Reevaluation of Southern African Unpaved Road Deterioration Models

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A number of models for the prediction of gravel loss, roughness progression, and roughness after blading were developed for use in unpaved road management systems from a large data base developed in southern Africa during the mid and late 1980s. These models differed considerably from models developed by the World Bank and were considered to be too simple, excluding a number of important parameters. This paper discusses the reevaluation of these models and concludes that the models developed were the most appropriate for the conditions under which they were developed. The inclusion of additional parameters would contribute little to their usefulness. However, application of these models on the Brazil data set (from which the World Bank models were developed) indicated major discrepancies. It is thus concluded that the transferability of this type of model requires calibration for different areas. Because of the problems associated with exponential models and low maintenance frequencies, the southern African data base was reanalyzed using nonlinear regression techniques as used in the World Bank study to provide a steady-state solution. This model is presented in the paper.

The transportation infrastructure is probably the most important factor affecting the economic viability of most developing countries. The bulk of this transportation infrastructure in most of these countries is the road network which, in nearly all sub-Saharan countries in Africa, consists primarily of unpaved roads. These unpaved roads typically make up more than 80 per cent of the total road network (*1*).

Nearly all the sub-Saharan countries can be classified as developing, and, since most of them are very poor, financial resources for road maintenance are minimal and maintenance is limited. The unpaved road network deteriorates rapidly with a concomitant increase in vehicle operating costs. In many cases poor roads result in damage to vehicle components that are often difficult to replace, and the vehicles become immobilized for long periods or even permanently.

The unpaved road network must be carefully managed in order to allocate the limited resources optimally and minimize the effects of poor roads. To do this effectively, models to predict the deterioration of the road condition are necessary. This paper analyses some pavement deterioration models for unpaved roads that have been derived under subtropical conditions in southern Africa, and makes recommendations regarding possible improvements following a comparison with the models used in HDM-III. A new roughness prediction model based on the HDM-III steady-state model has been developed for southern African conditions.

Background and Objectives

Between 1983 and 1989 an extensive project was carried out in southern Africa to investigate the performance of materials in unpaved roads in terms of their specification and rates of deterioration under traffic and climatic influences (*1*). This project resulted in the development of, *inter alia*, models to predict the rate of roughness progression, the roughness after blading, and the rate of gravel loss from the roads.

These results were widely published and are currently being implemented in all the provinces in South Africa as well as in other southern African countries. Earlier evaluation of the effectiveness of the models developed by the World Bank and utilized in HDM-III (*2*) on the southern African data base indicated that the local models produced a better estimate of the maintenance needs for roads in South Africa and Namibia (*3*). However, when the new models are used under conditions of infrequent maintenance, their exponential component results in a tendency to predict very high roughness, which the steady-state models used in HDM-III (*2*) avoid. It should be noted that the traffic conditions and typical maintenance procedures in South Africa and Namibia tend to result in relatively high maintenance frequencies.

In collaboration with the World Bank, the southern African models were thus reevaluated. Three aspects were specifically identified:

1. The southern African models incorporate fewer variables, and they could perhaps be made stronger by adding parameters such as grade, curvature, and different traffic classes.
2. The southern African models should be run using the Brazil data sets to evaluate the transferability of this type of model.
3. The southern African roughness data base should be reanalyzed using a nonlinear, steady-state model to eliminate the explosive tendency of the roughness progression under conditions of infrequent maintenance, which are typical of many developing and third world countries. New coefficients for the World Bank model forms should be determined.

The background and experimental design of the project were described at a previous Low Volume Roads Conference (*4*), and the models were presented fully at the fifth Low Volume Roads Conference (*3*) and are discussed only briefly in this paper.

The model for the prediction of gravel loss developed during the southern African unpaved roads study is

$$GL = D[ADT(0.059 + 0.0027N - 0.0006P26) - 0.367N - 0.0014PF + 0.0474P26] \quad (2.1)$$

where

GL = gravel thickness loss (mm);
D = time period under consideration (days/100);
ADT = average daily traffic in both directions;
N = Weinert N-value (*5*), which ranges from 1 in wet areas to more than 10 in arid areas and incorporates annual rainfall;
PF = plastic limit × percentage passing 0.075-mm sieve; and
$P26$ = percentage passing 26.5-mm sieve.

As highlighted previously, one of the main advantages of the southern African model for gravel loss prediction over the HDM-III equivalent is its simplicity. Aspects such as the vertical grade and horizontal curvature that need to be averaged for the various links in a road network are excluded from the southern African model to eliminate a possible source of inaccuracy. No estimate of the rainfall is necessary [it is difficult to take cyclical (seasonal or drought) conditions into account, anyway], and the required laboratory testing is minimal. All the parameters required can be easily obtained by relatively unskilled staff in unsophisticated laboratories.

The best model determined for southern African conditions to predict the change in roughness [in Quarter-car Index (QI) counts/km] with time was as follows:

$$\ln R = D[-13.8 + 0.00022PF + 0.064S1 + 0.137P26 + 0.0003N\ ADT + GM(6.42 - 0.063P26)] \quad (2.2)$$

where

$\ln R$ = natural logarithm of change of roughness with time, i.e.,
D = number of days since last blading in hundreds (days/100),
PF = product of plastic limit and percentage passing 0.075-mm sieve,
$S1$ = season dummy variable ($S1 = 1$ for dry season, 0 for wet season),
$P26$ = percentage passing 26.5-mm sieve,
N = Weinert N-value (*5*),
ADT = average daily traffic, and
GM = grading modulus (sum of percentages retained on 2.0-, 0.425-, and 0.075-mm sieves/100).

The HDM-III model requires essentially the same input but was considered to be particularly cumbersome for developing areas.

The change in roughness needs to be related to a datum for use in a maintenance management system. For this purpose, the following model to predict the roughness after blading (the starting point of roughness progression after each maintenance operation) was developed (*1*):

$$LRA = 1.07 + 0.699LRB + 0.0004ADT - 0.13DR + 0.0019LMS \quad (2.3)$$

where

- LRA = natural logarithm of roughness after blading (QI counts/km),
- LRB = natural logarithm of roughness before blading (QI counts/km),
- ADT = average daily traffic in both directions,
- DR = dust ratio (ratio of percentage passing 0.075- and 0.425-mm sieves), and
- LMS = laboratory determined maximum size (mm) (not greater than 75 mm).

Analysis

Effect of Variables Excluded from Current Models

Gravel Loss Models

The southern African models are considerably simpler than those used in HDM-III, and concern was expressed that the simplification may have reduced their effectiveness, particularly with respect to the effect grade and curvature have on the performance criteria. In order to investigate this possibility, detailed analyses of the residuals were conducted. By regressing the residuals from the prediction model against the predictor variables and the variables that were excluded from the analysis during the modelling, it is possible to identify whether missing terms or other signs of model misfit occur (6). The residuals of the prediction model were thus regressed against those parameters used in the southern African model, and those variables used in the HDM-III model but excluded from the local model and plots of the residuals checked for randomness. The regression models obtained were also evaluated to help identify any trends.

The residuals were determined by subtracting the gravel loss predicted using Model 2.1 (calculated for the time at which each gravel loss measurement was made) from the actual gravel loss recorded at each measurement. The SAS (7) suite of programs was used to carry out the statistical analyses.

The regression parameters of the residual analyses and the best-fit regression models are summarized in Table 1; 463 observations were used in the analyses.

As some multicollinearity existed between the Weinert N-value and the grade and curvature, further regression analyses were carried out on subsets with N-values less than and greater than or equal to 3 (Table 1).

TABLE 1 Statistical Data for Gravel Loss Analyses

Regression parameters for gravel loss analyses

Variable	R-square	F value	Pr > F
Variables in model 2.1			
N-value	0.0000	0.05	0.831
ADT	0.0000	0.00	0.996
P26	0.0079	3.66	0.057
PF	0.0016	0.74	0.391
Variables not in model 2.1 but in model 2.2			
Curvature	0.0121	5.65	0.018
Grade	0.0038	1.72	0.191
Number of cars	0.0098	4.67	0.033
Number of trucks	0.0147	6.93	0.009

Best fit models for residuals versus parameters for gravel loss

Residual = -2.194 - 0.025 x N-value
Residual = -0.350 - 0.00002 x ADT
Residual = 0.015 - 0.244 x Grade
Residual = 2.269 - 0.001 x Curvature
Residual = -13.75 + 0.140 x P26
Residual = 0.190 - 0.001 x PP
Residual = -1.494 + 0.016 x Cars
Residual = 0.418 - 0.024 x Trucks
Residual = 0.750 - 0.338 x Grade (N < 3)
Residual = 3.394 - 0.002 x Curvature (N < 3)
Residual = -0.291 - 0.381 x Grade (N ≥ 3)
Residual = 1.879 - 0.001 x Curvature (N ≥ 3)

Effect of grade on models within climate subsets

N- value	R-square	F-value	Pr >F
< 3	0.0104	1.96	0.163
≥ 3	0.0029	0.78	0.379

Effect of curvature on models within climate subsets

N- value	R-square	F-value	Pr >F
< 3	0.0118	2.20	0.139
≥ 3	0.0146	4.07	0.045

Roughness Progression Models

Analysis of the roughness progression models was a little more complex since numerous cycles make up the temporal variable. In order to compare the predicted and actual roughness, the values predicted from Model 2.2 were calculated for each roughness measurement. The predicted value (change in roughness) was added to the first roughness measurement after blading in order to simulate the temporal variation of the roughness that increases exponentially with time. The difference between the actual measured value and the predicted value at each measurement point was calculated as the residual. It was then regressed against all the parameters included in the model and those that perhaps should have been included. The results and the best-fit regression models are summarized in Table 2; 7,000 observations were used in the analyses.

TABLE 2 Statistical Data for Roughness Development Analyses

Results of regressing residuals against various parameters for prediction of change in roughness with time

Variable	R-square	F value	Pr > F
Variables in model 2.3			
N-value	0.0033	23.23	0.000
ADT	0.0066	46.65	0.000
P26	0.0010	6.70	0.010
PF	0.0029	20.58	0.000
GM	0.0002	1.59	0.207
DAYS	0.0331	239.34	0.000
Variables not in model 2.3 but in 2.4			
Curvature	0.0004	2.63	0.105
Grade	0.0007	4.74	0.030
Cars per day	0.0017	11.86	0.001
Trucks per day	0.0110	77.25	0.000
Dust ratio	0.0060	42.2	0.000
Mean monthly precipitation	0.0019	13.0	0.000

Best fit models for residuals versus parameters for roughness development

Residual = -2.194 - 0.025 x N-value

Residual = -0.350 - 0.00002 x ADT

Residual = 0.015 - 0.244 x Grade

Residual = 2.269 - 0.001 x Curvature

Residual = -13.75 + 0.140 x P26

Residual = 0.190 - 0.001 x PP

Residual = -1.494 + 0.016 x Cars

Residual = 0.418 - 0.024 x Trucks

Residual = 0.750 - 0.338 x Grade (N < 3)

Residual = 3.394 - 0.002 x Curvature (N < 3)

Residual = -0.291 - 0.381 x Grade (N ≥ 3)

Residual = 1.879 - 0.001 x Curvature (N ≥ 3)

Roughness after Blading

The predicted roughness after blading was calculated using Model 2.3 and was regressed against the actual roughness measured during the first visit after each section was bladed. The first visit was not always immediately after grading, and up to 20 days could have elapsed between grading and the roughness measurement. It was not possible to realistically take this factor into account in the analyses.

The results obtained for the regression models and the best-fit models are summarized in Table 3. Almost 2,200 results were used in the analyses.

Use of SA Models on Brazil Data Base

The analyses were carried out only on the roughness data since the gravel loss data from Brazil were not available at the time.

Roughness Progression

The Brazil data base was scanned from printed output, manually checked and corrected, and analyzed using SAS (7). The roughness was predicted using Model 2.2 for each field measurement, taking into account the measured roughness after blading for each observation within each blading cycle. The predicted roughness and residuals were plotted against the actual measured roughness. In order to investigate whether the infrequent blading had an effect, the residuals were plotted against the number of days since blading.

As some of the variables used in the model were not available from the Brazil data, the following assumptions were made:

- A Weinert *N*-value of 1.5 was used for all sections since the minimum annual rainfall in Brazil was in excess of 1200 mm^2,
- Since no values for the percentage passing the 2-mm sieve were available, the average of the 5- and

TABLE 3 Statistical Data for Roughness after Blading Analyses

Results of analysis of model for predicting roughness after blading

Variable	R-square	F value	Pr > F
Variables in model 2.5			
Dust ratio	0.0175	38.87	0.000
ADT	0.6974	5026.9	0.000
Maximum size	0.0031	6.75	0.010
Roughness before blading	0.0972	234.94	0.000
Variables not in model 2.5 but in model 2.6			
Grading modulus	0.0059	13.03	0.000
Cars	0.6371	3828.2	0.000
Trucks	0.3317	1082.6	0.000

Best fit models for residuals versus parameters for roughness after blading

Residual = 135.2 - 39.79 x Log of roughness before blading
Residual = -12.6 - 53.88 x Dust ratio
Residual = 31.12 - 0.662 x Average daily traffic
Residual = -30.36 - 0.243 x Maximum size
Residual = 11.68 - 14.95 x Grading modulus
Residual = 27.83 - 0.868 x Number of cars per day
Residual = -8.44 - 1.037 x Number of trucks per day

0.425-mm sieves was used to calculate the grading modulus, and

- The transitional season was considered as wet.

The best-fit regression model obtained (not forced through the origin) for the actual versus predicted data was

Predicted roughness 72.30 + 0.397 × QI

Roughness after Blading

The roughness after blading was modelled in the same way as the regression of the residuals for the southern African models. The first roughness measurement after blading was taken as the actual roughness after blading and was regressed against the value predicted from Model 2.3. The following model was obtained for the regression:

Predicted roughness after blading = 104.5 + 1.058 × roughness after blading

The minimum predicted roughness will always be in excess of the actual measurement, this excess being at least 105 units higher than the recorded measurement.

Steady-State Modelling of Southern African Data

The southern African data base of roughness measurements was originally analyzed using the modelling procedure followed for the Brazil study (*8*). Under conditions of minimal maintenance, the exponential model predicts extremely high roughness values toward the end of the blading cycle. The steady-state model developed by the World Bank eliminates this explosive tendency by constraining the maximum roughness to an upper level dependent on the material properties, road geometry, and so on.

The modelling procedure used attempted to follow the World Bank method in which the centroids of the roughness and dates for the first and last three results in each blading cycle were calculated. The grade of the line connecting the centroids was considered to represent the rate of roughness progression for that material, environment, and traffic milieu.

The data collected during the southern African study did not, however, provide an adequate number of points within many of the blading cycles to use the six-point centroid system, and it was also found that the roughnesses immediately after blading were relatively high and biased the initial reading inordinately. In addition, the last few roughness measurements in each blading cycle were often significantly lower than the maximum recorded for that cycle because the vehicles moved from the initial wheel tracks. In order to reduce the bias as much as possible, the first and last measurements in each blading cycle were deleted, and the minima and maxima of the remaining measurements in the cycle were determined for each cycle. These figures were taken as the lowest and highest roughness measurements for each cycle over the duration between the second and second last roughness measurement dates.

A nonlinear regression using the same parameters and initial coefficients as the World Bank model was then carried out. The actual results are plotted against the predicted values in Figure 1. The data were then reanalyzed using different variables (mostly based on the non-steady-state southern African model) and a plot of the predicted versus actual results is shown in Figure 2. The new model is:

$$RG(t_2) = RG_{max} - p[RG_{max} - RG(t_1)] \qquad (2.4)$$

where

$RG(t_1)$ = roughness at time t_1 (QI counts/km),
$RG(t_2)$ = roughness at time t_2 (QI counts/km),
t_1, t_2 = times elapsed since blading (days),
$p = \exp\{-0.016 - [0.001 * (t_2 - t_1)(-0.17 - 0.000067 * ADT - 0.00019 * N * ADT]\}$, and
$RG_{max} = -30.09 + 0.03 * PP + 294.76 * GM + 3.556 * P26$,

where the parameters are those defined for Model 2.2.

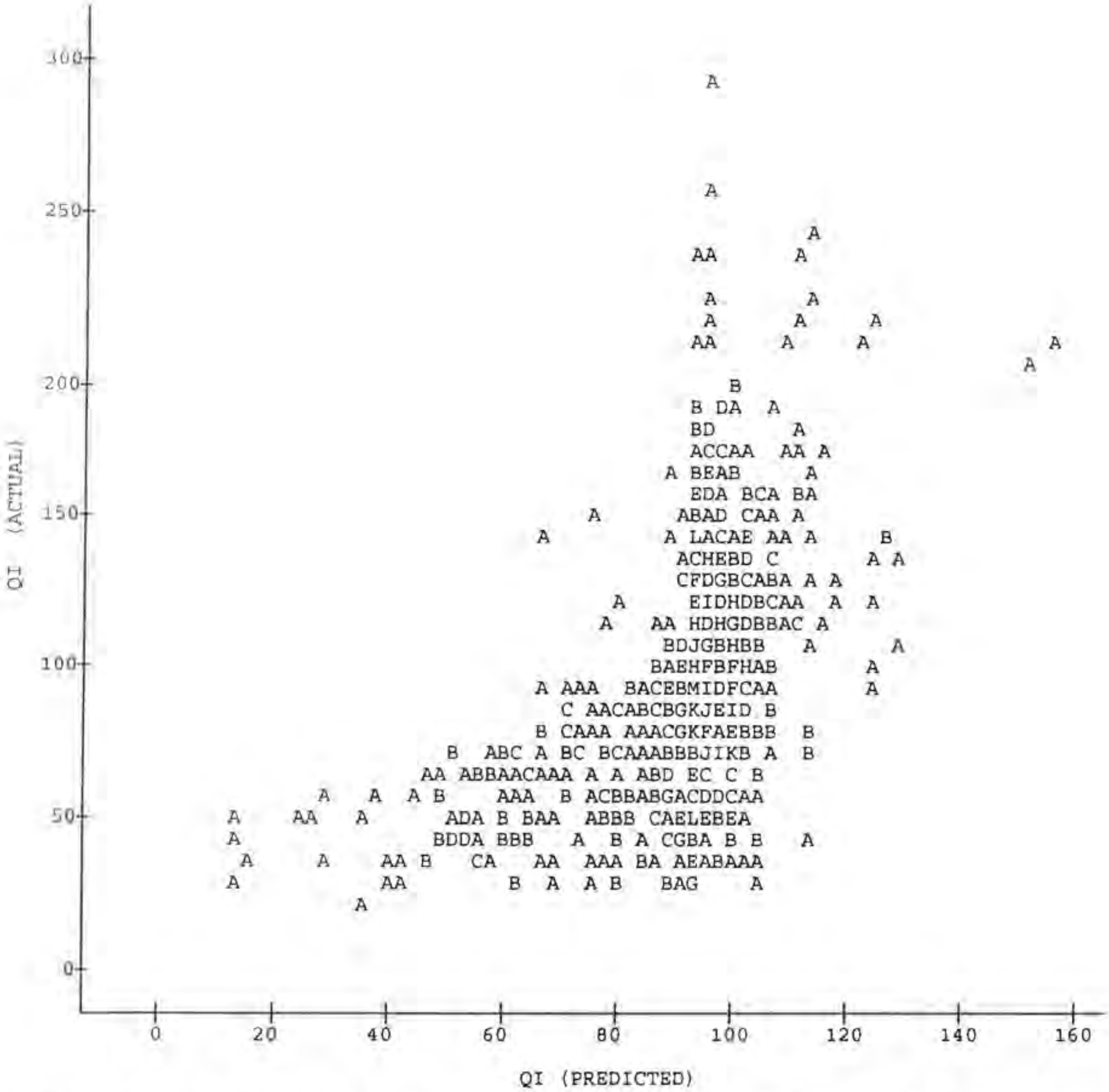

FIGURE 1 Actual versus predicted roughness using nonlinear analysis with HCM III model and southern African data.

The roughness after blading using the actual values recorded during the monitoring (but excluding obvious outliers when the value after blading was higher than that before blading) was determined following the World Bank procedure. The prediction model is presented below, and a plot of the actual versus predicted values is shown in Figure 3.

$$RG_a = RG_{min} + q(RG_b - RG_{min}) \tag{2.5}$$

where

RG_a = roughness after blading (QI counts/km),
RG_b = roughness before blading (QI counts/km),
$q = 0.144 - 0.087 * DR$,
$RG_{min} = 42.2 + 0.555 *$ Labmax $- 10.98 * MG$,
DR = dust ratio,
Labmax = maximum particle size from laboratory test, and
MG = particle grading parameter as discussed in Model 2.6 (MGD_i).

Additional analyses to develop a steady-state model for a subset of the full data base using a limited climatic and material range have been carried out recently. Similar modelling techniques were utilized, and the results are discussed later in the paper.

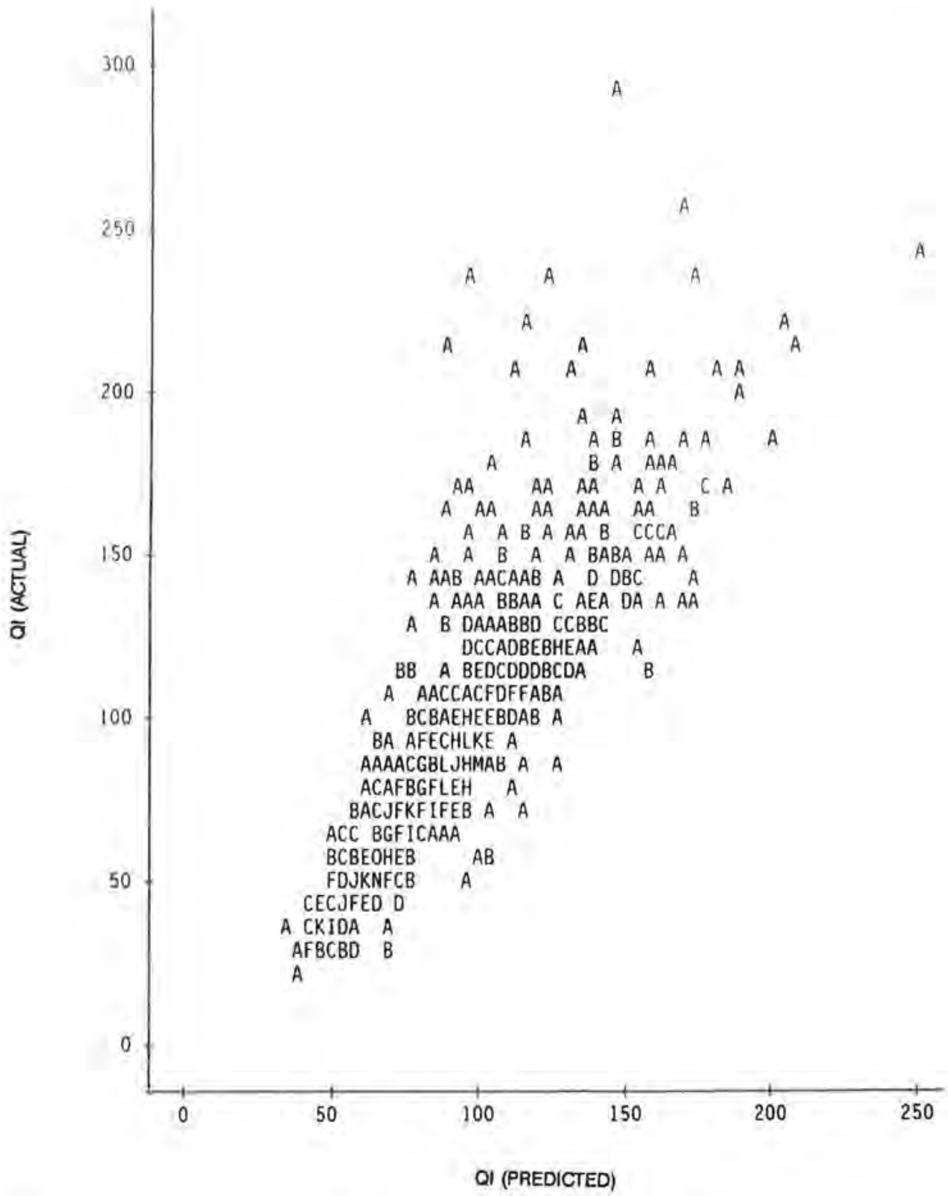

FIGURE 2 Actual versus predicted roughness values using Model 2.4.

Discussion of Results

Evaluation of Current Southern African Models

Gravel Loss Model

It is clear from the results and models in Table 1 that none of the regressions between the parameters included in the model and the residuals showed statistically significant correlations; the best correlation (percentage passing 26.5-mm sieve) was significant at worse than the 5 percent level. Inspection of the residual plots supports these results with random plots in all cases (examples of the residual plots for average daily traffic and Weinert *N*-value are shown in Figure 4). The regression models in Table 1 all show very flat slopes with intercepts near zero, supporting the randomness of the residuals.

The evaluation of the parameters included in the World Bank model but excluded from the southern African model shows some correlation for curvature and the number of cars and trucks. The plots of the residuals, however, indicate influential points at high traffic counts that somewhat improve the degree of correlation. At counts of less than 200 cars or trucks per

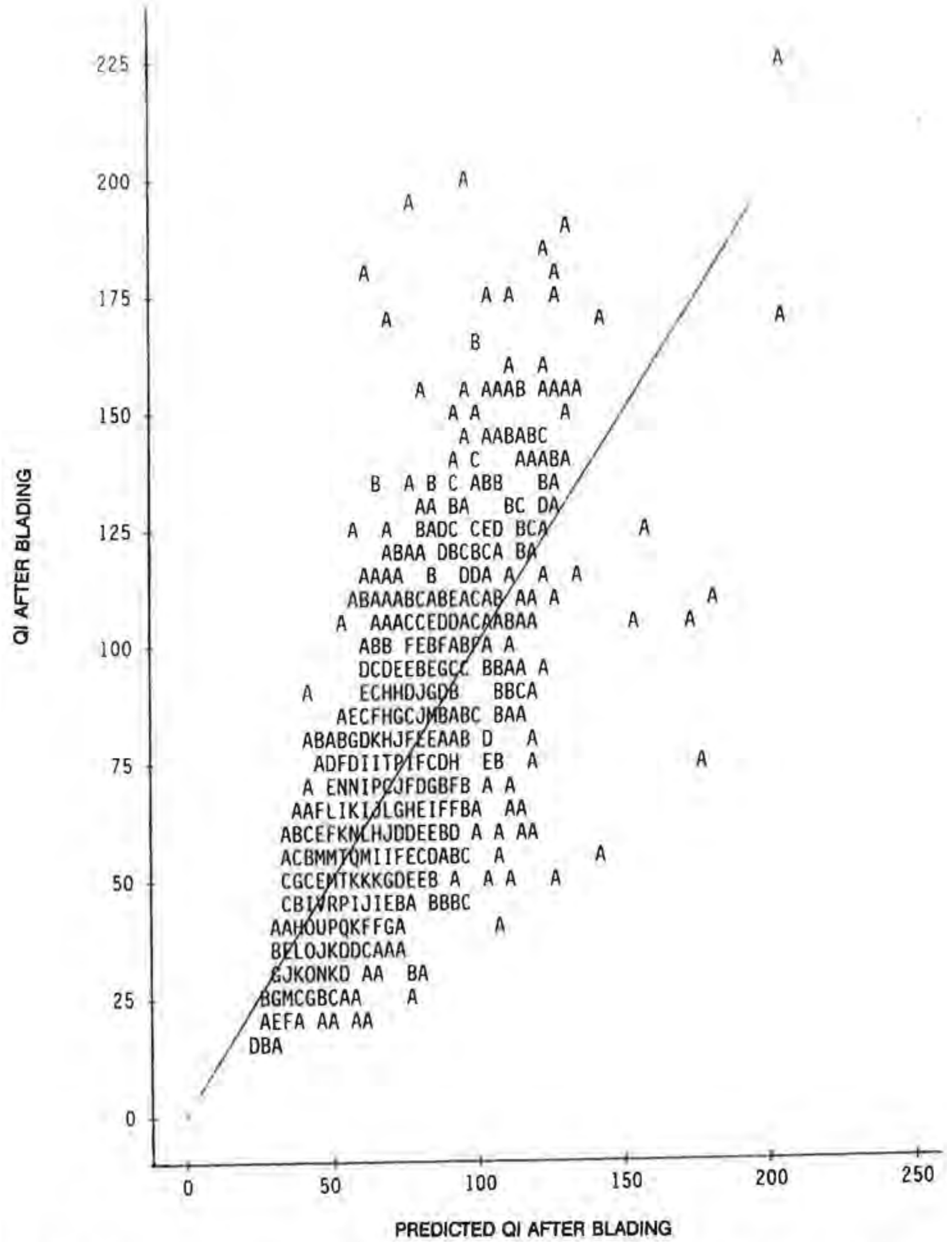

FIGURE 3 Actual roughness after blading versus values predicted using Model 2.5.

day, the residuals plot randomly. The plots for grade and curvature also show good randomness (Figure 5) even for the climatic subsets.

It can thus be concluded that, for the southern African data base, the model would not be significantly improved by incorporating additional variables, and the existing model (Model 2.1) should be used for most roads. Aspects such as the skill technique of grader operators carrying out routine maintenance are most likely to result in incorrect prediction of gravel loss.

Roughness Progression Model

The results in Table 2 show significant correlations between the regressors and residuals in nearly every case. These results are not unexpected since the number of data points is very large (7,000). However, all the best-fit models (Table 2) pass very close to the origin and have small slopes. The discussion is thus based mostly on the visual randomness of the residuals.

The residuals of the Weinert *N*-value, grading modulus, average daily traffic, and days since blading can be

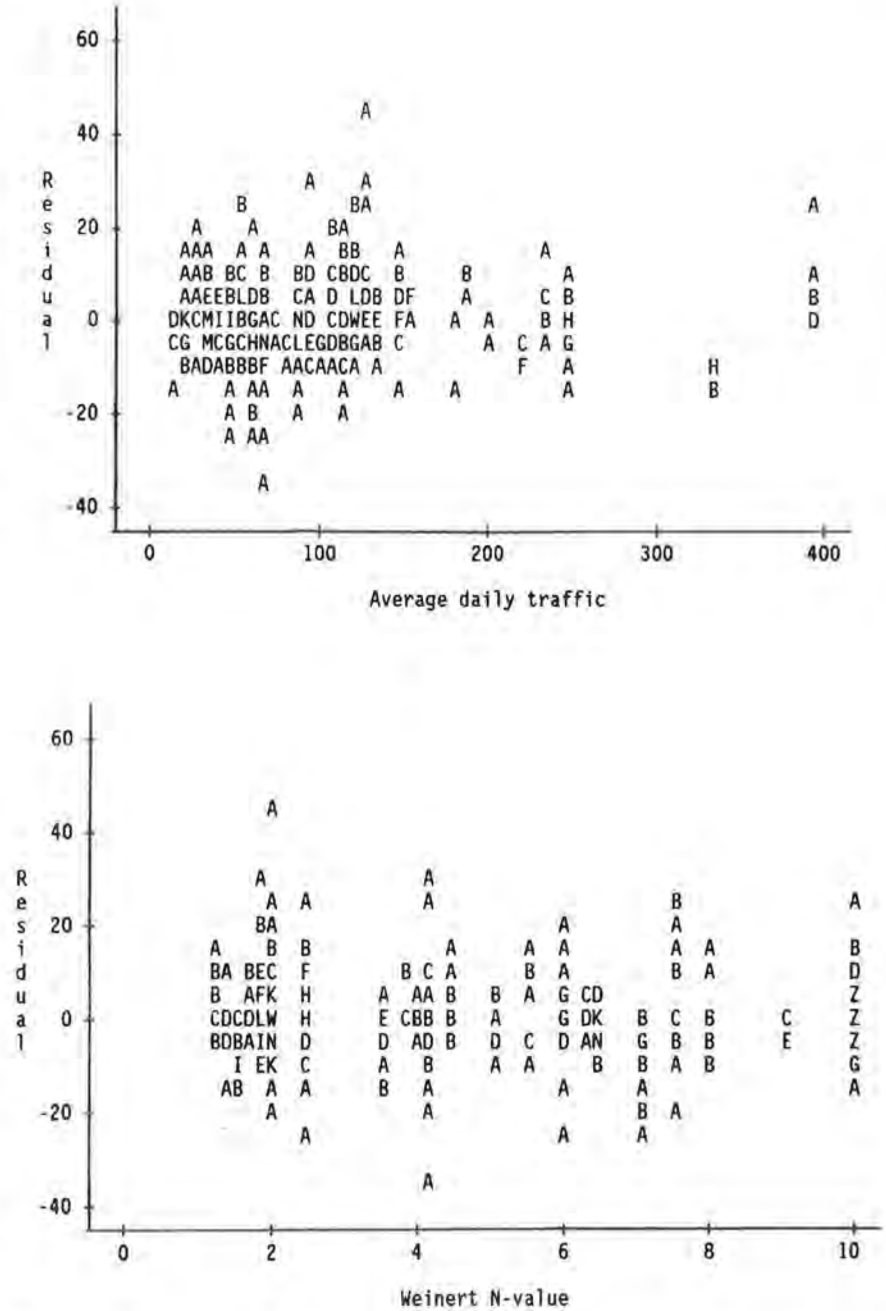

FIGURE 4 Gravel loss residuals versus average daily traffic and Weinert *N*-values using Model 2.1.

considered to be perfectly random. The percentage passing the 26.5-mm sieve shows a trend toward the upper limit, but this trend is primarily related to the preponderance of materials with 100 percent passing this sieve size; that is, a skewed distribution of these observations occurred and should perhaps have been transformed in order to normalize the distribution before analysis. The plastic factor (product of plastic limit and percentage passing the 0.075-mm sieve) shows a slight trend, but this is again associated with a preponderance of materials with low values. Relatively few of the residuals are greater than 50.

When evaluated in terms of the number of observations, the residuals of the parameters not included in the model but included in the World Bank model show no significant trends. These parameters include the dust

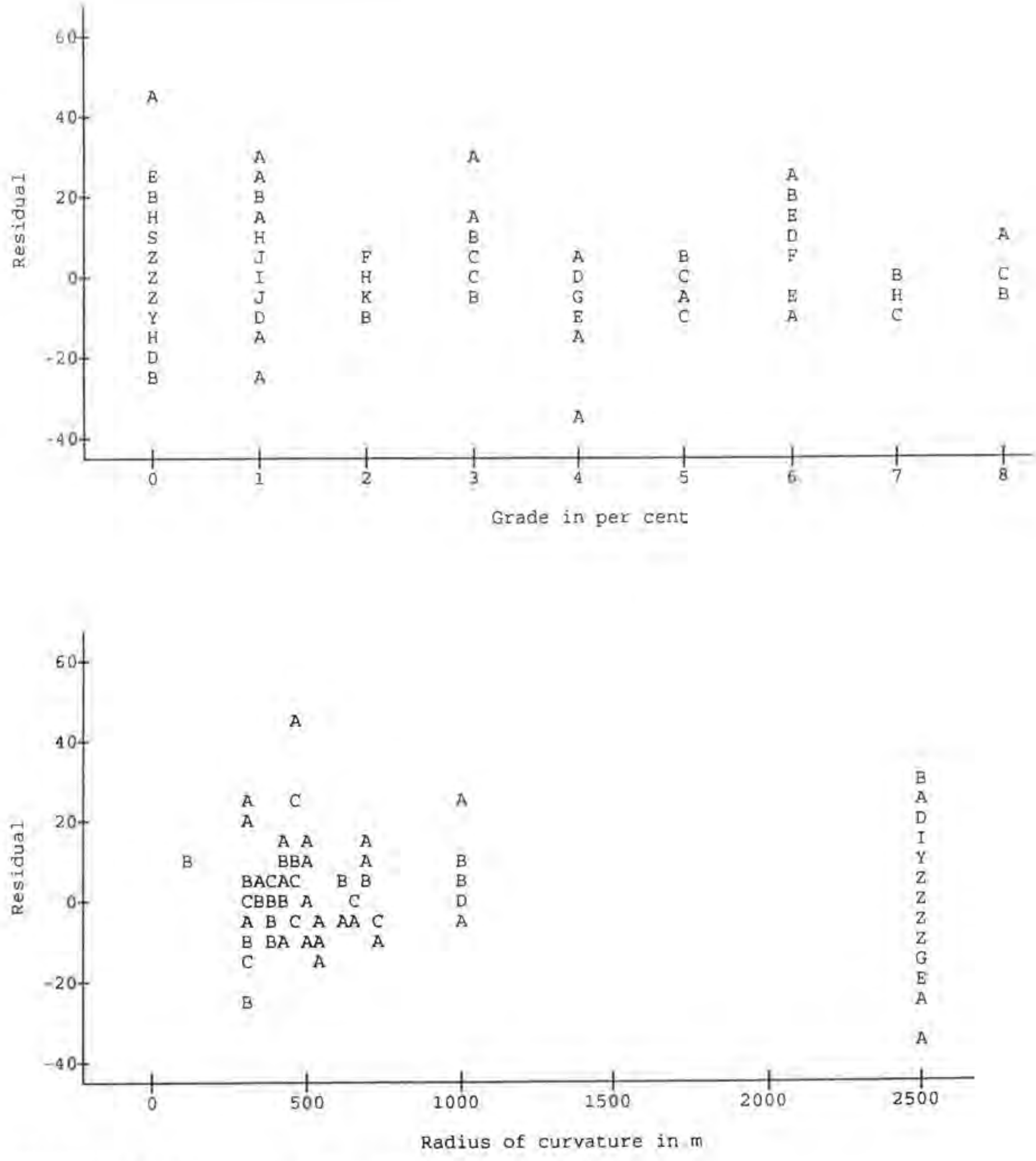

FIGURE 5 Gravel loss residuals versus grade and curvature (Model 2.1).

ratio, mean monthly precipitation, number of cars and trucks per day, and the radius of curvature and grade. Examples are shown in Figure 6.

Roughness after Blading

Although the initial model for the roughness after blading (Model 2.3) was highly significant, many of the predicted values were actually rougher after blading than before. This problem was noted and reasons given during the original study (*1*).

The roughness before blading is the dominant parameter in the model, and the residuals showed a strong bias toward overprediction with an otherwise generally random distribution of the residuals. A similar pattern was obtained for the dust ratio, maximum size, and grading modulus residuals with good randomness but biased toward overpredicting and one material being

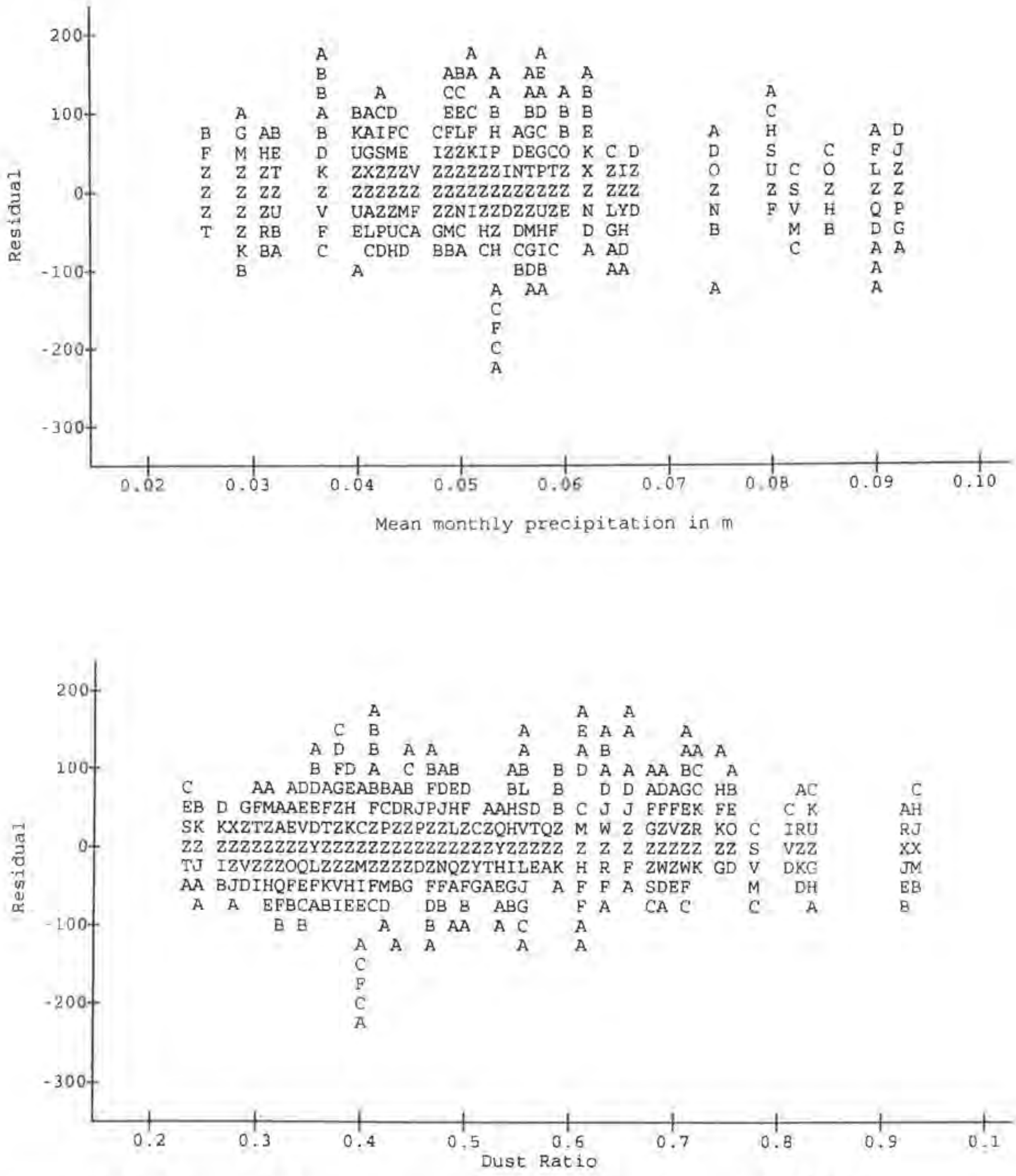

FIGURE 6 Roughness residuals versus mean monthly precipitation and dust ratio (Model 2.1).

particularly bad. The residuals for cars, trucks, and average daily traffic showed a trend to overpredict as the traffic increases.

Certain data (attributable to one or two specific sections monitored) were particularly badly overpredicted. It became evident from analysis of all the results that these outliers with the very high predicted values were from roads that were permanently in the shade of tall trees and were continuously moist during the experiment.

It can be concluded that the current model, although showing some trends and minor misfit, is unlikely to be significantly improved by including any of the additional parameters investigated. Transformation of some of the current parameters may, however, prove useful.

Evaluation Using Brazil Data Set

The result of running the southern African prediction models on the roughness data set developed in Brazil (*8*) illustrates a clear trend toward overprediction of the roughness at low roughness levels (by up to a factor of 7; a minimum predicted roughness of 72 counts/km is obtained when the measured QI is zero) and underprediction of roughness at higher roughness levels (by a factor of 2 to 3). Regression of the residuals against time after blading shows that this trend is strongly related to infrequent blading, particularly when the blading is delayed for more than about 8 months. The bulk of the predicted values, however, correlate well with the actual measured values although there is a wide variation.

The roughness after blading shows significant discrepancies with residuals in excess of 1,000 counts/km. Underprediction is almost nonexistent (the minimum possible predicted value is 104 counts/km). Although the bulk of the residuals are less than 125 counts/km, the southern African prediction model is considered to be unsatisfactory for the Brazil data.

It can generally be concluded that the southern African prediction models (Models 2.2 and 2.3) are not applicable to the Brazil data set. When this conclusion is viewed in relation to the reciprocal process [Brazil models (*8*) used in southern African data base (*3*)], it can be concluded that the transferability of the various prediction models from country to country is poor, and calibration is necessary for individual applications.

This inability to transfer models appears to be geographically related. The Brazil data set was developed in areas with a general tropical climate [predominantly Af and Aw (*9*)], and the southern African data set was developed in a subtropical climate [predominantly BS and BW (*9*)]. Small areas of both the Brazil and southern African experimental area fall within temperate climates [Cf and Cw (*9*)] which gives a little commonality to the data sets. Apart from the marked climatic differences in terms of seasonal temperature and rainfall variations, the soil-forming processes are significantly different. Typical tropical soils such as laterites developed by chemical decomposition predominate in Brazil whereas soils resulting mostly from physical disintegration or arid pedogenesis predominate in southern Africa. This difference would be expected to affect the performance of the materials in the different regions, which may account to a large extent for the differences between the HDM-III and the southern African models.

Steady-state Modelling of Roughness Prediction Models

The results of the steady-state modelling using the World Bank models and parameters as the initial input values in the nonlinear regression of the southern African data produced the plot shown in Figure 1. The model converged rapidly with a residual sum of squares of 1.1×10^6. The R-squared value of the measured QI versus the predicted QI was a significant 0.238 (F-value = 252; $RMSE$ = 36.96). It was clear from the residual plots that strong trends occur in the minimum and maximum QI, and the predicted versus actual plot shows a very weak relationship.

The data were then reanalyzed using the parameters identified in the earlier southern African model (Model 2.2). The R-squared value obtained was 0.742 (n = 807; F-value = 2321) with a root-mean-square error of 21.5. The predicted versus actual data are plotted in Figure 2. The model statistics are not as good as those of the World Bank model but are considerably better than the best model using the World Bank parameters and coefficients on the southern African data. It is considered that, given further manipulation, this model could be improved slightly. Analysis of the results by section resulted in an R-squared value of 0.819 (n = 105; F-value = 469; $RMSE$ = 14.75). This model was developed after repeated statistical analysis, and although it was by far the best model obtained, it is considered to be somewhat inelegant. RG_{max} is initially negative and is strongly influenced by the particle size distribution parameters. However, the prediction capability is high.

Examination of the residuals of both the parameters included and those in the World Bank model but excluded from the local model shows good randomness throughout. The plots of the residual versus the roughness show that most of the spread of the data points is a result of underprediction. These are also mainly fine materials (100 percent passing the 26.5-mm sieve) with low plastic factors in wet areas. It would appear that some other as yet unidentified parameter should be included in the model. None of the parameters included in the World Bank model but excluded from the new southern African model show trends in the residuals, and their inclusion is thus unlikely to improve the model.

The nonlinear evaluation of the roughness after blading using the World Bank parameters and coefficients as seed values converged rapidly producing the plot shown in Figure 3. The overall R-squared value was 0.564 (n = 1600; F-value = 2067; $RMSE$ = 20.4), and the section-specific R-squared value was 0.89 (F-value = 873; $RMSE$ = 7.55). The plot of the residuals versus the actual values shows an increasing trend as the actual roughness after blading increases. This trend was also evident in the World Bank model and would indicate some other unidentified source of error (possibly operator related).

Examination of the residuals of the other parameters included in the model (mostly the same as the World Bank model) shows good randomness.

Since the average daily traffic was a significant parameter in the southern African model (Model 2.3) it was included in the analysis and resulted in a marginal improvement in the R-squared value to 0.568 (F-value = 2103; $RMSE$ = 20.3). The residuals gave a random pattern, indicating that the parameter should stay in the model.

The analysis of the data subset including only basic igneous materials in a wet environment showed similar trends and also produced a somewhat inelegant model with a good prediction capability. Examination of the results of the model showed that an inordinately high maximum roughness was predicted, but, in the overall model (Equation 2.4), this neutralized itself, and a good estimate of the roughness progression was obtained within the inference space of the data. The high predicted maximum roughness is thought to be a consequence of the maximum roughness seldom being achieved in the data set because the vehicles moved to new wheel paths when the road attained a certain roughness and many of the sections of the road were maintained before they reached their maximum roughnesses

The reevaluation of the roughness prediction models using nonlinear regression has, however, resulted in new models that, although similar in structure to the HDM-III models, contain simple data input parameters. It is suggested that these new models be used in southern Africa when the blading frequencies on unpaved roads are low (less than twice a year).

Conclusions

From the reevaluation of the southern African unpaved road data base the following can be concluded:

- The existing southern African gravel loss model would not be improved by the incorporation of additional parameters;
- The existing models for roughness progression and roughness after blading would only be improved marginally by incorporating additional variables;
- The transferability of models developed in one area to other areas is not reliable without careful calibration;
- The steady-state model for roughness progression and the effect of blading developed by the World Bank does not include the most appropriate predictor variables for southern African conditions;
- New steady-state models incorporating the same parameters that were found to be the most significant in the southern African exponential model have been developed for use locally;
- It is recommended that, for southern African roads subject to regular maintenance (i.e., more than once a quarter), the exponential model (2.2) is the most appropriate;
- For roads that undergo only sporadic maintenance, the steady-state model should be used;
- The geographic differences among the source areas for the data sets result in significant differences between the prediction capabilities of the respective models outside their climatic classification areas. Calibration of all prediction models is thus recommended to ensure useful results.

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REFERENCES

1. Paige-Green, P. *The Influence of Geotechnical Properties on the Performance of Gravel Wearing Course Materials.* Ph.D. thesis. University of Pretoria, South Africa, 1989.
2. Paterson, W. D. O. *Road Deterioration and Maintenance Effects: Models for Planning and Management.* Highway Design and Maintenance Standards Series. Transportation Department, World Bank, Johns Hopkins University Press, Baltimore, Md., 1987.
3. Paige-Green, P., and A. T. Visser. Comparison of the Impact of Various Unpaved Road Performance Models on Management Decisions. In *Transportation Research Record 1291*, Vol. 2, TRB, National Research Council, Washington, D.C., 1991.
4. Paige-Green, P., and F. Netterberg. Requirements and Properties of Wearing Course Materials for Unpaved Roads in Relation to Their Performance. In *Transportation Research Record 1106*, Vol. 1, TRB, NRC, Washington D.C., 1987.
5. Weinert, H. H. *The Natural Road Construction Materials in Southern Africa.* H and R Academica, Cape Town, South Africa, 1980.
6. Galpin, J. S. *Regression Package REGPAC.* Special Report SWISK 25. National Research Institute for Mathmatical Sciences, CSIR, Pretoria, South Africa, 1981.
7. Statistical Analysis System. *SAS/STAT User's Guide: Version 6*, Vols. 1 and 2. Cary, N.C., 1992.
8. Visser, A. T. *An Evaluation of Unpaved Road Performance and Maintenance.* Ph.D. thesis. University of Texas, Austin, 1981.
9. Anonymous. *Philips Atlas of Southern Africa and the World.* George Philip and Son, London, 1986.