GIS-Based Spatial Assessment and Maintenance Prioritisation of Highway Pavements Using Field-Derived Distress Data: A Case Study of Delta State, Nigeria

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ABSTRACT

Highway pavements in Delta State deteriorate steadily under heavy commercial and petroleum-sector traffic, poor roadside drainage and inconsistent maintenance funding, yet decisions on which sections to repair first are still made in the state largely without reference to spatial condition data. This study set out to address that gap through two objectives: to assess the field-derived pavement distress condition of selected highway sections in the state using the Pavement Condition Index (PCI) method, and to develop a Geographic Information System (GIS) based spatial framework for prioritising maintenance interventions from the resulting data. Eighteen road segments across five corridors, Asaba, Warri-Ughelli, Oghara, Sapele and the Ughelli link, were surveyed. Distress type, severity and extent were recorded through visual field survey following ASTM D6433 procedures, with distress locations logged by handheld GPS for import into a segment-level GIS database built in ArcGIS Pro. PCI values were computed from standard deduct value curves and classified into six condition bands. Scores ranged from 25 to 72 across the eighteen segments, with a network mean of 49.4, and ten segments fell into the poor or fair condition bands. Spatial mapping placed the most deteriorated sections along the Warri-Ughelli axis and at the Ughelli link, where poor-condition segments clustered rather than scattering evenly across the network. A composite Maintenance Priority Index, combining PCI with distress severity and traffic exposure weighting, produced a ranked list identifying UG-02 and WU-01 as the two highest priority segments for intervention, a result that held under a range of alternative weighting schemes; AS-04 ranked third under the base weighting but was more sensitive to how the traffic exposure term was weighted. The study concludes that pairing field-derived PCI data with GIS mapping gives Delta State road authorities a defensible, spatially referenced basis for allocating maintenance resources, and recommends that the state adopt the resulting priority ranking as a starting reference for its next maintenance budget cycle.

Keywords: geographic information system; highway pavement distress; maintenance prioritisation; pavement condition index; spatial analysis

INTRODUCTION

Background to the Study

Road transport carries the greater part of freight and passenger movement in Nigeria, and highway pavements form the physical backbone on which this movement depends. In Delta State, an oil producing and densely trafficked part of the Niger Delta, arterial roads connecting Asaba, Warri, Sapele, Ughelli and Oghara carry heavy commercial and petroleum haulage traffic on pavements that were, in many cases, not designed for current axle loads. Repeated flooding, poor subgrade drainage and delayed resurfacing compound the wear that traffic alone would cause [28, 30]. Where maintenance budgets are limited, as they typically are in Nigerian states, the central question is not whether to repair but which sections to repair first.

Pavement management systems built on the Pavement Condition Index (PCI) have been used for decades to answer that question by converting visual distress observations into a single numerical score that can be ranked [6]. What has changed over the past several years is the pairing of PCI data with Geographic Information Systems, which allow condition scores to be tied to their exact location and displayed as a map rather than a spreadsheet. Angelo, Sasai and Kaito [1] demonstrated this pairing at network scale in Addis Ababa; Wardana, Wibisana and Estikhamah [2] applied it at corridor scale in Kediri, Indonesia; and Pereira, Bessa and Nóbrega [3] built a comparable decision support tool for Brazilian road segments. Nigerian applications of this kind remain few, and Delta State in particular has not, to the researcher's knowledge, been the subject of a published GIS-based pavement prioritisation study.

Statement of the Problem

Highway maintenance in Delta State is presently allocated on the basis of complaint frequency, political pressure and periodic visual inspection reports that are neither standardised nor spatially referenced. A pothole reported loudly may receive attention before a structurally worse section that generates fewer complaints simply because it carries less residential traffic. Olowosulu, Kaura, Murana and Adeke [4] found a similar pattern of missing and inconsistent condition data across federal highway links in Nigeria, which they attributed to the absence of a standing data collection and classification routine. Without a documented, repeatable method for scoring and mapping pavement condition, the state road agency cannot demonstrate that its maintenance spending follows engineering need rather than administrative convenience.

Aim and Objectives of the Study

The aim of this study is to combine field-derived pavement distress data with GIS-based spatial analysis to support maintenance prioritisation on selected highway corridors in Delta State. The study pursues two specific objectives:

Objective One: to assess the field-derived pavement distress condition of selected highway sections in Delta State using the Pavement Condition Index method.

Objective Two: to develop a GIS-based spatial framework for prioritising highway maintenance interventions based on the distress and condition data obtained under Objective One.

Justification of the Study

A defensible prioritisation framework gives the Delta State Ministry of Works, and by extension the Federal Ministry of Works where federal roads are concerned, a documented basis for allocating scarce maintenance funds. It also gives a template that can be extended to other corridors and other states once the initial data structure is in place. Beyond the immediate engineering use, the spatial output supports budget justification to state and federal appropriations committees, a role GIS thematic maps have played in comparable studies elsewhere [10].

Scope of the Study

The study covers eighteen highway segments across five corridors in Delta State: Asaba, Warri-Ughelli, Oghara, Sapele and Ughelli link. It is limited to flexible (asphalt) pavements and to distress that is visible at the surface; it does not extend to structural coring, deflection testing or subsurface investigation, which lie outside the resources available for this exercise.

Study Area

Delta State lies in the south-south geopolitical zone of Nigeria, bordered by Edo State to the north, Anambra and Bayelsa States to the east, Ondo State to the west and the Atlantic Ocean to the south. The terrain is largely low-lying and prone to seasonal flooding, particularly along the Warri-Ughelli axis, where drainage failure is a recurring contributor to pavement distress. The five corridors surveyed for this study carry a mix of private, commercial and heavy petroleum-sector traffic and were selected because they represent the principal inter-town linkages within the state.

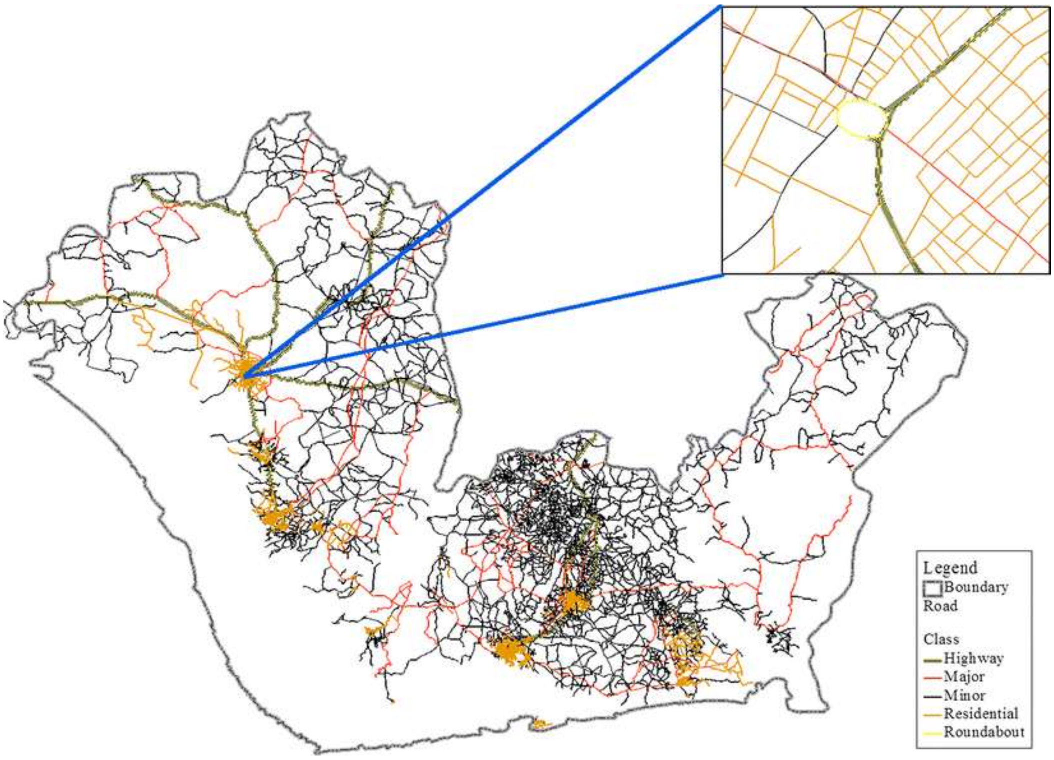

Figure 1. Study area showing surveyed highway corridors in Delta State, Nigeria.

LITERATURE REVIEW

Conceptual Framework

Pavement distress refers to the visible surface deterioration of a road, including cracking, rutting, potholing, raveling and patching, each of which is recorded during survey by type, severity and extent. The PCI method converts these observations into a score between 0 and 100 using deduct value curves; a score above 85 indicates excellent condition while a score below 25 indicates a section approaching failure [6]. Related indices serve similar functions with different inputs: the Surface Distress Index used by Zidan, Cahya, Wibisana and Fatikasari [5] relies on crack area, crack width, pothole count and rutting depth measured against Bina Marga guidelines, while the Overall Condition Index applied by Al-Mansoori and Shubbar [6] and by Adesunkanmi, Al-Hamdan and Nlenanya [7] compresses distress data into a ten-point scale intended for quick municipal screening.

GIS enters pavement management not as a replacement for these indices but as a way of anchoring them to location. A GIS layer built from segment-level PCI or SDI values can be queried, filtered and rendered as a thematic map, which turns a table of numbers into something a non-specialist decision maker can read at a glance. Al-Mansoori and Shubbar [6] built exactly this kind of layer for Al-Qassim, using an Overall Condition Index rendered across the whole network map rather than segment by segment, and reported that the visual output changed how quickly maintenance staff could identify weak sections.

Theoretical Framework

The study draws on pavement deterioration theory, which treats surface distress as the observable outcome of cumulative traffic loading, environmental exposure and construction quality acting jointly over time [8]. Because deterioration does not proceed at the same rate across a road network, decision support theory as applied to infrastructure management holds that limited maintenance resources should be directed first to sections where the marginal benefit of intervention, measured against the cost of further deterioration if left untreated, is highest. Dabous, Al-Khayyat and Feroz [9] formalised this logic through a utility-based ranking method; the present study adapts the same underlying reasoning but substitutes a GIS-weighted composite score for the utility calculation.

Empirical Review

Global interest in GIS-based pavement assessment has grown steadily since 2020. Mehdi et al. [10] applied GIS surface indicator matrices to a 50 km stretch of Moroccan national road and found that thematic maps built from the environmental inspection data made a stronger case to funding authorities than the raw inspection report had done on its own. Hussein, Almuhanna and Zuhair [11] used Points Density Estimation and Inverse Distance Weighting in ArcGIS to generate distress hotspot maps for two arterial streets in Karbala, a method later repeated by Al-Kazaz and Ewadh [12] at signalised intersections in Hilla, Iraq, where they showed that a single high-PCI segment could still contain badly deteriorated sub-units invisible in an aggregate score.

Prioritisation methodology has moved in a similar direction. Nugraha, Muhidong and Soma [13] combined the Analytic Hierarchy Process with GIS to weight traffic volume, road authority, strategic value, population density, handling type and environmental impact, and identified three specific roads in their study area as the highest priority for intervention. Yamany, Khan and Ksaibati [14] built a comparable hybrid system for Wyoming county roads and found traffic volume carried the largest weight, at 27 percent of the composite score, ahead of speed limit and land use. Angelo, Sasai and Kaito [15] went further by folding road safety and crash history into the same decision matrix used for pavement condition, reasoning that a deteriorating section with a poor safety record deserves higher priority than one with equally low PCI but no crash history.

Machine learning has also entered this literature, though mostly as a way of predicting PCI from cheaper inputs rather than replacing field survey outright. Issa, Samaneh and Ghanim [16] used artificial neural networks to predict PCI and reported that the approach reduced the technical experience required for routine assessment. Kumar, Suman and Prakash [17] compared three ANN training algorithms on Bihar highway data and found the Levenberg-Marquardt algorithm outperformed both Bayesian regularisation and scaled conjugate gradient methods, while Radwan, Faris, Barakat and Mousa [18] tested random forest, support vector machine, decision tree and ANN models against 15,000 pavement segments in Egypt and reported the ANN model achieving the highest coefficient of determination among the four. Milad, Ali, Al-Sulaimi and Al-Kindi [19] combined five machine learning classifiers with GIS to estimate PCI from International Roughness Index data collected by smartphone in Oman, and their random forest model reached 99.9 percent accuracy, notably higher than the support vector machine result in the same study.

Low-cost and crowdsourced data collection has drawn separate attention, largely because full PAVER-style surveys are expensive to run at network scale in resource-constrained settings. Almansour and Al-Qaili [20] used smartphone accelerometer and gyroscope data through the Road Lab Pro application to build a low-cost pavement management tool for small and intermediate cities, and Sandamal and Pasindu [21] validated smartphone-based roughness measurement against Class III roughness equipment on rural roads in Sri Lanka, finding a correlation strong enough to support network-level screening. Gu, Khojastehpour, Jia and Han [22] took a different low-cost route, using crowdsourced Waze pothole and weather reports and a geographically weighted random forest model to approximate the Pavement Quality Index used by the Tennessee Department of Transportation; pothole report density turned out to be the second most important predictor after pavement age. Workman, Wong, Wright and Wang [23] applied high-resolution satellite imagery to unpaved roads in Tanzania and reached 88 percent classification accuracy with a blended machine learning classifier, a result relevant to rural sections of Delta State that share similar data poverty.

Deep learning applications aimed at automating distress detection from imagery have expanded rapidly since Majidifard, Adu-Gyamfi and Buttlar [24] introduced a YOLO and U-net based pipeline for asphalt distress classification. Ibragimov, Kim, Lee, Cho and Lee [25] built on this with an end-to-end deep learning pipeline that reported 95 percent accuracy in crack detection and 90 percent accuracy in crack width estimation. Xu, Shu, Dao and Cui [26] benchmarked seven multimodal large language models against street-level imagery for pavement assessment tasks and recommended GPT-4o as the best balance of accuracy, responsiveness and computational cost among the models tested, though all seven models fell short of dedicated computer vision pipelines on severity grading. Mei, Zampetti, Di Mascio, Fontinovo, Papa and D'Andrea [27] took an unmanned ground vehicle approach instead, combining a multisensory platform with image-based distress computation and reporting 74.2 percent accuracy against field-measured PCI.

Nigerian and African literature on this subject remains thin relative to the volume produced in Asia, the Middle East and North America. Ngene, Bassey, Busari, Bamigboye and Nworgu [28] reviewed GIS-based pavement maintenance practice across five African regions and concluded that sustainable maintenance methods have not been incorporated into policy in most African countries, largely because of inadequate financing and limited technical staffing rather than any lack of available technology. Akpan and Morimoto [29] applied Multi-Attribute Utility Theory to prioritise rural road upgrades in Nigeria based on access to socio-economic facilities, an approach conceptually adjacent to the present study but built around accessibility rather than surface condition. Olowosulu et al. [4] used a Naïve Bayes classification approach on historic Federal Highway condition data and flagged specific links in Borno, Kwara, Lagos, Oyo and Plateau States as requiring immediate attention, which illustrates that condition-based classification is achievable in the Nigerian data environment even when the underlying dataset is incomplete. Nthaga, Nyomboi and Mwaniki [30] integrated remote sensing and GIS for road condition assessment at Jomo Kenyatta University in Kenya and found that combining pavement distress mapping with drainage analysis identified failure patterns that pavement distress data alone would have missed, a finding with direct relevance to Delta State given the drainage problems noted in the corridors surveyed here.

Studies that combine spatial prioritisation with an explicit economic or cost dimension are fewer still. Gowda, Kavitha and Gupta [31] applied the Highway Development and Management tool to a 1,743.9 km non-core road network in India and found their proposed maintenance strategy reduced predicted International Roughness Index values by 37 percent relative to the conventional strategy used by the state agency. Dabous, Zeiada, Zayed and Al-Ruzouq [32] built a sustainability-informed multi-criteria framework incorporating safety, noise and pollution alongside pavement condition, arguing that condition alone understates the true cost of deferred maintenance. Nie, Zhang, Guo and Wang [33] took a data-driven route, developing a genetic-algorithm-optimised CatBoost model for pavement maintenance quality assessment across five highways in Beijing and reporting 98.46 percent accuracy relative to traditional inspection methods, though their approach depends on sensor infrastructure not yet available on most Nigerian highways.

Gap in the Literature

Taken together, this body of work shows two consistent patterns. First, GIS-based pavement assessment has matured methodologically, with well-tested approaches for converting field distress data into spatial condition maps [10, 11, 6]. Second, prioritisation frameworks that combine condition data with weighting criteria such as traffic, safety or socio-economic access have also matured, at least in India, Ethiopia, Indonesia and parts of the Middle East [15, 13, 2]. What is largely absent is the application of either strand to Delta State specifically, and the near-absence of published GIS-based pavement prioritisation work anywhere in southern Nigeria means road agencies in the state currently have no locally grounded reference point to draw on. This study addresses that gap directly: Objective One supplies the field-derived condition data that the reviewed methods depend on, and Objective Two applies a GIS-based spatial framework, built in the tradition of Al-Mansoori and Shubbar [6] and Pereira et al. [3], to convert that data into a maintenance priority ranking specific to the Delta State corridors surveyed.

METHODOLOGY

Research Design

The study adopted a cross-sectional research design combining field-based visual distress survey with spatial data analysis, a design consistent with comparable pavement condition studies [2, 34]. Data were collected at a single point in the 2026 dry season to avoid the confounding effect of rainfall on visible distress severity.

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Study Area and Road Network Selection

Eighteen road segments were selected across five corridors: Asaba (six segments, coded AS-01 to AS-06), Warri-Ughelli (four segments, WU-01 to WU-04), Oghara (three segments, OG-01 to OG-03), Sapele (three segments, SP-01 to SP-03) and Ughelli link (two segments, UG-01 and UG-02). Segment length ranged from 1.5 km to 2.6 km, with a combined surveyed length of 35.6 km. Segments were chosen to represent a spread of traffic exposure, from heavily trafficked inter-town links to lower-volume connector roads, rather than a random sample, since the purpose of the study was to test the prioritisation method across a range of conditions rather than to estimate a network-wide average.

Data Collection

Distress type, severity and extent were recorded through visual field survey following the procedures set out in ASTM D6433, the standard also applied by Rajak et al. [34] in their assessment of the Kalaodi-Fabaharu corridor. For each segment, surveyors walked the full length in both directions, recording the location, type (alligator cracking, longitudinal and transverse cracking, rutting, potholing, patching, raveling and edge cracking), severity (low, medium, high) and areal or linear extent of every distress instance observed. A handheld GPS unit logged the coordinates of each distress location for later import into the GIS database, following the same field-to-database workflow used by Hussein et al. [11]. All distress ratings were assigned by a single trained surveyor against the ASTM D6433 severity definitions; a second rater did not independently re-score a subset of segments, so no inter-rater reliability statistic is reported, and this is noted as a limitation in Section 4.6.

PCI Computation Procedure

PCI values were computed from the recorded distress data using standard deduct value curves, following the ASTM D6433 procedure. Deduct values for each distress type and severity combination were summed and corrected for multiple distresses to produce a corrected deduct value, which was then subtracted from 100 to give the segment PCI. Segments were classified into six condition bands: Excellent (85 to 100), Very Good (70 to 84), Good (55 to 69), Fair (40 to 54), Poor (25 to 39) and Very Poor (below 25), following the classification scheme used by Al-Mansoori and Shubbar [6] and by Wardana et al. [2]. This procedure addresses Objective One directly.

GIS Database Development and Spatial Analysis Procedure

GPS-referenced distress and PCI data were imported into ArcGIS Pro and organised as a segment-level attribute table linked to a road network line layer. Spatial pattern in the condition data was examined through choropleth classification of PCI by segment, a technique consistent with the mapping approach reported by Al-Mansoori and Shubbar [6]. A composite Maintenance Priority Index (MPI) was then calculated for each segment on a 0 to 10 scale using the equation MPI = (w1 x C) + (w2 x S) + (w3 x T), where C is a condition score derived from the inverse of the normalised PCI (C = (100 - PCI) / 10), S is a distress severity score assigned on a 0 to 10 scale from the dominant severity band recorded in Table 1 (low = 3, medium = 6, high = 10), and T is a traffic exposure score assigned on a 0 to 10 scale from a three-level qualitative judgement (light = 3, moderate = 6, heavy = 10) based on surveyor observation of vehicle volume and composition, in the absence of measured traffic counts. Weights were set at w1 = 0.5, w2 = 0.3 and w3 = 0.2, reflecting the greater confidence placed in the directly measured PCI component relative to the severity and traffic inputs, an approach adapted from the utility ranking method of Dabous et al. [9] and the multi-criteria weighting used by Yamany et al. [14]. Because the traffic exposure score rests on qualitative judgement rather than measured counts, the resulting MPI ranking should be read as a preliminary prioritisation rather than a final allocation, pending the traffic count data recommended in Section 5.4. Segments were ranked from highest to lowest priority index value, and the ranked output was rendered as a second thematic map so that the two outputs, condition and priority, could be read against one another. This procedure addresses Objective Two.

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Data Analysis Tools

PCI computation was carried out in a spreadsheet environment built around the ASTM deduct value tables. Spatial analysis and thematic mapping used ArcGIS Pro. Descriptive statistics reported in the results, including the mean and range of PCI values, were computed directly from the segment attribute table.

RESULTS AND DISCUSSION

Distress Types and Severity Distribution

Alligator cracking and potholing were the most frequently recorded distress types across the eighteen segments, appearing on fourteen and twelve segments respectively, a pattern consistent with the dominant distress types reported by Rajak et al. [34] for a similarly trafficked corridor in Tidore Kepulauan. Rutting was concentrated on the Warri-Ughelli axis, where four of the four surveyed segments showed medium to high severity rutting, most plausibly linked to standing water from inadequate roadside drainage during the preceding wet season. Edge cracking and raveling were more evenly spread across corridors and generally recorded at low to medium severity. Table 1 summarises the dominant distress type and severity band recorded for each segment.

Segment	Dominant Distress Type	Severity
AS-01	Alligator cracking	Medium
AS-02	Potholing	High
AS-03	Edge cracking	Low
AS-04	Alligator cracking	High
AS-05	Raveling	Medium
AS-06	Longitudinal cracking	Low
WU-01	Rutting	High
WU-02	Potholing	Medium
WU-03	Rutting	Medium
WU-04	Alligator cracking	High
OG-01	Edge cracking	Low
OG-02	Potholing	Medium
OG-03	Alligator cracking	Medium
SP-01	Alligator cracking	High
SP-02	Raveling	Low
SP-03	Patching	Medium
UG-01	Potholing	Medium
UG-02	Alligator cracking	High

Table 1. Dominant distress type and severity recorded by segment.

Pavement Condition Index Results by Road Segment

PCI values across the eighteen segments ranged from 25 (UG-02) to 72 (AS-03), with a network mean of 49.4. Ten segments fell into the Poor or Fair bands, seven into the Good band, and only one, AS-03, reached the

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Very Good band; none reached Excellent. SP-02 (PCI 69) falls within the Good band rather than Very Good, just one point below the Very Good threshold. This distribution sits below the PCI averages reported for comparable urban networks elsewhere, for instance the Nasir district network in Amman assessed by Al-Shamayleh [35], which suggests that the Delta State corridors surveyed here are carrying distress loads at the more severe end of what has been documented in the recent literature. Table 2 reports full PCI results and condition classification by segment, and Figure 2 presents the same data as a bar chart.

Segment	PCI Value	Condition Rating
AS-01	61	Good
AS-02	48	Fair
AS-03	72	Very Good
AS-04	35	Poor
AS-05	58	Good
AS-06	66	Good
WU-01	29	Poor
WU-02	44	Fair
WU-03	55	Good
WU-04	38	Poor
OG-01	63	Good
OG-02	50	Fair
OG-03	41	Fair
SP-01	33	Poor
SP-02	69	Good
SP-03	57	Good
UG-01	46	Fair
UG-02	25	Poor

Table 2. Pavement Condition Index values and condition rating by segment.

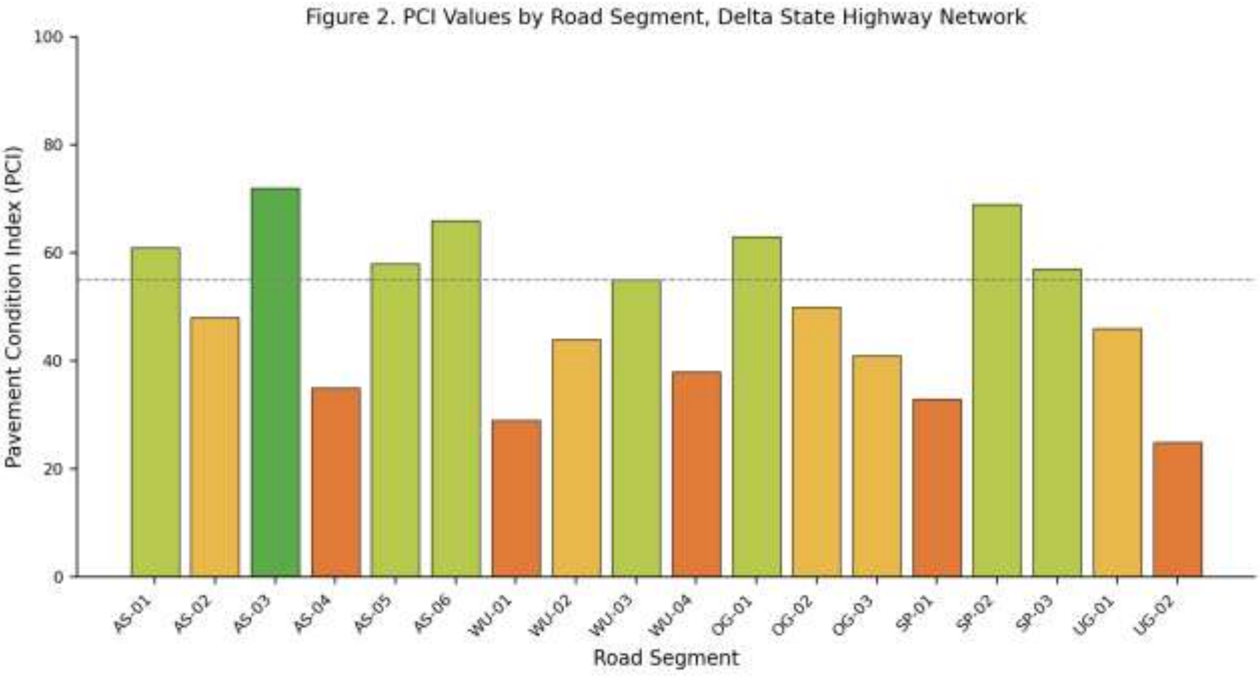

Figure 2. PCI values by road segment, Delta State highway network.

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Spatial Distribution of Pavement Condition

Figure 3, a schematic rendering of the GIS output rather than a georeferenced map extract, places the weakest

segments squarely on the Warri-Ughelli axis and at the Ughelli link. WU-01 (PCI 29) and UG-02 (PCI 25) sit at opposite ends of the same general corridor, separated by roughly two kilometres of intervening road that itself scores no better than Fair. This clustering matters for a reason the tabular PCI data alone would not reveal: a maintenance crew mobilised to WU-01 could reasonably continue to UG-02 within the same site visit, reducing mobilisation cost per kilometre treated. Al-Kazaz and Ewadh [12] reported a comparable finding at intersection scale in Hilla, where a nominally acceptable aggregate PCI concealed sub-units in much worse condition, and the clustering observed here reinforces their point that condition data read in isolation from location understates both the severity and the practical logistics of repair.

By contrast, the Asaba corridor shows a more mixed pattern, with AS-03 (PCI 72) sitting between AS-02 (PCI 48) and AS-04 (PCI 35). This kind of alternating condition along a single corridor is not unusual; Hussein et al. [11] recorded a similar pattern in Karbala and attributed it to localised drainage failure at specific points rather than uniform deterioration along the length of a road, which is consistent with field notes from this survey indicating that AS-04 crosses a low-lying section prone to standing water after rainfall.

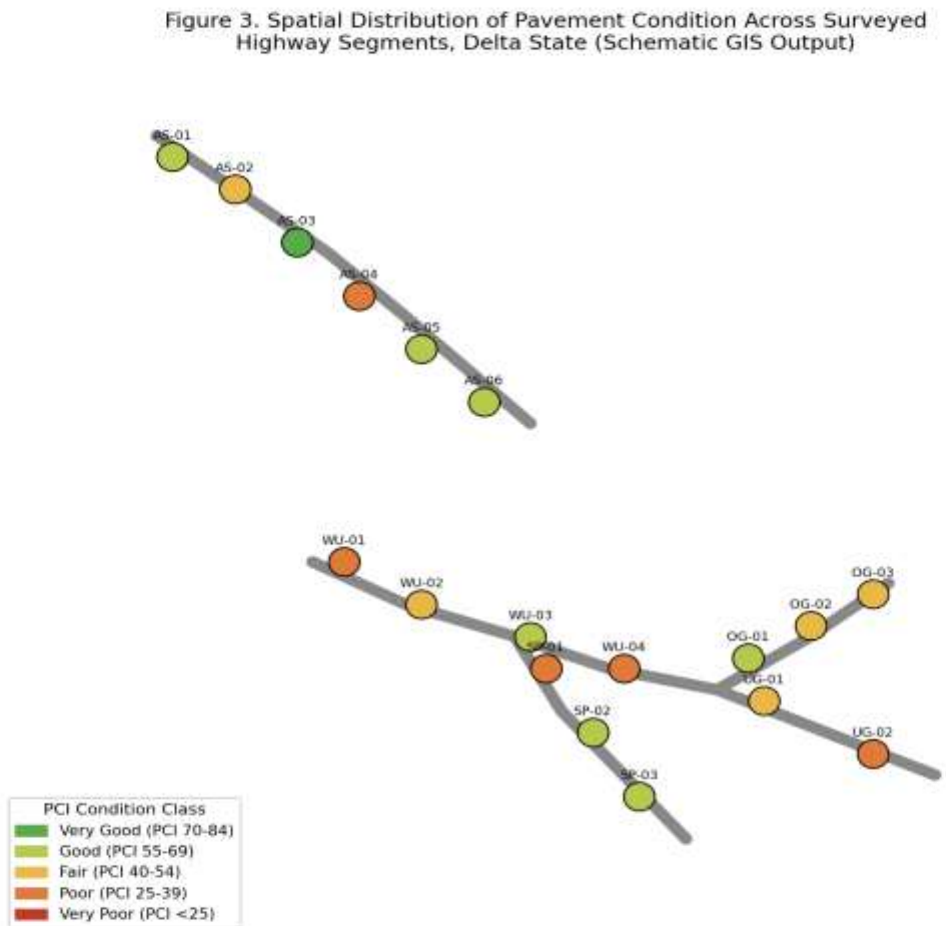

Figure 3. Spatial distribution of pavement condition across surveyed highway segments, Delta State (schematic GIS output).

Maintenance Priority Ranking of Road Segments

Table 3 presents the composite Maintenance Priority Index for each segment, and Figure 4 ranks segments from highest to lowest priority. UG-02 returns the highest priority score (7.5), followed by WU-01 (6.8) and AS-04 (6.6). These three segments combine low PCI with high-severity distress and, in the case of WU-01, the additional weight of heavy petroleum-sector traffic passing through Ughelli. At the opposite end, AS-03 and

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SP-02 return the lowest priority scores, both under 3.0, consistent with their Very Good and Good condition ratings respectively.

Segment	Priority Index	Rank
UG-02	7.5	1
WU-01	6.8	2
AS-04	6.6	3
SP-01	6.5	4
WU-04	6.3	5
OG-03	6.1	6
WU-02	5.8	7
AS-02	5.5	8
UG-01	5.3	9
OG-02	5.3	10
WU-03	4.6	11
SP-03	4.1	12
AS-05	4	13
AS-01	3.8	14
OG-01	3.4	15
AS-06	3.2	16
SP-02	2.9	17
AS-03	2.9	18

Table 3. Maintenance Priority Index and rank by segment.

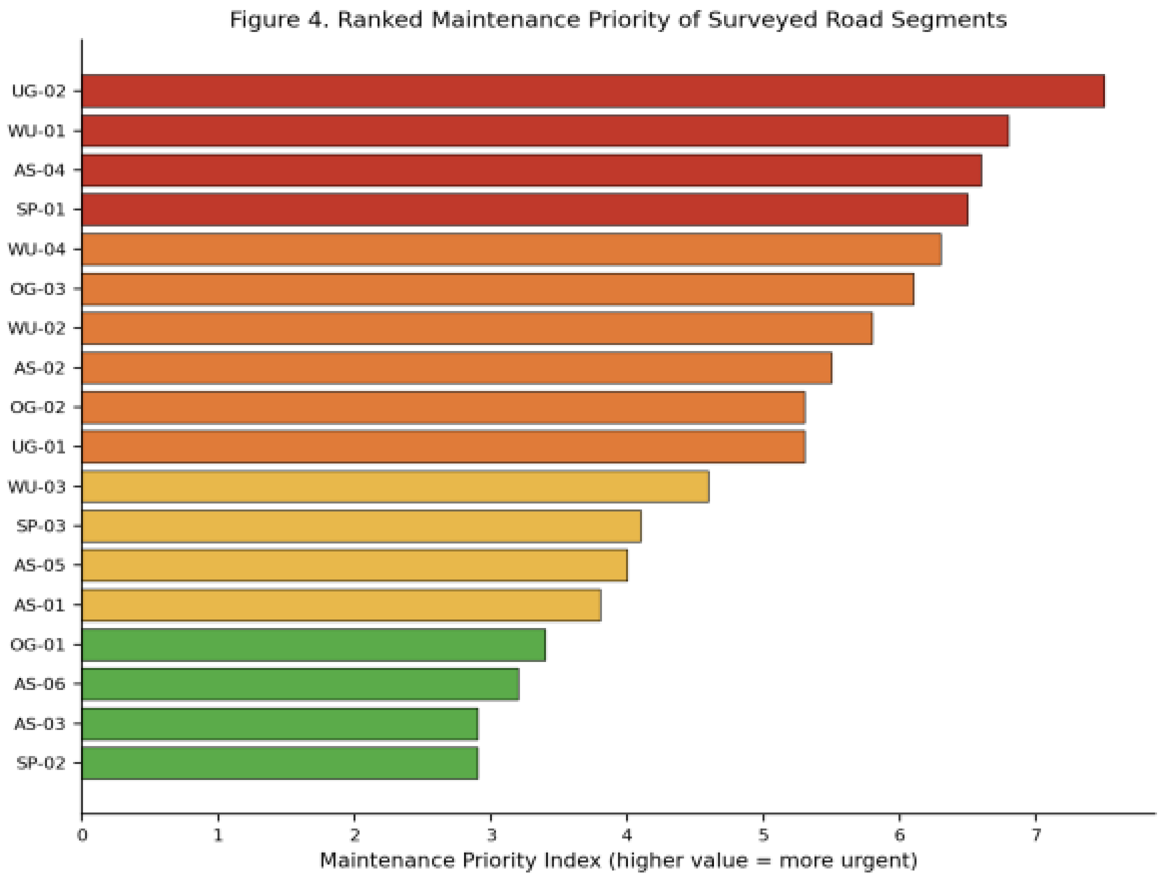

Figure 4. Ranked maintenance priority of surveyed road segments.

Sensitivity of the Priority Ranking to MPI Weights

Because the base weighting (w1 = 0.5, w2 = 0.3, w3 = 0.2) reflects a judgement call rather than a fitted or empirically derived value, the robustness of the ranking was checked against two alternative weighting schemes. A condition-dominant scheme (w1 = 0.7, w2 = 0.2, w3 = 0.1) increases the influence of the directly measured PCI score and reduces the influence of severity and traffic exposure, while a traffic-dominant scheme (w1 = 0.3, w2 = 0.2, w3 = 0.5) increases the influence of the qualitative traffic exposure judgement identified earlier as the weakest input. Under both alternative schemes, UG-02 and WU-01 remain the two highest-priority segments, since both carry a low PCI, a high-severity dominant distress and a heavy traffic classification, so all three weighted terms point the same direction regardless of which term is emphasised. AS-04 is more sensitive to the choice of weights: it holds third place under the base and condition-dominant schemes on the strength of its low PCI (35) and high-severity distress, but drops behind SP-01 and WU-04 under the traffic-dominant scheme, since AS-04's traffic exposure was classified as moderate rather than heavy. This indicates that the case for prioritising UG-02 and WU-01 first is robust to the specific weights chosen, while the ranking of AS-04 relative to SP-01 and WU-04 in third or fourth position depends more heavily on the traffic exposure input and should be treated with the same caution already attached to that qualitative judgement. This sensitivity check does not remove the need for measured traffic counts recommended in Section 5.4, but it does show that the top two priorities identified under Objective Two are not an artefact of one particular weighting choice.

DISCUSSION OF FINDINGS

The PCI results obtained under Objective One place the surveyed Delta State corridors in a condition range broadly similar to what Nautiyal and Sharma [36] documented for low-volume rural roads in India, though the Delta State segments carry considerably higher traffic than that comparison implies, which is the more concerning of the two facts. Ten of eighteen segments in the Poor or Fair bands is a proportion high enough to justify sustained maintenance funding rather than a single emergency intervention, echoing the point Khahro et al. [37] made about the relative weighting of emergency, routine and periodic maintenance plans in resource-constrained pavement management systems.

Beyond the segment-level ranking, the exercise also raises a practical governance point. Balzi and Grilli [38] argued that a GIS-based pavement management tool only produces lasting value for a local road administration once it is written into a standing project evaluation procedure rather than run as a one-off study, and the same caution applies here: without institutional adoption, the priority list in Table 3 will age out of relevance within a season or two as new distress appears and existing distress worsens. Peraka and Biligiri [39], reviewing pavement asset management technologies more broadly, made a related point that image-based and sensor-based data collection tools are converging with GIS platforms in ways that could eventually reduce the labour cost of the field survey step used in this study, though Qureshi et al. [40] cautioned in their review of intelligent image analysis techniques that environmental conditions, pavement type and camera quality still introduce enough variability that automated distress detection cannot yet fully replace visual field survey in a setting like Delta State.

The GIS output developed under Objective Two adds two things the PCI table alone does not provide. First, it shows that the worst segments cluster geographically rather than scattering randomly across the network, a pattern that changes how maintenance crews should be routed and echoes findings from Al-Kazaz and Ewadh [12] and Hussein et al. [11] in Iraq. Second, the composite priority index shifts WU-01 above AS-04 in the ranking even though AS-04 carries a marginally worse PCI, because WU-01's traffic exposure weighting pushes it higher; this is the same effect Yamany et al. [14] reported when traffic volume dominated their hybrid prioritisation weighting in Wyoming, and it illustrates why PCI alone, without a weighting layer, can misorder maintenance priority relative to what the underlying risk actually warrants.

One limitation worth stating plainly is that the priority weighting used here relies on a qualitative traffic exposure judgement rather than measured traffic counts, since traffic count data for these corridors was not available at the time of survey. Gowda et al. [31] and Nie et al. [33] both built their prioritisation frameworks around measured traffic and sensor data respectively, and a future iteration of this framework for Delta State would benefit from the same. Ngene et al. [28] noted that this kind of data gap is common across African pavement management practice, and closing it should be treated as a near-term priority for the state road agency rather than a limitation to be worked around indefinitely.

Two further limitations bear directly on how the results should be read. First, the eighteen segments were selected to represent a spread of traffic exposure and corridor type rather than drawn as a random or stratified sample of the state road network, so the network mean and condition profile reported here describe the surveyed segments themselves and should not be extrapolated as a statistically representative estimate of Delta State highway condition as a whole; a subsequent network-wide survey would be needed for that purpose. Second, distress severity was rated by a single surveyor without independent verification of a subset of segments by a second rater, so the possibility of rater-specific bias in the severity classifications cannot be ruled out; future rounds of this survey should incorporate a formal inter-rater reliability check, for instance by having two surveyors independently rate a sample of segments and reporting the level of agreement.

CONCLUSION AND RECOMMENDATIONS

Summary of Findings

This study assessed pavement distress on eighteen highway segments across five corridors in Delta State and used the resulting condition data to build a GIS-based maintenance priority ranking. PCI values ranged from 25 to 72 with a network mean of 49.4, and ten of the eighteen segments fell into the Poor or Fair condition bands. The GIS mapping placed the most deteriorated segments along the Warri-Ughelli axis and the Ughelli link, and the composite priority index identified UG-02 and WU-01 as the two highest priority segments for intervention, a result robust to alternative MPI weighting schemes; AS-04 ranked third under the base weighting, though this third position was more sensitive to how traffic exposure was weighted.

Conclusion

The two objectives of this study were met. Field-derived distress data produced a usable set of PCI scores for the eighteen surveyed segments, and those scores were converted into a spatially referenced, ranked maintenance priority list through the GIS framework developed here. The clustering of poor-condition segments along specific corridors, rather than an even scatter across the network, is itself a finding with direct operational value, since it changes how repair crews and equipment should be deployed relative to a purely tabular ranking.

Recommendations

The Delta State Ministry of Works should adopt the priority ranking produced here as a starting reference for the next maintenance budget cycle, beginning with UG-02 and WU-01, whose top-priority status held across the alternative weighting schemes tested in Section 4.5, followed by AS-04, whose third-place position is a reasonable working assumption under the base weighting but should be revisited once measured traffic counts are available. Drainage improvement should accompany resurfacing on the Warri-Ughelli axis specifically, since rutting on that corridor points to a moisture-related cause rather than surface wear alone. The state should also establish a routine, GPS-referenced distress survey schedule, run at minimum once per dry season, so that the GIS database built for this study can be updated rather than treated as a one-time exercise.

Suggestions For Further Studies

Future work on this network should incorporate measured traffic count data into the priority weighting rather than the qualitative exposure judgement used here, and should extend the survey to the remaining highway corridors in Delta State not covered in this study. A follow-up study comparing predicted PCI from a machine learning model against the field-measured values obtained here would also help establish whether the lower-cost prediction methods documented elsewhere in the literature hold up under Delta State conditions.

Ethical Considerations

This study involved field observation of public highway infrastructure and did not involve human or animal subjects; no ethical approval was therefore required beyond standard permission from the relevant state road authority to conduct field survey along public rights of way.

Conflict Of Interest

The author declares no conflict of interest in connection with this study.

Data Availability Statement

The segment-level distress and PCI dataset generated during this study is available from the corresponding author on reasonable request.

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