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A review of water quality factors in water main failure prediction models

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ABSTRACT

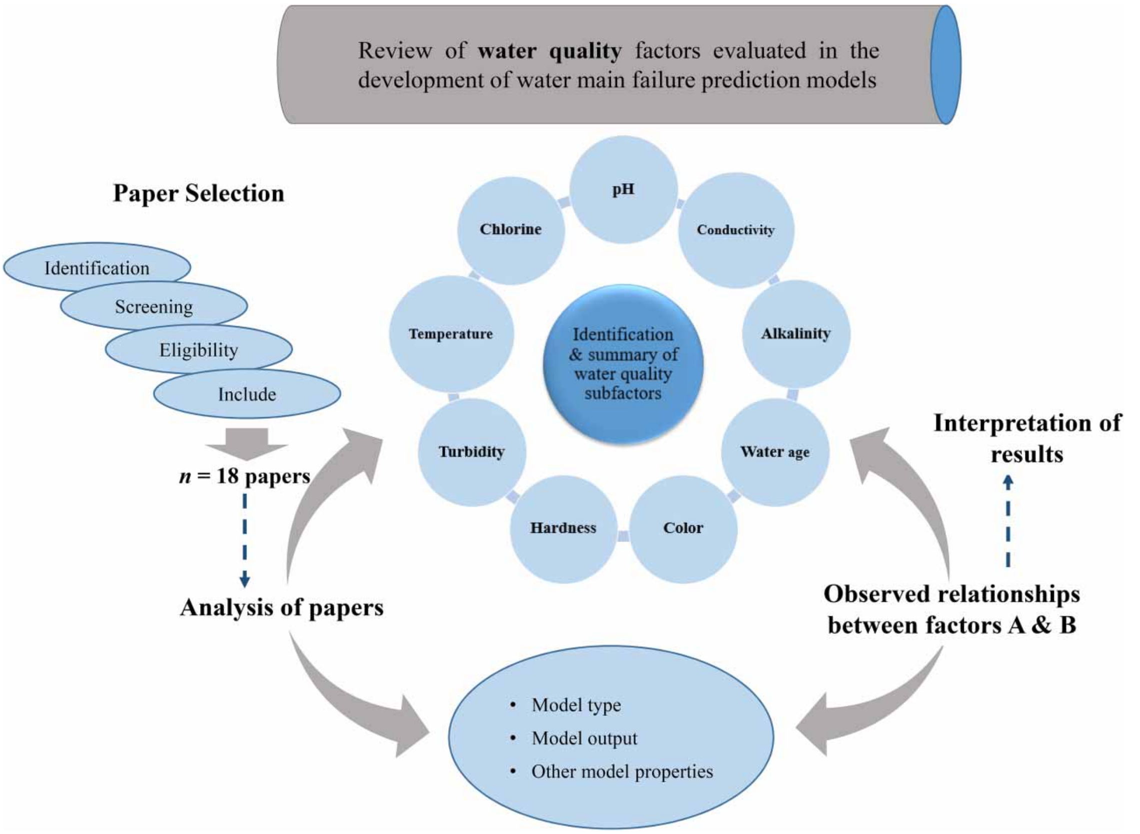
Water main failure can result from structural failure of the pipes, changes in water quality, or a combination. This paper is a review of articles evaluating water quality factors and subfactors in the development of water main failure prediction models since 2000. A systematic process was implemented to capture the most relevant current published papers. Of 4598 published papers, 304 were screened for water main failure prediction models. The resulting set was further screened for water quality factors and subfactors (e.g., pH, temperature, etc.). This led to the identification of 18 relevant research papers, and each of these was reviewed comprehensively. The water quality-related findings, as well as combinations with other information – such as type of prediction model and type of prediction – are summarized and discussed.

Key words: failure prediction models, prediction model factors, water mains, water main condition assessment, water quality factors, water quality subfactors

HIGHLIGHTS

- Summary of water quality factors for use in condition assessment of water mains based on a comprehensive literature review.
- Impact of water quality factors on water main failures, considering pipe material.
- Relationship between water quality factors and other model parameters, type of failure prediction model, and output.
- Water pH is the water quality factor that is most frequently included in water main failure prediction models.

GRAPHICAL ABSTRACT



INTRODUCTION

Municipalities are facing increasing challenges related to deteriorating water supply systems. Based on a survey of water systems in North America, Folkman (2018) reported that water main break rates increased by 27% from 2012 to 2018, equivalent to a break every two minutes across North America. Furthermore, of all the materials used in water systems, the break rates for cast iron and asbestos cement pipes increased significantly between 2012 and 2018. ASCE (2021) reported that water utilities across the US planned to replace more than 12,000 miles (~19,300 km) of water pipes in 2020. The Canadian Infrastructure (CI) Report Card (2012) reported that 15.4% of Canadian water distribution systems (WDS) were in fair to very poor condition, with a cost estimate of CAD 25.9 billion for replacement. More recently CI (2019) reported that the proportion had increased to 25%.

Service interruptions due to pipe failures in potable water systems are not only inconvenient but have economic and social impacts. These include increased maintenance, rehabilitation and renewal costs, degradation of drinking water quality, flooding, creation of sink holes, and disruption to traffic and business, and so on (Folkman *et al.* 2012; Folkman 2018). Since about 2000, significant effort and funds have been directed towards research on water main condition assessment, as water utilities become more proactive in managing water systems. Increasingly, utilities are trying to stretch limited budgets and base asset management decisions on data reflecting actual pipe conditions rather than taking a replace-as-pipes-break approach. Researchers, in turn, have proposed various water failure prediction models to determine the performance and durability of water mains, considering a wide range of factors (physical, operational and environmental). This research increases the information available on which to base future pipe replacement decisions but, despite the widespread work in this area and numerous papers published, the information is unconsolidated and difficult to navigate.

Most research on water main failure prediction is focused on three aspects: (1) development of models to predict water main failure; (2) predictive factors for failure; and (3) prediction model outputs – for example, failure rate, probability of failure, and so on. These efforts have been summarized and discussed in many literature reviews, which generally focus on existing types of prediction model and their evolution (Kleiner & Rajani 2001; Rajani & Kleiner 2001; Clair & Sinha 2012; Nishiyama & Filion 2013b; Ogutu *et al.* 2017; Wilson *et al.* 2017; Wu & Liu 2017; Dawood *et al.* 2020). Less effort has been expended on reviewing model factors and other aspects of this research (Gao 2017). For example, Clair & Sinha (2012) reviewed more than 50 articles from 2000 to 2010 and presented an explanation of each prediction model, classifying them as deterministic, statistical, probabilistic, artificial neural network (ANN) and fuzzy logic models. Wilson *et al.* (2017) reviewed articles published from 2000 to 2013 and proposed a failure prediction model for large diameter water mains (>500 mm), but only one specific output – time to next failure – was considered. In this work, models were classified as either physical or statistical. Nishiyama & Filion (2013b) covered developments from 2002 to 2012, focusing on statistical general linear and soft computing (ANN) models. Gao (2017) reviewed 64 papers published after 2008, summarizing information about failure prediction models, model parameters, and major findings, but without a comprehensive discussion related to model inputs and outputs, and/or the relationships between them.

Since an important consideration in successful model development relates to the physical, operational and environmental factors included, this review focuses on model factors and their interrelationships. The literature published from 2000 to 2020 was reviewed comprehensively, with a focus on water quality (and related subfactors) in developing water main failure prediction models. In this paper, water quality as an operational factor and water quality subfactors are discussed, as well as the inclusion of these factors in different model types. The systematic approach used to identify the most relevant papers and findings is also described.

METHOD

Many water main failure models are based on physical data. These have been excluded from this research, since obtaining the data required for physical models can be expensive (Rajani & Kleiner 2001; Wilson *et al.* 2017). Since many papers have been published in relation to water systems (e.g., more than 1,000 from a search of general key words), a systematic procedure was developed to identify relevant papers.

Figure 1 shows the basic structure of this study and outlines the procedure used to identify relevant papers. General key words (including pipeline, water pipeline, water network, water distribution, failure analysis, failure model, risk management, pipe deterioration, pipe break and pipe burst) were chosen for the database searches in order to avoid missing relevant papers. Sequential screening questions were used to filter the preliminary article set. Of the 304 articles identified involving water main pipe failure prediction models, only 18 mentioned water quality as a variable. Each of these eighteen papers was assigned an ID number.

Microsoft Excel was used to systematically record the data from the included papers, and an Excel spreadsheet was developed to digitize the information, with numbers assigned to each parameter – for example, 1 and 2 were assigned to water pressure and quality, respectively. If an article included more than one factor, the corresponding numbers were assigned to it. If an article did not contain the factor, 0 was assigned. To determine the relationship between water quality and other factors, a computer code was developed to detect any overlap between water quality, water quality subfactors, and other factors in the papers.

Data extracted from the papers were categorized into six groups: water main failure prediction models, physical parameters, operating parameters, environmental parameters, output, and other information (Gao 2017). Prediction models can be subdivided into six categories: deterministic, statistical, probabilistic, artificial intelligence (AI), risk assessment and multi-criteria decision models. Each may include various methods (Karimian 2015; Kabir *et al.* 2015a, 2015b; Francisque *et al.* 2017), including ANN, fuzzy logic, genetic algorithm, Bayesian belief network, etc, – so the specific modelling method was also recorded. There are three main categories that contribute to water main deterioration: physical, environmental and operational factors (Stacha 1978; National Research Council 2003; Al-Barqawi & Zayed 2006; Francisque *et al.* 2014; Mounce *et al.* 2014; Kabir *et al.* 2015a, 2015b; Karimian 2015). Certain factors, such as soil properties and climate (environmental parameters) and water quality (an operating parameter) can be divided into additional subfactors.

RESULTS

Literature review

Some 147 of the 304 papers selected were published in North America (US and Canada)—Figure 2—with 88 published in Europe. More than 50% of the papers selected were published between 2010 and 2020—Figure 3—and only 1% before 2000. The latter were collected via citations in other papers reviewed.

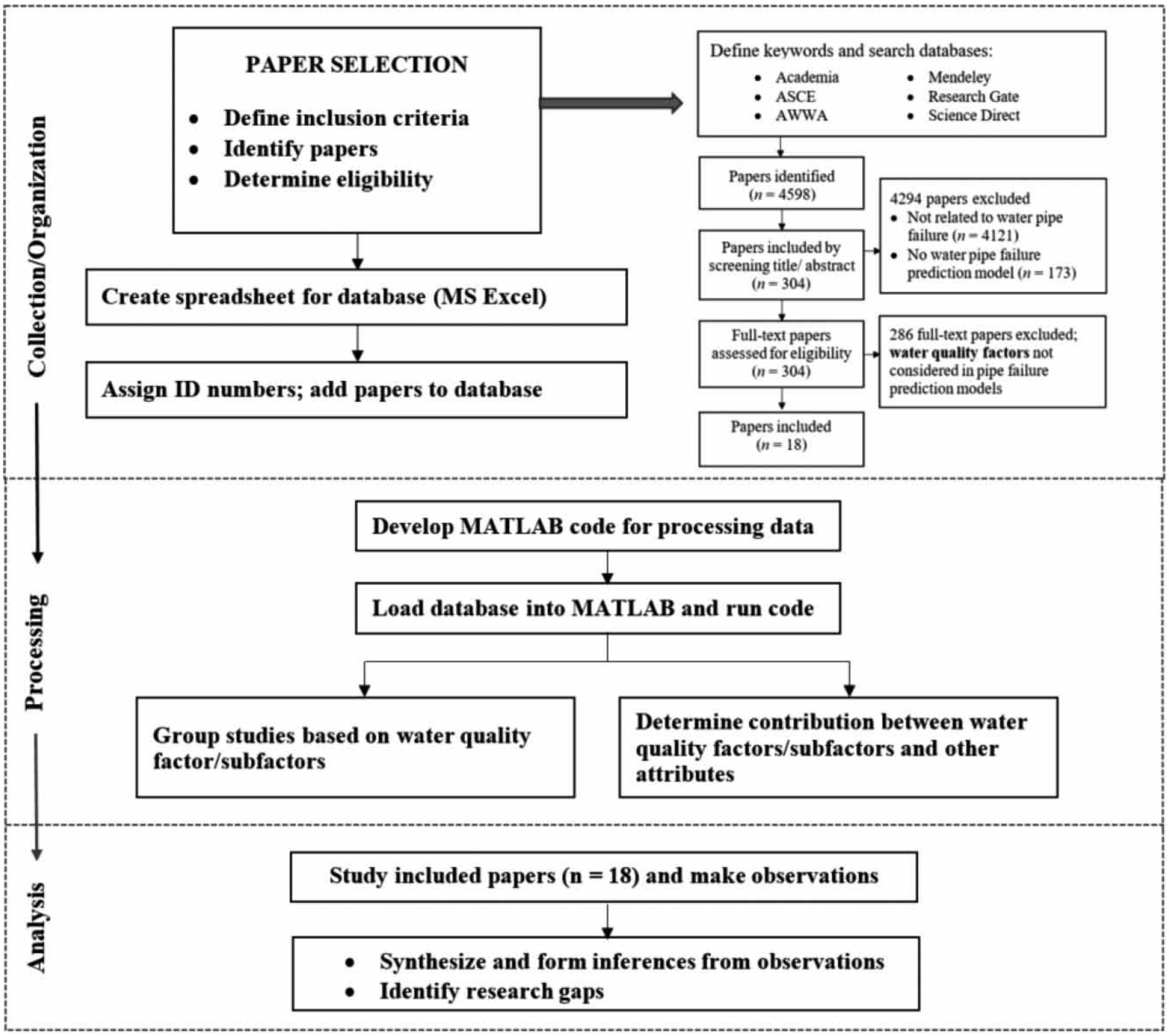


Figure 1 | Methodology flow diagram.

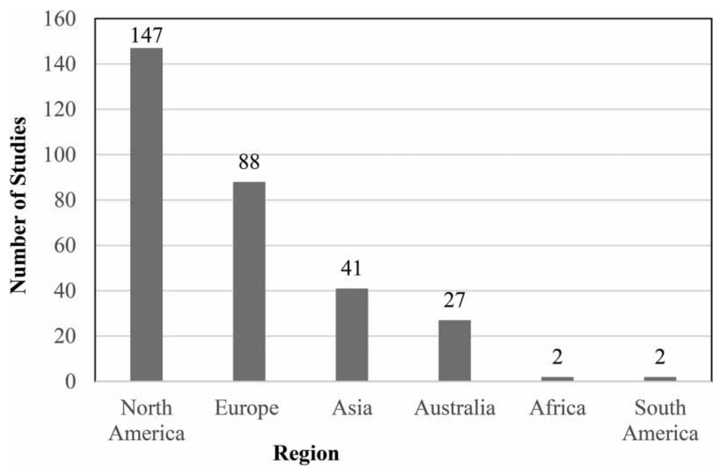


Figure 2 | Distribution of water main prediction model studies by region.

Water quality subfactors

Most research papers on water main prediction models include only physical factors (e.g., pipe material, diameter, age, and length). Although it has been observed that water quality is a significant factor in making

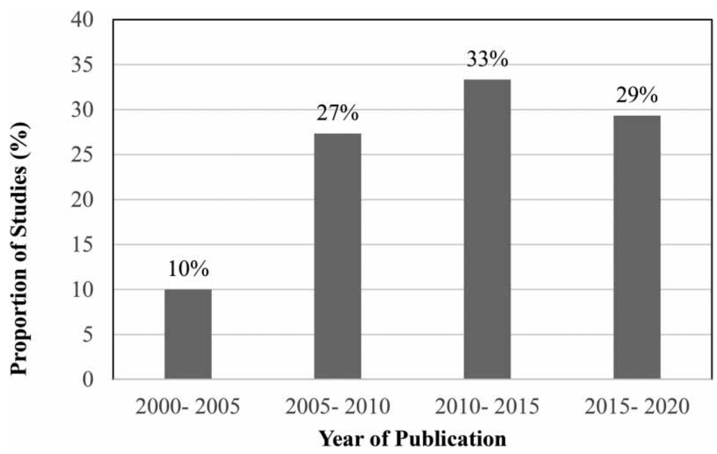


Figure 3 | Water main failure prediction model publications by date of publication (between 2000 and 2020).

decisions regarding replacement or rehabilitation of water mains, water quality factors have only been included in eighteen papers related to water main prediction models. Table 1 summarizes the main aspects of the papers using water quality as a prediction model factor. Most (61%) of the papers were based on data from North America, particularly Canada, and the majority (77%) were published between 2010 and 2020. The main water quality subfactors used in the water main failure prediction models reviewed are listed in Table 2. Of the eighteen papers analyzed, thirteen included water quality subfactors. The impacts of these subfactors were also evaluated in the papers.

Table 1 | Summary of the main aspects of papers related to water main failure prediction models that contain water quality as a factor

Authors	Region	Year Published	Model Type	Output
Ismaeel & Zayed (2018)	North America	2018	Multi-criteria decision	Probability of next failure
Francisque *et al.* (2017)	North America	2017		Assign priority to water mains
Choi *et al.* (2017)	Asia	2017		Assign priority to water mains
El Chanati *et al.* (2016)	Asia	2016		Assign priority to water mains
Fares & Zayed (2010)	North America	2010		Assign priority to water mains
Gardels *et al.* (2018)	North America	2018	Statistical	Pipe failure rate
Rathor & Sinha (2013)	North America	2013		Assign Priority to water mains
Bubtiena *et al.* (2011)	Asia	2011		Number of breaks
Røstum (2000)	Europe	2000		Number of breaks
El-Abbasy *et al.* (2019)	North America	2019	AI	Assign priority to water mains
Nishiyama & Filion (2013a)	North America	2013a		Pipe failure rate
Mounce *et al.* (2014)	Europe	2014		Burst detection
Zantingh (2018)	North America	2018	Risk assessment	Assign priority to water mains
Kabir *et al.* (2015a)	North America	2015a		Assign priority to water mains
Francisque *et al.* (2014)	North America	2014		Assign priority to water mains
Yaminighaeshi (2009)	North America	2009	Probabilistic	Probability of failure
De Silva *et al.* (2006)	Australia	2006		Pipe failure rate
Ojdrovic *et al.* (2007)	Europe	2007	Deterministic	Pipe failure rate

The number of water quality subfactors used in model development depends on the model type. Tavakoli (2018) noted that developing models to evaluate all physical, environmental and operational factors would be complex. Model complexity increases with increasing numbers of subfactors. Some subfactors are also not completely independent, such as alkalinity and hardness. Therefore, interdependence between factors should be

Table 2 | Water quality subfactors included in water main failure prediction models

Subfactor	Frequency
pH	9/13
Chlorine[a]	5/13
Temperature	3/13
Turbidity	3/13
Hardness	2/13
Color	2/13
Water age	2/13
Alkalinity	1/13
Conductivity	1/13

[a]Includes free residual chlorine, chlorine decay, and chlorine concentration.

considered in model development. Multi-criteria decision and risk assessment models typically take more factors into account, while probabilistic and statistical models are very sensitive to parameter precision and any interdependencies between subfactors. Addressing these considerations can complicate model development and may also increase uncertainty in the results. Among the papers using water quality as a predictive factor, the most common model type was the multi-criteria decision model used to assign priority ranking.

Water pH

Changes in pH can affect the rate of degradation of cement-based materials (e.g., in cement and asbestos cement pipes, and cement coatings/liners). pH also affects the corrosion of metal pipes and fittings, including metal fittings on plastic pipes.

As shown in Table 3, five of the nine studies that include pH were risk assessment or multi-criteria decision models, which are better equipped to evaluate higher numbers of covariates.

In terms of prediction type, ranking water mains is the most common. Such ranking or prioritization is important in deciding whether to renovate or rehabilitate mains. More than half the papers reviewed consider the impact of pH on water main ranking of both cementitious and metal pipes. Almost all of the metal pipe condition assessment papers include pH in their models. Four focus specifically on ductile iron (DI) and cast iron (CI) pipes. Yaminighaeshi (2009) considered corrosion in CI pipes, the other four included the impact of pH on cement-based pipes (Francisque *et al.* 2014, 2017; Kabir *et al.* 2015a; Zantingh 2018).

As pH increases, dissolution of iron decreases – i.e., the water's corrosivity is reduced (Sadiq & Tesfamariam 2007; Francisque *et al.* 2009). The rate of deterioration of cementitious pipes also decreases as scale forms under alkaline conditions. In fact, pH >7 is recommended for cement-based materials to reduce their dissolution rates (Vik *et al.* 1990; Wąsowski *et al.* 2019).

Francisque *et al.* (2014, 2017) defined and used the aggressiveness index to evaluate a pipe vulnerability index. The vulnerability index is calculated by aggregating the pipe structural integrity and hydraulic capacity indexes. Francisque *et al.* (2014, 2017) applied a weighted average incorporating pH and free residual chlorine to estimate the aggressiveness index for metal pipes. For cementitious pipes, the aggressiveness index was estimated using the equation presented by Hu & Hubble (2007), which is based on pH, total alkalinity and calcium hardness. Since water aggressivity is a long-term effect, it was not discussed for plastic pipes (Francisque *et al.* 2014), which have a lower rate of deterioration.

pH contribution compared with other subfactors

In Francisque *et al.* (2014) risk assessment model, pH and free residual chlorine have the same weight in estimating the aggressiveness index for metal pipes; however, the aggressiveness index was considered less important than the structural failure index and soil corrosiveness index.

Francisque *et al.* (2009) studied the impact of pH, trihalomethanes, heterotrophic plate count, free residual chlorine, water temperature and turbidity on the risk of water main failure. In this model, pH was assigned a weight of 0.25. Water temperature and free residual chlorine were assigned the highest weights in the model (almost 0.65).

Table 3 | Inclusion of pH in water main failure prediction models

	Model						Output				Pipe material		
Research	**Deterministic**	**Statistical**	**Probabilistic**	**Artificial intelligence**	**Risk assessment**	**Multi- criteria decision making**	**Probability of failure**	**Pipe failure rate**	**Burst detection**	**Priority assignment of water mains**	**Metal**	**Cement-based**	**Plastic**
Francisque *et al.* (2014)					•					•	•	•	
Choi *et al.* (2017)						•				•	• (DI)		
Mounce *et al.* (2014)				•					•				
Ojdrovic *et al.* (2007)	•							•			• (DI)		
Kabir *et al.* (2015a)					•					•	•	•	
Francisque *et al.* (2017)						•				•	•	•	
Nishiyama & Filion (2013a)		•						•			• (CI)		
Yaminighaeshi (2009)			•				•				• (CI)		
Zantingh (2018)					•					•	•	•	
Frequency	1/9	1/9	1/9	1/9	3/9	2/9	1/9	1/9	1/9	5/9	8/9	4/9	0/9

Chlorine

Chlorine is the most common disinfectant in water treatment and used worldwide, but it can also affect pipe corrosion. Free residual chlorine is the chlorine left after the initial disinfection that is available to inactivate microorganisms (WHO 2017). Almost half of the studies investigated incorporate chlorine, in some form, as a covariate (Yaminighaeshi 2009; Francisque *et al.* 2014, 2017; Kabir *et al.* 2015a). However, only Francisque *et al.* (2014) and Kabir *et al.* (2015a) considered the impact of chlorine on both changes in water quality and water aggressivity in their models. Both defined water quality and structural integrity indexes in models to evaluate the risk of water main failure.

According to Francisque *et al.* (2014), low free residual chlorine concentrations are desirable for metal water mains. However, this needs to be balanced with considerations related to water quality, since higher concentrations are recommended.

All papers that take chlorine into consideration mention a positive correlation between residual chlorine and the rate of internal corrosion (Frateur *et al.* 1999; Ojdrovic *et al.* 2007; Yamini & Lence 2007; Tamminen *et al.* 2008; Francisque *et al.* 2009, 2014, 2017; Yaminighaeshi 2009; Bubtiena *et al.* 2011; Kabir *et al.* 2015a). Three of the five papers investigating the effect of chlorine on water main condition applied risk assessment and multi-criteria decision models – Table 4 – and used water main ranking as the output.

In the five studies that met inclusion criteria, the impact of chlorine on pipe condition was only considered for metal water mains. Chlorine consumption is assumed to be a rough indicator of the internal corrosion rate for CI water mains (Yamini & Lence 2007; Yaminighaeshi 2009). Yaminighaeshi (2009) developed a model to determine the probability of mechanical failure of CI pipes due to internal corrosion, taking into account the relationship between chlorine consumption and corrosion rate. Frateur *et al.* (1999) studied the correlation between free chlorine consumption and pipe material. Comparison of plastic pipes (PE and PVC), aged CI (uncoated), and steel pipes indicates that CI pipes, not plastic ones, are associated with the most chlorine consumption. Tamminen *et al.* (2008) and Yamini & Lence (2007) also reported that chlorine consumption is higher in CI than PE networks.

Mounce *et al.* (2014) studied water distribution system time-series data and observed that chlorine concentration has a periodic sinusoidal behavior. Francisque *et al.* (2014) also mentioned that uncertainties in chlorine concentration are significant within the same and between networks, both temporally and occasionally, because of high variability.

Chlorine contribution compared to other subfactors

Kabir *et al.* (2015a) stated that free residual chlorine has the lowest contribution among water quality factors, on the basis of a sensitivity analysis of their risk assessment model for prioritizing water mains. However, Yaminighaeshi (2009) reported that (compared to water velocity) the ratio of current to initial chlorine concentration and the chlorine decay constant are more significant factors affecting the failure probability of CI mains.

According to Francisque *et al.* (2014), pH and free residual chlorine have the same weight in estimating the aggressiveness index for metal pipes, although the index is weighted lower than the structural failure or soil corrosiveness indices in evaluating the structural integrity index. Among all covariates related to water quality (e.g., turbidity, color, free residual chlorine, water age), however, free residual chorine has the highest preference weight (0.52) (Francisque *et al.* 2014). The analytic hierarchy process (AHP) developed by Saaty (2008) was applied to assign each parameter as a preference weight. Francisque *et al.* (2009) reported that, among water quality subfactors, free residual chlorine and water temperature had the highest preference weights (almost 0.65) in their risk assessment model. Their sensitivity analysis showed that just two factors – free residual chlorine and pipe breaks – accounted for 85% of the variability in risk index.

Water temperature

Typically, chemical reaction rates increase with increasing temperature (Ball & Key 2014). Thus, the water temperature in a distribution network can influence corrosion rates, and so on, and affect water quality. Temperature is also important in bacterial growth kinetics (Francisque *et al.* 2009). Despite its known significance, the effects of water temperature were only assessed in four papers (Yaminighaeshi 2009; Nishiyama & Filion 2013a; Mounce *et al.* 2014; Gardels *et al.* 2018).

Some water utilities specify that water temperature must be considered in water main condition assessment (Gardels *et al.* 2018), in line with industry experience and institutional knowledge. Many water main condition

Table 4 | Summary of water main failure models including chlorine (chlorine concentration, free residual chlorine and chlorine decay)

	Model				Output			Pipe Material		
Research	**Statistical**	**Probabilistic**	**Risk assessment**	**Multi- criteria decision making**	**Probability of failure**	**Prioritize water mains**	**Number of breaks**	**Metal**	**Cement-based**	**Plastic**
Francisque *et al.* (2014)			•			•		•		
Kabir *et al.* (2015a)			•			•		•		
Francisque *et al.* (2017)				•		•		•		
Bubtiena *et al.* (2011)	•						•	• (DI)		
Yaminighaeshi (2009)		•			•			• (CI)		
Frequency	1/5	1/5	2/5	1/5	1/5	3/5	1/5	5/5	0/5	0/5

models include water temperature: for instance, Nishiyama & Filion (2013a) applied water temperature in a statistical model to predict water main failure rates, although no explanation for its inclusion was given. Yaminighaeshi (2009) discussed the effects of water temperature on the intensity of internal corrosion in CI pipes, but temperature was not considered to be as significant as chlorine concentration.

Francisque *et al.* (2009) worked on quantifying the risk of water main failure based on water quality parameters, with a weight assigned to each parameter. pH, turbidity, free residual chlorine and water temperature were studied. Of these, temperature was assigned the highest weight, 0.66, followed by free residual chlorine (0.65), indicating almost equal importance. Sadiq & Tesfamariam (2007) also stated that corrosion rates (in metal pipes) increase in waters with high temperature (as well as low pH, high dissolved oxygen and/or high concentrations of dissolved solids).

Unlike other factors, such as chlorine content and pH, water temperature is not considered in risk assessment or decision-making models. However, in the three papers that included water temperature, its impact was studied for all pipe materials. One of the three papers related to prediction models developed specifically for CI pipes (Nishiyama & Filion 2013a). Gardels *et al.* (2018) evaluated a prediction model including temperature for metal pipes, as well as PVC and concrete.

Turbidity

Only three of the models reviewed in this study include turbidity (Francisque *et al.* 2014; Mounce *et al.* 2014; Kabir *et al.* 2015a). Generally, water with NTU <1 (NTU=nephelometric turbidity units) is acceptable but NTU >1 is not (Kabir *et al.* 2015a).

In the risk assessment models developed by Francisque *et al.* (2014) and Kabir *et al.* (2015a), either water quality failure or pipe failure constituted water main failure. Turbidity is a microbial parameter, and thus Francisque *et al.* (2014) studied its use as a water quality subfactor to estimate the water quality index. Since turbidity has been found to be less variable than free residual chlorine (both within and between networks) it is a better factor for use in regulation (Francisque *et al.* 2014) and thus may be more readily available for use in water prediction models.

Mounce *et al.* (2014) studied time-series data for water distribution systems and observed that turbidity shows the same behavior as observed for chlorine concentration (i.e., a periodic, sinusoidal-like time series). Turbidity also corresponds to the trends usually encountered for real-time monitoring of other water quality parameters, such as conductivity (which is non-periodic). Therefore, turbidity can have both characteristics.

Inclusion of turbidity in studies

Francisque *et al.* (2014) gave turbidity the highest weight (0.22) after free residual chlorine in a water quality index evaluation model. The other covariates included color, and water age and velocity. In a previous study, Francisque *et al.* (2009) assessed the risk of water quality failure for metal pipes in a single group (CI, DI, steel and copper) and evaluated each factor's contribution to the model. In this case, turbidity was assigned a weight of 0.27, placing it above pH, which had a weight of about 0.22.

Hardness

Like alkalinity, hardness affects internal corrosion and deterioration in both metal and cementitious pipes, with more significant impacts in the latter. If the hardness is low (i.e., below 10 mg-$CaCO_3$/L) in water carried by a cementitious main, the water is considered very aggressive (Francisque *et al.* 2014). The threshold between soft and moderately hard water is generally taken as being 60 mg-$CaCO_3$/L (WHO 2010). Hardness above 10 mg-$CaCO_3$/L has been reported to cause a significant decline in the dissolution of cement-based materials in cement and asbestos cement pipes, as well as cement coatings (Vik *et al.* 1990). In contrast, for metal pipes, calcium carbonate composites can deposit on pipe walls and reduce the rate of corrosion.

Although hardness is cited as a major factor affecting pipe corrosion and degradation, it is included in only two of the papers reviewed. Francisque *et al.* (2014) applied an aggressiveness index in their risk assessment model to consider water quality covariate effects on corrosion of metal pipes and degradation of cementitious pipes. Water hardness is only considered (along with alkalinity and pH) in the aggressiveness index proposed by Hu & Hubble (2007) for cement-based water mains, likely because carbonate has no direct role in metal pipe corrosion. El-Abbasy *et al.* (2019) evaluated the impact of all water quality subfactors (including water hardness) together in a single combined factor. They did this by defining three water quality classes – poor, fair and good. Like

Francisque *et al.* (2014), El-Abbasy *et al.* (2019) developed a model to detect and rank the most vulnerable metal and cementitious pipes.

Color

Color is only included in two papers on water quality effects in pipe failure prediction models (Francisque *et al.* 2014; Kabir *et al.* 2015a). Reddish or rusty-coloured water can indicate corrosion in metal pipes (Sadiq & Tesfamariam 2007; Francisque *et al.* 2009) because iron corrosion products are reddish (Yaminighaeshi 2009) due to the presence of Fe^{3+}.

Both Francisque *et al.* (2014) and Kabir *et al.* (2015a) used risk assessment models to prioritize the maintenance, renovation or replacement of water mains according to the level of risk. Color was one of the factors used to estimate the water quality index (a step in evaluating the risk). In the model developed by Francisque *et al.* (2014), color had the lowest covariate preference weight in estimating the water quality index.

Water age

Water age is the length of time water spends in a distribution network (Kourbasis *et al.* 2020). Kourbasis *et al.* (2020) and Francisque *et al.* (2014) state that water age is an indicator of water quality. Bio-film growth and residual disinfectant level are both influenced by water age or residence (Carter *et al.* 2000; Francisque *et al.* 2009; Kabir *et al.* 2015a; Kourbasis *et al.* 2020). Increasing water age is also connected to increased temperature and sedimentation (Kourbasis *et al.* 2020). Water age can only be determined by network models, and depends on water distribution velocity and demand, pipe length, and the water distribution design (radial or looped) (Fares & Zayed 2010; Francisque *et al.* 2014; Kabir *et al.* 2015a; Kourbasis *et al.* 2020).

Water age differs between networks. A survey of more than 800 distribution networks in the USA showed an average water age of around 1.3 days and a maximum of three days (Shamsaei *et al.* 2013; Chondronasios *et al.* 2017). Kabir *et al.* (2015a) defined and ranked water age ranges to evaluate its effect in a risk assessment model. This employed three water age boundaries: 30 hours or less – acceptable, between 30 and 70 hours – moderate, and more than 70 hours – inadequate.

Inclusion of water age alongside other subfactors

Francisque *et al.* (2014) gave water age a preference weight of 0.13, ranking it third among five water quality subfactors included in the model. Water age was determined to be less important than turbidity or free residual chlorine, but much more significant than color. However, on the basis of a sensitivity analysis, Kabir *et al.* (2015a) concluded that water age was more important than other covariates (specifically, free residual chlorine).

Alkalinity

Alkalinity influences cementitious pipe degradation and metal pipe corrosion. Low alkalinity water is more corrosive (Vik *et al.* 1990; Francisque *et al.* 2014; Wąsowski *et al.* 2019). Vik *et al.* (1990) mention that alkalinity above 15 mg-$CaCO_3$/L reduced the rate of dissolution of cement-based materials in both pipes and cement coatings. Hu *et al.* (2018) mentioned that increasing alkalinity and calcium hardness inhibit iron release in corrosion processes.

Although alkalinity is known to affect the internal corrosion rate of metal pipes, it is only included (as a structural integrity index) in one paper on cementitious pipes. Francisque *et al.* (2014) applied an aggressiveness index to estimate the structural integrity index for cementitious pipes, as a means to consider the impact of water quality on pipe degradation. Francisque *et al.* (2014) applied the aggressiveness index equation proposed by Hu & Hubble (2007), which includes alkalinity for cementitious pipes, in a risk assessment model to prioritize more vulnerable pipes.

Conductivity

Mounce *et al.* (2014) applied AI methods to develop a model to identify burst patterns in water distribution networks, using conductivity as one of the parameters. They found that deviation in conductivity from expected values can be a significant indicator of pipe bursts.

Li *et al.* (2016) studied water quality covariate variation alongside iron corrosion in water mains and showed that, once iron is released, conductivity exceeds the baseline value, while a fast decline in iron release caused a rapid drop and quicker recovery in conductivity. The researchers state that turbidity and color can be considered appropriate indicators for iron release in water mains, since they are slow to recover after a disturbance, while conductivity can be regarded as an auxiliary measure.

Inclusion of water quality subfactors in models for specific pipe materials

Pipe material – a physical factor – was most often included in models based on water quality subfactors, so there is more information on them than other physical factors. Of the 304 papers reviewed, 248 papers include pipe material in their models, while of the 18 that include water quality factors, 15 include pipe material.

Table 5 shows the inclusion of water quality subfactors in water main failure models for specific pipe materials. Most water quality subfactors seem to be significant for the condition evaluation of metal pipes. For cement-based pipes, the subfactors that are included most often in modelling are alkalinity, hardness, temperature and pH – all of which affect the degradation process of cementitious materials. In contrast, neither water age nor turbidity was included in relation to any material. Mounce *et al.* (2014) studied the impact of operational factors in burst detection, but did not take into account any interdependence with physical factors. The contributions of pH and pipe material may be considerable, however, and their inclusion could result in more effective water main prediction models.

Table 5 | Inclusion of water quality subfactors in models for specific pipe materials (thirteen papers)

	Pipe material		
Water quality subfactors	**Metal**	**Cement-based**	**Plastic**
pH	7	4	_
Chlorine[a]	5	_	_
Temperature	2	1	1
Turbidity	_	_	_
Hardness	_	2	_
Color	2	_	_
Water age	_	_	_
Alkalinity	_	1	_
Conductivity	1	_	_

[a]Including free residual chlorine, chlorine decay, and chlorine concentration.

CONCLUSION

A potential benefit of using water quality factors as a basis for water main failure prediction is that water quality data are already monitored and more easily accessible than other types of data, such as soil parameters. The goal of this study was to conduct a comprehensive review of papers published from 2000 to 2020 that include water quality and its subfactors in water main failure prediction model development. Papers that met the study criteria of inclusion of water quality factors and subfactors in water main failure prediction models were reviewed in detail. This review resulted in the identification of nine water quality subfactors that have been evaluated for use in water main condition assessment.

The subfactors most frequently included in water main failure prediction models were pH and chlorine (whether as chlorine concentration, free residual chlorine, or chlorine decay). As noted, some authors studied the importance and sensitivity of pH and chlorine as model parameters, and, in some cases, assigned weights to these factors. This type of analysis depends on factors such as the type of prediction model, data availability and precision, and case study characteristics (e.g., size of water distribution network). For these reasons, it can be difficult to determine which factors are the most important in developing a water main failure prediction model. Generally, the impact of water quality subfactors on water main failure was considered most often for metal pipes.

The results suggest a lack of publications evaluating water quality subfactors in water main condition assessment. Most reviews seem to relate to water main failure prediction models, with less work reported in relation to water main failure factors. It is also possible, however, that attempts to develop water main failure models based on water quality subfactors have been made but have met with little success.

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DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

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