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Potential Impacts of Groundwater Pumping on Stream Temperature Are Greatest in Streams With Substantial Cold Groundwater Inflows

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ABSTRACT

Groundwater pumping-induced reductions in streamflow (known as 'streamflow depletion') have been documented worldwide, but potential impacts of streamflow depletion on stream temperature are not well understood. Here, we use two types of models to identify potential impacts of pumping on stream temperature across the conterminous United States (CONUS) to determine which aspects of a stream's annual thermograph (thermal signatures) can be used to monitor and manage streamflow depletion impacts on stream temperature. We used long-term streamflow and stream temperature data from 30 streamgages across CONUS and surrogate models of streamflow depletion to analyse potential stream temperature impacts at each site. We compared two different stream temperature modelling approaches: (i) a process-based energy balance model and (ii) statistical regression models based on air temperature and stream discharge. We calculated a suite of thermal signatures under depleted and non-depleted conditions for each stream and found that maximum annual 7-day temperature and annual temperature range are potentially the most sensitive to streamflow depletion, with potential changes of at least 2°C at > 70% of the sites when using the process-based model. We also found that the regression-based models predicted much less sensitivity of stream temperature to streamflow depletion than the process-based model. This work provides an initial evaluation and sensitivity analysis of the potential impacts of streamflow depletion on stream temperature. We demonstrate that stream temperature may be most sensitive to pumping in streams with a high proportion of flow sourced from relatively cold groundwater inputs, and that regression-based stream temperature models may underpredict stream temperature changes caused by streamflow depletion.

1 | Introduction

Groundwater pumping has reduced streamflow in waterways worldwide, and pumping impacts on streamflow are projected to increase into the future (de Graaf et al. 2019). Reductions in streamflow caused by groundwater pumping, known as 'streamflow depletion', are key elements of integrated groundwater-surface water management strategies due to their implications for human water users, aquatic organisms, culturally significant water resources and outdoor recreation (S. C. Zipper, Farmer, et al. 2022; Barlow and Leake 2012). In addition to water quantity reductions, streamflow depletion may impact stream temperature, which could endanger aquatic and riparian ecosystems even when flows remain sufficient (Lapides et al. 2022). For example, groundwater inflows are known to be a major control over salmonid persistence, potentially through the persistence of relatively cool stream temperatures in otherwise warm streams (Larsen and Woelfle-Erskine 2018) or by increasing temperatures in systems where growth is constrained by cold surface waters, and water temperature is a key control over aquatic refugia (McLaughlin et al. 2017). However, the impacts of streamflow depletion on stream temperature have not yet been systematically evaluated.

Stream temperature can be strongly influenced by changes in streamflow, as evidenced by studies linking temperature to changes in low flows induced by drought (e.g., Fennell et al. 2020; Stewart et al. 2020; Nelson and Palmer 2007; Schultz et al. 2017). While pumping can affect streamflow to a similar extent as hydrologic drought, depletion-induced low flow conditions are driven by different hydrological processes than drought-induced low flows. During drought, surface flow contributions to streamflow tend to decline more rapidly than groundwater inputs (e.g., Dewson et al. 2007; Wawrzyniak et al. 2017; B. Webb and Walling 1997), meaning that the stability and volume of groundwater flows can be primary determinants of water temperature and availability in streams. However, streamflow depletion is characterised by reductions in groundwater inflows to streams, and therefore may have a different thermal impact on streamflow than drought (Barlow and Leake 2012). Thus, the impacts of streamflow depletion on stream temperature merits further investigation.

Previous modelling studies have suggested that streamflow depletion can lead to warmer summer and cooler winter stream temperatures (Risley et al. 2010; Lapides et al. 2022), but these results are based on a limited set of streams and (in the case of Lapides et al. 2022) use a highly simplified temperature mixing model to estimate pumping impacts on stream temperature. Observations and field studies of the impacts of streamflow depletion on stream temperatures have had mixed results, with some indicating increases in summer temperatures of 2°C–3°C caused by streamflow depletion (Folegot et al. 2018) and others indicating little impact (Fennell et al. 2020; Wright and Hatfield 2023; Booker and Whitehead 2022; Van Vliet et al. 2011). Thus, the potential impacts of streamflow depletion on stream temperature are poorly understood (White et al. 2023), and the best ways to measure those impacts have yet to be identified across a broad range of climate, geology and other site characteristics.

There are two primary mechanisms by which streamflow depletion could impact stream temperature: (i) heating or cooling from increased thermal response or exposure to surface energy inputs and (ii) adjusting the relative fraction of water sourced from groundwater (White et al. 2023). Streamflow depletion can affect the first mechanism by reducing the velocity and/or the stream surface area to volume ratio. Lower velocity increases the amount of time that water is exposed to the atmosphere, which increases the amount of time that water in a reach is exposed to surface energy inputs (Folegot et al. 2018). Slower velocity also reduces the impact of longitudinal advection of cooler water from upstream. The extent to which streamflow reductions affect water depth and surface area are controlled by channel geometry (Folegot et al. 2018; Jackson et al. 2017). A stream with less flow may have similar surface water area but reduced volume, enhancing the thermal response in the reach for a given radiative, turbulent or advective exchange. Streamflow depletion can affect the second mechanism by reducing groundwater inflows to streams. Groundwater plays an important role in regulating stream temperature as well as stream chemistry, which are both essential to the survival of aquatic organisms (Baron et al. 2002; Hayashi and Rosenberry 2002; Stonestrom and Constantz 2003; Risley et al. 2010). Groundwater tends to have more stable temperature throughout the course of the year than surface water, with groundwater inflows warmer than surface flows in the winter and cooler in the summer. As a result, groundwater inflow can provide thermal refugia for aquatic organisms that are key to survival and thriving at different times of year (e.g., Mackenzie-Grieve and Post 2006; Sutton et al. 2007; Caldwell et al. 2020; Stevens and DuPont 2011), and groundwater contributions provide substantial cooling in the summer (B. Webb and Zhang 1997, 1999; Fennell et al. 2020; M. F. Johnson et al. 2014). However, the relative importance of and interactions between these two mechanisms have not yet been tested.

In sum, the stream temperature response to streamflow depletion caused by groundwater pumping has not been systematically evaluated either with field studies or in a modelling context, leading to numerous uncertainties. Here, given a dearth of experimental field data, we quantify the potential impacts of streamflow depletion on stream temperature across a wide range of streams spanning the conterminous United States (CONUS) using empirical and process-based models. In doing so, we address three key research questions: (1) What aspects of the stream temperature regime are likely to be most sensitive to groundwater pumping? (2) How does the choice of a stream temperature modelling approach affect the estimated sensitivity of stream temperature to groundwater pumping? (3) Which types of streams are most likely to be highly sensitive to potential streamflow depletion? The last question draws on the strengths of process-based modelling to identify the prevalent process drivers determining stream sensitivity to thermal impacts. Conversely, empirical models represent fewer processes than process-based models, but they are commonly used and often perform very well on historical data (Benyahya et al. 2007). An approach combining both process-based and regression models allows us to use the process-based models to learn more about the relative importance of different process drivers, while the two model structures together allow for a more comprehensive assessment of potential thermal impacts. By addressing these questions, this study provides a theory-driven set of potential impacts of streamflow depletion on stream temperature across a broad range of streams.

2 | Methods

2.1 | Overview

Since the goal of this study is to understand the mechanisms by which streamflow depletion can impact stream temperature and how those changes arise quantitatively in the thermograph, we applied a surrogate modelling approach, which involves a simple but consistent modelling framework across multiple sites (Asher et al. 2015). Here, we describe our approach to identifying study sites, model input data, modelling approaches and sensitivity analyses used to address our research questions.

2.2 | Site Selection

Stream gauging stations were selected from the Geospatial Attributes of Gages for Evaluating Streamflow, version II, (GAGES-II) database (Falcone 2011; Falcone et al. 2010), which includes 1633 stations that have at least 20 years of streamflow data with minimal gaps in data coverage since 1950. Since the GAGES-II database does not provide metadata about stream temperature monitoring, we queried USGS NWIS to identify all GAGES-II stations with stream temperature records. We then downloaded data for each of the GAGES-II stations with stream temperature data and determined the continuous period of record with gaps no longer than 120 days. There were 311 gauging stations with at least 15 years of daily streamflow and stream temperature data. Since reservoir management can have a large impact on stream temperature (Webb et al. 2008), we limited our analysis to the 46 sites with no upstream dams. From this set of 46 sites, 16 sites were missing necessary input data during the gauged period (either due to missing streamflow data or too short of an overlap with available climate data, 1979–2020), so a set of 30 sites was used for this study for which stream temperature models could be developed. The final set of sites is shown in Figure 1a, and a list of attributes is shown in Table S1.

We used these criteria to identify sites with sufficient streamflow and temperature data that cover as many different geographic and hydroclimatic settings as possible. While sites are concentrated on the west coast of the United States, they span multiple ecoregions, drainage areas (5–15 000 km^2), and streamflow regimes (67–2140 mm/year). Given limitations in data availability for stream temperature, we include all basins that meet the data availability criteria, although not all of these streams may be at risk from groundwater pumping, to better explore potential physical drivers of stream sensitivity to pumping. Groundwater pumping is widespread and impacts basins with wide-ranging geology and climate characteristics (Condon and Maxwell 2019), so we include as many different types of streams as possible in this analysis to try to represent this range.

Detailed modelling is conducted at each of these 30 sites with available records of overlapping streamflow, stream temperature and climate datasets (Sections 2.5–2.7). To span a broader

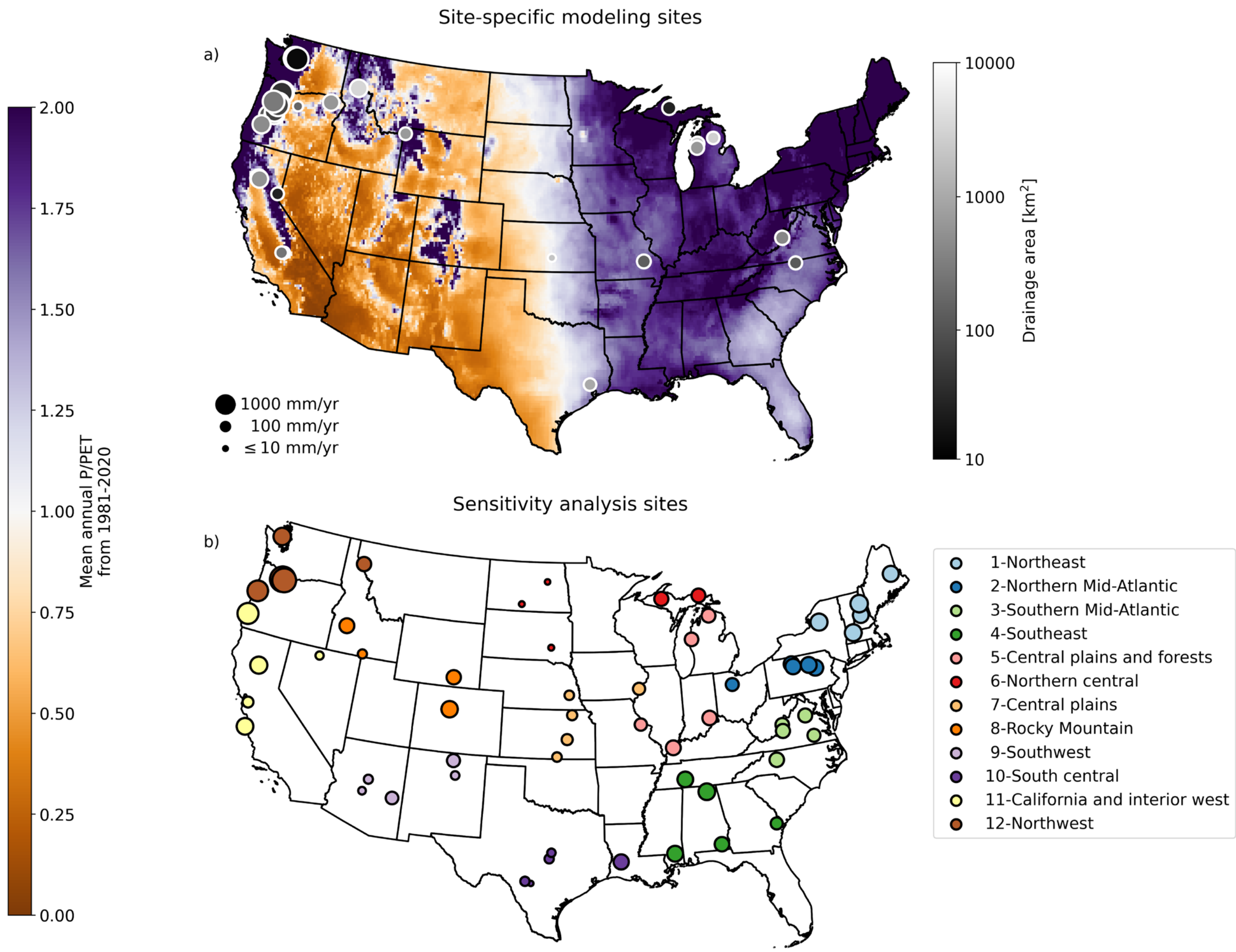

FIGURE 1 | Map of the conterminous United States showing (a) aridity index (background colour), defined as mean annual precipitation over potential evapotranspiration (P/PET), with study sites coloured by drainage area and (b) sensitivity analysis sites marked with circles coloured by hydroregion. The size of the circle indicates the mean annual flow in both panels.

range of hydrologic conditions, we conduct an additional set of sensitivity analyses using 60 sites distributed across the United States (Section 2.8) with stream temperature modelled using the process-based model described in Section 2.4.2.

2.3 | Climate and Stream Temperature Data

For daily meteorological data (minimum air temperature, maximum air temperature, incident solar radiation, relative humidity, wind speed and daily precipitation), we downloaded gridMET (Abatzoglou 2013) products for the years 1979–2020. Daily precipitation was aggregated by catchment for each gauging station, while air temperature, incident solar radiation, relative humidity and wind speed values were used for the gridMET pixel containing each gauging station. Precipitation was used only to calculate aridity indices for Figure 1a. Mean daily air temperature was calculated as the mean of the maximum and minimum daily air temperature from gridMET. Shading from topography and riparian vegetation is accounted for by the inclusion of a shading term in the process-based model, as described in Section 2.4.2 and Supporting Information S1. The gridMET input data has a 4 km spatial resolution, and therefore may be unable to capture fine-scale microclimatic variation in complex terrain. However, fine-scale meteorological variations are not essential to our modelling, and gridMET performs better at air temperature than other available distributed products (Blankenau et al. 2020). Values for each gridMET meteorological variable were summarised to make sure that they fit within logical ranges and daily time series were analysed to verify that they match regional patterns of intra- and inter-annual variability.

Stream temperature data were obtained from USGS using United States Geological Survey (USGS) National Water Information System (NWIS) (U.S. Geological Survey 2022) queried via the hydrofunctions python package (https://github.com/mroberge/hydrofunctions) and dataRetrieval R package (Hirsch and DeCicco 2015). The USGS follows set procedures for the observation of stream temperature as described in U.S. Geological Survey (2024) and Heck et al. (2018), which include guidance and requirements for maintenance, calibration and verification of sensors and data loggers, as well data reporting. Stream temperature measurements are susceptible to errors arising from observations being taken at different locations within a stream segment through time, changes in solar radiation through time (e.g., a change in forest canopy), and sensors becoming exposed to air, so care must be taken pre- and post-deployment to ensure that the data accurately reflect water temperatures (Sowder and Steel 2012). In this study, we screened stream temperature observation sites using available data on human impacts and visually inspected all records to ensure anomalous values were not present in the time series used to calibrate and test models developed. No suspect values were identified.

2.4 | Stream Temperature Models

To evaluate the sensitivity of our site-specific results to model selection, we explored two different types of temperature models: linear regression models and a process-based energy balance model. Each modelling methodology has strengths and weaknesses, so the results from the two approaches are complementary in understanding the ways that streamflow depletion affects stream temperature as well as the sensitivity of predicted streamflow depletion impacts to model selection, and it is generally recommended to use multiple stream temperature models given differences in projections (Piotrowski et al. 2021). This approach follows that of previous studies, such as Hockey et al. (1982), who used an approach with both empirical and process-based models to assess impacts of reduced discharge on stream temperature. The regression models capture existing relationships in the data, so if streamflow is generally an important driver of stream temperature, then the regression models will potentially capture the quantitative relationship. Regression models have been applied with success when air temperature is an important predictor of stream temperature (e.g., Crisp and Howson 1982; Jourdonnais et al. 1992; Stefan and Preud'homme 1993; Mohseni et al. 1998), and Asarian et al. (2023) previously used data-driven models with air temperature and streamflow as predictors to study the effects of reduced flows on stream temperature. However, if the relationship is nonlinear or varies in a different way than in the historical dataset when groundwater pumping is introduced, the regression models may not capture the impacts.

In contrast, process-based models are typically used when there are changes in drivers throughout the study period like a shift in vegetation or some other physically relevant attribute. These models are often used to simulate streams under natural conditions (e.g., Brown 1969), to identify the importance of different physical terms (Sinokrot and Stefan 1993; Caissie et al. 2007; Toffolon and Piccolroaz 2015; Bogan et al. 2004) and to evaluate the impact of anthropogenic changes to a stream environment (Morin et al. 1994; Sinokrot and Gulliver 2000; Bogan et al. 2004). Process-based models are particularly well adapted to studying the impacts of flow reduction or alteration on stream temperature (Caissie et al. 2007), as demonstrated by Gu et al. (1998). However, process-based models have embedded assumptions about the processes driving stream temperature variability, requiring in some cases a significant amount of data to constrain all parameters and ensure that processes are properly represented. The flexibility to extend to unobserved situations, though, provides conceptual information about the relative importance of different described processes, which is not possible with regression models.

2.4.1 | Regression Models for Stream Temperature

Statistical models, including regression models, have become important tools for stream temperature modelling due to their low data requirements and strong model performance (Benyahya et al. 2007). Most commonly, regression models for stream temperature rely solely on air temperature (e.g., Smith 1981; Crisp and Howson 1982; Mackey and Berrie 1991; Stefan and Preud'homme 1993). While less common, stream discharge has also been found to exert a statistically significant impact on stream temperature (e.g., B. Webb et al. 2003; Michel et al. 2020; Hockey et al. 1982). In order to detect the impact of streamflow depletion independently of climatic conditions, we used a linear regression model that predicts daily stream temperature as a function of both air temperature and streamflow:

$$T_{stream} = a + bT_{air} + cQ, \tag{1}$$

where T_{stream} (°C) is daily mean stream temperature from NWIS, T_{air} (°C) is mean daily air temperature, Q (L^3/T) is mean daily streamflow queried from NWIS, and a, b and c are fitted regression constants. Many different variations on this regression model exist in the literature. We tested some variations with very similar outcomes. A common variation is to use the $\log(Q)$ instead of Q (e.g., Hockey et al. 1982). We included model fits for this version in the code supplement (figures available to view without running code), but results are essentially identical, so we do not show results from this analysis. Since stream temperature relationships may vary based on season (e.g., Langan et al. 2001), we trained a different regression model for each site for each season, defined as four 3-month intervals: Winter (January–March), Spring (April–June), Summer (July–September) and Fall (October–December). Langan et al. (2001) found that training separate models for each season improves performance, and the procedure followed here is similar to that used in that study.

We trained the models using the first half of the historical record of overlapping stream temperature, discharge and meteorological data (range from 7.5 to 20 years) and then used the second half of the record to test model performance. A final model for each site was trained using the full overlapping historical record (15–40 years). This approach allows for both evaluating model performance and using the maximum amount of data to train the model used to explore the research questions.

2.4.2 | Energy Balance Model for Stream Temperature

Energy balance models use process-based equations to simulate the stream water energy balance and stream temperature response, and therefore are well-suited for evaluating stream temperature under alternative scenarios, particularly those outside the range of historical observed conditions (St-Hilaire et al. 2000; Dugdale et al. 2017). The basis of these models is typically the heat advection-dispersion equation for an open channel of constant cross-section and homogeneous temperature neglecting longitudinal dispersion and longitudinal advection (in this case, the point model), given by Bogan et al. (2004) and Caissie et al. (2007):

$$\frac{dT_{stream}}{dt} = \frac{H_{total}}{\rho c_p d}, \tag{2}$$

where t (T) is time, ρ (M/L^3) is the density of water, c_p (E/M°C) is the specific heat of water, d (L) is mean channel depth and H_{total} (E/L^2) is the net energy gains or losses by radiative, latent, sensible and advective heat exchange. To calculate each component of H_{total}, we use equations commonly used in stream temperature modelling literature (e.g., J. Leach and Moore 2010; Sinokrot and Stefan 1993; Maheu et al. 2014; Szeitz and Moore 2020; Caissie 2016). Please see the Supporting Information for additional details on the model equations and assumptions. Equation (2) is solved using Euler integration with an hourly timestep. Hourly values are then averaged by calendar day for a daily stream temperature timeseries. There are three tuned parameters encoded within these equations. One is a term that represents the fraction of incident shortwave radiation that passes through the canopy (M). The other two parameterise the relationship between streamflow and stream depth using a power law function of the form:

$$D = d_1 Q^{d_2}, \tag{3}$$

where d_1 and d_2 are fitted parameters, an approach that is commonly used in stream temperature modelling literature (Caissie et al. 2007; Garner et al. 2014). Parameters d_1 and d_2 are typically referred to as c and f in geomorphology literature, following Leopold and Maddock (1953). Stream depth is updated daily.

Each day, the temperature from the previous day is updated using Equation (2) to get an intermediary stream water temperature $T_{stream,int}$. Then, groundwater inflows are incorporated using a simple mixing model:

$$T_{stream} = Gfrac\, T_{groundwater} + (1 - Gfrac) T_{stream,int}, \tag{4}$$

where $Gfrac$ (·) is the fraction of flow from groundwater at a given day, and $T_{groundwater}$ (°C) is the temperature of groundwater. We extracted groundwater temperature from the global raster of shallow groundwater temperature produced by Benz et al. (2017). *Gfrac* is estimated as the fraction of baseflow at each timestep. At each site, we perform baseflow separation using the Eckhardt baseflow separation algorithm (Eckhardt 2005) as implemented in the 'hydro' python package (https://github.com/hydrogeog/hydro/). We use the baseflow index for each site from the GAGES-II dataset as the BFI_{max} input parameter to the Eckhardt baseflow separation. For the depleted scenarios (Figure 2), the amount of streamflow depletion is deducted from groundwater inflows first if they are available. Since baseflow may consist of groundwater that enters in the current reach or upstream of the current reach, we incorporate a further groundwater inflow term so that:

$$Gfrac = F_{baseflow} \times Ifrac \tag{5}$$

where $F_{baseflow}$ (·) is the fraction of streamflow that is baseflow following the Echkardt baseflow separation, and *Ifrac* (·) is a tuned parameter that represents the fraction of baseflow that is provided by groundwater flows into the current reach or in nearby upstream locations. There are three tuned parameters, including *Ifrac*. The other two parameters are used to define a relationship between streamflow and stream depth (Equation 3). Ice formation is not included in this model, but water temperatures are capped to a minimum value of 0°C.

Prior to conducting any further analyses, daily records of stream temperature from regression models and process-based models were inspected visually in time series plots and through the use of histograms to confirm that stream temperatures fell within a reasonable range and check for the presence of outliers, although no unexpected values were identified.

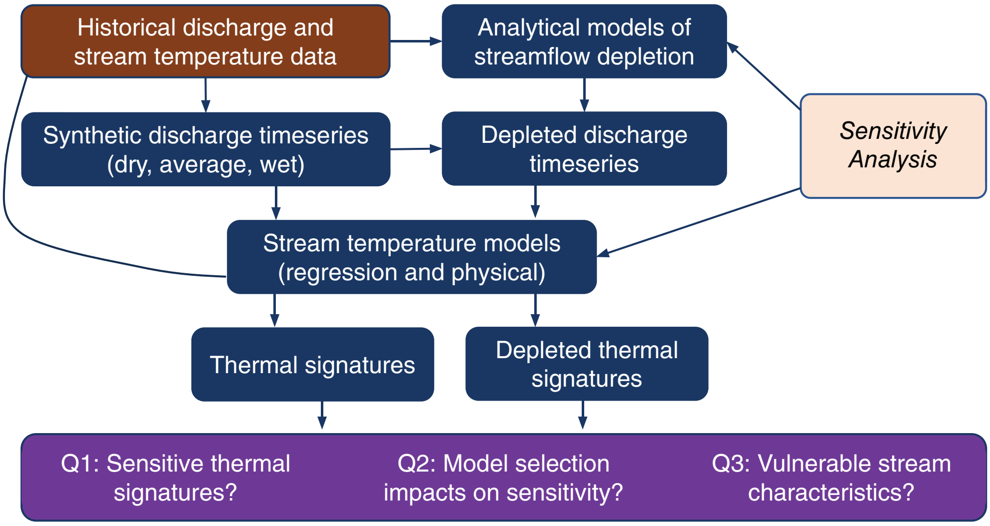

FIGURE 2 | Workflow and data used to address each of the study's research questions.

2.4.3 | Data Limitations

While we excluded sites with no upstream dams, there may be existing groundwater pumping in some of the study basins. Existing pumping could actually improve applicability of regression models since pumping could be a driver of stream temperature variability in the dataset. For instance, if pumping increases the impact of streamflow changes on stream temperature, then this impact would show up in training data and be captured by the fitted model terms. While the simulated pumping would still be outside the range of observations, the existing groundwater pumping in the record may mean that important processes are better represented in the modelled coefficients. Conversely, existing pumping could alter the calibration in the process-based model, resulting in a lower-than-natural groundwater inflow term *Ifrac*. This could lead to more rapid impacts on stream temperature with pumping or limited potential for the effect of groundwater inflow reductions but would not affect the overall functioning of the model.

2.5 | Streamflow Depletion Scenarios and Data

We built on the modelling framework developed by Lapides et al. (2023a) for identifying streamflow signatures impacted by streamflow depletion, which we summarise here and graphically in Figure 2, and adapt it in this study to assess potential changes in stream temperature. We simulated a suite of streamflow depletion scenarios based on a factorial combination of: (i) three streamflow scenarios per site (dry year, based on 10th percentile flow for each calendar day; average year, based on 50th percentile flow; and wet year, based on 90th percentile flow) and (ii) pumping scenarios simulated for 50 years using the Glover model (Glover and Balmer 1954) with 1000 randomly generated parameter sets for hydrostratigraphic and well parameters (using the following data as reference; Huscroft et al. 2018; Zell and Sanford 2020; Jasechko et al. 2021), an annual pumping rate equal to 5% of the annual streamflow at each site, and constant versus periodic pumping as in S. C. Zipper et al. (2019). In the periodic pumping scenario, a static pumping rate was used from May through September, and the total annual volume of pumping is equivalent between the constant and periodic pumping cases. Defining pumping as a constant fraction of streamflow at all sites allowed us to explore the potential stream temperature response to a normalised amount of streamflow depletion at all sites, rather than conduct a site-specific assessment of actual streamflow depletion impacts on temperature. For full details on streamflow depletion modelling approach and uncertainty analysis, see Lapides et al. (2023a) which used the same methodological approach, figure 3 in Lapides et al. (2023a) in particular provides a visual overview of the streamflow and pumping scenarios.

We found there were generally similar types and patterns of responses among wet, dry and average year scenarios, with typically the largest magnitude of response in the dry year scenarios, and therefore here we show only the dry year scenarios for simplicity, with wet and average year results included in the Supporting Information. The higher response magnitude in dry years is likely most applicable from a management and ecological perspective as well, since dry years typically have the greatest amounts of groundwater pumping (S. Zipper, Kastens, et al. 2024; Whittemore et al. 2023) and the highest stream temperatures (e.g., Fennell et al. 2020) and, therefore, may be the most important years to consider for potential pumping-driven ecological impacts on species that require more moderate thermal regimes. These simulations are meant to provide a representative depiction of potential streamflow depletion conditions at each site under different hydroclimatic and management scenarios, rather than a calibrated historical or present-day estimate of the actual streamflow depletion.

Throughout the manuscript, we show results only for the constant pumping scenario since results are very similar for the periodic pumping scenario (both scenarios ultimately result in a very similar amount of flow reduction since they are pumping the same volumes at an annual resolution). Results for the periodic pumping scenario can be found in Figures S1 and S2.

2.6 | Summary of Study Analyses

In this work, we proceeded with two main analyses: a site-specific analysis focused on 30 sites with long-term stream temperature and streamflow data and a sensitivity analysis for 60 sites distributed across a wide range of hydroregions.

For the site-specific analysis, we use the set of 30 sites with both long-term streamflow and stream temperature data (Section 2.2). We then used actual streamflow and stream temperature timeseries to train two different types of models to model stream temperature at each site: a set of regression models and a process-based model. The details of these models are described in Section 2.4. The process-based models were parameterised using the top percentile of simulations run with 3000 random parameter sets. Trained temperature models were then used to develop stream temperature timeseries for each streamflow depletion scenario at each gauge. To isolate the impacts of pumping on stream temperature, we kept climate constant every year for 50 years for each scenario using a repeating annual signal with the day of year median value for each gridMET climate variable over the full time period of overlap between stream temperature and climate data at each site, including air temperature, wind speed, incident solar radiation and relative humidity. By maintaining a constant climate across all years and scenarios, we ensured that any detected differences between stream temperature time series are due entirely to modelled 50-year streamflow depletion. We then compared stream temperature signatures without pumping and after 50 years of pumping to determine the potential impacts on stream temperature for a reach located at each of the 30 gauge locations.

For the sensitivity analysis, we used a larger set of 60 sites distributed across hydroregions in the Conterminous United States simulated with the process-based model (Section 2.8). This sensitivity analysis uses a single year of climate and streamflow data with randomly generated parameters for stream characteristics that impact stream temperature. This single year is repeated 50 times with the modelled streamflow depletion as described for the site-specific analysis. Potential impacts of groundwater pumping on stream temperature were then evaluated for each synthetic scenario. Across the ensemble of scenarios, we then developed an understanding of how different stream characteristics can drive vulnerability to stream temperature impacts from groundwater pumping.

2.7 | Thermal Signatures and Change Detection

To evaluate streamflow depletion impacts on stream temperature, we introduce the concept of 'thermal signatures' as a tool to characterise aspects of a stream's thermograph that can be used to describe its temperature behaviour. Thermal signatures are the stream temperature analogue to 'hydrologic signatures', which describe the streamflow hydrograph and can be related to specific hydrological processes to guide streamflow depletion management (McMillan 2020). Since recent work has found hydrologic signatures can significantly respond to groundwater pumping (Lapides et al. 2023a), thermal signatures could be a useful approach to link stream temperature changes to groundwater depletion.

Here, we suggest a set of 12 thermal signatures (Table 1) that represent different components of aquatic thermal regimes (Arismendi et al. 2013). For each streamflow and pumping scenario and each temperature model, we calculated each signature at annual resolution and 10 of the signatures at seasonal resolution. We defined seasons as: Winter = January–March, Spring = April–June, Summer = July–September and Fall = October–December.

TABLE 1 | Thermal signatures tested for sensitivity to streamflow depletion.

Signature	Description	Seasonal or annual?
Mean temperature	Mean daily temperature (°C)	*S* + *A*
Minimum temperature	Minimum daily temperature (°C)	*S* + *A*
Maximum temperature	Maximum daily temperature (°C)	*S* + *A*
Standard deviation	Standard deviation of daily temperatures (°C)	*S* + *A*
Degree days	Calculated following Charnov and Gillooly (2003) (°C)	*S* + *A*
Number of cold days	Days in normalised timeseries below *z*-score of −1 (days)	*S* + *A*
Number of warm days	Days in normalised timeseries above *z*-score of 1 (days)	*S* + *A*
Temperature range	Difference annually between minimum and maximum daily temperature (°C)	*A*
Coefficient of variation	Coefficient of variation of daily temperature	*A*

Note: In the final column, *S* indicates that the signatures are calculated seasonally and *A* indicates that the signatures are calculated annually. Seasons are defined as: Winter = January–March, Spring = April–June, Summer = July–September and Fall = October–December.

Since our experiment was designed to eliminate climatic variability between years through the use of representative synthetic hydrographs, all differences between stream temperature timeseries can be attributed to streamflow depletion. To detect changes, we used a percent change threshold ($S_{\%change}$) for signatures that do not have units of °C (degree days, cold days, warm days and coefficient of variation) and an absolute difference for all other signatures (S_{change}). We chose to consider an absolute difference in °C when possible to better capture the impact of temperature on aquatic organisms (e.g., Hartman and Cox 2008; Hayes et al. 2000). These metrics are defined as:

$$S_{\%\text{change}} = \frac{S_{50} - S_0}{S_0} \times 100 \tag{6}$$

and

$$S_{\text{change}} = S_{50} - S_0, \tag{7}$$

where S_{50} is the value of the signature after 50 years of streamflow depletion and S_0 is the value of the signature in the synthetic non-depleted timeseries. In general, we report S_{change} and $S_{\%\text{change}}$ using the median value of S_{50} across the range of simulated change values for each site and scenario. A measure of uncertainty can be calculated by using S_{50} from the 0.2 and 0.8 quantiles. The range from 0.2 to 0.8 quantile was arbitrarily selected to represent the majority of the likely data spread. When reporting a binary indicator of whether change is detected at a site for a given scenario, we use a percent change threshold of 20% and an absolute change threshold of 2°C. While binary indicators do not capture the magnitude and variability in changes, they have the advantage of allowing us to simplify a dataset across multiple sites with ensembles of outcomes for clear visualisation of findings. Small changes in these thresholds do not have much impact on results.

2.8 | Sensitivity Analysis to Identify Characteristics of Vulnerable Streams

The stream temperature analysis in this study is limited by available stream temperature records, which are relatively infrequent and not evenly distributed across CONUS (Figure 1a). To explore potential streamflow depletion impacts on a wider range of hydrologic conditions, we conducted a sensitivity and uncertainty analysis using data from 60 sites spread across CONUS (Figure 1b). To ensure these 60 sites spanned a range of different hydrologic conditions, we randomly selected five sites from each of the 12 hydroregions identified in McCabe and Wolock (2022). We then followed a five-step process to evaluate the sensitivity of estimated stream temperature changes to different parameters and generalise our results across CONUS. There is only one calibrated parameter in the process-based model (groundwater inflow fraction). Even without stream temperature data at these sites, we are able to estimate the other parameters. Thus, the described sensitivity analysis allows us to use the parameters we know along with a suite of process-based model runs to understand how streams will respond with different groundwater inflow fractions.

2.8.1 | Step 1: Develop Baseline Annual Hydrograph

This analysis is different from that described for the 30 sites with long-term stream temperature data in that we do not separately assess wet/dry/average years. We instead select a single baseline annual hydrograph shape for each site. For each site, we developed a baseline annual hydrograph by randomly selecting one calendar year from the streamflow record (Goodall et al. 2008) and normalised streamflow by the mean streamflow across all years. For representative climate timeseries, we selected the same year as used for streamflow from gridMET timeseries (Abatzoglou 2013) for air temperature, wind speed, incident solar radiation, relative humidity and daylight hours. We then generated 10 000 random parameter sets using the parameter ranges in Table 2 to alter conditions and adjusted the streamflow

TABLE 2 | Summary of randomly selected parameters for stream temperature sensitivity analysis.

Parameter	Description	Range
Landscape and stream parameters		
BFI	Baseflow index (%)	5–95
Groundwater temperature	Groundwater temperature (°C)	5–25
Inflow fraction	Fraction of water added to reach that has groundwater temperature vs. upstream reach temperature	0–1
Streamflow	Mean streamflow (m^3/s). Values not randomly selected. Listed values used for all sites and scenarios	0.1–100
d_1	Coefficient in Equation (3)	0–1
d_2	Exponent in Equation (3)	0–1
M	Fraction of solar radiation that passes through the canopy	0–1
Streamflow depletion parameters		
Well distance	Distance between well and first stream reach (m)	Sampled from Jasechko et al. (2021)
Transmissivity	Aquifer transmissivity (m^2/day)	Normal distribution, $\log(T)$ mean = 1.5 and $\log(T)$ stdev = 0.75
Storativity	Aquifer storativity	Normal distribution, S mean = 0.2 and S stdev = 0.04

hydrograph for each set of conditions by multiplying the normalised streamflow timeseries by the scenario's mean streamflow. While parameters d_1 and d_2 are not necessarily constrained to the range 0–1, we constrain them to the range 0–1 since all sites included in this study had parameterised ranges between 0 and 1 for both parameters in the HyG dataset (Enzminger et al. 2024).

2.8.2 | Step 2: Streamflow Depletion Timeseries

The streamflow depletion timeseries were then generated using the Glover model (Glover and Balmer 1954), as in the site-specific analysis described above. We randomly selected 1000 combinations of these parameters based on the ranges shown in Table 2. For each parameter set, a streamflow depletion timeseries was generated using constant pumping and periodic pumping, as defined in Section 2.7, resulting in 2000 streamflow depletion timeseries. Since streamflow varied widely across our scenarios, we generated streamflow depletion timeseries as the depletion fraction of the total pumping rate and then scaled streamflow depletion to each streamflow scenario assuming a pumping rate of 5% of the mean annual streamflow.

2.8.3 | Step 3: Stream Temperature Modelling

For each model run, the process-based stream temperature model was run for 2 years with reference streamflow followed by 2 years with identical conditions other than depleted streamflow using year 50 (the final year) of the streamflow depletion timeseries. We chose to run for 2 years only in each case since initial testing showed that the temperature model stabilised within a week of initialisation, and model run times were slow. Year 2 was identical to each of the following years, so we opted to minimise run time by running only 2 years of simulations for each set of conditions. This analysis did not require stream temperature data to calibrate temperate models, and was instead meant to evaluate the sensitivity of different thermal signatures to stream and landscape parameters.

2.8.4 | Step 4: Evaluation of Sensitive Parameters for Stream Temperature Changes

After stream temperature modelling, there were 60 000 distinct stream temperature timeseries produced using the combination of different site characteristics, climate and streamflow depletion modelling parameters. These 60 000 timeseries represent potential streams throughout the space of possible real streams rather than specific real streams. The large number of simulations ensures that we capture behaviour across the parameter space, and the findings can be used to evaluate which part of the parameter space is associated with different types of sensitivity to stream temperature changes from groundwater pumping. Real streams that fall in this part of the parameter space would be potentially vulnerable to stream temperature changes due to groundwater pumping.

We used minimum and maximum 7-day temperature as focal thermal signatures for each scenario, as the most likely signatures to indicate changes based on the results of our site-specific analyses. After running the temperature models, we calculated a change in each signature as an absolute difference between year 2 of the no-pumping timeseries and year 2 of the depleted timeseries, as described in Section 2.7. We then identified the landscape and stream parameters under which stream temperature was sensitive to streamflow depletion. For each parameter, sensitivity was measured as the fraction of parameter sets with a given value of that parameter that show impacts in a thermal signature of at least 2°C.

3 | Results

3.1 | Stream Temperature Model Evaluation

The model over the full year has KGE > 0.5 for the process-based models for nearly all sites (Figure 3j). Seasonally, KGE is generally 0.5 or above except during winter and summer for some sites, when performance is lower (Figure 3k–n). For this reason and due to the complexity of freeze–thaw cycles that are not accounted-for in our models, we do not show results for winter. We still show results for summer since RMSE is not higher than other seasons, and summer is an important time for high stream temperatures. RMSE for the full year is 2°C–4°C and typically closer to 2°C in all seasons (Figure 3e–i). These findings support a change threshold of 2°C, which is typically larger than model error. These errors are of a similar order of magnitude, although larger than errors found in other studies modelling the impacts of streamflow reductions on stream temperature (e.g., 0.5°C for a site-specific process-based model in Hockey et al. (1982) and 1.2°C for a more complex statistical model in Asarian et al. 2023).

Examples from six study sites are shown in Figure 4. These timeseries show that the empirical model is able to closely capture much of the variability and pattern in stream temperature in the historical dataset. While the process-based model matches the data less closely at many sites, it is still able to capture a variety of different stream temperature patterns (compare Figure 4d,g, for example). Together, these performance findings suggest that both types of models are able to simulate historical stream temperature with reasonable accuracy.

3.2 | Identifying Stream Thermal Signatures That Are Sensitive to Modelled Groundwater Pumping

Overall, the process-based models predict widespread impacts on stream temperature across sites, with changes of more than 2°C showing up primarily in annual mean daily temperature, minimum 7-day temperature, maximum 7-day temperature, standard deviation of daily temperature, and annual temperature range (Figure 5a). At a seasonal scale, impacted signatures are very similar (mean daily temperature, minimum and maximum 7-day temperature, standard deviation in daily temperature), but since impacts may show up more in some seasons than others, the fractions of impacted sites are lower, and most impacts show up in summer. See Figure S7 for a visual depiction of the projected impacts of streamflow depletion on stream temperature.

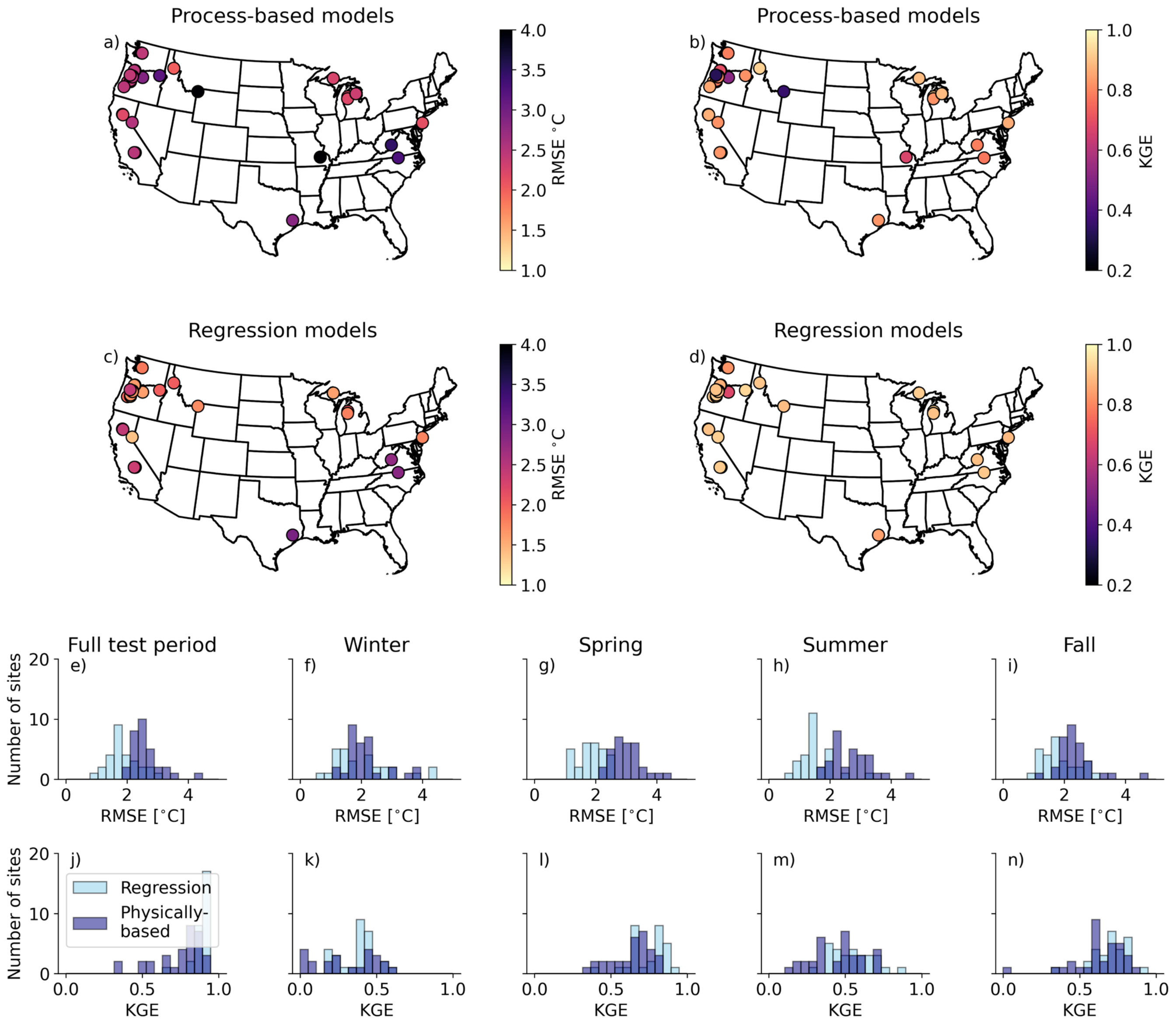

FIGURE 3 | Model performance for physically based and regression models shown (a–d) spatially and (e–n) as histograms of model performance in modelling daily stream temperature for each site. Performance is shown in terms of (a, c, e–i) RMSE and (b, d, j–n) KGE annually and by season.

3.3 | Comparing Stream Temperature Model Performance and Sensitivity to Pumping

The process-based models generally predicted greater impacts of streamflow depletion on temperature than the regression models at the sites we investigated. Very few sites have modelled impacts in any signatures when using the regression models (Figure 5, light blue) compared to the process-based models (Figure 5, brown). For annual signatures, 2% of sites or less are impacted in any signature, with the largest impacts to mean daily temperature and maximum 7-day annual and fall temperature (Figure 5). For the regression models, different models are trained for each season. When a single model is used for the whole year, no impacts are observed in any signatures (Figure S3).

Although the process-based and regression models disagree on the extent of impacts, there is a set of signatures identified as most likely to be impacted by both model structures: annual maximum temperature, mean daily temperature, annual temperature range and maximum fall temperature. In all cases, the magnitude of impacts suggested by the process-based model exceeds that suggested by the regression models. Overall, the process-based model suggests widespread potential impacts to stream temperature, whereas the regression models suggest minimal potential impacts.

The model performance for the regression models for daily stream temperature for the full year (Figure 3e,j) shows stronger agreement with observations than the process-based models. In terms of KGE, though, performance by season is quite similar between model structures (Figure 3j–n). RMSE for regression models is a little lower than for the process-based models, typically around 2°C and even lower during spring and summer (Figure 3e–i). However, this strong agreement does not necessarily indicate that the regression models

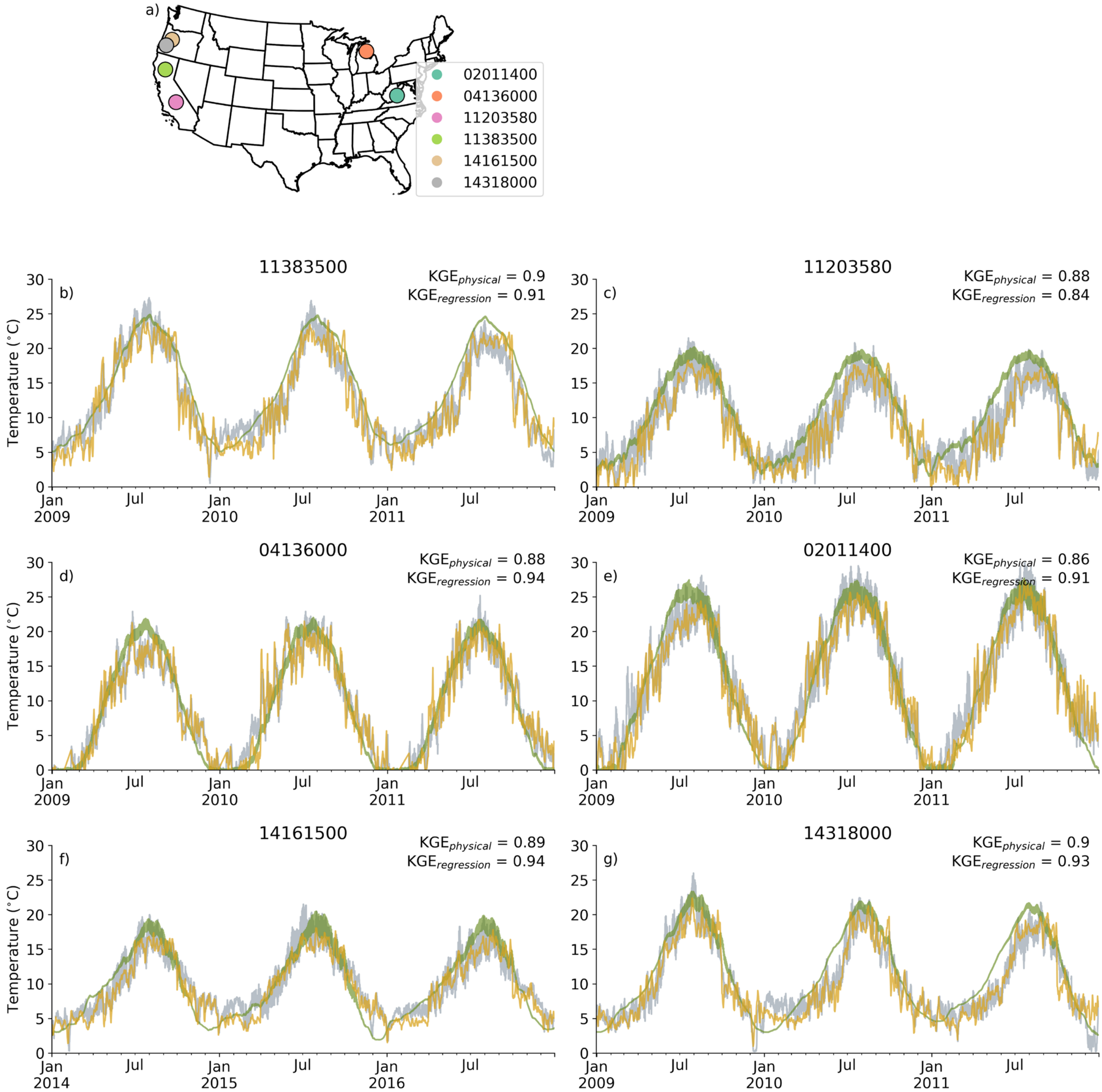

FIGURE 4 | Observed (grey) and modelled stream temperature (process-based model in green, regression in orange) for six example sites (b–g). USGS gauge number is at the top of each subplot. KGE$_{\text{physical}}$ and KGE$_{\text{regression}}$ are the KGE for the process-based and regression stream temperature models shown in the subplot. The locations of these sites in the USA are shown in (a).

captured the underlying relationships well. Partial residual plots (shown in the code supplement, visible without running code) indicate that air temperature is generally a much stronger driver of stream temperature than streamflow (indicated by steeper slopes in plots for air temperature than streamflow). Dependence on streamflow is often minimal (low slope), but for some sites, there is a clear negative relationship between streamflow and stream temperature in warmer seasons (summer and/or spring, lower discharge means higher temperatures) and a positive relationship in cooler seasons (fall and/or winter, lower discharge means lower temperatures). For other sites, the relationships may not follow these rules. These findings indicate that, while the regression models have exceptional model performance, they may not be able to predict stream temperature under changing conditions.

3.4 | Which Types of Streams Are Vulnerable to Temperature Impacts From Streamflow Depletion?

Across 60 000 randomly generated parameter sets, sensitivity of stream temperature to streamflow depletion using the

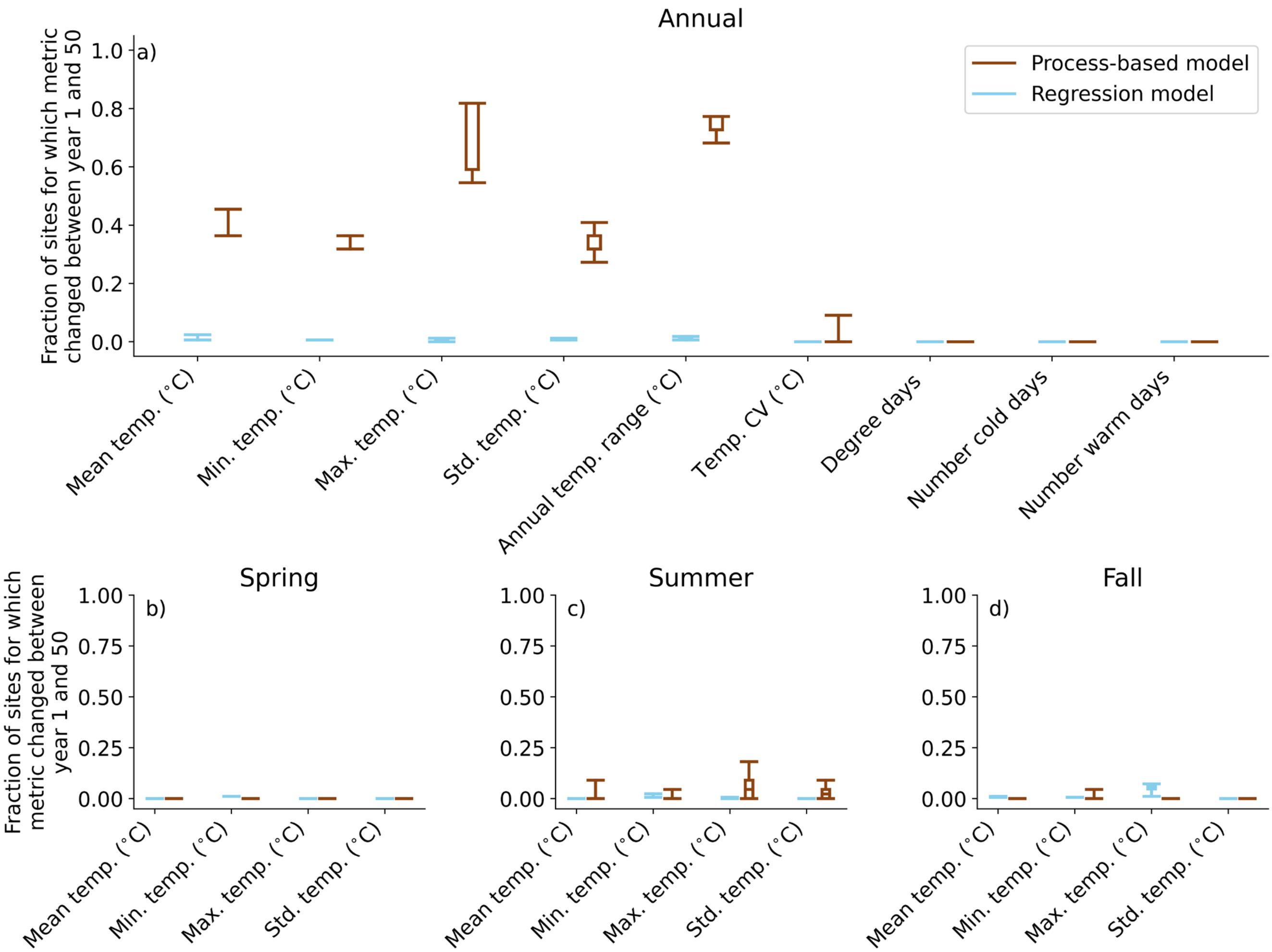

FIGURE 5 | Summary of detected impacts of streamflow depletion on stream temperature using the process-based (brown) and regression (light blue) temperature models with constant pumping for select (a) annually-calculated signatures and (b)–(d) seasonally calculated thermal signatures. A signature is considered to change if there is at least 2°C change for metrics with units degrees Celsius or at least 20% change for Degree days, number cold days and number warm days.

simple point-scale process-based model in each of the two studied thermal signatures (7-day maximum temperature, 7-day minimum temperature) is primarily driven by groundwater temperature, BFI, groundwater inflow fraction, fitted parameters relating streamflow to stream depth (d_1 and d_2), M and streamflow (relationships shown in Figure 6). Most prominent impacts appear with combinations of extreme values in multiple parameters (Figure 7). In terms of the two mechanisms by which groundwater pumping may impact stream temperature (increased exposure to atmospheric conditions and decreased groundwater inflows), the importance of groundwater temperature, BFI and groundwater inflow fraction are related to the changes in groundwater inflows, while d_1, d_2, M and streamflow are more closely related to exposure to atmospheric conditions since depth and volume are primary determinants of the extent to which atmospheric conditions are translated to stream temperature. For all of the other possible drivers in Table 2, simulations that show impacts of streamflow depletion on temperature are equally likely to occur at any parameter value (Figure S4).

Across the parameter space, there is a similar fraction of sites that show impacts on 7-day maximum temperature (64%) as 7-day minimum temperature (72%). Streamflow depletion has the greatest impacts on 7-day maximum temperature (Figure 6a) at sites with colder groundwater since, at these sites, reductions in cold groundwater inflows caused by pumping lead to warmer stream temperatures. The opposite holds for 7-day minimum temperature (Figure 6b), which is most sensitive to streamflow depletion at sites with warmer groundwater temperatures. For streamflow depletion impacts on 7-day maximum temperature, groundwater temperature is the most influential parameter, while BFI is the most influential parameter for 7-day minimum temperature. For both signatures, high enough BFI and groundwater inflow fraction are required for stream temperature to be sensitive to streamflow depletion. In these scenarios, pumping-induced reductions in groundwater discharge to streams have a greater impact on overall stream temperature. Relationships with other parameters are weaker but still apparent. The patterns suggest higher sensitivity for streams that change depth more quickly with changes in streamflow and have less shading.

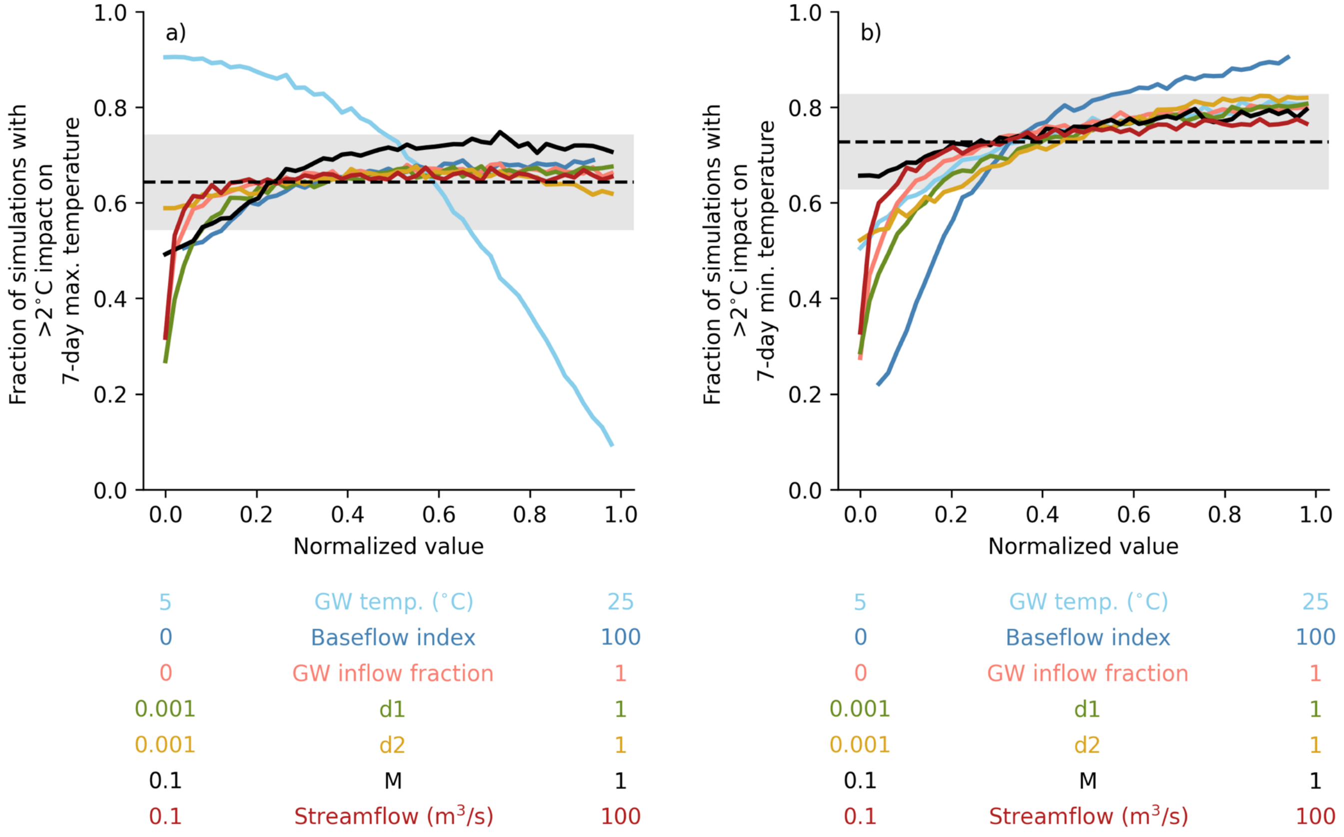

FIGURE 6 | Fraction of simulations with impacts to (a) 7-day maximum temperature and (b) 7-day minimum temperature as a function of parameter value for the five most important parameters. Sensitivity is defined as the fraction of parameter sets for which the signature is impacted by at least 2°C for a given value of the selected parameter. The dashed line in each panel indicates the fraction of simulations for which the signature is impacted. The shaded region covers an area of size 0.1 above and below that value. See Table 2 for a full list of parameters explored in the sensitivity analysis.

4 | Discussion

4.1 | Streamflow Depletion Impacts Most Common on Temperature Extremes

The process-based models used in this study indicated that annual and seasonal (especially summer) 7-day maximum temperatures, 7-day minimum temperatures, annual temperature range, standard deviation in daily temperature and mean daily stream temperature are the thermal signatures with the most likely potential impacts from groundwater pumping, and very few other signature were impacted at any sites with long-term streamflow and stream temperature data. The affected thermal signatures were sensitive to streamflow depletion at many sites, with impacts at ~80% of the sites for 7-day maximum and annual temperature range (Figure 5). Further sensitivity analysis across 60000 randomly generated parameter sets using the process-based model indicated which types of streams are most likely to experience temperature impacts from streamflow depletion (Figure 8). Generally, streams with impacts in 7-day extreme temperatures (Figure 8) have substantial groundwater contributions (high BFI, high groundwater inflow fraction), which means that pumping-induced reductions in groundwater discharge can significantly impact stream temperatures. We also found that smaller streams or headwater streams may be more vulnerable to impacts. Our analysis used a constant percent pumping relative to streamflow across basin size in order to isolate the effects of pumping on stream temperature. However, in smaller streams, even relatively minor groundwater withdrawals can be large relative to mean annual flow. As a result, smaller streams may experience higher percent pumping in addition to greater sensitivity to changes, making them particularly vulnerable to the impacts of streamflow depletion on stream temperature.

Whether impacts are evident on maximum or minimum stream temperature is largely determined by the groundwater temperature in the region and the magnitude of groundwater inflows to the reach (BFI and groundwater inflow fraction) based on our models, with additional smaller effects of shading and streamflow-depth relationships. These findings indicate the importance of groundwater inflows for regulating stream temperature. We observed potential impacts on 7-day minimum temperature where groundwater temperatures are warm (more than around 15°C), and potential impacts on 7-day maximum temperature where groundwater temperatures are cold (less than around 15°C). This is because streams warm when cold groundwater is depleted in the summer, and streams cool when warm groundwater is depleted in the winter. Streams with smaller groundwater contributions or with warm (cold) groundwater temperatures are less sensitive to impacts in 7-day maximum (minimum) temperatures (Figure 8, bottom left). Since their temperature is less regulated by groundwater inflows, the loss of groundwater does not have a large impact on the stream temperature. Along a

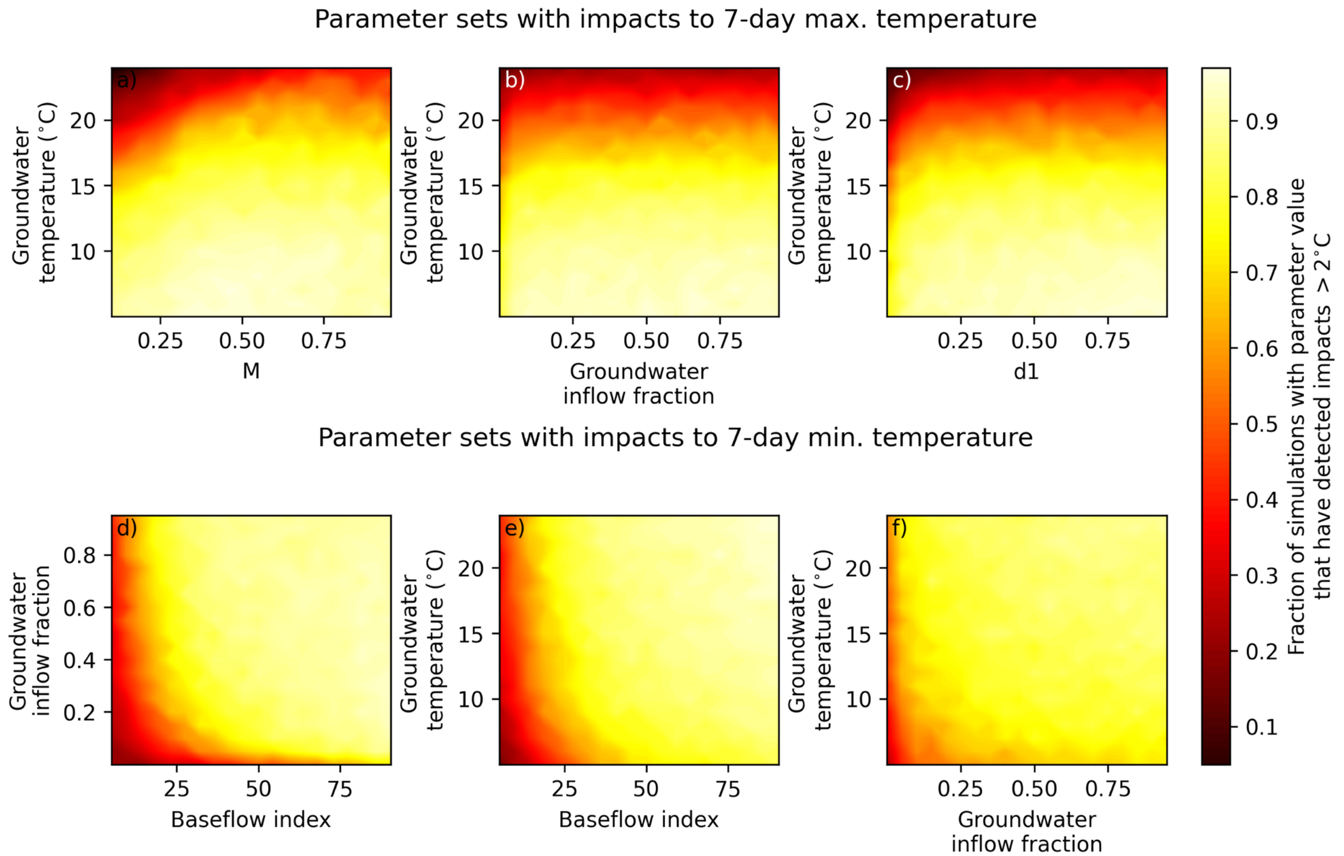

FIGURE 7 | Relationships between the most important parameters among parameter sets for which (a–c) 7-day maximum temperature and (d–f) 7-day min temperature are impacted. See Table 2 for a full list of parameters explored in the sensitivity analysis. Not all combinations are included in the covariance plots since behaviour of some variables in covariance plots is nearly identical. For each row, the three most representative spaces are shown, and the similar covariates are marked on the axis labels.

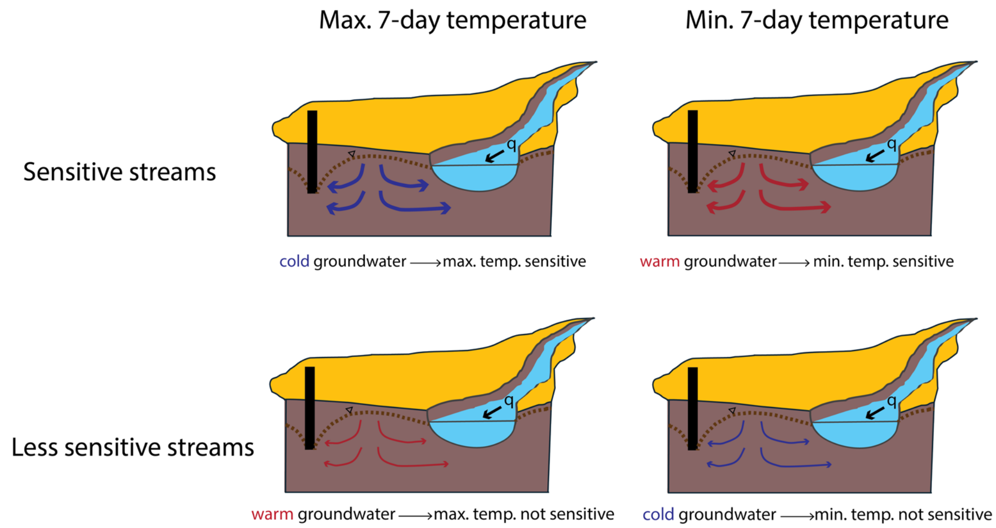

FIGURE 8 | Schematic diagram demonstrating the characteristics of streams that are conceptually more (top row) or less (bottom row) sensitive to the impacts of streamflow depletion on thermal signatures, considering (left) minimum 7-day temperatures and (right) maximum 7-day temperatures. In each panel, a groundwater pumping well is shown with a cone of depression marked with a dashed line. Arrows denote possible groundwater flow paths, and thickness of arrows denotes magnitude of flows.

stream network, reaches with higher groundwater inputs or further upstream may be more vulnerable relative to other reaches with lower groundwater inputs even for the same baseflow index (since losses of groundwater inflow will tend to have strong impacts on stream thermal regulation, which may threaten refugia).

Overall, the results of this study suggest that 7-day maximum temperatures and annual temperature range may be the thermal signatures most widely impacted by streamflow depletion. As suggested by the greater detected impacts in dry years relative to wet and average years (see supplementary results in code supplement), these impacts may exacerbate hydrologic drought conditions (e.g., Foglia et al. 2013), which are often associated with increased stream temperatures (e.g., Cowx et al. 1987; Crisp and Howson 1982; B. Webb and Walling 1993; Elliott 2000; Neal 2004; Bowes et al. 2011, and others cited in White et al. 2023). Since pumping requirements (such as irrigation) are often greatest during drought (Glose et al. 2022; Whittemore et al. 2023), streamflow depletion could increase the intensity, duration and impacts of hydrologic drought and further stress stream temperatures by reducing the groundwater inflows that provide hydrologic refugia in many settings (McLaughlin et al. 2017). Given that streamflow depletion impacts tended to be greatest in dry years, this suggests a potential compound effect of pumping and dry meteorological conditions on stream temperature and, therefore, aquatic ecosystems (Van Loon et al. 2016). However, additional research is needed to understand how these reach-level temperature models relate to watershed-scale temperature impacts and interact with other stressors such as drought (S. Zipper, Brookfield, et al. 2024).

4.2 | Process-Based Models May Be More Appropriate Than Regression Models for Stream Temperature Response to Streamflow Depletion

Across 30 sites with long-term stream temperature modelling, process-based and regression models disagreed on the extent and type of stream temperature impacts caused by streamflow depletion from groundwater pumping. Since both types of models were calibrated and able to successfully reproduce historical temperature dynamics at the sites, it is difficult to say definitively which result is more accurate without a benchmark dataset. However, as described in the introduction, the impacts of streamflow depletion caused by groundwater pumping would likely have different effects on stream temperature than natural variations in streamflow due to climatic conditions. Thus, a regression model trained on historical conditions (in the absence of significant streamflow depletion) may be less likely to represent stream temperature variations resulting from streamflow depletion. In particular, the regression models in this study use only streamflow and air temperature for inputs, and therefore streamflow depletion impacts are not able to specifically affect the groundwater component of streamflow. Air temperature is also only a proxy for radiative inputs and may not capture essential aspects of the heat budget (S. L. Johnson 2003). Training a different regression model for each season allows for seasonal variation in runoff generation that may impact how stream temperature responds to variations in streamflow. However, it cannot account for changes in runoff generation pathways within a season since it has no knowledge of these changes.

The minimal sensitivity across all signatures at all sites when using the regression models and the separate sensitivity analysis both suggest that the reduction in groundwater inflow is the primary way that stream temperature may be impacted by streamflow depletion. This observation suggests that process-based models, which are able to attribute pumping-induced streamflow depletion specifically to reductions in stream groundwater inflows, may be better-prepared to simulate changes in stream temperature. Similarly, a data-driven model could be appropriate if groundwater inflows or some proxy were used as a predictor, but these data are generally not available. In this study, we modelled a timeseries of groundwater inflows for the process-based model, so a data-driven model with a more complex structure may also be able to infer patterns in groundwater inflows given information such as a baseflow index or physical details about runoff pathways under different conditions. Further work would be needed to understand whether data-driven models without good proxies for groundwater inflows would be able to capture changes in runoff processes that ultimately can affect stream temperature sensitivity to streamflow depletion.

The finding that regression models may not capture potential stream temperature changes due to streamflow depletion is in alignment with previous work assessing the viability of regression models for assessing stream temperature changes due to climate change. Regression models were found to predict less severe impacts to stream temperature from climate change than process-based models (J. A. Leach and Moore 2019). Arismendi et al. (2014) and J. A. Leach and Moore (2019) found that regression models were less reliable under different climate conditions than those under which they were trained. This result parallels our finding of less impacts using the regression models and suggests that the greater impacts found using the process-based models may be more realistic, despite the fact that performance metrics were typically higher for regression models than process-based models in our study. Although the process-based model used in this study is simple, prior studies that have used more complex process-based models have similarly found greater sensitivity in stream temperature with process-based models than regression models. Examples include J. A. Leach and Moore (2019) and the case study described in Asarian et al. (2023).

Our process-based model also had some limitations impacting its ability to assess potential impacts of streamflow depletion on stream temperature. We have neglected some of what tend to be the less important heat budget terms, but these terms could be important in certain stream systems. For instance, some studies have found that hyporheic exchange across the streambed can have important temperature impacts (cooling or warming) as well (J. A. Leach et al. 2023; King and Neilson 2019), although these impacts are more important for diel range than daily mean temperature (J. A. Leach et al. 2021; King and Neilson 2019). We also neglected a sheltering term, which has been used in prior studies to capture the effect of decreased wind speed in forested riparian corridors relative to weather stations in nearby open areas (Sinokrot and Stefan 1993; Bogan et al. 2004). Neglecting this term may lead to overestimation of sensible and latent heat fluxes for some streams. The largest limitation of the process-based model, though, is that it is a point-scale model rather than a watershed-scale model. We worked with a point-scale model for this assessment of potential impacts since it is easier to calibrate and run and includes minimal parameters and input data. However, the propagating impact of reduced streamflow, stream depth or groundwater inputs over a network may be substantially larger as surface water moves downstream and has increased exposure to the atmosphere. Further, simplifications about groundwater temperature can have a large impact on how process-based models behave (Isaak and Luce 2023).

Given the large spatial scale of this study, it was not feasible to account for every physical process in our process-based or regression models. Further, the streamflow depletion scenarios we simulated were general and used a relatively simple analytical model. These simplifications together mean that the results in this study should be considered as a general sensitivity analysis to determine potential streamflow depletion impacts on stream temperature and controlling factors, rather than a site-specific investigation of actual impacts. A prior study in California using a detailed, site-specific model found that doubling or halving streamflow had an impact of about 2°C on stream temperature (NCRWQCB [North Coast Regional Water Quality Control Board] 2005). More modest streamflow losses of 5%–15% were found to increase summer temperatures by 0.5°C–1°C at basins in Idaho and California (Loinaz et al. 2013; Liu et al. 2018). In a managed basin in Nebraska using a complex process-based model, Sinokrot and Gulliver (2000) found a strong relationship between minimum flow requirement and number of days exceeding a stream water temperature of 32°C. Doubling the minimum flow requirement reduced the number of hot days by about 5%–50% depending on the monitoring location and flow change. These findings using more complex models are comparable to the findings using the simpler point-scale process-based model used in this study, which results in stream temperature increases of a median of 2.2°C with a range of 0°C–6°C across the study sites. While our results are comparable to these site-specific analyses, they should still be viewed as sensitivities more than explicit predictions since the models used in this study are relatively simple. More site-specific studies are needed to examine the potential impacts of streamflow depletion to confirm whether mechanisms not accounted for may enhance or diminish impacts on stream temperature.

Further, where streamflow reductions due to pumping are extreme, streams can dry completely (S. Zipper, Popescu, et al. 2022, Zipper et al. 2026), potentially leading to warming of shallow groundwater during the summer and reduced evaporative cooling in the river corridor, which would result in warmer summer air and groundwater temperatures around streams (with reverse effects leading to cooler temperatures in the winter). Alternatively, as found in the context of tree harvesting, dry streambeds may limit thermal impacts by preventing advection of warm water downstream since surface flow is discontinuous (Janisch et al. 2012; J. A. Leach et al. 2022). In cases of flow disconnection, warm surface water from upstream is not delivered to downstream reaches, and when flow resumes, the source is subsurface water, which is typically cooler, so stream network disconnection could result in stream cooling in some locations (e.g., Story et al. 2003). These complex terrestrial-aquatic feedbacks together could substantially increase the impacts of streamflow depletion on stream temperatures and merit further investigation. These effects would also not be accounted for in the regression models if stream networks enter drier states or dry differently than in the historical record. The spatial pattern of groundwater pumping could dry stream networks out in a way that is distinct from natural stream drying (Datry et al. 2023), potentially resulting in different along-stream temperature impacts. Overall, there are significant complexities in stream temperature modelling that arise when considering how pumping-induced changes in stream temperature would propagate from an affected reach to downstream portions of the watershed. Understanding these complexities would require additional study, and the actual impacts on stream temperature when considering network dynamics could differ from the point-scale results in this study. Thus, the findings of this work should be considered a conservative analysis of potential impacts.

4.3 | Linking to Integrated Surface Water-Groundwater Management

Most studies that assess pumping impacts on streamflow focus solely on water quantity, whether using field observations (Hunt et al. 2001; Flores et al. 2020) numerical models (Nyholm et al. 2002; Foster et al. 2021), analytical models (S. C. Zipper et al. 2019, 2021) or statistical models (Holtschlag 2019; Feinstein et al. 2016). Few studies have been able to quantify a mechanistic link between pumping, streamflow change and stream temperature change (Lapides et al. 2022). Since stream temperature can have a major impact on aquatic ecosystems, human water supply, recreation and other ecosystem services (i.e., through elevated water temperatures promoting harmful algal blooms; Glibert and Burkholder 2018), improved methods are needed to quantify streamflow depletion impacts on water temperature. In our work, we use modelling methods to identify specific thermal signatures (e.g., maximum and minimum annual 7-day temperature and mean daily temperature) that may be useful indicators for identifying settings where streamflow depletion has potentially impacted water temperature. However, additional field observations are needed to ground truth model predictions and provide a baseline for developing more robust models for how groundwater pumping may impact streamflow and stream temperature (S. Zipper, Brookfield, et al. 2024).

Given the potential for widespread impacts of streamflow depletion on temperature, there is a need for expanded stream temperature monitoring. Across CONUS, we identified only 46 sites with no upstream dams that have stream temperature timeseries of at least 15 years, and only 30 sites had sufficient overlapping hydrological and weather data to develop process-based models. These sites are predominantly located in the western United States (Figure 1a). This means that the vast majority of stream types and hydrologic settings across the CONUS are lacking reliable stream temperature data, including in many areas with substantial streamflow depletion such as the High Plains Aquifer (S. C. Zipper et al. 2021), Basin & Range (Prudic et al. 2006), southwest (Tolley et al. 2019; Zektser et al. 2005), southeast (Rugel et al. 2012) and upper midwest (Fienen et al. 2018; Kniffin et al. 2020). While most stream temperature monitoring is skewed towards temperate near-natural systems (Ouellet et al. 2020), our search through the USGS records indicates that stream temperature data may be sparse, or at the very least inaccessible (Hannah et al. 2011), everywhere. This presents a major challenge for observing changes in stream temperature over time and developing reliable stream temperature models that can predict stream thermal response to different management actions. Given that stream temperature has been identified as a 'master' water quality variable (Ficklin et al. 2023; Olden and Naiman 2010), it suggests even greater limitations in our ability to evaluate impacts of streamflow depletion on other changes in water quality.

5 | Conclusions

Streamflow depletion caused by groundwater pumping can impact stream temperature by reducing groundwater inflows to the stream, which changes the relative contributions of different water sources to the stream. Streamflow depletion also affects stream temperature by altering stream discharge, volume, depth and area. In this study, we developed a process-based point-scale energy balance model and statistical regression models for stream temperature at 30 sites across the United States with long-term stream temperature records. We then used these models to explore the potential impacts of streamflow depletion on stream temperature. The regression models indicated little to no impact from streamflow depletion, while the process-based models identified widespread potential impacts, particularly in mean daily and 7-day maximum/minimum stream temperatures. Given the limited set of sites with stream temperature data, we randomly generated 60 000 parameter sets to explore the characteristics of streams that do exhibit impacts on 7-day maximum and 7-day minimum temperature. We found that streams with large groundwater contributions are most likely to experience impacts in all signatures. A colder regional groundwater temperature results in more impacts for 7-day maximum temperature, and a warmer regional groundwater temperature results in more impacts on 7-day minimum temperature. Generally, these results indicate the importance of both mechanisms whereby streamflow depletion may impact stream temperature (enhanced exposure to atmospheric conditions and reduction in groundwater inflows). The specific importance of reductions in groundwater inflows in particular motivates the need for studying streamflow depletion from groundwater pumping separately from streamflow reductions due to drought. The results in this study should be considered as point-scale and preliminary, suitable for hypothesis generation. Further work is needed to explore how streamflow depletion may affect stream temperature using watershed-scale models, which may result in more substantial impacts.

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Data Availability Statement

All code and data generated for this study are available at: https://www.hydroshare.org/resource/954ebc6ec03340b5b96dd36a5aaf08bd/ (Lapides et al. 2023b).

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1:** hyp70444-sup-0001-Supinfo.pdf.