Maximum Stream Temperature Estimation from Air Temperature Data and its Relationship to Brook Trout (Salvelinus fontinalis) Habitat Requirements in Rhode Island

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Abstract

A literature review of critical maximum stream temperatures for brook trout was made. In addition, various stream temperature models were examined in order to assess their value. Analysis of annual local air temperature records indicated a significant increase of about 2.66 degrees centigrade in data from the Kingston, Rhode Island weather station. No significant changes in the ground water levels or precipitation were found in data available from the same area. Five daily weather related inputs (maximum air temperature, minimum air temperature, precipitation, evaporation and dry bulb temperature) and one output variable (maximum daily stream temperature) were utilized to train, calibrate and validate a neural network model designed to predict maximum summer stream temperatures from the above-mentioned atmospheric input variables. The predictive performance of the model was found to be very good. An application of the predictive model was made to assess the probable effects of an observed drought year (2002) on water temperatures related to brook trout survival. It was determined that somewhat higher stream temperatures were indicated for the drought period when compared with the year 2003 data from a nearby source. The potential utility of the neural network model for predicting critical maximum daily stream temperatures when water temperatures are not available was demonstrated.

Introduction

Stream water temperature is one of the most important parameters in watershed level ecosystem studies. It is important in relation to chemical processes as well as influencing many biological processes, such as growth and mortality of aquatic organisms. Variations in stream water temperatures are also important in limnological studies. For example, water temperature determines the rate of the decomposition of organic matter and the saturation concentration of dissolved oxygen (Nemerow, 1985). Perturbations of the thermal regime in a stream can significantly impact the utilization of fish habitats, and stream water temperature can be one of the limiting factors in determining the habitat potential of a stream (Bovee, 1982). Indeed, Stoneman and Jones (2000) have clearly demonstrated the importance of water temperature at distinguishing sites with differing trout biomasses. High stream temperatures in the range of 23-25 degrees Celsius (C) have been observed to adversely affect mortality of salmonid fishes (Lee and Rinne, 1980; and Bjornn and Reiser, 1991). Studies related to the effects of climate warming on fish thermal habitat have been conducted at a national level which indicate that stream habitat for cold and cool water fishes would be substantially reduced (approximately 50%), based on an estimated doubling of the current atmospheric carbon dioxide concentration (Eaton and Scheller, 1996). A temperature increase of from 2 to 6 degrees C has been estimated from these studies. Meisner (1990) indicated that brook trout distribution in the southern limits of its range is largely determined by the inflow to low order streams of cooler groundwater. He suggested that the range limits of this species correspond somewhat to an annual groundwater mean of about 15 degrees C.

In spite of the importance of water temperature to stream ecosystems, extensive time series of water temperature data in streams are relatively scarce, at least in Rhode Island, where this study has been conducted. For this reason it was considered desirable to develop a model for the purpose of predicting maximum daily stream temperatures during past years, especially during severe drought conditions such as during 2002 when no systematic stream temperature records were available in the Wood-Pawcatuck Watershed area. Several models have already been developed and utilized for predicting stream water temperature under various conditions. These have been classified into two major categories, namely a) deterministic or physical models and b) stochastic models. Deterministic models consider relevant meteorological factors, such as solar radiation and wind velocity, which are used in energy budget equations (radiation, evaporation, conduction, etc.) to calculate thermal exchange between the atmosphere and the stream. Physical characteristics of the stream, such as average depth, amount of flow, and the amount of cover are also significant model parameters. Examples of such deterministic models include Sinokrot and Stephan (1993), Gu et al (1998), Gu and Li (2002), Morin and Couillard (1990), Theurer et al (1984), and Bartholow (1999). These models are used to calculate the heat gained or lost from a parcel of water as it passes through a stream segment. They require numerous inputs including stream geometry as well as steady state hydrology and meteorology. These models seem to be most useful for large streams for which there is a considerable amount of input data.

On the other hand models termed as stochastic models are often based on linear statistical functions. Application of a stochastic model usually requires information only on air temperature and a continuous time series of stream water temperature for model calibration. The statistical relationship between air and water temperatures is traditionally established by classical regression analysis or by using time series analysis procedures. The advantage of this latter approach is its simplicity and minimal data requirements in contrast to the deterministic models which require much more data and are more complex mathematically. Examples of early stochastic stream temperature modeling include Kothandaraman (1972) and Cluis (1972). Among the many stochastic model studies pertaining to stream temperature/air temperature relationships, some reports are considered especially relevant to this work. These include a report by Stephan and Preud'homme (1993) who examined errors associated with linear relationships between stream temperatures and air temperatures for 11 streams in the central United States. Water temperatures were shown to respond to air temperatures with time lags, ranging from a few hours for small streams to seven days for large rivers up to five meters in depth. More recently Pilgrim et al (1998) examined linear relationships between stream water temperature and air temperature for 35 Minnesota streams. Equations were derived for daily, monthly, and annual mean temperatures. Standard deviations between all measured and predicted temperatures decreased from about 3.5 to 1.3 degrees C for increasing time intervals from daily to annual averages. No time lags were taken into account in these models and ice cover periods were excluded from analyses. A 4.6 degree C temperature rise was projected as the stream temperature increment from a doubling of the atmospheric carbon dioxide level from its current value. Mohseni and Stefan (1999) developed a four parameter nonlinear regression model to estimate temperatures for fish habitat evaluation through an entire annual cycle. Application of this model to the data for an entire year seemed to account for hysteresis- which involves lags in stream temperature response times at extremely low or extremely high temperatures. Caissie et al (1998) and Caissie et al (2001) modeled maximum daily water temperatures in a relatively small stream using air temperatures as the independent variable. Their preferred methodology involved estimating an annual component in stream temperatures by fitting a Fourier series to the data and a second order Markov process model to the short term residuals.

Other models have also been developed to assess relations between stream temperature and ambient air temperature. Stoneman and Jones (1996) developed a nomogram for classifying streams into three broad classes based on a single measure of water temperature at 1600 hours and a maximum air temperature for the same day. More recently, Gardner et al (2003) demonstrated geostatistical metrics for predicting stream temperatures in a Catskill Mountain watershed area. A stream temperature-equilibrium temperature relationship was developed by Bogan et al (2003) by fitting an equilibrium temperature linearly to recorded stream temperatures at weekly intervals to identify anthropogenic and hydrologic inputs to streams. Weekly averaging of equilibrium temperatures was done to reduce variability occurring at shorter intervals.

The objectives of this study were to develop and test a stochastic model to accurately predict maximum daily water temperatures during the summer season for small streams in the Wood-Pawcatuck Watershed using local air temperature and other available meteorological data to compensate for the lack of extensive water temperature observations in the study area. This model was then utilized to more precisely define and predict the extent of suitable habitat for brook trout in the study area under past drought or other adverse environmental conditions. Since it is generally recognized that local stream temperatures respond primarily to local rather than national or global climate changes, a preliminary analysis of available air temperature was made from a local weather station at the University of Rhode Island, Kingston, Rhode Island. This station is within a radius of approximately 25 kilometers from stream sampling stations where some water temperature data had been collected with data loggers. An initial part of this study involved estimating the degree of change, if any, in maximum air temperature over the available 72 year time series record and to compare these results with more global estimates. Two other hydrological variables were also briefly examined. However, the major objective was to develop a model based on air temperature and other available meteorological data from the Kingston weather station which could be used to accurately predict daily maximum summer water temperatures in local streams exclusively from past weather data. It is believed that daily maximum temperatures during the summer are very critical in defining brook trout habitat as well as habitats for other species.

Scott and Crossman (1973) indicate that brook trout tend to seek temperatures below 20 degrees C when surface waters warm up. The acceptable range of temperature for both juvenile and adult brook trout is believed to lie in the 10-20 degree C range during the warm part of the year (May to September). Although the annual temperature range has been cited as 0-24 degrees C by MacCrimmon and Campbell (1969), it is believed that adverse effects of temperature in natural environments may occur below the temperature tolerances estimated from laboratory studies, such as critical thermal maxima (CTM) as reported by Lee and Rinne (1980). Instead, the highest sustainable temperature for cold water fish, such as brook trout in their natural environment, is estimated at about 23 degrees C (Drake and Taylor, 1996). Elliott (1994) has described temperature tolerances for several salmonid species, including brook trout in his Table 4.1 (p. 73). The mean incipient lethal temperature is listed as 25.3 degrees C. This is the upper limit of temperature below which the fish may live for a considerable time under ideal conditions with respect to dissolved oxygen, pH and other variables. However, it is clear that this value is lower for effective feeding and growth as well as lower under less than ideal dissolved oxygen and pH values of the water in the stream.

Temperature and Related Data

Figure 1 illustrates the mean annual air temperature at the University of Rhode Island weather station in Kingston, which consists of a 72 year record of data commencing in 1931. Visual inspection of the data of Figure 1 shows that there may be some evidence for differences roughly between the first and second half of this data set, suggesting a break point in these data. A formal test for this partition of the data was made. Somerton (1980) described a method in which a break point in the slopes of a data set is found, such that it minimizes the residual sum of squares for regression pooled over both segments fitted to the data before and after the break point. A computer program termed SEGREG was written by the author and it is described in Saila, Recksiek and Prager (1988). It is an extension of Somerton's initial work and was applied to the data of Figure 1. Table 1a and 1b indicate some of the results from the segmented regression application to the Kingston air temperature data. A grid search for the optimum break point indicated that a it is found at year 38.5. This occurs between calendar years 1968 and 1969. Panel 1 of Table 1a indicates the results from an all points regression which shows a weak positive slope but one that is statistically significant. The first panel of Table 1b indicates the best fitting model to the second set of the data based on a conjoint regression. The FPI term in Table 1 refers to Akaike's FPI statistic (Akaike, 1969) which is used to rank the models in the grid search. FPI is an unbiased estimator of the mean square error of prediction on new data, assuming the regressions are fixed and the method is correct. The second panel of Table 1a shows the results from application of a regression model to the first segment of the partitioned data. A slight but non-significant negative slope was estimated for the first 38 years of observation. The third panel of Table 1a shows the ANOVA and regression analysis results for the second segment of the annual time series consisting of 34 years. Note that the slope of this segment is positive and is statistically significant at an alpha level of less than 0.05. The rate of increase as measured by this calculated regression is about 2.66 degrees C over the 34 year period. If this were to continue for a second period of 34 years, then the average expected increase in air temperature would be similar. It is evident from this analysis that air temperature has been increasing during the past 34 years, and that this rate of increase projected into the future for a similar period would further increase air temperature by nearly 3 degrees C. Obviously, this air temperature increase would be reflected in increased stream water temperatures of nearly the same magnitude. These would result in significant additional reductions of suitable brook trout habitat.

A plot of the maximum daily Kingston air temperature and the daily maximum stream temperature at Queen River near Dawley Road is illustated in Figure 2. There appears to be a high degree of association between these two data sets. Results of fitting a simple OLS regression with the daily air temperature as the independent variable against the Dawley Road site stream temperatures are shown in Figure 3 with 95 percent confidence and prediction intervals. The regression model is shown in the lower portion of Fig, 3. It indicates that the model explains less than 60 percent of the variability in these daily data although the regression is highly significant statistically. A similar analysis was made for the same data but with weekly average data values in contrast to the daily data described previously. Note that the regression model of Fig. 4 based on weekly data explains more than 80 percent of the variability. These results are similar to those previously reported in the literature. That is, the increased time scale reduces variability.

A brief examination was also made of available local data on precipitation and the groundwater table to determine whether or not these may have also changed during the available observation periods. Annual total precipitation for a 72 year period in the Kingston area is shown in Figure 5. These data were not autocorrelated, and a nonparametric trend analysis did not indicate any statistically significant trend during the past 36 years as shown in Table 2. A 48 year record of Kingston well data is shown in Figure 6. These data describe the annual average depth of the water table. No significant trends were found in either the first 20 years nor in the last 28 years using a nonparametric trend analysis procedure (Table 3a and 3b). These observations and analyses suggest that there were no substantial changes in these two variables over the observed time periods.

The available water temperature data used in the first phase of this study was kindly provided by the U.S. Geological Survey and consists of digital records of water temperature at hourly intervals from eight stations in the Queen River area, which is a portion of the Wood-Pawcatuck Watershed of Rhode Island. These data were collected for a period of 94 days commencing on June 24th, 2000 and ending on September 24th, 2000. These data and station locations are described in the U.S. Geological Survey Usquepaug-Queen River Basin temperature data summer 2002, and they include the following stream station locations: Fisherville Brook, Church Road; Locke Brook, Mail Road; Queen River, Dawley Road; Queen River , Mail Road; Queen River, Route 102; Queen River, William Reynolds Road; Usquepaug River, Route 138; and Usquepaug River, Route 2. The first 6 sites are in Exeter, RI and the last two are in South Kingston, RI. The data was collected using Onset Computer StowAway Tidbit data loggers. Quality assurance tests of the data loggers showed the results from the data loggers corresponding to independent measurements with errors of less than 1 degree. Additional data on water temperature at the above- mentioned stream sampling stations was obtained by the Wood Pawcatuck Watershed Association personnel during the summer of 2003. These data were collected using small temperature data loggers know as I-Buttons and quality-control for these data was achieved by comparing the observations with data collected by hand using YSI temperature loggers at intervals.

Temperature and Habitat Assessment Methodology

At this time it is generally accepted that aquatic ecosystems are both complex as well as poorly understood. Castleberry et al (1996) indicated that there does not appear to be in any currently defensible method for defining instream flows needed to protect particular species of fish or aquatic ecosystems. In complex systems, empirical relationships are often employed to estimate model parameters and properties. These complex systems are characterized by a number of interacting factors. The relationships among these factors are not precisely known. The data associated with these factors are also often sparse and/or noisy. The extraction of knowledge from data of the sort mentioned above in order to develop empirical relationships is a formidable task requiring sophisticated modeling techniques and considerable experience as well as intuition. Stephan and Preud'homme (1993) have indicated that weather parameters and water temperatures are related in a nonlinear way. This has been further confirmed by Bogan et al (2003).

It is becoming increasingly apparent that the use of neural networks may contribute to the alleviation of some of the above mentioned problems. There is a growing interest in neural networks, and this interest seems to be associated with their excellent performance in recognizing patterns and in modeling nonlinear relationships which include a large number of poorly defined variables. An artificial neural network (ANN) is a parallel distributed information system (computer model) that consists of simple but adaptable interconnected processing elements. The ANN is perceived as a statistical model which performs an input/output transformation by adjusting a set of parameters which are called weights (Bishop, 1997). An important advantage of ANNs over traditional statistical models is that they impose fewer and more flexible constraints in their application. No effort is made herein to provide a summary of the numerous and diverse neural network methodologies. However, the basic architecture of neural networks is nicely summarized in a recent book by Principe et al (2000) and in an earlier book by Eberhart and Dobbins (1990). Lippmann (1987) and Hammerstrom (1993) provide concise introductions and indications of available neural network development tools. Some applications of neural networks in a fishery science context include a study of variable genetic markers of brown trout (Aurelle et al, 1999), predicting trout population density (Baran et al, 1996 and Lek et al, 1996a) and predicting the abundance of a minnow species in a river (Mastrorillo et al, 1997). Neural networks have also been applied in a study of relationships between fish and habitat in lakes by Oldan and Jackson (2001). Lek et al (1996b) described a neural network in a broader context, namely modeling nonlinear relationships in ecology.

The neural network primarily used in this study consisted of a back propagation algorithm. This is a universal architecture which has been shown to be capable of approximating any continuous function if there are sufficient hidden neurons (Hornick et al 1989). The basic mathematical concepts of the back-propagation algorithm are described in Eberhart and Dobbins (1990). The specific software utilized in this study is called Neuroshell2 TM and it is available from the Ward Systems Group, Frederick, Md. The implementation of the back-propagation neural network model involved identification of the input parameters and acquiring the necessary data. In this case five weather related input variables were utilized from the Kingston, Rhode Island weather station and daily maximum stream temperature were utilized as the output variable to train the network to predict the daily maximum stream temperature. Conventional statistical tests in the form of simple correlation and regression analyses as well as multiple regression were applied to the data for initial examination. Because some of the raw data were autocorrelated a recurrent neural network was also applied to these data to see if it produced substantially more accurate results than the simpler back-propagation method. The latter produced the most consistent results and was utilized for the stream temperature prediction in this study. The specific neural network architecture utilized in this work is termed a Ward network with three slabs in the hidden layer. A slab is a group of neurons, and Ward Systems Group has developed three back-propagation models with multiple hidden layers (slabs). As stated previously, the Ward network with three hidden slabs and different activation functions was found to be the most satisfactory for the purposes of hand because it provided the smallest prediction error. When a neural network is trained with data, it will work at making a model which performs better and better and ultimately approaches a condition which virtually memorizes the data. This is known as over-training because generalization by the model is then lost. The approach used herein to avoid over-training is known as calibration. This involves randomly removing a test data set from the training data set. Calibration trains on the training set but it also reads in the test data set and computes an average error for it at intervals. In practice the error for the training set continues to decrease, and the error in the test set tends to get smaller up to a point. At this point (the optimal point) the test set error starts to increase. When one specifies that the network is to be saved with the best test then calibration will save the network at the optimal point. This was done with the ANN analyses reported here.

Another important step necessary in neural network development is termed validation. This procedure involves applying the trained neural network to an entirely new set of input data which has not been previously utilized in either the training or test data set. The model results from this application to the validation data is then compared with actual data which was withheld from the analysis. A comparison is then made with results obtained from the initial training set which now includes the response variables. In general, it is expected that there will be some loss of accuracy in this procedure. However, if the network model validation results compare reasonably well with the withheld data from a different source then this is an indication of the predictive value of the model with new data.

Stream Temperature Prediction Results

The data set used to develop the predictive maximum daily stream temperature model by applying the ANN described in the previous section consisted of five input variables and one output variable over a period of 94 days commencing on June 24, 2000 and ending on September 25, 2000. The five model inputs were obtained from the Kingston, Rhode Island weather station consisted of daily records of maximum air temperature, minimum air temperature, rainfall, evaporation and dry bulb temperature. The output variable used for training the network consisted of daily maximum stream water temperatures obtained by a data logger in the Queen River at the Dawley Road site. Twenty percent of the 94 day data was randomly chosen to provide a test set for calibration. The validation sample test set consisted of 30 days of weather input data which was obtained from the Kingston weather station for the period of August 5 to September 3, 2003. Although output data in the form of the maximum daily stream temperatures were available from a data logger located at Mail Road in the Queen River, these data were not included in the validation procedure. Instead, these data were later compared with the ANN model's predictions for this time period of 30 days in order to provide a proper validation.

Certain statistical calculations were made from the results of the initial training and test set predictions as well as those from the validation procedure results which provided an indication of the utility of the stream temperature prediction model. These statistical calculations are summarized in Table 4, which consists of two panels, namely panel *a* (the original training and test set) and panel *b* (the validation data set). From panel *a* it is evident that the model performed very well in predicting daily maximum stream temperatures from the test and training datasets from which it had been trained. Panel *b* refers to model outputs derived from predictions without output variables. Later comparisons were made with actual maximum daily steam temperatures obtained by a data logger located at Mail Road on the Queen River and compared with the predictions from the exclusively weather related inputs. It is noted that some accuracy and precision is lost in panel *b* statistics. This may be due to several factors. These include the fact that the Mail Road data logger site is about one kilometer downstream from the original Dawley Road site. Another factor is that the comparison was made three years after the initial deployment. In spite of these factors the observed reduction in accuracy and precision was small and suggests that the derived model may be useful in estimating probable maximum stream temperatures when no water temperature measurements are available.

One of the statistics in Table 4 deserves some further explanation. R squared is the coefficient of multiple determination, and it is a statistical indicator often applied to multiple regression analysis problems. It compares the accuracy of the model to the accuracy of a trivial benchmark model wherein the prediction is just the mean of all of the samples. This statistic should not be confused with r squared, which is the coefficient of determination nor with r which is the standard correlation coefficient. The other statistics in this table are thought to be self explanatory.

Table 5 illustrates all of the raw data and results obtained by comparing the actual output with the ANN model prediction and the difference between model results and the actual observed values of stream water temperature. Note that some variables (precipitation and evaporation) have been scaled in order to provide more similar weights to the other input variables. The first 94 rows of this table show both training and test set data and the predictions of the ANN model applied to the test and training set. These predictions were then compared with actual field data and differences between ANN predictions and actual stream measurements are illustrated in the last column. The next 30 rows beyond 94 in Table 5 show the results of the validation test. In this case the trained neural network was applied to input data exclusively. After the model predictions from these input data were calculated they were compared with actual stream temperature data which had been withheld up to this time. It is evident that the model predicted somewhat higher temperature values than the actual stream temperatures during the last several days. This may be because the ANN was trained with higher temperatures. However, the overall model predictions were found to be relatively accurate.

The primary purpose of this stream temperature model was to estimate maximum summer stream temperatures during adverse conditions which were not monitored with stream temperature loggers. An excellent example is the severe drought condition which occurred during the summer of 2002. Regretfully, no stream temperature loggers had been deployed in the Queen River area of interest during that summer. The estimates of the summer stream temperatures during the drought of 2002 were obtained exclusively from weather data shown in Table 6. The data in the last two columns show the predicted maximum temperature derived exclusively from weather data which is compared with stream temperature data from a nearby site (Mail Road) on the Queen River in the year 2003. Table 6 illustrates some summary statistics as well as the results of a t test for these data. The formal test for homogeneity of variances was rejected and the test based on unequal variances was applied. The difference between the two temperature data series was statistically significant at an alpha level of 0.086. It is concluded from this test that the drought conditions did indeed influence the stream temperature adversely during the drought period (Figure 8). Therefore, it is suggested that flow regulation may have a positive effect evidenced by more suitable stream temperatures for brook trout habitat during the summer period, especially during summer drought conditions.

Conclusions

1. Results from a review of literature related to the effects of stream temperature on the survival of brook trout suggest that about 23 degrees C is a reasonable upper limit for the survival of this species during the summer period under field conditions.
2. According to the Intergovernmental Panel on Climate Change (IPCC), established by the United Nations Environmental Program and the World Meteorological Organization (WMO), the panel has estimated in its Third Annual Report that "the globally averaged surface temperature is projected to increase by 1.4 to 5.8 degrees C. over the period 1990 to 2100." Analysis of a local (Kingston, Rhode Island) data set of average annual air temperatures over a period of 72 years indicated an estimated 2.66 degree C increase over a period of the last 34 years of available data. This estimate of air temperature increase translates to a nearly similar increase in groundwater temperature. It suggests that the available habitat for brook trout has been substantially reduced as a result of this increase. If this trend continues in a similar fashion during the next period of similar duration, then the brook trout habitat in Rhode Island is expected to be at or above its southern temperature limit with an annual mean groundwater temperature of about 15 degrees C.
3. Examination of local (Kingston, Rhode Island) annual precipitation records and ground water levels did not indicate any significant trends over the available time periods.
4. Because adequate time series data regarding low order stream temperatures were not available in Rhode Island, efforts were made to develop a predictive model for maximum daily stream temperature during the summer based on the atmospheric weather data. A back-propagation artificial neural network (ANN) was developed using five weather related variables as inputs and Queen River stream temperature data as the output. The results of the neural network training were considered to be

very accurate, and the validation test also indicated very satisfactory prediction accuracy.

5. The developed ANN was then applied to atmospheric data from the Kingston weather station during a portion of the drought period in 2002. The predicted maximum daily stream temperatures during the summer were then compared with actual stream temperatures during similar time periods obtained in 2003. It was shown that there were some differences between the two data sets at alpha levels between five and 10 %. The drought data had the higher average temperature values. This would suggest that stream flow control during times of high temperatures and drought conditions would probably ameliorate the higher temperature effects obtained during the drought.
6. It is evident that this model can be utilized for predicting maximum daily stream temperatures in other low order stream environments based entirely on atmospheric weather data. However, for new sites not in close proximity to this one , stream water temperatures at some time are necessary for initial model development. The current availability of low cost stream temperature loggers makes this feasible and their future widespread deployment is anticipated in the Wood-Pawcatuck Watershed Area.

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Figures

Figure 1. Time series plot of Kingston, Rhode Island weather station average annual air temperatures from 1931 to 2002.

Figure 2. Maximum daily air temperatures (top line) from the Kingston, RI weather station and daily maximum stream temperatures (bottom line) from the Queen River at the Dawley Road location.

Figure 3. Ordinary least squares (OLS) plot of the daily maximum air temperature versus the daily maximum stream temperature data of Figure 2 along with 95 percent confidence and prediction limits. The regression model is: DMAXT=6.4473+0.5252 MAXATC. Details of the regression model are shown below the figure.

Figure 4. Ordinary least squares (OLS) plot of the weekly average data from Figure 2. The regression model is: CDAWWAT= 4.6621+ 0.7623 CKAIRTAT with 95 percent confidence and prediction limits. Details of the regression model are shown below the figure.

Figure 5. Plot of 72 annual total precipitation values from the Kingston, RI weather station for the period 1931-2002.

Figure 6. Plot of 48 years of data for annual levels of groundwater at Kingston, RI as well as summary statistics for these data.

Figure 7. Graph of Table 5, comparing temperature measurements at the Dawley Road site of the Queen river done by USGS in 2000 and the temperature predictions done by the model after training.

Figure 8. An example of the possible applications for the model. Temperature data collected by WPWA personnel at a site on the Queen River in 2003 is compared to predictions made using air temperature from the same dates in 2002 at a nearby site, based on Table 6.

Tables

Table 1. Analysis of data from Figure 1 utilizing a segmented regression technique.

Table 2. Analysis of Kingston RI weather station annual precipitation data of Figure 5, including an auto correlation plot, a simple exponential smoothing and prediction model and a nonparametric trend analysis for the last 36 years.

Table 3. Nonparametric trend analysis of data from Figure 6. The first panel refers to analysis of the initial 28 years and the second panel refers to analysis of the next 20 years.

Table 4. Results describing the various measures of fit of the neural network model to the training set data (part a) and to the validation data (part b). The lower part of this table indicates the relative contribution factors of each of the input variables.

Table 5. Description of the neural network inputs (first 5 columns) and inputs for training the network (column 6). The last column (Act-Net) shows the difference between the / known actual value and the calculated value. Rows beyond 94 were estimated by the network without any training inputs in order to validate the model.

Table 6. Input data for the neural network prediction of maximum stream temperatures during the drought period from August 5-August 19, 2002. These results are shown in the column entitled NN predicted. The last column in this table shows the observed stream temperatures from a nearby source (Mail Road) obtained at exactly the same dates during 2003.

Table 7. Results from a comparison of the estimated 2002 stream temperatures at Dawley Road with actual data obtained with a data logger at Mail Road during the same period in 2003.