Pipes, Pavement, and Replacement Policy:
Insights from City of Madison Infrastructure Data

Wen Ye, Gautam Agarwal, *Eleanor Anderson, Bryan Jin, Tyler Caraza-Harter

University of Wisconsin-Madison *City of Madison

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Executive Summary

The Madison Water Utility delivers water through a complex system of water mains. The goal of this water infrastructure maintenance analysis is to expand the ability of the City of Madison, Wisconsin and other cities of similar sizes with aging pipes and cold climates to take preventative actions against vulnerable water mains by making recommendations on future water mains repair, replacement, and installation work. This project analyzes various factors responsible for water-main breakages including characteristics intrinsic to pipes, season and temperature, surrounding conditions such as soil type. Winter is particularly detrimental to water mains and compounds with other factors. Pipes made of cast iron and spun-cast iron break 10 times more in winter than summer. On the other hand, pipes laid in gravel are affected by winter conditions to a much smaller extent than pipes laid in other soil types, especially corrosive soil types like clay. Examining the frequency of breaks and the duration between these breaks, 56.3% of water mains with break records only break once. For water mains with multiple break incidents, a break is followed by a repeated break within 10 years 29.7% of the time. Moreover, 18.4% of breaks are followed by another break within 5 years.

Predictive models taking into account previous factors examined and breakage history information are then used to identify streets with both poor pavements and damaged water mains underneath, leading to a coherent repair plan. We use a decision tree model to predict the probability of a road segment having a water main breakage underneath within 5 years with an accuracy of 78.54% under cross-validation. We list 9 road segments as potential candidates to be scoped in an integrated water mains repair/replacement and road resurfacing program.

We highlight the area between Stonefield and Spring Harbor in West Madison and the area around La Follette High School in East Madison for prioritizing such a program. We recommend the continuation of reducing the use of cast iron and spun-cast iron pipes, shifting towards ductile iron which is also larger in diameter with greater strengths in general. When possible, we suggest installing new water mains in mixtures of gravel and other soil types. For example, lacing trenches with gravel in regions with unfavorable soil types is a best practice supported by our findings. By taking proactive actions, the city can reduce the cost of emergency repairs, which are costly and inconvenient. Finally, we recommend other municipalities likewise to centralize data and record data consistently which enables projects such as this one.

1 Introduction

Potable water is a critical resource. Founded as a public utility in 1882, Madison Water Utility (MWU) brings potable water to more than 250,000 people in Wisconsin across Madison, Shorewood Hills, Blooming Grove, Maple Bluff, parts of Fitchburg, the Town of Madison, and the Town of Burke through a complex network of 23 deep wells located at well facilities across the city, 895 miles of water main 9,009 hydrants, 21,728 valves, 33 reservoirs providing over 43 million gallons of storage, 10 district pressure zones, and 64,839 service connections and pipes to individual properties (City of Madison n.d.; Water Utility About). However, much of the water-main infrastructure in Madison dates back to World War II and the postwar era when pipe materials were unreliable (City of Madison n.d.; Infrastructure Overhaul). These materials, when subjected to extreme winter weather, are prone to breaking. Consequently, every year the MWU repairs over 200 water mains. When water mains break, houses in the surrounding face outages for hours if not days (City of Madison n.d.; Water Main Breaks).

The deteriorating water infrastructure caused the MWU to spend $7.5 million replacing water mains in 2013 and is estimated to have increased to $12.7 million in 2020 (City of Madison, 2014; Why all the main breaks). In 2021, the water utility approved $6.6 million of the budget with $4.8 million related to water mains. Project #12507 aims to install new water mains throughout the city. Project #11894 aims to replace existing water mains in conjunction with repaving roads. Project #10440 focuses on the maintenance of water facilities to provide reliable service and reduce emergency repairs. (City of Madison 2021; 2021 Capital Budget). The allocation of funds to upgrade pipes raises an important policy question: which pipes should receive priority for being replaced first?

Water main repairs affect the entire neighborhood. The construction is a hassle for all the inhabitants due to the complex nature of the process. Roads are dug up, mains are evaluated and repaired, followed by the re-development of the roads. This lengthy process also costs a lot of money. It is ideal to repair the pipes when they are at high risk, and even better to replace those in areas where road repairs are scheduled or should be scheduled.

In this work, we build a predictive model for predicting future water-main breakages beneath the roads. With this model, we incorporate road segments' pavement quality and provide recommendations regarding prioritizing water mains and road segments improvement plans. We take into account popular best practices like replacing existing water mains if future maintenance of the mains requires cutting of new pavement (Dallas Water Utility 2015).

To build the predictive model, however, we must address the following question: what influences the number of water-main breakages, and how does this influence affect the frequency of water-main breakages? We use data describing historical water main breaks in Madison and information on all existing water mains. This data is analyzed to examine factors that may relate to the number of water main breakages. By answering the above question, we focus on how the factors that make water mains vulnerable to breakage provide insight into future water mains installation and replacement work.

After deciding the factors responsible for the breakages, we build a decision tree model to estimate the probability of pipes that are near some roads breaking in the next 5 years. The model is first tested using cross-validation and then on a separate test set where it proves to be about 78.54% and 77.79% effective respectively. We combine our probability with feedback on the road and pavement quality to build the maintenance plan.

The rest of the paper is structured as follows. We explore the available datasets (section 2) and analyze the various factors that can affect the water mains' health (section 2). We then use some of the factors explored and breakage history information to predict the probability of future breaks (section 4). We combine the predictions with pavement quality to suggest an optimized maintenance plan (section 5). In the end, we summarize all the general policy recommendations and key areas of focus for maintenance (section 6) and discuss other related research projects (section 7).

2 Dataset

This report examines three datasets: the water main breaks dataset, the water mains dataset (which includes pipes that have never broken), and street centerlines and pavement dataset. Both the breakage dataset (City of Madison n.d. ; Water Main Breaks) and road segments dataset (City of Madison n.d.; Street Centerlines and Pavement Data) are from the open data portal of the City of Madison. The dataset of all the water mains is from the Madison Water Utility Department and is not public.

The breakage dataset describes all the historically recorded water main breakages in the City of Madison. The break information includes location which is a single point with GPS coordinates, MainID, and the date on which the water main broke. For some breakages, the breakage metadata includes soil type, depth, size/diameter. Among all the break records, 45.7% of them have a break date of January 1st, 1970, a placeholder date where the specific date on which the water main broke is unknown. However, 99.7% of these records with the placeholder date do have a valid break year. Since we are interested in the duration between breaks, we filtered out the data where the date of breakage was recorded to be 1970/01/01 and the break year recorded was invalid or missing. We then have 6985 break records remaining over 41 years from 1980 to 2020. Among these water mains, 96.8% of them are still active today while the other 3.2% pipe IDs are no longer in the dataset for all water mains, which we will discuss next.

The dataset of all water mains (with breakage history or not) consists of 882.4 miles of all the current active water mains in the City of Madison. This dataset gives the FacilityID of the water main, the year installed, the diameter of the pipe, the material of the pipe, and its location as a geometry line. This dataset cannot be found on the open data portal as knowing complete location data could pose a security risk to the city. The FacilityID in this dataset is the same as the MainID in the Water Main Breaks dataset. There are six instances where we see records of pipes being replaced where the FacilityID is the same and the material of the pipe is different. There are three instances where a Cast Iron (CI) pipe was replaced with Ductile Iron (DI) pipe, one instance of a CI pipe with new lining becoming a Cured In Place Pipe (CIPP), one instance of a Spun Cast Iron (SPUN) to CI, and one instance of a CI to COPPER. Only two of these pipes with replacement records show up in the water main breaks dataset.

The road segments dataset describes all the road segments in the City of Madison. Each road segment has a unique identifier (i.e. Segment ID), the name of the street, the name of the two streets that it connects, the geometric location, and the pavement rating. Every two years, the City Engineering Division rates the road segments by the Pavement Surface Evaluation and Rating (PASER) rating system (City of Madison, 2021; Resurfacing Program,) according to distresses including surface defects, surface deformation, cracks, patches, and potholes. Road segments with longitudinal cracks near the edge, poor drainage design, often mean a lack of gutter can have a rating of at most 5 (University of Wisconsin-Madison Transportation Information Center, 2002; PASER Manual Asphalt Roads). Road segments rated nine or above are in excellent condition, eight means in very good condition, six to seven means in good condition, four to five is in fair condition, and any road segments rated three or below are in poor condition. To suggest an integrated water main replacement and road resurfacing plan, we will focus on road segments with a pavement rating of three or below.

3 Analysis of Water Mains and Breaks

Many factors could potentially affect the likelihood that a water main pipe will break and require repair or replacement. In this section, we characterize the pipes in the Madison Water Utility (MWU) water distribution network and explore breakage factors. We consider the following questions: what are the basic physical properties of pipes in Madison (material and diameter), and what kind of pipes break most frequently (Section 3.1)? In what soil are these pipes laid (Section 3.2)? How is breakage frequency affected by Wisconsin winters (Section 3.3)?

3.1 Pipe Construction

The MWU network consists of 22276 unique pipes of varying length and material; Figure 1 shows the distribution of these pipes by material. The blue bars show the subset of pipes that have broken at least once where the percentage on top of each bar is the rate at which these pipes have broken. The first four categories are different varieties of iron pipe: ductile iron (DI), cast iron (CI), sand-cast iron (SAND), and spun-cast iron (SPUN). The remaining non-iron types are PVC, copper, cured-in-place pipe (CIPP), and HDPE; these non-iron types account for only 2.5% of all pipes and 0.4% of all breaks.

The ductile iron, invented in 1943 (Reliance Foundry n.d.; Ductile Iron vs. Cast Iron), is the material of choice for newly laid pipe, and now accounts for 67.2% of the MWU network . Whereas only 3% of ductile pipes in the network have broken, 18% of sand-cast pipes and a majority of the cast and spun-cast irons have broken at least once. The low break rate of the ductile iron pipes is likely due to a combination of it being a better material and the fact that these pipes are newer than the legacy iron pipes.

Figure 2 shows a scatter point for every MWU pipe, by type and install year. Ductile iron pipes are the youngest, most of which are installed in the recent 50 years. We see a handful of scatter points for the ductile iron where the install year recorded is before the invention of the material; we assume these are typos or errors in the dataset. Surprisingly, sand-cast pipes (70 to 140 years old) have fewer recorded breaks in the dataset than the other legacy iron pipes (cast and spun-cast are 50 to 80 years old).

Figure 3 shows how the most common iron-type at each location has evolved over recent decades. Gaps in the <1990 map are perhaps due to some older pipes not being in the dataset we used (we assume the downtown area must have been connected at that time). We see that ductile iron is broadly used for the most recent outward expansion of the city and is also now the dominant type downtown. In figure 6 we can also witness pocket areas like Regent Neighborhood, Midvale Heights Community, Schenk-Atwood-Starkweather-Yahara Neighborhood, Capitol Neighborhoods, and Schenk-Atwood where legacy iron is used.

Throughout the MWU network, pipes have varying diameters. Pipes that have a larger diameter generally need to be laid at greater depth from the ground surface to make sure the distance between the ground surface and the top of the pipe is large enough to prevent the water in the pipe from freezing in the winter and to reduce the damage that occurs due to the seismic vibrations (Western Municipal Water District, 2011; Design Criteria for Water Distribution System).

Figure 4 shows the distribution of pipe diameter for both legacy irons and ductile irons (solid black and solid red lines, respectively). The plot on the left describes the distribution for all the water mains while the one on the right shows the breaks. We see that the newer ductile iron pipes being laid are generally larger than the legacy irons (8 inches and 6 inches median, respectively). We also see that ductile iron pipes that break are generally smaller.

Policy Implications: as the City of Madison has expanded outward over the last 50 years, reliable ductile iron has been the material of choice for new pipes. However, there are many geographic pockets where legacy iron remains prevalent. Whereas prioritizing the replacements of the oldest pipes first may be the most intuitive policy, we find that sand-cast pipes (the oldest material in use) have had fewer breaks than somewhat newer cast iron and spun-cast pipes. Different materials were rolled out over different decades, so the material used may be a proxy for the best practices of the time and other variables. Regardless of why MWU's sand-cast pipes are outperforming other legacy iron, prioritizing upgrade efforts on somewhat newer cast iron and spun-cast iron is a policy likely to reduce future breaks.

3.2 Soil Type

The type of soil a pipe is laid in is known to affect reliability; for example, expansive clay is considered a corrosive environment (DIPRA 2017; Corrosion Control Polyethylene Encasement). The breakage dataset describes the composition of the soil at each break location as a single type (e.g., clay or sand) or a combination of types (e.g., clay and gravel, or sand and dirt and rock). Figure 5 shows the frequency of each soil type at recorded break locations. Clay is most common, being present at 74% of break locations where soil type is recorded; 65.8% of these times, clay is the sole type. Sand is the second most common, appearing at 28.8% of break locations, but usually as a part of a mixture (68.5% of these times). Rock (the third most common soil type) almost always presents as a mixture with other types.

Only 2.5% of instances involve the presence of three or more soil types. Figure 6 focuses on the instances of the soil type variable where two types are recorded as part of the mixture. The leftmost bar shows that when clay appears as one of two types, the other atomic type is either sand or rock in 80% of the instances. The next bar shows that when sand appears as one of two atomic types, the other atomic type is either clay or rock in 80% of the instances. The three bars on the right indicate that when gravel, dirt, or rock appear in a pair, they are always paired with clay or sand.

Figure 7 shows a map of soil types in the City of Madison. Each area is colored according to the most common soil type at each location, according to breakage records. There are many gaps in the data because some locations have never had breaks, and soil type is not recorded in a majority of breakage records. We see that clay is the predominant soil type present in the city with sand scattered throughout the city.

Policy Implications: 74% of MWU breaks with recorded soil information occur in pipes laid in clay, a soil type known to be corrosive. We do not have data on the soil type of pipes that did not break, so we cannot directly compute a per-soil breakage rate. We note, however, that it is best practice to backfill trenches in which new pipes are laid with sand, gravel, or limestone screenings (DIPRA 2016; Installation Guide for Ductile Iron Pipe).

3.3 Temperature and Seasonality

In this section, we explore seasonal break patterns and how pipe material and soil type (Sections 3.1 and 3.2) interact with temperature. Figure 8 shows the average breaks per month over 40 years, from 1980 to 2020. We observe that most breaks occur in the winter months, with the January break rate being 7.5 times worse than the April break rate. Relative to the system overall, we see ductile iron is less impacted during winter.

Figure 9 is the prediction of the expected number of breakages on a day of a given temperature and season from a simple linear regression model. In this model, months between December and February are classified as Winter, those between March and May are classified as Spring, those between June and August are classified as Summer, and those between September and November are classified as Fall. This figure also gives a more detailed comparison to differentiate the influence of temperature and season. We see that winter almost always has more breaks on days with the same minimum temperature as Summer, Spring, and Fall. This indicates that temperature is not the absolute determinant of the number of breaks on a given day and that season also matters. We do note that some combinations of temperature and season are not applicable and hence should be ignored (i.e., the extension of the summer line to sub-zero temperatures is a hypothetical extrapolation; Wisconsin summers are not that cold).

Figure 10 shows the distribution of water main breaks across soil types for each season. Breaks in multiple soil types are double-counted in each category that it belongs to. Breaks in all soil types are more common in winter than summer; the percentages in the legend indicate how much more. Whereas clay breaks increase by 628%, gravel breaks only increase by 54%.

Figure 11 similarly shows the distribution of water main breaks across iron type materials for each season. Here, we see cast iron and spun cast iron pipes break about 10 times more often in winter, in contrast to ductile iron pipes, which break only 150% more frequently. Surprisingly, the oldest iron pipes in the MWU network (sand-cast iron) appear to be the least affected by winter.

Policy Implications: Wisconsin winters are hard on pipes in general. Fortunately, newer ductile iron pipes are less susceptible than cast iron and spun cast iron; the local climate is thus an additional reason to fund upgrades. Surprisingly, the oldest pipes in the MWU (sand-cast iron) are even less affected by winter than ductile iron pipes, so replacement policies aimed at improving the reliability of the MWU network in winter should prioritize based on material rather than just age. We also saw that pipes laid in gravel are significantly less vulnerable to winters, perhaps because the porous nature of gravel makes it useful for drainage (Gillespie, 2021). Our findings show that the current best practice of backfilling new trenches with gravel (DIPRA 2016; Installation Guide for Ductile Iron Pipe) is a good policy.

4 Forecasting Future Breaks

We have identified several factors related (though not necessarily causally) to pipe breakage: pipe material, soil type, temperature, and season (Section 3). In this section, we explore modeling approaches to forecast the probability of future breaks; these forecasts are a cornerstone of our replacement policy suggestions (Section 5). We first study how breakage history affects future breakage (Section 4.1), then compare different modeling approaches based on history and other factors (Section 4.2), and finally, we forecast which road segments in the City of Madison are most likely to be affected by water main breaks in the next 5 years (Section 4.3).

4.1 Breakage History Features

We consider two historical features of pipes: how many times have they broken, and how long after a break is a re-break likely to occur? Figure 12 (a CDF) shows the distribution of breaks per pipe (for pipes that have broken at least once). Although most pipes with breakage history have broken exactly once, 43.7% of pipes with breakage history have broken multiple times, and 5.9% have broken at least 5 times. Overall, 70.5% percent of all breaks happen to a pipe with multiple breakage records in the dataset.

For every break in our dataset that has a valid break year, we compute the time between their breaks. Figure 13 (a CDF) shows the distribution of these intervals within 10 years, looking at break records from 1980 to 2010 (the data only goes into 2020, so we do not know the complete 10-year future for pipes following a break in 2011 or afterwards). Among all the break instances, we observe that 29.7% of them are followed by another break within 10 years. And 62% of these subsequent breaks occur within 5 years. Looking at the y-intercept, we also notice that some pipes have 0 duration between their breaks, meaning two breaks for the same pipe in the same year.

Policy Implications: breakage history can help us make predictions about breaks in the future; in particular, among pipes that have been broken, 18.4% of them have a break followed by repeat breaks within 5 years. However, replacing every pipe that breaks with a new pipe is likely too aggressive; two-thirds of pipes that break go another 10 years without further recorded incident.

4.2 Model Training Dataset

Although our breakage dataset is in terms of pipes, we want to forecast breakage incidents on a per-road basis (pipes usually run beneath city streets). The reason is that we want to use our forecasts as a factor in a proposed road maintenance policy that prioritizes construction work at sites with both bad roads and bad pipes to minimize digging expenses (Section 5). To construct a dataset suitable for training our models, we need historical examples describing a given road's status at a given point in time and whether that road was affected by water main breakages over some future interval (we choose 5 years) after that point in time.

Towards that end, we generate a dataset with a row for every combination of road segment and year (from 1980 to 2016). Many road segments overlay one or more water main pipes, as becomes evident when we observe an incident record in the breakage dataset at a GPS location overlapping the location of a road segment from our pavement dataset. By spatially joining on location, we can add features to each row indicating the number of prior overlapping breaks and the time (in years) since this road segment's last break underneath.

Considering rows with zero prior breaks, we compute the probability that a road with no breakage history will experience the first break at some point in the next 5 years as 6.8%. For roads with at least one prior break, we have more interesting metadata (regarding pipe material, etc.) that we can integrate from the breakage dataset and then use to make more informed probability estimates. In some cases, multiple pipes of different materials may have previously broken beneath the same road. In that case, we record all the pipe material types present among the water mains underneath that road. Similarly, we also take into account the age of the pipe that most recently broke (in years) and the year it was installed. We did not include soil type information for the training data because it is missing 49.7% of the times in the break records. After spatially joining break records onto road segments, soil type information is missing for 73.4% of the road rows. Taking into account the soil type beneath the road would largely truncate our available training data and hence, we decided not to include soil type metadata.

Policy Implications: when municipalities publish water main breakage data to public portals, making available the GPS location of breaks (as the City of Madison does) or provide some other simple way to associate breaks with affected roads (or other related infrastructure) enables the type of analysis we do here. We also recommend municipalities to have consistent ways in recording metadata such as soil type as break locations with a mixture of soil types were separated by a variety of symbols such as ampersand, commas, spaces, slashes with different styles of capitalizations in the dataset.

4.3 Risk Models

For all roads for which there is no breakage history, we estimate the probability of a break within 5 years as 6.8%, based on the overall rate for roads without history. In this section, we explore models for estimating the probability of future breaks affecting roads for which breakage history is recorded. We thus retain rows from the dataset in the previous section for which there is at least some history (and thus metadata about the pipes involved in previous incidents).

We select two classification models from Scikit Learn: LogisticRegression (LogR) and DecisionTreeClassifier (DT). In addition to being able to make simple break vs. no break predictions (as any classification model would be able), these two models are desirable because they are also able to give a probability estimate of future breakage.

For logistic regression, we try many configurations: a linear model based only on history, a linear model based on all features, including material, and a polynomial model (2nd degree) based on all features. In all cases, we apply standard scaling to our data. The first three bars of Figure 14 compare these configurations under 12-fold cross-validation on our training data (the error bars indicate standard deviation of accuracy scores). There is not much difference between the first two logistic regression models which compare only history to all features (they score 72.77% and 72.55% respectively). However, the polynomial version of all the features has an accuracy improvement to 75.81%.

Figure 15 shows the coefficients of all the features for the second-degree polynomial logistic regression model. As expected, recent breaks and old age are both predictive of future breaks. Per our earlier analysis, we see that cast iron and spun cast iron breaks are more likely to have follow-up breaks in the 5-year window. We also see the larger the number of years elapsed from the last break is, the smaller the predicted probability that this road segment will have a break within 5 years will be as the years since the last break feature has a large negative coefficient estimate.

The fourth bar of Figure 14 is a decision tree, created using default parameters and incorporating all the features; it is our best performing model (with an accuracy of 84.44%) and is what we recommend in scenarios where either a break vs. no break forecast is needed. Unfortunately, this default tree tends to be deep, with many leaf nodes and few samples per leaf node. This becomes problematic when a probability estimate is required of the model. According to the Scikit Learn documentation, these probability estimates are computed as "the fraction of samples of the same class in a leaf." This leads to extreme probabilities (0% or 100%) when there are only a few samples per leaf node.

To overcome this difficulty, we set a minimum number of samples required per leaf node. In general, a higher minimum is a tradeoff where the tree will be simpler (and perhaps less accurate as a result), but the probability estimates based on larger per-leaf samples will be better. Figure 17 shows the decision tree's performance against different values of the minimum split leaf. While it looks like having 5 minimum leaves is the best option, we choose a minimum of 85 to improve probability estimates. The fifth bar of Figure 14 shows the accuracy of this model under cross-validation: 78.54%. After selecting this model, we evaluated it against the test data we had held back at the beginning, finding an accuracy score of 77.79%.

With logistic regression models, it is easy to see what matters with a coefficient plot. With very large decision trees (our version with the highest accuracy has 11 levels), human understanding of what the model is doing is more difficult. Figure 18 shows a highly simplified decision tree (with depth capped to 5) with the default parameters trying to use all the features. Although we would not use this shallow tree for predictions, the top-level split decisions can inform us about the important features. Here, we see that the time since the last break and the total number of breaks are important features.

Policy Implications: a variety of maintenance and upgrade policies could conceivably be based on the probability that a given pipe or road will be affected by breaks soon. Where such a probability estimate is needed to implement a particular policy, we recommend using a decision tree with minimum leaf size.

4.4 Current Outlook for Madison Roads

For every road segment in the City of Madison in 2021, we now estimate the probability it will be affected by a water main breakage in the next 5 years. For roads with no breakage history, we use the base rate of 6.8% as our estimate. For other roads, we use the decision tree with a minimum leaf size (as described in the previous section) to estimate the probability of a break in the next 5 years.

Figure 19 shows a road map, colored to indicate our risk estimates. The downtown area and the outskirts look to be in fairly good condition, likely because there are many new DI water mains installed recently in the isthmus. Comparatively, the area in between downtown and the outskirts of the city is more concerning than the rest of the city which is dominated by legacy iron, shown earlier by Figure 3.

Depending on how our classifier is used, either false positives (model predicts a pipe will break, but then it does not) or false negatives (model predicts a pipe will not break, but then it does) may be more important to minimize. Our decision tree model outputs a probability estimate for each road segment, so we can apply thresholding on that probability to obtain different precision and recall performance, as desired. To explore this space of tradeoffs, we try different thresholds and measure the precision and recall for each, as shown in Figure 16.

One approach to choosing a classifier threshold is to optimize the F1 score (a kind of weighted average of precision and recall). In this case, a 68% threshold results in the highest F1 score of 86.1%. Alternatively, if upgrade budgets are very limited, the figure shows us that we could tune the threshold high such that our model only identifies 0.2 pipes for service (recall), but 96.8% of those pipes identified are destined to break otherwise (precision). Alternatively, under a scenario where budgets are large, one might prefer to optimize for high recall, at the cost of lower precision.

Policy Implications: roads that are downtown and at the edges of Madison are at relatively low risk for breakages. Upgrade efforts should instead focus on the large in-between band where pipes are likely to break. The tradeoff between false positives and false negatives is tunable with our model. As budgets increase, the model's threshold should be tuned to reduce false negatives.

5 Co-Maintenance Policy: Pavement Case Study

In section 4, we introduced a decision tree model for estimating the probability that there will be a water main breakage incident impacting a given road segment over a 5-year horizon. In terms of policy and decision making, these estimates should be one factor in determining which pipes should receive proactive maintenance or replacement; other factors to consider might include the impact of a water outage (e.g., how many homes, hospitals, or other businesses rely on a specific water main) and cost of maintenance or replacement. In this section, we explore how to combine our water main risk estimates with other infrastructure quality data (specifically, a pavement rating dataset) to identify potential joint projects, to reduce cost and road closure time.

The pavement quality dataset (City of Madison n.d.; Street Centerlines and Pavement Data) rates every road segment in the City of Madison on the 1-10 PASER scale (Walker, 2013; PASER

Asphalt Roads Manual.); the scores capture both the quality of the road (e.g., presence of cracks) and current design (e.g., are there gutters?). Figure 20 shows the distribution of segment ratings across the city. The median segment has a rating of 7; 38.7% are rated 8 or better, and 2.4% are rated 3 or worse.

Figure 21 shows the map of Madison roads colored in shades of red according to their pavement ratings; the background indicates the risk of corresponding pipe breakage (this is a less granular aggregation over Figure 19 results). From this map, we see multiple areas that are prime candidates for joint road-and-water projects, including the area between StoneField and Spring Harbor in West Madison and the area around Laffolette High School in East Madison by Lake Monona.

Figure 22 shows the scatter plot of road segments' risk level against their pavement rating (points are jittered horizontally and vertically to avoid overlap). According to the city's pavement rating code, pavement rating between 1-3 is considered poor, and pavement rating between 4-5 is considered fair. There are 15 road segments in the top left grid divided by the reference lines that separate several the probability of break above 50% over 5 years and the pavement rating below 4 from the rest of the road segments. The 9 segments in this quadrant account for 0.16% of all road segments in the city. We recommend prioritizing these locations (listed in Table 1) for water main and road maintenance in the near future.

Policy Implications: the publication of both road quality data and breakage records in a centralized location (in this case a public data portal) enables analysis to identify possible opportunities for joint maintenance projects aimed at reducing costs and construction time. Other municipalities should have policies in place requiring the collection and sharing of such data across agencies.

6 Summary of Policy Recommendations

We have made a number of policy recommendations throughout this paper (Sections 3-5). The recommendations fall under three broad categories: (1) policies regarding which pipes to prioritize for replacement and how new pipes should be laid, (2) policies regarding infrastructure data collection to support failure predictions, and (3) policies regarding coordinated projects across different types of infrastructure.

Upgrade Policy: When upgrading existing water mains in the network, the City of Madison should prioritize the replacement of spun-cast iron and cast iron over the replacement of the older sand-cast pipe, as the sand-cast pipes in the network appear less vulnerable to Wisconsin winters. In general, cities should not automatically assume the oldest pipes in a system are the most vulnerable. We also suggest refraining from immediately replacing pipes that break as two-thirds of them will continue another 10 years without incident. Replacing broken pipes right away would incur unnecessary costs. For new pipes, the best practice of laying larger ductile iron pipes in gravel-filled trenches is supported by our analysis, which shows these practices are especially beneficial in colder climates (like that of Madison, Wisconsin).

Data Policy: The availability of City of Madison infrastructure data enabled this project. An in-depth analysis of several infrastructures through data can lead to meaningful discussions and healthy takeaways for the entire community. Cities should maintain detailed records of every break (like the MWU does). More specifically, soil type appears to interact with temperature to cause breaks, so soil type information should be recorded consistently as part of this data collection (MWU sometimes collects this information, but not all the time, and not in a consistent format). Cities that have collected such data should use it to train models that forecast future breaks, then factor those forecasts into project planning and prioritization. For MWU specifically, we recommend using a decision tree with a minimum leaf size of 85 over features including the year the pipes were installed, the material of the pipes, the number of times the pipes have broken, the age of the pipe, and the time since the pipe's last break. We recommend tuning the model's prediction threshold as a function of the available budget (which determines the importance of false positives relative to false negatives). Diverse infrastructure data (including water main data and pavement quality data) should be published in a centralized location (ideally an online portal) to facilitate coordinated project planning. We recommend other cities pass ordinances requiring an open data portal (as the City of Madison has done). By identifying risky water mains during the early stage, costly and inconvenient emergent repairs can be reduced. The adoption of the above recommendations will give municipalities better knowledge on the status of existing water mains in the city and facilitate a healthier network of water mains.

Co-Maintenance Policy: Dallas Water Utilities has developed replacement guidelines for minimizing cutting into the pavement to minimize cost and traffic disruption. We recommend other cities adopt similar policy goals and use breakage models and pavement data (when available) to realize these goals. For the City of Madison, specifically, we recommend initiating a repair plan at the area between Stonefield and Spring Harbor in West Madison and the area around La Follette High School in East Madison by Lake Monona, as our analysis has identified these locations as having both vulnerable pipes and low-rated pavement.

7 Related Work

Modeling pipe breaks is an active field of research with a variety of approaches. Rajani and Kleiner survey a wide range of physical models (Rajani et al. 2001; physically-based models); these approaches generally try to calculate when a pipe will deteriorate to the point of breakage based on many factors (e.g., pipe material and thickness, weather, frost load, operating pressure, etc).

Unfortunately, "the physical mechanisms that lead to pipe breakage are often very complex and not completely understood", and the measurements necessary to use these models are often not available, so statistical methods (also surveyed by Rajani and Kleiner) are often more useful in practice (Kleiner et al. 2001; statistical models). Some of these models operate on a per-network or per-cohort (of similar pipes) basis, forecasting the number of breaks across a collection. Such forecasts are useful for estimating future maintenance costs. Other models make predictions on a per-pipe basis, with clear application for upgrading and rehabilitation planning; in this work, we predict on a per-road basis, as our goal is to recommend locations for project coordination between the water utility and streets division.

Kleiner et al. described a common problem with statistical models that we also encountered with our machine learning model (a decision tree): "the partitioning of data into groups warrants careful attention because two conflicting objectives are involved. On one hand the groups have to be small enough to be uniform but, at the same time, the groups have to be large enough to provide results that are statistically significant" (Kleiner et al. 2001; statistical models). Each leaf of a decision tree has an associated collection of samples, from which probability estimates are computed as ratios at each leaf. Although training the decision tree with default parameters produced the highest overall prediction accuracy, it would sometimes create leaves with very few samples, leading to extreme probability estimates (0% or 100%). We thus had to configure a minimum leaf size, sacrificing some accuracy in favor of better probability estimates.

There is a long history of applying machine learning models to predict water main breaks. Fernando Sacluti's Master's thesis (Sacluti 1999) explores the application of artificial neural networks (ANNs) to the problem. More recently, a gradient boosting model outperformed Random Forest and ANN models on a dataset of ductile iron pipes that have broken at least once (Snider et al. 2018). A gradient boosting model is an ensemble of simple decision trees (we evaluated a single larger decision tree).

Many predictive models incorporated are part of larger systems for decision-making. For example, UTILNETS takes into account breakage forecasts along with the expected cost of neglect and rehabilitation and other factors to inform maintenance decisions (Hadzilacos et al. 2002). Other work has attempted to identify Pareto optimal cost/benefit tradeoffs for rehabilitation decisions (Giustolisi et al. 2006). WARP is a recent system under development that should eventually be able to suggest priorities for the renewal of individual water mains (Rajani et al. 2020).

Scheduled work for other kinds of infrastructure is an important decision-making factor for water main maintenance (Kleiner et al. 2001; statistical models). In this paper, we recommend coordinating to improve low-quality roads and risky water mains simultaneously. The Dallas Water Utilities (DWU) has a similar policy to minimize cutting into pavement: "existing water mains may be replaced if future maintenance of the main requires cutting of new pavement within next 10 years" (Dallas Water Utility 2015).

8 Conclusion

The development of predictive models is a prerequisite for the implementation of seemingly obvious policies, such as "replace bad pipes with larger, ductile iron pipes" (models can help us quantify how "bad" a pipe is as its probability of breaking soon). Our study shows that intuition (e.g., oldest pipes should be replaced first) sometimes runs counter to actual breakage patterns (breakage of sand-cast pipes, the oldest in the MWU network, is seemingly less impacted by Wisconsin winters). In other cases, our findings support current best practices (a form of soft policy); for example, the switch to larger ductile iron pipes will likely reduce breakage.

The success of policies based on predictive models will always be limited by the accuracy of the models used; model accuracy depends greatly on the availability and quality of training data. The City of Madison was the first Wisconsin city to formalize its open data policy as an ordinance (City of Madison, 2012; New City of Madison Open Data Ordinance). We recommend other municipalities enact similar policies facilitating the publication of infrastructure data. We also recommend that Madison Water Utility continue to refine its data collection policies and practices to provide more complete and uniform metadata about breaks (particularly regarding soil type) for future model training.

Finally, Madison's open data ordinance mandates that data be "accessible through a single web portal"; this centrality requirement would be a good policy for other local governments with more scattered open data to adopt. As we have demonstrated in this work, centralized access to data for both road and water mains facilitates the possibility of co-maintenance. We believe centralized access to many types of infrastructure data will more generally create new opportunities for co-maintenance and cost reduction.

Acknowledgments

We thank the City of Madison, the Department of Water Utility, the Department of Public Work Streets Division and the Finance Department for inspiring this project, maintaining the Open Data Portal where we obtained most of the data, and providing background knowledge. We specifically thank Kathy Schwenn and Peter Braselton from the Water Utility Department for giving feedback and sharing the private dataset on all water mains. We also thank the peers from the University of Wisconsin-Madison COMP SCI 638 Fall 2020 course for giving support and feedback as this project progressed.

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Figures

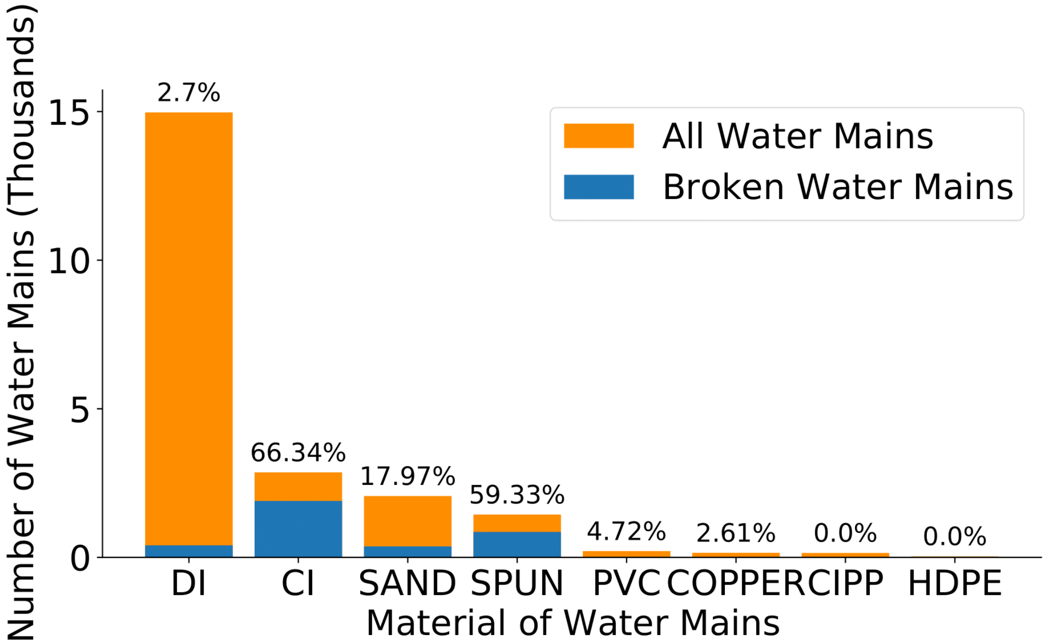

Figure 1**. Material of Water Mains.** *This shows the number of water mains in the City of Madison made of each material. The percentage of pipes made of different materials that have been broken are compared.*

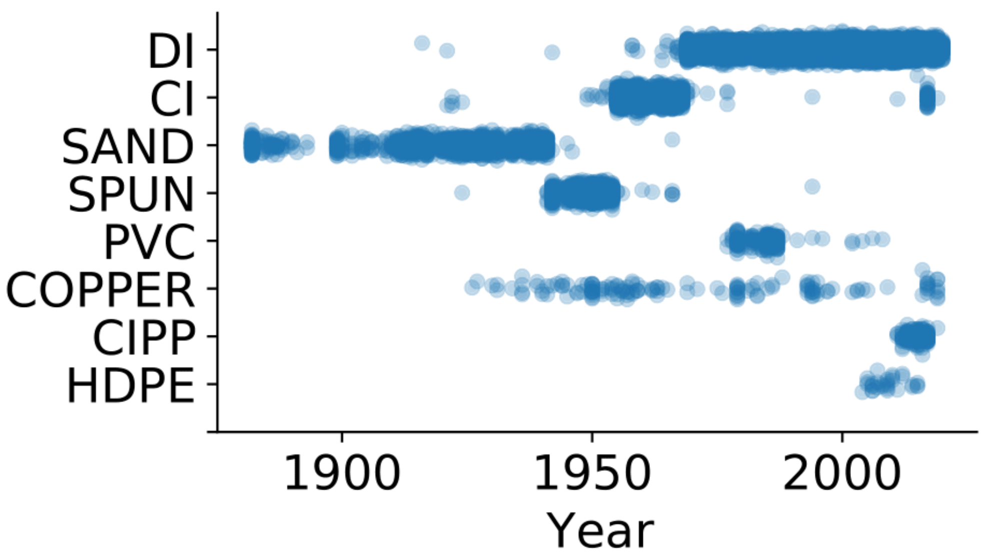

Figure 2**. Install Year of Water Mains.** *This shows the distribution of the install year of all the current active water mains in the City of Madison. The y-axis is in descending order of the number of water mains made of this material. The scatter points are jittered vertically to reduce overlap.*

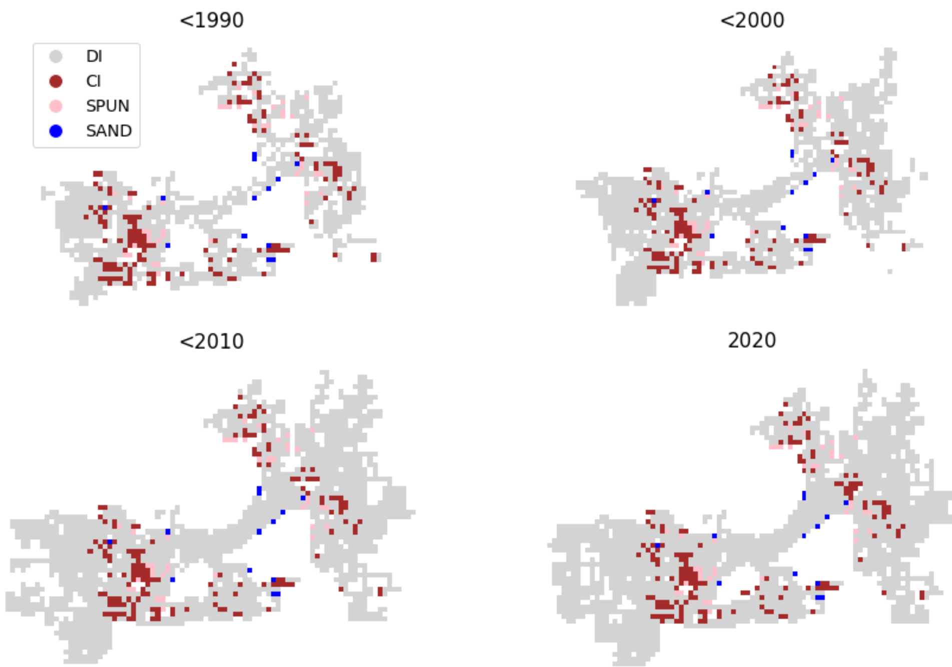

Figure 3**. Distribution of Pipes by Material.** *This shows fours snapshots (for four decades) of the City of Madison Water Main Network differentiated by the material.*

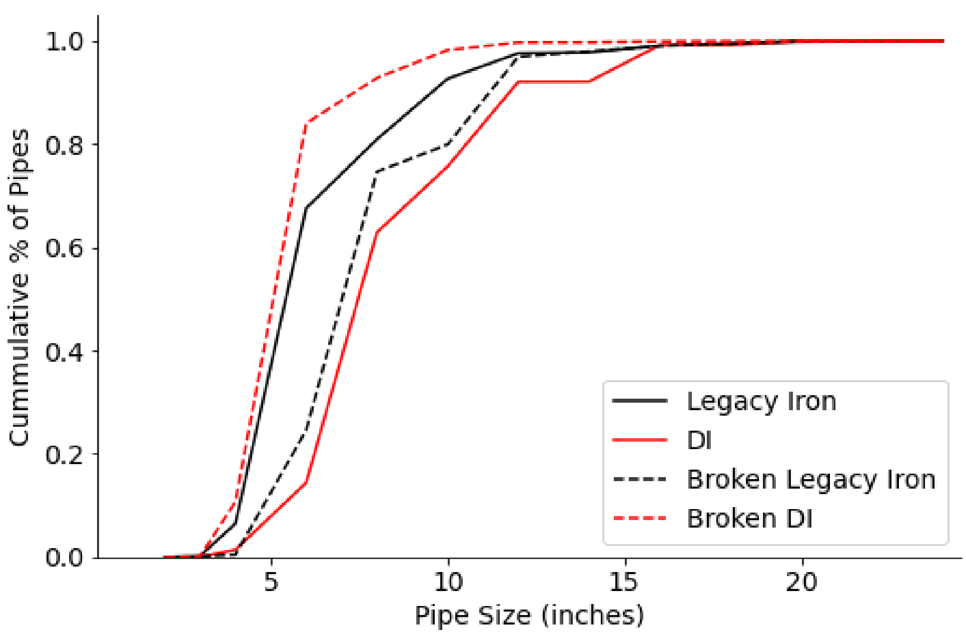

Figure 4**. Cumulative Distributive Frequency of Size.** *This shows the cumulative distribution of the two kinds of pipes: newer DI pipes and older legacy iron pipes (CI, SAND, and SPUN), under two scenarios: pipes broken and all the pipes present*

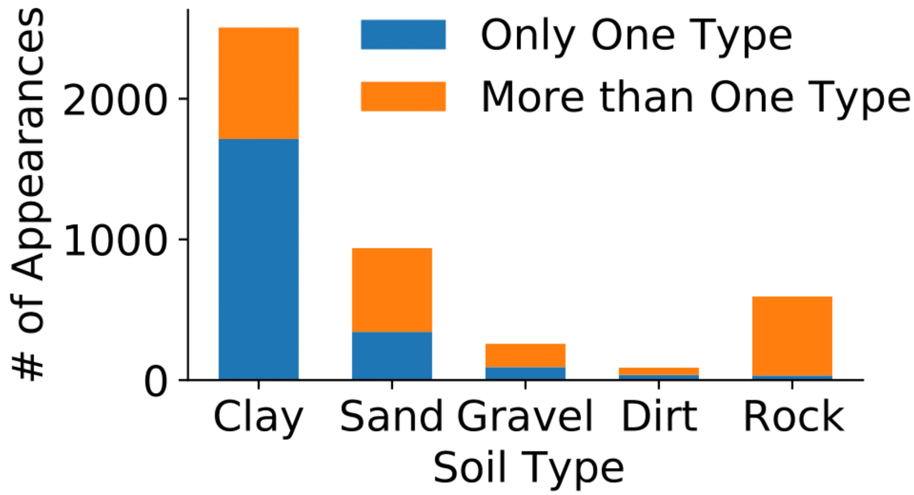

Figure 5**. One vs Multiple Soil Types.** *This shows how many times each soil type shows up as the only soil type at a break location as opposed to being part of a mixture of soil types.*

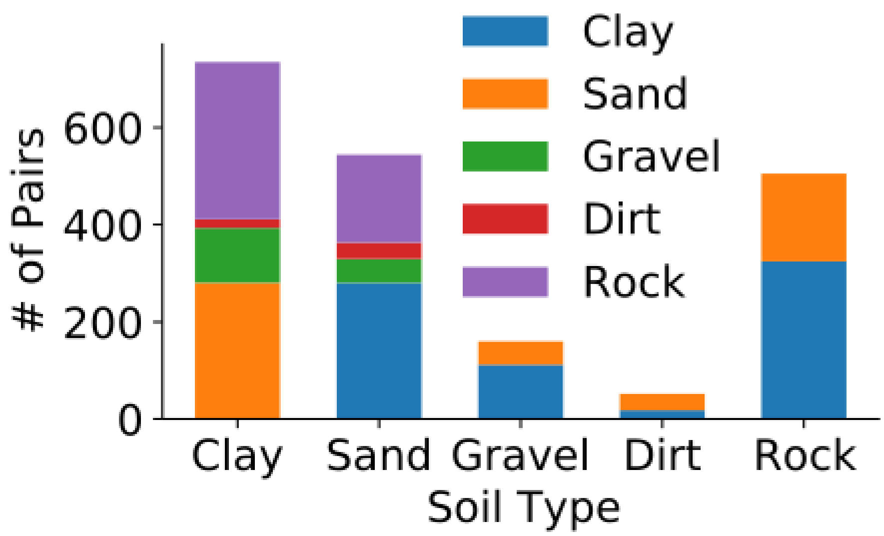

Figure 6**. Soil Type Pairs**. *The pairing between soil types for break locations with a mixture of soil types is shown. Clay and Sand look to be primary soil types while Gravel and Dirt look to be secondary soil types.*

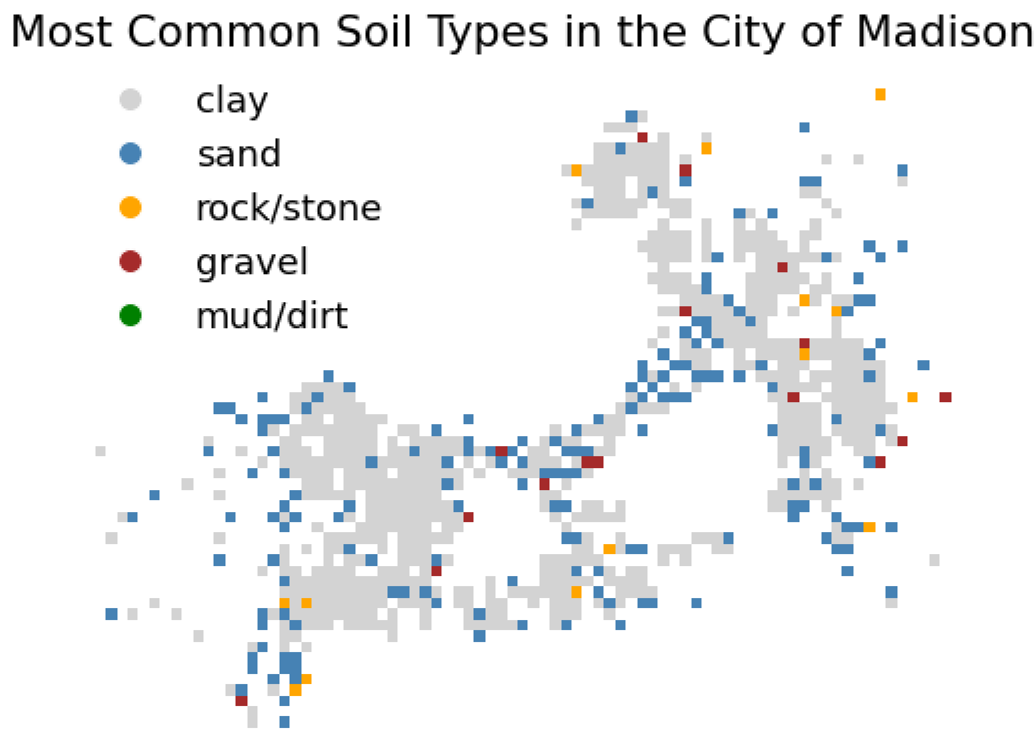

Figure 7**. Soil Type Map.** *This map shows the distribution of the most common soil types in each area in the City of Madison where there was a break and the soil type was recorded.*

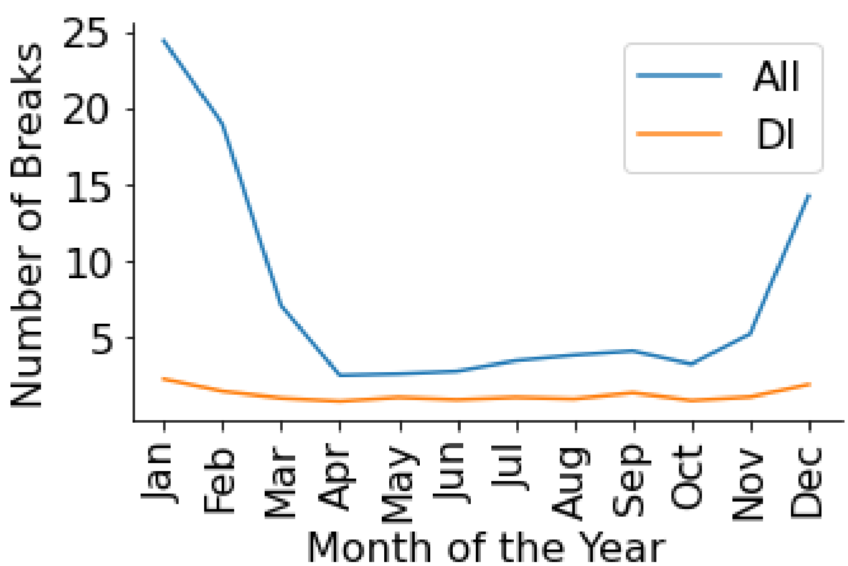

Figure 8**. Breaks by Month.** *The two lines show the average number of water main breaks in each month of the year for all pipes and pipes made of DI respectively.*

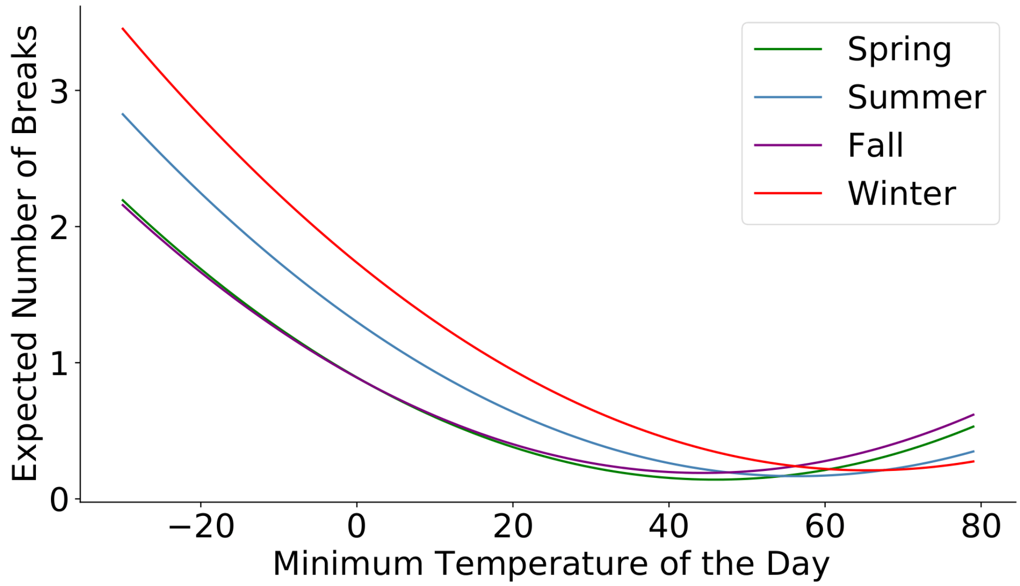

Figure 9**. Predicted Breaks by Season and Temperature.** *The effects of season and temperature on the predicted number of breaks on a given day by a simple linear regression are compared.*

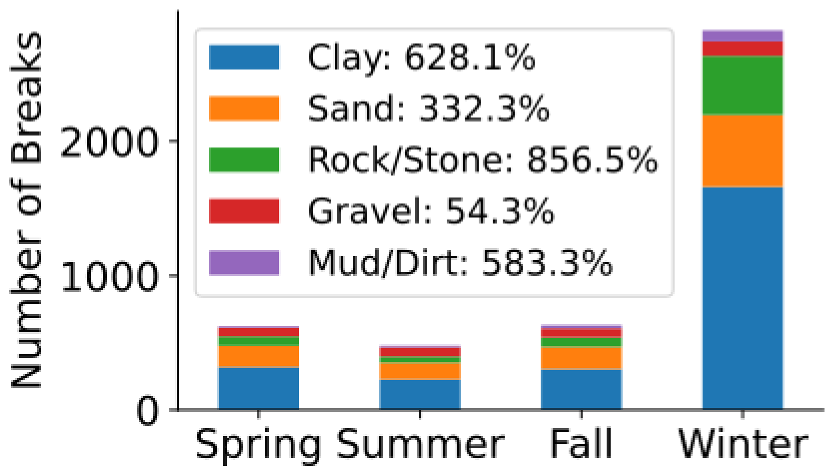

Figure 10**. Seasonal Effects on Breaks by Soil Type.** *The number of breaks is shown against the season and soil type of the break location. The legend compares the percentage of increase in the number of breakages from summer to winter.*

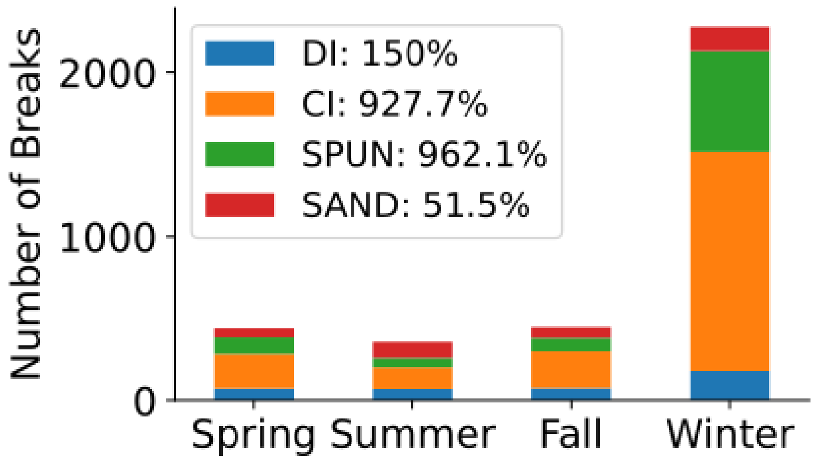

Figure 11**. Seasonal Effects on Breaks by Material.** *The number of breaks is shown against the season and material of the broken pipe. The legend compares the percentage of increase in the number of breakages from summer to winter.*

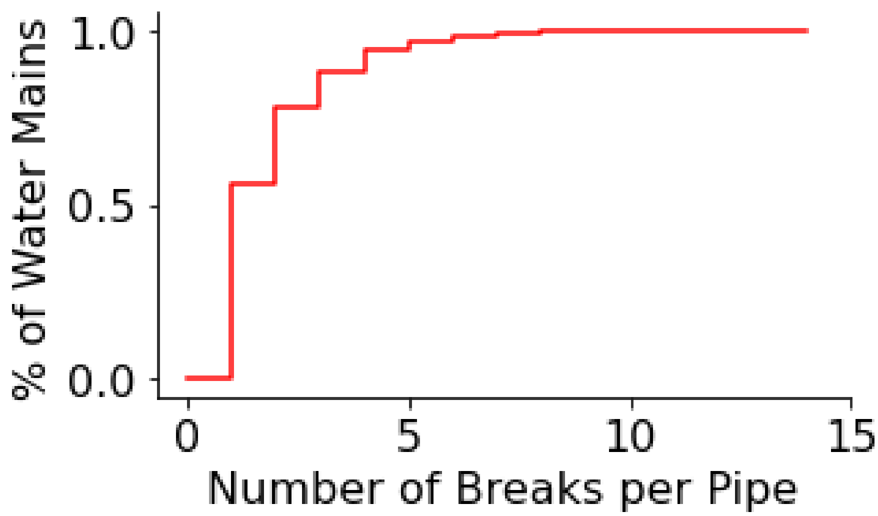

Figure 12**. Number of Breaks per Pipe.** *The CDF shows the cumulative distribution frequency of water mains by the number of breaks this pipe has on records.*

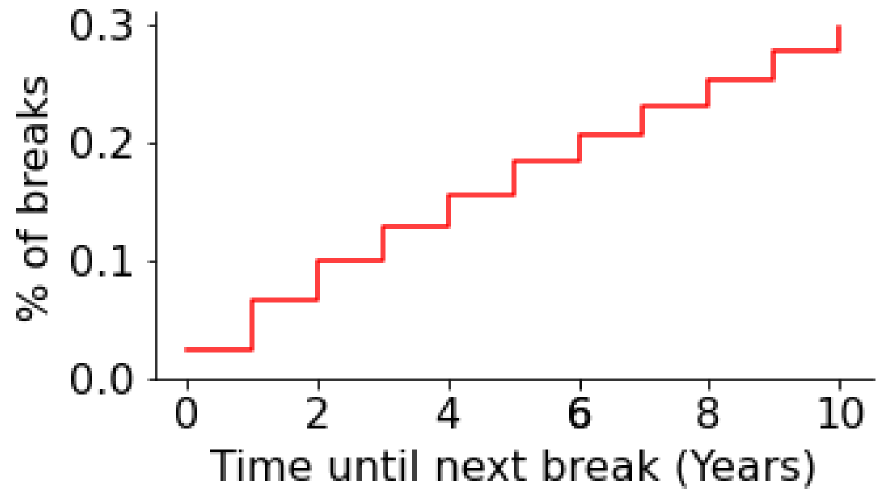

Figure 13**. Time until Next Break.** *The CDF shows the cumulative distribution frequency of breaks that are followed by subsequent breaks within 10 years examining the break records from 1980 to 2010.*

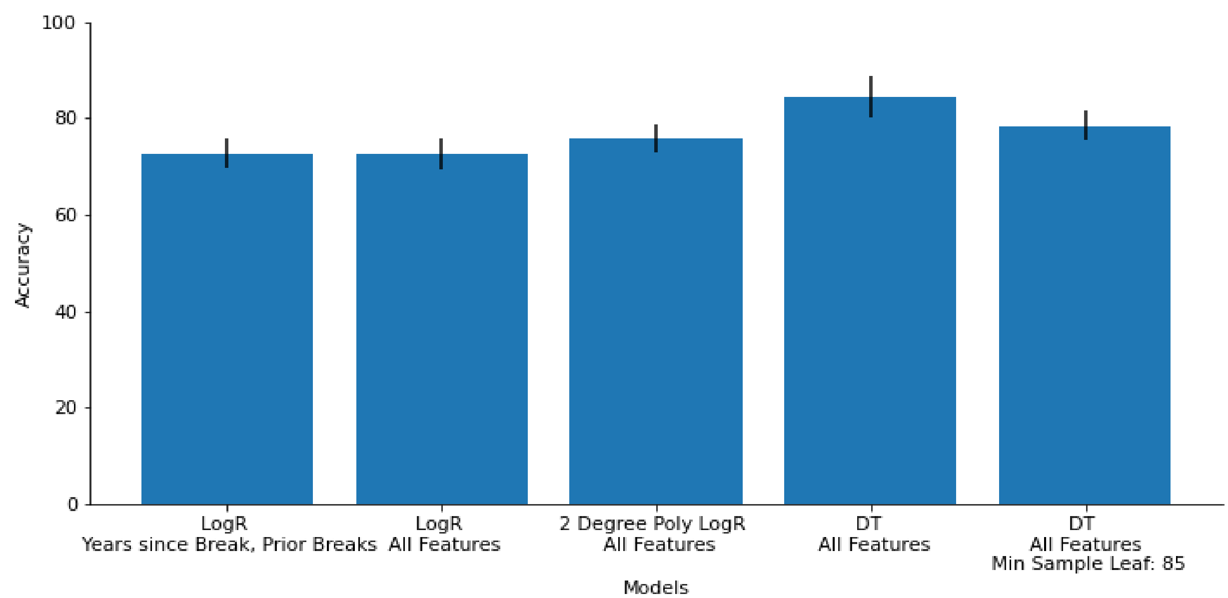

Figure 14**. Model Comparison.** *This plot compares several models by their mean 12-fold cross-validation score and the corresponding standard deviation*

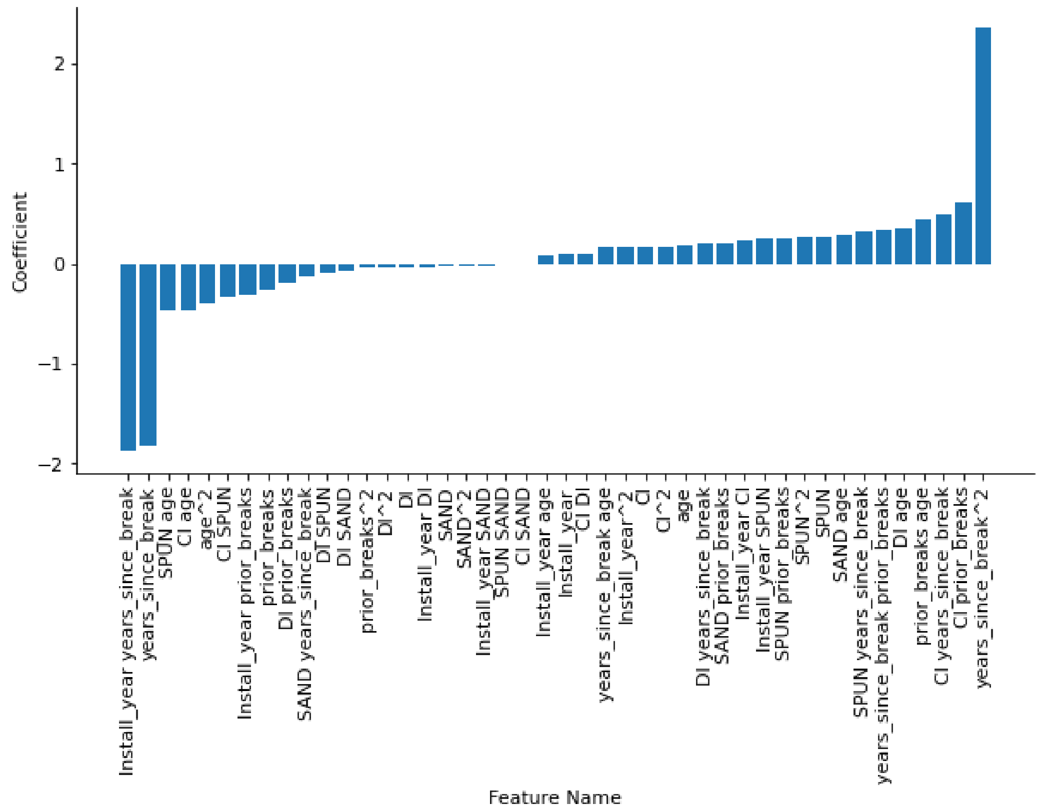

Figure 15**. logistic regression coefficients.** *This figure depicts the coefficients of the Polynomial Logistic Regression Model.*

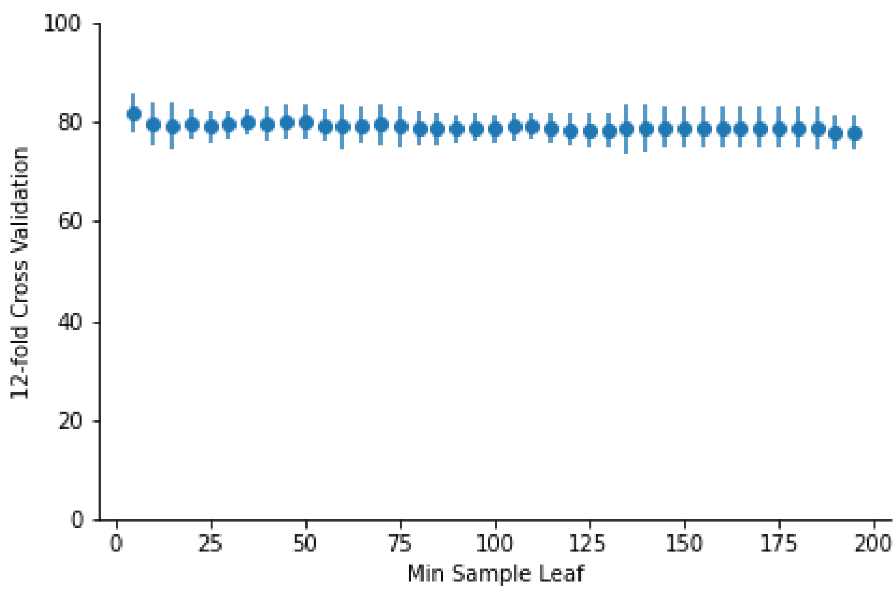

Figure 17**. Min Sample Leaf Accuracy.** *This plot depicts the 12-fold cross-validation accuracy score obtained when a Decision Tree Classifier is constructed with the corresponding minimum sample leaf sizes.*

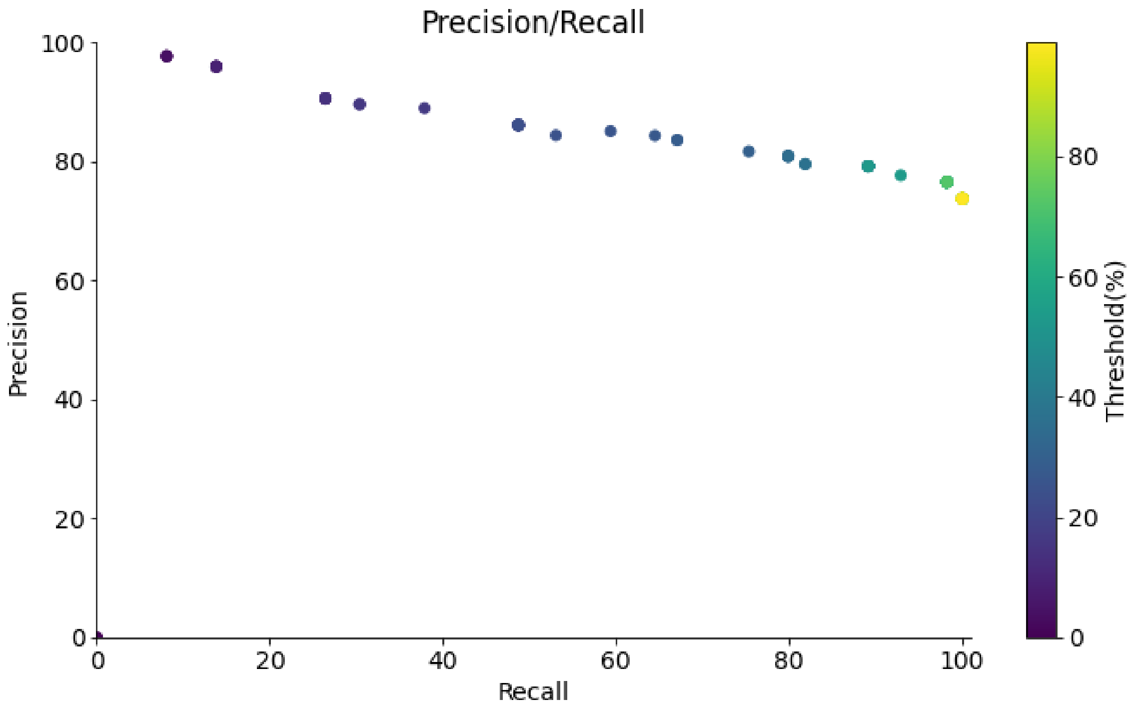

Figure 16**. Thresholding Plot.** *This plot shows the Precision and Recall for various thresholds to the probability model.*

```
|--- years_since_break <= 0.50
|   |--- class: 1
|--- years_since_break >  0.50
|   |--- prior_breaks <= 4.50
|   |   |--- prior_breaks <= 1.50
|   |   |   |--- Install_year <= 1939.00
|   |   |   |   |--- age <= 69.50
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- age >  69.50
|   |   |   |   |   |--- class: 0
|   |   |   |--- Install_year >  1939.00
|   |   |   |   |--- Install_year <= 1946.50
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- Install_year >  1946.50
|   |   |   |   |   |--- class: 0
|   |   |--- prior_breaks >  1.50
|   |   |   |--- Install_year <= 1973.17
|   |   |   |   |--- age <= 42.75
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- age >  42.75
|   |   |   |   |   |--- class: 0
|   |   |   |--- Install_year >  1973.17
|   |   |   |   |--- age <= 27.33
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- age >  27.33
|   |   |   |   |   |--- class: 1
|   |--- prior_breaks >  4.50
|   |   |--- Install_year <= 1967.00
|   |   |   |--- prior_breaks <= 7.50
|   |   |   |   |--- age <= 46.75
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- age >  46.75
|   |   |   |   |   |--- class: 0
|   |   |   |--- prior_breaks >  7.50
|   |   |   |   |--- age <= 54.50
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- age >  54.50
|   |   |   |   |   |--- class: 1
|   |   |--- Install_year >  1967.00
|   |   |   |--- DI <= 0.50
|   |   |   |   |--- class: 0
|   |   |   |--- DI >  0.50
|   |   |   |   |--- Install_year <= 1973.17
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- Install_year >  1973.17
|   |   |   |   |   |--- class: 1
```

Figure 18**. Decision Tree.** *This text plot depicts a simple Decision Tree Classifier. It is a miniature version of the model we use for predicting whether a water main near a road will break in the future*

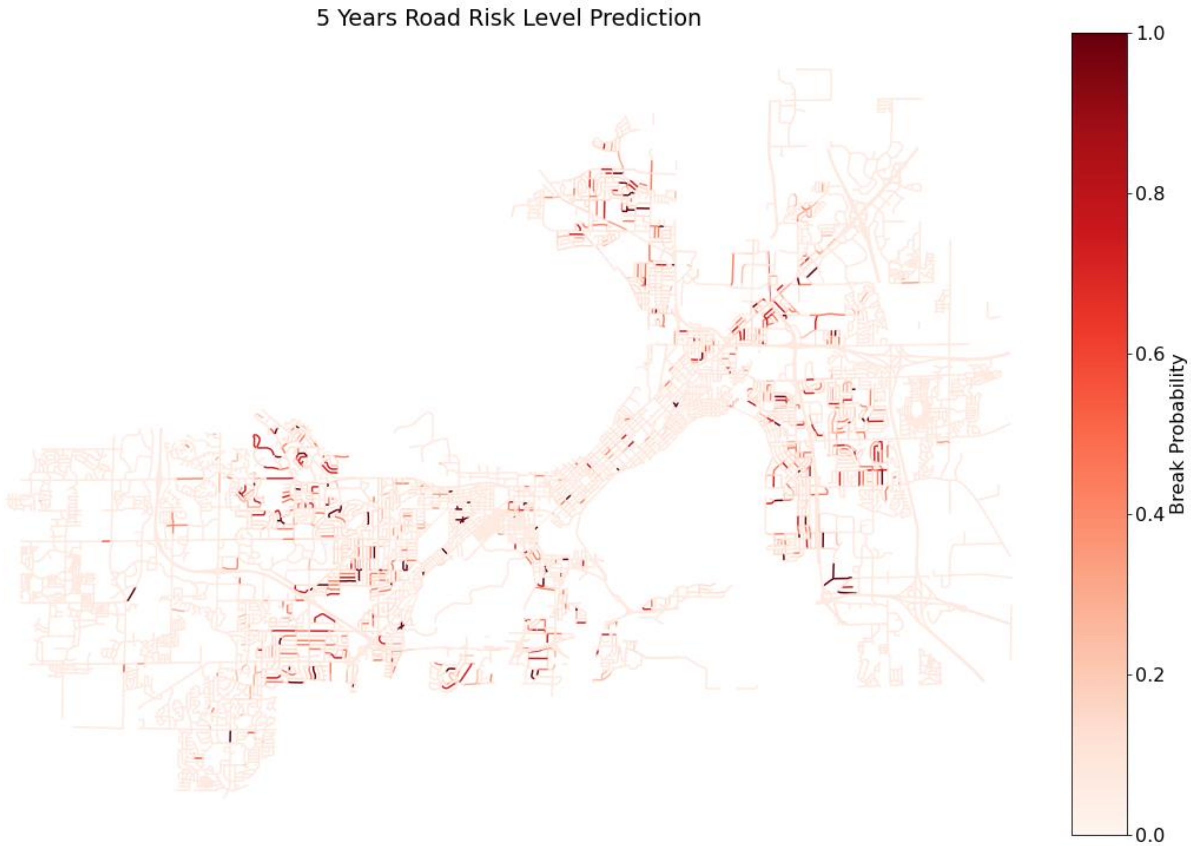

Figure 19**. Road Segments' Break Probability.** *This map shows the road segments in the City of Madison colored according to their predicted probability of break within 5 years by the Decision Tree model.*

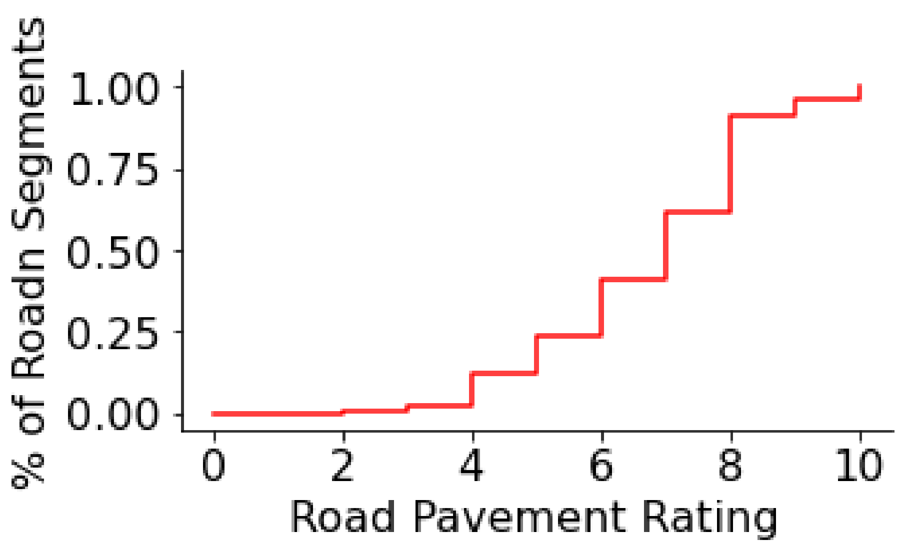

Figure 20**. Pavement Rating CDF.** *This CDF shows the cumulative distribution frequency of road segments' pavement rating according to the PASER rating system.*

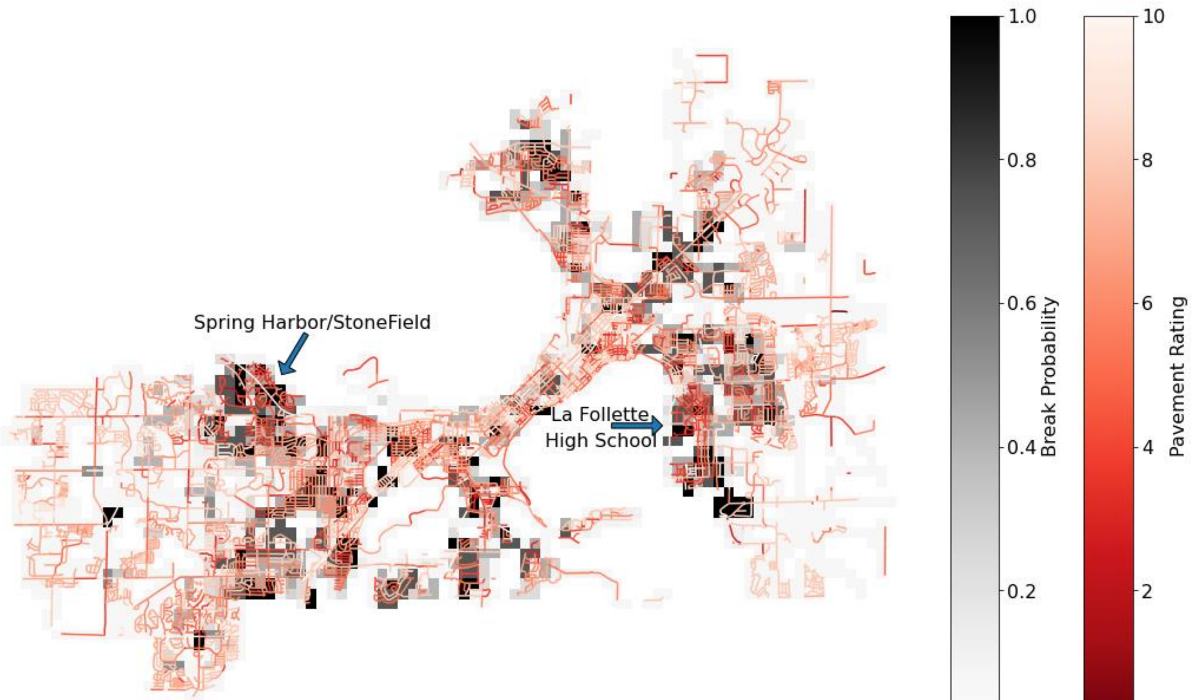

Figure 21**. Risk Level Map.** *This map shows the pavement rating of road segments in the City of Madison with darker colors indicating worse pavement ratings. The background pixels indicate the probability of the road segments' break probability. Two areas are highlighted as examples of low-quality roads with risky water mains underneath.*

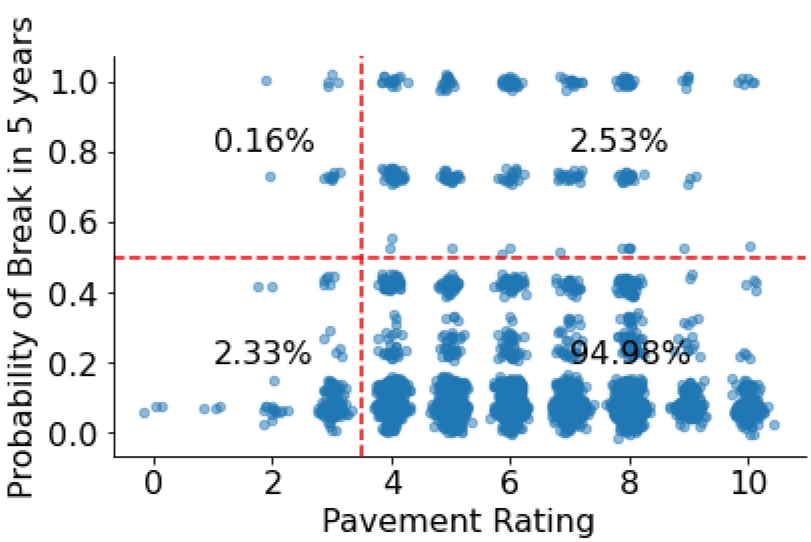

Figure 22**. Risk Level and Pavement Rating.** *This scatter plot shows the distribution of road segments of various pavement ratings and break probabilities. Roads in the top left quadrant are the ones to be concerned with which will be shown in Table 1.*

	segment_name	from_segment	to_segment	pavement_rating	prediction_probability
0	E DEAN AVE	TYLER CIR	LANCE LN	2.0	1.000000
1	HICKORY ST	SPRUCE ST	CEDAR ST	3.0	1.000000
2	SOUTH ST	MIDLAND ST	549 FT S OF MIDLAND ST	3.0	1.000000
3	SOUTH ST	W WINGRA DR	APPLETON RD	3.0	1.000000
4	HIGH ST	MIDLAND ST	S END	3.0	1.000000
5	N HIGHLANDS AVE	HILLSIDE AVE	S HIGHLANDS AVE	2.0	0.729927
6	S ORCHARD ST	ERIN ST	N WINGRA DR	3.0	0.729927
7	DONCASTER DR	SEMINOLE HWY	DANBURY ST	3.0	0.729927
8	STARKER AVE	HOMBERG LN	VONDRON RD	3.0	0.729927
9	STARKER AVE	NATIONAL AVE	ELLEN AVE	3.0	0.729927
10	DONDEE RD	STARKER AVE	E BUCKEYE RD	3.0	0.729927
11	PINECREST DR	BURKE AVE	E WASHINGTON AVE	3.0	0.729927
12	MEDICAL CIR	S WHITNEY WAY	ODANA RD	3.0	0.729927
13	E BADGER RD	RIMROCK RD	NOB HILL RD	3.0	0.729927
14	E DEAN AVE	MONONA DR	TYLER CIR	3.0	0.729927

Table 1. Candidate Road Segments. *This table lists the names of road segments that are predicted to be highly likely to experience a water main breakage within 5 years and have a low pavement rating.*