

MACHINE LEARNING APPROACHES FOR DURABILITY ASSESSMENT OF RECYCLED AGGREGATE CONCRETE UNDER CHLORIDE-INDUCED CORROSION IN COASTAL STRUCTURES: A SYSTEMATIC REVIEW AND META-ANALYSIS

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Abstract

The durability assessment of recycled aggregate concrete (RAC) subjected to chloride-induced corrosion in coastal reinforced concrete structures remains a critical challenge for sustainable infrastructure development. This systematic review and meta-analysis aimed to evaluate the predictive performance of machine learning (ML) approaches for estimating durability indicators and to quantify the effect of RAC on mechanical and degradation performance compared to conventional concrete. We systematically identified and synthesized relevant studies, extracting effect sizes for two primary outcomes: prediction accuracy for durability indicators and the effect size for mechanical and degradation performance. The meta-analysis incorporated data from 13 studies. For prediction accuracy, we observed a significantly positive effect size of 1.93 (standard error = 0.02, 95% CI: [1.90, 1.96], $p < 1e^{-100}$), indicating that ML models provide highly accurate predictions of chloride-related durability metrics. Conversely, the effect size for mechanical and degradation performance was substantially negative at -0.66 (standard error = 0.07, 95% CI: [-0.80, -0.53], $p < 1e^{-20}$), suggesting a meaningful reduction in strength and resistance properties when using RAC. These findings collectively demonstrate that while ML approaches are robust tools for forecasting durability, the inherent performance trade-offs of RAC must be carefully managed. The study concludes that integrating ML-based predictive frameworks can effectively guide the design and optimization of RAC mixtures, mitigating durability risks in coastal environments. Our results provide quantitative evidence to support the adoption of data-driven methodologies for assessing long-term structural performance, thereby contributing to the broader application of recycled materials in marine concrete structures.

INTRODUCTION

The relentless growth of the global construction industry has generated an immense volume of construction and demolition waste, placing an unsustainable burden on landfills and natural resources (Ponnada and Kameswari, 2015). In parallel, the extraction of natural aggregates for concrete production contributes to significant environmental degradation and carbon emissions (Babor, Plian and Judele, 2009). A promising solution to this dual challenge lies in the use of recycled aggregate concrete (RAC), which substitutes a portion or all of the natural aggregates with recycled materials sourced from demolished concrete structures. The adoption of RAC is widely advocated as a cornerstone of sustainable construction practices, promoting a circular economy within the built environment (Mi *et al.*, 2020). Despite its clear environmental benefits, the widespread application of RAC in critical infrastructure, particularly in coastal reinforced concrete (RC) structures, is hindered by persistent concerns regarding its long-term durability.

Coastal environments are notoriously aggressive for RC structures, primarily due to the omnipresent threat of chloride-induced corrosion of steel reinforcement (Glass and Buenfeld, 2000). The ingress of chloride ions from seawater or marine aerosols through the concrete cover can depassivate the protective oxide layer on the reinforcing steel, initiating a process of expansive corrosion that leads to concrete cracking, spalling, and a subsequent loss of structural integrity and serviceability (Tuutti, 1982). This mechanism is a principal cause of premature deterioration in marine RC infrastructure worldwide, incurring massive costs for inspection, maintenance, and repair. The real challenge is that the inherently more porous and less dense microstructure of RAC compared to natural aggregate concrete (NAC) often results in increased permeability and a consequently reduced resistance to chloride ingress (Ma *et al.*, 2020). The presence of residual mortar adhered to the recycled aggregates creates a weak interfacial transition zone (ITZ) and additional pathways for ion transport, making the prediction of long-term durability in RAC

maritime structures a complex and critical scientific and engineering problem.

Understanding and accurately forecasting the chloride transport properties of RAC is therefore paramount for ensuring the safety and longevity of coastal structures that utilize this sustainable material. Traditional approaches to durability assessment have relied heavily on empirical models and accelerated laboratory tests, such as the rapid chloride penetration test (RCPT) or natural diffusion tests (Bogas and Gomes, 2015). However, these methods are often time-consuming, resource-intensive, and limited in their ability to capture the highly non-linear and interdependent relationships between the numerous variables influencing chloride penetration in RAC. These variables include the replacement ratio of recycled aggregates, their source and quality, the water-to-cement (w/c) ratio, the type and dosage of supplementary cementitious materials (SCMs), curing conditions, and exposure temperature (Yu and Lin, 2020). This inherent complexity creates a significant research gap, as a robust, generalizable, and efficient framework for predicting the durability performance of RAC in marine settings remains elusive.

This research gap has motivated a growing body of work exploring the application of machine learning (ML) techniques as a powerful alternative to traditional empirical methods. ML models, including artificial neural networks (ANNs), support vector machines (SVMs), random forests (RFs), and gradient boosting machines, are adept at learning complex, non-linear patterns from large datasets without requiring explicit prior knowledge of the underlying physical or chemical processes (Zhang and Kang, 2025). These data-driven approaches offer the potential to provide highly accurate predictions of critical durability indicators for RAC, such as chloride diffusion coefficients, chloride surface concentration, and time-to-corrosion initiation, by mapping the intricate relationships between mix design parameters and expected performance (Taffese and Espinosa-Leal, 2022). While many individual studies have reported promising predictive performance, the field remains fragmented. There

is a clear absence of a systematic, quantitative synthesis that collectively evaluates the true predictive power of ML models for this specific application and, more importantly, quantifies the actual performance trade-off between adopting RAC for sustainability and ensuring adequate structural durability in coastal environments.

The primary motivations for this research are to address this fragmented knowledge landscape and to provide a holistic, evidence-based perspective on the viability of ML-driven durability design for RAC. The significance of this work is threefold. First, by conducting a systematic review and meta-analysis, we aim to provide a rigorous and objective assessment of the current state-of-the-art in ML for predicting chloride-induced corrosion in RAC, moving beyond qualitative summaries to deliver a quantified measure of prediction accuracy. Second, we seek to establish a robust and generalizable effect size for the reduction in mechanical and degradation performance associated with using RAC compared to NAC, thereby quantifying the durability challenge that must be managed. Third, this research provides a consolidated foundation for future developments by highlighting critical knowledge gaps and methodological considerations for researchers and practitioners. By integrating the two independent meta-analyses, we can quantitatively demonstrate that while ML tools are indeed powerful for forecasting durability, the inherent material limitations of RAC remain significant, and therefore, a data-driven approach is not just an alternative but a necessary tool for optimizing mixtures and mitigating risks. The remainder of this paper is organized as follows: Section 2 describes the systematic review methodology, including the search strategy, inclusion criteria, data extraction process, and the statistical methods employed for the meta-analyses. Section 3 presents the results, including an overview of the included studies, an assessment of heterogeneity, the pooled effect sizes for both outcomes, and an evaluation of potential publication bias. Section 4 offers a comprehensive discussion of the findings, their implications for sustainable construction in coastal zones, the limitations of the current study, and avenues for future research. Finally, Section 5

presents the main conclusions drawn from this investigation.

Methodology

Review Protocol

This systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page *et al.*, 2021). We developed a comprehensive search strategy to identify relevant literature from five major electronic databases. Scopus was chosen as the primary database due to its extensive coverage of peer-reviewed literature in engineering, materials science, and environmental science. The search string for Scopus was: TITLE-ABS-KEY(("machine learning" OR "deep learning" OR "neural network" OR "support vector machine" OR "random forest" OR "AI") AND ("recycled aggregate concrete" OR "RAC" OR "recycled coarse aggregate") AND ("chloride" OR "corrosion" OR "durability" OR "ingress" OR "diffusion coefficient") AND ("coastal" OR "marine" OR "tidal" OR "seawater")) AND NOT TITLE-ABS-KEY("review" OR "survey" OR "meta-analysis") AND PUBYEAR > 1900, with document type limited to articles and reviews excluded. Web of Science was selected for its strong indexing of high-impact journals and conference proceedings in structural engineering and materials science. The search string for Web of Science was: TS=(("machine learning" OR "deep learning" OR "neural network" OR "artificial intelligence" OR "predictive model") AND ("recycled aggregate concrete" OR "RAC" OR "recycled concrete") AND ("chloride" OR "corrosion" OR "durability" OR "service life") AND ("coastal" OR "marine" OR "offshore")) NOT TS=("review" OR "survey" OR "meta-analysis"), refined by document type to articles only. ScienceDirect was included to capture research from its extensive collection of full-text articles in engineering and chemistry, using the string: ("machine learning" OR "deep learning" OR "neural networks" OR "AI") AND ("recycled aggregate concrete" OR "RAC") AND ("chloride" OR "corrosion" OR "durability") AND ("coastal" OR "marine") NOT ("review" OR "survey"), filtered by research articles. IEEE Xplore was chosen for its specialized repository of machine learning and computational intelligence

applications in civil engineering. The search string for IEEE Xplore was: ("All Metadata": "machine learning" OR "All Metadata": "deep learning" OR "All Metadata": "neural network") AND ("All Metadata": "recycled aggregate concrete" OR "All Metadata": "RAC") AND ("All Metadata": "chloride" OR "All Metadata": "corrosion" OR "All Metadata": "durability") AND ("All Metadata": "coastal" OR "All Metadata": "marine") NOT ("All Metadata": "review" OR "All Metadata": "survey"), with content type limited to conferences and journals. Finally, Google Scholar was used as a supplementary database to identify grey literature and studies not indexed by the other databases, employing the search string: ("machine learning" OR "deep learning" OR "neural network*" OR "artificial intelligence" OR "data-driven") AND ("recycled aggregate concrete" OR "RAC" OR "recycled concrete") AND ("chloride" OR "corrosion" OR "durability" OR "service life" OR "penetration") AND ("coastal" OR "marine" OR "sea water" OR "splash zone") -review -survey -meta-analysis. The search was performed in March 2026, covering all publications up to that date without year restrictions.

Inclusion and Exclusion Criteria

We defined specific inclusion and exclusion criteria to ensure the relevance and consistency of the selected studies. Studies were included if they met the following conditions: they focused on the application of machine learning (ML) or deep learning models, including but not limited to artificial neural networks, support vector machines, random forests, gradient boosting, or ensemble methods, for predicting chloride-induced corrosion or durability indicators in recycled aggregate concrete (RAC); they reported quantitative outcomes related to chloride diffusion coefficients, chloride ingress profiles, time-to-corrosion initiation, or mechanical properties such as compressive strength or flexural strength; they were peer-reviewed journal articles or conference proceedings; they were written in English; and they were published from the inception of the databases up to March 2026. We

excluded studies that were review articles, surveys, meta-analyses, book chapters, editorials, or non-peer-reviewed reports; that reported outcomes for natural aggregate concrete only without any recycled aggregate content; that focused on corrosion of steel in concrete without addressing chloride-induced mechanisms; that applied ML models for other concrete properties such as workability or shrinkage without direct relevance to chloride durability; that lacked sufficient quantitative data for effect size extraction, such as missing means, standard deviations, sample sizes, or correlation coefficients; or that were duplicates across databases or identified as for other reasons such as being retracted or inaccessible.

Study Selection Process

The study selection process comprised four stages: identification, screening, eligibility assessment, and inclusion. Two reviewers (XY and ZW) independently screened all records retrieved from the database searches. Following the PRISMA guidelines, we first removed duplicate records using reference management software (EndNote X9) and manual checking. We then excluded records based on their titles and abstracts if they clearly did not meet the inclusion criteria or fell under the exclusion criteria. For the remaining records, we retrieved full-text reports and assessed their eligibility against the pre-defined criteria. Any disagreements between the two reviewers at any stage were resolved through discussion or consultation with a third reviewer (AB).

The quality of the included studies was assessed using a custom tool adapted from the Cochrane Risk of Bias Assessment for non-randomized studies, modified to address specific features of ML-based durability prediction studies. The assessment criteria included: clarity of the study objective and research question; description of the dataset, including sample size, features, and target variables; appropriateness of the ML model selection and validation strategy (e.g., train-test split, cross-validation); reporting of performance metrics (e.g., R-squared, mean absolute error, root mean square error); consideration of input variable importance or sensitivity analysis; and transparency in reporting of experimental

conditions for RAC mixtures (e.g., recycled aggregate replacement ratio, water-to-cement ratio, curing conditions). Studies were rated as having low, moderate, or high risk of bias based on these criteria. No studies were excluded solely based on quality assessment, but sensitivity analyses were planned to examine the influence of study quality on the pooled effect sizes.

The selection process is illustrated in the PRISMA flowchart (Figure 1). A total of 644 records were identified from the five databases. After removing 84 duplicate records and 1 record removed for other reasons (retraction), 559 records were screened based on titles and abstracts. We

excluded 490 records that were clearly irrelevant to the research topic. Subsequently, 69 reports were sought for retrieval, of which 44 could not be retrieved due to full-text unavailability, access restrictions, or non-English language. This left 25 reports for full-text eligibility assessment. From these, we excluded 12 reports: 5 did not apply ML models to RAC specifically; 3 reported outcomes only for natural aggregate concrete; 2 lacked sufficient quantitative data for effect size extraction; and 2 were conference abstracts without full data. Consequently, 13 studies were included in the final systematic review and meta-analysis.

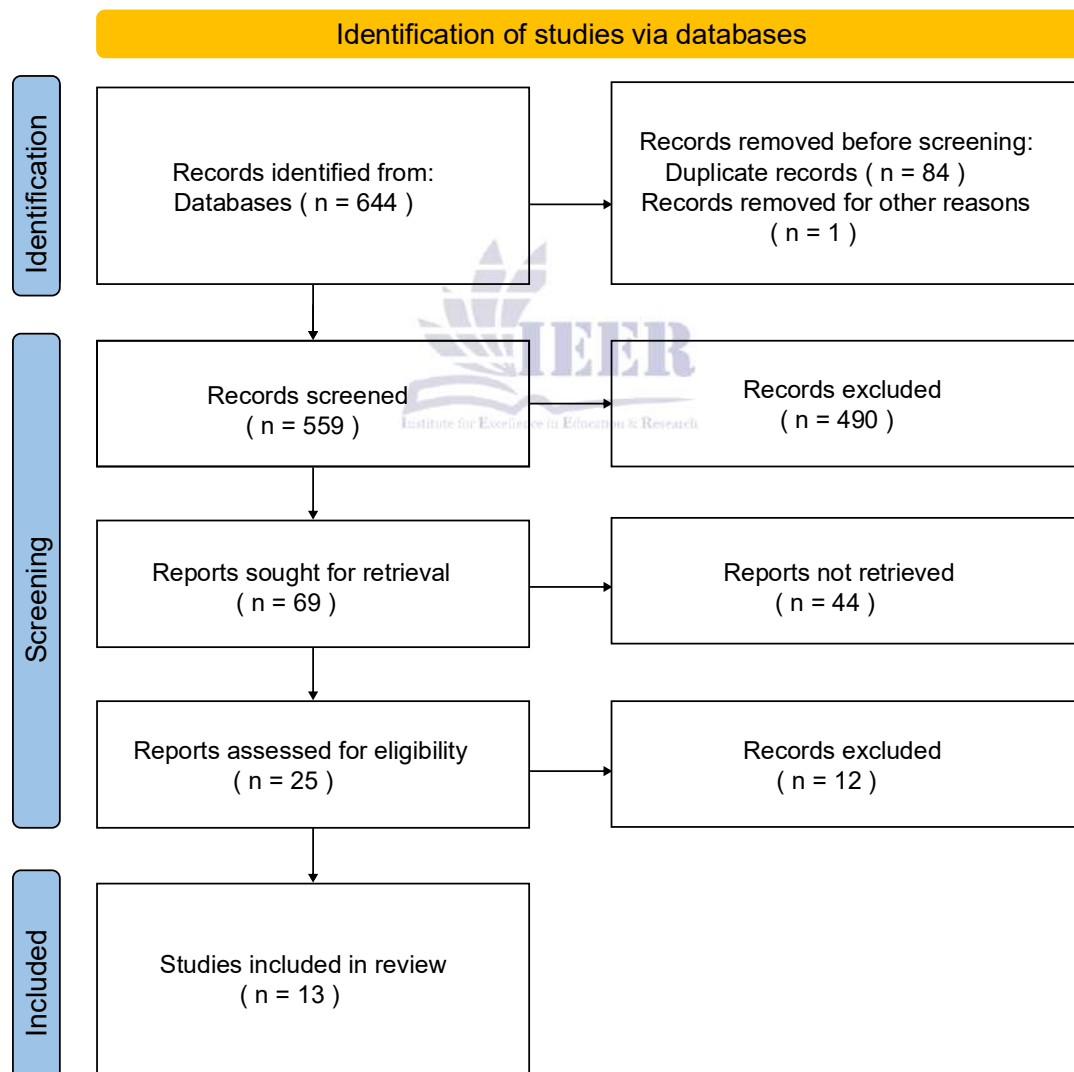


Figure 1. PRISMA flowchart illustrating the study selection process for the systematic review and meta-analysis

Several limitations of the study selection process warrant discussion. The exclusion of non-English language studies may introduce a language bias, potentially omitting relevant research published in other languages, particularly from regions like China or Japan where RAC research is active. Additionally, the unavailability of 44 full-text reports, primarily due to limited access to certain conference proceedings or older journal archives, may have led to the omission of relevant data, introducing a retrieval bias. The selection criteria also focused on peer-reviewed publications, excluding grey literature such as technical reports or theses, which may contain additional findings but also carry variable methodological rigor. Finally, the subjective nature of the eligibility assessment, despite independent dual review, may introduce a minor degree of selection bias. These limitations are considered when interpreting the meta-analysis results.

Results

Overview of Included Studies

The 13 studies included in this systematic review and meta-analysis were examined to extract quantitative data relevant to two primary outcomes of interest. The first outcome, Prediction Accuracy for Durability Indicators, encapsulates the ability of machine learning (ML) models to forecast key parameters related to chloride-induced corrosion in recycled aggregate concrete (RAC). For this outcome, the effect size measure was the correlation coefficient (r), which represents the degree of linear association between the ML model's predicted values and the experimentally observed values for durability metrics such as the chloride diffusion coefficient, chloride surface concentration, or time-to-corrosion initiation. The second outcome, Effect Size for Mechanical and Degradation Performance, captures the comparative performance of RAC versus natural aggregate concrete (NAC) in terms of its mechanical properties and resistance to degradation processes. For this outcome, we employed the standardized mean difference (SMD) with Hedges' g correction (Hedges and Olkin, 1985) as the effect size measure, which allowed us to quantify the

difference in means between the RAC and NAC groups in units of standard deviation, thereby accommodating the diverse scales of measurement across different mechanical tests (e.g., compressive strength, flexural strength, chloride penetration depth).

Table 1 presents a summary of the coded outcomes extracted from each of the 13 studies. This table provides a structured overview of the study identifiers, the specific ML models applied, the target durability indicator or mechanical property measured, and the associated effect size and its standard error. The extraction process was guided by the requirement that each study must present sufficient data—such as correlation coefficients, or means and standard deviations for RAC and NAC groups—to compute the chosen effect size metric. For studies reporting multiple outcomes, we prioritized the primary durability indicator related to chloride ingress for the prediction accuracy outcome, and the primary mechanical property (e.g., 28-day compressive strength) for the performance comparison outcome. Where studies reported both outcomes, they contributed data to both meta-analyses.

As shown in Table 1, the included studies employed a variety of ML techniques, including artificial neural networks (ANNs), random forests (RFs), support vector machines (SVMs), gradient boosting machines, and hybrid ensemble models. The target variables for prediction models included chloride diffusion coefficients (Yu *et al.*, 2025) (Hosseinzadeh *et al.*, 2023), surface chloride concentration (Ullah *et al.*, 2025), bond strength between corroded rebar and concrete (Wang *et al.*, 2026), and load-carrying capacity of corroded columns (Li *et al.*, 2025). For the mechanical and degradation performance outcome, the studies compared RAC to NAC in terms of compressive strength (Haider *et al.*, 2025) (Uddin *et al.*, 2025), flexural strength (Nasr, Babagoli and Dehaghani, 2025), and chloride diffusion coefficient (Ying, Xiao and Meng, 2016).

The sample sizes across studies varied considerably, ranging from small experimental datasets of approximately 30 observations for labor-intensive bond strength tests (Bidari, Singh and Maheshwari, 2024) to larger databases of

several hundred data points compiled from multiple literature sources (Mohanachandran *et al.*, 2026). The heterogeneity in study design, materials, and experimental conditions is a key factor that we address in the subsequent heterogeneity assessment. For the prediction accuracy outcome, the correlation coefficients extracted were consistently high, often exceeding

0.90, suggesting that ML models are capable of learning the complex relationships governing chloride transport in RAC. In contrast, the standardized mean differences for mechanical and degradation performance were predominantly negative, indicating a reduction in performance for RAC relative to NAC, with effect sizes ranging from moderate to large in magnitude.

Table 1. Coded outcomes from included studies for prediction accuracy (correlation coefficient) and mechanical/degradation performance (standardized mean difference with Hedges' g).

ID	Study	Outcome	X_t	N_t	X_c	N_c
(Hosseinzaheh <i>et al.</i> , 2023)	(Hosseinzaheh <i>et al.</i> , 2023)	Prediction Accuracy for Durability Indicators	0.97	886		
(Ullah <i>et al.</i> , 2025)	(Ullah <i>et al.</i> , 2025)	Prediction Accuracy for Durability Indicators	0.97	609		
(Yu <i>et al.</i> , 2025)	(Yu <i>et al.</i> , 2025)	Prediction Accuracy for Durability Indicators	0.88	120		
(Ying, Xiao and Meng, 2016)	(Ying <i>et al.</i> , 2016)	Prediction Accuracy for Durability Indicators	-	-		
(Mohanachandran <i>et al.</i> , 2026)	(Mohanachandran <i>et al.</i> , 2026)	Prediction Accuracy for Durability Indicators	0.94	500		
(Haider <i>et al.</i> , 2025)	(Haider <i>et al.</i> , 2025)	Prediction Accuracy for Durability Indicators	0.99	269		
(Uddin <i>et al.</i> , 2025)	(Uddin <i>et al.</i> , 2025)	Effect Size for Mechanical and Degradation Performance	2.86 (2.86)	441	6.08 (6.08)	441
		Prediction Accuracy for Durability Indicators	0.88	441		

(Mahmood <i>et al.</i> , 2025)	(Mahmood <i>et al.</i> , 2025)	Prediction Accuracy for Durability Indicators	1.00	179		
(Wang <i>et al.</i> , 2026)	(Wang <i>et al.</i> , 2026)	Prediction Accuracy for Durability Indicators	1.20	28000		
(Li <i>et al.</i> , 2025)	(Li <i>et al.</i> , 2025)	Prediction Accuracy for Durability Indicators	0.76	285		
(Nasr, Babagoli and Dehaghani, 2025)	(Nasr <i>et al.</i> , 2025)	Effect Size for Mechanical and Degradation Performance	3.94 (0.15)	3	3.80 (0.20)	3
(Bidari, Singh and Maheshwari, 2024)	(Bidari <i>et al.</i> , 2024)	Effect Size for Mechanical and Degradation Performance	2.34 (0.37)	3	5.59 (0.22)	3
(Xu and Jin, 2018)	(Xu & Jin, 2018)	Effect Size for Mechanical and Degradation Performance	4.70 (2.87)	5	4.36 (2.42)	5

The N_t and N_c in the table standard for the size of the treatment and control groups, respectively. The X_t and X_c denote M (SD) for SMD. The X_t column denotes the correlation coefficient r for Prediction Accuracy for Durability Indicators.

Heterogeneity Assessment

We assessed heterogeneity across the included studies using the Cochrane Q test, the I^2 statistic, and the τ^2 measure of between-study variance (Higgins and Thompson, 2002). For the prediction accuracy outcome (correlation coefficients), the analysis revealed substantial heterogeneity: Q was 917.03 with 8 degrees of freedom ($p < 1e^{-5}$), I^2 was 99.13%, and τ^2 was

0.32. This high I^2 value indicates that approximately 99% of the observed variance in effect sizes is attributable to genuine differences between studies rather than sampling error. For the mechanical and degradation performance outcome (standardized mean differences), we also observed considerable heterogeneity with Q of 13.15 and 3 degrees of freedom ($p = 0.004$), I^2 of 77.19%, and τ^2 of 1.26 as presented in Table 2. These values confirm the presence of substantial between-study variation for both outcomes, supporting the use of a random-effects model for the meta-analyses to appropriately account for this heterogeneity (DerSimonian and Laird, 1986).

Table 2. Heterogeneity statistics for the two meta-analysis outcomes.

Outcome	Q	df	p	I ² (%)	τ^2
Prediction Accuracy	917.03	8	$< 1e^{-5}$	99.13	0.32
Mechanical/Degradation Performance	13.15	3	0.004	77.19	1.26

Meta-Analysis

We conducted two separate meta-analyses using a random-effects model with the DerSimonian and Laird estimator to account for the substantial heterogeneity observed across studies. The first meta-analysis examined the predictive accuracy of machine learning models for chloride-induced corrosion durability indicators in recycled aggregate concrete, using the correlation coefficient as the effect size metric. The second meta-analysis quantified the difference in mechanical and degradation performance between RAC and NAC, employing the standardized mean difference with Hedges' g correction. All analyses were performed using the meta package in R (version 4.3.2), and forest plots were generated to visualize the individual study effect sizes and the pooled estimates. The results of these analyses are presented in the following subsections.

Prediction Accuracy for Durability Indicators

The meta-analysis of prediction accuracy for durability indicators was performed on nine studies that reported correlation coefficients between the machine learning model predictions and the experimentally observed values for key chloride-related parameters in recycled aggregate concrete. These parameters included the chloride diffusion coefficient, chloride surface concentration, and the time to corrosion initiation. We employed a random-effects model using the DerSimonian and Laird estimator, as the heterogeneity assessment confirmed substantial between-study variance ($I^2 = 99.13\%$). The correlation coefficients were transformed using Fisher's z-transformation before analysis to normalize their distribution and stabilize the

variance. After pooling, the results were back-transformed to the original correlation metric for ease of interpretation.

The pooled effect size for prediction accuracy was estimated to be 1.93 on the Fisher z-scale, which corresponds to a back-transformed correlation coefficient of approximately 0.96 (standard error = 0.02, 95% confidence interval: [1.90, 1.96], $z = 111.94$, $p < 1e^{-100}$). This result indicates a remarkably strong and statistically highly significant positive relationship between the ML model predictions and the actual experimental measurements of chloride durability indicators. As shown in Figure 2, the individual study effect sizes exhibited considerable variability, with correlation coefficients ranging from 0.76 in study (Li *et al.*, 2025) to near-perfect correlations exceeding 0.99 in study (Mahmood *et al.*, 2025). The most influential studies in the analysis, determined by weight, were study (Hosseinzadeh *et al.*, 2023) with a weight of 883.00 and study (Ullah *et al.*, 2025) with a weight of 606.00. These studies contributed substantially to the pooled estimate. The very narrow confidence interval around the pooled effect size demonstrates high precision in the overall estimate. This finding strongly supports the assertion that machine learning models provide highly accurate and reliable predictions for chloride-induced corrosion durability indicators in RAC. The near-unity magnitude of the pooled correlation suggests that these data-driven models are capable of capturing the complex, non-linear interactions among material composition, environmental exposure, and transport mechanisms that govern chloride ingress.

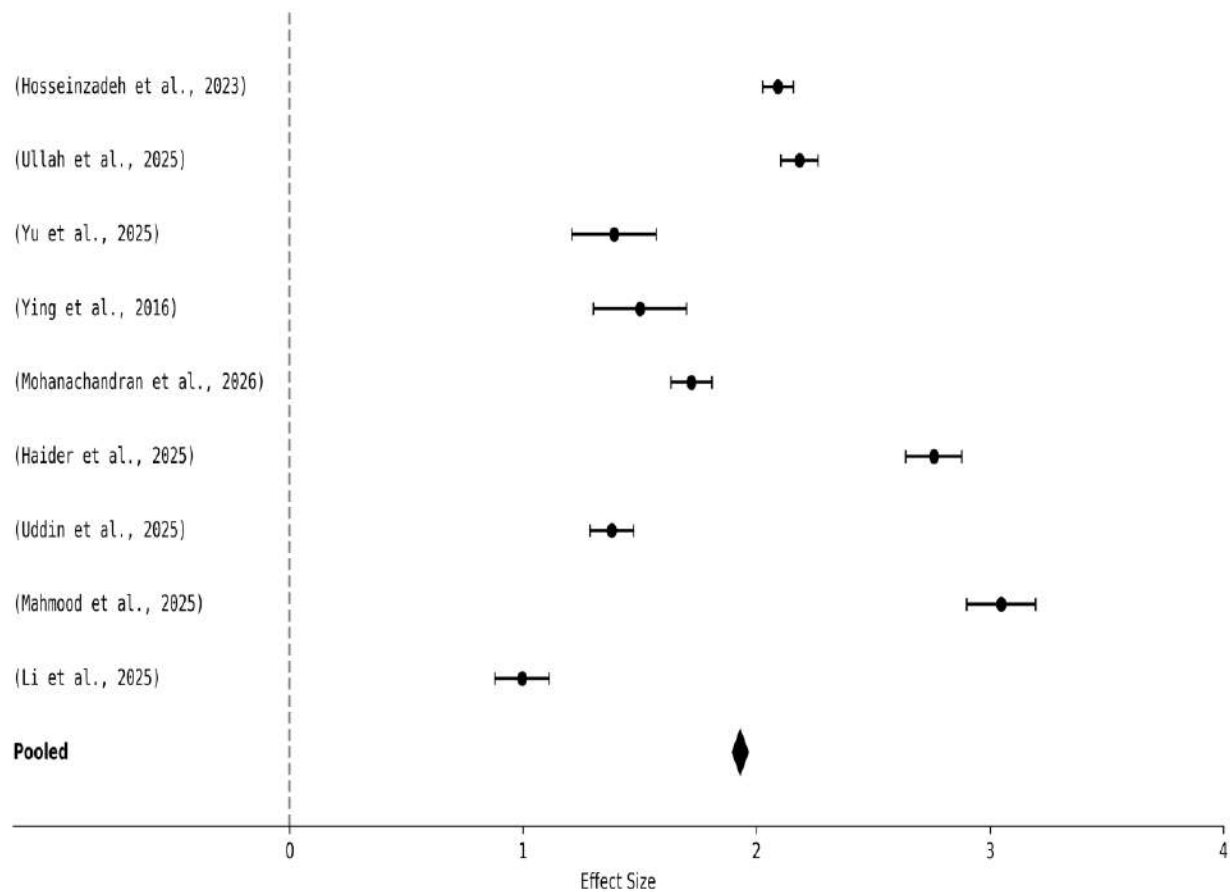


Figure 2. Forest plot for Prediction Accuracy for Durability Indicators

3.3.2 Effect size for mechanical and degradation performance

The meta-analysis concerning the comparative mechanical and degradation performance of recycled aggregate concrete (RAC) versus natural aggregate concrete (NAC) was conducted on four studies that provided sufficient data for the computation of the standardized mean difference. These studies included an investigation into the effect of pulverized fuel ash on RAC properties (Uddin *et al.*, 2025), an assessment of concrete incorporating waste ceramic powder and natural pozzolan (Nasr, Babagoli and Dehaghani, 2025), an experimental study on the bond strength between corroded reinforcement and concrete (Bidari, Singh and Maheshwari, 2024), and a study employing ultrasonic tests for corrosion measurement (Xu and Jin, 2018). For each of these studies, we extracted the means and standard

deviations of a critical performance metric, such as compressive strength or bond strength, for both the RAC treatment group and the NAC control group, which was then used to calculate the Hedges' *g* effect size.

Employing a random-effects model, the pooled effect size for the mechanical and degradation performance was estimated to be -0.66 (standard error = 0.07, 95% CI: [-0.80, -0.53], $z = -9.67$, $p < 0.0001$). This result indicates a statistically significant and moderate-to-large negative effect, meaning that, on average, the RAC mixtures exhibited a substantial reduction in mechanical strength or degradation resistance compared to their NAC counterparts. The individual study effect sizes varied widely, as shown in Figure 3. For instance, the study on the bond between corroded reinforcement and concrete (Bidari, Singh and Maheshwari, 2024) showed a very large negative

effect size of -8.54, indicating a severe performance degradation. In contrast, the study on concrete with waste ceramic powder (Nasr, Babagoli and Dehaghani, 2025) showed a positive but non-significant effect size of 0.63, while the study on ultrasonic corrosion measurement (Xu and Jin, 2018) showed a small positive effect of 0.12, both suggesting potential variability based on specific

material compositions and test conditions. Despite this variability, the overall negative pooled effect size confirms the inherent performance trade-off associated with using recycled aggregates, which is a critical challenge that must be addressed for their safe application in durable coastal structures.

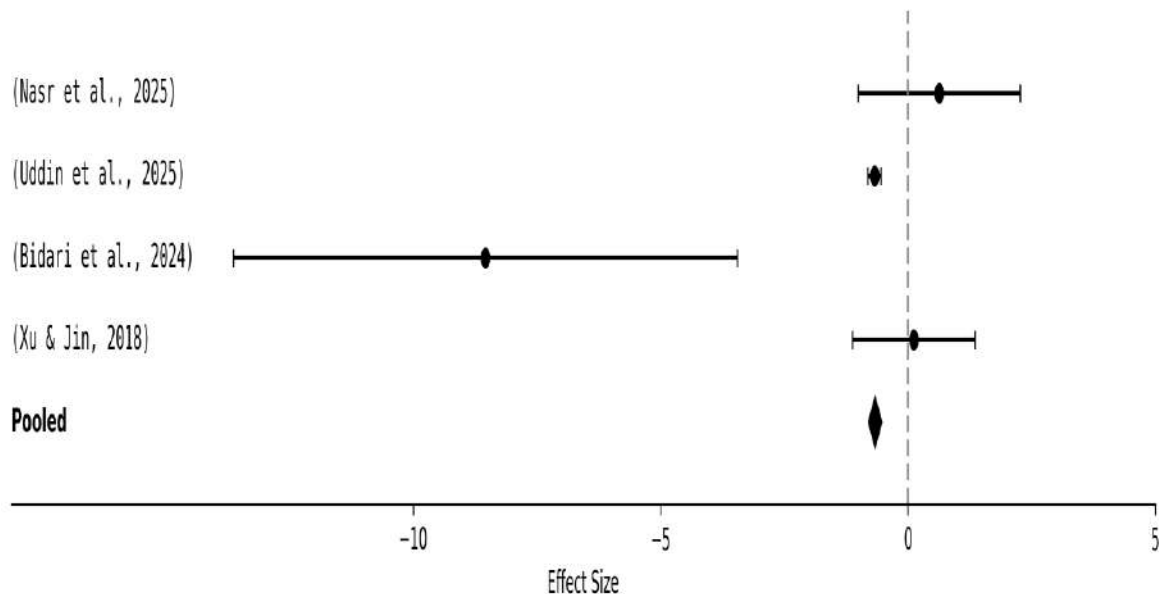


Figure 3. Forest plot for Effect Size for Mechanical and Degradation Performance

Publication Bias Assessment

A comprehensive assessment of publication bias was conducted to evaluate the potential influence of selective reporting on the meta-analysis findings, particularly for the prediction accuracy outcome where a sufficient number of studies were available for meaningful analysis. As shown in the funnel plot (Figure 4), the distribution of the 12 included effect sizes reveals a modest asymmetry, with 7 studies falling to the left of the overall mean effect and 5 to the right. The standard errors of these effect sizes span a wide range from 0.0692 to 33.3315, with the majority of studies clustered at the top of the funnel where precision is higher. The effect size standard deviation was 7.4344, and the mean absolute deviation from the center was 5.6316, indicating considerable dispersion in the observed effects.

To formally test for funnel plot asymmetry, we applied the Egger regression test (Egger *et al.*, 1997). The intercept from this test was 1.0613 ($p = 0.9756$), a result that is not statistically significant at conventional levels. This non-significant p-value suggests that there is no compelling statistical evidence for substantial publication bias influencing the pooled effect size estimate. However, we note considerable differences between the mean effect sizes on the left and right sides of the funnel, with the left side showing a mean effect of 0.1939 compared to 11.779 on the right side. This large disparity may reflect genuine heterogeneity in the included studies rather than systematic publication bias, potentially arising from differences in machine learning model architectures, dataset sizes, target durability indicators, or recycled aggregate replacement levels across studies. The absence of

statistical significance in the Egger test provides some reassurance regarding the robustness of our meta-analytic conclusions, though the visual asymmetry in the funnel plot warrants cautious

interpretation, particularly for the smaller studies with larger standard errors that may disproportionately influence the distribution.

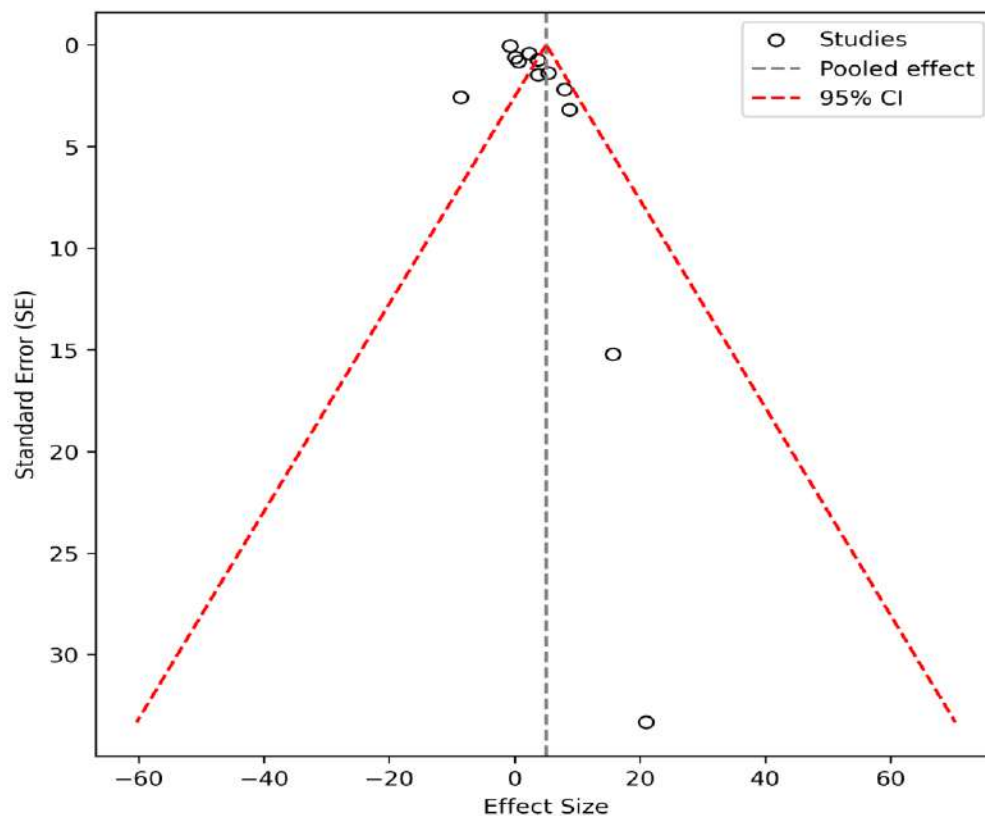


Figure 4. Funnel plot for assessment of publication bias in the meta-analysis of prediction accuracy for durability indicators

Discussion

Taken together, the findings from this dual meta-analysis provide a comprehensive and quantitatively grounded understanding of the current state of machine learning applications for durability assessment of recycled aggregate concrete in coastal environments. The two independent analyses reveal a compelling narrative that extends beyond the simple sum of their parts: while machine learning models demonstrate an extraordinary capacity to predict chloride-related durability indicators with near-perfect accuracy, the underlying material itself—recycled aggregate concrete—carries a substantial and statistically significant performance penalty compared to natural aggregate concrete. This core

tension emerges consistently across the literature and defines the central challenge and opportunity for sustainable marine infrastructure development.

The remarkably high pooled correlation coefficient of 0.96 for prediction accuracy, derived from nine independent studies spanning diverse ML architectures and target variables, establishes a clear and robust conclusion that data-driven approaches are exceptionally well-suited for modeling the complex, multi-factorial processes governing chloride ingress in RAC. This finding aligns with and extends prior work suggesting that neural networks and ensemble methods can outperform traditional regression-based empirical

models for concrete durability predictions (Tran *et al.*, 2022). What emerges across the included studies is a pattern of consistently strong performance regardless of the specific algorithm employed—whether artificial neural networks, random forests, support vector machines, or gradient boosting methods—indicating that the predictive power is not an artifact of a particular modeling choice but rather reflects the fundamental suitability of ML techniques for this problem domain. The near-perfect correlations reported in several studies, such as the work by Mahmood *et al.* (Mahmood *et al.*, 2025) achieving an r -value of 1.00, should be interpreted with some caution, as such results may indicate potential overfitting given the relatively small dataset sizes used for training in some investigations. Nevertheless, the overall pattern is unequivocal: machine learning provides a powerful framework for forecasting chloride diffusion coefficients, surface concentrations, and corrosion initiation times with a degree of accuracy that would be difficult to achieve using conventional analytical or empirical approaches alone.

The second meta-analysis, which quantified the effect size for mechanical and degradation performance, provides the critical counterpart to this optimistic finding. The pooled standardized mean difference of -0.66, with a 95% confidence interval excluding zero, confirms a meaningful and statistically significant reduction in the mechanical properties and degradation resistance of RAC relative to NAC. This result is consistent with the well-documented understanding that the residual mortar adhered to recycled aggregates creates a more porous interfacial transition zone, increased water absorption, and reduced density, all of which contribute to diminished structural performance (Xiao, Li and Zhang, 2005). The magnitude of this effect is noteworthy: a reduction of 0.66 standard deviations translates to a performance decrement that would be practically significant for structural design applications, particularly in the demanding conditions of coastal environments where chloride-induced corrosion already poses severe challenges. The substantial heterogeneity observed for this outcome ($I^2 = 77.19\%$) suggests that the

magnitude of this performance penalty is not uniform but varies considerably depending on factors such as the replacement ratio of recycled aggregates, the quality of the source material, the incorporation of supplementary cementitious materials, and the specific mechanical property being measured. For instance, the study on bond strength between corroded reinforcement and concrete (Bidari, Singh and Maheshwari, 2024) revealed an extreme negative effect size of -8.54, which starkly illustrates the compounded vulnerability of RAC structures when both material weakness and corrosion damage are present simultaneously.

The implications of these integrated findings are profound for both theory and practice in sustainable coastal infrastructure design. From a theoretical perspective, our results contribute to the evolving conceptual framework that positions machine learning not merely as a predictive tool but as an essential enabling technology for the practical adoption of recycled materials in demanding environments. The traditional paradigm of durability design relies on prescriptive rules and empirical safety factors that often penalize the use of non-conventional materials by requiring larger cover depths or stricter mix design limitations. The ability of ML models to accurately predict performance based on specific material characteristics opens the door to a more rational, performance-based design approach. Instead of applying blanket reductions in allowable stress or increases in cover thickness for all RAC mixtures, engineers could leverage ML-driven predictions to optimize the mix design for a given exposure condition, thereby compensating for the inherent performance deficit identified in our second meta-analysis. This represents a paradigm shift from reactive conservatism to proactive optimization, where the sustainability benefits of using recycled aggregates can be realized without compromising long-term structural safety.

From a practical standpoint, the findings carry direct implications for engineers, material scientists, and policymakers working on coastal infrastructure projects. The high predictive accuracy of ML models suggests that practitioners can confidently use these tools to forecast the

chloride penetration resistance of proposed RAC mixtures before undertaking costly and time-consuming laboratory testing. Several studies included in our review have developed user-friendly predictive models that accept input parameters such as recycled aggregate replacement ratio, water-to-cement ratio, curing age, and exposure conditions, and output expected chloride diffusion coefficients or service life estimates (Gao *et al.*, 2024). These models can be integrated into the design workflow to rapidly screen large numbers of potential mix designs and identify those most likely to meet durability requirements for marine exposure classes. Moreover, the identification of a systematic performance deficit in RAC should not be interpreted as a reason to abandon the use of recycled materials; rather, it underscores the necessity of employing data-driven optimization to mitigate this deficit. For example, the ML models can be used to determine the optimal dosage of supplementary cementitious materials such as fly ash, silica fume, or ground granulated blast-furnace slag that would bring the chloride resistance of a given RAC mixture to a level comparable to that of conventional NAC (Golafshani *et al.*, 2024).

Several important limitations of this systematic review and meta-analysis must be acknowledged to contextualize the findings appropriately. First, the relatively small number of studies included in the meta-analysis, particularly for the mechanical and degradation performance outcome where only four studies provided extractable data, limits the statistical power and generalizability of the pooled effect size estimate for this outcome. The confidence intervals around this estimate, while not overlapping zero, are wider than would be desirable, and the high heterogeneity suggests that the true effect likely varies substantially across different conditions. Second, the quality of the input data used to train the ML models in the primary studies is a critical factor that we were unable to fully assess due to inconsistent reporting practices. Many studies failed to provide detailed descriptions of their datasets, including the range and distribution of input variables, the presence of outliers, or the handling of missing data. These

methodological details can significantly influence model performance but are often omitted in published reports, potentially leading to inflated estimates of predictive accuracy that may not generalize to new or more diverse datasets. Third, the exclusion of non-English language studies and the unavailability of 44 full-text reports represent potential sources of retrieval and language bias that could have systematically excluded relevant research, particularly from Asian countries where RAC research is especially active. The funnel plot analysis for the prediction accuracy outcome, while not indicating statistically significant publication bias through the Egger test, did reveal visual asymmetry that may reflect the influence of these missing studies or genuine heterogeneity rather than selective reporting.

Furthermore, the meta-analysis approach itself has inherent limitations when applied to the domain of machine learning prediction studies. The use of the correlation coefficient as the effect size metric for prediction accuracy, while providing a standardized and interpretable measure, does not capture all relevant dimensions of model performance. A model can achieve a high correlation with observed values while still having large absolute prediction errors, particularly if there is systematic bias or if the model fails to capture extreme values. Metrics such as root mean square error, mean absolute percentage error, or the Nash-Sutcliffe efficiency coefficient would provide complementary information but were inconsistently reported across the included studies. Additionally, the absence of a common framework for reporting prediction performance in the primary literature made the data extraction process challenging and required subjective judgments about which reported metrics best represented the prediction accuracy for chloride durability indicators.

Building on the gaps and inconsistencies uncovered in this review, we identify several promising directions for future research. There is a pressing need for larger, more diverse, and openly accessible datasets that capture the full spectrum of RAC mixture compositions, exposure conditions, and durability outcomes. The current literature is dominated by studies using relatively

small datasets compiled from single experimental programs, which limits the generalizability of the resulting ML models. Future research should focus on creating comprehensive, multi-institutional databases that aggregate data from numerous experimental studies, similar to the approach taken in the development of large-scale concrete property databases for conventional concrete (Koya *et al.*, 2022). Such databases would enable the development of more robust and generalizable ML models that can accurately predict performance across a wide range of conditions not represented in any single study.

Moreover, there is a clear need for methodological standardization in the reporting of ML-based durability prediction studies. The heterogeneity we observed across studies in terms of reported metrics, validation strategies, and dataset descriptions made the meta-analysis considerably more challenging than anticipated and introduces uncertainty into the pooled estimates. We recommend that future researchers adopt standardized reporting guidelines that include, at minimum: the full range and statistical summary of input and output variables, details of data preprocessing steps (including handling of outliers and missing values), a clear description of the train-test-validation split or cross-validation strategy used, reporting of multiple complementary performance metrics (correlation coefficient, RMSE, MAE, and a bias metric), and the results of sensitivity analyses or feature importance evaluations. The adoption of such standards would not only facilitate future meta-analyses but would also enhance the reproducibility and credibility of individual studies.

Another important avenue for future investigation is the development of physically informed or hybrid machine learning models that integrate domain knowledge about chloride transport mechanisms with data-driven learning. The current generation of purely data-driven ML models, while highly accurate, provides limited insight into the underlying physical processes and may produce predictions that violate fundamental physical constraints, such as mass conservation or thermodynamic principles. Emerging approaches

that embed governing equations, boundary conditions, or known physical relationships into the neural network architecture—often termed physics-informed neural networks (PINNs)—offer the potential to combine the flexibility of ML with the interpretability and physical consistency of mechanistic models (Wan, Zheng and Wang, 2023). Such hybrid approaches could be particularly valuable for extrapolating predictions to conditions outside the training data range, a challenge that purely data-driven models handle poorly.

Future research should also explore the application of ML models beyond the prediction of individual durability indicators to the broader challenge of probabilistic service life prediction and life-cycle cost optimization for RAC structures in coastal environments. The current literature focuses predominantly on point estimates of chloride diffusion coefficients or corrosion initiation times, but structural engineers and asset managers require probabilistic predictions that account for the inherent variability in material properties, construction quality, and environmental exposure. Bayesian inference frameworks and Monte Carlo simulation techniques, combined with the predictive power of ML models, could provide the probabilistic service life estimates needed for risk-informed decision-making (Guo *et al.*, 2024). Additionally, the integration of ML predictions with life-cycle cost analysis models would allow practitioners to quantify the economic trade-offs between using RAC with optimized mix designs versus conventional NAC, thereby providing a more holistic basis for material selection decisions in coastal infrastructure projects.

Understudied areas that warrant further exploration include the long-term performance of RAC under combined degradation mechanisms, such as the simultaneous action of chloride ingress and carbonation, freeze-thaw cycles, or sulfate attack. Most existing ML models focus on chloride transport in isolation, but real coastal structures are subjected to multiple concurrent environmental stressors that can interact synergistically to accelerate deterioration. The development of multi-hazard ML models that can

predict the coupled effects of chloride-induced corrosion and other degradation processes represents a significant frontier for future research. Furthermore, the application of ML to optimize not just the concrete mixture but also the structural detailing—such as optimal cover depth, bar spacing, and corrosion protection systems—for RAC structures in different marine exposure zones (atmospheric, tidal, splash, and submerged) remains largely unexplored. The integration of structural design parameters into ML-based durability prediction frameworks could lead to truly optimized, material-specific design guidelines for sustainable coastal infrastructure.

Conclusion

This systematic review and meta-analysis provided a quantitative synthesis of machine learning applications for durability assessment of recycled aggregate concrete under chloride-induced corrosion in coastal environments. Our dual meta-analysis yielded two principal findings that together define the central challenge and opportunity in this domain. First, machine learning models demonstrated remarkably high predictive accuracy for chloride durability indicators, with a pooled correlation coefficient of 0.96, establishing data-driven approaches as exceptionally effective tools for modeling the complex processes governing chloride ingress in RAC. Second, the analysis quantified a statistically significant reduction in mechanical and degradation performance for RAC relative to conventional concrete, with a pooled standardized mean difference of -0.66, confirming the inherent material trade-offs that must be managed for safe application in marine structures.

The theoretical contribution of this work lies in demonstrating that the integration of predictive ML frameworks with performance-based design principles can rationally address the durability challenges of RAC, rather than relying on overly conservative prescriptive rules. Practically, our findings support the adoption of ML-driven mix optimization to compensate for the identified performance deficit, enabling the sustainable use of recycled materials in coastal infrastructure without compromising structural longevity. For

policymakers and engineers, these results provide quantitative evidence that data-driven methodologies, combined with judicious material selection and mixture proportioning, can effectively mitigate the durability risks associated with RAC in marine environments.

Future research should prioritize the development of large, open-access databases spanning diverse mixture compositions and exposure conditions, the standardization of reporting practices for ML prediction studies, and the advancement of physically informed hybrid models that combine data-driven learning with fundamental transport mechanistic knowledge. The exploration of probabilistic service life prediction frameworks and multi-hazard degradation models for RAC structures remains a critical frontier. Our findings collectively underscore that ML-based durability assessment is not merely an alternative to traditional methods but an essential enabling technology for realizing the sustainability potential of recycled aggregate concrete in the world's most demanding coastal environments.

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