COMPARISON OF INDIVIDUAL, COMBINED AND SERIES ARTIFICIAL NEURAL NETWORK MODELS FOR AIR TEMPERATURE AND DEW POINT TEMPERATURE PREDICTION

by

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(Under the Direction of Dr. Walter D. Potter)

ABSTRACT

Agricultural producers suffer economic losses in crops and livestock due to frost, freeze and heat stress. Freezing temperatures are responsible for reduced crop yields due to damage to leaves and fruit, especially blueberries and peaches. Heat stress could severely impact livestock, and similar temperature conditions could cause heat stroke in humans. Accurate prediction of air temperature and dew point temperature can help managers minimize the losses to crops and livestock. The research presented in this thesis compares artificial neural network models predicting air and dew point temperatures for twelve prediction horizons. The models are compared, using mean absolute error and number of prediction anomaly, with current web-based models available on the University of Georgia's Automated Environmental Monitoring Network website, www.georgiaweather.net.

INDEX WORDS: Air Temperature, Dew Point Temperature, Artificial Neural Networks, Decision Support System, Frost Protection, Weather Modeling

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DEDICATION

I dedicate this thesis to Tom Horton for being there for me during my tough times and for being the voice of reason and to Zhang Shu, my best friend.

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CHAPTER 1

INTRODUCTION

Extreme temperature conditions and weather events are responsible for reduced crop production and loss of livestock in most regions across the U.S. Heat stress creates dangerous working conditions for the farmers, and it has also been shown to decrease dairy production in cows by about 20 to 30% (Jones et al., 1999). In Summer 1995, a heat wave in the Midwestern United States caused death of over 1000 people, and deaths were attributed to a combination of high air temperature and high dew point temperature (Sandstorm et al, 2004). 1n 1990, 450,000 ha of fruit trees were impacted by frost damages resulting in $500 million in losses and damages (Attaway, 1997). In Florida due to frost damages the citrus industry incurred several billions of dollars in losses (Cooper et al., 1964; Martsolf, et al., 1984; Attaway, 1997). In April of 2007, 50% of Georgia's peach crop and 80% of its blueberry crop were lost due to frost. Agricultural producers can minimize the damages if warning was given ahead of time. Accurate prediction of air temperature and dew point temperatures is essential to avoid severe damages to crops.

The University of Georgia's Automated Environmental Monitoring Network (AEMN), established in 1991, collects meteorological data using the 81 solar powered weather stations mainly from rural areas across the state of Georgia (Hoogenboom, 2000). The stations monitor weather variables every second and the averages and sums were recorded until March 1996 at hourly intervals and since then at fifteen minute intervals. The dew point temperature monitoring was added to the stations in 2002. The collected data is downloaded to the AEMN server, and is made available through the AEMN website, www.georgiaweather.net.

Predictions for air and dew point temperature are made using the data available from AEMN and Artificial Neural Networks (ANNs). The air temperature models were developed by Smith et al., (2009) and were based on previous research by (Jain et al., 2003; Smith et al., 2008). The dew point temperature models were developed by Shank et al., (2008). The predicted air temperature and dew point temperature are available on the AEMN website.

The ANN models for air and dew point temperature, which produced the predictions available on AEMN website, were developed separately. Thus, a total of 24 individual models were used to obtain the air and dew point predictions for twelve hours. Under high relative humidity conditions the ANN models often predict air temperature lower than the dew point temperature. The observed air temperature may approach the observed dew point temperature but is never lower than the dew point temperature. Herein, this prediction error is referred to as the prediction anomaly.

In Chapter 1 the need for more accurate air and dew point temperature predictions is discussed. The overall goal of the thesis is stated. The current web-based ANN models are briefly introduced. A brief review of the background information and related work is provided. In Chapter 2, the individual and the combined model are compared using mean absolute errors (MAE) and number of prediction anomalies. Also a methodology to develop the combined models is discussed. The combined models were developed and were compared against the ANNs developed using previous studies. In Chapter 3, the individual and time series models are compared using MAE and the number of prediction anomalies. Also a methodology to develop time series models for four, six and twelve hour range is discussed. The time series models were developed for air temperature, dew point temperature and for the combined model from Chapter 2. The models developed in chapter were compared with ANNs developed in previous studies. In

Chapter 4 the research conducted in this study was summarized and possible areas for future work are suggested.

CHAPTER 2

COMPARISON OF INDIVIDUAL AND COMBINED ANN MODELS FOR PREDICTION OF AIR AND DEW POINT TEMPERATURE[1]

[1] Nadig, K., G. Hoogenboom, W.D. Potter, and R. W. McClendon. To be submitted to *Journal of Applied Meteorology and Climatology*

2.1 ABSTRACT

Predicted air and dew point temperatures can be valuable in decision making related to protecting crops from damage, avoiding heat stress on animals and humans, and in planning related to energy management. Current web-based artificial neural network (ANN) models on the Automated Environment Monitoring Network (AEMN) in Georgia predict hourly air and dew point temperature for twelve prediction horizons, using 24 models. The observed air temperature may approach the observed dew point temperature, but never goes below it. Current web based ANN models have prediction errors which, when the air and dew point temperatures are close, may cause air temperature to be predicted below the dew point temperature. Herein this error is referred to as a prediction anomaly. The goal of this research was to improve the prediction accuracy of existing air and dew point temperature ANN models by combining the two weather variables into a single ANN model for each prediction horizon. The objectives of this study were to reduce the mean absolute error (MAE) of prediction and to reduce the number of prediction anomalies. The combined models produced a reduction in the air temperature MAE for ten of twelve prediction horizons with an average reduction in MAE of 1.93%. However, the combined models produced a reduction in the dew point temperature MAE for only six of twelve prediction horizons with essentially no average decrease in MAE. The combined models showed a marked reduction in prediction anomalies for all twelve prediction horizons with an average reduction of 34.1%. The reduction in prediction anomalies ranged from 4.6% at the one-hour horizon to 60.5% at the eleven-hour horizon.

2.2 INTRODUCTION

Dew point temperature is the temperature at which humid air, under constant barometric pressure, will cause the water vapor to condense into liquid water. The dew point is the saturation temperature at which water vapor forms droplets on a solid surface. Hence, dew point temperature is always less than or equal to the air temperature. Air and dew point temperature predictions could be used to prepare for events such as frost, freeze and heat stress. Frost occurs when water vapor in the air gets deposited on a solid surface as ice without turning into liquid water during the transition (Perry, 1998). Freeze event occurs when the temperature drops below the freezing point of water. Frost damage is caused by the sharp ice crystals which form on the surface of the leaves. The crystals damage the cuticle and epidermis of the leaves, making the plant vulnerable to a further decrease in air temperature. Frost damage is mainly due to crystallization of liquid inside the individual cells (Perry, 1998). Freeze damage occurs when the temperature remains below 0°C and the amount of damage depends on the length of the freeze event. However, frost damage is usually noticeable due to visible physical impact on the plants. Freeze damage mainly impacts tender parts of the plants such as buds and shoots. This damage may not be evident immediately (Perry, 1998). Heat stress occurs when the body of a human or animal becomes overheated and the body is unable to regulate the temperature to cool down (Fauci, 2008). Severe cases of heat stress can cause heat stroke and could lead to death if proper and immediate treatment is not provided (Grundstein et al., 2012). Occurrence of heat stress could be estimated using dew point temperature (Sandstrom et al., 2004).

Low temperature conditions reduce crop yields due to frost damage to leaves and fruit, which could severely affect fruit crops such as blueberries and peaches. The duration of the extreme temperatures also determines the severity of damage that could be caused by the event.

Predicting weather variables gives sufficient time to minimize the loss of crops through the use of preventive measures such as orchard heaters and irrigation (Hochmuth et al., 1993). In Spring of 2002, a large area of blueberry and peach crops in South Georgia was destroyed due to unusually severe and unexpected low temperature conditions. In early April of 2007, 50% of Georgia's peach crop and 87% of blueberry crop were lost due to frost (Fonsah et al., 2007; Warmund et al., 2008). Crop managers can minimize these damages by using orchard heaters, irrigation or wind machines if they are given a warning with sufficient time. Accurate weather prediction thus plays a crucial role in managing crops.

Dew point temperature can be used to estimate the amount of moisture in the air, near-surface humidity, evapotranspiration, relative humidity, and frost. Each of these can have an effect on crop production. Plants in arid regions which do not receive frequent rainfall rely on the dew formation. The dew point temperature could also give an insight into the long-term climatic changes (Robinson, 2000).

Irrigation is a common method of frost protection, in which a layer of ice forms on the flowers insulates the peach and blueberry blossoms from damages due to frost. To effectively apply these preventive measures the farmers need accurate predictions about weather events several hours in advance. A prediction that fails to indicate the occurrence of a frost event could lead to extensive damages to crops. Similarly, a false frost event prediction could cause economic loss due to the cost of the frost damage prevention procedures.

Prediction of air and dew point temperature relies on prior observations of weather variables, such as air temperature, relative humidity, rainfall, wind speed, solar radiation, vapor pressure, vapor pressure deficit. The infrastructure needed to record the observations is provided by the University of Georgia's Automated Environment Monitoring Network (AEMN), which takes observations every second and calculates an average or total every 15 minutes (Hoogenboom, 2000; Hoogenboom et al., 2003). This network of weather stations collects data and records essential information required to keep track of the weather conditions, or perform analysis and prediction (Hoogenboom, 2005). The Georgia AEMN network currently has over 80 sites and the data for all the sites are accumulated at a central server located at Griffin, Georgia. Previous research has determined the variables needed for prediction of air temperature and dew point temperature, amount of historical data needed for accurate prediction and other such dependencies (Smith et al., 2009; Shank et al., 2008). The accumulated data are used as inputs to currently deployed individual ANN models to predict air and dew point temperature for the next twelve hours at an hourly interval. The accumulated data are parsed and the values of the weather variables are extracted from the data which includes current and prior values. This process is applied to both air and dew point temperature models for each of the twelve horizons. The predictions of air temperature and dew point temperature from the 24 models are updated every 15 minutes and made available on the AEMN website www.georgiaweather.net website (Hoogenboom, 2000).

The ANN models were initially designed to predict air temperature between Winter and early Spring (Jain et al., 2003). The inputs to the air temperature ANNs included five weather variables, temperature, relative humidity, wind speed, solar radiation and rainfall. The models were developed using data from the first 100 days of the year. The observations were also restricted to those in which the temperature at the time of prediction was less than or equal to 20°C. In addition to the current values for each observation, prior data for 24 hours spaced at one hour intervals were also included. Hourly first difference terms for the current and prior weather variables were also included. The models needed 24 hours of prior observations, time of day, seasonal terms as input, and the models had 120 neurons in the hidden layer and they predicted air temperature for a particular horizon (Jain, 2003). The ANN models were improved by Smith (2008) by adding the time of day and day of year as a part of the input, after transforming them using fuzzy logic membership functions, with a resulting decrease in MAE ranging from 6% to 14% for the twelve prediction horizons. However their models were only designed to predict between Winter and early Spring and had the same limitations of the previous models. A model was developed for each of the twelve prediction horizons. Air temperature ANN models were developed to predict year-round by Smith et al. (2009) and implemented on the AEMN website. These ANN models were used to generate short term air temperature predictions by the AEMN. The ANNs were based on Ward-style network architecture (Ward System Group, 1993) and were trained using the error back-propagation (EBP) (Haykin, 1999). The input layer of the model consisted of 258 neurons for inputs. The hidden layer of the model consisted of 120 nodes equally distributed among the three slabs with hyperbolic tangent, Gaussian and inverse Gaussian as the activation functions. The prediction accuracy of the year-round models was comparable to the previous Winter models, yet was developed to predict air temperature throughout the year. It was found that unanticipated cooling events were the most significant obstacle with the year-round models. Several ANN parameters such as the activation function of output, number of hours of prior data, additional values and rate of change for observations at 15 min intervals and the data scaling ranges for both input and output, were varied. However, no improvement in accuracy was produced. Bagging and boosting only slightly improved the accuracy, but at a high computational cost (Smith et al., 2009).

Support Vector Machine (SVM) based regression models were also developed to predict air temperature and the accuracy was compared with the existing ANNs (Chevalier et al., 2011). For a reduced training set with 300,000 patterns, the SVM models were slightly more accurate than the ANN models. However, the ANN models predicted more accurately when the number of training patterns was increased to 1.5 million.

ANN models for twelve hour prediction of dew point temperature were developed by Shank et al. (2008) and are included on the AEMN website. Inputs to the dew point ANNs included the same weather variables used in the existing air temperature models, plus weather variables vapor pressure and vapor pressure deficit, and their hourly rates of change. The models were developed similarly to those developed by Smith et al. (2009). Ensemble artificial neural network were developed by Shank et al. (2008) to improve the prediction accuracy. Approximately four years of weather data were available that included the additional weather variables (Shank et al., 2008). The twelve ANN models to predict dew point were implemented on the AEMN site similar to the air temperature models.

A fuzzy expert system, Georgia Extreme-weather Neural-network Informed Expert (GENIE), was developed to interpret the predicted air temperature, predicted dew point temperature and the observed wind speed in order to generate frost and freeze warning levels (Chevalier et al., 2012). The numeric warning levels generate by GENIE provide higher granularity than the textual warnings provided by the National Weather Service (NWS). A web interface was developed for GENIE to provide a convenient means of access to the warnings.

The air temperature and dew point temperature models have prediction errors measured in terms of mean absolute error (MAE). The MAE for the twelve air temperature models varies between 0.516°C and 1.873°C. Similarly the MAE for dew point temperature models varies between 0.508°C and 2.081°C. Under high relative humidity conditions the observed air temperature will approach the observed dew point temperature, but never goes below it. Under these conditions the predicted air temperature will frequently drop below the predicted dew point temperature. Herein this prediction error is referred to as a prediction anomaly. Further improvement of the ANN models for air and dew point temperature involves not only reducing the MAE but also reducing the number of prediction anomalies. The architecture of the ANNs plays a key role in the prediction capabilities of the ANNs. Previous research explored the ANN parameters such as the nodes in the hidden layers, varying the number of inputs, and larger datasets. Another possible ANN architecture parameter is the number of outputs. Impact on each output according to the inputs for ANN based models was examined by Gevrey et al. (2003), and the influence of outputs on learning in ANN models was examined by Narendra et al. (1994). The current implemented air and dew point temperature ANN models have only one output. Additional output could be any weather variable or other prediction horizons. A model that predicts more than one weather variable is herein referred to as the combined model. Such a model could predict air and dew point temperature for a single or multiple prediction horizons. Predicting multiple values in a single model provides an opportunity for interaction among the outputs.

The goal of this research was to improve the prediction accuracy of air temperature and dew point temperature ANN models by developing combined models to predict both air and dew point temperature for each prediction horizon. The research objectives are as follows: (1) to determine if MAE for predicted air temperature and predicted dew point temperature are reduced for the combined model in comparison with the individual models, and (2) to determine if the number of occurrences of the prediction anomaly can be reduced using the combined models. The hypothesis is that by predicting air and dew point temperature for a single prediction horizon in a single combined model, the prediction MAE may be reduced and the number of prediction anomalies may decrease. The air and dew point temperature are related weather variables, thus predicting both in a single model might aid in reducing the MAE and decreasing the number of prediction anomalies. These anomalies do not occur in the observed data thus training the combined models might decrease the number of prediction anomalies.

2.3 METHODOLOGY

2.3.1 DATA SETS

The AEMN measures weather variables each second and then stores the averages or totals of the values every 15 minutes. Data from the initial sites were available from 1991. However, the data selected for this research were from 2002 to 2010 because the dew point temperature observations were initiated in 2002. Routines were developed to perform error checking on the raw data to remove missing variables, incomplete records, instrument malfunctions and erroneous records. The data were partitioned into a model development set and a model evaluation set. The two sets were chosen so that they were mutually exclusive of years and locations, as shown in Table 1. The model development set was further partitioned into a training set and a selection set. The training set was used to train the ANN models using resilient propagation (Riedmiller et al., 1993) to adjust the ANN weights. The selection set was presented to the ANNs in feed forward mode only to choose the model with the lowest MAE. The chosen model was treated as the final model for a given prediction horizon. The training set and selection set were mutually exclusive by locations. The model evaluation set was presented to the ANNs in feed forward mode and the resulting MAE was used as a metric to compare with other models. The training set consisted of 297,974 patterns, the selection set had 306,972 patterns and the evaluation set included 507,347 patterns. This would be strongest evaluation of the models, since the final ANNs will be evaluated with data from sites and years which were not used in model development. The approach to partitioning the data was modified from the partitioning used to develop the current web-based ANN temperature models in order to include the additional sites and years. The current web-based ANN air temperature models were developed with data from 1997 to 2005, and over 20 locations (Smith et al., 2009). The current web-based ANN dew point temperature models were developed with data from 2002 to 2005, with over 20 locations (Shank et al., 2008). Additional years from 2006 to 2010 and locations were included herein to provide for more robust models.

The data partitions were subjected to constraints to ensure a fair distribution of patterns. The locations and years involved in the partitioning were chosen to minimize the difference in the range and average air temperatures between model development and evaluation. The years and locations were distributed among the sets until the difference in the range and average air temperatures among the three sets was minimized. This was done to ensure that the model development set and the model evaluation set were representative of the population.

Input and output patterns were generated from each of the datasets by transforming and scaling the data. The input patterns consisted of current and 24-hours of prior hourly values of air temperature, relative humidity, rainfall, wind speed, solar radiation, vapor pressure, vapor pressure deficit and their hourly rates of change. Each input pattern also had the time-of-day and day-of-year cyclic values obtained by using fuzzy membership functions (Smith et al., 2008). The pattern included observed air and dew point temperature as target for the twelve prediction horizons. All the values in the pattern were scaled to the range [-0.9, 0.9] since the domain of operation of the activation functions used in the ANNs was in the range [-1, 1]. The range [-0.9, 0.9] was chosen since it captured the range of values for each of the variables and transformed them to the domain of the activation functions. Inverse scaling was used to transform value of prediction from the domain of the activation function to the domain of the predicted variable. There were a total of 358 inputs and two output values per pattern. Patterns were generated for each of the twelve prediction horizons and the three data partitions.

2.3.2 MODEL DEVELOPMENT

All models were developed using the Ward-style network architecture (Ward System Group, 1993), consisting of a three layered neural network with input, hidden and output layers. The input layer consisted of neurons with linear activation functions. The hidden layer consisted of 120 neurons in three equally sized slabs of 40 neurons. The neurons in the slabs had hyperbolic tangent, Gaussian and inverse Gaussian activation functions. The output layer neurons used the symmetric sigmoid activation function. Only the number of inputs or outputs varied with the models.

Ten instances of each model were trained. Each instance is an ANN whose initial weights were selected randomly. Although all the model instances were presented with the same set of patterns the order was randomized. This provided the training algorithm a different starting point for each instance. Thus the training process took a different path while searching for the set of weights which could minimize the prediction error and improve the accuracy of the model. Selecting among multiple instances made it more likely that the training algorithm will approach the optimal set of ANN weights (Smith et al., 2009).

Resilient propagation (R-Prop) training algorithm was used to train the models (Riedmiller et al., 1993). R-Prop tends to converge faster and is more stable in comparison with the back-propagation algorithm (Anastasiadis et al., 2005; Igel et al., 2003). Resilient propagation is similar to back-propagation algorithm except that the error update in R-Prop is dependent on a constant value. This constant value exists for each synapse and is updated by increasing or decreasing the constant based on the sign of the error value. If the sign of the error value changes frequently then the magnitude of the constant value is decreased. If the sign does not change, then the magnitude of constant value is increased. Resilient propagation does not depend on the derivative of the activation function (Riedmiller et al., 1993). EnCog 3.0.0.0 (runtime v2.0.50727) package was used to develop and train the models.

All models were trained using the training dataset until the change in error was less than 0.01%. After training the models, the ten instances were presented with the selection set in feed forward mode to obtain the selection set MAEs. The instance with the lowest selection set MAE was chosen. That completed the model development part of the process. The selected models were then presented with the evaluation set once in feed forward mode to obtain the evaluation set MAE.

Individual ANNs to predict air temperature and dew point temperature were developed using the partitioned data as a base line for the prediction accuracy in terms of MAE. These individual models correspond to the existing air temperature and dew point temperature ANN models currently implemented on the AEMN. However, they take advantage of additional years and sites. The individual models have only one output since they were designed to predict either air temperature or dew point temperature. Each model was developed to predict a single weather variable for a single horizon. Hence, there were a total of 24 models, twelve for air temperature and twelve for dew point temperature. The individual air temperature model had 258 input neurons and one output neuron based on Smith et al. (2009). The dew point temperature model had 358 input neurons and one output neuron, based on Shank et al. (2008). In this research only combined model that predict air and dew point temperature for a single prediction horizon are considered. The combined model had 358 input neurons and the two outputs predicted air temperature and dew point temperature. The MAEs for individual and combined models were calculated and compared.

While obtaining the evaluation set MAEs for both individual and combined models, the occurrence of prediction anomalies was recorded. The predicted air temperature and the predicted dew point temperature obtained from the individual models of corresponding prediction horizon were compared. The number of instances where the predicted air temperature was lower than the predicted dew point temperature was calculated for each prediction horizon. Similarly the number of instances of the anomaly was computed for the combined model. The number of instances of anomaly for individual and combined model was calculated and compared. The day of the year was used to compare prediction anomalies by seasons. The count of prediction anomalies was grouped by seasons and prediction horizons to analyze the seasonal variation in the ANN models.

2.4 RESULT AND DISCUSSION

The air temperature and dew point temperature MAE values were obtained by presenting the evaluation dataset to the individual and combined ANNs in feed forward mode only as shown in Table 2. For air temperature, ten of twelve combined models produced an MAE lower than the individual models. The combined model showed an average reduction in MAE for air temperature by 1.93%. The two prediction horizons in which the individual model provided a lower MAE were the seven and eleven hour horizons. The Figure 1 shows the generally observed trend of increasing MAEs for longer horizons, with a slight decrease in MAEs for air temperature prediction from the combined model. This suggests that the combined model was able to predict the air temperature with a lower MAE when predicting both air temperature and dew point temperature. From Table 2, six of twelve combined models predicted the dew point temperature with lower MAE than the individual dew point temperature models. The combined model produced a slight increase in MAE and the average % increase in MAE was 0.08%. Both the individual and the combined models maintained the expected trend of increasing MAE with longer horizons as shown in Figure 2. From Table 2, of the ten combined models with lower MAE for air temperature, five also produced a lower MAE for dew point temperature in comparison with individual models.

Second approach to assess the accuracy of the ANNs was performed by determining the number of prediction anomalies found with individual and combined models, as shown in Table 3. The models were presented with the evaluation set in feed forward mode to count the number of prediction anomalies. The evaluation set had 507,347 patterns, and the number of prediction anomalies for the worst case was 6.55% of the evaluation set patterns. Twelve of twelve combined ANNs model showed a reduction in the number of prediction anomalies over the individual models. The average reduction in prediction anomalies for the combined model was 34.1%, and the reduction ranged from 4.6% at the one-hour horizon to 60.5% at the eleven-hour horizon. The Figure 3 shows a comparison between the number of prediction anomalies found in individual and combined models for each prediction horizon. The highest number of prediction anomalies occurred at the one hour horizon for both individual and combined models. The combined models provided a slight reduction in the number of prediction anomalies for the one-hour horizon. Other horizons showed a marked reduction in the number of prediction anomalies.

The models were further examined to compare the occurrence in prediction anomalies by seasons. The prediction anomalies were classified into following seasons: Winter (Dec – Feb), Spring (Mar – May), Summer (Jun-Aug) and Fall (Sep – Nov). Figure 4 compares the prediction anomalies for individual and combined models for all twelve prediction horizons, classified by seasons. The highest number of prediction anomalies occurred in the Winter season, with reduction in prediction anomalies of 23.3%. The lowest number of prediction anomalies occurred in the Spring season, with a reduction of 41.6%. In Summer, the combined models produced the highest reduction in the number of prediction anomalies with a value of 43.1%. In Fall, the number of prediction anomalies was slightly higher than the number of prediction anomalies produced during both Spring and Summer, and the combined models produced a reduction in the number of anomalies by 34.6%. The number of prediction anomalies for the individual and combined ANNs by season and horizons is shown in Table 4. In Winter, eleven of twelve combined models reduced the number of prediction anomalies in comparison with the individual models. During the Spring season only nine of twelve combined models showed reduction in the number of prediction anomalies. Consistent reduction was produced in Summer where twelve of twelve combined models showed reduction and in Fall ten of twelve combined models showed reduction. The total row shows sum of the number of prediction anomalies that occurred for all prediction horizons for each season using the evaluation set.

The anomalies from the combined models were further analyzed to determine the extent to which the air temperature prediction dropped below the predicted dew point temperature or severity. The severity of the prediction anomaly was classified using increments of 0.25°C as shown in Table 5. Green indicates few or no prediction anomalies. Yellow indicates that the number of prediction anomalies is in the range greater than 95 and less than or equal to 2000. Red or orange indicates that the number of prediction anomalies is greater than 2000. The Table 5 shows that a large portion of the anomalies are between 0°C and 1.5°C. The combined models produced a total of 146,466 prediction anomalies. The number of prediction anomalies with severity greater than 1°C was 11395, or 0.2% of the number of predictions in the evaluation set for all prediction horizons. The two-hour, four-hour and twelve-hour horizon models did not generate any anomalies greater than 2.25°C. The one-hour, eight-hour and nine-hour horizon models did not generate any anomalies greater than 3.25°C. Only 105 of the 146,466 prediction anomalies, for the combined models across all twelve prediction horizons, had severity greater than 3°C. The Table 6 shows a similar analysis of the individual models. Green indicates few or no prediction anomalies. Yellow indicates that the number of prediction anomalies is in the range greater than 95 and less than or equal to 2000. Red or orange indicates that the number of prediction anomalies is greater than 2000. The individual models showed higher prevalence of prediction anomalies, produced a total of 216,142 prediction anomalies. Approximately 10.7%, or 23067 prediction anomalies, of the total number of prediction anomalies across all twelve prediction horizons had severity greater than 1°C. However, 310 of the 216,142 prediction anomalies, for the combined models across all twelve prediction horizons, had severity greater than 3°C. The combined models showed an overall reduction of 32.2% in the total number of prediction anomalies across all twelve horizons. Since the combined models produced similar MAEs as the individual models and the combined models considerably reduced the prediction anomalies, based on these two metrics the results suggests that combined models are more accurate than individual models.

The Figure 5 shows the scatter plot for the air temperature predictions using the combined model for the prediction horizons of one, three, six, nine and twelve. As expected the observed scatter about the 1:1 line increases and the R2 value decreases as the prediction horizon increases. The plot for the one hour horizon, Figure 5.a, shows a narrower scatter, which indicates a large portion of the predicted air temperatures are in close proximity to the observed value. The regression line had a slope of 0.96, the intercept was 0.69 and the R2 was 0.98. At low observed temperatures the model tends to over-predict and at high observed temperatures the model tends to under-predict. This trend is observed in other horizons as well. The scatter plot for three-hour horizon model, shown in Figure 5.b, the regression line had a slope of 0.97, the intercept was 0.63 and the R2 was 0.97. The scatter plot for six-hour model had a slightly greater distribution about the 1:1 line as compared with the plot for three-hour horizon model, as shown in Figure 5.c. The regression line had a slope of 0.94, and the intercept was 1.21, and the R2 was 0.95. The nine hour scatter plot had observably greater distribution about the 1:1 line, as shown in Figure 5.d. The regression line had a slope of 0.91, and the intercept was 1.6, and the R2 was 0.92. This was expected as the MAEs of the six and nine models are higher than that of the one hour model. Lastly, the twelve hour scatter plot had markedly greater distribution about the 1:1 line, as shown in Figure 5.e, and it was the highest distribution among the other horizons. The regression line had a slope of 0.9, and the intercept was 1.8, and the R2 was 0.91.

Dew point temperature predictions from the combined model were used to generate the scatter plots shown in Figure 6, for the prediction horizons one, three, six, nine and twelve. The low observed temperatures were over-predicted and high observed temperatures were under-predicted. The plots show a similar trend that was observed in air temperature scatter plots. The one hour horizon plots, Figure 6.a, shows a narrow dense region but a much greater distribution about the 1:1 for the low density region as compared with the scatter plot of one hour horizon air temperature model shown in Figure 5.a. In the scatter plot for one-hour horizon dew point temperature model, as shown in Figure 6.a, the regression line had a slope of 0.97, the intercept was 0.4 and the R2 was 0.98. In the scatter plot for three-hour horizon model, as shown in Figure 6.b, the dense region was similar to dew point temperature scatter plot for the one-hour horizon model, but showed greater distribution about the 1:1 line for the low density region. The regression line had a slope of 0.97, the intercept was 0.26 and the R2 was 0.97, for the three-hour horizon model. Both the scatter plots of one and three hour horizons for dew point temperature are narrow compared to the six, nine and twelve hour horizons scatter plots. The scatter plot for the six-hour model, as shown in Figure 6.c, had greater distribution about the 1:1 line as compared to that of the three-hour model. The regression line had a slope of 0.94, the intercept was 0.64 and the R2 was 0.94. The scatter plots for nine and six hour model were similar in the distribution about the 1:1 line. However, the nine-hour model, as shown in Figure 6.d, had slightly greater distribution about the 1:1 line and the regression line had a slope of 0.91, the intercept was 0.95 and the R2 was 0.91. Lastly, the scatter plot for twelve-hour model, as shown in Figure 6.e, had the highest distribution about the 1:1 line. The slope of 0.88 was the lowest and the intercept of 1.23, was the highest among the other horizons. The R2 for the twelve-hour horizon model was 0.88, which was lowest among the other horizons. The dew point temperature scatter plots had greater distribution about the 1:1 line as compared with the corresponding air temperature scatter plots possible because of higher MAEs of the dew point temperature models.

2.5 SUMMARY AND CONCLUSIONS

Combined air temperature and dew point temperature models were developed for the twelve prediction horizons. The air temperature predictions from the combined model showed reduction in MAE for ten of twelve prediction horizons over the corresponding individual models, with a corresponding average reduction in MAE of 1.9%. The dew point temperature predictions from the combined model showed reduction in MAE for six of twelve prediction horizons over the corresponding individual models. However, averaging over the twelve prediction horizons showed that there was essentially no difference in MAE for the dew point temperature predictions. The combined models showed a marked reduction in the number of prediction anomalies as compared with the individual models. Also, experiments showed that the anomalies occurred most often in Winter and least frequently in Spring season for individual and combined models. The combined models reduced prediction anomalies for each season, with reduction ranging from 23.3% in Winter to 43.1% in Summer.

In this research, the ANN architecture used was based on previous work by Smith et al. (2009) and Shank et al. (2008). In future research the ANN parameters such as activation functions, number of nodes in the hidden layer, and distribution of nodes between the slabs of the Ward-style model could be explored for improvement in MAE or reduction in the number of anomalies. Also, longer duration of prior data, the inclusion of other weather variables, and different resolution of input data could be explored. Alternate architectures such as recurrent neural networks, hybrid neural networks, and alternative training algorithms such as scaled conjugate gradient propagation, quick-propagation, Manhattan-propagation, Lavenberg-Marquardt algorithm and evolutionary training algorithms could be applied. The training data could be further examined so that the patterns are distributed evenly for the various temperature values. Future work could also be focused on combining the models for various prediction horizons into a single model. This could include combining a time series of one through twelve prediction horizons for air temperature or dew point temperature or both into a single model.

2.6 REFERENCES

Anastasiadis, A. D., Magoulas, G. D., & Vrahatis, M. N. (2005). New globally convergent training scheme based on the resilient propagation algorithm. *Neurocomputing, 64, 253 - 270*.

Attaway, J. A. (1997). *A History of Florida Citrus Freezes.* Lake Alfred, FL: Florida Science Source, Inc.

Chevalier, R., Hoogenboom, G., McClendon, R., & Paz, J. (2011). Support vector regression with reduced training sets for air temperature prediction: a comparison with artificial neural networks. *Neural Comput. Appl., 20, 151-159.*

Chevalier, R., Hoogenboom, G., McClendon, R., & Paz, J. (2012). A web-based fuzzy expert system for frost warnings in horticultural crops. *Environmental Modelling & Software (In Press).*

Cooper, W. C., Young, R. H., & Turrell, F. M. (1964). Microclimate and physiology of citrus: Their relation to cold protection. *38-50.*

Fauci, A. (2008). Harrison's Principles of Internal Medicine. *McGraw-Hill Professional*.

Fonsah, E. G., Taylor, K. C., & Funderburk, F. (2007). Enterprise cost analysis for middle. *Technical Report*(AGECON-06-118).

Gevrey, M., Dimopoulos, I., & Lek, S. (2003). Review and comparison of methods to study the contribution of variables in artificial neural network models. *Ecological Modelling, 160, 249 - 264*.

Grundstein, A., Ramseyer, C., Zhao, F., Pesses, J., Akers, P., Qureshi, A., et al. (2012). A retrospective analysis of American football hyperthermia deaths in the United States. *International Journal of Biometeorology, 56, 11-20*.

Haykin, S. (1999). *Neural networks: a comprehensive foundation, 2nd edition.* Upper Saddle River, NJ: Prentice Hall.

Hochmuth, G. J., Kostewicz, S., & Martin, F. (1993). Irrigation Method and Rowcover Use for Strawberry Freeze Protection. *Journal of the American Society for Horticultural Science, 118, 575-579*.

Hoogenboom, G. (2000). The Georgia Automated Enviromnental Monitoring Network. *Preprints of the 24th Conference On Agricultural and Forest Meteorology* (pp. *24-25*). American Meteorological Society.

Hoogenboom, G. (2005). The Georgia Automated Environmental Monitoring Network: experiences with the development of a state-wide automated weather station network. *Proceedings of the 13th Symposium on Meteorological Observations and Instrumentation & 15th Conference on Applied Climatology*. Boston: American Society of Meteorology.

Hoogenboom, G., Coker, Edenfield, Evans, & Fang. (2003, April). The georgia automated environmental monitoring network: ten years of weather information for water resources management. *Proceedings of the 2003 Georgia Water Resources Conference*.

Igel, C., & Hüsken, M. (2003). Empirical evaluation of the improved Rprop learning algorithms. *Neurocomputing, 50, 105 - 123*.

Jain, A. (2003). Frost prediction using artificial neural networks: A temperature prediction approach. *M.S. thesis*.

Jain, A., McClendon, R. W., Hoogenboom, G., & Ramyaa, R. (2003). Prediction of frost for fruit protection using artificial neural networks. *American Society of Agricultural Engineers, 03,* 3075.

Jones, G. M., & Stallings, C. C. (1999). *Reducing heat stress for dairy cattle.* Virginia Cooperative Extension.

Martsolf, J. D., Gerber, J. F., Chen, E. Y., Jackson, H. L., & Rose, A. J. (1984). What do satellite and other data suggest about past and future florida freezes? *In Proceedings of the Florida State Horticultural Society*, (pp. *17-21*).

Narendra, K. S., & Mukhopadhyay, S. (1994). Adaptive control of nonlinear multivariable systems using neural networks. *7*(5), *737 - 752*.

Perry, K. B. (1998). *Basics of Frost and Freeze Protection for Horticultural Crops* (8 ed.). HortTechnology.

Riedmiller, M., & Braun, H. (1993). A direct adaptive method for faster backpropagation learning: the RPROP algorithm. *IEEE International Conference on Neural Networks*, (pp. *586 -591*).

Robinson, P. J. (2000). Temporal trends in United States dew point temperatures. *International Journal of Climatology, 985-1002*.

Sandstrom, M. A., Lauritsen, R. G., & Changnon, D. (2004, May-June). A Central-U.S. Summer Extreme Dew-Point Climatology (1949-2000). *Physical Geography, 25*(3), *191-207*.

Shank, D. B., McClendon, R. W., & Paz, J. a. (2008). Ensemble artificial neural networks for prediction of dew point temperature. *Applied Artificial Intelligence, 22*(6), *523-542*.

Shank, D., Hoogenboom, G., & McClendon, R. (2008). Dewpoint Temperature Prediction Using Artificial Neural Networks. *Journal of Applied Meteorology and Climatology, 47*, 1757.

Smith, B. A., Hoogenboom, G., & McClendon, R. W. (2009). Artificial neural networks for automated year-round temperature prediction. *Computers and Electronics in Agriculture, 68*, *52-61*.

Smith, B. A., McClendon, R. W., & Hoogenboom, G. (2008). Improving Air Temperature Prediction with Artificial Neural Networks.

Ward System Group. (1993). *Manual of NeuroShell 2*. Frederick, MD.

Warmund, M. R., Guinan, P., & Fernandez, G. (2008). Temperatures and Cold Damage to Small Fruit Crops Across the Eastern United States Associated with the April 2007 Freeze. *HortScience, 43*(6), *1643-1647*.

Table 1: Locations used for training, selection and evaluation datasets.

Model Development		**Model Evaluation**
2002, 2003, 2004, 2005, 2007, 2009		2006, 2008, 2010
Training Set	**Selection Set**	**Evaluation Set**
ATLANTA	ALMA	ALAPAHA
BRUNSWICK	ARABI	ALPHARETTA
CALLAWAY	BLEDSOE	ARLINGTON
COVINGTON	BOWEN	ATTAPULGUS
DALLAS	DEMPSEY	BLUE RIDGE
DAWSON	DIXIE	BYROMVILLE
DEARING	EATONTON	CAIRO
DULUTH	GEORGETOWN	CALHOUN
HOMERVILLE	GRIFFIN	CAMILLA
OAKWOOD	HOWARD	CLARKS HILL
SHELLMAN	JEFFERSONVILLE	CORDELE
TIFTON	LAFAYETTE	DANIELSVILLE
TIGER	PLAINS	DOUGLAS
WOODBINE	SPARTA	ELLIJAY
-	TENNILLE	HHERC*
-	-	MOULTRIE
-	-	NAHUNTA
-	-	NEWTON
-	-	ODUM
-	-	OSSABAW
-	-	SASSER
-	-	SAVANNAH
-	-	VALDOSTA
-	-	VIDALIA

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Table 2: Comparison of the individual ANN models for air and dew point temperature with combined models, evaluation dataset.

Horizons	Air Temperature MAE °C			Dew Point Temperature MAE °C		
	Individual	**Combined**	**% Reduction in MAE**	**Individual**	**Combined**	**% Reduction in MAE**
1	0.889	**0.846**	4.84	**0.818**	0.842	-2.93
2	0.959	**0.942**	1.77	0.890	**0.880**	1.12
3	1.170	**1.080**	7.69	**1.073**	1.081	-0.75
4	1.262	**1.256**	0.48	**1.261**	1.264	-0.24
5	1.413	**1.383**	2.12	1.424	**1.416**	0.56
6	1.565	**1.543**	1.41	1.600	**1.585**	0.94
7	**1.617**	1.621	-0.25	**1.711**	1.720	-0.53
8	1.707	**1.705**	0.12	1.836	**1.809**	1.47
9	1.825	**1.787**	2.08	**1.954**	1.965	-0.56
10	1.848	**1.830**	0.97	2.052	**2.030**	1.07
11	**1.916**	1.918	-0.10	2.155	**2.151**	0.19
12	2.016	**1.975**	2.03	**2.247**	2.276	-1.29
Models	2/12	**10/12**	(**Avg.**) 1.93	6/12	**6/12**	(**Avg.**) -0.08

Table 3: Number of prediction anomalies for individual and combined model, model evaluation dataset.[2]

Horizon	Individual		Combined		% Reduction
	#	%	#	%	
1	33252	6.6	**31723**	6.3	4.6
2	21161	4.2	**12857**	2.5	39.24
3	14367	2.8	**7331**	1.4	48.97
4	18775	3.7	**11142**	2.2	40.66
5	17885	3.5	**11394**	2.2	36.29
6	16593	3.3	**11989**	2.4	27.75
7	19345	3.8	**15054**	3.0	22.18
8	15595	3.1	**13292**	2.6	14.77
9	11845	2.3	**8281**	1.6	30.09
10	12815	2.5	**9061**	1.8	29.29
11	21833	4.3	**8619**	1.7	60.52
12	12676	2.5	**5723**	1.1	54.85
					(Average) 34.10

[2] The prediction anomalies were obtained after presenting the models with all 507,347 patterns from the evaluation set.

Table 4: Comparison of number of anomalies in individual (indv.) and combined (comb.) models by seasons, model evaluation dataset.[3]

	Winter		Spring		Summer		Fall	
Horizons	**Indv.**	**Comb.**	**Indv.**	**Comb.**	**Indv.**	**Comb.**	**Indv.**	**Comb.**
1	**17570**	21310	2610	**1581**	5565	**4842**	7507	**3990**
2	9168	**7570**	1002	**575**	5060	**1433**	5931	**3279**
3	6814	**3985**	1109	**402**	2037	**1233**	4407	**1711**
4	6267	**4490**	1296	**133**	5619	**2911**	5593	**3608**
5	7709	**6068**	**554**	899	5405	**1347**	4217	**3080**
6	6897	**4797**	1373	**808**	4231	**2176**	**4092**	4208
7	6975	**5262**	705	**322**	5239	**4283**	6426	**5187**
8	4795	**3883**	**433**	815	4103	**4073**	6264	**4521**
9	5571	**2714**	977	**310**	1971	**1415**	**3326**	3842
10	6345	**3201**	**527**	919	2009	**1623**	3934	**3318**
11	7106	**2399**	987	**396**	5037	**1297**	8703	**4527**
12	3704	**2515**	863	**107**	1138	**333**	6971	**2768**
Total	88921	**68194**	12436	**7267**	47414	**26966**	67371	**44039**
	1/12	**11/12**	3/12	**9/12**	0/12	**12/12**	2/12	**10/12**

[3] The prediction anomalies were obtained after presenting the models with all 507,347 patterns from the evaluation set.

Table 5: Distribution of prediction anomalies by severity of error, combined models, model evaluation dataset.[4]

Horizons (Hr) / (°C) $T_{DP} - T_A$	1	2	3	4	5	6	7	8	9	10	11	12
0.00 - 0.25	10034	7164	4439	7536	5814	5830	6283	6008	4742	4306	3967	3366
0.25 - 0.50	7678	3176	1705	2563	2694	3036	3996	3510	2183	2419	2334	1520
0.50 - 0.75	5279	1515	710	712	1258	1534	2279	2009	769	1177	1188	547
0.75 - 1.00	3645	631	267	204	631	732	1153	996	244	544	577	167
% severity 0.00 - 1.00	5.25	2.46	1.40	2.17	2.05	2.19	2.70	2.47	1.56	1.66	1.59	1.10
1.00 - 1.25	2320	267	117	76	327	391	616	454	166	292	261	66
1.25 - 1.50	1424	75	44	35	241	205	313	175	81	155	137	28
1.50 - 1.75	780	19	22	11	126	114	161	75	29	77	62	20
1.75 - 2.00	372	8	10	4	97	67	99	41	31	42	39	8
% severity 0.00 - 2.00	6.22	2.53	1.44	2.20	2.21	2.35	2.94	2.62	1.63	1.78	1.69	1.13
2.00 - 2.25	137	2	1	1	68	37	59	11	16	15	21	1
2.25 - 2.50	32	0	4	0	39	18	38	8	9	17	10	0
2.50 - 2.75	16	0	6	0	26	11	20	2	3	4	13	0
2.75 - 3.00	5	0	2	0	19	8	11	2	7	7	4	0
% severity 0.00 - 3.00	6.25	2.53	1.44	2.20	2.24	2.36	2.96	2.62	1.63	1.78	1.70	1.13
3.00 - 3.25	1	0	2	0	19	0	9	1	1	2	3	0
3.25 - 3.50	0	0	2	0	14	4	5	0	0	3	0	0
3.50 - 3.75	0	0	0	0	6	1	3	0	0	0	3	0
3.75 - 4.00	0	0	0	0	8	1	3	0	0	1	0	0
4.00 - 4.25	0	0	0	0	6	0	0	0	0	0	0	0
4.25 - 4.50	0	0	0	0	0	0	5	0	0	0	0	0
4.50 - 4.75	0	0	0	0	1	0	0	0	0	0	0	0
4.75 - 5.00	0	0	0	0	0	0	1	0	0	0	0	0
Total	31723	12857	7331	11142	11394	11989	15054	13292	8281	9061	8619	5723

[4] The prediction anomalies were obtained after presenting the models with all 507,347 patterns from the evaluation set.

Table 6: Distribution of prediction anomalies by severity of error, individual models, model evaluation dataset.[5]

Horizons (Hr) / (°C) $T_{DP} - T_A$	1	2	3	4	5	6	7	8	9	10	11	12
0.00 - 0.25	11105	10227	9349	8464	7660	7635	7626	6080	5334	4836	6366	5941
0.25 - 0.50	8125	5816	2517	5065	4682	4741	5243	4112	2531	2994	4757	2567
0.50 - 0.75	5583	2853	1168	2596	2572	1357	3168	2529	1990	1740	3472	1513
0.75 - 1.00	3725	1276	973	1311	1380	1422	1550	1399	1029	1108	2445	1143
% severity 0.00 - 1.00	5.62	3.98	2.76	3.44	3.21	2.99	3.47	2.78	2.15	2.10	3.36	2.20
1.00 - 1.25	2220	555	257	658	770	851	861	656	551	716	1659	752
1.25 - 1.50	1250	231	83	327	405	417	432	342	222	474	1148	571
1.50 - 1.75	634	118	15	185	198	115	237	183	109	332	654	116
1.75 - 2.00	295	46	4	108	88	42	108	110	61	220	461	51
% severity 0.00 - 2.00	6.49	4.16	2.83	3.69	3.50	3.27	3.79	3.04	2.33	2.45	4.13	2.49
2.00 - 2.25	158	27	0	38	52	9	65	68	12	144	321	11
2.25 - 2.50	79	5	1	14	26	3	24	48	3	100	176	7
2.50 - 2.75	32	4	0	8	23	0	17	20	0	67	128	3
2.75 - 3.00	16	1	0	1	10	1	6	16	2	30	82	1
% severity 0.00 - 3.00	6.55	4.17	2.83	3.70	3.52	3.27	3.81	3.07	2.33	2.52	4.27	2.50
3.00 - 3.25	12	2	0	0	5	0	3	15	1	15	52	0
3.25 - 3.50	6	0	0	0	4	0	2	9	0	10	37	0
3.50 - 3.75	5	0	0	0	3	0	2	3	0	8	28	0
3.75 - 4.00	7	0	0	0	0	0	1	4	0	8	12	0
4.00 - 4.25	0	0	0	0	2	0	0	1	0	4	13	0
4.25 - 4.50	0	0	0	0	5	0	0	0	0	3	8	0
4.50 - 4.75	0	0	0	0	0	0	0	0	0	2	3	0
4.75 - 5.00	0	0	0	0	0	0	0	0	0	1	5	0
5.00 - 5.25	0	0	0	0	0	0	0	0	0	0	1	0
5.25 - 5.50	0	0	0	0	0	0	0	0	0	1	1	0
5.50 - 5.75	0	0	0	0	0	0	0	0	0	0	2	0
5.75 - 6.00	0	0	0	0	0	0	0	0	0	1	0	0
6.00 - 6.25	0	0	0	0	0	0	0	0	0	0	1	0
6.25 - 6.50	0	0	0	0	0	0	0	0	0	0	1	0
6.50 - 6.75	0	0	0	0	0	0	0	0	0	1	0	0
Total	33252	21161	14367	18775	17885	16593	19345	15595	11845	12815	21833	12676

[5] The prediction anomalies were obtained after presenting the models with all 507,347 patterns from the evaluation set.

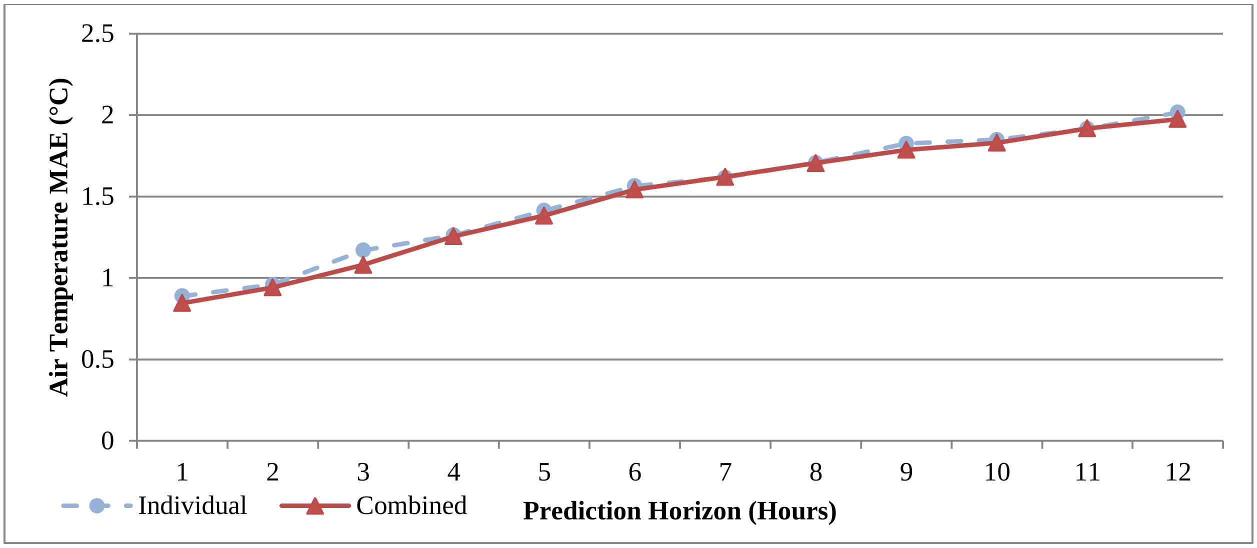

Figure 1. Comparison of air temperature MAEs for prediction horizons, individual and combined models, model evaluation set.

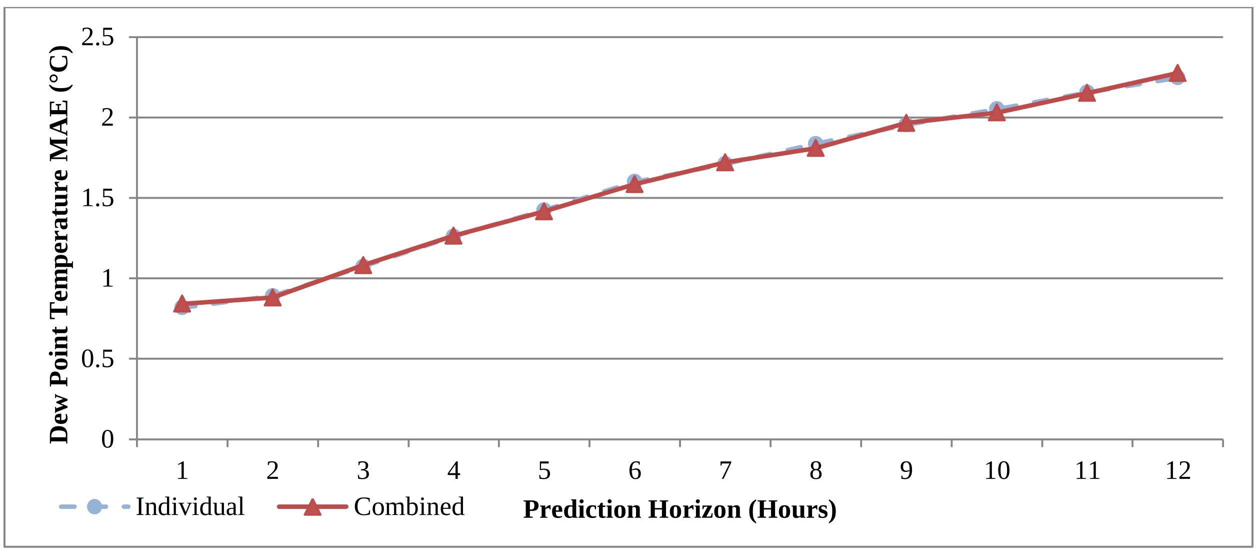

Figure 2. Comparison of dew point temperature MAEs for prediction horizons, individual and combined models, model evaluation dataset.

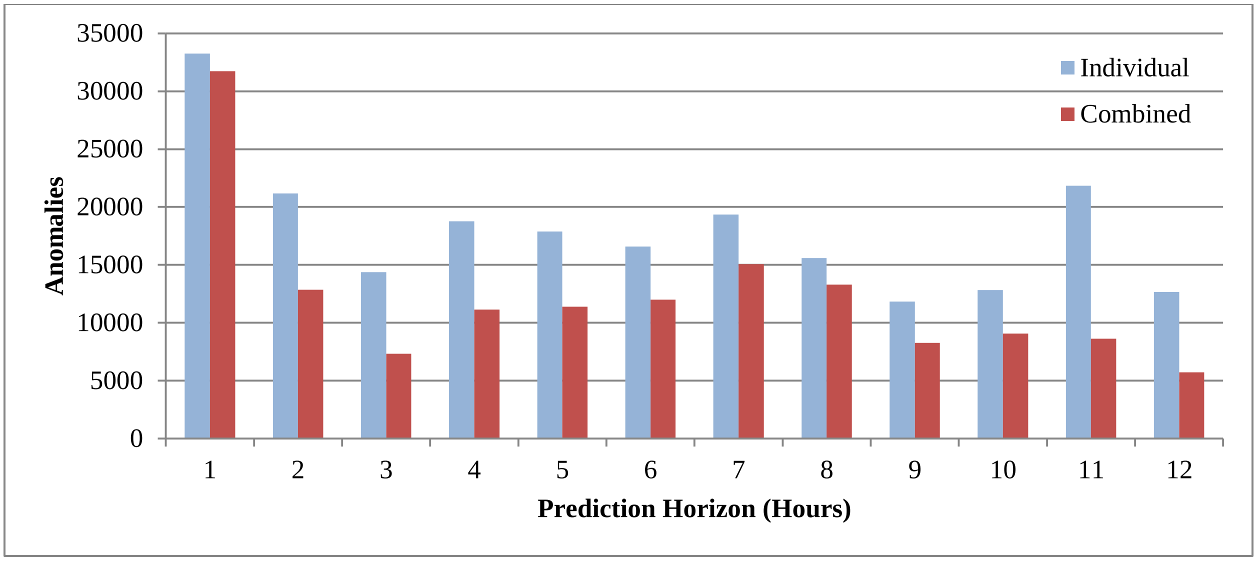

Figure 3. Comparison of number of prediction anomalies for individual and combined models, model evaluation dataset.[6]

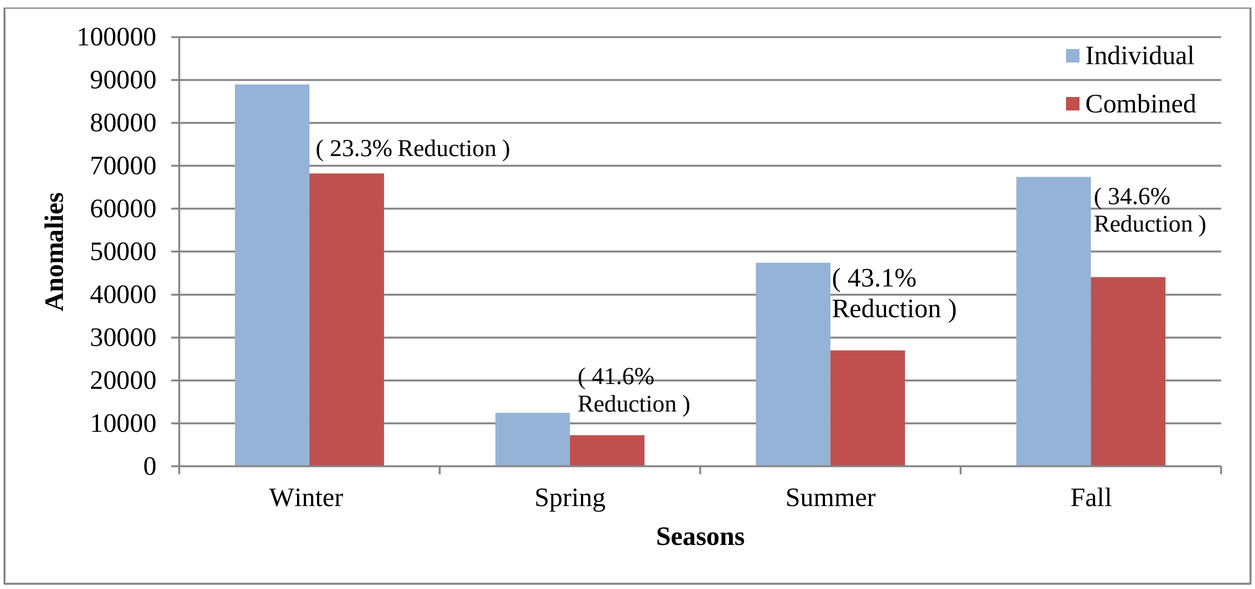

Figure 4. Comparison of anomalies by season, summed over the twelve prediction horizons, model evaluation dataset.[6]

[6] The prediction anomalies were obtained after presenting the models with all 507,347 patterns from the evaluation set.

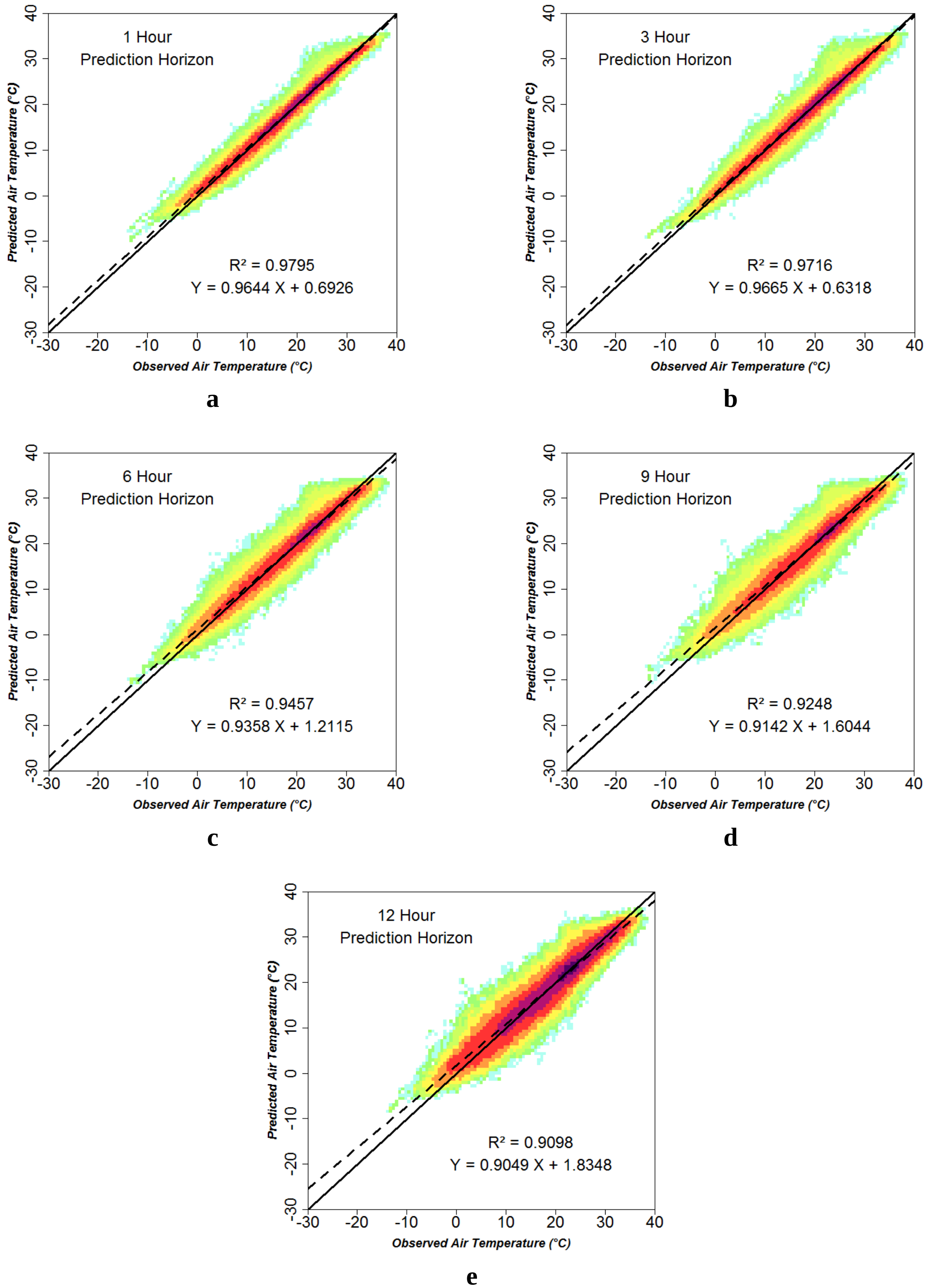

Figure 5. Predicted and observed air temperature, combined model, model evaluation dataset.

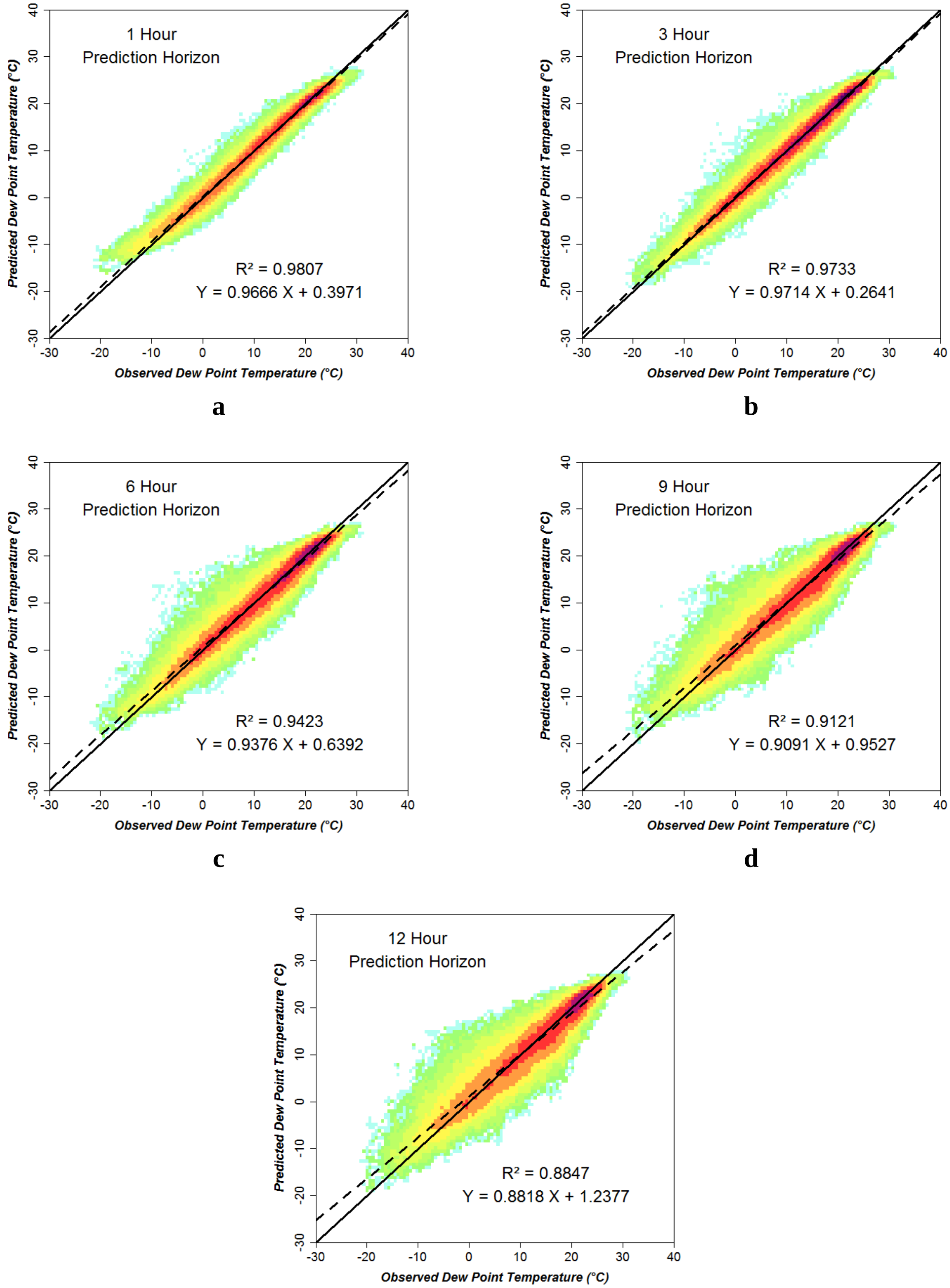

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Figure 6. Predicted and observed dew point temperature, combined model, model evaluation dataset.

CHAPTER 3

AIR AND DEW POINT TEMPERATURE PREDICTION USING TIME SERIES OUTPUT ARTIFICIAL NEURAL NETWORKS[7]

[7] Nadig, K., W. D. Potter, G. Hoogenboom and R. W. McClendon. To be submitted to *Environmental Modelling & Software*

3.1 ABSTRACT

Decision making in the management of agricultural production often depends on accurately predicted weather condition. Frost, freeze and heat stress are few examples of weather related events which are of interest to people involved in agricultural production. Currently use 24 models to predict Hourly air and dew point temperatures up to 12 hours ahead, on the Automated Environment Monitoring Network (AEMN) in Georgia using web-based artificial neural network (ANN) models. Individual models predict each temperature variable at each prediction horizon. The current 24 web-based ANN models have errors associated with the predictions. Under high relative humidity conditions, the air temperature approaches but does not go below the observed dew point temperature. A prediction anomaly occurs when the predicted air temperature is lower than the predicted dew point temperature. The goal of this research was to improve the prediction accuracy of existing air and dew point temperature ANN models by predicting the time series output for various prediction horizons using a single ANN model. The research objectives of this study were to determine if the time series models could reduce the mean absolute error (MAE) of prediction and to reduce the number of prediction anomalies. The time series considered were four-hours, six-hours and twelve-hours. The combined four-hour time series models produced lowest mean absolute error (MAE) for four of twelve prediction horizons for air temperature, with average reduction of 2.63% and the MAEs ranged from 0.65°C at one-hour to 1.98 at twelve-hour horizon. It produced lowest MAEs for five of twelve prediction horizons for dew point temperature, with average reduction of 2.22% and the MAEs ranged from 0.6°C at one-hour to 2.23°C at twelve-hour horizon. The combined four-hour time series models produced lowest number of prediction anomalies for two of twelve models, with

average reduction of 25.7%. The combined four-hour time series model produced overall improvement in reduction of both MAEs and prediction anomalies.

3.2 INTRODUCTION

Air temperature is the ambient temperature indicated by a thermometer exposed to the air but sheltered from direct solar radiation. The dew point temperature is the temperature at which the water vapor in humid air under constant barometric pressure is condensed into liquid, resulting in formation of droplets on solid surface. Air and dew point temperature predictions could be used to anticipate weather events. Frost is a type of weather event which occurs when water vapor gets deposited, on solid surfaces, as ice without transitioning into liquid (Perry, 1998). The surface of the leaves is damaged by the formation of sharp ice crystals due to frost. Damages to the epidermis of leaves and the epidermal cuticle can make the plants susceptible to low air temperature conditions. Crystallization of liquid inside the individual cells causes the frost damage (Perry, 1998). Freeze is another type of weather event which occurs when the temperature drops below the freezing point of water. If the air temperature remains below 0°C it can cause freeze damage and the duration of the freeze event determines the amount of damage. Noticeable or visual damage to the plants is caused by frost. Freeze damage usually occurs in the tender regions of the plants, and may not show any visible signs (Perry, 1998). Heat stress causes temperature regulation issues due to overheating in humans or animals (Fauci, 2008) and under extreme circumstances may cause death (Grundstein et al., 2012). The dew point temperature is useful in estimating the occurrence of heat stress (Sandstrom et al., 2004).

Predicting weather variables could give sufficient time to managers to minimize frost losses through the use of preventive measures such as orchard heaters and irrigation (Hochmuth et al., 1993). A large area of blueberry and peach crops in South Georgia was destroyed due to unusually severe and unexpected low temperature conditions in spring of 2002. In early April of 2007, 50% of Georgia's peach crop and 87% of blueberry crop were lost due to frost (Fonsah et al., 2007; Warmund et al., 2008). Orchard heaters, irrigation and wind machines are few of the techniques used by the crop produces to reduce the damage to the crops. In crop management, accurate prediction of weather variables crucial to the decision making process.

The estimation of the amount of moisture in the air, near-surface humidity, evapotranspiration, relative humidity, frost could be done using air and dew point temperature. Dew formation is especially important to plants which thrive in the arid regions. The dew point temperature could also give an insight into the long-term climatic changes (Robinson, 2000).

One of the common modes of crop protection against frost is irrigation, especially for peach and blueberry blossoms. The water from the irrigation process forms a layer on the surface of the blossoms insulating them from the dropping air temperature, protecting the blossoms from damage due to frost. Crop managers could benefit from the predictions as it allows them to take preventive measures and reduce the damages. Thus, accurate prediction of weather events is essential and must be provided several hours in advance. Failure to predict a weather event or false positives can also lead to losses due to damages to crops or expenses incurred applying the frost damage prevention.

Air and dew point temperature predictions are based on current and prior observations of weather variables, such as air temperature, relative humidity, rainfall, wind speed, solar radiation, vapor pressure, vapor pressure deficit. Monitoring, tracking and recording weather variables require equipment and data transfer medium. The Georgia Automated Environment Monitoring Network (AEMN) provides the needed infrastructure. AEMN keeps track of weather variables by collecting measurement every second and the averages and sums are recorded at 15 minute intervals (Hoogenboom, 2000; Hoogenboom et al., 2003). The network transfers data from 81 sites to a server at Griffin, Georgia, and accumulated data is used by AEMN for analysis, predictions, and tracking weather conditions (Hoogenboom, 2005). The variables needed for prediction of air temperature and dew point temperature, amount of historical data needed for accurate prediction and other such dependencies were determined in previous research (Smith et al., 2009; Shank et al., 2008). Current web-based ANN models use the accumulated data as inputs to generate predicted air and dew point temperature values for next twelve hours at hourly intervals. The weather variables are extracted from the accumulated data which includes current and prior observations. The predicted air and dew point temperature values are disseminated through the AEMN website. The predictions are updated every 15 minutes (Hoogenboom, 2000).

Current web-based ANN models for air temperature were developed by Smith et al. (2009) and implemented on the AEMN website. Weather variables of temperature, relative humidity, wind speed, solar radiation and rainfall were used as the inputs to the air temperature ANNs. Prior data for 24 hours and current values for each observation at one-hour intervals were also included as inputs. The inputs also included hourly first difference terms for the current and prior weather variables, time of day and day of the year. The ANN models predicted air temperature for a particular horizon, and a model was developed for each of the twelve prediction horizons (Smith et al., 2009). Ward-style network architecture was used to develop the ANN models (Ward System Group, 1993) and they were trained using the error back-propagation (EBP) (Haykin, 1999). The input layer of the model consisted of 258 neurons for inputs, the hidden layer had 120 neurons and the output layer had one neuron. In the hidden layer of the model equally distributed the types of activation functions among the three slabs with hyperbolic tangent, Gaussian and inverse Gaussian. Several ANN parameters including the activation function of output, number of hours of prior data, additional values and rate of change for observations at 15 min intervals and the data scaling ranges for both input and output, were varied, no reduction in MAE was produced, and bagging and boosting only slightly reduced the MAE (Smith et al., 2009). Chevalier et al., (2011) used Support Vector Machines (SVM) to develop air temperature prediction models and compared their accuracy with the implemented ANN models. The SVM models showed improvement when trained with 300000 patterns and the ANN models predicted with higher accuracy when trained with 1 million patterns.

Hourly dew point temperature prediction models for up to twelve hour prediction horizons were developed by Shank et al. (2008) and are included on the AEMN website. Inputs to dew point temperature models were same as the inputs as to the existing air temperature models, plus weather variables vapor pressure and vapor pressure deficit, and their hourly rates of change. The models were developed similarly to those developed by Smith et al. (2009). Ensemble artificial neural network, were also developed by Shank et al. (2008) to improve the prediction accuracy.

Georgia Extreme-weather Neural-network Informed Expert (GENIE), a fuzzy expert system, was developed to interpret the predicted and observed to generate frost and freeze warnings (Chevalier et al., 2012). The system produced numeric warnings and a web-based interface was developed to interact with the system.

The prediction errors in MAE for the twelve air temperature models varied between 0.516°C and 1.873°C. For the twelve dew point temperature models the MAE varied between

0.508°C and 2.081°C. The observed air temperature approaches the observed dew point temperature under high relative humidity conditions. However, air temperature never goes below the dew point temperature. Given the MAE values, the predicted air temperature will frequently drop below the predicted dew point temperature under high relative humidity conditions. Herein this prediction error is referred to as a prediction anomaly. To reduce the number of prediction anomalies, combined models were developed which could predict both air and dew point temperature in a single model (Nadig et al., 2012). The combined models produced a reduction in the number of prediction anomalies of about 34%. The combined models produced slight reduction in air temperature MAEs and no reduction is dew point temperature MAEs. However, the research did not focus on predicting multiple horizons in a single model. It is possible that the models could be further improved by including more values to the output of the ANNs. One way could be to include multiple prediction horizons, since the air temperature or dew point temperature data represent a time series (Chakraborty et al., 1992; Zhang et al., 2005). This could further reduce prediction anomalies and the MAEs. The models, herein, are referred to as the time series models. The time series models could provide an opportunity for interaction among the output during training.

The goal of this research is to improve the prediction accuracy of existing air temperature and dew point temperature ANN models by developing time series ANN models for prediction of air and dew point temperature for each prediction horizon from one to twelve hours. The research objectives are as follows: (1) to determine if MAE for predicted air temperature and predicted dew point temperature are reduced for the time series models in comparison with the individual models, and (2) to determine if the number of occurrences of the prediction anomaly can be reduced using the time series models.

3.3 METHODOLOGY

3.3.1. Data Sets

The data were partitioned into a model development set and a model evaluation set using the same locations and years as the study by Nadig et al, (2012). The two sets were chosen so that they were mutually exclusive of years and locations, as shown in Table 1. The model development set was further partitioned into a training set and selection set. The training set was used to train the ANN models. The models were chosen based on the lowest selection set MAE which was obtained by presenting the models the selection set in feed forward mode. The chosen model was treated as the final model for a given prediction horizon. The training set and selection set were mutually exclusive of only locations. The model evaluation set was used to evaluate the models in feed forward mode and the resulting MAE is used as a metric to compare with other models. The training set consisted of 297,974 patterns, the selection set had 306,972 patterns and the evaluation set had 507,347 patterns. The input and output patterns were generated from each of the datasets and normalized and scaled to the range [-0.9, 0.9]. There were a total of 358 input values per input pattern and twenty four output values per output pattern. Patterns were generated for each of the twelve prediction horizons and the three data partitions.

3.3.2. Model Development

Ward-style network architecture (Ward System Group, 1993) was used to develop all models. It was a three layered neural network, which includes input, hidden and output layers. The input layer consists of neurons with linear activation function. The hidden layer was made of 120 neurons, in three equally sized slabs with 40 neurons each. The neurons in the slabs had the following activation functions, hyperbolic tangent, Gaussian and inverse Gaussian. The output layer was made of neurons with symmetric sigmoid activation function. Only the number of inputs or outputs varied with the models.

To improve the chances of reducing the MAEs ten instances of each model were created. The initial weights for each of the models were randomly selected. This randomization allowed the training to start from a different location. The models were presented with patterns from the same datasets but in random order during training. This randomization ensured different path during the training process. Selecting among multiple instances makes it more likely that the training algorithm will approach the optimal set of ANN weights. The combined models developed in the previous research by Nadig et al., (2012) used resilient propagation algorithm for training to benefit from its faster convergence and stability in comparison with the back-propagation algorithm (Anastasiadis et al., 2005; Igel et al., 2003). The same development package EnCog 3.0.0.0 (runtime v2.0.50727) was used to develop and train the models.

All models were trained using the training dataset until the change in error was less than 0.01%. After training the models, they were presented with the selection set in feed forward mode to obtain the selection set MAEs. The instance with the lowest selection set MAE was chosen. The selected models were then presented with evaluation set once in feed forward mode to obtain the evaluation set MAE.

The result of the individual models and combined models from Nadig et al., (2012) were used for comparison. The individual models served as analogues of the current web-based models. The individual models were developed to predict only one weather variable at one prediction horizon hence the models had only one output. To predict twelve hours of air and dew point temperature 24 models were needed. The individual air temperature model had 258 input neurons and one output neuron, based on Smith et al. (2009). The dew point temperature model had 358 input neurons and one output neuron, based on Shank et al. (2008).

The time series output air temperature models predict only air temperature for four, six and twelve hour horizon groups. The four-hour time series ANN models predict air temperature for the following horizon groups, one through four, five through eight, and nine through twelve hours. Therefore, three four-hour time series models are needed to predict air temperature for all twelve of the prediction horizons. Each four-hour time series ANN model for air temperature prediction had four output neurons. The six-hour time series ANN models predict air temperature for the following horizon groups, one through six, and seven through twelve. So, two six-hour time series models are needed to predict air temperature for all twelve of the prediction horizons. Each six-hour time series ANN model for air temperature had six output neurons. The twelve-hour time series ANN models predict air temperature for all twelve prediction horizons, and only one twelve-hour time series model is needed. The twelve-hour time series ANN model for air temperature had twelve output neurons. All the time series output air temperature models had 258 inputs and 120 hidden layer neurons. The time series dew point temperature models were also developed is a similar manner. The dew point temperature models had 358 inputs.

The combined models developed by Nadig et al., (2012) predicted air and dew point temperature for a single prediction horizon. Except for the number of outputs all other ANN architecture parameters were identical to individual dew point temperature models for single horizon. The combined time series models predicted both air and dew point temperature in a single model for four, six and twelve hour horizon groups. The architecture of the ANNs was similar to that of the time series dew point models. However, combined four-hour time series, combined six-hour time series and the combined twelve-hour time series ANN models had eight, twelve and 24 outputs respectively, because the combined time series models predicted air and dew point temperature for each prediction horizon in a single model.

3.4 RESULTS AND DISCUSSION

The air temperature MAE values were obtained by presenting the evaluation dataset to the individual and series air temperature ANNs in feed forward mode only with results as shown in Table 2. The four-hour time series models predict the twelve hourly horizons in three groups, the six-hour time series models predict in two groups and the twelve-hour time series in a single model. The individual air temperature MAEs were used as a base line for comparison because this is the architecture of the currently implemented ANN models. Three of twelve individual models produced the lowest MAEs, in comparison with four-hour time series, six-hour time series and twelve-hour time series models. The four-hour time series air temperature model produced lowest MAE for seven of twelve prediction horizons, in comparison with individual, six-hour time series and twelve-hour time series models. The percent change if compared with the individual models ranged from 30% reduction at one-hour horizon to 2.1% increase at eight-hour horizon. The four-hour time series models produced an average reduction in MAE of about 4.28% across all twelve prediction horizons. The six-hour time series air temperature model produced lowest MAE for two of the twelve prediction horizons, in comparison with individual, four-hour time series and twelve-hour time series models. The percent change if compared with the individual models ranged from 29.5% reduction at one-hour horizon to 2.4% increase at seven-hour horizon. The six-hour time series model produced an average reduction in MAE of about 3.69% across all twelve prediction horizons. The twelve-hour time series air temperature model did not produce lowest MAE when compared with individual, four-hour time series and six-hour time series models. The percent change if compared with the individual models ranged from 20.5% reduction at one-hour horizon to 1.8% increase at four-hour horizon. The twelve-hour time series model produced an average reduction in MAE of about 1.74% across all twelve prediction horizons. From Table 2 four-hour time series air temperature model produced the largest average reduction in MAE for air temperature in comparison with the individual models.

The air temperature MAE values were obtained by presenting the evaluation dataset to the combined and combined series ANNs in feed forward mode only as shown in Table 3. The result of the individual models is repeated from Table 2 for comparison. The combined model produced lowest air temperature MAE for six of twelve prediction horizons, in comparison with individual, combined four-hour time series, combined six-hour time series and combined twelve-hour time series models. The percent change if compared with the individual models ranged from about 4.8% reduction at one-hour horizon to 0.25% increase at seven-hour horizon. The combined models produced an average reduction in air temperature MAE of about 1.93% across all twelve prediction horizons. The combined four-hour time series model produced lowest air temperature MAE for four of twelve prediction horizons, in comparison with individual, combined, combined six-hour time series and combined twelve-hour time series models. The percent change if compared with the individual models ranged from about 27.4% reduction at one-hour horizon to 2.7% increase at four-hour horizon. The combined four-hour time series models produced an average reduction in air temperature MAE of about 2.63% across all twelve prediction horizons. The combined six-hour time series model produced lowest air temperature MAE for only one of twelve prediction horizons, in comparison with individual, combined, combined four-hour time series and combined twelve-hour time series models. The percent change if compared with the individual models ranged from about 23.1% reduction at one-hour horizon to 4.07% increase at four-hour horizon. The combined six-hour time series models produced an average reduction in air temperature MAE of about 2.26% across all twelve prediction horizons. The combined twelve-hour time series model did not produce lowest air temperature MAE for any of twelve prediction horizons, in comparison with individual, combined, combined four-hour time series and combined six-hour time series models. The percent change if compared with the individual models ranged from about 17.5% at one-hour horizon to 8.8% increase at four-hour horizon. The combined twelve-hour time series model produced on average increased the air temperature MAE by 0.47%. From Table 3 combined four-hour time series models produced the largest average reduction in MAE for air temperature in comparison with the individual models. However combined models produced lowest MAE for more horizons than combined four-hour time series.

The air temperature MAEs from Table 2 for individual, four-hour time series, six-hour time series and twelve-hour time series, and from Table 3 for combined, combined four-hour time series, combined six-hour time series, and combined twelve-hour time series are consolidated into Table 4 for an overall comparison. The individual models produced lowest MAE only for the seven-hour horizon. The four-hour time series air temperature models produced lowest MAE for four of twelve prediction horizons, from one through four hour horizons. The six-hour time series air temperature models produced lowest MAE only for the six-hour horizon. The twelve-hour time series air temperature model did not produce lowest MAE for any of the twelve prediction horizons. The combined models produced lowest MAE for four of twelve prediction horizons. The combined four-hour time series models produced lowest MAE only for the eleven-hour horizon. The combined six-hour time series models produced lowest MAE only for the twelve-hour horizon. Finally, the combined twelve-hour time series model did not produce lowest MAE for any of the twelve prediction horizons. Thus the four-hour time series air temperature models and the combined models both produced lowest MAE for four of twelve prediction horizons.

The dew point temperature MAE values were obtained by presenting the evaluation dataset to the individual and series dew point temperature ANNs in feed forward mode only as shown in Table 5. The four-hour time series models predict the twelve horizons in three groups, the six-hour time series models predict in two groups and the twelve-hour time series in a single model. The individual dew point temperature MAEs were used as a base line for comparison. Individual models produced lower MAEs for nine of twelve horizons, in comparison with four-hour time series, six-hour time series and twelve-hour time series models. The four-hour time series dew point temperature model produced lowest MAE for three of twelve prediction horizons, in comparison with individual, six-hour time series and twelve-hour time series models. The percent change if compared with the individual models ranged from 18.1% reduction at one-hour horizon to 4.5% increase at three-hour horizon. The four-hour time series models on average increased the MAE by about 0.04% across all twelve prediction horizons. The six-hour time series dew point temperature model did not produce lowest in MAE for any of the twelve prediction horizons, in comparison with individual, four-hour time series and twelve-hour time series models. The percent change if compared with the individual models was 17.7% reduction at one-hour horizon to 5.52% increase at three-hour horizon. Except for the one-hour horizon there was no reduction for other horizons. The six-hour time series model on average increased the MAE by 1% across all twelve prediction horizons. The twelve-hour time series dew point temperature model did not produce reduction in MAE when compared with individual, four-hour time series and six-hour time series models. The percent change if compared with the individual models was 7.8% reduction at one-hour horizon to 10.4% increase at two-hour horizon. Except for one-hour there was no reduction for other horizons. The twelve-hour time series model on average increased the MAE by 3.26% across all twelve prediction horizons. From Table 5 individual dew point temperature model produced the lowest MAE for dew point temperature for most horizons.

The dew point temperature MAE values were obtained by presenting the evaluation dataset to the combined and combined series ANNs in feed forward mode only as shown in Table 6. The result of the individual models is repeated from Table 5 for comparison. The combined model produced lowest dew point temperature MAE for three of twelve prediction horizons, in comparison with individual, combined four-hour time series, combined six-hour time series and combined twelve-hour time series models. The percent change if compared with the individual model ranged from about 1.5% reduction at eight-hour horizon to 2.9% increase at one-hour horizon. The combined models on average increased the dew point temperature MAE by about 0.08% across all twelve prediction horizons. The combined four-hour time series model produced lowest dew point temperature MAE for five of twelve prediction horizons, in comparison with individual, combined, combined six-hour time series and combined twelve-hour time series models. The percent change if compared with the individual models ranged from about 26.6% reduction at one-hour horizon to 3.4% increase at four-hour horizon. The combined four-hour time series models produced an average reduction in dew point temperature MAE of about 2.22% across all twelve prediction horizons. The combined six-hour time series model did not produce lowest dew point temperature MAE for any of twelve prediction horizons, in comparison with individual, combined, combined four-hour time series and combined twelve-hour time series models. The percent change if compared with the individual models ranged from about 18.5% at increase one-hour horizon to 2.1% increase at three-hour horizon. The combined six-hour time series models produced an average reduction in dew point temperature MAE of about 1.08% across all twelve prediction horizons. The combined twelve-hour time series model produced lowest dew point temperature MAE for two of twelve prediction horizons, in comparison with individual, combined, combined four-hour time series and combined six-hour time series models. The percent change if compared with the individual models ranged from about 17.4% reduction at one-hour horizon to 4.9% increase at three-hour horizon. The combined twelve-hour time series model produced an average reduction in dew point temperature MAE of about 0.23%. From Table 6 combined four-hour time series models produced the largest reduction in MAE for dew point temperature.

The dew point temperature MAEs from Table 5 for individual, four-hour time series, six-hour time series and twelve-hour time series, and from Table 6 for combined, combined four-hour time series, combined six-hour time series, and combined twelve-hour time series are consolidated into Table 7 for an overall comparison. The individual models produced lowest MAE for two of twelve prediction horizons. The four-hour time series, six-hour time series and twelve-hour time series dew point temperature models did not produce lowest MAE for any of the twelve prediction horizons. The combined models produced lowest MAE for three of twelve prediction horizons. The combined four-hour time series models produced lowest MAE for four of twelve prediction horizons. The combined six-hour time series models did not produce lowest MAE for any of the twelve prediction horizons. Finally, the combined twelve-hour time series model produced lowest MAE for two of twelve prediction horizons. Thus the combined four-hour time series dew point temperature models produced lowest MAE for five of twelve prediction horizons.

The prediction anomalies for individual, four-hour time series, six-hour time series and twelve-hour time series models were obtained by presenting the model evaluation dataset to the models in feed forward mode, as shown in Table 8. The evaluation set contained 507,347 patterns for each prediction horizon. The largest number of prediction anomalies for the individual models occurred at the one hour prediction horizon with a value of 33252. This would be an occurrence of approximately 6.55% of the total patterns in the evaluation set. The individual models had the lowest number of prediction anomalies for eight of twelve prediction horizons. The four-hour time series models produced lowest number of prediction anomalies for three of twelve prediction horizons. The percent change if compared with individual models ranged from 37.6% reduction at one-hour horizon to 55% increase at six-hour horizon. On average the four-hour time series models produced an increase in the number of prediction anomalies by 14.98%. The six-hour time series models produced lowest number of prediction anomalies only for the two-hour horizon. The percent change if compared with individual models ranged from 35.6% reduction at one-hour horizon to 183% increase at nine-hour horizon. On average the six-hour time series models produced an increase in the number of prediction anomalies by about 61.54%. The twelve-hour time series models did not produce lowest number of prediction anomalies and on average increased the prediction anomalies by about 81.7%. From Table 8 the series models did not produce any improvement in the reduction of prediction anomalies as compared to the individual models.

The prediction anomalies for combined, combined four-hour time series, combined six-hour time series and combined twelve-hour time series models were obtained by presenting the model evaluation dataset to the models in feed forward mode, as shown in Table 9. The combined models produced lowest number of prediction anomalies in seven of twelve prediction horizons. The percent change if compared with individual models ranged from 60.5% reduction at eleven-hour horizon to 4.6% reduction at one-hour horizon. The combined models produced an average reduction in prediction anomalies of about 34.1%. The combined four-hour time series models produced lowest number of prediction anomalies in two of twelve prediction horizons. The percent change if compared with individual models ranged from 68.3% reduction at one-hour horizon to 35.5% increase at nine-hour horizon. The combined four-hour time series models produced an average reduction in prediction anomalies of about 25.7%. The combined six-hour time series models produced lowest number of prediction anomalies in three of twelve prediction horizons. The percent change if compared with individual models ranged from 69.96% reduction at eleven-hour horizon to 30.86% increase at three-hour horizon. The combined six-hour time series models produced an average reduction in prediction anomalies of about 27.5%. The combined twelve-hour time series model did not produce lowest number of prediction anomalies for any of the twelve prediction horizons, in comparison with individual, combined, combined four-hour time series and combined six-hour time series. The percent change if compared with individual models ranged from 22.25% reduction at one-hour horizon to 72.3% increase at six-hour horizon. The combined twelve-hour time series model on average increased the number of prediction anomalies by about 36.66%. From Table 9 combined models produced the lowest number of prediction anomalies for the largest number of prediction horizons in comparison with individual, combined four-hour time series, combined six-hour time series and combined twelve-hour time series models.

The number of prediction anomalies from Table 8 for individual, four-hour time series, six-hour time series and twelve-hour time series and from Table 9 for combined, combined four-hour time series, combined six-hour time series, and combined twelve-hour time series are consolidated into Table 10 for comparison. The individual, four-hour time series, six-hour time series, twelve-hour time series and combined twelve-hour time series models did not produce the lowest number of prediction anomalies for any of the twelve prediction horizons. The combined models produced the lowest number of prediction anomalies for seven of twelve prediction horizons. The combined four-hour time series model produced a reduction in two of twelve prediction horizons. The combined six-hour time series model produced a reduction in three of twelve prediction horizons.

The model development approach that is most accurate overall is determined by the two metrics of MAE and prediction anomalies. These metrics could be addressed separately or together. An approach could be chosen on greatest reduction in air temperature or dew point temperature MAE. Also, an approach could be chosen based on greatest reduction in the number of prediction anomalies. To address both MAE and prediction anomaly, an approach could be chosen such that it produced the largest reduction in MAE and prediction anomalies through some arbitrary combination of the two metrics. However, such a model may not produce greatest reduction when considering the metrics of MAE and prediction anomalies individually.

From Table 4, the four-hour time series model and the combined models both produced lowest MAEs for four of twelve prediction horizons for air temperature prediction. However, the four-hour time series model produced larger average reduction in MAE in comparison with combined model. Thus the four-hour time series model predicted air temperature more accurately than other model development approaches.

From Table 7, the combined four-hour time series model produced a reduction in dew point temperature MAE in the largest number of prediction horizons in comparison with other approaches. It also produced the largest reduction in average MAE. Thus, the combined four-hour time series model predicted dew point temperature more accurately than other model.

From Table 10, the four-hour, six-hour and twelve-hour time series models did not produce a reduction in the number of prediction anomalies for any prediction horizon. The combined model produced the largest reduction in the number of prediction anomalies. If reduction in prediction anomalies was more important than either or both air and dew point temperature MAEs then combined model would be chosen.

Overall, considering results from Table 4, Table 7 and Table 10, there are three candidate solutions based on reduction in either MAE for air and dew point temperature or prediction anomalies: Combined model, combined four-hour time series model and combined six-hour time series model. The combined model produced marked reduction in number of prediction anomalies and average air temperature MAE, but no change in the average dew point temperature MAE. Although the combined four-hour time series model produced lower reduction in the number of prediction anomalies compared to combined or combined six-hour time series model, it showed marked reduction in average MAEs for air temperature and dew point temperature. Although the combined six-hour time series model produced slightly greater reduction in the number of anomalies as compared to combined four-hour time series model, it produced a lower reduction in MAE for both air and dew point temperature. If reduction in MAE is more important than reduction in prediction anomalies then combined four-hour time series model would be chosen. If reduction in prediction anomalies is more important than reduction in either or both air and dew point temperature MAEs then the combined six-hour time series model would be chosen.

Alternatively, the approaches could be compared using an overall sum of the average % air temperature MAE reduction, average % dew point temperature MAE reduction and average % reduction in prediction anomalies. The combined four-hour and six-hour time series models were considered, since they were the only two approaches that produced reduction in air and dew point temperature MAEs and prediction anomalies, as shown in Table 11. The model with highest value could be considered the most accurate model overall. Using the sum of % reductions, the combined four-hour time series model has a value of 30.6 and the combined six-hour time series model has a value of 30.9. Based on this criterion the combined four-hour time series model and the combined six-hour time series model are approximately equal.

3.5 SUMMARY AND CONCLUSIONS

Time series models which predicted either air temperature or dew point temperature were developed to predict four, six and twelve hour horizons in a single model. Combined time series models which predicted both air and dew point temperature for four, six and twelve hour horizons in a single model were also developed. Four-hour time series air temperature models produced largest reduction in the air temperature MAEs making them possible candidate solutions for air temperature prediction. The combined four-hour time series models produced largest reduction in dew point temperature MAEs making it a possible candidate solution for dew point temperature prediction. Analyzing the models based only on prediction anomalies revealed that the combined model produced the lowest number of prediction anomalies making it a possible candidate for prediction of both air and dew point temperatures. The combined four-hour time series model and combined six-hour time series model both produced overall reduction in MAEs and prediction anomalies.

In this research, the ANN architecture used was based on previous work by Smith (Smith et al., 2009) and Shank (Shank et al., 2008). In future research the ANN parameters such as activation functions, number of nodes in the hidden layer, distribution of nodes between the slabs of the Ward-style model, could be explored for reducing MAE or reducing the number of prediction anomalies. The ANN architecture could be explored using evolutionary algorithms. Also, longer duration of prior data, additional weather variable inputs, and different resolution of input data could be explored. The input data could be transformed using fuzzy membership functions. The training data could be sampled evenly over the prediction range and the models could be selectively trained for shorter range of temperatures and outputs from the models could be accumulated to obtain the result for the entire range.

3.6 REFERENCES

Anastasiadis, A. D., Magoulas, G. D., & Vrahatis, M. N. (2005). New globally convergent training scheme based on the resilient propagation algorithm. *Neurocomputing, 64*(0), 253 - 270.

Attaway, J. A. (1997). *A History of Florida Citrus Freezes.* Lake Alfred, FL: Florida Science Source, Inc.

Chakraborty, K., Mehrotra, K., Mohan, C. K., & Ranka, S. (1992). Forecasting the behavior of multivariate time series using neural networks. *Neural Networks, 5*(6), 961 - 970.

Chevalier, R., Hoogenboom, G., McClendon, R., & Paz, J. (2011). Support vector regression with reduced training sets for air temperature prediction: a comparison with artificial neural networks. *Neural Comput. Appl., 20*, 151-159.

Chevalier, R., Hoogenboom, G., McClendon, R., & Paz, J. (2012). A web-based fuzzy expert system for frost warnings in horticultural crops. *Environmental Modelling & Software (In Press)*.

Cooper, W. C., Young, R. H., & Turrell, F. M. (1964). Microclimate and physiology of citrus: Their relation to cold protection. 38-50.

Fauci, A. (2008). *Harrison's Principles of Internal Medicine.* McGraw-Hill Professional.

Fonsah, E. G., Taylor, K. C., & Funderburk, F. (2007). Enterprise cost analysis for middle. *Technical Report*(AGECON-06-118).

Gevrey, M., Dimopoulos, I., & Lek, S. (2003). Review and comparison of methods to study the contribution of variables in artificial neural network models. *Ecological Modelling, 160,* 249 - 264.

Grundstein, A., Ramseyer, C., Zhao, F., Pesses, J., Akers, P., Qureshi, A., et al. (2012). A retrospective analysis of American football hyperthermia deaths in the United States. *International Journal of Biometeorology, 56*, 11-20.

Haykin, S. (1999). *Neural networks: a comprehensive foundation, 2nd edition.* Upper Saddle River, NJ: Prentice Hall.

Hochmuth, G. J., Kostewicz, S., & Martin, F. (1993). Irrigation Method and Rowcover Use for Strawberry Freeze Protection. *Journal of the American Society for Horticultural Science, 118*, 575-579.

Hoogenboom, G. (2000). The Georgia Automated Enviromnental Monitoring Network. *Preprints of the 24th Conference On Agricultural and Forest Meteorology* (pp. 24-25). American Meteorological Society.

Hoogenboom, G. (2005). The Georgia Automated Environmental Monitoring Network: experiences with the development of a state-wide automated weather station network. *Proceedings of the 13th Symposium on Meteorological Observations and Instrumentation & 15th Conference on Applied Climatology.* Boston: American Society of Meteorology.

Hoogenboom, G., Coker, Edenfield, Evans, & Fang. (2003, April). The georgia automated environmental monitoring network: ten years of weather information for water resources management. *Proceedings of the 2003 Georgia Water Resources Conference*.

Igel, C., & Hüsken, M. (2003). Empirical evaluation of the improved Rprop learning algorithms. *Neurocomputing, 50*(0), 105 - 123.

Nadig, K., Hoogenboom, G., Potter, W. D., & McClendon, R. W. (2012). Comparison of individual and combined ANN models for prediction of air and dew point tmeperature. *Journal of Applied Meteorology and Climatology (to be submitted)*.

Perry, K. B. (1998). *Basics of Frost and Freeze Protection for Horticultural Crops* (8 ed.). HortTechnology.

Riedmiller, M., & Braun, H. (1993). A direct adaptive method for faster backpropagation learning: the RPROP algorithm. *IEEE International Conference on Neural Networks,* (pp. 586 -591).

Robinson, P. J. (2000). Temporal trends in United States dew point temperatures. *International Journal of Climatology*, 985-1002.

Sandstrom, M. A., Lauritsen, R. G., & Changnon, D. (2004, May-June). A Central-U.S. Summer Extreme Dew-Point Climatology (1949-2000). *Physical Geography, 25*(3), 191-207.

Shank, D. B., McClendon, R. W., & Paz, J. a. (2008). Ensemble artificial neural networks for prediction of dew point temperature. *Applied Artificial Intelligence, 22*(6), 523-542.

Shank, D., Hoogenboom, G., & McClendon, R. (2008). Dewpoint Temperature Prediction Using Artificial Neural Networks. *Journal of Applied Meteorology and Climatology*, *47*, 1757.

Smith, B. A., Hoogenboom, G., & McClendon, R. W. (2009). Artificial neural networks for automated year-round temperature prediction. *Computers and Electronics in Agriculture, 68*, 52-61.

Smith, B. A., McClendon, R. W., & Hoogenboom, G. (2008). Improving Air Temperature Prediction with Artificial Neural Networks.

Ward System Group. (1993). *Manual of NeuroShell 2.* Frederick, MD.

Warmund, M. R., Guinan, P., & Fernandez, G. (2008). Temperatures and Cold Damage to Small Fruit Crops Across the Eastern United States Associated with the April 2007 Freeze. *HortScience*, *43*(6), 1643-1647.

Zhang, G., & Qi, M. (2005). Neural network forecasting for seasonal and trend time series. *European Journal of Operational Research, 160*(2), 501 - 514.

Table 1: Locations and years used partitioning weather data.

Model Development		**Model Evaluation**
2002, 2003, 2004, 2005, 2007, 2009		2006, 2008, 2010
Training Set	**Selection Set**	**Evaluation Set**
ATLANTA	ALMA	ALAPAHA
BRUNSWICK	ARABI	ALPHARETTA
CALLAWAY	BLEDSOE	ARLINGTON
COVINGTON	BOWEN	ATTAPULGUS
DALLAS	DEMPSEY	BLUE RIDGE
DAWSON	DIXIE	BYROMVILLE
DEARING	EATONTON	CAIRO
DULUTH	GEORGETOWN	CALHOUN
HOMERVILLE	GRIFFIN	CAMILLA
OAKWOOD	HOWARD	CLARKS HILL
SHELLMAN	JEFFERSONVILLE	CORDELE
TIFTON	LAFAYETTE	DANIELSVILLE
TIGER	PLAINS	DOUGLAS
WOODBINE	SPARTA	ELLIJAY
-	TENNILLE	HHERC*
-	-	MOULTRIE
-	-	NAHUNTA
-	-	NEWTON
-	-	ODUM
-	-	OSSABAW
-	-	SASSER
-	-	SAVANNAH
-	-	VALDOSTA
-	-	VIDALIA

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Table 2: Comparison of air temperature prediction by individual, individual series 4, individual series 6 and individual series 12, evaluation dataset.

Horizons	Individual	Series 4	% Reduction in MAE	Series 6	% Reduction in MAE	Series 12	% Reduction in MAE
1	0.889	**0.615**	30.79	0.627	29.53	0.707	20.52
2	0.959	**0.865**	9.78	0.886	7.60	0.952	0.73
3	1.170	**1.064**	9.10	1.082	7.54	1.134	3.07
4	1.262	**1.233**	2.32	1.263	-0.09	1.285	-1.84
5	1.413	1.438	-1.77	**1.391**	1.53	1.432	-1.34
6	1.565	1.544	1.35	**1.522**	2.73	1.543	1.43
7	**1.617**	1.638	-1.33	1.655	-2.36	1.634	-1.07
8	**1.707**	1.743	-2.12	1.737	-1.73	1.724	-0.97
9	1.825	**1.796**	1.58	1.805	1.12	1.806	1.05
10	1.848	**1.847**	0.06	1.856	-0.40	1.875	-1.45
11	**1.916**	1.924	-0.40	1.945	-1.51	1.925	-0.48
12	2.016	**1.977**	1.94	2.010	0.30	1.992	1.2
	3/12	7/12	(Avg.) 4.28	2/12	(Avg.) 3.69	0/12	(Avg.) 1.74

Table 3: Comparison of air temperature prediction by individual, combined, combined series 4, combined series 6 and combined series 12, evaluation dataset.

Horizons	Individual	Comb.	% Reduction	Comb. 4	% Reduction	Comb. 6	% Reduction	Comb. 12	% Reduction
1	0.889	0.846	4.84	**0.646**	27.37	0.684	23.11	0.733	17.51
2	0.959	0.942	1.77	**0.922**	3.85	0.932	2.87	0.988	-3.01
3	1.170	**1.080**	7.69	1.135	3.02	1.132	3.27	1.157	1.15
4	1.262	**1.256**	0.48	1.296	-2.73	1.313	-4.07	1.373	-8.81
5	1.413	**1.383**	2.12	1.428	-1.05	1.424	-0.77	1.490	-5.46
6	1.565	1.543	1.41	**1.523**	2.67	1.550	0.98	1.605	-2.53
7	**1.617**	1.621	-0.25	1.631	-0.85	1.658	-2.50	1.669	-3.20
8	1.707	**1.705**	0.12	1.709	-0.14	1.715	-0.45	1.721	-0.80
9	1.825	**1.787**	2.08	1.834	-0.47	1.787	2.07	1.808	0.91
10	1.848	**1.830**	0.97	1.893	-2.41	1.848	-0.01	1.874	-1.42
11	1.916	1.918	-0.10	**1.909**	0.36	1.910	0.34	1.929	-0.68
12	2.016	1.975	2.03	1.977	1.91	**1.969**	2.33	2.003	0.65
	1/12	6/12	(Avg.) 1.93	4/12	(Avg.) 2.63	1/12	(Avg.) 2.26	0/12	(Avg.) -0.47

Table 4: Comparison of air temperature MAE for Individual, Combined and Series models

Horizon	Individual	Series 4	Series 6	Series 12	Combined	Combined 4	Combined 6	Combined 12
1	0.889	**0.615**	0.627	0.707	0.846	0.646	0.684	0.733
2	0.959	**0.865**	0.886	0.952	0.942	0.922	0.932	0.988
3	1.170	**1.064**	1.082	1.134	1.080	1.135	1.132	1.157
4	1.262	**1.233**	1.263	1.285	1.256	1.296	1.313	1.373
5	1.413	1.438	1.391	1.432	**1.383**	1.428	1.424	1.490
6	1.565	1.544	**1.522**	1.543	1.543	1.523	1.550	1.605
7	**1.617**	1.638	1.655	1.634	1.621	1.631	1.658	1.669
8	1.707	1.743	1.737	1.724	**1.705**	1.709	1.715	1.721
9	1.825	1.796	1.805	1.806	**1.787**	1.834	1.787	1.808
10	1.848	1.847	1.856	1.875	**1.830**	1.893	1.848	1.874
11	1.916	1.924	1.945	1.925	1.918	**1.909**	1.910	1.929
12	2.016	1.977	2.010	1.992	1.975	1.977	**1.969**	2.003
	1/12	4/12	1/12	0/12	4/12	1/12	1/12	0/12
	-	4.28	3.69	1.74	1.93	2.63	2.26	-0.47

Table 5: Comparison of dew point temperature prediction by individual, individual series 4, individual series 6 and individual series 12, evaluation dataset.

Horizons	Individual	Series 4	% Reduction in MAE	Series 6	% Reduction in MAE	Series 12	% Reduction in MAE
1	0.818	**0.670**	18.11	0.674	17.66	0.754	7.84
2	**0.890**	0.911	-2.36	0.912	-2.49	0.983	-10.4
3	**1.073**	1.121	-4.46	1.132	-5.52	1.182	-10.2
4	**1.261**	1.295	-2.70	1.311	-3.99	1.350	-7.03
5	**1.424**	1.466	-2.94	1.479	-3.88	1.537	-7.94
6	1.600	**1.597**	0.19	1.608	-0.49	1.636	-2.24
7	**1.711**	1.733	-1.26	1.798	-5.11	1.762	-2.95
8	1.836	**1.833**	0.18	1.893	-3.08	1.874	-2.06
9	**1.954**	2.000	-2.35	1.991	-1.89	1.974	-1.04
10	**2.052**	2.077	-1.21	2.091	-1.92	2.093	-2.01
11	**2.155**	2.182	-1.25	2.172	-0.78	2.163	-0.38
12	**2.247**	2.258	-0.47	2.259	-0.52	2.264	-0.74
	9/12	3/12	(Avg.) -0.04	0/12	(Avg.) -1.00	0/12	(Avg.) -3.26

Table 6: Comparison of dew point temperature prediction by individual, combined, combined series 4, combined series 6 and combined series 12, evaluation dataset.

Horizons	Individual	Comb.	% Reduction	Comb. 4	% Reduction	Comb. 6	% Reduction	Comb. 12	% Reduction
1	0.818	0.842	-2.93	**0.601**	26.59	0.667	18.45	0.676	17.39
2	0.890	0.880	1.12	**0.866**	2.73	0.900	-1.08	0.918	-3.18
3	**1.073**	1.081	-0.75	1.075	-0.17	1.096	-2.14	1.125	-4.85
4	**1.261**	1.264	-0.24	1.304	-3.41	1.276	-1.22	1.319	-4.59
5	1.424	**1.416**	0.56	1.437	-0.89	1.430	-0.39	1.483	-4.12
6	1.600	1.585	0.94	**1.570**	1.91	1.577	1.45	1.610	-0.65
7	1.711	1.720	-0.53	**1.705**	0.37	1.734	-1.36	1.716	-0.27
8	1.836	**1.809**	1.47	1.823	0.70	1.838	-0.10	1.835	0.06
9	1.954	1.965	-0.56	1.977	-1.17	1.961	-0.35	**1.931**	1.18
10	2.052	**2.030**	1.07	2.065	-0.62	2.065	-0.64	2.033	0.92
11	2.155	2.151	0.19	2.156	-0.04	2.146	0.42	**2.137**	0.85
12	2.247	2.276	-1.29	**2.233**	0.62	2.249	-0.08	2.248	-0.04
	2/12	3/12	(Avg.) -0.08	5/12	(Avg.) 2.22	0/12	(Avg.) 1.08	2/12	(Avg.) 0.23

Table 7: Comparison of dew point temperature MAE for Individual, Combined and Series models.

Horizon	Individual	Series 4	Series 6	Series 12	Combined	Combined 4	Combined 6	Combined 12
1	0.818	0.670	0.674	0.754	0.842	**0.601**	0.667	0.676
2	0.890	0.911	0.912	0.983	0.880	**0.866**	0.900	0.918
3	**1.073**	1.121	1.132	1.182	1.081	1.075	1.096	1.125
4	**1.261**	1.295	1.311	1.350	1.264	1.304	1.276	1.319
5	1.424	1.466	1.479	1.537	**1.416**	1.437	1.430	1.483
6	1.600	1.597	1.608	1.636	1.585	**1.570**	1.577	1.610
7	1.711	1.733	1.798	1.762	1.720	**1.705**	1.734	1.716
8	1.836	1.833	1.893	1.874	**1.809**	1.823	1.838	1.835
9	1.954	2.000	1.991	1.974	1.965	1.977	1.961	**1.931**
10	2.052	2.077	2.091	2.093	**2.030**	2.065	2.065	2.033
11	2.155	2.182	2.172	2.163	2.151	2.156	2.146	**2.137**
12	2.247	2.258	2.259	2.264	2.276	**2.233**	2.249	2.248
	2/12	0/12	0/12	0/12	3/12	5/12	0/12	2/12
	-	-0.04	-1.00	-3.26	-0.08	2.22	1.08	0.23

Table 8: Comparison of prediction anomalies produced by individual, individual series 4, individual series 6 and individual series 12, evaluation set.[8]

Horizons	Individual		Series 4			Series 6			Series 12		
	#	%	#	%	% Reduction	#	%	% Reduction	#	%	% Reduction
1	33252	6.6	**20743**	4.1	37.62	21422	4.2	35.58	33851	6.7	-1.80
2	21161	4.2	19725	3.9	6.79	**19667**	3.9	7.06	38935	7.7	-83.99
3	**14367**	2.8	18713	3.7	-30.25	20647	4.1	-43.71	33783	6.7	-135.14
4	18775	3.7	**15993**	3.2	14.82	21216	4.2	-13.00	34664	6.8	-84.63
5	**17885**	3.5	26961	5.3	-50.75	20399	4.0	-14.06	31603	6.2	-76.70
6	**16593**	3.3	25744	5.1	-55.15	17953	3.5	-8.20	30771	6.1	-85.45
7	**19345**	3.8	21120	4.2	-9.18	37466	7.4	-93.67	28296	5.6	-46.27
8	**15595**	3.1	22220	4.4	-42.48	34826	6.9	-123.32	29190	5.8	-87.18
9	**11845**	2.3	17153	3.4	-44.81	33575	6.6	-183.45	30095	5.9	-154.07
10	**12815**	2.5	15293	3.0	-19.34	29404	5.8	-129.45	27558	5.4	-115.04
11	21833	4.3	**16225**	3.2	25.69	28536	5.6	-30.70	25729	5.1	-17.84
12	**12676**	2.5	14284	2.8	-12.69	30615	6.0	-141.52	24364	4.8	-92.21
	8/12		3/12		(Avg.) -14.98	1/12		(Avg.) -61.54	0/12		(Avg.) -81.69

[8] The prediction anomalies were obtained after presenting the models with all 507,347 patterns from the evaluation set.

Table 9: Comparison of prediction anomalies produced by individual, combined, combined series 4, combined series 6 and combined series 12, evaluation set.[9]

Horizons	Individual		Combined			Combined Series 4			Combined Series 6			Combined Series 12		
	#	%	#	%	% Redt.	#	%	% Redt.	#	%	% Redt.	#	%	% Redt.
1	33252	6.6	31723	6.3	4.60	**10524**	2.1	68.35	24006	4.7	27.81	25855	5.1	22.25
2	21161	4.2	**12857**	2.5	39.24	16419	3.2	22.41	15852	3.1	25.09	25754	5.1	-21.71
3	14367	2.8	**7331**	1.4	48.97	9805	1.9	31.75	18800	3.7	-30.86	24558	4.8	-70.93
4	18775	3.7	11142	2.2	40.66	**10271**	2.0	45.29	12586	2.5	32.96	27468	5.4	-46.30
5	17885	3.5	**11394**	2.2	36.29	14931	2.9	16.52	11949	2.4	33.19	24642	4.9	-37.78
6	16593	3.3	11989	2.4	27.75	11995	2.4	27.71	**9435**	1.9	43.14	28590	5.6	-72.30
7	19345	3.8	**15054**	3.0	22.18	17017	3.4	12.03	15151	3.0	21.68	25733	5.1	-33.02
8	15595	3.1	13292	2.6	14.77	14626	2.9	6.21	**11000**	2.2	29.46	24579	4.8	-57.61
9	11845	2.3	**8281**	1.6	30.09	16047	3.2	-35.47	10893	2.1	8.04	17288	3.4	-45.95
10	12815	2.5	**9061**	1.8	29.29	9589	1.9	25.17	9669	1.9	24.55	19664	3.9	-53.45
11	21833	4.3	8619	1.7	60.52	11395	2.2	47.81	**6559**	1.3	69.96	17279	3.4	20.86
12	12676	2.5	**5723**	1.1	54.85	7520	1.5	40.68	6917	1.4	45.43	18249	3.6	-43.96
		0/12		7/12	(Avg.) 34.10		2/12	(Avg.) 25.71		3/12	(Avg.) 27.54		0/12	(Avg.) -36.66

[9] The prediction anomalies were obtained after presenting the models with all 507,347 patterns from the evaluation set.

Table 10: Comparison of prediction anomalies for Individual, Combined and Series models.[10]

Horizon	Individual	Series 4	Series 6	Series 12	Combined	Combined 4	Combined 6	Combined 12
1	33252	20743	21422	33851	31723	**10524**	24006	25855
2	21161	19725	19667	38935	**12857**	16419	15852	25754
3	14367	18713	20647	33783	**7331**	9805	18800	24558
4	18775	15993	21216	34664	11142	**10271**	12586	27468
5	17885	26961	20399	31603	**11394**	14931	11949	24642
6	16593	25744	17953	30771	11989	11995	**9435**	28590
7	19345	21120	37466	28296	**15054**	17017	15151	25733
8	15595	22220	34826	29190	13292	14626	**11000**	24579
9	11845	17153	33575	30095	**8281**	16047	10893	17288
10	12815	15293	29404	27558	**9061**	9589	9669	19664
11	21833	16225	28536	25729	8619	11395	**6559**	17279
12	12676	14284	30615	24364	**5723**	7520	6917	18249
	0/12	0/12	0/12	0/12	7/12	2/12	3/12	0/12
	-	-14.98	-61.54	-8169	34.10	25.71	27.54	-36.66

[10] The prediction anomalies were obtained after presenting the models with all 507,347 patterns from the evaluation set.

Table 11: Comparison of average % reduction in air temperature MAE, dew point temperature MAE and number of prediction anomalies.

Model Type	Average % Reduction		
	Air Temperature	**Dew Point Temperature**	**Prediction Anomalies**
Series 4	4.28	-0.04	-14.98
Series 6	3.69	-1	-61.54
Series 12	1.74	-3.26	-81.69
Combined	1.93	-0.08	34.1
Combined Series 4	**2.63**	**2.22**	**25.71**
Combined Series 6	**2.26**	**1.08**	**27.54**
Combined Series 12	-0.47	0.23	-36.66

CHAPTER 4

SUMMARY AND CONCLUSIONS

The two goals in this research were to (1) evaluate the combined models in predicting the air and dew point temperatures by comparing the reduction in MAE and prediction anomalies (2) evaluate the time series models in predicting air and dew point temperatures by comparing the reduction in MAE and prediction anomalies.

In Chapter 2, the individual and the combined model are compared using mean absolute errors (MAE) for air and dew point temperature and number of prediction anomalies. A methodology was proposed to combine the air temperature model and the dew point temperature model to develop a single model. Using this methodology combined models were developed. The MAE for air and dew point temperature, and the number of prediction anomalies were calculated. It was found that the combined models were able to produce considerable reduction in the number of prediction anomalies, meanwhile producing slight reduction in MAEs in comparison with the individual air temperature and dew point temperature models. In Chapter 3 the individual and the time series model are compared using mean absolute errors (MAE) for air and dew point temperature and number of prediction anomalies. A methodology was proposed to combine the models across the prediction horizons. Using this methodology time series models for four, six and twelve hour prediction horizons were developed. The MAE for air and dew point temperature, and prediction anomalies were calculated. The four-hour time series air temperature model produced largest reduction in the air temperature MAEs making it a possible candidate solution for air temperature prediction. The combined four-hour time series model produced largest reduction in dew point temperature MAEs making it a possible candidate solution for dew point temperature prediction. The combined model for single prediction horizon produced the largest reduction in the number of prediction anomalies making it a possible candidate solution for both air and dew point temperature prediction based only on reduction in prediction anomalies. The combined four-hour time series model and combined six-hour time series model both produced reduction in MAEs and prediction anomalies making them candidate solutions for air temperature and dew temperature predictions.

Models developed in this research were based on previous work. In future research the ANN parameters such as number of nodes in the hidden layer could be explored for improvement in MAE or reduction in the number of anomalies. Also, a longer duration of prior data and different resolution of input data, different activation functions, and the input data could be transformed using fuzzy membership functions. Alternate architectures such as recurrent neural networks, hybrid neural networks, and alternative training algorithms such as scaled conjugate gradient propagation, quick-propagation, Manhattan-propagation, Lavenberg-Marquardt algorithm and evolutionary training algorithms could be applied. The training data could be further examined so that the patterns are distributed evenly for the various temperature values.

BIBLIOGRAPHY

Anastasiadis, A. D., Magoulas, G. D., & Vrahatis, M. N. (2005). New globally convergent training scheme based on the resilient propagation algorithm. *Neurocomputing, 64*, 253 - 270.

Attaway, J. A. (1997). *A History of Florida Citrus Freezes.* Lake Alfred, FL: Florida Science Source, Inc.

Chakraborty, K., Mehrotra, K., Mohan, C. K., & Ranka, S. (1992). Forecasting the behavior of multivariate time series using neural networks. *Neural Networks, 5*(6), 961 - 970.

Chevalier, R., Hoogenboom, G., McClendon, R., & Paz, J. (2011). Support vector regression with reduced training sets for air temperature prediction: a comparison with artificial neural networks. *Neural Comput. Appl., 20*, 151-159.

Chevalier, R., Hoogenboom, G., McClendon, R., & Paz, J. (2012). A web-based fuzzy expert system for frost warnings in horticultural crops. *Environmental Modelling & Software (In Press).*

Cooper, W. C., Young, R. H., & Turrell, F. M. (1964). Microclimate and physiology of citrus: Their relation to cold protection. 38-50.

Fauci, A. (2008). Harrison's Principles of Internal Medicine. *McGraw-Hill Professional*.

Fonsah, E. G., Taylor, K. C., & Funderburk, F. (2007). Enterprise cost analysis for middle. *Technical Report*(AGECON-06-118).

Gevrey, M., Dimopoulos, I., & Lek, S. (2003). Review and comparison of methods to study the contribution of variables in artificial neural network models. *Ecological Modelling, 160*, 249 - 264.

Grundstein, A., Ramseyer, C., Zhao, F., Pesses, J., Akers, P., Qureshi, A., et al. (2012). A retrospective analysis of American football hyperthermia deaths in the United States. *International Journal of Biometeorology, 56*, 11-20.

Haykin, S. (1999). *Neural networks: a comprehensive foundation, 2nd edition.* Upper Saddle River, NJ: Prentice Hall.

Hochmuth, G. J., Kostewicz, S., & Martin, F. (1993). Irrigation Method and Rowcover Use for Strawberry Freeze Protection. *Journal of the American Society for Horticultural Science, 118*, 575-579.

Hoogenboom, G. (2000). The Georgia Automated Enviromnental Monitoring Network. *Preprints of the 24th Conference On Agricultural and Forest Meteorology* (pp. 24-25). American Meteorological Society.

Hoogenboom, G. (2005). The Georgia Automated Environmental Monitoring Network: experiences with the development of a state-wide automated weather station network. *Proceedings of the 13th Symposium on Meteorological Observations and Instrumentation & 15th Conference on Applied Climatology.* Boston: American Society of Meteorology.

Hoogenboom, G., Coker, Edenfield, Evans, & Fang. (2003, April). The georgia automated environmental monitoring network: ten years of weather information for water resources management. *Proceedings of the 2003 Georgia Water Resources Conference*.

Igel, C., & Hüsken, M. (2003). Empirical evaluation of the improved Rprop learning algorithms. *Neurocomputing, 50*(0), 105 - 123.

Jain, A. (2003). Frost prediction using artificial neural networks: A temperature prediction approach. *M.S. thesis*.

Jain, A., McClendon, R. W., Hoogenboom, G., & Ramyaa, R. (2003). Prediction of frost for fruit protection using artificial neural networks. *American Society of Agricultural Engineers, 03*, 3075.

Jones, G. M., & Stallings, C. C. (1999). *Reducing heat stress for dairy cattle.* Virginia Cooperative Extension.

Martsolf, J. D., Gerber, J. F., Chen, E. Y., Jackson, H. L., & Rose, A. J. (1984). What do satellite and other data suggest about past and future florida freezes? *In Proceedings of the Florida State Horticultural Society*, (pp. 17-21).

Narendra, K. S., & Mukhopadhyay, S. (1994). Adaptive control of nonlinear multivariable systems using neural networks. *7*(5), 737 - 752.

Perry, K. B. (1998). *Basics of Frost and Freeze Protection for Horticultural Crops* (8 ed.). HortTechnology.

Riedmiller, M., & Braun, H. (1993). A direct adaptive method for faster backpropagation learning: the RPROP algorithm. *IEEE International Conference on Neural Networks*, (pp. 586 -591).

Robinson, P. J. (2000). Temporal trends in United States dew point temperatures. *International Journal of Climatology*, 985-1002.

Sandstrom, M. A., Lauritsen, R. G., & Changnon, D. (2004, May-June). A Central-U.S. Summer Extreme Dew-Point Climatology (1949-2000). *Physical Geography, 25*(3), 191-207.

Shank, D. B., McClendon, R. W., & Paz, J. a. (2008). Ensemble artificial neural networks for prediction of dew point temperature. *Applied Artificial Intelligence, 22*(6), 523-542.

Shank, D., Hoogenboom, G., & McClendon, R. (2008). Dewpoint Temperature Prediction Using Artificial Neural Networks. *Journal of Applied Meteorology and Climatology, 47*, 1757.

Smith, B. A., Hoogenboom, G., & McClendon, R. W. (2009). Artificial neural networks for automated year-round temperature prediction. *Computers and Electronics in Agriculture, 68,* 52-61.

Smith, B. A., McClendon, R. W., & Hoogenboom, G. (2008). Improving Air Temperature Prediction with Artificial Neural Networks.

Ward System Group. (1993). *Manual of NeuroShell 2.* Frederick, MD.

Warmund, M. R., Guinan, P., & Fernandez, G. (2008). Temperatures and Cold Damage to Small Fruit Crops Across the Eastern United States Associated with the April 2007 Freeze. *HortScience, 43*(6), 1643-1647.

Zhang, G., & Qi, M. (2005). Neural network forecasting for seasonal and trend time series. *European Journal of Operational Research, 160*(2), 501 - 514.