Projected Changes to Streamflow and Stream Temperature in Central Texas: How Much Will the River Flow?

ADRIENNE M. WOOTTEN,[a] ELINOR MARTIN,[b] CHARLES R. RANDKLEV,[c] AND RYAN SMITH[d]

[a] *South Central Climate Adaptation Science Center, University of Oklahoma, Norman, Oklahoma*
[b] *School of Meteorology, University of Oklahoma, Norman, Oklahoma*
[c] *Texas A&M Natural Resources Institute, Texas A&M AgriLife Research Center, Dallas, Texas*
[d] *The Nature Conservancy, San Antonio, Texas*

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ABSTRACT: Riverine ecosystems are dependent in large part on the climate of the region, and climate change is expected to alter climatic factors of interest, such as precipitation, temperature, and evapotranspiration. In central Texas, precipitation is expected to decrease while temperature increases as the climate changes. Drought and flooding events are also expected to increase in the region, which will also affect streamflow and stream temperature in riverine ecosystems. Numerous studies have assessed the potential impacts of climate change on riverine species. This study examines the projected climate changes, determines potential changes in streamflow and stream temperature for river basins in central Texas, and assesses the appropriate uses of climate projections for riverine species impact assessments, using the Texas fatmucket (*Lampsilis bracteata*) as a case study. Previously established regression methods were used to produce projections of streamflow and stream temperature. This study finds that streamflow is projected to decrease and stream temperature is projected to increase. Using thermal tolerance thresholds previously determined for the *Lampsilis bracteata*, this study also finds that the lethal temperature events for the *Lampsilis bracteata* will increase. This study makes several recommendations on the use of downscaled climate projections for impact assessments for riverine species such as the *Lampsilis bracteata*.

KEYWORDS: Ecology; Climate change; Climate prediction; Climate models; Hydrologic models

1. Introduction

Riverine ecosystems are strongly dependent on the hydrology of their respective river systems, and the hydrology of these river systems is dependent on the climate among other factors. In particular, precipitation, temperature, evapotranspiration rates, and the frequency of floods and droughts can affect runoff, streamflow, and stream temperature. Various studies and reports now indicate that climate change will alter all of these climate variables (Wuebbles et al. 2017; IPCC 2021).

Numerous studies have examined the impact of climate change on the hydrology of multiple river basins, particularly focusing on streamflow and stream temperature. In the case of streamflow, studies have suggested that streamflow generally will decrease with increases in temperature and evapotranspiration (Ficklin et al. 2013a), leading to concerns about water supply and efforts to adapt to them (e.g., Lymbery et al. 2021; Yufeng et al. 2021). In addition, changes in the frequency of meteorological droughts will lead to more low streamflow events, and changes in the frequency of high precipitation events will lead to more high streamflow events (Naz et al. 2018; Maurer et al. 2018). Finally, there is also recognition that climate change and land-use/land-cover changes will both have significant impacts on the hydrology and ecology of river systems (Daraio and Bales 2014; Thomas et al. 2019; Kiser et al. 2022).

Stream temperature is influenced by streamflow, and human-mediated disruptions of the natural flow regime, such as damming, pollution, water withdrawals and transfers, and sedimentation, can lead to shifts in water temperature (Olden and Naiman 2010). Climate change is expected to also have a direct effect on stream temperature and will likely exacerbate human impacts. Generally, organisms are limited to a certain temperature range for survival, within which they have narrower thermal windows for growth, movement, and reproduction (Pörtner et al. 2017). Complex freshwater ecosystems generally and freshwater mussels specifically provide such ecosystem services as the provisioning of freshwater, nutrient processing, and water filtration (Brauman et al. 2007; Dodds et al. 2013; Atkinson et al. 2014; Strayer 2014; Atkinson and Vaughn 2015; Vaughn et al. 2015). Thus, changes to a river's thermal regime can significantly impact ecosystem services and function through changes in species population performance (i.e., growth, survivorship, and reproduction) and community composition (e.g., Ficklin et al. 2013b; Kędra and Wiejaczka 2018; Song et al. 2018; Crozier et al. 2019; Khan et al. 2020; Rogers et al. 2020; Michel et al. 2022).

Freshwater mussels are among the species of concern that will be affected by climate change. This is because mussels are

Corresponding author: Adrienne M. Wootten, amwootte@ou.edu

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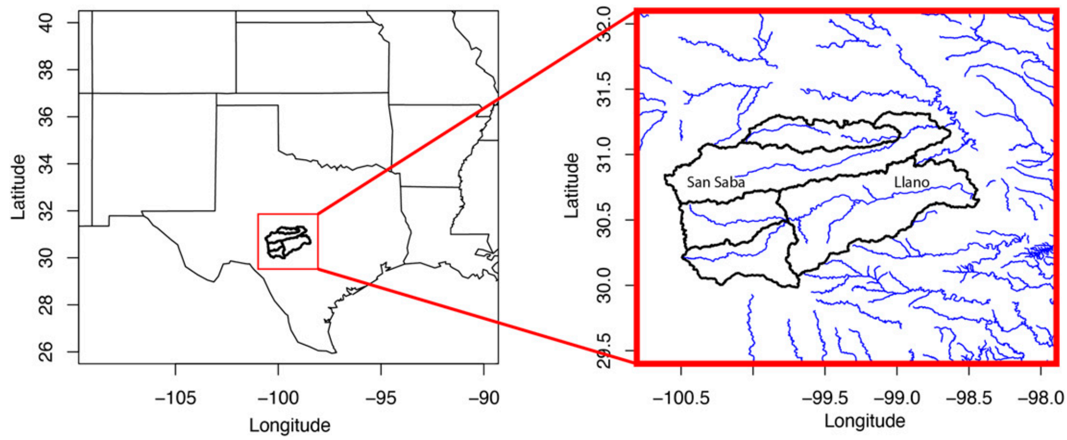

FIG. 1. San Saba and Llano River basins in central Texas. The blue lines in the right-hand graphic are the rivers in the region.

particularly sensitive to environmental change due to several species' traits. Unionids are filter-feeding ectotherms that are generally sedentary and require a host fish to successfully reproduce (Haag 2012). Because of these traits, mussels are unable to effectively cope or move out of harm's way when changes in flow and water temperature occur. Recent studies have shown that many species of freshwater mussels are considered to be already living near their thermal optima and likely will be imperiled further by climate change, though exact responses will vary between species and regions (Pandolfo et al. 2010; Ganser et al. 2013; Daraio et al. 2014; Black et al. 2010). For example, Bolotov et al. (2018) found that climate warming in the past 100 years likely contributed to the decline of margaritiferid mussels in Europe and that future climate change would exacerbate this. In addition, increasing air temperatures also makes drought conditions more likely, increasing the potential for drought related mass mortality of all freshwater mussel species and a degradation of the ecosystem services provided by these species (DuBose et al. 2019; Vaughn et al. 2015). Aside from the changes in ecosystem function from the loss of freshwater mussel species, it is also predicted that the perennial rivers systems in which these species reside will transition to intermittent or ephemeral systems with vastly different ecological features to the current systems (Datry et al. 2017).

Texas, located in the southern United States, is expected to experience significant climate change impacts, which will likely have negative consequences for mussels in streams already overallocated for human use. Increases in drought frequency and intensity under climate change in Texas is likely to cause species declines and community shifts in unionid mussels (Tarter et al. 2023; Mitchell et al. 2021). Projections of streamflow and stream temperature that can be used to assess climate impacts on freshwater mussels, or other species of concern, are typically derived using downscaled climate projections.

For example, the City of Austin (2018) created streamflow projections using downscaled climate projections matched to U.S. Geological Survey (USGS) stream gauge data. The process of downscaling translates change signals projected by global climate models (GCMs) to local scales, but downscaling also represents a significant source of uncertainty in precipitation projections (Wootten et al. 2017). The training data used for the statistical downscaling efforts are gridded observation datasets (also referred to as gridded observations). Gridded observations are processed products based upon weather station data that are interpolated to a grid to account for missing data and spatial/temporal incoherence. The differences between gridded observations, the influence on downscaled climate projections, and the influence on hydrology and ecosystem modeling have been demonstrated in several studies (Behnke et al. 2016; Werner and Cannon 2016; Elsner et al. 2014; Wootten et al. 2021). There are known relationships between temperature and precipitation and hydrological

TABLE 1. Locations of observation stations used in this study.

Site name	Site No.	Lat (°)	Lon (°)	Basin	Variable used
San Saba at Menard (USGS)	8144500	30.919	−99.786	San Saba	Streamflow
San Saba near Brady (USGS)	8144600	31.004	−99.269	San Saba	Streamflow
San Saba near San Saba (USGS)	8146000	31.213	−98.719	San Saba	Streamflow
Llano near Junction (USGS)	8150000	30.504	−99.734	Llano	Streamflow
Llano near Mason (USGS)	8150700	30.661	−99.109	Llano	Streamflow
Llano at Llano (USGS)	8151500	30.751	−98.669	Llano	Streamflow
Bois d'Arc (TAMU)	—	30.901	−99.915	San Saba	Stream temperature
Charlies (TAMU)	—	30.911	−99.518	San Saba	Stream temperature
CR340 (TAMU)	—	31.190	−98.903	San Saba	Stream temperature

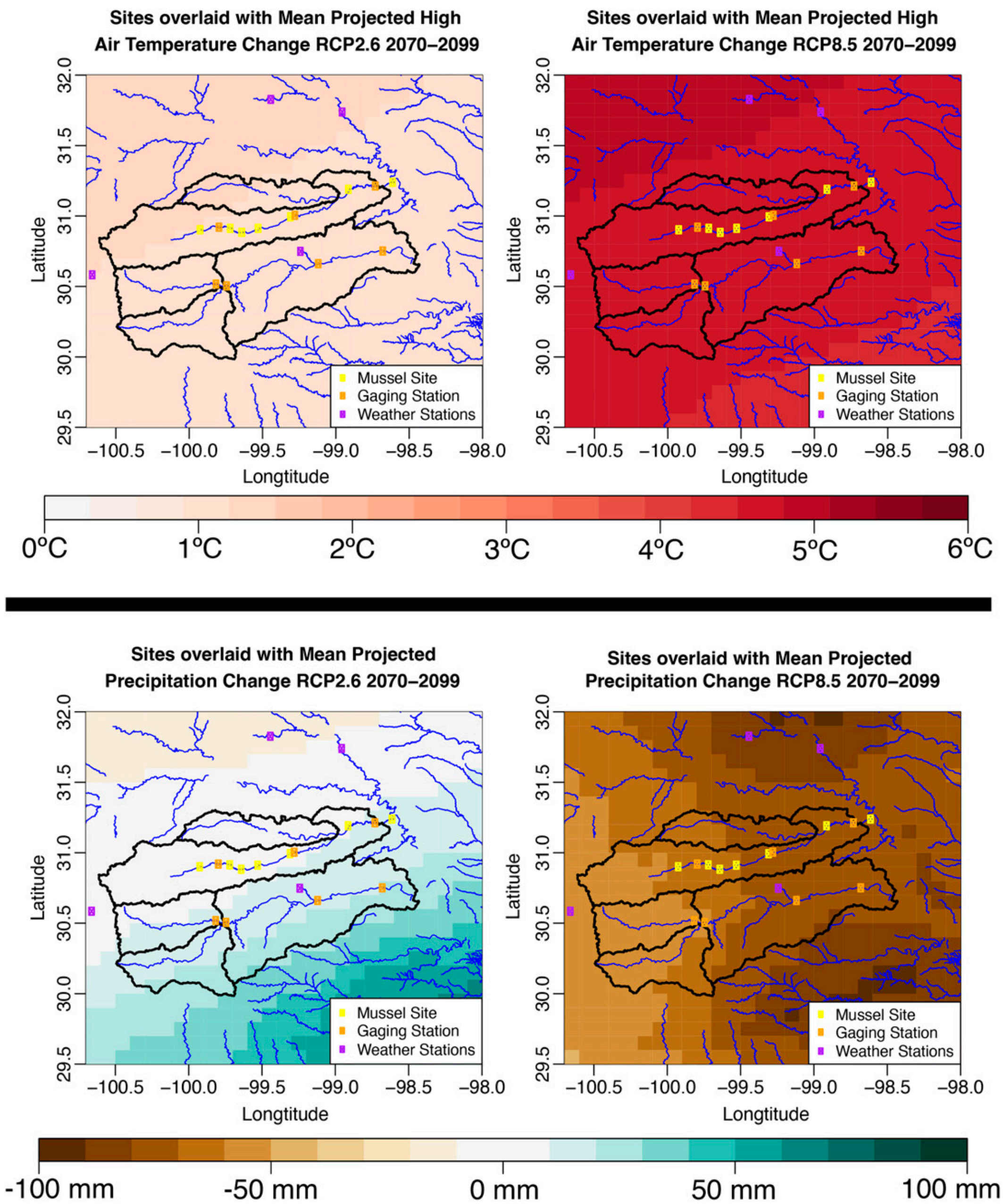

FIG. 2. The 2070–99 ensemble mean projected changes in (top) average annual high air temperature (°C) and (bottom) average annual total precipitation (mm) for the (left) RCP2.6 and (right) RCP8.5. Various gauging stations considered in the study are overlaid on the projected changes. Black lines overlaid outline the basins in question, and blue lines are rivers in the area.

statistics (such as streamflow and stream temperature) with some prior studies pointing to the GCM as a significant source of uncertainty in streamflow projections (e.g., Chen et al. 2011) while others point to both GCMs and regional climate models as significant sources of uncertainty for streamflow projections (e.g., Winter et al. 2015). Additional studies have noted that downscaling techniques are a significant source of uncertainty in recharge estimates (Crosbie et al. 2011) and that hydrologic models of streamflow and stream temperature are also a significant source of uncertainty (Chen et al. 2011; Piotrowski et al. 2021).

While previous efforts have examined various components of climate projections and their influence upon streamflow and stream temperature projections, they have not, to our knowledge, examined the full range of sensitivities associated with downscaled climate projections. Downscaled climate projections can be used to assess the impact of climate change on the *Lampsilis bracteata* similarly to other efforts for other species and sectors (e.g., Wang et al. 2017; Elgaali and Tarawneh 2021; Polasky et al. 2022; John et al. 2022; Wilson et al. 2022). However, any effort to assess the potential impacts of climate change on the *Lampsilis bracteata* must incorporate the various sources of uncertainty in the climate projections to provide the appropriate levels of confidence to the assessment.

This study examines the projected changes in the streamflow and stream temperature in the San Saba and Llano Rivers of central Texas using a suite of climate projections that encompasses all the components of downscaled climate projections. In addition, this study illustrates the usefulness of ecologically relevant climate projections for assessing the vulnerability of a species to climate change using the *Lampsilis bracteata* as a case study. Specifically, this study focuses on three questions:

1) What are the projected changes in streamflow for the San Saba and Llano Rivers in Texas and in the stream temperature in the San Saba River?
2) How sensitive are streamflow and stream temperature projections in the San Saba River to the components of the climate projections?
3) Given the uncertainty in the streamflow and stream temperature projections, what are the potential implications of climate change for the *Lampsilis bracteata* mussels in these rivers and what are the appropriate uses of the climate projections for impact assessments for species such as the *Lampsilis bracteata*?

2. Methods and data

a. Study region, species, and gauge data

The focus of this study is on the San Saba and Llano Rivers in central Texas, northwest of the city of Austin, Texas (Fig. 1). Both rivers are tributaries to the Colorado River basin and have observed populations of the *Lampsilis bracteata*. *Lampsilis bracteata* occurs in tributaries of the Colorado River drainage in central Texas. This species is currently being considered for listing under the U.S. Endangered Species Act (Fish and Wildlife Service 2009, 2021). Recent studies suggest that all mussel species may be sensitive to changes in water temperature. Increases in water temperature and changes to the flow regime in both rivers have been implicated as contributing factors to the decline of this species (Randklev et al. 2018). Other studies have shown that the *Lampsilis bracteata* tends to have higher numbers of brooding females during the winter and spring before peak water temperatures are reached (Seagroves et al. 2019).

Along the San Saba and Llano Rivers multiple gauges measure streamflow and stream temperature. For this analysis, six USGS streamflow gauges, three in the San Saba and three in the Llano, were used as the predictors for the streamflow regression (section 2c). In addition to examining changes in streamflow, we make use of three stream temperature measurement stations maintained by Texas A&M University (TAMU; Table 1) available from 24 July 2017 to 31 August 2021. The Texas A&M measurements of stream temperature are used here since stream temperature is currently not measured at USGS stream gauges. The stream temperature observations are used as the predictor in a separate regression for stream temperature projections (section 2d).

TABLE 2. Correlations for regressions using raw and smoothed air temperature data.

Smoothing	Variable	Bois d'Arc	Charlies	CR340
No smoothing	High temperature	0.88	0.89	0.89
	Low temperature	0.84	0.86	0.85
3-day smooth	High temperature	0.9	0.92	0.91
	Low temperature	0.86	0.88	0.88
5-day smooth	High temperature	0.91	0.93	0.91
	Low temperature	0.87	0.89	0.88
7-day smooth	High temperature	0.92	0.93	0.92
	Low temperature	0.87	0.89	0.88
10-day smooth	High temperature	0.91	0.93	0.91
	Low temperature	0.86	0.89	0.88
14-day smooth	High temperature	0.91	0.92	0.91
	Low temperature	0.85	0.89	0.87

b. Downscaled climate projections

The downscaled climate projections used in this study are those from the Climate Projections Evaluation Project (C-PrEP; Dixon et al. 2020). This set of projections was designed to capture the multiple sources of uncertainty associated with the climate projections. The C-PrEP data were created using three GCMs from phase 5 of the Coupled Model Intercomparison Project (CMIP5, Taylor et al. 2012) representative of the south-central United States (Bertrand and McPherson 2019), three representative concentration pathways (RCPs; van Vuuren et al. 2011), three statistical downscaling techniques, and three gridded observations used as training data (Daymet, version 1.3; Livneh, version 1.2; and PRISM AN81d). In prior research, Wang et al. (2020) recommended the use of at least 10 GCMs to be able to capture and thoroughly quantify the uncertainty. Per RCP and variable, the C-PrEP projections represent a 27-member ensemble that captures the various sources of uncertainty of interest for this study. In addition, the C-PrEP projections provide 10-km-resolution output for daily high temperature, daily low temperature, and daily precipitation projections for 2006–2100. The available variables allow the ability to derive any additional variables used for the streamflow and stream temperature regressions at the available gauges.

c. Streamflow regression

To produce streamflow projections, we make use of the regression approach used by the City of Austin (2018) during the development of the city's water plan. Here we briefly summarize that approach and discuss the changes made for this study. The streamflow regression is performed separately at each gauge owing to the differences between watersheds and along each river. For the initial stage of analysis, 120 climate indicators are derived from the daily high temperature, daily low temperature, and daily precipitation and used in a correlation analysis with the daily streamflow. For the initial

TABLE 3. Observed yearly average streamflow at each gauge location.

Site name	Yearly average streamflow (1981–2005)
San Saba at Menard (USGS)	47.45 cfs (1.34 $m^3 s^{-1}$)
San Saba near Brady (USGS)	68.79 cfs (1.95 $m^3 s^{-1}$)
San Saba near San Saba (USGS)	147.33 cfs (4.17 $m^3 s^{-1}$)
Llano near Junction (USGS)	213.56 cfs (6.05 $m^3 s^{-1}$)
Llano near Mason (USGS)	307.89 cfs (8.72 $m^3 s^{-1}$)
Llano at Llano (USGS)	416.74 cfs (11.80 $m^3 s^{-1}$)

analysis in this study and following the method of the City of Austin (2018), the daily streamflow from the USGS gauges from 1981 to 2005 is paired with climate indicators from the closest weather station (see Fig. 2) with data from 1981 to 2005. This period of 1981–2005 is used as it is the range available from the historical simulations of the downscaled climate projections. Following the correlation analysis, the pool of potential climate indicators used is reduced to 14 by grouping the indicators by the associated climate variable (temperature or precipitation) and time frame (1–3 days, 1–4 weeks, and 3–6 and 12–24 months) and selecting two indicators within each group that are strongly correlated with streamflow and represent either extremes or averages. For the 1–3 day group, only one indicator for temperature and precipitation is used as this period is only representative of extremes. Following the variable selection, the least absolute shrinkage and selection operator (LASSO) regression analysis is used iteratively to determine the appropriate model combination with the 14 selected indicators. The resulting regression models were cross validated using an odd and even years' approach, using one group to build the model and the other to validate it.

As with the method used for the city of Austin water plan, the regression is derived using the closest weather station to each USGS streamflow gauge station. However, unlike the city of Austin water plan, the regression was applied to the C-PrEP values of the climate indicators for the grid cell directly over the USGS streamflow gauge as opposed to the nearest weather station, which is sometimes many kilometers from the river (Fig. 2). After comparing the resulting streamflow from using both the weather station regression and the C-PrEP regression, the differences did not impact the sign of the change signal in the future projections. Therefore, the regression was applied using the nearest C-PrEP grid cell to each USGS gauge in our analysis. In addition, and unlike the city of Austin method, during the regression analysis described above, our study makes use of the 3-day rolling mean

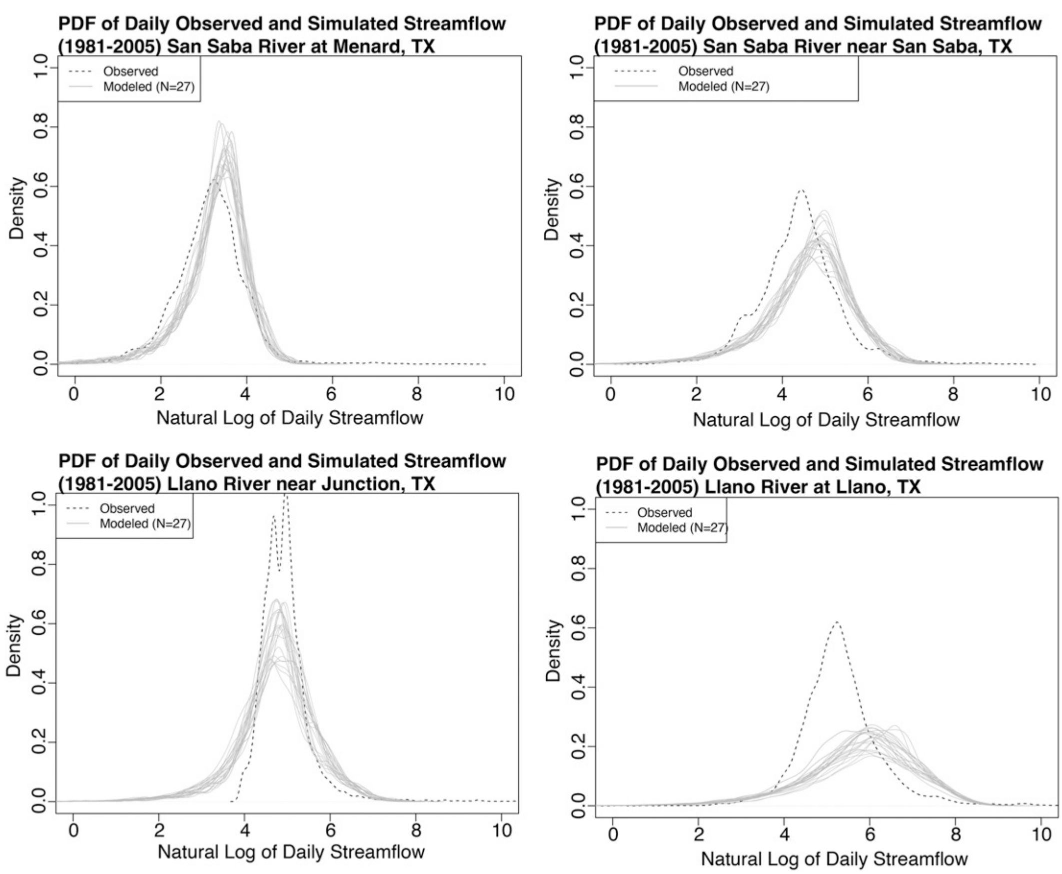

FIG. 3. PDF of historical simulations of streamflow vs PDF of observed streamflow at four locations, (top) two along the San Saba River and (bottom) two along the Llano River.

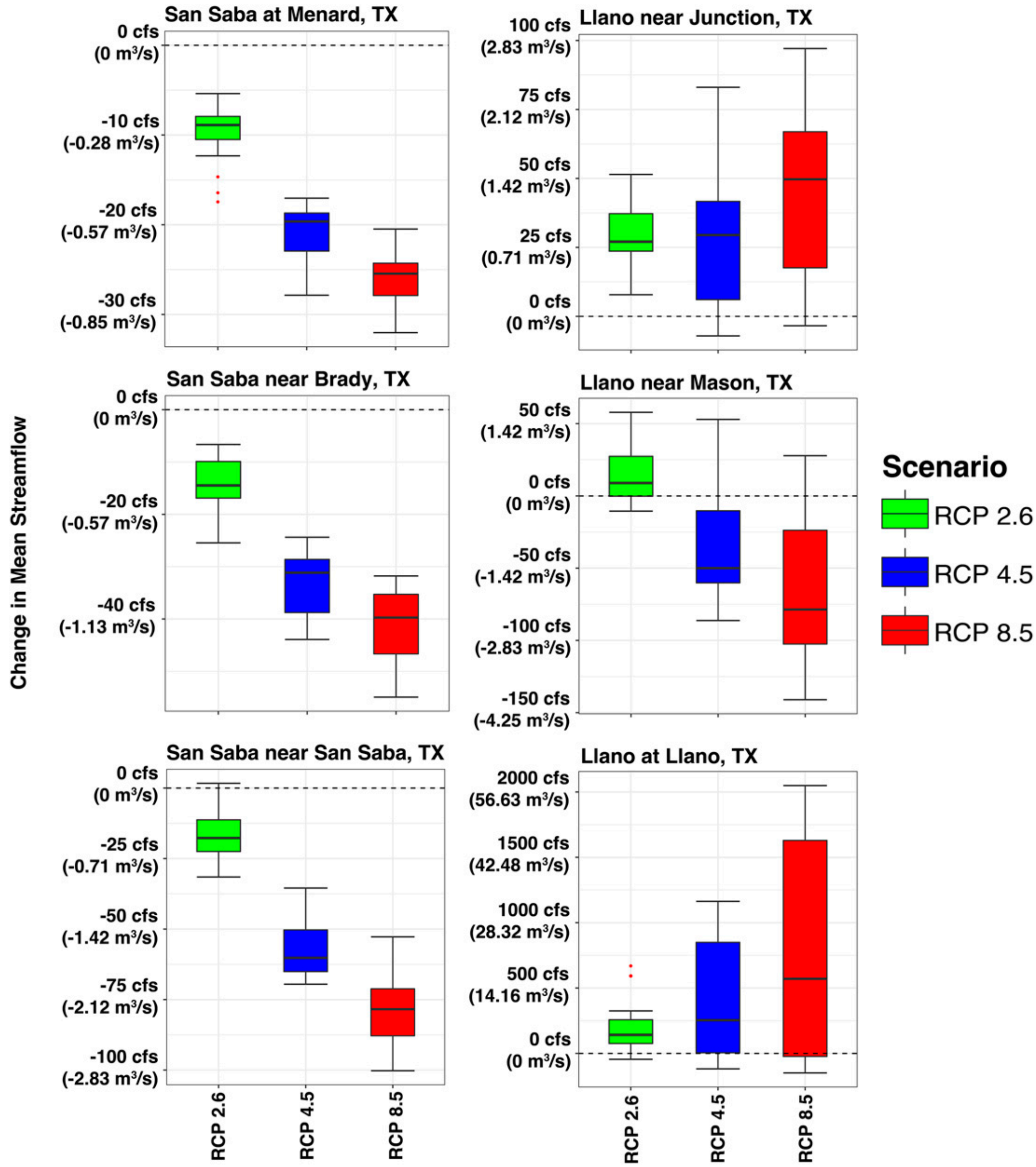

FIG. 4. Projected changes (2070–99) in yearly average streamflow for all six gauges: (left) the San Saba River gauges and (right) the Llano River gauges.

of daily streamflow. We find (not shown) that using the 3-day rolling mean of streamflow results in a higher correlation between the streamflow and climate indicators. In the final step, the regression is applied using the future projections of the climate indicators derived from the C-PrEP projections, which is the final step in the original method used in the city of Austin water plan (City of Austin 2018).

The streamflow regression is also used to produce projections of the frequency that streamflows fall below subsistence levels. The subsistence flow is the minimum streamflow required to maintain tolerable water quality conditions and minimal aquatic habitat for the survival of aquatic species (Texas Instream Flow Program 2008). Subsistence flows are, by definition, flows that occur infrequently and primarily during drought (Texas Instream Flow Program 2008; Opdyke et al. 2014). As a descriptive flow metric, subsistence flows are a utilization of the environment flow component concept (e.g., Richter et al. 2006) and are usually defined by season or month. In the method commonly utilized in Texas, subsistence flows are quantified using desktop hydrologic tools such as the Indicators of Hydrologic Alteration (IHA; The Nature Conservancy 2009) and/or the Hydrology-Based Environmental Flow Regime (HEFR; Opdyke et al. 2014). The subsistence flows for the San Saba River gauges were developed as part of the Great Plains Environmental Flow Information Toolkit project (Texas Parks and Wildlife Department 2019, 2020).

TABLE 4. Subsistence levels calculated by USGS for each season and the average number of days per year from 1981 to 2005 where streamflow fell below subsistence levels for each gauge in the San Saba River.

	San Saba at Menard		San Saba near Brady		San Saba near San Saba	
Season	Subsistence level	Obs avg no. of days below subsistence	Subsistence level	Obs avg no. of days below subsistence	Subsistence level	Obs avg no. of days below subsistence
Winter (Dec–Feb)	2.1 cfs (0.06 $m^3\ s^{-1}$)	0	20 cfs (0.57 $m^3\ s^{-1}$)	1	29 cfs (0.82 $m^3\ s^{-1}$)	0
Spring (Mar–May)	1.5 cfs (0.04 $m^3\ s^{-1}$)	0	1.5 cfs (0.04 $m^3\ s^{-1}$)	2.76	22 cfs (0.62 $m^3\ s^{-1}$)	2.88
Summer (Jun–Aug)	1 cfs (0.03 $m^3\ s^{-1}$)	0.28	1 cfs (0.03 $m^3\ s^{-1}$)	10.96	3 cfs (0.08 $m^3\ s^{-1}$)	1.28
Autumn (Sep–Nov)	1 cfs (0.03 $m^3\ s^{-1}$)	0	1 cfs (0.03 $m^3\ s^{-1}$)	7.36	13 cfs (0.37 $m^3\ s^{-1}$)	1.52

d. *Stream temperature regression*

USGS gauges do not provide stream temperature measurements in either basin, and stream temperature measurements in the region are scarce. Stream temperature is measured at three stations maintained by Texas A&M University where *Lampsilis bracteata* mussels are also observed. At these stations, stream temperature measurements are available on a 15-min time scale from July 2017 through August 2021. From these data, we derived daily high and low stream temperatures to match the available daily high and low air temperature from the gridded observations. The gridded observations of daily high and low air temperature from Daymet (Thornton et al. 2020) are used for this simple linear regression analysis over the period of the stream temperature observations. In addition to the regression analysis using daily high and low air temperature, this study also examined the stream temperature regression using 3-, 5-, 7-, 10-, and 14-day moving averages (smoothing) of air temperature. The resulting correlation analysis revealed the strongest relationship (correlation values of 0.87–0.93) in the separate regressions for daily high and low stream temperature using 5-day moving averages of daily high and low air temperature (Table 2). We note that linear regressions between air and stream temperature are generally not recommended as a linear relationship breaks down as the stream temperature approaches 0°C (Mohseni and Stefan 1999). However, at this location, the observed high and low stream temperatures remain near or above 5°C, which allows for a more linear relationship to air temperature. In addition, we recognize that streamflow and stream temperature have a known relationship to each other. However, we also note that air temperature has the strongest relationship to stream temperature based on prior work (Durfee et al. 2021).

The stream temperature regression was crafted using the Daymet gridded observations of daily high and low air temperature but ultimately applied to the C-PrEP projections to produce projections of daily high and low stream temperature. Previous studies comparing the Daymet, Livneh, and PRISM gridded observations with weather station data have found that the temperature biases of all three are similar to each other in the region of central Texas (Behnke et al. 2016). Given this previous work, it is our judgment that the regression created with other gridded observations will have similar results to the regression created with Daymet observations. As for streamflow, the regression is applied to future projections of stream temperature from the C-PrEP projections. Using the projections of stream temperature and the previous estimates by Goldsmith et al. (2021), projected changes in the occurrence of the threshold of 5% mortality during the glochidia stage (24-h LT05) and in the occurrence of the threshold of 5% mortality during the juvenile stages are calculated. In this case, LT05 is used given that such temperature thresholds have been crossed in the observed stream temperature records used in this study, where the LT50 thresholds have not been reached, which allows a point of comparison for the projected changes of the LT05 frequency.

3. Results

The region of central Texas will likely experience significant changes in air temperature by the end of the century (2070–99). In the region of the San Saba and Llano River basins, the mean projected change by end of the century (2070–99) of the high temperature is ~1°C under the RCP2.6 and ~4°C under RCP8.5 (Fig. 2, top row). While temperatures are consistently projected to increase, the precipitation projections are much less consistent. Under RCP2.6, there is little change projected in precipitation except for a projected increase of less than 25 mm in the Llano River basin. Under RCP8.5, the mean projected change in precipitation across the region is a decrease of 50–100 mm across both river basins (Fig. 2, bottom row). As discussed previously, streamflow and stream temperature both have known relationships to air temperature, precipitation, and evapotranspiration (Ficklin et al. 2013a). Therefore, we expect that as the air temperature rises and precipitation decreases, the stream temperature will increase and the streamflow will decrease.

a. *Streamflow*

The San Saba at Menard, Texas, gauge and the San Saba at San Saba, Texas, gauge are the westernmost and easternmost gauges, respectively, used in this study for the San Saba River. The streamflow along the San Saba increases from west to east with the yearly average streamflow at San Saba almost 3 times that of the yearly averaged streamflow at Menard (Table 3). For these two example gauges, the regression for daily streamflow using the historical simulations of the C-PrEP downscaled projections consistently captures the daily streamflow though with a tendency to overestimate (Fig. 3, top row). The root-mean-square error (RMSE) of the simulated yearly average streamflow created with the ensemble of historical simulations of the climate projections is 15 cfs (i.e., $ft^3\ s^{-1}$; 0.42 $m^3\ s^{-1}$) for the San Saba at Menard gauge and 14 cfs (0.40 $m^3\ s^{-1}$) for the San Saba at San Saba gauge.

While the streamflow regression procedure used in this study is consistently accurate for all three gauge locations on the San Saba River, the regression procedure is not consistently accurate along the Llano River, which has a higher streamflow than the San Saba (Table 3). The Llano near Junction, Texas, gauge and the Llano at Llano, Texas, gauge are the westernmost and easternmost gauges, respectively, used in this study for the Llano River. For the Llano River gauges, it is clear that the streamflow regression is more accurate for the westernmost gauge (Fig. 3, bottom row). The RMSE of the simulated yearly average streamflow created with the ensemble of historical simulations of the climate projections is 51 cfs (1.44 $m^3\ s^{-1}$) for the Llano near Junction gauge and 405 cfs (11.47 $m^3\ s^{-1}$) for the Llano at Llano gauge, which is almost equal to the annual mean streamflow. Since the regression *procedure* is the same everywhere and uses only climatic variables (e.g., temperature and precipitation), it is likely the inconsistent accuracy in the Llano River streamflow simulations is due to nonclimatic factors (such as groundwater flows, land use, and land cover, or river management practices). The Llano River is more managed, with human interaction along the river via several dams in the study region that does have an impact on streamflow along the river. The San Saba River in the study area is not subject to the same level of management via dams although agricultural pumping has resulted in flow intermittency in the middle San Saba River (RPS Espey 2013). We speculate that the effects of human management of the Llano River influence the observed streamflow, which degrades the relationship between the climate variables and streamflow downstream of the origins of the Llano River (the eastern portion of the domain). In addition, we also note that the regression equation used does not include the influence of groundwater input on streamflow, which likely affects the predictions for both rivers.

Given the streamflow regression developed for each gauge location, the C-PrEP projections of climate variables are used to project changes to the yearly average streamflow. Streamflow in the San Saba River is projected to decrease at all three gauges along the river in this study (Fig. 4, top row) by the end of the century (2070–99). The largest magnitude of the projected change in streamflow is under the RCP8.5, with a mean decrease of 26 cfs (0.74 $m^3\ s^{-1}$, standard deviation of 3 cfs or 0.08 $m^3\ s^{-1}$) at the San Saba at Menard gauge, and a mean decrease of 77 cfs (2.18 $m^3\ s^{-1}$, standard deviation of 14 cfs or 0.4 $m^3\ s^{-1}$) at the San Saba near San Saba gauge, which in each case is approximately a 50% decrease relative to observed streamflow (Table 3). The San Saba River, which is less managed, shows a consistent decrease in streamflow. The increase in temperatures under a changing climate would cause an increase in evapotranspiration resulting in a decrease in water flowing into the river and groundwater. In addition, a decrease in precipitation would also cause a decrease in runoff into the river. Therefore, both the increase in temperatures and decrease in precipitation would cause a decrease in streamflow in the San Saba River.

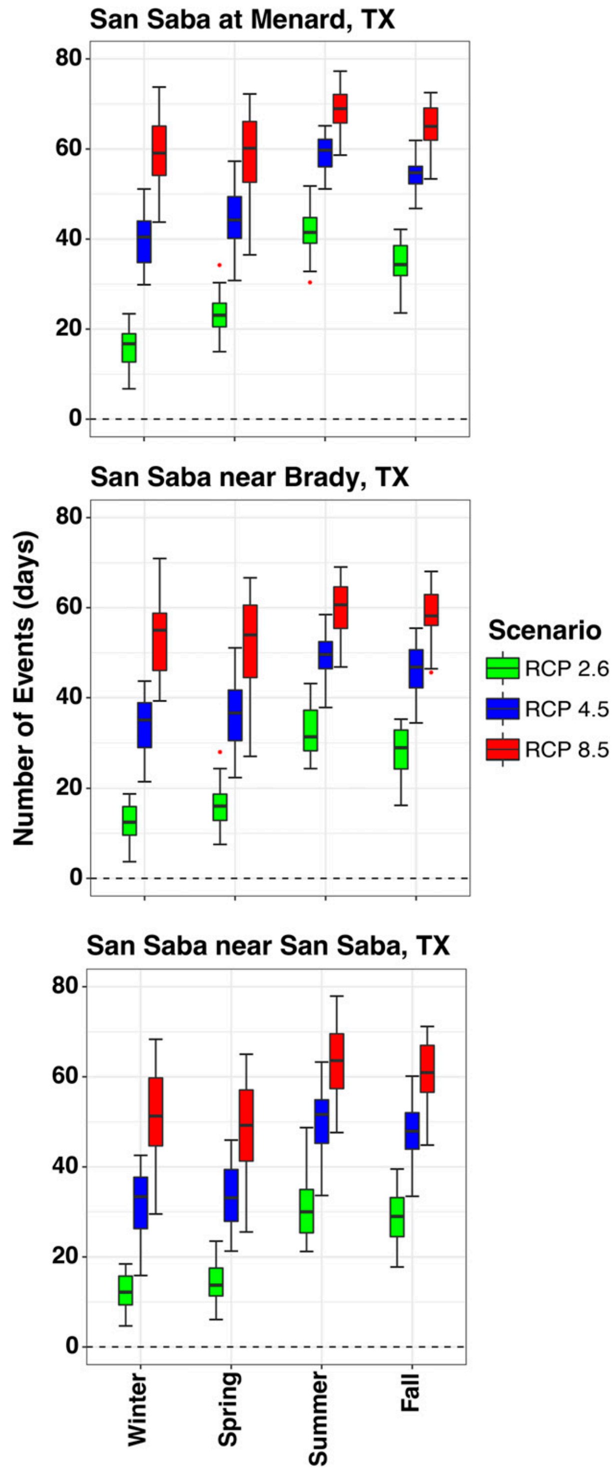

FIG. 5. Projected changes (2070–99) in the average number of days per season that streamflow falls below subsistence levels for all gauges along the San Saba River.

TABLE 5. Average high and low stream temperature (2017–21), the average number of days per year where 5% mortality rate for glochidia is reached, and average number of events per year where 5% mortality rate for juveniles is reached across the San Saba River.

Site name	Yearly avg high stream temperature (°C)	Yearly avg low stream temperature (°C)	Avg no. of days per year where 5% mortality rate for glochidia is reached	Avg no. of events per year where 5% mortality rate for juveniles is reached
Bois d'Arc (TAMU)	18.51	16.61	1.8	0
Charlies (TAMU)	18.30	16.65	1.4	0
CR340 (TAMU)	18.98	17.40	0	0

The streamflow projections from the Llano River are much less consistent across the river (Fig. 4, bottom row). Streamflow at the Llano near Junction gauge is projected to increase by 44 cfs (1.25 $m^3\ s^{-1}$) on average under RCP8.5 (standard deviation of 29 cfs or 0.82 $m^3\ s^{-1}$), streamflow at the Llano near Mason gauge is projected to decrease by 67 cfs (1.90 $m^3\ s^{-1}$) on average under RCP8.5 (standard deviation of 50 cfs or 1.42 $m^3\ s^{-1}$), and streamflow at the Llano at Llano gauge is projected to increase by 760 cfs (21.52 $m^3\ s^{-1}$) on average under RCP8.5 (standard deviation of 783 cfs or 22.17 $m^3\ s^{-1}$). We suspect that the amount of management along the river and groundwater inputs, which are not captured by the streamflow regression, are the primary causes for the vastly different projected changes over the distance between the western and easternmost gauges on the Llano River (65 miles from the westernmost to easternmost gauge).

The subsistence levels for the San Saba, broken down by season are shown in Table 4, along with the observed frequency by which these values were exceeded in the historical observations. As seen in Table 4, flow levels below subsistence occur infrequently in historical observations. Subsistence flows were not developed in the Great Plains Environmental Flow Information Toolkit (GP EFIT) project for the gauges on the Llano River, so they were not included in this analysis.

Projected changes to the average number of days with streamflow below subsistence levels are critically important to understand for both species and societal interests and are shown in Fig. 5 for the San Saba River. The projected decrease in yearly average streamflow is matched by a projected increase in the number of days the streamflow is below subsistence levels in every 3-month season [by 63 days on average under RCP8.5 (standard deviation of 8 days) at the San Saba River near San Saba gauge]. The increase in the number of days below subsistence levels is greatest in summer under RCP8.5. The increase in the number of days below subsistence levels follows from the decrease in streamflow brought on by increasing temperatures and evapotranspiration and the decrease in precipitation and runoff. However, the projected increase in the number of days below subsistence levels represents a stressor to the freshwater mussels in the San Saba River as the minimum flow for the survival of the species is projected to occur much less frequently, likely leading to more instances where thermal thresholds are exceeded.

b. Stream temperature

As USGS gauges in the San Saba and Llano Rivers do not provide measurements of stream temperature, the analysis of stream temperature is restricted to the three gauges maintained by Texas A&M University on the San Saba River (Table 1). Each of these three gauges has stream temperature measurements available from 24 July 2017 to 31 August 2021 (Table 5). The error of the high and low stream temperature regression was similar across the three gauges (Fig. 6). The projected changes in average stream temperature across the San Saba River range from less than 1°C under RCP2.6 (Fig. 7). Under RCP8.5, the average stream temperature is expected to have an average increase of 2.36°C (standard deviation 0.24°C), 2.52°C (standard deviation 0.25°C), and 2.36°C (standard deviation 0.24°C) for Bois d'Arc, Charlies, and CR340, respectively.

The increase in average stream temperatures suggests an increased danger to the *Lampsilis bracteata* mussels. Previous research on the *Lampsilis bracteata* in the San Saba River indicated stream temperature thresholds for the lethality of the species during different life stages. Goldsmith et al. (2021) determined that the *Lampsilis bracteata* in the San Saba River would have a 5% mortality rate during the glochidia stage if the 24-h average stream temperature (24-h LT05) rose above 27.9°C or during the juvenile stage if the 96-h average stream temperature (96-h LT05) rose above 30.8°C. The thermal tolerance estimates made by Goldsmith et al. (2021) are near or below current summer water temperatures. Table 5 illustrates that these lethality thresholds were infrequently (fewer than 2 days on average) exceeded for glochidia and never exceeded for juveniles during the 2017–21 observational record. Using these thresholds and the projections of stream temperature, one can project the change in the number of events where these thresholds are met. The number of events meeting the glochidia and juvenile thresholds is projected to increase dramatically (Fig. 8). For example, by the end of the century (2070–99), the number of occurrences of 24-h LT05 is projected to increase by up to 80 days per year on average (standard deviation of 8 days) under RCP8.5 at Bois d'Arc. However, by the end of the century, the number of occurrences of the 96 h LT05 threshold increases by up to 90 more events per year on average (standard deviation of 14 days) under RCP8.5 at Bois d'Arc. The majority of these events occur during the summer months (not shown).

c. Sensitivity to climate projections

Thus far, the regressions for streamflow and stream temperature, applied with downscaled climate projections, show a projected decrease in streamflow and a projected increase in stream temperatures. However, previous research has shown

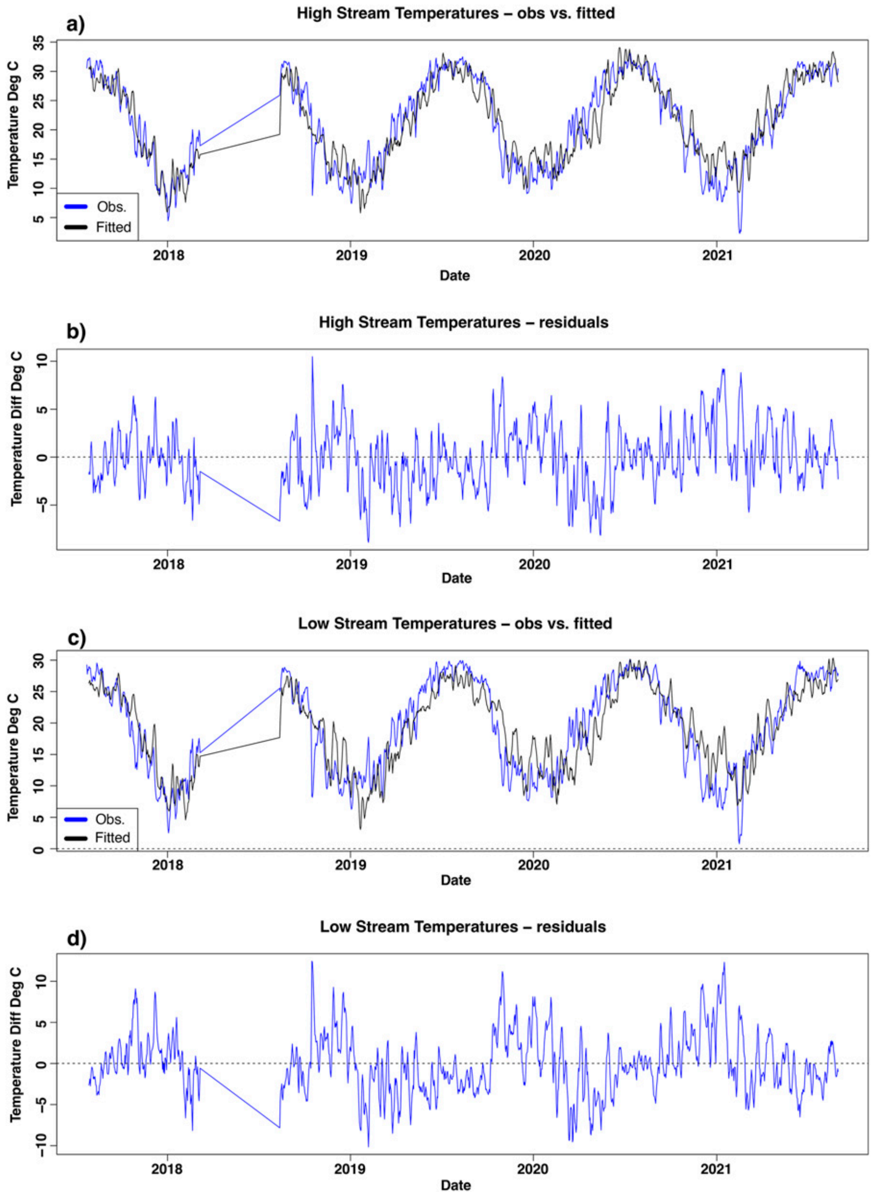

FIG. 6. (a) Observed and simulated high stream temperatures, (b) residuals from high stream temperature regression, (c) observed and simulated low stream temperatures, and (d) residuals from low stream temperature regression for Bois d'Arc.

that downscaled climate projections of precipitation can be sensitive to choices made in the downscaling process (Wootten et al. 2021) and that such choices can influence the output of impact models (e.g., Pourmokhtarian et al. 2016). Building on previous research, this section examines the sensitivity of the streamflow and stream temperature projections in the San Saba River to the various components of the downscaled climate projections. To maximize the change signal present, this section focuses on the projected changes for the end of this century (2070–99) under RCP8.5.

Streamflow projections along the San Saba River are sensitive to the training data used in the downscaled process. The magnitude of projected changes in streamflow is 20–30 cfs (0.57–0.85 $m^3 s^{-1}$) smaller when the PRISM data are used for training than when the Livneh or Daymet data are used for training (Fig. 9). While both temperature and precipitation variables are used in the streamflow regression, the only observable difference that matches the streamflow is the historical and future simulations of precipitation. The precipitation simulations that use the PRISM data for training are up to 4 in. drier than the other simulations (Fig. 10). The dry tendency of the PRISM observed here aligns with previous research that demonstrated that the PRISM precipitation is biased drier than others in this region (Behnke et al. 2016).

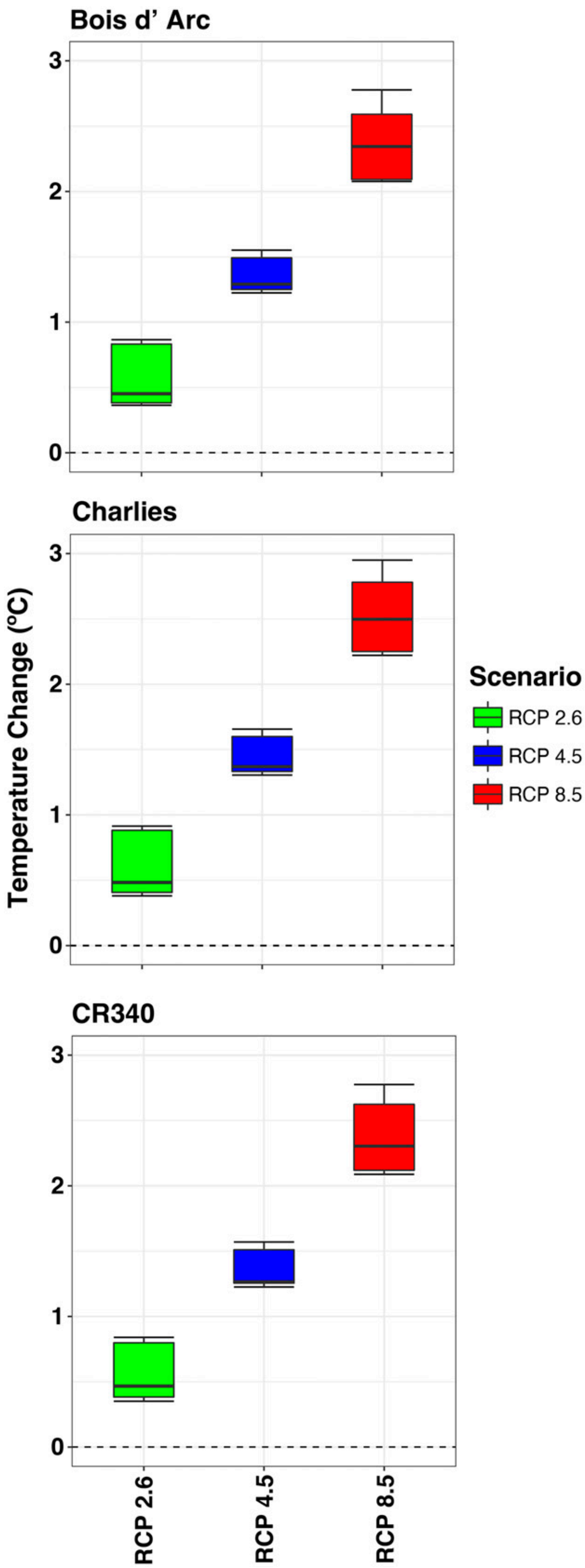

FIG. 7. Projected changes (2070–99) in annual average stream temperature for the San Saba River.

Downscaling attempts to create an estimate of future "observations" based on the training data provided. As such, any statistical downscaling technique will retain and transfer any biases in the training data to the output dataset. We speculate that the precipitation bias in the PRISM data in the region was translated through the streamflow regression, causing a similar effect on the projected streamflow in the San Saba River.

The stream temperature regression makes use of the daily high air temperature and daily low air temperature to estimate daily high and low stream temperature. As such, any sensitivity in projections of air temperature will likely be translated to projections of stream temperature. The projected changes in stream temperatures share similar patterns to the projected changes in air temperature. For daily high air temperature and daily high stream temperature, the projected increase is ~1° and ~0.5°C larger, respectively, for simulations using MIROC5 (Fig. 11). For the daily low stream temperature and daily low air temperature, the projected increase is up to ~1° and ~0.5°C smaller, respectively, for simulations using the CCSM4 (Fig. 12). The GCMs have known biases and differences in climate sensitivity (Sheffield et al. 2013a,b; Maloney et al. 2014). Statistical downscaling corrects for the biases present in every GCM while retaining the change signal unique to each GCM. Each GCM responds somewhat differently to the radiative forcing applied in the simulation, which in part causes distinct differences in the change signal between GCMs (Hawkins and Sutton 2009). In addition, while numerous statistical downscaling techniques exist, there are distinct differences in performance and sensitivity between downscaling techniques related to how each technique translates the change signal of the GCM to local scales (e.g., Lanzante et al. 2020; Wootten et al. 2021). However, the downscaled projections of air temperature are less sensitive to the downscaling approach than downscaled projections of precipitation (Wootten et al. 2017). Given that the air temperature projections are less sensitive to the downscaling technique, it follows that the stream temperature projections created in this study are also less sensitive to downscaling technique, but more sensitive to the GCM used when focusing on projections using a single emissions scenario for the end of the century. As noted in Wootten et al. (2017), the largest source of uncertainty in downscaled climate projections of air temperature is the scenario uncertainty, followed by the GCM uncertainty, while the uncertainty associated with downscaled projections is minimal. Given the direct relationship between stream temperature and air temperature used in this study and other studies (Mohseni and Stefan 1999), it follows that the uncertainty of stream temperature projections has a similar pattern to the uncertainty of air temperature projections.

d. Discussion

According to the projections of streamflow and stream temperature shown here, the average streamflow in the San Saba and Llano Rivers is expected to decrease, while the stream temperature is expected to increase. In addition, the number of days with flows below subsistence and temperatures above lethal thresholds for 5% mortality rates is also projected to

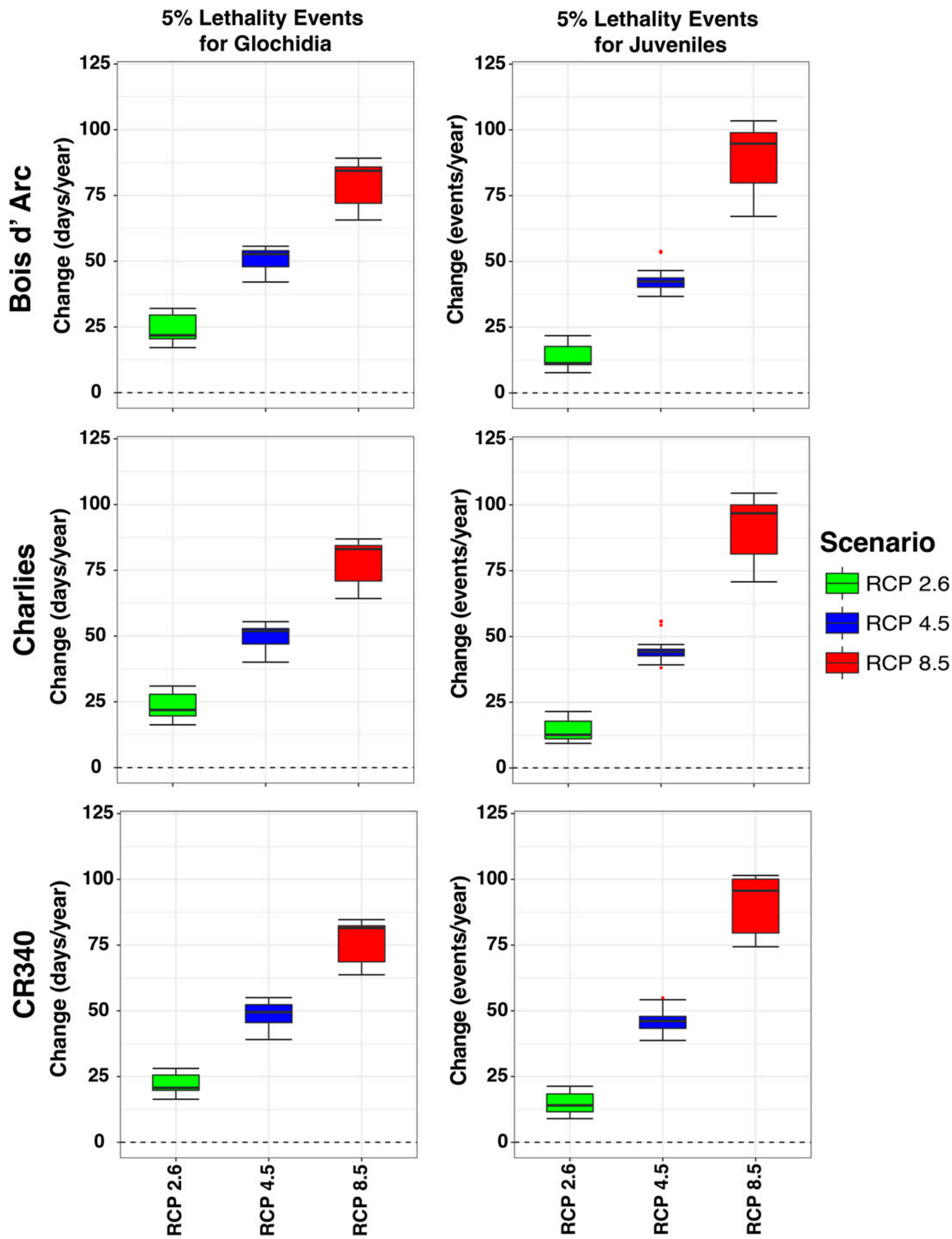

FIG. 8. Projected changes (2070–99) in the number of 5% lethality events for *Lampsilis bracteata* (left) glochidia and (right) juveniles for (top) Bois d'Arc, (middle) Charlies, and (bottom) CR340.

increase. Previous research has already identified the thermal limits for glochidia and juvenile *Lampsilis bracteata* and changes to streamflow that would be detrimental (Goldsmith et al. 2021).

The projections of streamflow are sensitive to the training data in the downscaled projections with this regression approach. However, this regression approach is relatively simple, and computationally inexpensive, in comparison with the breadth of hydrology that one could use to model and project streamflow using downscaled climate projections as inputs. The relationships between streamflow and climate variables (temperature and precipitation) are often nonlinear in other hydrology modeling exercises. As such, it is prudent that hydrology modeling efforts to project streamflow examine how the biases in training data (which may be used for the calibration of a

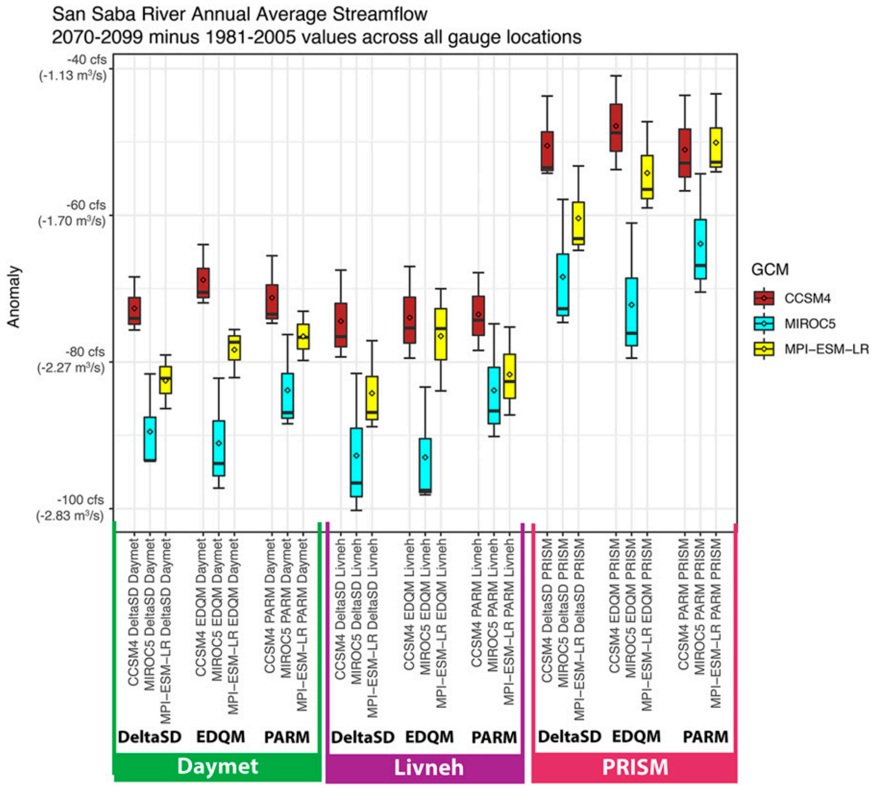

FIG. 9. RCP8.5 projected changes (2070–99) in annual average streamflow for all ensemble members along the San Saba River.

hydrology model) may influence the output projections of streamflow. Though the magnitude varies among the simulations, the simulations in this study consistently project a decrease in streamflow in the San Saba River, which lends confidence to our results. There is less confidence in the projections of decreasing streamflow in the Llano River. The Llano River basin is more managed via dams in the study region than the San Saba River, and we speculate that the error of the regression is larger as a number of nonclimatic factors influence the streamflow in the Llano River. The regression also does not include a representation of groundwater inflows that affect streamflow and stream temperatures. In this case, groundwater is not included in this regression as it is not measured at the gauges used in this study. This represents a limitation of the streamflow regression used in this study. For example, high groundwater inputs may result in underestimates in parts of the rivers during low streamflow conditions. In addition, low groundwater levels lead to losses of streamflow to the subsurface (e.g., via groundwater extraction or pumping), ignoring surface–groundwater interactions can also lead to overestimates of streamflow conditions. The streamflow regression is limited to relationships between climatic variables and streamflow and cannot capture nonclimatic factors affecting streamflow. This is a caveat of the streamflow projections in this study that might be better addressed with more complex hydrology modeling that can incorporate nonclimatic factors.

The stream temperature projections are less sensitive to different downscaling techniques and training data and are primarily sensitive to the GCM and scenario used. The regression used here is based solely on air temperature given prior research (Mohseni and Stefan 1999). Although there are minor differences between GCMs, the stream temperatures are still projected to increase along the San Saba River with the largest source of uncertainty likely from the emissions scenario. The difference between the stream temperature and streamflow projections highlights the challenges of determining the potential impacts of climate change on local hydrology from climate projections. Stream temperature and streamflow are also related to each other (Durfee et al. 2021; Rahmani et al. 2021) and are related to the health of riparian ecosystems (Rogers et al. 2020; Lee et al. 2020; Chang et al. 2018). The relationship between streamflow and stream temperature and sensitivity to the climate projections is a topic of future research.

The decrease in streamflow and increase in temperatures projected in this study imply that the *Lampsilis bracteata* will face increasing stress to survive in the current habitat. The decreasing streamflow and increasing temperatures will result in a greater tendency to exceed thresholds of thermal tolerance of glochidia and juvenile *Lampsilis bracteata*, which is already living near thermal limits. This does not affect adult populations specifically, but the recruitment of adults would be adversely affected if glochidia and juveniles experience increased mortality.

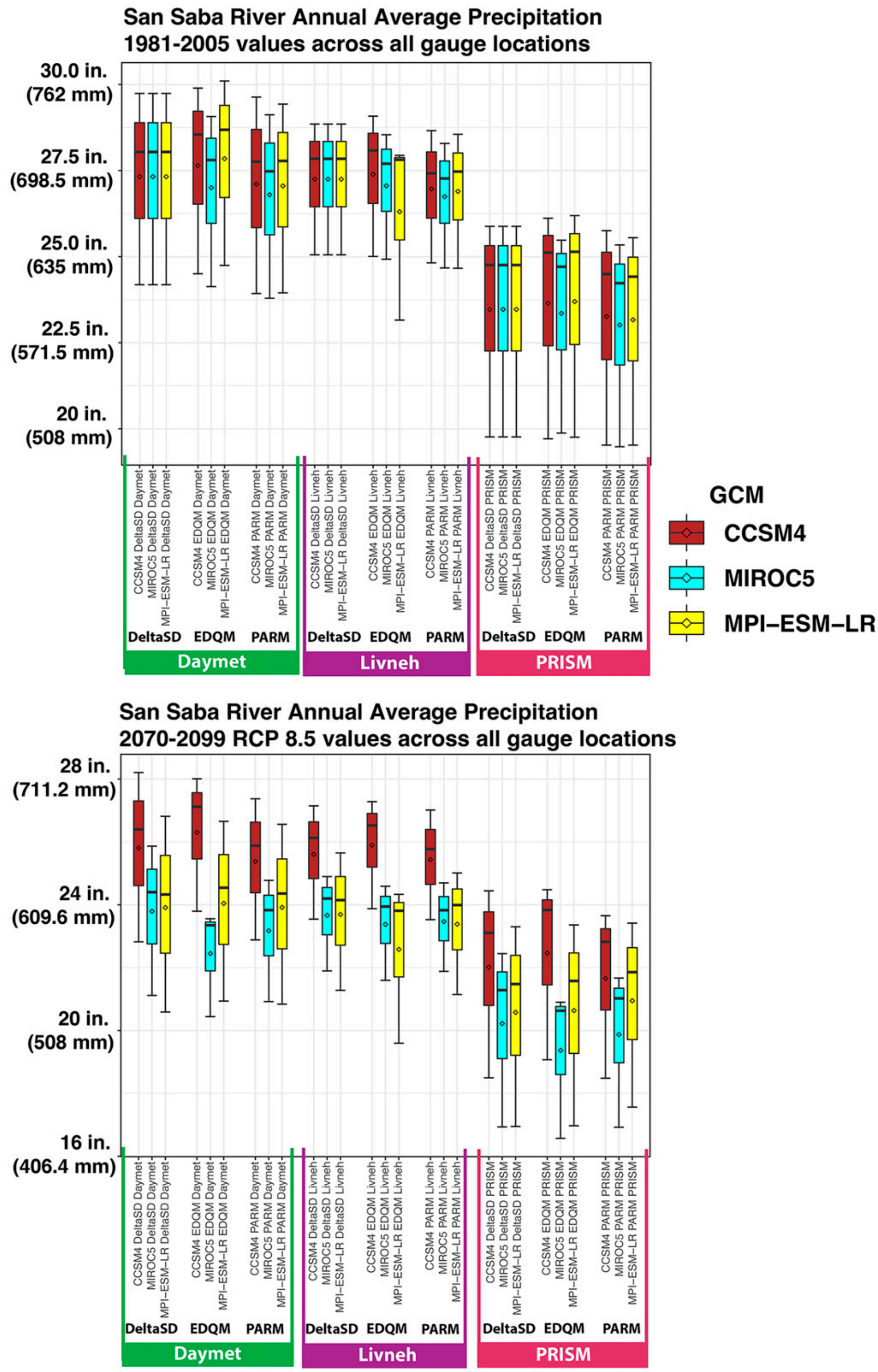

FIG. 10. (top) Historical annual average precipitation (1981–2005) and (bottom) RCP8.5 annual average precipitation (2070–99) from all ensemble members along the San Saba River.

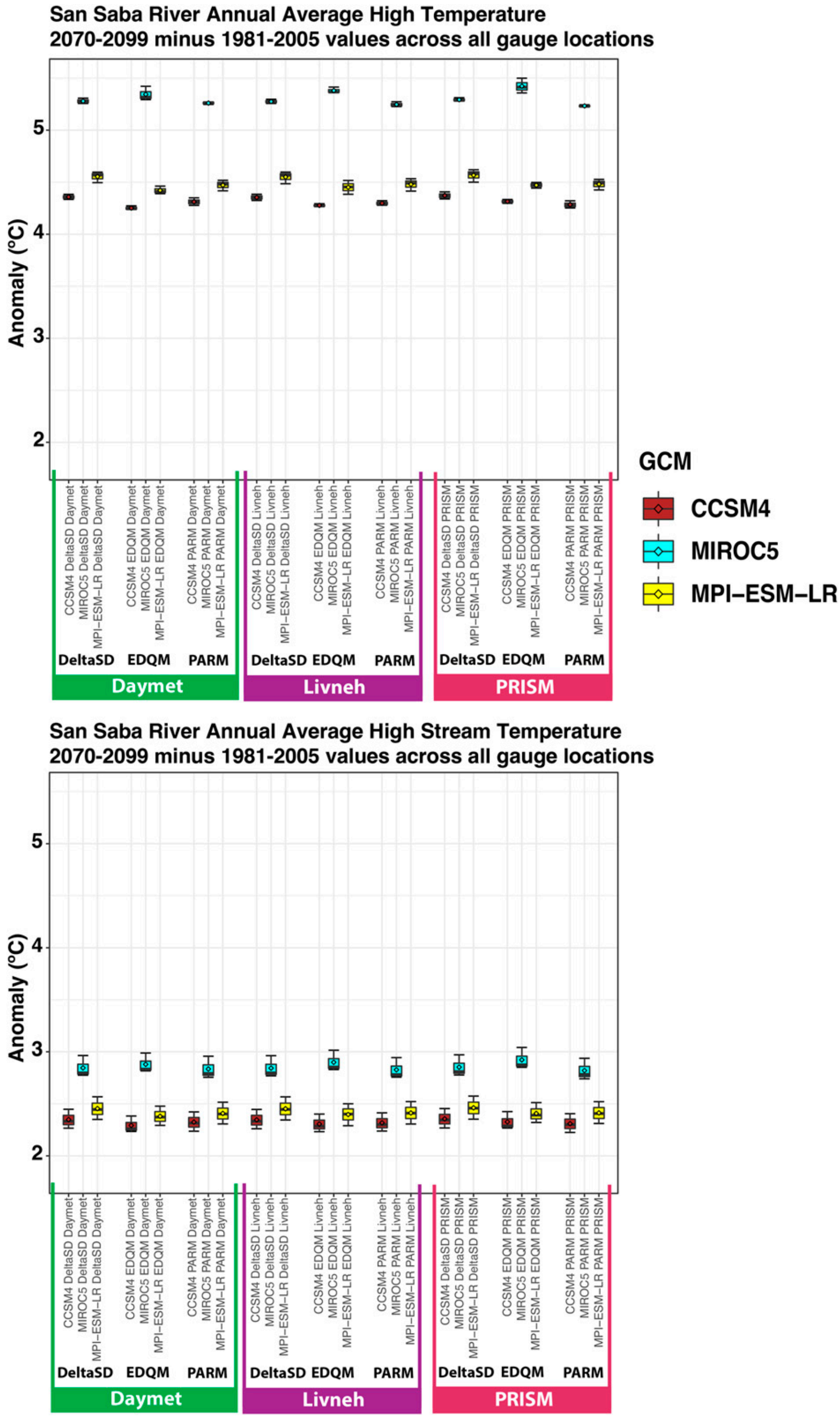

FIG. 11. RCP8.5 projected changes (2070–99) in (top) annual average high air temperature and (bottom) annual average high stream temperature for all gauges along the San Saba River.

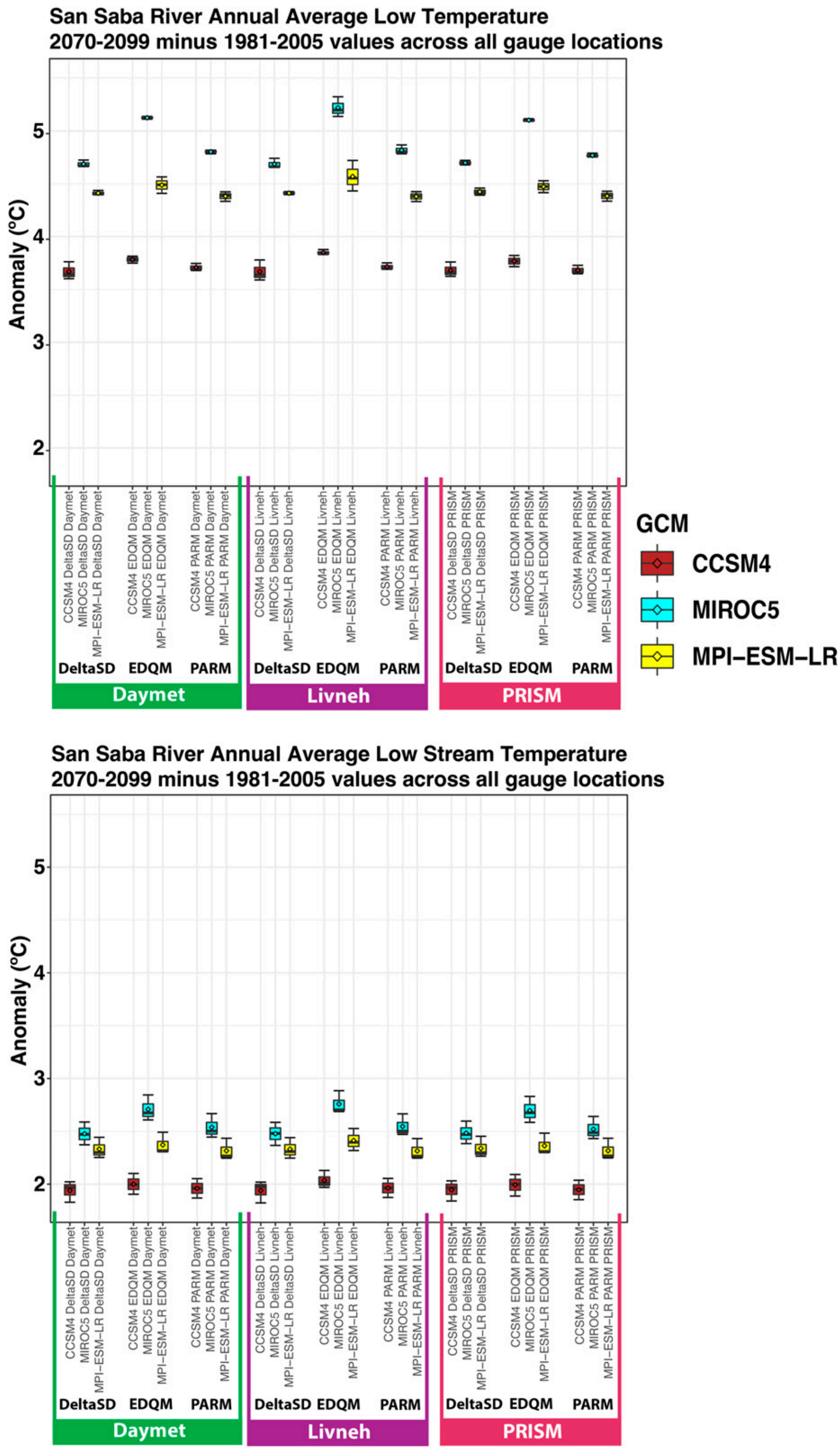

FIG. 12. RCP8.5 projected changes (2070–99) in (top) annual average low air temperature and (bottom) annual average low stream temperature for all gauges along the San Saba River.

Based on the analysis in this study, which used thresholds and information that are region specific (Goldsmith et al. 2021), the resulting projections are also applicable to other species of interest (such as host species for freshwater mussels and other freshwater mussel species, e.g., Modesto et al. 2018) and may be used to assist managers in determining potential changes to water availability and temperatures that impact riparian ecosystems and species. The relative simplicity of the methods used here also makes this a viable approach for an assessment of projected streamflow and stream temperature changes in other regions and for other smaller river systems. However, given the sensitivities identified here and the interrelationship between streamflow and stream temperature, using the regression approach here is a baseline analysis to inform potential impacts and should be paired with approaches using climate projections to inform hydrology modeling to produce projections of streamflow and stream temperature. Given that the stream temperature projections are primarily sensitive to emissions scenarios, one can conclude that the *Lampsilis bracteata* and similar species will face greater stresses under higher emissions scenarios. Since the projections of streamflow are more uncertain, it is more difficult to make the same leap. However, future analyses similar to this one that incorporate hydrologic modeling will allow for future efforts to incorporate potential changes to land use and land cover alongside downscaled climate projections. As such, future efforts that incorporate hydrology models will make additional assessments more robust and provide additional valuable information for impact assessments and adaptation planning for multiple species sensitive to thermal thresholds.

4. Conclusions

This study used climate projections for the south-central United States to create a regression to estimate stream temperature and streamflow. This study also examined the sensitivity of the streamflow and stream temperature projections to the sources of uncertainty in the climate projections.

Yearly average streamflow in the San Saba and Llano Rivers is projected to decrease by up to 80 cfs (2.27 $m^3\ s^{-1}$), while the average number of days the streamflow is below subsistence levels is projected to increase by up to 80 days in the easternmost portion of the San Saba River basin in summer. In addition, the average high and low stream temperatures are also projected to increase by up to 3°C, which results in an increase in the average number of events with 5% mortality for the *Lampsilis bracteata* glochidia by up to 55 days and *Lampsilis bracteata* juveniles by up to 100 days. The projected increase in stream temperatures and projected decrease in streamflow indicate that recruitment *Lampsilis bracteata* will decline and ultimately extirpated under the high emission scenario.

The streamflow projections are primarily sensitive to the training data used in downscaling, which is possibly the result of a known negative bias in precipitation in the PRISM data in this region. While physically based hydrology modeling can incorporate nonclimatic factors, the regression used here provides a useful baseline for projected changes in streamflow, and other similar approaches should carefully consider the training data used for downscaling to create streamflow projections. In contrast, the stream temperature projections are primarily sensitive to the GCM and emissions scenario, which mirrors prior research for projections of air temperature.

Other species of freshwater mussels and aquatic species have their own thresholds of stream temperature and streamflow under which they would face intense stress or mortality. While some studies note that knowledge of lethal temperatures is limited to 5% of known North American mussel species (Khan et al. 2019), other studies indicate that *Lampsilis bracteata* is more sensitive to dry conditions and desiccation than other species (Mitchell et al. 2018). Given the strong relationship between air temperature and stream temperature, the primary source of uncertainty in stream temperature projections that use downscaled projections is the emissions scenario. Therefore, we conclude that with larger increases in temperature associated with higher emissions scenarios, one can expect a greater increase in stream temperature and a higher likelihood of exceeding thermal tolerances of species based on the climate projections alone. However, one cannot ignore the influence of changes in streamflow or local land use and land cover that also affects stream temperatures. Therefore, while this study focuses on the impacts of climate change on streamflow and stream temperature with respect to a single species, future research should assess the potential impacts on related species and their ecosystem services in perennial, intermittent, and ephemeral river systems while considering both climatic and nonclimatic factors.

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Data availability statement. The downscaled climate projections from the Climate Projections Evaluation Project (C-PrEP) are publicly available through the USGS GeoData Portal.

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