Air-Sea Forcing of Coastal Ocean Sea Surface Temperature

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***Abstract*— Nearshore sea surface temperatures show both strong seasonal trends and rapid changes associated with local weather events. As a result, commercial fishing operations search and rescue services, and recreational users have a very limited capability to predict expected sea surface temperatures for any given day. We use empirical and neural net modeling techniques to describe the seasonal relationships between wind velocity, offshore sea surface temperature, air temperature, wave energy and nearshore sea surface temperature along the Outer Banks of North Carolina. In the winter months, nearshore sea surface temperature is influenced by both offshore sea surface temperatures and air temperature, both of which reflect solar input. During the summer months, the ocean is stratified. Consequently, winds influence nearshore sea surface temperatures by inducing upwelling and downwelling phenomena, resulting in decreases and increases in nearshore SSTs respectively. The spring and fall seasons exhibit trends from both the summer and the winter, but these trends are weaker. We also look at how the greater prevalence of winds and waves during various seasons also influences nearshore sea surface temperatures. The resulting neural net model can predict nearshore sea surface temperature with a reasonable amount of accuracy.**

Keywords—nearshore sea surface temperature; upwelling; winds; seasonal trends

I. BACKGROUND

Along the northern Outer Banks of North Carolina, nearshore sea surface temperatures (SSTs) show strong seasonal trends and rapid changes associated with local weather events. Summer nearshore SSTs in particular change rapidly. The Outer Banks is a popular summer tourist destination used both recreationally and commercially. Currently there is no reliable method for providing forecasted nearshore SSTs along the Outer Banks; measurements only come from sporadically located research and fishing piers. Without this information, commercial fishing operations, search and rescue services, and recreational users have a very limited capability to predict expected nearshore SSTs for any given day.

Past research indicates that wind events induce coastal upwelling and downwelling in the summer months. Wind has been acknowledged as a main factor in promoting coastal upwelling (Smith, 1968). Carbonel (2003) used an empirical model to determine that summer upwelling and downwelling phenomena along the Cabo Frio Coast (Rio de Janerio, Brazil) resulted from the combined effects of stratification and wind events. Furthermore, Clemente-Colón and Yan (1999) conducted a study along the New Jersey coast, in which they attributed upwelling to "the duration and intensity of wind events". In a 1999 study, Austin and Lentz describe the occurrence of upwelling and downwelling along the Outer Banks. Austin and Lentz state that upwelling occurs when the ocean is stratified and the winds are blowing in a direction to induce upwelling. They also stated that upwelling, which brings colder water to the ocean's surface results in a disparity between sea surface temperature and air temperature.

We use a 35-year observation data set collected at the USACE Field Research Facility (FRF), in Duck North Carolina, to test a neural net approach to determine what physical factors govern nearshore SSTs. We use the model and the FRF data to predict nearshore SSTs on both a seasonal and annual basis. Observations made by the FRF (Figure 1) indicate that nearshore SSTs decrease dramatically in the summer, with SST drops of 10^{o} possible in just 18 hours (Figure 2). These decreases appear to be strongly correlated with southwest wind events. When local winds, come from the southwest they induce upwelling along the northern Outer Banks coast (north of Cape Hatteras), which leads to decreases in nearshore SSTs. Southwestern winds bring colder bottom waters of the stratified water column up to the surface, thereby decreasing nearshore SSTs. These local observations coincide with the aforementioned studies in that upwelling is a summer phenomenon, is driven by local winds, and occurs over stratified oceans.

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Fig.1. Google Map showing FRF location

Past research coupled with local observations has led us to address the following key questions: (1) What local and physical factors govern nearshore SSTs? (2) How do these factors influence nearshore SSTs on a seasonal basis? There are currently no nearshore SST forecasts available for the Outer Banks. Spurred on by the need for a reliable forecast and academic curiosity we attempt to determine if a reasonably accurate model to predict nearshore SSTs can be developed using existing data and modern neural net approaches.

II. DATA

The following is a description of the data sets used in this study. Measurement details are provided in Table 1. Sample 8-day time series appear in Figure 2. Our target variable is nearshore SSTs. Our input variables include: time of year, wind history, offshore SST, air temperature, and wave power.

Winds are set to be relative to the beach angle at Duck (Figure 1); hence wind directions are rotated 19^o clockwise. Winds are then separated into u (cross-shore) and v (along-shore) components, based on the rotated wind directions. The positive u-component is from the northeast and the positive v- component from the northwest.

The neural net model is set to predict nearshore SST; nearshore SST is our target variable. In this analysis we look at the continuous nearshore SST data from January 2010 through December 2012. All of the input variables are interpolated to the recorded times for the nearshore SST data.

There is a seasonal correlation between how the various input variables influence the nearshore SST. In order to determine the relevance of the time of year to the nearshore SST we created a sequential day of the year variable (1 to 365). We base the days of the year on the nearshore SST data's recorded times.

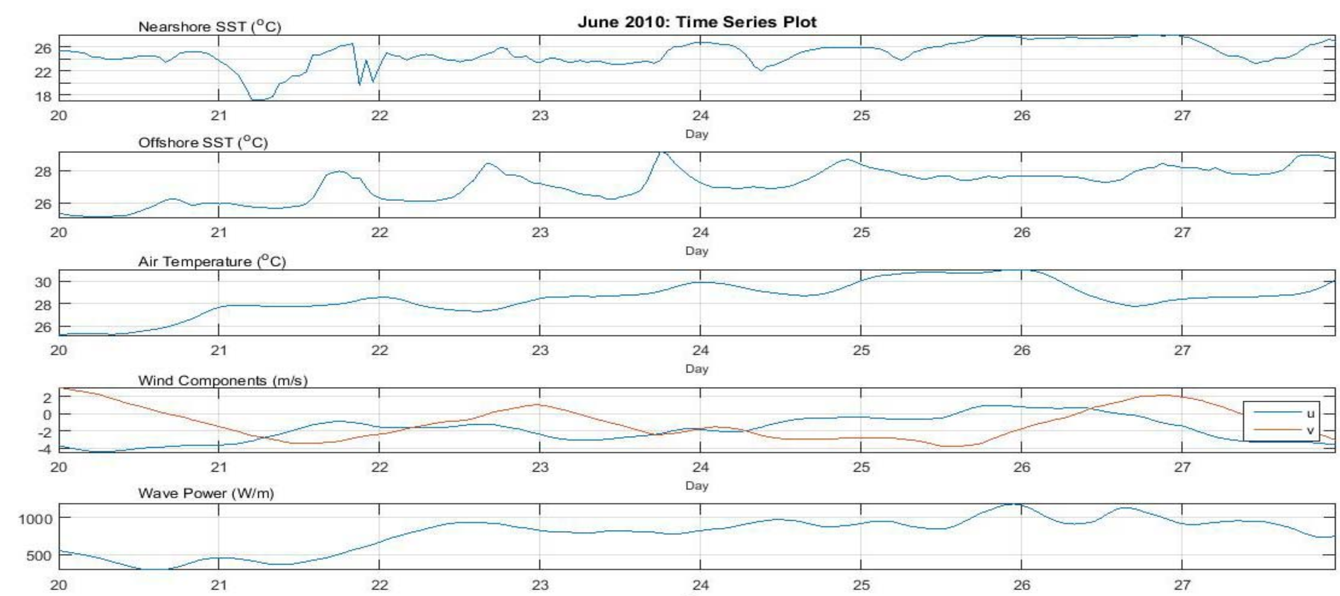

Fig. 2. Sample time series of air-sea parameters used in this study. Nearshore SST temperature drops occur when both u and v swing negative, which corresponds to winds from the southwest quadrant.

TABLE I. FRF MEASHREMENT DETAILS

Station	Thermistor String	RM Young Marine Anemometer	Waverider Buoy Station 430	Waverider Buoy Station 630	Weather Station
Parameter	Nearshore SST (^{o}C)	Wind data (m/s)	Offshore SST (^{o}C)	Offshore SST (^{o}C) Wave Power (W/m)	Air Temperature (^{o}C)
Elevation (Sea level = 0)	0m (tide not considered)	19.4 m	Water Depth -26m	Water Depth -17.4m	2.5 m
Latitude	36^o 11.02336’N	36°11.017’N	36°15.461’N	36°11.993’N	36°10.95’N
Longitude	75^o 44.708858’ W	75°44.70’W	75.479’W	75°42.843’W	75°45.1’W
Distance Offshore	end of pier (561m from dune)	end of pier (561m from dune)	18.5km	3km	150 m onshore behind dunes

III. APPROACH

Based on observations from the FRF, as well as past research, seasonal variations in nearshore SST on the northern Outer Banks are hypothesized to be a function of water column stratification and local wind history. Furthermore we hypothesize that water column stratification can be described using time of year, wind forcing, air temperature, offshore SSTs, and wave forcing parameters.

We conducted a preliminary study along the Outer Banks to establish the influence of FRF wind history and offshore SST data on nearshore SSTs. First we created seasonal plots of nearshore SST versus offshore SST (Figure 3a – 3d). We also created seasonal Cartesian plots in which we look for a relationship between wind and nearshore SSTs (Figure 4a – 4d). We looked at the change in nearshore SST as a function of wind speed, wind direction, and wind duration. Winter includes December, January and February. Spring includes March, April and May. Summer includes June, July, and August. Fall includes September, October and November.

We use neural net modeling techniques in Matlab^{TM} to develop a model for nearshore SSTs based on the results from our data correlation studies described above. In this study we continue to use meteorological and oceanographic observations made at the FRF. The neural net model is set to determine how the input variables (time of year, wind history, offshore SST, air temperature, and wave power) influence the target variable (nearshore SST).

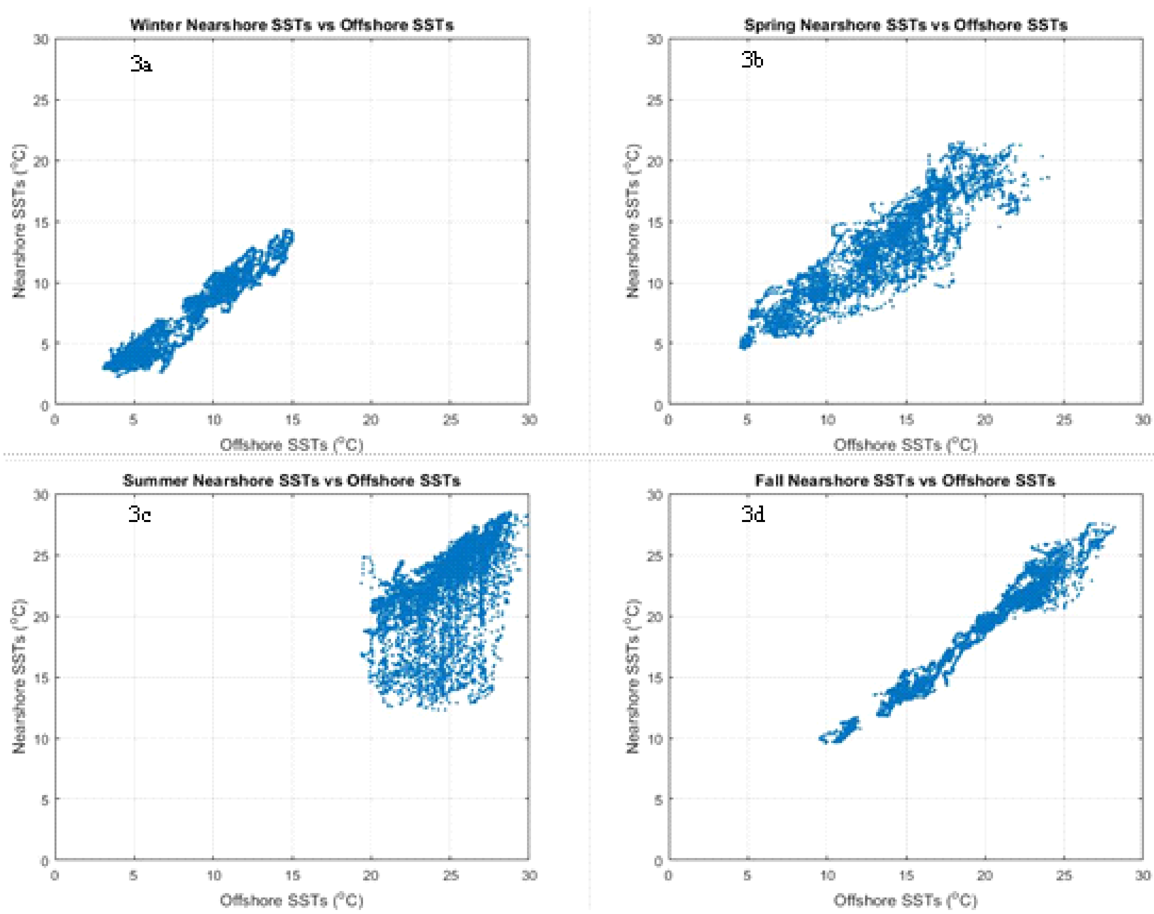

Fig. 3. Seasonal correlation plot of nearshore SSTs vs offshore SSTs

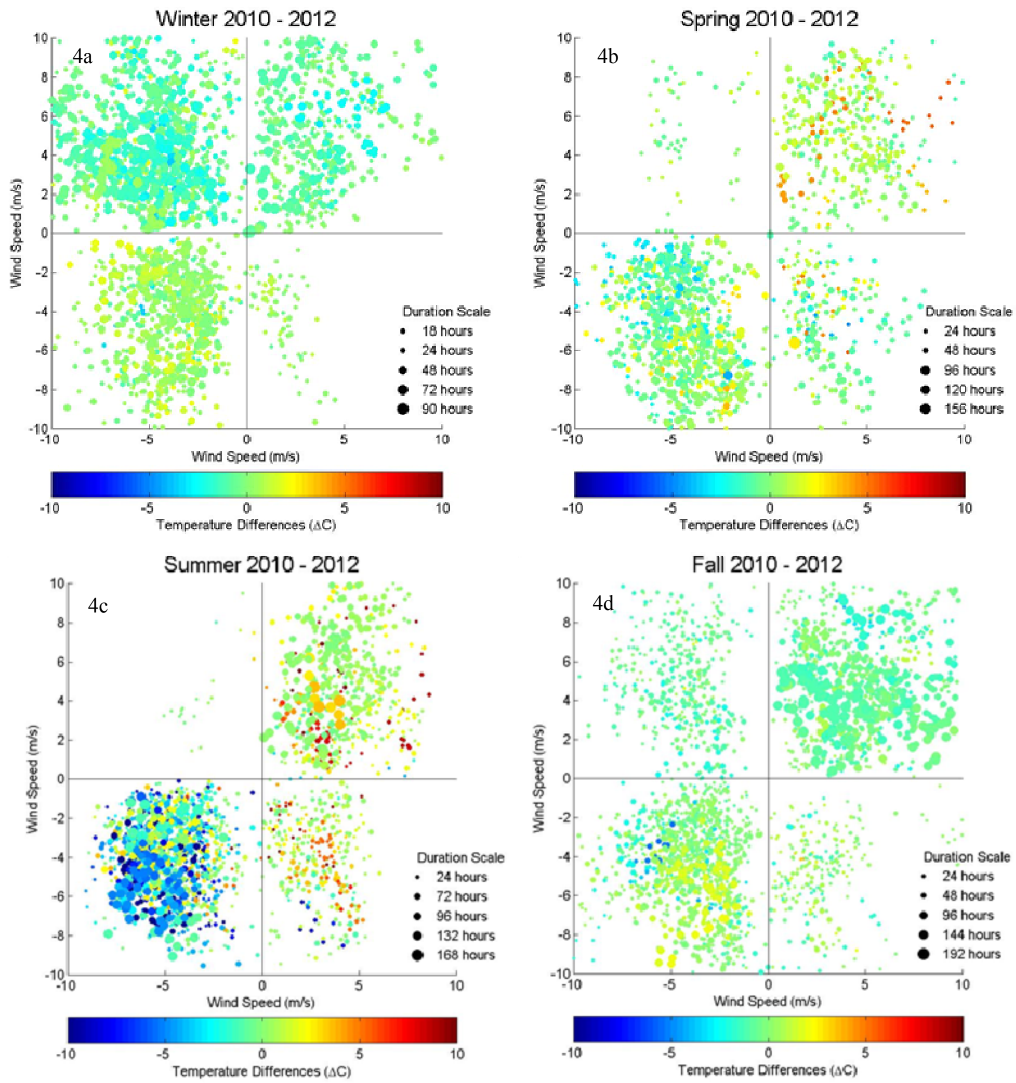

Fig. 4. Seasonal wind history plots. See text for explanation.

Each time we run the model a random sample of data from the input variables is selected (the training set). The training set is then run against the validation set, which consists of the remaining input variables. The validation set serves to test the accuracy of the training set. A single run-through between the training set and the validation set is considered one "epoch" or "iteration". The number of iterations the model goes through in each individual test is chosen at random but never exceeds 1000.

To measure modeling accuracy, we use the correlation coefficient (R). The R value is an indication of the relationship between the predicted and observed nearshore SSTs. If $R = 1$, this indicates that there is an exact linear relationship between the model estimates and the observations. If R is close to zero, then there is no linear relationship between them.

We run the model five times with each separate input variable and calculate the average R value to determine the importance of each input's contribution to predicting the target value. We have a total of 25,698 data points. Our training set consists of 70% of our data (17,988 samples). 15% of our data (3,855 samples) is used for validation, and the remaining 15% (3,855 samples) is used for testing. Once the relevance of each individual input value is determined, we successively re-combine the input variables (in order of importance) to see how the combination of inputs also impacts the prediction of the target variable. Finally we examine the model using all of the input variables to predict the target variable. We perform this analysis for each season, as well as for our entire three-year data set. We separate the seasons into months, the same way we did for our previous study.

The wind has a delayed influence on nearshore SST, hence the need for back-averaged wind values. Air temperature and wave power (like the wind history) also have delayed influences on nearshore SST and need to be back-averaged. In order to determine the optimal interval for back-averaging we ran the model with different back-average intervals five times to see which intervals generate the most efficient average R value. We test the model to find the best back-average interval for the each of the variables (winds, air temperature, wave energy), with no back-average intervals for the other variables. We use these back-average intervals in our neural net analysis.

IV. Results

A. Data Correlations

Our preliminary study indicates that nearshore SSTs are seasonally correlated with offshore SSTs (Figures 3a – 3d), and local wind histories (Figures 4a – 4d). Figures 3a – 3d are comprised of four seasonal scatter plots plotting data from 2010 through 2012. The x-axis is offshore SSTs and the y-axis is nearshore SSTs.

Four seasonal scatter plots, with data from 2010 through 2012 were created in order to visualize the relationship between the wind and the ocean's temperature (Figures 4a – 4d). The wind data is broken into u - and v - components and then divided into "wind events." For this analysis, a "wind event" is defined as a series of winds blowing from the same directional quadrant. The plots are Cartesian, with the y- axis representing the north and south wind components and the x-axis representing the east and west wind components. For example, a northeast wind plots in the first quadrant of the Cartesian plot and a southwest wind plots in the third quadrant of the Cartesian plot. Each point represents a particular instance in time and are plotted based on the wind components. The points are colored to show the change in temperature from that instant in time to the start of the nearest wind event preceding it. The scatter points are scaled to the approximate duration of the wind from the start of the wind event to the current time. These plots show that the wind does play a crucial role in changing the ocean's temperature.

The study determined that nearshore SSTs exhibit a seasonal variation and can be related to both offshore SSTs and wind trends. The plots indicate that there is a direct correlation between nearshore SSTs and offshore SSTs. Evidence of summer upwelling events generated by southwestern winds is seen in Figure 4c, in the outbreaks of cooler nearshore SSTs. During the winter (Figure 4a), winds from the north bring colder air temperatures leading to decreases in nearshore SSTs, while winds from the south bring relatively warmer air temperatures resulting in increases in nearshore SSTs. The spring and fall seasons (Figures 3b, 3d, 4b, and 4d) are transition time periods which exhibit trends from both the winter and summer seasons.

B. Neural Net Model

Wind history, air temperatures, and wave power have a delayed effect on nearshore SSTs. After testing the model, we determined that the effect of the winds on nearshore SSTs is best characterized by a 36-hour interval; the rotated u - and v - wind components are back-averaged every 36 hours. The effect of air temperature on nearshore SSTs is best characterized by a 30-hour interval. Air temperatures are back-averaged over 30 hours. Additionally, wave energy is best characterized by a 9-hour interval. R versus back-average-time plots display the optimal time for each of the variables, in Figure 5.

Neural net results, recorded in Table 2, list the average R values generated by the model during our analysis. Column 1 lists the input variables in order of importance (from top to bottom) for each season as well as for the full year and column 2 lists the average R values when the model is run with each of the individual input variables. Columns 3 through 5 list the average R value when the model successively combines the most important variables (based on the average R value). Column 6 presents the average R values when the model is run with all of the input values for each season and for the full year.

Scatter plots for each of the seasons and for the full year when all of the input variables are used in the model are shown in Figures 6a – 6e. These plots are one of the five plots used to calculate the average R values in Table 2. The

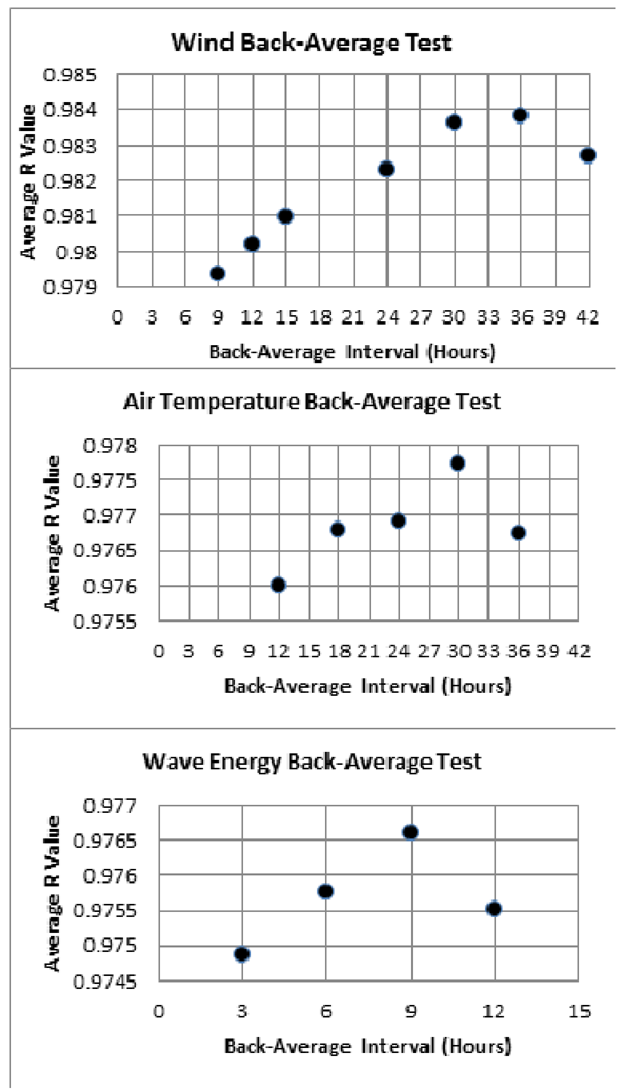

Fig. 5. Test plots to determine back-averaging intervals for winds (top panel), air temperature (middle panel) and wave energy (bottom panel)

summer model results (Figure 6c) tend to over-predict nearshore SST but still generate an average R value of 0.884 (Table 2). The other seasons as well as the full analysis exhibit tight scatter plots with average R values greater than 0.97 (Table 2). The fall season generates the tightest scatter plot (Figure 6d).

TABLE II. RESULTS: AVERAGE R VALUE

2010 through 2012: Inputs	Averaged R values	Averaged R values	Averaged R values	Averaged R values	Averaged R values
Offshore SST	0.960	0.964	0.970	0.984	**0.984**
Day Number	0.908				
Air Temperature	0.869				
Winds	0.379				
Wave Power	0.110				
Winter: Inputs	Averaged R values	Averaged R values	Averaged R values	Averaged R values	Averaged R values
Offshore SST	0.965	0.977	0.980	0.988	**0.989**
Air Temperature	0.683				
Day Number	0.637				
Winds	0.340				
Wave Power	0.206				
Spring: Inputs	Averaged R values	Averaged R values	Averaged R values	Averaged R values	Averaged R values
Offshore SST	0.911	0.924	0.940	0.970	**0.971**
Day Number	0.884				
Air Temperature	0.664				
Winds	0.377				
Wave Power	0.184				
Summer: Inputs	Averaged R values	Averaged R values	Averaged R values	Averaged R values	Averaged R values
Winds	0.729	0.843	0.857	0.873	**0.884**
Offshore SST	0.532				
Day Number	0.343				
Air Temperature	0.242				
Wave Power	0.205				
Fall: Input	Averaged R values	Averaged R values	Averaged R values	Averaged R values	Averaged R values
Offshore SST	0.983	0.986	0.988	0.992	**0.993**
Day Number	0.956				
Air Temperature	0.882				
Winds	0.417				
Wave Power	0.230				

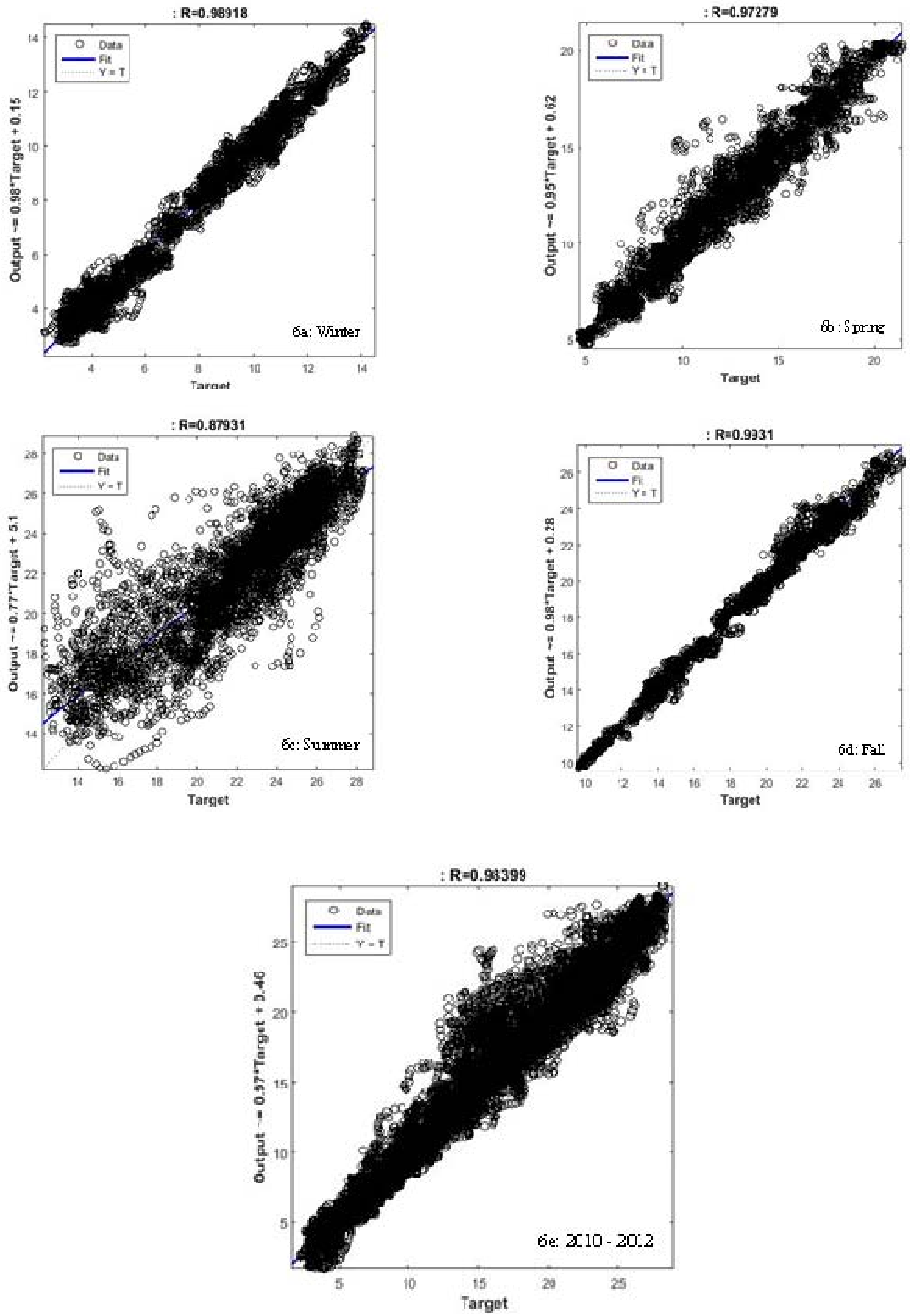

Fig. 6. Correlation of neural net model SSTs (Output) with observed SSTs (Target) for each season (a-d) and all time periods combined (e).

V. Discussion

A. Winter

In winter offshore SST is highly correlated with nearshore SST. Additionally, nearshore SSTs are influenced by winter air temperatures, transported by cold northerly winds or by warm southerly winds. Cold northerly winds decrease nearshore and offshore SSTs. On the contrary, warm southerly winds raise nearshore and offshore SSTs. The strong relationship between nearshore SSTs with offshore SSTs and air temperatures is supported by the fact the model yields high R values when run individually with each of these variables. The main factor governing winter nearshore SSTs is solar input. In our model, offshore SST and air temperature indicate solar input. These variables have the highest R values and so play the greatest role in influencing nearshore SST, during the winter.

Winds mostly influence nearshore SSTs by inducing upwelling and downwelling. Even though winds are the strongest in the winter (and in the spring), winds do not have much influence on winter nearshore SSTs because the winter ocean is not stratified. In addition, waves are the strongest in the winter and the fall, and further work to decrease stratification by causing vertical mixing in the water column. Without stratification, the winds and the waves do very little to influence nearshore SST. Hence the wind history and wave power have low R values when run as the only input variable in the model (Table 2).

By successively combining the input variables, we see the biggest increase in the average R value (Table 2) is with the addition of offshore SST, air temperature, and the time of the year. Combining the winds and the wave power does improve the prediction of nearshore SST as well. The resulting 5-parameter model predicts winter nearshore SSTs relatively well (Figure 6a).

B. Summer

Winds are the most influential input variable in determining nearshore SSTs during summer. The winds yield the highest average R value when the inputs are run individually in the model (Table 2). Summer months exhibit a well-stratified ocean, which enables local winds to induce coastal upwelling and downwelling phenomena. Upwelling brings colder, nutrient-rich bottom waters up to the surface, thereby decreasing nearshore SSTs, whereas downwelling brings warmer offshore waters into the nearshore region

During the summer, as in the other seasons, solar input is reflected in both offshore SSTs and air temperature (both of which are higher during the summer when compared to other seasons). Although offshore SSTs do influence nearshore SSTs in the summer, offshore SSTs have a smaller influence on nearshore SSTs (in the summer) when compared to other seasons. Upwelling and downwelling events induce cold or warm nearshore SST outbreaks which lead to miscorrelations between nearshore and offshore SSTs. Hence the summer season is the only season in which offshore SSTs do not have the highest individual R value and is the season with the lowest individual offshore SST R value (Table 2).

Upwelling and downwelling also contribute to the disparity between air temperature and summer nearshore SSTs. The strength of the summer solar input is reflected in air temperature, but upwelling events decrease nearshore SSTs leading to a miscorrelation between air temperature and nearshore SSTs. Upwelling events appear to override the influence of air temperature; individually air temperature has a relatively low R value (Table 2). Although wind is the main mechanism behind upwelling and downwelling, waves also have the potential to vertically mix the water column, and so can have a more significant impact on nearshore SST when the water column is stratified. Waves mix the upper ocean, however wave energy is lowest in summer.

The combination of all the input variables improves nearshore SST prediction in the summer (Table 2).The neural net model predicts the nearshore SSTs for the other seasons, as well as for the entire data set, more accurately than in the summer season (Table 2). Scatter plots of the summer season (Figure 6c) reveal that there are periods when the model both over- and under-predicted nearshore SST, with a greater tendency towards over-predictions. This could be contributed to a variety of factors including: the proximity of the Gulf Stream to the coast at any given time over the summer, coastal plumes originating from the Chesapeake Bay directly to the north, and/or the presence of wave-induced currents. Any or all of these factors can impact the wind's ability to effectively induce upwelling and downwelling events. In other seasons, the ocean is less stratified, not only because of decreased solar input, but also because of increased winds, waves, and currents. Consequently, the effects of these other variables may be over shadowed outside of the summer.

C. Spring

Offshore SST and the time of year are the most influential factors in determining nearshore SST during the spring; these factors have the highest individual average R values (Table 2). The spring months serve as a transition between winter and summer seasons. The main factor in controlling nearshore SST summer trends is ocean stratification. During the spring, the winter season exerts a greater influence on nearshore SST because the spring season starts with an un-stratified ocean. Not until the end of the spring season does the sun start to strengthen enabling the ocean to begin to develop some stratification. Consequently, offshore SST and air temperature play an important role in determining nearshore SST, similar to how these factors do in the winter.

Being a transition season, spring nearshore SSTs are predicted by factors that govern both the winter and the summer nearshore SSTs. Offshore SSTs and air temperature are more important for determining winter nearshore SSTs and winds play more of a role in influencing summer nearshore SSTs. The largest impact to the model was the successive combination of not only the offshore SST, the time of year, and the air temperature variables, but also the combination of these variables along with the winds. This statement is supported by the fact that the average R values increase by the largest amount when all four of these variables serve as input variables for the model. The model performs well during spring (Figure 6b).

D. Fall

The fall season, like spring, is a transition month. In addition, wave energy is stronger in the fall, which can lessen the impact of summer factors by decreasing ocean stratification. Still summer factors do influence nearshore SSTs. Individual analyses of the winds and waves yield greater average R values in the fall than in the spring.

Similar to the spring season, the successive combination of offshore SST, the time of year, the air temperature, and the winds exert the greatest impact on the model. This is supported by the fact that the successive combination of these four factors led to the greatest increase in the average R value (Table 2). The waves exert a greater influence in the fall than in the spring, which can be attributed to the fact that the fall season is more similar to the summer season, than the spring season. The model for the fall season is the most successful at predicting nearshore SST; the fall season generated the highest average R values (Table 2) and the tightest fitting scatter plot (Figure 6d). A possible explanation for this is that hurricanes occur along the Outer Banks in the fall. During the fall, the Outer Banks are exposed to the longest wave periods, which are most effective at vertical mixing. In fact, the individual average R value of wave power was greatest in the fall season (Table 2).

E. Full Analysis

Offshore SST is the most influential in predicting nearshore SST year-round; offshore SST has the highest individual average R values (Table 2). The importance of offshore SST is logical given that for three out of the four seasons (all save for the summer season in which offshore SST is the second most important input variable) offshore SST is the most influential variable. The time of year, although not as influential as offshore SST, is also very important for predicting nearshore SST (time of year has the second highest individual average R value). This further exemplifies the importance of seasonality in determining nearshore SST. Air temperature also exerts an important influence year-round on nearshore SST. Offshore SST and air temperature reflect solar input. The sun is overall the most influential factor in all air-sea processes as the sun warms the atmosphere and stratifies the ocean. The sun drives the dynamic physical processes occurring throughout the coastal region.

The influence of the winds is mostly restricted to the summer season (and to a lesser degree at the start of the fall and at the end of the spring) when the ocean is stratified. The lack of ocean stratification year-round, explains the winds' smaller impact on a year-long scale and the winds' smaller individual average R value (Table 2). The waves are also more influential when the water is stratified, but still remain as the least influential variable throughout all of the seasons, having the lowest individual average R value (Table 2).

Combining most of the input variables is necessary to create the best model for predicting nearshore SST, generating the highest average R values (Table 2). The contribution of wave power to the model is very small. The waves vertically mix the water column, and so can decrease ocean stratification. Waves are strongest in the winter and in the fall, often when the ocean is not very stratified. For the full year the addition of wave power to the model only increases the average R value by less than 0.001. This value is insignificant when error is considered (error is discussed in the next section). The"2010 – 2012" scatter plot in Figure 6e shows that the model occasionally over-predicts the nearshore SSTs in summer.

F. Sources of Error

In our model, we treat each of our input variables as independent entities, but in actuality they are related to each other. Offshore SST and air temperature reflect solar radiation. Winds are generated by uneven heating and cooling of the Earth's surface by the sun. The sun also stratifies the oceans. The interaction between the winds and the ocean surface leads to upwelling and downwelling. Additionally, the winds create the waves which work to vertically mix the ocean (from the top down). All of these physical mechanisms are interrelated and so to treat them as independent variables (as we do in our analysis) is an oversimplification and can contribute to error in our findings.

Additionally, we do not use a direct indicator of stratification. We do have bottom temperature measurements, but as they are not available as a forecast input, they are not included in our input variables. Consequently our references to stratification are based only on indirect observations.

Furthermore, we back-average the wind history, air temperature and wave history in our model. We simply average the wind history, air temperature, and wave history variables over a determined time despite the fact that the winds and the waves are more prevalent during different seasons. This average is an oversimplification as it treats all of these variables over their respective back-average intervals equally. In addition, the determined back-average times is based on all the data points. Some seasons or specific months may be better represented by a different back-average interval. Our back-averaging technique generalizes these variables over our entire data set.

The air-sea boundary zone, particularly along the coast, is very dynamic and complex. Many physical forcing mechanisms are at work influencing various processes in addition to nearshore SSTs. We look at a few of these mechanisms and attempt to describe nearshore SSTs with observations and averaging techniques. Therefore, any errors in our results can also be due to the simplifications we have made in order to better understand the processes involved in determining nearshore SSTs. Additional errors can be contributed to errors in our measurements.

VI. Conclusion

There is seasonal variability in the correlation of air-sea variables (time of year, wind history, offshore SST, air temperature, and wave power) with nearshore SST. In the winter, nearshore SST is best described by offshore SST and air temperature. Colder air temperatures from northern land masses result in colder SSTs, while warmer air temperatures from southern land masses cause warner SSTs. During summer, the sun is strong enough to create a stratified ocean. When the ocean is stratified local winds can induce coastal upwelling events (decreasing nearshore SST) and coastal downwelling events (increasing nearshore SST). Spring and fall are transition seasons, and exhibit trends from both winter and summer seasons. Looking at the year as a whole, offshore SST and time of year have the greatest impact on nearshore SST. The importance of the time of year attests to the concept that nearshore SST varies based on seasonal conditions.

We proved our hypothesis that northern Outer Banks nearshore SST is a function of water column stratification and local wind history. Summer wind patterns cause coastal upwelling and downwelling phenomena to occur due to the fact that the summer ocean is stratified. In addition the time of year (hence the seasonal trends) plays a role in determining how various factors influence nearshore SSTs. Offshore SSTs have the greatest impact on nearshore SSTs. All of our results are supported by our average R values. For the seasonal analyses as well as the full year analysis (using all of the input variables) the model generates average R values ranging from 0.884 to 0.993. Additionally, aside from the summer season (which has the lowest average R value) the other seasons and the full year analysis all generate average R values greater than 0.97. The scatter plots (Figure 6a – 6e) visually exemplify the effectiveness of the model in predicting nearshore SSTs.

Wave power does not have any significant influence in predicting nearshore SSTs. For each season, as well as for the full year, wave power individually has the lowest average R value (Table 2). Moreover, adding wave power into the model with the other variables did not significantly improve the model. The addition of wave power to the model increases the R value by 0.011 or less. These values are insignificant when error is considered and thus wave power can be dropped as a valid input to the model.

Future studies should focus on improving the model for the summer season. There are portions of the summer season during which the model over-predicts nearshore SSTs. This can likely be contributed to the fact that our wind averaging is a generalization of our entire data set. During the summer the back-average interval for the winds is the same generalized interval used throughout our entire analysis. Likely during the summer, and during different portions of the summer, our simple back-averaging technique is not the most accurate way to describe the accumulated influence of the winds on nearshore SSTs. In addition the model should be tested with data collected in other locations along the Outer Banks, aside from the FRF. One possible location for such a study is Jennette's Pier, which is located south of Duck. Overall this study was successful in that for the first time there is a model with the potential to predict nearshore SST along the Outer Banks.

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