Utilization of Traffic Speed Deflectometer for Pavement Management

FINAL REPORT

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16. Abstract

This project investigated how the Traffic Speed Deflectometer (TSD) data the South Carolina Department of Transportation (SCDOT) obtained as part of the pooled fund studies (i.e., TPF-5(282) and 5(385)) can be used to improve the selection of candidate projects for rehabilitation. The analysis using approximately 950 miles of TSD data collected on eight SC primary routes indicated that there is a low correlation between Structural Condition Index (SCI) and Pavement Quality Index (PQI). This finding confirmed prior knowledge that PQI does not accurately portray the pavement's underlying conditions related to remaining service life or the potential for future deterioration. The SCI_{12} performance indicator was selected to quantify the structural condition of a pavement, where *good* pavements are those with SCI_{12} values below 1.6, *fair* are those with SCI_{12} values between 1.6 and 3.3, and *poor* are those with SCI_{12} values above 3.3. A TSD score was developed using the percentages of *poo*r pavements to assist the SCDOT with candidate project selection. This TSD score can be easily incorporated into the current workflow of project selection with the implemented Excel-based tool.

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EXECUTIVE SUMMARY

This project investigated how the Traffic Speed Deflectometer (TSD) data the South Carolina Department of Transportation (SCDOT) obtained as part of the pooled fund studies (i.e., TPF-5(282) and 5(385)) can be used to improve the selection of candidate projects for rehabilitation. The objectives of this project were to: 1) develop a method to use TSD data to classify pavement sections as structurally good, fair, or poor for primary routes, and 2) develop a method to use TSD data to assist the SCDOT with the selection of potential rehabilitation candidates.

An online survey was conducted to understand the state-of-the-practice on the use of TSD data for pavement management. A total of 25 states Department of Transportation (DOTs) responded to the survey. Eighty percent (80%) of the respondents indicated that they collect structural condition data. The majority of the respondents (60%) use only Falling Weight Deflectometers (FWD) to collect the data. Twenty percent (20%) of the respondents use both FWD and TSD. One respondent (4%) indicated their agency use only TSD. Only 13% of the respondents indicated they have developed guidelines to utilize structural conditions to manage their pavement systems at the network level. About 48% indicated they have not done this but plan to in the future, and about 35% indicated that they do not intend to pursue this. Only one respondent indicated their agency has developed guidelines to utilize TSD data for project-level decision-making. About 39% indicated they have not done this but plan to in the future, and an equal percentage of respondents indicated that they do not intend to pursue this. Four respondents (17.4%) indicated they have investigated the cost effectiveness of collecting structural condition data for use at both the network and project levels, with five (21.7%) planning to and nine (39.1%) not planning to pursue this.

Approximately 950 miles of TSD data were analyzed in this study. The Structural Condition Index, SCI_{12}, was selected to quantify the structural condition of a pavement, where *good* pavements are those with SCI_{12} values below 1.6, *fair* are those with SCI_{12} values between 1.6 and 3.3, and *poor* are those with SCI_{12} values above 3.3. Pavement Quality Index (PQI) was used to quantify the functional condition of a pavement, where *good* pavements are those with PQI values above 3.34, *fair* are those with PQI values between 2.64 and 3.34, and *poor* are those with PQI values below 2.64. The correlation between SCI_{12} and PQI was assessed for all routes. Based on the calculated Pearson correlation, it was found that 50% has low correlation (below ± 0.29), 27.5% has moderate correlation (between ± 0.30 and ± 0.49), and 22.5% has high correlation (between ± 0.5 and ± 1.0). This finding confirmed prior knowledge that PQI does not accurately portray the pavement's underlying conditions related to remaining service life or the potential for future deterioration. Using the combination of SCI_{12} and PQI, the length of areas of interest for each route was determined. Areas of interest are those pavement sections with fair or good PQI and poor SCI_{12} or those with poor PQI and good SCI_{12}. These areas of interest are where utilization of TSD data has the greatest potential benefit for the SCDOT. That is, TSD data could help the SCDOT pavement engineers make informed decisions on whether field investigation is needed for a project and/or which type of rehabilitation should be performed. The following table provides the length of areas of interest for each route:

Route	Length of area of interest (mi)	Total route length (mi)	Percentage (%)
SC–9	44.4	231	19
US–321	55.89	216	26
US–378	45.81	201	23
US–178	52.47	181	29
US–29	5.8	37	16
US–78	3.1	36	9
US–17	5.96	19	31
US–501	4.4	12	37

A TSD score was developed to help inform the district pavement engineers of the structural condition of various segments. This score is intended to be used as another criterion, along with relative condition, corridor continuity, connectivity, and contractability at the second stage after the top 20% of candidate projects have been identified via Engineering Directive 63. Like other criteria, the TSD score ranges from 0 to 100, where a 0 indicates excellent structural condition and a 100 indicates extremely poor structural condition. To demonstrate the potential impact of using TSD scores, the scores were applied to the 2020 top 20% candidate projects sent to district engineers. The results indicated that the TSD scores may have an impact on project selection as summarized below. For example, for US-378 in Lexington County, 8 out of 22 pavement condition segments or 7.64 miles out of 14.38 miles, require field investigation or do not require full-depth reclamation. Pavement condition segments are defined in Integrated Transportation Management System (ITMS) as those with common pavement quality, AADT, and number of lanes. To assist the SCDOT with integrating the TSD scores into their existing workflow for project selection, an easy-to-use Excel-based tool was developed and delivered as part of this project.

Route	County	TSD score potential impact on project selection
US-378	Lexington	8 out of 22 segments*, 7.64 miles out of 14.38 miles
US-78	Charleston	3 out of 10 segments, 1.04 miles out of 4.13 miles
US-178	Saluda	1 out of 11 segments, 0.24 miles out of 15.65 miles
US-321	Chester	1 out of 13 segments, 0.27 miles out of 8.70 miles
US-321	Lexington	3 out of 20 segments, 2.74 miles out of 12.60 miles
US-321	York	2 out of 25 segments, 1.8 miles out of 13.19 miles

* Segment length is defined as sections with common pavement quality, AADT and number of lanes

From this project's findings, it is recommended that the SCDOT conduct a benefit-cost analysis to determine the potential savings with TSD data. There are three situations where TSD data would be beneficial. The first is where the pavement has *good* PQI but *poor* SCI_{12}. These sections need to be rehabilitated but do not make the top 20% of candidate projects using the current procedure in Engineering Directive 63. The second is where the pavement has *fair* PQI and *poor* SCI_{12}. These sections are unlikely to make the top 20% cut because they have *fair* PQI instead of *poor*, but they may get selected due to other criteria. In this case, the TSD data can be utilized to help guide the field investigation. The third is where the pavement has *poor* PQI but *good* SCI_{12}. These sections will most likely meet the 15% full-depth patch criterion. Thus, they may undergo reconstruction where preservation would suffice. The annual cost savings will determine how often TSD data should be acquired.

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CHAPTER 1: INTRODUCTION

In 2007, the South Carolina General Assembly enacted Act 114 which required the South Carolina Department of Transportation (SCDOT) to establish a project prioritization process. In 2016, the General Assembly enacted Act 275 which eliminated some of the requirements in Act 114, but retained the requirement for project prioritization (Engineering Directives 63 – 65). Currently, the SCDOT selects projects based on a set of relevant criteria and associated weightings as specified in Engineering Directives 63 (for Primary system), 64 (for Federal-Aid Eligible Secondary system) and 65 (for Non-Federal-Aid Eligible Secondary). These criteria and weightings are shown in Table 1.1.

Table 1-1 SCDOT relevant criteria and associated weightings for project selection (source: SCDOT Engineering Directive 63-65).

Criteria	Weight (%)	Points
Pavement Quality Index	40	0 to 400
International Roughness Index	15	15 to 150
Average Daily Traffic	15	15 to 150
Percent Patching	5	5 to 50
Average Daily Truck Traffic	5	5 to 50
State Freight Network	5	5 to 50
Strategic Corridor Network	5	5 to 50
Functional Classification	5	5 to 50
State Safety Programs	5	5 to 50
		1,000

Using the criteria shown in Table 1.1, candidate projects are ranked on a scale of 0 to 1,000 points; the higher the point value, the higher the chance the project will get selected for rehabilitation. Once eligible candidate projects are identified, district pavement engineers will use the following field review criteria, which are worth a maximum of 400 points, to complete the ranking process (Engineering Directive 63):

- Relative Condition (minus 100 to 100 points) – This criterion is used so that Pavement Quality Index (PQI) data accurately reflects the current condition of the pavement due to localized improvements made by SCDOT maintenance forces or accelerated deterioration due to increased loads.
- Corridor Continuity (0 to 100 points) – This criterion is used for route segments that would complete the resurfacing of, or add to the completion of the resurfacing of, a route corridor through a county or a district.
- Connectivity (0 to 100 points) – This criterion is used for routes that provide connectivity to economic centers, schools, emergency facilities or other key points of public interest.
- Contractibility (0 to 100 points) – Contractibility can be the grouping of roads in a specific geographical area into one project to achieve economies of scale or group roads with like treatments into a single project to reduce project costs.

The current ranking system relies heavily on the PQI to quantify pavement quality. While PQI can be an effective measure for ride quality and surface distresses, it may not be indicative of the pavement structural condition. Flora (2009) and Bryce et. al. (2012) found that there is little correlation between pavement functional condition and pavement structural condition. A number of researchers have recommended the consideration of both pavement functional and structural conditions for pavement management (Zaghloul et. al., 1998; Ferne et. al., 2013; Steele et. al., 2015, and Katicha et al., 2016). Moreover, earlier SCDOT-funded research conducted at the University of South Carolina (UofSC) by Baus et al., (2001) concluded that the "addition of a separate deflection-based structural assessment would be valuable for identifying structurally weak sections, developing rehabilitation strategies based on structurally homogeneous sections, and, once a database has been established, for evaluating the structural performance of pavements."

Recognizing the importance of pavement structural condition data and anticipating that future practice may require the use of such data, the South Carolina Department of Transportation (SCDOT) participated in two pooled fund studies entitled "Demonstration of Network Level Pavement Structural Evaluation with Traffic Speed Deflectometer" (TPF-5(282)) and "Pavement Structural Evaluation with Traffic Speed Deflection Devices (TSDDs)" (TPF-5(385)). As part of these studies, the SCDOT obtained approximately 950 miles of TSD data in 2019 within a period of four days. The aim of this research project is to determine how this data can be used effectively to assist the SCDOT with the selection of rehabilitation candidate projects for primary routes.

The objectives of this study are:

1) to develop a method to use TSD data to classify pavement sections as structurally good, fair, or poor for primary routes, and
2) to develop a method to use TSD data to assist the SCDOT with the selection of potential rehabilitation candidates.

CHAPTER 2: BACKGROUND AND LITERATURE REVIEW

2.1 Background

Traffic Speed Deflectometer (TSD) is a rolling wheel deflectometer that measures pavement response to an applied load. It was developed by Greenwood Engineering in the early 2000's using doppler laser-based technology (Manoharan et al., 2020). TSDs are being used by many transportation agencies around the world (Greenwood Engineering, 2019). The two main advantages of TSD when compared to other pavement structural condition measurement methods are: 1) it can measure pavement deflections continuously rather than at discrete points, and 2) it can collect pavement structural condition data while traveling at traffic speed, and therefore, does not require lane closures as is the case with the commonly used Falling Weight Deflectometer (FWD) (Chai et al., 2016). These advantages make TSD suitable to be used for pavement network-level management.

As part of the pooled fund studies (i.e., TPF-5(282) and 5(385)), the SCDOT obtained TSD data for approximately 950 miles along 8 primary routes. A map of the routes selected by SCDOT to obtain TSD data is shown in Figure 2-1. The length of TSD measurements obtained for each route is summarized below, in descending order.

- SC-9: 231 miles
- US-321: 216 miles
- US-378: 201 miles
- US-178: 181 miles
- US-29: 37 miles
- US-78: 36 miles
- US-17: 19 miles
- US-501: 12 miles

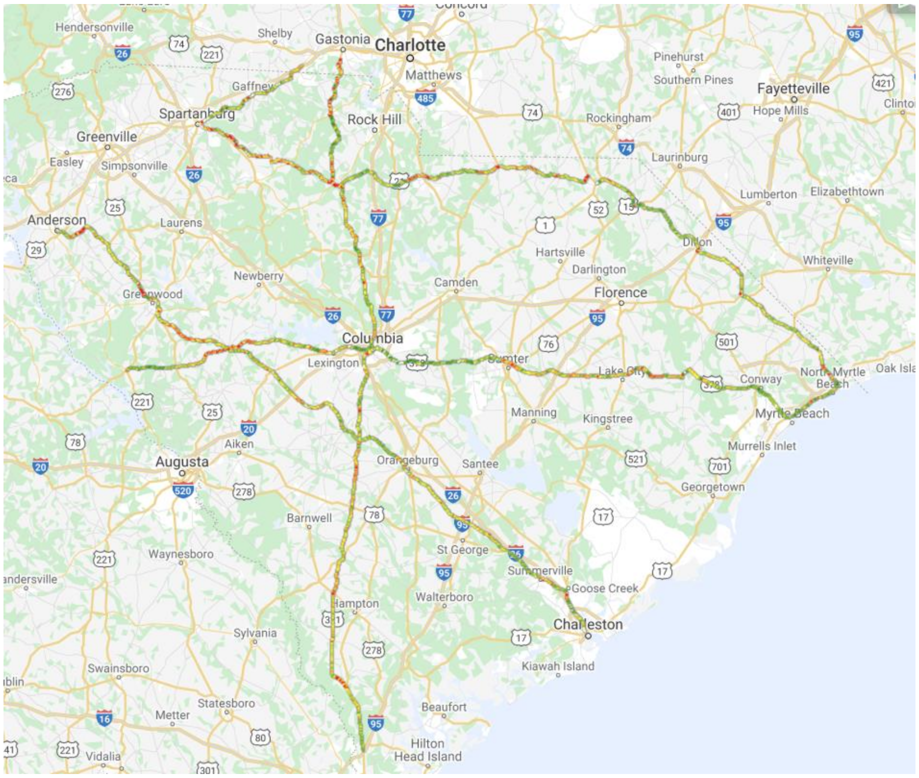

Figure 2-1 Primary routes selected by SCDOT to have TSD data collected.

The TSD data were obtained by ARRB using their Intelligent Pavement Assessment Vehicle (IPAVe). IPAVe (shown in Figure 2-2) is a semi-trailer truck that is equipped with six Doppler sensors to measure pavement deflection located at 110 mm (~4 in.), 210 mm (~8 in.), 310 mm (~12 in.), 610 mm (~24 in.), 910 mm (~36 in.), and 1510 mm (~60 in.) from the center of the wheel load. The Doppler sensors measure the velocity of the deflection, from which deflection slope can be obtained as illustrated in Figure 2-3. The pavement structural condition index or structural condition index (SCI) can be derived from the deflection slope. In this project, SCI_{300} is used to quantify pavement structural condition. It is the differences between D_0 and D_{300}, where D_0 is the maximum deflection (under the applied load) and D_{300} is the deflection at 300 mm (or 12 in.) from the applied load.

Figure 2-2 iPAVe used to collect pavement condition data in South Carolina (source: https://www.arrb.com.au/ipave).

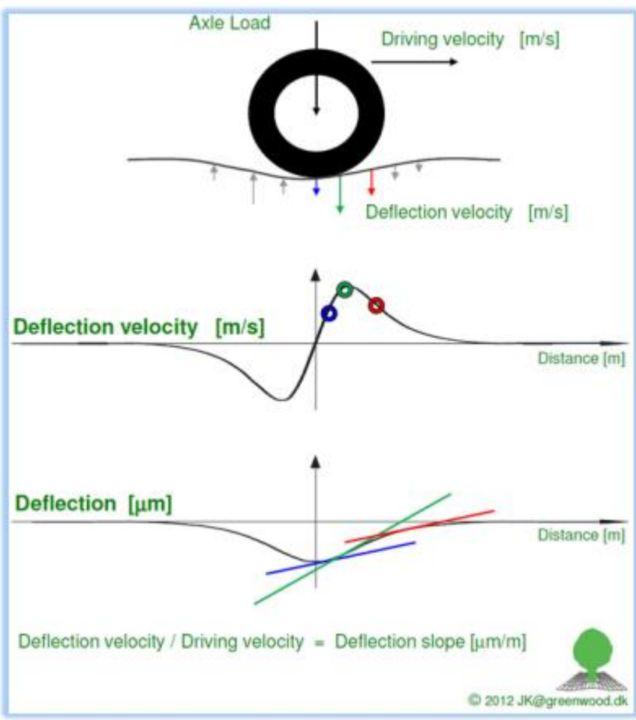

Figure 2-3 Relationship between driving velocity, deflection velocity, and deflection slope (source: https://greenwood.dk/road/tsd/).

2.2 Literature Review

Several different indicators have been proposed to quantify pavement structural condition. Manoharan et. al. (2020) proposed the use of Remaining Structural Life (RSL) and developed a method to derive RSL from D_0. Shrestha et al. (2018a) proposed the use of SCI_{300}. SCI_{300} (or SCI_{12} in English Customary). Subsequently, Shrestha et. al. (2018b) proposed the use of Deflection Slope Index (DSI) and developed a pavement deterioration model based on pavement age and DSI. Virginia DOT (VDOT) currently uses effective SN, calculated using Equation 2.1 (Katicha et al., 2020).

$$SN_{eff} = k_1 SIP^{k2} H_P^{k3} \quad (2.1)$$

where

SN_{eff} = effective Structural Number

H_P = total pavement thickness (mm)

SIP = structural index of pavement, calculated as $D_0 - D_{1.5H_P}$

k_1, k_2, k_3 = parameters to be estimated using data

Rohde (1994) estimated coefficients k_1, k_2, and k_3 for an asphalt pavement to be 0.4728, -0.4810, and 0.7581, respectively. Nasimifar et al. (2019) recommended that these coefficients be adjusted to 0.4369, -0.4768, and 0.8182 if the deflection measurements are obtained using a TSD.

Several studies have developed threshold values to quantify the pavement structural condition as good, fair, or poor. Shrestha et al. (2018b) developed thresholds for Deflection Slope Index (DSI). Pavement sections with DSI values below 5.90 are considered good, between 5.90 and 15.90 are considered fair, and above 15.90 are considered poor. Shrestha et. al. (2018a) also developed threshold values for SCI_{300}. For primary routes, their suggested threshold value for good pavement is less than 4.9, fair is between 4.9 and 6.2, and poor is greater than 6.2. Manoharan et al. (2018) developed threshold values for adjusted Structural Number (SNP) and D_0 as shown in The *relationship* between SNP and D0 (obtained using TSD data) is shown in Equations 2.2 and 2.3. SNP in Equations 2.2 and 2.3 are determined using FWD data.

$$SNP = 82.3 \times TSD_{D_0}^{-0.47} \quad (2.2)$$

$$SNP = 3.2 \times TSD_{D_0}^{-0.52} \quad (2.3)$$

Table 2-1. The relationship between SNP and D_0 (obtained using TSD data) is shown in Equations 2.2 and 2.3. SNP in Equations 2.2 and 2.3 are determined using FWD data.

$$SNP = 82.3 \times {TSD_{D_0}}^{-0.47} \quad (2.2)$$

$$SNP = 3.2 \times {TSD_{D_0}}^{-0.52} \quad (2.3)$$

Table 2-1 Pavement structural condition based on SNP and D_0.

Category	Adjusted Structural Number (SNP)		TSD Maximum Deflection (D_0)	
	Lower limit	Upper limit	Lower limit	Upper limit
Very good	≥ 8		≤ 160	
Good	≥ 6	<8	≤ 300	>160
Fair	≥ 4	<6	≤ 650	>300
Poor	≥ 2.5	<4	≤ 1535	>650

The only study, to the authors' knowledge, that has investigated the use of pavement structural condition data for system-wide pavement management is by Shrestha et al. (2019a), where a framework to assist VDOT to utilize SCI_{300} in their Pavement Management System (PMS) was developed. VDOT uses levels of pavement distresses to select pavement maintenance categories and Critical Condition Index (CCI) as an additional filter; CCI is equivalent to the SCDOT's PQI and it ranges from 0 to 100 where a 0 indicates very poor pavement and a 100 indicates an excellent pavement. Shrestha et al. (2019a) recommended the use of SCI_{300} at the second stage to make the final rehabilitation decision.

Anticipating the use of TSD data in future practices, several studies have begun to explore how to make use of such data. Maser et al. (2017) developed a geodatabase using ArcGIS to incorporate pavement condition data to assist DOT personnel to visualize pavement condition and select a suitable rehabilitation strategy. Nasimifar et al. (2017) proposed two approaches to back-calculate flexible pavement layer moduli from TSD data. Similarly, Elbagalati et al. (2017) and Nielson (2019) developed methodologies to incorporate TSD measurements in the back-calculation analysis. Elbagalati et al. (2017) found that the back-calculated moduli obtained from TSD and FWD deflection measurements had good agreement. Zofka et al. 2015 examined external factors that may have a significant effect on the TSD measurements. They proposed a probabilistic model to account for wind and pavement roughness. Nasimifar et al. (2018) developed a method to adjust SCI to a reference temperature. The authors stated that the temperature adjustment is essential to correctly assess the pavement structural evaluation since the asphalt layer is sensitive to temperature. Nasimifar et al. (2015) and Nasimifar et al. (2016) have investigated the use of 3D-Move Analysis Software to simulate TSD measurements.

This project did not seek to verify the validity of TSD data as directed by the project steering committee. It should be noted that a number of studies have compared the measurements obtained from TSD against FWD. Chai et al. (2016), Manoharan et al. (2018) and Muller and Roberts (2013) showed that TSD and FWD maximum deflections (D_0) are highly correlated. The goodness of fit of their linear regression models (R^2) are 0.88, 0.883 and 0.888, respectively. Muller and Roberts (2013) also showed that TSD and FWD SCI_{300} are highly correlated with $R^2 = 0.853$. All three of these studies used data collected from Queensland, Australia. Zihan et al. (2018) used TSD and FWD data from Louisiana and Idaho to compare the Structural Number (SN) calculated using these measurements. They found that the SN calculated using TSD data to be highly correlated with the SN calculated using FWD data; their linear regression model's R^2 value was 0.931 for the training dataset and 0.887 for the test dataset. Instead of using linear regression as those mentioned above, Levenberg et al. (2019) proposed the use of a Taylor diagram to visualize the similarity between TSD and FWD data as shown in Figure 2-4. In this figure, the markers indicate TSD measurements collected at different speeds. The distance of these markers from the origin represents the standard deviation of the TSD_{300} values, which is labeled by the dotted arcs. The correlation between TSD and FWD can be inferred by their Pearson correlation coefficients labeled in the outer arc.

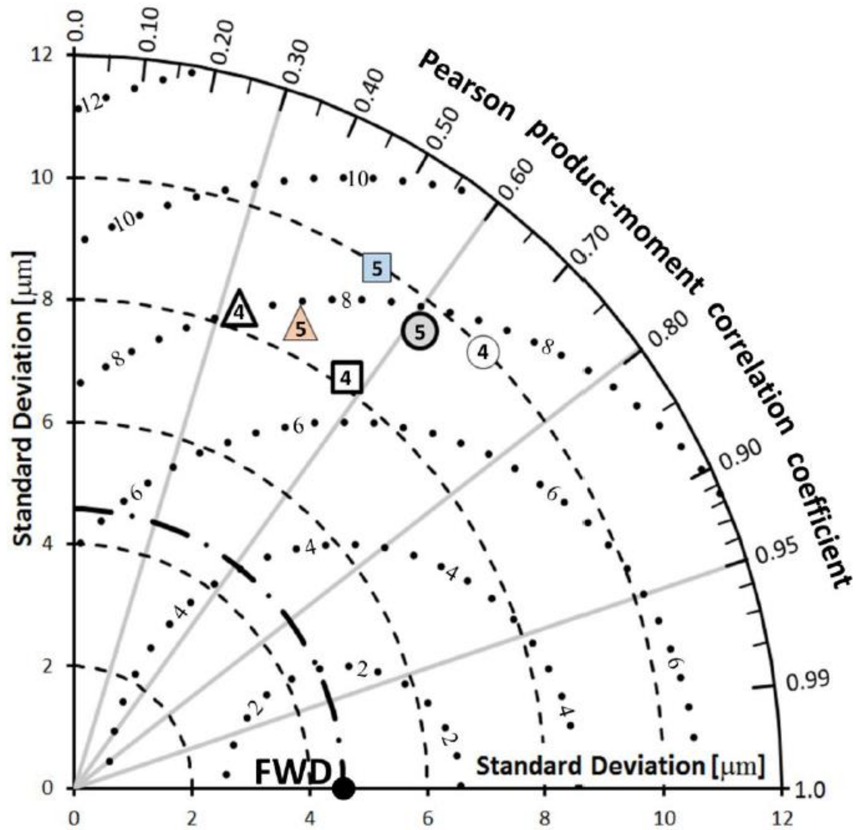

Figure 2-4 Taylor diagram of TSD_{300} index statistics for comparing FWD and TSD measurements at three different speeds: 40 km/h (triangular markers), 60 km/h (square markers), and 70 km/h (circular markers) [source: Levenberg et al., 2019].

2.3 State-of-the-Practice on Utilization of TSD for Pavement Management

As part of this study, an online survey was conducted to understand the state-of-practice on TSD utilization for pavement management in the United States. The survey was distributed to other state DOTs on April 15, 2020. A total of 25 state DOTs responded to the survey.

The questions and responses are summarized below. The questions are numbered and shown in italics.

1. *Does your agency collect pavement structural condition data?*

Table 2-2 Agency practice regarding pavement structural condition data.

Responses	No. of Responses	Percent of Responses
Yes	20	80%
Not yet, but we plan to	2	8%

Responses	No. of Responses	Percent of Responses
No, we do not intend to	0	0%
Other	3	12%
Total	25	100%

As shown in Table 2-2, most of the respondents (80%) indicated that their agencies collect pavement structural condition data.

2. Which method(s) is used to obtain pavement structural condition data?

Table 2-3 Methods being used to obtain pavement structural condition data.

	No. of Responses	Percent of Responses
FWD	15	60%
FWD and TSD	5	20%
FWD, TSD and other	1	4%
TSD	1	4%
Other	1	4%
Not yet but they have a plan	2	8%

As shown in Table 2-3, most of the agencies (60%) indicated that they use only FWD to collect pavement structural condition data. Twenty percent (20%) of the respondents use both FWD and TSD. One respondent (4%) indicated their agency use only TSD.

3. Has your agency developed guidelines to incorporate pavement structural condition data into your agency's network-level pavement management system?

Table 2-4 Development of guidelines to use structural condition for network-level pavement management.

Responses	No. of Responses	Percent of Responses
Yes	3	13%
Not yet, but we plan to	11	47.8%
No, we do not intend to	8	34.8%
Other	1	4.3%
Total	23	100%

As shown in Table 2-4, only 13% of the respondents indicated they have developed guidelines to utilize structural conditions to manage their pavement systems at the network level. About 48% indicated they have not done this but plan to in the future, and about 35% indicated that they do not intend to. Two state DOTs did not provide a response to this question.

4. Has your agency developed guidelines for how structural condition collected from TSDs can be used to support project level decision-making?

Table 2-5 Development of guidelines to use TSD data for project-level decision making.

Responses	No. of Responses	Percent of Responses
Yes	1	4.3%
Not yet, but we plan to	9	39.1%
No, we do not intend to	9	39.1%
Other	4	17.4%
Total	23	100%

As shown in
Table 2-5, only one respondent indicated their agency has developed guidelines to utilize TSD data for project-level decision making. About 39% indicated they have not done this but plan to in the future, and an equal percentage of respondents indicated that they do not intend to. Two state DOTs did not provide a response to this question.

5. Has your agency performed a study to evaluate the cost effectiveness of collecting structural condition data at both the network and project levels?

Table 2-6 Cost-effectiveness of collecting structural condition data.

Responses	No. of Responses	Percent of Responses
Yes	4	17.4%
Not yet, but we plan to	5	21.7%
No, we do not intend to	9	39.1%
Other	5	21.7%
Total	23	100%

As shown in Table 2-6, four respondents (17.4%) indicated they have investigated the cost effectiveness of collecting structural condition data for use at both the network and project levels, with 5 (21.7%) planning to and 9 (39.1%) not planning to. Two state DOTs did not provide a response to this question.

CHAPTER 3: METHODOLOGY

3.1 TSD and PQI Data

TSD data from ARRB and PSI, PDI, and PQI data from SCDOT were provided to the project team. Appendix A provides a description of the TSD data and Appendix B provides a description of the PSI and PDI data. The SCDOT collects pavement performance data annually for the interstate system, every two years for federal aid roadways, every three years for non-federal aid roadways and those that have AADT > 400, and every six years for roadways with AADT < 400. For this reason, the PSI and PDI values used in the analysis for each primary route are not of the same year. The most recent year when both PSI and PDI data are available was used in the analysis. The PSI and PDI data collection year used for each county and route are provided in Appendix C.

Although PQI data were provided, it was observed that for some 0.1-mile segments, the PDI values were zero when the distress values were non-zero. For this reason, the project team computed both PSI and PDI values using the provided roughness and distress data. The following provides equations used to compute PSI, PDI and PQI. It should be noted that our calculated PQI values match those provided by the SCDOT when they are non-zero.

3.1.1 Pavement Serviceability Index (PSI)

PSI is an index of pavement functional condition and it measures the quality of riding conditions from the point of view of the traveling public. The method used by the SCDOT to determine PSI considers only pavement roughness in the form of the International Roughness Index (IRI), which is calculated from elevation measurements along the left and right wheel path profiles in a pavement section. Given IRI measured in in./mile, PSI is calculated as follows (Stantec, 2014).

$$PSI = 5 \times e^{(-0.004 \times IRI)} \tag{3.1}$$

In Equation 3.1, 5 is the index scale and 0.0040 is the local calibration factor. This equation converts the IRI into a scale common with other indices. In South Carolina, newly constructed and rehabilitated pavements must have acceptable IRI values at the 100% pay range as specified in the rideability specifications (SC-M-403 and SC-M-502). Surface roughness increases as the pavement ages, resulting in increased IRI and decreased PSI values.

3.1.2 Pavement Distress Index (PDI)

To calculate PDI, detailed distress data must be converted into a single scale index. For flexible (bituminous and composite) pavements, there are six recognized types of distresses: fatigue cracking, transverse cracking, longitudinal cracking, rut depth, patching, and raveling. For rigid (concrete) pavements, eight types of distresses are observed: surface deterioration, transverse cracking, longitudinal cracking, patching, punchouts, spalling, faulting, and pumping. The distress data are input in terms of the extent (percent distressed area) and severity (low, moderate, high) for each observed distress location. The steps to determine PDI are as follows.

Step 1: Each distress is converted to a deduct value on a scale of 0 to 5 using Equation 3.2 (Stantec, 2014):

$$DV = 10^{\left(a + b \times \log_{10}(PDA)\right)} \tag{3.2}$$

where

DV = the deduct value for the distress / severity
PDA = percent distressed area (or other extent value)
a, *b* = model coefficients by distress type and severity

The coefficients for *a* and *b* are listed in Table 3-1 for asphalt pavements (bituminous). A different set of *a* and *b* coefficients are used for bituminous over concrete, jointed concrete pavements, continuously reinforced pavements.

Table 3-1 SCDOT HPMA DV model coefficients for asphalt pavements (source: Stantec, 2014).

Distress	Low Severity		Moderate Severity		High Severity	
Types	a	b	a	b	a	b
Fatigue cracking	-0.636	0.6	-0.398	0.526	-0.241	0.487
Transverse cracking	-0.832	0.642	-0.671	0.614	-0.528	0.596
Longitudinal cracking	-0.832	0.642	-0.671	0.614	-0.528	0.596
Raveling/weathering	-1.123	0.525	-1.054	0.644	-0.56	0.557
Rutting	0.418	0.802	0	0	0	0
Patching	-1.063	0.721	-0.905	0.71	-0.774	0.705

Step 2: The Total Deduct Value (TDV) is then calculated as the sum of the individual distress values using Equation 2.3 (Stantec, 2014):

$$TDV = \sum_{i} DV_i \tag{3.3}$$

Step 3: An Equivalent Distress (ED) value is then calculated for each distress / severity as the ratio of each DV to the highest observed DV as shown in Equation 3.4. It should be noted that DVmax in Equation 3.4 is the maximum distress value for *all* distress, not the maximum for distress *i*.

$$ED = \frac{DV_i}{DV_{\max}} \tag{3.4}$$

The Number of Equivalent Distresses (NED) is the sum of the individual distress / severity EDs as shown in Equation 3.5.

$$NED = \sum \frac{DV_i}{DV_{\max}} = \frac{TDV}{DV_{\max}} \tag{3.5}$$

The Adjusted Deduct Value (ADV) is calculated from the Total Deduct Value (TDV) using the ADV-TDV model as shown in Equation 3.6.

$$ADV = 10^{\left(0.0014 - 0.3958\times\log_{10}(NED) + 0.9565\times\log_{10}(TDV)\right)}$$

Step 4: Lastly, the PDI is calculated as the algebraic difference between a perfect (distress-free) pavement, given by a value of 5.0, and the calculated ADV, as shown in Equation 3.6. The higher the ADV, the lower the PDI value.

$$PDI = 5.0 - ADV \tag{3.6}$$

3.1.3 Pavement Quality Index (PQI)

PQI is an overall rating index with a theoretical scale from 0 to 5, where 5 is considered a perfectly plane and distress-free pavement. PQI is calculated as a weighted geometric average of PSI and PDI for a given pavement section (Stantec, 2104).

$$PQI = PDI^{0.76} \times PSI^{0.20} \tag{3.7}$$

3.2 Comparison of TSD and PQI Data

The TSD data from ARRB were collected at 0.01-mile increments, and the GPS coordinates provided for these segments are in World Geodetic System (WGS84) coordinate system. The PSI and PDI from SCDOT were collected at 0.1-mile increments and mile-points were provided for these segments. The SCDOT assisted the project team in converting the mile-points to GPS coordinates, but they were provided in North American Datum (NAD83) coordinate system. ESRI's ArMap 10.8.1 was used to convert TSD's GPS coordinates from WGS84 to NAD83. To compare the TSD data against PQI data, the TSD data were aggregated to match that of SCDOT's PQI data. The 0.1-mile segments with SCI_{12} data and 0.1-mile segments with PQI data were matched based on route name, county and Euclidean distance. Figure 3-1 illustrates how the TSD data were matched against PQI data using their GPS coordinates. As shown, given the start and end GPS coordinates of the PSI or PDI 0.1-mile segment, a Python program was written (codes are shown in Appendix D) to find the best matching starting 0.01-mile TSD segment and best matching ending 0.01-mile TSD segment. Note that the "from" coordinate is used for the starting TSD segment and the "to" coordinate is used for the TSD ending segment.

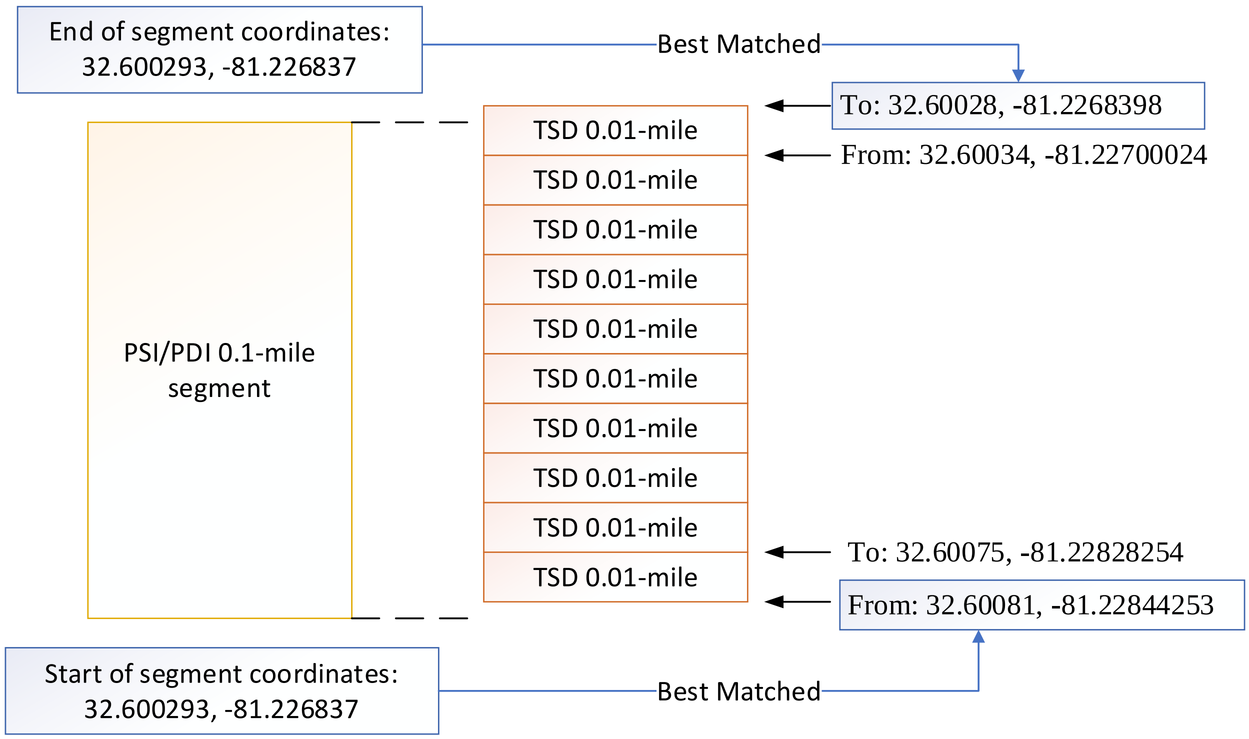

Figure 3-1 Illustration of method used to match TSD data to PQI data.

3.3 Pearson's Correlation

The Pearson correlation coefficient (Equation 3.8) was used to examine the strength and direction of the linear relationship between SCI_{12} and PQI. It was obtained using Python. The correlation coefficient ranges between a negative 1.0 and a positive 1.0. The larger the absolute value of the coefficient, the stronger the relationship between the variables. An absolute value of 1 indicates a perfect linear relationship. A value close to zero indicates no linear relationship between SCI_{12} and PQI. The sign of the coefficient indicates the direction of the relationship. If both SCI_{12} and PQI tend to increase or decrease together, then the coefficient will be positive, and the line that represents the correlation slopes upward. If SCI_{12} tends to increase as PQI decreases, or vice-versa, then the coefficient will be negative, and the line that represents the correlation slopes downward. The correlation was classified as weak, moderate or strong. The thresholds used to determine these are as follows.

- Strong correlation: If the absolute value of the Pearson coefficient is between 0.50 and 1.0.
- Moderate correlation: If the absolute value of the Pearson coefficient is between 0.30 and 0.49.
- Weak correlation: If the absolute value of the Pearson coefficient is less than 0.29.

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}} \tag{3.8}$$

where

r = Pearson correlation coefficient
x_i = SCI_{12} values in a sample
$\bar{x}$ = mean of the SCI_{12} values
y_i = PQI values in a sample
$\bar{y}$ = mean of the PQI values

3.4 Box Plots

To show how TSD and PQI data vary between routes and counties and the variability of the data within each route or county, Box plots are used in this study; they were generated using Python. Figure 3-2 shows the different components of a Box plot: minimum, 25th percentile, median, 75th percentile, and maximum. Outliers were defined as any point that is greater than 1.5 × IQR or less than 1.5 × IQR; where IQR is the interquartile range and represents the middle 50% of the data. The larger the IQR and difference between maximum and minimum, the higher the spread in the data. When the median is in the middle of the box and the whiskers are about the same on both sides of the box, then the data follows a Normal distribution. If the data are skewed, and thus not normally distributed, the median will be closer to the bottom or top of the box. It is said to be "skewed right" if the median is closer to the bottom of the box (i.e., mean > median). Similarly, it is skewed left if the median is closer to the top of the box (i.e., mean < median).

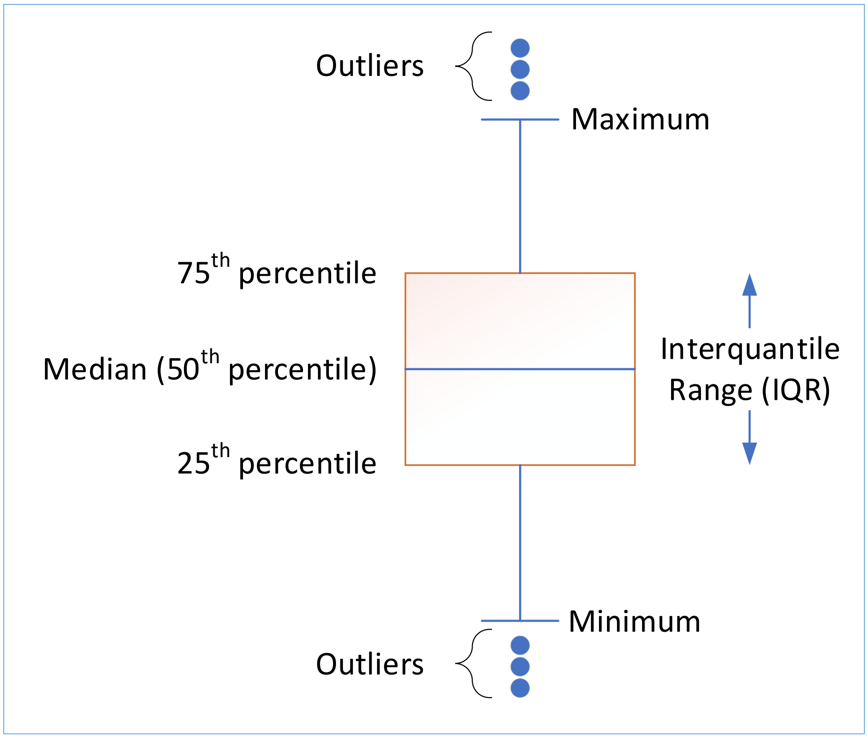

Figure 3-2 Components of a Box plot.

CHAPTER 4: FINDINGS AND DISCUSSION

4.1 SCI_{12} and PQI of TSD Routes

This section presents descriptive statistics at the route level. The same analyses were performed at the county level for each TSD route. This information can be found in Appendix E. Figure 4-1 shows a Box plot of SCI_{12} data for those primary routes selected to have TSD data collected as part of the pooled fund studies (will be referred to as *TSD routes* hereafter). It can be seen that the SCI_{12} data for all of the TSD routes are right-skewed. This suggests that some segments along these route have a very poor structural condition, and thus, making the mean > median. It can be seen that US-321 and US-378 have the worst structural condition among the TSD routes and US-17 has the best structural condition.

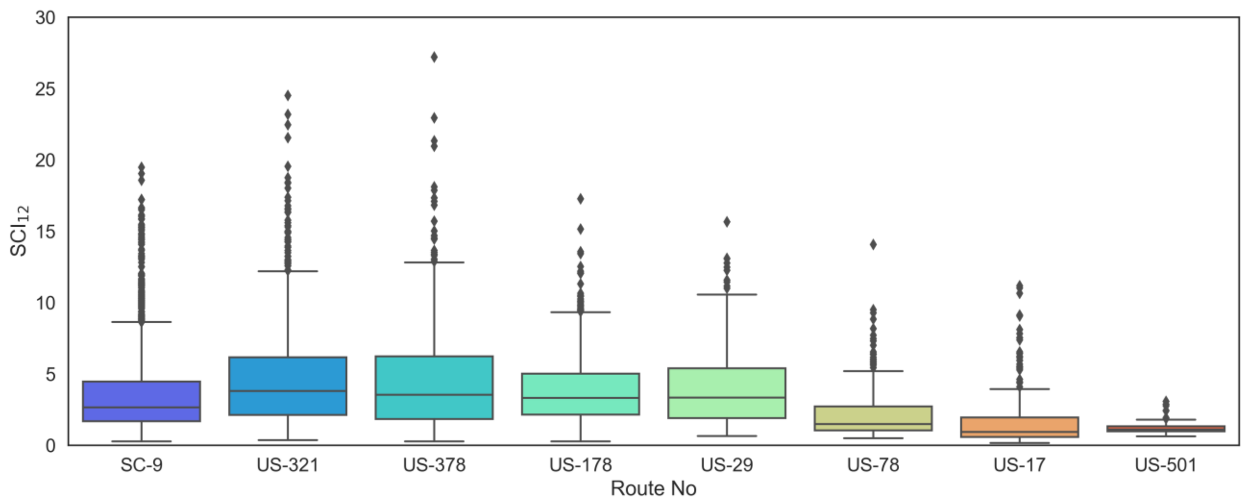

Figure 4-1 Box plot of SCI_{12} for TSD routes.

Figure 4-2 shows a Box plot of PQI for the TSD routes. The y-axis in Figure 4-2 is oriented such that lower is better. Similar to SCI_{12} data, the PQI data for all of the TSD routes are also right-skewed. It can be seen that US-78 has the best functional condition among the TSD routes, and US-17 has the worst. US-17 serves as a prime example of why PQI alone does not accurately capture the condition of the pavement. Considering that US-17 has the best structural condition among the TSD routes (per Figure 4-1), this pavement is less likely to have accumulated distresses, such as bottom-up cracking, and field investigation would most likely show only reflective cracking. Thus, a standard mill-and-fill would address the functional condition issue. The US-17 example illustrates the potential of having insight about a pavement's structural condition. Equipped with this knowledge, the SCDOT will be able to identify the appropriate maintenance activity (preservation or rehabilitation) for each project.

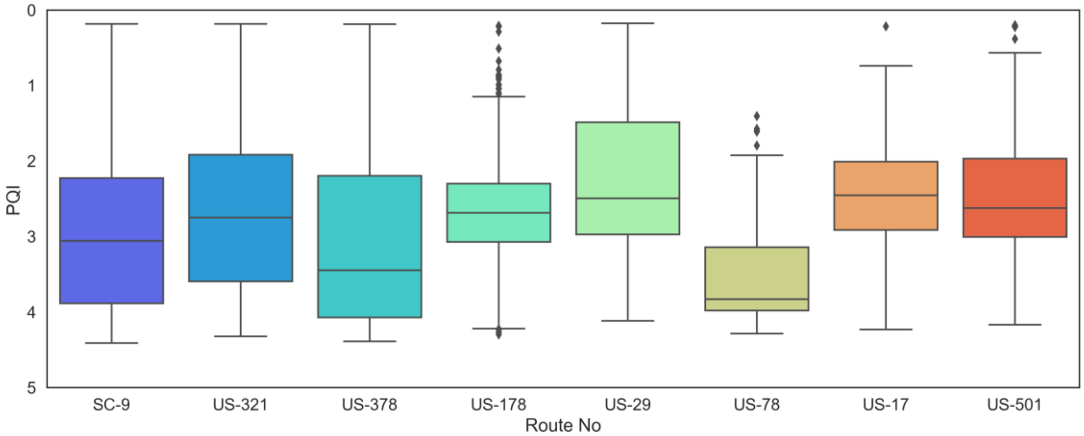

Figure 4-2 Box plot of PQI for TSD routes.

4.2 Pavement Structural Condition Classification

Figure 4-3 shows a histogram of SCI_{12} for the TSD routes. The data indicates a lognormal distribution, where the majority of the 0.1-mile segments along the TSD routes have SCI_{12} values less than 5. The number of 0.1-mile segments in the subsequent SCI_{12} intervals of 5-10, 10-15, 15-20 and 20-25 decreases. Of interest are the threshold values for classifying the structural condition of a pavement as good, fair or poor.

Three different approaches for utilizing the SCI_{12} data to classify pavement condition were considered in this study. The first is to classify the structural condition as *good* if the SCI_{12} value is below the 25^{th} percentile, *fair* if it is between the 25th and 75^{th} percentile (i.e., IQR), and *poor* if it is greater than the 75^{th} percentile. This is the approach considered by VDOT (Shrestha 2019).

The second approach was developed in consultation with the project steering committee and it relates the threshold values to the SCDOT functional condition. The approach uses the SCDOT's Transportation Asset Management Plan's (TAMP, 2018) documented percentages of *good*, *fair* and *poor* pavement for non-interstate National High System (NHS) based on federal guidelines. From these percentages, the SCI_{12} values were back-calculated to provide the same percentages of *good*, *fair* and *poor*. The SCI_{12} threshold values shown in Table 4-1 demarcate the distribution of SCI_{12} data such that 28% of TSD route segments have SCI values less than 1.6 and are considered *good*, 27% have SCI_{12} values between 1.6 and 3.3 and are considered *fair*, and 45% have SCI_{12} values above 3.3 which are considered *poor*.

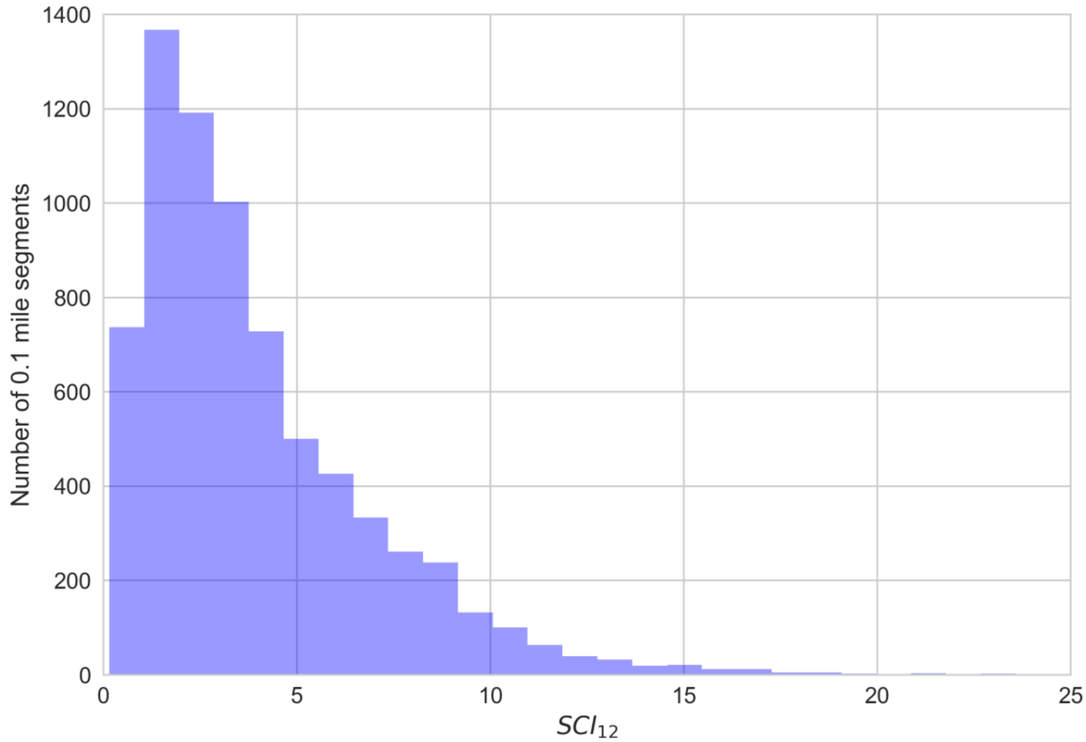

Figure 4-3 Histogram of SCI_{12} for TSD routes.

Table 4-1 SCI_{12} thresholds for classifying pavement structural condition.

Pavement Condition	Percentage	SCI_{12} Thresholds
Good	28%	< 1.6
Fair	27%	1.6 – 3.3
Poor	45%	> 3.3

The third approach found the demarcations for SCI_{12} data such that they produce the same percentages of *good*, *fair* and *poor* pavements as classified by PQI, where a pavement segment with a PQI value above a 3.35 is classified as *good*, between 2.65 and 3.34 is classified as *fair* and below 2.64 is classified as *poor*. The percentages of structurally *good*, *fair* and *poor* pavements using this approach for the TSD routes did not align with the steering committee's field observation. Therefore, the second approach is recommended.

4.3 Comparison of SCI_{12} and PQI Data

This section presents the results of the correlation analysis at the route level. The same analyses were performed at the county level for each TSD route. This information can be found in Appendix F. Table 4-2 shows the Pearson correlation coefficients and degree of correlation between SCI_{12} and PQI for each route. The p-values shown in the last column indicates that all of the correlation coefficients are statistically significant (i.e., different from 0). All TSD routes, except for one (US-178), have a negative correlation. The positive coefficient means that as PQI increases, SCI_{12} will decrease. Recall that a lower SCI_{12} value indicates better structural condition. A plot of SCI_{12} vs. PQI for SC-9 is shown in Figure 4-4 as an example. Collectively, about 50% of TSD route segments have low correlation (below ± 0.29), 27.5% have moderate correlation (between ± 0.30 and ± 0.49), and 22.5% have high correlation (between ± 0.5 and 1.0). This finding confirmed the expectation that PQI does not accurately portray the pavement's underlying conditions related to remaining service life or the potential for future deterioration. In this case, the value of having TSD data is significant. That is, the data can be used to make informed rehabilitation decisions.

Table 4-2 Correlation between SCI_{12} and PQI

Counties	Pearson Correlation	Degree of Correlation	p-value
SC-9	-0.30	Moderate	~0
US-321	-0.29	Low	~0
US-378	-0.34	Moderate	~0
US-178	0.32	Moderate	~0
US-29	-0.23	Low	~0
US-78	-0.57	Strong	~0
US-17	-0.63	Strong	~0
US-501	-0.26	Low	0.01

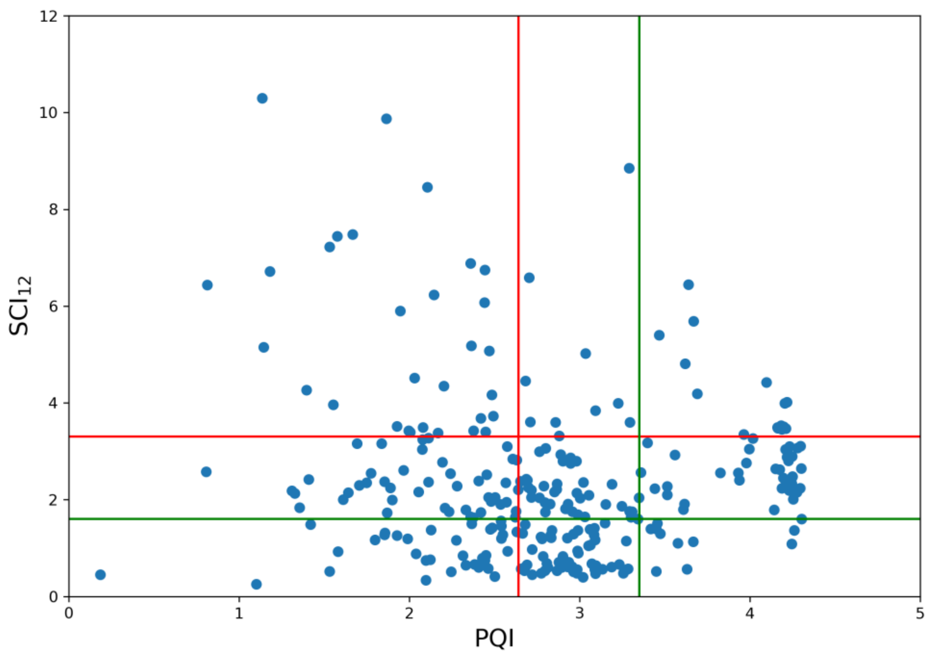

Figure 4-4 Correlation between SCI_{12} and PQI for SC-9 in Chester county.

There are nine "areas" in which a pavement section can be classified based on its structural condition (*good, fair* or *poor* based on SCI_{12} value) and functional condition (*good, fair* or *poor* based on PQI value) as illustrated in Figure 4-5 and applied to SC-9 as shown in Figure 4-4. It can be seen in Figure 4-7 that more TSD route segments are in Area 1 than any other areas. As defined, these segments have poor functional condition and poor structural condition. These segments, due to poor PQI, are likely to be ranked among the top 20% of candidate projects to be selected for rehabilitation. Thus, the current procedure is suitable for identifying pavement segments in Area 1, without the need for structural condition data. The areas where utilization of TSD data has the greatest potential benefit for the SCDOT are 2, 3 and 7. Pavement segments in Area 3 have good PQI but poor SCI_{12}. These segments will need to be continually and frequently rehabilitated if the underlying structural problems are not addressed. Pavement segments in Area 2 have fair PQI and poor SCI_{12}. These segments will likely not make the top 20% cut because the PQI is fair instead of poor, but some may get selected due to criteria other than PQI. In these cases, the TSD data can be utilized to help guide the field investigation. Pavement segments in Area 7 have poor PQI but good SCI_{12}. These segments, at the network level, may be flagged as a reconstruction project but it may only be a preservation or rehabilitation candidate. Table *1-1*Table 4-3 shows the percentage of segments in Areas 2, 3 and 7 and their combined length for each TSD route.

Area 1: Poor functional and poor structural	Area 2: Fair functional and poor structural	Area 3: Good functional and poor structural
Area 4: Poor functional and fair structural	Area 5: Fair functional and fair structural	Area 6: Good functional and fair structural
Area 7: Poor functional and good structural	Area 8: Fair functional and good structural	Area 9: Good functional and good structural

Figure 4-5 Pavement section classifications.

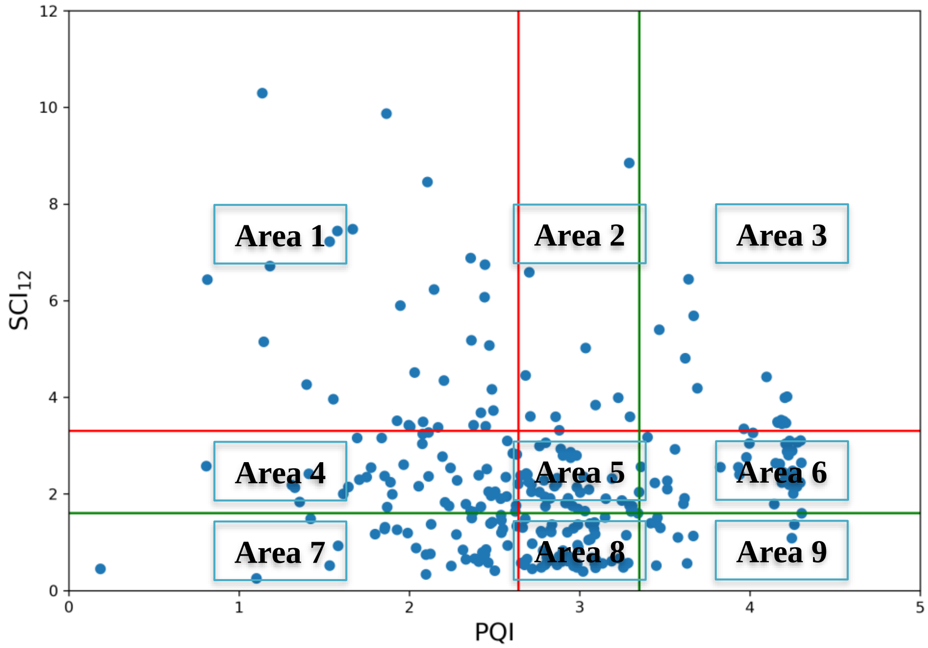

Figure 4-6 Pavement section classifications for SC-9 in Chester county.

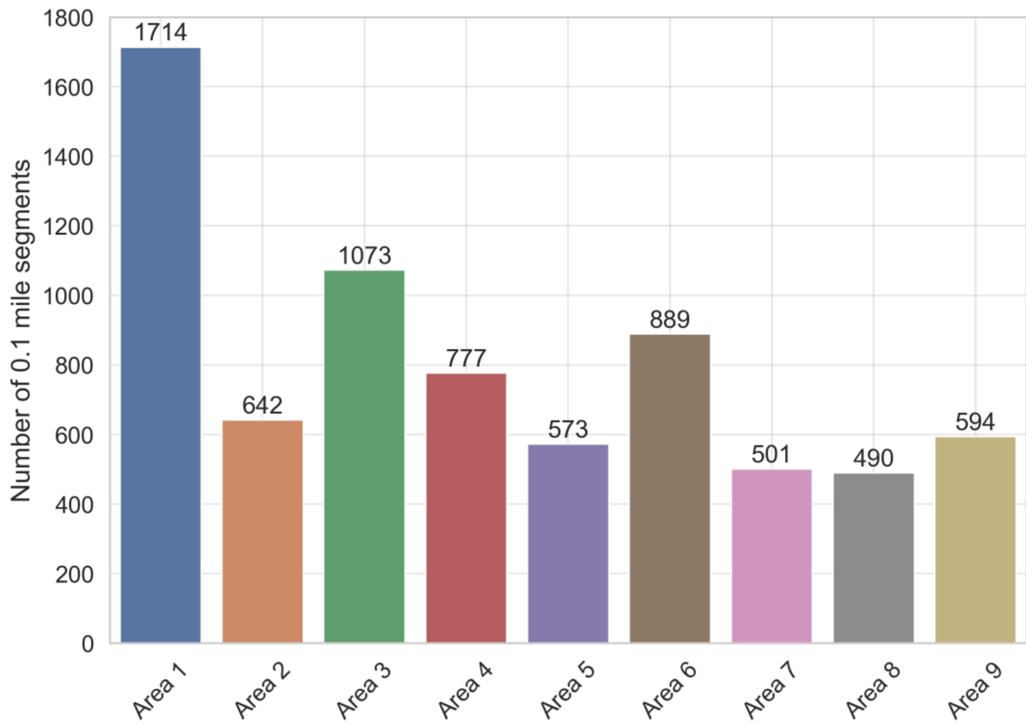

Figure 4-7 Number of TSD route segments in each classification area.

Table 4-3 Percentage and length of segments in areas of interest.

Route	Area 2*	Area 3†	Area 7‡	Combined Length (miles)
SC-9	7.45%	11.18%	5.27%	44.4 out of 231
US-321	7.50%	17.94%	6.60%	55.89 out of 216
US-378	4.91%	24.62%	3.83%	45.81 out of 201
US-178	16.70%	13.19%	7.81%	52.47 out of 181
US-29	10.73%	3.11%	6.23%	5.8 out of 37
US-78	7.63%	4.66%	0.85%	3.1 out of 36
US-17	0.56%	0%	32.97%	5.96 out of 19
US-501	0%	0%	36.67%	4.4 out of 12

* Area 2 = Fair functional and poor structural

† Area 3 = Good functional and poor structural

‡ Area 7 = Poor functional and good structural

4.4 Application of SCI_{12} Data

The SCI_{12} data can serve as a "secondary filter" for SCDOT district pavement engineers. That is, given the top 20% candidate projects, they could use the structural condition data as an additional criterion for selecting projects. To provide the district pavement engineers with a quantitative measure of a candidate project's structural condition, a TSD Score was developed in consultation with the project steering committee. The TSD Score is calculated as follows.

$$\text{TSD Score} = \frac{L_p}{T} \times P_p \tag{5.1}$$

where

L_p = length of pavement with poor structural condition (i.e., Areas 1, 2 and 3) in miles
T = length of candidate project in miles
P_p = percentage of pavement with poor structural condition (in percent)

For a candidate project that is 10 miles in length, of which 30% (or 2 miles) has poor structural condition, its TSD Score is 6 (i.e., [2/10]*30 = 6). By design, the TSD score ranges between 0 and 100. The higher the score, the poorer the structural condition and the more likely the project will be selected. This scoring convention is consistent with how other criteria are rated in SCDOT Engineering Directive 63. To facilitate the use of the TSD Score, if adopted by the SCDOT, an Excel-based tool has been implemented to assist headquarters personnel to generate these scores for candidate projects. District pavement engineers will receive the same Excel file as before but with an added column to show the TSD Score for each project that made the top 20% cut. If requested, the district pavement engineers can also obtain the location of the areas of interest (i.e., Areas 2, 3 and 7) for further inspection. US-17 is shown as an example in Figure 4-8; the areas of interest are shown as red circles along the route. This figure has been generated for other TSD routes and can be found in Appendix G.

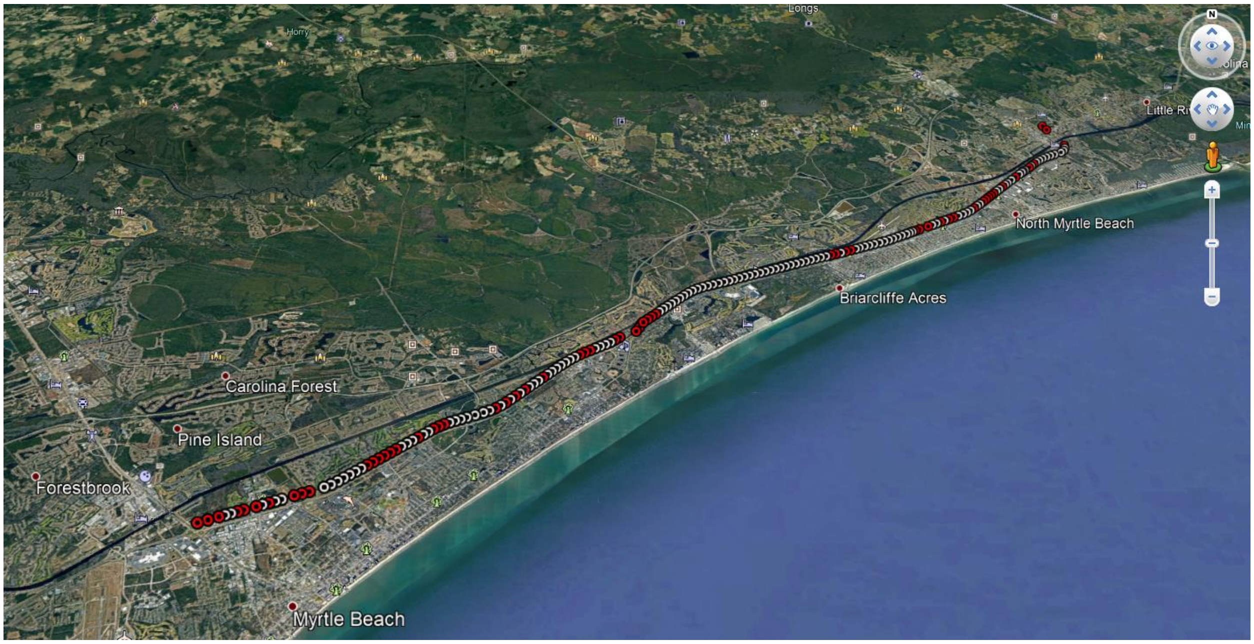

Figure 4-8 Location of areas of interest on US-17 (highlighted in red).

The use of TSD scores may have an impact on project selection as summarized in Table 4-4. For example, for US-378 in Lexington County, 8 out of 22 "pavement condition" segments or 7.64 miles out of 14.38 miles, are in Areas 2, 3 or 7. Thus, having pavement structural condition data could aid the SCDOT in making a more informed decisions in selecting candidates for rehabilitation. Pavement condition segments are defined in ITMS as those with common pavement quality, AADT, and number of lanes.

Table 4-4 TSD score potential impact on project selection.

Route	County	Number of pavement condition segments§ and length
US-378	Lexington	8 out of 22, 7.64 miles out of 14.38 miles
US-78	Charleston	3 out of 10, 1.04 miles out of 4.13 miles
US-178	Saluda	1 out of 11, 0.24 miles out of 15.65 miles
US-321	Chester	1 out of 13, 0.27 miles out of 8.70 miles
US-321	Lexington	3 out of 20, 2.74 miles out of 12.60 miles
US-321	York	2 out of 25, 1.8 miles out of 13.19 miles

§ Pavement condition segment: length is based on common pavement quality, AADT, and number of lanes.

CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

Having TSD data could potentially help the SCDOT identify more optimal and cost effective pavement preservation and rehabilitation strategies. US-17 serves as a prime example. It has good structural condition but poor functional condition. Thus, US-17 may be flagged as a reconstruction project in current SCDOT practice. The TSD data will help inform and reassure the SCDOT about its decision to proceed with a preservation treatment at the project level. Other state DOTs recognize the benefit of having structural condition data, and the majority indicated that they plan to utilize structural condition data to manage their pavement systems at the network level as well as at the project level.

A pavement's structural condition cannot be inferred from its functional condition since the correlation between SCI_{12} and PQI for the TSD routes is mostly low to moderate. Therefore, in order for the SCDOT to utilize structural condition data to manage its pavement systems at the network level, it will need to obtain structural condition data by some means. Collecting structural condition data for 2,752 centerline miles of Federal-Aid Non-Interstate NHS Primary system using FWD over a short period of time (to minimize effect of temperature difference) would not be practical. This task is achievable with TSD as demonstrated by the pooled fund studies where about 950 miles of TSD data were collected in a span of 4 days.

5.2 Recommendations

From this project's findings, it is recommended that the SCDOT consider obtaining TSD data and use the developed TSD scores to guide the selection of candidate projects. There are three uses for the TSD data and scores. The first is the identification of the top 20% of candidate projects using the current procedure in Engineering Directive 63. This list could be expanded to include projects with high TSD scores (i.e., poor structural condition). The second is when district pavement engineers need to make the final selection. The TSD score, specifically a threshold value, can be used to guide the selection. Lastly, TSD data can be utilized to help guide field investigations. That is, knowing the locations where pavements have poor structural conditions will expedite the field investigation process and reduce the overall effort involved.

5.3 Implementation Plan

To obtain TSD scores for projects, the SCDOT headquarters maintenance personnel can use the developed Excel-based tool, named "Secondary Filter." This tool considers the SCDOT's current workflow and minimizes the effort required. Figure 5-1 shows the graphical user interface of Secondary Filter. Four simple point-and-click operations is all that is needed to add TSD scores into the the Excel file that headquarters maintenance personnel typically prepare for district engineers.

- Step 1. Import the Excel file typically prepared for the districts. Upon clicking the "Import Top 20% Projects" button, the user will be prompted to select a file from the user's computer using standard Windows File Dialog.

- Step 2. Import the Excel file with TSD data provided by ARRB. Upon clicking the "Import TSD Data" button, the user will be prompted to select a file from the user's computer using standard Windows File Dialog.
- Step 3. Generate TSD scores for each candidate project. It should be noted that both files from Step 1 and Step 2 must have route type, route number, county, beginning mile point (BMP) and ending mile point (EMP).
- Step 4. Export the Excel file imported in Step 1 with the TSD scores added. Upon clicking on the "Export Data" button, the user will be prompted to select the destination for the output file.

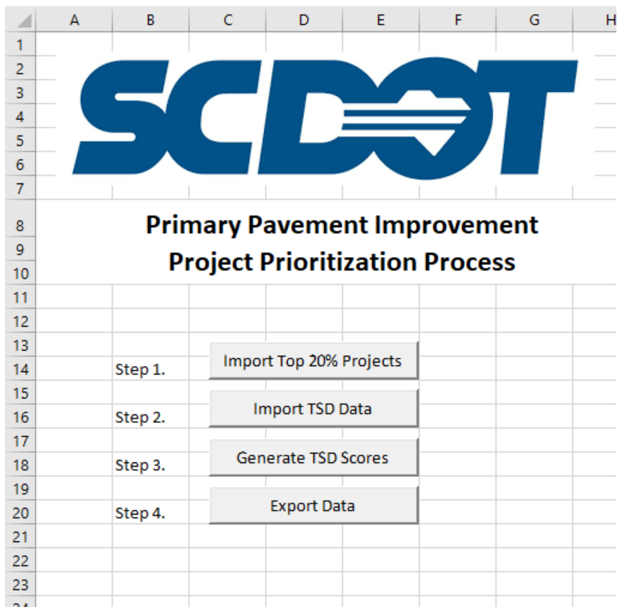

Figure 5-1 Graphical user interface of secondary filter tool.

District	County	Route Type	Route Num	Direction	BMP	EMP	TSD Score
4	CHEROKEE	US	29	N	0.92	3.72	19.36
4	CHEROKEE	US	29	N	3.72	5.5	2.04
4	CHEROKEE	US	29	N	5.5	5.93	0
4	CHEROKEE	US	29	N	15.1	15.5	25
4	CHEROKEE	US	29	N	15.5	16.8	7.44
4	CHEROKEE	US	29	N	23.7	24.086	25
4	CHEROKEE	US	29	N	24.086	24.09	N/A
4	CHEROKEE	US	29	N	24.09	24.1	N/A
4	CHEROKEE	US	29	N	24.1	24.13	N/A
4	CHEROKEE	US	29	N	24.13	24.42	N/A

Figure 5-2 Sample output file with TSD scores added.

In this project, we converted TSD data recorded in WGS84 coordinate system to SCDOT's NAD83 using ESRI's ArcMap 10.8.1. Instructions to accomplish this are provided in Appendix H. To generate the TSD data file mentioned in Step 2, run the provided Python program.

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APPENDIX A

TSD Data Description

Field name	Description
ROAD_ID	Route Identification Number
S_CHAINAGE	Distance of start of interval from start of section
E_CHAINAGE	Distance of of interval from start of section
IRI_AVG	IRI Roughness value-lane quarter car model
IRI_Right	IRI Roughness value-right outer wheel path-quarter car model
IRI_Left	IRI Roughness value-left inner wheel path-quarter car model
IRI_Lane	IRI Roughness value-lane half car model
SMTD_Left	Sensor Measured Texture Depth left (single spot laser)
SPTD_Left	Sand Patch Texture Depth left (single spot laser correlation)
SMTD_Centr	Sensor Measured Texture Depth center (single spot laser)
SPTD_Centr	Sand Patch Texture Depth center (single spot laser correlation)
SMTD_Right	Sensor Measured Texture Depth right (single spot laser)
SPTD_Right	Sand Patch Texture Depth right (single spot laser correlation)
MPD_Left	Mean Profile Depth texture left
ETD_Left	Estimated Profile Depth texture left
MPD_Center	Mean Profile Depth texture center
ETD_Center	Estimated Profile Depth texture center
MPD_Right	Mean profile depth texture right
ETD_Right	Estimated Profile Depth texture right
Cell_Crack	Percentage of all cells with any type of cracking (excluding straight lines) (Total cracked cells/Total cells)
Allig_Crck	Percentage of all cells with alligator cracking (Total alligator cracking cells/Total cells)
Long_Crck	Percentage of all cells with longitudinal cracking (Total longitudinal cracking cells/Total cells)
Trans_Crck	Percentage of all cells with transverse cracking (Total longitudinal cracking cells/Total cells)
Rut_Right	Taut wire rut depth Right
Rut_Left	Taut wire rut depth Left
Rut_Lane	Taut wire rut depth Lane
Rut_Avg	Taut wire rut depth Average
Pot_Num	Number of potholes
Pot_Depth	Average pothole depth
Pot_Area	Total area of potholes
Rav_Index	Reveling index
Poro_Index	Road porosity index
Ravel_Area	Area of ravelling
MPD_Zone_1	3D Mean Profile Depth texture AASHTO zone 1
MPD_Zone_2	3D Mean Profile Depth texture AASHTO zone 2
MPD_Zone_3	3D Mean Profile Depth texture AASHTO zone 1
MPD_Zone_4	3D Mean Profile Depth texture AASHTO zone 1
MPD_Zone_5	3D Mean Profile Depth texture AASHTO zone 1
SCI_{12}	Surface Curvature Index (D_{12} - D_0)
SCI_8	Surface Curvature Index (D_{12} - D_8)

SCI_Sub	Surface Curvature Index Subgrade (D_{60} - D_{36})
Max_Defl	Deflection calculation at 0 mm from load

APPENDIX B

PSI and PDI Data Description

PSI Field Name	Description
HR_ROUTCOD	Route Code
HR_COUNTY	County Number
HR_CNTYSQ	County Sequence
HR_ROUTTYP	Route Type
HR_ROUTNUM	Route Number
HR_ROUTAUX	Route Auxiliary
HR_DIRECTN	Route Direction
HR_INTCHG	Interchange Number
HR_RAMPID	Ramp ID Number
HR_LANEID	Lane ID
HR_DATYEAR	Data Year
HR_DATE	Data Collection Date
HR_BEGMILE	Route Beginning Milepost
HR_ENDMILE	Route Ending Milepost
HR_IRI_RT	IRI Rt
HR_IRI_LT	IRI Lt
HR_RUT_RT	Rut Rt
HR_RUT_LT	Rut Lt
HR_PSI	SCDOT Pavement Servicability Index
HR_PSI_OVD	Override
HR_SOURCE	Source
HR_SPEED	Speed
HR_RUT_DL	Rut Dual
HR_SLOPE	Slope
HR_RUTMAXL	Rut Max.L
HR_RUTMAXR	Rut Max.R
HR_FAULT	Fault Height
HR_HC_IRI	Half-Car IRI
HR_SEGNUM	Route Segmentation Number
HR_LANES	Number of Lanes
HR_OPNO	Operator ID
HR_RATER	Rater ID

PDI Field Name	**Description**
HC_ROUTCOD	Route Code
HC_COUNTY	County Number
HC_CNTYSQ	County Sequence
HC_ROUTTYP	Route Type
HC_ROUTNUM	Route Number
HC_ROUTAUX	Route Auxiliary
HC_DIRECTN	Route Direction
HC_INTCHG	Interchange Number
HC_RAMPID	Ramp ID Number
HC_LANEID	Lane ID Number
HC_DATYEAR	Data Year
HC_DATE	Data Collection Date
HC_BEGMILE	Route Beginning Milepost
HC_ENDMILE	Route Ending Milepost
HC_PAVETYP	Pavement Type
HC_PDI	SCDOT Pavement Distress Index
HC_PDI_OVD	Index Override
HC_SOURCE	Data Source
D_01_S1	Distress 1 - Low Severity
D_01_S2	Distress 1 - Moderate Severity
D_01_S3	Distress 1 - High Severity
D_02_S1	Distress 2 - Low Severity
D_02_S2	Distress 2 - Moderate Severity
D_02_S3	Distress 2 - High Severity
D_03_S1	Distress 3 - Low Severity
D_03_S2	Distress 3 - Moderate Severity
D_03_S3	Distress 3 - High Severity
D_04_S1	Distress 4 - Low Severity
D_04_S2	Distress 4 - Moderate Severity
D_04_S3	Distress 4 - High Severity
D_05_S1	Distress 5 - Low Severity
D_05_S2	Distress 5 - Moderate Severity
D_05_S3	Distress 5 - High Severity
D_06_S1	Distress 6 - Low Severity
D_06_S2	Distress 6 - Moderate Severity
D_06_S3	Distress 6 - High Severity
D_07_S1	Distress 7 - Low Severity
D_07_S2	Distress 7 - Moderate Severity
D_07_S3	Distress 7 - High Severity
D_08_S1	Distress 8 - Low Severity
D_08_S2	Distress 8 - Moderate Severity
D_08_S3	Distress 8 - High Severity
D_09_S1	Distress 9 - Low Severity
D_09_S2	Distress 9 - Moderate Severity
D_09_S3	Distress 9 - High Severity
D_10_S1	Distress 10 - Low Severity
D_10_S2	Distress 10 - Moderate Severity

D_10_S3	Distress 10 - High Severity
HC_OPNO	Operator Number
HC_PDI2	Secondary PDI Calculation
HC_SEGNUM	Route Segmentation Number
D_01_INDEX	Distress 1 Index Value
D_02_INDEX	Distress 1 Index Value
D_03_INDEX	Distress 1 Index Value
D_04_INDEX	Distress 1 Index Value
D_05_INDEX	Distress 1 Index Value
D_06_INDEX	Distress 1 Index Value
D_07_INDEX	Distress 1 Index Value
D_08_INDEX	Distress 1 Index Value
D_09_INDEX	Distress 1 Index Value
D_10_INDEX	Distress 1 Index Value
HC_LANES	Number of Lanes
HC_RATER	Rater ID

APPENDIX C

PSI and PDI Data Collection Year

SC-9 PSI and PDI data collection year

County	PSI	PDI
Chester	2018	2018
Chesterfield	2018	2018
Dillon	2017	2017
Horry	2016	2016
Lancaster	2018	2018
Marion	2017	2017
Marlboro	2017	2017
Spartanburg	2018	2018
Union	2018	2018

US-321 PSI and PDI data collection year

County	PSI	PDI
Allendale	2017	2017
Bamberg	2015	2015
Chester	2018	2018
Fairfield	2018	2018
Hampton	2018	2018
Jasper	2015	2015
Lexington	2018	2018
Orangeburg	2017	2017
Richland	2018	2018
York	2018	2018

US-378 PSI and PDI data collection year

County	PSI	PDI
Clarendon	2015	2015
Edgefield	2018	2018
Florence	2016	2016
Horry	2016	2016
Lexington	2018	2018
McCormick	2018	2018
Marion	2017	2017
Saluda	2018	2018
Sumter	2015	2015
Williamsburg	2016	2016

US-178 PSI and PDI data collection year

County	PSI	PDI
Abbeville	2017	2017
Dorchester	2016	2016
Greenwood	2017	2017
Lexington	2017	2017
Orangeburg	2017	2017
Saluda	2017	2017

US-29 PSI and PDI data collection year

County	PSI	PDI
Cherokee	2017	2017
Spartanburg	2018	2018

US-78 PSI and PDI data collection year

County	PSI	PDI
Charleston	2016	2016
Dorchester	2016	2016

US-17 PSI and PDI data collection year

County	PSI	PDI
Horry	2016	2016

US-501 PSI and PDI data collection year

County	PSI	PDI
Horry	2016	2016

APPENDIX D

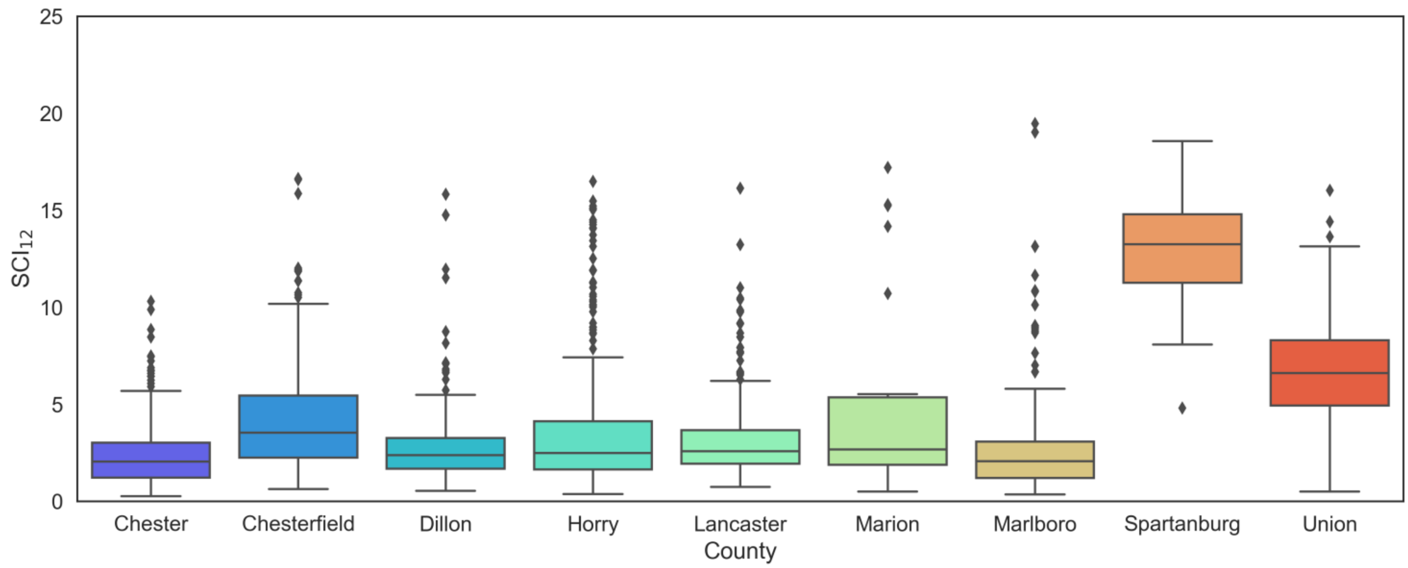
Python Code Developed to match TSD Data to PQI Data

```
import pandas as pd
import numpy as np
from numpy import math, random, sqrt, log, sin, cos, pi
from matplotlib import pyplot as plt

df321 = pd.read_excel("US321.xlsx")
df321_county_psi = pd.read_excel("county5psi.xlsx")
df321_county_pdi = pd.read_excel("county5pdi.xlsx")
df = pd.read_excel("US321_ARRB.xlsx")
df = df[['S_CHAINAGE', 'E_CHAINAGE','SCI_12','Y _NAD83','X_NAD83']]

df321_county_psi['HR_DATYEAR'].astype('category')

df321_county_pdi['HC_DATYEAR'].astype('category')

print(df321.columns)

#df321.rename(columns = {'BEG_MILEPOINT':'BMP', 'END_MILEPOINT':'EMP'},
inplace = True)

df321 = df321[['COUNTY', 'BMP', 'EMP', 'BMP_LAT', 'BMP_LONG']]
#df378 = df378.iloc[0:1580]
df321_county = df321.loc[(df321['COUNTY']) == 'Jasper']

df321_county_psi = df321_county_psi.loc[(df321_county_psi['HR_DATYEAR']) ==
2015]
df321_county_psi = df321_county_psi[['HR_BEGMILE', 'HR_ENDMILE', 'HR_PSI']]
df321_county_psi = df321_county_psi.reset_index(drop =True)

df321_county_pdi = df321_county_pdi.loc[(df321_county_pdi['HC_DATYEAR']) ==
2015]
df321_county_pdi = df321_county_pdi[['HC_BEGMILE', 'HC_ENDMILE', 'HC_PDI']]
df321_county_pdi = df321_county_pdi.reset_index(drop =True)

df321_county_pdi

df321_county_psi.rename(columns = {'HR_BEGMILE':'BMP', 'HR_ENDMILE':'EMP',
'HR_PSI':'psi'}, inplace = True)
df321_county_pdi.rename(columns = {'HC_BEGMILE':'BMP', 'HC_ENDMILE':'EMP',
'HC_PDI':'pdi'}, inplace = True)

df321_county_psi = df321_county_psi.round({"BMP":1, "EMP":1})
df321_county = df321_county.round({"BMP":1, "EMP":1})
df321_county_pdi = df321_county_pdi.round({"BMP":1, "EMP":1})

df321_county_psi

df321_county = pd.merge(df321_county, df321_county_psi, on = ['BMP', 'EMP'])
df321_county= pd.merge(df321_county, df321_county_pdi, on = ['BMP', 'EMP'])
df321_county['pqi'] = np.power(df321_county['psi'], 0.20) *
np.power(df321_county['pdi'], 0.76)

df321_county

B = df['X_NAD83']
A = df['Y _NAD83']
C = df321_county['BMP_LAT']
```

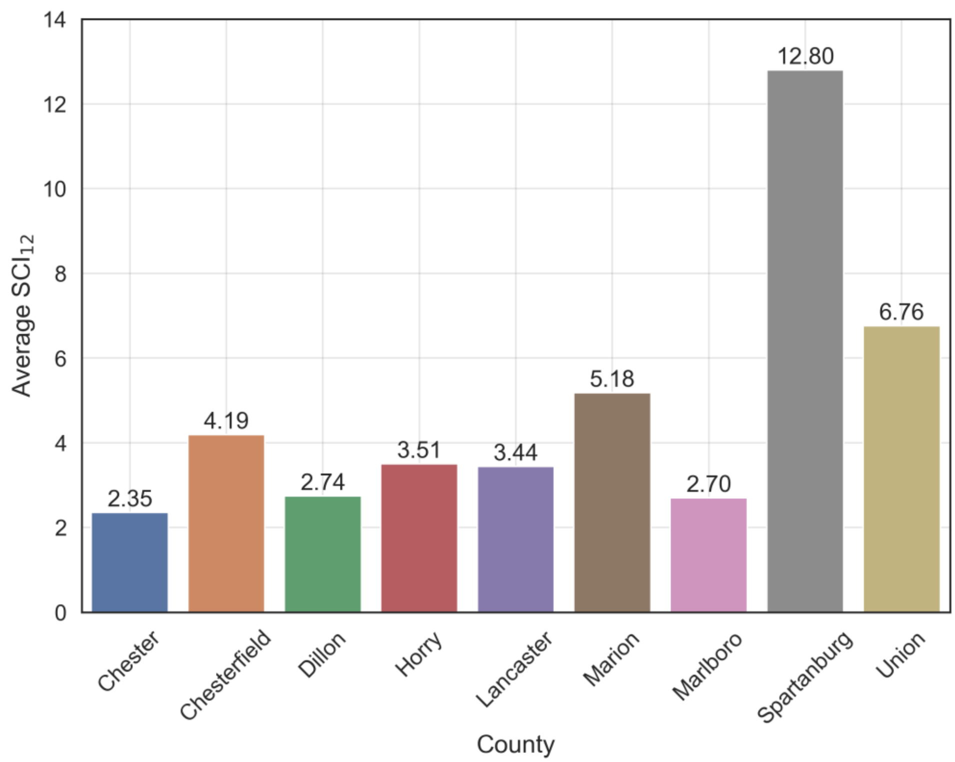
```
D = df321_county['BMP_LONG']

X=[]
for i in range(len(C)):
    distance=9999999
    closest=0
    for j in range(len(A)):
        calculated_distance = sqrt((A[j]-C[i])**2 +(B[j]-D[i])**2)
        if calculated_distance < distance: #needs to correct for different
        co-ordinate system
            distance = calculated_distance
            closest=j

    X.append(closest)
print(X)

sci=[]
for j in range(len(X)-1):
    df_1st = df.iloc[X[j+1]:X[j]+1]
    sci.append(df_1st['SCI_12'].mean())
print(sci)

df_sci = pd.Series(data= sci)
df_sci = df_sci.to_frame()
df_sci = pd.DataFrame(data=sci, columns=['sci'])

df321_county = pd.concat([df321_county, df_sci], axis =1)
df321_county.to_excel("df321_jasper_for_checking.xlsx", index = False)
```

APPENDIX E

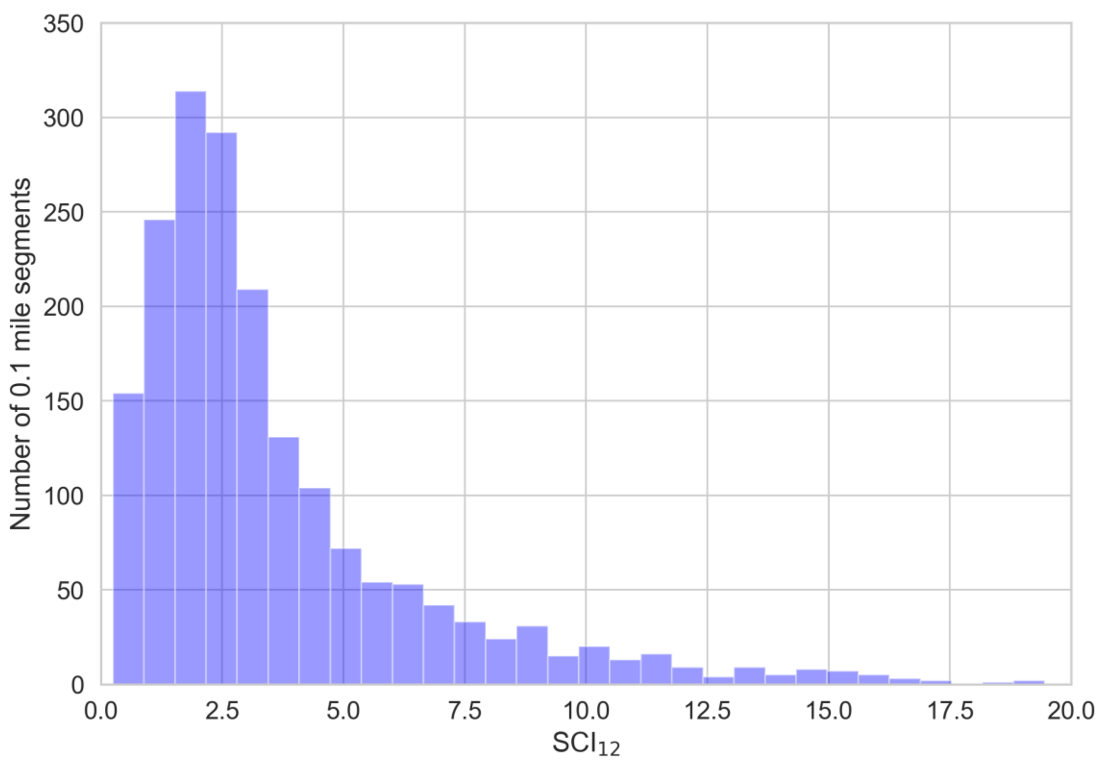
Descriptive Statistics of TSD Routes



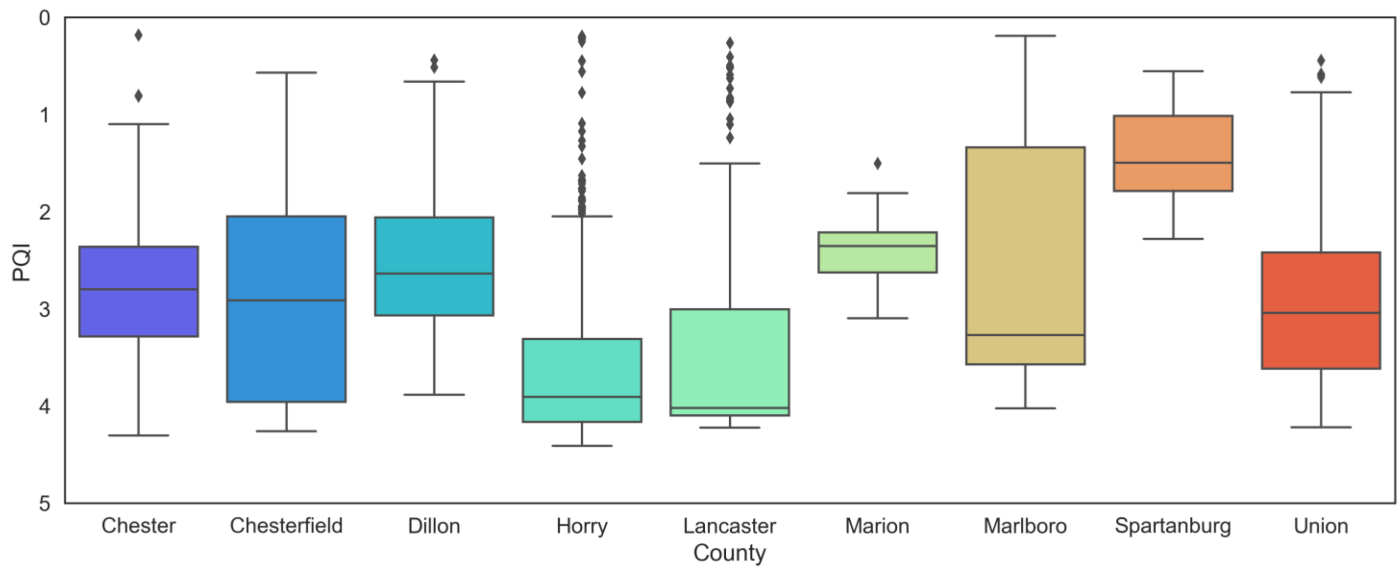
Boxplot of SCI_{12} for SC-9



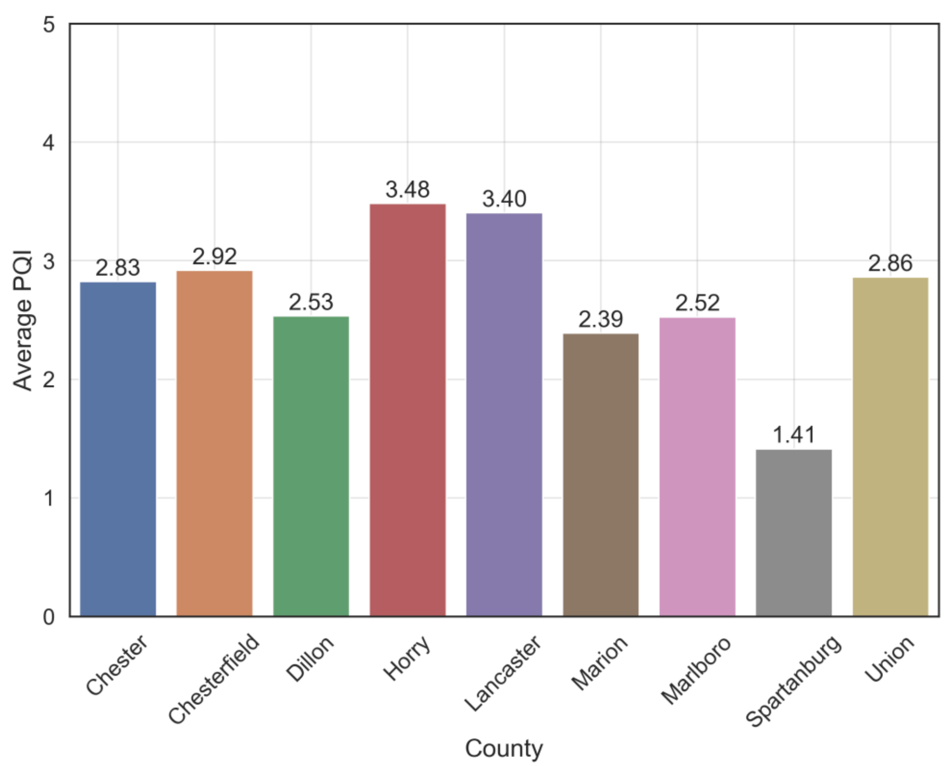
Mean of SCI_{12} for SC-9



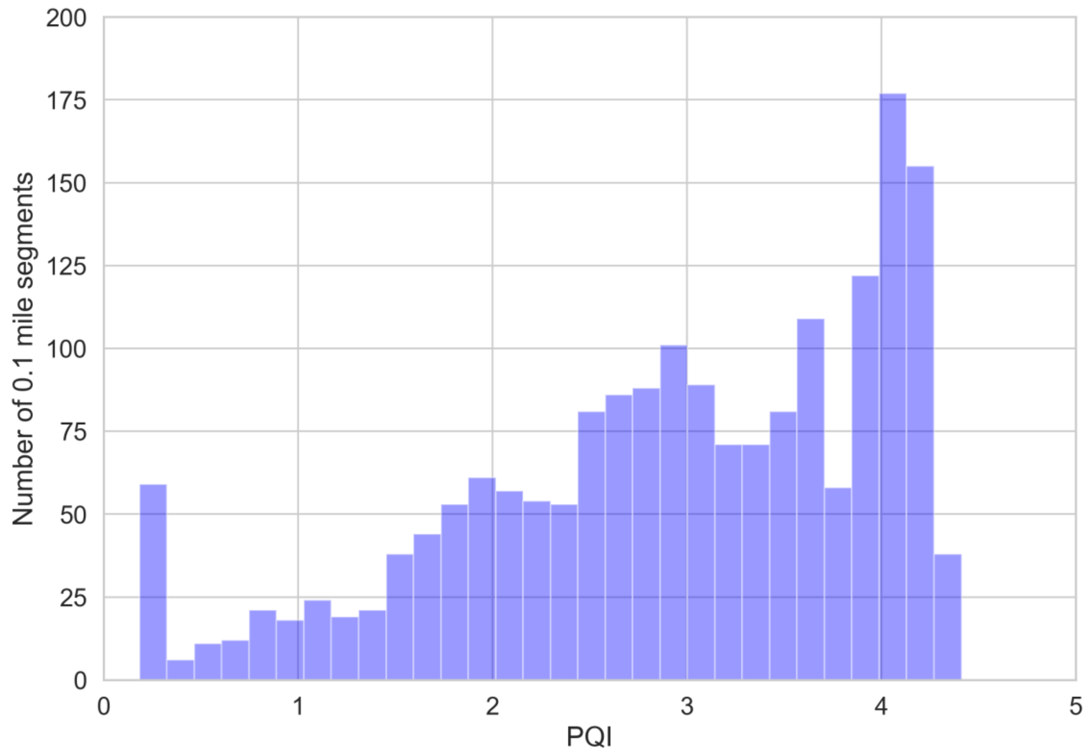
Histogram of SCI_{12} for SC-9



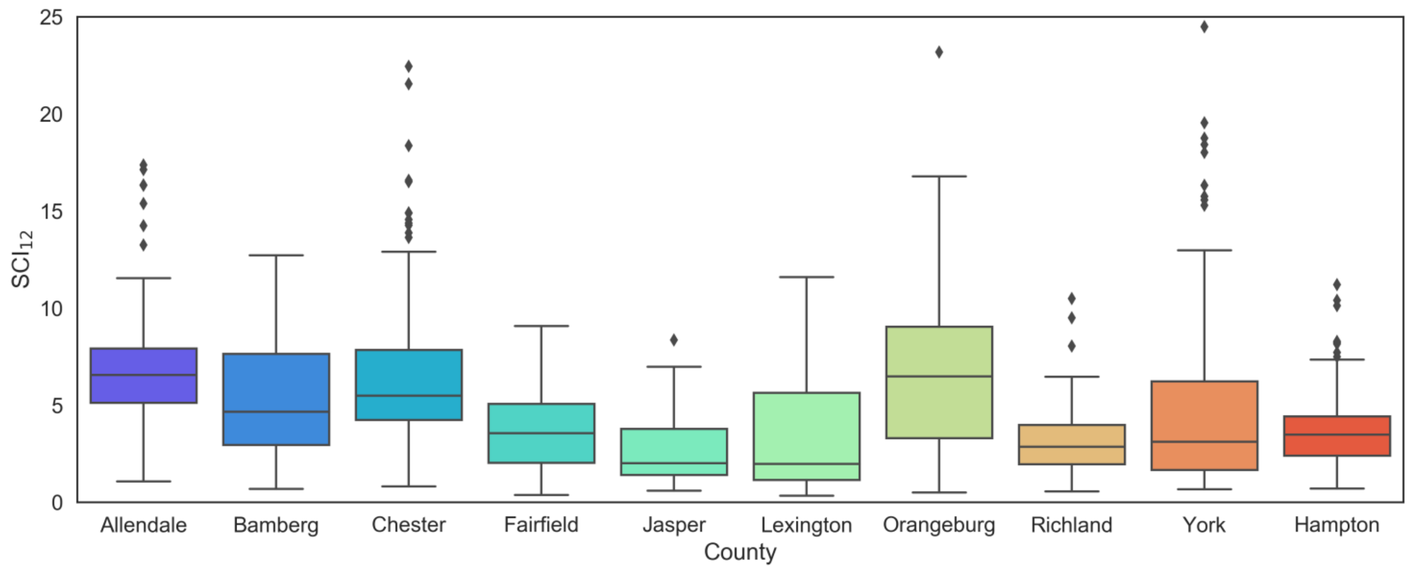
Histogram of PQI for SC-9



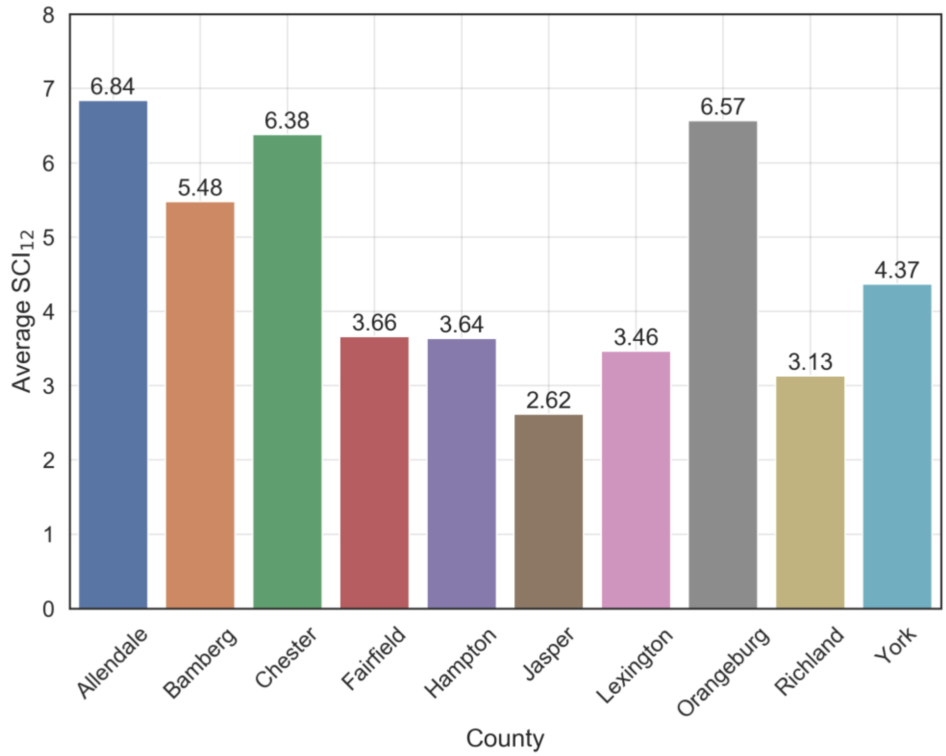
Mean of PQI for SC-9



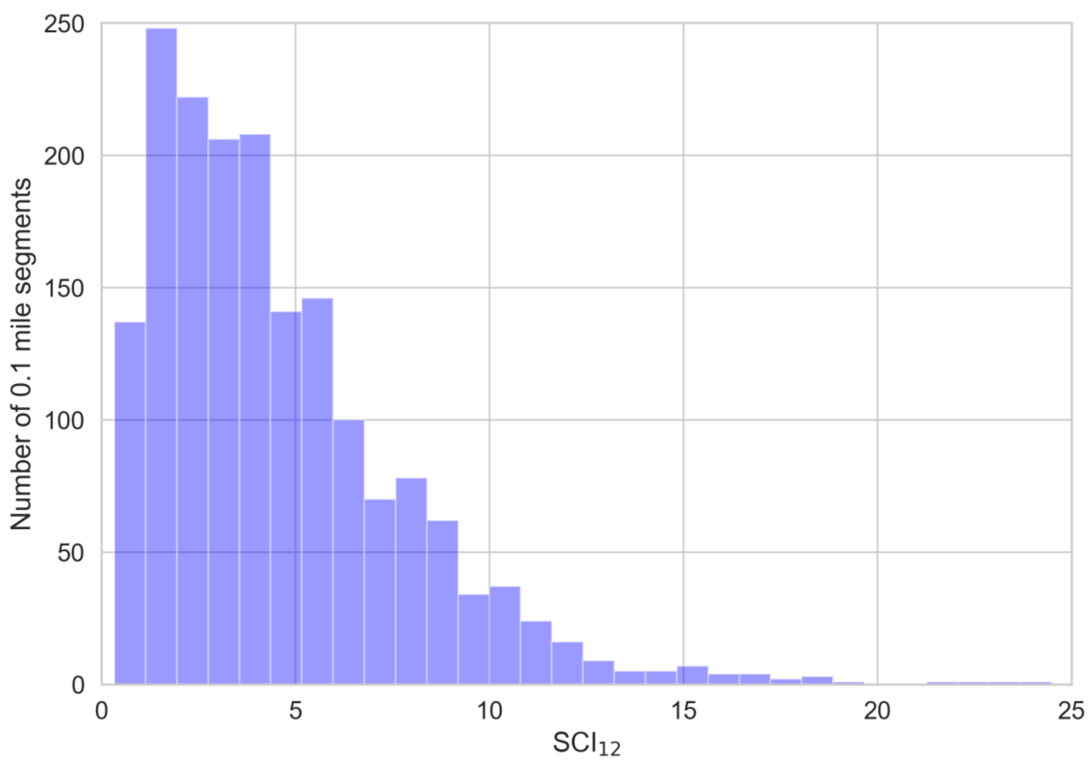
Histogram of PQI for SC-9



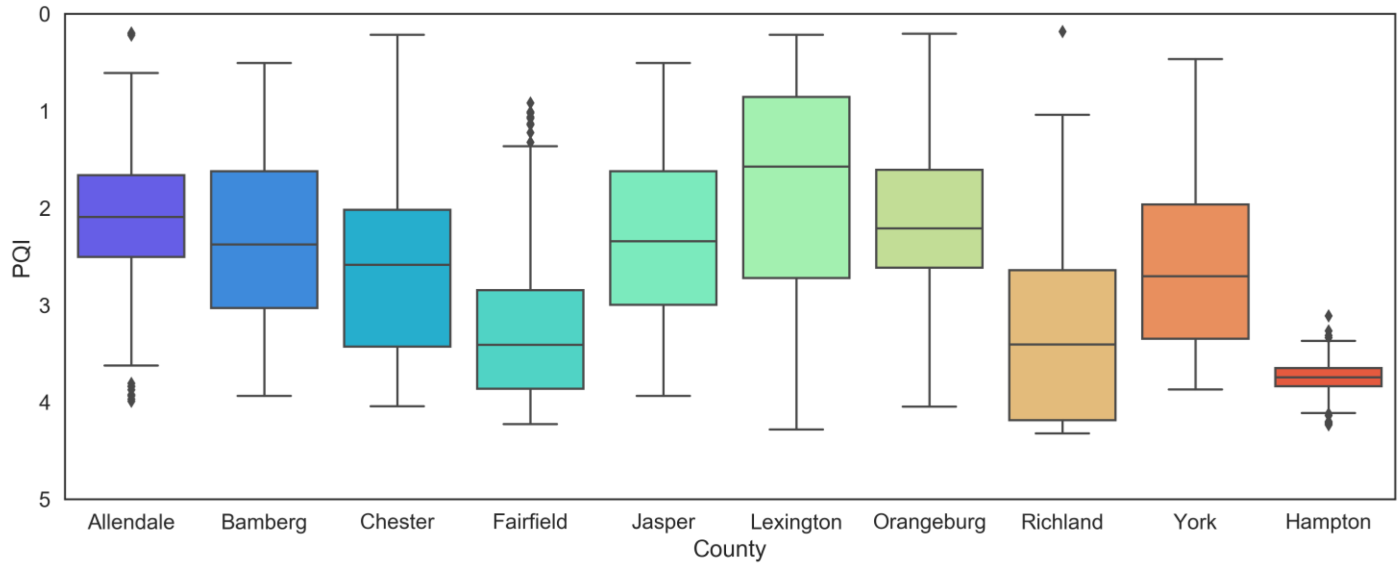
Boxplot of SCI_{12} for US-321



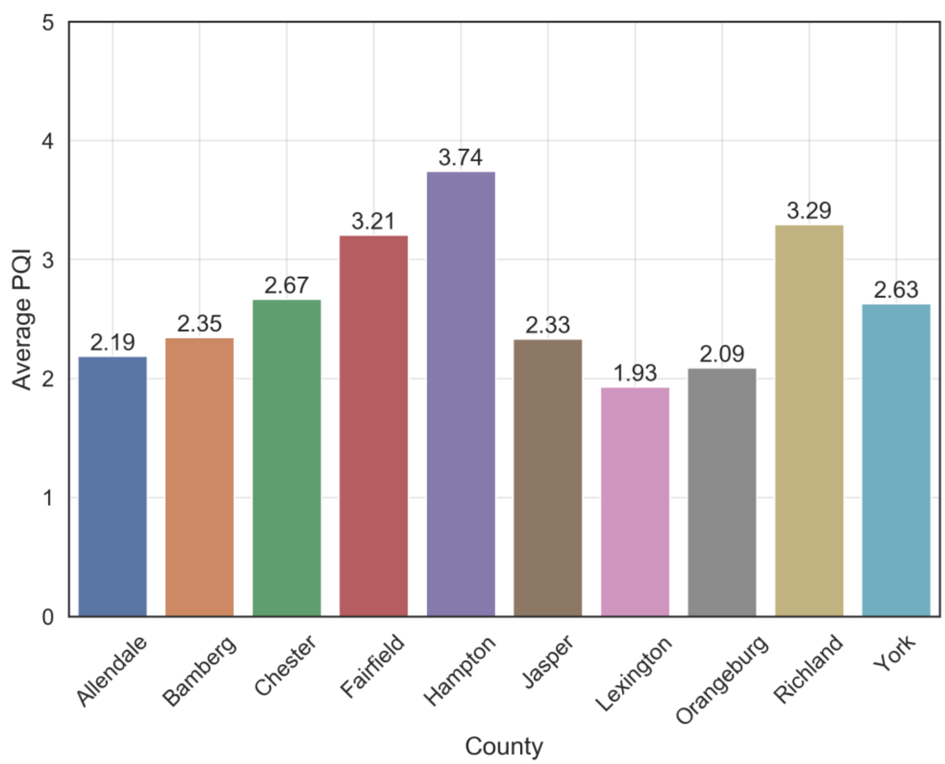
Mean of SCI_{12} for US-321



Histigram of SCI_{12} for US-321



Boxplot of PQI for US-321



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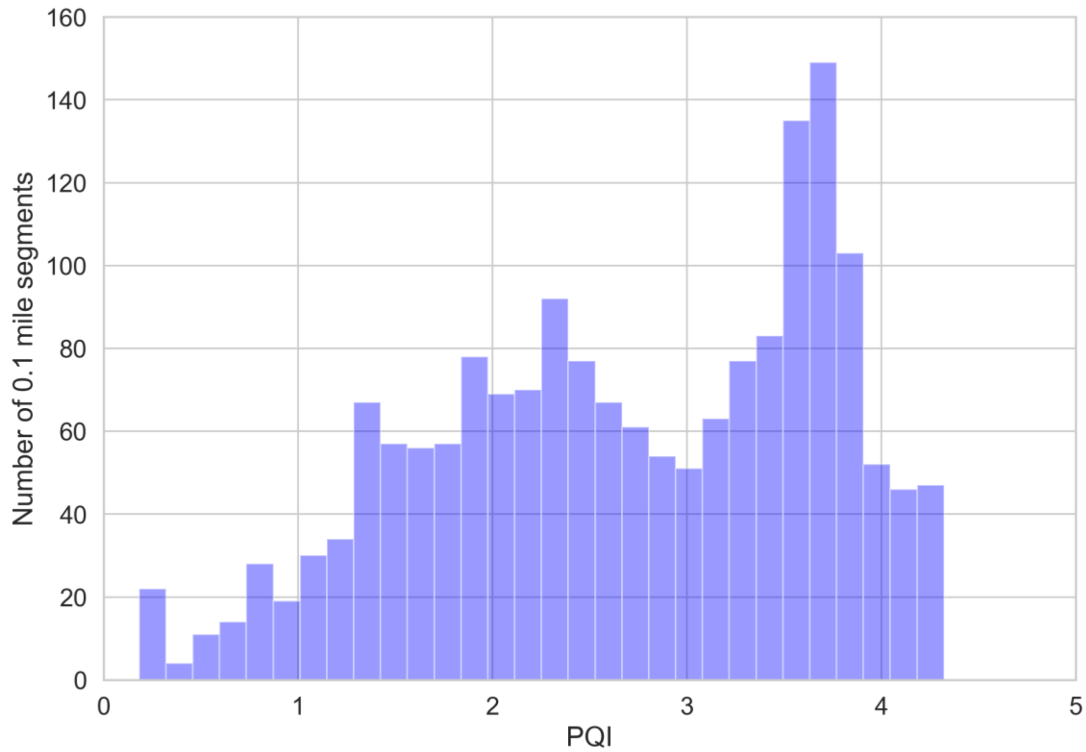
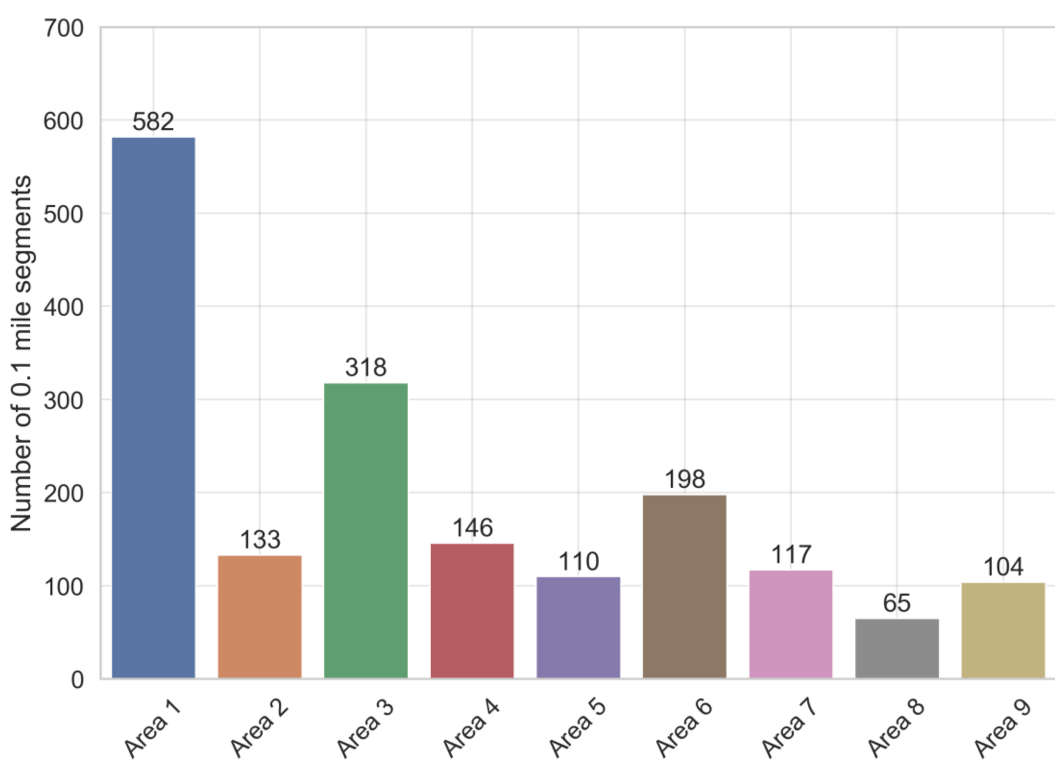
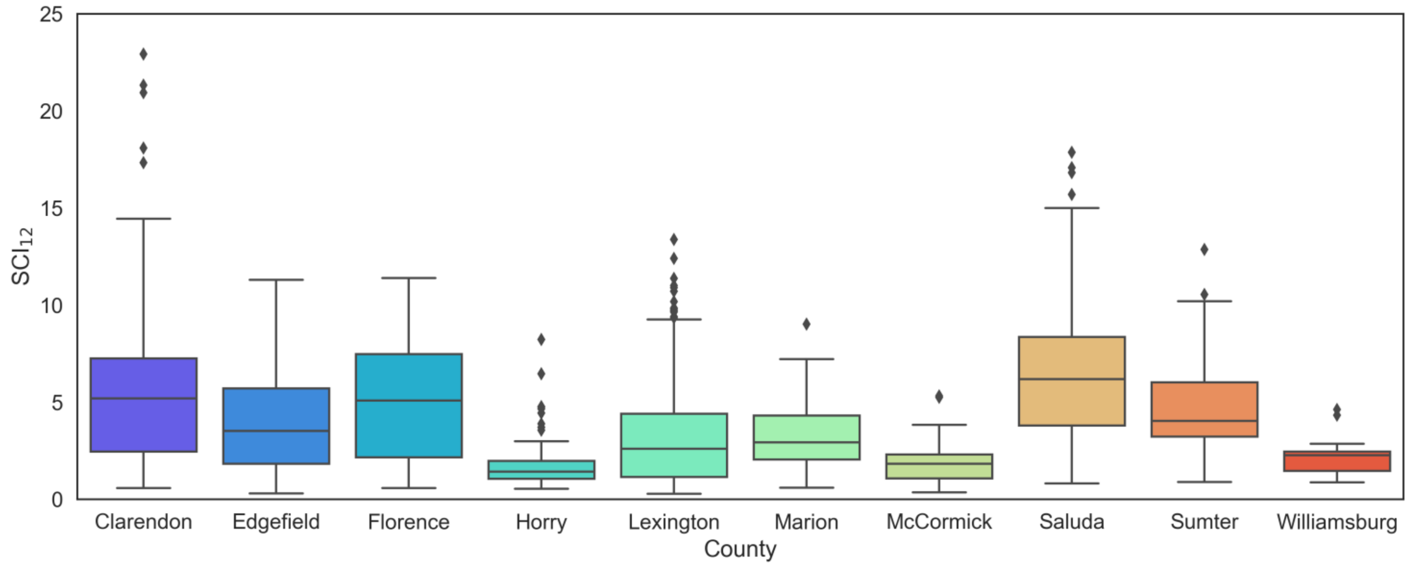


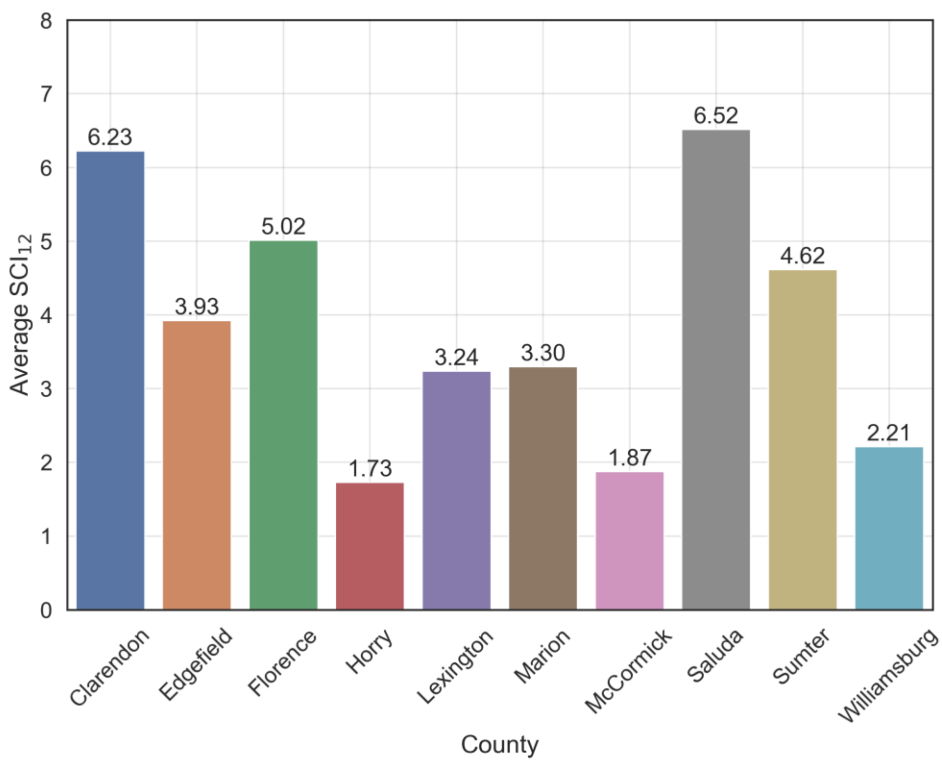
Histogram of PQI for US-321



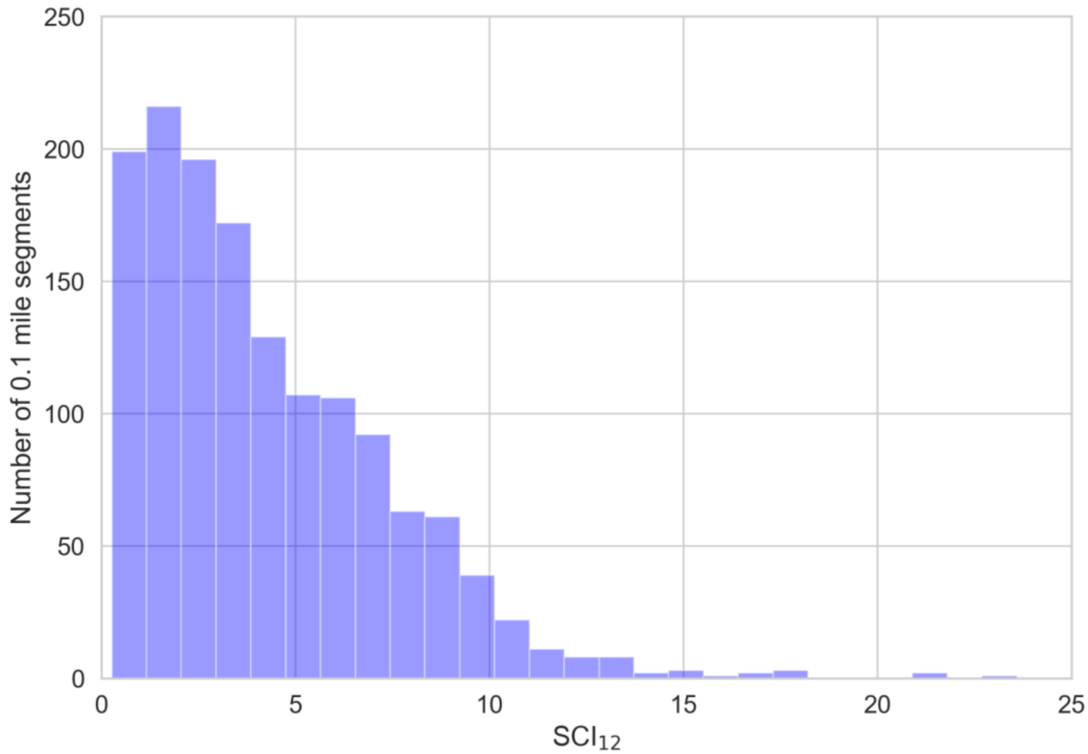
Distribution US-321 segments among the 9 classification segments



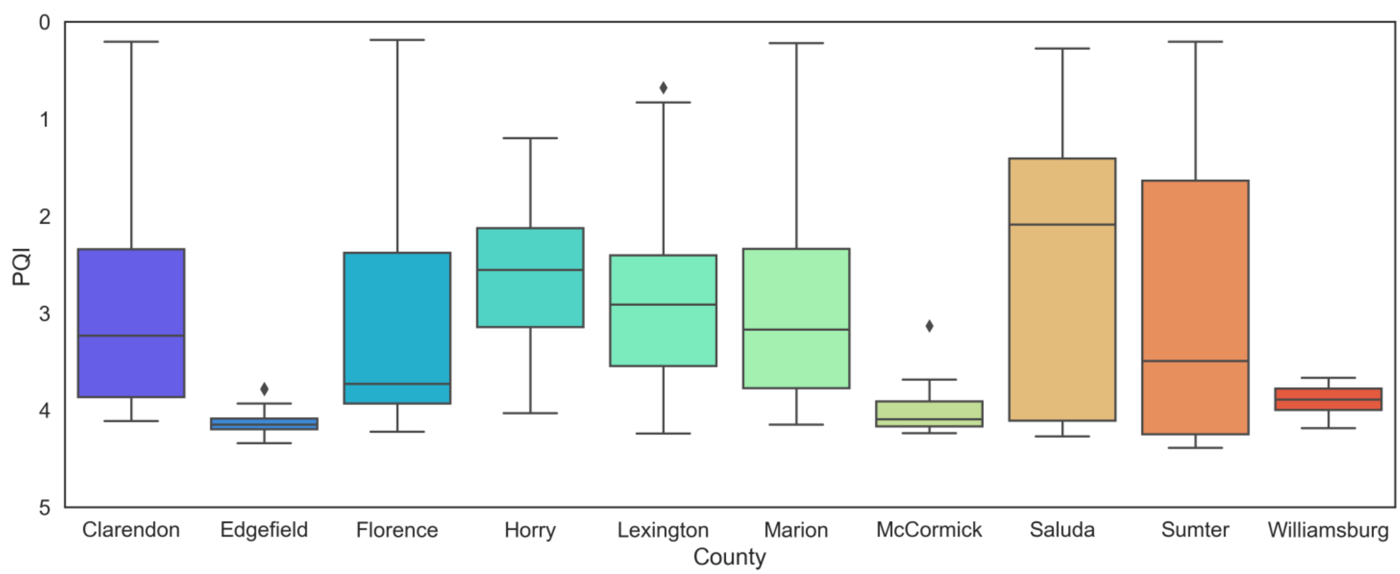
Boxplot of SCI_{12} for US-378



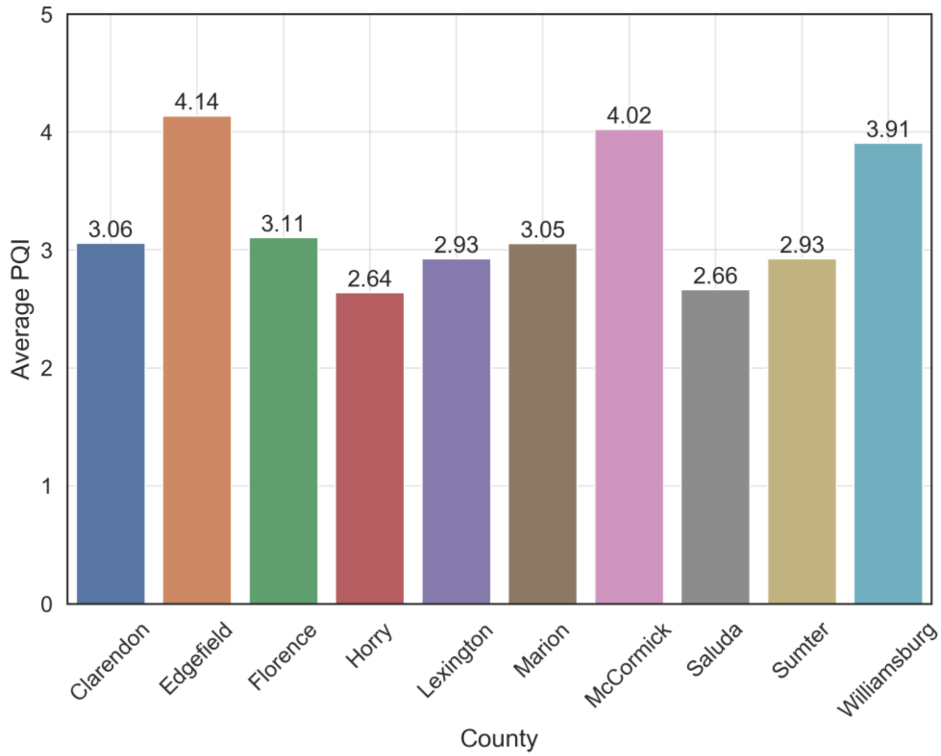
Mean of SCI_{12} for US-378



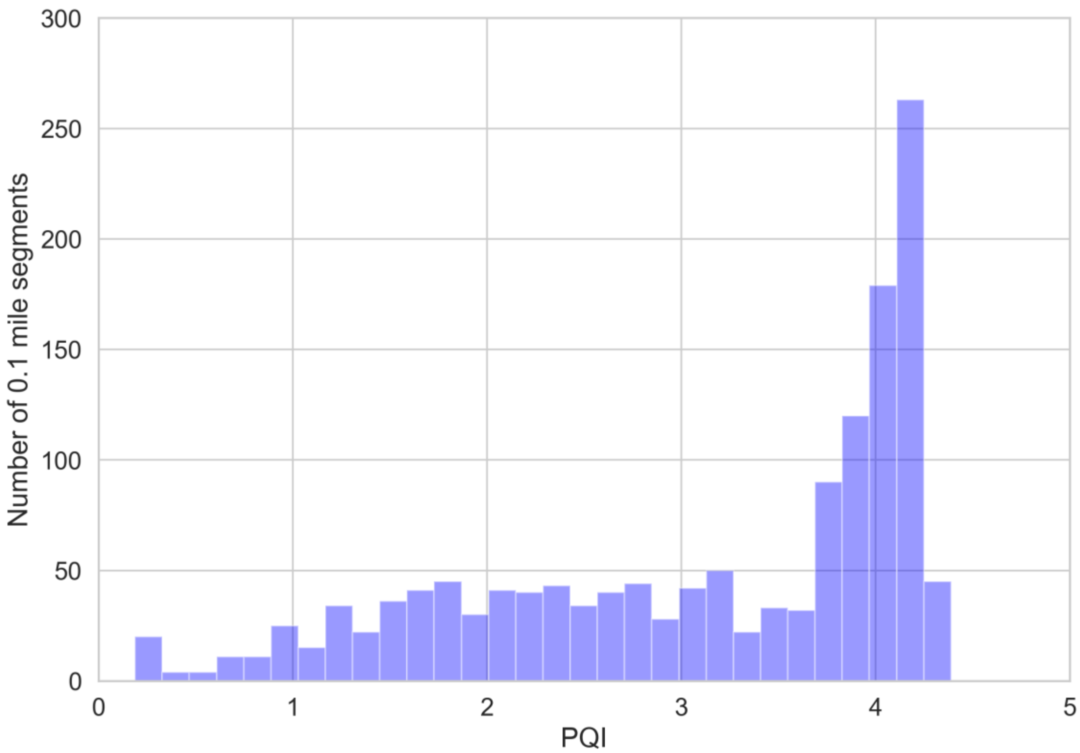
Histogram of SCI_{12} for US-378



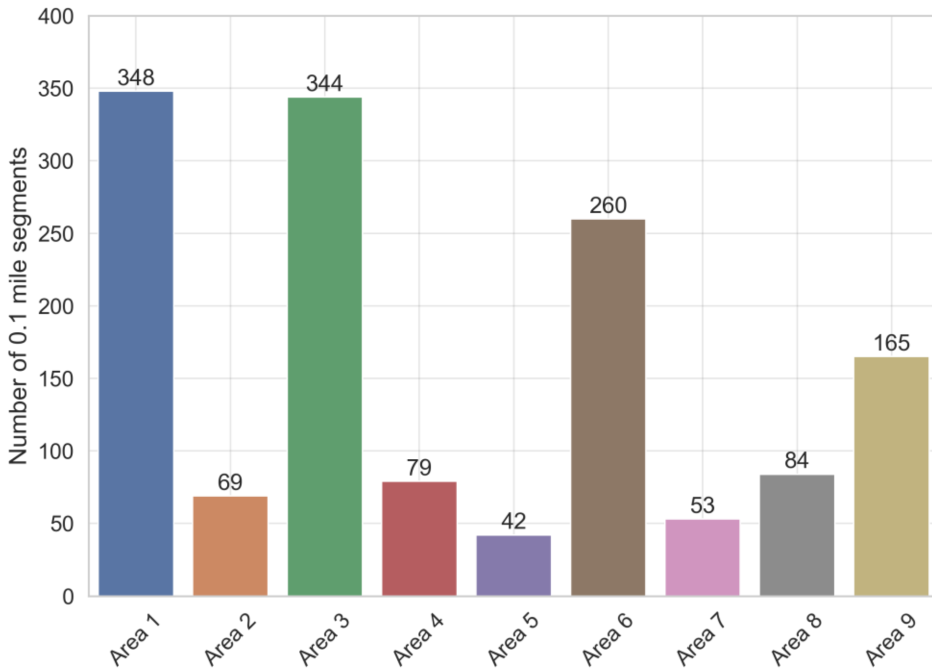
Boxplot of PQI for US-378



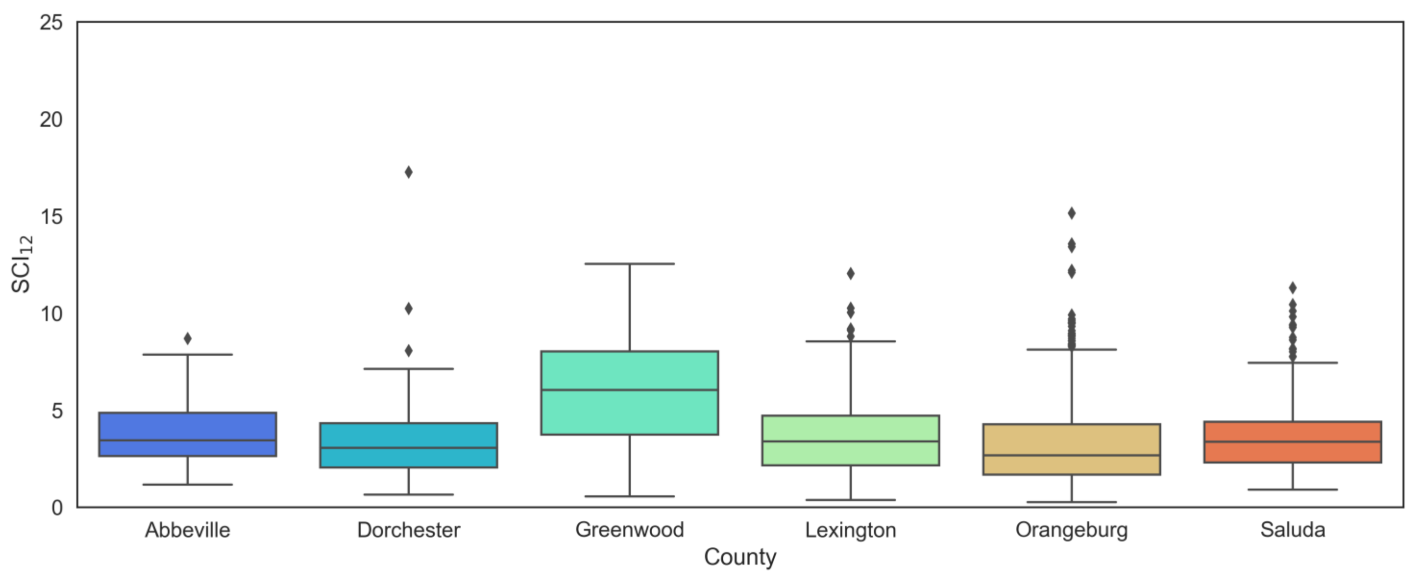
Mean of PQI for US-378



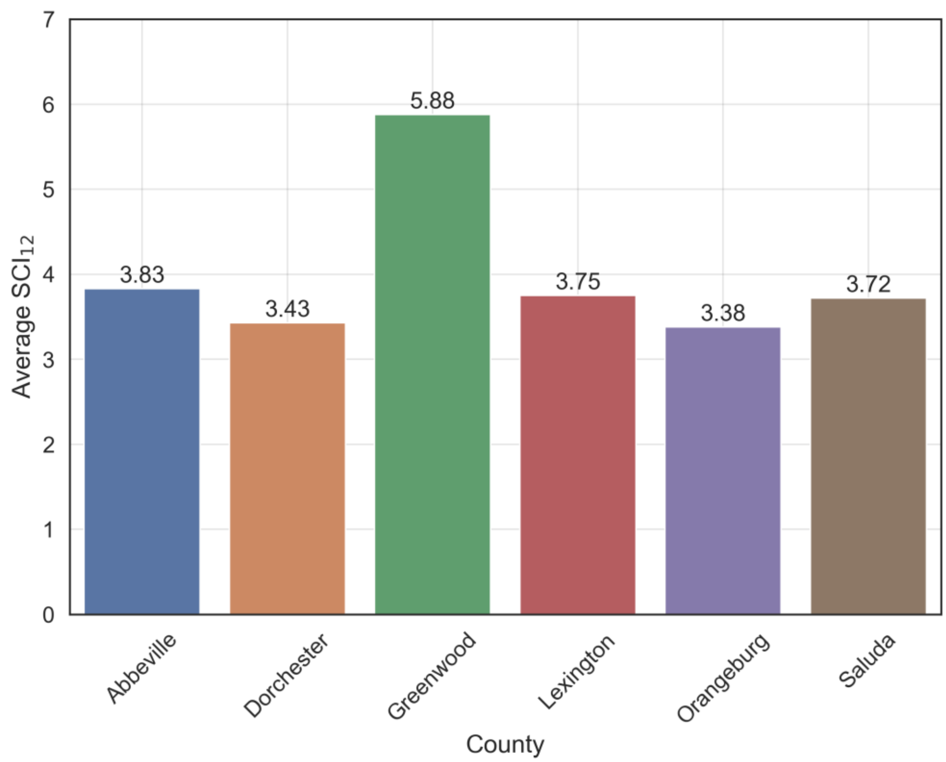
Histogram of PQI for US-378



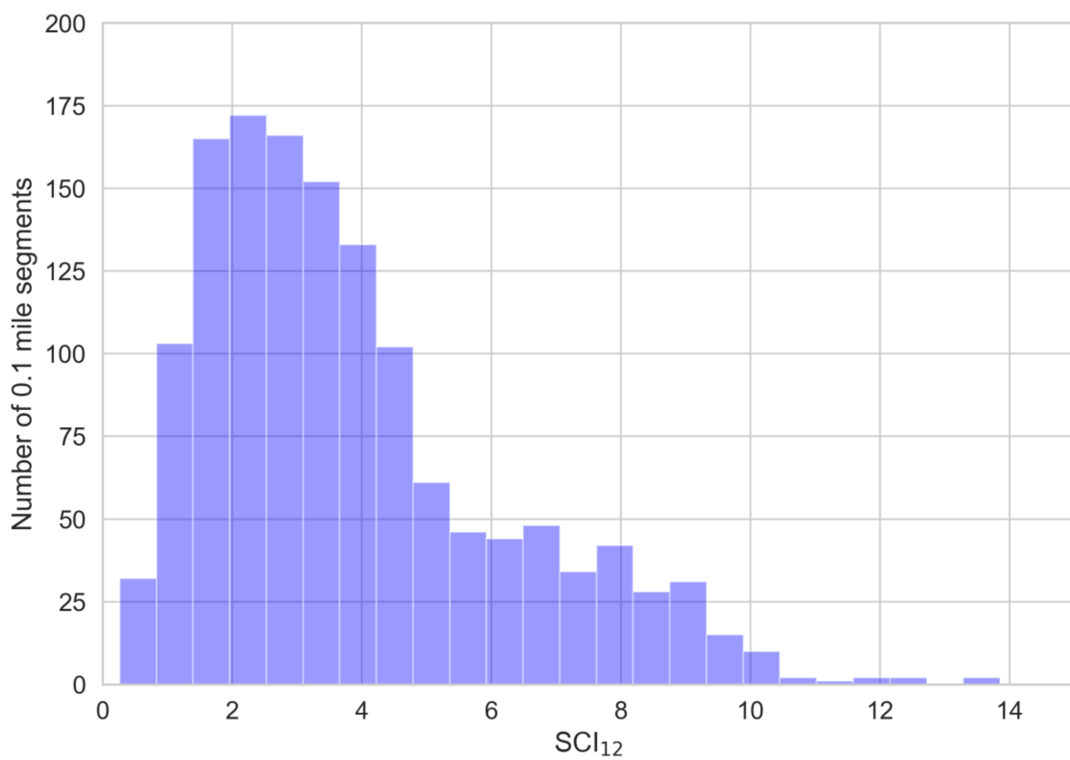
Distribution US-378 segments among the 9 classification segments



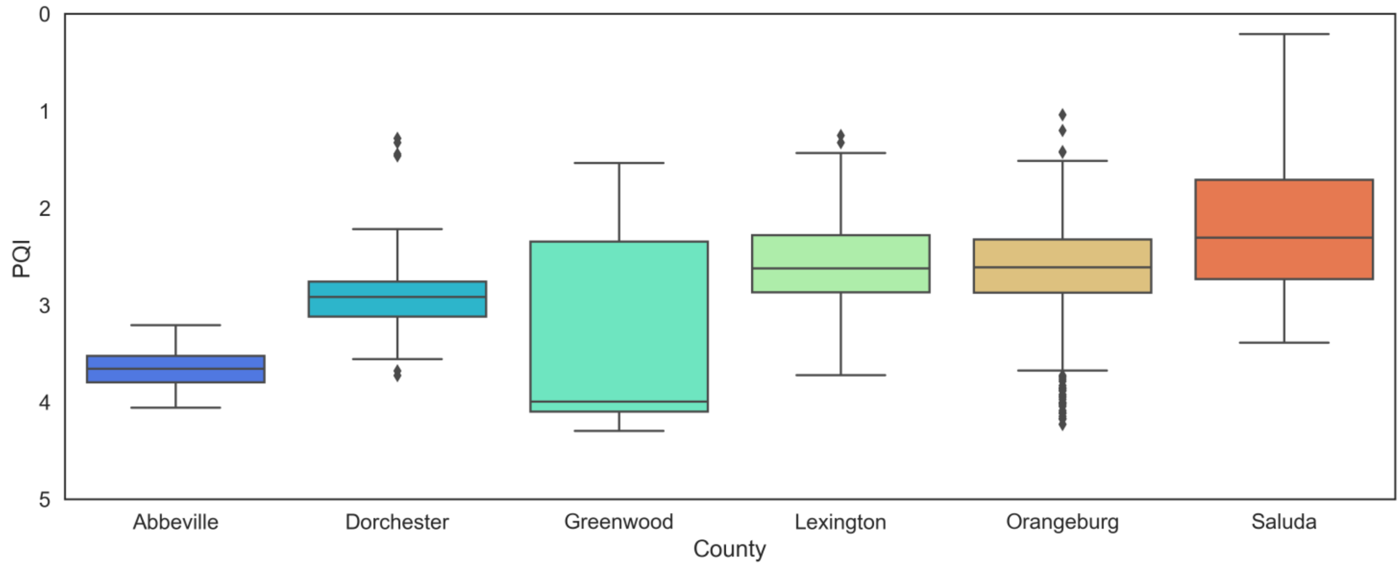
Boxplot of SCI_{12} for US-178



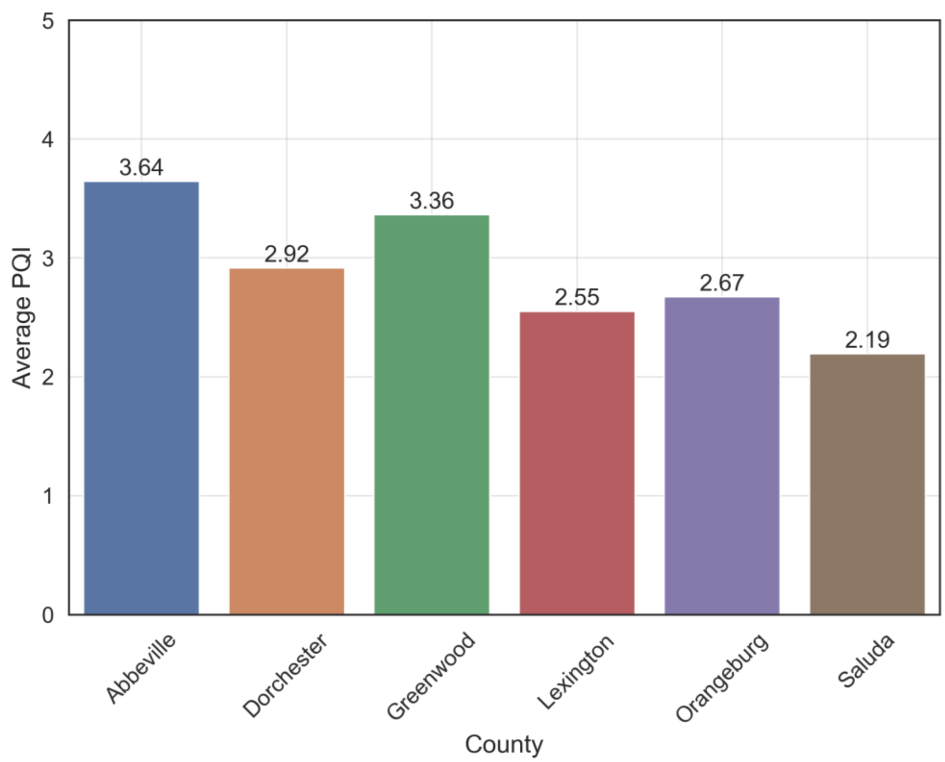
Mean of SCI_{12} for US-178



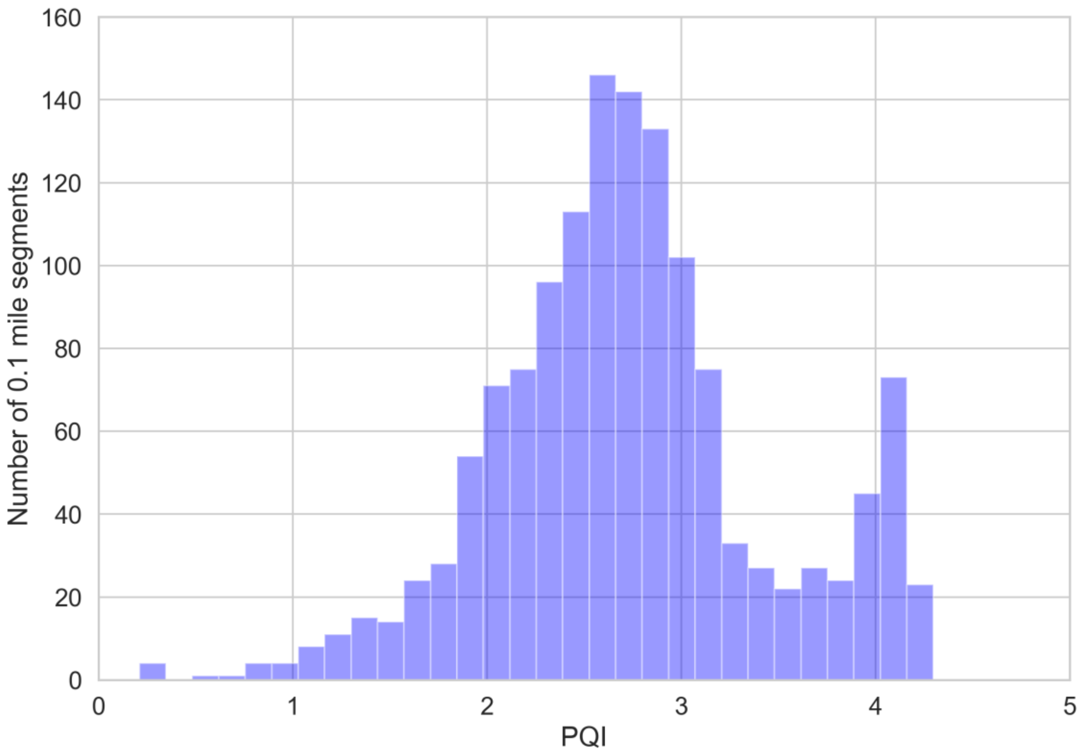
Histogram of SCI_{12} for US-178



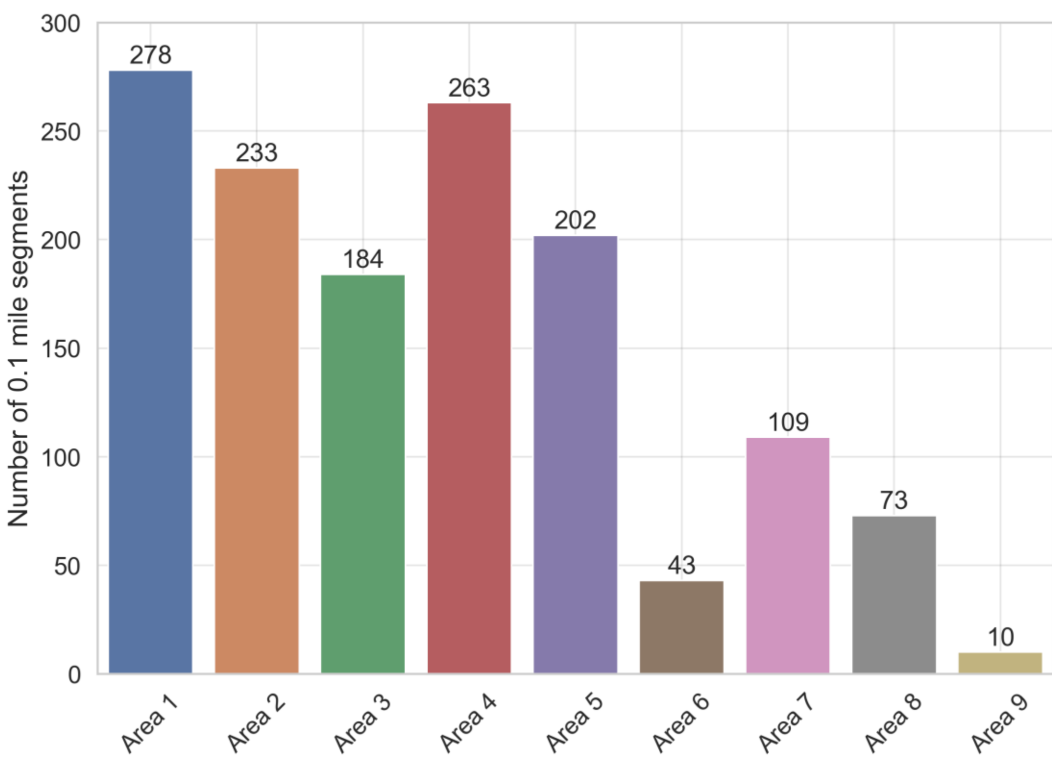
Boxplot of PQI for US-178



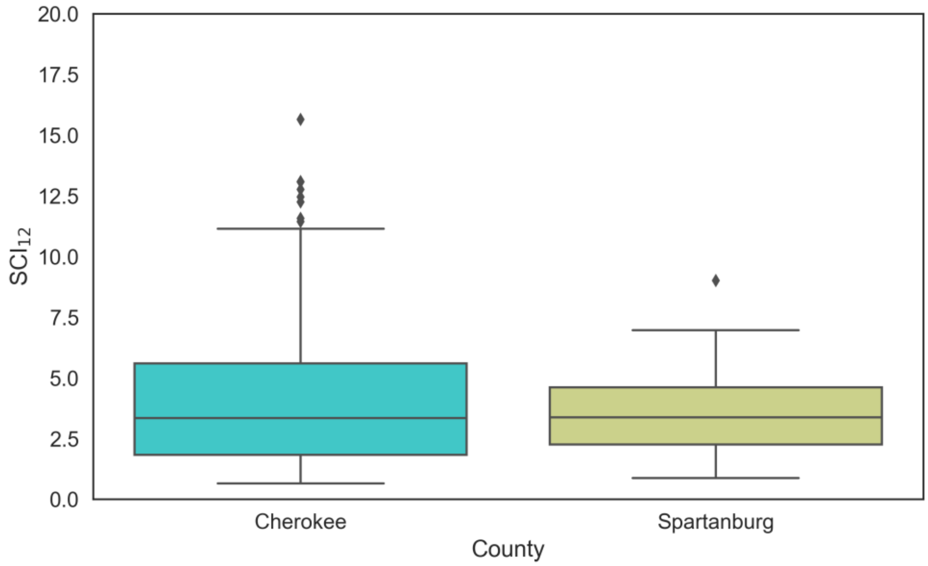
Mean of PQI for US-178



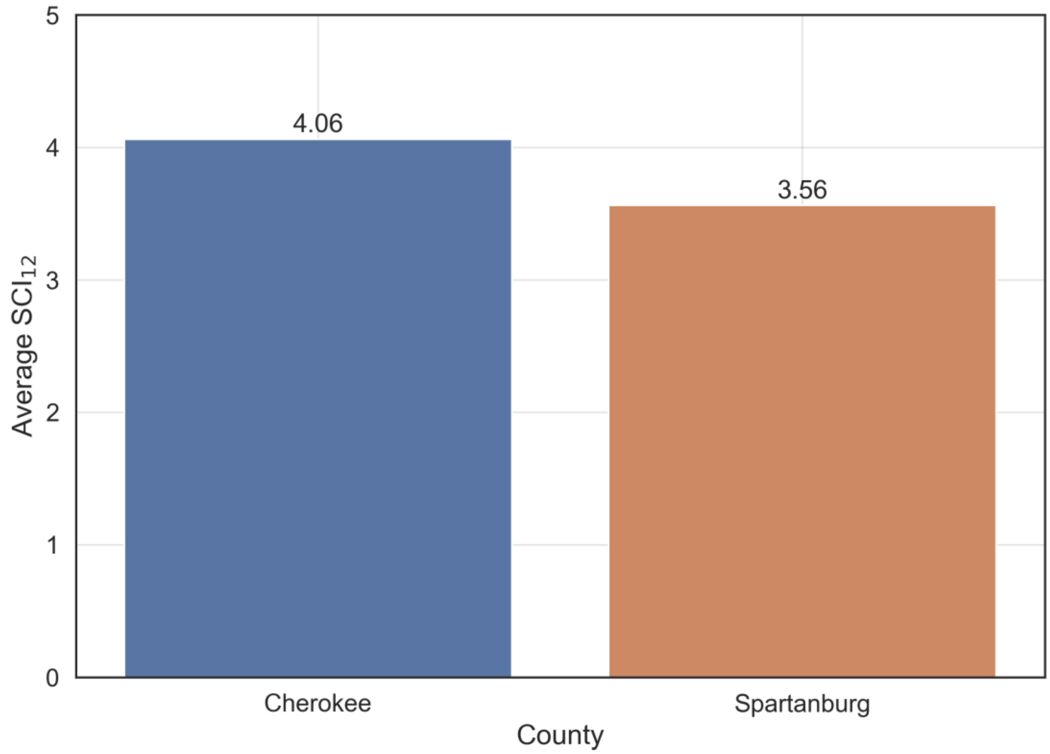
Histogram of PQI for US-178



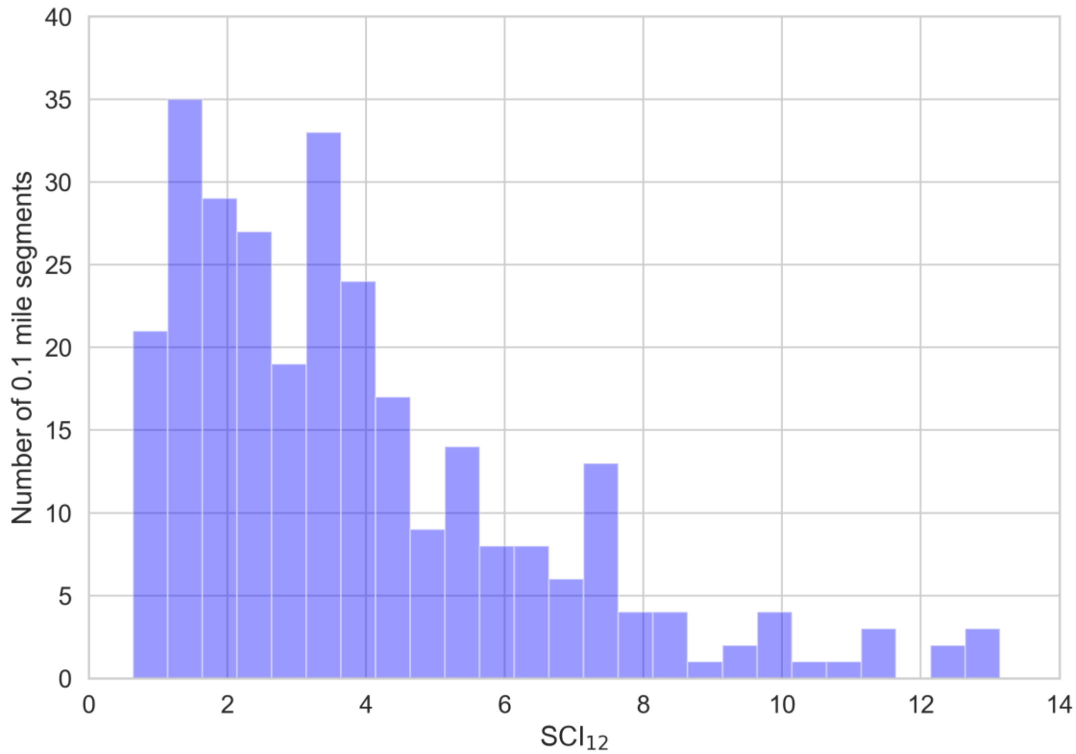
Distribution US-178 segments among the 9 classification segments



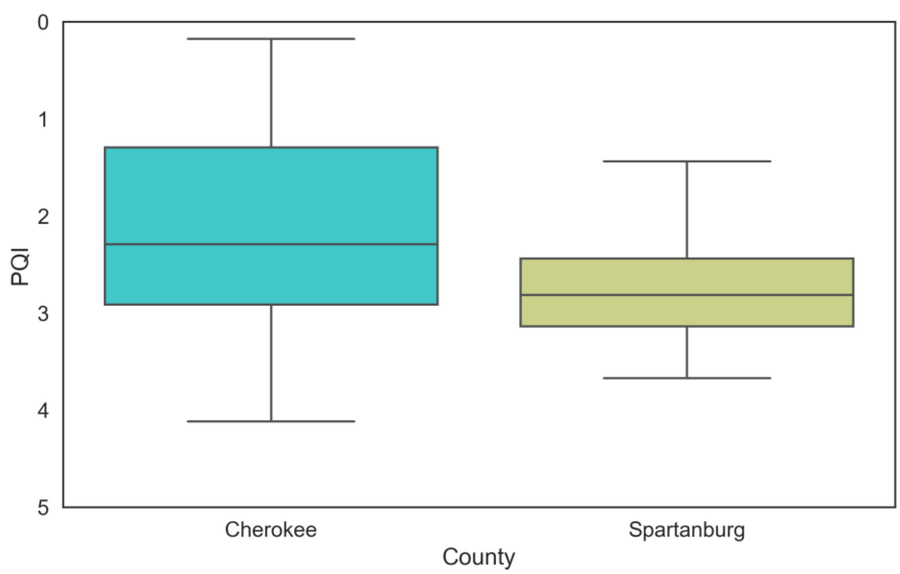
Boxplot of SCI_{12} for US-29



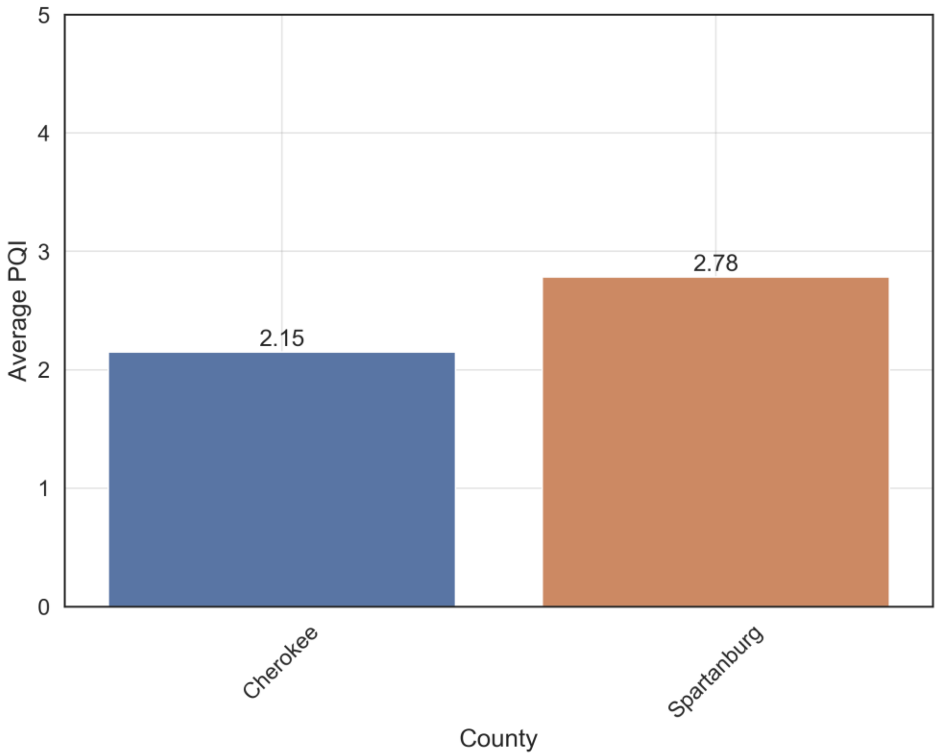
Mean of SCI_{12} for US-29



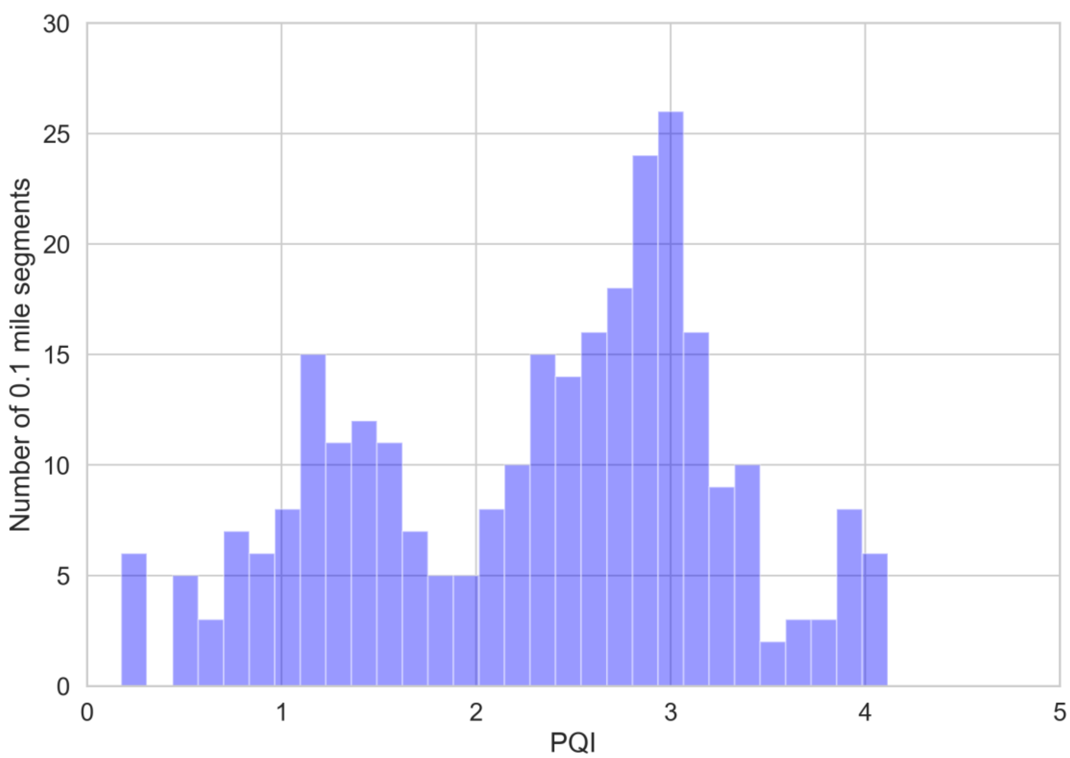
Histogram of SCI_{12} for US-29



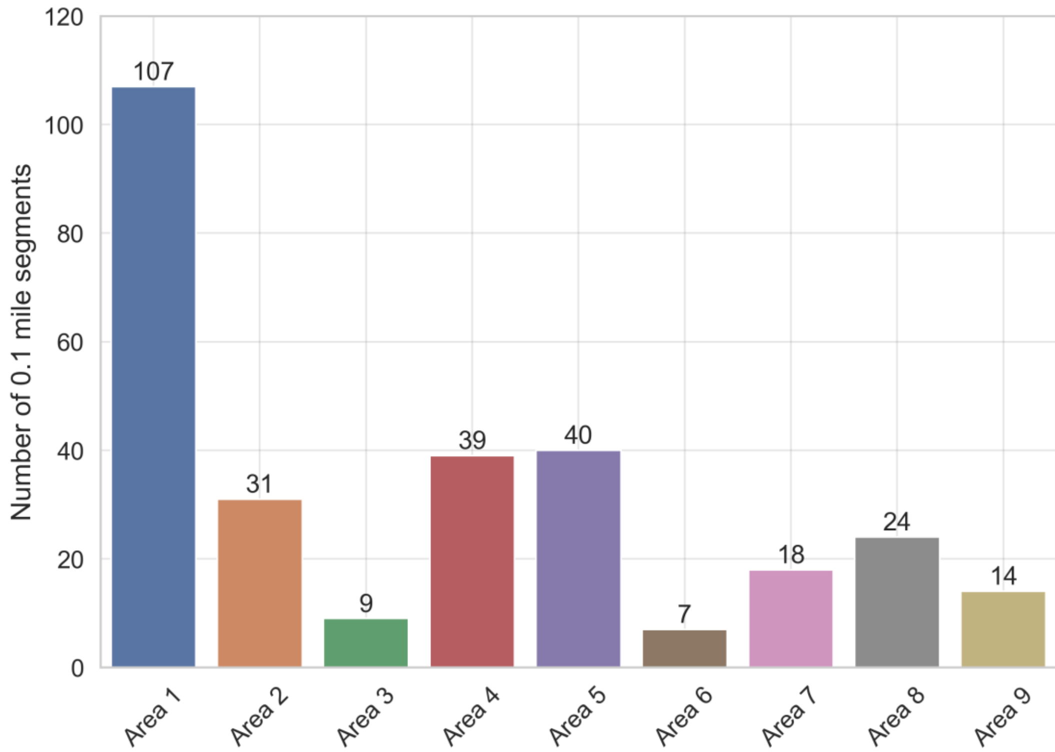
Boxplot of PQI for US-29



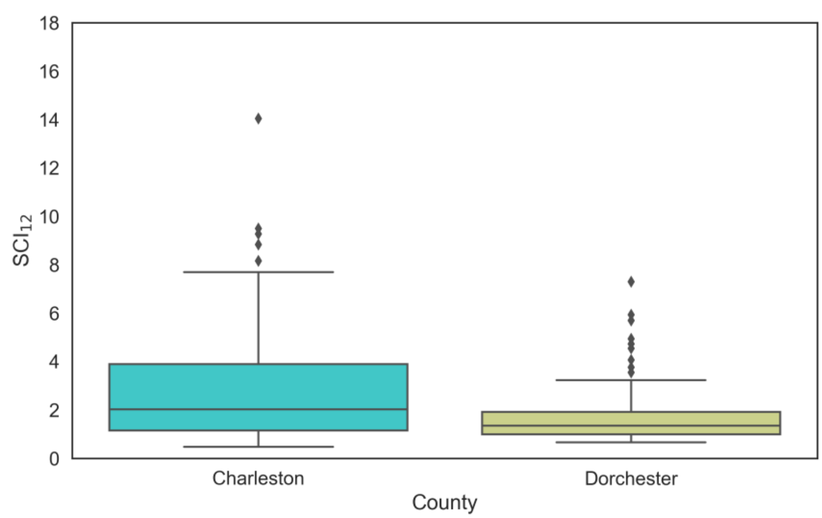
Mean of PQI for US-29



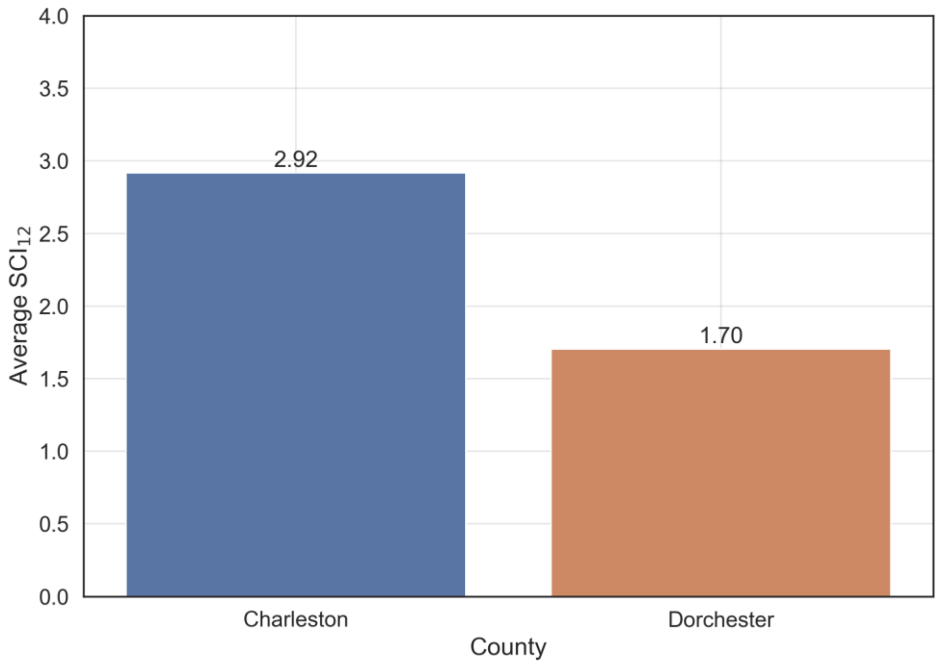
Histogram of PQI for US-29



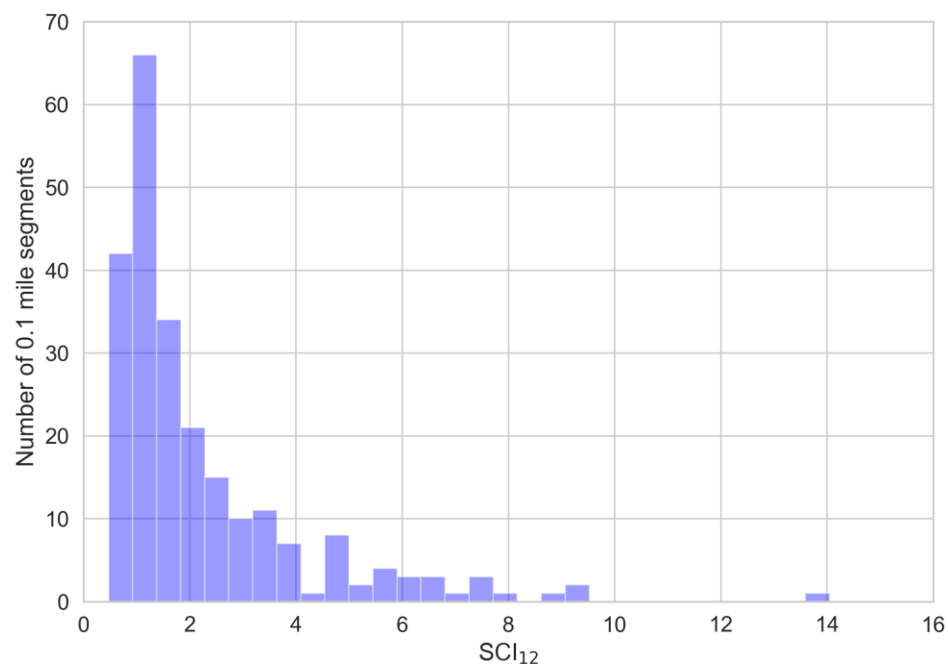
Distribution US-29 segments among the 9 classification segments



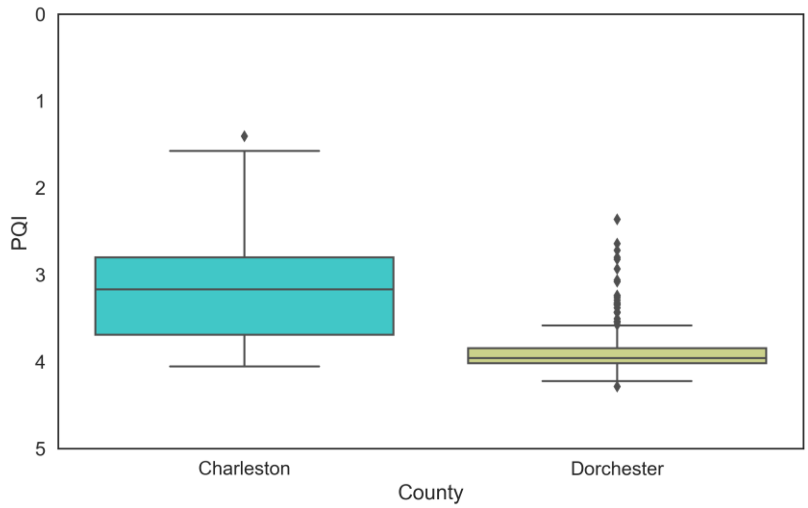
Boxplot of SCI_{12} for US-78



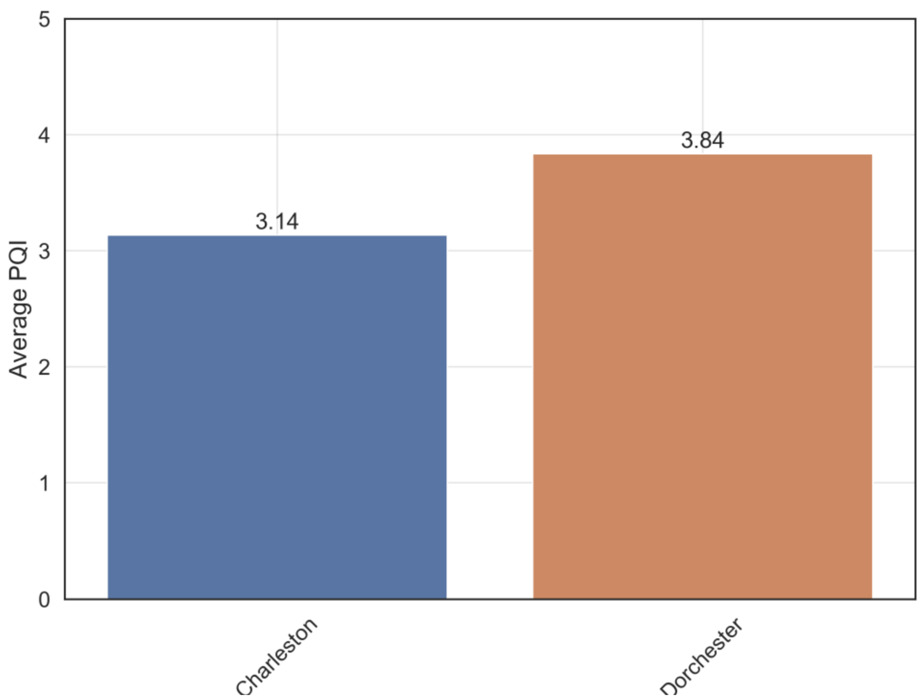
Mean of SCI_{12} for US-78



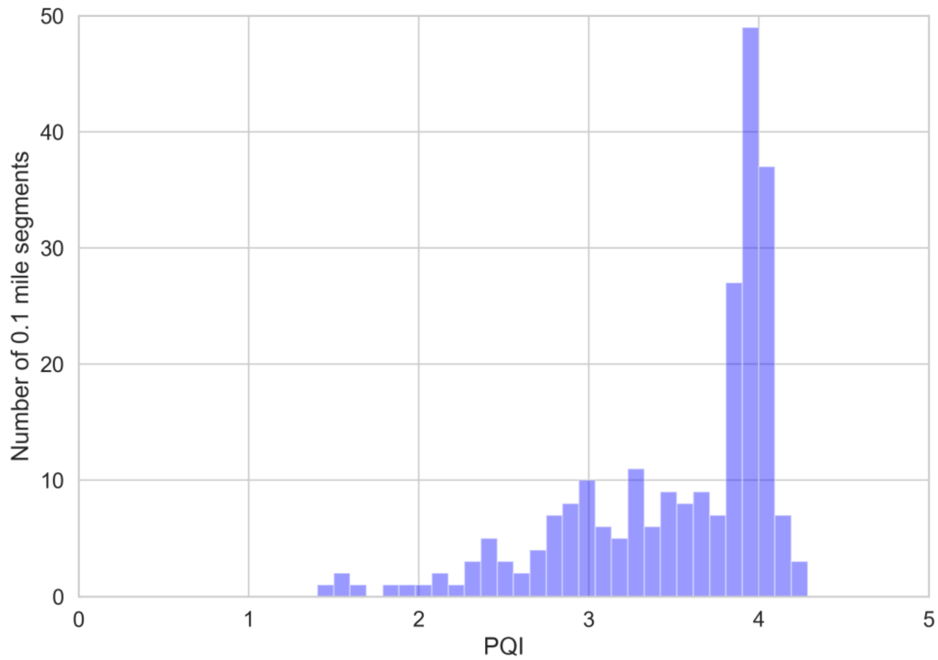
Histogram of SCI_{12} for US-78



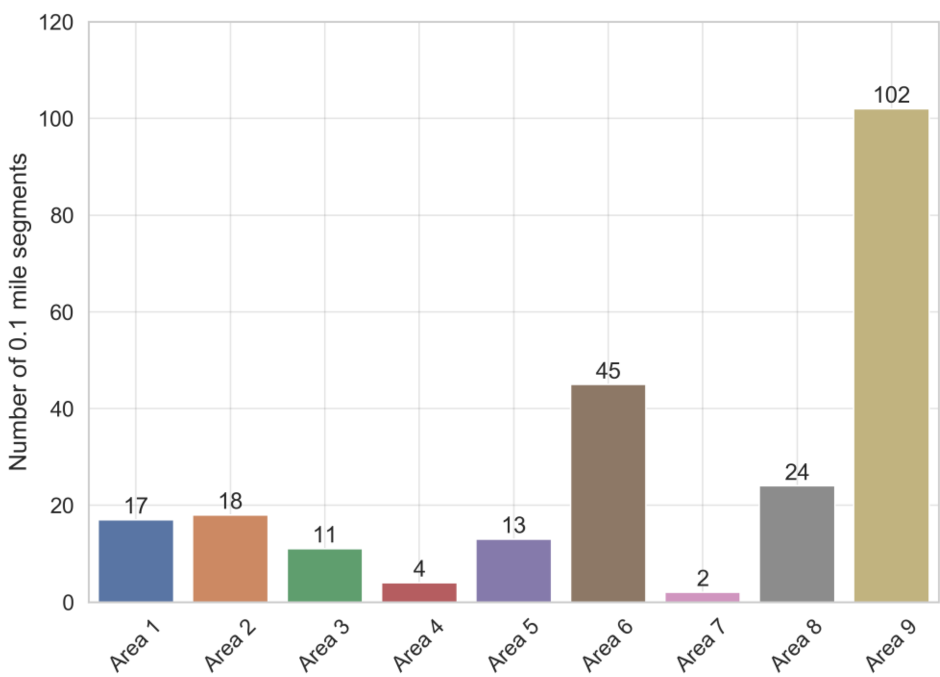
Boxplot of PQI for US-78



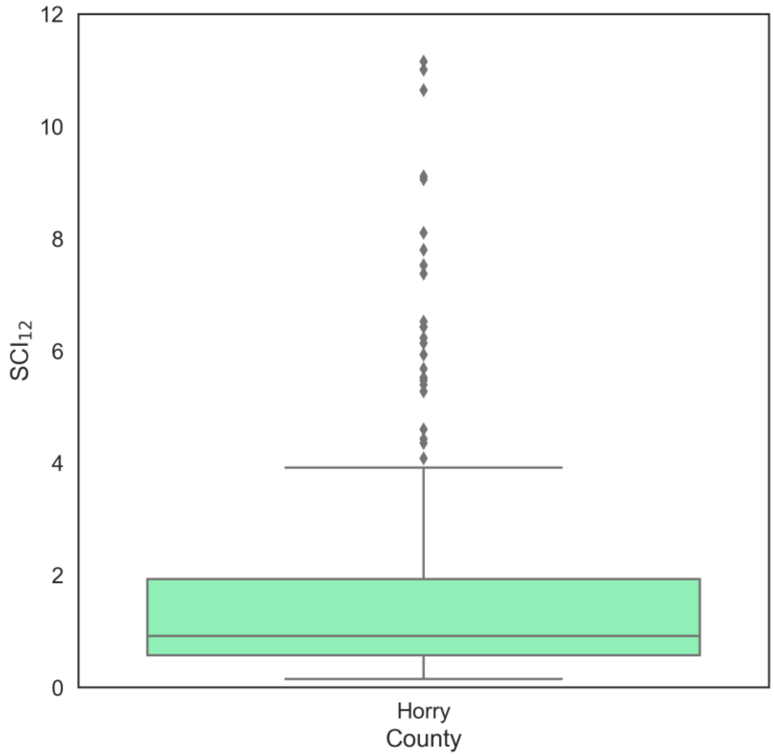
Mean of PQI for US-78



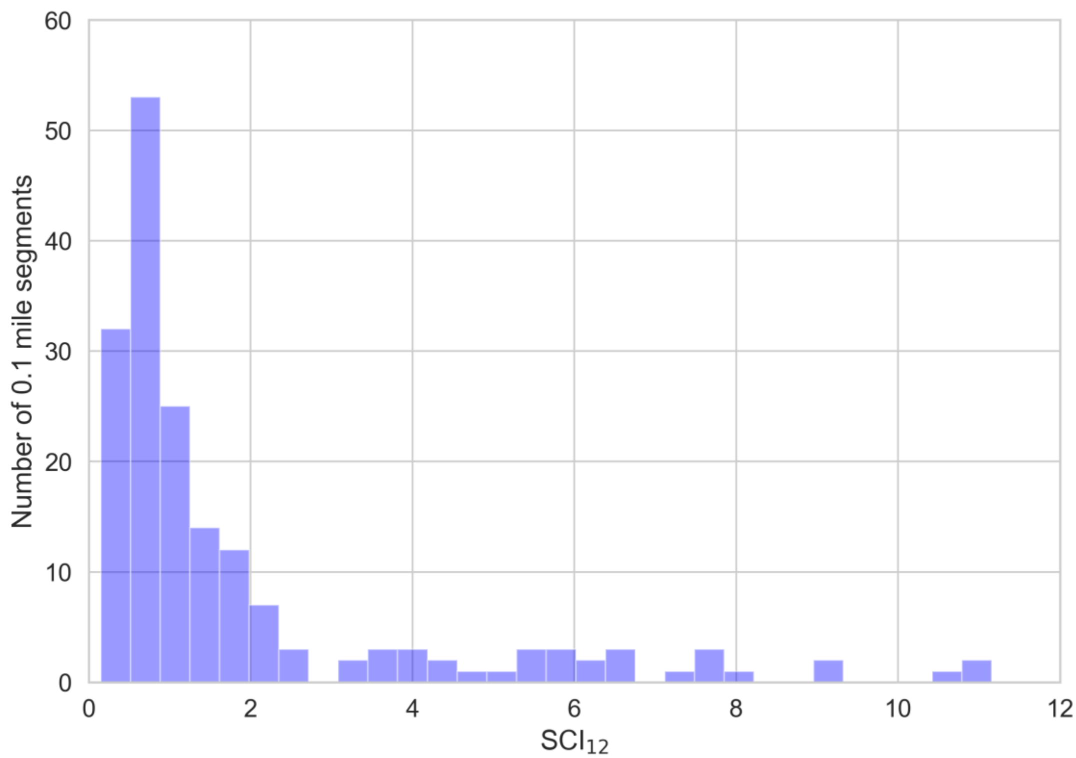
Histogram of PQI for US-78



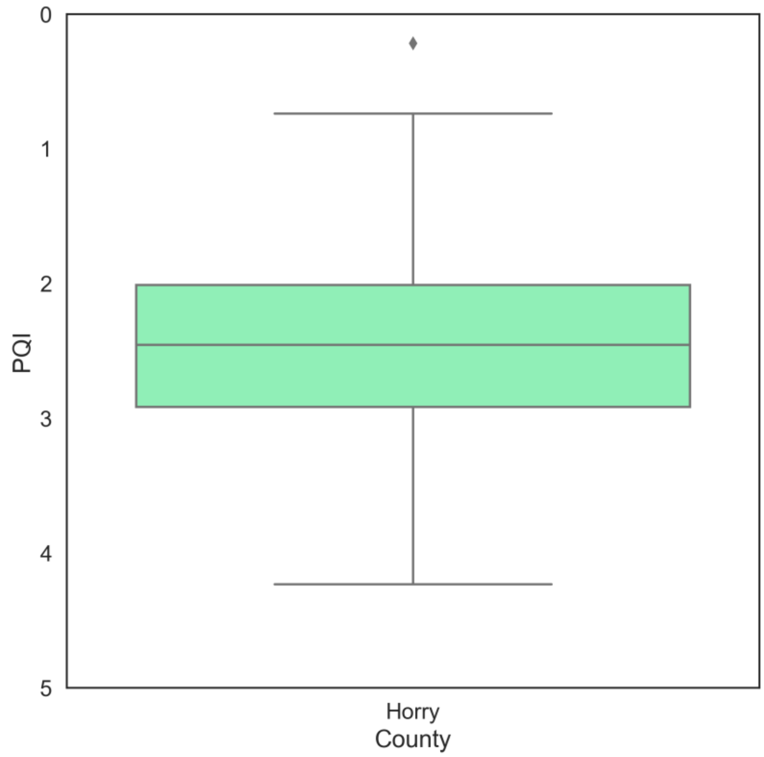
Distribution US-78 segments among the 9 classification segments



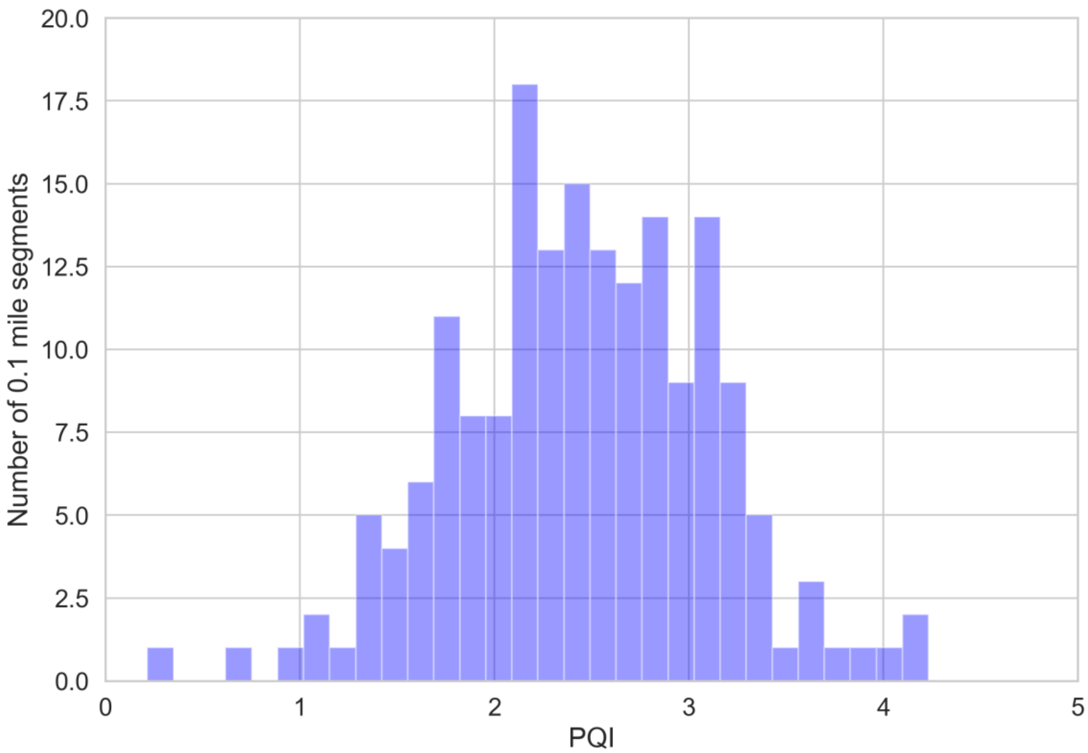
Boxplot of SCI_{12} for US-17



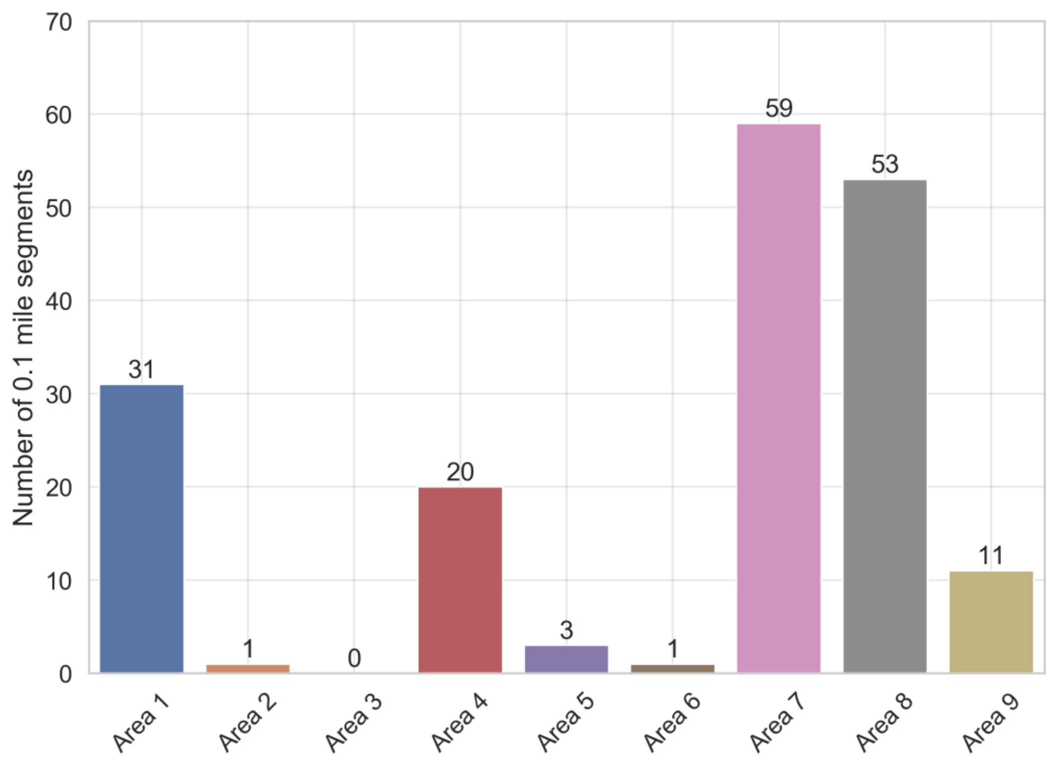
Histogram of SCI_{12} for US-17



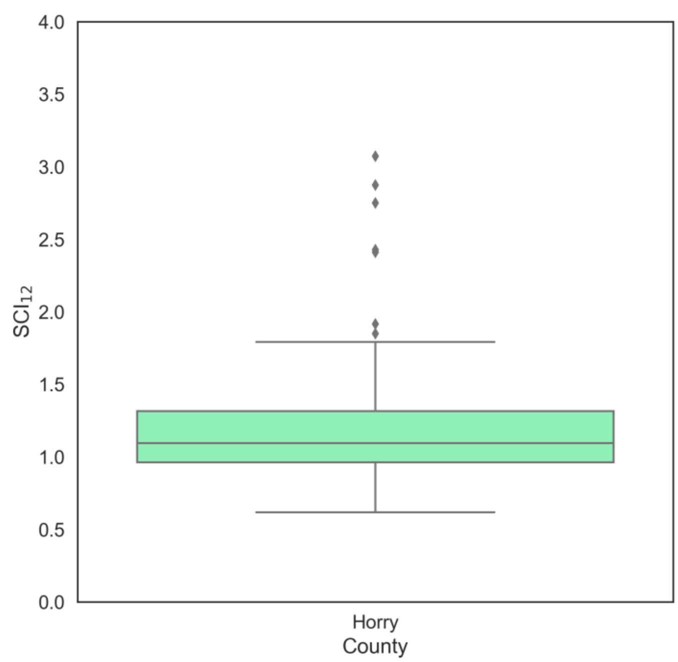
Boxplot of PQI for US-17



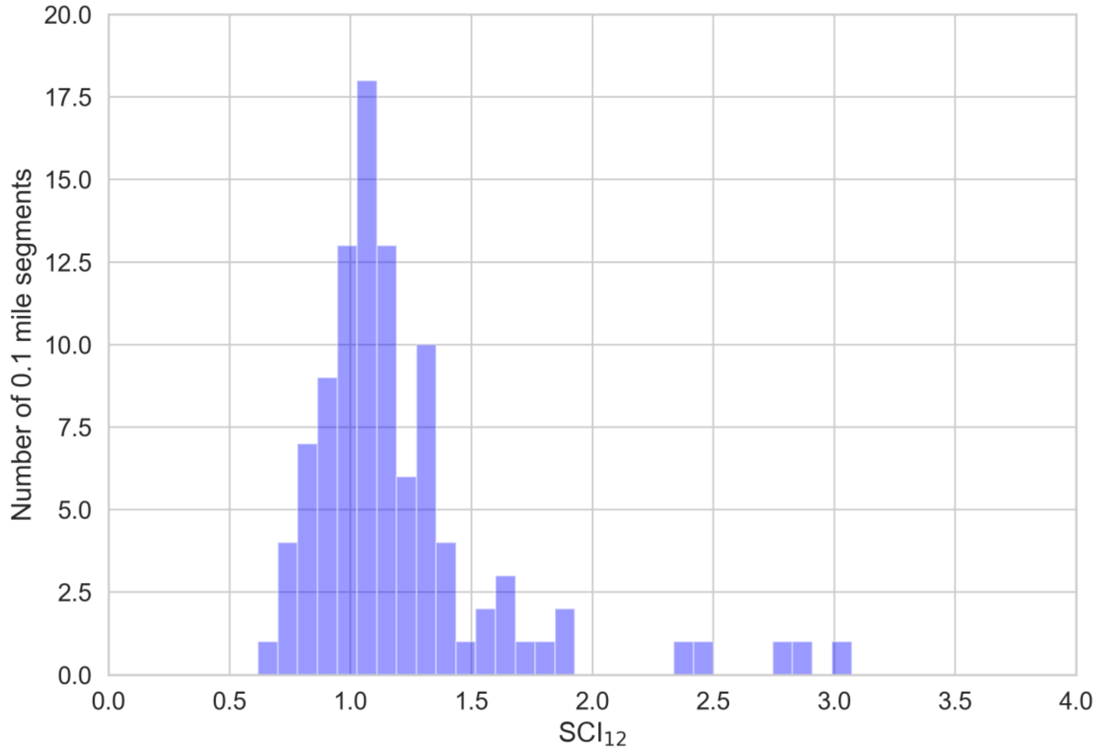
Histogram of PQI for US-17



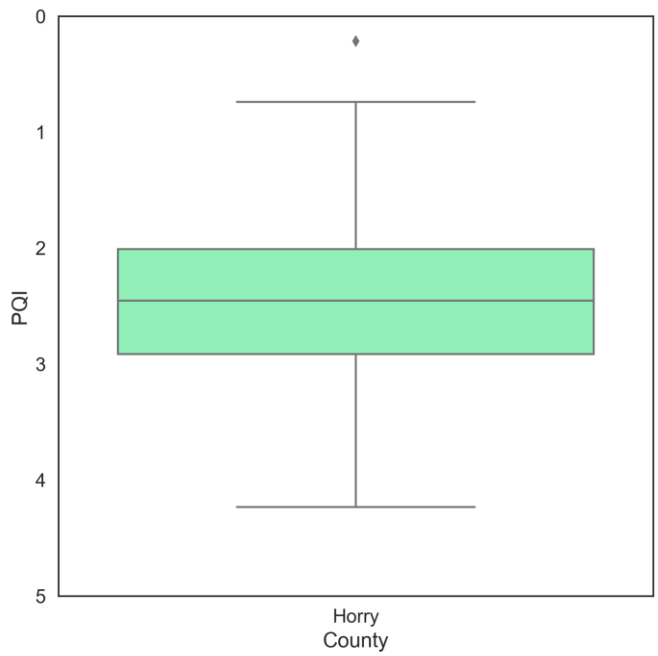
Distribution US-17 segments among the 9 classification segments



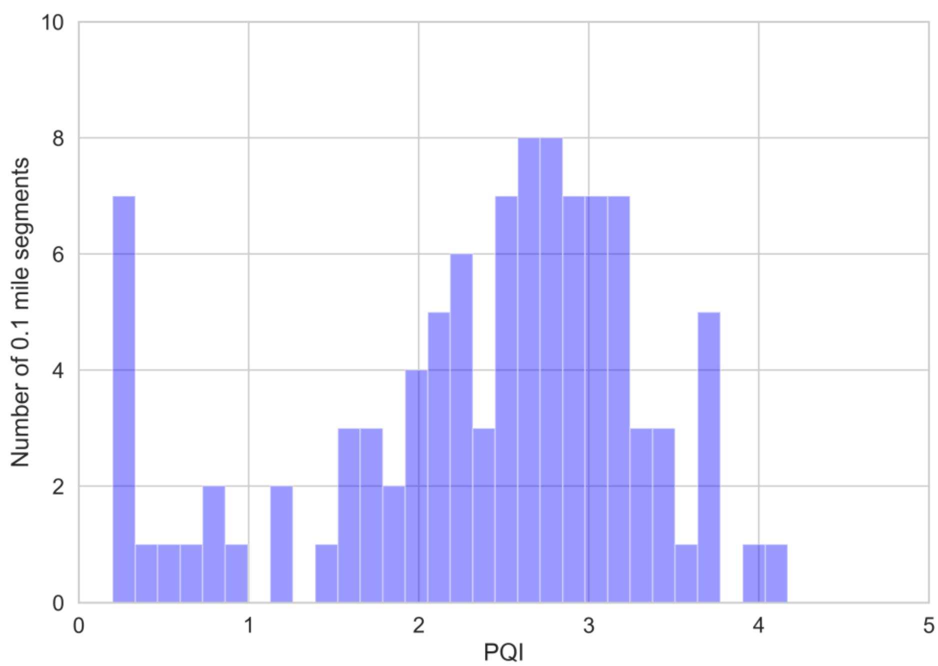
Boxplot of SCI_{12} for US-501



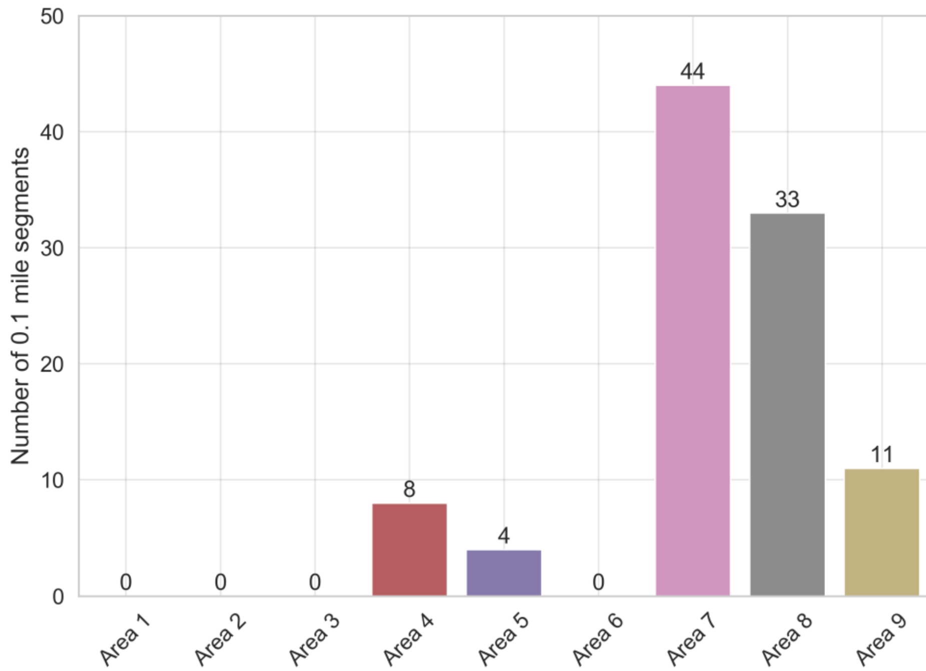
Histogram of SCI_{12} for US-501



Boxplot of PQI for US-501



Histogram of PQI of US-501



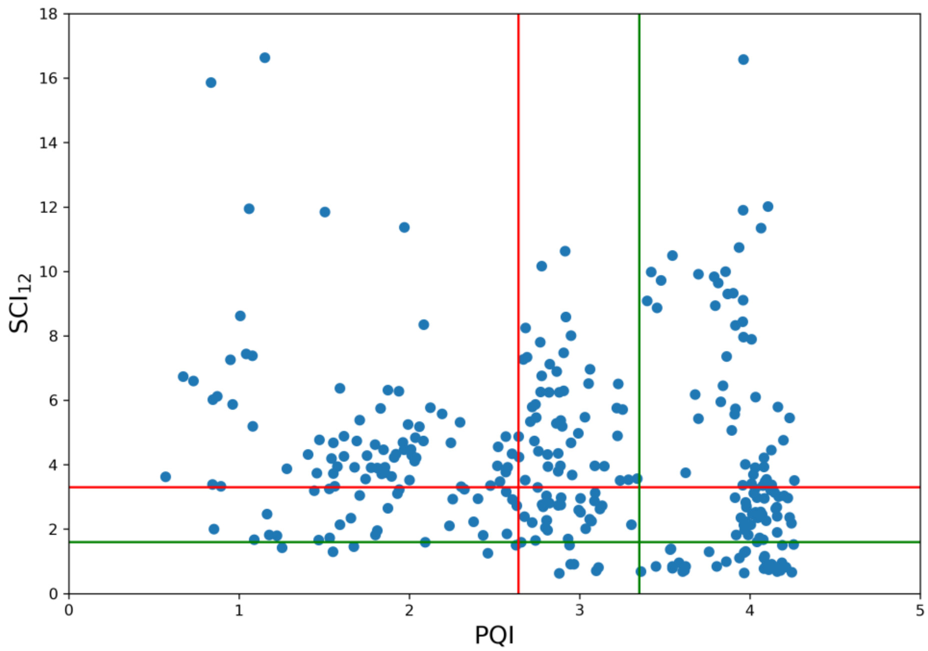
Distribution US-501 segments among the 9 classification segments

APPENDIX F

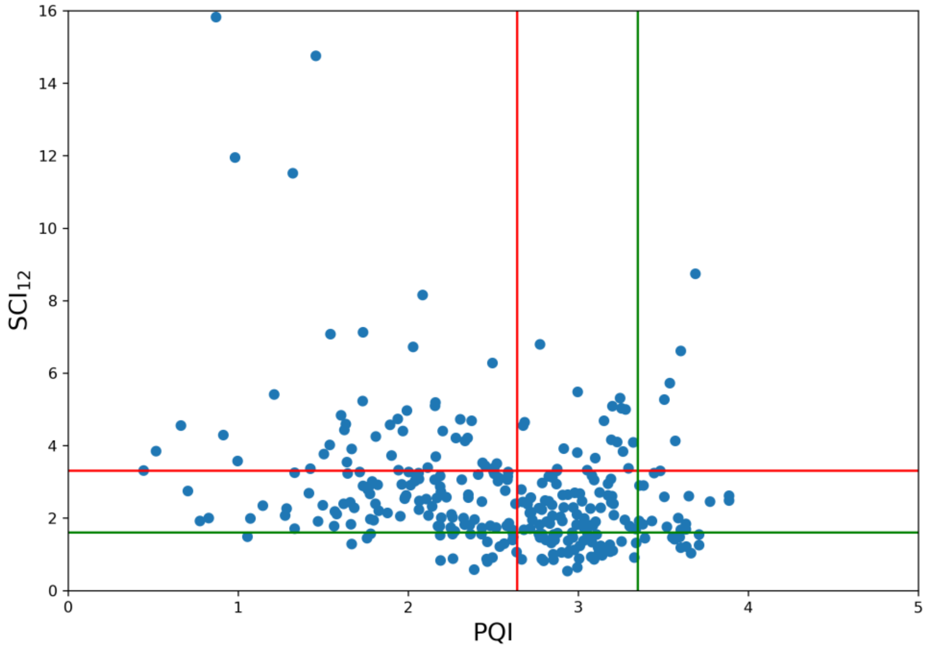
Correlation Analysis of each TSD Route

Correlation between SCI_{12} and PQI of SC-9

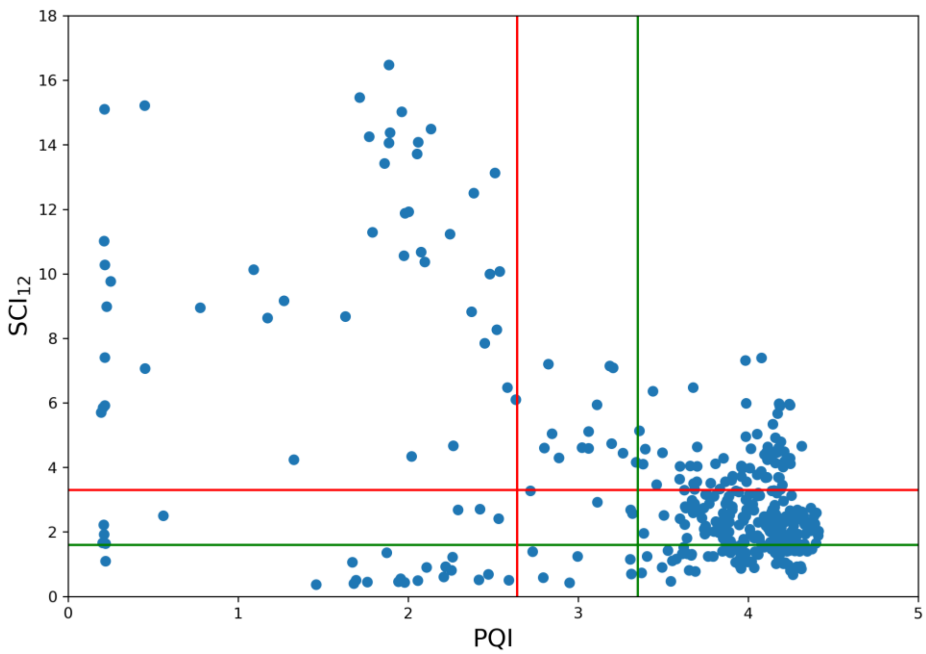
County	Pearson Correlation	Degree of Correlation	p-value
Chester	-0.1	Low	0.11
Chesterfield	-0.15	Low	0.01
Dillon	-0.29	Low	~0
Horry	-0.51	Strong	~0
Lancaster	-0.79	Strong	~0
Marion	-0.03	Low	0.89
Spartanburg	-0.2	Low	0.42
Union	-0.27	Low	~0



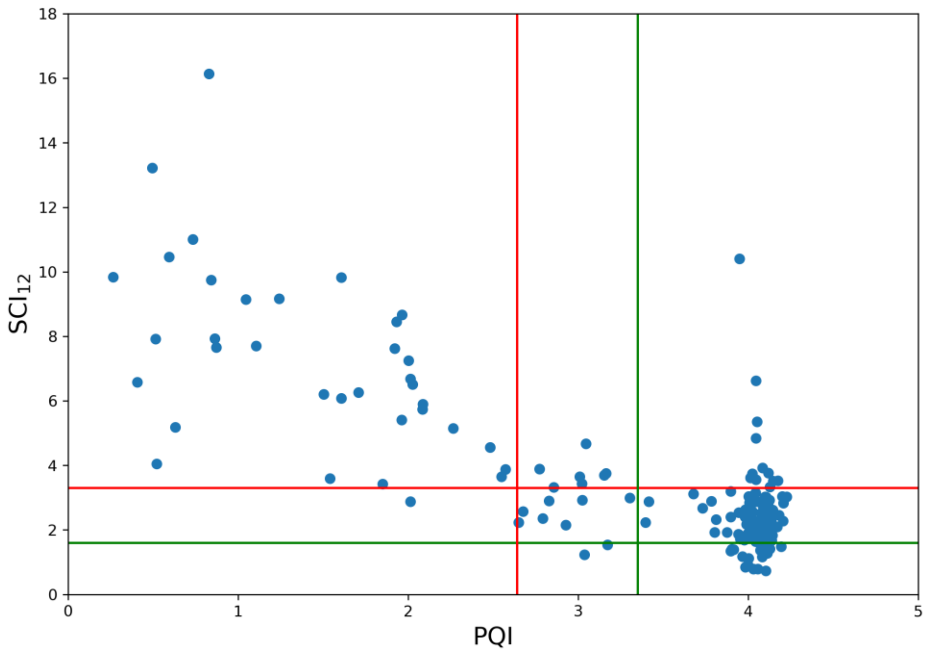
Correlation between SCI_{12} and PQI of SC-9 (Chesterfield county)



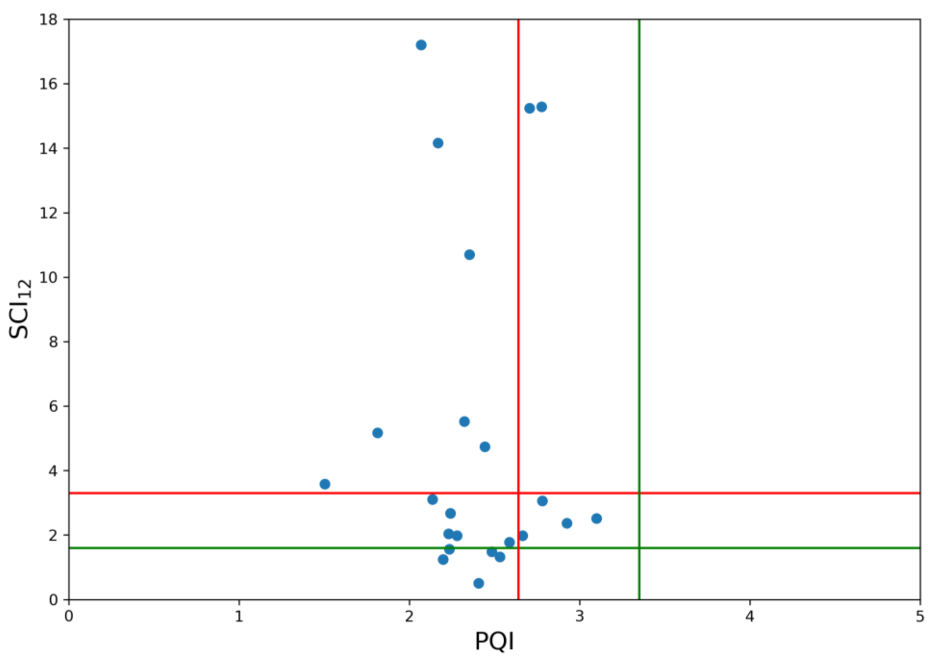
Correlation between SCI_{12} and PQI of SC-9 (Dillon county)



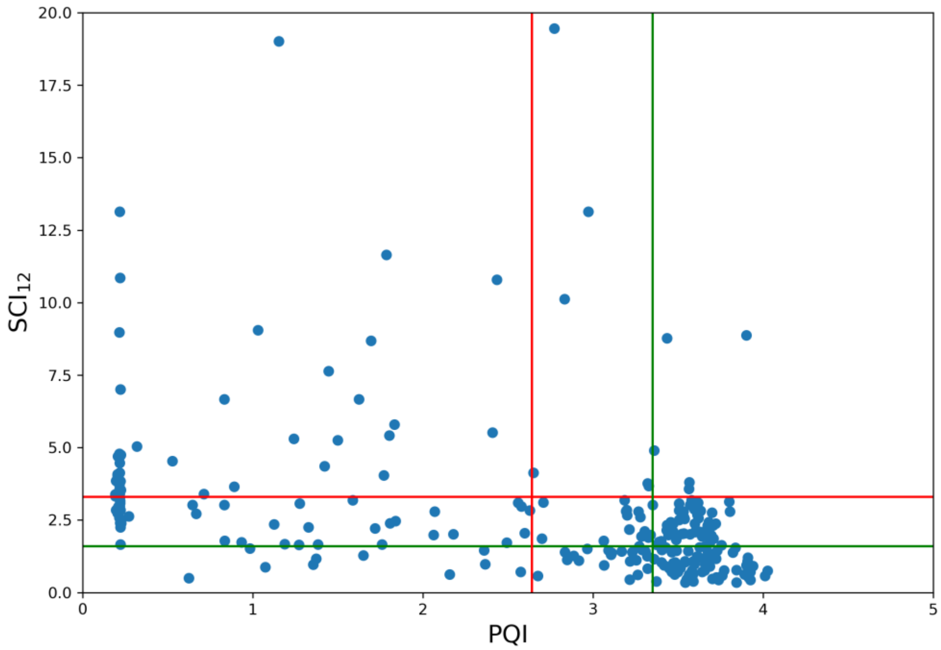
Correlation between SCI_{12} and PQI of SC-9 (Horry county)



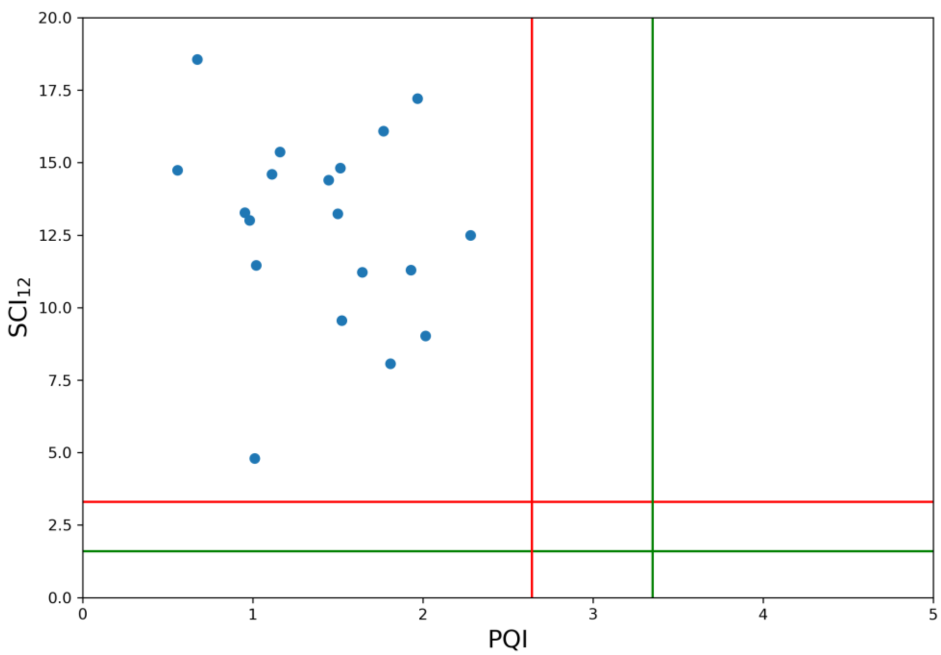
Correlation between SCI_{12} and PQI of SC-9 (Lancaster county)



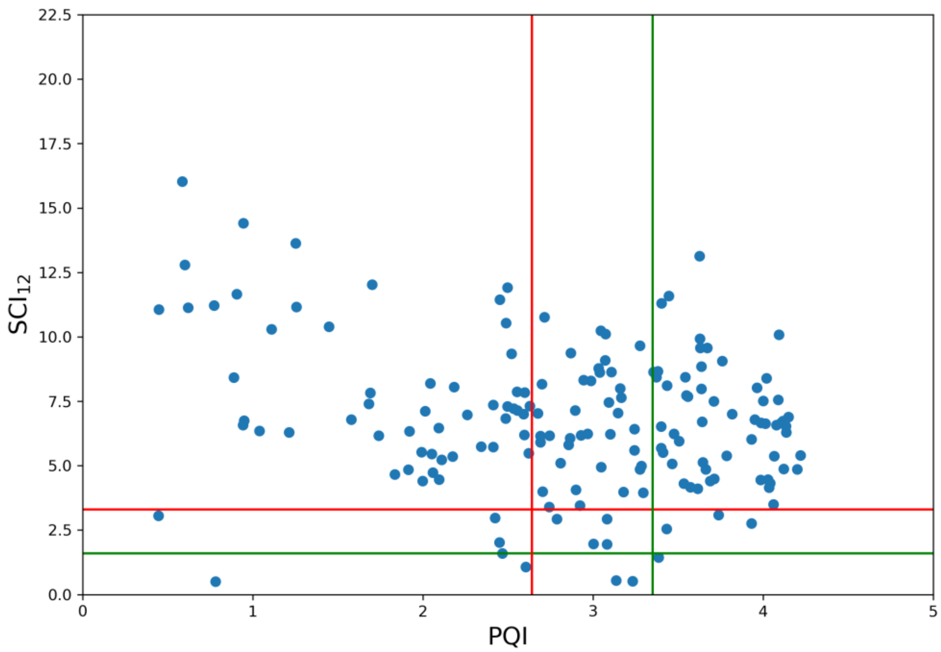
Correlation between SCI_{12} and PQI of SC-9 (Marion county)



Correlation between SCI_{12} and PQI of SC-9 (Marlboro county)



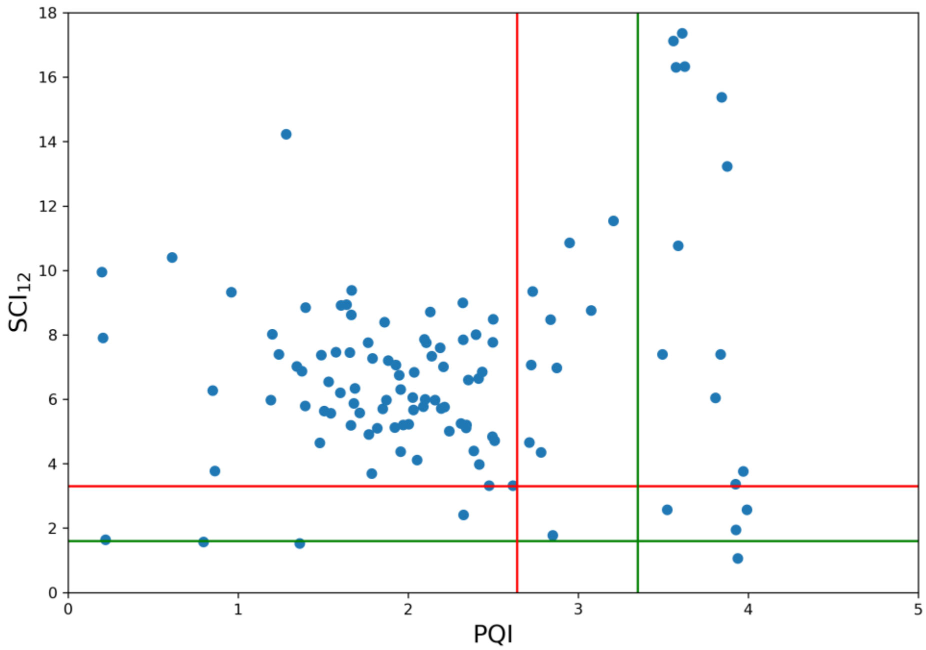
Correlation between SCI_{12} and PQI of SC-9 (Spartanburg county)



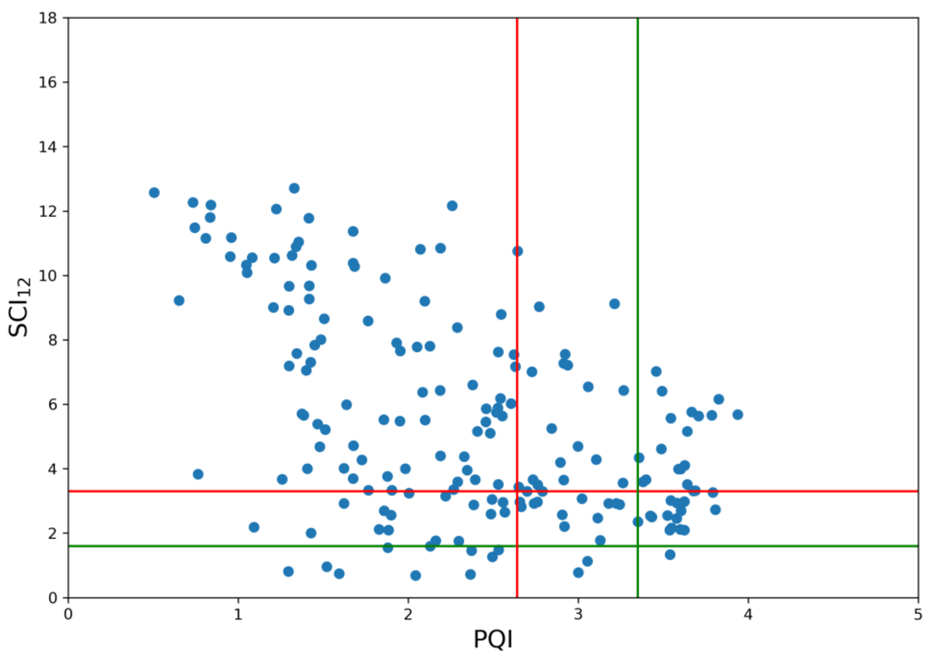
Correlation between SCI_{12} and PQI of SC-9 (Union county)

Correlation between SCI_{12} and PQI of US-321

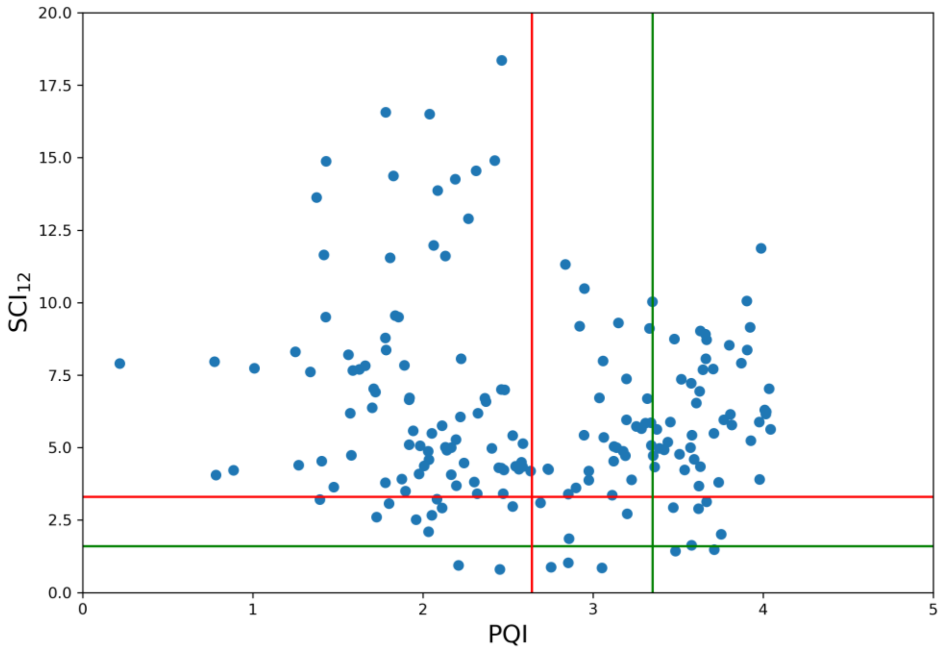
County	Pearson Correlation	Degree of Correlation	p-value
Allendale	0.17	Low	0.08
Bamberg	-0.51	Strong	~0
Chester	-0.14	Low	0.05
Fairfield	0.21	Low	0.01
Hampton	0.07	Low	0.30
Jasper	-0.32	Moderate	~0
Lexington	-0.08	Low	0.40
Orangeburg	-0.39	Moderate	~0
Richland	-0.50	Strong	~0
York	-0.48	Moderate	~0



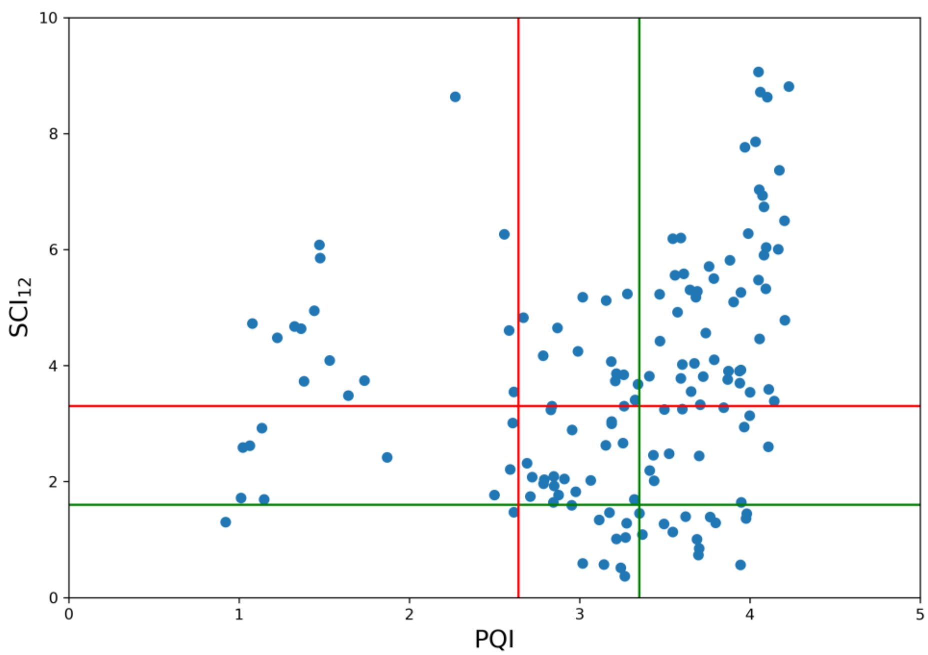
Correlation between SCI_{12} and PQI of US-321 (Allendale county)



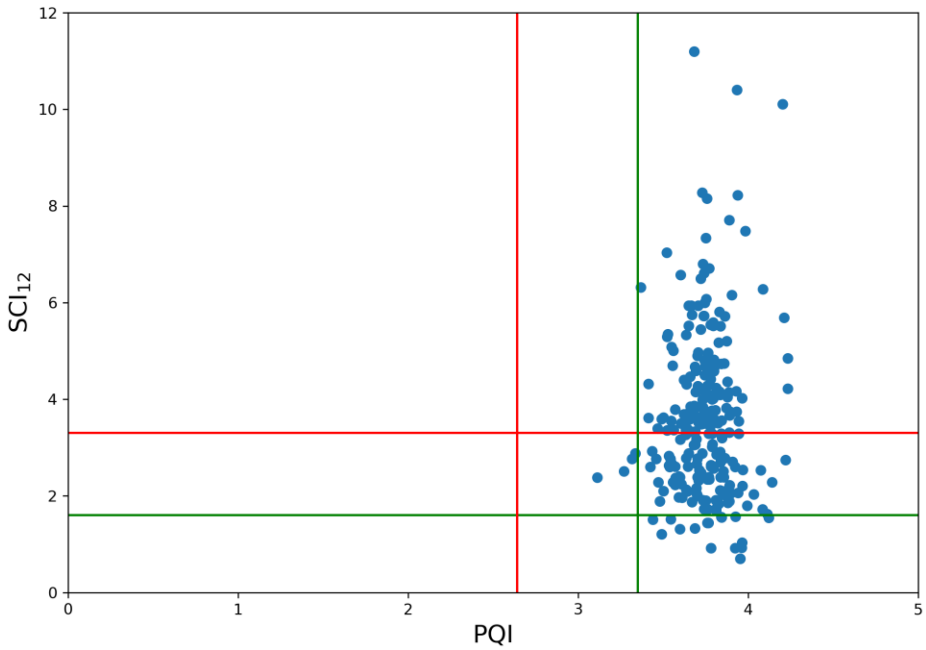
Correlation between SCI_{12} and PQI of US-321 (Bamberg county)



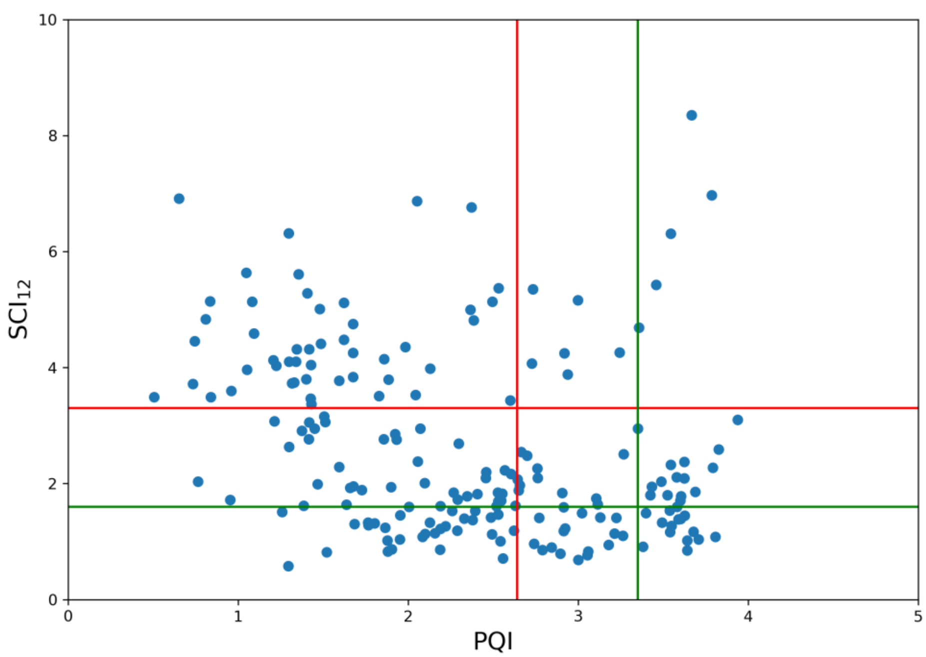
Correlation between SCI_{12} and PQI of US-321 (Chester county)



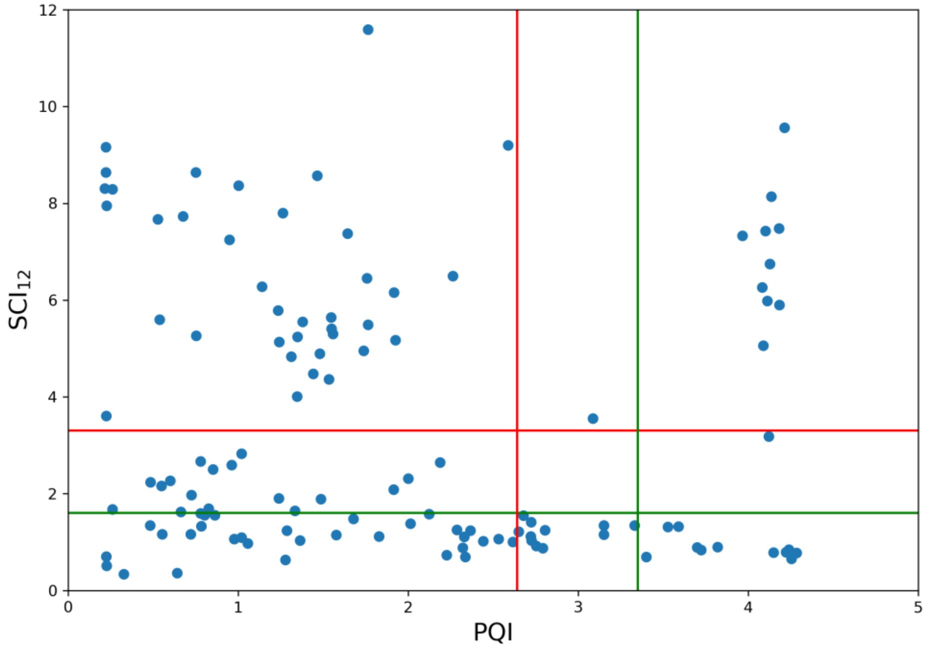
Correlation between SCI_{12} and PQI of US-321 (Chester county)



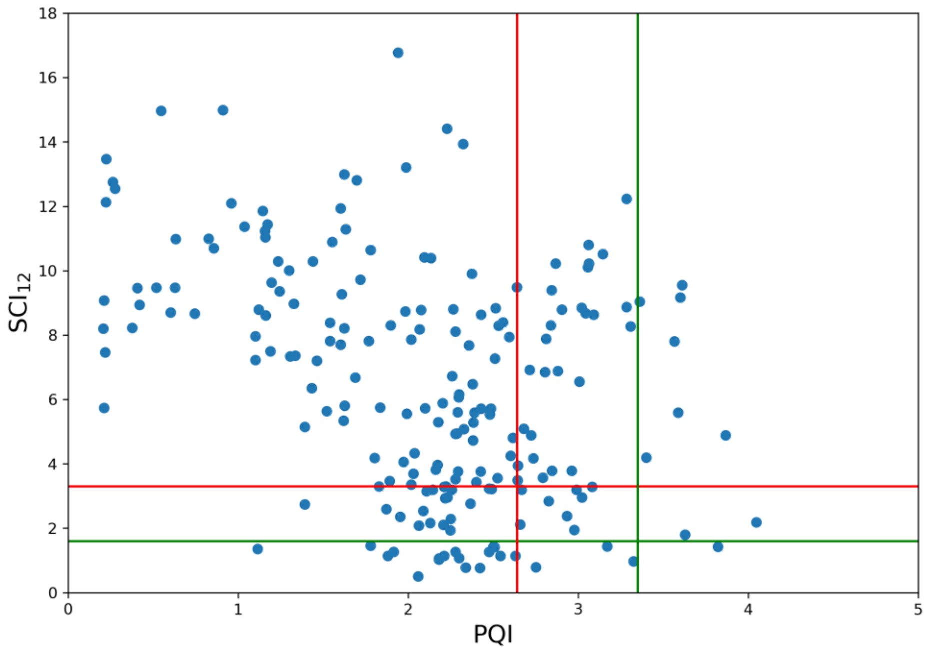
Correlation between SCI_{12} and PQI of US-321 (Hampton county)



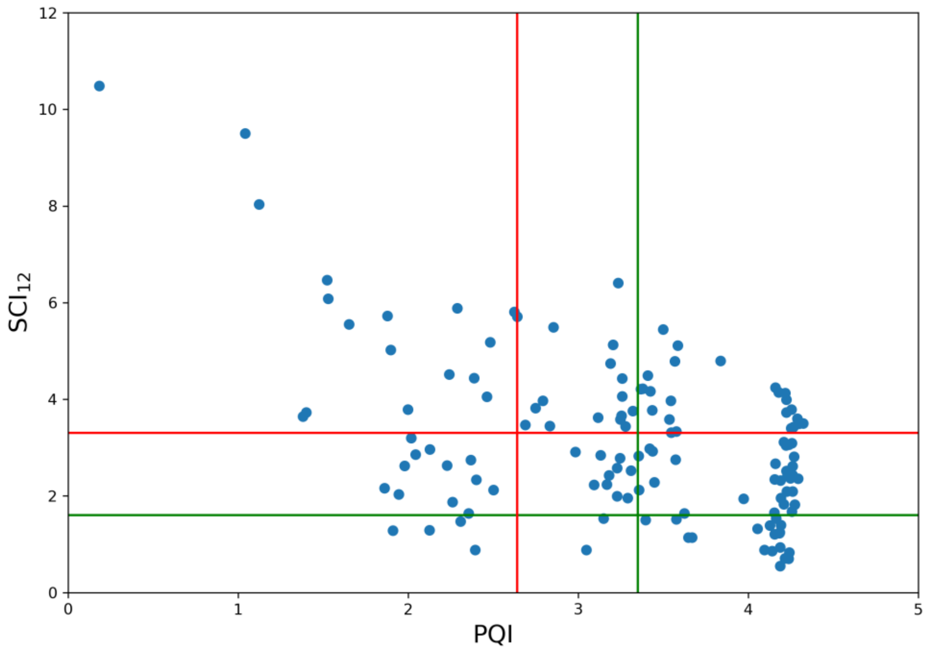
Correlation between SCI_{12} and PQI of US-321 (Jasper county)



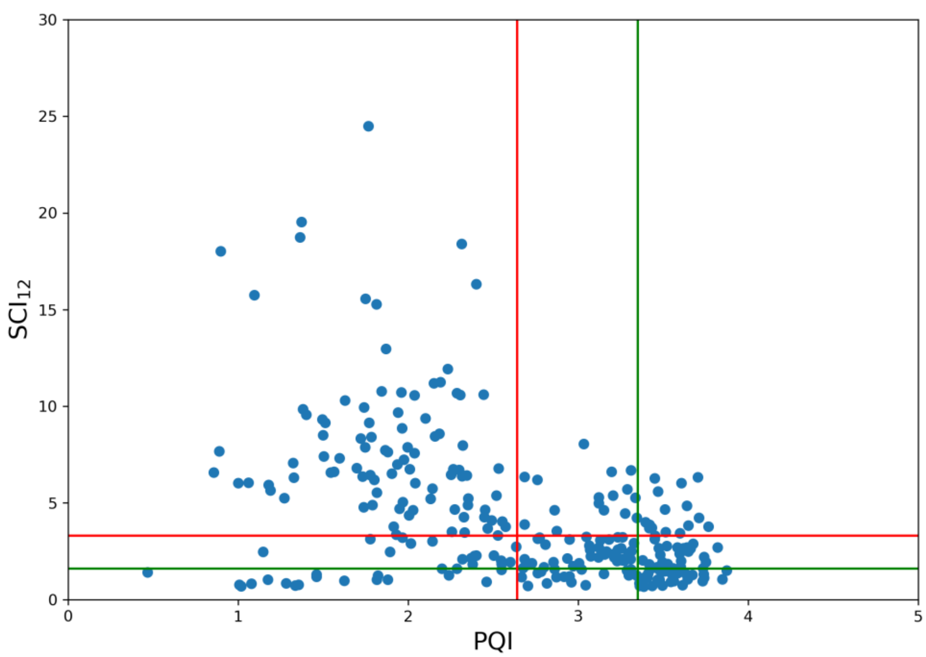
Correlation between SCI_{12} and PQI of US-321 (Lexington county)



Correlation between SCI_{12} and PQI of US-321 (Orangeburg county)



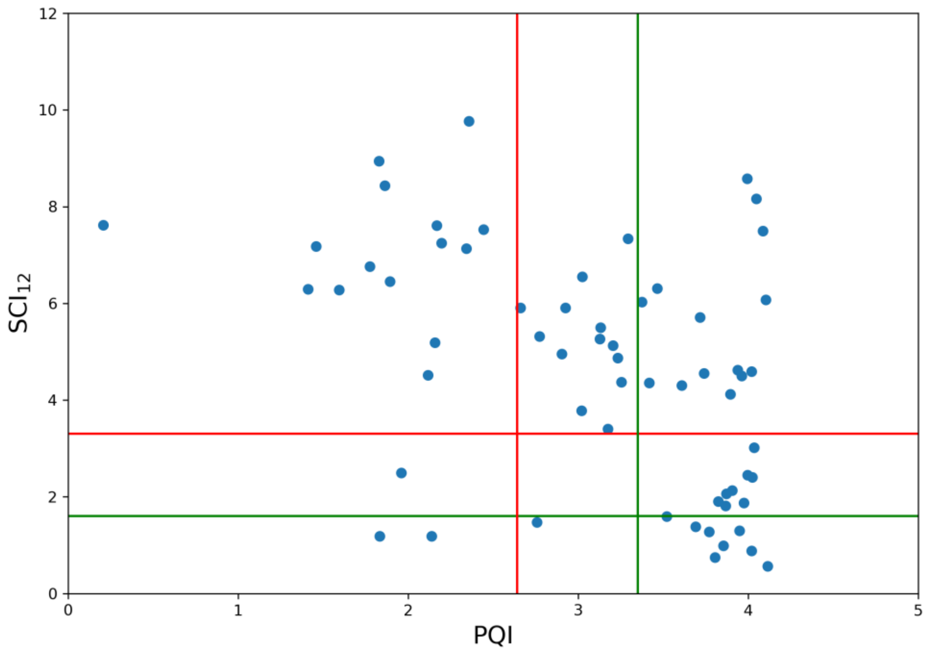
Correlation between SCI_{12} and PQI of US-321 (Richland county)



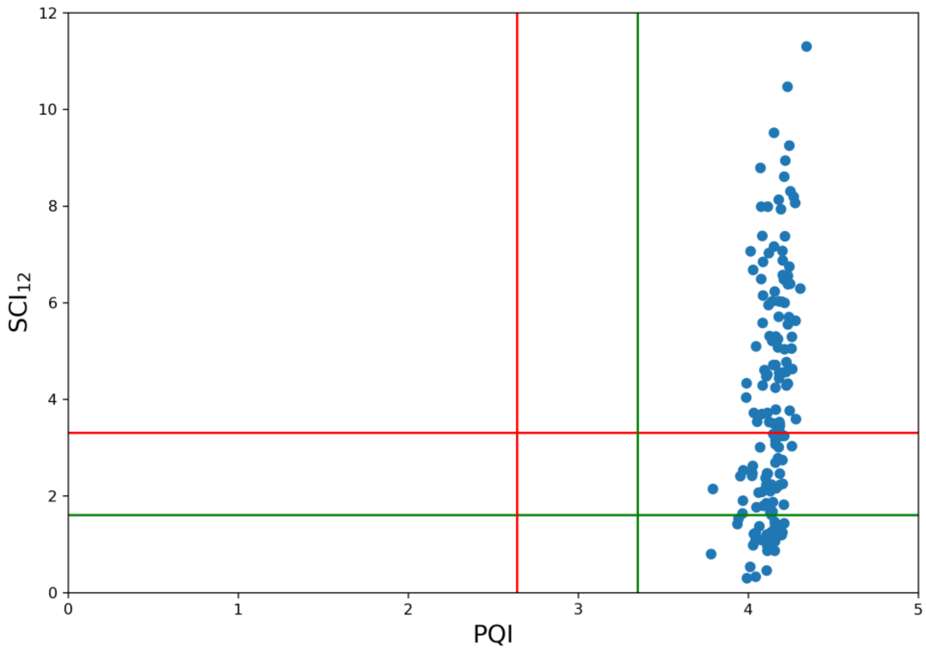
Correlation between SCI_{12} and PQI of US-321 (York county)

Correlation between SCI_{12} and PQI of US-378

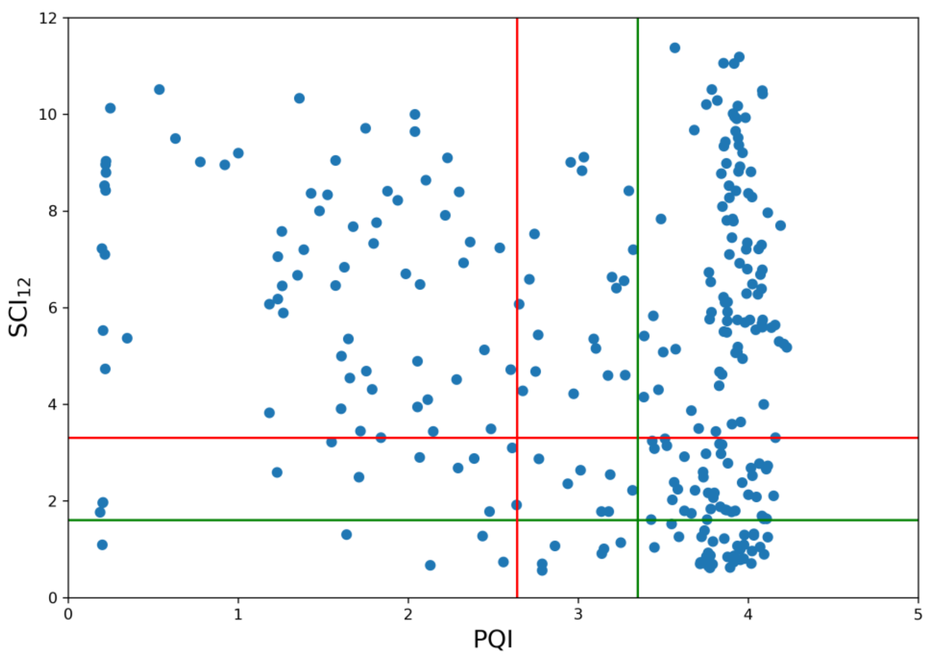
Counties	Pearson Correlation	Degree of Correlation	p-value
Clarendon	-0.32	Moderate	0.01
Edgefield	0.42	Moderate	~0
Florence	-0.19	Low	~0
Horry	-0.39	Moderate	~0
Lexington	-0.43	Moderate	~0
Marion	-0.7	Strong	~0
McCormick	-0.1	Low	0.47
Saluda	-0.59	Strong	~0
Sumter	-0.49	Moderate	~0
Williamsburg	0.22	Low	0.38



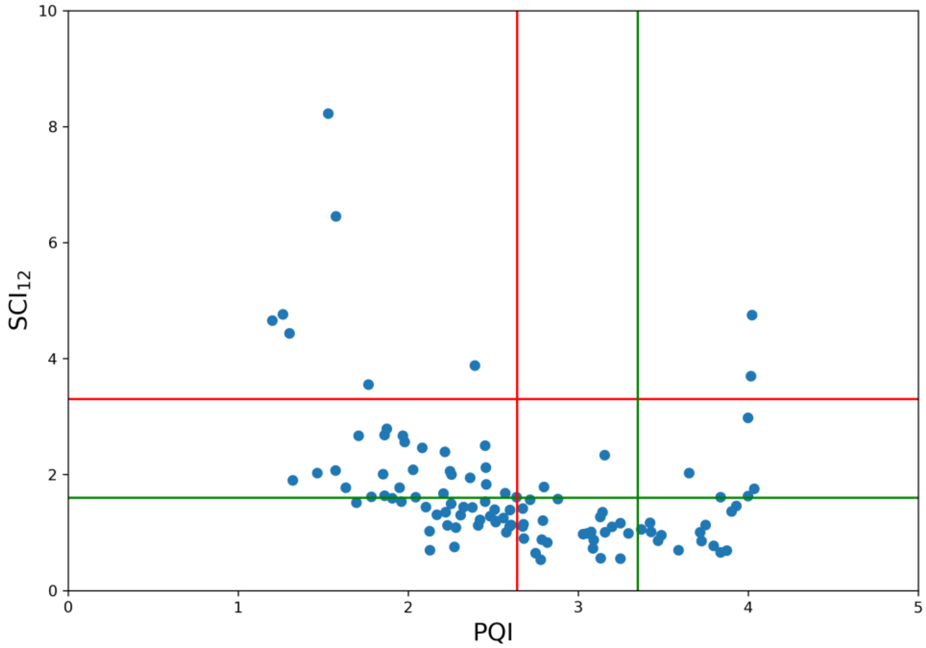
Correlation between SCI_{12} and PQI of US-378 (Clarendon county)



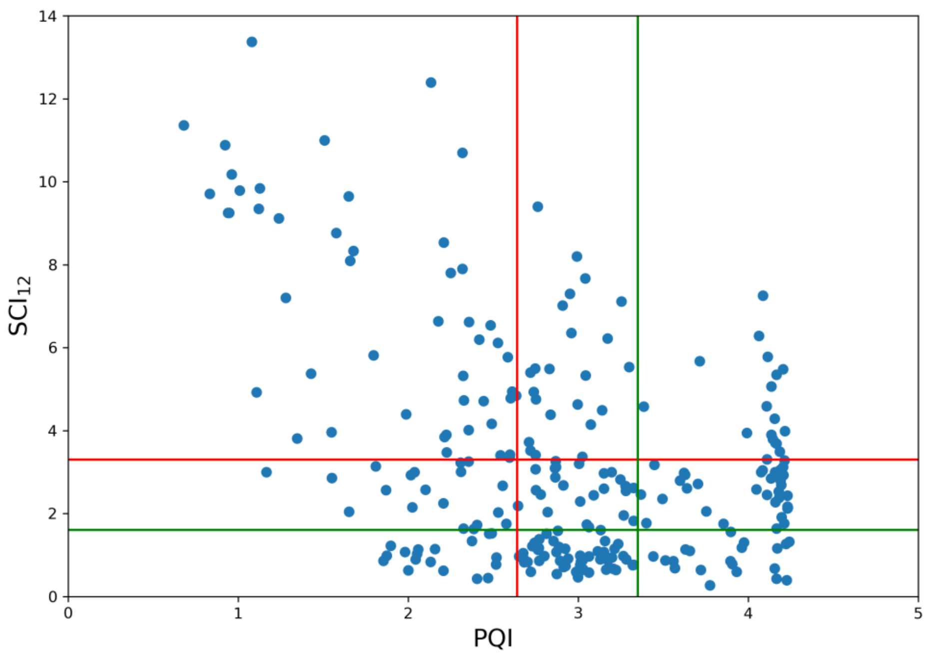
Correlation between SCI_{12} and PQI of US-378 (Edgefield county)



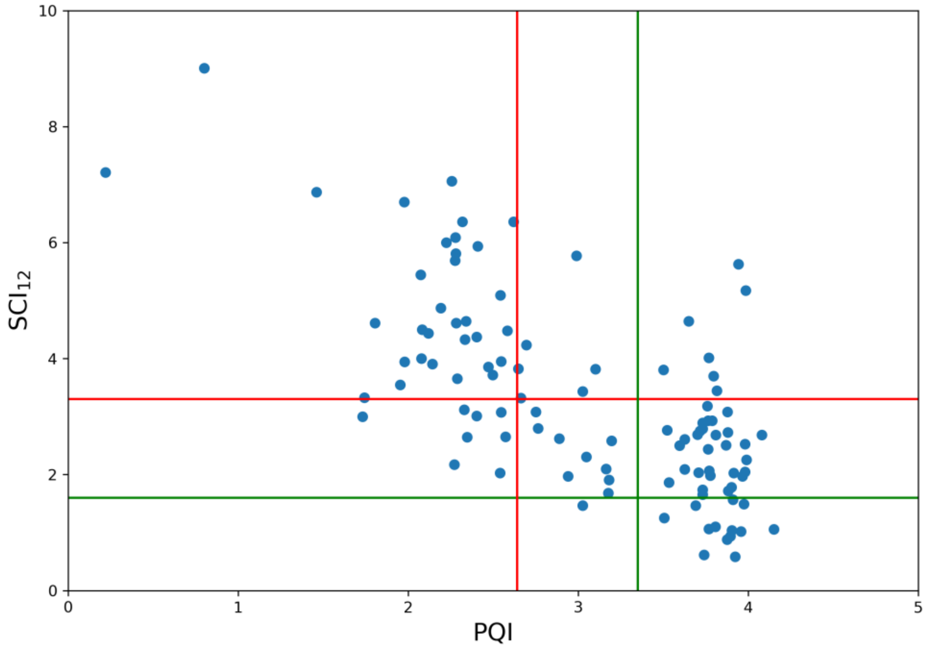
Correlation between SCI_{12} and PQI of US-378 (Florence county)



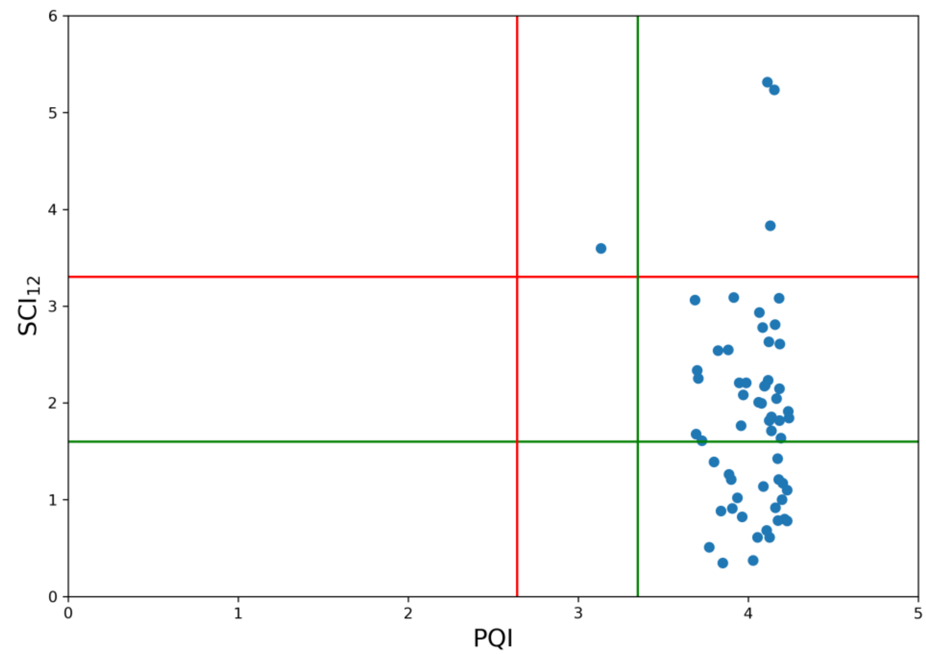
Correlation between SCI_{12} and PQI of US-378 (Horry county)



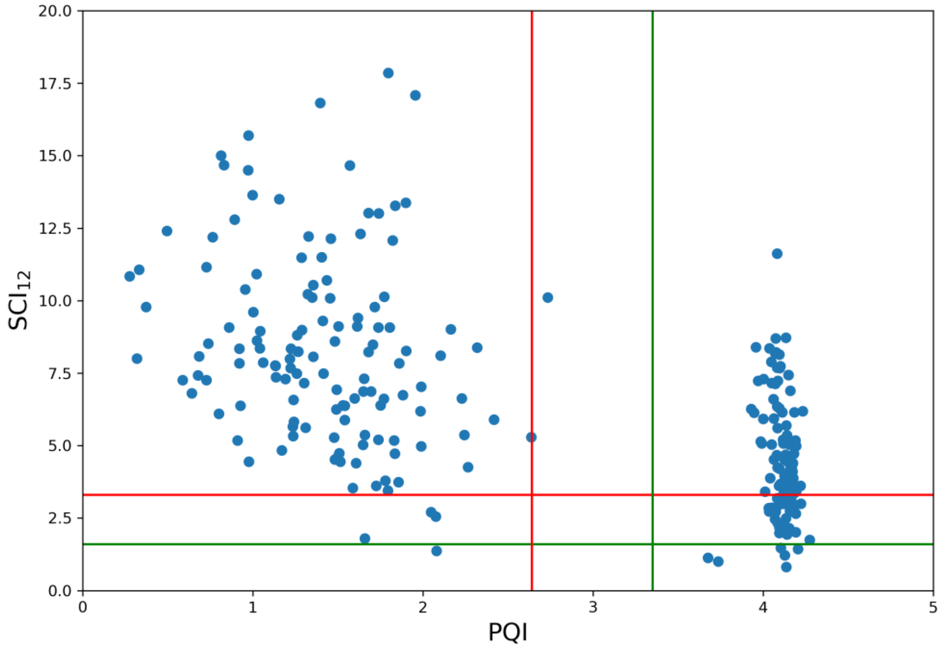
Correlation between SCI_{12} and PQI of US-378 (Lexington county)



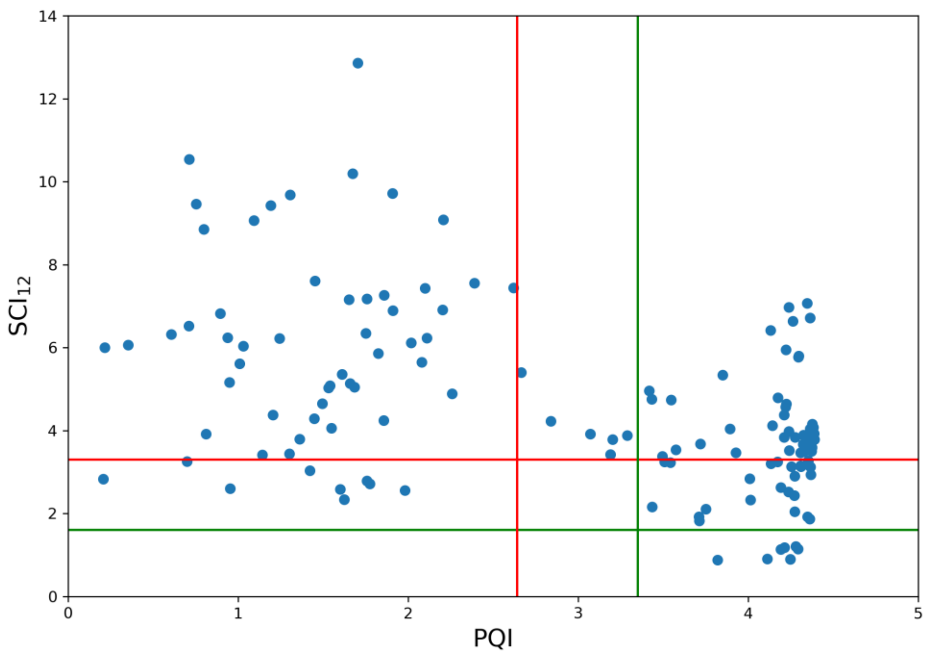
Correlation between SCI_{12} and PQI of US-378 (Marion county)



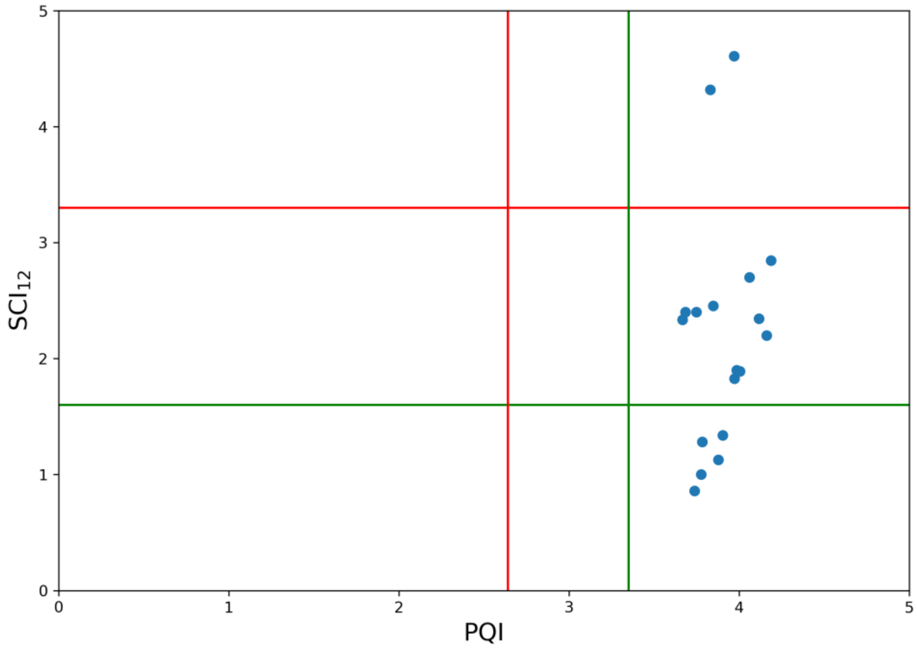
Correlation between SCI_{12} and PQI of US-378 (McCormick county)



Correlation between SCI_{12} and PQI of US-378 (Saluda county)



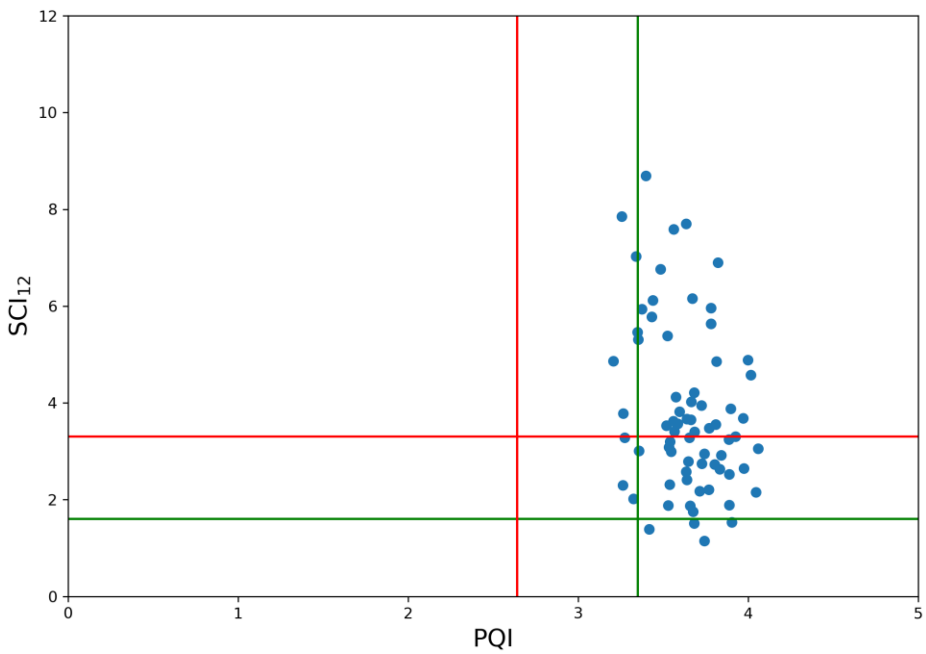
Correlation between SCI_{12} and PQI of US-378 (Sumter county)



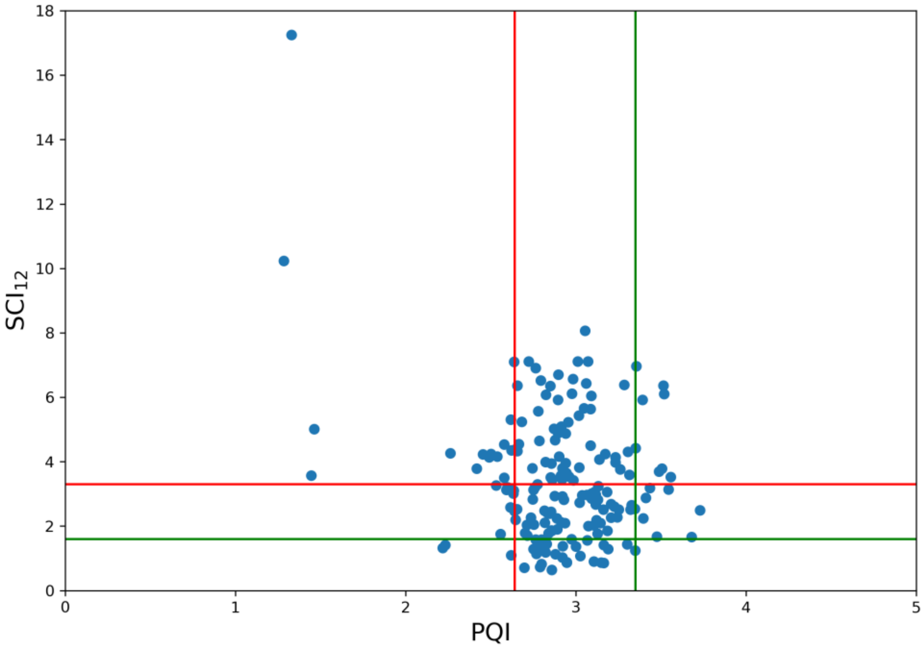
Correlation between SCI_{12} and PQI of US-378 (Williamsburg county)

Correlation between SCI_{12} and PQI of US-178

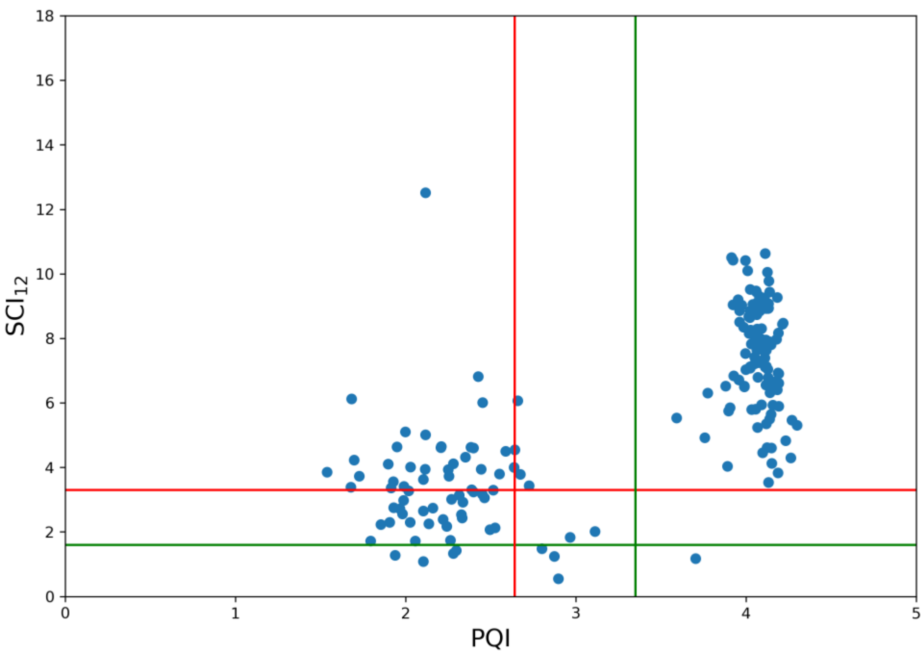
County	Pearson Correlation	Degree of Correlation	p-value
Abbeville	-0.29	Low	0.02
Dorchester	-0.27	Low	~0
Greenwood	0.721	Strong	~0
Lexington	-0.001	Low	0.99
Orangeburg	0.24	Low	~0
Saluda	0.24	Low	~0



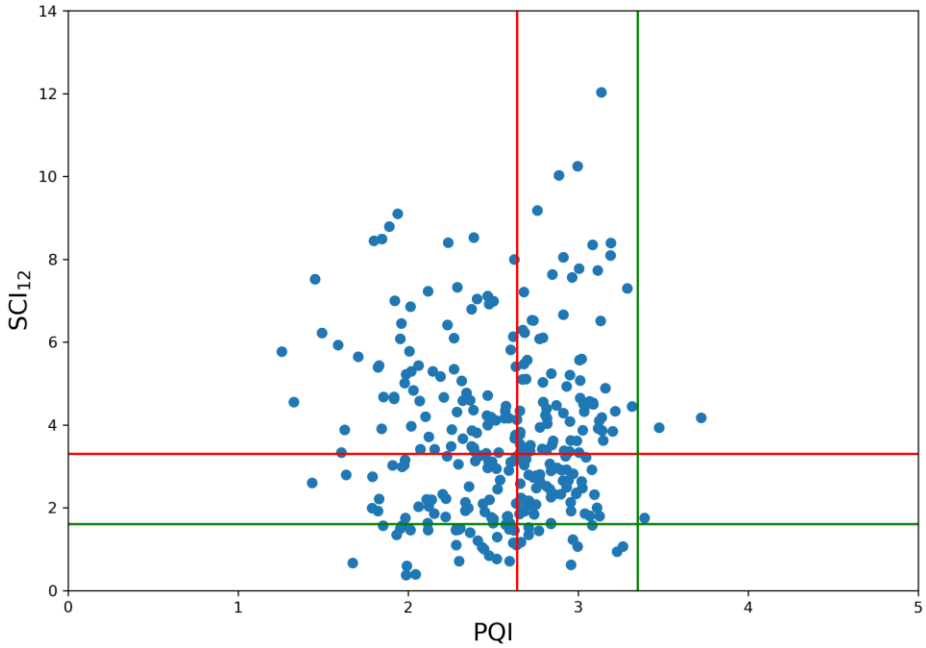
Correlation between SCI_{12} and PQI of US-178 (Abbeville county)



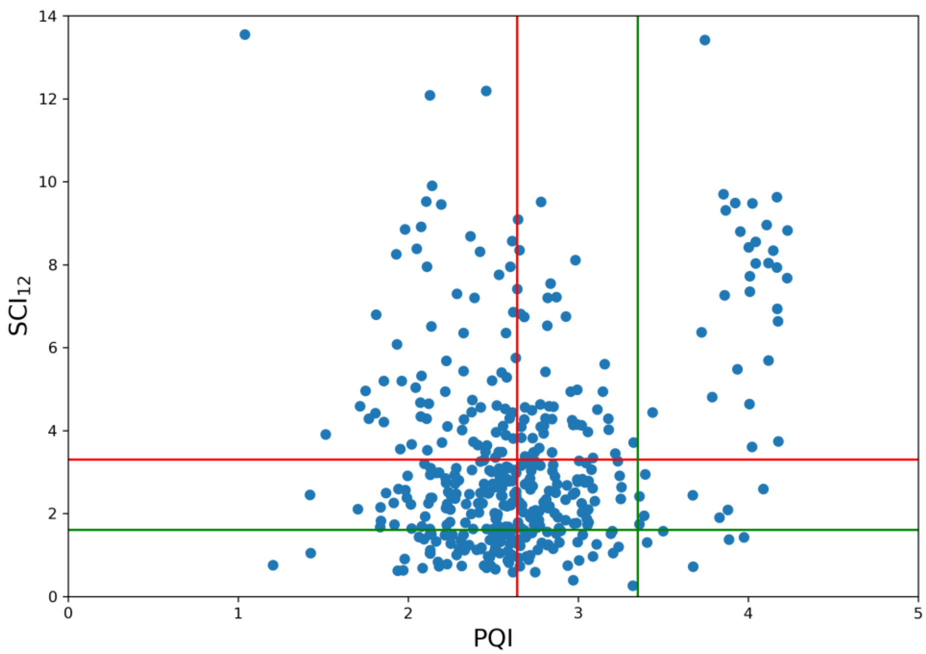
Correlation between SCI_{12} and PQI of US-178 (Dorchester county)



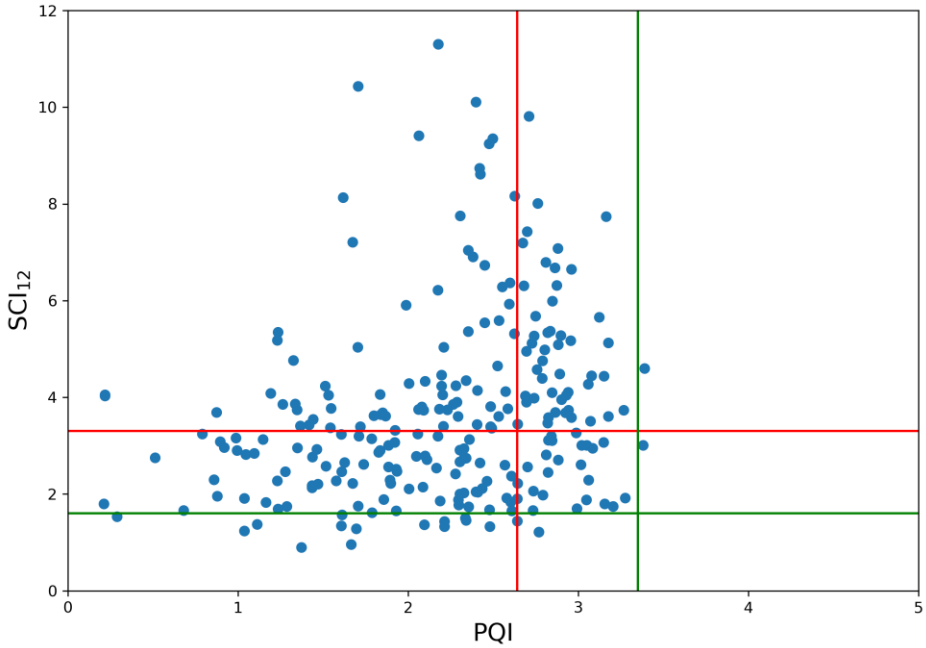
Correlation between SCI_{12} and PQI of US-178 (Greenwood county)



Correlation between SCI_{12} and PQI of US-178 (Lexington county)



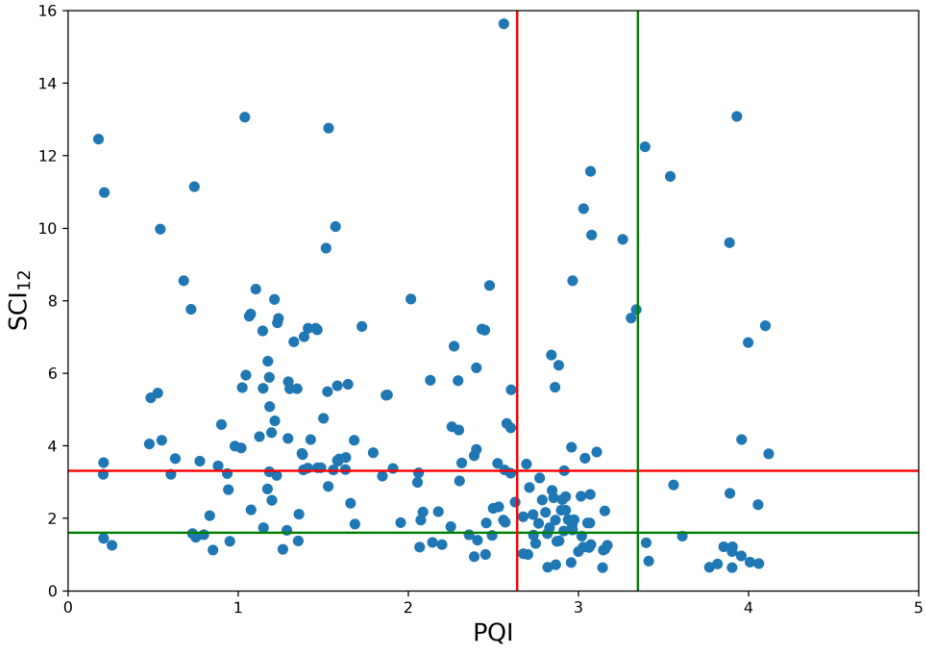
Correlation between SCI_{12} and PQI of US-178 (Orangeburg county)



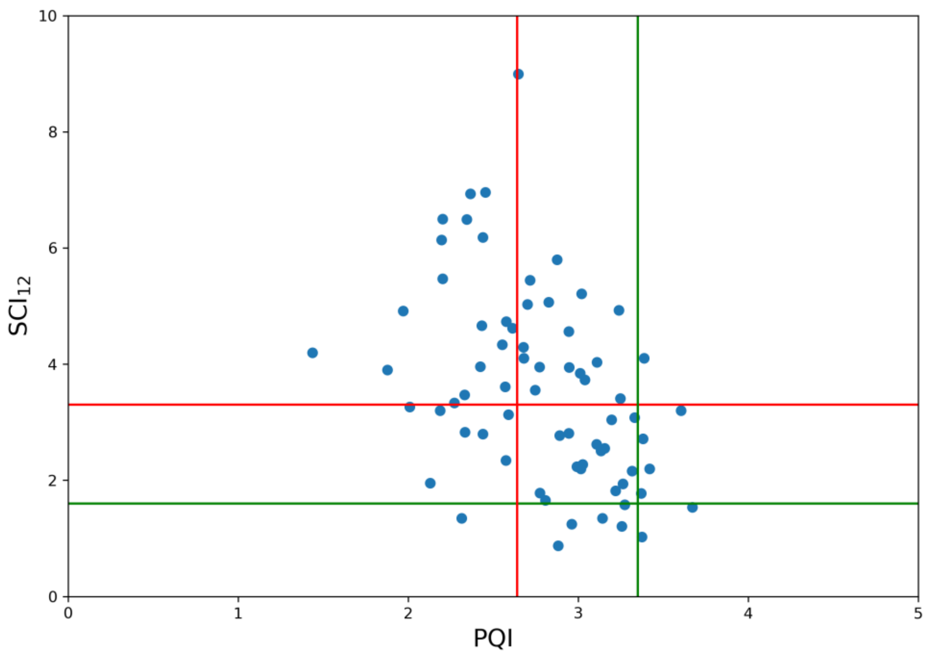
Correlation between SCI_{12} and PQI of US-178 (Saluda county)

Correlation between SCI_{12} and PQI of US-29

County	Pearson Correlation	Degree of Correlation	p-value
Cherokee	-0.2	Low	~0
Spartanburg	-0.43	Moderate	~0



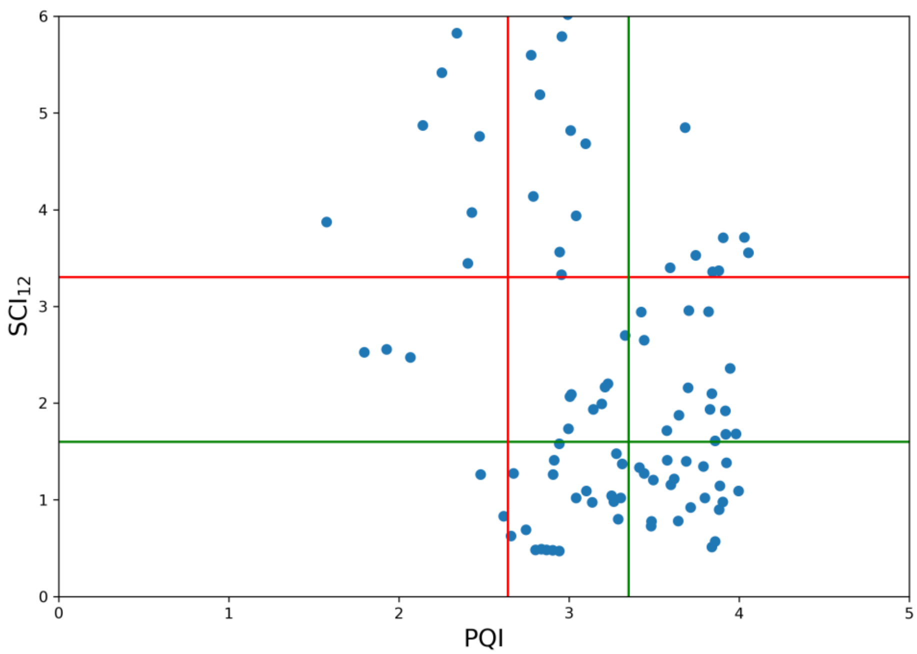
Correlation between SCI_{12} and PQI of US-29 (Cherokee county)



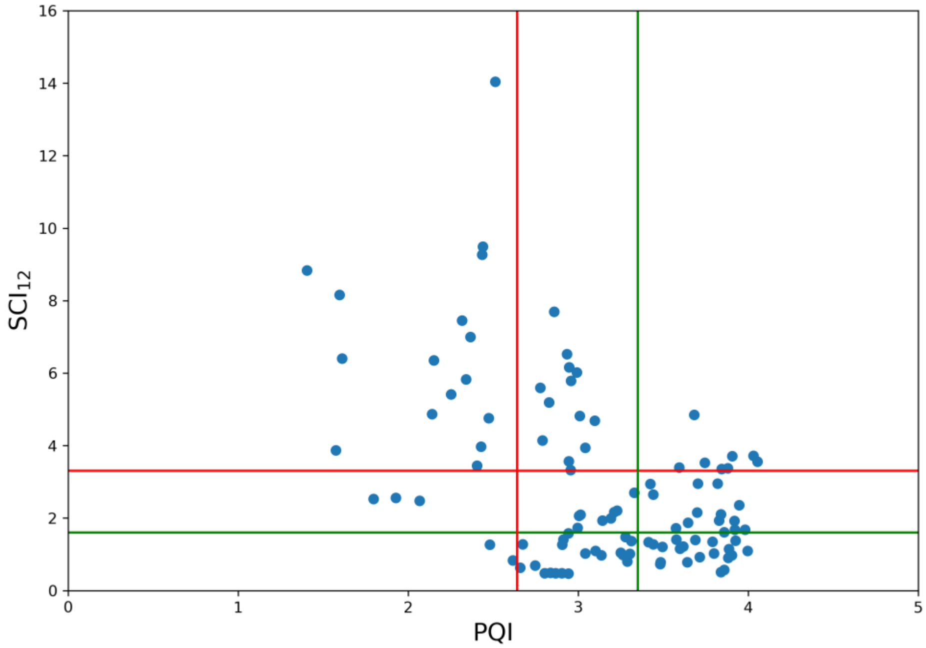
Correlation between SCI_{12} and PQI of US-29 (Spartanburg county)

Correlation between SCI_{12} and PQI of US-78

Counties	Pearson Correlation	Degree of Correlation	p-value
Charleston	-0.5	Strong	~0
Dorchester	-0.49	Moderate	~0



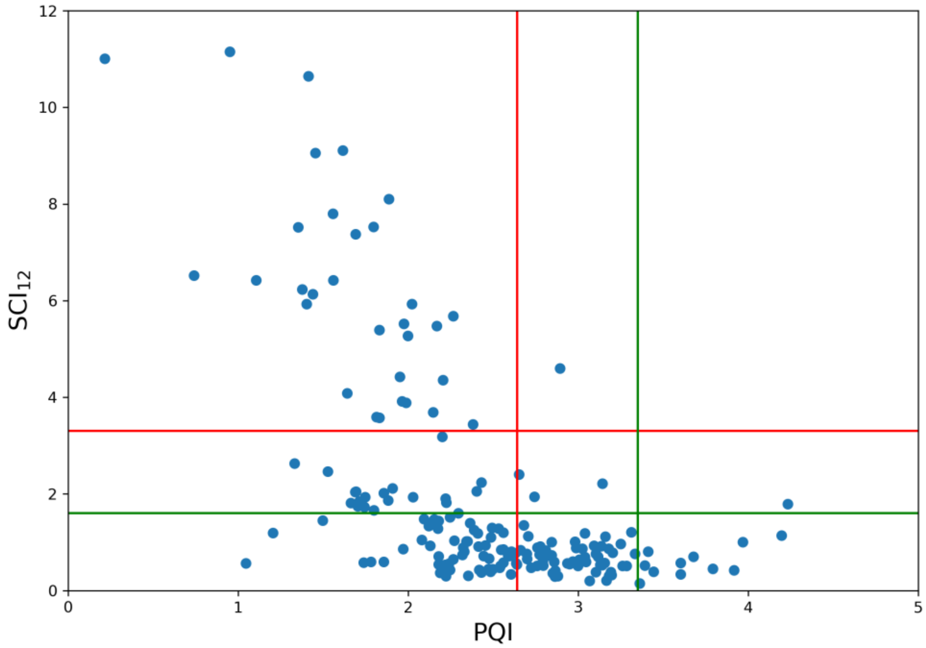
Correlation between SCI_{12} and PQI of US-78 (Charleston county)



Correlation between SCI_{12} and PQI of US-78 (Dorchester county)

Correlation between SCI_{12} and PQI of US-17

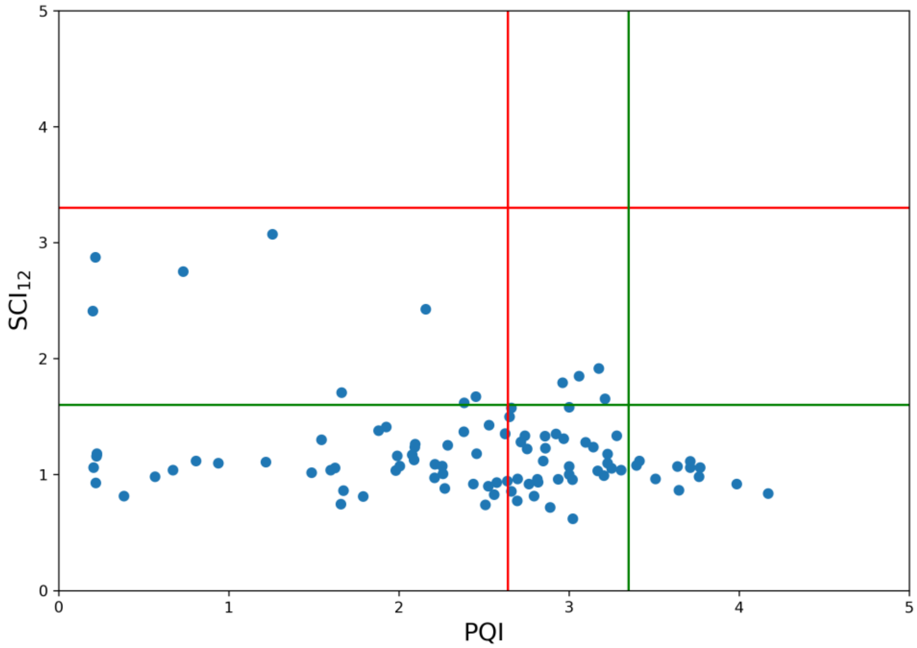
Counties	Pearson Correlation	Degree of Correlation	p-value
Horry	-0.63	Strong	~0



Correlation between SCI_{12} and PQI of US-17 (Horry county)

Correlation between SCI_{12} and PQI of US-501

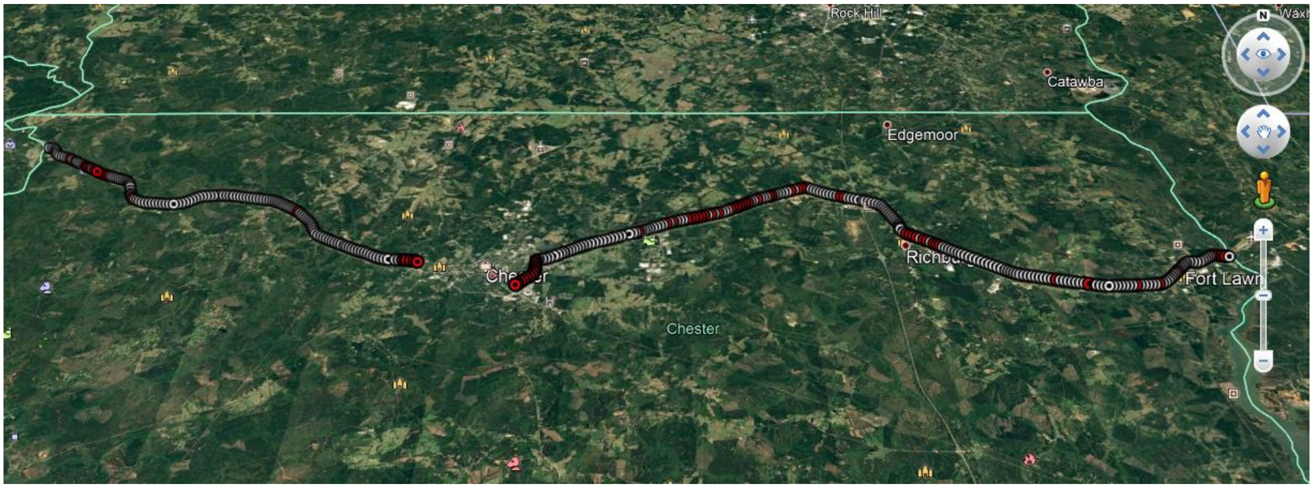
Counties	Pearson Correlation	Degree of Correlation	p-value
Horry	-0.26	Low	0.01



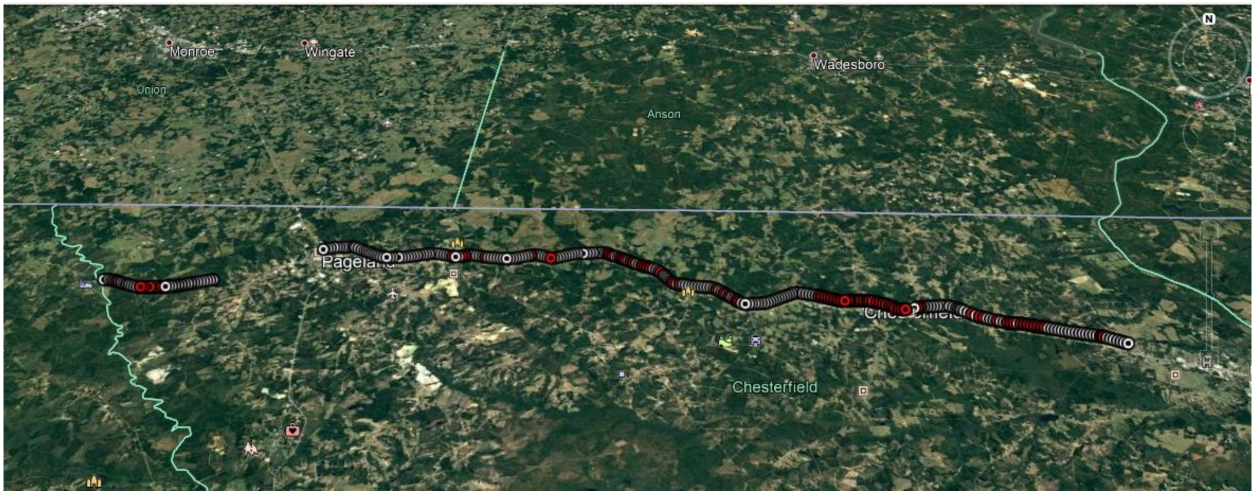
Correlation between SCI_{12} and PQI of US-501 (Horry county)

APPENDIX G

Areas of Interest

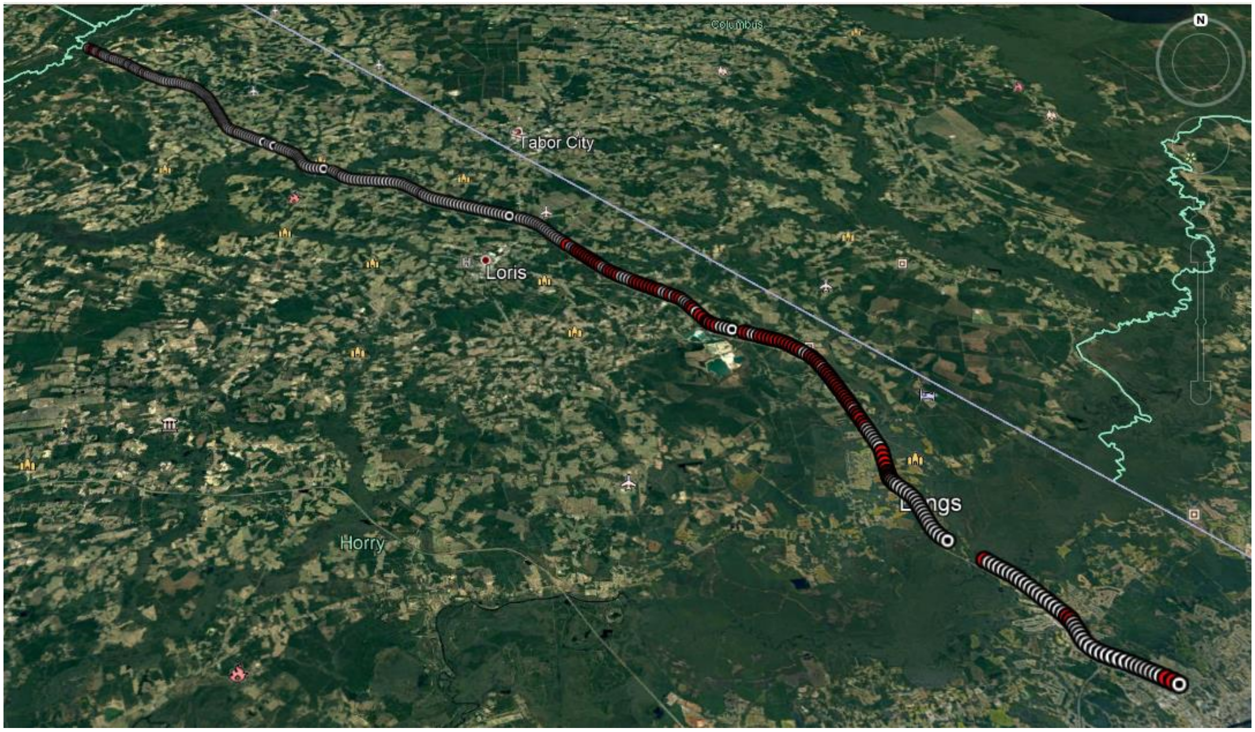


Location of areas of interest on SC-9 (Chester county)

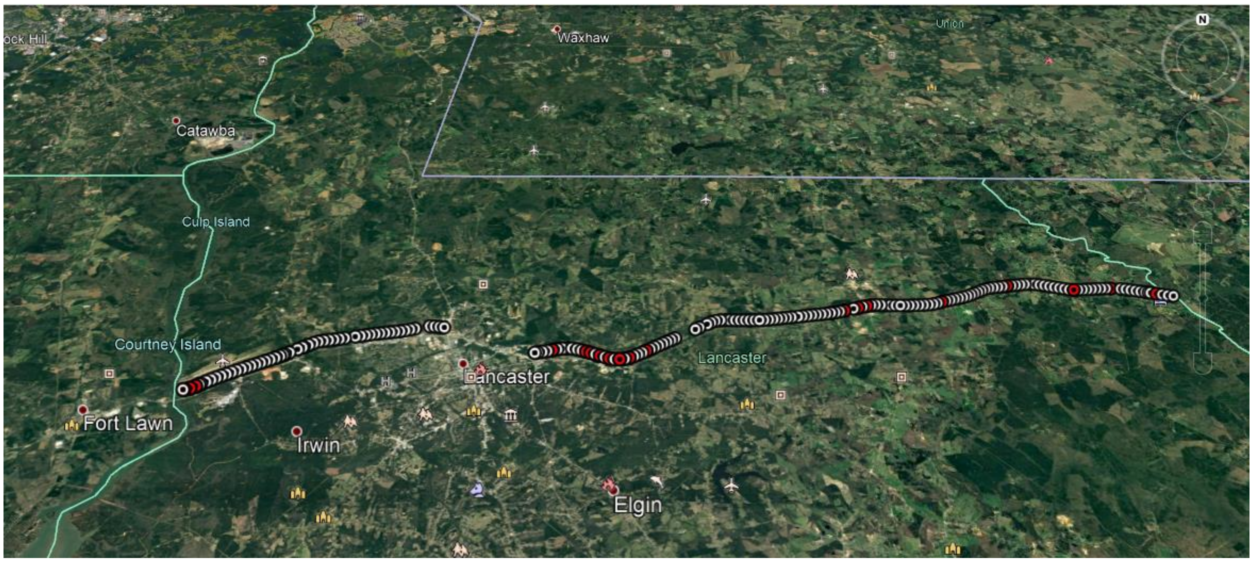


Location of areas of interest on SC-9 (Chesterfield county)

Location of areas of interest on SC-9 (Dillon county)

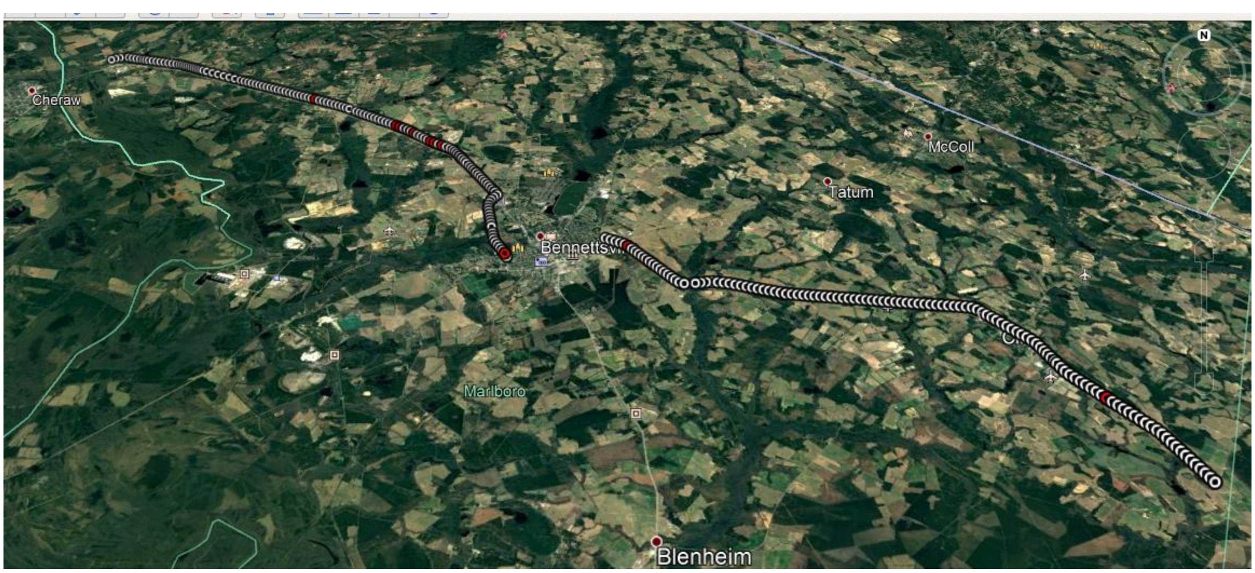


Location of areas of interest on SC-9 (Horry county)

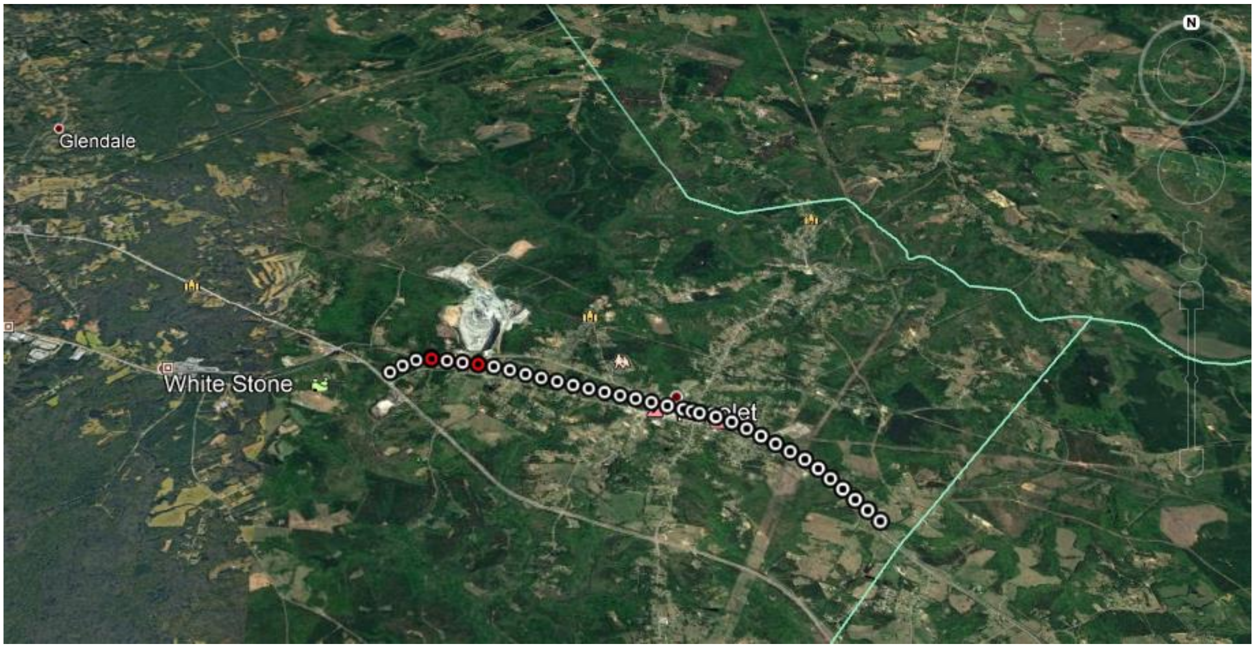


Location of areas of interest on SC-9 (Lancaster county)

Location of areas of interest on SC-9 (Marion county)



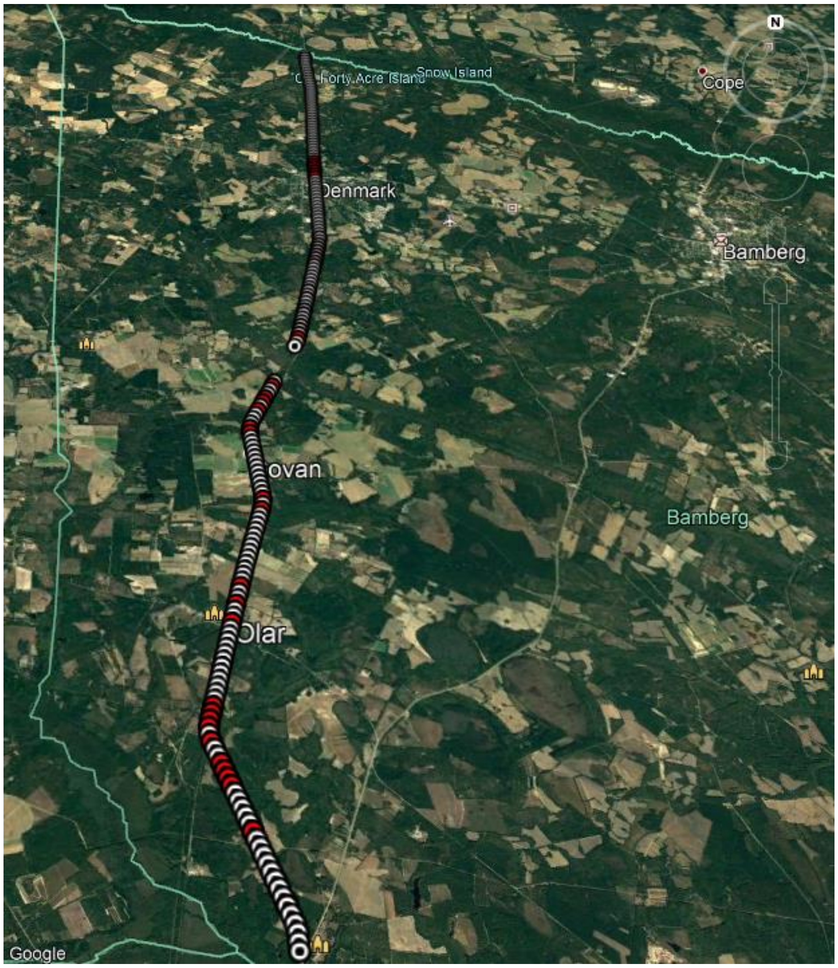
Location of areas of interest on SC-9 (Marlboro county)



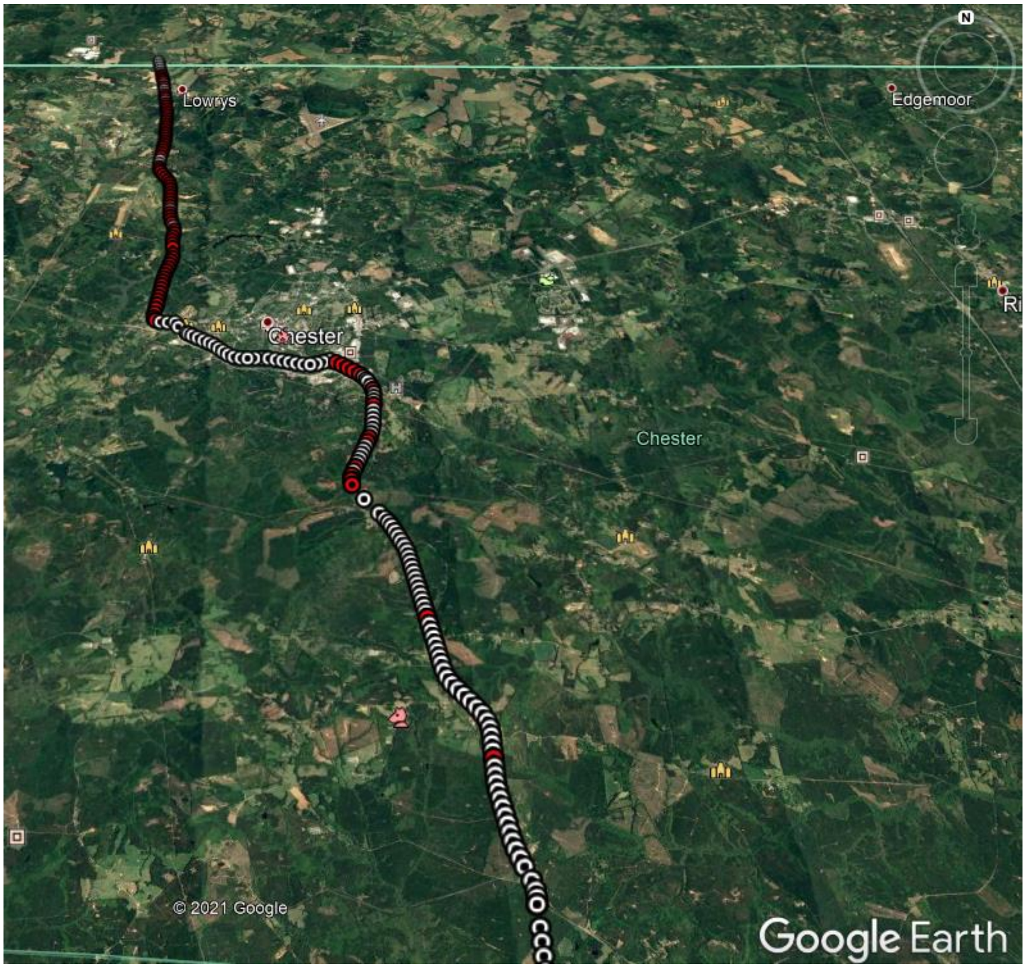
Location of areas of interest on SC-9 (Spartanburg county)

Location of areas of interest on SC-9 (Union county)

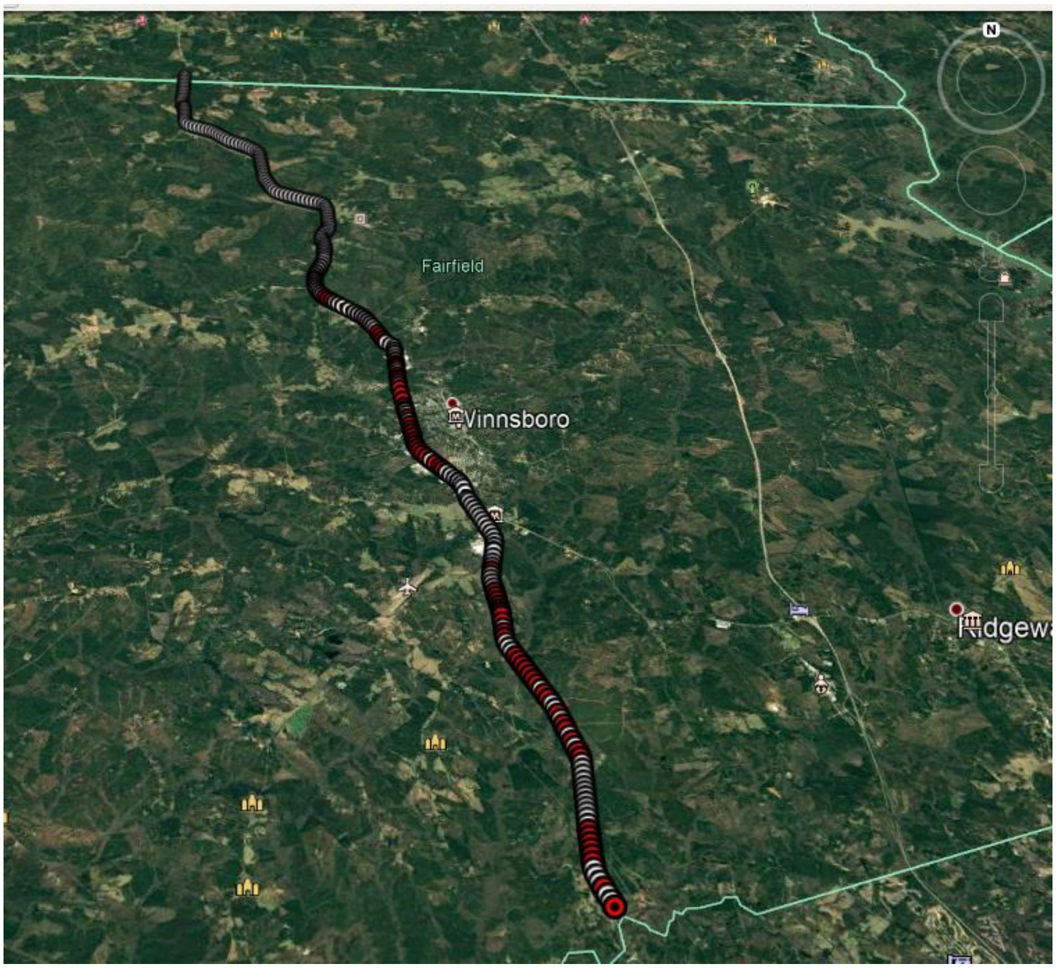
Location of areas of interest on US-321 (Allendale county)



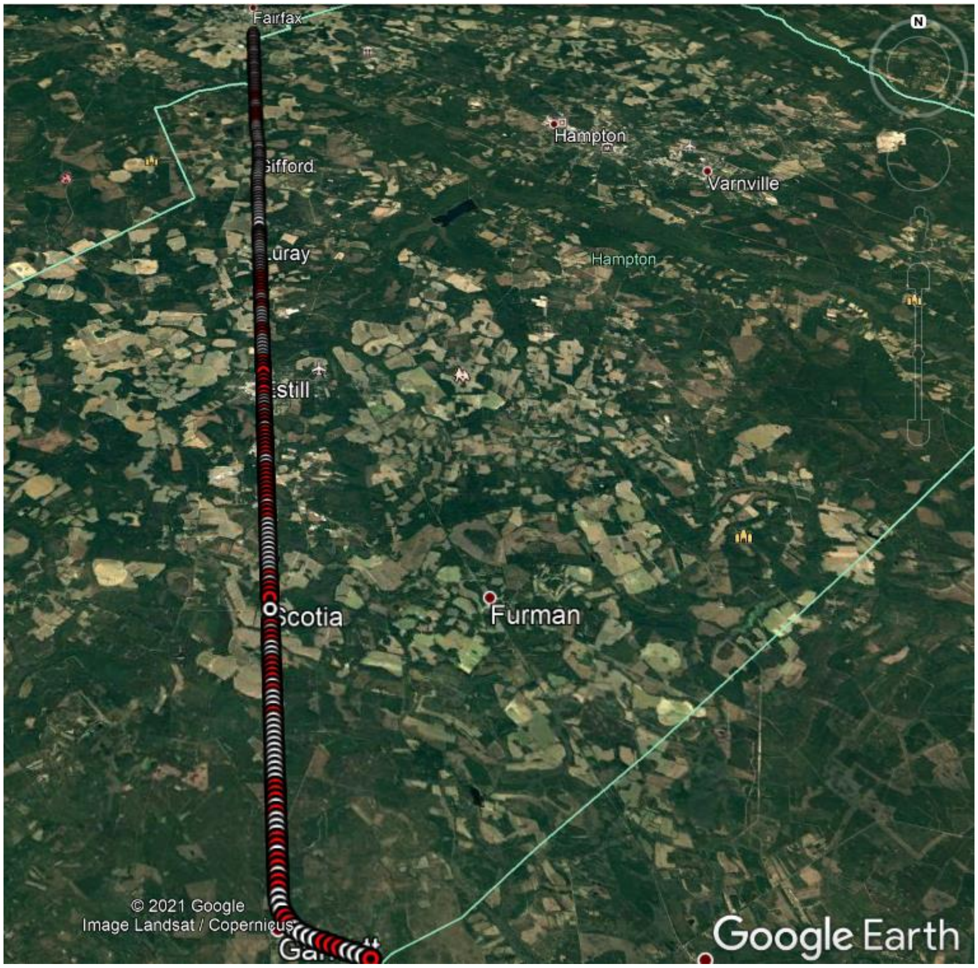
Location of areas of interest on US-321 (Bamberg county)



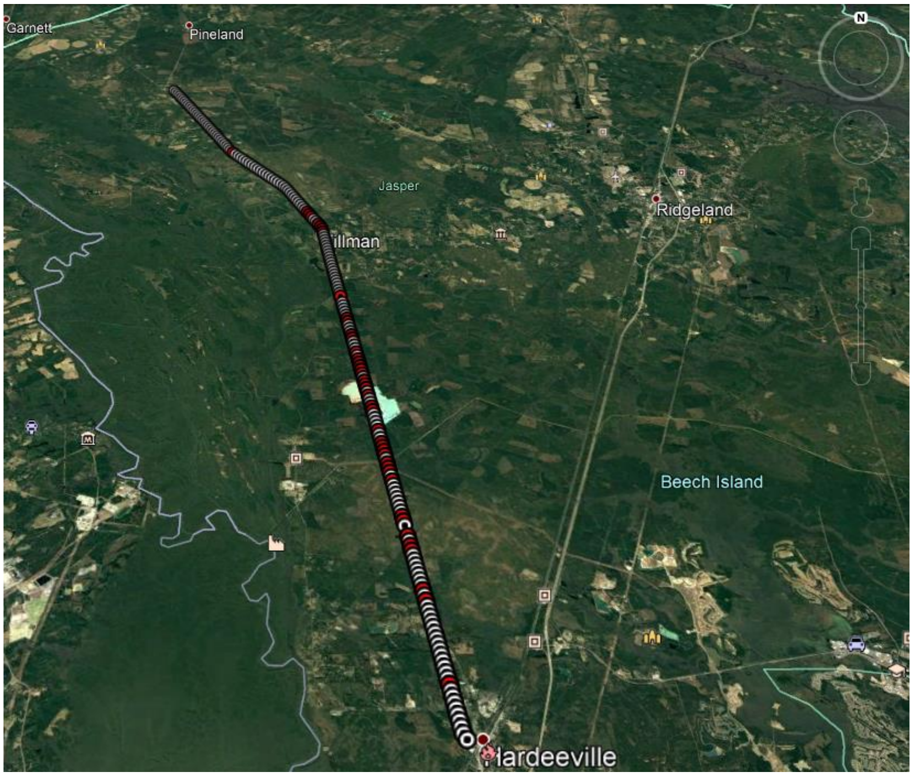
Location of areas of interest on US-321 (Chester county)



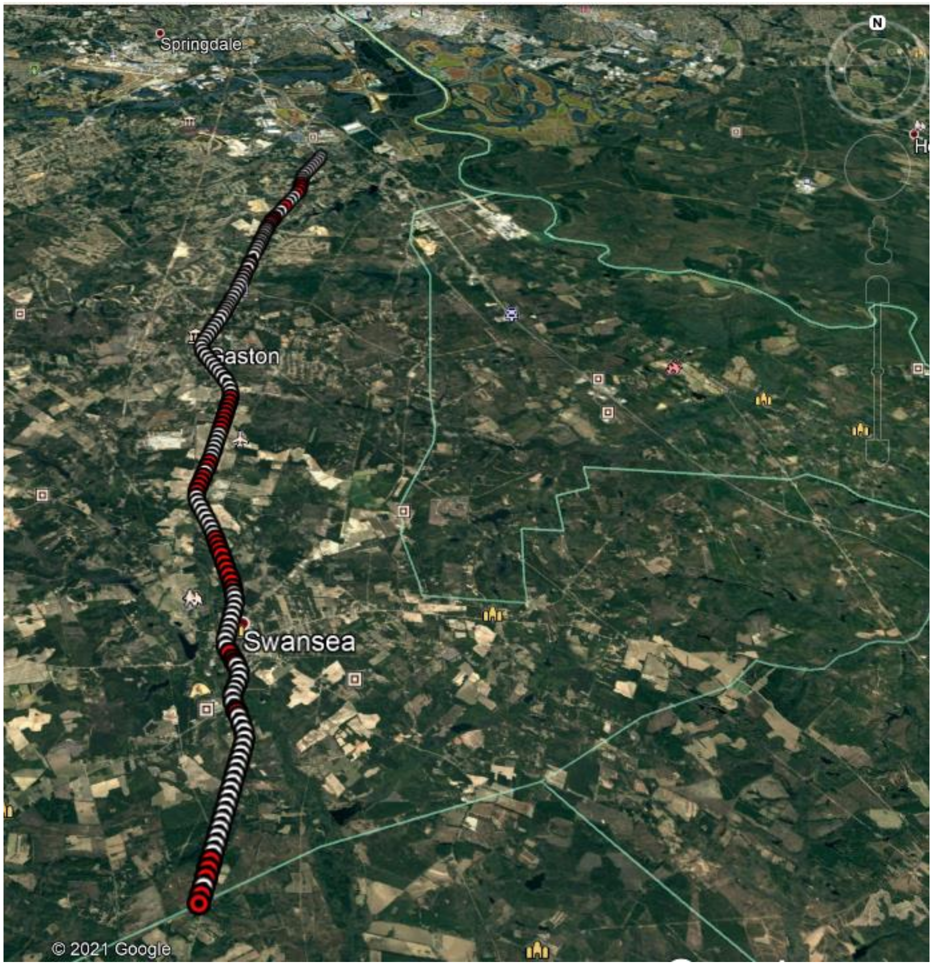
Location of areas of interest on US-321 (Fairfield county)



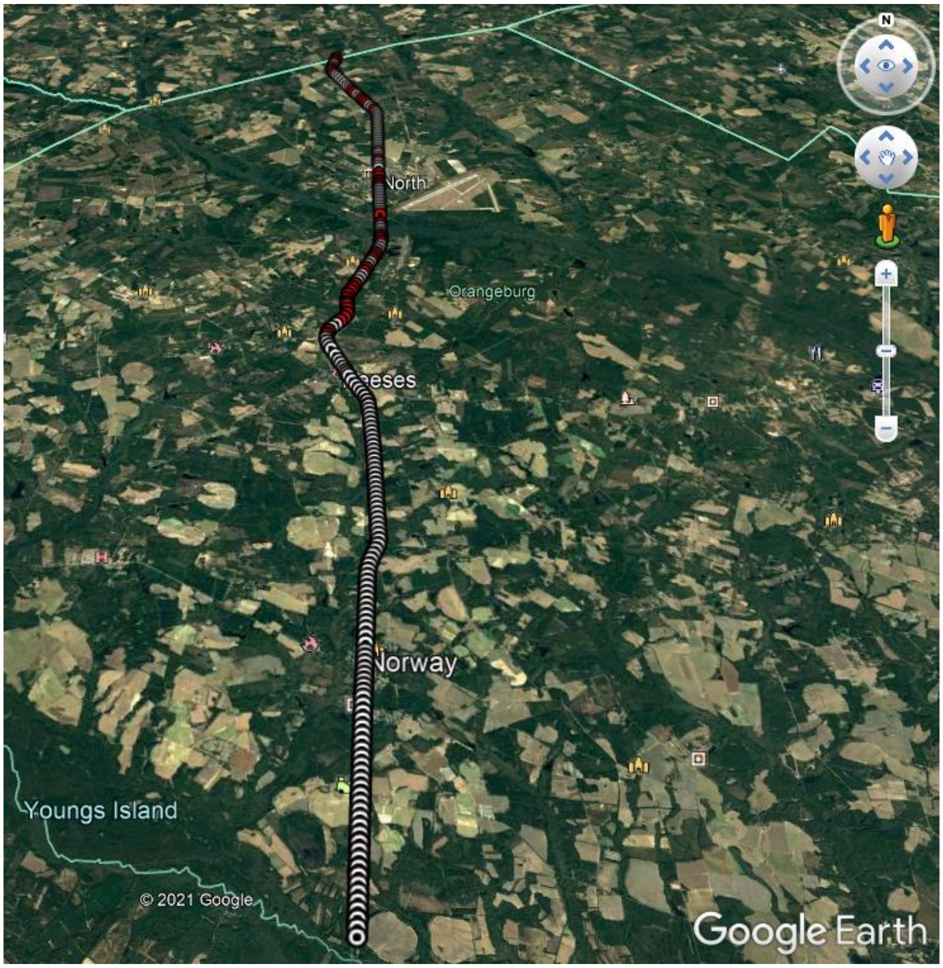
Location of areas of interest on US-321 (Hampton county)



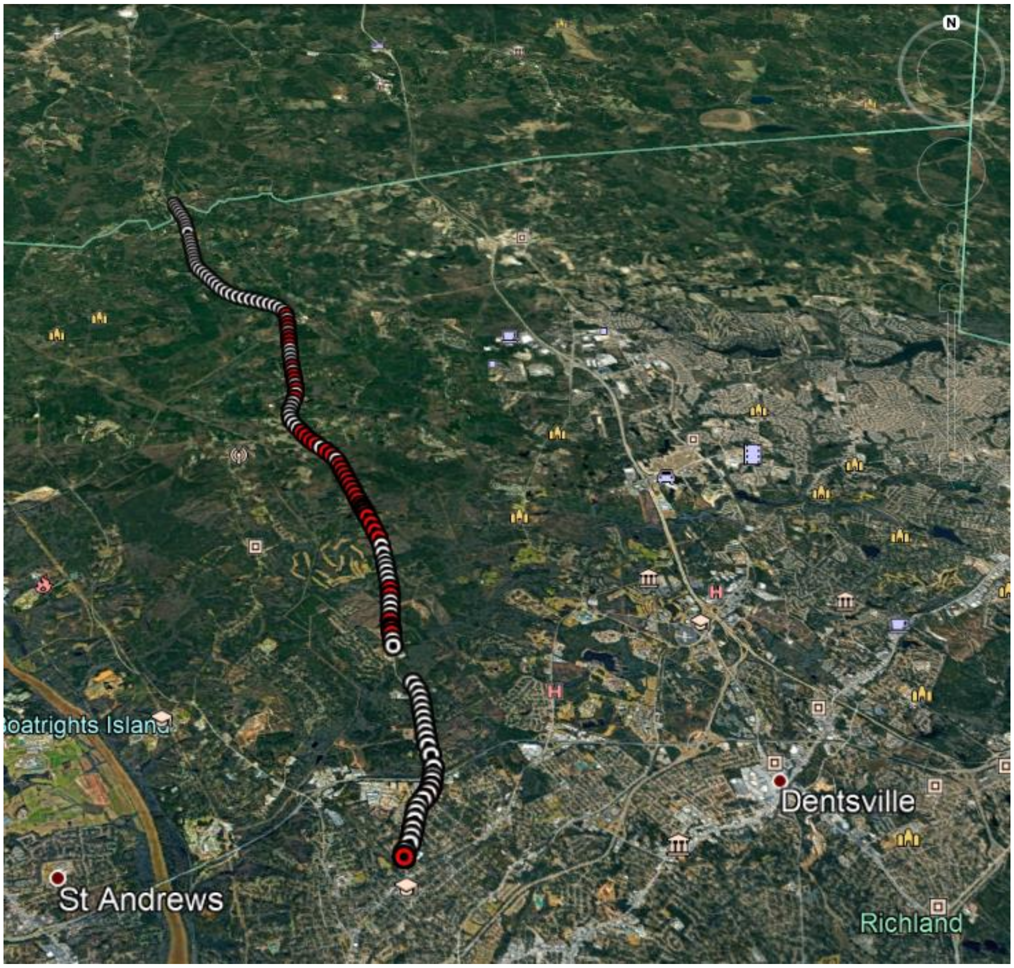
Location of areas of interest on US-321 (Jasper county)



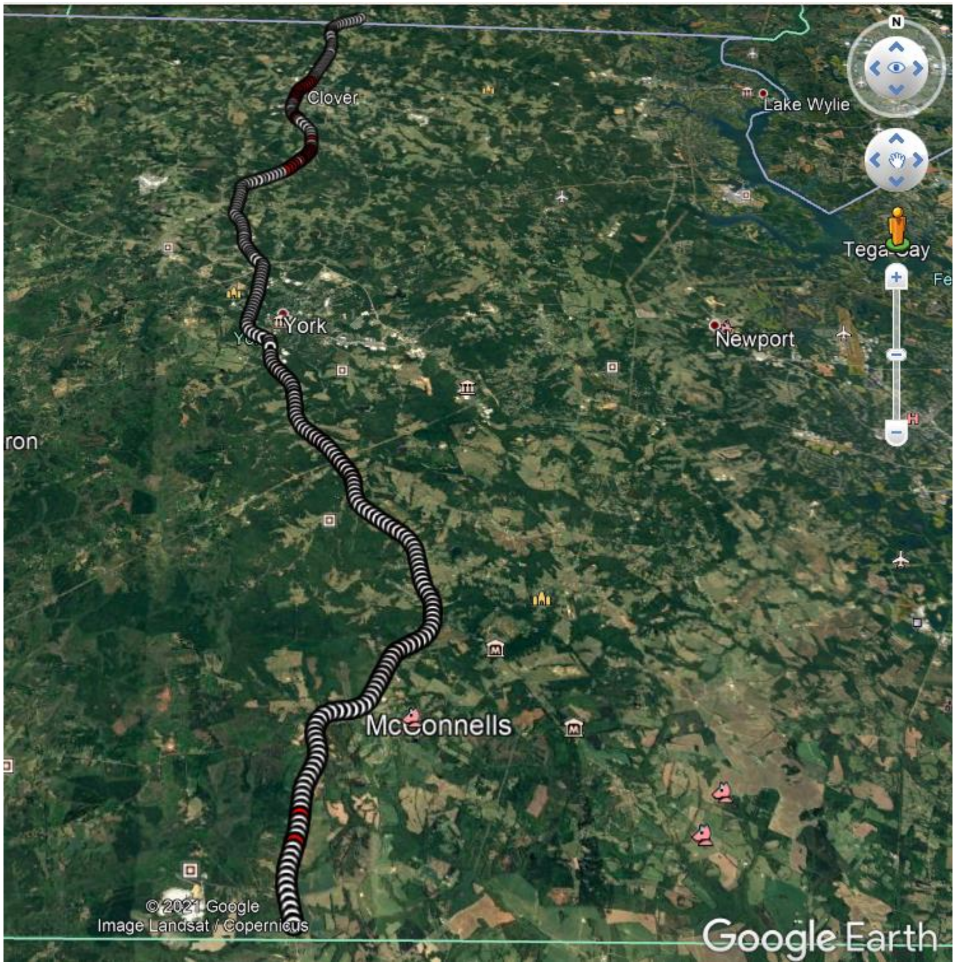
Location of areas of interest on US-321 (Lexington county)



Location of areas of interest on US-321 (Orangeburg county)



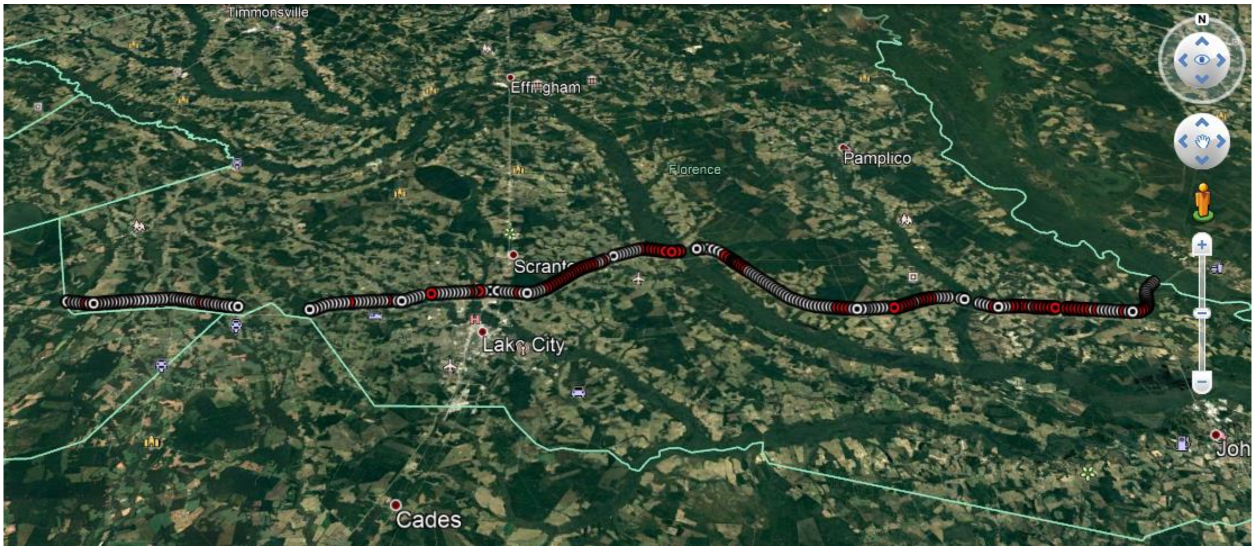
Location of areas of interest on US-321 (Richland county)



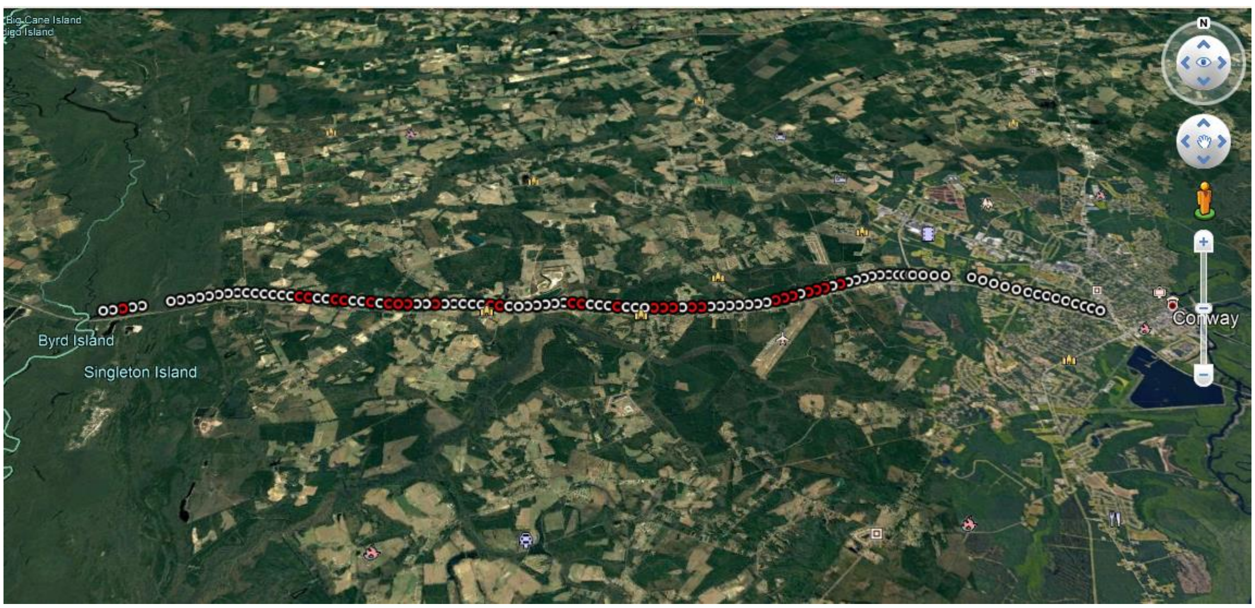
Location of areas of interest on US-321 (York county)

Location of areas of interest on US-378 (Clrendon county)

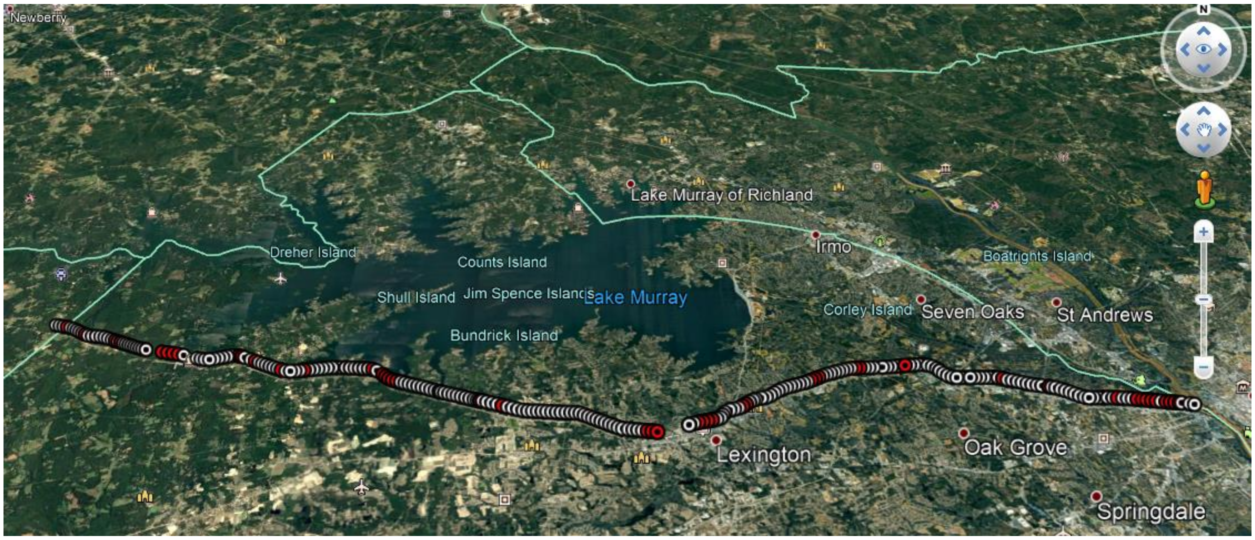

Location of areas of interest on US-378 (Edgefield county)



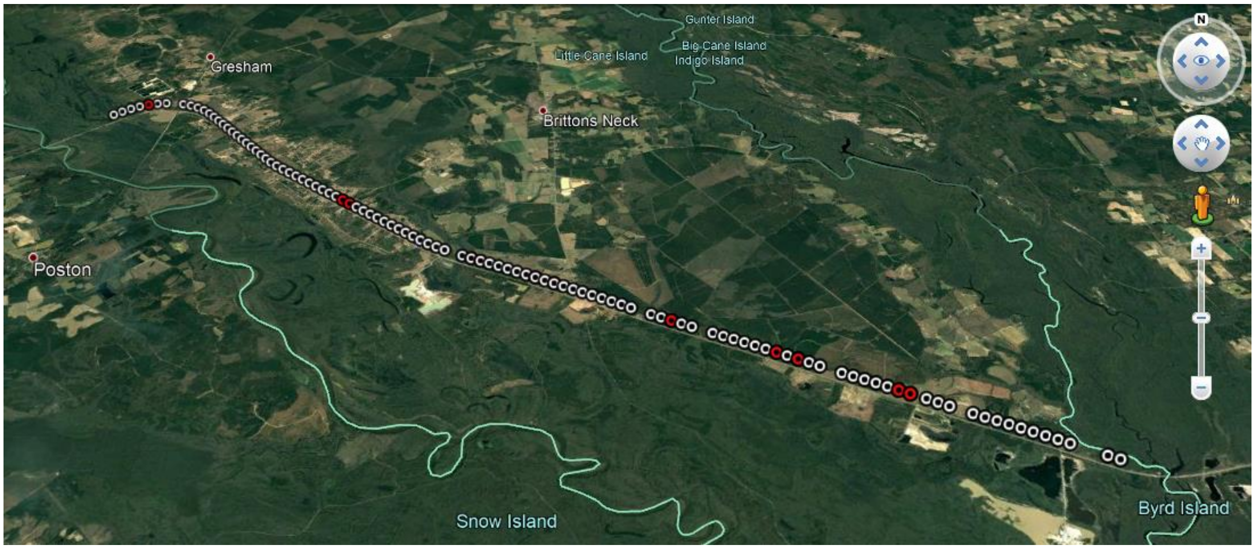
Location of areas of interest on US-378 (Florence county)



Location of areas of interest on US-378 (Horry county)



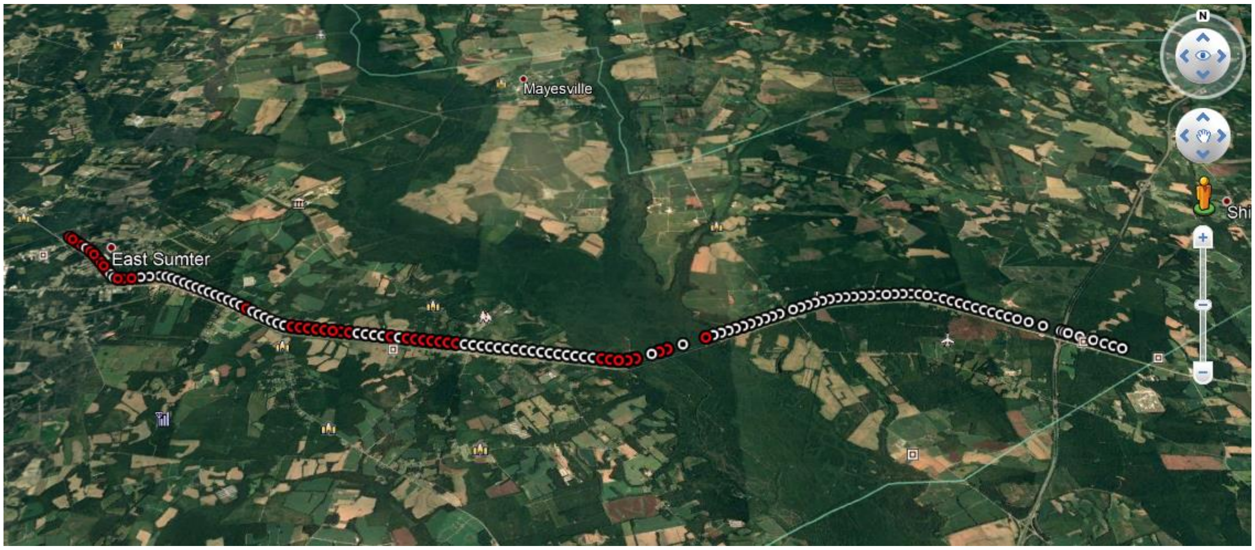
Location of areas of interest on US-378 (Lexington county)



Location of areas of interest on US-378 (Marion county)

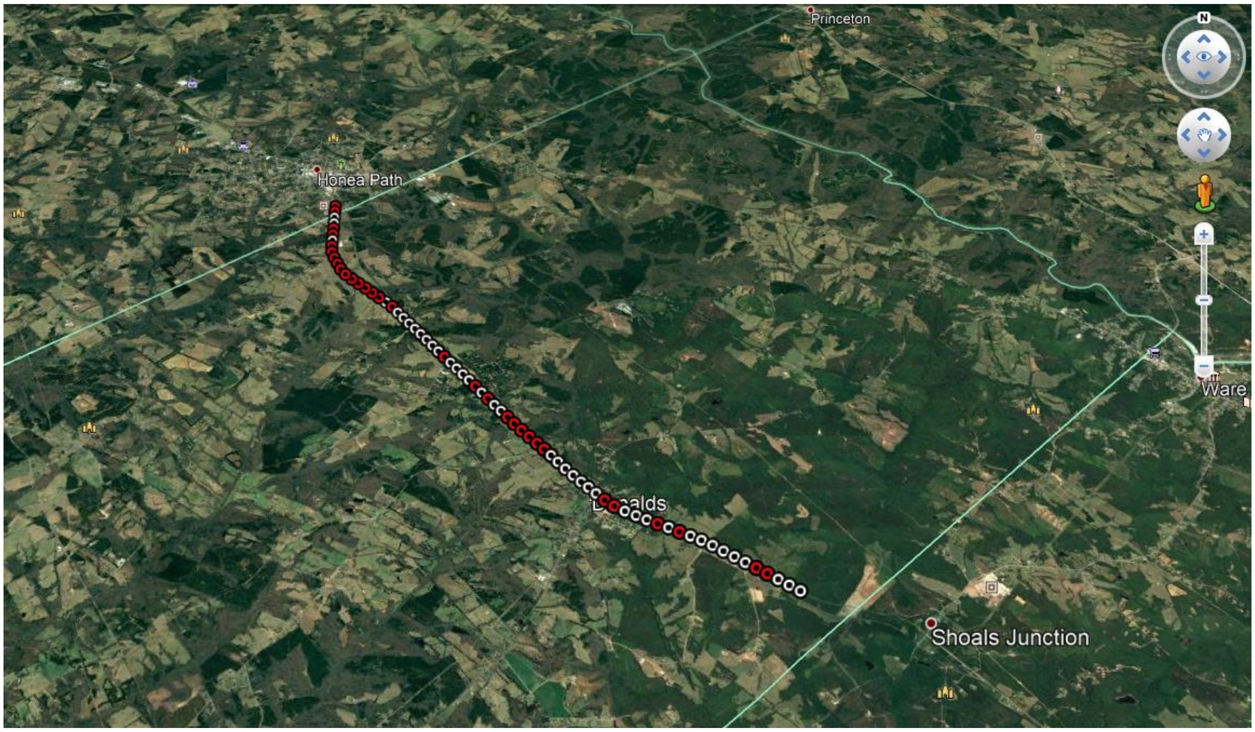
Location of areas of interest on US-378 (McCormick county)

Location of areas of interest on US-378 (Saluda county)



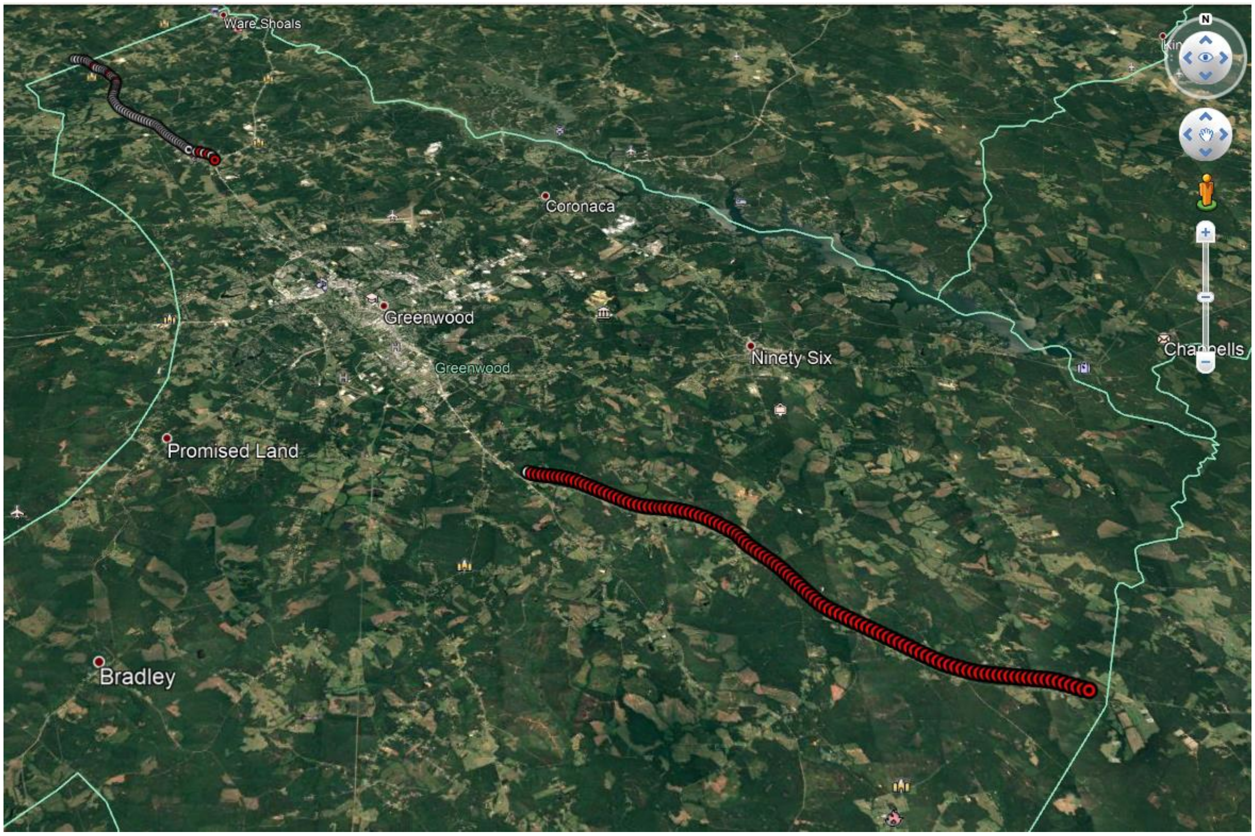
Location of areas of interest on US-378 (Sumter county)

Location of areas of interest on US-378 (Williamsburg county)



Location of areas of interest on US-178 (Abbeville county)

Location of areas of interest on US-178 (Dorchester county)

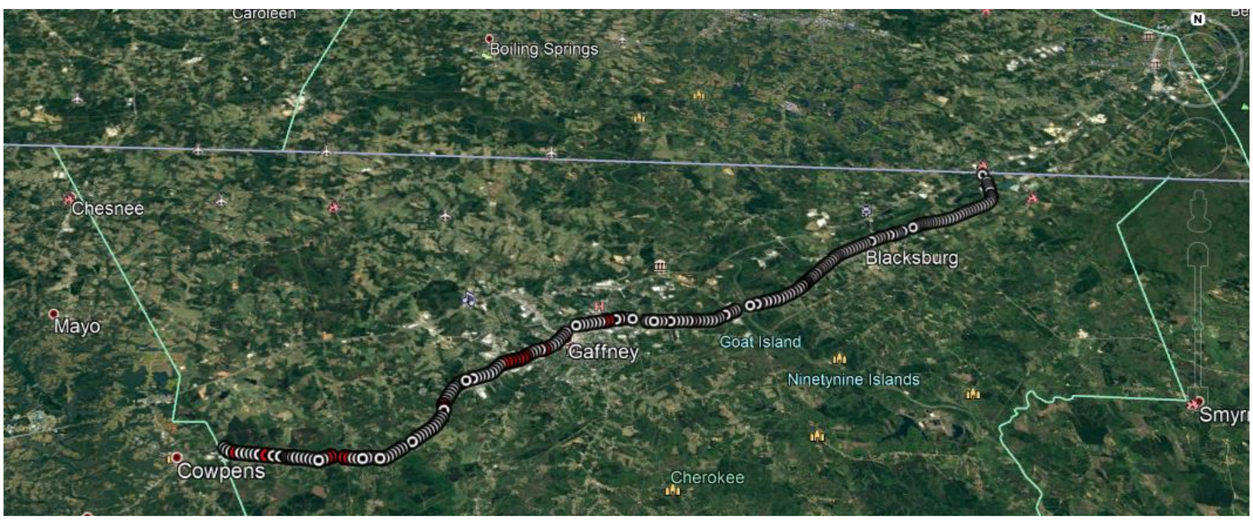


Location of areas of interest on US-178 (Greenwood county)

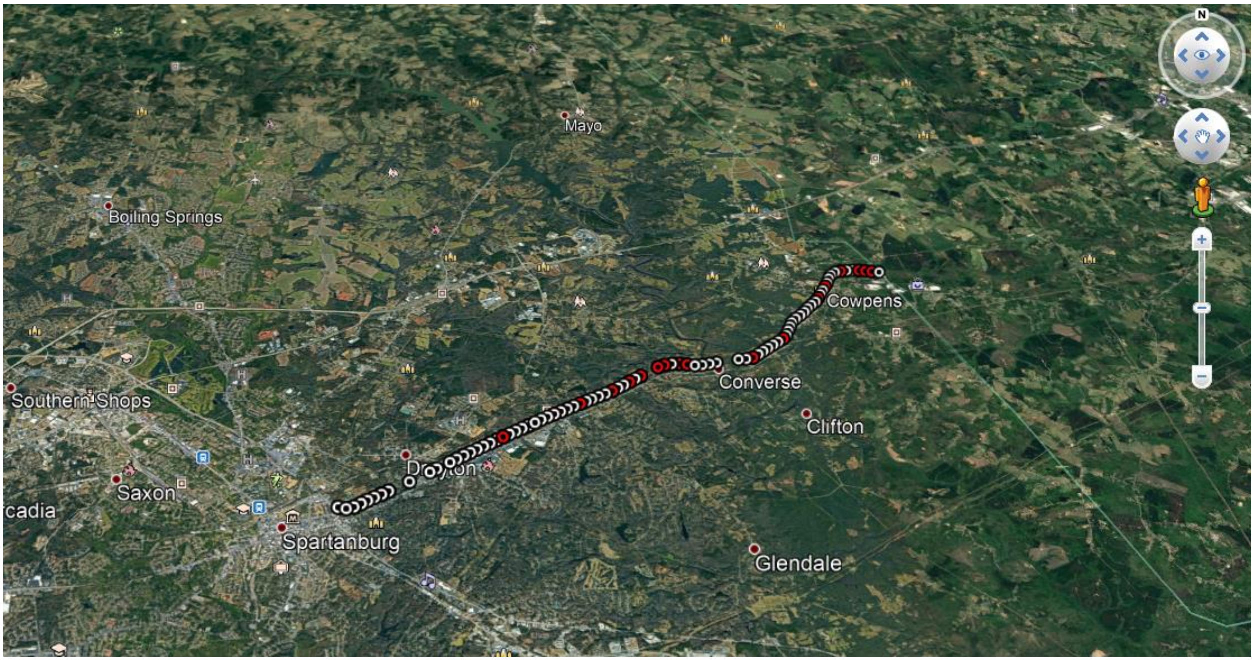
Location of areas of interest on US-178 (Lexington county)

Location of areas of interest on US-178 (Orangeburg county)

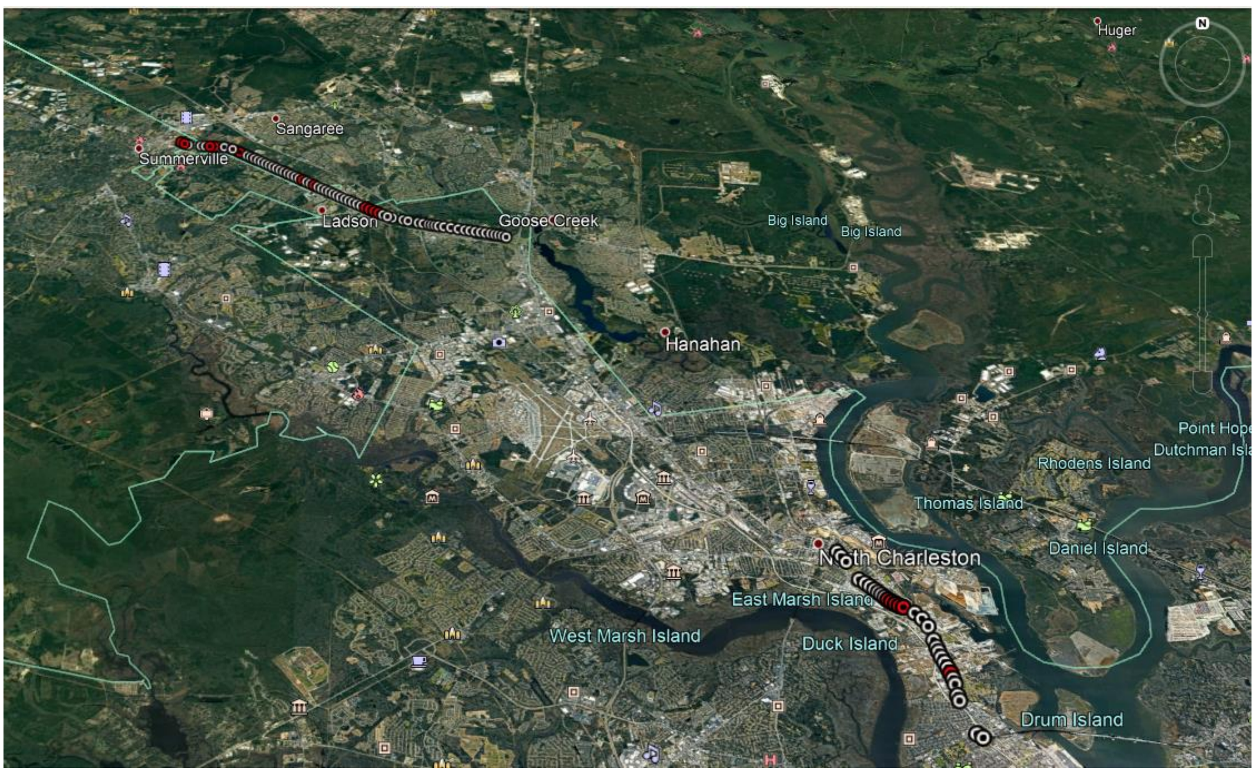
Location of areas of interest on US-178 (Saluda county)



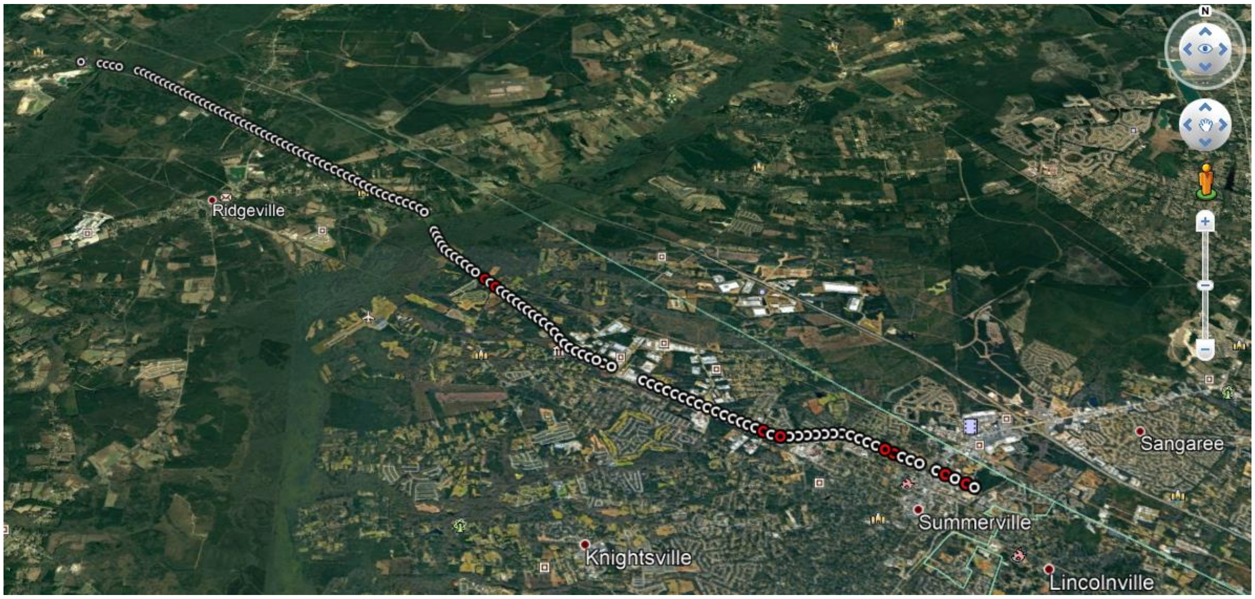
Location of areas of interest on US-29 (Cherokee county)



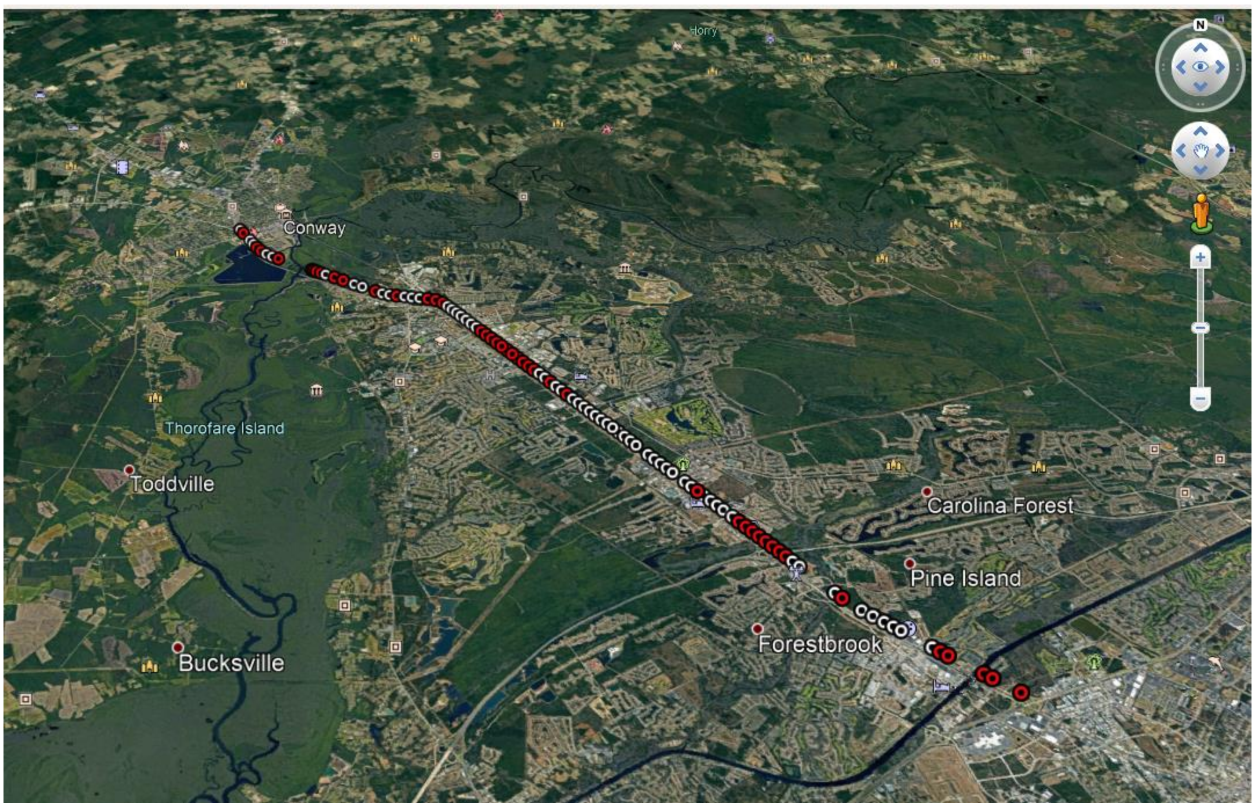
Location of areas of interest on US-29 (Spartanburg county)



Location of areas of interest on US-78 (Charleston county)



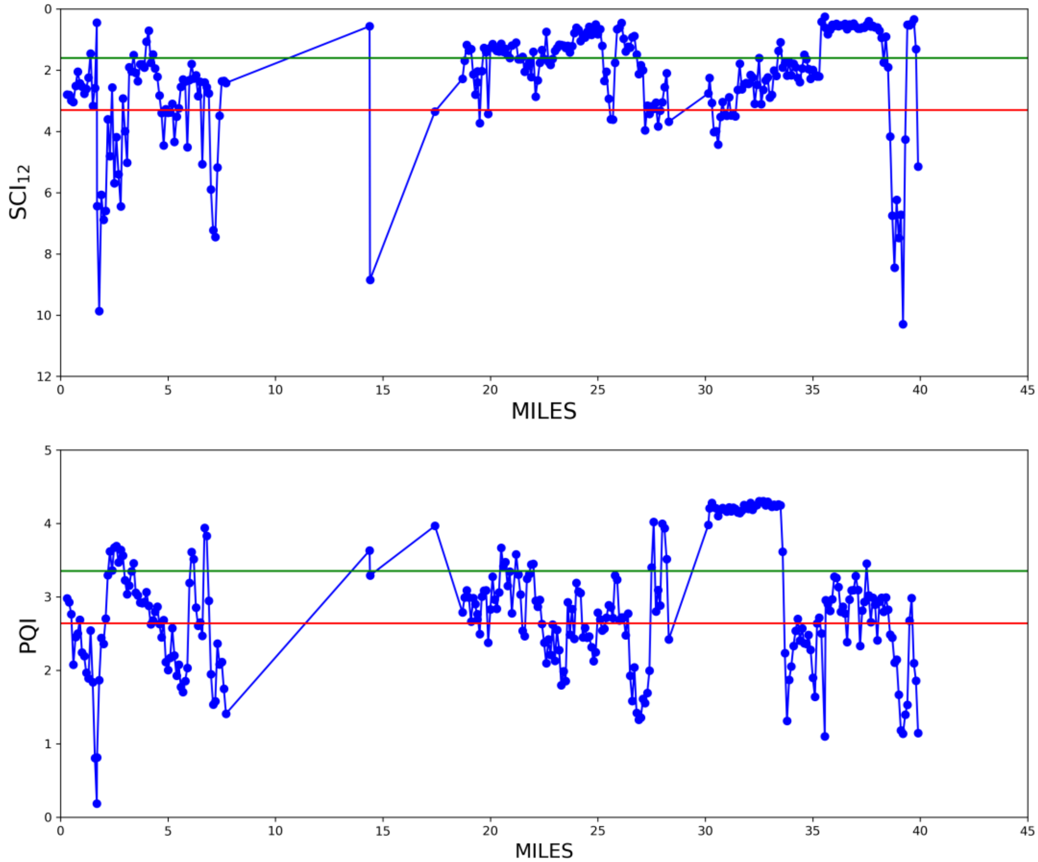
Location of areas of interest on US-78 (Dorchester county)



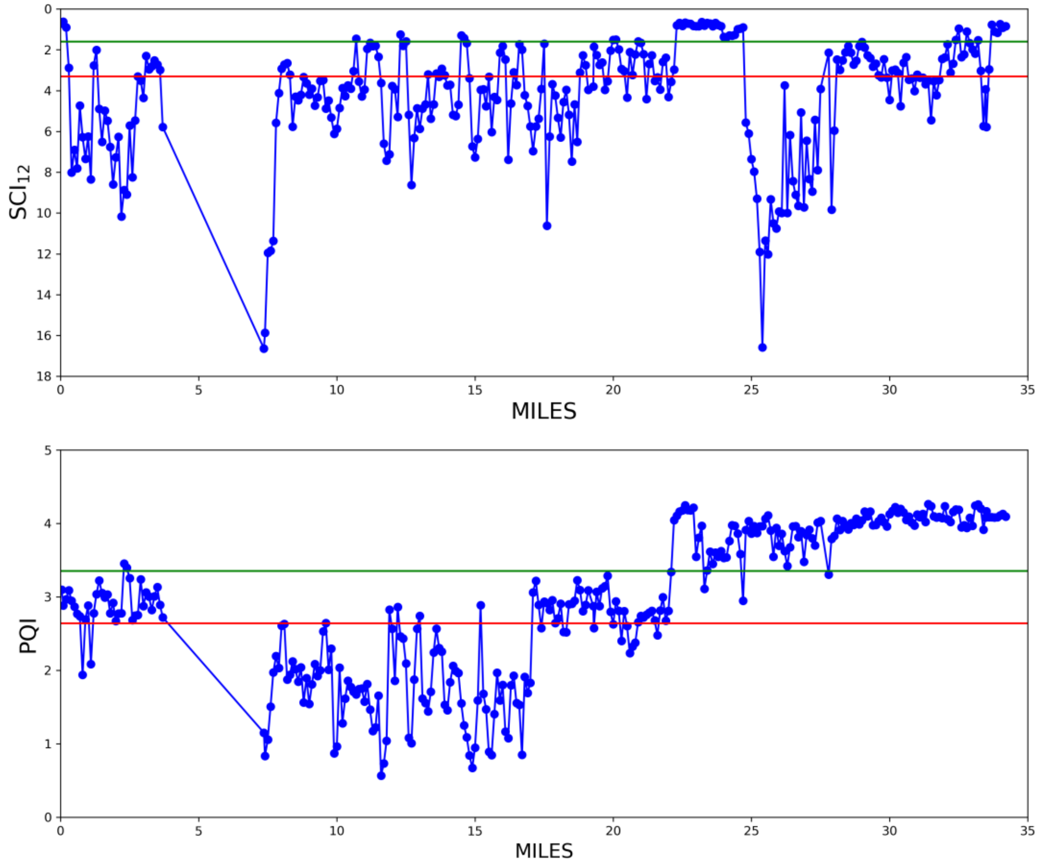
Location of areas of interest on US-501 (Horry county)

APPENDIX H

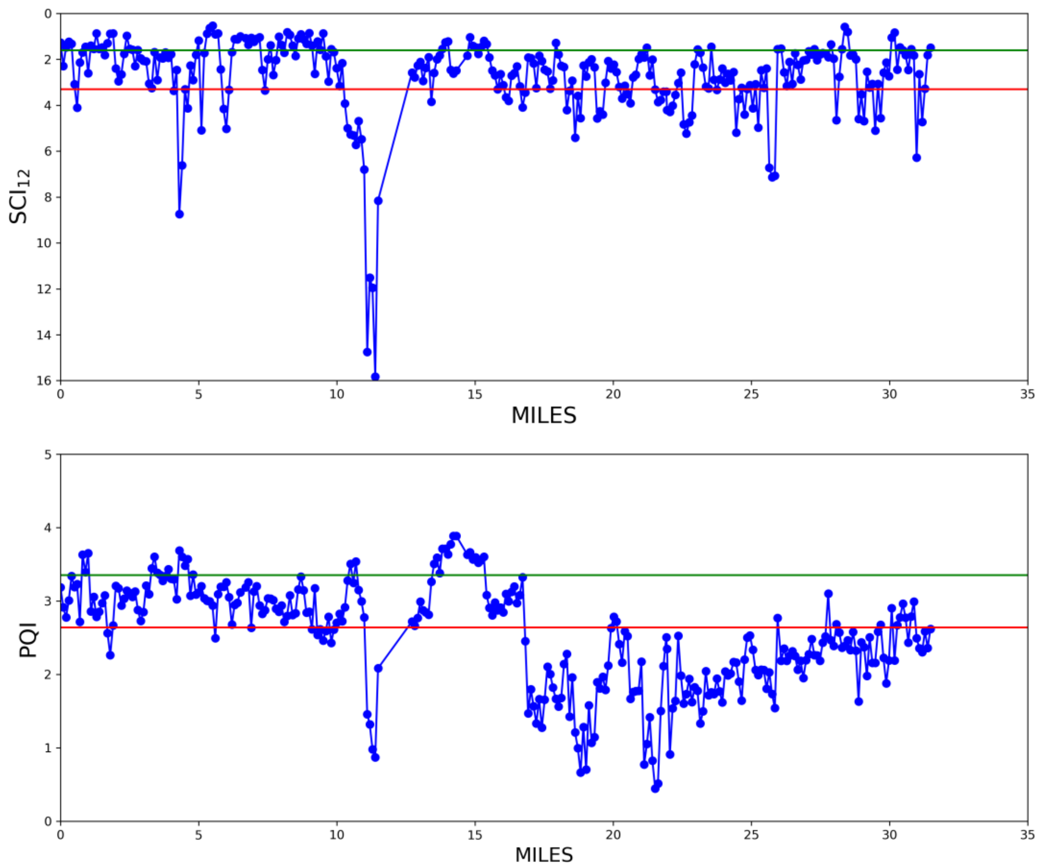
Comparison of SCI_{12} and PQI for TSD Routes



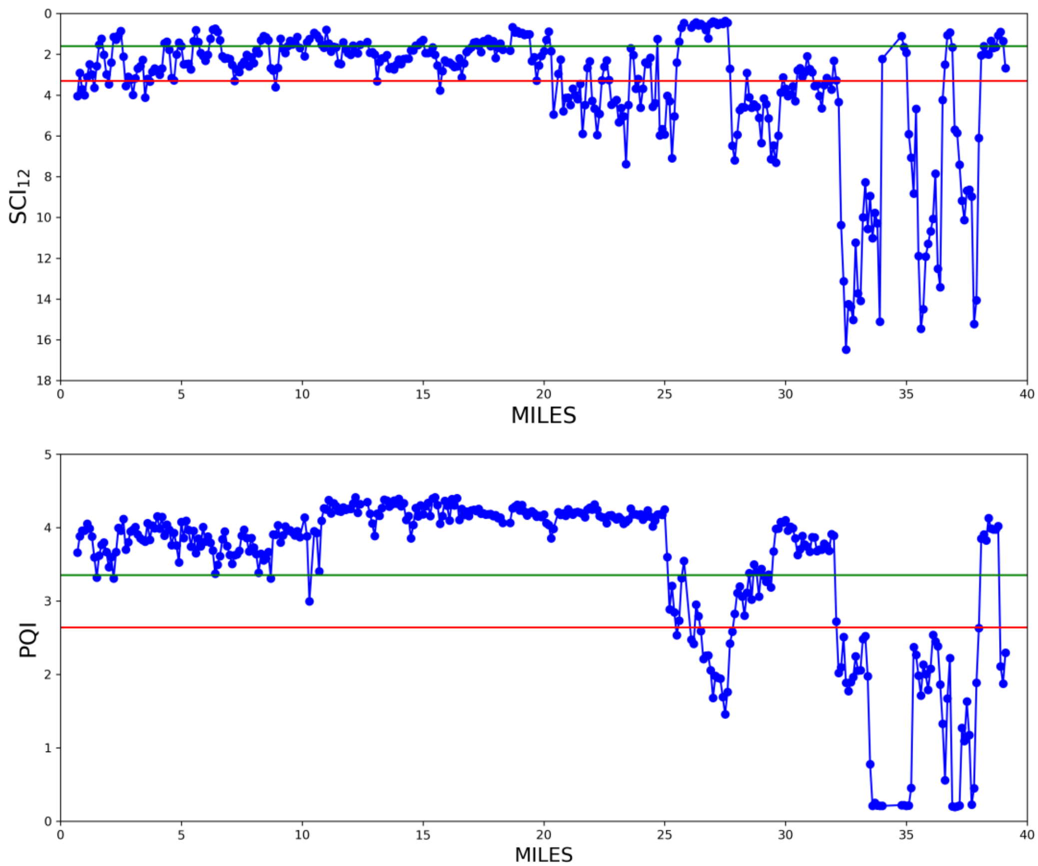
SCI$_{12}$ and PQI of Chester County of SC-9



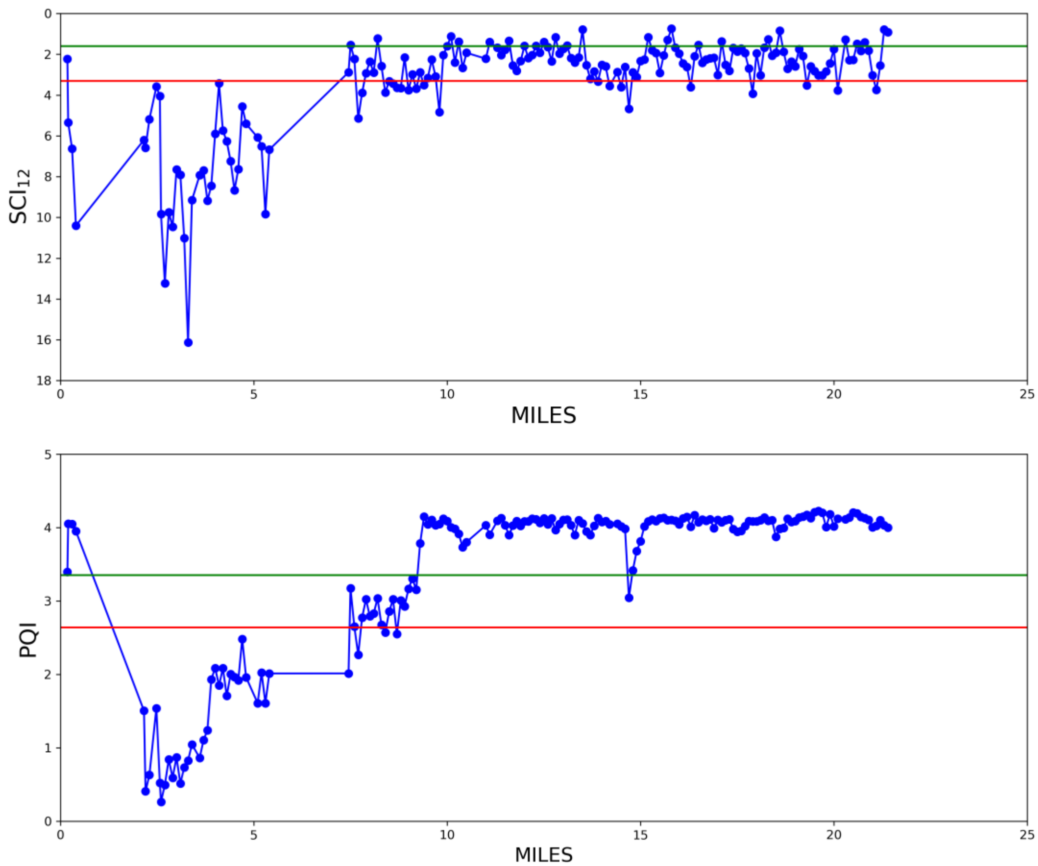
SCI$_{12}$ and PQI of Chesterfield County of SC-9



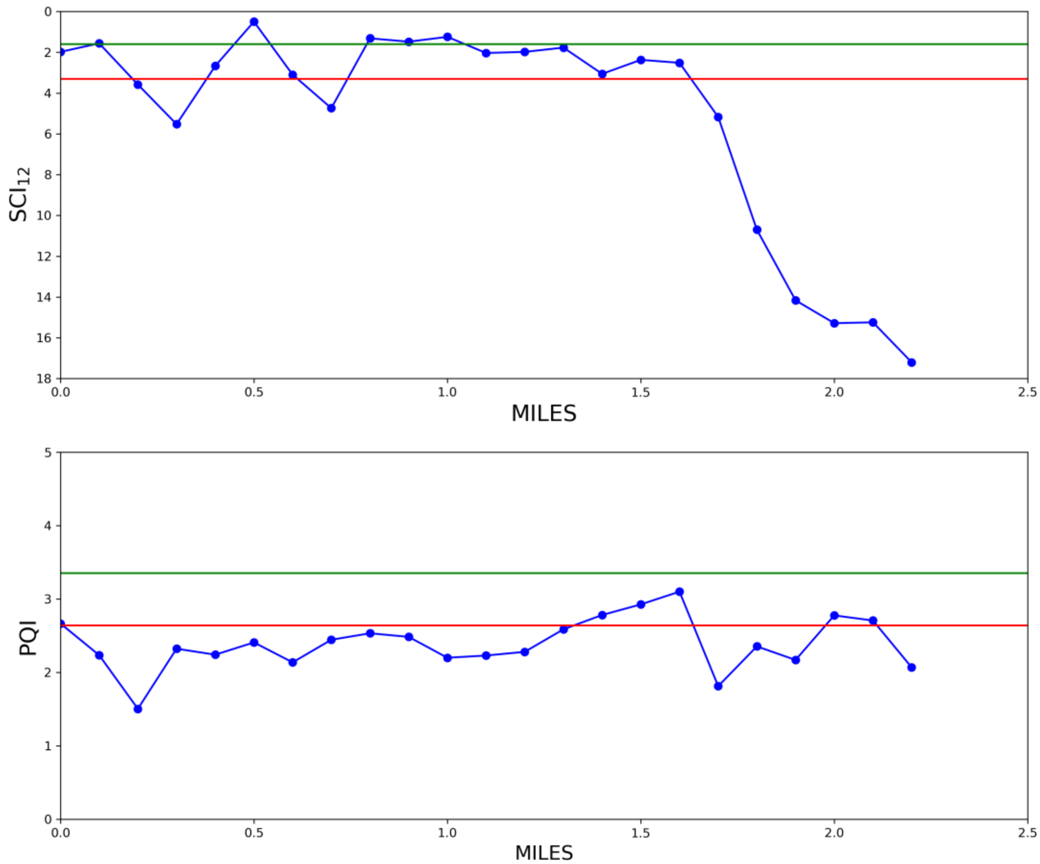
SCI$_{12}$ and PQI of Dillon County of SC-9



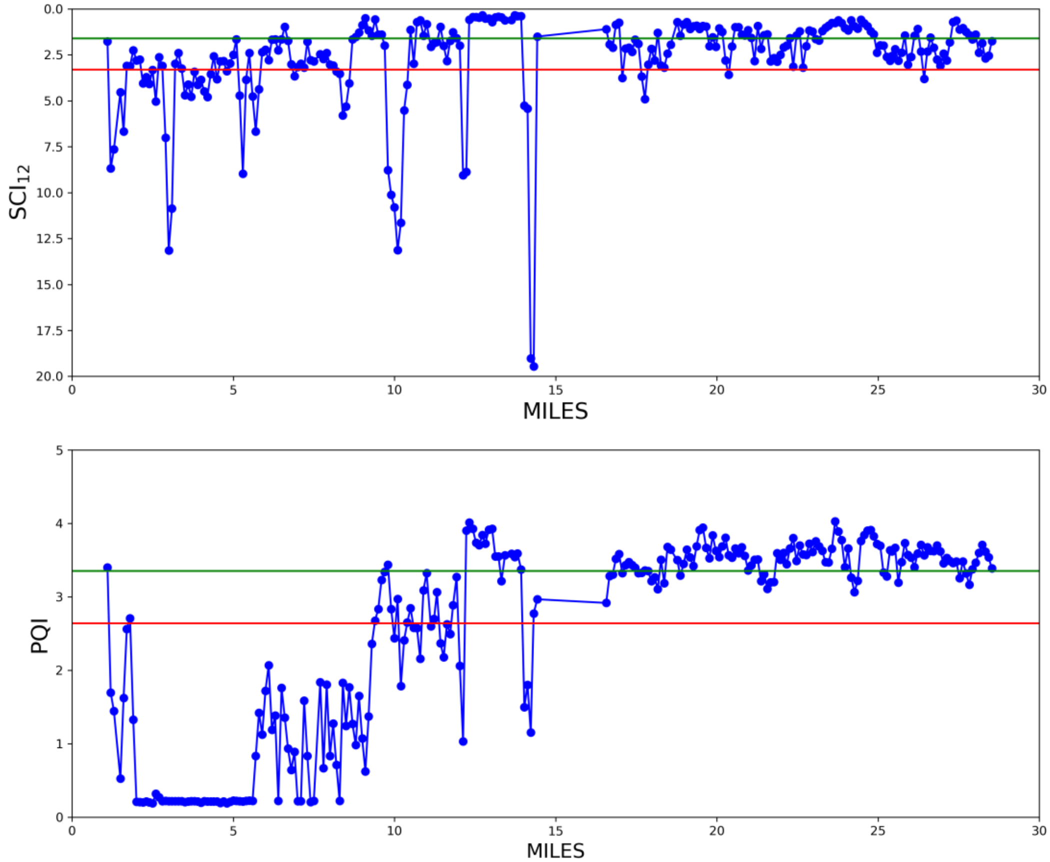
SCI$_{12}$ and PQI of Horry County of SC-9



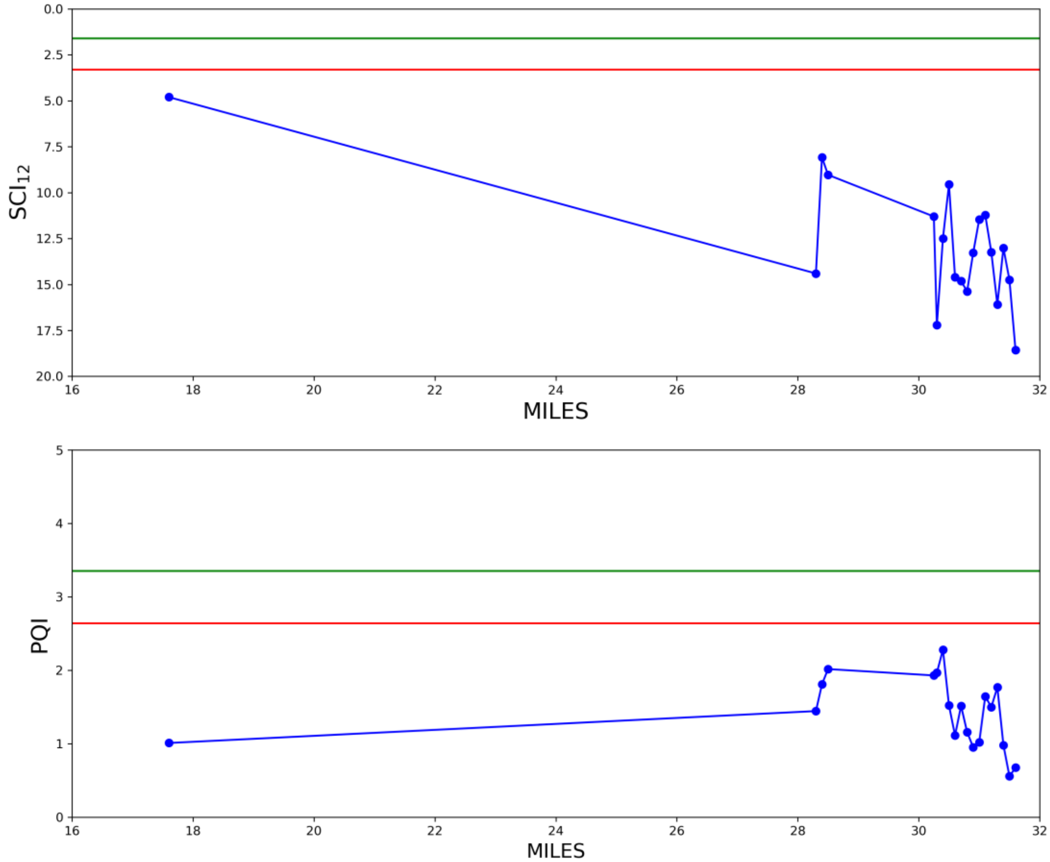
SCI_{12} and PQI of Lancaster County of SC-9



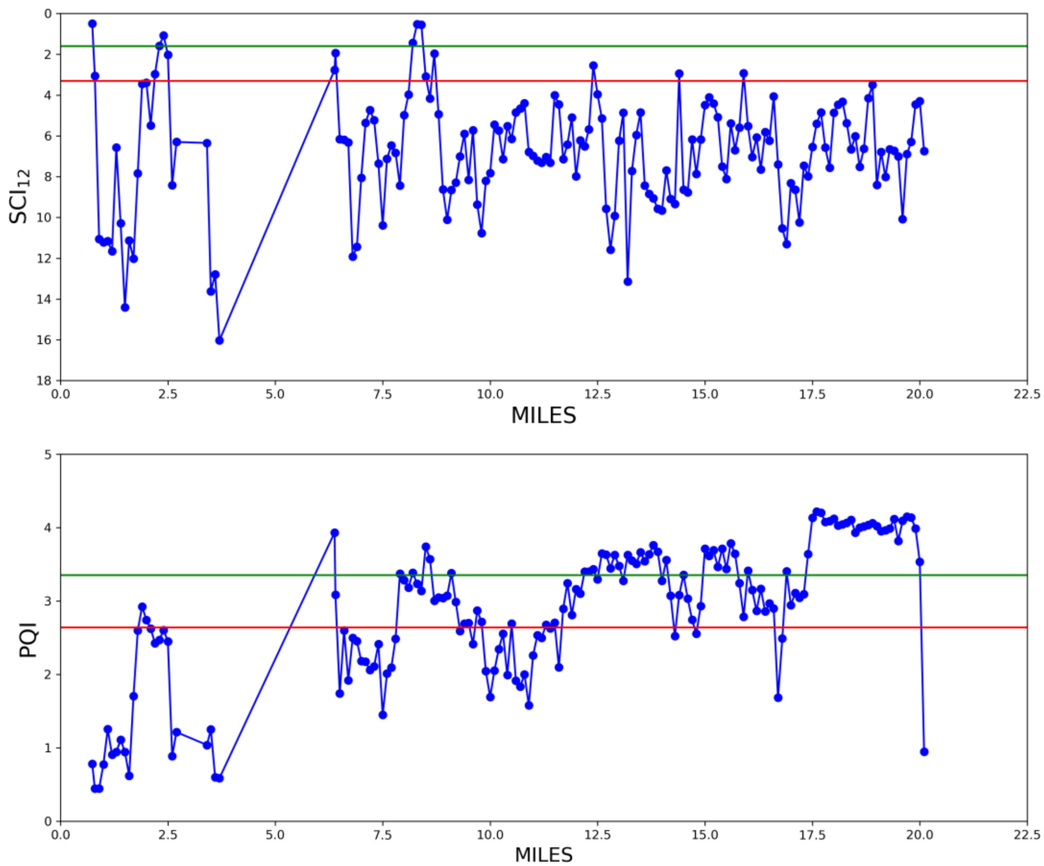
SCI$_{12}$ and PQI of Marion County of SC-9



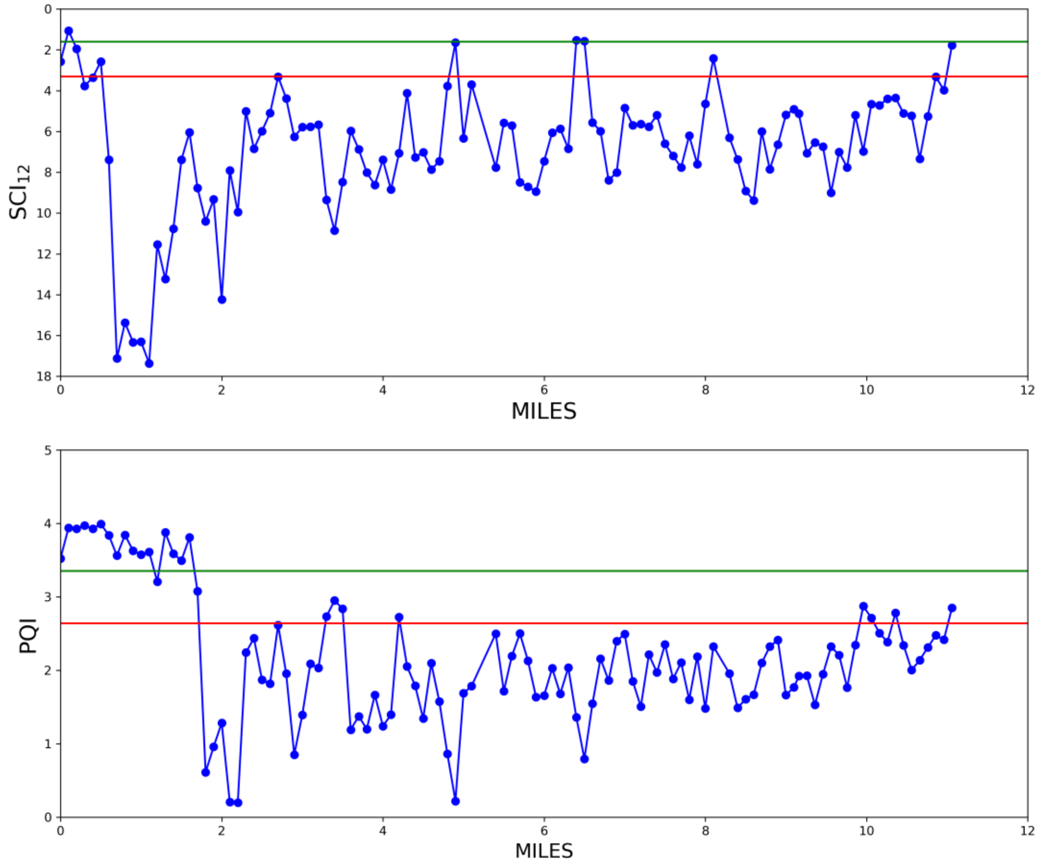
SCI$_{12}$ and PQI of Marlboro County of SC-9



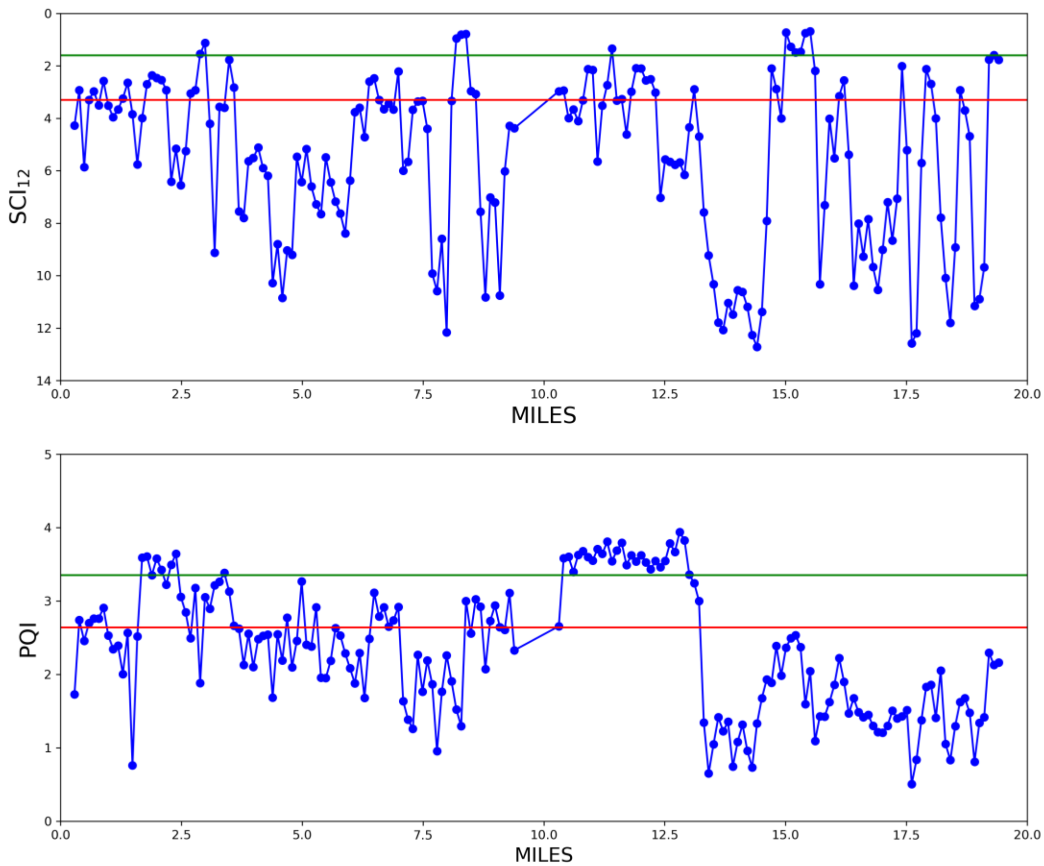
SCI_{12} and PQI of Spartanburg County of SC-9



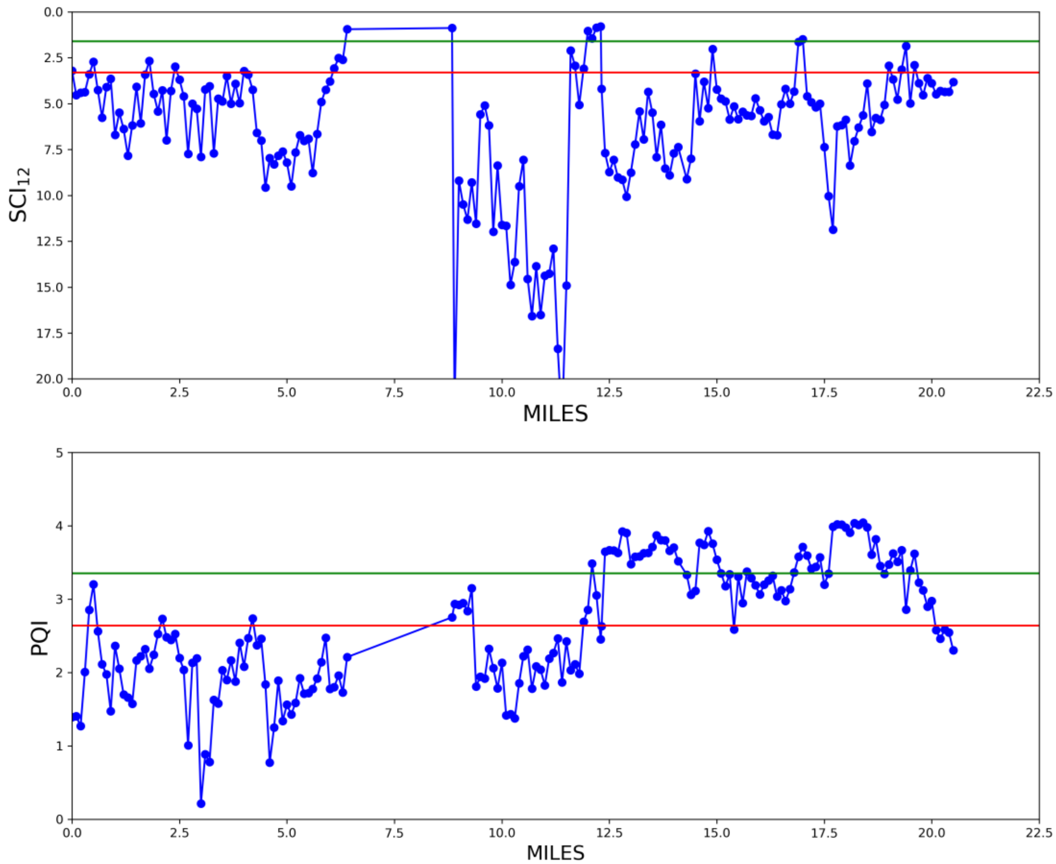
SCI$_{12}$ and PQI of Union County of SC-9



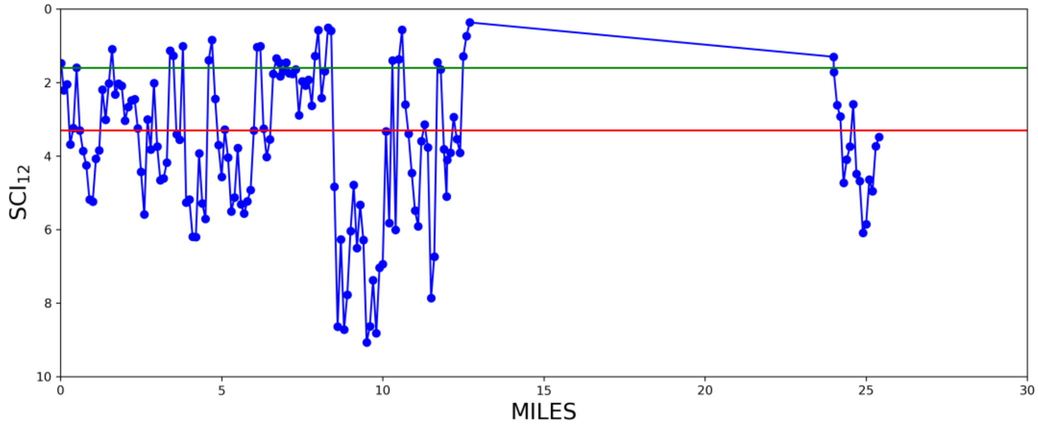
SCI$_{12}$ and PQI of Allendale County of US-321

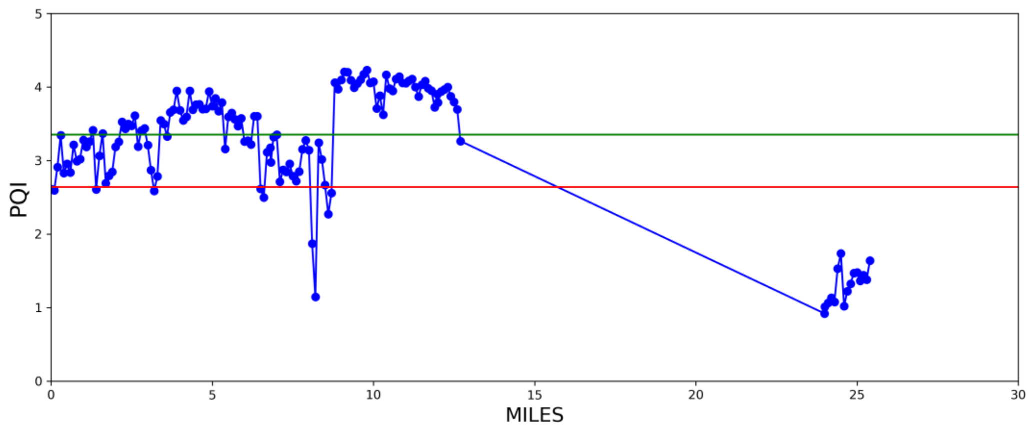


SCI$_{12}$ and PQI of Bamberg County of US-321

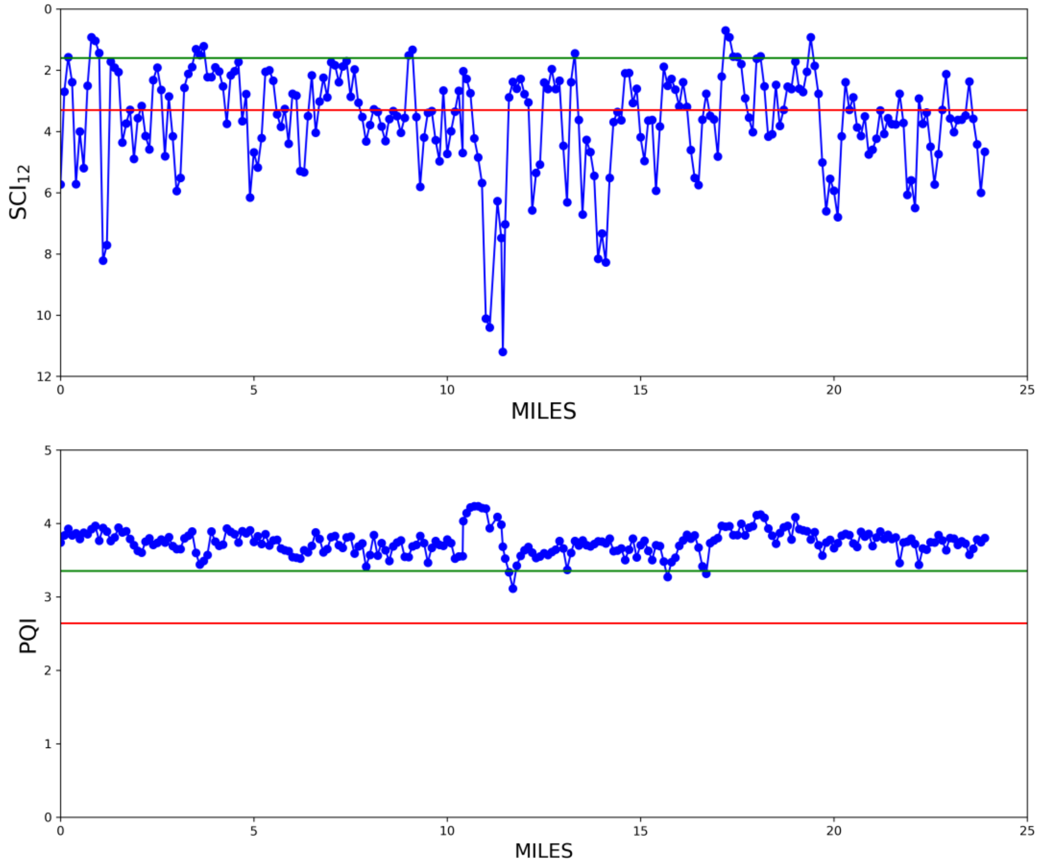


SCI_{12} and PQI of Chester County of US-321

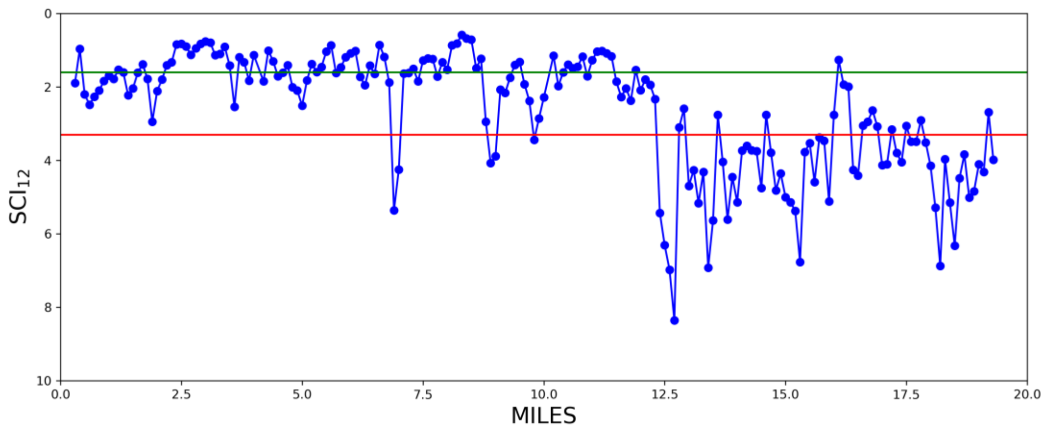


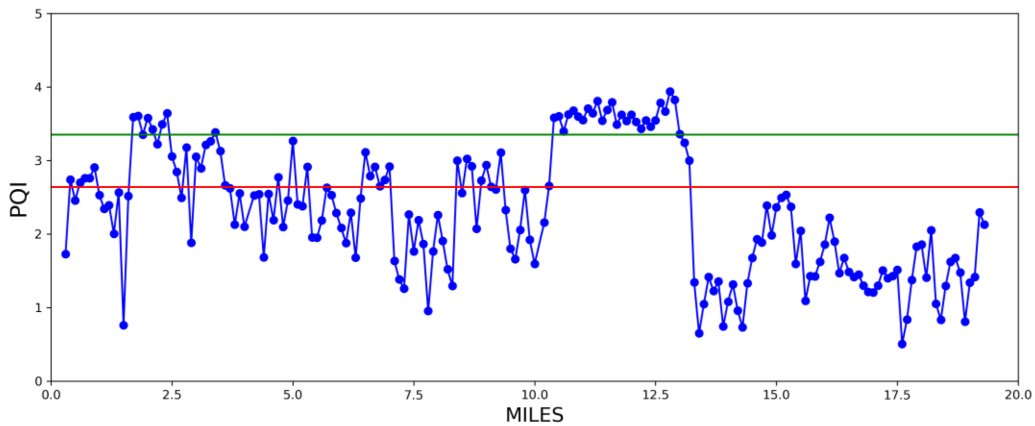


SCI$_{12}$ and PQI of Fairfield County of US-321

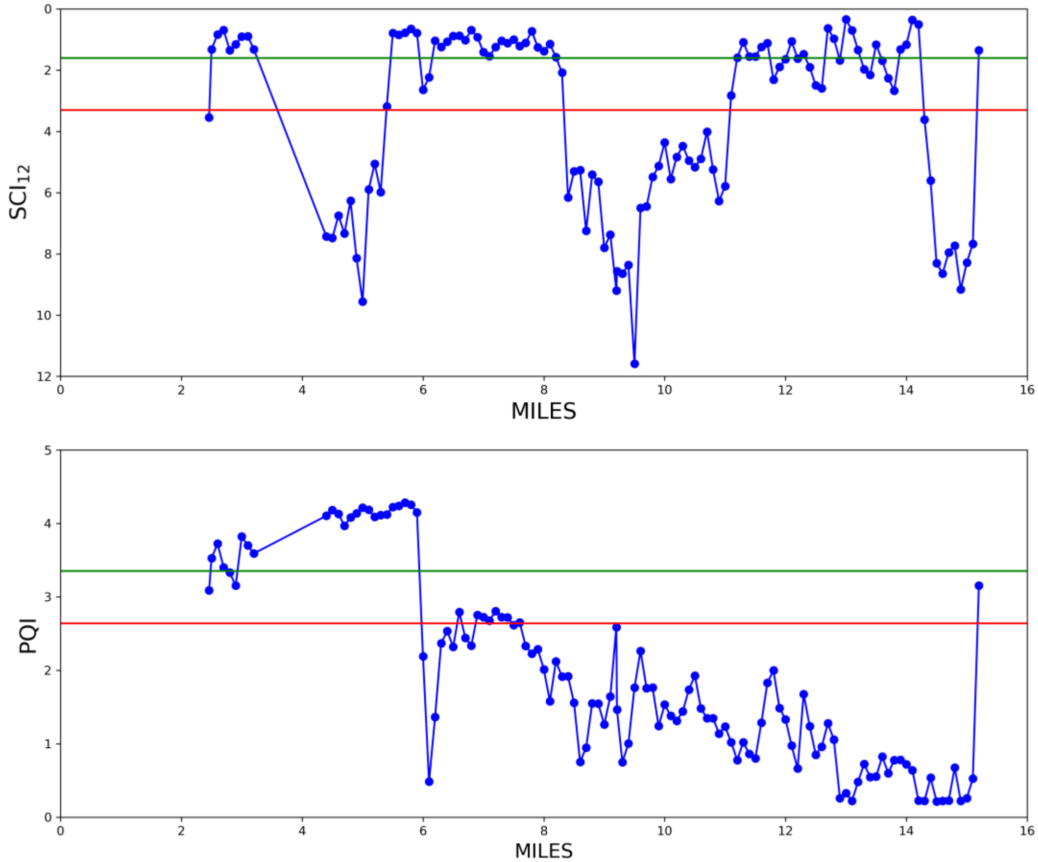


SCI$_{12}$ and PQI of Hampton County of US-321

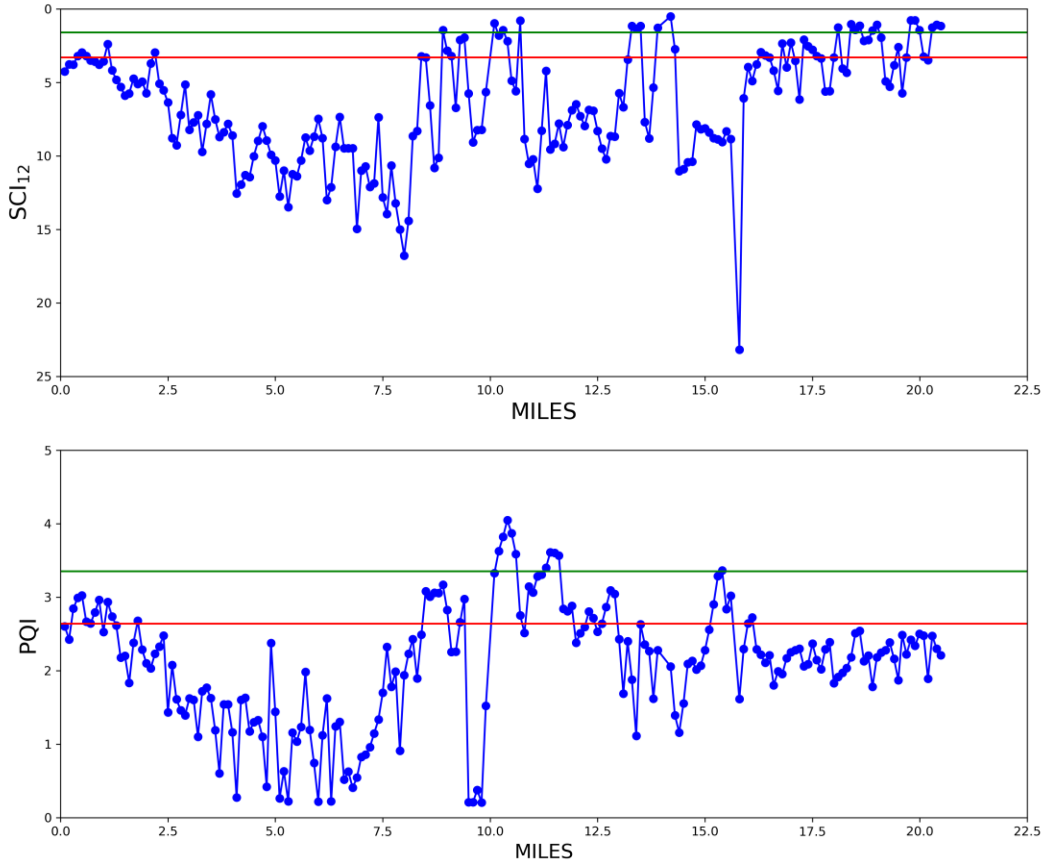




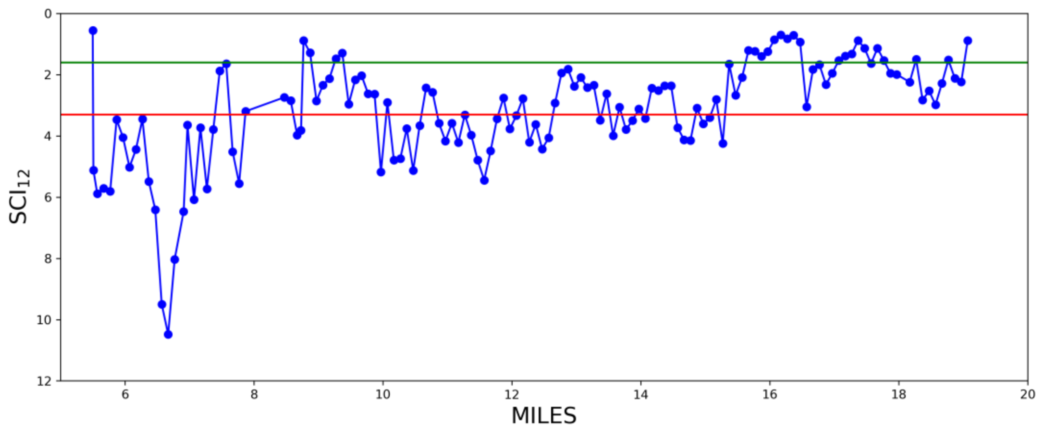
SCI_{12} and PQI of Jasper County of US-321

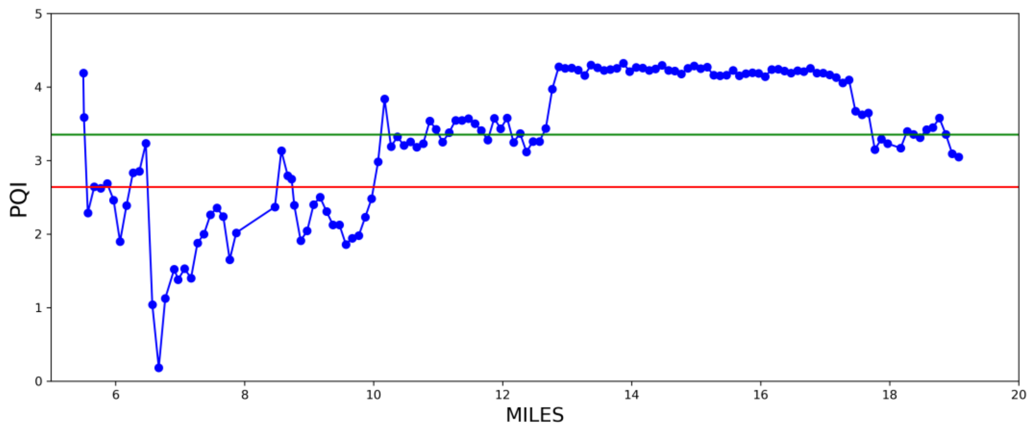


SCI$_{12}$ and PQI of Lexington County of US-321

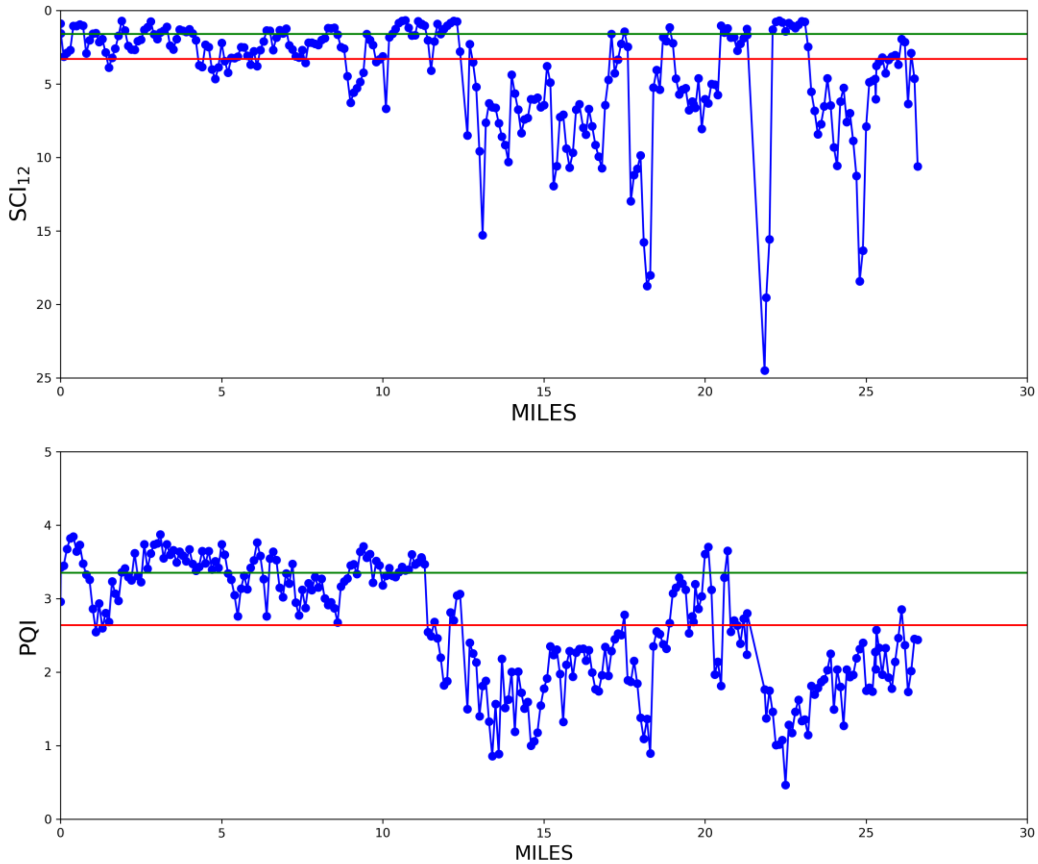


SCI_{12} and PQI of Orangeburg County of US-321

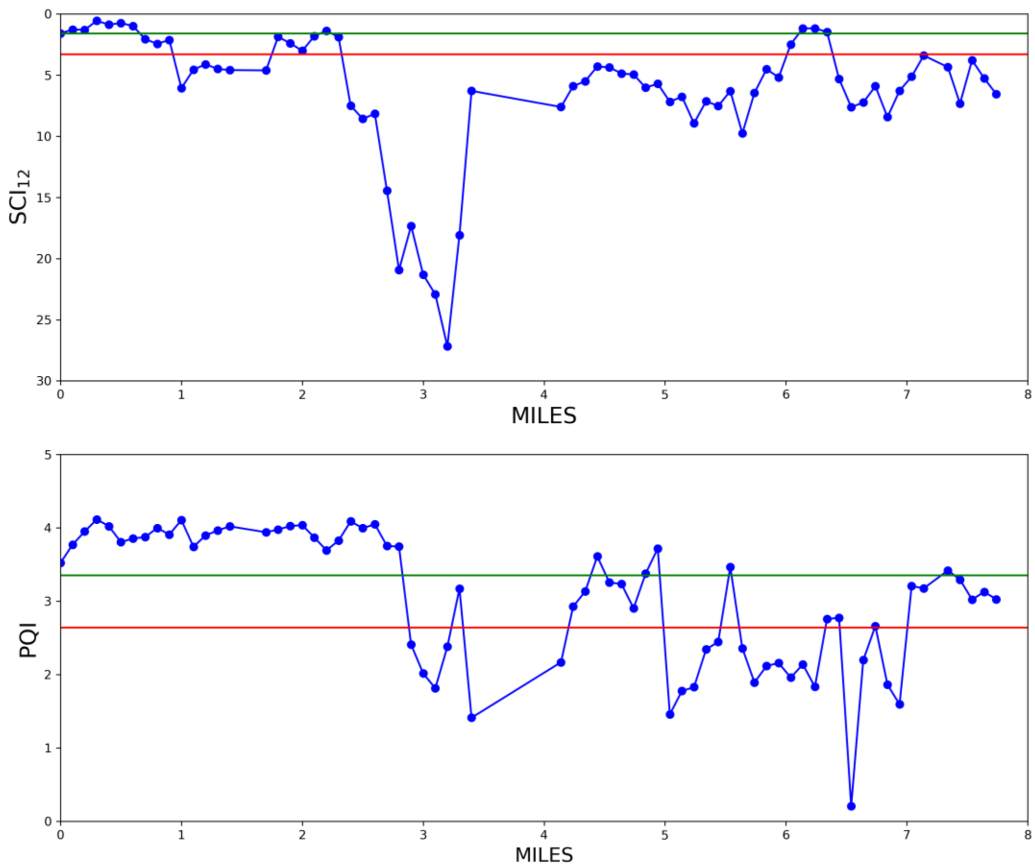




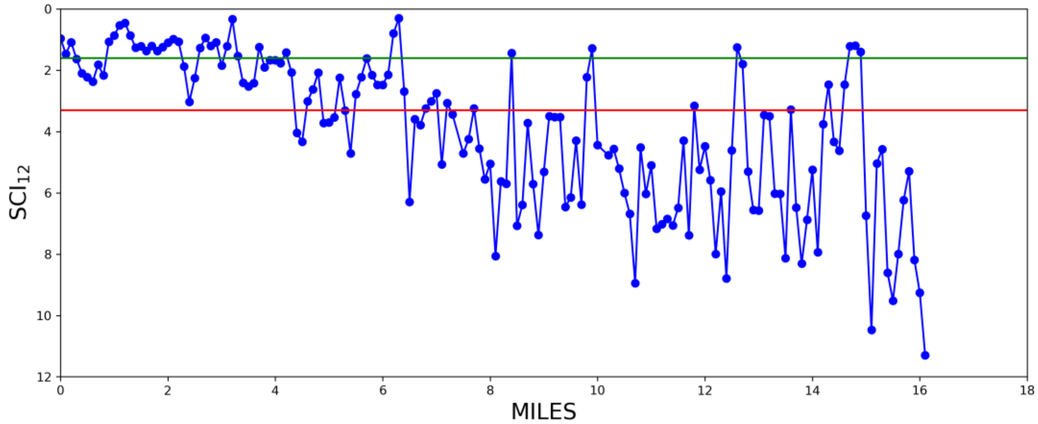
SCI$_{12}$ and PQI of Richland County of US-321

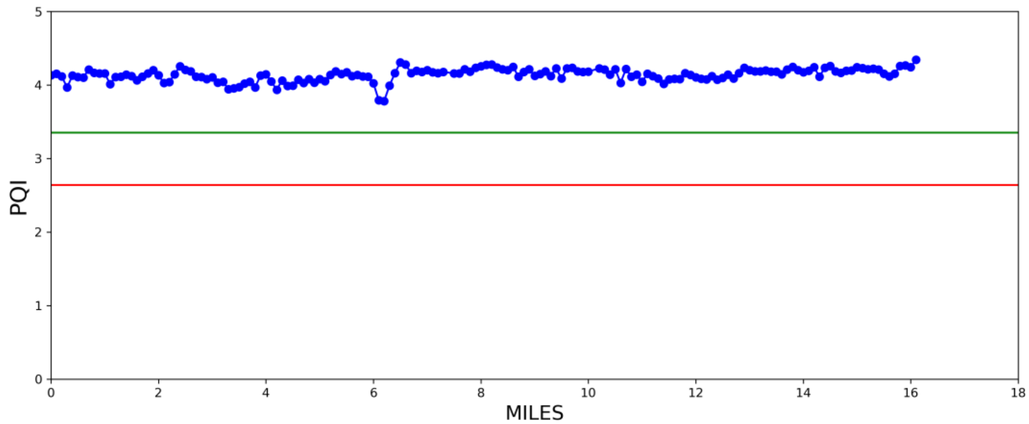


SCI$_{12}$ and PQI of York County of US-321

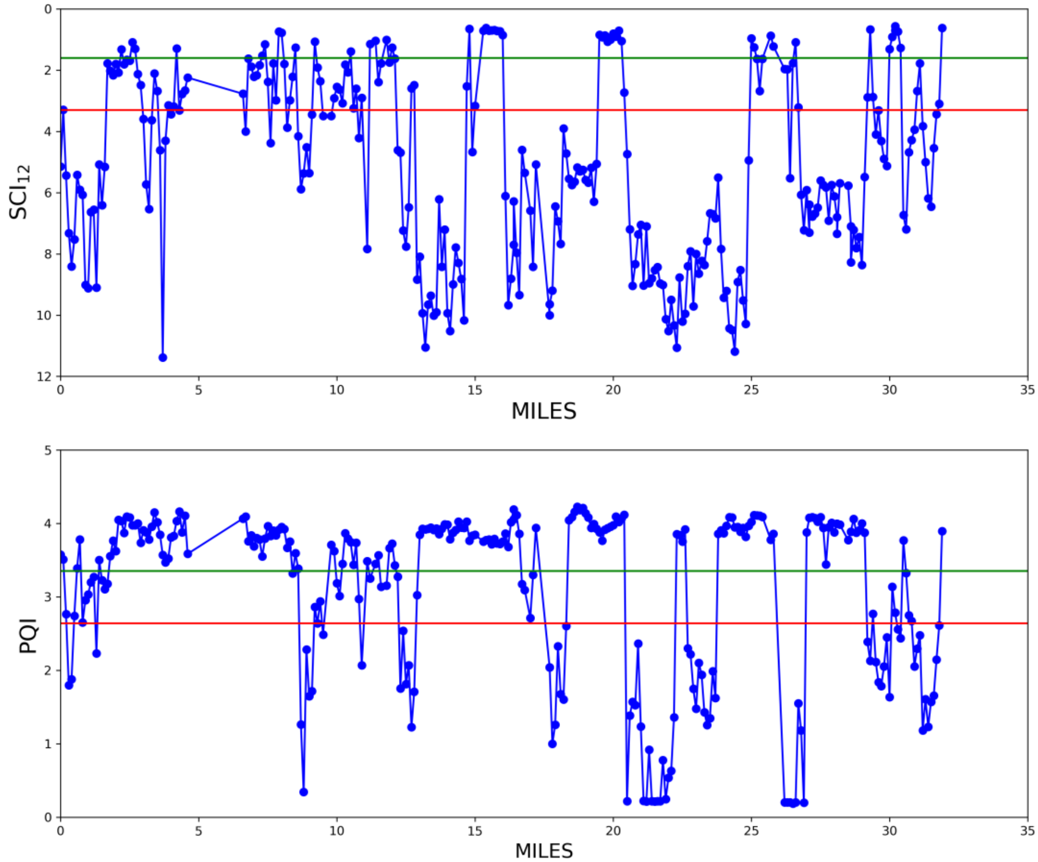


SCI_{12} and PQI of Clarendon County of US-378

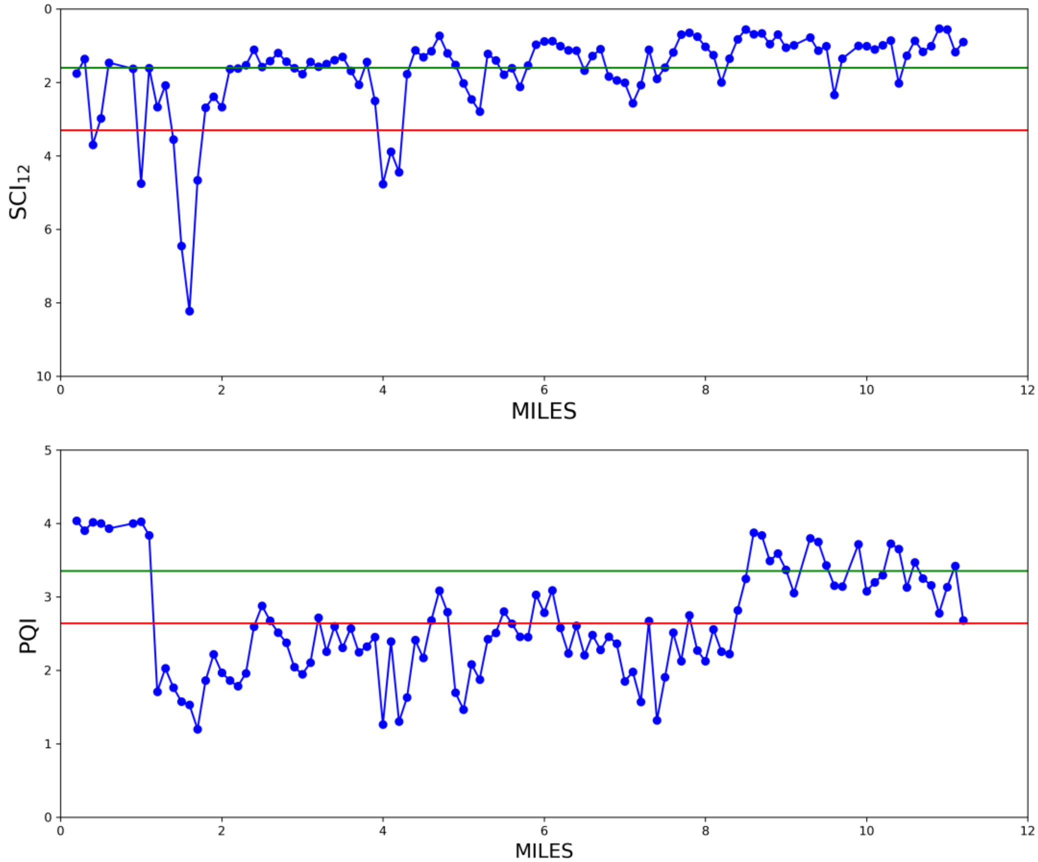




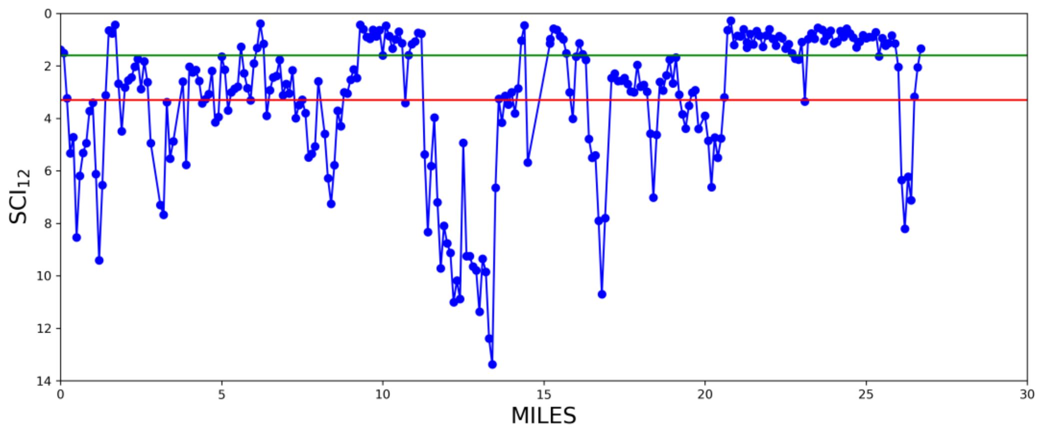
SCI_{12} and PQI of Edgefield County of US-378

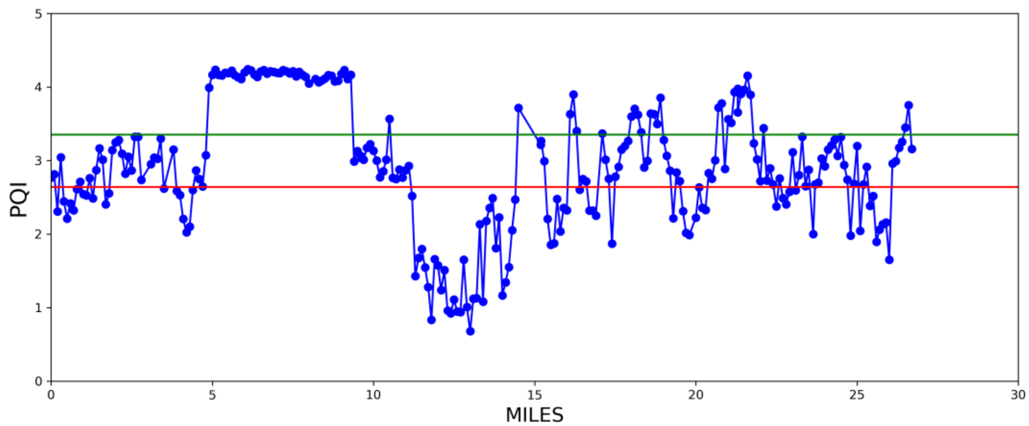


SCI_{12} and PQI of Florence County of US-378

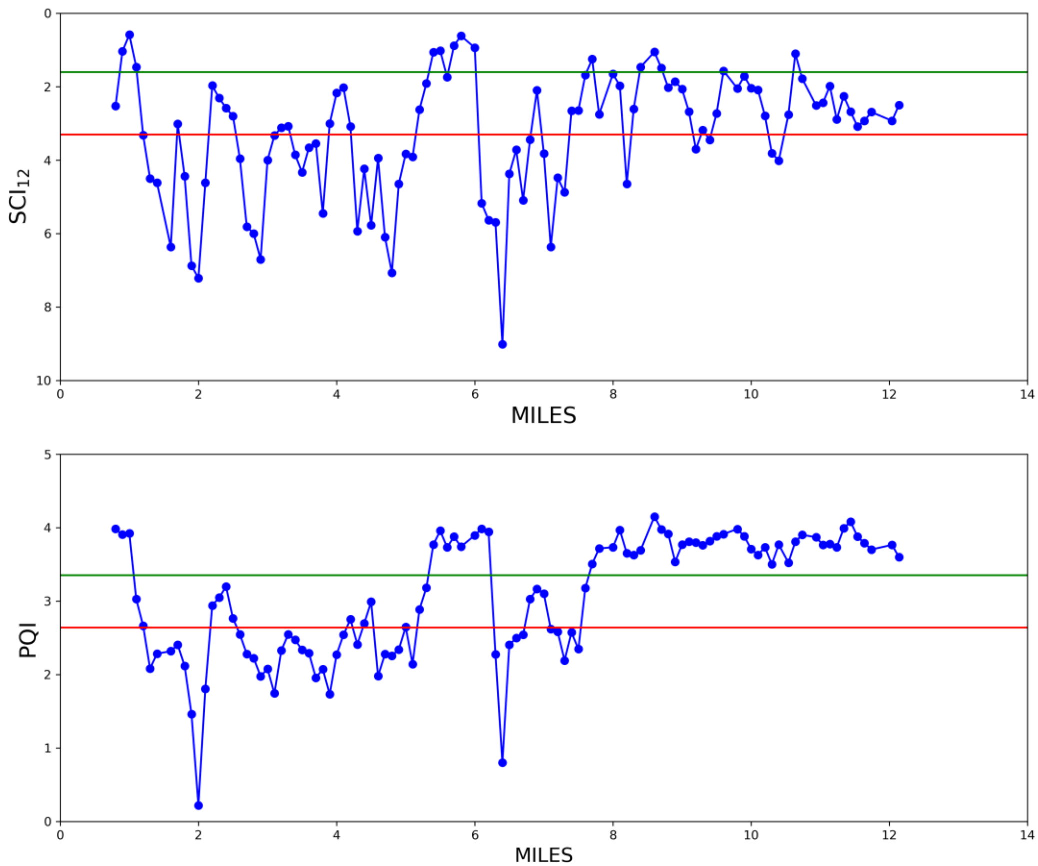


SCI$_{12}$ and PQI of Horry County of US-378

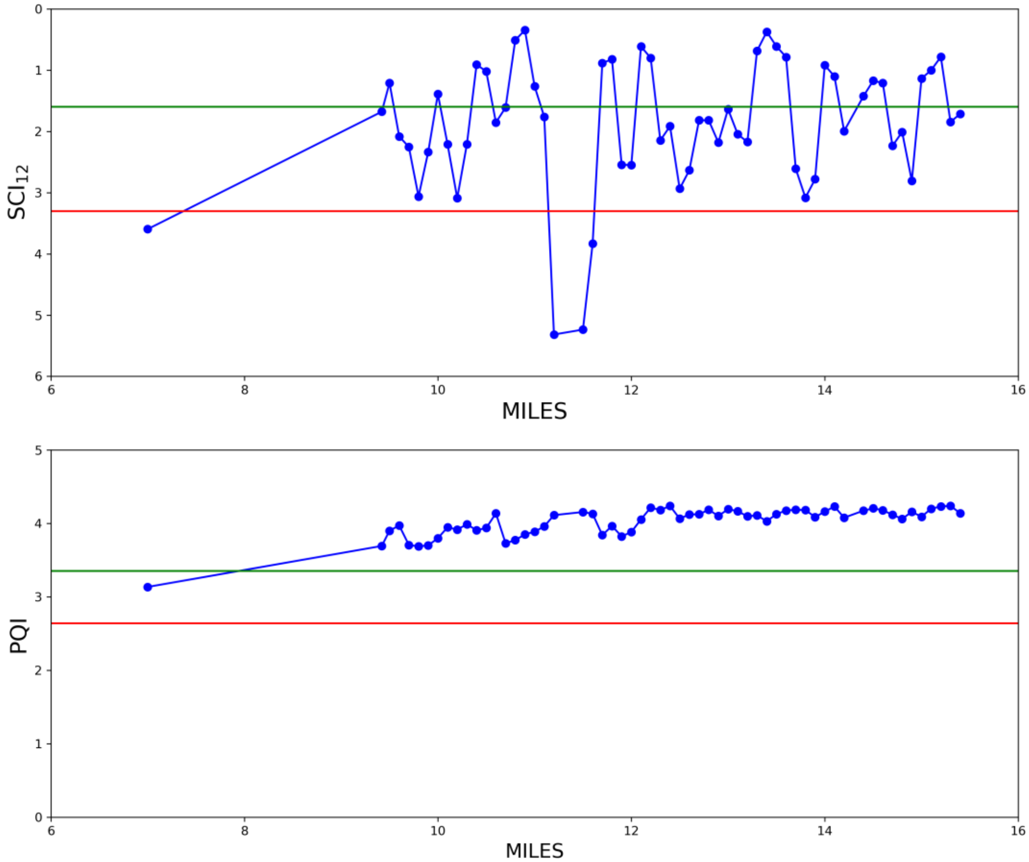




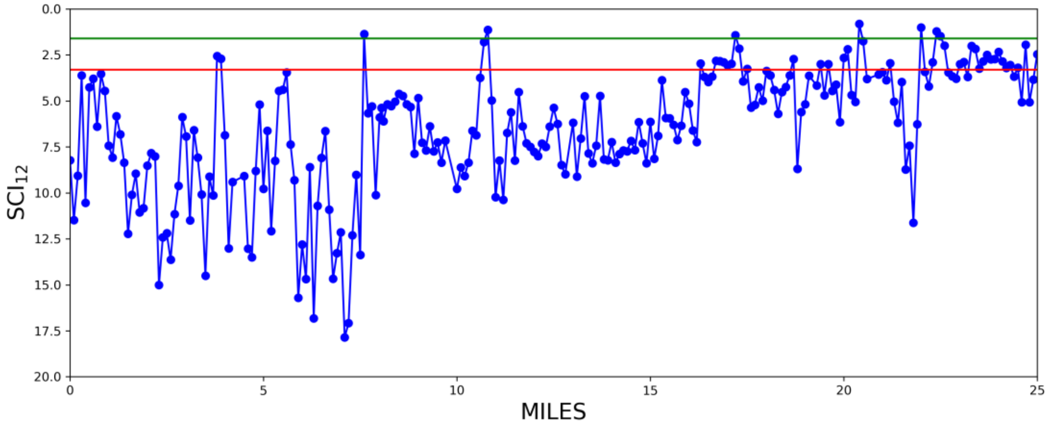
SCI$_{12}$ and PQI of Lexington County of US-378

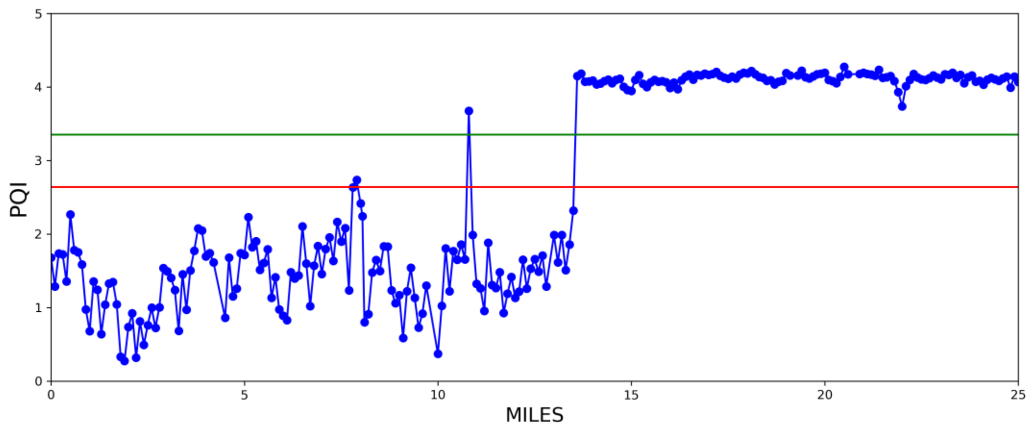


SCI$_{12}$ and PQI of Marion County of US-378

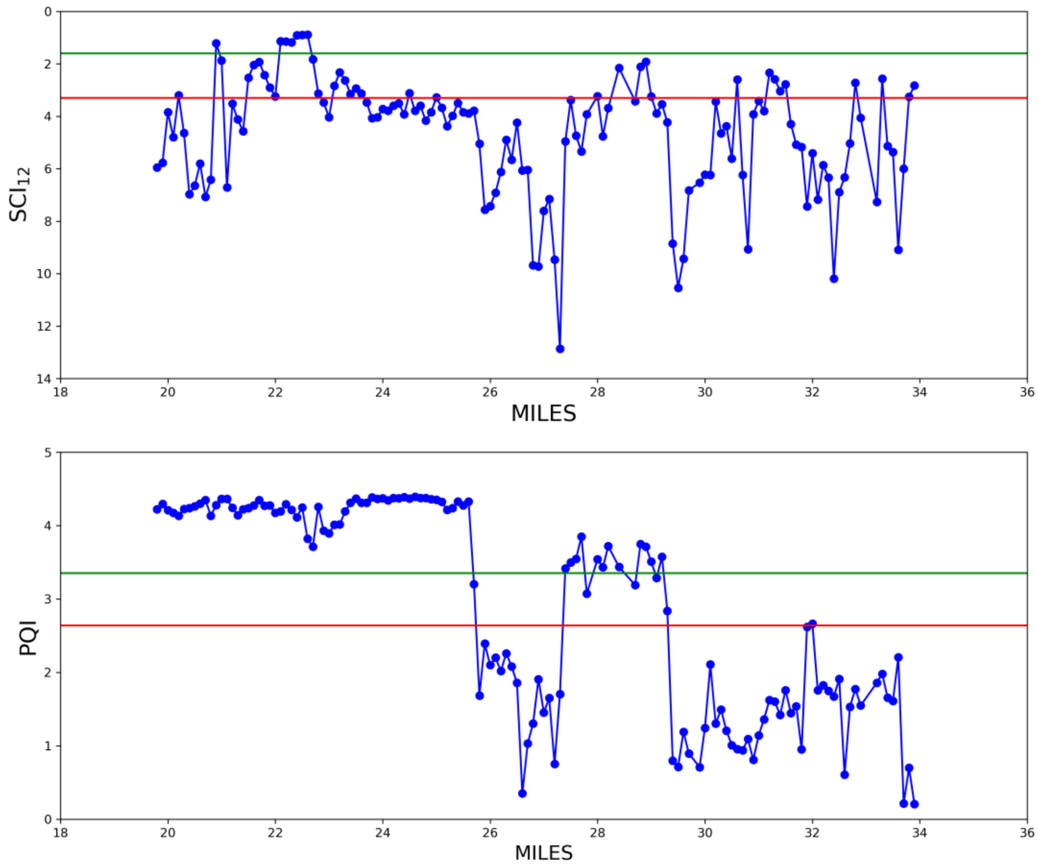


SCI$_{12}$ and PQI of McCormick County of US-378

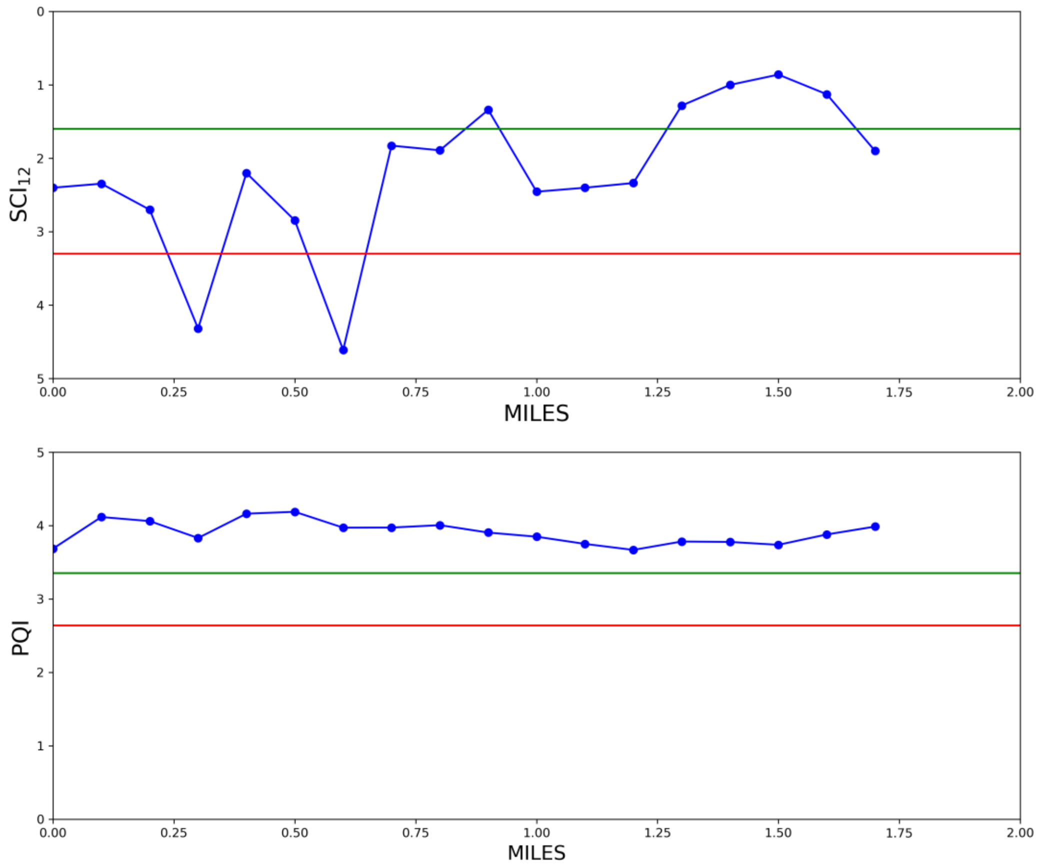




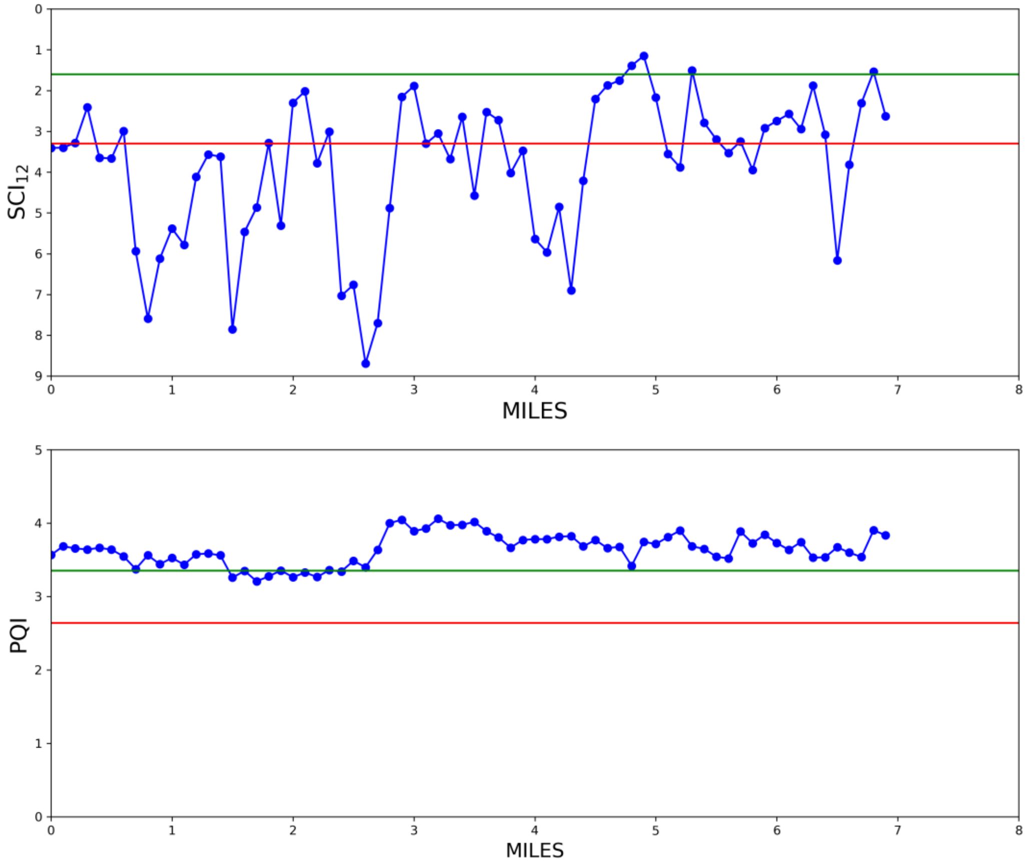
SCI$_{12}$ and PQI of Saluda County of US-378



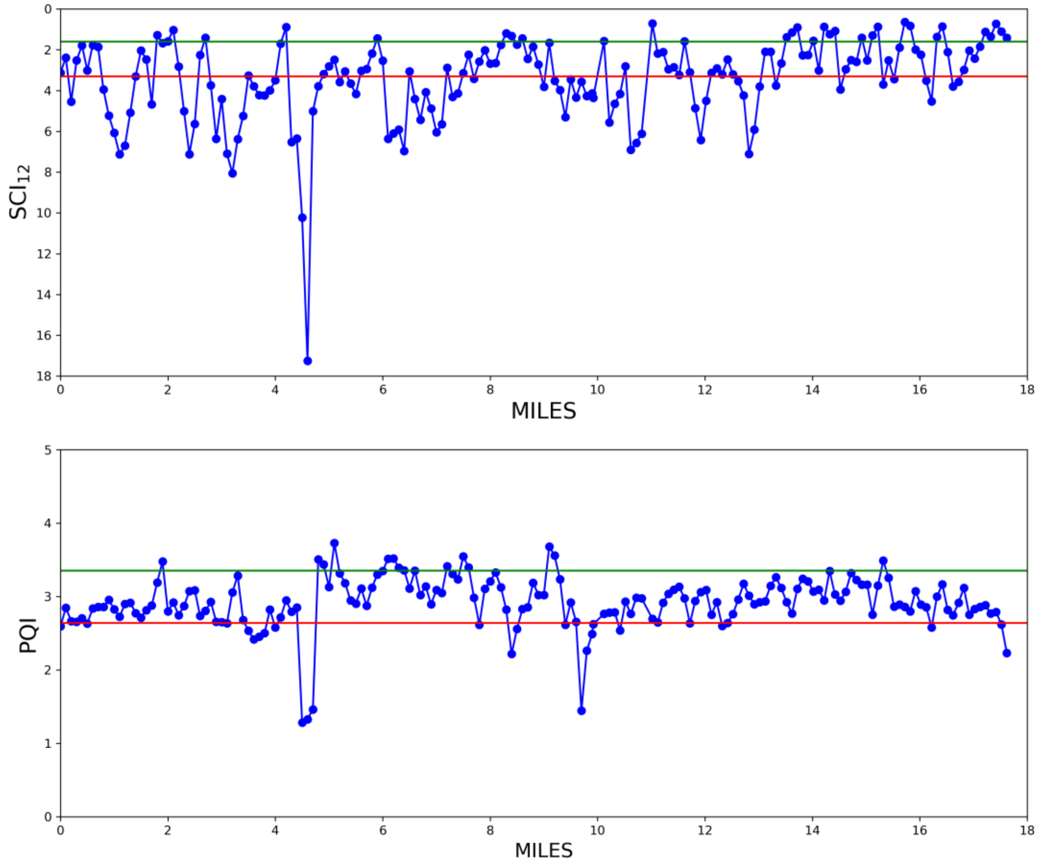
SCI$_{12}$ and PQI of Sumter County of US-378



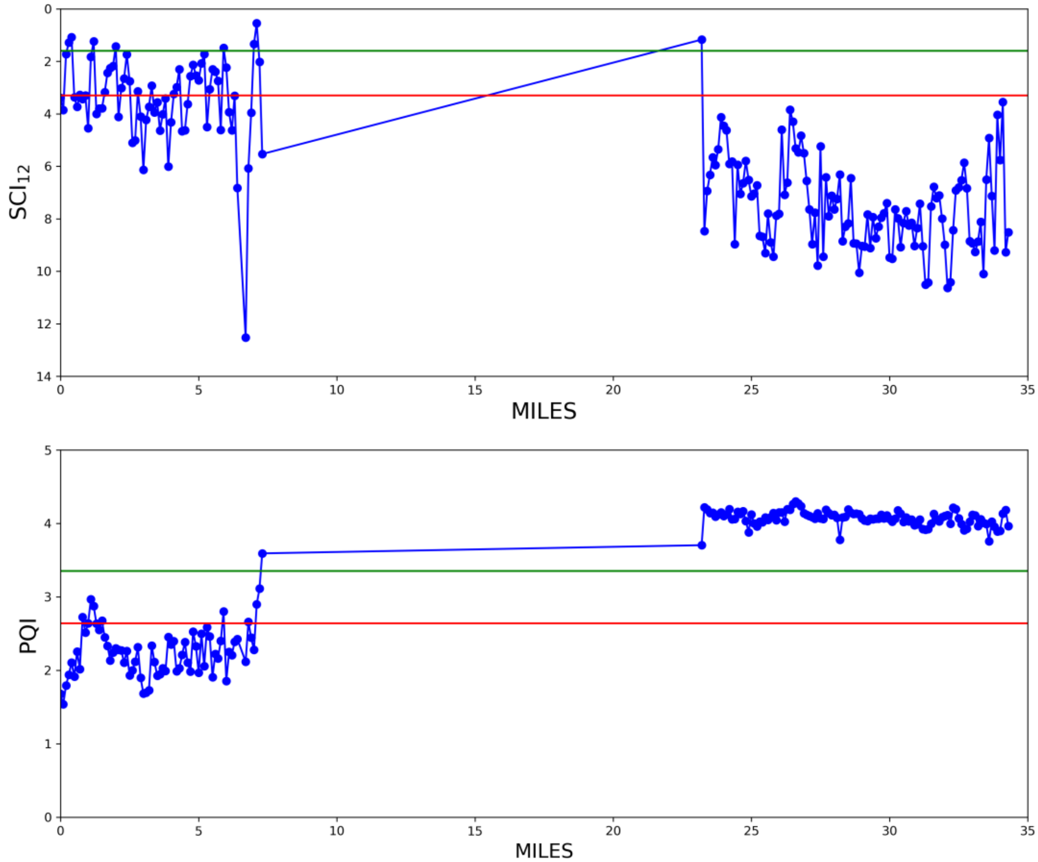
SCI$_{12}$ and PQI of Williamsburg County of US-378



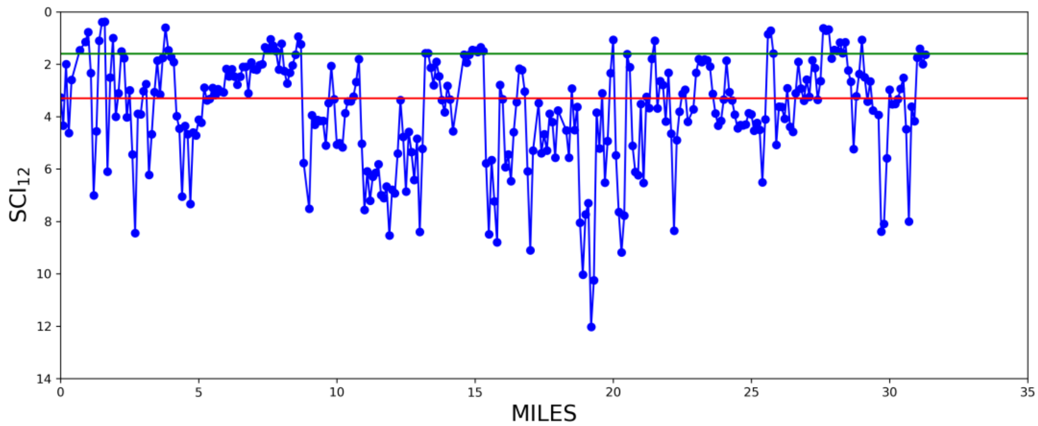
SCI$_{12}$ and PQI of Abbeville County of US-178

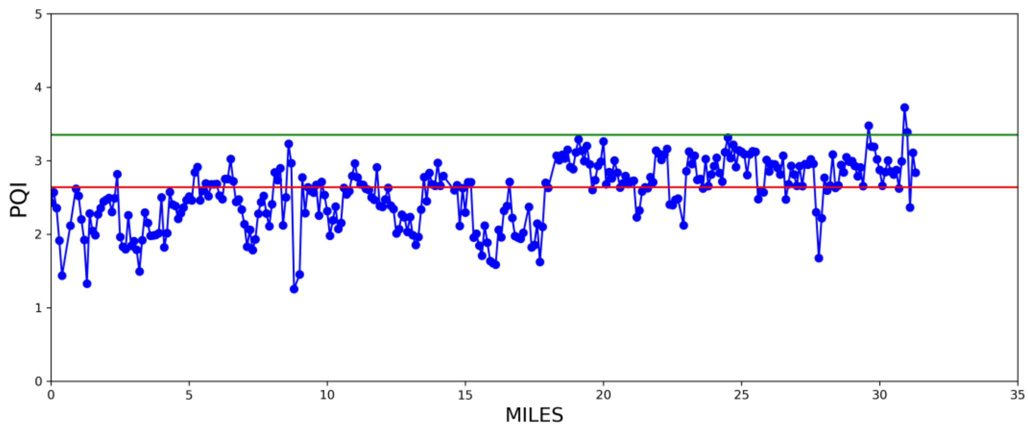


SCI_{12} and PQI of Dorchester County of US-178

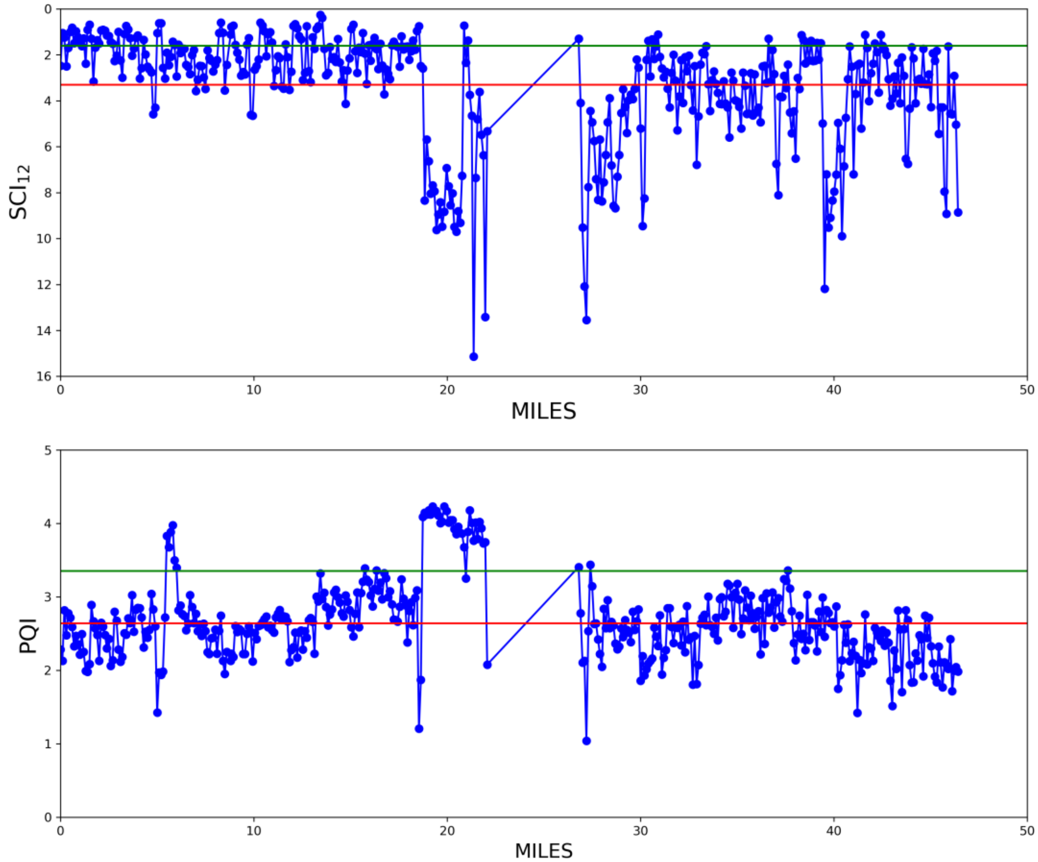


SCI$_{12}$ and PQI of Greenwood County of US-178

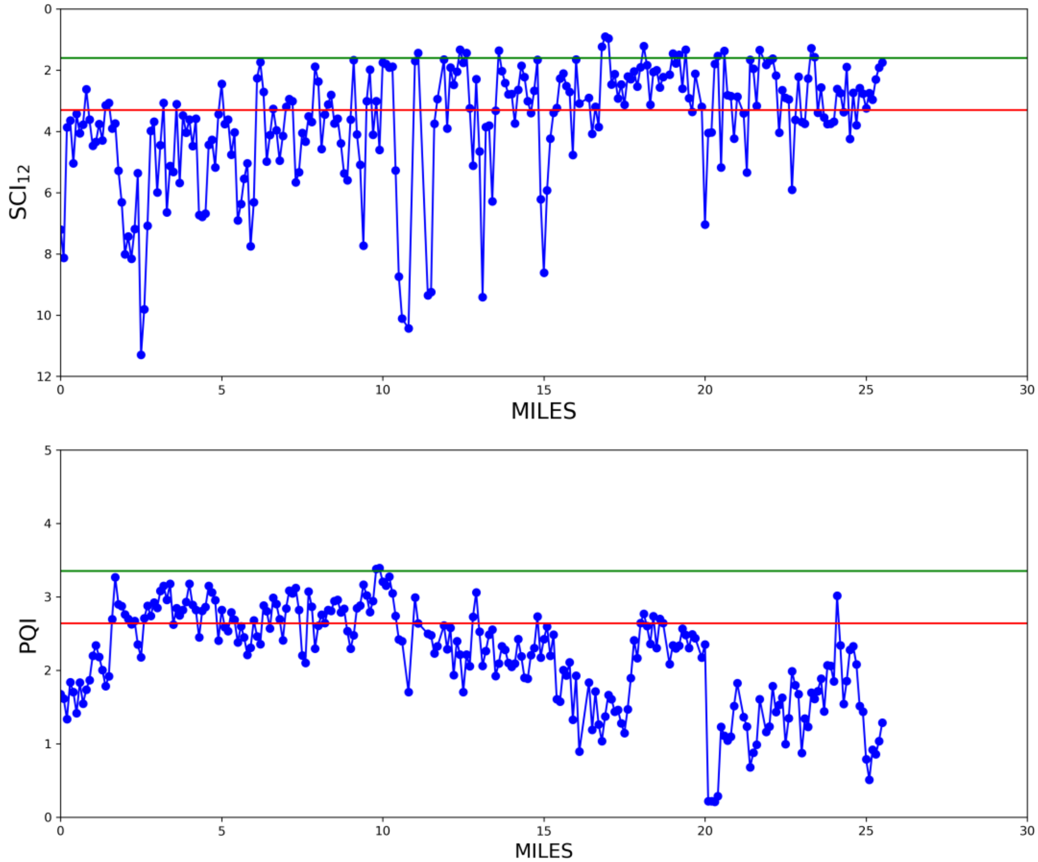




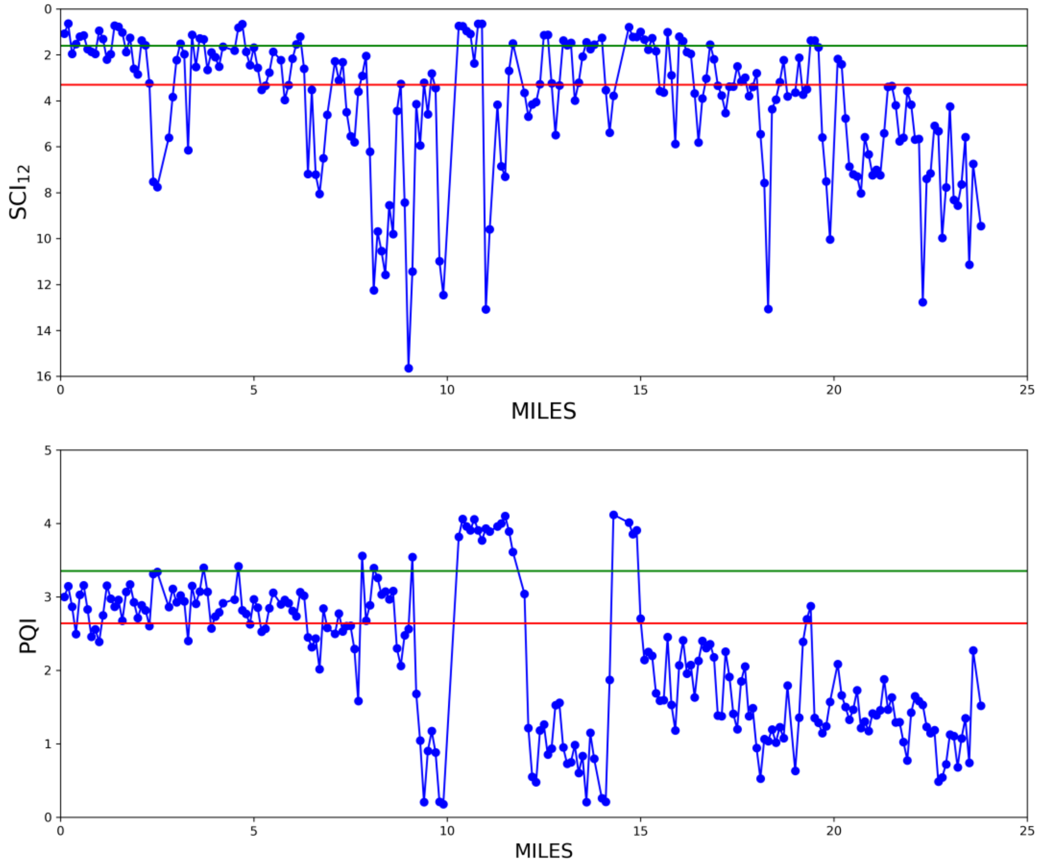
SCI$_{12}$ and PQI of Lexington County of US-178



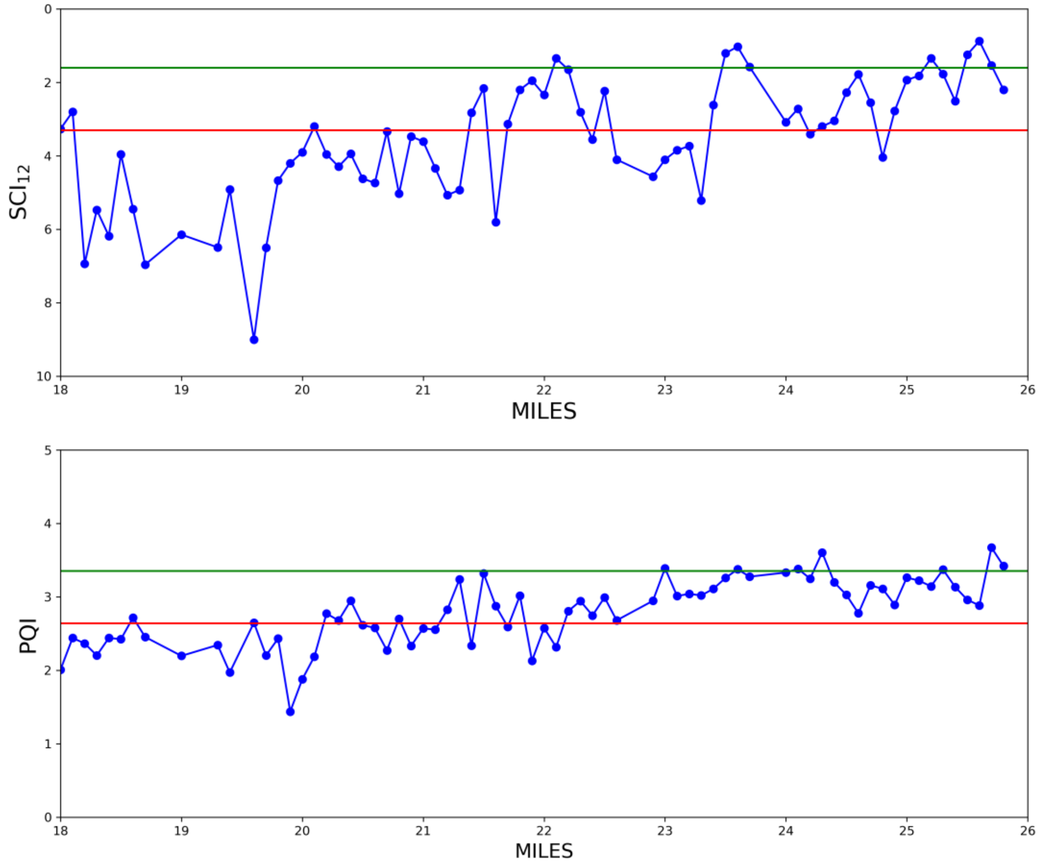
SCI$_{12}$ and PQI of Orangeburg County of US-178



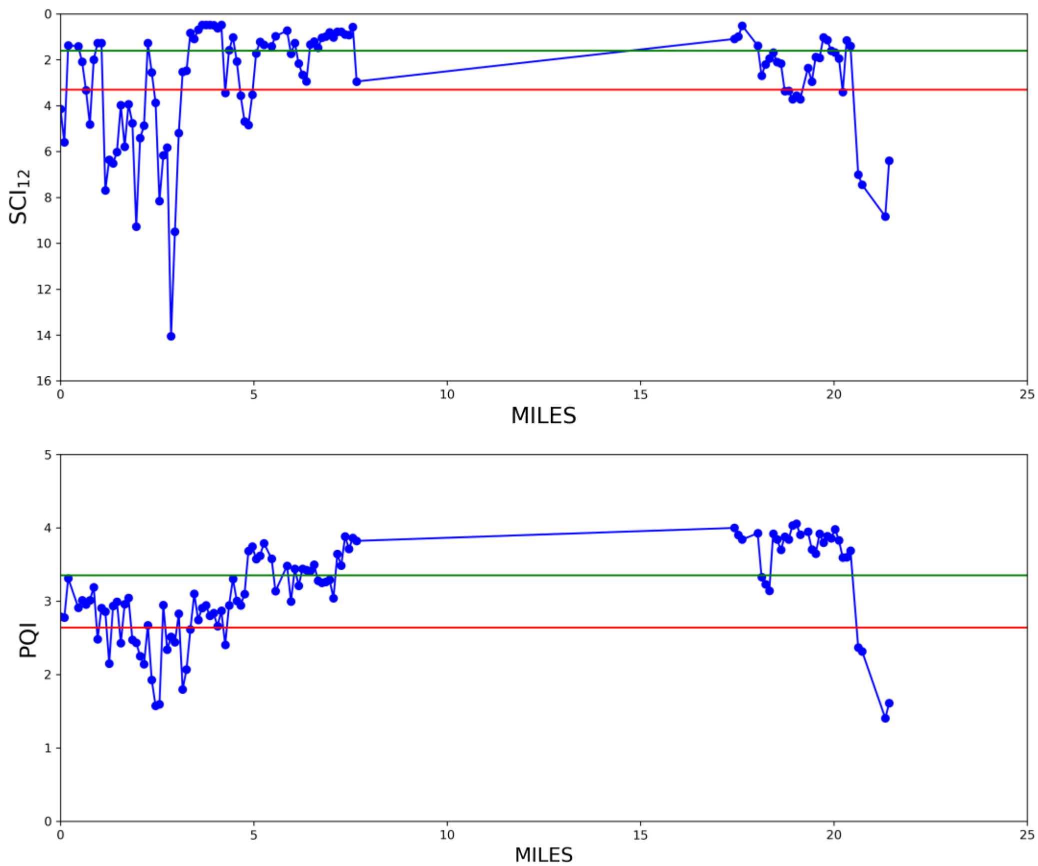
SCI$_{12}$ and PQI of Saluda County of US-178



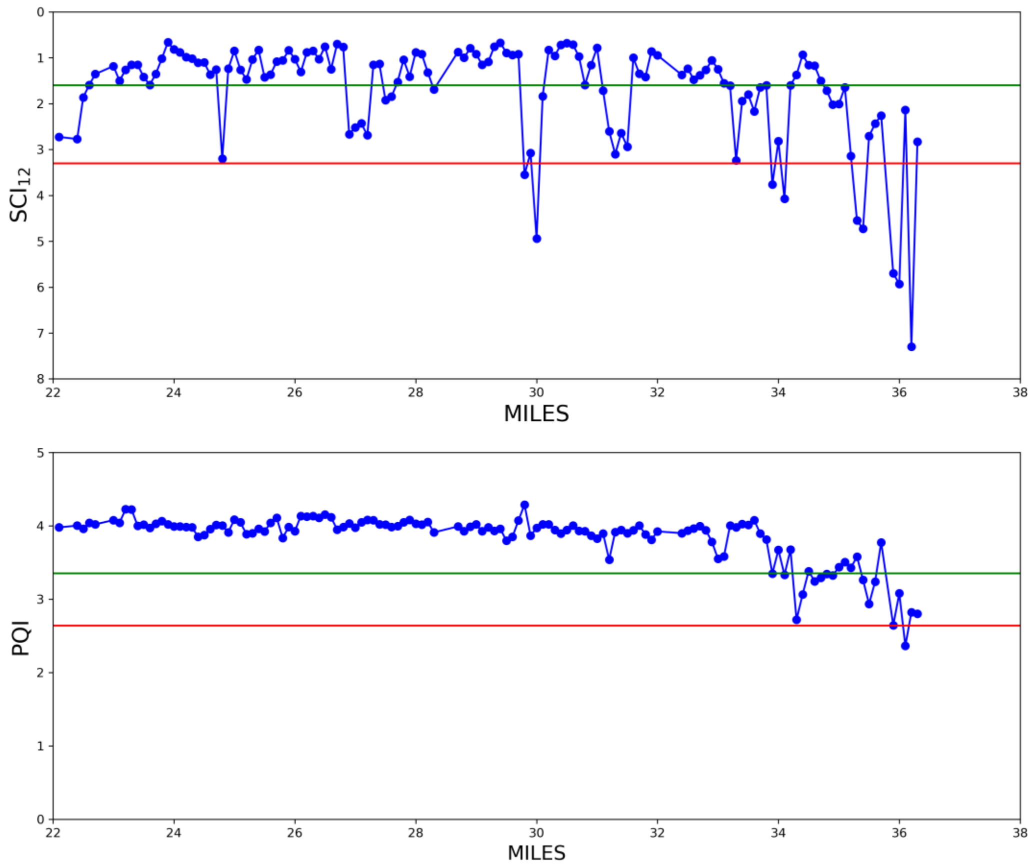
SCI$_{12}$ and PQI of Cherokee County of US-29



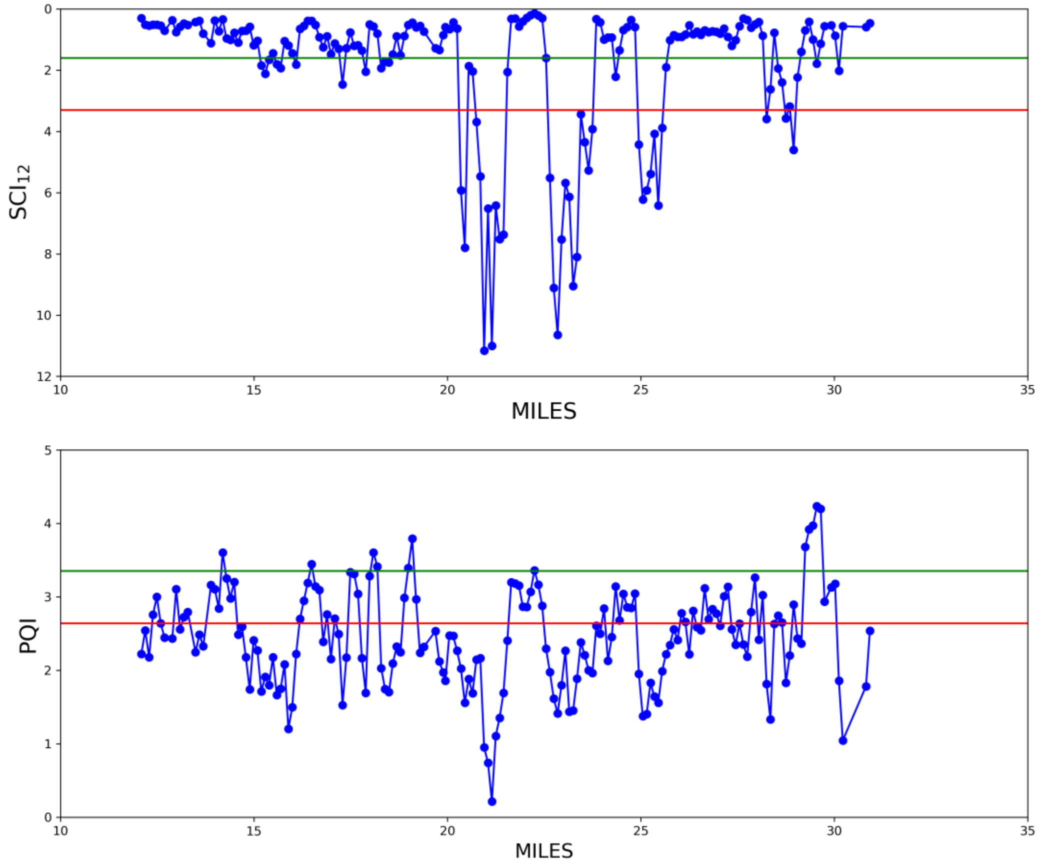
SCI$_{12}$ and PQI of Sparatnburg County of US-29



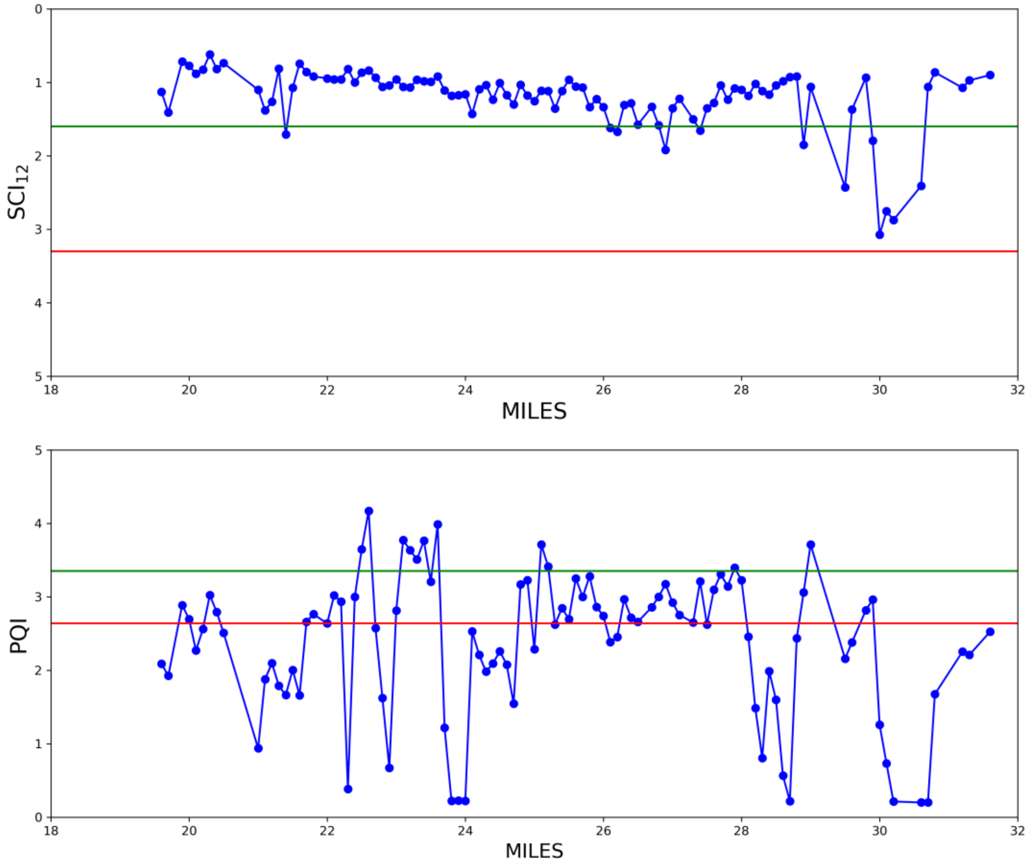
SCI_{12} and PQI of Charleston County of US-78



SCI$_{12}$ and PQI of Dorchester County of US-78



SCI$_{12}$ and PQI of Horry County of US-17

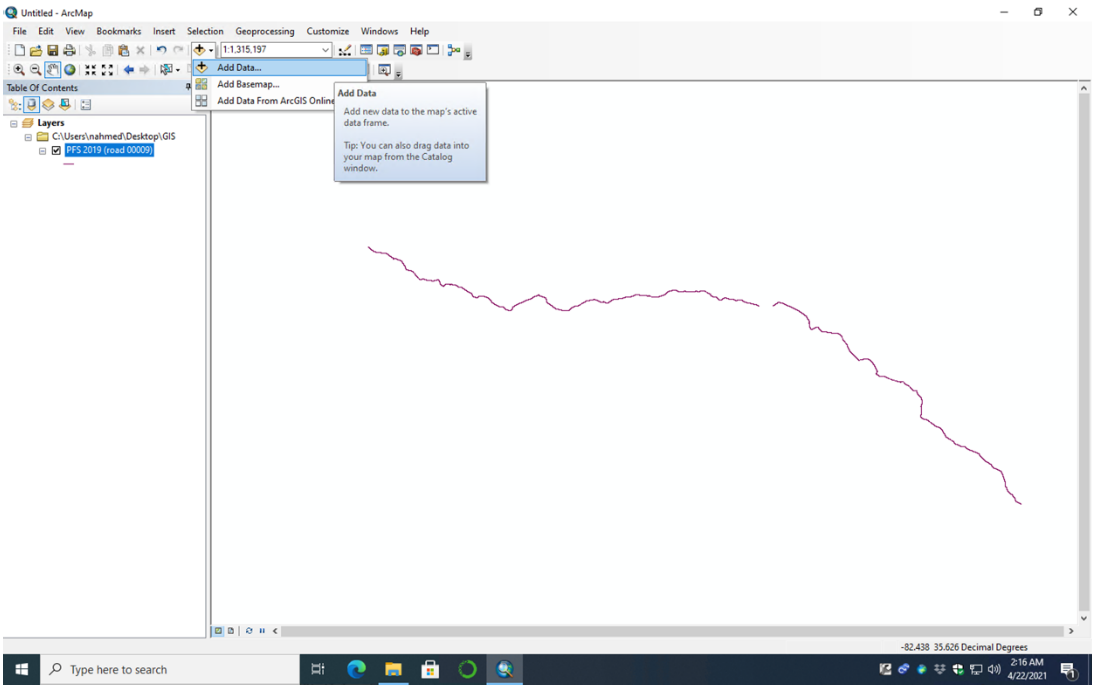


SCI$_{12}$ and PQI of Horry County of US-501

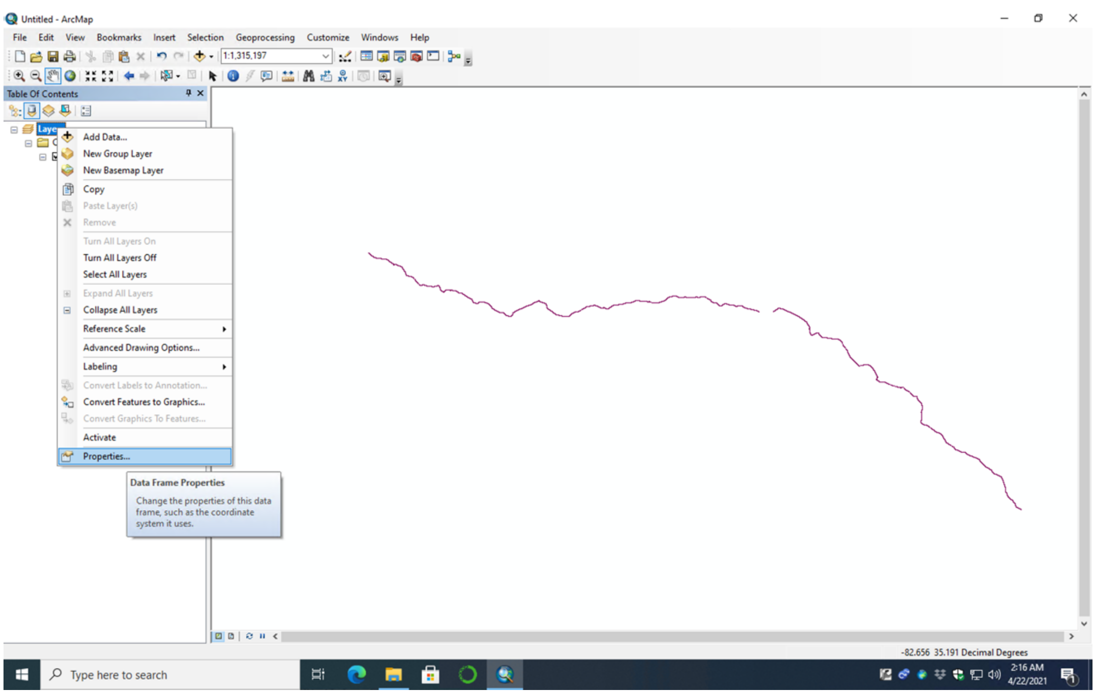
APPENDIX H

Converting TSD Data in WGS84 to NAD83 Coordinate System

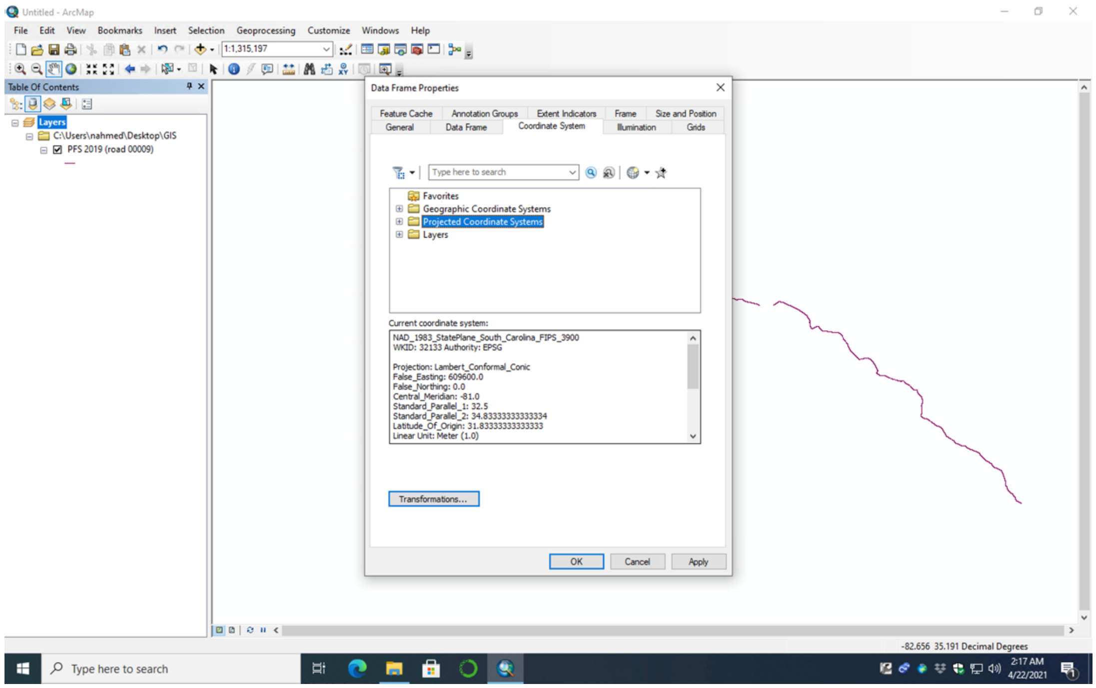
- Step 1: Open ArcMap (version 10.8.1 was used at the time of this project). Then select the "Add Data" icon as shown below. This option will open Windows File Diaglog. Select the file that contains the shapefile of the TSD route. This can be accomplished using Hawkeye Insight via the option "Export Shapefile".



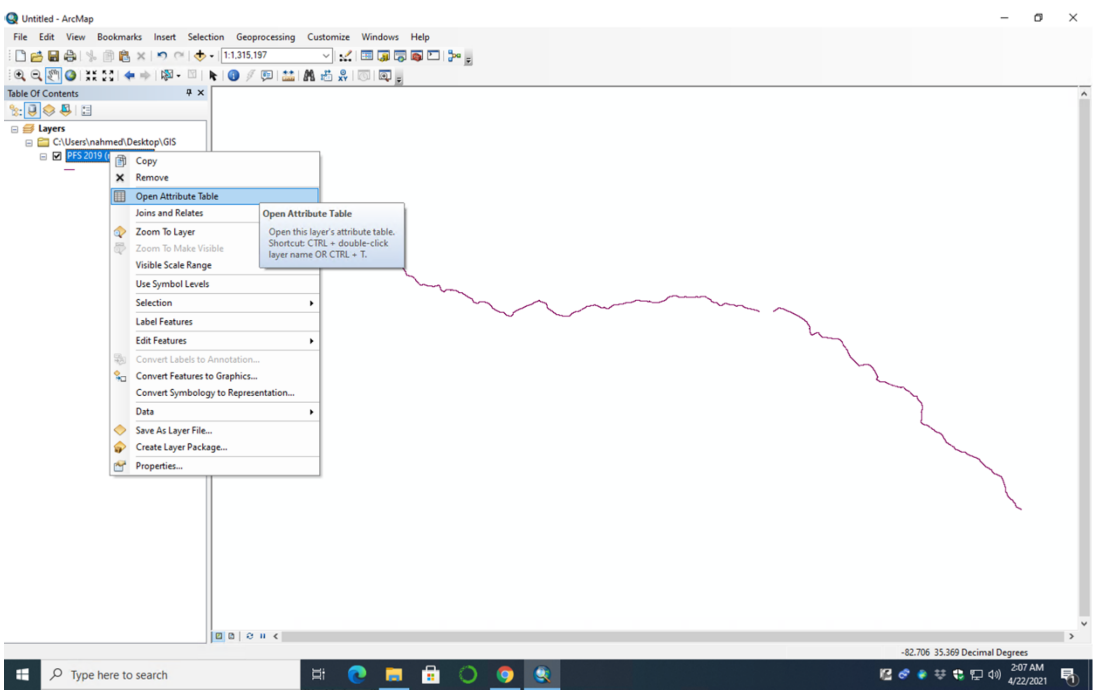
- Step 2: Right click on the "Layers" icon and thenselect "Properties" as shown below.



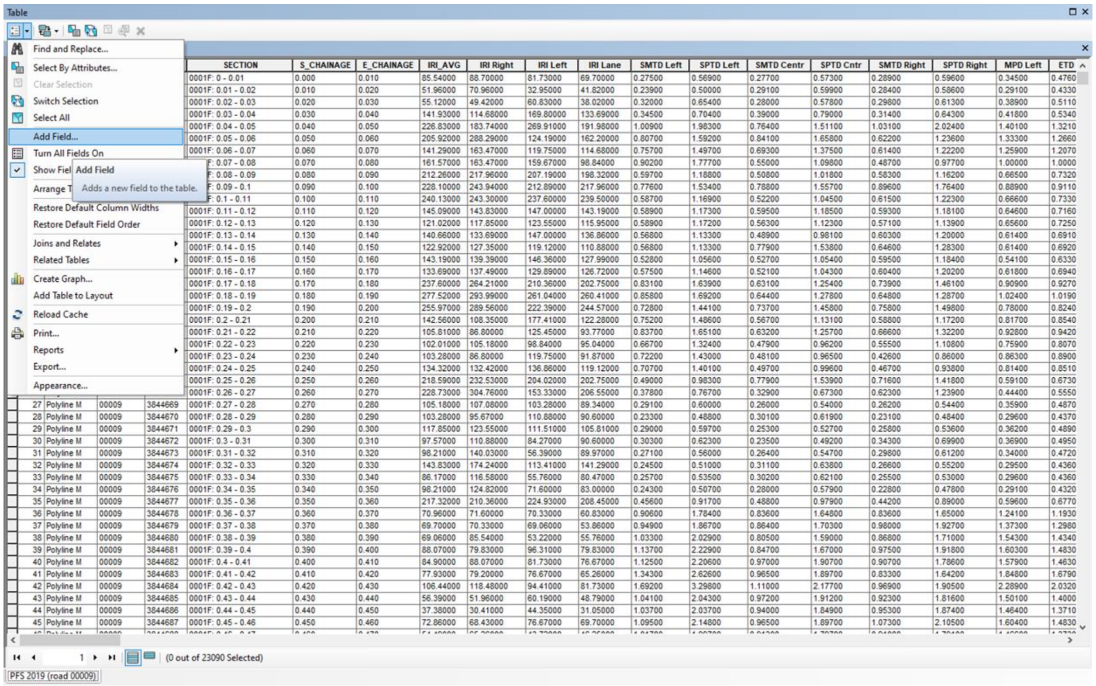
- Step 3: Expand the option “Projected Coordinate Systems”, select the option “NAD 1983 StatePlane South Carolina FIPS 3900 (Meters)”, click Apply and then click OK.



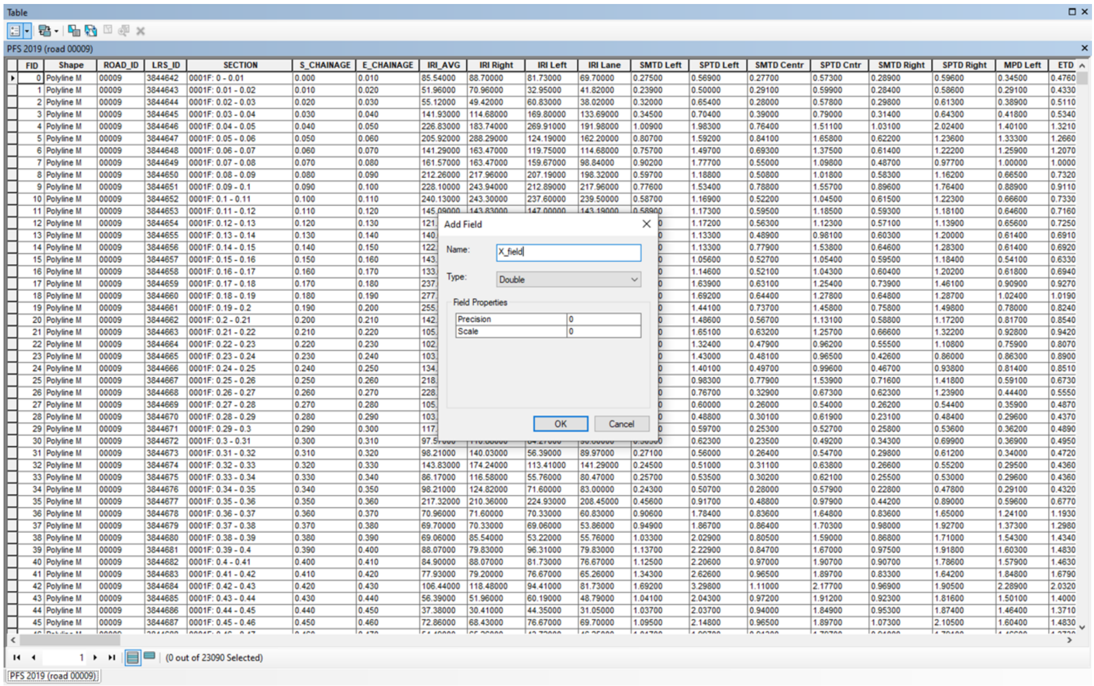
- Step 4: Right click on the option “Open Attribute Table” as shown below.



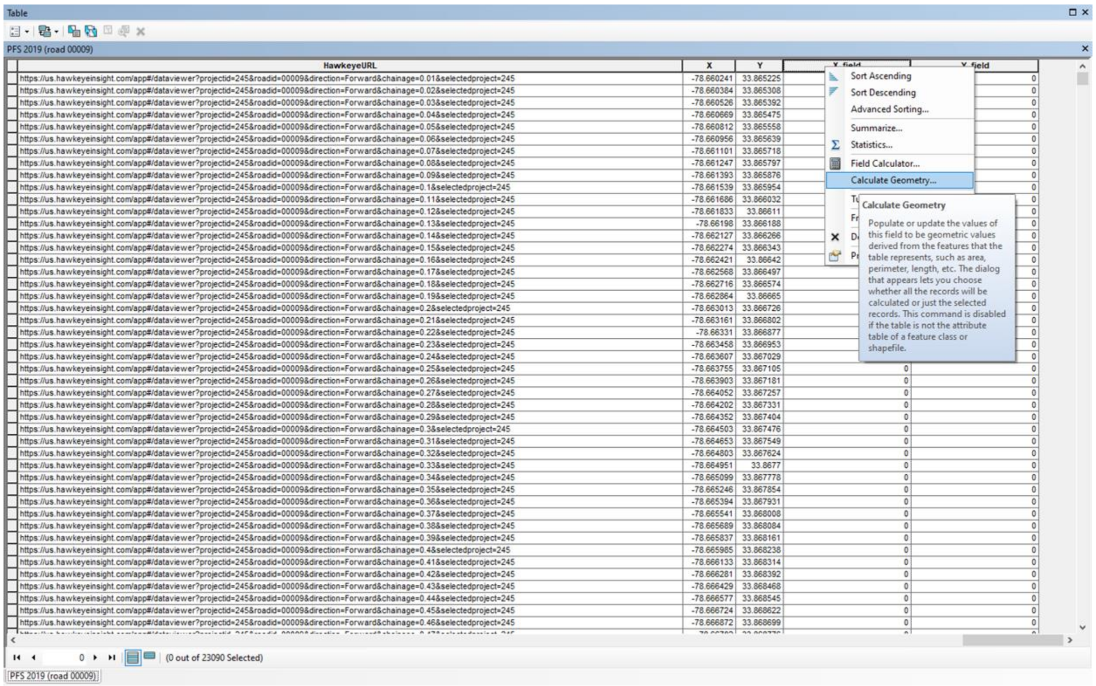
- Step 5: After completing the previous step, you should a table like the one shown below. Click on “Add Field” as shown below.



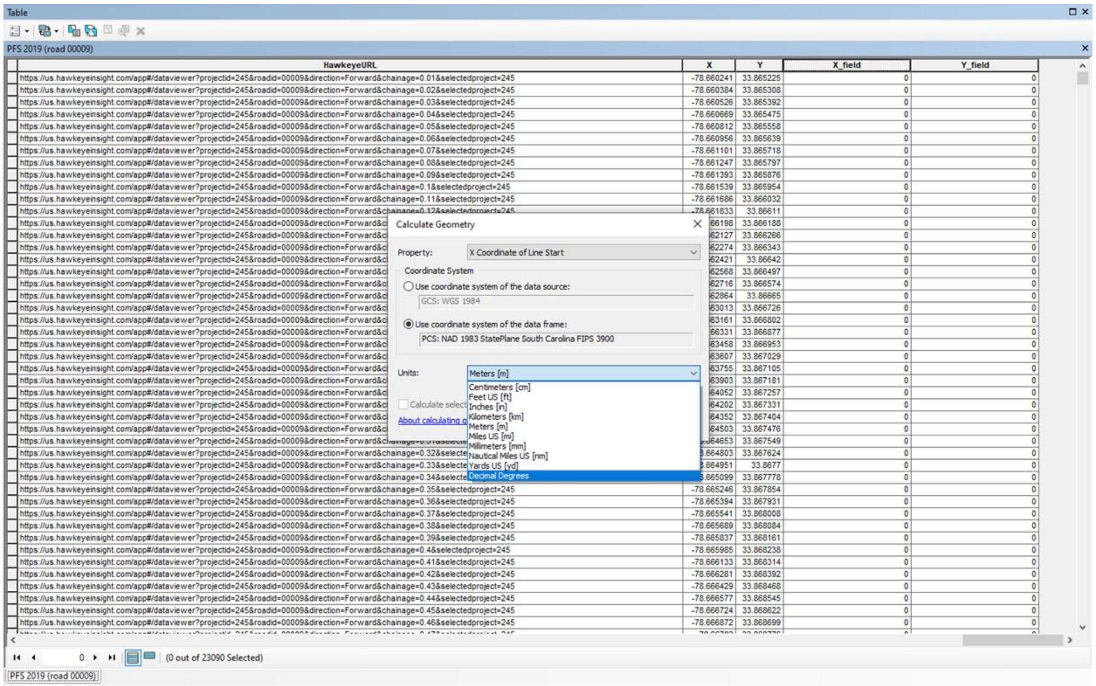
- Step 6: Write X_field in the textbox as shown below and then click “OK”. Repeat Steps 5 and 6 and enter “Y_field” instead of “X_field”.



- Step 7: Right click on the column named "X_field" and select "Calculate Geometry".



- Step 8: Select the option "X Coordinate of Line Start" and "Decimal Degrees" as shown below, and then click "OK". Repeat Steps 7 and Step 8 in for the column "Y_field" and select the option "Y Coordinate of Line Start" and "Decimal Degrees". After completing Step 8, X_field and Y_field columns will show the longitude and latitude values in NAD83 coordinate system.



- Step 9: The last step is to export this table. When exporting this table, select the option “dBASE table” as shown below. A file with the extension “.dbf” will be saved to the local drive. This file can be opened using Excel.