adjacent groin is ‘present’, then groin is ‘likely’. |
| Rule 4. | If land use is ‘not conducive’, then groin is ‘not likely’. |

Each set of rules defined each system such that, as the inputs to the system changed, the outputs behaved appropriately. Calibration of the models was achieved by investigating the effects of inputs on the output for each model and adjusting the model parameters so that each variable had the desired impact on the output. The final calculations of truth values, values from 0 to 1 indicating likelihood of each structure type based on each model, were accomplished by linking input values from the data set to the input variables in the model and running each model. The result was a set of truth values that correspond to each acre parcel that represents likelihood of installation of a particular structure for each FIS.

The truth values were then used to investigate scenarios of 5%, 10%, and 20% additional structure applied in proportion to existing structure, using the same methodology as the logistic prediction. The likelihood of change results associated with FLPred 1 were used to rank each type of shoreline structure and increases in structure were assigned in the order of current prevalence: bulkhead, riprap, and groin. The results from analysis of the FLPred 2 were used to assign increases in shoreline structure in the same manner. These results were then incorporated back into the GIS data set for analysis and map display.
Prediction Comparison

Comparison of the three shoreline structure prediction methods was undertaken by examining the overlap of the top 100 ranked acre parcels using each prediction method. The top 100 parcels were chosen so that the predictions could be examined with relation to location in the ranking and amount of overlap. In essence, this comparison indicates whether the prediction models are forecasting change in the same locations. To compare the top ranked 100 parcels by each structure type and prediction method, all prediction scores for bulkhead, riprap and groin were pulled into individual databases. The prediction scores were then coded 1 through 10 in the order in which it would change. The first ten changing parcels were coded with a ‘1’, the second 10 were coded with a ‘2’, and so on. This ranking method was used so that comparisons could be made across the prediction methods, and the rank number can be used as an indicator of its position in the top 100 likely to change parcels. Each prediction method’s top 100 was compared with the other two prediction methods, and the predictions were analyzed for overlap and location in the top 100 parcels.

Storm Surge Risk Categories

To incorporate the elevation data into the acre parcel data, the contour lines generated for the elevation model were converted to a polygon data set. The polygon data set was then joined with the acre parcel data so that the elevation that covered the largest area within an acre parcel was coded to the entire acre parcel. This process was accomplished using an AML program (Appendix 13: elev_maj.txt) that generated a new item (majority elevation), calculated which elevation covered the largest area of the parcel, and joined it to the acre parcel coverage.
The storm surge risk categories were established using the Saffir-Simpson Hurricane Scale (Iman, et al., 2002) estimates of storm surge for Category One through Category Five hurricanes. The estimated storm surge for a Category One hurricane is 4-5 feet above normal, and Category Two hurricanes are usually accompanied by 6-8 feet of surge. Since the elevation model is categorized into elevations 1 ft. through 5 ft. and above 5 ft., the two categories or storm surge risk for this area are ‘high risk’ and ‘moderate risk’.

RESULTS

Land Use Prediction

Land use trends for ‘undeveloped’ and ‘residential’ acre parcels in Guinea Neck follow a linear trend. The overall trends for ‘agricultural’ and ‘developed’ parcels are better fit with a polynomial equation. In figure 16, the 2002 time step depicts an important point where ‘agricultural’ land use is surpassed by ‘residential’ land use in total acres. It also indicates no substantial acceleration or deceleration in overall land use conversion in the last 60 years; this is especially true for ‘undeveloped’ and ‘residential’. If the conversion of land use continues at this proportion, ‘residential’ acre parcels will approach surpassing ‘undeveloped’ acre parcels in the 2025 time step.
Examination of historic trends in specific conversions of land use was necessary to make a reasonable estimate of demand for land use and a prediction of future land use. Linear regression was appropriate for this analysis because percent change of land use over time was consistently linear in the large categories of land use change. Categories that represent smaller amounts of land use change had some variability not fully represented by linear regression, but, overall, the relationships were no better represented by higher order equations. Land use conversions that fluctuated somewhat and represented a small percent change were estimated linearly in order to elucidate the general trend over time, rather than period-to-period fluctuations. This method of estimation was proven to be appropriate in the results of the linear prediction, which did not account for the total number of parcels. Using individual linear predictions of change to determine number of parcels converted, the prediction accounted for land use of 7460 of 7461 parcels. Conversion of each land use to every possible land use was considered, and the linear regression was converted to percent change in order to integrate demand.
for land use change into the 2025 prediction. Percent change in land use between the
time steps is represented in Figure 17.

<table>
<thead>
<tr>
<th>change in parcels</th>
<th># in 37-59</th>
<th>% in 37-59</th>
<th># in 59-82</th>
<th>% in 59-82</th>
<th># in 82-02</th>
<th>% in 82-02</th>
</tr>
</thead>
<tbody>
<tr>
<td>undeveloped to undeveloped</td>
<td>4841</td>
<td>91.46%</td>
<td>4396</td>
<td>90.81%</td>
<td>3875</td>
<td>88.15%</td>
</tr>
<tr>
<td>undeveloped to agriculture</td>
<td>363</td>
<td>6.86%</td>
<td>132</td>
<td>2.73%</td>
<td>229</td>
<td>5.21%</td>
</tr>
<tr>
<td>undeveloped to residential</td>
<td>88</td>
<td>1.66%</td>
<td>303</td>
<td>6.28%</td>
<td>287</td>
<td>6.53%</td>
</tr>
<tr>
<td>undeveloped to developed</td>
<td>1</td>
<td>0.02%</td>
<td>10</td>
<td>0.21%</td>
<td>5</td>
<td>0.11%</td>
</tr>
<tr>
<td>agriculture to agriculture</td>
<td>1745</td>
<td>84.50%</td>
<td>1608</td>
<td>76.28%</td>
<td>1354</td>
<td>77.82%</td>
</tr>
<tr>
<td>agriculture to residential</td>
<td>320</td>
<td>15.50%</td>
<td>475</td>
<td>22.53%</td>
<td>376</td>
<td>21.61%</td>
</tr>
<tr>
<td>agriculture to developed</td>
<td>0</td>
<td>0.00%</td>
<td>25</td>
<td>1.19%</td>
<td>10</td>
<td>0.57%</td>
</tr>
<tr>
<td>residential to residential</td>
<td>103</td>
<td>100.00%</td>
<td>505</td>
<td>98.83%</td>
<td>1259</td>
<td>98.13%</td>
</tr>
<tr>
<td>residential to developed</td>
<td>0</td>
<td>0.00%</td>
<td>6</td>
<td>1.17%</td>
<td>24</td>
<td>1.87%</td>
</tr>
<tr>
<td>developed to developed</td>
<td>0</td>
<td>0.00%</td>
<td>1</td>
<td>100.00%</td>
<td>42</td>
<td>100.00%</td>
</tr>
</tbody>
</table>

TABLE 2: PERCENT LAND USE CHANGE BETWEEN TIME STEPS BY CATEGORIES OF LAND USE

The demand for land use change, as determined by linear regression, was
calculated as a linear estimate and converted to percent change. The percentage change
was then used in the allocation procedure to calculate the number of acre parcels
undergoing each type of land use conversion in the 2025. Both the linear estimate and
percent change for the 2002 to 2025 time step are shown in Figure 18.

<table>
<thead>
<tr>
<th>2002-2025</th>
<th># parcel change</th>
<th>% parcel change</th>
</tr>
</thead>
<tbody>
<tr>
<td>undeveloped to undeveloped</td>
<td>3385</td>
<td>86.22%</td>
</tr>
<tr>
<td>undeveloped to agriculture</td>
<td>97</td>
<td>2.46%</td>
</tr>
<tr>
<td>undeveloped to residential</td>
<td>435</td>
<td>11.07%</td>
</tr>
<tr>
<td>undeveloped to developed</td>
<td>10</td>
<td>0.25%</td>
</tr>
<tr>
<td>agriculture to agriculture</td>
<td>1172</td>
<td>71.10%</td>
</tr>
<tr>
<td>agriculture to residential</td>
<td>454</td>
<td>27.51%</td>
</tr>
<tr>
<td>agriculture to developed</td>
<td>23</td>
<td>1.39%</td>
</tr>
<tr>
<td>residential to residential</td>
<td>1794</td>
<td>98.12%</td>
</tr>
<tr>
<td>residential to developed</td>
<td>34</td>
<td>1.88%</td>
</tr>
<tr>
<td>developed to developed</td>
<td>56</td>
<td>100.00%</td>
</tr>
</tbody>
</table>

TABLE 3: PREDICTED LAND USE CHANGE FOR THE 2002-2025 TIME STEP, USING LINEAR REGRESSION

The allocation procedure used a logistic regression analysis to assess the
likelihood of specific acre parcels to a land conversion. A separate regression equation
was used to assess the likelihood of conversion of each parcel in each land use type.
Detailed information about the logistic regression equations can be found in Appendix 14.

For ‘undeveloped’ acre parcels, the significant variables in the regression equation were all types of surrounding land use and distance to shoreline (Equation 1). The regression equation had a ROC value of 0.952, where 1 is a perfect fit and 0.5 is the possible fit due to chance.

\[ \text{Equation 1} \]
\[
\log \left( \frac{P_i}{1-P_i} \right) = -1.259 + 0.001 B_{shldist,i} - 0.420 B_{#ag,i} - 0.487 B_{#dev,i} + 0.575 B_{#undev,i} - 0.398 B_{#resid,i}
\]

where \( shldist \) is distance from shoreline, \( #ag \) is the number of surrounding parcels of agriculture, \( #dev \) is the number of surrounding parcels of developed land, \( #undev \) is the number of surrounding parcels of undeveloped land, and \( #resid \) is the number of surrounding parcels of residential land for a given parcel, \( i \).

The regression equation for ‘agricultural’ parcels found only the number of surrounding parcels of ‘agricultural’ and ‘undeveloped’ lands to be significant (Equation 2). Because there are only two significant variables, it may be more difficult to target the ‘agricultural’ parcels that are likely to undergo change. Fortunately, only a small amount of ‘undeveloped’ land is converted to ‘agricultural’ land, so this lack of significant variables will not affect the model to a great degree. The ROC value for this analysis was 0.955, indicating a good fit of the regression equation to the data.

\[ \text{Equation 2} \]
\[
\log \left( \frac{P_i}{1-P_i} \right) = -3.721 + 1.043 B_{#ag,i} - 0.045 B_{#undev,i}
\]

For ‘residential’ acre parcels, the regression equation indicated significance for all variables except the distance to roads (equation 3). Significance of several variables in this equation and the equation for ‘undeveloped’ will help to pinpoint the likely location.
of change with greater accuracy. This equation was also a good fit to the model with a ROC value of 0.983.

Equation 3
\[
\log\left(\frac{P_i}{1-P_i}\right) = 0.780 + 0.001B_{shdist, i} - 0.523B_{ag, i} - 0.635B_{#dev, i} + 0.447B_{undeV, i} - 0.518B_{#resid, i}
\]

The regression analysis for ‘developed’ acre parcels found only the number of ‘developed’ surrounding parcels as significant (Equation 4). The lack of significant variables in this analysis is likely caused by the small number of developed parcels (81 in the 2002 data set) in comparison to the total number of parcels in the data set (7461). In further analyses of land conversion in subsequent sections, this regression equation and its lack of significant variables causes possible difficulty with indicating the location of change to ‘developed’. Though the regression had few significant variables, the ROC value was 0.997.

Equation 4
\[
\log\left(\frac{P_i}{1-P_i}\right) = -6.441 + 2.127B_{#dev, i}
\]

These regression equations were used to score each parcel according to its likelihood of conversion, and these values were used to predict 2025 land use conditions as well as the alternate scenarios. The combination of the linear percent change estimates and the data from the 2002 time step were used to calculate the number of parcels that were converted to form the 2025 prediction. The number of acre parcels changed between 2002 and 2025 is shown below in Figure 19.
The land conversion that impacts the greatest amount of land is the conversion to ‘residential’. In the forecast, 11.07% of ‘undeveloped’ acre parcels and 27.51% of ‘agricultural’ parcels are converted to ‘residential’ that translates to 486 converted acre parcels. A far second in land conversion percentage is the change from ‘undeveloped’ to ‘agriculture’ with a 2.46% change, resulting in 95 converted parcels. The third largest conversion is to ‘developed’ with 32 parcels changing, but it is clear that the largest source of land use demand in the study area is ‘residential’ development. The breakdown of land use change over time and in the 2025 prediction can be represented as a percentage of land in each land use category (Figure 16).

<table>
<thead>
<tr>
<th>Conversion Type</th>
<th># Parcel Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>undeveloped to undeveloped</td>
<td>3341</td>
</tr>
<tr>
<td>undeveloped to agriculture</td>
<td>95</td>
</tr>
<tr>
<td>undeveloped to residential</td>
<td>429</td>
</tr>
<tr>
<td>undeveloped to developed</td>
<td>10</td>
</tr>
<tr>
<td>agriculture to agriculture</td>
<td>1126</td>
</tr>
<tr>
<td>agriculture to residential</td>
<td>435</td>
</tr>
<tr>
<td>agriculture to developed</td>
<td>22</td>
</tr>
<tr>
<td>residential to residential</td>
<td>1886</td>
</tr>
<tr>
<td>residential to developed</td>
<td>36</td>
</tr>
<tr>
<td>developed to developed</td>
<td>81</td>
</tr>
</tbody>
</table>

**Table 4: Predicted Amount of Land Use Conversion in the 2002-2005 Time Step, Using Linear and Logistic Regression**
In order to look at the trends in land use change over time and the impact of allocation on the 2025 land use prediction, visual representation of the data sets for each time step is necessary. GIS representation of 1937, 1959, 1982, 2002, and 2025 data sets can be found in Figure 20 through 24, where green indicates ‘undeveloped’, orange indicates ‘agricultural’, blue indicates ‘residential’, and red indicates ‘developed’.
Figure 18: 1959 Land Use for Guinea Neck

Figure 19: 1982 Land Use for Guinea Neck
In 1937, the clearly dominant land use is agriculture. The 1959 time step also shows a dominance of 'agricultural' parcels, but its domination of the landscape begins to diminish in 1982 and continues through 2002. 'Residential' development in 1937 is sparse, but increases in 'residential' acre parcels in subsequent time steps tend to cluster...
around major roads and shoreline. ‘Developed’ parcels are virtually nonexistent in the first two time steps, but begin to emerge in 1982 and 2002. Primarily this development occurs in the center of the study area and on the shoreline. The reason change to ‘developed’ areas on the shoreline is that the commercial interests represented in this area are primarily water related, such as marinas and fish packing houses. The 2025 prediction shows increases in ‘residential’ acre parcels adjacent to other ‘residential’ parcels and at the interface of ‘agricultural’ and ‘undeveloped’ lands.

In 1937, the majority of the shoreline parcels that are disturbed (not ‘undeveloped’) are ‘agricultural’, and this trend persists through the 1959 time step. ‘Residential’ development begins to take over by the 1982 time step and is clearly dominant in the 2002 time step. In examining only the shoreline parcels that were allowed to change and had complete shoreline condition information, only 42 acre parcels that were ‘undeveloped’ in the 2002 time step (92 acre parcels) remained ‘undeveloped’ in the 2025 time step. The majority of the conversion was to ‘residential’ (22). Six of these acre parcels were converted to ‘agriculture’ and 2 were converted to ‘developed’. ‘Agricultural’ shoreline acre parcels also experienced heavy conversion to residential (47 of 97), and only 48 remained ‘agricultural’. The remaining 2 were converted to ‘developed’. Not surprisingly, 516 out of 520 ‘residential’ parcels remained ‘residential’, and 4 were converted to ‘developed’. It is clear in the analysis of trends within time steps and in the prediction that ‘residential’ development has dominated the land use of the shoreline.
Alternate Future Land Use Scenarios

In order to assess the likely range of future land use change and the trends that are revealed with accelerated change of one type of land use, alternate prediction scenarios were developed. All scenarios used the 2025 prediction as the base. Alternate scenarios and percentage change over the 2025 prediction is summarized in Figure 25.

<table>
<thead>
<tr>
<th></th>
<th>change in 'residential'</th>
<th>change in 'developed'</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alternate Scenario 1</td>
<td>10.00%</td>
<td>5.00%</td>
</tr>
<tr>
<td>Alternate Scenario 2</td>
<td>20.00%</td>
<td>10.00%</td>
</tr>
<tr>
<td>Alternate Scenario 3</td>
<td>30.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>Alternate Scenario 4</td>
<td>0.00%</td>
<td>30.00%</td>
</tr>
<tr>
<td>Alternate Scenario 5</td>
<td>-10.00%</td>
<td>0.00%</td>
</tr>
</tbody>
</table>

Table 5: Alternate Land Use Change Scenarios, Percentages Added to or Subtracted From 2025 Prediction

Alternate scenario 1 investigated the effects of a 10% increase in residential areas and a 5% increase in developed areas, and alternate scenario 2 considers a 20% increase in residential areas and a 10% increase in developed areas. While change to residential areas has been relatively steady across the time steps, an increase of residential areas over the prediction is entirely possible, given the rate of population growth in Gloucester County and the uncertainty associated with predicting future condition. For instance, there is currently a $2.00 toll to cross the Coleman Bridge, which connects the more developed areas of Hampton Roads with Gloucester County. If this toll were removed, there would likely be a significant increase in immigration to Gloucester County. Since Guinea Neck is one of the regions nearest the bridge, homebuyers interested in proximity to Hampton Roads would probably consider purchasing or building in Guinea Neck.

Developed areas nearly doubled from 1982 to 2002, and this could indicate acceleration in the rate of conversion to developed areas that would project future development over the original prediction estimate. A 5% or 10% increase in developed areas is certainly
possible, especially if increases in residential development create a need for developed infrastructure to support the growing population.

In examining a 10 to 20% increase in residential areas combined with a 5 to 10% increase in developed areas, the conversion of land from ‘undeveloped’ in 2002 to ‘residential’ or ‘developed’ in 2025 increases significantly. In alternate scenario 1, the percent conversion from ‘undeveloped’ to ‘residential’ is 13.94%, up from 11.07% in the 2025 prediction. In both alternate scenario 1 and 2, every percentage change value is affected, and the differences are represented in Figures 26, 27, and 28. For simplicity, the 2025 prediction is labeled ‘2025’, the 10% increase in ‘residential’ with the 5% increase in ‘developed’ is labeled ‘10r/5d’, and the 20% increase in ‘residential’ with the 10% increase in ‘developed’ is labeled ‘20r/10d’. Also, in all analyses, green indicates conversion to ‘undeveloped’, orange indicates conversion to ‘agricultural’, blue indicates conversion to ‘residential’, and red indicates conversion to ‘developed’.

**Figure 22: Percent change in ‘undeveloped’ areas under three growth scenarios**
The developed lands do not change as an assumption of the model; 100% of developed lands in 2002 remain developed lands in 2025 by all scenarios. As you can see from the charts, the largest impact of these alternate scenarios is on the existing ‘undeveloped’ and ‘agricultural’ lands. The increase in conversion from ‘agricultural’ to ‘residential’ is particularly noteworthy as conversion to ‘residential’ is increased.
Percentage representation of land conversion in future scenarios must be considered with respect to the total number of parcels available to change in each land category. Also, the number of parcels that changed land uses within each land category helps to put land change into perspective. Below we see the number of parcels available for change in the 2002 data set, 2025 prediction data, and information for number of parcels changing in alternate scenarios 1 and 2 (Figure 29).

<table>
<thead>
<tr>
<th>Observed change 82-02</th>
<th>2002 land use</th>
<th>2025 prediction</th>
<th>alt.scen 1</th>
<th>alt.scen 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>undeveloped to undeveloped</td>
<td>3875</td>
<td>3875</td>
<td>3341</td>
<td>3216</td>
</tr>
<tr>
<td>undeveloped to agriculture</td>
<td>229</td>
<td>95</td>
<td>95</td>
<td>95</td>
</tr>
<tr>
<td>undeveloped to residential</td>
<td>287</td>
<td>429</td>
<td>540</td>
<td>651</td>
</tr>
<tr>
<td>undeveloped to developed</td>
<td>5</td>
<td>10</td>
<td>24</td>
<td>37</td>
</tr>
<tr>
<td>agriculture to agriculture</td>
<td>1354</td>
<td>1583</td>
<td>1126</td>
<td>981</td>
</tr>
<tr>
<td>agriculture to residential</td>
<td>376</td>
<td>435</td>
<td>548</td>
<td>661</td>
</tr>
<tr>
<td>agriculture to developed</td>
<td>10</td>
<td>22</td>
<td>53</td>
<td>85</td>
</tr>
<tr>
<td>residential to residential</td>
<td>1259</td>
<td>1922</td>
<td>1886</td>
<td>1835</td>
</tr>
<tr>
<td>residential to developed</td>
<td>24</td>
<td>36</td>
<td>87</td>
<td>139</td>
</tr>
<tr>
<td>developed to developed</td>
<td>42</td>
<td>81</td>
<td>81</td>
<td>81</td>
</tr>
</tbody>
</table>

Table 6. Comparison of Alternate Scenarios 1 and 2 with Observed Change and 2025 Prediction

The locations of change in scenarios 1 and 2 are dependent on the regression equations associated with each type of land use change. These two scenarios begin to show trends associated with predicted change to residential. In general, conversion to 'residential' lands in occurring at the interface of 'agricultural' lands and 'undeveloped' lands and both land uses are undergoing conversion (Figure 30 and 31), though agricultural lands are more impacted than undeveloped lands. The increase of 'residential' and 'developed' concurrently is important to investigate overlap in suitability for change to these particular land uses. In comparing the areas of new residential development with the new developed areas, no similar trends seem to emerge.

Conversion to developed areas is somewhat scattered across the landscape, with the exception of a few areas of clustered development (Figure 30 and 31). This could be due
to the lack of significant variables in the regression equation to predict the location of conversion to 'developed'. A contributing factor to the lack of significant variables could be the low number of 'developed' parcels in the study area in comparison to the data set as a whole.

**Figure 25: Land use in alternate scenario 1**

**Figure 26: Land use in alternate scenario 2**
Alternate Scenarios 3 and 4 examine a 30% increase in residential areas and a 30% increase in developed areas, respectively, over the original 2025 prediction. An increase of 30% of either type of land use over the 2025 prediction is possible but unlikely. The purpose of investigating these scenarios was to look at the general trends associated with large amounts conversion into one type of land use. Holding all other land conversion categories constant and affecting only the target land conversion category allows investigation of the location and impacts of future conversion to this target land category.

Alternate scenario 3, with a 30% increase in conversion to residential acre parcels affected ‘undeveloped’ and ‘agricultural’ acre parcels. The reason for this is that no other land use categories were allowed to change to residential, based on the lack of evidence that developed parcels revert to residential parcels. With a 30% increase in residential acre parcel allocated based on linear regression trends, percentage change from ‘undeveloped’ to ‘residential’ increased from the 2025 estimate of 11.07% to 19.68%, and percentage change from ‘agricultural’ to ‘residential’ increased from 27.51% to 48.90%. These percentage changes resulted in conversion of an additional 334 acre parcels of ‘undeveloped’ over the original 429 acre parcel change prediction and conversion of an additional 339 acre parcels of ‘agricultural’ over the original 435 acre parcel change prediction. As we began to see in alternate scenarios 1 and 2, the location of this increase in change is occurring in acre parcels at the interface of ‘undeveloped’ and ‘agricultural’ lands. The resulting map shows ‘residential’ areas almost as a buffer between ‘undeveloped’ and ‘agricultural’, and this land use conversion corresponds with
the significant variables in the logistic regression equation used to predict location of conversion (Figure 32).

Alternate scenario 4, a 30% increase of conversion to ‘developed’ parcels, affected all other land use categories, as all other land uses are allowed to change to developed within the constraints of the model. Given the trends of land use change in Guinea Neck, a 30% increase in ‘developed’ lands above the prediction is possible but unlikely. This analysis attempts to show the primary locations of development in the event of large amounts of conversion to ‘developed’ land. The 30% increase was allocated among ‘undeveloped’, ‘agricultural’, and ‘residential’ acre parcels so that the conversion of ‘undeveloped’ to ‘developed’ increased from 0.61% to 2.38%, the conversion of ‘agricultural’ to ‘developed’ increased from 1.39% to 13.24%, and the conversion of ‘residential’ to ‘developed’ increased from 1.88% to 17.90%. The resulting increase in conversion of ‘undeveloped’ acre parcels was 82 additional parcels converted in addition to the original 2025 prediction of 10 acre parcels converted.
‘Agricultural’ parcels underwent an additional conversion of 88 parcels in addition to the 22 parcels converted for the 2025 prediction, and ‘residential’ parcels experienced an increase of 310 parcels over the original 34 parcels converted. The allocation trends associated with alternate scenario 4 were not as distinctive as those represented in the 30% increase in ‘residential’ conversion. The corridor along the major road and areas with large amounts of ‘residential’ acre parcels experienced a large amount of conversion to ‘developed’. However, the patterns of location of change were quite dispersed into areas where no prior development had taken place (Figure 33). As noted in alternate scenarios 1 and 2, the likely reason for this is the lack of significant variables in the logistic regression equation describing conversion to ‘developed’ and the low number of ‘developed’ parcels in the data set.

Alternate scenario 5 investigated the effects of a 10% reduction in conversion to ‘residential’. This scenario is a possible but not likely. As discussed earlier, the 2025 prediction is possibly an underestimate of future land use condition due to the rate of
growth in Gloucester County, and it is not likely that this growth will slow down.

Because prediction of future condition can be influenced by unforeseen influences in the actual future condition, it is possible that an outside influence would slow the growth of residential development in Guinea Neck. Possibilities would be an increase in the price of the toll to cross the Coleman Bridge or a change in zoning ordinances limiting residential development. The analysis of a 10% reduction in conversion to ‘residential’ acre parcels affected the conversion percentages of ‘undeveloped’ and ‘agricultural’ acre parcels and the number of parcels converted to ‘residential’ as shown in Figure 34.

<table>
<thead>
<tr>
<th>Land Use Conversion</th>
<th>2002 Land Use</th>
<th>2025 Prediction, # Parcels</th>
<th>Alt. Scenario 5, # Parcels</th>
<th>2025 Prediction, % Parcels</th>
<th>Alt Scenario 5, % Parcels</th>
</tr>
</thead>
<tbody>
<tr>
<td>undeveloped to undeveloped</td>
<td>3875</td>
<td>3341</td>
<td>3452</td>
<td>86.22%</td>
<td>89.09%</td>
</tr>
<tr>
<td>undeveloped to agriculture</td>
<td>95</td>
<td>95</td>
<td>2.46%</td>
<td>2.46%</td>
<td></td>
</tr>
<tr>
<td>undeveloped to residential</td>
<td>429</td>
<td>318</td>
<td>11.07%</td>
<td>8.20%</td>
<td></td>
</tr>
<tr>
<td>undeveloped to developed</td>
<td>10</td>
<td>10</td>
<td>0.25%</td>
<td>0.25%</td>
<td></td>
</tr>
<tr>
<td>agriculture to agriculture</td>
<td>1583</td>
<td>1126</td>
<td>1242</td>
<td>71.10%</td>
<td>78.43%</td>
</tr>
<tr>
<td>agriculture to residential</td>
<td>435</td>
<td>319</td>
<td>27.51%</td>
<td>20.18%</td>
<td></td>
</tr>
<tr>
<td>agriculture to developed</td>
<td>22</td>
<td>22</td>
<td>1.39%</td>
<td>1.39%</td>
<td></td>
</tr>
<tr>
<td>residential to residential</td>
<td>1922</td>
<td>1886</td>
<td>1886</td>
<td>98.12%</td>
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<td>residential to developed</td>
<td>36</td>
<td>36</td>
<td>1.88%</td>
<td>1.88%</td>
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</tr>
<tr>
<td>developed to developed</td>
<td>81</td>
<td>81</td>
<td>100.00%</td>
<td>100.00%</td>
<td></td>
</tr>
</tbody>
</table>

TABLE 7: COMPARISON OF 2025 PREDICTION WITH NUMBER AND PERCENT CHANGE IN ALTERNATE SCENARIO 5

As expected, the land use category most impacted by a reduction in conversion to ‘residential’ is ‘agricultural’. The percent conversion dropped from 27.51% in the 2025 prediction to 20.18% in alternate prediction scenario 5 (Figure 34). Since the conversion of agricultural land to residential land is the largest conversion percentage in the prediction and conversion of undeveloped land to residential land is second, these land use types were impacted less by land use change with a 10% decrease in residential development. The general location trends of additional residential development remain true. In alternate scenario 5, the residential development primarily occurs adjacent to residential development and at the interface of ‘agricultural’ and ‘undeveloped’ lands.
Logistic Regression Prediction

In order to examine how land use and shoreline condition affect the location of structure on the shoreline, logistic prediction was used to better understand the relationships. Regression equations were formulated for each structure type: riprap, bulkhead, groin, and breakwater. Each shoreline parcel that was allowed to change, had complete shoreline condition information, and did not have an engineered structure in place was evaluated according to the regression equation which indicated the likelihood of structure being installed. Detailed analysis of logistic regression for structure prediction can be found in Appendix 15.

For riprap, percent of surrounding land use coded ‘residential’, percent of surrounding land use coded ‘developed’, presence of beach, presence of marsh, and presence of erosion were significant in the regression equation (equation 5). The regression equation that resulted from this analysis is as follows:
Equation 5

\[
\log\left(\frac{P_i}{1-P_i}\right) = -3.178 + 0.054B_{\%\text{dev}} - 1.203B_{\text{no\_bch}} - 1.907B_{\text{yes\_marsh}} + 3.578B_{\text{lo\_erosion}}
\]

The regression analysis for bulkhead found percentages of all surrounding land uses and presence of marsh significant, resulting in the following regression equation (equation 6).

Equation 6

\[
\log\left(\frac{P_i}{1-P_i}\right) = 84.604 - 0.870B_{\%\text{ag}} - 0.853B_{\%\text{undevel}} - 0.840B_{\%\text{res}} - 0.757B_{\%\text{dev}} - 2.049B_{\text{yes\_marsh}}
\]

The regression equation for groin included only shoreline condition variables as significant: presence of marsh, presence of beach, and presence of erosion (equation 7).

Equation 7

\[
\log\left(\frac{P_i}{1-P_i}\right) = -2.961 + 3.004B_{\text{lo\_erosion}} - 3.228B_{\text{yes\_marsh}} - 3.759B_{\text{no\_bch}}
\]

The regression for breakwater was not significant, since there was only one shoreline parcel that contained a breakwater. Because of this, breakwaters were not incorporated into the shoreline prediction.

Once the parcels were evaluated with the regression equations, the regression scores were used to rank them according to likelihood of each of the structure types being installed on the shoreline. The scenarios that were investigated were a 5%, 10%, and 20% increase in structure on the shoreline. The allocation methodology for this procedure was in order of prevalence: bulkhead, riprap, and groin. There was some overlap in suitability for each structure on a shoreline. As you might expect, a section of shoreline suitable for bulkhead may also be suitable for riprap or groin. Especially in the 5% and 10% forecasts, the regression equations differentiated among the structure types so that the overlap was not a significant problem in allocation. The 20% forecast of
shoreline structure had quite a bit more overlap due to the large amount of structure allowed by the scenario.

The reasoning behind using a 5%, 10%, and 20% increase in shoreline structure in conjunction with the logistic prediction is both because land use was proved not to be significant in the regression equations and because shoreline land use did not undergo considerable change in type of land use. As noted earlier, the majority of shoreline parcels at the 2002 and 2025 time steps are residential, and it is important to consider how residential land use has likely changed over time with shoreline parcels. As land values increase, lot sizes become smaller and houses become larger. It is likely that the average shoreline lot size in 1959 and 1982 were much larger than those found in 2002 and those that will be found in 2025. Because property owners will have smaller lots of land with more valuable structure, the incentive will be to protect the shoreline to defend this smaller lot. The 5%, 10%, and 20% scenarios show the possible range of shoreline armoring due to these circumstances.

The non-significance of dominant land use of the parcel was surprising in that, logically, the use of the land would be a large indicator of whether the shoreline will be defended. This is probably attributed to the resolution of the data set. Because the unit of analysis is an acre parcel and shoreline structure is often less than a hundred meters, difficulty arises when making inferences about structure on the acre parcel resolution. Because of the non-linear nature of shoreline in the study area, there is no way to standardize for length of shoreline in each acre parcel. In addition, an ‘agricultural’ parcel denotes that the dominant land use is agriculture, but there could be a residence on the parcel that is defended. This would result in the ‘agricultural’ parcel labeled as
having engineered shoreline structure if the length of shoreline defense is greater than 5m. The reason for attributing a parcel with structure only if the length is greater than 5m was to control for individual properties that are split between two acre parcels. If a small amount of structure overlaps into another parcel and the length is less than 5m, the parcel will not be attributed with structure. It was not advantageous to set the limit greater than 5m because in parcels with small lengths of shoreline and multiple sections of code on the shoreline, it is possible that less than 5m of defended shoreline would be attributed as not defended even though the majority of the parcel is defended. A greater limit would eliminate this parcel from being coded with the appropriate structure type. The risk in this case is the chance that a length of shoreline in a parcel of 60m has one section of structure with a length of 5m, and the entire acre parcel will be coded as having structure. To minimize the effects of this possible introduction of error, acre parcels were analyzed for presence or absence of structure rather than length.

The scenario proportions and the number of parcels that underwent change to each type of shoreline structure for each shoreline scenario can be found in Figure 36. Assuming the increase in shoreline structure actually occurs in proportion to current hardening, these estimates forecast the likely amount of change to the shoreline.

<table>
<thead>
<tr>
<th></th>
<th>5% structure scenario</th>
<th>10% structure scenario</th>
<th>20% structure scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td>orig. amt</td>
<td># of parcels</td>
<td># parcels ch</td>
<td># of parcels</td>
</tr>
<tr>
<td>none</td>
<td>450</td>
<td>413</td>
<td>-37</td>
</tr>
<tr>
<td>bulkhead</td>
<td>161</td>
<td>183</td>
<td>22</td>
</tr>
<tr>
<td>groin</td>
<td>19</td>
<td>22</td>
<td>3</td>
</tr>
<tr>
<td>riprap</td>
<td>87</td>
<td>99</td>
<td>12</td>
</tr>
</tbody>
</table>

**Table 8: Shoreline structure scenarios**

Even though the presence of bulkhead or structure was not a consideration in the logistic prediction, in general, acre parcels attributed with bulkhead in the 5% and 10% increase scenarios were near acre parcels that already contained bulkhead or another
structure. The 20% increase tended to allocate bulkhead to more individual parcels. This might be because the regression score of the last parcels converted in the 20% prediction is not as high as those converted first, indicating that bulkhead is not as likely in these parcels.

The regression equation for riprap attributes new parcels of shoreline with riprap in an order that is not concentrated around the location of current riprap or shoreline structure. This regression almost colonizes new areas where engineered shoreline structure may be installed. The growth from 5% to 10% to 20% clusters in these new areas suitable for riprap and have a considerable amount of individual areas of riprap. This seems appropriate since riprap can be installed on most shorelines, but bulkhead and groin installation tends to occur in sections rather than individually.

While current placement of groins along the shoreline occurred on the southern shore of Guinea neck, the logistic prediction estimated that converted parcels in all scenarios would be located in the tributaries. This difference in current and predicted location may be due to the allocation process. Because bulkhead and riprap were converted before groin, some of the parcels more likely to convert to groin may have already been converted to another shoreline structure. Also, because groins tend to occur on relatively linear shoreline on larger bodies of water and are likely to have a source of sediment (sand), the converted parcels would probably not be found in tributaries.

Fuzzy Logic Prediction

Six fuzzy logic inference systems (FIS) were constructed to estimate the likelihood of installation of structure on natural shoreline for three different shoreline types using two different methods of modeling (using logistic regression scores and using
conventional knowledge). Overall one difficulty with modeling using FIS is the enigmatic nature of the implication, aggregation, and fuzzification methods. There is a startling lack of information concerning their description and how they can best be used. The implication method used was the ‘minimum’, which truncates the fuzzy output. Another method of implication is ‘product’, which scales the output so that each rule affects the composite function to the same degree. This method would have been ideal for this analysis in order to give equal weighting to each input to the system. However, this analysis only returned truth values of 1, rather than truth values ranging from 0 to 1. Investigation of ways to use the ‘product’ implication method proved to be fruitless, so the ‘minimum’ function was used instead. Because the ‘minimum’ function does not naturally function to scale the output, membership functions and rules were altered so that the desired output for each FIS allowed all rules to influence the system.

A FIS analyzes the fuzzy output, or the set of numbers associated with the composite function, and defuzzifies it through the defuzzification method. The defuzzification method for these analyses was ‘middle of maximum’, where the truth value returned is the average of the maximum values of the output set. For each acre parcel, one truth value is the output for each inference system. A truth value is the measure of how close to true (or 1) are the conditions in the selected parcel. The end result of analyses with the six FIS are six sets of truth values, indicating how much each parcel fits to the rules that define the FIS. Truth values range from 0 to 1, where 0 is not true and 1 is true.

The first FIS if the FLPred 1 set of inference systems addressed likelihood of bulkhead. The system was set up so that ‘undeveloped’ and ‘agricultural’ parcels had
truth values ranging from 0.075 to 0.15. The range encompasses all variations of adjacent bulkhead and high logistic regression scores. ‘Residential’ and ‘developed’ ranged from 0.86 to 0.99. A ‘residential’ acre parcel with no adjacent bulkhead would have a truth value of 0.86, whereas one with adjacent bulkhead would return a value of 0.94. The top ranked logistic regression scores could boost these truth values to 0.99. For ‘developed’, a truth value of 0.97 was the output regardless of the presence of adjacent bulkhead, and the value could be boosted to 0.99 with a top ranked regression score. In general, developed parcels were bulkheaded first, residential parcels with adjacent bulkhead next, and residential parcels with no adjacent bulkhead following that. The high logistic regression scores had the ability to boost an acre parcel’s truth value over the value that it would have based on land use and adjacent bulkhead alone. The truth values for the FLPred 1 system are shown below in Figure 30.

![Figure 30: Fuzzy Logic Truth Values (FLPred 1) for Predicting Location of Bulkhead, Riprap, and Groin](image)

The FIS built for riprap as part of the FLPred 1 system was constructed using the same system as for bulkhead, although the ranges are slightly different. Truth values for
'undeveloped' and 'agricultural' acre parcels range from 0 to 0.14 with higher values for parcels adjacent to structure. 'Residential' and 'developed' parcels ranged from 0.915 to 0.965 based on land use and adjacent structure alone, but could be boosted up to 0.98 with a high logistic regression value. As for the previous FIS, 'residential' acre parcels adjacent to structure returned a higher truth value than those not adjacent to structure.

The FIS built for groin in the FLPred 1 system was constructed similarly to the other two FIS in the FLPred 1 system, but, since it had an additional input, an additional rule and minor adjustments were necessary. 'Undeveloped' and 'agricultural' acre parcels returned truth values ranging from 0 to 0.09, with consideration for all variations in adjacent groin, logistic regression score, and number of surrounding parcels.

'Residential' and 'developed' acre parcels ranged from 0.85 to 0.96. For both 'residential' and 'developed', the value was boosted for being adjacent to groin, having a high logistic regression score, and having a favorable number of surrounding parcels.

The FLPred 2 system was constructed using the same general goals for output but was slightly different since the variables were different. All variables, with the exception of land use, were binary variables. This works with the membership function system, but does not maximize its potential analysis powers. The distribution of the truth values for the FLPred 2 system are represented below in Figure 31.
The first FIS in the FLPred 2 system addressed bulkhead. ‘Undeveloped’ and ‘agricultural’ acre parcels ranged from 0 to 0.09 under all circumstances of adjacent bulkhead, bank height, and erosion. The ‘residential’ acre parcels ranged from 0.54 to 0.91 with increases in truth value for adjacent bulkhead, low bank height, and high erosion. ‘Developed’ parcels ranged from 0.54 to 1. Larger truth values were assigned to parcels with adjacent bulkhead, low bank height, or high erosion (or any combination of the three).

The FIS for riprap in the FLPred 2 system resulted in a truth value of 0 for ‘undeveloped’ and 0.075 for ‘agricultural’ under all circumstances. ‘Residential’ truth values ranged from 0.76 to 0.9. Higher truth values were assigned to ‘residential’ parcels with adjacent structure or high erosion or both. ‘Developed’ parcels had a range of truth values from 0.825 to 0.975, and larger truth values were assigned to parcels with adjacent structure or high erosion.
The FIS for groin in the FLPred 2 system returned truth values of 0 for 'undeveloped' and 0.075 for 'agricultural' under all circumstances. 'Residential' acre parcels had a range of truth values from 0.76 to 0.9. Increases in truth value were assigned for parcels with the favorable number of surrounding parcels, adjacent groin, and high erosion. Combinations of these conditions resulted in higher truth values also. Truth values for 'developed' acre parcels ranged from 0.81 to 0.975. Larger truth values were assigned to parcels with a favorable number of surrounding parcels, adjacent groin, and high erosion.

As you might expect from the way the models were built, the parcels that were first to change had the highest values for the variables contained within the models. Parcels with favorable land use, high erosion, high regression scores, adjacent structure, favorable number of surrounding parcels were the first to be converted from natural shoreline to structure. In the 5%, 10% and 20% increase in structure forecasts, there was some overlap in suitability of parcels, especially for riprap and bulkhead. In the 5% increase in structure prediction for FLPred 1, the two parcels ranked for riprap were also ranked high for bulkhead, and the two highest ranked groin parcels were ranked for riprap. In this prediction, the small amount of overlap indicates that the model did well at differentiating among the locations most favorable for a particular type of shoreline structure. In the 10% increase in structure prediction, there was considerably more overlap in suitability. Since bulkhead was allocated first, the overlap for riprap was only impacted by bulkhead. Similarly, the groin allocation was impacted by the rankings for both bulkhead and riprap. When allocating riprap for the 10% increase, parcels ranked 3-8 and 18-54 were already occupied by bulkhead. The overlap for groin was less, as the
top two rankings were occupied and 7-21 were occupied. These conditions indicate that
the suitability for groin is most different from the suitability for riprap and bulkhead. The
20% prediction had the most overlap, as you might expect since the number of changing
parcels is the largest. When allocating riprap, parcels ranked 3-16 and 18-89 were
occupied by bulkhead. For groin, the top 3 and parcels ranked 7-38 had already
undergone shoreline structure. Of these predictions, the 5% and 10% increases tend to
show the possible future allocation of structure better than the 20% increase in shoreline
structure due to the amount of overlap in suitability.

When examining the amount of shoreline resources impacted by the structure
predicted in the 5% and 10% shoreline structure scenarios, there is a substantially larger
impact to marsh land when predicting structure with the fuzzy logic methodologies.
Where the logistic prediction takes presence of marsh and beach into account in the
prediction, the impact to marsh is less than a third of selected parcels. The fuzzy logic
method does not directly take into account presence of marsh or beach, and the impact to
marsh exceeds 75% in some cases.

<table>
<thead>
<tr>
<th>Prediction Method</th>
<th>Scenario</th>
<th>% marsh</th>
<th>% beach</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logistic Prediction</td>
<td>5%</td>
<td>27.8%</td>
<td>36.1%</td>
</tr>
<tr>
<td></td>
<td>10%</td>
<td>31.9%</td>
<td>22.2%</td>
</tr>
<tr>
<td>Fuzzy Logic 1</td>
<td>5%</td>
<td>83.3%</td>
<td>22.2%</td>
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<tr>
<td></td>
<td>10%</td>
<td>69.4%</td>
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</tr>
<tr>
<td>Fuzzy Logic 2</td>
<td>5%</td>
<td>75.0%</td>
<td>36.1%</td>
</tr>
<tr>
<td></td>
<td>10%</td>
<td>66.7%</td>
<td>23.6%</td>
</tr>
</tbody>
</table>

**Table 9: Shoreline Resources Impacted by Addition of Shoreline Structure in the 5% and 10% Scenarios for Each Prediction Method**

The increases in shoreline structure for the FLPred 2 system showed more overlap
in suitability than the FLPred 1 system. This is probably because of the number of binary
variables used in the FLPred 2 system. In the 5% prediction, acre parcels ranked in the
top 4 and 9-22 for riprap were already allocated to bulkhead, and acre parcels ranked in the top 27 for groin were already allocated. The 10% prediction allocation of riprap showed overlap in the top 4 ranked parcels, 9-22, and 34-58. The first 28 ranked parcels for groin were already allocated to another shoreline structure. In the 20% increase in structure prediction, the overlap for riprap was the top 5 ranked parcels, 9-22, and 34-100, and the overlap for groin was the top 30 ranked parcels. These predictions again show a difference in suitability for groin installation than for bulkhead and riprap. Similar to the FLPred 1 prediction set, the 5% and 10% predictions show the possible future allocation of shoreline structure with far less overlap than the 20% prediction.

**Modeling Comparison**

In examining the differences between the modeling methods, each prediction method’s top 100 changing parcels were examined for overlap with other prediction top 100 lists and location within the ranking. The models were examined by structure type across each modeling method. For simplicity in referring to the modeling methods, the prediction using logistic regression will be referred to as LogPred, the prediction using fuzzy logic and logistic regression will be referred to as FLPred 1, and the prediction using fuzzy logic with no logistic regression will be referred to as FLPred 2.

The first analysis is similarities and differences in the methods for predicting location of future bulkhead. The first comparison is of the top 100 ranked parcels of LogPred and FLPred 1. The overlapping parcels are categorized in the table below (Figure 37).
The number of overlapping parcels is in the column ‘# overlap’, and the ranking category of the comparison method is across the top. The shaded cells indicate where a direct correlation of overlap would be for ranking category.

There is a 20% overlap between LogPred and FLPred 1, but there is agreement and disagreement as far as placement in the top 100. For instance, the three parcels ranked in category 1 in LogPred are ranked in category 10 in FLPred 1. Though they overlap, their likelihood of being converted from natural shoreline to bulkhead is very different. The overlap for categories 2, 3, and 4 in LogPred are closer associated in the top 100 parcels in FLPred 1. Overall, the overlap of LogPred and FLPred 1 is only 20% and not very closely associated in terms of ranking categories.

The analysis between LogPred and FLPred 2 indicates that there is a 20% overlap, and the location within the top 100 is both polar opposite and fairly closely associated. Figure 38 shows great disparity between ranking category 1 for LogPred and the corresponding ranking category for FLPred 2 (9 and 10). However, the ranking category

<table>
<thead>
<tr>
<th>ranking category in LogPred</th>
<th>FLPred 1</th>
</tr>
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<tbody>
<tr>
<td>1</td>
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<tr>
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<td>3</td>
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<table>
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</tr>
</tbody>
</table>

**Table 10: Comparison of LogPred and FLPred 1 for bulkhead.fis**
for 3, 4, 5, and 9 for LogPred are closely associated with the ranking category for FLPred 2.

<table>
<thead>
<tr>
<th>ranking category in LogPred</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td># overlap</td>
<td>6</td>
<td>3</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>4</td>
<td>3</td>
<td></td>
</tr>
</tbody>
</table>

**Table 11: Comparison of LogPred and FLPred 2 for bulkhead.fis**

The comparison between FLPred 1 and FLPred 2 had a considerably larger overlap at 95%. While there is some disparity between ranking category of the reference method and FLPred 2, generally the ranking categories of FLPred 1 are close to the corresponding ranking category of FLPred 2 (Figure 39).

<table>
<thead>
<tr>
<th>ranking category in FLPred 2</th>
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**Table 12: Comparison of FLPred 1 and FLPred 2 for bulkhead.fis**

The second set of analyses is for the models used to predict suitability for riprap. The same methodology for comparison of methods used for bulkhead was used to compare riprap models.

90
The first comparison is between LogPred and FLPred 1, which had an overlap of 15% of the top 100. This analysis shows almost no similarity between ranking categories of the reference model and FLPred 1 (Figure 40). When this is taken into consideration with the low percentage of overlap, LogPred and FLPred 1 used to predict likelihood of riprap produce very different results.

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**Table 13: Comparison of LogPred and FLPred 1 for riprap.fis**

The comparison between LogPred and FLPred 2 resulted in only a 4% overlap in the top 100 parcels. The location of the parcels within the top 100 is also not similar. In this case, evaluating likelihood of riprap with these two methods produce very different results.

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**Table 14: Comparison of LogPred and FLPred 2 for riprap.fis**

91
Comparison of FLPred 1 and FLPred 2 revealed an 85% overlap in the top 100 and many similarities between reference categories. This analysis indicates that there are several category 1 ranked parcels that receive lower ranking using the FLPred 1 model.

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The third comparison of similarities and differences in modeling results evaluated the models' ability to predict the suitability of a parcel for groin installation. The first comparison is LogPred and FLPred 1. There is only a 6% overlap between the two modeling techniques, and there is little to no similarity in placement in the top 100 list using either model as the reference category.

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The third comparison of similarities and differences in modeling results evaluated the models' ability to predict the suitability of a parcel for groin installation. The first comparison is LogPred and FLPred 1. There is only a 6% overlap between the two modeling techniques, and there is little to no similarity in placement in the top 100 list using either model as the reference category.
Comparing the modeling techniques of LogPred and FLPred 2 produces similarly poor results in overlap and correlation with ranking categories (Figure 44). Here we see a 12% overlap whose parcels do not share the same location in the ranked categories.

In comparing FLPred 1 and FLPred 2 modeling techniques, there is a 92% overlap and strong similarities in ranking categories using either modeling technique as a reference.

In general, the large amount of overlap between FLPred 1 and FLPred 2 indicates that the two prediction models are more similar for prediction of each type of structure. This is due to the way the model was specified. In FLPred 1, the regression score only
took precedence over other variables if the regression score was very high. This was necessary in building the model because other ways of specifying the model resulted in regression score dominating the prediction. While overlap between FLPred 1 and FLPred 2 was large, the top and bottom ranking categories often showed disparities, though many of the categories between 2 and 9 showed correlation between the two ranking categories.

The differences seen in the logistic regression method and the two fuzzy logic methods are likely due to the dissimilarity of the variables used in the prediction. While many of the same variables used in the fuzzy logic prediction were used for the logistic prediction, they were not significant and could not be used in the regression equation.

Another analysis was undertaken to examine the acre parcels that are predicted to undergo structure in all three analyses. In the 5% scenario, 1 of 37 acre parcels underwent using all three prediction methodologies, and 3 of 71 acre parcels changed using all scenarios in the 10% shoreline increase. The 20% shoreline structure increase scenario shows an overlap of 20 out of 143 for all shoreline parcels. The spatial location of shoreline parcels that were found to undergo structure using all three prediction methodologies can be found in Figure 32. Generally these are the areas that underwent the majority of the shoreline structure in shoreline prediction analyses.
Storm Surge Risk Categories

Because of discrepancies between the elevation model and the land use prediction model, 10632 acre parcels of the total 10743 were coded with the appropriate storm surge risk category. The discrepancies arise because the elevation model and the land use/shoreline prediction model were not standardized using the same method. This analysis is based on 10632 acre parcels of data, rather than the full set. The missing data is likely to be in the ‘moderate risk’ category since it is landward instead of near the shoreline. Parcels in the storm surge risk category of ‘high risk’ numbered 5526 and covered 52% of the study area. The remaining 5106 were coded as ‘moderate risk’, as they would likely experience the effects of storm surge during a Category Two hurricane.

The ‘high risk’ areas, especially in the Eastern part of the study area, infiltrate or intertwine with the ‘moderate risk’ areas to a great degree. This may cause increased risk for the property owners who own ‘moderate risk’ property due to flooding of roads leading out to the property or proximity to ‘high risk’ areas (Figure 46: ‘high risk’ = red,
‘moderate risk’ = orange). The owners of ‘moderate risk’ property in the Western side of the study area are in less danger of proximity effects of ‘high risk’ areas and flooding out of roads leading to their property.

**DISCUSSION**

This research is the first attempt at assessing the relationships between land use and shoreline condition and the first attempt at elucidating the future condition of shoreline based on these relationships. While the problem of resolution clouded the relationships between shoreline land use and shoreline condition in the logistic regression, the fuzzy logic methods were able to establish a framework for relating land use change to increases in shoreline structure. The parcels that underwent the most amount of hardening were residential and developed parcels, and much of this development occurred adjacent to currently hardened parcels. The condition of the shoreline was used for prediction of placement of structure in all three analyses, however,
the way the models use the shoreline condition is quite different. In the logistic analyses, regression equations were formulated based on the present condition of shoreline with structure and the present condition of shoreline without structure. It is reasonable to assume that an area of shoreline with a bulkhead is not likely to have a marsh or a beach. The logistic regression "sees" this as a correlation between absence of marsh or beach with suitability for bulkhead, though this may not be the case. For this reason, the fuzzy logic analyses did not use presence or absence of marsh or beach as a correlary to structure. Instead, the fuzzy logic analyses used erosion and adjacent structure as indicators of shoreline condition. This enabled the use of logic and common knowledge in the model as opposed to simply examining the apparent correlations. This is likely why the predicted impact to marshland was so much greater using the fuzzy logic analyses rather than the logistic prediction.

In general, the first parcel to be structured using the logistic regression model was a parcel that is surrounded by 'residential' and 'developed' acre parcels, has no marsh or beach, and has high erosion. In the first fuzzy logic analysis, the parcel with the highest "score" for suitability of structure is a parcel with a high logistic regression score, has adjacent structure, and has a land use that is 'residential' or 'developed'. The second fuzzy logic analysis indicates that the first parcel to change would be one with adjacent structure, 'residential' or 'developed' land use, and presence of erosion. It is important to note that these analyses are all different ways of examining the same data set to establish a prediction of shoreline condition.

For the land use prediction, the logistic regression method was able to differentiate between the likelihood of parcels to change based mostly on adjacent land
use. In this way, the model was able to evaluate the composition of the surrounding land uses and translate the composition into likelihood of change. For example, an agricultural parcel surrounded by ‘agricultural’ parcels would have a much smaller probability of change than an ‘agricultural’ parcel surrounded by ‘residential’ or ‘developed’ parcels.

The largest pattern of development resulting from the land use change analyses is the formation of a “buffer” of ‘residential’ land between ‘agricultural’ and ‘undeveloped’ land. Since the two largest land use conversions were from ‘agricultural’ to ‘residential’ and from ‘undeveloped’ to ‘residential’, it would make sense to find a large amount of change at the intersection of these lands. It also stands to reason that someone interested in building a home would prefer to build adjacent to current residential areas. This homebuilder, based on historic land conversion and the 2025 prediction, seems to prefer to convert ‘agricultural’ land over converting ‘undeveloped’ land. It is perfectly logical that this homebuilder would prefer not to incur the expense of clearing the land, making ‘agricultural’ land adjacent to residential land the easiest to convert. Testing the conclusions of the logistic regression against common knowledge of how conversion occurs, the logit method appears to have captured many of the important characteristics of land change in the prediction model for residential land.

The second most prevalent land use conversion was the conversion to ‘developed’ land. As with the ‘residential’ conversion, much of this conversion was at the expense of ‘undeveloped’ and ‘residential’ land. The logistic prediction for the location of change to ‘developed’ land only had one significant variable, the number of surrounding parcels of developed land. The reason for the lack of significant variables in this equation is largely
due to the small number of ‘developed’ parcels in the data set. In the 2002 data set, only 81 parcels of 7461 parcels were developed, and previous years had even fewer numbers of ‘developed’ parcels. This small data set made it difficult to make accurate conclusions as to the location of change to ‘developed’ land. This is exhibited in the land use prediction and the alternate scenarios by a “dotting” of the landscape with ‘developed’ parcels. While generally this development follows the established network of roads and builds on established areas of development, the model lacks the perspective necessary to make conclusions about the most likely areas for increases in ‘developed’ land.

Scale and resolution issues permeated much of the analyses. It is important to note that land use of the acre parcel was not found to be significant in the logistic regression predicting shoreline condition. Because the way the resolution portrays the shoreline data, the logistic prediction may have lost some of its effectiveness. Since one of the drivers for this research was to see how change in land use affects shoreline condition, it is evident that the expected result was to have land use be significant in the logistic regression predicting suitability for shoreline structure. Because land use was not significant in the logistic regression, it is not surprising that the fuzzy logic predictions (using land use and shoreline conditions) returned different parcel ranks than the logistic regression.

The largest limitation to this research is the lack of consideration of social and economic factors. Examining primarily the physical characteristics of shoreline change with some incorporation of social change only takes into account some of the variables important in the equation for prediction location of future shoreline structure. All the models predict location of engineered bank stabilization based on land use and shoreline
condition factors, but the model does not take into account the largest factor in bank stabilization, human preference. Just because a stretch of shoreline is suitable for structure, the shoreline will not become bulkheaded if the property owners are not interested in stabilizing it. Consideration of risk perception, property value, income, and individual preference are essential to building a better model of likelihood of shoreline structure. This information could be obtained through an analysis using a survey and stated-preference methodology. This methodology serves to investigate the decision-making structure of the individual (Caldas and Black, 1997). Incorporation of social and economic information would also allow for a more complex econometric analysis that looks not just at change but attempts to "explain" why change is occurring (Irwin and Geoghegan, 2001). The largest enhancement of this work would be an investigation of individual decision-making with respect to shoreline structure installation and its impacts at the aggregate level.

The ideal data set for this research would include a full assessment of individual decision-making, small-scale resolution land use data, and access to the currently used shoreline condition information. One important research limitation to keep in mind even given this ideal data set is that aggregation in order to make conclusions is necessary. Using the highest resolution data sets will likely yield extremely detailed results, but, at some level, it is necessary to aggregate this data into a manageable spatial resolution for analysis and conclusions.

Through the process conducting the project, some limitations were brought to light. The major limitations were the resolution of the land use prediction and the lack of
social and economic considerations in the models. Applications of these models in the future would benefit from addressing these issues.

The resolution of the land use prediction was an issue that not only affected the land use prediction, but also affected the shoreline structure likelihood analyses. In particular, the resolution effects on the logistic prediction were damaging to the prediction ability of the model. The problem with the resolution was the size of the parcels or the unit of analysis. The project would have benefited from a smaller unit of analysis. Ideally, this unit of analysis would be the property owner tax map information. However, constructing a GIS database of historic land use change at the ownership parcel level would be quite an arduous process. In order to construct a historical model of land use change based on parcel specific changes, all paper documents indicating sale of property would have to be digitized for the last 60 years. This information is not available digitally, except for current property boundaries, and is, therefore, not conducive to an investigation of land use change over time.

Since land conversion is the aggregation of multiple individual actions, it is best to look at the smallest level possible (Irwin and Bockstael, 2004). The difficulty with resolution arises in this analysis when attributing existing shoreline condition and structure to the acre parcels. In all cases, the majority land use was used to describe the composition of the acre parcel. Of course, land is not sold in perfectly square one-acre lots that correspond with my GPS anchored fishnet overlay, so multiple land uses can (and were) contained within parcels. When examining general trends in land use change, the resolution is not really a problem, as general trends over a 65 year period can be assessed using this method. When attributing the shoreline condition and structure
information to the acre parcel resolution, often there were 3 or more sections of shoreline
code for one particular acre parcel. Because of the need to match one acre parcel to one
description of shoreline\(^6\), only the majority of shoreline attributes were coded and used in
the analysis. The shoreline condition information is collected at a much finer scale than
that of the land use acre parcel information, but because of the need for combining the
information, the shoreline information is reduced in resolution in order to be combined
with the the acre parcel data set. This is the reason that we see ‘agricultural’ and
‘undeveloped’ lands coded with shoreline structure. In reality, shoreline structure is not
found on these types of lands. Because only the majority land use is used, there may be a
residence on the ‘agricultural’ acre with a shoreline structure.

This research opens doors to interesting further work improving the model and
building on the framework provided by this research. Improvements to the model include
spectral differencing, validation, addition of another time step to the land use prediction,
and using an alternate method of land use prediction. Spectral differencing is a process
by which aerial photography is analyzed for differences in darkness and pattern, each
combination indicating a different land use. This application can only be used on photos
that were collected using the same method and with similar time of year and exposure.
The idea behind spectral differencing is using the contrast within a photograph to locate
land use change (Volcani et. al, \textit{in press}). For incorporation into this project, spectral
differencing would be a great way to look at historical land use change over time, either
for prediction purposes or for verification purposes. The difficulty with this method is
finding photographs of the same quality, resolution, and type for a particular area,
especially for historical imagery.

\(^6\) GIS only allows a one to one data match, not a one to many association.
The need for validation is discussed at length in earlier sections. This project did not contain validation in the strict sense of the word, but validation for a prediction model is impossible (except to wait it out and see how the prediction fared). For prediction models in the past, validation has been accomplished with an interpolation of land use within the time period of the model. In this case, the two outcomes possible from an interpolation technique for validation would be either that, in between time steps, the prediction continues to be linear or the prediction is not linear in between time steps. This is a tremendously uninteresting result that does not add much information to the analysis, so in this research, validation was replaced with an examination of possible future scenarios of land use change. This was undertaken to examine the range of possible land use change and the result of extreme change in one land use type. However, validation for this model, including an examination of linearity in the last time step, would benefit the model and enhance its prediction ability.

The model also would have benefited from an additional land use prediction in between the 2002 dataset and the 2025 prediction. The reason for this is that the prediction does not take into account the changes that happen in between 2002 and 2025. Proximity effects of land use change as it happens (i.e. not all at once) can influence the location of future land use change. An intermediate time step of 2010 may have changed the allocation prediction for the 2025 timestep, although the demand for land use change will not be affected by this additional analysis. Since the model uses surrounding land use at the 2002 time step only for prediction of future land use, the impacts of gradual change in land use throughout the time period is not considered and therefore cannot affect the allocation of future land use change.
Land use conversion was predicted using one logistic regression equation for each type of land use, but did not take into account the starting land use of the parcel in the prediction. An alternate method of predicting which parcels will change first (rather than allocating ‘developed’, ‘residential’, then ‘agricultural’) would be to formulate regression equations for each possible land use conversion. This method would add depth to the analysis, however, in this project, the result may not be very different from the results presented. Having a regression score for each possible conversion would allow the most accurate allocation of changing parcels. Difficulty with this method is the treatment of overlapping rankings of logistic prediction scores and the impact of allocation method on the overall results (i.e. which land use change you allocate first, which takes precedence in the event of an overlap). Another possible difficulty could be the lack of significant variables in the regression, especially for ‘developed’ parcels. Using one logistic regression equation for each land use type is less precise and does not take into account the starting land use, which has been shown to be important in other studies (Irwin and Bockstael, 2004). In this case, the use of one logistic regression equation adequately predicts land use due to the small fractions of conversion to ‘developed’ and ‘agricultural’. The number parcels converted to ‘developed’ in the future time step is small in relation to the total amount of change taking place. By far, the largest category of change is to ‘residential’. Change to ‘agricultural’ does not encompass a large fraction of the total changing parcels either. Because most of the change is centered around conversion to ‘residential,’ the method used results in a logistic prediction that is more general but gives a solid indication of which acre parcels will change first. Using the method that employs a logistic regression equation for each land use conversion (because
consideration of starting state and ending state are important to prediction) would enhance the prediction. Substitution of this method for the one used in the project would improve the overall prediction ability of the model.

This model lays the groundwork for future work addressing environmental consequences of land use change in light of increased risk associated with climate change. Investigation of climate change and sea level rise in this research has been somewhat cursory, but preliminary investigation of risk categories allows for further work in this area. A particularly interesting future project would involve taking into account sea level rise and coupling it with likely responses from individual property owners (installing shoreline structure, abandoning property, etc.). If a full investigation of effects of sea level rise were undertaken in conjunction with sociological and economic preference, the model would be able to produce a more complete picture of landowner response, wetland succession, installation of structure and climate change.

The additional perspective on the future of coastal resources provided by the models developed in this research, as well as in future work, can help to develop the foundation for incentive-based management mechanisms and regulations that work both to preserve the function of the shoreline habitat as well as the economic value of the shoreline. In order to ensure protection of riparian benefits, prediction of future land use and impacts of shoreline condition change are integral to accurately estimating the future shoreline condition and investigating its impacts on natural coastal habitats.

Population growth in Gloucester County has grown exponentially in the past 45 years, but the trend in conversion of land use in Guinea Neck is linear. Due to the lack of availability of census tract data for population, the trends in Guinea Neck were unable to
be investigated. Because Guinea Neck has been under intense development pressure during this period, it is safe to assume for these purposes that population growth in Guinea Neck has also been more or less exponential. At first it seems unreasonable that population growth in an area doesn't correspond to the land use change, but factors such as smaller lot sizes, larger houses, increased land value, and increases in multi-family dwellings shed some light on how this is possible. As demand and land value increase, lot sizes tend to get smaller. Whereas, 10 years ago the average lot size might have been 5 acres, the current average lot size is likely to be much smaller. The reasons for this are increased land value and increased demand for housing. As land values increase, lot sizes get smaller and the homes on the property generally have a larger value. In this way there is an increase in population density with increased land value. The implications for shoreline defense as a result of increased population density can be quite large. If shoreline property owners have a smaller lot, it is likely that they will be more willing to install structure to prevent erosion and loss of property.

In conjunction with the consideration of how population affects land use, the subject of asymptotic build out is an important concept to address. The land use prediction extends to 2025, where the number of 'residential' acre parcels is approaching the number of 'undeveloped' parcels. It is important to note that the linear trends in land use change will not continue indefinitely. As 'undeveloped' land becomes a smaller percentage of the study area, the parcels will be harder to convert. Likewise, as 'residential' and 'developed' land takes over 'agricultural' land, the remaining 'agricultural' acre parcels will be more difficult to convert. The linear relationship will eventually become an asymptotic relationship. Under continued development pressure,
as percentages of ‘undeveloped’ and ‘agricultural’ acre parcels approaches 0 % of parcels, fewer parcels of these land will be converted to an alternate land use. Similarly, ‘residential’ and ‘developed’ acre parcels, as they approach saturation of the landscape, are unlikely to convert every other parcel to their land use. The recognition of this eventual asymptotic relationship is important to note in further research, as predictions of 50 or 100 years of development are likely to encounter this phase of development.

Land use change modeling and prediction of the condition of shoreline resources can be useful in crafting management strategies in order to guide the use of land and coastal resources. GIS datasets comprised of biological, environmental, and socio-economic data are a natural framework for assessing land change in the coastal zone and the impacts of that change. Integrating dissimilar data types is a complex process and is often ignored in the spatially and temporally dynamic coastal systems. Coastal systems are increasingly under pressure of development, so it is likely that integration of information about these areas for management is most important to integrate (Stanbury and Starr, 1999). Information about regions and predictions of likely scenarios help decision-makers envision the consequences of management actions (Pontius, 2001).

Past uses of watershed modeling and forecasting have considered the effects of management strategies on the forecast. One land use change investigation included evaluation of the effects of various management strategies on land use outcomes. Strategies examined were current regulation, mandating larger lot sizes for properties with a septic system, increasing the buffer zone around all wetlands and streams, and aggressively protecting open space on the forecast. Discouragingly, none of the regulation scenarios “substantially limited the negative impacts of future urban growth on
the water or terrestrial resources in this study.” This study was conducted in the Barnegat Bay watershed, characterized as an “urbanizing watershed” (Conway and Lathrop, 2005).

While much of the Chesapeake Bay watershed is urbanizing, considerable portions are less developed. The Gloucester County landscape is still dominated by forests, forested wetlands, and marsh. Arguably one of the most developed area in the County is Guinea Neck, and even it has a large proportion of undeveloped land. In areas like Gloucester County, introduction of incentives and regulation for planned use of resources and active conservation goals would have more of an impact than in more urban areas of the watershed. Like most other less developed counties in Virginia, Gloucester is one of the less economically affluent counties. Because of this there is a push to offer incentives to large businesses (Home Depot, Wal-Mart, etc.) to open stores in Gloucester. The county government is in favor of this because it increases county revenue and supplies jobs for county residents. Environmental impacts of this development are not high on the county’s list of considerations.

Models such as the ones presented in this research can be helpful to rural counties undergoing development pressure, both for the prediction in land use change and visualizing the potential impact to shoreline resources. This information can be used at the locality level to give decision-makers a clearer picture of what resources are at stake in the absence of protection. Models such as these can also be applied to a broader scale, such as the Chesapeake Bay watershed for investigation of impacts of urbanization and land use change on environmental resources.

The combination of natural science and social science in the construction of this model allow for a unique perspective on shoreline resource prediction. To my
knowledge, this research is the only attempt at prediction of shoreline resources represented in the scientific literature. The models that result from this research provide a resource for decision makers to envision the likely future state of shoreline condition. As a result, planning mechanisms can be designed in order to preserve the biodiversity and ecosystem integrity of the coastline as well as preserve the human uses. Because the prediction indicates a future state, managers can look at present and future conditions and guide development in a way that alters the future condition to a desired resource allocation. This insight into resource use allows for the use of incentive based mechanisms and non-regulatory options, as opposed to relying on command-and-control regulation. For instance, incentives for using less destructive methods of shoreline hardening or easement programs can be developed to encourage responsible stewardship of shoreline resources. Additional information about property owner preference would greatly enhance the predictive capability of the models, but this research succeeds in laying the groundwork for further work. Using the scientific principles associated with remote sensing and shoreline change in conjunction with econometric and fuzzy logic modeling commonly used in social science, this model begins to integrate the information necessary to truly examine predictors of shoreline change.
APPENDICES

Appendix 1: fishnet.lu.aml

/* union landuse and fishnet
/* Determine percent landuse scores for each acre and write the scores to
/* the original fishnet coverage.

&sv f [response 'Enter name for fishnet coverage']
&sv lu [response 'Enter name of landuse coverage']
&sv y [response 'Enter the year of landuse data']

precision double

/* copy original fishnet coverage to fishnet coverage with date
copy %f %f%y%

/* combine the landuse and the fishnet coverages
union $lu %f%y% union%y% .01

/* run a frequency
frequency union%y%.pat union%y%.dat
acre-id
acre_area
landuse
end
area
end

tables
additem union%y%.dat prcnt_ag 8 8 f 2
additem union%y%.dat prcnt_undev 8 8 f 2
additem union%y%.dat prcnt_resid 8 8 f 2
additem union%y%.dat prcnt_dev 8 8 f 2

/* calculate the percent of each landuse type
sel union%y%.dat
resel landuse = 'ag'
resel acre-id ne 0
calc prcnt_ag = area / acre_area * 100
asel
resel landuse = 'dev'
resel acre-id ne 0
calc prcnt_dev = area / acre_area * 100
asel
resel landuse = 'resid'
resel acre-id ne 0
calc prcnt_resid = area / acre_area * 100
asel
resel landuse = 'undev'
resel acre-id ne 0
calc prcnt_undev = area / acre_area * 100
asel

/* Create separate files to hold each landuse, delete all other landuses
copy union%y%.dat ag%y%.dat
copy union%y%.dat resid%y%.dat
copy union%y%.dat dev%y%.dat

sel ag%y%.dat
resel landuse ne 'ag'
purge
y
alter
area
area_ag
-
-
-
-

sel resid%y%.dat
resel landuse ne 'resid'
purge
y
-
alter
area
area_resid
-
-
-
-

sel dev%y%.dat
resel landuse ne 'dev'
purge
y
-
alter
area
area_dev
-
-
-
-

sel undev%y%.dat
resel landuse ne 'undev'
purge
y
-
alter
area
area_undev
-
-
-
-

sel
dropitem ag%y%.dat prcnt_undev prcnt_resid prcnt_dev landuse case# frequency
dropitem resid%y%.dat prcnt_undev prcnt_ag prcnt_dev landuse case# frequency
dropitem dev%y%.dat prcnt_undev prcnt_resid prcnt_ag landuse case# frequency
dropitem undev%y%.dat prcnt_ag prcnt_resid prcnt_dev landuse case# frequency

q

/* join the separate landuse files containing percentage back to the fishnet-year coverage. */
joinitem %y%.pat ag%y%.dat %y%.pat acre-id acre-id
joinitem %y%.pat undev%y%.dat %y%.pat acre-id prcnt_ag
joinitem %y%.pat resid%y%.dat %y%.pat acre-id prcnt_dev
joinitem %y%.pat dev%y%.dat %y%.pat acre-id prcnt_resid

/* Determine the predominate landuse for each acre cell */
dropitem %y%.pat dominant_lu 6 6 c
sel %y%.pat
resel prcnt_ag > 50
calc dominant_lu = 'ag'
  asel
  rese l prcnt_dev > 50
  calc dominant_lu = 'dev'
  asel
  rese l prcnt_resid > 50
  calc dominant_lu = 'resid'
  asel
  rese l prcnt_undev > 50
  calc dominant_lu = 'undev'
  asel
rese l dominant_lu = ' '
rese l prcnt_undev > 0 and prcnt_undev le 50
rese l prcnt_ag = 0 and prcnt_resid = 0 and prcnt_dev = 0
calc dominant_lu = 'undev'
  asel
rese l dominant_lu = ' '
rese l prcnt_undev > 0 and prcnt_ag le 50
rese l prcnt_undev = 0 and prcnt_resid = 0 and prcnt_dev = 0
calc dominant_lu = 'ag'
  asel
rese l dominant_lu = ' '
rese l prcnt_resid > 0 and prcnt_resid le 50
rese l prcnt_undev = 0 and prcnt_ag = 0 and prcnt_dev = 0
calc dominant_lu = 'resid'
  asel
rese l dominant_lu = ' '
rese l prcnt_dev > 0 and prcnt_dev le 50
rese l prcnt_undev = 0 and prcnt_ag = 0 and prcnt_resid = 0
calc dominant_lu = 'dev'
  asel
rese l dominant_lu = ' '
rese l prcnt_undev > 0 and prcnt_undev le 50
rese l prcnt_ag = 0 and prcnt_undev = 0 and prcnt_dev = 0
calc dominant_lu = 'none'
  asel
rese l dominant_lu = ' '
rese l prcnt_undev > 0 and prcnt_undev le 50
rese l prcnt_dev = 0 and prcnt_undev = 0 and prcnt_resid = 0
calc dominant_lu = 'undev'
  asel
rese l dominant_lu = ' '
rese l prcnt_undev > 0 and prcnt_undev le 50
rese l prcnt_dev = 0 and prcnt_undev = 0 and prcnt_resid = 0
calc dominant_lu = 'dev'
  asel
rese l dominant_lu = ' '
rese l prcnt_undev > 0 and prcnt_undev le 50
rese l prcnt_undev < prcnt_ag
calc dominant_lu = 'ag'
  asel
rese l dominant_lu = ' '
rese l prcnt_undev > 0 and prcnt_undev le 50
rese l prcnt_ag = 0 and prcnt_undev = 0 and prcnt_dev = 0
calc dominant_lu = 'dev'
  asel
rese l dominant_lu = ' '
rese l prcnt_undev > 0 and prcnt_undev le 50
resel prcnt_ag = 0 and prcnt_dev = 0
resel prcnt_undev < prcnt_resid
calc dominant_lu = 'resid'
asel
resel dominant_lu = '
resel prcnt_ag > 0 and prcnt_ag le 50
resel prcnt_dev = 0 and prcnt_resid = 0
resel prcnt_ag > prcnt_undev
calc dominant_lu = 'ag'
asel
resel dominant_lu = '
resel prcnt_ag > 0 and prcnt_ag le 50
resel prcnt_dev = 0 and prcnt_undev = 0
resel prcnt_ag > prcnt_resid
calc dominant_lu = 'ag'
asel
resel dominant_lu = '
resel prcnt_ag > 0 and prcnt_ag le 50
resel prcnt_undev = 0 and prcnt_resid = 0
resel prcnt_ag > prcnt_dev
calc dominant_lu = 'ag'
asel
resel dominant_lu = '
resel prcnt_undev > prcnt_ag
resel prcnt_undev > prcnt_resid
resel prcnt_undev > prcnt_dev
calc dominant_lu = 'undev'
asel
resel dominant_lu = '
resel prcnt_ag > prcnt_undev
resel prcnt_ag > prcnt_resid
resel prcnt_ag > prcnt_dev
calc dominant_lu = 'ag'
asel
resel dominant_lu = '
resel prcnt_resid > prcnt_ag
resel prcnt_resid > prcnt_undev
resel prcnt_resid > prcnt_dev
calc dominant_lu = 'resid'
asel
resel dominant_lu = '
resel prcnt_dev > prcnt_ag
resel prcnt_dev > prcnt_resid
resel prcnt_dev > prcnt_undev
calc dominant_lu = 'dev'
asel
q

&type This ami i is completed.
&return
Appendix 2: standardization.aml

/* standardization.aml - This aml looks
/* at the dominant landuse within each 1 acre parcel and compares it to the
/* preceeding year. It determines if the landuse stays the same or changes, and
/* calculates a new landuse value if necessary. It works from the most recent
/* landuse to the oldest landuse dataset, and makes the assumption the the
/* newest landuse is the most accurate dataset.

/*sv yr1 fishnetall37
/*sv yr2 fishnetall59
/*sv yr3 fishnetall82
/*sv yr4 fishnetall02

precision double

/*union %yr1% %yr2% union1 .01
/*union %yr3% union1 union2 .01
/*union %yr4% union2 fishnetalllu .01

/*sv yrall fishnetallu

sv yrall [response 'Enter the name of the coverage containing all 4 years']

/* create a list of id numbers to use to loop through each 1 acre parcel.
/* check for parcels that have 3 or le s s  years with 'none' as the land use.
/* Fix so that all parcels either have a landuse or a 'none'

if not [exists list.txt -file] &then
 &do
tables
 &if not [iteminfo %yrall%.pat -info id_recnum -exists] &then
 &additem %yrall%.pat id_recnum 4 5 b
 &sel %yrall%.pat
calc id_recnum = %yrall##
resel dominant_lu37 = 'none' and dominant_lu59 = 'none' and dominant_lu82 = 'none' and
dominant_lu02 = 'none'
sel
unload list.txt id_recnum
q
 &end
/* add items to hold new data
/* "ok" if lu stays the same or digresses. "no" if lu progresses
/* (ex resid -> undev) * remember * we are looking backwards in time.

if not [iteminfo %yrall%.pat -info y4-3 -exists] &then
additem %yrall%.pat %yrall%.pat y4-3 4 4 c
if not [iteminfo %yrall%.pat -info y3-2 -exists] &then
additem %yrall%.pat %yrall%.pat y3-2 4 4 c
if not [iteminfo %yrall%.pat -info y2-1 -exists] &then
additem %yrall%.pat %yrall%.pat y2-1 4 4 c
if not [iteminfo %yrall%.pat -info new_dom_lu82 -exists] &then
additem %yrall%.pat %yrall%.pat new_dom_lu82 6 6 c
if not [iteminfo %yrall%.pat -info new_dom_lu59 -exists] &then
additem %yrall%.pat %yrall%.pat new_dom_lu59 6 6 c
if not [iteminfo %yrall%.pat -info new_dom_lu37 -exists] &then
additem %yrall%.pat %yrall%.pat new_dom_lu37 6 6 c
tables
if [exists list.txt -file] &then
 &do
 &sv fileerr = [open list.txt openerr -read]
/* Check for errors in opening file.
&if %openerr% <> 0 &then  
  sreturn &warning Error opening file.

/* Read from file */
&sv record = [read %fileerr% readerr]
&if %readerr% <> 0 &then  
  sreturn &warning Could not read file.

&sv num = [TRIM %record% ]
&setvar num [subst %num% , '']
&do until %readerr% = 102

/* set variables to default value */
&sv dlu1 0
&sv dlu2 0
&sv dlu3 0
&sv dlu4 0
&sv v43 0
&sv v32 0
&sv v21 0
&sv nn 0
&sv prcnt1 0
&sv prcnt2 0
&sv prcnt3 0
&sv prcnt4 0
&sv ml 0
&sv m2 0

/* set variables */
sel %yrall%.pat
reselect id_recnum = %num%
&sv dlu1 = [show record %num% item dominant_lu37]
&sv dlu2 = [show record %num% item dominant_lu59]
&sv dlu3 = [show record %num% item dominant_lu82]
&sv dlu4 = [show record %num% item dominant_lu02]
&if %dlu1% ne 'none' &then &sv prcnt1 = [round [show record %num% item prcnt_%dlu1%37]]
&if %dlu2% ne 'none' &then &sv prcnt2 = [round [show record %num% item prcnt_%dlu2%59]]
&if %dlu3% ne 'none' &then &sv prcnt3 = [round [show record %num% item prcnt_%dlu3%82]]
&if %dlu4% ne 'none' &then &sv prcnt4 = [round [show record %num% item prcnt_%dlu4%02]]

/* check for the occurrence of 'none' in the parcel. If found, then fix as */
/* follows: */
/* * if 2 or 3 yrs have a value of 'none', then all years = 'none.' */
/* * if 1 yr = 'none' & largest land use acres is <30% of parcel size, then */
/* * set year equal to 'none.' */
/* * if 1 yr = 'none' & largest land use size is >30% of parcel size, then */
/* * set yr = the dominant landuse. */
&if %dlu1% = none or %dlu2% = none or %dlu3% = none or %dlu4% = none &then  
&do  
&if %dlu1% = none and %dlu2% = none &then  
  &do  
  calc dominant_lu37 = 'none'
  calc dominant_lu59 = 'none'
  calc dominant_lu82 = 'none'
  calc dominant_lu02 = 'none'
  &sv nn 1  
&end
&if %dlu1% = none and %dlu3% = none &then  
&do  
  calc dominant_lu37 = 'none'
  calc dominant_lu59 = 'none'
  calc dominant_lu82 = 'none'
  calc dominant_lu02 = 'none'
  &sv nn 1  
&end
&if %dlu1% = none and %dlu4% = none &then  
&do  
  calc dominant_lu37 = 'none'
  calc dominant_lu59 = 'none'
  calc dominant_lu82 = 'none'
&end
calc dominant_lu02 = 'none'  
&sv nn 1  
&end  
&if %dlu2% = none and %dlu3% = none &then  
&do  
calc dominant_lu37 = 'none'  
calc dominant_lu59 = 'none'  
calc dominant_lu82 = 'none'  
calc dominant_lu02 = 'none'  
&sv nn 1  
&end  
&if %dlu2% = none and %dlu4% = none &then  
&do  
calc dominant_lu37 = 'none'  
calc dominant_lu59 = 'none'  
calc dominant_lu82 = 'none'  
calc dominant_lu02 = 'none'  
&sv nn 1  
&end  
&if %dlu3% = none and %dlu4% = none &then  
&do  
calc dominant_lu37 = 'none'  
calc dominant_lu59 = 'none'  
calc dominant_lu82 = 'none'  
calc dominant_lu02 = 'none'  
&sv nn 1  
&end  
&if %nn% = 0 and %dlu1% = none &then  
&do  
&sv m1 = [max %prcnt2% %prcnt3%]  
&sv m2 = [max %ml% %prcnt4%]  
&if %m2% < 30 &then  
&do  
calc dominant_lu37 = 'none'  
calc dominant_lu59 = 'none'  
calc dominant_lu82 = 'none'  
calc dominant_lu02 = 'none'  
&sv nn 1  
&end  
&if %m2% ge 30 &then  
&do  
&if %m2% = %prcnt2% &then  
&do  
calc dominant_lu37 = [quote %dlu2%]  
&sv dl1 = %dlu2%  
&end  
&if %m2% = %prcnt3% &then  
&do  
calc dominant_lu37 = [quote %dlu3%]  
&sv dl1 = %dlu3%  
&end  
&if %m2% = %prcnt4% &then  
&do  
calc dominant_lu37 = [quote %dlu4%]  
&sv dl1 = %dlu4%  
&end  
&end  
&end  
&if %nn% = 0 and %dlu2% = none &then  
&do  
&sv m1 = [max %prcnt1% %prcnt3%]  
&sv m2 = [max %ml% %prcnt4%]  
&if %m2% < 30 &then  
&do  
calc dominant_lu37 = 'none'  
calc dominant_lu59 = 'none'  
calc dominant_lu82 = 'none'  
calc dominant_lu02 = 'none'  
&sv nn 1  

116
&end
&if %m2% ge 30 &then
&do
&if %m2% = %prcnt1% &then
&do
calc dominant_lu59 = [quote %dlul1%]
&s v dlu2 = %dlul1%
&end
&if %m2% = %prcnt3% &then
&do
calc dominant_lu59 = [quote %dlul3%]
&s v dlu2 = %dlul3%
&end
&if %m2% = %prcnt4% &then
&do
calc dominant_lu59 = [quote %dlul4%]
&s v dlu2 = %dlul4%
&end
&end
&end
&if %nn% = 0 and %dlu3% = none &then
&do
&s v m1 = [max %prcnt1% %prcnt2%]
&s v m2 = [max %m1% %prcnt4%]
&if %m2% < 30 &then
&do
calc dominant_lu37 = 'none'
calc dominant_lu59 = 'none'
calc dominant_lu82 = 'none'
calc dominant_lu02 = 'none'
&s v nn 1
&end
&if %m2% ge 30 &then
&do
&if %m2% = %prcnt1% &then
&do
calc dominant_lu82 = [quote %dlul1%]
&s v dlu3 = %dlul1%
&end
&if %m2% = %prcnt2% &then
&do
calc dominant_lu82 = [quote %dlu2%]
&s v dlu3 = %dlu2%
&end
&if %m2% = %prcnt4% &then
&do
calc dominant_lu82 = [quote %dlu4%]
&s v dlu3 = %dlu4%
&end
&end
&end
&if %nn% = 0 and %dlu4% = none &then
&do
&s v m1 = [max %prcnt2% %prcnt3%]
&s v m2 = [max %m1% %prcnt4%]
&if %m2% < 30 &then
&do
calc dominant_lu37 = 'none'
calc dominant_lu59 = 'none'
calc dominant_lu82 = 'none'
calc dominant_lu02 = 'none'
&s v nn 1
&end
&if %m2% ge 30 &then
&do
&if %m2% = %prcnt1% &then
&do
calc dominant_lu02 = [quote %dlul1%]
&s v dlu4 = %dlul1%
&end
&end
&if %m2%  = %prcnt2% &then
&do
calc dominant_lu02 = [quote %dlu2%]
&sv dlu4 = %dlu2%
&end
&if %m2%  = %prcnt3% &then
&do
calc dominant_lu02 = [quote %dlu3%]
&sv dlu4 = %dlu3%
&end
&end
&end
&if %nn%  = 0 &then
&do
/* landuse doesn't change */
&if %dlul%  = %dlu2% and %dlu2%  = %dlu3% and %dlu3%  = %dlu4% &then
&do
calc y4-3 = 'ok'
calc y3-2 = 'ok'
calc y2-1 = 'ok'
calc new_dom_lu59 = [quote %dlu2%]
calc new_dom_lu82 = [quote %dlu3%]
calc new_dom_lu37 = [quote %dlu1%]
&end
/* landuse yr4 = yr3 & yr3 = yr2, but yr1 is different */
&if %dlu4%  = %dlu3% and %dlu3%  = %dlu2% and %dlu2%  ne %dlul% &then
&do
calc y4-3 = 'ok'
calc y3-2 = 'ok'
calc new_dom_lu82 = [quote %dlu3%]
calc new_dom_lu59 = [quote %dlu2%]
&if %dlul%  = ag and %dlul%  = resid &then calc y2-1 = 'no'
&if %dlul%  = ag and %dlul%  = dev &then calc y2-1 = 'no'
&if %dlul%  = undev and %dlul%  = resid &then calc y2-1 = 'ok'
&if %dlul%  = undev and %dlul%  = dev &then calc y2-1 = 'ok'
&if %dlul%  = resid and %dlul%  = undev &then calc y2-1 = 'ok'
&if %dlul%  = resid and %dlul%  = dev &then calc y2-1 = 'ok'
&if %dlul%  = resid and %dlul%  = ag &then calc y2-1 = 'no'
&if %dlul%  = dev and %dlul%  = resid &then calc y2-1 = 'ok'
&if %dlul%  = dev and %dlul%  = dev &then calc y2-1 = 'ok'
&if %dlul%  = dev and %dlul%  = ag &then calc y2-1 = 'ok'
&sv v21 = [show record %num% item y2-1]
&if %v21% = ok &then calc new_dom_lu37 = [quote %dlu1%]
&if %v21% = no &then calc new_dom_lu37 = [quote %dlu2%]
&end
/* landuse yr4 = yr3, but yr2 is different */
&if %dlu4%  = %dlu3% and %dlu3%  ne %dlu2% &then
&do
calc y4-3 = 'ok'
calc new_dom_lu82 = [quote %dlu3%]
&if %dlu4%  = ag and %dlu2%  = resid &then calc y3-2 = 'no'
&if %dlu4%  = ag and %dlu2%  = dev &then calc y3-2 = 'no'
&if %dlu4%  = ag and %dlu2%  = undev &then calc y3-2 = 'ok'
&if %dlu4%  = undev and %dlu2%  = dev &then calc y3-2 = 'ok'
&if %dlu4%  = undev and %dlu2%  = undev &then calc y3-2 = 'no'
&if %dlu4%  = undev and %dlu2%  = ag &then calc y3-2 = 'no'
&if %dlu4%  = dev and %dlu2%  = resid &then calc y3-2 = 'no'
&if %dlu4%  = dev and %dlu2%  = dev &then calc y3-2 = 'ok'
&if %dlu4%  = dev and %dlu2%  = undev &then calc y3-2 = 'ok'
&if %dlu4%  = dev and %dlu2%  = ag &then calc y3-2 = 'ok'
&sv v32 = [show record %num% item y3-2]
if \$v32\$ = ok &then calc new_dom_lu59 = [quote \$dlu2\$]
if \$v32\$ = no &then calc new_dom_lu59 = [quote \$dlu3\$]

/* landuse yr4 ne yr3
if \$dlu4\$ ne \$dlu3\$ &then
   do
      if \$dlu4\$ = ag and \$dlu3\$ = resid &then calc y4-3 = 'no'
      if \$dlu4\$ = ag and \$dlu3\$ = dev &then calc y4-3 = 'no'
      if \$dlu4\$ = ag and \$dlu3\$ = undev &then calc y4-3 = 'ok'
      if \$dlu4\$ = undev and \$dlu3\$ = resid &then calc y4-3 = 'no'
      if \$dlu4\$ = undev and \$dlu3\$ = ag &then calc y4-3 = 'no'
      if \$dlu4\$ = undev and \$dlu3\$ = dev &then calc y4-3 = 'ok'
      if \$dlu4\$ = resid and \$dlu3\$ = dev &then calc y4-3 = 'no'
      if \$dlu4\$ = resid and \$dlu3\$ = ag &then calc y4-3 = 'no'
      if \$dlu4\$ = resid and \$dlu3\$ = undev &then calc y4-3 = 'ok'
      if \$dlu4\$ = dev and \$dlu3\$ = resid &then calc y4-3 = 'ok'
      if \$dlu4\$ = dev and \$dlu3\$ = undev &then calc y4-3 = 'ok'
      if \$dlu4\$ = dev and \$dlu3\$ = dev &then calc y4-3 = 'no'
      if \$dlu4\$ = dev and \$dlu3\$ = ag &then calc y4-3 = 'ok'
      if \$dlu4\$ = resid and \$dlu3\$ = undev &then calc y4-3 = 'ok'
      if \$dlu4\$ = resid and \$dlu3\$ = dev &then calc y4-3 = 'ok'
      if \$dlu4\$ = resid and \$dlu3\$ = resid &then calc y4-3 = 'ok'
   calc y4-3 = [show record \$num\$ item y4-3]
   if \$v43\$ = ok &then calc new_dom_lu59 = [quote \$dlu3\$]
   if \$v43\$ = no &then calc new_dom_lu59 = [quote \$dlu4\$]
   end

/* landuse yr4 ne yr3 and yr3 = yr2
if \$dlu4\$ ne \$dlu3\$ and \$dlu3\$ = \$dlu2\$ &then
   do
      calc y3-2 = 'ok'
   if \$v43\$ = ok &then calc new_dom_lu59 = [quote \$dlu2\$]
      if \$v43\$ = no &then calc new_dom_lu59 = [quote \$dlu3\$]
   end
   end

/* landuse yr4 ne yr3 and yr3 ne yr2
if \$dlu4\$ ne \$dlu3\$ and \$dlu3\$ ne \$dlu2\$ &then
   do
      calc y4-3 = [show record \$num\$ item y4-3]
      if \$v43\$ = ok &then calc new_dom_lu59 = [quote \$dlu2\$]
      if \$v43\$ = no &then calc new_dom_lu59 = [quote \$dlu3\$]
      if \$v43\$ = 'no' &then calc new_dom_lu59 = [quote \$dlu4\$]
   end
end
if %dlu4% = undev and %dlu2% = resid then calc y3-2 = 'no'
if %dlu4% = undev and %dlu2% = dev then calc y3-2 = 'no'
if %dlu4% = undev and %dlu2% = ag then calc y3-2 = 'ok'
if %dlu4% = resid and %dlu2% = undev then calc y3-2 = 'ok'
if %dlu4% = resid and %dlu2% = dev then calc y3-2 = 'no'
if %dlu4% = resid and %dlu2% = ag then calc y3-2 = 'ok'
if %dlu4% = dev and %dlu2% = resid then calc y3-2 = 'ok'
if %dlu4% = dev and %dlu2% = undev then calc y3-2 = 'ok'
if %dlu4% = dev and %dlu2% = ag then calc y3-2 = 'ok'
sv v32 = [show record %num% item y3-2]
if %v32% = ok then calc new_dom_lu59 = [quote %dlu2%]
if %v32% = no then calc new_dom_lu59 = [quote %dlu4%]
end

/* landuse yr3 ne yr2 and yr2 = yrl
if %dlu3% ne %dlu2% and %dlu2% = %dlu1% then
  do
    sv v43 = [show record %num% item y4-3]
    sv v32 = [show record %num% item y3-2]
    if %v43% = ok and %v32% = ok then
      do
        calc y2-1 = 'ok'
        calc new_dom_lu37 = [quote %dlu1%]
      end
    if %v43% = ok and %v32% = no then
      do
        calc y2-1 = 'no'
        calc new_dom_lu37 = [quote %dlu3%]
      end
    if %v43% = no and %v32% = ok then
      do
        calc y2-1 = 'ok'
        calc new_dom_lu37 = [quote %dlu4%]
      end
    if %v43% = no and %v32% = no then
      do
        calc y2-1 = 'no'
        calc new_dom_lu37 = [quote %dlu4%]
      end
  end
end

/* landuse yr3 ne yr2 and yr2 ne yrl
if %dlu3% ne %dlu2% and %dlu2% ne %dlu1% then
  do
    sv v43 = [show record %num% item y4-3]
    sv v32 = [show record %num% item y3-2]
    if %v43% = ok and %v32% = ok then
      do
        if %dlu2% = ag and %dlu1% = resid then calc y2-1 = 'no'
        if %dlu2% = ag and %dlu1% = dev then calc y2-1 = 'no'
        if %dlu2% = ag and %dlu1% = undev then calc y2-1 = 'ok'
        if %dlu2% = undev and %dlu1% = resid then calc y2-1 = 'no'
        if %dlu2% = undev and %dlu1% = dev then calc y2-1 = 'no'
        if %dlu2% = undev and %dlu1% = undev then calc y2-1 = 'ok'
        if %dlu2% = dev and %dlu1% = resid then calc y2-1 = 'ok'
        if %dlu2% = dev and %dlu1% = dev then calc y2-1 = 'ok'
        if %dlu2% = dev and %dlu1% = undev then calc y2-1 = 'ok'
        if %dlu2% = dev and %dlu1% = ag then calc y2-1 = 'ok'
        if %v21% = ok then calc new_dom_lu37 = [quote %dlu1%]
      end
    if %v21% = ok then calc new_dom_lu37 = [quote %dlu3%]
  end
*/
\textbf{if} \%v21\% = no \&then calc new_dom_lu37 = [quote \%dlu2\%]
\textbf{end}

\textbf{if} \%v43\% = ok \& \%v32\% = no \&then
\begin{verbatim}
&do
  &if \%dlu3\% = ag \& \%dlul\% = resid \&then calc y2-l = 'no'
  &if \%dlu3\% = ag \& \%dlul\% = dev \&then calc y2-l = 'no'
  &if \%dlu3\% = undev \& \%dlul\% = resid \&then calc y2-l = 'ok'
  &if \%dlu3\% = undev \& \%dlul\% = dev \& then calc y2-l = 'no'
  &if \%dlu3\% = undev \& \%dlul\% = ag \& then calc y2-l = 'ok'
  &if \%dlu3\% = undev \& \%dlul\% = undev \& then calc y2-l = 'ok'
  &if \%dlu3\% = resid \& \%dlul\% = undev \& then calc y2-l = 'ok'
  &if \%dlu3\% = resid \& \%dlul\% = dev \& then calc y2-l = 'no'
  &if \%dlu3\% = resid \& \%dlul\% = ag \& then calc y2-l = 'ok'
  &if \%dlu3\% = resid \& \%dlul\% = resid \& then calc y2-l = 'ok'
  &if \%dlu3\% = dev \& \%dlul\% = resid \& then calc y2-l = 'ok'
  &if \%dlu3\% = dev \& \%dlul\% = undev \& then calc y2-l = 'ok'
  &if \%dlu3\% = dev \& \%dlul\% = ag \& then calc y2-l = 'ok'
  &if \%dlu3\% = dev \& \%dlul\% = dev \& then calc y2-l = 'ok'
  &sv v21 = [show record \$num\% item y2-1]
&do
  &if \%dlu4\% = ag \& \%dlul\% = resid \& then calc y2-l = 'no'
  &if \%dlu4\% = ag \& \%dlul\% = dev \& then calc y2-l = 'no'
  &if \%dlu4\% = ag \& \%dlul\% = undev \& then calc y2-l = 'ok'
  &if \%dlu4\% = undev \& \%dlul\% = resid \& then calc y2-l = 'no'
  &if \%dlu4\% = undev \& \%dlul\% = dev \& then calc y2-l = 'no'
  &if \%dlu4\% = undev \& \%dlul\% = undev \& then calc y2-l = 'ok'
  &if \%dlu4\% = resid \& \%dlul\% = undev \& then calc y2-l = 'ok'
  &if \%dlu4\% = resid \& \%dlul\% = dev \& then calc y2-l = 'no'
  &if \%dlu4\% = resid \& \%dlul\% = ag \& then calc y2-l = 'ok'
  &if \%dlu4\% = resid \& \%dlul\% = resid \& then calc y2-l = 'ok'
  &if \%dlu4\% = dev \& \%dlul\% = resid \& then calc y2-l = 'ok'
  &if \%dlu4\% = dev \& \%dlul\% = undev \& then calc y2-l = 'ok'
  &if \%dlu4\% = dev \& \%dlul\% = dev \& then calc y2-l = 'ok'
  &sv v21 = [show record \$num\% item y2-1]
&do
  &if \%v21\% = ok \&then calc new_dom_lu37 = [quote \%dlul\%]
  &if \%v21\% = no \&then calc new_dom_lu37 = [quote \%dlu3\%]
\end{verbatim}
\textbf{end}

\textbf{if} \%v43\% = no \& \%v32\% = ok \&then
\begin{verbatim}
&do
  &if \%dlu2\% = ag \& \%dlul\% = resid \&then calc y2-l = 'no'
  &if \%dlu2\% = ag \& \%dlul\% = dev \&then calc y2-l = 'no'
  &if \%dlu2\% = undev \& \%dlul\% = resid \&then calc y2-l = 'ok'
  &if \%dlu2\% = undev \& \%dlul\% = dev \& then calc y2-l = 'no'
  &if \%dlu2\% = undev \& \%dlul\% = ag \& then calc y2-l = 'ok'
  &if \%dlu2\% = undev \& \%dlul\% = undev \& then calc y2-l = 'ok'
  &if \%dlu2\% = resid \& \%dlul\% = undev \& then calc y2-l = 'ok'
  &if \%dlu2\% = resid \& \%dlul\% = dev \& then calc y2-l = 'no'
  &if \%dlu2\% = resid \& \%dlul\% = ag \& then calc y2-l = 'ok'
  &if \%dlu2\% = resid \& \%dlul\% = resid \& then calc y2-l = 'ok'
  &if \%dlu2\% = dev \& \%dlul\% = resid \& then calc y2-l = 'ok'
  &if \%dlu2\% = dev \& \%dlul\% = undev \& then calc y2-l = 'ok'
  &if \%dlu2\% = dev \& \%dlul\% = ag \& then calc y2-l = 'ok'
  &if \%dlu2\% = dev \& \%dlul\% = dev \& then calc y2-l = 'ok'
  &sv v21 = [show record \$num\% item y2-1]
&do
  &if \%v21\% = ok \&then calc new_dom_lu37 = [quote \%dlul\%]
  &if \%v21\% = no \&then calc new_dom_lu37 = [quote \%dlu2\%]
\end{verbatim}
\textbf{end}

\textbf{if} \%v43\% = no \& \%v32\% = no \&then
\begin{verbatim}
&do
  &if \%dlu4\% = ag \& \%dlul\% = resid \& then calc y2-l = 'no'
  &if \%dlu4\% = ag \& \%dlul\% = dev \& then calc y2-l = 'no'
  &if \%dlu4\% = ag \& \%dlul\% = undev \& then calc y2-l = 'ok'
  &if \%dlu4\% = undev \& \%dlul\% = resid \& then calc y2-l = 'no'
  &if \%dlu4\% = undev \& \%dlul\% = dev \& then calc y2-l = 'no'
  &if \%dlu4\% = undev \& \%dlul\% = undev \& then calc y2-l = 'ok'
  &if \%dlu4\% = resid \& \%dlul\% = undev \& then calc y2-l = 'ok'
  &if \%dlu4\% = resid \& \%dlul\% = dev \& then calc y2-l = 'no'
  &if \%dlu4\% = resid \& \%dlul\% = ag \& then calc y2-l = 'ok'
  &if \%dlu4\% = resid \& \%dlul\% = resid \& then calc y2-l = 'ok'
  &if \%dlu4\% = dev \& \%dlul\% = resid \& then calc y2-l = 'ok'
  &if \%dlu4\% = dev \& \%dlul\% = undev \& then calc y2-l = 'ok'
  &if \%dlu4\% = dev \& \%dlul\% = dev \& then calc y2-l = 'ok'
  &sv v21 = [show record \$num\% item y2-1]
&do
  &if \%v21\% = ok \&then calc new_dom_lu37 = [quote \%dlul\%]
  &if \%v21\% = no \&then calc new_dom_lu37 = [quote \%dlu4\%]
\end{verbatim}
\textbf{end}
/* landuse yr4 ne yr3 and yr3 = yr2 and yr2 ne yr1
if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
  do
    if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
      do
        if %dlu2% = ag and %dlu1% = resid then calc y2-l = 'no'
        if %dlu2% = ag and %dlu1% = undev then calc y2-l = 'ok'
        if %dlu2% = undev and %dlu1% = resid then calc y2-l = 'no'
        if %dlu2% = undev and %dlu1% = dev then calc y2-l = 'no'
        if %dlu2% = undev and %dlu1% = ag then calc y2-l = 'no'
        if %dlu2% = undev and %dlu1% = undev then calc y2-l = 'ok'
        if %dlu2% = resid and %dlu1% = undev then calc y2-l = 'ok'
        if %dlu2% = resid and %dlu1% = dev then calc y2-l = 'no'
        if %dlu2% = resid and %dlu1% = ag then calc y2-l = 'ok'
        if %dlu2% = resid and %dlu1% = undev then calc y2-l = 'ok'
        if %dlu2% = resid and %dlu1% = dev then calc y2-l = 'no'
        if %dlu2% = dev and %dlu1% = resid then calc y2-l = 'ok'
        if %dlu2% = dev and %dlu1% = undev then calc y2-l = 'ok'
        if %dlu2% = dev and %dlu1% = dev then calc y2-l = 'ok'
        if %dlu2% = dev and %dlu1% = ag then calc y2-l = 'ok'
        v21 = [show record %num% item y2-l]
        if %v21% = ok then calc new_dom_lu37 = [quote %dlu1%]
        if %v21% = no then calc new_dom_lu37 = [quote %dlu2%]
      end
    end
  end
end

/* landuse yr4 ne yr3 and yr3 = yr2 and yr2 ne yr1
if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
  do
    if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
      do
        if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
          do
            if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
              do
                if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                  do
                    if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                      do
                        if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                          do
                            if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                              do
                                if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                                  do
                                    if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                                      do
                                        if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                                          do
                                            if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                                              do
                                                if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                                                  do
                                                    if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                                                      do
                                                        if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                                                          do
                                                            if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                                                              do
                                                                if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                                                                  do
                                                                    if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                                                                      do
                                                                        if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                                                                          do
                                                                            if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                                                                              do
                                                                                if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                                                                                  do
                                                                                    if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                                                                                      do
                                                                                        if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                                                                                      end
                                                                                      end
                                                                end
                                                              end
                                                            end
                                                          end
                                                        end
                                                      end
                                                    end
                                                  end
                                                end
                                              end
                                            end
                                          end
                                        end
                                      end
                                    end
                                  end
                                end
                              end
                            end
                          end
                        end
                      end
                    end
                  end
                end
              end
            end
          end
        end
      end
    end
  end
end

/* landuse yr4 ne yr3 and yr3 = yr2 and yr2 ne yr1
if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
  do
    if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
      do
        if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
          do
            if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
              do
                if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                  do
                    if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                      do
                        if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                          do
                            if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                              do
                                if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                                  do
                                    if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                                      do
                                        if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                                          do
                                            if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                                              do
                                                if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                                                  do
                                                    if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                                                      do
                                                        if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                                                          do
                                                            if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                                                              do
                                                                if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                                                                  do
                                                                    if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                                                                      do
                                                                                        if %dlu4% ne %dlu3% and %dlu3% = %dlu2% and %dlu2% ne %dlu1% then
                                                                                      do
                                                                                        end
                                                                                      end
                                                                end
                                                              end
                                                            end
                                                          end
                                                        end
                                                      end
                                                    end
                                                  end
                                                end
                                              end
                                            end
                                          end
                                        end
                                      end
                                    end
                                  end
                                end
                              end
                            end
                          end
                        end
                      end
                    end
                  end
                end
              end
            end
          end
        end
      end
    end
  end
end
end
end
end

/* Get next record. */
&sv record = [read &fileerr% readerr]
&sv num = [TRIM %record% ]
&setvar num [subst %num% , '']
&type $num$
&end

&type Process complete.
&return
Appendix 3: adjacent.lu.aml

/* adjacent.lu.aml - this aml looks at each parcel and
/* determines the number of adjacent parcels with ag, dev, undev, and resid
/* dominant landuse for the 4 years present.
/* created March 4, 2005

precision double
&s v yr all fishnetallu

/* create a list of id numbers to use to loop through each 1 acre parcel.

&if not [exists list.txt -file] &then
&do
	tables
	&if not [iteminfo %yrall%.pat -info id_recnum -exists] &then
	additem %yrall%.pat id_recnum 4 5 b
	sel %yrall%.pat
	dom id_recnum = %yrall%

calc id_recnum = id_recnum ne 'none'
	unload list.txt id_recnum
&end

/* add items to hold new data
&if not [iteminfo %yrall%.pat -info no_ag37 -exists] &then
additem %yrall%.pat %yrall%.pat no_ag37 2 4 n
&if not [iteminfo %yrall%.pat -info no_dev37 -exists] &then
additem %yrall%.pat %yrall%.pat no_dev37 2 4 n
&if not [iteminfo %yrall%.pat -info no_undev37 -exists] &then
additem %yrall%.pat %yrall%.pat no_undev37 2 4 n
&if not [iteminfo %yrall%.pat -info no_resid37 -exists] &then
additem %yrall%.pat %yrall%.pat no_resid37 2 4 n
&if not [iteminfo %yrall%.pat -info no_ag59 -exists] &then
additem %yrall%.pat %yrall%.pat no_ag59 2 4 n
&if not [iteminfo %yrall%.pat -info no_dev59 -exists] &then
additem %yrall%.pat %yrall%.pat no_dev59 2 4 n
&if not [iteminfo %yrall%.pat -info no_undev59 -exists] &then
additem %yrall%.pat %yrall%.pat no_undev59 2 4 n
&if not [iteminfo %yrall%.pat -info no_resid59 -exists] &then
additem %yrall%.pat %yrall%.pat no_resid59 2 4 n
&if not [iteminfo %yrall%.pat -info no_ag82 -exists] &then
additem %yrall%.pat %yrall%.pat no_ag82 2 4 n
&if not [iteminfo %yrall%.pat -info no_dev82 -exists] &then
additem %yrall%.pat %yrall%.pat no_dev82 2 4 n
&if not [iteminfo %yrall%.pat -info no_undev82 -exists] &then
additem %yrall%.pat %yrall%.pat no_undev82 2 4 n
&if not [iteminfo %yrall%.pat -info no_resid82 -exists] &then
additem %yrall%.pat %yrall%.pat no_resid82 2 4 n
&if not [iteminfo %yrall%.pat -info no_ag02 -exists] &then
additem %yrall%.pat %yrall%.pat no_ag02 2 4 n
&if not [iteminfo %yrall%.pat -info no_dev02 -exists] &then
additem %yrall%.pat %yrall%.pat no_dev02 2 4 n
&if not [iteminfo %yrall%.pat -info no_undev02 -exists] &then
additem %yrall%.pat %yrall%.pat no_undev02 2 4 n
&if not [iteminfo %yrall%.pat -info no_resid02 -exists] &then
additem %yrall%.pat %yrall%.pat no_resid02 2 4 n
&if [exists list.txt -file] &then
&do
	&s v fileerr = [open list.txt openerr -read]
/* Check for errors in opening file.
&if %openerr% <> 0 &then
	&return &warning Error opening opening file.
/* Read from file */
$sv record = [read %fileerr% readerr]
if readerr <> 0 then
  return &warning Could not read file.
$sv num = [TRIM %record% ]
&setvar num [subst %num% , '']
do &until %readerr% = 102
/* set variables */
$sv a37 0
$sv a59 0
$sv a82 0
$sv a02 0
$sv u37 0
$sv u59 0
$sv u82 0
$sv u02 0
$sv r37 0
$sv r59 0
$sv r82 0
$sv r02 0
$sv d37 0
$sv d59 0
$sv d82 0
$sv d02 0
/* select the parcel, put it into a new coverage, buffer parcel and use to */
/* select its neighbors. */
ae
ec %yrall%
ef poly
sel id_recnum = %num%
put p%num% q
build p%num%
buffer p%num% p%num%b # # 30 .01 poly
ae
ec %yrall%
ef poly
apc resel p%num%b poly inside = 100
apc resel $yrall poly overlap p%num%b poly
selectget
unsel id_recnum = %num%
put ps%num% q
/* run frequencies to count the landuses around the parcel */
frequency ps%num%.pat ps%num%_37.tab
new_dom_lu37
end
area
end
frequency ps%num%.pat ps%num%_59.tab
new_dom_lu59
end
area
end
frequency ps%num%.pat ps%num%_82.tab
new_dom_lu82
end
area
end
frequency ps%num%.pat ps%num%_02.tab
dominant_lu02
/* find the frequency and assign to variables ae */

edit ps%num%_37.tab info
sel new_dom.lu37 = 'ag'
&if [show number select] > 0 &then
&do
  statistics # # init
  sum frequency
  end
&sv a37 [show statistic 1 1]
&end

edit ps%num%_37.tab info
sel new_dom.lu37 = 'undev'
&if [show number select] > 0 &then
&do
  statistics # # init
  sum frequency
  end
&sv u37 [show statistic 1 1]
&end

edit ps%num%_37.tab info
sel new_dom.lu37 = 'resid'
&if [show number select] > 0 &then
&do
  statistics # # init
  sum frequency
  end
&sv r37 [show statistic 1 1]
&end

edit ps%num%_37.tab info
sel new_dom.lu37 = 'ag'
&if [show number select] > 0 &then
&do
  statistics # # init
  sum frequency
  end
&sv a59 [show statistic 1 1]
&end

edit ps%num%_59.tab info
sel new_dom.lu59 = 'undev'
&if [show number select] > 0 &then
&do
  statistics # # init
  sum frequency
  end
&sv u59 [show statistic 1 1]
&end

edit ps%num%_59.tab info
sel new_dom.lu59 = 'resid'
&if [show number select] > 0 &then
&do
  statistics # # init

sum frequency
end
&sv r59 [show statistic 1 1]
&end

edit ps$num%_59.tab info
sel new_dom_lu59 = 'dev'
&if [show number select] > 0 &then
&do
  statistics # # init
  sum frequency
end
&sv d59 [show statistic 1 1]
&end

edit ps$num%_82.tab info
sel new_dom_lu82 = 'ag'
&if [show number select] > 0 &then
&do
  statistics # # init
  sum frequency
end
&sv a82 [show statistic 1 1]
&end

edit ps$num%_82.tab info
sel new_dom_lu82 = 'undev'
&if [show number select] > 0 &then
&do
  statistics # # init
  sum frequency
end
&sv u82 [show statistic 1 1]
&end

edit ps$num%_82.tab info
sel new_dom_lu82 = 'resid'
&if [show number select] > 0 &then
&do
  statistics # # init
  sum frequency
end
&sv r82 [show statistic 1 1]
&end

edit ps$num%_02.tab info
sel dominant_lu02 = 'ag'
&if [show number select] > 0 &then
&do
  statistics # # init
  sum frequency
end
&sv a02 [show statistic 1 1]
&end

edit ps$num%_02.tab info
sel dominant_lu02 = 'undev'
&if [show number select] > 0 &then
&do
  statistics # # init
  sum frequency
end
&sv u02 [show statistic 1 1]
&end

edit ps%num%_02.tab info
sel dominant_lu02 = 'resid'
&if [show number select] > 0 &then
  &do
    statistics # # init
    sum frequency
  end
&sv r02 [show statistic 1 1]
&end

edit ps%num%_02.tab info
sel dominant_lu02 = 'dev'
&if [show number select] > 0 &then
  &do
    statistics # # init
    sum frequency
  end
&sv d02 [show statistic 1 1]
&end

q

/* add numbers to the parcel attribute table tables
sel %yrall%.pat
resel id_recnum = %num%
calc no_ag37 = %a37%
calc no_dev37 = %d37%
calc no_resid37 = %r37%
calc no_undev37 = %u37%
calc no_ag59 = %a59%
calc no_dev59 = %d59%
calc no_resid59 = %r59%
calc no_undev59 = %u59%
calc no_ag82 = %a82%
calc no_dev82 = %d82%
calc no_resid82 = %r82%
calc no_undev82 = %u82%
calc no_ag02 = %a02%
calc no_dev02 = %d02%
calc no_resid02 = %r02%
calc no_undev02 = %u02%
q

/* clean up coverages
kill ps%num% all
kill ps%num% all
kill p%num%b all
tables
&if [exists ps%num%_37.tab -info] &then kill ps%num%_37.tab
&if [exists ps%num%_59.tab -info] &then kill ps%num%_59.tab
&if [exists ps%num%_82.tab -info] &then kill ps%num%_82.tab
&if [exists ps%num%_02.tab -info] &then kill ps%num%_02.tab
q

/* Get next record.
&sv record = [read %fileerr% readerr]
&sv num = [TRIM %record% ]
&setvar num [subst %num% , '']
stype %num%
&end

stype Process complete.
&return

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Proximity to roads and shoreline:
- Convert gn_shl_82 shapefile into shl82 line coverage.
- remove the land arc that closed gloucestor shoreline into a polygon.
- create bigbox - a rectangle to use for clipping Tiger roads to the general Gloucester study area. build bigbox
- clip tiger roads with bigbox. name new coverage gloursds.
  (clip /ccci/gis/data/tiger2000/statewide_covs/roads/tgr2000_rds bigbox
  gloursds line .01)
- cellsize .63.61m

- determine road distances using GRID:
  Grid: setwindow fishnet1102
  Grid: outrds = linedist(gloursds, length, 63.61, dist, 600)
  convert floating point grid to integer grid: rd_dist = int(outrds)
  convert from grid back to polygon: rd_distp = gridpoly(rd_dist, .01)

- determine shoreline distances using grid:
  Grid: setwindow fishnet1102
  Grid: outshl = linedist(shl82, length, 63.61, dist, 2000)
  convert floating point grid to integer grid: shl_distg = int(outshl)
  convert from grid back to polygon: shl_distp = gridpoly(shl_distg, .01)

- alter items: grid-code in rd_distp -> rd_dist
  grid-code in shl_distp -> shldist

- union: union shl_distp rd_distp dist_cov .01

- in tables, dropitems:
  dropitem dist_cov.pat shl_distp# shl_distp-id rd_distp# rd_distp-id

- Use identity to combine the dist_cov with testa1l2 coverage:
  identity testa1l2 dist_cov newtesta1l poly .01

- clean up newtesta1l.pat by dropping some unimportant items:
  dropitem newtesta1l.pat union2# union2-id yr82# yr82-id union1# union1-id
  yr37# yr37-id yr59# yr59-id testa1l2# testa1l2-id yr02# yr02-id dist_cov#
  dist_cov-id perimeter59 perimeter82 perimeter37 perimeter02
Appendix 5: lu_stru_sum.aml

/* lu_str_sum.aml : This aml summarizes bank erosion, bank height, marsh, /* beach, and shoreline structures of each acre parcel. /* May 17, 2005

/* make sure all coverages have a unique id that is not the # or -id tables
&if not [iteminfo lushldr.pat -info id_recnum -exists] &then
  &do
  additem lushldr.pat id_recnum 4 5 b lushldr-id
  sel lushldr.pat
  calc id_recnum = lushldr#
  &end

&if not [iteminfo lushldr_lubc.aat -info id_recnum -exists] &then
  &do
  additem lushldr_lubc.aat id_recnum 4 5 b lushldr#
  sel lushldr_lubc.aat
  calc id_recnum = lushldr#
  &end

&if not [iteminfo lushldr_sstru.aat -info id_recnum -exists] &then
  &do
  additem lushldr_sstru.aat id_recnum 4 5 b lushldr#
  sel lushldr_sstru.aat
  calc id_recnum = lushldr#
  &end

/* run frequencies on the different attributes for lubc and structures.
&if not [exists lushldr_er.tab -info] &then
  &do
  frequency lushldr_lubc.aat lushldr_er.tab id_recnum erosion end
  length end
  &end

&if not [exists lushldr_mar.tab -info] &then
  &do
  frequency lushldr_lubc.aat lushldr_mar.tab id_recnum marsh end
  length end
  &end

&if not [exists lushldr_bea.tab -info] &then
  &do
  frequency lushldr_lubc.aat lushldr_bea.tab id_recnum beach end
  length end
  &end

&if not [exists lushldr_hgt.tab -info] &then
  &do
  frequency lushldr_lubc.aat lushldr_hgt.tab id_recnum height end
  length end
&end
&if not [exists lushrld_str.tab -info] &then
 &do
 frequency lushrld_str.tab lushrld_str.tab id_recnum
 structure
 end
 length
 &end
/* add item to .tab files. This item will hold the structure or land use
/* characteristic most common for the acre parcel.
 tables
 &if not [iteminfo lushrld_str.tab -info maj_structure -exists] &then
 additem lushrld_str.tab maj_structure 20 20 c structure
 &if not [iteminfo lushrld_mar.tab -info maj_marsh -exists] &then
 additem lushrld_mar.tab maj_marsh 20 20 c marsh
 &if not [iteminfo lushrld_bea.tab -info maj_beach -exists] &then
 additem lushrld_bea.tab maj_beach 20 20 c beach
 &if not [iteminfo lushrld_hgt.tab -info maj_height -exists] &then
 additem lushrld_hgt.tab maj_height 20 20 c height
 &if not [iteminfo lushrld_er.tab -info maj_erosion -exists] &then
 additem lushrld_er.tab maj_erosion 20 20 c erosion
 q

 /* create a list of id numbers to use to loop through 1 acre parcels.
 /* only want one of each number, so need to select, run frequency and then
 /* make list.
 &if not [exists shllist.txt -file] &then
 &do
 tables
 sel lushrld_lubc.aat
 resel feature ne ' '
 unload shllisttemp.txt id_recnum
 define shllist.dat
 id_recnum 4 5 b
 ~
 add from shllisttemp.txt
 q
 frequency shllist.dat shllist.tab id_recnum
 end
 end
 tables
 sel shllist.tab
 resel id_recnum ne 1
 unload shllist.txt id_recnum
 q &end
 ae
&if [exists shllist.txt -file] &then
 &do
 &sv fileerr = [open shllist.txt openerr -read]
 /* Check for errors in opening file.
 &if %openerr% <> 0 &then
 &return &warning Error opening file.
 /* Read from file
 &sv record = [read %fileerr% readerr]
 &if %readerr% <> 0 &then
 &return &warning Could not read file.
 &sv num = [TRIM %record% ]
 &setvar num [subst %num% , '"']
&do &until %readerr$ = 102
/* set variables to zero
%sv slen = 0
%sv rn = 0
%sv na = 0
%sv slen1 = 0
%sv rn1 = 0
%sv na1 = 0
%sv slen2 = 0
%sv rn2 = 0
%sv na2 = 0
%sv slen3 = 0
%sv rn3 = 0
%sv na3 = 0
%sv slen4 = 0
%sv rn4 = 0
%sv na4 = 0
/* rule 1 - for structures: if only one structure occurs within an acre
/* parcel, that structure must be atleast 10m in length to keep the code
/* for the acre parcel.
/* structure
edit lushlrld_str.tab info
sel id_recnum = %num%
&if [show number select] = 1 &then
calc maj_structure = structure
&if [show number select] > 1 &then
&do
resel structure ne ' '
&if [show number select] > 0 &then
&do
statistics # # init
max length
end
%sv slen [show statistic 1 1]
&if %slen% ge 5 &then
&do
resel length ge %slen% or length ge [truncate %slen%]
%sv rn = [show select 1]
%sv na = [show info %rn% item structure]
sel id_recnum = %num%
calc maj_structure = [quote %na%]
&end
&end
&end
/* edit marsh
edit lushlrld_mar.tab info
sel id_recnum = %num%
&if [show number select] = 1 &then
calc maj_marsh = marsh
&if [show number select] > 1 &then
&do
resel marsh lk 'Yes*'
&if [show number select] > 0 &then
&do
statistics # # init
max length
end
%sv slen1 [show statistic 1 1]
&if %slen1% ge 5 &then
&do
resel length ge %slen1% or length ge [truncate %slen1%]
%sv rn1 = [show select 1]
%sv na1 = [show info %rn1% item marsh]
```sql
select id_recnum = %num%
calc maj_marsh = [quote %na1%]
&end
&end

/* edit beach
edit lushlrdbea.tab info
sel id_recnum = %num%
&if [show number select] = 1 &then
calc maj_beach = beach
&if [show number select] > 1 &then
&do
resel beach lk 'Yes*'
&if [show number select] > 0 &then
&do
  statistics # # init
  max length
  end
  &sv slen2 [show statistic 1 1]
  &if %slen2% ge 5 &then
  &do
    resel length ge %slen2% or length ge [truncate %slen2%]
    &sv rn2 = [show select 1]
    &sv na2 = [show info %rn2% item beach]
    sel id_recnum = %num%
calc maj_beach = [quote %na2%]
  &end
  &end
&end
&end

/* edit erosion
edit lushlrder.tab info
sel id_recnum = %num%
&if [show number select] = 1 &then
calc maj_erosion = erosion
&if [show number select] > 1 &then
&do
resel erosion ne ' '
&if [show number select] > 0 &then
&do
  statistics # # init
  max length
  end
  &sv slen3 [show statistic 1 1]
  &if %slen3% ge 5 &then
  &do
    resel length ge %slen3% or length ge [truncate %slen3%]
    &sv rn3 = [show select 1]
    &sv na3 = [show info %rn3% item erosion]
    sel id_recnum = %num%
calc maj_erosion = [quote %na3%]
  &end
  &end
&end
&end

/* edit height
edit lushlrhdg.tab info
sel id_recnum = %num%
&if [show number select] = 1 &then
calc maj_height = height
&if [show number select] > 1 &then
&do
resel height ne ' '
&if [show number select] > 0 &then
```
&do
statistics # # init
max length
end
&sv slen4 [show statistic 1 1]
&if %slen4% ge 5 &then
&do
resel length ge %slen4% or length ge [truncate %slen4%]
&sv rn4 = [show select 1]
&sv na4 = [show info %rn4% item height]
sel id_recnum = %num%
calc maj_height = [quote %na4%]
&end
&end
&end

/* Get next record. */
&sv record = [read %fileerr% readerr]
&sv num = [TRIM %record%]
&se tvar num [subst %num% , ' ']
&type Acre parcel number is %num%
&end
q yes

/* Run frequencies again to condense data, then do joinitem to get data into */
/* lushlrd coverage. */
frequency lushlrd_str.tab stru.tab
id_recnum
maj_structure
end
length
end

frequency lushlrd_mar.tab marsh.tab
id_recnum
maj_marsh
end
length
end

frequency lushlrd_bea.tab beach.tab
id_recnum
maj_beach
end
length
end

frequency lushlrd_hgt.tab hgt.tab
id_recnum
maj_height
end
length
end

frequency lushlrd_er.tab erosion.tab
id_recnum
maj_erosion
end
length
end

joinitem lushlrd.pat hgt.tab lushlrd.pat id_recnum
joinitem lushlrd.pat erosion.tab lushlrd.pat id_recnum maj_height
joinitem lushlrd.pat marsh.tab lushlrd.pat id_recnum maj_erosion
joinitem lushlrd.pat beach.tab lushlrd.pat id_recnum maj_marsh
joinitem lushlrd.pat stru.tab lushlrd.pat id_recnum maj_beach

tables
dropitem lushlrd.pat case# frequency
q
/* struct_sum.aml 
/* Look at adjacent acre parcels to determine if they contain any structures. 
/* If they contain structures, count number. Are they bulkhead or groins? 

precision double

&sv c lushlrld
&sv list [response 'Enter complete name of list file you wish to use']

/* add items to hold new data
&if not [iteminfo %c%.pat -info no_structures -exists] &then
additem %c%.pat %c%.pat no_structures 2 4 n
&if not [iteminfo %c%.pat -info bulkhead -exists] &then
additem %c%.pat %c%.pat bulkhead 3 3 c
&if not [iteminfo %c%.pat -info groin -exists] &then
additem %c%.pat %c%.pat groin 3 3 c

&if [exists %list% -file] &then
&do
&sv fileerr = [open %list% openerr -read]
/* Check for errors in opening file.
&if %openerr% <> 0 &then
&return &warning Error opening file.
/* Read from file
&sv record = [read %fileerr% readerr]
&if %readerr% <> 0 &then
&return &warning Could not read file.
&sv num = [TRIM %record% ]
&setvar num [subst $num% , '']
&do &until %readerr% = 102
/* set variables
&sv sr '0'
&sv bu 'no'
&sv gr 'no'

/* select the parcel, put it into a new coverage, buffer parcel and use to 
/* select its neighbors.
ae
ec %c%
ef poly
sel id_recnum = %num%
put p%num% 
q
build p%num%
buffer p%num% p%num%b # # 30 .01 poly

ae
ec %c%
ef poly
apc resel p%num%b poly inside = 100
apc resel %c% poly overlap p%num%b poly
selectget
unsel id_recnum = %num%
put p%num% 
q
/* run frequency to count the structures around the parcel 
frequency ps%num%.pat ps%num%_str.tab
maj_structure
end
area
end

/* find the frequency and assign to variables ae
edit ps%num%_str.tab info
sel maj_structure = 'bulkhead'
&if [show number select] > 0 &then
  &sv bu = 'yes'
&if [show number select] > 0 &then
  &sv gr = 'yes'
end
edit ps%num%_str.tab info
sel maj_structure ne ' '
&if [show number select] > 0 sthen
  &sv bu = 'yes'
&if [show number select] > 0 sthen
  &sv gr = 'yes'
end

/* add values to the parcel attribute table
sel %c%.pat
resel id_recnum = %num%
calc no_structures = %st%
calc bulkhead = %bu%
calc groin = %gr%
q

/* clean up coverages
kill ps%num% all
kill ps%num% all
kill ps%num% all
tables
&if [exists ps%num%_str.tab -info] &then kill ps%num%_str.tab
&if [exists ps%num%_59.tab -info] &then kill ps%num%_59.tab
&if [exists ps%num%_82.tab -info] &then kill ps%num%_82.tab
&if [exists ps%num%_02.tab -info] &then kill ps%num%_02.tab
q

/* Get next record.
&sv record = [read %fileerr% readerr]
&sv num = [TRIM %record% ]
&setvar num [subst %num% , ' ']
&type %num%
&end
&type Process complete.
&return
Appendix 7: bulkhead.fis

[System]
Name='bulkhead'
Type='mamdani'
Version=2.0
NumInputs=3
NumOutputs=1
NumRules=5
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='sum'
DefuzzMethod='mom'

[Input1]
Name='blkregscore'
Range=[-5 5]
NumMFs=2
MF1='blklikely': 'gaussmf', [2.02 -5.54195767195767]
MF2='blknotlikely': 'gaussmf', [2.12 5.15873015873016]

[Input2]
Name='luaall25'
Range=[0 1]
NumMFs=2
MF1='luconduciveness': 'gaussmf', [0.304 1.07380952380952]
MF2='luconduciveness': 'gaussmf', [0.257 -0.0445104761904762]

[Input3]
Name='adjbulk'
Range=[0 1]
NumMFs=2
MF1='adjbulk': 'gaussmf', [0.209 1.07]
MF2='noadjbulk': 'gaussmf', [0.212 -0.161375661375661]

[Output1]
Name='bulkhead'
Range=[0 1]
NumMFs=2
MF1='blklikelihood': 'gaussmf', [0.343 1.05026455026455]
MF2='blknotlikely': 'gaussmf', [0.212 -0.0106]

[Rules]
1 -2 0, 1 (1) : 1
0 1 0, 1 (1) : 1
0 2 1, 2 (1) : 1
0 -2 1, 1 (1) : 1
0 2 2, 2 (1) : 1
Appendix 8: riprap.fis

[System]
Name='riprap'
Type='mamdani'
Version=2.0
NumInputs=3
NumOutputs=1
NumRules=5
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='sum'
DefuzzMethod='mom'

[Input1]
Name='ripregscore'
Range=[-5 25]
NumMFs=2
MF1='riplikely': 'gaussmf', [3.73 -5.6237619047619]
MF2='ripnolikely': 'gaussmf', [5.19704053985764 26]

[Input2]
Name='luall25'
Range=[0 1]
NumMFs=2
MF1='luconducive': 'gaussmf', [0.213 1.08658201058201]
MF2='lunotconducive': 'gaussmf', [0.145 -0.018539682539683]

[Input3]
Name='adjstruct'
Range=[0 1]
NumMFs=2
MF1='nostruct': 'gaussmf', [0.1 0.00261798941798942]
MF2='struct': 'gaussmf', [0.0887 1.0326455026455]

[Output1]
Name='riprap'
Range=[0 1]
NumMFs=2
MF1='riplikely': 'gaussmf', [0.194355385515645 1]
MF2='ripnolikely': 'gaussmf', [0.207882520347533 -0.0318]

[Rules]
1 -2 0, 1 (1) : 1
0 1 0, 1 (1) : 1
0 2 2, 2 (1) : 1
0 -2 2, 1 (1) : 1
0 2 1, 2 (1) : 1
Appendix 9: groin.fis

[System]
Name='groin'
Type='mamdani'
Version=2.0
NumInputs=4
NumOutputs=1
NumRules=6
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='sum'
DefuzzMethod='mom'

[Input1]
Name='grgresscore'
Range=[-10 0.5]
NumMFs=2
MF1='grlikely': 'gaussmf',[1.783 -10]
MF2='grnotlikely': 'gaussmf',[1.783 0.5]

[Input2]
Name='totalru25'
Range=[0 8]
NumMFs=2
MF1='grnotlikely': 'gaussmf',[1.359 5.551e-017]
MF2='grlikely': 'gaussmf',[1.36 5.5026455026455]

[Input3]
Name='lual25'
Range=[0 1]
NumMFs=2
MF1='lunotconducive': 'gaussmf',[0.183120970167919 0]
MF2='luc conducive': 'gaussmf',[0.192 1.08201058201058]

[Input4]
Name='adjgroin'
Range=[0 1]
NumMFs=2
MF1='noadjgroin': 'gaussmf',[0.1699 6.939e-018]
MF2='adjgroin': 'gaussmf',[0.17 1.05026455026455]

[Output1]
Name='groin'
Range=[0 1]
NumMFs=2
MF1='grnotlikely': 'gaussmf',[0.1699 6.939e-018]
MF2='grlikely': 'gaussmf',[0.17 1]

[Rules]
1 0 -1 0, 2 (1) : 1
0 0 2 0, 2 (1) : 1
0 0 1 2, 1 (1) : 1
0 0 -1 2, 2 (1) : 1
0 0 1 1, 1 (1) : 1
0 2 -1 0, 2 (1) : 1
Appendix 10: bulkhead2.fis

[System]
Name='bulkhead2'
Type='mamdani'
Version=2.0
NumInputs=4
NumOutputs=1
NumRules=3
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='sum'
DefuzzMethod='mom'

[Input1]
Name='lual125'
Range=[0 1]
NumMFs=2
MF1='lunotconducive': 'gaussmf', [0.1699 6.939e-018]
MF2='luconducive': 'gaussmf', [0.1699 1]

[Input2]
Name='adjbulk'
Range=[0 1]
NumMFs=2
MF1='noadjbulk': 'gaussmf', [0.1699 6.939e-018]
MF2='adjbulk': 'gaussmf', [0.1699 1]

[Input3]
Name='htcode'
Range=[0 1]
NumMFs=2
MF1='low': 'gaussmf', [0.17 -0.0979]
MF2='high': 'gaussmf', [0.17 1.23015873015873]

[Input4]
Name='erocode'
Range=[0 1]
NumMFs=1
MF1='erocode': 'gaussmf', [0.853 1.68518518518519]

[Output1]
Name='structure2'
Range=[0 1]
NumMFs=2
MF1='blknotlikely': 'gaussmf', [0.1699 6.939e-018]
MF2='blklikely': 'gaussmf', [0.1699 1]

[Rules]
2 2 0 0, 2 (1) : 1
1 0 2 0, 1 (1) : 2
0 0 1 1, 2 (1) : 1
Appendix 11: riprap2.fis

```plaintext
[System]
Name='riprap2'
Type='mamdani'
Version=2.0
NumInputs=3
NumOutputs=1
NumRules=3
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='sum'
DefuzzMethod='mom'

[Input1]
Name='lua1l25'
Range=[0 1]
NumMFs=2
MF1='lunotconducive': 'gaussmf', [0.1699 6.939e-018]
MF2='luconducive': 'gaussmf', [0.17 1.05820105820106]

[Input2]
Name='adjstruct'
Range=[0 1]
NumMFs=2
MF1='nostuct': 'gaussmf', [0.1699 6.939e-018]
MF2='adjstruct': 'gaussmf', [0.17 1.05026455026455]

[Input3]
Name='erocode'
Range=[0 1]
NumMFs=1
MF1='erocode': 'gaussmf', [1.1 2.29910052910053]

[Output1]
Name='output1'
Range=[0 1]
NumMFs=2
MF1='ripnotlikely': 'gaussmf', [0.1699 6.939e-018]
MF2='riplikely': 'gaussmf', [0.1699 1]

[Rules]
2 2 0, 2 (1) : 1
1 0 0, 1 (1) : 1
2 0 1, 2 (1) : 1
```

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Appendix 12: groin2.fis

[System]
Name='groin2'
Type='mamdani'
Version=2.0
NumInputs=4
NumOutputs=1
NumRules=4
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='sum'
DefuzzMethod='mom'

[Input1]
Name='totsurrlu25'
Range=[3 8]
NumMFs=1
MF1='surrlu': 'gauss2mf', [0.437 4.99 0.38513590256592 6.00925925925926]

[Input2]
Name='lual125'
Range=[0 1]
NumMFs=2
MF1='lunotconducive': 'gaussmf', [0.1699 6.939e-018]
MF2='lucconducive': 'gaussmf', [0.17 1.05089947089947]

[Input3]
Name='adjgroin'
Range=[0 1]
NumMFs=2
MF1='noadjgroin': 'gaussmf', [0.1699 6.939e-018]
MF2='adjgroin': 'gaussmf', [0.17 1.11]

[Input4]
Name='erocode'
Range=[0 1]
NumMFs=1
MF1='erosion': 'gaussmf', [0.859 1.92857142857143]

[Output1]
Name='groin'
Range=[0 1]
NumMFs=2
MF1='groinnotlikely': 'gaussmf', [0.1699 6.939e-018]
MF2='groinlikely': 'gaussmf', [0.1699 1]

[Rules]
0 2 0 1, 2 (1) : 1
1 2 0 0, 2 (1) : 1
0 -1 2 0, 2 (1) : 1
0 1 0 0, 1 (1) : 1
Appendix 13: elev_maj.txt

/* elev_maj.aml : This aml summarizes elevation for each acre parcel.
/* May 20, 2005

/* join coverages lushlrd.pat and elevationrl.pat
union lushlrd elevationrl lushlrd_elev

/* run frequencies on elevation.
&if not [exists lushlrd_elev.tab -info] &then
 &do
 frequency lushlrd_elev.pat lushlrd_elev.tab
     id_recnum
 elevation
     area
     end
 &end

/* add item to .tab files. This item will hold the elevation
/* characteristic for the majority of the acre parcel.
tables
&if not [iteminfo lushlrd_elev.tab -info maj_elev -exists] &then
   &additem lushlrd_elev.tab maj_elev 5 5 c
 &end

/* create a list of id numbers to use to loop through 1 acre parcels.
/* only want one of each number, so need to select, run frequency and then
/* make list.
&if not [exists list2.txt -file] &then
 &do
tables
     sel lushlrd.pat
     resel id_recnum ne 0
     unload list2.txt id_recnum
 &end
 &if [exists list2.txt -file] &then
 &do
     &sv fileerr = [open list2.txt openerr -read]
 /* Check for errors in opening file.
 &if %openerr% <> 0 &then
     &return &warning Error opening file.
 /* Read from file
 &sv record = [read %fileerr% readerr]
 &if %readerr% <> 0 &then
     &return &warning Could not read file.
 &sv num = [TRIM %record% ]
 &setvar num [subst %num% , ' ']
 &do &until %readerr% = 102
 /* set variables to zero
 &sv slen = 0
 &sv rn = 0
 &sv na = 0
 &sv slenl = 0
 &sv rnl = 0
 &sv nal = 0
 &sv slen2 = 0
 &sv rnl2 = 0

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\& sv \ na2 = 0
\& sv \ slen3 = 0
\& sv \ rn3 = 0
\& sv \ na3 = 0
\& sv \ slen4 = 0
\& sv \ rn4 = 0
\& sv \ na4 = 0

/* for elevation: parcel will be coded with the elevation that takes up
/* most of the area

/* elevation
edit lushlrd_elev.tab info
sel id_recnum = %num%

&if [show number select] = 1 &then
calc maj_elev = elevation
&if [show number select] > 1 &then
&do
resel elevation ne ' ' 
&if [show number select] > 0 &then
&do
statistics # # init
  max area
end
&sv slen [show statistic 1 1]
  resel area ge %slen% or area ge [truncate %slen%]
&sv rn = [show select 1]
&sv na = [show info %rn% item elevation]
  sel id_recnum = %num%
  calc maj_elev = [quote %na%]
&end
&end
&end

/* Get next record.
&sv record = [read %fileerr% readderr]
&sv num = [TRIM %record% ]
&setvar num [subst %num% , ' ']
&type Acre parcel number is %num%
&end
q yes

/* Run frequencies again to condense data, then do joinitem to get data into
/* lushlrd coverage.

frequency lushlrd_elev.tab elev.tab
id_recnum
maj_elev
end
area
end

joinitem lushlrd.pat elev.tab lushlrd.pat id_recnum

tables
dropitem lushlrd.pat case# frequency
q

&type This program has finished!
&return
Appendix 14: Logistic Regression Output (in SPSS) for Land Use Prediction

Variable descriptions:

LU02UNDEV = Land use of the parcel is 'undeveloped'
LU02AG = Land use of the parcel is 'agricultural'
LU02RESID = Land use of the parcel is 'residential'
LU02DEV = Land use of the parcel is 'developed'
NO_UNDEV02 = Number of surrounding parcels that are 'undeveloped'
NO_AG02 = Number of surrounding parcels that are 'agricultural'
NO_RESID02 = Number of surrounding parcels that are 'residential'
NO_DEV02 = Number of surrounding parcels that are 'developed'
SHLDIST = Distance from the center of the parcel to the nearest shoreline
RDDIST = Distance from the center of the parcel to the nearest road

Classification Table(a,b)

<table>
<thead>
<tr>
<th>Observed</th>
<th>Predicted</th>
<th>Percentage</th>
<th>Correct</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LU02UNDEV</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>3586</td>
<td>.0</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>3875</td>
<td>100.0</td>
</tr>
</tbody>
</table>

Overall Percentage 51.9

Variables not in the Equation

<table>
<thead>
<tr>
<th>Step 0: Variables</th>
<th>Score</th>
<th>df</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>NO_AG02</td>
<td>1600.686</td>
<td>1</td>
<td>.000</td>
</tr>
<tr>
<td>NO_DEV02</td>
<td>72.210</td>
<td>1</td>
<td>.000</td>
</tr>
<tr>
<td>NO_UNDEV02</td>
<td>4724.310</td>
<td>1</td>
<td>.000</td>
</tr>
<tr>
<td>NO_RESID02</td>
<td>1896.083</td>
<td>1</td>
<td>.000</td>
</tr>
<tr>
<td>SHLDIST</td>
<td>561.762</td>
<td>1</td>
<td>.000</td>
</tr>
<tr>
<td>RDDIST</td>
<td>75.325</td>
<td>1</td>
<td>.000</td>
</tr>
<tr>
<td>Overall Statistics</td>
<td>4754.320</td>
<td>6</td>
<td>.000</td>
</tr>
</tbody>
</table>

Variables in the Equation

<table>
<thead>
<tr>
<th>Step 1(a) NO_UNDEV02</th>
<th>B</th>
<th>S.E.</th>
<th>Wald</th>
<th>df</th>
<th>Sig.</th>
<th>Exp(B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-4.121</td>
<td>.098</td>
<td>1776.779</td>
<td>1</td>
<td>.000</td>
<td>.16</td>
</tr>
<tr>
<td>NO_UNDEV02</td>
<td>.975</td>
<td>.021</td>
<td>2174.277</td>
<td>1</td>
<td>.000</td>
<td>2.651</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Step 2(b) NO_UNDEV02</th>
<th>B</th>
<th>S.E.</th>
<th>Wald</th>
<th>df</th>
<th>Sig.</th>
<th>Exp(B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-4.121</td>
<td>.098</td>
<td>1776.779</td>
<td>1</td>
<td>.000</td>
<td>.16</td>
</tr>
<tr>
<td>NO_UNDEV02</td>
<td>.963</td>
<td>.021</td>
<td>2084.639</td>
<td>1</td>
<td>.000</td>
<td>2.619</td>
</tr>
<tr>
<td>Step</td>
<td>Variable(s) entered</td>
<td>Coefficients</td>
<td>Standard Error</td>
<td>t Value</td>
<td>df</td>
<td>Significance</td>
</tr>
<tr>
<td>------</td>
<td>---------------------</td>
<td>--------------</td>
<td>----------------</td>
<td>--------</td>
<td>----</td>
<td>--------------</td>
</tr>
<tr>
<td>3(c)</td>
<td>NO_UNDE V02, SHLDIST, RDDIST</td>
<td>-4.267</td>
<td>.107</td>
<td>42.29</td>
<td>1585.133</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Constant</td>
<td>-.281</td>
<td>.108</td>
<td>2.63</td>
<td>1581.246</td>
<td>1</td>
</tr>
<tr>
<td>4(d)</td>
<td>NO_AG02, NO_UNDE V02, SHLDIST, RDDIST</td>
<td>-4.281</td>
<td>.108</td>
<td>42.29</td>
<td>1581.246</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Constant</td>
<td>.969</td>
<td>.021</td>
<td>46.74</td>
<td>1553.849</td>
<td>1</td>
</tr>
<tr>
<td>5(e)</td>
<td>NO_AG02, NO_UNDE V02, NO_RESID 02, SHLDIST, RDDIST</td>
<td>-2.665</td>
<td>.325</td>
<td>8.17</td>
<td>67.172</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Constant</td>
<td>.758</td>
<td>.045</td>
<td>16.78</td>
<td>22.295</td>
<td>1</td>
</tr>
<tr>
<td>6(f)</td>
<td>NO_AG02, NO_DEV0 2, NO_UNDE V02, NO_RESID 02, SHLDIST, RDDIST</td>
<td>-2.665</td>
<td>.325</td>
<td>8.17</td>
<td>67.172</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Constant</td>
<td>-.401</td>
<td>.057</td>
<td>7.29</td>
<td>49.897</td>
<td>1</td>
</tr>
</tbody>
</table>

a Variable(s) entered on step 1: NO_UNDEV02.
b Variable(s) entered on step 2: SHLDIST.
c Variable(s) entered on step 3: RDDIST.
d Variable(s) entered on step 4: NO_AG02.
e Variable(s) entered on step 5: NO_RESID02.
f Variable(s) entered on step 6: NO_DEV02.

ROC Curve

Case Processing Summary
Larger values of the test result variable(s) indicate stronger evidence for a positive actual state.
a The positive actual state is 1.

Test Result Variable(s): Predicted probability

<table>
<thead>
<tr>
<th>Area</th>
<th>Std. Error(a)</th>
<th>Asymptotic Sig.(b)</th>
<th>Asymptotic 95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>.952</td>
<td>.002</td>
<td>.000</td>
<td>.948</td>
</tr>
</tbody>
</table>

The test result variable(s): Predicted probability has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.
a Under the nonparametric assumption
b Null hypothesis: true area = 0.5

Classification Table(a,b)

<table>
<thead>
<tr>
<th>Observed</th>
<th>Predicted</th>
<th>Percentage Correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 0</td>
<td>LU02AG</td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>5878</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1583</td>
</tr>
<tr>
<td>Overall</td>
<td>Percentage</td>
<td></td>
</tr>
<tr>
<td>78.8</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Variables not in the Equation

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### Variables in the Equation

<table>
<thead>
<tr>
<th>Step 0 Variables</th>
<th>Score</th>
<th>df</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>NO_AG02</td>
<td>4374.543</td>
<td>1</td>
<td>.000</td>
</tr>
<tr>
<td>NO_DEV02</td>
<td>5.532</td>
<td>1</td>
<td>.019</td>
</tr>
<tr>
<td>NO_UNDEV02</td>
<td>1426.392</td>
<td>1</td>
<td>.000</td>
</tr>
<tr>
<td>NO_RESID02</td>
<td>197.556</td>
<td>1</td>
<td>.000</td>
</tr>
<tr>
<td>SHLDIST</td>
<td>.000</td>
<td>1</td>
<td>.991</td>
</tr>
<tr>
<td>RDDIST</td>
<td>8.117</td>
<td>1</td>
<td>.004</td>
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<tr>
<td><strong>Overall Statistics</strong></td>
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</table>

### Variables in the Equation

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<thead>
<tr>
<th>Step</th>
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<th>S.E.</th>
<th>Wald</th>
<th>df</th>
<th>Sig.</th>
<th>Exp(B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 1a</td>
<td>NO_AG02</td>
<td>1.075</td>
<td>.026</td>
<td>1747.810</td>
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<td>.000</td>
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<td>.000</td>
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<td>Step 2b</td>
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<td>.030</td>
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<td>.000</td>
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<tr>
<td></td>
<td>NO_UNDEV02</td>
<td>-.045</td>
<td>.022</td>
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*a Variable(s) entered on step 1: NO_AG02.*  
*b Variable(s) entered on step 2: NO_UNDEV02.*

### ROC Curve

**Case Processing Summary**

<table>
<thead>
<tr>
<th>LU02AG</th>
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</tr>
</thead>
<tbody>
<tr>
<td>Positive(a)</td>
<td>1583</td>
</tr>
<tr>
<td>Negative</td>
<td>5878</td>
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</tbody>
</table>

Larger values of the test result variable(s) indicate stronger evidence for a positive actual state.  
*a The positive actual state is 1.*
Area Under the Curve

Test Result Variable(s): Predicted probability

<table>
<thead>
<tr>
<th>Area</th>
<th>Std. Error(a)</th>
<th>Asymptotic Sig.(b)</th>
<th>Asymptotic 95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>.955</td>
<td>.002</td>
<td>.000</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Lower Bound Upper Bound</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>.950 .960</td>
</tr>
</tbody>
</table>

The test result variable(s): Predicted probability has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

a Under the nonparametric assumption
b Null hypothesis: true area = 0.5

Classification Table(a,b)

<table>
<thead>
<tr>
<th>Observed</th>
<th>Predicted</th>
<th>Percentage Correct</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LU02RESID</td>
<td></td>
</tr>
<tr>
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<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
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<tr>
<td>Step 0</td>
<td>LU02RESID</td>
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<tr>
<td>Overall</td>
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</table>

a Constant is included in the model.
b The cut value is .500

Variables not in the Equation

<table>
<thead>
<tr>
<th></th>
<th>Score</th>
<th>df</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 0</td>
<td>Variables</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>NOAgregar02</td>
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</tr>
<tr>
<td></td>
<td>NO_dev2</td>
<td>13.652</td>
<td>1</td>
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<tr>
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<td>NO_undev2</td>
<td>1720.512</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>NO_resid2</td>
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</tr>
<tr>
<td></td>
<td>Shldist</td>
<td>696.075</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Rddist</td>
<td>48.603</td>
<td>1</td>
</tr>
<tr>
<td></td>
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Variables in the Equation

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<th>S.E.</th>
<th>Wald</th>
<th>df</th>
<th>Sig.</th>
<th>Exp(B)</th>
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</thead>
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<tr>
<td>Step 1(a)</td>
<td>NO_resid02</td>
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<td>.023</td>
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<td>Shldist</td>
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<td>.000</td>
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<td>.000</td>
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<td></td>
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<td>Step 3(c)</td>
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**Case Processing Summary**

<table>
<thead>
<tr>
<th>LU02RESID</th>
<th>Valid N (listwise)</th>
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</thead>
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<tr>
<td>Positive(a)</td>
<td>1922</td>
</tr>
<tr>
<td>Negative</td>
<td>5539</td>
</tr>
</tbody>
</table>

Larger values of the test result variable(s) indicate stronger evidence for a positive actual state.

a The positive actual state is 1.

**ROC Curve**

The ROC curve shows the trade-off between the true positive rate (sensitivity) and the false positive rate (1 - specificity) at various threshold settings. The curve is used to assess the performance of a binary classifier system as its discrimination threshold is varied.

Diagonal segments are produced by ties.
Area Under the Curve

Test Result Variable(s): Predicted probability

<table>
<thead>
<tr>
<th>Area</th>
<th>Std. Error(a)</th>
<th>Asymptotic Sig.(b)</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>.938</td>
<td>.003</td>
<td>.000</td>
<td>.932</td>
<td>.944</td>
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</table>

The test result variable(s): Predicted probability has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

a Under the nonparametric assumption
b Null hypothesis: true area = 0.5

Classification Table(a,b)

<table>
<thead>
<tr>
<th>Observed</th>
<th>Predicted</th>
<th>Percentage Correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 0</td>
<td>LU02DEV</td>
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<td></td>
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<td></td>
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<td>81</td>
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<tr>
<td>Overall</td>
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</table>

a Constant is included in the model.
b The cut value is .500

Variables not in the Equation

<table>
<thead>
<tr>
<th>Step 0</th>
<th>Variables</th>
<th>Score</th>
<th>df</th>
<th>Sig.</th>
</tr>
</thead>
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Variables in the Equation

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<th>NO_DEV02</th>
<th>NO_DEV02</th>
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<th>NO_DEV02</th>
<th>NO_DEV02</th>
<th>NO_DEV02</th>
<th>NO_DEV02</th>
<th>NO_DEV02</th>
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<tbody>
<tr>
<td></td>
<td>2.127</td>
<td>.129</td>
<td>273.006</td>
<td>1</td>
<td>.000</td>
<td>8.393</td>
<td>2.127</td>
<td>.129</td>
<td>273.006</td>
<td>1</td>
<td>.000</td>
</tr>
<tr>
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<td>.000</td>
<td>.002</td>
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</table>

a Variable(s) entered on step 1: NO_DEV02.

ROC Curve

Case Processing Summary

<table>
<thead>
<tr>
<th>LU02DEV</th>
<th>Valid N (listwise)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>152</td>
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</table>
Larger values of the test result variable(s) indicate stronger evidence for a positive actual state.

a The positive actual state is 1.

ROC Curve

Area Under the Curve

Test Result Variable(s): Predicted probability

<table>
<thead>
<tr>
<th>Area</th>
<th>Std. Error(a)</th>
<th>Asymptotic Sig.(b)</th>
<th>Asymptotic 95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>.997</td>
<td>.001</td>
<td>.000</td>
<td>.996</td>
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</tbody>
</table>

The test result variable(s): Predicted probability has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

a Under the nonparametric assumption
b Null hypothesis: true area = 0.5
Appendix 15: Logistic Regression Output (in SPSS) for Shoreline Prediction

Regression Variables:

### Classification Table (a,b)

<table>
<thead>
<tr>
<th>Observed</th>
<th>Predicted</th>
<th>MAJ_STRUCT</th>
<th>Percentage Correct</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>none</td>
<td>450</td>
</tr>
<tr>
<td></td>
<td></td>
<td>bulk</td>
<td>161</td>
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<tr>
<td></td>
<td>Overall Percentage</td>
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</table>

a Constant is included in the model.
b The cut value is .500

### Variables not in the Equation (a)

<table>
<thead>
<tr>
<th>Step 0 Variables</th>
<th>Score</th>
<th>df</th>
<th>Sig.</th>
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<tr>
<td>PRCNT_AG</td>
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<td>.000</td>
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<tr>
<td>PRCNT_UNDE</td>
<td>23.132</td>
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<td>.000</td>
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<tr>
<td>PRCNT_RESI</td>
<td>15.482</td>
<td>1</td>
<td>.000</td>
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<tr>
<td>PRCNT_DEV</td>
<td>71.583</td>
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<td>.000</td>
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<tr>
<td>MAJ_HEIGHT(1)</td>
<td>22.784</td>
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<td>.000</td>
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<tr>
<td>MAJ_MARSH(1)</td>
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<td>.000</td>
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<tr>
<td>MAJ_Beach(1)</td>
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<td>1</td>
<td>.731</td>
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<td>.009</td>
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<td>LU02AG</td>
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<td>.000</td>
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<td>.000</td>
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</table>

a Residual Chi-Squares are not computed because of redundancies.

### Variables in the Equation

<table>
<thead>
<tr>
<th>Step</th>
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<th>B</th>
<th>S.E.</th>
<th>Wald</th>
<th>df</th>
<th>Sig.</th>
<th>Exp(B)</th>
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</thead>
<tbody>
<tr>
<td>1(a)</td>
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<td>.000</td>
<td>.124</td>
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<tr>
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<td>MAJ_MARSH(1)</td>
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<td>.133</td>
<td>.218</td>
<td>1</td>
<td>.641</td>
<td>1.064</td>
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</table>

<table>
<thead>
<tr>
<th>Step 2(b) MAJ_MARSH(1)</th>
<th>-2.019</th>
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<th>.000</th>
<th>.133</th>
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</thead>
<tbody>
<tr>
<td>LU02DEV</td>
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<td>16.356</td>
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<td>.000</td>
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<tr>
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<td>.877</td>
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</table>

| Step 3(c) PRCNT_RESI | .020   | .004 | 29.890 | 1 | .000 | 1.021 |

154
<table>
<thead>
<tr>
<th>Step 4(d)</th>
<th>Variable(s) entered on step 4: PRCNT_DEV.</th>
</tr>
</thead>
<tbody>
<tr>
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<td>-1.917  0.225  72.878  1  0.000  0.147</td>
</tr>
<tr>
<td>LU02DEV</td>
<td>5.420  1.077  25.303  1  0.000  225.846</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.566  0.307  25.976  1  0.000  0.209</td>
</tr>
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<td>PRCNT_RE_SI</td>
<td>0.022  0.004  32.377  1  0.000  1.022</td>
</tr>
<tr>
<td>PRCNT_DEV</td>
<td>0.070  0.024  8.556  1  0.003  1.077</td>
</tr>
<tr>
<td>MAJ_MAR</td>
<td>-1.913  0.227  71.074  1  0.000  0.148</td>
</tr>
<tr>
<td>LU02DEV</td>
<td>2.518  1.392  3.272  1  0.070  12.403</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.729  0.321  29.044  1  0.000  0.177</td>
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<table>
<thead>
<tr>
<th>Step 5(e)</th>
<th>Variable(s) entered on step 5: PRCNT_AG.</th>
</tr>
</thead>
<tbody>
<tr>
<td>PRCNT_AG</td>
<td>-0.016  0.008  3.852  1  0.050  0.984</td>
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<tr>
<td>PRCNT_RE_SI</td>
<td>0.016  0.005  13.178  1  0.000  1.017</td>
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<tr>
<td>PRCNT_DEV</td>
<td>0.065  0.024  7.461  1  0.006  1.067</td>
</tr>
<tr>
<td>MAJ_MAR</td>
<td>-1.960  0.229  73.132  1  0.000  0.141</td>
</tr>
<tr>
<td>LU02DEV</td>
<td>2.344  1.388  2.851  1  0.091  10.423</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.164  0.410  8.038  1  0.004  0.312</td>
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<table>
<thead>
<tr>
<th>Step 6(f)</th>
<th>Variable(s) entered on step 6: PRCNT_UNDE.</th>
</tr>
</thead>
<tbody>
<tr>
<td>PRCNT_AG</td>
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</tr>
<tr>
<td>PRCNT_UNDE</td>
<td>-0.810  0.294  7.578  1  0.006  0.445</td>
</tr>
<tr>
<td>PRCNT_RE_SI</td>
<td>-0.796  0.295  7.282  1  0.007  0.451</td>
</tr>
<tr>
<td>PRCNT_DEV</td>
<td>-0.740  0.293  6.388  1  0.011  0.477</td>
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<tr>
<td>MAJ_MAR</td>
<td>-2.043  0.235  75.794  1  0.000  0.130</td>
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<td>LU02DEV</td>
<td>1.968  1.409  1.949  1  0.163  7.154</td>
</tr>
<tr>
<td>Constant</td>
<td>80.219  29.548  7.371  1  0.007  0.438</td>
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</table>

<table>
<thead>
<tr>
<th>Step 7(f)</th>
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<tbody>
<tr>
<td>PRCNT_AG</td>
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<tr>
<td>PRCNT_UNDE</td>
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</tr>
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<td>PRCNT_RE_SI</td>
<td>-0.840  0.294  8.186  1  0.004  0.432</td>
</tr>
<tr>
<td>PRCNT_DEV</td>
<td>-0.757  0.292  6.706  1  0.010  0.469</td>
</tr>
<tr>
<td>MAJ_MAR</td>
<td>-2.049  0.234  76.581  1  0.000  0.129</td>
</tr>
<tr>
<td>Constant</td>
<td>84.604  29.407  8.277  1  0.004  0.419</td>
</tr>
</tbody>
</table>

a Variable(s) entered on step 1: MAJ_MARSH.
b Variable(s) entered on step 2: LU02DEV.
c Variable(s) entered on step 3: PRCNT_RESI.
d Variable(s) entered on step 4: PRCNT_DEV.
e Variable(s) entered on step 5: PRCNT_AG.
f Variable(s) entered on step 6: PRCNT_UNDE.
ROC Curve

Case Processing Summary

<table>
<thead>
<tr>
<th>MAJ_STRUCT</th>
<th>Valid N (listwise)</th>
</tr>
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<tr>
<td>Positive(a)</td>
<td>161</td>
</tr>
<tr>
<td>Negative</td>
<td>450</td>
</tr>
</tbody>
</table>

Larger values of the test result variable(s) indicate stronger evidence for a positive actual state.

a The positive actual state is bulk.

ROC Curve

Diagonal segments are produced by ties.

Area Under the Curve

<table>
<thead>
<tr>
<th>Test Result Variable(s): Predicted probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area</td>
</tr>
<tr>
<td>-------</td>
</tr>
<tr>
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</tbody>
</table>

The test result variable(s): Predicted probability has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.
**Classification Table (a,b)**

<table>
<thead>
<tr>
<th>Observed</th>
<th>Predicted</th>
<th>Percentage Correct</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>MAJ_STRUCT</td>
</tr>
<tr>
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<tr>
<td>Overall</td>
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</table>

(a) Constant is included in the model.

(b) The cut value is .500

**Variables not in the Equation (a)**

<table>
<thead>
<tr>
<th>Step</th>
<th>Variables</th>
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<th>df</th>
<th>Sig.</th>
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<td>MAJ_Beach(1)</td>
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</tbody>
</table>

(a) Residual Chi-Squares are not computed because of redundancies.

**Variables in the Equation**

<table>
<thead>
<tr>
<th></th>
<th>B</th>
<th>S.E.</th>
<th>Wald</th>
<th>df</th>
<th>Sig.</th>
<th>Exp(B)</th>
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</thead>
<tbody>
<tr>
<td>Step 1(a)</td>
<td>MAJ_MARS H(1)</td>
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<td>52.676</td>
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<td></td>
<td>Constant</td>
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<td>.000</td>
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<td>Step 2(b)</td>
<td>MAJ_EROS IO(1)</td>
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<tr>
<td></td>
<td>MAJ_MARS H(1)</td>
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<td>Constant</td>
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### Step 3(c) MAJ EROS

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<tr>
<th>Variable(s)</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>t Value</th>
<th>Significance</th>
<th>95% Confidence Interval</th>
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</thead>
<tbody>
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### Step 4(d) PRCNT_DEV

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<th>Variable(s)</th>
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<th>t Value</th>
<th>Significance</th>
<th>95% Confidence Interval</th>
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a Variable(s) entered on step 1: MAJ_MARSH.
b Variable(s) entered on step 2: MAJ_EROSIO.
c Variable(s) entered on step 3: MAJ_BEACH.
d Variable(s) entered on step 4: PRCNT_DEV.

### ROC Curve

#### Case Processing Summary

<table>
<thead>
<tr>
<th>Variable(s)</th>
<th>Valid N (listwise)</th>
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</thead>
<tbody>
<tr>
<td>MAJ STRUCT</td>
<td>Positive(a): 87</td>
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</table>

Larger values of the test result variable(s) indicate stronger evidence for a positive actual state.
a The positive actual state is riprap.

![ROC Curve Diagram]

Diagonal segments are produced by ties.

#### Area Under the Curve

158
Test Result Variable(s): Predicted probability

<table>
<thead>
<tr>
<th>Area</th>
<th>Std. Error(a)</th>
<th>Asymptotic Sig.(b)</th>
<th>Asymptotic 95% Confidence Interval</th>
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The test result variable(s): Predicted probability has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

a  Under the nonparametric assumption
b  Null hypothesis: true area = 0.5

Classification Table(a,b)

<table>
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<tr>
<th>Observed</th>
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<th>Percentage Correct</th>
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a  Constant is included in the model.
b  The cut value is .500

Variables not in the Equation(a)

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</tr>
</tbody>
</table>

a  Residual Chi-Squares are not computed because of redundancies.

Variables in the Equation

<table>
<thead>
<tr>
<th>Step 1(a)</th>
<th>MAJ_BEAC H(1)</th>
<th>Constant</th>
<th>MAJ_MARS H(1)</th>
<th>MAJ_BEAC H(1)</th>
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<tbody>
<tr>
<td>B</td>
<td>S.E.</td>
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<td>Sig.</td>
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</table>
Step 3(c)

<table>
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<tr>
<th>Variable</th>
<th>Coefficient</th>
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<th>Wald Statistic</th>
<th>df</th>
<th>Sig.</th>
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<td>1</td>
<td>.000</td>
<td>Lower Bound: 0.000, Upper Bound: 0.000</td>
</tr>
</tbody>
</table>

a Variable(s) entered on step 1: MAJ_BEACH.
b Variable(s) entered on step 2: MAJ_MARSH.
c Variable(s) entered on step 3: MAJ_EROSIO.

ROC Curve

Case Processing Summary

<table>
<thead>
<tr>
<th>Variable</th>
<th>Valid N (listwise)</th>
</tr>
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<tbody>
<tr>
<td>Positive(a)</td>
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<tr>
<td>Negative</td>
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</table>

Larger values of the test result variable(s) indicate stronger evidence for a positive actual state.
a The positive actual state is groi.

Area Under the Curve

Test Result Variable(s): Predicted probability

<table>
<thead>
<tr>
<th>Area</th>
<th>Std. Error(a)</th>
<th>Asymptotic Sig.(b)</th>
<th>Asymptotic 95% Confidence Interval</th>
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</thead>
<tbody>
<tr>
<td>.948</td>
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<td>.000</td>
<td>Lower Bound: .912, Upper Bound: .984</td>
</tr>
</tbody>
</table>

The test result variable(s): Predicted probability has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.
a Under the nonparametric assumption
b Null hypothesis: true area = 0.5
REFERENCES


Center for Coastal Resources Management, Digital Tidal Marsh Inventory Series, 1992. Comprehensive Coastal Inventory Program, Virginia Institute of Marine Science, College of William and Mary, Gloucester Point, Virginia, 23062


Lindy Dingerson came to VIMS from the University of Mississippi, where she completed a B.S. in Biology in 2000. At the College of William and Mary, she has involved herself with the concurrent degree program between VIMS and the Thomas Jefferson Program in Public Policy. Upon completion of this thesis, she will receive both a M.S. in Marine Science as well as a Masters in Public Policy.

The curriculum for the Masters in Public Policy includes rigorous coursework covering many aspects of economics, law, and political science as well as a three-month internship and a client driven course. Lindy chose to complete her internship at the Virginia Department of Environmental Quality Coastal Resource Management Program, and she worked on the Virginia Ecotour Guide Certification Program and the Clean Marina Program. The requirements for the VIMS degree are coursework and completion of thesis research. In addition to her work at VIMS, Lindy has involved herself in the organization and facilitation of the Coastal Zone Asia Pacific 2002 conference in Bangkok, Thailand and many workshops including the Coastal Managers Workshop and the 4WFC Fisheries Management Workshop.

Lindy has competed for and been awarded the John A. Knauss Marine Policy Fellowship for 2006-2007. Also, she is currently in the final stages of application for a Physical Scientist position at the Coastal Services Center. The position focuses on coastal remote sensing and its application to coastal hazards and coastal hazard management. Her background in marine science, resource management, and policy will aid her in beginning a promising career in marine policy and resource management.