DEW POINT TEMPERATURE PREDICTION USING ARTIFICIAL NEURAL NETWORKS

by

DANIEL B. SHANK

(Under the Direction of Ronald W. McClendon)

ABSTRACT

Dew point temperature is the temperature at which water vapor condenses. It is an important weather variable used to estimate frost, fog, rain, snow, dew, evapotranspiration, near-surface humidity, and other meteorological variables. Dew point temperature directly or indirectly contributes to productivity of plants, crop damage during freezes, human comfort levels, and the loss of human life during heat waves. Although several studies have focused on the estimation of dew point temperature, little attention has been given to short term prediction. An artificial neural network (ANN) is a robust computational tool useful for prediction. The goal of this research was to develop ANNs that predict hourly dew point temperatures for up to twelve hours. This system of ANNs was trained on historical weather data from stations located throughout the state of Georgia. These ANNs will be implemented as part of a web-based decision support system.

INDEX WORDS: Artificial Neural Networks, Dew Point Temperature, Ensemble Networks, Decision Support System, Air Temperature, Weather Data, Fuzzy Logic.

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DANIEL B. SHANK

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DANIEL B. SHANK

Major Professor: Dr. Ronald W. McClendon

Committee: Dr. Gerrit Hoogenboom
Dr. Michael A. Covington

Electronic Version Approved:

Maureen Grasso
Dean of the Graduate School
The University of Georgia
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DEDICATION

I dedicate this thesis to Tim Baird, Steve Baber, and Scott Ragsdale, who influenced my academic priorities and more importantly my life priorities.

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CHAPTER 1

INTRODUCTION

Dew point temperature is the temperature at which water vapor in the air will condense into dew, frost, or water droplets given a constant air pressure. It can be defined alternately as the temperature at which the saturation vapor pressure and actual vapor pressure are equal (Merva, 1975). Dew point temperature together with relative humidity can be used to determine the moisture content in the air. A dew point temperature below 0˚C is referred to as the frost point because frost is produced when the air cools to that temperature.

Dew point temperature is a good estimate of near-surface humidity and can affect the stomatal closure in plants, where the productivity of the plants can be reduced by low humidity (Kimball et al., 1997). Dew can be essential to plant survival, especially in arid regions that infrequently have rainfall (Agam and Berliner, 2006). Many agronomical, ecological, hydrological, and climatological models require dew point temperature as an input to estimate evapotranspiration (Hubbard et al., 2003). Dew point temperature may be used in calculating actual vapor pressure or estimating relative humidity (Mahmood and Hubbard, 2005). Dew point temperature coupled with wet-bulb temperature can be used to calculate critical damage air temperature, allowing producers to respond to potential frosts that may damage crops (Snyder and Melo-Abreu, 2005). During a summer heat wave in of 1995 in the Midwestern United States, over 1000 people died due to a combination of high air temperatures and high dew point temperatures (Sandstrom et al., 2004).

Hubbard et al. (2003) developed a regression model for estimating daily average dew point temperature with a mean absolute error (MAE) of 2.20˚C. Although estimations of this type are useful for determining values for missing historical weather data, they do not allow the prediction of values in the future. Diab and Saade (1999) used a fuzzy logic inference system to predict dew point temperature one day ahead with absolute errors ranging to 8˚C.

An artificial neural network (ANN) is a robust computational technique primarily used for pattern recognition, classification, and prediction (Bose and Liang, 1996; Haykin, 1999). The use of ANNs in meteorological applications includes prediction of ozone concentration, sulfur dioxide concentration, tornadoes, storms, solar radiation, carbon dioxide, pollutants, and monsoon rainfall (Gardner and Dorling, 1998), monthly and year precipitation levels (Bodri and Cermak, 2000), tide charts (Steidley et al., 2005), wave heights (Wedge et al., 2005), flash floods (Luk et al., 2000), and air temperature (Jain et al., 2003; Smith et al., 2006). Mittal and Zhang (2003) developed an ANN model for estimation, not prediction, of dew point temperature and other weather variables using dry-bulb temperature and relative humidity as inputs. Psychrometric charts were used for their dataset instead of actual historical data with an estimated dew point temperature MAE of 0.305˚C.

Multiple ANNs can be combined into one model in what is referred to as an ensemble ANN. Maqsood et al. (2004) use single ANNs and ensemble ANNs for prediction of air temperature, wind speed, and humidity. Each of these models was not only trained and evaluated individually, but also was incorporated into two ensemble network types: a winner-take-all and a weighted average, both based on classification certainty of the member networks. Cannon and Lord (2000) used ensemble networks for the prediction of maximum hourly ozone concentration, useful for predicting extreme ozone conditions which may be hazardous. They developed multiple resilient error backpropagation ANNs to form an ensemble networks using bootstrap aggregation with resulting MAEs of 4.6 ppb to 6.6 ppb.

Dew point temperature has been estimated (Kimball et al., 1997; Mahmood and Hubbard, 2005; Mittal and Zhang, 2003; Parlange and Katz, 2000) and analyzed for long-term trends (Robinson, 1998; Robinson, 2000; Sandstrom et al., 2004), but there is little research on short-term dew point temperature prediction. The goal of this thesis research is to develop ANN models to predicted dew point temperature for up to twelve hours ahead. To accomplish this goal, Georgia statewide historical weather data from the University of Georgia Automated Environmental Monitoring Network (AEMN) is used. The AEMN provides applications through their website (www.georgiaweather.net) useful for natural resource management and agricultural decision-making (Hoogenboom, 2000). Over 70 weather stations spread throughout Georgia collect and aggregated weather data every 15 minutes into totals or averages from values collected each second. The ANN dew point temperature prediction models will be incorporated as a decision support system application for the AEMN website.

Chapter 1 provides background information to the dew point temperature domain, a brief review of related literature, and the goal of this thesis. Chapter 2 introduces the problem fully, and then describes the model development, methodology, experiment results, and primary conclusions and application potential. Chapter 3 enhances the Chapter 2 model by introducing alternate ANN stopping criteria, seasonal models, and ensemble ANN networks with seasonal member ANNs and provides a discussion of the application of this model as part of a decision support system. Chapter 4 summarizes all the research and draws conclusions suggesting possible future research.

CHAPTER 2

DEW POINT TEMPERATURE PREDICTION USING ARTIFICIAL NEURAL NETWORKS[1]

[1] Shank, D.B., G. Hoogenboom, and R. W. McClendon. To be submitted to *Agricultural and Forest Meteorology*.

ABSTRACT

Dew point temperature is the temperature at which water vapor in the air will condense into liquid. This temperature can be useful in estimating frost, fog, rain, snow, dew, evapotranspiration, and other meteorological variables. Dew point temperature is useful in the estimation of near-surface humidity, which can affect the stomatal closure in plants and contributes to human and animal comfort levels. The goal of this study was to use artificial neural networks (ANNs) to predict dew point temperature from one to twelve hours ahead using prior weather data as inputs. This study explores using three-layer backpropagation ANNs and weather data combined for three year from 20 locations in Georgia, United States, to develop non-location-specific models for dew point temperature prediction. Specific objectives included selection of the important weather related inputs, setting of ANN parameters, and selection of the duration of prior data. An iterative search found that in addition to dew point temperature, important weather related ANN inputs included relative humidity, solar radiation, air temperature, wind speed, and vapor pressure. Experiments also showed the best models included 60 nodes in the ANN hidden layer, a ±0.15 initial range for the ANN weights, a 0.35 ANN learning rate, and a duration of prior weather related data used as inputs ranging from six to 30 hours based on the prediction period. The evaluation of the final models with weather data from 20 separate locations and a different year showed that the one-hour prediction had a mean absolute error (MAE) of 0.550˚C, the four-hour prediction model had an MAE of 1.234˚C, the eight-hour prediction had an MAE of 1.799˚C, and the twelve-hour prediction had an MAE of 2.280˚C. These final models adequately predicted dew point temperature using previously unseen weather data, including difficult freeze and heat

stress extremes. Future research could include exploring alternate stopping criteria for ANN training and developing seasonal ANN models that could be combined into an ensemble ANN.

INTRODUCTION

Dew point temperature is the temperature at which water vapor in the air will condense into dew or water droplets given that the air pressure remains constant. Alternatively, it can be defined as the temperature at which the saturation vapor pressure and actual vapor pressure are equal (Merva, 1975). Dew point temperature coupled with relative humidity can be used to determine the amount of moisture in the air. Dew point temperature is a good estimate of near-surface humidity, which can affect the stomatal closure in plants, where a low humidity can reduce the productivity of the plants (Kimball et al., 1997). When the surface air temperature drops to the level of the dew point temperature, dew forms. Especially in arid regions that have infrequent rainfall, the dew can be essential to plant survival (Agam and Berliner, 2006).

Many agronomical, ecological, hydrological, and climatological models require dew point temperature as an input to estimate evapotranspiration (Hubbard et al., 2003). Dew point temperature may also be used to calculate actual vapor pressure or estimate relative humidity (Mahmood and Hubbard, 2005). Dew point temperature coupled with wet-bulb temperature can be used to calculate critical damage air temperature for specific crops, allowing producers to respond to potential frosts that may damage them (Snyder and Melo-Abreu, 2005). Heat waves, which cause damage and take the lives of people, are intensified by high dew point temperatures (Sandstrom et al., 2004). A study by Robinson (2000) suggests that the dew point temperature in the United States is slowly increasing over time and, therefore, could be an important weather variable for studies on long-term climate change.

Hubbard et al. (2003) developed a regression model for estimating the daily average dew point temperature, using the daily mean, minimum, and maximum air temperature as inputs. Their research used 14 years of data for six cities from South Dakota, Nebraska, Colorado, and Kansas in the United States. Their regression equation based on multiple cities was more accurate than the regression equations for each of the individual cities, with a mean absolute error (MAE) of 2.2˚C for the most accurate regression equation. These types of estimations are useful for determining the values for missing historical weather data, but do not allow the prediction of future values.

Diab and Saade (1999) used a fuzzy inference system with rules developed based on their own intuition about the correlation of weather variables to predict dew point temperature for exactly 24 hours ahead. The inference rules used the season of the year, barometric pressure, air temperature, and wind speed as inputs, each with their own fuzzy membership functions while the output dew point temperature membership functions were expressed as low, medium, and high. The evaluation with 40 uniformly distributed days for all four seasons in 1994 resulted in absolute errors ranging to a maximum of 8˚C with no mean error presented.

An artificial neural network (ANN) is a robust computational technique modeled after biological neuron connections found in human brains (Bose and Liang, 1996; Haykin, 1999). ANNs have been used for to help solve many real world problems such as pattern matching, classification, and prediction (Bose and Liang, 1996; Gardner and Dorling, 1998; Haykin, 1999). Often ANNs have been often used in the atmospheric sciences. Gardner and Dorling (1998) review ANNs used for prediction of ozone concentration and daily maximum ozone, sulfur dioxide concentration, tornadoes, thunderstorms, solar radiation, carbon dioxide, pollutants and monsoon rainfall. More recently, Bodri and Cermack (2000) used an ANN and 38 years of rainfall data to predict monthly and yearly precipitation levels for multiple sites in the Czech Republic. Using spatial and temporal data of recent rainfall, Luk et al. (2000) developed an ANN for short-term precipitation prediction focused on predicting flash flood rainfall amounts for 15 minutes ahead for various areas of western Sydney, Australia. Maqsood et al. (2004) used an ensemble of ANNs to provide 24-hour predictions for air temperature, wind speed, and humidity at the Regina Airport in Canada. Wedge et al.(2005) developed an ANN for prediction of waves spilling over sea walls in using sea conditions and wall properties as inputs. Steidley et al. (2005) use ANNs to predict tide charts for periods of 3 to 48 hours ahead for a shallow embayment on the coast of Texas, United States.

Jain et al. (2003) developed ANNs to predict hourly air temperatures for one to twelve hours for three locations in Georgia, United States using inputs of current air temperature, relative humidity, solar radiation, and wind speed along with up to six hours of prior data. The MAEs for each location varied from 0.6˚C to 0.7˚C for the one-hour prediction period and 2.4˚C to 3.0˚C for the twelve-hour prediction period. Smith et al. (2006) improved on the results of Jain et al. (2003) by using cyclic variables to represent the day of year and time of day as additional inputs to the ANN. Smith at el. (2006) also trained multiple ANNs with the same parameters but different initial weights and found that the minimum error on multiple networks provided an improved comparison during model development, with an MAE of 0.54˚C for a one-hour prediction and 2.33˚C for a twelve-hour prediction for the evaluation dataset.

Mittal and Zhang (2003) developed ANNs to estimate several weather variables using other weather variables, a process used for estimating missing historical data. Their ANN estimations provided an alternative to the traditional estimations done with psychrometric charts and mathematical models. They developed an ANN model to estimate wet-bulb temperature, enthalpy, humidity ratio, specific volume, and dew point temperature using dry-bulb temperature and relative humidity as inputs. Their dataset included values obtained from the psychrometric charts which did not correspond to actual historical data or specific locations, but rather to known relationships among weather variables. The MAE for the dew point temperature estimation was 0.305˚C.

Dew point temperature has been estimated (Kimball et al., 1997; Mahmood and Hubbard, 2005; Mittal and Zhang, 2003; Parlange and Katz, 2000) and analyzed for long-term trends (Robinson, 1998; Robinson, 2000; Sandstrom et al., 2004), but there is little research on short-term dew point temperature prediction. The overall goal of this project was to develop ANN models for predicting hourly dew point temperatures for up to twelve hours in advance. Specific objectives included to identify the important weather related inputs that affect dew point temperature prediction, to determine the preferred values of the ANN parameters, and to determine the preferred duration of prior data for each prediction period.

METHODOLOGY

The University of Georgia Automated Environmental Monitoring Network (AEMN) provides web-based delivery of current and historical weather data, as well as weather-based tools and applications useful for decision-making in agricultural production and natural resource management (www.georgiaweather.net) (Hoogenboom, 2000). With over 70 weather stations distributed throughout Georgia, each station collects weather data for variables such as air temperature, relative humidity, vapor pressure, wind speed and wind direction, solar radiation, atmospheric pressure, and rainfall. Vapor pressure deficit and dew point temperature are calculated based on these variables. The totals or averages, depending on the variable, are determined for each 15-minute interval based on one-second observations. Although the AEMN data collection began for some locations in 1992, the determination of dew point temperature only started in September 2002 following requests from the horticultural industry.

Data from 40 of the AEMN weather stations were used in this study. Twenty sites were used for model development, and 20 different sites were used for model evaluation. These sites were selected to represent the geographic and regional diversity of Georgia as shown in Figure 2.1. The years 2002 through 2004 were used for model development and the year 2005 was reserved for a final evaluation.

The initial weather related inputs considered included current and prior values of air temperature, relative humidity, vapor pressure, vapor pressure deficit, wind speed, solar radiation, rainfall, and dew point temperature. A sequence of prior values through the current value constitutes a history of that variable and is referred to as prior data. For each of the weather related variables, an hourly rate of change was calculated for prior points in time and used as an additional input. For example, the rate of change for dew point temperature between two and three hours prior to the time of prediction t is $T_{d(t-2)} - T_{d(t-3)}$. Smith et al. (2006) found that including the rate of change of weather related input variables reduced the MAE for air temperature prediction. Both time of day and day of year were included as inputs and encoded, due to the cyclic nature of days and years, using four cyclical variables with fuzzy logic type membership functions. An example of the fuzzy logic type membership function used for time of day is shown in Figure 2.2. If the time of day is 1200 hours, then the fuzzy logic membership functions shows 1.0 as the degree to which it is noon, and the degree to which it is the other three as 0.0. If the time of day is 0900, the fuzzy logic membership function shows the degree to which it is noon and morning as 0.5, and the degree to which it is evening and midnight as 0.0. If the time of day is an intermediate value, the fuzzy membership function gives a scaled value indicating how much that time of day is represented by the adjacent cyclic categories. Four similar fuzzy membership functions for seasons were used to represent the day of year.

An error backpropagation (EBP) algorithm was used as described by Haykin (1999) with a separate ANN model developed for each prediction period. The ANN had a Ward architecture with three fully-connected layers: input, hidden, and output. This architecture has three slabs of nodes in the single hidden layer with each the nodes in each slab using an alternative activation function (Ward System Group, 1993). The Ward architecture has been used for air temperature prediction (Jain et al., 2003; Smith et al., 2006) and dew point temperature estimation (Mittal and Zhang, 2003). Each of the three slabs had the same number of nodes and used the Gaussian, Gaussian complement, and hyperbolic tangent activation functions as shown in Figure 2.3. The number of nodes in each slab of the hidden-layer and number of input nodes were varied during model development. The output layer always consisted of a single node using a logistic activation function, and it represented the predicted dew point temperature (°C). Twelve separate models were developed to predict hourly dew point temperatures for prediction periods of one to twelve hours. The input layer was scaled to a range of 0.1 to 0.9 based on the extreme values for each input in the development dataset. These settings were based on previous work by Jain at al. (2003) and Smith et al. (2006), who showed that this type of ANN was suitable for air temperature prediction.

An EBP ANN model of this type has two modes. The first is a feed-forward mode where a set of inputs, x_i, where i ranges from 1 to I, is mapped to a single output z, by the following equations:

$$z = g\left(\beta_0 + \sum_{j=1}^{J} \beta_j \cdot y_j\right) \tag{1}$$

and

$$y_j = f_j\left(\alpha_{j0} + \sum_{i=1}^{I} \alpha_{ji} \cdot x_i\right) \tag{2}$$

where α_{ji} are the weights from the input layer to the hidden layer, β_j are the weights from the hidden layer to the output node, and y_j is output of the nodes in the hidden layer, where j ranged from 1 to J. The logistic activation function g is defined as follows:

$$g(n) = \frac{1}{1 + e^{-n}} \tag{3}$$

where n is the input to the activation function. The hyperbolic tangent, Gaussian, and Gaussian complement are the respective components of the hidden layer activation function f, defined as follows:

$$f_j(n) = \begin{cases} \tanh(n) & \textit{for } 0 < j \le \frac{1}{3}J \\ e^{-n^2} & \textit{for } \frac{1}{3}J < j \le \frac{2}{3}J \\ 1 - e^{-n^2} & \textit{for } \frac{2}{3}J < j \le J \end{cases} \tag{4}$$

where n is the input to the activation function. The second mode of the ANN is backpropagating the error to adjust the weights. The weight adjustment $\Delta(\beta_j)$ for each weight from the hidden layer to the output node β_j is defined as:

$$\Delta(\beta_j) = \eta \cdot g'\left(\beta_0 + \sum_{j=1}^{J} \beta_j \cdot y_j\right) \cdot (t - z) \cdot y_j \tag{5}$$

and the weight adjustment $\Delta(\alpha_{ji})$ for each weight from the input layer to the hidden layer α_{ji} is defined as:

$$\Delta(\alpha_{ji}) = \eta \cdot f_j'\left(\alpha_{j0} + \sum_{i=1}^{I} \alpha_{ji} \cdot x_i\right) \cdot g'\left(\beta_0 + \sum_{j=1}^{J} \beta_j \cdot y_j\right) \cdot (t - z) \cdot \beta_j \cdot x_i \tag{6}$$

where η is the learning rate and t is the target output value. The nodes y_0 and x_0 are bias nodes that are always set to one. The adjustments for all the weights were added after every training pattern and this is referred to as a learning event. An EBP ANN with all the parameters including inputs, initial weight range, number of hidden nodes per slab, and learning rate was referred to herein as a *model*. A single instantiation of the model with random initial weights and a randomly ordered set of training patterns selected from the development dataset was referred to as a *network*.

Traditionally, EBP ANNs use patterns in a training dataset to search iteratively for an optimal set of weights that connect the nodes between adjacent layers. The testing dataset is used to stop the training when the testing dataset error reaches a minimum. The selection dataset is used as a dataset to judge the error of that network after training has been stopped and a comparison of selection dataset errors is used for selection of parameters during model development. All model development was conducted using data from the development dataset, which consisted of approximately 1,560,000 observations. Preliminary tests indicated that a testing dataset was not necessary if the training dataset was sufficiently large. The error of the training and testing datasets, though slightly different, always tracked each other with as few as 20,000 independent observations in each dataset. For example, as the training dataset error continued to decrease, the testing dataset error did as well. Overtraining, where the ANN is able to make accurate predictions on the training dataset, but not on the testing and selection datasets, can be a problem for ANNs. These preliminary tests indicated overtraining was not a concern as the error continued to decrease on both training and testing datasets even after 5,000,000 learning events when the training and testing datasets consisted of at least 100,000 observations. Based on this it was decided that a testing dataset would not be used and a fixed number of learning events would be used to stop training. An epoch is one pass through all the patterns in the training dataset. With 100,000 observations in the training dataset the decrease in the error from epoch nine to ten was typically less than 0.01˚C and always less than 0.06˚C, so the stopping criteria for training was arbitrarily fixed at ten epochs of 100,000 patterns each, i.e., 1,000,000 learning events. For model development, the selection dataset errors were compared in order to select values of ANN parameters for determining the most accurate model.

Because the development data spanned less than three years, it was not partitioned into separate years for the training and selection datasets. To obtain the best representative sample the training and selection datasets consisted of 100,000 patterns randomly selected without replacement from the development dataset for each network. The training and selection datasets were non-overlapping in patterns, and each represented 20 cities for three years of data from 2002 to 2004.

In the first experiment, the preferred set of weather related inputs was determined using a six-hour prediction period. Dew point temperature, air temperature, relative humidity, vapor pressure, vapor pressure deficit, wind speed, solar radiation, and rainfall were the inputs considered in this search. Using an iterative approach, dew point temperature was the only weather related input considered, followed by the input that resulted in the minimum error when only one additional weather related input was considered. This model was then taken as the current preferred model, and the approach was continued to select the input that produced the minimum error when three weather related inputs were considered. This process was continued until all the possible inputs were included or models with additional inputs did not produce a smaller error than the previous preferred model. The initial ANN parameters were arbitrarily chosen to be 20 hidden nodes per slab for a total of 60 nodes in the hidden layer, a learning rate of 0.1, and an initial weight of ±0.2. An 18-hour duration of prior data was also used in this experiment.

In the second experiment, the preferred values were determined using a six-hour prediction period for the following ANN parameters: number of hidden nodes per slab, initial weight range, and learning rate. As each parameter was varied, the current preferred model was determined by the model with the minimum error. In the third experiment the preferred duration of prior data was determined for each prediction period ranging from one to twelve hours. Preliminary tests indicated that the duration of prior data was correlated to the prediction period and a search for the preferred model for all prediction periods should range from 6 to 30 hours. To help ensure the reliability of the preferred model for each prediction period, two models with longer durations of prior data and two models with shorter durations of prior data were developed.

The training for the final evaluation was conducted by training 30 networks for each of the twelve prediction periods using half of the development dataset, i.e. approximately 780,000 patterns, for a training dataset instead of the 100,000 patterns used during model development. The other half was used as a selection dataset to choose the preferred network for each prediction period model. The twelve preferred networks, which represented the twelve final models, were used in feed-forward mode for model evaluation on the evaluation dataset.

The mean absolute error (MAE) between predicted and observed dew point temperature for a particular dataset was selected as the measure of accuracy. For model development this was the selection dataset, and for model evaluation this was the evaluation dataset. Because each network was instantiated with random weights and the training and selection datasets were selected and ordered randomly, networks representing the same model produced different MAEs. 30 observations were considered as an adequate population sample to closely approximate statistical measurements such as the mean for the population (Freund and Wilson, 1993). Therefore, it was arbitrarily decided that 30 networks, referred to as a *network set*, would be used to determine the accuracy of a model during model development. The population then would be all instances of a model, and each network would be one sampling. As with any distribution, the more samples the higher the statistical validity, but computational time was also a consideration. One network trained for 1,000,000 learning events required one to six hours of computational time depending on the parameters, making 30 networks require

30 to 180 hours of computational time. Once trained, a network evaluated in feed-forward mode on 100,000 observations required only several minutes. All tests were conducted on 36 computers, i.e. 32 Pentium 4 and 4 Pentium 3, in the computer laboratories of the Department of Biological and Agricultural Engineering at the University of Georgia.

Because of the non-normal distribution for a network set, a number of different statistical measurements were considered to approximate the error of a model based on a network set. A preliminary test considered seven statistical measurements. Four statistical measurements of central tendency were considered: the mean, the mean truncated 20%, the mean truncated 40%, and the median. A truncated or trimmed mean is the mean of the remaining values after a percentage is removed, half from the minimums and half from the maximums. The truncated mean is useful as a robust measure of central tendency, especially for asymmetric distributions (Marazzi and Ruffieux, 1999). Three minimums were considered: the minimum, the average of the minimum five, and the average of the minimum ten. Of all seven statistical measures, the average of the minimum five provided the smallest range and standard deviation for the preliminary test. Therefore, the average of the minimum five MAEs for a network set was used to approximate the error of a model and was referred to as the MAE for that model during model development.

RESULTS AND DISCUSSION

Model Development

During the search for the important weather related inputs, several values were held constant including 20 hidden nodes per slab, an 18 hour duration of prior data, a 0.1 learning rate, a 0.2 initial weight range and a prediction period of six hours. The fuzzy membership function inputs for time of day and day of year (Figure 2.2) were also included in each model that was developed. When only dew point temperature was considered as a weather related input, the MAE was 1.620˚C (Table 2.1). The dew point temperature only model was then coupled with each possible remaining weather related input to determine the best two-weather-variable ANN. The model with dew point temperature and relative humidity produced the lowest MAE of 1.521˚C. Continuing with this approach, the weather related inputs in order of importance with respect to weather variables three through six were solar radiation, air temperature, wind speed, and vapor pressure. The ANN with six weather related inputs resulted in the lowest MAE, 1.463˚C (Table 2.1). Vapor pressure deficit and rain did not improve model accuracy when they were included. Vapor pressure deficit was calculated from vapor pressure so there was a covariance in predicting dew point temperature.

The number of hidden nodes per slab was varied from 10 to 70 in increments of 10. The MAE decreased from 1.471˚C to 1.463˚C when the number of hidden nodes was increased from 10 to 20 nodes per slab, but thereafter increasing the number of nodes per slab had a negligible effect on accuracy. Therefore, the number of hidden nodes per slab selected was 20.

The range of initial weights was varied from ±0.05 to ±0.40 in increments of 0.05. An initial weight range of ±0.15 resulted in the lowest MAE of 1.463˚C and was therefore selected for further model development. The learning rate was varied from 0.05 to 0.60 in increments of 0.05. A model with a learning rate of 0.35 had the lowest MAE, 1.445˚C, and was selected for further model development.

The duration of prior data was varied from six to 30 hours in increments of six hours for the twelve prediction periods, and in some cases the range of the duration was extended (Table 2.2). The model with the lowest MAE and, in the case of a tie, the lowest coefficient of variation (CV) for the MAE, for each prediction period was selected as the best model for model development. The best models for the one- and two-hour prediction periods were the models that included six hours of prior data; the best models for the five-, six-, seven-, nine- and twelve-hour prediction periods included 18 hours of prior data; the best models for the three-, four-, ten-, and eleven-hour prediction periods included 24 hours of prior data; and the best model for the eight-hour prediction period included 30 hours of prior data.

Model Evaluation

The final results for model evaluation are depicted in Figure 2.4. The MAEs for the one-, four-, eight-, and twelve-hour prediction models were 0.550˚C, 1.234˚C, 1.799˚C, and 2.281˚C, respectively, with a coefficient of determination (r^2) of 0.993, 0.964, 0.924, and 0.889, respectively. As expected the MAE values increased and the r^2 values decreased as the prediction period increased. There was also a tendency to overpredict at low dew point temperatures.

Sample periods were selected that included the extremes of low and high air temperature conditions to demonstrate the prediction of dew point temperature for these conditions. A sample period from March 18 to 20, 2005, for Dahlonega, Georgia, was selected as an example of two early morning freezes in late winter. This scenario would represent a situation in which a fruit crop could experience catastrophic damage from frost during the blooming phase of the crop. The predictions of dew point temperature for the one-, four-, eight-, and twelve-hour models indicate more accurate predictions for the shorter than the longer prediction periods during these winter freezes (Figure 2.5). The one- and four-hour predictions showed a drop in dew point temperature during the freeze event, but the four-hour model placed it later than it actually occurred. In contrast, the eight- and twelve-hour models did not predict the drop in dew point temperature, but instead predicted that it would remain steady around 1˚C to 3˚C. Similarly, the low dew point temperature between 1200 and 1800 on March 19 was predicted well by the one-hour prediction, fairly accurately with the four-hour model predicting an even lower dew point temperature, and less accurately by the eight- and twelve-hour models that predicted higher values for the dew point temperature than actually occurred.

For the prediction of a high dew point temperature associated with an extreme of high air temperature, a sample period from August 22 to 23, 2005, for Statesboro, GA, was selected. The highest observed dew point temperature in Statesboro during 2005 occurred on the August 22. The predictions of dew point temperature for the one-, four-, eight-, and twelve-hour models again indicate more accurate predictions for shorter prediction periods compared to longer prediction periods for this extreme event during summertime (Figure 2.6). The one-, four-, and eight-hour models predicted the dew point temperature accurately from 1200 to 1800, the highest air temperature portion of August 22, where the twelve-hour model prediction did not vary during that time as the observed dew point temperature changed. All models were less accurate for the high dew point temperature that occurred between 1800 and 2100 on August 22. Only the one-hour model predicted the climbing dew point temperature during this period, yet it did not accurately predict the maximum value. The four-, eight-, and twelve-hour models predicted a relatively stable dew point temperature for this period.

The twelve ANN models can be sequenced in order to provide a twelve-hour prediction track for dew point temperature. This is illustrated in Figure 2.7 using an early morning freeze example from March 14 to 15, 2005, for Tiger, GA. The 2100 prediction track shows a slight decrease in the dew point temperature, but it overpredicted the dew point temperature during the freeze by 4˚C to 5˚C. Yet predicting only three hours later at midnight, the prediction track more closely followed the actual freeze that occurred. It also indicated that the dew point temperature would remain slightly above 0˚C until 0400 to 0500, while the observed dew point temperature fell below 0˚C around 0200. Even with that inaccuracy, the midnight prediction track compared to the 2100 prediction track is extremely accurate and correctly shows that the dew point temperature would decrease to below 0˚C, that the minimum dew point temperature would occur between 0600 and 0700, and that the dew point temperature would increase from 0700 to 1200.

The models developed in this research show how dew point temperature can be predicted with an ANN, instead of being calculated or estimated by other weather variables. Although the results varied, the ANN models were able to adequately predict in many difficult conditions, including during extreme heat and freezing conditions.

These types of predictions are useful in decision making for ecologists, meteorologists, and agricultural producers and researchers.

APPLICATION AND FUTURE WORK

As shown, the twelve ANN models can be used in sequence to represent a continuous dew point temperature prediction from the prediction time to twelve hours ahead. These types of prediction tracks will be implemented as part of a decision support system on the AEMN website (www.georgiaweather.net), a weather-based information system. In future work, possible experiments could include examining different criteria for stopping training and examining the use of momentum in combination with various learning rates to produce the optimal results. Because dew point temperature varies dramatically with season, another approach would be to train four ANNs, one for each season. The four seasonal ANNs could be used individually or they could be combined with an ensemble ANN approach.

ACKNOWLEDGEMENTS

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Table 2.1
The effect of selected weather related variable input combinations on dew point temperature prediction using for the development dataset using artificial neural networks

Dew point temperature (°C)	Relative humidity (%)	Solar radiation (W/m^2)	Air temperature (°C)	Wind speed (m/s)	Vapor pressure (kPa)	Vapor pressure deficit (kPa)	Rain (mm)	MAE* (°C)
Dew point temperature only								
X								1.620
Two variables								
X	X							1.521†
X		X						1.579
X			X					1.535
X				X				1.585
X					X			1.602
X						X		1.524
X							X	1.614
Three variables								
X	X	X						1.498†
X	X		X					1.509
X	X			X				1.503
X	X				X			1.509
X	X					X		1.516
X	X						X	1.508
Four variables								
X	X	X	X					1.480†
X	X	X		X				1.487
X	X	X			X			1.497
X	X	X				X		1.488
X	X	X					X	1.492
Five variables								
X	X	X	X	X				1.477†
X	X	X	X		X			1.485
X	X	X	X			X		1.481
X	X	X	X				X	1.499
Six variables								
X	X	X	X	X	X			1.463†
X	X	X	X	X		X		1.474
X	X	X	X	X			X	1.483
Seven variables								
X	X	X	X	X	X	X		1.470
X	X	X	X	X	X		X	1.470

*Average of the minimum five mean absolute errors (MAEs) of the selection dataset out of 30 networks

†The best variables selected based on the minimum MAE

Table 2.2
The effect of the duration of prior data and prediction period on dew point temperature prediction based on the MAE* and its coefficient of variation (CV)

Mean absolute error (MAE)* (°C) (Coefficient of variation) (%)												
Prediction period (hours) / Duration of prior data (hours)	1	2	3	4	5	6	7	8	9	10	11	12
2	0.503 (0.13)	0.778 (0.95)	–	–	–	–	–	–	–	–	–	–
4	0.502 (0.63)	0.776 (0.31)	–	–	–	–	–	–	–	–	–	–
6	0.500† (0.35)	0.772† (0.43)	0.996 (0.38)	1.178 (0.19)	1.338 (0.46)	1.476 (0.54)	1.599 (0.13)	1.728 (0.50)	1.831 (0.39)	1.944 (0.96)	2.028 (0.30)	2.118 (0.11)
12	0.502 (0.45)	0.785 (0.30)	0.991 (0.79)	1.181 (0.82)	1.323 (0.44)	1.458 (0.58)	1.585 (0.57)	1.711 (0.56)	1.813 (0.50)	1.907 (0.36)	2.010 (0.21)	2.084 (0.60)
18	0.507 (0.68)	0.775 (0.75)	0.993 (0.79)	1.158 (0.72)	1.318† (0.16)	1.445† (0.69)	1.581† (0.58)	1.697 (0.79)	1.801† (0.61)	1.895 (0.21)	2.007 (0.80)	2.076† (0.36)
24	0.508 (0.27)	0.776 (0.52)	0.981† (0.45)	1.158† (0.30)	1.318 (0.79)	1.446 (0.48)	1.591 (0.57)	1.694 (0.28)	1.807 (0.42)	1.876† (0.70)	1.987† (0.49)	2.081 (0.25)
30	0.507 (0.53)	0.778 (0.48)	0.990 (0.37)	1.174 (0.96)	1.320 (0.26)	1.461 (1.00)	1.587 (0.44)	1.693† (0.36)	1.821 (0.63)	1.912 (0.79)	1.996 (0.63)	2.083 (0.79)
36	–	–	0.992 (0.66)	–	–	–	–	1.714 (1.16)	–	1.905 (0.50)	1.999 (0.86)	–
42	–	–	–	–	–	–	–	1.720 (0.33)	–	–	–	–

*Average of the minimum five MAEs of the selection dataset for 30 networks
†Duration of prior data selected for each prediction period

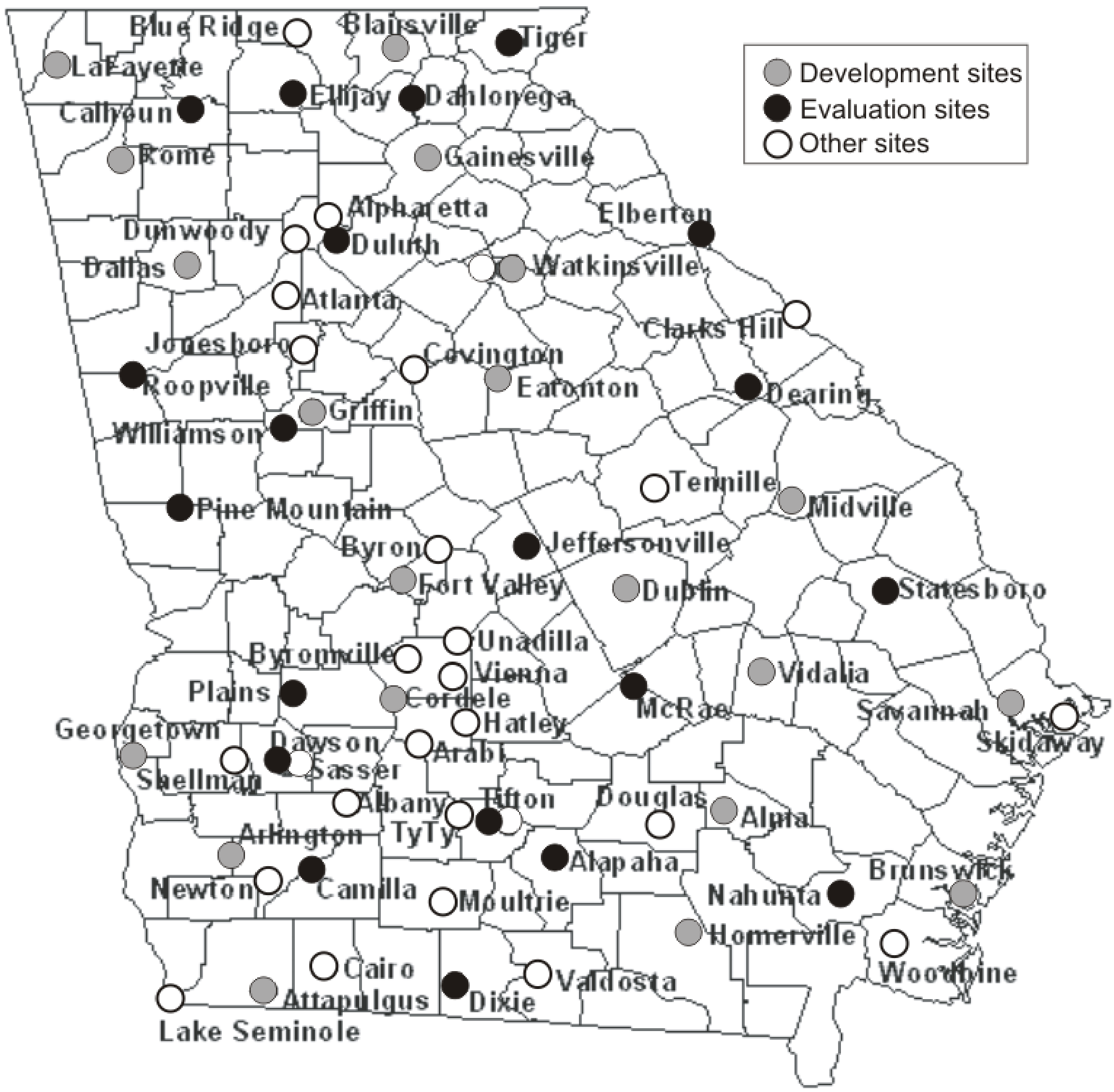

Figure 2.1: Automated Environmental Monitoring Network (AEMN) weather stations, 20 sites selected for model development and 20 sites selected for model evaluation

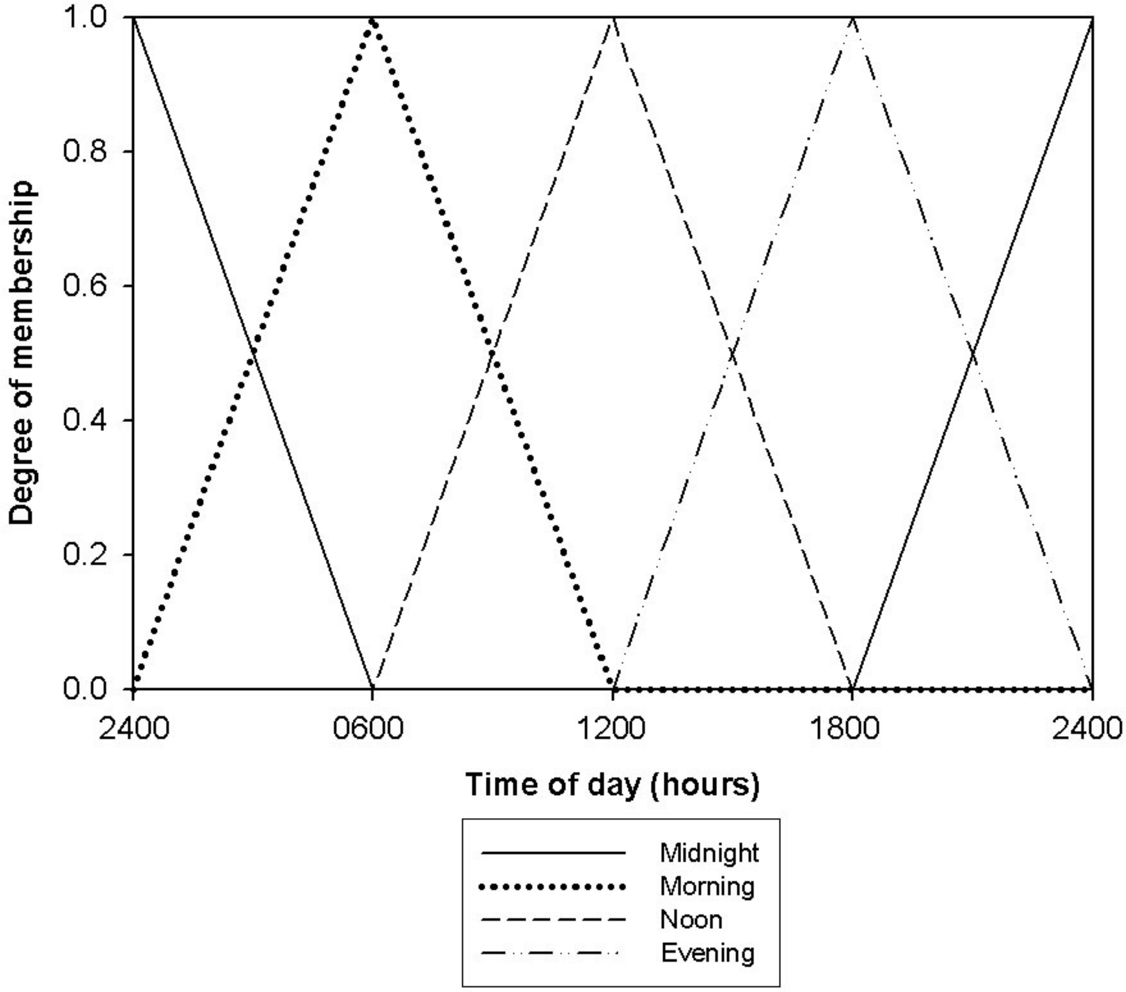

Figure 2.2: The degree of membership for four cyclic input variables for time of day as determined by the fuzzy membership functions

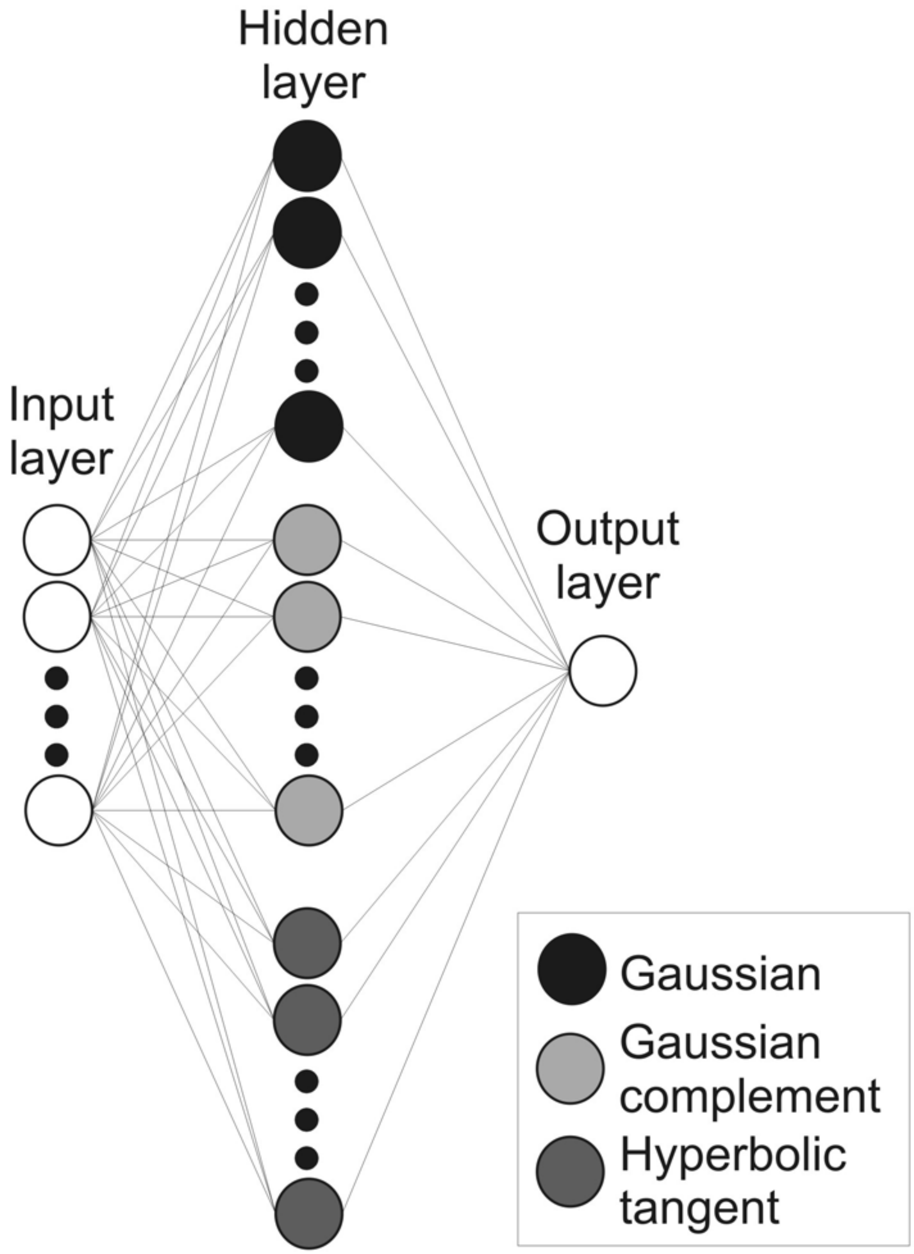

Figure 2.3: Ward error backpropagation (EBP) artificial neural network (ANN) architecture with a single hidden layer consisting of three slabs of hidden nodes with different activation functions: Gaussian, Gaussian complement, and hyperbolic tangent

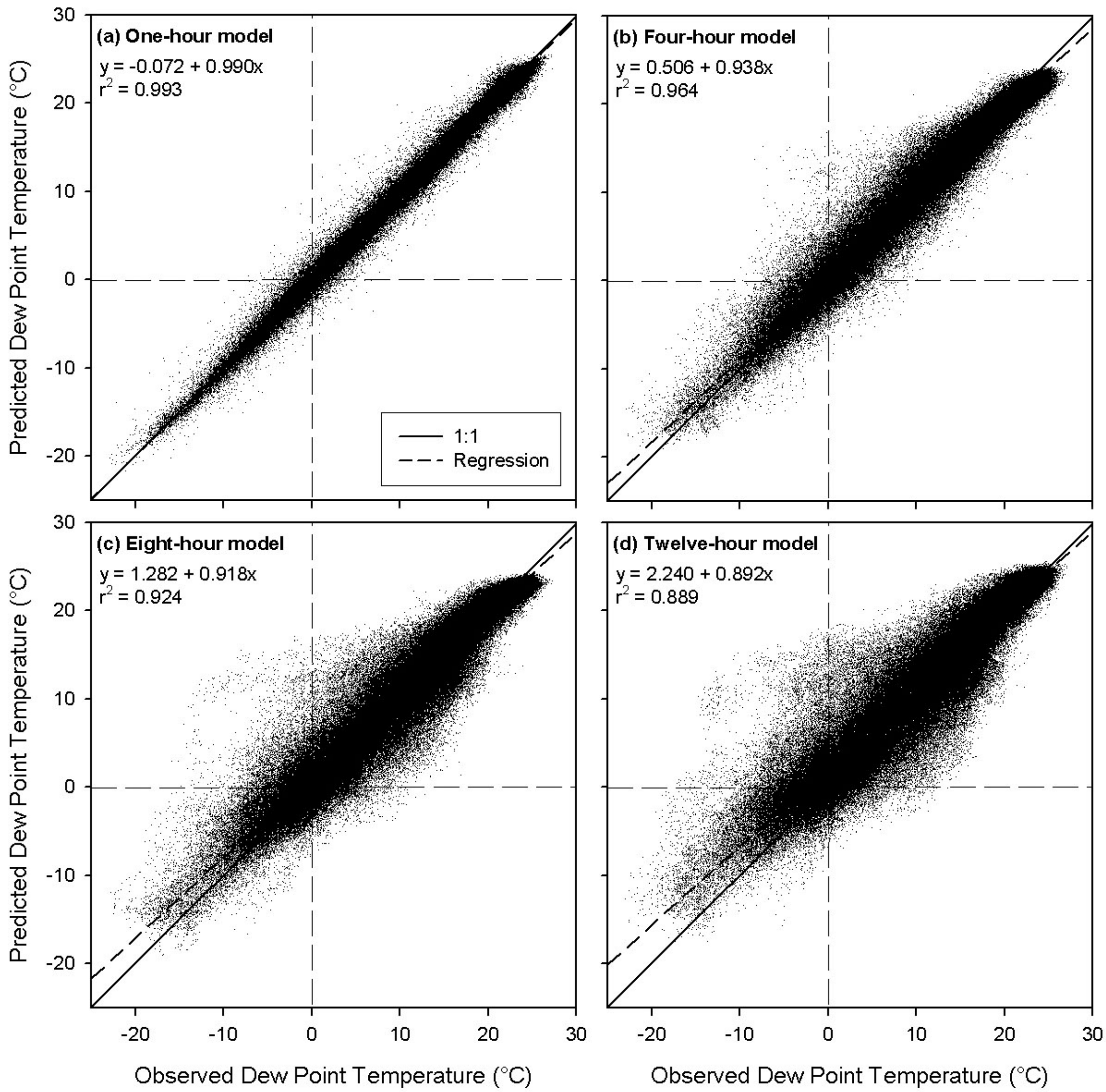

Figure 2.4: Performance of predicted dew point temperature for the evaluation dataset for the (a) one-hour, (b) four-hour, (c) eight-hour, and (d) twelve-hour prediction models

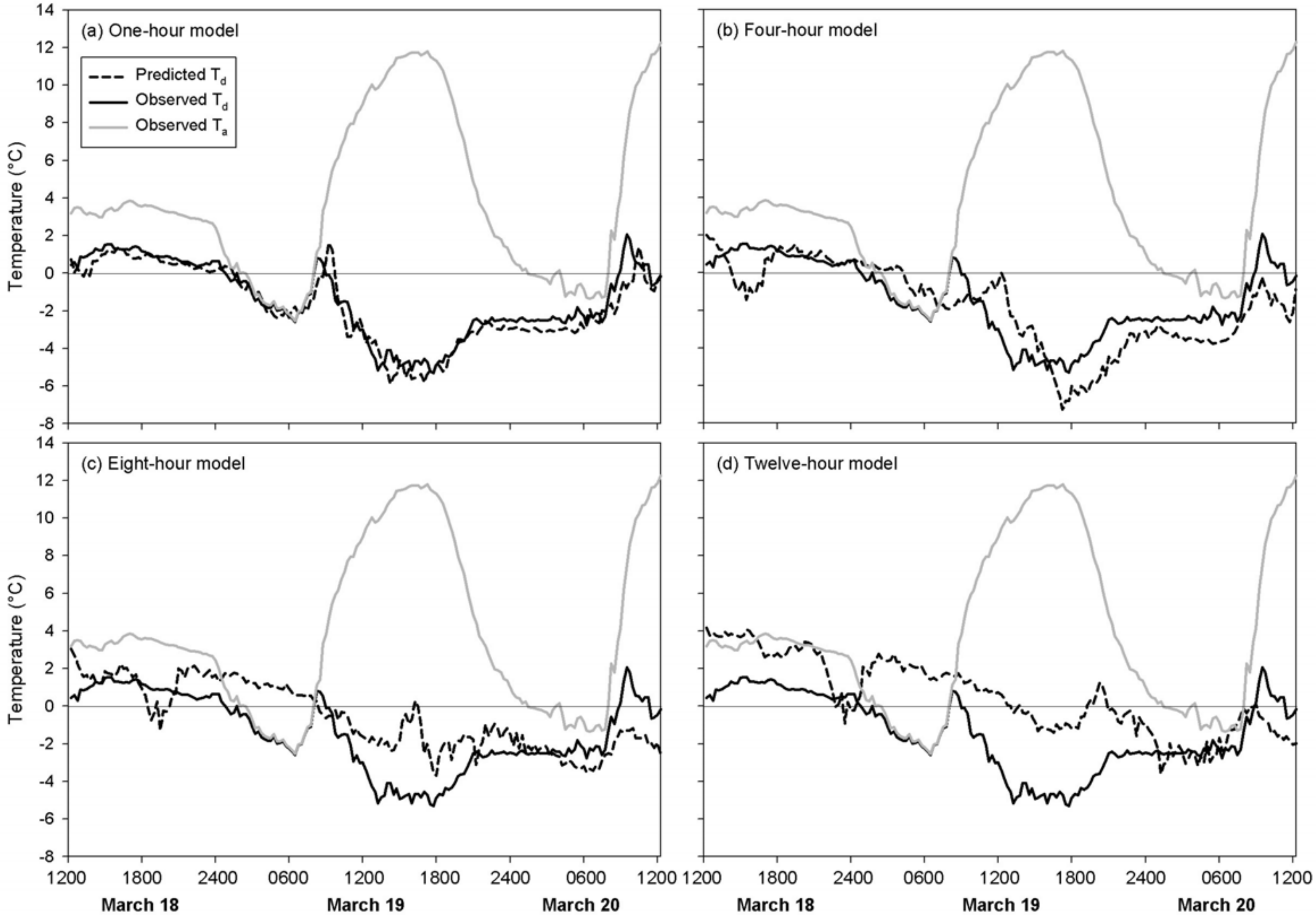

Figure 2.5: Predicted dew point temperature for Dahlonega, GA with (a) one-hour, (b) four-hour, (c) eight-hour and (d) twelve-hour prediction models. Observed dew point temperature and air temperature are also shown.

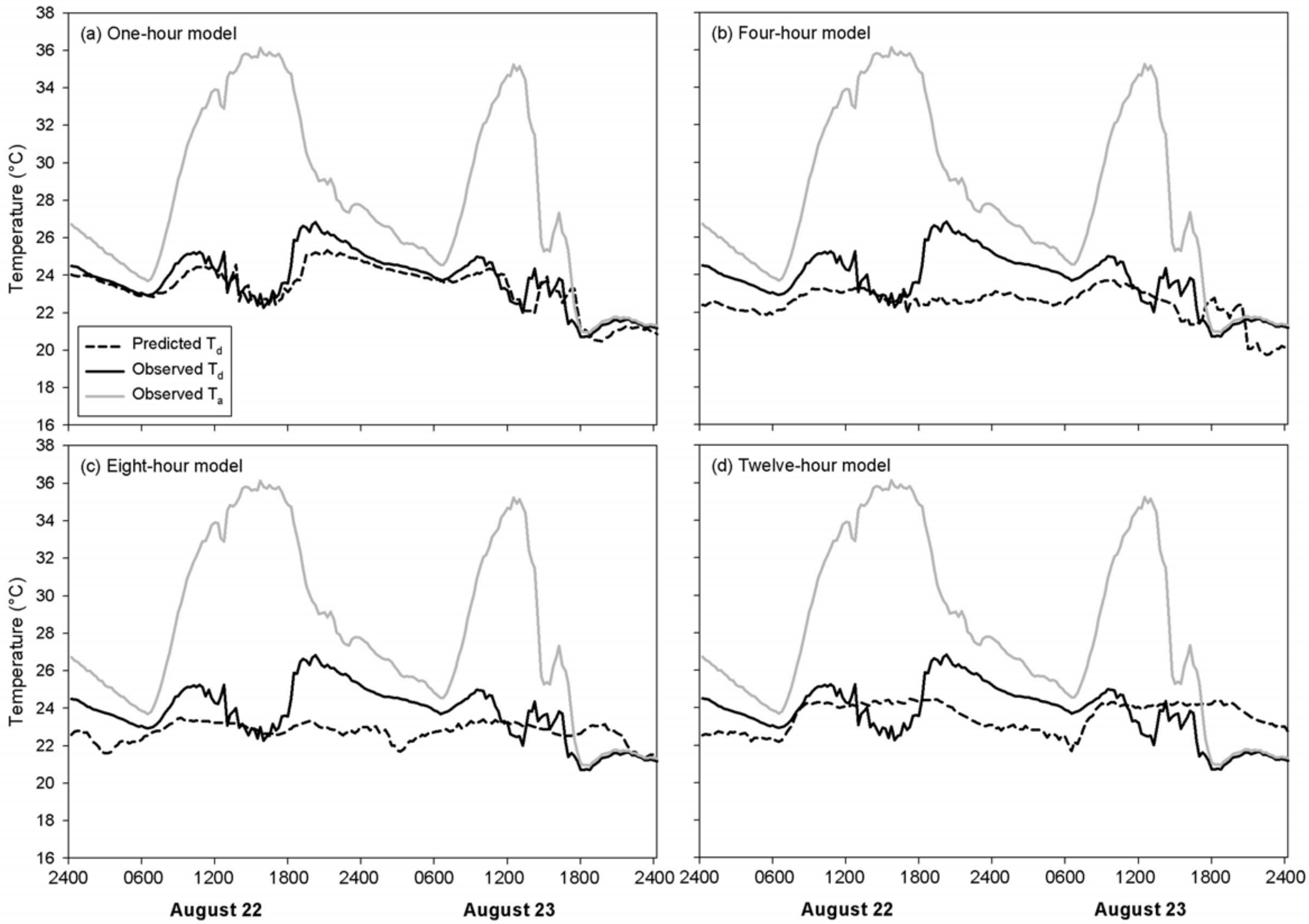

Figure 2.6: Predicted dew point temperature for Statesboro, GA with (a) one-hour, (b) four-hour, (c) eight-hour and (d) twelve-hour prediction models. Observed dew point temperature and air temperature are also shown.

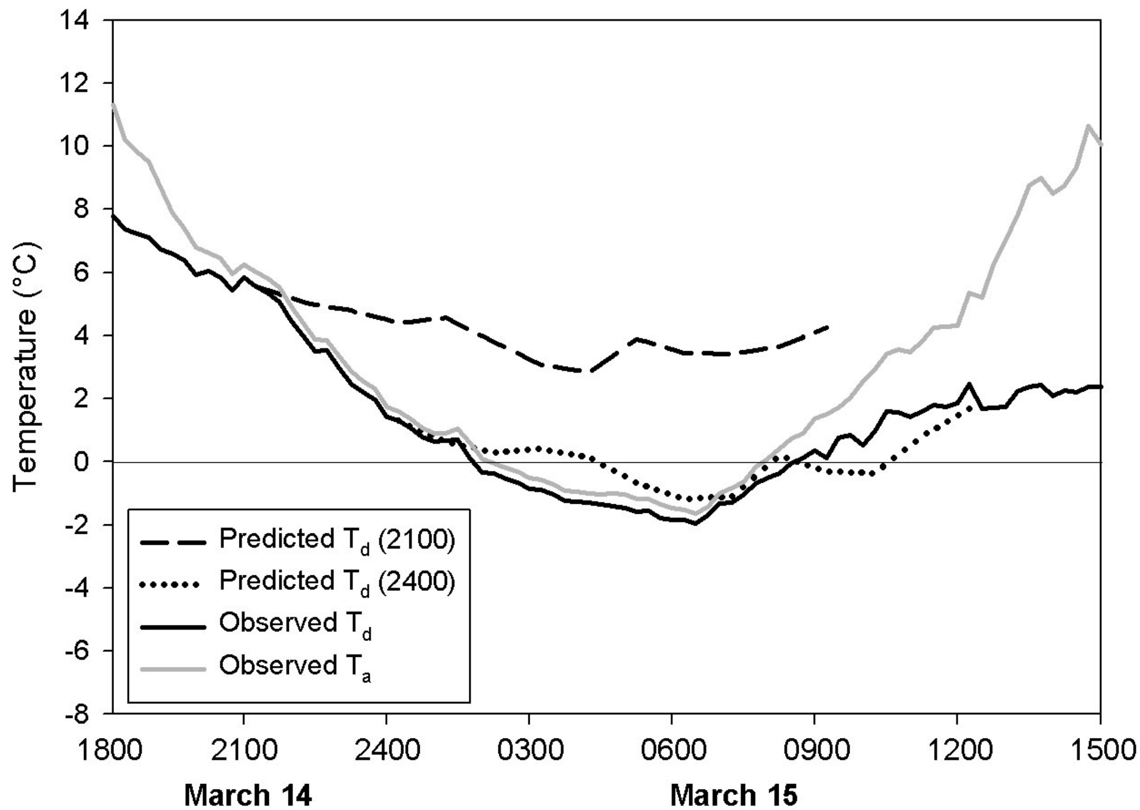

Figure 2.7: Predicted dew point temperature at 2100 and 2400 on March 14 to 15, 2005, based on a sequence of twelve models for Tiger, GA. Observed dew point temperature and air temperature are also shown.

CHAPTER 3

ENSEMBLE ARTIFICIAL NEURAL NETWORKS FOR DEW POINT TEMPERATURE PREDICTION[2]

[2] Shank, D.B., R. W. McClendon, G. Hoogenboom, and J. O. Paz. To be submitted to *Applied Artificial Intelligence*.

ABSTRACT

Dew point temperature is the temperature at which water vapor condenses into water droplets, dew or frost. Dew point temperature is needed as an input to estimate or calculate several meteorological variables, and it contributes to human and animal comfort levels. In conjunction with air temperature, dew point temperature determines the severity of freezes, which can cause damage to crops, and heat waves, which can injure people. The goal of this study was to develop artificial neural network (ANN) models to improve on previous ANN dew point temperature prediction research. These improvements include optimizing ANN stopping criteria, comparing seasonal models to year-round models, and developing ensemble ANNs to blend the output of seasonal models. For an ANN trained with 100,000 patterns per epoch, the error was reduced by using a 2000-pattern testing set at an interval of 20 learning events to decide when to stop training. Seasonal ANN models were blended together in an ensemble ANN with the weight of member networks determined using a fuzzy-membership function based on the day of year. These ensemble models were shown to produce lower errors than year-round, non-ensemble models. The mean absolute errors (MAEs) of the final models evaluated with an independent dataset included 0.795˚C for a two-hour prediction, 1.485˚C for a six-hour prediction, and 2.146˚C for a twelve-hour prediction. The final model MAEs when compared to the previous research were reduced by 0.008˚C, 0.081˚C and 0.135˚C, respectively. It can be concluded that the methods used in this research were affective in more accurately predicting year-round dew point temperature, yet a more complete exploration of each of the methods is left to future research. The ANN models for different prediction periods were sequenced to provide a twelve-hour dew

point temperature prediction system which will be implemented on the Automated Environmental Monitoring Network website (www.georgiaweather.net).

INTRODUCTION

As air temperature decreases, dew point temperature is the temperature at which water vapor will condense into liquid water or dew, assuming that air pressure remains constant. The dew point temperature below 0˚C, referred to as the frost point, is the temperature the air must cool to for frost. Applications for dew point temperature include estimating near surface humidity, calculating vapor pressure (Mahmood and Hubbard, 2005), and estimating evapotranspiration (Hubbard et al., 2003). Dew point temperature is particularly important during the hottest and coldest seasons because of the potential effect of the extreme dew point temperatures. Low dew point temperatures, along with wet-bulb temperature, can be used to calculate critical damage air temperature in crop specific conditions, helping agricultural producers prepare for damaging frosts (Snyder and Melo-Abreu, 2005). Although some plants have developed resistance and tolerance to frost, it still causes damage to most of the agricultural, especially horticultural, crops (Agrawal et al., 2004; Snyder and Melo-Abreu, 2005). Over 1000 people died in a 1995 summer heat wave in the Midwestern United States, and the deaths were attributed to both the high air temperatures and the high dew point temperatures (Sandstrom et al., 2004). Extremely high dew point temperatures can also affect air conditioning use and can decrease the efficiency of air conditioning units that use evaporative cooling (Sparks et al., 2002).

Sandstrom et al. (2004) analyzed extreme summer dew point temperatures using 52 years of data for 68 locations throughout the central United States. They define daily average dew point temperatures greater than or equal to 22˚C to constitute an extreme day. A region bordering the Gulf of Mexico, including approximately half of Georgia, produced an appreciably higher average yearly number of extreme days due to the moisture produced by the Gulf of Mexico. Of the two locations in Georgia, Macon was in this region with an average of 27 extreme days per year, while Atlanta was not in the region with an average of only 7 extreme days per year. Likewise, Chattanooga, TN, near the northern border of Georgia had an average of 11 extreme days per year, while Tallahassee, FL, near the Gulf and southern border of Georgia had an average of 54 extreme days per year. Robinson (1998) used national historical data from 1961 to 1990 from 222 weather stations to show a climatology of monthly dew point temperature averages for the contiguous United States. The average monthly dew point temperature for Georgia ranged from 0˚C to 10˚C for January through March, 10˚C to 20˚C for April through June, 15˚C to 25˚C for July through September, and 0˚C to 15˚C for October through December. These analyses illustrate the diverse seasonal dew point temperature conditions seen throughout Georgia.

Hubbard et al. (2003) developed a regression model for estimating daily average dew point temperature using air temperature parameters as inputs. Based on 14 years of data and six locations in the Great Plains of the United States, the regression equation had an MAE of 2.2˚C. Although estimations of this type are useful for determining values for missing historical weather data, they do not allow the prediction of values in the future. Diab and Saade (1999) used a fuzzy logic inference system to predict dew point temperature one day ahead. The inference rules used fuzzy membership functions with inputs of barometric pressure, wind speed, and air temperature and outputs of three membership functions, which were combined to make one dew point temperature prediction. The evaluation for 40 uniformly distributed days from 1994 resulted in an absolute error that ranged to a maximum of 8˚C.

An artificial neural network (ANN) is a robust computational technique, primarily used for pattern recognition, classification, and prediction (Bose and Liang, 1996; Haykin, 1999). ANNs have been used for meteorological applications including prediction of ozone concentration, sulfur dioxide concentration, tornadoes, storms, solar radiation, carbon dioxide, pollutants, and monsoon rainfall (Gardner and Dorling, 1998), monthly and year precipitation levels (Bodri and Cermak, 2000), tide charts (Steidley et al., 2005), ocean waves overtopping sea walls (Wedge et al., 2005), flash floods (Luk et al., 2000), and air temperature (Jain et al., 2003; Smith et al., 2006). Mittal and Zhang (2003) developed an ANN model for estimation of wet-bulb temperature, enthalpy, humidity ratio, specific volume, and dew point temperature using dry-bulb temperature and relative humidity as inputs. Estimations of this type are used to fill in missing historical dew point temperature data (Kimball et al., 1997), but do not allow for dew point temperature prediction. Mittal and Zhang (2003) developed ANNs as alternatives to the estimations traditionally done with mathematical models and psychrometric charts using data from the psychrometric charts instead of actual historical data, and the MAE for the estimated dew point temperature was 0.305˚C.

An ensemble ANN combines the outputs of multiple ANNs to provide one unified prediction or classification. Yang and Browne (2004) discussed two properties of ensemble ANNs: accuracy, which is the measure of a network error, and diversity, which is the difference between networks in terms of the results produced for the same inputs. One theory behind using ensemble networks is that several less accurate networks that are diverse can be combined into a more-accurate ensemble network (Naftaly et al., 1997; Yang and Browne, 2004).

Maqsood et al. (2004) used single ANNs and ensemble ANNs for prediction of air temperature, wind speed, and relative humidity at Regina Airport, Canada. Each of these models was trained and evaluated individually, as well as being incorporated into two ensemble network types: a winner-take-all and a weighted average, both based on classification certainty of the member networks. The air temperature, wind speed, and relative humidity data for 2001 were partitioned into four seasons, and each network was trained on bootstrapped resamplings for each individual season. The evaluation for each season was for only one day selected from the training dataset. Cannon and Lord (2000) applied ensemble networks for the prediction of maximum hourly ozone concentration for ten sites in British Columbia, and they focused on extreme hourly ozone concentration from May to September that exceeded 82 parts per billion (ppb), which is the level at which a public advisory is issued for the region. They developed multiple resilient error backpropagation ANNs to form an ensemble network using bootstrap aggregation, i.e. bagging, and a cross validation of dataset years for 1991 to 1996, which resulted in MAEs that ranged from 4.6 ppb to 6.6 ppb.

Shank et al. (2006) developed three-layer, error backpropagation ANNs to predict dew point temperature for up to twelve hours in advance for Georgia, USA. Their dataset consisted of statewide weather data from 2002 to 2004 for model development and 2005 for model evaluation. Twenty sites were selected for model development, and 20 additional sites were selected for model evaluation, each dataset representing the geographical diversity of the state of Georgia. Their training dataset consisted of 100,000 patterns randomly selected from the development dataset and the stopping criteria was ten epochs, i.e. 1,000,000 learning events.

During model development, Shank et al. (2006) performed iterative searches to determine important weather related inputs, the preferred values for the duration of prior input data, and ANN parameters including the number of nodes in the hidden layer, initial weight range, and learning rate. The preferred weather related inputs included dew point temperature, air temperature, relative humidity, vapor pressure, wind speed, and solar radiation. In addition to the current values of these variables, prior values representing a history of each variable were included as inputs and were referred to as prior data. The preferred durations of prior data were as follows: six hours for the two-hour prediction period, 18 hours for the six- and twelve-hour predictions periods, 24 hours for the four- and ten-hour prediction periods, and 30 hours for the eight-hour prediction period. For each of the prior weather related inputs an hourly rate of change was used as an additional input. They included as inputs the day of year and the time of day, each encoded as cyclic variables with fuzzy logic membership functions. They found preferred values for the ANN parameters to be 60 nodes in the hidden layer, an initial weight range of ±0.15, and a learning rate of 0.35. Their final models for the two-, six-, and twelve-hour prediction periods produced MAEs of 0.803˚C, 1.566˚C, and 2.281˚C, respectively, for the evaluation dataset.

The goal of this research project was to develop enhanced ANN models for predicting dew point temperature for up to twelve hours ahead. Specific objectives were to determine the best criteria for stopping the ANN during training, to compare the accuracy of seasonal ANN models with year-round models, and to evaluate application of ensemble ANN models which blend the output of seasonal ANN models.

MATERIALS AND METHODS

Model Development

The Automated Environmental Monitoring Network (AEMN) of the University of Georgia provides web-based applications (www.georgiaweather.net) for agricultural decision-making and natural resource management (Hoogenboom, 2000). Over 70 weather stations located throughout Georgia collect weather data every second and aggregate it every 15 minutes into totals or averages, depending on the variable. The weather variables collected include air temperature, relative humidity, vapor pressure, wind speed and direction, and solar radiation. Dew point temperature is calculated from the collected variables. Figure 3.1 shows the sites and years chosen for model development and model evaluation. These are the same as those used in Shank et al. (2006) to allow for a direct comparison with their work. Other choices about the ANN models were based on this previous research, including the number of nodes in the hidden layer, initial weight range, learning rate, weather related inputs, duration of prior data, and the cyclic input variables for time of day and day of year.

A fully-connected, error backpropagation (EBP) architecture ANN with an input layer, a single hidden layer, and an output layer was used in this study. All inputs were scaled to a range from 0.1 to 0.9 based on the extreme values for each input type in the development dataset. The single fully-connected hidden layer consisted of 60 nodes divided into three equal-sized slabs with different activation functions used for each slab:

Gaussian, Gaussian complement, and hyperbolic tangent (Ward System Group, 1993). This architecture is known as a Ward network and a 60 node Ward network has been shown to be effective in dew point temperature prediction (Shank et al., 2006). The output layer contained a single node with a logistic activation function that corresponded to the scaled value of the predicted dew point temperature.

An EBP ANN model operates in two phases. The first is a feed forward phase where a set of scaled inputs, x_i, where i ranges from 1 to I, are mapped to a single output z, by the following equations:

$$z = g\left(\beta_0 + \sum_{j=1}^{J} \beta_j \cdot y_j\right) \tag{1}$$

and

$$y_j = f_j\left(\alpha_{j0} + \sum_{i=1}^{I} \alpha_{ji} \cdot x_i\right) \tag{2}$$

and α_{ji} are the weights from the input layer to the hidden layer, β_j are the weights from the hidden layer to the output node, and y_j is the set of hidden node outputs with j ranging from 1 to J. The logistic activation function $g(n)$ for an input n is defined as:

$$g(n) = \frac{1}{1+e^{-n}}. \tag{3}$$

The function $f_j(n)$ for an input n is the hidden layer activation function containing the hyperbolic tangent, Gaussian, and Gaussian complement, respectively:

$$f_j(n) = \begin{cases} \tanh(n) & for\ 0 < j \le \frac{1}{3}J \\ e^{-n^2} & for\ \frac{1}{3}J < j \le \frac{2}{3}J \\ 1 - e^{-n^2} & for\ \frac{2}{3}J < j \le J \end{cases} \quad . \tag{4}$$

A second phase of the ANN is backpropagating the error to adjust the weights. The adjustment $\Delta(\beta_j)$ for each weight from the hidden layer to the output node is defined as

$$\Delta(\beta_j) = \eta \cdot g'\left(\beta_0 + \sum_{j=1}^{J} \beta_j \cdot y_j\right) \cdot (t - z) \cdot y_j \tag{5}$$

and the weight adjustment $\Delta(\alpha_{ji})$ for each weight from the input layer to the hidden layer is defined as

$$\Delta(\alpha_{ji}) = \eta \cdot f_j'\left(\alpha_{j0} + \sum_{i=1}^{I} \alpha_{ji} \cdot x_i\right) \cdot g'\left(\beta_0 + \sum_{j=1}^{J} \beta_j \cdot y_j\right) \cdot (t - z) \cdot \beta_j \cdot x_i \,. \tag{6}$$

η is the learning rate, *t* is the target output value, α_{ji} are the weights from the input layer to the hidden layer, and β_j are the weights from the hidden layer to the output node. The nodes y_0 and x_0 are bias nodes for the output and hidden layers, respectively, and are always set to one. The adjustments for each weight were added to the weights after each training pattern. During model development an ANN with a specific set of parameters and inputs was referred to as a *model*. Separate models were developed for each prediction period.

An EBP ANN would traditionally have a training dataset used to iteratively search for an optimal set of network weights. A testing dataset would be used in feed-forward mode during this iterative search to determine when to stop training by testing the ability of the ANN to predict patterns not used for training. The training should be stopped at the point where the testing dataset error is minimized. A separate selection dataset would then be used in feed-forward mode to select among alternative model configurations. For this reason, a training, testing, and selection dataset should not overlap in patterns.

Preliminary experiments indicated that when a testing dataset was evaluated at intervals within an epoch, the testing dataset error showed considerable variability. A typical example of this variability is shown in Figure 3.2, in which a testing dataset of 2000 patterns was evaluated every 20 learning events during the tenth epoch of training a network. The 5000 calculations of MAE for the testing dataset ranged from 1.432˚C to 3.318˚C, with a mean of 1.561˚C, and a standard deviation of 0.113˚C. Shank et al. (2006) used a stopping criteria in which the error was only evaluated at the end of the epoch. The MAE for the testing dataset, therefore, would be one sample drawn from this left-skewed distribution. Additional preliminary experiments showed that the rate of change of the minimum MAE for all intervals from the ninth to the tenth epoch for the testing dataset was always less than 0.01˚C. Therefore the tenth epoch, i.e. 900,000 to 1,000,000 learning events, was arbitrarily selected the epoch during which training was stopped. Because of this preliminary work, the stopping criteria was set to the interval that produced the minimum testing dataset MAE during training of the tenth epoch. The patterns from the training, testing, and selection datasets were chosen without replacement from the entire development dataset. Both the training and selection datasets contained 100,000 patterns each.

Although there are many ways to combine the outputs of member networks into an ensemble network output, an effective method is using a weighted average of the outputs according to the individual performance or diversity of the network (Granitto et al., 2005; Yang and Browne, 2004). It was decided that for the ensemble networks developed herein, the output of the ensemble network, z_{EN}, would be a weighted average of member networks, z_n where n ranged from 1 to N, according to the formula:

$$z_{EN} = \sum_{n=1}^{N} w_n \cdot z_n . \tag{7}$$

w_n, where n ranges from 1 to N, are the weights corresponding to the member networks where the sum of all w_n is always equal to one.

Using the same approach as Shank et al. (2006), the mean absolute error (MAE) of the predicted dew point temperature was selected as the error measurement. They used the average of the minimum five MAEs from a set of 30 network instantiations of the same ANN model for determining the best model parameters during model development. This method was also used for model development in this research. For model evaluation, ten network instantiations for each of the final seasonal and year-round models were developed, and the one with the minimum MAE for the selection dataset was chosen to represent the model. One instantiation required six to twelve hours of computational time to train and select a stopping interval. Evaluating this model in feed-forward mode required approximately one hour of computational time. All experiments were conducted on 34 Pentium 3 and 4 computers in the computer laboratories of the Department of Biological and Agricultural Engineering at the University of Georgia.

Experiments

In the first experiment, the optimal number of patterns in the testing dataset was determined using a six-hour prediction period. Identical network instantiations with identical training and selection datasets were trained and stopped using testing datasets of varying sizes. The testing intervals were held constant at 500 learning events. In the second experiment, the optimal testing interval was determined using a six-hour prediction period. Identical network instantiations with identical training and selection datasets were trained again and stopped according to the minimum MAE for the testing dataset based on different interval sizes. Using the value determined by the previous experiment, the size of the testing dataset was held constant.

In the third experiment, seasonal models were developed and compared to similarly-trained year-round models. The development and evaluation datasets for each season were the subset of the year-round, respective datasets which included patterns for that season. The seasons herein are defined as January 1 to March 31 as winter, April 1 to July 1 as spring, July 2 to September 30 as summer, and October 1 to December 31 as fall. Although these are up to twelve days off from the northern hemisphere seasons as defined by the equinoxes and solstices, this allowed for the winter season not to be split between years. Ten networks were trained for each of the six prediction periods, e.g. two-, four-, six-, eight-, ten-, and twelve-hour, for each of the four seasonal models and for the year-round model. In each case, the chosen network was the one with the minimum MAE for its selection dataset.

In the fourth experiment, seasonal models were developed for amalgamation into ensemble ANNs. The approach was the same as the one used for the third experiment, except the seasonal development datasets were extended to include patterns from the midpoint of each adjacent season. This allowed for overlap of adjacent seasonal membership functions. For example, the spring ANN model would be trained with a development dataset consisting of patterns from the last half of winter, all of spring, and the first half of summer. For each feed-forward pattern, the day of year for that pattern determined the weights for each member network of the ensemble ANN. This was done with fuzzy-membership functions that determine the degree of membership for each network, i.e. the weight of the member network, as shown in Figure 3.3. For example, as the day of year changes from the midpoint of winter to the midpoint of spring, the weight for the winter network decreases linearly from one to zero, while the weight for the spring network increases linearly from zero to one. During this time of year the weights for the summer and fall networks are set to zero.

RESULTS AND DISCUSSION

In the first experiment, the testing dataset size was varied from 100 to 100,000 patterns in order to determine the preferred size of the testing dataset. A size of 1000 patterns or greater produced nearly identical errors of 1.430˚C to 1.431˚C for the selection dataset, whereas a testing dataset size that was less than 1000 patterns produced higher errors. A testing dataset size of 2000 patterns was arbitrarily selected for further model development. In the second experiment, the testing interval was varied from 10 to 10,000 learning events. A testing interval of 20 learning events resulted in a minimum error of 1.420˚C for the selection dataset. This testing interval for epochs of 100,000 patterns required that the network was checked 5000 times to determine the optimal point to stop training.

In the third experiment, models were developed for two-, four-, six-, eight-, ten-, and twelve-hour prediction periods for each of the four seasons and for the entire year for comparison. For each of these 30 models, ten network instantiations were trained and the network with the minimum MAE for the selection dataset was chosen to represent that model. The selected seasonal networks were evaluated for the corresponding seasonal evaluation datasets. Although each seasonal model showed differences in the pattern distribution for the six-hour prediction period, the r^2 values ranged from 0.807 to 0.910

(Figure 3.4). The winter (Figure 3.4a) encompassed the largest range of observations, from -20˚C to 20˚C, and had the maximum MAE for the six-hour prediction seasonal models, 1.892˚C, with an r^2 of 0.889. The spring (Figure 3.4b) had a range of observations from -5˚C to 25˚C with an r^2 of 0.910 and an MAE of 1.394˚C. The summer (Figure 3.4c) had both the smallest range of observed dew point temperatures, 10˚C to 25˚C, and the minimum MAE of the seasonal models with a six-hour prediction period, 0.923˚C. Although the MAE for summer model was the lowest, the range was smaller, thus the r^2 was less than for other seasons, e.g. 0.807. The fall (Figure 3.4d) observed dew point temperatures ranged from -15˚C to 25˚C with an r^2 of 0.907 and an MAE of 1.777˚C.

The year-round models were also evaluated on the seasonal evaluation datasets and compared to the seasonal models evaluation on the corresponding dataset for each prediction period (Table 3.1). For the spring and summer evaluations, the respective seasonal networks produced lower MAEs than the year-round network for all prediction periods. The fall seasonal network produced equal to or lower MAEs than the year-round for all prediction periods except for the twelve-hour prediction. The results for winter were different in that the year-round network produced lower MAEs than the seasonal network for all prediction periods except for the two-hour prediction. One possible explanation was that winter experienced conditions representative of the entire year due to the large range of observed dew point temperatures. In this case, training for the entire year would have exposed the network to a greater variety of weather patterns, which could have improved the accuracy of the network. Another possibility was that certain times of the year, specifically winter and fall, contained more unexpected dew point temperature variation which made it more difficult for any model to predict. This idea was consistent with greater variance in dew point temperature and the higher MAEs for the winter and fall when compared to the spring and summer. The seasonal networks as a whole tended to predict dew point temperature better than the year-round network.

For the fourth experiment, models were developed for two-, four-, six-, eight-, ten-, and twelve-hour prediction periods for all four seasons using the extended seasonal data. For each of these 24 models, ten network instantiations were trained and the network with the minimum MAE for the selection dataset was selected to represent that model. The four selected networks, one for each season, were combined into a single ensemble network for each prediction period which was evaluated on the entire evaluation dataset. A combined seasonal network is when seasonal networks were combined sequentially with each network predicting for its specific season. The fuzzy ensemble models were compared to the models from previous research (Shank et al., 2006), the year-round models, and the combined seasonal models for the evaluation dataset (Table 3.2). The year-round models showed improvement when compared to the models of Shank et al. (2006) for all prediction periods except for two-hour, which had a slightly higher MAE. This improvement showed that the testing dataset stopping criteria used for ANN training was beneficial. The fuzzy ensemble models produced the minimum MAE for all prediction periods except for the two-hour prediction, for which it was only 0.001˚C higher than the combined seasonal network. The total improvements in the MAE for this study compared to the previous research by Shank et al. (2006) for the two-, six-, and twelve-hour prediction periods were 0.008˚C, 0.081˚C, and 0.135˚C, respectively.

For year-round weather data, the predicted versus observed dew point temperatures for the fuzzy ensemble networks for the two-, six-, and twelve-hour prediction periods are shown in Figure 3.5. The r^2 values were 0.984, 0.947, 0.890, respectively, which indicated that the longer prediction period models were less accurate. For the six- and twelve-hour prediction periods there was a tendency to overpredict for low dew point temperatures. In general the low dew point temperature predictions were less accurate than the high dew point temperature predictions, which corresponded to the larger prediction MAEs for the colder seasons.

The predicted and observed dew point temperature as a function of time for the fuzzy ensemble network of the six-hour prediction period is shown in Figure 3.6. Four example periods from evaluation locations were chosen in order to illustrate conditions of extreme dew point temperature. Ellijay, GA, (Figure 3.6a) had an early morning freeze beginning on March 11, 2005, at 0430 and the observed dew point temperature followed the air temperature during the freeze. The predicted dew point temperature underpredicted by 1°C to 2°C directly preceding the freeze as well as during the freeze. The prediction indicated that the dew point temperature was increasing as the freeze ended, but continued to underpredict. Tiger, GA, (Figure 3.6b) had a lengthy nighttime freeze from 2300 to 0800 on March 17 to 18, 2005, of the type that could damage the vineyards found in this region. As the observed dew point temperature decreased with the air temperature, the predicted dew point temperature followed it closely. The minimum predicted dew point temperature was also similar to the minimum observed dew point temperature which is an important factor in crop damage caused by freezes.

Dixie, GA, (Figure 3.6c) showed observed dew point temperatures in excess of 25°C while the air temperature increased during the morning of August 21, 2005. The predicted dew point temperature tracked the observed dew point temperature until 0700 when the observed dew point temperature increased more rapidly than the predicted dew point temperature. As the observed dew point temperature decreased to below 24°C at 1300 the predicted dew point temperature continued to track the observed without adjusting to small variances, but predicting the average trend throughout the late afternoon. Nahunta, GA, (Figure 3.6d) illustrated two rapid increases in the observed dew point temperature on July 1, 2005: one around 0730 and the other from 1700 to 1900. The first, accompanied by a rapid increase in air temperature, was missed by the prediction. The second, which brought the observed dew point temperature to over 26°C, was also missed by the prediction with a difference of about 2°C from 1800 to 2100. Rapid increases in dew point temperature were uncommon in summer, and this example illustrated the difficulty of the model to make accurate predictions when such rapid increases occurred.

Models developed with new stopping criteria showed improvement when compared to the previous research models of Shank at el. (2006). Then seasonal models were developed and compared for each season to a year-round model. In all seasons except winter, the seasonal models did better than the year-round. Using similar seasonal models, ensemble ANN models were developed with fuzzy membership functions for weighting of member networks, and the ensemble models generally did better than the previous best models. The six-hour ensemble model adequately predicted for extreme conditions, both freezes and high dew point temperatures.

APPLICATION AND CONCLUSION

The outputs of all six prediction period models were sequenced to generate a prediction track from the time of prediction to twelve hours in advance. This dew point temperature prediction system could be implemented as part of a decision support system to help identify future dew point temperature conditions. Figure 3.7 shows four examples of extreme dew point temperature conditions and two selected prediction tracks for each that focus on predicting extreme conditions. Tiger, GA, (Figure 3.7a) experienced a freeze from 2300 until just after 0800 on February 25 to 26, 2005, and the observed dew point temperature closely followed the air temperature during this freeze. The prediction at 2000 hours indicated the decreasing of the dew point temperature to below 0°C and predicted that this would occur two hours later than was observed. The prediction at 2400, after the freeze event had begun, was slightly overpredicted, but showed the dew point temperature increasing to 0°C at 1030, the same time the observed dew point temperature increased to 0°C. In Dahlonega, GA, (Figure 3.7b) a freeze occurred from 0400 to 0930 on March 1, 2005. The observed dew point temperature decreased to approximately -5°C prior to midnight and decreased to approximately -7°C during the freeze event in the early morning hours. The 2200 prediction track from February 28, 2005, showed that dew point temperature prediction was 2°C to 7°C higher than observed values. However, the 2400 prediction track was not only close to the level of the observed dew point temperature, but also the 2400 prediction track indicated the dip in observed dew point temperature during the freeze.

Plains, GA, (Figure 3.7c) sustained a three-hour high dew point temperature of approximately 25°C from 1900 to 2200 on July 27, 2005. The 1400 prediction indicated dew point temperatures exceeding 24°C, and then a decrease in dew point temperature starting at 2000. The observed decrease in the dew point temperature actually occurred at 2200, which the track at 1800 predicted more accurately. Although it slightly underpredicted the maximum dew point temperature value, the 1800 prediction track showed the duration of the extreme dew point temperatures and was accurate in showing the nighttime decreasing values from 2300 to 0600. In Camilla, GA, (Figure 3.7d) the observed dew point temperature tracked air temperature from 0000 to 0900 on June 9, 2005. The dew point temperature 0200 prediction was close to the observed until the observed dew point temperature increased at 0800, and it was underpredicted by approximately 1°C. The 0600 prediction, however, missed the quick rise in observed dew point temperature from 0800 to 0900, but then only slightly underpredicted the observed dew point temperature from 1000 to 1800.

A sequence of dew point temperature networks can be used to make prediction tracks and can be useful for predicting extreme conditions. Although these predictions are not perfectly accurate, when used as one component of a decision support system, producers, meteorologists, and the general public can all benefit from the predictions these systems provide. Dew point temperature prediction tracks are in the process of being implemented on the AEMN website (www.georgiaweather.net). Prediction tracks for air temperature are already available, and the dew point temperature prediction can be used in conjunction with them to predict conditions such as dew, frost, and heat stress.

RECOMMENDATIONS FOR FUTURE WORK

The optimization of stopping criteria and the development of ensemble networks has been shown to be helpful in dew point temperature prediction, but many details of their implementations have not been tested. Future work could include optimizing the ANN parameters and inputs for dew point temperature prediction for each of the seasonal models. In addition, partitioning the seasons based on observed dew point temperatures may help the diversity of the member components of the ensemble ANN. It may be possible to find alternate fuzzy membership functions that blend the ANN model outputs to generate more accurate dew point temperature predictions. Because the fuzzy membership functions were ways to determine the weights of each network in the ensemble, more complex functions could be generated, even using a genetic algorithm, a Bayesian classification system, or output from each member network to decide on the optimal weights for the ensemble ANN.

ACKNOWLEDGEMENTS

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Table 3.1
Comparison of the performance of year-round and individual season models for all four seasons for different prediction periods for the evaluation dataset

Mean absolute error (MAE) (°C)								
Prediction Period (hours)	Winter		Spring		Summer		Fall	
	Year-Round	Winter only	Year-Round	Spring only	Year-Round	Summer only	Year-Round	Fall only
2	0.915	0.913*	0.810	0.794*	0.609	0.597*	0.885	0.875*
4	1.453*	1.456	1.174	1.160*	0.801	0.784*	1.384	1.360*
6	1.862*	1.892	1.426	1.394*	0.945	0.923*	1.806	1.777*
8	2.275*	2.309	1.658	1.645*	1.030	0.995*	2.150*	2.150*
10	2.587*	2.617	1.812	1.762*	1.077	1.059*	2.508	2.436*
12	2.842*	2.893	1.946	1.896*	1.117	1.082*	2.720*	2.739

*Best model for each season and prediction period

Table 3.2

Comparison of the performance of different models for all prediction periods for the evaluation dataset

Mean absolute error (MAE) (°C)				
Prediction Period (hours)	Previous research model†	Year-round model	Combined seasonal model	Fuzzy ensemble model
2	0.803	0.805	0.795*	0.796
4	1.234	1.202	1.189	1.184*
6	1.566	1.508	1.495	1.485*
8	1.799	1.777	1.773	1.740*
10	2.011	1.994	1.966	1.941*
12	2.281	2.154	2.150	2.146*

*Best model for each prediction period

†Shank et al. (2006)

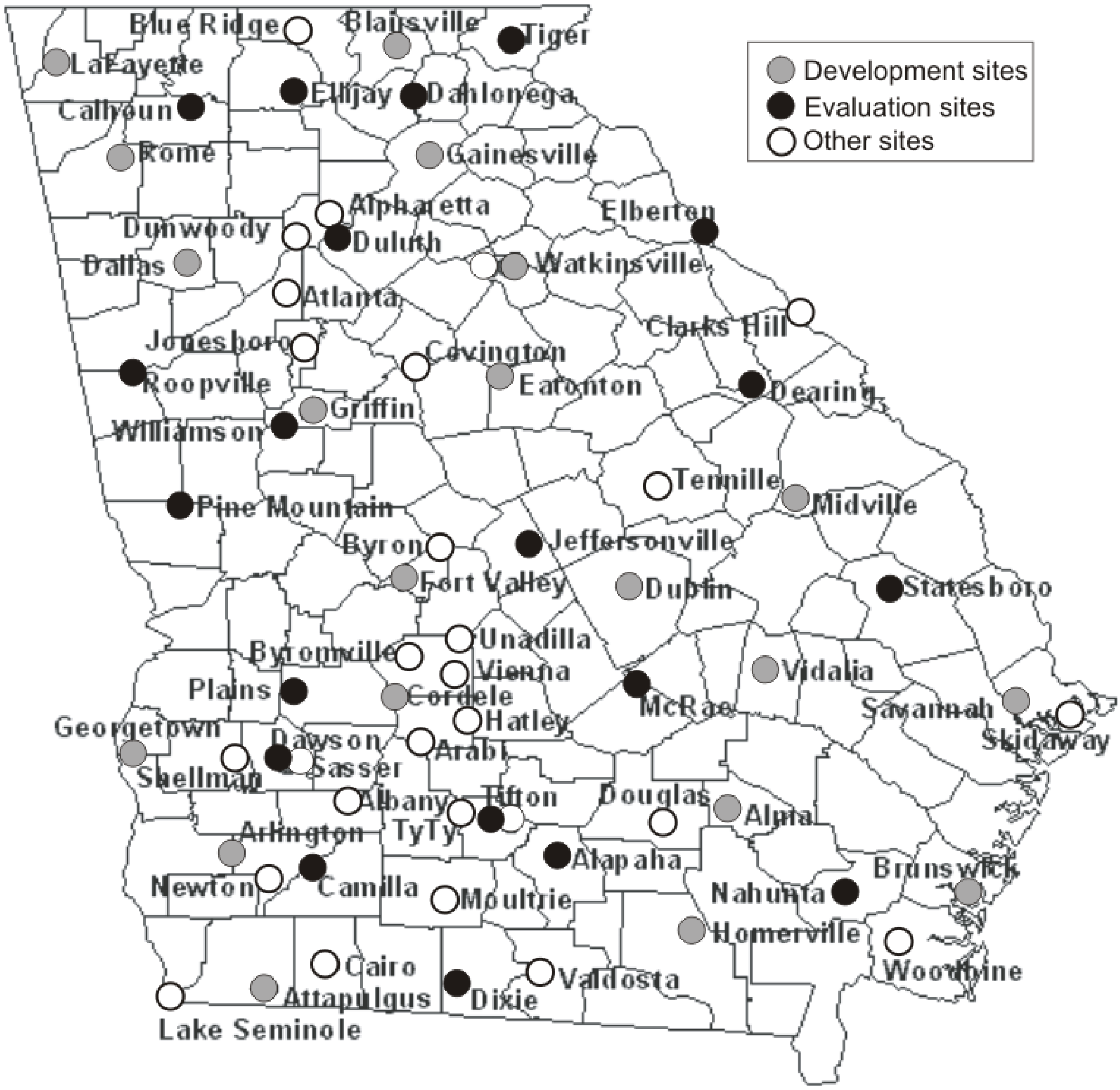

Figure 3.1: AEMN weather stations, twenty sites selected for model development and twenty sites selected for model evaluation

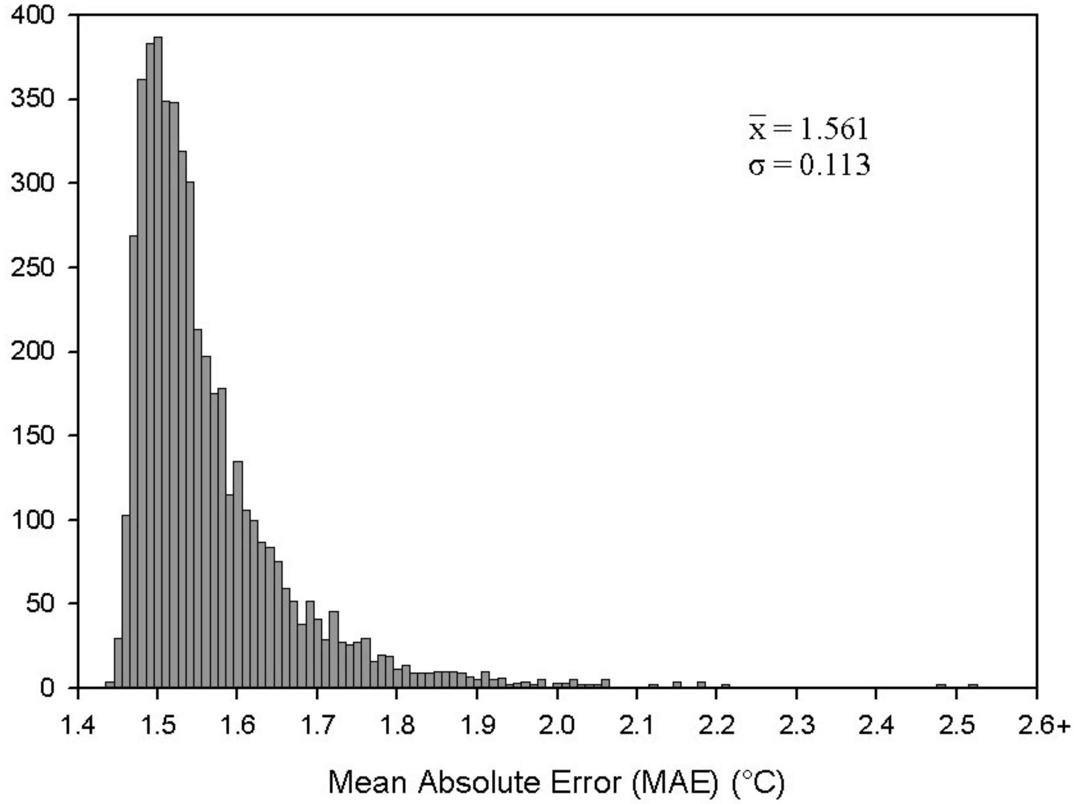

Figure 3.2: Histogram of 5000 MAEs taken at increments of 20 learning events during the tenth epoch of a network training for a testing dataset of 2000 patterns

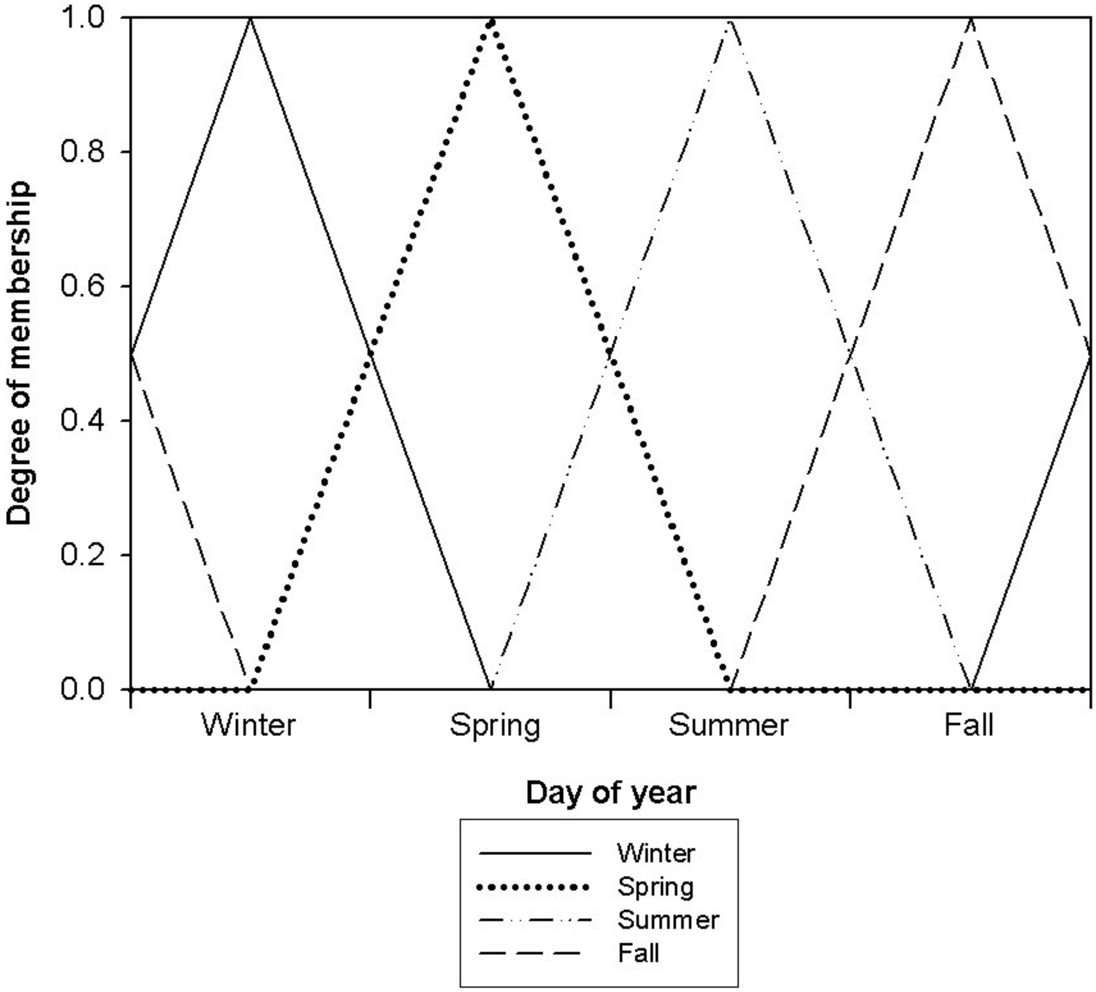

Figure 3.3: Cyclic fuzzy membership function for determining the ensemble weights for each member network based on day of year

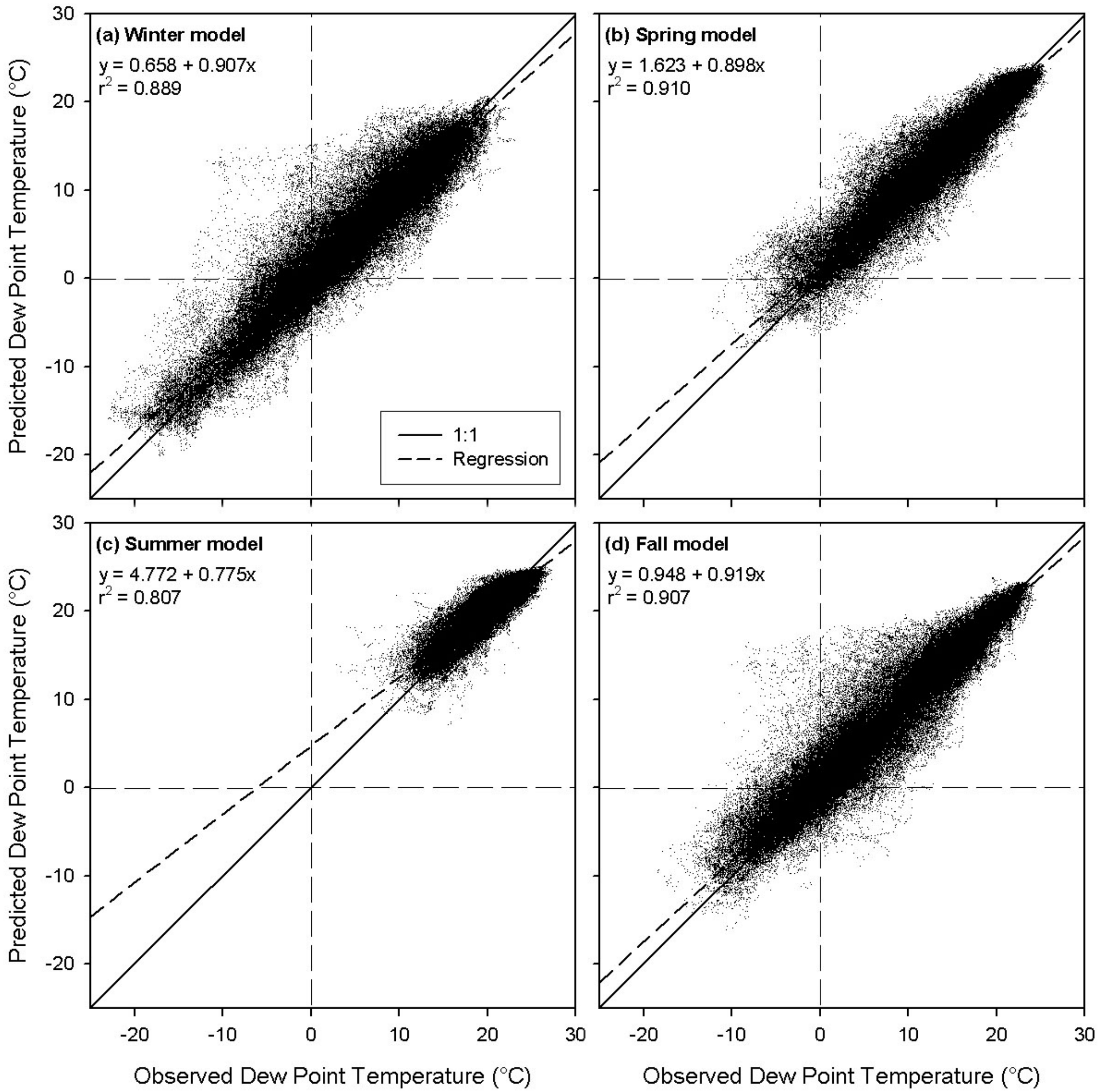

Figure 3.4: Performance of predicted dew point temperature for each seasonal model for a six-hour prediction period for the evaluation dataset for each corresponding season (a) winter, (b) spring, (c) summer, and (d) fall

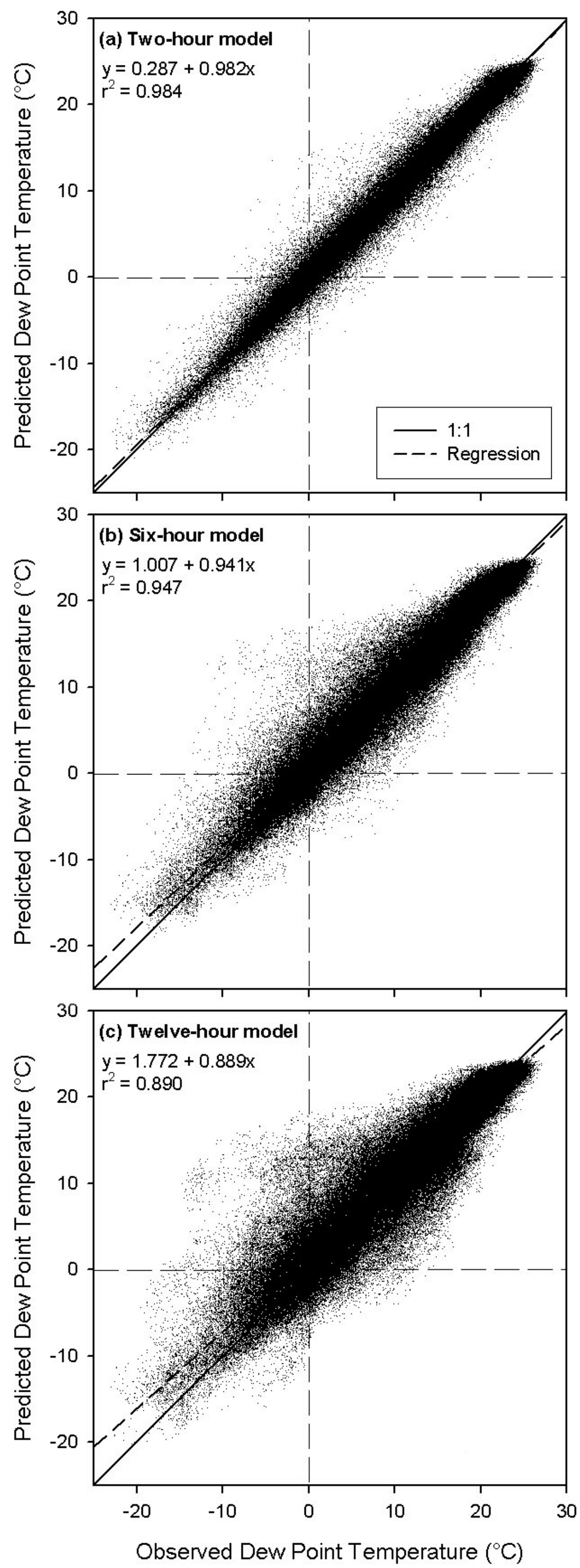

Figure 3.5: Performance of predicted dew point temperature for the evaluation dataset for the (a) two-hour, (b) six-hour, and (c) twelve-hour prediction models

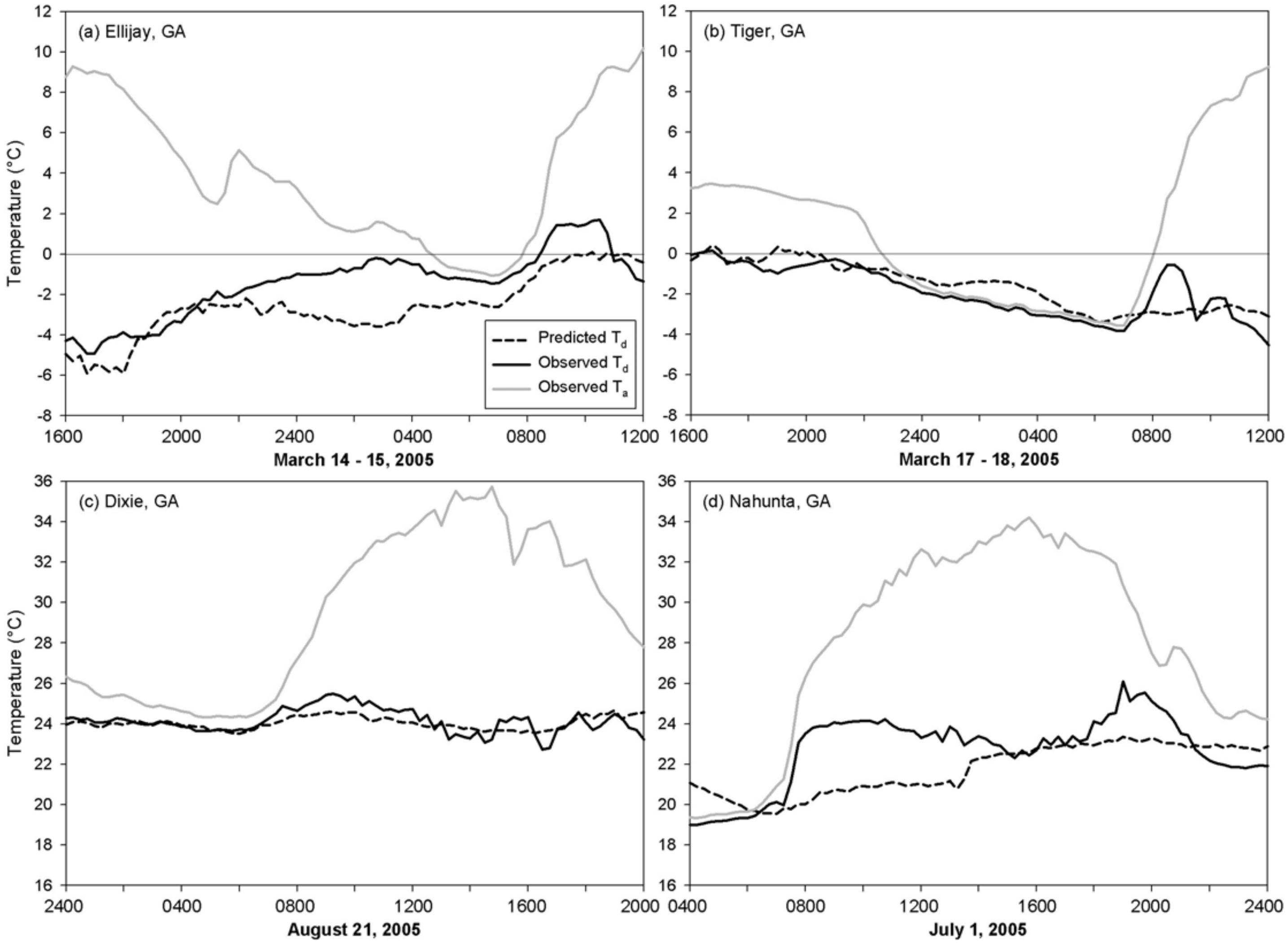

Figure 3.6: Predicted dew point temperature for a six-hour prediction model for (a) Ellijay, GA, (b) Tiger, GA, (c) Dixie, GA, and (d) Nahunta, GA. Observed dew point temperature and air temperature are also shown.

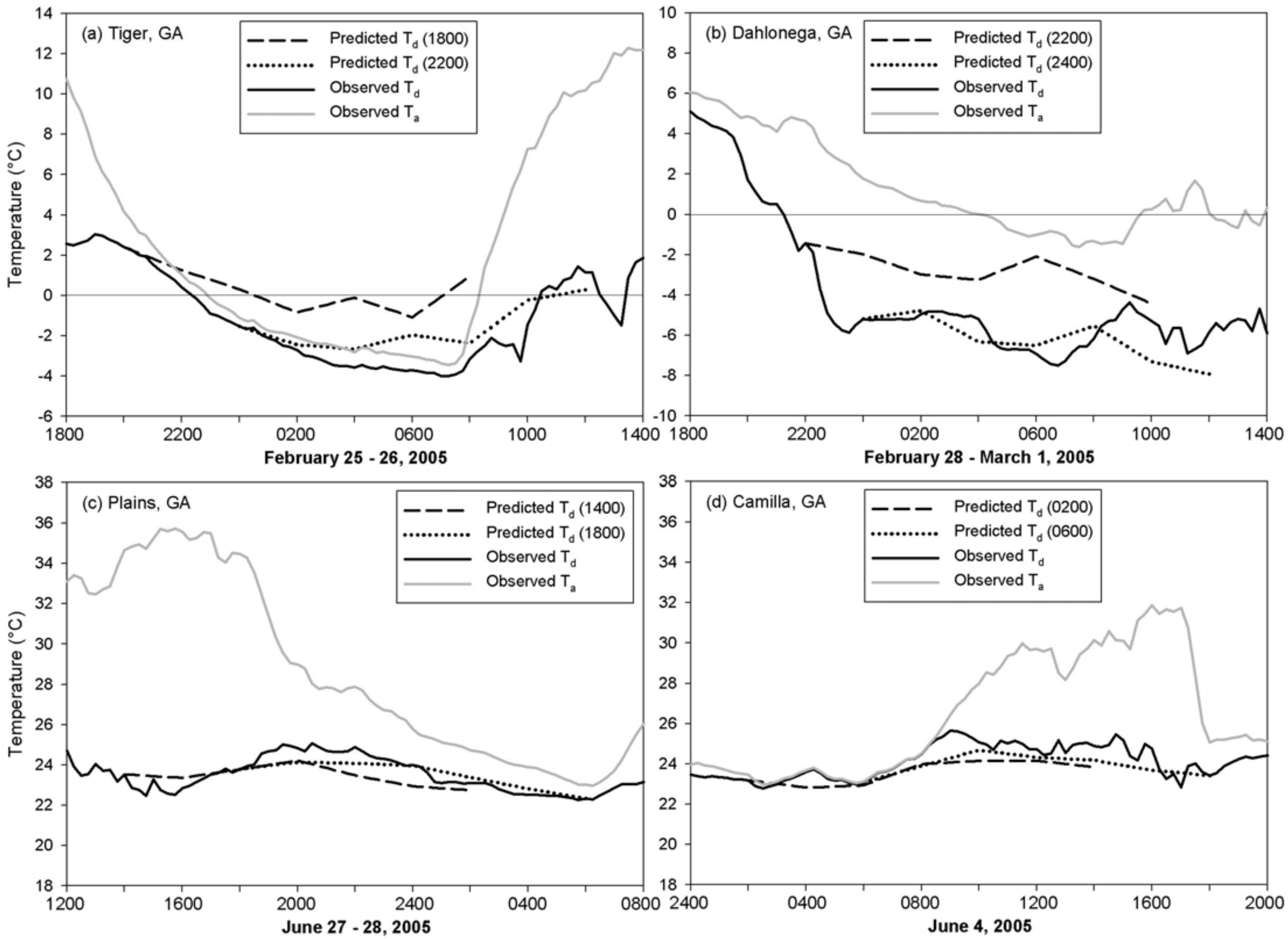

Figure 3.7: Predicted dew point temperature at two prediction times based on a sequence of twelve models for (a) Tiger, GA, (b) Dahlonega, GA, (c) Plains, GA, and (d) Camilla, GA. Observed dew point temperature and air temperature are also shown.

CHAPTER 4

SUMMARY AND CONCLUSION

The goal of this thesis was to develop ANN models that could predict dew point temperature for up to twelve hours using a Georgia statewide data. In Chapter 2, this was accomplished by determining the preferred weather related inputs for the model, by optimizing ANN parameters for the number of nodes per slab in the hidden layer, the initial weight, and the learning rate, and by searching for the preferred duration of data for each of the twelve prediction periods. These models were shown to be more accurate for the shorter prediction periods and able to predict dew point temperature for a wide variety of meteorological conditions. The resulting models were shown to be useful as part of a decision support system.

In Chapter 3, the ANN models were improved by determining new stopping criteria based on a testing set, by showing the value of seasonal models compared with year-round models in dew point temperature prediction, and by developing an ensemble network of seasonal models with fuzzy logic membership functions. These enhanced models were shown to be more accurate than the models presented in Chapter 2. These models were evaluated under the most difficult cases, conditions of extreme dew point temperature. Although the accuracy of the predictions was variable, most of them were able to show the general tendency of the observed dew point temperature. In Chapter 3, more cases of this type of prediction applied to extreme meteorological conditions were presented than in Chapter 2.

Final ANN models will be implemented on University of Georgia Automated Environmental Monitoring Network website (www.georgiaweather.net). Future research for dew point temperature prediction can build on the work in this thesis. One area would be to examine some of the parameters and methods not fully explored in this thesis including the ensemble network parameters and the stopping criteria. Other areas of interest would be to study dew point temperature for longer prediction periods or develop a model for location-specific dew point temperature predictions. Finally, because of the interaction between weather variables, it may be useful to have an ANN ensemble with each member network predicting different, yet related weather variables such as air temperature, relative humidity, vapor pressure, and dew point temperature.

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