GIS-Based Artificial Neural Network and Processed-Based HSPF Model for Watershed Runoff in Sinclair and Dyes Inlet, WA[1]

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ABSTRACT

Sinclair Inlet and Dyes Inlet are two inter-connected sub-estuaries of the Puget Sound estuarine system, located in the region of (-122^0 43’, 47^0 39’) and (-122^0 37’, 47^0 32’), north of Bremerton, WA. Pacific Ocean tides enter through the mouth of the Puget Sound and propagate to both Inlets from Brownsville, to the north and Clam Bay, to the South. The Inlets receive freshwater inflows and land-based contaminant loadings from industrial and stormwater discharges, sewage treatment plants and runoff from the surrounding watersheds. As part of a Total Maximum Daily Load (TMDL) modeling study, which is collaboratively supported by an agreement among the Puget Sound Naval Shipyard (PSNS), the Environmental Protection Agency (EPA), and the Washington State Department of Ecology, the watershed model HSPF (Hydrologic Simulation Program-FORTRAN), is currently being used to quantify runoff from eleven basins draining into the two Inlets.

While the HSPF models provide hydrographs and pollutographs, the model development and calibration for the eleven watersheds is nontrivial, let alone the large amount of field data required for model calibration. As such, a simple, and computationally fast model using an Artificial Neural Network (ANN) was developed to predict relationships between precipitation and freshwater inflows to the Inlets. The ANN uses a feed-forward, back-propagating neural network and consists of three layers: an input layer, hidden layer, and output layer. The ANN model uses a finite number of input nodes representing precipitation prior to the time of prediction. The ANN model is trained using the measured creekflow data and the corresponding precipitation data. With a back-propagation algorithm, the training optimizes the two weighting function matrices between the input and hidden layers as well as the hidden and output layers. With adequate training (learning), the ANN model is then capable of predicting creekflow resulting from precipitation. ANN-predicted flows for 3 creeks are compared with those predicted by the HSPF model. Results of both the ANN model and the process-based HSPF model bear similar accuracy levels. Considering the cost/product factor, this study shows that the ANN modeling approach provides a cost-effective alternative tool for predicting rainfall-runoff relationships.

KEYWORDS
Watershed, modeling, HSPF, Artificial Neural Network, ANN, TMDL

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[1] Paper presented at WATERSHED 2002, Specialty Conference, Wyndham Bonaventure, Ft. Lauderdale, FL, February 24-27, 2002.

INTRODUCTION

The Clean Water Act (CWA), enacted in 1972 and re-authorized in 1987, sets as a national goal that all waters be safe for fishing and swimming. Under the Section 303(d) of the CWA, EPA and states are obligated to implement Total Maximum Daily Load program, in which the total maximum daily load a waterbody can receive and still meet water quality standards needs to be developed. Under this TMDL program, fate and transport of contaminants from both point and non-point sources will be assessed, quantified, and evaluated for managing and controlling loadings.

Dyes Inlet and Sinclair Inlet, located in Bremerton, Washington, are two semi-enclosed waterbodies (Figure 1), connected through a narrow channel. Total surface area of the Dyes Inlet is about three times that of the Sinclair Inlet. Further east, the waterbody connects to Puget Sound through Port Orchard Passage to the north and Rich Passage to the southeast. Compared to Puget Sound, which is a Fjord type of estuary, Dyes Inlet is relatively shallow; depths in the Inlet vary from over 10 meters near the mouth connecting to Sinclair Inlet to 1-4 meters in the shallow shore regions. Depths along the two passages increase toward Puget Sound with maximum depths reaching ~25 meters in the two passages.

Both Inlets receive treated sewage discharges from POTWs that serve the cities of Silverdale, Bremerton, and Port Orchard. Treated and untreated runoffs enter the Inlets from a number of storm drains distributed around the shoreline. Contaminants from PSNS operations enter the Inlet by ways of runoffs, seepage and fugitive losses. The impacts on water quality, including bottom sediments and sorbed contaminants, in the Inlet from these external contaminant sources are not well known.

Flows in the Inlets are governed primarily by tides that propagate from the Pacific Ocean into Puget Sound and then into the Inlet through the two narrow passages, Port Orchard in the north and Rich Passage in the southeast. Tides in the Puget Sound regions are semi-diurnal and diurnal mixed modes with two high and two low tides every diurnal cycle (24.8 hours). Once reaching the entrances to the two passages and into the Inlet, the tides are further modulated in a nonlinear fashion by a number of forcing mechanisms, including freshwater inflows, wind, water depth variations and waterbody geometry. Tidal flows in the Inlet are modulated both spatially and temporally, with maximum tidal ranges (from low tide to high tide) reaching 5.5 meters during spring tides.

Freshwater enters into Dyes Inlet from four creeks: Barker Creek, Clear Creek and Strawberry Creek from the north and Chico Creek from the west (Figure 1). There are several (about 20) smaller creeks discharging freshwater to the Inlet. The Silverdale POTW discharges treated sewage effluent into the northern near-shore regions. Storm drains distributed around the shores of the Inlet also discharge untreated storm water into the Inlet during rainy seasons.

Rainfalls concentrate during the months of November-March with an average precipitation of 50 in/yr. The average air temperature ranges between 70-80 degrees

Fahrenheit during the day and 40-50 degrees Fahrenheit during the night. The Inlets are surrounded by the Olympic Mountains, the Cascade Range and the mountains of Vancouver Island. Wind in the Inlet region is low, with an average speed less than 5 m/s. Gust winds seldom exceed 10 m/s. Long-term data show that winds are predominantly from the southwest and northeast quadrants. during fall and winter. The spring and summer are characterized by northwesterly wind .

As part of a TMDL study, runoffs from three Dyes Inlet watersheds, the Barker Creek, Clear Creek and Strawberry Creek, have been simulated by two models: the Hydrological Simulation Program in Fortran (HSPF) model and an Artificial Neural Network (ANN) model. HSPF, a lumped parametric model, simulates daily creekflows that result from the corresponding rainfall over the surrounding watersheds. GIS data were used for HSPF model setup and model calibrations were conducted by adjusting model parameters until a best fit between model results and measured data was obtained. An alternative model using the Artificial Neural Network (ANN) was also developed for two objectives: 1) to provide independent solutions for model comparison with HSPF and 2) to provide fast and efficient engineering solutions.

ANN models are particularly suitable for applications involving complicated nonlinear processes, such as those for the watershed runoffs. The ANN model is based on a Multi-Layer Feedforward, Back-propagating scheme. The model was setup for one-day-ahead creekflow prediction and it was assumed that current creekflow can be predicted from known information from previous time steps about rainfall data and creakflow. Creekflows predicted by both the ANN model and HSPF were compared and discussed. Because ANN models can produce predictions by directly "learning" recursively from the data, they can result in significant savings of time in model setup, cpu time, and data required for model calibration.

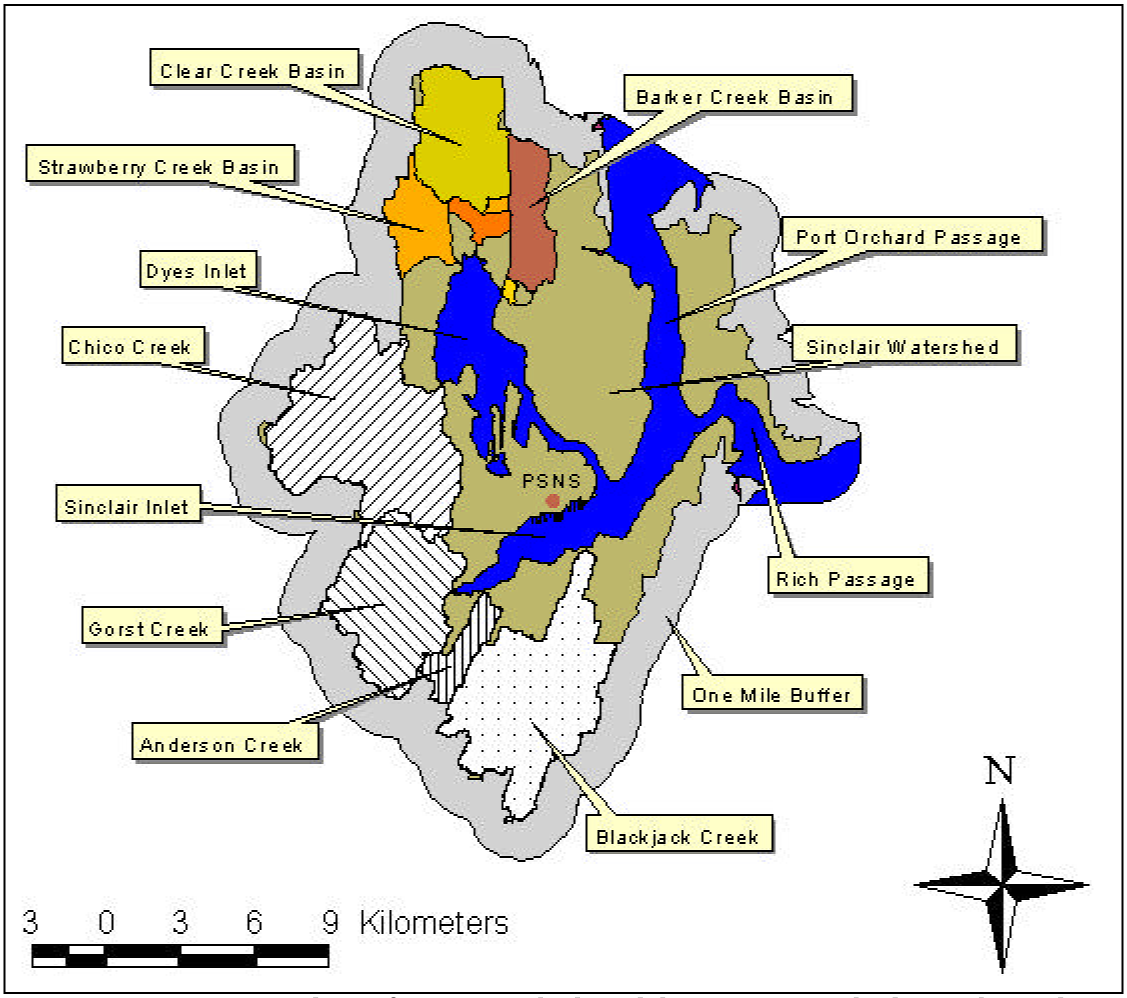

Figure 1. PSNS and significant watersheds and the marine waterbodies in the study

Precipitation and Creekflow Data

A climate summary of mean monthly temperatures for Bremerton, Washington, obtained from the Western Regional Climate Center, indicated that it would not be necessary to model snow accumulation and melt for the Barker Creek, Clear Creek, and Strawberry Creek watersheds. As a result, the meteorologic time series data requirements for an HSPF model included precipitation and potential evapotranspiration. The Silverdale-Wixon rain gage provides precipitation data for the Barker Creek, Clear Creek, and Strawberry Creek watersheds.

The Silverdale-Wixon rain gage has collected daily rainfall data since January 1990. Since October 2000, this gage, as part of a new watershed monitoring program, has been collecting rainfall data with a temporal resolution of fifteen minutes. The Silverdale-Wixon rain gage has an almost complete record of daily totals from January 1990 – September 2000. Missing daily rainfall data at the Silverdale-Wixon rain gage were filled using daily totals from the SeaTac gage, and subsequently disaggregated to an hourly time step using the hourly data from the SeaTac gage.

Flow data for the Barker Creek, Clear Creek, and Strawberry Creek were collected to calibrate and validate the HSPF models for these three watersheds. Daily creekflow data were provided for all creeks. The locations of the creekflow gages within each of these three watersheds is shown in Figure 2. Precipitation creekflow data during the periods (Table 1) were used for both HSPF and the ANN model.

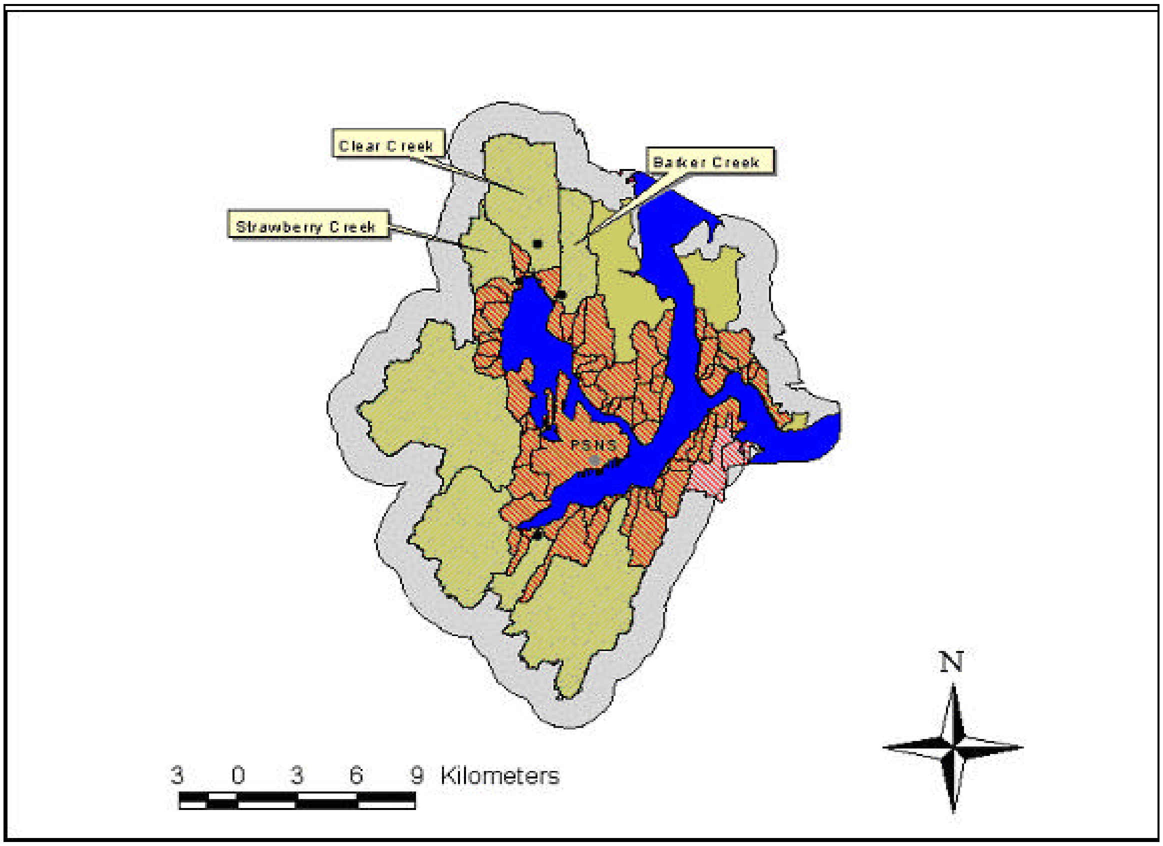

Figure 2. Creekflow gage locations for Barker Creek, Clear Creek, and Strawberry Creek.

MODELING METHODOLOGY

The HSPF model and two ANN models were set up for predicting flows from precipitation for 3 creeks, Barker Creek, Clear Creek and Strawberry Creek. The modeling setup, and approaches are described next.

HSPF-Model

HSPF hydrologic models were developed for three watersheds to estimate diffuse contaminant loading into the marine water bodies of interest, including the Sinclair Inlet, Dyes Inlet, Port Orchard Passage, and Rich Passage. As part of the PSNS watershed modeling project, the Marine Environmental Quality Branch of the U.S. Space and Naval Warfare Systems Center, San Diego (SSC SD) was tasked to develop HSPF models for the 3 afore-mentioned watersheds, which drain into the northern end of Dyes Inlet (Figure 2). The HSPF hydrologic model development and calibration conducted by SSC SD for Barker Creek, Clear Creek, and Strawberry Creek are described in the following.

Data requirements for an HSPF model application can be grouped into three broad categories (Munson, 1998): 1) physical watershed-specific data, 2) meteorologic data, and 3) calibration data. Physical watershed-specific data relevant to HSPF model development and calibration (e.g., elevation, channel geometry, soils, vegetation, and land use and land cover, LULC) were obtained from GIS databases and field observations. The ArcView and Geographic Resources Analysis Support System (GRASS) (USACERL, 1993) GIS software packages were utilized for mapping and evaluation at multiple scales. Meteorologic data were collected from weather stations maintained by the National Weather Service (NWS), and other organizations, within and surrounding the three watersheds. Flow data for the Barker Creek, Clear Creek, and Strawberry Creek were collected to calibrate and validate the HSPF models developed for these three watersheds. The ANNIE (Flynn et al., 1995) and WDMUtil (USEPA, 1999a) utility software packages were used to input and subsequently manage the meteorologic and calibration time series data in a Watershed Data Management (WDM) file.

Physical watershed-specific data, in a GIS format, were obtained from United States Geologic Survey (USGS) 10-meter Digital Elevation Models (DEMs) , LULC (and percent impervious data, for 1999, that were derived from Landsat 7 Thematic Mapper satellite imagery using standard image processing techniques, the Soil Survey Geographic (SSURGO) database for the Kitsap County Area, Washington, and a map of the project study area. Channel cross section data for Barker Creek, Clear Creek, and Strawberry Creek were approximated based on field observations.

For HSPF, potential evapotranspiration is typically prescribed by multiplying pan evaporation data by a pan coefficient. Actual evapotranspiration is subsequently simulated based on the input potential evapotranspiration data, model algorithms, and evapotranspiration parameters. Pan evaporation data were obtained from the following sources: 1) the WDM data file for the state of Washington that is packaged with the BASINS system from the EPA (USEPA, 1999b) , and
2) pan evaporation data for Puyallup, Washington, which was provided by AQUA TERRA Consultants, Everett, Washington.

The pan coefficient for the hourly pan evaporation data within the WDM data file for the state of Washington that is packaged with the BASINS system from the EPA was set to the recommended value of 0.82. AQUA TERRA Consultants, Everett, and the state of Washington recommended using a pan coefficient of 0.80 for the daily pan evaporation data for Puyallup, Washington. The daily pan evaporation data for Puyallup, Washington were disaggregated using the WDMUtil utility software package.

The principal software tool that was utilized to develop an initial HSPF model for Barker Creek, Clear Creek, and Strawberry Creek was the Watershed Modeling System (WMS) (Brigham Young University -, 1999). The WMS DEM module was initially used to delineate each watershed, using the DEM data that was obtained for the project study area. The WMS TIN module was subsequently used to triangulate the delineated watershed, and map land surface response data to the watershed triangulation. The WMS MAP module was used to display various ArcView data layers that were imported to support model development (e.g., coastline, stream gage locations, hydrography). The WMS HSPF module was used to develop the Users Control Input (UCI) file, the main HSPF model input file, for each watershed.

WMSTOPAZ was used to delineate each watershed using the DEM data that was obtained for the project study area. WMSTOPAZ is a limited version of the TOPAZ (TOpographic PArameteriZation) model (Garbrecht and Martz, 1999). TOPAZ automatically extracts topographic information, in raster and tabular form (e.g., watershed boundary, drainage direction at each cell, upstream drainage area, slope of the outflowing drainage direction, the channel network within the watershed boundary, channel link information) from a raster DEM. The approximate delineated basin area for Barker Creek, Clear Creek, and Strawberry Creek are 10.4 km^2, 20.8 km^2, and 7.6 km^2, respectively.

The purpose of land segmentation within a watershed is to construct a conceptual model with the minimum number of land segments needed to simulate the hydrologic processes within the watershed (Dinicola, 1990). Infiltration is a significant process in the hydrologic cycle, notably influencing surface runoff volume. The principal infiltration parameter in HSPF, INFILT, is primarily a function of soil characteristics, and value ranges have been related to SCS hydrologic soil groups (USEPA, 2000). To account for the spatial variability within a watershed and support parameter assignment, Land Use and Land Cover (LULC) data are typically used to describe distinct hydrologically homogeneous units within a watershed, with typical applications utilizing approximately five to six distinct land use classes (Northwest Hydraulic Consultants Inc., 1993a; 1993b; Munson, 1998; HydroGeoLogic, Inc. and AQUA TERRA Consultants, 1999; Lohani et al., 2000; Bergman and Donnangelo, 2000). USEPA (2000) provides guidance for the selection of several HSPF model parameter values based on land surface conditions. The LULC data was reclassified to generate a more manageable number of distinct land use classes. The reclassification of the original classification unit numeric codes involved neglecting the second of the two integers from the original numeric code. Pervious land segments within each of the three watersheds were defined based on a cross product of the re-classed LULC data and hydrologic soils group data.

Consistent with the understanding that, for HSPF, impervious area is directly connected impervious surface, impervious land segments were identified within each of the three watersheds as described below. First, a continuous distance grid theme and/or buffer, related to the hydrography data, was generated for each watershed. Second, using the continuous distance grid theme and/or buffer of the hydrography data within the watershed, highly impervious surfaces within 400 meters of a water body were identified.

Raster GIS analysis allowed for the determination of a single "land surface response" grid for each watershed, which included the information from the definition of pervious land segments, and also identified impervious surfaces, which were arbitrarily assigned an additional numeric code

For each watershed, the "land surface response" grid was converted to a shapefile and subsequently imported into WMS. Once within WMS, the land surface response map was mapped to the triangulation of the watershed; whereupon, a Users Control Input (UCI) file was automatically generated. At this point, using the HSPF interface within WMS, various modules and compartments could be activated (see section two), and parameters for the respective compartments initially estimated. The PERLND/ PWATER, IMPLND/IWATER, and RCHRES/HYDR application modules and associated compartments were activated to model Barker Creek, Clear Creek, and Strawberry Creek.

Initial parameter estimates were based on guidance provided by USEPA (2000), Munson (1998), USACE and USEPA (2000), GIS-based analysis, and data stored for a particular watershed in WMS. For example, the lower zone nominal soil moisture storage, LZSN, parameter values were based on the mean annual precipitation for the given watershed and guidance provided by USEPA (2000) and Donigian and Davis (1978).

Stage-discharge relationships for each reach within each watershed were specified based on application of Manning's equation and information obtained from field visits the three creeks. The channel geometry data that was estimated from these field visits is quite coarse. While Munson (1998) noted that water quantity simulations with HSPF are not overly sensitive to the specified channel geometry, it was also noted that many water quality processes depend on river depth.

HSPF model parameters are not available from field data, and must be determined through model calibration. HSPF hydrologic model calibration was performed manually by comparing simulated and observed flow volumes for various runoff categories: total runoff, fifty percent lowest flows, ten percent highest flows, storm flows, and seasonal runoff. Other criteria that were also used to support the manual calibration for each HSPF model included: 1) visually inspecting the match of simulated and observed flows, and 2) validation of the calibration results.

The expert system calibration tool HSPEXP (Lumb et al., 1994a) was the principal tool that was used to support the manual hydrologic model calibration for each HSPF model. HSPEXP produces a standard set of mass balance, statistical, and hydrograph comparisons that greatly facilitate manual HSPF hydrologic model calibration. The HSPEXP system also provides advice on parameter adjustments related to various user specified error criteria for deciding whether each phase of calibration is satisfactory

Table 1. Model simulation periods for Barker Creek, Clear Creek, and Strawberry Creek

Watershed	Simulation Periods
Barker Creek	**11/01/1991 - 11/30/1994**
Clear Creek	**12/01/1994 - 12/31/1996**
Strawberry Creek	**10/01/1991 - 09/30/1993**

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It has been noticed that, at times, the HSPEXP calibration tool provides advice that would adjust a parameter out of its acceptable or known range. In these cases, the advice provided by the HSPEXP calibration tool was not strictly followed. To date, it has been observed that while calibrating the HSPF hydrologic models for Barker Creek, Clear Creek, and Strawberry Creek, at times, there have been competing demands to satisfy the specified volume error criteria across the various calibration phases. For example, the calibration for Strawberry Creek has been a balance between satisfying the error criteria for the 50% lowest flows and the seasonal flow. Barker Creek possesses a significant baseflow component, and the Barker Creek HSPF model calibration has depended on inspecting the visual match of simulated and observed flows to ensure that the observed baseflow is adequately simulated. .

ANN-Model

Over the past decades, Artificial Neural Network has been rapidly developed in cognitive science that studies and simulates functioning of human brains and nervous system. Only until recently, ANNs have seldom been employed in water and environmental science and engineering, in spite of their significant successes over the past decades in many other disciplines, such as medical science, mechanical, electrical and control engineering (Bartlett and Anthony, 1999). Although ANN models do not explicitly describe the processes, that govern the systems, in contrast to most of the process-based models, such as HSPF, the ANN models can predict output from input in a non-linear fashion by learning from data. Specifically, ANN models are capable of determining non-linear relationships between the input and output of a physical system by a network of interconnecting nodes that adjust their connecting weights (parameters) based on training samples, and discover the rules governing the association between the inputs and outputs.

The ANN model used for this study is based on the Multi-Layer, Feedforward, Back-propagating scheme (Figure 3). There are three layers, the input layer, the hidden layer and the output layer.

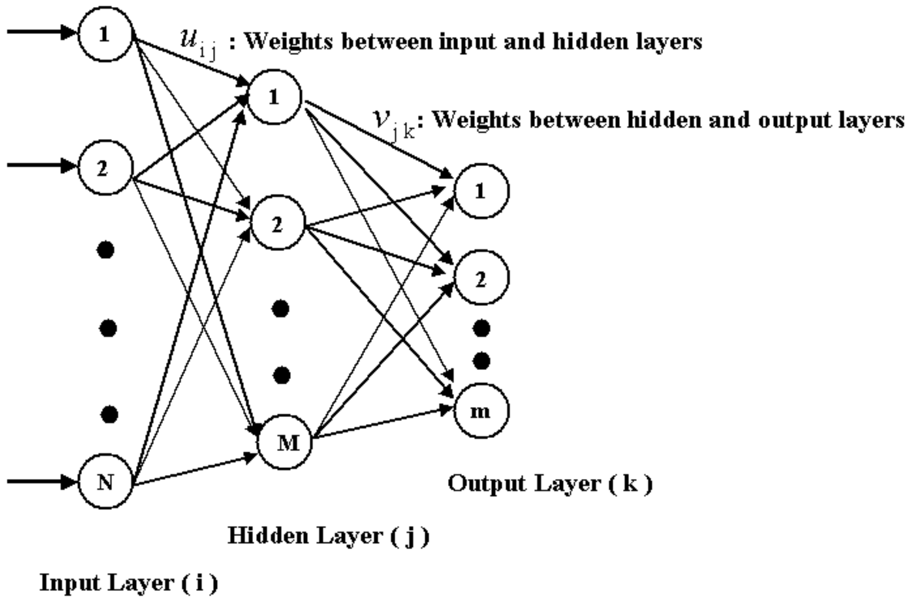


Figure 3. Schematic ANN Architecture and Flow Chart

In the ANN architecture, illustrated in Figure 3, each input is multiplied by a weight, u, and the weighted value is then fed into each of the hidden nodes. Output from each of the hidden nodes is regulated by a threshold, the hyperbolic tangent function. Each output from the hidden layer is then sent to each of the output node after multiplied by another weight, v. Output is then obtained by the sum of the weighted output from the hidden layer. These processes can be described by the following equation:

$$Y(x_k, w) = f\left(\sum_{j=0}^{M} v_{jk} \cdot g\left(\sum_{i=0}^{n} u_{ij} x_i\right)\right) \qquad (1)$$

in which the weights, w, represent the weights, u and v in the equation. The activation function, g, can be either sigmoid or hyderbolic tangent function (Gupta et al., 2000).

Feed-forward back-propagating ANN learns to best fit network output to measured data by adjusting the weights. This learning process is iterative until the sum of the Mean-Square-Error (MSE) reaches a minimum. To carry out this, we first express the MSE as

$$F(w) = \frac{1}{N}\sum_{k=1}^{N} \left| y_k - Y(x_k, w) \right|^2 \qquad (2)$$

where (x_k, y_k) is the dataset measured and $Y(x_k, w)$ is the ANN output for the input of x_k and the weights, w. The leaning process re-adjusts the weights as follows:

$$w^{new} = w^{old} - \alpha \nabla_w F(w)\Big|_{w=w^{old}} \qquad (3)$$

where α, a small parameter, is called the "learning rate".

The input layer reads in rainfall data and creekflow data, both assumed to be known for several days prior (< t) to the present day (t). The hidden layer serves as an activation gate that processes the input data in a nonlinear fashion. The output layer predicts creekflow data at the present day (t) (Gupta et al., 2000)

$$F_{pre}(t) = f\left(P_{obs}(t-n),..., P_{obs}(t), F_{obs}(t-m),..., F_{obs}(t-1),\right) \qquad (4)$$

where $F_{pre}(t)$ is the predicted creekflow, and P_{obs} and F_{obs} represent observed precipitation and creekflows respectively.

For this study, two sets of model parameters were selected: ANN1: n=3,m=2 and ANN2: n=4, m=0. For the ANN1 case, 4 precipitation datasets, including data from previous 3 days, t-3, t-2, t-1 and the present day (t), along with 2 creekflow datasets observed from the previous 2 days, t-2, and t-1, were used as model input. For the second case, ANN2, only 5 precipitation datasets, including 4 previous days and the present day, and no creekflows were used as model input. For both cases, the ANN network predicts creekflow for the present day, F(t).

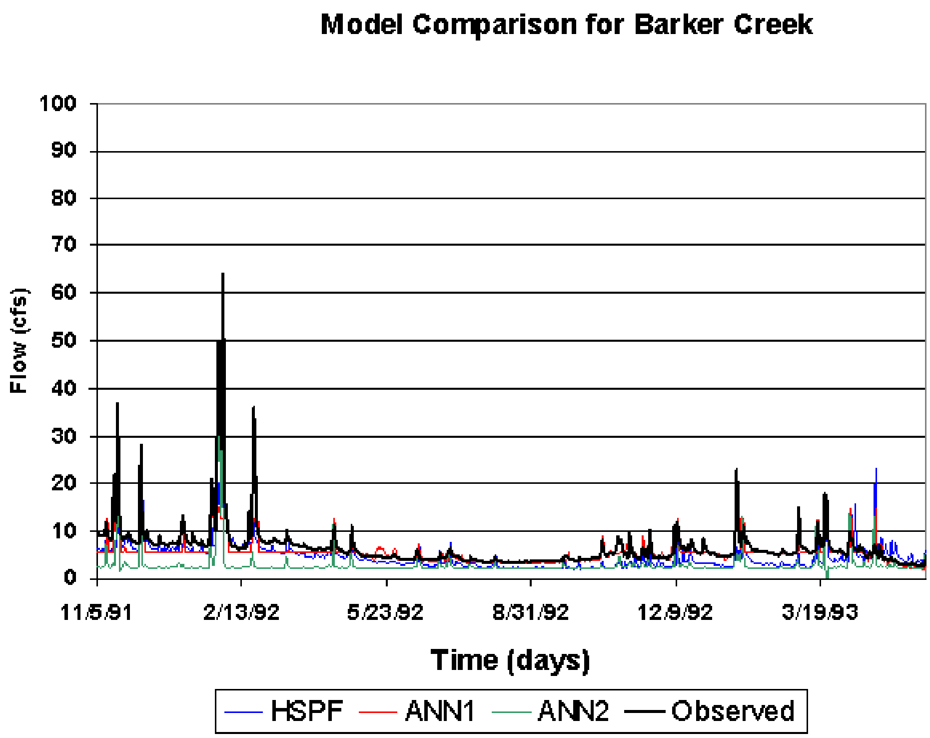
Daily precipitation and creekflows were used for training of the ANN. The training (Eqs. (2) and (3)) continues until the MSE is below 1.0E-10. A total of 760 daily datasets were used for Clear Creek, 1122 and 727 daily datasets for Barker Creek and Strawberry Creek, respectively.

RESULTS AND DISCUSSIONS

Figures 4-6 show the comparison of predicted for Barker Creek, Clear Creek, and Strawberry Creek, respectively. Table 2 shows correlation coefficient (r), and root-mean-square of creekflows between measurements and the models. In general, HSPF, ANN1 and ANN2 all fluctuate with measured creekflow throughout the simulation periods. HSPF overshoots at high flows, and predicts with the best accuracy. HSPF over-predicts Barker Creek flows during the spring of 1994.

Table 2. Comparisons of models, HSPF, ANN1 and ANN2

Creek	Correlation Coefficient (r)			Root-Mean –Square (CFS)		
	HSPF	ANN1	ANN2	HSPF	ANN1	ANN2
Barker	0.43	0.73	0.49	5.4	3.2	4.4
Clear	0.72	0.81	0.69	15.7	11.4	16.1
Strawberry	0.73	0.91	0.57	1.7	1.1	1.8



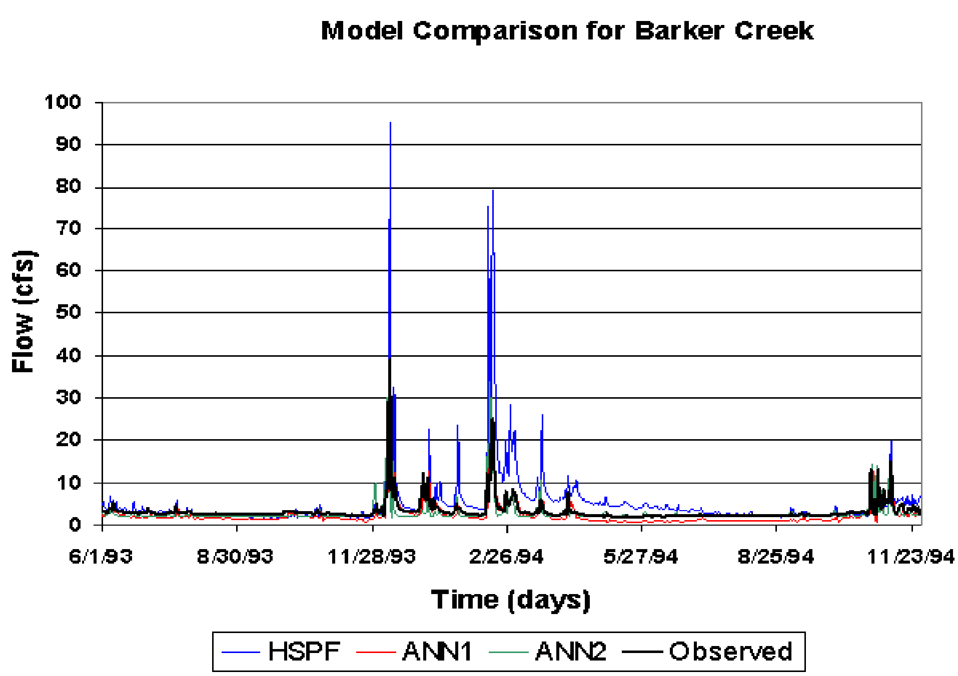
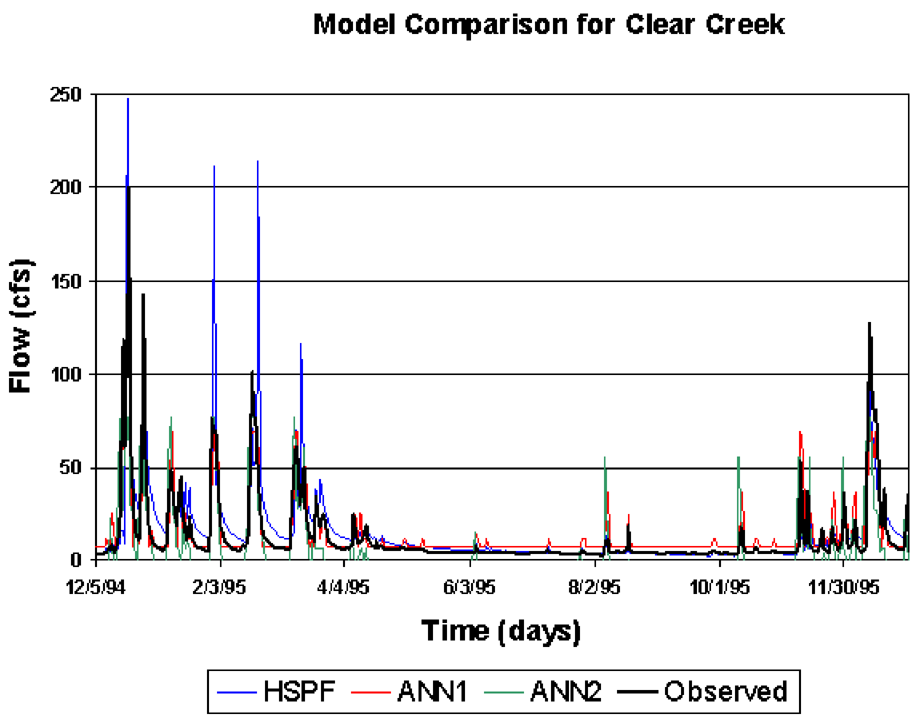


Figure 4. Simulated and observed flows for Barker Creek



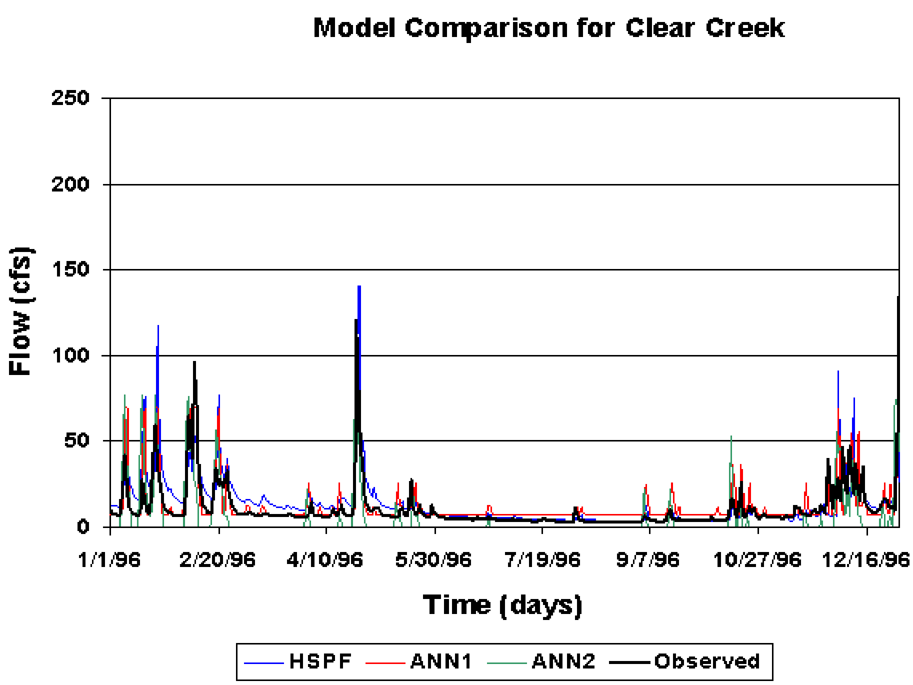
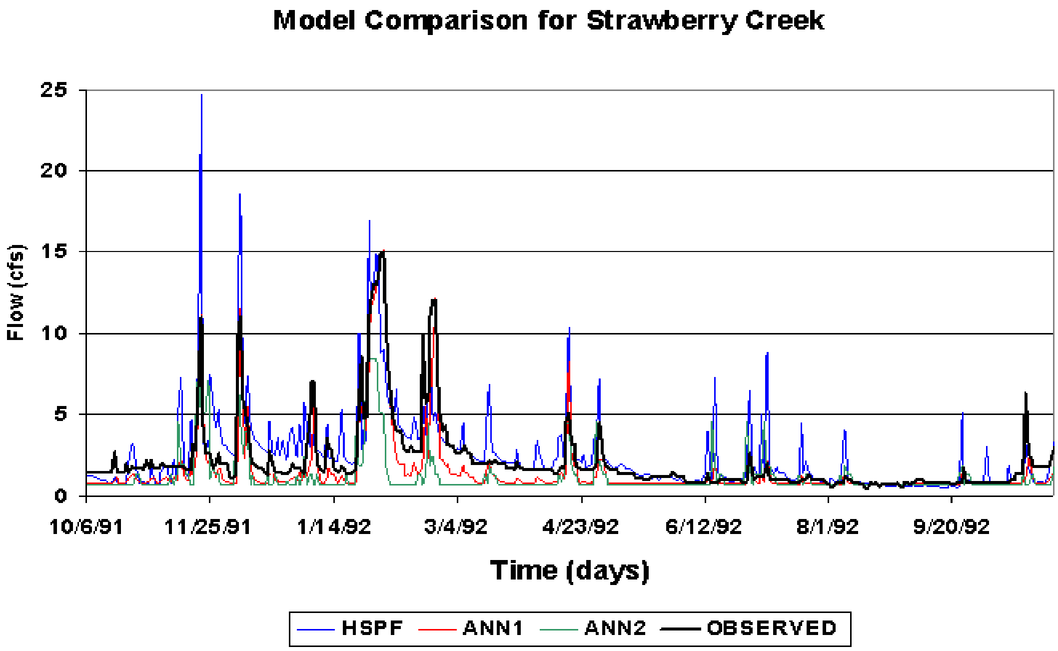


Figure 5. Simulated and observed flows for Clear Creek



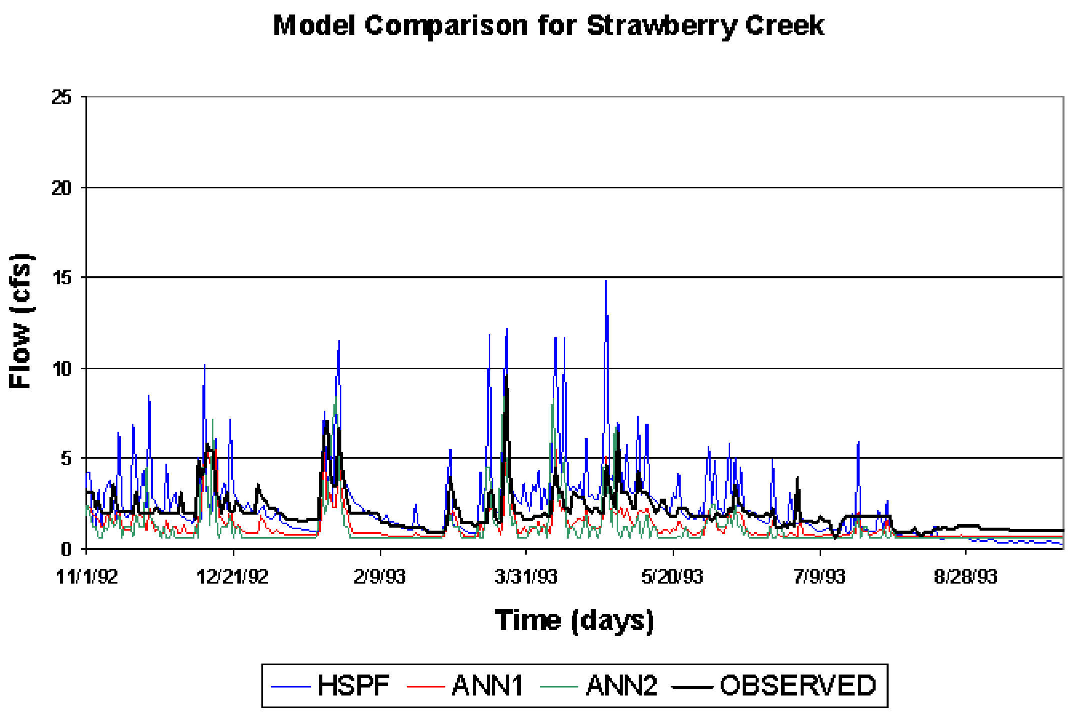


Figure 6. Simulated and observed flows for Strawberry Creek

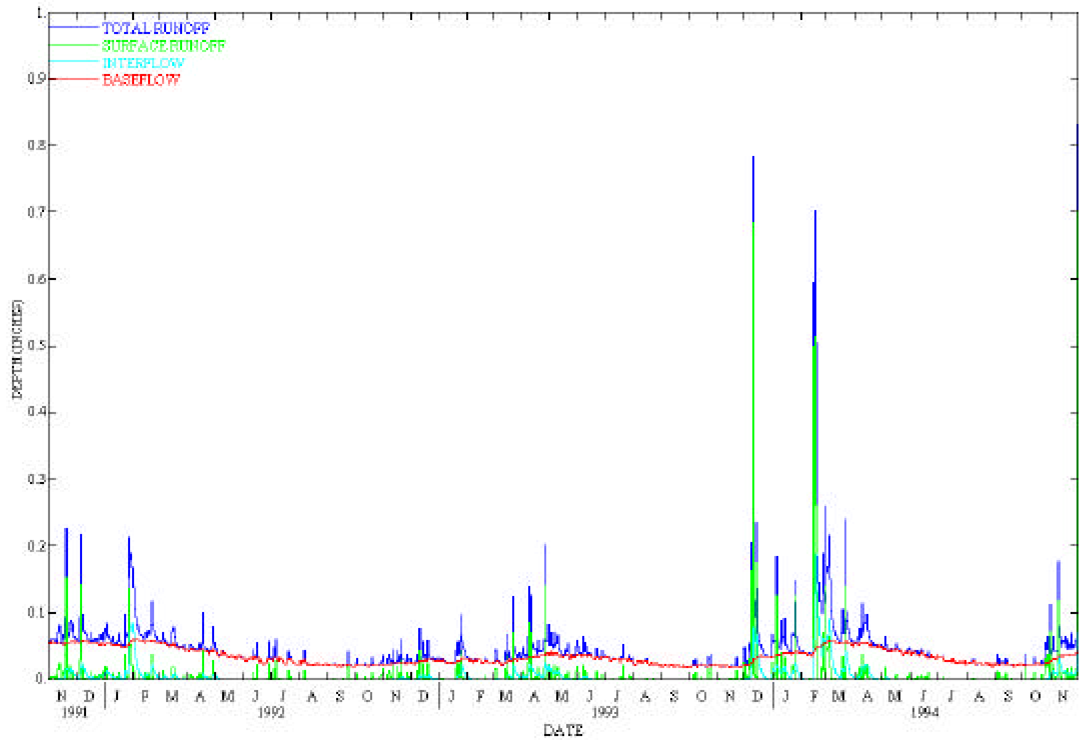


Figure 7. Partition of simulated flow across surface runoff, interflow, and baseflow for the Barker Creek HSPF model

Of the three models, the ANN1 model has the best flow predictions for all the three creeks during the simulation periods. In general, ANN1 predictions mimic closely to the observed values. Baseflow predictions are equally well between ANN1 and HSPF. ANN1. Of the three models, ANN2 produces the largest model-data discrepancies. Furthermore, ANN2 seems to be completely incapable of predicting baseflows. Although both ANN1 and ANN2 are based on the similar neural network principles, their prediction capabilities are quite different. The primary reason is that ANN1 uses both the precipitation data (the previous 3 daysplus today) and measured creekflow data (previous 2 days plus today), while ANN2 only use the precipitation data (the previous 4 days plus today). Measured creekflows data have two functions: 1) provide more correlated information to the predicted creekflow at the present day, and 2) creekflow history (2 previous days) tends to improve correlation with baseflows, which ANN2 lacks and totally failed.

In spite of the fact that the ANN and HSPF model predictions are at about same accuracy, they are two fundamentally distinctive models. The ANN model is essentially a nonlinear fitting model between the input (precipitation and known creekflows) and output (present creekflow), whereas the HSPF model is process-based model. Each of these processes can be evaluated separately, or combined with the rest of the processes for better understanding key mechanisms that govern the runoffs. Figure 7 illustrates that one can obtain the partition of simulated flow across surface runoff, interflow, and baseflow for a given HSPF model. Employment of either or both models should be based on several factors, including project goals, resources, data availability, and management requirement.

ACKNOWLEDGEMENTS

The authors would like to thank Mr. Gerald Sherrell of PSNS for support during the study. Dr. Billy Johnson of ERDC, formerly with the Concurrent Technology Corporation, provided some of the data.

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