FROST PREDICTION USING ARTIFICIAL NEURAL NETWORKS: A CLASSIFICATION APPROACH

by

RAMYAA

(Under the Direction of Ronald W. McClendon)

ABSTRACT

Air temperatures below freezing can damage plants. Irrigation is the most widely practiced frost protection measure. However, growers need information about when to start irrigating, as the process has to be commenced prior to the temperature dropping below freezing. The goal of this study was to develop Artificial Neural Networks (ANNs) to predict if frost would occur during the near future. A classification approach to develop the ANNs was used. This would require a method to predict frosts, but a model for frost prediction would typically require access to local weather. Many locations that could potentially benefit from frost prediction do not have historical weather data, or even a local weather station. An additional goal was to develop ANNs to predict frost for any given location in the state of Georgia. ANNs were developed using weather data from multiple locations and were evaluated for other locations.

INDEX WORDS: Artificial Neural Networks, Classification systems, Weather Prediction.

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RAMYAA

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RAMYAA

Major Professor: Ronald W. McClendon

Committee: Gerrit Hoogenboom
Walter W. Potter

Electronic Version Approved:

Maureen Grasso
Dean of the Graduate School
The University of Georgia
August 2004

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CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

Weather is one of the most important factors in agricultural production, especially in rain-fed agricultural production systems. In such systems, up to 90% of the variability in the yield can be attributed to weather differences (Hoogenboom, 2000c). Fruit crops such as blueberries and peaches are particularly susceptible to low temperatures. Temperatures below freezing damage the plants and temperatures near but above freezing might slow down plant growth and development. The severity of damage is determined by the duration of low temperature, the temperature itself and factors such as the type of plant, variety, stage of development, amount of leaf cover and wind speed (Tyson et al., 2002).

Farmers can provide some protection against frost by using wind machines or through irrigation. Wind machines induce air movement, through heating the air by using orchard heaters. Irrigation works by forming a layer of ice that keeps the temperature of the flower near freezing, preventing it from dropping to lower temperatures. Irrigation is the most widely practiced frost protection measure for crops like peaches and blueberries. Farmers need information about when to start irrigating, as the process has to be commenced prior to the temperature dropping below freezing. In addition to the expected low temperatures, farmers also need information about local wind speed, dew point or vapor pressure deficit to determine the point to initiate the frost protection measures (Hoogenboom, 2002). Thus there is a need for accurate local weather information and short-term weather forecasts.

Traditionally weather forecasts have been provided by the National Weather Service (NWS). However, changes in the USA laws do not allow NWS to provides data for agricultural applications. In addition, the NWS collects data from urban centers and at airports, thus the data is not useful for rural areas where farming is mostly done. In response to this need, the University of Georgia initiated the Georgia Automated Environmental Monitoring Network (AEMN) (Hoogenboom, 1996, 2000a, 2000b, Hoogenboom et al., 2000). This is a network of over 57 automated weather stations that are mainly located in the remote areas of Georgia, USA. These weather stations measure air temperature, relative humidity, soil temperature at depths of 2 cm, 5 cm and 10 cm, wind speed, wind direction, solar radiation, vapor pressure deficit and soil moisture every second. The averages, or totals depending on the variable, are calculated for every fifteen minutes and stored in the data logger. In addition, daily summaries are also calculated at midnight. The data are downloaded to a central computer located in Griffin. The AEMN program has a website (www.Georgiaweather.net) that disseminates this information as well as simple calculators that can dynamically calculate degree days, chilling hours, a water balance for management of irrigation and other data summaries (Georgiev and Hoogenboom, 1998, 1999, Hoogenboom et al. 1998). The web page has proven to be very popular; however it does not have a forecasting component.

A study was conducted by Jain et al. (2003) to develop a model for forecasting temperature. There have been projects that have tried to forecast the daily minimum temperature (Sutherland (1980), Dmiri et al., (2002), Li et al., (2004)). Forecasting temperature is relevant to protecting crops from cold damage since they can be used in predicting frosts, which damage the crops, and near frosts, which slow plant growth and development. However, these models are general purpose temperature forecasting models which are not dedicated to predicting frosts and near frosts.

ANNs have been developed to predict frost or freeze formation. Robinson and Mort (1996) developed an ANN-based system to predict overnight frost formation in Sicily, Italy. Their output classified the input as weather conditions that would or would not lead to a frost in the next 24 hours. They found that the best ANN predicted two false alarms and one failure over the course of a 50-day model evaluation set. This study was limited by the fact that it only classified a given 24 hour period as a non-freezing or freezing period. It is desirable to also have a model that can predict near frosts.

Chill is defined to be the temperature below 7^{o}C, (Okie et al., 1998) which indicates that low temperatures above freezing are significant. In addition, the temperature of the canopy at the surface can be slightly below the air temperature. This would mean that predicting air temperatures slightly above zero could also be appropriate in predicting frosts.

Jain et al. (2003) developed ANN models to forecast air temperature in hourly increments from 1 to 12 hours for Alma, Fort Valley and Blairsville in Georgia, USA. However, this study was limited by the fact that the model was not specifically developed to predict frosts. So, even though the model could give a good overall performance, a dedicated model might be able to perform better on the near freezing and freeing temperatures.

The goal of this study was to develop artificial neural network (ANN) models would predict frosts and near frosts. The specific objectives included 1) To develop ANNs that can predict short-term frosts and near frosts for a given location when trained with historical weather data from that same location and 2) To develop ANNs that can predict short term frosts and near frosts for a location that does not have sufficient historical weather data.

In chapter 1, e.g., this chapter, the problem is introduced and the overall goal of the research is presented along with some background information and literature review. This chapter also provides information about the organization of the thesis and contents of chapter two, three and four.

Chapter 2 describes the objectives, methodology, results and preliminary conclusions dealing with development of location specific models (i.e. objective 1). The discussion would be restricted to the location specific models of Fort Valley, Alma and Blairsville.

In chapter 3 describes the development of a general model for temperature prediction (i.e. objective 2). A general model is developed based on data from many locations and which can then be used for predicting temperature at any location.

In chapter 4 the overall research results are summarized, conclusions are presented and recommendations are provided for future research.

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CHAPTER 2

FROST PREDICTION USING ARTIFICIAL NEURAL NETWORKS: A CLASSIFICATION APPROACH[1]

[1] Ramyaa, R.W. McClendon and G. Hoogemboom. To Be Submitted to ASAE.

ABSTRACT

Air temperatures below freezing can permanently damage and kill plants during certain growth stages, while temperatures near but above freezing can slow down plant growth and development. Irrigation is the most widely practiced frost protection measure for many crops, including peaches and blueberries. However, growers need information about when to start irrigating, as the process has to be commenced prior to the temperature dropping below freezing. Frost is defined as air temperature falling below $0^{o}C$. The goal of this study was to develop Artificial Neural Networks (ANNs) to predict if frost would occur during the next twelve hours. A classification approach to develop the ANNs was used, i.e. if the prediction period included a frost event, then the period was classified as a *frost*. ANN models were developed for four, eight, and twelve-hour periods. Meteorological data including air temperature, relative humidity, wind speed, rainfall and solar radiation were obtained from the Georgia Automated Environmental Monitoring Network (AEMN) for three locations in Georgia, including Fort Valley, Blairsville, and Alma. Model development included data from 1993 through 2000 and model evaluation included data from 2001 and 2002. The models were first evaluated using the data from the locations for which they were trained. In addition, the models developed for a specific location were also evaluated using data from the other two locations. Various performance measures were investigated and a non-dimensional error measure was developed. The models developed using data from locations with more frost events proved to be more accurate. Blairsville averaged 40 frost events per year, and Fort Valley and Alma averaged 17 and 10 frost events, respectively. The model developed for Blairsville had an error measure of 0.089 averaged over evaluations for Blairsville, Fort Valley and Alma. Using the same evaluation data, the models developed for Fort Valley and for Alma data both averaged 0.104. Future research will focus on developing a general ANN model based on data from multiple locations.

INTRODUCTION

One of the most important factors affecting agricultural production is weather (Hoogenboom, 2000c). Fruit crops such as blueberries and peaches are particularly susceptible to damage from low temperatures at certain growth stages. Frost occurs when air temperature drops below $0^{o}C$ and these temperatures may damage plants. However, temperatures just above $0^{o}C$ can also slow plant growth and development. Growers can provide some protection against frost by using wind machines or irrigation (Powell and Himelrick, 2003). Irrigation is the most popular method of frost protection for horticultural crops such as blueberries and peaches (Tyson et al., 2002). Irrigation forms a layer of ice that keeps the temperature of the flower just above the freezing temperature, preventing it from dropping to lower temperatures. However, irrigation has to be started prior to the temperature dropping below $0^{o}C$. Thus, there is a need for short-term weather predictions for use by growers, especially during the period that the plants are in bloom or susceptible to freezing temperatures in general.

Traditionally, weather forecasts have been provided by the National Weather Service (NWS). However, the NWS mainly collects data from urban centers and at airports which are not useful for the regions where agriculture is the dominant sector. In response to this need, the University of Georgia developed the Georgia Automated Environmental Monitoring Network (AEMN) (Hoogenboom, 1996, 2000a, 2000b, Hoogenboom et al., 2000). This is a network of 57 automated weather stations located in remote areas of the state of Georgia, USA. These weather stations measure air temperature, relative humidity, soil temperature at depths of 2 cm, 5 cm and 10 cm, wind speed, wind direction, solar radiation, vapor pressure deficit and soil moisture at one-second intervals. The website of the AEMN (www.Georgiaweather.net) disseminates near real-time weather information (Georgiev and Hoogenboom, 1998, 1999, Hoogenboom et al. 1998). However, it currently does not have the capability to provide a local temperature prediction based on real-time local weather data.

Artificial Neural Networks

Artificial Neural Networks (ANNs) are artificial intelligence-based computational procedures for mapping input patterns to outputs consisting of real-valued or discrete-valued functions. Traditional statistical learning techniques can, in general, only learn combinations of linear functions, whereas neural networks can learn non-linear functions of arbitrary complexity. For problems where the mapping of inputs into outputs is complex or obscure, ANNs are among the most efficient of learning techniques known (Smith, 1993).

ANNs mimic the behavior of neurons in the brain. Neurons are primarily computational units which sum inputs, present the net input to an activation function and output the result. The neurons are connected by weighted links through which the outputs of neurons reach other neurons. ANNs work by capturing the complex relationships between inputs and outputs through the weights of the links. Learning is a process of determining the optimal values of the weight for each link. The error between the ANN output and the target output is used to adjust the weights of the connections by using the method of gradient descent.

Model development is conducted using training and testing data sets and a separate model evaluation data set is used to determine the accuracy of the trained network. The data used for updating weights in the standard back propagation architecture are called the training data. The process of pattern presentation and weight update is repeated until the error for the testing data, which is distinct from the training set, reaches a minimum. For the testing set the data are applied only in the feed forward mode and the weights are not updated.

ANNs have been used in several studies for estimating meteorological variables. Elizondo et al. (1994) developed an ANN for estimating daily solar radiation. Felker and Han (1997) used a radial basis function ANN to estimate daily soil water evaporation, while Bruton et al. (2000) developed various ANNs to estimate daily pan evaporation. Mehuys et al. (1997) created ANNs to simulate daily fluctuations of soil temperature at various depths.

ANNs have only been used in a few studies for frost prediction. The traditional method of frost prediction is to develop statistical or analytical models to forecast the minimum temperature, which is then used to predict frost. For instance, Figuerola and Mazzeo (1997) developed an analytical model for prediction of nocturnal and dawn surface temperatures in order to predict frost. Sutherland (1980) simulated air and soil temperatures by means of numerical solutions. Dmiri et al. (2002) developed a statistical model for predicting the maximum and minimum temperatures at Manali, India, while Raible et al. (1999) developed a statistical model for short-term weather forecasting. There have been many empirical and theoretical formulae developed for predicting minimum temperatures, as reviewed by Bagdonas et al. (1978). However, the state-of-art of predicting minimum temperatures and frost is not sufficiently developed to meet the present needs.

As mentioned previously, ANNs are not limited in complexity, which makes them very powerful, unlike statistical methods which are typically linear. However, powerful machine learning methods are prone to overfitting. In ANNs overfitting can be prevented by limiting the training time and number of hidden nodes. Thus, it is possible to develop a system which has just the right complexity to capture the patterns in the weather that is needed to predict frost. Robinson and Mort (1996) developed an ANN-based system to predict overnight frost formation in Sicily, Italy. The input variables were the previous day's minimum and maximum temperatures, cloud cover, maximum wind speed and direction, humidity, wind speed and wind direction at 1900 hrs. Their output classified the input as weather conditions that would lead to a frost (defined as any temperature below 1^{o}C) during the next 24 hours. They reported that the best ANN predicted two false alarms and one failure over the course of a 50-day model evaluation set. Jain et al. (2003) developed an ANN model based on Ward networks to predict air temperature in hourly increments from one to twelve hours for Alma, Fort Valley and Blairsville, Georgia. They experimented with the importance of different inputs as well as various neural network architectures and found that temperature, relative humidity, solar radiation, and wind speed were important in generating temperature forecasts. The mean absolute error (MAE) for predicting air temperature one hour and twelve hours ahead was 0.6^{o}C and 2.4^{o}C for Fort Valley, 0.7^{o}C and 3.0^{o}C for Blairsville, and 0.6^{o}C and 2.6^{o}C for Alma, Georgia.

<u>Classifications Models</u>

To make a decision regarding the initiation of irrigation, the information that is needed is whether or not a frost will occur in the near future, i.e. a classification into *frost* and *no frost*. However, almost all the existing systems predict the future temperature, which is a continuous valued function. The predicted temperatures can then be interpreted to classify conditions as *frost* or *no frost*. An alternative approach would be to directly classify a subsequent period as having frost conditions or not. Such a model would aim at classification, i.e. learning a discrete valued target function. A classification model would be dedicated to learning the weather patterns leading to frost, as opposed to a general temperature prediction model, which would learn the weather patterns leading to temperatures of a wide range.

Furthermore, it would be desirable to predict *near frosts* as well. Chill has been defined as temperatures between 0 ^{o}C and 7^{o}C (Okie et al., 1998), which indicates that low temperatures above freezing are important. In addition, the temperature of the surface of the canopy can be slightly below the air temperature. It is well understood that canopy surface temperature can be lower than ambient temperature due to radiative heat losses (Monteith, 1973; Nobel, 1991) Therefore, a model that could use the current weather to classify subsequent periods as *frost, near frost* and *no frost*, would be useful.

The overall goal of this research was to develop a Decision Support System (DSS) for classifying the subsequent period into *frost*, *near frost* or *no frost*, using ANNs. The specific objectives of this study were to determine (1) the preferred set of inputs and the corresponding architecture for an ANN that can classify frost predictions, (2) how accurately the ANNs developed for a specific location can forecast frosts for that location, and (3) if models developed with data for multiple locations are more accurate than location specific models.

MATERIALS AND METHODS

Weather data:

The weather data for this study were obtained from the Georgia AEMN for the years 1993 through 2003. The data represent selected fruit producing areas of Georgia, including Alma, Blairsville and Fort Valley. Only data from the months of January through April were used because during this period the air temperature varies between freezing and non-freezing and the crops are susceptible to damage from frost conditions.

The weather data from each location were partitioned by year into model development and model evaluation sets. Data prior to 2001 were used for model development and data from the years 2001 and 2002 were used for evaluation. The model development set was randomly subdivided into a training set with 60% of the data patterns and the remaining patterns were placed into a testing set. A final evaluation of the models was performed with data from 2003.

ANN model observations or patterns consist of associated inputs and outputs. The inputs consisted of weather variables, day of year and the time of day. In the preliminary study, the output was a classification into *frost* or *no frost*, depending on the minimum temperature (T_{min}) during the specified prediction period. Frost was defined as the temperature passing through 0^oC from positive to negative. The networks predicted if frost occurred during, the subsequent period. Thus, a single observed frost event will generate several patterns of frost for developing the ANN models. The models were developed for the subsequent four, eight and twelve hour periods.

The question of whether or not a frost will occur in the near future is meaningless if frost conditions are currently known to exist. Therefore, no data patterns were developed for conditions when the current air temperature was below 0^oC. Also the models were dedicated to frost prediction, which is needed only when there is a reasonable chance that a frost may occur during the next twelve hours. It was observed that the temperature did not fall from above 20^oC to 0^oC within twelve hours over a period of seven years based on the data from the locations used in this study. Therefore, the models were developed for conditions when current temperatures were above 0^oC and below 20^oC.

Preliminary analysis (two-state classification model):

A preliminary study using a two-state classification model to predict *frost or no frost* was conducted to determine the preferred ANN architecture, importance of rainfall as an input, preferred representation of change in weather variables as inputs, and the preferred number of output nodes. NeuroShell™ software (Ward System Group Inc., Frederic, MD, 1993) was used to develop the ANNs in this study. The various types of ANNs that were evaluated included probabilistic neural networks (PNNs), Ward ANNs and standard back propagation (BP).

In the BP ANN architecture, the nodes of the input layer receive the inputs and pass the results of their computations to the nodes of the output layer through the hidden layer(s). The BP ANNs learn by adjusting their weights to minimize the sum of squares of errors in their prediction of the target or known output (Smith, 1993). A Ward ANN is a modification of the BP ANN with three slabs of hidden nodes in a single hidden layer that have different activation functions (Ward System Group Inc., Frederic, MD, 1993). The input and output layers may also have different activation functions. PNNs are traditionally used for classification problems. They include input, pattern and summation units as well as an output unit. Each pattern unit directly corresponds to a training pattern. After training, each of the pattern units computes a distance function, such as dot product or Euclidean distance, between itself and the given pattern to be classified. The output for an evaluation data set is the probability that a pattern is similar to a pattern in the training data set (Andries, 2002).

Jain et al. (2003) studied the importance of the weather variables such as temperature, relative humidity, wind speed, solar radiation, and rainfall as inputs for estimating temperature. Other inputs included time of day, converted into a cyclic variable and change in the values of the weather variables. They found that all the inputs that were considered, except for rainfall, were useful in forecasting air temperature. We conducted experiments to determine if rainfall was a critical input in the classification approach.

Experiments were also conducted to determine the benefit of including the change in the selected input variables during previous periods as an input. The study also considered the best method for representing the change in the values of the weather variables (Δ) using two approaches: a) difference between the current value and the value n hours prior to the current observation b) the difference between hourly values, i.e., between n and n-1 hours earlier.

Experiments were conducted to determine the preferred approach for representing the outputs. The two approaches considered included: a) one output node with a continuous output classified as *frost* and *no frost* using a threshold value of 0.5 or b) two output nodes with one for *frost* and one for *no frost* and a winner take all interpretation of output. Networks were trained with both representations and their accuracy was compared with an evaluation data set to determine the preferred representation.

Three-State Classification Models:

The three-state classification problem included an additional classification category of *near frost*, along with the *frost* and *no frost* from the two-state classification problem. A threshold temperature of $3^{o}C$ was arbitrarily selected to create this classification of *near frost*, while the frost classification was unchanged. The *no frost* classification was now defined for periods with $T_{min} > 3^{o}C$.

In creating the data sets for developing the models for estimating a continuous target function using machine learning techniques, it is important to have representative data. A representative sample is one in which the ratios of patterns from various classes are the same as that of the population from which the sample is selected. A stratified sample is one in which the number of instances of various classes are equal, although they are not equal in the original population from which the sample is drawn. Usually, the sample data used in model development are representative of the distribution in the population. However, in classification problems where one class occurs much more frequently than another class, stratification of sample data can yield improved results (Smith, 1993). In the population of this study, the observed patterns for *frost* and *near frost* have a much lower probability of occurrence than *no frost*. The *frost* and the *near frost* patterns were duplicated in the model development data set to obtain a stratified data set, e.g., containing approximately an equal number of each of the three classes. Experiments were also conducted in which noise up to 5% was sampled from a normal distribution and added to the duplicated patterns.

Weather data from Blairsville, Alma and Fort Valley were used to develop location specific models, using data from a single location. These models were evaluated with the model evaluation data from the same location for which they were developed. In addition, these ANN models were evaluated with data from the other two locations to determine how accurately the models performed for other locations. Subsequently, models were developed with data from different combinations of these three locations. The following combinations of these three locations were used to develop various multi-location models: (a) Fort Valley and Alma, (b) Fort Valley and Blairsville, (c) Blairsville and Alma, and (d)Fort Valley, Blairsville and Alma,. These models were then evaluated for each of the three individual locations, including Blairsville, Fort Valley and Alma. To summarize, we developed a total of seven models, three site-specific and four combinations of various locations.

Performance measure

It is important to establish a performance measure that determines the accuracy of a classification model, but it is often highly problem specific. For the two-state classification models a simple performance measure was used which consisted of selecting the model which had the lowest number of false negatives. A false negative is a *frost* predicted as *no frost*. If two networks had the same number of false negatives, then, the one with the lower number of false positives was selected. The number of frost events missed (or predicted) is relative to the number of frost events present, which depends on the location. In order to standardize this measure, the percentage or ratio of the number of patterns classified by the network to the observed number is used. Thus, the results are presented in the raw number format (Percentage %), where the raw number is the number of frost events missed (or predicted). The statement false negatives are “x (y%)” means there were x patterns that were actually frosts, but not predicted as *frosts* by the network and y is the percentage:

$$y = \frac{x}{total\_number\_of\_frosts} \times 100 . \qquad (1)$$

We also evaluated each model using the Chi squared test, odds skill score (OSS) and Gilbert skill score (GSS). Chi squared test, a traditional statistical test, is calculated as the sum (over all the classes’ totals) of squares of the difference between the observed number of events and expected number of events, and divided by the expected number of events. Although the Chi squared test is standard, it is not very common for use in weather forecasting. Odds Skill Score uses Hit ratio (H), which is the relative number of times an event (frost) was predicted when it actually occurred, and False alarm ratio (F), which is the relative number of times an event (frost) was predicted when it did not occur. The Odds Skill Score is calculated as follows:

$$OSS = \frac{(H - F)}{(H + F - 2HF)} \qquad (2)$$

Gilbert Skill Score uses bias (B), which is the ratio of number of times an event (frost) is predicted to the number of times the event (frost) occurred, and is calculated as follows:

$$GSS = \frac{H}{(1 + B - H)} \qquad (3)$$

The problem studied needed a measure that considered the false positives, but would give them less importance than the false negatives. The Chi squared test and OSS skill measures give equal importance to *frost* and *no frost* predictions whereas GSS ignores the false positives.

For this study, the three categories that were selected for model development were ordinal. The *near frost* category had a T_{min} which was lower than that of the *no frost* category. Similarly, the *frost* category contained a T_{min} which was lower than that of the *near frost* category. Thus, *no frost* was more closely related to *near frost* than to *frost.* Therefore, frost conditions classified as *near frost* should be regarded as less of an error than *frost* conditions classified as *no frost*. Another consideration was that *frost* and *near frost* were rare compared to the number of *no frost* events.

Utility measures estimate the performance of a model from a particular user's perspective in which every misclassification is given the different importance. The standard statistical procedure is to estimate the cost incurred by the misclassifications. A model's performance is then assumed to be the cost-weighted sum of its misclassifications. However, in the frost prediction problem, the severity of damage due to frost depends on factors such as plant type and the stage of development of the crops. It is, therefore, rather difficult to estimate the cost incurred by missing a frost event and it can also be highly variable. Hence, we used weighting factors instead of cost as a performance measure. For the three-state classification system the misclassifications were arranged in the relative order of the associated damage from most damaging to least damaging:

1) *frost* predicted as *no frost*,

2) *near frost* predicted as *no frost*,

3) *frost* predicted as *near frost*,

4) *no frost* predicted as *near frost,*

5) *near frost* predicted as *frost* and

6) *no frost* predicted as *frost*.

Different weight sets were considered ranging from 1 – 10 to 1 – 10,000, for least damaging weight to most damaging weight. This measure also included a normalizing factor to balance the difference in the probability of occurrence of the different events, and a scaling factor to limit the measure to a range between 0 and 1.

These error measures were applied to these studies to measure the performance of location specific models and models developed using data from multiple locations. For each error measure, the ANN models were ordered based on their error measures for each evaluation location. We found that the range of weights had no effect on the ordering of the ANN models. Therefore, the maximum weight of 500 was arbitrarily selected to be representative of the various weight sets.

RESULTS AND DISCUSSION

Classification ANN models were developed to predict frosts occurring during the subsequent four, eight and twelve hour periods. All the experiments were conducted using data from the three locations. However, methodological choices were made using Fort Valley, as it is an example of "typical" or moderate weather in the state of Georgia. All the results reported are for the evaluation data sets. In particular, the twelve-hour period network for the Fort Valley weather data was used in the ANN parameter selection process, as it was the longest time period considered. The results for this case were found to be consistent with the results for the other locations and time periods. Hence, the results of the preliminary analysis are presented for the model developed using Fort Valley data for twelve hours.

Preliminary Analysis:

PNNs, Ward networks, and BP ANNs were considered to determine the best ANN network structure for a twelve-hour prediction for Fort Valley. The false negative and false positive counts for the three networks considered were 156 and 55 for PNN, 160 and 54 for Ward, and 155 and 51 for BP ANNs. Based on this preliminary study it was concluded that the BP ANNs produced slightly better results, and the BP ANN network structure was used in all subsequent model development experiments. The structure of the BP ANN is shown in Figure 2.1

To determine the effect of including rainfall as an input, networks were trained with and without rainfall as input for Fort Valley data for a twelve-hour prediction period. The false negative and false positive counts for the network with rainfall were 153 and 52, whereas for the network without rainfall were 155 and 51. Rainfall was therefore determined to be a useful input for predicting frosts using the classification approach.

Experiments were conducted to determine the benefit of including the change in input variables as an additional input. The network is provided with the value of the chosen weather variables at the time of decision and the hourly values hourly, up to six hours prior to the time of decision. These weather variables change over time and this change (Δ) may be a useful input. The difference between the value at the time of decision, t_0, and the values *i* hours prior to the time of decision, t_i, were represented in several ways and presented to the network as inputs. Networks trained with the change corresponding to time *i* represented as $t_0 - t_i$ had a false negative count of 153 and a false positive count of 52. When the change corresponding to time *i* calculated as $t_i - t_{i-1,}$ the network had a false negative count of 157 and a false positive count of 50. It can be seen that the representation that includes the change in the values of the weather variables as inputs performed the best and therefore used for all subsequent model developments.

The experiment to determine the best mode of output resulted in the following: the network with one output node with a continuous output classified as *frost* and *no frost* using a threshold of 0.5 had a false negative count of 153 and a false positive count of 52. The network with two output nodesconsisting of one for *frost* and one for *no frost* with a winner take all policy had a false negative count of 158 and a false positive count of 49. Therefore, one output node was used in all further experiments.

The statistical measures of Chi squared, Odds skill score, and Gilbert skill score were also included as performance measures to help determine the best networks. Table 2.1 summarizes the false positives and false negatives for the best networks for all three locations for all three time periods. The best four-hour model out of the three locations considered was found for Blairsville based on a false negative percentage of 26% ,followed by Fort Valley with 48% and Alma with 55%. This ordering was also supported by the Chi Squared error measure that showed a 1.2 for Blairsville, 18.2 for Fort Valley and 18.8 for Alma. Blairsville also had the highest GSS of 0.61, followed by Fort Valley with 0.46 and Alma with 0.4 However, the OSS analysis ranked Alma and Fort Valley the best with a score of 0.99, followed by Blairsville with a slightly lower OSS score of 0.98.

The best eight-hour model for the three locations considered was found for Blairsville based on a false negative percentage of 30%, followed by Fort Valley with 49% and Alma with 53%. This ranking was also supported by the Chi Squared error measure, which was 11.9 for Blairsville, 51.7 for Fort Valley and 36.7 for Alma. Blairsville also had the highest GSS of 0.59, followed by Fort Valley with a GSS of 0.48 and Alma with 0.43. However, the OSS analysis ranked Fort Valley the best with a score of 0.99, followed by Alma with 0.98 and then Blairsville with 0.96.

The best twelve-hour model for the three locations considered was found for Blairsville based on a false negative percentage of 28%, followed by Fort Valley with 43% and Alma with 48%. This ranking was also supported by the Chi Squared error measure, which was 13.5 for Blairsville, 30.4 for Fort Valley and 34.2 for Alma. Blairsville also had the highest GSS of 0.61, followed by Alma with a GSS of 0.5 and Fort Valley with 0.48. However, the OSS analysis ranked Alma the best with a score of 0.99, followed by Fort Valley with a slightly lower score of 0.98 and Blairsville with a score of 0.95.

For all three time periods, most of the statistical measures ranked the models for Blairsville to be the best, followed by the models for Fort Valley and then Alma. OSS, which gives equal importance to false negatives and false positives, did not rank the networks in the same order. However, the problem considered herein requires a measure that rates false negatives as more important than false positives.

When the twelve-hour model was applied to a restricted domain and used to predict frosts only for the successive eight hours, it performed better than the eight-hour network which was trained for the eight-hour time period. That is, the twelve-hour network missed fewer frost patterns which occurred during the next eight hours than the eight-hour network. For instance, the twelve-hour model developed for Blairsville and evaluated for Blairsville for eight-hour periods classified 55 *frost* patterns as *no frost* compared to the eight-hour model with 65 misclassifications. Similarly, the eight-hour network missed fewer *frost* patterns in the next four hours than the four-hour network. For instance, the eight hour model developed for Blairsville and evaluated for Blairsville for four hours predicted eight *frosts* as *no frosts* compared to the four hour model with 23 misclassifications. However, the model developed for Blairsville eight hours performed better then the twelve-hour model when both these models were evaluated for the restricted period of four hours. The eight-hour model had 10 misclassifications of frost patterns into no frost patterns while the twelve hour model had eight such misclassifications. The twelve-hour model is the model of choice for periods from four to twelve hours in the future. For the subsequent four hours, the eight hour model is best.

<u>Three-State Classification models:</u>

Temperature just above 0oC might slow down plant growth. So, networks predicting near frosts in addition to frosts could be useful. The following section presents the results of three-state classification model which classifies the future into frosts, near frosts and no frosts. A consistency matrix shows how the patterns of each category are classified. The rows of the consistency matrix represent the observed categories and the columns represent the predicted categories into which the observed categories are classified. Table 2.2 gives the consistency matrix for networks predicting twelve hours ahead for Fort Valley using stratified data. Although the frost patterns predicted as no frost patterns decreased, e.g., 39 (11%) with duplication and 46 (12%) without duplication, the other misclassifications increased. For instance, the number of no frost predicted as frosts was 60 (2%) with duplication and 12 (0.4%) without duplication. Though this appeared to be good from the point of view of this study, this was an artificial, forced model which “moved” some patterns from other categories into frosts. The number of frost events missed was reduced, but the number of non-frost events predicted as frosts were increased, e.g., the number of false negatives decreased but the number of false positives increased. Therefore, subsequent experiments did not use stratified data.

The results of the models developed using data from site specific locations for the prediction period of twelve hours evaluated for the locations for which they were developed is summarized in Table 2.3. The model developed for Blairsville misclassified 7% of frost patterns as no frost patterns, while the model developed for Fort Valley misclassified 13% of frost patterns as no frost patterns. And the model developed for Alma misclassified 16% of frost patterns as no frost patterns. Based on the percentage of frost patterns misclassified as no frosts, it can be seen that Blairsville performed best, followed by Fort Valley and Alma. The misclassifications can be divided into two categories analogous to false positives and false negatives. If frost is misclassified, it is false negative. If no frost is misclassified, it is false positive. If near frost is classified as frost, it is false positive, and if it is classified as no frost, it is false negative. Though the model for Blairsville performs the best in terms of false negatives, it has the highest percentage of false positives.

The results of the networks developed using different combinations of the three locations for all three prediction periods are summarized in Table 2.4 which gives the error measure developed for these networks. For the prediction period of four hours, when evaluated for Fort Valley, the model developed for Fort Valley performed the best with an error measure of 0.051, followed by Blairsville with an error measure of 0.065.

For the same prediction period, when evaluated for Blairsville, the model developed for Blairsville performed the best with an error measure of 0.069, followed by the model developed for Blairsville and Alma with an error measure of 0.074. When evaluated for Alma, the model developed for Blairsville performed the best with an error measure of 0.0761 followed by the model developed for Fort Valley with an error measure of 0.0763.

For the prediction period of eight hours, when evaluated for Fort Valley, the model developed for Blairsville and Alma performed the best with an error measure of 0.068, followed by the model developed for Blairsville and Fort Valley with an error measure of 0.076. For the same prediction period, when evaluated for Blairsville, the model developed for Blairsville and Alma performed the best with an error measure of 0.072, followed by the model developed for Blairsville with an error measure of 0.083. When evaluated for Alma, the two-site model developed for Blairsville and Alma performed the best with an error measure of 0.078 followed by the single-site model developed for Blairsville with an error measure of 0.092.

For the prediction period of twelve hours, when evaluated for Fort Valley, the single-site model developed for Blairsville performed the best with an error measure of 0.082, followed by the two-site model developed for Blairsville and Alma with an error measure of 0.085. For the same prediction period, when evaluated for Blairsville, the model developed for Blairsville performed the best with an error measure of 0.085, followed by the model developed for Blairsville and Alma with an error measure of 0.088. When evaluated with data from Alma, the model developed for Blairsville performed the best with an error measure of 0.1 followed by the model developed for Blairsville and Alma with an error measure of 0.105.

The models developed using Blairsville data typically provided the lowest error measure. For instance, the model developed for Blairsville for twelve hour period, when evaluated for Fort Valley had an error measure of 0.082, which was the lowest, compared to an error measure of 0.091 for the model developed for Fort Valley and evaluated for Fort Valley. The model developed for Alma for twelve hour period, when evaluated for Fort Valley had an error measure of 0.95, which was the highest. The only time a model performed best without Blairsville included was for Fort Valley for a prediction period of four hours, for which the model for Fort Valley performed the best.

It can be seen that a model that was developed with data from Blairsville consistently lowest error measure. A possible explanation is that the data from Blairsville included more frequent temperatures around freezing when compared to the other two sites. The weather data contained more frost events which gave the model more robustness. Some models that were developed with a combination of data from Blairsville and Alma, two-site models, also performed well. As an example, the error measure when evaluated for Fort Valley was for the two-site model for Blairsville and Alma 0.085, which was only slightly higher than the single-site model developed for Blairsville, which had an error measure of 0.082 Interestingly, Alma had a low percentage of frost events, e.g., ten frost events per year on an average. The two-site model developed for Blairsville and Alma for the twelve hour period, had an error measure of 0.85 when evaluated for Fort Valley, second only to the single-site model developed for Blairsville and evaluated for Fort Valley. It is possible that the data from this combination of locations made the model robust.

Frost events vs. Frost patterns

The results discussed previously were presented in terms of number of frost patterns. A single observed frost event can generate many frost patterns. A potential user of this system would be interested to see how well the frost events are predicted. An analysis was conducted to determine the accuracy of the models in terms of frost events. It is possible for the models to incorrectly classify some of the frost patterns for a frost event, yet predict the frost event. For instance, assume that a frost event occurs at 5:00 am. A twelve-hour model should predict a frost on the previous day from 5.00 pm onward. However, the model might miss predicting the frost at 5.00 pm and 6.00 pm but predict a frost from 7.00 pm onwards. Thus, the model missed the correct prediction of the first two patterns, but it ultimately predicted the frost event. In the evaluation data set the number of observed frost events for Fort Valley, Blairsville, and Alma were 32, 96 and 21, respectively. It was found that the models for all three locations, evaluated for the location for which they were developed, successfully predicted every frost event for all three prediction periods. For this simulation, the network was considered successful in predicting a frost event if it correctly predicted the event at least once. However this occurred only twice for Fort Valley and Blairsville and once for Alma. For the majority of the frost events, out of (typically) twelve predictions, the predictions for the eight hours immediately prior to the frost event was predicted correctly. Figure 2.2 shows a graph plotting the number of freeze events against the percentage of possible patterns predicted. For instance, the first bar corresponds to the number of freeze events for which the network predicted only less than 10% of the possible patterns correctly. In 39 out of the possible 96 frost events, the model predicted at least 90% of the possible frost patterns correctly. Also in 83% of the 96 events the model correctly predicted over half of the possible frost patterns.

<u>Non-numeric performance measures</u>

There are some desirable characteristics of an ANN output in terms of its use in decision support. The ANN output is a continuous value ranging from 0 to 1, therefore it would be desirable if the certainty of the output could be reflected in this numerical value. The decision maker would then be able to use this tool along with their level of risk aversion to make choices. For the two-state classification system, the output was interpreted as *frost* if the output had at least a value of 0.5, otherwise it was interpreted as a *no frost*. It would be useful if outputs near 1 and 0 could be interpreted as having greater certainty than outputs near 0.5. For example, if the ANN output is either 0.9 or 0.6, the patterns would be interpreted in both cases as a *frost*. However, the ANN with an output 0.9 would represent a greater certainty than 0.6. Values closer to 0 and 1 would correspond to the greatest certainty and values closer to 0.5 would correspond to least certainty. Figure 2.3 shows a graph that illustrates how well the numerical output of the ANN corresponds to certainty. The network considered was a two-state network for Blairsville for the prediction period of twelve hours. The first category defines the network output from 0.0 to 0.1. The height of the bar represents the percentage of correct classifications, i.e., percentage of *no frosts* for this output. The shape of the graph shows that when the network output is closer to the boundaries (0 or 1), the percentage of correct classifications is higher. This indicates that the network output can be interpreted as an indication of certainty. Figure 2.4 shows a graph that plots certainty in another manner for three state systems. It is a histogram of frost patterns versus the corresponding numerical output of the ANN. For instance, the first bar corresponds to the number of freeze patterns for which the network output a value from 0.0 to 0.1. For 770 of the 980 frost patterns or 79 %, the ANN output was 0.6 or greater. For only 63 of the 980 frost patterns or approximately 6%, the ANN output was less than 0.3. Moreover, the greatest number of patterns was in the >0.9 cell i.e. had a numerical output greater than 0.9.

It would also be helpful if the ANN model had a higher accuracy for short-term predictions than for longer term ones. For example, it would be desirable if the model had a higher accuracy when predicting a frost two hours ahead compared to one twelve hours ahead. The error is more critical to the crop manager if the network misses a short term frost event than if it misses a frost event. For three-state classification models, Figure 2.5 gives a graph plotting the percentage of correct classifications versus the length of time until the event occurred for Blairsville for the predication period of twelve hours. As expected, the accuracy was greater for shorter prediction periods. For instance, the dark section of the first bar represents the number of frost events successfully predicted one hour ahead. The gray section represents the number of frost events predicted as near frost event one hour ahead and the white section represents the number of frost events predicted as no frost events one hour ahead. This shows that the network is more accurate in predicting near-term frosts than frost that are twelve hours ahead. Also, the accuracy of prediction decreases almost monotonically with the number of hours in the prediction period. The twelve-hour model is not effective in predicting frosts beyond ten hours ahead. These graphs show that the network has the qualitative properties of certainty and higher accuracy when the event is nearer.

SUMMARY AND CONCLUSIONS

ANN models were developed to predict *frosts* and *near frosts* four, eight and twelve hours ahead for three locations in Georgia, including Alma, Blairsville and Fort Valley. Experiments were conducted to determine the preferred architecture, usefulness of some inputs, preferred output representation, and usefulness of stratified data. The best networks were those that used the BP ANN approach. Experiments indicated that rainfall and the rate of change of variables were useful inputs. Single output node ANNs gave the best results.

For the two-state classification systems for twelve hours, the false positive percentage and false negative percentage were 28% and 5% for Blairsville, 43% and 1% for Fort Valley, 48% and 0.6% for Alma. The error measure, i.e., a normalized, weighted sum of the misclassifications, of the three-state classification system for twelve hours was 0.091 for Fort Valley, 0.085 for Blairsville, and 0.112 for Alma. The location specific three-state classification systems were more accurate in predicating *frosts* for the location for which they were developed then for predicting frost for the other two locations.

Also, models were developed with various combinations of the three locations. The models that were developed based Blairsville, on the location that had the most frost events, in general performed best. Models developed with data from Blairsville and Alma also proved to be good and robust models. For instance, when the twelve-hour two-site model developed with data form Blairsville and Alma was evaluated for Fort Valley, it had an error measure of 0.085, which was only slightly higher than a single-site model developed with data for Blairsville only, with an error measure of 0.082, and the model developed for Fort Valley with an error measure of 0.091. In general, models developed with data from multiple locations were comparable in accuracy to the location-specific models.

The frost predictions were also analyzed to determine the certainty of the numerical output, accuracy of predictions with respect to frost events instead of frost patterns and accuracy of predictions with respect to period of prediction. The two-state networks' certainty was related to its numerical output in that when the network's output was close to the threshold, it was less accurate. The three-state network's numerical outputs also reflected their certainty in predicting frost, in that, for most of the frost patterns, the numerical output was close to 1. It was also found that the networks were accurate in predicting frost events. The accuracy of prediction decreased with the period of prediction. This analysis can aid managers in their decision to when to take action to protect their crops.

Future research should involve incorporating these analyses in a web–based DSS. Further research will also focus on developing a general ANN temperature predictor based on data from multiple locations. Such a general model is needed because a particular location may not have adequate historical weather data to be able to develop a location-specific model.

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Table 2.1 Two-state classification results[1] for location specific models for Fort Valley, Blairsville, and Alma, four, eight and twelve hours prediction periods.

Period of Prediction	4 hours		8 hours		12 hours	
Predicted / Observed	Frost	No Frost	Frost	No Frost	Frost	No Frost
Fort Valley						
Frost	67(52%)	63(48%)	128(51%)	124(49%)	202(57%)	153(43%)
No Frost	15(0.3%)	4368(99.7%)	13(0.3%)	4248(99.7%)	52(1%)	4106(99%)
Blairsville						
Frost	277(74%)	98(26%)	511(70%)	218(30%)	745(72%)	285(28%)
No Frost	77(2%)	3856(98%)	133(4%)	3446(96%)	182(5%)	3096(95%)
Alma						
Frost	43(45%)	53(55%)	91(47%)	101(53%)	146(52%)	132(48%)
No Frost	11(0.3%)	4055(99.7%)	19(0.5%)	3951(99.5%)	23(0.6%)	3861(99.4%)

[1] x(y%): x=count of (mis)classification patterns;y= percentage of (mis)classification w.r.t. the actual total

Table 2.2 Consistency matrix for the ANN model developed and evaluated with stratified data from Ft. Valley, twelve hour prediction period[2]

Observed \ Predicted	Frost	Near Frost	No Frost	Sum
Frost	284 (80%)	32 (9%)	39 (11%)	355
Near Frost	220 (32%)	188 (27%)	274 (40%)	682
No Frost	60 (2%)	87 (3%)	3329 (95%)	3476
Sum	564	307	3642	4513

[2]x(y%): x=count of (mis)classification patterns;y= percentage of (mis)classification w.r.t. the actual total

Table 2.3 Consistency matrices for the site-specific ANN model developed for Fort Valley, Blairsville and Alma ; twelve hour prediction period; evaluation data from same location [3]

Observed \ Predicted	Frost	Near Frost	No Frost
Fort Valley			
Frost	240 (68%)	68 (19%)	46 (13%)
Near Frost	85 (12%)	310 (45%)	287 (42%)
No Frost	13 (0%)	115 (3%)	3349 (96%)
Blairsville			
Frost	765 (74%)	189 (18%)	76 (7%)
Near Frost	150 (22%)	274 (41%)	244 (37%)
No Frost	54 (2%)	217 (8%)	2339 (90%)
Alma			
Frost	172 (62%)	62 (22%)	44 (16%)
Near Frost	27 (8%)	109 (34%)	186 (58%)
No Frost	8 (0%)	75 (2%)	3479 (98%)

[3] x(y%): x=count of (mis)classification patterns;y= percentage of (mis)classification w.r.t. the actual total

Table 2.4 Error measure for evaluating models developed with various combinations of sites when evaluated for Fort Valley, Blairsville and Alma. FV = Fort Valley; B = Blairsville; A = Alma.

Period of prediction	4 hours		8 hours		12 hours	
Evaluation location	Model development location	Error measure	Model development location	Error measure	Model development location	Error measure
Fort Valley	FV	0.051	B & A	0.068	B	0.082
	B	0.065	B & FV	0.076	B & A	0.085
	B & FV	0.068	B	0.077	B & FV	0.086
	B & A	0.070	A	0.082	FV	0.091
	B & FV & A	0.074	FV & A	0.085	B & FV & A	0.093
	FV & A	0.077	B & FV & A	0.086	FV & A	0.094
	A	0.081	FV	0.091	A	0.095
Blairsville	B	0.069	B & A	0.072	B	0.085
	B & A	0.074	B	0.083	B & A	0.088
	FV	0.078	B & FV	0.096	B & FV	0.097
	B & FV	0.080	B & FV & A	0.100	B & FV & A	0.100
	B & FV & A	0.084	A	0.103	A	0.104
	A	0.093	FV	0.112	FV	0.110
	FV & A	0.094	FV & A	0.115	FV & A	0.112
Alma	B	0.076	B & A	0.078	B	0.100
	FV	0.076	B	0.092	B & A	0.105
	B & A	0.078	B & FV	0.097	B & FV	0.110
	B & FV	0.079	FV	0.109	FV	0.112
	B & FV & A	0.082	B & FV & A	0.110	A	0.112
	A	0.092	FV & A	0.115	FV & A	0.118
	FV & A	0.094	A	0.117	B & FV & A	0.139

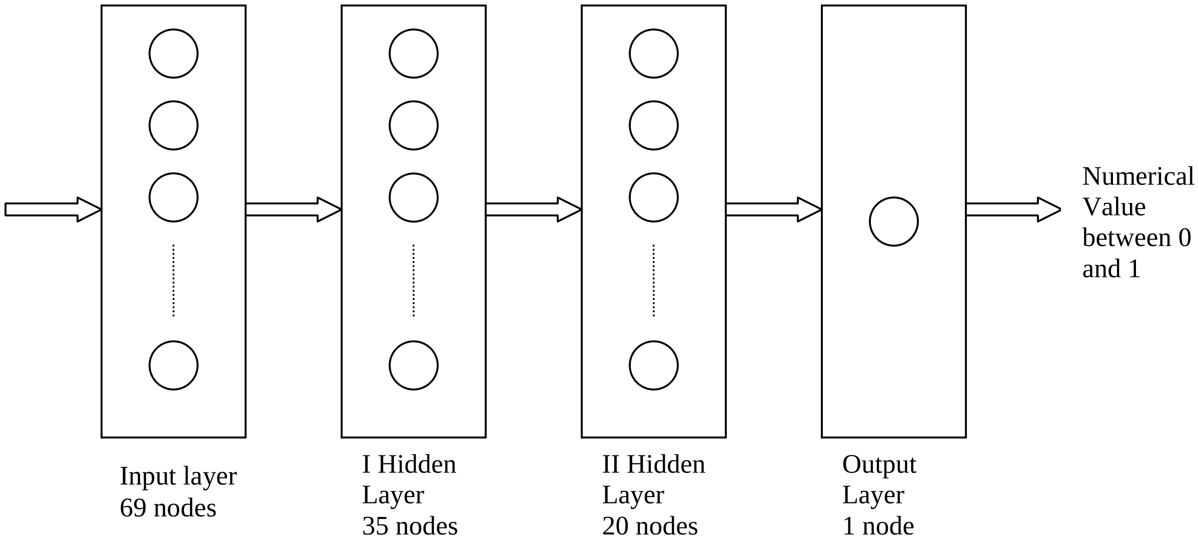

Figure 2. 1 Back Propagation Artificial Neural Network for Three-state classification system for Fort Valley for a prediction period of twelve hours.

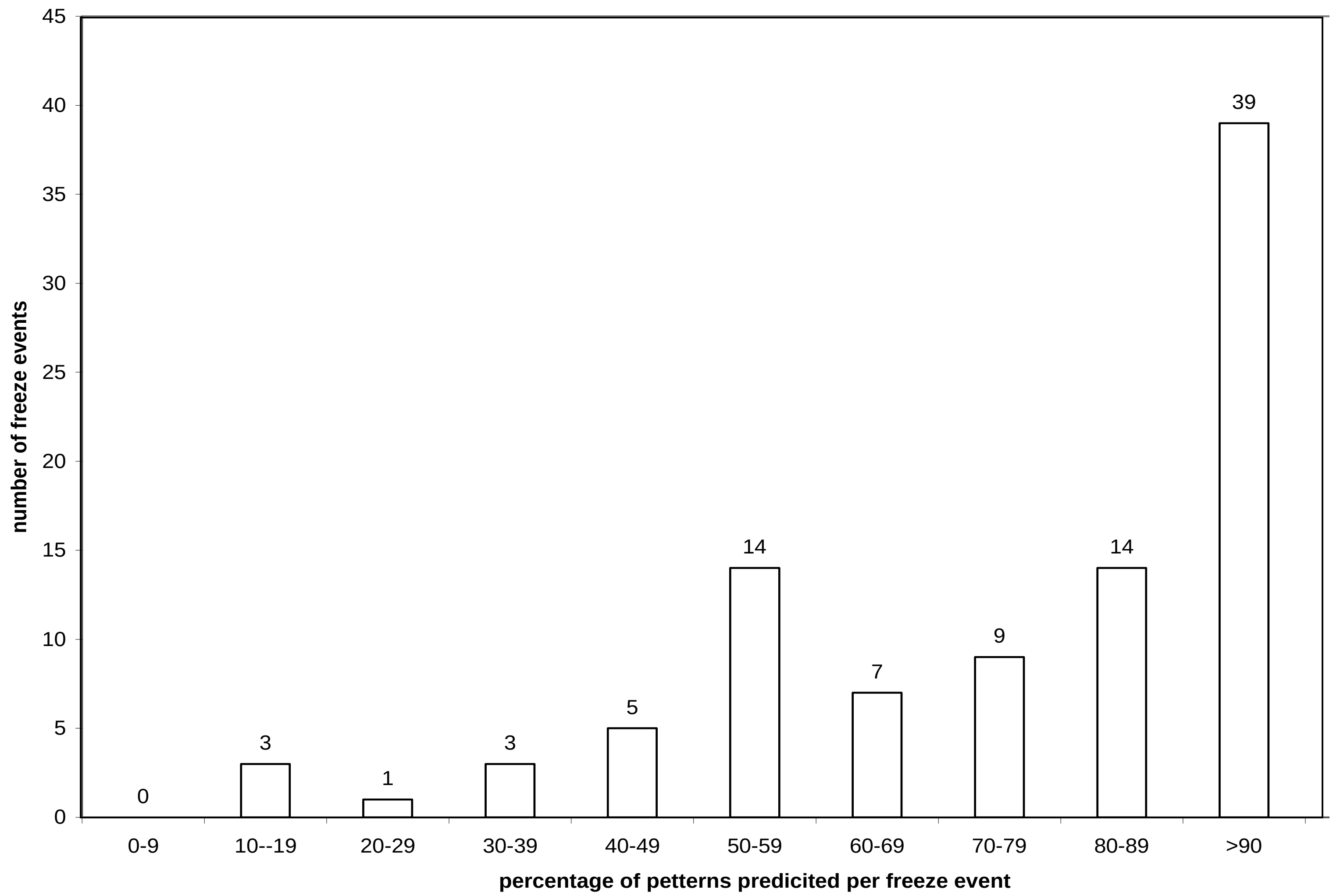

Figure 2.2 Histogram of the number of freeze events against the percentage of patterns generated by then that were predicted correctly Blairsville model development and evaluation data, twelve-hour prediction period.

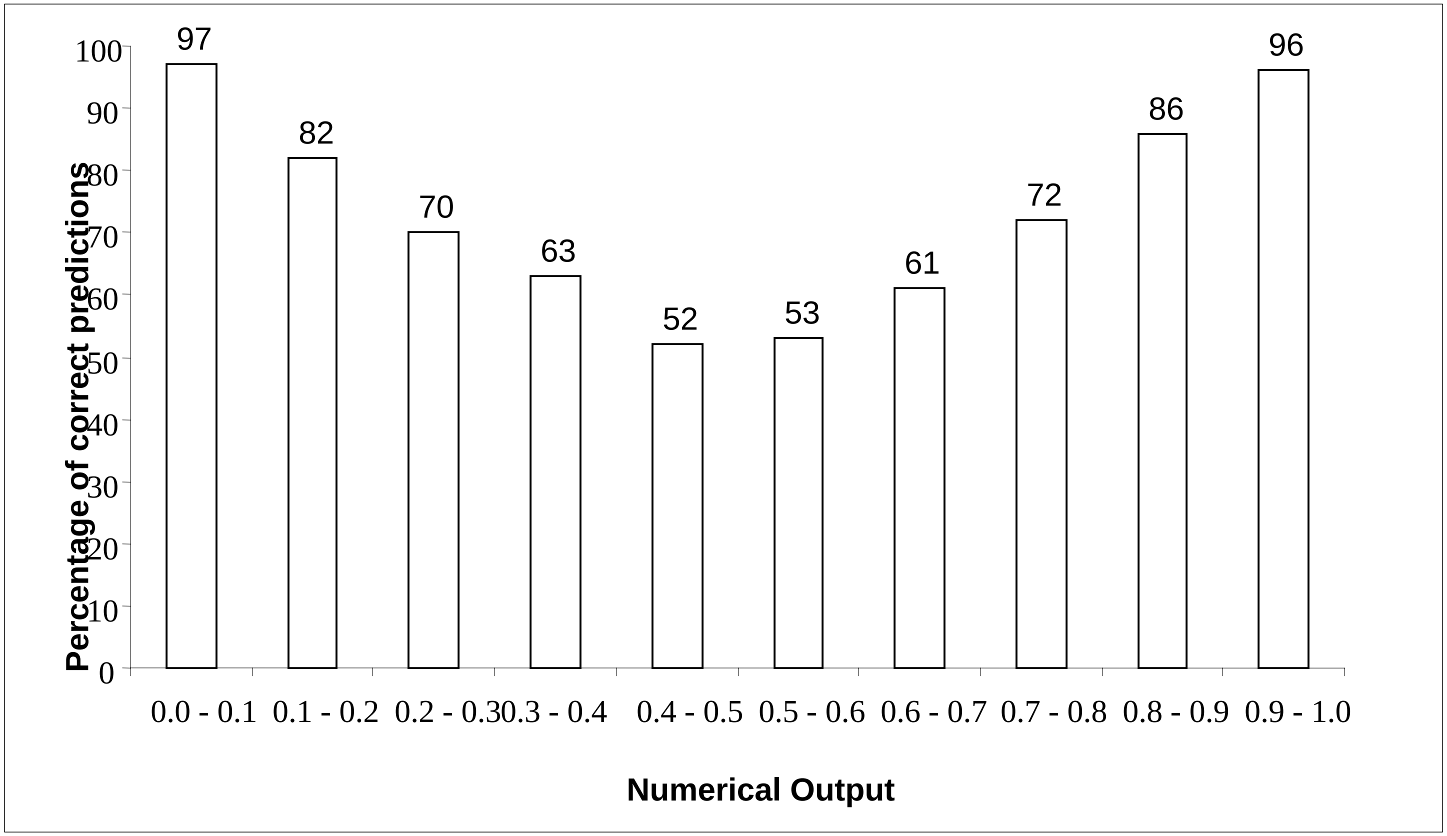

Figure 2.3 Histogram of the accuracy of the predictions as a function of the numerical value of the ANN output (certainty), Blairsville model development and evaluation data, twelve-hour prediction period two state system.

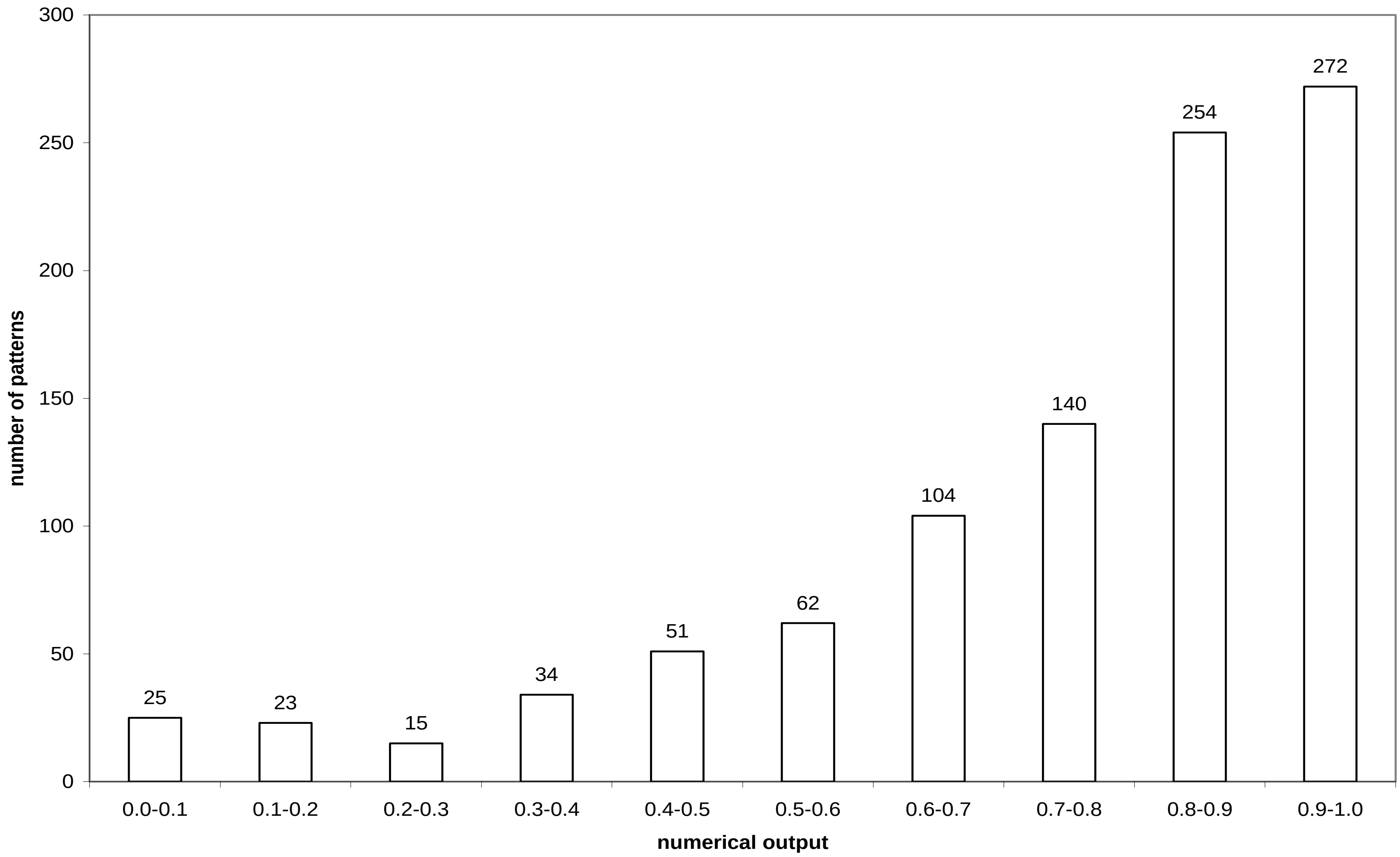

Figure 2.4 Histogram of the accuracy of the predictions as a function of the numerical value of the ANN output (certainty), Blairsville model development and evaluation data, twelve-hour prediction period three state system.

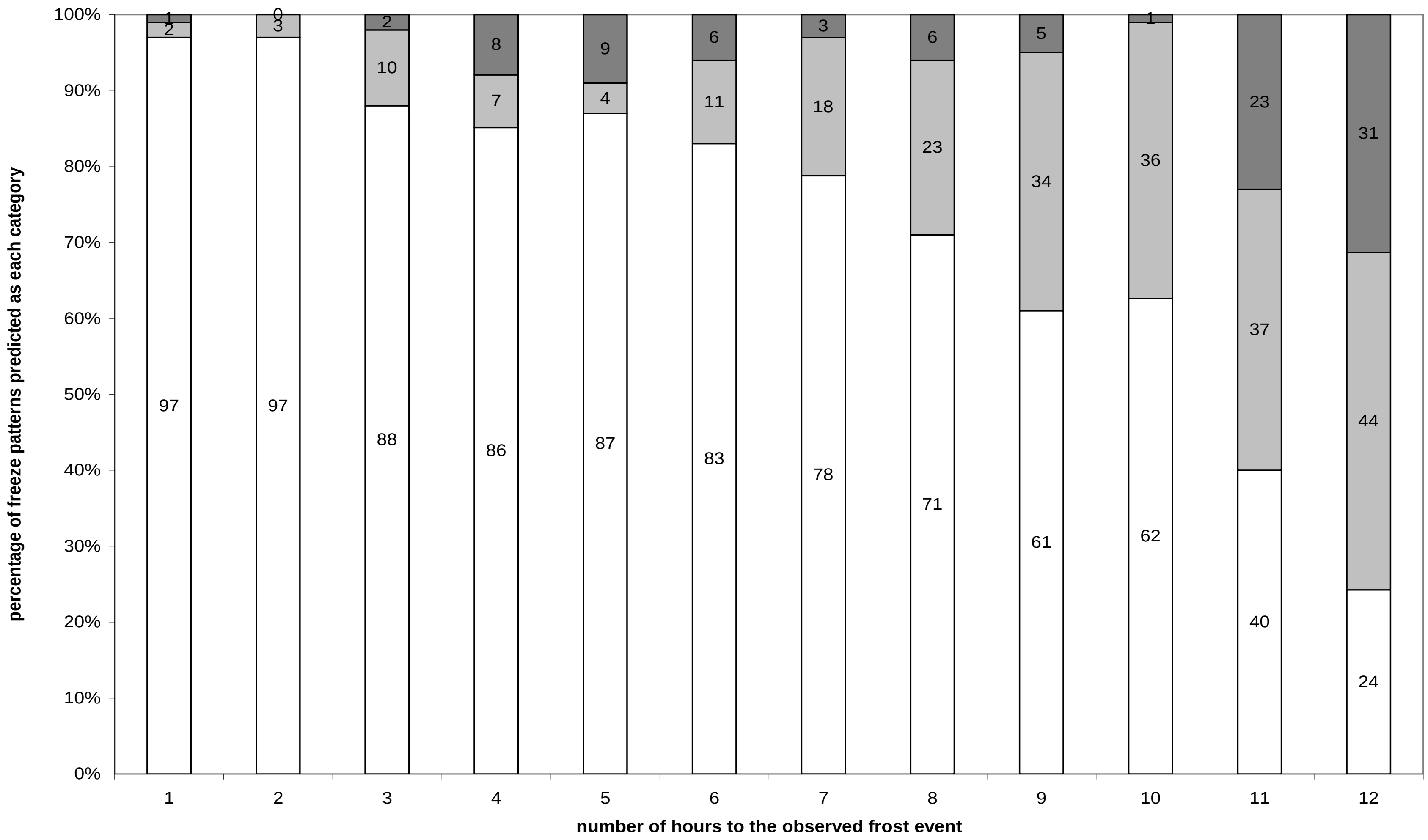

Figure 2.5 Histogram of the percentage of freeze patterns predicted as function of the number of hours of the prediction period. Blairsville model development and evaluation data, twelve-hour ANN model.

	Predicted as freeze
	Predicted as near freeze
	Predicted as no freeze

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CHAPTER 3

FROST PREDICTION USING ARTIFICIAL NEURAL NETWORKS: A GENERALIZED CLASSIFICATION MODEL[2]

[2] Ramyaa, R.W. McClendon and G. Hoogemboom. To Be Submitted to ASAE.

ABSTRACT

Although frost can be desirable in some stages of horticultural plant development, frost during bloom or budding phases can seriously damage the plant causing a reduction in yield. Crops can be protected from frost damage using measures such as irrigation, provided irrigation is started prior to the temperature dropping below freezing. This would require a method to predict frosts, but a model for frost prediction would typically require access to local weather. Many locations that could potentially benefit from frost prediction do not have historical weather data, or even a local weather station. The goal of this study was to develop Artificial Neural Networks (ANNs) to predict frost for any given location in the state of Georgia. ANNs were developed using weather data from multiple locations and these ANNs were then evaluated for other locations where no historical weather data were available. It was found that the general ANN models could predict temperatures for a given location without historical data with reasonable accuracy. For instance, the average error measure of the general model developed using data from nine locations, when evaluated for 23 locations was 0.0957, which was only slightly higher than the average error measure of location-specific models which was 0.0951. For 19 out of 23 locations, this general model performed as well or better than the location-specific models. The four locations for which location-specific model out performed this general model were Blairsville, Dixie, Dublin and Savannah. Of these locations, Blairsville and Savannah were used to develop the general model, while the other two were not. Thus, the performance of this general model for a given location does not depend on the inclusion of this location for model development, or geographical proximity of a location to locations used for general model development.

Future research will focus on incorporating the general frost prediction model into a pre-existing web-based information dissemination program, where it can be used as a decision support tool to aid farmers in protecting their crops from frost damage.

INTRODUCTION

Fruit crops such as blueberries and peaches are particularly susceptible to damage due to low temperatures during certain crop phases, especially flowering and early reproductive development. During these periods temperatures below freezing may damage the plants and temperatures near but above freezing might slow down plant growth and development. Frost is defined as the air temperature below $0^{o}C$.

To some extent, plants can be protected against frost using wind machines or irrigation. Irrigation is the most widely used means for frost protection of horticultural crops such as peaches and blueberries. However, for irrigation to be effective it must be started prior to the temperature dropping below freezing. Thus, there is a need for accurate local weather information and short-term weather predictions. The University of Georgia initiated the Georgia Automated Environmental Monitoring Network (AEMN) (Hoogenboom, 1996, 2000a, 2000b, Hoogenboom et al., 2000) to provide local current weather information. The AEMN is a network of 57 automated weather stations that measure air temperature, relative humidity, soil temperature at depths of 2 cm, 5 cm and 10 cm, wind speed, wind direction, solar radiation, vapor pressure deficit and soil moisture at one-second intervals. The AEMN website (www.Georgiaweather.net) provides fruit growers and other users with access to near real-time weather information (Georgiev and Hoogenboom, 1998, 1999, Hoogenboom et al. 1998). However. the AEMN web-site currently does not have the capability to provide a local temperature prediction based on the most-recently observed data.

A machine learning system developed for predicting weather typically would use prior weather data to extract knowledge about weather patterns and use this to predict weather in the near future. A weather forecasting model developed for a single specific location using data from that location may not perform well for other locations, due to the differences in weather patterns between various locations (Ramyaa, 2004). Hence, location-specific models developed for each weather station might not be uniformly accurate throughout the state. In addition, there are many crop growing locations across the states that do not have historical weather data. However, decision makers at those locations could benefit from weather prediction. Thus, a general model that can predict *frosts* and *near frosts* for any given location is needed.

Artificial Neural Networks (ANNs) are a modeling tool that provide a robust approach to approximating real-valued as well as discrete-valued functions. These functions have traditionally been modeled using statistical methods. However, statistical modeling techniques such as linear regression can typically only approximate linear functions, whereas ANNS can learn functions of arbitrary complexity. For problems where the mapping of inputs into outputs is complex or obscure, ANNs are among the most efficient learning techniques currently known (Smith 1993).

ANNs mimic the behavior of neurons in the brain. Computational neurons are the basic components of an ANN. Neurons are connected by links which have weights associated with them. These are computational units which calculate the activation function value of the sum of its inputs and pass it to other neurons via the links. ANNs work by capturing the complex relationships between inputs and outputs in their weights. Learning is a process of trying to correct the weight for each link. The error between the ANN output and the target output is used to adjust the weights of the links by using gradient descent. The data that are used are called the training data. Weight updating is repeated until the error for the testing data, which is a data set disjoint from the training set, reaches a minimum. The training and testing data comprise the model development data set. Once training is complete, the ANN is applied to the evaluation data set, yet another data set disjoint from both training set and testing set, to determine its accuracy.

ANNs have been used in several studies for estimating temperature and predicting frost. Robinson and Mort (1996) developed an ANN-based system to predict overnight frost formation in Sicily, Italy. Their output classified the input as weather conditions that would lead to a frost, e.g., defined as temperature below 1^{o}C, during the next 24 hours or conditions that would not lead to a frost. They reported that the best ANN predicted two false alarms and one failure over the course of a 50-day model evaluation set.

Ramyaa (2004) conducted a study to develop ANN models to classify the subsequent hours into *frost*, *near frost* and *no frost*. Data used in this study were for Alma, Blairsville and Fort Valley, which are locations representative of the main fruit growing regions in Georgia. Individual models were developed for these specific locations and these models were then evaluated for the other two locations. Though the study considered models developed using two locations, it was not geared towards developing and analyzing generalized models, i.e. models that are developed using several locations and expected to perform well for any arbitrary location.

There have been previous studies that developed a generalized, heterogeneous model for forecasting temperature and predicting frosts. Blennow and Persson (1998) used a Geographic Information System (GIS) and a stepwise linear regression model to determine where frost could occur over an area covering 7.5 km^2 of forested and heterogeneous region in Sweden. The model generated a map with areas delineated that were prone to low temperature and frost after clear-cutting. The map provided useful information for efficient implementation of frost protection measures in forestry and was based on a simple methodology that can be applied in practical forestry.

Bagdonas et al. (1978) reported several theoretical techniques for predicting minimum temperature. These theoretical methods should technically be usable for multiple locations when the correct values of the parameters in the equations are provided into the equations for each location. However, the difficulty of finding reliable values for parameters makes these equations have little practical value. Kanazawa (1999) developed a model for predicting temperature for specific climates depending on geographical location and time of season.

Li et al. (2004) conducted a study in which they used weather data from neighboring weather stations to develop artificial neural network (ANN) models for estimating and interpolating daily maximum and minimum air temperature, and total solar radiation. Though this study helped the regions which do not have a local weather station, it did not predict future temperatures.

Jain et al. (2003) developed a general ANN model to forecast air temperature for any given location in Georgia. They also developed location-specific models and found that the general models could predict temperatures for a given location without historical data with reasonable accuracy when compared to a location-specific model. They attempted to deliver a prediction of a discrete function, i.e., *frost* or *no frost* for a given period, using the estimation of temperature, a continuous valued target function. This study was limited by the fact that it attempted to predict temperature, a continuous variable, which was then used to classify the future into *frost* or *near frost*.

Forecasting temperature is relevant to protecting crops from cold damage only because they can be used in forecasting frosts and near frosts. Hence, what is needed is a model that can classify the present weather conditions as leading to a) *frost* or b) a *near frost* or c) *no frost*. Most computer modeling tools require historical data to learn existing weather patterns in order to be able to predict future weather. A single weather station covering a large area might not give collect data that are representative for the entire area (Blennow and Persson, 1998), especially if the area is heterogeneous. Further, there are many locations which do not have historical weather data or with no weather data since they do not have a weather station/observation system. However, these locations will also benefit from weather prediction.

The goal of this study was to develop a general ANN model which could be used for frost forecasting for any location in Georgia. The specific objectives of this study were 1) determine the accuracy of a general model developed using historical data from multiple locations to predict frost for locations without historical data, 2) determine the number of locations needed to maximize the accuracy of a general model for each period of prediction, 3) compare the accuracy of a general model developed with data from multiple locations with models developed for specific locations.

MATERIALS AND METHODS

The models that were considered are three way classification systems, i.e., they classify the given weather pattern as leading to a) *frost*, b*) near frost*, or c) *no frost*. If the minimum temperature drops below $0^{o}C$ within the prediction period, the prediction period is considered as having a *frost*. If the minimum temperature drops below $3^{o}C$ but stays above 0°C within the prediction period, the period is considered as having a *near frost*. If the minimum temperature within the prediction period remains above 3°C, the period is classified as having a *no frost*. The prediction periods considered were four hours, eight hours and twelve hours.

The weather data were obtained from the Georgia AEMN for the years 1993 to 2003. The locations that were selected covered most of the state of Georgia. Weather data from the following 23 locations were used in this study: Alma, Arlington, Attapulgus, Blairsville, Brunswick, Byron, Cairo, Camilla, Cordele, Dearing, Dixie, Dublin, Fort Valley, Griffin, Homerville, Midville, Nahunta, Newton, Plains, Savannah, Tifton, Valdosta, and Vidalia. Model development data were based on historical weather data for the years prior to 2001, although the installation date and starting year varied for each location. Depending on the location, four to nine years of data were available for these locations as summarized in Table 3.1. Model evaluation data were based on historical weather data from 2001 to 2003. All the locations had data from 2001 onward except Homerville, which had data beginning in 2003 and Nahunta, which had data beginning on day 82 of 2002 i.e. March 23, 2002. The model development and model evaluation data were restricted to the first four months of the year, as these are the months when frost conditions are likely to occur and can potentially cause damage to the crops.

NeuroShell™ software (Ward Systems Group Inc. Frederic, MD, 1993) was used in this study to develop the ANNs. The ANN architecture used was standard back propagation ANNs based on prior research results (Ramyaa, 2004). Inputs for the ANN model included temperature, wind speed, humidity, solar radiation and rainfall, both current and prior values, along with the rate of change. Timing variables included day of year and time of day. Models in this study were developed to predict frosts in three subsequent time periods: four, eight and twelve hours.

Generalization in stages:

One objective was to determine the accuracy of a general ANN model, developed using historical data from multiple locations, to predict frost for locations without historical data. An additional objective was to determine the number of locations needed to maximize the accuracy of a general model for each period of prediction. Then, the accuracy of models at various stages of generalization was compared.

Generalization was conducted in stages so as to study its effect on the accuracy of the prediction. The first stage of model development was location-specific, i.e., models were developed with data from a single location. In the second stage, models were developed with data from two locations. The third stage consisted of models developed with data from four locations, and the fourth stage consisted of models developed withg data from nine locations.

A set of locations was defined as a configuration. For instance, the set of locations of Blairsville and Alma form a configuration. In the second stage of model development, three configurations were considered. Three sets of two locations each were used in this stage. For the third stage in which models developed with four locations, three configurations were also considered. Three sets of locations, each set consisting of four locations were used in this stage. For the fourth stage of model development, one nine-location configuration was considered.

In the first stage, location-specific models were developed for Alma, Arlington, Attapulgus, Blairsville, Brunswick, Cairo, Camilla, Cordele, Dearing, Dixie, Dublin, Fort

Valley, Griffin, Midville, Newton, Plains, Savannah, Tifton, Valdosta, and Vidalia for all three prediction periods. Models were not developed for Byron, Homerville and Nahunta as they lacked data prior to 2001. For the second stage of the study, models were developed using three configurations consisting of two locations each. For the first configuration, data from Blairsville and Fort Valley prior to 2001 were used. The second two-location configuration models were developed using the data from Alma and Blairsville and the third two-location configuration data set which consisted of data from Alma and Fort Valley. The third stage of the study had three configurations, each consisting of four locations. The first configuration consisted of model development data from Alma, Attapulgus, Fort Valley and Savannah. The second configuration of model development data used data from Alma, Attapulgus, Fort Valley and Blairsville. The third four-location configuration used data from Alma, Attapulgus, Fort Valley and Griffin. The fourth stage of the study consisted of one configuration with nine different locations. The model was developed using weather data from locations of Alma, Arlington, Attapulgus, Blairsville, Fort Valley, Griffin, Midville, Plains and Savannah. As above, the data used for model development were from the years prior to 2001.

Data layouts:

An unusual weather occurrence in one year of data for the chosen location may bias the results. Therefore, each configuration consisted of five different data layouts. A data layout consisted of a random sampling of years of data from the locations in a configuration, with the total number of years restricted to nine years. Thus, different data layouts for the same configuration will contain different years of the chosen locations(s). For instance, a stage two configuration of Blairsville and Alma might included weather from 1992, 1994, 1995 and 1997 for Blairsville and 1991, 1995, 1998, 1999 and 2000 for Alma. Nine years of data were used in each layout because the earliest weather data were from 1991, thus allowing for nine years of pre-2001 weather data. By keeping the number of years constant at nine years, it was ensured that no layout or configuration was advantaged or disadvantaged by having more or less years of data available.

The ANNs for the three prediction periods were developed for each of the five data layouts. For each evaluation location, the error measures from the five different data layouts were then averaged to provide the error measure associated with a particular configuration for that time period of prediction. The error measure associated with a particular configuration for a particular period of prediction was then calculated.

Performance Measure:

The performance measure developed in Ramyaa (2004) was used to quantify the error of the network on the evaluation data set. The misclassifications were sorted in the order of the damage they caused. Sorted from most damaging to least damaging is:

(i) *frost* predicted as *no frosts*,

(ii) *near frost* predicted as *no frost*,

(iii) *frost* predicted as *near frost*,

(iv) *no frost* predicted as *near frost*,

(v) *near frost* predicted as *frost* and

(vi) *no frost* predicted as *frost*.

The weighted sum of the misclassifications was calculated using the weight set which gives the weight 1 to the least damaging misclassification and weight 500 to the most damaging misclassification. The measure also included a normalizing factor to balance the difference in the probability of occurrence of the different events, and a scaling factor to limit the measure between 0 and 1.

RESULTS AND DISCUSSION

Four-hour predictions:

The results for the models with a prediction period of four hours are presented in Table 3.2. The results are summarized by stages, i.e. results for the location-specific models evaluated for all locations and then the models developed using data from two locations, four locations and nine locations. For the location-specific models of the first stage, the average of the error measures evaluated for 20 locations was 0.077 (SD: 0.013). The error measures ranged from 0.054 (SD: 0.047) for Dixie to 0.107 for Alma (SD: 0.04) and Nahunta (SD: 0.42).

For the models developed using data from two locations, the average error measure, when evaluated for 23 locations was 0.081(SD: 0.013) for the model developed for Blairsville and Fort Valley, 0.078 (SD: 0.011) for the model developed for Fort Valley and Alma, and 0.081 (SD: 0.012) for the model developed for Blairsville and Alma. The overall average for all the models developed using two locations over all configurations was 0.080. The error measure ranged from 0.060 (SD: 0.05) for the model developed for Fort Valley and Alma and evaluated for Brunswick to a maximum error measure of 0.114 (SD: 0.051) for the model developed using Fort Valley and Blairsville when evaluated for Nahunta.

For the models developed using data from 4 locations, the average error measure, when evaluated for 23 locations for the model developed for Blairsville, Alma, Attapulgus and Fort Valley was 0.091 (SD: 0.027), 0.083 (SD: 0.012) for the model developed for Savannah, Alma, Attapulgus and Fort Valley, and 0.092 (SD: 0.015) for the model developed for Griffin, Alma, Attapulgus and Fort Valley. The overall average for all the models developed using four locations over all configurations was 0.089. The error measure ranged from 0.056 (SD: 0.054) for the model developed for Savannah, Alma, Attapulgus and Fort Valley evaluated for Brunswick to a maximum of 0.119 (SD: 0.043) for the model developed using Griffin, Alma, Attapulgus and Fort Valley evaluated for Nahunta.

The average of the error measure for the models developed using data from nine locations evaluated for 23 locations was 0.073 with a standard deviation of 0.014. The error measure ranged from 0.054 (SD: 0.045) for Brunswick to 0.107 (SD: 0.059) for Nahunta.

To summarize, the average error measure was 0.073 for 23 locations for the nine location model, 0.077 for the location-specific models evaluated for the locations for which they were trained, 0.080 for the two-location model averaged for all the three data layouts, 0.089 for the four-location model averaged for all the three data layouts. The nine-location model had the minimum error measure in 19 locations out of the 23 locations selected for evaluation. The locations for which the nine-location model was not the best model were Blairsville, Dixie, Dublin and Savannah. For each of these four locations, the best results were obtained with the location-specific models. For the four locations where the site- specific model was better than the nine-location model, two of the sites, e.g., Dixie and Dublin, were included in the nine-location model and the other two, e.g., Blairsville and Savannah, were not. This indicated that the geographical proximity of the evaluation site to the sites included in model development did not directly impact the performance. The four-location models and the two-location models did not produce the minimum error measure for any of the locations.

<u>Eight-hour predictions:</u>

The results for the models with a prediction period of eight hours are presented in Table 3.3. The results are summarized by stages, i.e. results for the location-specific models evaluated for all locations followed by the models developed with data from two locations, four locations and nine locations. For the location-specific models of the first stage, the average of the error measures evaluated for 20 locations was 0.087 (SD: 0.015). Error measure ranged from 0.064 (SD: 0.05) for Dixie to 0.128 (SD: 0.05) for Nahunta.

The average error measure for the two-location models, when evaluated for 23 locations was 0.102 (SD: 0.055) for the model developed with data from Blairsville and Fort Valley, 0.100 (SD: 0.055) for the model developed with data from Fort Valley and Alma, and 0.098 (SD: 0.012) for the model developed with data from Blairsville and Alma. The overall average for all the models developed using two locations over all configurations was 0.094. The error measure ranged from 0.068 (SD: 0.053) for the model developed with data from Fort Valley and Blairsville and evaluated for Homerville to a maximum error measure of 0.150 (SD: 0.051) for the model developed with data from Fort Valley and Blairsville evaluated for Cordele.

For the four-location model, the average error measure, when evaluated for 23 locations, was 0.099 (SD: 0.027) for the model developed with data from Blairsville, Alma, Attapulgus and Fort Valley, 0.094 (SD: 0.012) for the model developed with data from Savannah, Alma, Attapulgus and Fort Valley was, and 0.103 (SD: 0.012) for the model developed with data from Griffin, Alma, Attapulgus and Fort Valley. The overall average for all the models developed using four locations over all configurations was 0.099. The error measure ranged from 0.067 (SD: 0.059) for the model developed with data from Savannah, Alma, Attapulgus and Fort Valley and evaluated for Brunswick to a maximum of 0.209 (SD: 0.061) for the model developed with data from Blairsville, Alma, Attapulgus and Fort Valley and evaluated on Fort Valley.

For the nine-location model, the average error measure for all 23 locations was 0.090 (SD: 0.016). The actual error measure ranged from 0.065 (SD: 0.053) for Brunswick to 0.128 (SD: 0.06) for Nahunta.

Comparing the averages of different stages of generalization, the location-specific models performed the best, followed by generalization using nine locations, the two-location and four-location models. The average error measure was 0.087 for the location-specific models when evaluated for the locations for which they were trained, 0.090 for the nine-location model when evaluated for 23 locations, 0.094 for the two-location model averaged for all the three data layouts, and 0.099 for the four-location model averaged for all the three data layouts. Note that the location-specific models were evaluated only for the locations they were trained for, and the general models were evaluated for all locations.

For the 23 locations that were selected for evaluation, the general model with nine locations gave the minimum error measure, or was tied for the minimum error measure, in 19 locations. The locations where it was not the best model were Blairsville, Dixie, Dublin and Savannah. For each of these locations, the best results were obtained using the location-specific models. Of the four locations where the site-specific model was better than the nine location model, two of the sites, e.g., Dixie and Dublin, were included in the nine-location model and two locations, e.g., Blairsville and Savannah, were not. This is in support of the claim that the geographical proximity of the evaluation site to the sites that were used for model development did not affect the performance. The two- and four-location models did not produce the minimum error measure for any of the locations, though their results were comparable to the location- specific models.

Twelve-hour predictions:

The results for the models with a prediction period of twelve hours are presented in Table 3.4. The results are summarized by stages, i.e. results for the location-specific models evaluated for all the locations and then the models developed using data from two locations, four locations and nine locations. For the location-specific models of the first stage, the average of the error measures evaluated for 20 locations was 0.092 (SD: 0.012). Error measure ranged from 0.074 (SD: 0.054) for Dixie to 0.128 (SD: 0.05) for Nahunta.

For two-location models, the average error measure, when evaluated for 23 locations was 0.121 (SD: 0.016) for the model developed with data from Blairsville and Fort Valley, 0.097 (SD: 0.012) for the model developed with data from Fort Valley and Alma, and 0.098 (SD: 0.012) for the model developed with data from Blairsville and Alma. The overall average for all the models developed using two locations over all configurations was 0.105. The error measure ranged from 0.068 (SD: 0.053) for the model developed with data from Fort Valley and Alma and evaluated for Brunswick to a maximum error measure of 0.148 (SD: 0.063) for the model developed with data from Fort Valley and Blairsville evaluated on Nahunta.

For four-location models, the average error measure, when evaluated for 23 locations for the model developed with data from Blairsville, Alma, Attapulgus and Fort Valley was 0.172 (SD: 0.040), 0.102 (SD: 0.012) for the model developed with data from Savannah, Alma, Attapulgus and Fort Valley, and 0.111 (SD: 0.015) for the model developed with data from Griffin, Alma, Attapulgus and Fort Valley. The overall average for all the models developed using four locations over all configurations was 0.128. The error measure ranged from 0.067 (SD: 0.059) for the model developed with data from Savannah, Alma, Attapulgus and Fort Valley evaluated for Brunswick to 0.206 (SD: 0.059) for the model developed with data from Blairsville, Alma, Attapulgus and Fort Valley and evaluated on Cairo.

For the nine-location models, the average of the error measures evaluated for 23 locations was 0.095 (SD: 0.013). The actual error measure ranged from 0.075 (SD: 0.05) for Brunswick to 0.128 (SD: 0.055) for Nahunta.

Comparing the averages of different stages of generalization, the location-specific models performed the best, followed by generalization using nine locations, the two-location models and then the four-location models. The average error measure was 0.095 for the location-specific models when evaluated for the locations for which they were trained, 0.092 for the nine-location model when evaluated on 23 locations, 0.105 for the two location models averaged over all the three data layouts, 0.128 for the four location models averaged over all the three data layouts. Not that, the location-specific models were evaluated only for the locations they were trained for, and the general models were evaluated on all the locations.

Out of the 23 locations that were selected for evaluation, the general model with nine locations gave the minimum error measure, or was tied for the minimum error measure, in 19 locations. The locations where it was not the best model were Blairsville, Dixie, Dublin and Savannah. For each of these locations, the best results were obtained using the location-specific models. Of the four locations where the site specific model was better than the nine site model, two of the sites, e.g. Dixie and Dublin, were included in the nine location model and two locations, e.g. Blairsville and Savannah, were not. This result is consistent for all three prediction periods and indicates that the performance of a model on an evaluation set is independent of the geographical proximity of the evaluation site to the sites included in model development. The two-location and four-location models and the two location models did not produce the minimum error measure for any of the locations, though their results were comparable to the location-specific models.

Discussion

The general model to predict *frosts* and *near frosts* for four, eight and twelve hours ahead was developed using two, four and nine locations. It was found that the performance of these general models performance was comparable to that of the location-specific models. The nine location model performed the best for all three prediction periods. For 19 out of the 23 locations for which the models were evaluated, the nine location model gave the least error measure. The four locations for which the general model consistently for all three prediction periods resulted in the highest error measures were: Blairsville, Dixie, Dublin and Savannah. From these four sites. Blairsville and Savannah were used in the general model development. Hence, inclusion of a location or the geographical proximity between the evaluation location and the locations included in training does not affect the performance in an obvious way.

The averages of the error measures of the various models were determined for each evaluation location. It was found that Nahunta had the highest average error measure for prediction periods of four and twelve hours and had the second highest average error measure for the prediction period of eight hours. Further, it was observed that Homerville also had the highest error measure for all three prediction periods. This might be because these two locations had less data that could be used for evaluation. Nahunta only included data for 2003, while Homerville had data starting on day 82 in 2002 (March 23rd 2002) and 2003. Additional experiments that were conducted supported the conclusion that a reduced evaluation data set had an impact on overall model performance for a particular site. For instance, the evaluation set for Brunswick consisted of the years 2001, 2002 and 2003. The general model with nine locations had an error measure of 0.75 when evaluated with this data set. When the general model was evaluated for a reduced data set of Brunswick with data for 2003 only, it had an error measure of 0.82.

In general, if the evaluation data set had less number of frost events, then it had a lower error measure. For instance, Brunswick had approximately seven frost events, the lowest number per year on average and it consistently had the lowest average error measure for all models and for all three prediction periods. Though it is generally the case that the average error measure increases with the number of frost events in the evaluation data set, this is not always true. For instance, Arlington has around 15 frost events per year on average, which was higher than many locations. However, Arlington had an error measure for all three locations that was below average.

SUMMARY AND CONCLUSIONS

The objectives of this study were to 1) determine the accuracy of a general model developed using historical data from multiple locations to predict frost for locations without historical data, 2) determine the number of locations needed to maximize the accuracy of a general model for each period of prediction, 3) compare the accuracy of a general model developed with data from multiple locations with models developed for specific locations.

To accomplish the first objective ANN models were developed to predict temperature at a location without historical weather data using a model developed with data from locations with historical data. The average error measure for evaluating on all 23 locations for the four-hour prediction for location-specific network was 0.079, for the two location models was 0.080, for the four location models was 0.088, and for the nine location models was 0.078.

Performance of models developed using location-specific data, data from two locations, four locations and nine locations were compared. The nine-location data configuration was the best configuration compared to the configurations that had data from four and two locations. The nine-location configuration consisted of data from Alma, Arlington, Attapulgus, Blairsville, Fort Valley, Griffin, Midville, Plains and Savannah. It was also observed that accuracy of the general models was comparable to the models that were developed specifically for a location. Future research will focus on developing hidden node optimized ANN models that can predict temperature for all durations starting from one hour to twelve hours in the future.

Once the ANNs have been developed they would be incorporated into the pre-existing web-based information dissemination programs, where they can be used as a Decision Support Tool to aid farmers in protecting their crops from frost damage. Also, further experimentation can be done with the number of locations. Other areas of future work would be in building an expert system with more than one of the chosen models, using fuzzy logic to combine these models' outputs into a system with better performance.

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Table 3.1 Weather stations from the Georgia Automated Environmental Monitoring Network (AEMN) that were used in this study

Locations	rs of available data	Pre- 2001 Data
Alma	1993 - 2003	8
Arlington	1997 - 2003	4
Attapulgus	1993 - 2003	8
Blairsville	1993 - 2003	8
Brunswick	2000 - 2003	1
Byron	2001 - 2003	0
Cairo	1998 - 2003	3
Camilla	1998 - 2003	3
Cordele	1998 - 2003	3
Dearing	1999 - 2003	2
Dixie	1999 - 2003	2
Dublin	1998 - 2003	3
Fort Valley	1993 - 2003	8
Griffin	1992 - 2003	9
Homerville	2003	0
Midville	1992 - 2003	9
Nahunta	2002* - 2003	0
Newton	2000 - 2003	1
Plains	1992 - 2003	9
Savannah	1993 - 2003	8
Tifton	1992 - 2003	9
Valdosta	1998 - 2003	3
Vidalia	1998 - 2003	3

Table 3.2 Average error measure for the prediction period of four hours averaged over five data layouts.

Development / Evaluation	Location-specific models	Two-location Models (a)*	(b)	(c)	Four-location Models (d)	(e)	(f)	Nine-location Models (g)	Min
Alma	0.107	0.099	0.098	0.101	0.097	0.095	0.104	0.092	0.092
Arlington	0.077	0.074	0.074	0.076	0.081	0.082	0.088	0.063	0.063
Attapulgus	0.094	0.086	0.085	0.088	0.089	0.088	0.096	0.074	0.074
Blairsville	0.073	0.083	0.081	0.086	0.096	0.09	0.103	0.081	0.073
Brnswk	0.069	0.061	0.06	0.063	0.061	0.056	0.066	0.054	0.054
Byron	N/A	0.075	0.076	0.078	0.077	0.079	0.085	0.074	0.074
Cairo	0.074	0.069	0.071	0.075	0.074	0.079	0.093	0.059	0.059
Camilla	0.074	0.073	0.075	0.077	0.082	0.089	0.096	0.062	0.062
Cordele	0.076	0.079	0.081	0.083	0.086	0.092	0.096	0.076	0.076
Dearing	0.09	0.083	0.083	0.085	0.082	0.082	0.088	0.078	0.078
Dixie	0.054	0.066	0.066	0.07	0.075	0.075	0.088	0.069	0.054
Dublin	0.068	0.084	0.087	0.091	0.089	0.098	0.111	0.095	0.068
Fort Valley	0.081	0.114	0.073	0.07	0.198	0.076	0.066	0.063	0.063
Griffin	0.072	0.068	0.065	0.066	0.073	0.064	0.068	0.059	0.059
Homerville	N/A	0.1	0.101	0.105	0.101	0.102	0.116	0.1	0.1
Midville	0.089	0.091	0.085	0.089	0.104	0.086	0.098	0.08	0.08
Nahunta	N/A	0.107	0.108	0.111	0.108	0.11	0.119	0.107	0.107
Newton	0.076	0.086	0.08	0.085	0.109	0.093	0.108	0.072	0.072
Plains	0.081	0.085	0.073	0.075	0.109	0.074	0.08	0.064	0.064
Savannah	0.06	0.073	0.081	0.086	0.07	0.094	0.11	0.089	0.06
Tifton	0.086	0.08	0.068	0.069	0.099	0.063	0.068	0.054	0.054
Valdsta	0.073	0.071	0.075	0.078	0.071	0.081	0.092	0.07	0.07
Vidalia	0.07	0.068	0.07	0.075	0.076	0.082	0.095	0.059	0.059

* (a) – Blairsville, Fort Valley; (b) - Fort Valley, Alma; (c) – Blairsville, Alma
(d) – Blairsville, Alma, Attapulgus, Fort Valley; (e) – Savannah, Alma, Attapulgus, Fort Valley; (f) Griffin, Alma, Attapulgus, Fort Valley
(g) - Alma, Arlington, Attapulgus, Blairsville, Fort Valley, Griffin, Midville, Plains and Savannah

Table 3.3 Average error measure for the prediction period of eight hours, averaged over five data layouts.

Development / Evaluation	Location-specific models	Two-location models			Four-locations models			Nine-location models	Min
		(a)*	(b)	(c)	(d)	(e)	(f)	(g)	
Alma	0.118	0.11	0.11	0.113	0.107	0.106	0.115	0.105	0.105
Arlington	0.087	0.087	0.088	0.09	0.091	0.093	0.099	0.084	0.084
Aattapulgus	0.105	0.1	0.1	0.099	0.099	0.099	0.107	0.095	0.095
Blairsville	0.084	0.097	0.096	0.101	0.106	0.101	0.114	0.102	0.084
Brnswk	0.08	0.072	0.071	0.08	0.071	0.067	0.077	0.065	0.065
Byron	N/A	0.089	0.09	0.096	0.087	0.09	0.096	0.086	0.086
Cairo	0.085	0.083	0.085	0.089	0.084	0.09	0.104	0.08	0.08
Camilla	0.085	0.087	0.089	0.096	0.093	0.1	0.107	0.083	0.083
Cordele	0.086	0.148	0.15	0.103	0.097	0.103	0.107	0.086	0.086
Dearing	0.1	0.097	0.097	0.1	0.092	0.093	0.099	0.09	0.09
Dixie	0.064	0.08	0.08	0.087	0.086	0.086	0.099	0.09	0.064
Dublin	0.078	0.098	0.101	0.108	0.1	0.109	0.122	0.116	0.078
Fort Valley	0.091	0.128	0.087	0.086	0.209	0.087	0.077	0.075	0.075
Griffin	0.083	0.082	0.079	0.083	0.083	0.075	0.079	0.074	0.074
Homerville	N/A	0.068	0.078	0.122	0.083	0.113	0.127	0.121	0.068
Midville	0.1	0.105	0.099	0.104	0.115	0.097	0.109	0.096	0.096
Nahunta	N/A	0.075	0.083	0.128	0.096	0.121	0.13	0.128	0.075
Newton	0.087	0.1	0.095	0.103	0.12	0.104	0.119	0.083	0.083
Plains	0.091	0.099	0.087	0.088	0.12	0.085	0.091	0.085	0.085
Savannah	0.071	0.087	0.095	0.106	0.08	0.105	0.121	0.11	0.071
Tifton	0.096	0.093	0.082	0.086	0.109	0.075	0.079	0.075	0.075
Valdsta	0.083	0.087	0.091	0.099	0.082	0.092	0.103	0.082	0.082
Vidalia	0.08	0.082	0.084	0.098	0.087	0.093	0.106	0.08	0.08

* (a) – Blairsville, Fort Valley; (b) - Fort Valley, Alma; (c) – Blairsville, Alma
(d) – Blairsville, Alma, Attapulgus, Fort Valley; (e) – Savannah, Alma, Attapulgus, Fort Valley; (f) Griffin, Alma, Attapulgus, Fort Valley
(g) - Alma, Arlington, Attapulgus, Blairsville, Fort Valley, Griffin, Midville, Plains and Savannah

Table 3.4 Average error measure for prediction period of twelve hours and four configurations, averaged over five data layouts.

Development / Evaluation	Location-Specific models	Two-location models			Four-location models			Nine-location models	Min
		(a)*	(b)	(c)	(d)	(e)	(f)	(g)	
Alma	0.112	0.111	0.113	0.113	0.109	0.114	0.123	0.103	0.103
Arlington	0.086	0.089	0.09	0.09	0.097	0.1	0.106	0.084	0.084
Attapulgus	0.097	0.098	0.1	0.099	0.102	0.107	0.114	0.095	0.095
Blairsville	0.085	0.097	0.098	0.101	0.103	0.108	0.121	0.102	0.085
Brnswk	0.085	0.113	0.078	0.08	0.178	0.075	0.084	0.075	0.075
Byron	N/A	0.125	0.096	0.096	0.184	0.098	0.104	0.095	0.095
Cairo	0.082	0.123	0.086	0.089	0.206	0.097	0.111	0.08	0.08
Camilla	0.089	0.126	0.095	0.096	0.2	0.107	0.115	0.089	0.089
Cordele	0.101	0.133	0.104	0.103	0.197	0.111	0.115	0.101	0.101
Dearing	0.101	0.133	0.1	0.1	0.198	0.1	0.107	0.099	0.099
Dixie	0.074	0.114	0.08	0.087	0.195	0.093	0.106	0.098	0.074
Dublin	0.086	0.134	0.106	0.108	0.201	0.117	0.129	0.116	0.086
Fort Valley	0.091	0.087	0.09	0.086	0.085	0.094	0.084	0.084	0.084
Griffin	0.087	0.115	0.083	0.083	0.178	0.083	0.086	0.08	0.08
Homerville	N/A	0.146	0.121	0.122	0.195	0.12	0.134	0.12	0.12
Midville	0.103	0.133	0.103	0.104	0.195	0.104	0.116	0.101	0.101
Nahunta	N/A	0.148	0.128	0.128	0.189	0.129	0.137	0.128	0.128
Newton	0.093	0.129	0.099	0.103	0.2	0.112	0.126	0.093	0.093
Plains	0.093	0.123	0.09	0.088	0.192	0.093	0.098	0.085	0.085
Savannah	0.082	0.127	0.101	0.106	0.19	0.112	0.128	0.11	0.082
Tifron	0.106	0.123	0.088	0.086	0.187	0.082	0.087	0.075	0.075
Valdsta	0.099	0.128	0.098	0.099	0.188	0.099	0.11	0.097	0.097
Vidalia	0.093	0.128	0.095	0.098	0.199	0.101	0.114	0.092	0.092

* (a) – Blairsville, Fort Valley; (b) - Fort Valley, Alma; (c) – Blairsville, Alma
(d) – Blairsville, Alma, Attapulgus, Fort Valley; (e) – Savannah, Alma, Attapulgus, Fort Valley; (f) Griffin, Alma, Attapulgus, Fort Valley
(g) - Alma, Arlington, Attapulgus, Blairsville, Fort Valley, Griffin, Midville, Plains and Savannah

CHAPTER 4

SUMMARY AND CONCLUSION

The ultimate goal of this study was to develop ANNs that predict frost and no frost and that can be incorporated in a DSS to help farmers with protecting their crops from cold damage. ANNs were developed to predict frosts and near frosts for four, eight and twelve hours ahead. Initially data from Fort Valley, Blairsville and Alma were used. Experiments involving duplication of frosts to stratify the data were conducted. Also, models were developed with various combinations of data from the three locations. The models with the most frost events, such as Blairsville, performed best. . For instance, for the two-state classification systems for twelve hours, the false positive percentage and false negative percentage were 28% and 5% for Blairsville, 43% and 1% for Fort Valley, 48% and 0.6% for Alma. The error measure, i.e., a normalized, weighted sum of the misclassifications, of the three-state classification system for twelve hours was 0.091 for Fort Valley, 0.085 for Blairsville, and 0.112 for Alma.

In the second part of this study models were developed to predict frost and near frost for a location that did not have historical weather data based on stations with historical weather data. The ANN models that were developed using data from the nine-location configuration were the most accurate models. The nine locations included Alma, Arlington, Attapulgus, Blairsville, Fort Valley, Griffin, Midville, Plains and Savannah, Georgia. The average error measures for evaluating on all 23 locations for the four-hour prediction for location specific network was 0.079, for the two location models was

0.080, for the four location models was 0.088, and for the nine location models was 0.078.

Future research will focus on developing programs that can use the ANNs developed and successfully incorporate them into the pre-existing web-based system to create the DSS that will help farmers protect their crops from frost. Expert systems that incorporate the four, eight and the twelve hour networks and form one system to predict frost would be desirable. Also, these frost predicting networks can be used in conjunction with the already existing temperature forecasting networks. The expert systems developed for the above mentioned systems can be enhanced by using fuzzy logic. Other machine learning techniques like decision trees, rule based systems developed using Genetic Algorithms can also be tried. Other areas to explore include more experimentation with the system studies – for instance, trying out three output nodes for the three state classification systems, with one node corresponding to each output category.