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Back cover photo: *Inside Busch Stadium - St. Louis, MO*. Credit: Jackie Gillespie

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Determinants of Water Source Choice for Irrigation in the Arkansas Delta

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Abstract: The use and the share of water applied from several irrigation water sources correlate with the irrigation practices in use by the peers of Arkansan farmers. From a sample of producers from an irrigation survey in Arkansas, a bivariate sample selection model accounts for how peer use of numerous irrigation practices affects the use and the share of irrigation that comes from a water source. The bivariate sample selection model controls for the bias in the statistical estimates that occur because producers who volunteer for an irrigation survey are likely to know about and use irrigation more than the population. We find that peer influence operates through multiple irrigation practices, and peer influence through an irrigation practice depends on an irrigator's location and current farm practices. For example, peer use of a tail-water recovery system and peer use of alternate wetting and drying both increase the probability of surface water use alone.

Keywords: *irrigation water source, reservoir, tail-water recovery, surface water*

Crop production in the Arkansas Delta uses substantial groundwater from the Mississippi River Valley Alluvial aquifer for irrigation (NASS 2018a), which spans several states such as Mississippi, Missouri, and Louisiana, and overdraft has led to declines in the aquifer abundance (ANRC 2014). A portfolio of sources for irrigation provides greater security for reliably meeting crop water needs throughout the growing season. Although several studies consider the determinants of irrigation practices to increase consumptive efficiency (Genius et al. 2014; Frisvold and Bai 2016; Sampson and Perry 2019a), the factors explaining the use of different irrigation water sources are less understood. We consider the use and the share of irrigation from five irrigation sources (natural surface water, surface water stored in a reservoir alone, surface water stored in a reservoir with a tail-water recovery system, groundwater, and reservoir filled by tail-water recovery alone) in the Arkansas Delta. Our focus is on the types of irrigation practices in use by a farmer's peers. We define a peer of a farmer as a family, friend, or neighbor who has used irrigation practice in the last 10 years. Conjunctive use of surface water and groundwater has been present in overdrafted parts of the Lower Mississippi River Basin (LMRB) since at least the 1950s. The most recent Arkansas Water Plan (ANRC 2014) encourages greater use of conjunctive water management to address groundwater decline in the alluvial aquifer. However, there have been no studies to our knowledge that consider the factors correlated with the use of surface water for irrigation. The role of the peer use of irrigation practices is a potential way for policy makers to make a difference in the greater adoption of surface water as an irrigation source.

The natural surface water source for irrigation refers to water taken from a bayou or other water body either on or adjacent to a farmer's field and applied directly to a field. The water source called surface water stored in a reservoir alone refers to water drawn from natural sources throughout the

Research Implications

- The use of surface water for irrigation correlates with the peer use of numerous irrigation practices.
- The use of surface water correlates with one set of peer irrigation practices, and the intensity of surface water use correlates with a different set of peer irrigation practices.
- Producers who use more surface water have less education and do not use the center pivot or zero-grade leveling practices.

year and stored in a reservoir for later irrigation. The third source is surface water stored in a reservoir with a tail-water recovery system which indicates water taken through the year from either natural sources or tail-water recovery systems and stored in a reservoir for later irrigation. The groundwater source comes from a well and is applied directly to a producer's field. The final water source is a reservoir filled by tail-water recovery alone, and this happens for the fields with no access to natural surface water. Farmers often rely on several alternative water sources since this provides greater water security for producers than reliance solely on groundwater.

We consider the share of water for irrigation from each source. A farmer may use surface water stored in a reservoir with a tail-water recovery system, but this might represent less than 5% of the water applied for irrigation. The share of water for irrigation that comes from a source reveals how much investment in that water source a farmer has made. Policy makers not only want producers to use a new irrigation source, but use that source enough that there is meaningful water conservation. Our methodological approach uses a bivariate sample selection model that allows for simultaneous consideration of a model for the use of an irrigation source and a model for the share of irrigation water applied that uses an irrigation source. A sample selection model corrects for bias by accounting for the correlation between the error terms of the models.

The likelihood of a farmer adopting irrigation or irrigation practices increases as the number of peers increases, proximity to the peer increases, and if they hear good news regarding a practice (Genius et al. 2014; Sampson and Perry 2019a; Maertens et al. 2020). Also, the information provided by extension agents influences irrigation practice adoption. The positive effect of extension visits on the adoption of drip irrigation found by Genius et al. (2014) is not borne out by studies that show extension interactions to have a negative or insignificant effect on new technology adoption (Conley and Udry 2010; Ward and Pede 2014). A literature review of the factors commonly affecting irrigation choices, including the previous studies about the role of peers, is in Appendix A1. However, there has been no examination of the determinants of the use of new water sources, especially in the Southern United States. We consider how 11 irrigation practices in the Arkansas Delta in use by peers (scientific scheduling, pivot, computerized hole selection, surge, precision leveling, end-blocking, zero grading, alternate wetting and drying, multiple-inlet, on-farm reservoirs, and tail-water recovery systems) affect the use and the share of irrigation water drawn from the five irrigation sources. The definition of the irrigation practices in the Arkansas Delta and their estimated water savings from conventional irrigation are in Table 1. A combination of several irrigation techniques in use by peers rather than a single irrigation technique has the potential to provide insights about a producer's choice of irrigation water sources. We also examine whether the influence of a peer differs by the location of a farm and the producer's current farming practices. Our findings suggest novel ways to bring together groups of producers with extension and other stakeholders to exchange information about irrigation and encourage greater use of conservation practices.

A producer considers the irrigation practices to use based on the personal view of the benefits and costs of the practices that depend on their own and their peers' experiences. The irrigation practices chosen by the producer in turn determine the irrigation sources for several reasons. One reason is that some irrigation practices and techniques operate more effectively with groundwater than surface water, namely center pivots. Another reason is that surface water use requires costly infrastructure (i.e., reservoirs and tail-water

Table 1. Definition of irrigation practices in the Arkansas Delta.

Variable	Definition	Water savings
TWR	Tail-water recovery system: collects runoff and reapplies the water to the field for a subsequent irrigation set	15%[a]
AltWetDry	Alternate wetting and drying: permitting a rice field to go dry for short periods before refilling the field with water for rice cultivation	16 to 28%[b]
CHS	Computerized hole selection: poly-pipe with alternate hole sizes to deliver water down furrows with an uneven length	25%[c]
Surge	Surge: pulsing of water along furrows by switching the flow rate during an irrigation set	51%[d]
Plevel	Precision leveling: the movement of soil to create a gentle slope for the flow of water down a furrow	--
Res	On-farm reservoirs: the storage of water collected throughout the year for irrigation later in the growing season	--
EndBlock	End-blocking: blocking or diking of the lower end of furrow irrigated fields to prevent the loss of water from the field	--
Sched	Scientific scheduling: soil moisture sensors, evapotranspiration (ET) monitors, and Woodruff charts	--
Pivot	Pivots: portable and mounted sprinkler systems	30%[e]
ZeroGrade	Zero-grading: movement of soil to create a field with no slope and a constant water level for rice production	40%[f]
MI	Multiple inlet irrigation: filling all the areas between the levees of a rice field with water at the same time	27 to 53%[g]

[a] Texas Water Development Board 2013; [b] Enriquez et al. 2021; [c] University of Arkansas Division of Agriculture 2023; [d] Nishihara and Shock 2001; [e] Stein 2011; [f] Henry et al. 2016; [g] Massey et al. 2022.

recovery systems) that may be viewed by the producer as either a complement or substitute with the irrigation practices that focus on consumptive efficiency (i.e., computerized hole selection or surge valves).

Next, we describe the study region and process for gathering the data, and this is followed by an explanation of the methods for the analysis. We finish with a section on the results followed by discussion and key findings in the conclusion.

Study Region

The Mississippi Valley Alluvial aquifer supplies most of the irrigation water for Eastern Arkansas. Regional depressions in the aquifer in the Arkansas Delta correspond to where rice is grown (ANRC 2014). Over the past decade, irrigated acres grew substantially in the Lower Mississippi Delta Region, and more than four million irrigated acres were present in Arkansas in 2018 (NASS 2018a; Kovacs et al. 2019). Climate change has the potential to increase precipitation in the winter while decreasing precipitation and increasing temperature in the growing season. The seasonal change in precipitation could increase farmer's interest in exploring water sources other than groundwater for irrigation during the spring and summer. The storage of water in a reservoir during the winter months along with the recovery and recycling of tail-water during the growing season can reduce farmer dependence on groundwater.

Gravity irrigation is common in Arkansas and includes field management practices (i.e., precision grade leveling, end blocking, and zero grade leveling) and water flow control practices (i.e., flow meters, computerized hole selection, and alternate wetting and drying) (Huang et al. 2017; Nian et al. 2020). Also common on farms that use gravity irrigation is the storage of water in reservoirs followed by the recovery and recycling of tail-water in the growing season (Kovacs et al. 2019). The use of recycled water occurs on about 18% of farms using recycled water for some irrigation (NASS 2018b). Groundwater is the only source of irrigation for three-fifths of farms and irrigated acres, but nearly nine-tenths of all farms and irrigated acres use groundwater (NASS 2018c). Almost a third of farms use on-farm surface water for irrigation, but this only constitutes a tenth of the irrigated acres. About 5% of farms use only on-farm surface water for irrigation, and this is less than 1% of the irrigated acres (NASS 2018c). Barriers to water conservation improvements are an inability to finance improvements, a landlord will not share in the cost, and improvements will not reduce costs enough to cover installation costs (NASS 2018d).

Materials and Methods

A team of agricultural scientists developed a telephone survey conducted by the Mississippi State University Social Science Research Center to understand the type of irrigation systems in the 2016 crop year. The contact information of the agricultural producers came from Survey Sampling International. There were 3,712 telephone numbers purchased for commercial crop growers from Dun & Bradstreet records for the state of Arkansas. There were at least 10 dials of each telephone number before the retirement of the number. In the four months available to conduct the survey, 913 unique phone numbers were dialed. Those reached by phone were asked at the start of the survey if they were farm operators and if they were irrigators. Of the 617 irrigators reached by phone and eligible to complete the survey, 247 refused the survey and 171 refused to continue the survey during the administration. The response rate for the survey was 32% based on the 199 fully completed surveys, but only 170 surveys had responses for all the questions in the analysis. Based on irrigators in the region reported by the Farm and Ranch Irrigation Survey (USDA NASS 2014), the margin of error for the survey is 4.6% with a 95% confidence interval (Edwards 2016).

We balance gathering a complete and extensive set of information on irrigation practices while not keeping respondents on the phone for a long conversation. The survey had nearly 150 questions and took about 40 minutes to complete. Irrigators are familiar with long surveys such as the 17-page Farm and Ranch Irrigation questionnaire and the even longer Census of Agriculture. The survey began with questions about the crops grown and general farm practices, followed by the types of irrigation practices, then the willingness to pay questions about off-farm water and on-farm surface water, and the final section asked about the peer irrigation practices and socio-demographics characteristics. Questions from all sections of the survey provide data input for addressing the research questions around the influence of the number and type of peer irrigation practices on the use and the share of land that irrigators devote to the irrigation water sources.

The summary statistics of the dependent variables for the use of an irrigation source (natural surface water, surface water stored in a reservoir alone, surface water stored in a reservoir with a tail-water recovery system, groundwater, and a reservoir filled by tail-water recovery alone) and the share of irrigation water from a source are in Tables A1 and A2 in the Appendix, respectively. The binary dependent variables in Table A1 have a value of 1 if an irrigation source is in use and 0 if an irrigation source is not in use. Figure 1 displays the information about the percentage of respondents that use an irrigation source. Groundwater (GW) is the most common irrigation source with 93.0% of respondents indicating the use of the aquifer. The next most heavily used irrigation source is natural surface water (SW) with 40.4% of respondents indicating use, followed by surface water stored in a reservoir with a tail-water recovery system (SWResTWR) at 28.7%, reservoir filled by a tail-water recovery system alone (ResTWR) at 21.1%, and surface water stored in a reservoir alone (SWRes) at 18.7%. Figure 2 and Table A2 indicate that groundwater is the source with the highest share of irrigation water in use on a farm at 73.6%.

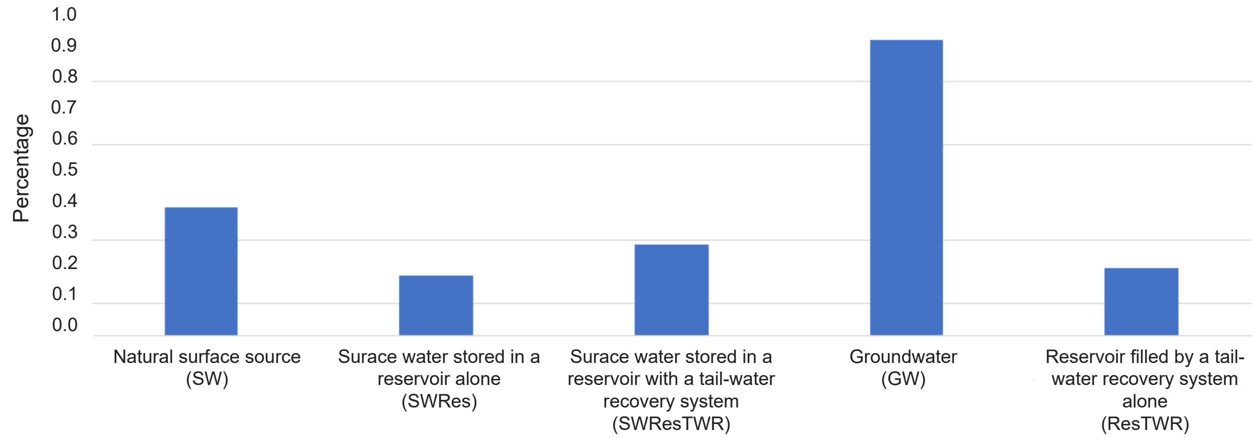

Figure 1. Percentage of respondents that use an irrigation source.

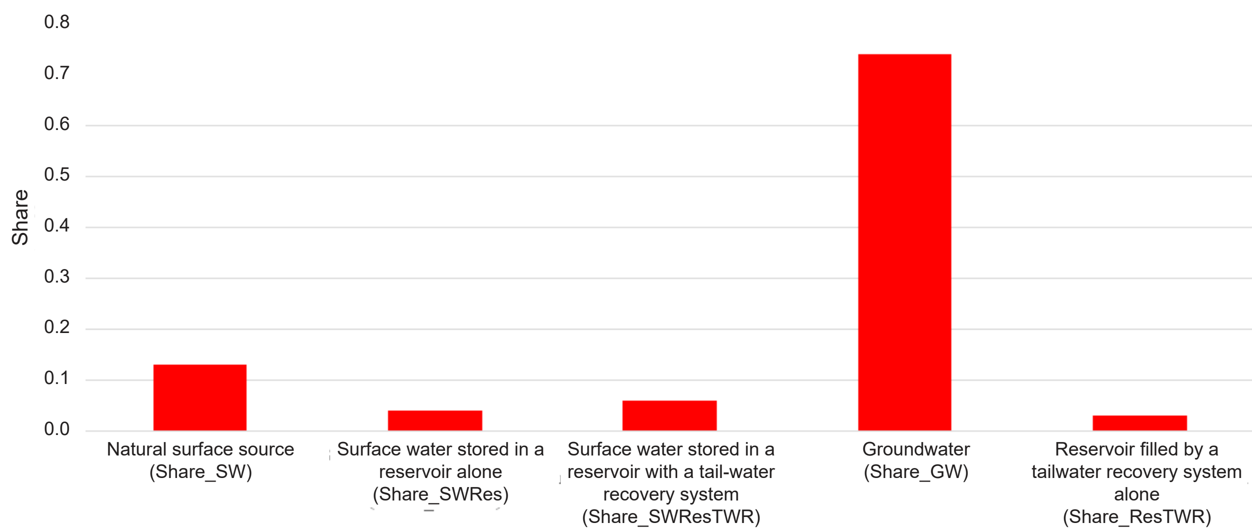

Figure 2. Share of water applied by irrigation source.

Natural surface water, surface water in a reservoir with a tail-water recovery system, reservoir filled by a tail-water recovery system alone, and surface water in a reservoir alone were on average 12.94, 6.24, 4.37, and 2.82% of a producer's source of irrigation water, respectively.

The explanatory variables for the choice of an irrigation source and the share of irrigation water from a source are in Table A3 in the Appendix. These explanatory variables have two categories 1) peer network of irrigation practice use, and 2) farm, irrigation, and socioeconomic characteristics. The variables that represent the peer network of irrigation practice use include family members, friends, or neighbors (i.e., a peer) in the past 10 years that used a type of irrigation practice. Nearly every respondent has a peer using precision leveling (PeerPlevel), around 90%, while only 35% of respondents have a peer using alternate wetting and drying for rice irrigation (PeerAltWetDry). We use the interaction variables of the peer network variables with the location and farm characteristic variables to understand how peer influence changes by location or farm practice. The Arkansas Delta locations are Crowley's Ridge (Ridge), Grand Prairie (GP), Mississippi River (River), and the North (ND) or South (SD) Delta. The Arkansas counties in each of the regions are in the definitions for those regions in Table A3. Another way we explore the influence of peer networks is through producer participation in conservation programs such as the Conservation Reserve Program (CRP) and other conservation programs (Other). The last way we modify the influence of a peer network is to consider if the primary reason for a tail-water recovery system or reservoir was financial assistance (ReasonFin). The peers of the survey respondents are not in the sample. We only know that a survey respondent has a peer that uses a particular irrigation practice. We examine if there is a correlation between the use of an irrigation practice by a peer of the survey respondent and the use of an irrigation source by the survey respondent.

Farm, irrigation, and socioeconomics characteristics include producer's education, type of pumps used on the farm, soil types, access to surface water sources, and proximity to urban areas. Although the survey did not ask for the farm size because this was deemed sensitive information to request from producers, we did ask how many irrigated acres were planted to each crop. The crop most frequently planted and that had the most planted acres was soybeans with 1,448 acres on average, but one farm had planted 12,000 acres. The second most frequently planted crop was rice with 1,058 acres on average and one farm had a maximum of 6,250 acres. Less than half report having a bachelor's degree (Bach), but more than half report having a degree related to agriculture (AgEdu). Nearly all respondents report using at least one diesel (DieselPump) and one electric pump (ElectricPump). Using information from the Soil Survey Geographic Database, on average about a quarter of the land in a county has a pH above 6 (pH>6.0). The typical county has a population of 20,000 or more and is not adjacent to a metro area according to the Rural-Urban continuum code for 2013 (USDA ERS 2013). Based on the National Hydrography Dataset, the average county has about 37 kilometers (23 miles) of canals and ditches (CanalDitch) and about 137 kilometers (85 miles) of streams and rivers (StreamRiver).

Data Analysis

Studies based on observation are rarely pure random samples (Heckman 1979). A sample of producers who volunteer to spend time on an irrigation survey likely have an interest in production with irrigation. A non-random sample results in the bias of parameter estimates that persist at large sample sizes. The bivariate sample selection model corrects for the bias by accounting for the correlation between the error in the model on the use of an irrigation source and the error in the model for the share of irrigation water applied that uses an irrigation source. The model for the use of an irrigation source has a binary dependent variable. The model for the share of irrigation water applied that uses an irrigation source has a continuous dependent variable.

The irrigation source dependent variable y_1 (e.g., =1 if use natural surface source for irrigation when considering SW), is an incompletely observed value of a latent dependent variable, y_1^* where the observation rule is

$$y_1 = \begin{cases} 1 \; if \; y_1^*>0, \\ 0 \; if \; y_1^* \leq 0 \end{cases}$$

and a resultant outcome equation such that

$$y_2 = \begin{cases} y_2^* \; if \; y_1^*>0 \\ - \;\; if \; y_1^* \leq 0. \end{cases}$$

This model indicates that the share of an irrigation water from an irrigation source, y_2 (e.g., when considering the share of water applied from a natural source, Share_SW), is observed when y_1^* >0 and there is no value for y_2 when $y_1^* \leq 0$. Since y_1^* and y_2^* are latent variables, the use and the share of irrigation water applied that uses an irrigation source are not observed for the population, only the sample. We then specify a linear model with additive errors for the latent variables, so

$$y_1^* = x_1'\beta_1 + \varepsilon_1,$$

$$y_2^* = x_2'\beta_2 + \varepsilon_2.$$

Bias will arise in the estimation of β_2 if ε_1 and ε_2 are correlated. However, through maximum likelihood and the assumption that the correlated errors have a joint normal distribution and are homoscedastic

$$\begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix} \sim \aleph \left[\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{bmatrix} \right],$$

then estimation is asymptotically efficient. The bivariate sample selection model corrects for the correlated errors that would lead to bias if the estimation of the equation for y_2^* was through ordinary least squares.

The likelihood function for the bivariate sample selection model is

$$L = \prod_{i=1}^{n} \{Pr[y_{1i}^{*} \leq 0]\}^{1-y_{1i}} \{f(y_{2i} \mid y_{1i}^{*} > 0) \times Pr[y_{1i}^{*} > 0]\}^{y_{1i}}$$

where an initial term in the irrigation source use equation is $y_{1i}^{*} \geq 0$, and the second term is the equation for the share of irrigation water applied that uses the irrigation source when $y_{1i}^{*} > 0$.

We report the marginal effects of irrigation source use as the change in the probability of use in response to a one-unit increase in an explanatory variable. The marginal effect for the share of irrigation water applied that uses an irrigation source depends indirectly on how an explanatory variable affects the use of an irrigation source and directly through the share of irrigation water applied that uses an irrigation source. Explanatory variables appearing only in the equation for the share of irrigation water applied that uses a source have a marginal effect equal to the coefficient estimate. If an explanatory variable appears only in the use equation, a unit change in the explanatory variable affects the expected value of the error term, and through correlation of the error terms in both equations, there is an expected change in y_2. When an explanatory variable appears in both equations, then the indirect effect through the use equation and the direct effect through the share of irrigation water equation result in an expected change to y_2. We conduct the maximum likelihood estimation with Stata® version 13.1 developed by StataCorp.

Results

The first two tables of results indicate the role of peer use of multiple irrigation practices (Table 2) and other farm and socioeconomic characteristics (Table 3) on the use of five irrigation water sources. The decision to use a surface water source for irrigation (a binary yes or no variable) is a first step toward the reduction of groundwater dependence, but the share of irrigation water from a surface source (a continuous variable) explains the level of investment in alternative sources of irrigation water. The last two results tables examine how peer use of multiple irrigation practices (Table 4) and the other farm and socioeconomic characteristics of the producer (Table 5) influence the share of irrigation water from the five irrigation sources. Other explanatory variables included in the analysis that did not have estimated coefficients significant at the 15% level or above have summary statistics in Table A4 and marginal effects in Tables A5 and A6.

A producer with a peer using a tail-water recovery system (PeerTWR) increases the likelihood of that producer using natural surface water (SW) by 38% (Table 2). However, if the producer uses a tail-water recovery system (TWR), this has no influence on the likelihood that the producer uses natural surface water. In fact, Table 2 indicates that no irrigation practice that the farmer uses themselves has an influence on the likelihood that the producer uses natural surface water, surface water with a reservoir alone (SWRes), groundwater (GW), or a reservoir filled by a tail-water recovery system alone (ResTWR). A producer with a peer using alternate wetting and drying (PeerAltWetDry) is 27% more likely to use natural surface water. The peer effect differs by location and whether financial assistance was a primary reason for using a reservoir or tail-water recovery system. We control for historical weather patterns in the analysis, and the location specific influence of the peer effects has more to do with the historical differences in crops grown and agricultural development across the wide geographic area. A producer with a peer using a tail-water recovery system who lives along the Mississippi River (PeerTWR*River) is 57% less likely to use natural surface water. A producer with a peer using computerized hole selection, and whose primary reason for using a reservoir or tail-water recovery system is financial assistance (PeerCHS*ReasonFin), is 26% more likely to use natural surface water.

A producer with a peer using surge (PeerSurge) decreases the likelihood of that producer using surface water with a reservoir alone by 9%. A producer with a peer using a tail-water recovery system and who participates in a conservation program other than the conservation reserve program, or the environmental quality incentives program (PeerTWR*Other) is 11% less likely to use surface water with a reservoir alone. A producer with a peer using computerized hole selection and who lives in the North Delta (PeerCHS*ND) is 24% more likely to use surface water with a reservoir alone. The lower precipitation in the

North Delta than in the South may partly explain this (PRISM 2022). A producer with a peer using a tail-water recovery system (PeerTWR) increases the likelihood of that producer using surface water with a reservoir and tail-water recovery system (SWResTWR) by 21%. A producer with a peer using precision leveling (PeerPlevel) increases the likelihood of a producer using surface water with a reservoir and tail-water recovery system by 23%. A producer with a peer using a reservoir and who lives in the North Delta (PeerRes*ND) is 19% less likely to use surface water with a reservoir and tail-water recovery system. The summary statistics for the Arkansas Delta regions in Table A3 indicate that 12% of the respondents come from the North Delta region, 32% from counties around Crowley's Ridge, 7% from South Delta counties, and the rest from other Delta counties. Three irrigation practices (alternate wetting and drying (AltWetDry), precision leveling (Plevel), and reservoirs (Res)) a producer uses themselves correlate positively with the likelihood of surface water use with a reservoir and tail-water recovery system.

A producer with a peer using end-blocking (PeerEndBlock) increases the likelihood of that producer using groundwater by 7%. A producer with a peer using alternate wetting and drying (PeerAltWetDry) decreases the likelihood of a producer using a reservoir filled by a tail-water recovery system alone by 10%. A producer with a peer using end-blocking increases the likelihood of a producer using a reservoir filled by a tail-water recovery system alone by 5%. A producer with a peer using scientific scheduling and who lives in the Crowley's Ridge region (PeerSched*Ridge) is 10% more likely to use a reservoir filled by a tail-water recovery system alone. A producer with a peer using scientific scheduling, and whose primary reason for using a reservoir or tail-water recovery system is financial assistance (Peer*ReasonFin), is 22% less likely to use a reservoir filled by a tail-water recovery system alone.

Table 2. Marginal effects[1] for the peer network variables to explain the use of an irrigation water source.

Variable	SW	SWRes	SWResTWR	GW	ResTWR
PeerTWR	0.38 (0.02)[b]	0.06 (0.21)	0.21 (0.09)[c]		
PeerAltWetDry	0.27 (0.06)[c]				-0.10 (0.06)[c]
PeerCHS	0.15 (0.16)	-0.09 (0.12)			
PeerSurge		-0.09 (0.09)[c]			
PeerPlevel			0.23 (0.12)[c]		
PeerRes			0.14 (0.17)		
PeerEndBlock				0.07 (0.09)[c]	0.05 (0.10)[c]
PeerSched					-0.04 (0.21)
PeerSched*Ridge					0.10 (0.10)[c]
PeerSched*ReasonFin					-0.22 (0.10)[c]
PeerRes*ND			-0.19 (0.07)[c]		
PeerTWR*River	-0.57 (0.03)[b]				
PeerTWR*Other		-0.11 (0.08)[c]			
PeerCHS*ND		0.24 (0.02)[b]			
PeerCHS*ReasonFin	0.26 (0.08)[c]				
PeerAltWetDry*ReasonFin	-0.31 (0.08)[c]				
Pseudo R^2	0.63	0.46	0.45	0.32	0.51

Number of observations: 170. Significance values: [a] = 1%, [b] = 5%, [c] = 10%. P-values from the probit model estimates in parentheses. [1]The marginal effects for the peer variables that also have interaction variables are the marginal effects assuming the interaction variables are zero. For example, the marginal effect on PeerTWR in the SW column assumes the variable River is zero. The marginal effect for PeerTWR*River in the SW column assumes that the variables PeerTWR and River are both one.

Table 3. Marginal effects for the farm, irrigation, and socioeconomics variables to explain the use of an irrigation water source.

Variable	SW	SWRes	SWResTWR	GW	ResTWR
AltWetDry			0.02 (0.01)[c]		
AdvEdu	-0.58 (0.05)[c]				-0.15 (0.10)[c]
AgEdu	0.19 (0.07)[c]				0.07 (0.10)[c]
AllClay	0.10 (0.00)[a]				
AllSand	0.03 (0.02)[b]	0.04 (0.10)[c]			
Bach	-0.52 (0.03)[b]				-0.07 (0.12)
CanalDitch	-0.04 (0.00)[a]		-0.01 (0.14)		
DieselPump	0.36 (0.05)[c]	-1.26 (0.03)[b]			
ElectricPump				0.07 (0.09)[c]	
GDD			-0.003 (0.07)[c]		
OrgMatter					-0.31 (0.05)[b]
Plevel			0.01 (0.005)[a]		
PPT			-0.02 (0.07)[c]		
Res			0.01 (0.002)[a]		
StreamRiver	0.002 (0.10)[a]		0.003 (0.01)[a]		
UsedFlowMeter		0.98 (0.01)[a]			
Pseudo R^2	0.63	0.46	0.45	0.32	0.51

Number of observations: 170. Significance values: [a] = 1%, [b] = 5%, [c] = 10%. P-values from the probit model estimates in parentheses.

The coefficient estimates for the explanatory factors of the farm, irrigation, and socioeconomic characteristics on the likelihood of irrigation source use are in Table 3. A producer with a graduate degree (AdvEdu) is 58% less likely to use natural surface water, and a producer with a bachelor's degree (Bach) is 52% less likely to use natural surface water. However, a producer with a degree in agriculture (AgEdu) is 19% more likely to use natural surface water. One possibility for the negative correlation with formal education and a positive relationship with an agricultural education is that surface water use may be viewed as a less efficient way to provide irrigation by those with a formal education. Another possibility is that a producer with an agricultural education is more willing to invest in conjunctive water management and agriculture in general than those with a formal education. A survey that collects information on producers' thoughts about irrigation efficiency or the willingness to make long-term agricultural investments might uncover what explanations are correct. An additional kilometer of canals and ditches (CanalDitch) in a county reduces the likelihood of natural surface water use by 4% while an additional kilometer of streams and rivers (StreamRiver) increases the likelihood by 0.2. An additional kilometer in canals and ditches in a county means a 1% decrease, while an additional kilometer in streams and rivers means a 0.3% increase in the use of surface water with a reservoir and tail-water recovery system. The likelihood of use of a reservoir with a tail-water recovery system alone is 15% lower if a producer has a graduate degree, but the likelihood is 7% greater if the producer has a degree related to education in agriculture. An additional percentage increase in organic matter in the soil (OrgMatter) lowers the likelihood of a reservoir with a tail-water recovery system by 31%. This finding suggests a substitution between desirable soil properties due to organic matter and the irrigation requirements of a crop.

The marginal effects associated with the peer network variables for the share of irrigation water applied that uses an irrigation source are in

Table 4. Producers with a peer using surge have a higher proportion of irrigation water from a natural surface water source (an increase of 0.48), but this proportion decreases by 0.34 if the producer is in the North Delta and by 0.40 if the producer is in the South Delta. A producer with a peer using zero-grade (PeerZeroGrade) has a lower proportion of irrigation water from a natural surface water source (a decrease of 0.24). A producer with a peer using pivot (PeerPivot) has a lower proportion of irrigation water from surface water with a reservoir alone (a decrease of 1.01), but the proportion increases by 1.25 if the producer is in the Grand Prairie and increases by 1.45 if the producer is along the Mississippi River. A producer with a peer using scientific scheduling (PeerSched) has a higher proportion of irrigation from surface water with a reservoir alone (an increase of 0.28).

Producers with a peer using computerized hole selection (PeerCHS) have a higher proportion of irrigation from surface water with a reservoir and tail-water recovery system (an increase of 0.18), but the proportion decreases by 0.46 if the producer lives near Crowley's Ridge (PeerCHS*Ridge) and decreases by 0.11 if the primary reason for the reservoir and tail-water recovery system is financial assistance (PeerCHS*ReasonFin). A producer with a peer using pivot has a higher proportion of irrigation from a reservoir with tail-water recovery (an increase of 0.53), but the proportion

Table 4. Marginal effects[1] for the peer network variables to explain the share of water applied by irrigation source.

Variable	Share_SW	Share_SWRes	Share_SWResTWR	Share_GW	Share_ResTWR
PeerCHS			0.18 (0.01)[a]		
PeerPLevel			-0.57 (0.00)[a]	0.04 (0.05)[b]	
PeerSurge	0.48 (0.11)[a]				
PeerPivot		-1.01 (0.13)	0.53 (0.00)[a]	0.05 (0.08)[c]	0.09 (0.11)[c]
PeerSched		0.28 (0.02)[a]			
PeerZeroGrade	-0.24 (0.08)[b]				
PeerMI					-0.48 (0.00)[a]
PeerMI*Ridge					0.62 (0.00)[a]
PeerMI*ND					0.31 (0.00)[a]
PeerCHS*Ridge			-0.46 (0.00)[a]		
PeerCHS*ReasonFin			-0.11 (0.07)[c]		
PeerSurge*ND	-0.34 (0.19)[c]				
PeerSurge*Ridge	-0.40 (0.19)[c]				
PeerPivot*GP		1.25 (0.07)[c]	-0.75 (0.00)[a]		0.25 (0.00)[a]
PeerPivot*ND			-0.53 (0.00)[a]		
PeerPivot*River		1.45 (0.04)[b]			1.23 (0.00)[a]
PeerPivot*CRP					-0.28 (0.00)[a]
Wald Chi2	62.89	190.35	396.32	$2.33*10^7$	154.46
LR test of independent equations: Chi squared statistics	2.60 (0.11)	0.86 (0.35)	0.99 (0.32)	11.89 (0.001)	1.16 (0.28)

Number of observations: 170. Significance values: [a] = 1%, [b] = 5%, [c] = 10%. P-values from the bivariate sample selection model estimates in parentheses. [1]The marginal effects for the peer variables that also have interaction variables assume the interaction variables are zero. For example, the marginal effect on PeerSurge in the Share_SW column assumes the variables ND and Ridge are zero. The marginal effect on PeerSurge*ND in the Share_SW column assumes that the variables PeerSurge and ND are both one.

decreases by 0.75 if the producer is in the Grand Prairie (PeerPivot*GP) and decreases by 0.53 if the producer is in the North Delta (PeerPivot*ND). This finding illustrates the diversity in irrigation approaches across the Arkansas Delta. Intensive rice production regions like the Grand Prairie and the North Delta view reservoir and tail-water recovery systems as substitutes for pivots. Other Arkansas Delta regions view pivots as complements to reservoir and tail-water recovery systems. A producer with a peer using precision leveling (PeerPLevel) or pivots has a higher proportion of irrigation from groundwater (an increase of 0.04 and 0.05, respectively).

A producer with a peer using a pivot has a higher proportion of irrigation from a reservoir supplied by a tail-water recovery system alone (an increase of 0.09), and the proportion increases by 0.25 if the producer is in the Grand Prairie (PeerPivot*GP) and increases by 1.23 if the producer lives along the Mississippi River (PeerPivot*River). The proportion decreases by 0.28, however, if the producer participates in the conservation reserve program (PeerPivot*CRP). There is a potential substitution between the conservation reserve program and the use of a reservoir with a tail-water recovery system alone. A producer with a peer using multiple inlets (PeerMI) has a lower proportion of an irrigation that uses a reservoir supplied by tail-water recovery alone (a decrease of 0.48), but the proportion increases by 0.62 if the producer lives near Crowley's Ridge (PeerMI*Ridge) and increases by 0.31 if the producer is in the North Delta (PeerMI*ND). This is additional evidence of a diversity of irrigation approaches across the Arkansas Delta, indicated here by different approaches for rice irrigation in the North Delta versus the Grand Prairie.

The marginal effects of the explanatory factors of the farm, irrigation, and socioeconomic characteristics on the share of irrigation from an irrigation source are in Table 5. For each additional growing degree day (GDD) in a county where a producer lives, the proportion of irrigation from natural surface water decreases by 0.003. The use of surge irrigation (Surge) correlates negatively with the proportion of irrigation from natural surface water by 0.18. A producer with a graduate degree has a higher proportion of irrigation (an increase of 0.84) from surface water with a reservoir alone. A farmer that lives in a more rural county, as measured by a step along the rural-urban continuum code (USDA ERS 2013), has a 0.28 higher proportion of irrigation from surface water with a reservoir alone. The use of alternate wetting and drying (AltWetDry) and end-blocking (EndBlock) increases the proportion of irrigation from surface water with a reservoir alone by 0.52 and 0.27, respectively. The use of pivots (Pivot) reduces the proportion of irrigation from surface water with a reservoir alone by 0.25.

A farmer with a graduate degree has a higher proportion of irrigation from surface water with a reservoir and tail-water recovery system by 0.27 than a farmer without a college degree. An additional kilometer of streams and rivers in a county increases the proportion of irrigation from surface water with a reservoir and tail-water recovery system by 0.01. The use of multiple inlets (MI) for rice irrigation and reservoirs (Res) increases the proportion of irrigation from surface water with a reservoir and tail-water recovery system by 0.09 and 0.14, respectively. The use of zero-grade leveling (ZeroGrade) reduces the proportion of irrigation from surface water with a reservoir and tail-water recovery system by 0.07. The use of computerized hole selection (CHS), reservoirs, and tail-water recovery systems decreases the proportion of irrigation from groundwater by 0.05, 0.13, and 0.07, respectively. The use of center pivots increases the proportion of irrigation from groundwater by 0.06. An additional kilometer of streams and rivers in a county where a producer lives lowers the proportion of irrigation from groundwater by 0.001. The use of end-blocking and zero-grade leveling influences the proportion of irrigation from reservoirs filled by a tail-water recovery system alone by 0.06 and -0.05, respectively.

Discussion and Conclusion

We are the first to consider the factors that influence the use of irrigation water sources in the LMRB, but previous studies looked at how such factors affect the use of efficient irrigation practices in other regions. For instance, studies show advanced education has a direct correlation with

Table 5. Marginal effects for the farm, irrigation, and socioeconomics variables for the share of water applied by irrigation source.

Variable	Share_SW	Share_SWRes	Share_ SWResTWR	Share_GW	Share_ ResTWR
AltWetDry		0.52 (0.27)b			
AdvEdu		0.84 (0.00)a	0.27 (0.00)s	0.11 (0.10)c	
AllClay		0.04 (0.09)c	0.02 (0.00)a		
AllSand	0.14 (0.06)c				0.03 (0.00)a
Bach	0.09 (0.05)c				
DieselPump		0.39 (0.00)a			
EndBlock		0.27 (0.17)c			0.06 (0.03)b
GDD	-0.003 (0.09)c	-0.002 (0.14)			
MI			0.09 (0.03)a		
OrgMatter		-2.54 (0.00)a			
pH>6.0		0.002 (0.01)a		0.003 (0.05)b	-0.06 (0.00)a
Pivot		-0.25 (0.13)c		0.06 (0.03)b	
Res			0.14 (0.05)a	-0.13 (0.038)a	
StreamRiver			0.01 (0.00)a	-0.001 (0.03)b	
Surge	-0.18 (0.09)b				
TWR				-0.07 (0.04)b	
ZeroGrade			-0.07 (0.03)a		-0.05 (0.03)c
Wald Chi2	63	190	396	233000	154
LR test of independent equations: Chi squared statistics	2.6 (0.12)	0.9 (0.35)	0.9 (0.32)	11.9 (0.001)	1.2 (0.28)

Number of observations: 170. Significance values: [a] = 1%, [b] = 5%, [c] = 10%. P-values from the bivariate sample selection model estimates in parentheses.

the use of new irrigation practices (Frisvold and Bai 2016). We find that the share of irrigation water applied from sources that involve reservoirs with natural surface water rise with greater education. Genius et al. (2014) indicate that the adoption of drip irrigation occurs more slowly on sandy soil. Our findings indicate that the use of natural surface water and surface water with a reservoir alone is more likely on sandy soil. Also, farms with sandy soil use a greater share of irrigation water from a reservoir with tail-water recovery alone.

Past studies have shown that the effectiveness of peer communication depends on how information spreads among peers, such as through the size of the peer group (Bandiera and Rasul 2006), the distance peers are from each other (Sampson and Perry 2019a;b), and whether an affirmative, neutral, or negative experience with the irrigation practice occurs in the communication (Conley and Udry 2010). The examination of the peer use of multiple irrigation practices reveals relationships not seen by looking at the producers' use of the irrigation practices themselves. For example, the use of water from a reservoir and tail-water recovery system decreases with the peer use of reservoirs only in the northern Arkansas Delta. Another example is that the share of reservoir and tail-water recovery water use increases the peer use of pivot except when in the Grand Prairie or North Delta. The findings reveal the diversity of irrigation source choice across the Arkansas Delta.

Crane-Droesch (2018) considers the role of social learning in the adoption of a soil amendment to improve fertility and shows that both the expected profitability and the associated risk transmit through social networks. This might explain why the influence of the peer use of irrigation practices differs in the use of an irrigation water source versus for the share of the water source applied. Natural surface water use increases with the peer use of a tail-water recovery system, but the share of natural surface water use increases with the peer use of surge and the peer use of pivot in certain locations. Another example is that the use of a reservoir and tail-water recovery system increases with the peer use of precision leveling, but the share of water from a reservoir and tail-water recovery system increases with the peer use of computerized hole selection. In California, Schoengold and Sunding (2014) find that if low-cost surface water is available with certainty, there is greater investment in sprinkler and drip irrigation because a producer is confident about repaying the investment loans.

In addition to the influence of social networks on the peer use of irrigation practices, the farm, irrigation, and socioeconomic characteristics also have a role in irrigation source choice. Those with a graduate degree are less likely to use natural surface water, use a larger share of surface water with a reservoir alone, use a larger share of water with a reservoir and tail-water recovery system, and use a larger share of groundwater. Although past studies have not been conclusive about the effects of education, Wheeler et al. (2010) show that as producers age, they are less likely to change farm practices during times of production uncertainty and less likely to engage in labor-intensive practices. A producer that uses pivots for irrigation uses a smaller share of surface water with a reservoir alone and uses a larger share of groundwater. A producer that uses zero-grading uses a smaller share of surface water with a reservoir alone and a smaller share of water from a reservoir filled by a tail-water recovery system alone. Green et al. (1996) show that the scale of a large farm allows for more investment in efficient irrigation practices, and this increases the likelihood of precision agriculture adoption.

An additional kilometer of streams and rivers in a county increases the likelihood of use of natural surface water and the use of surface water with a reservoir and tail-water recovery, and producers use a larger share of water with a reservoir and tail-water recovery system and use a larger share of groundwater. More sandy soil increases the likelihood of the use of natural surface water and increases the share of water from a reservoir and tail-water recovery system. Genius et al. (2014) find that farmers are slow to adopt drip irrigation on soils derived from sandy limestone than from soils of differing texture. Producers with desirable properties in the soil and high fertility are more likely to use drip irrigation while producers with low fertility soils are less likely to use drip irrigation (Shrestha and Gopalakrishnan 1993). A 1% increase in the slope steepness in California increases the likelihood of sprinkler irrigation by 0.01% and precision irrigation by 9.81%, and the likelihood of furrow irrigation decreases by 0.32% (Green et al. 1996).

Policy efforts to conserve groundwater in the LMRB include providing information and incentives on the conjunctive use of surface water with groundwater. By understanding what positively correlates with surface water use for current farmers, we may better encourage new farmers to adopt surface water and allow for the continued use of surface water by farmers that have already adopted. Extension personnel and other stakeholders can use these findings to help identify which farmers are the best candidates for the adoption of surface water for irrigation. For example, from the highlighted findings in the prior two paragraphs, stakeholders are likely to have more success with farmer's that have greater education, do not currently use pivots or zero-grade leveling, and live in counties with abundant surface water and sandy soils. Also, the peer use of several types of irrigation practices correlates with the use of surface water, but this correlation is found to depend on where the farmer is within the Arkansas Delta. Stakeholders that want to target the use of surface water should find out if the producer has peers that use a tail-water recovery system or precision leveling. However, for targeting a greater share of surface water from irrigation, the stakeholders should find out if the producers have peers that use surge valves and computerized hole selection.

The evaluation of how the practices by peers affect irrigation source choice offers insight into the diversity of irrigation within the region. The irrigation sources other than groundwater that are common are natural surface water and surface water from a reservoir and tail-water recovery system. Peer use of a tail-water recovery system increases the use of both irrigation sources. However, peer use of alternate wetting and drying is important for natural surface water use, and peer use of precision leveling is important for surface water from a reservoir and tail-water recovery system. This diversity of peer influence by irrigation practice in the Arkansas Delta reflects the large geography and the heterogeneity in the access to surface water and the depletion of groundwater over the region.

Peer use of irrigation practices correlates with farmers' irrigation source decisions, but more research could illuminate how peers have this influence on irrigation sources. A new producer survey could provide additional information about the peers who use the common irrigation practices. This information could include who the peer is (i.e., family or friend), spatial proximity of the peer to the farmer, and the type of information shared between the peers. Other explanatory factors would be worthwhile to further investigating too. Education appears to influence the use and the share of the irrigation sources, and this raises the question whether more formal education or the more specific technical information provided by stakeholders is valuable. The soil texture and acidity also play a frequent role in the sharing of water from irrigation sources, likely because these are indicators of the suitability of the land for rice.

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References

Arkansas Natural Resources Commission (ANRC). 2014. Arkansas Water Plan 2014 Update. Available at: https://arwaterplan.arkansas.gov/plan/ArkansasWaterPlan/Default.htm. Accessed November 23, 2022.

Bandiera, O. and I. Rasul. 2006. Social networks and technology adoption in northern Mozambique. *The Economic Journal* 116(514): 869-902.

Conley, T. and C. Udry. 2010. Learning about a new technology: Pineapple in Ghana. *American Economic Review* 100(1): 35-69.

Crane-Droesch, A. 2018. Technology diffusion, outcome variability, and social learning: Evidence from a field experiment in Kenya. *American Journal of Agricultural Economics* 100(3): 955-974.

Edwards, J.F. 2016. Crop Irrigation Survey: Final Report. Social Science Research Center, Survey Research Laboratory, Mississippi State University, Starksville, MS.

Enriquez, Y., S. Yadaz, G.K. Evangelista, D. Villanueva, M.A. Burac, and V. Pede. 2021. Disentangling challenges to scaling alternate wetting and drying technology for rice cultivation: Distilling lessons from 20 years of experience in the Philippines. *Frontiers in Sustainable Food Systems* 5: 675818.

Frisvold, G. and T. Bai. 2016. Irrigation technology choice as adaptation to climate change in the western United States. *Journal of Contemporary Water Research and Education* 158(1): 62-77.

Genius, M., P. Koundouri, C. Nauges, and V. Tzouvelekas. 2014. Information transmission in irrigation technology adoption and diffusion: Social learning, extension services, and spatial effects. *American Journal of Agricultural Economics* 96(1): 344-382.

Green, G., D. Sunding, D. Zilberman, and D. Parker. 1996. Explaining irrigation technology choices: A microparameter approach. *American Journal of Agricultural Economics* 78(4): 1064-1072.

Heckman, J.J. 1979. Sample selection as a specification error. *Econometrica* 47(1): 153-161.

Henry, C.G., S.L. Hirsch, M.M. Anders, E.D. Vories, M.L. Reba, K.B. Watkins, and J.T. Hardke. 2016. Annual irrigation water use for Arkansas rice production. *Journal of Irrigation and Drainage Engineering* 142(11): 05016006.

Huang, Q., Y. Xu, K. Kovacs, and G. West. 2017. Analysis of factors that influence the use of irrigation technologies and water management practices in Arkansas. *Journal of Agricultural and Applied Economics* 49(2): 159-185.

Kovacs, K., J. Lee, C. Henry, L.J. Krutz, R. Nayga, and F. Tsiboe. 2019. Factors influencing the willingness to pay for on-farm water infrastructure. *Journal of Soil and Water Conservation* 74(3): 259-268.

Maertens, A. and C.B. Barrett. 2013. Measuring social networks' effects on agricultural technology adoption. *American Journal of Agriculture Economics* 95(2): 353-359.

Maertens, A., H. Michelson, and V. Nourani. 2020. How do farmers learn from extension services?: Evidence from Malawi. *American Journal of Agricultual Economics* 103(2): 569-595.

Massey, J.H., M.L. Reba, M.A. Adviento-Borbe, Y.L Chiu, and G.K. Payne. 2022. Direct comparisons of four irrigation systems on a commercial rice farm: Irrigation water use efficiencies and water dynamics. *Agricultural Water Management* 266(1): 107606.

National Agricultural Statistics Service (NASS). 2018a. 2018 Irrigation and Water Management Survey. Table 2: Irrigated Farms by Acres Irrigated: 2018 and 2013. U.S. Department of Agriculture. Available at: https://www.nass.usda.gov/Publications/AgCensus/2017/Online_Resources/Farm_and_Ranch_Irrigation_Survey/fris_1_0002_0002.pdf. Accessed January 22, 2024.

National Agricultural Statistics Service (NASS). 2018b. Irrigation and Water Management Survey. Table 29: Gravity Irrigation in Fields in the Open: 2018 and 2013. U.S. Department of Agriculture. Available at: https://www.nass.usda.gov/Publications/AgCensus/2017/Online_Resources/Farm_and_Ranch_Irrigation_Survey/fris_2_0029_0029.pdf. Accessed January 22, 2024.

National Agricultural Statistics Service (NASS). 2018c. Irrigation and Water Management Survey. Table 30: Sprinkler Irrigation in Fields in the Open: 2018 and 2013. U.S. Department of Agriculture. Available at: https://www.nass.usda.gov/Publications/AgCensus/2017/Online_Resources/Farm_and_Ranch_Irrigation_Survey/fris_2_0030_0030.pdf. Accessed January 22, 2024.

National Agricultural Statistics Service (NASS). 2018d. Irrigation and Water Management Survey. Table 39: Water Management Practices Used by Producers with Gravity Systems for Acres in the Open: 2018 and 2013. U.S. Department of Agriculture. Available at: https://www.nass.usda.gov/Publications/AgCensus/2017/Online_Resources/Farm_and_Ranch_Irrigation_Survey/

fris_2_0039_0039.pdf. Accessed January 22, 2024.

National Agricultural Statistics Service (NASS). 2018e. Irrigation and Water Management Survey. Table 25: Barriers to Making Improvements to Reduce Energy Use or Conserve Water: 2018. U.S. Department of Agriculture. Available at: https://www.nass.usda.gov/Publications/AgCensus/2017/Online_Resources/Farm_and_Ranch_Irrigation_Survey/fris_1_0025_0025.pdf. Accessed January 22, 2024.

Nian, Y., Q. Huang, K. Kovacs, C. Henry, and J. Krutz. 2020. Water management practices: Use patterns, related factors, and correlations with irrigated acres. *Water Resources Research* 56: e2019WR025360.

Nishihara, A. and C. Shock. 2001. Cost and benefits of surge irrigation. Malheur Experiment Station, College of Agricultural Sciences, Oregon State University. Available at: https://agsci.oregonstate.edu/mes/irrigation/cost-and-benefits-surge-irrigation#:~:text=Surge%20Irrigation%20can%20reduce%20irrigating,lost%20from%20furrow%2Dirrigated%20fields. Accessed April 30, 2024.

Pokhrel, B., K. Paudel, and E. Segarra. 2018. Factors affecting the choice, intensity, and allocation of irrigation technologies by U.S. cotton farmers. *Water* 10(6): 706.

PRISM Climate Group. 2022. Average Annual Precipitation for Arkansas (1991-2020). Northwest Alliance for Computational Science and Engineering. Available at: https://prism.oregonstate.edu/projects/gallery_view.php?state=AR. Accessed January 22, 2024.

Sampson, G. and E. Perry. 2019a. The role of peer effects in natural resource appropriation: The case of groundwater. *American Journal of Agriculture Economics* 101(1): 154-171.

Sampson, G. and E. Perry. 2019b. Peer effects in the diffusion of water-saving agricultural technologies. *Agricultural Economics* 50(6): 693-706.

Schoengold, K. and D. Sunding. 2014. The impact of water price uncertainty on the adoption of precision irrigation systems. *Agricultural Economics* 45 (6): 729-743.

Schuck, E.C., W.M. Frasier, R.S. Webb, L.J. Ellingson, and W.J. Umberger. 2005. Adoption of more technically efficient irrigation systems as a drought response. *Water Resources Development* 21(4): 651-662.

Shrestha, R.B. and C. Gopalakrishnan. 1993. Adoption and diffusion of drip irrigation technology: An econometric analysis. *Economic Development and Cultural Change* 41(2): 407-418.

Stein, L. 2011. The Way We Irrigate Can and Should Make a Difference. Earth-Kind Landscaping. Texas A&M AgriLife Extension Service. Available at: https://aggie-horticulture.tamu.edu/earthkind/drought/drought-management-for-commercial-horticulture/the-way-we-irrigate-can-and-should-make-a-difference/. Accessed January 22, 2024.

Texas Water Development Board. 2013. Best Management Practices for Agricultural Water Users. Available at: https://www.twdb.texas.gov/conservation/BMPs/Ag/doc/AgMiniGuide.pdf. Accessed January 22, 2024.

Tjernström, E. 2016. Signals, similarity and seeds: Social learning in the presence of imperfect information and heterogeneity. In: *Learning for Adopting: Technology Adoption in Developing Country Agriculture.* FERDI Policy Brief, No. B157, June 1-2 , 2016, Clermont-Ferrand, France.

U.S. Department of Agriculture, Economic Research Service (USDA ERS). 2013. Rural-Urban Continuum Codes. January 2013. Available at: https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/. Accessed May 3, 2024.

U.S. Department of Agriculture/National Agricultural Statistics Service (USDA NASS). 2014. Farm and Ranch Irrigation Survey. Volume 3, Special Studies, Part 1 AC-12-SS-1. Available at: https://omb.report/icr/201805-0535-001/doc/83052201. Accessed January 22, 2024.

University of Arkansas. 2023. Computerized Hole Selection. Division of Agriculture Research and Extension. Available at: https://www.uaex.uada.edu/environment-nature/water/agriculture-irrigation/computerized-hole-selection.aspx. Accessed January 22, 2024.

Ward, P. and V. Pede. 2014. Capturing social network effects in technology adoption: The spatial diffusion of hybrid rice in Bangladesh. *Australian Journal of Agricultural and Resource Economics* 59(2): 225-241.

Wheeler, S., H. Bjornlund, T. Olsen, K.K. Klein, and L. Nicol. 2010. Modelling the adoption of different types of irrigation water technology in Alberta, Canada. In: *Sustainable Irrigation Management, Technologies and Policies III*. C.A. Brebbia, A.M. Marinov, and H. Bjornlund (Eds.). WIT Press, Southampton, UK, pp. 189-201.

Appendix

Appendix A1 has a more expansive literature review than that provided in the introduction. Appendix A2 has additional tables with summary statistics and marginal effects for probit estimation of variables significant at the 15% level or above. Tables A1 and A2 have summary statistics for the dependent variables, and Table A3 has the summary statistics for the explanatory variables significant at the 10% level or below. Table A4 has the summary statistics for the other explanatory variables, significant at the 15% level or above, in the bivariate sample selection analysis for the modeling of the irrigation sources. Table A5 has the marginal effects of the probit estimation for the use of an irrigation source for all variables significant at the 15% level or above. Table A6 has the marginal effects for the explanatory variables for explaining the share of an irrigation source for all variables significant at the 15% level or above.

Appendix A1: Literature Review

We first look at the literature surrounding the influence of peer communication on irrigation choice and the role of outside influencer communication such as extension agents. Next, we look at the literature that considers the influence of the sociodemographic and environmental characteristics of the farm on irrigation choice.

The effectiveness of peer communication depends on how information spreads among peers, such as through the size of the peer group, the distance peers are from each other, and whether an affirmative, neutral, or negative experience with the irrigation practice occurs in the communication. Sampson and Perry (2019a;b) observe that a greater distance among farmers corresponds to a diminishing effect on the influence that one farmer who adopted irrigation has on the other farmer adopting irrigation. Likewise, the larger distance among farmers has a similar effect related to irrigation practice adoption (Maertens and Barrett 2013; Genius et al. 2014). Bandiera and Rasul (2006) find, that as the number of peers in the social group increases, the adoption of sunflower seeds exhibits an inverse-U shape with producers having a 0.271% likelihood to adopt with one to five peers, 0.557% likelihood to adopt with five to ten peers, and 0.300% likelihood to adopt with 10+ peers, respectively. The result indicates that an emerging number of adopters provides more encouragement to a producer to try a new technology or input than a fully established number of adopters.

A peer with good news about an input increases the likelihood of the adoption of an input, but a peer with bad news about an input often decreases the likelihood of the adoption of an input by a greater magnitude (Conley and Udry 2010). An exception to this rule is that Conley and Udry (2010) found that good news about fertilizer increases the chance of fertilizer use more than bad news about the fertilizer decreases the chance of fertilizer use. If the profitability of the technology depends on the variability in the characteristics of the potential adopters (e.g., irrigation feasibility), then the social network has a weaker influence (Tjernström 2016). The ability to learn from others is more challenging if important characteristics of the farm that determine the success of the new technology are unobservable. Crane-Droesch (2018) considers the role of social learning in the adoption of a soil amendment to improve fertility and shows that both the expected profitability and the associated risk transmit through social networks.

Outside influencer communication includes extension agents that promote alternative farming practices for the sake of reducing input costs and conserving natural resources. However, the role of extension agents in the adoption of new farming practices is negative or insignificant in some cases (Conley and Udry 2010; Ward and Pede 2014) while the role is positive in other studies (Genius et al. 2014). As the distance between the farm and an extension office increases, the extension agents spend less time at the farm. Rural farms likely receive less information from the extension personnel (Genius et al. 2014). The influence of peer interaction on input choice and farm practices is stronger than information from extension agents (Ward and Pede 2014).

The irrigation water sources and practices chosen also depend on the sociodemographics of the farm operator and the environmental characteristics of the farm. Pokhrel et al. (2018) find that as age increases, the likelihood of a cotton producer using conventional furrow irrigation rises, while the likelihood of pivot and drip does not change. As producers age, they are less likely to change farm practices during times of production uncertainty and less likely to engage in labor-intensive practices (Wheeler et al. 2010). The scale of a large farm allows for more investment in efficient irrigation practices, and this increases the likelihood of precision agriculture adoption (Green et al. 1996). Uncertainty in precipitation makes Coloradan producers more likely to adopt sprinkler systems (Schuck et al. 2005), but California producers are less likely to use precision irrigation (Schoengold and Sunding 2014).

High income from on-farm activities increases the likelihood of irrigation practice adoption, but high income from off-site activities decreases irrigation practice adoption (Wheeler et al. 2010; Frisvold and Bai 2016). As water prices increase through fuel expenses at a well, producers are more likely to use efficient irrigation practices such as sprinkler and drip but less likely to use inefficient practices such as furrow (Schoengold and Sunding 2014; Frisvold and Bai 2016). However, if low-cost surface water is available with certainty, Schoengold and Sunding (2014) find greater investment in sprinkler and drip irrigation because a producer is confident about repaying the investment loans.

The environmental characteristics (e.g., soil and slope) also can affect irrigation choices. Farmers are slow to adopt drip irrigation on soils derived from sandy limestone than from soils of differing texture (Genius et al. 2014). Other properties of the soil such as bulk density, pH, and total water stable aggregates affect the irrigation practices too. Producers with desirable properties in the soil and high fertility are more likely to use drip irrigation while producers with low fertility soils are less likely to use drip irrigation (Shrestha and Gopalakrishnan 1993). A 1% increase in the slope steepness in California increases the likelihood of drip irrigation by 0.23%, sprinkler irrigation by 0.01%, precision irrigation by 9.81%, and the likelihood of furrow irrigation decreases by 0.32% (Green et al. 1996).

Appendix A2: Table of Summary Statistics and the Marginal Effects of Explanatory Variables Significant at the 15% Level or Above

Table A1. Summary statistics for dependent variables of irrigation source choice.

Variable	Definition	Percentage
SW	=1 if use natural surface source	0.404
SWRes	=1 if use surface water stored in a reservoir alone	0.187
SWResTWR	=1 if use surface water stored in a reservoir with a tail-water recovery system	0.287
GW	=1 if use a groundwater source	0.930
ResTWR	=1 if use a reservoir filled by a tail-water recovery system alone	0.211

Number of observations: 170.

Table A2. Summary statistics for dependent variables for the share of water applied by irrigation source.

Variable	Definition	Mean	Std. Dev	10th Percentile	90th Percentile
Share_SW	Share of water applied from a natural source	0.13	0.24	0	1
Share_SWRes	Share of water applied from surface water stored in reservoir alone	0.04	0.16	0	1
Share_SWResTWR	Share of water applied from surface water stored in a reservoir with a tail-water recovery system	0.06	0.15	0	1
Share_GW	Share of water applied from groundwater	0.74	0.32	1	1
Share_ResTWR	Share of water applied from a reservoir filled by a tail-water recovery system alone	0.03	0.08	0	1

Number of observations: 170.

Table A3. Explanatory variables for irrigation source modeling.

Variable	Definition	Percentage
PeerTWR	=1 if peers* used a tail-water recovery system	0.71
PeerAltWetDry	=1 if peers used alternate wetting and drying for rice irrigation	0.35
PeerCHS	=1 peers used computerized hole selection	0.56
PeerSurge	=1 if peers used surge irrigation	0.36
PeerPlevel	=1 if peers used precision leveling	0.90
PeerRes	=1 if peers used storage reservoir	0.65
PeerEndBlock	=1 if peers used end blocking, cutback irrigation, or furrow diking in irrigation	0.55
PeerSched	=1 if peers used scientific scheduling	0.53
PeerPivot	=1 if peers used center pivot	0.66
PeerMI	=1 if used multiple inlets for rice irrigation	0.70
PeerZeroGrade	=1 if peers used zero grade leveling	0.75

*Peers include family members, friends, or neighbors using a practice within the past 10 years.

Farm, irrigation, and socioeconomic characteristics

Variable	Definition	Percentage
AltWetDry	=1 if use alternate wetting and drying for rice irrigation on farm	0.05
AdvEdu	= 1 if producer has a graduate degree	0.09
Bach	= 1 if producer has a Bachelor's degree	0.44
CHS	=1 if use computerized hole selection on farm	0.35
DieselPump	=1 if use diesel pump on farm	0.91
ElectricPump	=1 if use electric pump on farm	0.88
EndBlock	=1 if use end-blocking, cutback irrigation, or furrow diking in irrigation	0.32
GP	=1 if county is in the Grand Prairie (i.e., Arkansas, Lonoke, Prairie, Pulaski, and White counties)	0.19
MI	=1 if use multiple inlets for rice irrigation on farm	0.27
ND	=1 if county is in the northern Arkansas Delta (i.e., Independence, Jackson, Lawrence, Monroe, Randolph, and Woodruff counties)	0.12
Pivot	=1 if use center pivot on farm	0.39
Plevel	=1 if precision leveling on farm	0.84
ReasonFin	=1 if primary reason for tail-water recovery system or reservoir was financial assistance	0.06
Ridge	=1 if county is in Crowley's Ridge (i.e., Clay, Craighead, Cross, Greene, Lee, Poinsett, and St. Francis counties)	0.32
River	=1 if county is along Mississippi River (i.e., Chicot, Crittenden, Desha, Mississippi, and Phillips counties)	0.23
Res	=1 if use reservoir on farm	0.38
Sched	=1 if use scientific scheduling on farm	0.05
SD	=1 if county is in the South Delta (i.e., Ashley, Drew, Jefferson, and Lincoln counties)	0.07
Surge	=1 if use surge irrigation on farm	0.39
TWR	=1 if use tail-water recovery system on farm	0.49
UsedFlowMeter	= 1 if flowmeter used	0.38
ZeroGrade	=1 if use zero grade leveling on farm	0.37

(Table A3 continued. Explanatory variables for irrigation source modeling.)

Variable	Definition	Mean	Std Dev.
AgEdu	=1 if holds an agriculture related degree	0.59	0.49
AllClay	Percent of land in the producer's county of residence with a clay and clay loam component in the soil	15.11	17.14
AllSand	Percent of land in the producer's county of residence with a fine sand, fine sandy loam, sand, sandy clay, sandy clay loam, sandy loam, and very fine sandy loam	9.24	7.65
AWS	Root zone between 0 to 150 centimeters available water storage (cm)	23.32	2.77
CanalDitch	Kilometer of canals and ditches in the county of the producer's residence	36.81	31.03
GDD	Average degree days between 283.15 and 304.82 Kelvin between 2005 and 2015 (degrees*days)	654,674	33,073
OrgMatter	Percent of organic matter in the producer's county of residence to a depth of 150 cm	1.6	0.24
pH>6.0	Percent of land in the county of the producer's residence with a pH greater than 6.0	24.27	16.86
PPT	Average growing season precipitation between 2005 and 2015 (cm)	68.28	11.61
RUCC2013	Rural-Urban Continuum code of site in 2013	5.12	2.07
StreamRiver	Kilometer of streams and rivers in the county of the producer's residence	137.30	70.78

Table A4. Additional explanatory variables for irrigation source modeling.

Variable	Definition	Percentage	
PeerTWR*ND	= 1 if peers^ used a tail-water recovery system in the northern Arkansas Delta region	0.09	
PeerTWR*CHS	= 1 if peers used a tail-water recovery and computerized hole selection	0.26	
PeerSurge*CHS	=1 if peers used surge irrigation and computerized hole selection	0.17	
PeerSurge*GP	=1 if peers used surge irrigation in the Grand Prairie region	0.05	
PeerCHS*SD	=1 if peers used computerized hole selection in the South Delta region	0.03	
PeerEndBlock*CRP	= 1 if peers used end blocking and participate in the conservation reserve program	0.28	
PeerEndBlock*EQIP	= 1 if peers used end blocking and participates in an environmental quality incentive program	0.35	
PeerEndBlock*ND	= 1 if peers used end blocking in the northern Arkansas Delta region	0.09	
PeerZeroGrade*GP	= 1 if peers used zero grade leveling in the Grand Prairie region	0.14	
PeerRes*FinReason	= 1 if peers used a reservoir and federal storage	0.24	
^Peers include family members, friends, or neighbors using an irrigation practice within the past 10 years.			
Farm and irrigation characteristics			
IrrCotton	= 1 if grows irrigated cotton	0.14	
ExpCorn	= 1 if corn yield expected in bushels/acre	102.19	
DepthIncrease	=1 if water tables have increased in height over past five years	0.12	
		Mean	**Std Dev.**
FineSand	Percent of land in the producer's county of residence with a fine sand	0.21	0.69
Socioeconomic characteristics			
IncomeNA	Net income not reported	0.24	0.43
IncomeHigh	Net income > $200,000	0.13	0.34

Table A5. Marginal effects from probit estimation: All variables significant at or above 15th percentile.

Variable	SW	SWRes	SWResTWR	GW	ResTWR
AltWetDry	0.09 (0.14)	0.01 (0.02)			0.02 (0.02)
CHS	-0.17 (0.18)	0.001 (0.02)	0.008 (0.66)	0.01 (0.01)	-0.003 (0.01)
EndBlock	-0.01 (0.05)	-0.01 (0.02)	0.22 (0.54)	-0.01 (0.01)	-0.01 (0.01)
ExpCorn			0.0002 (0.50)		
IncomeNA	-0.11 (0.27)				0.07 (0.16)
IncomeHigh	0.001 (0.99)				0.07 (0.19)
DepthIncrease			0.13 (0.16)		
MI	0.03 (0.06)	-0.04 (0.04)	-0.63 (0.58)	0.001 (0.01)	0.003 (0.01)
PeerRes			0.12 (0.16)		
PeerCHS	0.15 (0.16)				
PeerSched					-0.04 (0.21)
PeerTWR		0.06 (0.21)			
PeerTWR*ND	0.28 (0.17)				
PeerTWR*CHS	-0.16 (0.15)				
PeerSurge*CHS		-0.06 (0.51)			
PeerCHS*SD		0.14 (0.15)			
PeerEndBlock*CRP				0.04 (0.26)	
PeerEndBlock*EQIP				-0.05 (0.21)	
Pivot	-0.03 (0.06)	0.02 (0.03)	0.28 (0.82)	0.01 (0.01)	-0.02 (0.02)
Plevel	-0.05 (0.07)	0.03 (0.03)		0.01 (0.01)	0.001 (0.01)
Res	-0.05 (0.07)	0.04 (0.04)		-0.001 (0.01)	0.02 (0.02)
Sched	-0.05 (0.15)		-1.72 (1.46)		0.01 (0.02)
Surge	0.07 (0.08)	0.03 (0.03)	-0.03 (0.72)	-0.004 (0.01)	-0.003 (0.01)
TWR	0.08 (0.09)	0.01 (0.02)		0.004 (0.01)	0.002 (0.01)
ZeroGrade	0.05 (0.06)	0.01 (0.02)	-0.43 (0.65)	-0.002 (0.01)	0.01 (0.01)

Table A6. Marginal effects from bivariate sample selection: All variables significant at or above 15th percentile.

Variable	SW	SWRes	SWResTWR	GW	ResTWR
AltWetDry	-0.05 (0.12)		-0.02 (0.15)	-0.01 (0.07)	-0.09 (0.07)
CHS	-0.01 (0.15)	-0.23 (0.28)	0.03 (0.04)		
EndBlock	0.11 (0.06)		-0.06 (0.12)	-0.04 (0.03)	
IrrCotton	-0.001 (0.24)				
ExpCorn	-0.002 (0.25)	0.002 (0.33)	-0.003 (0.31)	-0.01 (0.50)	
DepthIncrease			0.03 (0.32)		
IncomeNA	-0.04 (0.66)				
IncomeMid				-1.57 (0.63)	-0.04 (0.40)
FineSand	0.08 (0.17)			2.40 (0.37)	
MI	-0.06 (0.06)	-0.27 (0.56)		-0.01 (0.03)	0.04 (0.03)
PeerZeroGrade*GP	-0.09 (0.28)				
PeerRes*FinReason	-0.08 (0.16)				
PeerSurge*GP					-0.03 (0.47)
PeerEndBlock*ND					-0.03 (0.41)
Pivot	-0.11 (0.08)		-0.07 (0.05)		
Plevel	-0.02 (0.09)	-0.33 (0.45)	-0.03 (0.18)	0.65 (0.03)	
Res	-0.12 (0.08)	-0.35 (0.41)			
Sched	-0.01 (0.16)	-0.07 (0.13)	0.02 (0.10)	0.03 (0.07)	
Surge		-0.21 (0.24)	-0.05 (0.21)	0.04 (0.04)	
TWR	-0.04 (0.11)		-0.13 (0.17)		
ZeroGrade	-0.04 (0.07)	-0.19 (0.21)		-0.06 (3.18)	

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Distribution of Per- and Polyfluoroalkyl Substances in the Rapidly Urbanizing Arroyo Colorado Watershed, Texas

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Abstract: This study presents the first report of per- and polyfluoroalkyl substances (PFAS) in water samples collected in the Arroyo Colorado (n = 15), irrigation canals (n = 6), stormwater and wastewater retention ponds (n = 7), as well as drinking waters (n = 2) across the Arroyo Colorado watershed. Of the 30 PFAS monitored in this study, 14 were detected in the samples in various combinations. Short-chain PFAS (less than 8 carbon atoms) were observed in most samples. Water collected from the Arroyo Colorado showed significant spatial variabilities, with high total PFAS concentrations observed near possible point sources - a municipal airport and wastewater treatment facilities. PFAS concentrations were generally higher in water samples collected in stormwater and wastewater retention ponds than in the Arroyo Colorado and irrigation canals. PFAS in stormwater retention ponds likely came from roadway runoff. Short-chain PFAS were observed in the two municipal water samples, but they were below the current U.S. EPA regulation limits or are not currently regulated. This study provides useful information for water quality in this region and provides insights into PFAS occurrence in a rapidly urbanizing area.

Keywords: *PFAS, urban water, agriculture*

Per- and polyfluoroalkyl substances (PFAS) are a diverse group of human-made chemicals with more than 10,000 chemicals found, to date, in the United States Environmental Protection Agency's CompTox Chemicals Dashboard (U.S. EPA 2023). PFAS are broadly used in many industrial and consumer products due to their unique physical-chemical properties. PFAS are in items we use every day, such as non-stick cookware, food packaging, textiles, cosmetics, and beyond (Trier et al. 2011; Glüge et al. 2020; Whitehead et al. 2021; Schellenberger et al. 2022). Aqueous film-forming foam (AFFF), which has been used to extinguish hydrocarbon-fuel fires for several decades, contains various PFAS compounds (Backe et al. 2013; Ruyle et al. 2021). Many PFAS are bioaccumulative and toxic to animals and humans (Giesy and Kannan 2001; Fenton et al. 2021; George et al. 2023).

PFAS are chemically diverse. Perfluorinated PFAS have fully fluorinated carbon chains, while polyfluorinated PFAS contain multiple carbon-fluorine bonds, but not all carbon atoms are bonded to fluorine. Additionally, PFAS are grouped based on the polar functional groups they contain, e.g., carboxylic, sulfonic, sulfonamide, etc. (Table 1). These chemical characteristics affect their fate and transport in the environment. PFAS with fully fluorinated carbon chains, i.e., perfluorinated, are extremely resistant to degradation and, thus, are persistent in the environment after release (Kwiatkowski et al. 2020). While polyfluorinated PFAS may be degraded in the environment, they are precursors to the perfluorinated compounds (Houtz

Research Implications

- This is the first report on PFAS concentrations in the rapidly urbanizing Arroyo Colorado watershed, and it provides critical information on water quality in this region.
- PFAS were found in almost all water samples in this study, particularly short-chain PFAS. Short-chain PFAS may be taken up by plants, such as crops.
- This survey showed significant spatial heterogeneity of PFAS concentrations across the Arroyo Colorado watershed, with more PFAS types closer to possible sources. Concentrations and type distributions are both critical for understanding PFAS fate and transport within a watershed. Future studies should also consider temporal distributions.

et al. 2013). PFAS are more mobile in the aqueous phase than non-polar legacy contaminants, such as dioxins, polychlorinated biphenyls (PCBs), and polybrominated diphenyl ethers (PBDEs), due to their amphiphilic properties. Therefore, PFAS are ubiquitously distributed in groundwater, surface waters, sediments, soil, air, and even our drinking water (Jahnke et al. 2009; Houtz et al. 2013; Domingo and Nadal 2019; Aly et al. 2020; Strivens et al. 2021; Teymoorian et al. 2023).

There are numerous sources of PFAS with various combinations of compounds within this chemical class. Therefore, it is critical to understand which PFAS and at what concentrations are found in the environment to better assess possible exposure risks. In the past decade, researchers have investigated PFAS occurrence in different waterbodies worldwide because water can transport PFAS for long distances and is closely related to human exposure through water supplies and fish (Scott et al. 2009; Moller et al. 2010; Lam et al. 2014; D'Agostino and Mabury 2017; Gebbink et al. 2017; Groffen et al. 2018; Aly et al. 2020; Goodrow et al. 2020; Guillette et al. 2020; Ruyle et al. 2021). However, the diverse chemical characteristics and sources of PFAS likely mean that data from other waterbodies may not be extrapolated in certain regions. To date, information on the occurrence of PFAS in Texas rivers is scarce. This study investigates the distribution of 30 PFAS in the Arroyo Colorado watershed (Figure 1).

The Arroyo Colorado Watershed

The Arroyo Colorado watershed is located in the Lower Rio Grande Valley of South Texas,

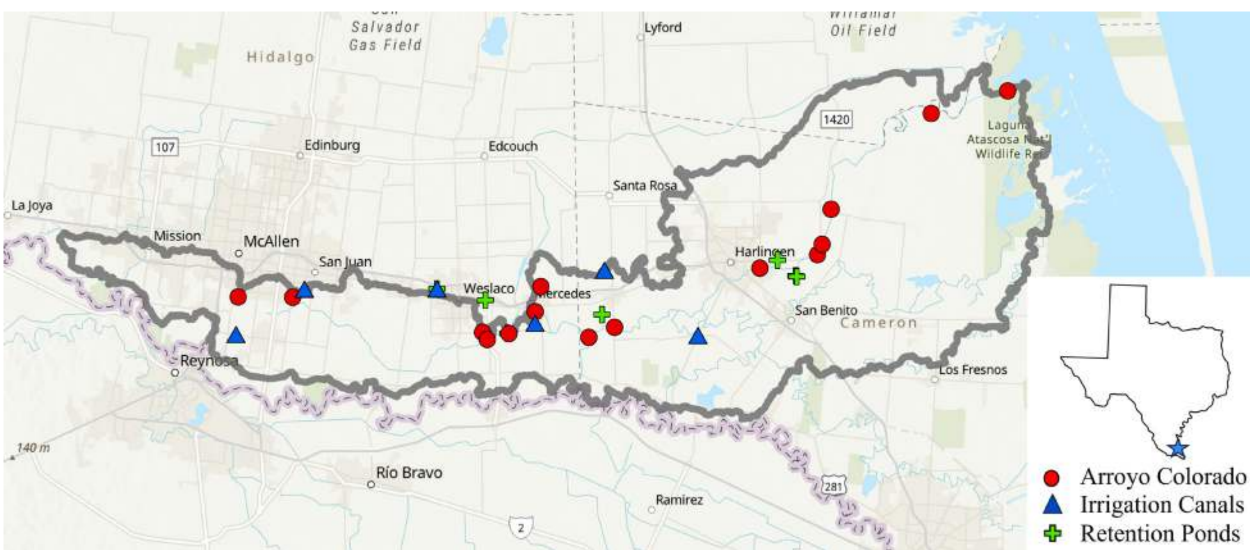

Figure 1. Sampling sites of this study. Red circles mark the locations of water samples collected in the Arroyo Colorado. Blue triangles mark the locations of water samples collected in irrigation canals. Green crosses mark the locations of water samples collected in stormwater or wastewater treatment plant retention ponds. The grey outline marks the boundary of the Arroyo Colorado watershed.

and includes portions of Cameron, Hidalgo, and Willacy counties. McAllen (Hidalgo County) and Harlingen (Cameron County), TX, are both considered urban areas in the 2020 U.S. Census. Smaller cities partly within the watershed include Mission, Pharr, San Juan, Alamo, Donna, Weslaco, Mercedes, La Feria, San Benito, and Rio Hondo. The entire area is undergoing urbanization, and many historically farmed lands are being converted to urban uses.

The Arroyo Colorado (~ 90 miles long), which flows eastward into the Lower Laguna Madre from its headwaters near Mission, is a historic distributary of the Rio Grande and lies within the Rio Grande delta. The Arroyo Colorado watershed is served by multiple irrigation districts that supply Rio Grande water across the Lower Rio Grande Valley for agricultural irrigation water and raw drinking water. Irrigation canals are hydrologically disconnected from the Arroyo Colorado, but irrigation return flows from these sources do flow into the Arroyo Colorado in many cases. In normal flow conditions, the Arroyo Colorado consists primarily of treated municipal wastewater effluent, agricultural irrigation return flows, and stormwater from the watershed. The lower 25 miles of the Arroyo Colorado are tidally influenced. This section has been dredged and is maintained as a ship and barge channel for the Port of Harlingen. In flood conditions, the Arroyo Colorado hydrologically connects to the Rio Grande and the North Floodway.

Approximately 706 square miles of land drains into the Arroyo Colorado. Primary land cover includes croplands (53%), rangelands/forests (14%), pastures (6%), mixed intensity developed spaces (19%), wetlands (8%), and waterbodies (Flores et al. 2017). Soils in the region range from sandy to silty loams across the larger Rio Grande delta and support large agricultural enterprises. Originally, cattle ranching dominated the region due to limited water resources. Large-scale irrigation changed this in the early 1900s, and the arrival of the railroad in 1904 allowed cultivated agriculture to expand rapidly (Vigness and Odintz 1952). This region is still agriculturally dominated, but has experienced rapid land use changes. Between 2001 and 2021, approximately 16,532 acres of agricultural working lands were converted into other uses, while developed space has increased by 14,268 acres representing a roughly 4% loss of open space across the watershed (Dewitz 2023). This rapid conversion continues today as importing goods and produce from Mexico has led to considerable industrial development. Agriculture and municipalities represent the largest scale water users in the watershed, and the return flows from these sources largely sustain flows in the Arroyo Colorado. These return flows carry nutrients, sediment, bacteria, and many pollutants (e.g., PCBs) into the water body, leading to various water quality impairments and concerns. However, PFAS concentrations have never been assessed in the Arroyo Colorado watershed. Therefore, this study will provide critical information on water resource quality in the Arroyo Colorado.

Methods

Sampling

All supplies, such as sample containers, laboratory consumables, solvents (Optima LC-grade), etc., were screened for PFAS to ensure the supplies were free of PFAS contamination before the study. Both field and laboratory blanks were ultrahigh-purity water (Milli-Q 18.2 MΩ·cm) contained in the same type of high-density polyethylene (HDPE) 250 mL bottles used for sample collection.

Sampling occurred on January 31st and February 1st, 2023, to cover areas across the Arroyo Colorado watershed. We collected samples in different sections of the Arroyo Colorado and irrigation canals to assess whether areas undergoing rapid urbanization experienced PFAS contamination and, if so, which PFAS. We collected 15 water samples in the Arroyo Colorado and 6 samples in irrigation channels. We also collected 7 samples from stormwater and wastewater treatment facility (WWTF) retention ponds in the region. To provide context to possible exposure to PFAS through drinking water, we also collected 2 drinking waters in the region.

Environmental water samples were collected via a HDPE bucket and rope. Prior to each sample collection, the bucket was triple rinsed with ambient water from the sampling site. Rinse water was deposited on the bank to minimize instream disturbance. Water samples were drawn as near to the middle of the waterway as possible, poured into 250 mL HDPE bottles, and kept cold (on ice) until they arrived in the Halo-Carbon Laboratory on the Texas A&M University Campus in College Station, TX. Water samples were stored at ~4°C in the laboratory until extraction. All water samples were extracted within 14 days of collection.

PFAS Quantification

Thirty PFAS were quantified based on established analytical methods (Aly et al. 2020; Strivens et al. 2021; Hayman et al. 2023) (Table 1). PFAS samples, spiked with isotopically labeled extraction standard, were extracted with Water's Oasis weak anion exchange (WAX) solid phase extraction. PFAS concentrations were analyzed by High-Performance Liquid Chromatography (HPLC, Agilent 1290 Infinity II) / Triple Quadrupole Mass Spectrometer (QqQ-MS, Agilent 6470) equipped with a Jet Stream electrospray ionization (ESI) source. Twenty µL of samples in 96% methanol were injected and then separated by an Agilent ZORBAX Eclipse Plus C-18 narrow bore (2.1 mm × 50 mm, 1.8 µm) HPLC column maintained at 50°C. The flow rate was 0.4 mL min^{-1}. Chromatographic separation was achieved on Solvent A (5 mM ammonium acetate in water) and Solvent B (95% MeOH and 5% water with 5 mM ammonium acetate). The separation gradient method used was 0 - 0.5 min (holding at 10% B), 0.6 - 2 min (10% B to 30% B), 2.1 - 14 min (30% B to 95% B), 14.1 - 14.5 min (95 % B to 100 % B), 14.6 to 16.5 min (holding at 100% B), and then stabilize the column at 10% B for 6 min before the next injection. Mass spectrometer parameters were optimized for PFAS compounds under direct infusion at 0.4 mL min^{-1} to identify the MRM transitions (precursor/product fragment ion pair). Sample acquisition and analysis were performed with MassHunter B.08.02 (Agilent). Limits of quantifications, which were determined by serial dilution of PFAS standards, were 0.313 ng mL^{-1} for the perfluoroalkyl carboxylic acids and perfluoroalkyl sulfonic acids, and 3.13 ng mL^{-1} for the fluorotelomer sulfonic acids, perfluoroalkane sulfonamides, perfluorooctane sulfonamidoacetic acids, per- and polyfluoroether carboxylic acids, and fluorotelomer carboxylic acids. Recoveries for all PFAS monitored in this study were 102 ± 17%. Sample triplicates were collected in a randomly selected location; one served as the regular sample, one served as a matrix spike, and one served as a matrix spike duplicate. Based on these samples, we confirmed that sampling and detection of PFAS were reproducible (< 5.1% variability).

Results and Discussion

PFAS in the Arroyo Colorado and Irrigation Canals

Of the 30 PFAS we monitored, 14 of them, namely, PFBA (C4), PFBS (C4), PFPeA (C5), PFPeS (C5), PFHxA (C6), PFHxS (C6), PFHpA (C7), PFHpS (C7), PFOA (C8), PFOS (C8), PFNA (C9), PFDA (C10), 6:2 FTS (C8), N-MeFOSAA (C11), were detected in various combinations in the samples (Table 1 and Table 2). Twenty of the 21 water samples (95%) collected in the Arroyo Colorado and irrigation canals have detectable amounts of PFAS. Most samples in the Arroyo Colorado and irrigation canals only contain shorter chain PFAS (less than 8 carbon atoms), besides a few isolated cases (Table 1 and Table 2). The total amounts of PFAS detected in these samples were spatially heterogeneous, with several locations having significantly higher concentrations than others (Figure 2). These samples were collected near sources known to release PFAS, such as WWTFs and airports (Clara et al. 2008; Houtz et al. 2018; Milley et al. 2018; Lenka et al. 2021; Carey et al. 2022; Helmer et al. 2022; Liu et al. 2022).

The highest total PFAS concentration (1259.88 ng L^{-1}) in the Arroyo Colorado was detected in AC13, which was collected south of the McAllen airport (Table 2 and Figure 2). This sample also contains a diverse number of PFAS with a wide range of carbon chain lengths (C4 to C8), namely PFBA, PFBS, PFPeA, PFPeS, PFHxA, PFHxS, PFHpA, PFHpS, PFOA, PFOS, and 6:2 FTS. AC13 is also the only site where 6:2 FTS was detected (698.06 ng L^{-1}). 6:2 FTS is found in AFFF formulations and AFFF-impacted sites (Houtz et al. 2013; Houtz et al. 2016; Méndez et al. 2022). 6:2 FTS concentration in AC13 was comparable to that found in certain locations in the Houston

Table 1. List of PFAS analytes with their abbreviations, number of carbon atoms per molecule, and number of total samples they were observed in.

Target Analyte Name	Abbreviation	Carbon Number	Number of Samples Observed In (Total = 30)
Perfluoroalkyl carboxylic acids			
Perfluorobutanoic acid	PFBA	4	24
Perfluoropentanoic acid	PFPeA	5	26
Perfluorohexanoic acid	PFHxA	6	27
Perfluoroheptanoic acid	PFHpA	7	3
Perfluorooctanoic acid	PFOA	8	4
Perfluorononanoic acid	PFNA	9	1
Perfluorodecanoic acid	PFDA	10	1
Perfluoroundecanoic acid	PFUdA	11	0
Perfluorododecanoic acid	PFDoA	12	0
Perfluorotridecanoic acid	PFTrDA	13	0
Perfluorotetradecanoic acid	PFTeDA	14	0
Perfluorohexadecanoic acid	PFHxDA	15	0
Perfluoroalkyl sulfonic acids			
Perfluorobutanesulfonic acid	PFBS	4	20
Perfluoropentansulfonic acid	PFPeS	5	2
Perfluorohexanesulfonic acid	PFHxS	6	2
Perfluoroheptanesulfonic acid	PFHpS	7	2
Perfluorooctanesulfonic acid	PFOS	8	5
Perfluorononanesulfonic acid	PFNS	9	0
Perfluorodecanesulfonic acid	PFDS	10	0
Perfluorododecanesulfonic acid	PFDoS	12	0
Fluorotelomer sulfonic acids			
1H,1H, 2H, 2H-Perfluorohexane sulfonic acid	4:2 FTS	6	0
1H,1H, 2H, 2H-Perfluorooctane sulfonic acid	6:2 FTS	8	1
1H,1H, 2H, 2H-Perfluorodecane sulfonic acid	8:2 FTS	10	0
Perfluoroalkane sulfonamides			
Perfluoro-1-octanesulfonamide	FOSA-I	8	0
Perfluorooctane sulfonamidoacetic acids			
N-methyl perfluorooctanesulfonamidoacetic acid	N-MeFOSAA	11	1
N-ethyl perfluorooctanesulfonamidoacetic acid	N-EtFOSAA	12	0
Per- and Polyfluoroether carboxylic acids			
Hexafluoropropylene oxide dimer acid	HFPO-DA (Gen-X)	6	0
Fluorotelomer carboxylic acids			
2-Perfluorohexyl ethanoic acid	FHEA	8	0
2-Perfluorooctyl ethanoic acid	FOEA	10	0
2-Perfluorodecyl ethanoic acid	FDEA	12	0

Table 2. PFAS concentrations (ng L^{-1}) in water samples collected from the Arroyo Colorado (AC), irrigation canals (IC), stormwater and wastewater treatment plant (WWTF) retention ponds (RP), and drinking water (municipal water supply and private well water) (PW).

	Sample ID	PFBA	PFBS	PFPeA	PFPeS	PFHxA	PFHxS	PFHpA	PFHpS	PFOA	PFOS	PFNA	PFDA	6:2 FTS	N-MeFOSAA	Total PFAS
Arroyo Colorado																
	AC01	5.48	4.41	11.65		8.23										29.77
	AC02	5.43	3.40	5.93		5.28										20.04
	AC03	4.05	3.51	10.61		7.11										25.28
	AC04	5.99	4.06	13.71		8.07										31.83
	AC05	4.57	3.20	4.49		4.83										17.09
	AC06	4.50	3.38	9.55		7.89										25.32
	AC07	4.29	3.67	12.19		8.88										29.03
	AC08		3.67	10.61		10.64										24.92
	AC09		6.14	18.26		15.95					5.76					46.11
	AC10	4.01	3.99	11.96		9.19										29.15
	AC11	4.05	3.85	11.80		8.94										28.64
	AC12			5.80		4.31										10.11
	AC13	33.92	50.01	113.56	32.01	125.08	140.17	22.92	3.42	12.13	28.60			698.06		1259.88
	AC14	4.97	8.23	28.87		15.47										57.54
	AC15															
Irrigation Canals																
	IC01	5.11		4.50		4.85										14.46
	IC02	4.09		5.83		4.51					3.59					18.02
	IC03	5.38		5.68		3.66										14.72
	IC04	4.71		3.27		3.71										11.69
	IC05	4.20		3.50		3.42										11.12
	IC06	4.57		5.44		5.23										15.24
Retention Ponds																
WWTP 1 Retention Pond	IP01	104.55	157.82	299.20	34.70	330.98	145.61	412.64	31.52	1391.30	553.54	198.96	110.05		39.47	3810.34
WWTP 1 Retention Pond	IP02	12.74	20.73	65.73		30.34		3.65		5.57						138.76
Stormwater 1	IP03	10.11	6.67	46.14		36.17				7.76						106.85
Stormwater 2	IP04	5.22	3.36	4.53		5.94					3.80					22.85
Stormwater 3	IP05															
Stormwater 4	IP06	8.92	7.83			3.85										20.60
WWTP 2 Effluent Pond	IP07	5.96	10.45	29.89		17.28										63.58
Private Water																
Tap Water	PW01	24.57		5.34		5.16										35.07
Groundwater	PW02		4.89													4.89

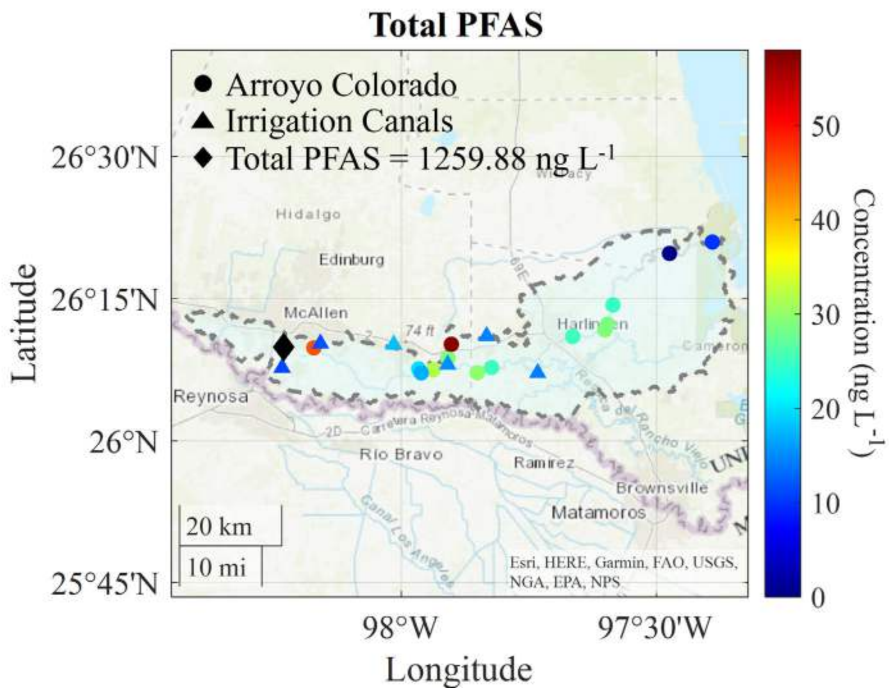

Figure 2. Total PFAS concentrations (ng L^{-1}) in samples collected in the Arroyo Colorado (circles) and irrigation canals (triangles). The black diamond marked the location of water sample collected in the Arroyo Colorado with total PFAS significantly higher than the other samples.

ship channel during the Intercontinental Terminals Company (ITC) fire in March 2019, during which AFFF was actively used (Aly et al. 2020). 6:2 FTS (C8) can be microbially degraded into other PFAS, such as shorter chain PFPeA (C5) and PFHxA (C6) (Méndez et al. 2022), which were also detected in this sample. In surface water, we expect 6:2 FTS concentrations to decrease drastically away from the source due to dilution and degradation, as observed during the ITC fire (Aly et al. 2020). Therefore, site AC13 was likely impacted by AFFF applications at the time of sampling.

Relatively high total PFAS concentrations were also found in samples AC09 (46.11 ng L^{-1}) and AC14 (57.54 ng L^{-1}) (Table 2 and Figure 2). These samples were collected downstream of WWTFs. It should be noted that these samples contain different types of PFAS. AC09 contained PFBS (C4), PFPeA (C5), PFHxA (C6), and PFOS (C8), while AC14 contained shorter chain PFAS, namely, PFBA (C4), PFBS (C4), PFPeA (C5), and PFHxA (C6). PFPeA and PFHxA were the dominant PFAS compounds in both samples (Table 2 and Figure 3). PFPeA accounted for 40% and 50% of the total PFAS detected in AC09 and AC14, respectively. PFHxA accounts for 35% and 27% of the total PFAS detected in AC09 and AC14, respectively. While it is not possible to deduce the sources for PFPeA and PFHxA in these two samples, it would be reasonable to assume they might, in part, be derived from precursor PFAS in WWTFs, such as fluorotelomers like 6:2 FTS. AC09 and AC14 also have elevated PFBS concentrations compared to other samples collected in the Arroyo Colorado, except for A13, which was collected near an airport.

PFBA, PFBS, PFPeA, and PFHxA were the most frequently detected PFAS in samples collected in the Arroyo Colorado and irrigation canals. This is to be expected because short-chain PFAS (less than 8 carbon atoms) are likely to be more mobile in water. PFBS, PFPeA, and PFHxA showed similar spatial heterogeneity (Figure 3), with significantly higher concentrations in sites near an airport or a WWTF. However, PFBA appeared more spatially homogeneous, with higher concentrations in the upper Arroyo Colorado. PFBA may be released directly from its point source or derived from the degradation of higher-chain PFAS in the environment. PFBA was found in Arctic ice cores along with other ultrashort-chain PFAS (less than 4 carbon atoms), suggesting it is highly mobile in water and possibly in the atmosphere. The high environmental mobility of PFBA likely explains the spatial homogeneity observed in this study. PFBA and other PFAS concentrations were lower in the lower Arroyo Colorado (Figures 2 and 3). The only sample (AC15) in the watershed that does not have any detectable PFAS was collected in this region. These findings suggest possible dilution due to tidal movements.

All samples collected in irrigation canals contained short-chain PFAS (C4 to C6). IC02 also contained PFOS (C8). PFAS-containing irrigation water can contaminate soil and plants (Brown et al. 2020). Gen-X and PFOA have been found to cause phototoxicity and bioaccumulation in plants (Chen et al. 2020). Additionally, short-chain PFAS, such as PFBA, PFPeA, and PFHxA, have been found in crop tissues (Mroczko et al. 2022). PFBA, PFPeA, and PFHxA were observed in most of the samples in this study, as well. This suggests that future studies on the occurrence of PFAS in crops in this area are necessary.

Studies of PFAS concentrations across a watershed are rather limited at this time, but the

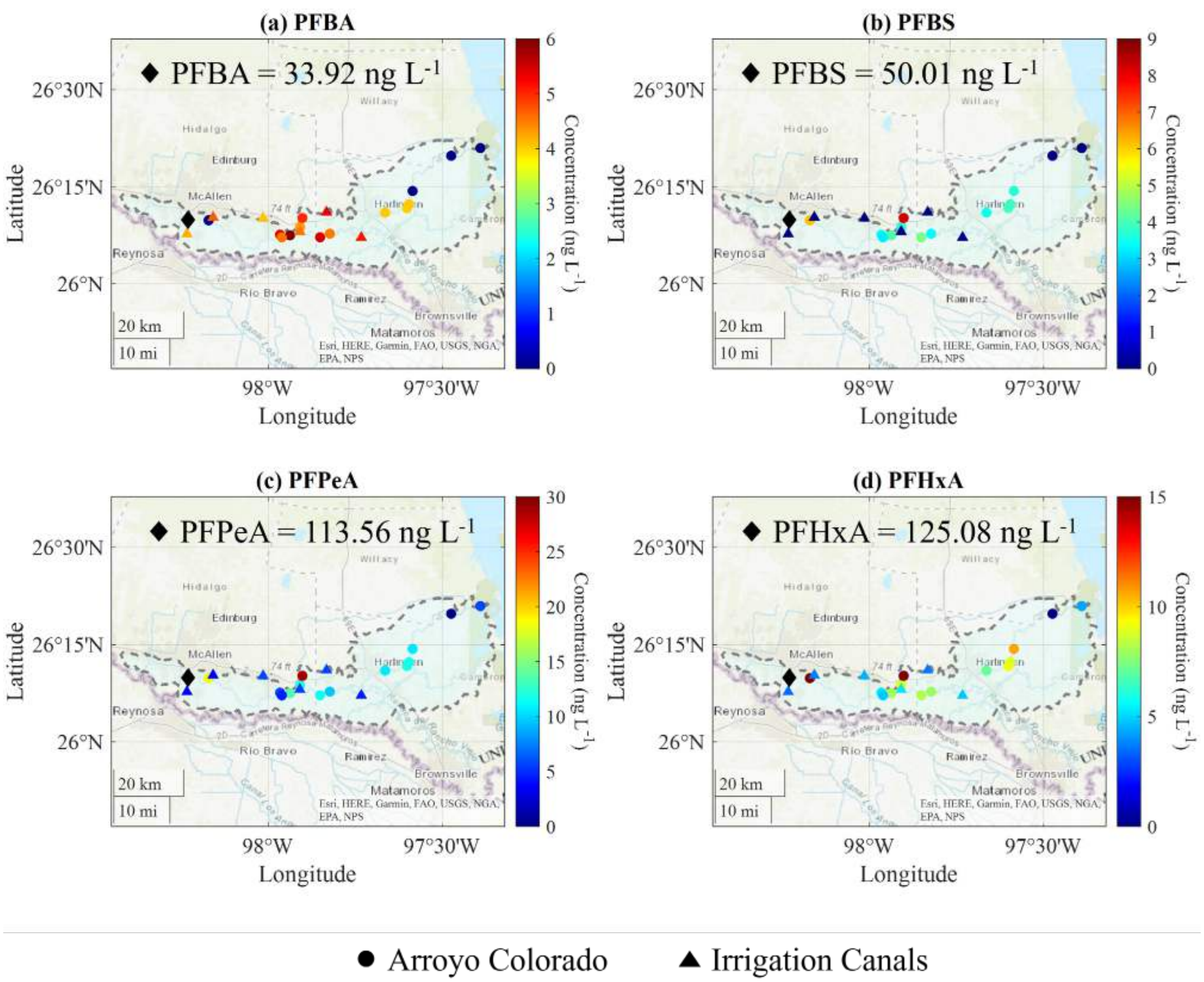

Figure 3. Concentration (ng L^{-1}) distributions of (a) PFBA, (b) PFBS, (c) PFPeA, and (d) PFHxA. Circles mark the locations of samples collected in the Arroyo Colorado. Triangles mark the locations of samples collected in irrigation canals. Black diamonds mark the location of samples collected in the Arroyo Colorado with PFAS significantly higher than the other samples, PFBA = 33.92 ng L^{-1}, PFBS = 50.01 ng L^{-1}, PFPeA = 113.56 ng L^{-1}, and PFHxA = 125.08 ng L^{-1}.

body of literature is rapidly growing. However, it is still difficult to make reasonable comparisons due to various geographical, hydrological, and environmental differences, e.g., the size of watersheds, the level of development, seasonality, river flow rates, or whether known manufacturing sources are present, etc. Here, we compared PFAS concentrations with other survey studies with one-time sample collection (i.e., no temporal coverage) across one or more watersheds. In general, PFAS concentrations in the Arroyo Colorado watershed were higher than in rivers and creeks in Canada and the Truckee River, which is a relatively pristine environment in Nevada, U.S. (Scott et al. 2009; Bai and Son 2021) (Table 3). However, comparisons with other urbanized or industrialized systems with known PFAS manufacturers or point sources are not as straightforward. For example, while total perfluorinated carboxylic acids (ΣPFCA) in the Arroyo Colorado was lower than in the Las Vagas Wash, total perfluorinated sulfonic acids (ΣPFSA) was higher in the Arroyo Colorado (Table 3). These two regions have different developments and, thus, likely have different sources/types of PFAS. Most of the compounds detected in this study were higher than those reported by Gebbink et al. (2017) from a river with a known PFAS production source (Table 3). However, Gebbink et al. (2017) reported elevated Gen-X downstream of the source, while Gen-X was below the detection limit for all samples in this study. ΣPFCA was generally lower than those observed in the Rhine River watershed, but ΣPFSA observed in this study was higher (Moller et al. 2010). It should be noted that even though ΣPFSA reported in this study appeared to be higher than other studies listed in Table 3, it is likely biased due to the fact that data for several PFSA compounds were not available in the other studies. However, besides PFBS, concentrations of the other individual PFSA compounds reported in this study were still higher (Table 3). PFAS concentrations in these studies all showed significant spatial heterogeneities, and the types of PFAS found in different surface waters also varied depending on the distance to the sources and source type. Within this study, we observed substantial spatial heterogeneity and variation of PFAS types closer to a source.

PFAS in Stormwater and WWTF Retention Ponds

Six water samples were collected from stormwater and WWTF retention ponds in the study area. Water from the WWTF retention ponds had been through primary (coagulation, flocculation, and sedimentation) and secondary (biodegradable matter removal) treatments. These ponds do not receive water directly from the Arroyo Colorado or irrigation channels, but some have permits to discharge to the Arroyo Colorado. In other words, we expect less dilution effect in PFAS concentrations. Indeed, PFAS concentrations observed in these samples were generally higher than in samples collected in the Arroyo Colorado and irrigation canals (Table 2). The highest total PFAS of all the samples collected in this study was found in a retention pond of a WWTF (IP01) at 3810.34 ng L^{-1}. IP01 also contains the most diverse PFAS, including long-chain PFAS (more than 8 carbon atoms), namely, PFBA (C4), PFBS (C4), PFPeA (C5), PFPeS (C5), PFHxA (C6), PFHxS (C6), PFHpA (C7), PFHpS (C7), PFOA (C8), PFOS (C8), PFNA (C9), PFDA (C9), and N-MeFOSAA (C11). PFAS were found in three of the four stormwater retention ponds (IP03, IP04, and IP05). It should be noted that it was rainy at the time of sample collection. Therefore, the elevated PFAS concentrations compared to samples collected in the Arroyo Colorado and irrigation canals may have come from road runoff.

PFAS in Drinking Water

We collected two drinking water samples, one from a municipal supply and one from a private well, to assess possible PFAS exposure in this region. While the number of samples was rather limited, it provided an opportunity to compare samples collected from the Arroyo Colorado watershed and retention ponds in the region (Table 2). PFBA (24.57 ng L^{-1}), PFPeA (5.34 ng L^{-1}), and PFHxA (5.16 ng L^{-1}) were found in the municipal water sample, while only PFBS (4.89 ng L^{-1}) was found in the private well sample. It should be noted that PFBA, PFPeA, and PFHxA are not currently regulated by the U.S. EPA for drinking water, while PFBS is proposed to be regulated based on a hazard index (unitless) considering the combination effects of PFNA, PFHxS, PFBS, and Gen-X.

Table 3. Mean PFAS concentrations (ng L^{-1}) in water samples collected from the Arroyo Colorado and irrigation canals in this study compared to other studies with one-time sampling across different watersheds. Number of samples (n) are presented if available. Red shades highlight relatively high values of a PFAS compound compared between the studies. Blue shades highlight relatively low values of a PFAS compound compared between the studies. "N.A." notes data are not available. "N.D." notes a PFAS compound was monitored but not detected.

	PFCA								PFSA					
	PFBA	PFPeA	PFHxA	PFHpA	PFOA	PFNA	PFDA	ΣPFCA	PFBS	PFPeS	PFHxS	PFHpS	PFOS	ΣPFSA
This study														
Arroyo Colorado (n = 15)	7.39	19.21	17.13	22.92	12.13	N.D.	N.D.	78.78	7.81	32.01	140.17	3.42	17.18	200.59
Irrigation Canals (n = 6)	4.68	4.70	4.23	N.D.	N.D.	N.D.	N.D.	13.61	N.D.	N.D.	N.D.	N.D.	3.59	3.59
Scott et al. 2009														
Canadian Rivers and Creeks	N.A.	N.A.	1.03	1.08	1.65	0.51	0.13	4.39	0.21	N.A.	0.72	0.13	2.15	3.21
Gebbink et al. 2017 (n = 18)														
Downstream of a fluorochemical production plant (n = 13)	7.78	4.82	5.34	1.85	4.62	0.67	0.41	25.50	21.00	N.A.	1.97	0.14	3.40	26.51
Upstream of a fluorochemical production plant (n = 3)	6.37	6.17	6.17	1.90	3.00	0.75	0.56	24.91	19.67	N.A.	2.10	0.16	4.77	26.70
Moller et al. 2010														
Rhine upstream Leverkusen (n = 27)	1.44	3.65	2.00	0.43	2.13	N.A.	N.A.	9.65	3.19	N.A.	3.04	N.A.	3.70	9.93
Rhine downstream Leverkusen (n = 9)	117.00	4.28	2.86	0.49	3.11	N.A.	N.A.	127.74	45.40	N.A.	1.93	N.A.	4.13	51.46
River Ruhr (n = 3)	16.60	21.35	8.74	0.99	14.30	N.A.	N.A.	61.98	7.08	N.A.	0.18	N.A.	4.21	11.47
River Moehne (n = 1)	115.00	59.30	49.90	5.78	42.10	N.A.	N.A.	272.08	31.10	N.A.	1.03	N.A.	3.11	35.24
Bai and Son 2021														
Truckee River (n = 8)	N.D.	5.80	18.00	1.70	6.90	N.D.	N.D.	32.40	5.20	0.70	6.40	N.D.	2.20	14.50
Las Vagas Wash (n = 10)	2.60	52.30	80.70	11.60	27.30	N.D.	N.D.	174.50	17.70	2.30	11.20	N.D.	12.90	44.10

Conclusions

This study presents the first report of PFAS in water samples collected in the Arroyo Colorado, irrigation canals, stormwater and WWTF retention ponds in the region, as well as a limited number of drinking waters. PFAS concentrations in water samples collected in the Arroyo Colorado watershed provide useful information for water quality in this region and provide insights into PFAS occurrence in a rapidly urbanizing area. When we compared our data with surveys in other watersheds, we noted many complicating factors, such as the size of watersheds, the level of development, seasonality, river flow rates, and the distance to known sources, making it challenging to systematically compare PFAS occurrence in different waterbodies. However, given that surface waters are one of the key factors for determining PFAS fate and transport and are closely connected to human and environmental health, it highlights the need for more data in different watersheds regardless of basin size. Long-term studies are necessary to capture temporal and spatial variabilities of PFAS types and concentrations to better understand whether different climatological and hydrological conditions affect PFAS distributions, fate, and transport across different watersheds. Additionally, water in the Arroyo Colorado as well as in many watersheds globally is used for agricultural irrigation. Therefore, long-term data on PFAS occurrence in crops should be collected.

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References

Aly, N.A., Y.-S. Luo, Y. Liu, G. Casillas, T.J. McDonald, J.M. Kaihatu, et al. 2020. Temporal and spatial analysis of per and polyfluoroalkyl substances in surface waters of Houston ship channel following a large-scale industrial fire incident. *Environmental Pollution* 265(B): 115009. Available at: https://doi.org/10.1016/j.envpol.2020.115009. Accessed May 2, 2024.

Backe, W.J., T.C. Day, and J.A. Field. 2013. Zwitterionic, cationic, and anionic fluorinated chemicals in aqueous film forming foam formulations and groundwater from U.S. military bases by nonaqueous large-volume injection HPLC-MS/MS. *Environmental Science & Technology* 47(10): 5226-5234. doi: 10.1021/es3034999.

Bai, X. and Y. Son. 2021. Perfluoroalkyl substances (PFAS) in surface water and sediments from two urban watersheds in Nevada, USA. *Science of The Total Environment* 751: 141622. Available at: https://doi.org/10.1016/j.scitotenv.2020.141622. Accessed May 2, 2024.

Brown, J.B., J.M. Conder, J.A. Arblaster, and C.P. Higgins. 2020. Assessing human health risks from per- and polyfluoroalkyl substance (PFAS)-impacted vegetable consumption: A tiered modeling approach. *Environmental Science & Technology* 54(23): 15202-15214. doi: 10.1021/acs.est.0c03411.

Carey, G.R., S.G. Hakimabadi, M. Singh, R. McGregor, C. Woodfield, P.J. Van Geel, and A.L.-T. Pham. 2022. Longevity of colloidal activated carbon for in situ PFAS remediation at AFFF-contaminated airport sites. *Remediation Journal* 33(1): 3-23. Available at: https://doi.org/10.1002/rem.21741. Accessed May 2, 2024.

Chen, C.-H., S.-H. Yang, Y. Liu, P. Jamieson, L. Shan, and S.-H. Chu. 2020. Accumulation and phytotoxicity of perfluorooctanoic acid and 2,3,3,3-tetrafluoro-2-(heptafluoropropoxy)propanoate in *Arabidopsis thaliana* and *Nicotiana benthamiana*. *Environmental Pollution* 259: 113817. Available at: https://doi.org/10.1016/j.envpol.2019.113817. Accessed May 2, 2024.

Clara, M., C. Scheffknecht, S. Scharf, S. Weiss, and O. Gans. 2008. Emissions of perfluorinated alkylated substances (PFAS) from point sources--Identification of relevant branches. *Water Science & Technology* 58(1): 59-66. doi: 10.2166/wst.2008.641.

D'Agostino, L.A. and S.A. Mabury. 2017. Certain perfluoroalkyl and polyfluoroalkyl substances associated with aqueous film forming foam are widespread in Canadian surface waters. *Environmental Science & Technology* 51(23): 13603-13613. doi: 10.1021/acs.est.7b03994.

Dewitz, J. 2023. National Land Cover Database (NLCD) 2021 Products. U.S. Geological Survey. Available at: https://www.sciencebase.gov/catalog/item/647626cbd34e4e58932d9d4e. Accessed May 2, 2024.

Domingo, J.L. and M. Nadal. 2019. Human exposure to per- and polyfluoroalkyl substances (PFAS) through drinking water: A review of the recent scientific literature. *Environmental Research* 177: 108648. Available at: https://doi.org/10.1016/j.envres.2019.M108648. Accessed May 2, 2024.

Fenton, S.E., A. Ducatman, A. Boobis, J.C. DeWitt, C. Lau, C. Ng, et al. 2021. Per- and polyfluoroalkyl substance toxicity and human health review: Current state of knowledge and strategies for informing future research. *Environmental Toxicology and Chemisty* 40(3): 606-630. Available at: https://doi.org/10.1002/etc.4890. Accessed May 2, 2024.

Flores, J., K. Wagner, G.L. Gregory, and J.A. Benavides. 2017. Update to the Arroyo Colorado Watershed Protection Plan. Texas Water Resources Institute, College Station, TX. Available at: https://twri.tamu.edu/publications/technical-reports/2017-technical-reports/tr-504/. Accessed May 2, 2024.

Gebbink, W.A., L. van Asseldonk, and S.P.J. van Leeuwen. 2017. Presence of emerging per- and polyfluoroalkyl substances (PFASs) in river and drinking water near a fluorochemical production plant in the Netherlands. *Environmental Science & Technology* 51(19): 11057-11065. doi: 10.1021/acs.est.7b02488.

George, S.E., T.R. Baker, and B.B. Baker. 2023. Nonlethal detection of PFAS bioaccumulation and biomagnification within fishes in an urban- and wastewater-dominant Great Lakes watershed. *Environmental Pollution* 321: 121123. Available at: https://doi.org/10.1016/j.envpol.2023.121123. Accessed May 2, 2024.

Giesy, J.P. and K. Kannan. 2001. Global distribution of perfluorooctane sulfonate in wildlife. *Environmental Science & Technology* 35(7): 1339-1342. doi: 10.1021/es001834k.

Glüge, J., M. Scheringer, I.T. Cousins, J.C. DeWitt, G. Goldenman, D. Herzke, et al. 2020. An overview of the uses of per- and polyfluoroalkyl substances (PFAS). *Environmental Science: Processes & Impacts* 22(12): 2345-2373. doi: 10.1039/D0EM00291G.

Goodrow, S.M., B. Ruppel, R.L. Lippincott, G.B. Post, and N.A. Procopio. 2020. Investigation of levels of perfluoroalkyl substances in surface water, sediment and fish tissue in New Jersey, USA. *Science of*

The Total Environment 729: 138839. Available at: https://doi.org/10.1016/j.scitotenv.2020.138839. Accessed May 2, 2024.

Groffen, T., V. Wepener, W. Malherbe, and L. Bervoets. 2018. Distribution of perfluorinated compounds (PFASs) in the aquatic environment of the industrially polluted Vaal River, South Africa. *Science of The Total Enviroment* 627: 1334-1344. doi: 10.1016/j.scitotenv.2018.02.023.

Guillette, T.C., J. McCord, M. Guillette, M.E. Polera, K.T. Rachels, C. Morgeson, et al. 2020. Elevated levels of per- and polyfluoroalkyl substances in Cape Fear River Striped Bass (*Morone saxatilis*) are associated with biomarkers of altered immune and liver function. *Environment International* 136: 105358. Available at: https://doi.org/10.1016/j.envint.2019.105358. Accessed May 2, 2024.

Hayman, N.T., J.E. Carilli, Y. Liu, M.R. Shields, L. Hsu, and R. George. 2023. Water quality impacts on sorbent efficacy for per- and polyfluoroalkyl substances treatment of groundwater. *Remediation Journal* 33(2): 89-100. Available at: https://doi.org/10.1002/rem.21747. Accessed May 2, 2024.

Helmer, R.W., D.M. Reeves, and D.P. Cassidy. 2022. Per- and polyfluorinated alkyl substances (PFAS) cycling within Michigan: Contaminated sites, landfills and wastewater treatment plants. *Water Research* 210: 117983. Available at: https://doi.org/10.1016/j.watres.2021.117983. Accessed May 2, 2024.

Houtz, E., M. Wang, and J.S. Park. 2018. Identification and fate of aqueous film forming foam derived per- and polyfluoroalkyl substances in a wastewater treatment plant. *Environmental Science & Technology* 52(22): 13212-13221. doi: 10.1021/acs.est.8b04028.

Houtz, E.F., C.P. Higgins, J.A. Field, and D.L. Sedlak. 2013. Persistence of perfluoroalkyl acid precursors in AFFF-impacted groundwater and soil. *Environmental Science & Technology* 47(15): 8187-8195. doi: 10.1021/es4018877.

Houtz, E.F., R. Sutton, J.S. Park, and M. Sedlak. 2016. Poly- and perfluoroalkyl substances in wastewater: Significance of unknown precursors, manufacturing shifts, and likely AFFF impacts. *Water Reources* 95: 142-149. doi: 10.1016/j.watres.2016.02.055.

Jahnke, A., J.L. Barber, K.C. Jones, and C. Temme. 2009. Quantitative trace analysis of polyfluorinated alkyl substances (PFAS) in ambient air samples from Mace Head (Ireland): A method intercomparison. *Atmospheric Environment* 43(4): 844-850. Available at: https://doi.org/10.1016/j.atmosenv.2008.10.049. Accessed May 2, 2024.

Kwiatkowski, C.F., D.Q. Andrews, L.S. Birnbaum, T.A. Bruton, J.C. DeWitt, D.R.U. Knappe, et al. 2020. Scientific basis for managing PFAS as a chemical class. *Environmental Science & Technology Letters* 7(8): 532-543. doi: 10.1021/acs.estlett.0c00255.

Lam, N.H., C.R. Cho, J.S. Lee, H.Y. Soh, B.C. Lee, J.A. Lee, et al. 2014. Perfluorinated alkyl substances in water, sediment, plankton and fish from Korean rivers and lakes: A nationwide survey. *Science of The Total Environment* 491-492: 154-162. doi: 10.1016/j.scitotenv.2014.01.045.

Lenka, S.P., M. Kah, and L.P. Padhye. 2021. A review of the occurrence, transformation, and removal of poly- and perfluoroalkyl substances (PFAS) in wastewater treatment plants. *Water Research* 199: 117187. Available at: https://doi.org/10.1016/j.watres.2021.117187. Accessed May 2, 2024.

Liu, M., G. Munoz, S. Vo Duy, S. Sauvé, and J. Liu. 2022. Per- and polyfluoroalkyl substances in contaminated soil and groundwater at airports: A Canadian case study. *Environmental Science & Technology* 56(2): 885-895. doi: 10.1021/acs.est.1c04798.

Méndez, V., S. Holland, S. Bhardwaj, J. McDonald, S. Khan, D. O'Carroll, et al. 2022. Aerobic biotransformation of 6:2 fluorotelomer sulfonate by *Dietzia aurantiaca* J3 under sulfur-limiting conditions. *Science of The Total Environment* 829: 154587. Available at: https://doi.org/10.1016/j.scitotenv.2022.154587. Accessed May 2, 2024.

Milley, S.A., I. Koch, P. Fortin, J. Archer, D. Reynolds, and K.P. Weber. 2018. Estimating the number of airports potentially contaminated with perfluoroalkyl and polyfluoroalkyl substances from aqueous film forming foam: A Canadian example. *Journal of Environmental Management* 222: 122-131. Available at: https://doi.org/10.1016/j.jenvman.2018.05.028. Accessed May 2, 2024.

Moller, A., L. Ahrens, R. Surm, J. Westerveld, F. van der Wielen, R. Ebinghaus, and P. de Voogt. 2010. Distribution and sources of polyfluoroalkyl substances (PFAS) in the River Rhine watershed. *Environmental Pollution* 158(10): 3243-3250. doi: 10.1016/j.envpol.2010.07.019.

Mroczko, O., H.E. Preisendanz, C. Wilson, M.L. Mashtare, H.A. Elliott, T.L. Veith, et al. 2022. Spatiotemporal patterns of PFAS in water and crop tissue at a beneficial wastewater reuse site in central Pennsylvania. *Journal of Environmental Quality* 51(6): 1282-1297. Available at: https://doi.org/10.1002/jeq2.20408. Accessed May 2, 2024.

Ruyle, B.J., H.M. Pickard, D.R. LeBlanc, A.K. Tokranov, C.P. Thackray, X.C. Hu, et al. 2021. Isolating the AFFF signature in coastal watersheds using oxidizable PFAS precursors and unexplained organofluorine. *Environmental Science & Technology* 55(6): 3686-3695. doi: 10.1021/acs.est.0c07296.

Schellenberger, S., I. Liagkouridis, R. Awad, S. Khan, M. Plassmann, G. Peters, et al. 2022. An outdoor aging study to investigate the release of per- and polyfluoroalkyl substances (PFAS) from functional textiles. *Environmental Science & Technology* 56(6): 3471-3479. doi: 10.1021/acs.est.1c06812.

Scott, B.F., C. Spencer, E. Lopez, and D.C.G. Muir. 2009. Perfluorinated alkyl acid concentrations in Canadian rivers and creeks. *Water Quality Research Journal* 44(3): 263-277. doi: 10.2166/wqrj.2009.028.

Strivens, J.E., L.-J. Kuo, Y. Liu, and K.L. Noor. 2021. Spatial and temporal baseline of perfluorooctanesulfonic acid retained in sediment core samples from Puget Sound, Washington, USA. *Marine Pollution Bulletin* 167: 112381. Available at: https://doi.org/10.1016/j.marpolbul.2021.112381. Accessed May 2, 2024.

Teymoorian, T., G. Munoz, S. Vo Duy, J. Liu, and S. Sauvé. 2023. Tracking PFAS in drinking water: A review of analytical methods and worldwide occurrence trends in tap water and bottled water. *ACS ES&T Water* 3(2): 246-261. doi: 10.1021/acsestwater.2c00387.

Trier, X., K. Granby, and J.H. Christensen. 2011. Polyfluorinated surfactants (PFS) in paper and board coatings for food packaging. *Environmental Science and Pollution Research* 18(7): 1108-1120. doi: 10.1007/s11356-010-0439-3.

U.S. Environmental Protection Agency (U.S. EPA). 2023. CompTox Chemicals Dashboard v2 4.1: Master List of PFAS Substances. Available at: https://comptox.epa.gov/dashboard/chemical-lists/pfasmaster. Accessed May 2, 2024.

Vigness, D. and M. Odintz. 1952. Rio Grande Valley. Texas State Historical Society, Austin, TX. Available at: https://www.tshaonline.org/handbook/entries/rio-grande-valley. Accessed May 2, 2024.

Whitehead, H.D., M. Venier, Y. Wu, E. Eastman, S. Urbanik, M.L. Diamond, et al. 2021. Fluorinated compounds in North American cosmetics. *Environmental Science & Technology Letters* 8(7): 538-544. doi: 10.1021/acs.estlett.1c00240.

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Feasibility of Wastewater-based Public Health Monitoring Systems in Texas' Small Rural Communities

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Abstract: In recent years, there has been much focus on the use of wastewater-based epidemiology (WBE) in urban centers, particularly for SARS-CoV-2 monitoring. However, less is known about the application of WBE in rural settings or in areas of limited resources. Most WBE programs in low-resource communities have occurred outside the United States. To reap the benefits, WBE would need to be tailored to better reflect the socioeconomic challenges, technical barriers, communication limitations, and variable wastewater infrastructures associated with rural communities. The objective of this review is to evaluate the potential opportunities and challenges of deploying the current SARS-CoV-2 monitoring methodologies in small, rural communities, with a particular focus on rural Texas. For this, we conducted an inventory of rural communities in the state of Texas and their wastewater infrastructure. Based on specific rural examples, we evaluated the potential of current WBE methodologies used in urban settings to monitor for emerging biological agents of concern such as SARS-CoV-2. Our findings include an overview of rural wastewater capacity across rural Texas, a look at current WBE efforts to detect SARS-CoV-2, and recommendations for future implementation in two cities in rural counties, Kerrville and Valentine. WBE is a rapidly evolving public health tool with several notable advantages associated with cost, access, and adaptability. It is of particular use in resource-limited communities that often exhibit healthcare disparities. This study presents the first overview of the feasibility of implementing WBE in the rural settings of Texas. We provide several recommendations and suggest alternatives that may be of use when planning an expansion of WBE into these areas.

Keywords: *rural, Texas, WBE (wastewater-based epidemiology)*

Wastewater-based epidemiology (WBE) is a means of examining public health concerns (disease, drug use, toxins in the human body) using wastewater as the medium of investigation rather than direct testing on individuals. WBE has several notable advantages over individual testing (Xagoraraki and O'Brien 2019; Wu et al. 2022). WBE uses samples that are derived from populations rather than individuals, allowing for anonymized monitoring of human diseases or other excreted biological or chemical markers. Another advantage is that the method is passive, making use of either grab or automated sampling of the water at the source. Individuals need not be present or provide their samples to test for the agents directly (Polo et al. 2020; Safford, Shapiro, and Bischel 2022; Wu et al. 2022). The wastewater flowing through a sampling location serves as a record of human health because of modern sanitation engineering.

Determining the role of contaminated water in the spread of infectious agents within a community can be traced back to the 1850s when Dr. John Snow deduced that the Broad Street Pump was the

Research Implications

- Wastewater-based epidemiology (WBE) has enabled surveillance for community transmission during the COVID-19 pandemic and helped inform policy actions based on infection trends at the specific wastewater catchment level.
- WBE has great potential for the detection of public health concerns including emerging infectious diseases, antibiotic-resistant pathogens, pharmaceuticals, and emerging toxins, such as PFAS. However, the implementation of WBE in rural areas of the U.S. has been limited.
- A tailored approach to WBE in rural communities would account for limited resources and technical and socioeconomic barriers, and provide supporting data for public health providers and decision-makers at the community level.

source of a cholera outbreak in England (Buechner, Constantine, and Gjelsvik 2004). In the 1930s, U.S.-based researchers began using wastewater from the city treatment plants to monitor the spread of the poliovirus in large communities such as Charleston (South Carolina), Detroit (Michigan), Windsor (Massachusetts), and Buffalo (New York) (Trask and Paul 1942). Salmonella bacteria were isolated from sewage in Belfast, Ireland as early as 1928 (Wilson 1933). WBE would continue to be of value in the detection of water-borne pathogens throughout the 1950s, 1960s, and into the late 1980s across the world (Brouwer et al. 2018; Joseph-Duran et al. 2022). It is the preferred method for polio surveillance around the globe today (GPEI 2023). Contemporary applications of WBE include the pandemic outbreaks of the 2000s such as H1N1, Ebola, Zika, Middle East Respiratory Syndrome (MERS), and Severe Acute Respiratory Syndrome (Joseph-Duran et al. 2022).

While there has been much focus on the use of WBE in urban centers, particularly in recent years owing to the COVID-19 pandemic, less is known about the application of WBE in rural settings or in areas of limited resources. Most documented studies in such areas have occurred outside the United States in countries such as China, Bangladesh, Finland, Australia, and New Zealand (Lai et al. 2013; Kankaanpää et al. 2016; Hou et al. 2020; Price et al. 2021; Jakariya et al. 2022). Several of these studies combine rural communities with urban communities rather than treating them as distinct entities. One of the first documented WBE applications in rural communities in the U.S. was in the late 1930s, when researchers studied wastewater from a rural community in Michigan for periodic examination for polio (Trask and Paul 1942). Over the years, very few studies have employed WBE to detect pathogens within rural areas of the United States (Bishop et al. 2020; Margetts et al. 2020; Jarvie et al. 2023).

The reasons for the low utilization of WBE in these communities are varied and complex. Unlike their urban counterparts, rural communities are faced with specific challenges that distinguish them from urban counterparts. First, there are several socioeconomic challenges. Studies have shown that rural residents tend to be older, impoverished, and lacking in access to job opportunities and adequate healthcare resources (Mueller et al. 2021; Rural Health Information Hub 2023). Rural communities are less resilient to outbreaks and experience a disproportionate number of negative outcomes (Perry, Aronson, and Pescosolido 2021). Such negative outcomes are exacerbated by a lack of financial capital at the local level and lower funding from federal programs (Perry, Aronson, and Pescosolido 2021). Rural communities also face challenges with access to staff who are available and trained to support wastewater testing. Wastewater testing protocols need to be validated and verified, including the use of blind testing, controls, and matrix spike-ins, to name a few (APHL 2022). Management of a wastewater testing laboratory with a focus on microbiology would now require advanced molecular microbiology training. However, training programs in WBE are rare at the present time, particularly in the use of cutting-edge techniques such as next-generation sequencing for variant detection and digital polymerase chain reaction (PCR). The bulk of the current protocol development for SARS-CoV-2 detection and other emerging pathogens, such as the human *Monkeypox virus,* is spearheaded by partnerships with academic laboratories. The technology is costly and beyond the budget of most utilities, which likely outsource testing to local or statewide/federal environmental laboratories. Most environmental laboratories are at staffing capacity, busy fulfilling regulatory and compliance testing needs; time and resources are lacking for research and development to broaden a multi-targeted approach for WBE (US EPA 2015a; Switzer, Teodoro, and Karasik 2016). As of March 15, 2024, according to the Texas Commission on Environmental Quality, there are 167 labs (out of 245) certified by the National Environmental Laboratory Accreditation Program to test non-potable water.

Lastly, rural communities are different from their urban counterparts from a wastewater infrastructure perspective. There can be wide variability in treatment unit selection, quality and quantity of the wastewater profile, expense on a per-capita basis, choice of a centralized or decentralized treatment system, and numbers of employees dedicated to wastewater treatment in the community (Boller 1997; Tokich and Hophmayer-Tokich 2006). With these socioeconomic and wastewater infrastructure challenges, it is imperative for rural communities to have information that best reflects their own community.

In Spring 2021, the Texas Legislature established the Texas Epidemic Public Health Institute (TEPHI), located at The University of Texas Health Science Center at Houston (UTHealth Houston) (Clark et al. 2023). The institute has a mandate that includes working collaboratively with state, local, and federal agencies, academic institutions, professional associations, businesses, and community organizations to better prepare the state for public health threats. We hope that our efforts will synergize with that of TEPHI's mission, with our specific focus on rural communities and the role of academic institutions located in these rural regions to support state-wide efforts. The need to tailor WBE efforts to best reflect the socioeconomic issues, communication barriers, and infrastructural challenges associated with rural communities remains.

In this paper, we present a synthesis of the potential opportunities and challenges of deploying WBE methodologies in small rural communities. Specifically, we identify rural communities in terms of their demographic characteristics and their wastewater infrastructure. We also address how WBE would be useful in two rural communities in Texas to provide: (a) representative, unbiased information on community health, (b) information in a timely manner, and (c) specific information needed for public health and regional leaders to make informed decisions. Ultimately, our goal is to provide a framework whereby rural communities could identify indicators of public health for events such as outbreaks of infectious diseases. We expect that this framework will help rural communities establish an early warning strategy that is cost-effective, in house, informative, and responsive to the concerns and needs of the community.

Methods

Answering the question, "What is rural?" is not a simple task. There are several U.S. governmental agencies that provide varying guidance on how to define rural areas in the form of individual neighborhoods, city boundaries, and counties (Ratcliffe et al. 2016; Surbhi et al. 2021; Sanders and Cromartie 2024b). Rather than attempt to define "rural" to fit all situations that can be found in Texas, we take a more conceptual approach. The concept of rural generally connotes a human population area which exhibits some or all of the following characteristics (as compared to urban areas) – less dense in population, farther from city amenities (e.g., hospitals, professional sports venues, large office buildings), less diverse in demographic characteristics, larger travel distances for daily commutes, and smaller local government with lower service capacity. These markers are not meant to assess the quality of life in such places. They merely help researchers, planners, and demographers to better define rural beyond strict determinations. Therefore, in this work we have made specific assessments of rurality according to data availability involving delineation of rural communities, which is explained in the following subsections. Further details on the diversity of definitions for rurality are in the Supporting Information at the end of this paper, for those interested to see the underpinnings of our conceptual understanding.

Texas Rural Population and Demographics

To determine the potential application of WBE for Texas rural communities, we measured the extent of rural communities in Texas. We used the U.S. Census definition based on population number (population size of < 5,000) (CDC 2008). Using the U.S. Census definition, we looked at the population density of rural cities and sampled four rural cities around the state in the approximate north, south, east, and west regions to look at the racial demographics in the cities. To cover a more inclusive extent of rural communities, and in addition to the U.S. Census definition of rurality, we discussed implications of considering *metro/non-metro* and urban/not-urban characteristics. Our population and location data were obtained from the Texas Legislative Council Capital Data Portal, which is based on population and city geographic extent taken from the 2020 U.S. Census. We converted all city boundaries to centroid point locations.

Wastewater Flow Data - Wastewater Infrastructure

To evaluate the potential need, opportunity, and viability of WBE for rural Texans, we determined the scale of wastewater generation by defining cities with centralized wastewater treatment, their dispersion within the state, their population density, and their wastewater generation rate per capita. To define rural cities in this section, we used the U.S. Census population number of less than 5,000 persons. We collected all the wastewater treatment plant (WWTP) facility information from the Environmental Pollution Agency (EPA) Permit Compliance System (PCS), accessed through EPA Envirofacts as of April 20, 2023.

WBE in Texas

We reviewed the published literature for sampling, concentration, extraction, and detection methods currently being used in Texas in the context of SARS-CoV-2 as an example of current technical needs for detecting a biological agent of concern. Keywords used in the literature search included: 'SARS-CoV-2', 'wastewater', 'surveillance', 'wastewater-based epidemiology', 'rural', and 'detection'. We considered the methods used, the frequency and nature of sampling, and the equipment and procedural approaches currently implemented in Texas cities (Table 1).

Case Study–Application of WBE in Rural Communities

To understand how WBE can be implemented in rural communities, we conducted an analysis of the distribution of rural communities across the state and considered the nature of wastewater infrastructure in those communities. For a more detailed look, we examined two cities in two different rural counties in the State of Texas - Valentine (Jeff Davis County; population 133 in 2019) and Kerrville (Kerr County; population 24,477 in 2021). Kerrville has a population over 24,000, defined as rural in terms of residing in a *non-metro* county per the United States Department of Agriculture (USDA) Economic Research Services (ERS). According to the USDA-ERS, a county is considered *non-metro* if it meets at least one of these three criteria—"open countryside, rural towns less than 5,000 people and 2,000 housing units, and urban areas with populations ranging up to 50,000 people that are not a part of larger labor areas (metropolitan areas)" (Sanders and Cromartie 2024a; 2024b). Considering Kerr County as a rural county is also consistent with other definitions as described by the Texas Department of Agriculture and Texas Department of Housing and Community Affairs (Texas State Office of Rural Health 2012; Texas Department of Housing and Community Affairs 2022). It is interesting to note that Jeff Davis County, the county in which Valentine is located, can also be considered a *non-metro* county.

The factors analyzed in both cities include the rural demographics, sewer network characteristics, distance from a major center city (defined as having a population greater than 200,000 people with an entity that has current support for WBE activity), and type of WWTP. Kerrville is in a rural county, and is, along with Valentine, representative of one of the two types of centralized treatment plants in Texas (Figure 1). Valentine has a pond/lagoon system, characterized by a series of holding ponds, and Kerrville has an activated sludge system, characterized by an oxidation ditch system. The characteristics of both cities are detailed in Table 2.

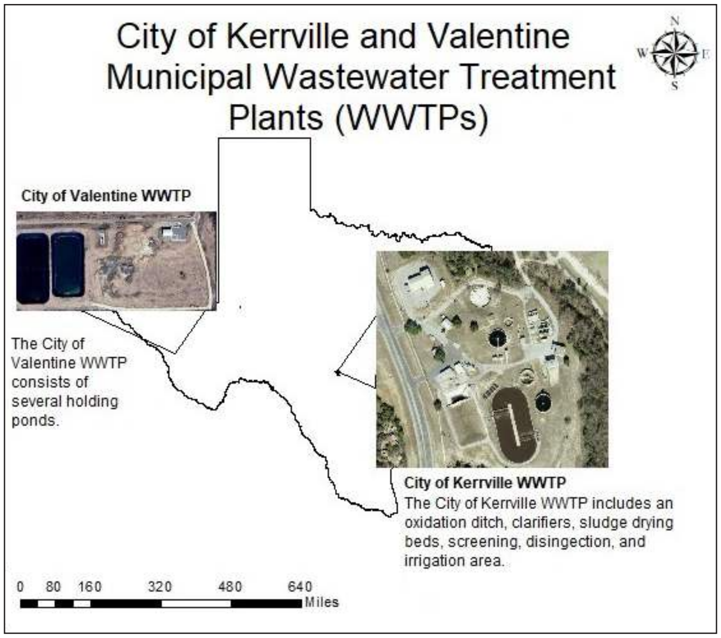


Figure 1. Characteristics of the centralized wastewater treatment plants in Kerrville and Valentine (Texas Department of Transportation 2015; 2024; ESRI 2021; Google Earth V 7.3 2024a; 2024b).

Health Outcomes and Literacy Data. The 2010 community health outcomes (HO) for Texas are publicly available from County Health Rankings produced by the University of Wisconsin, Population Health Institute. HO are a combination of length of life and quality of life, and can be influenced by a variety of factors, such as access to clean water, affordable housing, the quality of medical care, and the availability of well-paying jobs, all of which are influenced by policies and programs (UWPHI 2023a). The HO rankings are based on an ordering of composite z-scores weighted according to the model in the report, which assigned weights to specific measures of heath, standardized the measures within each state using a z-score, calculated weighted sums of the standardized measures within each state and sorted these composite scores to create an ordering of counties which determined the rank (UWPHI 2023a). Because the HO ranks are based on z-scores they do not have units, and they range from 1 (healthiest) to 221. The following counties had insufficient data to be ranked in 2010: Armstrong, Borden, Briscoe, Coke, Concho, Cottle, Dickens, Edwards, Foard, Glasscock, Hemphill, Irion, Jeff Davis, Kenedy, Kent, King, Lipscomb, Loving, Mason, McMullen, Menard, Motley, Oldham, Reagan, Roberts, Schleicher, Shackelford, Sherman, Sterling, Stonewall, Terrell, Throckmorton, and Upton. We used the HO rankings broken down by location to understand why HO might differ across a county. We focused on our two rural cities of Kerrville and Valentine, in Kerr and Jeff Davis counties, respectively, both of which are rural counties (UWPHI 2023b). We also examined the health literacy (HL) scores for our two communities (National Health Literacy 2010). HL is defined as the ability to find, understand, and easily use health information and services to make informed decisions and take informed actions (Health Literacy Texas 2023). The HL scores on the dashboard range from 177 to 280, with higher numbers indicating a higher level of HL. Rural and urban communities with low literacy may exhibit difficulties with reading and interpreting basic health information such as pamphlets about a condition.

Results and Discussion

Texas Rural Population and Demographics

Using the U.S. Census definition based on population number, there are 868 rural cities (population size of < 5,000) found in Texas, out of

Table 1. Published WBE schemes in Texas.

City	Study Purpose	Collection Location	Collection Frequency*	Wastewater Concentration Method(s)	RNA Extraction Method	RNA Detection Technique(s)	Reference
Houston (2021 Pop: 2,288,250[1])	Evaluation of varying methods for wastewater sampling, concentration, RNA extraction, and RNA detection	WWTP influent from six city treatment plants	One sample every hour for 24 hrs	Each sample is spiked with bovine coronavirus (BCoV) before concentration. HA extraction with bead beating. HA extraction with elution. PEG precipitation. Ultrafiltration	Chemagic Prime Viral DNA/RNA 300 Kit H96	One-Step RT-ddPCR Advanced Kit for Probes on QX200 AutoDG Droplet Digital PCR System with N1 and N2 SARS-CoV-2 primers; BCoV primers. qPCRBIO Probe 1-Step Go Separate-ROX on QuantStudio. Real Time PCR System with VGP pMMoV primers.	LaTurner et al. 2021
Austin (2021 Pop: 964,177[1])	Use wastewater and daily COVID-19 cases to identify sewersheds (via zip codes) in which COVID-19 was the most prevalent	WWTP primary clarifier effluent from two city treatment plants	Two to three times a week for 39 weeks	Pasteurization and centrifugation	MagMax Microbiome Ultra Nucleic Acid Isolation kit on the KingFisher Flex System	ViiA7 Real Time System with CDC nCOV_N2 primer	Nelson et al. 2022
Houston (2021 Pop: 2,288,250[1])	Assess how effective wastewater can be as a forecasting tool in comparison with other indicators of "disease surveillance" across a city	WWTP influent from all 39 city treatment plants	Weekly for 86 weeks	Electronegative filtration	Chemagic 360 automated platform, Viral DNA/RNA 300 Kit H96	One-Step RT-ddPCR Advanced Kit for Probes on QX200 AutoDG Droplet Digital PCR System and C100 Thermo Cycler. Water SARS-CoV-2 RT-PCR test kit	Hopkins et al. 2023
Houston (2021 Pop: 2,288,250[1])	Employment of modeling software to simulate SARS-CoV-2 presence in various sized sewersheds, and to identify preferable sampling locations in a watershed	WWTP influent from six city treatment plants	Not listed	HA filtration with bead beating	Qiagen Allprep Powerviral DNA/RNA kit	One-Step RT-ddPCR Advanced Kit for Probes on QX200 AutoDG Droplet Digital PCR System	McCall et al. 2022

Table 1, continued. Published WBE schemes in Texas.

City	Study Purpose	Collection Location	Collection Frequency*	Wastewater Concentration Method(s)	RNA Extraction Method	RNA Detection Technique(s)	Reference
Austin (2021 Pop: 964,177[1])	A comparison of methods, specifically wastewater concentration, sample collection, and RNA extraction/detection	WWTP primary clarifier effluent from two city treatment plants	Six times throughout an eight-week period; 14 times throughout a 39-week period	Samples are first either pasteurized and/or centrifuged. Samples undergo vacuum filtration and nanofiltration regardless of being pasteurized or centrifuged	MagMax Microbiome Ultra Nucleic Acid Isolation kit on the KingFisher Flex System	ViiA7 Real-Time System with CDC nCOV_N1 primer	Palmer et al. 2021
San Antonio (2021 Pop: 1,451,853[1])	A temporal study of the change in viral concentration entering a city WWTP	WWTP influent	Weekly for 12 weeks every Tuesday	Adsorption-extraction by means of electronegative membranes. Bovine coronavirus as surrogate for recovery validation.	RNeasy Power Microbiome Kit with QIACube Connect	BioRad QX200 Droplet Digital PCR System with one-step RT-ddPCR	Al-Duroobi et al. 2021
El Paso (2021 Pop: 678,415[1])	An assessment of a two-year city monitoring program	WWTP influent from four city treatment plants	Weekly for 98 weeks	Electronegative filtration	Chemagic Prime Viral DNA/RNA 300 Kit H96	7500 Fast Dx Real-Time PCR Instrument	Gitter et al. 2023

*24 hr. composite samples were taken in each case.

Table 2. Characteristics of two cities in rural Texas, Valentine, and Kerrville.

City	Population	Sewer Network Characteristics	Distance from Major City Center	WWTP Description	Data Source
Valentine	133 (2019)	● Three different pipe sizes— 19,000 linear feet 6-10", 38 manholes ● Two locations with 200 linear feet, 16" steel casing ● Lift station, 15,000 linear feet, 3-inch force main; unknown staff number	159 miles southeast of El Paso	Pond system (bar screen, facultative lagoon, storage pond)	City of Valentine 2003; City-Data 2023
Kerrville	24,477 (2021)	200 mi of collection lines, 3,163 sewer manholes, 27 lift stations; 2.2 MGD daily average flow; a staff of 13	65 miles northwest of San Antonio	Preliminary (screening, grit, equalization), aerobic/anoxic, oxidation ditch, clarifiers, rapid sand filters, chlorine disinfection, dechlorination	City of Kerrville, Texas 2023; U.S. Census Bureau 2023a

a total of 1,223 municipalities. These rural cities are distributed all over the state (Figure 2), with 75% having populations of less than 2,000.

The size distribution and population density of all rural cities, as well as demographics of four representative cities taken from east, west, north, and south Texas are provided in Figure 3. The histogram (Figure 3a) highlights the right-skewed distribution of small city populations, indicating that many of the towns we examined are particularly small with about half (438 cities) having population sizes of less than 1,000 persons. We sampled four cities around the state in the approximate north, south, east, and west regions to look at the racial demographics in the cities (Figure 3b). The sample also contains cities that fit into one of the four quartiles for rural population size (Q1: 22-422, Q2: 423-989, Q3: 990-2,062, Q4: 2,063-4,974). In the far west and south of Texas a greater Hispanic population is evident while in the north and east, there is a much greater Anglo population. Varying cultural and social differences among these communities is likely to influence the level of acceptance and trust in emerging methods such as WBE. These trends are important to consider as inclusive, ethical, and effective strategies for implementation are developed (Medina et al. 2022; National Academies of Sciences, Engineering, and Medicine 2023). Using the population size of < 5,000, a statistical summary of rural Texas city population density is shown in Figure 3c. Population density helps validate the rural designation of these cities and informs some aspects of community cooperation that can be influenced by population density (Smailes 1996). Higher population density can increase human interaction, which has impacts on disease transmission and, potentially, residential interest in public health. It has been reported that rural public health workers engage with communities that tend to be skeptical of the role of government (Leider et al. 2020). Our results show that the mean population density of rural Texas cities in 2020 was 680 ± 470 people per square mile (mean ± sd); 867 cities were included with viable population density values, when notable outliers were excluded (5% of cities are outliers). This results in a coefficient of variation (CV) of 69%, indicating a fair amount of variation in rural community population density. Overall, 75% of Texas rural cities in this selection

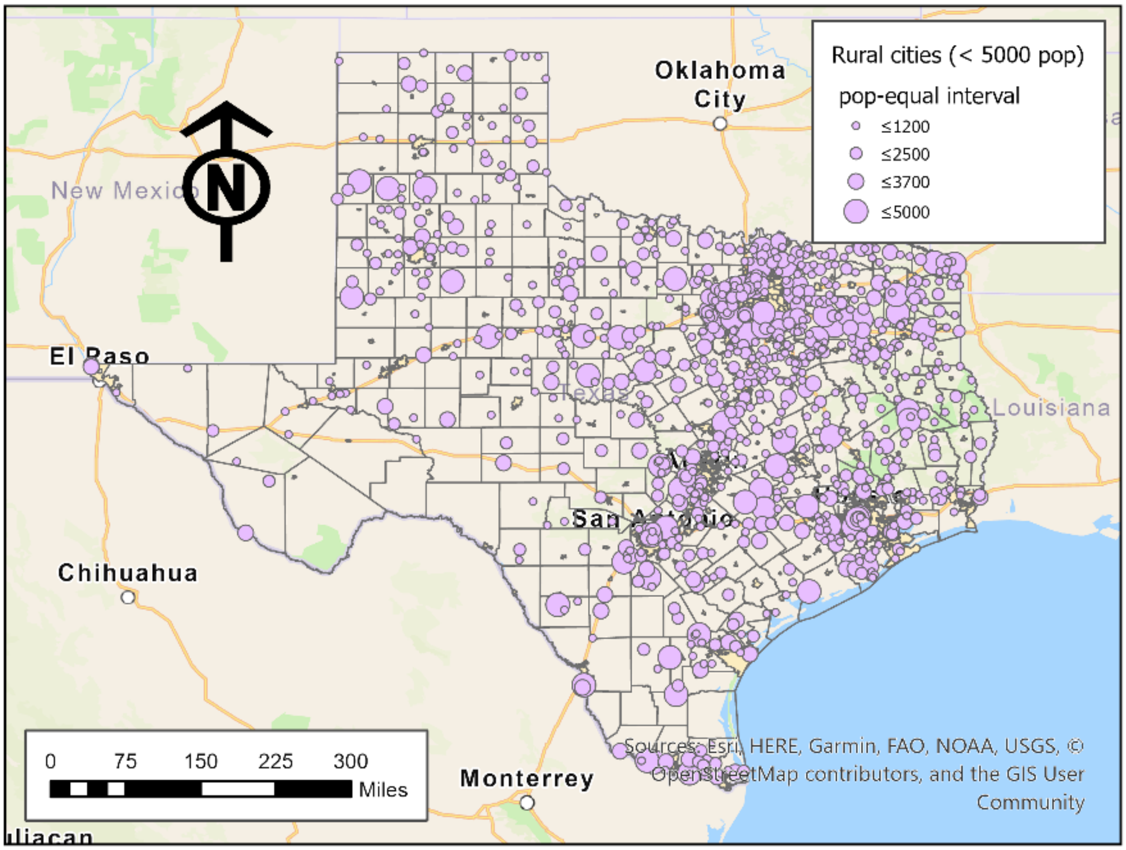


Figure 2. Distribution of rural communities (n=868) within the state of Texas. All data taken from the 2020 U.S. Census, with inclusion criteria of less than 5,000 in total population. Size classes are determined as convenient intervals from minimum to maximum size.

were at a density of < 1,000 people per square mile (pop/mi²).

Using the < 5,000 population criterion, 71% of all cities in Texas are rural. However, the proportion of the population living in areas of the state considered rural is small. Out of a total Texas population of 29.1 million in 2020, rural cities account for 1.24 million people (4.3%) (U.S. Census Bureau 2023b). There is a sizable amount of the Texas population that lives outside of incorporated cities (8 million), while all incorporated cities have a total population of 21.1 million. This population may not necessarily be classified as "rural" if the population measurement of < 5,000 is used, i.e., they may live near a city limit boundary but just outside of it. Consequently, we consider it likely that communities outside of city limits could also be classified as rural. A more inclusive delineation of rural communities is found when considering *metro/non-metro* and urban/not-urban characteristics. A *metro* area is defined as a core area containing a large population nucleus with adjacent communities that are integrated to that core (U.S. Census Bureau 2023b). *Non-metro* counties are outside the boundaries of *metro* areas and could have or not have a population larger than 5,000. The Rural Health Information Hub (RHIhub) (2023) shows that if counties are determined to be either *metro or non-metro* based on various parameters, including eligibility criteria for federal programs, 10.8% of all Texans in 2020 live in *non-metro* areas. Using *non-metro* could be a more inclusive way to classify communities as being rural. The U.S. Census Bureau's (2023b) official fraction of rural for 2020 in Texas was reported as 16.3%. The Bureau defines any population which is not found in an urban designated area as "rural." Using a population residual calculation, the Bureau determines that "not urban" is equivalent

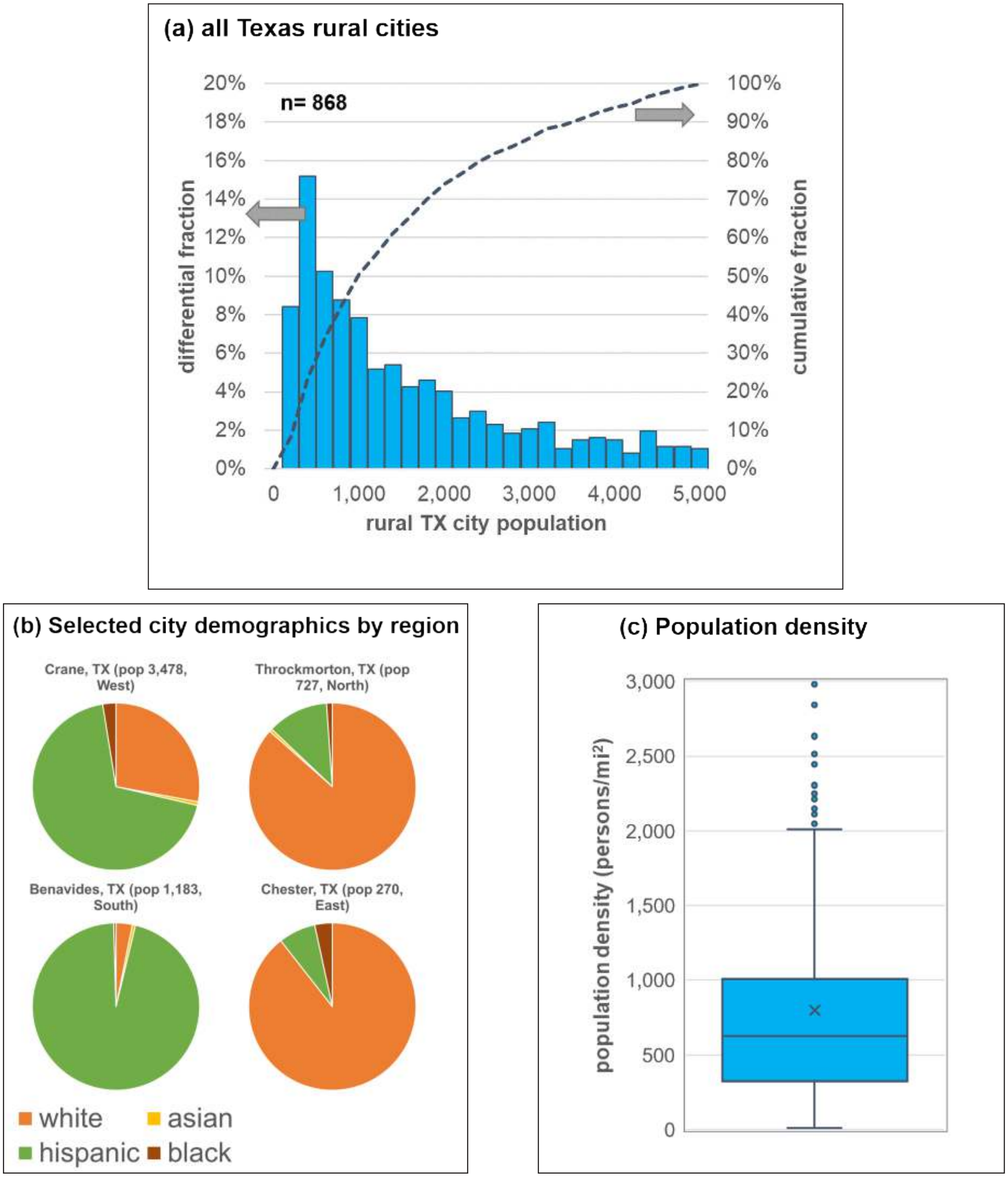


Figure 3. Texas rural city population data. (a) The statistical distribution of population size ranges from 22 to 4,974 as differential histogram and cumulative population (dashed line). (b) The demographics by race in four cities that span the four areas of Texas (North, East, South, West). Each city was selected so that one city each was in a different quartile of rural populations (Q1: 22-422, Q2: 423-989, Q3: 990-2,062, Q4: 2,063-4,974). (c) Rural Texas town population density; the sign "x" represents the mean. A total of 867 cities were included with viable population density values. The use of an outlier determination criteria of 1.5IQR reveals an upper outlier threshold of 2000 person/mi^2 which then identifies that 5% of cities are outliers in the rural Texas town class.

to rural. Based upon the data we have presented here at the city boundary level, Texas is in practice approximately 10% rural, with the fraction of rural population variable according to the region of the state, *non-metro* and "not-urban" characteristics.

Wastewater Flow Data - Wastewater Infrastructure

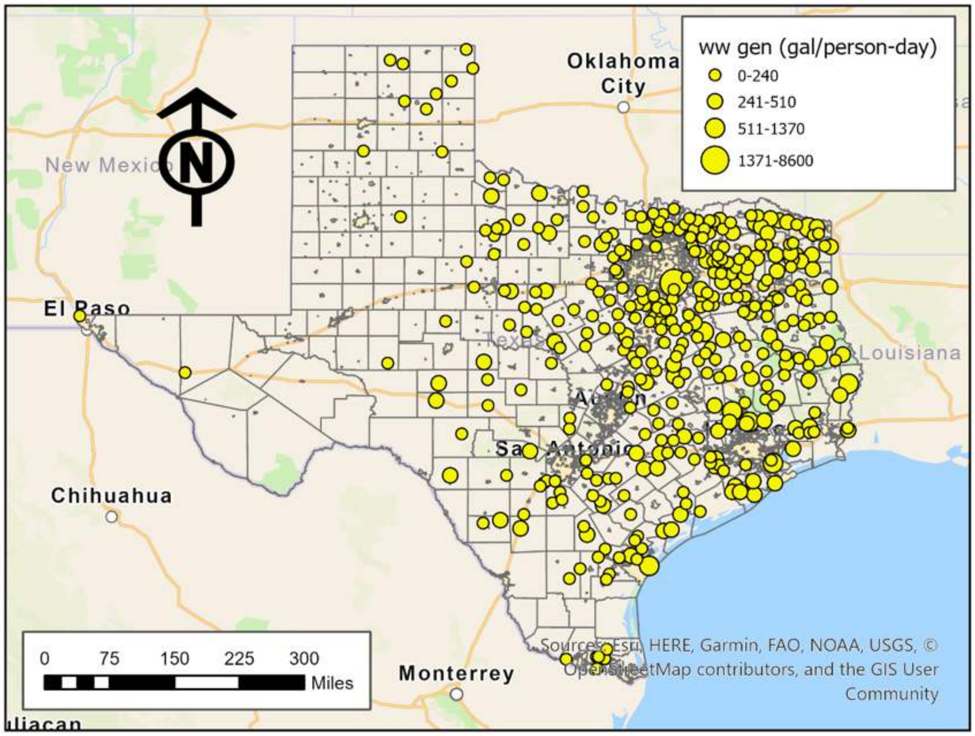
The use of population data could provide greater accuracy on daily wastewater flow and variation, but for the purpose of this study, we used the design flow of the WWTP to determine the scale of wastewater generation. We focused our study on which cities have centralized wastewater treatment, their dispersion within the state, their population density, and their wastewater generation rate per capita, in order to evaluate the potential need, opportunity, and viability of WBE for public health benefits for rural Texans.

The examination of wastewater quantity and infrastructure in particular communities we identified as rural requires that there be data in each community on both population and wastewater. We therefore had to find a match between the Census 2020 city name and the city name in EPA permit records. Out of 868 rural communities we identified (using the population < 5,000 threshold), we were able to identify 371 cities for which we could obtain wastewater flow data, which constitutes a match rate of 43%. We considered this subset of cities likely to represent what typically occurs in rural communities across the state, as the mean population for all the rural cities we identified (n=868 cities) was 1,430 (range of 22-4,974), whereas the mean value of cities that had matching wastewater data (n=371) was 1,724 (range of 116-4,969), a slightly higher population mean. We hypothesize that this may be because larger rural cities are more likely to have centralized wastewater treatment, and thus more likely to have current permit records available in the EPA permit records database. However, cities as small as Cuney, TX (pop. 115), reported a wastewater treatment permit for even a very small design flow of 0.05 millions of gallons per day (MGD), suggesting that size alone does not necessarily predict if a city has centralized wastewater treatment or if their treatment structure and/or strategy is available in the EPA permit system.

Figure 4 provides a spatial outlay of the rural cities where wastewater treatment matching was possible in terms of wastewater generated per capita. In Figure 4a, we see the variation in wastewater generation rate per capita. The wastewater generation rate per capita is 234±39 gal/person-day (mean±95% conf), and the 90th percentile of wastewater generation is 353 gal/person-day. Therefore, there are some unique instances where wastewater generation per capita is relatively high, but for most rural areas the 95% confidence span of 195-273 gal/person-day is representative. When comparing wastewater generation rate per capita in rural cities (< 5,000 pop.) and urban (> 5,000 pop.) cities we found a nominal decrease in the urban mean (199 gal/person-day, n=228) compared to the rural mean (234 gal/person-day, n=371). However, there was no statistical difference via an independent sample t-test ($p > 0.05$) between these means. We can conclude that the wastewater generation rate of urban cities versus rural cities is approximately the same, at least based on the treatment plant design flow rate (Figure 4b). The wastewater generation rates or design flow do not correlate strongly with geography. However, there is a spatial pattern of more rural centralized treatment systems with permits in the eastern third of the state. We think that this is due to a greater proportion of the Texas population overall residing in the eastern third as compared with the central and western thirds. The census data would support this hypothesis, despite the growth in population in certain counties along the border.

Figure 5 shows the overall change in the design flow rate of treatment plants (i.e., the general treatment capacity) across the state for rural cities. There are some notable examples of higher flow rates in the 2.4-3.2 MGD but only a few. Out of all wastewater flows, 95% of flows in these rural cities were 0.96 MGD or less. To put this scale of flow into perspective, we first compared it to larger cities of population > 5,000. In this dataset, 95% of all design flows were 24.7 MGD or less. At the median level, urban cities had flows that were about 10x larger (0.25 MGD rural vs. 2.6 MGD urban). We also considered the size of the inflow pipe to the single WWTP that a rural location would receive (typically, all rural cities

(a) Wastewater generation per capita



(b) Wastewater treatment design flows

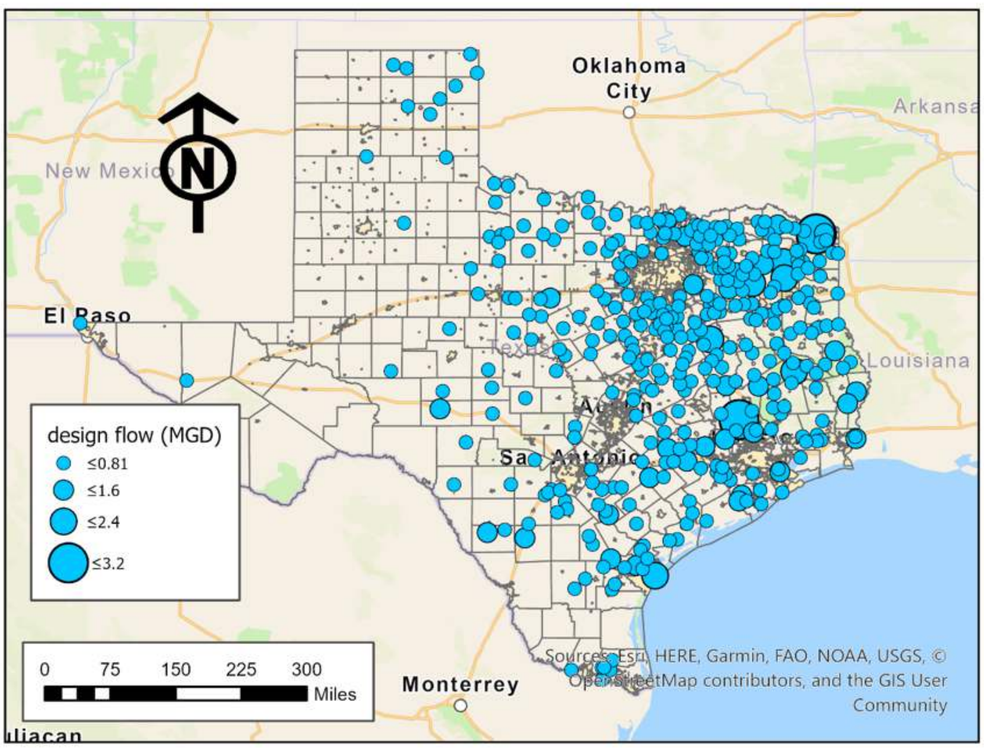


Figure 4. Wastewater treatment and rural population data linkages in rural Texas cities. (a) The wastewater generation rate per capita as design flow of wastewater per unit of the 2020 Census population is provided as gallons per person per day. (b) The total design flow is for the entire rural community.

have only one centralized treatment facility). The median flow rate to wastewater facilities in a rural city is 0.25 MGD. Figure 5 illustrates the way such a flow would fill a sanitary sewer main feeding the plant influent, demonstrating how different pipe sizes would be filled at the rural wastewater flow rate for the entire town.

Given that a practical design of such an influent pipe at the design flow should be at 20-50% full (to balance cost and capacity to deal with flow variations), the influent pipe size for this typical small-town wastewater treatment facility would be 7-14 inches in diameter. A similar analysis for the urban median flow (2.6 MGD), if it were concentrated into a single facility influent, would be an 18–36-inch diameter pipe.

On average, rural cities in Texas have total wastewater flows which are 10x smaller than the typical urban setting. Such differences in pipe size and flow depth would impact the results of any WBE strategy. The water depths may be shallower, and the pipe sizes smaller. An operator's ability to easily obtain a wastewater sample would be affected by this flow depth; at times of lower flow it could become more difficult to obtain. Despite these challenges, most rural Texas cities are likely to have only one WWTP and outfall, which allows for the entire community to be evaluated for public health concerns at a single location. The fact that rural towns have slightly larger wastewater per capita generation rates may indicate that there is a greater dilution of fecal matter-influenced wastewater (the portion most used for WBE) with other wastewater sources (showers, sinks, local industry, car washes, etc.). This dilution could obscure the signal of pathogens or other WBE constituents of interest, another area of difficulty that rural WBE schemes in Texas would need to surmount.

WBE in Texas

As detailed studies of methods for SARS-CoV-2 are available, we focused on detecting a pathogen such as SARS-CoV-2 when determining an idealized protocol for a rural setting. We based our suggestions on comparing techniques used in Texas cities, when possible, as research in rural communities is lacking. These suggestions would also be applicable to sites and locations beyond Texas with similar processes and population sizes.

Sampling Frequency and Location. Developing a sampling protocol in a rural community would require balancing detection errors and resources. A sampling protocol would ideally include a daily sampling schedule and composite samples to avoid errors in non-detectable targets (Table 3) (Ahmed et al. 2022). However, daily sampling would not be feasible for most communities, nor would it be cost-effective. Sampling twice per week for SARS-CoV-2 was determined to be sufficient to avoid detection inaccuracies and was

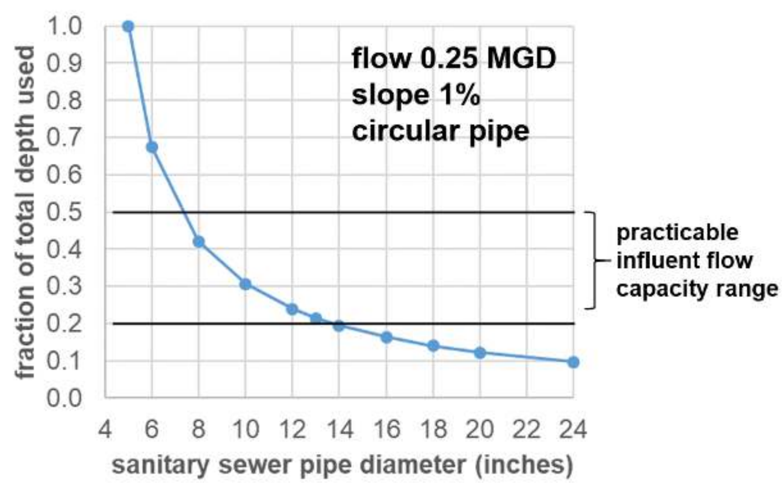


Figure 5. Representative influent pipe sizes for a single rural wastewater centralized treatment facility providing treatment for the entire city. Calculation conducted at uniform open channel flow at a flow of 0.25 MGD on a 1% in a concrete sanitary sewer circular pipe.

Table 3. Recommended practices for the detection of SARS-CoV-2 in wastewater samples.

Method Component	Description	Recommendation	Reference
Sampling		QA/QC protocols to avoid contamination during sampling based on drinking water sampling protocols	US EPA 2015b
		Composite sampling is recommended to minimize false negatives due to temporal fluctuations or collection of multiple grab samples within a 3-4 hr period using passive samplers. Single-grab samples are adequate if viral load is expected to be high.	Ahmed et al. 2022
		Large volume for collections (1-2 L) especially when low incidence of COVID cases is expected	Ahmed et al. 2022
	Composite influent samples over a 24-hr period sampled one to two days per week at 12 WWTPs and daily for five days per week for two WWTPs	A three-day per week sampling frequency evenly spaced apart will not compromise surveillance and a non-consecutive two-day per week frequency has minimal impact on surveillance	Feng et al. 2021
Concentration	Seeded wastewater with gamma-irradiated SARS-CoV-2	Aluminum-based precipitation with manual extraction (< 40%) was considered the best strategy due to time (less than 2h) versus an overnight incubation using PEG	Pérez-Cataluña et al. 2022
		If COVID cases are low, both liquid and solid fractions should be concentrated	Ahmed et al. 2022
	Grab samples of wastewater from a manhole and influent from two WWTPs	Solid precipitation that concentrated 400 mL sample by 100-fold provided detectable SARS-CoV-2 RNAs compared to methods using supernatant from initial centrifugation	Kitamura et al. 2021
	24-hr composite influent samples spiked with bovine coronavirus (BCoV) and quantified by ddPCR	HA filtration with bead beating provides SARS-CoV-2 RNA concentrations consistently above the LOQ compared to centrifugation followed by direct extraction	LaTurner et al. 2021
Extraction	Seeded wastewater with gamma-irradiated SARS-CoV-2	Automated extraction provides higher sensitivity	Pérez-Cataluña et al. 2022
	Grab samples of manholes or lift stations associated with individual buildings or clusters on university academic, dormitory, research, and hospital facilities	Smaller RNA extraction eluents improve sensitivity likely due to PCR inhibitory substances: 10 µL for elution (Ct 33) compared to 40 µL (Ct 35)	Sharkey et al. 2021

Table 3, continued. Recommended practices for the detection of SARS-CoV-2 in wastewater samples.

Method Component	Description	Recommendation	Reference
Assay	Seeded wastewater with gamma-irradiated SARS-CoV-2	Genomic RNA of SARS-CoV-2 as positive control when evaluating assay efficiency	Pérez-Cataluña et al. 2022
		A surrogate virus should be used as a positive sample process control for at least 10-20% of samples or an endogenous control	Ahmed et al. 2022
	24-hr composite influent samples spiked with bovine coronavirus (BCoV) and quantified by ddPCR	BCoV as a process control and normalization factor for recovery has low variability	LaTurner et al. 2021
	Influent wastewater samples with aluminum-based adsorption-precipitation method and RT-qPCR	N1 and N2 primers provide higher positivity rates compared to primer sets E, IP2, IP4, and RdRp	Pérez-Cataluña et al. 2022
	Composite influent samples over a 24-hr period sampled one to two days per week at 12 WWTPs and daily for five days per week for two WWTPs	If selecting one set of primers, N1 primers are more sensitive and have higher correlation to SARS-CoV-2 case numbers	Feng et al. 2021
	Grab samples of manholes or lift stations associated with individual buildings or clusters on university academic, dormitory, research, and hospital facilities	V2G-qPCR and N1 or N2 RT-qPCR similar in terms of limit of detection (LOD) or quantitation (LOQ) with N1 RT-PCR providing results higher than V2G-qPCR (approximately 10%)	Sharkey et al. 2021
	Detection of SARS-CoV-2 RNA isolate strain in diluted RNA from isolate extraction. Grab samples of wastewater from a manhole and influent from two WWTPs	Duplex RT-qPCR using N1 and N2 primers, compared to NIID_2019-nCoV_N primer sets, was more sensitive in detection (< 10 gc/reaction of diluted RNA samples) and detected higher numbers in wastewater samples.	Kitamura et al. 2021

sufficient to correlate with a 7- to 8-day lag time in case detection at two Austin WWTPs (Feng et al. 2021; Nelson et al. 2022). In El Paso, a nearly weekly sampling approach had a 4- to 24-day lag time (Gitter et al. 2023); therefore, a biweekly sampling strategy would be more practical when limited resources and personnel are considered, especially in a rural community (Feng et al. 2021). Extending the time between sampling events would be expected to increase detection errors for environmental monitoring; however, an increase in the concentration of biological or chemical contaminants observed at multiple sampling points within a community would then warrant a strategic increase in sample frequency and location of sampling points (Levine et al. 2014). Such a temporal and spatial approach would facilitate source tracking (chemical or biological) and localization of the problem while reducing the costs and barriers for utilities and laboratory personnel. The Balanced Approach Survey (BAS) considers spatial variation in sampling locations and targeted sampling sites based on a determination of more susceptible populations within an ecological context (Brown, Robertson, and McDonald 2015).

Our recommendation for the rural cities selected is that WBE should consider a multi-dimensional environmental sampling approach to reduce sampling size while capturing critical data. Regarding application of the BAS (Brown, Robertson, and McDonald 2015), sampling sites should be selected based on representation of wastewater in the geographic area (two-dimensional points) and include additional dimensions that determine the sensitivity of communities or severity of the environmental impact on subsections of the community. These could include limited public health resources, social and economic factors, and the health behaviors of a population such as those tracked to determine county health rankings (UWPHI 2023b). Considering the higher impact that SARS-CoV-2 had on minority populations, including more sampling points within these communities would be crucial (CDC 2020). From our review of the published literature, WBE sampling points in what we consider to be rural communities are currently rare in Texas, with the focus being on major metropolitan areas such as Austin, Houston, San Antonio, and El Paso (Table 1). Addressing this gap would preemptively address hospital stress resulting in higher deaths (Soria et al. 2021).

Techniques and Approaches to Sampling. Several cost-effective alternatives for sampling have been proposed, such as the "Moore swab," a gauze pad suspended by a string in water to provide a composite sample of human fecal matter by continuously filtering flowing water over a 24-hr period (Sikorski and Levine 2020). Testing of this sampling matrix could be incorporated into a citizen or community science program for water surveillance, such as one being conducted by Texas Stream Teams (a collaborative effort across the State looking at environmental water quality), in collaboration with academic or non-profit entities. Such programs would empower rural residents to participate and engage in local public health efforts. Research has demonstrated the feasibility of passive sampling as a viable method for the collection of wastewaters to monitor the changes in viral presence throughout the COVID-19 pandemic, many of which occurred either during times of low prevalence or in smaller wastewater communities such as universities (Hayes et al. 2021; Hayes, Stoddart, and Gagnon 2022; Li et al. 2022). In the only North American rural community wastewater surveillance study, sampling locations were compared between a pumping station upstream from a wastewater lagoon and a lagoon pool (D'Aoust et al. 2021). At both sampling sites, a 24-hour composite sample, taken every three to seven days for approximately five months, was collected using an autosampler. Pumping station samples had higher levels of SARS-CoV-2, likely due to the higher fecal-associated material present at the pumping station site which had degraded within the lagoon given the high residence time (80 h to 10 days), as well as to low water flow velocity and particle settling from the use of polyaluminum sulfate. Total RNA concentrations were up to five-fold higher at the pumping station, confirming the degradation of biological material for detection. Travel time from the wastewater source and sampling location require consideration of viral decay. In a Houston study, SARS-CoV-2 viral decay was $\geq$ 50% at wastewater sampling points with a higher number of remote regions (McCall et al. 2022). Depending on the location of the lagoon and the geographical area being served, upstream sampling may be needed.

For rural communities with lagoon wastewater treatment, such as Valentine, samples collected from the last pumping station within a series could represent the influent collection point of an urban wastewater treatment. Pumping station viral load data in the rural community study (D'Aoust et al. 2021) showed similar trends to the clinical positivity rate, indicating that the lagoon sampling location would not be representative of community trends. In rural communities where cost and energy supply must be considered, grab samples taken at a biweekly frequency would need to be sufficient. The analyses performed by the National Wastewater Surveillance System (NWSS) used a 15-day surveillance window for trend reporting (CDC 2023). There is emerging evidence that grab samples, depending on the context and sampling targets, are comparable to composite samples collected over 24 hrs using an autosampler (George et al. 2022). Unlike grab sampling methods, autosamplers, while ubiquitous at urban plants, are costly and it would be difficult to scale up sampling if many autosamplers were required to maintain a surveillance program in a rural setting.

Extraction Methods. The choice of concentration and extraction method also warrants consideration in the context of rural settings, as many of these methods are pathogen-specific and require equipment and technical prowess which may not be present in a rural, environmental laboratory. Detection of SARS-CoV-2 in suspended solids is likely to be more consistent than detection in the liquid phase (Palmer et al. 2021). In comparisons of extraction methods from raw wastewater, electronegative filtration (HA filtration) with bead beating was determined to be the best approach based on consistent results above the limit of quantitation (LoQ), and was the most sensitive in terms of C_t (cycle threshold) value with a strong correlation to clinical data (Ahmed et al. 2020; LaTurner et al. 2021; Sharkey et al. 2021). Direct extraction (centrifugation of a sample followed by RNA extraction from supernatant) was the cheapest method in terms of startup costs and consumables, and even provided the highest concentrations of SARS-CoV-2 based on genome copies per L of wastewater. However, direct extraction was less likely to have a positive relationship with N1 and N2 gene copy numbers (LaTurner et al. 2021). The structural form of SARS-CoV-2 and a surrogate control requires investigation to understand how the concentration method affects recovery (LaTurner et al. 2021; Palmer et al. 2021). The methods for SARS-CoV-2 recovery may not work for all pathogens and different kits would be required for other viruses and pathogens such as bacteria and parasites. There is no method currently that works for all agents and some commercial kits are very costly and require additional equipment. The WBE studies in Texas have also relied on automated methods which would not be present in a typical environmental testing lab. In summary, we believe that extraction methods are critical when designing monitoring methods and require extensive resources. This step might need high expertise involvement to define a clear prioritization for targeting agents of public health concern.

Detection and Quantification. To be able to rely on the results obtained one would need to include controls. Recovery controls can be used in two ways: to evaluate the entire processing of a sample (process control) and to confirm the presence of fecal matter (fecal indicator). Both have the potential to be used as a recovery factor for normalization of quantifiable data, critical given the range in population densities among rural communities. Pepper mild mottle virus (PMMoV) has been used as a human fecal indicator and as an internal control for normalizing SARS-CoV-2 detection between sampling events (Rosario et al. 2009; Kitamura et al. 2021). When compared to bovine coronavirus (BCoV) as a process control, PMMoV detection was more variable, yet had higher recoveries (LaTurner et al. 2021). In the rural community study by D'Aoust et al. (2021), PMMoV was used for the recovery of SARS-CoV-2 in wastewater and showed trends like that of clinical data. As a possible limitation of the study, however, the clinical data obtained was for a larger geographic region that potentially did not represent the regions being served by the rural wastewater lagoon treatment location (D'Aoust et al. 2021). Other markers such as CrAssphage and HF183 can be used as indicators for the presence of human fecal matter (Ahmed, Masters, and Toze 2012; Wilder et al. 2021; Sabar, Honda, and

Haramoto 2022). While BCoV would be suitable for normalization, it would need to be reexamined for rural communities where bovine fecal matter could be a potential contaminant (LaTurner et al. 2021). Human coronavirus 229E (HCoV 229E) spiked into samples was used as another effective surrogate for monitoring infections within college campus residences at the University of Arizona (Betancourt et al. 2021). An alternative to genetic data for normalization was used in South India; quantification of caffeine levels in influent samples had greater than a 75% concurrence with N1 and N2 gene copies (Chakraborty et al. 2021).

Another consideration is the use of quantitative or droplet digital PCR (ddPCR), with ddPCR rapidly becoming the gold standard owing to its advantages in dealing with PCR inhibitors and direct quantification capacity (Al-Duroobi et al. 2021; Ciesielski et al. 2021; LaTurner et al. 2021; McCall et al. 2022; Hopkins et al. 2023; Jarvie et al. 2023). Droplet digital PCR allows for absolute nucleic acid quantification, with higher sensitivity and specificity than other PCR methods (Hindson et al. 2013; Kojabad et al. 2021). The target analyte molecule, DNA/RNA, is encapsulated into nanoliter-sized droplets that serve as a reaction chamber for amplification. Ciesielski et al. (2021) compared SARS-CoV-2 levels in influent wastewater detected by RT-ddPCR and RT-qPCR and found that RT-ddPCR signals were detected earlier during the study, likely when viral loads were lower. The assay limit of quantification (ALOD) for RT-qPCR was greater (60 copies/reaction) than RT-ddPCR (0.25 copies/reaction) using the N2 gene of the SARS-CoV-2 virus. Although RT-ddPCR is more sensitive, it may be difficult to differentiate background levels at low concentrations of viral RNA (Park et al. 2021). Ahmed et al. (2022) suggested that RT-qPCR should be used for wastewater samples because of the subjectivity in differentiating between a positive and negative signal with RT-ddPCR.

In the D'Aoust et al. (2021) study, samples were concentrated using settling at 4°C for one hour followed by centrifugation for RNA extraction from pelleted solids (Qiagen RNeasy PowerMicrobiome kit). SARS-CoV-2 viral signals were quantified using the primers for the N1 and N2 regions of the gene and singleplex one-step RT-qPCR, followed by normalization using PMMoV detection. Based on internal control (vesicular stomatitis virus, VSV), extraction recovery was between 3 and 4.5%. As mentioned above, the quantification of SARS-CoV-2 showed similar trends to the community data; however, the epidemiological data was only available for the larger geographic region (population of approximately 200,000) and not the regional community (population of approximately 4,000) that represented only 2% of the obtained clinical data. The availability of localized clinical data may also present a challenge to establishing a rural WBE scheme.

Case Study–Application of WBE in Rural Communities

We have recommendations that are based on the characteristics of our two cities (Table 4), derived from our consideration of rural communities and the unique challenges associated with rural WBE strategies because of diversity in size, wastewater characteristics, and treatment method selection. The major limiting factor in the deployment of any WBE strategy is the cost.

Case Study Valentine. While establishing WBE can be challenging, the case study of Valentine provides support for the need to adopt WBE within rural communities. There appears to be no SARS-CoV-2 case data readily available for Valentine, and so county-level data must be used. Reviewing the epidemiological data (as of April 17, 2023) for Jeff Davis County, there was a reported total of 278 cases with 10 deaths (Huang et al. 2021). There are a few challenges to consider with data collection and reporting for a city the size of Valentine. First, this data represents the entire county, and not necessarily the city of Valentine. Valentine is not the county seat of Jeff Davis County–it is Fort Davis, a city slightly larger than Valentine and so one could infer that more of the cases reported for the county could be from citizens in Fort Davis. Further support for this inference can be seen in the second challenge– the lack of testing centers relatively close to Valentine. Currently, the closest testing center to Valentine is in Alpine, TX, a 60-minute drive away. This testing center could also be used by residents from Fort Davis, which is only 30 minutes away from Fort Davis residents. In addition, Fort Davis had at least one instance of testing being done in the community in June of 2020.

Table 4. Recommendations for considering a WBE approach in a rural community such as Valentine or Kerrville.

Factor	Valentine (pop size=133 in 2019)	Kerrville (pop size=24,477 in 2021)
Sample Collection	Grab sampling might be recommended for this city because the number of staff might not be adequate to complete more than just one task at a time.	Any sampling method might be applicable to this city if strategically planned appropriately.
Sample Location	Collection within the sewer network or after the bar screen.	Collection within the sewer network, at the headworks, or before the aerobic/anoxic tank.
Sample Frequency	Recommend using a similar schedule as employed for BOD5 collection.	Twice per week.
Sampling Processing and Assessment	Consider partnering with local university partners in El Paso or an environmental lab.	Consider an in-house method such as purchasing a turnkey device that detects the pollutant.

Note: Our recommendations consider technical features, however, social factors should also be considered, such as building capacity, communication with, and characteristics of the community.

Case Study Kerrville. If we consider the sampling processing and assessment for the city of Kerrville, using in-house methods would require the city to procure the necessary equipment to detect the agent of concern. Equipment costs can vary based on the precision and complexity of the instrument, along with the need to continue to invest capital for consumables, maintenance and training, and management of personnel. If enough personnel were trained and capable of using the equipment, the cost per sample would be less than outsourcing the work to a commercial lab, which can be beyond the budget of a rural city. The cost per sample analyzed, shipping costs, and sample and shipping preparation costs to an outsourced lab could be prohibitive. The locations of our rural cities also suggest the need for collaboration with a local academic unit or college to support WBE development. This would require funding support and the development of training programs to be implemented at universities and community colleges in or near rural regions of Texas.

HO and HL Data. The HO and HL for Kerr (home of Kerrville) and Jeff Davis (home of Valentine) counties are shown in Figure 6.

Both rural cities demonstrated low HL scores compared with their urban counterparts. Kerr had a HL score of 246.84 compared with that of Travis, home of Austin (248.41) and Bexar, home to San Antonio (237.72), while Jeff Davis had a score of 244.24, compared with that of Midland (247.23). The range of reported values is from 177 to 280, with higher numbers indicating a higher level of HL. When HO was included (ranging from 1 to 221, with a value of 999 indicating the county was unranked), the low HO for Jeff Davis (HO:999) and Kerr (HO:126) compared with Travis (HO:7), Bexar (HO:78), and Midland (HO:18) gave further support for the establishment of WBE in these rural communities. Certainly, with these challenges for Valentine, WBE monitoring would be an appropriate tool to complement the health center testing data and give the city officials of Valentine a more localized profile to track the spread of the virus within their community.

Regardless of the method selected, it is our opinion that the value of information derived from the analysis should drive decision-making. In communities with poor HO and low HL, this type of population-level screening could make a difference

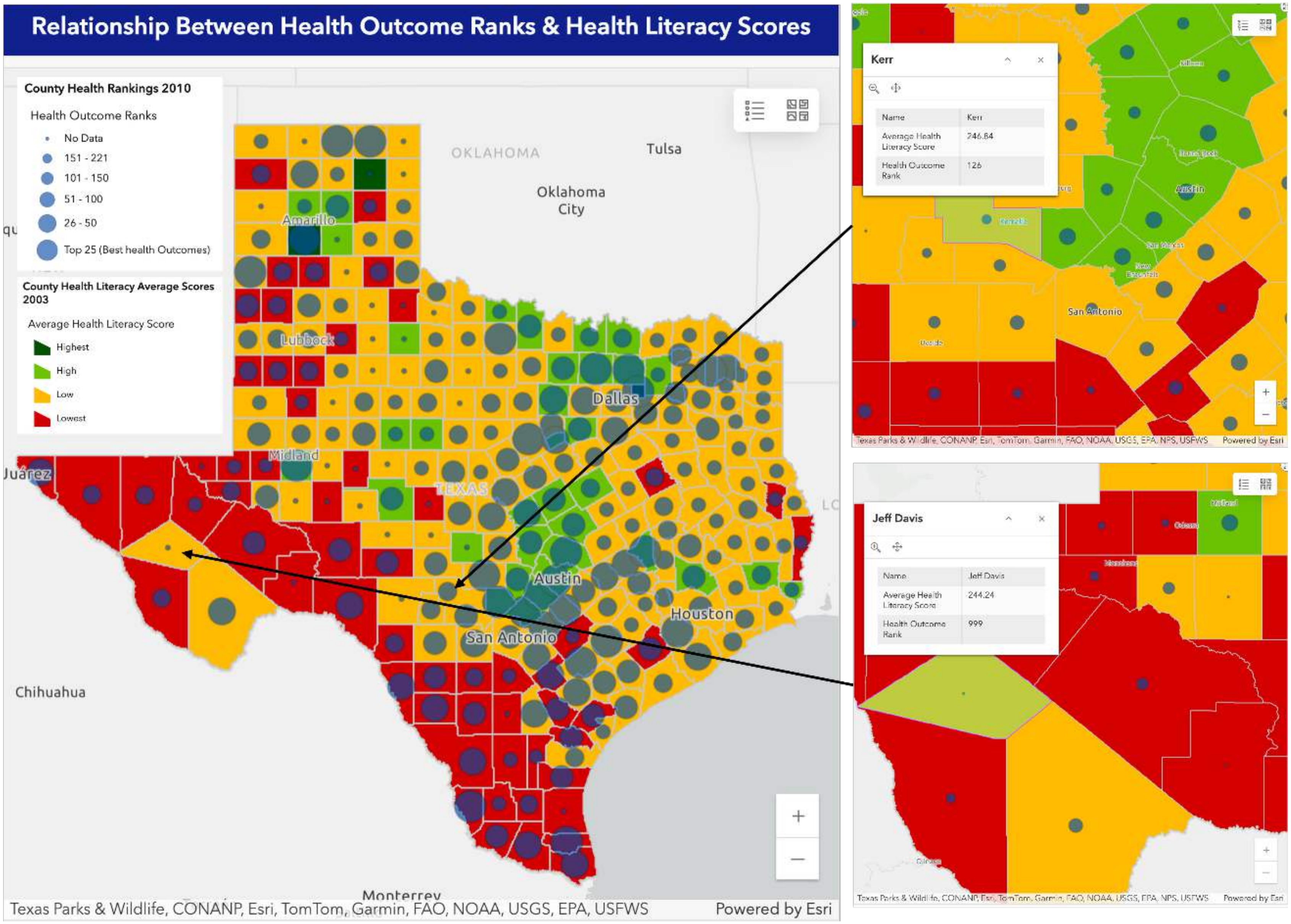


Figure 6. Health literacy and health outcome scores for Texas with panels showing the scores for Kerr and Jeff Davis. The colors indicate health literacy, with dark green having the highest score and red having the lowest score based on quartile scores for health literacy. The size of the circles within each county indicates the health outcome score; the larger the circle the higher the score. Stars show the location of Kerr and Jeff Davis on the map.

in morbidity and mortality in the event of a public health emergency. Several reports and studies have recommended WBE for rural communities and made suggestions as to implementation (Shrestha et al. 2021; National Academies of Sciences, Engineering, and Medicine 2023). Importantly, the results must be useful enough to make informed decisions by providing valuable and timely information where clinical sampling is lacking or access to sampling is unavailable to the appropriate decision-makers at the utility, local government, and state and federal levels. A reliance on data from urban centers would likely miss emerging agents of concern in regions that lack clinical surveillance.

Challenges for Implementing WBE in Other Rural Systems and Implications for Stakeholders

Our goal was to understand the potential for rural communities to employ WBE for measuring agents of concern such as outbreaks of infectious diseases (Gruchlik, Linge, and Joll 2018). There are many practical considerations when developing a contextualized WBE strategy beyond socioeconomic and wastewater infrastructure concerns, including the sampling collection method, sample processing and assessment, sampling location, and sampling frequency (Figure 7).

Wastewater Surveillance in Septic Systems. An important consideration for wastewater surveillance within rural communities is implementation within septic systems, also known as on-site sewage facilities (OSSFs) or decentralized systems. According to estimates from the American Society of Civil Engineers (ASCE), approximately 20% of U.S. citizens, including 60% of rural residents (Maxcy-Brown et al. 2021), have their wastewater treated by means of OSSF (Texas Water Resources Institute 2024). In many places worldwide, decentralized treatment is still a primary method of processing municipal wastewater (Shrestha et al. 2021; Gonçalves et al. 2022). With Texans comprising 5.8 million of those residents on OSSF (Texas Water Resources Institute 2024), it is important to consider strategies that will enable surveillance to be easily implemented within communities that employ OSSFs.

There are several important questions that must be answered when thinking about the implementation of wastewater surveillance within these communities. This work will address two fundamental questions. First, can the samples collected from OSSFs best represent the population within a community, given that sampling will most likely occur in individual households? Septic systems have hydraulic and pollutant characteristics that are different from a municipal WWTP (Iwamoto et al. 2022). For example, it is suggested that ideal retention time for solids within a septic tank can range between 12 and 24 hours (Nnaji and Agunwamba 2012), while at municipal plants that time is a few days (Li et al. 2023). This can result in two different outcomes. On one hand, the concentration of viruses within an OSSF waste stream could be higher than at a municipal plant. Since the operation of an OSSF is different from a municipal treatment plant, viruses are not always removed as efficiently as in centralized facilities. This results in viruses being concentrated within the waste stream not only because the treatment methods employed are not designed to remove these agents of concern, but also because there are no dilution effects or pathways for viral reduction, as are present in municipal waste streams. Wastewater in an OSSF is not being transferred long distances from the wastewater source (i.e., homes, apartments, schools) through a distribution network, as it would be in a municipal system. This pathway presents the opportunity for the concentration of these agents to be reduced by the time the wastewater reaches the plant, and temperatures during hauling might increase viral decay (Gwenzi 2022; Li et al. 2023).

Another outcome is that the concentration of viruses within solids from OSSFs might be different from the concentration of viruses in municipal systems. This happens because the solids in a septic tank stratify from shallow to deep. Amongst this stratification, the virus attached to the solids typically will concentrate within the deepest layers of the tank, which Li et al. (2023) surmise might result in a possible increase in viral decay, depending on holding time of the sludge. Factors such as viral decay, accessibility to household tanks, temperature, and sampling depth within a tank could also result in a misrepresentation of viral load in samples collected (Aslan et al. 2020; Li et al. 2023). Also, unlike a municipal treatment

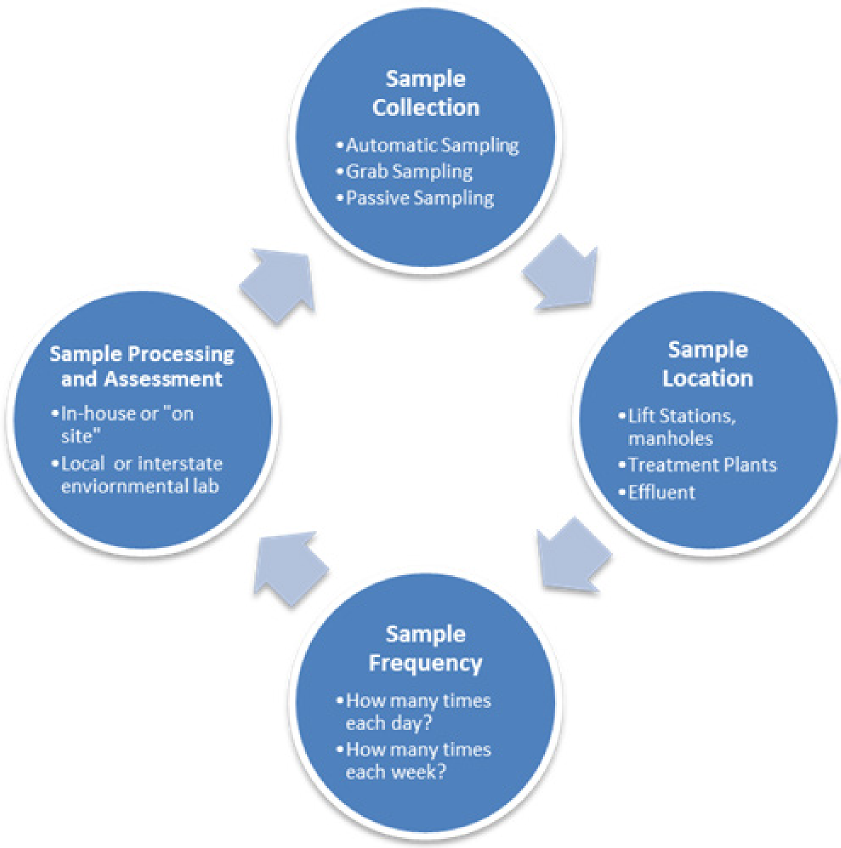


Figure 7. A diagram of the main factors that must be considered when instituting a WBE program. Each factor includes bullet points that outline key points and/or questions that provide context on how each factor relates to the establishment of WBE within a city.

facility where the wastewater amalgamates together giving some representation of the individuals in the community (Minnesota Pollution Control Agency 2024), OSSF wastewater is not always collated. In those scenarios, samples will need to be done at individual homes in order to obtain a community profile. This poses not only a time and financial constraint, but also raises potential ethical challenges as well (Shrestha et al. 2021). In cases such as these, it would be more feasible to sample pumped, hauled sewage rather than individual septic tanks (Li et al. 2023).

A second important question to address is where and with what methods do we sample? Currently, there have only been a few studies that have considered surveillance within OSSFs systems, and so guidance on this question is limited. Examples of studies published include the assessment of communities in Bangladesh (Amin et al. 2020; 2023), Japan (Iwamoto et al. 2022), Saudi Arabia (Hong et al. 2021), and China (Zhang et al. 2020; Dong et al. 2022). However, five of those six studies were assessing wastewater from hospitals (Zhang et al. 2020; Hong et al. 2021; Dong et al. 2022; Iwamoto et al. 2022; Amin et al. 2023), with three of those five facilities being temporary quarantine facilities for COVID-19 patients (Zhang et al. 2020; Hong et al. 2021; Iwamoto et al. 2022). A recently published study on wastewater surveillance in OSSF facilities evaluating wastewater from public beach restrooms in Malibu, CA (Li et al. 2023) was the only study found highlighting a United States study location. Please note that this study was not evaluating OSSFs in U.S. rural communities. However, this work does enable us to see that common public spaces (i.e., schools, community centers, churches) in communities employing OSSFs might provide a better way to sample wastewater within a community using septic systems, while at the same time resolve some of the logistical and ethical concerns of sampling at individual homes.

In closing, the lack of studies within U.S. rural communities at OSSFs presents an opportunity for future researchers to address the unknowns currently missing in literature. While there are other prevailing questions that must be addressed, the questions addressed in this study highlight and provide initial discussion topics on what should be considered.

Conclusions

It is a challenge to define what constitutes rural wastewater infrastructure in the United States and this has major implications when considering the feasibility (in terms of funding and available resources) of a public health strategy such as WBE. WBE has been shown to have utility for the detection of a wide variety of agents of public health concern, but an understanding of the challenges faced by rural communities is essential when attempting to design a feasible strategy for implementation.

Data Availability

All data analyzed in this paper are publicly available with data sources provided in the reference list.

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The authors declare no competing interests.

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References

Ahmed, W., N., Masters, and S. Toze. 2012. Consistency in the host specificity and host sensitivity of the bacteroides HF183 marker for sewage pollution tracking. *Letters in Applied Microbiology* 55(4): 283-289. Available at: https://doi.org/10.1111/j.1472-765X.2012.03291.x. Accessed May 3, 2024.

Ahmed, W., N. Angel, J. Edson, K. Bibby, A. Bivins, J.W. O'Brien, P.M. Choi, et al. 2020. First confirmed detection of SARS-CoV-2 in untreated wastewater in Australia: A proof of concept for the wastewater surveillance of COVID-19 in the community. *Science of The Total Environment* 728: 138764. Available at: https://doi.org/10.1016/j.scitotenv.2020.138764. Accessed May 3, 2024.

Ahmed, W., S.L. Simpson, P.M. Bertsch, K. Bibby, A. Bivins, L.L. Blackall, S. Bofill-Mas, et al. 2022. Minimizing errors in RT-PCR detection and quantification of SARS-CoV-2 RNA for wastewater surveillance. *Science of The Total Environment* 805: 149877. Available at: https://doi.org/10.1016/j.scitotenv.2021.149877. Accessed May 3, 2024.

Al-Duroobi, H., S.V. Moghadam, D.C. Phan, A. Jafarzadeh, A. Matta, and V. Kapoor. 2021. Wastewater surveillance of SARS-CoV-2 corroborates heightened community infection during the initial peak of COVID-19 in Bexar County, Texas. *FEMS Microbes* 2: xtab015. Available at: https://doi.org/10.1093/femsmc/xtab015. Accessed May 3, 2024.

Amin, N., R. Haque, M.Z. Rahman, M.Z. Rahman, Z.H. Mahmud, R. Hasan, M.T. Islam, et al. 2023. Dependency of sanitation infrastructure on the discharge of faecal coliform and SARS-CoV-2 viral RNA in wastewater from COVID and non-COVID hospitals in Dhaka, Bangladesh. *Science of The Total Environment* 867: 161424. Available at: https://doi.org/10.1016/j.scitotenv.2023.161424. Accessed May 3, 2024.

Amin, N., P. Liu, T. Foster, M. Rahman, M.R. Miah, G.B. Ahmed, M. Kabir, S. Raj, C.L. Moe, and J. Willetts. 2020. Pathogen flows from on-site sanitation systems in low-income urban neighborhoods, Dhaka: A quantitative environmental assessment. *International Journal of Hygiene and Environmental Health* 230: 113619. Available at: https://doi.org/10.1016/j.ijheh.2020.113619. Accessed May 3, 2024.

Aslan, A., G. Shah, V. Sittaramane, and P. Shankar. 2020. Sewage monitoring in rural communities: A powerful strategy for COVID-19 surveillance. *Journal of Environmental Health* 83(5): 8-11.

Association of Public Health Laboratories (APHL). 2022. SARS-CoV-2 Wastewater Surveillance Testing Guide for Public Health Laboratories. Silver Spring, MD. Available at: https://www.aphl.org/aboutAPHL/publications/Documents/EH-2022-SARSCoV2-Wastewater-Surveillance-Testing-Guide.pdf. Accessed May 3, 2024.

Betancourt, W.Q., B.W. Schmitz, G.K. Innes, S.M. Prasek, K.M.P. Brown, E.R. Stark, A.R. Foster, et al. 2021. COVID-19 containment on a college campus via wastewater-based epidemiology, targeted clinical testing and an intervention. *Science of The Total Environment* 779: 146408. Available at: https://doi.org/10.1016/j.scitotenv.2021.146408. Accessed May 3, 2024.

Bishop, N., T. Jones-Lepp, M. Margetts, J. Sykes, D. Alvarez, and D.E. Keil. 2020. Wastewater-based epidemiology pilot study to examine drug use in the western United States. *Science of the Total Environment* 745: 140697. Available at: https://doi.org/10.1016/j.scitotenv.2020.140697. Accessed May 3, 2024.

Boller, M. 1997. Small wastewater treatment plants- a challenge to wastewater engineers. *Water Science and Technology* 35(6): 1-12. Available at: https://doi.org/10.1016/S0273-1223(97)00089-9. Accessed May 3, 2024.

Brouwer, A.F., J.N.S. Eisenberg, C.D. Pomeroy, L.M. Shulman, M. Hindiyeh, Y. Manor, I. Grotto, J.S.

Koopman, and M.C. Eisenberg. 2018. Epidemiology of the silent polio outbreak in Rahat, Israel, based on modeling of environmental surveillance data. *Applied Mathematics* 115(45): E10625-E10633. Available at: https://doi.org/10.1073/pnas.1808798115. Accessed May 3, 2024.

Brown, J.A., B.L. Robertson, and T. McDonald. 2015. Spatially balanced sampling: Application to environmental surveys. *Procedia Environmental Sciences* 27: 6-9. Available at: https://doi.org/10.1016/j.proenv.2015.07.108. Accessed May 3, 2024.

Buechner, J.S., H. Constantine, and A. Gjelsvik. 2004. John Snow and the Broad Street pump: 150 years of epidemiology. *Medicine and Health*, Rhode Island 87(10): 314-315.

Centers for Disease Control and Prevention (CDC). 2008. Healthy Housing Inspection Manual. U.S. Department of Health and Human Services and U.S. Department of Housing and Urban Development, Atlanta, Georgia. Available at: https://stacks.cdc.gov/view/cdc/7020/cdc_7020_DS1.pdf. Accessed May 3, 2024.

Centers for Disease Control and Prevention (CDC). 2020. Risk for COVID-19 Infection, Hospitalization, and Death by Race/Ethnicity. Available at: https://www.cdc.gov/coronavirus/2019-ncov/covid-data/investigations-discovery/hospitalization-death-by-race-ethnicity.html. Accessed May 3, 2024.

Centers for Disease Control and Prevention (CDC). 2023. Developing a Wastewater Surveillance Sampling Strategy. National Wastewater Surveillance System. Available at: https://www.cdc.gov/nwss/sampling.html. Accessed May 4, 2024.

Chakraborty, P., M. Pasupuleti, M.R.J. Shankar, G.K. Bharat, S. Krishnasamy, S.C. Dasgupta, S.K. Sarkar, and K.C. Jones. 2021. First surveillance of SARS-CoV-2 and organic tracers in community wastewater during post lockdown in Chennai, South India: Methods, occurrence and concurrence. *Science of The Total Environment* 778: 146252. Available at: https://doi.org/10.1016/j.scitotenv.2021.146252. Accessed May 3, 2024.

Ciesielski, M., D. Blackwood, T. Clerkin, R. Gonzalez, H. Thompson, A. Larson, and R. Noble. 2021. Assessing sensitivity and reproducibility of RT-ddPCR and RT-qPCR for the quantification of SARS-CoV-2 in wastewater. *Journal of Virological Methods* 297: 114230. Available at: https://doi.org/10.1016/j.jviromet.2021.114230. Accessed May 3, 2024.

City-Data. 2023. Valentine, Texas (TX 79854). Available at: http://www.city-data.com/city/Valentine-Texas.html. Accessed April 29, 2023.

City of Kerrville, Texas. 2023. Water Reclamation Facility Tour. Available at: https://www.kerrvilletx.gov/1573/Water-Reclamation-Facility-Tour. Accessed April 29, 2023.

City of Valentine. 2003. Water and Wastewater Systems Improvements, Valentine, Texas. Rapid Assessment Process Project Strategic Plan. Available at: https://www.slideserve.com/aelan/city-of-valentine-water-wastewater-systems-improvements-valentine-texas. Accessed May 3, 2024.

Clark, J.R., A. Terwilliger, V. Avadhanula, M. Tisza, J. Cormier, S. Javornik-Cregeen, M.C. Ross, et al. 2023. Wastewater pandemic preparedness: Toward an end-to-end pathogen monitoring program. *Frontiers in Public Health* 11. Available at: https://www.frontiersin.org/articles/10.3389/fpubh.2023.1137881. Accessed May 3, 2024.

D'Aoust, P.M., S.T. Towhid, É. Mercier, N. Hegazy, X. Tian, K. Bhatnagar, Z. Zhang, et al. 2021. COVID-19 wastewater surveillance in rural communities: Comparison of lagoon and pumping station samples. *Science of the Total Environment* 801: 149618. Available at: https://doi.org/10.1016/j.scitotenv.2021.149618. Accessed May 4, 2024.

Dong, Q., J-X. Cai, Y-C. Liu, H-B. Ling, Q. Wang, L-J. Xiang, S-L. Yang, et al. 2022. Occurrence and decay of SARS-CoV-2 in community sewage drainage systems. *Engineering* 26: 214-219. Available at: https://doi.org/10.1016/j.eng.2022.03.012. Accessed May 4, 2024.

Environmental Systems Research Institute, Inc. (ESRI). 2021. Esri Releases Guide Teaching ArcGIS Desktop10.8. Redlands, CA. Available at: https://www.esri.com/about/newsroom/announcements/esri-releases-guide-teaching-arcgis-desktop-10-8/. Accessed May 4, 2024.

Feng, S., A. Roguet, J.S. McClary-Gutierrez, R.J. Newton, N. Kloczko, J.G. Meiman, and S.L. McLellan. 2021. Evaluation of sampling, analysis, and normalization methods for SARS-CoV-2 concentrations in wastewater to assess COVID-19 burdens in Wisconsin communities. *ACS ES&T Water* 1(8): 1955-1965. Available at: https://doi.org/10.1021/acsestwater.1c00160. Accessed May 4, 2024.

George, A.D., D. Kaya, B.A. Layton, K. Bailey, C. Kelly, K.J. Williamson, and T.S. Radniecki. 2022. The impact of sampling type, frequency and scale of collection system on SARS-CoV-2 quantification fidelity. *Environmental Science & Technology Letters*. Available at: https://doi.org/10.1021/acs.estlett.1c00882. Accessed May 4, 2024.

Gitter, A., C. Bauer, F. Wu, R. Ramphul, C. Chavarria, K. Zhang, J. Petrosino, et al. 2023. Assessment of a

SARS-CoV-2 wastewater monitoring program in El Paso, Texas, from November 2020 to June 2022. *International Journal of Environmental Health Research* 34(1): 564-574. Available at: https://doi.org/10.1080/09603123.2022.2159017. Accessed May 4, 2024.

Global Polio Eradication Initiative, World Health Organization. (GPEI). 2023. The Global Polio Laboratory Network. Available at: https://polioeradication.org/polio-today/polio-now/surveillance-indicators/the-global-polio-laboratory-network-gpln/. Accessed April 28, 2023.

Gonçalves, J., A. Torres-Franco, E. Rodriguéz, I. Diaz, T. Koritnik, P. Gomes da Silva, J.R. Mesquita, et al. 2022. Centralized and decentralized wastewater-based epidemiology to infer COVID-19 transmission – A brief review. *One Health* 15: 100405. Available at: https://doi.org/10.1016/j.onehlt.2022.100405. Accessed May 4, 2024.

Google Earth Pro V. 7.3. 2024a. City of Valentine. 30.59208, -104.50771, 100 ft. Airbus, CNES/Airbus, Maxar Technologies. Available at: https://www.google.com/maps/place/Valentine,+TX+79854/@30.5913472,-104.5079627,319m/data=!3m1!1e3!4m6!3m5!1s0x86ef6fb636bbd7d7:0xaad57af6cb216d87!8m2!3d30.5873662!4d-104.4965912!16zL20vMDEwNGxk?entry=ttu. Accessed April 26, 2024.

Google Earth Pro V. 7.3. 2024b. Kerrville Wastewater Treatment Plant. 30.02545, -99.11353, 100 ft. Airbus, CNES/Airbus, Maxar Technologies. Available at: https://www.google.com/maps/place/Kerrville+Wastewater+Treatment/@30.0247437,-99.1136541,321m/data=!3m1!1e3!4m6!3m5!1s0x865be351b98fb8fb:0xcf4b996cee59b84d!8m2!3d30.0253196!4d-99.1135414!16s%2Fg%2F1tgn54j3?entry=ttu. Accessed April 26, 2024.

Gruchlik, Y., K. Linge, and C. Joll. 2018. Removal of organic micropollutants in waste stabilisation ponds: A review. *Journal of Environmental Management* 206: 202-214. Available at: https://doi.org/10.1016/j.jenvman.2017.10.020. Accessed May 4, 2024.

Gwenzi, W. 2022. Wastewater, waste, and water-based epidemiology (WWW-BE): A novel hypothesis and decision-support tool to unravel COVID-19 in low-income settings? *Science of the Total Environment* 806(Part 3): 150680. Available at: https://doi.org/10.1016/j.scitotenv.2021.150680. Accessed May 4, 2024.

Hayes, E.K., C.L. Sweeney, L.E. Anderson, B. Li, G.B. Erjavec, M.T. Gouthro, W.H. Krkosek, A.K. Stoddart, and G.A. Gagnon. 2021. A novel passive sampling approach for SARS-CoV-2 in wastewater in a Canadian province with low prevalence of COVID-19. *Environmental Science: Water Research & Technology* 7(9): 1576-1586. Available at: https://doi.org/10.1039/D1EW00207D. Accessed May 4, 2024.

Hayes, E.K., A.K. Stoddart, and G.A. Gagnon. 2022. Adsorption of SARS-CoV-2 onto granular activated carbon (GAC) in wastewater: Implications for improvements in passive sampling. *Science of the Total Environment* 847: 157548. Available at: https://doi.org/10.1016/j.scitotenv.2022.157548. Accessed May 4, 2024.

Health Literacy Texas. 2023. About Health Literacy. Available at: https://www.healthliteracytx.org/about-health-literacy. Accessed May 3, 2024.

Hindson, C.M., J.R. Chevillet, H.A. Briggs, E.N. Gallichotte, I.K. Ruf, B.J. Hindson, R.L. Vessella, and M. Tewari. 2013. Absolute quantification by droplet digital PCR versus analog real-time PCR. *Nature Methods* 10: 1003-1005. Available at: https://doi.org/10.1038/nmeth.2633. Accessed May 4, 2024.

Hong, P-Y., A.T. Rachmadi, D. Mantilla-Calderon, M. Alkahtani, Y.M. Bashawri, H. Al Qarni, K.M. O'Reilly, and J. Zhou. 2021. Estimating the minimum number of SARS-CoV-2 infected cases needed to detect viral RNA in wastewater: To what extent of the outbreak can surveillance of wastewater tell us? *Environmental Research* 195: 110748. Available at: https://doi.org/10.1016/j.envres.2021.110748. Accessed May 4, 2024.

Hopkins, L., D. Persse, K. Caton, K. Ensor, R. Schneider, C. McCall, and L.B. Stadler. 2023. Citywide wastewater SARS-CoV-2 levels strongly correlated with multiple disease surveillance indicators and outcomes over three COVID-19 waves. *Science of the Total Environment* 855: 158967. Available at: https://doi.org/10.1016/j.scitotenv.2022.158967. Accessed May 4, 2024.

Hou, C., Z. Hua, P. Xu, H. Xu, Y. Wang, J. Liao, and B. Di. 2020. Estimating the prevalence of hepatitis B by wastewater-based epidemiology in 19 cities in China. *Science of the Total Environment* 740: 139696. Available at: https://doi.org/10.1016/j.scitotenv.2020.139696. Accessed May 4, 2024.

Huang, J., S. Jacoby, J.C. Lee, J-M. Murphy, C. Smart, and A. Sun. 2021. Jeff Davis County, Texas Covid Case and Risk Tracker. *The New York Times*, January 27, 2021. Available at: https://www.nytimes.com/interactive/2023/us/jeff-davis-texas-covid-cases.html. Accessed May 4, 2024.

Iwamoto, R., K. Yamaguchi, C. Arakawa, H. Ando, E. Haramoto, K-I. Setsukinai, K. Katayama, et al. 2022. The detectability and removal efficiency of SARS-CoV-2 in a large-scale septic tank of a COVID-19 quarantine facility in Japan. *Science of the Total Environment* 849: 157869. Available at: https://doi.org/10.1016/j.scitotenv.2022.157869. Accessed May 4, 2024.

Jakariya, Md., F. Ahmed, Md.A. Islam, A. Al Marzan, M.N. Hasan, M. Hossain, T. Ahmed, et al. 2022. Wastewater-based epidemiological surveillance to monitor the prevalence of SARS-CoV-2 in developing countries with onsite sanitation facilities. *Environmental Pollution* 311: 119679. Available at: https://doi.org/10.1016/j.envpol.2022.119679. Accessed May 4, 2024.

Jarvie, M.M., M. Reed-Lukomski, B. Southwell, D. Wright, and T.N.T. Nguyen. 2023. Monitoring of COVID-19 in wastewater across the eastern upper peninsula of Michigan. *Environmental Advances* 11: 100326. Available at: https://doi.org/10.1016/j.envadv.2022.100326. Accessed May 4, 2024.

Joseph-Duran, B., A. Serra-Compte, M. Sàrrias, S. Gonzalez, D. López, C. Prats, M. Català, E. Alvarez-Lacalle, S. Alonso, and M. Arnaldos. 2022. Assessing wastewater-based epidemiology for the prediction of SARS-CoV-2 incidence in Catalonia. *Scientific Reports* 12: 15073. Available at: https://doi.org/10.1038/s41598-022-18518-9. Accessed May 4, 2024.

Kankaanpää, A., K. Ariniemi, M. Heinonen, K. Kuoppasalmi, and T. Gunnar. 2016. Current trends in Finnish drug abuse: Wastewater based epidemiology combined with other national indicators. *Science of the Total Environment* 568: 864-874. Available at: https://doi.org/10.1016/j.scitotenv.2016.06.060. Accessed May 4, 2024.

Kitamura, K., K. Sadamasu, M. Muramatsu, and H. Yoshida. 2021. Efficient detection of SARS-CoV-2 RNA in the solid fraction of wastewater. *Science of The Total Environment* 763: 144587. Available at: https://doi.org/10.1016/j.scitotenv.2020.144587. Accessed May 4, 2024.

Kojabad, A.A., M. Farzanehpour, H.E.G. Galeh, R. Dorostkar, A. Jafarpour, M. Bolandian, and M.M. Nodooshan. 2021. Droplet digital PCR of viral DNA/RNA, current progress, challenges, and future perspectives. *Journal of Medical Virology* 93(7): 4182-4197. Available at: https://doi.org/10.1002/jmv.26846. Accessed May 4, 2024.

Lai, F.Y., R. Bruno, W. Hall, C. Gartner, C. Ort, P. Kirkbride, J. Prichard, P.K. Thai, S. Carter, and J.F. Mueller. 2013. Profiles of illicit drug use during annual key holiday and control periods in Australia: Wastewater analysis in an urban, a semi-rural and a vacation area. *Addiction* 108(3): 556-565. Available at: https://doi.org/10.1111/add.12006. Accessed May 4, 2024.

LaTurner, Z.W., D.M. Zong, P. Kalvapalle, K.R. Gamas, A. Terwilliger, T. Crosby, P. Ali, et al. 2021. Evaluating recovery, cost, and throughput of different concentration methods for SARS-CoV-2 wastewater-based epidemiology. *Water Research* 197: 117043. Available at: https://doi.org/10.1016/j.watres.2021.117043. Accessed May 4, 2024.

Leider, J.P., M. Meit, J.M. McCullough, B. Resnick, D. Dekker, Y.N. Alfonso, and D. Bishai. 2020. The state of rural public health: Enduring needs in a new decade. *American Journal of Public Health* 110(9): 1283-1290. Available at: https://doi.org/10.2105/AJPH.2020.305728. Accessed May 4, 2024.

Levine, C.R., R.D. Yanai, G.G. Lampman, D.A. Burns, C.T. Driscoll, G.B. Lawrence, J.A. Lynch, and N. Schoch. 2014. Evaluating the efficiency of environmental monitoring programs. *Ecological Indicators* 39: 94-101. Available at: https://doi.org/10.1016/j.ecolind.2013.12.010. Accessed May 4, 2024.

Li, D., H. Quon, J. Ervin, S. Jiang, D. Rosso, L.C. Van De Werfhorst, B. Steets, and P.A. Holden. 2023. Modeled and measured SARS-CoV-2 virus in septic tank systems for wastewater surveillance. *Journal of Water and Health* 21(9): 1242-1256. Available at: https://doi.org/10.2166/wh.2023.128. Accessed May 4, 2024.

Li, J., W. Ahmed, S. Metcalfe, W.J.M. Smith, B. Tscharke, P. Lynch, P. Sherman, et al. 2022. Monitoring of SARS-CoV-2 in sewersheds with low COVID-19 cases using a passive sampling technique. *Water Research* 218: 118481. Available at: https://doi.org/10.1016/j.watres.2022.118481. Accessed May 4, 2024.

Margetts, M., A. Keshaviah, X.C. Hu, V. Troeger, J. Sykes, N. Bishop, T. Jones-Lepp, M. Henry, and D.E. Keil. 2020. Using wastewater-based epidemiology with local indicators of opioid and illicit drug use to overcome data gaps in Montana. medRxiv. Available at: https://doi.org/10.1101/2020.04.18.20064113. Accessed May 4, 2024.

Maxcy-Brown, J., M.A. Elliott, L.A. Krometis, J. Brown, K.D. White, and U. Lall. 2021. Making waves: Right in our backyard- Surface discharge of untreated wastewater from homes in the United States. *Water Research* 190: 116647. Available at: https://doi.org/10.1016/j.watres.2020.116647. Accessed May 4, 2024.

McCall, C., Z.N. Fang, D. Li, A.J. Czubai, A. Juan, Z.W. LaTurner, K. Ensor, L. Hopkins, P.B. Bedient, and L.B. Stadler. 2022. Modeling SARS-CoV-2 RNA degradation in small and large sewersheds. *Environmental Science: Water Research & Technology* 8(2): 290-300. Available at: https://doi.org/10.1039/

D1EW00717C. Accessed May 4, 2024.

Medina, C.Y., K.F. Kadonsky, F.A. Roman, A.Q. Tariqi, R.G. Sinclair, P.M. D'Aoust, R. Delatolla, H.N. Bischel, and C.C. Naughton. 2022. The need of an environmental justice approach for wastewater based epidemiology for rural and disadvantaged communities: A review in California. *Current Opinion in Environmental Science & Health* 27: 100348. Available at: https://doi.org/10.1016/j.coesh.2022.100348. Accessed May 4, 2024.

Minnesota Pollution Control Agency. 2024. Wastewater Permitting. Available at: https://www.pca.state.mn.us/air-water-land-climate/wastewater-permitting. Accessed April 14, 2024.

Mueller, J.T., K. McConnell, P.B. Burow, K. Pofahl, A.A. Merdjanoff, and J. Farrell. 2021. Impacts of the COVID-19 pandemic on rural America. *Proceedings of the National Academy of Sciences* 118(1): 2019378118. Available at: https://doi.org/10.1073/pnas.2019378118. Accessed May 4, 2024.

National Academies of Sciences, Engineering, and Medicine. 2023. *Wastewater-Based Disease Surveillance for Public Health Action*. The National Academies Press, Washington, D.C. Available at: https://doi.org/10.17226/26767. Accessed May 4, 2024.

National Health Literacy Mapping to Inform Health Care Policy. 2010. Health Literacy Scores in Texas. Available at: https://www.arcgis.com/apps/dashboards/943c5859937843fbbb947ea6d81ea738. Accessed April 29, 2023.

Nelson, J.R., A. Lu, J.P. Maestre, E.J. Palmer, D. Jarma, K.A. Kinney, T.H. Grubesic, and M.J. Kirisits. 2022. Space-time analysis of COVID-19 cases and SARS-CoV-2 wastewater loading: A geodemographic perspective. *Spatial and Spatio-temporal Epidemiology* 42: 100521. Available at: https://doi.org/10.1016/j.sste.2022.100521. Accessed May 4, 2024.

Nnaji, C.C. and J.C. Agunwamba. 2012. Detention time as a critical parameter in septic tank design. *Asian Journal of Water, Environment and Pollution* 9(1): 31-38. Available at: https://www.researchgate.net/profile/Chidozie-Nnaji/publication/237102381_Detention_Time_as_a_Critical_Parameter_in_Septic_Tank_Design/links/0deec51caf378a6a68000000/Detention-Time-as-a-Critical-Parameter-in-Septic-Tank-Design.pdf. Accessed May 4, 2024.

Palmer, E.J., J.P. Maestre, D. Jarma, A. Lu, E. Willmann, K.A. Kinney, and M.J. Kirisits. 2021. Development of a reproducible method for monitoring SARS-CoV-2 in wastewater. *Science of the Total Environment* 799: 149405. Available at: https://doi.org/10.1016/j.scitotenv.2021.149405. Accessed May 4, 2024.

Park, C., J. Lee, Z. ul Hassan, K.B. Ku, S-J. Kim, H.G. Kim, E.C. Park, et al. 2021. Comparison of digital PCR and quantitative PCR with various SARS-CoV-2 primer-probe sets. *Journal of Microbiology and Biotechnology* 31(3): 358-367. Available at: https://doi.org/10.4014/jmb.2009.09006. Accessed May 4, 2024.

Pérez-Cataluña, A., Á. Chiner-Oms, E. Cuevas-Ferrando, A. Díaz-Reolid, I. Falcó, W. Randazzo, I. Girón-Guzmán, et al. 2022. Spatial and temporal distribution of SARS-CoV-2 diversity circulating in wastewater. *Water Research* 211: 118007. Available at: https://doi.org/10.1016/j.watres.2021.118007. Accessed May 4, 2024.

Perry, B.L., B. Aronson, and B.A. Pescosolido. 2021. Pandemic precarity: COVID-19 is exposing and exacerbating inequalities in the American heartland. *Proceedings of the National Academy of Sciences* 118(8): e2020685118. Available at: https://doi.org/10.1073/pnas.2020685118. Accessed May 4, 2024.

Polo, D., M. Quintela-Baluja, A. Corbishley, D.L. Jones, A.C. Singer, D.W. Graham, and J.L. Romalde. 2020. Making waves: Wastewater-based epidemiology for COVID-19 - Approaches and challenges for surveillance and prediction. *Water Research* 186: 116404. Available at: https://doi.org/10.1016/j.watres.2020.116404. Accessed May 4, 2024.

Price, M., C. Wilkins, B.J. Tscharke, T. Baker, J.F. Mueller, and S. Trowsdale. 2021. Spatial, temporal and socioeconomic patterns of illicit drug use in New Zealand assessed using wastewater-based epidemiology timed to coincide with the census. *The New Zealand Medical Journal* 134(1537): 11-26. Available at: https://pubmed.ncbi.nlm.nih.gov/34239158/. Accessed May 4, 2024.

Ratcliffe, M., C. Burd, K. Holder, and A. Fields. 2016. Defining Rural at the U.S. Census Bureau. U.S. Census Bureau Report Number ACSGEO-1. Available at: https://www.census.gov/library/publications/2016/acs/acsgeo-1.html. Accessed May 4, 2024.

Rosario, K., E.M. Symonds, C. Sinigalliano, J. Stewart, and M. Breitbart. 2009. Pepper mild mottle virus as an indicator of fecal pollution. *Applied and Environmental Microbiology* 75(22): 7261-7267. Available at: https://doi.org/10.1128/AEM.00410-09. Accessed May 4, 2024.

Rural Health Information Hub. 2023. Texas. Available at: https://www.ruralhealthinfo.org/states/texas. Accessed April 28, 2023.

Sabar, M.A., R. Honda, and E. Haramoto. 2022. CrAssphage as an indicator of human-fecal contamination in water environment and virus reduction in wastewater treatment. *Water Research* 221: 118827. Available at: https://doi.org/10.1016/j.watres.2022.118827. Accessed May 4, 2024.

Safford, H.R., K. Shapiro, and H.N. Bischel. 2022. Wastewater analysis can be a powerful public health tool—If it's done sensibly. *Proceedings of the National Academy of Sciences* 119(6): e2119600119. Available at: https://doi.org/10.1073/pnas.2119600119. Accessed May 4, 2024.

Sanders, A. and J. Cromartie. 2024a. Rural Classifications. USDA-ERS. Available at: https://www.ers.usda.gov/topics/rural-economy-population/rural-classifications/. Accessed May 4, 2024.

Sanders, A. and J. Cromartie. 2024b. What is Rural? USDA-ERS. Available at: https://www.ers.usda.gov/topics/rural-economy-population/rural-classifications/what-is-rural/. Accessed May 4, 2024.

Sharkey, M.E., N. Kumar, A.M.A. Mantero, K.M. Babler, M.M. Boone, Y. Cardentey, E.M. Cortizas, et al. 2021. Lessons learned from SARS-CoV-2 measurements in wastewater. *Science of The Total Environment* 798: 149177. Available at: https://doi.org/10.1016/j.scitotenv.2021.149177. Accessed May 4, 2024.

Shrestha, S., E. Yoshinaga, S.K. Chapagain, G. Mohan, A. Gasparatos, and K. Fukushi. 2021. Wastewater-based epidemiology for cost-effective mass surveillance of COVID-19 in low- and middle- income countries: Challenges and opportunities. *Water* 13(20): 2897. Available at: https://doi.org/10.3390/w13202897. Accessed May 4, 2024.

Sikorski, M.J. and M.M. Levine. 2020. Reviving the 'Moore swab': A classic environmental surveillance tool involving filtration of flowing surface water and sewage water to recover typhoidal *Salmonella* bacteria. *Applied and Environmental Microbiology* 86(13): e00060-20. Available at: https://doi.org/10.1128/AEM.00060-20. Accessed May 4, 2024.

Smailes, P.J. 1996. Demographic response to rural restructuring and counterurbanisation in South Australia, 1981-1991. *International Journal of Population Geography* 2(3): 261-287. Available at: https://doi.org/10.1002/(SICI)1099-1220(199609)2:3<261::AID-IJPG38>3.0.CO;2-L. Accessed May 4, 2024.

Soria, A., S. Galimberti, G. Lapadula, F. Visco, A. Ardini, M.G. Valsecchi, and P. Bonfanti. 2021. The high volume of patients admitted during the SARS-CoV-2 pandemic has an independent harmful impact on in-hospital mortality from COVID-19. *PLOS ONE* 16(1): e0246170. Available at: https://doi.org/10.1371/journal.pone.0246170. Accessed May 4, 2024.

Surbhi, S., E.A. Tolley, R.E. Cossman, A.A. Dashputre, and J.E. Bailey. 2021. Refining a traditional urban-rural classification approach to better assess heterogeneity of treatment effects in patient-centered outcomes research. *MethodsX* 8: 101299. Available at: https://doi.org/10.1016/j.mex.2021.101299. Accessed May 4, 2024.

Switzer, D., M.P. Teodoro, and S. Karasik. 2016. The human capital resource challenge: Recognizing and overcoming small utility workforce obstacles. *Journal AWWA* 108(8): E416-E424. Available at: https://doi.org/10.5942/jawwa.2016.108.0093. Accessed May 4, 2024.

Texas Department of Housing and Community Affairs. 2022. 2022 Index of Texas Counties. Available at: https://www.tdhca.state.tx.us/home-division/docs/22-IndexCounties.pdf. Accessed May 4, 2024.

Texas Department of Transportation. 2024. Texas Cities [map]. Version 10.8.2. Available at: https://gis-txdot.opendata.arcgis.com/datasets/texas-cities/explore?location=30.334664%2C-100.887837%2C8.00. Accessed March 22, 2024.

Texas Department of Transportation. 2015. Texas State Boundary [map]. Version 10.8.2. Available at: https://gis-txdot.opendata.arcgis.com/datasets/texas-state-boundary/explore. Accessed May 4, 2024.

Texas State Office of Rural Health, Office of Rural Affairs, Texas Department of Agriculture. 2012. Texas County Designations. Available at: https://texasagriculture.gov/portals/0/forms/er/rural-metro%20counties.pdf. Accessed May 23, 2024.

Texas Water Resources Institute. 2024. Bigger Is Not Always Better: Decentralizing Texas' Wastewater Infrastructure. Available at: https://twri.tamu.edu/publications/txh2o/2022/winter-2022/bigger-is-not-always-better-decentralizing-texas-wastewater-infrastructure/. Accessed April 14, 2024.

Tokich, S.H. and S. Hophmayer-Tokich. 2006. Wastewater Management Strategy: Centralized v. Decentralized Technologies for Small Communities. Center for Clean Technology and Environmental Policy. Available at: https://research.utwente.nl/en/publications/wastewater-management-strategy-centralized-v-decentralized-techno. Accessed May 4, 2024.

Trask, J.D. and J.R. Paul. 1942. Periodic examination of sewage for the virus of poliomyelitis. *Journal of Experimental Medicine* 75(1): 1-6. Available at: https://doi.org/10.1084%2Fjem.75.1.1. Accessed May 4, 2024.

U.S. Census Bureau. 2023a. QuickFacts: Kerrville City, Texas. Available at: https://www.census.gov/quickfacts/kerrvillecitytexas. Accessed April 29, 2023.

U.S. Census Bureau. 2023b. Urban and Rural. Available at: https://www.census.gov/programs-surveys/geography/guidance/geo-areas/urban-rural.html. Accessed April 28, 2023.

U.S. Environmental Protection Agency (US EPA). 2015a. About Small Wastewater Systems. Available at: https://www.epa.gov/small-and-rural-wastewater-systems/about-small-wastewater-systems. Accessed May 4, 2024.

U.S. Environmental Protection Agency (US EPA). 2015b. Sampling Guidance for Unknown Contaminants in Drinking Water. Available at: https://www.epa.gov/waterlabnetwork/sampling-guidance-unknown-contaminants-drinking-water. Accessed May 4, 2024.

University of Wisconsin Population Health Institute (UWPHI). 2023a. Health Outcomes. County Health Rankings & Roadmaps. Available at: https://www.countyhealthrankings.org/explore-health-rankings/county-health-rankings-model/health-outcomes. Accessed April 30, 2023.

University of Wisconsin Population Health Institute (UWPHI). 2023b. How Healthy Is Your Community? County Health Rankings & Roadmaps. Available at: https://www.countyhealthrankings.org/county-health-rankings-roadmaps. Accessed April 29, 2023.

Wilder, M.L., F. Middleton, D.A. Larsen, Q. Du, A. Fenty, T. Zeng, T. Insaf, et al. 2021. Co-Quantification of crAssphage increases confidence in wastewater-based epidemiology for SARS-CoV-2 in low prevalence areas. *Water Research X* 11: 100100. Available at: https://doi.org/10.1016/j.wroa.2021.100100. Accessed May 4, 2024.

Wilson, W.J. 1933. Isolation of enteric bacilli from sewage and water and its bearing on epidemiology. *British Medical Journal* 2(3794): 560-562. Available at: https://doi.org/10.1136/bmj.2.3794.560. Accessed May 4, 2024.

Wu, F., W.L. Lee, H. Chen, X. Gu, F. Chandra, F. Armas, A. Xiao, et al. 2022. Making waves: Wastewater surveillance of SARS-CoV-2 in an endemic future. *Water Research* 219: 118535. Available at: https://doi.org/10.1016/j.watres.2022.118535. Accessed May 4, 2024.

Xagoraraki, I. and E. O'Brien. 2019. Wastewater-based epidemiology for early detection of viral outbreaks. In: *Women in Water Quality: Investigations by Prominent Female Engineers.* D.J. O'Bannon (Ed.). Springer, pp. 75-97. Available at: https://doi.org/10.1007/978-3-030-17819-2_5. Accessed May 4, 2024.

Zhang, D., H. Ling, X. Huang, J. Li, W. Li, C. Yi, T. Zhang, et al. 2020. Potential spreading risks and disinfection challenges of medical wastewater by the presence of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) viral RNA in septic tanks of Fangcang Hospital. *Science of The Total Environment* 741: 140445. Available at: https://doi.org/10.1016/j.scitotenv.2020.140445. Accessed May 4, 2024.

Supporting Information

Rural Definition

The question, "What is rural?" for the purposes of demography is not a simple one. There are several ways to reach the definition, and they may all yield different results. Briefly, the most common ways are (1) communities with less than a threshold maximum population, (2) residing in a county which has a population density less than a maximum threshold, (3) residing in any place which is outside of a U.S. Census Metropolitan Statistical Area (MSA), (4) examining levels of isolation or distance from more heavily populated areas, or (5) the presence or absence of significant agricultural activities. As stressed by one USDA-ERS article, there is not a consistent definition of rural, and this may be appropriate. It is not that "rural" is meant to be a subjective concept. Rather, it is that there is generally a greater purpose (certainly from a planning or governmental perspective) in calling an area rural, urban, or peri-urban. The definition of rural should fit this purpose (Sanders and Cromartie 2024).

A short examination of other studies having many varied purposes illustrates the point of having a workable definition for rural, as opposed to a universal definition. We outline five studies that have strong emphasis on how to define rurality over the last 25 years in Table 1. A few common themes emerge. First, there is the need to relate rurality to the lived experiences of those who are being studied. Despite many demographic metrics that could be used, it is important to examine the finding from these metrics according to both the lived experience of residents and inquiring how they themselves define rurality (Berry et al. 2000; Krutsinger et al. 2024). Second, geospatial metrics of rurality would do well to consider at least two major types of data. The two most common are population density and distances to services, but most researchers acknowledge that more metrics could be added to these to improve the rural definition (Nelson and Nguyen 2023; Krutsinger et al. 2024). Third, it may sometimes be inaccurate to speak of rural and urban as a dualism or dichotomy. In these studies, there are instances where those in areas that were significantly labeled as urban core self-identified as rural. In other cases, the definition of rural versus urban is fuzzy (Bennett et al. 2019; Johnson and Scala 2022). It may not be as simple as either rural or urban since there is a continuum between some extremes. Leaning into the work of Bennett et al. (2019), we are being careful to define precisely what our definition of rural is, depending on the analysis we conduct and with some justification why that analysis is appropriate in each case of its use (Johnson and Scala 2022).

There are two definitions of rural that we use in our study.

Method 1 - Community Population Size

Given that it is our aim to examine the landscape of rural wastewater-based epidemiology potential, it seemed appropriate to think of rurality in terms of places that were smaller in size and fully incorporated with centralized water utilities. This is predominantly a size threshold approach. While there are certainly places outside of incorporated cities that are rural, these places are not very likely to have centralized sewerage. We selected a minimum population threshold of < 5,000 residents for this definition, based primarily on practical concerns. While there are communities larger than this which might be considered rural by some definitions, these locations are frequently more suburban and have a greater tax base and workforce to use WBE. This is the definition that we used to determine inclusion for rural communities on all statewide GIS analyses.

Method 2 – County Population and Presence of Metropolitan Area

Another method for rurality is to look at the population density of a county. A definition given by USDA-ERS is that a county should have rural towns < 5,000 people with urban areas with populations as high as 50,000 people, and not otherwise holding any metropolitan areas (Sanders and Cromartie 2024). This definition is admittedly fuzzier since it has room for towns which are

Table 1. Studies involving critical examination on the definition and conceptualization of rurality.

Study	Purpose	Method(s) for Identifying Rurality
Berry et al. 2000	Classifications of counties in the Western U.S.	Attempted to find U.S. Census metrics to describe rural according to interviews with county commissioners. Found three criteria that most fit with qualitative data-(1) population density, (2) population, and (3) agricultural land base.
Bennett et al. 2019	Rural health and creating more certainty in the definition of rural in general	Definitions of rurality are highly variable, and many reasonable definitions are possible. Thus, researchers should "include the specific definition and clearly define how rurality is operationalized in their work." Also, they encourage reporting rurality down to the smallest possible unit and to note any limitations in whatever definition is chosen in a given study.
Johnson and Scala 2022	Evaluation of U.S. political landscape by culture and geography	Examining political ideology, they find that rural and urban are two poles of extremes. Much of the U.S. is in a continuum between the dense urban core and the isolated community. They emphasize finding degrees of rural along the continuum.
Nelson and Nguyen 2023	Concerns about the inequities and disadvantages of those who are rural	Created a single metric, Community Assets and Relative Rurality (CARR), which evaluates rurality according to traditional population measures (remoteness, population density) and ease of access to services and amenities (geographic metrics of access and availability).
Krutsinger et al. 2024	Rural health and access to healthcare	Examined the viability of the Rural-Urban Commuting Area (RUCA) according to alignment with self-identification of people saying they reside in a rural or urban area. The lack of alignment between RUCA and self-perceptions points to a need to use more "patient-centered" definitions of rural in healthcare.

called "rural" and areas that are urban but non-metro. It is based on this definition that we selected case study communities for detailed examination into wastewater treatment process units and conveyances. More detail on more specific rural criteria for these communities is found in the presentation of the results.

References

Bennett, K.J., T.F. Borders, G.M. Holmes, K.B. Kozhimannil, and E. Ziller. 2019. What is rural? Challenges and implications of definitions that inadequately encompass rural people and places. *Health Affairs* 38(12): 1985-1992. Available at: https://doi.org/10.1377/hlthaff.2019.00910. Accessed May 25, 2024.

Berry, K.A., N.L. Markee, N. Fowler, and G.R. Giewat. 2000. Interpreting what is rural and urban for western U.S. counties. *The Professional Geographer* 52(1): 93-105. Available at: https://doi.org/10.1111/0033-0124.00208. Accessed May 25, 2024.

Johnson, K.M. and D.J. Scala. 2022. The rural-urban continuum and the 2020 U.S. Presidential election. *Forum - A Journal of Applied Research in Contemporary Politics* 20(2): 229-255. Available at: https://doi.org/10.1515/for-2022-2057. Accessed May 25, 2024.

Krutsinger, D.C., K.N. Yadav, and J.L. Hart. 2024. Self-identified rurality in a nationally representative population in the US. *Rural and Remote Health* 24(1): 8483. Available at: https://doi.org/10.22605/rrh8483. Accessed June 6, 2024.

Nelson, K.S. and T.D. Nguyen. 2023. Community assets and relative rurality index: A multi-dimensional measure of rurality. *Journal of Rural Studies* 97: 322-333. Available at: https://doi.org/10.1016/j.jrurstud.2022.12.025. Accessed May 25, 2024.

Sanders, A. and J. Cromartie. 2024. What is Rural? USDA-ERS. Available at: https://www.ers.usda.gov/topics/rural-economy-population/rural-classifications/what-is-rural/. Accessed May 4, 2024.

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