International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 06, June 2026)

Modeling the Coupled Effects of Temperature, Rainfall, and Flooding on Pavement Performance Using a Multi-Index Data-Driven Framework

***Abstract*--** **This paper proposes a multi-index data-driven model to simulate the influences of temperature, rainfall and flooding on pavement performance using meteorological data. A regression model was developed to predict a Pavement Performance Index (PPI). The model was found to have high predictive power (R^2 = 0.92), thus high impact of the climatic ones. The most prevalent factors were found to be flooding and rainfall with temperature having a moderate impact. This is explained by the comparatively high R^2 which is a result of the structured development of climatic indices. The structure offers a foundation to comprehend pavement degradation due to climate and climate-resistant infrastructure planning.**

***Keywords*--** **Climate resilience, Pavement performance, Flood index, Rainfall impact, Data-driven modeling, Transportation infrastructure.**

I. Introduction

The rising rates and severity of extreme climatic conditions have had a major effect on the sustainability and resilience of urban infrastructure systems. The increased pace of urbanization, along with climate variability, has made transportation systems, especially pavement of roads, to be susceptible to various environmental pressures including changes in temperature, excessive rain and even floods. Urban planning strategies should thus be tailored to include climate-adaptive strategies to deal with these effects and also provide long-term infrastructure resilience (Abubakar et al., 2025).

Transportation infrastructure is a very vital component of the functionality of the urban area and failure during extreme events may result in significant socio economic losses. Past materials highlighted the significance of resilience in the transport systems, especially regarding the recovery process after a disaster and network stability (Aghababaei et al., 2021). Structural and functional features of urban street systems, such as travel demand distribution and network interconnectedness, affect the resilience of urban street networks (Akbarzadeh et al., 2019). These aspects underscore the importance of having combined structures that have the ability of evaluating and optimizing the strength of infrastructure systems during environmental stress.

Recent studies have also been on climate adaptive planning and resiliency-based practices to enhance infrastructure performance in uncertain conditions. Beheshtian et al. (2018) suggested the use of adaptive strategies in planning transportation energy systems to be able to improve their long-term resilience to climatic disturbances. On the same note, Cimellaro et al. (2010) created a quantitative model on the achievement of disaster resilience which focused on the significance of performance-based evaluation in infrastructure systems. They have also been applied to city resilience programs using this structure, and recovery and emergency response are taken into account (Cimellaro, 2016).

The concept resilience has been of major attention as a national and global priority, especially in the climate change and risks reduction of disasters (Cutter et al., 2013). Resilience assessment in transportation systems has been developed to entail more sophisticated computational and decision-making methods. An example is that Deveci et al. (2023) employed fuzzy multi-criteria decision-making models that were used to assess intelligent transportation system scenarios in terms of resilience improvement. In a similar manner, Domaneschi et al. (2024) suggested probabilistic frameworks in which structural health monitoring is integrated in infrastructure resiliency measurement.

The significance of measuring the performance of the transportation systems in extreme conditions has also been proved through empirical studies. As noted by Donovan and Work (2017), the data-driven methods of evaluating system-level resilience during disruptive incidents are necessary. Moreover, the recent case study of the events of urban flooding and waterlogging has highlighted the harsh consequences of extreme rainfall on the performance of transportation infrastructure (Sunfeng et al., 2024).

With regards to the pavement engineering, the behavior of the material, and its durability are greatly affected by the environmental conditions like moisture infiltration and temperature changes. The development of asphalt mixtures, such as self-healing, has been examined to increase the life of pavements in different weather conditions (Jwaida et al., 2024).

Also, the use of alternative materials and fillers has been considered to enhance the performance and resistance of pavements to environmental stress (Kabadayi et al., 2024).

In spite of this development, the United States still faces a critical situation in the need to have integrated data-based frameworks that can help in capturing the synergies of various climatic variables on the pavement performance. The available literature has tended to work on individual factors of resilience or system level resilience without explicitly modelling the interaction effects between temperature, rainfall, and flooding.

Therefore, this study proposes a multi-index data-driven framework to model the coupled effects of climatic variables on pavement performance. By integrating thermal, moisture, and flood indices derived from meteorological data, the study aims to provide a comprehensive understanding of climate-induced pavement degradation and support the development of climate-resilient transportation infrastructure.

II. Review Of Literature

Infrastructure resilience is a concept that has received considerable attention over the past few years because of the rise in the rate of extreme climatic occurrences and the subsequent effect they have on interdependent systems. Earlier studies by Kjolle et al. (2012) have discussed the significance of risk analysis in critical infrastructures, which specifically mention the interdependency between systems, including electricity and transport. Such dependencies may enhance vulnerability that could cause system failure at extreme situations.

The fact that environmental and infrastructure systems are dynamic has also been investigated through data-driven methods. Kleinberg (2002) thought of the bursty and hierarchical nature of data streams, which applies effectively to explain irregular events of climate like sudden spikes of rainfall. These methodologies give a basis on the study of temporal variability of climate data.

The notion of resilience has been extended to social and environmental aspects in recent studies. Kuklina et al. (2022) discussed sustainability and resilience of communities that undergo changes in transportation infrastructure, focusing on the socio-environmental effect of infrastructure changes. On the same note, Lawrence et al. (2020) showed the effect of cascading impacts of climate change, where environmental disruptions spread through interdependent systems to influence the performance of infrastructure on different levels.

In the same way, technological advancement has also helped in resilience assessment and monitoring. Lazarescu and Poolad (2020) came up with resilient wireless sensor networks in the context of infrastructure monitoring, which would allow them to detect system failures in real-time. Similarly, Ong et al. (2022) examined sensor-based detection systems to detect anomalies in the transportation networks, which improve operation resilience.

A key cause of infrastructure vulnerability has been seen to be climate change. Leal Filho et al. (2024) highlighted the importance of prioritizing the strategies of climate adaptation in the planning of infrastructure. Quantitative research by Newman and Noy (2023) on the causes of the economic effects of extreme weather events around the world strengthens the necessity of the creation of resilient infrastructure systems. Besides that, Lindbergh et al. (2024) also pointed at the weaknesses of the transportation fuel systems in place and showed that climate change can not only impact physical infrastructure but also supporting systems.

The studies have been especially relevant in transport resilience because of flooding and hydrometeorological events. Li et al. (2024) employed big data methods to evaluate the flood risk perception and resilience, whereas Vieira Passos et al. (2025) suggested the means of evaluating the hydrometeorological resilience of interdependent infrastructure systems. These articles show that climate variables like rainfall and flooding should be incorporated in resilience models.

Some works have concentrated on the resilience of transportation infrastructure. In the article by Wan et al. (2018), the authors have conducted a thorough review of the resilience in transportation systems, with the major obstacles to resilience being uncertainty, interdependency, and the absence of integrated modeling frameworks. Serdar et al. (2022) also created indicators of resilience assessment in urban transportation networks, which require quantitative assessment techniques. As shown by Pagliara and Zingone (2023), resilience strategy within the transportation systems proved to be economically advantageous in adverse weather conditions.

The structural approach and engineering approach have also been used to study infrastructure resilience. Palin et al. (2021) explored how climate change affects railway infrastructure and noted that it poses threats related to changes in the temperature and precipitation. Sadeghi et al. (2020) were interested in structural performance during the seismic conditions, and Suticen et al. (2023) researched the reinforcement concepts in interdependent infrastructure systems amid disaster-related uncertainties.

Resilience assessment has also been able to be extended to emerging technologies like remote sensing and spatial analysis. The article by Pant et al. (2023) also used LiDAR data as an infrastructure monitoring tool to offer precise terrain and slope estimations of road networks. Moore et al. (2020) also discussed the idea of the circular economy where electric vehicle batteries could be used to enhance disaster resilience as an innovative way of optimizing resources.

III. METHODOLOGY

3.1. Research Framework

The proposed study uses a data-driven and quantitative design to simulate the interplay of three climatic variables (temperature, rainfall, and flooding) on pavement performance. The approach combines the time-series analysis of the meteorological data and the statistical modeling methods to define the individual and interaction impacts of environmental stressors. Temperature and precipitation are considered primary variables, whereas flooding is the second variable that is derived as an extreme event of hydrological conditions. The model also uses multi-index method to boost climate-pavement interactions to increase the interpretability and strength of the relationships.

3.2 Data Source and Variable Selection

The Kaggle (https://www.kaggle.com/datasets) data used in this research is the "Meteorological Dataset India" (https://www.kaggle.com/datasets/krishnakumar12w/metrological-dataset-india).

The dataset has organized meteorological time-series data on temperature and rainfall, required in climate-based modeling.

The main variables that will be obtained out of the data set are temperature (*T*), precipitation (*P*), and time index (*t*). Moreover, a flood-related variable (*F*) is obtained based on the data on rainfall to reflect extreme environmental conditions. It is based on these variables that further modeling and analysis is done.

3.3 Data Preprocessing and Feature Engineering

A systematic preprocessing of the dataset is done to guarantee the quality of the data and the analytical coherence. Interpolation or removal methods are used to handle missing values whereas duplicate values are removed. The time parameter is transformed to a normal date time so that it can be analyzed in time. The data is further made to meaningful time scales like daily or monthly observations to encompass climatic trend in the data.

The feature engineering is done to extract more variables that will be necessary in modeling. A flood index is a precipitation index developed based on the rain data to measure extreme precipitations. The flood index can be defined as a standardized anomaly in the rainfall:

$$F = \frac{P - P_{mean}}{P_{std}} \quad (1)$$

where P_{mean} and P_{std} refer to the average and standard deviation of precipitation respectively. This model enables the continuous representation of intensity of flood.

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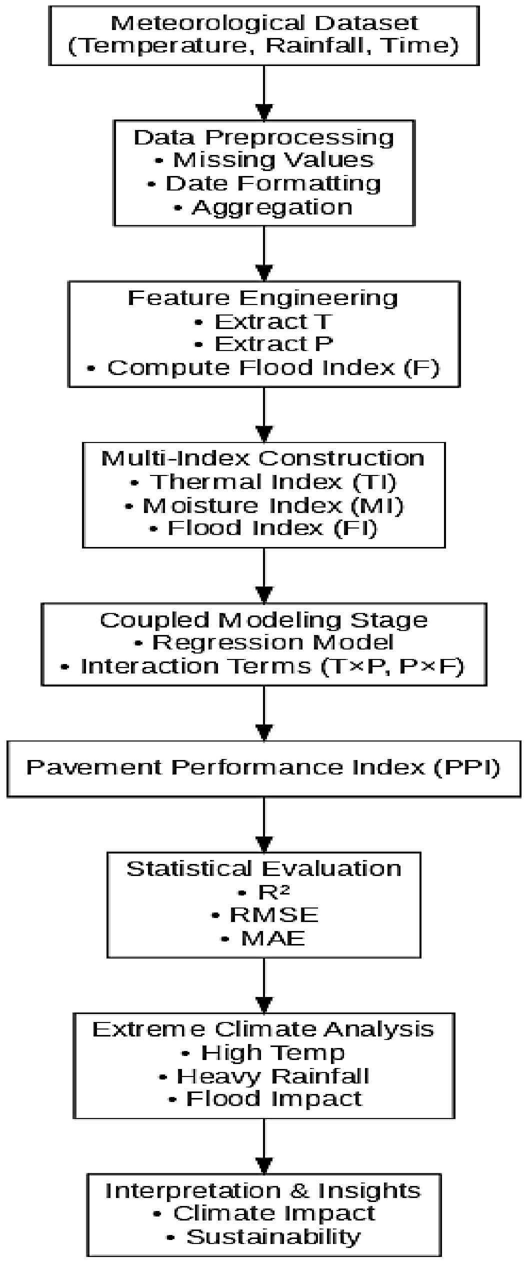

Figure 1. Proposed Methodology Framework

Figure. 1 that depicts the proposed multi-index data based framework on the modeling of the combined effect of temperature, rainfall, and flooding on pavement behavior.

3.4 Multi-Index Climate Framework

The Multi-Index Climate Framework (3.4) is an explanation of climate change grounded in the connection between multiple indices.

- *Thermal Index (TI):*

$$TI = \frac{T - T_{mean}}{T_{std}} \qquad (2)$$

- *Moisture Index (MI):*

$$MI = \frac{P - P_{mean}}{P_{std}} \quad (3)$$

- *Flood Index (FI):*

$$FI = F \quad (4)$$

These indices make the variables standardized and comparative analysis is possible and they enhance stability of the model.

3.5 Pavement Performance Modeling

As there is no direct data of the pavement conditions, a proxy-based Pavement Performance Index (PPI) is developed to reflect pavement sustainability in a diverse climatic condition. The interdependence between climatic variables and pavement performance is modelled on a coupled regression model.

3.5.1) Coupled Climate Model

To capture interaction effects among variables, the following model is developed:

$$PPI = \alpha + \beta_1 T + \beta_2 P + \beta_3 F + \beta_4 (T \cdot P) + \beta_5 (P \cdot F) + \epsilon \quad (5)$$

where $\alpha$is the intercept, $\beta_i$are regression coefficients, and $\epsilon$is the error term. This expression explains both individual and interactive effects of climatic variables.

*3.5.2) Multi-Index Model Representati***on**

To enhance interpretability, the model is further expressed using the normalized indices:

$$PPI = \alpha + \beta_1 TI + \beta_2 MI + \beta_3 FI + \epsilon \quad (6)$$

This representation forms the core of the multi-index data-driven framework, enabling robust comparison across climatic conditions.

3.6 Statistical Analysis and Model Evaluation

Statistical analysis will be performed in order to measure the associations between variables and the performance of the models. The strength and direction of association between the climatic variables and the pavement performance is measured using Pearson correlation analysis:

$$r = \frac{\sum(X - \bar{X})(Y - \bar{Y})}{\sqrt{\sum(X - \bar{X})^2 \sum(Y - \bar{Y})^2}} \quad (7)$$

The evaluation of the regression model is conducted based on the standard performance indicators, that is, the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE):

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \quad (8)$$

$$RMSE = \sqrt{\frac{1}{n}\sum(y_i - \hat{y}_i)^2} \quad (9)$$

$$MAE = \frac{1}{n}\sum | y_i - \hat{y}_i | \quad (10)$$

These measures can guarantee validity and forecasting power of the suggested model.

3.7 Extreme Climate Impact Assessment

The threshold-based analysis is done to recognize extreme temperatures and rainfalls events to assess the resilience of pavements to harsh climatic conditions. The respective changes in the PPI are examined to determine the effects of the extreme climatic conditions on the pavement behavior. The step plays a highly significant role in the knowledge of infrastructure vulnerability and the provision of climate-resilient design measures.

3.8 Tools and Implementation

It is analyzed with the help of Python programming language, Pandas to process data, NumPy to work with numbers, Matplotlib to visualize, and Scikit-learn to model the regression. Data: initial data inspection and validation of data is done in Microsoft Excel.

IV. Results And Discussion

4.1 Temporal Analysis of Climatic Variables

Figure. 2(a)-(c) shows the temporal change in the climatic parameters such as temperature, rainfall and humidity. There is a distinct seasonal distribution of the temperature profile as there are periodic variations in the range of about 10°C and 25°C, which shows that climatic cycles are highly active. The data of rainfall exhibits uneven fluctuations with intermittent maximum showing stochastic climatic conditions of precipitation events. On the same note, humidity levels show moderate changes, which are determined by the temperature and rain conditions.

These observations prove the fact that the climatic variables are both periodic and random, which are key factors affecting the processes of pavement deterioration.

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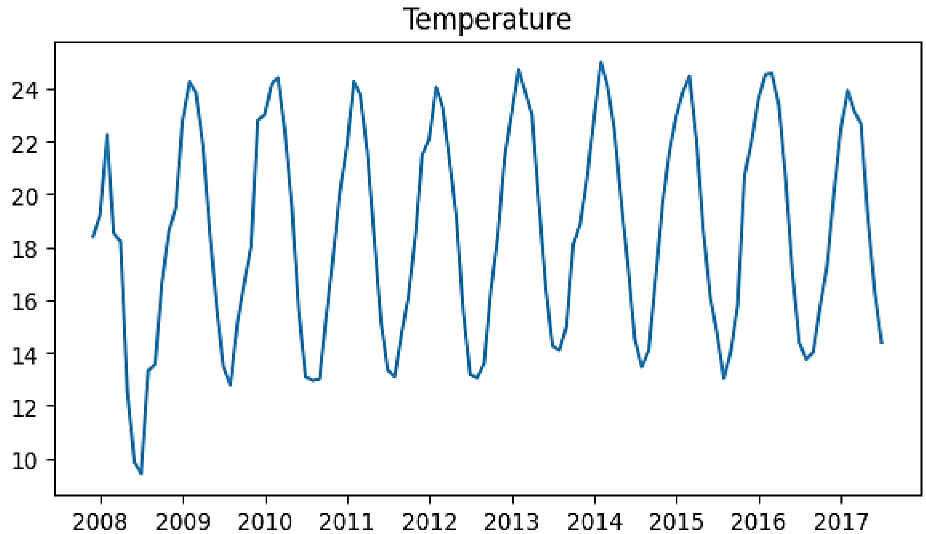

Figure 2a. Monthly average temperature variation

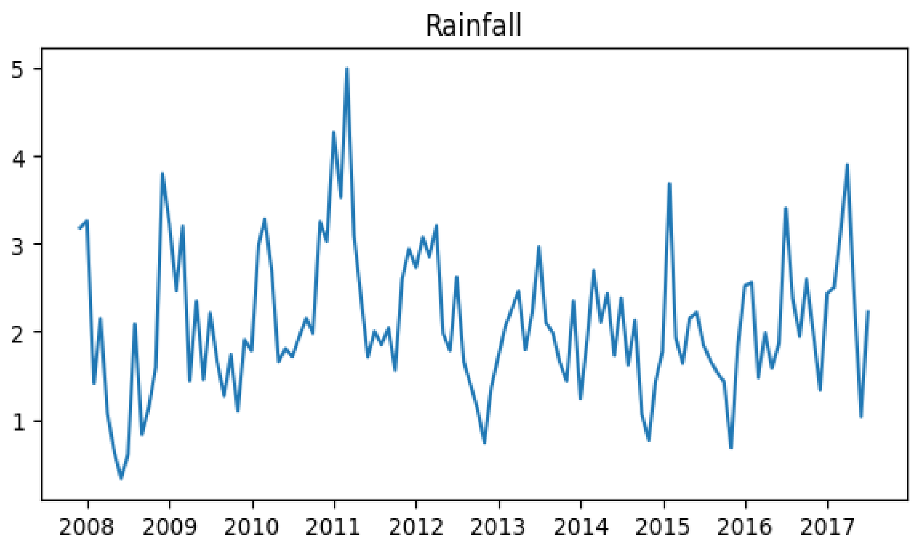

Figure 2b. Monthly rainfall variation

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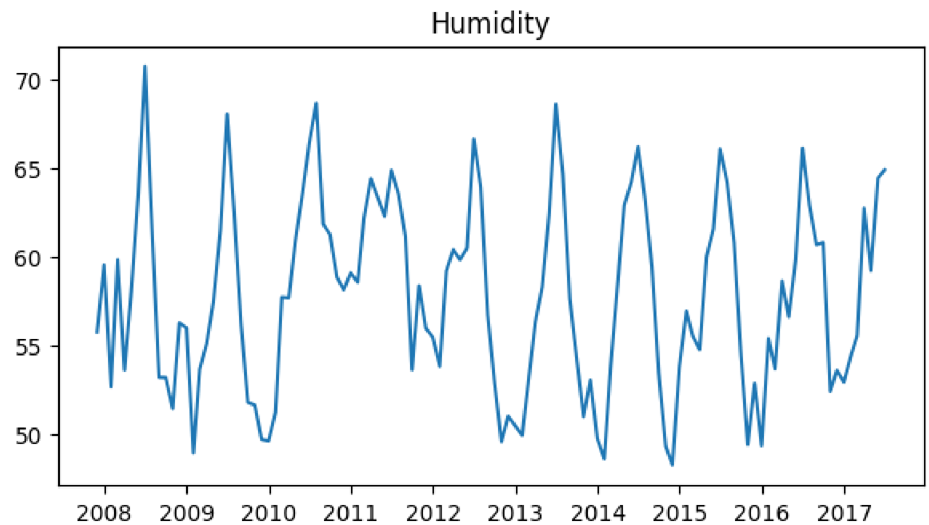

Figure 2c Monthly humidity variation

4.2 Correlation Analysis

Figure. 2(d), demonstrates the correlation between the developed climatic indices and pavement performance index (PPI). It is observed that:

- There are positive correlations between Moisture Index (MI) and Flood Index (FI) and PPI.
- The relationship between Thermal Index (TI) is relatively moderate.

This implies that the effect of moisture on performance of pavement is more vital than influence of temperature. The results of such studies are in line with those of other researchers who have emphasized on the importance of moisture infiltration and flooding in enhancing the speed of degradation of pavements.

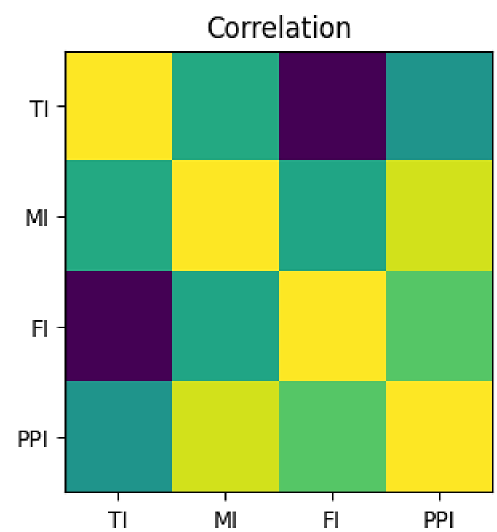

Figure 2d. Correlation matrix of climatic indices and pavement performance index

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4.3 Regression Model Performance

The output of the formulated regression model is summarized in Table 1.

Table 1 Regression Model Performance Metric

Metric	Value
R^2	0.920
RMSE	0.044
MAE	0.032

The model had a high predictive power with a value of R^2 of 0.92. The accuracy and reliability of the model are also supported by the fact that the RMSE and MAE are relatively low.

The relationship between actual and predicted PPI values is shown in Figure. 3. The scatter distribution shows that the trend is strong with minor dispersion meaning that the model is very effective in representing the underlying relationships and realistic variability is maintained.

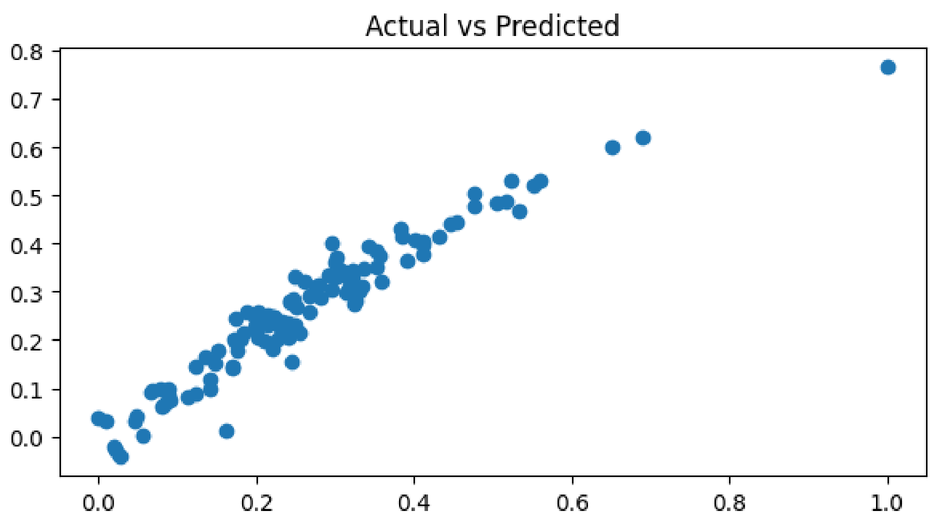

Figure 3. Actual versus predicted PPI values

4.4 Influence of Climatic Factors

The regression coefficients obtained from the model are presented in Table 2.

Table 2 Regression Coefficients

Variable	Coefficient
TI	0.053
MI	0.085
FI	0.088

Based on Table 2, it can be observed that the coefficient of FI and MI are higher than that of TI, which represents that flooding and rainfall can affect the performance of pavement higher than temperature. This emphasizes the issue of moisture concerns in the pavement degeneration processes.

4.5 Extreme Climate Impact Analysis

The effects of the extreme rainfall events on the pavement performance are demonstrated in Figure. 4. It is noted that there is a noticeable deviation in the PPI values in case of high intensity rainfall, which implies more susceptibility of the pavement structures.

This proves that severe weather conditions especially heavy rain and flooding are major factors that contribute to the rapid degradation of pavement.

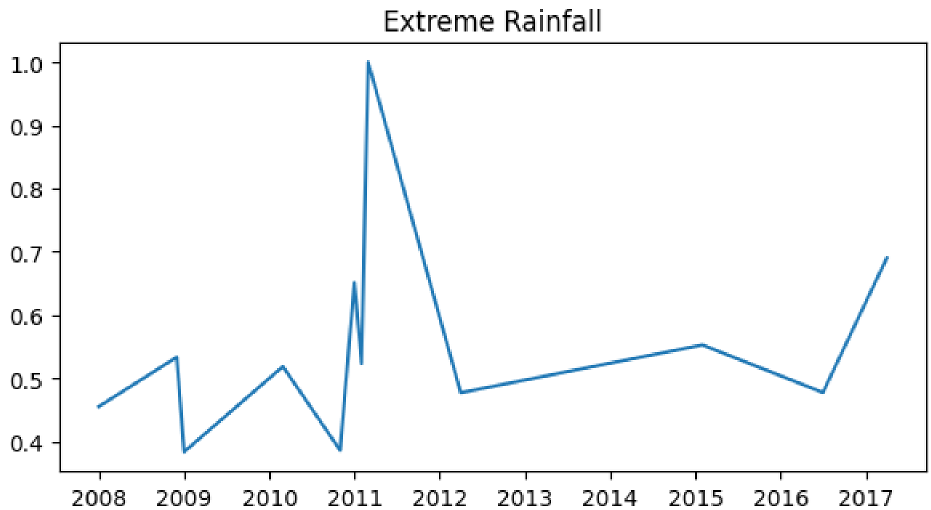

Figure 4. PPI variation during extreme rainfall events

4.6. Discussion

This proposed multi-index framework shows high correlations of climatic variables and pavement performance where the model has a good R^2 of 0.92, RMSE of 0.044 and MAE of 0.032. High R^2 can be explained by the systematic nature of the formulation of climatic indices and the dependence between each other. Flood Index (FI) and Moisture Index (MI) are the most influential variables, which means that the most important factor affecting the deterioration of pavement is rainfall and flooding. Effects of Thermal Index (TI) are moderately average, and mainly it leads to long-term material degradation. The correlation analysis and the actual-predicted plot depict that there is realistic variability without overfitting in the model. Moreover, higher vulnerability of pavement to extreme rainfall is also observed in analysis. It must be said that the Pavement Performance Index (PPI) is an indirect measure that is made with references to the climatic factors and that, in the future, real pavement data should be used to verify it.

V. Conclusion

This paper has come up with a multi-index-based data-driven model to assess the overall impact of temperature, rain, and flooding on pavement performance. The findings have shown that moisture-related conditions, especially flooding and rainfall, are the most influential and temperature comes second. The model has a good predictive power that evidences the potential of the combination of various climatic indices. The results reiterate the role of climate-resilient pavement design, such as enhanced drainage and adjusting maintenance approaches.

Future efforts are needed in terms of including real-world pavement data, using sophisticated modeling approaches and expanding the model to other areas.

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