Quarterly Report – Public Page

Date of Report: 2nd Quarterly Report-March 31st, 2020
Contract Number: 693JK31910018POTA
Prepared for: DOT PHMSA
Project Title: Mapping Indication Severity Using Bayesian Machine Learning from Indirect Inspection Data into Corrosion Severity for Decision-Making in Pipeline Maintenance
Prepared by: TEES (Texas A&M Engineering Experiment Station) and University of Dayton
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For quarterly period ending: March 31st, 2020

1: Items Completed During this Quarterly Period:

Per the contract, Task 1 is associated with the second quarterly report. The following activities have been completed

Item #	*Task #*	*Activity/Deliverable/Title*	*Federal Cost*	*Cost Share*
2	1	Preprocess the indirect and/or direct measurements from the industry partners	10,000	5,000
5	1	2nd Quarterly Report	4,000	0.00

2: Items Not-Completed During this Quarterly Period:

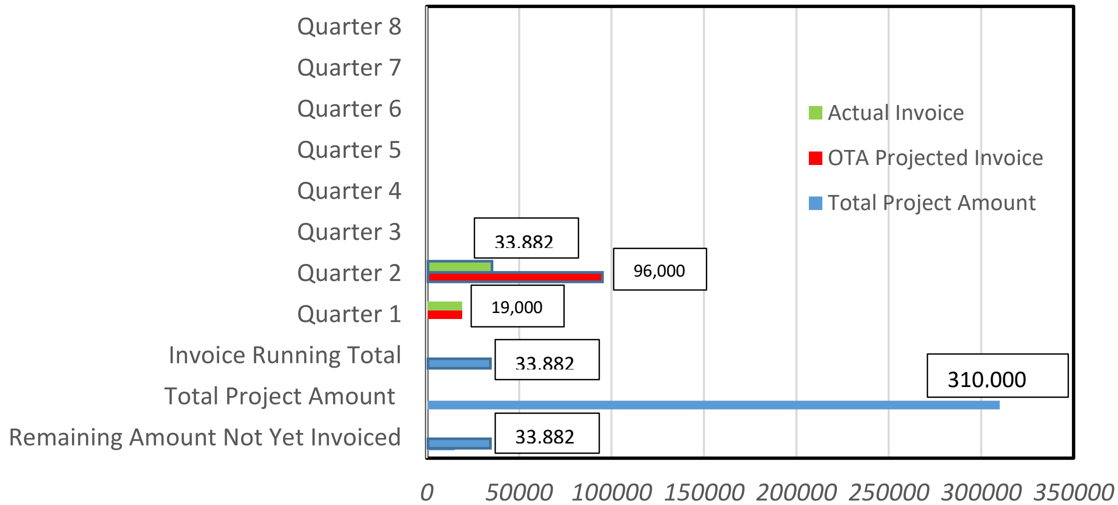
Task number 2, laboratory set up and extract basic corrosion model parameters started during this quarter report. Part of Task 2 will be cover in the following partial report.

Item #	*Task #*	*Activity/Deliverable/Title*	*Federal Cost*	*Cost Share*
6	1	Mapping available data via GIS tools and geographically co-register all datasets.	20,000.00	10,000.00
7	2	Laboratory set up and electrochemistry mechanisms and corrosion assessment	55,000.00	0.00
9	2	Extract basic corrosion model and embed into the previously developed stochastic corrosion rate model framework	24,000.00	0.00

3: Project Financial Tracking During this Quarterly Period:

The figure below provides details on the overall financial status of the project.

Quarterly Payable Milestones/Invoices 693JK31910018POTA



4: Project Technical Status –

The following tasks are included in the project:

- *Task 1:* **Establishing a database**
- *Task 2:* **Experiments and analyses to bridge gaps in prior knowledge**
- *Task 3:* **Bayesian machine learning to bridge gaps in uncertainty quantification.**
- *Task 4* **Finalize and evaluate/validate the model.**

During the second quarter, the team members from Texas A&M University (TAMU) and the University of Dayton (UD) had different meetings and a workshop conducted to deepen the understanding of characterization methods used in pipelines.

The team organized and participated in a web-conference Workshop entitled *"Quantification and characterization of parameters obtained by indirect inspection in buried pipelines"*

The outcomes of the workshop helped the PhD students in both TAMU and UD teams with different knowledge backgrounds to understand the corrosion mechanisms in buried pipelines and how the indirect inspection tools and technologies can be complemented by different parameters due to the corrosion mechanism. The ECDA (External Corrosion Direct Assessment) methodology was also discussed to indicate the steps to take for integrity management in buried pipelines and how indirect inspections can be integrated with survey recommended practices.

During the internal team meeting, we discussed different actions to cover task 1 and task 2.

Some of the results and highlights are summarized in this report as follows:

Task 1 – Establishing a database. The digital database was generated from direct, indirect, and survey technologies with sub-meter location, in-line inspection, and direct characterization. The initial data frame was screened and different parameters were included based on the corrosion mechanism. Since we are considering corrosion as the main threat for the buried pipelines we defined different parameters that influences or affects corrosion.

Previously we developed two different set of data, the section first considers an X65 API steel pipeline of 37.5 miles and the second section includes 68 miles of X52 steel. The following characteristics were included in the database (Table 1):

Table 1: Basic information of the selected pipeline systems

Pipeline Section	37.5 miles X65 API steel	68 miles X52 steel
Thickness	0.343 in	0.374 in
Diameter	30 in	18 in
CIS Inspections	Year 1 , Year 2	Year 1 , Year 2
DCVG Inspections	Year 1 , Year 2	Year 1 , Year 2
ILI Inspections	NDT, MFL	MFL

The metrics of corrosivity have been queried, integrated and aligned with field measurements. The parameters have been defined as different layers for the corrosion process. Following the direct and indirect inspection technologies: in line inspection (ILI) as displayed In Figure 1a, close interval potential survey (CIPS) and direct current voltage gradient (DCVG) are the first layer for the detection and corrosion identification. The rest of the survey parameters, such as pH, resistivity, soil ionic concentration, potential redox are considered as the secondary layer of corrosion detection as illustrated in Figure 1b. A third layer is created by parameters that can be estimated based on environmental conditions, such as precipitation, soil drainage, topography and water accumulation.

Start Static	Pipeline diameter-i	Material and grade	Origil wall thickness,	Pigging date	Metal loss %	Metal Loss in mm	Metal Loss Rate	defect longitude, in	Defect orientation	Active
0	18	52000	0.252							
0	18	52000	0.252					122	6.13	
0	18	52000	0.252	1/12/2005						
0.01	18	52000	0.252	3/16/2010						
0.01	18	52000	0.252							
0.56	18	52000	0.252	1/12/2005						
0.66	18	52000	0.252	3/16/2010						
0.66	18	52000	0.252							
0.9	18	52000	0.252							
1.4	18	52000	0.252							
2.03	18	52000	0.252							
2.98	18	52000	0.252	3/16/2010						
2.98	18	52000	0.252							
3.32	18	52000	0.252	3/16/2010						
3.37	18	52000	0.252					346	9	

(a)

Resistivity @ 1m (ohm.cm	Resistivity a 2m (ohm.cm	pH	CO3 (mmol L-1)	HCO3 (mmol L-1	Cl (mmol L-1)	SO4 (mmol L-1)	Soil Moisture	Soil Type
6283.18531	2956.79309	5.454	0.516	4.902	8.25	0.090096	0.2834	5
6283.18531	2956.79309	5.454	0.516	4.902	8.25	0.090096	0.2834	5
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6283.18531	2956.79309	5.454	0.516	4.902	8.25	0.090096	0.2834	5

(b)

Figure 1. Sample screen shots of the master file for each pipeline section (a) characteristics of the pipeline, ILI (b) characteristics of the soil

The definition of each layer and how it influences the corrosion mechanism helped to screen each parameter in the database and how the laboratory experiments can help to characterize and quantify when necessary.

The following are some highlights of each set of data and definition based on each layer:

Direct and indirect inspections

- In line inspection presents different magnitudes following the survey, longitude, position (clockwise) and depth of the external defect. The defects are assumed to have a semi-ellipsoid geometry and are resulted from the activation of the corrosion process.
- CIPS is based on the open circuit potential concept for steels in soil conditions. The soil/coating/steel system is considered.
- DCVG is based on potential gradients and current distribution due to a leakage at the defect or coating event location.

Different survey magnitudes

- pH is used primarily as the corrosivity of the soil and local electrochemical conditions
- Ionic concentration is used primarily to the corrosivity of the soil and how potential measurements can be affected by these magnitudes
- Resistivity of the soil is used primarily to the corrosivity of the soil

Estimation of parameters from environmental conditions

- Precipitation is used for water distribution in the soil and to generate a corrosivity index.
- Type of soil is used for water drainage and distribution to quantify soil corrosivity
- The normalized difference vegetation index (NDVI) is used for water evaporation and distribution.
- Topography is used for water distribution.

The consolidated data was analyzed to discuss about the assumptions and characterization to be made in order to start the modeling process. One example is illustrated in figure 2.

The soil type, water precipitation and drainage at five different depth ranges (0-20 cm, 20-40 cm, 40-60 cm, 60-80 cm and 80-100cm) were obtained for the four seasons (spring, summer, fall and winter). Based on this data, the pipeline at the various locations will be placed into a qualitative ranking system that depend on whether it is partially, fully or not immersed completely in the water in the soil. Based on the water precipitation and distribution, the corrosivity will be normalized and included in the database for additional information.

	A	B	C	D	E	F	G	H
1	id	pH	Soil Type		Soil Moisture Layer 5 (80-100 cm)			
2			Layer 5 (80-100 cm)	Layer 5 (80-100 cm)	Spring	Summer	Fall	Winter
3	2	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
4	4	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
5	5	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
6	6	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
7	8	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
8	9	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
9	10	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
10	11	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
11	12	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
12	15	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
13	17	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
14	18	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
15	20	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
16	22	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
17	24	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
18	26	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
19	27	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
20	28	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
21	29	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
22	30	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
23	31	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
24	32	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
25	33	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
26	35	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
27	36	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
28	38	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
29	39	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
30	40	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
31	41	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618
32	43	7.957918	Clay Loam	5	0.2689	0.2729	0.2834	0.2618

Figure 2. Sample screen shot of the soil moisture data.

A portion of the collected database has been georeferenced and co-registered for a better understanding of the spatial distribution. Several georeferenced layers of data showing rivers, vegetation coverage, topological elevation, soil type have been produced.

The first dataset is regarding the water body distribution within the region of interest and the sample plot is shown in figure 3. Blue lines on the plot shows the river water sources.

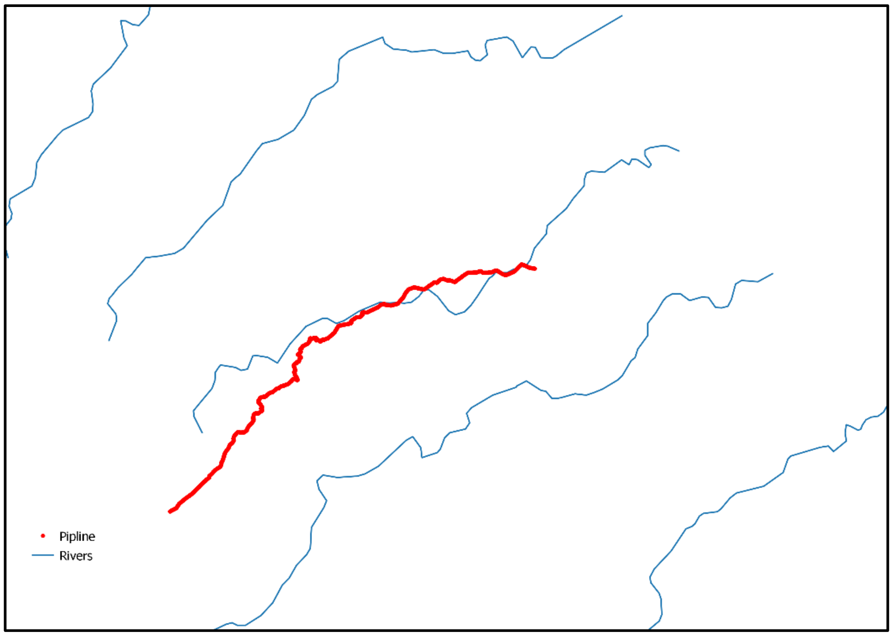

Figure 3. The map of the water body within the region of interest covering the pipeline right-of-way.

The second dataset is the spatial distribution of the NDVI, which is one of the most successful of many attempts to simply and quickly identify vegetated areas and their growing condition, and it remains the most well-known and used index to detect live green plant canopies. In this project, NDVI is assumed to be correlated with large scale soil condition and the seasonable variation of the NDVI images of the region of interest may reflect the information of the soil moisture and soil type. A sample image is shown in Figure 4.

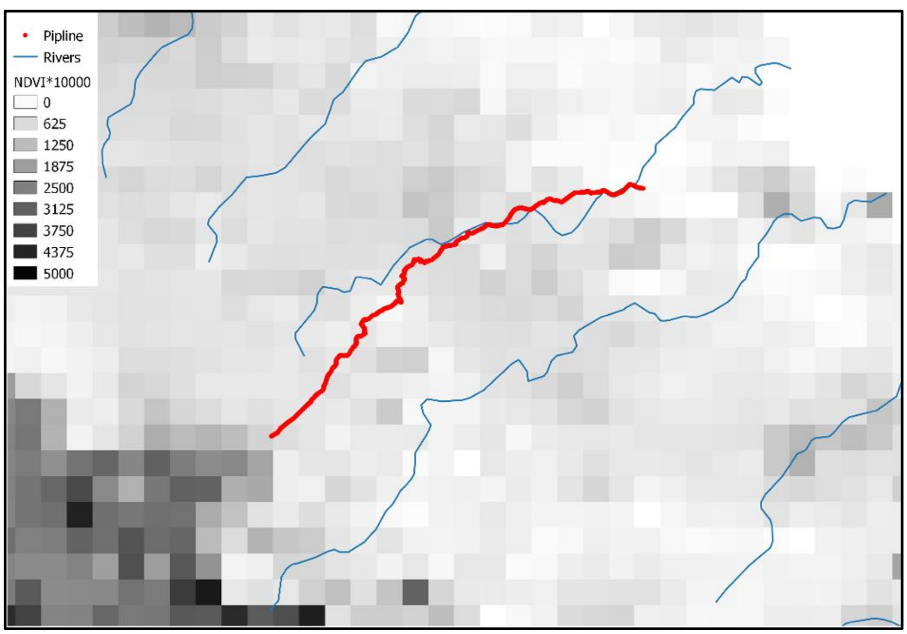

Figure 4. Sample NDVI image of the region of interest

The third dataset is the digital terrain model of the region of interest. The topography will affect the water distribution, soil type distribution, and the vegetation distribution as illustrated in figure 5. We are currently working on linking all these datasets together into a multi-layer georeferenced database. Each pipeline segment is expected to be linked with a set of information as described above

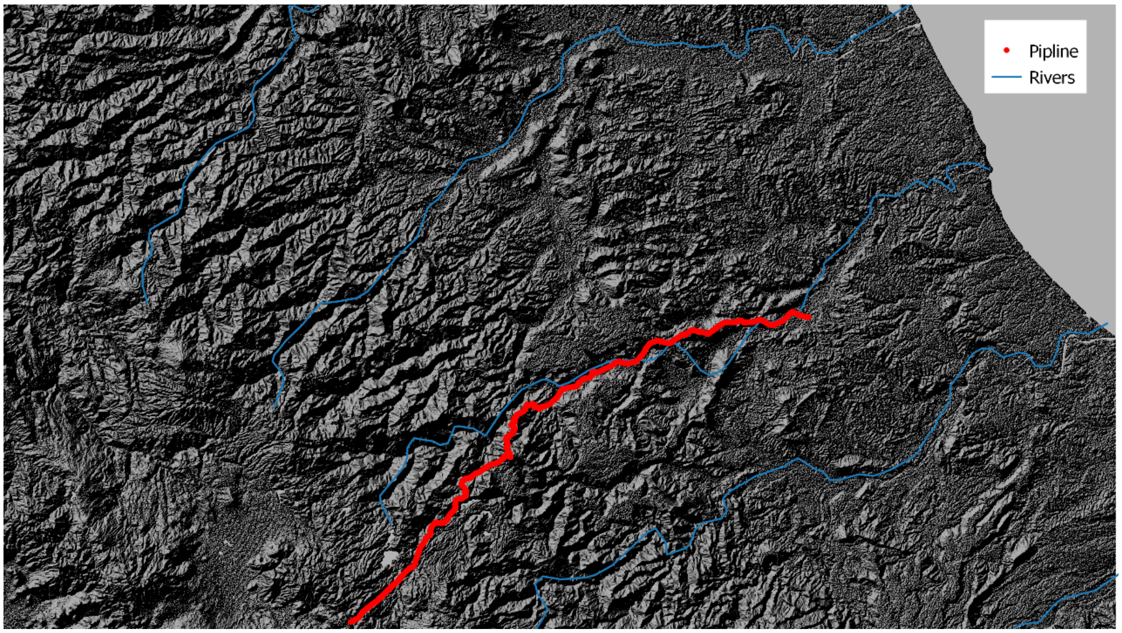

Figure 5. The DTM covering the region of interest and the overlaying pipeline right-of-way

5: Project Schedule –

The project is on-schedule as originally-proposed.

*During the following quarter, the team will perform the experimental laboratory testing. During the set up and experimental development will consider g*aps in prior knowledge relating coating conditions and corrosion severity under controlled environmental factors. Fieldwork will involve pipelines whose RoW reflects conditions of different soil scenarios, and a host of topographic conditions will be included, to cover the range of typical US conditions. Trends in the outcomes will be examined and/or deterministic or semi-empirical models or expressions will be developed to quantify the damage evolution in the pipeline/soil system.

The activity for mapping available data via GIS tools and geographically co-register all datasets will be continue to have the task completed.

6. Publication

On Feb 25th, 2020, the research manuscript "Statistical Analysis of Spatial Distribution of External Corrosion Defects in Buried Pipelines Using a Multivariate Poisson-lognormal Model" was accepted by the journal *Structure and Infrastructure Engineering*. Currently, the manuscript is going through the typesetting and proofreading.

Observations: The experimental set up and development might be affected for the current proposed timeframe due to the current world circumstances. Laboratory activities and research operations might be affected.