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Counterfactual Modelling for Evaluating Pipeline Replacement Strategies

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Abstract. Water utilities companies increasingly rely on predictive models to prioritise pipeline replacement, yet they rarely evaluate whether these decisions actually prevent failures. This study applies a counterfactual modelling approach to assess the effectiveness of *Brabant Water*'s replacement strategy in the Netherlands. Using rare-events logistic regression on pipeline and environmental characteristics, failure probabilities were estimated for pipelines replaced between 2020 and 2023 and simulated a no-replacement scenario. Comparing simulated counterfactual failures with observed post-replacement failures shows that executed replacements reduced failure rates by more than 80%. Spatial hotspot analysis further reveals that most simulated high-risk areas did not experience failures after replacement, indicating successful risk mitigation. The study demonstrates that counterfactual reasoning provides a powerful framework for evaluating infrastructure policies, provided that predictive models are well calibrated.

Submission type. Analysis, Case study

BoK concepts. [AM7] Spatial Statistics, [AM3] Spatial Modeling, [AM5] Spatial Pattern Analysis

Keywords. Counterfactual analysis, Logistic regression, Asset management, Pipeline infrastructure

1 Introduction

Access to safe and clean drinking water is fundamental to public health and sustainable development (Jimenez-Roa et al., 2023). Water distribution networks therefore require continuous maintenance to prevent deterioration resulting from aging, corrosion, soil conditions and climatic influences (Chen et al., 2017; Dawood et al., 2020; Mazumder et al., 2018; Ramos-Salgado et al., 2021; Wols et al., 2019). If not adequately maintained, deteriorating pipelines can lead to service disruptions, water losses, and increased operational costs (Chen et al., 2017; Mazumder et al., 2018; Scheidegger et al., 2015). Varying models have been created to predict the failure of water pipelines, based on environmental and asset-related factors (Jimenez-Roa et al., 2023; Ramos-Salgado et al., 2021).

Replacing deteriorated water pipelines in time is therefore crucial to maintain network reliability (Verwegen et al., 2024). However, due to financial, logistical and time-related constraints, the number of water pipelines that can be replaced within a year is limited (Jimenez-Roa et al., 2023; Mazumder et al., 2018). This makes careful prioritisation of replacement plans necessary, to ensure the greatest possible reduction in failure risk (Chen et al., 2017).

Asset-related factors such as pipe age and material consistently show correlation with failure of pipelines (Chen et al., 2017; Dawood et al., 2020; Ramos-Salgado et al., 2021; Scheidegger et al., 2015). Pipe diameter and installation quality also influence vulnerability: smaller or shallow-buried pipes are more sensitive to pressure transients, ground movement, and frost action (Wols et al., 2019). Environmental factors, such as soil type, soil corrosivity, and climate variability, play a key role in pipeline degradation (Almheiri et al., 2020; Dawood et al., 2020; Hussein Farh et al., 2023). Climatic effects such as freeze–thaw cycles, temperature fluctuations, wind surges that cause trees to unroot, and precipitation extremes further exacerbate stress on pipes (Chen et al., 2017; Jimenez-Roa et al., 2023; Wols et al., 2019).

Furthermore, recent studies demonstrate that pipeline failures often exhibit spatial clustering, suggesting that local neighbourhood effects and shared environmental conditions amplify failure risk (Chen and Guikema, 2020). This exemplifies why GIS-based analysis is relevant for modelling pipeline failure (Chen et al., 2017; Jimenez-Roa et al., 2023). Incorporating a geospatial dimension through GIS allows for the spatial visualisation and analysis of water pipeline performance, revealing location-dependent patterns and environmental influences that might otherwise remain hidden (Pickard, 2006).

While many studies focus on predicting failures, considerably fewer assess whether executed replacement plans actually reduce failure rates in the real network (Dawood et al., 2020; Robles-Velasco et al., 2021; Scheidegger et al., 2015). This research addresses this gap by evaluating *Brabant Water*'s replacement strategy and model using counterfactual modelling.

Brabant Water is a drinking water utility company for the province of Noord-Brabant in the Netherlands, which manages a network of approximately 20.000 kilometres of water pipelines (Vernieuwing waterleidingnet Brabant, 2025). Each year, portions of this network are scheduled for replacement to maintain network reliability, but not all planned projects are ultimately executed. Understanding whether the right plans are being prioritised and executed can help the company allocate its resources more efficiently, reduce failure risks, and optimise future replacement strategies (Chen et al., 2017; Mazumder et al., 2018). The results of this study can provide insights to enhance the effectiveness of long-term maintenance planning.

In this research, the following questions will be answered:

What is the difference in failure rate between pipelines that were replaced, had a replacement status of delayed or denied and were not selected for replacement between 2020 and 2023?

To what extent do environmental (frost occurrence, groundwater fluctuation, soil type, land use, wind surges and proximity to roads) and asset-related (age, material and diameter) factors influence failure occurrence, and how have executed replacement plans affected failure rates across replaced pipelines?

How effective was the replacement strategy of Brabant Water between 2020 and 2023?

2 Data & Methods

2.1 Data

Tables 1 and 2 show the datasets that were used in the analysis, the source and why it is fit for the analysis.

This study combines internal asset and failure datasets from Brabant Water with publicly available environmental datasets to capture both asset-related and environmental drivers of pipeline failure. Asset data include pipeline characteristics, replacement status, and recorded failures for pipelines in use between 2020 and 2023 (Table 1). Environmental variables comprise soil type, land use, meteorological indicators (frost events and wind surges), groundwater level fluctuation, and proximity to roads (Table 2).

Failure locations were linked to pipelines using a relational identifier, resulting in 1,605 recorded failures across 500,227 pipeline segments. Asset characteristics such as age, diameter, and material were directly available in the pipeline dataset, with materials grouped into five categories to improve interpretability. Environmental datasets were processed using standard GIS operations, including spatial joins, interpolation, and classification, to derive pipeline-level predictors suitable for regression analysis.

2.2 Data and Software availability

This study uses internal pipeline and failure datasets provided by Brabant Water at the 28th of October, 2025, which contain sensitive infrastructure information and cannot be publicly shared. Access to these datasets is restricted for security reasons. External environmental datasets (soil type, land use, groundwater levels, and meteorological observations) were obtained from publicly available Dutch government sources, but the processed versions used in this study include spatial joins and derived variables based on the confidential pipeline network and therefore cannot be released.

All statistical analyses were conducted in R (version 4.5.2) using standard packages for spatial processing, regression modelling, and rare-events correction. The spatial joins and other GIS-based actions were performed in ArcGIS pro (version 3.6.1).

2.3 Methods

Analyses were performed for the replacement plans of the years 2020 - 2023, to evaluate the effectiveness of Brabant Water's current selection criteria, i.e. the prioritisation rules used to decide which pipelines are immediately replaced, delayed, denied or not selected at all. This timeframe was chosen so that enough failures had occurred to allow meaningful comparison. A flowchart of used methods can be found in figure 1.

Table 1. Asset-related datasets

	Title	Source	Year	Scale	Format	Fit for purpose
Asset-related factors	*Distributieleidingen in bedrijf* (Pipelines in use)	*Brabant Water*	2025	Province of Noord-Brabant	Vector (lines)	Contains asset-related characteristics
	Distributieleidingen buiten bedrijf (Pipelines out of use)	*Brabant Water*	2025	Province of Noord-Brabant	Vector (lines)	Contains asset-related characteristics for the pre-replacement group
	Distributieleidingen uitgenomen (Removed pipelines)	*Brabant Water*	2025	Province of Noord-Brabant	Vector (lines)	Contains asset-related characteristics for the pre-replacement group
	Reparatielocaties (Reparation locations)	*Brabant Water*	2025	Province of Noord-Brabant	Vector (point)	Indicates where, when and why a failure took place
	Vervangingsplannen (Replacement plans)	*Brabant Water*	2025	Province of Noord-Brabant	Vector (polygons)	Contains the group of pipelines that were replaced, with attribute information such as replacement date

Table 2. Environment-related datasets

	Title	Source	Year	Scale	Format	Fit for purpose
Environment-related factors	*BRO bodemkaart* (Soil type)	Wageningen Environmental Research	2018, updated 2025	The Netherlands	Vector (polygons)	Different soils have different chemical and mechanical impacts
	Bestand Bodemgebruik (Land use)	CBS	2017	The Netherlands	Vector (polygons)	Urban loadings and road traffic increase stress
	Dagwaarnemingen (Daily weather observations)	KNMI	2015 – 2025	The Netherlands	CSV converted to point data, then interpolated to raster	Frost-thaw cycles cause ground movement and stress on pipes. Wind surges can uproot trees which may impact pipelines
	BRO model Grondwaterspiegeldiepte (Groundwater levels)	PDOK	2021, updated 2025	The Netherlands	Raster	Corrosion risk increases with fluctuating or shallow groundwater.
	NWB wegen (Roads)	Rijkswaterstaat	2025	The Netherlands	Vector (lines)	Higher stress near heavy traffic

The pipeline network was categorised into four groups, based on replacement status: a) selected pipelines that were replaced; b) selected pipelines that were delayed; c) selected pipelines that were denied and d) pipelines that were not selected. These groups were compared to test the hypothesis that pipelines prioritised for replacement (delayed or denied) would show higher baseline failure rates than non-selected pipelines, reflecting the current selection strategy to identify risk-prone segments. Further, it is used to test whether replacement brings down failure rates: replaced pipelines are hypothesised to have lower failure rates than all other groups.

The dataset contained a lot of pipelines with no failures. Only 0.3% of pipelines experienced at least one failure. Therefore, the dataset violated assumptions of normality. A non-parametric alternative to analysis of variance

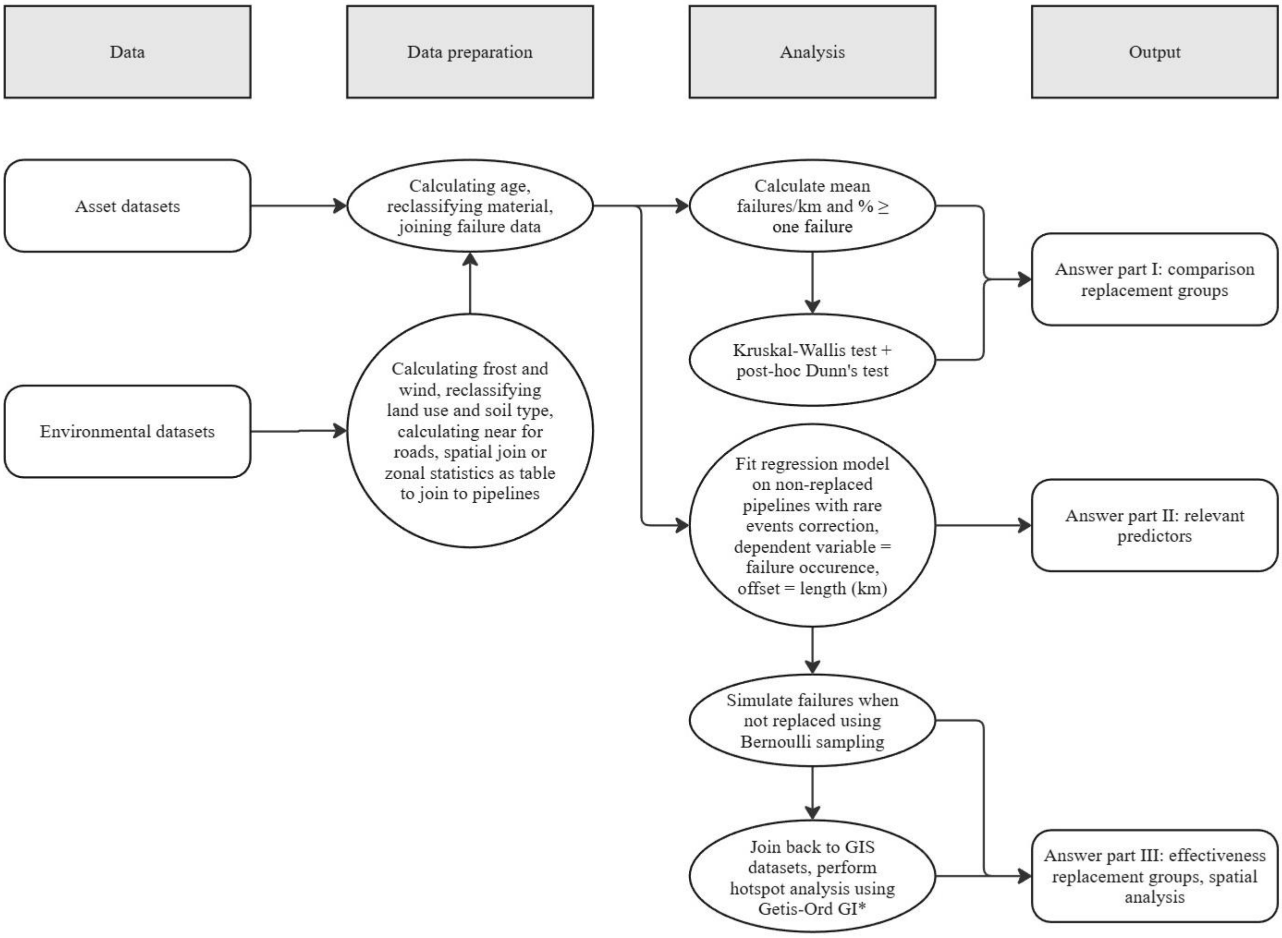

Figure 1. Flowchart of used methods

(Kruskal-Wallis test with pairwise Dunn post-hoc comparisons) was applied to analyse the differences between the four replacement groups.

To identify predictors of pipeline failure and to train the model for counterfactual simulation, a rare events logistic regression model was fitted using the dataset of the 478,578 pipelines that were not replaced between 2020-2023.

To account for the zero-inflation and avoid inflated probability estimates, a rare-events logistic regression model was applied (King and Zeng, 2001). Alternative modelling approaches, such as linear regression and count-based models, were explored but offered limited additional explanatory value given the low incidence of repeated failures. Logistic regression was therefore selected for its interpretability and suitability for modelling binary failure outcomes, consistent with previous studies (Karadirek et al., 2023; Ramos-Salgado et al., 2021). Replaced pipelines were excluded from the model because long-term effects could not be measured, as not enough time had passed.

The model included continuous variables (age, diameter, frost exposure, wind surges, distance to road, groundwater fluctuation), categorical variables (pipeline material, soil type, land use) and an offset for pipeline length (log(length)). Continuous variables were tested for non-linearity using cubic splines (df=3).

Model fit was assessed using area under the curve (AUC), Brier score and calibration plot assessment. The Brier score is a measure of the accuracy of probabilistic predictions for binary models, like the mean squared error for continuous models (Fenlon et al., 2018; Rufibach, 2010). A lower Brier score means that predictions are calibrated better (Rufibach, 2010). Calibration plot assessment refers to testing whether predicted probabilities align with observed frequencies: a slope close to 1 and intercept near 0 indicate well-calibrated predictions (Fenlon et al., 2018).

The regression model was used to predict failure probabilities using the pre-replacement features of the replaced pipelines. Probabilities were then converted to a failure scenario by taking a Bernoulli sample (Deshmukh, 1991). The purpose of this procedure was not to predict failure rates or uncertainty distributions, but to generate a counterfactual scenario of failure occurrence under pre-replacement conditions (Baer and Fleming, 1976). The Bernoulli sample was run multiple times to see whether the outcome changed drastically but showed little difference between runs (maximum 1).

To allow for direct comparison between the counterfactual and actual scenario, only the 19,591 pipelines that had a geometry in both pre-replacement dataset, which contained the simulated failures, and post-replacement dataset, which contained the observed failures, were included in further analysis.

The counterfactual scenario was compared to the actual situation by calculating the number of failures and the failure rate (failures/km pipeline) for both scenarios and calculating the decrease due to replacement.

To evaluate spatial clustering of the simulated and observed pipeline failures, a hotspot analysis was conducted using the Getis-Ord G_i* statistic in ArcGIS (Garciá et al., 2018; Getis and Ord, 1992; Ord and Getis, 1995). This method identifies statistically significant concentrations of high or low values by comparing the local sum of attribute values within a defined neighbourhood to the global sum across the study area (Garciá et al., 2018; Getis and Ord, 1992; Ord and Getis, 1995).

The G_i* statistic was calculated for observed post-replacement failures and simulated counterfactual failures, both aggregated to a grid of 5 km^2 to show spatial patterns more clearly. This produced two hotspot maps, allowing direct comparison of spatial risk patterns under actual and hypothetical scenarios.

3 Results & Discussion

Failure incidence differed modestly across replacement status groups. Pipelines selected for replacement but ultimately delayed or denied exhibited higher failure rates

Table 3. Association of predictors with failure from logistic regression: OR, SE, 95% CI and p-values

Variable	OR	*p*
Road	1.00	.03
Frost	0.95	< .001
Wind	1.00	.18
Groundwater	1.00	.02
Soil: Clay	0.81	.07
Soil: Leam	1.14	.84
Soil: Peat	0.64	< .001
Soil: Sand	0.52	< .001
Material: Iron/Steel	0.68	<.001
Material: Other	0.48	.32
Material: PVC	0.29	< .001
Material: Synthetic	0.18	< .001
Land use: Built up	1.68	< .001
Land use: Infrastructure	1.28	.007
Land use: Nature	1.14	.45
Land use: Urban	1.29	.009

Note. Reference categories for categorical variables are Soil: Unknown, Material: AC and Land use: Agricultural

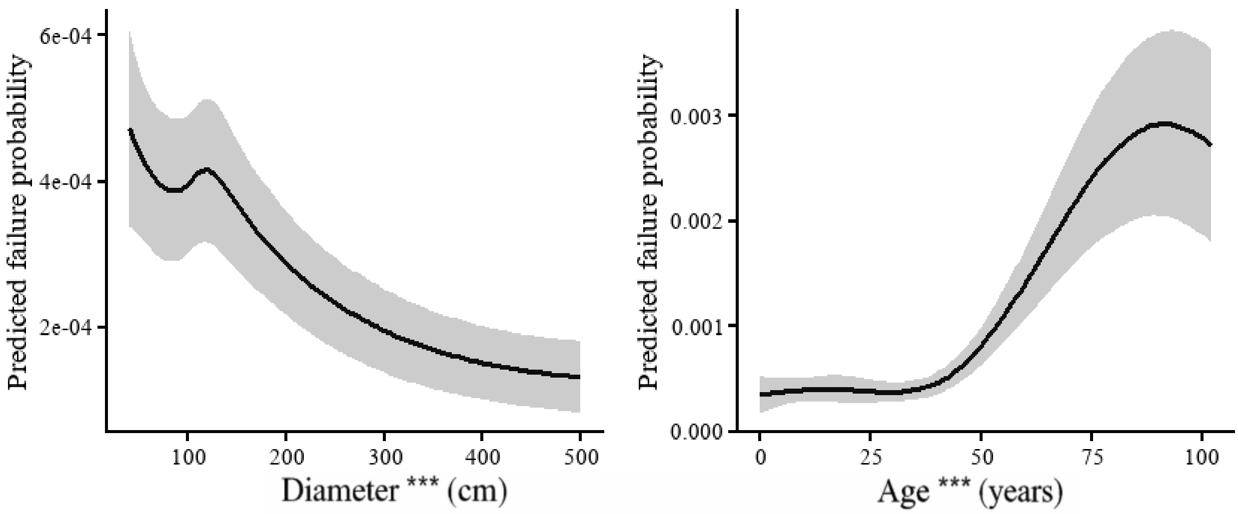

Figure 2. Effect plots of the splined variables diameter and age with 95% CI intervals

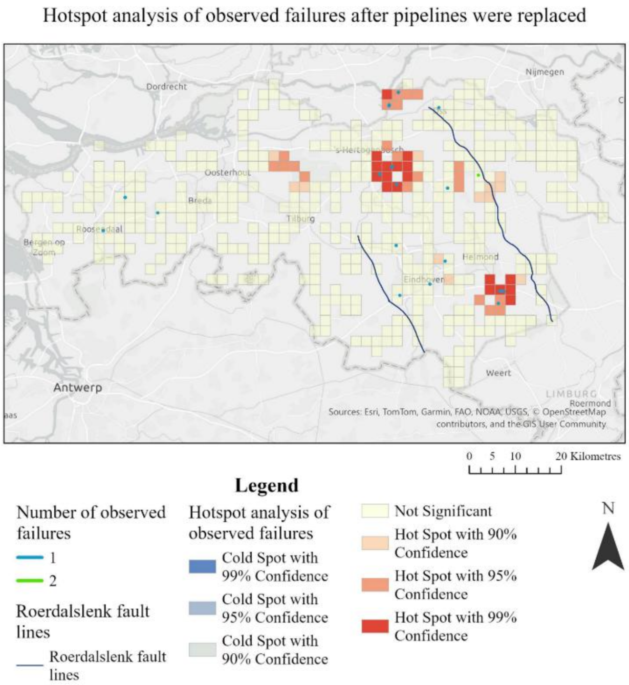

Figure 3. Map of observed failure hotspots (Getis-Ord Gi*), grid size of 2,5 · 2,5 km for visualisation purposes.

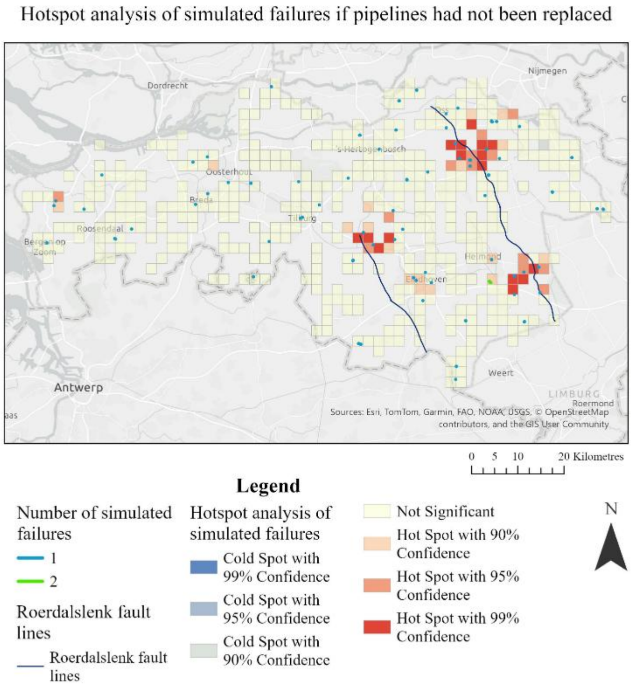

Figure 4. Map of simulated failure hotspots (Getis Ord Gi*), grid size of 2,5 · 2,5 km for visualisation purposes.

than non-selected pipelines, while replaced pipelines showed comparatively low failure incidence. A Kruskal–Wallis test indicated statistically significant differences between groups ($\chi^2(3) = 15.83$, $p = .001$), although the effect size was negligible due to the strong zero-inflation of the data. Pairwise comparisons showed that replaced pipelines differed significantly from denied and non-selected pipelines, whereas other contrasts were not significant.

The rare-events logistic regression demonstrated strong discriminatory performance (AUC = 0.872) and good overall calibration (Brier score = 0.003), although probabilities were slightly overestimated, as expected in rare-event settings (King and Zeng, 2001). Material, soil type, land use, age, and diameter were the strongest predictors of failure (table 3). PVC and synthetic materials showed substantially lower failure odds compared to *Asbestcement* (Asbestos cement), while built-up land use was associated with increased risk (table 3). Diameter exhibited a strong inverse relationship with failure probability, and failure risk increased with pipeline age up to approximately 95 years (Fig. 2). Other continuous predictors were statistically significant but showed negligible practical effects.

Post-replacement failures were recorded from the date of replacement up to the present. Based on the counterfactual scenario, the simulated number of failures for the pre-replacement pipelines was 73, corresponding to a failure rate (failures per kilometre) of 0.23. For the post-replacement pipelines, failure count was 23. corresponding to a failure rate of 0.04. This suggests that the replacement of these pipelines leads to an 80.3% reduction in failure rates and a 68.5% reduction in occurrence of failures, which would indicate that the replacement plans that were executed between 2020 – 2023 were highly effective in reducing failures.

Figure 3 shows the results of hotspot analysis for observed pipeline failures. Grid cells that contained no replaced pipelines were left out of the map. Statistically significant ($p < .05$) hotspots are concentrated around 's Hertogenbosch, north of Tilburg and south of Helmond. Most failures appear to be in urban or built area, which is logical as there are more pipelines there.

Figure 4 shows the results of hotspot analysis for simulated pipeline failures. Most significant ($p < .05$) simulated hotspots are situated in the east of the province, between Tilburg and Eindhoven, south of Helmond and west of Oss.

The simulated and observed hotspots generally do not overlap, which means that replacement plans sufficiently prevented those failures (figure 3 & 4). However, observed failures that occurred in locations not predicted by the model suggest that additional, unexplored spatially varying variables may be influencing risk. The results also confirm that pipeline attributes are the most influential for failure probability, because these variables change the most with replacement (age decreases, modern materials). Environmental variables generally stay the same after replacement.

The occurrence of simulated and observed failures overlap with the Roer valley rift, which is a tectonic fault area that moves vertically in the east of Brabant (figure A1 and A2) (Geluk et al., 1994). The area between the two fault lines moves down, while the surrounding area moves up (Michon and van Balen, 2005). The rift functions as an active valley where ongoing subsidence and seismicity concentrate stress along fault zones. This geodynamic movement might explain the spatial pattern of the simulated and observed failures.

The novel contribution of this study lies in combining counterfactual simulation with hotspot analysis. Whereas most literature focuses on prediction, this approach revealed that executed replacement plans substantially reduced simulated failures. This evaluation could improve future decision-making, not only in water pipeline management but also in other planning- or policy-based disciplines. A requirement for this approach to work, is that the model used to simulate the alternative scenario is accurate. Otherwise, a non-realistic comparison is made that does not provide an accurate conclusion.

Several limitations should be acknowledged. Environmental datasets vary in temporal resolution (e.g., land use 2017; soil 2018), which introduces potential temporal mismatch with failure records. Due to time constraints and lack of data, the model does not incorporate all relevant variables such as hydraulic pressure, transient events, or operational data such as valve operations, which are known to influence pipe integrity. Future studies could investigate these.

For statistical tests, non-parametric alternatives had to be used because of the zero-inflated nature of the data. Further, this zero-inflation may have influenced the predictive capacity of the regression model. The intercept and slope of the model shows that the model may overestimate failures. To create a more accurate simulation, other models such as machine-learning approaches or different regression methods could be explored in further studies (Asadi, 2024). Bernoulli sampling introduced stochastic variability, meaning simulated outcomes may differ across runs and may not fully capture uncertainty in real-world replacement scenarios (Isham, 1991).

Further, the omission of replaced pipelines in the training dataset introduced a selection bias because the pipelines that deteriorated the fastest were not used, which may diminish the effects of the predictors.

Finally, the spatial pattern of observed failures differs from the simulated hotspots, suggesting that while many risks were mitigated, some failures still emerged in locations not anticipated by the model. This shift in spatial distribution may reflect the influence of unmodeled factors, such as operational stressors or localised environmental conditions. An example that followed from this study is the influence of tectonic movements. This could be examined further in future research. It should be noted that the difference in hotspots may also occur due to modelling errors or spatial aggregation effects.

4 Conclusion

This study evaluated the effectiveness of *Brabant Water*'s replacement programme between 2020 and 2023 using a counterfactual spatial modelling approach. While predictive models are commonly used to create policy, they are rarely applied to assess whether executed interventions actually reduce failure risk. By explicitly simulating a no-replacement scenario, this study demonstrates that the executed replacement decisions substantially reduced failures, with observed post-replacement failure rates more than 80% lower than the counterfactual estimate.

The results confirm that material, diameter, and age are dominant drivers of failure risk, consistent with previous studies, while environmental factors such as land use and soil type modulate risk spatially (Chen et al., 2017; Mazumder et al., 2018; Ramos-Salgado et al., 2021; Scheidegger et al., 2015). Importantly, the spatial comparison of simulated and observed failures shows that replacement not only reduced overall failure rates but also altered the spatial pattern of risk, preventing failures in areas that would otherwise have formed significant hotspots.

Simultaneously, some results diverge from prior research. Climatic variables (frost and wind), often reported as important, played only a minor role in this dataset, suggesting regional context or data smoothing (IDW) moderated their impact (Dawood et al., 2020). Similarly, the lower risk observed in peat soils contrasts with studies that identified this as high-risk soils, pointing to possible interactions with material choice (Robles-Velasco et al., 2021).

For *Brabant Water*, the findings suggest that the current replacement strategy is successful. The strong influence of material and diameter indicates that targeted replacement of small-diameter AC or older metal pipes should remain a priority. Meanwhile, environmental layers such as land use and soil type could be incorporated more into the internal risk model. Modelling influence of tectonic movement might also improve prediction of failures. By incorporating these findings into future replacement strategies, *Brabant Water* and similar water utility companies can optimise resource allocation, reduce service disruptions, and reinforce long-term network resilience.

Declaration of Generative AI in writing

The authors declare that they have not used Generative AI tools in the preparation of this manuscript. All intellectual and creative work, including the analysis and interpretation of data, is original and has been conducted by the authors without AI assistance.

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