

Monitoring spatial and temporal variation of dissolved oxygen and water temperature in the Savannah River using a sensor network

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Abstract Dissolved oxygen is a critical component of river water quality. This study investigated average weekly dissolved oxygen (AWDO) and average weekly water temperature (AWT) in the Savannah River during 2015 and 2016 using data from the Intelligent River[®] sensor network. Weekly data and seasonal summary statistics revealed distinct seasonal patterns that impact both AWDO and AWT regardless of location along the river. Within seasons, spatial patterns of AWDO and AWT along the river are also evident. Linear mixed effects models indicate that AWT and low and high river flow conditions had a significant impact on AWDO, but added little predictive information to the models. Low and high river flow conditions had a significant impact on AWT, but also added little predictive information to the models. Spatial linear mixed effects models yielded parameter estimates that were effectively the same as non-spatial linear mixed effects models. However,

components of variance from spatial linear mixed effects models indicate that 23–32% of the total variance in AWDO and that 12–18% of total variance in AWT can be apportioned to the effect of spatial covariance. These results indicate that location, week, and flow-directional spatial relationships are critically important considerations for investigating relationships between space- and time-varying water quality metrics.

Keywords Intelligent River[®] · Geographic information systems (GIS) · Spatial stream networks · Water quality monitoring

Introduction

In the southeastern USA, the Savannah River provides drinking water, hydroelectric energy, and recreational opportunities for the states of Georgia and South Carolina (U.S. Army Corps of Engineers 2013). In addition, the river is home to the second largest population of Atlantic sturgeon (*Acipenser oxyrinchus oxyrinchus*), which is known to be an endangered species (Bahr and Peterson 2016). Modern environmental pressures from agriculture, industry, urbanization, and climate change make it challenging to manage water quality in many river systems, including the Savannah River.

Dissolved oxygen is a key water quality metric that is often the subject of monitoring and analysis efforts. Hypoxia (dissolved oxygen <2 mg/L⁻¹) threatens the health of river systems resulting in great economic loss

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and a reduction in biodiversity (Wilson and Carpenter 1999). Low levels of dissolved oxygen reduce fish development and growth, leading to mortality, and create condition suitable for eutrophication, making the water unsuitable for consumption. Foul odors resulting from hypoxic conditions can also reduce the economic gain from human recreation (Cox 2003). Runoff from agricultural land, sewage treatment plants, or industrial facilities often contains excess nutrients that can lead to hypoxic conditions in river systems (Bianchi et al. 2010). In the Savannah River, specific potential sources of nutrients and other chemical constituents that may deplete dissolved oxygen include poultry feedlots, corn and soy fields, leakage or runoff from coal ash storage, and effluent water from nuclear cooling towers (Wilde and Shealy 1992).

Internal river metrics are thought to drastically impact dissolved oxygen at different spatial and temporal scales (Huang and Scmitt 2013). Water temperature is the primary regulating metric that determines how much dissolved oxygen water can hold; dissolved oxygen is inversely dependent on water temperature. Heat exchange at the water's surface is the primary contributor to water temperature changes (Ficklin et al. 2013). Projected effects of climate change create a pressing need for further understanding of the relationship between dissolved oxygen and water temperature in rivers and streams (van Vliet et al. 2013; Kaushal et al. 2010). As air warming intensifies in many areas of the globe, rivers and streams will likely warm as well (Kaushal et al. 2010). Increases in water temperature would thus further reduce dissolved oxygen and negatively impact water quality. This creates a pressing need to monitor and learn about the spatial and temporal dynamics of water temperature and dissolved oxygen in rivers and streams.

Seasonality is very important to consider when assessing water quality, as seasonal effects on surface water flow can reveal important trends or annual cycles that have important management or forecasting implications. Qian et al. (2007) detected seasonal patterns that were nearly identical among several nutrients in the Indian River Lagoon in Florida. Richards and Baker (2002) saw seasonal patterns in phosphate and nitrate loads in Ohio. Similarly, Tufford et al. (1998) observed seasonality in nutrient loads in Lake Marion drainage just slightly northeast of the current study area. Seasonal variation may affect dissolved oxygen through indirect processes, such as the depletion of dissolved oxygen

during eutrophication of surface water during warmer months (Minaudo et al. 2015). Young and Isely (2011) described seasonal distributions of water temperature and dissolved oxygen in the Thurmond Reservoir immediately upstream from the current study area. However, it is unknown how representative their estimates may be for water temperature and dissolved oxygen along the large section of the Savannah River below the Thurmond Dam.

New technologies for monitoring and assessing water quality are being developed at a rapid pace to keep up with increasing management demands created by the changing environment. Recent developments in sensor technologies allow for continuous in situ monitoring of water quality (Sherson et al. 2015). Sensor technologies have a clear advantage over traditional sampling methods, which do not allow for safe or simple sampling during less than desirable weather conditions. The continuous collection of water data allows for studies into the dynamics of inorganic nutrients in the water and the effects of wildfires on water quality (Sherson et al. 2015; Mast et al. 2016). This study utilizes the Intelligent River[®] system, a network of sensors that collect information on the Savannah River and other sites. Water quality data is collected from in situ sensors, which are attached to buoys along the Savannah River, and is transmitted to an online database (<https://www.intelligentriver.org/data>), where it can be retrieved for any or all active sensors for specified time periods. The data export module allows users to gather, share, and apply environmental data on immense temporal and spatial scales. The system includes novel data collection, processing, and storage platforms, wireless transmission technology, and presentation tools. With the Intelligent River[®] system, environments can be continuously monitored inexpensively, on a fine scale, and over a long period, amassing a large amount of publicly available information (White et al. 2010; Eidson et al. 2010).

Perhaps the primary challenge of modeling relationships between water quality metrics in river networks is that these metrics are space- and time-varying, and contained in a spatial network that is flow-directional. Not only may data be spatially dependent, but spatially dependent on upstream water and land conditions. Ver Hoef and Peterson (2010) developed and implemented spatial covariance functions as part of a generalized or mixed linear modeling strategy that has yielded promising results for spatially modeling water quality in stream

or river networks. This modeling strategy has been used to spatially model mean summer stream temperature (Isaak et al. 2010), summer median stream temperature (Detenbeck et al. 2016), and 13 different stream temperature metrics (Steel et al. 2016) at various spatial scales in river networks. A common theme from these studies is the use of spatially variable, but temporally static, stream temperature metrics. Another common theme is the use of external predictor variables outside of the water body. Dissolved oxygen has not been considered in this modeling strategy, and space- and time-varying predictor variables in the river body have also not been considered. Estimates of spatial effects from the mixed model could provide insight as to whether there is inherent spatial correlation in water temperature and dissolved oxygen data in the river, and as to whether this information may be useful for spatiotemporal prediction of water quality.

This study uses Intelligent River[®] data collected continuously during 2015 and 2016 on the Savannah River to investigate the seasonality of water quality and relationships between space- and time-varying water quality metrics. The objectives of this study were to (1) summarize seasonal and within-season spatial distributions of average weekly dissolved oxygen (AWDO) and average weekly water temperature (AWT) on the Savannah River during 2015 and 2016, (2) evaluate in situ correlations between AWDO and AWT at Intelligent River[®] sensor sites during 2015 and 2016, and (3) investigate relationships between AWDO, AWT, and river flow conditions using a random and mixed effects linear modeling strategy, including the use of components of the spatial stream network modeling strategy.

Materials and methods

Study area

The entire Savannah River basin covers approximately 2,739,900 ha and contains portions of North Carolina, South Carolina, and Georgia. This includes portions of the following biogeographic regions: Blue Ridge, Carolina Piedmont, Carolina Sand Hills, and Atlantic Coastal Plains. The U.S. Army Corps of Engineers constructed and maintains three major dams (J. Strom

Thurmond, Richard B. Russell, and Hartwell) on the Savannah River for hydroelectric power, flood control, water supply, and recreational purposes (U.S. Army Corps of Engineers 2013). The J. Strom Thurmond Dam is farthest downstream, approximately 350 km from the Atlantic Ocean. Water quality and subsequent analyses for this study focus on the Savannah River portion below J. Strom Thurmond Dam.

Data collection

The data used in this study were collected from the Intelligent River[®]. The data were recorded by ten sensors along the Savannah River below J. Strom Thurmond Dam (Table 1, Fig. 1). The sensors continuously record several water quality variables at ≈ 10 -min intervals. Time stamps of data records from all sensors in the Intelligent River[®] system are synchronized on Eastern Standard Time. Dissolved oxygen (DO) readings were taken using a YSI EXO2 multiparameter sonde with an optical DO sensor and a temperature sensor (as part of a combined temperature conductivity probe). All sensors were equipped with a central mechanical wiper that limited bio-fouling of sensors by wiping sensors in between readings. Sensors were calibrated in the lab using manufacturers standard calibration procedures and were exchanged at regular service intervals (typically every 30 days). Temperature and salinity were adjusted for during the laboratory calibration for field use. To further access sensor function, data were visually inspected directly before and after each sensor exchange to verify readings were consistent and that data from a replaced sensor was valid. In each case, data did not display noticeable changes between sensor exchanges, indicating sensor function and bio-fouling did not impact reported values. For this study, all recordings of DO and water temperature from January 1, 2015 until December 31, 2016 were downloaded from the Intelligent River[®] data export module (<https://www.intelligentriver.org/export?p=6>). River flow conditions are not available at Intelligent River[®] sensor sites, but seven USGS gage stations are located along the section of the Savannah River used in this study, some of which are near to Intelligent River[®] sensor sites. Gage

Table 1 Descriptions of Intelligent River[®] sensor sites used in this study

	Intelligent River [®] sensor site	Weeks with complete data	Distance (km) from outlet node	Upstream area (km ²)	Nearest USGS gage station
Flow direction ↓	STM215	94	297.8	494	02195520
	STM206	99	285.5	2585	021964832
	STM198	94	271.6	2773	021964832
	STM190	94	262.3	3497	02197000
	STM185	89	248.6	3568	02197000
	STM179	92	239.1	3839	02197000
	STM150	89	196.7	5326	02173269
	STM119	67	147.2	6580	02197500
	STM061	85	58.8	9726	02198500
	STM027	96	4.0	10,692	02198840

height (feet) data from these USGS gage stations were retrieved (<https://waterdata.usgs.gov/nwis/sw>)

and associated with the nearest Intelligent River[®] sensor sites (Table 1).

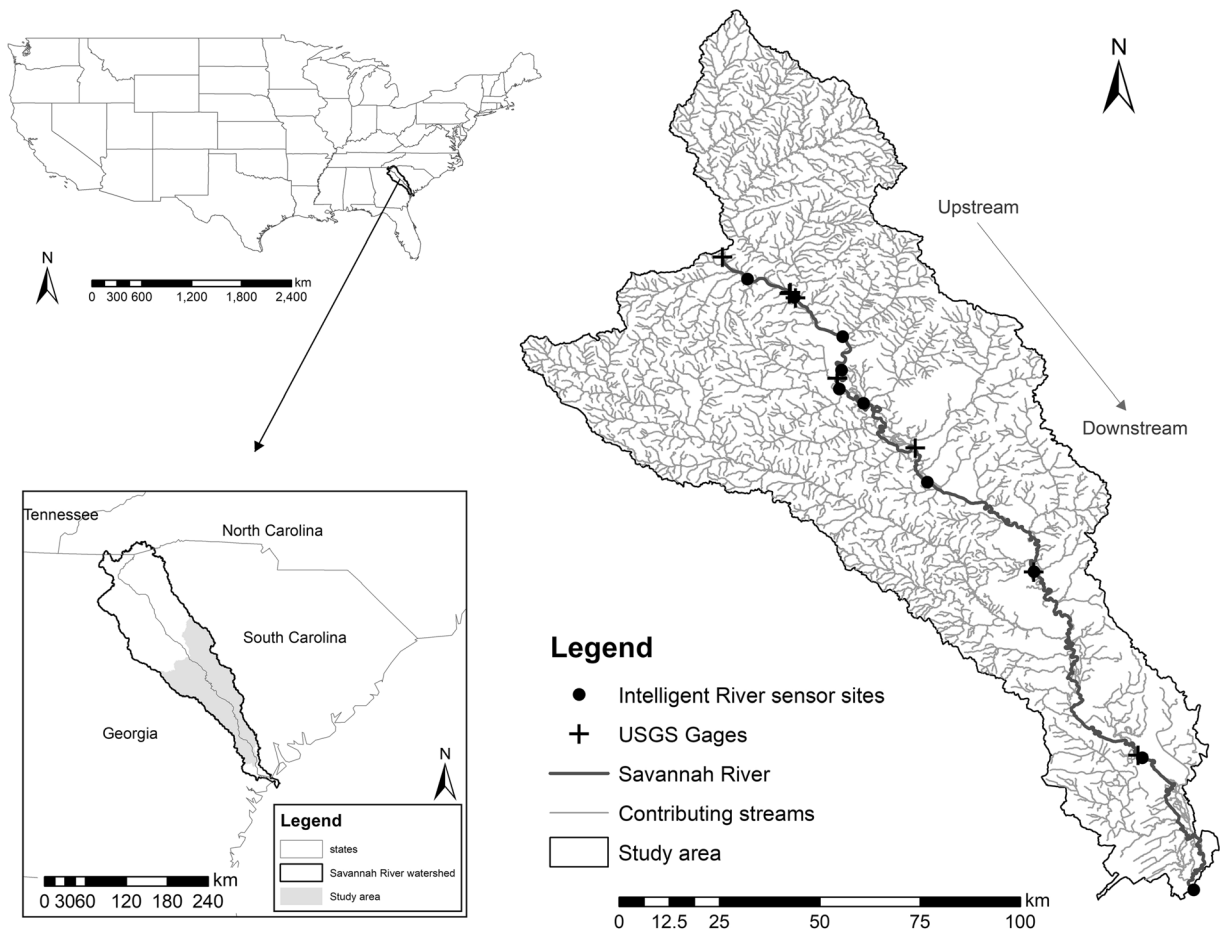


Fig. 1 Map of the study area with locations of intelligent River[®] sensors and USGS gage stations

Data aggregation

Data were aggregated to average weekly dissolved oxygen (AWDO) and average weekly temperature (AWT) at each sensor site. The sensor platform did not always report values at each location for each expected sensor reading, and each sensor is missing at least several weeks of data during the study period (Table 1). In cases where sensor values were reported, the laboratory calibration and sensor exchange process did not highlight data for omission from the analysis. The quality and temporal density of the data indicate that the missing data is inconsequential for the analyses performed in this study. For plotting purposes, weekly gage height data was standardized at each site; gage heights are heights above an arbitrary point below the water surface, meaning raw values can be artificially variable between gages based on the arbitrary point from which measurements are made. No transformations were applied to Intelligent River[®] data. All sensor sites used in this study are flow connected to the main channel of the Savannah River.

Seasonal statistics

Seasons were defined using northern meteorological seasons: spring (03/01–05/31), summer (06/01–08/31), autumn (09/01–11/30), and winter (12/01–02/28). These seasons begin 21–22 days earlier than astronomical seasons. For each season, summary statistics were computed from AWDO and AWT at each Intelligent River[®] sensor site. Autumn summary statistics were not computed for STM119 because a majority of the data was missing. The seasonal means at each sensor site were evaluated in an upstream-downstream manner to identify any additive or diffusive patterns in AWDO and AWT along the river.

Correlation between AWDO and AWT

Pearson correlations were computed between AWDO and AWT at each Intelligent River[®] sensor site. It was recognized that AWDO and AWT may both be correlated with time, and that this in itself may have important management applications with regard to tracking dissolved oxygen across time using water temperature values. Thus, correlations were computed over time using the AWDO and AWT values. In order to assess whether or not correlations between AWDO and AWT might also represent a site-level relationship independent

of temporal processes, correlations were also computed on residuals that resulted from subtracting the weekly mean (among all sites) from each observation of AWDO and AWT. These analyses were carried out in R Studio (R Core Team 2014).

Random and mixed effects linear modeling

A random and mixed effects linear modeling strategy was used to assess the relationship between AWDO, AWT, and river flow conditions. To establish a baseline to compare against models that used dynamic space-time predictors (AWT or river flow conditions), random effects models were fit for AWDO and AWT using the week of observation and sensor site as random effects. Space-time predictors were then used to fit mixed effects linear models of AWDO and AWT, where again the week of observation and sensor site were used as random effects. This random effects design was selected because it was viewed as the most appropriate modeling structure by removing weekly variability and variability between sites to estimate model parameters. Since some sensors share the same USGS gage data (Table 1), river flow conditions were generalized for river sections by using binary low flow (25th percentile) and high flow (75th percentile) variables computed from the weekly mean gage height at the nearest USGS gage station.

Spatial random and mixed effects linear modeling

The relationship between AWDO, AWT, and river flow conditions were also assessed using spatial random and mixed effects linear models. The same set of model statements used in random and linear mixed effects models of AWDO and AWT were used, but the random effects design differed in spatial random and linear mixed effects models. Week was again used as a random effect, but two random spatial effects were used in place of sensor site as a random effect. These were estimated using “tail-up” and “tail-down” spatial covariance functions (Ver Hoef and Peterson 2010). Generally, tail-down covariance can be viewed through the traditional lens of spatial covariance, but the function uses distance estimated along the stream network. Tail-up covariance is an additional, extended spatial covariance function intended to help adjust for situations where spatial covariance may depend on upstream conditions; a sensor site is only allowed to be spatially correlated with upstream sensor sites. This random effects design was used

because it was viewed as the most appropriate spatial analog to the non-spatial random and mixed effects linear models, as the effect of sensor site may be spatially dependent on other sensor sites regardless of weekly variability. All spatial models were fit using exponential spatial weights, in addition to the upstream area (km²) in the case of tail-up spatial covariance. The spatial stream network (SSN) dataset was compiled in ArcGIS 10.4 (ESRI 2014) using methods detailed by Peterson (2015); a modified National Hydrography Dataset (NHDPlusV2, VPU03b) and a 30-m digital elevation model were used for the analyses. All models were fit using the SSN package (Ver Hoef et al. 2014) in R Studio (R Core Team 2014).

Results

Seasonal and within-season spatial distribution of AWDO and AWT

AWDO had a distinct seasonal pattern within each study year (Fig. 2a). All sites reached peak annual AWDO levels in February or March, and the lowest AWDO levels at all sites occurred around the beginning of September. In all seasons, STM185 had the highest AWDO (all seasonal results Table 2). In spring and winter, the most downstream sensor site, STM027, had the lowest AWDO. In summer and autumn, the most upstream sensor site, STM215, had the lowest AWDO. In all seasons, AWDO slightly increased when moving downstream from STM215 to STM185, and then slightly decreased when moving downstream from STM185 to STM027.

AWT also had a distinct seasonal pattern within each study year, but this pattern was opposite from AWDO (Fig. 2b). Peak AWT at all sites occurred between June and September, and lowest AWT at all sites occurred in February or March. In all seasons except autumn, STM027 had the highest AWT. In spring and summer, STM215 had the lowest AWT. STM206 had the lowest AWT in autumn and STM119 the lowest AWT in winter. Variation in AWT among sites was quite pronounced in spring and summer. There was less variation in AWT among sites in autumn, and very little variation in AWT among sites in winter. Generally, there was a progressive increase in AWT when moving downstream from STM215 during spring and summer. In autumn and winter, there were no clear upstream or downstream

patterns in AWT. Weekly gage height showed no clear seasonal patterns (Fig. 2c), but the effects and aftermath of the “1000-year rainstorm” of October–November, 2015 can be seen clearly (Holmes 2017). The spatial and temporal dynamics of this “storm complex” have not been fully assessed for the study area. No obvious disturbances to AWT or AWDO are apparent during or after the storm complex in the weekly data used in this study. A closer look at the impact of this event on water quality is a potentially exciting research opportunity, but will likely require analysis at a much higher temporal frequency than used in this study.

Correlations between AWDO and AWT at sensor sites

Pearson correlation analysis was conducted between AWDO and AWT for each sensor site over time. Results suggest a strong and significant negative correlation between AWDO and AWT before the time adjustment (Table 3). The three most downstream sensor sites, STM027, STM061, and STM119, had the lowest correlation coefficients of -0.6590 , -0.6894 , and -0.6611 respectively. All other correlations between AWDO and AWT were particularly strong and negative ($r < -0.90$ in all cases). After adjusting for weekly variation by subtracting the weekly average among all sites from each AWDO and AWT observation, the correlations are much weaker and mostly non-significant (Table 3). In fact, STM215 had a significant positive correlation ($r = 0.2786$) after adjusting for weekly variation.

AWDO models

A set of five random and mixed effects linear models were developed to investigate the relationship of AWDO to AWT and river flow conditions (Table 4). These five models were fit in non-spatial and spatial contexts. In non-spatial models, week and sensor captured the vast majority of the total observed variance of AWDO. For space-time predictors, AWT had a significant negative impact on AWDO in all models. Low river flow conditions (25th percentile) had a significant positive impact on AWDO, while high river flow conditions (75th percentile) had a significant negative impact on AWDO. However, in this modeling strategy, the space-time covariates accounted for a relatively small portion (generalized $R^2 < 0.10$ in all models) of the total observed variance of AWDO. In fact, the proportion of

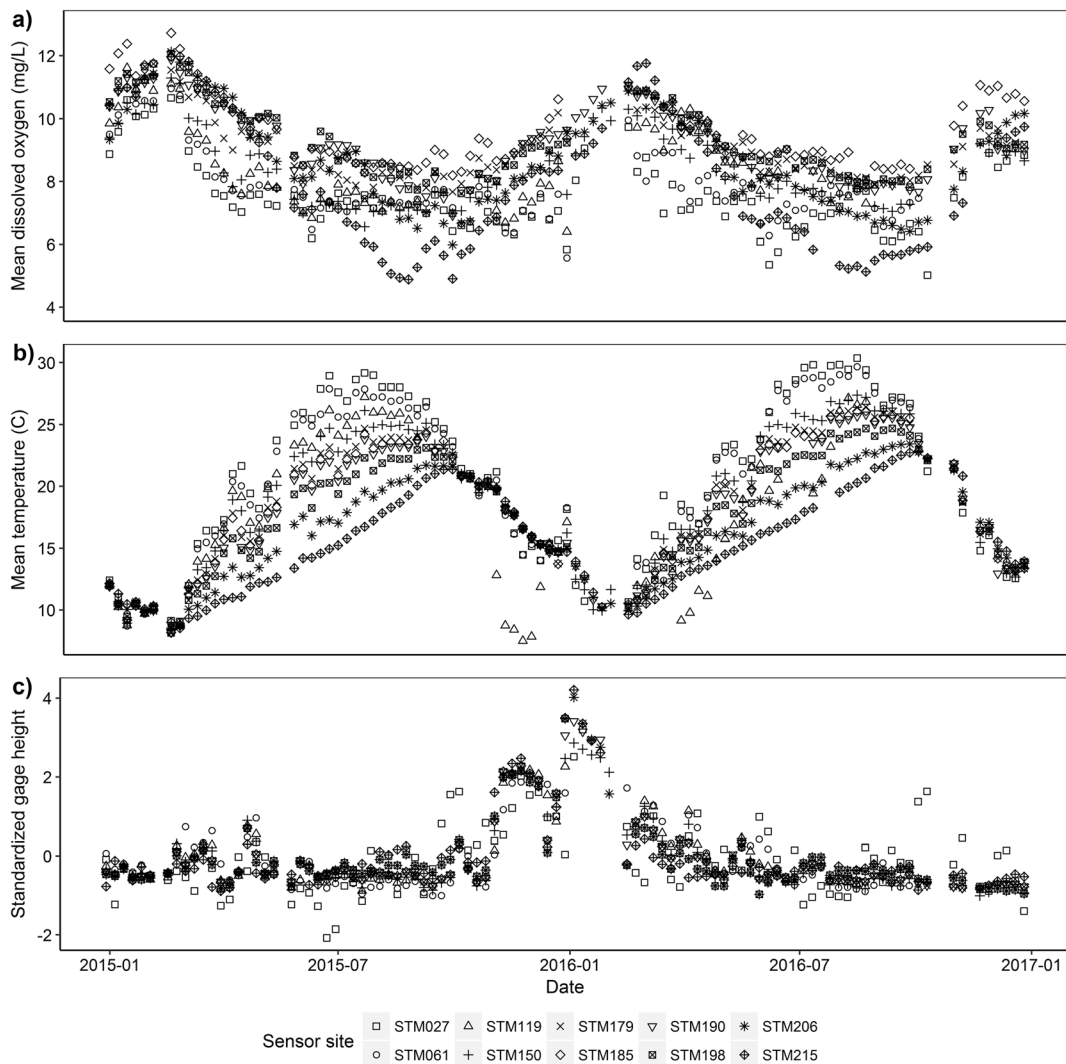


Fig. 2 Average weekly: **a**) dissolved oxygen (mg/L), **b**) water temperature (C°), and **c**) standardized gage height (feet) at Intelligent River® sensor sites along the Savannah River during 2015 and 2016

unexplained variance (nugget = 0.16) of the random effects model, which only includes an intercept model parameter, was lower than all other non-spatial models. This model also had the smallest prediction error [root mean square error (RMSE) = 0.64].

In spatial models, tail-up and tail-down spatial covariance functions were used in place of the sensor as a random effect (Table 4). In the spatial models, week and tail-up spatial covariance captured the vast majority of the total observed variance of AWDO. Interestingly, tail-up spatial covariance seems to capture a slightly larger portion of AWDO variance than sensor as a random effect in non-spatial models. Tail-down spatial covariance

captured a very small portion of the total variance in AWDO. The spatial models yielded parameter estimates that were effectively the same as non-spatial models, though the intercepts did differ slightly from the non-spatial models. As was the case with non-spatial models, space-time predictors accounted for a relatively small portion (generalized $R^2 < 0.08$ in all models) of the total observed variance of AWDO. Also similar to the non-spatial models, the random effects model that only included an intercept model parameter had the lowest proportion of unexplained variance (nugget = 0.16) and smallest prediction error (RMSE = 0.64) of all the spatial models.

Table 2 Seasonal summary statistics for average weekly dissolved oxygen (AWDO) and average weekly water temperature (AWT) at Intelligent River® sensor sites along the Savannah River during 2015 and 2016. Sensor sites are ordered vertically from the most upstream site (STM2015) to the most downstream site (STM027)

Variable	Sensor	Spring (03/01–05/31)				Summer (06/01–08/31)				Autumn (09/01–11/30)				Winter (12/01–02/28)			
		Min.	Max.	Mean.	S.D.	Min.	Max.	Mean.	S.D.	Min.	Max.	Mean.	S.D.	Min.	Max.	Mean.	S.D.
AWDO																	
	STM215	6.65	11.82	9.31	1.54	4.88	7.67	6.14	0.90	4.91	8.26	6.40	0.93	8.30	11.98	10.13	1.24
	STM206	7.68	11.75	9.73	1.17	6.51	8.96	7.68	0.73	5.99	9.28	7.35	0.89	8.45	12.13	10.21	0.94
	STM198	8.68	11.47	9.96	0.76	7.74	9.60	8.51	0.44	6.99	9.92	8.36	0.72	8.99	12.07	10.39	1.14
	STM190	8.14	11.08	9.71	0.83	7.27	9.18	8.29	0.53	6.91	10.28	8.37	0.89	8.91	11.89	10.33	0.90
	STM185	8.78	11.67	10.06	0.75	7.77	9.04	8.65	0.33	8.19	11.07	9.10	0.82	9.42	12.73	11.22	0.88
	STM179	8.30	10.78	9.54	0.63	7.46	8.71	8.22	0.30	7.67	9.71	8.48	0.55	9.02	11.55	10.38	0.88
	STM150	7.43	10.05	8.79	0.76	6.56	8.01	7.40	0.36	6.99	9.20	7.64	0.68	7.58	11.29	9.72	0.93
	STM119	7.36	10.30	8.74	0.86	6.83	8.32	7.51	0.43	6.68	7.49	7.08	0.34	6.40	11.61	9.81	1.55
	STM061	6.68	9.32	8.05	0.65	6.28	7.87	7.28	0.37	6.36	7.84	7.08	0.47	5.56	10.99	9.22	1.72
	STM027	6.08	8.97	7.49	0.57	5.35	8.41	7.10	0.71	5.02	9.25	6.94	0.93	5.84	10.67	8.90	1.34
AWT																	
	STM215	9.33	16.15	12.47	1.90	14.20	21.47	17.55	2.09	15.96	22.85	20.57	1.87	8.53	15.51	12.06	2.27
	STM206	10.06	18.87	13.90	2.25	16.00	22.72	19.72	1.83	15.85	23.43	20.43	2.32	8.54	15.25	11.87	2.19
	STM198	10.79	21.31	15.42	2.65	18.24	24.68	22.01	1.64	15.87	24.69	20.67	2.82	8.15	15.30	11.92	2.37
	STM190	11.16	22.81	16.21	2.93	19.66	25.81	23.23	1.66	15.85	25.56	21.00	3.09	8.19	15.42	11.87	2.14
	STM185	11.27	22.95	16.44	2.93	20.06	26.09	23.60	1.53	15.86	25.81	20.91	3.34	8.16	15.32	11.80	2.25
	STM179	11.48	23.31	16.80	2.96	20.62	26.41	24.04	1.47	15.94	26.00	21.08	3.26	8.28	15.34	11.82	2.23
	STM150	11.79	24.04	17.53	3.08	21.98	27.39	25.09	1.35	15.48	26.34	22.11	3.49	8.43	16.22	11.58	2.09
	STM119	9.15	23.32	16.03	3.88	19.43	27.24	24.44	2.39	–	–	–	–	8.56	17.09	11.57	2.60
	STM061	11.74	25.87	18.59	3.81	24.89	29.66	27.33	1.30	14.47	26.99	21.92	4.14	8.71	18.27	11.96	2.86
	STM027	11.97	24.95	19.53	3.24	25.48	30.37	28.25	1.31	14.47	27.23	21.35	4.28	8.97	18.15	12.32	2.46

AWT models

A set of four models were developed to investigate the relationship between AWT and river flow conditions (Table 5). These four models were fit in non-spatial and spatial contexts. In non-spatial models, week alone captured the vast majority of the total observed variance of AWT, while sensor site captured a relatively small portion of the total variance. Low weekly river flow conditions (25th percentile) had a significant positive impact on AWT, while high weekly river flow conditions (75th percentile) had a significant negative impact on AWT. Separately or collectively, river flow conditions as space-time predictors explained a very small portion of the total variance (generalized $R^2 < 0.03$ in all models) of AWT. However,

the addition of river flow conditions as space-time predictors slightly reduced the prediction error in these models when comparing against the random effects model that only included an intercept model parameter.

In spatial models of AWT, tail-up and tail-down spatial covariance functions were used in place of sensor site as a random effect (Table 5). In these models, week captured less of the total observed variance of AWT than in the non-spatial models, while tail-down spatial covariance captured more variance than sensor as a random effect in non-spatial models. Tail-up spatial covariance in these models captured a very small portion of the total variance of AWT. Again, spatial models of AWT yielded parameter estimates that were effectively the same as non-spatial models. Prediction errors

Table 3 Pearson correlations between average weekly dissolved oxygen and average weekly water temperature at Intelligent River[®] sites during 2015 and 2016. Correlations over time were computed with the weekly values and correlations adjusted for time were computed on the residuals after subtracting the weekly average (among all sites) from each observation

Site ID	Over time <i>R</i>	Adjusted for time <i>R</i>
STM027	-0.6590***	0.0035
STM061	-0.6894***	0.0554
STM119	-0.6611***	-0.2966**
STM150	-0.9106***	-0.0869
STM179	-0.9262***	0.1881
STM185	-0.9226***	-0.1388
STM190	-0.9048***	-0.0550
STM198	-0.9043***	-0.4674***
STM206	-0.9503***	-0.1835
STM215	-0.9099***	0.2786**

Asterisks indicate significance at $p < 0.10$ (*), $p < 0.01$ (**), and $p < 0.001$ (***)

(RMSE) were also effectively the same when comparing non-spatial and spatial models of AWT.

Discussion

Seasonality of water quality

Results from the current study and Young and Isely study (2011) in the Thurmond Reservoir generally agree in terms of the seasonal distribution of both water temperature and dissolved oxygen. Both Young and Isely (2011) and the current study agree with the review of stream and river temperature research by Webb et al. 2008 that states microthermal conditions are the most variable in summer months. Many studies discuss the temporal variation of dissolved oxygen (e.g., Williams et al. 2000; Young and Isely 2011) and spatial variations of dissolved oxygen in terms of variation between locations (e.g., Xia et al. 2010), but few studies discuss dissolved oxygen in terms of upstream or downstream spatial distributions. Mandal et al. (2010) noted that dissolved oxygen dropped to worrisome levels in the middle and downstream sections of the Yamuna River in Northern India, presumably due to wastewater discharge from the city of Delhi. Sharp et al. (2009) noted varying average dissolved oxygen levels in different sections of

the Delaware River, but these variations, like AWDO in the current study, did not exhibit a clear upstream or downstream trend.

Relationships between AWDO, AWT, and river flow conditions

Given the strength of Pearson correlations between AWDO and AWT over time in this study, it is tempting to assume there is a causal relationship (i.e., increasing water temperature causes dissolved oxygen to decrease). He et al. (2011) also found a strong negative correlation between dissolved oxygen and water temperature using daily measurements from two sensor sites over the course of 1 year in Alberta, Canada. Harvey et al. (2011) used temperature to model dissolved oxygen at daily, weekly, and monthly time steps, and also concluded there was a strong negative relationship between water temperature and dissolved oxygen in Newfoundland rivers. There are also chemistry-based reasons to assume a causal relationship between water temperature and dissolved oxygen, as gases tend to become more soluble in colder water (Vega et al. 1998).

However, the results of the current study suggest that water temperature is actually not a very useful spatial predictor of dissolved oxygen at any given time. When weekly variation and variation among sites or possible spatial correlation among sites was removed, the water temperature had little impact on dissolved oxygen. The SSN statistical software estimates spatial random effects on the model residuals, meaning in this case that spatial random effects were estimated on dissolved oxygen values that were adjusted for variation associated with seasonal variation in water temperature. Therefore, results of spatial models indicate there could be a temporally consistent spatial pattern in dissolved oxygen that is weakly dependent on water temperature. It is thus reasonable to suspect that there may be another process playing out that is strongly correlated with both water temperature and dissolved oxygen. Ozaki et al. (2003) suggested that increases in water temperature led to increased biological oxygen demand in several rivers of Japan, which then led to depleted dissolved oxygen. Biological oxygen demand may be a variable that interacts with both water temperature and dissolved oxygen (Schindler et al. 2017). Whether or not this invalidates the use of water temperature to predict dissolved oxygen is open to interpretation, as water temperature might be viewed as a potential

Table 4 Non-spatial and spatial linear random and mixed effects models of average weekly dissolved oxygen at Intelligent River® sites along the Savannah River during 2015 and 2016. All model parameters were significant at $p < 0.05$

Type	Model statement (random effects)	Parameter estimate (standard error)					Proportion of total observed variance					
		β_0	Temperature	Low flow	High flow	Gen. r^2	Week	Sensor	Tail up	Tail down	Nugget	RMSE
Non-spatial												
	(Sensor, week)	8.62 (0.25)	–	–	–	0.00	0.63	0.21	–	–	0.16	0.64
	Temperature (sensor, week)	9.88 (0.29)	–0.07 (0.01)	–	–	0.05	0.46	0.26	–	–	0.23	0.66
	Temperature + low flow (sensor, week)	9.94 (0.29)	–0.08 (0.01)	0.38 (0.07)	–	0.08	0.43	0.26	–	–	0.23	0.65
	Temperature + low flow + high flow (sensor, week)	10.1 (0.30)	–0.08 (0.01)	0.36 (0.07)	–0.23 (0.09)	0.09	0.43	0.26	–	–	0.22	0.66
	Temperature + high flow (sensor, week)	10.0 (0.30)	–0.07 (0.01)	–	–0.28 (0.09)	0.06	0.45	0.26	–	–	0.23	0.65
Spatial												
	(Week, tail up, tail down)	8.20 (0.53)	–	–	–	0.00	0.59	–	0.23	0.02	0.16	0.64
	Temperature (week, tail up, tail down)	9.39 (0.58)	–0.07 (0.01)	–	–	0.05	0.41	–	0.32	0.02	0.20	0.66
	Temperature + low flow (week, tail up, tail down)	9.51 (0.54)	–0.08 (0.01)	0.38 (0.07)	–	0.08	0.40	–	0.26	0.05	0.21	0.65
	Temperature + low flow + high flow (week, tail up, tail down)	9.57 (0.58)	–0.08 (0.01)	0.36 (0.07)	–0.23 (0.09)	0.08	0.39	–	0.31	0.02	0.20	0.66
	Temperature + high flow (week, tail up, tail down)	9.55 (0.58)	–0.07 (0.01)	–	–0.28 (0.09)	0.06	0.40	–	0.32	0.02	0.20	0.65

Table 5 Non-spatial and spatial linear random and mixed effects models of average weekly water temperature at Intelligent River® sites along the Savannah River during 2015 and 2016

Type	Model statement (random effects)	Parameter estimate (standard error)			Proportion of total observed variance						
		β_0	Low flow	High flow	Gen. r^2	Week	Sensor	Tail up	Tail down	Nugget	RMSE
Non-spatial											
	(Sensor, week)	18.3 (0.71)	–	–	0.00	0.82	0.08	–	–	0.10	1.90
	Low flow (sensor, week)	18.1 (0.70)	0.84 (0.19)	–	0.02	0.80	0.08	–	–	0.10	1.88
	Low flow + high flow (sensor, week)	18.3 (0.70)	0.78 (0.19)	–0.75 (0.27)	0.03	0.79	0.08	–	–	0.10	1.88
	High flow (sensor, week)	18.5 (0.70)	–	–0.86 (0.28)	0.01	0.80	0.08	–	–	0.11	1.89
Spatial											
	(Week, tail up, tail down)	18.3 (1.90)	–	–	0.00	0.74	–	0.04	0.12	0.10	1.90
	Low flow (week, tail up, tail down)	18.1 (2.16)	0.84 (0.19)	–	0.02	0.71	–	0.01	0.17	0.09	1.88
	Low flow + high flow (week, tail up, tail down)	18.5 (2.14)	0.78 (0.20)	–0.75 (0.28)	0.03	0.70	–	0.01	0.16	0.10	1.88
	High flow (week, tail up, tail down)	18.5 (2.14)	–	–0.88 (0.27)	0.01	0.69	–	0.02	0.18	0.10	1.89

All model parameters were significant at $p < 0.05$

proxy for biological oxygen demand. Water temperature and dissolved oxygen may also be more or less related at shorter time scales.

The impact of river flow conditions on water temperature in this study was expected. That runoff during and after rainfall decreases stream temperatures is intuitive, and this relationship has been observed in several studies (Kieser et al. 2004). Isaak et al. (2010) included flow as a significant predictor of stream temperature in their models, but they only used data from two USGS gage stations, and their estimates were annual summer summaries of flow. The impact of river flow conditions on dissolved oxygen in this study is counter to results of He et al. (2011), who concluded increasing river flow conditions had a positive impact on dissolved oxygen. Results of the current study also confuse the interpretation of the relationship between water temperature and dissolved oxygen, as low river flow conditions had a positive impact on both water temperature and dissolved oxygen. Given the rarity of the 1000-year rainstorm, it is difficult to assess how it may have impacted model estimates of relationships between river flow conditions, water temperature, and dissolved oxygen when investigating at the weekly scale. A separate study is needed to quantify the spatial and temporal extent of this event in the

study area, and to evaluate river metrics at a higher temporal resolution before, during, and after this event.

There are also other factors not considered in this study that could affect dissolved oxygen, water temperature, and river flow conditions. Geomorphology may affect these variables because the Savannah River watershed is a geographically large area. The entire watershed ranges from very cool, highly oxygenated headwaters in the southern Blue Ridge mountains (Price and Leigh 2006) to coastal plain and tidal marsh. In between these two extremes, the river receives drainage from large areas of the Carolina Piedmont and Sandhill biogeographic regions. It is unknown how either the soils or vegetation of Piedmont or Sandhill regions may impact dissolved oxygen, water temperature, or river flow conditions. Closer to the Atlantic Ocean, the Savannah River receives flow from several small Coastal Plain rivers. Coastal Plain rivers in the region are typically high in dissolved organic material, have a distinct dark water color, and are lower in dissolved oxygen than alluvial rivers (Ensign et al. 2014).

Another potentially critical factor affecting dissolved oxygen, water temperature, and river flow are impoundments. There are numerous dams in the watershed with a range of sizes and functionality. Dams

in large rivers have been shown to reduce dissolved oxygen and increase temperature (Zhao et al. 2013), and different types of water release regimes from dams can also impact dissolved oxygen and water temperature (Bednarek and Hart 2005). The type of release mechanism (e.g., top or bottom release) has also been shown to have an impact on dissolved oxygen and water temperature in some smaller contributing streams of the Savannah and Altamaha Rivers (Ignatius and Rasmussen 2016). The impact of the Thurmond Dam on dissolved oxygen in this study may be apparent in the seasonal statistics. For example, the summer and autumn dissolved oxygen and water temperature values at STM215 just several miles downstream from the Thurmond Dam (Table 2) closely match summer and autumn dissolved oxygen in the Thurmond Reservoir reported by Young and Isely (2011). Further downstream, summer and autumn dissolved oxygen are higher than at STM215. However, the Thurmond Dam releases water from both the top and lower sections of the water column in Thurmond Reservoir, for flood control and hydroelectric energy production, respectively. More information on dam release is needed in order to fully evaluate the impact that releases from the Thurmond Dam may have on water quality in the Savannah River.

Strengths, limitations, and applications of the study

This study used data from an advanced monitoring network of water quality sensors on the Savannah River. Having near real-time data has several advantages, including the ability to determine if data is being collected (or requires service) and the ability to access the general status of the sensors. It also provides a way for other domain scientists and concerned members of the public to observe sensor data as soon as it is collected through the open Intelligent River[®] website (<http://www.intelligentriver.org>). Related technologies are expected to become less expensive over time, so the added cost of implementing a sensor network should eventually become negligible when compared to the cost of deploying sensors with non-networked data loggers.

Modeling relationships between space- and time-varying water quality metrics in a flow-directional spatial network is difficult to say the least. The Spatial Stream Network (SSN; Ver Hoef et al. 2014) model is valuable for modeling spatial correlation structure in linear regression models.

However, these models estimate spatial correlation in stream and river networks as being temporally static. This study showed that weekly or seasonal fluctuations are the dominant source of variation in dissolved oxygen and water temperature in the Savannah River (Tables 2, 4, and 5). Therefore, the main criticism of the SSN models in this study would be that the spatial effects were constant throughout the study period, while AWDO and AWT varied seasonally and weekly. Despite this, SSN models estimated that spatial correlation was a source of 23–32% of the total observed variance in AWDO (Table 4). This indicates that even in temporally dense distributed sensor data, temporally static spatial effects estimated using SSN models could still be useful for spatially predicting dissolved oxygen along the studied section of the Savannah River if basin-scale weekly or seasonal variation is accounted for first. Moving forward, more work is needed to understand if or how spatial correlation in distributed water quality sensor data may vary at different times and temporal scales.

Together, distributed water quality sensor networks and SSN modeling could be used to support management of water resources and wildlife. For example, sensor networks could be important for establishing background water quality levels, which is important for determining the impact of various human activities in the watershed (Jahn and Srezov 2017). The endangered Atlantic (*Acipenser oxyrinchus*) and shortnose (*Acipenser brevirostrum*) sturgeon utilize the Savannah River system year-round, as well as populations of other migratory fish species, such as blueback herring (*Alosa estivalis*), American shad (*Alosa sapidissima*), and robust redhorse (*Moxostoma robustum*). Dissolved oxygen (DO) can be considered a limiting factor in fish habitat use, movements, and survival (Kramer 1987). Atlantic sturgeon in southern populations exhibit fall spawning migrations, and individuals acoustically transmitted in the nearby Altamaha River tend to enter the system during hot summer months (Ingram and Peterson 2016). Dissolved oxygen levels observed during these times in this study are not expected to directly imperil sturgeon species in the Savannah River, but may affect their migration and selection of spawning habitat. The combined use of distributed water quality sensor networks and SSN modeling can help managers understand and predict when and where water quality problems may be anticipated so that specific management strategies can be formulated.

Conclusions

This study investigated dissolved oxygen (AWDO) and water temperature (AWT) along the Savannah River during 2015 and 2016 using data downloaded from the Intelligent River[®]. Distinct seasonal patterns impact both AWDO and AWT regardless of location along the river. When evaluating summary statistics of individual seasons, spatial patterns of AWDO and AWT along the river were also evident. Pearson correlations of weekly AWDO and AWT at sensor sites were highly negative and significant over time, but after attempting to control for time, correlations at sensor sites were much less negative and mostly non-significant. AWT had a significant impact on DO at Intelligent River[®] sensor sites in both spatial and non-spatial linear mixed effects models. Low and high river flow conditions also had a significant impact on AWDO and AWT. Components of variance in AWDO and AWT in these models suggest that location, week, and perhaps flow-directional spatial relationships are much more important than space-time predictors for predicting AWDO and AWT at a weekly scale.

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