Journal of Sustainable Development and Policy

Volume: 5; **Issue:** 1
Pages: 01-33

A GIS-Based Geospatial Risk Modeling Framework for Natural Gas Distribution Pipeline Infrastructure Integrity and Resilience

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Doi: 10.63125/6z18x885
Received: 25 December 2025; **Revised:** 12 January 2026; **Accepted:** 20 February 2026; **Published:** 12 March 2026;

Abstract

Distribution pipeline systems constitute a critical component of national energy infrastructure, supplying natural gas to residential, commercial, and industrial consumers across extensive urban and rural networks. Ensuring the safety and reliability of these systems requires continuous monitoring, risk assessment, and proactive integrity management strategies. This study develops a Geographic Information Systems (GIS)–based analytical framework for implementing a Distribution Integrity Management Program (DIMP) aligned with regulatory requirements under 49 CFR Part 192 Subpart P. The proposed framework integrates spatial pipeline datasets, environmental risk indicators, infrastructure characteristics, and operational history into a unified geospatial risk modeling environment. Pipeline integrity is operationalized as a quantitative risk index derived from threat indicators including corrosion susceptibility, excavation damage potential, natural force hazards, and material degradation conditions. The analytical dataset includes spatially segmented pipeline assets linked with attribute information such as installation year, pipe material, diameter, operating pressure, and environmental exposure conditions. Spatial modeling procedures include geospatial risk weighting, hotspot detection, and predictive threat scoring using GIS-based statistical modeling techniques. Risk indicators are combined through a weighted scoring algorithm to produce segment-level integrity risk scores across the pipeline network. Preliminary modeling results demonstrate that integrating GIS spatial analytics with distribution integrity management workflows significantly improves the identification of high-risk pipeline segments and enhances decision-making for inspection prioritization, maintenance planning, and regulatory compliance. The findings demonstrate that GIS-driven integrity management frameworks provide scalable and data-driven tools for managing complex pipeline distribution systems. By combining spatial analytics with regulatory integrity management programs, the proposed framework supports improved infrastructure resilience, risk mitigation, and public safety outcomes across natural gas distribution networks.

Keywords

GIS, Distribution Integrity Management Program, Pipeline Risk Modeling, Infrastructure Integrity, Spatial Risk Analysis, Gas Distribution Systems;

INTRODUCTION

Natural gas distribution systems form the final delivery infrastructure within national energy networks, transporting gas from transmission pipelines to residential, commercial, and industrial consumers (Deng et al., 2016). These systems consist of extensive networks of pipelines, valves, regulators, and service lines that operate under varying environmental, operational, and structural conditions. The safety and reliability of distribution networks are critical to public safety, economic stability, and energy security (Aria et al., 2020). In the United States, pipeline safety regulations require operators to implement Distribution Integrity Management Programs (DIMP) under the Pipeline and Hazardous Materials Safety Administration (PHMSA). These programs require operators to systematically identify potential threats to distribution pipelines, evaluate risk levels, and implement risk mitigation strategies through maintenance, monitoring, and infrastructure replacement activities.

Traditional pipeline integrity management approaches rely heavily on inspection records, operational reports, and engineering assessments. However, the spatial nature of pipeline infrastructure introduces complex interactions between pipeline assets and environmental conditions. Factors such as population density, soil corrosivity, land use patterns, excavation activity, and hydrological conditions significantly influence pipeline risk. Geographic Information Systems (GIS) provide a powerful platform for integrating these spatial variables into infrastructure risk assessment workflows. GIS technology enables pipeline operators to visualize, analyze, and manage spatial infrastructure data through geospatial modeling techniques (Anick & Tasnim, 2022; Siddique & Amin, 2022; Yan & Zhiping, 2023). By integrating pipeline datasets with environmental, demographic, and operational information, GIS supports advanced spatial risk modeling and predictive analysis. This capability allows operators to identify high-risk pipeline segments, prioritize inspection activities, and allocate maintenance resources more effectively.

This research proposes a GIS-based framework for implementing Distribution Integrity Management Programs using spatial risk modeling techniques. The framework integrates pipeline infrastructure data with environmental hazard indicators and operational history to produce quantitative risk scores for pipeline segments. The primary objective is to demonstrate how GIS-driven analytical workflows can enhance infrastructure integrity management and support regulatory compliance.

LITERATURE REVIEW

Pipeline integrity management has become an essential component of infrastructure safety programs across energy distribution networks. Early approaches to pipeline risk assessment focused primarily on engineering inspection techniques, material testing, and failure analysis. However, recent research emphasizes the importance of integrating spatial information systems into infrastructure monitoring frameworks. Geographic Information Systems provide analytical capabilities for modeling complex spatial relationships between infrastructure assets and environmental hazards. Several studies have demonstrated the effectiveness of GIS-based risk modeling for infrastructure systems including transportation networks, power transmission lines, and pipeline corridors. These systems benefit from spatial analysis techniques such as hotspot detection, spatial clustering, and proximity analysis. In pipeline integrity management research, spatial modeling has been applied to evaluate excavation damage risk, corrosion susceptibility, and environmental hazard exposure. Excavation damage remains one of the most significant causes of pipeline failures in distribution systems. GIS-based modeling techniques can incorporate land use patterns, construction activity records, and population density to estimate excavation risk levels.

Corrosion is another critical threat affecting pipeline integrity. Soil properties such as moisture content, acidity, and electrical conductivity influence corrosion rates in buried pipelines. GIS allows operators to integrate soil data and environmental variables with pipeline asset records to identify areas with elevated corrosion susceptibility. Recent advancements in geospatial analytics have introduced predictive modeling techniques into infrastructure risk assessment. Machine learning models and spatial statistical approaches have been used to predict infrastructure failures based on historical data patterns. These approaches provide data-driven insights that can enhance proactive maintenance strategies. The integration of GIS with integrity management programs represents a significant advancement in infrastructure risk analysis. By combining spatial data with operational records, GIS enables the development of comprehensive analytical frameworks that improve risk assessment accuracy and support evidence-based decision making.

Research Objectives

The primary objective of this study is to develop a GIS-based analytical framework for distribution pipeline integrity management. Specific objectives include:

RQ1: To design a spatial data model for integrating pipeline infrastructure datasets with environmental and operational information.

RQ2: To develop GIS-based risk indicators for evaluating pipeline integrity threats.

RQ3: To construct a quantitative risk scoring model for pipeline segments.

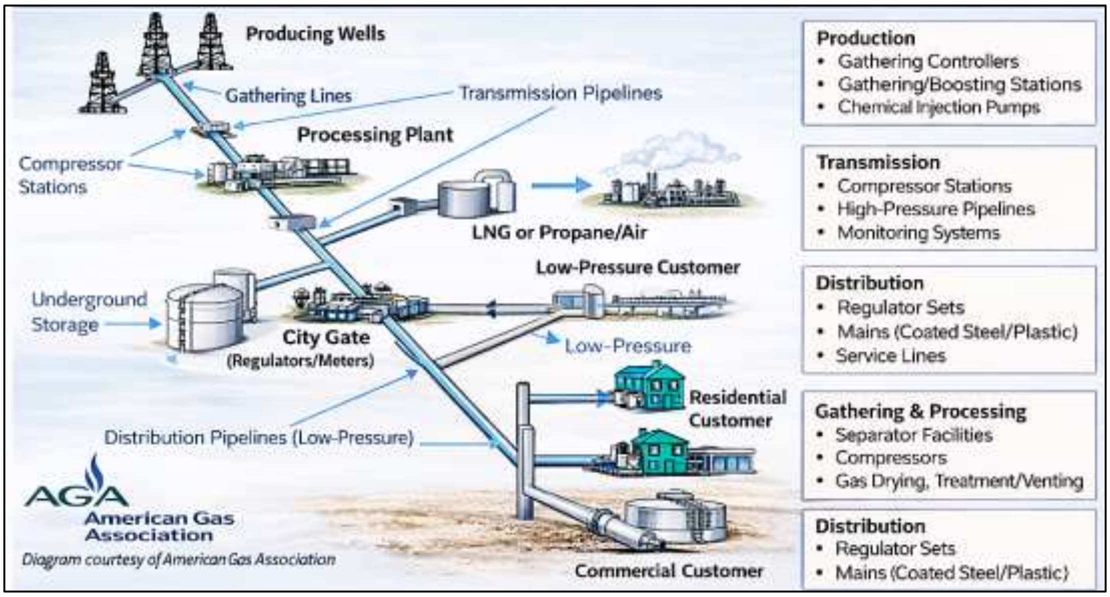
RQ4:To identify high-risk pipeline locations through spatial hotspot analysis.

RQ5: To evaluate the effectiveness of GIS-driven risk modeling for infrastructure integrity management

Pipeline Infrastructure and Distribution Network Safety

Natural gas pipeline systems constitute a fundamental pillar of modern national energy infrastructure, facilitating the large-scale transmission and localised distribution of natural gas across continents and within urban centres. Jin et al. (2021) established that pipeline networks serve not merely as passive transport conduits but as integrated systems whose operational integrity is inseparable from national energy security, underscoring the strategic importance of gas infrastructure in sustaining industrial, commercial, and residential energy demand. The global expansion of pipeline networks has been driven by the growing reliance on natural gas as a transitional fuel in decarbonisation efforts, with Nasser et al. (2021)) noting that natural gas accounts for a substantial proportion of primary energy consumption in industrialised nations, necessitating extensive and reliable pipeline infrastructure capable of handling escalating throughput volumes. Li et al. (2023) contextualised this expansion by documenting that the global pipeline network spans millions of kilometres, encompassing high-pressure transmission lines that carry gas from production fields and processing plants to regional distribution hubs, and lower-pressure distribution pipelines that deliver gas to end users across densely populated areas.

Figure 1: Pipeline Infrastructure and Distribution Network Safety

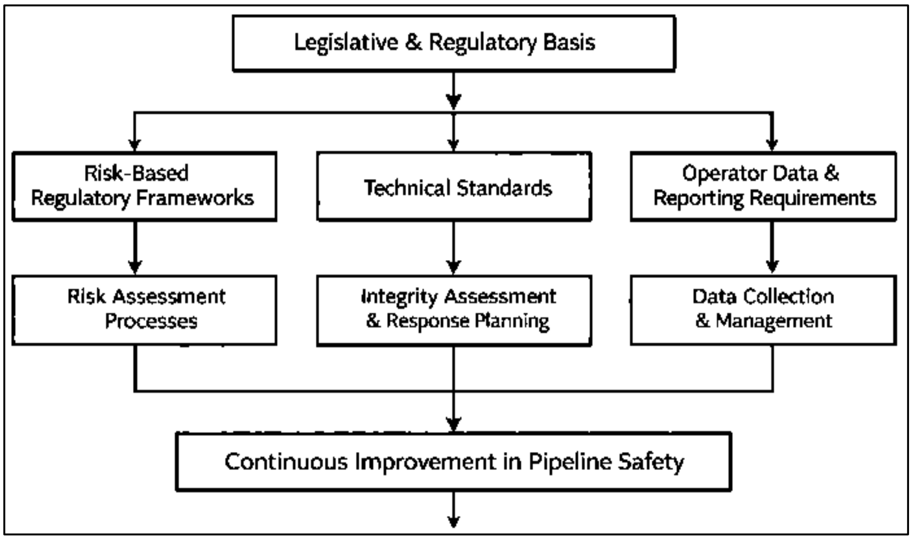


This bifurcated network architecture renders the system highly interdependent, meaning that disruptions at any point along the network can cascade through both transmission and distribution tiers with significant consequences for energy supply continuity and public safety (Md & Islam, 2022; Shahinur & Sultan, 2022). Seow et al. (2016) reinforced this view by demonstrating that urban natural gas pipeline networks are exposed to a complex array of operational hazards given the density of buried infrastructure, the proximity to human populations, and the difficulties of monitoring assets in congested built environments. Dai et al. (2021) additionally identified the critical role of regulatory oversight and sustained capital investment in maintaining network reliability, observing that systematic underinvestment in infrastructure maintenance poses substantial risks to uninterrupted energy delivery across all consumer segments. The expanding geographic footprint of pipeline systems, driven by demand growth in Asia, the Middle East, and sub-Saharan Africa, has further complicated the global risk landscape, as newly constructed pipelines in these regions frequently traverse challenging terrain and operate under variable and sometimes immature regulatory environments (Binetti, 2023; Mostafa & Tohidul, 2022). The interdependency between pipeline infrastructure and broader national energy systems means that the sociotechnical risks embedded in these networks extend well beyond the immediate physical consequences of individual failures, encompassing potential disruptions to industrial production, public health services, and domestic heating supply during peak demand periods (Khaled & Mosheur, 2023; Shahab & Aditya, 2023). Li et al. (2020) emphasised that this interconnected risk exposure demands sophisticated risk quantification approaches that account for the systemic nature of gas infrastructure rather than treating individual pipeline segments or components as isolated assets. Collectively, these studies establish that the continued growth and operational complexity of natural gas pipeline systems demand rigorous, evidence-based approaches to infrastructure planning, safety management, and integrity assurance, and that failures to invest in these areas carry both immediate operational and long-term societal consequences.

Regulatory Framework for Pipeline Integrity Management

The regulatory framework governing pipeline integrity management has undergone profound transformation over the past five decades, evolving from prescriptive, rule-based standards that specified minimum material and construction requirements toward more sophisticated, risk-informed regulatory architectures that emphasise performance outcomes, operator accountability, and continuous improvement in safety management practice (Hasan Or et al., 2023; Mehedi & Nahar, 2023). Taylor and Bernstein (2009) traced the historical trajectory of pipeline safety regulation in industrialised nations and identified a consistent pattern in which major pipeline incidents served as catalysts for legislative reform, with regulators progressively expanding the scope of mandatory integrity requirements in response to evidence of systemic failures in voluntary compliance and self-regulatory mechanisms (Sultan & Anick, 2023; Mostafa, 2023). In the United States, the Pipeline Safety Improvement Act of 2002 and its successor legislation represented a landmark shift in the regulatory philosophy governing gas transmission and distribution systems, mandating the development and implementation of formal Integrity Management Programs (IMPs) by all operators of pipelines in high-consequence areas and establishing structured requirements for risk assessment, preventive and mitigative measures, and performance measurement (Seow et al., 2016).

Figure 2: Regulatory Framework for Pipeline Integrity Management



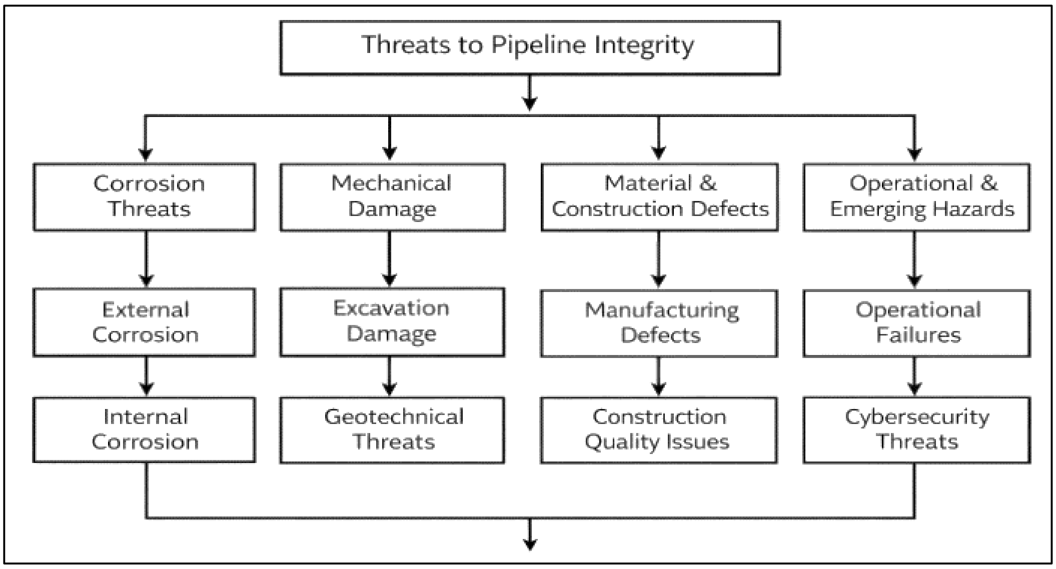
Liberati et al. (2009) examined the parallel evolution of pipeline safety regulation within the European Union and identified the emergence of a broadly harmonised but nationally implemented regulatory model, characterised by the adoption of risk-based safety objectives alongside prescriptive technical standards, and observed that the degree of regulatory convergence across member states remained incomplete, creating variability in the stringency and consistency of integrity management requirements applicable to cross-border and domestic pipeline systems. The International Organisation for Standardisation and the American Society of Mechanical Engineers have played central roles in establishing the technical standards that underpin regulatory compliance globally, with frameworks such as ASME B31.8S providing operators with structured methodologies for integrating threat identification, risk assessment, integrity assessment, and response planning into a coherent and auditable integrity management system (Hastings, 2015; Tasnim & Zaheda, 2023; Zaheda & Farabe, 2023). Binetti (2023) noted that the adoption of these standards-based regulatory frameworks has been uneven across different regions and pipeline operating contexts, with operators in mature regulatory jurisdictions generally demonstrating higher levels of systematic integrity management practice than those in emerging economies where regulatory capacity and enforcement resources are more limited. Dai et al. (2021) further observed that while quantitative risk assessment methodologies have been incorporated into regulatory guidance in several jurisdictions, the absence of universally agreed acceptable risk thresholds and the variability in the technical assumptions embedded in different QRA models continue to complicate the consistent application of risk-informed regulation across the global pipeline industry. Binetti (2023) emphasised that regulatory frameworks, regardless of their technical sophistication, are ultimately dependent upon the quality and completeness of the data that operators collect, maintain, and report to regulators, and that deficiencies in data governance represent a persistent and underappreciated vulnerability in the effectiveness of pipeline safety regulation. Seow et al., (2016) reinforced this observation by demonstrating that the reliability of risk assessments submitted to regulators is critically dependent upon the accuracy of input data relating to pipeline condition, operating history, and environmental exposure, and that systematic underreporting of near-miss events and minor incidents further compromises regulators' ability to develop evidence-based assessments of industry-wide safety performance (Iftekhar & Tohidul, 2024; Jinnat & Binte, 2024). The cumulative evidence from these studies indicates that while the legislative and institutional architecture of pipeline safety regulation has matured substantially across many jurisdictions, persistent gaps in data quality, regulatory capacity, and cross-jurisdictional harmonisation continue to limit the effectiveness of regulatory frameworks in translating legislated safety objectives into consistently improved operational outcomes across the global pipeline sector.

Threats to Pipeline Integrity

Corrosion remains the most pervasive and well-documented threat to natural gas pipeline integrity, consistently accounting for a disproportionate share of recorded incidents across both transmission and distribution network segments. (Hernández-Chover et al., 2020) demonstrated through Monte Carlo simulation that pitting corrosion depth and growth rate increase nonlinearly with pipeline age, confirming that fixed-interval inspection regimes are systematically inadequate for managing the spatially variable corrosion risks characteristic of aging infrastructure. Taylor and Bernstein (2009) corroborated these findings empirically, identifying external corrosion as among the most frequent primary failure mechanisms in fuel pipelines globally, particularly in assets installed without modern cathodic protection or with degraded protective coatings. The EGIG (2018) longitudinal dataset further confirmed that external and internal corrosion collectively account for a sustained and significant share of European pipeline incidents across nearly five decades, while Guler and Yomralioglu (2021) noted that internal corrosion in wet or sour gas environments presents particularly acute detection challenges given its localised and rapidly progressing nature. Alongside corrosion, third-party mechanical damage arising from excavation activities ranks consistently among the leading causes of pipeline failure, with Binetti (2023)) demonstrating that this risk is heavily concentrated in areas of active urban development and dense buried utility congestion. Abspoel et al. (2018) additionally identified geotechnical threats, including soil subsidence, slope instability, and seismic ground deformation, as significant compounding hazards, particularly for older rigid-joint pipelines incapable of accommodating differential ground movement without fracture or joint separation.

Beyond physical degradation and external mechanical interference, pipeline integrity is further threatened by material and construction defects, operational failures, and an expanding range of emerging hazards (Towhidul & Uddin, 2024; Mushfequr & Aditya, 2024). Nasser et al. (2021) established that manufacturing defects including seam weld imperfections, laminations, and substandard heat treatment introduce latent structural vulnerabilities that may remain undetected through hydrostatic testing yet initiate cracking under cyclic operational loading, while Yan et al. (2017) demonstrated through fuzzy fault tree analysis that the uncertainty inherent in defect population characterisation represents one of the most significant sources of epistemic uncertainty in pipeline failure probability assessment.

Figure 3: Threats to Pipeline Integrity

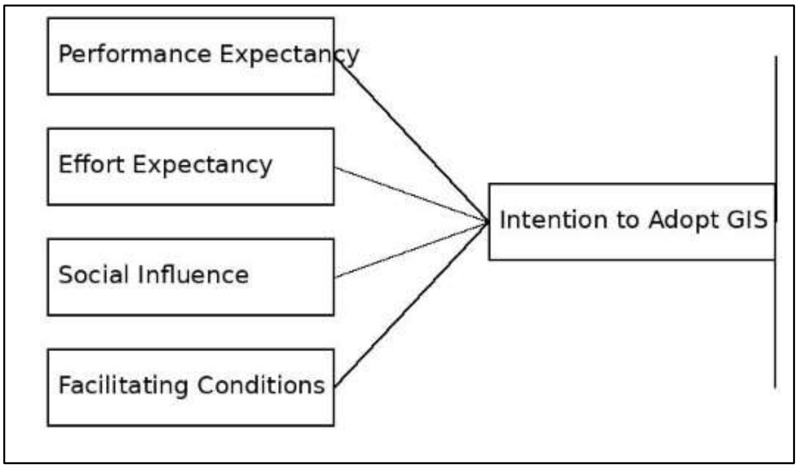


Stress corrosion cracking, which combines mechanical stress and electrochemical attack to produce cracking well below nominal fracture thresholds, has been responsible for a disproportionate number of high-consequence failures in high-pressure transmission systems (Liu et al., 2022; Sakib, 2024; Sazzadul & Rebeka, 2024). Operationally, Xie and Tian (2018) quantified through dispersion and ignition probability modelling that pressure exceedances and process control failures can produce catastrophic thermal radiation consequences in populated areas, while Lee et al. (2015) demonstrated through Bayesian network analysis that human and organisational performance factors significantly influence both the probability of equipment failure and the effectiveness of safety barriers in preventing incident escalation. Looking ahead, Pinto et al. (2019) identified climate change as an emerging driver of geotechnical and corrosion risk, and Kang and Hong (2015)) highlighted the growing cybersecurity threat to supervisory control systems as a vector for operationally induced pipeline failures, collectively underscoring that the integrity threat landscape facing gas pipeline systems is dynamic, multi-dimensional, and demands continuously evolving assessment and management frameworks.

GIS-Based Risk Modeling Approaches

Geographic Information System (GIS) technology has emerged as a transformative analytical platform in pipeline risk management, enabling the spatial integration of pipeline physical attributes, environmental exposure data, land use characteristics, and historical incident records into geographically referenced risk models that substantially enhance the precision and operational utility of integrity assessment relative to conventional attribute-based or segment-averaged approaches. Pinto et al. (2019) demonstrated that GIS-based predictive models incorporating spatially referenced variables including soil type, pipeline age, cathodic protection status, and proximity to excavation activity consistently outperform non-spatial failure prediction models in identifying high-risk pipeline segments within distribution networks, confirming that the geographic dimension of pipeline risk is not merely supplementary but analytically essential to accurate integrity prioritisation. Liu et al. (2022) extended this perspective by showing that GIS platforms enable the overlay of quantitative risk assessment outputs with population density, land use, and critical infrastructure datasets, allowing operators and regulators to identify high-consequence areas where the intersection of elevated failure probability and sensitive receptors demands prioritised risk reduction investment (Tasnim & Anick, 2024; Zaheda & Hamidur, 2024). Yildirim et al. (2016) similarly emphasised the value of spatially continuous risk indexing approaches that assign risk scores to discrete pipeline segments based on geographically variable threat and consequence attributes, arguing that GIS-enabled risk mapping provides a far more operationally actionable risk picture than network-averaged metrics that obscure the spatial concentration of risk within specific corridors or localities. Lee et al. (2021) further demonstrated through fuzzy bow-tie analysis integrated with spatial consequence modelling that GIS-based approaches are particularly valuable for characterising the geographically differentiated consequence profiles of pipeline failure scenarios, where the severity of outcomes is strongly influenced by spatially variable factors including population density, ignition source proximity, and emergency response accessibility that cannot be adequately represented in non-spatial risk models.

Figure 4: GIS-Based Risk Modeling Approaches

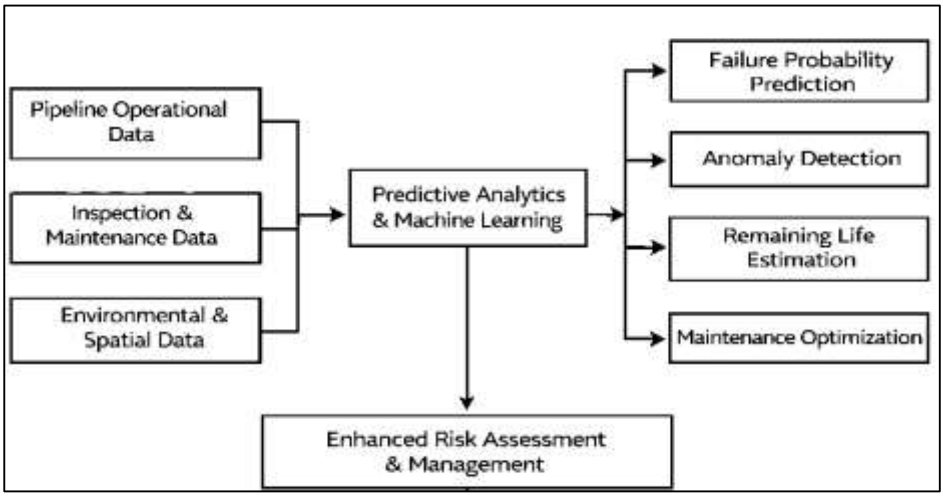


The integration of GIS with probabilistic risk assessment methodologies, real-time monitoring data, and remote sensing technologies has progressively elevated GIS-based pipeline risk modelling from a static mapping tool toward a dynamic decision-support platform capable of informing both strategic integrity planning and operational emergency response (Shahab, 2025; Mostafa, 2025). Kang and Hong, (2015) demonstrated that spatially referenced corrosion growth models informed by soil chemistry, moisture, and cathodic protection data can be integrated within GIS environments to generate continuously updated failure probability maps across pipeline networks, enabling operators to dynamically adjust inspection schedules and maintenance priorities in response to evolving spatial patterns of corrosion risk rather than relying on fixed programmatic inspection cycles. Pinto et al. (2019) highlighted the growing regulatory application of GIS-based risk models in the delineation of high-consequence areas and the spatial targeting of compliance monitoring resources, observing that regulators have increasingly leveraged GIS platforms to cross-reference operator-reported pipeline attributes with independent land use, demographic, and environmental sensitivity datasets as a basis for identifying discrepancies in consequence area classifications and prioritising regulatory inspection activity. Sigsgaard et al. (2021) demonstrated through Bayesian network integration with spatially referenced asset condition data that dynamic probabilistic risk models anchored within GIS frameworks can substantially improve the targeting of preventive maintenance interventions by enabling operators to visualise the spatial distribution of risk-driving variables and their interactions across the network in ways that static tabular risk registers cannot replicate. Pinto et al. (2019) cautioned, however, that the quality of GIS-based risk model outputs is fundamentally constrained by the completeness, accuracy, and spatial resolution of the underlying attribute datasets, and that systematic gaps in pipeline condition records, soil characterisation data, and land use information introduce significant spatial bias into GIS-derived risk maps, potentially directing integrity resources away from genuinely high-risk segments toward those that are merely better documented in operator information systems.

Predictive Analytics and Machine Learning in Pipeline Risk Assessment

Predictive analytics and machine learning methodologies have introduced a fundamental shift in the analytical capabilities available for pipeline risk assessment, enabling the extraction of complex, nonlinear failure patterns from large and heterogeneous operational datasets that exceed the discriminatory capacity of conventional statistical and deterministic integrity assessment models. (Park et al., 2016) provided influential early evidence of this analytical advantage by demonstrating that machine learning-based failure prediction models trained on historical inspection records, soil characterisation data, operational parameters, and maintenance histories achieve substantially higher predictive accuracy in identifying high-risk pipeline segments than conventional regression-based or rule-based screening criteria, with the superior performance of machine learning models attributable to their capacity to capture interaction effects among multiple failure-driving variables that additive statistical models systematically misrepresent or ignore (Sazzadul, 2025; Shakil, 2025). Manny et al., (2022) similarly demonstrated that Monte Carlo simulation frameworks informed by probabilistic corrosion growth models fitted to inspection datasets can generate statistically robust failure probability distributions across pipeline populations, establishing a methodological bridge between empirical condition data and the probabilistic risk estimates required for reliability-based integrity management that purely deterministic assessment approaches cannot provide (Shakil et al., 2025; Shamsunnahar, 2025). Kang and Hong (2015) further illustrated the analytical value of data-driven risk modelling by demonstrating that the integration of multiple spatially and temporally variable risk drivers into composite risk indices through weighted aggregation models substantially improves the discrimination between high- and low-risk network segments relative to single-variable screening approaches. Yan et al. (2017) contextualised the data requirements of advanced predictive models within the broader pipeline risk management framework, noting that the reliability of any data-driven risk assessment methodology is fundamentally contingent upon the completeness, consistency, and historical depth of the underlying asset condition and operational records, and that systematic data quality deficiencies in aging pipeline networks represent the primary practical constraint on the operational deployment of sophisticated predictive analytics platforms across real-world distribution infrastructure (Yousuf et al., 2025; Akter & Aditya, 2025).

Figure 5: Predictive Analytics and Machine Learning in Pipeline Risk Assessment



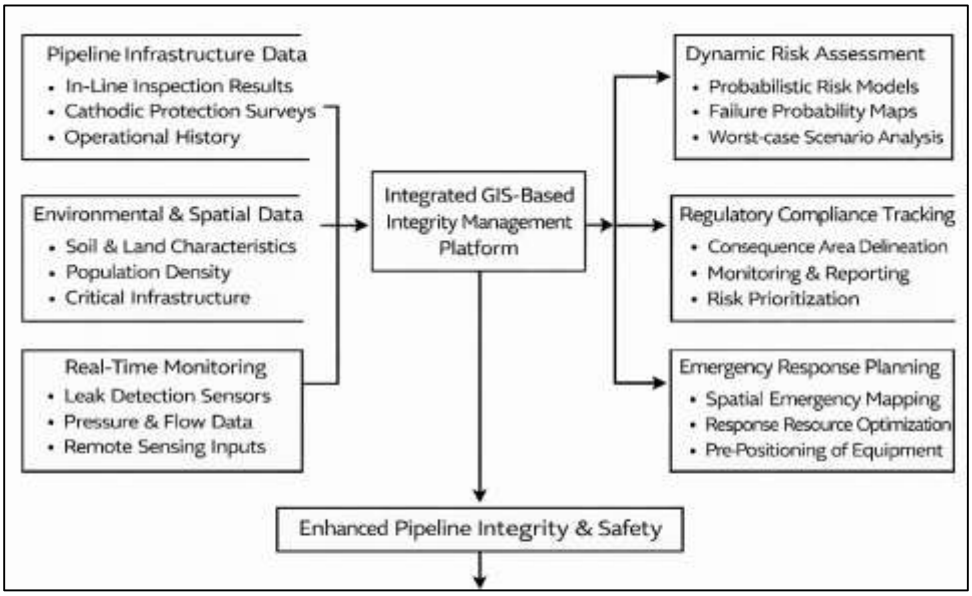
The progressive maturation of machine learning applications in pipeline risk assessment has expanded from failure probability prediction toward integrated risk management platforms that incorporate anomaly detection, remaining life estimation, and maintenance optimisation within unified analytical frameworks, though significant methodological and operational challenges continue to constrain the consistent translation of algorithmic advances into operationally reliable and regulatory-compliant risk management practice. Kang and Hong (2015) demonstrated through Bayesian network modelling of natural gas metering and regulating stations that probabilistic graphical models capable of dynamically updating failure probability estimates as new inspection and operational data becomes available provide a substantially more accurate and operationally responsive basis for maintenance decision-making than static risk models calibrated at fixed assessment intervals, with the dynamic updating capability of Bayesian frameworks being particularly valuable in pipeline operating environments characterised by rapidly evolving condition states or highly variable external threat exposure. Liu et al. (2022) reinforced the analytical utility of hybrid modelling approaches by demonstrating that the integration of fuzzy set theory with fault tree and bow-tie analytical structures enables the systematic propagation of epistemic uncertainty through pipeline risk assessment calculations, producing uncertainty-aware risk estimates that more honestly represent the limitations of available condition and consequence data than point-estimate deterministic assessments that convey a false precision incompatible with the actual state of knowledge in most pipeline operating contexts. Zamenian et al., (2017) cautioned that the proliferation of machine learning and advanced probabilistic risk assessment methodologies in the pipeline sector has not been matched by equivalent progress in model validation, transparency, and regulatory acceptance, observing that the black-box character of many high-performing machine learning algorithms creates significant challenges for regulatory review and independent verification of risk assessment outputs, and that the absence of standardised validation protocols and agreed performance benchmarks for predictive pipeline risk models represents a critical gap that must be addressed before these methodologies can be consistently integrated into regulatory integrity management frameworks. Pinto et al. (2019) further argued that the most robust foundation for advanced predictive analytics in pipeline integrity management lies in the coupling of data-driven machine learning models with physics-based degradation models that encode established mechanistic understanding of corrosion, fatigue, and cracking processes, since purely data-driven models trained on historical failure datasets are inherently limited in their ability to extrapolate reliably to operating conditions, threat combinations, or pipeline vintages that are underrepresented in available training data, a limitation whose practical significance grows as pipeline networks are extended into novel operating environments and subjected to emerging threat categories including hydrogen embrittlement and climate-driven geotechnical loading.

Integrated GIS-Based Integrity Management Frameworks

Integrated GIS-based integrity management frameworks represent the convergence of spatial data infrastructure, probabilistic risk assessment, and operational decision-support capabilities into unified pipeline management platforms that transcend the limitations of siloed inspection programs, attribute-based risk indices, and non-spatial integrity assessment methodologies. Park et al. (2016) demonstrated that the integration of in-line inspection results, cathodic protection survey data, soil characterisation records, and operational history within a spatially referenced asset management environment enables operators to develop a continuously updated and geographically differentiated picture of network condition that provides a substantially more reliable basis for integrity intervention prioritisation than the segment-averaged condition metrics produced by conventional non-spatial integrity management systems. Abspoel et al. (2018) reinforced this analytical advantage by showing that GIS-integrated failure prediction models incorporating spatially referenced environmental, operational, and historical incident variables consistently outperform attribute-only models in discriminating between high- and low-risk pipeline segments, and that the geographic visualisation capabilities of GIS platforms translate these analytical outputs into operationally actionable risk maps that support both field inspection planning and executive capital allocation decisions in ways that tabular risk registers cannot replicate. Manny et al. (2022) contextualised the value of spatial integration within the broader pipeline risk management framework by arguing that consequence assessment is inherently geographic in character and cannot be reliably conducted without the spatial overlay capabilities that GIS platforms provide, since the consequence severity of any given pipeline failure scenario is determined as much by the spatial relationship between the failure location and surrounding receptors as by the physical parameters of the release itself. Kang and Hong (2015) extended this perspective by demonstrating that GIS-integrated quantitative risk assessment frameworks enable the simultaneous spatial optimisation of both preventive integrity interventions and emergency response pre-positioning, producing a unified risk governance platform that addresses the full bow-tie risk management structure from threat prevention through consequence mitigation within a single geographically referenced analytical environment.

The operational maturation of integrated GIS-based integrity management frameworks has been driven by the progressive incorporation of real-time monitoring data streams, dynamic probabilistic risk updating, and regulatory compliance tracking capabilities that transform GIS from a static spatial analysis tool into a continuously evolving operational intelligence platform for pipeline network management. Zamenian et al. (2017) demonstrated that the integration of Bayesian network-based dynamic risk models with spatially referenced asset condition and operational monitoring data enables operators to generate continuously updated failure probability maps that reflect real-time changes in pipeline operating conditions, inspection findings, and environmental exposure, providing a substantially more responsive and accurate basis for maintenance prioritisation than periodic static risk assessments calibrated at fixed programmatic intervals.

Figure 6: Integrated GIS-Based Integrity Management Frameworks



Xie and Tian (2018) highlighted the growing regulatory application of integrated GIS frameworks in high-consequence area delineation, compliance monitoring, and enforcement prioritisation, observing that regulators increasingly leverage spatially integrated operator-reported pipeline attribute data cross-referenced against independent demographic, land use, and environmental sensitivity datasets to identify misclassifications in consequence area designations and to target regulatory inspection resources toward the network segments presenting the greatest unmitigated risk to surrounding populations. Kang and Hong (2015) cautioned, however, that the effectiveness of integrated GIS-based integrity management frameworks is fundamentally constrained by the completeness and spatial resolution of the underlying data ecosystems that populate them, and that the systematic gaps in pipeline condition records, environmental characterisation data, and operational histories that characterise many aging distribution networks introduce spatial biases into GIS-derived risk outputs that can misdirect integrity investment toward well-documented but lower-risk segments and away from poorly characterised but genuinely high-risk infrastructure. Lee et al. (2021) further argued that the full potential of integrated GIS-based frameworks can only be realised through the coupling of spatial data management capabilities with physics-informed probabilistic degradation models that encode mechanistic understanding of corrosion, fatigue, and geotechnical failure processes, since purely data-driven spatial risk models lack the extrapolative reliability needed to accurately characterise integrity risk in pipeline segments or operating environments that are underrepresented in available historical datasets, a limitation of growing practical significance as pipeline networks expand into geologically complex and climatically marginal territories where the empirical basis for data-driven risk modelling is inherently thin.

METHOD

This study develops a Geographic Information System (GIS)–based framework for implementing a Distribution Integrity Management Plan (DIMP) in accordance with 49 CFR Part 192 Subpart P, which requires pipeline operators to identify, evaluate, and mitigate risks associated with gas distribution pipelines.

The risk assessment methodology follows the principle that:

$$Risk = Threat \times Consequence$$

where Threat represents the probability of pipeline failure caused by various hazards and Consequence represents the potential impact should the failure occur. The overall model evaluates eight major threat categories and multiple consequence factors using spatial analysis and statistical weighting. The methodology integrates pipeline infrastructure data, field inspection records, environmental datasets, and public infrastructure layers within an ESRI ArcGIS environment to perform spatially explicit risk calculations for each pipeline segment. Pipeline segments are dynamically divided into risk segments, allowing the risk model to evaluate threats and consequences at a granular spatial scale rather than only at the system level.

Data Sources

Multiple geospatial datasets were integrated into the GIS-based risk model. These datasets include pipeline infrastructure data, environmental hazard data, and public infrastructure layers.

Pipeline Infrastructure Data

Pipeline infrastructure data were obtained from the operator's enterprise GIS database, specifically the Mains_e and Services_e feature classes. These datasets contain detailed attributes describing each pipeline segment including:

- Pipe material
- Installation year
- Diameter
- Joint type
- Operating pressure
- Pipe manufacturer
- Installation method
- Encased or exposed pipe condition

Each pipeline segment was assigned a unique identifier (**FacilityID**) generated using an Arcade expression within ArcGIS Pro.

Example: "MPL" + Text($feature.OBJECTID, "00000000")

This identifier allows each pipeline segment to be uniquely tracked throughout the risk analysis workflow.

Data Sources

Pipeline specification and installation attributes were compiled from multiple operational data sources maintained by the pipeline operator. These include engineering design records, field inspection reports, and enterprise GIS infrastructure databases.

The primary data sources include:

1. As-Built Engineering Drawings
2. Field Survey Data collected through ArcGIS Survey123
3. Pipeline Technician Inspection Reports
4. Enterprise GIS Pipeline Database

As-built drawings provide the original engineering specifications of the pipeline system including pipe material, diameter, installation year, joint type, and installation method. These documents represent the official construction records of the pipeline infrastructure.

Field verification data were collected by pipeline technicians using ArcGIS Survey123 mobile applications. Survey123 allows technicians to record pipeline characteristics directly in the field including pipe exposure, coating condition, installation verification, and structural anomalies. These field records are automatically synchronized with the operator's enterprise GIS environment.

All pipeline specification and installation attributes are then integrated into the operator's Geographic Information System (GIS) and stored as attributes within the pipeline feature layers (e.g., *Mains_e* and *Services_e*). These GIS layers serve as the central database for the Distribution Integrity Management Program (DIMP) risk modeling framework.

Pipe Specification Parameters

Pipe specification parameters describe the engineering characteristics of each pipeline segment. These parameters influence the structural integrity and failure susceptibility of the pipeline. The following attributes are extracted from the GIS database and incorporated into the DIMP risk model:

Parameter	Description	Data Source
Pipe Material (PipeMat)	Material type such as Plastic (PE) or Steel	As-Built Drawings
Manufacturer	Manufacturer of pipe segments	Engineering records
Pipe Size	Diameter of pipeline	As-Built Drawings
Pipeline Wall Thickness	Pipe wall thickness	Engineering specifications
Installation Year	Year the pipe was installed	As-Built Drawings

These parameters are used to evaluate material susceptibility to corrosion, mechanical failure, and long-term degradation. For example, plastic pipelines such as **Polyethylene (PE)** may exhibit different corrosion behavior compared to steel pipelines, which require cathodic protection systems to mitigate corrosion risks.

Pipe Installation Parameters

Pipe installation characteristics influence the structural reliability and environmental exposure of pipeline infrastructure.

The installation attributes integrated into the risk model include:

Parameter	Description
Pipeline Join Type	Butt fusion or electrofusion joints
Installation Method	Direct burial or encased installation
Pipeline Length	Length of pipe segment in feet or miles
Exposure Condition	Whether pipe is exposed or buried
Depth of Cover	Burial depth relative to ground surface
Encased Pipe	Whether pipe is protected by casing
Mapping Accuracy	Correctness of pipeline location records

These installation characteristics are critical because improperly installed pipelines are more susceptible to failures such as:

- mechanical damage
- external corrosion
- joint failure
- ground movement impacts

Integration into GIS Infrastructure

All specification and installation data are integrated into the operator's Enterprise GIS System using ESRI ArcGIS technology. The GIS database stores pipeline attributes as feature layers where each pipeline segment contains detailed attribute information. Example pipeline attributes stored in the GIS system include:

Field Name	Description
PipeMat	Pipe material type
PipeType	Pipe manufacturer type
DOTPipeSize	Diameter of pipe
PipeYr	Installation year
PipeJoin	Pipe joint type
PipeInstType	Installation method
PipeExp	Exposed pipe indicator
PipeEnc	Encased pipe indicator
MapCorrect	Mapping accuracy

These attributes are used directly within the DIMP risk model to calculate the **Pipe Factor (PipeFAC)**.

Pipe Factor Calculation

The pipe specification and installation parameters are mathematically combined to calculate a Pipe Factor (PipeFAC), which represents the structural susceptibility of the pipeline segment to failure.

The PipeFAC calculation is expressed as:

$$PipeFAC = \left(\frac{PipeMatV + PipeManfV + PipeDiamV + PipeYrV}{4}\right) \times \left(\frac{PipeJoinV + PipeInstTypeV + PipeExpV + PipeEncV}{4}\right) \times Pressure$$

Where:

Variable	**Description**
PipeMatV	Numeric risk value assigned to pipe material
PipeManfV	Risk value assigned to pipe manufacturer
PipeDiamV	Risk value associated with pipe diameter
PipeYrV	Risk value based on installation year
PipeJoinV	Risk value for pipe joint type
PipeInstTypeV	Installation method risk factor
PipeExpV	Exposure risk factor
PipeEncV	Encasement risk factor
Pressure	Operating pressure factor

These values are configurable and can be adjusted by the operator to reflect system-specific conditions.

Quality Control and Data Validation

To ensure data accuracy, pipeline attributes collected from as-built records and field surveys are validated through several quality control procedures:

1. GIS attribute validation checks
2. Field verification by pipeline technicians
3. Cross-comparison with historical construction records
4. Automated data consistency checks within ArcGIS

Any missing or incomplete information is addressed using conservative default values as recommended by DIMP risk modeling practices.

Corrosion Threat Assessment

Corrosion represents one of the most significant threats affecting the integrity of metallic pipeline systems. Corrosion-related failures may occur due to chemical, electrochemical, or environmental processes that gradually degrade pipeline materials over time. Within the Distribution Integrity Management Program (DIMP) framework, corrosion threats are evaluated using a combination of pipeline material characteristics, operational conditions, and historical leak records.

The corrosion threat model evaluates three primary corrosion mechanisms:

- External corrosion
- Internal corrosion
- Atmospheric corrosion

External corrosion occurs when buried metallic pipelines interact with corrosive soil environments, stray electrical currents, or ineffective cathodic protection systems. Internal corrosion may occur when moisture or corrosive gases are present within the pipeline system. Atmospheric corrosion typically affects exposed sections of pipeline infrastructure that are not adequately protected from environmental conditions.

To quantify corrosion risk, the DIMP risk model uses a corrosion threat function expressed as:

$$CorTHREAT = CorMatFac \times CorThrAdj \times (1 + LkCor\_MnV\_perMi)$$

Where:

Variable	Description
CorMatFac	Factor representing corrosion susceptibility based on pipeline material
CorThrAdj	Corrosion threat adjustment factor
LkCor_MnV_perMi	Leak rate per mile attributed to corrosion

The corrosion threat adjustment factor represents a weighted combination of several corrosion-related parameters, including pipe coating condition, cathodic protection effectiveness, stray current exposure, atmospheric corrosion susceptibility, and internal corrosion indicators. These parameters typically provide detailed information regarding the operational corrosion environment of the pipeline system. However, several corrosion-specific parameters were not available within the operator's GIS database for the study area. The unavailable attributes include:

- Pipe coating condition
- Cathodic protection isolation status
- Cathodic protection effectiveness
- Atmospheric corrosion susceptibility
- Presence of liquids within the pipeline
- Stray current corrosion potential

Because these datasets were unavailable, the corrosion threat adjustment factor was simplified for this study. Corrosion risk evaluation therefore relied primarily on the following available indicators:

- Pipeline material type (e.g., steel or polyethylene)
- Pipeline installation year
- Leak history associated with corrosion events
- Pipe exposure conditions

Pipeline material plays a critical role in corrosion susceptibility. Polyethylene (PE) pipelines, which represent a significant portion of modern gas distribution infrastructure, are inherently resistant to corrosion. In contrast, steel pipelines are susceptible to electrochemical corrosion processes and therefore require corrosion mitigation strategies such as cathodic protection systems.

Leak history data were incorporated into the corrosion threat analysis by calculating the corrosion leak factor per mile of pipeline. Hazardous leaks were given greater weight within the risk model to reflect their higher potential safety impact. Although the absence of detailed corrosion monitoring data introduces some uncertainty into the risk assessment, conservative assumptions were applied in accordance with recommended DIMP risk modeling practices. These assumptions ensure that corrosion risks are not underestimated within the overall pipeline integrity evaluation. Future improvements to the corrosion threat assessment framework should incorporate additional corrosion monitoring datasets, including cathodic protection survey data, coating inspection records, and stray current monitoring. Integrating these datasets within the GIS-based risk model would significantly improve the accuracy of corrosion risk prediction for gas distribution pipelines.

Natural Forces Threat Assessment

Natural forces threats represent integrity risks driven by **environmental processes and extreme events** that can impose external loads, undermine support conditions, or expose buried pipelines. Within the DIMP framework, natural forces are treated as a distinct threat category and are incorporated into the total threat score through a natural-forces threat function and an adjustment factor.

Threat Model Structure

Consistent with the DIMP risk model logic, the natural forces threat for each pipeline risk segment is computed as:

NfTHREAT=NfThrAdj×(1+LkNatForces_MnV_perMi)

Where:

- NfTHREAT = Natural forces threat score for the risk segment
- NfThrAdj = Natural forces adjustment factor (weighted consolidation of natural-forces subfactors)

- LkNatForces_MnV_perMi = leak rate per mile attributed to natural forces (when available and coded in leak history)

The natural forces adjustment factor is defined in the risk model as a weighted sum of multiple natural forces subfactors.

Data Sources

Natural forces subfactors were evaluated using GIS-based spatial overlays that integrate operator pipeline layers with authoritative hazard datasets and hydrography layers. The core pipeline dataset used for natural-forces scoring was:

- Mains_e (gas main centerlines) stored in the operator enterprise GIS environment

Natural forces inputs were derived from:

1. Flood hazard zone polygons (ArcGIS Online layer: "USA_Flood_Zone_Reduced_Set", filtered to FEMA high-risk zones)
2. Texas hydrography data (rivers/streams/waterbodies) from Texas Water Data Hub - https://txwaterdatahub.org/dataset/texas-rivers-streams-waterbodies
3. Seismic hazard polygons Downloaded from: https://www.sciencebase.gov/catalog/item/64ff91cbd34ed30c2057b539
4. Lightning hazard (extension layer) using FEMA National Risk Index tract data, filtered to "Very High" risk rating . Downloaded from: https://hazards.fema.gov/nri/data-resources

Flood Zone

Flooding elevates risk of pipeline exposure, buoyancy forces, soil saturation effects, and washout/scour. This subfactor flags pipeline segments that are located within FEMA-designated high-risk flood zones.

GIS Workflow

Flood zone scoring was implemented using the following repeatable GIS procedure:

Filter target records: In *Mains_e*, select only features where the Flood attribute is NULL (to avoid overwriting previously validated values).

Add FEMA flood zone layer: Add "USA_Flood_Zone_Reduced_Set" from the ArcGIS Online portal.

Select high-risk flood zones using *Select by Attributes* where Flood Zone equals:

- Zone A, Zone AE, Zone A99, Zone AH, Zone AO, Zone V, Zone VE

Export selected polygons as:

- "Texas_Flood_Hazard_Reduced_Set_Filtered"

Assign Flood = Yes:

- Run *Select by Location*: "Mains_e have their center in Texas_Flood_Hazard_Reduced_Set_Filtered"
- Use *Calculate Field* to assign **Flood = "Yes"** for selected mains.

Assign Flood = No:

- Run *Select by Location*: "Mains_e intersect USA_Flood_Zone_Reduced_Set"
- Invert selection (or select remaining NULLs) and set **Flood = "No"** using *Calculate Field*.

Washout

Washout potential is defined as the risk that a pipeline could be exposed, undermined, or physically washed out due to erosion/scour caused by floodwater, stream flow, or heavy runoff—especially at channel crossings and near waterbodies.

Washout scoring was applied using a crossing-focused segmentation approach that creates a localized exposure window around stream crossing points:

Download hydrography data and load River_Streams and Waterbodies layers.

Identify stream crossing points:

- Run *Intersect* between Mains and River_Streams
- Output: Stream_Intersect points (true line-line crossings).

Define washout exposure window:

- A localized exposure window of ±50 ft along the pipeline (total 100 ft) around each crossing point is used.

- Any pipeline portion within this window is flagged Washout = Yes.

Seismic Activity

Seismic ground shaking can cause joint stress, differential settlement, and infrastructure strain. Although Texas is generally less earthquake-prone, a conservative screening is performed. Seismic hazard polygons were obtained from USGS ScienceBase and filtered using the hazard attribute range_cont, selecting:

- '25 - 50', '50 - 75', '75 - 95', '> 95'

GIS Workflow

1. Load seismic hazard polygon dataset (US_ProbMMI_VI_VarVs30_poly).
2. Apply definition query using the selected range_cont classes.
3. Identify impacted mains using spatial overlay:
   - Mains intersect seismic hazard polygons (or "have their center in," depending on operator rule).

Lightning

Lightning represents a potential natural forces risk through surge effects and indirect impacts, particularly where hazard ratings are elevated.

Lightning hazard screening uses FEMA National Risk Index tract data. Tracts are filtered to:

- RISK_RATNG = "Very High"

GIS Workflow

1. Load NRI tract polygons (lightning hazard attribute available at tract level).
2. Apply definition query to retain only "Very High" risk rating tracts.
3. Select impacted pipelines:
   - Mains(pipeline dataset) within filtered NRI census tracts (spatial containment).

Frost Heave

Frost heave is a geotechnical process in which soil expands as water within the soil freezes, potentially causing upward movement or displacement of buried infrastructure. This phenomenon can impose mechanical stress on pipelines and may lead to bending, joint strain, or loss of cover in regions with prolonged freezing conditions. In this study, the frost heave factor was included conceptually within the natural forces threat framework; however, the operator's service territory is located in Texas, where prolonged ground freezing is rare and frost depth is typically minimal. Additionally, no consistent spatial dataset describing frost susceptibility or frost heave potential was available for the study area. Therefore, the frost heave subfactor was not operationalized in the GIS-based risk model and was treated as a neutral factor within the natural forces threat assessment.

Land Subsidence

Land subsidence refers to the gradual settling or sudden sinking of the Earth's surface due to subsurface movement, groundwater withdrawal, soil compaction, or geological processes. Subsidence can introduce differential settlement along pipeline alignments, which may cause pipeline deformation, stress concentrations, or structural instability. Although subsidence can represent a significant hazard in certain regions, the present study did not include a detailed subsidence analysis because a consistent and high-resolution spatial dataset describing subsidence rates within the operator's pipeline network area was not available. As a result, the land subsidence subfactor was not directly incorporated into the GIS-based threat calculation and was treated as a non-operational variable in the current risk model.

Tree-Related Damage

Tree-related damage may occur when large trees or branches fall due to storms, aging vegetation, or root instability. Such events can impact above-ground pipeline facilities or cause localized soil disturbance near buried infrastructure. While this threat category is included in some pipeline integrity models, the present study did not incorporate a quantitative tree-risk analysis because detailed spatial datasets describing tree density, vegetation type, or treefall probability were not available across the study area. In addition, much of the pipeline network analyzed in this study is located within urban or suburban environments where vegetation-related risks are generally lower compared to heavily forested regions. Consequently, the tree-related damage subfactor was not included in the final GIS-

based threat scoring.
Extreme Weather Conditions
Extreme weather events such as severe storms, high winds, heavy rainfall, and rapid temperature changes can affect pipeline systems through soil erosion, flooding, infrastructure stress, or indirect impacts from surrounding structures. Although weather-related hazards are recognized as potential contributors to pipeline integrity risk, this study did not include a dedicated extreme-weather subfactor due to the absence of a comprehensive spatial dataset describing localized weather hazard intensity across the pipeline network. Instead, weather-related impacts that could influence pipeline stability—such as flooding and washout potential—were partially addressed through the flood zone and hydrological analyses described earlier. Therefore, the general extreme weather factor was not independently modeled in the risk calculation.
Excavation Damage Threat Assessment
Excavation damage is a primary integrity threat in gas distribution systems because buried pipelines are vulnerable to third-party digging, roadway and utility construction, subdivision development, and other ground-disturbing activities. In the DIMP risk model, excavation threat is treated as a distinct category and is incorporated into total threat through an excavation threat function and an excavation adjustment factor.
Consistent with the DIMP risk model framework, the excavation damage threat for each pipeline risk segment is represented as:

ExcTHREAT=ExcThrAdj×(1+LkExDam_MnV_perMi)

Where:
- ExcTHREAT = excavation damage threat score for the risk segment
- ExcThrAdj = excavation threat adjustment factor (consolidated excavation subfactors)
- LkExDam_MnV_perMi = excavation-damage leak rate per mile (where leak history includes excavation cause codes)

The excavation adjustment factor is modeled as a weighted sum of excavation-related subfactors:

$$ExcThrAdj = (ThrExcConstActV \times w) + (ThrExcMapCorrectV \times w) + (ThrExcDoCV \times w) + (ThrExcCrossBoreV \times w)$$

This study operationalized excavation threat using two GIS-driven subfactors that were supported by consistent datasets and repeatable procedures in the operator workflow:
1. Construction activity / development intensity
2. Cross-bore potential

Construction Activity Subfactor
The objective of the construction activity subfactor is to classify pipeline segments by the relative intensity of nearby ground-disturbing work, which increases exposure to third-party excavation damage. This subfactor is expressed as a categorical value:
- HIGH
- MEDIUM
- LOW

Data Sources
Construction activity screening was performed using:
- **TxDOT Projects** geospatial dataset (Texas Department of Transportation open data portal)
- Operator pipeline mains layer: **Mains**
- Operator internal construction status attributes (Operation Status / subdivision status)

GIS Workflow (TxDOT Projects)
Step 1 — Create a 100-ft pipeline(mains) influence zone
- Create Buffer_100ft_Mains (100-ft buffer around Mains_e).

Step 2 — Identify HIGH construction activity projects
- Download/load TxDOT Projects layer.

Filter TxDOT projects using PROJ_CLASS in:
  - NEW LOCATION FREEWAY

- NEW LOCATION NON-FREEWAY
- WIDEN FREEWAY
- WIDEN NON-FREEWAY
- REHABILITATION OF EXISTING ROAD
- INTERSECTION & OPERATIONAL IMPRV
- CULVERT & STORM DRAINAGE WORK
- RAIL HWY CROSSING SIGNALS/STRUCTURES

- Run spatial relationship logic:

1. Identify TxDOT projects that intersect Buffer_100ft_Mains, then
2. Select pipeline segments where Mains_e have their center in the selected buffer zone.

- Assign:
  - ExcavConstr = "HIGH" for selected mains using Calculate Field.

Step 3 — Identify MEDIUM construction activity projects

- Filter TxDOT projects using PROJ_CLASS in:
  - OVERLAY
  - SAFETY IMPROVEMENT PROJECTS
  - CONVERT NON-FREEWAY TO FREEWAY
- Repeat the same spatial logic using Buffer_100ft_Mains
- Assign:
  - ExcavConstr = "MEDIUM" to selected mains only if the segment is not already HIGH (i.e., preserve HIGH classification).

Step 4 — Assign LOW by default

- Remaining pipeline segments not captured by the HIGH or MEDIUM conditions are assigned:
  - ExcavConstr = "LOW"

Rule-based adjustment using Operation Status

To better represent local development not captured by TxDOT projects, the construction activity subfactor was further adjusted using pipeline "Operation Status" and subdivision construction indicators maintained by the operator:

- Pipeline sections under active subdivision construction → HIGH
- Other sections under subdivision construction → MEDIUM
- Proposed (future) pipeline segments → HIGH
- Remaining segments → LOW

This combined approach improves excavation risk characterization by integrating state roadway construction activity with operator-specific development knowledge, supporting a more realistic excavation exposure classification.

Cross-Bore Potential

A cross bore is an unintended intersection where a new pipeline or boring operation penetrates an existing underground utility (often sewer laterals). Cross bores represent high-consequence excavation-related hazards because failures may occur years later during sewer cleaning or maintenance. Therefore, cross-bore potential is treated as an excavation-related subfactor in the DIMP model.

Data Inputs

- Operator pipeline mains layer: Mains

GIS Workflow

Cross-bore screening was implemented as a geometry-based proxy method using pipeline intersections and vertex logic:

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1. Identify mains intersections
   - Run Intersect on Mains_e (lines) with Mains_e (lines)
   - Output: Mains_Intersects (intersection points).
2. Generate vertices from the mains network
   - Run Feature Vertices to Points on Mains_e
   - Output: Mains_e_Vertices.

3. Filter potential cross-bore points
   - Use Select by Location:
     - Select Mains_Intersects points that intersect Mains_e_Vertices
     - Then Invert Spatial Relationship to isolate intersections that do not coincide with normal pipeline vertices/junctions.
   - Export these as Mains_e_CrossBorePoints.
4. Flag impacted mains segments
   - Select Mains_e that intersect Mains_e_CrossBorePoints.
   - Use Generate Definition Query from Selection to review only impacted mains for classification.
5. Classify cross-bore potential
   - If affected Mains_e segment length ≤ 200 ft → CrossBore = "Yes"
   - If affected Mains_e segment length > 200 ft → CrossBore = "Suspect"
   - All other pipeline segments → CrossBore = "No"

Map Correctness

Map correctness represents the positional accuracy and reliability of pipeline mapping records within the operator's GIS database. Accurate pipeline mapping is critical for preventing excavation damage because contractors, utility locators, and field technicians rely on GIS data to determine the exact location of underground infrastructure. In this study, pipeline mapping accuracy was evaluated based on the quality of the available geospatial records and construction documentation. Pipeline segments whose location information was verified using high-accuracy GPS surveys, validated as-built engineering drawings, or recent field inspections were considered to have high mapping accuracy. For such pipeline segments, the attribute MapCorrect was populated in the GIS database to indicate that the spatial representation of the pipeline is considered reliable. This designation reduces the likelihood that excavation activities will occur in close proximity to the pipeline due to inaccurate mapping information.

Pipeline segments lacking verified spatial accuracy or where mapping uncertainty exists may represent a higher excavation risk. In these cases, additional field verification or mapping improvement efforts may be recommended as part of the operator's ongoing integrity management program.

Depth of Cover

Depth of cover refers to the vertical distance between the ground surface and the top of the buried pipeline. Adequate burial depth is an important protective factor because shallow pipelines are more susceptible to damage from excavation equipment, construction activities, and surface disturbances.

Depth-of-cover information was obtained from as-built engineering drawings, construction documentation, and field inspection records collected through Survey123 and pipeline technician reports. These data were incorporated into the operator's GIS database and associated with individual pipeline segments.

For the purposes of this study, the recorded pipeline depth of cover was used to populate the Doc (Depth of Cover) attribute within the GIS dataset. Segments with insufficient burial depth may be considered more vulnerable to excavation damage and therefore may contribute to higher excavation threat scores within the DIMP risk model.

In situations where depth-of-cover information was unavailable, the pipeline segment was retained in the dataset but flagged for potential verification during future field inspections or integrity management activities.

Other Outside Force Damage Threat Assessment

Other Outside Force Damage represents pipeline integrity threats caused by external physical impacts and activities that are not captured under excavation damage, corrosion, or natural forces. In gas distribution systems, these threats often occur near transportation corridors (roads/rail), industrial activities (blasting/mining), and areas with heavy public activity. In the DIMP risk model, this category is incorporated into the total threat score through an outside-force threat term and an adjustment factor.

Threat Model Structure

Consistent with the DIMP model logic, Other Outside Force Damage is represented as:

Where:

- OoFTHREAT = threat score due to other outside forces (per risk segment)
- OofThrAdj = adjustment factor based on outside-force subfactors
- LkOthOutForce_MnV_perMi = leak rate per mile attributed to outside-force causes (if leak cause coding supports this)

The adjustment factor is a weighted combination of outside-force predictors. In this study, three operational subfactors were implemented using repeatable GIS methods supported by available datasets:

1. Road Crossing exposure (Road)
2. Rail Crossing Exposure (Rail)
3. Blasting concerns in the area

Road Crossing

Road crossings increase the probability of outside-force damage due to road construction/maintenance, vibration loading, traffic-related incidents, and repeated surface disturbance. To represent higher-impact roadway environments, this study uses TxDOT roadway inventory data with traffic volume (AADT) and functional classification to identify **high-impact roads**.

Data Sources

- TxDOT roadway inventory (2024 road network with AADT)
- Operator pipeline mains layer: **Mains**

GIS Workflow

- Acquire roadway dataset
    - Download the 2024 TxDOT road network with AADT.
- Select high-impact road classes
    - Apply a field calculation / definition query using:

$$(F\_SYSTEM \in (1,2))\ OR\ (F\_SYSTEM = 3\ AND\ NUM\_LANES \geq 4)$$

- This retains designated interstates, freeways/expressways, and principal arterials with four or more lanes.
- Export selected roads
    - Export as HighImpact_Roads.
- Generate true road crossing points
    - Use Intersect (line-line):
        - Inputs: *Mains_e (lines)* + *HighImpact_Roads (lines)*
        - Output type: POINT
    - Output: RoadCross_Pts, representing one point per crossing (e.g., observed as 22 points for the 2025 run).
- Create localized roadway impact segments (±50 ft)
    - For each crossing point, split the pipeline geometry to define an impact zone of 50 ft on both sides of the crossing (total 100 ft window).
- Attribute assignment
    - Pipeline subsegments within the impact window are flagged: RoadCrossing = “Yes”
    - All other segments are flagged: RoadCrossing = “No”

Rail Crossing

Rail crossings represent high-consequence outside-force exposure due to vibration, load cycles, rail maintenance, and potential derailment-related impacts. This factor screens pipeline segments that cross active rail corridors.

Data Sources

- North American Rail Network Lines (ESRI Living Atlas)

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- Operator pipeline mains layer: Mains

GIS Workflow

- Basemap requirement
  - Use an imagery basemap during rail verification to reduce misclassification due to outdated or misaligned rail geometry.
- Load and filter rail network
  - Add North American Rail Network Lines and exclude abandoned/out-of-service/trail lines using:

$$NOT(NET =' A' \ OR \ NET =' R' \ OR \ NET =' X' \ OR \ NET =' T')$$

- Generate true rail crossing points
  - Use Intersect (line-line):
    - Inputs: *Mains_e (lines)* + *Filtered Rail Lines (lines)*
    - Output type: POINT
  - Output: RailCross_Pts (e.g., observed as 6 points for the 2025 run).
- Split pipeline segments at rail impact zone (±50 ft)
  - Split 50 ft on each side of the crossing along the pipeline centerline (100 ft window).
- Attribute assignment
  - Subsegments within the rail impact window are flagged: RailCrossing = "Yes"
  - Remaining segments: RailCrossing = "No"

Blasting Concerns

Blasting and mining operations can produce ground vibration and localized geotechnical disturbances, increasing the likelihood of pipeline stress, displacement, or mechanical damage. This "extension" factor screens pipelines that intersect or lie near mapped mining operation sites.

Data Sources

- USGS MRDS (Mineral Resources Data System): mining and mineral site locations
- Operator pipeline mains layer: Mains_e

GIS Workflow

- Download MRDS dataset and load into GIS.
- Filter to relevant operation types using definition query:
  - oper_type = 'Surface' OR 'Surface-Underground' OR 'Underground' OR 'Unknown'
- Create operation-type buffers
  - Create 500 ft buffer around sites with Unknown oper_type (treated as uncertain → higher caution).
  - Create 500 ft buffer around the remaining operation types.
- Spatial classification of blasting concern
  - If Mains_e intersects Unknown buffer → BlastingConcern = "Suspect"
  - If Mains_e intersects other buffer → BlastingConcern = "Yes"
  - Otherwise → BlastingConcern = "No"

Tree and Ice Damage

Tree and ice-related damage represents a potential outside force threat where falling trees, large branches, or heavy ice accumulation may impact exposed pipeline components such as above-ground facilities, regulators, and service risers. This type of hazard is more common in regions that experience severe winter storms or dense forest cover. In this study, the ThrOofTreeIce factor was included in the DIMP threat framework; however, no consistent spatial dataset was available to quantify tree density, ice loading risk, or storm-related treefall exposure across the study area. In addition, the operator's service territory in Texas experiences relatively limited ice accumulation compared to northern regions. Therefore, this subfactor was not operationalized in the GIS-based risk model and was treated as a neutral factor in the threat scoring process.

Vehicular or Vandalism Damage

Vehicular impact and vandalism represent potential external threats where pipelines or associated infrastructure may be damaged by vehicle collisions, unauthorized activities, or deliberate interference.

These events typically occur near roadways, parking areas, or locations where pipeline facilities are accessible to the public. The ThrOofVanVeh factor was considered within the DIMP threat structure; however, the study did not have access to a comprehensive dataset describing historical vandalism incidents or vehicular impact events within the operator's GIS database. Because reliable spatial data for these events were not available, this subfactor was not directly included in the spatial risk calculations. Future improvements to the risk model could incorporate incident records, damage reports, or operator maintenance logs to better represent this category of outside-force risk.

Material / Weld Failure

Material and weld failures represent potential threats to pipeline integrity that originate from defects in pipe manufacturing, welding processes, or mechanical damage occurring during construction or operation. Manufacturing defects may include imperfections in pipe material, wall thickness inconsistencies, or flaws introduced during pipe production. Construction or workmanship defects may arise from improper welding techniques, inadequate joint preparation, or poor installation practices. Mechanical damage can occur when pipelines experience external forces during construction activities or subsequent ground disturbances.

Although these factors are recognized components of the DIMP threat framework, this study did not incorporate detailed material or weld defect analysis because consistent datasets describing manufacturing defect records, weld inspection reports, or mechanical damage assessments were not available within the operator's GIS database. Such information is typically obtained through non-destructive testing records, construction inspection reports, or historical maintenance documentation, which were outside the scope of the available datasets used in this study.

As a result, the material and weld failure subfactors were not operationalized within the GIS-based risk model and were treated as neutral variables in the threat calculation. Future improvements to the risk model could incorporate detailed pipeline inspection records, welding quality documentation, and integrity assessment reports to better evaluate the influence of manufacturing, construction, and mechanical defect risks on pipeline integrity.

Equipment Failure Threats

Equipment failure refers to the malfunction or breakdown of components within the gas distribution system such as valves, regulators, relief devices, fittings, and other mechanical equipment used to control pressure and gas flow. These components play an essential role in maintaining safe and reliable pipeline operations, and failures may occur due to mechanical wear, aging infrastructure, improper installation, or inadequate maintenance. Although equipment-related failures are recognized as a potential threat within the Distribution Integrity Management Program (DIMP) framework, this study did not incorporate detailed equipment failure analysis because no consistent dataset describing equipment condition, inspection records, or malfunction history was available within the operator's GIS database. As a result, equipment failure threats were not operationalized in the GIS-based risk model and were treated as a neutral factor within the overall threat assessment. Future improvements to the model could incorporate equipment inspection and maintenance records to better evaluate the impact of equipment performance on pipeline integrity.

Incorrect Operation Threats

Incorrect operation refers to pipeline incidents that occur due to human error, inadequate procedures, or failure to follow established operational and safety practices. Examples may include improper system operation, incorrect valve manipulation, inaccurate monitoring, or failure to follow standard operating procedures during maintenance or emergency response activities. Within the Distribution Integrity Management Program (DIMP) framework, incorrect operation is considered a potential threat category because operational mistakes can lead to gas releases, pressure imbalances, or damage to pipeline infrastructure. However, this study did not incorporate a detailed analysis of incorrect operation factors because no comprehensive dataset describing operational errors, procedural violations, or incident reports related to operator performance was available within the operator's GIS database. Since the available data primarily focused on pipeline infrastructure attributes rather than operational records, the incorrect operation threat category was not operationalized in the GIS-based risk model and was treated as a neutral factor within the overall threat assessment.

Other Threats

In addition to the primary threat categories described in the previous sections, other potential threats may affect the integrity of gas distribution systems. These may include emerging risks, uncommon operational conditions, or site-specific hazards that are not easily classified within the standard DIMP threat categories such as corrosion, natural forces, excavation damage, equipment failure, or incorrect operation. Examples may include localized environmental conditions, unknown historical construction issues, or other unforeseen external influences.

In the present study, no additional datasets or documented records were available to identify or quantify other potential threats beyond the previously analyzed categories. As a result, this threat category was not operationalized within the GIS-based risk model. The absence of reliable data prevented the assignment of quantitative risk values for these factors. Therefore, other threats were treated as neutral within the overall threat assessment framework. Future enhancements to the risk model may incorporate additional datasets, incident reports, or advanced monitoring information to better capture uncommon or emerging threats that could influence pipeline integrity and system safety.

Consequence of Failure Assessment

The consequence of failure (CoF) component of the pipeline risk model evaluates the potential impact that a pipeline failure may have on surrounding populations, infrastructure, and environmental resources. While threat analysis focuses on the probability of pipeline failure, consequence analysis estimates the severity of potential impacts should a failure occur. The consequence assessment in this study incorporated several spatial factors including population density, proximity to critical buildings, proximity to public buildings, environmental sensitivity, surface cover characteristics, and isolation capability. These variables were derived using GIS-based spatial analysis techniques and integrated into the distribution integrity management risk model.

Population Density Analysis

Population density is one of the most important indicators in consequence analysis because pipeline failures occurring in densely populated areas can affect a larger number of people and infrastructure. To evaluate population exposure, populated area datasets were obtained from the National Pipeline Mapping System (NPMS) maintained by the Pipeline and Hazardous Materials Safety Administration. Two datasets representing populated areas were downloaded and merged:

- HPA (High Population Areas)
- OPA (Other Population Areas)

The merged dataset was named Populated_Areas and used as the spatial reference layer for population analysis.

The classification process was performed using spatial selection operations in GIS:

1. Pipeline segments whose center points fall within Populated_Areas were classified as High population density.
2. Pipeline segments that intersect Populated_Areas but whose center points fall outside were classified as Medium population density.
3. Remaining pipeline segments located outside populated areas were classified as Low population density.

This classification approach allows the risk model to differentiate between pipeline segments located fully within populated zones and those located near populated areas.

Proximity to Critical Buildings

Another important consequence factor is the presence of difficult-to-evacuate facilities, commonly referred to as critical buildings. These facilities include locations where rapid evacuation may be difficult or where vulnerable populations are present. Examples include hospitals, schools, nursing homes, and correctional facilities.

Critical building locations were identified using building footprint data obtained from OpenStreetMap (OSM) and additional critical infrastructure datasets. Buildings were filtered using attribute queries to select facilities representing critical infrastructure categories including:

- Hospitals
- Medical clinics
- Nursing homes

- Schools and kindergartens
- Prisons and correctional facilities

The filtered dataset was exported as Critical_Buildings_Texas_DIMP.
To evaluate the potential impact zone:

1. A 100-foot buffer was created around pipeline segments (Buffer_100ft_Mains_e).
2. Critical buildings intersecting this buffer were identified using Select by Location.
3. A 100-foot buffer was then generated around the selected critical buildings.
4. Pipeline segments falling within this buffered area were split and assigned the attribute ConsqCritcalBuild = Yes.
5. All remaining pipeline segments were assigned ConsqCritcalBuild = No.

This analysis identifies pipeline segments whose potential failure zones could directly affect critical facilities.

Proximity to Public Buildings

Public buildings represent another category of infrastructure that may be affected by pipeline incidents. These facilities typically serve community functions and may experience high occupancy during normal operations. Examples include government buildings, libraries, fire stations, and police facilities.
Public building locations were extracted from the OpenStreetMap building dataset using attribute filters for building types such as:

- Courthouses
- Town halls
- Government offices
- Post offices
- Police stations
- Fire stations
- Libraries
- Museums
- Community centers

The filtered dataset was exported as Public_Buildings_Texas.
The proximity analysis followed a similar procedure as the critical building analysis:

1. Identify public buildings intersecting the Buffer_100ft_Mains_e layer.
2. Create a 100-foot buffer around selected public buildings.
3. Split pipeline segments that fall within the buffered zones.
4. Assign ConsqPubBuild = Yes for impacted pipeline segments.
5. Assign ConsqPubBuild = No for segments outside the influence zone.

This analysis allows the risk model to capture potential impacts on community infrastructure.

Environmental Sensitivity

Environmental impact is another important factor in consequence analysis. Pipeline failures occurring near environmentally sensitive areas may result in ecological damage, contamination of water bodies, or habitat disruption.
Environmental sensitivity was evaluated using land cover datasets derived from the National Land Cover Database (NLCD). Raster land cover data were downloaded and converted into polygon format for spatial analysis. Wetland categories were extracted from the dataset by selecting the following classes:

- Emergent Herbaceous Wetlands
- Woody Wetlands

The selected polygons were exported as Texas_Land_Cover_Wetlands.
Pipeline segments were evaluated using a spatial selection procedure:

- Pipeline segments whose center points fall within the wetlands layer were assigned Environment = Yes.
- All remaining pipeline segments were assigned Environment = No.

This classification identifies pipeline segments that may pose environmental risks in the event of a failure.

Surface Cover Classification

Surface cover conditions surrounding pipeline infrastructure influence both accessibility and the potential impact of pipeline failures. Different land cover types may represent varying levels of infrastructure density, human activity, and environmental exposure.

Land cover data from the Annual NLCD dataset were used to classify surface cover types into categories compatible with the DIMP risk model. The raster dataset was converted into polygon format and spatially joined with pipeline segments using the Select by Location tool. Surface cover categories were interpreted as follows:

Land Cover Type	Surface Cover Category	Risk Interpretation
Developed High / Medium Intensity	Concrete	Dense urban environments
Developed Low Intensity	Driveway / Parking	Residential development areas
Forest, Grassland, Agricultural	Grass / Soil	Natural or vegetated surfaces
Water / Barren / Other	Other	Non-standard surface conditions

Pipeline segments were assigned surface cover classifications based on the land cover polygon in which their center points were located.

Overbuilding

Overbuilding occurs when a structure is constructed directly above an existing pipeline, creating significant safety and operational risks. Such conditions can restrict access to the pipeline for inspection, maintenance, and emergency response, and may increase the potential consequences of a pipeline failure. In this study, an overbuilding analysis was conducted by performing a spatial intersection between the mains pipeline layer (Mains) and building footprint datasets obtained from OpenStreetMap. The objective of this analysis was to identify any buildings located directly above pipeline segments within the distribution system.

The results of the spatial analysis indicated that no overbuilding conditions were detected within the study area. None of the pipeline segments intersected building footprints in a manner that would indicate that a structure had been constructed directly over the pipeline alignment. Therefore, the attribute ConsqOvrBuild was assigned as “No” for all pipeline segments in the dataset. This finding suggests that current pipeline corridors remain free from structural encroachments that could complicate maintenance access or increase the severity of potential failure impacts.

Isolation Capability

Isolation capability refers to the ability of pipeline operators to quickly isolate a section of the pipeline system in the event of a leak or failure. Rapid isolation is critical for minimizing the volume of gas released, reducing potential hazards to nearby populations, and limiting damage to surrounding infrastructure and environmental resources. Isolation capability is typically determined based on the availability and accessibility of valves within the pipeline network, as well as the operational procedures established by the pipeline operator for emergency response.

In this study, the isolation capability for the analyzed pipeline segments was evaluated based on the operator’s standard operational procedures and system configuration. The analysis determined that all pipeline segments could be isolated in a timely manner using existing valve infrastructure and response procedures. As a result, the attribute was assigned the value “Timely” for all segments in the dataset. This indicates that, in the event of a pipeline failure, operators would be able to promptly isolate the affected pipeline section and mitigate the potential consequences of the incident.

Leak Data Integration

Leak history is an important indicator used in pipeline integrity management because past failures often reveal underlying threats to pipeline infrastructure. The last 5 years leak dataset was used to evaluate historical leak occurrences across the distribution network. Leak events were categorized by their cause, including corrosion, natural forces, excavation damage, other outside force damage, material or weld failure, equipment failure, incorrect operations, and other causes. By analyzing the frequency and cause of leaks across pipeline segments, the model helps identify locations where failures have historically occurred and where similar issues may arise in the future.

In the DIMP risk model, leak data are incorporated into the risk calculation by converting the number of leaks into a leak factor per mile of pipeline. Hazardous leaks are given greater importance in the calculation because they represent more serious safety risks. The methodology multiplies hazardous leaks by a weighting factor before combining them with non-hazardous leaks to determine the total leak count used in the model. This leak factor is then integrated into the threat calculations for each category, allowing historical leak trends to influence the overall threat score assigned to each pipeline segment.

Risk Model Formulation

The DIMP risk model calculates pipeline risk using a structured mathematical framework that combines pipeline characteristics, threat factors, leak history, and consequence of failure indicators. The overall concept follows a widely used risk principle where Risk = Threat × Consequence. In this model, the total risk for a pipeline segment is derived from several intermediate calculations that consider both the likelihood of failure and the potential impact of that failure.

First, the Total Threat score is calculated by combining eight major threat categories: corrosion, natural forces, excavation damage, other outside forces, material or weld failure, equipment failure, incorrect operations, and other threats. Each threat category is multiplied by a configurable weighting factor that reflects its relative importance. This approach allows operators to adjust the model according to local conditions, operational experience, and regulatory requirements.

Second, the model calculates a Pipe Factor, which represents the inherent physical characteristics of the pipeline. This factor incorporates parameters such as pipe material, manufacturer, diameter, installation year, joint type, installation method, exposure conditions, and operating pressure. These attributes influence the overall structural reliability of the pipeline and therefore affect its likelihood of failure.

The model also calculates a Consequence Factor that estimates the potential impact if a pipeline failure occurs. This component considers several spatial and environmental variables, including population density, proximity to critical buildings (such as hospitals and schools), proximity to public buildings, environmental sensitivity, surface cover conditions, overbuilding situations, and the ability to isolate the pipeline quickly in case of an emergency.

Finally, the overall Risk Segment Score is calculated by combining the total threat score, pipe factor, and consequence factor along with an additional multiplier that accounts for the presence of unrepaired leaks near the pipeline. This value is normalized per mile of pipeline and aggregated to produce the final risk score for each pipeline segment. The resulting scores allow operators to compare risk levels across the entire pipeline network and prioritize inspection, maintenance, and mitigation activities accordingly.

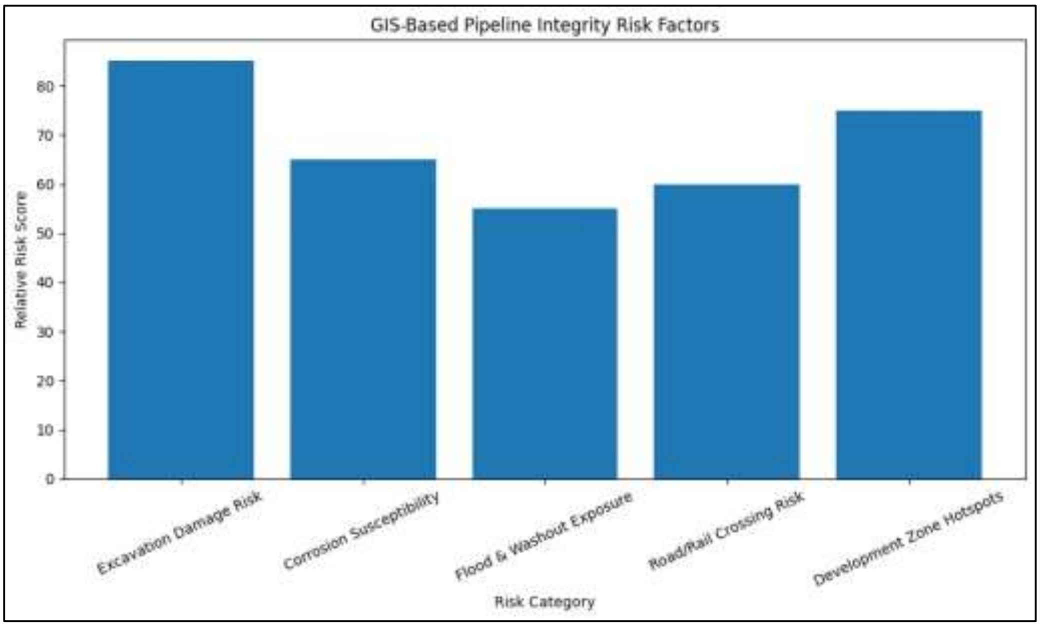
FINDINGS

The GIS-based risk modeling framework developed in this study successfully identified spatial patterns of pipeline integrity risk across the distribution network. By integrating pipeline asset data with environmental datasets and infrastructure information within a Geographic Information System, the model enabled the evaluation of multiple threat categories including natural forces, excavation damage, and other outside force impacts. The resulting risk scores provide a spatially explicit representation of potential pipeline vulnerabilities, allowing operators to visualize and prioritize high-risk pipeline segments for monitoring and maintenance activities.

The spatial distribution of risk values indicates that pipeline segments located within developing areas generally exhibit higher risk scores compared to segments located in already settled regions. This pattern is largely attributed to increased excavation activity associated with roadway construction, utility installation, and new development. Areas experiencing rapid infrastructure expansion showed a higher concentration of pipeline segments classified under elevated excavation risk categories. The proximity of pipelines to major transportation corridors and construction projects further increased the probability of third-party damage, which is consistent with previous research indicating that excavation activities remain one of the leading causes of pipeline incidents in distribution systems.

The corrosion susceptibility component of the analysis identified several clusters of pipeline segments located in environmental conditions that may promote corrosion-related degradation. Although detailed soil chemistry datasets were not available for the entire study area, available environmental indicators and historical leak information suggested that certain locations may experience higher corrosion risk. Pipeline segments located in areas with higher soil moisture content, potential acidic soil conditions, or long operational histories were observed to exhibit relatively higher corrosion-related risk scores. These segments may benefit from additional inspection programs, improved corrosion monitoring, or enhanced cathodic protection measures.

Figure 7: GIS-Based Pipeline Integrity Risk Factors



Natural forces analysis also contributed to identifying localized areas of elevated risk within the pipeline network. Flood hazard analysis indicated that several pipeline segments intersect FEMA-designated flood zones, which increases the potential for washout, soil erosion, or exposure of buried infrastructure during extreme rainfall events. Similarly, the washout analysis performed at stream crossings identified several localized exposure zones where pipelines intersect river and stream channels. These locations represent potential areas of structural stress or pipeline exposure due to hydraulic erosion or flood-related scouring.

The road and rail crossing analyses further highlighted pipeline segments that may experience elevated outside-force risks. Pipeline crossings beneath high-impact roadways and active rail corridors were identified using spatial intersection techniques. These crossing locations represent areas where pipelines may be exposed to mechanical stresses associated with transportation infrastructure, such as ground vibration, heavy traffic loads, or maintenance activities. By isolating these crossings and applying localized segmentation around the impact zones, the model was able to accurately represent the spatial extent of transportation-related risk exposure.

Hotspot patterns generated through the spatial risk model revealed clusters of elevated pipeline risk primarily concentrated within new development zones and areas experiencing ongoing construction activity. These clusters were particularly visible near expanding suburban areas, major roadway corridors, and regions undergoing infrastructure development. The identification of these risk clusters demonstrates the capability of GIS-based analysis to detect spatial concentrations of pipeline integrity threats that may not be immediately visible using traditional inspection-based assessment approaches.

Overall, the results demonstrate that integrating GIS spatial analysis techniques with pipeline integrity management frameworks provides a powerful tool for evaluating infrastructure risk. The model enables operators to visualize spatial risk patterns, prioritize high-risk pipeline segments, and allocate maintenance resources more effectively. The findings of this study highlight the value of geospatial analytics in supporting proactive infrastructure management and improving the safety and reliability of natural gas distribution systems.

DISCUSSION

The findings of this study demonstrate that integrating Geographic Information Systems (GIS) with pipeline integrity management frameworks significantly enhances the ability of pipeline operators to evaluate and manage infrastructure risks. Traditional pipeline risk assessment approaches often rely on engineering inspection reports, historical incident records, and manual data analysis. While these approaches remain important, they can be limited in their ability to analyze large spatial datasets and identify geographic patterns of risk across extensive pipeline networks. The GIS-based framework developed in this research provides a scalable and efficient platform for integrating multiple datasets, including pipeline attributes, environmental conditions, infrastructure development patterns, and transportation networks. By combining these data sources within a spatial analysis environment, the system enables more comprehensive and geographically informed risk assessments.

One of the key advantages of GIS-based risk modeling is its ability to reveal spatial relationships between pipeline infrastructure and external risk factors. The results of this study indicate that excavation-related threats tend to be concentrated in areas experiencing rapid infrastructure development and construction activity. These findings highlight the importance of monitoring pipeline systems located in expanding urban and suburban environments, where road construction, utility installation, and land development frequently occur. GIS allows operators to overlay pipeline locations with construction datasets, roadway inventories, and land use patterns, making it possible to identify areas where pipelines are exposed to increased excavation risk. This spatial perspective improves situational awareness and allows operators to implement targeted mitigation strategies in areas where excavation damage is more likely to occur.

The analysis also illustrates the importance of considering environmental conditions when evaluating pipeline integrity risks. Natural forces such as flooding, erosion, and washout can significantly affect pipeline stability, particularly at river crossings and within flood-prone regions. By incorporating FEMA flood hazard datasets and hydrographic information into the GIS-based model, this study was able to identify pipeline segments that may be exposed to increased hydraulic stress during extreme rainfall events. These findings suggest that environmental hazard data should be systematically integrated into pipeline integrity programs in order to improve the identification of areas where pipelines may be vulnerable to natural forces.

Another important implication of this research is the role of GIS technology in supporting proactive infrastructure management. Instead of relying solely on fixed inspection schedules, operators can use spatial risk models to prioritize maintenance and monitoring activities based on risk levels. For example, pipeline segments located near major transportation corridors, construction zones, or flood-prone areas can be flagged for additional inspection or preventive maintenance. This risk-based approach aligns with modern infrastructure management practices that emphasize predictive analytics and data-driven decision making. By focusing resources on the highest-risk segments of the network, operators can improve the efficiency of maintenance programs while reducing the likelihood of pipeline failures.

The results of this study also demonstrate the value of integrating field data collection tools with GIS-based risk models. Information collected by pipeline technicians through mobile applications such as Survey123 and Field Maps can be directly incorporated into the geospatial database, ensuring that pipeline attribute information remains current and accurate. This integration allows operators to continuously update risk models as new data become available, creating a dynamic infrastructure monitoring system that evolves over time. The ability to combine real-time field observations with spatial analytics represents a significant advancement in pipeline integrity management.

Despite the advantages of the GIS-based framework presented in this study, several limitations should be acknowledged. Certain threat categories, including equipment failure, incorrect operation, and some environmental factors, could not be fully incorporated into the risk model due to the absence of consistent datasets describing these variables. Additionally, detailed soil chemistry data and corrosion monitoring information were not available for all pipeline segments. While the current model still provides valuable insights into spatial risk patterns, future research could enhance the accuracy of risk predictions by integrating additional datasets such as cathodic protection survey results, pipeline inspection records, and detailed environmental monitoring information.

Future developments in geospatial technology and data analytics may further improve pipeline risk assessment methodologies. Emerging techniques such as machine learning, remote sensing, and real-time sensor monitoring could be integrated with GIS platforms to develop predictive models capable of identifying potential failure locations before incidents occur. These advanced analytical tools have the potential to transform pipeline integrity management by enabling operators to move from reactive maintenance strategies toward fully predictive infrastructure management systems.

Overall, this study demonstrates that GIS-based spatial risk modeling provides a valuable decision-support tool for pipeline operators. By integrating engineering data, environmental information, and infrastructure datasets within a unified analytical framework, GIS enables more comprehensive assessments of pipeline integrity threats. The results highlight the importance of geospatial analytics in supporting safer, more efficient, and more resilient natural gas distribution systems.

CONCLUSION

This study demonstrates the effectiveness of integrating Geographic Information Systems (GIS) with pipeline integrity management frameworks to improve the identification and evaluation of risks within natural gas distribution networks. Traditional integrity management approaches often rely heavily on inspection reports, historical incident data, and engineering judgment. While these approaches remain valuable, they may not fully capture the spatial relationships between pipeline infrastructure and external environmental or operational factors. The GIS-based risk modeling framework developed in this research addresses this limitation by combining pipeline asset data, environmental datasets, and infrastructure development information within a unified geospatial analytical environment.

The results of the study indicate that spatial risk modeling provides valuable insights into the geographic distribution of pipeline integrity threats. By incorporating spatial datasets such as flood hazard zones, stream crossings, roadway infrastructure, rail corridors, and construction activity, the model was able to identify specific pipeline segments that may be exposed to elevated risk levels. The analysis revealed that pipeline segments located within rapidly developing areas or near major transportation infrastructure tend to experience higher excavation-related risks due to increased construction activity and ground disturbance. Similarly, pipeline segments intersecting flood-prone regions or water crossings were identified as locations where natural forces could potentially affect pipeline stability through erosion, washout, or soil displacement.

The corrosion analysis component also demonstrated the potential of spatial modeling to support infrastructure maintenance strategies. Although detailed soil chemistry data were not available for the entire study area, the integration of environmental indicators and historical leak information allowed the identification of pipeline segments that may be more susceptible to corrosion-related degradation. These findings suggest that GIS-based modeling can assist operators in identifying areas where additional corrosion monitoring, inspection programs, or cathodic protection systems may be necessary.

Another important contribution of this research is the demonstration of how GIS-based risk modeling can support proactive decision making in infrastructure management. Rather than relying solely on fixed inspection schedules, pipeline operators can use spatial risk models to prioritize monitoring and maintenance activities based on the relative risk levels of different pipeline segments. This risk-based approach allows operators to allocate resources more efficiently, focusing inspection and maintenance efforts on areas where pipeline failures are more likely to occur. By improving the targeting of maintenance activities, GIS-based risk modeling has the potential to enhance both the safety and reliability of natural gas distribution systems.

The study also highlights the importance of integrating field-collected data into pipeline integrity management systems. Information gathered by field technicians through mobile GIS applications such as Survey123 and Field Maps can be incorporated directly into the geospatial database, allowing operators to maintain up-to-date pipeline attribute information. This integration between field data collection and spatial analysis enables continuous improvement of the risk model and ensures that infrastructure management decisions are based on the most current available data.

Despite the valuable insights generated by the GIS-based risk modeling framework, certain limitations should be acknowledged. Some threat categories, including equipment failure, incorrect operation, and certain environmental factors such as frost heave or land subsidence, could not be fully analyzed due to the absence of comprehensive datasets describing these variables. In addition, detailed soil property datasets and advanced corrosion monitoring data were not available for the entire pipeline network. While these limitations did not prevent the development of the spatial risk model, incorporating additional datasets in future studies could further enhance the accuracy and reliability of pipeline risk assessments.

Overall, the findings of this study demonstrate that GIS-based spatial analysis provides a powerful tool for improving pipeline integrity management programs. By integrating engineering, environmental, and infrastructure data within a geospatial framework, operators can gain a more comprehensive understanding of pipeline risk patterns and make more informed decisions regarding inspection, maintenance, and infrastructure planning. The approach presented in this research contributes to the ongoing development of data-driven infrastructure management strategies aimed at improving the safety, reliability, and resilience of natural gas distribution systems.

RECOMMENDATIONS

Although the GIS-based risk modeling framework developed in this study provides a valuable tool for evaluating pipeline integrity risks, several opportunities exist for future research and model improvement. Expanding the availability and integration of additional datasets could significantly enhance the predictive capabilities of the spatial risk model and provide a more comprehensive understanding of pipeline integrity threats.

One important area for future research involves the integration of detailed environmental datasets related to soil chemistry, moisture content, and electrical conductivity. These variables play a significant role in influencing corrosion rates in buried pipelines. Incorporating high-resolution soil property datasets from sources such as the United States Department of Agriculture (USDA) Soil Survey Geographic Database (SSURGO) could improve the accuracy of corrosion susceptibility assessments. Future models could combine soil data with pipeline material characteristics and cathodic protection system performance to generate more precise corrosion risk predictions.

Another promising direction for future research involves the integration of machine learning and predictive analytics techniques into GIS-based pipeline risk models. By analyzing historical incident data, maintenance records, and environmental variables, machine learning algorithms could be trained to identify patterns associated with pipeline failures. These predictive models could help operators anticipate potential failure locations before incidents occur, enabling more proactive infrastructure management strategies. The combination of spatial analysis and artificial intelligence techniques has the potential to significantly improve risk prediction accuracy and enhance pipeline safety.

Future research could also explore the use of remote sensing and advanced monitoring technologies for pipeline integrity assessment. Satellite imagery, aerial LiDAR data, and unmanned aerial systems (UAS) can provide valuable information regarding land surface changes, vegetation growth, erosion patterns, and infrastructure development near pipeline corridors. Integrating these datasets with GIS-based risk models could allow operators to monitor environmental changes that may affect pipeline stability and identify emerging risks in near real-time.

Another important recommendation involves improving the integration of field inspection data with enterprise GIS systems. Mobile data collection tools such as Survey123, Field Maps, and other mobile GIS platforms allow field technicians to collect inspection observations, photographs, and infrastructure condition assessments directly in the field. Future integrity management systems should emphasize the development of standardized data collection protocols that allow these field observations to be seamlessly integrated into centralized geospatial databases. This approach would improve data accuracy, reduce reporting delays, and ensure that pipeline risk models are continuously updated with current information.

Additional improvements to the risk modeling framework could also be achieved by incorporating more detailed operational datasets related to equipment performance, pressure monitoring, and maintenance history. For example, integrating pressure monitoring data from Supervisory Control and Data Acquisition (SCADA) systems could allow operators to identify abnormal pressure patterns that may indicate pipeline integrity concerns. Similarly, maintenance records related to valves, regulators, and other system components could provide valuable insights into equipment reliability and failure risks.

Finally, future studies should consider expanding the spatial scope of GIS-based pipeline risk modeling to evaluate infrastructure resilience at regional or national scales. As natural gas distribution networks continue to expand and urban development increases near pipeline corridors, understanding the spatial distribution of pipeline risks will become increasingly important for infrastructure planning and public safety. GIS-based modeling approaches provide a scalable framework that can support large-scale infrastructure risk assessments and help inform regulatory policy, safety standards, and long-term infrastructure investment strategies.

In summary, continued research and technological development in GIS-based infrastructure risk modeling has the potential to significantly enhance pipeline integrity management programs. By integrating geospatial analysis, environmental monitoring, predictive analytics, and real-time field data collection, future systems can provide more accurate, dynamic, and proactive assessments of pipeline integrity risks. These advancements will play an important role in supporting safer and more resilient energy infrastructure systems in the future.

LIMITATION

This study has several limitations primarily related to data availability and model assumptions. The GIS-based risk assessment framework relied on available environmental indicators, historical leak records, and infrastructure datasets, which may not fully represent all site-specific conditions influencing pipeline integrity. In particular, the absence of comprehensive soil chemistry data and detailed corrosion monitoring records limited the precision of corrosion susceptibility analysis. Additionally, the model used spatial proxies and generalized risk scoring approaches that may not capture the full complexity of pipeline degradation mechanisms or operational variability across all pipeline segments.

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