Condition Prediction of Highway Assets Based on Spatial Proximity and Interrelations of Asset Classes: A Case Study

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Abstract – Deterioration models significantly contribute to increasing the efficiency of life-cycle planning for highway assets. Therefore, asset managers strive to maximize the accuracy of such models and intensify the efficacy of the life-cycle plan. Even though nearby assets have been thought to have an impact on each other's conditions, usually, such interrelations have not been considered in previous deterioration models. To this end, in this paper, we focused on investigating the impact of considering nearby assets interrelations on the accuracy of prediction models. Our results show that this consideration resulted in more accurate prediction models in comparison to considering each asset individually.

Keywords – Highway Asset Management; Condition Prediction; Logistic Regression; Nearby Assets

1 Introduction

The optimization of budget allocation in highway asset management programs is gaining more attention due to the massive maintenance needs of the existing aged roadways. Furthermore, in recent years, the constrained budget has resulted in an ever-growing backlog of funding. As an example, the amount of budget shortage for preserving the U.S. roadways in a good state of repair was estimated $836 billion in 2017. As a result, this budget deficit emphasizes the need for optimal and smart investments in highway asset management programs [1]. Therefore, in the pursuit of optimal allocation of the available funds, highway decision makers look for procedures that maximize the level of service with minimal expenditure. To this end, information modeling and management are the keys in establishing optimized Life Cycle Plans (LCPs) and maintenance works [2; 3; 4; 5]. In the meantime, the accuracy of deterioration prediction models highly affects the efficiency of LCPs and, in turn, highway asset management programs. Therefore, decision makers strive to increase the accuracy of data-driven deterioration prediction models given the limited extent of available data so that they could better predict possible future deficiencies in roadways.

In a highway system, several asset classes can be found next to each other. According to the first law of geography that specifies there is a relation between everything with nearby elements being more related, it can be hypothesized that the conditions of neighboring assets are correlated [6]. For instance, the condition of neighboring pavements, shoulders, and slopes might be correlated because of the similar impact of the identical temperature variations and precipitation rates that happen in their vicinity. Also, defects in adjacent asset items could be affected by possible interrelations between the degradation of neighboring elements. For example, the deformation of a slope next to a shoulder might cause the shoulder's subsidence.

However, the majority of previous studies developed their condition prediction models when each asset was considered individually [7, 8, 9, 10, 11]. For this reason, the possible interrelations of nearby asset classes have not been fairly considered in previous deterioration models. To address this challenge, the main motivation of this study is to examine the impact of incorporating the condition of neighboring asset classes into condition prediction models on the accuracy of condition forecasts. To this end, we selected flexible pavement, paved shoulder, and slope to perform the analysis. We selected these assets because: (i) they are made of similar materials, (ii) they are located in close proximity, and (iii) similar factors affect their degradation rates. Then, we developed deterioration models for the selected asset types in a case study. We then performed a comparative study to measure the impact of including the conditions of neighboring assets in the developed prediction frameworks for the selected asset items. The following section moves on to the review of the literature in deterioration prediction models of the selected asset items.

2 Background

Several studies targeted developing deterioration models for pavements and bridges. However, other roadway assets have received less attention. In addition, agencies have focused more on measuring the performance of pavements and bridges in comparison to the other assets [12]. Therefore, sometimes agencies do not own enough performance data of other assets such as slopes and shoulders. Yet, in a roadway asset management system, all asset types are required to be considered together under a framework wherein their performance prediction models specify their maintenance investment needs. Consequently, adding the information of assets with abundant data (e.g. pavement) in condition prediction of other assets with less available data could mitigate uncertainties and contribute toward a better budget allocation.

We identified two main shortcomings in previous works. The first found gap is that the majority of prediction models were developed based on the data of a single asset type, where each asset was modeled individually. For instance, [7], [13], and [14] developed prediction models for the condition of pavements only based on the historical data of pavement segments. Another identified shortcoming in the literature is that even though the condition of nearby assets might be dependent, this dependency was not considered in developing prediction models. For example, in spite of the probable impacts of underlying pavements on the condition of pavement markings, the majority of studies investigated their conditions separately [15, 16]. In addition, several studies performed individual investigations of degradations for other asset types, such as signs, barriers, and culverts [17, 18, 9]. Therefore, the possible interrelations between neighboring assets have not been fairly considered in previous studies. However, a few of the past studies partially investigated the mutual impacts of some of the neighboring assets on each other. For example, the impact of drained and undrained base and subbase layers on the condition of pavement were examined in some works, where the outcomes unveiled that the presence of water in the subsurface layer and its surroundings can significantly influence the pavement's stiffness [19, 20]. In addition, [21] studied the role of routine maintenance of paved shoulders on the condition of adjacent flexible pavement. In another study, [22] investigated the influences of shoulders' rumble strip on the pavement condition. Finally, [23] performed a correlational study between the condition of nearby flexible pavements, paved ditches, and paved shoulders. They identified some interrelations that mutually impact the condition of the selected asset items. However, they did not study the possible impacts of these correlations in the condition prediction models of each asset.

To fill the identified gaps in the body of knowledge, the main objective of this study is to examine how including the condition of nearby assets as a predictor in the condition prediction of a particular asset improves the accuracy compared to single asset modeling where the deteriorations are predicted based on the information of each asset individually. The next section moves on to the step-by-step methodology proposed in this study and explains each step in more detail.

3 Methodology

In this study, we selected three asset classes for our analysis: flexible pavement, shoulder, and slope. We used a wide range of contributing factors to degradation in our analysis under three main categories: weather, traffic, and historical asset's condition due to their importance and data availability. We developed the prediction model of each asset in two different scenarios: when the conditions of its adjacent assets were considered (i.e. nearby-asset modeling) and ignored (i.e. single asset modeling). Prior to developing prediction models, we performed a feature reduction step to ensure there was no multicollinearity in the input dataset. Next, we used logistic regression to predict the existence of pothole defects in flexible pavement and shoulder, and erosion and erosion patterns in slope under the scenarios as mentioned earlier.

To measure the capability of the proposed framework, we applied it on 321.4 kilometers of I-81, I-77, and I-381 highways in Virginia as our case study. Selected roadways were split into 84 segments, each of which has a length of 3.2 kilometers (2 miles). The utilized datasets in this study recorded the corresponding values of weather, traffic, and historical conditions between 2015 and 2019. Fig. 1 shows the framework of the proposed methodology. The following sections provide a detailed description of each step.

3.1 Data Collection and Preparation

The utilized data in this study were categorized into three groups: weather, traffic, and condition. First, we collected data from available resources and then audited the data to detect and correct possible errors, abnormalities, and irregularities.

3.1.1 Traffic

The traffic dataset was extracted from a public portal [24]. We performed a cleaning step to identify missing information and inaccuracies in the dataset. Next, in order to prevent the occurrence of bias in the results, we used the min-max scaling in our analysis to linearly map the features between 0 and 1 [25]. We applied this scaler on each feature of the cleaned traffic dataset separately. The summary of the utilized traffic features, as well as their descriptive statistics, including minimum, maximum, 25th percentile, median, and 75th percentile before scaling are provided in Table 1 and Figure 2, respectively.

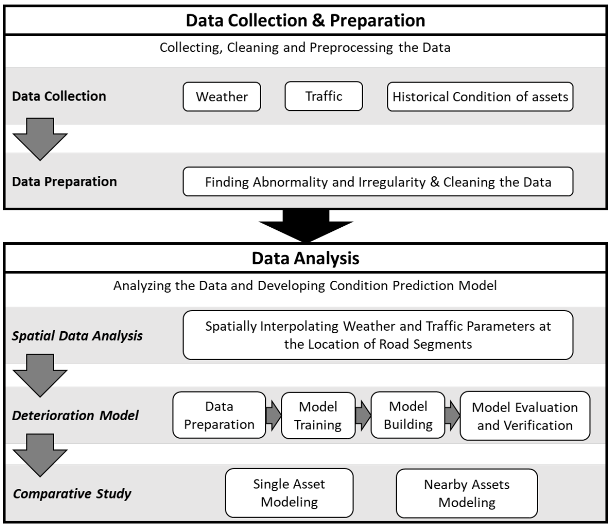

Figure 1. Proposed methodology framework

Table 1. Traffic features

Parameter	Definition
ADT	average daily traffic
AAWDT	average annual weekday traffic
ADT_4	average daily traffic of 4-tire vehicles
ADT_BU	average daily traffic of buses
ADT_TR	average daily traffic of trucks with 1 trailer
ADT_1	average daily traffic of trucks with 2 axles
ADT_2	average daily traffic of trucks with 2 trailers
ADT_3	average daily traffic of trucks with 3 axles

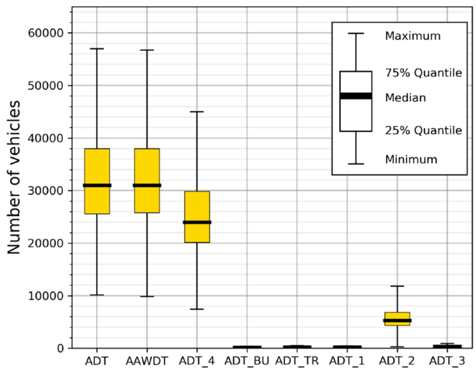

Figure 2. Traffic feature statistical description

3.1.2 Weather

We extracted the weather data from the National Oceanic Atmospheric Administration (NOAA) database. We collected the data from 24 weather stations to cover our case study. Figure 3 shows the selected weather stations and their location with respect to the case study.

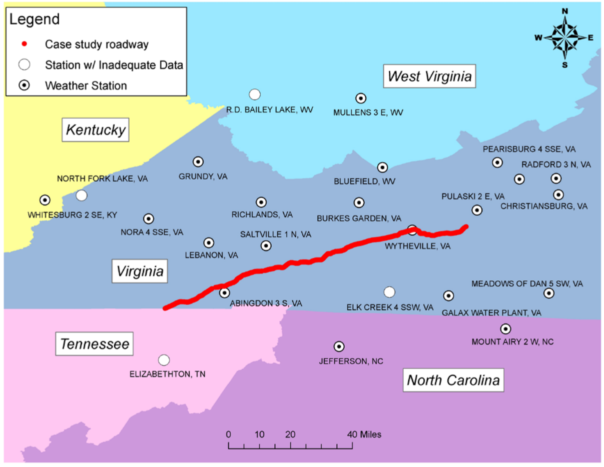

Figure 3. Selected weather stations and the case study

We cleaned the dataset to minimize inaccuracies and missing information. We filtered the stations to the ones with more than 250 days of recorded data, which reduced the number of remaining stations to 20. Table 2 provides a summary of the weather features used in our analysis.

We used the ordinary kriging to interpolate the extracted weather features onto each segment. We used this technique due to its acceptable accuracy for weather-related features [26, 27, 28]. In addition to the common weather features, we devised and considered more attributes to incorporate temperature variations. For instance, the average daily maximum-minimum temperature difference in a year, TMAXTMIN, is one of the attributes that we used to take into account the daily fluctuation of the temperature. TMAXTMIN ranges between two extremums: the upper bound, which takes place in desert-like regions, and the lower bound being observed in low-lying humid areas.

Table 2. Weather features

Parameter	Definition
TMAX	annual maximum daily temperature (° C)
TMIN	annual minimum daily temperature (° C)
TMAXMIN	annual average of daily max_min temperature difference (° C)
DWT32	number of days with minimum temperature<0° C (32° F) in a year
DWT80	number of days with maximum temperature>26.7° C (80° F) in a year
DWTMXN30	number of days with Tmax-Tmin>16.7° C (30° F) in a year
DSNW	number of days with snow depth > 2.54 cm (1 inch) in a year
EMSD	maximum annual daily snow depth (cm)
EMXP	maximum annual daily precipitation depth (cm)
PRCP	total annual precipitation (cm)
SNOW	total annual snow depth (cm)

We additionally added another feature to our analysis to include the number of days with maximum-minimum temperature difference greater than 16.7 degrees Celsius (30 degrees Fahrenheit), called DWTMXN30. Then, like traffic data, we used min-max scaling to map the weather data as well. Figure 4 provides the statistical descriptions of the extracted weather features through a set of boxplots prior to scaling.

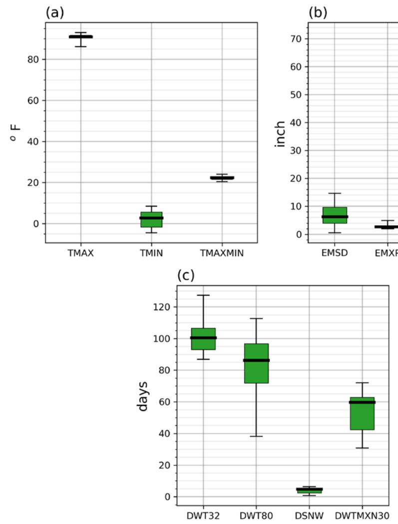

Figure 4. Weather features' statistical description

3.1.3 Condition

The condition of each asset corresponds to its physical characteristics that affect its performance at the time of inspection [29]. We extracted the condition data from a Maintenance Quality Assurance Program (MQAP) that inspected and recorded the condition of the selected assets (i.e. flexible pavement, paved shoulder, and slope) in our case study between 2015 and 2019. The MQAP recorded pothole defects on flexible pavement and shoulder in each segment of roadways, and erosion and erosion patterns in slopes. Being a common defect on flexible pavements and shoulders, potholes pose extreme dangers to vehicles and drivers. Driving over potholes can harm different parts of vehicles and could force drivers to show dangerous maneuvers for avoiding driving over them. Like potholes in flexible pavements and shoulders, erosion and erosion patterns are major probable defects in slopes that endanger their stability. They could cause dangerous failures in slopes. Therefore, we considered these defects in our analysis. The utilized MQAP rated the recorded conditions in 4 classes: very poor, poor, good, and very good. The definitions of all classes of recorded conditions for each asset are provided in Table 3 to Table 6.

Table 3. Condition descriptions for flexible pavement - pothole

Condition	Description
Very Poor	More than one pothole present
Poor	One pothole present
Good	No pothole
Very Good	No pothole or any sign of distressed asphalt such as rutting, heaving, or troughing

Table 4. Condition descriptions for shoulder - pothole

Condition	Description
Very Poor	More than one pothole present
Poor	One pothole present
Good	No pothole
Very Good	No pothole or any sign of distressed asphalt such as rutting, heaving, or troughing

Table 5. Condition descriptions for slope - erosion

Condition	Description
Very Poor	Multiple erosion along slope greater than 8 inches deep
Poor	Erosion along slope greater than 8 inches deep
Good	Less than or equal to 8 inches deep erosion.
Very Good	No slope erosion.

Table 6. Condition descriptions for slope - erosion pattern

Condition	Description
Very Poor	Pattern of erosion that endangers the stability of at least 25% of the slope.
Poor	Pattern of erosion that endangers the stability of less than 25% of the slope.
Good	No pattern of erosion that endangers the stability of the slope.
Very Good	N/A

3.2 Prediction Model

We used logistic regression to develop prediction models and to predict the future condition of selected assets. In developing prediction models, we aggregated the defects into pass or fail classes. This new classification is aligned with trigger levels in maintenance decision making systems that highlights the necessity of repairs for very poor and poor classes. Therefore, in each asset, very poor and poor conditions were merged into the fail class while good and very good into the pass class. As a result, the output of the model would be a binary value (pass/fail), which corresponds to the predicted condition of each asset in the considered segment.

Prediction models in this study were developed in two different scenarios so that the interrelations of neighboring assets could be investigated. In the first scenario, we only considered weather, traffic, and the condition of each individual asset in the modeling (single asset modeling). The condition feature only contains the recorded condition in the prior year of the targeted prediction time. For example, to forecast the condition of the flexible pavement in 2017, the single asset prediction model uses only the condition of flexible pavement in 2016 as a predictor, as well as other weather and traffic features. Figure 5 schematically shows the single asset prediction modeling used in this study.

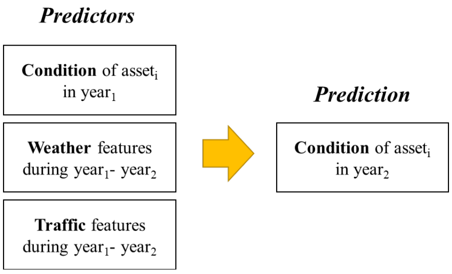

Figure 5. Single asset prediction modeling procedure

In the other scenario, we added the historical condition of the nearby assets in both the prior and the prediction years into the feature space as well (nearby-asset prediction modeling). For instance, for predicting the recorded condition of slope (i.e. slope erosion) in 2017, in addition to weather, traffic, and conditions of the slope (slope erosion and erosion patterns) in 2016, the condition of nearby flexible pavement, shoulder, and the condition of the slope under erosion pattern in 2017 were also included in the modeling. In this way, the interrelations between the condition of neighboring assets in the past and also in the year of prediction are taken into account. Figure 6 schematically describes the modeling process used in this study.

In both scenarios, we first performed a feature reduction step to ensure that the considered features are not highly correlated.

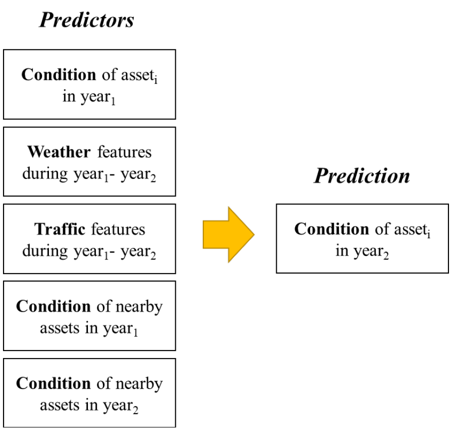

Figure 6. Nearby-asset modeling procedure

3.2.1 Feature Reduction

The efficiency of a multivariable analysis could be highly impacted by multicollinearity among features. Multicollinearity corresponds to the existence of high correlations among some attributes in a dataset, which can bias the result toward correlated attributes [30]. Therefore, we used a correlational investigation to find high correlations between features and to remove multicollinearity.

Given the essence of the considered inputs, we performed the feature reduction in two steps. First, we ensured that there was not any high correlation among continuous features, i.e. weather and traffic, using Pearson correlation coefficients. As a rule of thumb, features whose pairwise absolute Pearson correlation coefficients are more than 0.9 are considered highly correlated [31, 30]. Therefore, we clustered such features and chose only one of them as the only representative of the group.

In the next step, we measured the correlation between the remaining continuous and categorical features, i.e. condition classes, utilizing absolute point-biserial correlation coefficients. Any group of attributes with a more significant correlation than 0.9 were considered as highly correlated and represented with only one of the considered features.

3.2.2 Logistic Regression

After feature reduction, we used logistic regression to develop the condition prediction model, which predicts the probability of each condition category, i.e. pass or fail, for each asset based on multiple independent variables that were available in the dataset, i.e. weather, traffic, and condition. Maximum likelihood estimation was used to evaluate the probability of categorical membership in the binary logistic regression [32, 33]. For example, if y_i is the dependent variable with two categories (0/1), the probability of being in category 1 could be denoted by $\pi_i^{(1)} = \Pr(y_i = 1)$ with the chosen reference category, $\pi_i^{(0)}$. If only one independent variable x_i existed, a logistic regression model would be written as Equation 1:

$$Log\left(\frac{\pi_i^{(1)}}{\pi_i^{(0)}}\right) = \beta_0^{(1)} + \beta_1^{(1)} x_i \quad (1)$$

Wherein $\beta_0^{(1)}$ is the intercept and $\beta_1^{(1)}$ is the regression coefficient. In addition, the probability of being y_i in the reference category (0) is written in Equation 2.

$$\pi_i^{(0)} = 1 - \pi_i^{(1)} = \frac{1}{1 + e^{(\beta_0^{(1)} + \beta_1^{(1)} x_i)}} \quad (2)$$

Therefore, $\pi_i^{(1)}$ can be calculated using Equation 3.

$$\pi_i^{(1)} = \frac{e^{(\beta_0^{(1)}+\beta_1^{(1)}x_i)}}{1+e^{(\beta_0^{(1)}+\beta_1^{(1)}x_i)}} \quad (3)$$

3.2.3 Validation of Prediction Models

After developing prediction models, we validated them using k-fold cross-validation that evaluates and controls the performance of the models over unseen data. We utilized five folds for this purpose.

4 Results and Discussion

This section provides the results that we obtained after applying the proposed methodology to our case study. Figure 7 shows the correlation matrix and corresponding pairwise absolute Pearson correlation coefficients among continuous features i.e. weather and traffic. As it can be observed, traffic features are highly correlated. In addition, TMAXTMIN and DWTMXN30 are highly correlated as well. Therefore, we only considered ADT as the representative of the traffic features, as well as all of the weather features except for TMAXTMIN in the final dataset.

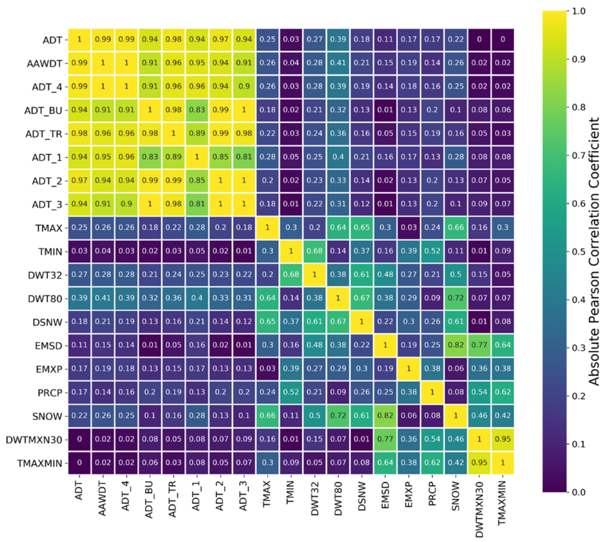

Figure 7. Correlation matrix of continuous features

In the next step, we measured the correlation between the remaining continuous and categorical features (i.e. conditions). The corresponding correlation matrix, using absolute point-biserial correlation, is provided in Figure 8.

Figure 8. Correlation matrix of mixed features

As Figure 8 suggests, there is not any high correlation in the mixed feature, and we proceeded with the remaining features ensuring that the multicollinearity has been removed.

Next, we fed the reduced dataset into the logistic regression to develop the condition prediction models. We developed the models for each asset in both single asset and nearby-asset modeling scenarios and reported the obtained confusion matrices in Figure 9 and 10, respectively. In addition, the results of the average accuracy of the final validated prediction models for the two considered scenarios are summarized in Table 7. It can be observed that in all cases when the conditions of the nearby asset items were considered in developing the condition prediction model, the accuracy of predictions increased in comparison to single asset prediction models.

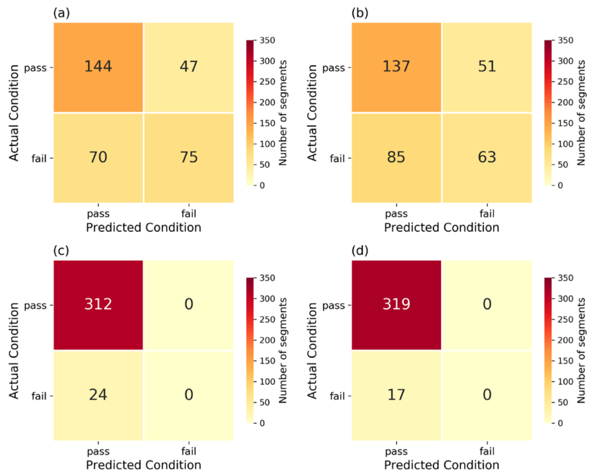

Figure 9. Confusion matrix of single asset modeling: (a) Flexible Pavement-Pothole, (b) Shoulder-Pothole, (c) Slope-erosion, (d) Slope-erosion pattern

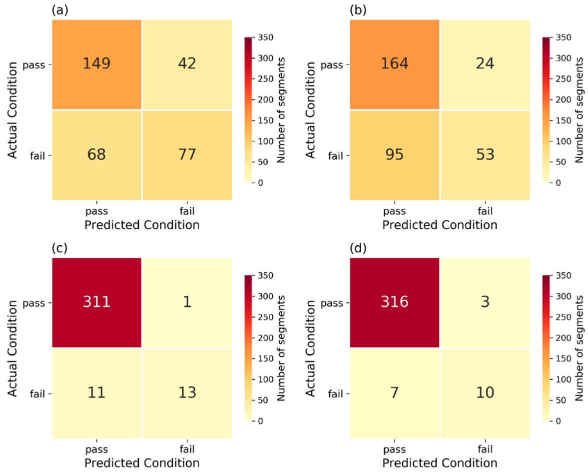

Figure 10. Confusion matrix of nearby-assets modeling: (a) Flexible Pavement-Pothole, (b) Shoulder-Pothole, (c) Slope-erosion, (d) Slope-erosion pattern

Table 7. Summary of the obtained accuracies

Asset/Defect	Accuracy		Improvement
	Single asset	**Nearby-asset**	
Flexible Pavement-Pothole	65.2%	67.3%	3.22%
Shoulder-Pothole	59.5%	64.6%	8.57%
Slope-Erosion	92.9%	96.4%	3.77%
Slope-Erosion Pattern	94.9%	97.0%	2.21%

5 Conclusion

In this study, we examined the impact of interrelations between nearby assets in the accuracy of their condition predictions. We selected three assets (flexible pavement, shoulder, and slope) to investigate how considering the condition of nearby assets into the condition prediction of each one improves the accuracy of predictions. To this end, we developed prediction models in two different scenarios: when the conditions of nearby assets were and were not considered as a predictor. We then implemented the proposed methodology on a case study in the state of Virginia. The results show that in all of the selected asset items, when the conditions of nearby assets were included in the modeling, the accuracy of condition predictions increased. This highlights the interrelation between nearby assets and its impact on the condition of individual asset items. With potentially increasing the accuracy of deterioration models, the results of this study could benefit the optimization and scheduling of maintenance activities and facilitate planning for an optimum and effective Life Cycle Plan (LCP). In this study, we applied the methodology on three assets. Similarly, the idea could be applied to the other highway asset items with more possible interrelations. Furthermore, we considered weather, traffic, and maintenance as major contributing factors to the degradation of the selected assets. However, other factors such as construction quality potentially impact the condition and could be taken into account in future studies. Another limitation of this study is that we performed the feature reduction using a traditional approach (correlation matrix). It is suggested that future studies utilize other techniques as well.

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