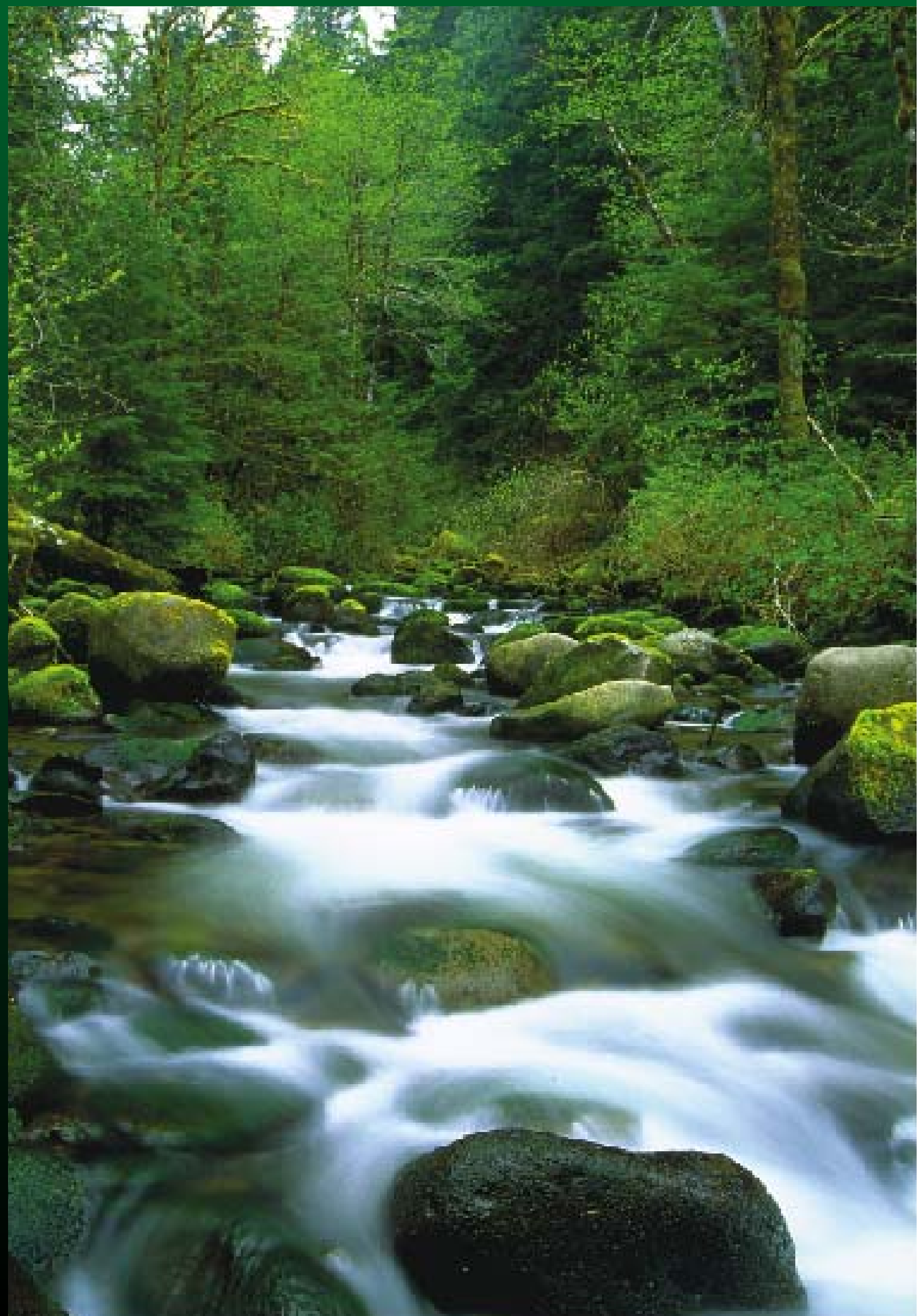
Estimating Water Temperatures in Small Streams in Western Oregon Using Neural Network Models



Prepared in cooperation with the

OREGON WATERSHED ENHANCEMENT BOARD

U.S. GEOLOGICAL SURVEY

Water-Resources Investigations Report 02-4218

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By John C. Risley, U.S. Geological Survey, Edwin A. Roehl, Jr., Advanced Data Mining, LLC, *and* Paul A. Conrads, U.S. Geological Survey

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U.S. DEPARTMENT OF THE INTERIOR

GALE A. NORTON, *Secretary*

U.S. GEOLOGICAL SURVEY

Charles G. Groat, *Director*

For additional information write to:

District Chief
U.S. Geological Survey
10615 S.E. Cherry Blossom Drive
Portland, Oregon 97216-3159
Email: info-or@usgs.gov
Internet: http://oregon.usgs.gov

Copies of this report can be purchased from:

U.S. Geological Survey
Information Services
Building 810
Box 25286, Federal Center
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CONVERSION FACTORS AND VERTICAL DATUM

Conversion Factors

Multiply	By	To obtain
cubic meter per second (m^3/s)	35.31	cubic foot per second (ft^3/s)
millimeter (mm)	0.03937	inch
meter (m)	3.281	foot (ft)
kilometer (km)	0.5400	mile (mi)
square kilometer (km^2)	0.3861	square mile (mi^2)
cubic meter (m^3)	1.308	cubic yard (yd^3)

Temperature in degrees Celsius (°C) may be converted to degrees Fahrenheit (°F) as follows:

$$°F=1.8\ °C+32$$

Vertical Datum

In this report, vertical coordinates are referenced to the North American Vertical Datum of 1988 (NAVD 88).

Estimating Water Temperatures in Small Streams in Western Oregon Using Neural Network Models

By John C. Risley[1], Edwin A. Roehl, Jr.[2], and Paul A. Conrads[3]

ABSTRACT

Artificial neural network models were developed to estimate water temperatures in small streams using data collected at 148 sites throughout western Oregon from June to September 1999. The sites were located on 1st-, 2nd-, or 3rd-order streams having undisturbed or minimally disturbed conditions. Data collected at each site for model development included continuous hourly water temperature and description of riparian habitat. Additional data pertaining to the landscape characteristics of the basins upstream of the sites were assembled using geographic information system (GIS) techniques. Hourly meteorological time series data collected at 25 locations within the study region also were assembled.

Clustering analysis was used to partition 142 sites into 3 groups. Separate models were developed for each group. The riparian habitat, basin characteristic, and meteorological time series data were independent variables and water temperature time series were dependent variables to the models, respectively. Approximately one-third of the data vectors were used for model training, and the remaining two-thirds were used for model testing. Critical input variables included riparian shade, site elevation, and percentage of forested area of the basin. Coefficient of determination and root mean square error for the models ranged from 0.88 to 0.99 and 0.05 to 0.59 ^{o}C, respectively. The models also were tested and validated using temperature time series, habitat, and basin landscape data from 6 sites that were separate from the 142 sites that were used to develop the models.

The models are capable of estimating water temperatures at locations along 1st-, 2nd-, and 3rd-order streams in western Oregon. The model user must assemble riparian habitat and basin landscape characteristics data for a site of interest. These data, in addition to meteorological data, are model inputs. Output from the models include simulated hourly water temperatures for the June to September period. Adjustments can be made to the shade input data to simulate the effects of minimum or maximum shade on water temperatures.

INTRODUCTION

Background

Stream water temperature has become a major concern in Oregon. Temperature affects dissolved oxygen concentrations, biochemical oxygen demand rates, algae production, and contaminant toxicity. Although warm water can occur naturally in Oregon, it is commonly induced by anthropogenic activities such as effluent point sources, removal of riparian shade, stream channel alterations, water diversions, and urbanization. Many States have adopted water temperature standards as a part of their compliance with the Federal Clean Water Act. Elevated water temperature is the single most common water-quality violation for streams in Oregon. Hundreds of stream reaches exceed the maximum State standard, which is 17.8-degrees Celsius (^{o}C) based on a 7-day moving

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[1]U.S. Geological Survey, Portland, Oregon.
[2]Advanced Data Mining, LLC, Greenville, South Carolina.
[3]U.S. Geological Survey, Columbia, South Carolina.

average maximum daily temperature for most streams with cold-water fisheries during summer low-flow conditions. Such reaches are designated “water-quality-limited” by the State. Once a waterway is designated water-quality-limited, the State must develop a Total Maximum Daily Load (TMDL) plan for that water body to meet the established water-quality standard.

Temperature has a major affect on the distribution, health, and survival of native salmonids (salmon, trout, and charr) and other aquatic species. Salmonid feeding, growth, resistance to disease, competitive ability, and predator avoidance are impaired when salmonids are exposed to unsuitable temperatures. Very high temperatures can cause direct mortality of salmonids. While lethal temperatures do occur naturally and can be locally problematic, temperatures in the range where sublethal effects occur are widespread and probably have the greatest effect on the overall well-being and patterns of occurrence of native fish populations (Poole and Berman, 2001). In recent years, a growing number of salmon, steelhead, and other species in Oregon have been listed as threatened and endangered under the Federal Endangered Species Act (ESA).

With the addition of ESA issues, the need to address water-quality violations associated with elevated temperatures has become more critical. However, developing water temperature TMDL plans can be expensive. In many TMDL plans, mechanistic models are used to determine current and potential water temperatures. For input, these models typically require extensive amounts of field collected water temperature and meteorological data. Mechanistic models must to be adequately calibrated and validated. Using preexisting water temperature statistical models, which use stream reach and basin characteristics as their only inputs, is one way to reduce costs in a TMDL plan. Statistical models might not be able to eliminate the need for using mechanistic models in the lower reaches of river basins, but they could eliminate the need for using mechanistic models in headwater 1st-, 2nd-, and 3rd-order streams. Water temperatures predicted by a statistical model can serve as upper boundary inputs to mechanistic models reducing the need for collecting water temperature data at many locations. A water temperature statistical model also can be used to efficiently identify and prioritize stream reaches that are grossly out of compliance and in most need of remediation and to establish attainable temperature-reduction goals for reaches that have naturally elevated water temperatures.

Aside from assisting TMDL plans, a water temperature statistical model will help researchers better understand the relationship between physical landscape characteristics and water temperature, and monitor stream health.

In response to the need for a relatively inexpensive method of developing temperature TMDLs for Oregon streams, in 1999, the U.S. Geological Survey began a cooperative study with the Oregon Watershed Enhancement Board to develop a statistical model capable of predicting water temperature time series for 1st-, 2nd-, and 3rd-order streams in western Oregon.

Purpose and Scope

The study design included field-data collection and statistical analyses. Continuous water temperature, riparian habitat, and basin landscape-characteristics data were collected at 148 sites having relatively undisturbed riparian zones located throughout western Oregon during the summer of 1999 by the U.S. Geological Survey and the Oregon Department of Environmental Quality. Available meteorological hourly time series data collected at various locations around the study region also were assembled. Clustering analysis was performed on the overall data set to determine optimal subsets. Artificial neural network (ANN) models were developed based on data from the subsets. The models were tested and validated on a group of stream sites that were not included in the set used to create the models. The models also were used to simulate the effect of varying shade conditions on water temperatures.

This report provides (1) a description of the data used to develop the water temperature models, (2) some background theory on ANN models, (3) a description of the model development, (4) examples of model application, and (5) a user’s guide for operating the models.

Study Area

Located in western Oregon, the boundaries of the study area are the Columbia River (north), the California border (south), the Pacific Ocean (west), and the Cascade Range divide (east) (fig. 1). This region covers approximately 80,000 square kilometers. Elevations range from sea level near the Columbia River to more than 3,000 meters in the mountains of the Cascade Range. Almost 3 million people, representing approximately 85 percent of the State's population (2000 census), live in the region. The region supports an economy based on agriculture, manufacturing, timber, and recreation, and contains extensive fish and wildlife habitat.

Western Oregon has a temperate marine climate characterized by dry summers and wet winters (fig. 2). Over 80 percent of annual precipitation typically falls between October and May. Mean annual precipitation ranges from about 500 millimeters in Medford to 4,000 millimeters at crests in the Coast Range. About 35 percent of the precipitation falls as snow at the 1,200 meter elevation, and more than 75 percent falls as snow at 2,100 meters. Because the region is largely dominated by maritime systems, the range of both seasonal and diurnal air temperatures is relatively small.

On the basis of various geologic, physiographic, biological, and climatic indices, the study area is divided into four ecoregions (U.S. Environmental Protection Agency, 1996). These ecoregions include the Coast Range, Willamette Valley, Cascades, and Klamath Mountains (fig. 1).

The Coast Range is characterized by highly productive, rain-drenched coniferous forests. Dominant tree species in the Oregon coastal region include Sitka spruce, western red cedar, western hemlock, and Douglas fir. The Coast Range is composed of Tertiary marine sandstone, shale, and mudstone interbedded with volcanic basalt flows and volcanic debris. Soils are typically loamy and well drained.

Prior to European settlement, the Willamette Valley consisted of rolling prairies, deciduous/coniferous forests, and extensive wetlands. Annual precipitation, less than the Coast Range or Cascades regions, is typically from 1,000 to 1,200 millimeters. Much of the terrain in the Willamette Valley up to an elevation of about 120 meters is covered by sandy to silty terrace deposits that settled from water ponded in the great glaciofluvial lake resulting from the Missoula Floods (Glenn, 1965; Allison, 1978). Alluvial deposits that border existing rivers and form alluvial fans near river mouths were derived from the surrounding mountains, and they consist of intermingled layers of clay, silt, sand, and gravel.

The Cascades, the most mountainous region of the study area, is characterized by steep ridges, highly productive coniferous forests, a moist temperate climate, dormant and active volcanos, and alpine glaciers at higher elevations. The region is composed of volcanic rocks consisting of Tertiary basaltic and andesitic rocks together with volcanic debris, primarily in the western part of the range, and Quaternary basaltic and andesitic lava flows, primarily in the High Cascades.

The Klamath Mountains region is located in the southern portion of the study area. The region is physically and biologically more diverse than the other three regions. The climate is mild and subhumid with hot dry summers. Forest vegetation is dominated by a mix of northern Californian and Pacific Northwest conifers. The topography of the region is characterized by highly dissected, folded mountains, foothill terraces, and floodplains. The region is underlain by igneous, sedimentary, and some metamorphic rock.

Previous Investigations

A large body of research has been generated in recent years in water temperature prediction. Models that predict water temperature are often classified as mechanistic or statistical.

A heat-transport model, an example of a mechanistic or process-base model, predicts water temperature using an energy-balance equation. Mathematical equations are used to represent the physical processes of heat transfer between the stream and the surrounding environment. Meteorological data (solar radiation, air temperature, wind speed, and humidity) are typical inputs to mechanistic models. Mechanistic water temperature models also typically contain, or are coupled with, a hydrologic flow model. Mechanistic models typically are applied to a specific stream reach. Boundary flow and water temperature time series data must be collected at the site. After the model has been calibrated and validated with the measred data, it is possible to use the model to simulate cooler water temperatures that could exist under a "natural" shade scenario.

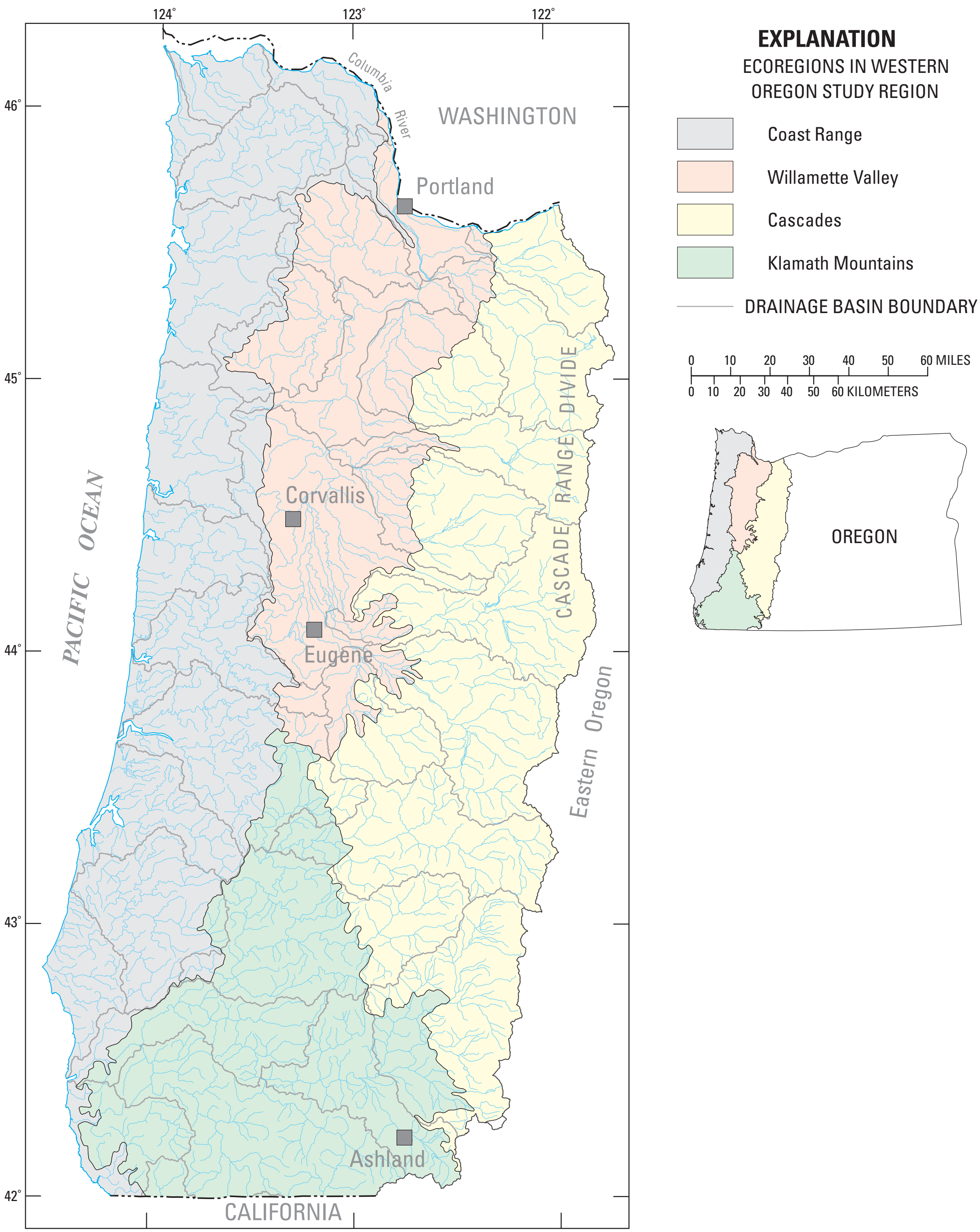

Figure 1. Western Oregon study region.

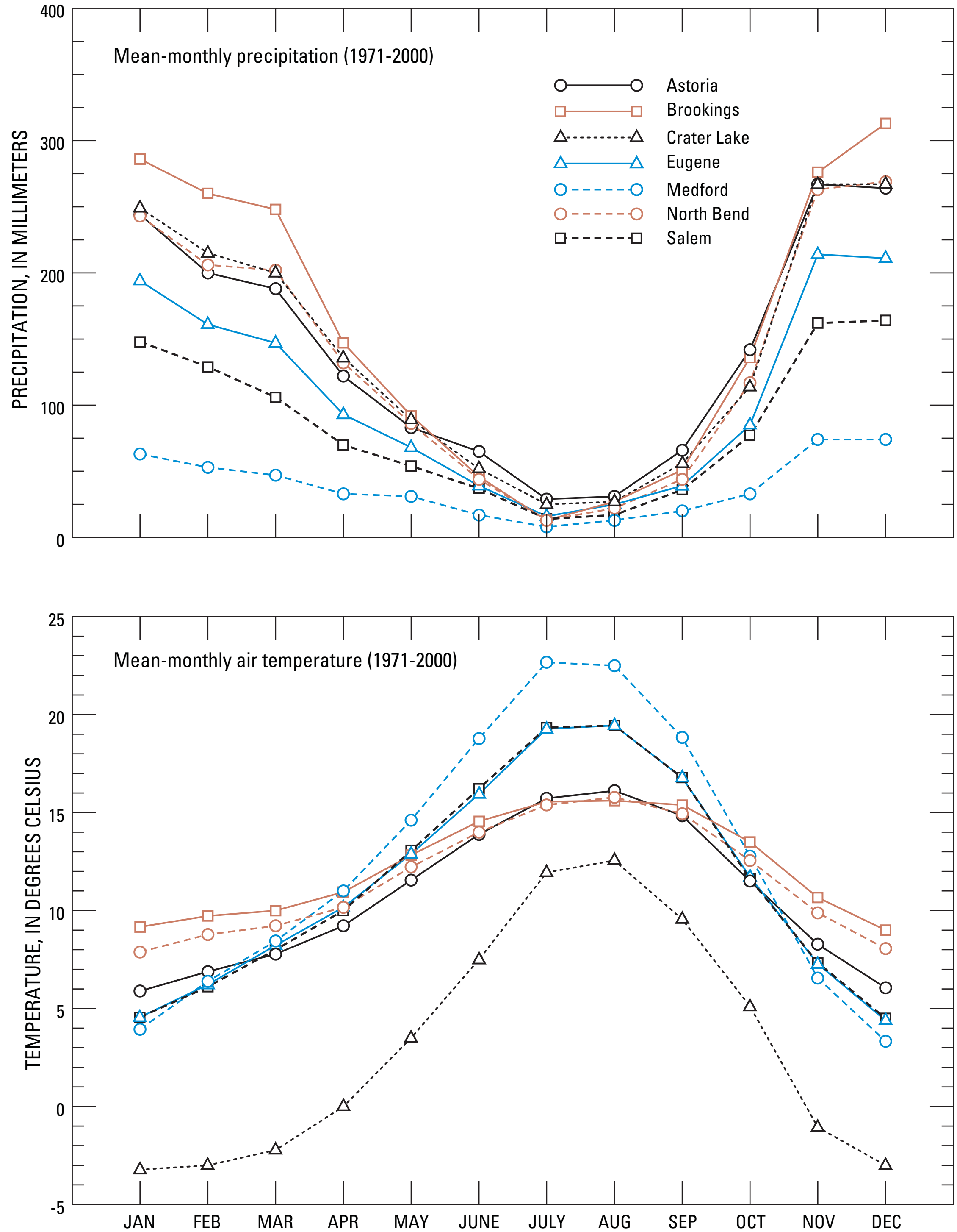

Figure 2. Mean monthly precipitation and air temperature at Astoria, Brookings, Crater Lake, Eugene, Medford, North Bend, and Salem, Oregon.

An early mechanistic model applied to small streams in Oregon was developed by Brown (1969). Examples of other mechanistic models include a steady-state model developed by Theurer and others (1984), one-dimensional dynamic flow and heat-transport models developed by Jobson (1989), Jobson and Schoellhamer (1987), and a two-dimensional, laterally averaged model developed by Edinger and Buchak (1975) and Cole and Buchak (1995).

To model water temperature over a broad region, such as western Oregon, a mechanistic modeling approach would not have been practical due to the substantial data requirements. Most statistical models that predict water temperatures use univariate or multivariate regression techniques. Some univariate regression models use air temperature as a predictor of water temperature because the two variables often have a high statistical correlation. Mohseni and others (1998) developed a four-parameter nonlinear regression model that uses weekly air temperature to predict weekly water temperatures. With multivariate statistical models, the temperature estimates are usually based on the physical characteristics of the stream site (elevation, stream morphology, channel aspect, riparian shade) and ambient climate conditions (air temperature, humidity, and solar radiation). Many of these multivariate models use a harmonic-analysis regression fit of annual variability (Ward, 1963; Collings, 1973; Tasker and Burns, 1974; and Dyar and Alhadeff, 1997). These models can be applied on a regional scale and used to predict temperatures at locations where no data have been collected. This approach is similar to using regionalized hydrologic statistical models which estimate flood or low-flow frequency streamflow statistics at ungaged sites (Riggs, 1973).

Some detailed studies generally on small streams have evaluated the relation between stream site physical characteristics, ambient climate conditions, and water temperatures (Moore, 1967; Pluhowski, 1970; Theurer and others, 1985; Lewis and others, 2000; and Poole and Berman, 2001). Additional studies by Brown and Krygier (1970), Feller (1981), Beschta and Taylor (1988), Bartholow (2000), and Johnson and Jones (2000) assessed the effects of forest practices on water temperatures. These studies confirmed that there is typically an increase in thermal loading in many streams as a result of the removal of riparian vegetation and increased solar radiation.

Acknowledgments

The authors gratefully acknowledge several agencies and individuals for assistance during the study. Approximately one-half of the water temperature and riparian habitat data used to develop the ANN models were collected by the Oregon Department of Environmental Quality. Rick Hafele and Mike Mulvey were especially helpful. Ken Bierly, Oregon Watershed Enhancement Board, was instrumental in securing funding for the study.

DATA COLLECTION

Continuous water temperature and riparian habitat data were collected at 148 sites located throughout western Oregon during the summer of 1999. Topographic data describing the basin upstream of each site were computed using geographic information system (GIS) techniques. Available climate time series data collected at various locations around the study region were assembled.

Water Temperature

Continuous half-hourly water temperature was collected by the USGS and the Oregon Department of Environmental Quality at 148 western Oregon stream sites during the 1999 low-flow period (May through September) (fig. 3). The sites were located on 1st-, 2nd-, or 3rd-order streams. The streams at these sites drained basins ranging in size from 0.31 to more than 300 square kilometers. Site elevations ranged from 7 to 1,446 meters above mean sea level. A list of the 148 sites and their locations is shown in Appendix A.

Sites were selected based on accessibility and a minimum of upstream anthropogenic impacts. Locations below point sources were not used. Also, most locations which had been extensively denuded of upstream riparian vegetation were not used. However, an attempt was made to provide an even distribution of sites across the study region. Locating sites with minimal anthropogenic impacts was more difficult in populated agricultural lowlands, such as the Willamette Valley, as opposed to forested regions in the Cascades.

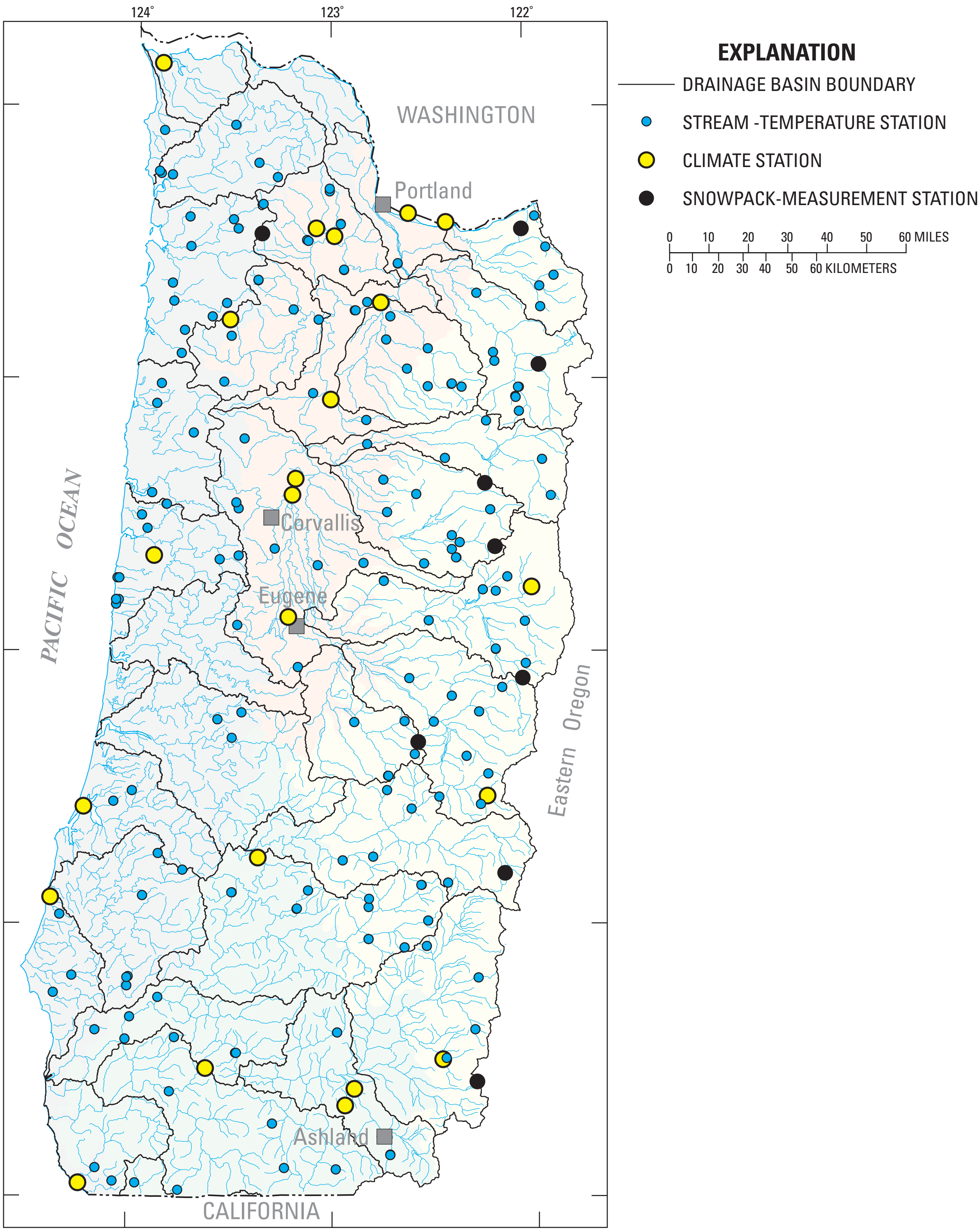

Figure 3. Locations of stream temperature stations, climate stations, and snowpack measurement stations in western Oregon.

Stream Habitat Surveys

Stream habitat surveys were conducted at all the sites during the summer of 1999. The surveys used the U.S. Environmental Protection Agency (EPA) Environmental Monitoring and Assessment Program (EMAP) field methods for measuring physical habitat in wadeable streams (Kaufman and Robison, 1994, 1998). The methodology used to compute metrics from the field data are described in Kaufmann and others (1999). Each survey was made along a stream reach just upstream of the temperature probe location. The length of the stream reach was 40 times the width of the stream at the temperature probe location, but no shorter than 150 meters. Habitat measurements were taken at 11 cross sections at equal intervals along the stream reach.

The EMAP habitat parameters measured for this study included stream bearing, stream gradient, canopy cover, stream wetted widths, stream depth, and streambed substrate (table 1).

Stream bearing for each site was computed from the mean of 10 compass bearing measurements between the 11 cross sections along the stream reach. The bearings, measured in an upstream to downstream direction, were in degrees from 0 to 360. Stream bearing, like basin aspect, is important to water temperature because of its relation to the amount of solar radiation reaching the water surface. South facing basins (in the northern hemisphere) typically have warmer water temperatures than north facing basins.

Stream gradient, defined as the rise over run ratio percent, was computed from the mean of 10 gradient measurements made with a clinometer between each of the 11 cross sections. Stream gradient has relevance to water temperature as an indication of stream velocity and residence time within the reach.

Summer canopy cover was measured using a Convex Spherical Densiometer, model B (Lemmon, 1957). At each of the 11 cross sections, 4 measurements were taken from the center of the channel facing upstream, downstream, and each bank. The 44 values were averaged and computed as a percentage. A second set of densiometer measurements were made, at each cross section, from both streambanks facing the water. These 22 values were averaged and computed as a percentage. Canopy cover directly affects water temperature because it controls the amount of short-wave solar radiation reaching the water surface.

Stream wetted width and depth were measured at each of the 11 cross sections. The depth to width ratio can affect water temperature. Deep narrow streams are typically cooler than wide shallow streams.

Streambed substrate was sampled at five locations at each cross section. These locations included both the left and right edge of water and within the channel (one-quarter, one-half, and three-quarters of the distance across the stream). At each location, the substrate material was visually evaluated as either bedrock (particle size greater than 4,000 millimeters), boulder (between 250 to 4,000 millimeters), cobble (between 64 to 250 millimeters), gravel (between 2 to 64 millimeters), sand (between 0.06 to 2 millimeters), or fine silt or muck (less than 0.06 millimeter). For the entire stream reach, the percentage breakdown for these 6 classes was computed using data from a total of 55 sampling locations (5 locations at each of 11 cross sections).

Basin Characteristics

For many streams, the temperature at a particular location is influenced by habitat and vegetation conditions that exist farther upstream than the length of the stream reach defined for the habitat field surveys (40 times the downstream channel width). Using GIS, topographic and vegetative characteristics of the drainage basin upstream of the temperature probe were computed (table 1). The 148 basins for the sites were delineated using 10-meter digital elevation models (DEM).

The percentage of forest cover and forest cover density were computed for each basin using a GIS coverage of forest vegetation in western Oregon that was created from LANDSAT imagery developed by Cohen and others (1995, 1998, 2001, and 2002). The LANDSAT imagery was taken in 1995 and resampled to a 25-meter cell resolution. For this study, all areas that contained forest vegetation were classified as “forested” and areas absent of forest vegetation (which included forest clear cuts and fire burns) were classified as “open.” Most regions outside of forested areas, such as agricultural or urban areas, were usually classified as “open.”

Mean summer air temperature data were computed for each basin using a GIS coverage of mean monthly air temperatures (1961-1990) developed by Daly and others (1997). The mean for the summer period was based on the months of May through September.

Table 1. Stream habitat and basin variables used as model inputs and their statistics

[Statistics are based on 142 sites. Six sites from the total set of 148 sites were held aside for later model validation]

Model label	Explanation	Mean	Standard deviation	Minimum	Maximum
STRMRB	Stream reach bearing (degrees)	206.93	98.67	0.00	360
SLOPEPCT	Slope (percent)	4.57	5.75	0.10	33.65
STRMBDEN	Streambank densiometer (percent)	90.20	11.87	29.95	100
MIDCHDEN	Mid-channel densiometer (percent)	78.94	18.94	2.27	100
DEPTH	Depth (centimeters)	33.13	19.86	3.67	126
WETTEDWD	Wetted width (meters)	5.93	3.89	0.54	19.56
SBSUBSTF	Streambed substrate percent Fines/others	17.60	24.07	0.00	100
SBSUBSTS	Streambed substrate percent Sand	7.08	8.23	0.00	42.59
SBSUBSTG	Streambed substrate percent Gravel	26.58	13.78	0.00	65.45
SBSUBSTC	Streambed substrate percent Cobble	23.60	14.31	0.00	63.64
SBSUBSBO	Streambed substrate percent Boulder	14.04	14.32	0.00	74.55
SBSUBSBE	Streambed substrate percent Bedrock	11.10	14.00	0.00	60.00
BASBEARA	Basin bearing (degrees)	204.07	103.07	4.00	359
BASBEARS	Basin bearing (sine)	-0.2719	0.6701	-1.0000	1.0000
BASBEARC	Basin bearing (cosine)	0.0299	0.6947	-0.9998	0.9998
STRMCHBE	Stream-channel bearing (degrees)	201.44	103.82	0.00	350
BASINKM2	Basin area (square kilometers)	34.06	47.77	0.32	300.65
BASMELEV	Basin mean elevation (meters)	725.11	475.69	50.71	2,871.10
BASOELEV	Basin outlet elevation (meters)	394.63	350.14	7.20	1,445.80
BASXELEV	Basin maximum elevation (meters)	1,142.41	639.24	61.00	4,470.00
STCHMELV	Stream-channel mean elevation (meters)	523.17	405.26	33.77	1,649.59
BASMSLOP	Basin mean slope (percent)	34.82	15.43	1.40	123.36
STMCHSLO	Stream-channel mean slope (percent)	3.51	3.17	0.07	16.30
BASFOREA	Basin forest area (percent)	79.38	25.12	0.00	100
BASOPENA	Basin open area (percent)	20.62	25.12	0.00	100
DENBASFA	Density of basin forest area (percent)	88.85	16.04	0.00	98.94
STCHFORA	Stream-channel forest area (percent)	82.16	29.43	0.00	100
STCHOPA	Stream-channel open area (percent)	17.84	29.43	0.00	100
DNSTCHFA	Density of stream-channel forest area (percent)	83.84	22.01	0.00	98.29
BASMSATC	Basin mean summer air temperature (degrees Celsius)	14.81	1.38	10.79	17.62
STMSUATC	Stream-channel mean summer air temperature (degrees Celsius)	14.93	1.38	11.04	17.67
OUTMSATC	Outlet mean summer air temperature (degrees Celsius)	15.41	1.82	11.67	24.94
XCOORD	Longitude (normalized decimal value)	0.4933	0.2546	0.0048	0.9426
YCOORD	Latitude (normalized decimal value)	0.5115	0.2587	0.0002	0.9444

Climate

Hourly climatological time series data collected at various stations around western Oregon also were assembled (table 2; fig. 3). The climate stations are operated by the U.S. National Weather Service, U.S. Bureau of Reclamation, and the U.S. Forest Service.

The climate parameters used in the study included air temperature, dew-point temperature, short-wave solar radiation, air pressure, and precipitation. Daily snowpack time series data collected by the U.S. Natural Resource Conservation Service at nine sites also were assembled (table 2; fig. 3).

Table 2. Climate time series data assembled for the model simulations

[**Agencys**: NRCS, U.S. Natural Resources Conservation Service; USBR, U.S. Bureau of Reclamation; NWS, U.S. National Weather Service; USFS, U.S. Forest Service; **Meteorological parameters:** AP, air pressure; SWE, snow water equivalent; DT, dewpoint temperature; AT, air temperature; SR, solar radiation; RN, rainfall]

Station name	Latitude	Longitude	Elevation (meters)	Agency	Meteorological parameter					
					AP	SWE	DT	AT	SR	RN
Corvallis	44 38 03	123 11 24	70.1	USBR			X	X	X	X
Aurora	45 16 55	122 45 01	42.7	USBR			X	X	X	X
Bandon	43 05 28	124 25 02	24.4	USBR			X	X	X	X
Dee Flat	45 34 25	121 38 50	384	USBR			X	X		
Forest Grove	45 33 11	123 05 01	54.9	USBR			X	X	X	X
Medford	42 19 52	122 56 16	408	USBR			X	X	X	X
Billie Creek Divide	42 25 00	122 17 00	1,615	NRCS		X				
Diamond Lake	43 11 00	122 08 00	1,620	NRCS		X				
Holland Meadows	43 40 00	122 34 00	1,494	NRCS		X				
Jump Off Joe	44 23 00	122 10 00	1,067	NRCS		X				
Little Meadows	44 37 00	122 13 00	1,219	NRCS		X				
North Fork	45 33 00	122 01 00	951	NRCS		X				
Peavine Ridge	45 03 00	121 56 00	1,067	NRCS		X				
Roaring River	43 54 00	122 02 00	1,494	NRCS		X				
Saddle Mountain	45 32 00	123 22 00	991	NRCS		X				
Astoria	46 09 00	123 53 00	2.13	NWS	X			X		
Brookings	42 02 00	124 15 00	7.32	NWS	X		X	X		
Eugene	44 07 00	123 13 00	34.7	NWS	X		X	X		
Hillsboro	45 31 00	122 59 00	18.9	NWS	X		X	X		
Medford	42 23 00	122 53 00	123	NWS	X					
North Bend	43 25 00	124 15 00	1.22	NWS	X		X	X		
Portland	45 36 00	122 36 00	3.66	NWS	X		X	X		
Roseburg	43 14 00	123 22 00	48.8	NWS	X		X	X		
Salem	44 55 00	123 00 00	18.6	NWS	X		X	X		
Cannible	44 21 00	123 55 00	593.1	USFS			X	X		X
Pebble	44 14 00	121 59 00	1,085	USFS	X		X	X		
Rye Mountain	45 13 00	123 32 00	610	USFS			X	X		X

Typically, ANN models are more efficient if the input time series data sets have been normalized to accentuate the variability within the data set. Normalizing the climate data can be done by selecting a centrally located climate station as a standard. Data measurements from the standard station are subtracted from corresponding data measurements collected at nonstandard stations. Being centrally located in the study area, Corvallis was selected as a standard. Hourly Corvallis climate data for air temperature, dewpoint temperature, rainfall, and solar radiation were used to normalize corresponding non-Corvallis station data. However, air pressure data were normalized with air pressure data from Eugene, because Corvallis air pressure data were unavailable.

MODEL DEVELOPMENT

Background Theory

An artificial neural network (ANN) model is a flexible mathematical structure capable of describing complex nonlinear relations between input and output data sets. Although used in industrial applications for years, ANN modeling is increasingly being used in environmental sciences, particularly for problems where the characteristics of the processes are difficult to simulate using a mechanistic modeling approach. Within hydrologic studies, ANN modeling has been used for a variety of purposes. Kuligowski and Barros (1998) used ANN modeling to estimate missing rainfall data. Karunanithi and others (1994) and Hsu and others (1998) used ANN modeling for streamflow forecasting. River stage also has been forecasted using ANN modeling (Thirumalaiah and Deo, 1998). Hsu and others (1995) and Shamseldin (1997) describe applications of ANN modeling to rainfall-runoff processes. In a water-quality application, Conrads and Roehl (1999) used an ANN model to simulate salinity, temperature, and dissolved oxygen in a complex tidal estuary. Morshed and Kaluarachchi (1998) present an ANN model used in complex ground-water flow and contaminant transport simulations. Cannon and Whitfield (2001) modeled transient pH depressions using an ANN model.

The architecture of ANN models is loosely based on the biological nervous system (Hinton, 1992). ANNs contain interconnected units that are analogous to neurons. The function of the synapse is modeled by a modifiable weight which is associated with each connection. Probably the most commonly used ANN model is the feed-forward neural network shown in figure 4. This example contains three nodes in the input layer, five nodes in the hidden layer, and a single node in the output layer. The model output is generated by feeding input data through the model from left to right. The output from each hidden layer node *hj* is computed in the following equation:

$$h_j = \tanh\left[\sum_i X_i {}^1w_{ij} + {}^1b_j\right] \qquad (1)$$

where

h_j	is the computed output from each hidden-layer node,
j	is the hidden-layer node index,
tanh	is the hyperbolic tangent,
i	is the input layer node index,
X_i	is the input variable,
${}^1w_{ij}$	is the hidden layer weight, and
${}^1b_j$	is hidden-layer bias.

Output from the ANN model is computed in the following:

$$Y = \sum_j h_j {}^2w_j + {}^2b \qquad (2)$$

where

Y	is the output variable
${}^2w_j$	is the output layer weights, and
${}^2b$	is the output layer bias.

Nonlinear relationships in the model are represented by the hyperbolic tangent function, a sigmoid-shaped function, in the hidden-layer nodes. However, the output variable, *Y*, is a linear function of the weighted hidden-layer outputs.

The root mean square error (RMSE) of the ANN model is defined as:

$$E = \sqrt{\frac{1}{N}\sum_{cases}(Y - Y_{obs})^2} \qquad (3)$$

where

E	is the root mean square error,
N	is the number of input and output cases,
Y	is the predicted output, and
Y_{obs}	is the measured output.

Training the ANN model involves minimizing the RMSE by continually adjusting the model weights and bias terms. Usually, training is accomplished using a nonlinear multivariate optimization algorithm. The back propagation algorithm (or gradient descent) is commonly used in many training applications.

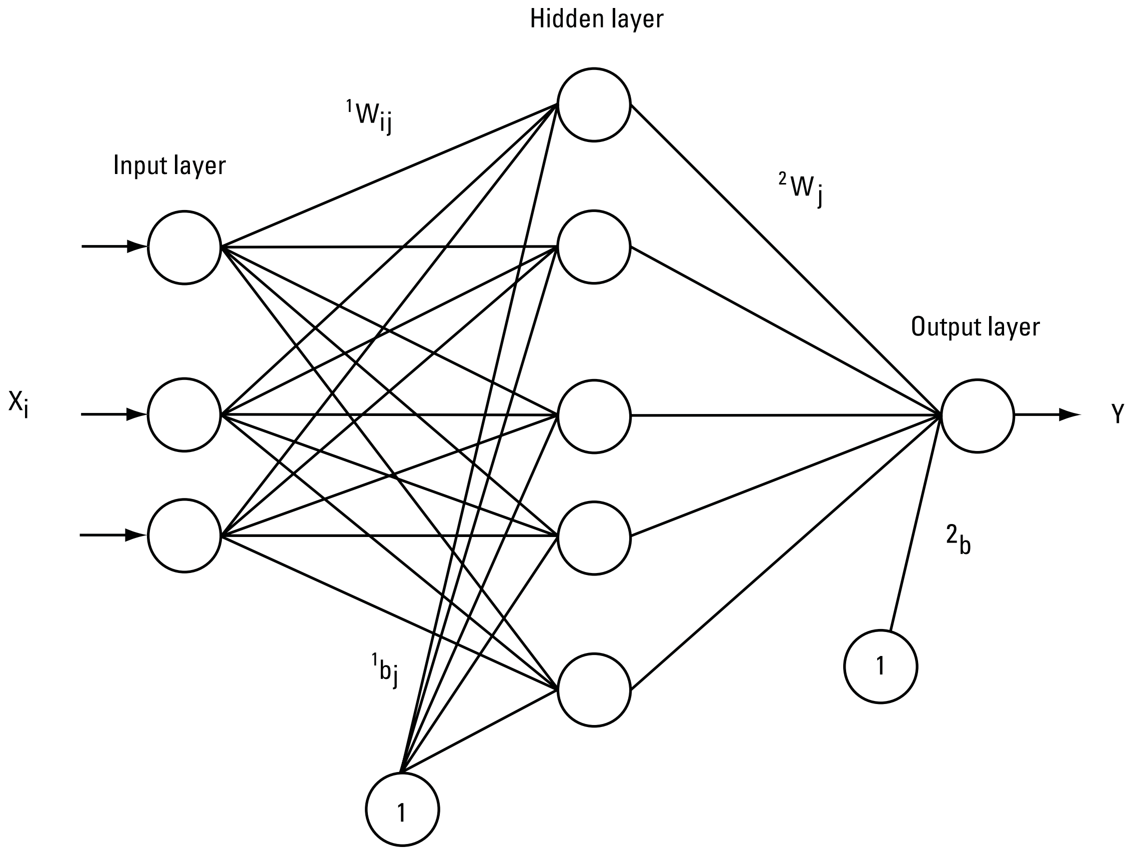

Figure 4. Feed-forward neural network architecture with three inputs, five hidden-layer nodes, and a single output.

Clustering Analysis

For many spatial modeling problems, it is necessary to subdivide a larger study area and create separate models for regions rather than create a single model for an entire study area. This approach is typically used in regional regression studies for flood statistic (Riggs, 1973). The western Oregon study area varies broadly with respect to climate, topography, and ecology. A preliminary assessment of the water temperature data revealed expected time series discontinuities. One large ANN model for all of western Oregon would not have been capable of simulating much of the time series discontinuities. However, instead of subdividing western Oregon into spatially contiguous regions, separate and more homogenous groups of temperature sites were created using clustering analysis. The clustering analysis, which is discussed in more detail below, was based on only continuous water temperature time series data collected in the summer of 1999 from 142 sites throughout western Oregon. (Six sites were randomly removed from the original set of 148 sites and set aside for post-model-development validation.) In addition to determining which specific sites fall into which groups, clustering analysis can be used to determine an optimal number of groups. A higher number of groups will create more distinct homogenous groups. However, these groups will contain a smaller number of sites, which may be insufficient for creating robust ANN models.

Prior to the clustering analysis, it was necessary to determine an optimal period of record for all 142 sites. The beginning and ending dates for the records of these sites varied within the period from early May to early October 1999. The period from June 21 to September 20, 1999, was selected as an optimum period having the highest density of records (fig. 5). This period also included the warmest part of the summer in western Oregon, which is when water temperature standard violations are mostly likely to occur. This same period also was used for the subsequent modeling after the clustering analysis. To improve file storage and simulation speed, hourly (instead of half-hourly) temperature values were used in the analysis. In analyzing water temperature records in the Pacific Northwest, Dunham and others (2001) found that accurate measures of the daily maximum and minimum temperatures are still retained if an hourly record is used rather than a half-hourly record.

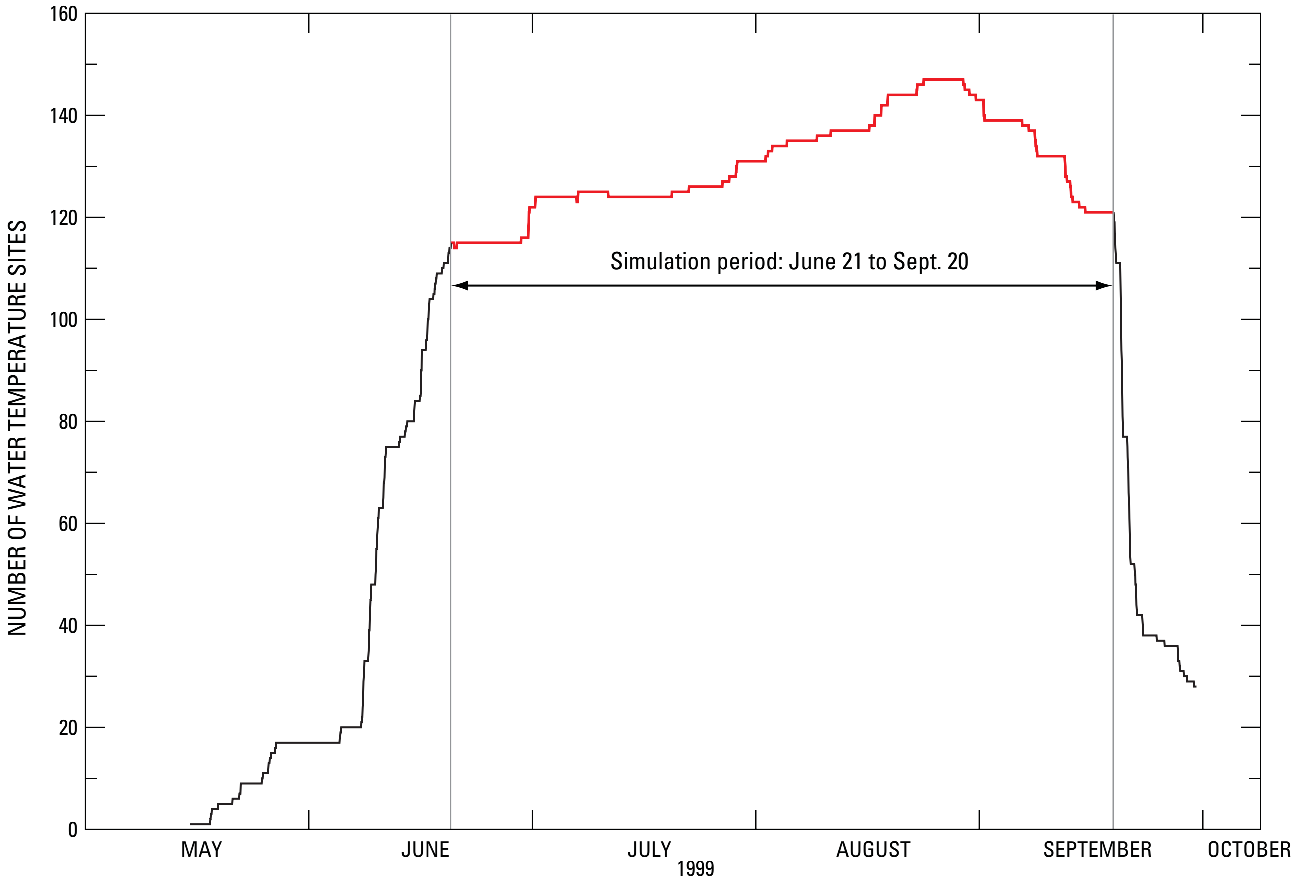

Figure 5. Density of water temperature records.

The actual clustering analysis was performed using a proprietary methodology developed by Advanced Data Mining, LLC of Greenville, South Carolina[1]. All continuous hourly water temperature time series data, for the period from June 21 to September 20, 1999, from all 142 sites were converted into an intermediate representation of characteristics to which k-means clustering is applied. The k-means clustering implementation used was provided by the Data Miner Software Kit (DMSK) package (Weiss and Indurkhya, 1998). For k number of groups, clustering analysis optimizes which members of the overall group of 142 should be in groups 1-k based on the cumulative distances between each vector and the mean of that vector's group.

As the number of groups is increased, the RMSE (which is computed by the DMSK software and described on pages 102-103 of Weiss and Indurkhya,1998) decreases as shown in figure 6. Sometimes the optimal number of groups can be selected at the inflection point between a sharp vertical decline and a horizontal plateau. However, this plot did not have a marked decline. The RMSE for three, four, and five group clustering was 0.104, 0.098, and 0.092, respectively. The three group clustering, which would yield three separate models, was the optimal number of groups. The four- or five-group clustering yielded lower RMSE; however, the number of sites in some of the groups was insufficient for model creation.

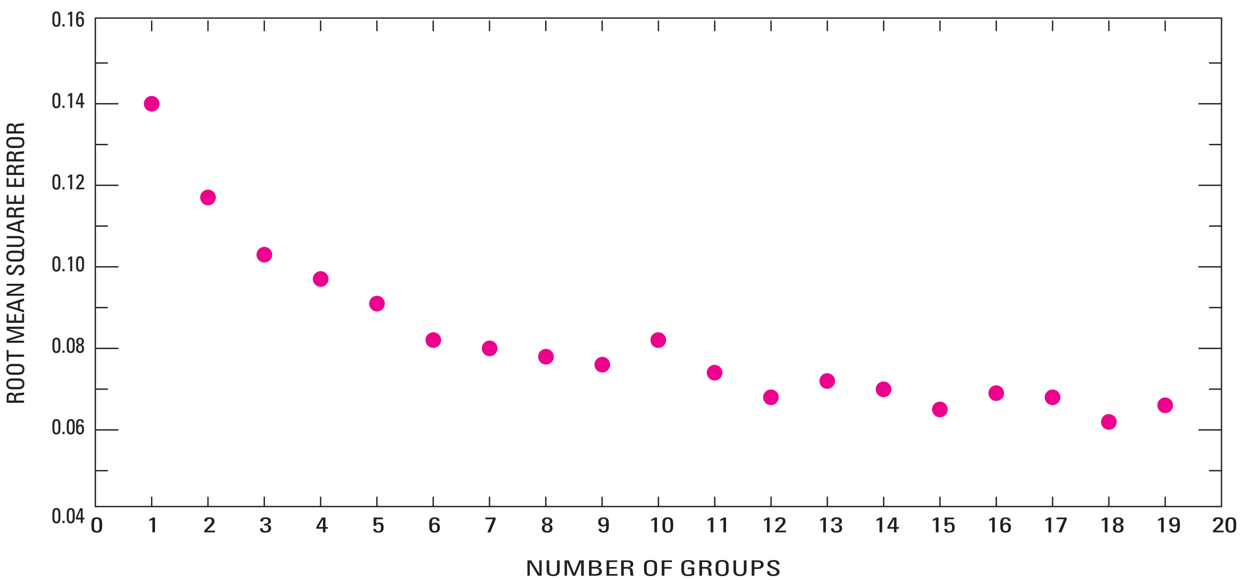

Figure 6. Results of clustering analysis.

[1]The proprietary clustering methodology is available through: Advanced Data Mining, LLC, 3620 Pelham Road, PMB #351, Greenville, South Carolina, 29615-5044; email: ed.roehl, ed@advdatamining.com; http://www.advdatamining.com, telephone: 864-676-9790.

The distribution of the sites across western Oregon for each of the three groups is shown in figure 7. Group 1 sites are generally located in warmer climate regions at lower elevations and in the southern portion of the study area. This includes the Klamath Mountains ecoregion and the Willamette River Valley lowlands. However, group 2 sites are more predominant at higher elevations, particularly in the Cascades. Group 3 sites are not restricted to any geographic area in western Oregon. Figure 8 shows the mean of all the normalized 24-hour moving average temperatures of all the sites for each of the three groups. All 24-hour moving average temperatures for all 142 time series (using a common period of record from June 21 to September 20, 1999) were normalized to values between 0 and 1. Normalizing was done by first subtracting the minimum 24-hour moving average temperature in a time series (for the period of record) from each 24-hour moving average temperature in that time series. All these values were then divided by the difference between the maximum and minimum 24-hour moving average temperatures (for the period of record) in that time series. The mean of the normalized values for all time series in a group was then calculated into a single time series for that group. These three time series, for the three groups, are what is shown in the figure.

Figure 8 shows that in June and July, temperatures for group 2 remained low (in relation to its period of record) due to the influence of an extended season of snowpack in 1999. Group 1, which has many sites at lower elevations and in the southern coast region, are influenced by maritime climatic changes and have some of their highest temperatures in June and July. Group 1 had its lowest temperatures in September, and group 2 had its highest temperatures in August. Group 3 followed a trend in between the two other groups. Because of these differences, it was possible to make more accurate and robust models by subdividing the pool of 142 sites into these 3 groups.

Model Framework

All the ANN models made in this study were developed using the Neural Fusion (NNModel32 Version1.0) software package[2]. The models were developed as a linked series which, when used in a consecutive order, can provide a user with a time series of simulated hourly temperatures for a stream site of interest (fig. 9). The period of the simulated time series, June 21 to September 20, encompasses the warmest period of a typical year.

The group assignment model determines into which of the three groups, determined in the clustering analysis, a site would fall. This model uses static site data (stream habitat and basin characteristics listed in table 1) as input variables.

Using a decomposition approach, the hourly time series was broken into static, chaotic, and periodic components (as shown in equation 4). Separate ANN models were created for each component. The static component predicts the mean temperature for the modeling period (June 21 to September 20). The chaotic component (as shown in equation 5) predicts the normalized 24-hour moving average temperature. The periodic component (as shown in equation 6) predicts the normalized residual of the 24 hour period. The breakdown of these components is shown in the following:

$$HOURLY = MEANT + NAVG24 + NHOURLY \quad (4)$$

where

HOURLY	is hourly temperature,
MEANT	is the mean of hourly temperature for the simulation period (static component),
NAVG24	is the normalized 24-hour moving average temperature (chaotic component), and
NHOURLY	is the normalized 24-hour residual (periodic component).

[2]All property rights of Neural Fusion software are owned by: EnvaPower, Inc, 90 Windom Street, Suite 2A, Boston, MA 02134 Phone: 617-254-5300; email: info@envapower.com; http://www.envapower.com.

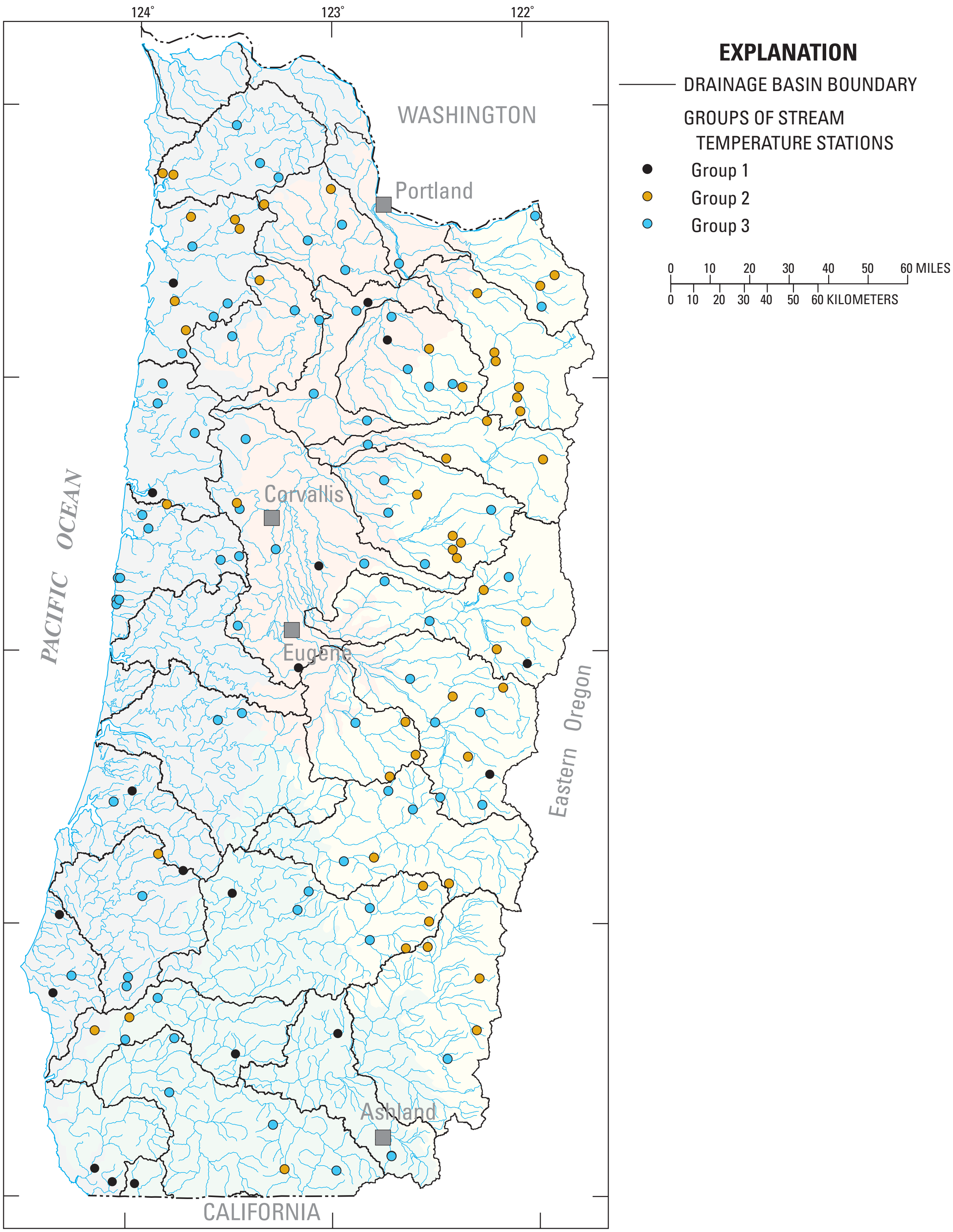

Figure 7. Distribution of the three groups of stream temperature stations within the study area.

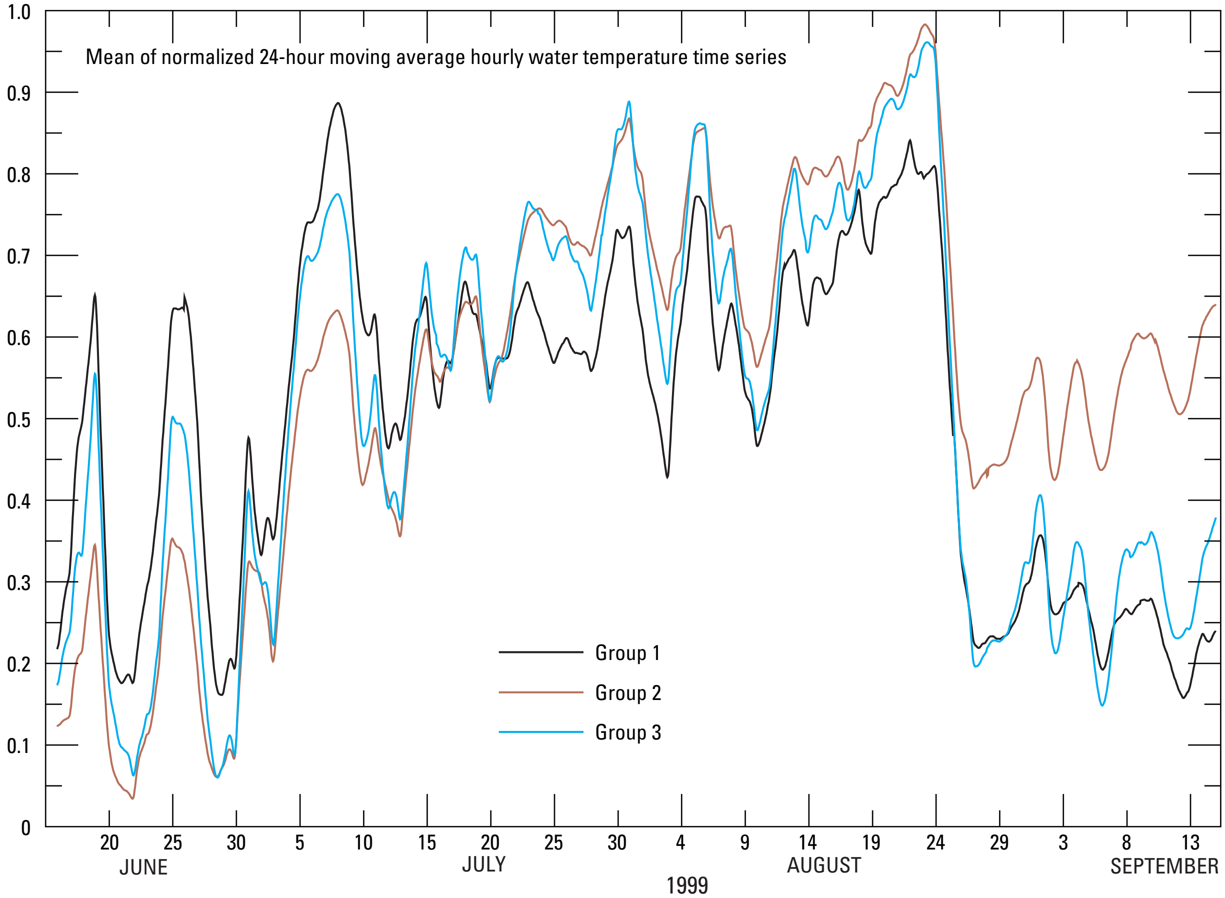

Figure 8. Mean of normalized 24-hour moving average hourly water temperature time series from each of the three groups.

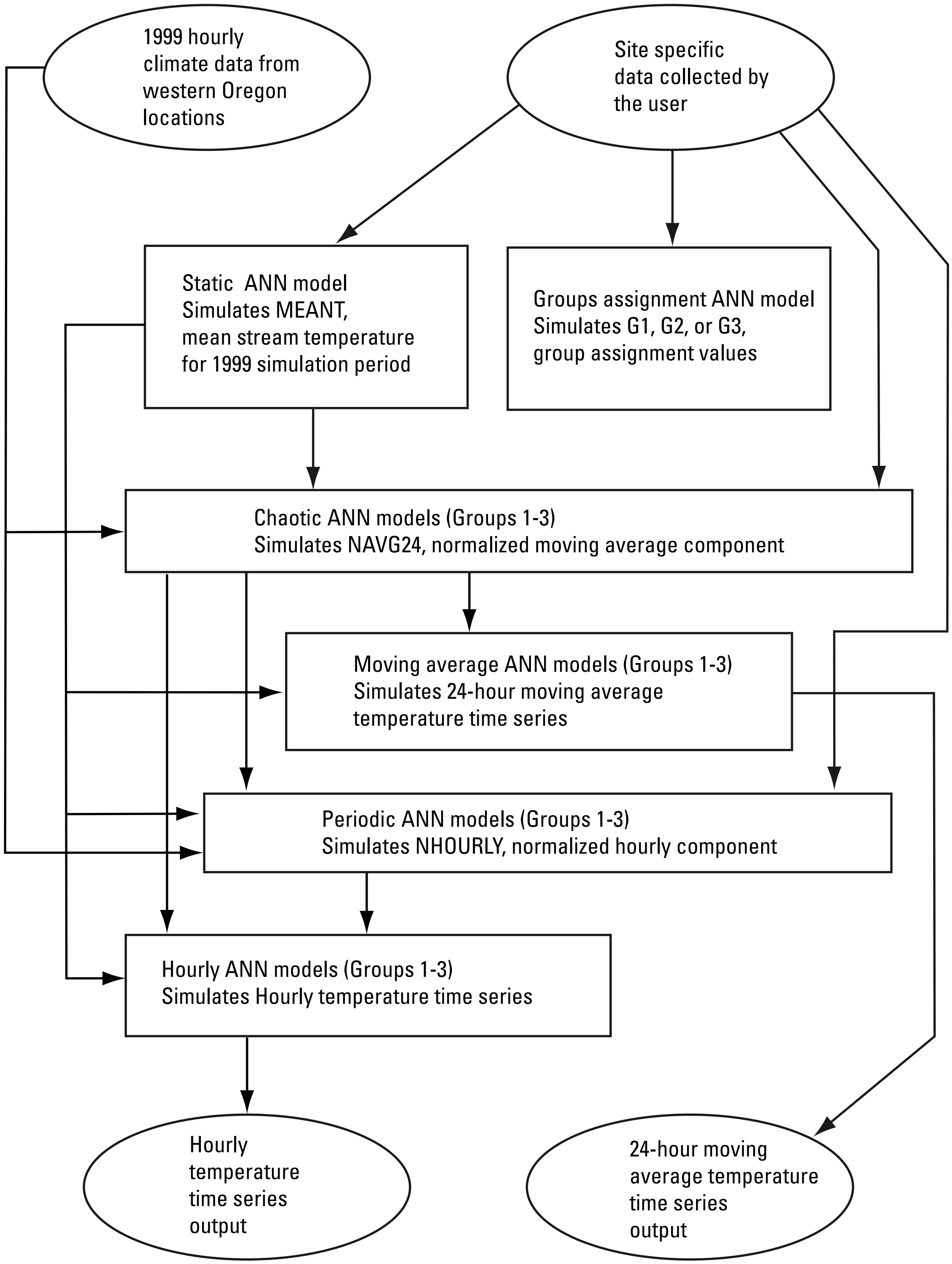

Figure 9. Components of artificial neural network water temperature models.

The chaotic component is computed as:

$$NAVG24 = 24AVG - MEANT \qquad (5)$$

where

24AVG is the 24-hour moving average hourly temperature data.

The periodic component is computed as:

$$NHOURLY = HOURLY - MEANT - NAVG24 \qquad (6)$$

To predict the static component, a single ANN model was used for all 142 sites. Like the group assignment model, only static site data (stream habitat and basin characteristics listed in table 1) were used as input variables.

For the chaotic and periodic components, separate sets of ANN models were created for each of the three groups. It was also necessary to subdivide both groups 2 and 3 into their own northern and southern zones. This was done because the size of the input files for these groups would have exceeded storage capacity of the ANN software. The dividing line separating group 2 is at latitude 44 degrees 34 minutes 12 seconds (44.57 in decimal degree units), and the dividing line separating group 3 is at latitude 44 degrees 18 minutes 0 seconds (44.30 in decimal degree units).

Separate sets of models were made for each zone in groups 2 and 3. In all, a total of five separate sets of models (for the chaotic and periodic components) were developed.

The input variables for the chaotic models included static site data (stream habitat and basin characteristics as listed in table 1) and normalized hourly 24-hour moving average climate station data for the period of June 21 to September 20, 1999. As described earlier, non-Corvallis climate stations (listed in table 2) were normalized using Corvallis data. The input variables for the periodic models included static site data and normalized hourly climate station data.

Two final models for each group and zone were developed to simulate hourly and 24-hour moving average water temperature time series. The hourly model used simulated static (MEANT), chaotic (NAVG24), and periodic (NHOURLY) values as input variables. The 24-hour moving average model used simulated static (MEANT) and chaotic (NAVG24) values as input variables. The linkages between the models are illustrated in figure 9.

Training

For each model, a training matrix was arranged with a row for each data vector and a column for each input or output variable. The matrices for the group assignment and static component models had 142 rows (or data vectors), which contained stream habitat and basin characteristics as input variables for each site. These matrices also contained 142 output variables for either group assignment or mean seasonal temperature. However, the matrices for the chaotic and periodic models, which used hourly meteorological time series data as input, contained thousands of rows (or data vectors). For example, the matrix for the northern zone of group 3, which has 41 sites, has 86,216 rows. Although each site contained a varying number of rows of data depending on the length of its data collection period from June to September, many sites contained approximately 2,000 rows of hourly time series data. The time series data sets for each site were stacked on top of each other in the matrix for that model. The chaotic and periodic model matrices also contained some columns of static variable data. These columns had the same value for all the rows (approximately 2,000) that pertained to the same site.

Analogous to statistical software used to create multiple regression models, the ANN modeling software creates a model based on input and output variable data sets and provides a coefficient of determination (R-square) and RMSE terms in the results. The software also allows the user to randomly divide the data points into separate training and testing sets. Approximately one-third of the data vectors were used for model training and the remaining two-thirds were used for model testing. During the training process, the ANN model is developed from just the training data set. The software then tests (or validates) the model using the testing data set. Often an indication of “overtraining” occurs if both the coefficient of determination and RMSE terms for the testing data set are significantly lower and higher, respectively, than these terms for training data set.

During each training session, continual adjustments are automatically made to the model weights and bias terms to maximize the coefficient of determination and minimize the RMSE. The simulation is completed when the coefficient of determination and RMSE terms have stabilized. At the beginning of the training process, all available input variables were used. For each subsequent training simulation, those input variables having an insignificant relation to the output variable, based on a sensitivity analysis, were removed. However, a model with too few input variables can produce a model that has a higher error and a lower coefficient of determination. The statistical results for all the models are shown in table 3. Coefficients of determination and the RMSE for the models ranged from 0.88 to 0.99 and 0.05 to 0.59 °C, respectively. Tables containing the model input variables used in the group assignment, static component, chaotic component, and periodic component models are in Appendix B. These tables also include the sensitivity analysis results for each model and lists the input variables in their order of importance. Critical input variables for most of the models typically included riparian shade, site elevation, and percent forested area of the basin. Model operation instructions are shown in Appendix C.

Table 3. Statistical results for the training and testing of simulations for each model

[**Abbreviations**: RSQ, coefficient of determination; N, number of data points; *Tobs*, measured hourly water temperature; *Tsim*, simulated hourly water temperature. A smaller root mean square error (RMSE) is an indication of more accurate model performance; –, number of data points was too small for testing. RMSE, root mean square error = $\sqrt{\frac{1}{N}\sum_{n=1}^{N}(Tobs - Tsim)^2}$]

Model	Training			Testing		
	RSQ	RMSE	N	RSQ	RMSE	N
Group assignment–Group 1	0.98	0.05	142	–	–	–
Group assignment–Group 2	0.93	0.13	142	–	–	–
Group assignment–Group 3	0.95	0.11	142	–	–	–
Static	0.96	0.59	142	–	–	–
Chaotic–Group 1	0.94	0.41	5,383	0.93	0.44	21,946
Periodic–Group 1	0.92	0.40	4,190	0.87	0.52	17,148
Moving average–Group 1	0.98	0.59	5,543	0.98	0.59	21,786
Hourly–Group 1	0.99	0.57	4,190	0.98	0.66	17,148
Chaotic Group 2 North	0.98	0.21	9,889	0.98	0.23	39,860
Periodic Group 2 North	0.88	0.26	8,436	0.86	0.29	33,466
Moving average–Group 2 North	0.99	0.23	9,997	0.99	0.23	39,752
Hourly–Group 2 North	0.99	0.29	8,436	0.98	0.32	33,466
Chaotic Group 2 South	0.98	0.24	8,254	0.98	0.26	33,267
Periodic Group 2 South	0.94	0.23	6,610	0.88	0.33	26,635
Moving average–Group 2 South	0.99	0.26	8,245	0.99	0.26	33,276
Hourly–Group 2 South	0.99	0.33	6,575	0.99	0.33	26,670
Chaotic Group 3 North	0.96	0.30	10,194	0.96	0.32	41,285
Periodic Group 3 North	0.89	0.34	8,156	0.85	0.39	32,323
Moving average–Group 3 North	0.98	0.32	10,440	0.98	0.32	41,039
Hourly–Group 3 North	0.98	0.36	8,156	0.98	0.40	32,323
Chaotic Group 3 South	0.98	0.22	9,382	0.97	0.25	38,459
Periodic Group 3 South	0.93	0.27	7,225	0.90	0.32	28,629
Moving average–Group 3 South	0.99	0.26	9,694	0.99	0.26	38,147
Hourly–Group 3 South	0.99	0.27	7,225	0.98	0.32	28,629

Validation

Prior to model development, 6 stream sites were randomly removed from the original data set of 148 sites and not used in the ANN model training process. The location of these sites is shown in figure 10, and their stream habitat and basin characteristics data are listed in table 4.

To determine the group assignment for each of the six sites, stream habitat and basin characteristics data from each site were entered into the group assignment model. The sites were all assigned to groups 2 and 3. Based on the latitude of each site, the sites were further assigned to either the northern or southern zone. None of the six sites happened to fall into group 1.

Stream habitat and basin characteristics data from each site also were entered into the static model to simulate the mean water temperatures for the simulation period from June 21, 1999 to September 20, 1999. A comparison of the difference between measured and simulated mean temperatures for the six sites is shown in table 5. With the exception of Palmer and Fisher Creeks, the differences were less than 1 °C.

The static model simulated mean temperature for Fisher Creek was approximately 3 °C warmer than the measured mean temperature. Out of the entire set of 148 sites that were used in the study, the elevation of the Fisher Creek site was one of the highest. Because of a limited representation of high elevation sites in the model, the static model may not have performed as well at this elevation. The Fisher Creek Basin also may have been an aberration compared to other basins in the same region. The influence of the heavy spring snowpack in 1999 could have been more persistent in the Fisher Creek Basin and made water temperatures cooler than expected. Cooler than expected water temperatures also could be the result of ground water inflows from possible springs and cold-water pockets just upstream of the site. As a result, the site specific data collected at Fisher Creek, and used for the model input variables, may not have adequately represented these cooling ground-water influences.

The static model simulated mean temperature for Palmer Creek was approximately 2 °C Celsius warmer than the measured mean temperature. The Palmer Creek site is a low elevation agricultural basin in the Willamette Valley. The streambank (STRMBDEN) and mid channel (MIDCHDEN) shade densiometer measurements for this site were high, because of the presence of thick riparian vegetation. However, the percentage of basin forest area (BASFOREA) and percentage of stream channel forest area (STCHFORA) estimations for this site were very low. It is possible that this discrepancy caused some problems for the static model in estimating a mean seasonal value. Higher BASFOREA and STCHFORA values would have yielded a lower mean seasonal value.

Using the chaotic and periodic models, 24-hour moving average and hourly water temperature time series were simulated for the six sites. A comparison of measured and simulated 24-hour moving average water temperatures for the sites are shown in figure 11. These figures show how well the combination of just the static and chaotic models (without the periodic model) performed. Figure 12 shows a comparison of measured and simulated hourly water temperatures. The RMSE between measured and simulated 24-hour moving average water temperatures for the sites are shown in table 5. These errors are a measure of the combined performance of the static and chaotic models. Table 5 also shows the RMSE between measured and simulated hourly water temperatures for the sites. These errors are a measure of the combined performance of static, chaotic, and periodic models. A measure of how well just the periodic models performed can be inferred by the difference between these two types of errors.

For Palmer Creek, the static model, which uses only site data (field measurements and GIS derived basin characteristics) as input, simulated a seasonal error greater than 2 °C. However, the effect of the chaotic and periodic models appears to have compensated and reduced the error. The RMSE for the hourly temperature values (table 5) was approximately 1 °C.

For Boardtree Creek, the RMSE for hourly temperatures was 0.6 °C greater than the RMSE for 24-hour moving average hourly temperatures. This difference was an indication of error from the periodic model as shown in figure 12*D*. Boardtree Creek is a well shaded low elevation site. Some of the low elevation sites included in the modeling data set of 142 sites were not as well shaded as Boardtree Creek. This would provide some explanation as to why the simulated daily variation was greater than the measured daily variation.

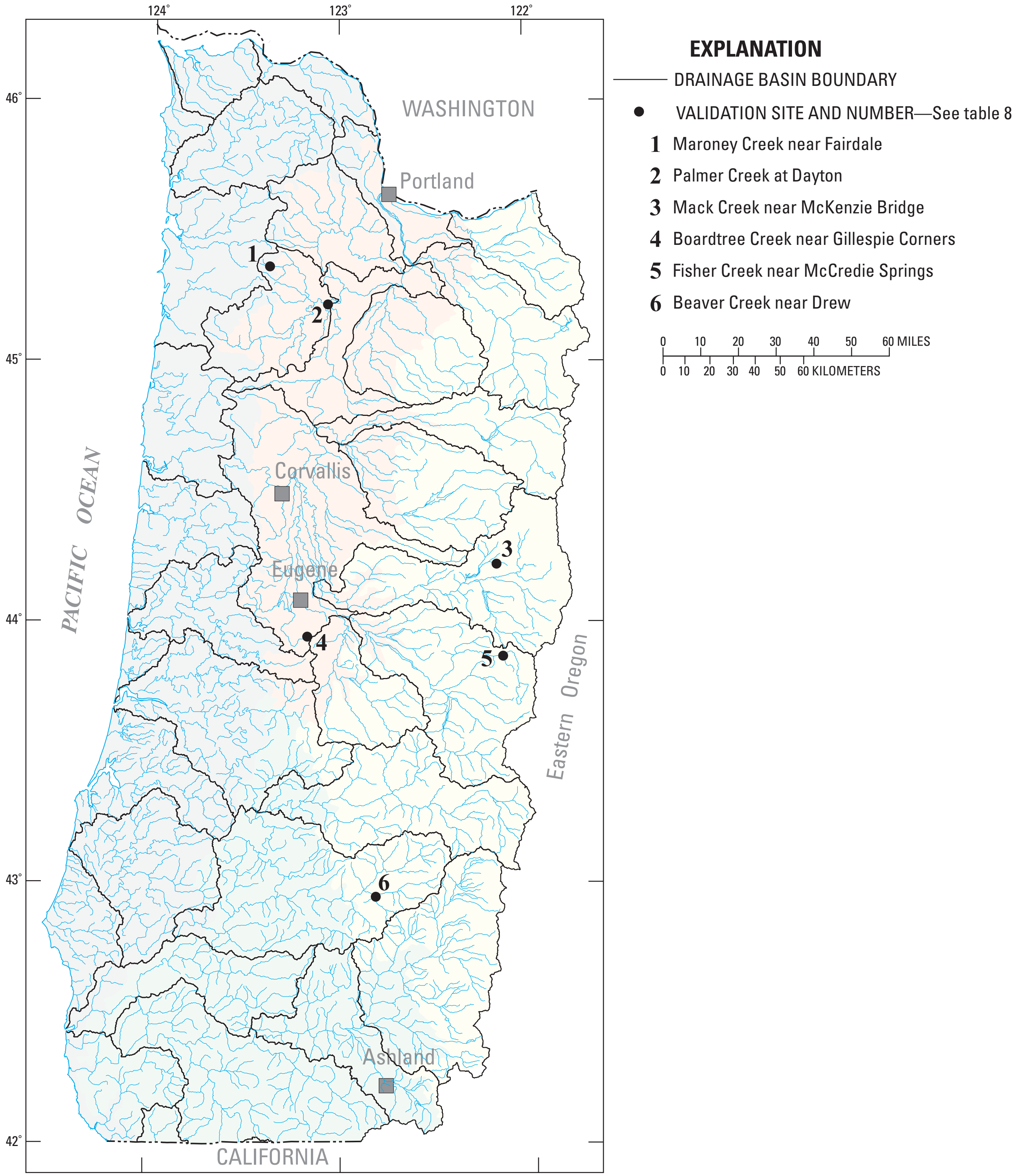

Figure 10. Location of model validation sites.

Table 4. Location, stream habitat, and basin characteristics data for the validation stream sites

Model label	Stream sites					
	Maroney Creek	Palmer Creek	Mack Creek	Boardtree Creek	Fisher Creek	Beaver Creek
Latitude (degree, minute, second)	45 21 48	45 13 09	44 13 10	43 56 31	43 51 56	42 56 34
Longitude (degree, minute, second)	123 23 10	123 04 15	122 10 02	123 10 41	122 08 11	122 49 05
STRMRB	8.5	315.95	333.67	301.11	250.87	359.81
SLOPEPCT	7.05	0.23	8.46	0.74	2.02	1.48
STRMBDEN	97.86	94.12	90.64	93.58	98.4	95.88
MIDCHDEN	92.11	79.28	80.08	87.57	97.59	82.62
DEPTH	21.82	107.73	18.51	51.45	34.2	12.64
WETTEDWD	2.73	5.83	4.52	3.03	6.05	6.31
SBSUBSTF	0	90.91	1.8	63.64	12.73	3.64
SBSUBSTS	14.55	0	0	10.91	5.45	9.09
SBSUBSTG	29.09	0	14.6	23.64	20	18.18
SBSUBSTC	38.18	9.09	41.8	0	50.91	41.82
SBSUBSBO	18.18	0	38.2	1.82	10.91	20
SBSUBSBE	0	0	3.6	0	0	7.27
BASBEARA	76	17	297	348	320	298
BASBEARS	0.9703	0.2924	-0.8910	-0.2079	-0.6428	-0.8829
BASBEARC	0.2419	0.9563	0.4540	0.9781	0.7660	0.4695
STRMCHBE	43	17	320	350	320	300
BASINKM2	3.38	82.35	5.27	4.6	28.16	89.03
BASMELEV	557.85	76.77	1221.49	302.71	1315.73	973.61
BASOELEV	216.4	23	779.9	197.2	815.1	410.9
BASXELEV	786	355	1625.8	423.6	1735.5	1563.4
STCHMELV	417.56	34.49	993.77	225.9	932.61	592.98
BASMSLOP	38.71	6.08	46.89	20.93	38.25	29.28
STMCHSLO	7.05	0.07	10.4	1.78	1.92	2.23
BASFOREA	85.93	0.85	100	89.44	99	89.4
BASOPENA	14.07	99.15	0	10.56	1	10.6
DENBASFA	97.18	98.04	91.32	94.86	90	85.28
STCHFORA	78.33	0	100	94.57	100	100
STCHOPA	21.67	100	0	5.43	0	0
DNSTCHFA	93.02	0	92.95	89.1	95.39	86.52
BASMSATC	13.76	16.74	14.26	16.34	13.67	15.69
STMSUATC	13.82	16.82	14.23	16.33	13.79	15.72
OUTMSATC	14.28	16.72	14.28	16.33	14.22	16.44
XCOORD	0.3809	0.4914	0.8636	0.4522	0.8267	0.5826
YCOORD	0.8060	0.7707	0.5590	0.4602	0.4425	0.2174

Table 5. Comparison of static, 24-hour moving average, and hourly model errors for the simulation period (June 21, 1999, to September 20, 1999) for the validation stream sites

[**Abbreviations:** ^{o}C, degrees Celsius; N, number of data points; *Tobs*, measured hourly water temperature; *Tsim*, simulated hourly water temperature; **Model error:** Static model error, measured mean temperature of the simulation period – simulated mean temperature of the simulation period; RMSE, root mean square error = $\sqrt{\frac{1}{N}\sum_{n=1}^{N}(Tobs - Tsim)^2}$

	Stream sites					
	Maroney Creek	**Palmer Creek**	**Mack Creek**	**Boardtree Creek**	**Fisher Creek**	**Beaver Creek**
Static model error (^{o}C)	-0.72	-2.21	0.32	0.31	-3.18	0.19
24-hour moving average model error (RMSE) (^{o}C)	0.70	0.95	2.77	0.97	2.41	0.49
Hourly model error (RMSE) (^{o}C)	0.84	1.05	3.04	1.63	2.32	0.64

For Mack Creek, the static model, which uses only site data (field measurements and GIS basin characteristics) as input, was able to simulate the mean temperature of the simulation period to within almost 0.3 ^{o}C of measured mean temperature (table 5). The periodic component also appeared accurate (fig. 12*C*). However, the chaotic model component generally under simulated. The chaotic component is dependent on various climatic time series inputs. Most of the climate data were collected at larger towns, which are at lower elevations. These climate stations may not have been adequate to represent the climate near Mack Creek, which is at a higher elevation than most basins and located closer to the eastern edge of the study region.

Interestingly, the chaotic and periodic simulated components for Fisher Creek did not appear to contribute significant error to the simulated 24-hour moving average and hourly temperatures (figs. 11*E* and 12*E*). However, the simulated mean temperature, for possible reasons explained above, was greater than the measured mean temperature. With the exception of being shifted upwards, the simulated hourly temperatures appear to be almost identical to the measured hourly temperatures.

If a model user were to make several instantaneous temperature measurements at a site during the simulation period (from June to September), it might be possible to combine this measured information with the simulated results. If the measured measurements are consistently above or below the simulated hourly time series by the same magnitude, it would seem reasonable for the model user to shift the simulated time series accordingly. During the 1999 field surveys to the 148 sites used in the study, a manual instantaneous temperature measurement was made at each site with a lab calibrated thermometer. (These measurements were made for verification of the temperature data loggers.) The Fisher Creek site field survey was made on August 24, 1999. The instantaneous water temperature measurement, made at 1430, was 10.8 ^{o}C. The model simulated a water temperature of 13.2 ^{o}C for the same date and time. With a difference of 2.4 ^{o}C, a downward shift was then applied to the simulated time series as shown in figures 11*E* and 12*E*. This resulted in a much closer match with the measured time series.

Although the models performed less adequately for some sites at higher elevations, the model error in this study were comparable to model error in other water temperature regionalization studies in Georgia and Washington (Dyar and Alhadeff, 1997; Collings, 1973). Those two studies used a harmonic (sinusoidal) function to predict daily mean water temperatures. Differences between the measured and predicted harmonic curves were sometimes greater than 5 ^{o}C for some sites.

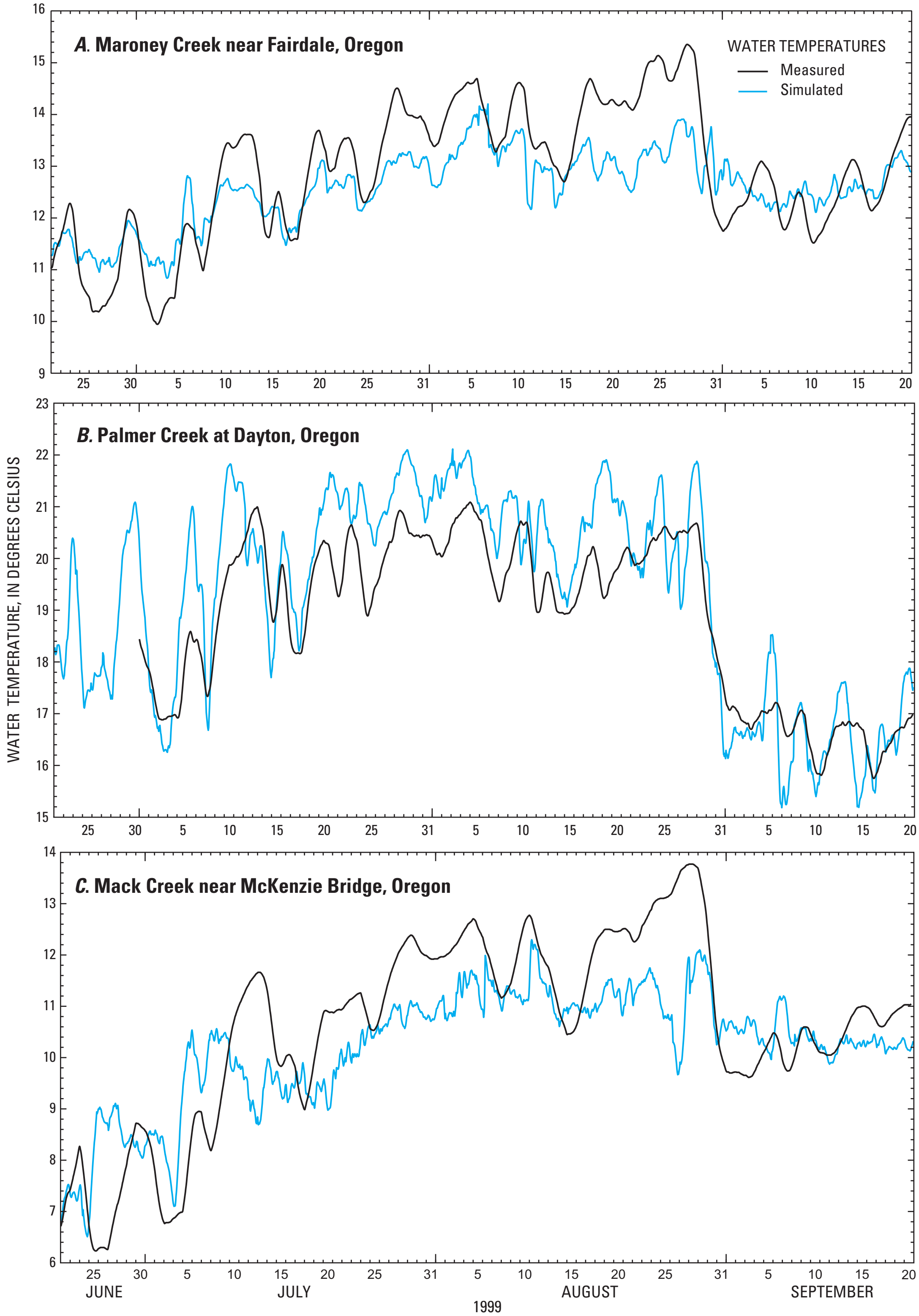

Figure 11. Measured and simulated 24-hour moving average hourly water temperatures for selected sites in western Oregon.

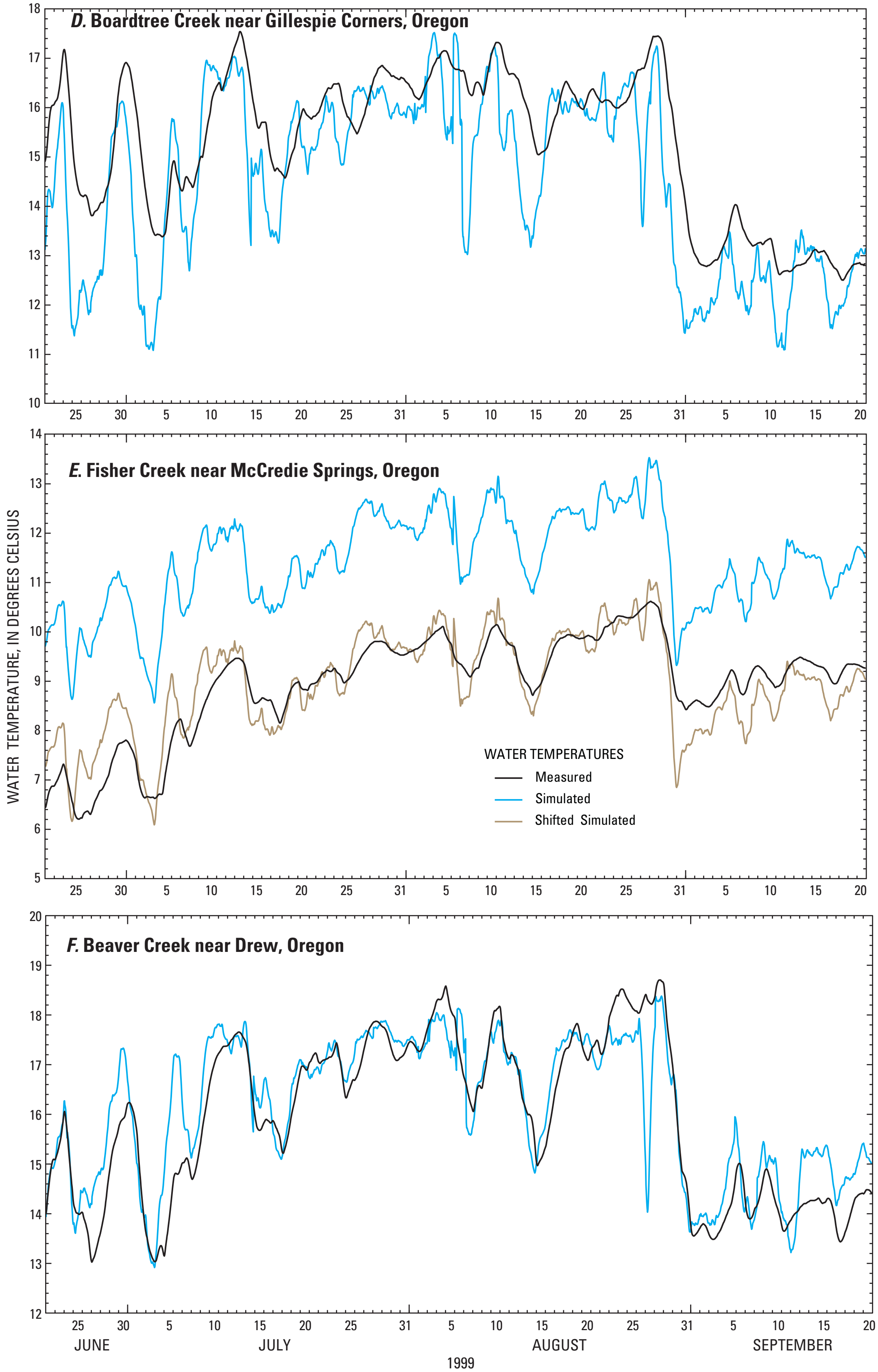

Figure 11.—*Continued.*

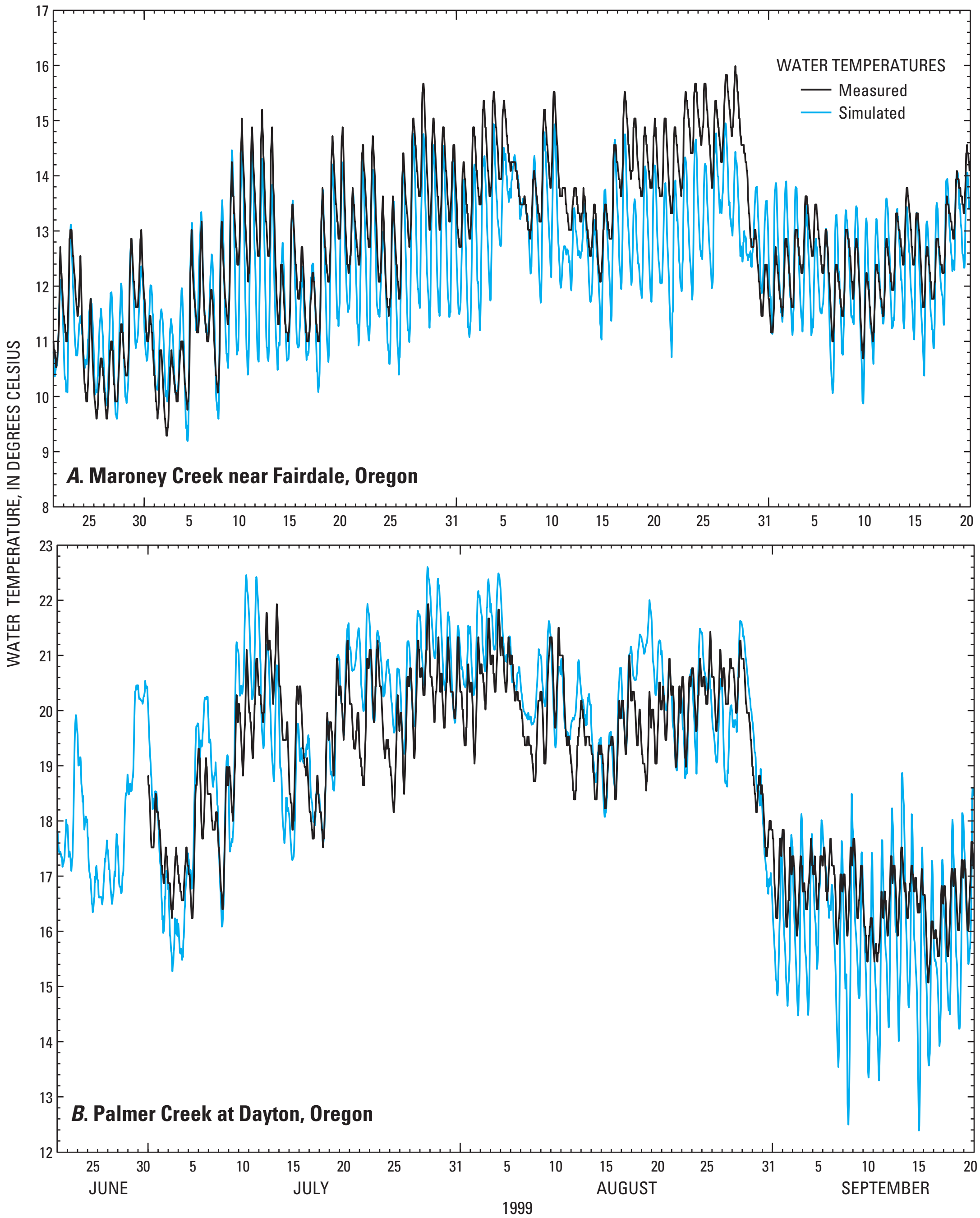

Figure 12. Measured and simulated hourly water temperatures for selected sites in western Oregon.

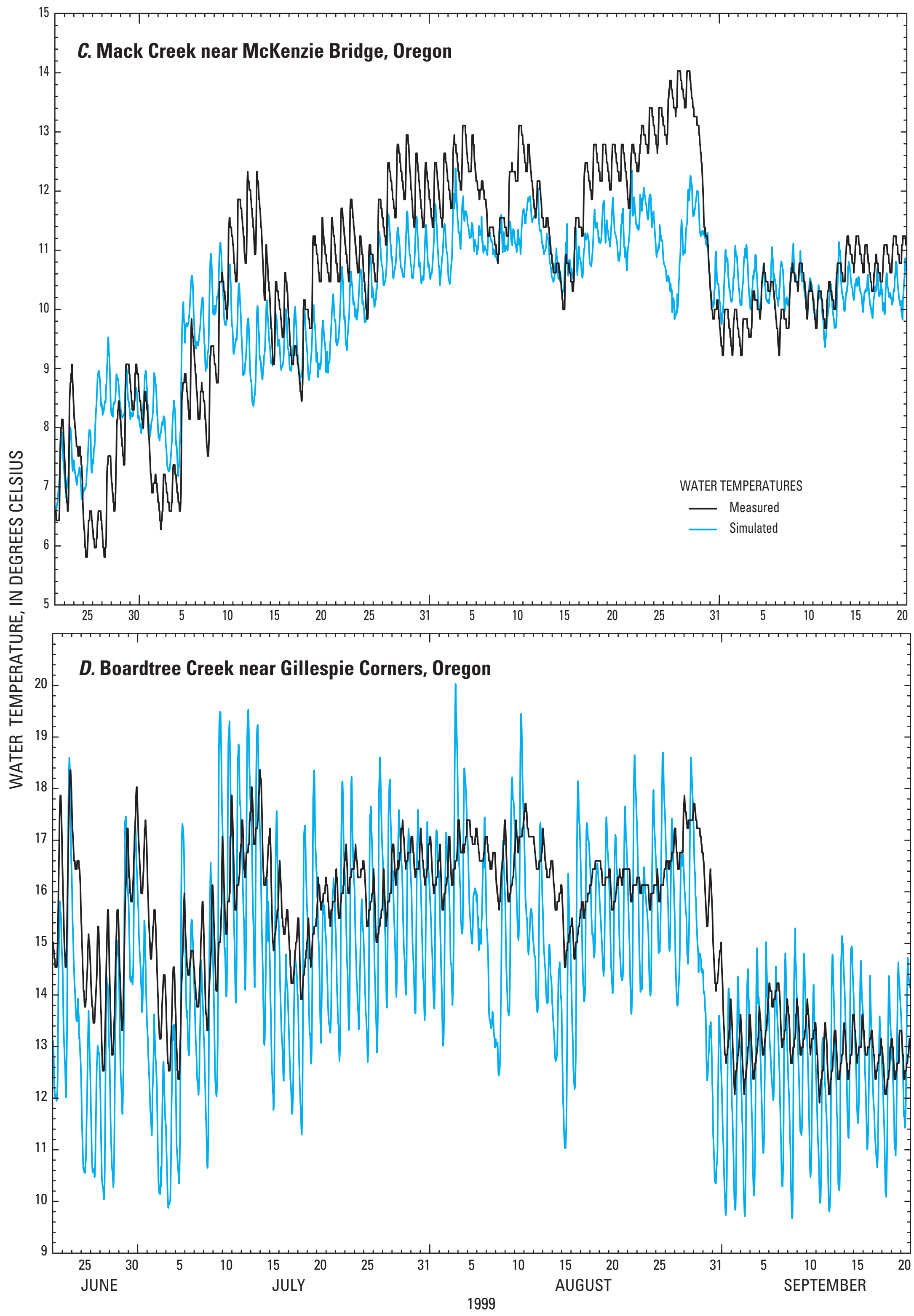

Figure 12.—*Continued.*

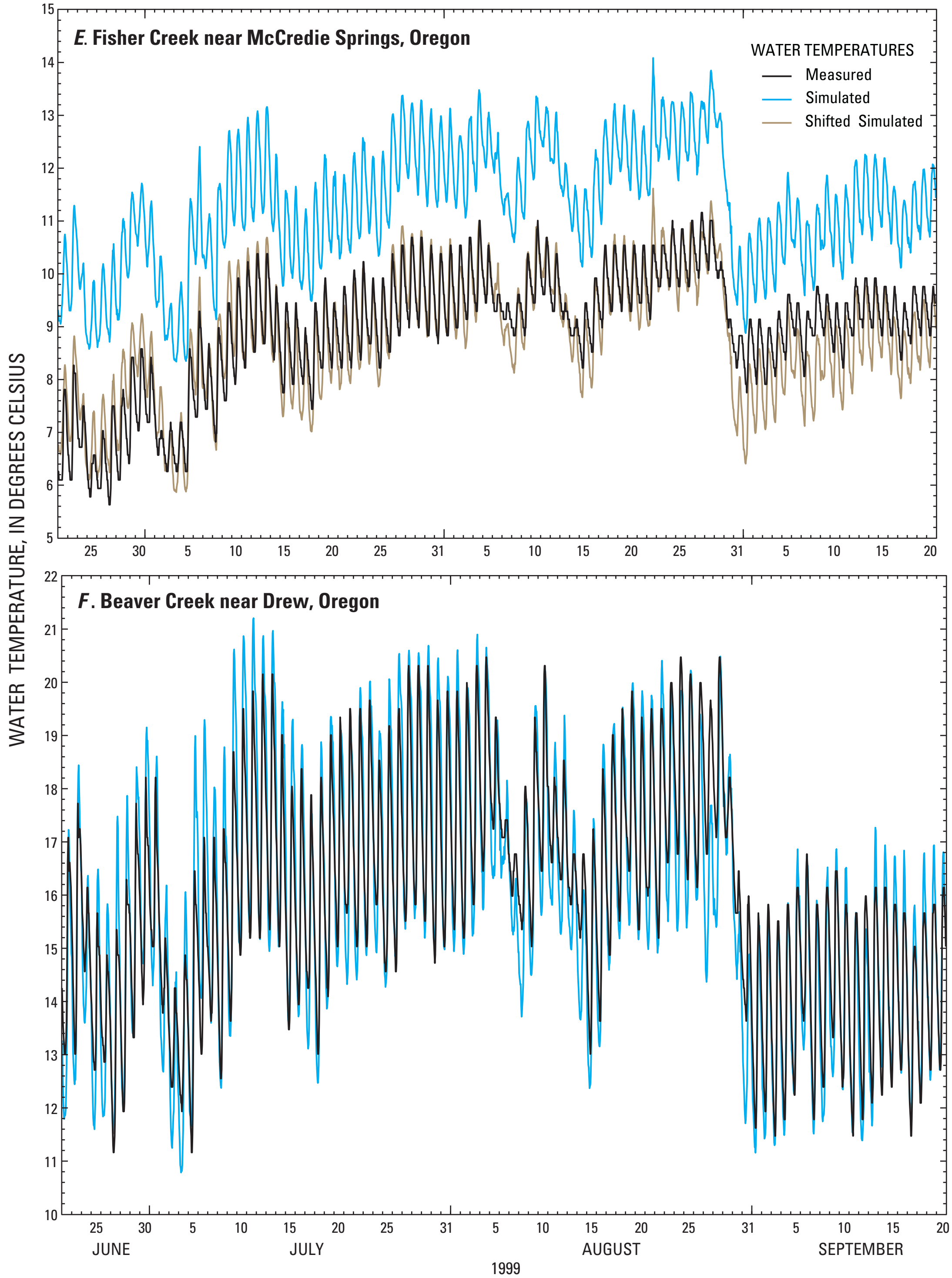

Figure 12.—*Continued.*

MODEL APPLICATION

Shade Adjustment

A major objective of the study was creating a model that could be used to simulate water temperatures representing “natural” (undisturbed) conditions at stream sites in western Oregon that currently are in a disturbed state. Water-quality professionals in regulatory agencies need this information to be able to (1) set reach-specific temperature standards that have a scientific basis, (2) identify and prioritize stream reaches that are grossly out of compliance and in most need of remediation, and (3) establish attainable temperature-reduction goals for reaches that have elevated water temperatures.

A model user must still measure and collect existing riparian field data at a site of interest. However, in addition to simulating water temperatures for existing conditions, it is possible to simulate water temperatures for minimum and maximum shade scenarios by adjusting the measured values used for the shade and vegetation variables. These variables include streambank and mid channel densiometer shade measurements in addition to estimated percent of the basin that is forested or open. Table 6 shows existing and adjusted shade and vegetation variable values for the validation sites.

Two of the six validation stream sites, Mack Creek and Fisher Creek, were in pristine settings. Measured values for the shade and vegetation variables for these two sites already represented near maximum shade conditions. However, the other four sites, Palmer Creek, Maroney Creek, Boardtree Creek, and Beaver Creek, had measured values that were between the maximum and minimum values for the shade and vegetation variables. Using the variable values shown in table 6, minimum and maximum shade scenarios were simulated for Maroney Creek, Boardtree Creek, and Beaver Creek. Because the existing shade for Palmer Creek was already minimal, only the maximum shade scenario was simulated for that site. Results for the adjusted shade simulations are shown in table 7. The simulated 24-hour moving average temperature time series for the minimum and maximum shade in addition to the existing conditions are shown in figure 13. Maximizing shade at Palmer Creek resulted in the greatest decrease in water temperature, approximately 4 ^{o}C on average. However, maximizing shade at Maroney Creek, which was already reasonably well shaded, decreased water temperature only by approximately 0.5 ^{o}C on average.

Like any statistical models, ANN models have their limitations as tools for extrapolation. These models become more unstable when they are asked to make predictions based on inputs that may be outside the boundaries of the input data set used to create the models. An indication of this instability can be seen in figure 13*A*. Simulated water temperatures under minimum shade conditions at Maroney Creek are unrealistically low for a few days in early July.

Table 6. Existing and adjusted shade and vegetation variable values for selected stream sites

Model label	Explanation	Existing conditions				Simulated conditions	
		Maroney Creek	Palmer Creek	Boardtree Creek	Beaver Creek	Minimum shade	Maximum shade
STRMBDEN	Stream bank densiometer (percent)	97.86	94.12	93.58	95.88	33	100
MIDCHDEN	Midchannel densiometer (percent)	92.11	79.28	87.57	82.62	5	100
BASFOREA	Basin forest area (percent)	85.93	0.85	89.44	89.4	5	100
BASOPENA	Basin open area (percent)	14.07	99.15	10.56	10.6	95	0
STCHFORA	Stream channel forest area (percent)	78.33	0	94.57	100	5	100
STCHOPA	Stream channel open area (percent)	21.67	100	5.43	0	95	0

Table 7. Mean of simulated hourly temperatures for varying shade conditions for selected stream sites

[**Mean temperature:** Mean of simulated hourly water temperatures for the simulation period from June 22, 1999, to September 20, 1999; **Abbreviations:** (ºC), degrees Celsius; –, no data]

Shade condition	Maroney Creek		Palmer Creek		Boardtree Creek		Beaver Creek	
	Mean temperature (ºC)	Difference from existing shade (ºC)	Mean temperature (ºC)	Difference from existing shade (ºC)	Mean temperature (ºC)	Difference from existing shade (ºC)	Mean temperature (ºC)	Difference from existing shade (ºC)
Minimum	15.44	+3.09	–	–	17.38	+3.07	17.64	+1.75
Existing	12.36	–	18.83	–	14.32	–	15.89	–
Maximum	11.83	-0.53	14.68	-4.15	12.72	-1.59	13.62	-2.27

Climate Adjustment

Time series output from the ANN models simulated hourly water temperatures representing climatic conditions from June 21 to September 20, 1999. However, the summer of 1999 in western Oregon was cooler and wetter than normal. Table 8 shows the departure of 1999 mean monthly water temperatures from the period of record of long-term USGS water temperature monitoring stations in western Oregon. These stations are located on relatively unregulated streams ranging from large rivers to creeks. They are generally in the northern and southern regions of the study area. Unregulated long-term stations in the central region of the study area were less common.

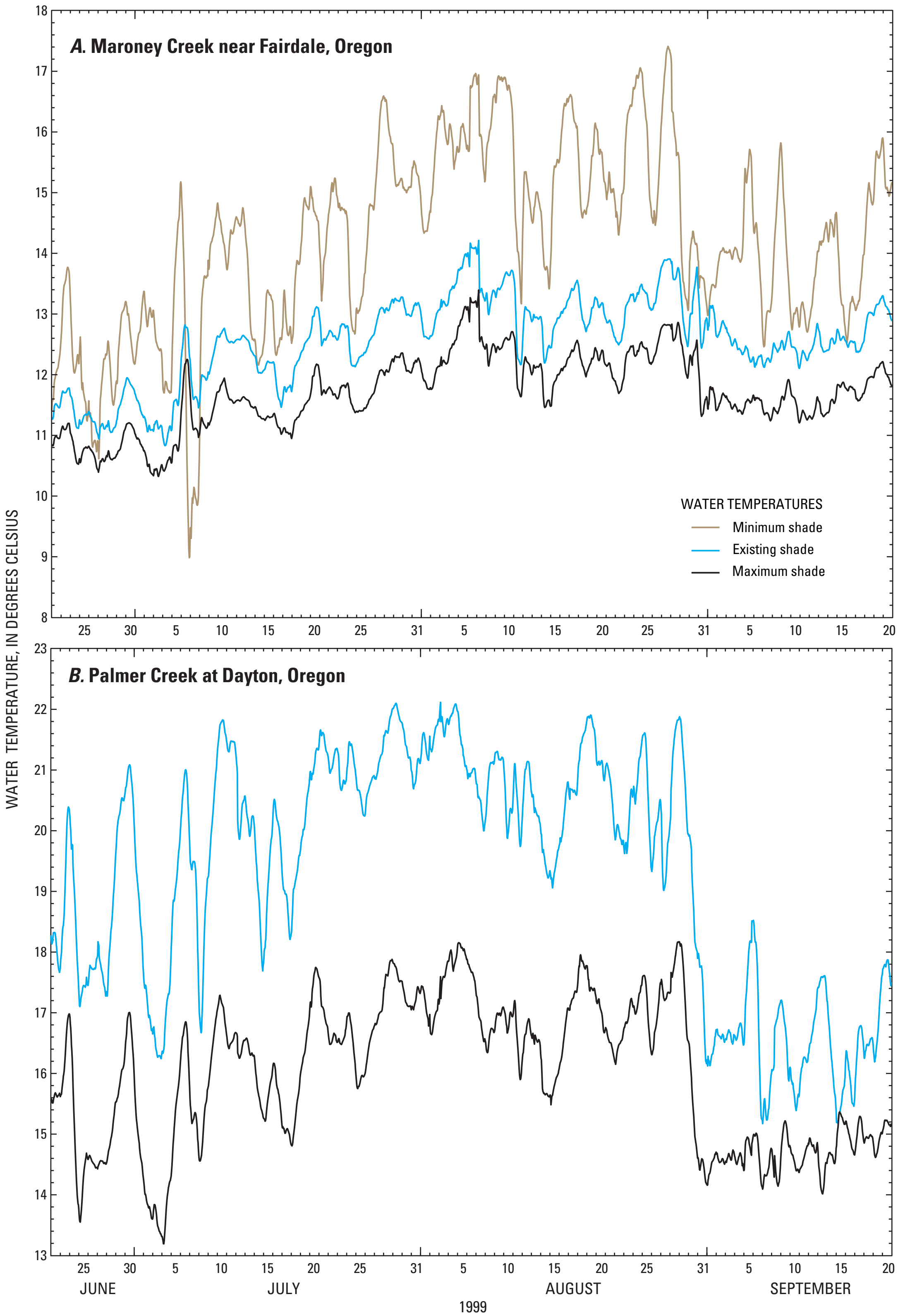

Figure 13. Simulated 24-hour moving average hourly water temperatures for varying shade conditions for selected sites in western Oregon.

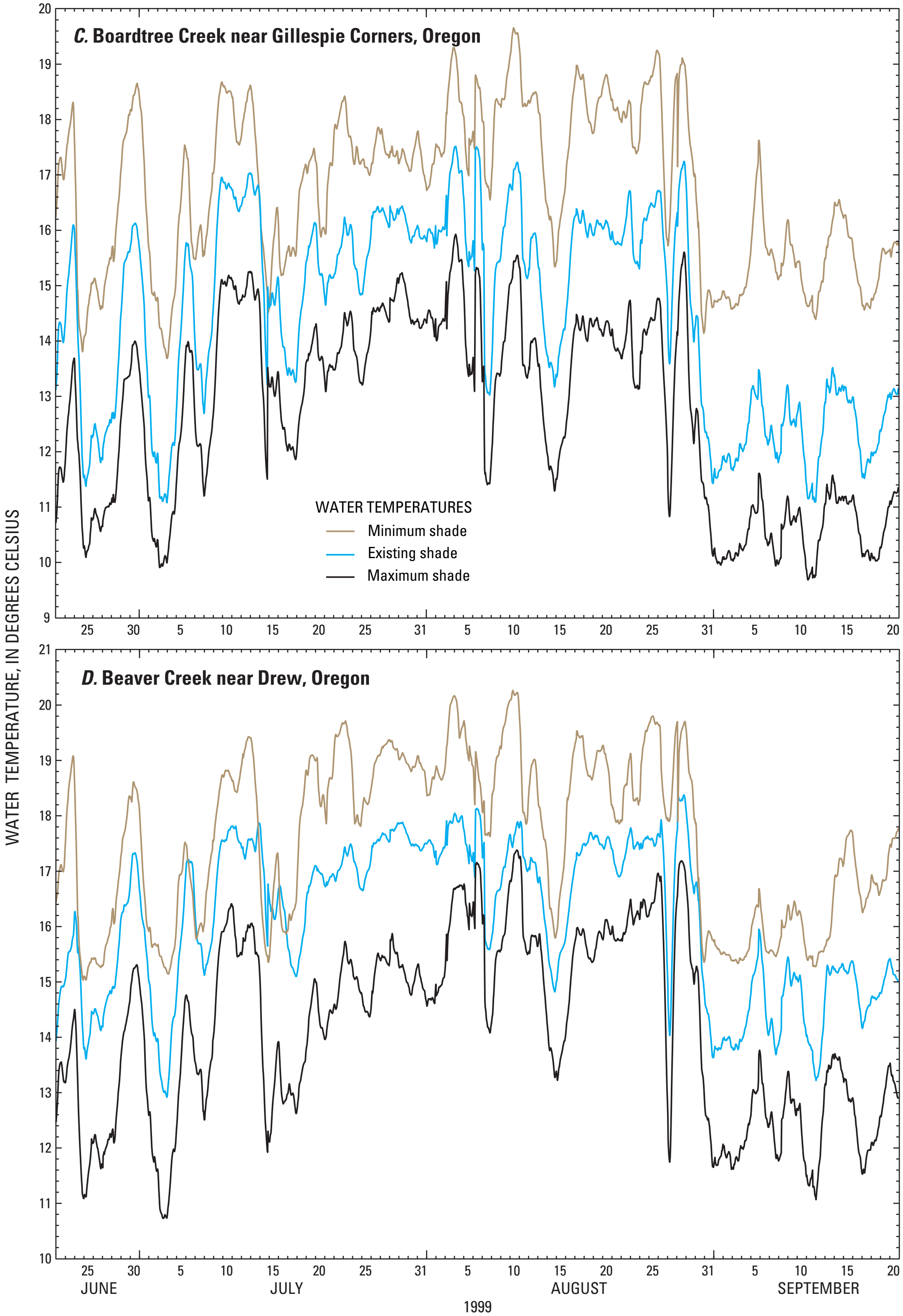

Figure 13.—*Continued.*

Table 8. Departure of 1999 mean monthly water temperatures from the period of record at selected stations in western Oregon

[**Abbreviations:** USGS, U.S. Geological Survey; (°C), temperature in degrees Celsius; (km^2), square kilometers; Sept., September; –, data not available]

USGS station No.	Station name	Drainage area (km^2)	Period of record	Temperature difference (°C)			
				June	July	August	Sept.
11492200	Crater Lake near Crater Lake, Oregon	67.9	1979-00	-2.3	-2.3	-1.1	-0.2
14138850	Bull Run River near Multnomah Falls, Oregon	124	1978-01	-1.9	-1.1	-0.1	-0.9
14138870	Fir Creek near Brightwood, Oregon	14.1	1978-00	-1.5	-0.9	-0.2	-0.4
14138900	North Fork Bull Run River near Multnomah Falls, Oregon	21.5	1979-00	-0.8	-0.5	-0.1	-0.6
14139800	South Fork Bull Run River near Bull Run, Oregon	39.9	1979-01	-1.4	-1.2	-0.2	-0.7
14200400	Little Abiqua Creek near Scotts Mills, Oregon	25.4	1993-00	-0.2	-0.5	0.39	0.0
14201300	Zollner Creek near Mount Angel, Oregon	38.8	1993-01	-0.6	-1.2	0.16	-1.0
14207200	Tualatin River at Oswego Dam near West Linn, Oregon	1,829	1991-01	-0.5	–	-0.1	-0.1
14246900	Columbia River at Beaver Army Terminal, Oregon	665,371	1993-00	-0.7	-1.1	-0.2	-0.2
14330000	Rogue River below Prospect, Oregon	982	1977-00	-2.0	-1.0	-0.3	-0.5
14337500	Big Butte Creek near McLeod, Oregon	635	1979-00	-1.0	-0.8	-0.2	-0.2
14337870	West Branch Elk Creek near Trail, Oregon	36.8	1978-00	-1.0	-1.1	-0.6	-1.6
14338000	Elk Creek near Trail, Oregon	334	1979-00	-2.5	-1.0	1.3	0.4
14369500	Applegate River near Applegate, Oregon	1,808	1979-01	-2.0	-1.1	-1.1	-1.1

Some possible options for the model user in dealing with year to year climate variations include:

(1) Simulate hourly water temperature time series for a non-1999 year (or years) of interest for a stream site of interest. To do this, the user would need to acquire hourly climatological time series data for the simulation period (June 21 to September 20) for the non-1999 year that were collected at the same 25 climate stations in western Oregon used in the model development. If data from a certain station were unavailable, interpolation techniques would have to be used to recreate the time series. The the non-1999 year climatological time-series data would also have to be normalized to Corvallis and Eugene climatological time-series data before it is used as input to the models.

(2) Adjust computed 1999 mean monthly water temperature values. The user would simulate a water temperature time series for 1999 for a stream site of interest, and then compute the mean monthly values. These values would be then adjusted to the long-term climate trend using the mean-monthly departures for an appropriate station that is listed in table 8. As an example, table 8 shows that the mean water temperature for June 1999 at the Elk Creek station was 2.5 °C less than the period of record mean water temperature for the month of June. A model user who is using the Elk Creek station as a guide would add 2.5 °C to the June mean water temperature.

(3) Simulate a water temperature time series for 1999 for a stream site of interest, and make no adjustments at all. The model user could state that their water temperatures time series output were simulated using 1999 climatological time-series as input, and that 1999 was cooler and wetter than average for most locations in western Oregon. They could also include data from table 8 to show how much 1999 water temperatures departed from long-term water temperatures.

Future Improvements

Simulation results using data from the six validation sites suggest that water temperatures may be affected by upstream ground-water processes at some stream sites to a greater extent than originally thought. The specific physical habitat variables measured in the field surveys, and then subsequently used as model input, may not be adequate in capturing these anomalies. Future water temperature ANN modeling studies should investigate other possible physical habitat variables to include in the field surveys. When more information about a site and its upstream environment can be collected, a more reliable a temperature estimate can be made. A series of temperature measurements collected along the reach, even upstream of the defined reach used in the habitat survey, might locate significant springs and cold water pockets that are affecting water temperature at the site. Also, additional temperature measurements collected at the site at different dates during the summer period could be used to shift the simulated temperature time series if needed.

SUMMARY AND CONCLUSIONS

Stream water temperature is a major concern in Oregon. Temperature affects dissolved oxygen concentrations, biochemical oxygen demand rates, algae production, and contaminant toxicity. Temperature also has a major effect on the distribution, health, and survival of native salmonids (salmon, trout, and charr) and other aquatic species. Although warm water temperatures occur naturally, they are also induced by anthropogenic activities such as effluent point sources, removal of riparian shade, stream channel alterations, water diversions, and urbanization. To reduce the effects of elevated water temperatures, the State of Oregon is developing Total Maximum Daily Load (TMDL) plans for stream reaches that exceed State standards. A reliable method of estimating water temperatures that reflect natural or undisturbed conditions for these currently disturbed reaches was needed. In response to this need, ANN models were developed to estimate “natural” water temperatures in small streams using data from at 148 sites throughout western Oregon from June to September 1999. The sites were located on 1st-, 2nd-, or 3rd-order streams having undisturbed or minimally disturbed conditions. Data collected at each site included continuous hourly water temperature and riparian habitat. Additional data pertaining to the landscape characteristics of the basins upstream of the sites were assembled using geographic information system techniques. Hourly meteorological time series data collected at 25 locations within the study region were also assembled.

Clustering analysis were used to partition 142 sites into 3 groups. Separate models were developed for each group. The riparian habitat, basin characteristic, and meteorological time series data were independent variables and water temperature time series were dependent variables to the models, respectively. Approximately one-third of the data vectors were used for model training and the remaining two-thirds were used for model testing. Critical input variables included riparian shade, site elevation, and percent forested area of the basin. Coefficient of determination and the RMSE for the models ranged from 0.88 to 0.98 and 0.05 to 0.59 ^{o}C, respectively. Final output from the models included simulated hourly and 24-hour moving average temperature time series from June to September.

The models also were tested using temperature time series, habitat, and basin landscape data from 6 validation sites, located throughout the study area, that were not among the 142 sites that were used to develop the models. The error between measured and simulated hourly water temperatures for the simulation period for these sites ranged from 0.84 to 3.04 ^{o}C. This range of error is comparable to error in other water temperature regionalization studies. It is possible that error at some of the validation sites could be the result of the effect of ground-water processes (such springs and cold-water pockets) on water temperatures upstream of the site. These processes may not have been adequately identified and quantified during the site field surveys, and subsequently not used in the model formulation. The capabilities of the models might be improved with further research into the interactions between ground-water processes and water temperature.

The validation sites were also used to simulate water temperatures for minimum and maximum shade scenarios by adjusting the measured values used for the shade and vegetation variables. Maximizing shade at one site resulted in a decrease in water temperature of about 4 ^{o}C on average. However, maximizing shade at another site that was already heavily forested decreased water temperature by only about 0.5 ^{o}C.

The water temperature models developed in the study can estimate approximate natural water temperatures in small unregulated streams in western Oregon having either disturbed or undisturbed riparian conditions. This methodology should useful to agencies engaged in monitoring stream health. Using the models may save the expense of installing water temperature data loggers at a site. Estimates of water temperature under natural shade conditions, which can be scientifically defended, are needed for future TMDL activities. These models would not substitute the use of mechanistic water temperature modeling in the lower reaches of rivers in a TMDL study. However, output from the ANN models could be used as the upstream boundary input to the mechanistic models.

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Appendix A. Site list for water temperature and habitat survey data collection

[**Agency/Project abbreviations:** USGS, U.S. Geological Survey; OWEB, Oregon Watershed Enhancement Board; ODEQ/COAST, Oregon Department of Environmental Quality coastal study sites; ODEQ/REMAP, Oregon Department of Environmental Quality REMAP study sites; USFS, U.S. Forest Service]

Site model label name	Latitude (degrees, minutes, and seconds)	Longitude (degrees, minutes, and seconds)	Agency/Project	Stream name
abbott15	42 54 58	122 31 37	USGS/OWEB	North Fork Abbott Creek near Union Creek, Oregon
anvil52	42 44 25	124 23 46	USGS/OWEB	Anvil Creek near Port Orford, Oregon
bauns3	45 41 23	123 00 58	USGS/OWEB	Unnamed tributary to Baunswick Canyon, Mountaindale, Oregon
bear29	44 58 54	123 52 57	USGS/OWEB	Bear Creek near Rose Lodge, Oregon
bear39	43 32 58	122 12 40	USGS/OWEB	Unnamed tributary to Bear Creek near Cascade Summit, Oregon
bear69	44 45 38	122 49 25	USGS/OWEB	Bear Branch near Sublimity, Oregon
beaver21	42 56 34	122 49 05	USGS/OWEB	Beaver Creek near Drew, Oregon
beaver25	44 51 01	122 49 29	USGS/OWEB	Beaver Creek near Sublimity, Oregon
bickmo46	44 19 32	122 50 24	USGS/OWEB	Bickmore Creek near Crawfordsville, Oregon
bigbnd56	43 25 20	122 36 01	USGS/OWEB	Big Bend Creek near Steamboat, Oregon
boardt41	43 56 31	123 10 41	USGS/OWEB	Boardtree Creek near Gillespie Corners, Oregon
canyon35	44 20 37	122 21 56	USGS/OWEB	Canyon Creek near Upper Soda, Oregon
cast60	45 22 39	121 51 01	USGS/OWEB	Cast Creek near Rhododendron, Oregon
champ67	45 15 10	122 52 58	USGS/OWEB	Champoeg Creek near Butteville, Oregon
cheat64	44 42 07	121 55 20	USGS/OWEB	Cheat Creek near Marion Forks, Oregon
coal36	44 58 21	122 30 23	USGS/OWEB	Coal Creek near Wilhoit, Oregon
coast6	45 09 26	123 31 23	USGS/OWEB	Coast Creek near Willamina, Oregon
cummin12	44 16 02	124 06 02	USGS/OWEB	Cummins Creek near Yachats, Oregon
dickey62	44 55 54	122 03 05	USGS/OWEB	Dickey Creek near Breitenbush Hotsprings, Oregon
dickey66	45 06 46	122 30 20	USGS/OWEB	Dickey Creek near Molalla, Oregon
drift14	44 26 58	123 56 56	USGS/OWEB	Drift Creek near Tidewater, Oregon
evans19	42 36 01	122 58 37	USGS/OWEB	Evans Creek near Sams Valley, Oregon
fisher38	43 51 56	122 08 11	USGS/OWEB	Fisher Creek near McCredie Springs, Oregon
fourbt18	42 30 15	122 26 08	USGS/OWEB	Fourbit Creek near Butte Falls, Oregon
fourth28	44 48 05	123 42 55	USGS/OWEB	Fourth of July Creek near Valsetz, Oregon
gales4	45 38 35	123 21 40	USGS/OWEB	Gales Creek near Glenwood, Oregon
gribbl72	45 13 51	122 41 57	USGS/OWEB	Gribble Creek near Barlow, Oregon
hamilt33	44 30 41	122 43 13	USGS/OWEB	Hamilton Creek near Waterloo, Oregon
image63	44 58 15	122 19 50	USGS/OWEB	Image Creek near Elkhorn, Oregon
indigo50	42 34 47	123 47 19	USGS/OWEB	East Fork Indigo Creek near Galice, Oregon
junipr45	43 36 53	122 19 16	USGS/OWEB	Juniper Creek near McCredie Springs, Oregon
kelsey10	43 46 38	122 15 23	USGS/OWEB	Kelsey Creek near McCredie Springs, Oregon
kentuck30	43 26 47	124 06 21	USGS/OWEB	Kentuck Creek near Allegany, Oregon
knob61	44 52 48	122 02 12	USGS/OWEB	Knobrock Creek near Breitenbush Hotsprings, Oregon
little42	44 18 59	123 04 31	USGS/OWEB	Little Muddy Creek near Halsey, Oregon
lobstr53	42 36 18	124 11 12	USGS/OWEB	South Fork Lobster Creek near Illahe, Oregon
lonewo20	43 00 35	122 31 14	USGS/OWEB	Lonewoman Creek near Union Creek, Oregon
marony40	45 21 48	123 23 10	USGS/OWEB	Maroney Creek near Fairdale, Oregon
mcfee1	45 24 05	122 56 22	USGS/OWEB	Mcfee Creek at Scholls, Oregon
moose34	44 25 32	122 23 16	USGS/OWEB	Moose Creek near Cascadia, Oregon

Appendix A. Site list for water temperature and habitat survey data collection—*Continued*

Site model label name	Latitude	Longitude	Agency/Project	Stream name
	(degrees, minutes, and seconds)			
muddy43	44 22 39	123 17 48	USGS/OWEB	Muddy Creek near Bellfountain, Oregon
nell54	42 05 54	124 10 39	USGS/OWEB	Nell Creek near Harbor, Oregon
nfpedee7	44 46 50	123 27 09	USGS/OWEB	North Fork Pedee Creek near Pedee, Oregon
olalla22	43 06 49	123 30 22	USGS/OWEB	Olalla Creek near Tenmile, Oregon
opal27	44 50 43	122 12 23	USGS/OWEB	Opal Creek near Elkhorn, Oregon
palmer71	45 13 09	123 04 15	USGS/OWEB	Palmer Creek at Dayton, Oregon
panther5	45 15 14	123 12 08	USGS/OWEB	Panther Creek near Carlton, Oregon
poodle44	44 05 48	123 29 16	USGS/OWEB	Poodle Creek near Noti, Oregon
powell55	42 15 51	123 18 00	USGS/OWEB	Powell Creek near Williams, Oregon
rain57	43 08 56	122 25 20	USGS/OWEB	Rainbow Creek near Clearwater, Oregon
redbl16	42 47 58	122 16 10	USGS/OWEB	Red Blanket Creek near Crater Lake, Oregon
rock13	44 11 14	124 06 24	USGS/OWEB	Rock Creek at Roosevelt Beach, Oregon
rock24	45 08 42	122 43 15	USGS/OWEB	Rock Creek near Yoder, Oregon
rock26	44 42 33	122 25 16	USGS/OWEB	Rock Creek near Gates, Oregon
sfm9	43 57 10	122 00 57	USGS/OWEB	South Fork McKenzie River near Foley Springs, Oregon
south23	43 06 04	123 57 27	USGS/OWEB	South Fork Elk Creek near Dora, Oregon
stilsn11	44 31 28	123 28 53	USGS/OWEB	Stilson Creek near Wren, Oregon
tanner59	45 35 47	121 56 37	USGS/OWEB	Tanner Creek near Bonneville, Oregon
tobe32	44 20 14	123 34 39	USGS/OWEB	Tobe Creek near Alsea, Oregon
trail37	44 00 23	122 10 18	USGS/OWEB	Trail Creek near Foley Springs, Oregon
trib68	45 16 58	122 49 21	USGS/OWEB	Unnamed tributary to Willamette River near Butteville, Oregon
trout65	44 23 58	122 20 48	USGS/OWEB	Trout Creek near Upper Soda, Oregon
tryon70	45 25 27	122 39 36	USGS/OWEB	Tryon Creek at Lake Oswego, Oregon
warble2	45 34 11	122 57 19	USGS/OWEB	Unnamed tributary to McKay Creek near North Plains, Oregon
wfa48	42 09 03	122 42 53	USGS/OWEB	West Fork Ashland Creek near Ashland, Oregon
wfmill31	43 29 11	124 00 45	USGS/OWEB	West Fork Millicoma River near Allegany, Oregon
wfmull51	42 43 38	123 52 31	USGS/OWEB	West Fork Mule Creek near Marial, Oregon
wikiup17	42 36 35	122 17 22	USGS/OWEB	Wickiup Creek near Rocky Point, Oregon
wolf58	43 13 53	122 56 52	USGS/OWEB	Wolf Creek near Peel, Oregon
woods47	44 32 44	123 29 39	USGS/OWEB	Woods Creek near Wren, Oregon
c3riv	45 10 42	123 45 57	ODEQ/COAST	Three Rivers at River mile 10.1
cands	45 45 43	123 54 15	ODEQ/COAST	Anderson Creek at River mile 2.73
cbensm	45 35 09	123 30 57	ODEQ/COAST	Ben Smith Creek at River mile 0.44
cbig1	44 10 15	124 06 21	ODEQ/COAST	Big Creek at River mile 0.79
cbrock	43 08 30	122 33 11	ODEQ/COAST	Black Rock Fork at River mile 4.8
cbvr6	42 05 47	122 59 02	ODEQ/COAST	Beaver Creek at River mile 6.44
cbvrm	45 17 05	123 49 21	ODEQ/COAST	Beaver Creek at River mile 0.79
ccant	43 29 25	122 43 24	ODEQ/COAST	Canton Creek at River mile 15.66
ccarp	45 30 29	123 07 30	ODEQ/COAST	Carpenter Creek at River mile 1.7
cchrm	42 02 43	123 58 47	ODEQ/COAST	Chrome Creek at River mile 0.22

Appendix A. Site list for water temperature and habitat survey data collection—*Continued*

Site model label name	Latitude	Longitude	Agency/Project	Stream name
	(degrees, minutes, and seconds)			
cco	45 35 42	123 44 32	ODEQ/COAST	Company Creek at River mile 0.76
ccoal	43 27 56	122 27 43	ODEQ/COAST	Coal Creek tributary at River mile 2.0
ccum	44 15 58	124 05 24	ODEQ/COAST	Cummins Creek at River mile 1.02
cdoneg	42 54 44	122 38 21	ODEQ/COAST	Donnegan Creek at River mile 2.62
cdumnt	43 05 28	122 48 56	ODEQ/COAST	Dumont Creek at River mile 4.95
cefwin	42 03 03	124 05 22	ODEQ/COAST	East Fork Winchuck River at River mile 1.18
celkh	44 29 59	123 58 47	ODEQ/COAST	Elkhorn Creek at River mile 1.56
cemile	43 14 44	122 47 40	ODEQ/COAST	Emile Creek tributary at River mile 0.76
cfhwk	45 55 56	123 30 25	ODEQ/COAST	Fishhawk Creek at River mile 1.07
cflyn	44 32 19	123 51 04	ODEQ/COAST	Flynn Creek at River mile 1.71
cglen	44 56 52	123 06 04	ODEQ/COAST	Glenn Creek at River mile 5.45
cgrav	45 44 55	123 50 15	ODEQ/COAST	Gravel Creek at River mile 0.34
chalf	43 44 57	123 34 59	ODEQ/COAST	Halfway Creek tributary at River mile 0.29
chall	42 46 07	124 01 45	ODEQ/COAST	Hall Creek at River mile 1.48
chicks	42 39 17	124 00 57	ODEQ/COAST	Hicks Creek off Highway 1160
cjjoe	42 31 25	123 29 00	ODEQ/COAST	Jumpoff Joe Creek at River mile 1.17
cjord	45 33 10	123 29 24	ODEQ/COAST	Jordan Creek at River mile 7.52
cking	43 44 26	122 53 22	ODEQ/COAST	King Creek at River mile 0.24
clnest	45 05 39	123 47 05	ODEQ/COAST	Little Nestucca at River mile 11.6
clnfw	45 29 08	123 44 08	ODEQ/COAST	Little North Fork at River mile 1.5
cmhwk	44 15 32	122 44 12	ODEQ/COAST	Mohawk River at River mile 22.13
cmidd	43 15 22	123 52 41	ODEQ/COAST	Middle Creek at River mile 23.2
cmina	45 13 44	123 37 19	ODEQ/COAST	Mina Creek at River mile 1.43
cmonty	44 34 50	123 55 43	ODEQ/COAST	Montgomery Creek at River mile 0.91
cneha	45 44 33	123 17 05	ODEQ/COAST	Nehalem River near River mile 109
cnest	45 16 41	123 33 02	ODEQ/COAST	Nestucca River at River mile 38.6
cnfwlf	45 47 41	123 23 01	ODEQ/COAST	North Fork Wolf Creek at River mile 0.45
cnmyrt	43 07 17	123 07 29	ODEQ/COAST	North Myrtle Creek at River mile 14.3
cnorth	44 54 33	123 54 26	ODEQ/COAST	North Creek at River mile 0.54
cobri	42 06 07	123 14 20	ODEQ/COAST	Obrien Creek at River mile 0.9
cpeak	44 21 06	123 28 55	ODEQ/COAST	Peak Creek at River mile 3.5
cpnthr	42 22 52	123 48 46	ODEQ/COAST	Panther Creek at River mile 0.17
crck	44 11 12	124 06 21	ODEQ/COAST	Rock Creek at River mile 1.5
credi	43 01 41	124 22 13	ODEQ/COAST	Redibaugh Creek at River mile 1.33
croarr	44 37 49	122 44 16	ODEQ/COAST	Roaring River at River mile 0.10
cschol	43 03 18	123 10 39	ODEQ/COAST	School Hollow Creek at River mile 1.64
csfsmt	43 46 27	123 27 50	ODEQ/COAST	South Fork Smith at River mile 0.83
cshas	42 34 23	124 02 03	ODEQ/COAST	Shasta Costa Creek at River mile 1.11
csixes	42 48 15	124 18 19	ODEQ/COAST	Sixes River at River mile 19.2
ctill	45 21 07	123 49 51	ODEQ/COAST	Tillamook River at River mile 14.9
ctiog	43 11 43	123 45 21	ODEQ/COAST	Tioga Creek at River mile 17.74
ctsfcm	42 47 55	124 01 43	ODEQ/COAST	South Fork Coquil at River mile 0.13
cwfash	42 08 56	122 42 52	ODEQ/COAST	West Fork Ashland at River mile 0.16

Appendix A. Site list for water temperature and habitat survey data collection—*Continued*

Site model label name	Latitude	Longitude	Agency/Project	Stream name
	(degrees, minutes, and seconds)			
rbeav089	45 02 14	122 36 46	ODEQ/REMAP	Beaver Creek
rbigh135	45 15 46	121 55 11	ODEQ/REMAP	Big Horn
rbric095	43 37 21	122 35 09	ODEQ/REMAP	Brice Creek
rcany049	44 22 26	122 23 20	ODEQ/REMAP	Canyon Creek
rcnty115	44 16 19	122 06 22	ODEQ/REMAP	County Creek
rcrab053	44 34 40	122 34 20	ODEQ/REMAP	Crabtree
rdona022	44 31 08	122 11 26	ODEQ/REMAP	Donaca Creek
reigt025	43 50 06	122 23 37	ODEQ/REMAP	Eight Creek
rfish057	45 05 51	122 10 02	ODEQ/REMAP	Fish Creek Low Creek
rfish087	45 03 52	122 09 39	ODEQ/REMAP	Fish Creek Up
rlook009	44 13 32	122 14 01	ODEQ/REMAP	Lookout Creek
rmart099	44 06 46	122 30 34	ODEQ/REMAP	Marten Creek
rmart021	43 32 31	122 43 05	ODEQ/REMAP	Martin Creek
rnfea037	45 18 50	122 15 06	ODEQ/REMAP	North Fork Eagle Creek
rnfwi045	43 54 04	122 36 31	ODEQ/REMAP	North Fork Winberry
rpeat119	44 58 03	122 02 18	ODEQ/REMAP	Peat Creek
rrone023	44 06 28	122 01 07	ODEQ/REMAP	Roney Creek
rsalt015	43 44 35	122 38 10	ODEQ/REMAP	Saltpeter
rshor019	43 44 27	122 29 09	ODEQ/REMAP	Shortridge Creek
rtabl029	44 58 53	122 22 59	ODEQ/REMAP	Table Rock Fork
rtumb085	43 26 15	122 15 01	ODEQ/REMAP	Tumblebug Creek
rwfho033	45 27 52	121 46 52	ODEQ/REMAP	West Fork Hood River
rwile109	44 19 18	122 31 52	ODEQ/REMAP	Wiley Creek
rzigz097	45 20 20	121 55 18	ODEQ/REMAP	Zigzag River
mack	44 13 10	122 10 02	USFS	Mack Creek near Blue River, Oregon

Appendix B. Model input variable tables and sensitivity analyses

Tables included in the appendix:

Explanation of climate station model input variable labels

Group assignment model input variables

Static model input variables

Chaotic model input variables--Group 1

Chaotic model input variables--Group 2, northern zone

Chaotic model input variables--Group 2, southern zone

Chaotic model input variables--Group 3, northern zone

Chaotic model input variables--Group 3, southern zone

Periodic model input variables--Group 1

Periodic model input variables--Group 2, northern zone

Periodic model input variables--Group 2, southern zone

Periodic model input variables--Group 3, northern zone

Periodic model input variables--Group 3, southern zone

Explanation of climate station model input variable labels

Model label for hourly values	Model label for 24-hour moving average values	Meteorological parameter and units	Station name	Latitude	Longitude	Elevation (feet)
BILLIEZNWS	na	Snow water equivalent (inches)	Billie Creek Divide	42 25 00	122 17 00	5,300
DIAMONDZ	na	Snow water equivalent (inches)	Diamond Lake	43 11 00	122 08 00	5,315
HOLLANDZ	na	Snow water equivalent (inches)	Holland Meadows	43 40 00	122 34 00	4,900
JUMPZ	na	Snow water equivalent (inches)	Jump Off Joe	44 23 00	122 10 00	3,500
LITTLEZ	na	Snow water equivalent (inches)	Little Meadows	44 37 00	122 13 00	4,000
NORTHZ	na	Snow water equivalent (inches)	North Fork	45 33 00	122 01 00	3,120
PEAVINEZ	na	Snow water equivalent (inches)	Peavine Ridge	45 03 00	121 56 00	3,500
ROARZ	na	Snow water equivalent (inches)	Roaring River	43 54 00	122 02 00	4,900
SADDLEZ	na	Snow water equivalent (inches)	Saddle Mountain	45 32 00	123 22 00	3,250
2DSTD*	1DSTD*	Dewpoint temperature (degrees Celsius)	Corvallis	44 38 03	123 11 24	230
2AURXRAD	1AURXRAD	Dewpoint temperature (degrees Celsius)	Aurora	45 16 55	122 45 01	140
2BANXOND	1BANXOND	Dewpoint temperature (degrees Celsius)	Bandon	43 05 28	124 25 02	80
2EEFXATD	1EEFXATD	Dewpoint temperature (degrees Celsius)	Dee Flat	45 34 25	121 38 50	1,260
2OREXTGD	1OREXTGD	Dewpoint temperature (degrees Celsius)	Forest Grove	45 33 11	123 05 01	180
2EDFXRDD	1EDFXRDD	Dewpoint temperature (degrees Celsius)	Medford	42 19 52	122 56 16	1,340
2ROOXIND	1ROOXIND	Dewpoint temperature (degrees Celsius)	Brookings	42 02 00	124 15 00	24
2EUGXNED	1EUGXNED	Dewpoint temperature (degrees Celsius)	Eugene	44 07 00	123 13 00	114
2ILLXBOD	1ILLXBOD	Dewpoint temperature (degrees Celsius)	Hillsboro	45 31 00	122 59 00	62
2ORTXBED	1ORTXBED	Dewpoint temperature (degrees Celsius)	North Bend	43 25 00	124 15 00	4
2ORTXAND	1ORTXAND	Dewpoint temperature (degrees Celsius)	Portland	45 36 00	122 36 00	12
2OSEXURD	1OSEXURD	Dewpoint temperature (degrees Celsius)	Roseburg	43 14 00	123 22 00	160
2SALXEMD	1SALXEMD	Dewpoint temperature (degrees Celsius)	Salem	44 55 00	123 00 00	61
2ANNXBLD	1ANNXBLD	Dewpoint temperature (degrees Celsius)	Cannible	44 21 00	123 55 00	1,946
2PEBXLED	1PEBXLED	Dewpoint temperature (degrees Celsius)	Pebble	44 14 00	121 59 00	3,560
2RYEXTND	1RYEXTND	Dewpoint temperature (degrees Celsius)	Rye Mountain	45 13 00	123 32 00	2,000
2PSTD*	1PSTD*	Air Pressure (millibar)	Eugene	44 07 00	123 13 00	114
2STOXIAP	1STOXIAP	Air Pressure (millibar)	Astoria	46 09 00	123 53 00	7
2ROOXINP	1ROOXINP	Air Pressure (millibar)	Brookings	42 02 00	124 15 00	24
2ILLXBOP	1ILLXBOP	Air Pressure (millibar)	Hillsboro	45 31 00	122 59 00	62
2EDFXRDP	1EDFXRDP	Air Pressure (millibar)	Medford	42 23 00	122 53 00	405
2ORTXBEP	1ORTXBEP	Air Pressure (millibar)	North Bend	43 25 00	124 15 00	4
2ORTXANP	1ORTXANP	Air Pressure (millibar)	Portland	45 36 00	122 36 00	12
2OSEXURP	1OSEXURP	Air Pressure (millibar)	Roseburg	43 14 00	123 22 00	160
2SALXEMP	1SALXEMP	Air Pressure (millibar)	Salem	44 55 00	123 00 00	61
2PEBXLEP	1PEBXLEP	Air Pressure (millibar)	Pebble	44 14 00	121 59 00	3,560
2AURORAR	1AURORAR	Rainfall (inches)	Aurora	45 16 55	122 45 01	140
2BANDONR	1BANDONR	Rainfall (inches)	Bandon	43 05 28	124 25 02	80
2ORVALLR	1ORVALLR	Rainfall (inches)	Corvallis	44 38 03	123 11 24	230
2ORESTGR	1ORESTGR	Rainfall (inches)	Forest Grove	45 33 11	123 05 01	180
2EDFORDR	1EDFORDR	Rainfall (inches)	Medford	42 19 52	122 56 16	1,340

Explanation of climate station model input variable labels

Model label for hourly values	Model label for 24-hour moving average values	Meteorological parameter and units	Station name	Latitude	Longitude	Elevation (feet)
2ANNIBLR	1ANNIBLR	Rainfall (inches)	Cannible	44 21 00	123 55 00	1,946
2RYEMTNR	1RYEMTNR	Rainfall (inches)	Rye Mountain	45 13 00	123 32 00	2,000
2SSTD*	1SSTD*	Solar Radiation (langleys)	Corvallis	44 38 03	123 11 24	230
2AURXRAS	1AURXRAS	Solar Radiation (langleys)	Aurora	45 16 55	122 45 01	140
2BANXONS	1BANXONS	Solar Radiation (langleys)	Bandon	43 05 28	124 25 02	80
2OREXTGS	1OREXTGS	Solar Radiation (langleys)	Forest Grove	45 33 11	123 05 01	180
2EDFXRDS	1EDFXRDS	Solar Radiation (langleys)	Medford	42 19 52	122 56 16	1,340
2TSTD*	1TSTD*	Air Temperature (degrees Celsius)	Corvallis	44 38 03	123 11 24	230
2AURXRAT	1AURXRAT	Air Temperature (degrees Celsius)	Aurora	45 16 55	122 45 01	140
2BANXONT	1BANXONT	Air Temperature (degrees Celsius)	Bandon	43 05 28	124 25 02	80
2EEFXATT	1EEFXATT	Air Temperature (degrees Celsius)	Dee Flat	45 34 25	121 38 50	1,260
2OREXTGT	1OREXTGT	Air Temperature (degrees Celsius)	Forest Grove	45 33 11	123 05 01	180
2EDFXRDT	1EDFXRDT	Air Temperature (degrees Celsius)	Medford	42 19 52	122 56 16	1,340
2STOXIAT	1STOXIAT	Air Temperature (degrees Celsius)	Astoria	46 09 00	123 53 00	7
2ROOXINT	1ROOXINT	Air Temperature (degrees Celsius)	Brookings	42 02 00	124 15 00	24
2EUGXNET	1EUGXNET	Air Temperature (degrees Celsius)	Eugene	44 07 00	123 13 00	114
2ILLXBOT	1ILLXBOT	Air Temperature (degrees Celsius)	Hillsboro	45 31 00	122 59 00	62
2ORTXBET	1ORTXBET	Air Temperature (degrees Celsius)	North Bend	43 25 00	124 15 00	4
2ORTXANT	1ORTXANT	Air Temperature (degrees Celsius)	Portland	45 36 00	122 36 00	12
2OSEXURT	1OSEXURT	Air Temperature (degrees Celsius)	Roseburg	43 14 00	123 22 00	160
2SALXEMT	1SALXEMT	Air Temperature (degrees Celsius)	Salem	44 55 00	123 00 00	61
2ANNXBLT	1ANNXBLT	Air Temperature (degrees Celsius)	Cannible	44 21 00	123 55 00	1,946
2PEBXLET	1PEBXLET	Air Temperature (degrees Celsius)	Pebble	44 14 00	121 59 00	3,560
2RYEXTNT	1RYEXTNT	Air Temperature (degrees Celsius)	Rye Mountain	45 13 00	123 32 00	2,000

Group assignment model input variables

Notes:

Output variables are G1, G2, and G3. Input variable labels are defined in table 1. Input variables are listed below in the order of their importance for each group. Weight, was determined through model sensitivity analysis. The sum of the weight values for each group equals 1.

Group 1		Group 2		Group 3	
Input Variable	**Weight**	**Input Variable**	**Weight**	**Input Variable**	**Weight**
BASFOREA	0.09339	BASFOREA	0.12899	BASFOREA	0.12637
BASXELEV	0.08896	DENBASFA	0.08123	DENBASFA	0.08317
XCOORD	0.07912	XCOORD	0.06593	XCOORD	0.06871
DENBASFA	0.07556	STCHFORA	0.06223	STRMRB	0.06389
STRMRB	0.07016	STRMRB	0.06037	STCHFORA	0.06025
MIDCHDEN	0.05439	BASMSATC	0.05682	BASMSATC	0.05560
YCOORD	0.05335	STRMBDEN	0.04952	YCOORD	0.04865
STRMBDEN	0.05017	MIDCHDEN	0.04907	BASXELEV	0.04841
STMSUATC	0.04391	YCOORD	0.04670	MIDCHDEN	0.04572
STCHFORA	0.04274	BASXELEV	0.04441	STRMBDEN	0.04403
STRMCHBE	0.03647	STRMCHBE	0.04034	STRMCHBE	0.04014
SBSUBSTC	0.03330	SBSUBSTC	0.03969	SBSUBSTC	0.03874
BASMSATC	0.03298	DNSTCHFA	0.03476	OUTMSATC	0.03327
DEPTH	0.03013	OUTMSATC	0.03207	WETTEDWD	0.03295
OUTMSATC	0.02733	WETTEDWD	0.03200	STMSUATC	0.03290
BASINKM2	0.02656	BASMSLOP	0.03169	BASMSLOP	0.03196
DNSTCHFA	0.02609	STMSUATC	0.02901	DNSTCHFA	0.03091
BASMSLOP	0.02506	BASINKM2	0.02336	BASOELEV	0.02391
STCHMELV	0.02455	DEPTH	0.02275	BASINKM2	0.02388
BASOELEV	0.02424	BASOELEV	0.02253	DEPTH	0.02088
BASBEARS	0.02163	BASBEARS	0.01676	STCHMELV	0.01933
WETTEDWD	0.02135	STCHMELV	0.01673	BASBEARS	0.01594
BASBEARC	0.01857	BASBEARC	0.01305	BASBEARC	0.01039

Static model input variables

Notes:

Output variable is MEANT, which is defined in equation 4 as the mean hourly temperature for the simulation period. Input variable labels are defined in table 1. Input variables are listed below in the order of their importance. Weight, was determined through model sensitivity analysis. The sum of the weight values equals 1.

Input Variable	Weight
XCOORD	0.11630
BASOELEV	0.10562
STMSUATC	0.10342
BASMSATC	0.10037
MIDCHDEN	0.08401
STCHMELV	0.08228
STCHFORA	0.07860
BASFOREA	0.06855
DNSTCHFA	0.06302
YCOORD	0.06300
BASXELEV	0.05761
SBSUBSTG	0.03330
BASINKM2	0.02941
SBSUBSBO	0.01450

Chaotic model input variables—Group 1

Notes:

Output variable is NAVG24, which is defined in equation 5 as the normalized 24-hour hourly moving average residual. Input variable labels are defined in table 1 and appendix b. Input variables are listed below in the order of their importance. Weight, was determined through model sensitivity analysis. The sum of the weight values equals 1.

Input Variable	Weight
1TSTD	0.09840
DENBASFA	0.07685
1PEBXLEP	0.05520
MEANTP	0.04683
1EDFXRDS	0.04528
OUTMSATC	0.04378
1ROOXINT	0.04196
BASOPENA	0.04187
1SSTD	0.04003
1ORTXANP	0.03869
SBSUBSTC	0.03822
BASMSATC	0.03372
1ILLXBOP	0.03099
BASXELEV	0.03093
STRMBDEN	0.03044
STCHOPA	0.03022
1OSEXURT	0.02995
1ROOXINP	0.02901
LITTLEZ	0.02604
MIDCHDEN	0.02526
1STOXIAP	0.02445
1BANXONT	0.02262
BASBEARA	0.02190
1PSTD	0.01905
1EDFXRDT	0.01840
X	0.01810
1EEFXATT	0.01598
DNSTCHFA	0.01394
DEPTH	0.01197

Chaotic model input variables—Group 2, northern zone

Notes:

Output variable is NAVG24, which is defined in equation 5 as the normalized 24-hour hourly moving average residual. Input variable labels are defined in table 1 and appendix b. Input variables are listed below in the order of their importance. Weight, was determined through model sensitivity analysis. The sum of the weight values equals 1.

Input Variable	Weight
1TSTD	0.07206
LITTLEZ	0.07111
STCHFORA	0.04389
1ILLXBOP	0.04205
1SSTD	0.03487
1EEFXATT	0.03239
1DSTD	0.02916
XCOORD	0.02784
1BANXONT	0.02706
BASFOREA	0.02539
1SALXEMT	0.02266
1ILLXBOT	0.02211
1ANNXBLD	0.02081
1ORTXANT	0.02004
BASOELEV	0.01962
BASBEARA	0.01927
1EDFXRDS	0.01825
1BANXONS	0.01795
1PEBXLEP	0.01795
1EDFXRDP	0.01754
1STOXIAP	0.01746
1SALXEMP	0.01734
1ILLXBOD	0.01677
1EDFXRDT	0.01622
DEPTH	0.01602
YCOORD	0.01577
1ORTXANP	0.01567
SBSUBSTG	0.01545
1OREXTGS	0.01505
1ORTXBET	0.01498
DENBASFA	0.01489
MIDCHDEN	0.01478
1PEBXLET	0.01420
OUTMSATC	0.01371
ROARZ	0.01352
STRMCHBE	0.01322
BASMSLOP	0.01303
1ORTXBEP	0.01256
1EUGXNET	0.01204
SBSUBSBO	0.01152
SBSUBSTC	0.01145
1OREXTGD	0.01134
SBSUBSTC	0.01132
SBSUBSTF	0.01092
1EDFXRDR	0.01089
1AURXRAS	0.01053
SBSUBSBE	0.01022
1BANXOND	0.01020
SLOPEPCT	0.00935
DNSTCHFA	0.00811

Chaotic model input variables—Group 2, southern zone

Notes:

Output variable is NAVG24, which is defined in equation 5 as the normalized 24-hour hourly moving average residual. Input variable labels are defined in table 1 and appendix b. Input variables are listed below in the order of their importance. Weight, was determined through model sensitivity analysis. The sum of the weight values equals 1.

Input Variable	Weight
LITTLEZ	0.05829
1TSTD	0.05542
DNSTCHFA	0.04284
DENBASFA	0.04173
MEANTP	0.03663
STCHFORA	0.03551
MIDCHDEN	0.03524
1DSTD	0.03158
BASOELEV	0.03144
1ROOXINP	0.02640
1ILLXBOP	0.02601
STRMBDEN	0.02494
BASBEARA	0.02449
BASMSLOP	0.02403
1ROOXINT	0.02374
1SSTD	0.02308
1SALXEMP	0.02257
1PEBXLEP	0.02176
ROARZ	0.02135
1EDFXRDT	0.02038
1STOXIAP	0.02000
STRMRB	0.01993
1ORTXANP	0.01896
1EDFXRDD	0.01755
1EDFXRDP	0.01718
1EDFXRDR	0.01647
XCOORD	0.01618
1EEFXATT	0.01581
YCOORD	0.01543
1OSEXURT	0.01527
BASFOREA	0.01506
1AURXRAS	0.01487
1ILLXBOD	0.01430
SBSUBSBO	0.01375
1PSTD	0.01234
BASBEARS	0.01230
1BANXONS	0.01225
1SALXEMT	0.01224
SLOPEPCT	0.01164
1ORTXANT	0.01137
STRMCHBE	0.01048
1ORTXBEP	0.01024
1EDFXRDS	0.01010
STCHMELV	0.00983
SBSUBSTF	0.00965
1EUGXNET	0.00850
SBSUBSBE	0.00594
SBSUBSTS	0.00540

Chaotic model input variables—Group 3, northern zone

Notes:

Output variable is NAVG24, which is defined in equation 5 as the normalized 24-hour hourly moving average residual. Input variable labels are defined in table 1 and appendix b. Input variables are listed below in the order of their importance. Weight, was determined through model sensitivity analysis. The sum of the weight values equals 1.

Input Variable	Weight
1TSTD	0.07957
MEANTP	0.04933
1DSTD	0.04886
BASFOREA	0.04406
DENBASFA	0.04013
STCHFORA	0.03689
1SALXEMT	0.02975
DNSTCHFA	0.02795
1ROOXINP	0.02750
1EDFXRDP	0.02662
1SALXEMP	0.02605
1PSTD	0.02344
XCOORD	0.02317
STRMBDEN	0.02256
1ORTXANP	0.02064
LITTLEZ	0.02045
1EDFXRDS	0.02019
1EDFXRDD	0.01928
1ORTXBEP	0.01793
1SSTD	0.01788

Input Variable	Weight
1ROOXINT	0.01787
1PEBXLEP	0.01786
1ILLXBOP	0.01781
MIDCHDEN	0.01763
BASBEARS	0.01702
YCOORD	0.01642
OUTMSATC	0.01429
1OSEXURT	0.01420
SBSUBSTC	0.01416
1BANXONS	0.01405
1AURXRAS	0.01352
1BANXOND	0.01326
1EEFXATT	0.01308
1BANXONT	0.01288
1STOXIAP	0.01266
SLOPEPCT	0.01254
STRMRB	0.01244
1ORTXANT	0.01121
BASINKM2	0.01100
BASBEARA	0.01094
1ANNXBLD	0.01068
ROARZ	0.01039
BASBEARC	0.01003
SBSUBSTF	0.00988
SBSUBSBE	0.00974
DEPTH	0.00940
1ORTXBET	0.00938
BASMSLOP	0.00834
STRMCHBE	0.00789
1EDFXRDR	0.00773

Chaotic model input variables—Group 3, southern zone

Notes:

Output variable is NAVG24, which is defined in equation 5 as the normalized 24-hour hourly moving average residual. Input variable labels are defined in table 1 and appendix B. Input variables are listed below in the order of their importance. Weight, was determined through model sensitivity analysis. The sum of the weight values equals 1.

Input Variable	Weight
MEANTP	0.06953
1DSTD	0.05887
1TSTD	0.05245
DENBASFA	0.03269
1EDFXRDP	0.03044
1SALXEMP	0.03019
STCHFORA	0.02817
1SSTD	0.02642
1OSEXURT	0.02528
1EDFXRDS	0.02456
STRMBDEN	0.02452
1ROOXINP	0.02378
LITTLEZ	0.02329
1ILLXBOP	0.02224
WETTEDWD	0.02175
XCOORD	0.02173
SBSUBSTG	0.02096
1ORTXBEP	0.02087
DNSTCHFA	0.02054
STCHMELV	0.02022
MIDCHDEN	0.01984
YCOORD	0.01921
1SALXEMT	0.01862
1STOXIAP	0.01749
1EDFXRDT	0.01656
1ROOXINT	0.01651
1EUGXNED	0.01638
1EUGXNET	0.01578
ROARZ	0.01568
1EDFXRDD	0.01550
1PSTD	0.01545
1BANXONS	0.01528
1ORTXANP	0.01402
1ORTXANT	0.01343
1PEBXLEP	0.01322
SLOPEPCT	0.01309
BASBEARA	0.01309
1BANXOND	0.01304
BASMSLOP	0.01301
BASOELEV	0.01208
DEPTH	0.01125
1EEFXATT	0.01102
1ORTXBET	0.01059
1ILLXBOT	0.01025
1ILLXBOD	0.00990
1OSEXURP	0.00941
STRMRB	0.00927
1EDFXRDR	0.00921
1ANNXBLD	0.00794
SBSUBSTF	0.00588

Periodic model input variables—Group 1

Notes:

Output variable is NHOURLY, which is defined in equation 6 as the normalized 24-hour residual. Input variable labels are defined in table 1 and appendix B. Labels with parentheses are time lagged in hours. Input variables are listed below in the order of their importance. Weight, was determined through model sensitivity analysis. The sum of the weight values equals 1.

Input Variable	Weight
NAVG24P	0.08667
NAVG24P(024)	0.06748
2EDFXRDS(006)	0.04437
2OSEXURT	0.03771
DENBASFA	0.02945
2PEBXLEP	0.02703
2BANXONT	0.02529
MEANTP	0.02427
STRMRB	0.02316
MIDCHDEN	0.02281
2SSTD(006)	0.02266
2EDFXRDP	0.02207
2ORTXANP(012)	0.02190
STMSUATC	0.02095
2EUGXNET	0.01952
1EDFXRDT(003)	0.01928
2EDFXRDT(006)	0.01925
1ORTXBET(003)	0.01921
OUTMSATC	0.01893
DNSTCHFA	0.01791
2EDFXRDT	0.01789
2ORTXBET	0.01720
1ROOXINT(003)	0.01714
2ROOXINP(006)	0.01659
BASBEARA	0.01655
1SALXEMT(003)	0.01648
STRMBDEN	0.01616
2OSEXURT(012)	0.01615
NAVG24P(012)	0.01610
1BANXONT(003)	0.01588
1OSEXURT(003)	0.01575
2EDFXRDT(012)	0.01561
2ANNXBLT(006)	0.01515
2PSTD(006)	0.01482
STRMCHBE	0.01479
2EUGXNET(006)	0.01411
2ORTXBEP(012)	0.01408
2PEBXLEP(012)	0.01387
1EEFXATT(003)	0.01343
2EEFXATT	0.01330
Y	0.01326
1EUGXNET(003)	0.01303
1ORTXANT(003)	0.01246
2SSTD	0.01186
2BANXONT(006)	0.01180
2PEBXLET(012)	0.01103
2BANXONT(012)	0.00919
BASMSLOP	0.00864
1ANNXBLT(003)	0.00788

Periodic model input variables—Group 2, northern zone

Notes:

Output variable is NHOURLY, which is defined in equation 6 as the normalized 24-hour residual. Input variable labels are defined in table 1 and appendix B. Labels with parentheses are time lagged in hours. Input variables are listed below in the order of their importance. Weight, was determined through model sensitivity analysis. The sum of the weight values equals 1.

Input Variable	Weight
NAVG24P	0.06882
2TSTD(003)	0.06107
NAVG24P(024)	0.05031
MEANTP	0.04159
2ORTXANP	0.03287
2TSTD(012)	0.02863
2PEBXLET(003)	0.02787
STRMBDEN	0.02445
2OSEXURT	0.02403
BASFOREA	0.02334
2OSEXURT(012)	0.02303
2ORTXANP(012)	0.02292
STRMCHBE	0.02167
2TSTD(006)	0.02138
2STOXIAT(003)	0.02098
2AURXRAT(006)	0.02077
2PEBXLET(012)	0.01999
BASBEARS	0.01999
2EUGXNET(006)	0.01997
2OREXTGT	0.01988
XCOORD	0.01889
2ORTXANT	0.01868
DENBASFA	0.01746
2ORTXBET(012)	0.01677
MIDCHDEN	0.01667
SBSUBSTC	0.01636
2RYEXTNT(003)	0.01613
2STOXIAP	0.01581
YCOORD	0.01488
2EEFXATT	0.01472
2BANXONT	0.01460
STCHFORA	0.01420
2EEFXATT(003)	0.01384
2STOXIAT	0.01365
DNSTCHFA	0.01351
2SALXEMT(003)	0.01316
BASMSLOP	0.01304
STRMRB	0.01302
2RYEXTNT(006)	0.01261
2STOXIAT(006)	0.01246
2EDFXRDT	0.01200
2SALXEMP(006)	0.01089
2STOXIAP(012)	0.01050
2STOXIAT(012)	0.01036
2AURXRAT(003)	0.01025
SLOPEPCT	0.00933
2EEFXATT(006)	0.00910
2ORTXBET(006)	0.00885
2ORTXBET(003)	0.00867
2EEFXATT(012)	0.00827
2ORTXANT(003)	0.00817

Periodic model variables—Group 2, southern zone

Notes:

Output variable is NHOURLY, which is defined in equation 6 as the normalized 24-hour residual. Input variable labels are defined in table 1 and appendix B. Labels with parentheses are time lagged in hours. Input variables are listed below in the order of their importance. Weight, was determined through model sensitivity analysis. The sum of the weight values equals 1.

Input Variable	Weight
NAVG24P	0.09582
NAVG24P(024)	0.04803
NAVG24P(012)	0.03511
DENBASFA	0.03360
MIDCHDEN	0.02891
STCHFORA	0.02770
2TSTD(003)	0.02596
MEANTP	0.02263
2EDFXRDT(006)	0.02128
STCHMELV	0.01989
2PEBXLET(003)	0.01885
2EDFXRDT	0.01884
BASMSATC	0.01873
2EDFXRDS	0.01828
2TSTD(006)	0.01753
BASOELEV	0.01711
DNSTCHFA	0.01701
STRMCHBE	0.01633
2OREXTGT(012)	0.01592
BASFOREA	0.01587
XCOORD	0.01559
2EDFXRDT(003)	0.01558
2OSEXURT	0.01519
YCOORD	0.01502
STRMRB	0.01495
2ORTXANT(006)	0.01478
2OSEXURT(012)	0.01444
2TSTD	0.01410
2BANXONT(003)	0.01404
STRMBDEN	0.01396
2ORTXANP(012)	0.01373
2SALXEMT(003)	0.01306
BASMSLOP	0.01295
2EUGXNET(003)	0.01268
2RYEXTNT(003)	0.01240
2EEFXATT	0.01232
2EUGXNET(006)	0.01201
2ORTXANP(006)	0.01200
2OREXTGT	0.01175
2PEBXLET(006)	0.01166
2ROOXINP	0.01163
BASBEARC	0.01160
2PEBXLET(012)	0.01133
2AURXRAT(003)	0.01126
2SSTD	0.01115
2AURXRAT(012)	0.01106
WETTEDWD	0.01102
SBSUBSTG	0.01101
2ORTXANT(012)	0.01052
2ROOXINP(006)	0.00982
2OSEXURT(003)	0.00979
2EDFXRDS(006)	0.00928
2PSTD(012)	0.00896
BASINKM2	0.00883
2EDFXRDP(006)	0.00876
2EDFXRDP	0.00848
2EEFXATT(003)	0.00821
LITTLEZ	0.00814
2DSTD(012)	0.00740
SLOPEPCT	0.00667

Periodic model input variables—Group 3, northern zone

Notes:

Output variable is NHOURLY, which is defined in equation 6 as the normalized 24-hour residual. Input variable labels are defined in table 1 and appendix B. Labels with parentheses are time lagged in hours. Input variables are listed below in the order of their importance. Weight, was determined through model sensitivity analysis. The sum of the weight values equals 1.

Input Variable	Weight
NAVG24P	0.07983
NAVG24P(024)	0.03873
NAVG24P(012)	0.03714
2OREXTGS(006)	0.02645
2TSTD	0.02626
2TSTD(006)	0.02590
DENBASFA	0.02523
NAVG24P(003)	0.02486
STCHFORA	0.02402
2ILLXBOT(006)	0.02030
2EUGXNET(003)	0.01957
2TSTD(012)	0.01952
2OREXTGT(003)	0.01931
XCOORD	0.01910
MEANTP	0.01904
2SSTD(006)	0.01825
NAVG24P(006)	0.01766
2EUGXNET	0.01760
2ORTXANT(012)	0.01691
2BANXONT(003)	0.01670
2ORTXANP(006)	0.01600
BASBEARC	0.01538
2AURXRAT	0.01531
STRMRB	0.01516
DEPTH	0.01491
MIDCHDEN	0.01485
SLOPEPCT	0.01482
2AURXRAT(006)	0.01447
2ORTXANT	0.01436
STRMBDEN	0.01418
2STOXIAT(003)	0.01407
YCOORD	0.01395
2RYEXTNT(003)	0.01383
2OREXTGT	0.01370
BASBEARS	0.01367
2STOXIAP(012)	0.01314
2SALXEMT(006)	0.01313
2EDFXRDS(006)	0.01286
STRMCHBE	0.01258
2SSTD	0.01255
2PEBXLET	0.01237
2SALXEMT(003)	0.01216
STMSUATC	0.01211
2EEFXATT(012)	0.01183
SBSUBSTF	0.01154
SBSUBSTC	0.01152
BASMSATC	0.01110
BASBEARA	0.01108
2RYEXTNT	0.01101
2EDFXRDP(012)	0.01055
DNSTCHFA	0.01038
2BANXONS	0.01017
SBSUBSTS	0.01005
2DSTD(012)	0.00948
2EDFXRDP	0.00928
2BANXONT	0.00915
2OSEXURT(012)	0.00902
WETTEDWD	0.00802
2STOXIAT(006)	0.00743
OUTMSATC	0.00693

Periodic model input variables—Group 3, southern zone

Notes:

Output variable is NHOURLY, which is defined in equation 6 as the normalized 24-hour residual. Input variable labels are defined in table 1 and appendix B. Labels with parentheses are time lagged in hours. Input variables are listed below in the order of their importance. Weight, was determined through model sensitivity analysis. The sum of the weight values equals 1.

Input Variable	Weight
NAVG24P	0.09025
2TSTD(003)	0.03659
NAVG24P(012)	0.03275
NAVG24P(024)	0.03247
MEANTP	0.02504
2EDFXRDS(006)	0.02483
2OSEXURT	0.02381
MIDCHDEN	0.02380
2ORTXANP	0.02283
DNSTCHFA	0.02150
2EDFXRDT	0.02130
2PEBXLET(003)	0.02059
2OSEXURT(003)	0.02042
2OREXTGS(006)	0.01964
2EDFXRDT(006)	0.01930
DENBASFA	0.01887
2EDFXRDS	0.01739
YCOORD	0.01730
XCOORD	0.01726
NAVG24P(006)	0.01715
STCHFORA	0.01672
STRMBDEN	0.01633
2TSTD(012)	0.01605
2AURXRAT(012)	0.01557
DEPTH	0.01510
2EUGXNET(003)	0.01501
2BANXONS	0.01500
2RYEXTNT(003)	0.01471
BASFOREA	0.01409
2STOXIAP(012)	0.01397
BASMSATC	0.01376
2SSTD(006)	0.01343
2TSTD(006)	0.01330
BASINKM2	0.01322
SLOPEPCT	0.01317
2AURXRAT	0.01315
2AURXRAT(003)	0.01287
SBSUBSTG	0.01203
2STOXIAP	0.01200
2EEFXATT	0.01127
2BANXONT(012)	0.01124
BASBEARA	0.01123
2OREXTGT	0.01108
BASMSLOP	0.01105
2ORTXBET(003)	0.01103
2EEFXATT(012)	0.01101
2ORTXANT	0.01053
2EDFXRDP	0.01025
2SSTD	0.01011
2PEBXLET(012)	0.00951
2ORTXBET(006)	0.00939
2OSEXURT(012)	0.00936
2DSTD(012)	0.00926
2EUGXNET(006)	0.00915
SBSUBSTC	0.00898
STMSUATC	0.00886
2PSTD	0.00793
2ROOXINT(003)	0.00751
2OREXTGT(003)	0.00744
2EDFXRDS(012)	0.00614
BASBEARC	0.00558

Appendix C. Model operation instructions

1. Downloading model files

From http://oregon.usgs.gov/projs_dir/or185/, click on “Model operation files” to go to the ftp directory. From there, download a file named “modelfiles.zip.” This file is a package containing various files used for processing the input data and operating the water temperature model. Some additional software and GIS coverages that were used in this study could not be included in this package file, because they must be acquired through other firms or agencies. Details regarding those firms or agencies are provided below.

2. Assembling model input parameters

Before running the model, the user must assemble the input data that is specific to their basin of interest for the 34 stream habitat and basin characteristics parameters listed in table 1. For proper model operation, it is critical that the data assembled by the user be within the maximum and minimum extremes shown in the table 1 for each parameter.

It is assumed that stream habitat data, the first 12 parameters listed in table 1, will have already been collected at and near the outlet of the user’s basin of interest. The habitat data should be collected and assembled using EMAP protocols described in (Kaufmann and Robison, 1994, 1998; and Kaufmann and others, 1999).

The next step is to estimate the basin characteristics, which are the remaining 22 parameters listed in table 1. Arc Macro Language (AML) scripts are provided in the “modelfiles.zip” file to assist the user in downloading most of these parameters from 10-meter digital elevation models (DEMs) and other GIS coverages.

The aml script files are:

“aml.start”

“aml.clip”

“aml.clean”

“aml.basin”

“aml.wipeout”

Instructions for running the scripts are in “README.gis_instructions.txt”

Using these specific scripts is not required if the user has access to other GIS tools or methods. However, a user (with some GIS skills) should examine these scripts to understand how the basin characteristic parameters were defined and computed for this study. The computed output for most of the basin characteristic parameters is provided in the “aml.basin” file. Running this script requires using proprietary forest and air temperature GIS coverages that may have to be purchased through non-USGS agencies listed in “README.gis_instructions.txt”. If the user already has forest and air temperature data for their basin, they could modify the “aml.basin” file to just compute the DEM derived basin characteristic parameters (such as drainage area, elevation, etc.)

Before running the scripts, the latitude and longitude coordinates of the site of interest must be converted into Universal Transverse Mercator, Zone 10 (UTM) 1927 North American Datum (NAD27) units. An easy to use coordinate conversion tool is available at http://jeeep.com/details/coord/.

The X and Y UTM coordinates then must be manually converted into normalized decimal units for use as model inputs: XCOOR and YCOOR.

$$XCOOR = (X_{utm} - 384{,}651) / 223,448$$
$$YCOOR = (Y_{utm} - 4{,}654{,}955) / 456{,}853$$

Values for BASBEARA, BASBEARS, BASBEARC, and STRMCHBE (listed in table 1) can be manually estimated from a topographic map. BASBEARA is the angle (0-360 degrees) of the line starting from the location on the basin divide that is furthermost away from the outlet and extending to the outlet. STRMCHBE is the is the angle (0-360 degrees) of the line that parallels the main stream channel. This line starts from a location one-third of the basin length up from the outlet and extends to the outlet.

3. Setting up the models

The water temperature models can be are run within an EXCEL spreadsheet using an EXCEL add-in called NNCALC. The NNCALC add-in file, “nncalc32.xll” is not provided in the “modelfiles.zip” package file. However, it can be purchased at a nominal price through:

Advanced Data Mining, LLC
3620 Pelham Road, PMB #351,
Greenville, South Carolina, 29615-5044
email: ed.roehl@advdatamining.com
Telephone: 864-676-9790

Having the NNCALC add-in file enables a user to operate the models without purchasing the entire Neural Fusion software package. If it is not possible to acquire the NNCALC add-in, a user could conceivably reconstruct the temperature models on their own in a spreadsheet using the 22 model text files (ending in *.txt, and listed below) and the EXCEL template “model_template.xls” file. The model text files contain the final hidden and output layer weights trained for each model. The “model_template.xls” file contains climate data necessary for the chaotic and periodic models. Figure 4 shows how the links between the input, hidden, and output layers would have to be set up for each model. Figure 9 shows how data would have to be passed from one model to another to simulate hourly or 24-hour moving average temperature time series output. However, by using the NNCALC add-in the user would only need to assemble the field habitat and basin characteristics data (listed in table 1) and insert them into “model_template.xls” to simulate a water temperature time series for their basin of interest. Using the NNCALC add-in, the “model_template.xls” spreadsheet is dynamically linked to 22 model files (ending in *.enn and listed below). The 22 *.enn files and the “model_template.xls” file need to all reside together in the same directory as the NNCALC add-in file “nncalc32.xll”.

4. Running the models

As a suggestion, the user should always make a copy of the “model_template.xls” for every new application. The “model_template.xls” file can be easily compromised if certain cells, rows, or columns are deleted by mistake.

4.1--After the required field habitat and basin characteristics data (table 1) for a basin of interest have been assembled, they are inserted into the cells in column B of the ‘group-static’ worksheet in the EXCEL template file “model_template.xls”

4.2--After the input data are entered, the three group assignment output values will appear in cells C2, D2, and E2. The cell with the highest value will be the group assignment for the site of interest. For assignments in groups 2 or 3, the cells D3 or E3 will indicate if the site of interest is in the northern or southern zone.

The dividing line between the northern and southern zones for group 2 is at:

Latitude (DMS): 44 degrees 34 minutes 12 seconds

Latitude (DD): 44.57

UTM: 4,935,450

YCOOR: 0.613972

The dividing line between the northern and southern zones for group 3 is at:

Latitude (DMS): 44 degrees 18 minutes 0 seconds

Latitude (DD): 44.30

UTM: 4,905,460

YCOOR: 0.548328

4.3--To compute 24-hour moving average and hourly water temperatures, the user must copy cell F2 (MEANTP) and then click on the worksheet for their group assignment (group1, group2n, group2s, group3n, or group3s). Once inside the group worksheet, the user must click on cell B2 and then click Edit-->Paste Special-->Values-->OK. Do not use Edit-->Paste. (“MEANTP”, output from the STATIC model, is the simulated mean water temperature [in degrees Celsius] for the entire simulation period [June 21, 1999, to September 20, 1999.])

4.4--Click on cell C2, which shows the results of the chaos model for the first time step. Highlight from C2 to C2209, and then click on Edit-->Fill-->Down. While these cells are still highlighted, click on Edit-->Copy. Click on cell D2, and then Edit-->Paste Special-->Values-->OK.

4.5--Click on cell E2, which shows the results of the periodic model for the first time step. Highlight from E2 to E2209, and then click on Edit-->Fill-->Down. While these cells are still highlighted, click on Edit-->Copy. Click on cell F2, and then Edit-->Paste Special-->Values-->OK.

4.6--Click on both cells G2 and H2, which show 24-hour moving average and hourly water temperatures (in degrees Celsius), respectively. To complete the time series, highlight and fill down cells G2 to G2209 and cells H2 to H2209. These simulated temperatures are based on 1999 climatic conditions for the user’s site of interest.

4.7--If the user is interested in simulating water temperatures for resulting different shade scenarios, they should repeat steps 4.1 through 4.6 using a new template file and new input values for the shade related parameters (listed in table 6).

Model files

Files for the 22 models are included in the “modelfiles.zip” file. File names with the *.enn ending are used in conjunction with the NNCALC add-in. File names with the *.txt ending are more easily understood text files and are included here as a backup alternative if the user is unable to acquire the NNCALC add-in.

Group assignment model:

“groupmod.enn” or “groupmod.txt”

Static model:

“static.enn” or “static.txt”

Chaos models:

“chaosg1.enn” or “chaosg1.txt”
“chaosg2n.enn” or “chaosg2n.txt”
“chaosg2s.enn” or “chaosg2s.txt”
“chaosg3n.enn” or “chaosg3n.txt”
“chaosg3s.enn” or “chaosg3s.txt”

Periodic models:

“perg1.enn” or “perg1.txt”
“perg2n.enn” or “perg2n.txt”
“perg2s.enn” or “perg2s.txt”
“perg3n.enn” or “perg3n.txt”
“perg3s.enn” or “perg3s.txt”

Moving average models:

“mavg1.enn” or “mavg1.txt”
“mavg2n.enn” or “mavg2n.txt”
“mavg2s.enn” or “mavg2s.txt”
“mavg3n.enn” or “mavg3n.txt”
“mavg3s.enn” or “mavg3s.txt”

Hourly models:

“hourg1.enn” or “hourg1.txt”
“hourg2n.enn” or “hourg2n.txt”
“hourg2s.enn” or “hourg2s.txt”
“hourg3n.enn” or “hourg3n.txt”
“hourg3s.enn” or “hourg3s.txt”