

EVALUATION OF A PERMITTIVITY SENSOR FOR CONTINUOUS MONITORING OF SUSPENDED SEDIMENT CONCENTRATION

Barbra C. Utley, Department of Watershed Sciences, Utah State University, Logan, UT, email: barbra.utley@usu.edu; Tess Wynn, Department of Biological Systems Engineering, Virginia Polytechnic and State University, Blacksburg, VA, email: thwynn@vt.edu; Niaqian Zhang, Department of Biological and Agricultural Engineering, Kansas State University, Manhattan, KS email: zhangn@ksu.edu

Abstract According to the US Environmental Protection Agency (USEPA), sediment is a leading cause of water quality impairment (US EPA, 2002). The annual costs of sediment pollution in North America alone are estimated to range between \$20 and \$50 billion (Pimentel et al., 1995; Osterkamp et al, 1998, 2004). Due to the large spatial and temporal variations inherent in sediment transport, suspended sediment measurement can be difficult.

The overall goal of this research was to develop and test an inexpensive sensor for continuous suspended sediment monitoring in streams. This study was designed to determine if the gain and phase components of permittivity could be used to predict suspended sediment concentrations (SSC). For this study, gain (dB) was the ratio of the input voltage to the output voltage and phase (deg) was the difference between the phase of the input signal to the output signal (Tang, 2009). To test this concept, prediction models for SSC were built with input variables of temperature, specific conductivity, and gain and/or phase at multiple frequencies. The permittivity sensor that was developed is comprised of an electrode, power source, and a control box or frequency generator.

Partial Least Squares (PLS) regression techniques were applied to gain and phase data for 127 of the 635 frequencies. The three models with the lowest error between predicted and actual values of SSC for validation were further tested with nine levels of independent validation data. The largest model error (error >50%) occurred for the top three models at 0 and 500 mg/L. At the higher concentrations error varied from 1-40%. The prediction accuracy for the independent validation data set increased for the top three models at levels of near 1000 mg/L. Model 3A, a phase-based model, performed the best. Model 3A was able to predict six of the nine independent validation treatment levels within 300 mg/L. Future research will provide additional laboratory and field testing of the prototype sensor.

INTRODUCTION

Suspended sediment is a global problem; the US Environmental Protection Agency (US EPA) identified sediment as a leading cause of water quality impairment in 2002 (US EPA, 2002). A survey of streams throughout the United States determined 46% of streams analyzed suffer from excessive siltation (Berkman and Rabeni, 1987). In North America the annual costs due to sediment pollution are estimated to range between \$20 billion and \$50 billion (Pimentel et al., 1995; Osterkamp et al, 1998, 2004). Due to the large spatial and temporal variations inherent in sediment transport, the precise and accurate measurement of suspended sediment is difficult to achieve (Wren et al., 2002). The majority of sediment movement occurs infrequently during large rainfall events, requiring the rapid mobilization of field personnel into potentially hazardous flood conditions. Traditional methods for measuring suspended sediment are also expensive. As of 2006 only a quarter of the USGS stations collecting daily sediment data in 1981 were still in service. The decrease in sediment monitoring stations is primarily due to cost (Gray and Gartner, 2009).

Currently the USGS is testing multiple new sensing technologies in U.S. rivers and in laboratories for measuring certain characteristics of suspended sediment, bed load, and bed material. The technologies include: bulk optic or turbidity, laser optic, pressure difference, and acoustic backscatter (Gray and Gartner, 2009). The informal Sediment Monitoring Instrument and Analysis Research Program with the USGS is working to determine if the above technologies can make the shift from research to operational applications (Gray and Gartner, 2009). The new technologies are being rigorously tested for accuracy and reliability across a range of physiographic conditions.

A more advantageous alternative to traditional SSC measuring techniques would have to be cost-effective, autonomous, and have increased temporal and spatial resolution. High-quality suspended sediment data will allow researchers to better quantify soil losses due to hillslope and channel erosion, the rate of reservoir sedimentation, and the results of landuse and climate change, management actions, and restoration efforts on aquatic systems (Wren et al., 2002).

The overall goal of this research was to develop and test an inexpensive sensor for continuous suspended sediment monitoring in streams. Specific objectives included developing a prototype permittivity electrode for use in stream systems and developing and assessing a prediction model for SSC.

Background on Permittivity Permittivity is a physical description of the effects of an electric field on a dielectric medium and how the medium then affects the electric field (Robinson et al., 1999). Permittivity is measured indirectly with an impedance sensor by monitoring the sensor and sample volume, and then removing the known geometric factors of the sensor to calculate permittivity of the sample volume (Lee et al., 2007a; Lee et al., 2007b). The following equations are necessary to calculate permittivity from impedance measurements:

$$\epsilon_r' = \frac{C}{\epsilon_0} g \quad (1)$$

$$\epsilon_r'' = \frac{G}{2\pi f \epsilon_0} g \quad (2)$$

where ϵ_r' is the real part of the relative permittivity, C is the capacitance between the plates (F), ϵ_0 is the permittivity of free space (8.85×10^{-12} F m⁻¹), g is the geometric factor of the sensor (m⁻¹), ϵ_r'' is the imaginary part of relative permittivity, G is the conductance between plates (S), and f is frequency (Hz). Further background and theory on permittivity sensors is available in Lee et al. (2007).

Permittivity Sensors and Suspended Sediment As noted by Lee et al. (2007b), applying permittivity measurements to complex, heterogeneous systems is still a very “black box” approach. This statement also applies to measuring SSC via a permittivity method. However, Figures 1-2 detail the potential reactions of multiple scenarios to low, medium, and high frequencies. High frequencies will be greater than or equal to the dielectric relaxation point of water (17 GHz; as stated by Robinson et al., 2003). Medium frequencies will be less than or equal to the relaxation point for soils (<1 GHz; as stated by Robinson et al., 2003). Low frequencies will be less than 10 MHz. The scenarios predict how the output signal will change with variations in the heterogeneous mixture within the sample volume. The sample volumes include water with ions present (Fig. 1) and water with sediment present (Fig. 2). The reaction of the sample volume to high, medium, or low frequency in each scenario will be discussed in terms of gain and phase, where signal loss can be due to ionic conductivity and dispersion. For this study, gain (dB) was the ratio of the *input* voltage to the *output* voltage (Equation 3) and phase (deg) was the difference between the phase of the *input* signal to the *output* signal (equation 4; Tang, 2009).

$$gain = \frac{V_{in}}{V_{out}} \quad (3)$$

$$phase = phase_{out} - phase_{in} \quad (4)$$

For the first scenario (Fig. 1) at 1 GHz, both gain and phase will be greater than one as energy is stored in the sample volume. At 17 GHz, gain will be greater than one due to conductive losses, but phase will be near zero as the ions in the water increase the conductive properties of the water. For the second scenario (Fig. 2) at 10 MHz, gain will be greater than one and phase will be much greater than one because both sediment and water will polarize and store energy within the system. However, it will take longer for the system to discharge, increasing the difference in phase between the input and output signals. At 1 GHz, both gain and phase will be significantly greater than one; only water will be able to polarize and store energy. The storage is less than in scenario one because it is believed that sediment will inhibit the polarization of water. At 17 GHz, gain will be greater than one due to conductive losses; phase will be close to zero due to the conductive properties of water.

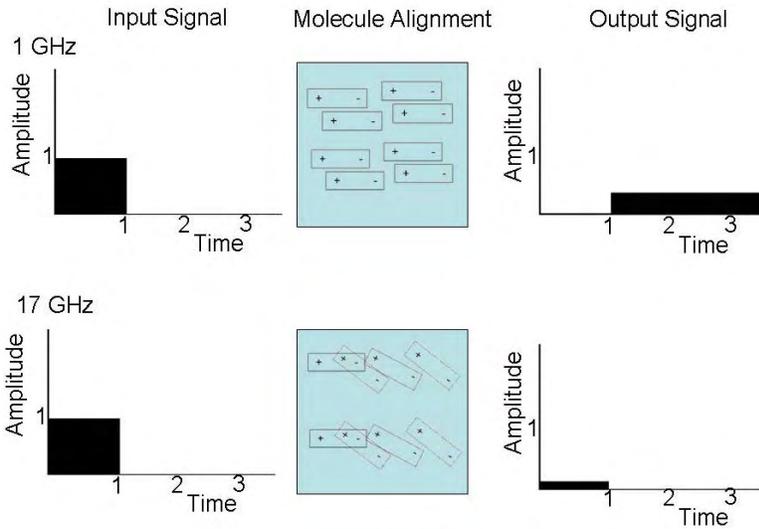


Figure 1 Predicted response of water with ions to the application of high and low electromagnetic currents. Input signals, molecular response to the signal, and the signal transmitted through the media are shown for both frequencies.

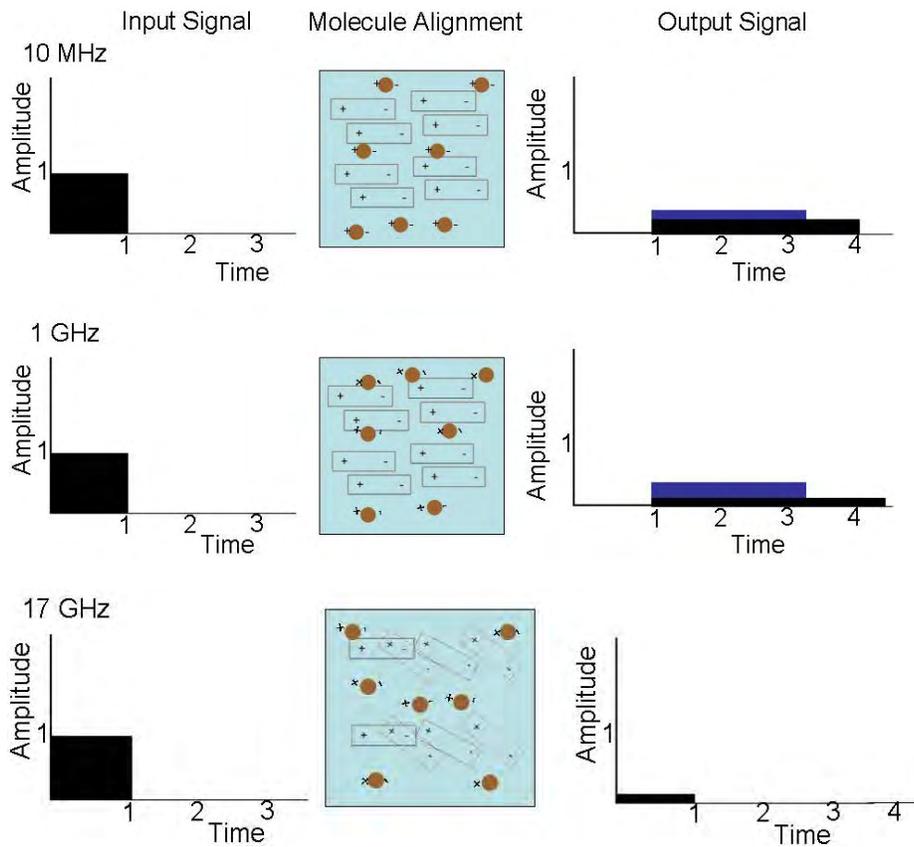


Figure 2 Predicted responses of water with suspended sediment to the application of low (10 MHz), medium (1 GHz), and high (17 GHz) electromagnetic currents. Input signals, molecular response to the signal, and the signal transmitted through the media are shown for all three frequencies. Brown signifies soil molecules and blue represents water. Blue bars on the output signal represent the response of just water as expressed in Figure 1.

METHODS FOR PERMITTIVITY SENSOR TESTING

Laboratory experiments were conducted to create a prediction model to accurately convert measured changes in solution permittivity to changes in sediment suspension of varying concentrations. The experiments took place in the Ecological Engineering Laboratory in the Department of Biological Systems Engineering at Virginia Tech. The study evaluated possible interactions between SSC, specific conductance, and temperature.

The permittivity sensor was comprised of an electrode, power source, and a control box or frequency generator. To complete the study, a bench-scale suspension system was built to maintain a homogeneous suspension throughout the testing period (Utley, 2009). The suspended sediment sensor was calibrated via a static calibration procedure using known concentrations over the required sensor range. The prediction model was verified by randomly generating nine concentrations, measuring the permittivity of each suspension, and predicting the SSC with the transfer function.

Bench-Scale Apparatus **Electrode design and manufacturing** The electrode consisted of four 22 gauge stainless steel plates constructed to make a parallel plate capacitor (Figure 3a). The top of the electrode was fabricated from a small plastic container with casting resin as the insulating medium to ensure the wire contact points with the plates remained dry. The plates had a surface area of 59.78 cm² with a 3-mm spacing between the plates to allow suspended sand grains to flow between the plates. The wiring of the plates followed an alternating plate polarity pattern.

Control Box and Power Source The Biological and Agricultural Engineering (BAE) Department at Kansas State University (KSU) is developing a frequency response (FR) permittivity sensor for water quality and soil applications. For this study a control box (2005 version) from KSU served as the frequency generator and microcontroller for the sediment electrode described above (Figure 3b). The control box used in this study generated 635 frequencies between 50 Hz and 120 MHz and monitored two output variables that compared the input voltage signal to the output signal at each frequency. Detailed information regarding the control box is available in Tang (2009).

The power supply for the permittivity sensor was an Extech Instruments, 80 watt switching DC power supply (model 382260; Waltham, MA). The Extech power supply provided the required maximum voltage of 9 V and the maximum current of 4 amps.

Permittivity Data Collection and Analysis The study was conducted using 10.57-L solutions at three different conductivities (0, 250, 500 $\mu\text{S}/\text{cm}$), seven different sediment concentrations of kaolinite (0, 500, 1000-5000 mg/L), and three temperatures (10, 20, 30°C) for a total of 63 treatment levels. Kaolinite is a 1:1 clay with a low surface charge and does not shrink or swell appreciably due to changes in moisture content. The kaolinite used in this study was from the Kaolin Company (Thiele B-80, Kaolin Filler Grade, CAS #1332-58-7) and contains crystalline silica (CAS #14808-60-7). Specific conductivity and temperature were monitored independently of the permittivity sensor. Temperature was monitored using a digital, traceable thermometer (Traceable Control Company, VWR model 61220416, Friendswood, Texas). Specific conductivity was monitored with a conductivity meter specifically calibrated for levels under 1990 $\mu\text{S}/\text{cm}$ (EC Testr waterproof microcontroller series, model 296102). SSC was also measured for each SSC-treatment level using five, 28-mL aliquots removed from the sample volume to determine the exact SSC within the sensor measurement volume.



Figure 3 a) Permittivity electrode, b) KSU BAE control box (version 2005).

For each conductivity, temperature, and SSC combination the suspension was analyzed at 635 frequencies from 50 Hz to 120 MHz to test the response behavior over a range of frequencies. The sample volume was analyzed by measuring gain and phase for each of the 635 frequencies.

The KSU control box collected three full sets of data with each run. In this study six runs or 18 individual replicates of gain and phase data were collected per treatment level. Data processing included collapsing the 18 replicates to three test data files by averaging six replicates of data into tests A, B, and C for the Partial Least Squares regression analysis. The data set was also reduced to prevent model “over-fitting” by selecting gain and phase data for every fifth frequency instead of all 635 frequencies.

The PLS regression analysis required explanatory (X) and predictor (Y) variables and the data had to be designated as training or validation data. Gain and phase values for all three replicates (tests A, B, and C) of seven treatment levels were removed from the statistical analysis for later model validation. The seven levels identified for validation were selected via a stratified, random sampling procedure with one validation point per concentration level. The combination of temperature and conductivity was randomly selected. Table 1 summarizes the treatment levels selected for validation. Multiple combinations of explanatory variables were analyzed to find the best combination for the prediction of SSC (Y). The PLS analysis was conducted in SAS JMP version 8.0 (2008 SAS Institute Inc., Cary, NC).

Table 1 Treatment levels randomly selected for validation.

Concentration (mg/L)	Treatment #	Temperature level (°C)	Conductivity level (µS/cm)
0	2	10	250
500	17	30	250
1000	19	10	0
2000	33	20	500
3000	43	30	0
4000	49	20	0
5000	60	20	500

Prediction Model Development Partial Least Squares regression balances two priorities, explaining predictor variation (x-variable) and response variation (y-variable). PLS maximizes the variation explained by both predictor and response variables by generalizing and combining features from principle component analysis (PCA) and multiple regression (Abdi, 2003). It is most appropriate to use in cases where there are more x-variables than observations because it is not affected by multicollinearity in the ways that plague traditional regression techniques (SAS JMP help, 2009; Abdi, 2003).

The X-matrix for each model created was composed of temperature, conductivity, and either gain and/or phase values for 127 frequencies. The X and Y matrices were also normalized; means and standard deviations for each variable were calculated based on data sets A and B only. The data were normalized to compare variable importance or significance. Normalizing all the data allows a “unit” change in one variable to equal the “unit” change in another. As the phase data were an order of magnitude larger than the gain data, this was a necessary step.

Models were created for three scenarios where gain, phase, and gain and phase data at the 127 frequencies were entered in the X matrix. Two models were created for each scenario. The first model used a “leave one out” cross validation procedure to select the number of latent variables to be included in the model. The cross validation selection procedure tries to minimize the Root Mean Square Error (RMSE) independent of the amount of variation explained in Y. For the second model the number of latent variables was selected by the user. The percent error between the treatment value and the predicted value was calculated. The six models created during the first analysis were repeated with one significant difference: all data for 0 mg/L were removed from the analysis to determine the change in accuracy by removing the concentration with the highest prediction error.

Validation Data Collection and Analysis Two types of validation procedures were completed on the prediction models. The first was briefly described above and was completed as part of the PLS analysis. The second validation procedure was completed on the three prediction models with the lowest overall validation error for

concentrations between 433.8 and 5000 mg/L with an independent data set. Nine treatment combinations of concentration, temperature, and conductivity were randomly selected and organized for the validation study. The range for each independent variable remained constant between model development and validation studies. Treatment levels are shown in table 2. Nine sets of data were collected for each treatment.

The validation data were post-processed following the procedure discussed earlier for PLS model development. Following post-processing, SSC levels were predicted using the top three models developed. Prediction values for the nine treatment levels were calculated for each data set (A, B, and C) and then averaged for the final prediction value.

Table 2 Nine treatment levels randomly generated for the validation study.

Concentration (mg/L)	Conductivity (μ S/cm)	Temperature (deg C)
2000	230	25
3800	330	25
800	80	12
3200	230	27
100	220	15
3000	350	25
4800	420	27
2400	280	19
1500	130	18

RESULTS FROM PERMITTIVITY SENSOR TESTING

Quality Control for Suspension System Once a collection technique was identified, five subsamples were collected to determine the actual concentration within the sample volume of the suspension system. In general, greater than 90% of the treatment level was recovered in the subsamples for each concentration level except the 500 mg/L treatment level. The sub-samples for each concentration were normally distributed based on Shapiro-Wilk test ($\alpha=0.05$). Sample means for each concentration were significantly different than the treatment levels based on a student t-test ($\alpha=0.05$). Therefore the measured concentration was used for model development instead of the treatment level.

Partial Least Squares Regression Results Twelve PLS regression models were developed, four for each set of input variables. Half of the models had the 0 mg/L treatments removed from the analysis because 0 mg/L had the highest error. Each model was based on three sets of training data. Seven treatment levels were excluded from the training data and were used as validation data. In general, 500 mg/L and 5000 mg/L were the most difficult levels to predict both with training and validation data when 0 mg/L was included in the analysis. The first two models for each input category used a cross validation procedure to determine the number of latent variable to include in the model, while for the third and fourth models the number of latent variables was specified by the user. A summary of the twelve PLS models is provided in Table 3.

Table 3 Summary of the 12 PLS regression models.

Model Name	Input variables	Cross Validation	# of Latent Variables	% of Y variation explained
Model 1A	Gain	yes	8	83.33
Model 1B	Gain	yes	6	78.48
Model 2A	Gain	no	15	90.83
Model 2B	Gain	no	15	93.39
Model 3A	Phase	yes	3	49.29
Model 3B	Phase	yes	8	77.23

Model 4A	Phase	no	15	86.43
Model 4B	Phase	no	15	88.48
Model 5A	gain and phase	yes	10	87.36
Model 5B	gain and phase	yes	5	76.24
Model 6A	gain and phase	no	15	92.65
Model 6B	gain and phase	no	15	95.99

The three models with the lowest overall validation error between predicted and actual SSC values from the 12 models described above were selected to test with the second set of validation data (table 4 and 5). Figure 4 compares the prediction error of both training and validation data sets for the three selected models: model 2A, model 3A, and model 6B. Models 2A and 3A had prediction errors greater than 50% at SSC of 0 mg/l; however, validation errors over the rest of the concentrations were less than most of the other models. The large error for 0 mg/L may be due to human error in cleaning the system between runs or may be an effect of conductivity when no sediment was present. All of the models performed best at concentrations from 1000 to 5000 mg/L with an accuracy of ± 140 mg/L for model 2A, ± 560 mg/L for model 3A, and ± 320 mg/L for model 6B. However, the error for models 2A and 6B increased for concentration around 3000 mg/L to ± 1200 mg/L.

Table 4 Summary of error for the training data of the 12 PLS models.

Model Conc. (mg/L)	1		2		3		4		5		6	
	A	B	A	B	A	B	A	B	A	B	A	B
0.0	1.10	N/A	1.41	N/A	0.33	N/A	2.09	N/A	2.04	N/A	2.29	N/A
433.8	-0.88	-0.08	-0.51	-0.13	-2.21	-0.77	-0.59	-0.22	-0.70	-0.58	0.42	-0.16
913.8	-0.48	-0.20	-0.15	-0.03	-1.02	-0.32	-0.28	-0.27	-0.32	-0.38	0.18	-0.06
1844.0	-0.21	-0.02	-0.08	-0.04	-0.41	-0.17	-0.11	-0.07	-0.11	-0.03	0.05	-0.02
2787.6	0.09	0.13	0.01	0.01	0.14	0.04	0.06	-0.02	0.04	0.03	0.02	0.00
3686.0	0.06	0.15	0.08	0.04	0.12	0.06	0.10	0.05	0.04	0.05	0.04	0.02
4590.7	0.11	0.18	0.06	0.05	0.45	0.14	0.06	0.06	0.10	0.17	0.02	0.02

Table 5 Summary of error for the validation data of the 12 PLS models.

Model Conc. (mg/L)	1		2		3		4		5		6	
	A	B	A*	B	A*	B	A	B	A	B	A	B*
0.0	19.71	N/A	8.57	N/A	12.35	N/A	1.34	N/A	16.20	N/A	11.03	N/A
433.8	-3.48	-3.80	-3.19	-2.94	-0.47	-3.84	-3.58	-1.92	-2.84	-3.11	-2.81	-2.65
913.8	-0.59	-0.67	0.22	0.61	-0.11	-2.40	-1.06	-1.22	-0.50	-1.00	0.22	0.06
1844.0	0.18	0.08	0.04	0.33	0.17	0.20	-0.09	0.26	0.28	-0.02	0.09	0.22
2787.6	-0.41	-0.41	-0.44	-0.51	-0.21	-0.23	-0.48	-0.38	-0.46	-0.29	-0.58	-0.43
3686.0	0.25	0.32	-0.02	0.13	0.25	0.52	0.54	0.27	0.19	0.37	0.21	0.21
4590.7	0.13	0.16	0.05	-0.17	0.20	0.17	0.07	0.12	0.10	0.24	0.07	-0.01

*Model selected for further validation testing.

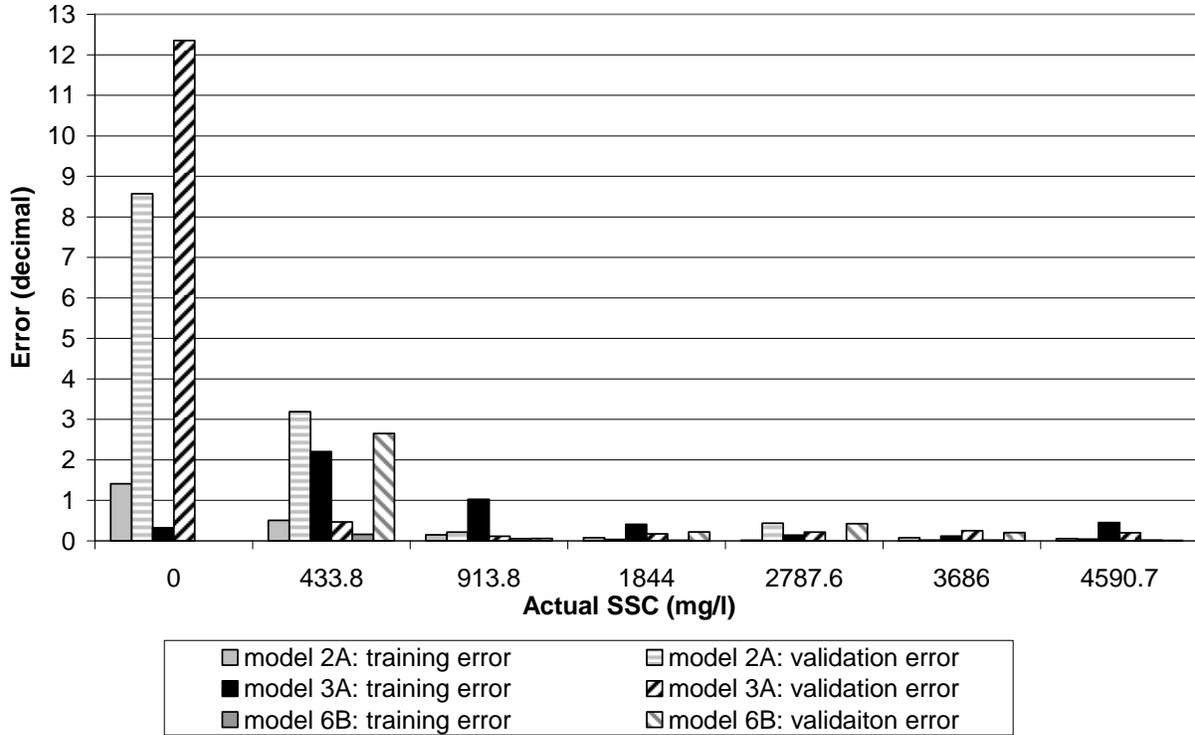


Figure 4 Error comparison of the training and validation data for the top three models: model 2A, model 3A, and 6B. All three models have the most difficulty predicting concentrations near 0 mg/L and 500 mg/L.

Validation Data Results Prediction values for nine treatment levels were calculated for each data set (A, B, and C) and then averaged for the final prediction value. Error between the predicted and actual values of SSC was calculated (Fig. 5). The first level (100 mg/L) was not shown in this plot because the error was orders of magnitude greater than the other concentration levels, greatly exaggerating the y-axis scale. All three models have the most difficulty predicting concentrations between 100 mg/L and 1500 mg/L. Model 3A does the best job predicting concentration.

The data used to develop the PLS models were normalized; therefore, when using the PLS models for independent validation, the input data must be normalized by the same standard deviation and mean values as used to develop the prediction models. The predicted values for the independent validation data were calculated with the following equations:

$$normalized_input_value = \frac{(x - \bar{x})}{stdev_x} \tag{5}$$

$$normalized_SSC_{predicted} = b + coef_t temp + coef_c cond + \sum_i coef_i x_i \tag{6}$$

where *normalized_input_value* is the gain or phase value once normalized; *x* is the gain (dB) or phase (deg) value measured by the KSU control box at a specific frequency; *x bar* is the mean value of *x*; *stdev_x* is the standard deviation of *x*; *normalized_SSC_{predicted}* is the normalized, predicted SSC from model 1, 2, and 3; *b* is the model intercept; *coef_t* is the coefficient for temperature; *temp* is the temperature recorded during sampling (°C); *coef_c* is the coefficient for specific conductivity; *cond* is the conductivity recorded during sampling (µS/cm); *i* is a counter variable for the number of frequency-based variables (gain and phase) included in the model (127 variables for model 2 and 254 variables for models 5 and 6); *coef_i* is the coefficient for variable *i*; and, *x_i* is the normalized gain or phase value measured by the KSU control box. Both the explanatory and predicted variables were normalized. Therefore, the predicted SSC must be reverse-transformed. The mean SSC for the models developed with all

concentration levels was 2037 mg/L and the standard deviation was 1602 mg/L. When 0 mg/L treatments were removed from the analysis (model 6B) the mean was 2376 mg/L and the standard deviation was 1478 mg/L.

Two of the three models selected for prediction with the independent validation data did a poor job of predicting the nine treatment levels. The predicted levels were orders of magnitude higher for 100 and 800 mg/L for all three models. Model 3A did the best job predicting concentration for all treatment levels except 100 and 4800 mg/L. It was expected that model 3A would have a difficult time predicting 100 mg/L based on the earlier validation results. Models 2A and 6B did the best job predicting concentration between 2000 and 4000 mg/L.

Investigations into the source of these poor predictions showed the distribution for many of the gain and phase variables in the independent validation data set had a different distribution than the prediction model data set. For most variables the mean gain and phase values did not vary significantly, but the standard deviation for 40-50 variables was double the size of the standard deviation values of the prediction model. The variation in standard deviations between data sets led to normalized values of gain within the validation data set as high as 20 instead of ranging between -2 and 2.

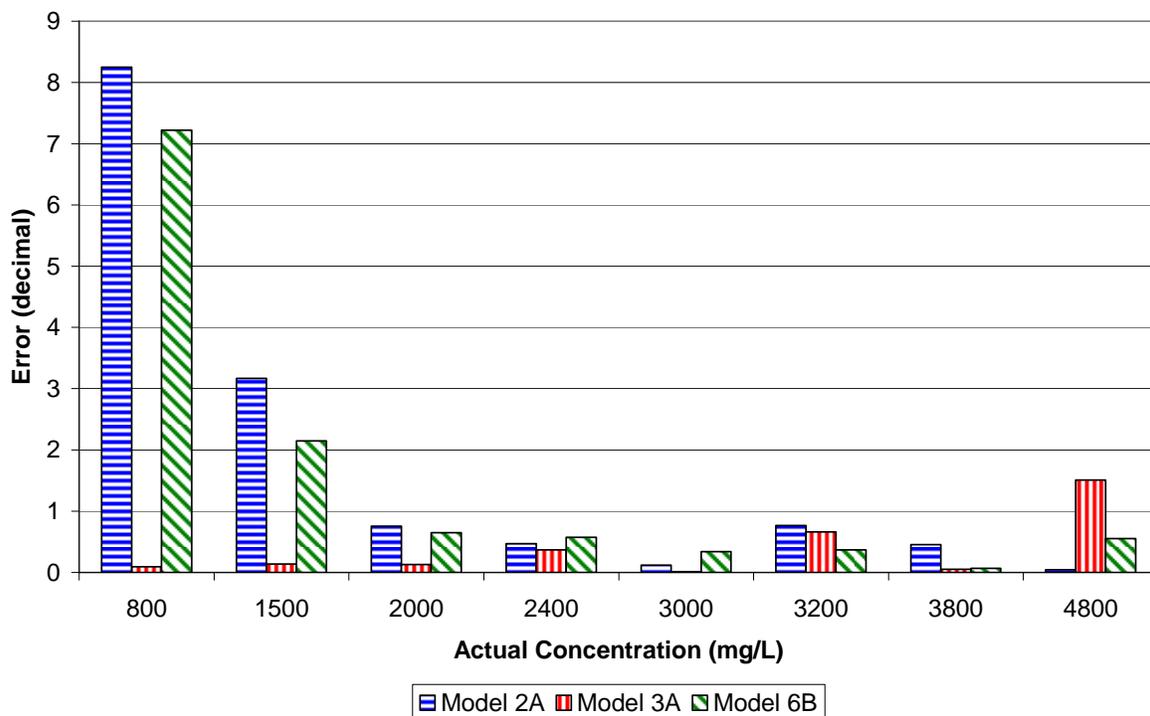


Figure 5 Error comparisons of the actual and predicted concentrations for eight of the nine validation treatment levels.

DISCUSSION OF PREDICTION MODELS

Accuracy of PLS Regression models Based on the initial training and validation data for models 2A, 3A, and 6B it was expected that the models would be able to predict SSC to ± 150 -500 mg/l over most of the study range (0-5000 mg/L) except for concentrations at or close to 0 mg/L. However, the error for models 2A and 6B increased for concentration around 3000 mg/L to ± 1200 mg/L.

This was not the case as seen in the analysis of the independent validation data set where all of the predicted levels for two of the models (2A and 6B) were significantly greater than the treatment levels (± 2000 mg/L). This drastic decrease in model accuracy was due to differences in the distributions of the gain and phase values between the prediction data and the independent validation data. At this point it is not clear if response to the shifted distribution is a weakness of PLS regression technique or there was a hardware malfunction in the measurement system,

resulting in validation data with a significantly different distribution than the prediction data even though similar treatments were applied. However model 3A which was based on temperature, specific conductivity, and 127 frequencies of phase data was able to predict six of the nine independent validation levels within ± 300 mg/L. The increased accuracy of model 3A could mean that phase values are less susceptible to variations within the hardware than gain values.

Conclusions on Permittivity Sensor Hardware Comparisons Traditional bottle or pump sampling techniques for SSC are time consuming, expensive (collection and analysis), and can be dangerous under storm and flood stage conditions. There is also a scale discrepancy between the measurement time-scale and the time-scale at which most desired calculations are completed (Gray and Gartner, 2009). Currently there are three surrogate technologies that are gaining credibility: turbidity or optical backscatter sensors, laser diffraction systems, and acoustic backscatter systems (Gray and Gartner, 2009). No one system provides the solution for all sediment monitoring challenges; therefore, the strengths and weaknesses of each measurement system compared to the conditions of the study site must be taken into account (Gray and Gartner, 2009). Some common weakness include particle size dependency, spatial or temporal resolution, and susceptibility to biofouling (Gray and Gartner, 2009; Wren et al. 2000).

This study supported the concept that permittivity measurements can predict SSC. The modeling predictions were most accurate (± 150 -500 mg/l) from 1000 to 5000 mg/L. This falls within the common measurement range of most turbidity (0-2000 mg/L or 0-5000 mg/L) and laser diffraction systems (0-2000 mg/L) currently available on the market (Gray and Gartner, 2009).

Cost Comparisons Currently the cost estimate for a common turbidity sensor is \$5000 (Gray and Gartner, 2009). Laser and acoustic systems can easily cost two to six times that amount (Gray and Gartner, 2009). It is believed that the permittivity system will be inexpensive to produce and may be on the scale of or less than a traditional turbidity sensor. Permittivity electrodes could potentially be multiplexed with one controlling system, allowing the user to deploy multiple electrodes at a field site with only one control system.

Conclusions for PLS Regression and Validation Multiple models generated within this study were able to predict treatment level with errors less than 10% during model development. However, SSC predictions made during a validation procedure were orders of magnitude greater than the treatment levels for concentrations under 1000 mg/L. At this time strong conclusions cannot be drawn regarding the feasibility of using permittivity to predict SSC. It is suspected that differences in the distribution of the validation data compared to the prediction model data set caused the poor predictions. Although two of three models tested with independent validation did not show promise, the phase-based model (model 3A) did predict six of the nine treatment levels within 300 mg/L. It would be beneficial to repeat the independent validation portion of this study. First, the control box and all system connectors would need to be tested to determine if the control box contributed to the error in the independent validation predictions for models with gain as input variables (models 2A and 6B). It may also be necessary, if significant changes are made to the KSU control box, for the entire prediction model data set to be collected again.

FUTURE WORK ON PERMITTIVITY SENSOR

Future work for sensor development The primary goal of this study was to determine if it was feasible to distinguish between different suspended sediment concentrations using a permittivity sensor. The previous sections present data and analyses that were able to distinguish differences over a large range of concentrations. It is recommended that future work on the application of permittivity measurements for predicting SSC include designing a more appropriate electrode for the environmental conditions present in lotic systems. Possible research question include:

- How can the design of the sensor electrode be manipulated to maximize capacitance and minimize flow effects?
- How does the electrode geometry affect sediment movement between the plates?
- How can electrode geometry and plate materials be optimized to prevent biofouling?
- Can a permittivity sensor predict both SSC and particle size distribution?
- With the optimal electrode geometry can the accuracy of SSC prediction be increased to the scale necessary for research?

Future Work for PLS Regression and Validation This project generated a significant amount of data because the exact modeling technique was not known at the onset. One modeling technique was presented in this paper. There are many more options available for modeling frequency based data. Future work on the prediction and validation components of this study includes the following:

- Can other multivariate modeling techniques predict SSC with higher accuracy than the PLS regression completed in this study?
- Are temperature and conductivity not significant in predicting SSC once sediment enters the system?
- Why does model performance decrease at concentrations at or near 0 mg/L?

REFERENCES

- Abdi, H. (2003). Partial least squares regression (PLS-regression). In M. Lewis-Beck, A. Bryman, T. Futing (Eds): *Encyclopedia for research methods for the social sciences*. Thousand Oaks (CA): Sage. pp. 792-795.
- Gray, J.R. and J.W. Gartner. 2009. Technological advances in suspended-sediment surrogate monitoring. *Water Resources Research*. 45, W00D29, doi:10.1029/2008WR007063.
- Lee, K.H., N. Zhang, W.B. Kuhn, G.J. Kluitenberg. 2007a. A frequency-response permittivity sensor for simultaneous measurement of multiple soil properties: Part I. The frequency-response method. *Trans. ASABE*. 50(6): 2315-2326.
- Lee, K.H., N. Zhang, and G. Kluitenberg. 2007b. A frequency-response permittivity sensor for simultaneous measurement of multiple soil properties: Part II. Calibration model tests. *Trans. ASABE*. 50(6): 2327-2336.
- Osterkamp, W. R., P. Heilman, and L. J. Land. 1998. Economic considerations of a continental sediment-monitoring program. *International Journal of Sediment Research*. 13(4): 12-24.
- Osterkamp, W. R., P. Heilman, and J. R. Gray (2004), An Invitation to Participate in a North American Sediment-Monitoring Network, *Eos Trans. AGU*, 85(40).
- Pimentel, D., C. Harvey, P. Resosudarmo, K. Sinclair, D. Kurz, M. McNair, S. Crist, L. Shpritz, L. Fitton, R. Saffouri, and R. Blair. 1995. Environmental and Economic Costs of Soil Erosion and Conservation Benefits. *Science*. 267 (5201): 1117-1123.
- Berkman, H.E. and C.F. Rabeni. 1987. Effect of siltation on stream fish communities. *Environmental Biology of Fishes*. 18(4): 285-294.
- Robinson, D.A., C.M.K. Gardner, and J.D. Cooper. 1999. Measurement of relative permittivity in sandy soils using TDR capacitance and theta probes: comparison, including the effects of bulk soil electrical conductivity. *J. Hydrology*. 223: 198-211.
- Robinson, D.A., S.B. Jones, J.M. Wraith, D. Or, and S.P. Friedman. 2003. A review of advances in dielectric and electrical conductivity measurement in soils using time domain reflectometry. *Vadose Zone Journal* 2: 444-475.
- Tang, N. 2009. A Real-time control system for a frequency response-based permittivity sensor. MS thesis. Manhattan, KS: Kansas State University, Department of Biological and Agricultural Engineering.
- USEPA. 2002. National Water Quality Inventory: 2000 Report. *EPA 841-R-02-001*. USEPA: Washington, DC.
- Utley, B.C. 2009. Evaluation of a Permittivity Sensor for Continuous Monitoring of Suspended Sediment Concentration. Ph.D. dissertation. Blacksburg, VA: Virginia Polytechnic and State University, Department of Biological Systems Engineering.
- Wren, D., S.Vadapurapu, J. Chambers, R. Kuhnle, and B. Barkdoll. 2002. Suspended-sediment measurements in laboratory flumes using acoustic techniques. *HMEM 2002*, ASCE.