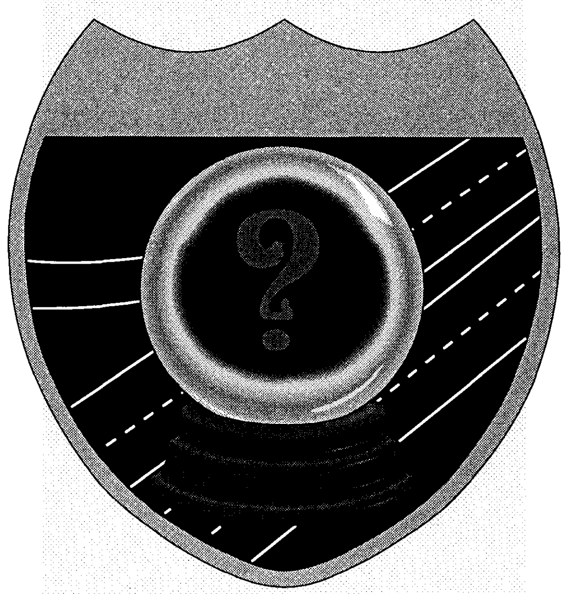
FINAL REPORT

THE DEVELOPMENT OF PERFORMANCE PREDICTION MODELS FOR VIRGINIA'S INTERSTATE HIGHWAY SYSTEM - VOLUME II: MODEL DEVELOPMENT



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16. Abstract

Performance prediction models are a key component of any well-designed pavement management system. This study used data compiled from condition surveys conducted annually on Virginia's pavement network to develop prediction models for the interstate system. The study is reported in two volumes.

Volume II describes the development and evaluation of the performance prediction models. An exploratory data analysis was first conducted to examine the data distribution, and to reveal the underlying relationships among the variables. "Robust" regression techniques were used to identify outlying observations that could adversely affect the regression analysis results. Stepwise regression was then used to select the significant predictors of deterioration.

Different models were examined to identify the most suitable for fitting the data. The models were evaluated by checking their goodness-of-fit statistics and conducting a series of sensitivity analyses. To further assess the models' accuracy, their predictions were compared against field-observed values. An ANOVA test was run to compare the accuracy of two model forms and two model adjustment proceduress. The developed models provided an adequate fit and generated predictions that conformed with accepted engineering judgement. Comparisons with field observations showed their accuracy to be quie reasonable even for long-range predictions. Finaly, the ANOVA results indicated that no significant differences existed between the two model forms tested or between the two adjustment procedures.

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ABSTRACT

Performance prediction models are a key component of any well-designed pavement management system. This study used data compiled from the condition surveys conducted annually on Virginia's pavement network to develop prediction models for the interstate system. The study is being reported in two volumes, of which this is the second.

The second volume describes the development and evaluation of the performance prediction models. An exploratory data analysis was first conducted to examine the data distribution, and to reveal the underlying relationships among the variables. "Robust" regression techniques were used to identify outlying observations that could adversely affect the regression analysis results. Stepwise regression was then used to select the significant predictors of deterioration.

Different model forms were examined to identify the most suitable for fitting the data. The models were evaluated by checking their goodness-of-fit statistics and conducting a series of sensitivity analyses. To further assess the models' accuracy, their predictions were compared against field-observed values. An analysis-of-variance *(ANOVA)* test was also conducted to compare between the accuracy of two model forms and two model adjustment procedures. In general, the developed models provided an adequate fit and generated predictions that conformed with accepted engineering judgement. Comparisons with field observations showed their accuracy to be quite reasonable even for long-range predictions. Finally, the *ANOVA* results indicated that no significant differences existed between the two model forms tested or between the two adjustment procedures.

The Development of Performance Prediction Models for Virginia's Interstate Highway System - Volume II : Model Development

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INTRODUCTION

Performance prediction models greatly enhance the capabilities of a pavement management system, allowing an agency to predict the timing for maintenance or rehabilitation activities and estimate the long-range funding requirements for preserving the pavement system. These functions are crucial to the success of any pavement management process.

In Virginia, a pavement performance model was developed by McGhee in 1984 from data collected on Interstate 81.[1] It related the pavement distress maintenance rating (DMR), a composite index of distress damage, to cumulative equivalent single axle loads (ESALs). The model is not currently used because the ESAL data it was based on are not now accessible from within the Pavement Management System (PMS). Also, when this model was developed the Virginia Department of Transportation's (VDOT) PMS was still evolving, and condition data were limited. The annual condition surveys conducted since the model was originally developed have compiled substantial condition data, making more refined models possible.

PURPOSE AND SCOPE

An earlier phase of this study used condition data to construct a screened data base to support the modeling effort.[2] In this phase, the data base was used to develop prediction models for Virginia's interstate system. Specifically, this study had the following objectives:

1. To identify the major factors affecting the condition of Virginia's pavements.

2. To experiment with various model types, forms, and modeling approaches, and identify the most appropriate for Virginia's data.

3. To compare the precision of the developed models and assess the accuracy of the overall prediction process.

METHODOLOGY

The research consisted of the following five major stages:

1. Literature review.
2. Preliminary data analysis and outlier detection.
3. Significant predictors identification.
4. Model development and evaluation.
5. Model verification and accuracy assessment.

The following sections describe each of these stages.

Stage 1 - Literature Review

Significant variables affecting pavement deterioration that were identified by earlier studies, different modeling approaches that have been used, and the mathematical form of previous prediction models were reviewed.

Significant Variables Affecting Pavement Deterioration

Factors affecting pavement condition can be divided into the following categories: traffic loading, environment, pavement structural capacity, soil type, drainage condition, type of pavement, and maintenance activities. Within each category, a number of variables characterize the factor under consideration. Traffic loading is typically characterized by the cumulative number of 18-kips single axle loads (ESALs). Variables used to characterize the pavement structural capacity will depend upon the type of the pavement; for flexible pavements, for example, the structural number developed in relation to the AASHO design equations is usually employed. Indices such as the Thornthwaite index or the freezing index can characterize environmental factors.[3]

Often, however, not all of these variables are available. Moreover, some variables may sometimes be statistically insignificant in predicting pavement condition. This happens when the variable does not show significant variation over the study area. For example, environmental conditions may virtually be uniform over one state, and would not need to be included in the models. Any modeling effort should start by establishing the available variables that significantly affect pavement deterioration in the area under consideration. Results may differ from case to case.

Iowa DOT's study of pavement performance models for composite and rigid pavements,[4] for example, showed that the major factors affecting pavement condition on interstates were pavement loadings, base material type, and aggregate durability. For primary roads, the significant variables were pavement age, pavement thickness, soil subgrade, and reinforcement types.

Gibby and Kitamura[5] identified factors affecting the condition of pavements owned by local governments:

1. Previous pavement condition,
2. Pavement age since last major rehabilitation or reconstruction work,
3. Soil classification,
4. Classification of roadway drainage,
5. Surface thickness,
6. Functional classification,
7. Presence or absence of bus service, and
8. Individual jurisdiction.

An accurate assessment of the effect of traffic was not possible, since the data files used for that study did not contain ESAL information.

As pointed out by Gibby,[5] because of the relationship between variables, some variables may be used as surrogates for others. For example, the road functional classification can be a surrogate variable for traffic levels, since the higher the classification of a road, the heavier the traffic. Another issue that needs special attention while selecting variables for model development is the problem of multicollinearity between variables.[6] Multicollinearity arises when independent variables that are highly correlated are included in the model. A common example is the high correlation between the age variable and the cumulative ESALs. To overcome this problem, their ratio (ESALs per year) may be used.

Modeling Approaches

The literature review showed that, with respect to deterministic models, there have been three basic approaches for modeling the deterioration of a particular network: a pavement "family" approach, a multivariate model approach, and a project-specific approach. A brief description of each of these approaches is given below.

Pavement "Family" Approach.

In this approach,[7-9] pavements with similar characteristics are grouped together to form "families" or categories. Several combinations of factors can be used to define these "families." For example, the PAVER PMS, developed by the U.S. Army Corps of Engineers Research Laboratories, defines a pavement family as a group of sections having the same type, pavement use and pavement rank.[9] A recent study of Minnesota DOT prediction models adopted finer groups based on pavement type, functional class, district, thickness, subgrade soil strength and traffic levels.[7]

Once the families are defined, two-variable models relating the pavement condition measure to age are developed. Grouping is assumed to account for the effect of the other variables, such as traffic or structural strength. The developed model will represent the mean behavior of all sections in a particular family. When the family model is used to predict the condition of a particular section, it is adjusted if the observed current condition is different from that predicted by the model. This is usually done by drawing a curve through the observed pavement condition-age point parallel to the family curve. The adjusted model can then be used to predict the section condition for future years.

Multivariate Model Approach

In the second approach,[10-13] pavement sections are broadly classified by factors like functional class, type or region. For each classification, models are developed relating the pavement condition to a number of variables such as pavement age, ESALs and structural capacity, not just to age as in the previous approach. Each pavement section within a classification will thus have its own performance pattern. Adjustments can still be made if the observed condition is different from the model prediction. This takes several additional factors into consideration, such as the inherent variations in materials quality and construction procedures, which the model did not consider. It also incorporates data feedback into the prediction process, since prediction is based on the most recent observation.

This approach is used by the performance prediction models of the Illinois Pavement Feedback System (IPFS),[13] where the interstate system is divided into five broad groups according to pavement type. Performance prediction models are developed for each pavement type relating the pavement condition to the age of the pavement, its structural capacity and the cumulative ESALs to which it has been subjected.

Project-Specific Approach

The third approach, used by the Washington State PMS,[14] develops project-specific prediction models, where a separate model relating the pavement condition to age is fitted for each project or analysis unit within the state system. The problem with this approach is that in some cases, such as a relatively new project, the number of points available for model fitting can be very small. For new projects, or when the project-specific curve provides unreasonable predictions, the approach is usually supplemented by standard or "family" curves.

Regression Techniques

In all of the above approaches, regression analysis is the basic tool for model development. The techniques used include simple linear, multiple linear, stepwise, and nonlinear regression. In addition, some modern regression techniques for outlier detection and optimal variable transformations were recently investigated by Lee and Darter.[15]

Prediction Model Form

The prediction model form should satisfy applicable engineering boundary conditions, which should be established before the statistical data analysis. Lytton[6] identified six boundary conditions for damage prediction models expressing pavement damage on a scale of 0-1: a) the initial value at time 0; b) the initial slope; c) the overall deterioration trend; d) the variation in slope along the service life of the section; e) the final slope; and f) the terminal value. A literature review revealed that not all of these conditions were actually satisfied in practice. Basically, previous prediction models assumed one of the following forms:

Linear Model

The linear model has the following general form:

$$Y = a_0 + a_1 x_1 + a_2 x_2 + \dots + a_n x_n \qquad (1)$$

where,

Y	=	pavement condition measure to be predicted;
$x_1 \dots x_n$	=	independent variables such as pavement age, traffic and structural capacity;
$a_1 \dots a_n$	=	regression coefficients.

This model form failed to satisfy most boundary conditions, and therefore was generally used as an interim until more data became available.[16] Owing to its simplicity, it was also used to identify the significant variables affecting the pavement condition in the study area,[5] and to point out major problems and unreasonable trends in the available data.[11]

Power Curve

The form of a power curve is given as:

$$Y = a_0\, x_1^{a_1}\, x_2^{a_2} \dots\dots\dots\dots x_n^{a_n} \qquad (2)$$

where all terms are as previously defined.

This model form was frequently used in previous studies,[5,12,17] and a number of states, including Washington and Illinois, adopted it in developing prediction models for their pavement management systems.[13,14] Unlike the linear form, the power curve can satisfy the initial boundary condition of zero distress at the beginning of the pavement service life.

Sigmoidal Curve

A sigmoidal (S-shaped) model is a curve with an inflection point and upper and lower asymptotes. This could be appropriate for predicting pavement condition indices, since such indices are typically bounded by an upper and lower value. By having an inflection point, the model can reflect the fact that the pavement rate of deterioration may differ throughout its service life. A simple sigmoidal model for prediction models can be expressed as :

$$Y = e^{\frac{-A}{T}} \qquad (3)$$

where,

Y	=	pavement condition measure to be predicted,
A	=	parameter representing pavement characteristics, and
T	=	pavement age, or cumulative ESALs or a function of age and ESALs.

Systems that use the sigmoidal form include Minnesota,[16] Ohio,[11] and the Metropolitan Transportation Commission (MTC) of the San Francisco Bay Area.[3]

Polynomial Equation

Polynomial prediction models have the following general form :

$$Y = a_0 + a_1 x + a_2 x^2 + \ldots\ldots\ldots a_n x^n \qquad (4)$$

where,

Y	=	the pavement condition measure,
x	=	the pavement age,
$a_1 \ldots a_n$	=	regression coefficients, and
n		refers to the degree of the equation.

Polynomial models were used in previous studies to develop 2-variables models relating condition to pavement age.[8, 9] However, because of data scatter, the polynomial curve would sometimes show an upward shift, suggesting that the pavement condition improved with time. To overcome this problem, the regression parameters were estimated using mathematical programming techniques, which allowed for imposing constraints on the slope of the curve.[9]

Since polynomial models are purely empirical, they are usually not recommended for extrapolation beyond the data range.

Stage 2 - Preliminary Data Analysis and Outlier Detection

After the data base construction stage,[2] the research effort proceeded to preliminary data analysis and outlier detection. This stage consisted of three main tasks. The first task was to formulate an appropriate modeling approach. This involved deciding upon an appropriate classification scheme, identifying the potential explanatory variables, and selecting the statistical packages to use in the analysis. The second task was a series of exploratory data analysis procedures. Finally, the third task addressed the critical issue of detecting outlying observations using robust regression techniques. These tasks are described below.

Task 1 - Formulating an Appropriate Modeling Approach

As previously discussed, the literature review revealed three basic approaches for prediction modeling: a "family" approach, a multivariate model approach, and a project-specific approach. The nature of the data suggested the multivariate model approach for this study. This approach permitted investigation of the effect of the different variables on pavement condition. It could be transformed into "family" modeling simply by using the pavement age as the single predictor, and adopting finer pavement groups or categories.

The project-specific approach, on the other hand, was ruled out because the surveyed sections changed every year, which limited the available number of points for distinct sections. The very nature of the DMR score as a subjective measure suggests that basing a model on a small number of points is quite dangerous, since any error in one point will appreciably affect the precision of the model.

The Categorization Scheme

The distribution of the available data was examined to identify a suitable classification scheme that would yield categories of pavement sections with an adequate number of data points per group for model development. Figure 1 shows the number of points available for modeling by district and pavement type. The exact figures are in Table 1. The overlaid flexible pavements category had the largest number of available points for all districts, except for Fredricksburg.

Based on the distribution of the available data points, the following sectioning scheme was adopted. Sections were first classified according to their pavement type into: a) overlaid flexible pavements, b) flexible pavements with no overlay, c) composite pavements with one overlay, and d) composite pavements with more than one overlay (the number of points available for the individual surface types within the "OTHER" category was inadequate for developing reliable models). Overlaid flexible pavement sections were then subdivided by district to give a separate model for each district; this controlled the variability arising from the fact that each district had its own rating team.

Figure 1 Number of Observation Points by District & Pavement Type

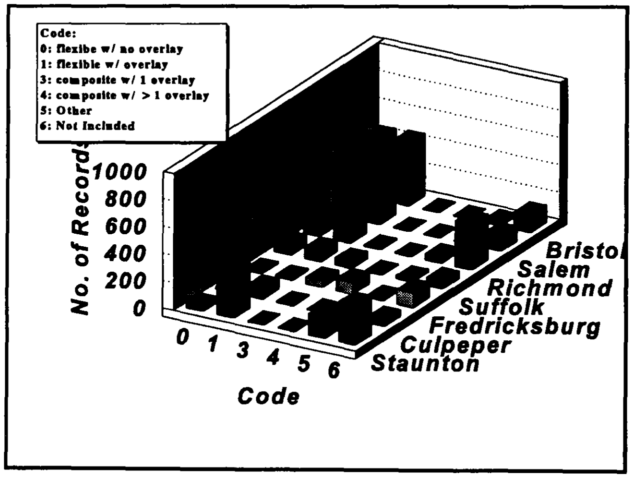


Table 1. Number of Observation Points by District and Pavement Type (after saving the 5 % sample)

District	Number of Points Available for Analysis					
	flexible w / no overlay	flexible w / overlay	composite w/ 1 overlay	composite w/ > 1 overlay	OTHER	Not included
Bristol	45	452	0	0	20	123
Salem	54	623	0	0	6	111
Richmond	167	989	7	0	42	335
Suffolk	76	81	49	6	18	53
Fredricksburg	13	11	45	85	10	108
Culpeper	19	77	6	0	2	46
Staunton	30	748	0	0	150	288

The other three pavement type categories had too few points to develop district-specific models, so sections were classified by geographic regions combining a number of contiguous districts. Virginia's three basic geographic regions are:

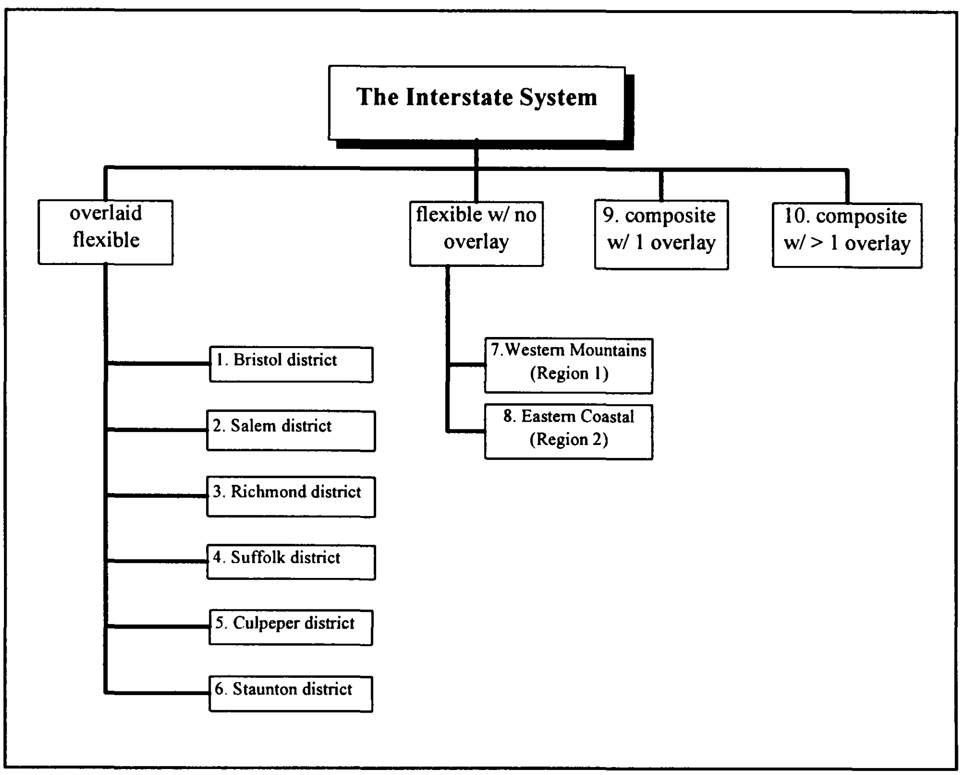
1. Valley and Ridge Western Mountains, containing Bristol, Salem and Staunton districts (denoted as Region 1).

2. Piedmont, encompassing Lynchburg, Culpeper and Northern Virginia.

3. Coastal Plain, containing Richmond, Suffolk and Fredricksburg districts (denoted as Region 2).

Although the maximum number of classes defined under this classification scheme was 18 (9 for overlaid flexible pavements and 3 each for flexible with no overlay, composite with one overlay and composite with more than one overlay), the scheme resulted in only 10 groups in our case (Figure 2). This is because data were not available for Lynchburg and Northern Virginia,[2] only some districts had composite pavement sections, and some groups contained very few observation points (less than 20). Adopting this classification scheme allowed the modeling process to capture differences in the deterioration trend of the various pavement types, as well as variations in the environmental conditions and paving materials.

Figure 2 The Classification Scheme



Potential Explanatory Variables

With the DMR representing the response variable for the models, the next step was to identify the potential explanatory variables that were expected to have an effect on the DMR. In general, explanatory or predictor variables may either be continuous or discrete (categorical) variables. The following paragraphs discuss the potential predictors identified for this study.

Continuous Explanatory Variables. The variables depended upon the pavement category. For overlaid flexible pavements, the following four variables were identified:

AGE:	the age of the pavement in years since last overlay;
DEPTH:	the thickness of the last overlay in inches;
STRNO:	the structural number of the underlying pavement structure; and
YESAL:	the average yearly equivalent single axle loads in million ESALs.

The YESALs were computed by dividing the cumulative ESALs to which a section had been subjected from the time of its construction to its rating date, by the section AGE. YESALs were used instead of the cumulative ESALs to avoid multicollinearity problems arising from the very high correlation between the cumulative ESALs and the section AGE.

For flexible pavements with no overlay, these variables were reduced to AGE, STRNO, and YESAL. For composite pavements with either one or more overlays, the predictors were AGE, DEPTH (which in this case equaled the total thickness of the last asphaltic concrete overlay), and YESAL.

Because of missing layer data, the DEPTH and STRNO variables were not available for all the records. This problem was especially evident for the structural number (STRNO) variable for overlaid flexible pavements in the Bristol, Richmond, Culpeper and Staunton districts, where records with a value for this variable were a very small fraction of the total number of points available. To avoid a drastic reduction in the number of points available for modeling, the STRNO variable was not used for these four groups. The unavailability of such an important variable inhibits the development of theoretically-based models.

Categorical Explanatory Variables. In addition to continuous variables, the effect of other categorical variables on the DMR score had to be considered. Capturing the effect of these categorical variables required the use of dummy variables, which are variables that assume only 2 values, usually a 1 and a 0 for linear models or 2.7183 and 1 for nonlinear models. The number of dummy variables needed to represent a certain categorical variable is equal to one less than the number of levels that the categorical variable assumes. The following four groups of dummy variables were needed.

1. Dummy variables to identify the lane being rated.

According to VDOT's rating practice, the lanes of the roadway section in a particular direction were rated as a one unit unless their construction histories were significantly different. Where individual lanes are rated separately, however, the deterioration trend of the traffic lane should be different from the inner lanes, which are subjected to lower truck traffic. To capture this effect, sections were divided into 2 groups, and a dummy variable, LANNO, was encoded as follows :

LANNO = 0 if rating was performed on the whole section or on lane 1 (traffic lane)
= 1 if any other lane (i.e. lane 2, 3 or 4) was rated.

The decision to adopt the two groups described above was made after discussions with the pavement coordinators from the different districts. The two cases of rating the section as a whole and rating the traffic lane were grouped together, since even when the whole section is rated, the rater is still required to emphasize distresses observed in the traffic lane.

2. Dummy variables for the number of lanes available per direction.

To include this effect in the models, sections were divided into three groups: sections with 1 lane per direction, sections with 2 lanes per direction, and sections with 3 or more lanes per direction. Two dummy variables, RDTYP1 and RDTYP2, were encoded to account for these levels.

3. Dummy variables to distinguish among the individual routes within a group.

To capture some characteristics that are specific to a particular route, dummy variables, ROUTID, were used to identify points belonging to the different routes within a district. The number of dummy variables equaled the number of different routes within a group minus one.

4. Dummy variables to identify individual districts within a geographic region.

Finally, for the cases where classification was based on geographic region rather than individual districts, dummy variables, DISTR, were used to identify points belonging to the individual districts within the region.

There were two main reasons for using dummy variables like the LANNO and RDTYP variables, to account for factors that might have been captured using traffic lane distribution factors. First, dummy variables will capture the above effects even if ESAL data is missing, which it often is. Second, the lane distribution factors are not precisely known, and the use of default values may obscure or distort the ESAL's role in prediction.

Statistical Software Packages Used in the Analysis

Three statistical packages were used for statistical analysis and modeling: S-PLUS software, Statistical Package for the Social Sciences (SPSS), and Number Cruncher Statistical System (NCSS). The combination of these three packages provided a powerful modeling tool, since each was employed where it offered certain advantages. For example, S-PLUS has very strong graphical capabilities, and was heavily used during the exploratory data analysis stage. It also contains modern regression techniques that enhanced the modeling effort. SPSS is very efficient in performing traditional linear and nonlinear regression procedures. NCSS is very well suited for quick preliminary experimentation with different model forms.

Task 2 - Exploratory Data Analysis

Exploratory data analysis was used to:

- study the extent, range and distribution of the data,
- identify possible coding errors,
- check conformity with the basic assumptions of regression analysis, and
- understand the general relationships between the variables.[15]

The exploratory data analysis procedures used in this study are described below.

Response Variable Distribution

Regression requires that the residuals from the fitted model be independent and normally distributed.[18] For this to be fulfilled, however, the response variable distribution should also be approximately normal. Therefore, the close-to-normal distribution for the DMR had to be verified for each of the 10 groups or data sets used. This was done by four exploratory analysis techniques available from the S-PLUS package,[15, 19] explained later in this report.

Explanatory Variables Range

As opposed to the response variable, explanatory variables are not required to satisfy any special conditions with respect to their distribution. It was only necessary to check the data range and potential errors by plotting the frequency histograms.

Relationships Among Variables

For a basic understanding of the interrelations among the variables, a scatter plot matrix was generated for each of the 10 basic groups. This matrix displayed the pairwise scatter plots for the different variables used in the analysis.

Task 3 - Outlier Detection Using Robust Regression Techniques

The screening of the data base during the data base construction stage was mainly to minimize the adverse effects of some *obvious* errors in the data base. However, other sources of error had not yet been considered, and possible outliers still needed to be detected and removed. Outlier detection was necessary because ordinary least square regression is highly sensitive to outliers; a single outlying observation can have a dramatic effect on the analysis results.

The last decade has seen a number of "robust" regression techniques which attempt to fit the bulk of the data first and then search for outliers. The Least Median Squared Regression (LMS) devised by Rousseeuw in 1984[20, 21] was recently investigated for use with pavement data by Lee and Darter,[15] and was adopted by this study for outlier detection and removal. Robust regression was employed to detect outliers as follows:

1. Robust regression was first run, and the standardized residuals from the LMS regression were determined.

2. Data points with a value for the standardized residuals greater than 2.5 were identified as potential outliers.

3. The detected points were closely investigated to determine those points with justifiable reasons warranting their exclusion.

4. Traditional regression techniques were then performed after excluding detected outliers.

One problem with the LMS method, however, is that the identified outliers are influenced by the assumed model form.[15] An inappropriate model will result in a number of points being flagged as outliers, even though the problem is the inability of the assumed model to fit the data, and not the alleged outliers. To minimize this problem, LMS regression was performed using two different model forms, and the potential outliers detected in each case were compared. Using different forms with different characteristics helped distinguish between "genuine" and "false" outliers. The two models used were:

1. A linear model having the general form

$$Y = a_0 + a_1.x_1 + a_2.x_2 + a_3.x_3 + a_4.x_4 + \ldots\ldots\ldots\ldots a_n.x_n \qquad (5)$$

where,

Y	=	response or dependent variable
$x_1 \ldots x_n$	=	explanatory or independent variables
$a_0 \ldots a_n$	=	regression coefficients.

2. *A nonlinear power model,* with the general form :

$$Y = a_0 \cdot x_1^{a_1} \cdot x_2^{a_2} \cdot x_3^{a_3} \cdot x_4^{a_4} \ldots\ldots x_n^{a_n} \qquad (6)$$

For LMS to be performed, however, this nonlinear model needed to be transformed into a linear form. This was done by taking the natural logarithm of both sides of the equation to yield:

$$\ln(DMR_{init.} - DMR) = \ln(a_0) + a_1.\ln(AGE) + a_2.\ln(DEPTH) + a_3.\ln(STRNO) + a_4.\ln(YESAL) + a_5.\ln(LANNO) + a_6.\ln(RDTYP) + a_7.\ln(ROUTID) + a_8.\ln(DISTR) + \ln(error) \qquad (7)$$

In the previous equation, $DMR_{init.}$ is equal to 100 since this is the rating before any distress develops. However, in order to avoid the numerical problems that arise when the DMR score is equal to 100 (in such case the left-hand side will be equal to ln (100-100) = ln(0) which is undefined), a constant value of 1 was added to give:

$$\ln(101 - DMR) = \ln(a_0) + a_1.\ln(AGE) + a_2.\ln(DEPTH) + a_3.\ln(STRNO) + a_4.\ln(YESAL) + a_5.\ln(LANNO) + a_6.\ln(RDTYP) + a_7.\ln(ROUTID) + a_8.\ln(DISTR) + \ln(error) \qquad (8)$$

To avoid multicollinearity problems which could adversely affect the results of the LMS regression, ordinary stepwise least squared regression was carried out first, and then LMS regression was run using only those variables that were included in the stepwise regression. The analysis resulted in two lists of potential outliers, one for each model form assumed. The two lists were compared and a second round of manual screening was performed. Extreme care was taken to delete points only when there were strong reasons supporting their exclusion. Essentially, points were removed if the section exhibited unexplainable fluctuations in its condition, or if the DMR value was beyond the range that should be expected for the corresponding age (for example, a section with a DMR value equal to 100 at an age of 8 years). Table 2 gives the number of points deleted as a result of this second iteration of data cleansing.

Stage 3 - Significant Predictors Identification

In this stage, the purpose was to select, from the available explanatory variables, a subset of good predictors to be included in the models. To this end, stepwise regression was performed on each of the 10 categories or groups assuming a linear model of the form:

$$DMR = a_0 + a_1.(AGE) + a_2.(DEPTH) + a_3.(STRNO) + a_4.(YESAL) + a_5.(LANNO) + a_6.(RDTYP) + a_7.(ROUTID) + a_8.(DISTR) + error \quad (9)$$

The Statistical Package for the Social Sciences (SPSS) was used to perform the stepwise regression analysis . The procedure uses a combination of forward selection and backward elimination for variable selection. For forward selection, a variable enters the model if the probability associated with the F-test for the hypothesis that its coefficient is 0 is less than or equal to 0.05. In backward elimination, the variable remains in the equation as long as the probability associated with an F-to-remove test does not exceed 0.10.[22]

Stepwise regression helped identify the least number of explanatory variables needed for reliable prediction, ensure that all variables included were statistically significant, and minimize multicollinearity problems in the developed models.

Table 2. Number of Outliers Deleted for Each Group

Group	Number of points deleted	Number of points remaining
1. Overlaid flexible-Bristol	12 pts.	404 pts.
2. Overlaid flexible-Salem	29 pts.	534 pts.
3. Overlaid flexible-Richmond	28 pts.	861 pts.
4. Overlaid flexible-Suffolk	4 pts.	63 pts.
5. Overlaid flexible-Culpeper	5 pts.	69 pts.
6. Overlaid flexible-Staunton	44 pts.	415 pts.
7. Flexible / no overlay-Region 1	7 pts.	96 pts.
8. Flexible / no overlay-Region 2	13 pts.	153 pts.
9. Composite with 1 overlay	11 pts.	88 pts.
10. Composite with > 1 overlay	10 pts.	80 pts.

Stage 4 - Model Development and Evaluation

With the significant predictors identified, the study moved into the model development and evaluation stage. This stage involved two major tasks. In the first task, a power model form was used to develop the required prediction models. The goodness-of-fit of the developed models was then evaluated and a sensitivity analysis conducted to assess the adequacy of their predictions. In task two, a sigmoidal (S-shaped) model was developed and evaluated. The performances of the power and sigmoidal models were then compared.

The linear model form failed to meet most of the boundary conditions established for a good performance prediction model. As just one example, the basic boundary condition for a section to have a DMR of 100 (no distress) at AGE 0 (beginning of service life) was rarely satisfied. There was a need to investigate more realistic model forms capable of satisfying some of the important boundary conditions and more accurately representing the actual deterioration trend. Compared with the simple linear model, the power curve was a more realistic form. This model, generally expressed as

$$DMR = DMR_{init.} - a_0 \cdot (AGE)^{a1} \cdot (DEPTH)^{a2} \cdot (STRNO)^{a3} \cdot (YESAL)^{a4} \cdot (LANNO)^{a5} \cdot (RDTYP)^{a6} \cdot (ROUTID)^{a7} \cdot (DISTR)^{a8} \quad (10)$$

is capable of satisfying the initial boundary condition of no distress at age zero, regardless of the values for the other variables.

Approaches for Fitting the Power Curve

There are two options for fitting the power curve to the observed data. The first option is to transform the model into a linear form by taking the logarithm of both sides of the equation. The second approach is to directly fit the model using nonlinear regression techniques. Each approach has its own assumptions, advantages, and disadvantages.

The basic assumption of the first approach is that the error term is *multiplicative*, as shown below.

$$DMR = DMR_{init.} - a_0 \cdot (AGE)^{a1} \cdot (DEPTH)^{a2} \cdot (STRNO)^{a3} \cdot (YESAL)^{a4} \cdot (LANNO)^{a5} \cdot (RDTYP)^{a6} \cdot (ROUTID)^{a7} \cdot (DISTR)^{a8} \cdot \underline{error} \quad (11)$$

This allows the logarithmic transformation to be performed by taking the natural logarithm of both sides of the equation, as was done previously when using LMS regression for outlier detection.

The problem, however, is that in our case interest was in the response variable in its original metric (the DMR before transformation). Consequently, a reverse transformation would have to be performed to convert the transformed predicted value back to its original metric. Such a procedure, although a common practice, has two complications. First, the parameter estimates after transformation are no longer the least square estimates of the true parameters.[23,24] Secondly, the goodness-of-fit statistics reported in this case strictly apply to the transformed model, and the detransformed regression equation will not usually have the same level of accuracy reported for the transformed one.[15]

In the second approach, the error term is assumed to be *additive*, and thus the model cannot be transformed.

$$DMR = DMR_{init.} - a_0 . (AGE)^{a1} . (DEPTH)^{a2} . (STRNO)^{a3} . (YESAL)^{a4} . (LANNO)^{a5} . (RDTYP)^{a6} . (ROUTID)^{a7} . (DISTR)^{a8} \pm \underline{error} \qquad (12)$$

This approach avoids the problems associated with variable transformation. The disadvantage, however, is mainly caused by the complex nature of nonlinear regression. For nonlinear models, there are no explicit expressions for the estimators, and the procedure has to use an iterative procedure which may fail to converge in some cases. Nonlinear regression also requires the user to specify the model form, and to guess at the initial values for the parameters to be used in the search procedure.[18]

In the current study, after examining the residuals resulting from the two approaches, the assumption of an additive error term seemed more plausible. Consequently, only the results from the nonlinear regression approach are reported.

The Use of Nonlinear Regression in Power Model Development

Equation (12) gives the general form for the power model. The predictor variables used for each group or data set were those identified from the stepwise regression. However, since the variables' significance could slightly change with the model form assumed, care was taken not to exclude any significant variable that would appreciably improve the fit in this case but that was not included in the previous stepwise regression step (this was only the case with one group in connection with the DEPTH variable).

To obtain the initial parameter estimates required by the nonlinear regression search algorithm, the model was transformed into a linear form as previously described, and the parameters were estimated using linear regression. These estimates were then used by the iterative algorithm to find the estimates that would minimize the sum of the square of the residuals. To ensure the development of reliable models, the asymptotic standard errors for the parameters were consistently monitored to ensure that they were within reasonable limits.

Evaluation of the Power Model

Plots were made of the predicted versus the actual DMR values for each category in order to assess the goodness-of-fit of the developed models. A sensitivity analysis was then conducted to ensure that the models' predictions conform with the basic engineering knowledge and to allow for an assessment of the relative importance of the different predictor variables. This mainly involved the generation of 3-dimensional and 2-dimensional plots showing the change in the DMR value with the variable/variables of interest.

Task 2 - The Development of a Sigmoidal Prediction Model

Since the characteristics of the sigmoidal (S-shaped) model suggested that it could be appropriate for performance prediction modeling, this type of model was investigated for its ability to fit Virginia's data. The performance of the developed sigmoidal models was then compared to the simpler power models developed in the previous step, to assess whether the sigmoidal model was likely to significantly enhance prediction accuracy.

Model Form and Initial Parameter Estimates

The assumed sigmoidal model had the following general form:

$$DMR = 100 - a_0 \cdot e^{\frac{-a_1 \cdot (DEPTH)^{a_2} \cdot (STRNO)^{a_3} \cdot (LANNO)^{a_4} \cdot (RDTYP)^{a_5} \cdot (ROUTID)^{a_6} \cdot DISTR^{a_7}}{(AGE)^{a_8} \cdot (YESAL)^{a_9}}} \tag{13}$$

The variables included for each category or data set were those identified from stepwise regression.

To obtain initial estimates for the regression parameters, the model was rearranged and transformed into a linear form by taking the logarithm of both sides of the equation twice to yield the following form:

$$\ln\left[-\ln\left(\frac{100 - DMR}{a_0}\right)\right] = \ln.a_1 + a_2.\ln(DEPTH) + a_3.\ln(STRNO) + a_4.\ln(LANNO) + a_5.\ln(RDTYP) + a_6.\ln(ROUTID) + a_7.\ln(DISTR) - a_8.\ln(YESAL) - a_9.\ln(AGE) \tag{14}$$

According to the above sigmoidal model specification, the parameter a_0 represents the difference between the values of the upper and lower asymptotes of the curve (that is to say, a_0 represents the difference between the upper and lower bounds of the DMR values as given by the model). Since the lower range for the available DMR data was generally around a DMR score of 70, the value for the parameter a_0 was initially assumed to be equal to 30. This allowed for calculating the left-hand side of the above equation, and linear regression was then used to estimate the remaining parameters. Since the sole purpose behind the above procedure was to provide reasonable initial estimates for the regression parameters, the assumption of a value for a_0 was not likely to appreciably affect the results of the subsequent analysis. Nonlinear regression was then performed to develop the final models.

Evaluation of the Sigmoidal Model

As done for the power model, the goodness of fit for the sigmoidal models was evaluated by plotting the predicted versus the actual DMR values. Sensitivity analyses were also conducted to ensure that the models were providing rational predictions. Finally, the deterioration trends predicted by the power and sigmoidal models, as well as the goodness-of-fit statistics for the two model forms, were compared.

Stage 5 - Model Verification and Accuracy Assessment

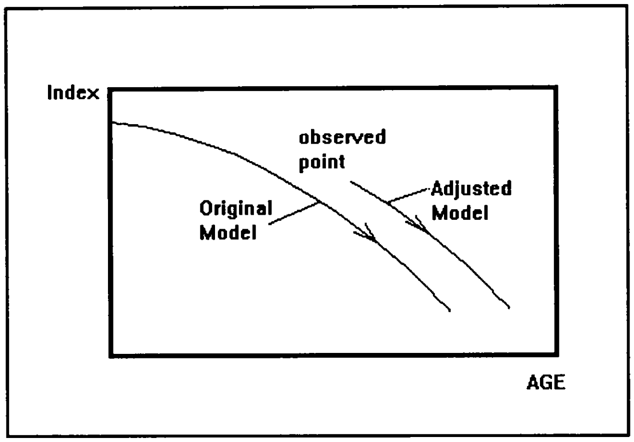
The final stage of the study assessed the accuracy of the developed models. The stage consisted of two major tasks. The first task used the previously saved 5% sample to assess the accuracy of the developed models when used to predict for different numbers of years into the future. In task two, the sample was employed to compare the predictive ability of the two model forms developed in the previous stage, and evaluate the effectiveness of two approaches for model adjustment that attempt to incorporate data feedback into the prediction process.

Assessing the Accuracy of the Prediction Process and Adjusting the Developed Models

Since the behavior of pavement structures is affected by many factors, the performance of a specific section typically differs from the mean response given by a deterioration model. In practice, therefore, when the observed condition of a section in a given year differs from that predicted by the model, the model should be adjusted to pass through the observed point. Predictions for future years are then made using this augmented curve.

The literature on prediction model development shows two basic approaches for model adjustment. The first approach, exemplified by the PAVER system and the Illinois Pavement Feedback System (IPFS), essentially draws a curve through the observed pavement condition-age point parallel to the developed model (Figure 3).

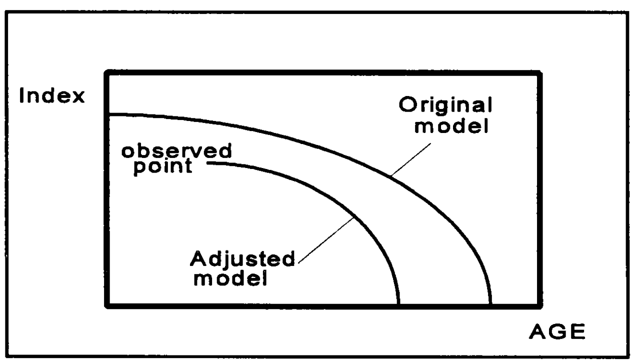
Figure 3. The Horizontal-Shift Model Adjustment Approach



Mathematically, this horizontal shift is performed by solving the model equation for the AGE value that corresponds to the observed pavement condition, AGE'. Future predictions are then made assuming that such calculated value, AGE' , is the current age for the section.

The second approach, adopted by Cook and Kazakov,[25] diverts the curve vertically instead of horizontally, so that it passes through the observed point (Figure 4).

Figure 4. The Vertical-Shift Model Adjustment Approach



This is done by using the actual drop in the pavement condition index from its initial value, D_1, versus the theoretical drop, D_2, to compute an adjustment factor, F, defined as: $F = D_1 / D_2$. Future predictions are made by multiplying the theoretical drop by F, which is usually constrained to the interval of 0.75 to 1.25.

Both adjustment methods were examined in the current study to determine if either was more appropriate than the other.

Preparing the Sample Data Set for the Analysis

Owing to the predominance of the overlaid flexible pavement category, the 5% sample for categories pertaining to the other pavement types resulted in very few data points for an assessment of the models' accuracy. The same was also true with the Suffolk and Culpeper overlaid pavement categories, where the number of points available for verification purposes was quite small. As a result, assessment was constrained to the prediction accuracy of the overlaid flexible pavement models in the Bristol, Salem, Richmond and Staunton districts.

Since the sample was randomly selected, its points belonged to different survey years and to sections with different ages. Consequently, to assess the models' accuracy when used to predict for different numbers of years into the future, the sample data set points were categorized into four groups:

1. Group A, used in the accuracy assessment of prediction for one year into the future, with the following two sets of points:

    - Points corresponding to pavement sections which had a DMR value recorded for the (t-1) survey year, where t refers to the survey year of a data point in the sample set. This DMR value and its accompanying AGE value were used to adjust the prediction model.

    - Points corresponding to sections that were less than one year old at the survey time. No adjustment was made in such cases.

2. Group B, used in the accuracy assessment of 2 years' prediction, containing:

    - Points belonging to sections with a DMR value recorded for the (t-2) survey year. Prediction was adjusted based on this DMR-AGE point.

    - Points corresponding to sections which were between 1 and 2 years old at the time of the survey. No adjustment was made, even if a DMR value for the preceding year existed, in order to simulate prediction for two years into the future.

3. Group C contained points to be used in measuring the accuracy of prediction for 3 to 4 years.

    - Predictions for 3 to 4 years were combined into one group in order to yield a sufficient number of points that can allow a reasonable assessment.

4. Group D contained points to be used in measuring the prediction accuracy for 5 or more years.

Table 3 gives the number of points that were available within each group for the four districts.

Table 3. The number of points available for model verification

Pavement Category	Number of Points			
	Group A	Group B	Group C	Group D
1. Overlaid flex in Bristol	13	12	15	9
2. Overlaid flex in Salem	17	19	14	16
3. Overlaid flex in Richmond	31	25	24	34
4. Overlaid flex in Staunton	17	15	18	12

The models' adjusted predictions were compared against the DMR observed values from this sample data set. For a quantitative assessment of the models' accuracy, the prediction error, defined as the difference between the observed and the predicted values, was calculated for each observation point. The mean of this prediction error, its standard deviation and 95% confidence intervals were then computed for each district and each prediction level (number of prediction years into the future).

Comparing the Performance of the Two Model Forms and the Two Adjustment Procedures

To compare between the different models and adjustment procedures, the predicted DMR values were computed according to the power and the sigmoidal models; each being adjusted using the horizontal and vertical shift approaches (the linear model was not considered in this comparison since it failed to meet the boundary conditions established for a deterioration model). For each data point, 4 predicted values were estimated (corresponding to the 2 model forms x 2 adjustment procedures), except for Richmond district where the sigmoidal model did not converge.

An analysis-of-variance *(ANOVA)* test procedure was then performed to assess the effect on the response variable (the prediction error) of the following three factors:

1. The number of years into the future for which prediction is performed,
   at levels :
   1 (prediction for one year)
   2 (prediction for two years)
   3 (prediction for three or four years)
   4 (prediction for five or more years).

2. The model form used in prediction,
   at levels : 1 (the power model)
   2 (the sigmoidal model).

3. The adjustment method used,
   at levels : 1 (the horizontal-shift adjustment procedure).
   2 (the vertical-shift adjustment procedure).

RESULTS AND DISCUSSION

Exploratory Data Analysis

Response Variable Distribution

Four exploratory data analysis techniques were employed to check the distribution of the response variable, the DMR. Figure 5 shows the results of applying such techniques to check the DMR distribution for the Salem overlaid flexible pavement category data set. Results for the other data sets were quite similar. The figure contains four plots.

- In the upper left corner is a histogram which gives a crude picture of the DMR distribution. A histogram is also an effective tool for detecting possible coding errors, since points lying outside the reasonable or feasible range for a particular variable are readily apparent.

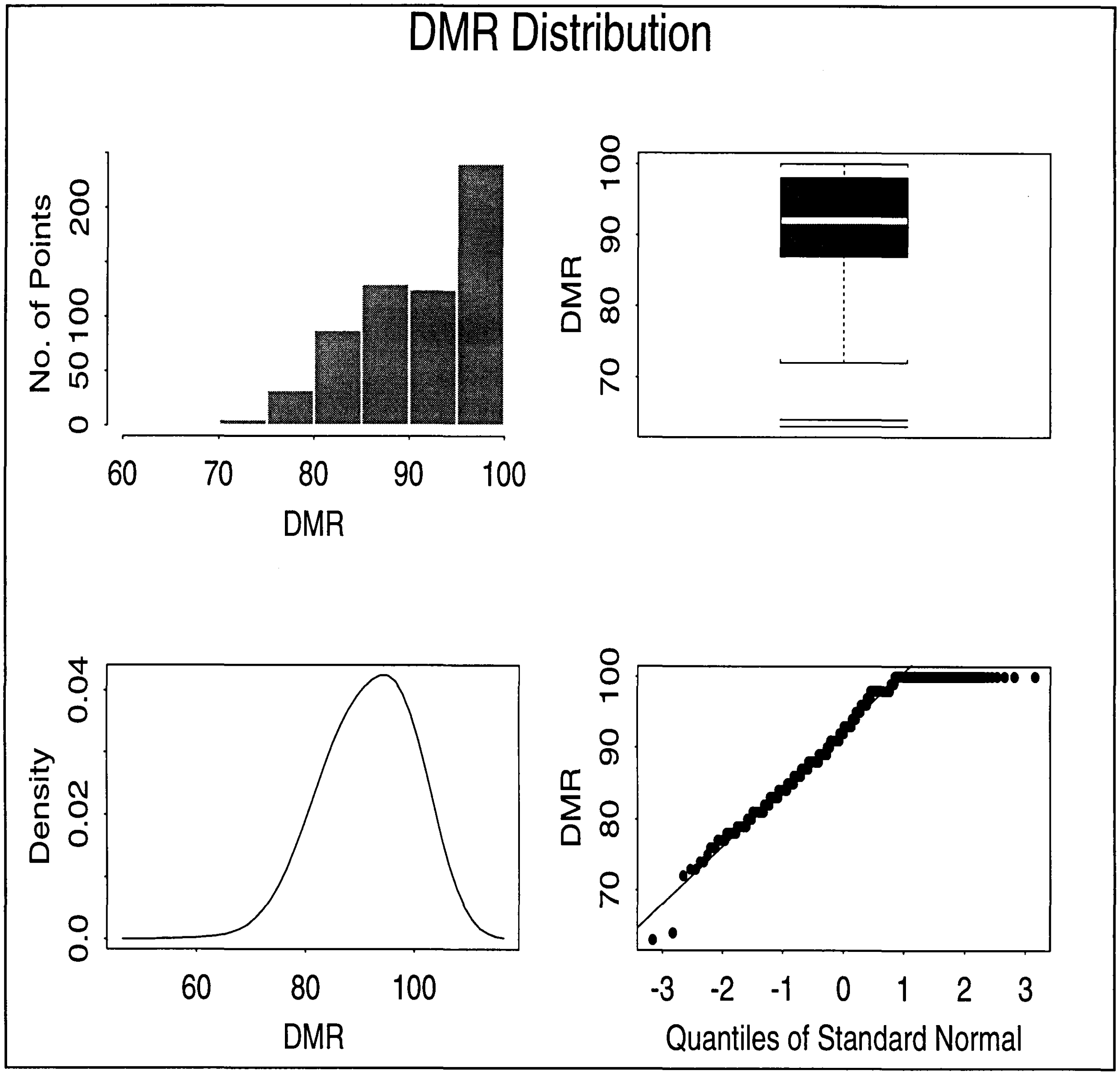
- The lower left plot shows a continuous curve representing a non-parametric estimate of the probability density function for the DMR. This curve provides a clear visualization of the variable distribution.

- A Box-and-Whisker plot is given in the upper right corner of the figure. In these plots, the box encloses the interquantile range for the variable, with the lower side giving the 25th percentile, the upper giving the 75th percentile, and the middle line showing the median. The whiskers extend to the 5th and 95th percentiles. Box plots depict the data range, skewness, and outliers.[26]

- Finally, a normal probability plot, or q-q plot, is provided in the lower right corner. In this plot, the quantiles or percentiles of the DMR distribution are plotted against the quantiles of a normal curve. Under normality assumption, points on the scatter plot should lie approximately on a straight line.[26]

The figure shows a quite normal distribution of the DMR, although it is somewhat skewed to the left because a high percentage of the sections were in the 98-100 DMR range, which signifies an excellent pavement condition.

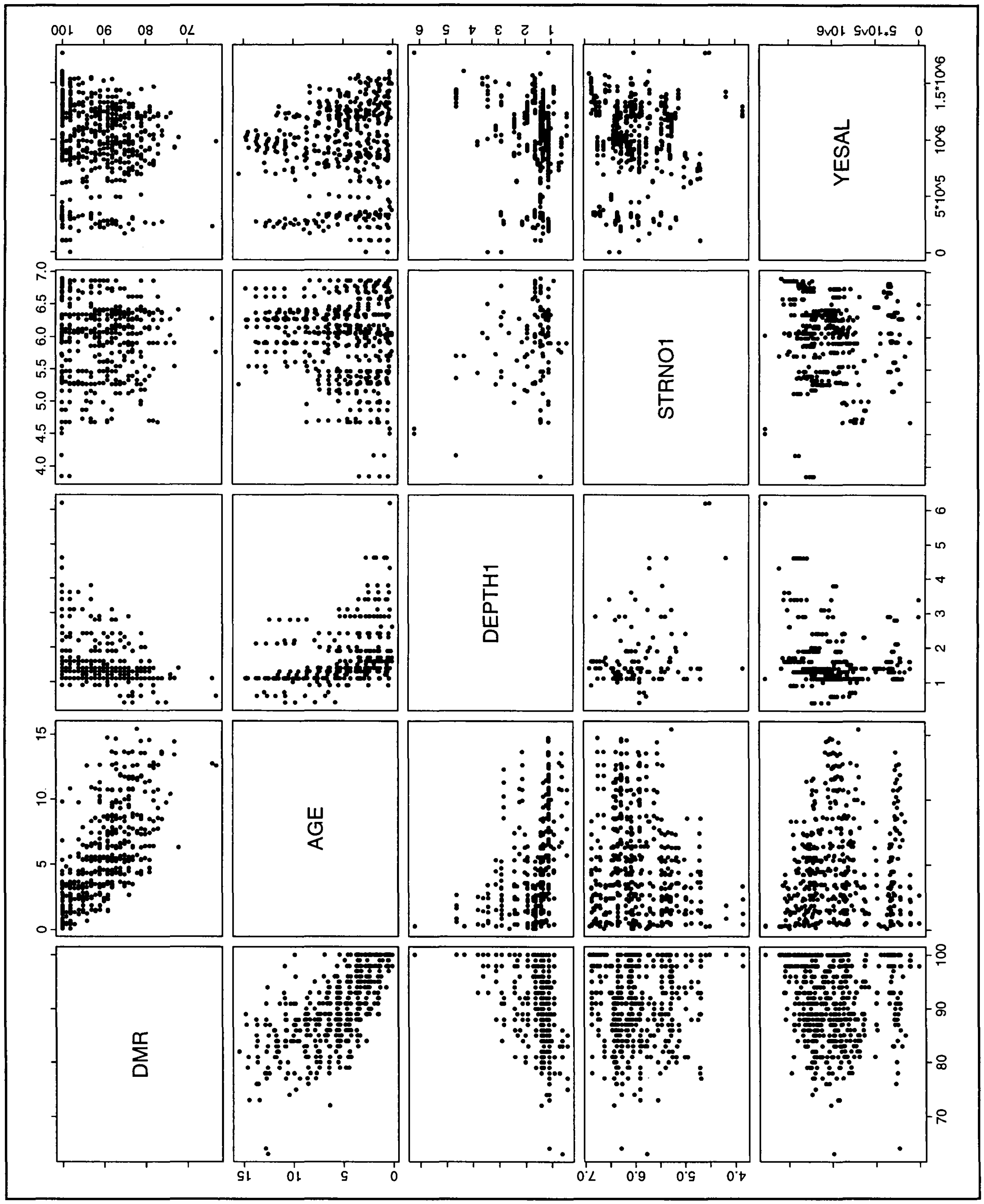
Figure 5. DMR Distribution for Salem Overlaid Flexible Pavements Data Set



Relationships Among Variables

Figure 6 shows the scatter plot matrix for the Salem overlaid flexible pavement category data set. The scatter matrices for the other data sets are included in Appendix A, figures A-1 through A-9. In these figures, variable names in the empty rectangles to the left and bottom of an individual scatter plot refer to variables plotted on the y- and x- axis respectively.

Figure 6. Scatter Plot Matrix for Salem Overlaid Flexible Pavements Data Set



The following observations can be deduced from the plots:

- Age, among all the other variables, seems to exhibit the strongest correlation with the DMR value.

- The relationship between the DMR and the AGE appears to be best represented by a concave or S-shaped curve.

- No significant interrelations among the independent variables can be readily detected, perhaps with the exception of the interrelationship between STRNO and YESAL in the data sets where STRNO was available. This indicates that, apart from the association between STRNO and YESAL, no major multicollinearity problems will be encountered.

Stepwise Regression

Stepwise Regression Models and Their Statistics

Table 4 gives the models resulting from the stepwise regression analysis along with their associated statistics, all variable definitions and notations being as previously described.

Discussion of Stepwise Regression Results

Table 5 summarizes the predictor variables included in each of the above 10 models. With reference to Table 5 and the developed models, the following observations are made:

AGE

This variable was included in all 10 models, and was consistently found to have the largest correlation with the DMR and, by far, be its most significant predictor. Table 6 shows the ratio of the R^2 value resulting from using AGE as the single independent variable to that resulting from using all the variables included in the stepwise regression. The ratio ranged from 75% to 100%. This finding accords with the findings of other researchers.[10]

DEPTH

DEPTH or the thickness of the overlay was included in 4 out of the 8 cases where it was applicable. The exclusion of the variable in some of the other cases was attributed to the fact that the available data set for the group had a distribution with a limited range for the values of this variable. For example, in Suffolk district, the thickness of the overlay ranged only from 1.0 to 1.6 inches. Such a small variation had an insignificant impact on the DMR value.

Table 4. Stepwise Models and Their Statistics

Group	Model	R^2	Standard Error	F-value	p-value	No. of points
1	DMR = 95.87 - 2.34(AGE) + 0.65(DEPTH) + 0.49(YESAL)	0.69	3.77	292.51	0.0000	404
2	DMR = 88.21 - 1.41(AGE) + 1.35(DEPTH) + 1.26(STRNO) + 2.92(LANNO)	0.66	4.02	253.65	0.0000	534
3	DMR = 99.87 - 1.01(AGE) - 7.15(YESAL) + 3.25(LANNO) - 4.78(RDTYP2) + 3.50(ROUT85) + 6.61(ROUT95)	0.44	4.41	115.06	0.0000	861
4	DMR = 114.94 - 1.56(AGE) - 2.91(STRNO) - 2.33(ROUT64)	0.72	3.13	55.09	0.0000	63
5	DMR = 100.99 - 1.76(AGE)	0.68	3.40	142.38	0.0000	69
6	DMR = 97.06 - 1.11(AGE) + 1.09(DEPTH) + 5.03(LANNO) - 1.39(ROUT81)	0.54	3.82	121.63	0.0000	415
7	DMR = 92.62 -1.11(AGE) + 2.32(LANNO)	0.50	4.73	48.94	0.0000	96
8	DMR = 105.82 - 1.09(AGE) - 1.68(STRNO) + 2.21(ROUT464)	0.66	3.78	100.51	0.0000	153
9	DMR = 95.68 - 1.45(AGE) + 4.25(DISTR5)	0.76	2.38	138.88	0.0000	88
10	DMR = 97 - 1.90(AGE) +1.54(DEPTH) + 4.07(LANNO)	0.85	2.36	146.25	0.0000	80

Group 1: overlaid flexible pavements - Bristol district
Group 2: overlaid flexible pavements - Salem district
Group 3: overlaid flexible pavements - Richmond district
Group 4: overlaid flexible pavements - Suffolk district
Group 5: overlaid flexible pavements - Culpeper district
Group 6: overlaid flexible pavements - Staunton district
Group 7: flexible pavements with no overlay - Region 1
Group 8: flexible pavements with no overlay - Region 2
Group 9: composite pavements with one overlay
Group 10: composite pavements with more than one overlay

Table 5. Predictor Variables Status

Group or Data set	AGE	DEPTH	YESAL	STRNO	LANNO	RDTYP	ROUTID	DISTR
1.overlaid flex- Bristol	included	included	included	*	not includ.	not includ.	not includ.	**
2.overlaid flex- Salem	included	included	not includ.	included	included	not includ.	not includ.	**
3.overlaid flex-Richmond	included	not includ.	included	*	included	included	included	**
4.overlaid flex- Suffolk	included	not includ.	not includ.	included	***	not includ.	included	**
5.overlaid flex-Culpeper	included	not includ.	not includ.	*	***	***	not includ.	**
6.overlaid flex- Staunton	included	included	not includ.	*	included	***	included	**
7.flex no overlay-region1	included	**	not includ.	not includ.	included	not includ.	not includ.	not includ.
8.flex no overlay-region2	included	**	not includ.	included	not includ.	not includ.	included	not includ.
9.composite- 1 overlay	included	not includ.	not includ.	**	***	not includ.	not includ.	included
10.composite->1 overlay	included	included	not includ.	**	included	***	***	***

* Explanatory variable was not available.
** Explanatory variable is not applicable.
*** All points belonged to the same level for the categorical variable, or only 6 points or less were available for the other level.

Table 6. The Contribution of AGE to DMR Prediction

Group	AGE contribution (%)
1. Overlaid flexible-Bristol	97.1 %
2. Overlaid flexible-Salem	92.4 %
3. Overlaid flexible-Richmond	74.9 %
4. Overlaid flexible-Suffolk	90.5 %
5. Overlaid flexible-Culpeper	100.0 %
6. Overlaid flexible-Staunton	87.2 %
7. Flexible / no overlay-Region 1	96.0 %
8. Flexible / no overlay-Region 2	96.1 %
9. Composite with 1 overlay	78.2 %
10. Composite with > 1 overlay	94.9 %

YESAL

This variable, which represented the average annual ESALs, was included in only 2 cases, despite its availability for all 10 data sets. This is quite encouraging, since it means that the adopted classification scheme and the use of dummy variables helped keep the YESAL virtually at a uniform level within each category. This reduced the significance of its role in the overall prediction process, allowing reasonable predictions to be made even in the absence of ESAL data.

With respect to the coefficient sign, the variable assumed the correct sign for group 3, which signifies that an increase in the YESAL will inflict more damage, but not for group 1. To resolve this problem, group 1 was broken down into 2 subgroups: group 1a for sections belonging to I-77, and group 1b for those belonging to I-81 or I-381. This subdivision resulted in more homogeneous characteristics within the two finer subgroups. Accordingly, the significance of the role of either the STRNO or the YESAL variables was reduced, and the YESAL disappeared from the equation. The two developed models are in Table 7.

Table 7. Refined Models for Group 1

Group	Model	R^2	Standard Error	F-value	p-value	No. of points
1a	DMR = 97.49 - 2.45(AGE)	0.74	3.66	229.03	0.0000	82
1b	DMR = 96.59 - 2.32(AGE) + 0.65(DEPTH)	0.66	3.84	306.69	0.0000	332

STRNO

The structural number of the pavement structure (STRNO) was only available and applicable in 4 data sets. Out of these, STRNO entered the models in 2 cases. However, STRNO did not always assume the correct sign. Normally, the model should indicate that the stronger the pavement structure, the less the damage; this was not the case for group 4. Consequently, in order to prevent incorrect conclusions and inferences from being drawn from the model, the regression analysis was repeated with this variable excluded. The new model for group 4 is shown below.

DMR=100.95 - 1.58(AGE) - 2.85(ROUT64)
R^2 = 0.70 & SE = 3.25

LANNO

This dummy variable, which accounts for the lane rated, entered the model in 5 out of the 7 cases where it was available. In the absence of ESAL data, the use of this variable was essential to account for the difference in the deterioration trends between the traffic and the inner lanes.

RDTYP

RDTYP, which accounts for the number of lanes per direction of the roadway section, was included in one out of 9 cases. Since the YESAL played a minor role in the prediction process, it should be expected that the number of lanes per direction, which influences the share of each lane in the traffic load, would also have an insignificant effect.

ROUTID

This set of dummy variables, which differentiates between the different routes within a certain group, was included in 4 out of 9 cases. The ROUTID helped account for some of the characteristics particular to a certain route, and reduced the significance of the role played by the YESAL and STRNO variables.

DISTR

DISTR, the set of dummy variables used to identify individual districts, was included in 1 out of 3 cases where classification was based upon geographic region. Statistical tests checking whether the deterioration trends for the overlaid flexible pavements category differed among the various districts indicated that DISTR was indeed a significant predictor. For example, when stepwise regression analysis was performed on an experimental data set pooling points from the three districts forming the Western Mountains region, the DISTR dummy variables were included in the model. This further justifies the subdivision of this category into groups of individual districts.

The Poor Fit for the Richmond Model

The fact that the majority of the categorical variables were included in the Richmond model, coupled with the large number of data points available for this group, suggested that the fit could be improved by breaking this category into finer subgroups. The subgroups adopted were as follows:

- Group 3a, for I-64 pavement sections,
- Group 3b, for I-85 pavement sections,
- Group 3c, for sections of I-95 with 2 lanes per direction, and
- Group 3d, for sections of I-95 with 3 or more sections per direction.

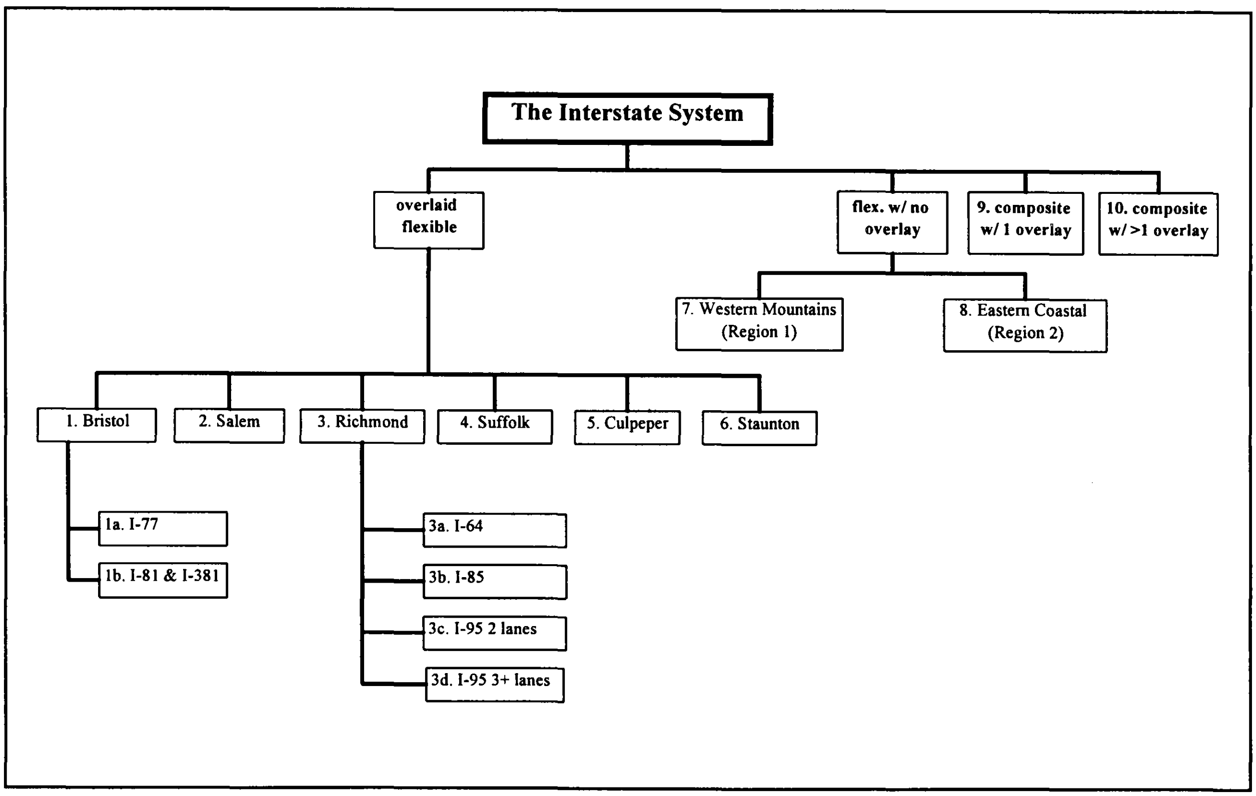
This subdivision resulted in a considerable improvement in the fit for three of these subgroups as is shown in Table 8.

The main purpose of linear stepwise regression analysis was to identify the significant predictors. The results were quite encouraging. The models were highly significant, with satisfactory coefficients of determination (R^2) values coupled with reasonable standard error. These were very satisfactory results for a preliminary model form. The simple linear model form was also useful, in that it led to the adoption of a refined classification scheme that enhanced the modeling process. Figure 7 shows the refined classification scheme used for the subsequent modeling stages.

Table 8. Refined Models for Group 3

Group	Model	R^2	Standard Error	F-value	p-value	No. of points
3a	DMR = 95.98 - 1.91(AGE)	0.68	3.61	161.10	0.0000	77
3b	DMR = 98.87 - 1.15(AGE) - 6.53(YESAL)	0.63	3.34	97.49	0.0000	116
3c	DMR = 107.12 - 1.57(AGE) - 9.60(YESAL)	0.71	3.00	61.88	0.0000	51
3d	DMR = 105.41 - 0.92(AGE) - 6.85(YESAL) + 2.94(LANNO)	0.37	4.66	117.76	0.0000	600

Figure 7. The Modified Classification Scheme



It is essential to raise a basic point about the nature of these models. All the models in the current study are empirical, and should not be applied beyond the range of the data used in their development. This is especially true here, since some important variables were missing, and others were excluded because their limited range had an insignificant effect on DMR prediction. Table 9 gives the range of the different variables for each group or data set.

Table 9. Variable Ranges for the Different Groups

Group	AGE	DEPTH	STRNO	YESAL	Rated Lane [c]	Lanes / direction	ROUTE	DISTRICT[d]
1a	0.2 - 12.8	1.1 - 2.7	a	0.2 - 1.2	0, 1, 2	2	77	1
1b	0.2 - 11.4	0.9 - 6.3	a	0.7 - 2.2	0,1, 2, 3	1,2,3	81, 381	1
2	0.0 - 14.8	0.6 - 4.6	3.8 - 6.9	0.7 - 2.2	0, 1, 2, 3	2,3	77, 81, 581	2
3a	0.0 - 10.5	1.0 - 2.2	a	0.2 - 0.8	0, 1	2	64	4
3b	0.4 - 15.6	0.5 - 1.5	a	0.5 - 1.5	0, 1	2	85	4
3c	0.1 - 12.5	0.9 - 3.8	a	0.8 - 1.6	0	2	95	4
3d	0.1 - 16.9	0.9 - 4.4	a	1.6 - 2.8	0 ,1, 2, 3	3,4	95	4
4	0.4 - 13.0	1.0 - 1.6	4.0 - 5.4	0.5 - 1.5	0	2,3	64,95,264,464	5
5	0.3 - 9.7	1.3 - 3.0	a	0.2 - 0.8	0, 1	2	64, 66	6
6	0.1 - 15.2	0.7 - 4.1	a	0.1 - 2.1	0, 1, 2	2	64, 66, 81	7
7	0.4 - 17.3	b	4.2 - 6.8	0.1 - 2.0	0,1,2,3	2,3	64, 77, 81	1, 2, 8
8	0.8 - 17.5	b	4.0 - 5.9	0.4 - 2.4	0, 1, 2, 3	2,3,4	64,95,264,464,664	4, 5, 6
9	0.2 - 14.0	1.9 - 7.9	b	0.6 - 2.5	0,1	2,3	64,95,264, 664	4, 5, 6
10	0.2 - 10.5	0.6 - 2.4	b	0.8 - 2.7	0, 1, 2	2	95	6

a Variable was not available.
b Variable is not applicable.
c A value of 0 for the rated lane means that rating was performed on the section as a whole; lane numbering starts from the outer or traffic lane toward the median.
d 1➪ Bristol ; 2 ➪ Salem ; 4 ➪ Richmond; 5 ➪ Suffolk; 6 ➪ Fredricksburg; 7 ➪ Culpeper; 8 ➪ Staunton.

The Power Model

Table 10 shows the developed models along with their R^2 and standard error (SE) values.

Table 10. Power Models and their Statistics

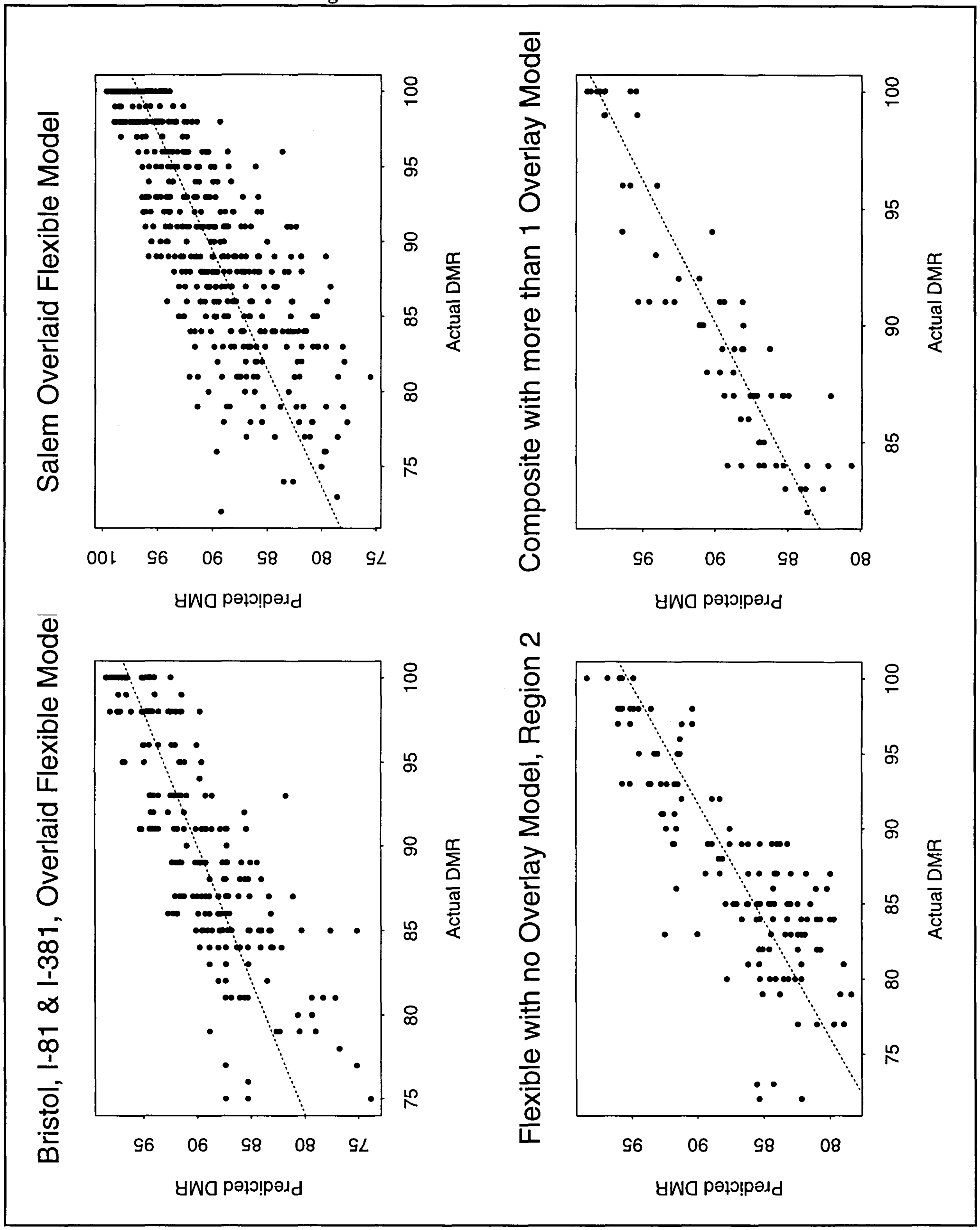
Group	Model	R^2	SE
1a	$DMR = 100 - 5.17.(AGE)^{0.68}$	0.80	3.24
1b	$DMR = 100 - 4.43.(AGE)^{0.73}.(DEPTH)^{-0.04}$	0.68	3.73
2	$DMR= 100 - 15.63.(AGE)^{0.75}.(DEPTH)^{-0.17}.(STRNO)^{-0.92}.(LANNO)^{-0.31}$	0.67	3.94
3a	$DMR = 100 - 7.08.(AGE)^{0.62}.(YESAL)^{0.28}$	0.72	3.42
3b	$DMR = 100 - 7.07.(AGE)^{0.44}.(YESAL)^{0.39}$	0.65	3.27
3c	$DMR = 100 - 5.06.(AGE)^{0.48}.(YESAL)^{1.29}.(DEPTH)^{-0.20}$	0.72	3.03
3d	$DMR = 100 - 2.30.(AGE)^{0.42}.(YESAL)^{1.53}.(LANNO)^{-0.16}$	0.50	4.15
4	$DMR = 100 - 1.67.(AGE)^{0.92}.(ROUT64)^{0.31}$	0.71	3.24
5	$DMR = 100 - 1.14.(AGE)^{1.18}$	0.68	3.40
6	$DMR = 100 - 3.14.(AGE)^{0.62}.(DEPTH)^{-0.15}.(LANNO)^{-0.59}.(ROUT81)^{0.08}$	0.57	3.69
7	$DMR = 100 - 6.03.(AGE)^{0.49}.(LANNO)^{-0.11}$	0.59	4.37
8	$DMR = 100 - 1.82.(AGE)^{0.79}.(LANNO)^{-0.21}.(ROUT95)^{0.21}$	0.68	3.74
9	$DMR = 100 - 3.45.(AGE)^{0.76}.(DISTR5)^{-0.35}$	0.74	2.50
10	$DMR = 100 - 3.43.(AGE)^{0.76}.(DEPTH)^{-0.23}.(LANNO)^{-0.68}$	0.87	2.21

Power Model Evaluation Results

Model's Goodness of Fit

Figure 8 shows plots of the predicted versus the actual DMR values for 4 models. Plots for the remaining 10 models are included in Appendix B, figures B-1 and B-2. As these plots show, no erratic pattern is apparent and the power model appears to adequately fit the data.

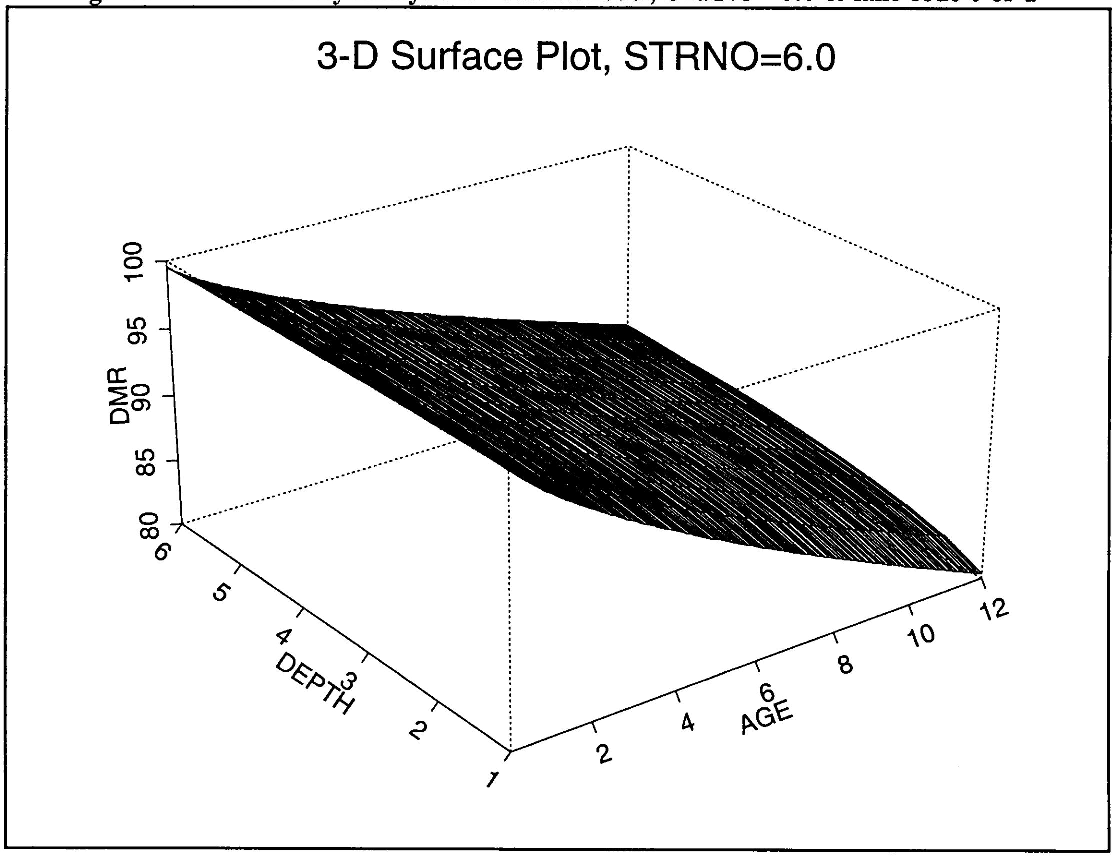
Figure 8. Power Model Goodness-of-Fit



Sensitivity Analysis

The results of a sensitivity analysis for the Salem overlaid flexible model appear in Figures 9 through 11. Figure 9 shows the sensitivity of the DMR prediction with respect to the pavement AGE and overlay thickness, DEPTH. Figure 10 depicts the sensitivity with respect to AGE and the structural number of the underlying structure. Figure 11 compares the deterioration trends of the different lanes. The performance of the model is quite reasonable and in agreement with basic engineering knowledge. Results for the other models are included in the Appendix B, figures B-3 through B-19.

Figure 9. 3-D Sensitivity Analysis for Salem Model, STRNO=6.0 & lane code 0 or 1*



* The lane code identifies the lane being rated with a "1" for the outer or traffic lane. In the usual case when the roadway is rated as a whole, a "0" is used.

Figure 10. 3-D Sensitivity Analysis for Salem Model, DEPTH=1.4 & lane code 0 or 1

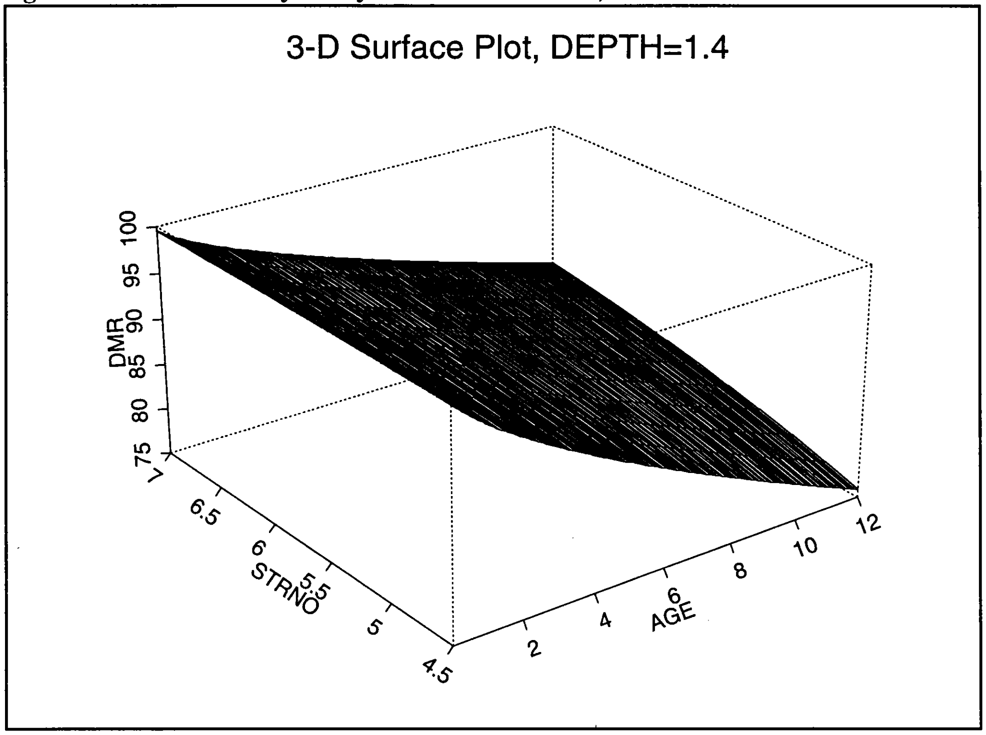
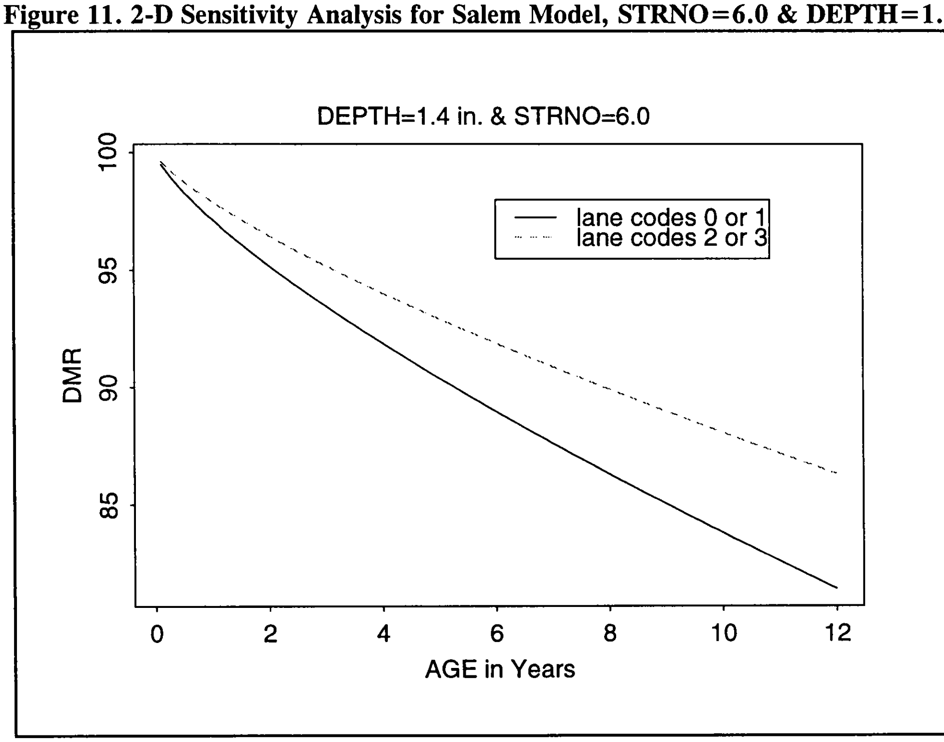


Figure 11. 2-D Sensitivity Analysis for Salem Model, STRNO=6.0 & DEPTH=1.4



The Sigmoidal Model

The developed models are shown in Table 11 along with their R^2 and SE values. As can be seen, a satisfactory model could be attained for only 8 groups; for the other 6 groups, the values for the asymptotic errors were too high to be acceptable.

Table 11. Sigmoidal Models and Their Statistics

Group	Model	R^2	SE
1a	$DMR = 100 - 43.96\, e^{\frac{-2.49}{(AGE)^{0.56}}}$	0.83	3.02
1b	$DMR = 100 - 23.52\, e^{\frac{-2.14\,.\,(DEPTH)^{0.21}}{(AGE)^{1.02}}}$	0.73	3.44
2	$DMR = 100 - 28.68\, e^{\frac{-0.74\,.\,(DEPTH)^{0.25}.\,(STRNO)^{0.80}.\,(LANNO)^{0.34}}{(AGE)^{0.76}}}$	0.70	3.78
3d	$DMR = 100 - 30.88\, e^{\frac{-6.05\,.\,(LANNO)^{0.24}}{(YESAL)^{1.81}.\,(AGE)^{0.50}}}$	0.52	4.08
6	$DMR = 100 - 18.46\, e^{\frac{-1.88\,.\,(DEPTH)^{0.66}.\,(LANNO)^{0.92}}{(AGE)^{0.83}}}$	0.62	3.51
7	$DMR = 100 - 21.22\, e^{\frac{-6.50\,.\,(LANNO)^{0.47}}{(AGE)^{1.85}}}$	0.70	3.77
8	$DMR = 100 - 25.67\, e^{\frac{-9.56\,.\,(LANNO)^{0.37}}{(ROUT95)^{0.16}.\,(AGE)^{1.18}}}$	0.71	3.55
10	$DMR = 100 - 25.74\, e^{\frac{-2.48\,.\,(DEPTH)^{0.36}.\,(LANNO)^{0.70}}{(AGE)^{0.80}}}$	0.90	1.95

Figures C-1 and C-2 (Appendix C) show plots of the predicted versus the actual DMR values for the sigmoidal models. The sensitivity analysis results are also in Appendix C, Figures C-3 through C-15. The evaluation results indicated that, *on convergence*, the sigmoidal model also yielded an adequate fit, and gave logical predictions.

The Sigmoidal Versus the Power Curve

Figure 12 contrasts the deterioration trends given by the power and sigmoidal models for the eight categories where a satisfactory sigmoidal model could be developed. These plots are for typical values for the section characteristics in each data set. The plots show that, unlike the power curve, the sigmoidal model can model a low deterioration rate region at the beginning of the section's life cycle. This explains to some extent the sigmoidal model nonconvergence for some groups; in such cases, sections essentially exhibited the same deterioration rate throughout their life.

The plots also indicate that the differences between the sigmoidal model low rate deterioration region and the power curve are of appreciable significance only in the case of the *flexible pavements with no overlay* category. This is a rational conclusion, since distress should be expected to develop in original flexible pavement designs at a slower rate than in overlays or composite pavements.

The R^2 and the standard error (SE) values for the two model forms in Tables 10 and 11 support the above conclusion. The sigmoidal model provided an improved fit for the groups where it converged, with the greatest improvement in fit obtained for the *flexible pavements with no overlay* category in region one.

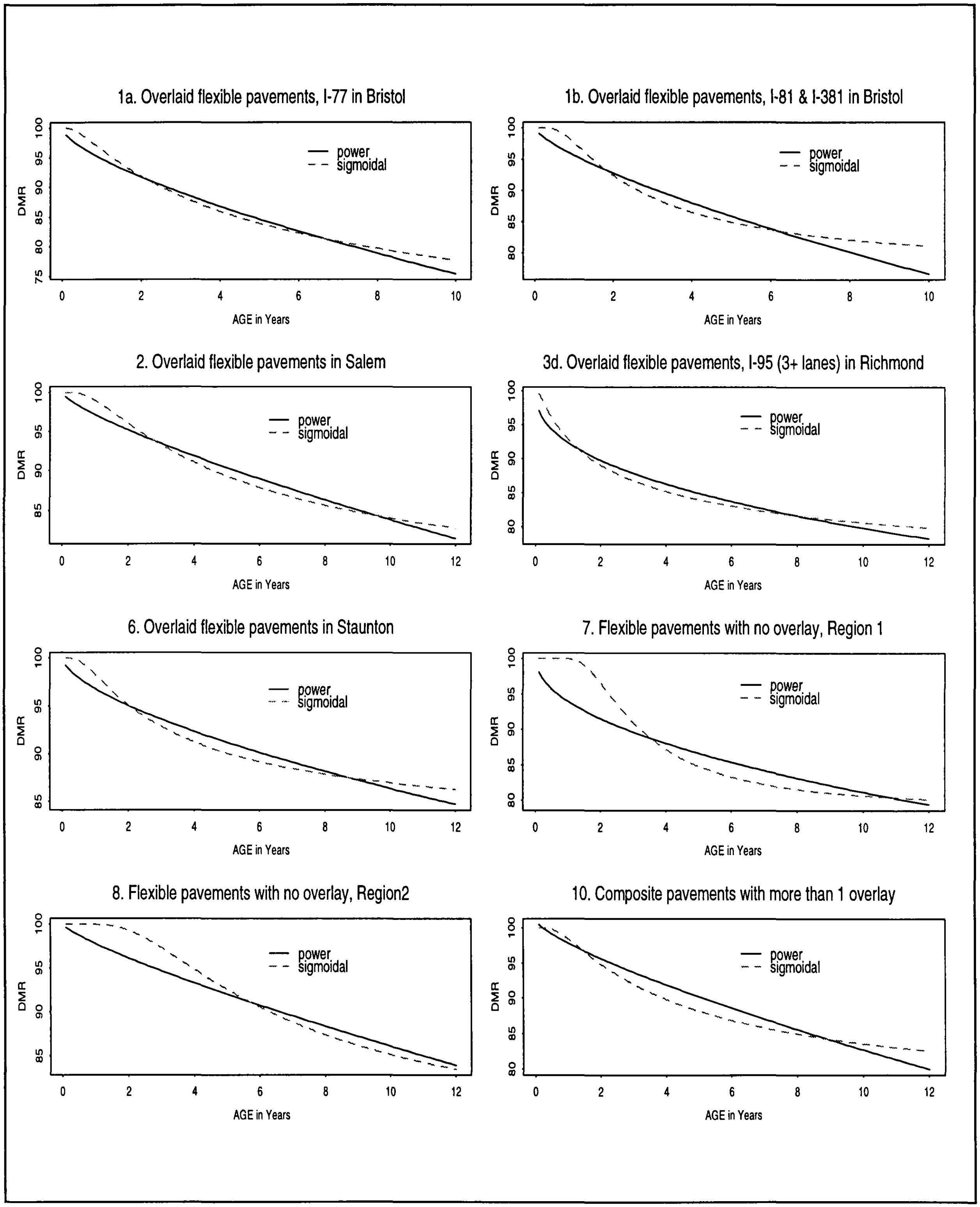
The following conclusions can be drawn from the available data :

- For all pavement types other than *the flexible pavements with no overlay* category the use of the simpler power curve seems to be adequate from a practical standpoint, although the sigmoidal model may provide for a slightly better fit. This conclusion is supported by the fact that the sigmoidal model failed to converge for some groups belonging to other pavement type categories.

- For *flexible pavements with no overlay*, the sigmoidal curve may be preferred over the power curve to reflect their initial slower deterioration rate compared to overlaid sections. The significant improvement in the fit for group seven justifies this conclusion.

Moreover, the use of the power curve may be safer from an extrapolation point of view. The lower asymptote of the sigmoidal model does not really represent the absolute minimum value for the DMR. It represents an "artificial" minimum, heavily influenced by the threshold DMR value currently adopted by VDOT, since the range of the available data will be bounded by the threshold value. Consequently, the sigmoidal model cannot be used to investigate the effect of adopting a new threshold value which falls below its lower asymptote.

Figure 12. Comparing the Sigmoidal and Power Models



Accuracy Assessment Results

Figures 13 through 16 show the models' adjusted predictions plotted against the observed sample data set DMR values for the four levels of prediction accuracy and for the four districts. In these figures, predictions were made using the non-linearly fit power model, and were adjusted using the horizontal-shift adjustment approach. The models provided good and reasonable predictions. Moreover, predictions for five or more years into the future were comparable to the one year prediction.

The mean, standard deviation and 95% confidence intervals for the prediction error for each district are provided in tables 12 through 15. These tables show a quite satisfactory prediction accuracy. For the Bristol district, for example, the mean error for predicting for 5 or more years into the future was -0.13. In addition, one can be 95 % confident that the average error in predicting the DMR for this district will be within ±2.0 DMR points.

ANOVA Test Results

The ANOVA results are provided in Appendix D, tables D-1 through D-4. In all four cases the interaction between the factors was insignificant (the p-value is greater than the usual α of 0.05). The absence of interaction effects allows for studying the effect of the individual factors, "the main effects," since it indicates that factor effects are not "averaging out" one another. Examining the p-values for the three factors for the four cases indicated that they were all greater than the 0.05 value. This led to the following conclusions:

1. There are no true differences among the predictive accuracies of the two model types.

2. The accuracy of predictions for different numbers of years is comparable.

3. The performance of the two adjustment procedures is similar.

Conclusion 1 was expected, since, as the previous stage of the study demonstrated, the performance of the three models was quite similar for overlaid pavements. Interestingly, the results indicated that the predictive accuracy for different years into the future was comparable. This conclusion, coupled with Conclusion 3 (the insignificant differences between the adjustment procedures), suggested that no appreciable improvement in the prediction process was obtained from using section-specific data to adjust the prediction models. This finding supported the assertion that a project or section-specific modeling approach for modeling the data currently available from VDOT was not quite appropriate. For the rather high level of contamination that the data exhibited, an approach that grouped similar pavements together seemed much safer. Such an approach was likely to minimize the problems associated with data errors, and helped reveal the overall deterioration trend.

Figure 13. Assessing the Prediction Accuracy for Salem District

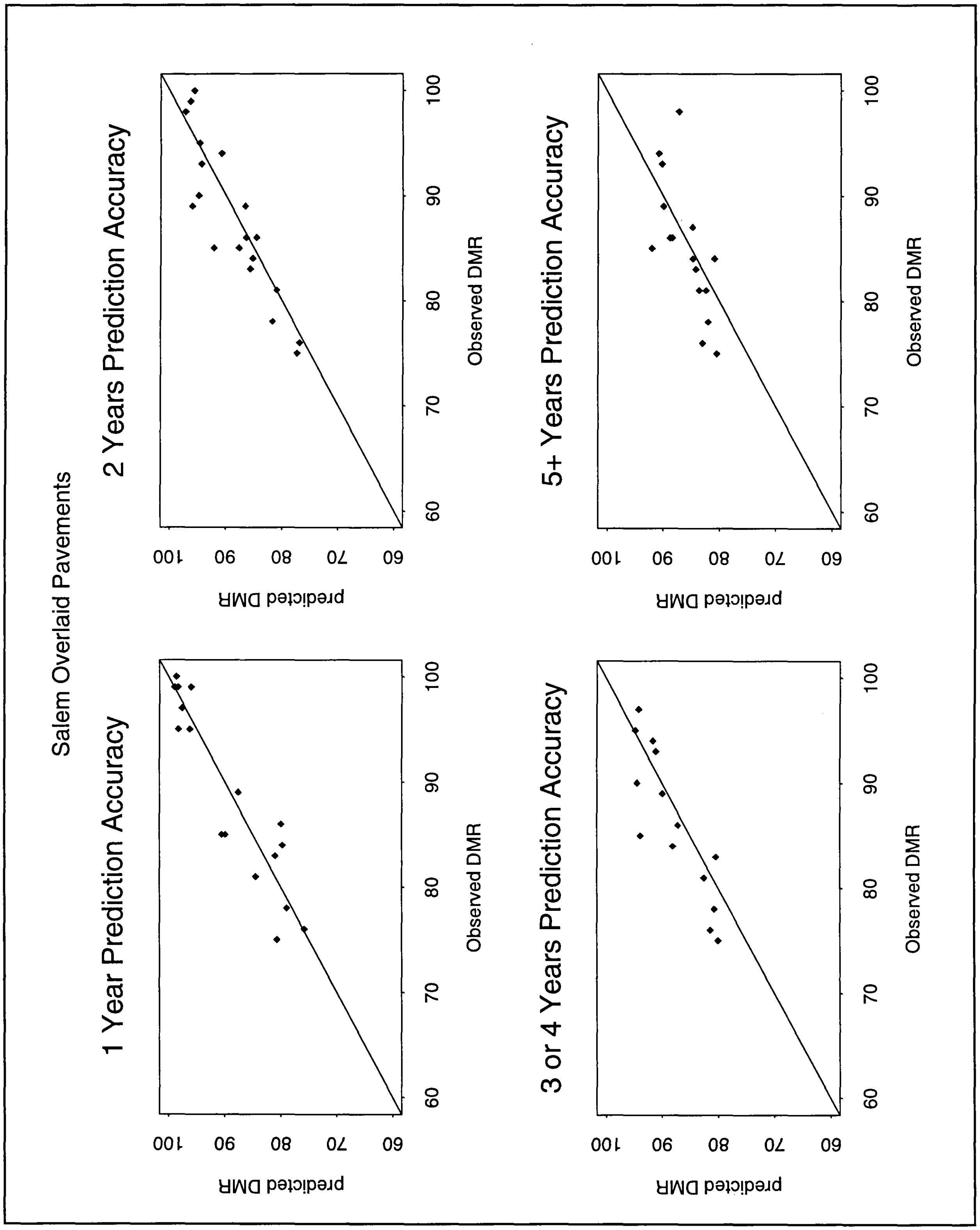


Figure 14. Assessing the Prediction Accuracy for Richmond District

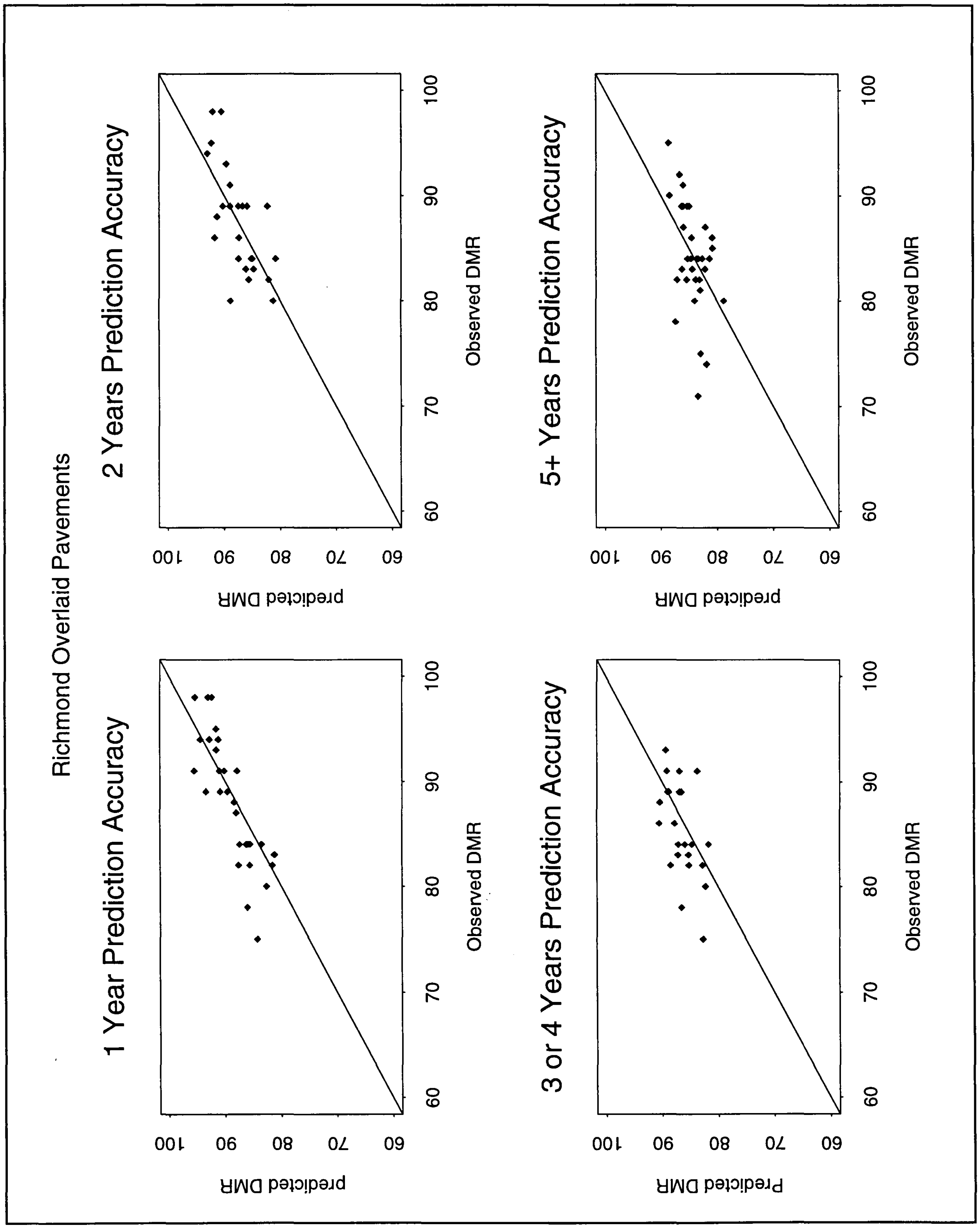


Figure 15. Assessing the Prediction Accuracy for Bristol District

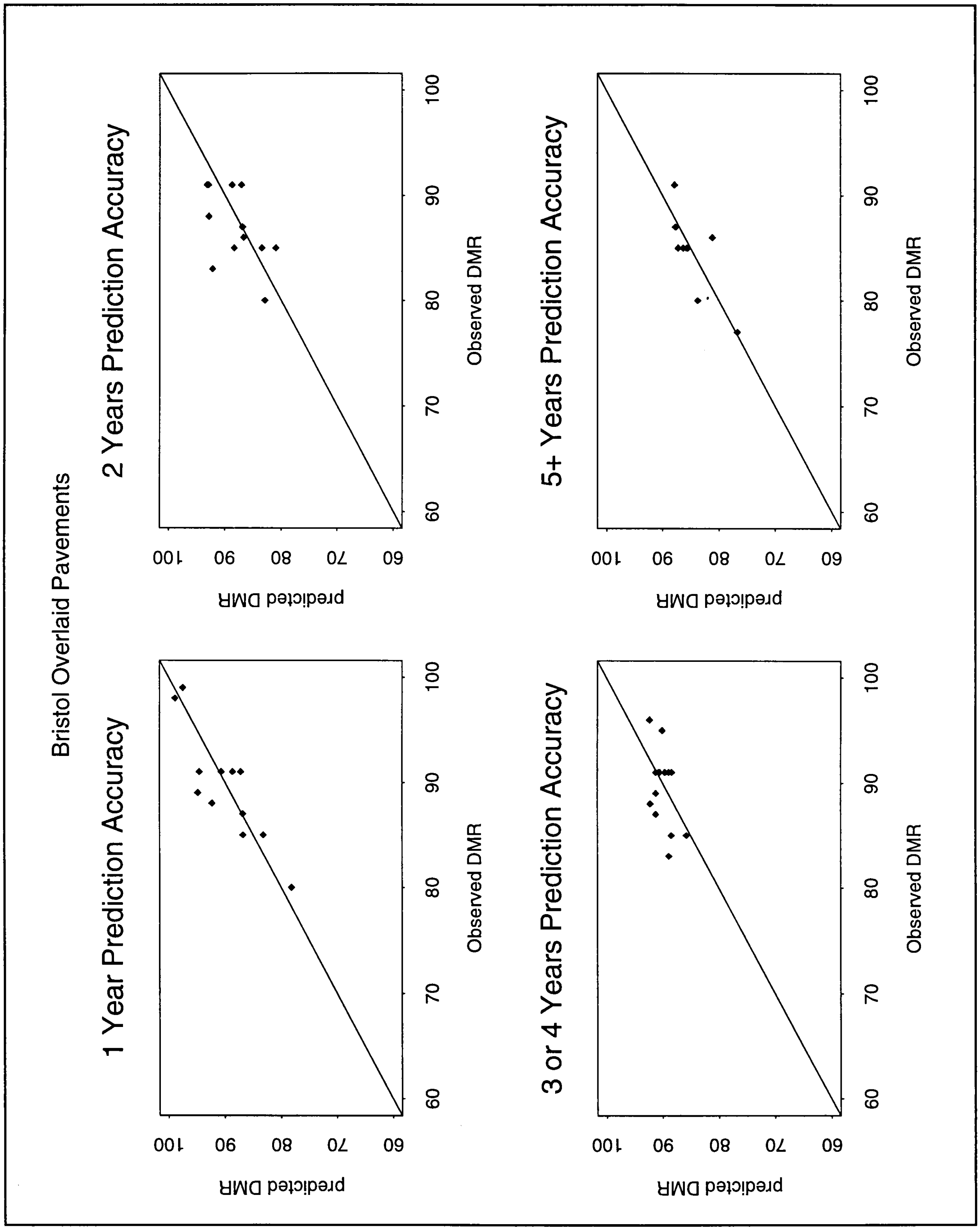


Figure 16. Assessing the Prediction Accuracy for Staunton District

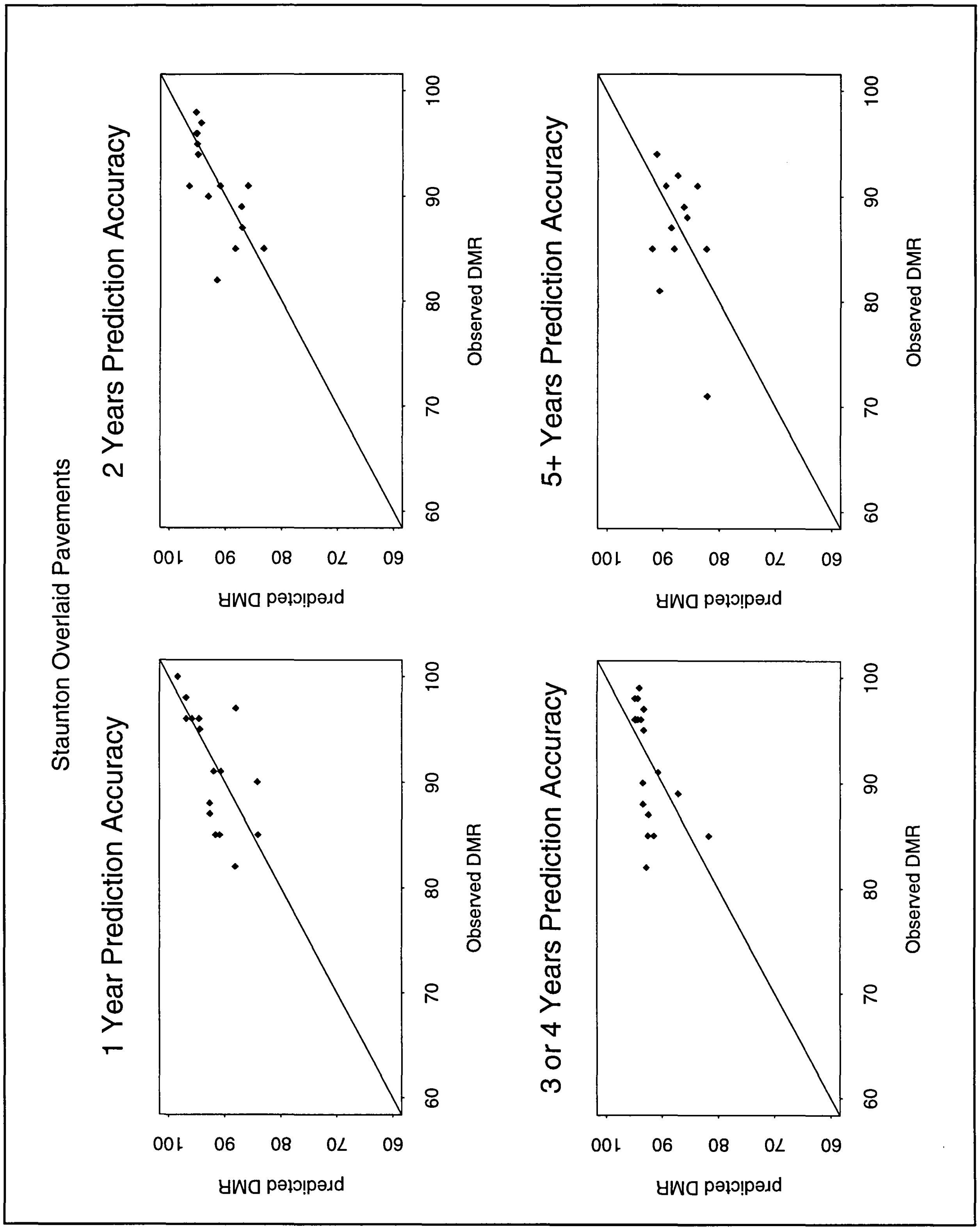


Table12. Prediction Error Statistics for Bristol District

Number of Years of Prediction into the future	Prediction Error Statistics		
	Mean	Standard Dev.	95 % Confid. Interval
1 Year	- 0.17	2.93	[- 1.94 ; 1.60]
2 Years	- 1.10	3.83	[- 3.53 ; 1.33]
3 or 4 Years	- 0.29	3.16	[- 2.04 ; 1.46]
5 + Years	- 0.13	2.64	[- 2.16 ; 1.90]

Table13. Prediction Error Statistics for Salem District

Number of Years of Prediction into the future	Prediction Error Statistics		
	Mean	Standard Dev.	95 % Confid. Interval
1 Year	- 0.38	3.37	[- 2.11 ; 1.35]
2 Years	- 0.97	3.23	[- 2.52 ; 0.60]
3 or 4 Years	- 1.76	3.54	[- 3.80 ; 0.28]
5 + Years	- 0.80	4.53	[- 3.20 ; 1.60]

Table 14. Prediction Error Statistics for Richmond District

Number of Years of Prediction into the future	Prediction Error Statistics		
	Mean	Standard Dev.	95 % Confid. Interval
1 Year	- 0.744	3.47	[- 2.02 ; 0.53]
2 Years	0.13	3.84	[- 1.45 ; 1.71]
3 or 4 Years	- 0.97	3.84	[- 2.59 ; 0.65]
5 + Years	- 0.09	4.54	[- 1.67 ; 1.49]

Table 15. Prediction Error Statistics for Staunton District

Number of Years of Prediction into the future	Prediction Error Statistics		
	Mean	Standard Dev.	95 % Confid. Interval
1 Year	- 0.50	4.25	[- 2.68 ; 1.68]
2 Years	- 0.41	3.65	[- 2.42 ; 1.60]
3 or 4 Years	- 0.57	4.66	[- 2.90 ; 1.74]
5 + Years	- 0.67	5.83	[- 4.37 ; 3.03]

CONCLUSIONS

Preliminary Data Analysis and Outlier Detection

The basic conclusions derived from this stage of the study were:

1. The majority of data points for the Interstate system belong to overlaid flexible pavements, thus allowing the development of a separate prediction model for each district. For the other categories, the number of data points available can only permit the classification scheme to be based on geographic regions, which groups 3 districts together.

2. For overlaid flexible pavements, the number of sections with sufficient layer information to compute the structural number is relatively small compared to the total number of available points.

3. The age of the section (AGE), among all other independent variables, exhibits the strongest correlation with the DMR, with their relationship best expressed as a concave or an S-shaped curve.

4. With the exception of the interrelationship between the structural number (STRNO) and the yearly ESALs (YESAL), no other significant correlation among the independent variables exists.

Significant Predictors Identification

Conclusions for the significant variables affecting the pavement condition on Virginia's Interstate System are:

1. AGE was by far the most significant predictor for the DMR score. Its contribution, measured by the ratio of the R^2 value resulting from its use as the sole predictor to that resulting from using all variables included in the stepwise regression, ranged between 75% and 100% for the different groups.

2. The overlay thickness, DEPTH, was significant in predicting the DMR value, provided that it varied significantly among the sections under consideration. The variable was excluded from the model if the data base had a limited range for the values of this variable.

3. No true assessment regarding the significance of the structural number, STRNO, in the prediction process could be made, since the variable was only available in a few cases. However, due to its high correlation with the yearly ESALs together with the absence of other variables, the variable could end up with the incorrect sign.

4. Yearly ESALs (YESAL) play a minor role in the prediction process, because the adopted classification scheme and the use of dummy variables helped preserve the variable virtually at a uniform level within each group. Reasonable predictions can thus be made even in the absence of this variable.

5. The deterioration trend of the outer or traffic lane is significantly different from the inner lanes.

6. All other factors being the same, the number of lanes available per direction does not seem to significantly affect the pavement condition.

7. The use of dummy variables to differentiate among the different routes within a group may help capture some of the characteristics particular to a specific route.

8. Differences among the deterioration trends of pavements belonging to different districts are detectable in some cases. This suggests that basing classification schemes on districts, whenever possible, is beneficial.

Model Development and Evaluation

From this phase of the study, the following conclusions, pertinent to Virginia's Interstate data, can be made:

1. The power model provides for a satisfactory fit with reasonably high R^2 values and low standard errors. Moreover, its predictions conform with basic engineering knowledge.

2. The sigmoidal model is capable of modeling a low rate deterioration region at the beginning of a section's service life.

3. Differences between the sigmoidal curve's low deterioration region and the power curve are practically insignificant, except for the flexible pavement with no overlay category.

4. From an extrapolation standpoint, the power model may be safer than the sigmoidal curve, because the sigmoidal curve's lower asymptote will typically reflect the lower limit of the available data, which is influenced by the current threshold value for the condition measure.

Model Verification and Accuracy Assessment

Based on the results from this part of the study, the conclusions regarding deterioration prediction for overlaid flexible pavements are:

1. No detectable differences between the prediction accuracy of the power model and the sigmoidal model exist.

2. The accuracy of predictions for different numbers of years into the future is comparable.

3. The performance of the two model adjustment procedures (the horizontal and the vertical shift) is similar.

4. Conclusions 2 and 3 suggest that using section-specific data did not appreciably improve the accuracy of the prediction process. This, in turn, implies that a project- or section-specific modeling approach is not quite appropriate for the data currently available in the system.

RECOMMENDATIONS

The following recommendations are based on the results and conclusions of the study.

1. For all pavement types other than the flexible pavements with no overlay category, the power curve is adequate for prediction, from a practical standpoint, even though the sigmoidal curve may provide a slightly improved fit.

2. For non-overlaid flexible pavements, the sigmoidal curve is preferred, to reflect their initial slower deterioration rate.

3. Given the quality of the data currently available, the development of section-specific prediction models is not highly recommended.

Utility of the Developed Models

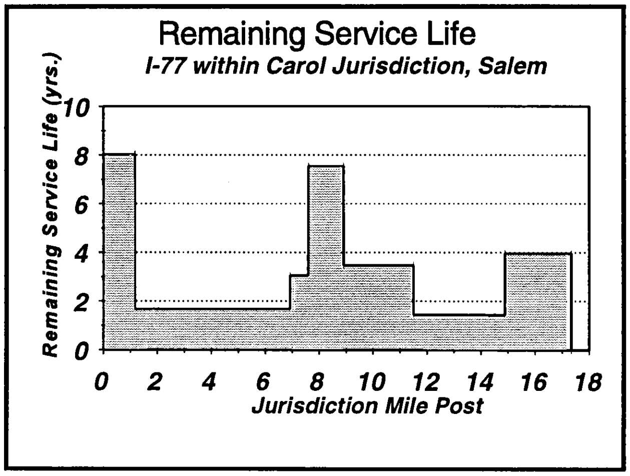
The deterioration prediction models developed under the current study could serve many functions for VDOT.

1. By predicting when maintenance or rehabilitation will be needed, the models will enable the Department to more accurately project the long-range funding needs for preserving Virginia's interstate network.

2. The models can aid in performing remaining service life analyses for the different interstate segments. An example appears in Figure 17, where the models are used to estimate the remaining service life for a portion of I-77 within the Carrol jurisdiction in the Salem

District. The remaining service life is based on the currently adopted DMR threshold value for interstate routes of 83.

Figure 17. Remaining Service Life from February 1994 to a DMR of 83



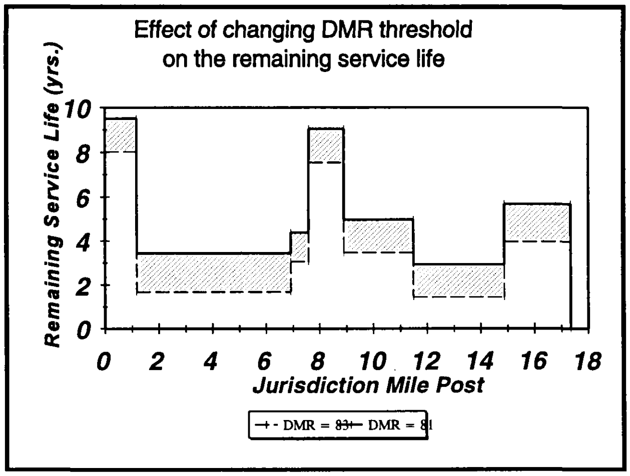
Through analyses like this one, decisions regarding rehabilitations can be based not only on the current DMR value, but also on the number of years the section is expected to remain in service. These analyses could also reveal sections with relatively uniform remaining lifespans, which could then be managed as a single unit.[13]

3. The developed models can also be used to study the effect of adopting different threshold values on the remaining service life of the network, and hence on funding requirements. Figure 18 is an example of such an analysis, where the models were employed to determine the gain in service life, represented by the shaded areas in the figure, resulting from lowering the threshold DMR from 83 to 81. Essentially, the developed models are a first step toward moving from the simplistic condition assessment analysis method currently used, to priority assessment and optimization analysis techniques.

Suggestions for Future Research

Although the developed models appeared to provide for reasonable predictions, the models were based on a database which suffered from a number of deficiencies and limitations.[2] In addition, the current practice for pavement condition assessment relies solely on a subjective windshield survey, which may fail to furnish a detailed and true picture of the section condition.

Figure 18. Effect of changing the threshold value on the remaining service life (I-77, Carrol jurisdiction, Salem District)



VDOT is moving towards the use of automated equipment for distress data collection, in an attempt to eliminate some of the problems associated with the manual survey method. The Department is planning to perform annual network-wide roughness surveys in coming years. Once enough data from these more reliable and less subjective sources have been compiled and the deficiencies of the database addressed, there will be an opportunity to develop additional performance models that can greatly enhance the prediction and analysis capabilities of the system. Specifically, models for predicting the individual distresses as well as roughness progression should be developed. Such models will allow more refined remaining service life analyses.[27]

Future studies should also consider adopting other approaches for performance prediction modeling. This could involve the development of probabilistic models, such as Markovian models and survivor curves, as well as the use of some of the nontraditional prediction tools that have recently received attention, including neural- and poly-networks.

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Appendix A

Preliminary Data Analysis Results

Figure A-1 Scatter Plot Matrix for Overlaid Flexible Pavements in Bristol Category

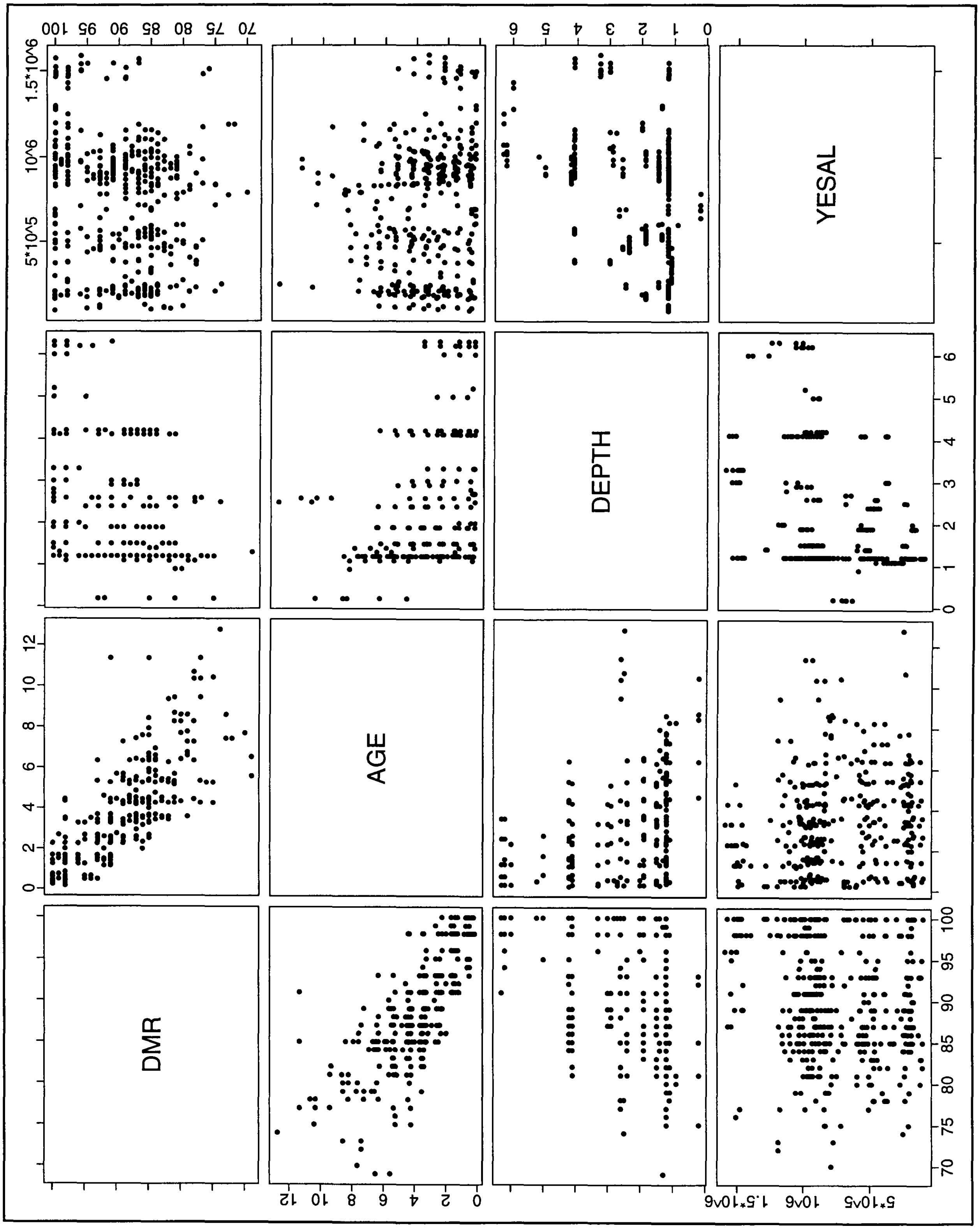


Figure A-2 Scatter Plot Matrix for Overlaid Flexible Pavements in Richmond Category

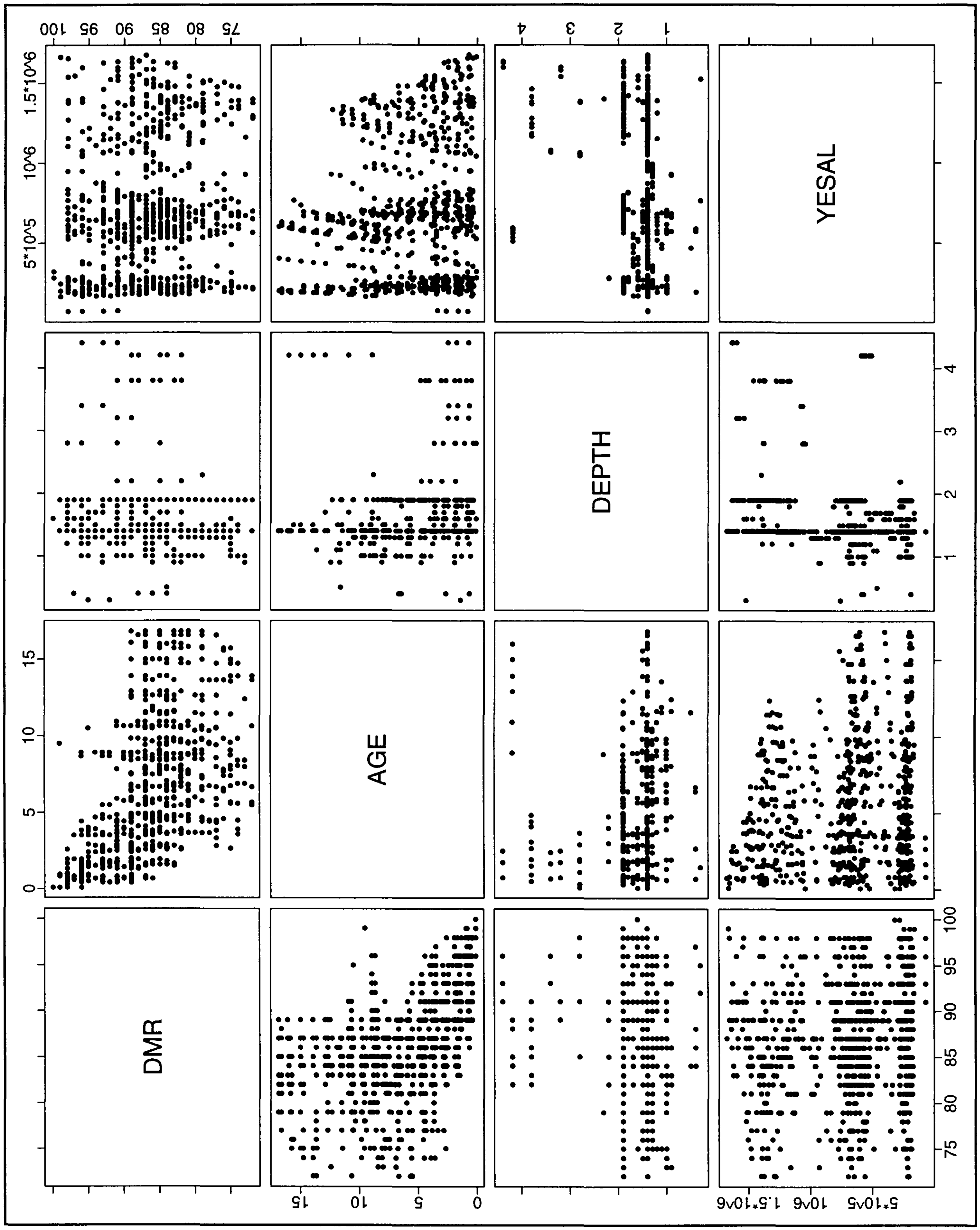


Figure A-3 Scatter Plot Matrix for Overlaid Flexible Pavements in Suffolk Category

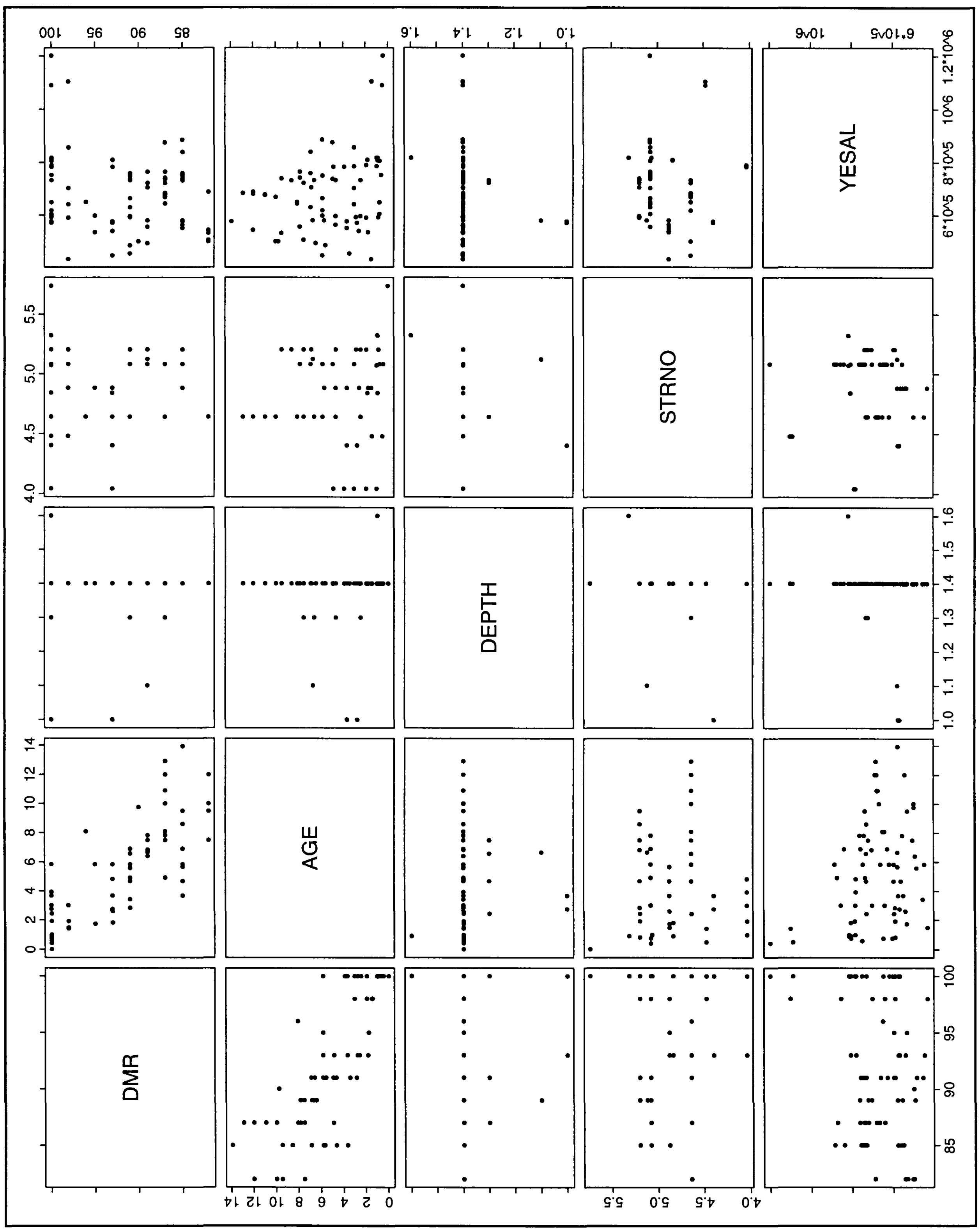


Figure A-4 Scatter Plot Matrix for Overlaid Flexible Pavements in Culpeper Category

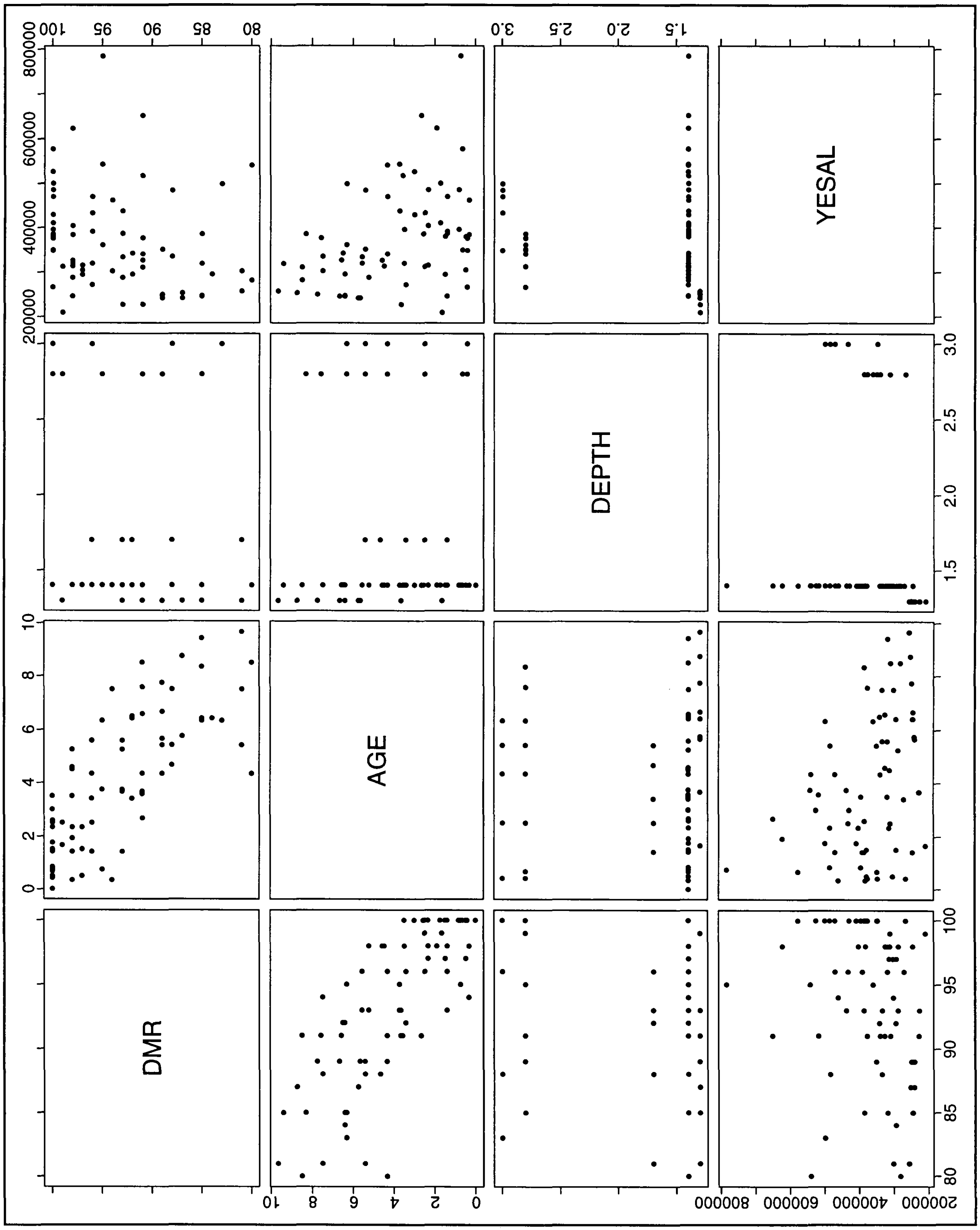


Figure A-5 Scatter Plot Matrix for Overlaid Flexible Pavements in Staunton Category

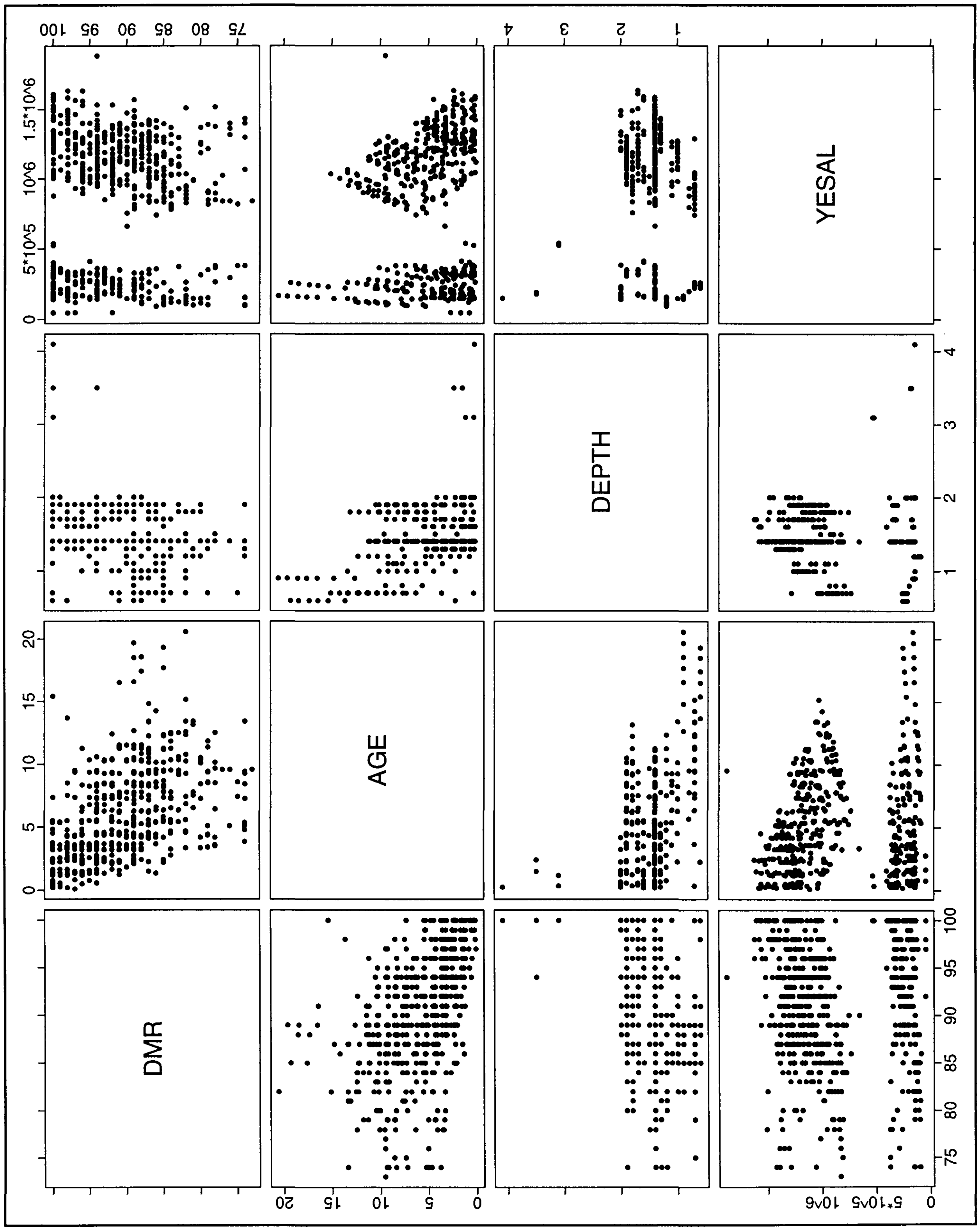


Figure A-6 Scatter Plot Matrix for Non-overlaid Flexible Pavements in Region 1

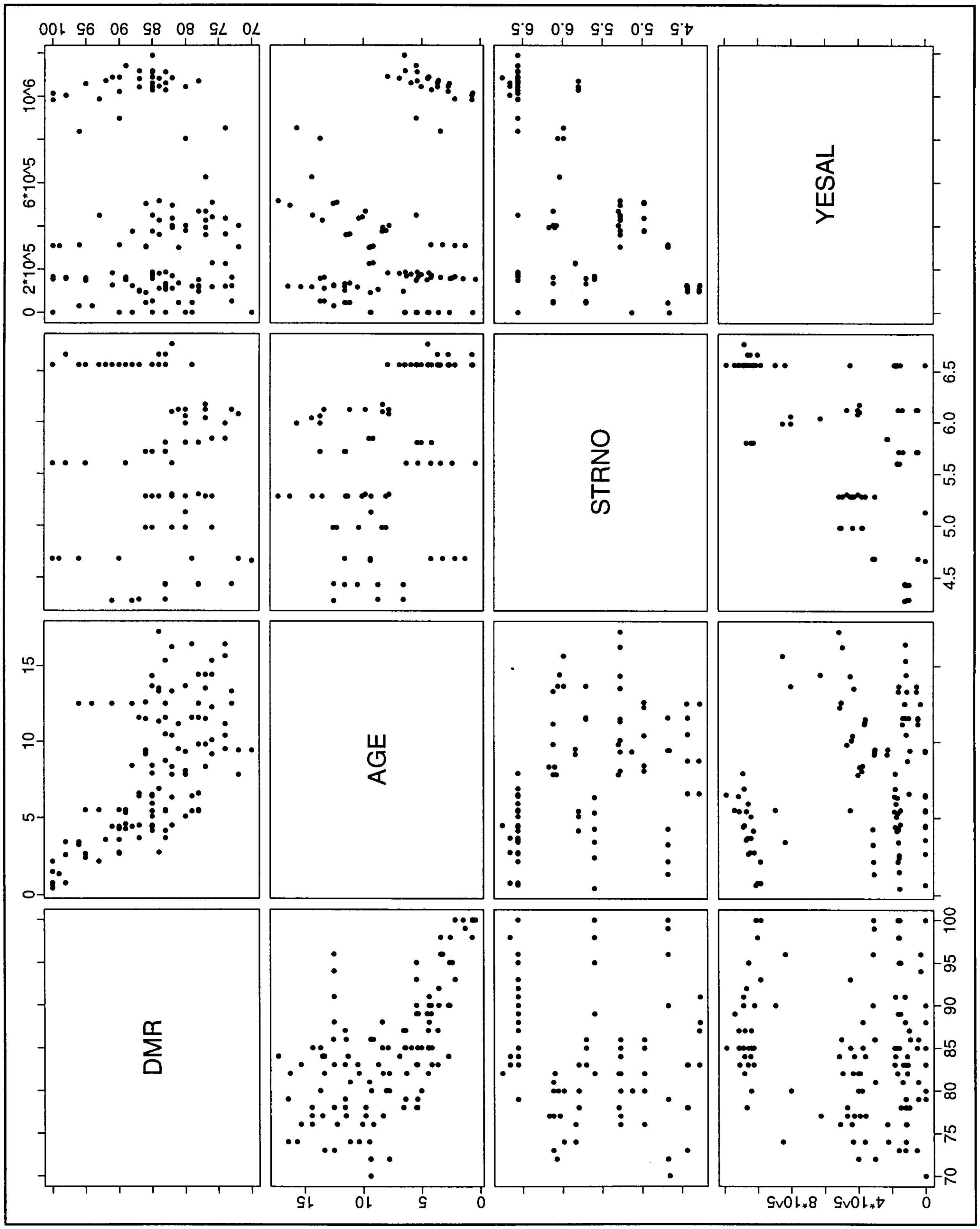


Figure A-7 Scatter Plot Matrix for Non-overlaid Flexible Pavements in Region 2

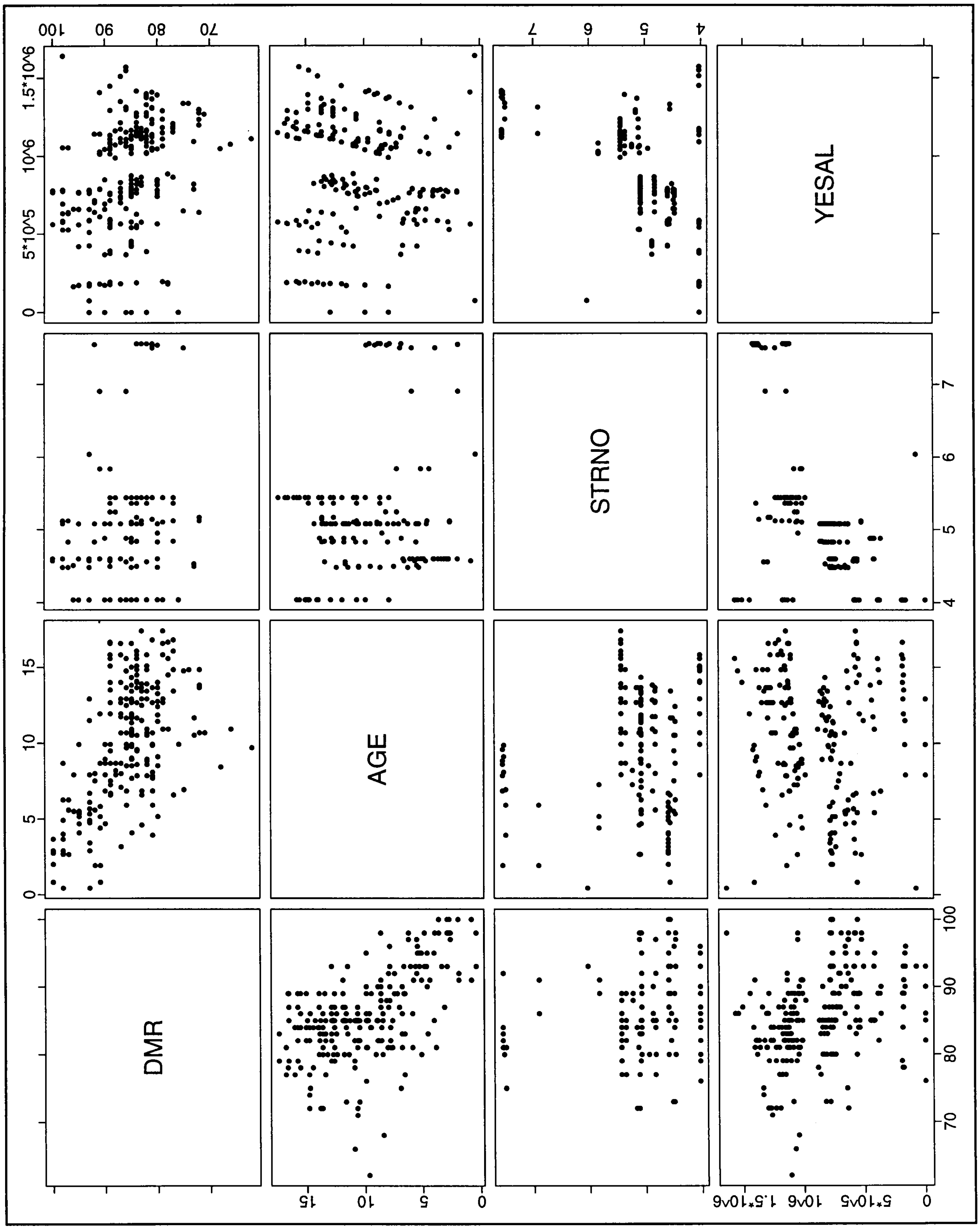


Figure A-8 Scatter Plot Matrix for Composite Pavements with One Overlay

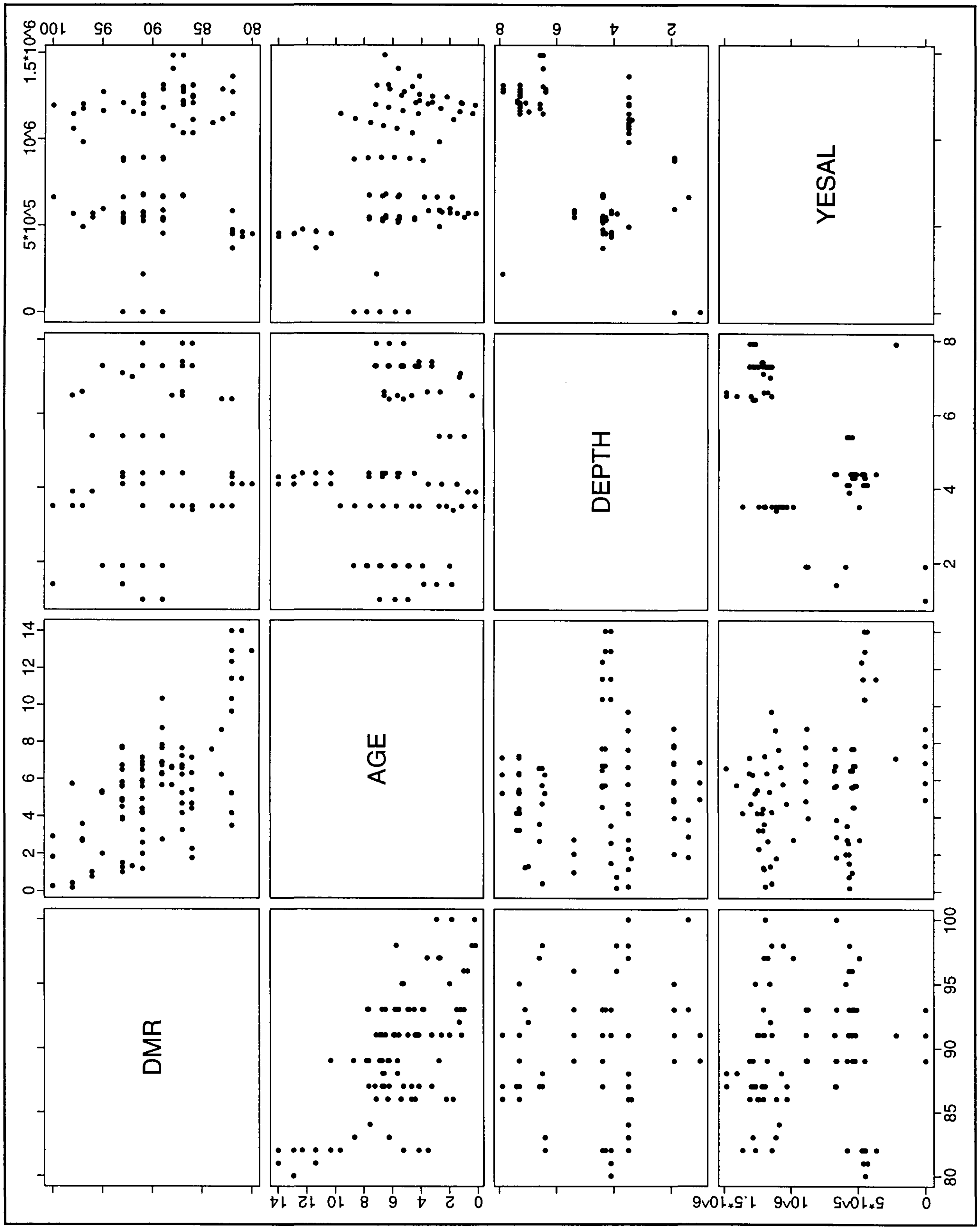
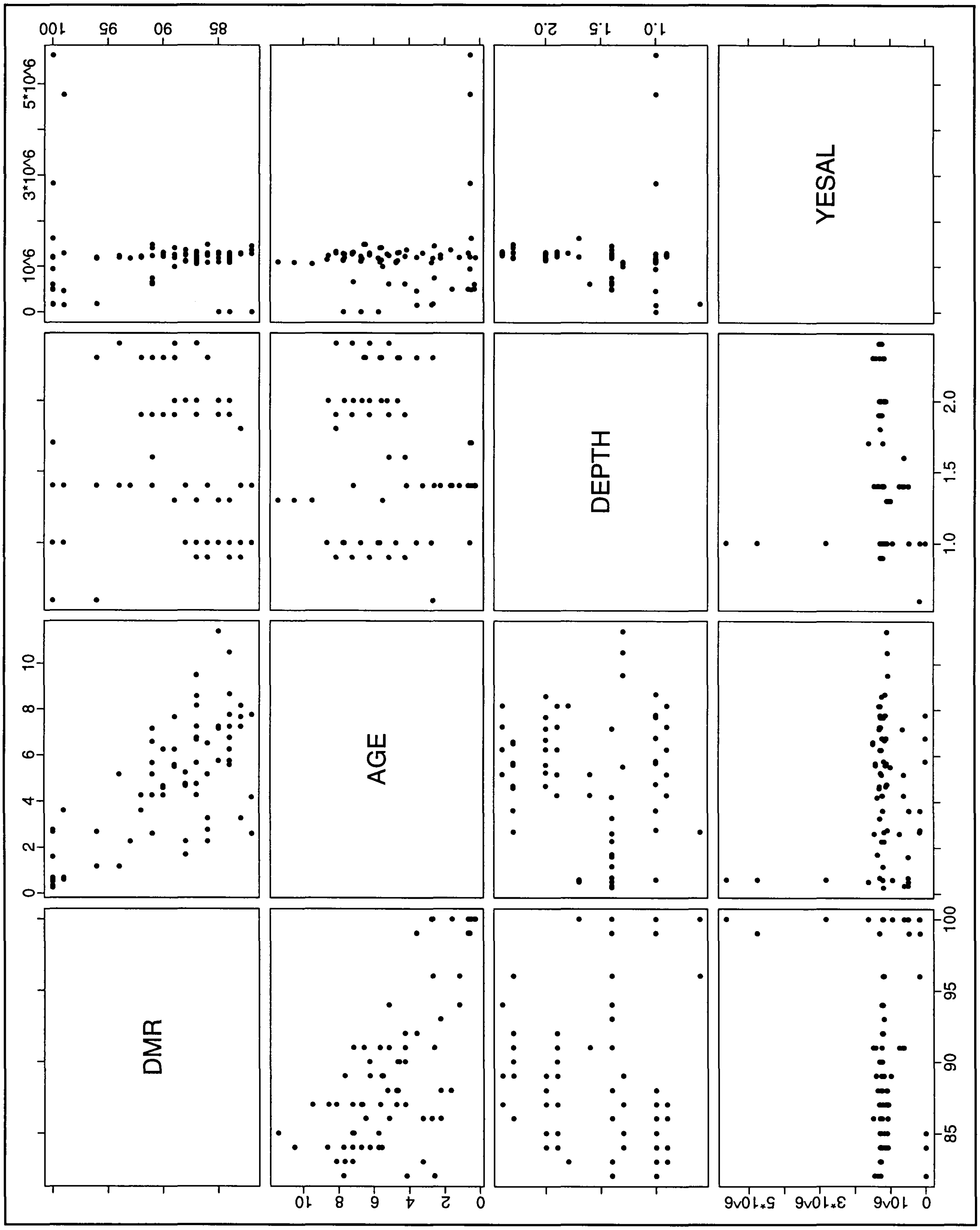


Figure A-9 Scatter Plot Matrix for Composite Pavements with more than one Overlay



Appendix B

Power Model Evaluation Results

Figure B-1 Power Model Goodness-of-Fit

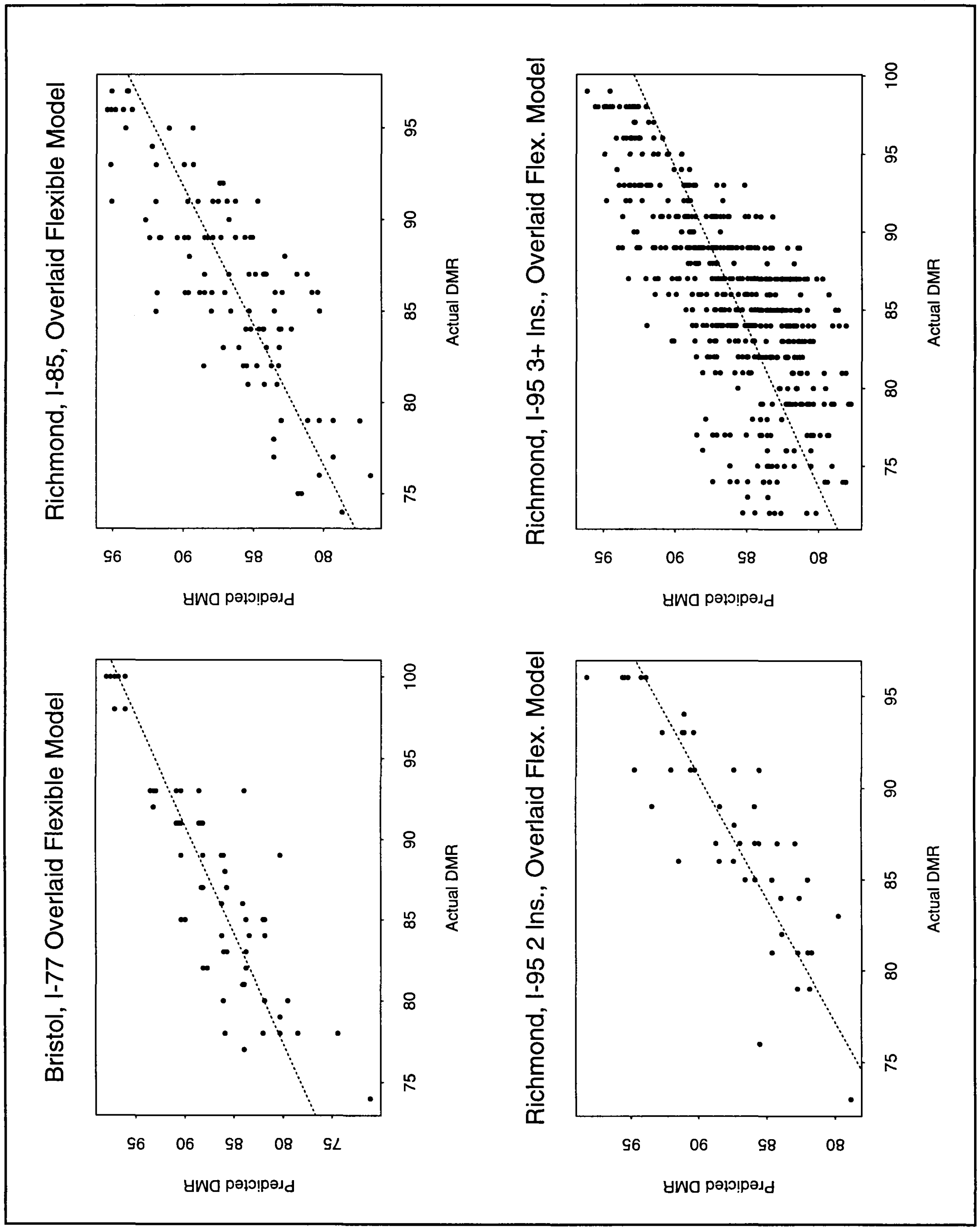


Figure B-2 Power Model Goodness-of-Fit

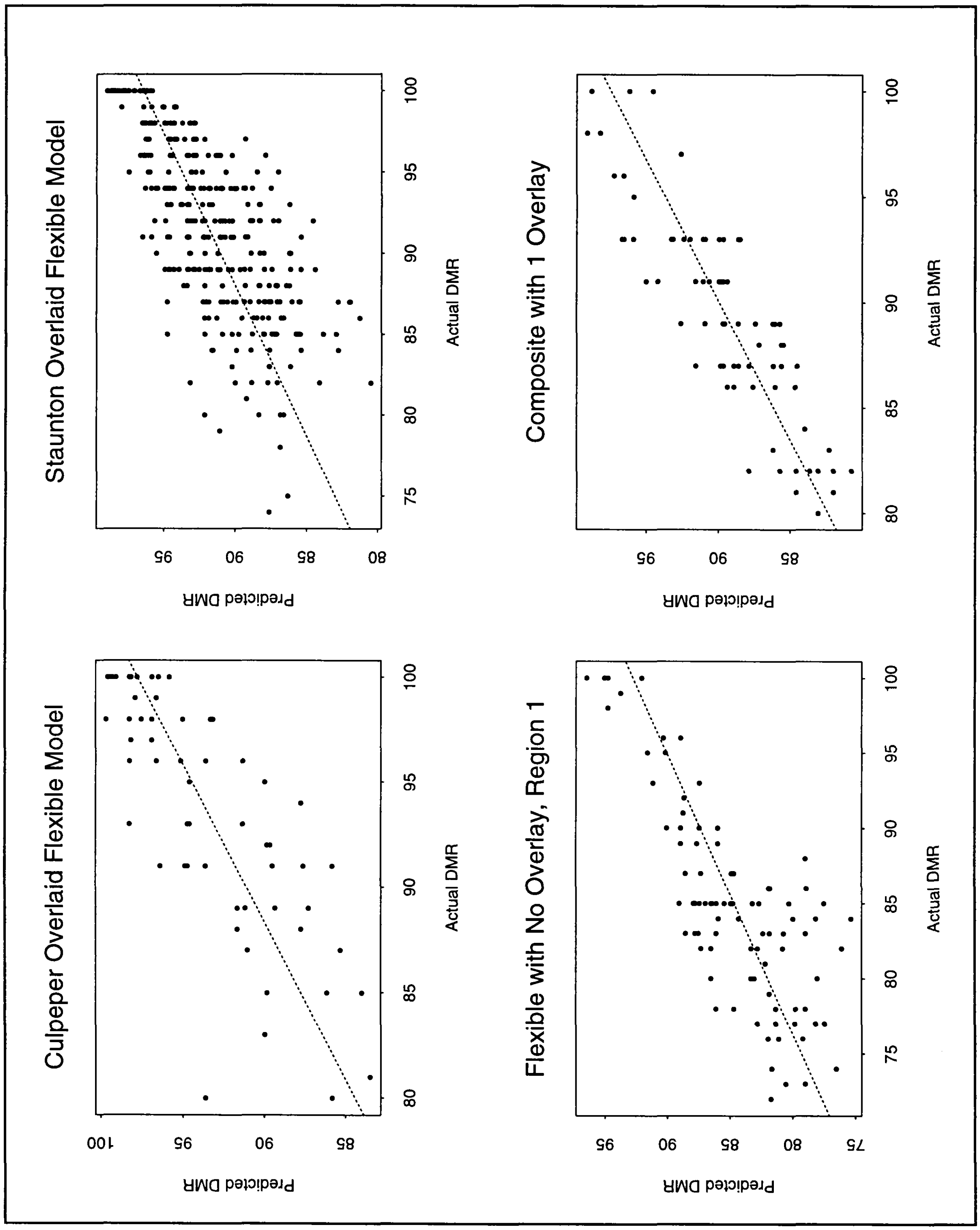


Figure B-3 3-D Sensitivity Analysis for Bristol I-81 & I-381 Overlaid Flex. Model

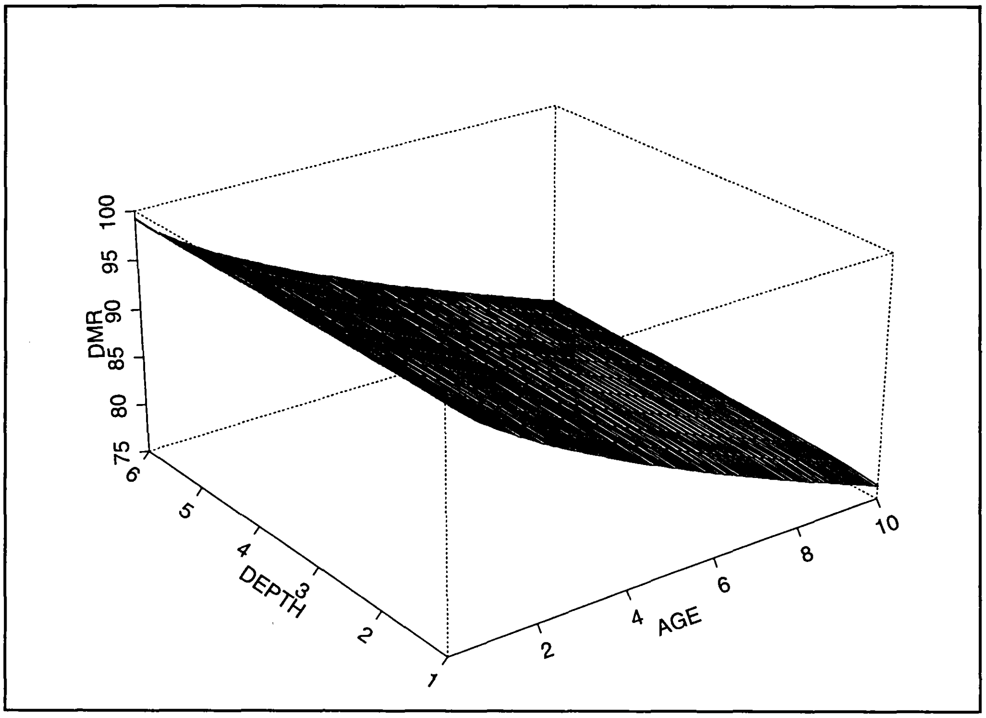


Figure B-4 3-D Sensitivity Analysis for Richmond I-64 Flex. Overlaid Model

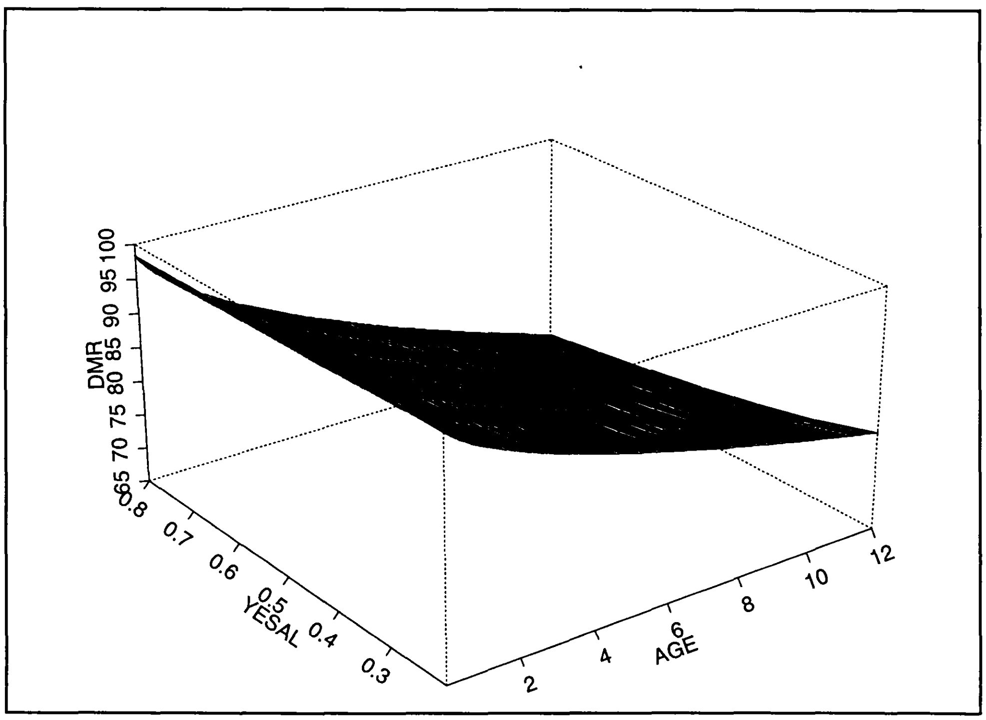


Figure B-5 3-D Sensitivity Analysis for Richmond I-85 Flex. Overlaid Model

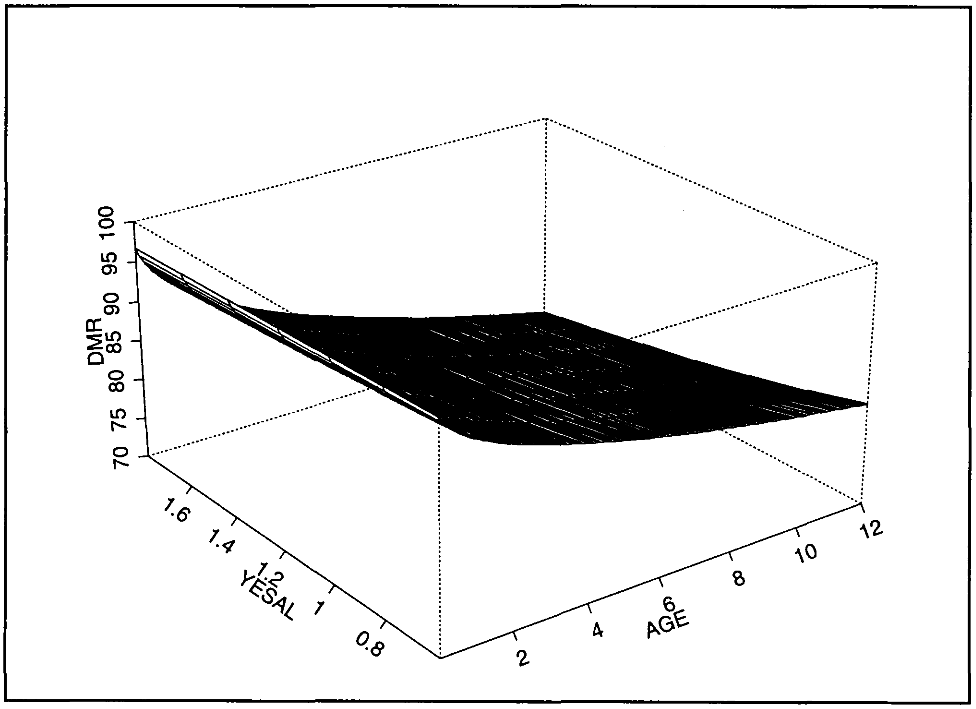


Figure B-6 3-D Sensitivity Analysis for Richmond I-95 (2 lanes) Flex. Overlaid Model
DEPTH = 1.4

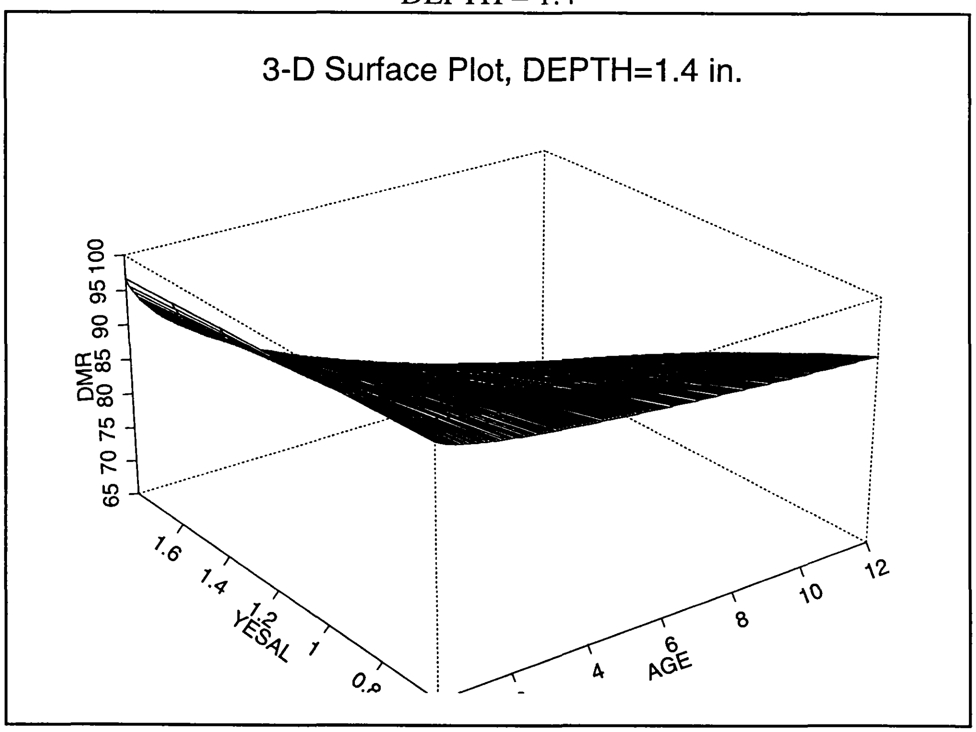


Figure B-7 3-D Sensitivity Analysis for Richmond I-95 (2 lanes) flex. Overlaid Model
YESAL = 1.2

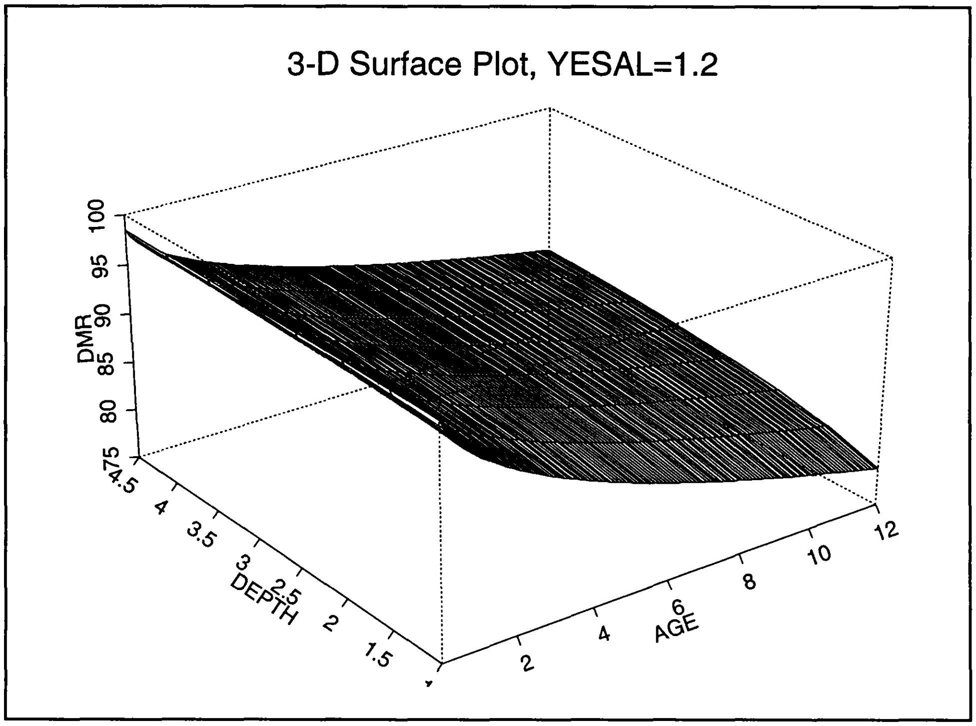


Figure B-8 3-D Sensitivity Analysis for Richmond I-95 (3+ lanes) Flex. Overlaid Model

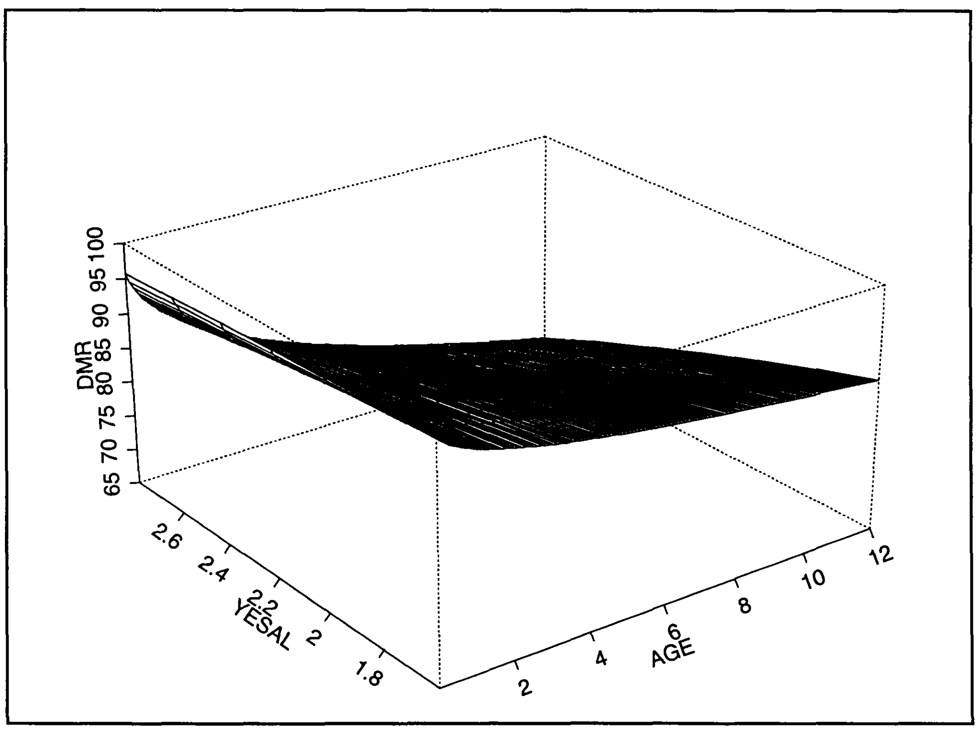


Figure B-9 3-D Sensitivity Analysis for Staunton Flexible Overlaid Model

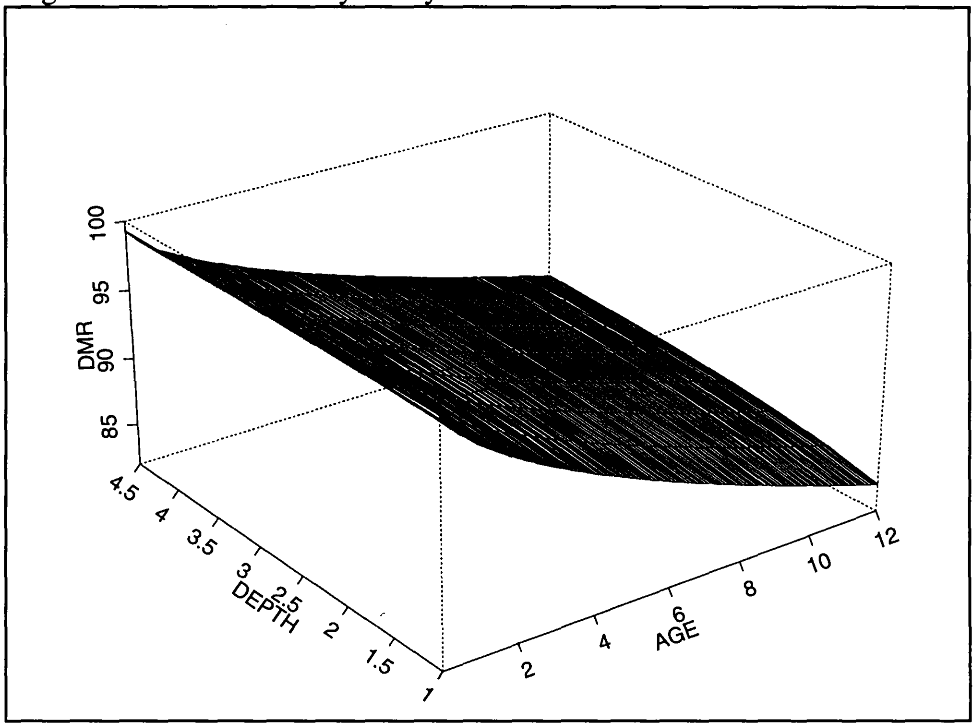


Figure B-10 3-D Sensitivity Analysis for Composite Pavements with > 1 Overlay

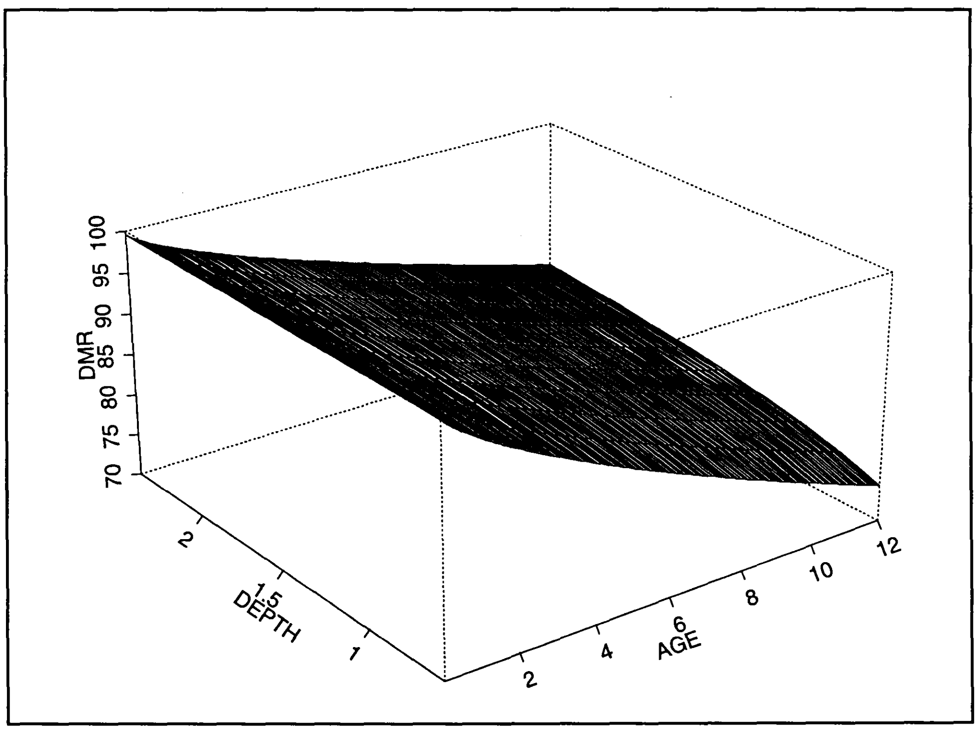


Figure B-11 2-D Sensitivity Analysis for Richmond I-95 (3+ lanes) Flex. Overlaid Model

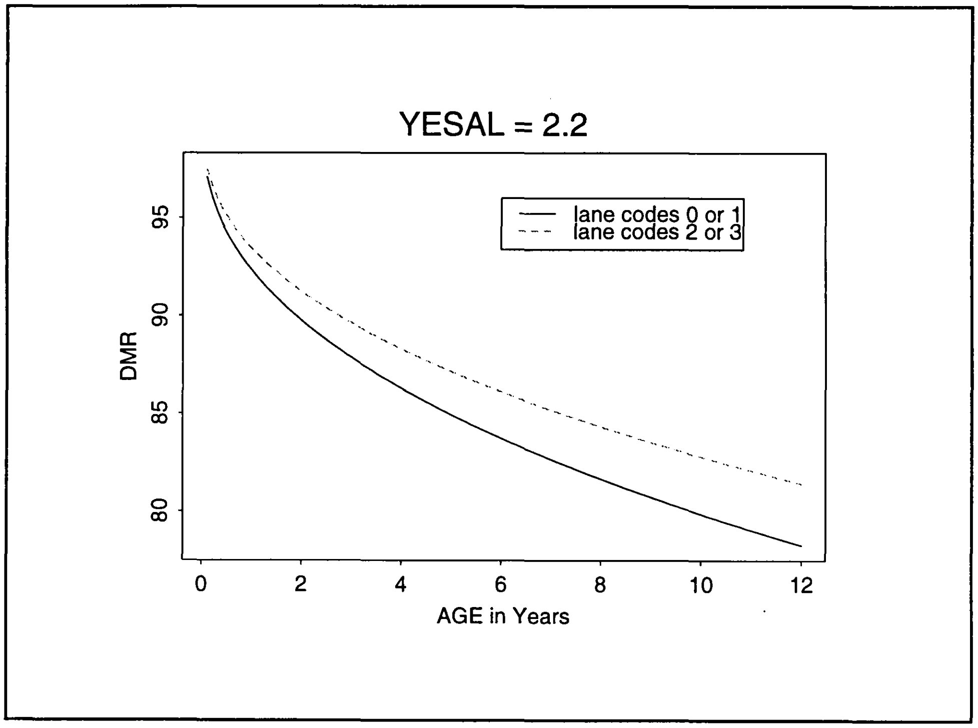


Figure B-12 2-D Sensitivity Analysis for Suffolk Flexible Overlaid Model

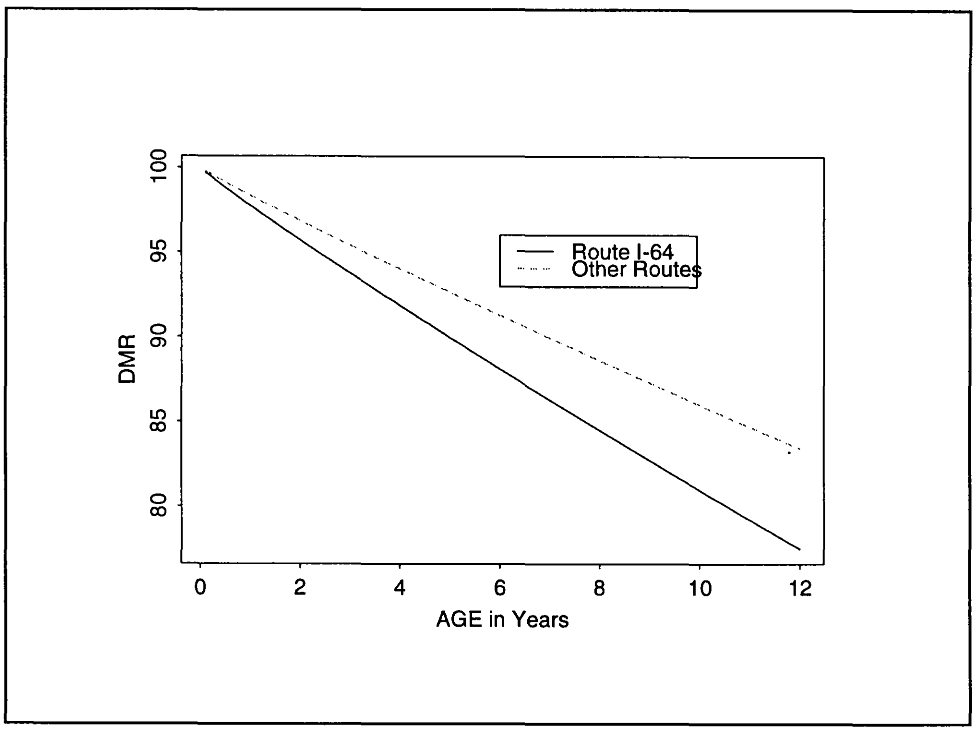


Figure B-13 2-D Sensitivity Analysis for Staunton Flexible Overlaid Model

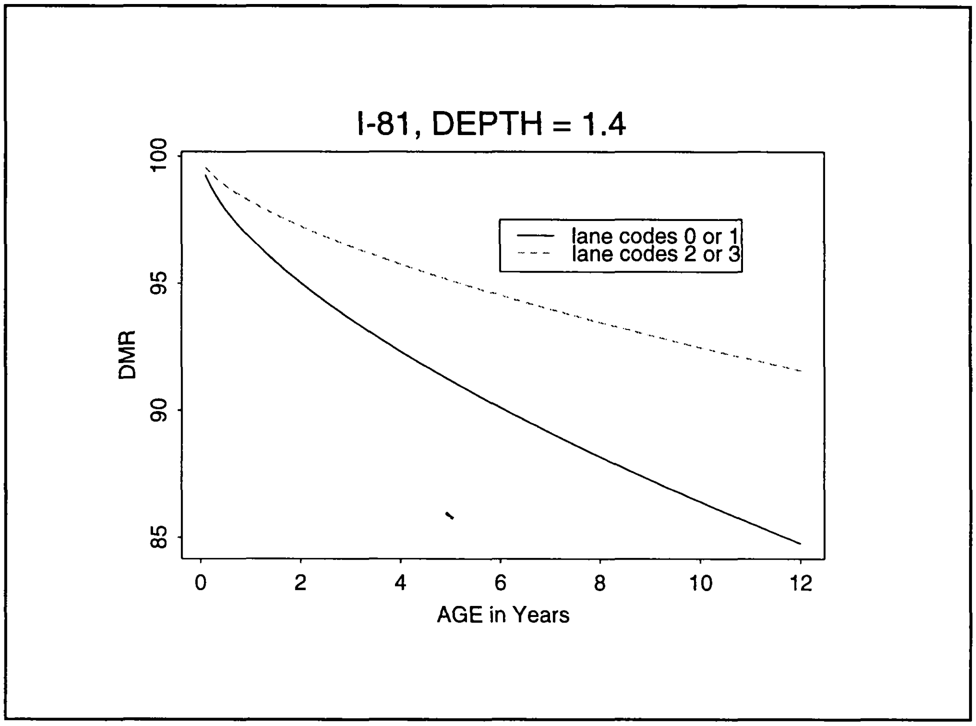


Figure B-14 2-D Sensitivity Analysis for Staunton Flexible Overlaid Model

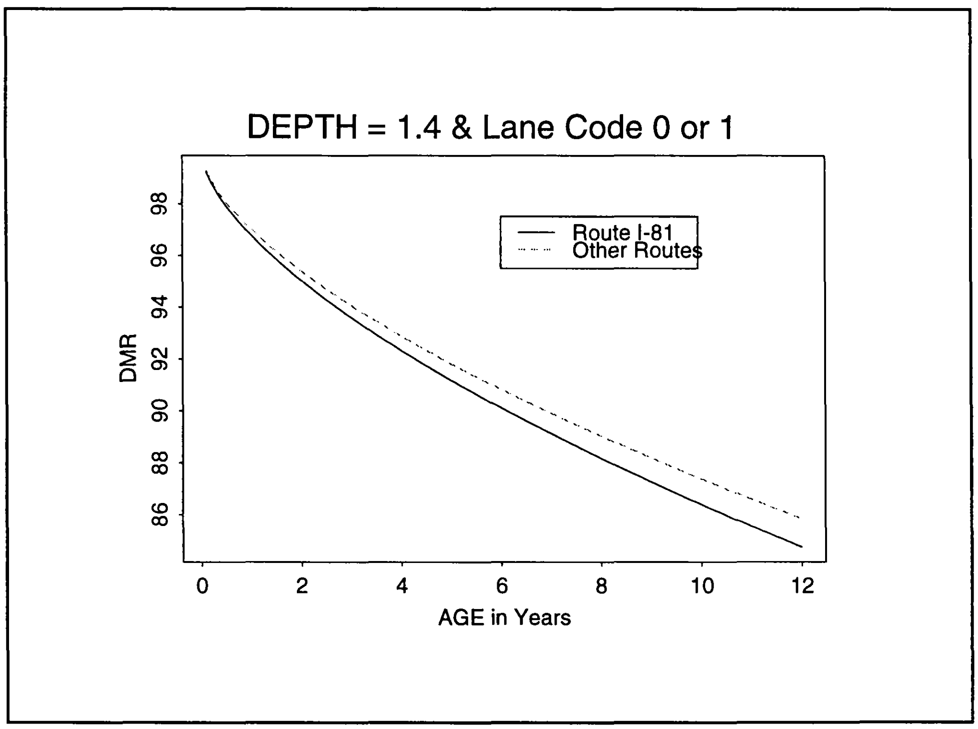


Figure B-15 2-D Sensitivity Analysis for Non-overlaid Pavements Model in Region 1

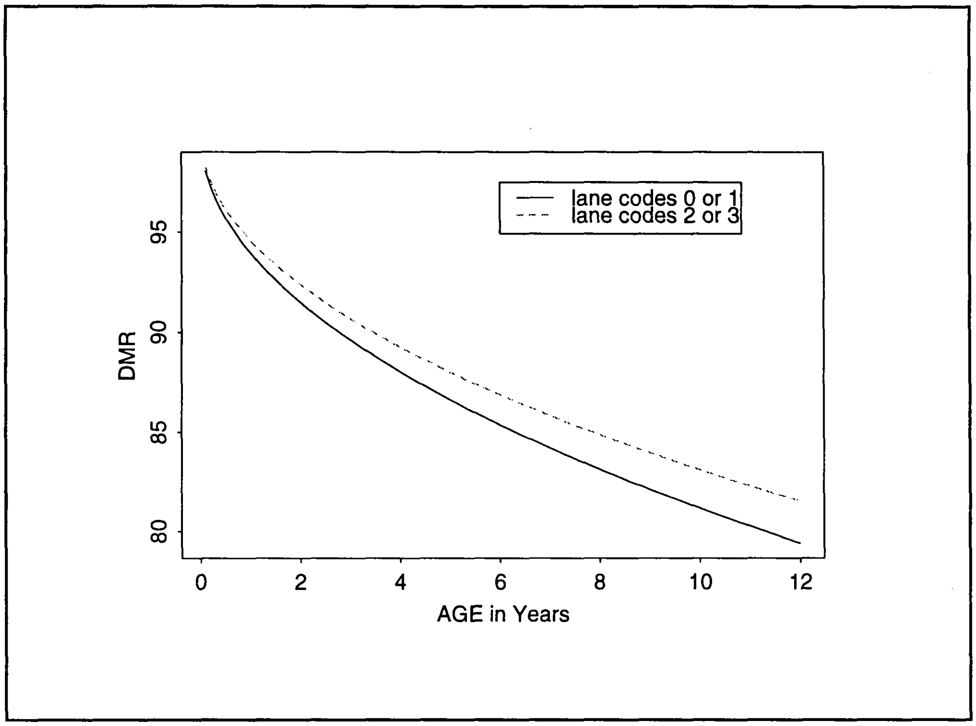


Figure B-16 2-D Sensitivity Analysis for Non-overlaid Pavements Model, Region 2

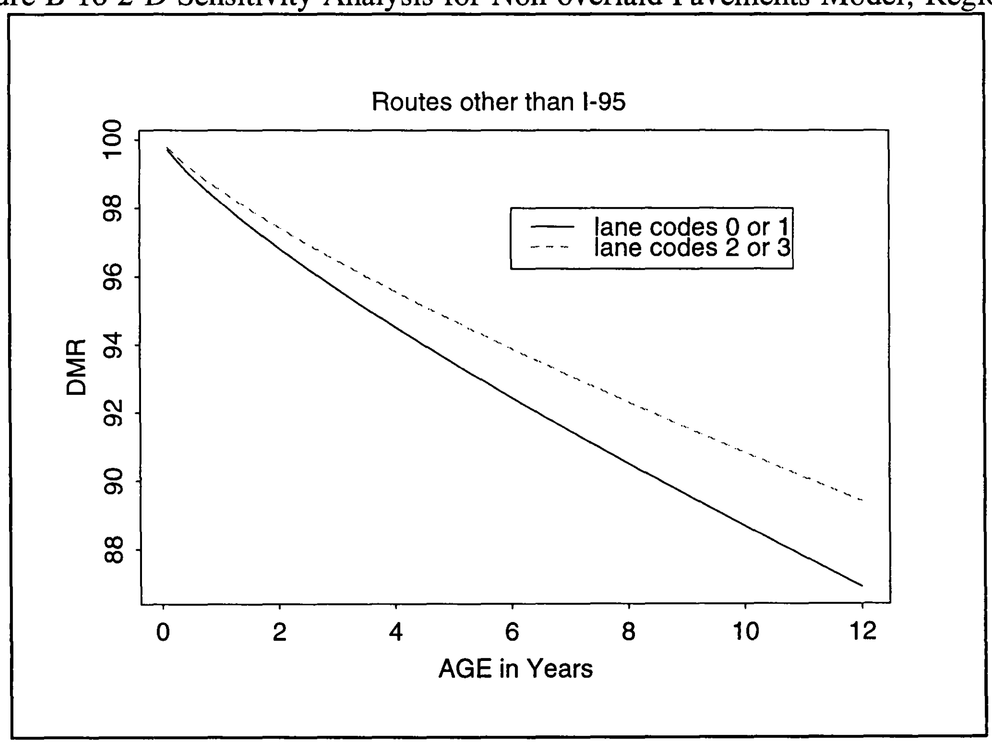


Figure B-17 2-D Sensitivity Analysis for Non-overlaid Pavements Model, Region 2

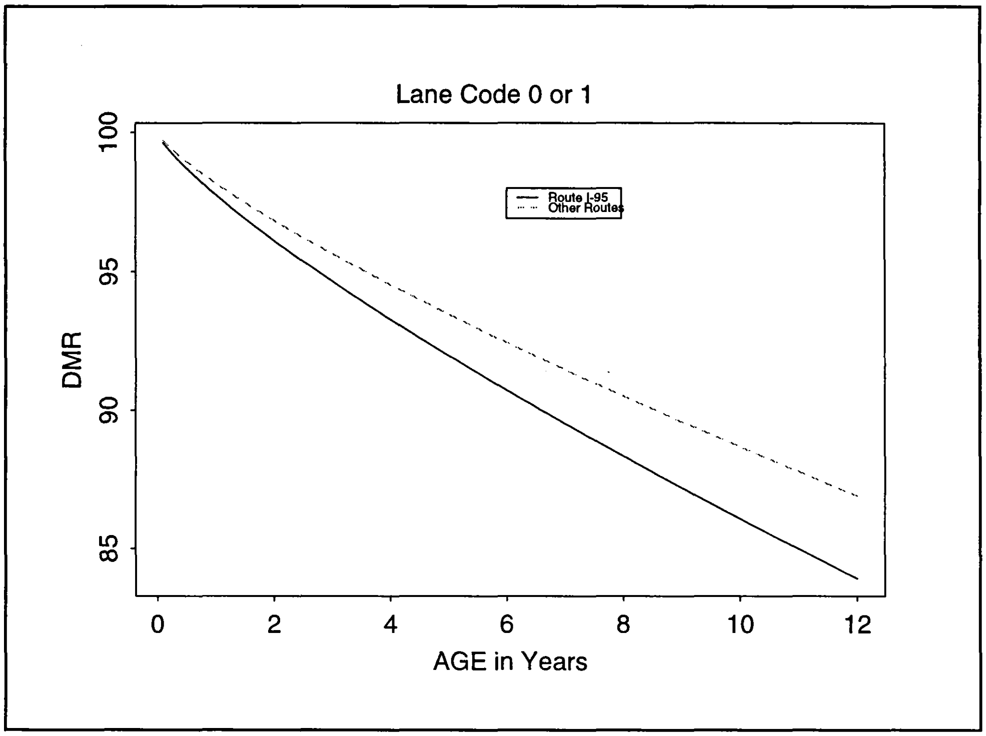


Figure B-18 2-D Sensitivity Analysis for Composite Pavements with One Overlay Model

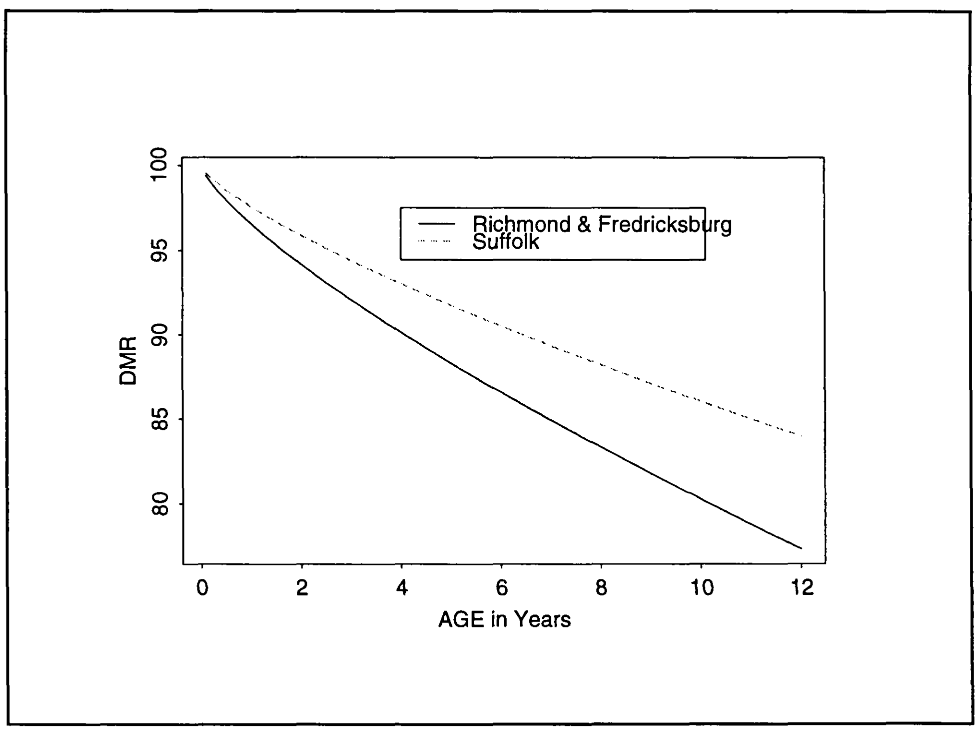
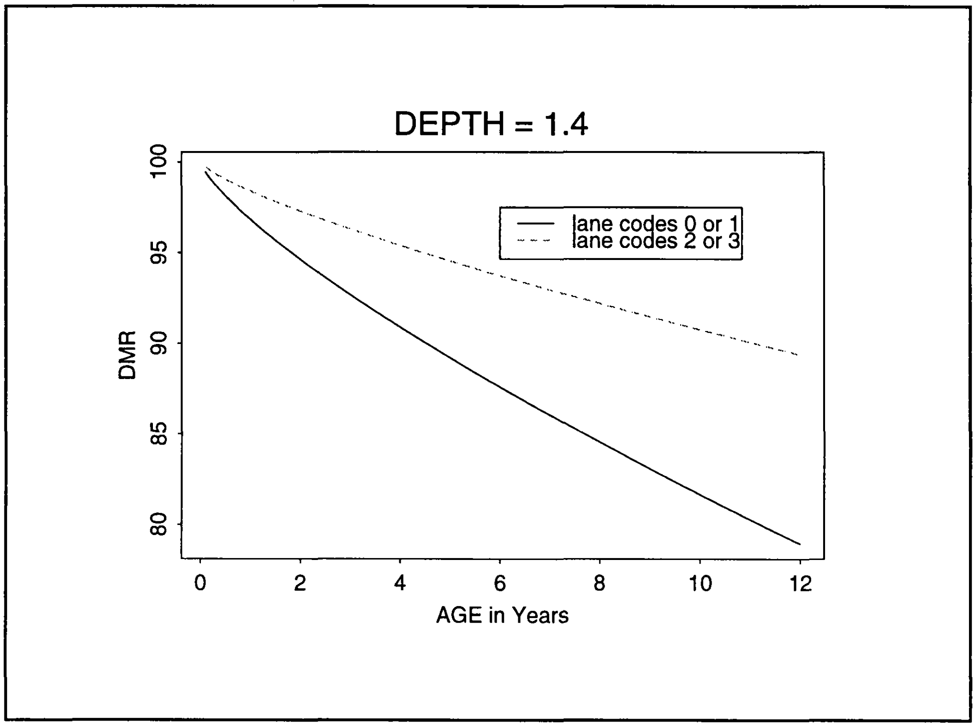


Figure B-19 2-D Sensitivity Analysis for Composite Pavements with > 1 Overlay Model



Appendix C

Sigmoidal Model Evaluation Results

Figure C-1 Sigmoidal Model Goodness-of-Fit

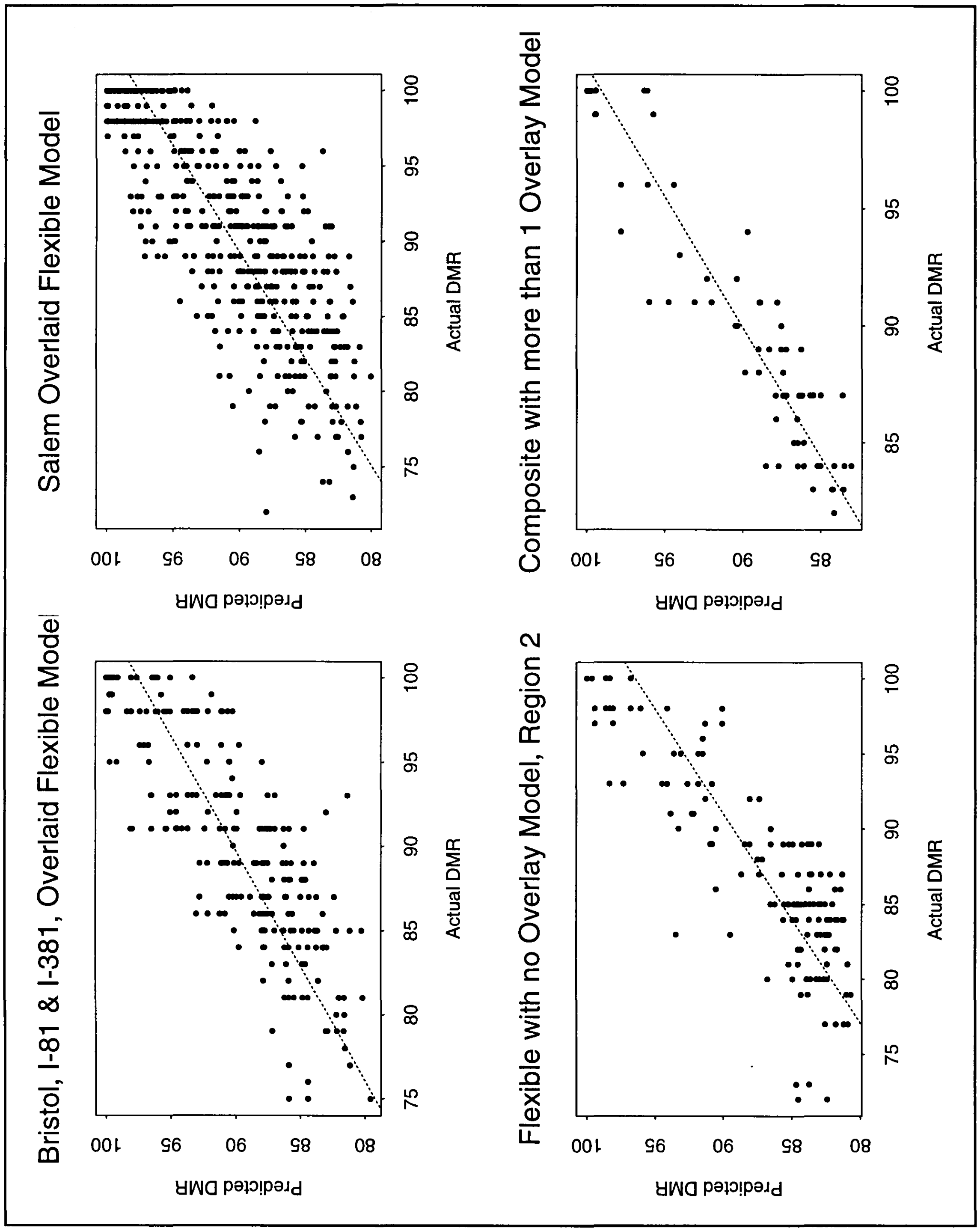


Figure C-2 Sigmoidal Model Goodness-of-Fit

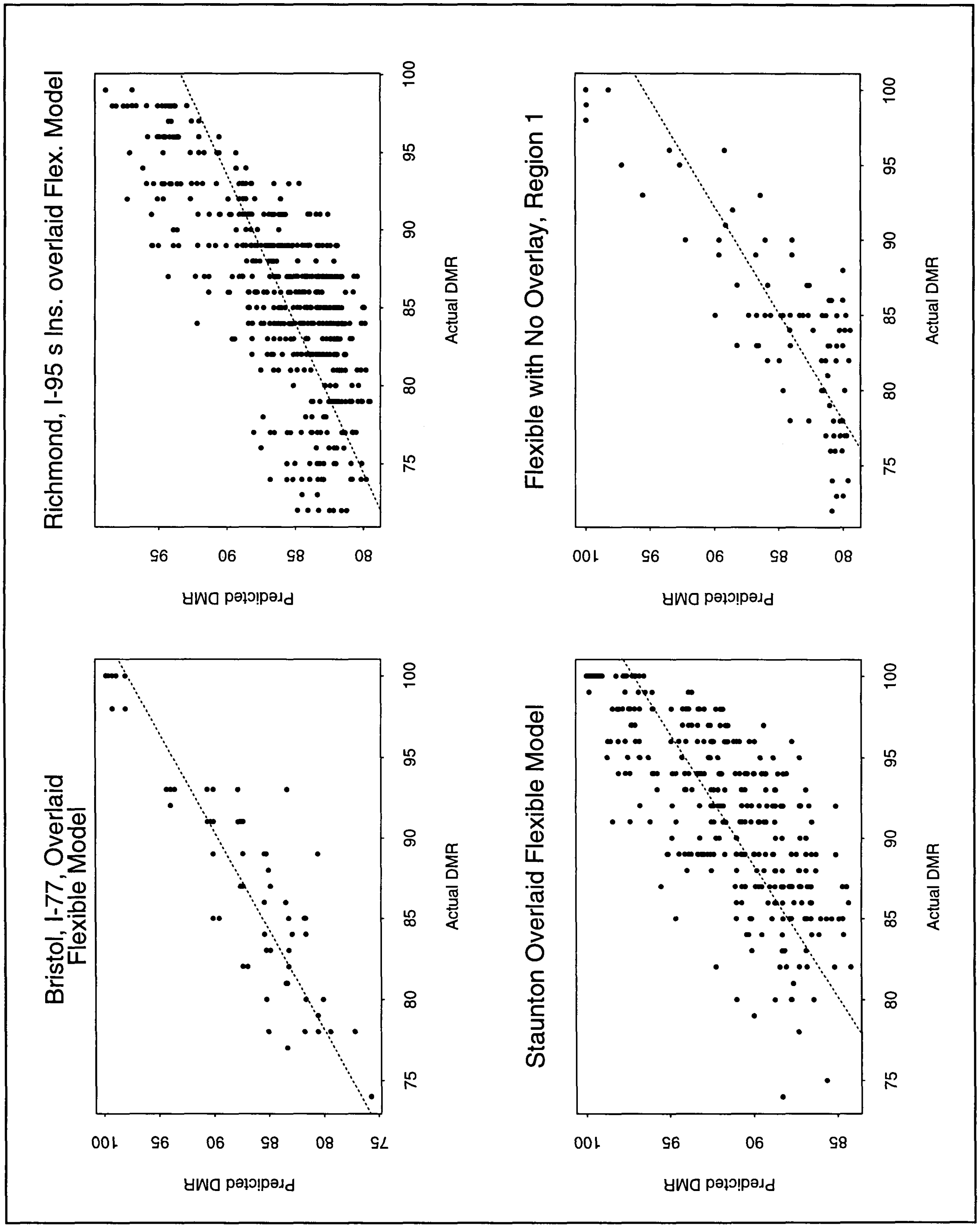


Figure C-3 3-D Sensitivity Analysis for Bristol I-81 Overlaid Flexible Model

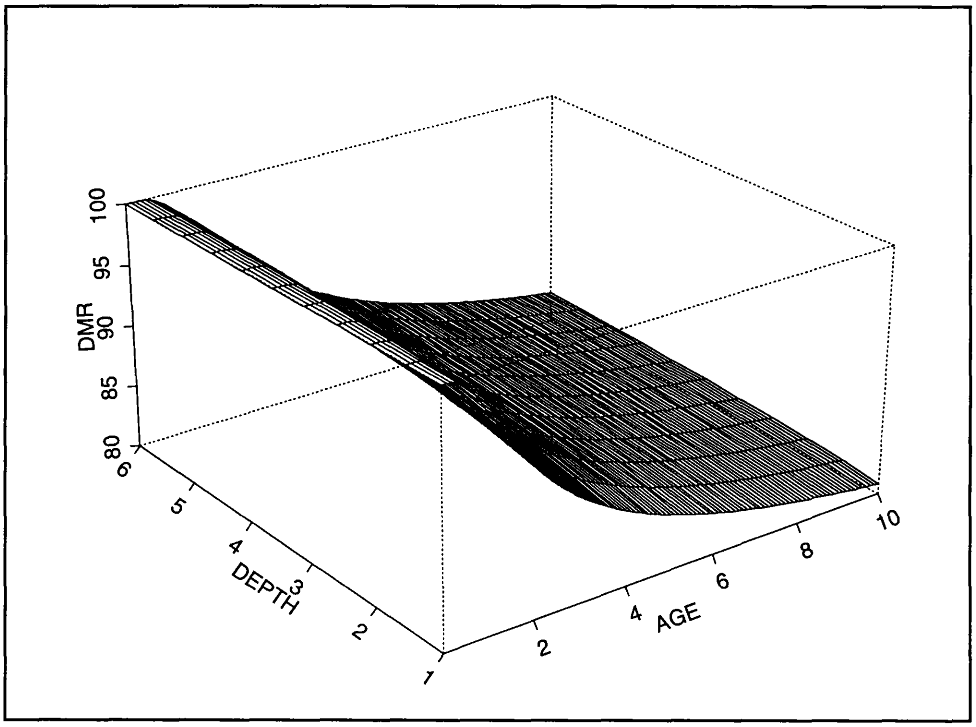


Figure C-4 3-D Sensitivity Analysis for Salem Model, STRNO=6.0 & lane code 0 or 1

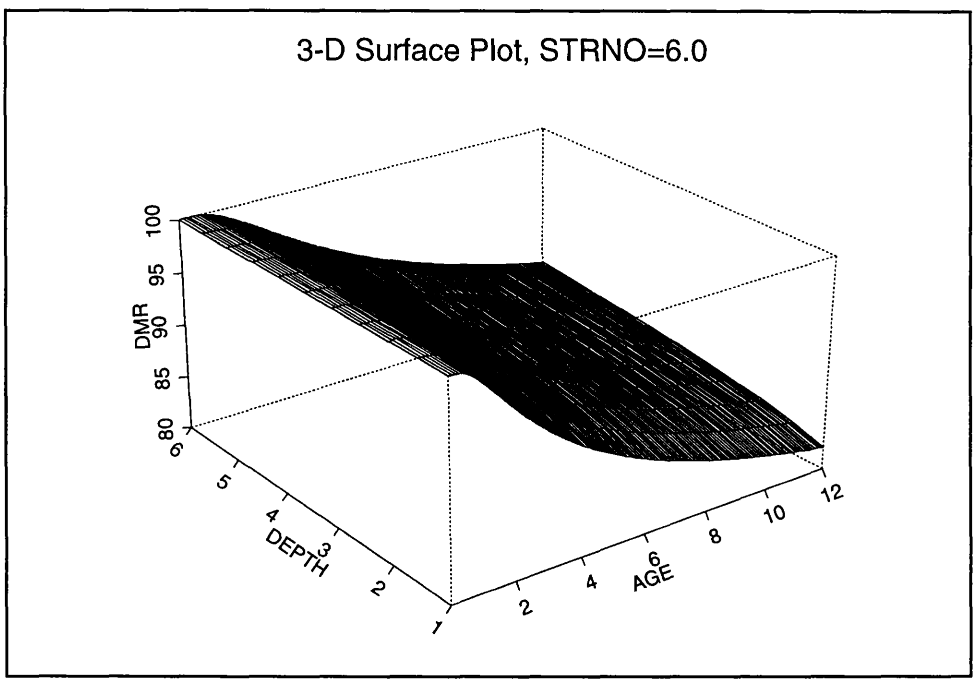


Figure C-5 3-D Sensitivity Analysis for Salem Model, DEPTH=1.4 & lane code 0 or 1

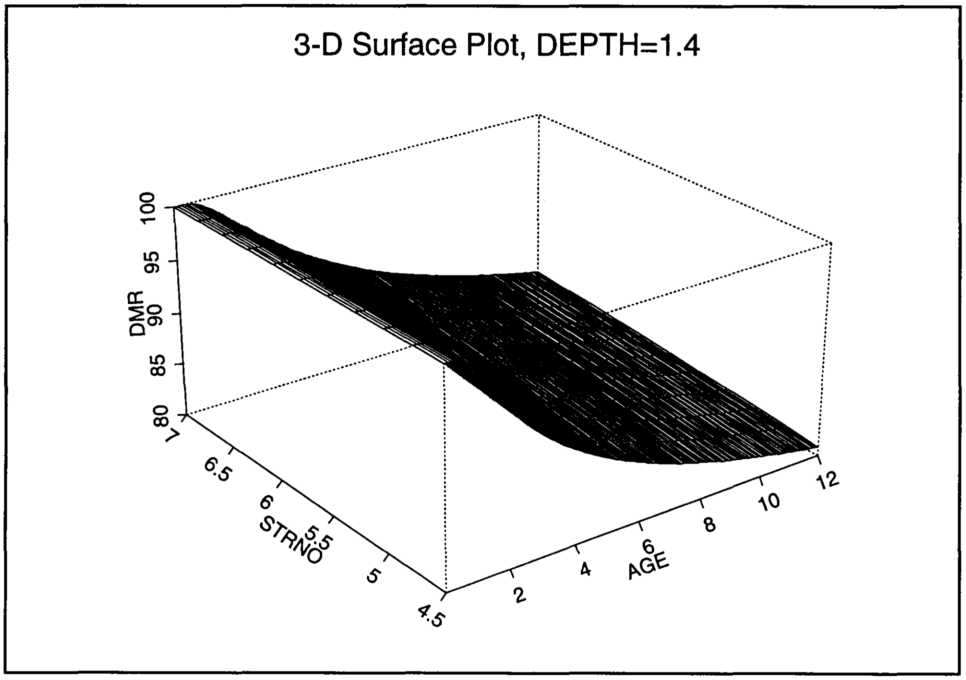


Figure C-6 3-D Sensitivity Analysis for Richmond I-95 (3+ lanes) Overlaid Flex. Model

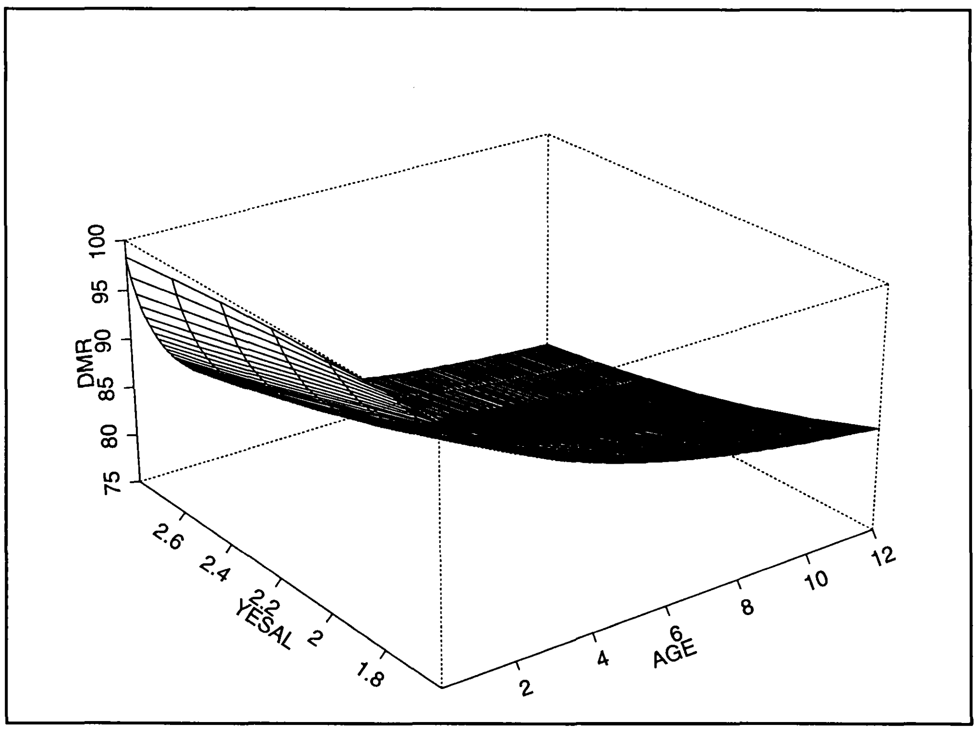


Figure C-7 3-D Sensitivity Analysis for Staunton Overlaid Flex. Model

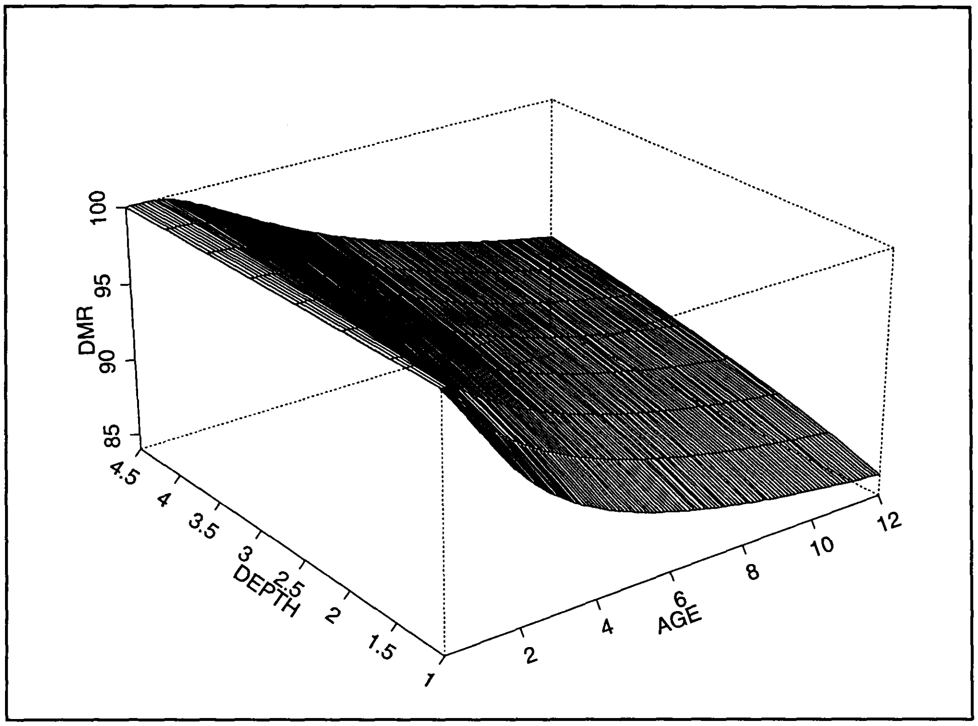


Figure C-8 3-D Sensitivity Analysis for the Composite with > 1 Overlay Model

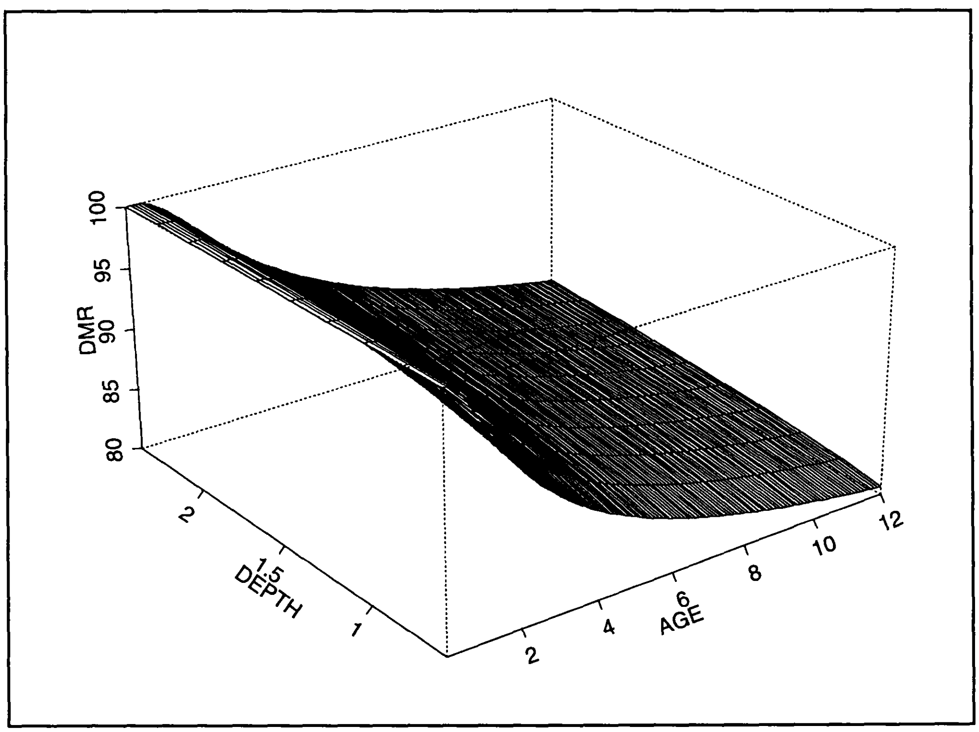


Figure C-9 2-D Sensitivity Analysis for Salem Model, STRNO=6.0 & DEPTH=1.4

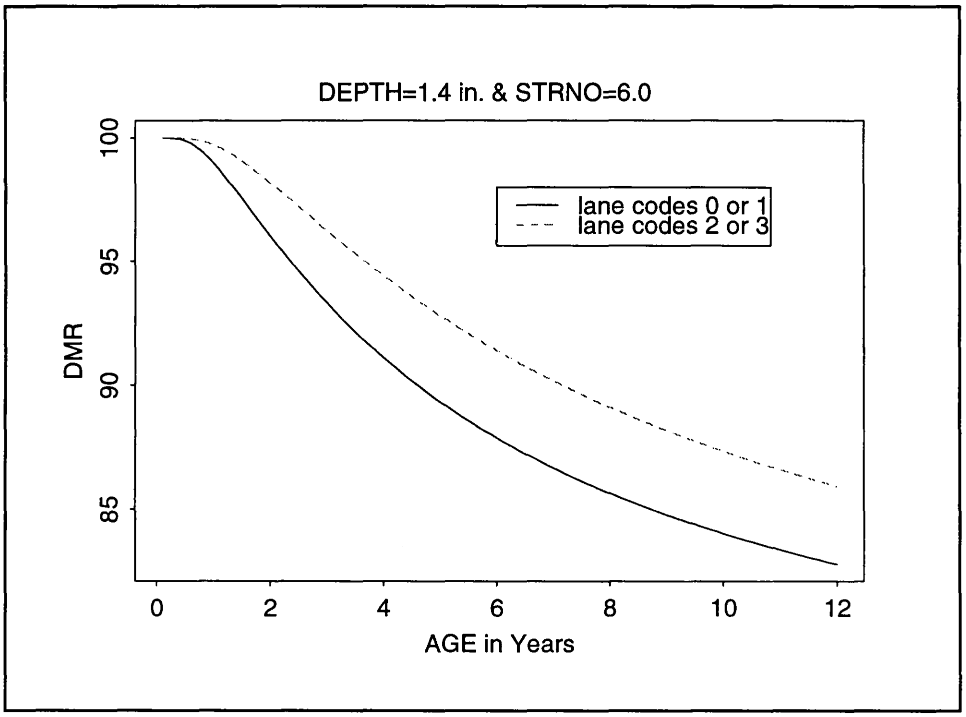


Figure C-10 2-D Sensitivity Analysis for Richmond I-95 (3+ lns.) Overlaid Flex. Model

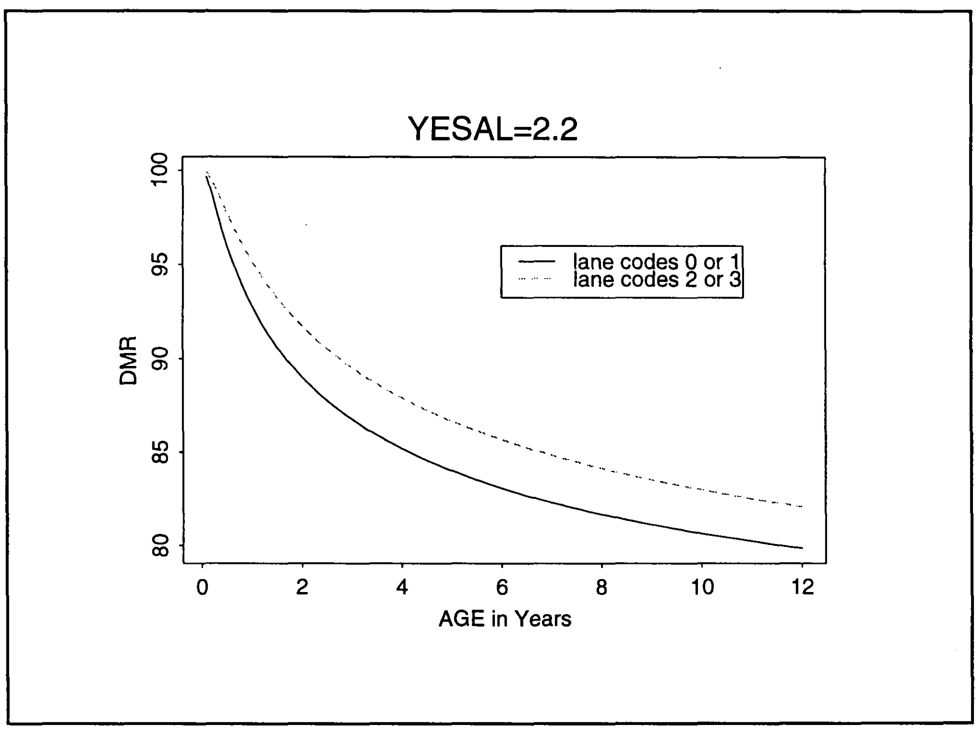


Figure C-11 2-D Sensitivity Analysis for Staunton Overlaid Flex. Model

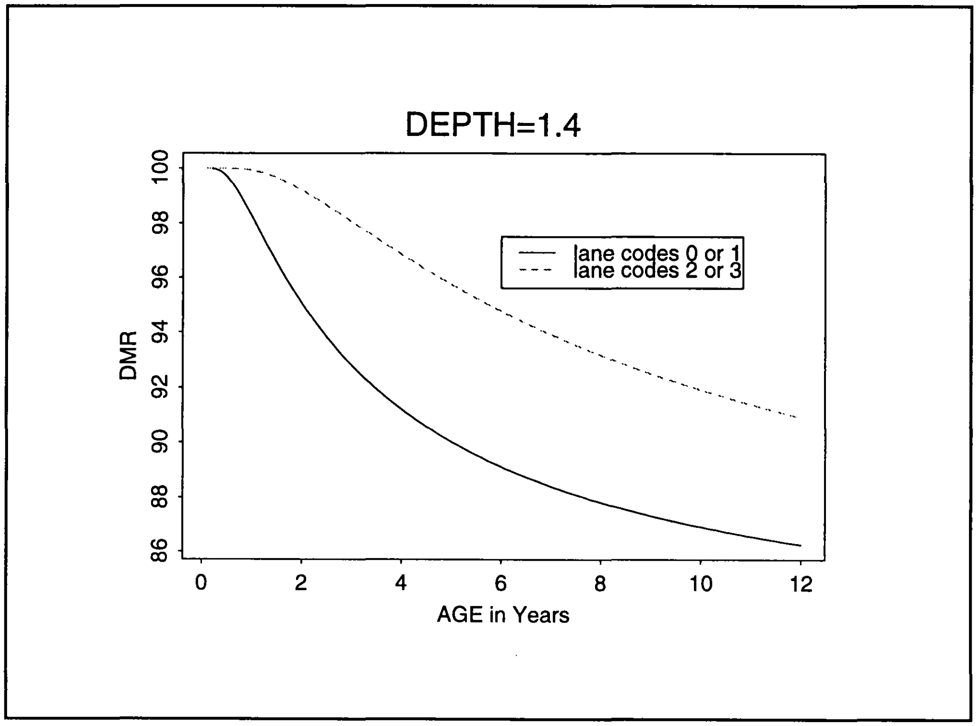


Figure C-12 2-D Sensitivity Analysis for the Non-overlaid Flex. Model for Region 1

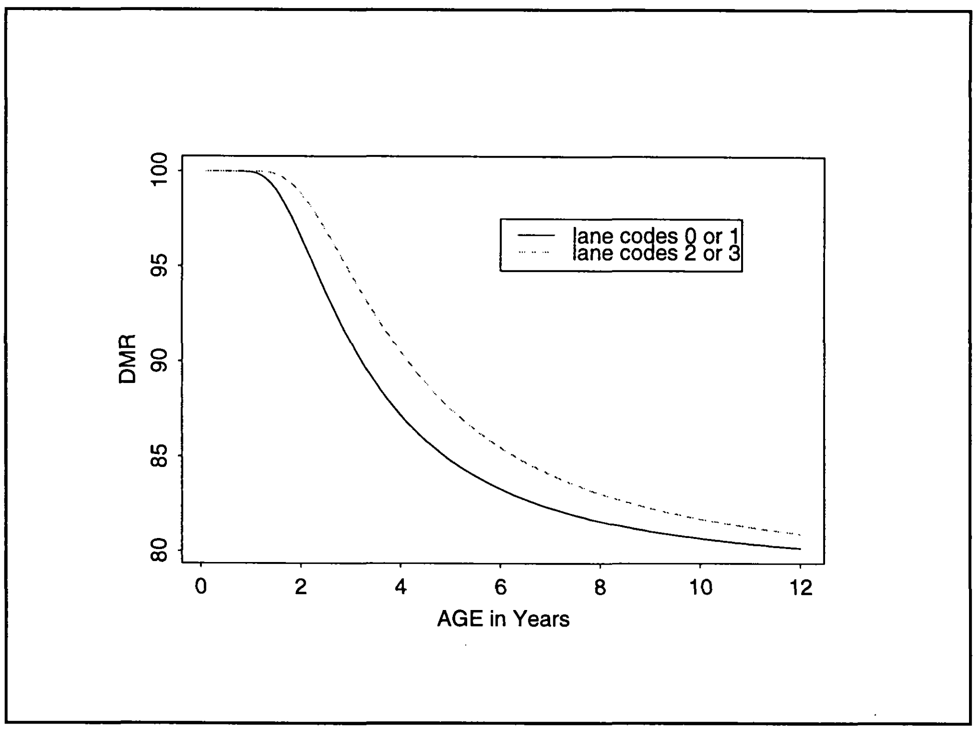


Figure C-13 2-D Sensitivity Analysis for Non-overlaid Pavements Model, Region 2

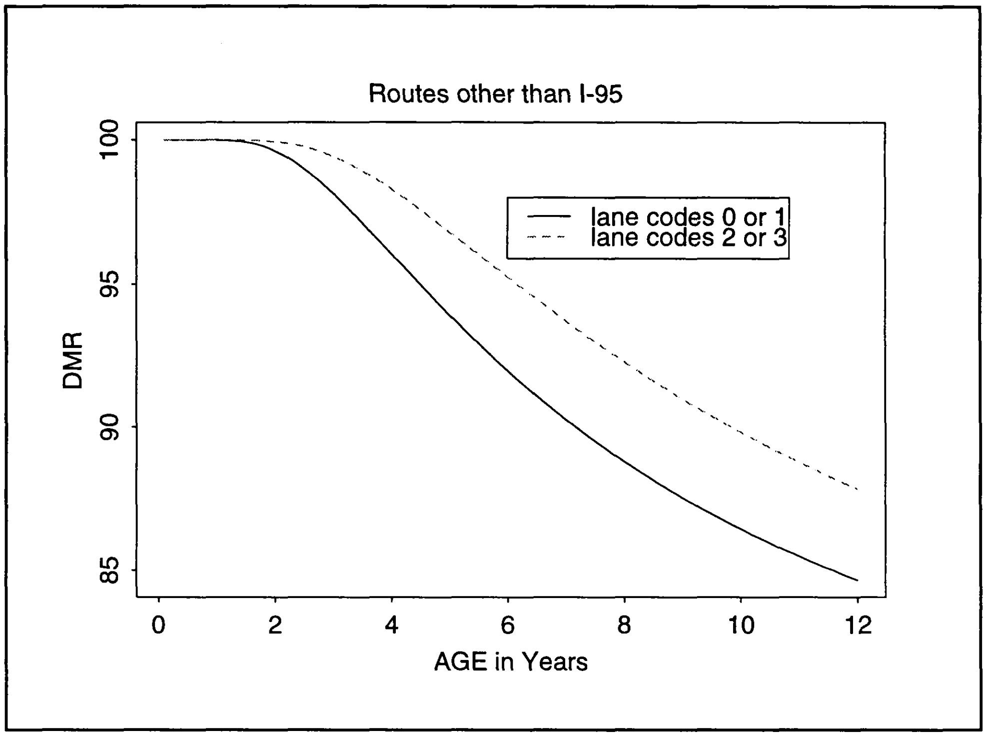


Figure C-14 2-D Sensitivity Analysis for Non-overlaid Pavements Model, Region 2

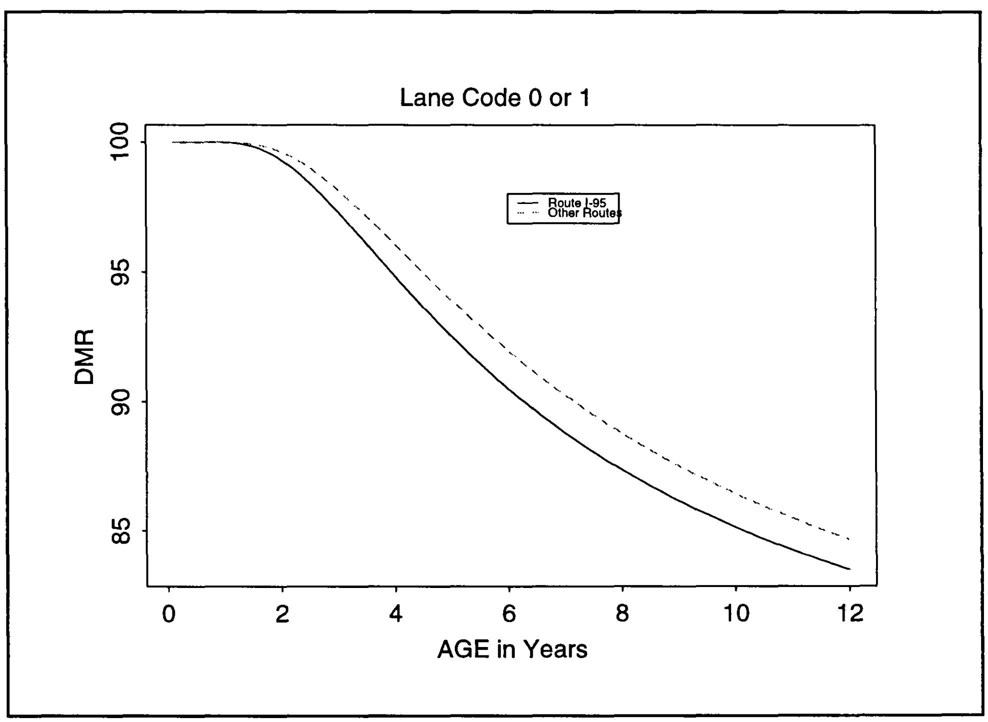
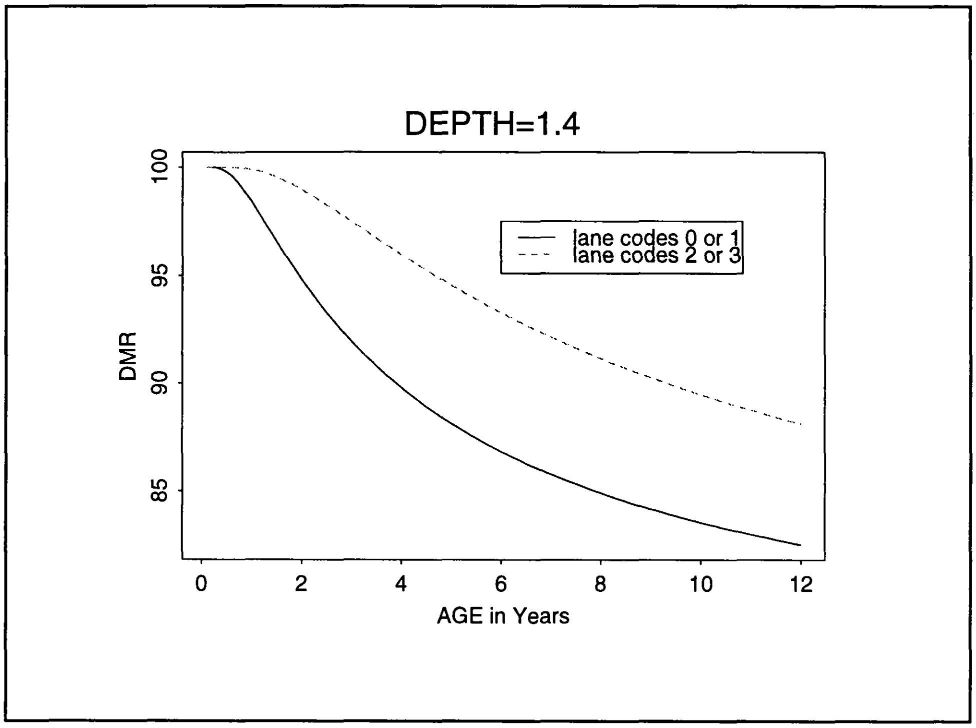


Figure C-15 2-D Sensitivity Analysis for the Composite with > 1 Overlay Model



Appendix D

Analysis-of-Variance (*ANOVA*) Test Results

Table D-1 *ANOVA* Test Results for Bristol District :

ANOVA Table for Response Variable: DIFF1

Source	DF	Sum-Squares	Mean Square	F-Ratio	Prob>F
A (YEAR)	3	19.18902	6.39634	0.62	0.6010
B (MODEL)	1	17.4265	17.4265	1.70	0.1943
AB	3	8.576534	2.858845	0.28	0.8409
C (ADJ)	1	.3175798	.3175798	0.03	0.8606
AC	3	2.842005	.947335	0.09	0.9642
BC	1	2.939E-02	2.939E-02	0.00	0.9574
ABC	3	.2058712	6.862E-02	0.01	0.9992
ERROR	180	1847.888	10.26604		
TOTAL(Adj)	195	1900.417			

Table D-2 *ANOVA* Test Results for Salem District :

ANOVA Table for Response Variable: DIFF1

Source	DF	Sum-Squares	Mean Square	F-Ratio	Prob>F
A (YEAR)	3	60.02439	20.00813	1.42	0.2384
B (MODEL)	1	2.562633	2.562633	0.18	0.6701
AB	3	3.787562	1.262521	0.09	0.9658
C (ADJ)	1	.9172266	.9172266	0.06	0.7988
AC	3	.8230723	.2743574	0.02	0.9963
BC	1	.3241027	.3241027	0.02	0.8796
ABC	3	.1426018	4.753E-02	0.00	0.9997
ERROR	248	3502.714	14.12385		
TOTAL(Adj)	263	3571.659			

Table D-3 *ANOVA* Test Results for Richmond District :

ANOVA Table for Response Variable: DIFF1

Source	DF	Sum-Squares	Mean Square	F-Ratio	Prob>F
A (YEAR)	3	47.45429	15.8181	0.93	0.4291
B (ADJ)	1	5.137249	5.137249	0.30	0.5834
AB	3	.8390875	.2796958	0.02	0.9971
ERROR	220	3758.526	17.08421		
TOTAL(Adj)	227	3811.753			

Table D-4 *ANOVA* Test Results for Staunton District :

ANOVA Table for Response Variable: DIFF1

Source	DF	Sum-Squares	Mean Square	F-Ratio	Prob>F
A (YEAR)	3	9.356613	3.118871	0.16	0.9243
B (MODEL)	1	.4035484	.4035484	0.02	0.8862
AB	3	3.84625	1.282083	0.07	0.9783
C (ADJ)	1	.8532386	.8532386	0.04	0.8352
AC	3	.2719283	9.064E-02	0.00	0.9996
BC	1	1.291E-02	1.291E-02	0.00	0.9796
ABC	3	.8791642	.2930547	0.01	0.9975
ERROR	232	4573.435	19.71308		
TOTAL(Adj)	247	4589.565			