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Identifying hydrologic signatures associated with streamflow depletion caused by groundwater pumping

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Abstract

Groundwater pumping can reduce streamflow in nearby waterways ('streamflow depletion'), a process which must be accounted for in integrated management of surface and groundwater resources. However, causal identification of streamflow depletion from hydrographs alone is challenging because pumping impacts are masked by other drivers of hydrologic variability. To identify potential indicators of streamflow depletion, we used synthetic hydrographs and an analytical streamflow depletion model to assess potential pumping impacts on specific hydrograph characteristics ('hydrologic signatures') for 215 streamgages spanning the conterminous United States (CONUS). We found that streamflow depletion commonly impacts signatures associated with seasonal and annual low flows and low flow recessions. The largest impacts occurred during dry years, suggesting streamflow depletion may be evident in dry years even where impacts are unmeasurable in wet years. Random forest models indicated that streamflow depletion could significantly impact Annual, Summer, and Fall signatures in most streams. Our finding that multiple hydrologic signatures are consistently responsive to streamflow depletion across CONUS suggests that the underlying hydrological processes linking pumping to streamflow reductions are consistent across diverse settings, information that will aid in identifying indicators of streamflow depletion from streamflow hydrographs.

KEYWORDS

anthropogenic impacts, hydrograph, hydrologic signatures, low flow, stream-aquifer interactions, water resources management

1 | INTRODUCTION

Groundwater pumping has led to a worldwide reduction in streamflow that is projected to continue to increase (de Graaf et al., 2019). Reductions in streamflow caused by groundwater pumping, known as 'streamflow depletion,' can be considerably lagged from when pumping occurs and obscured by other causes of streamflow variability (Barlow & Leake, 2012). These confounding factors make it impossible to quantify streamflow depletion from observational streamflow data alone, presenting a major challenge to water management in settings with interacting groundwater and surface water resources (Zipper et al., 2022).

Streamflow is often used to set targets and thresholds for hydrological and ecological management; therefore, causally relating streamflow depletion to specific aspects of hydrologic change is an essential step towards integrating streamflow depletion standards into water resources management (Lapides, Maitland, et al., 2022). Hydrologic signatures, which are metrics derived from hydrographs, offer a potential approach to link different types of changes in the

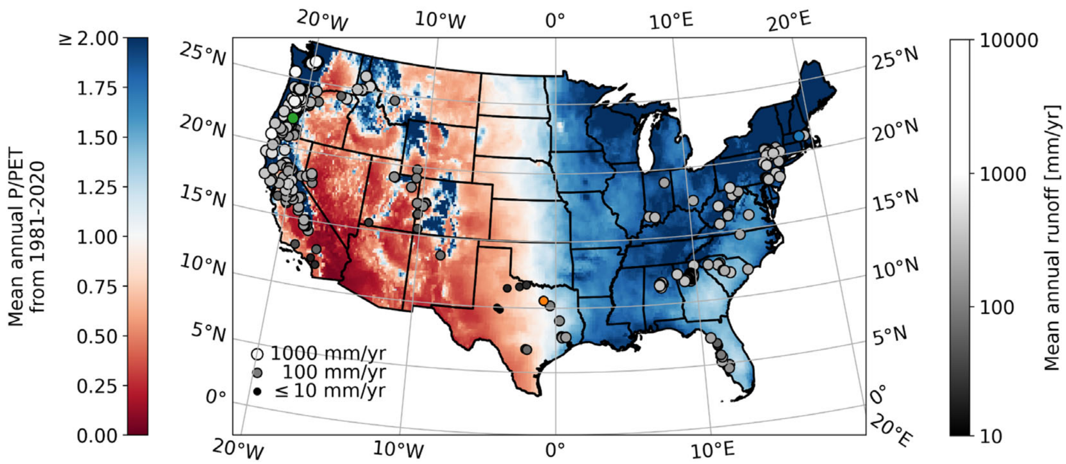

FIGURE 1 Map of the 215 U.S. Geological Survey streamgage locations across the conterminous United States, coloured and sized by mean annual runoff from the GAGES-II dataset (Falcone, 2011). Map background is mean annual precipitation as a fraction of potential evapotranspiration from gridMET (Abatzoglou, 2013). Blue, orange, and green dots mark the locations of sites used as examples in Figure 3.

hydrograph to specific hydrologic processes (McMillan, 2020). Whilst recent work has suggested that certain aspects of the hydrograph, such as low-flows during baseflow periods, are more sensitive to streamflow depletion than others (Lapides, Maitland, et al., 2022), this is based on a small number of streams in the upper Midwest United States. As a result, it remains unknown whether the hydrological processes linking streamflow depletion to specific hydrologic signatures are generalizable to other regions with substantially different climate, geological, or other characteristics.

Our goal is to investigate which hydrologic signatures are most sensitive to streamflow depletion across a wide range of environmental conditions. To do this, we aggregated streamflow data from 215 streamgages across the conterminous United States (CONUS) and estimated potential streamflow depletion impacts for dry, average, and wet conditions using synthetic hydrograph scenarios developed from long-term streamflow data. We then calculated a suite of hydrologic signatures for each of the non-depleted and depleted hydrographs to evaluate the degree to which each signature was affected by pumping at each streamgage. By identifying the hydrologic signatures and streamgages that are most sensitive to streamflow depletion, we provide a quantitative perspective that will aid in developing causal linkages between streamflow hydrographs and the hydrological process of streamflow depletion to promote effective streamflow depletion assessment and management.

2 | MATERIALS AND METHODS

2.1 | Study sites and streamflow scenarios

We selected streamgages from the Geospatial Attributes of Gages for Evaluating Streamflow, version II, (GAGES-II) database (Falcone, 2011). Of the >3000 streamgages included in the GAGES-II database with at least 20 years of high-quality streamflow data, we selected 215 streamgages (Figure 1) that also had high-quality stream temperature for our analysis since planned future work will investigate streamflow depletion-induced changes in stream temperature.

Streamgages cover the range of climates and physiographic provinces represented in CONUS (excluding desert environments in the Southwest). The gages we use span gradients of mean annual precipitation (360 to 3330 mm/yr), snow fraction (0 to 70% of precipitation), drainage area (4 to 9800 km^2), mean annual streamflow (24 to 2100 mm/yr), and baseflow index (11 to 85%) (Falcone, 2011).

2.2 | Streamflow depletion model

Because our goal was to link streamflow depletion to different hydrologic signatures, we elected to use a surrogate modelling approach (Asher et al., 2015) by applying a simplified but consistent modelling framework across sites. Our approach (Figure 2) is intended to isolate the dominant hydrological process of interest (streamflow depletion impacts on hydrologic signatures), rather than try to approximate the historical streamflow hydrograph for each streamgage using real-world historical pumping data, which is rarely known due to a lack of monitoring data (Foster et al., 2020). The scenarios we simulated were based on a factorial combination of three streamflow scenarios (dry, average, and wet synthetic hydrographs) and two pumping scenarios (constant and periodic):

- *Streamflow scenarios*: We developed a synthetic daily hydrograph for each site representing a dry, average, and wet year based on the 10th percentile, 50th percentile, and 90th percentile flow, respectively, for each day of the year. Since our focus was not on event-scale changes, we smoothed the synthetic hydrographs with a 7-day moving average to eliminate high-frequency variability (i.e., individual flood peaks). An example set of synthetic hydrographs for one site is shown in Figure 3a.

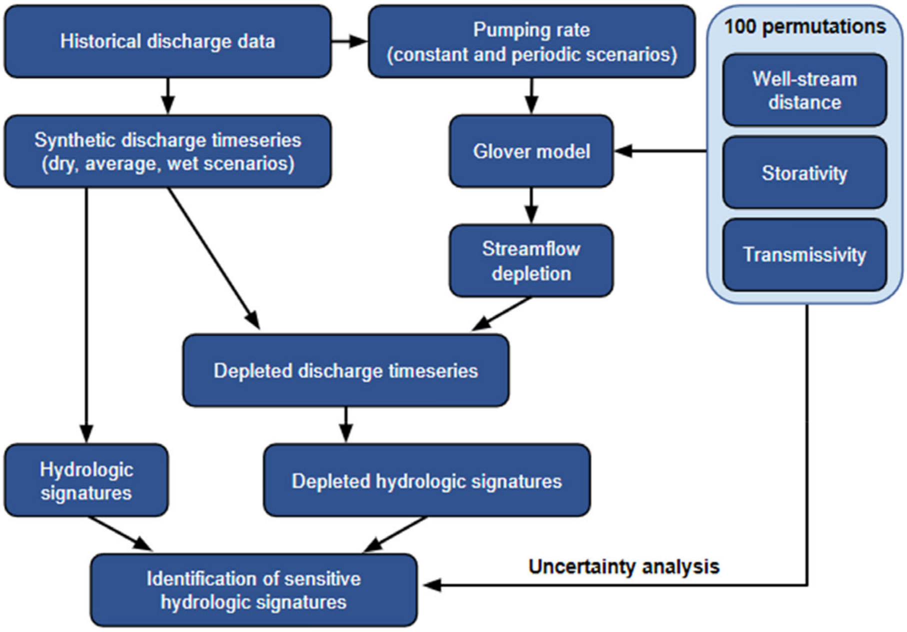

FIGURE 2 Workflow showing datasets and methods used to evaluate sensitivity of hydrologic signatures to streamflow depletion.

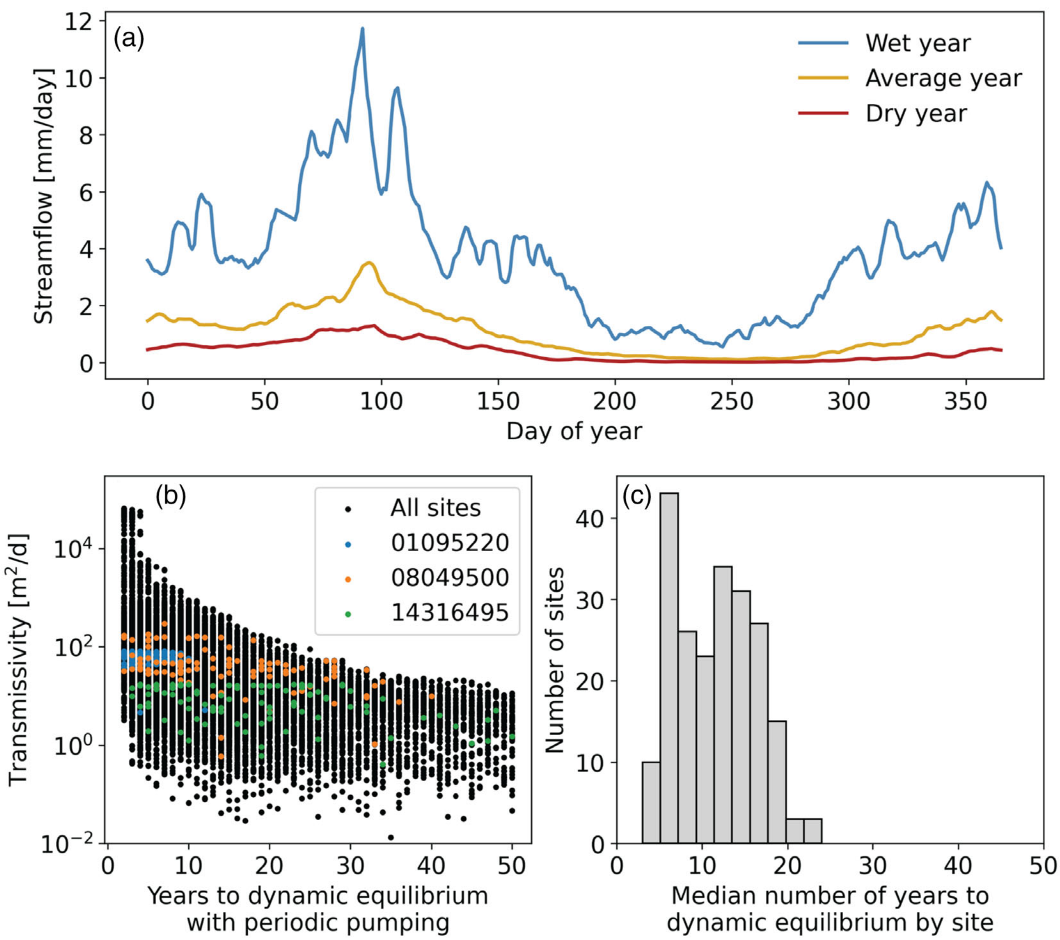

FIGURE 3 (a) Example synthetic hydrographs for site 01095220, marked in blue in Figure 1. (b) The relationship between transmissivity and years after the onset of pumping before streamflow depletion using the Glover model reaches dynamic equilibrium. Colours show three example gages for a visual indication of intra- and inter-gage variability, locations marked by colour in Figure 1. The range of transmissivity values is different for each site, as described in Section 2.2. (c) The median number of years to dynamic equilibrium across all parameter combinations for each site using the Glover model.

- *Pumping scenarios*: We simulated constant and periodic pumping, as in Zipper et al. (2019). In both scenarios, the total volume of water pumped over the course of the year was equivalent to 5% of mean annual streamflow at the streamgage, which was within the range of pumping fractions across the GAGES-II dataset from Falcone (2011) via Hutson et al. (2004). This level of pumping was chosen to be large enough for impacts to be visible without causing all streams to go dry but well within the range of groundwater pumping in real basins (median across data available from Falcone (2011) via Hutson et al. (2004), Figure S1). The volume of pumping was distributed evenly over the pumping period, which was year-round for the constant scenario and May 1 to September 30 for the period scenario.

A range of approaches is used to model streamflow depletion from analytical models to statistical models and complex numerical models (Zipper et al., 2022). The most appropriate model varies depending on diverse factors including the research question of interest, data availability, and hydrological processes under investigation (Huang et al., 2018). More complex models require more knowledge of the system and more computational power. Given the intention of this study to evaluate sensitivity of hydrological signatures to streamflow depletion rather than accurately reflect real aquifer conditions and groundwater use (which are in general mostly unknown; Foster et al., 2020; Marston et al., 2022), we modelled streamflow depletion using the Glover and Balmer (1954) analytical solution, hereafter referred to as the Glover model. The Glover model has low input data requirements and widespread past application including evaluation through comparisons to other analytical and numerical models (Flores et al., 2020; Li et al., 2020, 2022; Sophocleous et al., 1995; Zipper et al., 2019; Zipper, Gleeson, et al., 2021). In the Glover model, streamflow depletion is calculated as follows:

$$Q_s = Q_w \operatorname{erfc}\left(\sqrt{\frac{Sd^2}{4Tt}}\right) \tag{1}$$

Where Q_s is volumetric streamflow depletion [m^3/d], Q_w is the pumping rate of the well [m^3/d], S is the aquifer storativity [−], d is the distance between the well and the stream [m], T is the transmissivity [m^2/d], and t is the time since pumping began [d].

Since each watershed includes many different wells and hydrostratigraphic conditions, we accounted for potential uncertainty associated with both the simplified streamflow depletion model and the lack of location-specific groundwater use data by calculating 100 different depletion timeseries permutations for each watershed whilst randomly varying S, T, and d based on real-world conditions. For S and T, we extracted the porosity for each watershed from the GLobal HYdrogeology MaPS (GLHYMPS) dataset (Huscroft et al., 2018) and the transmissivity for each watershed from the Zell and Sanford (2020) dataset, respectively. For each of the 100 permutations, a pixel was randomly chosen from within the contributing area for each streamgage. For d, we used distances from wells to the closest stream from the dataset compiled by Jasechko et al. (2021), which we sampled randomly 100 times from the entire dataset. Daily Q_w was the same for all permutations and based on the mean annual streamflow and pumping scenario, as described above. For each scenario, we randomly selected a value for S, T, and d and simulated daily depletion for 50 years (t from 1 to 18 250 days). This uncertainty analysis demonstrates that our results are robust to variations in S, T, and d (Figures S13–S15) and that 50 years was nearly always adequate time for simulations to reach dynamic equilibrium (Figure 3b,c).

To obtain depleted streamflow timeseries, we subtracted Q_s calculated by each permutation from the 50-year long dry, average, and wet synthetic hydrographs. We focus on periodic pumping and the dry climate scenario in the results since impacts in this scenario are largest but otherwise similar across all scenarios. Constant pumping versions of all figures are included in the Supplemental Information. For a visual representation of the study workflow, see Figure 2.

2.3 | Hydrologic signatures and change detection

For each streamflow and pumping scenario, we computed a suite of 11 annual and 5 seasonal hydrologic signatures (Table S1). Signatures were selected based on hypothesized likelihood of detecting changes during low flow periods compared to wetter times of the year (Lapides, Maitland, et al., 2022; Smakhtin, 2001). Computed annual and seasonal hydrologic signatures included the total flow volume, the minimum 7-day flow and the date on which it occurred, and the recession rate for 7, 14 and 30 days prior to the minimum 7-day flow. We also computed several low flow signatures based on the use of a long-term 10th percentile of streamflow values to define low flow. These signatures included the low flow duration, as the number of days below the low flow threshold (long-term 10th percentile of streamflow); the low flow deficit, as the accumulated flow departure below the low flow threshold calculated from the first year of each scenario (e.g., Fleming et al., 2021; Hammond & Fleming, 2021); the number of discrete low flow periods, and the mean and maximum length of these discrete low flow periods in days. We defined seasons as: Winter = January–March, Spring = April–June, Summer = July–September, Fall = October–December. Since the synthetic hydrographs exhibit no interannual variability due to climate, all differences between years in each timeseries are due to streamflow depletion.

To detect change in hydrologic signatures between the measured and depleted scenarios, we used a percent change threshold calculated as:

$$S_{\text{change}} = \frac{S_{50} - S_0}{S_0} \times 100 \tag{2}$$

Where S_{change} is the % change in a signature, S_{50} is the metric value for a pumping scenario in year 50, and S_0 is the signature value on the synthetic non-depleted timeseries. Generally, we report % 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 (for example) the 0.2 and 0.8 quantiles.

2.4 | Drivers of change and likely impacted basins

We developed a set of random forest models using the python package scikit-learn (Pedregosa et al., 2011) to extend the study results to other streams based on landscape attributes. Random forest models are widely used for hydrologic signature prediction due to their flexible data input requirements, ability to integrate nonlinear responses, and relatively low risk of overfitting compared to other statistical modelling approaches (Addor et al., 2018; Eng et al., 2017; Hammond et al., 2021; Zipper, Hammond, et al., 2021). Each of the models predicts whether a group of signatures (6 groups, see Figure 5) is expected to detect a hydrograph change of at least 20% due to streamflow depletion at each site. Training variables included were derived from the GAGES-II database. We chose 50 process-relevant variables that include indicators of geography, physiography, soils, climate, land use, and human modification (full list in Table S2), all factors that drive changes in hydrology and therefore the potential importance of surface water-groundwater interaction. We used a random train-test split (randomly selected 25% of data for testing, the remaining 75% for training) to assess model accuracy and trained a final model on the full set of study data. Accuracy was measured as the percent of correctly labelled sites (impacted more than 20% or not). The range of values for each variable included in the training data and predicted data sets are shown in Table S2. In general, the training data captures well the range of values represented in the prediction data set, as only 3% of sites in the prediction set have more than two characteristics that fall more than 25% beyond the values represented by the training data. We applied the final model to all streamgages in the GAGES-II database to predict where streamflow depletion could impact hydrologic signatures.

3 | RESULTS

3.1 | Sensitivity of hydrologic signatures to streamflow depletion

Streamflow depletion impacted most of the hydrologic signatures investigated in this study, and the proportion of impacted streamgages varied by hydrologic signature, streamflow scenario, and season (Figure 4, Figure S2). The primary hydrologic signatures impacted by streamflow depletion were related to annual, summer, and fall low-

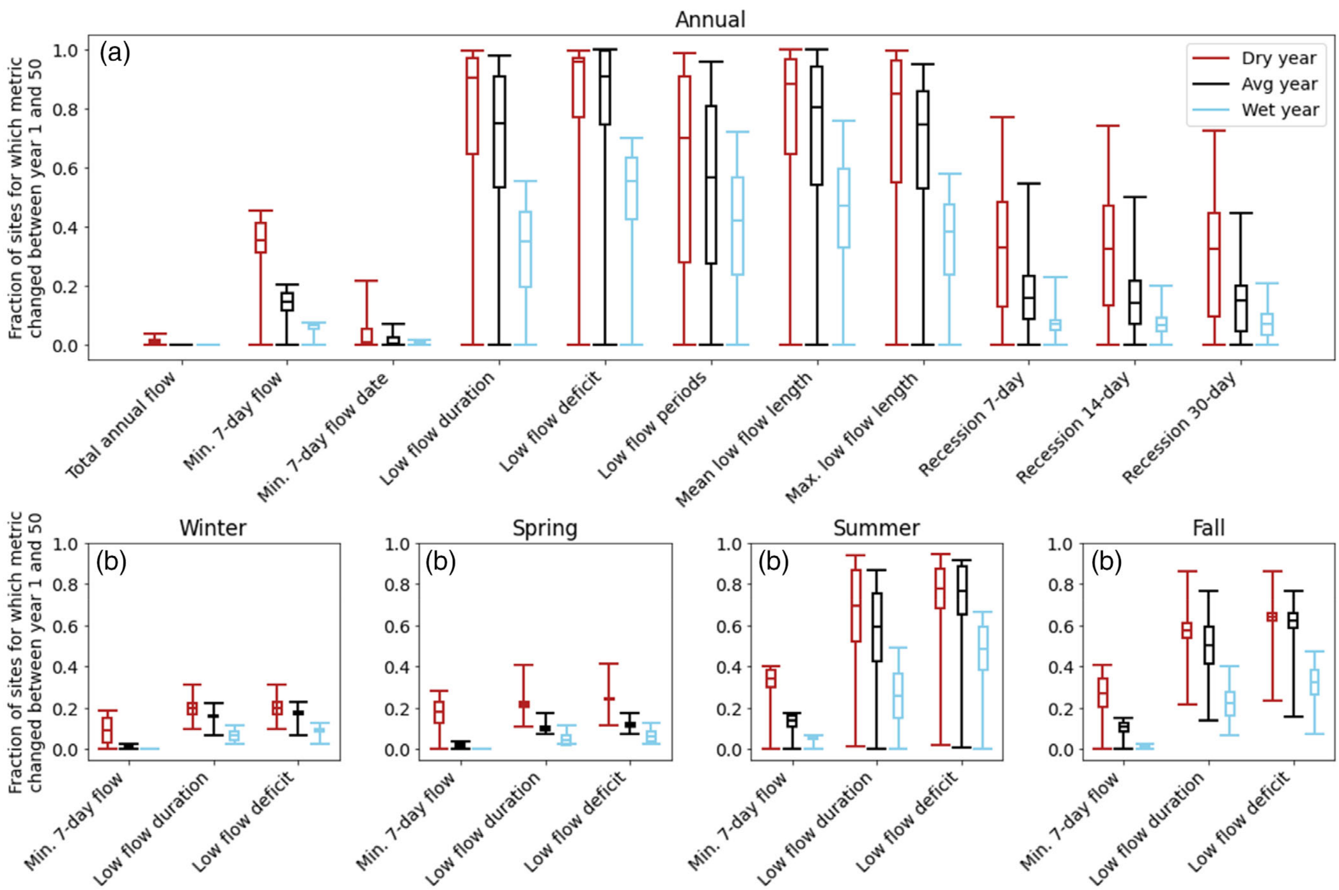

FIGURE 4 Boxplots for signature sensitivities across all sites, box plots indicate parameter uncertainty for streamflow. Boxplots show the range of sites impacted using the 25-75th percentile across the range of 100 parameter sets for each site with the median number marked. Whiskers denote the minimum and maximum number of sites impacted considering all parameter sets for each site. Results are shown using the periodic pumping scenario and a 20% change threshold for percent different from the no-pumping scenario.

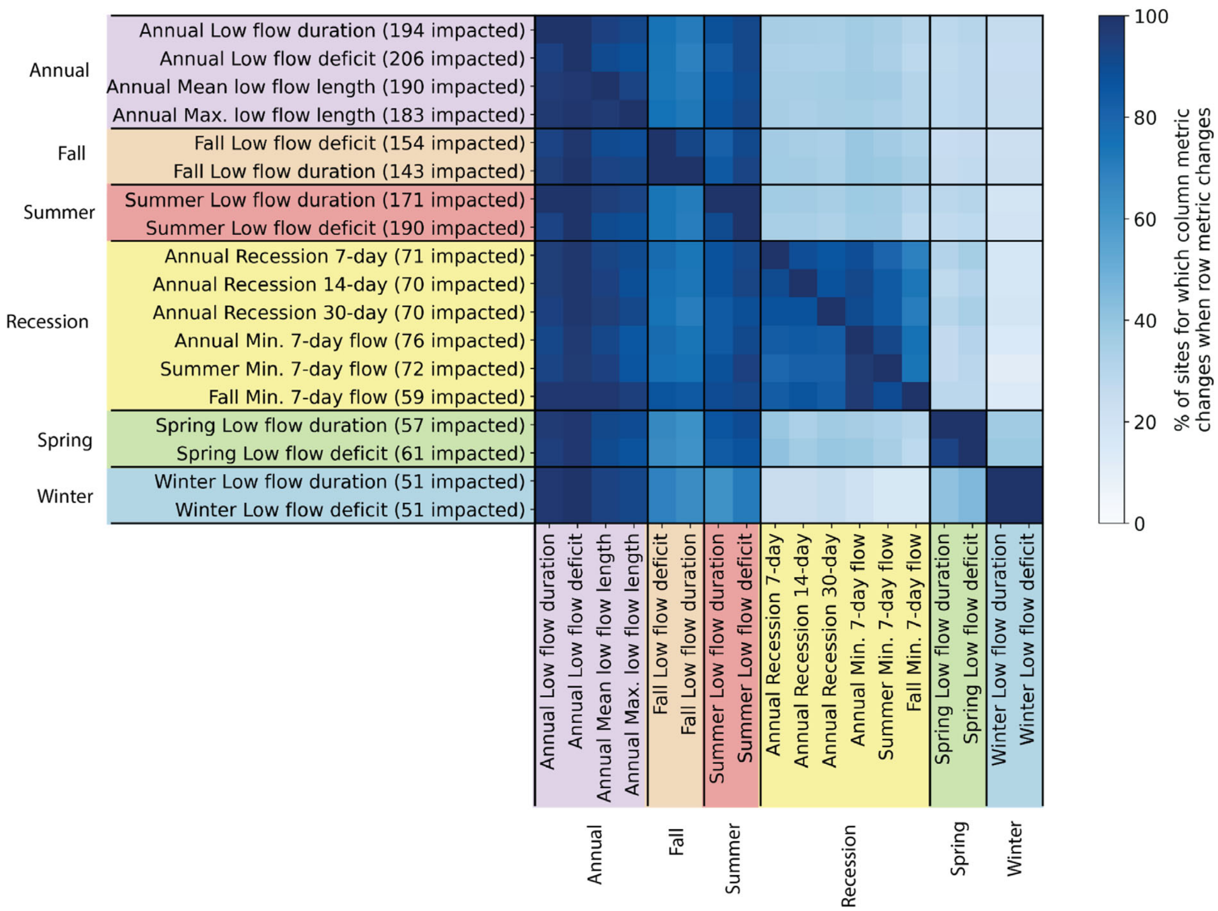

FIGURE 5 For each grid box, the percent of sites for which the column signature changed amongst the subset of sites for which the row signature changed. A score of 100 indicates that the column signature always changed when the row signature changed. For reference, the number of sites in each row's subset is noted next to the signature name for each row. Results are shown for a change threshold of 20%, the dry climate scenario, and periodic pumping. Colour groups on axes indicate categories used to refer to signatures in text.

flows (i.e., mean low flow length, low flow deficit), which changed in response to pumping in 70%–90% of sites for both the dry and average scenario and 30%–50% of sites in the wet scenario. Signatures related to recession (i.e., 7-, 14-, and 30-day Recession rate) were also widely responsive to streamflow depletion, with median changes in 33% of streamgages for the dry scenario, 15% for the average scenario, and 7% for the wet scenario. There were no distinct regional patterns in the gages where signatures were affected by pumping (Figures S3 and S4). However, regardless of the hydrologic signature under investigation, impacts were observed the most for the dry scenario, a smaller number of streamgages in the average scenario, and the least streamgages in the wet scenario.

Since many hydrologic signatures measure similar aspects of the hydrograph (Olden & Poff, 2003), changes in signatures are correlated in many cases. The signatures in this study grouped into six clusters that were typically impacted in tandem and appear as dark square-shaped features along the diagonal in Figure 5. These clusters were (1) annual signatures that describe annual low flows, (2) recession signatures that describe dry-down rates, and (3–6) a pair of signatures for each season that describe seasonal low-flow deficit and duration. Annual metrics were generally strongly correlated with each of the other clusters. Figure 5 is asymmetrical because the subset of sites for which the row metric is impacted generally differs from the subset of sites for which the column metric is impacted. For example, more sites show impacts for the Annual low flow duration than Fall low flow deficit, so most of the time when Fall low flow deficit is impacted, Annual Low flow duration is impacted, but the opposite is less true. This is indicative of the fact that Annual low-flow metrics are strongly correlated with the seasonal metrics for seasons where flow is lowest (Summer and Fall) for most gages. The same groups arise for the constant pumping scenario (Figure S5). Since signatures in each group show similar behaviour, we present results for signature groups for the remainder of this study.

For the hydrologic signatures that are impacted by streamflow depletion, impacts tended to appear within 1 year, and essentially all appeared by year 10 (Figure 6 for the periodic pumping scenario, Figure S6 for the constant pumping scenario). Only 6 (Annual signatures) to 12 (Recession and Spring signatures) sites had impacts delayed beyond 10 years. Delayed impacts were most commonly found in the Recession, Winter, and Spring hydrologic signature groups (Figures S9 and S10), and likely associated with low transmissivity environments that take longer for streamflow depletion to reach

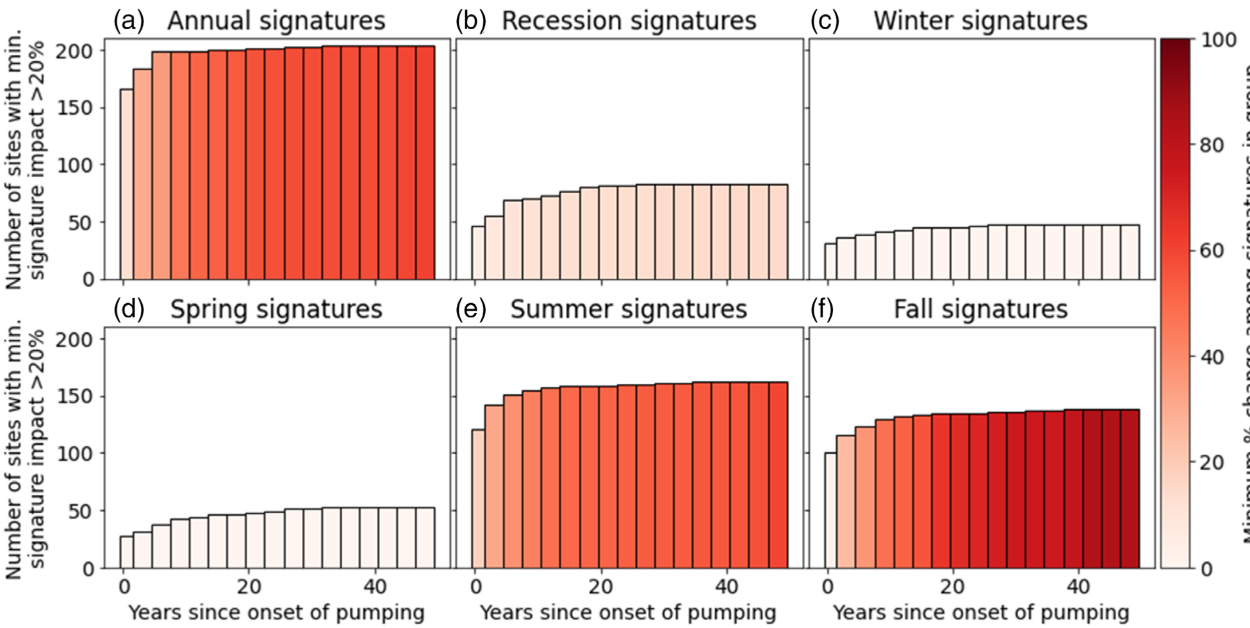

FIGURE 6 Number of sites with at least two signatures in a signature group impacted more than 20% after a given number of years of pumping. Shading on bars indicates the median minimum change amongst the signatures in the group. Results shown for the dry climate and periodic pumping schedule.

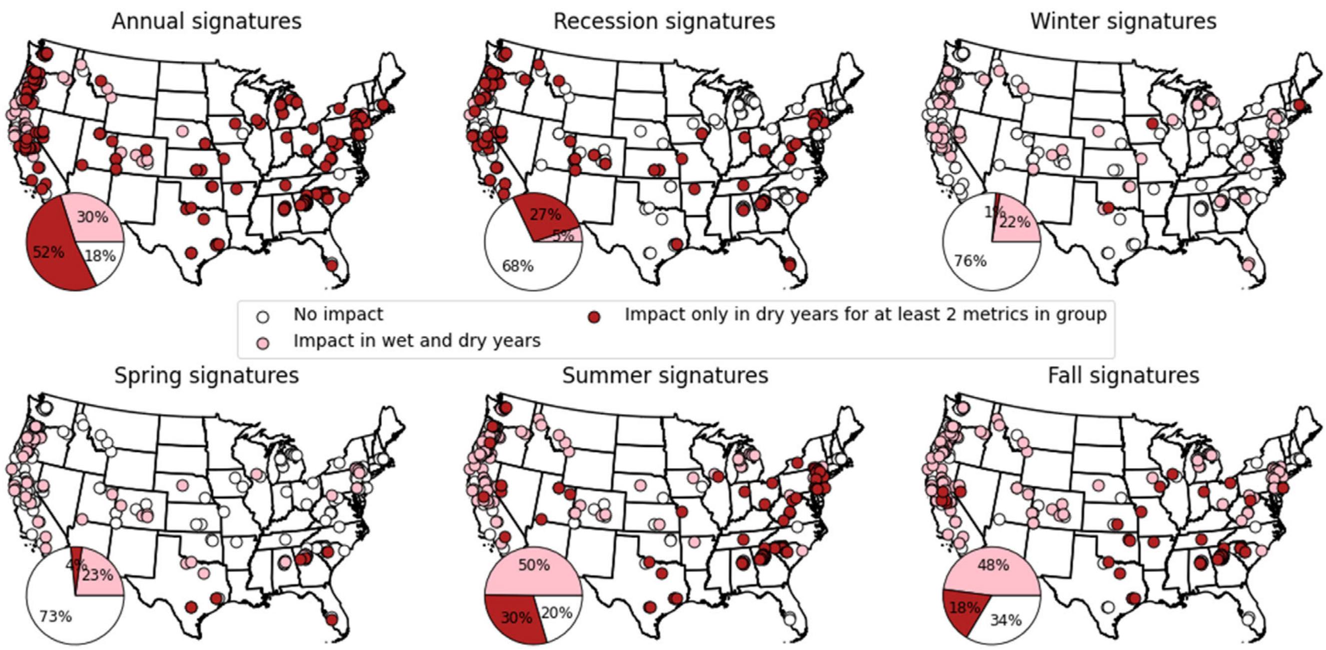

FIGURE 7 Maps showing streamflow scenarios where impacts were evident in the dry climate scenario but not the wet climate scenario for at least two signatures in the signature group using a change threshold of 20% and a periodic pumping schedule.

dynamic equilibrium (Figure 1). See Figures S7 (periodic pumping) and S8 (constant pumping) for magnitudes of impacts over time and Figures S9 (periodic pumping) and S10 (constant pumping) for maps of years until impacts exceed 20% by signature group. There were 12 (Annual signatures) to 167 (Winter signatures) sites not impacted within the 50 year simulations across the signature groups even in the dry climate scenario.

3.2 | Differing impacts in dry versus wet years

For many streamgages, hydrologic signatures that exhibited changes in the dry climate scenario did not exhibit changes in the average or wet scenarios. All signature groups except Winter and Spring signatures had a significant portion of gages that were impacted in the dry but not wet climate scenario (Figure 7, Figure S11). For Annual and

Recession groups, the majority of sites for which the signature group was impacted showed impacts only in the dry climate scenario. Whilst our experimental design used consistent year-to-year streamflow based on the synthetic hydrographs, in a real stream, this means that a series of average or wet years could overwhelm the effects of groundwater pumping or falsely suggest a lack of streamflow depletion impacts that would then emerge as a surprise during dry conditions.

3.3 | Identifying which basins are likely to be impacted by streamflow depletion

Random forest models to explain which streams are sensitive to groundwater pumping had relatively high accuracy (67%–96%, Figure 8), which is consistent with past efforts to predict hydrologic signatures from catchment attributes (Addor et al., 2018). Annual, Summer, and Fall signatures were broadly predicted to be altered more than 20% from the no-pumping scenario at nearly all streamgages in the GAGES-II database for the simulated level of pumping, whereas Winter, Spring, and Recession signatures were predicted to show impacts at fewer sites. Recession signatures were not expected to show impacts except for areas in the upper Midwest, Northeast, and Southeast. Summer signatures were expected to be impacted less in the center CONUS, Florida, and Massachusetts. This effect was stronger for the constant pumping scenario (Figure S12), but patterns with constant pumping are otherwise very similar. Across GAGES-II streamgages, random forest models predicted that 98% of streamgages would show impacts in Annual signatures, 86% in both Summer and Fall, 41% in Recession, 10% in Spring, and 5% in Winter signatures at the level of groundwater pumping used in this study and with a change threshold of 20%.

Across all signature groups, landscape attributes, hydrologic attributes, and land cover are amongst the most important features for determining whether a stream has detectable impacts from streamflow depletion (Figure 9). Network properties rank as important for Recession signatures, substrate for Annual and Spring signatures, and Anthropogenic impacts for Fall signatures. Drainage area (DRAIN_SQKM) stands out as one of the most important features overall, with more impacts in smaller basins (see data supplement for partial dependence plots). Longitude (LONG_CENT) is of high importance for annual signatures, indicating that region is likely very important as well, with more impacts showing up at intermediate longitudes and fewer at more western longitudes. Open water land cover (WATERNLCD06) is important for Recession, Winter, and Fall signatures with more impacts at intermediate coverage values and fewer at very low coverage values.

4 | DISCUSSION

4.1 | Drought indicators best capture the hydrological impacts of streamflow depletion

Low flow metrics, such as 7-day low flow, are commonly used in management contexts (Lapides, Maitland, et al., 2022). Whilst 7-day minimum flow was impacted at many sites in the dry climate scenario, low flow duration and deficit were more consistently impacted; the maximum fraction of sites with 7-day minimum flow impacts is smaller than the 25th percentile for duration and deficit signatures under all

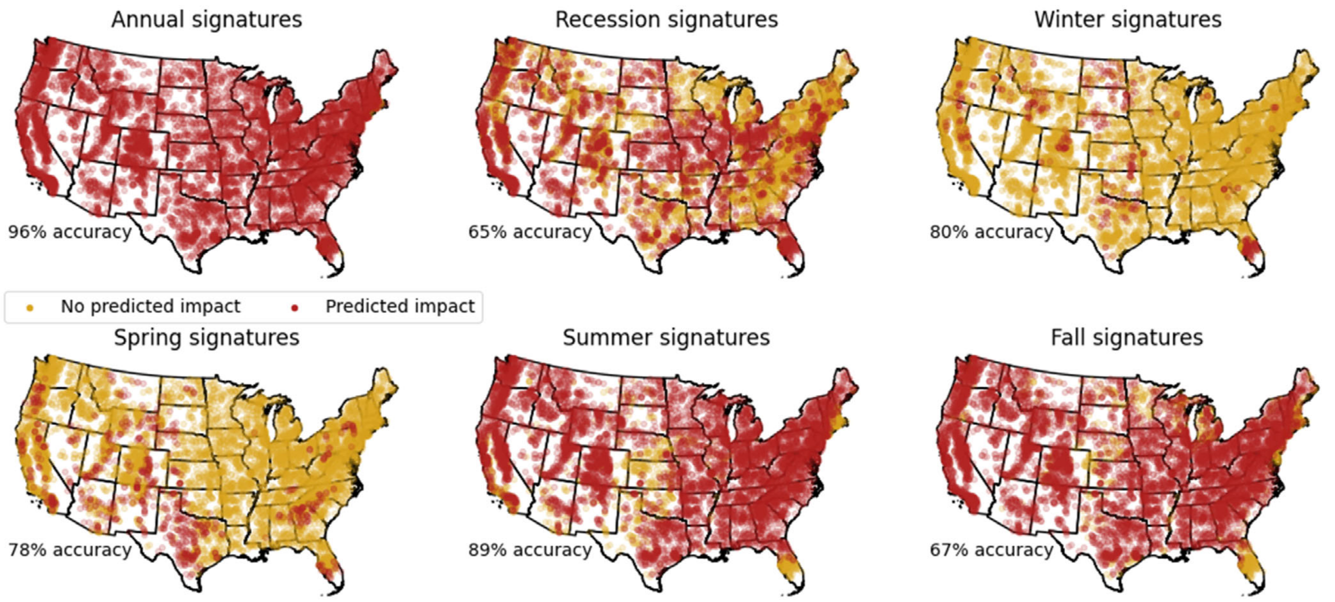

FIGURE 8 Random forest prediction of where GAGES-II streams were predicted to see changes in each signature group within 50 years based on the dry climate and periodic pumping scenario. Accuracy percentages show the accuracy of the model on the test set.

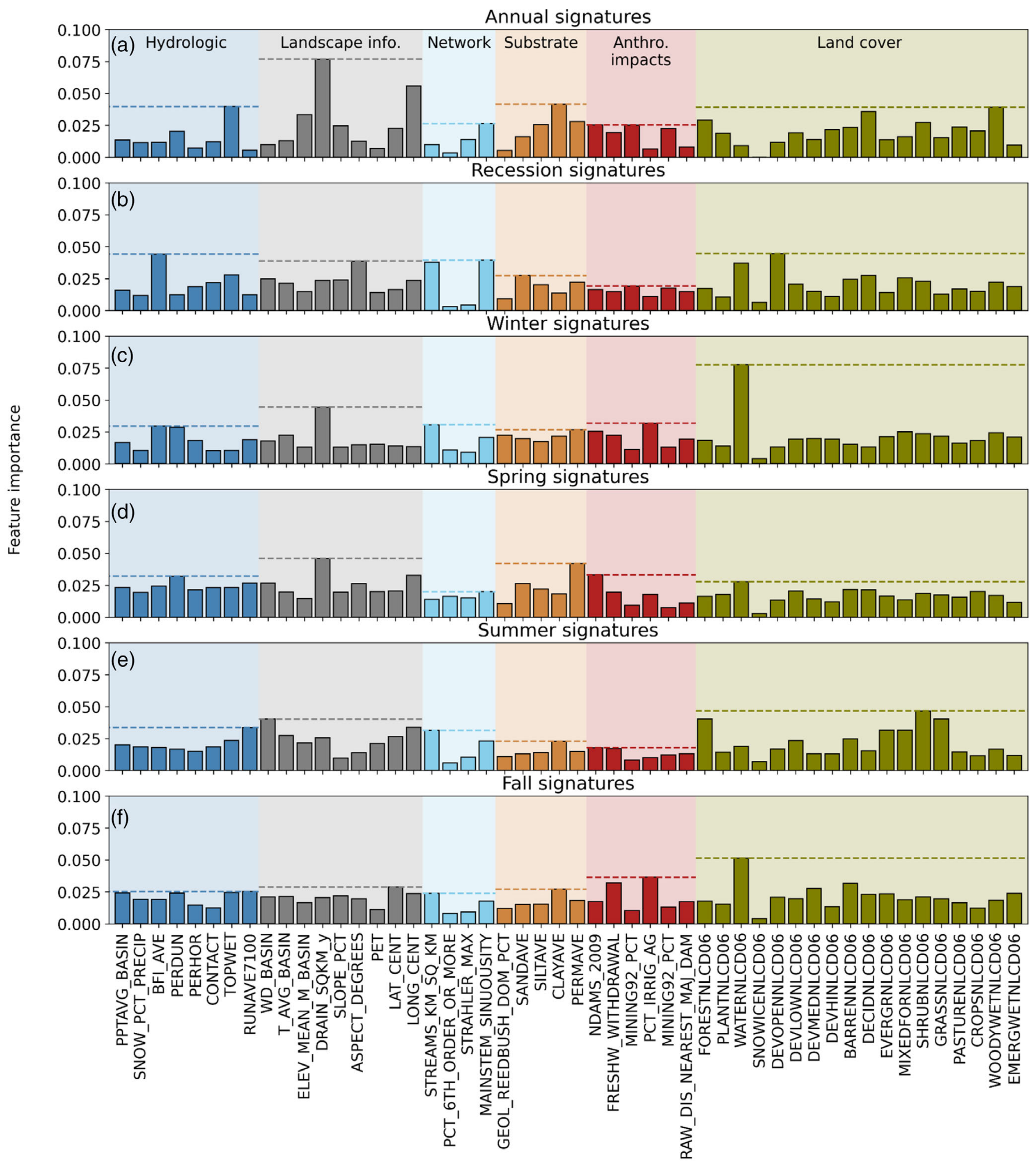

FIGURE 9 Random forest permutation feature importance for each of the six random forest models developed (one for each signature group to predict whether signatures change by more than 20% due to groundwater pumping). Features are grouped by the type of catchment information they describe, labelled in panel (a). The horizontal dashed lines indicate the maximum feature importance in each feature group for each model. Descriptions of the feature attributes can be found in Table S2.

climate scenarios (Figure 4). This finding emphasizes the importance of using streamflow drought metrics to detect low flows, as suggested by Hammond et al. (2022), and our results indicate that these processes are generalizable across climates and geologic provinces (Section 3.3). Whilst aquatic ecosystems are sensitive to low flows (Bogan & Lytle, 2011; Perkin et al., 2017, 2019), there has not been much research documenting the relationship between specific hydrologic signatures and ecosystem health. The results of this study suggest that these signatures may be more sensitive to changes in the hydrograph than more commonly used signatures; however, further research is needed to identify whether the impacts detected with drought metrics correspond to changes relevant to ecosystem health.

More broadly, the coherence of signature groups suggested that, within a given group of hydrologic signatures, the impacts of streamflow depletion would likely be apparent regardless of the specific signature calculated, and the random forest model suggests that the utility of Annual, Summer, and Fall signatures for detecting streamflow depletion is general across CONUS. Combined, these results provide a degree of flexibility to match specific management targets. For instance, the grouping of low flow duration and deficit signatures aligns well with correlated trends between low flow duration and deficit (Hammond et al., 2022) and suggests that many of these signatures would perform similarly in terms of documenting streamflow depletion impacts in hydrograph data. Given the similar response to streamflow depletion, this indicates that hydrologic signatures can be targeted to the functional needs of relevant species (Yarnell et al., 2020).

4.2 | Streamflow depletion impacts are strongest in dry periods

Our results indicate that streamflow depletion is most consistently detectable in the dry year scenario, and often impacts are measurable in dry years within a short time period when they are not measurable at all in the wet year scenario (Figure 7). This finding suggests that a wet climate period can buffer streams against the impacts of streamflow depletion, which is consistent with prior work indicating accentuated effects of groundwater pumping on streamflow during dry conditions (Zektser et al., 2005). This implies that even streams that appear unimpaired during a wet period may exhibit noticeable changes in hydrologic signatures during a dry period. Not only do dry conditions enhance the visibility of stream depletion impacts, but dry conditions are typically associated with increased groundwater use and well installations (Glose et al., 2022; Zipper, Helm Smith, et al., 2017) and stressed surface water resources (Van Loon, Gleeson, et al., 2016). This suggests that a waterway with unmeasurable streamflow depletion impacts during a wetter period may still experience streamflow depletion as a prominent factor that intensifies hydrologic drought (He et al., 2017; Van Loon, Stahl, et al., 2016).

4.3 | Are streamflow depletion impacts fast or slow?

In this study, we found that streamflow depletion impacts were evident rapidly in most gages (Figures S10 and S11) despite the fact that we chose *S* to represent unconfined conditions, which should lead to the slowest estimate for when impacts reach the stream. This finding is at odds with the fact that streamflow depletion is typically dampened and lagged relative to pumping (Leake, 2011). We believe this apparent discrepancy can be explained by two factors. The first is that the pumping rates used in this study, which were defined as 5% of mean annual flow based on typical estimated pumping volumes across the GAGES-II dataset, are substantial. This translates to evident impacts within 1–5 years, even whilst the total volume of streamflow depletion continues to increase before equilibrating in the 5–20 year range (Figure 3c). Thus, whilst we identify relative rapid onset of impacts, the largest impacts of pumping are delayed for many years beyond the onset of pumping. This suggests that in cases with lower magnitudes of groundwater pumping, the same hydrological signatures would be appropriate, but it may take longer for the impacts to be detectable.

The second factor stems from our study design. We used synthetic hydrographs that are consistent from year to year and therefore eliminated other drivers of hydrologic variability that mask streamflow depletion including hydroclimatic variability, surface water diversions, and land use/land cover change (Zipper et al., 2022). This controlled experimental approach allowed us to causally attribute changes in the hydrographs to streamflow depletion without having to disentangle confounding drivers of hydrologic change, giving us the ability to confidently identify streamflow depletion impacts after short periods of time. Our results therefore provide an idealized case to identify characteristic changes to look for that may be distinguishable from other drivers of hydrograph variability.

4.4 | Limitations to the study approach

We used a simplified, synthetic hydrograph and modelling approach to investigate the processes by which hydrograph changes can be attributed to streamflow depletion. Our synthetic hydrograph scenarios do not directly correspond to any year's actual hydrograph, and we use a relatively simple analytical model to estimate streamflow depletion impacts. In this study, these simplifications were intentional as they allowed us to isolate the impacts of streamflow depletion, the specific hydrological process under investigation. This approach, often called surrogate modelling (Asher et al., 2015; Razavi et al., 2012), archetypal modelling (Zipper et al., 2018; Zipper, Soylu, et al., 2017), or meta-modelling (Fienen et al., 2016, 2018), is widely used to simplify hydrological systems in order to study specific stress-response relationships.

Nonetheless, these simplifications introduce some limitations to our work. For one, the Glover analytical model makes many simplifying assumptions about real-world conditions and we parameterize this model using best-available national and global datasets, rather than site-specific field studies. Whilst the Glover model has been shown to be appropriate for modelling streamflow depletion in a variety of scenarios (Li et al., 2020, 2022; Sophocleous et al., 1995; Zipper et al., 2022; Zipper, Gleeson, et al., 2021), it is unable to capture all of the complexity of many real-world scenarios, and there may be alternative models that are better-suited for a detailed site-specific investigation at any of these gages (Huang et al., 2018; Hunt, 2014). With a large number of sites, limited geological knowledge, and little basis for specifying well locations and detailed pumping schedules, the small number of parameters allowed for a manageable level of parameter space exploration and permitted us to conduct a detailed sensitivity analysis (see SI Text S3), which found that our results and conclusions were robust across a wide range of potential parameterizations. These results, however, can be considered a worst-case scenario since the Glover model assumes that the stream fully penetrates the aquifer with no impedance to flow across the streambed. In areas with lower-conductivity streambeds and/or confining or semi-confining layers between the stream and wells, the Glover model will likely overestimate streamflow depletion, which can be mediated by a weaker connection between the stream and the groundwater system.

Another potential limitation is related to extrapolation beyond our study sites. The random forest models trained in this study are limited by the training data, which does not comprehensively cover all catchment types and, in particular, underrepresents non-perennial watersheds, small watersheds, and watersheds with relatively small human impacts (Krabbenhoft et al., 2022). The attributes used for training were selected from GAGES-II, which has a comprehensive set of attributes, but it does not include all possible relevant information, like aquifer type and streambed substrate. Despite this, we believe that our approach allows us to broadly estimate the characteristics of catchments that may have impacts to specific groups of hydrologic signatures.

5 | CONCLUSIONS

This study demonstrates that Annual, Summer, and Fall low flow duration and deficit signatures can be effective and valuable indicators of streamflow depletion across a wide variety of hydroclimatic and hydrographic settings. We found that, when hydroclimatic variability is eliminated, streamflow depletion impacts are measurable generally within several years of pumping onset if impacts will be measurable at all. More sites have impacts under the dry climate scenario than the wet climate scenario, suggesting that transitions from wet period to dry periods could quickly manifest streamflow depletion impacts. Given the results of the random forest model indicating that these findings should be apparent across most streams in the United States, it seems surprising that streamflow depletion is so difficult to detect in real streams (Lapides, Maitland, et al., 2022; Zipper et al., 2022). In general, when examining observed hydrograph data with climatic variability, analysts must first account for that variability before attempting to determine whether there are any significant hydrograph changes that may be due to streamflow depletion. In this study, we simplify the issue of detection by (i) using hydrographs without interannual variability and (ii) directly comparing between pre- and post-pumping scenarios. This suggests that statistically controlling for hydroclimatic variability may be a promising approach for identifying streamflow depletion from hydrographs. Trend analysis on streamflow signatures may reveal hydrograph changes potentially caused by streamflow depletion where trends attributable to climate differ from expected trends due to streamflow depletion (Juracek, 2015; Kustu et al., 2010; Lucas et al., 2021); however, estimates of groundwater pumping would bolster confidence in the occurrence and magnitude of streamflow depletion. The results of this study provide a more robust accounting of expected changes due to streamflow depletion and help prioritize sensitive hydrologic signatures that can form a basis for subsequent efforts on streamflow depletion detection.

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DATA AVAILABILITY STATEMENT

All code and data generated for this study are accessible at https://github.com/lapidesd/streamflow_depletion_metrics_replacement/tree/flow_only (Lapides, Zipper, & Hammond, 2022).

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SUPPORTING INFORMATION

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