4.4 ANN PREDICTIVE WATER TEMPERATURE MODELING OF COLD WATER EVENTS IN A SHALLOW LAGOON

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1. INTRODUCTION

The Laguna Madre is the longest hypersaline lagoon in the United States and extends southward for over 250 miles from Corpus Christi, Texas to La Pesca, Tamulipas, Mexico. The Laguna Madre is home and habitat to numerous species of larval, juvenile, and adult finfish and shellfish as well as a host of endemic and migratory birds (Britton and Morton, 1989). The passage of cold fronts can dramatically lower air temperatures by more than 10°C in less than 24 hours which leads to a considerable decrease in water temperature. Records from the past 20 years reveal that some of these cold water events resulted in massive fish kills. In 1997, more than 94,000 fish died in the Lower Laguna Madre and over 48,000 fish died in the Upper Laguna Madre (TPWD, 1997). To mitigate the impact of these cold events, local agencies and stakeholders are considering interrupting activities such as fishing and boating during these events. To help manage such interruptions accurate predictions of occurrences and length of cold water events are critical.

At present there is no specific predictive model for water temperature other than regional weather forecasts. The main objective of this study is to design and assess the performance of Artificial Neural Network (ANN) models predicting water temperatures in the Upper Laguna Madre during both normal and cold front conditions.

2. SITE AND DATA DESCRIPTION

The study takes advantage of real-time and archived measurements collected for the Texas coast by Texas A&M University-Corpus Christi, Division of Nearshore Research (DNR). DNR operates the Texas Coastal Ocean Observation Network (TCOON). This study focuses on the conditions at the TCOON South Bird Island Station, located south of Corpus Christi Bay in the Upper Laguna Madre. This study site was selected because of its northern location, leading to somewhat cooler temperatures, and the availability of extensive records of archived measurements. Data from other stations was included to account for the influence of nearby water bodies, i.e. Corpus Christi Bay and the Gulf of Mexico. Bob Hall Pier station is located on the shores of the Gulf of Mexico and Ingleside Station is located on the North shore of Corpus Christi Bay. The location of all study stations is illustrated in Figure 1.

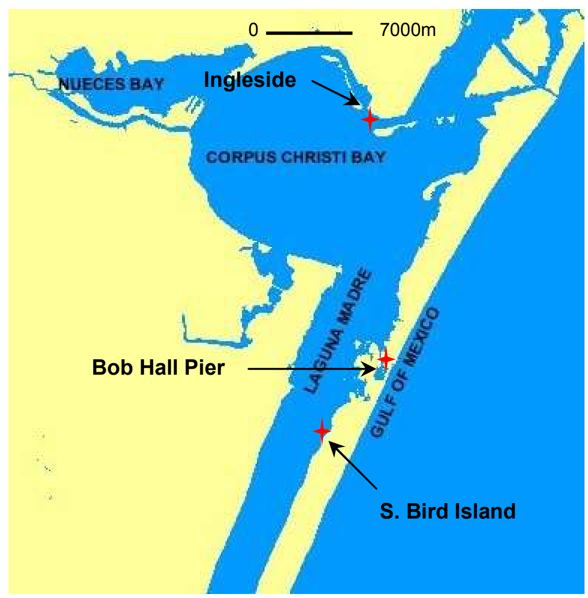

Figure 1. Map of TCOON Stations used in this study.

Bird Island station data used in the descriptive statistics consists of eleven yearly records (1995 to 2005) of air and water temperature. Data used in the training and optimization of the ANN model include yearly data sets 1995, 1996, 2000, and 2001 from Bird Island, Bob Hall Pier, and Ingleside Stations. These data sets consist of air temperature, water temperature, wind speed and wind direction, as well as measured and harmonically predicted water levels. More information on the data, including a

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table with data quality for each variable and station, can be accessed at the following link: http://lighthouse.tamucc.edu/Main/RobynBall. Additional graphs and tables related to this study are also available through this link.

The water temperature measurement sensors are located mid-depth in the water column at each station. The harmonic forecasts are computed using DNR harman & harmpred web based software (Mostella et al., 2002). The programs implement NOAA procedures (Schureman, 1958). The harmonic coefficient computations are based on one year of observations of water levels and a set of 26 harmonic constituents. Wind speed and wind direction are included in the model as squared winds along and across the local shoreline (angle of 25° from North). Gaps in the data used with the neural network models were filled using linear interpolation between the closest known measurements.

For the purpose of this study, a cold event is defined as any period during two days with one or more occurrences of water temperature falling below 7.2°C (~45°F). This threshold value is based on the experience of scientists from the Texas Department of Parks and Wildlife regarding the onset of fish mortality. Another important parameter for the onset and severity of fish kills is the length of time the water temperature remains below 7.2°C. Between 1995 and 2005 at Bird Island 24 such cold water events occurred, 23 of them ranging in length from 1 to 110 hours. One event in January of 1997 lasted 214 hours (Figure 2) and resulted in significant fish mortality (TPWD, 1997).

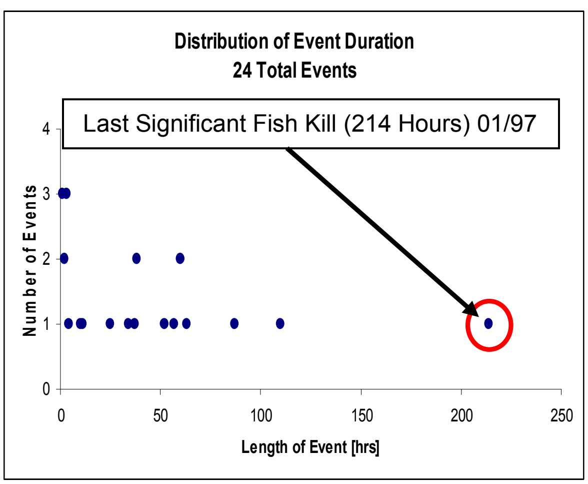

Figure 2. Distribution of event duration at Bird Island from 1995 to 2005.

3. METHODOLOGY

The ANN model design follows a stepwise method, progressively adding and comparing possible inputs to the model. A neural net model was selected for this work over other techniques because of its ability to model non-linear systems, robustness to noisy data, and generic modeling capability (Hagan, et al., 1996, Rumelhart and Chauvin, 1995). Rather than experimenting with the number of neurons and the number of hidden layers, our initial model follows the approach taken by Tissot, et al. This study found that simple [1,1] neural networks performed best for predictive modeling of water levels at the same location (Tissot et al., 2003). A tansig function is used for the hidden layer neuron and a purelin function is used for the output layer neuron.

The ANN models were developed, trained, and tested within the Matlab R2006b computational environment, utilizing the Neural Network Toolbox (The MathWorks, Inc., 2006). All ANN models were trained using the Levenberg-Marquardt algorithm.

Because of the number and variation in length of events, 1996 with six cold water events ranging from 2 to 110 hours, was selected as the training year. A significant amount of missing measurements during the cold water event of 1997, which resulted in a significant fish kill, ruled out that year as a test year. We selected three other test years instead: 1995 with two events (60 and 63 hrs), 2000 with four events (1, 3, 3, and 39 hrs), and 2001 with three events (3, 10, and 87 hrs).

Inputs to the neural networks consist of time series of previous water and air temperature measurements at Bird Island, water temperature measurements at Bob Hall Pier, and forecasted air temperature at Bird Island. In this study, forecasted air temperatures are replaced by measured air temperatures at Bird Island. For model implementation, air temperature forecasts will be provided by the local National Weather Service office. Sets of NAM (North American Model) predictions have been provided four times daily to DNR since 2002. Future models may include time series of air temperatures at other locations along typical tracks of incoming cold fronts.

Although we are most interested in accurately predicting cold events, the ANN models are initially optimized based on training and testing over yearly data sets. This methodology was adopted in large part because the cold events are sparse. Once the model is optimized, this initial approach is also compared to seasonal training. The ability of the ANN models to perform well, as compared to linear models during both regular and cold event situations, is also tested. The model performance is computed for both average and cold water event conditions and is assessed by the average absolute error $E_{absavg} = (1/N)\sum_{i=1}^{N}|e_i|$ over the full data sets, one year of water temperature measurements.

Based on persistence of water temperature, initial input selection for the ANN included only previous water temperature at Bird Island Station. During the optimization process, it was observed that short-term (3 and 12 hour) forecasts behaved similarly and longer term (24 and 48 hour) forecasts, while dissimilar to short-term forecasts, compared well to one another. Based on this observation, one model was designed for short 3 and 12 hour forecasts and another model was optimized for longer 24 and 48 hour forecasts. A stepwise method (Wilks, 2006) was employed to determine the optimal number of previous measurements to include in the model, with the first model including only present water temperature (wtp(0)). Up to 60 hours of previous water temperature measurements were consecutively added, producing a series of 61 water temperature models: wtp(0), wtp(0:1), wtp(0:2)…wtp(0:60) for both the training and test years. In total, for previous water temperature measurements, 244 models (Figure 4) were compared for each forecast. Based on the performance over the 3 yearly testing sets, model improvements are measurable up to the inclusion of the previous 26 hours of water temperature measurements (wtp(0:26)) for both short term and long term forecasts.

Once the basic ANN model is constructed, the next step is to select and test other possible models against this base model (wtp(0:26)) and determine whether including other inputs will lead to a significant performance improvement. These inputs were selected based on the physical understanding of the system as well as availability of data. Possible inputs considered include:

Atmospheric forcing of water temperature

- Previous air temperature at Bird Island
- Forecasted air temperature for Bird Island
- Future models may include air temperatures at a remote location along typical cold front tracks

Air/Water mixing

- Wind along and wind across shore squared at Bird Island

Heat input from nearby water bodies

- Primary water level at Bird Island
- Harmonic water level forecasts at Bird Island
- Water level difference between Bob Hall Pier and Bird Island Stations
- Previous water temperature measurements at Bob Hall Pier and Ingleside Stations

Day/night cycles

- 24 hour time stamp

For each of the additional possible inputs in the above list, new models were assembled by adding their input to previous water temperatures (wtp(0:26)). These other models were evaluated one at a time. The same stepwise method discussed previously was utilized for each of these other models with the number of previous measurements progressively increased to include up to 60 hours of previous measurements. The possible input models were assessed based on the average absolute error reduction. To justify adding an input time series, results from all test years are compared. Additional inputs are included if there is a substantial improvement (average absolute temperature difference of 0.02°C or larger) for the majority of the test years.

Along with previous measurements, models including air temperature forecasts and harmonically predicted water levels were also considered. We employed the same stepwise method with the exception that the models included forecasts up to the water temperature forecast time (3, 12, 24, and 48 hours).

The optimal model was obtained by adding to the past water temperatures (wtp(0:26)) all the other series of inputs that improved upon the base model. Other inputs were discarded.

4. RESULTS

For previous water temperature input (see Figure 4), the model's average absolute error continues to decrease over the entire 60 hours of added inputs for every test year. The 48 hour forecast errors decrease in a linear fashion, while the other forecast errors steeply decrease between approximately 0 and 5 and 15 to 20 hours. The error levels off after approximately 26 hours of previous measurements. Based on these results, 26 hours of previous water temperature at Bird Island are included in all ANN models.

The results for other possible input variables are represented in Table 2. The optimized ANN models include previous water and air temperature at Bird Island as well as forecasted air

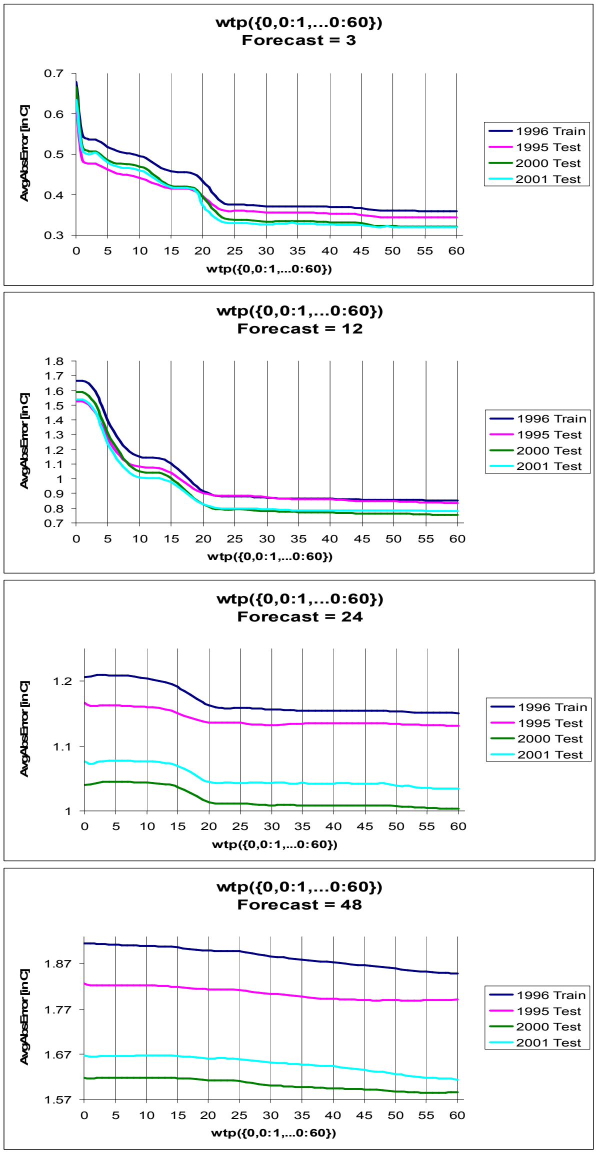

Figure 4. Average absolute errors for 3, 12, 24, and 48, hour forecasts. Previous water temperatures at Bird Island (ranging from 0 to the past 60 hours) are the only inputs.

temperature at Bird Island. The short-term model (3 and 12 hour forecasts) also includes the previous 16 hours of a 24 hour time stamp [0.1,2.4] and the long-term model includes the current water temperature measurement at Bob Hall Pier. The performance of the final ANN model is presented in Table 3.

5. DISCUSSION

The optimized ANN model performance presented in Table 3 shows that the accuracy of the model decreases from 0.3°C for 3 hour forecasts to between 0.6°C and 0.9°C for 48 hour

	Series Included	
Possible Inputs Considered	Short Term	Long Term
Bird Island wtp	wtp(0:26)	wtp(0:26)
Bird Island atp	atp(0:22)	atp(0:16)
Bird Island forecasted atp	ALL	ALL
Wind along and across shore	None	None
Bird Island pwl	None	None
Bird Island harmwl	None	None
Bird Island & Bob Hall pwldiff	None	None
Bob Hall wtp	None	Current
Ingleside wtp	None	None
24 hr time stamp	time(0:16)	None

Table 2. Possible inputs and series of inputs included in the model. (wtp = water temperature, atp = air temperature, pwl = water level, harmwl = harmonic predicted water level, pwldiff = water level difference, time = time stamp)

Average Absolute Error of Optimized ANN [in °C]					
	Forecast	1996	1995	2000	2001
Year	3 hours	0.314	0.301	0.281	0.292
Cold Events		0.418	0.223	0.425	0.294
Year	12 hours	0.557	0.534	0.488	0.549
Cold Events		0.816	0.445	0.419	0.794
Year	24 hours	0.592	0.565	0.533	0.662
Cold Events		0.916	0.393	0.457	0.783
Year	48 hours	0.693	0.650	0.636	0.869
Cold Events		0.994	0.449	0.477	0.397

Table 3. Average absolute errors in the optimized ANN model for both the training year (1996) and test years (1995, 2000, 2001).

forecasts when evaluated over yearly data sets. Interestingly, the model is more accurate for cold water temperature predictions; however, there is greater year to year variability. The variability is likely due to the smaller number of predictions as well as the variability in the intensity of the frontal passages generating these cold events. During cold events, the accuracy decreases from 0.2°C to 0.4°C for 3 hour forecasts to 0.4°C to 0.5°C for 48 hour forecasts.

It is hypothesized that the better performance during cold events, as compared to the performance averaged over the overall data set, is due to the more systematic behavior of the water temperature during such events. In particular, the water temperature is strongly correlated to previous air temperatures during cold events. Such correlation should lead to a model performance sensitive to the accuracy of air temperature predictions. To assess the importance of air temperature predictions the model was further tested without such predictions. Results are presented in Table 4.

As can be observed in Table 4, model accuracy for cold events is now considerably below average model performance. The average absolute errors increase dramatically during test years by 2.3°C to 4.7°C for 48 hour forecasts; a 400% to 900% increase. The differences between the results with and without air temperature predictions emphasize the importance of this parameter, particularly during cold events.

Average Absolute Error of Optimized ANN without Air Temperature Predictions [in °C]					
	Forecast	1996	1995	2000	2001
Year	3 hours	0.33	0.32	0.29	0.31
Cold Events		0.44	0.25	0.46	0.30
Year	12 hours	0.78	0.77	0.67	0.75
Cold Events		1.21	0.93	0.92	1.07
Year	24 hours	1.09	1.07	0.94	1.02
Cold Events		2.07	1.74	1.59	0.90
Year	48 hours	1.81	1.72	1.51	1.59
Cold Events		5.28	4.06	4.75	2.26

Table 4. Average absolute errors in the optimized ANN model without air temperature predictions for both the training year (1996) and the test years (1995, 2000, 2001).

Current work is underway to replace the perfect predictions with historical NAM model output. The performance of the ANN model with NAM air temperature inputs will give a more realistic performance of the model. That said, even a substantial degradation of the performance will still lead to a very useful predictive tool.

This study utilizes a tansig transfer function for the hidden layer neuron and a purelin function for the output layer neuron (tansig/purelin). To estimate the importance of including the nonlinear modeling capability an additional linear model was tested with the same inputs, but using a purelin transfer function for both the hidden layer and output neurons (purelin/purelin). Models were compared based on the average absolute error. The performance of the purelin/purelin model was similar to the nonlinear ANN design over the full yearly data sets. The nonlinear model, however, outperformed the linear model during cold events, as can be seen in Table 5. The mean of the average absolute error of all test years during cold events is lower for all forecast times and, as the forecast time increases, so does the difference in the error between the linear and nonlinear models.

Figure 6 and 7 further illustrate the better performance of the nonlinear model during cold events. The figures also suggest that the linear model is negatively biased for low temperatures.

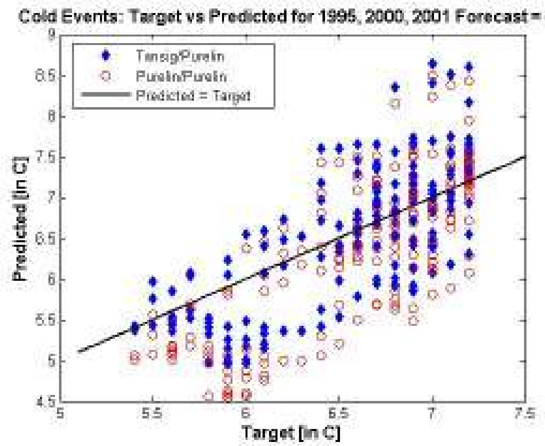

Figure 6. Target vs. Predicted. tansig/purelin and purelin/purelin transfer function combinations during cold events. 1995, 2000, 2001. 48 hour forecast.

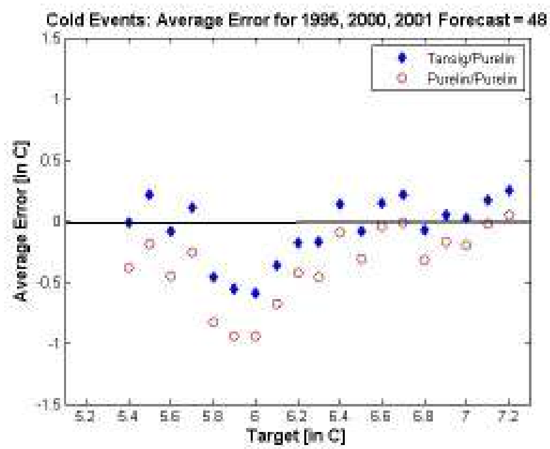

Figure 7. Linear and non linear model average error (bias) vs. measured target temperature.

Mean of 1995, 2000, and 2001 Average Absolute Errors during Cold Events [in °C]				
Forecast	**3 hrs**	**12 hrs**	**24 hrs**	**48 hrs**
Tansig/Purelin	0.282	0.533	0.494	0.448
Purelin/Purelin	0.292	0.540	0.544	0.519

Table 5. Mean of 1995, 2000, and 2001 average absolute errors during cold events.

It is hypothesized that the modeling capability of the non linear ANN design allows for an unbiased or less biased prediction of water temperatures during cold events.

Initially, the models were trained and tested on yearly data sets. This method was compared to training seasonally with the same inputs. Because of the distribution of events, the models were trained on data from December 1995 – April 1996, and consisted of 6 events (2, 4, 38, 57, 63, and 110 hrs). Both seasonally trained and yearly trained models were tested on data from December 2000 – March 2001, also consisting of 6 cold events (1, 3, 3, 3, 10, and 87 hrs).

For average conditions, seasonally and yearly trained models yielded similar results for short-term forecasts. For longer term forecasts, the yearly training method performed slightly better for average conditions. The seasonal model performance was mixed during cold events. Although the error decreased by more than 15% for 12 hour forecasts, the error increased by over 7% for 48 hour forecasts. Because of the distribution of cold water events over the available data, there was only one season with a substantial number of cold events (6) on which to test the model. More testing will be required to evaluate potential benefits of seasonally trained models.

6. CONCLUSION

An Artificial Neural Network model was designed to predict water temperatures in the Laguna Madre. A successful model will be an important management tool to help mitigate the impact of cold water events on fish mortality by, for example, regulating fishing and shipping activities during the predicted cold events.

A short term model was designed for 3 and 12 hour forecasts and a longer term model was constructed for 24 and 48 hour forecasts. The models were designed following a stepwise method, consecutively adding possible inputs and then comparing the average absolute error of the models. Both models included the previous 26 hours of water temperature at Bird Island and air temperature forecasts. The short term model inputs also consisted of the previous 22 hours of air temperature measurements and the past 16 hours of a 24 hour time stamp. Long term model inputs included the previous 16 hours of air temperature measurements along with the last water temperature measurement at Bob Hall Pier.

Model performance was excellent, with an accuracy of better than 0.5°C for all forecast times, up to 48 hours during cold events. The present model is, however, based on perfect air temperature predictions and work is ongoing to evaluate a model based on historical NAM predictions provided by the Corpus Christi Weather Forecasting office.

Other observations from the study include better performance of nonlinear ANN models during cold events as compared to a linear model and the absence of significant performance difference during average conditions. A real time model including NAM predictions will be implemented as one of the online forecasting tools of the TAMU-CC Division of Nearshore Research.

7. ACKNOWLEDGEMENTS

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