Temperature Sensitivity of Guatemala's Rio Dulce to Climate Change

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ABSTRACT

Water temperature is an important indicator of river system health. Temperatures occurring outside the norm for a particular system cause stress to the biological community. Climate change is expected to intensify extreme river water temperature, especially in high biodiversity areas such as Central America. I constructed a deterministic water temperature model for Guatemala's Rio Dulce using meteorological and temperature data I collected *in situ* from August 5 – 15, 2014. I used this model to predict water temperatures in Rio Dulce for two of the climate change scenarios expected during the 21st century. I found the model to predict summer midday water temperatures with a mean standard error of 0.57 °C. And I found that Rio Dulce water temperature is expected to increase by 2 – 5 °C by year 2100. This temperature increase will adversely affect local biota. Specifically, I expect growth reduction and mortality in Rio Dulce fish populations. This will impact local Guatemalan communities that rely on subsistence fishing in Rio Dulce and nearby river systems.

KEYWORDS

INTRODUCTION

Water temperature is an important indicator of river system health. Temperature conditions occurring outside the normal range for a particular river system are stressors to the local biota (Caissie et al. 2007). Extreme river temperatures impair fish spawning ability, and can be detrimental to fish populations (Monismith et al. 2009). High water temperatures cause a reduction in dissolved oxygen and an increase in fish metabolism, which leads to growth reduction and mortality in many fish species (Brown et al. 2013; Webb et al. 2008). Water temperature also impacts the location and duration that certain nutrients are available in river systems (Webb et al. 2008). Rapid changes in water temperature often lead to temperature stratification, which together with hypoxia facilitate the development of toxic cyanobacteria, (Bormans and Webster 1998). For these reasons, it's important accurately gauge river temperature as a means of assessing river system health.

Deterministic modeling is a technique often applied to river systems to study water temperature. One method of deterministically modeling river temperature is with a one-dimension advection-dispersion equation (e.g., Fischer et al. 1979), and is given by

$$A(x)\frac{\partial T}{\partial t} - Q_f \frac{\partial T}{\partial x} = \frac{\partial}{\partial x}\left(K(x)A(x)\frac{\partial T}{\partial x}\right) - \frac{WH_f}{\rho c_p} \tag{1}$$

where A is the cross sectional river area (m^2), T is water temperature (°C), x is upstream river location (m), Q_f is streamflow (m^3 s^{-1}), K is the empirical dispersion coefficient (m^2 s^{-1}), W is river width (m), H_f is heat flux at the air-water interface (W m^{-2}) and is determined by local meteorological conditions, ρ and c_p are water density and heat capacity, respectively (Fischer et al 1979). The theory for this 1-D application is an energy balance implemented on a given reach of river (Monismith et al. 2009). Equation 1 quantifies heat fluxes associated with river discharge and meteorological conditions, and can be used to predict water temperature (Caissie 2006; Gooseff et al. 2005; Gu et al. 1998; Sinokrot and Stefan 1993; Monismith et al., 2009). This modeling technique is especially accurate in describing river temperature during extreme climate conditions, such as heat waves or droughts (Gooseff at al. 2005).

Climate change is increasing the frequency and intensity of extreme temperature episodes in rivers (Brown et al. 2013; Gooseff et al. 2005; Cloern et al. 2011). General Circulation Models

(GCMs) of climate change scenarios predict an increase in air temperature for the remainder of this century (IPCC 2013). This increase will directly affect the meteorological and upstream boundary conditions of the deterministic temperature model, and produce higher river temperatures (Fischer et al. 1979). Variability in climate change-induced shifts in precipitation patterns leads to uncertainty in projections of future river discharge rates (Maurer et al. 2008). For most rivers, a decrease in precipitation would likely warm the system, while an increase in precipitation would have a cooling effect (Fischer et al. 1979; Caissie et al. 2007). Predicting river temperature under scenarios of climate change has been done for cases in the United States and other mid-latitude regions (Gooseff et al. 2005; Brown at al. 2013; Cloern et al. 2011), but no extensive work has been done on this topic in Central America (Maurer et al. 2008).

This study was developed to estimate the impact that various climate change scenarios will have on river temperature in Central America for this century. My hypothesis was that net warming would occur in these rivers, along with an increase in the frequency and intensity of high water temperature episodes. To test this hypothesis, I used Guatemala's Rio Dulce as a sample site for estimating river temperature under scenarios of climate change. To predict river temperature for this century, I used Equation 1 to construct a deterministic temperature model of Rio Dulce. I then extracted meteorological conditions and precipitation patters from GCMs covering a range of climate change scenarios, and applied those conditions and patterns as inputs to the Rio Dulce temperature model. The results from this model application predict the thermal regime of Rio Dulce under future scenarios of climate change, and provide a first-order approximation of water temperatures expected in other Central American rivers.

Site description

Guatemala's Rio Dulce is a 43-km tidal river that flows northeast from Lake Izabal into Amatique Bay (Figure 1). Midway along Rio Dulce is the long, narrow lake, Golfete. Golfete is approximately 15 km long, 4 km wide, and an average of 4.5 meters deep (Brinson et al., 1974). Golfete divides the river into Upper Rio Dulce and Lower Rio Dulce. Upper Rio Dulce flows from Lake Izabal to Golfete, and is characterized by the flatness of the surrounding land. Lower Rio Dulce (hereafter called Rio Dulce) is the 12 km span of river flowing from Golfete to Amatique Bay, and serves as the test site for this study. Rio Dulce is an attraction to visitors in Guatemala

due to the gorge formation that it runs through in the five kilometers near Livingston. The gorge walls rise approximately 90 meters on either side, and leave overhangs that small transport boats (lanchas) can drive under. Apart from being a tourist attraction, Rio Dulce serves as a vital fishing location for local residents. The main catch is the common snook (*Centropomus undecimalis*), which is fished from personal canoes using the handlining technique.

Figure 1. Image of Lake Izabal, El Golfete, and Rio Dulce. The border between Guatemala and Honduras, and the Atlantic Ocean, provide a spatial reference. The gage station monitors height in the Polochic River three times daily. Original figure was taken from UNEP Report (Yanez-Arancibia et al. 2005).

METHODS

Data collection and model development

To construct a temperature model of Rio Dulce, I measured water temperature, air temperature, relative humidity, and wind speed at 11 stations along the river (Figure 2). I chose these stations at 1 km intervals along Rio Dulce to get a representative sample of the river parameters. The 2 km of river closest to Livingston was omitted from the analysis due to the mixing that occurs with the bay.

Figure 2. Data collection stations along Rio Dulce. Stations are 1 km apart. Figure was taken from Google earth.

I collected data twice daily at each site during the study period, August 5-15, 2014. The time of collection was consistent for each station (within 1 hour), with all measurements taken from 08:00-11:00 and again from 13:00-16:00. To measure water temperature, air temperature, wind speed, and relative humidity, I used the Extech 45170 Hygro-Thermo-Anemometer-Light Meter. I measured water temperature (°C) at 1-meter depth intervals to obtain a cross sectional-average temperature. I measured wind speed (m s^{-1}), relative humidity (%), and air temperature (°C) at the river surface to be used in the surface heat flux calculation. I made cloud cover observations in oktas, with 0 being no cloud cover and 8 being sky completed covered.

To quantify the heat flux term in the advection-diffusion equation (H_f in Equation 1), I deconstructed it into incoming shortwave radiation (Q_{sw}), net longwave radiation (Q_{lw}), latent heat transfer (Q_l), and sensible heat transfer (Q_s) (see, e.g., Aeschbach-Hertig, 2011; Monismith et al., 2009; Gooseff et al., 2005). The total surface heat flux can be written as

$$H_f = Q_{sw} + Q_{lw} + H_l + H_s \qquad (2)$$

with all values in W m^{-2}. To calculate the four constituent factors on the right side of Equation 2 I used the *in situ* measured meteorological conditions and the following parameterizations described by Aeschbach-Hertig (2011).

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$$Q_{SW} = -(1 - \rho_{SW})Q_{Sw}^0(1 - 0.65B) \tag{3}$$

$$Q_{LW} = \varepsilon_W \sigma T_W^4 - (1 - \rho_{LW})\varepsilon_A \sigma T_A^4 \tag{4}$$

$$Q_L = \rho_{air} L_e c_L u_{10} \cdot (q_s(T_w) - q_A) \tag{5}$$

$$Q_S = \rho_{air} c_p c_s u_{10} \cdot (T_W - T_A) \tag{6}$$

The subscripts W and A refer to water and air, respectively, ρ_{SW} and ρ_{LW} are reflectivity in shortwave and longwave radiation, respectively, Q_{Sw}^0 is the clear sky radiation, B is cloud cover fraction, ε is emissivity, σ is the Stefan-Boltzmann constant, T is temperature (K), ρ_{air} is density of humid air, L_e is latent heat of evaporation, c_p is specific heat of air, c_L and c_S are bulk transfer coefficients (~0.001), u_{10} is wind speed, q_s is saturation specific humidity at T_W, and q_A is specific humidity of air.

       To estimate discharge for Rio Dulce (Q_f in Equation 1), I used a stock-flow model for water in Lake Izabal and known ratios of surface flow in the Izabal-Rio Dulce watershed. The Polochic River contributes 70% of all surface water to Lake Izabal, and Upper Rio Dulce contributes 90% of all surface water to El Golfete (Medina et al., 2010). Guatemala's National Institution for Seismology, Volcanology, Meteorology, and Hydrology monitors height of the Polochic River at the Teleman gage station (Figure 1) and provides annual average river discharge. Using Manning's Formula and 2013 average river height and discharge, I determined the relationship between volumetric flow rate and river height in the Polochic River. Manning's Formula operates under the assumption of flow at the normal depth and is given by

$$Q_f = \frac{A}{n} R_h^{2/3} S_0^{1/2} \tag{7}$$

with Q_f being volumetric flow rate (m^3 s^{-1}), A is cross-sectional area (m^2), n is Manning's roughness coefficient, R_h is hydraulic radius (m) and is a function of the river width and water height, and S_0 is the channel slope. Imposing the rectangular channel assumption, Equation 7 can be written as

$$\frac{Q_f}{y^{5/3}} = \frac{W}{n} S_0^{1/2} \tag{8}$$

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with *W* (channel width in meters), *n*, and *S₀* assumed to be constant and therefore provide the relationship between discharge and river height in the Polochic River. I used this relationship, river heights in the Polochic River during the study period, the Izabal-Rio Dulce flow ratios, and precipitation records for Eastern Guatemala to estimate volumetric flow rate in Lower Rio Dulce during the study period.

Model calibration and validation

To determine the dispersion coefficient (*K(x)* in Equation 1), I rearranged Equation 1 and assumed the river to be uniform, rectangular, and steady. This yields *K* as a function of river parameters and is given by

$$K = \frac{H_f \overline{W}(x - x_0)}{-\rho c_p \overline{A}\frac{dT}{dx}} - \frac{Q_f(T(x) - T(x_0))}{-\overline{A}\frac{dT}{dx}} \tag{9}$$

where over bars indicate study site means, *x₀* is at the mouth of the river, and *x* is a location upstream. I determined *K* for the study period using measured river parameters and meteorological conditions. I used the mean *K* from August 5-10, 2014 (calibration period) for model calibration, and August 11-14, 2014 (validation period) for model validation. I used average midday values for all model parameters. By testing this predicted water temperature against the observed water temperature for Rio Dulce during the validation period, I was able to determine the RMSE and accuracy of the temperature model.

Climate change data extraction and application

To approximate Rio Dulce water temperature under scenarios of climate change, I used regional climate projections provided by the IPCC in the Fifth Assessment Report on Climate Change (IPCC, 2013). These climate projections are based on outputs from the Coupled Model Intercomparison Project Phase 5, which uses data sets from 42 climate models (IPCC, 2013). The IPCC provides projections of regional (sub continental) air temperature change and precipitation change for each of the four Representative Concentration Pathways (RCPs) by season and by time

span. These representative concentration pathways are RCP 2.6, 4.5, 6.0, and 8.5 and represent four possible climate change scenarios, in which four different concentrations of greenhouse gasses are present in the atmosphere. These RCPs can be described as intensities of climate change, with RCP 2.6 being the lowest and RCP 8.5 the highest. I extracted changes in precipitation and air temperature associated with RCP 4.5 and RCP 8.5 for the summer months for the time spans of 2016-2035, 2046-2065, and 2081-2100 (Table 1). I then applied these six scenarios and their corresponding meteorological conditions to the temperature model of Rio Dulce. I assumed the percent change in river flow to be equal to the percent change in precipitation. In reality, a change in precipitation would lead to an amplified change in discharge. This is well understood by the fact that discharge is only a fraction of precipitation (Maurer et al., 2008). This model application yielded predications of Rio Dulce water temperature as a function of climate change scenario, time span, and position along the river.

Table 1. Central American Climate Projections for RCP 4.5: June-August

Period	RCP	Change in Air Temp (°C)	Change in Precipitation (%)
2016-2035	4.5	+0.5 to 1.0	-20 to -10
	8.5	+0.5 to 1.5	-20 to -10
2046-2065	4.5	+1.5 to 2.0	-20 to -10
	8.5	+1.5 to 2.5	-30 to -20
2081-2100	4.5	+2.0 to 3.0	-30 to -20
	8.5	+3.5 to 4.5	-40 to -30

RESULTS

Model development

Measurements of water temperature, meteorological conditions, and flow characteristics allowed me to develop a temperature model for Rio Dulce. I found that mean midday water temperature increased with distance upriver (Figure 3). There is an initial decrease in mean water temperature from 1 to 2 km upriver from the mouth, and another decrease from 4 to 6 km upriver.

A linear model indicates a longitudinal temperature gradient of 0.1 °C km^{-1} (P < 0.001). I also found the longitudinal temperature gradient to vary with time during the study period (Figure 1). Positive values indicate warmer water temperatures upriver. Gradients range from 0.02 to 0.24 °C km^{-1} with a mean of 0.14 °C km^{-1} and a standard deviation of 0.06 °C km^{-1}. I represented the entire length study site by using temperature differences between stations 1 and 6 and temperature differences between stations 6 and 11.
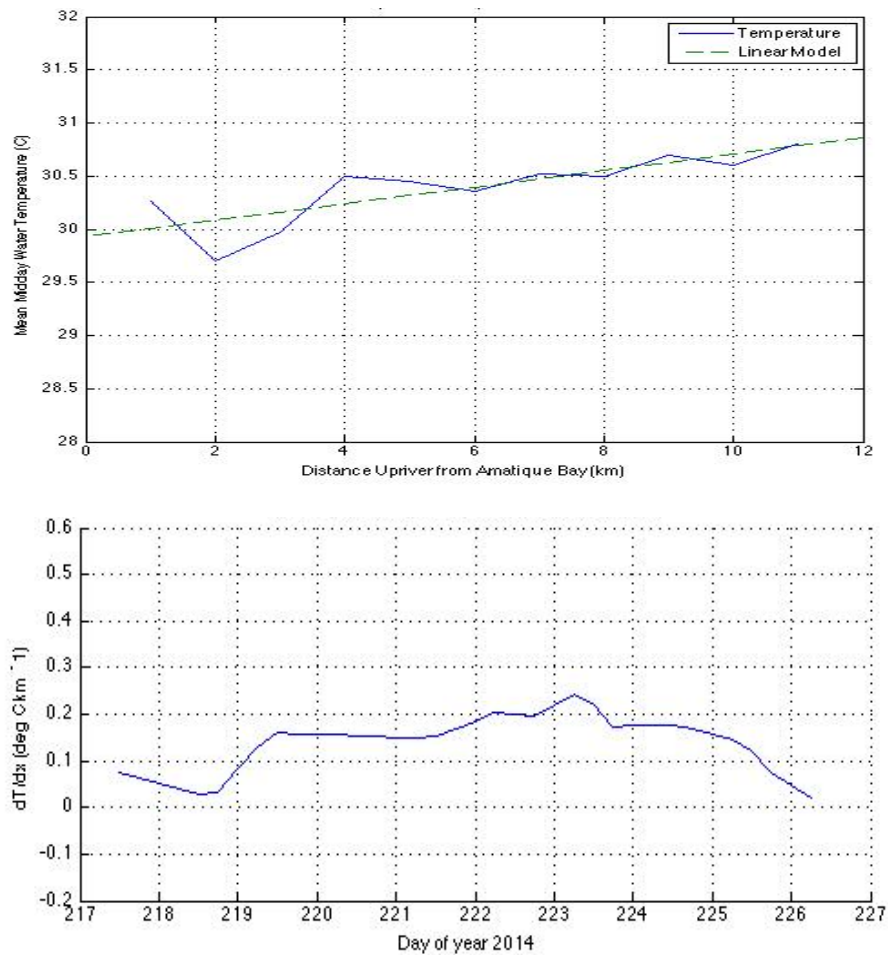

Figure 3. Mean water temperature and temperature gradient in Rio Dulce. Water temperatures (top) as a function of position along Rio Dulce are depth-average means that I measured twice daily (late morning and early afternoon) at 11 stations along the river. Positive values for the longitudinal temperature gradient (bottom) indicate warmer upriver water temperatures.

I found the total midday surface heat flux (*H$_f$* in Equation 1) to be consistently negative during the study period, indicating heating of the water column (Figure 4). Figure 4 also shows the constituent factors of the total surface heat flux. Factors that contribute to daytime warming of the water column are incoming shortwave radiation and sensible heat transfer. Net longwave radiation

and latent heat transfer warm the water column. The mean of the total surface heat flux is -505 W m^{-2} with a standard deviation of 97 W m^{-2}.
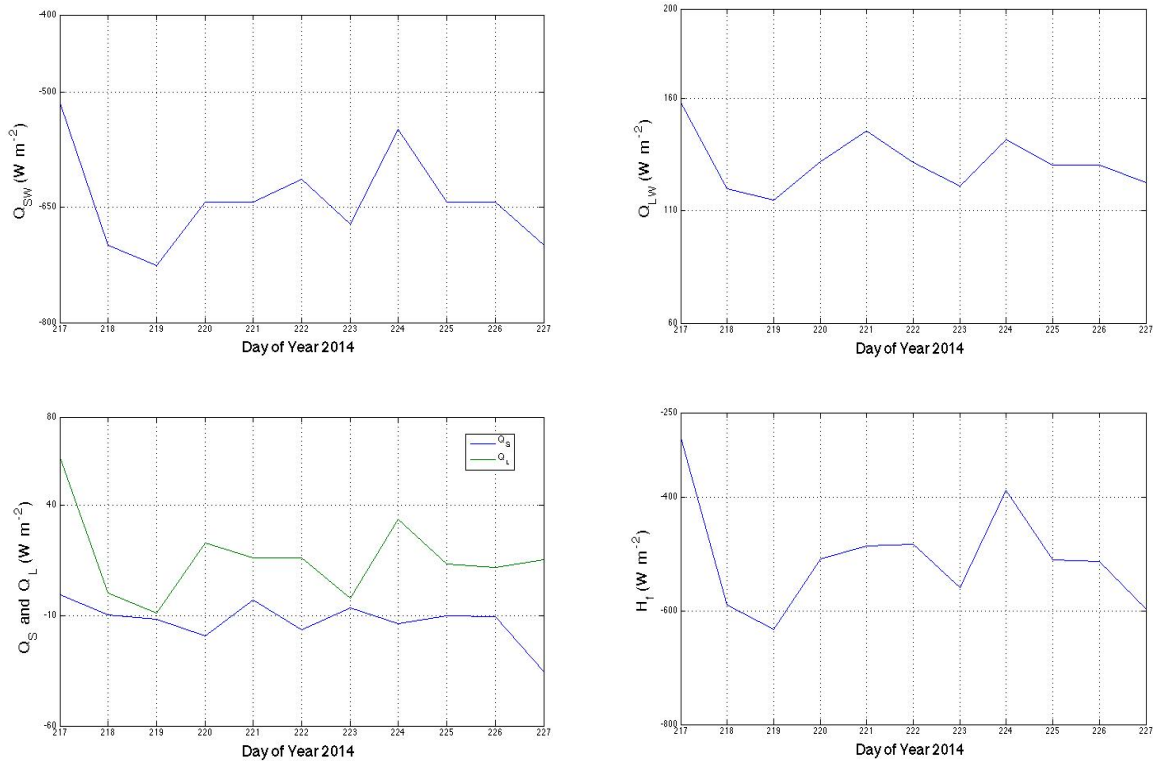

Figure 4. Surface heat fluxes over Rio Dulce; August 5-15, 2014. Negative values indicate warming of the water column; (top-left) incoming shortwave radiation, (top-right) net longwave radiation, (bottom-left) latent and sensible heat transfer, (bottom-right) total heat flux. All values are based on midday (11:00-15:00) mean air temperature, wind speed, relative humidity, and water temperature that I observed *in situ*, and do not show diurnal variation.

A stock-flow model of Rio Dulce discharge indicated that river flow rates can vary substantially from day to day (Figure 5). Discharge values range from 290 to 490 m^3 s^{-1}, with a mean flow rate of 360 m^3 s^{-1}. Most of the discharge values are between 300 and 400 m^3 s^{-1}. There highest increase in discharge occurs at day 223, immediately following a high precipitation event the night of Julian day 222.
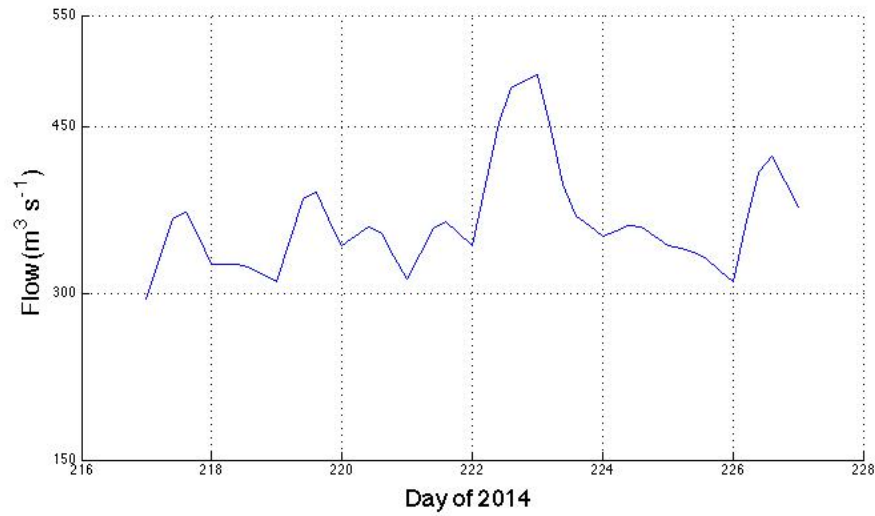
Figure 5. Estimated discharge in Rio Dulce; August 5-15, 2014. I estimated values using a stock-flow model that relies on precipitation records and know flow ratios in Rio Dulce. I used two values per day and 1-D linear interpolation for the connecting values.

Model calibration and validation

Using the relationships given by Equation 9, I found the longitudinal dispersion coefficient for the study period (Figure 6). Values range from 230 to 280 m^2 s^{-1}, with a mean of 260 m^2 s^{-1} and a standard deviation of 13 m^2 s^{-1}. To better understand where these calculated *K* values fit with others in rivers and streams, I used the approximation of longitudinal dispersion coefficient associated with an oscillating shear flow given by

$$K = 0.011 \left(\frac{u}{u_*}\right)^2 \left(\frac{B}{H}\right)^2 Hu_* \qquad (10)$$

where *u* is fluid velocity (m^2 s^{-1}), u_* is shear velocity (m^2 s^{-1}), *B* is river width (m), and *H* is river height (m) (Fischer et al., 1979). Equation 10 suggests that a river with physical characteristics such as Rio Dulce is expected to have a $K \approx 4.3$ $m^2\,s^{-1}$.
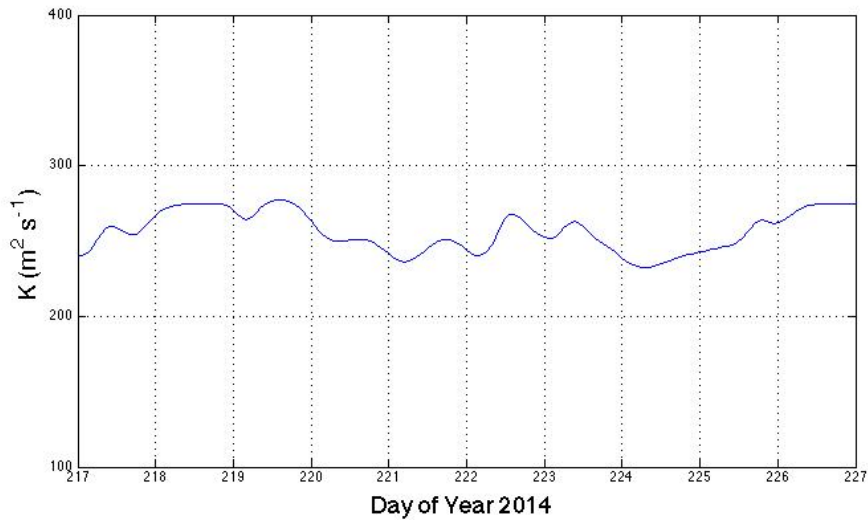
Figure 6. Calculated longitudinal dispersion coefficient for Rio Dulce; August 5-10, 2014. I calculated the dispersion coefficients using the relationships in Equation 9, and time-series data from Figures 3, 4, and 5. I used 1-D linear interpolation for the intraday values.

Using the mean inferred *K* value for the calibration period, I plotted observed and simulated water temperature for Stations 3, 7 and 10 (see location in Figure 2) during the entire study period of August 5-15, 2014 (Figure 7). The RMSE values for the calibration period are 0.25 at Station 3, 0.59 at Station 7 and 0.78 at Station 10. The RMSE for the validation period are 0.35 at Station 3, 0.63 at Station 7, and 0.73 at Station 10, with a mean standard error of 0.57 °C. The model performs better at locations nearer the river mouth at Amatique Bay, and does not capture the daily variations in water temperature from August 9-11, 2014. There is a slight model bias for simulating cooler water temperatures, with 59% of the observed water temperatures being warmer than their modeled counterparts.
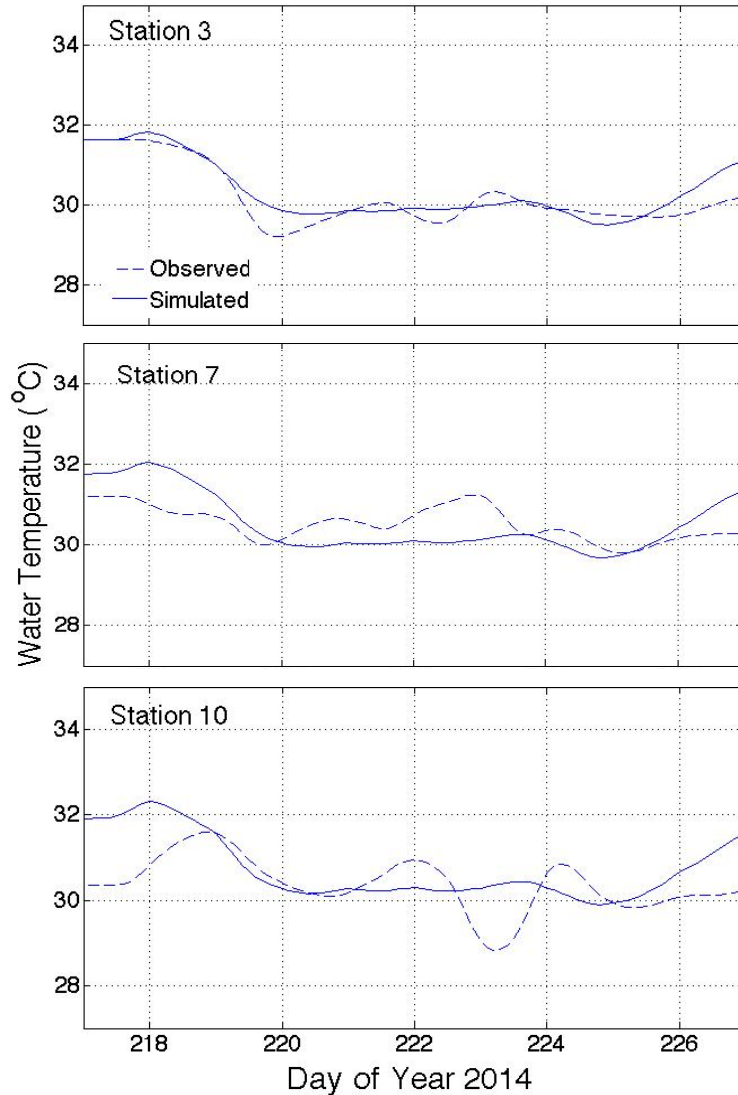
Figure 7. Observed and simulated water temperatures for three Rio Dulce stations. I used August 5-10, 2014 values for the model calibration and August 11-15, 2014 values for validation. The observations and modeled values represent midday temperatures (11:00-15:00) and do not show diurnal variations.

Climate change scenarios

The model suggests that IPCC-forecasted changes in air temperature and precipitation will substantially influence river parameters. Using the relative air temperature increases and precipitation decreases predicted for RCP 4.5 and RCP 8.5, and projected ocean temperatures, I estimated mean Rio Dulce water temperature to be increasing during the remainder of this century (Figure 8). Figure 8 does not display the uncertainty associated with the projects, as that is not the focus of this research. Water temperature increases at similar rates for RCPs 4.5 and 8.5 until

approximately the year 2060, at which time mean water temperature for RCP 4.5 begins to plateau and mean water temperature for RCP 8.5 increases more rapidly.
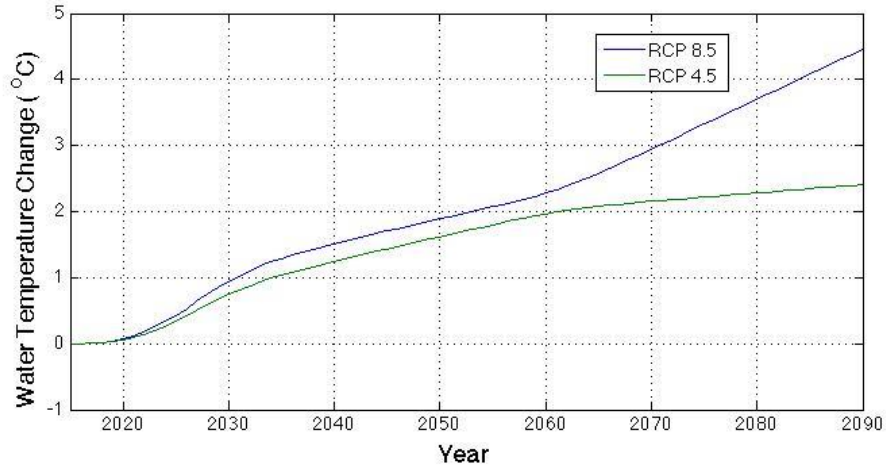

Figure 8. Mean temperature in Rio Dulce in the 21st century for RCPs 8.5 and 4.5. Water temperatures are mean temperatures throughout the 11 km study site. RCP 8.5 (blue) and RCP 4.5 (red) represent changes in radiative forcing associated with greenhouse gas emission scenarios described in the Fifth Assessment Report on Climate Change created by the Intergovernmental Panel on Climate Change.

DISCUSSION AND CONCLUSIONS

Understanding river water temperature is important because many biological processes that occur in rivers are impaired by extreme thermal conditions (Caissie 2006). In the reality of a warming climate, this understanding is essential for maintaining the health of riverine systems. For this study, I developed an advection-dispersion model of water temperature for Rio Dulce, and applied climate change scenarios to the model to estimate future water temperatures. The model displayed acceptable accuracy (RMSE of 0.57 °C) for predicting summer midday water temperatures. Our findings of increasing water temperature throughout the remainder of this century suggest that the amount of stress days for local biota will increase in Rio Dulce. One result of this biological stressor will be harm to the substance fishing industry in Guatemala.

Temperature model

Warmer upriver temperatures in Rio Dulce suggest a dominant air to water heat flux exists in the headwaters, Lake Golfete. Because Golfete is shallow (mean depth of 4.5 m), rapid radiative heating occurs during the day, sending a warm source water flux down Rio Dulce (Brinson et al. 1974; Fischer et al. 1979). This temperature gradient is atypical of most rivers, with the more common thermal regime being cooler headwaters flowing toward a warmer river mouth (Wetzel 2001). This standard thermal regime is related to the direct dependence of water temperature on surface air temperature (Wetzel 2001). Rivers flow from higher altitude (lower air temperatures) to lower altitude (higher air temperatures), and water temperature typically follows that same pattern. Although this altitude gradient is the same for Rio Dulce, proper modeling must also account for the cooling effect that Amatique Bay and the Atlantic Ocean have on coastal air temperatures in summer. This cooling effect suggests that air temperatures (and thereby water temperatures) are cooler at the mouth of Rio Dulce, which is consistent with my findings.

The mean dispersion coefficient of 260 m^2 s^{-1} in Rio Dulce suggests that the dispersive heat flux is relatively large compared to what would be expected for a river with similar flow characteristics. Elder (1959) presented the first published formula for estimating the longitudinal dispersion coefficient for open channel flow, which suggests a coefficient for Rio Dulce of 19 m^2 s^{-1} (Kashefipour 2001). The formula put forth by McQuivey and Keefer (1974) suggest a coefficient of 100 m^2 s^{-1}. Fischer et al. (1979) suggests the smallest coefficient of 4.3 m^2 s^{-1}. The large *K* value for Rio Dulce is most likely due to the channel geometry. Rio Dulce has an inverted acute triangular shape caused by the high rising cliffs on either side. These formulas for dispersion coefficients are based on the assumption of a rectangular channel cross-section. Natural channels have been found to have dispersion coefficients with values 150% greater than those found in rectangular channels (Kashefipour 2001). Another reason the measured *K* value for Rio Dulce was high may be that I was not able to directly include a groundwater heat flux in the temperature model. Low temperature groundwater, not subject to radiative fluxes, infiltrates the river resulting in a cooling effect (Wetzel 2001). This cooling effect was represented in the model by the empirical dispersion coefficient. The higher coefficient contributes to more dispersive heat leaving the control volume (i.e. lower river temperature).

The calibration and validation of the Rio Dulce temperature model suggest that we can describe summer day water temperature to ±0.57 °C. Table 2 describes how this model compares to other deterministic temperature models in the literature. The variation in RMSE from the studies in Table 2 is most likely due to length of study period, with a longer study period leading to higher model accuracy. Caissie et al. (2007) suggest that their relatively poor model performance was influenced by snowmelt conditions, which were not accounted for in the analysis. Although the Rio Dulce model performs well, I'll note that this model is for summer midday water temperatures only, and does not display diurnal variation. This limits its application in making climate-based predictions.

Table 2. Standard error for deterministic river temperature models

Model	River	RMSE (°C)
Gooseff et al. (2006)	Madison River	0.17
Yearsley (2009)	Columbia River	0.29
Sinokrot and Stefan (1993)	Zumbro River	0.52
Marchese, D. (2015)	*Rio Dulce*	*0.57*
Caissie et al. (2007)	Miramichi River	1.5

Climate change

Before I interpret the results of Rio Dulce water temperature response to climate change, I'll note that this study provides only two of infinitely many scenarios that are possible for the 21st century. This range of possibilities is primarily caused by the lack of precision between individual GCMs (Sillmann et al. 2013; Nohara et al. 2006; Cloern et al. 2011). This study attempts to mitigate that lack of precision by using a multi-model ensemble of GCMs. The benefit of using this type of climate ensemble is that we can describe the prediction uncertainty (Maurer et al. 2008). However, a drawback of such an approach is that the climate extremes that are likely to occur are removed from the projection (Maurer at al. 2008).

The 42 GCM multi-model ensemble used in this study suggests that water temperature will increase in Rio Dulce for both RCP 4.5 and RCP 8.5. The plateau in water temperature that occurs at approximately year 2060 for RCP 4.5 is due to a projected reduction in GHG emission growth

rate by year 2030 (IPCC 2013). This plateau occurs at water temperatures that will increase stress days for the local biota (Baron-Aguilar et al. 2013). In contrast to water temperature plateauing, the increase in rate of river warming projected for RCP 8.5 at year 2060 describes conditions under "business as usual" GHG emissions (IPCC 2013). This acceleration in river warming is expected to cause high mortality rates for local fish populations in Rio Dulce (Taylor et al. 1998). The diversion of projected water temperature between RCP 4.5 and RCP 8.5 that occurs at year 2060 is due to differences in GHG emissions as well as climate forcing feedback loops, such as reduced carbon sink capacity of the land and oceans for RCP 8.5 (Arora et al. 2011). Although the seemingly comprehensive multi-model ensemble used in this study provides an estimate of future climate change, higher resolution climate modeling is needed to reduce uncertainly in the predictions.

Limitations and future directions

The temperature model described here is limited by the short study period and lack of available data for Rio Dulce. This study relies on a relatively small data set (10 days), and would be improved by a longer study period. The longer study period would decrease the model error and increase the effectiveness with which we can predict water temperatures (Caissie et al. 2007). The only data available for Rio Dulce was summer day values of meteorological conditions and river parameters. To make statements about the annual cycle of water temperature in Rio Dulce, a more diverse sample period would need to be modeled.

Although this study captures mean values of water temperature well, it is limited in predications of climate extremes. These climate extremes are best captured by using watershed scale climate models (Maurer et al. 2008). Watershed models present the extreme variations in air temperature and precipitation needed to predict extreme water temperatures. However, fine scale resolution models rely on long-term meteorological data and are not available for most Central American watersheds.

These findings suggest future research should be done in downscaling regional climate models in Central America, and continuous water temperature monitoring should be undertaken. Climate modeling at the watershed scale is needed to better predict future water temperatures

(Gooseff et al. 2011). Although deterministic models are useful in predicting temperature means, stochastic models are better suited at capturing temperature extremes (Morrison et al. 2002)

Broader implications

The forecast increases in mean water temperature for Rio Dulce suggest an increase in stress days for local fish species. The most important catch for subsistence fishing in Rio Dulce is snook. Although temperature stress for snook is most commonly due to extreme low temperatures (< 15 °C), high temperatures can also impact the health of snook populations (Taylor et al. 1998; Baron-Aguilar et al. 2013). High water temperatures cause reduced dissolved oxygen and increased fish metabolism, which lead to high mortality in the early development of snook. Baron-Aguilar et al. (2013) found that at 31 °C, only 37.2% of snook larvae survived at 24 hours after hatching, compared to 89.3% survival at 25 °C. Because snook spawn from May-September (Taylor et al. 1998), the increased summer water temperature presented in this study would cause high snook mortality during the first days post-hatching.

It is important to discuss that climate change impacts should be put in context with other drivers of ecosystem change. These drivers include pollution, population growth, increased tropical storms, urbanization, etc. (Cloern et al. 2011). And some of these drivers will have a much greater impact on river systems than climate change. Through a combination of climate modeling and smart development practices, we may be able to limit the stress on river systems, which is especially important for the sensitive natural environment of Central America.

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