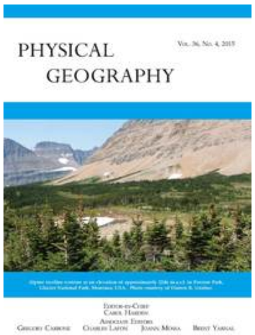

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Comparison of dew point temperature estimation methods in Southwestern Georgia

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Recent upward trends in acres irrigated have been linked to increasing near-surface moisture. Unfortunately, stations with dew point data for monitoring near-surface moisture are sparse. Thus, models that estimate dew points from more readily observed data sources are useful. Daily average dew temperatures were estimated and evaluated at 14 stations in Southwest Georgia using linear regression models and artificial neural networks (ANN). Estimation methods were drawn from simple and readily available meteorological observations, therefore only temperature and precipitation were considered as input variables. In total, three linear regression models and 27 ANN were analyzed. The two methods were evaluated using root mean square error (RMSE), mean absolute error (MAE), and other model evaluation techniques to assess the skill of the estimation methods. Both methods produced adequate estimates of daily averaged dew point temperatures, with the ANN displaying the best overall skill. The optimal performance of both models was during the warm season. Both methods had higher error associated with colder dew points, potentially due to the lack of observed values at those ranges. On average, the ANN reduced RMSE by 6.86% and MAE by 8.30% when compared to the best performing linear regression model.

Keywords: artificial neural network; dew point temperature; irrigation; land-use change; linear regression

Introduction

Changing land cover can have important effects on local climate (Mahmood et al., 2014; Marshall, Pielke, Steyaert, & Willard, 2004; Pielke et al., 2002; Shepherd, Pierce, & Negri, 2002). The state of the land cover directly influences how incoming solar radiation is partitioned into other energy budget terms, such as sensible and latent heat. Agriculture is a predominant form of land cover with croplands accounting for nearly 15 million km^2 (Ramankutty, Evan, Monfreda, & Foley, 2008), or roughly 40% of the global land cover when combined with pastures (Foley, 2005). Agricultural land cover is expected to increase with projected rises in population and the growing demand for biofuel production (Evans & Cohen, 2009). While some agricultural landscapes rely on natural precipitation for irrigation, there has been rapid growth toward artificially irrigated landscapes (Harrison, 2001; Tilman, 2001). This introduction of water at the surface has the ability to change the near-surface moisture content (Ferguson &

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Maxwell, 2011). Changnon, Sandstrom, and Schaffer (2003) stated that recent short duration heat events in the Chicago region have experienced higher dew points than those that occurred earlier in the period of record. Their research attributed these changes to changes in agricultural practices that increased evapotranspiration (ET) rates in the region. They noted the importance that small scale, local land cover changes can have on regional climate variability. Hot humid weather can cause heat stress in humans (Gaffen & Ross, 1998), increasing their chances of experiencing heat-related morbidity or mortality (Bentley & Stallins, 2008, Lippmann, Fuhrmann, Waller, & Richardson, 2013). It is difficult to assess these postulated changes in moisture content at local scales because of the lack of sufficient data outside of first-order observation stations. Thus, there is a need to model and estimate near-surface moisture from readily available meteorological data.

Early methods for estimating near-surface moisture involved using daily minimum temperature as a proxy for dew point temperature (T_d). This assumption is not always valid if there are large diurnal variations in T_d and if minimum temperature stays well above T_d (Kimball, Running, & Nemani, 1997). Kimball et al. (1997) used annual precipitation, potential ET, mean daily net solar radiation, as well as temperature (maximum, minimum, and mean) to produce a more accurate assessment of daily T_d across the United States and Alaska, primarily at first-order observation stations. Hubbard, Mahmood, and Carlson (2003) expanded on the efforts of Kimball and evaluated an additional four regression equations for the Northern Great Plains in the United States. The goal of their study was to produce a T_d estimation method that required less complex input data than Kimball et al. (1997). They wanted to take advantage of meteorological data provided by the National Weather Service Cooperative (NWS Coop) weather stations. Their analysis found that a combination of maximum (T_x), minimum (T_n), and mean (T_m) temperature are the best estimators for daily T_d. An alternative method for estimating near-surface moisture is through artificial neural networks (ANN). Jain, Nayak, and Sudheer (2008) estimated ET using an ANN from limited input variables. Their estimation model included hourly temperature, dew point, sunshine radiation, wind speed, and humidity in Reynolds Creek Experimental Watershed. Shank, McClendon, Paz, and Hoogenboom (2008) developed ANN models to predict T_d at 2-h intervals, up to 12 h in advance. Their methods incorporated T_d, relative humidity, vapor pressure, wind speed, and solar radiation from the Georgia Automated Environmental Monitoring Network (GAEMN) to develop and train the ANN.

The purpose of this study is to estimate daily T_d using linear regression models and an ANN for portions of Southwest Georgia using daily meteorological data, an understudied area that has undergone rapid agricultural expansion since the 1970s (Harrison, 2001). This study aims to give insight into which meteorological variables sufficiently estimate T_d in the analysis region. A secondary objective is to evaluate the performance of the linear regression models in an area outside of the Great Plains to determine whether there are any differences in the variables needed to successfully estimate dew point temperature. Southwest Georgia experiences a higher amount of annual precipitation than the Great Plains and two major climate controls, latitude and continentality, are different between the two regions (Rohli & Vega, 2008). Precipitation could be an important factor in estimating daily dew point, as the highest dew point ever recorded in the United States was partly caused by heavy rains the morning of the event (Webmaster, 2008). Shank et al. (2008) gave insight as to how an ANN performed in the region from an error standpoint, but their analysis included observed dew point temperatures as an input variable. This study analyzes a different geographic location from that of Hubbard et al. (2003) and focuses on a smaller spatial extent than that used by Kimball et al. (1997). The ANN analysis is not aided by the inclusion of dew point temperature or any moisture parameter because the focus is on producing a daily estimate vs. a prediction. Qualitative comparisons of the performance of the two estimation techniques are assessed from an error standpoint. The development of a valid estimation technique is a vital step in the goal of characterizing the influence of irrigation on climate in the study region. This region has experienced rapid growth in acres irrigated (Harrison, 2001), but little is known about the influence of irrigation on the climate in Southwest Georgia. From a hydrological standpoint, Rugel et al. (2012) analyzed pre- and post-irrigation flow-duration curves for two sites in southwestern Georgia. Their research found significant reductions in 1-, 7-, and 14-day low flows. Also, the relationship between winter and summer flows that existed prior to irrigation was not present in the post-irrigation period. They attributed these changes to intensification of agricultural irrigation because they found no discernible changes in drought frequency or precipitation patterns during pre- and post-irrigation regimes. This research aims to develop a valid estimation technique for dew point in the analysis region that ultimately could be used to measure the influence of irrigation on climate.

Data and methodology

Data

The data-set used in this study is the Georgia Automated Environmental Monitoring Network (GAEMN; Hoogenboom, 2000). The GAEMN is maintained by the University of Georgia and has a 1-s temporal resolution that is aggregated into 15-min averages or totals. There are over 75 stations in the network throughout Georgia that record weather variables including air temperature, relative humidity, vapor pressure, wind speed and direction, and solar radiation. Dew point temperature is calculated from the collected variables. This study uses daily aggregates of maximum and minimum temperature, precipitation, and dew point.

Linear regression

The regression equations are adapted from Hubbard et al. (2003). The analysis herein employed three out of the five total regression equations developed by Hubbard et al. (2003). The equations used are as follows:

Hubbard et al. (2003) Method 1:

$$T_d = \alpha T_n + \beta(T_x - T_n) + \gamma \tag{1}$$

Hubbard et al. (2003) Method 3:

$$T_d = \alpha T_m + \beta(T_n) + \gamma(T_x - T_n) + \lambda \tag{2}$$

Hubbard et al. (2003) Method 4:

$$T_d = \alpha T_n + \beta(T_x - T_n) + \gamma(P_{daily}) + \lambda \tag{3}$$

where T_d, T_x, T_n, T_m, and P_{daily} are the daily dew point temperature; maximum, minimum, and mean daily temperature; and daily precipitation, respectively. The coefficients of the regression equations are represented by $\propto$, β, and λ. Figure 1 shows the GEAMN

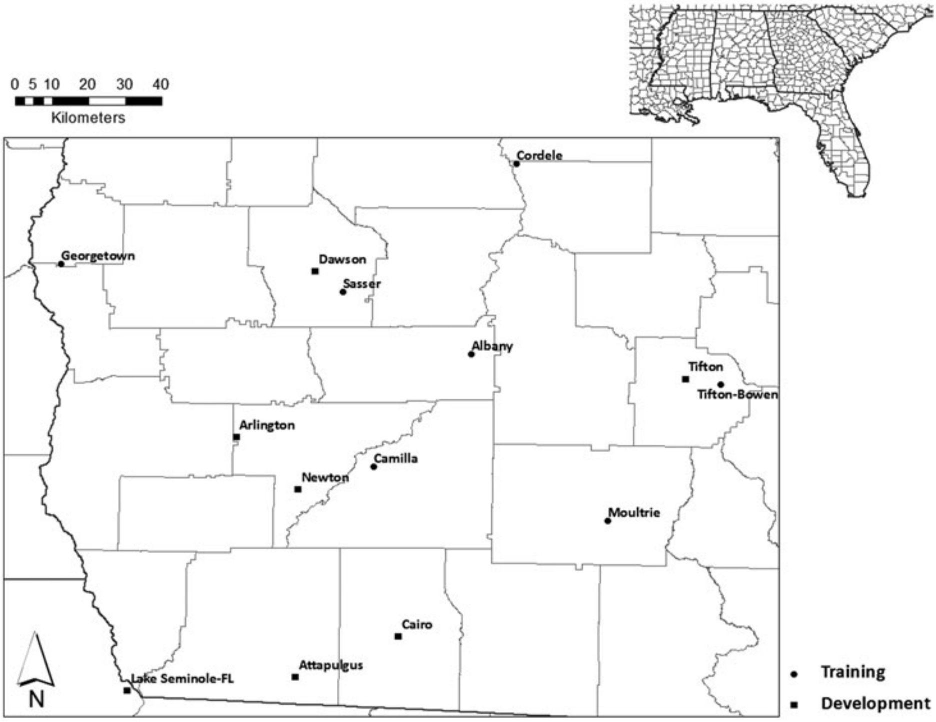

Figure 1. Map of stations used in development of the regression models (circles) and testing of the regression models (squares).

stations used in this study. The circles represent the stations used in the development of the regression models and the squares represent the independent stations. Method 1 (Equation (1)) uses minimum temperature and the diurnal temperature range (DTR) to estimate dew point. Method 3 (Equation (2)) includes the mean temperature in addition to the minimum temperature and the DTR. Method 4 (Equation (3)) uses minimum temperature, DTR, and daily precipitation to estimate daily dew point temperature.

Different configurations of precipitation were also included in Equation (3), in place of the P_{daily} variable, to determine whether there was any improvement in model skill. The different configurations include 3-, 5-, and 7-day totals and averages. The different configurations of precipitation showed no improved model skill, so P_{daily} is the primary configuration of precipitation used in the analysis.

To determine the coefficients for the regression models and to evaluate the initial performance of the regression models, a subset of seven stations with the longest continuous period of record within the region (Figure 1, circles) are selected. The data from the seven stations are aggregated to determine the coefficients only, and then each station is analyzed on an individual basis. The performances of the three models are evaluated for each station before choosing the best model to perform test on independent data not used in model training. The independent stations in the analysis (Figure 1, squares) are not used in the development of the model coefficients or in the initial estimates of the model performance. The model evaluation parameters presented in this analysis are selected to ensure a robust viewpoint of possible error and biases, and to avoid solely relying on correlation parameters as high correlations can be achieved by poor models (Legates & McCabe, 1999). The three models are evaluated using the root mean square error (RMSE), the mean absolute error (MAE), the Pearson correlation coefficient (R), the Index of Agreement (d), and the Coefficient of Efficiency (E). Readers are encouraged to review Legates and McCabe (1999) for a detailed overview of the d and E model validation statistics. As previously stated, a single set of coefficients is developed from a combination of the seven developmental stations. The decision to merge the data sets is made to ensure the models can adequately estimate dew point temperatures for varying climatic regimes within the region.

Artificial neural network

The ANN used in this study is a feed-forward multilayer perceptron with one hidden layer using sigmoid activation functions and trained using back-propagation as implemented in pyBrain version 0.3.1 (Schaul et al., 2010) with python programming language version 2.7.3. The basic network design is shown in Figure 2. A number of potential networks were evaluated. These networks differ in the number of input variables and the number of processing nodes in the hidden layer. Inputs to the network include minimum temperature, temperature range, and 0–5 days of antecedent precipitation. A constant bias input node with a value of unity is also included. The number of nodes in the hidden layer varies from a minimum of two to a maximum equal to the number of inputs for the network (up to eight). In total, 27 ANNs are evaluated. Data for ANN training and testing are partitioned in an identical manner to the regression models.

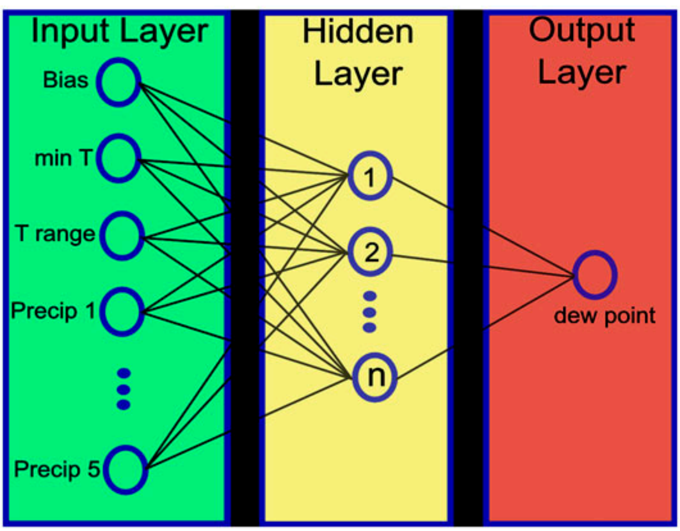

Figure 2. Basic network design of the ANN. This ANN is a feed-forward multilayer perceptron with one hidden layer using sigmoid activation functions and trained using back-propagation. The ANN consists of an input layer, a hidden layer, and an output layer.

Results and discussion

Linear regression

The three methods performed comparably from an error and model evaluation standpoint. The RMSE, MAE, R, d, and E values were only separated by hundredths for all three models for all stations within the training data-set. The Pearson correlation coefficient (R), d, and E all indicate improved performance when they are closer to unity. Overall, Equation (3) had the lowest errors and the highest model evaluation statistics. This was a different result than that obtained by Hubbard et al. (2003), as Equation (2) in our analysis was their best performing method. As expected, their analysis region has a different climatic regime from our analysis region. This result shows that daily precipitation makes a valuable contribution to estimates of daily dew point values. As a refresher, Equation (3) incorporated minimum temperature, the difference between maximum and minimum temperatures, and the addition of daily precipitation. The equation with included coefficients is as follows:

$$T_{\mathrm{d}} = 1.00681512(T_{\mathrm{n}}) + 0.17912155(T_{\mathrm{x}} - T_{\mathrm{n}}) + 0.05591049(P_{\mathrm{daily}}) - 1.789463 \quad (4)$$

The results of the model evaluation and error statistics are displayed in Table 1. For most of the stations in the developmental data-set, the R and d statistics were nearly identical among the three methods, thus were omitted from most of the tables. For most stations, R ranged from 0.94 to 0.96. The only noticeable variation was in the RMSE, MAE, and the E statistic. This speaks to the robustness of the equations developed by Hubbard et al. (2003).

In our study region, we found that minimum temperature, DTR, and precipitation (Equation (3)) were the best input parameters for estimating dew point temperatures. The three variables displayed a strong relationship with dew point, with minimum temperature explaining 90% of the variability in dew point, DTR explaining 0.42%, and precipitation explaining 0.46% of the variability. Physically, minimum temperature provides a baseline value for the dew point because the minimum temperature can never be lower than the dew point temperature. As air temperatures approach the saturation point, condensation will occur that will prevent air temperatures from falling below the dew point temperature. The DTR is the difference between the daily maximum and minimum temperature, and is an expression of solar radiation and vapor pressure deficit, which are both related to ET, and rates of ET are indicated by the magnitude of the

Table 1. Error and model evaluation statistics of Equations (1)–(3) for the training stations. The coefficients for the regression equation are derived from a merged data-set containing data from all seven stations listed below.

	Equation 1		Equation 2		Equation 3	
	RMSE	MAE	RSME	MAE	RSME	MAE
Arlington	2.25	1.69	2.24	1.73	2.20	1.65
Attapulgus	2.68	1.99	2.65	1.99	2.62	1.95
Cairo	2.40	1.77	2.38	1.78	2.33	1.72
Dawson	2.80	1.91	2.69	1.93	2.72	1.87
Newton	2.31	1.70	2.31	1.74	2.26	1.67
Sneads	2.57	1.82	2.54	1.81	2.52	1.79
Tifton	2.58	1.94	2.59	1.98	2.52	1.91
Average	**2.51**	**1.83**	**2.48**	**1.85**	**2.45**	**1.79**

vapor pressure deficit (Rosenberg, 1983). Essentially, DTR yields information about the mass transfer of moisture toward and away from the surface, which impacts the dew point temperature Hubbard et al. (2003). A lower DTR indicates a moist air mass Hubbard et al. (2003), which was the case in our analysis region, as DTR and mean dew point were negatively correlated. A large DTR is associated with less moisture because more radiant energy is partitioned into sensible heating during the day or radiant cooling occurs at night, which would also influence the dew point temperature. Precipitation is a useful variable because after a rainfall event, near-surface moisture may increase due to increased ET from the landscape (Rohli & Vega, 2008). The increased moisture at the surface has the ability to moderate minimum and maximum temperatures, altering the DTR, which would influence the dew point. Although the model used in this study is purely a statistical model, the physical underpinnings of the parameters used and their association with dew point temperatures are evident.

We observed some biases in the models at high and low dew points. This result was present in all three methods, although only Equation (3) is shown here. This is captured in the scatter plot of estimated vs. observed minus estimated dew point values from the Arlington automated weather station (Figure 3). Figure 3 shows a greater tendency for the model to underestimate values on the low end of dew point spectrum. Arlington is used as a representative station because it has the lowest RMSE and MAE for the selected method. Other stations are expected to perform comparably to the Arlington station. There is also a tendency for the overestimation of dew point at the high end. Even with the discrepancies mentioned above, equation three does an adequate job of capturing the observed variability. The overall performance of the model is adequate as well, as approximately 85% of the estimated values are within 3 °C of the observed values (Figure 4).

Since the method that included precipitation performed best, it was a natural inquiry to see whether different variations of precipitation improved the skill of the model. The

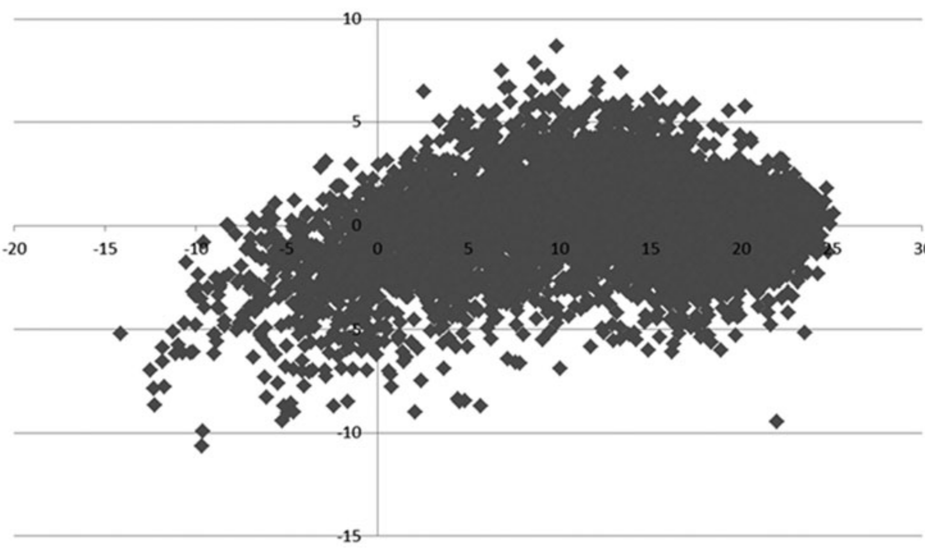

Figure 3. Observed vs. the difference between Estimated and Observed scatter plot for Arlington GEAMN station. The *x*-axis and *y*-axis are shown in degrees Celsius.

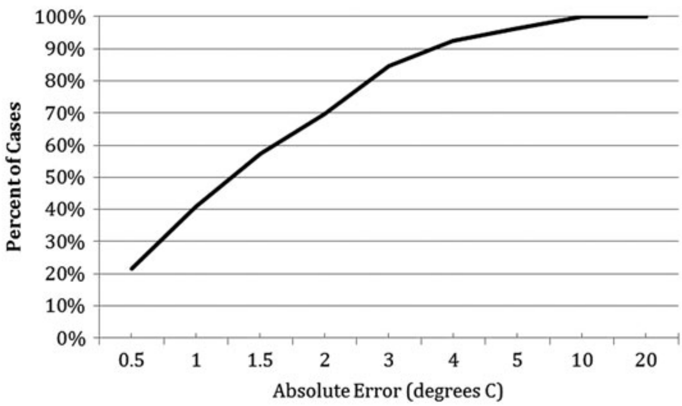

Figure 4. Performance of Equation (3) for the Arlington automated weather station. The *x*-axis represents the absolute error in degrees and the *y*-axis represents the percent of cases associated with the corresponding error.

underlying premise of this hypothesis is to analyze whether there is a 'soil moisture memory' component to the estimation of dew point, as modeling studies suggest that wet soils are thought to influence ET rates, thus influencing the dew point temperature (Dirmeyer et al., 2012; Dirmeyer, Schlosser, & Brubaker, 2009; Koster & Suarez, 2001). To test this theory, 3-, 5-, and 7-day totals and averages were added in place of the daily precipitation. It was also required to develop a new set of coefficients for each variation of precipitation tested. The additional precipitation metric slightly degraded the model performance when compared to the regression model with daily precipitation (Table 2).

The model performance was evaluated on an annual basis. This measure was taken to ensure a robust model performance, capable of handling a wide array of climatic conditions. Essentially, the model will be applied when irrigation rates are at their highest, the growing season (April–September). During the growing season, the model displays an improved skill and has an optimal performance during this period. This was tested by developing a set of coefficients for October–November for all years. The coefficients of the growing season data-set are then applied to the Arlington training station. The growing season regression model reduced the RMSE and the MAE by 17% (Table 2).

Artificial neural network

The first step in applying an ANN to the problem of estimating dew point temperature is to determine the combination of inputs and hidden nodes that provide the best

Table 2. Error and model evaluation for Arlington during the growing season, daily precipitation, and 3-day precipitation using Equation (3).

	RMSE	MAE	R	D	E
Growing	1.82	1.37	0.96	0.98	0.91
Daily precipitation	2.20	1.65	0.96	0.98	0.93
3-day precipitation	2.29	1.74	0.96	0.98	0.92
Average	**2.10**	**1.58**	**0.96**	**0.98**	**0.92**

performance. The number of inputs is dependent upon the number of days worth of precipitation data, we wish to include in the analysis and ranges from zero to five. Other inputs included in all networks are minimum temperature, temperature range and a constant bias neuron whose value is always equal to unity. There is no formula for determining the optimal number of nodes in the hidden layer of a network. It is generally suggested that the number of hidden nodes should be between the number of inputs and the number of outputs (Heaton, 2013). For this study, we will test networks with number of hidden nodes ranging from two to the number of inputs.

Figure 5 shows how number of inputs and hidden nodes affected network performance as expressed by mean absolute and RMSEs for 27 different networks. Examining the figure from left to right, the first network (3_2) relies on only minimum temperature and temperature range to determine dew point. Addition of an additional hidden node (3_3) allows the network to better fit the data. Addition of the current day's precipitation (4_2) allows for further improvement in the network performance. Expanding the network beyond four inputs and two hidden nodes did not lead to an appreciable improvement in network performance. For the remainder of the study, the ANN architecture used is that of four inputs (minimum temperature, temperature range, daily precipitation, and a constant) with two hidden nodes.

Overall, the ANN outperformed the regression methods of Hubbard et al. (2003), as shown in Table 3 for the training data and Table 4 for the validation data. For all stations, the ANN displayed lower error values and was equal to or better on the other performance metrics as well. Direct comparison between the ANN and Equation (3) shows that, on average, the ANN reduced RMSE by 6.86% and MAE by 8.30% (Table 4). One area where the ANN offered little improvement is for low dew point temperatures (Figure 6). For dew points in the 20–30 °C range, the ANN has an absolute error within 2 °C of the observed for 90% of the cases, and 60% of the time the error is 1 °C. However, performance for the lower end of the dew point spectrum drops

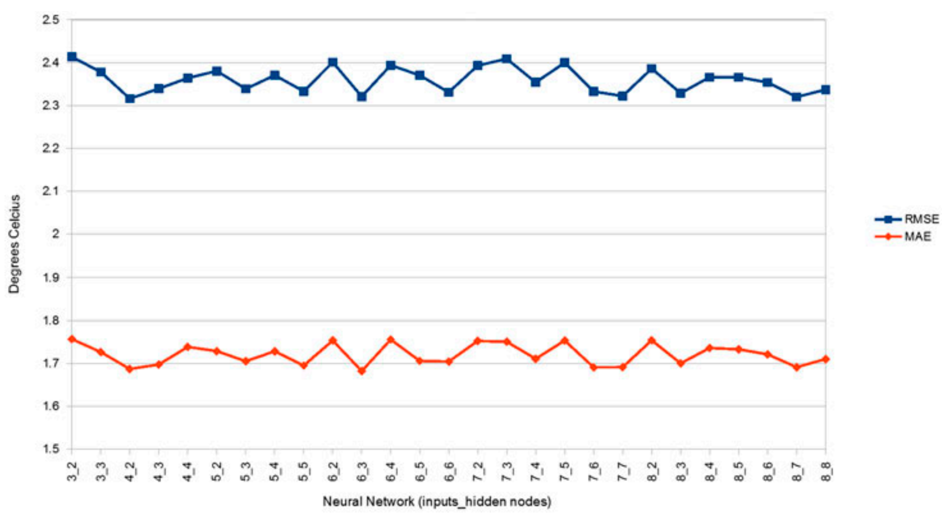

Figure 5. Performance comparison of various neural network architectures for dew point estimation. Network architectures are given on *x*-axis and are defined by the number of input and hidden nodes: 3_2 represents a network with three inputs and two hidden nodes.

Table 3. Error and model evaluation statistics of the ANN for the training stations.

	RMSE	MAE	R	D	E
Arlington	2.08	1.57	0.97	0.98	0.93
Attapulgus	2.55	1.88	0.95	0.97	0.90
Cairo	2.22	1.59	0.96	0.98	0.92
Dawson	2.36	1.72	0.96	0.98	0.92
Newton	2.13	1.58	0.97	0.98	0.93
Sneads	2.46	1.71	0.95	0.97	0.90
Tifton	2.35	1.77	0.96	0.98	0.92
Average	**2.31**	**1.69**	**0.96**	**0.98**	**0.92**

Table 4. Comparison of RMSE and MAE for Equation (3) and the ANN for the independent stations.

	Neural Network		Regression		Percent Improvement	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
Albany	2.70	2.01	2.90	2.21	6.85%	8.92%
Cordele	2.26	1.68	2.46	1.87	8.04%	10.11%
Georgetown	2.24	1.67	2.43	1.83	7.74%	8.61%
Moultrie	2.25	1.67	2.35	1.72	4.24%	2.93%
Sasser	2.27	1.66	2.50	1.86	9.93%	10.79%
Tifton-Bowen	2.32	1.68	2.44	1.83	4.99%	8.44%
Average	**2.34**	**1.73**	**2.51**	**1.89**	**6.86%**	**8.30%**

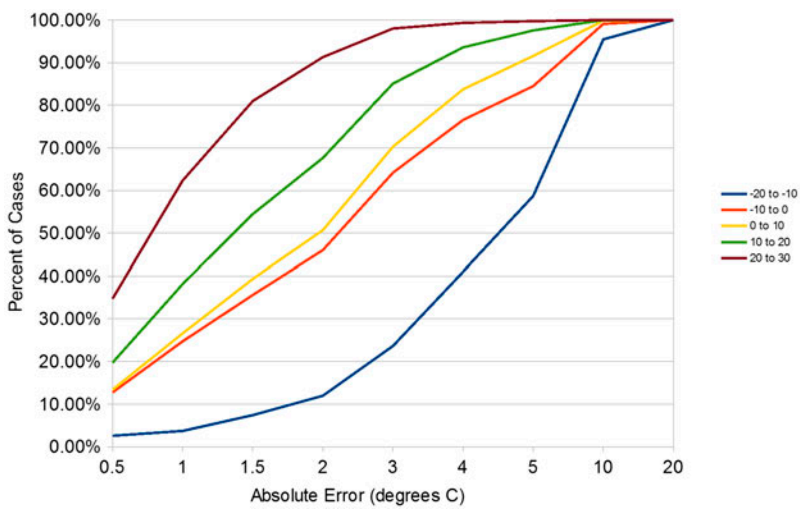

Figure 6. Performance of the ANN represented as a percentage for varying dew point temperature ranges. The *x*-axis represents the absolute error in degrees and the *y*-axis represents the percent of cases for the given absolute error.

off quickly. When the dew points are between 0 and 10 °C, only 50% of cases are within 2° of the observed dew point and only 24% within 1 °C. Fortunately, the growing season of Southwest Georgia is characterized by dew point values in the range where the ANN estimates are most accurate. Note that the ANN was not retrained using only growing season data as was done for the regression model.

Conclusion

The overarching goal of this study was to develop a daily dew point estimation method adapted for Southwest Georgia, as dew point is an expression of moisture in the atmosphere. An estimation method is needed because of the poor availability of long-term dew point observations in the region, as data on most atmospheric humidity parameters are not as available as data on temperature. With this in mind, it was desired to make the estimation draw from readily available temperature and precipitation observation from NWS COOP stations in the region. The linear regression equations developed by Hubbard et al. (2003) were adapted and applied to our region of interest. Three of the five methods used by Hubbard et al. (2003) were used here, with Equation (3) performing the best from an error standpoint. On average, Equation (3) performed equal to, or better, in all five measures of performance for the training stations (Table 1). It was shown that the model performs best during the growing season, when irrigation rates are at their highest, and that additional precipitation information actually degrades model performance. An ANN is also employed to estimate dew point.

Seven automated weather stations from the GEAMN were selected to train and validate each the estimation model for each technique. On an annual basis, the ANN performed best, only bettered by the growing season version of the regression model. A growing season only version of the ANN was not tested and is something that can be explored in the future to see whether there is any improvement in the skill of its estimation. Each technique tested performed adequately for the region and should be able to assist in a retroactive analysis in dew point estimation in the study region. Estimating dew point from limited meteorological variables has been successfully demonstrated in the Great Plains region, and now in Southwest Georgia. This gives confidence into the validity of dew point estimates derived from other variables, which can be applied to construct dew point climatology for data poor regions. It was also demonstrated that the ANN provided a better overall estimate than the regression method and this result could be applicable to other regions.

A possible future application of this analysis is to study the influence of agricultural irrigation in the region. Irrigation has increased in Southwest Georgia since the early 1970s (Harrison, 2001). Irrigation is a consumptive form of water use, and most of the water used to irrigate crops is transpired back into the atmosphere. Irrigation wets the soil, which partitions more incoming solar radiation into latent heating, resulting in increased near-surface dew point temperatures (Adegoke, Pielke, Eastman, Mahmood, & Hubbard, 2003; Harding & Synder, 2012). Data for atmospheric humidity, including dew point temperature, are not as available as temperature data, thus an adequate method to model humidity is needed. Our work has analyzed two viable methods to estimate dew point. Now that an acceptable method has been developed to estimate dew point temperatures, we have a tool that can potentially capture possible long-term changes in near-surface humidity caused by changes in agricultural practices. This method can aid in creating a proxy data-set of long-term dew point temperatures that would have not otherwise been available, as first-order stations are not representative of our area of interest.

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