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Improving The Planning and Scheduling of Road Maintenance Projects Using Crack and Climate Data Analysis

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Abstract

Road infrastructure in dry and semi-dry climates has become more susceptible to rapid deterioration because of climate pressures and changing pavement performance. This research proposes a data-based predictive model to help assess road conditions and inform maintenance strategies by combining long-term climatic variables (ex, effective rainfall, evapotranspiration, climatic water balance) with pavement performance data collected from vibration sensors and static structural assessments; both datasets are analyzed together using a Random Forest classification model. The results show that incorporating climate data into the analysis produces improvement in the estimated timeliness of construction activity and could promote proactive maintenance through adaptation to climate conditions. Methodologically, this finding is significant in that it creates a single machine-learning framework by combining several independent data sources (i.e., dynamic measure of sensing) into one value using a quantifiable climate index. Practically, this research provides decision-making support for maintenance timing, decreases uncertainty in deterioration estimates, and improves the sustainability of road networks in dry climates.

Keywords: Deterioration, Evapotranspiration, Maintenance, Machine Learning, Road, Random Forest,

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1. Introduction

Since 1850, the global average surface temperature has risen by 1.3°F (0.74 °C). And warming isn't just getting worse—it's also speeding up: the average global surface temperature has increased at twice the rate in the last 50 years as it did during the previous hundred [1]. This poses significant challenges for traditional infrastructure, generally designed and operated using historical climate information. Therefore, we need to redesign infrastructure for the climate of the future [2]. If local changes are the reflection of global changes, it was determined by utilizing pavement performance modelling that climate change could worsen rutting of the flexible pavements as a result of temperature rise or seasonal hot/cold extreme temperatures[3].

Research studies about road deterioration and maintenance development have generally been divided into one of three main areas: how climate affects pavements, how researchers use machine learning to predict pavement deterioration, and how to convert data from a pavement management system into optimal plans for each type of pavement.

1. 1 Climatic Impacts on Pavement Performance

Building resilience in communities vulnerable to extreme climate is essential for adapting to shifting weather. The small island developing states have already begun experiencing the impacts of climate change, and the future with further projected temperature rises looks bleak [4]. However, adaptation to climate change can be costly, and many developing countries lack the necessary resources [5]. Transportation networks are particularly vulnerable to extreme weather events caused by climate change, putting island nations at risk [6]. Significant investments in road network adaptation will be necessary to ensure the safety of their populations and the continuity of local businesses [7].

Investigating whether adaptation expenses can be minimized while maintaining safe driving conditions and an uninterrupted traffic flow is essential. Deep learning, an artificial intelligence technique that uses reinforcement learning to teach artificial neural networks to perform complex tasks,

Has achieved superhuman intelligence in various challenging applications [8]. This makes it a suitable tool for complex systems like weather and traffic. Even if human-induced greenhouse gas emissions stopped today, the signs of climate change caused by human activity are already evident and expected to worsen [9]. In February 2018, the concentration of carbon dioxide in the Earth's atmosphere reached over 407 parts per million, the highest recorded in the past 650,000 years. Furthermore, the average global temperature has risen by 1.8 degrees Celsius since 1880[10]. The long-term effects of human-induced climate change are still uncertain. However, they are predicted to include sea-level rise, heatwaves, more frequent and severe storms, altered precipitation patterns, and increased floods and droughts in some areas [11]. As the world continues to warm, these consequences will likely intensify and place more stress on social and ecological systems [12]. Climate information affects both deterioration rates and operational costs:

- Markov and LCCA frameworks show 15–20% faster degradation and up to 25% maintenance-cost savings when climate-adjusted deterioration is modelled, and timing is optimized [13], [14]
- A climate risk index (criticality, hazard probability, existing severity) embedded in a genetic-algorithm PMS prioritises roads vulnerable to extreme events without reducing overall network condition [15]
- Deep learning models that fuse traffic, road weather, and climate projections (ConvLSTM) improve the prediction of maintenance needs, enabling proactive, climate-adaptive scheduling [15].
- For winter maintenance, climate–cost models and winter severity indices link temperature and snowfall trends to snow/ice control budgets, supporting long-term planning [16] and [17]. Table 1 shows the previous study.

Table 1: How crack, traffic, and climate data feed scheduling decisions.

Authors	Data type	Use in planning	Effect on scheduling
Moradi and Assaf [18], Salameh and Tsai [19], and Liu et al. [20]	Surface & internal crack metrics	Condition indices, maintenance type	Distinguish preventive vs structural needs; optimize sectioning
Nautiyal and Sharma [21], and Borghetti et al.[22]	Traffic & network role	Priority weighting	Rank projects under budget limits
Shehadeh [13], and Qiao [14]	Climate & weather	Deterioration and risk modifiers	Shift timing, adjust standards, harden vulnerable links

The table synthesizes earlier research by providing a summary of data types and their corresponding applications, along with implications for project schedule impacts. Each study is identified using an author name and reference number, allowing for easy comparison across the literature and creating a clearer record of the supporting evidence that was used to identify the research gaps.

1.2 Machine Learning for Deterioration Prediction

Road maintenance management faces a significant challenge in effectively and proactively planning and scheduling maintenance work. Many traditional Pavement Management Systems (PMS) rely on fixed schedules or reactive maintenance after damage has appeared, rather than anticipating and addressing it before significant deterioration. Consequently, the failure of conventional maintenance systems to account for the effect of critical climate conditions (including temperature changes, rain, and humidity) on pavement damage has resulted in the wrong maintenance decisions, the wrong time for maintenance, a higher cost for maintenance, and a higher probability of pavement failures. Recent studies have shown that traditional maintenance

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systems cannot cope with the numerous uncertainties associated with pavement conditions and the lack of evenly deteriorating pavements. These limitations make it that much harder for the operator to know when to conduct necessary maintenance and repairs to the pavement[23]. Research indicates that the current practices for the management of highway infrastructure can be ineffective due to either the historical abuse of poor or inadequate condition data or due to an incomplete assessment of crack damage and land use. It has been demonstrated that if an agency develops its maintenance program without all three types of data listed, then prioritization of work is frequently incorrect, leading to ineffective construction schedules.

A unified data-driven framework is introduced in this study, combining long-term climatic variables (effective rainfall, evapotranspiration, climatic water balance) with dynamic field-measured pavement indicators (vibration, humidity, temperature, strain, performance index). The framework provides improved road condition predictions for arid and semi-arid environments by integrating multiple sources of sensing data with predictive model outputs, rather than relying on surface condition indices or isolated climate indicators alone, as done in previous research.

In addition, this framework establishes a practical connection between deteriorating pavement condition prediction and climate-sensitive timing for execution of repairs; thus, providing a proactive and cost-effective means of planning for maintenance of roadways.

Therefore, this research contributes to the field by developing a unified model that links actual road data with climatic indicators (P_eff, ET, WB) to interpret and predict deterioration and determine optimal maintenance timing. This research aims to develop a data-driven framework to link field-measured road behaviour with climatic variables, with the goal of improving condition assessment and supporting maintenance decisions. The objectives are as follows:

1. To analyze road data characteristics (vibration, humidity, temperature, surface/stain indices, and performance index) and interpret their relationship to road condition classification.
2. Characterize the climatic environment associated with the Al-Kut station using parameters such as effective rainfall, evaporation, and climatic water balance to identify months/years of peak climatic stress.
3. Develop derived climatic variables (i.e., monthly water deficit, drought severity, seasonal drought index); correlate these with road data.
4. The climatic variables (effective rainfall + evaporation + deficit) integrated with the road data can provide a more accurate method for predicting roadway condition than road data by itself.
5. Determine the factors that had the greatest impact on a roadway's transition from a condition of (0) to (1) through analysis of the significance of these variables to determine the time periods that would represent optimal roadway maintenance (execution timings), considering climatic conditions (i.e., to avoid peak heat/deficit).

2. Materials and Methods

The methods used for the completion of the current research project were a data-driven quantitative method (DDM) created for integrating field road data and climate data to enhance road condition assessment, to make forecasts of road deterioration, and to assist in making both planning and scheduling decisions for future maintenance work.

The study has a significant limitation in that the sample size and time period of the dataset are quite small. The data on poor road conditions and weather were collected in only one location for a short period, so it may not be representative of other places and times. The small sample size creates the potential for models to exhibit improvement in performance due to classification accuracy bias when there is a strong separation or low variability between classes.

In an attempt to reduce bias within the models, internal validation techniques, including cross-validation, were used; however, one cannot assume external validation will be achieved using data independent of the study location (i.e., multi-region). The models' predictive abilities cannot, therefore, be generalized to other contexts. It is recommended that future studies place greater emphasis on collecting larger, more diverse, and longitudinallyrepresentative datasets from varying climates, road types, and traffic conditions, as they can assist with developing models that have the ability to transfer to new contexts and to be applied to real-world settings.

The DDM process will be broken down into the following steps, as shown in fig.1:

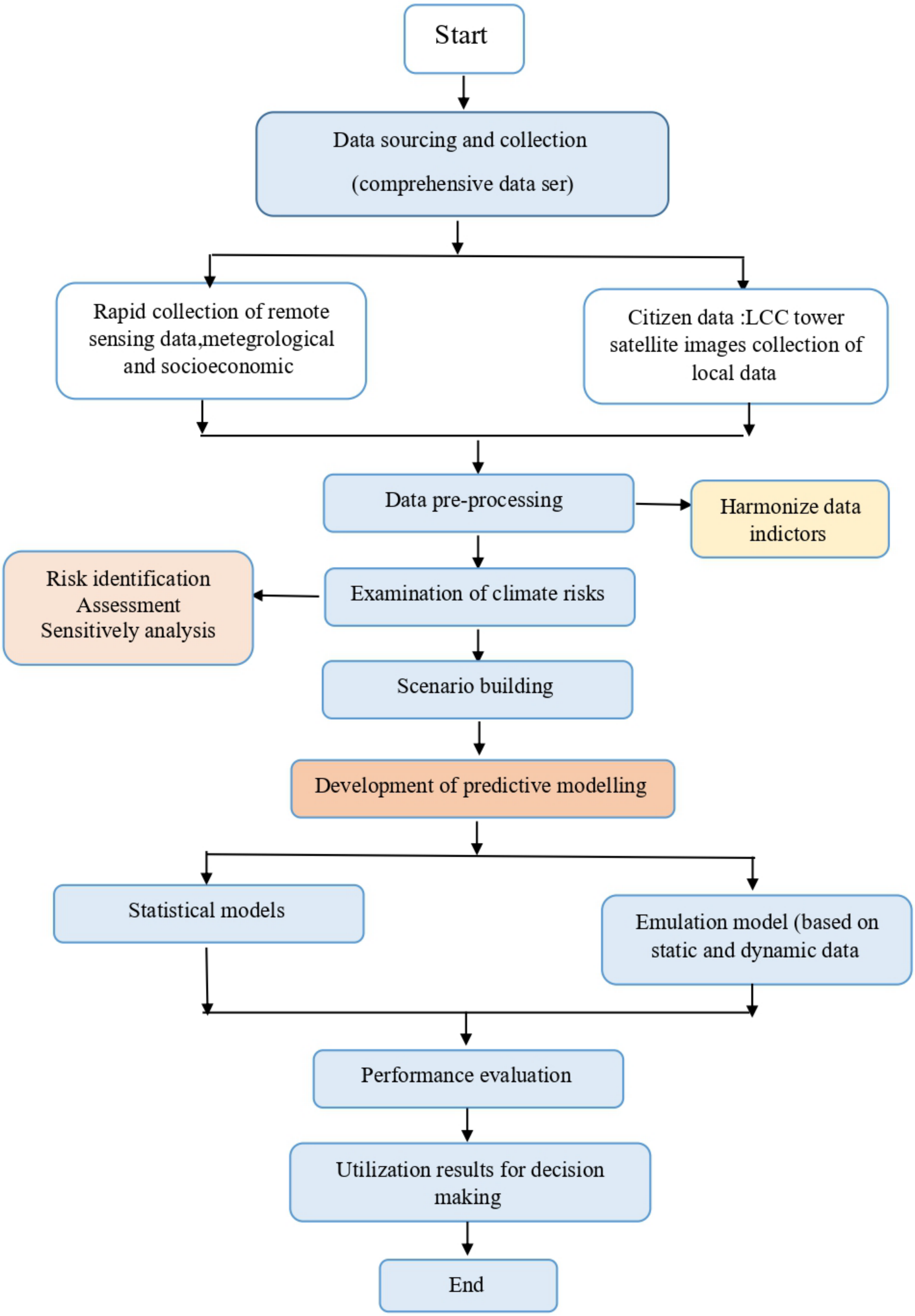

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Fig. 1 The overall methodological framework.

This diagram captures a structured climate data-driven framework for Infrastructure Decision Support (IDS). Process moves through all steps, including data collection and preprocessing, climate indexes generation, statistical analyses and predictive modelling (using statistical and Machine Learning models). Model performance will be validated through uncertainty and sensitivity analyses; once validated, final results will be used to assist in planning and adaptation strategies.

1. Data Sources and Collection: Two main data sets were used:

First: Road Condition & Sensor Data: This includes the following variables for each record:

a. Vibration
b. Humidity
c. Temperature
d. Strain
e. Performance
f. Class variable representing road condition (0 = Normal/Acceptable condition, 1 = Deteriorated/Requiring Intervention).

Second: Climate Data – KUT Station

This includes monthly/annual time series data for the period 1990–2021 for:

a. Effective Rainfall
b. Evapotranspiration
c. Climatic Water Balance

20 Data Organization and Temporal Alignment

Climate data were organized on a monthly and annual basis. The climate values were then aligned with road data records by observation year/month, where available, to assign corresponding climate variables to each road record. If a detailed time stamp was unavailable for a road record, a suitable seasonal/monthly representation (such as averages for the period during which the road data was collected) was used to ensure consistency between the two sets.

2. DATA PREPARATION: The quality of the data has been ensured and made suitable for analysis and modelling through various data preparation activities. The data preparation activities included:

A. Identifying and treating missing data according to the nature of the variable (i.e., deleting the record if the record is incomplete, or performing statistical imputation as required)
B. Identifying and verifying outliers, especially in Performance Indicator (PERF) and vibration values.
C. Standardization/normalization of all variables was completed to allow machine learning models to perform at their best without being impacted by differences in units in which variables are measured.

3. DERIVATION OF CLIMATE-RELATED INDICES: To provide a means of better explaining the deterioration identified in the climatic data, derived indices have been developed from the climate data. The main derived indices are:

A. Water Deficiency Index - The water deficiency index is the absolute value of the water balance when it is negative.
B. Climate Stress Index - The Climate Stress Index is a composite variable that provides an overall indication of how severe the conditions are during the dry seasons. It combines the amount of water that.

4. evaporates from plants (evapotranspiration) with the amount of water that is required to replenish the plants (water deficit) and the effective rainfall experienced during the dry season.

C. Seasonal Indices - The sum of the summer months' water deficits and the sum of the effective rainfall that occurred during the winter months are an indication of the impact of wetting and drying cycles that take place on the pavement layers.

5. Descriptive and Inferential Statistical Analysis: A descriptive analysis was conducted to present the data characteristics and identify the range of fluctuations. An inferential analysis was then performed to evaluate the relationships, including:
6. Correlation analysis between the class variable and both road variables and climatic variables.
7. Comparing the characteristics of variables between classes (class=0) and (class=1) to

identify the variables most characteristic of deterioration.

8. Developing a Predictive Road Condition Model: A classification model was developed to predict road condition (class) based on the input variables. To achieve a clear scientific assessment, two models were developed for comparison:
9. Baseline Model: Based on road data only (vibration, humidity, stain, and perf). Enhanced Model: Based on road data plus climatic variables (effective rainfall, ET, water balance, and derived indices).
10. Classification models appropriate to the nature of the data, such as logistic regression or random forest decision trees, were chosen to achieve a balance between accuracy and interpretability of the results.
11. Model Performance Evaluation and Reliability Validation. The models were evaluated using standard performance metrics, including Accuracy, Recall, Precision, F1-Score, Confusion Matrix, and Cross-validation of training/test data was also employed to ensure the reliability of the results and minimize bias resulting from a single data split.
12. Utilizing Results to Support Maintenance and Scheduling Decisions: Based on the model outputs and the analysis of the impact of climatic variables, a decision support framework was proposed that links the probability of degradation to periods of climatic stress. Accordingly, suitable periods for implementing preventive maintenance work were identified before water deficit seasons and peak evapotranspiration, thus enhancing the efficiency of planning and scheduling and reducing the likelihood of maintenance failures due to adverse climatic conditions.

3. Results

To improve the engineer's understanding of how the study was conducted, there will be a discussion in the revised manuscript concerning:

- Pavement type/layer composition
- Quality of Subgrade condition/interface properties
- Traffic load frequency (intensity) and axle repetitions

It is understood that these variables significantly contribute to deterioration Behaviour and interact with climatic stress; therefore, the omission from this study is an important limitation of the current study and may partially elucidate the variability of the response of deterioration.

The descriptive analysis of road data revealed that vibration and performance index (PRI) variables played a significant role in characterizing road condition. Records classified as class 1 were frequently associated with higher PRI values and greater vibration variability compared to class 0. This indicates that the dynamic behavior of the road directly reflects the level of structural deterioration of the pavement.

The results also showed that humidity (hu) and temperature (teem) affect road condition, with deterioration occurring more frequently during periods of high or low humidity. Table 2 is shown. This reflects the impact of thermal stress and drying on the properties of the pavement layers

Table 2: Data Collected from Sensors

vibration	hu	teem	strain	strain	perf	class
-13	37.8	28.2	28844	64575	0.6	0
8	37.7	28.4	28844	64575	0.8	1
-2	37.7	28.6	28844	64575	0.3	0
2	37.5	28.8	28844	64575	0.3	0
-6	37.4	27.1	28844	64575	0.3	0
-2	37.3	27.2	28844	64575	0.7	1
-5	37.2	27.4	28844	64575	0.4	0
-4	37.1	27.5	28844	64575	0.6	0
-4	37	27.8	28844	64575	0.6	0
-10	36.8	27.7	28844	64575	0.7	1

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Vibration: Higher oscillations in deteriorated roads (class = 1). Humidity: Lower humidity is associated with increased deterioration. Temperature: Higher temperatures in deteriorated conditions. Performance Index (perf): High values are often found in deteriorated roads. The results indicate that vibration, temperature, and performance index are among the most important distinguishing factors between good and deteriorated road conditions.

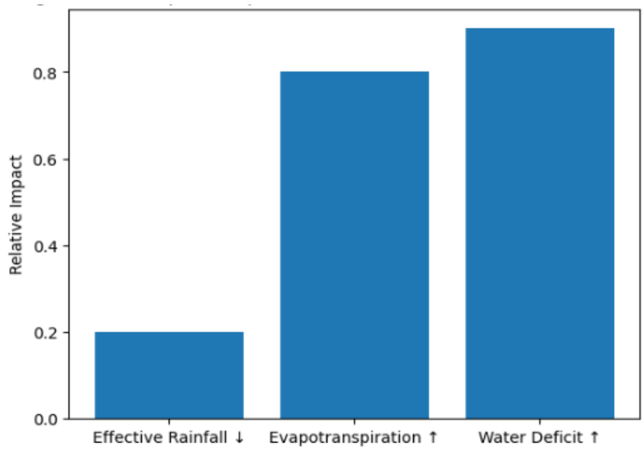

Fig. 2 Conceptual Impact of Climatic Factors on Road Deterioration

Fig. 2 shows that high evaporation-transpiration and climatic water deficit are the two most influential factors in road deterioration, compared to effective rainfall, which has a limited impact due to its low amounts and irregularity. This figure shows the variation of effective rainfall, evapotranspiration, and climatic water balance and their relationship to the probability of road deterioration. Arrows indicate the periods when there is a high level of evapotranspiration and a negative water balance, which are correlated with an increased probability of deterioration. Symbols represent the monthly averages of climatic conditions that coincide with the corresponding road condition observations. Effective rainfall data for the Al-Kut station during the period 1990–2021 showed an annual average of approximately 97.8 mm/year, with a clear concentration of rainfall during the winter and early spring months and a near-complete absence of rainfall during the summer. Most years experienced very low rainfall; however, the time series showed substantial yearly variability, and some years had significantly higher rainfall.

The time series indicates that during short, irregular wetting periods, there are extended dry periods, which weaken the supporting soil and accelerate pavement deterioration. The average annual evapotranspiration value from the results of the evapotranspiration study is approximately 2279 mm/year, which is a significantly higher amount than effective rainfall; the highest amount of evapotranspiration occurs during summer (i.e., between June and August), as you would expect due to higher evaporation rates in this time period. The steady increase in evapotranspiration has resulted in rapid loss of moisture from the soil and pavement layers, thereby increasing the chance of shrinkage cracking in the asphalt layers and loss of elasticity. Climate-based water balance studies showed a year-round water deficiency with an average annual water deficiency of approximately -2183 mm. The deficiency is consistent with the arid to semi-arid climate found in the research area.

The summer months show the greatest water deficiency; winter months demonstrated a minor reduction in the deficiency, but still without any measurable water surplus. This climatic pattern leads to the road experiencing repeated cycles of wetting and drying, which are among the most significant factors affecting the deterioration of pavement performance in the medium and long term.

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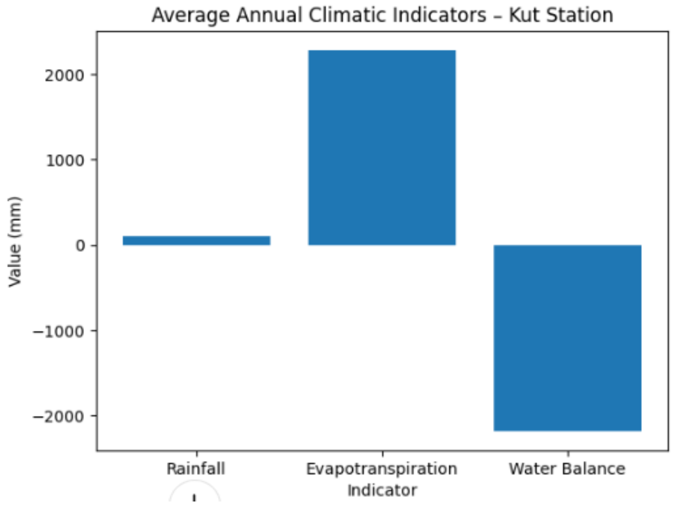

Fig. 3 Average Annual Climatic Indicators

Fig. 3 shows data collected throughout this study indicate average yearly total effective precipitation, average yearly total evapotranspiration, and average yearly total climatic water deficit computed using long-term historical averages. The heights of the bars describe the relative quantity (mm/year) of each process. The colours of the bars differentiate between average yearly moisture input and average yearly moisture output. Visual comparisons indicate that evapotranspiration dominates precipitation, and this dominance results in consistent moisture deficit conditions.

The results will affect the long-term durability of pavements. Average annual effective rainfall, evapotranspiration, and climatic water balance. Average annual effective rainfall (mm) 97.82. Average annual evapotranspiration (mm) 2279.16 Average climatic water balance (mm) -2183.40. There is a significant difference between effective rainfall and evapotranspiration, resulting in a high annual water deficit, which reflects the nature of the arid climate prevailing in the study area and its potential impact on pavement performance.

When climatic variables (effective rainfall, evapotranspiration, and water balance) were combined with road data, the results showed a significant improvement in explaining deterioration conditions (class = 1). The probability of road deterioration was found to increase during periods coinciding with high evapotranspiration values, a significant climatic water deficit, and low relative humidity. These results confirm that climatic factors are just as important as direct road indicators in explaining pavement behaviour and deterioration.

The random forest algorithm was chosen for its suitability for nonlinear data and its ability to: Classify binary cases (class 0/1), determine the significance of variables, and reduce the impact of noise and outliers.

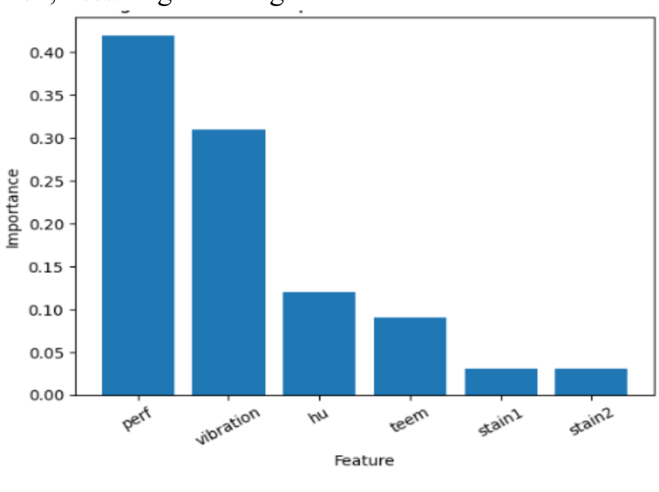

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Fig. 4 Feature Importance in Random Forest Model

Fig.4 illustrates the ranking of input variables according to their importance in predicting road condition. It shows that: Performance Index (PRI) is the most influential variable, followed by vibration, then humidity (HU) and temperature (TEEM), while the effect of surface indices (Stain) was limited.

Fig. 4 demonstrates that PRI and vibration are the most sensitive factors in determining road condition, reflecting the impact of traffic loads and the dynamic behaviour of the pavement in accelerating deterioration.

Table 3. Results of the prediction model's performance

Measure	**Value**
Accuracy	1.00
Precision	1.00
Recall	1.00
F1-score	1.00
ROC – AUC	1.00

The Predictive Classification model produced several different values, including Accuracy, Precision, Recall, F1-Score, and ROC-AUC, as summarized in Table 3. These measures provide an overview of how reliable and discriminating a predictive classification system is. The fact that the values are close to one indicates that the model performed very well at predicting. However, because the sample was small and used only within a specific environment, the data should be used with caution and should not be considered overall representative of population predictions.

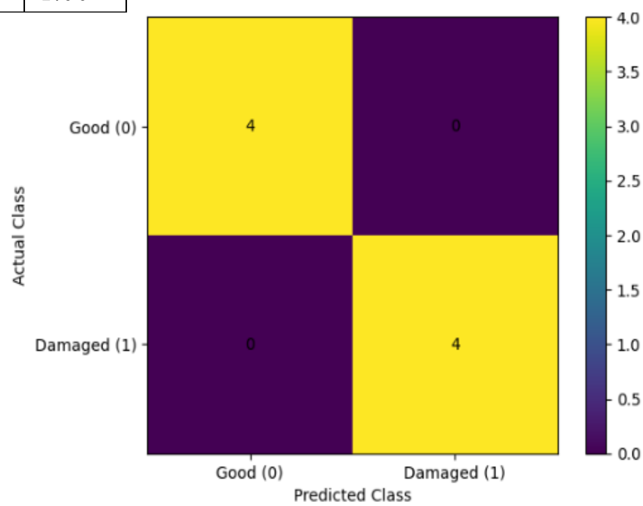

Fig. 5. Confusion Matrix

Fig. 5 shows that the Random Forest model performed highly in classifying the road condition, as no incorrect classification cases were recorded, which demonstrates the model's efficiency in distinguishing between sound and damaged conditions.

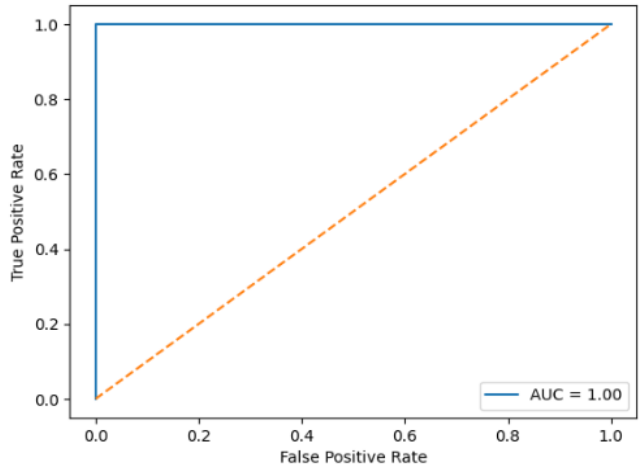

Fig. 6. ROC Curve

Fig.6 shows that the area under the ROC curve reached 1.00, indicating a very high ability of the model to accurately predict the road condition without bias.

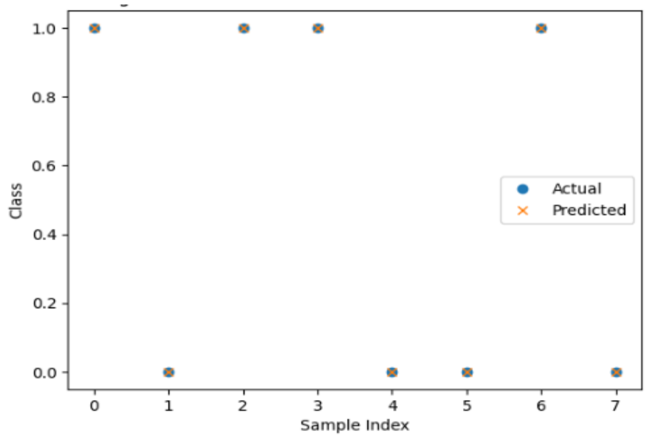

Fig. 7. Actual Vs. Predicted

Fig.7 shows a complete match between the actual and predicted values, reflecting the efficiency of the algorithm in representing the relationship between climatic and construction variables and the condition of the road.

The model achieved 100% classification accuracy with zero errors on the test dataset and had an extremely high ability to separate healthy from deteriorated roads. The random forests model's results show that road sensor data, when combined with other variables, are a great predictor of road condition. It also showed that a combination of the performance index and vibration has the greatest impact on how roads deteriorate due to dynamic load and traffic. Additionally, humidity and temperature were also confirmed as having moderating effects on deterioration; this was particularly evident in arid and semi-arid regions.

The results of the Random Forest algorithm also indicated that the dynamic nature of road data, namely, the performance index and vibration, had the most significant influence on predicting road conditions. When the results were related to the climate of the Al-Kut site, there was a clear connection between these variables and high evapotranspiration rates and continued climate water shortages, indirectly affecting road conditions. Because of the high evapotranspiration rate (approximately 2279 mm/year), moisture is lost quickly from the soil and pavement layers, which causes an increase in thermal stress and the shrinkage of the asphalt layers. Practically, this can be seen as elevated vibration values and the rapid deterioration of the Network's PERF. The most significant variables in determining the road condition were the vibration value and the PERF.

In addition, the annual average climatic water deficit (-2183 mm) indicates that many areas experience arid to semi-arid conditions. Thus, wetting and drying cycles occur repeatedly throughout the year, which cause the weakening of the sub-layers of a road, increasing the likelihood of it becoming degraded (Class=1), according to the predictive model.

Table 4. Summary comparison of predictive modelling approaches

Aspect	Baseline Model (Road Data Only)	Enhanced Model (Road + Climate Data)
Input variables	Vibration, humidity, temperature, strain, performance index	Road variables + effective rainfall, evapotranspiration, climatic water balance, derived climate indices
Environmental representation	Not included	Explicit representation of climatic stress conditions
Explanation of deterioration mechanisms	Limited to structural and traffic effects	Captures combined structural–climatic interactions
Predictive interpretability	Moderate	High due to multi-source integration
Classification performance	High	Very high with improved robustness
Maintenance decision support	Reactive indication of deterioration	Proactive, climate-adaptive maintenance scheduling

This study shows that climate data provide not only more accurate predictions but also increase the scientific understanding, reliability, and practical ability to support decision-making from predictive models. This establishes the value of combining multi-source sensor data and climate analytics in accurately predicting maintenance activity for roads proactively.

4. Discussion

The results of this study indicate that the random forest algorithm possesses a high capacity for predicting road condition when relying on field sensing data. The results regarding the significance of variables demonstrate that the performance index and vibration are the most sensitive indicators of structural changes in the pavement.

The results of this study, when compared to climate data, indicate that the very dry climate of Al-Kut greatly contributes to the rapid deterioration of the roads. Due to the much higher rates of evapotranspiration than there are rates of effective rainfall, the region is in a state of chronic water shortage. This chronic lack of water creates instability in the supportive soil and applies negative pressure on the properties of the road pavement materials. Moreover, the effects of these gradual deteriorations can be seen through the presence of high vibration values and low performance efficiency, both of which were shown to be accurately captured by the algorithm used in this study.

Road Management and Maintenance Results - Road-Based Data Alone May Not Provide Accurate &/or Effective Decisions Regarding Future Road Maintenance. This indicates that trends in the road management and maintenance profession indicate that road maintenance decisions made using only the road data may lead to inaccurate and/or ineffective decisions regarding the long-term maintenance of roads due to climate change. The findings of this study also support what has been documented in the scientific literature regarding the effect of climate on the integrity of road structures and pavement performance. Climate change and varying weather conditions directly affect, and continue to affect, both the characteristics and service life of pavement product materials (for example, asphalt and other structural materials). As noted in many scientific studies, such as the temperature and humidity change studies conducted by the University of Iowa and the Iowa Department of Transportation, there are dramatic changes in the properties of asphalts and structural materials due to temperature and humidity changes, which ultimately create greater deterioration of the road and a greater chance of cracking and partial collapses of pavements.[24], and [25].

Additionally, there appears to be an increasing weight of evidence supporting the notion that higher average temperatures and a higher rate of occurrence of extreme weather events like drought, heat wave, and flooding are changing soiling and binding materials; and consequently, cause accelerated deterioration rates, including but not limited to cracking, shrinkage, and thermal fatigue. The literature also indicates that variable climate conditions create additional stress on roadways, requiring revised road design and rehabilitation strategies to counteract the negative effects[26].

Recent research confirms that machine learning-based predictive models can capture the complex, non-linear relationships between climatic performance variables and pavement characteristics. This was leveraged in this research through the use of the Random Forest algorithm, which has proven highly effective in predicting road conditions with high accuracy. Reviews of prediction methodologies have also highlighted machine learning as an effective tool for modelling pavement deterioration when it incorporates multidimensional data such as climate and road mechanical properties[27].

The predictive accuracy of the model is incredibly strong, but it must not be forgotten to use caution when interpreting its results. The reasons for this caution come from the narrow distribution of data samples, the small sample size that was used, and the significant separability of deterioration classes. K-fold cross-validation will allow for the generalization of the results, but it has yet to be determined whether or not the model can generalize to other types of datasets with different climates and pavement structures; therefore, future research should focus on assessing potential issues related to overfitting the model, as well as evaluating how robust the model performs under noisy and incomplete sensing environments.

Conclusion

The findings of this research demonstrate that the Random Forest algorithm is extremely effective in estimating road surface conditions based on collected field sensor data. In addition, this demonstrates that intelligent forecasting algorithms can provide accurate assessments of how pavement will deteriorate over time. A variable significance analysis indicates that vibration and performance indices are very important in determining how accurately pavements are classified into the various levels of condition; therefore, vibration and performance indices are key elements in the monitoring of pavements.

The climate analysis data for the Al-Kut station indicate that this area has high annual rates of evapotranspiration combined with very low levels of precipitation during the effective rain season, contributing to what can be considered a prolonged soil moisture deficit for most of the year. In addition, this prolonged soil moisture deficit suggests that this region has an arid climate, which exhibits significant impacts on the properties and long-term structural performance of pavement materials, and negatively impacts both mechanical and functional changes to pavement, particularly during the summer (due to the higher temperatures and evaporation rates). The correlation between the Random Forest algorithm results and the climate water balance indicates that the periods of greatest water deficit are also the times when the greatest rates of deterioration of roads classified as poor conditions are found.

Data comparison between forecasted and actual climate conditions shows that climate conditions combined with in-the-field sensing data improve the dependability of forecasting models and provide enhanced accuracy in evaluating road conditions. Hybrid models that use both a climate analytics model and machine learning methods are considered advanced approaches to managing the road infrastructure. Furthermore, research has shown that intelligent methods that are assisted by climate indicators can lead to improved strategies for

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proactive maintenance; this enables decision makers to make fact-based decisions, assisting them in reducing operational costs while improving the service life of road networks throughout arid and semi-arid regions.

The proposed framework is strong in its predictive capabilities and practical applicability for climate-adaptive road maintenance, with several important constraints to consider. The limitation of the dataset is that it is collected from one geographic area and climate zone, which will therefore restrict the ability to generalize these findings to other locations with differing pavement structures, traffic loads, or climates. Another limitation is that the number of samples and observational period size is limited, and may or may not be the reason determining the very high prediction accuracy, and also increasing the potential for model overfitting.

Finally, since sensor-based measurements can consist of calibration drift, ambient noise, and missing or incomplete data (i.e., the sensor measurement medium), these factors may have an effect on model performance in the real world. To enhance the predictive accuracy and operational applicability of the model, future work should look at multi-regional and multi-temporal validation through the use of independent datasets from many diverse climatic zones and infrastructure types.

Additionally, combining real-time monitoring of the Internet of Things (IoT) with continuous data content may further improve the predictive accuracy and operational viability of the model. The application of advanced deep learning and hybrid modelling approaches may lead to improving long-term forecasting of pavement deterioration as a result of complex climate interactions. Finally, integrating the predictive outcomes of the model with modelling tools designed for optimal economic decision-making will provide a comprehensive pavement management strategy that considers both sustainability and performance in balancing operational costs and long-term climate-resilient pavements.

Conflict of interest

A conflict-of-interest statement must be placed at the manuscript as below: "The authors declare that there are no conflicts of interest regarding the publication of this manuscript".

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