Characterizing the sound speed variability in laboratory water tank

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A senior thesis submitted to the faculty of
Brigham Young University
in partial fulfillment of the requirements for the degree of

Bachelor of Science

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ABSTRACT

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The variation of temperature in the ocean causes changes in sound propagation. This can be difficult to model, however, the advent of machine learning has allowed for the development of accurate 3D propagation models with limited environmental knowledge. To simulate the naturally occurring variability in an ocean environment and for testing the robustness of machine learning algorithms, this project quantified the sound speed variation achievable in a laboratory water tank. The rectangular tank (1.2 m x 3.6 m with 0.5 m depth) has anechoic paneling that minimizes lateral reflections. In this experiment, temperature was measured from two temperature sensors. The temperature was used to calculate the sound speed in the tank as a function of time while the water was cooled with ice, heated, and naturally warmed back to room temperature. Sound speed values were calculated using the freshwater Marczak equation. We found that while the temperature varies in time, the temperature remains relatively uniform across a single depth. Heating the tank for 2 hours increases the sound speed by 7 m/s while adding ice in various quantities decreases the temperature rapidly. After rapid cooling, the water near the surface of the tank warms faster than the water near the bottom, creating a sound speed gradient. Eight hours after adding 380 pounds of pebble ice, the sound speed gradient was 10.7 m/s per m. By adding an additional degree of variability to the tank measurements, a portion of the variability seen in the ocean can be replicated. This sound speed variability can then be used to test the robustness of machine learning algorithms.

Keywords: water tank, temperature, sound speed, machine learning, underwater acoustics, sound variability

1. INTRODUCTION

In the field of ocean acoustics, large amounts of data are collected and required for accurate modeling. Identifying key acoustics features in such large and variable data sets, however, requires a lot of human effort. With the advent of machine learning, which is a relatively new area of research within ocean acoustics, large data sets can be processed to discover new complex acoustics models. Machine learning, which is entirely data-driven, bypasses the human effort required to identify acoustics features in data sets by identifying patterns in data and providing a general framework for acoustics models. Machine learning has a lot of potential for accurate and real-time acoustics predictions.[1]

Conversely, matched-field processing (MFP), which is a beam-forming method derived from the Green's function to accurately locate sources in range, depth, and azimuth, has been an attractive method for source localization for decades. The method can be extremely accurate when detailed environment knowledge is known and accounted for.[2,3] However, a paper published about noise data from ships in the Santa Barbara Channel proved that machine learning processes outperform MFP for greater distances when limited environmental knowledge is known. Niu *et al.*[4] used data collected by VLAs from 7 to 20 of September in 2016 from one shipping track for training purposes and used two other ship paths for testing. What they found is that MFP techniques can localize the ships accurately up to 4 km away, however, after 4 km, MFP loses accuracy. The predicted location of the two ships based on machine learning methods, however, remained accurate for the entire 9 km range, as shown in their Fig. 3.

From this study and others, we can determine that a large benefit of using machine learning for source localization is that it does not depend on a model of sound propagation because the environmental parameters will be considered during training.[4,5] A study done by Van Komen *et al.*[6] shows the importance of accounting for ocean variability during the training step of machine learning. The conclusion was that training with greater sound speed variability leads to better generalization. As this is a new field and sound propagation in the ocean can be extremely complex,[7] it is imperative that machine learning algorithms are tested for their robustness for a variety of environmental complexities.

For this reason, we plan to use a water tank with variable sound speeds to measure acoustics data for deep learning and testing of how ML models can handle variations of sound speed and still make accurate predictions. The goal of this paper is to demonstrate the sound speed variability possible in our laboratory tank due to an advanced filtration system and adding ice. A description of the experimental setup and the results of several experiments are presented.

2. BACKGROUND

A. SOUND SPEED VARIABILITY

There are many causes for variation in sound speed in the shallow ocean. These variations depend on weather, seasons, latitude and are influenced by internal gravity waves. Rossing[8] discusses some of the seasonal effects on sound speed profiles in the *Springer Handbook of Acoustics*. Winter months typically show an isovelociy effect due to mixing, so sound speed profiles are relatively constant with depth. In summer months, however, water is typically warmer near the surface from heating. From the text, Fig. 5.4 on page 152 shows general sound speed profiles in winter versus summer months. In winter months from the surface to a depth of 100 meters, the sound velocity stays close to 1500 m/s. For summer months, however, the first 20 meters is well mixed at around 1530 m/s but from 20 meters to 40 meters, the sound speed drops rapidly to 1500 m/s and stays fairly constant to the bottom.[8]

Differences in sound speeds change the acoustic propagation paths. An experiment published by Sertlek *et al.*[9] examines how assuming a constant sound speed rather than a sound speed gradient affects the accuracy of shipping sound maps. The study was done on the Dutch North Sea, where sound speed in the summer months can vary as a function of depth from 1480 m/s to 1515 m/s while varying in winter between 1465 m/s and 1480 m/s for a depth of 70 m. (See Fig. 2 from that paper.) They compared sound pressure level measurements from an isovelocity sound speed with winter and summer measurements. Relative to isovelocity measurements, the winter measurements differed by 2.5 dB and the summer measurements by 5 dB over a wide frequency band.

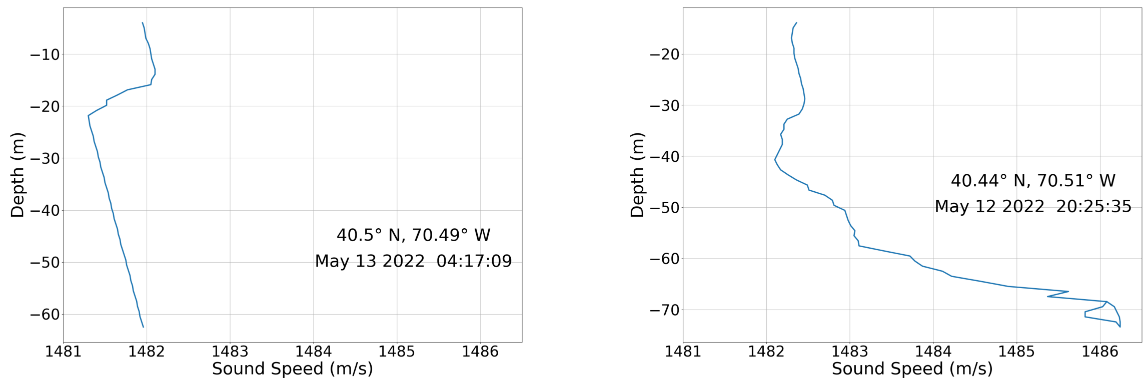
There are often spatial variations in sound speed as well. During the Seabed Characterization Experiment (2022), sound speed profiles (SSP) from the New England Mud patch were taken at various locations. In the northern regions of the New England Mud patch, the sound speed stayed nearly uniform from the middle of the water column to the ocean floor. However, as seen in Fig. 1, the SSP at the southern location showed a rapid increase in sound speed near the ocean floor due to warmer southern water brought up by currents. The distance between the two SSPs was only 5.56 km. Spatial variations in the SSP in the New England Mud Patch add a layer of complication to the analysis of data collected during the experiment.

The last cause of sound speed variation in the ocean discussed here is internal gravity waves, which are found in greater quantities near the coast. These waves introduce more scattering and a time-dependent complexity that is difficult to model.[7] Badiey *et al.*[10] analyzed data from the Shallow Water Acoustic Experiment 2006 (SW06) conducted on the New Jersey continental shelf to record the time-varying environment induced by nonlinear internal waves (NLIWs). Figure 3d of their publication shows time-varying temperature fluctuations over a span of 5 hours. At times, the water temperature at the specified location is isothermal, however, at other times large spikes in the water temperature cause up to a 15 °C increases. The temperature fluctuations vary in depth, repetition rate, and have duration of up to 10 minutes. Their Fig. 1e also shows the range-dependent temperature fluctuations of about 20 °C from shore out to 3 km.

B. WATER TANKS

Many labs choose to use a laboratory water tank for collecting scale-model acoustics data. Sagers and Ballard[11] discuss the use of scale-model laboratory experiments as useful for the development of three-dimensional numeric acoustic propagation models. They assert that laboratory tanks can be used to collect benchmark data, as data measured in the ocean has insufficient environmental information for modeling, along with time-dependent variations in the ocean environment. In contrast, water tank measurements allow for greater control and knowledge of environmental information that provides more consistent modeling. In a water tank, temperature, bathymetry, source/receiver geometry, sea surface, seafloor roughness, etc. can all be maintained. Additionally, complications resulting from additional sounds from shipping lanes and other ambient noises in the ocean are eliminated.

Though laboratory tanks are used to create a controlled environment for testing acoustics mod-



(a) Northern SSP ***(b) Southern SSP***

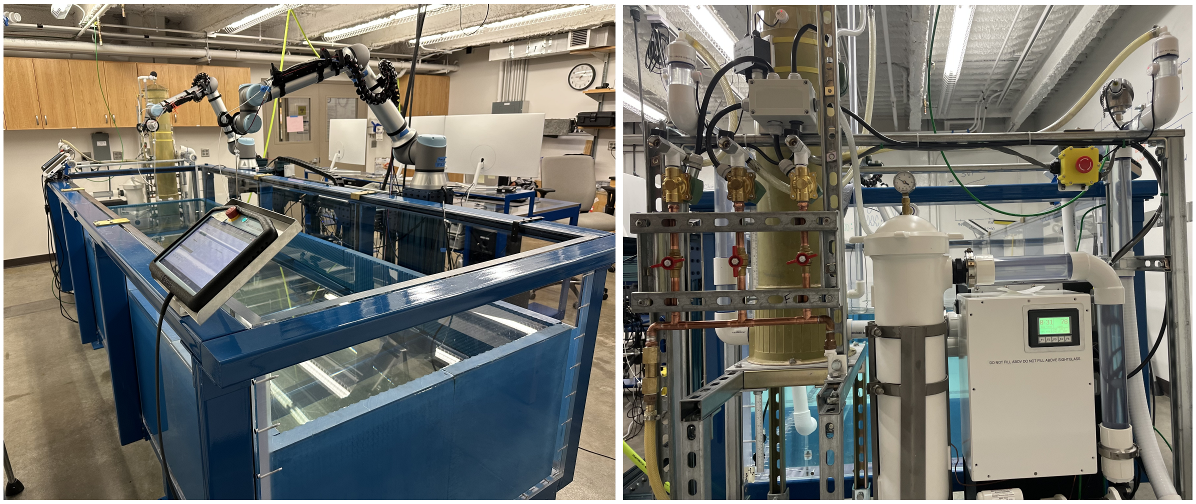
Figure 1: Two sound speed profiles taken in the New England Mud Patch in May. The southern SSP cast was taken 5.56 km south of the northern cast. The southern cast shows the effect of warmer water currents increasing the temperature of the water near the bottom.

els, complications arise in making the tank into a scale model of the ocean. Some of these complications arise due to lateral reflections and the materials used for the bottom of the laboratory tank. Attempts to scale frequency and distances are complicated by the fact that attenuation is not a linear function of frequency. Finally, a room-temperature water tank defaults to uniform sound speed, where SSPs vary widely in the ocean, as detailed above.

In addition, attempts to mitigate the sound speed limitation of water tanks have been undertaken by two labs that successfully varied the sound speed gradient in a laboratory water tank. Zhang and Swinney[12] created a sound speed gradient in their tank by linearly increasing the salinity (density) of the water in their 0.9 m long and 0.45 m wide tank at a depth of 0.5 m. The density and thereby sound speed varies continuously, achieving speeds of 1500 to 1700 m/s, obtaining a depth-dependant sound speed gradient of 0.377 m/s per mm.

In another paper, Rabau[13] discussed their different approach of using liquids of different densities to create the sound speed gradient. The dimensions of the tank were 4.5 m long and 0.88 m wide. The fluids used included two aqueous alcohol mixtures and four saline solutions and totaled a depth of 20 cm. The sound speed profile the laboratory replicated was that of a tropical eastern summer in the deep ocean (4 km depth). They were able to create a laboratory sound speed profile with an axis of minimum sound speed or a SOFAR channel. The sound speeds ranged from 1490 to 1520 m/s. Furthermore, the layered liquids were able to maintain their separation for several hours. Their Fig. 8 shows the sound speed profile evolution over one week.

Tank data have also previously been used in machine-learning applications.[5,14] Because machine learning is dependent on having a large source of data, water tanks make an ideal place for training and testing machine-learning models. Yangzhou *et al.*[14] conducted an experiment to test a deep neural network (DNN) approach to source localization and compared results to several MFP approaches. For their experiment, they used uncalibrated hydrophones to demonstrate the robustness of a DNN method in a 1.1 m x 1.4 m tank with a water depth of 10 mm. For each frequency,



(a) Tank *(b) Filter*

Figure 2: (a) Water tank. (b) Filter which can heat water ranging from 19 °C to 38 °C.

they gathered 8000 samples of data and used 7200 for training purposes and the rest for testing. Their Table II shows that a DNN method far surpasses MFP in accuracy. The primary conclusion of their work is that DNN method is advantageous because it does not rely on an acoustic forward model or sensor calibration.

With all of this in mind, the goal of the experiment reported here is to use temperature to vary the sound speed of a laboratory water tank for testing the robustness of machine learning algorithms. Other labs have either created variable sound speeds in water tanks or have performed machine-learning experiments with tank data. Our lab hopes to combine the two by introducing sound speed variability into a machine-learning experiment.

3. METHODS

A. MEASUREMENT SETUP

The water tank in this experiment, shown in Fig. 2a, has dimensions of 1.2 m x 3.6 m and holds a maximum depth of 0.91 meters, which equates to a max water volume of 4077.6 L. The tank is made of acrylic because its acoustic impedance is more similar to water than tanks made from steel, concrete, or glass. The material has added benefits of being transparent and non-corrosive. To further minimize reflections from the sides of the tank, panels made of polyurethane are placed in the tank. This attenuating material from Precision Acoustics advertises echo reduction greater than 30 dB for frequencies in the 20-200 kHz range.

On one side of the tank is a water filter and heater, as shown in Fig. 2b. The water filter was specially designed with a debubbler column to keep the water well sanitized. Additionally, chemicals are added to the tank weekly to ensure consistent conditions of the water. Tap water is used to fill the tank as it is less corrosive to the acrylic than distilled. The heater attached to the water filter can output water ranging from 19 °C to 38 °C.

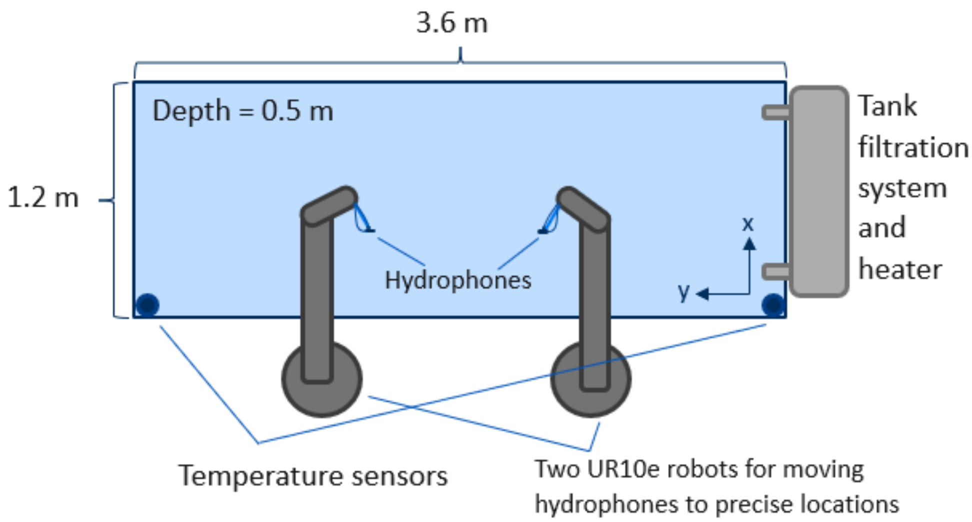


Figure 3: Diagram of water tank.

Alongside the water tank are two UR10e robots from Universal-Robots. The robots are used as a positioning system as they each have six axes of motion and a reach of 1.3 m. One of the robots is mounted on an extender track, giving it 1.4 m added reach. This underwater positioning system has an uncertainty of +/- 0.01 mm for repeat measurement. The robots move transmitters, receivers, and temperature sensors to precise locations in the tank. A diagram of the water tank is included in Fig. 3.

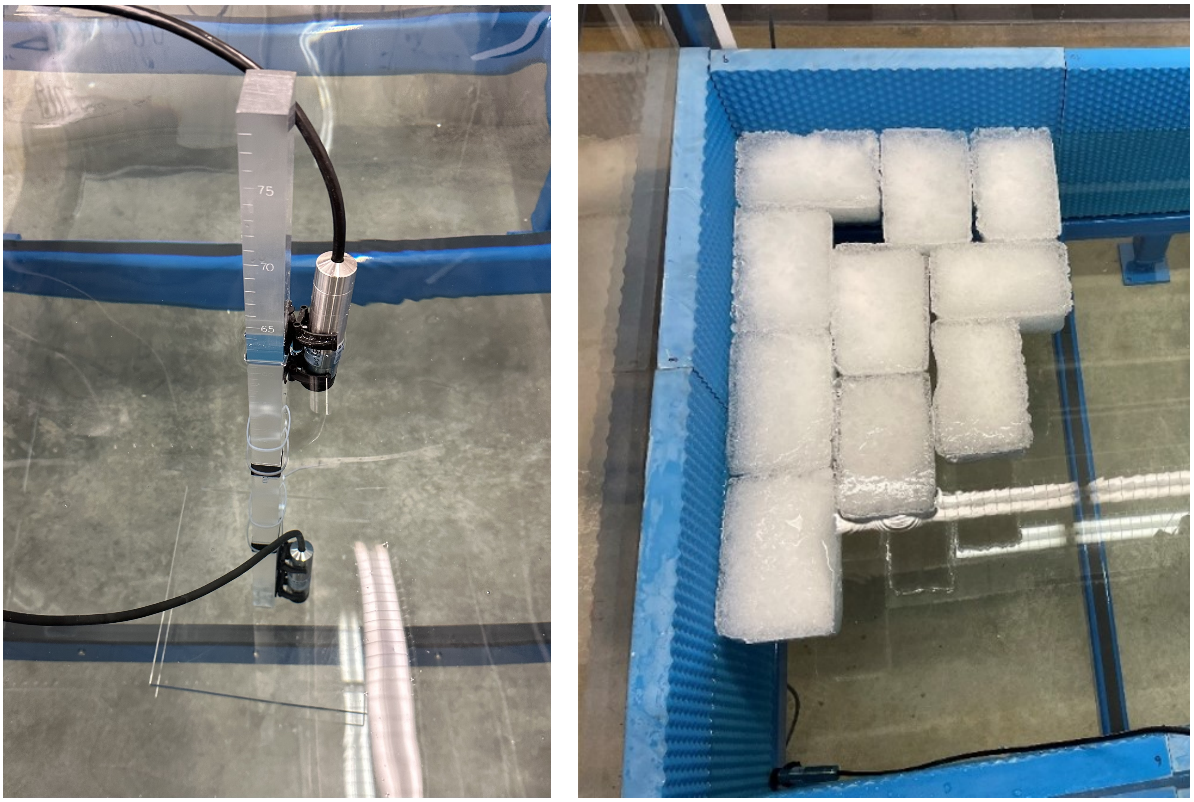
The positions and data acquisition are controlled via a custom LabVIEW software called Easy Spectrum Acoustics Underwater (ESAU) because it uses spectrum 16-bit data acquisition cards. For the scope of this experiment, this software was edited to include a temperature recording capability for a selected number of hours. More information on the design of the laboratory water tank used in this experiment can be found in the Vongsawad *et al.*[15]

B. TEMPERATURE EXPERIMENTS

At room temperature, a shallow water tank has spatially uniform water temperature, so we observe constant sound speed throughout the water. Experiments were performed to test the sound speed variation attainable in our water tank using heating and adding ice. From these experiments, we can assess the minimum and maximum sound speed caused by ice and the tank heater as well as the sound speed gradient (depth-dependant sound speed) from surface to bottom at various stages of warming and cooling.

Temperature measurements are made with two LMP 307T level and temperature transmitters, which specify an accuracy of less than or equal to 1 degree Celsius. During the experiments, the temperature is sampled every 5 seconds and saved to Excel spreadsheets. These data are then plotted and converted to water sound speed with Python.

The time-dependent water temperatures were used in the Marczak[16] empirical equation for converting fresh water to sound speed as a function of temperature only. The equation is a fifth-



(a) Temperature sensor stand *(b) 100 lbs Block Ice*

Figure 4: (a) Stand used to mount temperature sensors to various depths within the water tank. (b) 100 lbs of block ice added to the tank.

order polynomial that is valid from 0 to 95 °C. Equation 1 and Table 2 from that paper show the equation used.

The locations of the temperature sensors for the various experiments are listed in Table 1. The coordinates for the temperature sensors are measured from the axis at the bottom right corner of the tank as illustrated in Fig. 3.

Experiments A and B were the first two time-dependent measurements taken. The temperature sensors were at the same depth in the water tank for the entirety of data collection. For Experiment A, the temperature sensors were at opposite ends of the tank located at the bottom and the depth was 0.5 m. The tank was heated for two hours with the filter temperature set at 38 °C, with Sensor 2 located closer to the outlet of the water heater. For Experiment B, the temperature sensors were once again placed on opposite ends of the water tank near the bottom. The water depth was 0.43 m for this experiment and 100 pounds of block ice were added. (See Fig. 3b.)

Experiments C and D were the two time and depth-dependent experiments, meaning the temperature sensors were placed at the center of the tank at different depths as seen in Fig. 4a. For Experiment C, the water depth was 0.6 m and Sensor 2 was 5 cm below the water line and Sensor 2 was located 1 cm from the bottom of the tank. During this experiment, the heater ran set at 38 °C for two hours, and 300 lbs of pebble ice were added. (See Fig. 5.) For Experiment D, 380 lbs of pebble ice were added and the heater was not on during the experiment. The water depth was 0.5

Table 1: Temperature Experiments.

Experiment	Method	Water Depth	Locations	
			Sensor 1	Sensor 2
A	2 hr heating	0.5 m	(0,L,0)	(0,0,0)
B	100 lbs block ice	0.43 m	(0,L,0)	(0,0,0)
C	300 lbs pebble ice and heat	0.6 m	(0.6,1.8,0.55)	(0.6,1.8,0.01)
D	380 lbs pebble ice	0.5 m	(0.6,1.8,0.43)	(0.6,1.8,0.01)

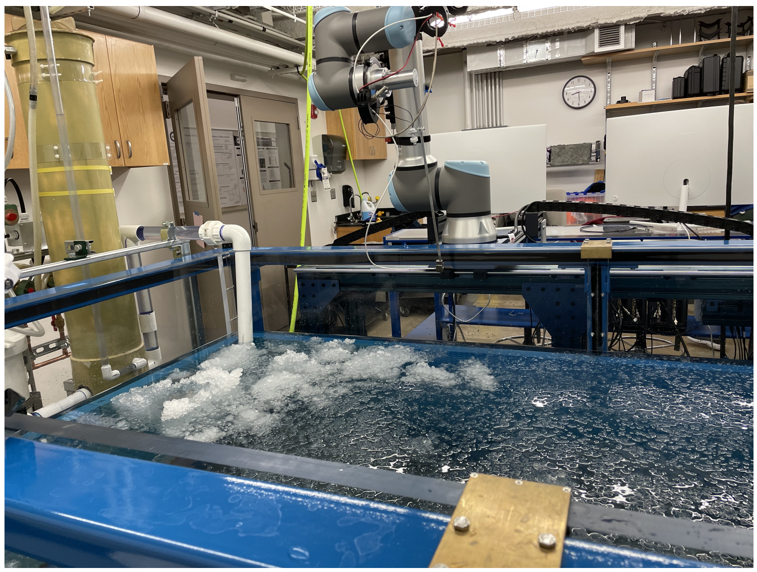


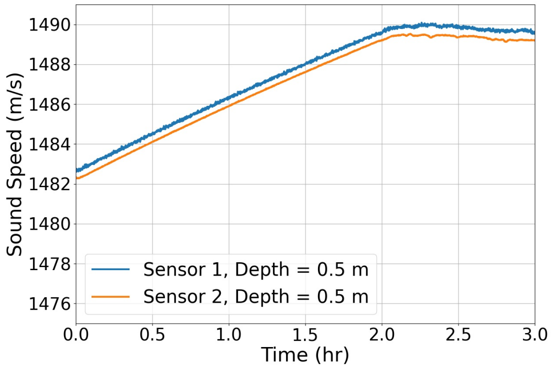
Figure 5: 300 lbs pebble ice in tank.

m and Sensor 1 was 7 cm below the water line and Sensor 2 was located 1 cm above the bottom of the tank.

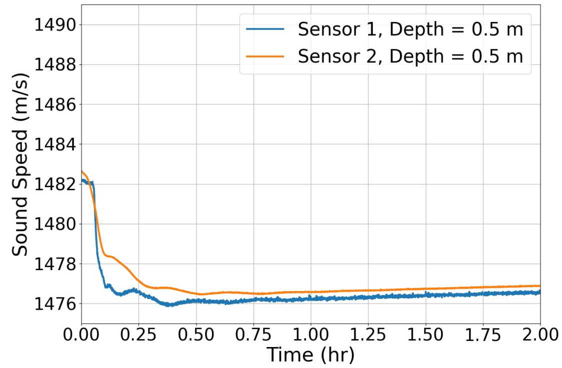
The predicted results are that ice added in hundreds of pounds to the surface of the tank decreases the sound speed near the surface, and the heater which better mixes water at the bottom of the tank increases sound speed faster lower in the water. This effect would ideally cause SSPs in our tank similar to profiles found where warm water currents traveling along the bottom of the ocean floor increase the sound speed at deeper depths, similar to the southern profile from the New England Mud Patch. (See Fig. 1.)

4. RESULTS

The results from all four experiments are presented. In all plots in this section, the blue line represents Sensor 1 and the orange line is Sensor 2. The legend of the plots gives information on the depth of the sensors, not the z-coordinates. (See Table 1 for details of the experiments.)



(a) Experiment A



(b) Experiment B

Figure 6: (a) The sound speed at the bottom of the tank was measured with two temperature sensors. The water was heated at 38 °C for 2 hours and cooling was tracked for an hour after. (b) The sound speed at the bottom of the tank after 100 lbs of block ice were added to the tank. Two hours of data are shown.

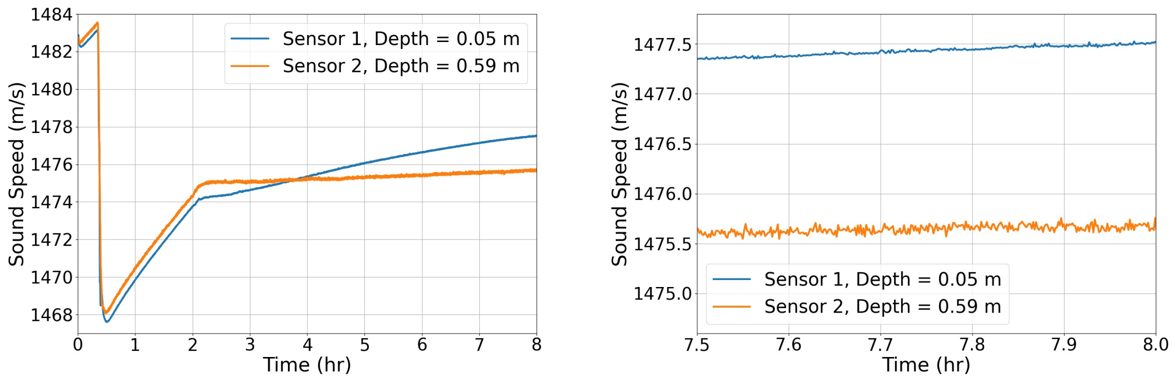
A. TIME-DEPENDENT

The sound speed for the time-dependent experiments A and B are shown in Fig. 6. The plot (a) for Experiment A shows that two hours of heating resulted in a 7 m/s increase in sound speed. The increase in sound speed was linear as the tank was heated at a rate of 3.5 m/s increase per hour. Comparing the temperature from Sensors 1 and 2, the sound speed in the tanks maintained a difference of approximately 0.3 m/s throughout the experiment. Though farther from the water heater, Sensor 1 measured higher water temperatures as soon as data acquisition began and the water heater was started. One explanation is that the water is well enough mixed to maintain uniform sound speed at a given depth and any difference in temperature is a result of slight differences in calibration. Additional trials have proved that additional hours of heating can extend the maximum sound speeds at the same linear rate.

The plot for Experiment B (Fig. 6b) shows that adding block ice rapidly decreased the sound speed in the water tank. One-hundred pounds of ice blocks decreased the temperature of the water at the bottom by 6 m/s. Sensor 1 was located closer to the block ice when they were added to the tank, which explains why the temperature near Sensor 1 dropped faster than Sensor 2. However, even with the water heater turned off, there is still enough mixing in the tank that the temperature at the bottom of the water tank quickly reached uniformity as shown by both sensors maintaining even spacing at 0.5 hours. Again, the 0.3 m/s difference in sound speed is assumed to be differences in calibration.

B. DEPTH-DEPENDENT

The variation in sound speed for the depth-dependent Experiment C is shown in Fig. 7. The full scan plot (a) shows that adding the pebble ice rapidly dropped the sound speed by 15 m/s. This decrease in temperature is constant from the surface to the bottom of the tank even while the heater



(a) Full Scan ***(b) Zoomed-in View***

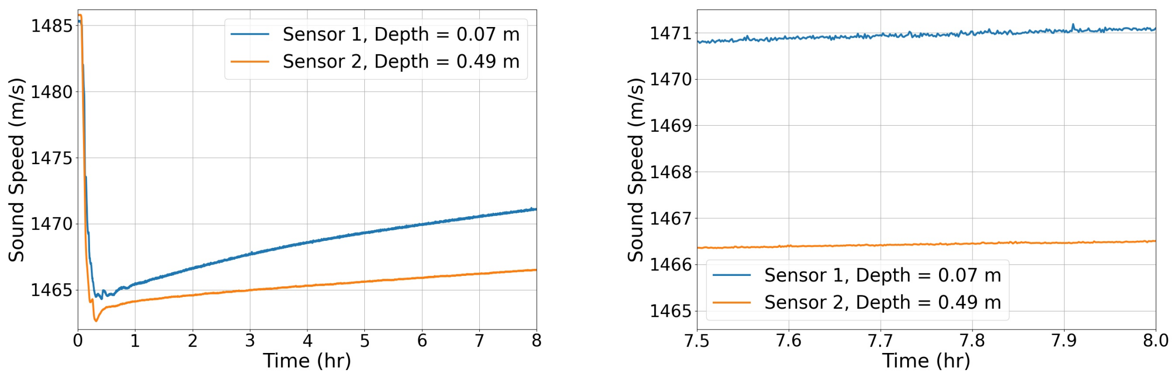
Figure 7: Plots for Experiment C. Added 300 lbs of ice and two hours of heating at 38 °C.

is running. Again, the heater increases the water temperature linearly. Additionally, these data show that this temperature increase is relatively uniform from surface to bottom. Once the heater is turned off, the water continues to warm back up to room temperature, and only then does the water temperature show a temperature gradient. The water near the surface of the water warmed faster than the water near the bottom, and the zoomed-in plot (b) shows that over the 0.54 m change in depth, a 1.8 m/s change in sound speed is established.

Experiment D was a test to see if adding ice without heating would allow for the temperature gradient from surface to bottom to be extended. Figure 8 shows that adding 380 lbs of ice rapidly decreased the temperature of the water between 21 and 22 m/s. From there, the water near the surface warmed faster. The zoomed-in plot (b) between 7.5 and 8 hours after dumping the ice shows about a 4.5 m/s change in sound speed for a 0.42 m change in depth, yielding a sound speed gradient of 10.7 m/s per m. A summary of the results of the temperature experiments is located in Table 2. Experiments A and B do not have values for the depth-dependent sound speed gradient because the sensors were at the same depth for the entirety of the experiment.

5. CONCLUSION

Based on the four temperature experiments that were conducted, we can conclude that we are able to successfully attain a time-dependent and a depth-dependent sound speed variation due to temperature changes. For the time-dependent experiments, two hours of heating results in a 7 m/s change and follows a linear relationship. Adding 100 pounds of block ice decreases the bottom water temperature by 6 m/s. The temperature all along the bottom of the tank remains uniform during both heating and ice experiments. The depth-dependent experiments showed that there is not much variation of temperature from surface to bottom while the heater is turned on or ice is melting due to mixing. The water near the surface, however, does warm faster than the bottom when going back to room temperature. Eight hours after adding 380 pounds of pebble ice, the sound speed gradient was 10.7 m/s per m. The thermal conductivity of acrylic is 200 mW/(m K)[17] which is about four times greater than that of air, which is 26 mW/(m K).[18] Thus, We can



(a) Full Scan ***(b) Zoomed-in View***

Figure 8: Plots for Experiment D. Added 380 lbs of pebble ice.

Table 2: Sound Speed Results.

Experiment	Max SS	Min SS	Max Change in SS	Max Depth-Dependant SS gradient
A	1490 m/s	1483 m/s	7 m/s	
B	1482 m/s	1476 m/s	6 m/s	
C	1483 m/s	1468 m/s	15 m/s	1.8 m/s at 8 hrs
D	1485 m/s	1463 m/s	22 m/s	4.5 m/s at 8.0 hrs

conclude that it is not the material of the acrylic that is causing the bottom water to warm slower. We believe that the effect is due to convection currents that result from warm material rising. In conclusion, we were able to characterize the sound speed variability in our tank. We obtained a time-dependent sound speed due to the heater and adding ice. We also achieved a sound speed gradient when naturally warming back to room temperature. Lastly, we predict that if we were to cool the bottom water and heat the surface water, the depth-dependent sound speeds would have even greater ranges and be more stable. Having characterized the temperature variability possible within our water tank will give us greater control over sound speed variables in this water tank for testing the robustness of our machine learning algorithms, which is the next step in the project.

ACKNOWLEDGMENTS

I would like to acknowledge Adam Kingsley and Jay Cliftman for helping update the LabVIEW software (ESAU) used for the temperature acquisition for these experiments. I thank the College of Physical and Mathematical Sciences at Brigham Young University for funding my research assistantship. I acknowledge the Office of Naval Research for funding the projects in our lab. Lastly, I would like to thank my advisor Tracianne Neilsen for the mentoring, guidance, and

assistance with this project.

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