ARTIFICIAL NEURAL NETWORKS AS WATERSHED NUTRIENT LOADING MODELS

A Thesis

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Master of Science

by

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ABSTRACT

Artificial neural network (ANN) is a computing architecture in the area of artificial intelligence. The present study aims at the wider use of ANN in the watershed loading prediction. An important aspect of these initiatives is the accurate forecasting nutrient load in runoff water. Accurate prediction of watershed loading has been recognized as an important measure for effective water management strategy. This study compares Haith's Generalized Watershed Loading Function (GWLF) and Arnold's Soil and Water Assessment Tool (SWAT) to multilayer artificial neural networks for monthly/daily watershed load forecast modeling. The comparison splits into two different parts; 1) performance of the ANN calibrated to the observed data; 2) performance of the ANN calibrated to simulated data. The first part includes comparison of model estimates from both the ANN and the GWLF to the collected observations from West Branch Delaware River watershed. The second part evaluates the performance of calibrated ANN model using simulated output using the SWAT. Feed-forward networks with one hidden layer of sigmoid nodes followed by an output layer of linear nodes were created for both comparisons. The model performances were evaluated using various statistical indices. For each of the ANN models, different numbers of nodes were tested in order to create the optimal structure. The modeling results indicate that calibrated feed-forward ANN models were found to provide reasonable prediction accuracy as the GWLF and the SWAT in most of the nutrient categories. With its flexibility and computation efficiency, the ANN is anticipated as a useful tool to obtain a quick preliminary assessment of nutrient loading variations.

BIOGRAPHICAL SKETCH

Raymond Jungwoo Kim was born September 11, 1983 in Seoul, South Korea. He received the Bachelor of Science in Environmental Systems Engineering from Hanyang University in 2009. He served in a military as a Drill Sergeant at Korea Army Training Center from 2006 to 2008. He is currently a graduate student at the school of Civil and Environmental Engineering at Cornell University. He is also a board member of the Korean Graduate Student's Association at Cornell.

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TABLE OF CONTENTS

CHAPTER 1

INTRODUCTION

Nutrients are indispensible for water bodies to remain healthy, but excessive amounts can be harmful. Nutrient pollution, especially from nitrogen and phosphorus, has consistently been one of the top causes of degradation in the water systems including streams, rivers, wetlands, estuaries, and coastal waters (US EPA 2007). High levels of nitrogen and phosphorus can lead to significant water quality problems such as propagation of harmful algae blooms. Decomposition of these algae blooms can reduce dissolved oxygen in a biotic environmental, and suffocate fish and other aquatic life. Wildlife is no longer able to survive in such conditions and will face decline in its population or even extinction. Excess amount of nitrogen and phosphorus can also result in higher amounts of toxic chemicals that can have harmful effects on humans (MPCA 2008). Some of the main causes to this nutrient pollution are agricultural fertilizers (both residential and agricultural usage), manure, rainfall flowing over cropland and urban/suburban areas, industrial wastewaters, and overflow from septic systems (Howarth et al. 2002). The control of these pollution sources has generated much interest with regard to evaluation of management options and development of accurate nutrient load forecasting models (Johnes 1996). To do this, several physical based models have been developed including the Generalized Watershed Loading Functions (GWLF) and the Soil and Water Assessment Tool (SWAT).

The GWLF by Haith (1987) is a widely used model that estimates dissolved and total monthly nitrogen and phosphorus loads in streamflow from complex watersheds. The GWLF model is unique in its ability to predict nutrient fluxes in streamflow without calibration. The SWAT is a river basin model developed by Arnold (1995) to predict the impact of land management practices on water, sediment, and agricultural chemical yields in large ungauged basins. The SWAT uses physically based input such as soil, weather, land use, and topographic data. The model conducts long-term simulations up to 100 years on a daily, monthly, or yearly time-step.

However, the essential information for calibration may not be readily accessible (Loke et al. 1999), which makes the model expensive and time-consuming (Suen et al. 2003) or even results in inaccurate estimation if parameterized without using the data from the site of interests (May et al. 2009). For instance, as it is stated in the GWLF manual (Haith 2010), to further improve the model performance, more detailed chemical simulation models would be needed. These would require additional data, necessitating extra computational requirements such as calibration to water quality sampling data. Also, Ndomba (2008) mentions some limitations of the SWAT that poor catchment representation of important hydrological features, such as precipitation, may lead to poor performance of the model. Thus, there is a great need for statistical models capable of predicting watershed loading at unmonitored sites (May et al. 2009).

As an alternative to these physically based models, an Artificial Neural Network (ANN) could be applied to watershed loading estimates. The ANN is inspired by the early models of sensory processing by the brain. It is designed to resemble the human thinking process in decision-making and strategy learning. By applying algorithms that mimic the processes of real neurons, one can make a network that learns to solve many types of problems. ANN has been well recognized for its great ability to handle complex systems and has been adopted throughout the technology industry, providing solutions for logistics, data mining, pattern recognition, medical diagnosis and many other fields (Soroush 2009). The main purpose of this study is to analyze and discuss the comparison between statistically based ANN model and physically based GWLF and SWAT models, in an effort to judge whether such an ANN might be suitable as a watershed nutrient loading model.

CHAPTER 2

BACKGROUND

ANN contains nodes and links in its network. The nodes take a number of input signals, then, process through an internal weighting system, and produces a single output signal that is typically sent as input to another node. Nodes are interconnected and organized into layers. After the input layer receives the input, it is processed though one or more hidden layer. Then, it is processed to the output layer, which produces the final output.

ANN typically begins with random weights for all its nodes. In other words, the nodes are not aware and need be trained in order to solve the problem for which they are intended. One of the training methods to be discussed in this study is a backpropagation method. For this training algorithm, the model evaluates whether the ANN's output is correct during the training period. If it is correct, weights of the nodes that produced that output are reinforced; if the output is incorrect, those weights responsible are diminished. This type is most often used for cognitive research and for problem-solving applications.

In backpropagation, a numerical optimization technique called gradient descent makes the computation simple. There are some learning parameters (learning rate and momentum) that need tuning when using backpropagation, and there are other problems to consider. For example, since the result of the training depends on the initial values of the weights, gradient descent is not always guaranteed to find the global minimum of the error.

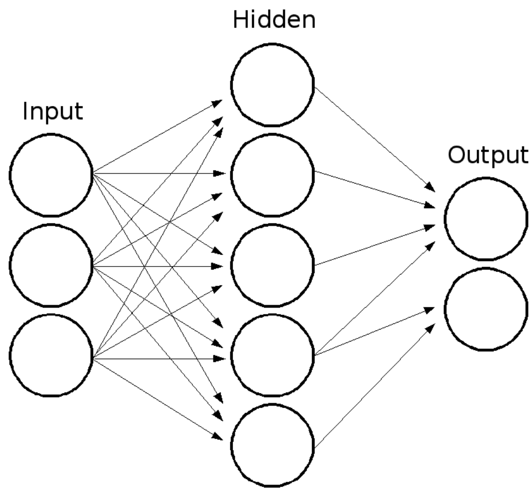


Fig. 1 Example schematic figure of ANN Architecture

A major advantage of ANN is its parallel nature. This allows the network to be built using multiple processors, giving it a great speed advantage at very little development cost. The parallel architecture also allows ANN to process a large amount of data very efficiently. Therefore, ANN operates considerably faster than other models when dealing with large, continuous streams of information.

For the last ten years, ANNs have been developed and used effectively in various research projects in water protection and water management in many other countries. ANN using the Fuzzy Logic has been developed in the Netherlands for the control of water levels in polder areas (Lobbrecht et al. 1999). Another ANN that performs river flow forecasting has been developed also in the Netherlands (Dibike et al. 1999). Also in the US, ANN has been developed for water quality prediction (Lek et al. 1999; Bowers et al. 2000; Maier et al. 2004; Sarangi et al. 2005; Sengorur et al. 2006; Fogelman et al. 2006), and reservoir operations (Aguilera et al. 2001; Suen et al. 2003, Zaheer et al. 2003; Tayfur et al. 2005). Epcor (US company) in cooperation with the American Water and Wastewater Association Research Foundation (AWWARF) has developed ANN for the process optimization for water and wastewater treatment (Iliyadis et al. 2007). ANNs have become popular in the analysis of non-linear and non-stationary hydrologic data such as river flow forecasting (Gopakumar et al. 2007; El-Shafie et al. 2009), forecasting surface water and groundwater level fluctuations (Nayak et al. 2006; Altunkaynak 2007; Mohanty et al. 2010), and rainfall runoff simulation modeling (Sohail et al. 2008; Lee et al. 2008; Nourani et al. 2009; Chen et al. 2010). Due to a growing number of successful researches in the field, the possibilities of ANN as water resources management tools are increasing rapidly. However, not many attempts have been made to develop watershed nutrient loading model with the ANN yet.

CHAPTER 3

STUDY AREAS AND DATA

3.1 West Branch Delaware River watershed

West Branch Delaware River (WBDR) watershed, also known as Cannonsville Basin watershed, covers 850km^2 of dairy farming area in southeast New York, which consists of 30% agricultural, 67% forested and 3% urban land uses (Appendix Fig. A-1) The WBDR watershed's drainage basin is the largest basin in the city's system, and includes parts of 17 towns, all in Delaware County: Andes, Bovina, Delhi, Deposit, Franklin, Hamden, Harpersfield, Jefferson, Kortright, Masonville, Meredith, Middletown, Roxbury, Sidney, Stamford, Tompkins and Walton. Cannonsville Reservoir was formed by damming the WBDR, which continues south and becomes part of the lower Delaware River, the border between New York and Pennsylvania. The reservoir is used for water supply source for the city of New York. The reservoir had a long history of eutrophication problems due to excess nutrient loading from the WBDR associated primarily with dairy agriculture and point source discharges. Sources of nonpoint source loading include land application of manure, rainfall overflow, overuse of fertilizer in cropland (New York City Watershed 2006).

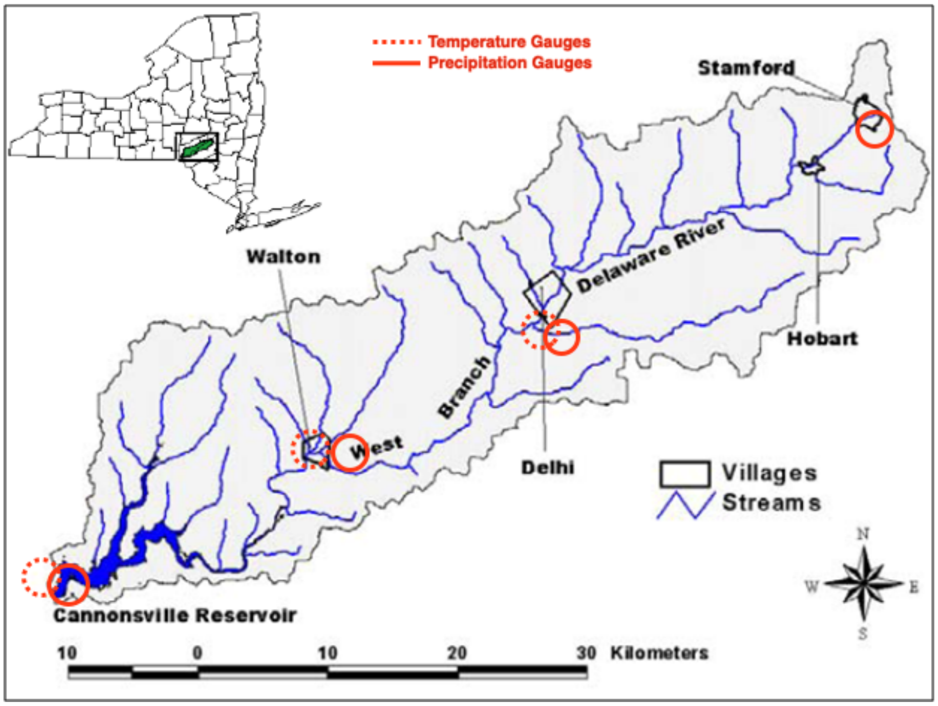


Fig. 2 West Branch Delaware River watershed and gauge locations

For the first part of the comparison, the ANN and the GWLF are tested for their model predictions of sediment, and nutrient loads from the WBDR watershed during a two-year period (March, 1980 – March, 1982). The GWLF is a mid-range watershed loading model developed to assess non-point source flow and sediment and nutrient loading from urban and rural watersheds. Both surface runoff and groundwater sources are included, as well as nutrient loads from point sources and on-site wastewater septic systems. Thus, the model requires three main sets of input data – historical weather data, transport data, and nutrient data. The historical data include daily temperature and precipitation. The transport data include basin size, land use/cover distribution, curve numbers by source area, evapotranspiration cover coefficients, erosivity coefficients, day light hours by month, growing season months, initial snow amount, and sediment delivery ratio soil water. The nutrient data include nitrogen and phosphorous point source loads, background nitrogen and phosphorus concentrations in groundwater, background nitrogen and phosphorus concentrations in soil, months of manure spreading, and population on septic systems. These components are segmented into 118 input parameters. Among these input parameters, the ANN model only uses time-dependent values. The daily precipitation and temperature records are obtained from the US Environmental Data and Information service weather station at Walton, New York. For the transport parameters, monthly bases of evapotranspiration cover factors, average daylight hours, growing season indicators, and rainfall erosivity coefficients are derived from the GWLF. For the nutrient parameters, monthly populations served by septic systems - normal, short-circuited, ponded, and direct discharge are used. Detailed procedures for estimating transport and nutrient parameters are described in *Generalized Watershed Loading Function Manual 3.0* (Haith 2010).

The following outputs from both models are predicted and compared with the observed data from WBDR:

- Monthly Sediment Yield
- Monthly Total Nitrogen and Phosphorus Loads in Streamflow
- Monthly Dissolved Nitrogen and Phosphorus Loads in Streamflow

The observation data are collected, analyzed and summarized by the N.Y. State Department of Environmental Conservation. Total and dissolved phosphorus and sediment data are collected from March, 1980 through March, 1982. The sampling periods for dissolved and total nitrogen are less extensive; March, 1980 – September, 1981 and January, 1981 – September, 1981, respectively.

For the second part of the comparison, the ANN is calibrated using the SWAT. Since SWAT is a widely used model for its accuracy and effectiveness for management purpose (Saleh et al. 2004), the second part of the comparison focuses on how well the ANN fits to the SWAT. The SWAT is developed to predict the impact of land management practices on water, sediment and agricultural chemical yields in large complex watersheds with varying soils, land use and management conditions over long periods of time. To satisfy this objective, the model is physically based. Rather than incorporating regression equations to describe the relationship between input and output variables, the SWAT requires specific information about weather, soil properties, topography, vegetation, and land management practices occurring in the watershed. In this study, the SWAT uses approximately 230 input parameters to estimate the nutrient loadings (sediment out, sediment concentration, mineral phosphorus, organic phosphorus) in the WBDR watershed on a daily basis from January 1, 1996 through December 30, 2000. The ANN is trained and validated using the sets of inputs and the simulated outputs from the SWAT. Since the selection of the input parameters is a very important aspect for the ANN modeling to avoid noise in its training process, the input parameters were be selected carefully for the efficiency of the model (Dogan et al. 2009). Among the 230 inputs from the SWAT, a total of 15 input variables are implemented into the ANN model; daily average temperature data from three gauges, daily precipitation data from four gauges (Fig. 2), daily average solar radiation, daily average wind speed, daily average dew temperature, grazing operation data, fertilizer operation data, and harvest index override data.

The following outputs were simulated using the ANN and compared with the estimates from the SWAT:

- Daily Sediment Load Out (tons)
- Daily Sediment Concentration (mg/kg)
- Daily Organic Phosphorus (kg)
- Daily Mineral Phosphorus (kg)

CHAPTER 4

MODEL DEVELOPMENT

4.1 ANN model using feed-forward network

The ANN used in this study is a feed-forward network trained with a backpropagation algorithm, which has previously been identified as the most common ANN model used in water resources applications (Maier et al. 1996). ANN with one hidden layer is capable of approximating any finite non-linear function with high accuracy (Schalkoff 1997), and using more hidden layers often cause unnecessary computational overload (Kim et al. 2008). Hence, following many previous studies, a feed-forward network with one hidden layer of sigmoid nodes followed by an output layer of linear nodes is created for this model. The input layer is just the layer of nodes receiving inputs directly from outside the network. There is only one input layer, and the number of nodes comprising that layer is equal to the number of input variables. A hidden layer with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors. The linear output layer lets the network produce values outside the range –1 to +1. Figure 1 shows the general architecture of the feed-forward network.

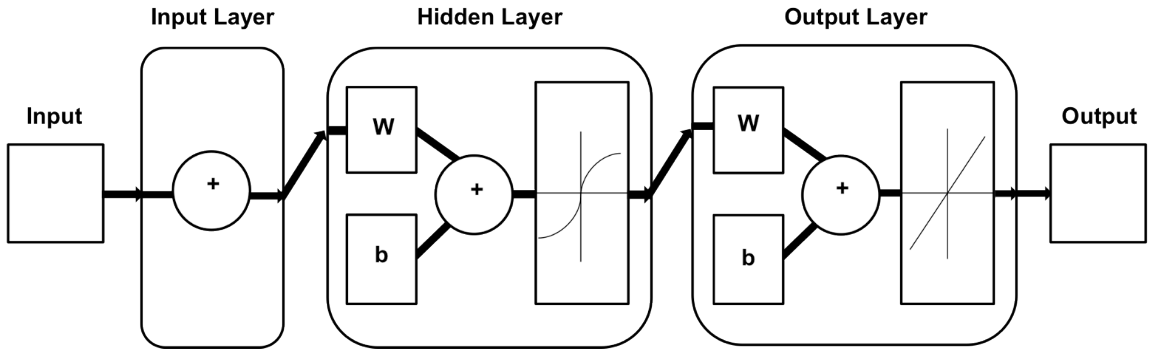


Fig. 3 ANN Feed-forward Network

The sum of the weighted inputs and the bias b forms the input to the transfer function *f*. Nodes can use any transfer function *f* to generate their output a.

$$a = f(W * I + b)$$

Before training the feed-forward network, the weights and biases must be initialized. Once the network weights and biases are initialized, training process is ready to begin. The training process requires a set of examples of network inputs and target outputs.

All training algorithms use the gradient of the performance function to determine how to adjust the weights to optimize performance. The gradient is determined using a technique called backpropagation, which involves performing computations backward through the network. The backpropagation uses supervised training and compares its resulting outputs against target outputs. Errors are propagated back through the system to adjust the weights of the nodes in each layer. More literature about backpropagation is discussed in *Theory of the Backpropagation Neural Network* (Hecht-Nielsen 1989).

There are many variations of the backpropagation algorithm. In this study, the network is trained using the variation called Levenberg-Marquardt algorithm (LMA). The LMA trains a neural network 10 to 100 times faster than standard gradient backpropagation method, and is the fastest method for training moderate-sized (up to several hundred nodes) feed-forward network (Catalao et al. 2007). The performance function for the ANN is measured in Root Mean Square Error (RMSE) – the average squared error between the network outputs and the target outputs.

Setting a right number of nodes in the feed-forward network is one of the most significant tasks. The best number of hidden nodes depends on (Tarassenko 1998):

- Numbers of input and output data
- Number of training cases
- Amount of noise in the target outputs
- Complexity of the function or classification to be learned
- Architecture
- Training algorithm

In most cases, there is no way to determine the best number of hidden nodes without training several networks and estimating the generalization error of each. If too few hidden nodes are used, high training error and high generalization error will occur due to underfitting and high statistical bias. If too many hidden nodes are used, the network will produce low training error but still produce high generalization error due to overfitting and high variance. Geman et al (1992) discuss how the number of hidden units affects the bias/variance trade-off. However, Blum (1992) mentions that a rule of thumb is for the size of hidden layer to be somewhere between the input layer and output layer size. Another rule of thumb discussed in the literature is that the network will never require more than twice the number of hidden nodes as used for inputs (Swingler, 1996).

For each model run, samples are randomly divided up in 70% for training, 15% for validation and 15% for testing. The training data are presented to the network to adjust according to its error. The validation data are used to measure network generalization, and to stop training when generalization stops improving. Testing data have no effect on training and so provides an independent measure of network performance during and after training.

4.2 ANN architecture for its performance evaluation against GWLF

A set of five ANN models using feed-forward network is created for each target output (sediment, dissolved nitrogen, dissolved phosphorus, total nitrogen, and total phosphorus). The target outputs are collected observation from the WBDR watershed. A set of ten input parameters is used for model training and Table 1 summarizes the symbols used in this study.

Table 1 Symbols for input parameters used for the ANN

Symbol	Meaning	Units
TMP	Average daily temperature	°C
PCP	Average daily precipitation	cm
DLH	Average daylight hours per day	hrs
GSI	Growing season indicators	1=Yes, 0=No
REC	Rainfall erosivity coefficient	-
ECC	Evapotranspiration cover coefficient	-
SSN	Population in septic system (normal)	person
SSP	Population in septic system (ponded)	person
SSSC	Population in septic system (short-circuited)	person
SSDD	Population in septic system (direct discharge)	person

Table 2 Percentage of total population served by each septic system. Retrieved from GWLF Manual 3.0 (Haith 2010)

Systems Type	% of Total Population	Population Served	
		Year-round	Seasonal (Jun-Aug)
Normal	86	7572	1835
Short-Circuited	1	88	21
Ponded	10	881	213
Direct Discharge	3	264	64

Septic systems (on-site wastewater disposal) are used for the nutrient data. Septic systems need estimates of the per capita nutrient load in septic system effluent and per capita nutrient losses due to plant uptake, as well as the number of people in the watershed served by each type of system. There are four types of septic systems; normal, short-circuited, ponded, and direct discharge. Normal septic system is a system whose construction and operation conforms to recommended procedures for on-site wastewater disposal systems by US Environmental Protection Agency. Effluents from these systems infiltrate into the soil and enter the shallow saturated zone. The nitrogen is transported to the stream by groundwater discharge, and phosphorus is retained by soil (no discharge). Short-circuited systems are located close enough to surface water (within 15m) so that adsorption of phosphorus is no more significant. Ponded systems exhibit hydraulic failure of the tank's absorption field and resulting surfacing of the effluent. Unless the surfaced effluent freezes, ponding systems deliver their nutrient loads to surface water. Direct discharge systems are illegal systems that discharge septic tank effluent directly into surface. The literature about the septic systems in detail is available from *Generalized Watershed Loading Functions version 3.0* (Haith 2010). The basic statistical parameters (minimum, median, maximum, mean, standard deviation, and coefficient of variation of the variables) used in this model are presented in Table 3, and the schematic representation is depicted in Fig. 4.

Table 3 Statistics of the variables used in the ANN

Variables	Maximum	Median	Minimum	Mean	SD	CV%
TMP	21.13	7.61	-10.23	7.00	9.97	142.38
PCP	0.60	0.31	0.09	0.30	0.12	40.14
DLH	14.60	11.70	1.00	10.86	3.49	32.14
GSI	1.00	0.00	0.00	0.48	0.51	106.23
REC	0.25	0.06	0.06	0.15	0.10	64.07
ECC	1.00	0.49	0.49	0.73	0.26	35.39
SSN	9407.00	7572.00	7572.00	8012.40	799.86	9.98
SSP	1094.00	881.00	881.00	932.12	92.84	9.96
SSSC	109.00	88.00	88.00	91.36	7.86	8.60
SSDD	328.00	264.00	264.00	279.36	27.90	9.99

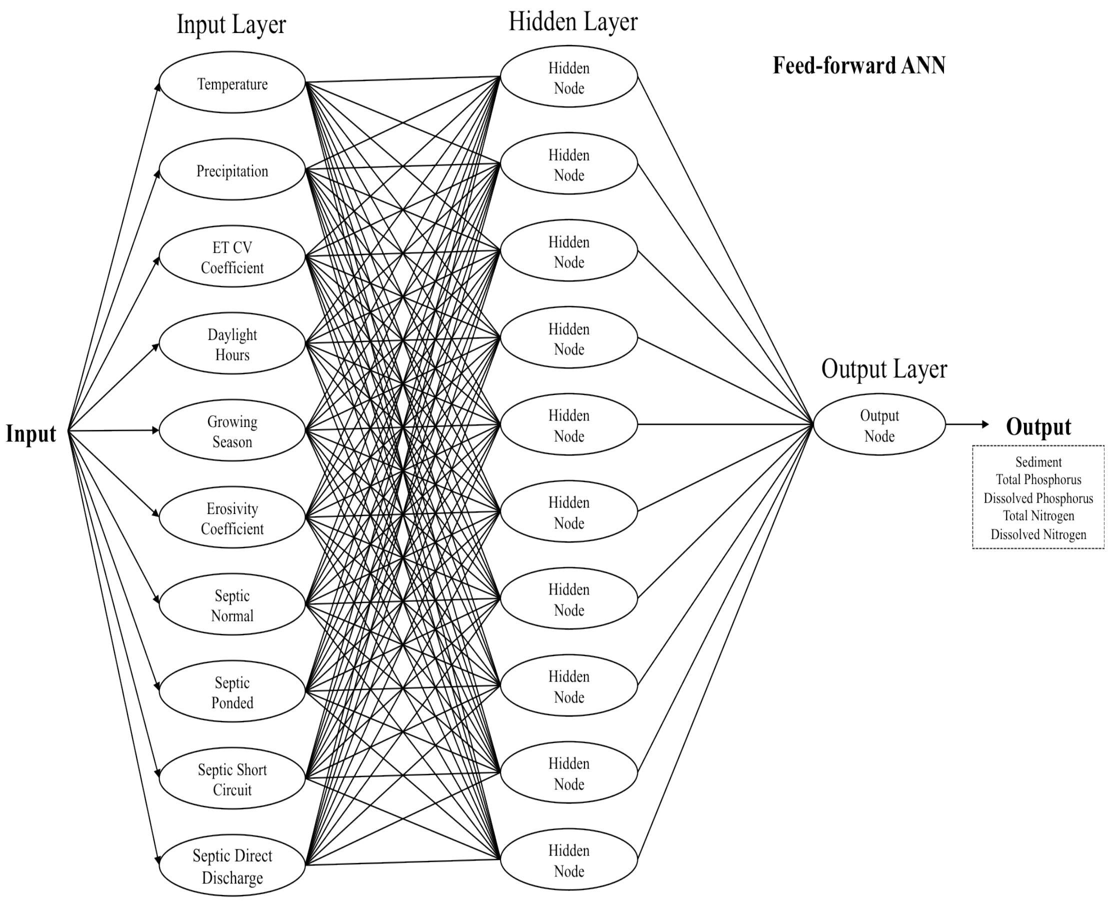


Fig. 4 A representation of a 3-layer feed-forward ANN with 10 inputs, 10 hidden nodes, and 1 output

4.3 ANN Model calibrated using SWAT

A set of five ANN models using feed-forward network is created for each target output (sediment out, sediment concentration, mineral phosphorus, and organic phosphorus). The target outputs are simulated estimates of the WBDR watershed using the SWAT. A set of ten input parameters is used for model training and Table 4 summarizes the symbols used in this study.

Table 4 Symbols for input parameters for the ANN (calibrated using the SWAT)

Symbol	Meaning	Units
SLR	Average daily solar radiation	MJ/m^2
DPT	Average daily dew point temperature	°C
WDS	Average daily wind speed	m/s
TMP1	Average daily temperature from gauge 1 (42.06 -75.3)	°C
TMP2	Average daily temperature from gauge 2 (42.16 -75.1)	°C
TMP3	Average daily temperature from gauge 3 (42.25 -74.9)	°C
PCP1	Average daily precipitation from gauge 1 (42.06 -75.3)	mm
PCP2	Average daily precipitation from gauge 2 (42.16 -75.1)	mm
PCP3	Average daily precipitation from gauge 3 (42.25 -74.9)	mm
PCP4	Average daily precipitation from gauge 4 (42.40 -74.6)	mm
DCW	Grazing operation (Delaware County West) –Total dairy	kg
DCS	Grazing operation (Delaware County South) –Total dairy	kg
N	Fertilizer operation – Total nitrogen	kg
P	Fertilizer operation – Total phosphorus	kg
HIO	Harvest index override	-

The SWAT model uses approximately 230 input parameters. Among these inputs, ten of them are used for model training and Table 4 summarizes the symbols used in the study. SLR is average daily solar radiation for month. This value is calculated by summing the total solar radiation for everyday in the month for all years of record and dividing by the number of days summed. DPT is average daily dew point temperature for each month or relative humidity (fraction) can be input. DPT is the temperature at which the actual vapor pressure present in the atmosphere is equal to the saturation vapor press. WDS is average daily wind speed in month. This value is calculated by summing the average or mean wind speed values for everyday in the month for all years of record and dividing by the number of days summed. Temperature data measured from three different gauges are used from records of the WBDR. The SWAT uses daily minimum and maximum temperature measured from each gauge, but these values are averaged into daily mean temperature for the ANN model to reduce noise. The daily precipitation data are measured from four different rain gauges and the gauge locations are shown in Fig. 2.

The SWAT itemizes the land and water management practices taking place within the system into management files for each HRU. The management files contain input data for planting, harvest, irrigation applications, nutrient applications, pesticide applications, and tillage operations. Three sets of operation parameters are derived from the SWAT; grazing operation, fertilizer application, and harvest operation. The grazing operation simulates plant biomass removal and manure deposition over a specified period of time. This operation is used to simulate pasture or rage grazed by animals, and cow dairy data from Delaware County (west and south) are implemented. The fertilizer operation applies fertilizer or manure to the soil. This includes the timing of the operation, the type and amount of fertilizer applied. Nitrogen and phosphorus data are used for this simulation. Harvest index override data are also used as input parameters. The harvest operation will remove grain or plant biomass without killing the plant and a harvest index override can be set for each day. Detailed information about the input parameters including the management operations is available in *Soil Water Assessment Tool Input/Output File Documentation Version 2009* (Neitsch et al. 2010). The basic statistical parameters (minimum, median, maximum, mean, standard deviation, and coefficient of variation of the variables) used in these models are presented in Table 5, and the schematic representation is depicted in Fig. 5.

Table 5 Statistics of the variables used in the ANN (calibrated using the SWAT)

Variables	Maximum	Median	Minimum	Mean	SD	CV%
SLR	20.57	13.87	4.44	12.58	5.67	45.04
DPT	15.37	5.69	-8.11	3.61	8.54	236.26
WDS	5.09	4.17	3.21	4.26	0.65	15.19
TMP1	25.85	7.80	-22.75	7.55	9.87	130.75
TMP2	26.35	8.05	-22.20	7.63	9.72	127.40
TMP3	26.35	9.15	-20.80	8.42	9.77	116.00
PCP1	124.50	0.00	0.00	3.28	8.07	246.49
PCP2	114.00	0.05	0.00	3.27	8.00	244.91
PCP3	102.40	0.10	0.00	3.34	7.98	238.77
PCP4	93.70	0.00	0.00	2.96	6.84	230.82
DCW	13.64	0.00	0.00	6.11	6.19	101.40
DCS	7.33	4.21	0.00	2.46	2.45	99.40
N	39.30	0.00	0.00	0.11	2.05	1908.93
P	17.10	0.00	0.00	0.05	0.89	1904.46
HIO	0.50	0.00	0.00	0.00	0.03	1356.30

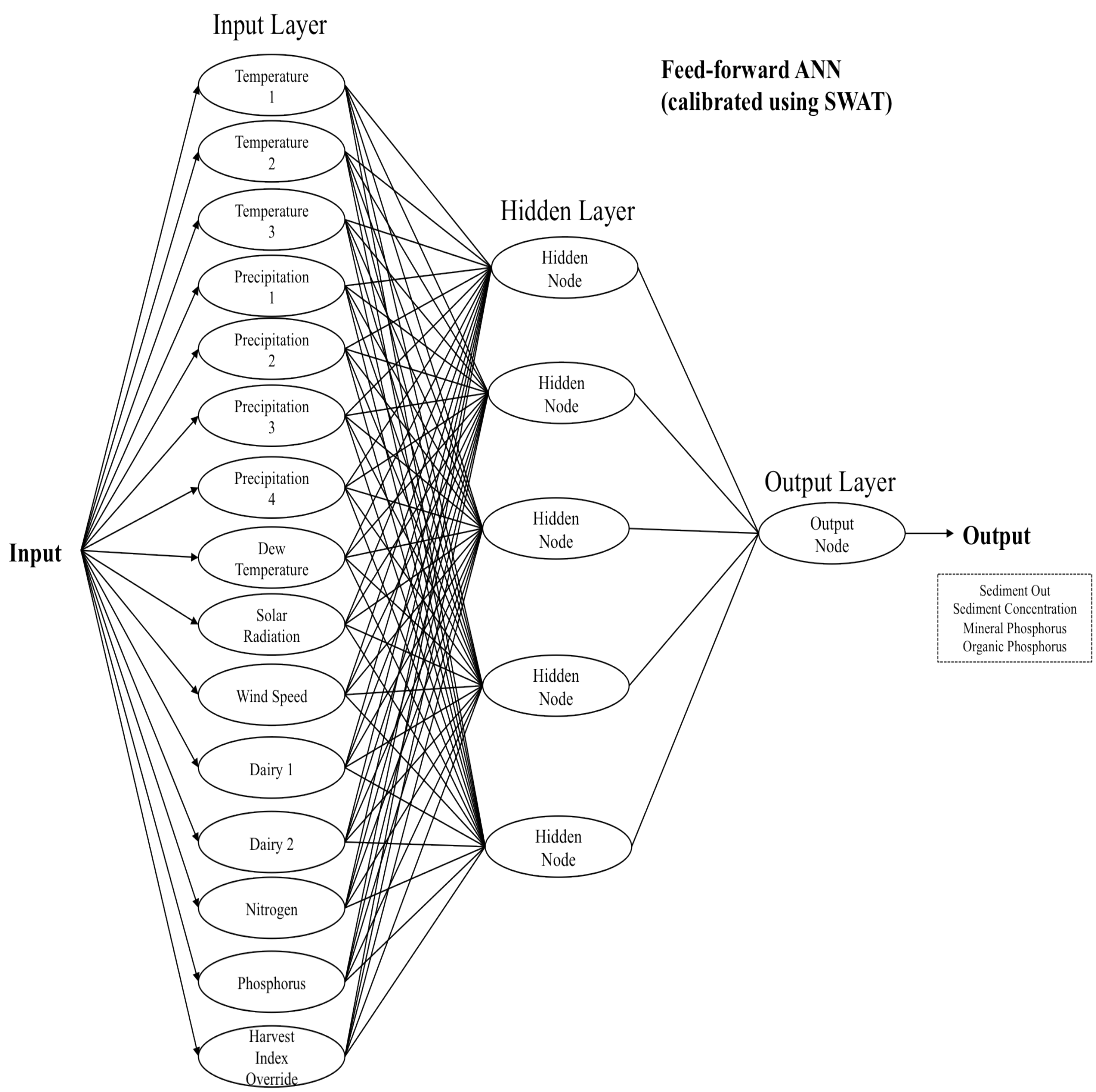


Fig. 5 A representation of a 3-layer feed-forward ANN with 15 inputs, 5 hidden nodes, and 1 output

4.4 Model Performance Comparison

The performance of developed models can be evaluated using several statistical tests that describe the errors associated with the model. After each of the model structures is calibrated using the training and validation data set, the performance can then be evaluated in terms of these statistical measures of goodness of fit. In order to provide an indication of goodness of fit between the observed and forecasted values, analyses such as, RMSE, correlation, F-test, and t-test can be used.

RMSE is a frequently used measure of the differences between values predicted (y) by a model or an estimator and the values actually observed (x) from the model with a good measure of precision. These individual differences are also called residuals, and the RMSE serves to aggregate them into a single measure of predictive power, and is given by:

$$RMSE = \sqrt{\frac{SEE}{n}}$$

where SEE = sum of squared errors, and n = number of data used. SEE is given by:

$$SEE = \sum_{i=1}^{N} (x - y)^2$$

with the variables having already been defined, SEE will always be nonnegative and, therefore, the smallest value SEE can assume is 0. The only way for SEE to equal 0 is for all the individual estimation errors to be 0, in which case the estimated regression line would fit the data perfectly. Because regression analysis finds the values of the parameter estimates that minimize the sum of squared estimation errors, it is sometimes referred to as the method of least squares. The smaller the RMSE, the better is the performance of the model. For purposes of communicating the results, it is usually best to report RMSE rather than mean squared error (MSE) because the RMSE is measured in the same units as the data, rather than in squared units, and is representative of the size of a 'typical' error.

The quantity R, called the linear correlation coefficient, measures the strength and the direction of a linear relationship between two variables. The measure of association most often used is Pearson's correlation coefficient. This association may be expressed as a number (the correlation coefficient) that ranges from –1 to +1. The mathematical formula for computing R is:

$$R = \frac{n\sum xy - (\sum x)(\sum y)}{\sqrt{n(\sum x^2) - (\sum x)^2}\sqrt{n(\sum y^2) - (\sum y)^2}}$$

where n is the number of pairs of data. The correlation measures how well a straight line fits through a scatter of points when plotted on an x–y axis. If the correlation is positive, it means that when one variable increases, the other tends to increase. If the correlation is negative, it means that when one variable increases, the other tends to decrease. When a correlation coefficient is close to +1 (or –1), it means that there is a strong correlation – the points are scattered along a straight line. If there is no linear correlation or a weak linear correlation, R is close to 0. A value near zero means that there is a random, nonlinear relationship between the two variables. A perfect correlation of ± 1 occurs only when the data points all lie exactly on a straight line. A correlation greater than 0.8 is generally described as strong, whereas a correlation less than 0.5 is generally described as weak. The closer a correlation coefficient gets to 0, the weaker the relationship, where the scatter of points is not close to a straight line.

The F-test is designed to test if two sample variances are equal. It does this by comparing the ratio of two variances. So, if the variances are equal, the ratio of the variances will be closer to 1, and the more this ratio deviates from 1, the stronger the evidence for unequal sample variances. The mathematical formula for computing F is:

$$F = \frac{{\sigma^2}_x}{{\sigma^2}_y}$$

where ${\sigma^2}_x$ is the variance of the first group and ${\sigma^2}_y$ is the variance of the second group. This test can be a two-tailed test or a one-tailed test. The two-tailed version tests against the alternative that the variances are not equal. The one-tailed version only tests in one direction that is the variance from the first sample is either greater than or less than (but not both) the second sample variance. The choice is determined by the problem. Since we are testing a new model performance to the actual data, one-tail test is used because we are interested in knowing if the result of the model is less variable than the actual data. The hypothesis that the two sample variances are equal is rejected if F ≤ F critical value (α ,df_x, df_y), where degree of freedom (df) is the sum of the samples in both groups minus 1, and α is a significance level 0.05. This means that five times out of a hundred we would find a statistically significant difference between the variances even if there were none (Snedecor et al. 1983).

The t-test is used to determine if two same means are equal. To enable this test, we need to decide (from the result of F-test) if the variances are equal in both groups, which determine the type of t-test to perform. Then, depending on our decision about the equality of variances you either perform the version of the t-test that assumes equality of variances or other one that does not make that assumption. The formula for the t-test is a ratio:

$$\frac{Signal}{Noise} = \frac{difference\ between\ group\ means}{variability\ of\ groups}$$

$$t = \frac{\bar{X}_x - \bar{X}_y}{\sqrt{\frac{\sigma^2{}_x}{n_x} + \frac{\sigma^2{}_y}{n_y}}}$$

The top part of the ratio is just the difference between the two means or averages. The bottom part is a measure of the variability of groups. This formula is essentially another example of the signal to noise metaphor in research; the difference between the means is the signal that is introduced into the data, and the bottom part of the formula is a measure of variability that is essentially noise that may make it harder to see the group difference. The t will be positive if the first mean is larger than the second and negative if it is smaller. The significant level α is set to 0.05. In the t-test, the df is the sum of the samples in both groups minus 2. Given the significance level, df, and t, computation was carried out using MS Excel 2011 and R-statistics to determine whether the t is large enough to be significant. If it is, the means for the two sample groups is different.

CHAPTER 5

RESULTS AND DISCUSSION

5.1 ANN vs. GWLF

As mentioned earlier in the study, there are three types of layers in the ANN model; input layer, hidden layer, and output layer. Input and target output data dimensions of the ANN determine the number of nodes in the input and the output layers, respectively, but the number of hidden layers and their nodes are determined heuristically (Hajnayeb et al 2011). Using the rules of thumb introduced by Geman et al. (1992) and Swingler (1996), the number of nodes is set between the sizes of input and output layers. In this test, a trial and error procedure for the hidden node selection was carried out by gradually varying the number of nodes in the hidden layer. Starting from three hidden nodes, the RMSE is gradually decreased as for every increment of node by one. At applying seven hidden nodes, the network produced the best performance. After increasing the number of hidden nodes over eight, the RMSE began increasing again. For each hidden node setup, the trials were tested for 20 times. All computation for the ANN was carried out using MATLAB R2011A, and the length of the computation was approximately 2 seconds.

Table 6 Performance (RMSE) of the ANN model at different number of hidden nodes

Model Output	Nodes								
	3	4	5	6	7	8	9	10	15
Sediment	1.44	1.33	1.30	1.27	1.06	1.31	1.57	1.80	1.92
Dissolved N	9.98	9.96	9.41	9.51	7.61	7.92	8.30	8.59	13.21
Total N	4.84	4.52	4.17	3.95	3.04	3.35	3.20	5.24	6.75
Dissolved P	1.52	1.40	1.34	1.23	0.92	1.19	1.49	1.77	1.94
Total P	3.52	3.38	3.37	3.03	2.63	2.84	2.93	3.10	3.48

Table 7 Standard deviation of the RMSE with seven hidden nodes

	Sediment	Dissolved N	Total N	Dissolved P	Total P
SD	0.26	0.42	0.33	0.25	0.39

As depicted in Table 6, for all categories, the networks produced the best performance with seven hidden nodes in the hidden layer. When between three to six hidden nodes were applied, the models were underfitting. Setting more than eight hidden nodes resulted in overfitting. This test was extended to increase the number of hidden nodes up to 15 to validate the magnitude of the overfitting. Since the feed-forward networks using seven hidden nodes performed the best, the final model performance was evaluated and analyzed based on simulated estimates using these settings.

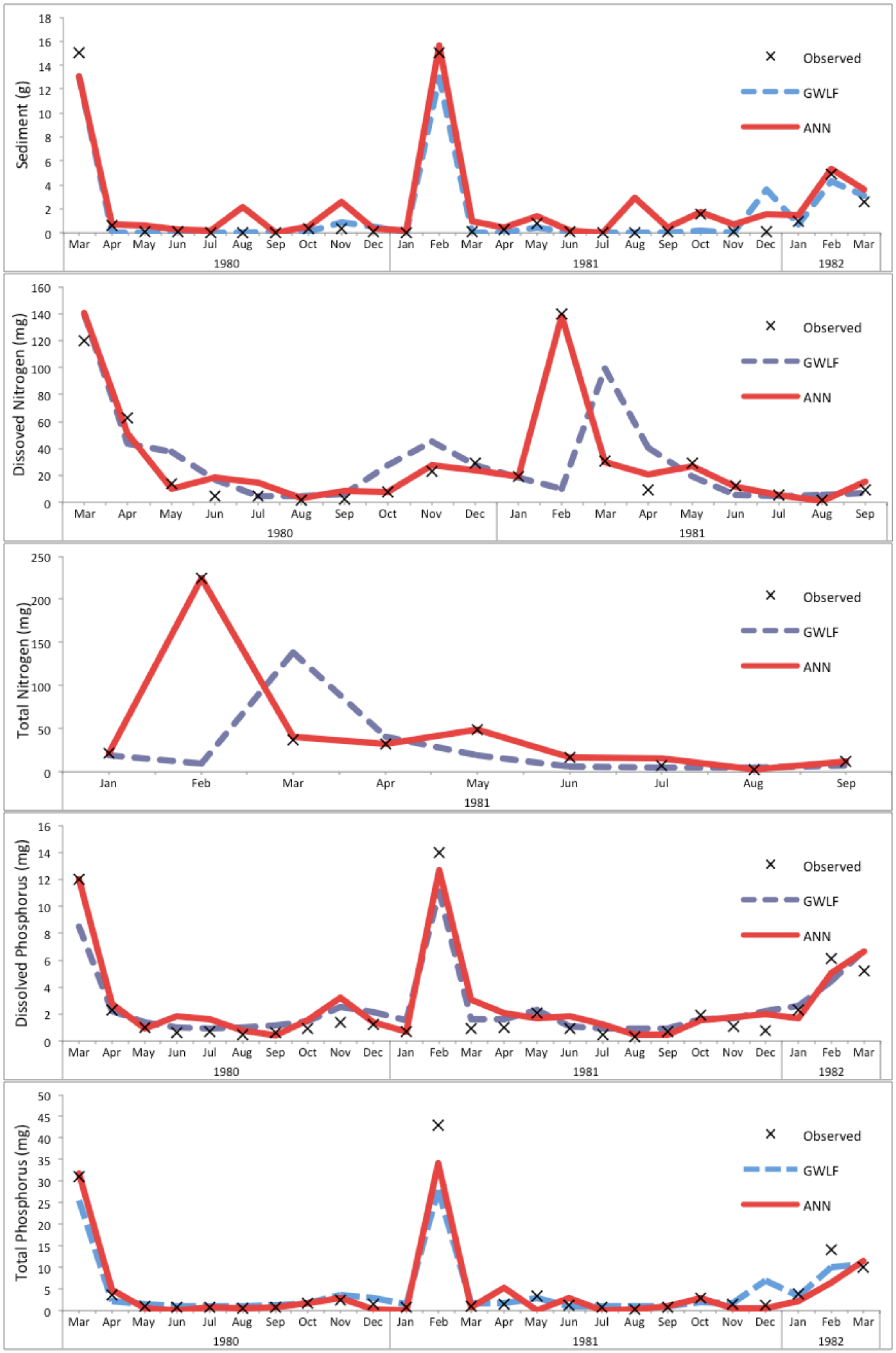


Fig. 6 Nutrient loading estimates using the ANN and the GWLF in comparison to the observed data

Performances of five nutrient loading outputs estimated by the GWLF and the ANN were compared – sediment, dissolved nitrogen, total nitrogen, dissolved phosphorus, and total phosphorus. The sediment, dissolved phosphorus, and total phosphorus estimates were predicted and validated from March, 1980 through March, 1982 (24 months). Dissolved nitrogen, and total nitrogen estimate were predicted and validated from March, 1980 through September, 1981, and January, 1981 through September, 1981, respectively.

For the sediment outputs, the ANN overestimated and the GWLF underestimated in general. The RMSE of the sediment estimates were 0.976 for the GWLF, and 1.061 for the ANN. The ANN seemed to produce unnecessary peaks during the summer due to noise in the input data. This noise can be filtered through sensitivity analysis for the model improvement in the future. For the dissolved and total nitrogen, the ANN estimates were much more accurate than the estimates of the GWLF, even though shorter period of time was used for the calibration. The ANN accurately estimated the peaks on February, 1981 while the GWLF did not catch the peak for both categories. The RMSE of dissolved and total nitrogen for the GWLF were 36.29 and 79.64, and for the ANN were 7.62 and 3.04. For the dissolved and total phosphorus, both models performed fairly well, but slightly underestimated the high peak on February, 1981. The RMSE of dissolve and total phosphorus for the GWLF were 1.17 and 3.54, and for the ANN were 0.92 and 2.64. Overall, the ANN performed better than the GWLF in 4 out of 5 categories from the results of the RMSE.

More closely looking at Fig. 7, the ANN models were highly correlated. The R for the ANN were; 0.98 (sediment), 0.98 (dissolved nitrogen), 0.99 (total nitrogen), 0.97

(dissolved phosphorus), 0.97 (total phosphorus). The R for the GWLF were; 0.98 (sediment), 0.50 (dissolved nitrogen), -0.03 (total nitrogen), 0.97 (dissolved phosphorus), 0.98 (total phosphorus). Again, the ANN performed better than then GWLF in 4 out of 5 categories from the results of correlation analysis.

F-test was performed to check if the variances of both model estimates and the observation data are equal. For all five categories of the ANN estimates, the probabilities (F ≤ F-critical) were higher than the α=0.05 (significance level), which means the variances of the ANN estimates and the observation data are assumed equal. The F-test for the GWLF showed that only three output estimates (sediment, dissolved nitrogen, and total nitrogen) had equal variances. The variances of other two output estimates (dissolved phosphorus, and total phosphorus) were either on the threshold or not assumed equal. In addition, t-test was performed to check if the means of both model estimates and the observation data are equal. As depicted in Appendix Table 2, the mean estimates of both the ANN and the GWLF were tested equal to the observed data in all five categories. So, both models estimate the sediment, dissolved nitrogen, total nitrogen, dissolved phosphorus, and total phosphorus with the same mean to observed data at a 95% confidence level.

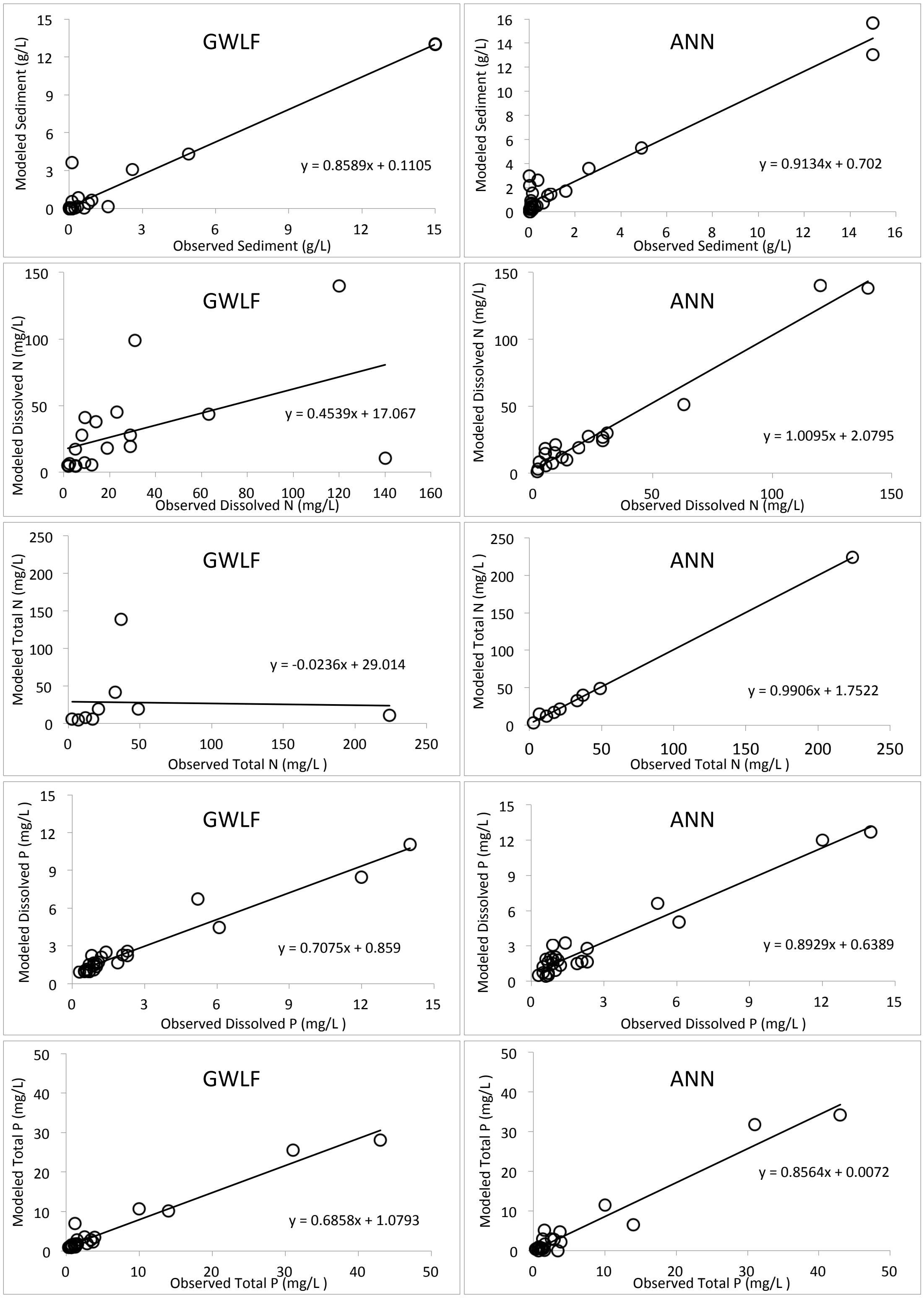


Fig. 7 Comparison of modeled vs. measured values of nutrient loadings for the ANN and the GWLF

5.2 ANN calibrated using SWAT

The ANN's input layer was prepared using combinations of weather data, and agricultural management data from the SWAT. To find the optimal number of hidden nodes, trial and error procedure was carried out by gradually varying the number of nodes in the hidden layer. Again, using the rules of thumb, the numbers of hidden nodes were set between 3 to 30.The hidden nodes were increased by one starting from three hidden nodes. Underfitting occurred for the networks using three and four hidden nodes. The networks performed the best when five hidden nodes were used. When six or more nodes were used the models resulted in greater variance and generalization error. The computation length was approximately 5 seconds when 30 hidden nodes were used, and less than 5 seconds when smaller sets were used. All computation was carried out using MATLAB R2011A.

Table 8 Performance (RMSE) of the ANN model at different number of hidden nodes

Model Outputs	Nodes										
	3	4	5	6	7	8	9	10	15	20	30
Sediment Out	6.21	4.80	3.90	4.83	5.12	5.33	5.54	6.69	6.33	7.06	8.55
Sediment Conc.	6.41	6.35	6.10	6.91	6.26	6.66	6.88	7.02	7.02	7.18	7.15
Organic P	31.89	37.37	14.54	26.05	31.81	36.95	37.99	31.50	42.60	32.68	37.94
Mineral P	7.49	6.55	6.22	6.67	9.11	9.28	7.82	9.03	6.40	8.31	8.74

Table 9 Standard deviation of the RMSE with five hidden nodes

	Sediment Out	Sediment Conc.	Organic P	Mineral P
SD	0.607	0.653	3.013	2.432

The simulated outputs (sediment out, sediment concentration, organic phosphorus, and mineral phosphorus) of the ANN model were compared to the output estimates of the SWAT model.

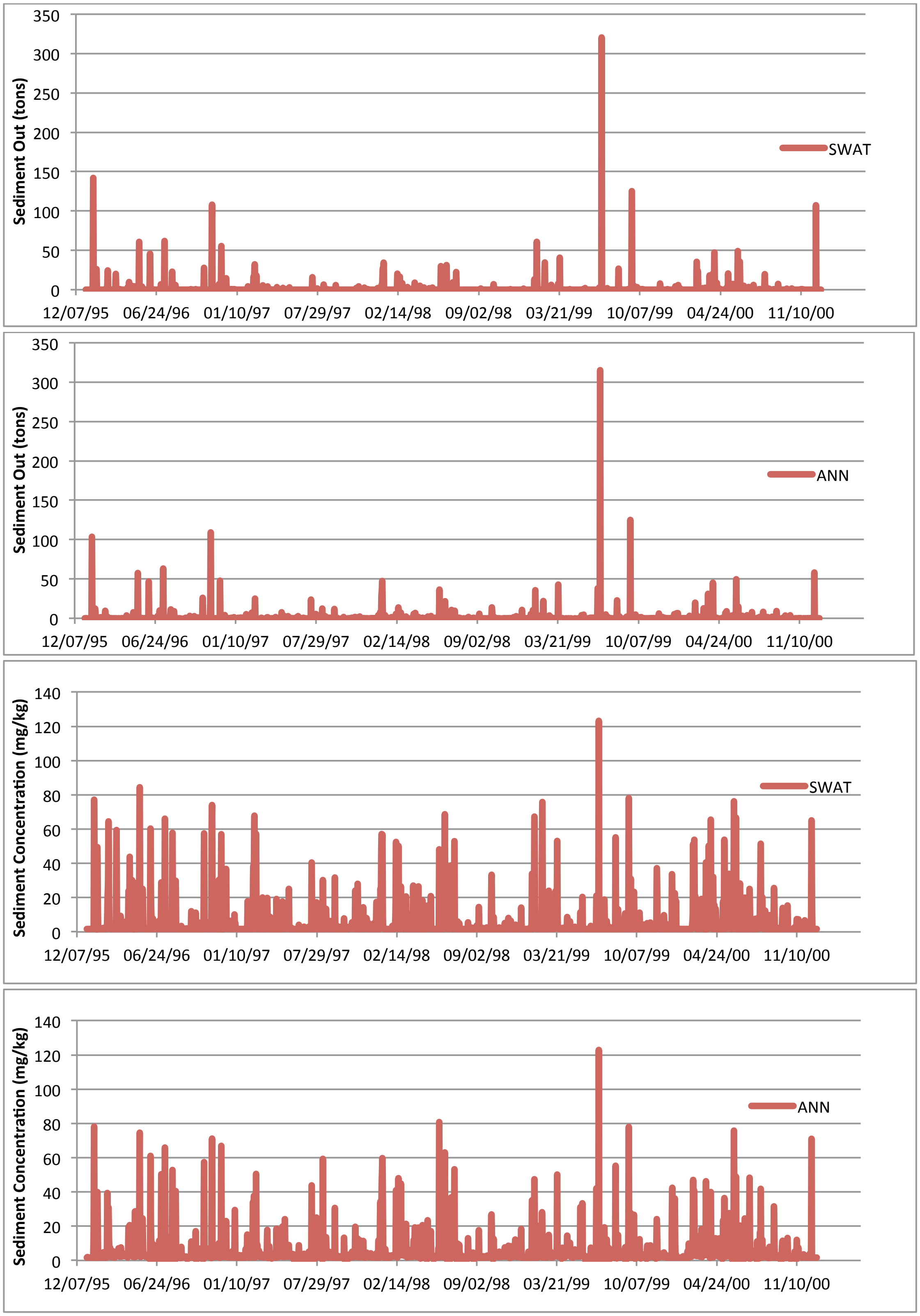


Fig. 8 Comparison of the sediment estimates of the ANN to the SWAT

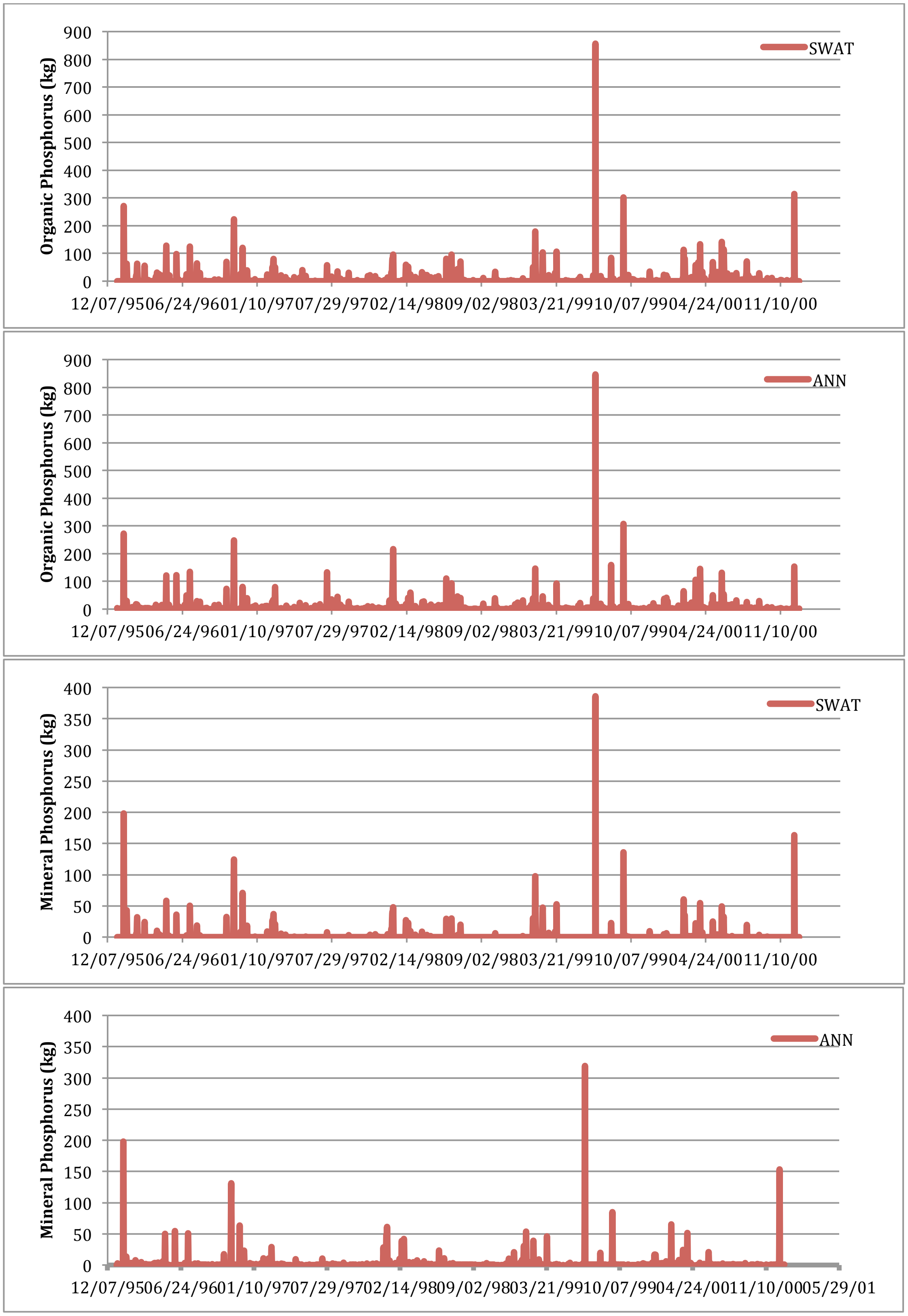


Fig. 9 Comparison of organic and mineral phosphorus estimates for the ANN to the SWAT

The RMSE of the ANN were 2.87 (sediment out), 4.88 (sediment concentration), 8.78 (organic phosphorus), and 3.95 (mineral phosphorus). The ANN models fit fairly well to the SWAT model, although at higher peaks they frequently show underestimation.

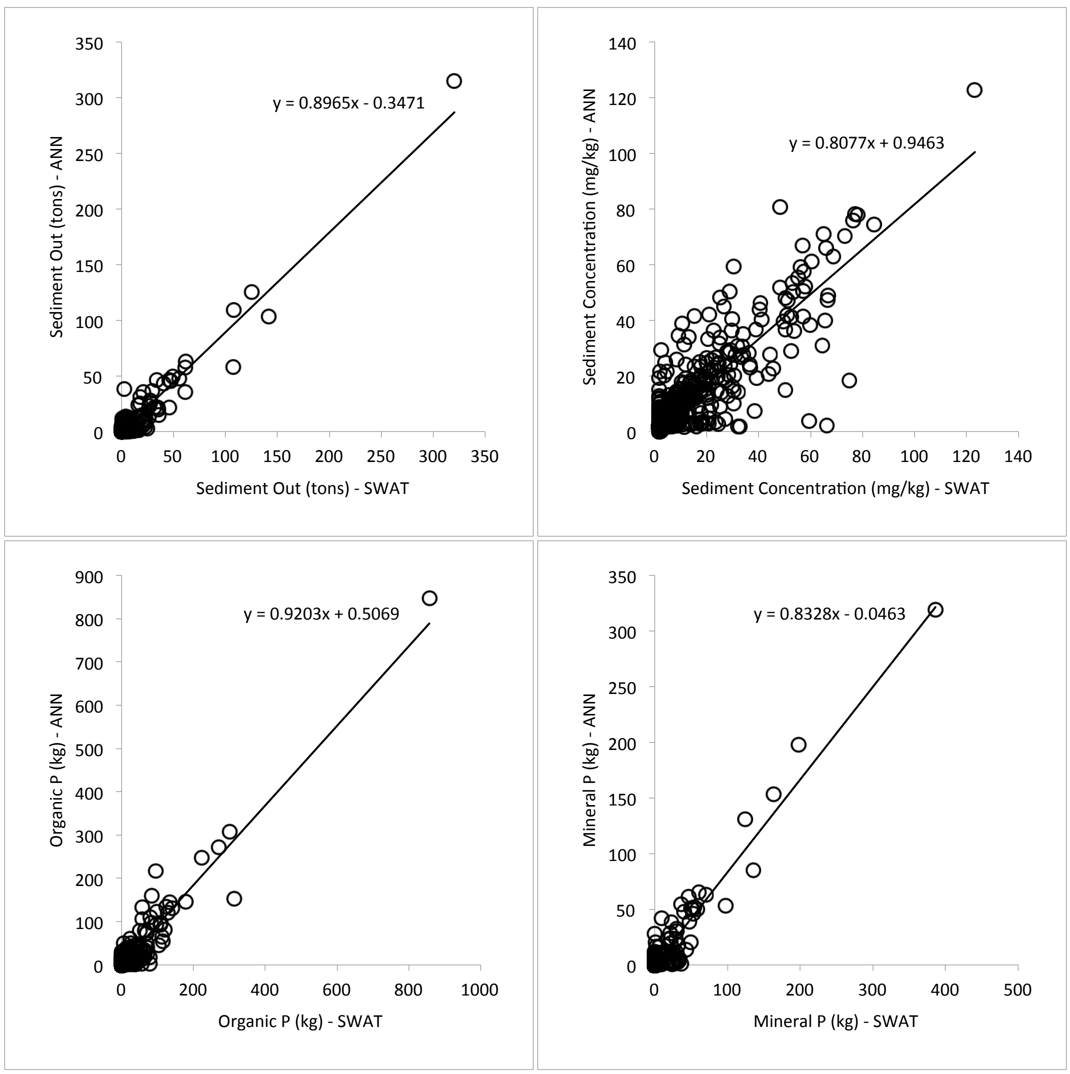


Fig. 10 Correlation Analysis of the ANN calibrated using the SWAT

As depicted in Fig. 10, the ANN models were highly correlated to the SWAT. The R for the sediment estimation was 0.96; sediment concentration was 0.88; organic phosphorus was 0.95; mineral phosphorus was 0.96. The F-test has shown that only organic phosphorus estimates of the ANN had equal variance with the SWAT. The t-test has shown that all model estimates of the ANN had equal means with the SWAT at 95% confidence level.

CONCLUSION

Having the ability to learn and train itself to solve complex problems efficiently with great computational speed, ANN is becoming one of the most promising tools in many industries. In this study, the ANN was applied as watershed loading models and its performance was compared with other physical models. The ANN used feed-forwarding architecture with the LMA for training. For the ANN model calibrated using the observed data, a structure having one hidden layer with seven hidden nodes gave the best estimates for all outputs. For the ANN model calibrated using the SWAT parameters, a structure having one hidden layer with five hidden nodes gave the best estimates for all outputs. When less than the specified numbers of nodes were applied, the models underfitted, and when more numbers were used they overfitted. Input variables used in the ANN models were time dependent parameters derived from the GWLF and the SWAT.

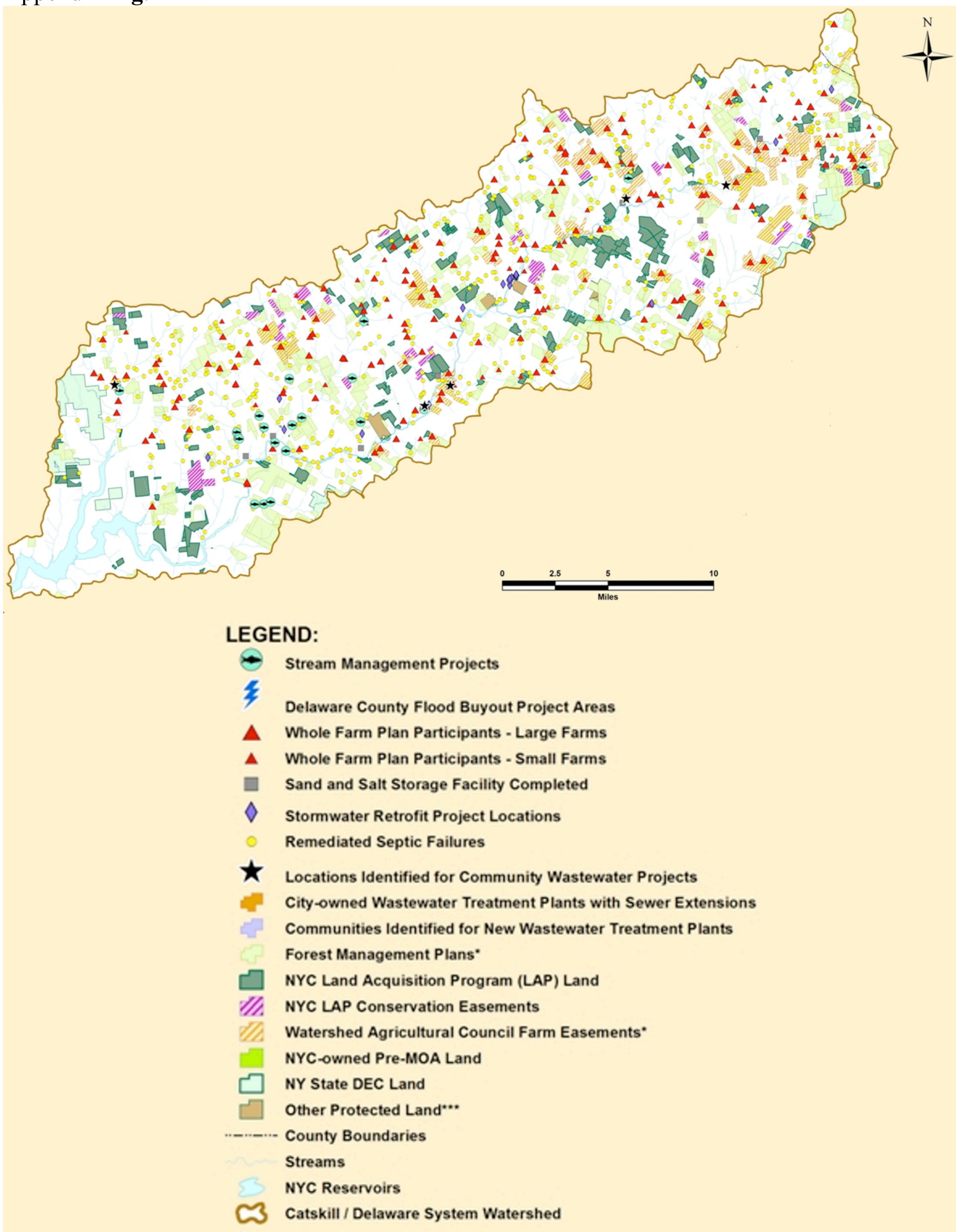
Model performances were measured using RMSE, correlation analysis, F-test, and t-test. From the results obtained, the ANN models gave satisfactory predictions of watershed nutrient loadings in most measures. The ANN model often estimated negative values (non-feasible) for the nutrient output. Also, the model often underestimated at some specific large observations and these are remaining as shortcomings of statistical models. Nevertheless, ANN model gives a great advantage of computation efficiency over other models when larger and more complex sets of samples must be tested. Despite the highly stochastic nature of the data, the ANN model was capable of mimicking the output estimations accurately with relatively small errors. The application to such environmental data in this study has a great potential in further work on prediction of watershed nutrient loading and provides a useful tool for water resources management.

FUTURE WORKS

To further improvement the ANNs as watershed nutrient loading models, a sensitivity analysis can be tested to avoid overfitting and to eliminate the noises in the data set. Since ANN structures are created and rapidly computed at low cost, numerous sensitivity analyses could be performed in order to identify the key variables as major inputs to the ANN models.

APPENDIX

Appendix **Fig. A-1**



Appendix **Table A-1**

Initial input parameters for the ANN

Month	TMP	PCP	DLH	GSI	REC	ECC	SSN	SSP	SSSC	SSDD
Mar-80	-0.16	0.48	11.70	0	0.06	0.49	7572	881	88	264
Apr-80	7.93	0.40	13.10	0	0.25	0.49	7572	881	88	264
May-80	14.06	0.10	14.30	1	0.25	1.00	7572	881	88	264
Jun-80	15.90	0.35	1.00	1	0.25	1.00	9407	1094	109	328
Jul-80	20.55	0.31	14.60	1	0.25	1.00	9407	1094	109	328
Aug-80	21.13	0.32	13.60	1	0.25	1.00	9407	1094	88	328
Sep-80	16.27	0.36	12.30	1	0.25	1.00	7572	881	88	264
Oct-80	7.61	0.32	10.90	1	0.06	1.00	7572	881	88	264
Nov-80	0.87	0.29	9.70	0	0.06	0.49	7572	881	88	264
Dec-80	-6.23	0.20	9.00	0	0.06	0.49	7572	881	88	264
Jan-81	-10.23	0.09	9.30	0	0.06	0.49	7572	881	88	264
Feb-81	-0.43	0.60	10.40	0	0.06	0.49	7572	881	88	264
Mar-81	0.81	0.14	11.70	0	0.06	0.49	7572	881	88	264
Apr-81	8.37	0.34	13.10	0	0.25	0.49	7572	881	88	264
May-81	13.52	0.42	14.30	1	0.25	1.00	7572	881	88	264
Jun-81	18.27	0.27	1.00	1	0.25	1.00	9407	1094	109	328
Jul-81	20.29	0.23	14.60	1	0.25	1.00	9407	1094	109	328
Aug-81	19.16	0.17	13.60	1	0.25	1.00	9407	1094	88	328
Sep-81	14.53	0.46	12.30	1	0.25	1.00	7572	881	88	264
Oct-81	7.39	0.42	10.90	1	0.06	1.00	7572	881	88	264
Nov-81	3.17	0.20	9.70	0	0.06	0.49	7572	881	88	264
Dec-81	-3.61	0.26	9.00	0	0.06	0.49	7572	881	88	264
Jan-82	-9.48	0.21	9.30	0	0.06	0.49	7572	881	88	264
Feb-82	-4.36	0.33	10.40	0	0.06	0.49	7572	881	88	264
Mar-82	-0.23	0.29	11.70	0	0.06	0.49	7572	881	88	264

Appendix **Table A-2**

Initial input parameters for the ANN calibrated using the SWAT

Day	SLR	DPT	WDS	TMP1	TMP2	TMP3	PCP1	PCP2	PCP3	PCP4	DCW	DCS	N	P	HIO
01/01/96	5.45	-8.11	4.99	-1.40	-3.90	-0.55	0.00	0.00	0.00	0.00	11.62	0.00	0.00	0.00	0.00
01/02/96	5.45	-8.11	4.99	-0.55	-2.50	-1.65	1.50	0.80	0.50	0.30	11.62	0.00	0.00	0.00	0.00
01/03/96	5.45	-8.11	4.99	-8.90	-7.20	-6.90	17.30	12.70	13.50	14.00	11.62	0.00	0.00	0.00	0.00
01/04/96	5.45	-8.11	4.99	-15.00	-14.70	-13.30	1.00	5.10	4.30	4.60	11.62	0.00	0.00	0.00	0.00
01/05/96	5.45	-8.11	4.99	-16.35	-15.85	-13.60	0.00	0.10	0.00	0.00	11.62	0.00	0.00	0.00	0.00
01/06/96	5.45	-8.11	4.99	-22.75	-22.20	-20.80	0.00	0.10	0.30	0.00	11.62	0.00	0.00	0.00	0.00
01/07/96	5.45	-8.11	4.99	-18.10	-17.25	-16.40	0.00	0.00	0.00	0.00	11.62	0.00	0.00	0.00	0.00
01/08/96	5.45	-8.11	4.99	-13.30	-11.40	-9.75	0.00	2.00	8.10	6.60	11.62	0.00	0.00	0.00	0.00
01/09/96	5.45	-8.11	4.99	-12.50	-13.35	-12.80	0.00	0.10	0.10	0.00	11.62	0.00	0.00	0.00	0.00
01/10/96	5.45	-8.11	4.99	-8.35	-8.65	-8.10	0.00	3.60	3.60	3.60	11.62	0.00	0.00	0.00	0.00
01/11/96	5.45	-8.11	4.99	-15.85	-16.65	-15.30	0.00	0.50	3.60	1.50	11.62	0.00	0.00	0.00	0.00
01/12/96	5.45	-8.11	4.99	-13.05	-8.30	-7.50	20.80	0.00	0.00	0.00	11.62	0.00	0.00	0.00	0.00
01/13/96	5.45	-8.11	4.99	-4.75	-3.65	-4.20	2.80	18.50	19.80	0.10	11.62	0.00	0.00	0.00	0.00
01/14/96	5.45	-8.11	4.99	-0.55	0.25	-1.40	0.00	0.10	0.00	0.00	11.62	0.00	0.00	0.00	0.00
01/15/96	5.45	-8.11	4.99	-3.35	-5.25	-3.60	0.00	0.00	0.00	0.00	11.62	0.00	0.00	0.00	0.00
01/16/96	5.45	-8.11	4.99	-13.35	-15.55	-14.70	0.00	0.00	0.00	0.00	11.62	0.00	0.00	0.00	0.00
01/17/96	5.45	-8.11	4.99	-7.20	1.95	-0.25	0.00	0.50	1.80	0.30	11.62	0.00	0.00	0.00	0.00
01/18/96	5.45	-8.11	4.99	6.40	6.40	4.70	0.00	1.80	1.50	0.00	11.62	0.00	0.00	0.00	0.00
01/19/96	5.45	-8.11	4.99	10.30	4.70	3.30	52.30	59.20	61.20	2.00	11.62	0.00	0.00	0.00	0.00
01/20/96	5.45	-8.11	4.99	-6.70	-6.95	-6.95	2.30	0.00	0.00	36.10	11.62	0.00	0.00	0.00	0.00
01/21/96	5.45	-8.11	4.99	-6.95	-6.95	-7.80	0.00	0.00	0.10	0.00	11.62	0.00	0.00	0.00	0.00
01/22/96	5.45	-8.11	4.99	-3.60	-3.60	-3.05	0.00	0.00	0.10	0.00	11.62	0.00	0.00	0.00	0.00
01/23/96	5.45	-8.11	4.99	-3.60	-1.10	-2.50	0.00	0.00	0.10	0.00	11.62	0.00	0.00	0.00	0.00
01/24/96	5.45	-8.11	4.99	3.30	3.90	3.60	17.00	5.10	4.60	4.10	11.62	0.00	0.00	0.00	0.00
01/25/96	5.45	-8.11	4.99	-2.50	-2.20	-3.35	2.00	12.20	0.10	12.70	11.62	0.00	0.00	0.00	0.00
01/26/96	5.45	-8.11	4.99	-6.40	-5.85	-5.85	0.00	0.00	0.30	0.00	11.62	0.00	0.00	0.00	0.00
01/27/96	5.45	-8.11	4.99	2.70	3.60	4.40	23.90	16.50	15.70	8.10	11.62	0.00	0.00	0.00	0.00
01/28/96	5.45	-8.11	4.99	2.50	-2.30	-3.60	3.00	15.70	22.90	11.70	11.62	0.00	0.00	0.00	0.00
01/29/96	5.45	-8.11	4.99	-7.50	-7.50	-7.20	0.00	0.00	0.10	0.00	11.62	0.00	0.00	0.00	0.00
01/30/96	5.45	-8.11	4.99	-3.90	-1.40	-3.60	0.00	0.80	1.30	0.50	11.62	0.00	0.00	0.00	0.00
01/31/96	5.45	-8.11	4.99	-6.95	-7.25	-8.35	2.30	2.50	2.30	16.80	11.62	0.00	0.00	0.00	0.00

Appendix **Table A-3**

Sediment (g/L)

F-Test Two-Sample for Variances

	Observed	*GWLF*	*ANN*
Mean	1.73	1.60	2.28
Variance	17.10	13.25	15.01
Observations	25	25	25
df	24	24	24
F		1.29	1.14
P(F<=f) one-tail		0.27	0.38
F Critical one-tail		1.98	1.98

t-Test: Two-Sample Assuming Equal Variances

	Observed	*GWLF*	*ANN*
Mean	1.73	1.60	2.29
Variance	17.10	13.25	14.99
Observations	25	25	25
Pooled Variance		15.18	16.05
Hypothesized Mean Difference		0	0
df		48	48
t Stat		0.12	-0.49
P(T<=t) one-tail		0.45	0.31
t Critical one-tail		1.68	1.68
P(T<=t) two-tail		0.90	0.63
t Critical two-tail		2.01	2.01

Dissolved nitrogen (mg/L)

F-Test Two-Sample for Variances

	Observed	*GWLF*	*ANN*
Mean	27.78	29.68	30.13
Variance	1527.63	1245.30	1611.93
Observations	19	19	19
df	18	18	18
F		1.23	0.95
P(F<=f) one-tail		0.33	0.46
F Critical one-tail		2.22	0.45

t-Test: Two-Sample Assuming Equal Variances

	Observed	*GWLF*	*ANN*
Mean	27.78	29.68	30.13
Variance	1527.63	1245.30	1611.93
Observations	19	19	19
Pooled Variance		1386.46	1569.78
Hypothesized Mean Difference		0	0
df		36	36
t Stat		-0.16	-0.18
P(T<=t) one-tail		0.44	0.43
t Critical one-tail		1.69	1.69
P(T<=t) two-tail		0.88	0.86
t Critical two-tail		2.03	2.03

Total nitrogen (mg/L)

F-Test Two-Sample for Variances

	Observed	*GWLF*	*ANN*
Mean	44.79	27.96	46.12
Variance	4740.12	1853.21	4659.62
Observations	9	9	9
df	8	8	8
F		2.56	1.02
P(F<=f) one-tail		0.10	0.49
F Critical one-tail		3.44	3.44

t-Test: Two-Sample Assuming Equal Variances

	Observed	*GWLF*	*ANN*
Mean	44.79	27.96	46.12
Variance	4740.12	1853.21	4659.62
Observations	9	9	9
Pooled Variance		3296.66	4699.87
Hypothesized Mean Difference		0	0
df		16	16
t Stat		0.62	-0.04
P(T<=t) one-tail		0.27	0.48
t Critical one-tail		1.75	1.75
P(T<=t) two-tail		0.54	0.97
t Critical two-tail		2.12	2.12

Dissolved phosphorus (mg/L)

F-Test Two-Sample for Variances

	Observed	*GWLF*	*ANN*
Mean	2.39	2.55	2.77
Variance	12.20	6.46	10.32
Observations	25	25	25
df	24	24	24
F		1.89	1.18
P(F<=f) one-tail		0.06	0.34
F Critical one-tail		1.98	1.98

t-Test: Two-Sample Assuming Equal Variances

	Observed	*GWLF*	*ANN*
Mean	2.39	2.55	2.77
Variance	12.20	6.46	10.32
Observations	25	25	25
Pooled Variance		9.33	11.26
Hypothesized Mean Difference		0	0
df		48.00	48.00
t Stat		-0.19	-0.40
P(T<=t) one-tail		0.43	0.34
t Critical one-tail		1.68	1.68
P(T<=t) two-tail		0.85	0.69
t Critical two-tail		2.01	2.01

Total phosphorus (mg/L)

F-Test Two-Sample for Variances

	Observed	*GWLF*	*ANN*
Mean	5.22	4.66	4.47
Variance	104.14	51.42	80.87
Observations	25	25	25
df	24	24	24
F		2.03	1.29
P(F<=f) one-tail		0.04	0.27
F Critical one-tail		1.98	1.98

t-Test: Two-Sample Assuming Unequal (GWLF) & Equal (ANN) Variances

	Observed	*GWLF*	*ANN*
Mean	5.22	4.66	4.47
Variance	104.14	51.42	80.87
Observations	25	25	25
Pooled Variance			92.50
Hypothesized Mean Difference		0	0
df		43.00	48.00
t Stat		0.22	0.27
P(T<=t) one-tail		0.41	0.39
t Critical one-tail		1.68	1.68
P(T<=t) two-tail		0.82	0.79
t Critical two-tail		2.02	2.01

Appendix **Table A-4**

Sediment out (tons)

F-Test Two-Sample for Variances

	SWAT	*ANN*
Mean	1.43	0.94
Variance	111.41	96.36
Observations	1826.00	1826.00
df	1825.00	1825.00
F	1.16	
P(F<=f) one-tail	0.00	
F Critical one-tail	1.08	

t-Test: Two-Sample Assuming Unequal Variances

	SWAT	*ANN*
Mean	1.43	0.94
Variance	111.41	96.36
Observations	1826.00	1826.00
Hypothesized Mean Difference	0.00	
df	3631.00	
t Stat	1.47	
P(T<=t) one-tail	0.07	
t Critical one-tail	1.65	
P(T<=t) two-tail	0.14	
t Critical two-tail	1.96	

Sediment concentration (mg/kg)

F-Test Two-Sample for Variances

	SWAT	*ANN*
Mean	5.07	5.04
Variance	106.91	89.70
Observations	1826.00	1826.00
df	1825.00	1825.00
F	1.19	
P(F<=f) one-tail	0.00	
F Critical one-tail	1.08	

t-Test: Two-Sample Assuming Unequal Variances

	SWAT	*ANN*
Mean	5.07	5.04
Variance	106.91	89.70
Observations	1826.00	1826.00
Hypothesized Mean Difference	0.00	
df	3622.00	
t Stat	0.09	
P(T<=t) one-tail	0.47	
t Critical one-tail	1.65	
P(T<=t) two-tail	0.93	
t Critical two-tail	1.96	

Organic phosphorus (kg)

F-Test Two-Sample for Variances

	SWAT	*ANN*
Mean	4.58	4.73
Variance	759.27	715.45
Observations	1826	1826
df	1825	1825
F	1.06	
P(F<=f) one-tail	0.10	
F Critical one-tail	1.08	

t-Test: Two-Sample Assuming Equal Variances

	SWAT	*ANN*
Mean	4.58	4.73
Variance	759.27	715.45
Observations	1826	1826
Pooled Variance	737.36	
Hypothesized Mean Difference	0	
df	3650	
t Stat	-0.16	
P(T<=t) one-tail	0.44	
t Critical one-tail	1.65	
P(T<=t) two-tail	0.87	
t Critical two-tail	1.96	

Mineral phosphorus (kg)

F-Test Two-Sample for Variances

	SWAT	*ANN*
Mean	1.74	1.40
Variance	169.66	128.42
Observations	1826	1826
df	1825	1825
F	1.32	
P(F<=f) one-tail	0	
F Critical one-tail	1.08	

t-Test: Two-Sample Assuming Unequal Variances

	SWAT	*ANN*
Mean	1.74	1.40
Variance	169.66	128.42
Observations	1826	1826
Hypothesized Mean Difference	0	
df	3581	
t Stat	0.83	
P(T<=t) one-tail	0.20	
t Critical one-tail	1.65	
P(T<=t) two-tail	0.41	
t Critical two-tail	1.96	

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