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Corrosion Monitoring and Predictive Modelling of Gas Processing Pipelines in Ghana and Sub-Saharan Africa: Evidence Gaps and a Research Agenda

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ABSTRACT

Gas-processing pipelines are central to gas monetisation and power stability in Ghana, yet peer-reviewed evidence on their corrosion behaviour remains limited compared with global literature. The regional operating environment combines internal wet-gas CO_2 and H_2S attack with marine atmospheric corrosion, corrosion under insulation and buried-coating failure, creating multi-mechanism degradation that cannot be represented by single-gas intuition or average rate models alone. At the same time, monitoring and predictive modelling have moved toward layered sensing architectures and probabilistic, machine-learning and hybrid approaches, although many studies rely on simulated data, weak validation and incomplete uncertainty treatment, which reduces confidence for safety-critical deployment. Using a structured narrative review with scoping features and conservative inclusion criteria, this article examines corrosion mechanisms, monitoring techniques, predictive models and the limited Ghana- and Sub-Saharan-specific evidence base. The review finds that model transfer without regional calibration is unsafe and that monitoring must be designed around deployability as much as technical capability. It proposes a research programme focused on long-term regional datasets, systematic recalibration of transferable oil-sector and analogue marine evidence, hybrid mechanistic-data-driven models with explicit uncertainty quantification, field validation under tropical coastal and onshore gas conditions, and open yet secure data structures and capacity building to support defensible integrity decisions in Ghanaian and Sub-Saharan gas- processing networks.

Keywords: pipeline integrity management, pipeline corrosion, predictive modelling, corrosion monitoring, uncertainty quantification.

INTRODUCTION

Gas pipelines and gas-processing networks are central to the monetisation of offshore and onshore gas and to the stability of gas-to-power systems, while also shaping the broader economics of petroleum value chains (Odumugbo, 2010). Available Ghana-focused technical literature includes studies on industrial pipeline corrosion and NDT-based wall-thickness assessment, but relatively little peer-reviewed work reports measured corrosion performance specifically for gas-processing pipelines in Ghana (Amoah et al., 2023). That imbalance matters because corrosion is not a generic maintenance issue in wet-gas service, since flow regime, wetting behaviour, and condensate accumulation can sharply alter corrosion severity and failure risk (Kamali et al., 2026; Dai, 2021; Zhao et al., 2018). Corrosion is a coupled material, chemistry, flow, and operations problem that influences failure risk, plant uptime, inhibitor demand, inspection intervals, and the credibility of integrity management itself (Ma et al., 2023). Even in settings with mature standards, internal and external corrosion remain persistent drivers of leakage and repair costs (Askari et al., 2019). In regions where climate exposure is aggressive and integrity data are sparse, the operational penalty of uncertainty is higher (Amoah et al., 2023; Seechurn et al., 2022). Ghana's upstream literature shows progress in local content and supplier participation, but persistent skill and institutional gaps remain, with implications for inspection quality, analytics adoption, and long-term integrity stewardship (Adjei & Ackah, 2023; Gbadago et al., 2023).

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The corrosion problem is especially acute for gas-processing and gas-gathering infrastructure because service conditions are unstable rather than neatly classified. Wet natural gas gathering pipelines are highly susceptible to CO_2 corrosion when water is present, because operating pressure, temperature, pH, flow regime, and pipe inclination can alter the stability of protective films and promote localised attack, such as pitting, mesa attack, and flow-induced corrosion (Abd et al., 2019). Carbon steel remains widely used because of its low cost, availability, and favourable mechanical properties, yet its corrosion performance depends on whether protective iron carbonate layers form and remain stable in CO_2-saturated environments (Jacklin et al., 2024). Foundational and recent studies agree that internal corrosion prediction remains challenging when protective scales, water chemistry, temperature, and multiphase flow interact (Obaseki et al., 2022; Nešić, 2007). Those same difficulties become more consequential in humid coastal environments, where chloride deposition, wet-dry cycling, and moisture trapped beneath insulation intensify external degradation in coastal and onshore gas infrastructure (Chen et al., 2021; Caines et al., 2015; Corvo et al., 2008).

A second reason for a focused review is the widening gap between monitoring practice and modelling practice. Monitoring technologies now include intrusive probes, ultrasonic testing, distributed optical systems, guided-wave methods, advanced radiography, and intelligent pigging (Yang et al., 2023; May et al., 2022; Ren et al., 2018).Predictive modelling has likewise moved from empirical corrosion relations and burst-pressure approaches toward neural networks, ensemble learning, Bayesian methods, and physics-informed or hybrid approaches (Akhlaghi et al., 2023; Song et al., 2023; Xie et al., 2021; Nešić, 2007). Yet the evidence base behind these tools is uneven. Many machine-learning studies report high fit metrics using simulation-derived or narrowly curated datasets, while field validation, uncertainty communication, and out-of-domain performance remain underdeveloped (Tan et al., 2025; Song et al., 2023; Akhlaghi et al., 2023; Sikorska et al., 2011). Corrosion-oriented machine learning remains constrained by data scarcity, small and fragmented datasets, inconsistent feature handling, and limited interpretability, which reduce confidence in deployment for safety-critical assets (Dong et al., 2024; Özkan et al., 2024; Sutojo et al., 2023; Nguyen et al., 2022).

A regional review is therefore warranted for two reasons. The first is mechanism relevance. Ghana and many sub-Saharan coastal gas corridors combine marine aerosol exposure, high humidity, elevated temperatures, and aggressive coastal corrosivity, while specialist capacity and infrastructure support remain uneven (Afrifa-Yamoah, 2024; Adjei & Ackah, 2023; Chen et al., 2021; Corvo et al., 2008). The structured search underpinning this review found limited peer-reviewed evidence that is directly usable for Ghanaian gas-processing pipeline corrosion prediction, especially studies reporting measured corrosion rates, time-series monitoring, inhibitor optimisation from field data, or open inspection datasets (Amoah et al., 2023). Regional consequence studies exist, including the broader literature on pipeline accidents in sub-Saharan Africa, but these do not substitute for corrosion evidence tied to operating envelopes, defect growth, and inspection observations (Hassan et al., 2022; (Carlson et al., 2015). The novelty of the present review, therefore, lies less in re-explaining corrosion science than in distinguishing what is transferable from global literature, what is deployable in the region, and what evidence is still missing for defensible prediction and decision-making (Ma et al., 2023; Wang et al., 2023; Coelho et al., 2022). The research agenda that follows prioritises long-term regional corrosion datasets, hybrid mechanistic and machine-learning models with uncertainty quantification, field validation of monitoring technologies under tropical coastal and onshore gas conditions, and open yet secure data structures that support local calibration and explainable deployment.

REVIEW METHODOLOGY

The review was designed as a structured narrative review with scoping features (Pollock et al., 2024; Turnbull et al., 2023). That design was chosen because the topic spans mechanistic corrosion science, sensing and inspection technologies, predictive analytics, and region-specific infrastructure studies, all of which differ in method, data source, and evidentiary depth. The search strategy was organised around the theme blocks provided for this review, namely gas-processing context, review methodology, corrosion mechanisms, monitoring techniques, predictive modelling, evidence from Ghana and sub-Saharan Africa infrastructure, and data-centred research directions. Methodological framing was informed by the PRISMA extension for scoping

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reviews and by SANRA, the Scale for the Assessment of Narrative Review Articles, because both sources emphasise transparency in search design, study selection logic, and synthesis structure even when meta-analysis is neither appropriate nor possible (Tricco et al., 2026; Baethge et al., 2019).

Eligibility was deliberately conservative. Only peer-reviewed journal articles and peer-reviewed conference papers from verifiable academic publishers were considered. The preferred publication window was 2015 to 2026, with earlier foundational papers retained only where they remain central to the corrosion mechanism or modelling formulation. Grey literature, company white papers, standards documents, news reports, and vendor material were excluded from the analytical core.

The same principle was applied to regional evidence. If a Ghana- or Africa-related claim could not be supported by peer-reviewed literature, it was either omitted or reframed as an evidence gap rather than asserted as fact. This approach was necessary because much operational knowledge in pipeline integrity is held in proprietary systems, consultancy reports, and regulatory archives that are not public or peer reviewed.

Study selection proceeded in three passes. The first pass identified review articles and foundational mechanistic papers on carbon dioxide corrosion, hydrogen sulfide corrosion, mixed-gas behaviour, atmospheric and under-insulation corrosion, and corrosion monitoring. The second pass targeted modelling studies, especially those applying machine learning, hybrid physics-data strategies, probabilistic approaches, and uncertainty analysis to corrosion rate or residual-strength prediction.

The third pass focused on Ghana and sub-Saharan Africa, including studies on pipeline design, inspection capability, local content, and consequence literature related to integrity failure. The goal was not exhaustiveness in a strict systematic review sense, but analytical saturation across the main themes needed for a publication-ready synthesis.

The analysis itself was thematic rather than paper-by-paper. Evidence was grouped according to five questions. Which corrosion mechanisms are most relevant to regional gas infrastructure? Which monitoring methods are technically useful and regionally deployable? What types of predictive models exist, and what evidence supports them? What the peer-reviewed literature actually says about Ghana and sub-Saharan African infrastructure. Which evidence gaps most directly limit safe and economic integrity management? Priority was given to contradictions, recurrent methodological weaknesses, and operational consequences. Reported model performance was interpreted with caution, especially when studies relied on simulated data, single-asset datasets, or insufficient external validation.

Corrosion Mechanisms in the Regional Operating Environment

For gas-processing pipelines, the dominant internal mechanism remains carbon dioxide corrosion in aqueous phases, often intensified by chloride-bearing brines and intermittent wetting rather than by continuously flooded conditions (Alsalem et al., 2023; Ma et al., 2021; Ezeh & Oriaku, 2020; Barker et al., 2018). As shown in Figure 1, carbon dioxide dissolves in condensed water to form carbonic acid, which accelerates anodic iron dissolution (Fonseca et al., 2024; Alsalem et al., 2023). Under favourable supersaturation, iron carbonate may precipitate and reduce general corrosion(Wang et al., 2022; Barker et al., 2018).

Yet this protective behaviour is conditional. Recent reviews and mechanistic studies show that iron carbonate films are heterogeneous, sensitive to local chemistry, and can stabilise broad areas of the steel surface while still promoting localised attack at crystal boundaries and crevice-like interstices (Fonseca et al., 2024; Lotz et al., 2024; Lazareva et al., 2021). Temperature, pH, salinity, and ferrous-ion availability, therefore, influence not only average corrosion rate but also the transition from general corrosion to localised metal loss, as $FeCO_3$ precipitation, morphology, and coverage depend strongly on growth conditions and chloride-assisted film breakdown (Ahmad et al., 2019; Pessu et al., 2015).

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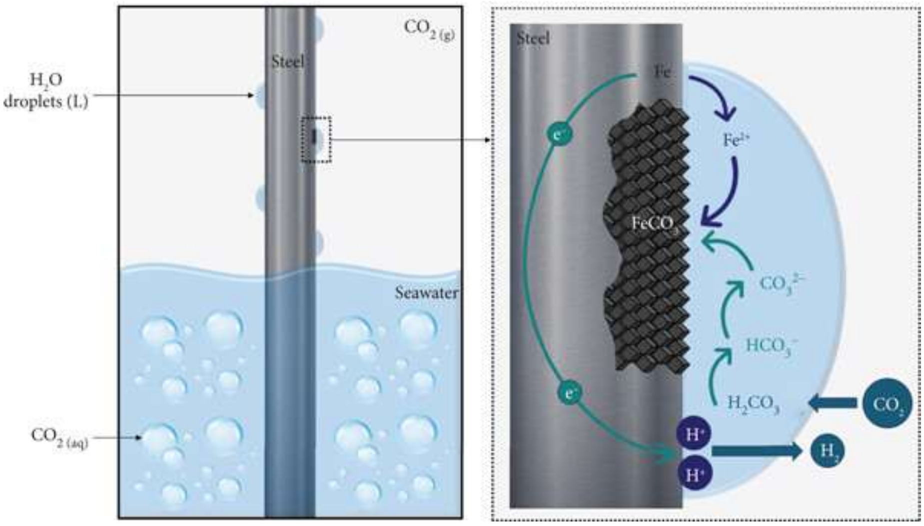

Figure 1. Mechanistic schematic of CO_2 corrosion and $FeCO_3$ film development in aqueous pipeline environments. Source: (Fonseca et al., 2024).

The picture becomes more severe when hydrogen sulfide is present. In sour environments, hydrogen sulfide changes corrosion behaviour by altering film composition, surface electrochemistry, hydrogen uptake, crack susceptibility, and failure mode (Zhou et al., 2025; Li et al., 2021). H_2S can promote iron sulfide formation, modify scale compactness, and increase the risk of sulfide stress cracking, hydrogen-induced cracking, and hydrogen-assisted embrittlement, especially in higher-strength pipeline steels or in stressed regions such as girth weld zones and cold-worked areas (Gou et al., 2023; Li et al., 2023; Liu & Case, 2022; Qin et al., 2022). Experimental studies on X80-type steels show that hydrogen charging in H_2S environments produces degradation that is not fully reversible, particularly after longer exposure or repeated charging cycles (Bai et al., 2020). Reviews of H_2S corrosion likewise emphasise that temperature, pH, flow regime, and H_2S partial pressure interact rather than act independently, so nominally similar gas chemistry can produce markedly different damage under different operating envelopes (Huang et al., 2023; K. Li et al., 2021).

Mixed CO_2 and H_2S environments are particularly relevant for regional gas systems because acid-gas composition can vary across fields, processing stages, and upset conditions (Chen et al., 2024; Huang et al., 2023). Huang et al. (2023) reported that corrosion of X80 steel in an H_2S/CO_2 coexisting environment varied with H_2S partial pressure, temperature, and applied stress, while Pessu et al. found that increasing H_2S altered the morphology of the iron sulfide film and could either increase or decrease uniform corrosion depending on the conditions. Further studies also show that flow conditions can intensify localised attack in CO_2/H_2S systems, while mixed-gas corrosion products may become mechanically unstable under certain operating regimes (Qin et al., 2022). Taken together, these mixed-gas studies suggest that corrosion cannot be represented well by single-gas intuition or by average corrosion-rate models alone (Huang et al., 2023; Liao et al., 2022; Pessu et al., 2015). In practical terms, the key question is whether the local chemistry and flow conditions favour a dense protective film, a porous film, or an unstable deposit.

External corrosion of pipelines is a significant concern in Ghana and other coastal sub-Saharan African regions, where industrial pipelines and exposed steel structures can suffer pitting, wall loss, and accelerated corrosion in aggressive marine or service environments (Amoah et al., 2023; Seechurn et al., 2023). Marine atmospheric corrosion of carbon steel is accelerated by high chloride deposition and persistent humidity, with corrosion kinetics in tropical marine sites showing transition behaviour near the coast (Alcántara et al., 2017; Ma et al., 2010). In tropical coastal exposures, corrosion kinetics may show an initial increase followed by slower behaviour as rust layers evolve, while site-specific salinity, humidity, rainfall, and microclimate can cause substantial variability in long-term corrosion rates (Seechurn et al., 2022; Chen et al., 2018; Corvo et al., 2008). For piping and pipelines near processing plants, damaged or degraded coatings and below-cladding areas are especially vulnerable to localised external corrosion (Farh et al., 2023; Ossai, 2012). Atmospheric

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corrosion reviews also show that prediction quality deteriorates when local environmental heterogeneity is ignored, a point that matters for gas assets spanning shore approaches, plant plots, and buried onshore tie-ins (Santa et al., 2022; Alcántara et al., 2017; Corvo et al., 2008).

Corrosion under insulation (CUI) deserves specific attention because gas-processing facilities routinely contain insulated piping, separators, heaters, and hot process lines that operate within the temperature ranges known to favour under-insulation moisture retention and hidden corrosion (Cao et al., 2022). Cao et al. (2022) further note that CUI is difficult to detect early, is often aggravated by insulation damage and chloride ingress, and can progress beneath apparently intact outer cladding. In tropical coastal settings, where ambient humidity is high and rainfall events are intense, the probability of water ingress and prolonged wetness is elevated (Cao et al., 2022; Seechurn et al., 2022). This mechanism is operationally significant because it can escape routine visual inspection, distort maintenance priorities, and generate unexpected failures at pipe supports and low-visibility locations (Cao et al., 2022; Ossai, 2012).

Taken together, the regional operating environment favours multi-mechanism corrosion rather than isolated mechanism categories. Internal wet-gas corrosion, hydrogen-assisted sour damage, atmospheric chloride attack, buried-coating failure, and CUI can all coexist within the same gas value chain (Zhou et al., 2025; Farh et al., 2023; Seechurn et al., 2022; Bai et al., 2020; Ossai, 2012). That reality has two consequences. First, corrosion surveillance must distinguish where the average corrosion rate is the right metric and where localised defect growth is the real hazard. Second, predictive models need regional calibration not because the underlying electrochemistry changes, but because the distribution and interaction of controlling variables differ across tropical coastal assets and are rarely captured by global default datasets.

Monitoring Techniques and Regional Deployability

Corrosion monitoring for gas-processing pipelines includes coupons, electrical resistance (ER) probes, linear polarisation resistance (LPR), ultrasonic testing (UT), and in-line inspection (ILI) tools. Coupons are the most transferable baseline because they are inexpensive, standardised, and easy to interpret, but they only provide delayed evidence and can miss short-lived wetting or localised damage. ER probes improve temporal resolution, while LPR offers near-real-time response under conductive aqueous conditions. However, both methods depend strongly on water continuity, flow conditions, and calibration context, which limits their reliability in intermittently wet natural-gas systems unless paired with chemistry surveillance and sound installation design (Orlikowski et al., 2024; Martinelli-Orlando & Angst, 2022; Wright et al., 2019).

From a deployability perspective, the appeal of coupons and ER probes in Ghana and comparable settings is not only lower cost but also lower dependence on advanced data infrastructure and specialist interpretation, which makes them practical where technical capacity and local skills are still developing. This aligns with Ghana’s local-content agenda, which aims to strengthen local mastery of technology and skills but still faces capacity and implementation constraints. When staffing is stretched, these tools can anchor a practical monitoring hierarchy, but they provide local rather than distributed information, so a few access points can give false reassurance in assets with strong spatial variability. This is why recent review literature increasingly recommends layered architectures in which intrusive probes characterise process corrosivity while ultrasonic or other non-intrusive systems track wall loss at high-risk locations (Orlikowski et al., 2024; Komary et al., 2023; Martinelli-Orlando & Angst, 2022; Wright et al., 2019).

Non-destructive methods broaden coverage but differ in skill and infrastructure demands. Conventional ultrasonic thickness measurement is mature and versatile for repeat readings at corrosion circuits, low points, and suspected CUI locations. Wireless ultrasonic systems can improve trend visibility, but they add cost and maintenance demands. Radiography remains useful where access is limited or insulation removal is undesirable, and Amoah et al. are notable because they show applied radiographic capability for wall-thickness and corrosion assessment in industrial pipelines in Ghana. Even so, radiography is labour- and safety-intensive, so it is unlikely to serve as a continuous monitoring backbone for long gas corridors (Pan et al., 2024; Amoah et al., 2023; Thibbotuwa et al., 2022; Khalili & Cawley, 2018; Edalati et al., 2006; Balaskó

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et al., 2005). Guided-wave ultrasonics, electromagnetic acoustic approaches, and acoustic-emission methods are increasingly attractive because they can screen larger lengths from fewer access points and can help target intrusive follow-up inspection. Reviews of guided-wave corrosion detection show clear strengths in long-range screening and hidden-location assessment, but also persistent trade-offs involving signal dispersion, defect characterisation limits, and sensitivity to geometric complexity. These methods are therefore best viewed as risk-screening tools rather than direct substitutes for thickness data or defect sizing. In resource-constrained environments, their greatest value may lie in periodic campaigns for inaccessible segments such as crossings, insulated runs, or supports, where conventional access is poor (Cawley, 2024; Lyu et al., 2024; Dhutti et al., 2021; Ghavamian et al., 2018; Khalili & Cawley, 2018;).

Inline inspection (ILI) remains the most data-rich option for transmission pipelines, particularly for metal loss, crack detection, and geometry distortion across large networks. ILI is carried out using instrumented tools known as smart pigs, which travel inside the pipeline driven by product flow and collect sensor data along the full bore. As shown in Figure 2, these tools span multiple classification dimensions, including sensor technology, problem category, and application context, reflecting the operational diversity of ILI as a discipline (Parlak et al., 2023). Deploying ILI effectively depends on piggable design, launcher and receiver facilities, flow-assurance compatibility, and the analytical capacity to interpret large datasets. For older or smaller-diameter lines, branch complexity, deposits, and operational constraints can narrow the feasible toolset, and ILI is therefore best understood in the regional context as a strategic rather than universal monitoring layer (Q. Ma et al., 2025; Orlikowski et al., 2024; Parlak & Yavasoglu, 2023).

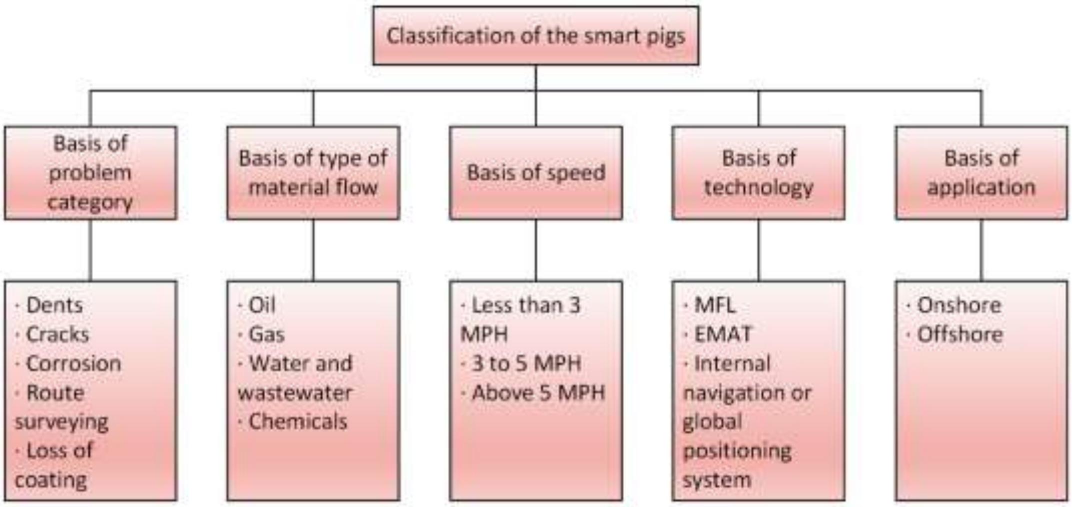

Figure 2. Classification of smart pig technologies used in inline inspection (ILI) of oil and gas pipelines, organised by problem category, material flow type, operating speed, sensor technology, and application context. Source: Parlak and Yavasoglu (2023).

Table 1 summarises a deployability-oriented interpretation of the monitoring literature.

Technique	Main strength	Main limitation	Best regional role	Key literature
Weight-loss coupons	Low cost and simple interpretation	Time-averaged and spatially local	Baseline corrosivity confirmation and inhibitor checking	Wright et al. (2019)
ER probes	Continuous metal-loss trend	Sensitive to installation context	Trend monitoring where wetting is recurrent	Martinelli-Orlando and Angst (2022);

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		and local representativeness		Shin et al. (2022)
LPR probes	Fast electrochemical response	Requires conductive aqueous phase	Wet sections, separators, and monitored low points	Shin et al. (2022)
UT spot monitoring	Accurate local wall-thickness data	Requires repeat access and disciplined circuits	Corrosion loops and verification of high-risk locations	Salgueiro et al. (2024)
Radiography	Works through some insulation	Safety burden and campaign cost	Targeted inspection in plants where access is difficult	Amoah et al. (2023)
Guided-wave UT	Screens longer lengths from fewer positions	Limited sizing precision and signal complexity	Inaccessible runs, supports, crossings, and CUI screening	Lyu et al. (2024)
Distributed fiber sensing	Continuous distributed response	Cost, installation complexity, and durability concerns	High-consequence pilot deployments rather than routine fleet-wide use	Wright et al. (2019)
Inline inspection (ILI)	Network-scale metal-loss or crack data	Requires piggability, run logistics, and advanced analytics	Strategic integrity campaigns on major transmission lines	Parlak et al. (2023); Ma et al. (2025)

Table 1 draws on peer-reviewed reviews and studies on corrosion sensing, NDT, and ILI. It reflects deployability rather than absolute technical superiority. Sources:(Amoah et al., 2023; Lyu et al., 2024; Ma et al., 2025; Martinelli-Orlando & Angst, 2022; Parlak & Yavasoglu, 2023; Salgueiro et al., 2024; Shin et al., 2022; Wright et al., 2019).

For Ghana and much of sub-Saharan Africa, deployability should be treated as a first-order design variable in any monitoring program. The most advanced method is not always the most useful one, and what matters is whether it survives local constraints on power supply, technical training, chemical stability, access, piggability, and data stewardship. Evidence from Ghana's petroleum sector indicates that capability is advancing but remains constrained by skills gaps and local-content limitations, making phased monitoring architectures more credible than high-technology substitution. A sound regional program would typically begin with chemistry surveillance, coupons, and selected probes, then progressively add fixed UT, guided-wave screening, and ILI, where the asset base and organisational capacity can sustain them (Amoah et al., 2023; Ma et al., 2025; Parlak & Yavasoglu, 2023; Salgueiro et al., 2024; Wright et al., 2019).

Predictive Modelling and Its Evidence Base

Predictive modelling of pipeline corrosion has shifted from deterministic growth equations to probabilistic and data-driven approaches that better capture uncertainty and complex degradation mechanisms. Recent reviews emphasise that model choice must reflect data availability, dominant corrosion mechanisms and operational context, rather than relying on a single universal methodology (Ma et al., 2023; Wang et al., 2023).

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Machine-learning studies using random forests, CatBoost, and related ensemble methods predict internal corrosion rates for crude oil and gas pipelines with high accuracy under simulated or monitored operating conditions. Deep and hybrid architectures for corrosion growth and pitting depth modelling improve performance over empirical models but raise interpretability and data-quality challenges (Fang et al., 2023; Ma et al., 2023; Wang et al., 2023; Xu et al., 2023).

Bayesian belief networks and Bayesian neural networks link corrosion predictors to failure probabilities, inspection planning and maintenance decision support in natural gas and transmission systems. Adapting these probabilistic and data-driven frameworks to Ghanaian and Sub-Saharan gas-processing pipelines will require context-specific calibration using local operating data and corrosion monitoring records (Y. T. Li et al., 2022; Shabarchin & Tesfamariam, 2016; Soomro et al., 2022; Xu et al., 2023).

What is Known About Corrosion in Ghana and Sub-Saharan African Infrastructure

The structured search confirms a pronounced asymmetry between the depth of the global corrosion literature and the thinness of evidence specific to Ghana and sub-Saharan Africa. What can be stated with confidence rests on a few studies demonstrating inspection and analytical capability rather than measured corrosion behaviour in operating gas-processing service. This does not imply that corrosion is absent, only that the quantitative basis for defensible prediction in Ghanaian gas-processing service has not yet been assembled (Amoah et al., 2023; Okyere, 2025).

The most directly relevant technical study is Amoah et al. (2023), who applied double-wall and tangential radiographic techniques to evaluate remaining wall thickness, pitting, and deposits in industrial pipes, validated against ultrasonic gauging. It demonstrates functioning local non-destructive inspection capability, yet reports detection accuracy under controlled conditions on industrial pipes rather than corrosion rates from operating gas-processing assets. Okyere (2025), applied computational fluid dynamics to assess internal corrosion risk in wet sour gas pipelines and compare mitigation strategies. The study evidences predictive expertise within a Ghanaian operator, but its modelled rates derive from the Kashagan offshore case in Kazakhstan and are simulation outputs, not field measurements.

Beyond Ghana, the sub-Saharan evidence base is dominated by Nigeria and is oil-oriented rather than gas-processing-oriented. Ossai et al. (2015) provide the most quantitatively complete regional study, modelling internal pitting corrosion from ten years of ultrasonic thickness data across sixty onshore Niger Delta oil-and-gas pipelines and validating the model against twelve operating transmission lines. Their analysis identifies carbon dioxide partial pressure, flow rate, and chloride concentration as the dominant controls on pit-depth growth, with hydrogen sulfide present only in trace amounts. Obike et al. (2020) document the regional consequence and cost burden over three decades and report a named pipeline case, the 89.9 km Warri-to-Benin carbon steel line, in which pitting, microbial, sulfide-stress and hydrogen-stress cracking were all identified alongside extensive cathodic-protection under-coverage. At the experimental scale, Mgbemere et al. (2025) measured corrosion rates on welded carbon steel coupons in cultured seawater and found that oxygen-scavenger and biocide injection failed to suppress corrosion and in several conditions accelerated it. Taken together, these studies confirm that measured corrosion data for the region are not absent, but they are concentrated in Nigerian oil and production systems, governed by CO_2-dominated internal pitting under operating envelopes that differ materially from Ghanaian wet-sour gas processing.

A substantial peer-reviewed literature situates regional integrity management within a constrained capability environment. Work on Ghana's local-content regime documents persistent skills gaps, weak enforcement, and continued expatriate dominance of high-skill technical roles, with slow knowledge transfer (Ablo, 2018; Ablo & Otchere-Darko, 2022; Adjei & Ackah, 2023). Afrifa-Yamoah (2024) identifies institutional characteristics as the central driver of local-content outcomes. This matters because inspection quality, analytics adoption, and integrity stewardship depend on the same human-capital and governance foundations, which remain uneven. Where quantitative corrosion data exist, they come largely from analogue tropical marine settings

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rather than Ghanaian gas assets, and cannot be transferred without local calibration (Chen et al., 2018; Corvo et al., 2008; Seechurn et al., 2022).

This evidence reframes rather than removes the gap. Sub-Saharan field corrosion data exist, but they are oil-dominated, Nigerian, and tied to operating conditions that cannot be assumed to represent Ghanaian gas-processing service without recalibration. For Ghana specifically, the record still offers demonstrated inspection and modelling capability (Amoah et al., 2023; Okyere, 2025) without measured corrosion rates from operating gas-processing assets. The decisive shortfall is therefore narrower and sharper than a regional data vacuum: it is the absence of Ghana-specific, gas-processing-specific corrosion measurements, time-series monitoring records, and field-validated inhibitor performance, against a regional backdrop where transferable oil-sector data and predictive methods already exist. Closing that specific gap, rather than re-establishing that corrosion occurs, is the central motivation for the research agenda that follows.

Research Agenda

The asymmetry between the rich global corrosion literature and the sparse Ghana-specific evidence base defines the shape of the required research programme. The decisive gap identified in this review is threefold: the absence of measured corrosion rates from operating Ghanaian gas-processing assets, the absence of time-series monitoring records linking those rates to operating conditions, and the absence of field-validated inhibitor performance data. Each element of the agenda below responds to one or more of these absences, and the strands are sequenced rather than parallel, because credible model benchmarking depends on the data infrastructure being built first.

The first and foundational priority is the creation of long-term regional corrosion datasets from operating gas-processing pipelines. These should couple gas composition, water chemistry, flow regime, temperature, pressure, inhibitor dosing practice and defect growth from repeat inspection, recorded at a frequency and duration sufficient to resolve seasonal wet-dry cycling and operational transients rather than annual averages. Asset selection should deliberately span coastal marine-exposed and inland buried service so that internal and external mechanisms can be separated in analysis.

The second priority is systematic recalibration of the evidence that already exists. Nigerian oil-sector field data and analogue tropical marine exposure data are transferable in principle but not directly, and the conditions under which transfer fails are themselves an open research question. Transfer-learning and domain-adaptation methods, and Bayesian formulations that treat regional data as priors updated by local measurements, should be benchmarked explicitly on out-of-domain predictive error rather than in-sample fit (Song et al., 2023; Tan et al., 2025). The third priority is hybrid predictive modelling that respects CO_2 and H_2S mechanism complexity while exploiting ensemble, deep and Bayesian architectures, with uncertainty quantification and interpretability treated as design requirements rather than reporting afterthoughts (Coelho et al., 2022; Ma et al., 2023). These models should be validated against the datasets from the first strand, not against simulation-derived surrogates.

The final priority is field validation and institutional embedding. Corrosion-focused SCADA and machine-learning pilots should run on selected assets under agreements that make anonymised integrity data open yet secure, with operators, the regulator and Ghanaian universities sharing defined roles. Capacity building should target the inspection, analytics and data-stewardship skills that the local-content literature identifies as persistently thin (Ablo & Otchere-Darko, 2022; Adjei & Ackah, 2023). The measure of success for the programme as a whole is not publication volume but whether integrity decisions on Ghanaian gas-processing assets can be defended from locally measured evidence within a decade.

CONCLUSION

The review shows that gas-processing pipelines in Ghana and Sub-Saharan Africa operate in environments where internal wetgas CO_2 and H_2S corrosion, atmospheric marine attack, corrosion under insulation and

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buried-coating failure act together rather than as isolated mechanisms. These combined conditions, alongside uneven specialist capacity and infrastructure support, mean that uncertainty carries a higher operational cost when integrity decisions rely on generic models rather than regionally grounded evidence. The peer-reviewed record for Ghanaian gas-processing assets is still thin, and most quantified corrosion data come from Nigerian oil systems and analogous tropical marine exposures, which cannot be used without careful recalibration.

For practice, the review points to monitoring and prediction that are built around what can be deployed and defended locally, rather than around the nominal sophistication of individual methods. Layered monitoring architectures that combine chemistry surveillance, coupons, probes, ultrasonic measurements, selected guided-wave campaigns and strategic inline inspection runs are more credible than reliance on a single technique, provided they are matched to asset configuration and organisational capability. On the modelling side, deterministic growth equations, probabilistic formulations, Bayesian networks and machine-learning approaches are useful only when data provenance, uncertainty treatment, validation and interpretability are treated as part of the core design, not as afterthoughts (Coelho et al., 2022; Ma et al., 2023; Wang et al., 2023; Xu et al., 2023).

The research agenda set out in the review follows directly from these observations. It places measured regional datasets for gas-processing pipelines, hybrid mechanistic–data-driven models with explicit uncertainty treatment, and field validation of monitoring technologies under tropical coastal and onshore gas conditions at the centre of future work. It also argues that open yet secure data structures and targeted capacity building within Ghanaian and Sub-Saharan institutions responsible for integrity management are essential if advances in corrosion prediction are to translate into safer and more economical decisions in the region's gas value chains.

Ethical Approval

This study is a structured narrative review of published, peer-reviewed literature. It did not involve human participants, human tissue, or animal subjects, and no primary experimental or field data were collected. Ethical approval was therefore not required. All sources analysed are previously published works that were subject to the ethical oversight of their respective publishers, and each is acknowledged in the reference list.

Conflict Of Interest

The author declares no financial, commercial, or personal relationships that could be construed as a potential conflict of interest in relation to this work. No funding was received for the conduct of this review or for the preparation of this manuscript. No commercial entity, pipeline operator, or technology vendor influenced the selection, interpretation, or presentation of the literature reviewed.

Data Availability

No new data were generated or analysed in the course of this review. All evidence discussed is drawn from peer-reviewed journal articles and conference papers that are publicly available through their publishers, and each source is fully identified in the reference list with its DOI where one exists. Figures 1 and 2 are reproduced from previously published works, cited in their respective captions, and are available from those sources. The search terms, eligibility criteria, and three-pass selection procedure underpinning the review are described in full in the Review Methodology section, so the evidence base can be reconstructed by any reader.

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