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Article

Data-Driven Prediction of Track Quality Index (TQI): A Comparative Study of Statistical and Ensemble Learning Models – A Case Study of the Kolašin–Podgorica Railway

Ivona Nedevska Trajkova ^{1,*}, Zlatko Zafirovski ¹, Jelena Dimitrijević ², Riste Ristov ¹ and Vasko Gacevski ¹

¹ Faculty of Civil Engineering, Ss. Cyril and Methodius University in Skopje, 1000 Skopje, North Macedonia

² Faculty of Civil Engineering and Architecture, University of Niš, 18000 Niš, Serbia

* Correspondence: nedevska@gf.ukim.edu.mk; Tel.: (+38970742824)

Abstract

Maintaining the geometric quality of railway tracks is essential for ensuring the safety and efficiency of railway operations. This study presents a comparative analysis of Multiple Linear Regression (MLR) and Random Forest (RF) models for predicting the Track Quality Index (TQI), based on historical inspection data collected from the mountainous Kolašin–Podgorica railway section between 2017 and 2022, with data from 2024 reserved for independent validation. The dataset includes high-resolution measurements divided into 20-meter homogeneous units, incorporating infrastructure, geometric, operational, and maintenance-related variables. Both models were trained on scaled input features, and their performance was evaluated using the coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE). The results demonstrate that the machine learning approach significantly outperformed the statistical baseline; the RF model achieved a higher goodness-of-fit ($R^2 = 0.69$ vs. 0.57) and reduced the average prediction error (MAE) by approximately 15% compared to the MLR model. Furthermore, RF exhibited superior stability in capturing severe localized degradation trends. These findings highlight the potential of ensemble machine learning methods to mitigate large prediction errors and enhance data-driven, proactive track maintenance planning in geometrically complex railway networks.

Keywords: Track Quality Index (TQI); railway track geometry; predictive maintenance; random forest; multiple linear regression; data-driven modeling; Western Balkans

1. Introduction

The geometric condition of railway track infrastructure directly affects the safety, ride comfort, and cost-efficiency of railway transport systems [1–3]. Over time, track geometry degrades due to cumulative dynamic loading and environmental influences, requiring systematic maintenance interventions [4,5]. One of the most commonly used indicators to quantify this condition is the Track Quality Index (TQI), which aggregates deviations in key geometric parameters [6–9].

In the context of railway maintenance in the Western Balkans, only a limited number of studies have been carried out. In North Macedonia, one of the few relevant works is the Study for the Renewal of Corridor X [10], which analyzed the technical and economic aspects of maintenance and rehabilitation along the Tabanovce–Gevgelija line. The study provided a systematic overview of track geometry degradation and maintenance activities between 1991 and 2000, highlighting the strong budgetary and institutional constraints that shaped the current state of the railway network. However, beyond this example, no extensive research has been conducted in the country that explicitly focuses on tracking degradation modeling and predictive maintenance.

At the regional level, the South-East Europe Transport Observatory (SEETO) produced the Report on Rail Maintenance on the TEN-T Core Network in the Western Balkans [11]. This report analyzed the railway infrastructure of Albania, Bosnia and Herzegovina, Montenegro, North Macedonia, Kosovo, and Serbia, concluding that nearly 30% of the core network was in poor condition. At the same time, maintenance budgets were often insufficient or allocated in an unsystematic manner. These findings emphasized the need for systematic maintenance strategies and reliable degradation models for railways in the Western Balkans.

Internationally, numerous studies have addressed railway track degradation using both statistical and machine learning approaches. Traditional deterministic and probabilistic models focused on traffic load, curvature radius, gradients, and tamping cycles to estimate track quality deterioration [12]. More recent contributions have applied data-driven and artificial intelligence methods, including artificial neural networks for predicting track geometry degradation [13] and hybrid decision-support models that combine degradation trends with life-cycle cost analysis. These studies confirmed the potential of predictive modeling in supporting maintenance planning, but also highlighted the need for case-specific applications on ageing railway networks such as those in the Western Balkans.

Existing research on railway track degradation has primarily focused on deterministic or probabilistic models that estimate quality deterioration based on traffic load, curvature, and tamping cycles [12]. While such models provide valuable baseline insights, they often fail to incorporate the combined effects of infrastructure conditions (e.g., tunnels, bridges, gradients) and operational factors (e.g., traffic intensity, speed restrictions). More recent contributions, utilizing artificial neural networks [13] or hybrid decision-support systems, have achieved higher predictive accuracy. However, their implementation has been limited to large railway networks in Western Europe or Scandinavia, where data availability and monitoring systems are considerably more advanced.

By contrast, the Western Balkans still lack case-specific applications of predictive models, especially in mountainous sections characterized by complex geometry and frequent maintenance constraints. This study addresses these gaps by combining both statistical and machine learning approaches and applying them to the Kolasin–Podgorica line, thereby providing one of the first data-driven predictive analyses of track quality in the region.

Table 1. Overview of previous studies and reports on railway track maintenance and degradation modeling, with emphasis on Corridor X and the Western Balkans region.

Approach / Study	Methods Applied	Main Limitation	Contribution of This Study
Krakovski (2009) – Corridor X Study	Technical & economic analysis; descriptive track degradation trends	No predictive modeling; focused only on rehabilitation costs and activities	Provided systematic data on maintenance/ rehabilitation in Macedonia
Jovanović et al. (2015)	Deterministic & probabilistic regression	Limited to traffic & curvature; no ML	Established baseline statistical models
Khajehei et al. (2022)	Artificial Neural Networks	Applied in Sweden; requires large datasets	Demonstrated ML potential for TQI prediction
SEETO Report (2016)	Descriptive infrastructure analysis	No predictive modeling	Identified poor maintenance in the Western Balkans
This study	Multiple Linear Regression & Random Forest	Applied to Kolasin–Podgorica (Western Balkans)	First comparative predictive modeling in a regional context

Forecasting future TQI values enables railway infrastructure managers to implement proactive and optimized maintenance strategies [14,15]. Traditional statistical methods, such as Multiple Linear Regression (MLR), provide interpretable baseline models but often fall short in capturing complex

nonlinear relationships [16–19]. In contrast, ensemble learning techniques like Random Forest (RF) offer improved accuracy and robustness in high-dimensional settings [20–22].

This paper compares the performance of MLR and RF models for predicting TQI in 2024 using historical data collected over three prior inspection intervals: 2017, 2019, and 2022. The analysis aims to evaluate the suitability of each method for practical use in infrastructure asset management.

2. Materials and Methods

2.1. Study Area and Dataset Description

The study was conducted on the Kolašin–Podgorica section of the Vrbnica–Bar railway line in Montenegro, a strategically important route that traverses mountainous terrain with variable elevation. The alignment includes tunnels, bridges, sharp curves, and steep gradients, creating technically demanding conditions for maintaining track geometry stability [23]. These engineering and operational characteristics make the section particularly suitable for analyzing real-world degradation phenomena.



Figure 1. Location of the Kolašin–Podgorica section on the Vrbnica–Bar railway line (highlighted in red circle). Source: Author's adaptation based on ŽICG data.

According to the geometric characteristics provided by Railway Infrastructure of Montenegro - AD Podgorica, the Kolašin–Podgorica section spans 39.7 km, with a minimum curve radius of 300 m and maximum longitudinal gradients of 24.9 %. More than 65% of the alignment consists of curves,

representing one of the highest proportions along the Vrbnica–Bar corridor. This combination of steep gradients and small-radius curves imposes intensified dynamic loading on the track structure, accelerating ballast settlement, rail wear, and geometric instability [24,25].

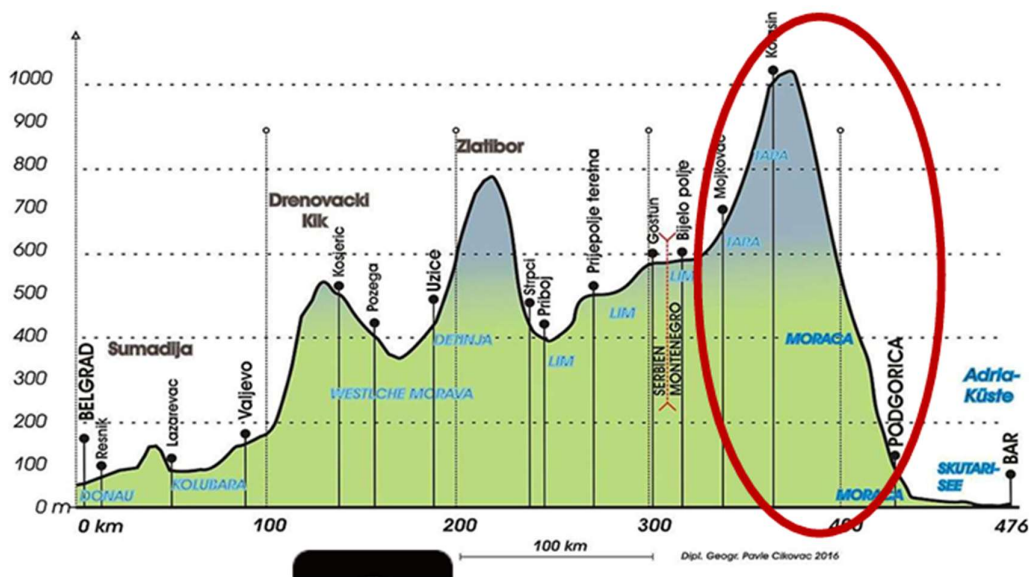


Figure 2. Longitudinal profile of the Belgrade–Bar railway, with the Kolašin–Podgorica section highlighted (red circle). Source: Author’s adaptation based on publicly available cartographic data (2016).

Such characteristics highlight the extreme operational challenges of this section compared to flatter and straighter railway alignments. From a maintenance perspective, the high curvature ratio and steep slopes increase the frequency of required interventions, while also limiting the long-term effectiveness of tamping operations [26,27]. Consequently, the Kolašin–Podgorica section provides an ideal case study for predictive modeling of degradation trends under harsh geometric and geotechnical conditions.

Track geometry measurements were collected during four independent inspection campaigns: 2017, 2019, 2022, and 2024. All inspections were carried out using a certified track recording vehicle that complies with European standards EN 13848-1:2019 and UIC Leaflet 518. Measurements were performed in autumn under comparable weather conditions to minimize the effects of seasonal variation. Notably, the 2024 data were excluded from model training and calibration and reserved exclusively for final validation, ensuring the objectivity and reliability of the predictive analysis.

2.2. Segmentation into Homogeneous Units

For analytical consistency, the Kolasin–Podgorica section was divided into 20-meter homogeneous segments. A review of the literature on segmentation techniques in railway track degradation analysis highlights the need to combine theoretical consistency with technical applicability. International standards such as UIC 518 [28] and EN 13848-1:2019 [29] define recording lengths of 10 m, 20 m, and 200 m to balance analytical resolution with operational efficiency, enabling both the detection of localized anomalies and the assessment of long-term track fatigue. This approach is reinforced by spatial network theory and segmentation practices in transportation research, where uniform lengths allow for consistent statistical evaluation of degradation processes [30].

Moreover, leveraging spatial abstraction methods in traffic and infrastructure studies provides valuable insights into how homogeneous segmentation supports integration of heterogeneous datasets and facilitates forecasting of deterioration patterns [31]. The adoption of such multiscale

segmentation ensures comparability of results, integrates diverse data sources, and improves the accuracy of deterioration diagnosis, ultimately strengthening the link between micro-level defects and macro-level performance [32].

The 20 m segmentation length was selected as a practical balance between precision and stability. Shorter intervals of 10 m increase the sensitivity to random fluctuations and measurement noise, often highlighting variations that are not critical from an engineering standpoint. Conversely, longer 200 m intervals tend to mask localized defects and smooth out critical irregularities, reducing the ability to identify sections with urgent maintenance needs. By contrast, the 20 m segmentation provides an intermediate resolution that ensures statistical representativeness while remaining sensitive to localized degradation zones.

This choice is particularly relevant for the Kolasin–Podgorica section, which traverses challenging mountainous terrain with frequent tunnels, bridges, sharp curves, and steep gradients. Under such conditions, finer segmentation is essential to capture the localized effects of infrastructure transitions—for example, increased ballast instability at tunnel exits or bridge approaches. At the same time, the 20 m interval minimizes noise within each segment, ensuring stable calculation of statistical indicators and supporting compatibility with international degradation studies.

From an engineering standpoint, this segmentation enables the precise spatial identification of degradation zones [33,34], improves the reliability of statistical indicators [35,36], and ensures that predictive models are trained on a sufficiently large number of observations to prevent overfitting [37]. Consequently, the 20 m segmentation provides both methodological rigor and practical engineering relevance, making it well-suited for predictive modeling of track quality in geometrically complex railway environments such as the Kolasin–Podgorica corridor.

2.3. Track Quality Index Calculation

The Track Quality Index (TQI) serves as the dependent variable in the predictive modeling process. TQI was calculated using the Combined Standard Deviation (CoSD) method, which integrates the standard deviations of multiple geometric parameters:

$$TQI = \sum_{j=1}^M w_j * \sigma_j \quad (1)$$

Where:

- σ_i is the standard deviation of geometry parameter j ,
- w_i is the weight factor assigned based on EN 13848 and UIC 518 standards [28,29],
- M is the number of geometry parameters included in the calculation.

The CoSD method uses the standard deviation as a statistical measure of dispersion to quantify variability across multiple geometric features of railway tracks [38]. Given that each geometric parameter contributes to the overall performance and safety of the railway, aggregating their standard deviations yields an index that is highly sensitive to anomalies and gradual degradations.

Weighting factors were defined according to engineering relevance and international standards. The adopted values are summarized in Table 2.

Table 2. Weighting factors used in the calculation of TQI.

Parameter	Weighting factor (w_i)	Engineering rationale
Twist	1.8 – 2.0	Highest influence due to its direct effect on vehicle stability
Longitudinal level	1.5	Strong effect on vertical dynamics and ride comfort
Gauge	1.2	Medium influence on wheel–rail contact and wear
Alignment	1.0 – 1.1	Lower influence, but relevant for lateral stability

This method ensures that parameters expressed in different units (mm , %, degrees) are normalized and meaningfully integrated. Higher TQI values indicate greater deviations and poorer quality, while lower values denote a well-maintained track. Table 3 summarizes the interpretation scale:

Table 3. Weighting factors used in the calculation of TQI.

TQI value	Interpretation
0 – 10	Excellent track quality – very low degradation, no intervention needed.
10 – 20	Good track quality – low degradation, but preventive inspection may be required.
20 – 30	Fair track quality – regular maintenance is recommended to prevent deterioration.
30 – 40	Poor track quality – maintenance is required in the near future to avoid defects.
>40	Critical track quality – urgent repairs are necessary to maintain safety.

The CoSD approach was selected because it provides a single synthetic indicator of track condition that captures both variability and severity across parameters, while remaining interpretable and widely used in practice. Compared to alternative methods, such as mean deviation or exceedance-based indices, CoSD ensures higher comparability between different track sections and inspection periods, which is particularly important for longitudinal degradation analysis and predictive modeling.

2.4. Input Features

For each 20-meter segment and measurement year, the following categories of variables were included:

2.4.1. Track Geometry Parameters

Track gauge: The track gauge is the distance between the inner faces of the rail heads, measured at a reference height, typically 14 mm below the running surface. This definition is critical because even minor deviations from the nominal value can have significant consequences for railway safety and operational stability, and large deviations can lead to speed restrictions or risk of derailment [39–41].

Cant (superelevation): Vertical difference between the two rails, measured at the rail head. Adequate cant is crucial in curves for balancing centrifugal forces; irregularities can induce excessive lateral forces and uneven rail wear [39–41].

Twist: Difference in cant measured over a fixed base length (typically 3–10 m). High twist values indicate abrupt vertical distortions between the two rails, which are critical for ride comfort and safety, especially for passenger trains [39–41].

Alignment (left and right): Lateral deviation of each rail from a 10 m reference chord. It reflects horizontal irregularities, such as kinks, that increase dynamic loading and may accelerate the deterioration of ballast and subgrade [39–41].

Longitudinal level (left and right): Vertical deviation of each rail from a smoothed reference plane in the longitudinal direction. Unevenness at the longitudinal level produces vertical dynamic forces that accelerate track degradation and directly influence TQI [39–41].

2.4.2. Infrastructure Parameters

Tunnel presence (0/1): Tunnel presence as a binary indicator captures whether a railway segment lies inside a tunnel. The confined environment of tunnels often results in constrained drainage and limited ballast ventilation, both of which can accelerate track geometry degradation. In tunnel sections, the reduced efficiency of drainage systems results in the accumulation of water and

moisture, leading to deterioration of ballast and the underlying support, while restricted ventilation hinders the evaporation of accumulated moisture. These conditions lead to faster degradation of track geometry than in open track sections. In detail, constrained drainage within tunnels can lead to prolonged exposure to water-related damage, such as frost action and chemical degradation of ballast materials, thereby directly impacting the long-term integrity of the track geometry. Moreover, the limited airflow in these enclosed environments exacerbates moisture retention, further accelerating material degradation and increasing maintenance requirements. Such tunnel-specific degradation phenomena have significant implications for predictive maintenance models that rely on track quality indicators, as tunnel sections are often associated with a higher risk of accelerated deterioration [42].

Bridge presence (0/1): The presence of a bridge can be represented as a binary indicator (0/1) in railway infrastructure monitoring, indicating whether a given track segment is on a bridge. This indicator is significant because bridges subject the track to higher dynamic forces, including vibration, impact loads, and differential motion, compared to conventional, embankment-supported tracks. These higher dynamic forces are known to contribute to localized settlement of the track structure and induce additional stresses in the track components, thereby increasing maintenance requirements. Specifically, the dynamic interaction among the train, track, and bridge has been examined in studies that reveal that the dynamic forces transmitted through a bridge structure under high-speed traffic loads can exceed those encountered on ground-level alignments [43,44].

Station proximity (0/1): The impact of station proximity on track geometry has been highlighted in the literature, noting that track segments located within or near stations are subjected to frequent acceleration and braking forces. These dynamic forces can induce ballast disturbance and geometric irregularities, necessitating more frequent maintenance interventions. The station proximity indicator (coded as 0/1) plays a crucial role in predictive track maintenance models because the dynamic conditions around stations are directly linked to the degradation rates of ballast and track geometry irregularities. Incorporating such an indicator into maintenance planning enables railway operators to allocate resources more effectively and tailor their intervention strategies to these high-risk areas [45].

Curve radius (in meters): The horizontal curve radius is a critical parameter for assessing track performance because smaller radii are strongly correlated with increased lateral forces, which lead to higher rail wear and accelerated degradation. As the curve radius decreases, the train negotiating the curve experiences higher centrifugal forces, resulting in increased lateral forces at the wheel-rail interface. This phenomenon increases rail wear rate and promotes conditions such as corrugation, which lead to geometric degradation. Conducted studies underscore that the horizontal curve radius is not merely a geometric descriptor but is fundamentally linked to the dynamic loading conditions that govern rail wear and degradation. Thus, accurate quantification and management of curve radius effects are essential for predicting maintenance needs and ensuring the long-term reliability of railway infrastructure [46,47].

Longitudinal gradient (in ‰): The longitudinal gradient, often reported in per mille (‰), characterizes the track slope and plays a significant role in track performance. Steeper gradients require higher traction and braking forces during train operation, which in turn impose additional stresses on the ballast and subgrade. These augmented forces can exacerbate track substructure settlement, leading to differential settlement over time. Experimental investigations have demonstrated that the additional longitudinal forces generated on sloping tracks are a major contributor to differential settlement, as increased traction and braking loads intensify the dynamic interactions between the train and the track [48]. Collectively, these studies underscore that the longitudinal gradient is not merely a geometric parameter but an influential factor that affects the mechanical response of the track substructure. As such, proper evaluation of track slope is critical for predictive maintenance models, as it enables anticipatory assessment of potential settlement issues and informs the formulation of maintenance strategies to mitigate the adverse effects of steep gradients [49,50].

2.4.3. Operational Parameters

Speed (km/h): The maximum allowed speed of a track segment, typically expressed in km/h, is determined based on both infrastructure condition and regulatory requirements. Higher permitted speeds require stricter geometric quality to ensure vehicle stability and safety, given the higher dynamic loads trains impose on the track. Segments designed for high speeds must meet tighter tolerances to maintain the kinematic and dynamic performance required for safe operation [51,52].

Traffic intensity (gross tons/year): The annual cumulative traffic load, measured in gross tons per year, is a vital indicator of the stress imposed on railway track segments. Higher traffic intensity translates into more frequent and intense dynamic forces acting on the track structure. These dynamic forces contribute to increased cumulative wear and accelerated geometry degradation. For example, heavy cyclic loading from freight and passenger services can exacerbate ballast deformation and subgrade settlement, leading to irregularities in track geometry that require more intensive maintenance [53,54]. Moreover, studies examining the quality assessment of track geometry have identified traffic load as a critical factor among other influential variables—suggesting that segments with higher gross tonnage tend to exhibit greater deterioration in geometric parameters over time [55]. Such findings underscore the need to incorporate traffic intensity into degradation-prediction models, thereby enabling more accurate forecasting of maintenance requirements and improved management of track infrastructure.

2.4.4. Maintenance Data

Track tamping/regulation: Track tamping is a fundamental maintenance intervention on ballasted railway tracks, wherein a specialized machine lifts and realigns the track by inserting vibrating tamping tines into the ballast under the sleepers. This procedure aims to restore the vertical level and horizontal alignment of the track, thereby temporarily correcting geometry defects caused by operational loads. However, while tamping effectively realigns the track, it inherently disturbs the ballast structure. The vibrations and mechanical actions of the tamping tines can break and degrade the ballast, potentially accelerating its degradation dynamics in subsequent loading cycles [56,57]. These insights underscore the engineering trade-offs involved in using tamping as a maintenance measure. Optimizing the tamping process to maximize geometry correction while minimizing ballast damage remains a critical focus for railway infrastructure management. Field investigations and simulation studies continue to provide valuable insights for refining both operational parameters and the scheduling of tamping interventions, ensuring the long-term performance and safety of the track system [58–60].

Ballast profiling and shaping: This machine-based maintenance activity plays a critical role in restoring the geometry of ballast shoulders and crib spaces. This restoration is essential to ensuring lateral stability of sleepers and improving drainage performance, both of which are crucial to maintaining track performance over time. Dedicated machines, such as dynamic track stabilizers, are deployed after tamping operations to reestablish the optimal ballast profile [61]. Ballast profiling and shaping are integral for re-establishing the functional configuration of the ballast layer. Through these maintenance interventions, the lateral stability of sleepers is maintained, and drainage is improved, both of which are critical for mitigating long-term degradation of railway infrastructure.

Counts per period: Total number of interventions (both tamping/regulation of track and ballast profiling/shaping) executed in the three analysis intervals (2017–2019, 2019–2022, 2022–2024). This metric provides explanatory power by linking the frequency of restorative actions with observed differences in track degradation rates [62]. In maintenance operations planning, knowing the precise number of interventions over defined periods helps quantify the workload imposed on the infrastructure and can indicate whether maintenance strategies effectively counteract degradation. When maintenance counts are analyzed against degradation trends over consistent time intervals (such as 2017–2019, 2019–2022, and 2022–2024), they enable a better understanding of the relationship between scheduled interventions and the long-term evolution of track geometry quality.

Track geometry variables are directly incorporated in the TQI calculation according to EN 13848 and UIC 518, while infrastructure, operational, and maintenance parameters represent boundary conditions that indirectly affect degradation processes. This integrated feature set enables the predictive models to capture both the intrinsic geometric condition of the track and the external factors influencing its evolution over time.

All numerical features were scaled using MinMaxScaler to ensure consistent ranges and eliminate scale bias.

2.5. Modeling Approach

This subsection outlines the modeling framework adopted in the study, including model selection, training strategy, and validation procedure. Two supervised regression models were implemented using Python's scikit-learn library. The modeling objective was to predict the TQI value for each 20-meter segment in the 2024 inspection, based on features derived from the 2017-2022 period. The models used were:

- Multiple Linear Regression (MLR): A classical statistical model implemented with Linear Regression. This method estimates the relationship between the target variable and the predictors, assuming a linear combination of the predictors. MLR was selected as a baseline due to its interpretability and ability to provide direct insights into the contribution of individual predictors. Additionally, it enables baseline interpretability and sensitivity analysis of predictors, providing the transparency essential in engineering decision-making [63,64].
- Random Forest Regressor (RF): An ensemble machine learning algorithm implemented using RandomForestRegressor (n_estimators=100, max_depth=8, random_state=42). It constructs multiple decision trees during training and outputs the mean prediction of the individual trees. RF was chosen as a more advanced non-linear method, capable of capturing feature interactions and complex degradation patterns that are difficult to model with traditional regression. By aggregating multiple trees, RF reduces variance and increases stability, while the built-in randomization enhances robustness against overfitting [65].

Both models were trained on the same set of scaled input features. Although Random Forest is not sensitive to feature scaling, MinMax scaling was applied to all numerical inputs to ensure fairness, consistency across models, and a unified analytical pipeline. After training, predictions for TQI_2024 were obtained and then inverse-transformed to the original scale for evaluation and comparison.

In addition to testing the models, a 5-fold cross-validation strategy was applied to assess model robustness and generalizability. In this process, the dataset was partitioned into five subsets: four for training and one for validation. This procedure was repeated five times, with each subgroup serving as the validation set once. Performance metrics were averaged across all folds to ensure results were not dependent on a particular data split. The choice of 5 folds represents a balance between statistical stability and computational efficiency, and is widely recognized as a standard practice in predictive engineering studies.

This unified framework ensures the comparability of results and provides a reliable basis for evaluating the relative suitability of statistical versus machine-learning approaches for predictive railway maintenance planning.

2.6. Software Tools and Computational Infrastructure

All modeling and evaluation tasks were performed in the Python programming environment, which provides a flexible, widely adopted platform for statistical analysis and machine learning. The following libraries and frameworks were used:

- scikit-learn: applied for the implementation of regression models, including Multiple Linear Regression (MLR) and Random Forest (RF), as well as for cross-validation procedures, ensuring a standardized framework (unified API) for defining, training, and validating predictive models [66,67].

- statsmodels: employed for detailed parameter diagnostics and statistical validation of the regression-based approaches, including confidence intervals, hypothesis testing, and residual diagnostics [66,68].
- Keras/TensorFlow: utilized in extended experiments with neural network models (MLP), providing advanced functionality for defining and training multi-layer architectures, with built-in support for GPU/TPU acceleration for faster training on large datasets [66,68].
- pandas and numpy: used for dataset integration, transformation, and numerical computation [68].
- matplotlib: applied for visualization of results, including error distributions, scatter plots, and comparative histograms [66].
- Google Colab: served as the computational environment, enabling access to GPU acceleration and ensuring reproducibility of the analyses through cloud-based scripting, while also allowing direct integration with Google Drive for organized storage and collaboration [68].

The use of these open-source tools guaranteed methodological transparency, computational efficiency, and full reproducibility of the study, aligning the research design with current best practices in infrastructure data analysis and predictive modeling.

2.7. Evaluation Metrics

To quantify model accuracy and error, the following evaluation metrics were calculated:

- R^2 (Coefficient of Determination)

R^2 indicates how well the predicted values approximate the actual target values. Higher values represent better model performance.

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

Where y_i are the observed values, (\hat{y}_i) are the predicted values, and \bar{y} is the mean of the observed values. In the context of track quality, a higher R^2 indicates that the model can better reproduce degradation trends [69,70].

- MAE (Mean Absolute Error):

MAE measures the average magnitude of the errors in a set of predictions, without considering their direction.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (3)$$

In railway applications, a lower MAE indicates that deviations between predicted and actual TQI are minor on average, which reduces the risk of misclassifying track segments based on their quality [71].

- RMSE (Root Mean Square Error)

RMSE penalizes larger errors more than MAE, providing a sense of the precision of the prediction.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (4)$$

Since extreme prediction errors can lead to underestimation of critically degraded segments, RMSE is crucial for evaluating reliability in maintenance planning [72].

These metrics were selected because they are widely used in both statistical and machine learning studies on infrastructure condition modeling, thereby ensuring comparability with the existing literature. Together, these metrics provide a balanced evaluation of both explanatory power and predictive accuracy, which is essential in railway infrastructure applications.

3. Results

This section presents the empirical and quantitative findings from the predictive modeling of Track Quality Index (TQI) degradation on the Kolašin–Podgorica railway section. The performance of the baseline Multiple Linear Regression (MLR) and the advanced Random Forest (RF) models is reported using a 5-fold cross-validation strategy applied to the historical dataset (2017–2022) and validated on the 2024 validation dataset.

3.1. Predictive Performance of MLR and RF

To minimize the risk of overfitting and evaluate robustness, a 5-fold cross-validation strategy was implemented. The dataset covering the period from 2017 to 2022 was randomly divided into five subsets. Each subset was used once as validation data, while the remaining four were used for training. Performance metrics were averaged across all folds to provide a reliable estimate of model generalization.

Table 2. Predictive performance of MLR and Random Forest models with cross-validation. (Source: Author).

Model	R ²	MAE	RMSE
Linear Regression	0.5696	4.6805	6.3013
Random Forest	0.6895	3.9630	5.3518

Results show a consistent performance trend, with Random Forest achieving higher R² values and lower errors than multiple linear regression. Under cross-validation, Random Forest retained its advantage and recorded an R² of 0.6895, an MAE of 3.9630, and an RMSE of 5.3518. Quantitatively, Random Forest reduced the average prediction error by approximately 15% (MAE) and 16% (RMSE) relative to MLR.

3.2. Error Distribution and Visual Analysis

The graphical comparison provides additional insight into the predictive behavior of the two models beyond the aggregated metrics.

Figure 3 presents the scatter plot of actual versus predicted TQI₂₀₂₄ values obtained with the Linear Regression model. The red line ($y = x$) represents the ideal fit, and the distance of the points from this line directly indicates the magnitude of the prediction error. Most points are concentrated in the lower range (TQI < 20). However, as TQI values increase, the dispersion of points around the diagonal becomes wider. For segments with a TQI greater than 30, the trend line (black dashed) in Figure 1 deviates notably from the ideal fit (red line).

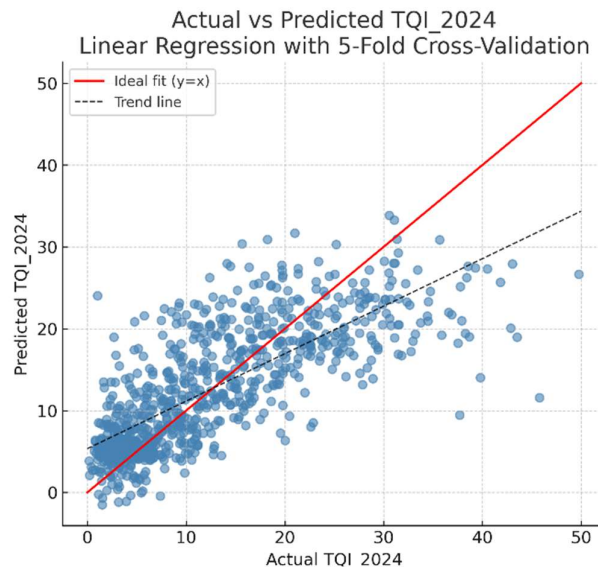


Figure 3. Actual vs predicted TQI_2024 values using Linear Regression with 5-fold cross-validation, with the red line ($y = x$) indicating the ideal fit. (Source: Author's calculations based on model outputs).

Figure 4 shows the histogram comparison between the actual and predicted distributions for the Linear Regression model. Within the range TQI = 0–20, the expected frequency closely follows the exact distribution. However, for higher values (TQI > 25), the model recorded lower frequencies than the actual distribution, while local deviations are also observed in the intermediate range (TQI = 10–15).

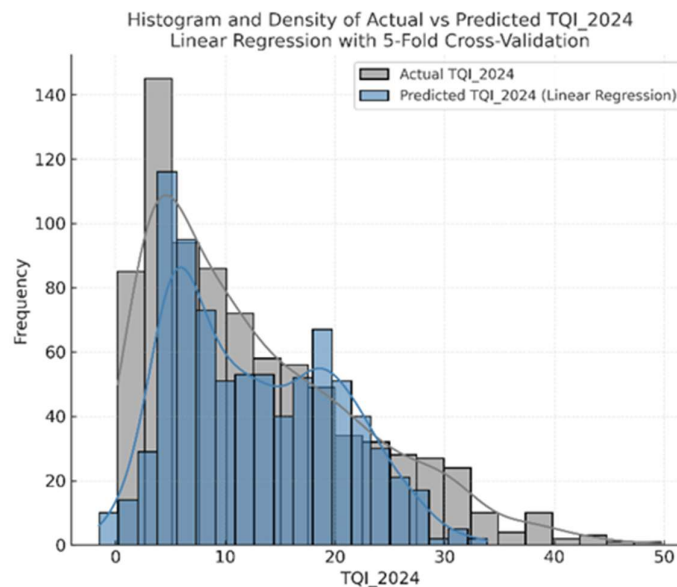


Figure 4. Histogram and density plots of actual vs. predicted TQI_2024 values obtained with Linear Regression (5-fold cross-validation). (Source: Author's calculations based on model outputs).

Figure 5 illustrates the scatter plot of actual versus predicted TQI_2024 values using the Random Forest model. Compared with Linear Regression, the dispersion around the diagonal is smaller, with a large proportion of points lying close to the ideal fit line ($y = x$) within the TQI range of 5–25. For higher TQI values (TQI > 30), some isolated outliers are present, but the trend line remains closer to the ideal fit compared to the linear model.

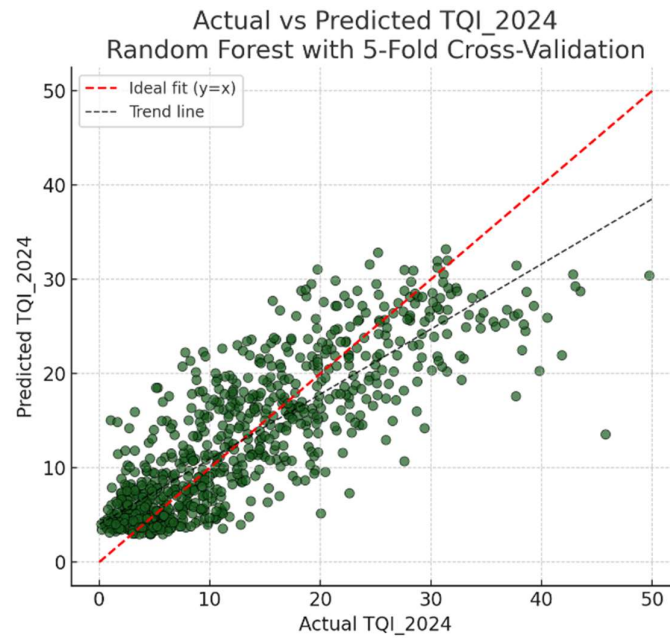


Figure 5. Actual vs predicted TQI_2024 values using Random Forest with 5-fold cross-validation, with the red line ($y = x$) indicating the ideal fit. (Source: Author's calculations based on model outputs).

Figure 6 presents the histogram comparison for Random Forest. The predicted distribution aligns with the actual distribution across the full TQI spectrum, encompassing both lower and higher degradation ranges ($TQI > 25$), with minor local deviations remaining around the $TQI = 10-15$ range.

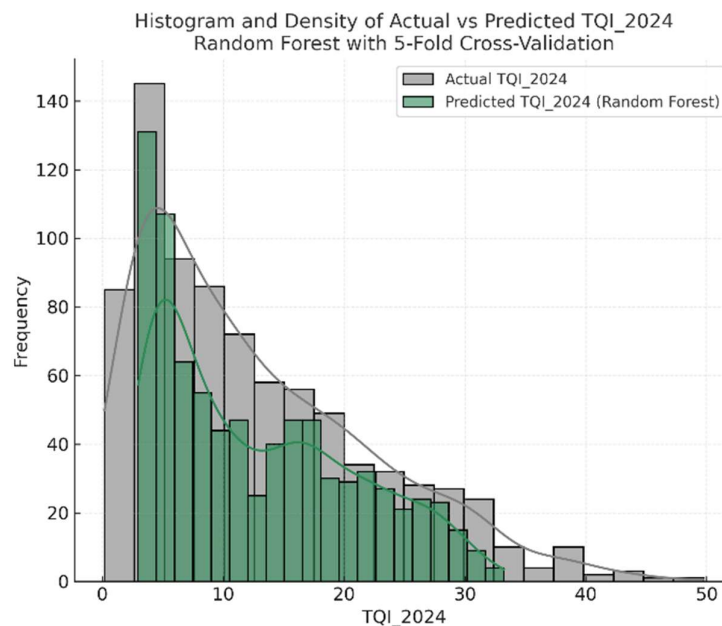


Figure 6. Histogram and density plots of actual vs. predicted TQI_2024 values obtained with Random Forest (5-fold cross-validation). (Source: Author's calculations based on model outputs).

4. Discussion

The comparative evaluation of Multiple Linear Regression (MLR) and Random Forest (RF) highlights the distinct theoretical and practical implications of using machine learning frameworks for infrastructure asset management.

4.1. Interpretation of Evaluation Metrics

To better understand the performance of both models, the statistical evaluation measures must be interpreted in the specific context of track quality assessment:

- **Coefficient of Determination (R^2):** For the Linear Regression model, $R^2 = 0.57$ indicates that the model explains 57% of the variance in the TQI_2024 data. This leaves 43% of the variance unexplained, confirming its limited ability to capture nonlinear processes. In contrast, Random Forest achieved an R^2 of 0.69, indicating that nearly 70% of the variance is captured. This substantial improvement underscores the advantages of ensemble methods for analyzing complex systems where geometry, infrastructure components, and operational variables interact nonlinearly.
- **Mean Absolute Error (MAE):** For linear regression, an MAE of 4.68 means that, on average, predictions deviate by ± 4.68 units from actual TQI values. From an engineering perspective, such errors can result in misclassification of priority segments, particularly in critical zones such as tunnels, bridges, and sharp-radius curves. Random Forest reduced this error to 3.96 (a 15% improvement), lowering the likelihood of misclassification and enabling more precise prioritization.
- **Root Mean Square Error (RMSE):** The Linear Regression model yielded an RMSE of 6.30, indicating that significant prediction errors occur relatively frequently. Because RMSE is highly sensitive to extreme deviations, a track segment with an actual TQI of 35 (poor quality) may be predicted as 28.7 (medium quality), resulting in an inappropriate downgrade of intervention priority. Random Forest improved the RMSE to 5.35, reducing the influence of extreme errors and demonstrating significantly better stability across all data ranges.

4.2. Interpretation and Model Suitability

The comparative evaluation of Multiple Linear Regression (MLR) and Random Forest (RF) highlights the added value of ensemble learning methods for modeling railway track degradation. While MLR provides a transparent and interpretable framework, its strict assumption of linearity limits its ability to capture complex, nonlinear dependencies in the dataset. Track degradation is strongly influenced by multiple interacting factors—geometric, infrastructural, operational, and maintenance-related—that frequently exhibit nonlinear dynamics which linear models cannot adequately reflect.

Random Forest, on the other hand, demonstrates a clear advantage in this context. By constructing multiple decision trees and aggregating their outputs, the method effectively captures feature interactions and nonlinear dependencies. This explains its consistently higher predictive accuracy and its closer alignment with the actual distribution of TQI values, as confirmed by both statistical metrics and visual analyses. From a practical engineering perspective, RF provides a more reliable basis for identifying track segments at higher risk of degradation, thereby enabling proactive maintenance planning.

Nevertheless, the role of MLR should not be dismissed. Its simplicity, computational efficiency, and interpretability make it suitable for rapid diagnostic assessments, preliminary evaluations, and situations requiring transparent relationships between predictors and outcomes. For example, infrastructure managers may employ MLR to identify broad trends or perform sensitivity analyses, while relying on RF for detailed predictive modeling.

In summary, RF offers substantial improvements in predictive performance and generalization, making it the more suitable candidate for integration into predictive maintenance systems,

particularly in geometrically demanding contexts such as the Kolašin–Podgorica section. At the same time, MLR remains a practical, complementary method when transparency, ease of implementation, and quick interpretation are prioritized.

4.3. Practical Implications for Maintenance Planning

The results of the comparative modeling have direct implications for railway maintenance planning and asset management. The superior performance of Random Forest indicates that ensemble-based machine learning models can provide more reliable forecasts of track geometry quality, particularly in complex environments such as mountainous railway sections with frequent tunnels, bridges, and sharp curves. By identifying segments that are most likely to experience rapid degradation, infrastructure managers can prioritize interventions and allocate resources more efficiently.

From an operational perspective, improved prediction accuracy reduces the risk of unexpected speed restrictions or safety incidents, as critical sections can be detected earlier and addressed through timely maintenance. This predictive capability reduces costly emergency interventions and helps maintain service continuity on heavily used corridors. Moreover, the ability of RF to capture nonlinear interactions between geometry, traffic, and maintenance variables supports the development of adaptive maintenance strategies tailored to specific local conditions.

At the same time, the continued use of multiple linear regression retains value in practical workflows. Its interpretability enables decision-makers to better understand the influence of individual parameters—such as traffic intensity or curvature—on TQI. This transparency is helpful for reporting, regulatory compliance, and communicating results to non-technical stakeholders. Thus, MLR can complement advanced ensemble models by providing diagnostic insights in contexts where simplicity and clarity are required.

Overall, the combination of interpretable linear models for diagnostic insight and advanced ensemble methods for predictive precision offers a balanced framework for enhancing railway maintenance planning. Such an integrated strategy enables railway operators to transition from reactive to proactive asset management, extend track life, optimize maintenance costs, and enhance service reliability.

5. Conclusions

This study conducted a systematic comparison of the predictive performance of Multiple Linear Regression (MLR) and Random Forest (RF) models for forecasting the Track Quality Index (TQI) on the geometrically and geotechnically demanding Kolašin–Podgorica railway section. Using data from three inspection campaigns (2017, 2019, 2022) and validating against 2024 measurements, the analysis demonstrated that RF consistently outperformed MLR in terms of explanatory power, error reduction, and generalization under 5-fold cross-validation.

Across the 5-fold cross-validation, RF consistently achieved an R^2 of 0.69 compared to 0.57 for MLR, with reductions in MAE (3.96 vs. 4.68) and RMSE (5.35 vs. 6.30). These values confirm RF's superior predictive ability in capturing nonlinear degradation patterns.

The results highlight several key findings:

- Predictive accuracy: RF achieved higher R^2 values and lower error metrics (MAE, RMSE) than MLR, confirming its superior ability to capture nonlinear degradation patterns.
- Error distribution: RF preserved the statistical distribution of TQI values more faithfully, which is essential for identifying both typical and extreme degradation cases.
- Practical suitability: RF provides a robust and reliable basis for predictive maintenance planning, especially in mountainous railway environments with steep gradients, sharp curves, tunnels, and bridges, where degradation dynamics are most pronounced. By contrast, MLR retains value as a complementary tool for diagnostic assessments and interpretability.

From an engineering perspective, integrating ensemble machine learning methods, such as Random Forest, into railway asset management systems can enhance proactive maintenance strategies, optimize resource allocation, and reduce life-cycle costs.

However, the scope of this study is limited to a single railway section and a four-period dataset, which constrains the broader generalization of the results. In addition, expanding the dataset to include more extended observation periods and incorporating additional railway sections across the Western Balkans would further validate the generalizability of the proposed approach.

Future work should also explore hybrid modeling approaches that combine the interpretability of statistical methods with the predictive power of advanced machine learning, extending the analysis to broader railway networks.

In conclusion, ensemble-based predictive modeling offers a powerful and scalable foundation for data-driven railway infrastructure management, contributing to safer, more resilient, and economically sustainable railway networks.

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