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Developing and testing temperature models for regulated systems: A case study on the Upper Delaware River

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SUMMARY

Water temperature is an important driver of many processes in riverine ecosystems. If reservoirs are present, their releases can greatly influence downstream water temperatures. Models are important tools in understanding the influence these releases may have on the thermal regimes of downstream rivers. In this study, we developed and tested a suite of models to predict river temperature at a location downstream of two reservoirs in the Upper Delaware River (USA), a section of river that is managed to support a world-class coldwater fishery. Three empirical models were tested, including a Generalized Least Squares Model with a cosine trend (GLScos), AutoRegressive Integrated Moving Average (ARIMA), and Artificial Neural Network (ANN). We also tested one mechanistic Heat Flux Model (HFM) that was based on energy gain and loss. Predictor variables used in model development included climate data (e.g., solar radiation, wind speed, etc.) collected from a nearby weather station and temperature and hydrologic data from upstream U.S. Geological Survey gages. Models were developed with a training dataset that consisted of data from 2008 to 2011; they were then independently validated with a test dataset from 2012. Model accuracy was evaluated using root mean square error (RMSE), Nash Sutcliffe efficiency (NSE), percent bias (PBIAS), and index of agreement (d) statistics. Model forecast success was evaluated using baseline-modified prime index of agreement (md) at the one, three, and five day predictions. All five models accurately predicted daily mean river temperature across the entire training dataset (RMSE = 0.58–1.311, NSE = 0.99–0.97, d = 0.98–0.99); ARIMA was most accurate (RMSE = 0.57, NSE = 0.99), but each model, other than ARIMA, showed short periods of under- or over-predicting observed warmer temperatures. For the training dataset, all models besides ARIMA had overestimation bias (PBIAS = −0.10 to −1.30). Validation analyses showed all models performed well; the HFM model was the most accurate compared other models (RMSE = 0.92, both NSE = 0.98, d = 0.99) and the ARIMA model was least accurate (RMSE = 2.06, NSE = 0.92, d = 0.98); however, all models had an overestimation bias (PBIAS = −4.1 to −10.20). Aside from the one day forecast ARIMA model (md = 0.53), all models forecasted fairly well at the one, three, and five day forecasts (md = 0.77–0.96). Overall, we were successful in developing models predicting daily mean temperature across a broad range of temperatures. These models, specifically the GLScos, ANN, and HFM, may serve as important tools for predicting conditions and managing thermal releases in regulated river systems such as the Delaware River. Further model development may be important in customizing predictions for particular biological or ecological needs, or for particular temporal or spatial scales.

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1. Introduction

Water temperature is an important factor driving many processes in riverine ecosystems (Jackson et al., 2001; Matthews, 1998). Many key abiotic processes, including nutrient cycles and characteristics of dissolved gases, are linked to river temperature (Webb et al., 2008). Similarly, many biotic activities, including life history traits of aquatic species, are affected by changing patterns of temperature over a variety of temporal scales (Vannote and Sweeney, 1980; Ward, 1985). This pattern of changing temperatures, or the natural thermal regime, is one key aspect of a functioning river ecosystem.

In unregulated rivers, temporal patterns in thermal regimes are primarily controlled by a set of factors that include climate (e.g. air temperature, precipitation, and solar radiation), groundwater

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inputs, and topography (Caissie, 2006). Crisp and Howson (1982) found air temperature explained almost 82% of variation in river temperature for streams in England. Norton and Bradford (2009) found stream temperature during summer months to be most sensitive to air temperature but also noted relative humidity to be important to stream temperatures in southern Ontario. Story et al. (2003) found that groundwater could affect a river's daily maximum temperature by up to 3 °C and Constantz (1998) found that groundwater inputs dampened the temperature fluctuation in receiving streams largely because of the constant temperature of groundwater. Fine-scaled resolution groundwater data have been studied at various scales but the intended spatial application of those study's results are important to consider (Scanlon et al., 2002).

The presence of reservoirs and reservoir releases can also alter a river's natural thermal regime; the magnitude and rate of change in temperature depending upon reservoir size, release volume, and the size of the downstream river (Baxter, 1977; Cole, 2007; Harmel and Smith, 2007). Releases from impoundments have a large influence on the thermal regime of downstream reaches, often altering the relative importance of other factors, such as groundwater inputs or warming or cooling due to atmospheric conditions (Baxter, 1977). This influence depends on season and on whether the release is from the bottom or top of the reservoir because reservoirs often show thermal stratification (Poff, 2002). For example, a bottom release during summer would dampen the magnitude of atmospheric warming (Bartholow, 1991). However, a surface release during summer could be used to mitigate groundwater influences to support warm water fisheries (Osmundson, 2011). Therefore, management of these impoundments can directly affect river temperatures through the quantity of release and whether the release comes from the bottom or top of the reservoir. Because reservoir releases affect multiple factors simultaneously (Graf, 2006), it can be difficult to predict their effects on downstream thermal regimes. Mathematical models may help understand how these various factors interact to influence river temperature.

Many models have been developed to predict thermal regimes in river systems using assorted climate variables and watershed characteristics as predictor variables. These can be generally grouped into two classes: empirical models (Johnson, 1971; Koch and Grünewald, 2010; Mackey, 1991; Smith, 1981) and mechanistic models (Allen et al., 2007; Bartholow, 1991). Empirical models are correlative or response models with known properties and error structures and are based on statistical analysis techniques (Bolker, 2008). Empirical models are based entirely on data. Multiple linear regression (MLR) is the most common and familiar example of an empirical model and has been used to model river temperature (Erickson, 2000; Mohseni and Stefan, 1999; Stefan and Preud'homme, 1993), but can violate independence assumptions because of the nature of time series data. Additional examples of empirical models that can handle time series data and have been used in river temperature modeling include Generalized Least Squares Models (GLS, Wehrly et al., 2009), Autoregressive Integrated Moving Average models (ARIMA, McMichael and Hunter, 1972), and Artificial Neural Networks (ANN, Chenard, 2008) that are built with an iterative process of data transformations fitting observed patterns of influential factors to temperature values, and nonlinear regression models (Mohseni et al., 1998). Recent advances in empirical modeling include combinations of these models (e.g., a hybrid ARIMA-ANN model, Ömer Faruk, 2010).

Mechanistic (theoretical) models are cause and effect models that use functions and distributions based on a theoretical understanding of how a given system works. They have been applied to estimate temperature in a variety of river systems and at a variety of spatial scales (Bartholow, 2005; Benyahya et al., 2007; Bolker, 2008; Caissie et al., 2007; Keller, 1989; Norton and Bradford, 2009). To develop mechanistic river temperature models, past studies have explored the use of a thermal budget balance that accounts for all thermal inputs and outputs for a given river system (Benyahya et al., 2007; Caissie et al., 2007). These may include solar radiation, long-wave radiation, evaporative heat flux, and convective heat flux (Caissie et al., 2007). These calculations result in a value for the net heat gain or loss from the system and an estimate of water temperature. Both empirical and mechanistic models have been applied in free flowing river systems to predict water temperature across a broad range of river conditions (Bartholow, 1991; McKenna et al., 2010; Younus et al., 2000); however, their utility in regulated systems has yet to be fully tested.

The Upper Delaware River (UPDE), USA, is an ecologically important river that has competing water demands, including water supply for nearly 17 million people (New York City area), recreational boating activities, and a world-class coldwater fishery. Several species of concern, including American eel, (*Anguilla rostrata*), American shad (*Alosa sapidissima*), and the US federally endangered dwarf wedgemussel (*Alasmidonta heterodon*) and bridle shiner (*Notropis bifrenatus*) are also located in the UPDE. Streamflow and thermal regimes in the UPDE are strongly influenced by releases from reservoirs on its major tributaries. Release scenarios are designed to balance the above needs. Understanding how these scenarios affect the thermal regime of the UPDE will help water and fisheries managers. In this study, our goal was to test how various temperature models performed in a regulated river system and explain the potential strengths and limitations of each model. To accomplish this, we developed and tested the ability of three empirical models (two statistical and one Artificial Neural Networks) and one mechanistic model (Heat Flux Model based on theoretical heat gain or loss) to predict average daily river temperature at a specific location in UPDE where river temperatures are strongly influenced by upstream reservoirs.

2. Methods

2.1. Study area

The Delaware River basin, located in the Northeast United States, drains 33,016 km^2 along 674 km of river (Fig. 1). The headwaters of the mainstem river begin in New York, USA, and the river flows south with portions in the states of Pennsylvania, New Jersey, and Delaware, USA. The river discharges into Delaware Bay near Philadelphia, Pennsylvania, and ultimately drains into the Atlantic Ocean. In this study, we focused on the portion of the river upstream of the U.S. Geological Survey (USGS) gage at Lordville, New York, USA (gage #1427207, drainage area 4118 km^2, river kilometer 483, Fig. 1) hereafter referred to as the Upper Delaware River (UPDE). This area is of particular interest because (1) this section of the Delaware River is managed as a coldwater fishery, (2) the flow and temperature of this portion of the river is affected by operation of three reservoirs (Cannonsville, Pepacton, and Neversink) that reside in the headwaters, and (3) previous studies (Bovee et al., 2007; Cole, 2007; Maloney et al., 2012, 2014) have documented the importance of reservoir management to species in this area. Temperatures at the Lordville USGS gage also provide the best indication of the upstream thermal regime; thus, developing a temperature model for this site would provide an important tool for natural resource managers in the UPDE.

2.2. Data collection and dataset development

We incorporated climate and hydrologic data into a suite of models to predict river temperature at the USGS Lordville gage (LD) in the Upper Delaware River. Climate data were obtained from