

USING RUT DEPTH SENSING TO CALCULATE SOIL STRENGTH FOR COMPARING ACCURACY TO GEOWATCH AND PHYSICAL MEASUREMENTS

Jason N. Fischell¹, Bradley S. Hansen, PhD¹, J. Rebekah Jackson¹, John B. Eylander²

¹Mobility Systems Branch, Geotechnical and Structures Laboratory

²Hydrologic Systems Branch, Coastal and Hydraulics Laboratory

U.S. Army Corps of Engineers, Engineer Research and Development Center
Vicksburg, MS

ABSTRACT

Ground vehicle soft soil mobility has been studied for decades. Standard measurements, such as cone penetrometer, determine soil strength which helps analyze vehicle mobility. These methods are only available where data can be collected. As off-road vehicles transition to autonomous and semi-autonomous, real time in-situ analysis of soil strength is becoming a necessity. Databases such as GeoWATCH provide coarse (30-90m geospatial resolution) mobility parameter estimates. Hydrologic events can cause rapid changes in mobility which may not be effectively captured by these databases. In order to make real time predictions for autonomous vehicles, it is necessary to develop a method to determine mobility parameters without operator intervention. A system using rut depth measurements (collected via optical and ultrasonic sensors) and vehicle parameters was developed from established methods to estimate soil strength. The results were compared to corresponding physical measurements and raw GeoWATCH data.

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1. INTRODUCTION

The US Army routinely conducts research to develop new methodologies to understand and predict ground vehicle performance in all weather and terrain conditions. A key component of this research involves understanding the strength of

soils based on soil classifications, water content, and pressure applied to the soil by equipment and vehicles. Additionally, the Army has developed a number of applications to support the computation of mobility based on vehicle characteristics and terrain information, including but not limited to the NATO Reference Mobility Model [1], Army Standard Mobility Application Interface (STNDMOB) [2], and Mobility Analysis Tool [3].

While developing models and applications to characterize vehicle performance is a key goal, linking those models with real time environmental information describing soils and weather information remains a major challenge because of the lack of accurate and precise maps of soil information world-wide, including the influence of weather on the soils.

The Engineer Research and Development Center continually investigates new methods, develops new datasets, and links applications to integrate weather and terrain knowledge with mobility applications. These resources are used to analyze and predict the impact of environmental conditions on vehicle-terrain performance. One of the latest weather-informed mobility tools being evaluated is the Geospatial Weather-Affected Terrain Conditions and Hazards (GeoWATCH) [4] application. GeoWATCH links weather data from the US Air Force 557th Weather Wing with global soils and terrain information to predict soil strength and supports an embedded execution of the STNDMOB application to compute cross-country vehicle speeds. However, accurate computation of soil strength and vehicle speed based on weather and terrain data alone is uncertain and still produces relatively coarse (~30 meter resolution) products compared to the resolution of drainage features and other terrain conditions that impact mobility. Also, soil strength and mobility predictions lack the use of automated, fielded sensors as a way to reduce uncertainty and increase accuracy of remotely observed weather patterns. Similarly, terrain, elevation, and vegetation information gathered using satellites or other airborne direct remote sensing methods lack the necessary levels of accuracy and reliability.

GeoWATCH soil classification allows for reasonable soil strength estimation. Knowing the strengths and weaknesses of GeoWATCH soil classification then becomes vitally important. In order to understand how

classification inaccuracies occur GeoWATCH soil classifications were compared to previous in situ soil classifications. The in situ soil classifications were completed in early 2020 and consisted of 18 test sites. Out of the 18 tests, GeoWATCH was 77% accurate (14:18) when compared to the sieve analysis classifications. One possible explanation for why GeoWATCH was less accurate is that GeoWATCH tends to classify soils based on the surface layer of the soil area. Therefore, GeoWATCH incorrectly classifies soils as mainly organic rather than the sandy soils seen in the testing area. The sieve analysis tended to take in the totality of the soil profile in making a soil prediction, often ignoring the initial top organic soil layer. In the four test sites that GeoWATCH incorrectly classified as organic/peat material, GeoWATCH utilized the data from the top organic soil layer. Through this comparison, it seemed that the main issue in false soil type classifications was the soil layer in which GeoWATCH was using to classify. Updating GeoWATCH in the future will mitigate these types of errors and increase the accuracy of soil type classifications and in turn, soil strength classifications. By continuing experiments such as in this paper, GeoWATCH can be refined and accuracy can be increased.

A key hypothesis of this study is that a vehicle equipped with a number of lightweight and low power sensors can support the automated detection of soil strength to increase the accuracy of those predictions and apply those observations to any modeling system without requiring personnel to frequently deploy soil probes to acquire in situ measurements. This project was designed to address the automated collection of soil strength measurements using an innovative, vehicle-based tire or track rut-depth detection approach. Specifically, this project evaluated placing a number of sensors on vehicles to measure the vehicle tire or track rut depths and determine whether those measurements can be used to approximate soil strength and predict future

mobility conditions when combined with model-based estimates through assimilation. Additionally, this project evaluated the computation of soil strength indices. A number of experiments were designed in order to test whether the rut-depths acquired from the sensors and the resulting soil strengths computed compared well with measured rut depths and GeoWATCH soil strengths. In situ measurements taken with standard tools (e.g., cone penetrometer) were part of the original experimental design, but were not available due to environmental conditions.

2. WHEELED VEHICLE RUT DEPTH AND SOIL STRENGTH RELATIONSHIPS

This paper uses three different rut depth and soil strength relationships for wheeled vehicles that were derived from existing equations [5, 6, 7]. The original equations calculated the rut depth using vehicle parameters and soil strength. These equations were rearranged by solving for the soil strength.

Equation (1) was derived from a semi-empirical equation for calculating rut depth [5], the purpose of which was to estimate rut depth in spring thaw conditions. The vehicles of interest in the original study were the Stryker (wheeled), HEMTT (wheeled), and M60A3 (tracked). Ultimately the estimation of rut depth using the equation under predicted rut depth in thawing and saturated conditions. However, the equation was able to predict single-pass rut depth in normal soil conditions.

$$RCI = \frac{\left(\frac{10*r*N^2}{z_{soil}}\right)^{\frac{1}{3}} * W * \left(1 - \frac{\delta}{h}\right)^{\frac{3}{2}} * 5^{\frac{1}{5}}}{2*r*b} \quad (1)$$

RCI= Rating cone index (kPa, psi)

r = Tire radius (m, in)

N = Number of passes

z_{soil} = Sinkage or rut depth (m, in)

W = Tire load (kN, lb)

δ = Tire deflection (m, in)

h = Unloaded section height (m, in)

b = Undeformed tire width (m, in)

s = Wheel slip (can assume 20-50%) or calculate using Equation (2)

$$s = \frac{V_w - V_v}{V_w} \quad (2)$$

V_w = Velocity of the wheel (mph)

V_v = Velocity of the vehicle (mph)

Equation (3) comes from a report that uses ground vehicle rut depths to predict aircraft ground performance [6]. It uses a tire-clay numeric to calculate a rut depth relationship. The equation was rearranged and solved for an airfield index which was then converted to a cone index (CI). As shown in Equation (4), CI is directly related to rating cone index (RCI), a measure of soil strength. The tire-clay numeric was found to be effective in consolidating rut depth and towed data to graphical relationships for each variable in the tire-clay numeric.

$$CI = \frac{50*W*\left(1 - \frac{\delta}{h}\right)^2 * \left(1 + \frac{b}{2*d}\right) * 10^{-2.27*N^{0.220}}}{b*d} \quad (3)$$

$$RCI = CI * RI \quad (4)$$

CI = Cone index

RI = Remold index

d = diameter

Equation (5) originated from a report designed to investigate changes to the methodology for estimating army training and testing area carrying capacity (ATTACC), vehicle severity factors, and local condition factors [7]. Ultimately, the authors mention that the sinkage equations, the original arrangement of Equation (5), can be used effectively but their applied methodology would need to be changed.

$$RCI = \left(\frac{5*d}{z_{soil}}\right)^3 * \frac{W_{veh}}{\#Wheels * d*b} * \left(1 - \frac{\delta}{h}\right)^2 * 0.7247797 \quad (5)$$

W_{veh} = Total vehicle weight (kN, lb)

These equations all have similarities that give credence to their use. This paper uses the equations in a slightly different way in support of solving problems relevant to real time off-road mobility. If a vehicle can determine in real time the soil strength based on rutting depth, it would be a significant contribution to the autonomy community and army capability.

3. TRACKED VEHICLE RUT DEPTH AND SOIL STRENGTH RELATIONSHIP

This paper uses one tracked equation from [5] which was rearranged to solve for RCI. The tracked Equation (6) can be seen below. Tracked vehicles had less available literature concerning rut depth and soil strength relationships than wheeled vehicles.

$$RCI = \frac{5.887*W}{b*L*\ln\left(\frac{z_{soil}}{\sqrt{N*0.0043*L}}\right)} \quad (6)$$

W = Track load (kPa)

b = Track width (m)

L = Track length (m)

4. SENSOR SUITE

Two means of quantifying rut depth were considered. The first was to use a scanning lidar or other such system to get a profile of the entire rut. These data would allow the researchers to quantify rut depth as well as other rut parameters such as the width of the rut and heights of the piles formed on either side of the rut. However, two major faults were found with this method.

First, the use of a scanning lidar would require significantly more data processing to determine rut depths. In order to profile a rut using the data from a scanning lidar system, one must consistently identify the bottom of the rut, the piles formed, and

the region of undisturbed soil on one or both sides of the rut. Second, preliminary tests using a Velodyne VLP-16 lidar revealed a great deal of discrepancy between even adjacent points scanned by the lidar. This inconsistency, as well as the relatively low accuracy and precision of the VLP-16, precluded its use in this project.

The second method of rut depth measurement considered was to take distance measurements at different locations behind the vehicle. While two distance measurements cannot be used to profile the rut in detail, it provides a simple method of determining rut depth. By mounting one sensor over the center of the rut caused by the vehicle and the other over the undisturbed soil between the two ruts, rut depth can be determined by taking the difference between the two measurements. It should be noted, however, that even high fidelity sensors are limited in their accuracy, precision, and consistency. As a result, determining rut depth from two distance measurements still requires some data post-processing.

Once the method of determining rut depth was decided upon, the next step was to determine the types of sensors to be used. Ultrasonic sensors (US) and solid-state lidar time-of-flight (ToF) sensors were considered for this project. ToF are much faster than US, and are significantly less susceptible to changes in temperature. ToF sensors also usually have a narrower field of view, making it easier to accurately measure the center or deepest part of the rut, rather than risking interference from the edges. However, one major disadvantage of ToF sensors is that they perform better on reflective surfaces, which the dirt or mud behind an off-road vehicle usually is not.

Similarly, US perform better on hard surfaces, which, for soft soil testing, is unlikely to be the case. However, US also have several significant advantages. First, US are not affected by sunlight, which was a strong consideration for the in situ testing of this system. Second, the US were believed to be less susceptible to interference from

dirt and mud kicked up by the vehicle and possibly adhered to the sensor surface.

Because of the natural advantages provided by each means of distance measurement, as well as the unanswered questions about the performance of each sensor type for this specific application, three US and three ToF were purchased and their performances were compared.

Bench testing was sufficient to identify the superior ToF and US sensors from the others of the same type. In both cases, the selected sensor yielded higher accuracy, precision, ease of use, and reliability than their counterparts, making them the obvious choice. Of the three US, the one selected was the MB7366 from the HRXL-MaxSonar-WR series by MaxBotix. Of the three ToF, the obvious choice was Benewake TFMini Plus. In bench tests, both sensors yielded millimeter level precision and an accuracy of ± 5 mm. The TFMini Plus sensors were much faster, while the MB7366 provided superior measurement-to-measurement stability.

An analysis of the propagation of uncertainty from sensor measurements to soil strength was conducted to determine whether these sensors would meet the needs of this project. It was determined that a rut depth measurement error of roughly 1 cm would yield a ± 10 psi uncertainty in the soil strength estimates. Based on the sub-cm accuracy of each of the sensors, these results suggested that the selected sensors would be sufficient for the requirements of this project. However, because of the wide variety of factors that affect sensor performance in practice, it was impossible to determine which sensor would be better suited to rut depth measurement from bench testing alone.

In order to provide a fair platform for the comparison of the sensors, as well as to provide a better means of data collection, both sensors were integrated into the same system. One of each type was mounted in a line over the center of one rut, and the others were mounted in the same order over the approximate center of each vehicle. In addition to these sensors, a Garmin 18x PC 1 Hz GPS was

integrated to determine the speed and position of the vehicle when the measurements were being taken. The position is advantageous for purposes of record keeping, as well as its relevance to the integration of this system and GeoWATCH data. The speed is helpful for some of the rut depth calculations mentioned in the previous sections. For the purposes of record keeping, comparison to GeoWATCH, and to verify the validity of the GPS data, the date, time, and age of each GPS reading were also recorded.

All of the data from each sensor were collected via an Arduino Mega and saved to an SD Card as a CSV file. Because of the inability of the Arduino to multithread, the system operates sequentially. First, the GPS data is saved to the SD card. Because of the 1 Hz update rate of the GPS, this process takes roughly 1.2 seconds. Next, the US sensors fire sequentially to minimize interference. Firing both US, reading their data output, and saving their data takes roughly 1.1 seconds. Finally, because reading a ToF and saving the appropriate data only take about 22 ms each, the ToFs are fired alternately (to minimize interference) 10 times each, over a period of 0.43 seconds. Over all, the program takes roughly 2.75 seconds per cycle (0.36 Hz) and provides the following measurements:

- Uptime at cycle start
- Date
- Time
- GPS Reading Age
- Position (latitude and longitude)
- Speed
- Uptime at US Start
- US1 and US2 Depths
- Uptime at ToF Start
- ToF 1 and 2 Board Temperatures
- 10 reading from each ToF1 and ToF2

5. EXPERIMENTAL PROGRAM

5.1. Vehicles

Five vehicles were intended to be tested for this effort. However, due to mechanical failures and

logistical conflicts only one wheeled vehicle and one tracked vehicle were available for testing when the selected site was accessible. Only one week of onsite testing was possible. The wheeled and tracked vehicle were the High Mobility Multi-purpose Wheeled Vehicle (HMMWV) and the Expeditionary Modular Autonomous Vehicle (EMAV), respectively. These vehicles are depicted in Figure 1. Table 1 displays the physical dimensions of each vehicle needed for the equations described in Sections 2 and 3.



a.) HMMWV



b.) EMAV

Figure 1. Vehicles successfully tested.

Table 1. Vehicle Dimensions

Vehicle	Avg. W (kN)	r (m)	δ (m)	h(m)	b (m)	L (m)
HMMWV	13.9	0.46	0.029	0.23	0.31	---
EMAV	16.5	---	---	---	0.30	1.95

5.2. Testing Methods

For this experiment, in situ tests, with the sensor system mounted on the vehicle, were conducted in

two distinct environments. First, tests were conducted on hard surfaces, namely asphalt and concrete, to determine the efficacy of the sensors and data analysis for conditions with no rutting. These hard surface tests were performed outdoors on several different days, to account for differing weather conditions, using the entire sensor suite. The hard surface tests were conducted both with the vehicle in motion and parked, but the poor quality of the data recorded while the vehicle was in motion resulted in the data being omitted from this paper. The preliminary results from the hard surface testing were used to establish a baseline for the performance of the sensor suite before more advanced testing methods were implemented.

Second, truly in situ tests were conducted with the HMMWV and the EMAV on soft soils. The requirements for the selected test site are described in the following section. These tests were conducted on two different days, one for each vehicle, over a variety of number of vehicle passes. Data were collected both while the vehicles were moving and parked, but as with the hard surface tests, data recorded while the vehicle was in motion was discarded due to its unreliability.

5.3. Testing Site

For any soft soil testing, site selection is vitally important. An ideal area contains a range of soil strengths that encompass “infinite” strength to practically zero strength or immobilization. This ideal area does not exist which means a variety of sites are typically screened for these characteristics to provide the best data. Three sites were screened in the following locations: Delta, LA; Flowers, MS; and Bovina, MS. The Louisiana site was inaccessible due to flooding of the Mississippi River. The Flowers site had tall grass which made it unusable. The Bovina site had short grass, and held enough water to yield lower soil strengths.

Ultimately, the Bovina site, near the Big Black River, was selected. The site is depicted in Figure 2 and Figure 3. The river is to the east and south of the test site location as indicated by the green line.

This site was prepared by removing the top grass layer and allowing rain to condition the site for lower soil strengths. Site conditions did not allow for the collection of cone penetrometer soil strength measurements (RCI).

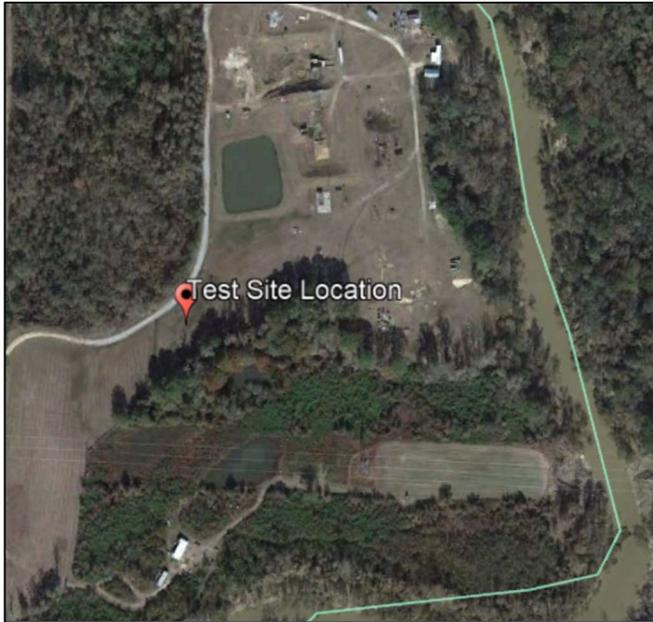


Figure 2. Test Site.



a.) Site before scraping



b.) Site after scraping

Figure 3. Site preparation.

5.4. In Situ Testing Procedures

As is common in developing new field testing practices, the methods of data collection were refined throughout the data collection process. The number and variety of tests conducted was limited not only by vehicle availability, but by the size of the test site and the restrictions of testing in flood prone regions. These limiting factors made it impossible to repeat the earliest tests as better practices were developed. However, in future iterations of this experiment, the improved practices will be implemented from the start.

Experimentation started with the EMVA in one lane of the test site on the afternoon of June 8, 2021. Data were collected by running the rut depth system as the EMVA was driven across the soft soil lane. After 10 one-way passes (five back-and-forth laps) were completed with the EMVA, data collection was transitioned from a continuous measurement while the vehicle was in motion to discrete measurements of rut depths at five separate points along the path. At each of the five points, the sensor system was used to collect data for at least 10 cycles (roughly 30 seconds), and a rut depth measurement was taken by hand according to the standard procedure.

This practice was repeated until a slight tilt in the vehicle was observed. At this point, an angular

measurement of the tilt of the vehicle was added to the data collection process. From that time on, each time the vehicle was stopped to record data, a measure of the transverse (left-to-right) incline of the vehicle was recorded by hand using a level with 1° resolution.

The same process was repeated for 25 and 50 one-way passes of the EMAV. For each, data were collected during the intervening passes while the vehicle was driving, as well as at five parked locations within the path. After the fifth point was collected in the 50-pass lane, testing of the EMAV was completed.

Upon analysis of the EMAV rut depth data, it was observed that there was a significant discrepancy between the depths observed by the ultrasonic and lidar sensors. It was assumed that this was due more to the heterogeneous nature of the mud than discrepancies between the sensors. As such, when testing was conducted on the HMMWV several days later, it was decided to record two measurements of the rut depth, one beneath each sensor, rather than the one measurement between the sensors recorded during the EMAV trials.

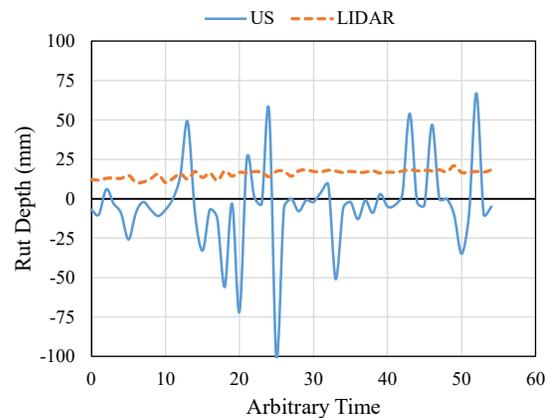
On the morning of June 11, 2021, data collection with the HMMWV proceeded as it had with the EMAV, including in-motion data collection and parked data collection after 10 and 25 passes. For each of the parked measurements, the transverse angle of the vehicle and the rut depth beneath each sensor was recorded.

During the last set of passes of the HMMWV, from 25 to 50 passes, it was observed that the vehicle was rapidly losing traction. As such, it was decided to take the final set of rut depth measurements after 40 passes of the HMMWV, rather than 50. While trying to get the vehicle out of the mud after the last data point had been collected, the vehicle became stuck and had to be towed out. This reinforced that the experimenters had made the correct decision in collecting data after 40 passes, rather than trying to complete 50 passes and being unable to collect any more data.

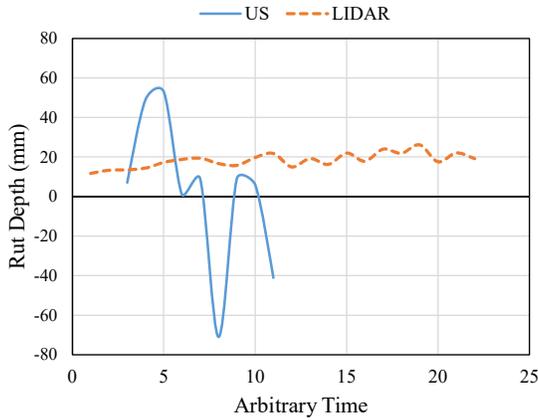
6. RESULTS

6.1. Parked Test

The first step was to test the sensors when attached to the vehicle (EMAV in this case) in a parked condition over 1-3 minute periods on asphalt and concrete. This can be seen in Figure 4. Arbitrary time was used as a measure instead of actual time due to the sequential reading of measurements that leads to a small discontinuity in time between LIDAR and US. The US did not show consistent measurements which was not fully understood. The LIDAR showed exceptional consistency in the parked condition on both asphalt and concrete. Respectively, the LIDAR and US measured an average rut depth of 16 and -4 mm on concrete and 18 and 0.3 mm for asphalt. After small angle corrections the averages went further away from zero. The accuracy of the parked, no rut condition was unimpressive. This data showed that a potential adjustment in sensor reading and/or low pass filtering of the data may be required. However, the authors believed a raw data adjustment to be unnecessary until in situ data were collected. The parked no rut condition is of no concern for mobility, so subpar results in this configuration were of little consequence.



a.) Concrete



b.) Asphalt

Figure 4. Vehicle Parked Tests.

6.2. In Situ Tests EMAV

The EMAV was the first vehicle tested, and as described earlier, had some small data collection changes that were instituted during testing. As such, the data for the EMAV should be expected to be a little less consistent than that from the HMMWV testing. The rut depth comparisons between the physically measured rut depths and the sensor rut depths are shown in Figure 5. Figure 5 shows an equality plot to determine how closely the rut depths obtained by the sensors compare to those collected by hand. The R^2 value is not a true coefficient of determination, but it does show a degree of linearity between the datasets.

The LIDAR showed a weak positive correlation approximately 35% lower on average than the measured value. The US performance was poor and throughout testing showed consistently poor performance. Figure 6 shows the average of all calculated soil strengths from each rut depth measurement mechanism using equation (6). These are compared to the expected soil strength from GeoWATCH for the date and time of testing. The comparison to GeoWATCH showed poor performance, which was predicted based on the scatter of rut depth measurements in Figure 5.

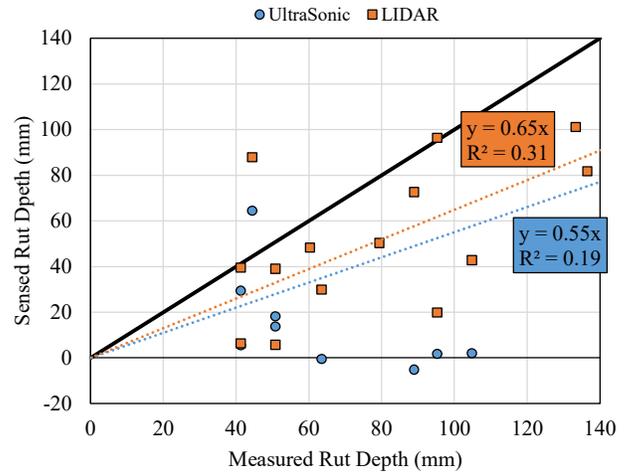


Figure 5. EMAV Rut Depth Results.

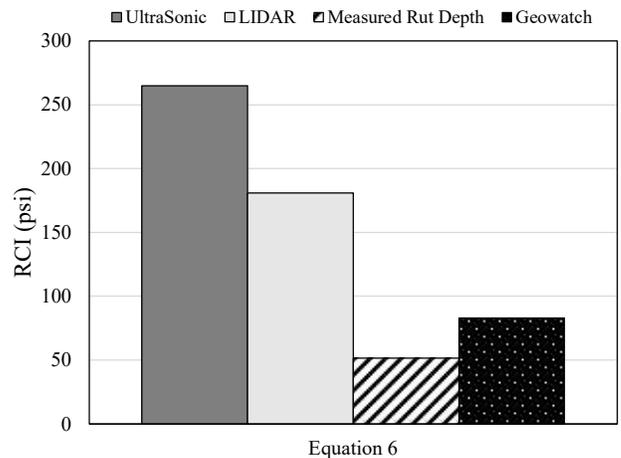


Figure 6. EMAV RCI Comparison.

6.3. In Situ Tests HMMWV

The second vehicle tested was the HMMWV. The data collection method was refined based on experience with the EMAV. Figure 7 shows much better rut depth comparisons for the HMMWV than the EMAV. This is most likely due to our adjusted data collection practices. The LIDAR had a moderate to strong agreement with the measured rut depth values being 32% lower on average. The US once again showed poor performance. One noteworthy limitation that the US sensors used for

testing cannot measure certain large rut depths. Once the sensors get closer than 500 mm it no longer registers a return. The largest rut depth for the HMMWV was around 250 mm which led to the central US being unable to accurately measure the distance to the ground. Figure 8 shows the average of all soil strengths calculated from each rut depth measurement mechanism using equations (1), (3), and (5). These are compared with the expected soil strength for the day and time of testing from GeoWATCH. When ignoring the US calculated soil strength, equation (3) showed the best overall performance. The LIDAR rut depth, manually measured rut depth, and GeoWATCH RCI were 89, 79, and 83 psi, respectively. This falls within the required accuracy of RCI measurements of 10-15 psi. This finding was exceptionally encouraging.

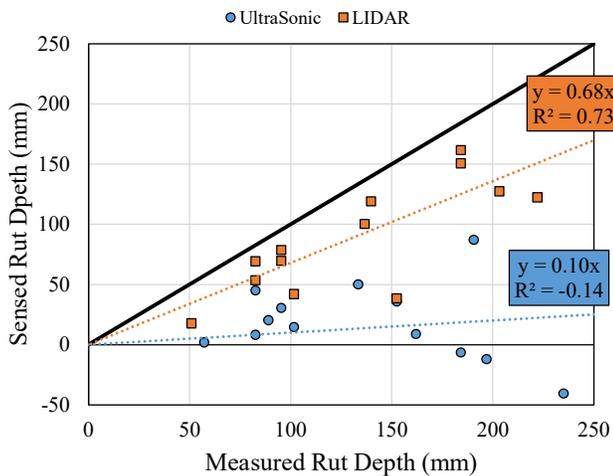


Figure 7. HMMWV Rut Depth Results.

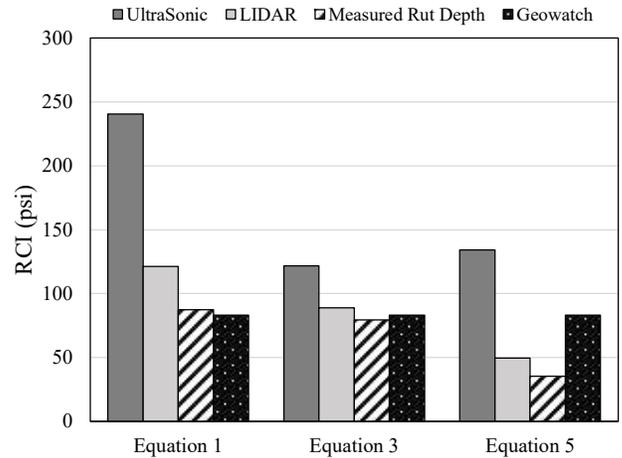


Figure 8. HMMWV RCI Comparison.

7. CONCLUSIONS & RECOMMENDATIONS

This paper explored a method of calculating soil strength based on dynamic in situ rut depth measurements. The results of this experiment demonstrate some promise that taking rut depth measurements may be a valuable asset to make real time mobility decisions in the field. However, in addition to that conclusion, many lessons were revealed throughout the experimental process.

The raw data recorded by the sensors revealed severe limitations in field data collection capabilities. The dynamic nature of the data collection process produces inconsistent measurements in some cases, such as when the vehicle is in motion. Because these measurements are the basis from which soil strength is being calculated, reliability of rut depth estimation is essential to the success of this project. Future iterations will consider more advanced means of sensor stabilization, such as the incorporation of a gimbal or gimbals between the vehicle chassis and the sensors. Any steps taken to reduce sensor vibration and instability will likely reduce both measurement error and inconsistency, and increase the accuracy of the results.

The sensors used in this experiment were explicitly unidirectional sensors. Any significant deviation from a perpendicular reflecting surface

caused measurement error for both sensor types, but especially the US. This was not particularly problematic, as the sensors were oriented at the ground, but is worthy of consideration in future experimentation. This drawback was an unexpected disadvantage of the use of distance sensing tool instead of a scanning lidar as discussed in the Sensor Suite section.

Another disadvantage of the point measurement approach is the effect of vehicle roll on the results. Because the center distance sensors were placed 0.7 meters away from the rut distance sensors, even slight angles along the roll axis of the vehicle could cause significant discrepancies in the results provided. For example, a vehicle roll of 1° resulted in an error of 1.2 cm, which is outside the accepted margin provided by the analysis of error propagation. However, unlike the directionality of the sensors discussed in the previous paragraph, this issue could be resolved by the incorporation of an accelerometer, gyroscope, or IMU into the system. For this work the angle was physically measured and accounted for in calculating the rut depths. However, incorporation into an automatic system would be more efficient.

This experiment has revealed many impediments to estimating soil strength from rut depth measurements. However, in the months of planning, testing, and data analysis, there has been no indication that using rut depth to approximate soil strength in real time is not possible. In fact, the HMMWV results showed that determining accurate soil strengths is possible, but more soil conditions and types still need to be investigated. In the years to come, this line of research will continue

to be explored in the hope of advancing off-road autonomy and real time mobility decision making.

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