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Comparing the Use of Mobile Device and Flow Data to Characterize Dynamic Populations in Wastewater Surveillance Monitoring Areas

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ABSTRACT: Mobile device data has the potential to capture fluctuations in populations contributing to a wastewater catchment area, which can aid in interpreting pathogen concentrations. As an alternative to flow rates which are commonly used to normalize pathogen concentrations, we evaluated the use of mobile device data to characterize population dynamics at the daily and monthly scale across 66 sewersheds in Colorado from August 2020 to December 2024. We compared monthly device counts to monthly average flow rates where available and evaluated the extent to which rainfall and snowmelt explained periods of decoupling between device counts and flow rates. Using K-Means clustering, we identified two distinct patterns of population dynamics, one comprised of high-tourism regions. There were significant temporal fluctuations in daily and monthly device counts, with more pronounced patterns at the monthly level. Flow and mobile device counts were not consistently well-correlated. Using mixed effects regression, we found that rainfall and snowmelt, in addition to device counts, were significantly associated with flow rates. Mobile device data can characterize dynamic populations over multiple geographical areas and over short and long timescales in ways that are distinct from flow. It should be considered in efforts to improve normalization algorithms for wastewater-based epidemiology.

KEYWORDS: wastewater-based epidemiology; mobile device data; population dynamics; temporal variability; sewersheds; normalization algorithms; rainfall and snowmelt

SYNOPSIS: Populations in wastewater monitoring areas fluctuate over short and long timescales. This study investigates the use of mobile device and flow data to characterize these fluctuations to improve normalization methods.

INTRODUCTION

Wastewater-based epidemiology (WBE) can provide public health officials with insights on community spread of pathogens and serve as an early indicator of infectious disease trends¹. Monitoring infectious diseases in municipal wastewater is advantageous because it draws samples from existing wastewater treatment plants, does not require clinical reporting, and is independent of care-seeking behavior.¹⁻³ Additionally, disease trends can be monitored at fine spatial scales, allowing identification of areas of concern at the community level. WBE has been used for decades to track poliovirus elimination.⁴ During the COVID-19 pandemic, WBE played an important role in monitoring emerging variants and disease trends.⁵ WBE today is a topic of global interest in the surveillance of multiple endemic and emerging infectious diseases from mpox to antimicrobial resistant bacteria to vector-borne diseases such as West Nile Virus.⁶⁻¹⁴ However, translating pathogen concentrations into actionable public health information can be challenging because viral concentrations in wastewater are noisy, impacted by a number of factors such as industrial discharges, infiltration of rainfall and snowmelt, sewershed-specific wastewater treatment protocols, viral shedding rates, and more, making it difficult to discern true changes in community infectious disease trends.

A key priority for WBE is developing normalization algorithms for viral concentrations in wastewater in order to separate the signal from the noise, refine data interpretation, and improve public health situational awareness for infectious diseases of public health importance.^{2, 15} At present, no consensus exists on normalization methods for wastewater data for trend monitoring.^{5, 16, 17} Some approaches include adjusting for the number of people contributing waste to the sewershed using human biomarkers, such as Pepper mild mottle virus, crAssphage, creatinine, and human DNA analytes.^{5, 15, 18} However, these biomarkers can introduce additional laboratory error

and studies evaluating human biomarkers for normalization have found mixed results regarding whether they meaningfully improve correlation between wastewater-based disease measures and other disease indicators.^{15, 16, 18}

Accurately interpreting pathogen concentrations in wastewater requires estimating the number of people contributing to a wastewater monitoring area (or sewershed), ideally at the time of measurement. However, populations fluctuate over time as people move for work, school, and recreation in ways that are challenging to characterize. This is a particular concern in sewersheds serving smaller populations and resort communities, which may experience large swings in populations over relatively short timescales that US Census or utility-based estimates do not capture. Daily wastewater flow is commonly used to normalize pathogen concentrations in wastewater, serving as a proxy for the number of people contributing to the sewersheds.¹⁹ However, flow-based normalization has limitations as it represents a combination of usage, precipitation infiltration and industrial discharge, and it is sensitive to measurement techniques (e.g., peak flow vs. 24 hour average).²⁰⁻²³

As an alternative to flow, mobile device data has the potential to account for short-term patterns (e.g., weekday vs. weekend commuting patterns, large-scale events) as well as longer-term trends (e.g., seasonal influxes of populations into high-tourism regions). Recent prior work has demonstrated the potential to use mobile device data to estimate dynamic populations, such as in the context of monitoring illegal drug use via wastewater in a European city,^{24, 25} and for WBE surveillance of infectious diseases in a small and medium European town.²⁶ In this study, we extend the use of mobile device data to estimate population fluctuations in a large network of established sewersheds in a geographically heterogeneous US state using over four years of data, allowing for a high level of spatial and temporal precision. In addition, we introduce methods for

working with US mobile device data, which is distinct from mobile device data in some other countries.

In 2020, the state of Colorado established a large network of sewersheds throughout the state in response to the COVID-19 pandemic.²⁷ These sewersheds reported SARS-CoV-2 viral concentrations and flow rates to the Colorado Department of Public Health & Environment (CDPHE) during various time periods over the course of several years. Over time, the surveillance network built in the capacity to test for influenza, respiratory syncytial virus (RSV), mpox, enterovirus D68, and measles.²⁸ This study is designed to characterize dynamic populations in these sewersheds using mobile device and flow data, and to investigate the relationships between the two. Specifically, we used clustering approaches to identify distinct patterns of populations dynamics across sewersheds, evaluated fluctuations in device counts at a daily to seasonal timescale, and compared them to fluctuations in flow rates. Additionally, we characterized how device counts and flow rates correlated over time and examined whether periods of decoupling could be explained by snowmelt or rainfall. Together, these analyses can set the stage for establishing normalization methods that account for dynamic populations within and across wastewater monitoring areas over short and long timescales.

MATERIALS AND METHODS

Data Sources

Sewersheds. Shapefile boundaries were available for 71 sewersheds that participated in Colorado's wastewater surveillance program, 66 of which reported flow data over the course of 365 consecutive days or more during the study period, which spans August 1, 2020 to December 31, 2024.

Mobile Devices. We used mobile device data obtained from Advan, via Dewey Data.²⁹ This dataset describes the movement of devices between origin and destination census block groups (CBGs) over time. Device pings, primarily from cell phones, are collected using a software development kit used by smartphone applications to obtain location information of the phone. Phones can be located through a variety of methods, including GPS, network information, IP address, and Bluetooth. All data is anonymized and aggregated to the CBG level using the 2010-2019 CBG boundaries. Mobile device data was accessed on March 03, 2025 and spans January 01, 2018 to January 31, 2025; we restricted this dataset to reflect the study period spanning August 1, 2020 to December 31, 2024.

To assign CBGs to sewersheds, we overlaid the sewershed area shapefile with the Colorado 2010 CBG boundaries from the TIGER/Line Shapefiles from the US Census Bureau in ArcGIS Pro 3.3 and calculated the areal overlap between a sewershed and any CBG it occupied.³² To ensure that each sewershed was assigned to at least one CBG, we assigned a CBG to a sewershed if the sewershed occupied at least 0.2% of the CBG's land mass. If a CBG was occupied by more than one sewershed, the sewershed that occupied the highest percentage of the CBG's land mass was assigned to that CBG.

We estimated the mobile device count by month for each sewershed using the US neighborhood patterns dataset. This dataset provides a count of total unique devices by month that enter all destination CBGs in the state from all origin CBGs associated with these unique devices, counted as one device per destination CBG per month. The distribution of origin CBGs across all devices entering each destination CBG is also provided. Advan assigns origin CBGs to each device in the data by analyzing six weeks of movement and determining the CBG in which a device spends most of its nighttime hours, defined as the time between 6pm and 7am.^{30, 33} Internal devices were

defined by summing, for all destination CBGs assigned to that sewershed, the monthly counts of devices whose origin CBGs matched their destination CBGs. External devices were defined by summing, for all destination CBGs assigned to that sewershed, the monthly counts of devices whose origin CBG was outside the sewershed. Devices whose origin CBG did not match the destination CBG, but still belonged to the same sewershed as the destination CBG, were excluded from the device count because these devices were already accounted for in the data. We aggregated monthly device counts to the sewershed level by combining the monthly internal and external device counts for all destination CBGs assigned to each sewershed. We used monthly device counts to evaluate patterns by month and season. We defined winter as December–February; spring as March–May; summer as June–August; and fall as September–November.

To investigate dynamics in device counts by day of the week and weekday/weekend, we estimated daily mobile device counts for each sewershed using a different feature in the neighborhood patterns dataset: device counts to a destination CBG for each day of the month, counted as one device per destination CBG per day. Daily device counts include both devices that reside in the destination CBG and devices entering from outside the destination CBG; device origin CBGs were not available at this timestep. We calculated daily total device counts for each sewershed by summing all daily device counts for all destination CBGs assigned to that sewershed. We used this data to investigate dynamics in device counts by day of the week and weekday/weekend, defining weekdays as Monday through Friday and weekends as Saturday and Sunday.

Because we were interested in the relative fluctuations in device counts within and across sewersheds, rather than absolute device counts, we transformed the data prior to analysis. Device counts were highly right skewed; we first natural log-transformed the data. Device counts reported as zero were imputed as 1 before log-transforming. To account for changing opt-in rates and data

collection practices over time, we z-score standardized device counts by sewershed and year. Outliers that were more than three standard deviations from the mean for each sewershed and year were removed (this accounted for approximately 0.3% of the mobile device data after applying all transformations).

Flow. Flow rate describes the volume of influent water to sewersheds for a given day over time in millions of gallons per day (MGD). Flow was typically reported twice per week, typically on the same days; however, the frequency and day of reporting varied by sewershed. Because flow data was generally only reported twice per week, and weekend reporting was rare, we did not examine flow dynamics by day of the week or weekday/weekend. Beginning August 1, 2024, only 20 sewersheds reported flow data as Colorado shifted its surveillance system to a sentinel network. Analyses used all flow data where available.

Because we were interested in the relative fluctuations in flow rates within and across sewersheds, rather than absolute flow rates, we transformed the data prior to analysis in a manner similar to the mobile device data. Flow rates were highly right-skewed; we first natural log-transformed the data. Flow rates of 0 MGD were imputed as 0.001 before log-transforming. To allow for comparisons between sewersheds and to account for changing laboratory methods over time, we z-score standardized flow rates by sewershed and year. Outliers that were more than three standard deviations from the mean for each sewershed and year were removed (this accounted for approximately 0.3% of the flow data after applying all transformations).

Precipitation. We used the GridMET database to obtain minimum temperature, maximum temperature, and precipitation (in millimeters of water) at the county-day level from January 01, 2020 to December 31, 2024.³⁴ We estimated the daily temperature for each county as the mean of

the maximum and minimum temperatures. Precipitation was classified as snow accumulation if the mean temperature on a given day was below 0° C. Snowmelt was calculated using the degree-day method from the USDA Hydrology and National Engineering Handbook when average temperature was above 0° C and snow accumulation was present (details and equation provided in the Supplementary Information).³⁵ Once total accumulation in a county reached 0mm, snowmelt values were imputed as zero. Rainfall and snowmelt were compiled for each county-day and assigned to sewersheds based on the county in which the sewershed address was located. When incorporated into models, rainfall and snowmelt were converted to centimeters for better interpretability.

Statistical Analysis

Analysis 1: Mobility Clusters. Given the variety of urban, rural, and resort communities represented throughout the state of Colorado, we first evaluated evidence of geographical patterns in population dynamics for the 66 sewersheds in this study. To do this, we used K-Means clustering to analyze the monthly mobile device data.³⁶ The clustering algorithm assigns each sample to one of K clusters, based on the sample's distance to each cluster's *centroid*, or average sample. The centroids for each cluster are then recomputed using the new cluster assignments. This process of cluster assignment and centroid computation continues iteratively until the cluster assignments stabilize (convergence). The only parameter required for K-Means is K , which defines the number of clusters. To find the optimal K , we ran K-Means clustering for $K = [2,14]$ and defined the optimal K using the silhouette metric, which tests how well the pairwise distances between the points in the data align with cluster labels.³⁷ As a sensitivity analysis, we also conducted the clustering analysis on daily device counts.

Analysis 2: Temporal Fluctuations in Device Counts and Flow Rates. We evaluated the extent to which mobile device counts varied at daily, monthly, and seasonal timescales, and the extent to which flow rates varied at monthly and seasonal timescales. Because flow rates were typically reported twice a week, we could not examine flow rates at daily timescales. Because Analysis 1 indicated distinct patterns of population fluctuations, all analyses were stratified by mobility cluster. We visualized the distribution of daily device counts in each cluster grouped by day of the week and weekday/weekend and calculated the mean and the quantile interval encompassing 66% of the data (approximately one standard deviation after normalizing) for each group. We used linear mixed regression to test whether differences in daily device counts by day of the week or weekday/weekend were due to chance. We modeled daily device counts as the dependent variable, included a fixed effect for day of the week and a random intercept for sewershed to account for repeated measures. Separate models were run for weekday/weekend comparisons. Hypothesis tests were conducted using the likelihood ratio test, comparing the aforementioned model to a baseline model with no fixed effects. As a sensitivity analysis, we ran another regression model for weekday/weekend where weekends were reclassified to include Friday. Regression model equations are provided in the Supplementary Information. Analysis was performed in R version 4.2.0 using the *lme4* package.

We used a similar approach to evaluate whether mobile device data and flow rates varied by month and season. We used monthly mobile device data and biweekly flow data, aggregated as a monthly mean, to compare the distributions of device counts and flow rates by month and season. As above, we calculated the mean and 66% quantile interval for each group. We used the linear mixed modeling approach described above to test whether fluctuations in mobile device counts and flow rates by month and seasons were due to chance, fitting a separate model for each outcome and

cluster, and for month and season. Because external device counts had a higher degree of fluctuation than internal device counts, we conducted a sensitivity analysis using internal device counts by month to determine if fluctuations by month and season were significant when accounting for internal devices only.

Analysis 3: Comparison of Mobile Device Data to Flow Data. To characterize the relationship between mobile device and flow data within each sewershed, we estimated dynamic Spearman correlations between device counts and flow rates over a 90-day rolling window using the *NonParRolCor* package in R.³⁸ We restricted the date range of each sewershed's combined mobile device and flow time series to begin on the date of the first non-missing value of the sewershed's flow data and ending on the last non-missing value of the sewershed's flow data or December 31, 2024, whichever came first. To achieve a daily timestep for flow data, missing values were filled with the previous non-missing value. No missing values existed for mobile device data. To reduce noise, both device counts and flow rates were converted into a right-justified 7-day moving average.

We were interested in the strength of correlation between mobile device counts and flow data across different sewersheds and whether there were consistent periods of higher or lower correlations. To this end, we estimated the percent of all correlation values > 0.5 across a sewershed's time series. High strength was defined as a correlation value of > 0.5 for $> 50\%$ of all observations; low strength was defined as a correlation value of > 0.5 for $\leq 50\%$ observations. We also characterized seasonal rolling correlations by taking the mean of rolling correlation coefficients across all sewersheds in each cluster over time on the last day of each previously described season (to capture the 90-day seasonal period prior) and year, defined as February 28 for winter, May 31 for spring, August 31 for summer, and November 30 for fall.

Analysis 4: What Else Impacts Flow Rates? To further characterize the relationship between device counts and flow rates, we evaluated the extent to which rainfall and snowmelt, in addition to mobile device counts, were associated with flow rates. We used multiple linear mixed regression analysis to model weekly flow as a function of weekly mobile device counts, rainfall, and snowmelt. For each sewershed, we included complete observations for daily mobile device counts, daily rainfall, daily snowmelt, and daily flow data to calculate the mean weekly values for each variable. Device counts and flow rates were log-transformed as in the aforementioned analyses but not standardized by sewershed or year; these variables were controlled for statistically. All models included a one-week lagged flow rate term to account for autocorrelation. Year was included as a dummy variable to account for long-term changes in opt-in rates and mobile device reporting practices. We used Bound Optimization BY Quadratic Approximation (BOBYQA) approximation,³⁹ incorporating a random intercept for sewershed and a random slope for mobile device counts by sewershed. Models were run separately for each mobility cluster. To understand if there was significant sewershed-specific variability on the impact of precipitation on the relationship between mobile device counts and flow rate, we evaluated an expanded model, adding a random slope for rainfall and snowmelt. We compared the BIC of the expanded model to the model without the random slopes for precipitation variables to determine whether these random slopes were justified. Analysis was performed in R version 4.2.0 using the *lme4* and *lmerTest* packages.

RESULTS AND DISCUSSION

Analysis 1: Mobility Clusters. The clustering analysis indicated two clusters (Figure 1), as the silhouette score was greatest at $K = 2$ (Supplementary Information, Figure S1). Cluster 1 sewersheds comprised Colorado's major ski resorts and adjoining towns. Sewersheds in Cluster

1 exhibited two annual peaks in device counts, one each during the summer and winter months with a drop in device counts during the spring and fall months. Cluster 2 sewersheds comprised metropolitan areas, rural areas, and high-tourism destinations outside of the major ski areas, and exhibited a single annual peak in device counts during the summer months and a drop in device counts during the winter months. The sensitivity analysis using daily device counts yielded the same clusters (Supplementary Information, Figures S2 and S3).

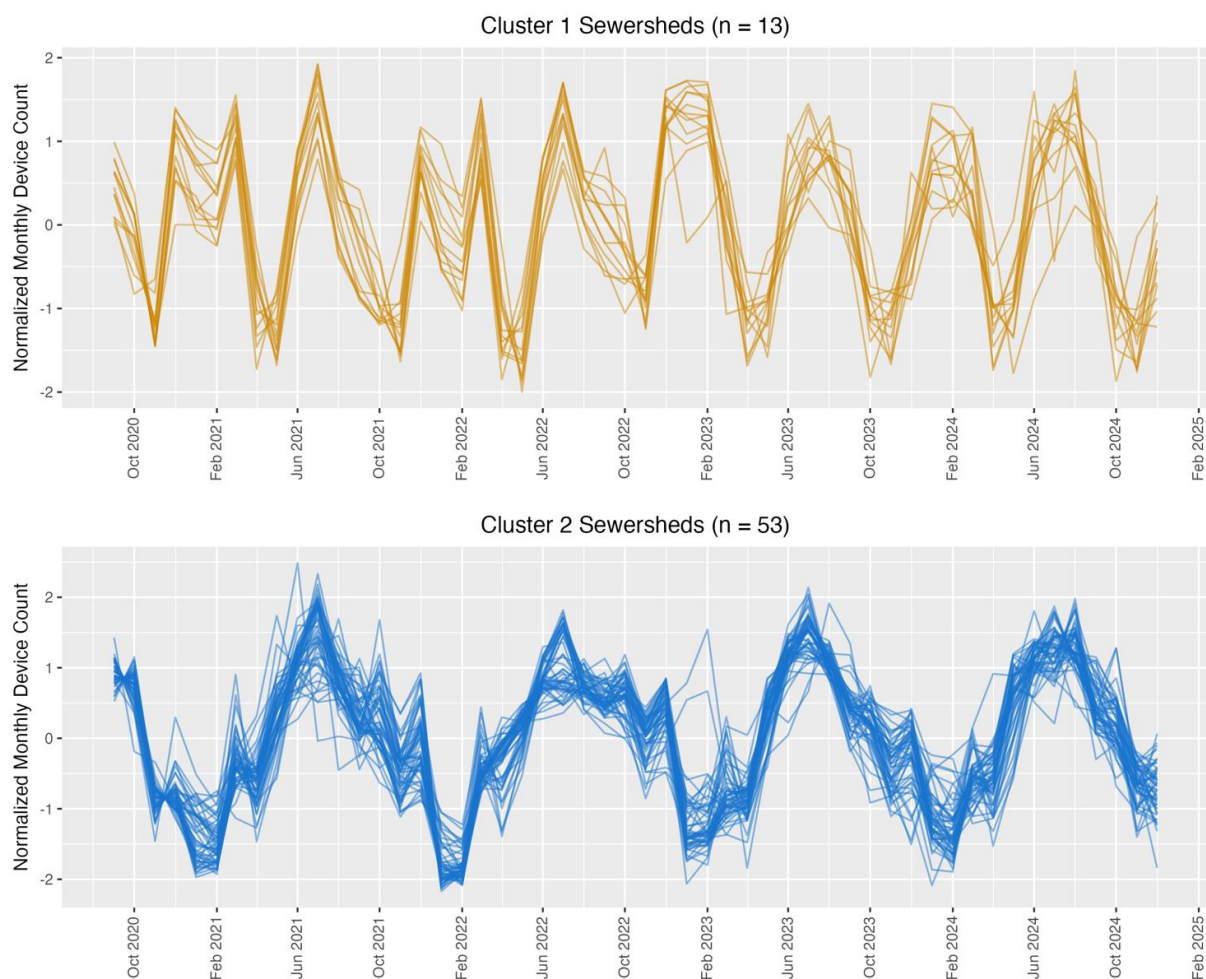


Figure 1. Spaghetti plot showing log-transformed, year-standardized monthly device counts for the two mobility clusters generated from K-Means clustering. Outliers more than three standard deviations from the mean were removed, which comprises approximately 0.3% of the data after

transforming. The optimal clustering ($K = 2$) was selected using silhouette score. Cluster 1 (top) comprises 13 sewersheds in and around Colorado's major ski resorts. Cluster 2 (bottom) comprises 53 sewersheds located in metropolitan areas, rural areas, and high-tourism areas outside of ski resorts.

Analysis 2: Temporal Fluctuations in Device Counts and Flow Rates. There was modest fluctuation in device counts at the day of the week and weekday/weekend (Figure 2, Table 1, Supplementary Information Figure S4). In Cluster 1, sewersheds showed a slight increase in device counts on Fridays and Saturdays and a similar decline on Sundays, while Cluster 2 sewersheds showed a more pronounced decrease in device counts on Sundays. Fluctuation in mobile device counts by day of the week was statistically significant for both clusters (LRT $p < 0.001$) and for weekday/weekends in Cluster 2 only (LRT $p < 0.001$). When weekends were reclassified to include Friday, fluctuation by weekday/weekend was significant for Cluster 1 sewersheds (LRT $p < 0.001$).

Device counts showed more pronounced patterns by month and season than by day of the week or weekday/weekend (Figure 3, Supplementary Information Figure S5). A sensitivity analysis on internal devices (Supplementary Information, Table S1) also showed significant fluctuations by month and season (LRT $p < 0.001$). Flow rates in both clusters also showed fluctuation by month and season; however, these fluctuations were less pronounced than the device counts. In Cluster 1 sewersheds, the largest discrepancies between device counts and flow rates occurred in April and May; in Cluster 2 sewersheds, the largest discrepancies between device counts and flow rates occurred in January and February. Variation in both mobile device counts and flow rates by month and season was statistically significant for both clusters (LRT $p < 0.001$).

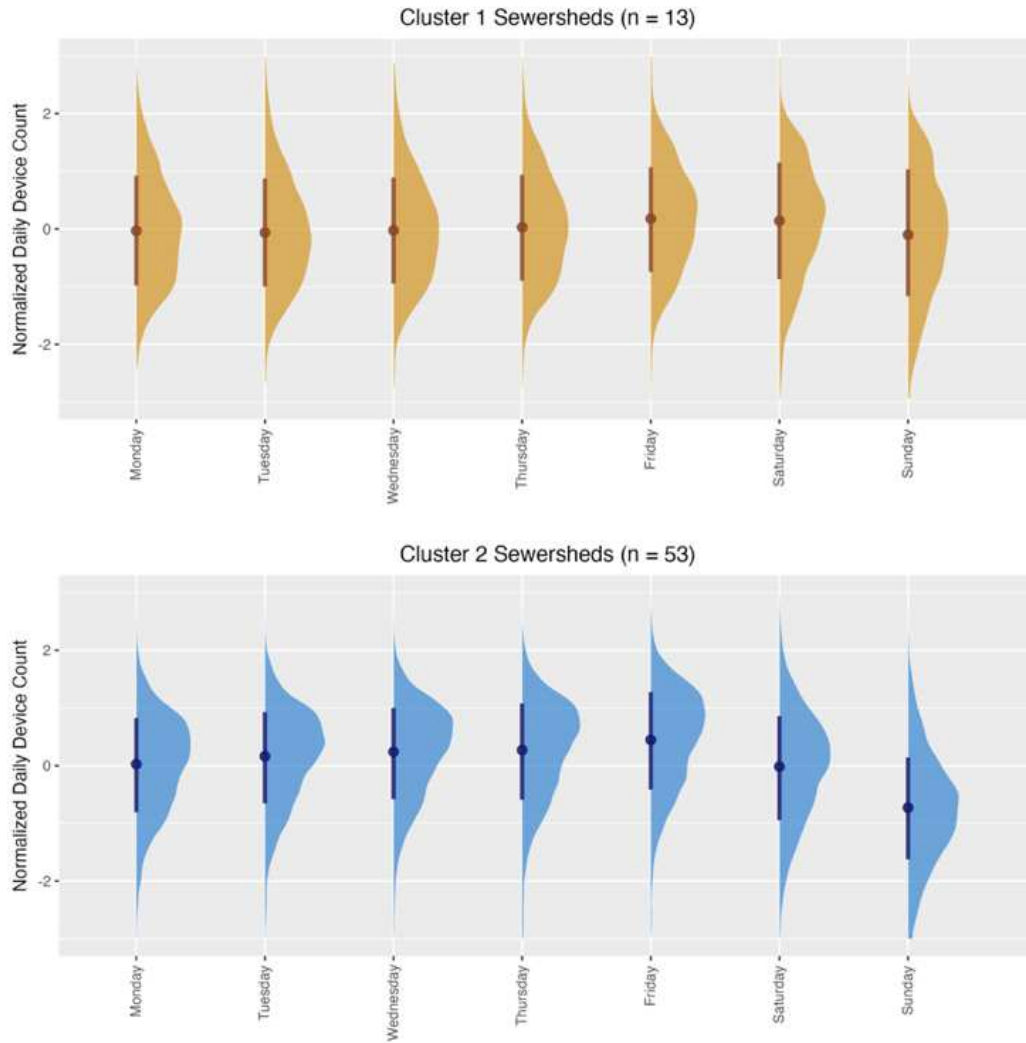


Figure 2. Density plots showing distributions of log-transformed device counts, z-score standardized by sewershed and year, grouped by day of the week across Cluster 1 (top) and Cluster 2 (bottom) sewersheds in Colorado using daily mobile device data from August 2, 2020 to December 30, 2024. Points represent the mean, while bars represent the quantile interval comprising 66% of the data (approximately one standard deviation after normalizing). Outliers more than three standard deviations from the mean were removed, which comprises approximately 0.3% of the data after transforming.

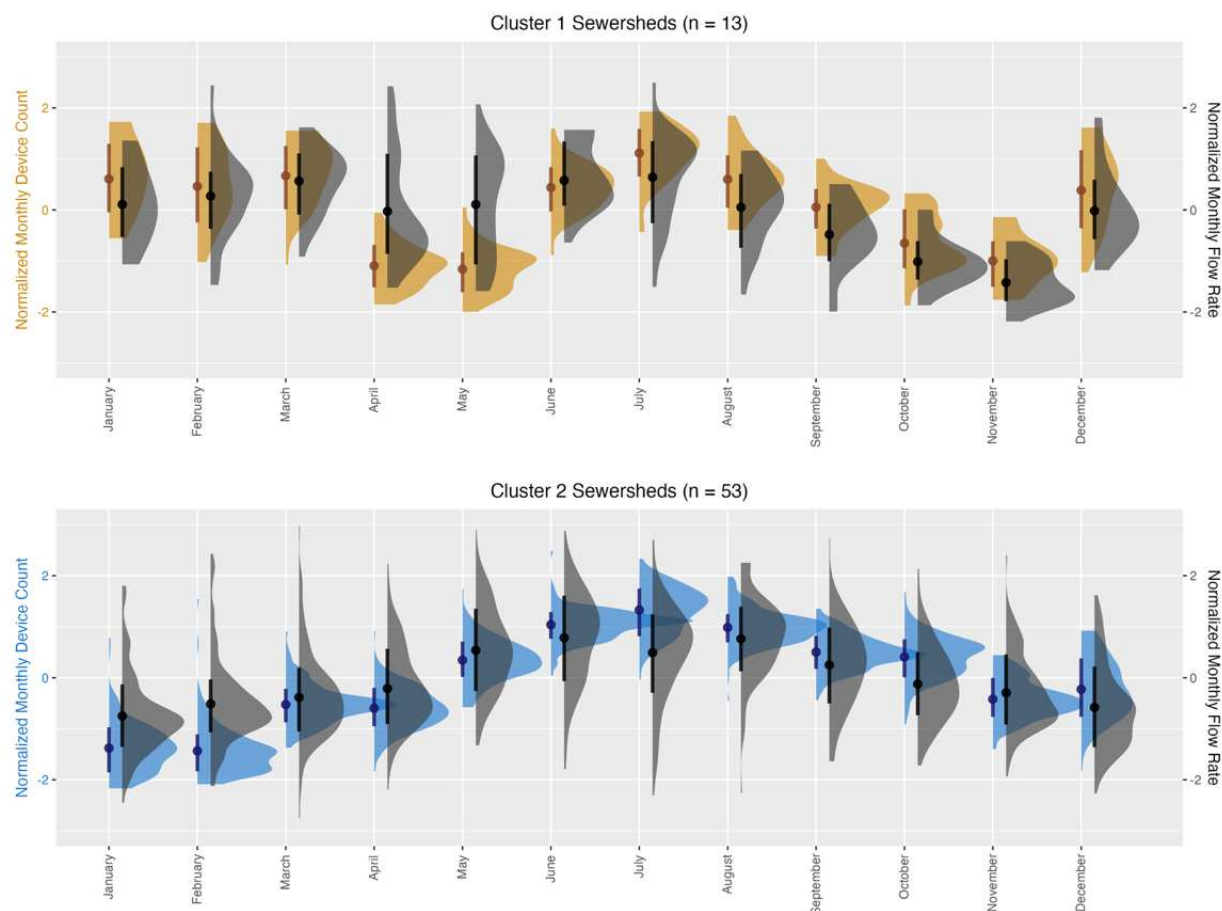


Figure 3. Density plots showing distributions of log-transformed monthly device counts (orange, blue) and monthly flow rates (black), z-score standardized by sewershed and year, grouped by month across Cluster 1 (top) and Cluster 2 (bottom) sewersheds in Colorado using mobile device and flow data from August 2, 2020 to December 30, 2024. Points represent the mean, while bars represent the quantile interval comprising 66% of the data (approximately one standard deviation after normalizing). Outliers more than three standard deviations from the mean were removed, which comprises approximately 0.3% of the data after transforming.

Table 1. Descriptive Assessment of Temporal Fluctuations in Mobile Device Counts in Colorado Wastewater Monitoring Areas Grouped by Day of Week, Weekday/Weekend, Month, and Season, August 2020 – December 2024.

	Cluster 1 Sewersheds (n = 13)			Cluster 2 Sewersheds (n = 53)		
Grouping	mean	sd	LRT p	mean	sd	LRT p
Day of Week			< 0.001			< 0.001
Monday	-0.030	0.938		0.002	0.896	
Tuesday	-0.060	0.948		0.153	0.849	
Wednesday	-0.020	0.939		0.202	0.907	
Thursday	0.035	0.926		0.233	0.940	
Friday	0.182	0.919		0.436	0.894	
Saturday	0.136	1.006		-0.049	1.013	
Sunday	-0.110	1.085		-0.784	1.047	
Weekday/ Weekend			0.840			< 0.001
Weekday	0.021	0.938		0.205	0.909	
Weekend	0.013	1.054		-0.417	1.094	
Month			< 0.001			< 0.001
January	0.608	0.647		-1.379	0.464	
February	0.462	0.731		-1.433	0.456	
March	0.669	0.593		-0.525	0.372	
April	-1.094	0.414		-0.597	0.400	
May	-1.161	0.428		0.345	0.391	
June	0.438	0.448		1.039	0.291	
July	1.114	0.517		1.327	0.439	
August	0.599	0.532		0.985	0.343	
September	0.053	0.449		0.502	0.325	
October	-0.652	0.545		0.408	0.402	
November	-0.997	0.440		-0.422	0.371	
December	0.385	0.737		-0.227	0.559	
Season			< 0.001			< 0.001
Winter	0.477	0.711		-0.952	0.761	

Spring	-0.529	0.977		-0.259	0.578	
Summer	0.717	0.575		1.117	0.392	
Fall	-0.532	0.649		0.163	0.554	

Footnote: Mean and standard deviation of total daily device counts for Cluster 1 and Cluster 2 sewersheds grouped by day of the week and weekday/weekend, and mean and standard deviation of total monthly device counts for Cluster 1 and Cluster 2 sewersheds grouped by month and season. Daily and monthly device counts were log-transformed and z-score standardized by sewershed and year; p-values derived from likelihood ratio tests (LRT) comparing a linear mixed regression model with random effect of sewershed and temporal grouping as a predictor to a baseline model with random effect of sewershed and no fixed effects.

Table 2. Descriptive Assessment of Temporal Fluctuations in Flow Rates in Colorado Wastewater Monitoring Areas Grouped by Month and Season, August 2020 – December 2024.

	Cluster 1 Sewersheds (n = 13)			Cluster 2 Sewersheds (n = 53)		
Grouping	mean	sd	LRT p	mean	sd	LRT p
Month			< 0.001			< 0.001
January	0.046	0.882		-0.552	0.921	
February	0.098	1.050		-0.428	1.000	
March	0.463	0.921		-0.298	0.996	
April	0.035	1.010		-0.107	0.842	
May	0.081	0.938		0.380	0.930	
June	0.554	0.642		0.604	0.939	
July	0.532	1.060		0.390	1.060	
August	0.147	0.597		0.494	0.963	
September	-0.313	0.655		0.213	0.815	
October	-0.854	0.789		-0.094	0.790	
November	-1.130	0.801		-0.210	0.810	
December	-0.070	0.939		-0.417	0.908	
Season			< 0.001			< 0.001
Winter	0.029	0.962		-0.466	0.945	
Spring	0.195	0.976		-0.006	0.967	
Summer	0.413	0.813		0.495	0.991	
Fall	-0.742	0.818		-0.026	0.824	

Footnote: Mean and standard deviation of flow rates in Cluster 1 and Cluster 2 sewersheds grouped by month and season, log-transformed and z-score standardized by sewershed and year. p-values derived from likelihood ratio tests (LRT) comparing a linear mixed regression model with random effect of sewershed and temporal grouping as a predictor to a baseline model with random effect of sewershed and no fixed effects.

Analysis 3: Comparison of Mobile Device Data to Flow Data. The correlation between mobile device counts and flow by sewershed varied markedly by sewershed (Figure 4). Notably, 8 of 13 Cluster 1 sewersheds were classified as high strength; however, only 1 of 53 Cluster 2 sewersheds was classified as high strength. When examining correlations by season, Cluster 1 sewersheds exhibited the highest mean rolling correlations in the fall and winter and the lowest mean rolling correlations in the spring and summer; Cluster 2 sewersheds showed less seasonal variability with the lowest mean rolling correlations in the winter and summer (Figure 5, Supplementary Information, Figure S6). Both clusters exhibited a wide distribution of rolling correlation values.

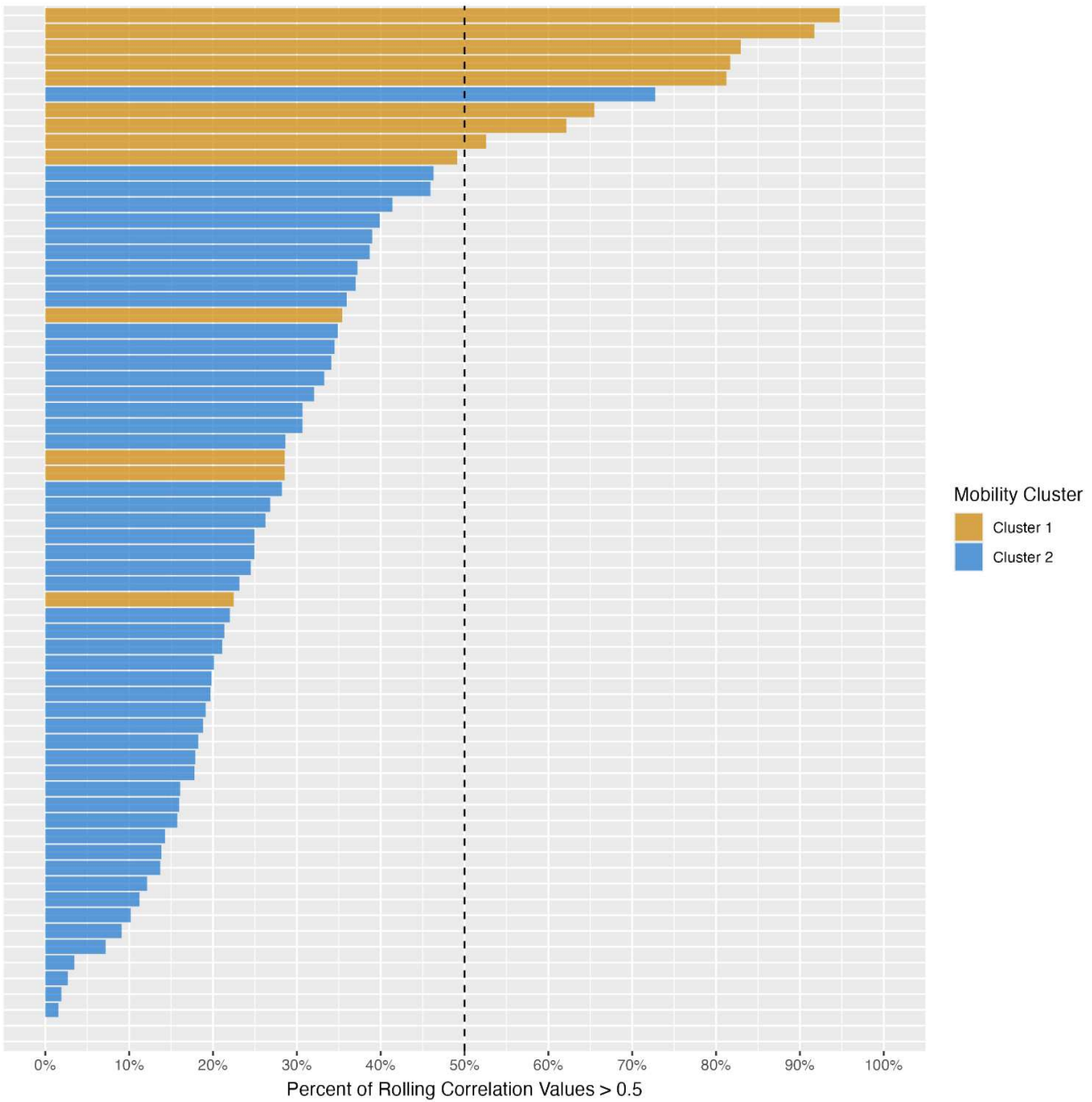


Figure 4. Ranked sewersheds by strength of 90-day rolling correlations across each sewershed's time series. The vertical dotted line represents the cut point for defining high strength ($> 50\%$ of rolling correlation values > 0.5) and low strength ($\leq 50\%$ of rolling correlation values > 0.5).

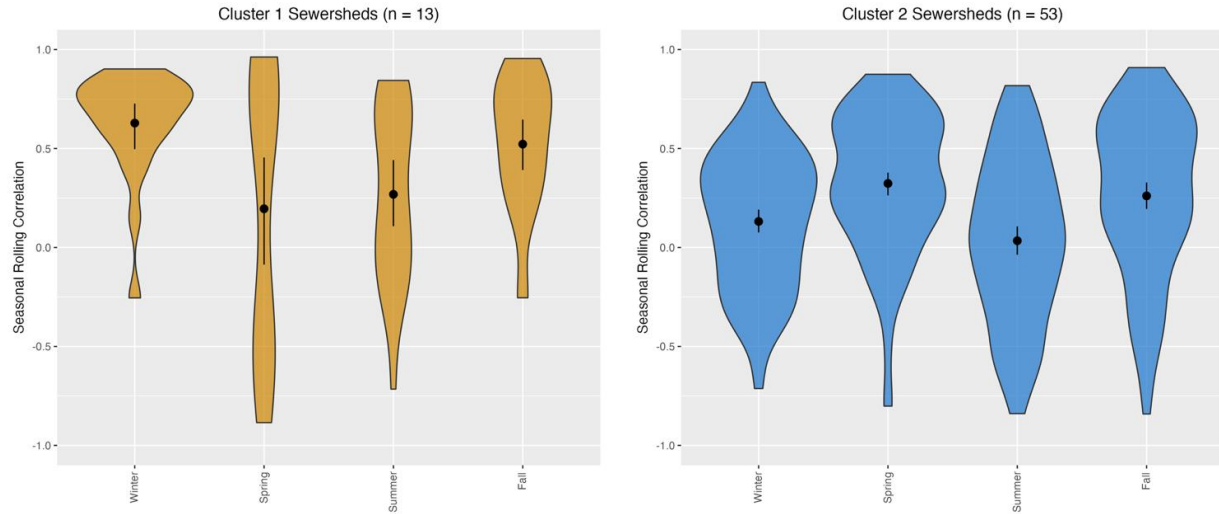


Figure 5. Distributions of seasonal Spearman 90-day rolling correlations in Cluster 1 (left) and Cluster 2 (right) sewersheds over time. Seasonal rolling correlations were determined based on each sewershed’s rolling correlation value on the last day of each season, defined in this analysis as February 28 for winter, May 31 for spring, August 31 for summer, and November 30 for fall. Points represent the mean, while bars represent the 95% confidence interval.

Analysis 4: What Else Impacts Flow Rates? Results of linear mixed regression evaluating the relationship between flow, mobile device counts, rainfall, and snowmelt are provided in Table 4. Mobile device counts, rainfall, and snowmelt were all positively associated with flow in models adjusted for year and autocorrelation. The association between precipitation and flow rates was markedly stronger in Cluster 1 sewersheds compared to Cluster 2 ($\beta_{\text{snowmelt}} = 0.069$ vs. 0.018, and $\beta_{\text{rainfall}} = 0.090$ vs. 0.031). We did not find evidence that random slopes for flow or precipitation by sewershed improved the models. The models with only a fixed effect for rainfall and snowmelt had a lower BIC in both clusters (Cluster 1 BIC: -227, Cluster 2 BIC: -1031) compared to the models that also included random slopes by sewershed for rainfall and snowmelt (Cluster 1 BIC: -205, Cluster 2 BIC: -972).

Table 4. Coefficients for Linear Mixed Regression Model on Device Counts and Flow Rates, Controlling for Year, Lagged Flow Rate, Rainfall, and Snowmelt.

	Cluster 1 Sewersheds (n = 13)		Cluster 2 Sewersheds (n = 53)	
	β	p	β	p
Intercept	-0.902 (-1.415, -0.386)	0.004*	-0.536 (-0.756,-0.312)	<0.001*
Device counts[†]	0.102 (0.060, 0.140)	<0.001*	0.083 (0.060, 0.108)	<0.001*
Year (2021)			0.033 (0.007, 0.059)	0.013*
Year (2022)			-0.015 (-0.043, 0.011)	0.250
Year (2023)	0.026 (0.00036, 0.052)	0.047*	-0.023 (-0.053, 0.006)	0.097
Year (2024)	0.062 (0.030, 0.094)	<0.001*	-0.023 (0.053, 0.0071)	0.110
Flow_{t-1}[†]	0.511 (0.468, 0.558)	<0.001*	0.617 (0.599, 0.636)	<0.001*
Rainfall (cm)[‡]	0.090 (0.034, 0.150)	0.002*	0.031 (0.014, 0.047)	<0.001*
Snowmelt (cm)[‡]	0.069 (0.039, 0.098)	<0.001*	0.0179 (-0.008, 0.044)	0.180

Footnote: Due to non-normally distributed data, models used log-transformed device counts and flow rates. This model also incorporated a random intercept and random slope for device count by sewershed.

*p-value < 0.05

[†]Device counts and flow rates were natural log-transformed.

[‡]cm of liquid water

Our analyses suggest that mobile device counts can capture fluctuations in the population contributing to a given sewershed over long and short timescales, and that mobile device data provides information that is distinct from flow rates. We found both mobile device counts and

influent flow rates in sewershed catchment areas fluctuate over time. However, these measures were not consistently correlated, rather exhibiting periods of both high and low correlation over time and across sewersheds. We also found that flow rates were associated with rainfall and snowmelt in Colorado, indicated flow rates capture more than just human activities. Together, this information suggests that flow rates alone are an imperfect proxy for short- and long-term changes in populations contributing to a sewershed. This has implications for WBE, as the interpretation of pathogen detections in wastewater should be informed, in part by regionally relevant data to capture a better approximation of the number of people contributing to a sewershed independent of environmental factors that can affect influent flow rates.

Mobile device data offers assets that could add value to WBE. First, parsing mobile device data into clusters can showcase the similarities and differences in population dynamics across multiple sewershed catchment areas in a state or region. In the case of Colorado, clustering approaches highlighted the unique population dynamics of ski resort communities. These are areas that experience high levels of winter and summer tourism in ways that are distinct from other areas of the state. Second, WBE programs could incorporate mobile device or similar types of data to better understand temporal patterns in population dynamics in their jurisdictions. Mobile device data can resolve fluctuations at very fine temporal scales such as day of the week (something that is not always possible with flow data), as well as longer monthly to season-scale patterns. Ideally, pathogen detections in wastewater are interpreted with knowledge of the size of the population contributing to the sewershed (simplistically, allowing calculations akin to a number of pathogens per capita). In both of the aforementioned cases, mobile device data can provide information on how the population is changing over space or time, improving interpretation of pathogen detections.

Our analyses suggest that flow rates alone are an imperfect proxy for estimating dynamic populations. Flow data itself has several limitations, such as limited reporting frequency and periods (Supplementary Information Figure S7), as well as the precision of flow estimates, which can vary by sewershed. We also found that rainfall and snowmelt (in addition to device counts) are significant predictors of flow and the relationship between flow and precipitation may vary regionally. While we observed similar coefficients describing associations between flow and mobile devices for both clusters when controlling for precipitation, the associations between flow and rainfall and snowmelt were stronger in Cluster 1 vs. Cluster 2. Possible explanations include increased susceptibility to infiltration, more total snowmelt, or a combination of both in the rural, high elevation sewersheds that comprised Cluster 1. This is important, indicating that flow may be differentially impacted by weather in different areas, further complicating the inference of contributing populations from flow data alone. Notably, our sensitivity analysis testing a random slope for summed rainfall and summed snowmelt did not appreciably change the model fit, indicating that the association between device counts and flow rates was not significantly different between sewersheds of the same cluster. In other words, there was evidence that inflow and infiltration differed between clusters, but it was similar within clusters.

Because flow captures both weather-related infiltration and population water use (specifically, the generation of wastewater through washing, toilet flushing, etc.), it has inherent error when used as a proxy for population counts and may obscure patterns. For example, in Cluster 1, device counts in April and May dropped more markedly than flow rates, suggesting that increasing snowmelt may attenuate the magnitude of the decrease in human contributions to the sewershed during periods of reduced ski visitation. In other words, flow rates seem to be influenced by and large by human water use; however, they are also impacted by infiltration by outside water sources.

While mobile device data offers several potential advantages to WBE, it also comes with several limitations. First, mobile device data is provided at scales distinct from sewersheds, which presents unique challenges when aggregating to the sewershed level and potential overcounting. For example, in the data we used, device counts are presented as one device per CBG per day or month, meaning that a device that passes through multiple CBGs in a given day or month will be counted as a separate device for that CBG, introducing the potential for multiple-counting when summing device counts across all CBGs assigned to a sewershed. To address this, we excluded counts of devices in the monthly data whose origin CBG was in the same sewershed as a nonmatching destination CBG; however, multiple-counting of the remaining devices in the monthly data, and all devices in the daily data, could not be avoided completely. Second, due to factors such as limited cell reception and opt-in rates for location tracking, the number of devices observed represents only a small fraction of true devices, and therefore people, in the area. Advan does not disclose this sampling fraction, so we used raw device count and standardized device counts by year to reduce the impact of changing opt-in rates. Inferring the opt-in rate and the true number of people served by a sewershed catchment area based on device counts requires additional assumptions that are beyond the scope of this analysis. Nevertheless, we expect that raw device counts serve as a satisfactory representation of relative changes in human population over time. Third, devices passing through a sewershed can be pinged and counted in the mobile device data even if their owners did not spend enough time in the sewershed to meaningfully contribute to pathogen spread in a region, especially in sewersheds that border major highways and experience high volumes of vehicle traffic. This could overestimate the number of devices that actually correspond to the sewershed in question.

Overall, our findings indicate that wastewater surveillance programs that flow-normalize wastewater concentration data may be missing key signals associated with high snowmelt due to dilution of the sample. Understanding environmental effects on a sewershed's influent flow rate is critical to accurate data interpretation. Flow rates alone are an insufficient proxy for population; this study indicates additional metrics are needed to adjust viral concentration data. We recommend refining wastewater surveillance trend methodology to include population movement and environmental effects to improve real-time trend classification, providing public health officials with more accurate information about regional viral activity and scale of impact on communities. This analysis indicates that data sources representing population mobility, precipitation and snowmelt measures may provide unique information for trend modeling.

In this analysis, we investigated the use of mobile device and flow data in Colorado wastewater monitoring areas to characterize dynamic populations, and compared the agreement between the two measures. Flow rates serve as the standard proxy for population dynamics in WBE data analytics, which may be impacted by external factors. Mobile device data may serve as an additional proxy for human population, especially in areas that experience large-scale precipitation events and may be more susceptible to inflow and infiltration. While both mobile device and flow data can provide unique and important information on population dynamics, it is important to note that our analyses cannot identify which, if any, can better predict clinical outcomes, such as cases or hospitalizations. Future work in this area could help further the use of WBE for surveillance to improve public health planning and response for a number of pathogens.

ASSOCIATED CONTENT

Supporting Information

The following files are available free of charge.

Snowmelt calculation equations, linear mixed regression equations, and supplemental tables and figures with detailed information on temporal variability in and correlations between device counts and flow rates (PDF)

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The manuscript was written through contributions of all authors. All authors have given approval to the final version of the manuscript.

Notes

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