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Independent Technical Evaluation and Modernization of a Transmission Integrity Management Risk Model: An Anonymized TIMP Risk-Assessment Case Study

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Abstract

This study evaluates the technical adequacy, internal consistency, current applicability, and modernization needs of a transmission integrity management risk framework using five anonymized artifacts: Transmission Integrity Management Program (TIMP), TIMP risk-assessment methodology, TIMP risk-model workbook, a transmission class-analysis procedure, and a structure-code dictionary. The assessment combined structured document review, formula-level reverse engineering, independent recalculation of all available route and segment metrics, HCA/MCA/class-location reconciliation, operational GIS-method assimilation, descriptive diagnostics, rank-correlation analysis, and comparison with current federal and Texas requirements and peer-reviewed pipeline-risk literature. The program documents establish several sound governance principles, including conservative treatment of missing data, periodic review, subject-matter-expert review, management of change, quality assurance, and use of risk ranking to prioritize integrity activities. The implemented workbook, however, is a dimensionless relative-risk index rather than a probabilistic failure or consequence model. It contains 594 dynamic risk segments across 11 routes and 11.7998 miles of coated-steel legacy pipeline, materially narrower than the 2024 TIMP portfolio description of approximately 103.66 miles across 30 systems containing steel and high-density polyethylene. The consequence-area review found that the program defines HCA and MCA identification processes, reports 18 HCAs totaling approximately 3.59 miles, and includes 28 MCA and 20 HCA segment entries in its portfolio table; however, another program passage reports 16 HCA segments, and the supplied materials do not reconcile these counting bases. The operational GIS procedure provides a practical workflow based on separate class-location and PIR/PIC geometries, structure inventory, a cluster boundary adjustment, HCA/MCA flags, and map outputs. Its integration requires controls because 660 feet is incorrectly labeled as 220 meters, the cluster provision is described too broadly, several structure codes combine distinct class and identified-site tests, multi-family dwelling counts are not explicit, MCA roadway evidence is not operationalized, and blank values cannot distinguish No, Unknown, and Not evaluated. The workbook itself contains no MCA status, PIR/PIC, identified-site, qualifying-roadway, or HCA-method field and treats HCA as a mutually exclusive ordinal population category alongside Classes 1-3. HCA-labeled workbook segments represent 8.63% of modeled mileage but 15.20% of total risk, with a length-weighted risk density of 21.90 compared with 12.36 for Class 3; the difference is driven primarily by consequence and pipe factors rather than higher mean threat. Routes 6, 10, and 8 account for 56.9% of the workbook total-risk index. The workbook route "risk per mile" sums segment risk-density indices and is therefore strongly segmentation dependent (Pearson r = 0.925); a length-weighted aggregation changes rankings materially (Spearman rank correlation = 0.418). Multiple threat categories are effectively static, the leak-history window ends in June 2016 with no nonzero leak inputs, several within-category weights do not sum to 1.00, and an additive longitudinal factor appears in implemented PipeFAC but not in the methodology. The legacy model remains useful as a transparent triage tool for the limited asset subset it represents, and the operational GIS procedure can be retained as the evidence-production layer after controlled revision.

Keywords

Transmission Integrity Management; Pipeline Risk Model; High Consequence Area; Moderate Consequence Area; Class Location; Potential Impact Radius; GIS Procedure;

INTRODUCTION

Transmission pipeline integrity management is a decision system rather than a single inspection program. It links asset information, threat identification, risk assessment, integrity assessment, anomaly response, preventive and mitigative actions, performance measurement, management of change, and quality assurance. The risk model is the analytical core of that system because it translates heterogeneous information into priorities and provides a basis for comparing candidate actions. If the model is poorly scoped, mathematically unstable, or dominated by defaults, the broader program can appear procedurally complete while producing weak or misleading risk insights.

Federal gas-transmission integrity requirements are organized principally in 49 C.F.R. Part 192, Subpart O. Current § 192.917 requires operators to identify and evaluate all potential threats, integrate pertinent data, analyze spatial and threat interrelationships, validate the risk method against operating and industry experience, perform sensitivity analysis, account for uncertainty, analyze interacting threats, and evaluate the potential risk reduction associated with candidate actions (49 C.F.R. § 192.917, 2026). These requirements reflect a wider evolution in pipeline risk practice. PHMSA's risk-modeling work concluded that the overriding purpose of a model is to support risk-reduction decisions and that quantitative system or probabilistic models generally offer greater versatility than simple index models, although model selection must remain proportionate to the operator's decisions and data (PHMSA, 2020).

The scientific literature similarly distinguishes relative scoring from quantitative risk. Index models combine ordinal or semi-quantitative factors to rank locations; quantitative models estimate failure frequency or probability and the magnitude or distribution of consequences. Han and Weng (2011) showed that the two model families can both be useful but produce fundamentally different outputs. Jo and Ahn (2005), Han and Weng (2010), and Ma et al. (2013) developed quantitative frameworks that explicitly combine failure likelihood with accident consequences. Other researchers have introduced Bayesian, fuzzy, bow-tie, and multicriteria methods to address sparse data, uncertainty, dependence, and multidimensional consequences (Brito & de Almeida, 2009; Dong & Yu, 2005; Jamshidi et al., 2013; Shahriar et al., 2012; Shan et al., 2017).

Problem statement

The reviewed TIMP materials present three core analytical layers developed at different times—a 2013 risk-methodology document, a 2019 Excel implementation, and a 2024 TIMP—plus two operational GIS artifacts: a 2024 transmission class-analysis procedure and a structure-code dictionary. The core documents are not merely successive versions of one artifact; they perform different functions and describe different system scopes. The supplementary artifacts show how class, HCA and MCA work was intended to be operationalized in GIS. The research problem is therefore to determine whether the implemented model remains consistent with the governing program, whether its formulas and aggregations are technically valid, whether its data represent the current portfolio, whether the operational class/HCA/MCA method is reproducible and correctly linked to risk, and what modernization is needed to support present-day integrity decisions.

Research questions

This study addresses six questions:

1. What risk-management architecture is established by the TIMP, and what analytical functions are assigned to the risk model?

2. How does the workbook calculate segment and route risk, and is its implementation consistent with the methodology?

3. Are the model's scope, inputs, defaults, and outputs sufficiently current and discriminating for the portfolio described in the TIMP?

4. How are class location, HCA, MCA, PIR/PIC, identified sites, and consequence-area changes represented, reconciled, and linked to risk prioritization?

5. How does the reviewed framework align technically with current regulatory requirements and peer-reviewed risk-modeling practice?

6. What practical modernization pathway preserves useful legacy features while improving validity, consequence-area traceability, uncertainty treatment, and decision support?

Contribution and boundaries

The study contributes a reproducible formula audit, independent route and segment recalculation, diagnostics of segmentation sensitivity and factor variability, an HCA/MCA/class-location reconciliation, assimilation and technical evaluation of an operational GIS procedure and structure-code taxonomy, a structured gap assessment, and a staged future-state architecture. It is limited to the five supplied artifacts and publicly available technical and regulatory sources. No operator incident database, pressure-test files, in-line inspection data, cathodic-protection history, populated GIS geodatabase, building or identified-site layer, qualifying-roadway layer, class-location study outputs, HCA/MCA geometry, geoprocessing logs, subject-matter-expert records, or audit packages were provided. Consequently, the paper is an independent technical evaluation of the supplied evidence; it is not a legal opinion, regulatory audit, boundary certification, or certification of compliance.

Regulatory and Scientific Foundation

The current federal framework requires more than a one-time rank ordering. Section 192.917(a) requires identification and evaluation of time-dependent, stable, time-independent, and human-error threats. Section 192.917(b) requires integration of pertinent information about the entire pipeline that could be relevant to covered segments, including material properties, construction records, pressure-test history, coatings, gas quality, operating pressure, leak and failure history, cathodic-protection performance, integrity-assessment findings, repairs, encroachments, external forces, and industry experience. The same section requires validated inputs to the maximum extent practicable, control of subject-matter-expert inputs, analysis of spatial relationships, and analysis of interrelationships among threats (49 C.F.R. § 192.917, 2026).

The risk-assessment provisions are particularly relevant to this case. The method must produce a characterization consistent with operator and industry experience, include sensitivity analysis of likelihood and consequence factors, analyze individual and interacting threats, compensate for uncertainty, and evaluate the potential risk reduction of candidate preventive, mitigative, remediation, and assessment actions. Risk analysis must then support additional preventive and mitigative measures under § 192.935 and periodic evaluation under § 192.937. Reassessment intervals remain governed by § 192.939 and the incorporated ASME B31.8S requirements (49 C.F.R. §§ 192.917, 192.935, 192.939, 2026).

As of this study, 49 C.F.R. § 192.7 incorporates ASME B31.8S-2018 for the relevant integrity-management provisions. The supplied TIMP contains references to older editions in portions of its bibliography. This does not by itself establish a substantive deficiency, but it creates a document-control risk because procedures, cross-references, and incorporated requirements should identify the edition actually governing the program.

Texas rules provide risk-based and prescriptive integrity-assessment options for covered intrastate pipelines and identify factors such as population density, environmental and public-safety exposure, pipeline configuration, prior inspection and pressure-test information, leak and incident data, operating characteristics, construction records, and pipeline specifications. Section 8.101 also requires periodic plan review and expressly states that it does not apply to plastic pipelines, while Texas § 8.1 adopts the applicable federal gas-pipeline standards. Plastic transmission pipe must nevertheless be addressed under federal § 192.917(d), including threats unique to plastic materials and joints (16 Tex. Admin. Code §§ 8.1, 8.101, 2026; 49 C.F.R. § 192.917(d), 2026).

This distinction matters because the 2024 TIMP describes both steel and high-density polyethylene assets, whereas the supplied workbook contains only coated-steel legacy segments. A current portfolio-wide risk framework therefore needs threat taxonomies and parameterization appropriate to both material classes, even when different regulatory provisions or assessment methods apply.

Table 1: Technical regulatory crosswalk

Source	Technical expectation	Evidence in supplied materials	Assessment
49 C.F.R. § 192.917(a)-(b)	Identify all applicable threats; integrate pertinent, validated data; analyze spatial and threat relationships.	TIMP states these principles and conservative treatment of missing data.	Workbook scope and stale/constant inputs do not demonstrate current full-portfolio integration.
49 C.F.R. § 192.917(c)	Validate risk results; conduct sensitivity analysis; compensate for uncertainty; analyze interactions; evaluate candidate risk reduction.	No explicit output or record for these functions was supplied.	Major evidence gap; not a legal determination.
49 C.F.R. § 192.935	Use risk analysis to identify additional preventive and mitigative measures.	TIMP contains preventive/mitigative program elements.	Workbook does not quantify action effectiveness or benefit.
49 C.F.R. § 192.939	Use integrity information and risk factors to establish reassessment intervals.	TIMP addresses reassessment and periodic evaluation.	Model support for current full-system intervals was not demonstrated.
49 C.F.R. § 192.7 / ASME B31.8S	Use the currently incorporated technical edition and controlled references.	TIMP cites ASME concepts and older editions in places.	Reconcile controlled references to ASME B31.8S-2018 and current cross-references.
16 Tex. Admin. Code §§ 8.1, 8.101	Texas adoption and state integrity provisions; § 8.101 distinguishes plastic applicability.	TIMP addresses Texas requirements and includes steel/HDPE assets.	Portfolio-wide model requires material-specific logic even when provisions differ.
49 C.F.R. §§ 192.5, 192.609, 192.611	Maintain current class-location records; study population-driven class changes; confirm or revise MAOP as required, including current eligible-Class-3 provisions.	The TIMP describes density/class review and change triggers; the workbook contains a population category but no class-study record, effective date, or eligible-Class-3 status.	Program concept is present; model linkage and current 2026 update are not demonstrated.
49 C.F.R. §§ 192.903, 192.905	Identify HCA by the selected method; retain PIR/PIC and receptor basis; incorporate newly identified HCA into the baseline plan.	The TIMP describes Method 2, GIS analysis, annual review, identified sites and HCA mileage; workbook has an HCA label but no method, PIR/PIC, receptor count or HCA ID.	Substantial traceability and reconciliation gap between determination and risk model.
49 C.F.R. §§ 192.3, 192.710	Identify MCA and qualifying Class 3/4 segments outside HCA; assess applicable onshore steel segments using a risk-prioritized schedule.	The TIMP defines MCA and portfolio table includes MCA segment entries; workbook has no MCA field or § 192.710 applicability/schedule logic.	Major current-scope evidence gap.

HCA, MCA, class location, and impact-zone requirements

Class location, HCA, and MCA are related but non-equivalent regulatory constructs. Class location is determined under 49 C.F.R. § 192.5 using a continuous one-mile class-location unit extending 220 yards on each side of the pipeline. Class 1 through Class 4 are based principally on building density, public-assembly proximity, and prevalence of buildings with four or more stories. Operators must maintain records documenting the current class location and the determination basis. A population increase that indicates a class change can trigger an immediate study under § 192.609 and, where the established MAOP is not commensurate with the new class, confirmation or revision actions under § 192.611 (49 C.F.R. §§ 192.5, 192.609, 192.611, 2026).

HCA is an integrity-management coverage overlay under § 192.903 rather than a higher numbered class location. The current definition permits Method 1 or Method 2 and incorporates Class 3/Class 4 locations, PIR/PIC building and identified-site criteria, and—following a 2026 amendment—eligible Class 3 segments whose MAOP is confirmed under § 192.611(a)(4). The PIR for natural gas is $r = 0.69 \times \sqrt{(p \times d^2)}$, where p is MAOP in psig and d is nominal diameter in inches. The operator must document the method applied to each portion of the system and incorporate a newly identified HCA into the baseline assessment plan within one year (49 C.F.R. §§ 192.903, 192.905, 2026).

MCA is defined separately in § 192.3 as a non-HCA onshore area within a PIC that contains at least five buildings intended for human occupancy or a qualifying interstate, freeway, expressway, or other principal arterial roadway with four or more lanes. Section 192.710 applies to qualifying onshore steel transmission segments operating at or above 30% SMYS in Class 3, Class 4, or an MCA outside an HCA; it requires risk-prioritized initial assessment and periodic reassessment at least every 10 years, with intervals not to exceed 126 months (49 C.F.R. §§ 192.3, 192.710, 2026). MCA status is therefore not merely a lower HCA score; it can establish a distinct assessment population and schedule.

The analytical implication is structural. Current class location, HCA status and method, MCA status and basis, PIR/PIC geometry, identified-site evidence, qualifying-roadway evidence, and effective dates should be stored as separate versioned attributes. A single ordinal field such as Class 1, Class 2, Class 3, HCA obscures overlap, change history, regulatory applicability, and the basis of a determination. These regulatory overlays should also be distinguished from physical consequence estimates to avoid double counting population and receptor effects.

The supplementary operational procedure implements these constructs through two GIS geometries: a 660-foot class-analysis corridor and a segment-specific PIR/PIC buffer. It then inventories structures, applies the § 192.5(c)(2) cluster boundary adjustment, and assigns HCA/MCA status ("Transmission Class Analysis Procedure," 2024). This is a useful operational bridge, but it requires precision. The source labels 660 feet as 220 meters; the regulatory equivalence is 220 yards, or approximately 200 meters. The cluster provision adjusts the endpoints of Class 2 or Class 3 areas and does not replace the required continuous one-mile class-location unit (49 C.F.R. § 192.5, 2026).

The accompanying structure-code dictionary classifies dwellings, nonoccupied structures, high-occupancy buildings, schools, limited-mobility facilities, four-or-more-story buildings, and public-assembly areas ("Structure Code Dictionary," n.d.). These codes can support class, HCA and MCA determination only if their regulatory functions remain distinct. A commercial building that does not meet identified-site occupancy criteria may still count as a building intended for human occupancy; a multi-family feature must carry a separate dwelling-unit count; and public-assembly codes must preserve the different spatial and temporal tests used for class location and identified-site determinations.

Table 2: Regulatory distinction among class location, HCA, MCA, identified sites, and PIR/PIC

Construct	Primary basis	Principal function	Required model representation
Class location	One-mile unit; 220 yards each side; building/public-assembly density; Classes 1-4.	Design, MAOP, operations, maintenance and certain assessment obligations.	Current class, study date, source records, boundary geometry and change history.
HCA	Method 1 or 2; Class 3/4, PIR/PIC buildings, identified sites, and current eligible-Class-3 provisions.	Defines covered segments and Subpart O integrity-management protection.	Separate HCA status, method, HCA ID, PIR/PIC, receptor basis, effective date and approval.
MCA	Non-HCA PIC with at least five occupied buildings or a qualifying four-or-more-lane roadway.	Establishes part of the assessment population outside HCA under § 192.710 for qualifying steel segments.	Separate MCA status and basis; qualifying-roadway/building evidence; § 192.710 applicability and schedule.
Identified site	Occupancy-frequency or difficult-to-evacuate facility criteria.	Can independently trigger HCA status.	Site type, occupancy basis, source, verification date and spatial relationship.
PIR/PIC	Pressure- and diameter-based impact radius and corresponding circle.	Spatial screening basis for HCA/MCA delineation and consequence analysis.	Calculated PIR, inputs, formula/version, PIC geometry and recalculation triggers.

Relative index, multicriteria, and quantitative risk models

Risk models can be organized into three broad families. Relative-index models assign scores to causal, condition, consequence, or management factors and combine them using arithmetic and weights. They are transparent and can operate with sparse information, but the resulting numbers are usually dimensionless and depend on scoring conventions. Cagno et al. (2000) noted the limitations of demerit-point approaches and developed a Bayesian alternative that combined sparse historical data with structured expert judgment. Han and Weng (2011) directly compared qualitative index and quantitative methods and emphasized that the former yields a ranking score while the latter yields individual and societal risk.

Multicriteria models are valuable when consequences are multidimensional and decision-maker preferences must be represented explicitly. Brito and de Almeida (2009) used multi-attribute utility theory to rank pipeline sections across multiple impact dimensions. Brito et al. (2010) integrated utility theory with ELECTRE TRI to sort segments into risk classes. Shahriar et al. (2012) expanded the consequence space to social, environmental, and economic outcomes through a fuzzy bow-tie framework. These approaches are particularly useful for decision preference and consequence valuation, but preference weights should not be confused with physical failure probability.

Quantitative risk analysis generally decomposes risk into event frequency or probability and consequence. Jo and Ahn (2005) proposed a simplified quantitative method for transmission pipelines. Han and Weng (2010) integrated accident probability, physical consequences, individual and societal risk, and network economic effects. Ma et al. (2013) combined empirical failure-rate estimation, consequence modeling, individual and societal risk, and GIS. Sklavounos and Rigas (2006) demonstrated scenario-based consequence and safety-distance analysis for pressurized gas pipelines. GIS-based approaches can improve spatial consistency and support high-resolution consequence mapping (Li et al., 2019; Ma et al., 2013).

Bayesian and fuzzy methods provide structured ways to represent uncertainty and update knowledge. Dong and Yu (2005) combined fault-tree analysis, expert elicitation, and fuzzy probabilities. Jamshidi et al. (2013) integrated fuzzy inference with a relative-risk score. Shan et al. (2017) converted a bow-tie into a fuzzy Bayesian network to support forward and diagnostic inference. Zhu et al. (2022) applied Bayesian networks to third-party damage. A review by Zakikhani et al. (2020) found a broad range of statistical, reliability, probabilistic, and machine-learning failure models, each requiring careful attention to data quality, validation, transferability, and decision context.

Recent work also illustrates the convergence of GIS, Bayesian belief networks, and data-driven corrosion modeling, although transferability and validation remain essential when models are moved between systems (Woldesellasse & Tesfamariam, 2025).

Table 3: Selected peer-reviewed pipeline risk-modeling literature

Study	Method	Principal contribution	Relevance to modernization
Cagno et al. (2000)	Bayesian/AHP	Combines sparse failure data with structured expert priors.	Supports explicit expert uncertainty rather than hidden default scoring.
Jo & Ahn (2005)	Quantitative risk assessment	Links failure frequency and gas-release consequences.	Illustrates interpretable likelihood × consequence formulation.
Dong & Yu (2005)	Fuzzy fault tree	Estimates failure probability under imprecise data.	Relevant to sparse or linguistic threat evidence.
Sklavounos & Rigas (2006)	Consequence analysis	Estimates hazard effects and safety distances for gas pipelines.	Supports scenario-based consequence libraries.
Brito & de Almeida (2009)	Multi-attribute utility	Ranks pipeline sections across multiple consequence dimensions.	Useful when social, environmental and economic impacts remain separate.
Han & Weng (2010)	Integrated QRA	Combines accident probability, consequences, individual/societal risk and network effects.	Demonstrates full-system quantitative decision metrics.
Brito et al. (2010)	ELECTRE TRI + utility	Sorts pipeline segments into risk classes.	Provides structured category assignment when preferences are explicit.
Han & Weng (2011)	Qualitative vs quantitative comparison	Shows that index scores and quantitative risk outputs are not interchangeable.	Directly informs interpretation of the TIMP index.
Shahriar et al. (2012)	Fuzzy bow-tie	Integrates causal pathways and sustainability consequences.	Supports interaction and multidimensional consequence analysis.
Jamshidi et al. (2013)	Fuzzy inference	Builds a rule-based pipeline relative-risk model.	Provides a structured alternative for imprecise expert inputs.
Ma et al. (2013)	GIS-based QRA	Combines failure rate, consequence, individual/societal risk and GIS.	Supports spatially consistent full-portfolio modeling.
Shan et al. (2017)	Fuzzy Bayesian network	Supports forward and diagnostic inference through a bow-tie network.	Applicable to interacting threats and updating.
Li et al. (2019)	Grid-based QRA/GIS	Produces spatially resolved urban pipeline pre-warning outputs.	Shows how GIS can support quantitative reporting.
Zakikhani et al. (2020)	Review	Synthesizes statistical, reliability, probabilistic and machine-learning failure models.	Frames method selection, data needs and validation.
Zhu et al. (2022)	Bayesian network	Models third-party damage causation.	Relevant to excavation and outside-force pathways.
Woldesellasse & Tesfamariam (2025)	Bayesian belief network + GIS	Integrates GIS, Bayesian networks and corrosion modeling.	Illustrates current hybrid spatial-probabilistic practice.

Evaluation criteria used in this study

Based on the regulations, PHMSA guidance, ASME concepts, literature, and the two operational GIS artifacts, the case model was evaluated against fourteen criteria: scope completeness; data currency and lineage; threat and consequence coverage; HCA/MCA/class-location traceability; regulatory-overlay separation; geoprocessing reproducibility; structure-code and status semantics; mathematical consistency; aggregation invariance; uncertainty representation; sensitivity analysis; interacting-threat capability; validation and calibration; and ability to evaluate the risk reduction of candidate actions. Transparency, usability, map production, and governance were treated as enabling attributes rather than substitutes for model validity.

Case Materials and Methods

Five anonymized source artifacts were reviewed. The first was the Transmission Integrity Management Program dated July 1, 2024, which defines the integrity-management framework and describes approximately 103.66 miles in 30 systems, including class-category and HCA/MCA information. The second was TIMP Risk Assessment Documentation, dated March 2013, which documents the intended index-model methodology. The third was the 2019 TIMP risk-model workbook, which implements the legacy calculation for an anonymized 11-route transmission subsystem. The fourth was a transmission class-analysis procedure updated June 5, 2024, which describes the GIS workflow for class-location, PIR/PIC, structure inventory, HCA/MCA flagging and map production. The fifth was a structure-code dictionary that defines the internal receptor categories used by that workflow. The artifacts were analyzed as distinct evidence layers: the TIMP as the governing program and consequence-area statement; the methodology as the intended analytical design; the workbook as the executed calculation; and the two GIS artifacts as the operational determination method and data taxonomy. Operator, developer, consultant, platform, layer, road, station, route-name, system-name, and original segment identifiers are intentionally omitted throughout this paper.

Table 4: Source artifacts and analytical roles

Artifact	Analytical role	Primary use in this paper
TIMP Program Document	Governing program statement	Scope, governance, data integration, threats, assessment, remediation, QA/QC, review and performance.
TIMP Risk Assessment Documentation	Intended analytical methodology	Parameters, equations, weighting structure, leak treatment and GIS segmentation.
TIMP Risk Model Workbook	Implemented legacy calculation	Formula trace, segment and route recalculation, data profiling, ranking and sensitivity diagnostics.
Transmission Class Analysis Procedure	Operational GIS work instruction	Class corridor and PIR/PIC setup, structure interpretation, cluster boundary adjustment, HCA/MCA status and map outputs.
Structure Code Dictionary	Operational GIS data dictionary	Structure, occupancy, public-assembly, limited-mobility and story-height categories used in class/HCA/MCA analysis.

Document review

The TIMP was coded for program scope, roles, data integration, class-location review, HCA/MCA identification, PIR/PIC logic, threat identification, risk calculation, prioritization, assessment methods, preventive and mitigative measures, change management, quality assurance, performance measurement, and review frequency. The methodology was coded for definitions, equations, configurable factors, GIS segmentation, population and receptor consequence parameters, leak treatment, and aggregation. The class-analysis procedure was coded for required layers, geometry construction, structure fields, cluster logic, HCA/MCA status, map production and file retention. The structure dictionary was coded by regulatory function: occupied-building count, dwelling-unit count, Class 3 public-assembly trigger, Class 4 indicator, HCA identified-site trigger, MCA building support, and exclusion/reference use. Statements of historical condition, HCA/MCA status, or absence of particular leak and incident types were treated as assertions made by the source documents rather than independently verified facts.

Workbook reverse engineering

The workbook was inspected at the Open XML level to obtain sheet structures, cell formulas, formula dependencies, and cached results. All 594 populated segment rows were reconstructed into a segment-level analytical table. Route boundaries were identified from the workbook's summary rows. The analysis verified formulas for threat-category adjustments, total weighted threat, PipeFAC, consequence factor, leak-rate factors, segment risk per mile, segment total risk, and route rollups. Formula outputs were independently recalculated and compared with cached workbook values.

The implemented segment equations can be summarized as follows:

Total weighted threat

$T_i = \Sigma_k (w_k \times t_{ik})$

where t_{ik} is the segment score for threat category k and w_k is the top-level category weight.

Implemented PipeFAC

P_i = [(mean of four pipe-specification factors) × (mean of four installation factors) × pressure factor] + longitudinal factor

Consequence factor

$C_i = \Sigma_j (v_j \times c_{ij})$

where c_{ij} is a consequence subfactor and v_j is its weight.

Segment risk-per-mile index

$r_i = T_i \times P_i \times C_i \times U_i$

where U_i equals 1.25 when the unrepaired-leak indicator is nonzero and 1.00 otherwise.

Segment total-risk index

$R_i = r_i \times L_i \times 1{,}000$

where L_i is segment length in miles.

3.4 Independent diagnostics

The following diagnostics were performed:

- completeness and frequency profiles for asset, threat, consequence, and leak inputs;
- minimum, maximum, mean, standard deviation, coefficient of variation, number of unique values, and modal percentage for principal factors;
- route total-risk shares and rankings;
- reconstruction of the workbook's route “risk per mile”;
- a corrected length-weighted route risk-density metric;
- Pearson correlation between route segment count and the workbook route metric;
- Spearman rank correlation between workbook and corrected normalized rankings;
- correlations between segment risk per mile and total threat, PipeFAC, consequence, and the longitudinal factor; and
- comparison of documented and implemented equations and weight totals.

The corrected route risk-density metric was defined as:

$r_{route} = [\Sigma_i (r_i \times L_i)] / \Sigma_i L_i = [\Sigma_i R_i] / [1{,}000 \times \Sigma_i L_i]$

This formulation is a length-weighted average of segment risk-per-mile values and is invariant to subdivision of a homogeneous segment.

HCA, MCA, and class-location analysis

The source-program HCA/MCA review extracted the stated identification method, PIR formula, identified-site and building criteria, roadway criteria, review frequency, change triggers, portfolio-level class flags, and reported HCA/MCA counts and mileage. The system table was independently reconstructed without retaining names. Its 51 material/diameter entries total 103.664 miles, matching the program total after rounding. The HCA and MCA segment-count columns were summed by material and compared with narrative counts elsewhere in the program.

The workbook analysis treated the populated consequence input as a categorical field and calculated, for each HCA/Class category, segment count, modeled mileage, total risk, mileage share, risk share, length-weighted risk density, mean ConseqFac, mean PipeFAC, and mean total threat. HCA-labeled rows were also summarized by Route 1 through Route 11. The consequence parameter table and formulas were reviewed to identify category scores and weights, while the segment table was checked for MCA, PIR/PIC, building-count, identified-site, roadway, HCA-method, and change-history fields.

The analysis distinguishes a source-record designation from an independently verified regulatory determination. No source GIS, class-location-unit geometry, PIC polygons, building/receptor points, identified-site inventory, qualifying-roadway layer, full-portfolio MAOP/diameter table, or approved determination record was provided. Therefore, the paper evaluates traceability, consistency, and model representation; it does not certify that any individual segment is or is not in a class location, HCA, or MCA.

Operational-method assimilation

The two supplementary GIS artifacts were assimilated as an operational-method layer rather than treated as completed or authoritative determination records. The procedure was decomposed into geometry generation, structure and roadway inventory, structure coding, class analysis, HCA logic, MCA logic, map production and record retention. The structure codes were cross-walked to five distinct functions: building count, dwelling-unit count, Class 3 public-assembly logic, Class 4 prevalence logic, and HCA identified-site logic. MCA building and roadway criteria were evaluated separately because MCA is a non-HCA construct.

Each procedural step was tested for dimensional correctness, consistency with current criteria, explicit determination basis, status semantics, reproducibility, data lineage, effective dating, independent review, change triggers and linkage to risk and assessment planning. Source ambiguities were preserved and reported rather than silently corrected. The recommended assimilated method in Section 6 and Appendix F retains the useful workflow elements while adding the controls necessary for an auditable production process. Each finding was assigned one of four technical significance levels. "Critical" indicates a condition capable of materially changing decisions or preventing current portfolio representation. "Major" indicates a substantial validity, traceability, or decision-support limitation. "Moderate" indicates an issue that should be corrected but is less likely to overturn priorities alone. "Positive practice" identifies a defensible feature that should be retained. Ratings describe the reviewed evidence and are not regulatory violation determinations.

The model was not recalibrated against actual failures because no complete event history, exposure history, inspection findings, or remediation outcomes were supplied. No independent verification of GIS features, structure codes, qualifying roadways, consequence receptors, class boundaries, HCA/MCA polygons, or completed map packages was possible. The operational procedure was evaluated from its text, embedded regulatory images and stated workflow; no populated geodatabase, geoprocessing history, field-verification package or approval record was supplied. Excel cached values were treated as the executed results in the supplied version. The analysis did not evaluate cybersecurity, user-access control, or macros because the relevant workbook did not contain evidence requiring those tests. External standards and regulations were assessed as of July 2026.

Results

The 2024 TIMP establishes a conventional integrity-management lifecycle. It identifies high-consequence and moderate-consequence areas, recognizes the ASME threat categories, requires data gathering and integration, uses risk analysis to prioritize segments, selects assessment methods based on applicable threats and technical feasibility, provides for remediation and preventive or mitigative measures, and includes management of change, quality assurance, performance measurement, and annual program review (TIMP Program Document, 2024).

Several program statements are technically sound and should be retained. The TIMP directs personnel not to exclude threats merely because data are missing or suspect; it calls for conservative assumptions and documentation of those assumptions. It requires risk recalculation when material new information becomes available, when mitigation changes conditions, when an inaccuracy is discovered, and during scheduled updates. The program also calls for review by personnel with multidisciplinary operating and engineering experience. These provisions align with the principle that risk models must be living decision tools rather than static spreadsheets.

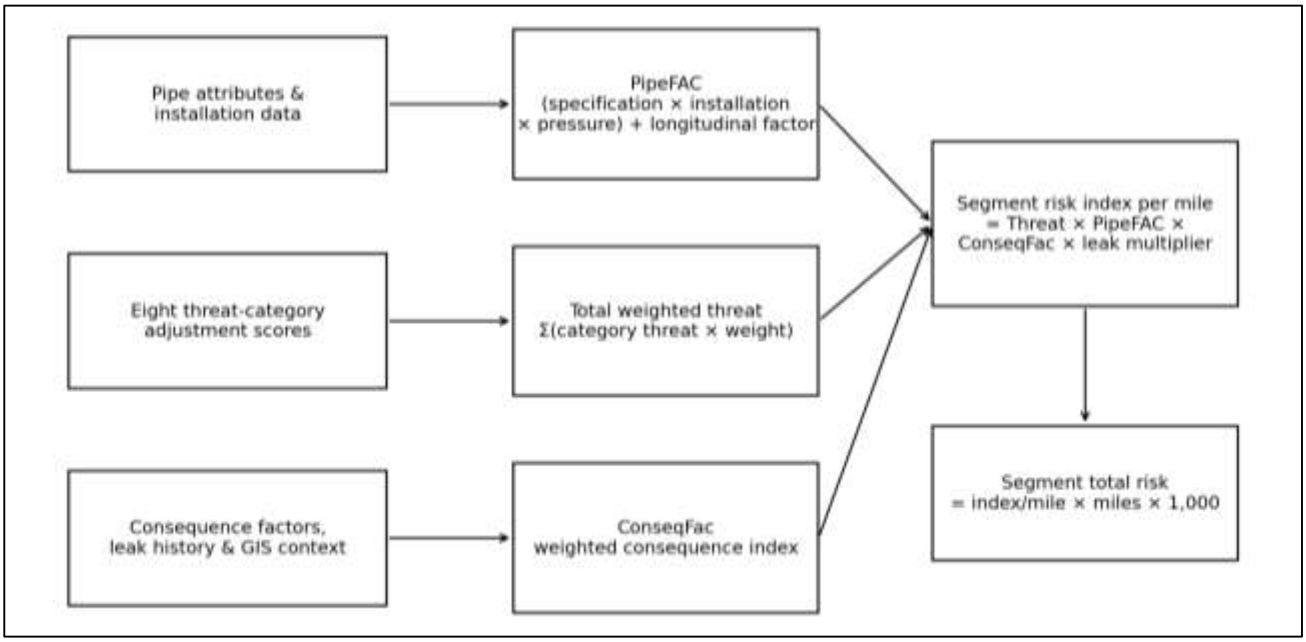
The quality-assurance section is comparatively robust. It identifies the risk-analysis process, threat assessment, remediation, preventive and mitigative measures, performance measurement, management of change, records, and mapping as audit subjects. It contemplates audit plans, qualified auditors, original notes, findings, recommended corrective actions, and documented resolution. It also requires an annual review, not to exceed 15 months, and distinguishes leading, operational, process,

and direct performance measures. These controls create an appropriate institutional basis for model modernization.
Two governance concerns remain. First, the TIMP references multiple document ages and, in places, older technical editions; the controlled reference list should be reconciled to the currently incorporated ASME B31.8S-2018 and current federal provisions. Second, update-frequency terms should be unambiguous. The word "biannual" can mean twice yearly or every two years and should be replaced with "semiannual" or "biennial," as intended. These are document-control issues rather than findings about pipeline condition.

Reconstructed model architecture

Figure 1 shows the implemented architecture. Asset specification and installation factors feed PipeFAC; eight threat-category adjustments feed a top-level weighted threat score; consequence and GIS-related inputs feed the consequence factor; and an unrepaired-leak indicator applies a binary multiplier. The result is a segment risk-per-mile index and a length-proportional segment total-risk index.
The architecture is understandable and auditable. It maintains a recognizable separation among hazard-related factors, pipe characteristics, consequence, and length. Dynamic GIS segmentation allows the model to create a new analytical segment when asset or spatial conditions change. These are positive features. The principal concern is not opacity but the validity and interpretation of how the components are scaled, combined, and aggregated.

Figure 1. Reconstructed architecture of the 2019 TIMP risk model. The outputs are dimensionless index values.



Portfolio and data profile

The workbook contains 594 populated dynamic risk segments in 11 routes. Total modeled length is 62,302.859 feet, or 11.799784 miles. Every segment is classified as cathodically protected coated steel. The asset years represented are 1951, 1983, 2008, 2011, 2012, 2013, 2015, and 2018, with 1951 and 1983 accounting for most segments. Pipe diameters are primarily 10 inches and 4 inches. All segment rows are recorded as welded, directly buried, at 36 inches of cover, and high pressure; map accuracy is marked "Correct" on every segment.
The consequence data contain more variation than the threat data. Population classifications include HCA, Class 3, Class 2, and Class 1. Environmental sensitivity is predominantly "No," with a small number of "Yes" and "Suspect" entries. Critical building, public building, overbuild, and isolation-response fields are invariant: every segment is recorded as having no critical building, no public building, no overbuild, and timely isolation. Such uniform values may be accurate for this specific

corridor, but they should be verified against current GIS and emergency-response data because they materially constrain consequence differentiation.

The leak-history columns are explicitly labeled "July 2013 thru June 2016." All 16 leak inputs are zero for all 594 segments, and the unrepaired-leak indicator is also zero everywhere. Consequently, the leak multiplier is never activated and leak history does not affect any supplied result. Even if historically correct, a data window ending in 2016 cannot represent subsequent operating experience without an external update mechanism.

The most consequential scope finding is the difference between model and program. The workbook represents 11.80 miles of legacy coated-steel pipe. The 2024 TIMP describes approximately 103.66 miles across 30 systems and states that the portfolio contains steel and HDPE. Thus, the supplied model covers approximately 11.4% of the mileage described by the current TIMP. The model can be interpreted as a legacy-subsystem analysis, but not as evidence of a current portfolio-wide risk calculation.

Table 5: Legacy workbook portfolio and data profile

Metric	Observed value	Interpretation
Populated dynamic risk segments	594	All independently reconstructed from workbook formulas and cached values.
Routes	11	Anonymized legacy subsystem only.
Modeled length	11.799784 mi	62,302.859 ft.
TIMP portfolio description	Approximately 103.66 mi / 30 systems	Includes coated steel and HDPE.
Approximate mileage represented	11.4%	Legacy workbook mileage divided by TIMP-described mileage.
Material in workbook	100% cathodically protected coated steel	No HDPE rows in the supplied model.
Leak-history window	July 2013-June 2016	All 16 leak input fields are zero on all 594 segments.
Unrepaired-leak indicator	Zero on all segments	The 1.25 multiplier is never activated.
Total model risk index	146,632.11	Dimensionless relative index; amplification factor = 1,000.
Workbook population/HCA categories	93 HCA; 325 Class 3; 110 Class 2; 66 Class 1	No MCA or populated Class 4 category in legacy workbook.
2024 portfolio consequence-area entries	20 HCA entries; 28 MCA entries; narrative reports 18 HCAs / 3.59 mi	Counts and units require controlled reconciliation.

HCA, MCA, class-location, and consequence-area analysis

The 2024 TIMP contains a substantive HCA identification process. It states that Method 2 is used, calculates PIR/PIC along the pipeline, evaluates occupied buildings and identified sites, delineates contiguous covered segments in GIS, and reviews newly identified areas at least annually. It also identifies change triggers such as MAOP changes, construction, building-use changes, class-location changes, centerline corrections, reroutes, diameter changes, and commodity changes. MCA is defined using the five-building and qualifying-roadway criteria and is intended to use the same geospatial process supplemented by roadway data, imagery and field verification (TIMP Program Document, 2024).

The supplementary class-analysis procedure adds an operational sequence to that program architecture: create a class-analysis corridor, compute PIR from controlled MAOP and diameter, generate the PIC buffer, inventory and classify structures, apply the class analysis and cluster boundary adjustment, then assign HCA/MCA status and publish separate maps ("Transmission Class Analysis Procedure," 2024). The structure-code dictionary supplies the associated receptor categories ("Structure Code Dictionary," n.d.). This materially strengthens the evidence that the program has an intended GIS workflow, while also creating new questions about unit control, criteria mapping, field semantics and record reproducibility.

The source package nevertheless contains three HCA counts that are not reconciled in the supplied text: one passage states 16 HCA segments; the Method 2 results state 18 HCAs totaling approximately 3.59

miles; and the HCA-segment column in the portfolio table sums to 20 entries. These values may represent different concepts—areas, covered segments, table entries, or revision dates—but the record provided does not state the crosswalk. The same portfolio table sums to 28 MCA segment entries but provides no MCA mileage total. An auditable program should maintain a single controlled register that explains area count, covered-segment count, table-entry count and mileage by effective date.

The reconstructed portfolio table contains 103.664 miles: 34.905 miles of steel and 68.759 miles of HDPE. Its count columns assign 13 HCA and 26 MCA segment entries to steel rows and 7 HCA and 2 MCA entries to HDPE rows. These counts are not direct measures of mileage or risk. They also require material-specific interpretation: § 192.710 applies to qualifying onshore steel segments outside HCA, whereas federal integrity-management requirements include plastic-transmission threat and preventive-measure provisions for covered segments. The source table includes class-category flags extending through Class 4, but those flags are multi-valued portfolio descriptors and cannot be converted into class-specific mileage without segment geometry.

Table 6: HCA/MCA/class-location evidence and reconciliation across the supplied artifacts

Evidence layer	Reported or calculated evidence	Technical evaluation
2024 program narrative	16 HCA segments in one passage; Method 2 results report 18 HCAs and approximately 3.59 HCA miles.	Counts appear to use different units or revision bases; no supplied reconciliation.
2024 portfolio table	103.664 total miles; 20 HCA segment entries and 28 MCA segment entries; class-category flags include Classes 1-4.	Entry counts are not equivalent to unique areas or mileage; class flags are multi-valued.
Portfolio material split	Steel: 34.905 mi, 13 HCA entries, 26 MCA entries. HDPE: 68.759 mi, 7 HCA entries, 2 MCA entries.	MCA and assessment applicability require material- and pressure-specific screening; counts alone are not decisions.
2019 workbook	93 HCA-labeled dynamic segments totaling 1.017838 mi; Classes 1-3 present; no populated Class 4; no MCA field.	Legacy-subsystem scope only; HCA is treated as an ordinal population category rather than a separate overlay.
2013 methodology	Population/class, critical/public building, environmental, surface, overbuild and isolation consequence factors.	Provides a transparent consequence index but predates MCA and does not document current HCA/MCA governance fields.
2024 operational GIS procedure and structure-code dictionary	Separate class and PIR geometries; structure/occupancy fields; cluster adjustment; HCA/MCA status; class/HCA/MCA map outputs; 12 structure codes.	Useful operational bridge, but no populated output was supplied. Unit, criterion, status, roadway, dwelling-count and version-control issues require correction before the procedure can serve as the authoritative determination process.

The workbook does not implement HCA, MCA and class location as separate regulatory attributes. Its population field is mutually exclusive and contains only HCA, Class 3, Class 2, or Class 1 in the populated data. The parameter table assigns values of 1, 2, 3, 4 and 5 to Class 1, Class 2, Class 3, Class 4 and HCA, respectively, and the population term receives a 0.25 weight in ConseqFac. Thus, HCA is treated analytically as "Class 5," even though HCA is an overlay that may be established through class location, PIR/PIC and receptor criteria and now includes a specific eligible-Class-3 pathway.

No MCA category or status field was found. The workbook also contains no explicit PIR, PIC ID, HCA method, HCA ID, identified-site type, building count, qualifying-roadway criterion, determination effective date, or § 192.710 applicability/schedule field. Critical-building, public-building and overbuild inputs are "No" for all 594 segments, and isolation is "Timely" for every segment; environmental sensitivity is "Yes" on 9 segments and "Suspect" on 2. These invariant or nearly invariant fields substantially limit receptor differentiation and should be validated against the current controlled GIS and field records rather than assumed correct or incorrect from the workbook alone.

Of the 594 dynamic workbook segments, 93 are labeled HCA, 325 Class 3, 110 Class 2 and 66 Class 1. HCA-labeled segments comprise 15.66% of segment count but only 8.63% of modeled mileage. They contribute 15.20% of total risk, producing a risk-share-to-mileage-share ratio of 1.76. Their length-weighted risk density is 21.90 index units per mile, 77.1% above Class 3, 104.5% above Class 2, and 118.6% above Class 1. This confirms that the workbook increases the relative priority of HCA-coded rows, but it does not validate the underlying HCA designation or demonstrate MCA coverage.

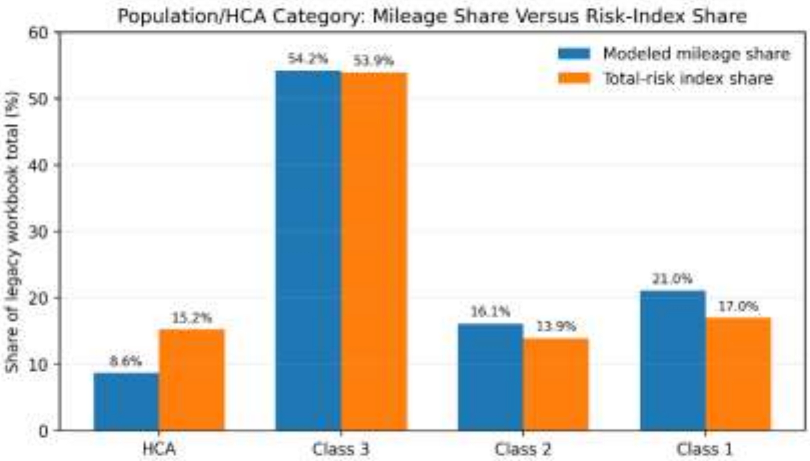
The HCA elevation is not caused by a higher average total-threat score: mean total threat is 1.082 for HCA versus 1.087 for Class 3. HCA rows instead have a higher mean ConseqFac (2.039 versus 1.548) and a higher mean PipeFAC (10.148 versus 7.797). The modeled HCA effect therefore combines the intended consequence-category uplift with asset-condition and pressure characteristics concentrated in the HCA-labeled subset. A modern analysis should preserve this physical co-location without conflating the regulatory designation itself with a universal consequence multiplier.

All 93 HCA-labeled rows occur on Routes 3, 6, 9 and 10. Route 10 contains 50 of those rows, 0.4267 HCA-labeled miles and 44.0% of HCA-labeled total risk. Route-level concentration can be operationally meaningful, but it also means that any stale HCA geometry, misclassification, or segmentation artifact on those four routes can materially influence the model output.

Table 7: Legacy workbook distribution and risk profile by population/HCA category

Category	Segments	Miles (share)	Total risk (share)	Weighted risk density	Mean profile: threat / PipeFAC / ConseqFac
HCA	93	1.017838 (8.63%)	22,291.12 (15.20%)	21.900	1.082 / 10.148 / 2.039
Class 3	325	6.396999 (54.21%)	79,093.51 (53.94%)	12.364	1.087 / 7.797 / 1.548
Class 2	110	1.901840 (16.12%)	20,367.08 (13.89%)	10.709	1.129 / 7.948 / 1.303
Class 1	66	2.483107 (21.04%)	24,880.41 (16.97%)	10.020	1.087 / 7.693 / 1.082
Total	594	11.799784 (100%)	146,632.11 (100%)	12.427	–

Figure 2. Legacy workbook mileage share versus total-risk index share by population/HCA category. HCA-labeled rows carry 15.2% of risk on 8.6% of mileage.



4.4.4 Reconciliation, regulatory currency, and decision implications

The 2024 program predates the 2026 federal amendment that added eligible Class 3 segments confirmed under § 192.611(a)(4) to the HCA definition and imposed detailed initial and recurring controls for that pathway. The absence of this provision from the 2024 document is therefore a currency issue rather than evidence that the program ignored a requirement existing at the time of issue. The next controlled revision should evaluate applicability, update the HCA definition and process, and create an explicit eligible-Class-3 status and evidence record.

The principal model deficiency is not that HCA receives no consequence emphasis; it clearly does. The deficiency is that classification, regulatory coverage, physical consequence and assessment applicability are compressed into one ordinal input. This prevents the workbook from demonstrating which HCA method applies, whether an MCA is excluded because it is already HCA, whether a non-HCA Class 3/4 or MCA steel segment is subject to § 192.710, when the determination became effective, and which GIS/receptor evidence supports it.

A controlled future architecture should therefore maintain four linked but distinct layers: (1) current class location and class-change studies; (2) HCA/MCA/eligible-Class-3 regulatory overlays and assessment schedules; (3) physical consequence scenarios and exposed receptors; and (4) the risk calculation and action-prioritization layer. Changes in MAOP, diameter, product, population, land use, identified sites, road classification, centerline geometry or portfolio configuration should trigger documented recomputation and impact analysis across all four layers.

Operational GIS method and structure-code assimilation

The supplementary 2024 class-analysis procedure provides the missing operational bridge between the program-level HCA/MCA language and the legacy workbook. It calls for an asset-centered 660-foot class-analysis corridor, a separate PIR buffer derived from MAOP and diameter, identification of current and historical structures, occupancy and identified-site attributes, use of the § 192.5(c)(2) cluster provision, binary HCA/MCA fields, and separate class, HCA and MCA map outputs (“Transmission Class Analysis Procedure,” 2024). The accompanying dictionary defines 12 structure codes covering dwellings, nonoccupied structures, high-occupancy buildings, schools, limited-mobility facilities, four-or-more-story buildings and public-assembly areas (“Structure Code Dictionary,” n.d.).

These artifacts are useful because they distinguish the class-location corridor from PIR/PIC geometry, recognize that structures require interpretation rather than simple point counts, and create repeatable map products. They also demonstrate that an operational process exists beyond the higher-level TIMP narrative. However, they are procedures and taxonomies, not completed determination records; no populated geodatabase, source snapshots, geoprocessing logs, field-verification package, approvals or route-level outputs were supplied for independent verification.

Four corrections are material. First, 660 feet equals 220 yards and approximately 200 meters, not 220 meters. Second, the cluster provision adjusts the endpoint of a Class 2 or Class 3 area after the continuous one-mile class-location analysis; it is not a substitute for that analysis. Third, the procedure’s outdoor identified-site description uses the 5-days-per-week-for-10-weeks pattern, whereas the HCA outside-area criterion is 20 or more persons on at least 50 days in a 12-month period. The tests overlap but are not equivalent. Fourth, the difficult-to-evacuate identified-site criterion does not require the 20-person/5-day/10-week threshold that appears in one procedure category. The separate limited-mobility code partly resolves this issue, but the procedure and dictionary should be formally reconciled.

Additional controls are required. Multi-family features must store the number of dwelling units because each unit is counted separately. “Non-qualifying” commercial buildings may still count as buildings intended for human occupancy. MCA logic must explicitly exclude HCA and include qualifying roadway evidence; a controlled roadway layer is not identified among the procedure’s required data. Yes/null fields should be replaced with Yes, No, Unknown and Not evaluated. Year-specific status columns should be replaced by an effective-dated overlay register. The code for features beyond 680 feet should be treated as a distance/reference flag rather than a structure type.

The assimilated treatment is therefore to retain the source workflow as the GIS and field evidence-production process, but route its outputs into separate controlled class, HCA, MCA, identified-site, roadway and physical-consequence tables. Table 5C summarizes the required integration controls;

Table 8: Operational class/HCA/MCA procedure: strengths, gaps, and assimilated controls

Procedure element	Useful source feature	Technical gap or ambiguity	Assimilated control
Class geometry	**660-foot corridor around the pipeline.**	Source calls 660 ft "220 m"; continuous one-mile unit is not stated in the instruction.	Use 220 yd/200 m and retain the continuous one-mile unit; store geometry and calculation version.
PIR/PIC	**Separate buffer based on MAOP and diameter.**	Inputs, formula version, effective date and review are not specified.	Store MAOP, diameter, gas factor, formula, result, centerline version, reviewer and effective date.
Structure inventory	**Current and historical structures; imagery and occupancy attributes.**	Lifecycle, source date, dwelling count and evidence confidence are not controlled.	Use persistent structure IDs, lifecycle status, source/date, dwelling-unit count, verification and confidence fields.
Class analysis	**Uses the § 192.5(c)(2) cluster provision.**	Cluster wording may be read as the entire method.	Perform the full one-mile class-unit analysis first; apply cluster endpoint adjustment second.
Identified sites	**High-occupancy, public-assembly and difficult-evacuation categories.**	Outdoor and limited-mobility thresholds are conflated or over-restricted.	Record identified-site basis separately for outside-area, building and limited-mobility criteria.
HCA	**PIR-based HCA flag and map.**	No method, basis, HCA ID, effective date or current eligible-Class-3 field.	Record Method 1/2, basis, HCA ID, geometry, effective date, approval and eligibility pathway.
MCA	**Separate MCA**	Non-HCA exclusion and qualifying-roadway evidence	Run MCA only after HCA exclusion; integrate controlled

	flag and map.	are not operationalized.	roadway classification and building evidence.
Status semantics	**Yes or blank/null.**	Blank conflates No, Unknown and Not evaluated.	Use controlled status values and a separate confidence/resolution workflow.
Outputs and risk link	Separate class, HCA and MCA maps.	Map PDFs alone are not reproducible determinations or risk-model links.	Archive data layers, source snapshots, geoprocessing log, map, approval and relational keys to risk/assessment records.

Formula traceability and consistency

The 2013 methodology defines "Total GDMain Risk" as a prorated expression in which segment total risk is multiplied by segment length and divided by total length (TIMP Risk Assessment Documentation, 2013). Because the methodology separately defines segment total risk as segment risk per mile multiplied by segment length and an amplification factor, the documented gas-main equation appears to apply length twice. The workbook does not implement that equation. Instead, it sums segment total-risk values at route boundary rows. The workbook implementation is more logically consistent for total route risk, but the difference is undocumented and should be resolved through a controlled technical basis.

The methodology defines PipeFAC as the product of an average specification score, an average installation score, and a pressure factor. The workbook implements that product and then adds a longitudinal factor derived from GIS proximity or intersection features. The longitudinal factor ranges from 1.000 to 3.889 and is therefore not negligible. Adding it to a multiplicative pipe-condition expression changes scale behavior and can create double counting if the same spatial features also influence threat or consequence. The term should either be incorporated into a revised, technically justified formula or moved to the threat or consequence component to which it physically belongs.

Top-level threat-category weights sum to 1.00, and consequence weights sum to 1.00. Several within-category weight sets do not. Corrosion subweights sum to 1.15, natural-force subweights to 0.98, material/weld to 1.04, equipment to 1.05, and "other" threats to 1.02. Excavation, other outside force, and incorrect operations sum to 1.00. These deviations establish different category baselines before top-level weights are applied. For example, the corrosion adjustment is 1.15 on every segment even when all inputs are at the lowest coded state. This is an implicit scaling choice that is not explained in the methodology.

Weights do not always need to sum to one if they are deliberately calibrated coefficients. In this workbook, however, the fields are labeled "Weighting," the methodology describes weighted factors, and no calibration record was supplied. The safer interpretation is that the sums should be normalized or explicitly documented as calibrated scales.

The 2013 methodology describes an amplification factor of 10, while noting that the value is configurable. The workbook multiplies segment risk per mile by length and 1,000. This difference does not change rankings within a single workbook run because it is a common scalar, but it changes the magnitude of every reported total-risk index by two orders of magnitude relative to the documented default. Historical comparisons are therefore valid only when the amplification factor and model version are known.

The unrepaired-leak factor is 1.25 when the indicator is nonzero and 1.00 otherwise. This creates a step change independent of leak severity, cause, recency, repair status, pressure, or proximity. A binary multiplier can be defensible as a conservative screen, but its 1.25 value should be tied to empirical calibration, expert elicitation, or a documented policy basis. In the supplied workbook it has no operational effect because every indicator is zero.

Table 9: Summary formula audit

Component	2013 methodology	2019 workbook	Technical finding
Total weighted threat	Σ(category threat × category weight)	Same top-level structure.	Generally traceable; lower-level category scales are not uniform.
PipeFAC	(mean specification) × (mean installation) × pressure	Documented product + additive longitudinal GIS factor.	Material formula divergence; risk of double counting and scale distortion.
Segment risk per mile	Threat × PipeFAC × consequence × unrepaired-leak factor	Same structure.	Traceable dimensionless index, not probability or expected loss.
Segment total risk	Risk/mile × miles × AmpFac; default AmpFac = 10	Risk/mile × miles × 1,000	Common scalar does not change ranks but changes magnitudes by 100× vs documented default.
Route total risk	Prorated expression that appears to multiply length twice	SUM(segment total risk)	Workbook approach is more coherent, but documentation and implementation diverge.
Route risk per mile	No basis for summing segment intensive values	SUM(segment risk per mile)	Mathematically segmentation-dependent; should be a length-weighted mean.
Leak multiplier	1.25 if unrepaired leak is present; otherwise 1.00	Implemented as documented.	All supplied indicators are zero; no current effect.

Route risk results

The total legacy-model risk index is 146,632.11. Route 6 has the highest total at 39,510.94 and represents 26.95% of the modeled total. Route 10 is second at 22,484.65, and Route 8 is third at 21,460.75. Together, these three routes account for 56.92% of total model risk. The top five routes account for 80.22%. Figure 2 displays the route totals.

Total route risk is length-dependent by design. It answers a cumulative exposure question: how much relative risk is distributed across the entire route? The normalized route metric should answer a different question: how intense is the relative risk per unit length? Those two questions require separate metrics and should not be interchanged.

Figure 3. Legacy model total-risk index by route. Route 6 is the largest contributor

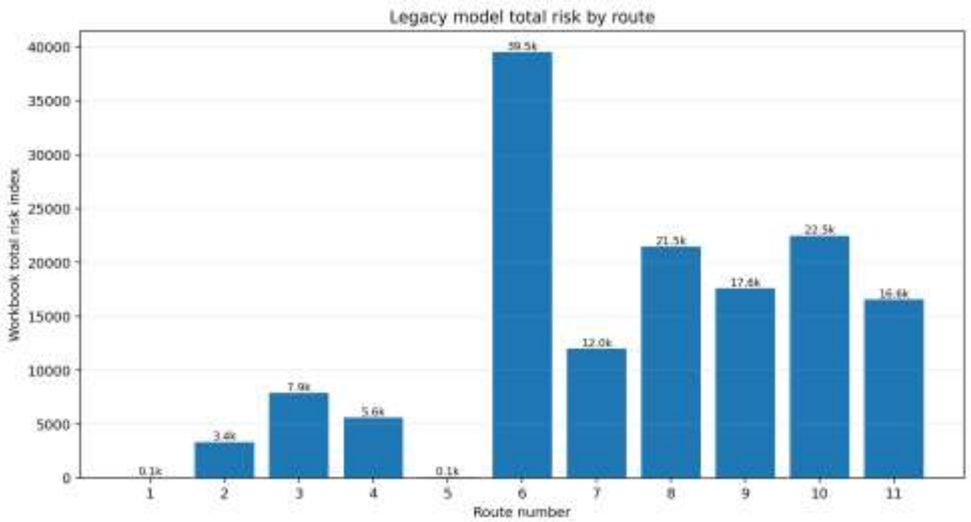


Table 10: Route-level legacy model results and rankings

Route	Segs	Miles	Total index	Share	Total rank	Workbook RPM rank	Corrected RPM rank
Route 1	6	0.0073	63.3	0.0%	11	10	8
Route 2	11	0.4308	3,354.2	2.3%	9	9	11
Route 3	45	0.4418	7,889.8	5.4%	7	6	1
Route 4	24	0.6768	5,616.5	3.8%	8	8	9
Route 5	3	0.0074	80.5	0.1%	10	11	6
Route 6	126	2.6534	39,510.9	26.9%	1	1	4
Route 7	61	0.9123	12,006.0	8.2%	6	4	5
Route 8	62	2.0440	21,460.7	14.6%	3	7	7
Route 9	50	1.1258	17,610.5	12.0%	4	5	2
Route 10	98	1.4415	22,484.7	15.3%	2	2	3
Route 11	108	2.0588	16,554.8	11.3%	5	3	10

Segmentation bias in the route "risk per mile" metric

The workbook route "risk per mile" is calculated as SUM(segment risk per mile). This is dimensionally inconsistent: adding multiple per-mile indices produces a value that increases when an otherwise identical route is divided into more segments. The relationship is visible in the data. The Pearson correlation between the number of dynamic segments and the workbook route metric is 0.925. This does not prove that segment count is the sole driver, but it demonstrates that segmentation structure is a dominant influence.

A corrected route risk density was calculated as the length-weighted mean of segment risk-per-mile values. The correction materially changes route ranks. Route 3 moves from sixth under the workbook metric to first under the corrected metric. Route 11 moves from third to tenth. Route 6 moves from first to fourth. The Spearman correlation between the two normalized rankings is only 0.418. Figures 3 and 4 show the segment-count dependence and resulting rank changes.

This defect does not change the workbook's separate total-risk rank, which is based on the sum of length-proportional segment risk. It does, however, make the displayed "risk per mile" values and rankings unreliable for normalized comparisons. Any decision, dashboard, threshold, or performance metric using that column should be recalculated.

Figure 3. Segmentation-count dependence of the workbook route risk-per-mile metric.

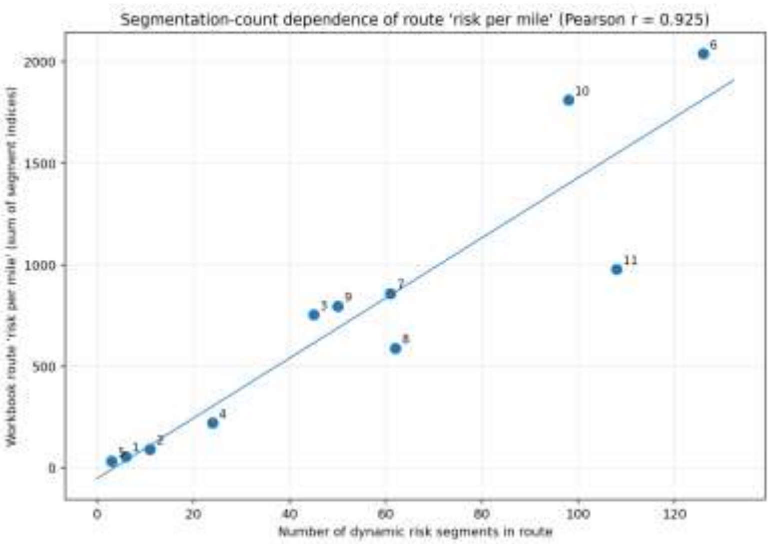


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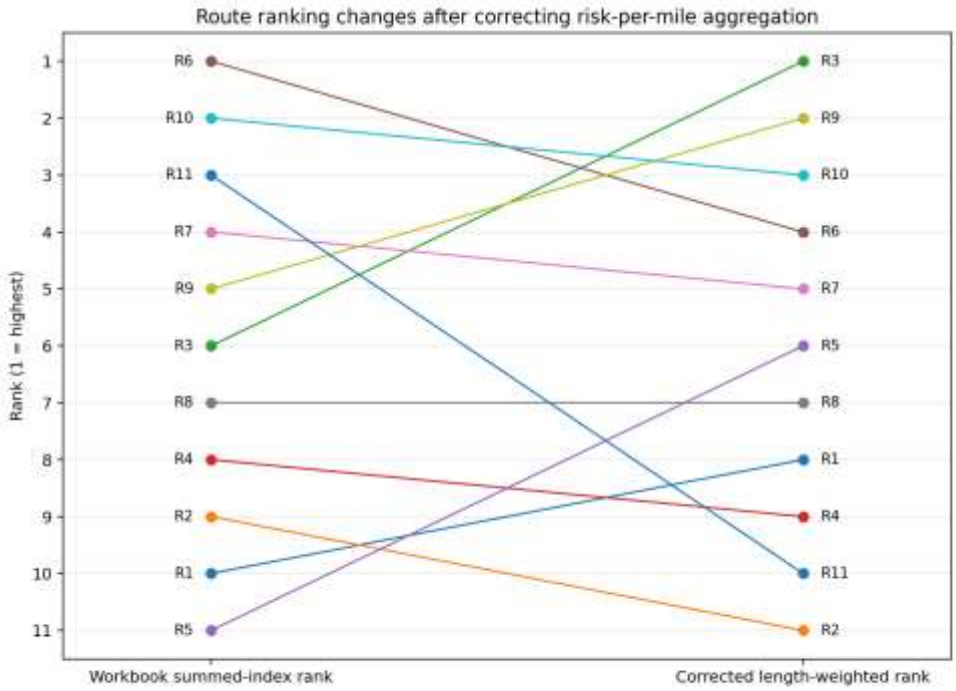
Figure 4. Route-ranking changes after replacing the summed segment index with a length-weighted route risk density.



The total weighted threat score ranges from 1.04975 to 1.36975 and has only six unique values across 594 segments. The modal value occurs on 73.1% of segments. Five of the eight threat-category adjustments are constant across every segment: corrosion (1.15), material/weld (1.04), equipment (1.05), incorrect operations (1.00), and other threats (1.02). Natural-force adjustment is at its modal value on 98.3% of segments; excavation is at its modal value on 96.0%; and other-outside-force is at its modal value on 78.5%.

Table 7. Factor variability and model discrimination

Factor	Min	Max	Unique	Modal share	Interpretation
Corrosion adjustment	1.150	1.150	1	100.0%	Constant baseline; no segment discrimination.
Natural-force adjustment	1.105	2.085	2	98.3%	Almost entirely at baseline.
Excavation adjustment	1.000	2.600	3	96.0%	Limited differentiation.
Other-outside-force adjustment	1.000	2.000	2	78.5%	Most variable threat category.
Material/weld adjustment	1.040	1.040	1	100.0%	Constant baseline.
Equipment adjustment	1.050	1.050	1	100.0%	Constant baseline.
Incorrect-operation adjustment	1.000	1.000	1	100.0%	Constant baseline.
Other-threat adjustment	1.020	1.020	1	100.0%	Constant baseline.
Total weighted threat	1.0498	1.3698	6	73.1%	Low dispersion; limited threat-driven ranking.
PipeFAC	4.750	12.326	53	9.1%	Primary source of segment-score variation.
Consequence factor	1.000	2.400	18	44.9%	Meaningful but partly constrained by invariant fields.
Segment risk per mile	5.336	32.535	218	4.7%	Driven principally by PipeFAC and consequence.

The risk-per-mile index is therefore much more sensitive to PipeFAC and consequence than to total threat. Pearson correlations with segment risk per mile are 0.839 for PipeFAC, 0.700 for consequence, and 0.150 for total weighted threat. The longitudinal factor alone has a correlation of 0.458. These statistics do not imply causation, but they confirm that the threat component contributes relatively little discrimination in the supplied data.

A risk model can legitimately conclude that threats are broadly similar across a homogeneous system. The concern here is evidentiary: several categories are constant because their underlying fields are constant or defaulted, and leak data are all zero in an outdated window. Without sensitivity analysis, updated operating data, or validation against events and inspection findings, it is not possible to distinguish a truly homogeneous threat profile from a model that lacks current discriminating inputs.

Threat rollup and baseline scaling

The workbook sums threat-category adjustment scores across all segments and ranks them as "threats of concern." Other outside force ranks first, corrosion second, and natural forces third. Because several within-category weights do not sum to one and every category has a positive baseline, the rollup combines actual spatial variation with arbitrary baseline scale. If the within-category sums are normalized, corrosion falls from second to fourth, while natural forces rises from third to second. This sensitivity illustrates why category scores should be placed on comparable scales before they are ranked. A better threat-of-concern measure would separate at least three quantities: estimated event frequency or probability by cause; exposure or susceptible mileage; and consequence contribution. A simple sum of index scores can still be used as a screening indicator, but it should not be described as a calibrated measure of threat frequency.

No explicit probability distributions, confidence intervals, data-quality scores, Monte Carlo simulation, or Bayesian updating were found in the workbook. Unknown or conservative values are embedded directly in physical risk factors, so the score does not reveal whether a segment is high because the evidence indicates hazardous conditions or because the data are uncertain. This makes it difficult to prioritize data acquisition separately from physical mitigation.

The workbook does not visibly model interacting threats. The additive weighted threat structure treats categories as independent contributors before multiplication by common pipe and consequence factors. Spatial features included in the longitudinal factor may indirectly represent co-location, but there is no explicit logic for combinations such as corrosion plus cyclic loading, a dent plus a crack, unstable ground plus a girth-weld susceptibility, or third-party activity plus inadequate cover.

No sensitivity-analysis output, back-testing result, calibration record, or comparison against operator and industry failure experience was supplied. Likewise, the model does not calculate the expected risk reduction from candidate actions. A user can manually alter factors to explore scenarios, but the workbook has no formal action library, intervention effectiveness model, cost basis, or uncertainty range. These are major gaps relative to the current decision functions described in § 192.917.

Summary gap assessment

The reviewed framework's strongest attributes are governance intent, transparency, conservative missing-data principles, GIS-based dynamic segmentation, clear separation of total and segment-level calculations, and the existence of an auditable spreadsheet implementation. The most significant weaknesses are incomplete current-portfolio scope, obsolete leak inputs, non-discriminating threat data, undocumented or inconsistent formulas, a biased normalized route metric, absence of explicit uncertainty and interaction logic, and lack of validation and candidate-action benefit analysis.

Table 8. Technical gap assessment

Finding	Significance	Evidence	Recommended control
Current portfolio coverage	**Critical**	11.80 modeled miles vs approximately 103.66 miles and 30 systems in the TIMP.	Rebuild the complete linear asset inventory and material-specific model scope.
Route risk-density aggregation	**Critical**	SUM of segment indices; segment-count correlation r = 0.925; corrected ranks materially differ.	Replace with length-weighted aggregation and re-evaluate dependent decisions.
Leak and operating-data currency	**Major**	Leak window ends June 2016 and all leak inputs are zero.	Integrate current leaks, damages, near misses, assessments, repairs and

			operations data.
Formula/version traceability	**Major**	Route formula, longitudinal factor and amplification factor differ from methodology.	Issue a controlled model-basis document and automated tests.
Threat differentiation	**Major**	Five categories are constant; total threat has only six unique values.	Refresh threat evidence and calibrate category-specific scales.
Uncertainty and sensitivity	**Major**	No explicit uncertainty distributions, confidence classes or sensitivity outputs supplied.	Separate data confidence and run sensitivity/uncertainty propagation.
Interacting threats	**Major**	Additive threat structure does not explicitly model conditional interactions.	Implement a screened interaction library using causal or Bayesian logic.
Candidate-action benefit	**Major**	No formal risk-reduction or cost-effectiveness calculation.	Model before/after risk for assessment, mitigation and data-acquisition options.
HCA/MCA/class-location linkage	Critical	HCA is an ordinal workbook code; no MCA, PIR/PIC, method, identified-site, roadway, effective-date or § 192.710 logic; source HCA counts are unreconciled.	Create a separate controlled GIS register and automated crosswalk to risk, assessment and MOC processes.
Operational class/HCA/MCA procedure	**Major**	Useful two-geometry GIS workflow and structure taxonomy, but unit, cluster, occupancy, dwelling-count, roadway, status and version-control issues remain.	Issue a controlled work instruction and data dictionary; implement the Appendix F workflow and independently verify the first production run.
Governance, QA and annual review	Positive practice	TIMP includes audits, MOC, annual review, lessons learned and performance measures.	Use existing controls to govern modernization, HCA/MCA reconciliation and model validation.

Discussion

The TIMP risk model workbook remains useful as a transparent screening instrument for the legacy steel corridor. Its inputs and formulas can be traced to individual cells, GIS segmentation provides spatial resolution, and route and segment outputs can be reproduced independently. These properties are valuable because a technically sophisticated model that cannot be explained, reviewed, or maintained may be less useful operationally than a simpler model with clear lineage.

The model's numerical outputs, however, are relative index values. They do not represent annual failure probabilities, event frequencies, expected fatalities, expected service interruption, or expected monetary loss. This distinction limits cross-system comparison, temporal interpretation, and benefit-cost analysis. An index of 20 is not twice the physical risk of an index of 10 unless the scale has been demonstrated to be ratio-consistent, which was not shown in the supplied materials. Han and Weng (2011) reached a similar conclusion in comparing qualitative and quantitative pipeline-risk methods: ranking scores and quantitative risk measures answer different questions and should not be treated as interchangeable.

The appropriate role for the current model is therefore bounded. It can support preliminary triage, structured multidisciplinary review, identification of unusual data combinations, and comparison within a stable asset subset after the formula defects are corrected. It should not be the sole analytical basis for current full-portfolio prioritization, interacting-threat analysis, reassessment optimization, or quantitative evaluation of candidate risk-reduction measures.

Dynamic segmentation is a sound GIS practice when boundaries reflect changes in pipe attributes, threats, receptors, or operating conditions. The error occurs when segment-level intensive quantities are added without exposure weighting. A route divided into 100 equal homogeneous pieces should have the same risk density as the same route represented by one segment. The workbook's summation formula violates that invariance.

This issue has practical consequences beyond mathematical form. If the segmenting rules change after a GIS refresh, route risk-per-mile rankings can change even when no physical condition changes. A segment may be split because a new road centerline, class-location boundary, parcel layer, or survey record was added. Under the current route formula, the split itself increases the route value. This can create false trends, distort resource comparisons, and make year-to-year performance measurement unreliable.

The correction is straightforward: aggregate extensive quantities by summation and intensive quantities by exposure-weighted averaging. Segment total risk is extensive and may be summed. Segment risk per mile is intensive and should be length-weighted. Comparable rules should be documented for every output, including threat frequency per mile, consequence per event, data-confidence scores, and system-level expected loss.

Conservative defaults are an accepted integrity-management response when information is missing. The TIMP properly states that absent or suspect data should not be used to exclude a threat. Yet a conservative physical-risk score and a data-uncertainty penalty are not analytically identical. Combining them in one number obscures the reason for the priority. A segment may be ranked high because it has verified adverse conditions, because a critical record is unavailable, or because both are true. Those cases imply different actions: physical mitigation, data acquisition, or both.

This distinction is particularly important in a model dominated by constant or modal inputs. When most threat factors are invariant, the model's apparent precision is largely driven by pipe and consequence coding. Updating leak history, patrol findings, encroachments, one-call activity, cathodic-protection performance, integrity-assessment results, environmental change, and material-specific defects could materially alter the ranking. A separate data-confidence layer would allow the operator to identify high-risk/high-confidence segments, high-risk/low-confidence segments, and low-risk/low-confidence segments and to assign different management responses.

Bayesian methods provide one formal way to treat sparse evidence because prior knowledge can be updated as operator-specific data accumulate (Cagno et al., 2000; Dong & Yu, 2005). Fuzzy systems can also represent linguistic or imprecise expert evidence, although their membership functions and rule bases require validation (Jamshidi et al., 2013). Neither method eliminates the need for authoritative source data, data lineage, and documented expert controls.

Threat interaction and material-specific applicability

The TIMP recognizes threat categories and notes that stable threats can become important when combined with other mechanisms. The workbook's top-level arithmetic, however, adds threat-category scores and then applies common pipe and consequence factors. It does not explicitly represent conditional dependence or acceleration among threats. This is a material limitation because pipeline failures often arise from interacting mechanisms rather than isolated categories.

A practical interaction model does not need to enumerate every conceivable combination. It can begin with a controlled library of technically plausible interactions relevant to the portfolio, such as corrosion with cyclic pressure, dents with gouges or cracks, ground movement with girth-weld susceptibility, coating damage with cathodic-protection shielding, and inadequate cover with excavation activity. Bow-tie and Bayesian-network methods are well suited to representing causal pathways and conditional dependence (Shahriar et al., 2012; Shan et al., 2017; Zhu et al., 2022).

Material scope is equally important. The supplied workbook's corrosion material factor and threat parameters were built for coated steel. The 2024 TIMP describes substantial HDPE mileage. Plastic-pipe risk requires material- and joint-specific logic, including installation damage, slow crack growth, squeeze-off history, joint quality, incompatible components, temperature effects, and other applicable mechanisms. A single steel-oriented parameter table should not be copied to HDPE without a separate technical basis.

The existing consequence factor uses population/class, critical and public buildings, environmental sensitivity, surface cover, overbuild, and isolation capability. These are sensible screening variables. The issue is that a weighted index does not explicitly model release size, ignition probability, thermal effects, occupancy, emergency response, service disruption, or environmental and economic outcomes. Quantitative consequence models estimate scenario-specific effects and can be linked to GIS receptors. Jo and Ahn (2005), Sklavounos and Rigas (2006), Han and Weng (2010), Ma et al. (2013), and Fang et al. (2019) demonstrate variations of this approach. For a small operator, a full computational-fluid-dynamics model is unnecessary for every segment. A defensible scenario library based on pipe diameter, pressure, release mode, ignition state, population exposure, and isolation time can provide substantially more interpretable consequences while remaining maintainable.

The current consequence index may remain as a screening layer during transition. Its variables should be refreshed from authoritative GIS, emergency-response, land-use, environmental, and facility records, and invariant fields should be specifically confirmed rather than assumed current.

Class location, HCA and MCA should not be combined as a single severity ladder. A segment can be in a particular class location and also be in an HCA through a class-based or PIR/PIC-based method. MCA is explicitly defined as non-HCA, and its regulatory significance depends on material, pressure, inspectability and § 192.710 applicability. Treating HCA as a population value above Class 4 masks these logical relationships and prevents a transparent audit of coverage decisions.

The workbook does increase scores for HCA-coded segments, but it cannot show whether the increase represents additional people, an identified site, a class-based rule, or another consequence mechanism. If population density, critical/public buildings, surface cover and HCA status are all weighted in the same consequence factor, the model can also double count the same underlying receptor unless dependencies are explicitly controlled. The future model should calculate exposed people, property, environmental and service consequences from source data and use HCA/MCA/class status primarily as regulatory, governance and segmentation overlays.

The complete portfolio introduces an additional distinction. The source table assigns both steel and HDPE entries to HCA and MCA columns, while the current Texas § 8.101 does not apply to plastic pipelines and federal § 192.710 applies to qualifying steel segments. Those exclusions do not eliminate federal integrity-management duties for covered plastic transmission segments; §§ 192.917(d) and 192.935(e) contain plastic-specific requirements. The model must therefore determine applicability at the segment level rather than infer it solely from an HCA/MCA label.

The unreconciled source counts are a governance concern even if each value is individually correct for its stated unit. The controlled program record should explicitly map each HCA area to one or more covered segments, each covered segment to linear mileage, and each portfolio-table entry to the effective GIS version. The same structure should be maintained for MCA, class-location units and eligible-Class-3 segments. Without that mapping, performance measures, assessment schedules and model coverage cannot be reconciled reliably.

The operational class-analysis procedure can be retained as the front-end GIS work instruction, but its outputs should be treated as evidence rather than direct risk scores. The structure codes should populate receptor counts, occupancy profiles, evacuation difficulty, class/HCA/MCA basis and data-confidence fields. They should not be converted into a single increasing severity code. One structure can serve several analytical functions: a multi-family feature affects class and PIC building counts; a four-story building affects Class 4 logic; a school or limited-mobility facility can establish an identified site; and a qualifying roadway can establish MCA without being a building.

This separation also avoids threshold artifacts. The regulatory layer can record whether a threshold is met, while the physical consequence layer retains continuous exposure variables, occupancy evidence and source confidence. The model can therefore respect class, HCA and MCA requirements without assigning zero physical consequence to a location just below a regulatory threshold or automatically multiplying consequence merely because an overlay status changes.

A risk model is validated when its structure, inputs, outputs, and decisions are shown to behave consistently with engineering knowledge, operating experience, and observed outcomes. Validation is not a one-time approval of a spreadsheet. It should include formula unit tests, independent calculation, sensitivity testing, ranking stability, back-casting against historical leaks and anomalies, comparison

with integrity-assessment findings, review of false positives and false negatives, and documented multidisciplinary challenge.
The supplied program has a strong procedural foundation for this work. It already calls for audits, annual review, lessons learned, benchmarking, quality assurance, management of change, and performance metrics. These mechanisms should be extended to the model itself. The performance dashboard should distinguish model health from pipeline health. Model-health measures can include source-data completeness, stale-data rate, unresolved default rate, formula test coverage, ranking stability, calibration statistics, and time to incorporate new information. Pipeline-health measures can include leaks, ruptures, anomalies, corrosion growth, excavation damages, encroachments, and risk reduction achieved.
The reviewed documents and operational procedure express several principles consistent with current integrity-management requirements. The evidence supplied for the model and GIS method does not, however, demonstrate a completed current class/HCA/MCA determination package, sensitivity analysis, explicit uncertainty compensation, interacting-threat analysis, validation against current incident and leak history, or evaluation of risk reduction for candidate actions. The technically appropriate conclusion is that these functions were not demonstrated in the supplied evidence. Determining legal compliance would require controlled procedures, source records, completed analyses, GIS outputs, approvals, assessment schedules and implementation evidence beyond the five artifacts reviewed.
This distinction should be preserved in internal governance. A modernization project should not merely add features to satisfy a checklist. It should create evidence that the model supports the decisions assigned to it and that those decisions are repeatable, technically justified, and reviewed under the operator's quality system.

Recommended Modernized Risk Framework

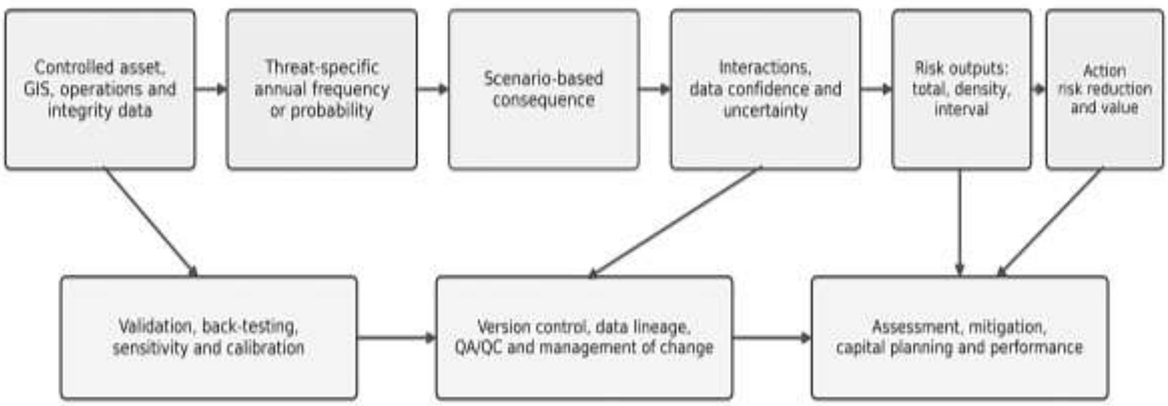
Design principles

The recommended future state is a hybrid, threat-specific, quantitative system model supported by the existing GIS segmentation and a retained index cross-check. “Hybrid” means that quantitative frequency and consequence estimates are used where evidence is adequate, while structured Bayesian, fuzzy, or expert-informed methods are used for sparse mechanisms with explicit uncertainty bounds. The framework should follow eight design principles:

1. Preserve source-data lineage from each score or estimate to an authoritative record.
2. Separate physical risk, data uncertainty, and management confidence.
3. Use material- and threat-specific likelihood models.
4. Use scenario-based consequences with interpretable units.
5. Represent selected interacting threats and conditional dependencies.
6. Aggregate quantities in a dimensionally consistent and segmentation-invariant manner.
7. Quantify uncertainty and sensitivity, rather than hiding them in point scores.
8. Evaluate the risk reduction and cost-effectiveness of candidate actions.

Figure 5 presents the recommended architecture and the relationship among data, likelihood, consequence, uncertainty, action analysis, and governance.

Figure 5. Recommended hybrid risk-system architecture



The legacy index can remain as a screening and cross-check layer.

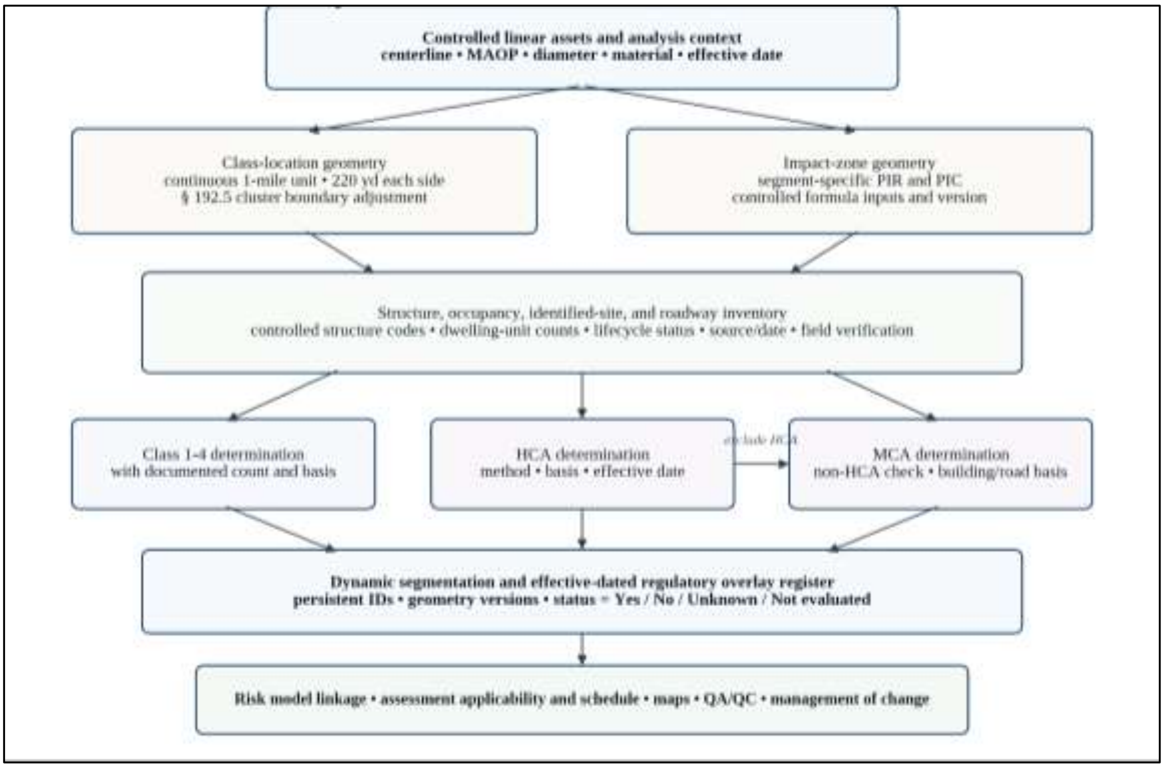
Data and segmentation layer

A controlled linear-referenced asset model should serve as the common analytical spine. Every risk segment should have a persistent identifier, route and system identifiers, begin and end measures, length, material, diameter, wall thickness, grade, seam or joint type, coating, installation year, pressure history, class and consequence geography, HCA/MCA status, and links to source records. Dynamic segmentation should occur at changes in asset characteristics, threat evidence, consequence receptors, assessment coverage, or mitigation state.

Each input should carry metadata: source system, record owner, effective date, extraction date, validation status, confidence class, default status, and next review date. Values derived by spatial overlay should store the GIS layer version and geoprocessing rule. Expert inputs should store the question, alternatives, rationale, participants, date, approval, and uncertainty range.

The assimilated operational workflow is shown in Figure 5A. It begins with controlled asset geometry and operating attributes; constructs separate class-location and PIR/PIC geometries; inventories and codes structures and roadways; makes separate class, HCA and MCA determinations; and then dynamically segments and effective-dates the overlays before linking them to risk and assessment planning.

Figure 6: Assimilated operational GIS workflow for class, HCA, and MCA determination and risk-model linkage.



At the structure level, the source taxonomy can remain as the user-facing code set, but the regulatory basis and counting fields should be separate. Minimum status values should be Yes, No, Unknown and Not evaluated; null should not carry a regulatory meaning. Historical structures should be retained with lifecycle dates but excluded from current counts when no longer present. GIS-derived values should retain the source layer, observation date, geometry version, geoprocessing rule, reviewer and exception status.

Threat-specific likelihood layer

For segment i and threat k, the model should estimate an annual failure frequency or probability, denoted λ_ik. The estimation method can differ by threat:

• external and internal corrosion: statistical or mechanistic models using assessment findings, corrosion

growth, cathodic-protection performance, coating condition, gas quality, pressure, and repair history;
• excavation damage: exposure models using one-call tickets, construction activity, patrol and encroachment data, depth of cover, land use, and damage-prevention performance;
• material, seam, and weld threats: cohort or Bayesian models using material vintage, manufacturing process, test history, pressure cycles, and assessment findings;
• natural forces: geospatial hazard and fragility models for flooding, subsidence, erosion, landslide, or other relevant mechanisms;
• equipment and incorrect operations: event-rate models informed by equipment population, inspection history, abnormal operating conditions, procedure deviations, and human-reliability evidence;
• plastic-pipe threats: material- and joint-specific models appropriate to HDPE and its installation and operating history.

A generic segment-frequency structure is:

$$\lambda_i = \Sigma_k \lambda_{ik}$$

where each λ_{ik} includes model uncertainty and, where applicable, conditional adjustments for interaction. A Bayesian hierarchical model can borrow strength from industry or fleet experience while allowing operator-specific updating. The approach is consistent with the literature's use of Bayesian priors, fault trees, fuzzy probability, and Bayesian networks under sparse data (Cagno et al., 2000; Dong & Yu, 2005; Shan et al., 2017).

Interacting-threat layer

The operator should establish a screened interaction library rather than multiplying all threat pairs. Each interaction should have a physical basis, triggering data, consequence for failure frequency or scenario selection, and a validation or review record. Interaction may be represented through:
• conditional probabilities in a Bayesian network;
• interaction terms in a statistical model;
• fault-tree or event-tree logic;
• state transitions in a degradation model; or
• conservative conditional multipliers with uncertainty bounds during an interim phase.

The model should also test for double counting. For example, depth of cover and excavation activity should not be independently counted in multiple components without a clear causal interpretation.

6.5 Consequence layer

For each threat-related failure, the model should define a small, controlled set of release scenarios, such as leak and rupture, each with ignition and non-ignition branches where applicable. Scenario probability should be conditioned on diameter, pressure, failure mode, gas properties, and operating context. Consequence calculations should consider:
• thermal or other public-safety effects;
• exposed population and occupancy;
• critical and public facilities;
• environmental receptors;
• isolation and emergency-response time;
• service interruption and customer impact;
• repair, property, and business costs; and
• uncertainty in receptor and scenario parameters.

The expected consequence for segment i and threat k is:

$$E(C_{ik}) = \Sigma_s P(s \mid i,k) \times C_{is}$$

where s indexes release and outcome scenarios. Consequences can be maintained as separate dimensions for life safety, environment, reliability, and cost, or converted to a common decision unit through an approved value framework. Multicriteria methods may be used to preserve noncommensurate outcomes, but preference weights should be governed separately from engineering likelihood inputs (Brito & de Almeida, 2009; Brito et al., 2010).

A modern consequence layer should separate regulatory overlays from physical outcome modeling. The regulatory layer answers whether a location is Class 1-4, HCA, MCA, an eligible Class 3 segment, or subject to a particular assessment schedule. The physical layer estimates scenario consequences such

as exposed people, injury/fatality potential, building damage, environmental effects, emergency-response constraints, service interruption, and cost. Both layers use common GIS and asset inputs but serve different decisions.
For natural gas, PIR/PIC should be calculated and retained with its MAOP, diameter, gas-property factor, formula version and effective date. HCA and MCA geometry should be derived from controlled building, identified-site and roadway layers, supplemented by documented field verification. The model should preserve both the regulatory threshold determination and continuous exposure variables; a building count of 19 versus 20 should not create an unexplained discontinuity in physical consequence, even though it can alter regulatory status.
The structure-code dictionary can support this layer through a controlled crosswalk rather than as a direct consequence scale. Single- and multi-family codes support occupied-building and dwelling counts; the high-occupancy building code supports identified-site evidence; school and limited-mobility codes support identified-site and evacuation logic; the four-story code supports Class 4 analysis; and the two outdoor public-assembly codes support different temporal tests. Nonoccupied, non-qualifying and out-of-corridor codes require explicit count and exclusion rules. Appendix F documents the recommended treatment.
To avoid double counting, the consequence model should not automatically add an HCA multiplier on top of the same population and receptor variables used to create the HCA. Any residual HCA/MCA governance multiplier must have a clearly defined decision purpose and sensitivity test. The preferred approach is to use HCA/MCA/class to establish coverage, segmentation, minimum controls and reporting, while the physical consequence model independently quantifies outcomes.
Outputs should include HCA and MCA mileage by system and material; class-location mileage; count and type of identified sites; § 192.710 applicable mileage and assessment status; risk and uncertainty by regulatory overlay; and the incremental risk reduction expected from actions. The reporting hierarchy should reconcile exactly to the controlled area/segment register.

Risk, aggregation, and reporting

Annual expected risk for segment i is:

$R\_i = \Sigma\_k [\lambda\_ik \times E(C\_ik)]$

System total risk is the sum of segment risks:

$R\_system = \Sigma\_i R\_i$

Risk density for a route or system is:

$R\_density = R\_system / total\ length$

This separation prevents the aggregation defect found in the legacy workbook. Extensive measures, such as expected annual loss or expected annual fatalities, are summed. Intensive measures, such as frequency per mile or risk per mile, are exposure-weighted. Reporting should include both total risk and density because long routes can have high total risk even when local intensity is moderate.
The model should report central estimates and uncertainty intervals, not only point estimates. At minimum, dashboards should include segment and route total risk, risk density, dominant threats, consequence drivers, data-confidence class, uncertainty range, and ranking stability.

Candidate-action analysis

Every major integrity decision should be representable as a change to model inputs or structure. Candidate actions may include pressure reduction, excavation-damage prevention, additional patrol, cathodic-protection remediation, coating rehabilitation, direct examination, pressure test, in-line inspection, valve or isolation improvement, replacement, or targeted data collection.
For action a, expected risk reduction is:

$\Delta R\_a = R\_baseline - R\_after,a$

Risk-reduction efficiency can be expressed as ΔR_a divided by lifecycle cost, subject to safety, legal, operational, and feasibility constraints. The model should report the range of ΔR_a under uncertainty and identify whether an action reduces physical risk, reduces uncertainty, or both. This directly connects the model to preventive and mitigative decision making rather than treating ranking as the final product.

Validation and governance

The future model should be controlled as an integrity-management analytical system. Required

controls include:
• approved model basis and data dictionary;
• source-code or workbook version control and release notes;
• independent formula and software verification;
• unit, regression, and boundary tests;
• documented calibration and back-testing;
• sensitivity and uncertainty analyses;
• structured multidisciplinary review;
• change-control thresholds and approval authorities;
• annual validation and post-event review;
• archival reproducibility of every official model run; and
• documented rationale for overrides or deviations.
• controlled reconciliation of HCA areas, covered segments, MCA segments, class-location units, eligible-Class-3 segments and mileage;
• automated validation that MCA does not overlap HCA in the official regulatory overlay and that § 192.710 applicability is material-, pressure- and inspectability-specific;
• required recomputation after changes in MAOP, diameter, product, centerline, buildings, identified sites, road classifications or class location;
• independent GIS and source-record review of HCA/MCA boundaries and the basis for inclusion or exclusion; and
• current-regulation review before each controlled program release, including the 2026 eligible-Class-3 provisions where applicable.

The current workbook can serve as a benchmark during transition. Large differences between the index and quantitative results should trigger investigation rather than automatic rejection of either result.

Implementation Roadmap

Phase 1: Stabilize the legacy model (0-90 days)

The first phase should freeze the supplied workbook and operational GIS procedure as controlled baselines; correct the route-density formula; remove or justify the longitudinal addition; reconcile the amplification factor; normalize or justify all weighting sets; add automated test cases; and explicitly label the workbook HCA field as a legacy consequence code rather than the authoritative regulatory determination. In parallel, issue a controlled revision of the class/HCA/MCA work instruction and structure dictionary that corrects the 660-foot unit description, clarifies the one-mile class unit and cluster adjustment, separates identified-site tests, requires multi-family dwelling counts, adds qualifying-roadway logic, defines HCA method and basis, replaces null status and establishes effective-dated records. The repaired model should show total route risk and length-weighted risk density with clear units or “dimensionless index” labels.

A model-basis document should identify every equation, factor domain, default, data owner, effective date and intended interpretation. A parallel HCA/MCA/class-location reconciliation should resolve the 16-segment, 18-HCA, 20-entry and 3.59-mile references; establish controlled identifiers and mileage; document the effective GIS version; and validate the revised procedure through an independently reviewed pilot route. A change log should record all corrections and their effect on historical ranks and consequence-area determinations. Any decision previously based on the summed route risk-per-mile column, the legacy HCA code, a yes/null GIS field or an unversioned map should be identified and re-evaluated with the corrected and reconciled data.

Phase 2: Build the current data foundation (1-6 months)

The operator should reconcile the complete current portfolio to a master linear asset inventory. The risk data set should include all systems, not only the legacy corridor, and should distinguish steel and HDPE with appropriate threat taxonomies. A controlled consequence-area data mart should integrate current class-location studies; HCA/MCA/eligible-Class-3 geometries; PIR/PIC calculations; building and identified-site records; qualifying roadways; § 192.710 applicability and schedules; and assessment, remediation and MOC status. The leak-history window should be extended through the current effective date, and integrity assessments, repairs, cathodic-protection data, one-call and excavation activity, encroachments, patrols, abnormal operating conditions, pressure history, and current

consequence receptors should be integrated.
Each data element should receive a lineage and confidence record. Defaults should be enumerated in a separate register with owners and closure dates. GIS overlays should be rerun using the controlled Appendix F workflow and approved layer versions. Structure records should include lifecycle, occupancy, dwelling-unit and identified-site evidence; roadway records should include functional class and lane count; and class/HCA/MCA counts should reconcile to mileage and segment registers. Automated checks should identify new or changed buildings, identified sites, roadways, MAOP, diameter, product and centerline geometry that could alter PIR/PIC, class, HCA or MCA status.

Phase 3: Pilot the hybrid model (4-12 months)

A pilot should be implemented on three representative scopes: the legacy steel system, a newer steel system, and an HDPE system. It should also include at least one HCA, one non-HCA § 192.710-applicable steel segment if present, one MCA building basis, one MCA roadway basis, one class-location-change scenario, and representative structure codes including multi-family, high-occupancy, limited-mobility, four-story and public-assembly features. The pilot should independently reproduce the GIS determinations, estimate threat-specific frequencies, use a controlled consequence scenario library, represent a limited set of high-value interactions, and run Monte Carlo or equivalent uncertainty propagation. It should calculate risk reduction for several actual candidate actions and verify that regulatory-overlay status changes do not create unintended score discontinuities or double counting.
The pilot should be compared with the repaired index model, operator judgment, inspection findings, and historical events. Differences should be reviewed in structured workshops. The objective is not to force identical rankings but to understand why they differ and which model behavior is better supported.

Phase 4: Production deployment (9-18 months)

Following pilot validation, the model should be extended to the full portfolio and integrated with GIS, HCA/MCA/class-location governance, document control, integrity-assessment planning, management of change, and performance measurement. A formal model-validation report should be approved before the first official production run. Users should receive role-based training on model interpretation, regulatory overlays, uncertainty, overrides, and limitations.
Production reports should preserve an archived input snapshot, model version, run date, approvals, and output package. Dashboards should distinguish risk, risk density, uncertainty, and data confidence. Candidate-action analysis should be incorporated into assessment, mitigation, and capital-planning decisions.

Phase 5: Continuous improvement (ongoing)

The model and consequence-area register should be updated after material new information, completed assessments, repairs, mitigation, incidents, near misses, pressure or diameter changes, and significant population, roadway, land-use or centerline changes. Annual validation should include HCA/MCA/class-location reconciliation, performance against actual events and findings, sensitivity analysis, ranking stability, § 192.710 schedule status, and model-health metrics. Major changes in equations, priors, consequence logic, regulatory definitions or data sources should pass management of change and independent technical review.

Table 11: Implementation roadmap

Phase	Timing	Primary actions	Deliverables	Decision gate
1. Stabilize	0-90 days	Freeze workbook and GIS procedure; correct route density and formula differences; revise unit/criteria/status logic; document weights/units; label legacy HCA code; reconcile HCA/MCA/class counts and identifiers; pilot procedure; add regression tests.	Repaired legacy model, controlled class/HCA/MCA procedure and code dictionary, reconciled overlay register, model-basis document, change log and decision-impact review.	Independent formula verification complete.
2. Data foundation	1-6 months	Reconcile all systems; execute the controlled GIS workflow; integrate class studies, HCA/MCA/PIR/PIC, structure codes, dwelling counts, identified sites, roadways, § 192.710 applicability, current integrity and consequence data; add lineage/confidence.	Controlled full-portfolio risk and consequence-area data mart, GIS layer package, structure/roadway evidence register, map package and default register.	Data completeness and quality thresholds met.
3. Hybrid pilot	4-12 months	Pilot on representative steel/HDPE and HCA/MCA/class scopes; independently reproduce GIS outputs; validate structure-code crosswalk; add frequency, consequence, interactions and uncertainty; test status-change and candidate-action scenarios.	Pilot model, sensitivity analysis, validation workshop and comparative report.	Technical committee approves scale-up.
4. Production	9-18 months	Deploy across portfolio; integrate GIS, HCA/MCA/class governance, MOC, assessment planning and dashboards; train users; archive official runs.	Validated production model and controlled reporting package.	Formal model-validation approval.
5. Continuous improvement	Ongoing	Update after new data/events/actions and consequence-area changes; annual reconciliation, back-testing, calibration, sensitivity and model-health review.	Annual validation record, release notes and performance results.	Management review accepts continued use or directs revision.

Limitations and Conclusion

This research evaluated only the five supplied artifacts. It did not have access to the complete GIS, event and near-miss database, pressure-cycle history, integrity-assessment results, cathodic-protection records, repair files, one-call and encroachment data, expert-elicitation records, audit reports, baseline assessment plan, management approvals, populated class-location study files, HCA/MCA determination records, PIC polygons, structure and identified-site layers, roadway classifications, geoprocessing logs, map approvals, or full-portfolio MAOP/diameter data. The supplementary class-analysis procedure and structure-code dictionary were evaluated as written methods, not as proof that a current production analysis was completed. The absence of an item from the supplied files does not prove that it has not been performed or retained elsewhere.

The analysis treated workbook cached values as the official output of the supplied version and independently reproduced the principal formulas, route calculations, and population/HCA summaries. It did not determine whether another controlled workbook or enterprise application supersedes the file. HCA/MCA and class-location counts were extracted from the supplied program and table but could not be spatially validated. Consequence receptors and pipeline attributes were not field verified. Statistical relationships reported in this paper are diagnostic of the supplied data and should not be interpreted as causal failure models or certified regulatory classifications.

The external comparison reflects regulations and sources reviewed through July 2026. Regulatory applicability can depend on facts, jurisdiction, effective dates, waivers, and operator-specific circumstances. The paper therefore provides technical findings and recommendations, not a legal compliance conclusion.

Conclusion

The reviewed TIMP integrity-management framework has a solid procedural foundation. The 2024 TIMP recognizes the essential lifecycle of data integration, class and HCA/MCA review, threat evaluation, risk ranking, assessment, remediation, preventive and mitigative measures, management of change, quality assurance, performance measurement, and periodic review. The 2013 methodology and 2019 workbook provide transparency, GIS segmentation and an auditable relative-risk structure. The 2024 class-analysis procedure and structure-code dictionary add a practical GIS evidence workflow that can be assimilated into the future system after correction and formal control.

The evidence nevertheless demonstrates that the supplied workbook is a legacy, limited-scope index model rather than a current full-system quantitative risk model. It represents 11.7998 miles of coated-steel legacy pipeline, while the current TIMP describes approximately 103.66 miles across 30 systems containing steel and HDPE. HCA is encoded as an ordinal population category, MCA is absent, and no PIR/PIC, determination method, identified-site, roadway, effective-date or § 192.710 logic is visible. The source program also reports HCA counts on different bases that are not reconciled. The operational GIS procedure usefully addresses class, PIR/PIC, structure inventory and HCA/MCA mapping, but its unit label, cluster description, identified-site criteria, dwelling-count logic, roadway coverage, null status and record controls require revision. In addition, route risk-per-mile is segmentation dependent; documented and implemented equations diverge; several weighting sets impose unexplained baselines; threat differentiation is weak; leak data end in 2016 and are uniformly zero; and explicit uncertainty, interaction, validation, and candidate-action benefit functions are not demonstrated.

The technically proportionate response is a controlled modernization rather than abrupt replacement. The operator should first repair and document the existing index; issue the controlled class/HCA/MCA procedure and structure-code crosswalk in Appendix F; independently validate the first production GIS run; reconcile and version the consequence-area data; refresh and extend the portfolio; and separate physical risk from data uncertainty and regulatory overlays. It should then transition to a hybrid threat-specific model that estimates interpretable likelihood and consequence, represents selected interactions, propagates uncertainty, aggregates consistently, and evaluates the risk reduction of candidate actions. The current index and revised GIS workflow can remain as transparent screening, evidence and cross-check layers.

The immediate decision controls are threefold. Until the route risk-per-mile formula is repaired, that metric should not be used for normalized route comparisons. Until HCA/MCA/class-location records are reconciled and linked to controlled GIS evidence, the workbook HCA code should not be treated as the authoritative determination or as proof of MCA assessment coverage. Until the operational procedure is corrected and its first official run independently reproduced, a yes/null field or exported map should not be treated as the complete determination record. The separate total-risk ranking remains mathematically consistent with workbook segment totals, but it applies only to the legacy subset and inherits the model data, classification and calibration limitations. Modernization should therefore proceed on parallel tracks: correct known calculation defects, establish authoritative consequence-area governance, operationalize the revised GIS method, and build the evidence-based full-portfolio decision model required for the future.

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