Utilizing spatiotemporal based business risk exposure to analyze cast iron water main failures in California

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ABSTRACT

Cast iron (CI) pipes are used in a significant proportion of US water distribution systems. Due to the number of old and deteriorated elements still in operation, the failure rates of CI pipes in most water utilities are higher compared with other materials. This study assessed the business risk exposure (BRE) for each CI water main in three selected service areas in California, taking into account both the likelihood of failure (LOF) and consequence of failure (COF). Spatiotemporal-based emerging hot spot analysis was used to examine LOF and unique critical facilities were considered for COF. The resulting BRE-based heat maps can be a helpful tool in enabling water utility executives to make more informed decisions and in mitigating the risks associated with the deteriorating CI pipe networks.

Key words | business risk exposure, cast iron pipe, consequence of failure, likelihood of failure, spatiotemporal analysis, water main failures

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INTRODUCTION

During the first half of the 20th century, cast iron (CI) was widely used for new installations of water distribution pipes in the United States, mainly because of its strength and relatively low manufacturing and installation costs. In 2004, the US Environmental Protection Agency (EPA) estimated that CI still represented about 29% of the total pipe length in drinking water distribution systems across the USA. Given that CI failure rates are markedly higher than for other pipe materials (Folkman *et al.* 2012), an immediate in-depth examination is clearly needed to better support water utilities' decisions regarding repair, replacement or rehabilitation of CI elements in their existing pipe networks.

In the study reported in this paper, a business risk exposure (BRE) approach is adopted to derive a risk-based prioritization ranking for individual CI assets. This method can be applied to any water distribution system that considers a BRE-based water mains integrity program. The EPA (2018) defines BRE as the product of the likelihood of failure (LOF) and the consequences of failure (COF). Historical failure data can be used to calculate LOF, while COF can be determined based on a variety of factors linked to the specifics of the service area (e.g., environmental and proximity concerns, failure to meet hydraulic and water quality performance requirements, the presence, type, and location of critical customers). In this particular study, LOF is based on the previous research results that historical failures actually produce future failures (Wang *et al.* 2009; de Oliveira *et al.* 2011; Kleiner & Rajani 2012). The regions with high concentration of failures indicate that there is an underlying phenomenon which is affecting structural integrity of water mains. Since these conditions are likely to remain the same (soil conditions, weather conditions, pressure, operating conditions), it is probable that more failures will appear in these zones. On the other hand, the COF analysis focused on a subset of variables: critical customers and facilities. More comprehensive COF

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assessments can take into account other COF factors such as detailed pressure drop, isolated demand, water quality, loss of revenue and loss of essential services. This new platform is expected to be a sound, data-driven, and transparent justification tool that can augment/replace the engineering judgment-based ('rule-of-thumb') decision frameworks/ methods that many water utilities rely on at present.

Many researchers have addressed CI failure problems, carrying out extensive explorations of the unique failure mechanisms involved. CI failures are known to be caused by a combination of:

- external and internal loadings (e.g. hydraulic pressure/ velocity, water quality, soil, traffic loads, weather/ temperature/freezing, faults, subsidence, groundwater level, operations and management practices);
- pipe characteristics (material, diameter, age, thickness, length, joint types, depth of installation, previous failure history, cathodic protection, lining/coating, bedding, and quality of installation/construction); and
- deterioration (corrosion rates) (Makar *et al.* 2001; Kleiner & Rajani 2001; Fahmy & Moselhi 2009; Nishiyama & Filion 2014).

These factors combine to attack a pipe's structural integrity, thus reducing its capacity to resist internal and external forces. Although many researchers have shown that a number of different parameters (e.g. external, internal and corrosion) are synergistic when it comes to CI failures, it remains challenging to determine specific causal factors.

In most water utilities, decisions to proceed with repair, replacement or rehabilitation are based on observed/ historical performance and/or engineers' experience (Rajani & Makar 2000; Fahmy & Moselhi 2009). Many utilities still operate in a reactive mode with little or no proactive maintenance programs. The research conducted for this study takes a different approach by addressing the uncertainty related to water mains failures, and by using the spatiotemporal clustering revealed in historical data as the basis for determining LOF. The concept of water main failure clustering has been studied by several researchers (de Oliveira *et al.* 2011; Martínez García *et al.* 2018). In this context, a cluster is defined as an area with a high number of pipe failures compared with the average number of failures. Also, the patterns identified by spatiotemporal clustering can indicate spatial correlations that make it possible to predict subsequent pipe failures more accurately (de Oliveira *et al.* 2009; Ganesan *et al.* 2017).

Although there have been many reports of research on water mains asset management that utilize clustering, those focusing specifically on CI pipe asset management issues are few and far between. Clustering techniques can be helpful where water utilities have been collecting and retaining historical failure data for these assets, making it possible to forecast future failure rates in such mains (Moglia *et al.* 2008; de Oliveira *et al.* 2009). When this data is available, the probability of failure (LOF) for each pipeline can be determined by applying emerging hot spot (EHS) analysis (ArcGIS 2016), which evaluates failure clustering patterns in both space and time. This type of analysis identifies areas where water mains failures have been increasing or decreasing with time. To estimate BRE for each CI main, COF can be calculated based on the number of critical facilities that are located close to and are served by each CI water main by considering the various impacts (and consequences) if that water main were to fail. As mentioned earlier, COF analysis usually considers multiple variables, but in this particular study, a subset of COF variables is used: critical customers and facilities.

OBJECTIVES

This study provides a proof of concept for innovative methods for water utilities to use to assess and prioritize water main repairs, replacements or rehabilitation projects, in order to continue providing safe and reliable water to its customers at a reasonable cost. The main purpose of this study is to assess CI pipe failure patterns in California by identifying areas with consecutive hot spots (high probability of failure – LOF) and estimating the number of critical facilities served (consequence of failure – COF) to help water managers determine the total BRE associated with CI water mains, and thus better plan future repair and/or replacement works. The study's specific objectives are as follows:

- To perform a spatiotemporal analysis to determine consecutive hot spot areas linked to a high probability of CI water main failures for three selected water districts in California.

- To identify the COF for all CI pipelines by identifying critical facilities located nearby.
- To present a combined BRE framework that will help water utility managers make more informed decisions with regard to CI asset management projects.

BACKGROUND

Cal Water

The California Water Service Company (Cal Water) supplies water to roughly 478,000 customers in 24 service districts, serving about 1.7 million people located in 83 communities across the State of California. The company is currently developing an Enterprise Asset Management Program (EAM) to manage the entire lifecycle of their assets with one objective: to deliver a high level of service to its customers with an acceptable level of risk exposure at an affordable cost. As part of this mission, Cal Water is increasing the amount of pipe replacements to be undertaken in future budgets, replacing an extra 48 km of high-risk pipelines every year in addition to the pipelines known to be suffering 'frequent-to-many' failures in order to improve the service it provides to customers (Keck & Lee 2015; Güngör-Demirci 2018a, 2018b).

Cast iron pipes in Cal Water

As with most US water utilities, CI is one of the most common materials used for water mains. About 14.7% of Cal Water's water mains are constructed of CI across all of its 24 service districts. Other materials include: asbestos cement (4,538 km (2,820 miles), 43.3%), ductile iron (822 km (511 miles), 7.9%), PVC (1,986 km (1,234 miles), 18.9%), steel (209 km (130 miles), 2%). Most of these CI pipes were installed during the 1920–1960 time period. Between 1991 and 2015, the company recorded 10,725 water failure events, with 3,345 of these failures involving CI pipes (31.1%). Failure count for other materials are: asbestos cement (4,001 failures, 37.7%), steel (1,413 failures, 13.2%), wrought iron (386 failures, 3.6%). Due to the widespread presence of CI pipes in the network, as well as the high number of observed failures (31.1%), Cal Water has a strong interest in analyzing the performance of CI water mains as part of the development of its new EAM Program.

METHODS

CI failure data

Two geographic information system (GIS) datasets were used for assessing CI failures: water mains and historical failure data. The water mains GIS dataset contains information about each individual pipe segment, including its diameter, material, date of installation, location, and length. The failure GIS dataset contains details of every water main failure for the last 25 years, including its reported date and its location. In this dataset, a failure is formally defined as a leak and/or break incident that required attention from Cal Water's field crews, and that was subsequently recorded in the Cal Water GIS database. Based on the failure count, the total CI pipe length, the number of failures per length, and in consultation with Cal Water engineers, the authors decided to focus on three Cal Water service areas: Bakersfield, the Bear Gulch District and Stockton.

BRE

This study sought to quantify BRE for all CI pipes based on the product of LOF and COF for each CI main located in each of the subject service areas.

Likelihood of failure

To evaluate the LOF for each CI pipe, the Space-Time Pattern Mining Tool in ArcGIS 10.4.1 was used to examine the spatial and temporal distribution of water main failures in the study areas. The objective of this procedure was to identify consecutive hot spot areas, which in practice means zones with a high concentration of failures during the periods of time under consideration that are therefore likely to fail again. The first step was to create a Space-Time Cube for each study site. The X and Y horizontal dimensions of the cube represent the geographical coordinates, while the vertical axis represents time. The cube is divided vertically and horizontally into multiple bins. The analysis requires a bin size and time-step to be specified. Here a time-step of 1 year is selected for the vertical dimension. Although the tool allows many different time-steps to be used (e.g., day, week, month), based on existing studies that have utilized the EHS tool in various disciplines, for the purposes of this study 1 year is deemed appropriate for analyzing water mains failures. Given that the failure data covers a 25-year period (1991–2015 inclusive), the cube was divided into 25-time slices.

Regarding the horizontal bin dimensions, multiple values were tested for comparing failure clustering intensity. The cube bin size is based on an appropriate scale related to the object of study. To find an appropriate distance, different bin sizes were tested ranging from 122 m (400 ft) (typical block in high density zones) to 1,524 m (5,000 ft) (rural areas). Because each water district has a different density and distribution of CI pipes and failures, the bin dimensions selected were 610 m × 610 m (2,000 × 2,000 feet) for Bakersfield, 1,219 m × 1,219 m (4,000 × 4,000 feet) for Bear Gulch, and 305 m × 305 m (1,000 × 1,000 feet) for Stockton. It is important to note that this evaluation also requires engineering judgment in terms of 'precision of results' and 'availability of data'. In this type of analysis, if the bin dimensions are too small, clustering cannot be detected because so many bins have zero values, but if the bin dimensions are too large, the analysis will not show any spatial variance. The values and dimensions utilized in this study correspond to the specific conditions for the selected water service districts.

The EHS analysis tool uses these inputs to calculate the *Getis-Ord Gi** statistic (Equation (1)), which identifies bins that contain statistically significant clusters of high failure count (hot spots) and low failure count (cold spots). The *Gi** statistic returned for each spatial location and for each year is a z-score. A z-score is a standard deviation associated with the normal distribution. If the local count of failures within a bin and its neighbors is very different from the expected value (average), and this difference is too large to be the result of randomness, the tool generates a statistically significant z-score associated with a low p-value. When the p-value is very small (i.e., very high or low negative z-scores are calculated), it means it is very unlikely (small probability) that the observed spatial pattern is the result of random processes; hence the null hypothesis can be rejected (ArcGIS 2016). This shows that there is evidence of a process (corrosion, age, pressure, or something else) that is causing an abnormally dense pattern of water main failures in that particular bin and its neighbors. The equation for the G_i^* statistic is as follows:

$$G_i* = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \bar{X}\sum_{j=1}^{n} w_{i,j}}{s\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}} \tag{1}$$

where x_j is the attribute value for feature j (failure count), w_{ij} is the spatial weight between features i and j, s is the standard deviation of the attribute value (failure count) and n is the total number of features (failures).

The next step is for the EHS analysis tool to evaluate the temporal trends of each location by analyzing the z-scores and p-values along the time dimension using the Mann-Kendall test. This analysis not only indicates areas with higher failure values but also the temporal patterns associated with the failures (ArcGIS 2016). For example, if many failures occurred at the beginning of the analyzed time window but then no failures were detected later, the EHS tool would categorize the location as 'hot spot' for the first few years and 'no pattern detected' for the rest. Then, using the Mann-Kendall test, the tool would likely assign a 'diminishing hot spot' label to that location due to decreasing temporal trend. On the other hand, if the majority of failures occurred in recent years, the tool would classify the location as 'new hot spot'. A complete list of EHS can be found in ArcGIS (2016).

The EHS analysis tool provides useful information for assessing the LOF because high z-scores indicate areas where the concentration of failures is higher than normal. However, this is not its only function; by focusing on one group of hot spots designated *consecutive* hot spot areas, it reveals whether an unusually high concentration of pipeline failures has been *consistently observed in the same area in recent years*. For example, areas close to pumping stations that are going through constant hydraulic transients (without adequate surge control appurtenances) may become a problematic zone. Zones with a constant landslide risk are another good example. This suggests (or raises a conjecture) that a specific process is causing this increased failure density.

Consequence of failure

Before the development of the EAM Program could begin, Cal Water defined and identified a set of critical facilities in the state. In a subsequent step, the spatial locations of these facilities were then identified using multiple GIS datasets. The resulting shapefiles contain information regarding the critical facilities that Cal Water identified as likely to suffer the most negative impacts in the event of a water main failure. Examples of these critical facilities include airport boundary, roads, highway, railroads, backyard easement, emergency center, fire station, healthcare facilities, police station, schools, marine protection areas and water bodies (including lakes, reservoirs, and pond layers).

Once the potentially critical facilities had been identified, the second step was to create a buffer around each CI pipe segment. This was done to calculate the number of critical facilities located near each pipe segment. Appropriate buffer zones were determined by considering the average lengths of the service lines connecting the water mains with the facilities and/or the distance between the longitudinal axis of the pipe and each facility's property line. Based on an extensive discussion with Cal Water Engineers, this distance was set at 60 m (200 feet) in each direction.

RESULTS AND DISCUSSION

LOF: emerging hot spots

The EHS analysis identifies trends in the way clusters of failure counts occur in specific space-time cubes (ArcGIS 2016). Figure 1 shows the results of this analysis for the three subject service areas. Each column represents a spatial location, and each bin represents one period of time. For each

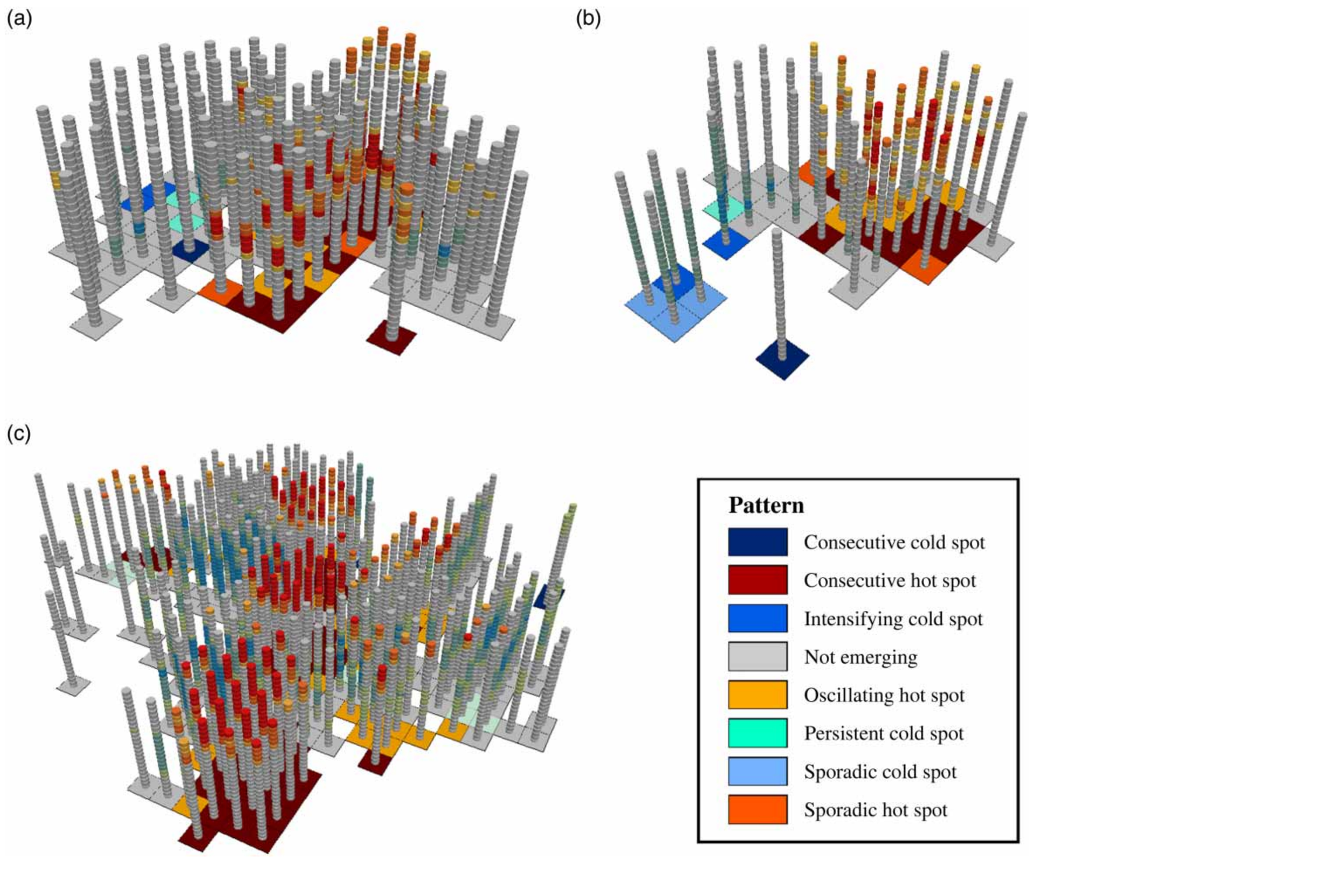

Figure 1 | Results of the emerging hot spot analysis: (a) Bakersfield (bin dimensions 610 m × 610 m), (b) Bear Gulch District (bin dimensions 1,219 m × 1,219 m), (c) Stockton (bin dimensions 305 m × 305 m). Please refer to the online version of this paper to see this figure in color: http://dx.doi.10.2166/aqua.2019.120.

individual location, red indicates that, for a given year, the bin is classified as a hot spot, while blue indicates that the bin is classified as a cold spot. Bins where the failure clustering is not significant at any particular time are shown in gray (i.e., no pattern detected).

In Bakersfield, 77 bins were identified where further examination is necessary, as were 36 in Bear Gulch, and 217 in Stockton. Of these, 20, 8 and 55 bins were classified as consecutive hot spots in Bakersfield, Bear Gulch and Stockton, respectively. Based on the different patterns observed in Figure 1, the EHS tool also classified each bin in a category according to its own time pattern. Although the EHS tool provides 16 different categories, in this study only certain categories were found, which are explained in the following. A complete list of categorizations can be found in ArcGIS (2016).

Based on these findings, the majority of bins are classified into four main groups as follows:

1. *No pattern detected*. The location is not classified as displaying any of the defined hot spot or cold spot patterns, i.e., no statistically significant spatial-temporal pattern is detected in these locations.
2. *Sporadic hot spots*. This category describes locations where intermittent hotpots are identified but these are present for less than 90% of the time (Figure 1).
3. *Oscillating hot spots*. Intermittent hot spots were found to be present in these locations for less than 90% of the total time (25 years). The main difference between these and sporadic hot spots is that in oscillating hot spots, cold spots are also present in the timeline, meaning that in some years, the occurrence of failures is high, but in others it is minimal. These categories do not show a specific trend in terms of water asset deterioration because of their variability (cold spots ↔ hot spots) and are not included in any further analyses for this study. Further research is suggested to examine possible reasons for this pattern.
4. *Consecutive hot spots*. These bins contain a continuous run of multiple years of statistically significant hot spot bins in the final (more recent) time-step intervals. It is one of the most important groups because it indicates regions with a higher number of water main failures (compared with the average in each region) and that this pattern has been detected in a consecutive number of years more than 90% of the time. Consecutive hot spots were found in all three of the study areas.

COF

As with LOF, all CI pipes currently in service were considered for the COF analysis. The three study areas contain a total of 12,737 CI pipe segments, of which 6,631 pipe segments are located in Bakersfield, 1,909 in Bear Gulch, and 4,196 in Stockton. The critical facilities in each area were classified into three groups for this analysis: point locations (such as police stations or schools), lines (railroads or highways) and polygons (airports, marine protection areas). This classification is important because the number of pipes that might affect critical facilities in the event of failure, repair, or replacement can be significant. For example, an arterial road or a railroad might traverse an entire city and include several intersections with the water distribution network, while a police station might only be affected by one or two pipelines. Some pipes may be in areas where the concentration of critical facilities is particularly high: for example, where a pipeline crosses underneath a large highway or transportation interchange.

Based on the number of critical facilities located in the area, heat maps were generated for each district (Figure 2). In these maps, the count of critical facilities near (60 m) each pipe segment is color-coded using three different categories to reflect their different characteristics: CI pipes that are near only a few (0–2) critical facilities are shown in green, those close to an intermediate number (3–10) are shown in yellow, and those with a high number of neighboring critical facilities (11+) are shown in red. These categories reflect the number of critical facilities likely to be affected in the case of water main failure, repair or replacement.

BRE

LOF and COF, which are the main components required to quantify and construct the BRE matrix, are depicted using color coding as shown in Table 1. In this matrix, the pipes are classified based on their LOF (EHS analysis) and COF (number of critical facilities).

The pipes located in consecutive hot spot areas and having 11 or more critical facilities within the buffer

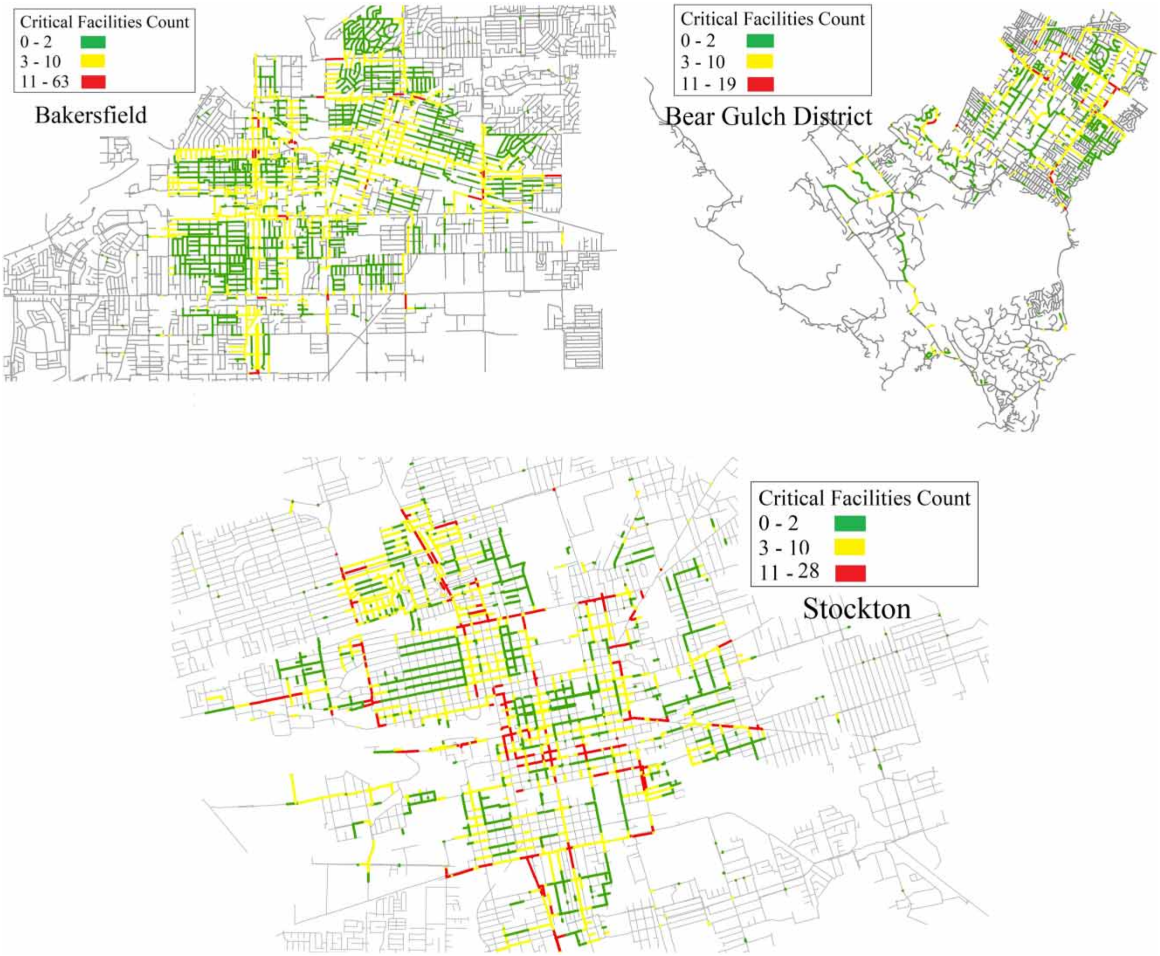

Figure 2 | Maps showing the number of critical facilities located within the buffer zone around each CI pipe segment. Grey lines indicate pipes made from other materials. Please refer to the online version of this paper to see this figure in color: http://dx.doi.10.2166/aqua.2019.120.

zone are categorized as belonging to the immediate risk mitigation group that requires immediate attention/action (Group 1 color-coded purple). This category covers about 7.8 km (4.9 miles) of CI pipe in Bakersfield (3%), 2.2 km (1.4 miles) in Bear Gulch (2%), and 7.1 km (4.4 miles) in Stockton (5%). The second category (Group 2 color-coded dark orange) indicates pipes that will need to be replaced soon, but due to their relatively lower LOF or COF scores they can be replaced when the utility has the capacity to do so. Two groups of pipes can be identified in this category: either pipes with a lower count of critical facilities located in consecutive hot spots or pipelines with a higher COF located in other hot spot areas, specifically oscillating and sporadic. These hot spot categories imply that for some years, there was a high count of failures but for others the count was low meaning that the phenomenon causing them is temporal (pressure peaks, temperature variations, etc.). This category includes 30.6 km (19.0 miles) in Bakersfield (11%), 22.7 km (14.1 miles) in Bear Gulch (24%), and 24.5 km (15.2 miles) in Stockton (17%).

The third category (Group 3 color-coded light orange) reflects a medium replacement priority. Based on factors such as age and failure rate, a further evaluation is recommended. There are three groups in this classification: pipes with a high LOF but with a low COF, pipes with a low LOF and a high COF and pipes with medium COF located in 'other hot spot' categories. In this category 75.8 km (47.1 miles) in Bakersfield (28%), 31.3 km (19.5 miles) in Bear Gulch (33%), and 42.6 km (26.5 miles) in Stockton (29%) are included (Table 2). The fourth category

Table 1 | BRE assessment matrix

LOF	**Consecutive hot spot (High)**	Medium priority Re-assess individual cases ***Group 3***	Close monitoring and maintenance ***Group 2***	Immediate risk mitigation ***Group 1***
	Other hot spot categories (sporadic – oscillating) (Medium)	Low priority Re-assess individual cases ***Group 4***	Medium priority Re-assess individual cases ***Group 3***	Close monitoring and maintenance ***Group 2***
	No pattern detected (Low)	Minimum priority ***Group 5***	Low priority Re-assess individual cases ***Group 4***	Medium priority Re-assess individual cases ***Group 3***
		No critical facilities (Low)	**1 to 10 critical facilities (Medium)**	**11 or more critical facilities (High)**
	COF			

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Table 2 | BRE summary

City	BRE group	1	2	3	4	5	Total
Bakersfield	Kilometres	7.8	30.6	75.8	105.3	54.7	274.2
	Miles	4.9	19.0	47.1	65.4	34.0	170.4
	%	3%	11%	28%	38%	20%	100%
Bear Gulch	Kilometres	2.2	22.7	31.3	32.6	6.5	95.4
	Miles	1.4	14.1	19.5	20.3	4.0	59.3
	%	2%	24%	33%	34%	7%	100%
Stockton	Kilometres	7.1	24.5	42.6	56.9	17.2	148.3
	Miles	4.4	15.2	26.5	35.4	10.7	92.2
	%	5%	17%	29%	38%	12%	100%

(Group 4 color-coded green) indicates pipes that can be left to operate until failure occurs, because they have a lower LOF or COF (i.e. low priority). However, periodic monitoring is recommended. This category includes 105.3 km (65.4 miles) in Bakersfield (38%), 32.6 km (20.3 miles) in Bear Gulch (34%), and 56.9 km (35.4 miles) in Stockton (38%).

Finally, Group 5 (color-coded light blue) represents minimum priority with no EHS pattern detected and/or no critical facilities located in the vicinity. This category includes the remaining 54.7 km (34 miles) in Bakersfield (20%), 6.5 km (4 miles) in Bear Gulch (7%) and 17.2 km (10.7 miles) in Stockton (12%). Based on the resulting matrix, a BRE-based prioritization heat map was developed for the three study areas (Figure 3) using the same color-coding for the five different BRE groups. It is the authors' opinion that the generated heat maps can serve as a helpful tool to enable water utility asset managers to make more informed decisions regarding EAM project prioritization.

CONCLUSIONS

This paper provides a proof of concept for Cal Water and other utility managers of innovative methods to assess and prioritize water utilities' asset management strategies by presenting the results of a clustering-based spatiotemporal analysis. The approach is designed to identify hot spot areas with a comparatively higher concentration (likelihood) of CI water main failures for three selected service areas in California. In this paper, both spatial and temporal trends were considered to define hot spots. CI pipe assets were also classified in terms of their COF by identifying nearby critical facilities that would be affected in the event of a water main failure, repair or replacement. By merging these two factors (LOF × COF), a resulting BRE analysis emerged. This analysis provided a color-coded, five group BRE classification to determine the conditions of each individual pipe segment based on LOF–COF parameters. The identified groups are: immediate risk mitigation (Group 1), close monitoring/maintenance (Group 2),

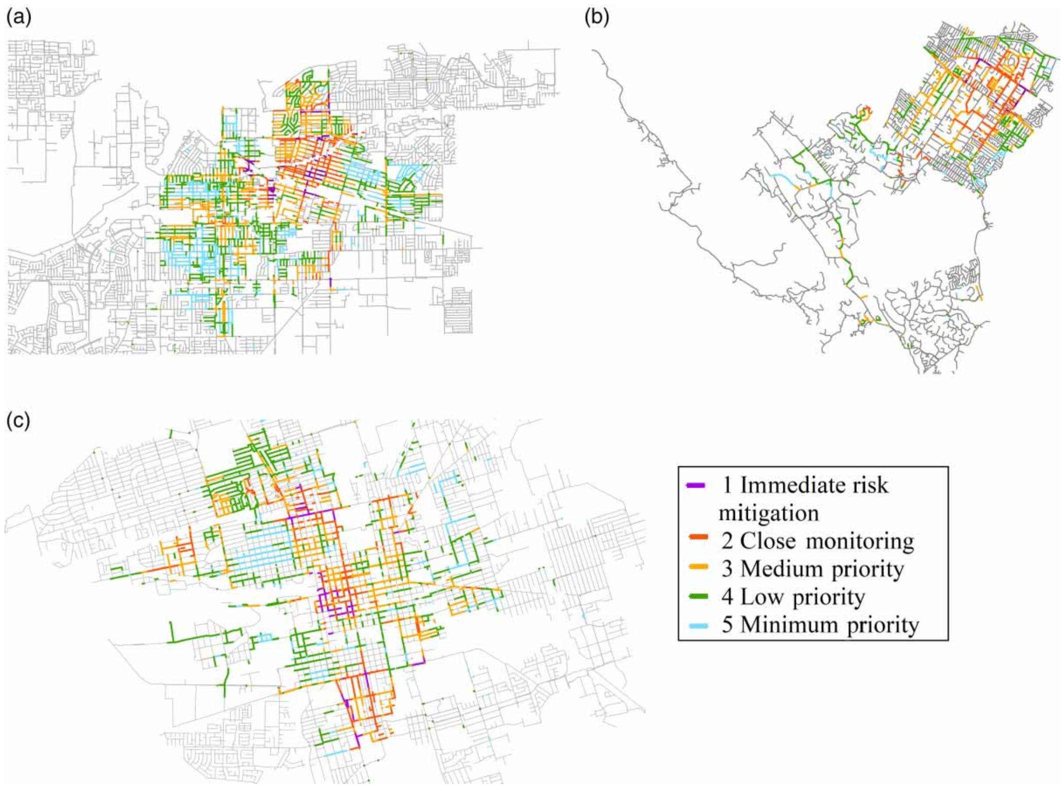

Figure 3 | Prioritization maps of the three study areas: (a) Bakersfield, (b) Bear Gulch, (c) Stockton.

re-assess individual case (Group 3), medium (Group 4), and low priority (Group 5). This BRE analysis can serve as a helpful tool to enable water utility managers/directors to make more informed decisions regarding the prioritization of EAM projects and to assess the risks associated with the rapidly deteriorating cast iron pipes in their networks.

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