Report of Preliminary Analyses

Task 3.1 & 3.2 Deliverable for the project

Synthesizing Detailed Expert Guidance on Florida Department of Environmental Protection's Septic Vulnerability Assessment Model and Pilot-Testing Recommended Improvements

DEP Agreement # AT006

For the Florida Department of Environmental Protection,

Office of Environmental Accountability and Transparency

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Task 3 Overview

This report focuses on the final component (Task 3) of a larger project supported by the Florida Department of Environmental Protection (DEP) focused on gathering and synthesizing expert input on a tool for assessing the potential vulnerability of waterbodies to Onsite Sewage Treatment and Disposal System (OSTDS) pollution in Florida. The tool includes an interactive map that projects an assessment of waterbody vulnerability to OSTDS pollution within a dashboard created by SAS for DEP; the assessment that the tool shares is based on parameters related to OSTDS pollutant load and transport, as well as the likelihood of OSTDS-derived pollution affecting sensitive waters. This 3-task project aims to deliver expert-vetted, literature-informed guidance about how to refine the tool, evaluate its performance, and recommend future improvements to the tool that may be achieved over time.

Task 1 entailed the completion of a literature review of assessment approaches and parameters commonly used in such assessments, as well as a survey of how experts in OSTDS, water quality, and other relevant topics in the state would prioritize parameters in such a tool. In Task 2, the project team hosted a workshop in which OSTDS experts identified a list of parameters important to influencing the potential for pollution from OSTDS to nearby water bodies, prioritized these parameters, and made recommendations related to the weights to be applied to the parameters in the assessment. Participants also identified areas of distinct geology and development around Florida that they felt would make suitable locations to pilot-test the assessment updated based on their input from the workshop. Task 3, which we summarize in the report below, builds upon the former task in its focus on implementing and evaluating the parameter ranking and weighting identified in the workshop and pilot testing its performance in a few representative locations.

While pilot testing and review of the new assessment has been completed and is summarized below, we acknowledge that there were limitations in both time and resources that affected the team's ability to implement all the suggestions identified by workshop participants. Prior to reviewing our Task 3 findings, we urge our readers to take note of these limitations. Specifically, although the participants recommended that we include 23 parameters in the assessment, the updated assessment our project team applied included only the 8 parameters that were already cleaned and integrated within the SAS dashboard. Thus, the updated assessment does not include parameters, such as topography and potential for flooding, that were identified as important by workshop participants. In addition, in this report, we related the initial and updated vulnerability assessment values to a water quality impairment metric that integrates water quality analytes, such as nitrogen levels, that may be affected by sources other than OSTDS. Suggestions for overcoming these challenges in the input parameters to the assessment and for addressing the water quality data limitations are provided in the recommendations section.

This report summarizes comparison methods, statistical results, and model comparison results of Task 3. The report first describes the method used for developing a new water quality vulnerability index (hereafter, 'WQVI-ST') due to OSTDS. The WQVI-ST was developed using expert guidance from workshop. For comparison, we also report findings based on the previously developed assessment calculated in the SAS dashboard prior to the start of this project. This initial assessment is hereafter referred to as the 'SAS OSTDS score'. To evaluate these indices, their statistical relation to the widely used NSF International's water quality index (WQI) was examined at the HUC 8 and HUC12 watershed levels. It is expected that a HUC12 unit with high WQVI-ST or SAS OSTDS score would have a low WQI. Next, the method of estimating WQI is described and the relation between WQI and WQVI-ST and between WQI and the SAS OSTDS score are examined for five HUC8 sub-basins which were selected based on guidance provided by the workshop participants in Task 2. Finally, comparison results are shown and recommendations are given.

Method of Estimating Vulnerability Index

This section explains the method for calculating a new water quality vulnerability index due to OSTDSs (WQVI-ST). The calculation is theoretically similar to the calculation of the SAS OSTDS score. WQVI-ST is calculated via Equation (1):

$$\text{WQVI-ST} = \sum_i W_i R_i \quad (1)$$

where W_i is the weight for the *i*-th parameter (i = 1, 2, …, 8) and R_i is the rating of the *i*-th parameter.

A higher WQVI-ST value means water quality is expected to be more vulnerable to OSTDS contamination. The methods for estimating weights and ratings are described below. In this project, WQVI-ST was developed by the FSU/UF project team, and calculations were implemented by DEP's data analytics contractor, SAS. SAS delivered the WQVI-ST results for parcels and HUC12 units to the FSU/UF team, and the HUC 12 results were used for analysis below.

Eight Parameters and Their Weights

Table 1 lists the eight parameters that were used for the WQVI-ST calculation. Note that these eight parameters were used by SAS for calculating the SAS OSTDS score, but are referred to as "factors" in SAS presentations. While pedality was used in the SAS OSTDS score calculation, it was not used for the WQVI-ST calculation because pedality was not recommended by attendants of the workshop that was held on May 5, 2022 and May 6, 2022.

Table 1. Names of eight parameters and their weights used for calculating water quality vulnerability index due to OSTDSs (WQVI-ST). SAS also used the eight parameters for calculating the SAS OSTDS score.

Parameter Name	Mean Priority	Temporary Weights	Final Weights
Depth to Groundwater	1.25	1.00	20.37%
Distance to NHD Waterbody	1.36	0.92	18.76%
Parcel Density	1.43	0.88	17.82%
OSTDS Age	2.11	0.59	12.08%
Weighted Hydraulic Conductivity	2.32	0.54	10.97%
Population	3.68	0.34	6.92%
Drainage Class	3.79	0.33	6.72%
Within a Springshed	4.00	0.31	6.36%

Sum		4.91	100%

The "Final Weights" listed in the last column of **Table 1** are the W_i values used for implementing Equation (1). The final weights were determined by following the procedure described in McClelland (1974) for estimating the weights of the NSF International WQI. The final weights were estimated in the following four steps:

Step 1: On Day 2 of the two-day workshop, the attendants were asked to assign priority to a total of 23 parameters compiled on Day 1 of the workshop. The priority scale is 1 through 5, with 1 being the highest priority (or highest relative value) and 5 being the lowest priority (or lowest relative value). Most workshop attendees only assigned priority values to a portion of the 23 parameters. For the parameters that did not have a priority value, a default value of 5 was used.

Step 2: Arithmetic means of the priority values were calculated for each of the 23 parameters. **Table 1** lists these arithmetic means (called mean priority in the table) of the eight parameters used in the index.

Step 3: A temporary parameter weight was calculated as the ratio between the minimum mean priority (i.e., 1.25 for depth to groundwater) and each parameter's mean priority. For example, the temporary weight of parameter "Depth to Groundwater" was calculated as 1.25/1.25 = 1.0, and the temporary weight of parameter "Distance to Nearest Surface Water body" was calculated as 1.25/1.36 = 0.92. The sum of the temporary weights is 4.91; see **Table 1**.

Step 4: Each temporary weight was divided by the sum of all temporary weights to obtain the final weights, W_i, listed in the last column of **Table 1**. The final weights sum to 100%.

The first five parameters in **Table 1** also received the most significant weights among the 23 parameters. However, the other three parameters (Population, Drainage Class, and Within a Springshed) listed in **Table 1** did not receive large weights. In other words, the workshop attendants did not think these three parameters were as highly relevant to water quality vulnerability due to OSTDSs.

Parameter Ranges and Ratings

The parameter ratings (R_i) were estimated in the manner of estimating parameter ratings for the U.S. Environmental Protection Agency (EPA) DRASTIC index documented in Aller et al. (1987). The DRASTIC Index uses the parameters: **D**epth to water table, net **R**echarge, **A**quifer media, **S**oil media, **T**opography (slope), **I**mpact of vadose zone, and **C**onductivity (hydraulic) of the aquifer. This estimation is done in the following two steps:

Step 1: Each parameter was divided into either ranges or types (categories).

Step 2: Ratings for each parameter range were set to reflect their relative effects on potential of water quality vulnerability due to OSTDSs. The rating scale ranges from 1 to 100, with 100 being the highest potential for water quality vulnerability.

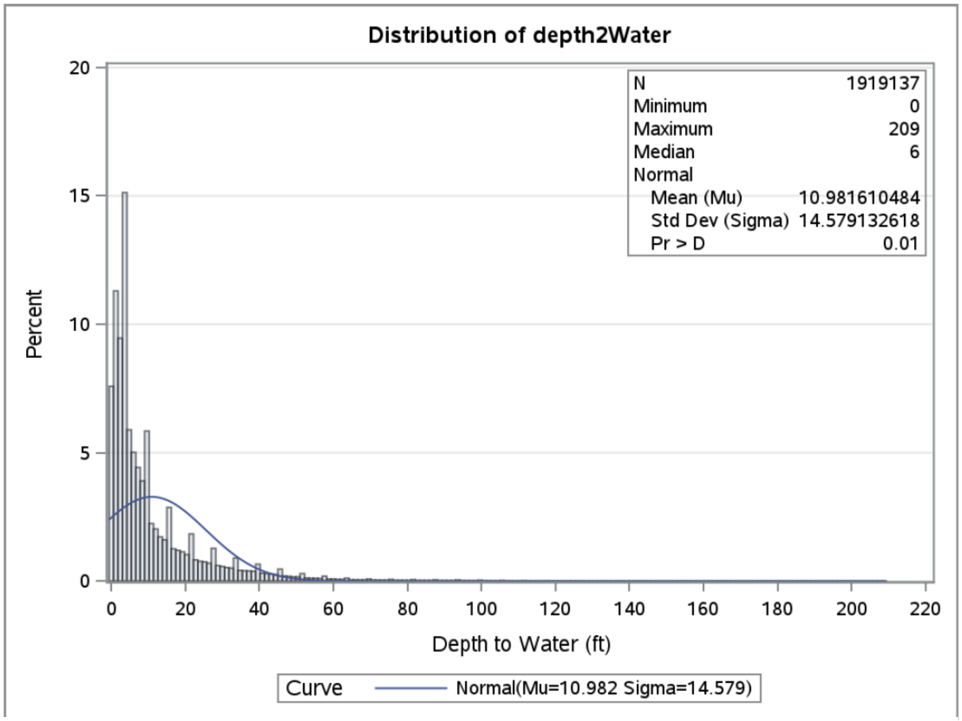
Neither the ranges nor the ratings were discussed during the workshop, and Ming Ye of the FSU/UF team determined them based on his experience and literature information.

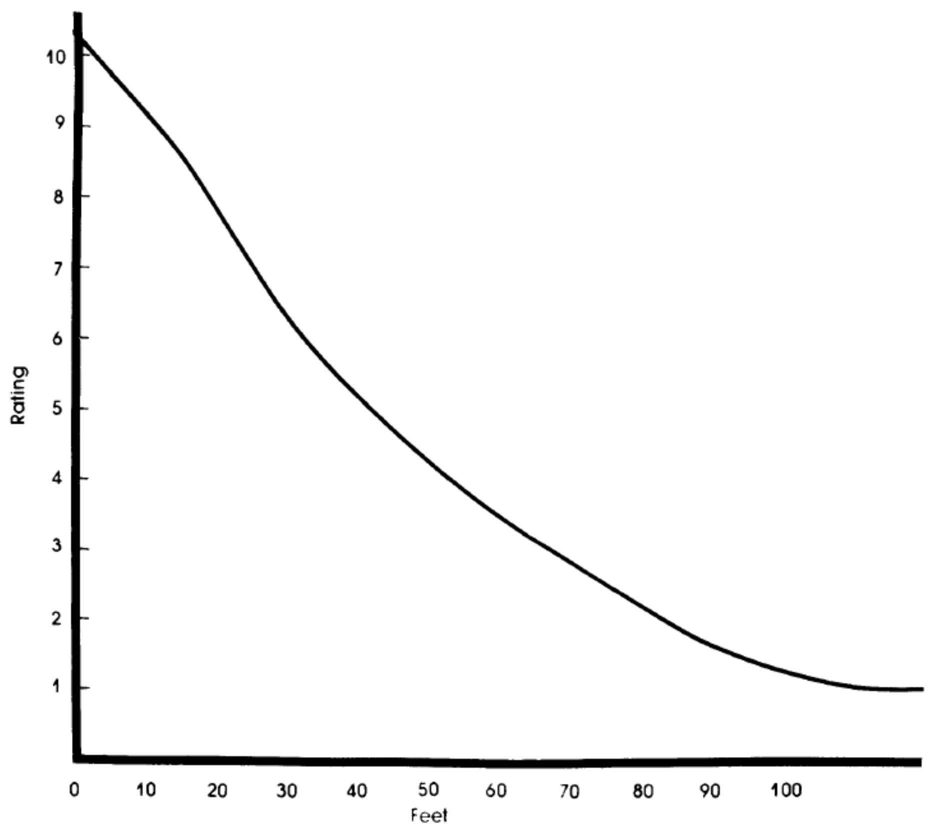
Depth to Groundwater (ft)

For Depth to Groundwater, the probability density function (PDF) of input data was provided by SAS and is shown in the top plot of **Figure 1**. The plot shows that the parameter ranges from 0 to 209 feet, with the median and mean of 6 feet and 10.98 feet, respectively. The percent (on the *y*-axis of the plot, i.e., relative frequency) decreases to zero after about 80 feet. Based on these data, and comparing parameter ranges with those used in the EPA DRASTIC (listed in **Table 2**), the rating scheme of EPA DRASTIC was adapted, with adjusted ranges as shown in **Table 2**. The adjustment was needed mainly because there were no values greater than 80 feet (see **Figure 1**). The bottom plot of **Figure 1** illustrates the variation of the ratings and is adopted from Aller et al. (1987) for EPA DRASTIC.

Table 2. Ranges and ratings for Depth to Groundwater were used for EPA DRASTIC and this study.

Range (EPA Drastic)	Rating (EPA DRASTIC)	Range (this study)	Rating (this study)
0-5	10	0-5	100
5-15	9	5-15	90
15-30	7	15-30	70
30-50	5	30-40	50
50-75	3	40-60	30
75-100	2	60-80	20
100+	1	80+	10


Distribution of depth2Water
N 1919137
Minimum 0
Maximum 209
Median 6
Normal
Mean (Mu) 10.981610484
Std Dev (Sigma) 14.579132618
Pr > D 0.01
Percent
Depth to Water (ft)
Curve
Normal(Mu=10.982 Sigma=14.579)


Rating
Feet

C

Distance to NHD Water Body (mile)

For the distance to the NHD Water Body, the top plot (provided by SAS) of **Figure 2** shows that the parameter ranges between 0 and 12.41 miles, with the median and mean of 0.14 miles and 0.28 miles, respectively. The percent (on the *y*-axis of the plot, i.e., relative frequency) decreases to zero after about 2 miles. Nitrogen load from a OSTDS to a surface water body decreases when the distance between the OSTDS and the water body increases. In other words, water quality vulnerability due to OSTDSs decreases when the distance to the surface water body increases. Ye et al. (2017) work in the St. Lucie River and Estuary watershed indicates that the decrease follows an exponential function, as shown in the middle plot of **Figure 2**. It is thus assumed that the rating of distance to NHD water body (R_{disw}) follows Equation (2):

$$R_{disw} = 100e^{-2.3disw} \tag{2}$$

where *disw* (in miles) is the distance to the NHD water body.

For reference, the rating is 100, 10, and 1 for distances of 0, 1, and 2 miles, respectively. The function is illustrated in the bottom plot of **Figure 2**.

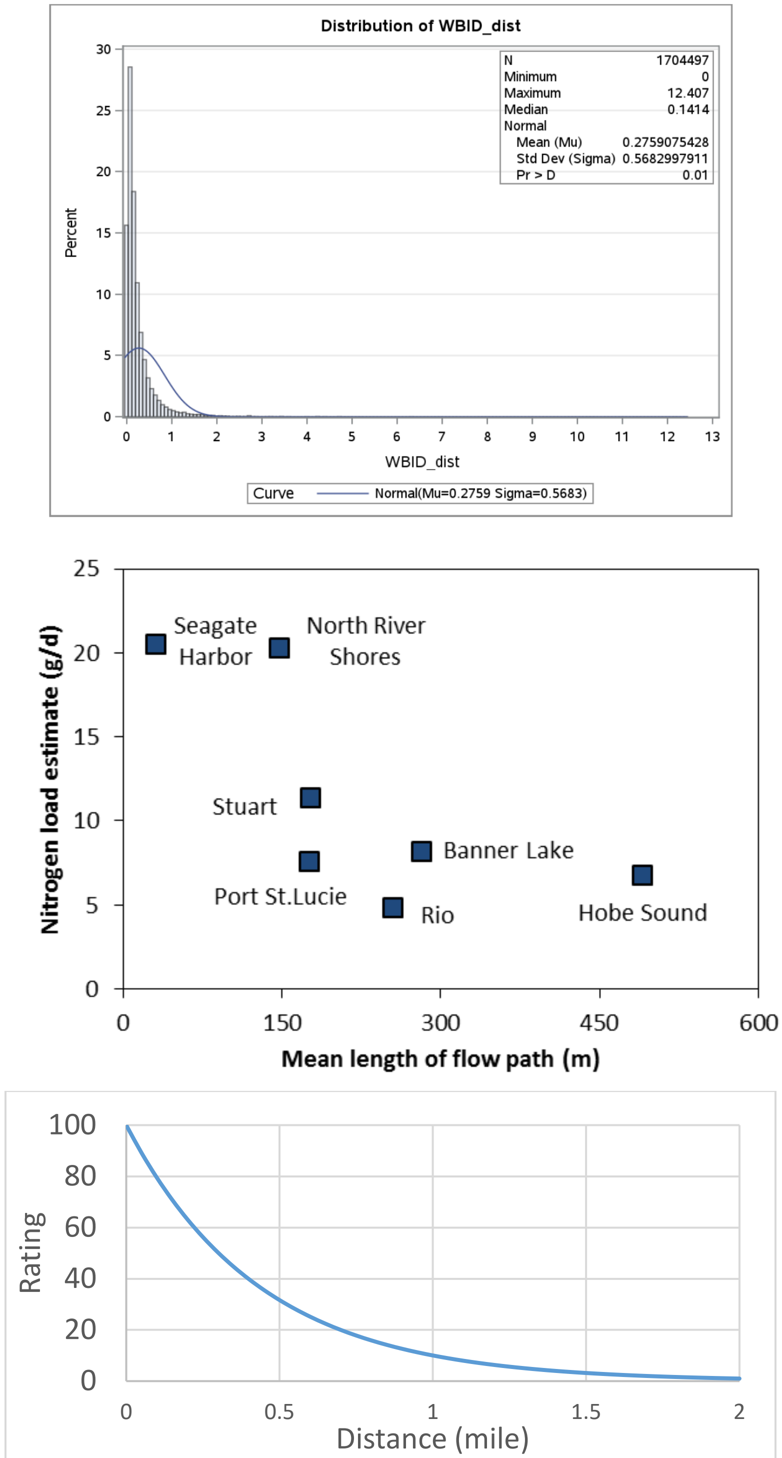


Figure 1. (Top) Probability density function (PDF) of Distance to NHD Water body (mi) provided by SAS. (Middle) Variation of nitrogen load estimate per OSTDS with mean lengths of flow paths at seven sites of St. Lucie River and Estuary Basin, Florida. The plot is adapted from Ye et al. (2017). (Bottom) Exponential function of ratings for the distance to NHD water body.

Parcel Density

While SAS provides statistics of parcel density (count/acre) for HUC8, HUC12, and BMAP levels, only the statistics of HUC12 were used for determining the ranges and ratings of parcel density. For the Parcel Density of HUC12, the top plot of **Figure 3** (provided by SAS) shows that the parameter ranges between 0 and 1 OSTDSs per acre, with a median and mean of 0.017 and 0.05 OSTDSs per acre, respectively. For about 80% of the data, the parcel density is 0.03 OSTDSs per acre, i.e., about one OSTDS per 30 acres. A smaller parcel density is expected to have a lower impact on water quality. This impact is illustrated in the middle plot of **Figure 3** based on the study of Ye and Sun (2013) in the St. Lucie River and Estuary basin. The plot shows the variation of estimated nitrogen load with the number of OSTDSs in six neighborhoods. It is observed from the plot that the relation between nitrogen load and OSTDS number is a nonlinear function. As a result, it is assumed that the rating (R_{pd}) of parcel density follows Equation (3):

$$R_{disw} = 100^{pd} \qquad (3)$$

where *pd* (count/acre) is the parcel density.

For reference, the rating is 1 and 100 for parcel densities of 0 and 1 per acre, respectively. The function is illustrated in the bottom plot of **Figure 3**. The function has a gradually increasing rate at low parcel densities and more rapid rise at higher densities. For example, the rating increases from 1 to 10 when parcel density increases from 0 to 0.5 OSTDS per acre. However, the rating increases from 10 to 100 when parcel density increases from 0.5 to 1 OSTDS per acre. This change reflects the nonlinear impacts of parcel density on water quality vulnerability.

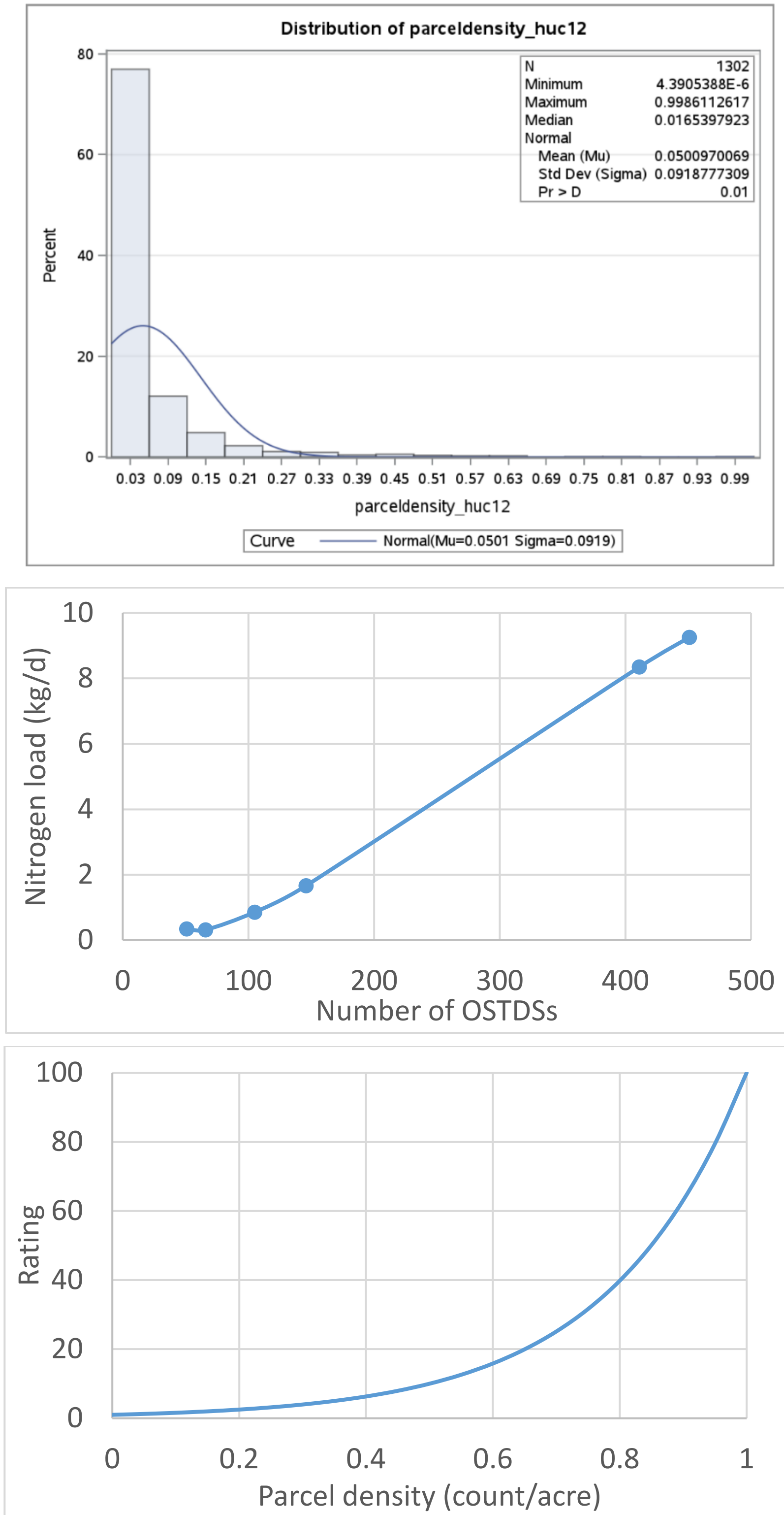


Figure 2. (Top) Probability density function (PDF) of Parcel Density (count/acre) provided by SAS. (Middle) Variation of nitrogen load estimate with the number of OSTDSs at six neighborhoods of the St. Lucie River and Estuary Basin, Florida. The plot is based on data from Ye and Sun's technical report (2013). (Bottom) Exponential function of ratings for parcel density.

OSTDS Age

Figure 4 shows the probability density function (PDF) of OSTDS Age provided by SAS. Since the maximum age turns out to be an outlier due to data input errors made by county appraisal offices, it is assumed that the maximum age is 100 years based on the PDF plot. There are several essential years relevant to OSTDSs in Florida. In 1972, 1983, 1992, and 2000 OSTDS regulations were modified. Before 1972, there was no density requirement; in 1983 and 1992, setback and siting requirements changed, respectively; voluntary inspections started in 2000. These lead to four critical ages, 50 years in 1972 (relative to the current year, 2022), ~40 years in 1983, 30 years in 1992, and ~20 years from 2000. The value of 30 years is close to the median of 32 years and the median of 34 years.

A total of five ranges were thus determined (**Table 3)**. When a OSTDS was built before 1972 (50 years before the density requirement), it was expected that the OSTDSs would significantly impact water quality, and a rating of 100 was assigned. From 1972 to 1983 (i.e., after the density requirement but before the setback requirement), because of the density requirement, the rating drops from 100 to 80. Between 1983 and 1992 (after the setback requirement but before the sitting requirement), because of the setback requirement, the rating drops from 80 to 60. Between 1992 and 2000 (after the sitting requirement and before the volunteer inspection), due to the sitting requirement, the rating drops from 60 to 40. From 2000 to 2012 (after the volunteer inspection until ten years before 2022), the rating drops from 40 to 30. A OSTDS of 10 years old or newer is considered to be in a reasonable operation condition, given that EPA recommends inspecting septic systems every 3 to 5 years. The corresponding rating drops from 30 to 20.

Table 3. Ranges and ratings for OSTDS Age (years).

Range	Rating
less than 10 years old	20
2000 - 2012	30
1992 - 2000	40
1983 – 1992	60
1972 – 1983	80
before 1972	100

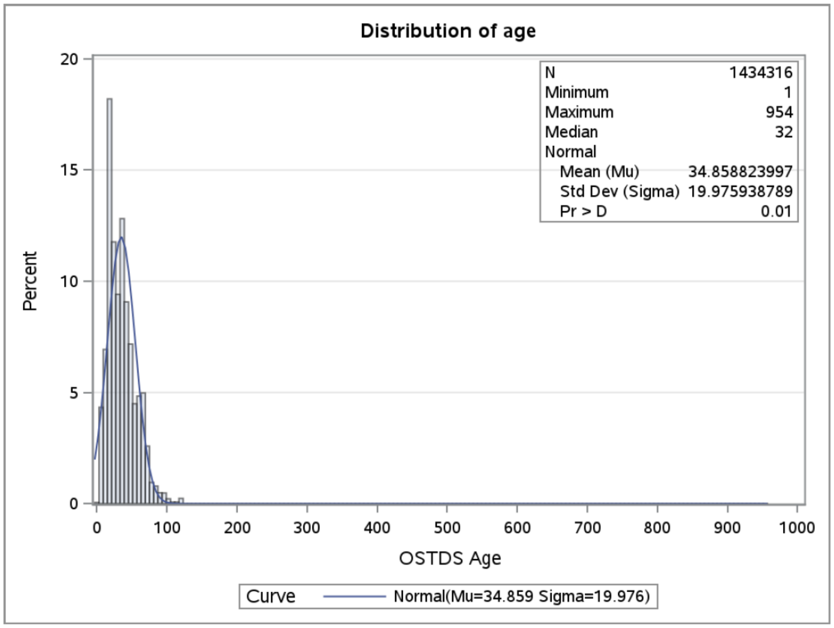


Figure 3. Probability density function (PDF) of OSTDS Age (year) provided by SAS.

Weighted Hydraulic Conductivity

The top plot of **Figure 5** (provided by SAS) shows the probability density function (PDF) of weighted hydraulic conductivity (mm/s). The maximum value of 423 mm/s is extremely high, resembling the value for unconsolidated gravel deposits, as shown in the diagram of hydraulic conductivity for various geological media shown in the bottom-left plot of **Figure 5** (source: https://en.wikipedia.org/wiki/Hydraulic_conductivity#/media/File:Groundwater_Freeze_and_Cherry_1979_Table_2-2.png. The median value of 15.7 mm/s (1.57 cm/s) and mean value of 24.75 mm/s (2.475 cm/s) are also in the range expected for unconsolidated gravel deposits or consolidated karst limestone. For most OSTDSs in Florida, clean sand is the most common soil type, and its corresponding hydraulic conductivity is one mm/s (0.1 cm/s) or less. The high values of hydraulic conductivity in the SAS data may be due to its calculation using the arithmetic mean. Using a harmonic mean is more appropriate from a hydrogeologic perspective, particularly for considering vertical hydraulic conductivity (Zhu 2008). Notably, a harmonic mean is substantially different from an arithmetic mean, which can be demonstrated by an example of two numbers, 1 and 100. Their arithmetic mean is 50.5, but their harmonic mean is 1.98. It is recommended to use harmonic mean in a future study.

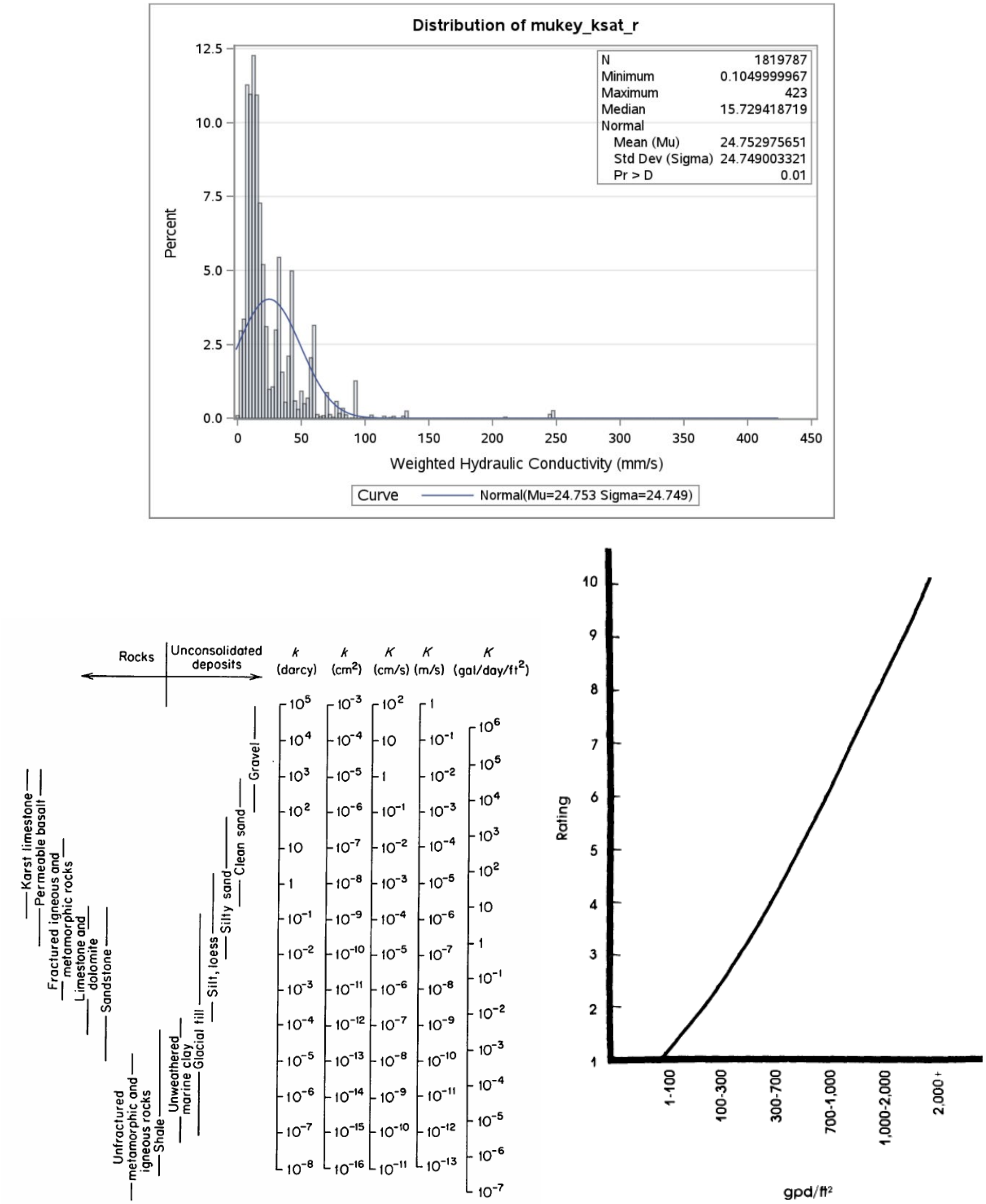


Figure 4. (Top) Probability density function (PDF) of Weighted Hydraulic Conductivity (mm/s) provided by SAS. (Bottom-Left) Hydraulic conductivity for various geological materials. (Bottom-Right) Relation between rating and hydraulic conductivity (gpd/ft2) used in EPA DRASTIC calculation.

Table 4 lists the hydraulic conductivity ranges and ratings used in EPA DRASTIC calculation. The unit of hydraulic conductivity was gpd/ft^2, and it was converted to mm/s, which is used for the SAS data. The bottom-right plot of **Figure 5** illustrates the relationship between the ranges and the ratings. It is reasonable to assign a significant rating for a large hydraulic conductivity. It is thus determined to adopt the DRASTIC rating scheme. However, the parameter ranges were adjusted by multiplying the EPA DRASTIC ranges by 100 to be consistent with the SAS weighted hydraulic conductivity magnitude. The ranges and ratings of this study are listed in **Table 4**.

Table 4. Ranges and ratings for Hydraulic Conductivity were used for EPA DRASTIC and this study.

Range (**gpd/ft^2**) (EPA)	Range (**mm/s**) (EPA)	Rating (EPA)	Range (mm/s) (this study)	Rating (this study)
1-100	0.0005-0.05	1	0-5	10
100-300	0.05-0.14	2	5-15	20
300-700	0.14-0.33	4	15-35	40
700-1000	0.33-0.47	6	35-45	60
1000-2000	0.47-0.94	8	45-95	80
2000+	0.94+	10	95+	100

Population

Figure 6 shows the PDF of the population provided by SAS. The maximum population of 2,282 may be for a commercial building (e.g., a high-rise condo) but is exceptionally uncommon. On the other hand, the median value of 2.25 and the mean value of 2.39 are typical for single-family houses. The ranges and ratings of the population are listed in **Table 5**. The ratings are expected to be linear regarding the population ranges.

Table 5. Ranges and ratings for OSTDS Age (years).

Range	Rating
1	10
2	20
3	30
4	40
5-10	60
10-20	80
20+	100

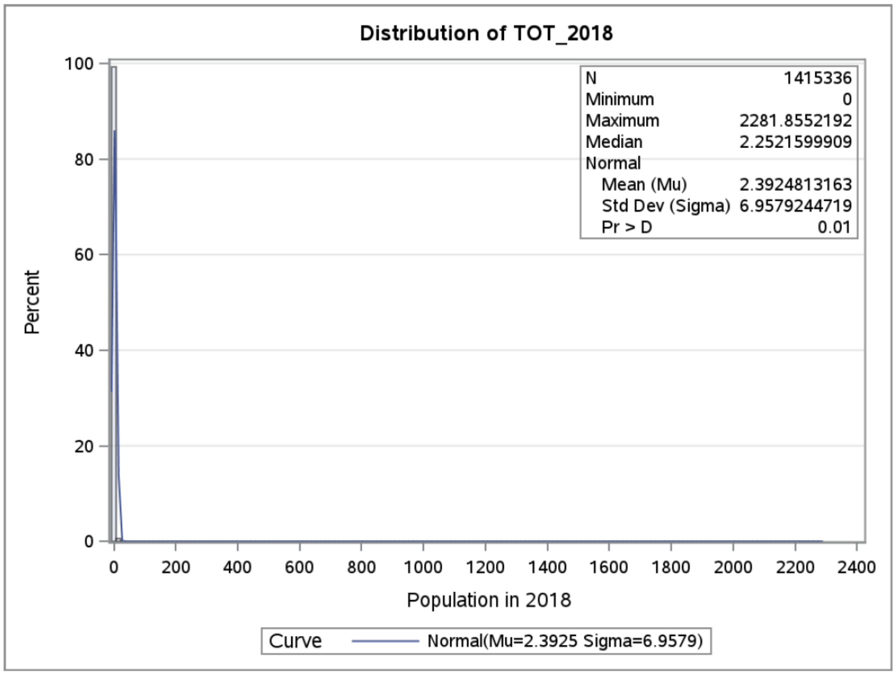


Figure 5. Probability density function (PDF) of Population provided by SAS.

Drainage Class

A total of seven Drainage Classes are used in SAS calculation, and they are excessively drained (ED), somewhat excessively drained (SED), well-drained (WD), moderately well-drained (MWD), somewhat poorly drained (SPD), poorly drained (PD), and very poorly drained (VPD). Nitrogen load from a OSTDS to a surface water body is significant for well-drained soils, and this is illustrated in **Figure 7** based on the work of Ye et al. (2017). **Figure 7** further indicates a linear relationship between nitrogen load and soil drainage conditions.

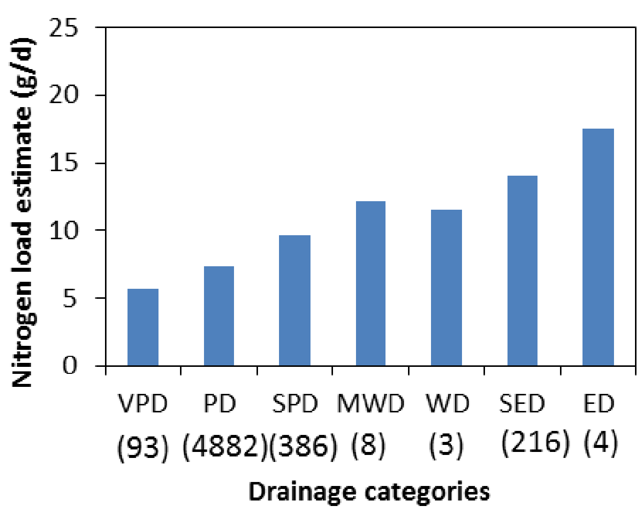


Figure 6. Variation of nitrogen load estimate per septic system with drainage conditions of the soil zones where septic systems are located at the Port St. Lucie site. This figure is adopted from Ye et al. (2017).

For the calculation of WQVI-ST, the seven drainage classes were assigned values 1 to 7 (**Table 6**); ratings for the seven drainage classes are determined Based on **Figure 7** and listed in **Table 6**.

Table 6. Ranges and ratings for Drainage Classes.

Drainage Class	Class Index	Rating function
Excessively drained (ED)	7	100
Somewhat excessively drained (SED)	6	80
Well drained (WD)	5	60
Moderately well-drained (MWD)	4	50
Somewhat poorly drained (SPD)	3	40
Poorly drained (PD)	2	30
Very poorly drained (VPD)	1	20

Within a Springshed

The SAS calculation also considered whether a OSTDS is within or outside a springshed. It is expected that a OSTDS within a Springshed has a more considerable impact on water quality than a OSTDS outside of a springshed. Therefore, two ratings of 90 and 1 were used (**Table 7)**. It was noted that not all springsheds are mapped, and that the dataset used for this calculation only includes the 30 Outstanding Florida Springs, identified by legislature in 2016.

Table 7. Ranges and ratings for Within a Springshed.

Within a Springshed	Rating
Yes	90
No	1

Method of Estimating Water Quality Index for Five HUC8 Sub-Basins

Although SAS estimated WQVI-ST for parcels, evaluating the parcel-level WQVI-ST is practically meaningless because a OSTDS at a parcel does not cause water quality problems. Instead, evaluating the impacts of many OSTDSs on water quality is practically meaningful. In this task, the evaluation was conducted at the HUC8 sub-basin and HUC12 sub-watershed scales by investigating the statistical correlation between WQVI-ST and the water quality index (WQI). The HUC8 and HUC12 scales were chosen because they are large enough to contain many OSTDSs and can reflect spatial variability of WQVI-ST, SAS OSTDS score, and WQI. Additionally, water quality data are available for HUC12 basins in the DEP WAVES dataset available at https://prodenv.dep.state.fl.us/DearWin/public/wavesSearchFilter?calledBy=menu. Since this project is a pilot study, it did not evaluate all HUC12s in the entire state, but only within five selected HUC8 sub-basins. Therefore, the statistical correlation between WQVI-ST and WQI was evaluated for the HUC12 sub-watersheds within the five HUC8 watersheds as well as using average scores at the HUC8 sub-basins.

This section first briefly discusses the estimation of the NSF International's WQI in the manner described in McClelland (1974). The five HUC8 sub-basins and water quality parameters available for each HUC8 are discussed next. The WQI calculation were adjusted because different HUC8 and HUC 12 units may have a different number of available water quality parameters. The adjusted method for estimating WQI is also described.

Method of estimating WQI and its adjustment

According to McClelland (1974), the NSF International's WQI is estimated via Equation (4):

$$WQI = \sum_i W_i Q_i \tag{4}$$

where W_i is the weight for the *i*-th parameter (i = 1, 2, …, 9), and Q_i is the sub-index of the *i*-th parameter ranging between 0 and 100. A larger *WQI* value means better water quality.

Table 8 lists the nine water quality parameters and their weights for the NSF International's WQI calculation. The sub-index is estimated based on a rating function curve, and an example curve for fecal coliform is shown in **Figure 8**. For example, if there are 10,000 colonies of fecal coliform per 100 ml of water, the corresponding sub-index value is 10. The sub-index can estimate a parameter value using a linear interpolation method, and a Java code is available at the website, https://www.water-research.net/watrqualindex/index.htm. The Java code was converted into Python code that was used in this project.

Table 8. Names and weights of nine water quality parameters used for estimating the NSF International's water quality index.

Parameter	Weights
Dissolved Oxygen	0.17
Fecal Coliform Density	0.16
pH	0.11
Biochemical Oxygen Demand	0.11
Nitrate	0.10
Phosphates	0.10
Temperature	0.10
Turbidity	0.08
Total Solids	0.07

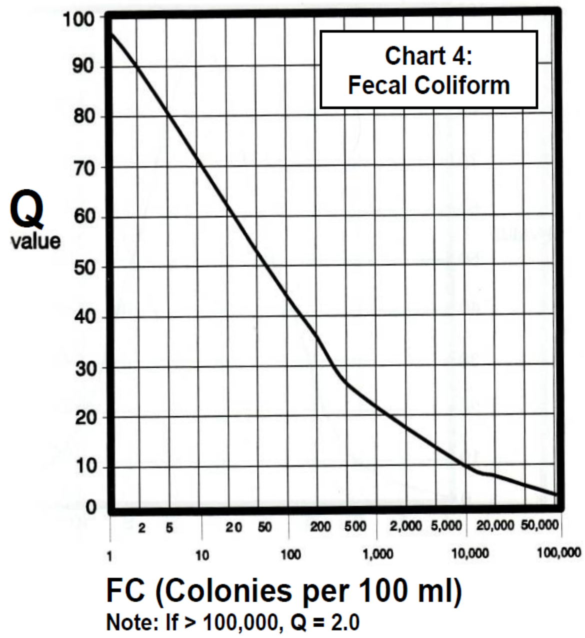


Figure 7. Rating function of fecal coliform (number of colonies (organisms) per 100 ml water) used for estimating the NSF International's water quality index. The figure is copied from the website at https://www.water-research.net/watrqualindex/index.htm. The Y-axis of the Q-value is another name for the sub-index used in Equation (4).

Five HUC8 Sub-Basins, Their HUC12 Sub-Watersheds, and Water Quality Parameters

In this project, five HUC8 sub-basins were selected for calculating WQI to evaluate WQVI-ST at their HUC12 sub-watersheds. The selection was based on the workshop results, where experts were asked to suggest suitable evaluation locations across Florida. **Figure 9** shows the suggested sites and also includes the rationale behind the experts' suggestions. A detailed discussion of the suggestions was supplied in the report of Task 2 of this project. Five HUC8 sub-basins were selected for index evaluation in this report (**Table 9**): Cape Canaveral, located in the Indian River Lagoon area of the Florida east coast; Lower Ochlockonee in the panhandle area with rural lands; Apalachee Bay-St. Marks in the panhandle area with a mix of rural and urban lands; Ocklawaha in the north ridge of central Florida; and Kissimmee in the south ridge of central Florida. Although the five sites are representative of the diversity of geologic and environmental conditions across Florida, selecting more study sites to comprehensively evaluate WQVI-ST in a future study is recommended (after addressing input parameter and water quality data limitations described under Recommendations).

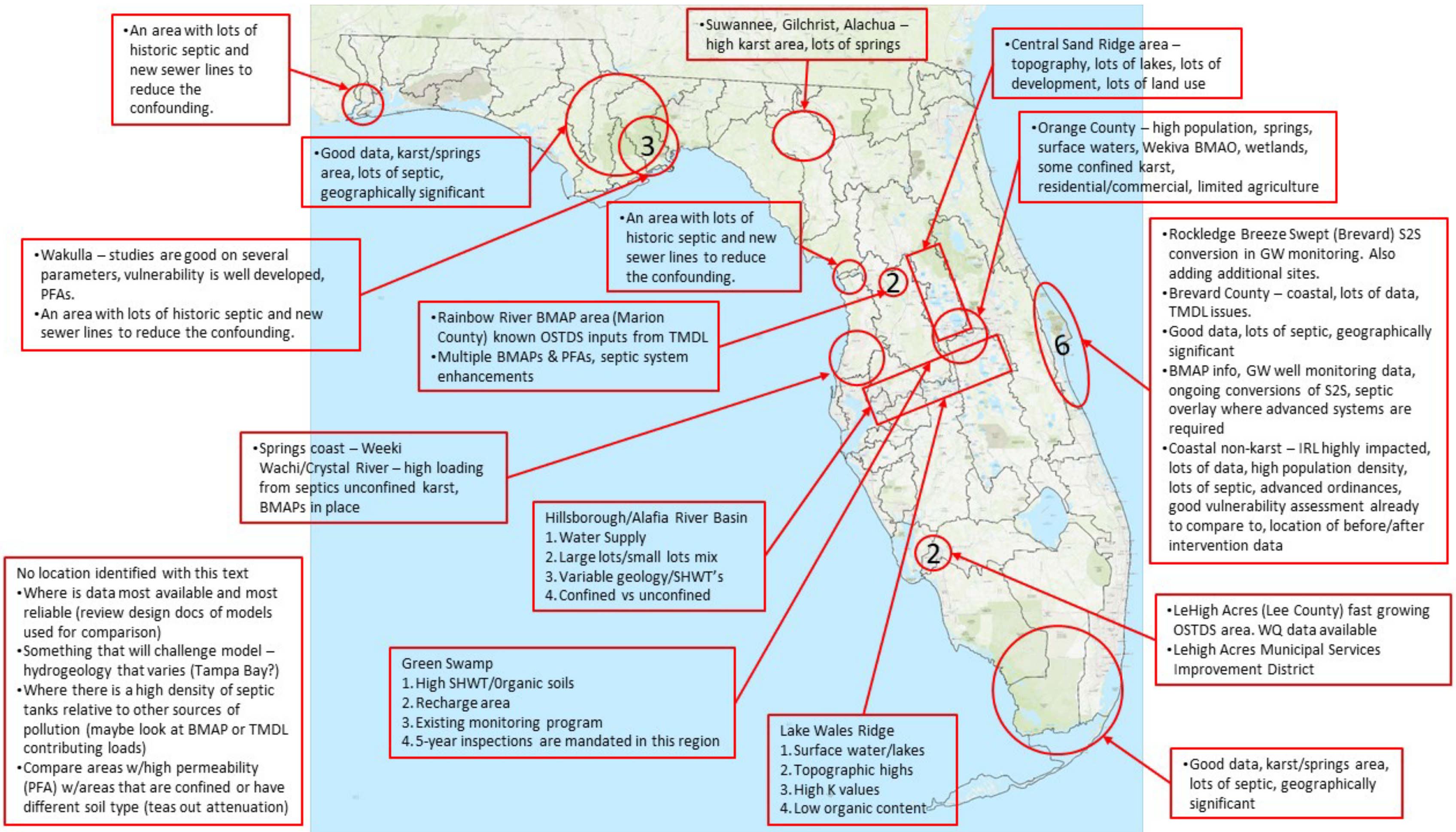


Figure 8. Synthesis of expert suggestions on pilot evaluation sites. Text in the boxes explains the rationale behind the suggestions, and a detailed discussion of the suggestions is given in the report of Task 2 of the project.

Table 9. Numbers, names, and locations of five HUC8 sub-basins, where WQVI-ST is evaluated in the HUC12 sub-watersheds of the HUC8 sub-basins.

HUC8 Number	HUC8 Name	Location	# HUC12 sub-basins
03080202	Cape Canaveral	East coast	12
03120003	Lower Ochlockonee	Panhandle (rural)	50
03120003	Apalachee Bay-St. Marks	Panhandle (rural and urban)	30
03080102	Ocklawaha	North ridge of central Florida	53
03090101	Kissimmee	South ridge of central Florida	69

For the five HUC8 sub-basins, the WIN WAVES database was queried for measurements of water quality parameters at HUC12 sub-watersheds for the period between January 01, 2018, and December 31, 2021. This period was selected based on the assumption that more recent data are representative of current water quality. At each HUC8, not every HUC12 had measurements for all nine water quality parameters listed in Table 8. In order to use the same parameters for all HUC12 in a HUC8, we had to remove several parameters and several HUC12 sub-watersheds from the analysis. Tables 10 and 11 list the water quality parameters used and excluded for each HUC8 for the estimation of the WQI. Note that the best available variable in the WIN WAVES database for total solids is residual-nonfilterable (i.e., total dissolved solids, TDS). For nitrate, the corresponding variable in the WIN WAVES database is Nitrate-Nitrite (N) (i.e., NOx-N), and the NOx-N concentrations were multiplied by 4.43 to obtain the nitrate concentrations used in the WQI calculation. Although the water quality parameters used for calculating WQI were the same for all the five HUC8 sub-basins (as were the excluded parameters), this is not necessarily a requirement of analysis. Table 12 lists the HUC12 sub-watersheds where WQI was not evaluated for each HUC8; for HUC8 Cape Canaveral, WQI was calculated for all HUC12 sub-watersheds.

It was noticed that WQVI-ST and SAS OSTDS score were not evaluated for the following HUC12 sub-watersheds: 030901011504 - Kissimmee - Duck Slough, 030901011601 - Kissimmee - Morgan Hole Creek, 030901012004 - Kissimmee - Istokpoga Creek, 030802020104 - Cape Canaveral - Goat Creek, 030802020105 - Cape Canaveral - Kid Creek, 030802020203 - Cape Canaveral - South Banana River, and 031200010801 – Apalachee Bay-St. Marks – Upper Lost Creek. These HUC12 were thus also excluded from further analysis in this report. In a future study, it would be necessary to ensure that the latest HUC12 sub-watersheds are used.

Table 10. Water quality parameters were used for calculating the water quality index for five HUC8 sub-basins (Cape Canaveral, Lower Ochlockonee, Oklawaha, Kissimmee, and Apalachee Bay-St. Marks).

Water Quality Parameters Used for Calculating the WQI
Turbidity
Total Solids (mg/L) [Residues-Nonfilterable (TDS)]
Total Phosphorus (mg/L)
pH
Nitrate (mg/L) [Nitrate-Nitrite (N)]
Dissolved Oxygen (% Saturation)

Table 11. Water quality parameters excluded from calculating the water quality index for five HUC8 sub-basins (Cape Canaveral, Lower Ochlockonee, Oklawaha, Kissimmee, and Apalachee Bay-St. Marks).

Water Quality Parameters Excluded from Calculating the WQI
Fecal Coliform (Colony-Forming Unit)
Biochemical Oxygen Demand (mg/L)
Temperature

Table 12.. The HUC12 sub-watersheds where WQI was not calculated for the five HUC8 sub-basins.

HUC8 Name	**HUC12 where WQI not calculated**
Cape Canaveral	None
Lower Ochlockonee	Little Attapulgus Creek, Devil's Branch-Telogia Creek, and Buckhorn Creek-Sopchoppy River
Oklawaha	Gooski Prairie, Lochloosa Creek, Saluda Swamp, Ledwith Lake, Johnson Lake, Daisy Creek, Lake Stafford, Brooks Branch, Marshall Swamp, and Little Creek-Palatlakaha River
Kissimmee	Cypress Slough-Chandler Slough, Pine Island Slough, South Fork of Pine Island Slough, Lonesome Camp Swamp, and Lake Conlin
Apalachee Bay-St. Marks	Jump Creek and Shepherd Branch

Figure 10 shows the seven likely contaminants stemming from of OSTDS-derived pollution in Florida waterbodies suggested by participants of the online survey in Task 1 of the project. Among the seven indicators, nitrogen and phosphorous were included in the water quality parameters used for WQI calculation. Unfortunately, two of the important parameters suggested by the online survey (fecal coliform and biochemical oxygen demand) were not available in the WIN WAVES database at a sufficient volume to include in the WQI calculation, which is a major limitation of these results. These two parameters generally cannot be measured in situ, and are thus measured substantially less frequently than other water quality parameters. Measuring these parameters in future studies is recommended to better characterize water quality. Temperature is another parameter that should be more consistently measured, however it should be noted that the WQI uses temperate change between two reference points, such as a waterbody and an upstream point, rather than only the waterbody, making this variable potentially irrelevant to understanding impacts of septic pollution.

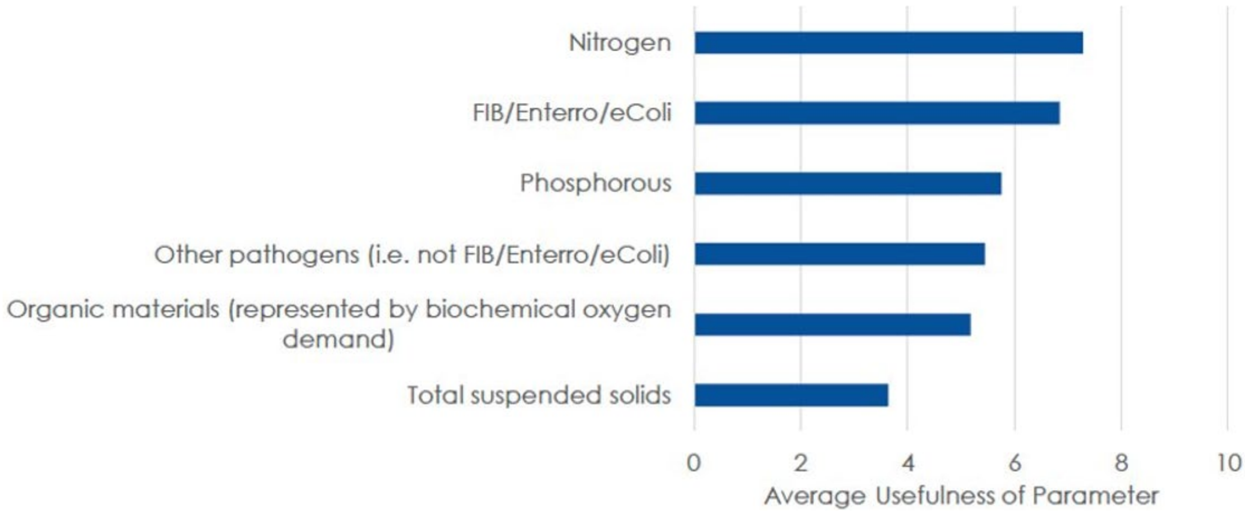


Figure 9. Likely contaminants stemming from OSTDS-derived pollution in Florida waterbodies were suggested by participants of an online survey conducted in Task 1 of the project.

The WQI calculation has the flexibility of using a portion of the parameters, e.g., six out of the nine parameters. Using fewer analytes does not require adjusting the sub-index of the selected parameters, but the weights of the parameters need to be adjusted. **Table 13** lists the adjusted weights for the six water quality parameters used for the WQI calculation given data limitations.

Table 13. Original and adjusted weights of the water quality parameters used for WQI calculation.

Water Quality Parameters	Original Weights	Adjusted Weights
Dissolved Oxygen	0.17	0.27
Fecal Coliform	0.16	*0.00*
pH	0.11	0.17
Biochemical Oxygen Demand	0.11	*0.00*
Temperature	0.10	*0.00*
Total Phosphate	0.10	0.16
Nitrates	0.10	0.16
Turbidity	0.08	0.13
Total Dissolved Solids	0.07	0.11
Totals	1.00	1.00

In a HUC12 sub-watershed, there were always multiple locations where the water quality parameters are measured over time. We first estimated temporal averages of the measurements over time and then estimated spatial averages over the HUC12 watershed. When estimating the spatial averages, we used two averaging schemes based on the shapes of the sub-index functions shown in **Figure 11**. The functions of nitrate, phosphate, TDS, and turbidity are monotonically decreasing functions, and the average of each parameter was estimated over a HUC12 sub-watershed. This technique may lead to an underestimation of the sub-index and thus an underestimation of water quality. By taking nitrate as an example, for the concentrations of 10 mg/L and 50 mg/L, their corresponding sub-index values are 50 and 10, respectively. The average concentration is 30 mg/L, and its corresponding sub-index is about 26. This value is smaller than the average of 30 for the two sub-index values. The rating functions for pH and DO are bell-shaped, which is inappropriate for average parameter values—taking pH as an example of its values of 4 and 10 correspond to small sub-index values. However, the average pH value is 7, corresponding to a very high sub-index value. It is, therefore, necessary to average sub-index values.

In summary, for nitrate, phosphate, TDS, and turbidity, the averages of their concentrations were estimated for each HUC12 sub-watershed. Afterward, the average concentrations were used to estimate the sub-index of the four parameters. For pH and DO, the sub-index of each concentration was estimated, and the average index was calculated for each HUC12 sub-watershed. Subsequently, the sub-index values were used for estimating WQI using the weights listed in **Table 13**. Calculated WQI at the HUC12 scale is illustrated in **Figure 12.**

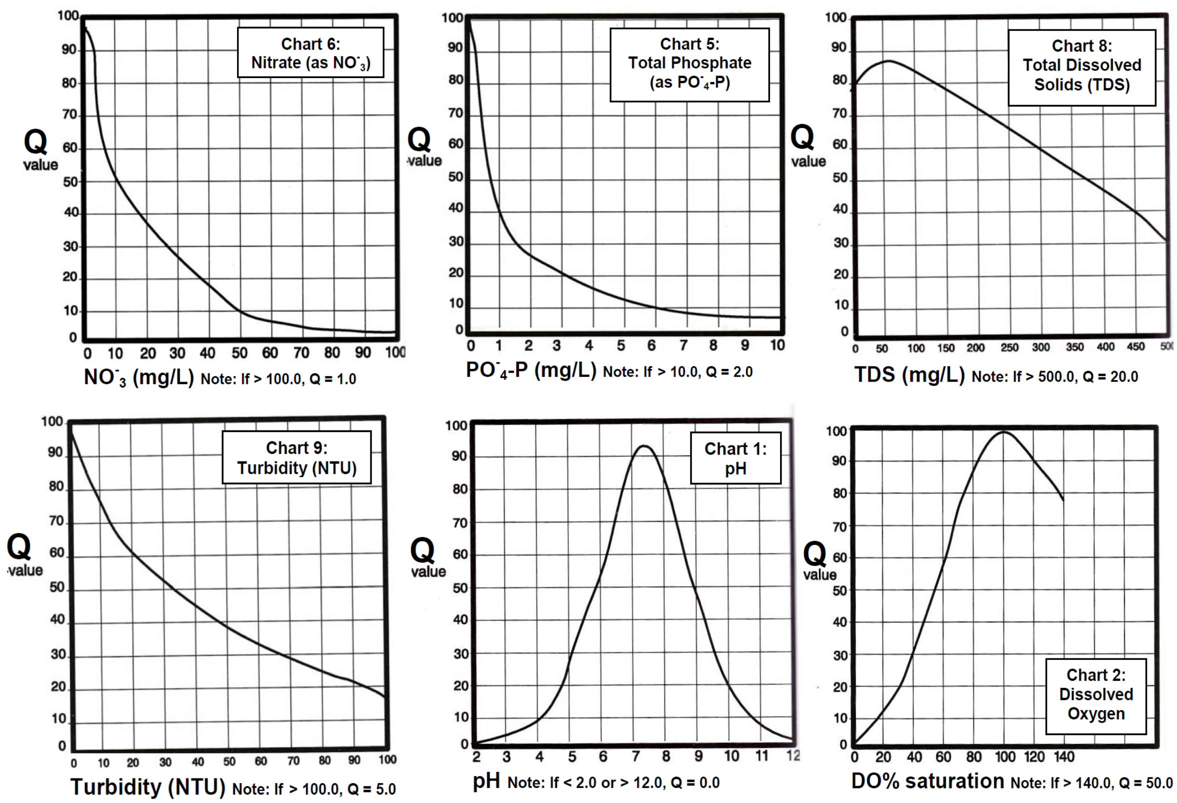


Figure 10. Rating functions of the six water quality parameters used for calculating the water quality index in this project. The figures were copied from the website at https://www.water-research.net/watrqualindex/index.htm. The Y-axis of the Q-value is another name for the sub-index used in Equation (4).

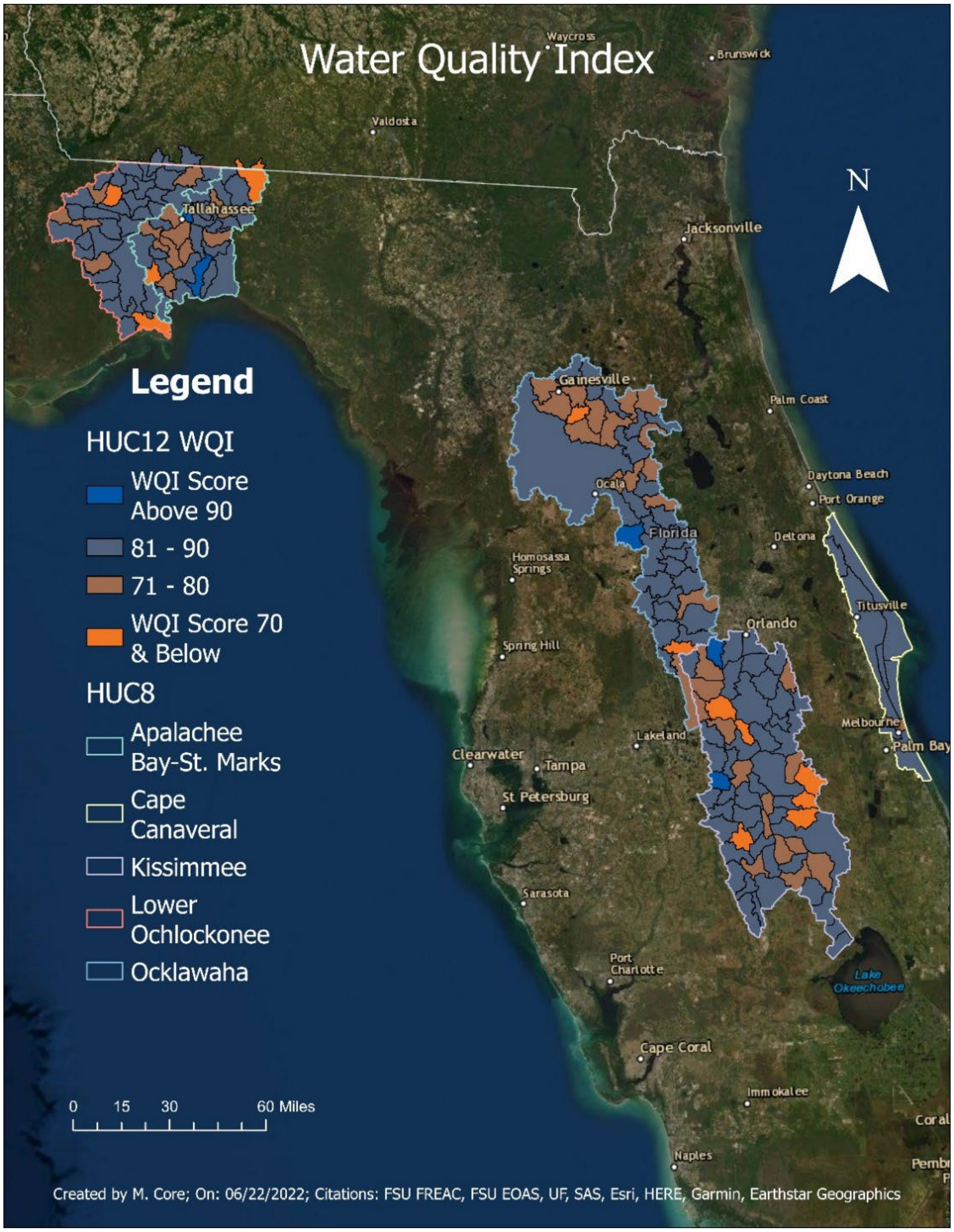


Figure 11. Estimated water quality index for HUC12 sub-watersheds of five HUC8 sub-basins.

Statistical Results Comparing WQVI-ST/SAS OSTDS score with WQI

Figure 13 plots the estimated WQVI-ST and SAS OSTDS score for the HUC12 sub-watersheds of the five HUC8 sub-basins. Since these two indices use different scales, it difficult to directly compare them. However, it is visually clear that they differ spatially (for example, see differences between scores in the eastern portion of the Kissimmee HUC8, which are relatively much higher for the WQVI-ST as compared to the SAS OSTDS score). It is also difficult to visually compare the two variables with the WQI index shown in **Figure 12**. Therefore, the statistical correlation between WQVI-ST and WQI was investigated to evaluate whether there was a negative correlation between the two indices, assuming that a high WQVI-ST/SAS OSTDS score would correspond to a low WQI at HUC12 and HUC8 levels.

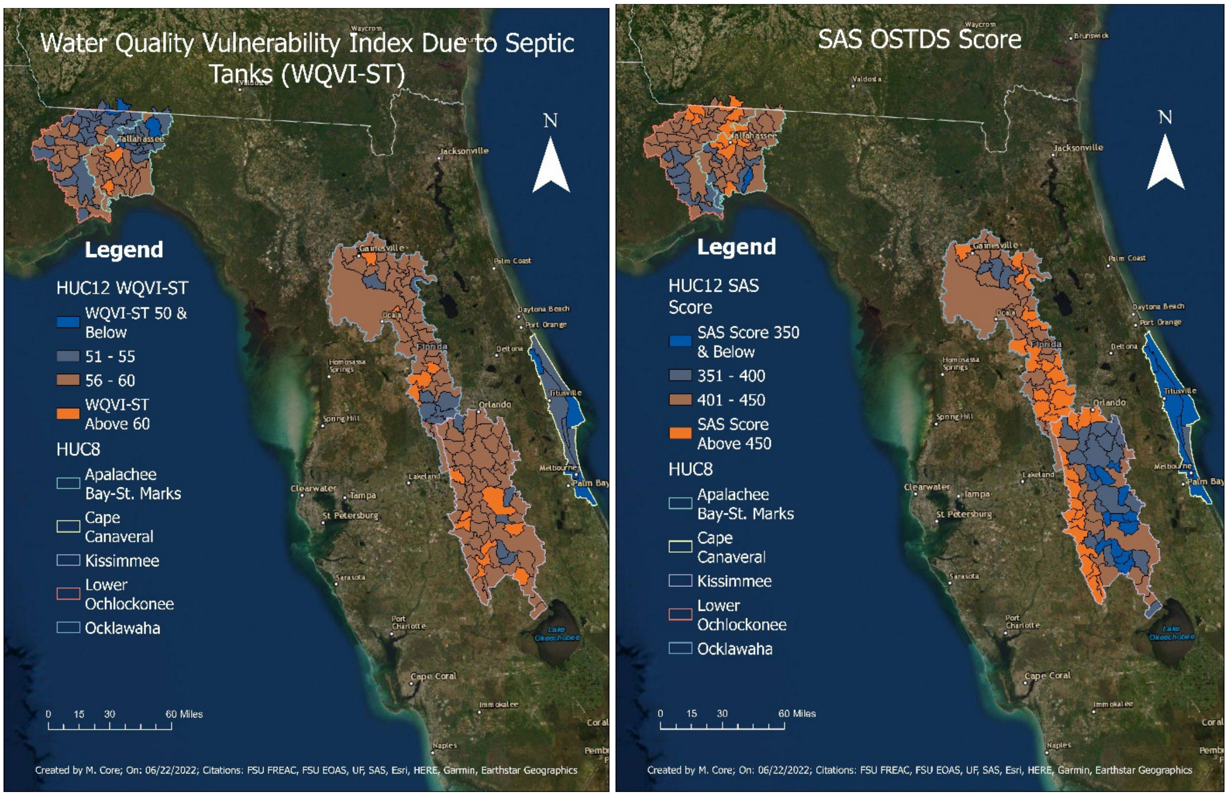


Figure 12. Estimated WQVI-ST (left) and SAS OSTDS score (right) at HUC12 sub-watersheds of five HUC8 sub-basins.

Figure 14 plots the correlation between WQVI-ST, WQI, SAS OSTDS score, and WQI for the five HUC8 sub-basins. The values listed in **Table 14** for WQI, WQVI-ST, and SAS OSTDS score of each HUC8 were averaged over the HUC12 of the HUC8. The figure shows a significant negative correlation between WQVI-ST/SAS OSTDS score and WQI. The correlation coefficient between WQVI-ST and WQI is -0.95, and the correlation coefficient between SAS OSTDS score and WQI is -0.97 (**Table 14**). These results indicate that both WQVI-ST and SAS OSTDS score are equally satisfactory indicators for WQI (as calculated using available water quality data) at the HUC8 level. However, as noted throughout this report, the modified WQI implemented in this analysis is constrained by data availability and limited in its ability to characterize the specific impacts of OSTDSs on surface water quality. This evaluation constraint applies to all of the HUC12-level results presented below.

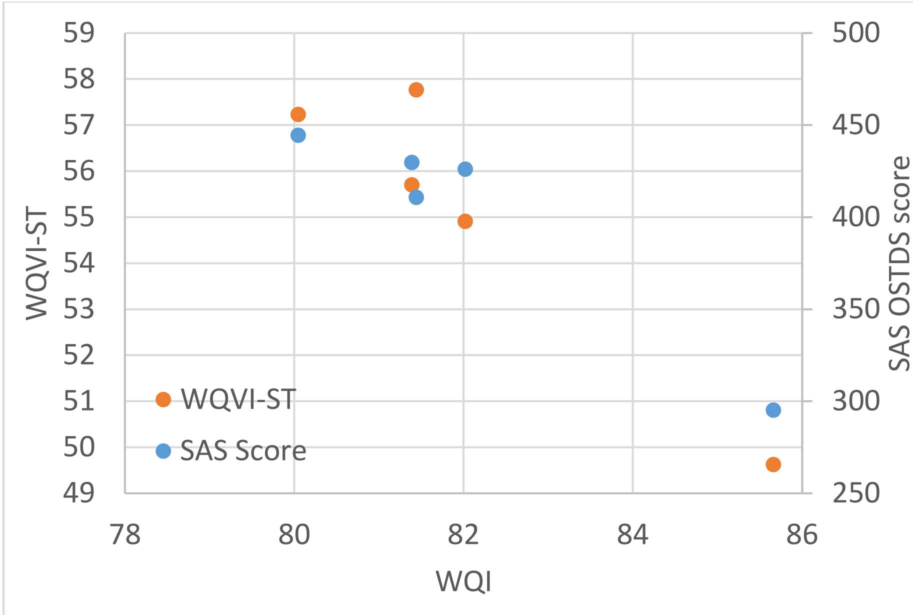


Figure 13. Correlation between WQVI-ST and WQI and between SAS OSTDS score and WQI for the five HUC8 sub-basins.

Table 14. WQI, WQVI-ST, and SAS OSTDS score of the five HUC8 sub-basins.

HUC8 Number	HUC8 Name	WQI	WQVI-ST	SAS OSTDS score
03080102	OKLAWAHA	80	57	445
03080202	CAPE CANAVERAL	86	50	295
03090101	KISSIMMEE	81	58	411
03120003	LOWER OCHLOCKONEE	82	55	426
03120001	APALACHEE BAY ST MARKS	81	56	430
	Correlation Coefficient		-0.95	-0.97

In contrast, WQVI-ST and SAS OSTDS score have varying and different performances for individual HUC8 sub-basins. **Figure 15** plots the correlation between WQVI-ST and WQI and between SAS OSTDS score and WQI for the eight HUC12 sub-watersheds of the Cape Canaveral HUC8. The values of WQI, WQVI-ST, and SAS OSTDS score of each HUC12 are listed in **Table 15**. The figure shows a negative correlation between WQVI-ST/SAS OSTDS score and WQI. The correlation coefficient between WQVI-ST and WQI is -0.55, and the correlation between SAS OSTDS score and WQI is -0.76 (Table 13); both are negative as expected, but the strength of the correlation is greater for the SAS OSTDS score.

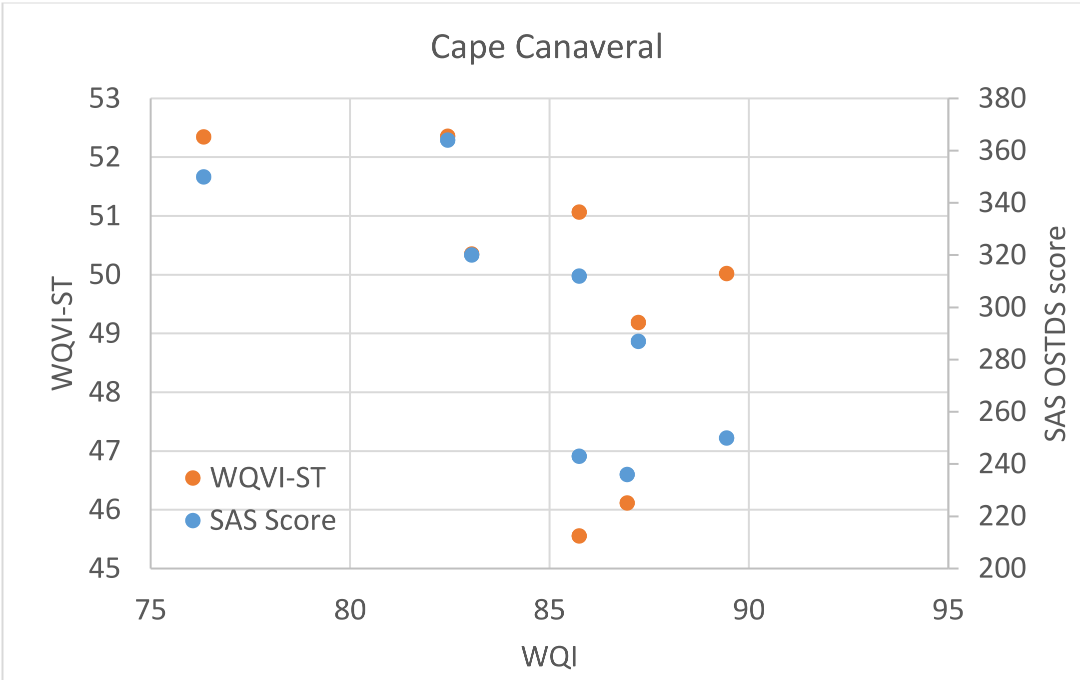


Figure 14. Correlation between WQVI-ST and WQI and SAS OSTDS score and WQI for the HUC12 sub-watersheds of HUC8 Cape Canaveral.

Table 15. WQI, WQVI-ST, and SAS OSTDS score of eight HUC12 sub-watersheds of HUC8 Cape Canaveral.

HUC12 Name and ID	WQI	WQVI-ST	SAS OSTDS score
NORTH BANANA RIVER, 030802020101	87	46	236
NEWFOUND HARBOR, 030802020102	83	50	320
SOUTH BANANA RIVER, 030802020103	82	52	364
TURNBULL HAMMOCK, 030802020201	86	46	243
INDIAN RIVER LAGOON, 030802020202	86	51	312
EAU GULLIE RIVER, 030802020301	76	52	350
CRANE CREEK, 030802020302	87	49	287
MOSQUITO LAGOON, 030802020400	89	50	250
Correlation Coefficient		-0.55	-0.76

Figure 16 plots the correlation between WQVI-ST and WQI and between SAS OSTDS score and WQI for the 32 HUC12 sub-watersheds of HUC8 Lower Ochlockonee. The values of WQI, WQVI-ST, and SAS OSTDS score of each HUC12 are listed in **Table 16**. The figure shows a negative correlation between WQVI-ST and WQI (as expected) with a correlation coefficient of -0.30. In contrast, there is a positive correlation coefficient between SAS OSTDS score and WQI, indicating that HUC12 sub-watersheds with

higher vulnerability (as assessed by the SAS OSTDS score) have “better” water quality in this region, which is the opposite of the expected relationship.

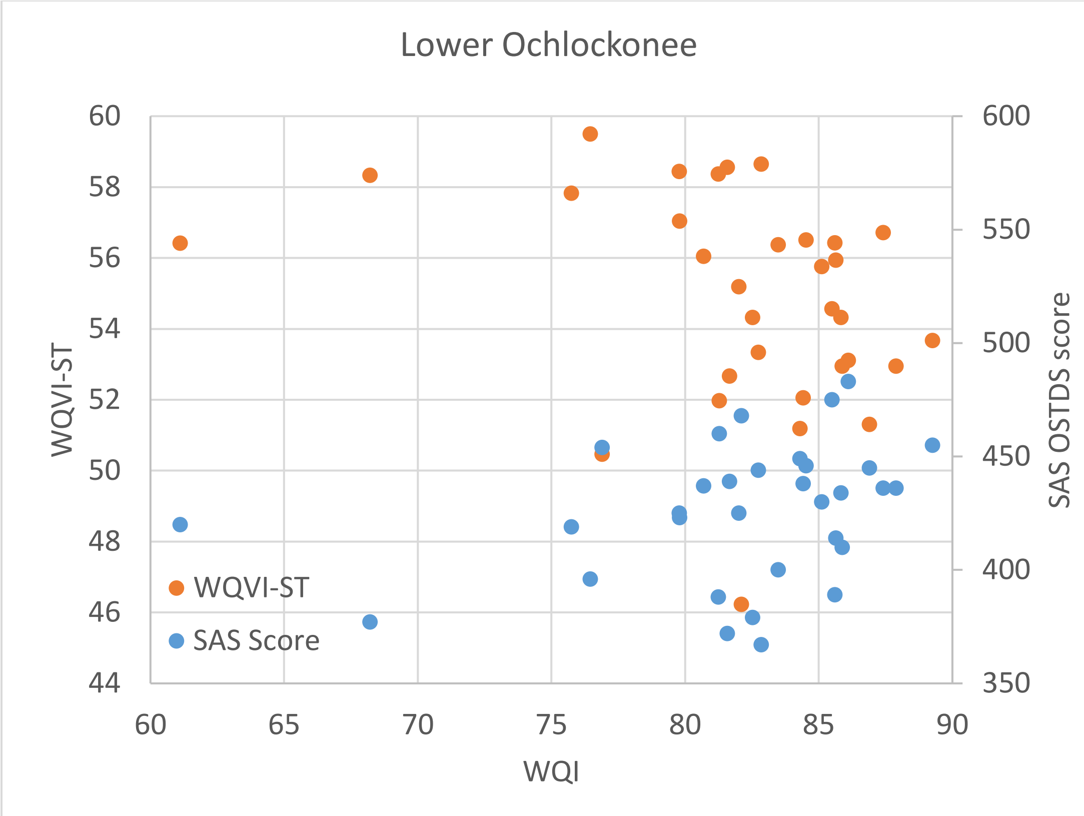


Figure 15. Correlation between WQVI-ST and WQI and between SAS OSTDS score and WQI for the HUC12 sub-watersheds of HUC8 Lower Ochlockonee.

Table 16. WQI, WQVI-ST, and SAS OSTDS score of 32 HUC12 sub-watersheds of HUC8 Lower Ochlockonee.

HUC12 Name and ID	WQI	WQVI-ST	SAS OSTDS score
SHAW CREEK, 031200030102	82	46	468
PICKLE POND, 031200030104	86	53	410
LAKE IAMONIA, 031200030105	77	50	454
ORCHARD POND, 031200030106	86	54	434
LOWER SWAMP CREEK, 031200030205	87	51	445
LOWER WILLACOOCHEE CREEK, 031200030207	81	52	460
LOWER ATTAPULGUS CREEK, 031200030208	84	51	449
LAKE JACKSON, 031200030301	86	53	483

HUC12 Name and ID	WQI	WQVI-ST	SAS OSTDS score
REED SWAMP, 031200030302	81	56	437
HOLLEY BRANCH, 031200030303	85	56	430
UPPER QUINCY CREEK, 031200030401	89	54	455
LOWER QUINCY CREEK, 031200030402	85	55	475
CRAB CREEK-UPPER LITTLE RIVER, 031200030403	83	53	444
LOWER LITTLE RIVER-LAKE TALQUIN, 031200030404	84	52	438
UPPER ROCKY COMFORT CREEK, 031200030501	61	56	420
LOWER ROCKY COMFORT CREEK, 031200030502	88	53	436
INDIAN SPRINGS, 031200030602	76	58	419
MULE CREEK, 031200030603	82	55	425
MILL BRANCH-TELOGIA CREEK, 031200030605	80	57	423
BIG CREEK-TELOGIA CREEK, 031200030703	80	58	425
STOKES BRANCH, 031200030704	83	56	400
EAST LAKE TALQUIN, 031200030801	82	53	439
OCKLAWAHA CREEK, 031200030802	87	57	436
CENTRAL LAKE TALQUIN, 031200030803	85	57	446
WEST LAKE TALQUIN, 031200030804	86	56	414
REEDY CREEK, 031200030805	86	56	389
HIGHLOG LAKE, 031200030901	76	59	396
WHITEHEAD LAKE, 031200030902	83	54	379
HITCHCOCK LAKE, 031200030903	82	59	372
BUCKHORN CREEK-SOPCHOPPY RIVER, 031200031101	81	58	388
WOMACK CREEK SWAMP, 031200031202	83	59	367
OCHLOCKONEE BAY, 031200031204	68	58	377
Correlation Coefficient		-0.30	0.29

Figure 17 plots the correlation between WQVI-ST and WQI and between SAS OSTDS score and WQI for the 40 HUC12 sub-watersheds of HUC8 Oklawaha. The values of WQI, WQVI-ST, and SAS OSTDS score of each HUC12 are listed in **Table 17**. The figure shows a positive correlation between both the WQVI-ST/SAS OSTDS score and WQI. The correlation coefficient between WQVI-ST and WQI is 0.17, and the correlation coefficient between SAS OSTDS score and WQI is 0.28. The positive correlations found here indicate that neither the WQVI-ST nor SAS OSTDS score perform as expected for correlating with water quality in this region.

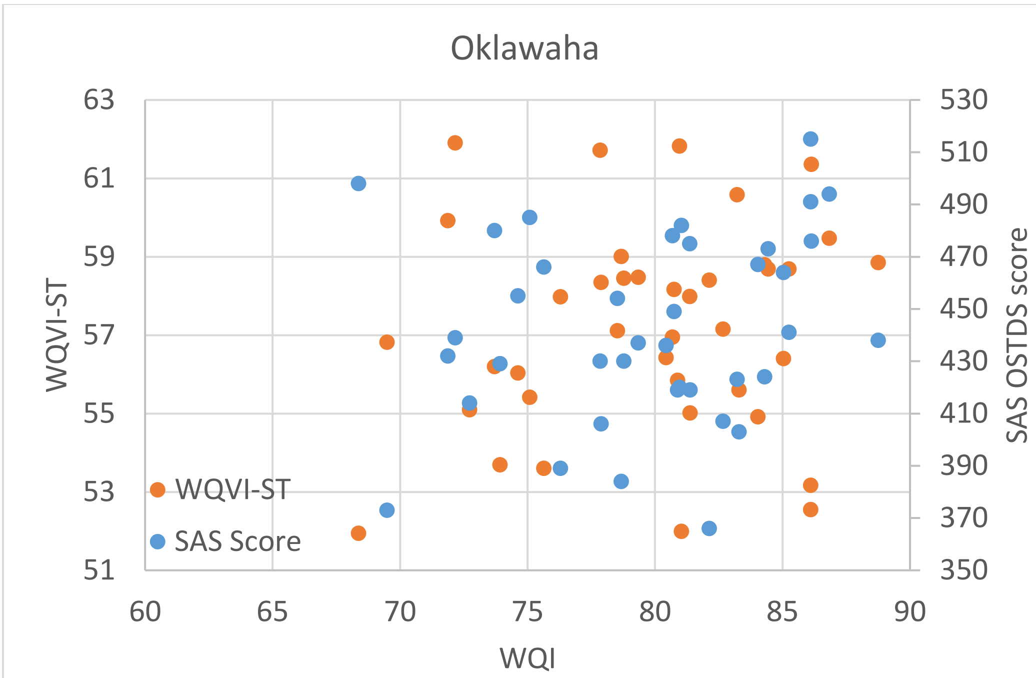


Figure 16. Correlation between WQVI-ST and WQI and between SAS OSTDS score and WQI for the HUC12 sub-watersheds of HUC8 Ocklawaha.

Table 17. WQI, WQVI-ST, and SAS OSTDS score of 40 HUC12 sub-watersheds of HUC8 Ocklawaha.

HUC Name and ID	WQI	WQVI-ST	SAS OSTDS score
BIG CREEK-PALATLAKAHA RIVER, 030801020101	72	60	432
LAKE LOUISA, 030801020103	68	52	498
LAKE MINEOLA, 030801020104	86	53	515
PALATLAKAHA RIVER, 030801020105	81	62	420
LITTLE EVERGLADES, 030801020201	81	52	482
LITTLE LAKE HARRIS, 030801020202	85	59	441
LAKE HARRIS, 030801020203	83	61	423

HUC Name and ID	WQI	WQVI-ST	SAS OSTDS score
JOHNS LAKE, 030801020301	86	53	491
LAKE APOPKA, 030801020302	84	55	467
APOPKA-BEAUCLAIR CANAL, 030801020303	74	56	480
LAKE DORA, 030801020304	87	59	494
LAKE BRACY, 030801020401	84	59	473
LAKE EUSTIS, 030801020402	86	61	476
ELUA LAKE, 030801020403	80	56	436
LAKE YALE, 030801020404	89	59	438
LAKE GRIFFIN, 030801020405	85	56	464
PECAN LAKE, 030801020501	81	58	449
LAKE WEIR, 030801020502	91	59	520
MUD PRAIRIE SWAMP, 030801020505	81	56	419
LAKE BRYANT, 030801020801	75	55	485
MILL DAM LAKE, 030801020802	81	57	478
MUD LAKE-OKLAWAHA RIVER, 030801020803	73	55	414
SILVER RIVER, 030801020804	72	62	439
STROUDS CREEK, 030801020806	78	58	406
HATCHET CREEK, 030801021102	83	57	407
HOGTOWN CREEK, 030801021103	79	57	454
GUM ROOT SLOUGH, 030801021104	82	58	366
PAYNES PRAIRIE, 030801021105	79	58	437
NEWNANS LAKE, 030801021106	78	62	430
RIVER STYX, 030801021107	69	57	373
LOCHLOOSA LAKE, 030801021202	76	58	389
ORANGE LAKE, 030801021205	74	54	429
LITTLE ORANGE CREEK, 030801021301	81	55	419
CABBAGE CREEK, 030801021302	75	56	455

HUC Name and ID	WQI	WQVI-ST	SAS OSTDS score
ORANGE CREEK, 030801021303	79	59	384
GRAVEYARD LAKE, 030801021402	84	59	424
PENNER PONDS, 030801021403	76	54	466
UPPER OCKLAWAHA LAKE, 030801021404	81	58	475
SWEETWATER BRANCH-OCKLAWAHA LAKE, 030801021405	79	58	430
LOWER OCKLAWAHA LAKE, 030801021406	83	56	403
Correlation Coefficient		0.17	0.28

Figure 18 plots the correlation between WQVI-ST and WQI and between SAS OSTDS score and WQI for the 58 HUC12 sub-watersheds of HUC8 Oklawaha. The values of WQI, WQVI-ST, and SAS OSTDS score of each HUC12 are listed in **Table 18**. The figure shows no correlation between WQVI-ST and WQI (correlation coefficient being -0.01) but a positive correlation between SAS OSTDS score and WQI with a correlation coefficient of 0.42. These correlations indicate that neither the WQVI-ST nor SAS OSTDS score perform as expected as indicators of surface water quality in this region.

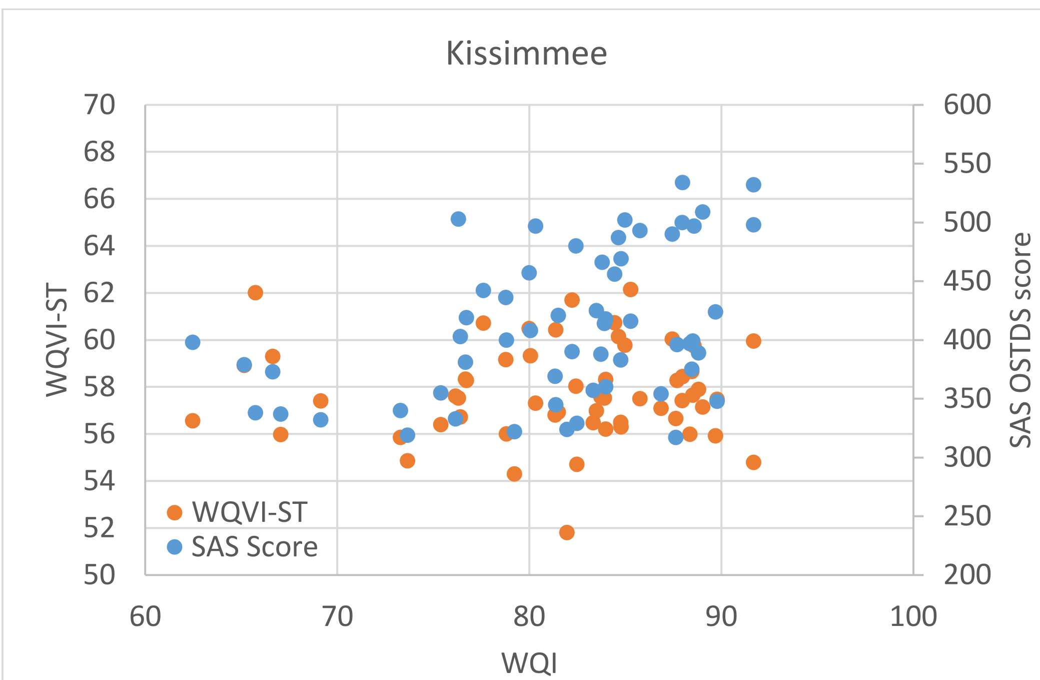


Figure 17. Correlation between WQVI-ST and WQI and between SAS OSTDS score and WQI for the HUC12 sub-watersheds of HUC8 Kissimmee.

Table 18. WQI, WQVI-ST, and SAS OSTDS score of 58 HUC12 sub-watersheds of HUC8 Kissimmee.

HUC12 Name and ID	WQI	WQVI-ST	SAS OSTDS score
LAKE CONWAY, 030901010101	88	58	534
BOGGY CREEK SWAMP, 030901010102	85	56	383
LAKE HART, 030901010103	88	59	375
EAST LAKE TOHOPEKALIGA, 030901010104	89	58	399
LAKE MYRTLE, 030901010201	77	58	381
BIG SAND LAKE, 030901010301	88	57	500
SHINGLE CREEK, 030901010302	88	58	396
LAKE TOHOPEKALIGA, 030901010400	89	58	389
KISSIMMEE-0501, 030901010501	92	55	498
KISSIMMEE-0502, 030901010502	85	56	469
KISSIMMEE-0503, 030901010503	79	56	400
DAVENPORT CREEK, 030901010504	77	58	419
REEDY CREEK SWAMP, 030901010601	65	59	379
LAKE RUSSEL, 030901010602	69	57	332
KISSIMMEE-0701, 030901010701	86	58	493
CATFISH CREEK, 030901010702	84	58	414
HORSE CREEK, 030901010801	76	58	503
LAKE MARION, 030901010802	87	60	490
LAKE MARION CREEK, 030901010803	79	59	436
LAKE HATCHINEA, 030901010804	87	57	354
ALLIGATOR LAKE, 030901010901	84	58	388
LAKE GENTRY, 030901010903	90	57	348
CYPRESS LAKE, 030901010905	88	57	317
LAKE MARIAN, 030901011001	67	59	373
FODDERSTACK SLOUGH, 030901011002	79	54	322
TIGER LAKE, 030901011102	84	58	360

HUC12 Name and ID	WQI	WQVI-ST	SAS OSTDS score
LAKE KISSIMMEE, 030901011103	82	62	390
LAKE ROSALIE, 030901011201	76	57	403
KISSIMMEE-1202, 030901011202	92	60	532
KISSIMMEE-1203, 030901011203	84	61	456
KISSIMMEE-1204, 030901011204	84	56	418
KISSIMMEE-1301, 030901011301	89	60	497
KISSIMMEE-1302, 030901011302	89	57	509
KISSIMMEE-1303, 030901011303	85	60	487
LAKE ARBUCKLE, 030901011304	83	57	425
BUTTERMILK SLOUGH, 030901011401	73	56	340
UPPER BLANKET BAY SLOUGH, 030901011402	67	56	337
LOWER BLANKET BAY SLOUGH, 030901011404	82	52	324
RATTLESNAKE HAMMOCK, 030901011405	66	62	338
KISSIMMEE-1505, 030901011505	74	55	319
BONNET CREEK, 030901011602	62	57	398
UPPER ARBUCKLE CREEK, 030901011603	83	56	357
MIDDLE ARBUCKLE CREEK, 030901011604	81	60	345
KISSIMMEE-1701, 030901011701	82	58	480
LAKE HUNTLEY, 030901011702	80	57	497
KISSIMMEE-1703, 030901011703	84	58	466
KISSIMMEE-1704, 030901011704	80	60	457
KISSIMMEE-1801, 030901011801	85	60	502
LOWER ARBUCKLE CREEK, 030901011802	78	61	442
ARBUCKLE BRANCH, 030901011803	81	57	369
LAKE ISTOKPOGA, 030901011804	90	56	424
HOLE IN THE WALL CREEK, 030901011901	82	55	329
ISTOKPOGA CREEK, 030901011902	76	58	333

HUC12 Name and ID	WQI	WQVI-ST	SAS OSTDS score
UPPER CHANDLER SLOUGH, 030901012002	75	56	355
LOWER CHANDLER SLOUGH, 030901012003	85	62	416
DOUGHTERY CUTOFF, 030901012101	80	59	408
GROGAN LAKE, 030901012102	82	57	421
BUCKHEAD RIDGE, 030901012103	88	56	397
Correlation Coefficient		-0.01	0.42

Figure 19 plots the correlation between WQVI-ST and WQI and between SAS OSTDS score and WQI for the 27 HUC12 sub-watersheds of HUC8 Apalachee Bay – St. Marks. The values of WQI, WQVI-ST, and SAS OSTDS score of each HUC12 are listed in **Table 19**. The figure shows a slightly negative correlation between WQVI-ST and WQI (correlation coefficient -0.27), but essentially no correlation between SAS OSTDS score and WQI with a correlation coefficient of -0.05. These correlations indicate that WQVI-ST is more associated with WQI (and in the expected direction) than is the SAS OSTDS score in this region.

Table 20 lists the correlation coefficients between WQVI-ST and WQI and between SAS OSTDS score and WQI for HUC12 sub-watersheds of all five HUC8 sub-basins. This table summarizes the strengths and weaknesses of using the WQVI-ST and SAS OSTDS scores as indicators or predictors of water quality, again considering the caveats regarding water quality data described above. Recommendations for future work to address these limitations are given in the next section.

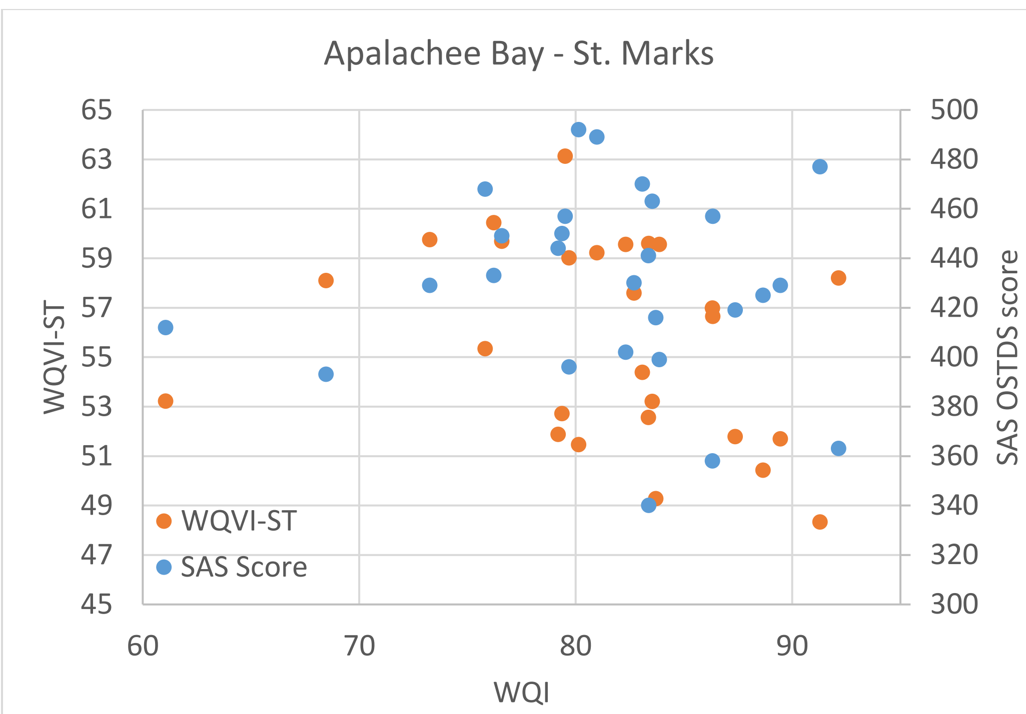


Figure 189. Correlation between WQVI-ST and WQI and SAS OSTDS score and WQI for the HUC12 sub-watersheds of HUC8 Apalachee Bay – St. Marks.

Table 19. WQI, WQVI-ST, and SAS OSTDS score of 58 HUC12 sub-watersheds of HUC8 Apalachee Bay – St. Marks.

HUC12 Name and ID	WQI	WQVI-ST	SAS OSTDS score
WARDS CREEK, 031200010201	61	53	412
LAKE MICCOSUKEE, 031200010203	84	49	416
PATTY SINK, 031200010301	87	52	419
BIRD SINK, 031200010302	79	52	444
LLOYD CREEK, 031200010303	89	52	429
LAKE KILLARNEY, 031200010401	83	54	470
ALFORD ARM, 031200010402	80	51	492
LAKE ELLA, 031200010403	91	48	477
LAKE LAFAYETTE, 031200010404	84	53	463
BURNT MILL CREEK, 031200010501	89	50	425
APALACHEE BAY-ST. MARKS-0502, 031200010502	83	53	441
CHICKEN BRANCH, 031200010503	79	53	450
HAMLIN BRANCH, 031200010504	86	57	358
LAKE BRADFORD, 031200010601	81	59	489
BLACK SWAMP-LAKE MUNSON, 031200010602	76	55	468
LAKE MUNSON, 031200010603	80	63	457
MCBRIDE SLOUGH, 031200010605	77	60	449
FISHER CREEK, 031200010701	80	59	396
BLACK CREEK-WAKULLA SPRINGS, 031200010702	82	60	402
WAKULLA SPRINGS, 031200010704	73	60	429
LOWER LOST CREEK, 031200010803	68	58	393
SPRINGS CREEK, 031200010901	76	60	433
GOOSE CREEK-WALKER CREEK FRONTAL, 031200010902	86	57	457
OLD CREEK-SKIPPER CREEK FRONTAL, 031200010903	84	60	399
WAKULLA RIVER, 031200011001	83	58	430
EAST RIVER, 031200011002	83	60	340
LOWER ST. MARKS RIVER, 031200011003	92	58	363
Correlation Coefficient		-0.27	-0.05

Table 20. Correlation coefficients between WQVI-ST and WQI and between SAS OSTDS score and WQI for HUC12 sub-watersheds of five HUC8 sub-basins.

HUC8 Number	HUC8 Name	# HUC12	WQVI-ST (Correlation Coefficient)	SAS OSTDS score (Correlation Coefficient)
03080202	Cape Canaveral	8	-0.55	-0.76
03120003	Lower Ochlockonee	32	-0.30	0.29
03120001	APALACHEE BAY ST MARKS	27	-0.27	-0.05
03080102	Ocklawaha	40	0.17	0.28
03090101	Kissimmee	58	-0.01	0.42

As a final analysis, for the HUC8 Apalachee Bay – St. Marks sub-basin, the Florida Geological Survey conducted the Wakulla County Aquifer Vulnerability Assessment (WCAVA) (Baker et al., 2009), which is phase II of the Florida Aquifer Vulnerability Assessment (FAVAII). **Table 21** lists the vulnerability of the HUC12 sub-watersheds located in Wakulla County, with vulnerability classified as most vulnerable, vulnerable, and less vulnerable. These categories were translated to three indices: 3 for the class of most vulnerable, 2 for vulnerable, and 1 for less vulnerable. The correlation coefficient between the WCAVA and WQI was 0.23 (**Figure 20**), indicating greater aquifer vulnerability was associated with *better* water quality, counter to expectations. As with several cases above where WQVI-ST and/or the SAS OSTDS score was positively, rather than negatively, correlated with WQI, these results suggest that further effort would be required to confidently apply FAVA-based vulnerability indices as predictors of water quality associated with OSTDS.

The positive correlation between WCAVA vulnerability and WQI was mainly caused by the data of Lower Lost Creek HUC12, which has karst features. After removing data of this HUC12, the correlation coefficient between WCAVA vulnerability index and WQI becomes -0.37 (the correlation coefficient between WCAVA and WQVI-ST/SAS OSTDS score becomes 0.19/0.22). While WCACA considered karst features, WQI, WQVI-ST, and SAS OSTDS score did not consider karst in their evaluation, although workshop attendants recommended to consider karst features in the OSTDS vulnerability analysis.

Table 21. Vulnerability classification, vulnerability index, WQI, WQVI-ST, and SAS OSTDS score for eight HUC12 sub-watersheds within Wakulla County. The Correlation coefficients between the vulnerability index and WQI/WQVI-ST/WQI are also listed.

HUC 12 Name and Number	Vulnerability	Vulnerability Index	WQI	WQVI_ST	SAS OSTDS score
BLACK CREEK-WAKULLA SPRINGS, 031200010702	Less Vulnerable	1	82	60	402
LOWER LOST CREEK, 031200010803	Less Vulnerable	1	68	58	393
SPRINGS CREEK, 031200010901	Most Vulnerable	3	76	60	433
GOOSE CREEK-WALKER CREEK FRONTAL, 031200010902	Vulnerable	2	86	57	457
OLD CREEK-SKIPPER CREEK FRONTAL, 031200010903	Vulnerable	2	84	60	399
WAKULLA RIVER, 031200011001	Vulnerable	2	83	58	430
EAST RIVER, 031200011002	Vulnerable	2	83	60	340
LOWER ST. MARKS RIVER, 031200011003	Vulnerable	2	92	58	363
Correlation			0.23	0.26	0.23

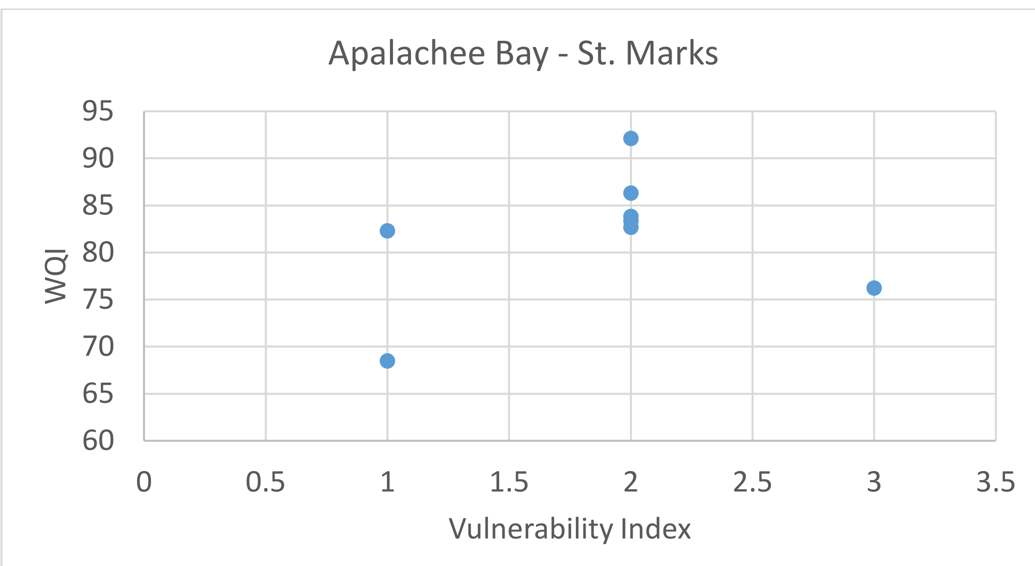


Figure 20. Correlation between vulnerability index and WQI for eight HUC12 sub-watersheds in Wakulla County.

Recommendations

The methodological approach and results above illustrate the potential for using expert knowledge to develop and evaluate alternate OSTDS-related water quality vulnerability indices. While the work summarized in this report should be considered a pilot analysis, constrained by time and data limitations, the results help assess the current utility of the developed vulnerability indices and develop recommendations for possible next steps.

Overall, these results demonstrate that the correspondence between vulnerability indices (as currently defined) and available water quality information is a function of the spatial scale over which they are applied (i.e., HUC8 vs. HUC12). Specifically, the expert-guided index developed here (WQVI-ST) and the previously developed index (SAS OSTDS score) showed similarly strong and expectedly negative correlation with the modified water quality index (WQI) when averaged at the HUC8 level (**Figure 14**, **Table 14**). While this scale of analysis may be useful for selecting regional focus areas for OSTDS mitigation, it is likely much too coarse to aid in specific project selection. At smaller scales, the two indices varied considerably in their correlation with WQI at the HUC12 level for the five selected HUC8, including several counterintuitive positive correlations (**Table 20**, **Figure 15-19**). Specifically, HUC12 SAS OSTDS scores were positively correlated with WQI for three out of five tested watersheds (i.e., showing *better* water quality in HUC12s with *higher* vulnerability scores). The WQVI-ST was positively correlated with WQI in one watershed and very weakly correlated in another.

At a minimum, these results suggest that the current indices should be applied with extreme caution, especially at smaller spatial scales. Furthermore, given the limitations of water quality parameter data and OSTDS-specific water quality data (described in detail below), additional data and effort are required to more robustly "evaluate whether the factors and weighting structures recommended in the workshop for the SAS-DEP dashboard can predict relationships between modeled septic vulnerability and surface water quality," as detailed in our contract with DEP. Recommendations for the continued improvement and expanded evaluation of septic vulnerability scores developed through the SAS-DEP dashboard are outlined below, organized into three main sections: 1) input parameters and data; 2) vulnerability score evaluation, and 3) recommendations for current and future applications.

Input Parameters and Data

An important recommendation is for DEP to gather and integrate additional parameters and data identified as a high priority in the workshop but which is not yet in the SAS dashboard. For example, while the top five parameters identified by workshop participants (Distance to Nearest Surface Water body, Depth to Groundwater, OSTDS Density, OSTDS Age, and Hydraulic Conductivity) are in the dashboard, none of the following five highest-ranked parameters were available (Drain field Depth to Seasonal High-Water Table, Onsite System Type, Topography, Potential for Flooding, Proximity to Karst, and Depth to Karst). Of these five parameters, drain field depth to the seasonal high-water table (ranked sixth) could potentially be estimated from USDA soil survey maps, topography (ranked seventh) could be extracted by calculating land surface slope from widely available digital elevation models, and proximity to Karst (ranked tenth) is likely available from the Florida Geological Survey (FGS) Florida Aquifer Vulnerability Assessment (FAVA or FAVA II).

The potential for flooding (ranked eighth) and onsite system type (ranked ninth) are potentially more challenging to add to the analysis. Onsite system type refers to whether the installed OSTDS is a standard or "advanced" system with enhanced nutrient removal. Future efforts by DEP to extract this information from OSTDS permits would allow the inclusion of this parameter in the future. Notably, advanced OSTDS systems are currently required for new permits on small lots in Priority Focus Areas (PFAs) within adopted Basin Management Action Plans (BMAPs) for impaired outstanding Florida Springs; parcels that meet these criteria could be assumed to have advanced systems installed. On the other hand, including a parameter quantifying the potential for flooding would require substantial further effort to define the parameter and develop a methodological approach for its estimation. This effort could vary from extracting flood zones from Federal Emergency Management Agency (FEMA) flood maps to developing probabilistic flooding models at the stateside scale, an effort recently initiated by the newly created Florida Flood Hub.

Additional potentially useful input parameters identified by workshop participants are also worthy of further exploration, including existing FAVA model outputs (i.e., vulnerability metrics) or the parameters underlying these metrics (e.g., presence of confining layer, depth to Karst, etc.). While FAVA is explicitly focused on groundwater and soil characteristics, pollution of surface waters by (functioning) OSTDS occurs via groundwater flow paths; as such, the inclusion of FAVA metrics could be a valuable complement to the existing parameter set. Workshop participants also suggested the potential consideration of historical land-use changes, especially in locations where agricultural or industrial areas were converted to residential land use due to their potential for legacy pollutants. Finally, participants recommended the inclusion of climate change-related factors and future population growth; if adding these parameters, DEP should differentiate between assessments of current vulnerability versus potential future vulnerability (discussed further below).

A second important recommendation regarding input data is to robustly QA/QC the parameter data used in the tool. DEP should consider identifying or collecting improved datasets for data sets with low reliability. Three examples of potential data reliability issues include depth to groundwater (ranked first), OSTDS Age (ranked fourth), and hydraulic conductivity (ranked fifth). Specifically, the parcel-level depth to groundwater data was extracted from FAVA, which adapted a terrain-following method (Sepulveda 2003) to develop statewide, gridded maps of water table elevation. To do so, FGS applied multiple linear regression equations for eleven regions in Florida using land surface elevation and water table elevations measured between 1990 and 2000. The reliability of the resulting spatially interpolated water table estimates is thus a function of three components: 1) the multi-linear models' ability to capture observed variance; 2) the accuracy of the underlying land elevation dataset (developed from USGS 7.5-minute quadrangle maps, which have a coarse elevation resolution); and 3) the availability of groundwater well data (which was relatively sparse and unequally distributed across the state). Despite these limitations, FAVA reports show good predictive ability, at least for the wells from which the correlations were derived. However, further assessment of the reliability and uncertainty in the FAVA model's depth to groundwater estimate at the parcel scale and in other areas (i.e., other than at the wells used in its development) is recommended.

Similarly, the reliability of the OSTDS Age data in the dashboard was raised by multiple workshop participants. <u>It should be noted that for those parcels for which no permit records were available, the estimated age was based on the age of first improvement of the parcel in the property appraisers' data.</u> It was suggested that OSTDS Age could be improved by adding and/or cross-referencing existing age data with information obtained through repair permits and property appraisal data, as well as from data in the Florida Water Management Inventory. Overall, this dataset should be reviewed for accuracy and cleaned of any spurious entries (**Figure 4**).

For hydraulic conductivity, the arithmetic means used in the current analysis should be replaced with harmonic means to represent soil layering better, and the dataset should be reviewed for accuracy. The range of current values in the database is higher than expected for Florida soils, with extremely high conductivities usually associated with gravel (**Figure 5**, **Table 4**). Overall, a robust assessment of data quality for the entire input parameter dataset is recommended.

Vulnerability Score Evaluation

As summarized in the Workshop 2 Final Report, workshop participants identified a range of possible evaluation approaches to assess the utility of the vulnerability scores (see **Table 3** in the Workshop 2 Final Report). The approach pursued in this report was the highest-ranked evaluation method, comparing vulnerability scores against water quality parameters/indices. However, it is important to note two significant limitations to this approach that may guide future work: 1) limited availability of the water quality data required for calculation of standard water quality indices (WQI) at the requisite spatial and temporal scales, and 2) non-specificity of available water quality parameters to uniquely identify OSTDS pollution.

DEP has developed and maintains an extensive water quality database, the Watershed Information Network (WIN), which compiles sample data from agencies, municipalities, utilities, and industries across Florida. Water quality data from WIN are accessible through the WIN Advanced View & Extraction System (WAVES) and include spatial information, facilitating the calculation of WQI at various spatial scales. Despite this wealth of accessible data, there was insufficient data for two critical components of the WQI applied in this study: fecal coliform and biochemical oxygen demand. These parameters are important indicators of sewage pollution and were among the parameters suggested by participants of the online survey in Task 1 as “reliable indicators of OSTDS-derived pollution in Florida waterbodies.” While still valid, the remaining water quality measures are less specifically indicative of wastewater pollution, limiting their utility in identifying regions affected specifically by OSTDS pollution (discussed further below). Expanding regular measurement of these two parameters is thus recommended to improve water quality characterization statewide.

As an additional step, it is suggested that DEP systematically assess water quality data available at various spatial scales (e.g., WBID, HUC12, HUC8, BMAP, etc.) and, over time, determine the feasibility of using WQI for broad-based water quality assessment. This assessment would help support the vulnerability scores evaluation as applied here and for spatial and temporal analysis of water quality trends.

Critically, even for regions (and time periods) with sufficient data to calculate the standard WQI, a significant limitation of this evaluation approach is that it is not specifically sensitive to OSTDS pollution. For example, none of the nine water quality parameters identified by workshop participants and/or included in the WQI, are uniquely directly related to wastewater pollution by OSTDS. Other pollutants, such as fecal coliform, nitrogen and phosphorus, are associated with a wide variety of pollutant sources, including point and nonpoint-source pollution from industry, agricultural, and residential areas, meaning that poor water quality associated with these parameters is not (necessarily) an indication of OSTDS pollution.

There are, however, several water quality analytes that are more directly associated with OSTDS-specific pollution. For example, Brewton et al. (2022) investigated septic pollution in the Caloosahatchee River Estuary using fecal indicator bacteria, specific molecular markers, sewage-associated chemical tracers (sucralose and various pharmaceuticals), and stable isotopes in water and organic matter samples.

Unfortunately, the data supporting the Brewton et al. (2022) study is not available statewide; however, a systematic assessment of what data are available (and a plan to expand the measurement of the most critical analytes) would support future assessment of septic vulnerability scores using a more OSTDS-specific water quality index.

In the meantime, DEP could use the existing vulnerability indices (or improved indices as recommended in above) along with the standard WQI to expand this analysis to other geographic regions of the state (beyond the five HUC8 watersheds analyzed here). This approach would support the evaluation of score performance more robustly across different geologic/anthropogenic regions and identify regions for which the scores do or do not reflect measured water quality.

Once satisfactory improvements and additions are made to input parameter datasets and the availability of relevant water quality analytes, vulnerability scores should be recalculated, and their correspondence to OSTDS-specific pollutants should be reevaluated. Once complete, a possible future approach would be to iteratively adjust parameter ratings and weightings to maximize correspondence between vulnerability scores and observed water quality. For example, this approach could calibrate in areas with substantial septic and validate in areas without septic, among other potential statistical optimization and validation approaches. However, pursuing this “fitting” procedure is not recommended until data availability, and quality issues are addressed, both for input parameters and the water quality data used for assessment.

In the meantime, DEP may pursue other approaches identified in Task 2, including expert elicitation and assessment of the changes in the vulnerability scores and water quality outcomes (measured or modeled) in locations where OSTDS intervention or mitigation programs have been implemented. DEP is also recommended to perform a sensitivity analysis of parameters in driving vulnerability scores. Of note, there was a limited and variable correlation between SAS OSTDS scores and WQVI-ST at the HUC12 scale (**Figure 21**), indicating the two indices are sensitive not only to the scale of application but also to the different weightings of input parameters underlying each method.

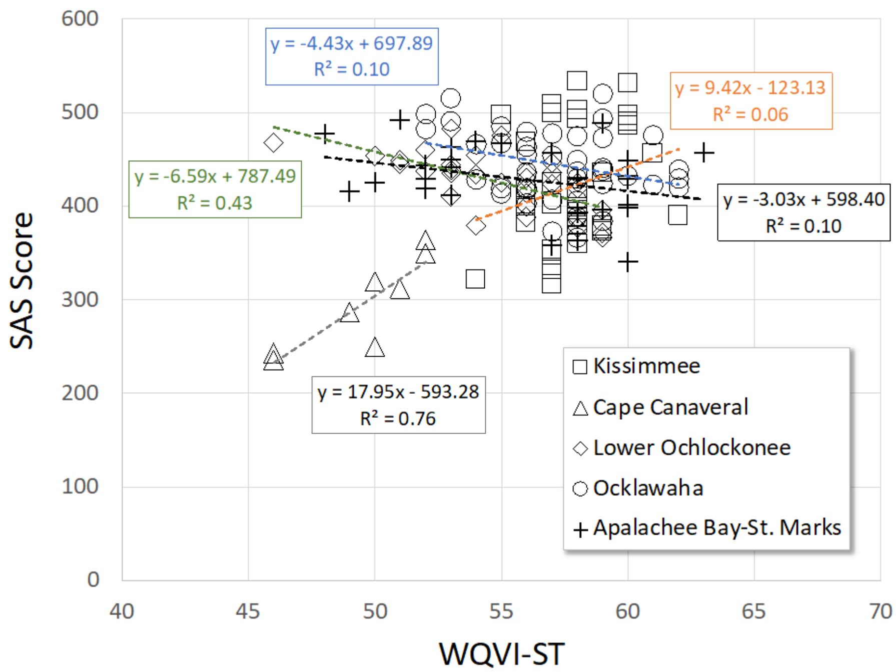


Figure 21. Correlation between HUC12 SAS OSTDS scores and WQVI-ST for the five HUC8 watersheds evaluated. Correlations between the two indices are low, except in the Cape Canaveral HUC8, the only watershed with low vulnerability scores according to both SAS and WQVI-ST scores (and for which correlations with WQI were highest).

Future Applications

As noted above, limitations in input parameter data and OSTDS-specific water quality data limit confidence in the ability of current vulnerability indices (WQVI-ST and SAS OSTDS scores) to predict septic-related water quality degradation. Once these limitations have been addressed, however, workshop participants suggested a variety of potential future applications for the dashboard beyond simply mapping and ranking current vulnerabilities. These applications can generally be described as scenario analyses to prioritize current decision-making and/or considering future climate and development scenarios to guide future decision-making.

For current-day applications, an improved dashboard would be useful for scenario analysis of the possible WQ improvements associated with specific septic-mitigation efforts being considered in a region (e.g., requiring advanced septic, transitioning from septic to sewer, changing zoning requirements for lot size, etc.). This scenario analysis would be useful for ranking and prioritizing projects based on expected water quality improvements for a given investment. These assessments could be further strengthened by explicitly integrating additional data related to the feasibility of project implementation (e.g., likelihood of septic-to-sewer conversion given existing infrastructure) and various socio-economic factors into the dashboard. The resulting analysis would potentially support ranking projects by benefit-cost ratios rather than only water quality impacts. Building upon this scenario analysis approach, DEP could consider adding future climate vulnerability (e.g., changes in flooding potential from sea-level rise and more extreme precipitation events) and projected land-use change (e.g., maps from the Florida 2070 population projections) to the dashboard to identify areas of future (rather than current) vulnerability.

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