Case Study in the Application of Probabilistic Framework for Pipeline Failure Estimation due to Landslides

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ABSTRACT: As transmission pipelines are present in diverse terrains, identification of the susceptible regions for landslides and slope movement requires significant effort, and the scale of the system often poses a challenging engineering task for site investigations. This case study presents the application of data-driven approaches for the probability estimation of the landslide susceptibility over a large gas transmission pipeline network in North America.

Landslides pose a significant integrity threat to buried oil and gas pipelines, causing failure that results in the loss of containment. As transmission pipelines span across diverse terrain, identification of sites susceptible to slope movement and landslides requires significant effort, and the scale of the pipeline system often poses a challenging engineering task for site investigations. The threat posed by the large-scale ground movement to pipeline integrity is often managed through aerial and satellite-based inspection systems as well as the inline inspection (ILI) of the pipelines through inertial mapping units (IMU) that provide indirect measurements of the pipeline curvature. Due to the limited spatial and temporal resolution of these inspection systems, there are significant uncertainties in the inference of slope hazard susceptibility of these sites. Furthermore, there are uncertainties in estimating the probability of pipeline failure due to the slope movement activity, as the pipeline response to the ground movement depends not only on the pipeline parameters, but also on the site-specific soil parameters.

The probability of failure (P_f) of a pipeline due to ground movement on a slope is commonly represented as

$$P_f = \mathrm{P}(S_d > S_c | \, d_s \geq D) \cdot \mathrm{P}(d_s \geq D) \qquad (1)$$

where S_d is the strain demand on the pipeline due to imposed ground movement, S_c is the strain capacity of pipe body and the girth weld joints to accommodate the displacement caused by the ground movement, d_s is the magnitude of the ground displacement and D is the threshold at which a slope is categorized as susceptible for landslide and can induce strain demand on the buried steel pipeline. $\mathrm{P}(d_s \geq D)$ is the probability of occurrence of a landslide and is commonly termed as 'landslide susceptibility'. $\mathrm{P}(S_d > S_c | \, d_s \geq D)$ is the conditional probability that the pipeline would have a loss of containment given the occurrence of the ground movement.

Most of the probabilistic landslide assessment models in the literature (Baumgard et al. 2016, Guthrie and Reid 2018, Newton et al. 2022) have focused on the landslide susceptibility. The susceptibility factors are derived as a combination of the regional geological, topographic and soil characteristics along with the field investigations and site-specific observations. The probability of occurrence of the landslide is derived based on the historical occurrence of landslides as a function of the susceptibility factors. This approach is amenable to landslide hazard management on a large regional scale and to identify the potential locations where further investigation and inspection is warranted. However, this approach is prone to providing probability estimates that vary only by an order of magnitude and thus lacks the granularity that is actionable at a spatial scale in pipeline integrity management.

In contrast to the landslide susceptibility models, the probabilistic models to estimate the conditional probability of the pipeline failure use structural reliability approaches (Sen and Hassanien 2019, Fowler et al. 2022). These models consider the site-specific characteristics such as soil type, slope angle, movement zone, angle of movement between the soil and the pipeline longitudinal axis to estimate the strain demand imposed by the soil movement, ideally through advanced finite-element analysis (FEA). This approach is feasible where landslide susceptible sites are known and instrumented with slope inclinometers to provide the ground movement rate. However, in a large scale pipeline system, instrumentation and monitoring of all landslide susceptible sites become impractical.

Although there have been previous efforts for data fusion between the landslide susceptibility factors and pipeline failure probability estimates (Koduru 2019), these were not extended to the pipeline system-wide application at a regional scale. More recently, a GIS-based data driven approach was developed to estimate the landslide susceptibility (Varela et al., 2022) and used high-resolution light detection and ranging (LiDAR) data along the pipeline corridor.

In the present case study, the GIS-based data driven approach is applied to a gas transmission pipeline system of over 18,000 miles spread across North America. The primary objectives of the study are (a) the verification of the model performance against standard statistical attributes and, (b) development of a model validation approach where the true landslide susceptibility is unknown until the occurrence of the event. Furthermore, a new probabilistic framework is introduced to account for the pipeline failure probability as a reformulation of the standard approach noted in the Eq. (1).

A brief description of the GIS-based data driven approach is presented first, followed by a description of the gas transmission pipeline system and the summary of the landslide susceptibility predictions. Next, a discussion of the model verification approach and summary of the model validation results are presented. This is followed by the reformulated framework for estimating the pipeline probability of failure. Finally, this study concludes with a discussion on the model validation approaches in the absence of the truth data sets.

1. MODEL AND SYSTEM DESCRIPTION

1.1. GIS-based data driven model

The GIS-based data driven model uses the high-resolution LiDAR data along the pipeline corridor as shown in Figure 1.

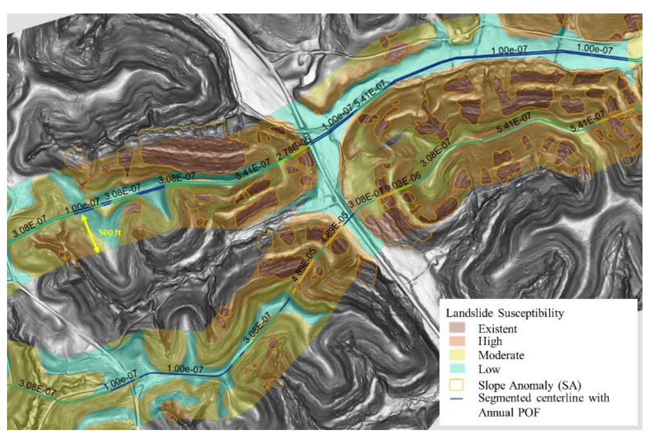

Figure 1: High-resolution LiDAR along the pipeline corridor where slope anomalies are marked (adopted from Varela et al. 2022)

The model consists of five model factors that are derived from a GIS-referenced polygon called 'slope anomaly' (SA). The high-resolution LiDAR data is used to delineate the polygons for slope anomalies, which are identified by the geomorphic review of the data by the geotechnical experts. The LiDAR data is overlaid with the public domain surficial soil characteristics available from Soil Survey Geographic Database (SSURGO) developed by the United States Department of Agriculture (USDA) Natural Resources Conservation Service (NRCS). For the pipeline system in Canada, the surficial and quaternary geology is used to infer the surficial soil characteristics. Once the slope anomalies and the associated soil characteristics are known, each slope anomaly is assigned a landslide susceptibility rating based on the existing geomorphology or potential for land movement. This is the first model factor to be assessed. Table 1 summarizes the qualitative classification and scores assigned to the 'landslide susceptibility' (LS) factor of the model.

The remaining four factors are derived based on the slope anomaly characteristics and their spatial relationship with the pipeline. These include the state of activity of the slope anomaly (A), distance of the slope anomaly from the pipe centerline (D), and spatial relationship of the slope anomaly with the pipeline location (PR). The final factor is the extent of the interaction, which depends on a combination of the length of intersection (LI) of the slope anomaly with the pipeline centerline, and the incidence angle (IA) between the expected direction of movement and the pipeline. Table 1 shows the classification and category scores for A, D and PR, while Table 2 shows the classification and scores for the combined factor of LI and IA.

The model factors and their category scores are assigned for a short section of pipeline, which has a length of a typical pipeline joint. All the factors are weighted equally to obtain an average score for susceptibility of pipeline to landslide. The susceptibility scores are calibrated against an annualized occurrence rate using the historical data. In this model, the occurrence event is defined as the presence of bending strain in the pipeline in the proximity of a slope anomaly. Therefore, the probability predicted by the model is the probability of occurrence of pipeline bending strains greater than 0.4%. Eq (2) shows the probability estimate as a function of average score, S.

$$P(S_d \geq 0.4\%) = 5.99 \times 10^{-9} \times 10^{1.22S} \quad (2)$$

Table 1: Classification of model factors (Varela et al. 2022).

Factor	*Classification*	*Score*
Landslide Susceptibility (LS)	*Existent*	*5.0*
	High	*4.0*
	Moderate	*3.0*
	Low	*1.0*
Activity (A)	*Active*	*5.0*
	Inactive	*3.0*
	No SA	*1.0*
Distance (D)	*D < 20ft*	*5.0*
	20 < D < 50ft	*4.0*
	D > 50ft	*1.0*
Spatial relationship to the pipeline (PR)	*Cross cutting the pipe centerline (CC)*	*5.0*
	Cross cutting only pipeline right-of-way (RC)	*4.0*
	Proximal to pipeline centerline, within 50ft (PC)	*3.0*
	Distal to pipeline centerline, greater than 50ft (DC)	*1.0*

Table 2: Combined factor of LI and IA (Varela et al. 2022).

Incidence Angle	*Length of Intersection (ft)*			
	0	*<40*	*40-120*	*>120*
0	*1.0*	*1.0*	*1.0*	*1.0*
<20^o (Axial)	*1.0*	*1.0*	*3.0*	*5.0*
20^o to 70^o (Oblique)	*1.0*	*1.0*	*3.0*	*5.0*
>70^o (Transverse)	*1.0*	*1.0*	*4.0*	*5.0*

During the calibration of the average score to the historical data, the sampling of the data subsets at high average score was too sparse, which introduced sample size uncertainty. Therefore, 90th percentile confidence bounds were also estimated corresponding to the average score values where historical incident rates were estimated. Table 3 shows the confidence bounds and the uncertainty associated with the calibration of the probability values to the average score.

The general trend in the calibration shows that the probability estimates decrease with decreasing average score except for the anomalous result at S = 4.0. This is due to the sample size being as low as two samples that meet the bending strain criterion at this average score.

Table 3: Confidence bounds on the probability calibration to the average score.

Average Score (S)	*Lower bound $P(S_d \geq 0.4\%)$*	*Upper bound $P(S_d \geq 0.4\%)$*
5.0	3.37×10^{-3}	1.37×10^{-2}
4.8	6.30×10^{-3}	1.66×10^{-2}
4.6	3.26×10^{-4}	3.02×10^{-3}
4.4	3.34×10^{-4}	3.09×10^{-3}
4.2	1.01×10^{-4}	1.76×10^{-3}
4.0	1.46×10^{-4}	2.54×10^{-3}
3.8	8.32×10^{-5}	1.46×10^{-3}

1.2. System description

The GIS-based data driven model was applied to a North American gas transmission pipeline system of approximately 18,000 miles over the geographical extent shown in Figure 2.

The transmission system consists of a wide range of pipeline vintage from pre-1950s to the 2010s, pipeline diameters, design classes, construction methods, pipe grades, soil characteristics, topography, and the climatic conditions. Given the nature and extent of the pipeline system, it is considered a satisfactory representation of the range of possible combinations of the geomorphological conditions and the pipeline characteristics of pipeline systems within the North America. The pipeline system was also extensively monitored through surface inspections such as satellite-based Interferometric Synthetic Aperture Radar (InSAR), and LiDAR, field visits, site-instrumentation, ILI and IMU. These independent inspections and evaluations have provided independent data sets to consider for model validation.

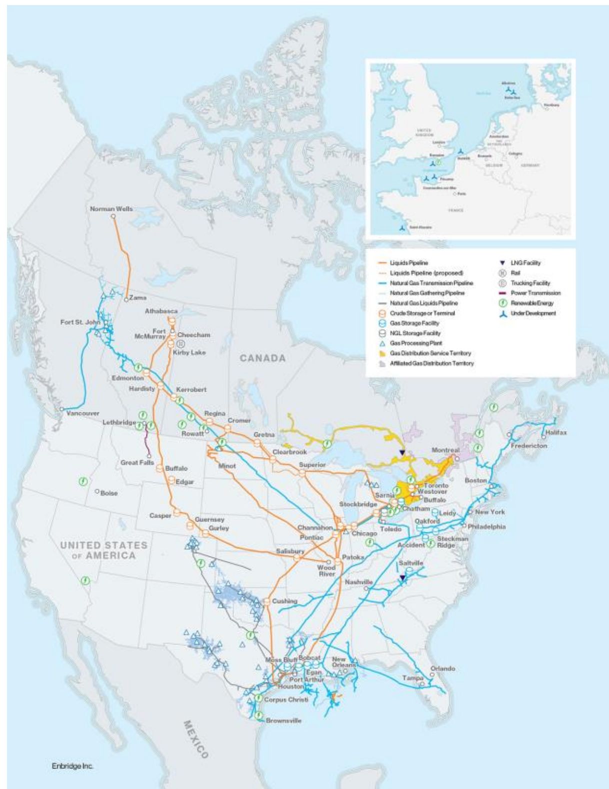

Figure 2: Geographical extent of the gas transmission pipeline system (shown in blue) in North America

2. SYSTEM-WIDE RESULTS AND VALIDATION

2.1. System-wide model results

The system-wide mileage is segmented to short length of pipeline termed as a 'pipeline fragment'. Each pipeline fragment is 50ft length except where a slope anomaly intersects with the pipeline. In such cases, i.e., when model factor PR is CC, the pipeline fragment length is equal to the intersecting length with the slope anomaly. The model predictions of the average score and probability of bending strain presence for each pipeline fragment are estimated across the system-wide mileage. Figure 3 shows the histogram of the average scores for all the pipeline fragments across the system.

There are close to 1.9 million pipeline fragments within the system. The distribution of frequencies is expected to follow an exponential distribution due to the natural phenomena occurring more frequently at low severity and less frequently at high severity. In Figure 3, the distribution shows a gap at average score 2.0, which indicates the model may have been overestimating average scores due to inherent correlation about the model factors such as distance to slope anomaly (D) and spatial relationship between the pipeline and slope anomaly (PR). Where the distance to slope anomaly to the pipeline is greater than 50 ft, both factors will score low, and when the slope anomaly intersects the pipelines, both factors would score high.

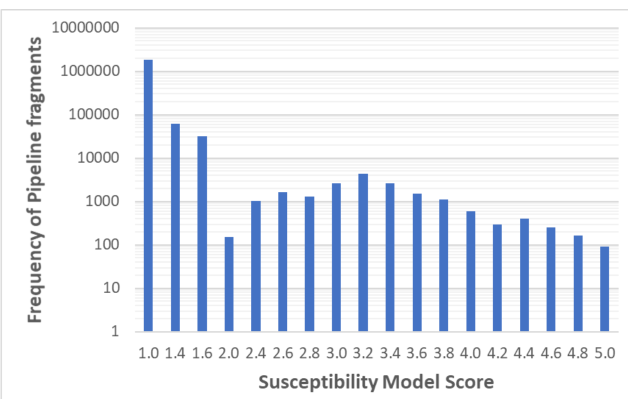

Figure 3: Frequency distribution of susceptibility model scores for the system-wide mileage

Figure 4 shows the frequency distribution of the system-wide pipeline fragments over the calibrated probability. The distribution is akin to the distribution of the model scores, which indicates a linear correlation between the average model scores and the probability estimates in the log scale. This is as expected from the relationship shown in Eq. (2).

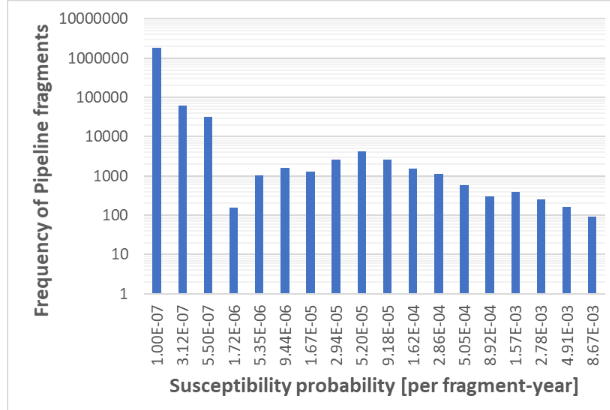

Figure 4: Frequency distribution of susceptibility probability for the system-wide mileage

2.2. Model validation

2.2.1. Description of validation datasets

Two validation datasets were available to compare the susceptibility model predictions against an independent assessment.

The first data set consisted of a 'qualitative ranking model' developed by a team of independent geotechnical experts. The model included the data from IMU inspection to consider the bending strain in addition to other factors such as activity, movement rate, and proximity of a landslide to the pipeline. This model was applied to approximately 3000 miles within the system, which enabled comparison over 300,000 pipeline fragments.

The second data set consisted of a 'field-data model' wherein the probability was assigned based on the data collected during the field visits by the geotechnical experts. This assignment was done by a different team independent of the team involved in the qualitative ranking model and GIS-based data driven model. As field visits are limited to areas with high susceptibility to landslides, the field-data model was applied to only 650 miles within the system. This enabled comparison over approximately 60,000 pipeline fragments.

2.2.2. Comparison to qualitative ranking model

Figure 5 shows the comparison of the average score to the qualitative rank for the pipeline fragments. The bigger the circle means the greater the number of fragments. A vast majority of the fragments have an average score of 1.0 as well as a qualitative rank of 1.0, where both models indicate a low susceptibility to the ground movement.

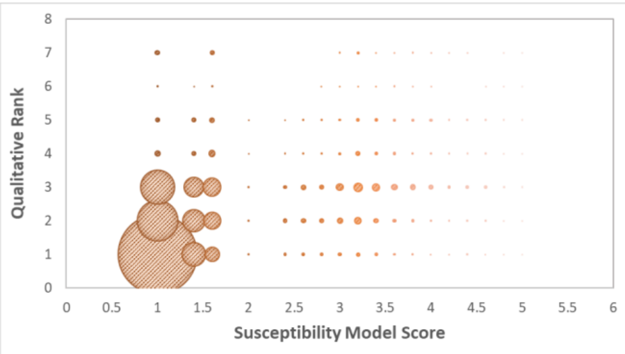

Figure 5: Comparison of average score with qualitative rank for the system-wide mileage

Although both models align well for the low susceptibility fragments, there are a few cases where the qualitative rank is 7.0, indicating a high susceptibility, whereas the average score is 1.0, indicating a low susceptibility. For a quantitative comparison between the two models, qualitative rank greater than 5.0 is categorized as 'high', and average score greater than 4.0 is categorized as 'high'. Table 4 shows the number of pipeline fragments that align with the same categorization between the two models and the cases where they deviate. Although, the total number of pipeline fragments with high susceptibility category are similar in number between both models, the models lack congruence in identifying the same pipeline fragment to be of high susceptibility. Reasons for the discrepancy are:

- Mitigations conducted based on the qualitative rank model would obscure the landslide features for the GIS-based data-driven model, as these models were developed over a three-year time period.
- Qualitative model is a lagging indicator of the landslide susceptibility as it is dependent on detected bending strain through IMU, while GIS-based data-driven model is a leading indicator for potential landslides that haven't materialized yet.

Table 4: Comparison of the Qualitative Rank model with the GIS-based Data-driven model

GIS-based Data-driven model	Qualitative Rank model	
	Low (Rank ≤5)	High (Rank > 5)
Low (S≤4.0)	300235	1174
High (S>4.0)	882	30

2.2.3. Comparison to field-data model

Figure 6 shows the comparison of the average score with probability estimates from the field-data model. Most of the pipeline fragments in the field-data model are categorized as low susceptibility with average score of 1.0 in the GIS-based data driven model.

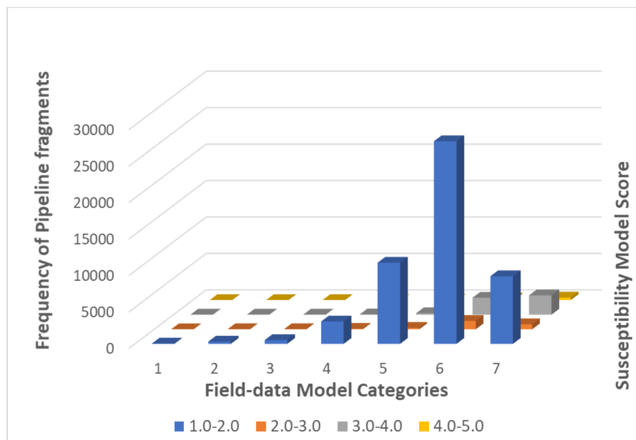

Figure 6: Comparison of average score with field data model for the system-wide mileage

Table 5 shows the distribution of the pipeline fragments for field-data model categories and the assigned probability values for each category. It is evident from the trend that the field-data model is more likely to assign a high probability for pipeline fragment. Another underlying reason for this trend is the categorization of the probability by the 'geotechnical site' by the field-data model, which may consist of multiple pipeline fragments. This results in overestimation of the pipeline fragments that are assigned a high probability.

The comparison of the field-data model with the GIS-based data driven model indicates a large discrepancy between the assigned categories for susceptibility of ground movement. However, the source of discrepancy is difficult to identify due to the subjective nature of susceptibility assignment in the field-data model.

Table 5: Field-data model categories and frequency distribution of pipeline fragments

Category	*Probability Range*	*Number of pipeline fragments*
1	$<2.0\times10^{-7}$	*41*
2	$\geq2.0\times10^{-7}$ & $<2.0\times10^{-6}$	*314*
3	$\geq2.0\times10^{-6}$ & $<2.0\times10^{-5}$	*529*
4	$\geq2.0\times10^{-5}$ & $<2.0\times10^{-4}$	*3163*
5	$\geq2.0\times10^{-4}$ & $<2.0\times10^{-3}$	*11535*
6	$\geq2.0\times10^{-3}$ & $<2.0\times10^{-2}$	*31470*
7	$\geq2.0\times10^{-2}$	*12927*

3. UPDATED PROBABILITY FRAMEWORK

3.1. Probability formulation

In the present study, the probability framework presented in Eq. (1) is updated to include the definition of the susceptibility based on the bending strain threshold. Eq. (3) shows the updated formulation to estimate the probability of pipeline failure,

$$P_f = \mathrm{P}(S_d > S_c | S_d \geq 0.4\%) \cdot \mathrm{P}(S_d \geq 0.4\%) \qquad (3)$$

Where $\mathrm{P}(S_d \geq 0.4\%)$ is estimated using Eq. (2), and $\mathrm{P}(S_d > S_c | S_d \geq 0.4\%)$ is estimated using a standard structural reliability approach. Generally, a mean-centered Monte-Carlo Sampling (MCS) is performed on strain capacity S_c modeled as an implicit function of random variables of a girth weld strain capacity model. The distribution for strain demand is obtained from the IMU inspection.

3.2. System-wide predictions

Figure 7 shows the distribution of the probability of failure over the system-wide mileage. The number of pipeline fragments with annualized probability greater than 2×10^{-3} is close to 400, which accounts for less than 4 miles in a system-wide mileage of approximately 18,000 miles. This implies that only a small percentage of the system has a high likelihood of failure due to landslides. It is noted here that the GIS-based data driven model did not include factors for mitigation such as installation of drainage, retaining walls at the toe of the slope, and re-grading of the slope. Inclusion of these factors would further reduce the estimated probability of failure.

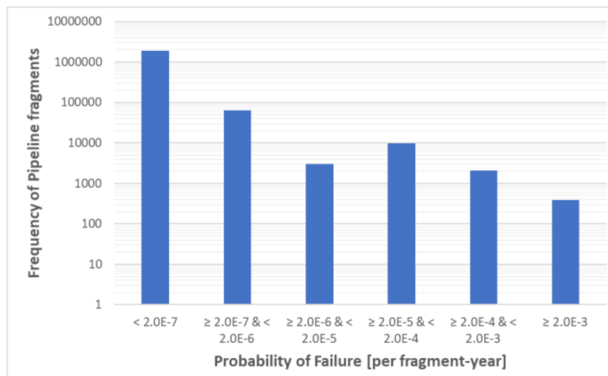

Figure 7: Frequency distribution of probability of failure estimation for the system-wide mileage

4. DISCUSSION

In this study, the application of a data-driven model with reproducible factors was presented. Model validation was performed by comparing the predictions with independent predictions of landslide susceptibility on a subset of the system-wide mileage. The models with similar underlying structure and factors, such as qualitative ranking model, have shown model congruence in identifying the pipe fragments of low susceptibility, even though the ranking for high susceptibility varied due to the reasons noted in Section 2.2.2.

In contrast, models based on field-data and expert opinion have differed largely from the data-driven models and do not present the opportunity to interrogate the reasons for this variation. As the true landslide susceptibility is unknown until the ground movement is observed, this creates a challenge to validate models if expert opinion is used as the basis of the validation. In the present study, the availability of multiple independent data sets has overcome this issue. Where such collection of large-scale independent data sets is not feasible, a Bayesian framework for iterative model updates is recommended.

5. CONCLUSIONS

The case study presented is an application of the GIS-based data driven model to the system-wide mileage of over 18,000 miles of pipelines in North America. The study provides an opportunity to demonstrate the challenges in applying and validating data-driven approach for landslides due to lack of verifiable public data sets for model validation.

6. ACKNOWLEDGEMENT AND DISCLAIMER

Authors would like to thank Enbridge for permission to publish the study.

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