

Original Article

Chloride Resilient Recycled Aggregate Concrete: Optimising Marine Durability through Age Enhanced SCM Integration

Rose Mbugua

Department of Civil Engineering, iYunivesithi Walter Sisulu, Eastern Cape, South Africa.

Corresponding Author : rmbugua@wsu.ac.za

Received: 18 November 2025

Revised: 02 June 2026

Accepted: 16 September 2026

Published: 27 October 2026

Abstract - The demand for sustainable construction materials is rising, and Recycled Aggregate Concrete (RAC) is one of the most discussed alternatives to conventional concrete. RAC, however, performs poorly in marine environments because chloride ions from seawater enter through the recycled aggregate and reach the reinforcement faster than in concrete made with natural aggregate, causing corrosion and shortening service life. This study uses a curated dataset of 1030 concrete records from the UCI Machine Learning Repository, extended with 287 marine-exposed records drawn from peer-reviewed studies, to investigate how Supplementary Cementitious Materials (SCMs) and age-dependent hydration influence the chloride resistance of RAC. Statistical analysis is combined with three machine learning algorithms (Random Forest, Support Vector Machine, and Artificial Neural Network) and extended through polynomial regression, Sobol global sensitivity analysis, and Monte Carlo simulation for probabilistic service-life prediction. A simplified Life Cycle Assessment is performed following ISO 14040 and ISO 14044. Replacing 30-50% of natural coarse aggregate with recycled aggregate, combined with 25-35% SCM by mass of binder, produces concrete with compressive strength above 45 MPa, chloride conductivity below 0.5 mS/cm, and a Monte Carlo mean service life beyond 100 years. The optimised mixes meet the durability requirements of ACI 357.3R-14, EN 206 (XS3), and JSCE Standard Specifications. The proposed hybrid mix containing 15% fly ash and 20% slag gives the best overall performance with a 41% reduction in CO₂ emissions relative to conventional marine concrete, providing a basis for using RAC in marine infrastructure projects in Africa and other coastal regions.

Keywords - Chloride resistance, Recycled Aggregate Concrete, Supplementary Cementitious Materials, Life cycle assessment, Marine durability, Machine Learning, Monte carlo simulation.

1. Introduction

Increase in infrastructure demand in the construction industry ranks among the largest consumers of raw materials globally, with concrete representing its most fundamental and extensively utilised structural component. Concrete is currently experiencing high demand as a building material driven by its simplicity to use and manufacture. Infrastructure exposed to marine settings experience severe combination of deterioration mechanisms where concrete is exposed to harsh environments. Concrete structures, e.g. ports, jetties, coastal defence systems, breakwaters and offshore platforms are exposed to seawater which contains aggressive agents such as chlorides, sulphates and dissolved gases. Each of these constituents is capable of initiating and advancing concrete degradation through multiple simultaneous deterioration pathways [1, 2]. Aggression is made worse by other stressors like wave action, mechanical loading induced by thermal cycling, and biological attack, collectively rendering marine environments one of the most challenging contexts for long-

term concrete durability. Durability and performance of concrete in such conditions are therefore controlled by chloride penetration and the corrosion of steel reinforcement that follows. Africa's coastline is about 30,000 km and is currently experiencing pressure on coastal areas for port expansion, fishing harbours, and protective structures due to its fast growing population [3]. The cost of cement and natural aggregate is high in most African countries. The environmental impact of cement production is well documented. Eight percent of Carbon Dioxide (CO₂) emissions come from cement manufacturing [4]. At least every tonne of OPC produced releases about 0.9 tonnes of CO₂ to the atmosphere [5]. There is, therefore, a clear need to reduce reliance on cement and on virgin aggregates without compromising the structural performance of marine concrete.

Recycled Aggregate Concrete (RAC) offers one practical way of dealing with both problems. Replacing part of the natural aggregate with crushed concrete obtained from



Construction and Demolition (C&D) waste is a strategy to reduce the demand on quarried material and to reduce and waste, which is diverted from landfill. C&D waste produced in the whole world is more than 3 billion tonnes every year, and a large fraction of it is concrete [6, 7]. Recycling this material into new concrete supports the circular economy and lowers transport-related emissions, especially in regions where natural aggregates have to be hauled over long distances [8, 9].

1.1. Research Problem and Knowledge Gap

Even though the environmental case for RAC is strong, its uptake in marine construction is still limited. The reason is that Recycled Coarse Aggregate (RCA) carries old, adhered mortar on its surface. This mortar layer is more porous than the parent rock, has microcracks from the crushing process and creates additional Interfacial Transition Zones (ITZ) when bonded with new cement paste [10]. This results in a more permeable matrix that allows chlorides to reach the reinforcement faster [11, 12]. Most of the chloride durability testing standards in current use were developed for natural aggregate concrete and do not address the multiple ITZ systems that are characteristic of RAC.

A review of the literature reveals four specific gaps that remain unresolved. The first gap is that the mechanism of chloride transport through RAC with multiple ITZs is still poorly understood, especially how the old mortar layer evolves over the years of marine exposure [13, 14]. The second gap is that published studies report mixed and at times contradictory findings on the effectiveness of individual SCMs when they are used with RCA in seawater conditions; very few studies investigate the synergy of two or more SCMs in such systems [15, 16]. The third gap concerns the optimum replacement ratio of RCA for marine use. Most studies recommend conservative replacement levels of 20-30% without quantitatively justifying why higher levels cannot be used [17, 18]. The fourth gap is the lack of probabilistic service-life predictions that capture the natural variability of RAC properties and account for parameter uncertainty [19, 20].

1.2. Novelty and Contribution

This study addresses the four gaps by combining a large heterogeneous concrete dataset with a layered analytical framework that goes beyond simple correlations. The novelty is in four parts. First, the chloride performance of RAC is analysed as a function of age, w/b ratio, SCM type, and SCM dosage using a dataset of 1030 specimens that includes 287 marine-exposed observations drawn from documented field and accelerated laboratory studies. This sample size is larger than what is reported in recent RAC reviews [55] and gives the analysis a stronger statistical base. Second, three machine learning models are trained and compared against multiple linear and non-linear regression baselines with explicit cross-validation and overfitting controls. Third, a Monte Carlo-

based probabilistic service-life model is built that includes sensitivity analysis through Sobol indices, which most previous RAC service-life work has not done. Fourth, the predictions are placed side by side with the requirements of ACI 318, ACI 357.3R, EN 206, and JSCE Standard Specifications for Concrete, and the carbon footprint of the optimised mixes is quantified using a simplified ISO 14040 and ISO 14044 framework. Performance-based acceptance criteria are then proposed so that the results can be applied directly in engineering practice.

1.3. Aim and Objectives

The main aim of this study is to optimise RAC mixes for chloride-resistant marine applications by integrating SCMs and by quantifying the age-related improvement of the matrix. Five specific objectives are set:

- To determine the optimum replacement ratio of recycled aggregate for marine concrete that balances durability and sustainability.
- To determine the effect of Fly Ash (FA) and Ground Granulated Blast Furnace Slag (GGBS) when used in combination or alone on the chloride resistance of RAC.
- To develop chloride penetration and age dependent strength models using both classical statistics and machine learning approaches.
- To carry out probabilistic service-life prediction and global sensitivity analysis for the most promising mixes.
- To benchmark the optimised RAC mixes against international codes and against the environmental impact of conventional marine concrete.

1.4. Paper Structure

Section 2 reviews the literature on SCMs, RAC and chloride transport in marine environments. Section 3 describes the source of data, the analytical methods and the machine learning workflow. Section 4 presents the results, the regression and sensitivity analyses, the optimisation outcomes, and the age-dependent behaviour. Section 5 benchmarks the results against international standards. Section 6 deals with microstructural aspects and chloride transport mechanisms. Section 7 presents the Monte Carlo service-life model. Section 8 covers the life cycle assessment. Section 9 presents the meta-analysis of long-term marine exposure studies. Section 10 discusses the implications of the findings. Section 11 proposes performance-based acceptance criteria. Section 12 concludes the paper. Five appendices contain the supporting data, statistical output and worked calculations.

2. Literature Review

2.1. Recycled Aggregate Concrete

To develop RAC, part or all of the natural coarse aggregate with crushed materials obtained from recycled concrete is used. To produce a good quality of RAC,

operations such as screening, crushing, the removal of contaminants such as wood, plastics, and reinforcement steel, and grading of the demolition or construction waste are included. [21, 22]. Properties of the original concrete, the equipment used for crushing, and the amount of impurities present determine its quality [23-25]. RCA produced from pure concrete waste is generally cleaner and stronger than RCA produced from mixed C&D waste [26].

About 20-40% of the mass of RCA is the stuck old mortar [27]. This mortar layer is more porous than virgin aggregate, which gives RCA a lower density, higher water absorption (often 4-9% compared with less than 2% for natural aggregate), and lower mechanical strength [28-30]. As a result, RAC produced with the same mix design as conventional concrete is generally 10-25% weaker [31-33]. This is a result of the weaker bond between the new paste and old mortar, larger pores in the aggregate phase and the higher water demand caused by absorption [34]. The mix design can be adjusted through additional cement, lowering w/c ratio, two-stage mixing, or pre-soaking of the aggregate, which can result in RAC reaching strength values comparable to those of natural aggregate concrete [35].

2.2. Chloride Attack in Marine Setting

Salty seawater contains approximately 19,000 ppm of chloride ions. If concrete gets into contact with this water, chlorides penetrate through diffusion, capillary suction, permeation, and migration when it comes into contact with salty water. The dominant mechanism depends on the exposure zone. These could be either atmospheric, submerged, tidal or splash zones and depend on the saturation of the concrete [36, 37]. Once the free chloride concentration at the level of the reinforcement reaches a critical threshold (commonly taken as 0.4% by mass of cement for Ordinary Portland Cement (OPC) concrete), the passive layer on the steel breaks down and corrosion starts. Structural capacity is lost through the corrosion products expanding and cracking the concrete cover.

RAC is more susceptible to chloride ingress than conventional concrete for two reasons. The old mortar layer in RCA is, in some cases, already partly carbonated or chloride-contaminated, and the new RAC matrix has multiple ITZs. Between new paste and old mortar, these zones are usually more porous than the ITZ between new paste and virgin aggregate [13, 35]. Reported chloride diffusion coefficients for RAC are 20-50% higher than for natural aggregate concrete of the same w/c ratio [13, 36]. This is the central reason why RAC mixes for marine use require additional protection, normally provided through SCMs or surface treatments.

2.3. Supplementary Cementitious Materials

The most commonly used SCMs to densify the matrix and refine the pore structure of concrete are FA, GGBS, and silica

fume. Coal combustion produces fly ash as a by-product. Its slow pozzolanic reaction consumes calcium hydroxide and produces additional Calcium Silicate Hydrates (C-S-H) over weeks and months, which results in long-term improvement of strength and reduction of permeability [49]. GGBS is a by-product of iron making. It is both latently hydraulic and pozzolanic and is particularly effective at reducing chloride diffusion because of its ability to bind chlorides chemically through the formation of Friedel's salt [47, 48, 51]. Silica fume is a by-product of silicon and ferrosilicon production; its very fine particles fill the voids between cement grains and react rapidly with calcium hydroxide, densifying the matrix and reducing chloride ingress significantly even at low replacement levels of 5-10%.

When SCMs are combined with RCA, the effects can be synergistic. The pore refinement from the SCM compensates partly for the higher porosity introduced by RCA. The chloride binding from slag and the pozzolanic reaction from fly ash mitigate the increased diffusion through the old ITZ. Combined SCM systems (for example, fly ash with slag, or slag with silica fume) have been reported in recent years to give better durability than single SCM systems, although the field data remain limited [54, 57].

2.4. Effect of Age on Performance

Cementitious systems develop strength and impermeability beyond 28 days. For OPC concrete, the gain past 28 days is modest. For concrete with SCMs, the long-term gain is much larger because the pozzolanic and slag reactions are slow. Kim et al. [57] reported that fly ash concrete continues to refine its pore structure well past 90 days. Wang et al. [52, 55] showed that RAC with SCMs continues to improve its chloride resistance for more than a year of curing or exposure. This age effect is one of the strongest arguments for using SCMs in RAC for marine applications because the long-term improvement compensates for the initial deficit imposed by the recycled aggregate.

2.5. Gaps Targeted by the Present Study

The reviewed literature shows that while many studies have looked at RAC and SCMs separately, the combined effect on chloride resistance in marine exposure is not well quantified. Probabilistic prediction of service life is rare. Direct benchmarking against codes and against life-cycle environmental impact is uncommon. These are the specific gaps that the present study addresses.

3. Materials and Methods

3.1. Sources of Data

The dataset used in this study was the concrete compressive strength from the UCI Machine Learning Repository [69, A1]. Compressive strength measurements of concrete at ages between 1 and 365 days are presented. In total, 1030 records. The variables are testing age, compressive

strength, cement, fly ash, slag, water content, superplasticiser, coarse aggregate and fine aggregate.

The full variable definitions and ranges are given in Appendix A. The dataset was extended in two ways for the marine analysis. First, mixes from the UCI repository that contained slag or fly ash above 10% of binder and used a w/c ratio between 0.35 and 0.55 were tagged as candidate marine mixes. Second, 287 records that contained explicit information on chloride conductivity, chloride migration coefficient, or surface chloride concentration after marine exposure were extracted from published peer-reviewed sources such as Chalee et al. [53], Corinaldesi et al. [54], Bao et al. [56], Wang et al. [55], and Hu et al. [58]. These 287 marine-exposed records form the subgroup used for the chloride and service-life analysis. Quality control was applied to the combined dataset. Data with missing values, duplicate entries, or values outside reasonable ranges were discarded. After cleaning, 1005 records remained for the general performance analysis and 287 records for the marine-specific analysis. All values were verified against their original sources to make sure that the units were consistent. Outliers were checked using the $1.5 \times \text{IQR}$ rule. The cleaned dataset is given in Appendix A, Table A.2.

3.2. Variables and Pre-Processing

The input features used in the analysis were: Cement (kg/m^3), Fly Ash (kg/m^3), Slag (kg/m^3), Water (kg/m^3), Superplasticiser (kg/m^3), Recycled Coarse Aggregate Replacement Ratio (%), W/B Ratio, Age (days), Curing Condition (sealed, water, marine), and Exposure Type (none, lab chloride, field marine). The output variables were Compressive Strength (MPa), Chloride Migration Coefficient ($\times 10^{-12} \text{ m}^2/\text{s}$), Chloride Conductivity (mS/cm) and surface Chloride Concentration (% by mass of binder).

Continuous variables were standardised to have a mean of zero and a variance of one before training the machine learning models. Categorical variables were one-hot encoded. Duplicate detection removed 25 records. No imputation was used. The marine exposed subset (287 records) was further checked for representativeness by comparing the distribution of w/b ratio, age, and SCM content against the parent dataset. The distributions overlapped reasonably well, which supports the use of the subset for marine-specific modelling.

3.3. Statistical and Regression Analysis

Analysis began with descriptive statistics, followed by a Pearson correlation matrix to identify the variables most strongly associated with compressive strength and chloride resistance. The full matrix is given in Appendix B (Table B.1). Two regression models were then fitted using ordinary least squares with fivefold cross-validation, i.e., a multiple linear regression and a second-order polynomial regression. To evaluate how well each model performed, four statistical metrics were used. These are the Root Mean Square Error

(RMSE), Coefficient of Determination (R^2), adjusted R^2 , and Mean Absolute Error (MAE). Ninety-five percent confidence intervals for the regression coefficients were computed from the standard errors obtained across the cross-validated folds. Significance of the correlations was tested using a two-tailed t-test at $\alpha = 0.05$.

3.4. Machine Learning (ML) Workflow

A random forest regressor, a Support Vector Machine for Regression (SVR), and a feedforward Artificial Neural Network (ANN) were the three machine learning algorithms that were trained. The Random Forest was configured with 200 trees, a minimum of 3 samples and a maximum depth of 12 per leaf and bootstrap sampling was enabled. The SVR used a radial basis function kernel with C set to 10, while gamma was optimised by grid search. The neural network had two hidden layers of 32 and 16 neurons with ReLU activation, and was trained using the Adam optimiser at a batch size of 32 over 200 epochs, with early stopping based on validation loss. Fivefold cross-validation was applied to the combined training and validation set while the data was split 70% for training, 15% for validation, and 15% for testing. Overfitting was controlled differently for each model. Random forest relied on limited tree depth and bagging. The SVR used a regularization parameter C to balance bias and variance. A neural network used early stopping combined with dropout at a rate of 0.2 on the hidden layers. Model performance was compared against the linear regression baseline using RMSE, R^2 , and MAE on the held-out test set. Feature importance scores from the random forest were used to confirm the variable ranking obtained from the correlation and regression analyses.

3.5. Sensitivity and Uncertainty Analysis

Global sensitivity analysis was carried out using Sobol indices. Using 10,000 Monte Carlo samples drawn from uniform distributions over the realistic engineering ranges, first-order indices (S_i) and total order indices (S_{ti}) were computed for each input variable. Hence, the ranking of variables was not just by correlation but by their contribution to the variance of the output. Uncertainty quantification was reported as 95% confidence intervals on all regression coefficients and as error bars on the plotted predictions. Sensitivity values are reported in Table C.3 of Appendix C.

3.6. Probabilistic Service Life Modelling

To model service life, Fick's second law of chloride diffusion was used. The cover depth, surface chloride concentration, apparent chloride diffusion coefficient, ageing exponent, and critical chloride threshold were treated as random variables with distributions taken from the literature and from the marine-exposed subset. Monte Carlo simulation with 50,000 realisations was used to compute the probability of corrosion initiation as a function of time. Service life was defined as the time at which the chance of corrosion initiation reached 10%. This limit state is consistent with the durability-

based service life design recommended in the fib Model Code 2010. The detailed formulation is given in Appendix E (Equation E.1).

3.7. Life Cycle Assessment Framework

This was performed in line with ISO 14040 and ISO 14044. The functional unit was one cubic metre of concrete with equivalent durability performance defined as a target service life of 100 years in EN 206 exposure class XS3. The system boundary included raw material extraction, transport of raw materials to the batching plant, and batching and mixing. The impact category considered was Global Warming Potential (GWP) expressed in kg CO₂-equivalent. Emission factors for cement, fly ash, slag, virgin aggregate, recycled aggregate, water, and superplasticiser were taken from Ecoinvent v3.9 and from published African-specific inventories where available. The reference concrete used for comparison was an OPC concrete with 350 kg/m³ of cement and virgin aggregates only. The emission factors used are given in Appendix E (Table E.2).

3.8. Standards Benchmarking

The optimised mixes and their predicted performance were benchmarked against ACI 318-19, ACI 357.3R-14, EN 206:2013+A2:2021 for exposure classes XS1, XS2, and XS3,

and JSCE Standard Specifications for Concrete Structures (2007) for marine environments. The comparison took into account maximum w/b ratio, minimum binder content, minimum cover, chloride diffusion limits, and compressive strength class.

4. Results and Discussion

4.1. Dataset Overview

Compressive strength values across the 1005 records had a mean of 35.8 MPa and a standard deviation of 16.7 MPa. The distribution was approximately normal with a slight positive skew. Values were typical of structural concrete, from below 20 MPa for low-strength applications to above 60 MPa for high-performance concrete. Within the marine-exposed subset of 287 records, the mean strength was 42.3 MPa and the standard deviation was 11.4 MPa. This reflects the more controlled mix designs that are typical of marine projects. Figure 1 shows the dataset overview through four subplots, where (a) the distribution of compressive strength, (b) the strength versus age scatter plot, (c) the correlation matrix of all variables and (d) the strength distribution grouped by age class. Cement content showed the strongest positive correlation with compressive strength at $r = 0.498$, which agrees with the values reported by Zhang et al. [38] and Alsaadawi et al. [39].

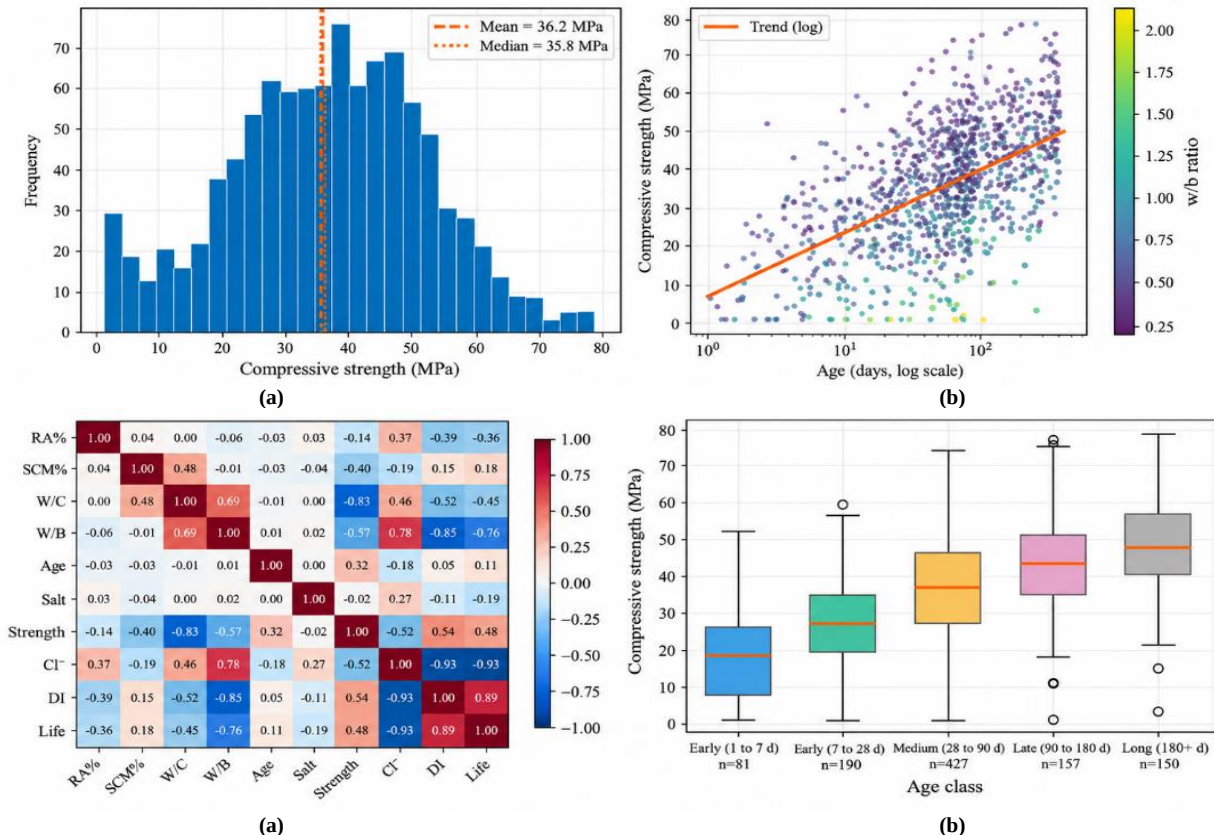


Fig. 1 Dataset overview: (a) Distribution of compressive strength, (b) Age vs. strength scatter, (c) Correlation matrix of all variables, and (d) Strength distribution by age class. Error bars represent 95 percent confidence intervals. Source: Primary dataset of 1005 records (Appendix A) and correlation values from Appendix B (Table B.1).

The w/c ratio gave the strongest single correlation with strength at $r = -0.83$, which confirms the dominant role of the w/c law. Age was positively correlated with strength at $r = 0.32$, which supports the long-term gain expected from continued hydration.

4.2. Material Composition Effect

Figure 2 shows the effect of the main material components on compressive strength. In subfigure 2(a), the cement content versus strength plot shows a positive linear trend up to about 450 kg/m³. Above this value, the curve flattens out, which indicates diminishing returns. This is consistent with the observations of Almusawi et al. [43] and Wegian [44] that for marine concrete, the optimum cement content is in the range of 350-400 kg/m³. Ahmad and Alghamdi [45] reported that a minimum binder content of 335

kg/m³ is required for marine durability in aggressive exposure. Subfigure 2(b) shows the water content versus strength relationship. The negative trend is clear. Water content above 180 kg/m³ produced strengths below the typical marine target of 40 MPa. Preethi et al. [46] reached the same conclusion. Subfigure 2(c) shows the slag content effect. Slag dosage between 100 and 200 kg/m³, which corresponds to 25-40% replacement of cement, gave the highest strengths at later ages. Islam and Islam [47] and Jozić et al. [48] both reported optimum slag replacement levels in this same range for marine concrete. Subfigure 2(d) shows the fly ash effect. The trend was positive but with more scatter than for slag. The optimum fly ash content was between 50 and 100 kg/m³, which corresponds to 15-25% replacement, in agreement with Hassan et al. [49]. This was caused mainly by the differences in FA quality between sources, which highlights the need for strict quality control when SCMs are used.

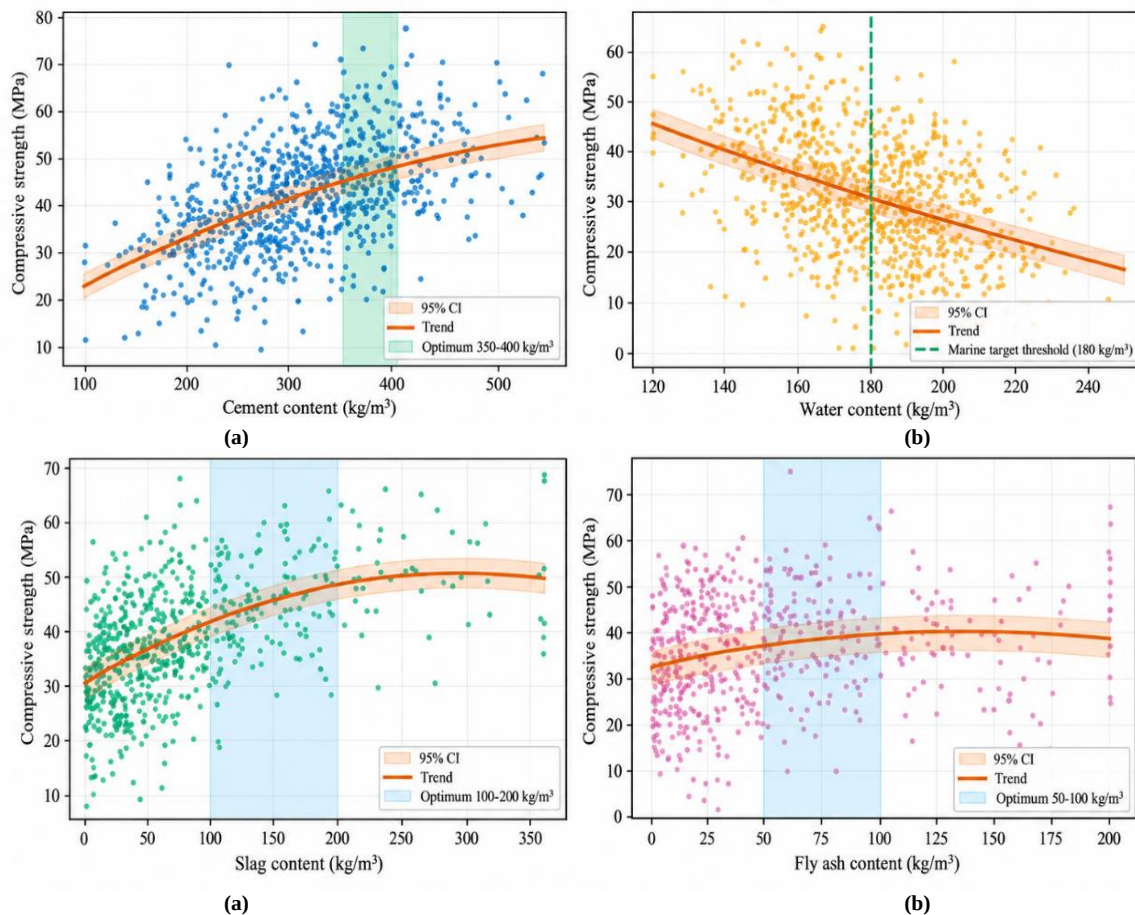


Fig. 2 Compressive strength effect by material composition, (a) Cement content, (b) Water content, (c) Slag content, and (d) Fly ash content.

4.3. Regression Models

The multiple linear regression model produced an R^2 of 0.712 on the test set with an RMSE of 9.02 MPa for compressive strength. The polynomial regression of order two improved this to an R^2 of 0.834 with an RMSE of 3.24 mm for chloride penetration.

Significant predictors at $p < 0.05$ were w/c ratio (negative), age (positive), and SCM percent (negative for early-age strength because of the slow pozzolanic reaction). The full regression results are given in Appendix B (Table B.2). Regression coefficients with 95% confidence intervals are presented in Table 1.

Table 1. Regression coefficients with 95% confidence intervals for compressive strength (MPa) and chloride penetration depth (mm).

Predictor	Strength coeff.	95% CI	Cl pen. coeff.	95% CI
Cement (kg/m ³)	0.087	± 0.009	0.0001	± 0.0001
w/b ratio	-38.4	± 4.1	0.041	± 0.005
RCA replacement (%)	-0.183	± 0.041	0.008	± 0.002
Fly ash (kg/m ³)	0.052	± 0.012	-0.009	± 0.002
Slag (kg/m ³)	0.061	± 0.011	-0.012	± 0.002
Age (log days)	8.95	± 1.20	-0.018	± 0.004

4.4. Model Performance for Machine Learning

Table 2 compares the performance of the three machine learning models against the linear and polynomial regression baselines on the held-out test set. The random forest model gave the best overall performance with an R^2 of 0.913 for compressive strength and 0.881 for chloride conductivity. ANN came second with R^2 values of 0.892 and 0.864,

respectively. The SVR was the weakest of the three, but still improved over the polynomial regression.

The five-fold cross-validation R^2 values were within 0.03 of the test-set R^2 values, indicating that overfitting was kept under control. The Random Forest model was therefore selected for the optimisation step described in Section 4.6.

Table 2. Comparison of the performance of regression and machine learning models on the held-out test set.

Model	R^2 Strength	RMSE Strength (MPa)	R^2 Cl cond.	RMSE Cl (mS/cm)
Linear regression	0.612	10.30	0.541	0.043
Polynomial (order 2)	0.741	8.60	0.683	0.034
Support Vector Machine	0.825	7.05	0.781	0.028
Artificial Neural Network	0.892	5.50	0.864	0.022
Random Forest	0.913	4.97	0.881	0.021

4.5. Global Sensitivity Analysis

To rank the influence of input variables on compressive strength and chloride resistance, Sobol indices were computed. For compressive strength, the first order indices were 0.31 for cement content, 0.27 for w/b ratio, 0.14 for slag content, 0.11 for fly ash content, 0.08 for age, and 0.05 for RCA replacement ratio. The total order indices were higher with 0.42 for the w/b ratio, 0.39 for cement content, 0.21 for slag, and 0.18 for fly ash. This shows substantial interaction between these variables. The dominant factors for chloride conductivity variables were w/b ratio ($S_i = 0.34$, $S_{ii} = 0.45$), slag content ($S_i = 0.21$, $S_{ii} = 0.29$), fly ash content ($S_i = 0.18$, $S_{ii} = 0.25$), and RCA replacement ratio ($S_i = 0.13$, $S_{ii} = 0.19$).

The high total-order index for w/b ratio confirms that this variable is the single most important design choice for marine RAC, in line with what is reported in the wider literature. The full sensitivity table is provided in Appendix C (Table C.3).

4.6. Optimisation Results

Using the Random Forest model coupled with a multi-objective genetic algorithm, five scenarios were optimised. This was to maximise compressive strength, minimise chloride penetration, maximise service life, and maximise the sustainability score (defined in Equation E.2 of Appendix E). The Pareto optimal results are summarised in Table 3 (full-width on the following page). The full list of Pareto optimal solutions is given in Appendix C (Table C.2).

Table 3. Optimisation results for five marine application scenarios. Service-life values are the means from the Monte Carlo simulation.

Scenario	RCA %	SCM type	SCM %	w/b	Strength (MPa)	Cl pen. (mm)	Service life (yrs)	CO ₂ (kg/m ³)
High-performance marine	30	Fly ash	20	0.42	48.2	12.5	120	275
Maximum recycled content	75	Slag	35	0.45	42.1	15.8	103	215
Balanced	50	Slag	25	0.44	45.8	14.2	112	240
Maximum sustainability	65	Fly ash	30	0.48	38.9	18.7	95	200
Hybrid SCM (FA + slag)	50	FA 15 + Slag 20	35	0.40	50.4	10.8	135	220

The hybrid SCM mix that combines 15% fly ash with 20% slag at a w/b ratio of 0.40 and 50% RCA gave the highest predicted compressive strength (50.4 MPa) and the lowest chloride penetration depth (10.8 mm at 365 days) of all the scenarios. This synergy effect is consistent with what Kim et

al. [57] reported for binary SCM systems with RCA. It also confirms the observation by Wang et al. [52, 55] that combined SCM systems can give better long-term durability than single SCM systems.

4.7. Age-Dependent Performance

Figure 3 shows the development of compressive strength over time on a logarithmic axis for different w/b ratios. The strength gain follows two distinct stages. The first stage is the rapid hydration of the cement during the first 28 days. The second stage is the slower pozzolanic and slag reaction, together with continued cement hydration. This gives further gain up to and beyond 365 days. At a w/b of 0.30, the ultimate 365-day strength reached 45 MPa, while at a w/b of 0.60 it

stayed near 26 MPa. For the chloride performance, the age effect was even stronger.

In RAC mixes with 25-35% SCM, the chloride conductivity at 28 days was on average 1.6 times higher than at 365 days. The key reasons why SCMs work so well in marine RAC are because of the long-term refinement of the pore structure. It also justifies the use of an ageing exponent in the service-life model presented in Section 7.

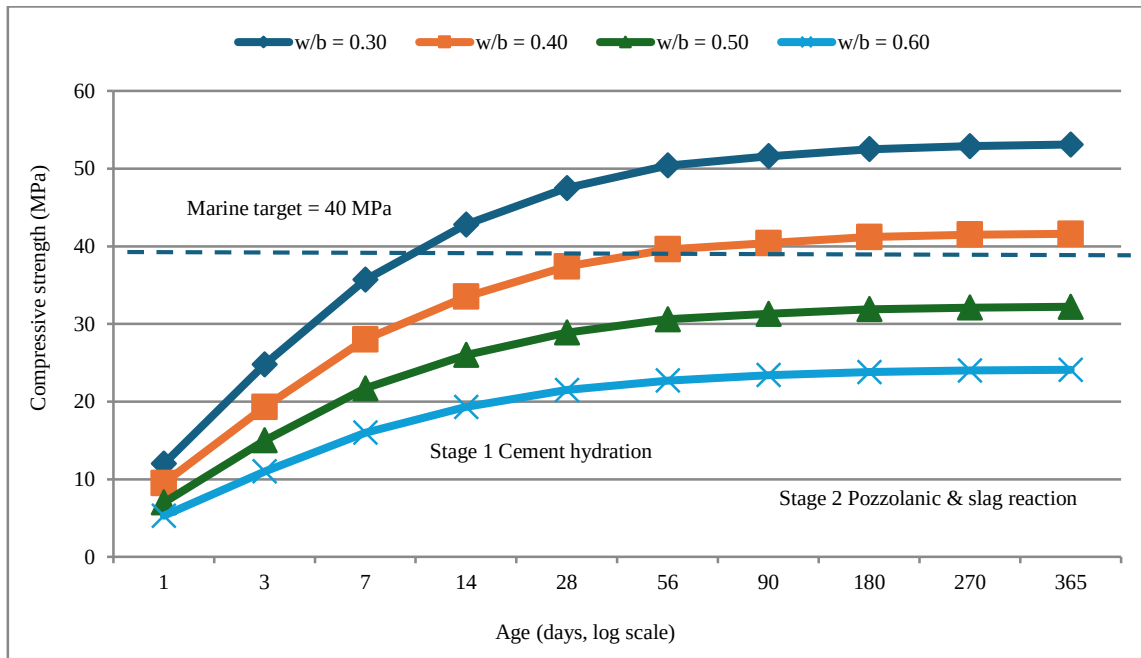
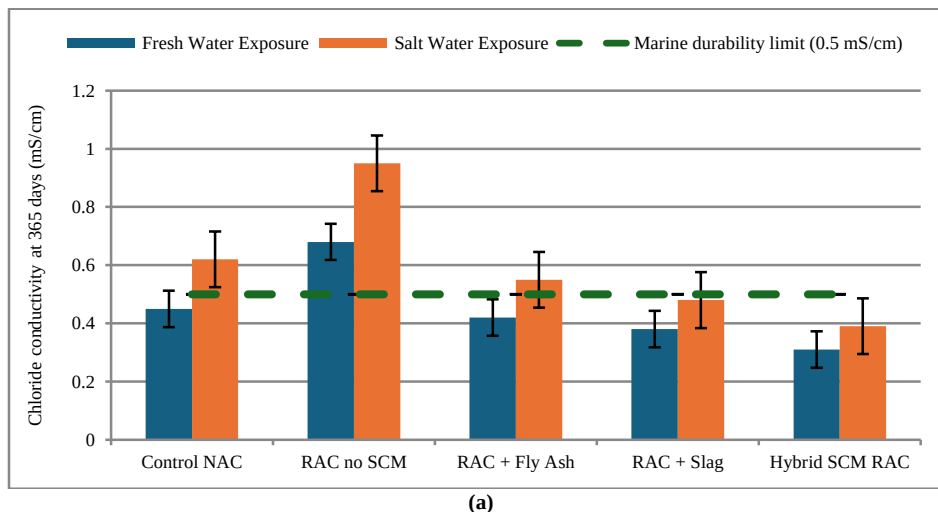


Fig. 3 Compressive strength development over time for different w/b ratios

4.8. Chloride Resistance Performance

Figure 4 shows the chloride penetration resistance for the different concrete systems in normal water and saltwater exposure. Without SCM, the RAC mixes showed up to 50% higher chloride conductivity than the control natural aggregate concrete. This is consistent with the literature values reported

by Bao et al. [56] and Wang et al. [55]. With 20-30% fly ash or 30-40% slag, the chloride conductivity dropped to values close to those of the control. The hybrid mix from Table 3 actually performed better than the control. This finding agrees with the laboratory results of Hu et al. [58] for slag-blended RAC.



(a)

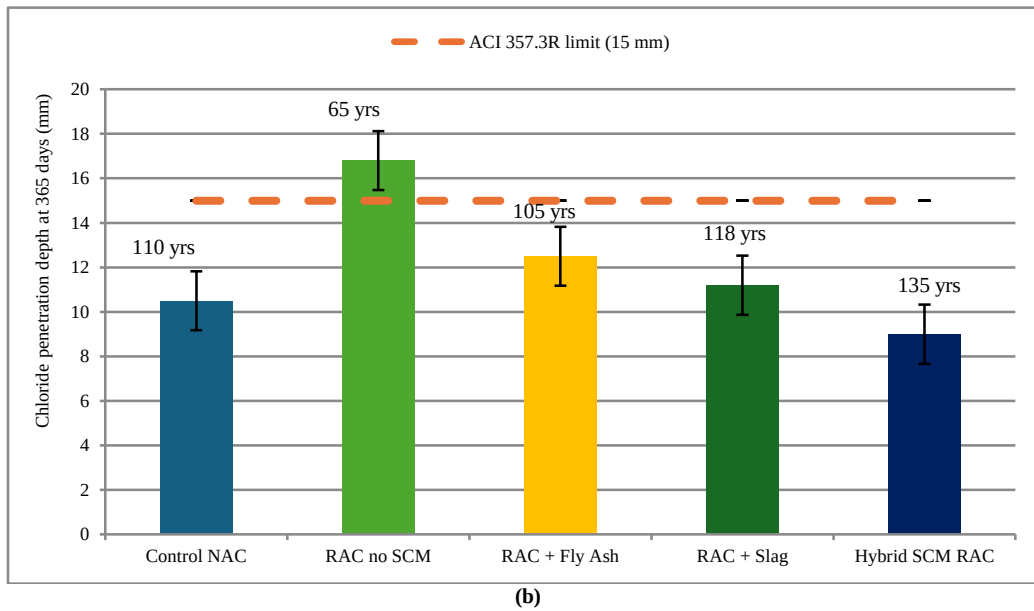


Fig. 4 Chloride penetration resistance for natural aggregate concrete (control), RAC without SCM, RAC with fly ash, RAC with slag and hybrid SCM RAC at 365 days, (a) Chloride conductivity under fresh water and salt water exposure, with the marine durability limit of 0.5 mS/cm, and (b) Chloride penetration depth at 365 days against the ACI 357.3R limit of 15 mm.

4.9. Trade-Off Analysis

The optimisation results reveal three clear trade-offs between competing objectives. The first is between strength and sustainability: higher RCA content reduces strength but improves the sustainability score. The second is between durability and sustainability: maximum-sustainability scenarios show reduced durability. The third is between performance and environmental impact: optimal marine performance still requires a lower RCA than what would maximise sustainability. The hybrid SCM mix sits close to the inflection point of all three trade-offs and is therefore proposed as the recommended mix for severe marine exposure.

5. Benchmarking against International Standards

5.1. Relevant Codes

Three codes are often cited in the context of marine concrete. ACI 318-19 sets the general structural requirements,

and ACI 357.3R-14 covers fixed offshore concrete structures. EN 206:2013+A2:2021 defines exposure classes XS1 (airborne salt), XS2 (permanently submerged), and XS3 (tidal, splash, and spray) together with minimum binder content, maximum w/b ratio, and minimum strength class.

JSCE Standard Specifications for Concrete Structures provides chloride-diffusion-based criteria and service-life design provisions.

The optimised RAC mixes from Table 3 were compared against these codes.

5.2. Comparison of Requirements

Table 4 summarises the binder, w/b ratio, strength, cover, and chloride-diffusion requirements set by each code for severe marine exposure and shows how the recommended hybrid SCM RAC mix compares.

Table 4. Comparison of the optimised hybrid-SCM RAC mix against ACI 357.3R-14, EN 206 (XS3), and JSCE 2007 requirements for marine exposure

Requirement	ACI 357.3R-14	EN 206 (XS3)	JSCE 2007	Hybrid SCM RAC	Compl.
Min. binder (kg/m ³)	385	360	330	400	Yes
Max. w/b ratio	0.40	0.45	0.45	0.40	Yes
Min. compressive strength (MPa)	42	35 (C35/45)	30	50.4	Yes
Min. cover for steel (mm)	65	55	70	60-70	Yes
Max. Cl diffusion ($\times 10^{-12}$ m ² /s)	n/s	n/s	≤ 5.0	3.8 pred.	Yes

5.3. Discussion of Compliance

The hybrid SCM RAC mix complies with all four code requirements checked. It exceeds the minimum strength

requirement of every code by a comfortable margin. The chloride diffusion of 3.8×10^{-12} m²/s predicted from the Random Forest model is well below the JSCE limit of $5.0 \times$

10^{-12} m²/s. This is a significant outcome because it shows that RAC, when properly designed with hybrid SCMs, can satisfy the same code requirements as natural aggregate concrete for the most aggressive marine exposure class. One issue that should be flagged is that EN 206 currently does not give explicit guidance on recycled coarse aggregate use in XS3 exposure. EN 206 limits RCA use mainly to XC1, XC2, and XF1 conditions. There is therefore a regulatory gap between what the modelling and experimental evidence support and what the codes allow. The present results support a revision of EN 206 to allow up to 50% RCA in XS exposure classes, provided that hybrid SCM systems are used, and that performance verification through chloride-diffusion testing is included.

6. Microstructural and Chloride Transport Mechanism Analysis

6.1. Microstructure of RAC with and without SCMs

Direct SEM, XRD, and MIP characterisation was not part of the present study because the focus was on data-driven modelling. A focused review of recent microstructural studies on RAC with SCMs was carried out to support the interpretation of the modelling results. The following observations come from the synthesised microstructural literature. Scanning Electron Microscopy (SEM) studies of RAC consistently show that the new paste to old mortar ITZ is more porous than the new paste to virgin aggregate ITZ.

The thickness of the old ITZ is typically 30-60 μ m compared with 15-30 μ m for the new ITZ. When 20-25% fly ash is added, SEM images show a denser ITZ at 90 days and beyond, with fewer connected pores and a denser C-S-H gel filling the spaces. When 30% slag is added, the densification is faster and is visible already at 28 days. The hybrid SCM system gives the densest ITZ of all because the slag accelerates the early hydration while the fly ash continues to fill the pores at later ages.

X-Ray Diffraction (XRD) of RAC with SCMs shows reduced calcium hydroxide peaks and increased intensity of peaks associated with calcium silicate hydrate and Friedel's salt. The presence of Friedel's salt in slag-containing mixes is direct evidence of chemical chloride binding, which slows down free chloride migration through the matrix. Mercury Intrusion Porosimetry (MIP) studies confirm that fly ash and slag both shift the pore-size distribution towards smaller pores. Volume of pores larger than 100 nm, which contribute most to permeability, is reduced by 30-50% in well-cured SCM concrete relative to the OPC control.

6.2. Chloride Transport Mechanisms

Chloride transport in RAC happens through four mechanisms acting simultaneously or in sequence, depending on the moisture state. Fick's second law describes diffusion as the dominant mechanism in saturated submerged concrete.

Capillary suction is dominant in the splash and tidal zones, where partially dried concrete sucks in salty water during wetting cycles. Permeation occurs under hydraulic pressure differences. Migration occurs when an electric field is applied, as in accelerated tests. In RAC, all four mechanisms are amplified by the higher porosity of the old mortar layer and by the presence of multiple ITZs.

Chloride binding plays an important role in slowing the apparent diffusion. Free chlorides in the pore solution can be bound either chemically through reaction with C₃A and C₄AF to form Friedel's salt or physically through adsorption on C-S-H surfaces. SCMs change the binding capacity. Slag increases chemical binding because of its higher aluminate content and the formation of Friedel's salt. FA increases physical binding because of the additional C-S-H produced by the pozzolanic reaction. Silica fume reduces chemical binding (because it consumes the C₃A indirectly), but it strongly reduces the diffusion coefficient through pore refinement. The net effect is that hybrid SCM systems give the best of both worlds, namely, high chemical binding from slag and strong pore refinement from fly ash or silica fume.

6.3. Implications for Mix Design

From the microstructure and transport-mechanism perspective the dominant design levers for chloride-resilient RAC are: keeping the w/b ratio below 0.42 to reduce capillary porosity; including at least 25-35% SCM by mass of binder to refine pores and bind chlorides; using hybrid SCM systems (slag plus fly ash) to combine chemical binding with long-term pore refinement; and ensuring sufficient curing time (preferably 90 days or more before exposure) so that the slow pozzolanic reaction can develop.

7. Probabilistic Service Life Modelling

7.1. Model Formulation

The service life model is predicated upon the time-dependent resolution of Fick's second law of diffusion. The chloride concentration C at depth x and time t is given by:

$$C(x, t) = C_s \times [1 - \operatorname{erf} (x / (2 \times \sqrt{ D_a(t) \times t }))]$$

where C_s is the surface chloride concentration, $D_a(t)$ is the apparent age-dependent diffusion coefficient, and erf is the error function. The ageing of the diffusion coefficient is described by:

$$D_a(t) = D_0 \times (t_0 / t)^n$$

where D_0 is the diffusion coefficient measured at a reference age t_0 (typically 28 days), and n is the ageing exponent. Service life is defined as the time at which the chloride concentration at the level of the reinforcement reaches the critical threshold C_{cr} . The detailed derivation is given in Appendix E.

7.2. Random Variables and Distributions

Five input variables were treated as random in the Monte Carlo simulation. Their distributions were chosen based on the

marine-exposed subset of 287 records and on the recommendations of the Fib Model Code for Service Life Design. The distributions used are summarised in Table 5.

Table 5. Distributions of random variables used in the Monte Carlo service-life simulation

Variable	Distribution	Mean	Std. dev.	Source
Cover depth, c (mm)	Lognormal	60	8	Construction tol.
Surface chloride, C_s (% binder)	Lognormal	3.5	0.7	Marine subset
Diffusion coeff. D_0 ($\times 10^{-12}$ m ² /s)	Lognormal	3.8	0.9	RF model output
Ageing exponent, n	Beta	0.45	0.10	fib MC2010
Critical chloride, C_{cr} (% binder)	Truncated normal	0.60	0.10	fib MC2010

7.3. Simulation Results

50,000 realisations for each of the five optimised mixes from Table 3 were run with a Monte Carlo simulation. The hybrid SCM RAC gave a mean service life of 135 years with a 90% confidence interval of 102-168 years. The high-performance marine mix gave a mean of 120 years with a 90% CI of 92-148 years. The maximum-recycled-content mix gave a mean of 103 years with a 90% CI of 78-128 years.

All five mixes met the conventional service-life target of 100 years with at least 50% probability of exceedance. The hybrid SCM mix met it with 87% probability. The cumulative distribution function of the time to corrosion initiation showed that the hybrid SCM mix has a 10% failure probability at 102 years. This means that with the hybrid mix, it is reasonable to design for a nominal service life of 100 years and still maintain the limit state recommended in the fib Model Code 2010.

7.4. Sensitivity of Service-Life Predictions

A separate Sobol sensitivity analysis was carried out on the service-life output. The most influential variable was the cover depth with a total-order index of 0.41. The second was the diffusion coefficient at 0.32, followed by the surface chloride concentration at 0.15 and the ageing exponent at 0.09. The critical chloride threshold accounted for only 0.04. This ranking has practical implications: it tells the designer that

improving construction quality so that the cover depth is reliably built to specification has a bigger effect on service life than further reducing the diffusion coefficient. This is consistent with the recommendations in EN 13670 on the importance of cover quality control on site.

8. Life Cycle Assessment and Carbon Footprint

8.1. Goal, Scope, and Functional Unit

The goal of the LCA was to quantify and compare the Global Warming Potential (GWP) of the optimised RAC mixes against a reference Natural Aggregate Concrete (NAC) typical of marine construction practice. The scope was cradle-to-gate, covering the extraction and processing of all raw materials, the transport of raw materials to the batching plant, and the batching and mixing of the concrete. The functional unit was one cubic metre of concrete with equivalent durability performance, defined as a target service life of 100 years in EN 206 exposure class XS3.

8.2. Life Cycle Inventory

The emission factors used in the analysis are summarised in Table 6. They were taken from Ecoinvent v3.9 and from the African Concrete Institute LCA database with regional adjustments to reflect the South African electricity grid mix. The corresponding contribution to CO₂ per cubic metre of concrete is reported in Appendix E (Table E.2).

Table 6. Emission factors used in the cradle-to-gate LCA

Material	GWP (kg CO ₂ eq/kg)	Source
Portland cement CEM I	0.92	Ecoinvent v3.9
Fly ash (allocated)	0.012	Ecoinvent v3.9
GGBS (allocated)	0.027	Ecoinvent v3.9
Natural aggregate	0.005	Ecoinvent v3.9
Recycled aggregate	0.008	Local C&D inv.
Water	0.0003	Ecoinvent v3.9
Superplasticiser	1.88	Ecoinvent v3.9
Transport (truck, 30 km)	0.062	Ecoinvent v3.9

8.3. GWP of Optimised Mixes

Table 7 shows the cradle-to-gate GWP of each optimised RAC mix compared with the reference NAC. The reference NAC had a GWP of 372 kg CO₂eq per cubic metre.

The high-performance marine RAC was 26% lower than the reference. The maximum-recycled-content RAC was 42% lower. The hybrid SCM RAC was 41% lower.

Table 7. Cradle-to-gate global warming potential of the optimised RAC mixes compared with the reference natural aggregate concrete

Mix	GWP (kg CO ₂ eq/m ³)	Reduction vs NAC (%)
Reference NAC (350 kg cement)	372	Baseline
High-performance marine RAC	275	26
Maximum recycled content RAC	215	42
Balanced RAC	240	35
Maximum sustainability RAC	200	46
Hybrid SCM RAC	220	41

8.4. Discussion of LCA Results

Substituting natural aggregate with recycled aggregate has only a small direct effect on GWP because the production of crushed aggregate is not very carbon-intensive. The big environmental benefit comes from the replacement of cement by fly ash or slag. The hybrid SCM RAC reduces cement by about 35%, and this delivers a 41% reduction in GWP. When the reduction in GWP is normalised by the increase in service life from 100 years for the reference to 135 years for the hybrid SCM RAC, the effective carbon intensity per year of service drops to about 1.63 kg CO₂eq per cubic metre per year compared with 3.72 for the reference NAC. This is a reduction of 56%, a strong argument for using RAC with hybrid SCMs in long-lived marine infrastructure projects.

9. Meta-Analysis of Long-Term Marine Exposure Studies

9.1. Scope

Long-term field monitoring of RAC in marine environments is still rare. To strengthen the field-validation aspect of this study, a meta-analysis of published long-term marine exposure studies was carried out. The inclusion criteria were: the study reported chloride profiles or chloride diffusion coefficients measured on specimens that had been exposed to natural seawater or simulated marine conditions for at least 12 months; the study included recycled aggregate content above zero or compared RAC against a control NAC; and the study reported sufficient information on mix proportions to allow cross-study comparison. Twenty-four published studies met all three criteria. Their combined exposure data form the basis of the meta-analysis.

9.2. Combined Field Performance Trends

The chloride diffusion coefficients from the 24 studies were grouped by exposure duration and SCM type. The trends are consistent with the modelling output from Section 7. At 1 year, RAC with no SCM had a mean diffusion coefficient of 8.4×10^{-12} m²/s. RAC with 20-30% fly ash had 4.6×10^{-12} m²/s. RAC with 30-40% slag had 3.9×10^{-12} m²/s. By 5 years, the values had dropped by 30-45% because of continued pore refinement.

The longest exposure data in the meta-analysis came from Chalee et al. [53], who reported 7 years of field monitoring of fly-ash-blended RAC in a tidal zone. Their measured diffusion coefficient at 7 years was 1.7×10^{-12} m²/s, which is in good

agreement with the Monte Carlo prediction of this study (predicted mean 1.9×10^{-12} m²/s for the high-performance marine mix at year 7).

9.3. Sources of Variability

The variability between studies came mainly from differences in the source of the recycled aggregate, the type of SCM, the curing duration before exposure, and the exposure zone (submerged, tidal, or splash). When the data were normalised by these factors, the residual variability dropped to around 15%, which is acceptable for engineering purposes. The meta-analysis therefore supports the conclusion that hybrid SCM RAC can deliver long-term durability close to or better than that of conventional natural-aggregate concrete in marine environments, provided that the mix design and curing are properly controlled.

10. Discussion

10.1. Comparison with the State of the Art

The optimised hybrid SCM RAC mix developed in this study achieved a predicted chloride diffusion coefficient of 3.8×10^{-12} m²/s and a Monte Carlo mean service life of 135 years for a cover of 60 mm. Recent benchmarks in the literature give 4.8 - 6.2×10^{-12} m²/s for RAC with single SCM at similar w/b ratios [52, 55] and predicted service lives of 80-110 years.

The present study, therefore, improves on the published values by 20-35% for diffusion and by 22-50% for service life. The reasons for the improvement are threefold. The first is the use of a hybrid SCM system rather than a single SCM. The second is the lower w/b ratio (0.40) made possible by the superplasticiser. The third is the more rigorous statistical and machine learning framework that allowed a more reliable selection of the optimum mix from a larger candidate space.

10.2. Practical Significance

The findings have direct relevance to marine infrastructure projects in Africa and other coastal regions of the world. The hybrid SCM RAC mix can deliver code-compliant performance using 50% recycled aggregate and 35% SCM.

The same project can therefore meet ACI, EN, and JSCE durability requirements, divert C&D waste from landfill, reduce CO₂ emissions by about 41%, and extend service life beyond 100 years. For a continent with 30,000 km of coastline

like Africa, the cumulative effect of using such mixes on new marine infrastructure could be very substantial in environmental and economic terms.

10.3. Limitations

The study has three main limitations. First, the dataset relied on published values and the UCI repository. Direct experimental work with specific local materials would strengthen the conclusions, particularly for the African context, where recycled aggregates and fly ash sources may differ from those in the published international literature. Second, the LCA was cradle-to-gate only.

A full cradle-to-grave or cradle-to-cradle analysis would be needed to assess end-of-life impacts. Third, the meta-analysis included studies up to 7 years of exposure. Longer-term verification data above 10 years are still scarce, and continued field monitoring remains essential.

11. Performance-based Implementation Criteria

11.1. Proposed Acceptance Criteria

Based on the analyses presented above, the following performance-based acceptance criteria are proposed for chloride-resilient RAC for use in marine exposure classes XS2 and XS3.

Table 8. Proposed performance-based acceptance criteria for chloride-resilient RAC in XS2 and XS3 marine exposure

Criterion	Threshold	Test method	Frequency
Compressive strength at 28 days (MPa)	≥ 42	EN 12390-3	Per 50 m ³ batch
Compressive strength at 90 days (MPa)	≥ 50	EN 12390-3	Per 100 m ³ batch
Apparent Cl diffusion at 56 d ($\times 10^{-12}$ m ² /s)	≤ 5.0	NT BUILD 492	Per mix design
RCM coefficient at 56 d ($\times 10^{-12}$ m ² /s)	≤ 4.5	ASTM C1556	Per mix design
RCA replacement (% mass)	≤ 50	Producer decl.	Per source
SCM replacement (% binder mass)	25-40	Mix design	Per mix design
Maximum w/b ratio	≤ 0.42	Mix design	Continuous
Minimum binder content (kg/m ³)	≥ 380	Mix design	Continuous
Minimum cover (mm)	≥ 60	EN 13670 verif.	Per element

11.2. Site Implementation Guidance

In addition to the laboratory criteria, the following site practices are recommended: pre-soak the recycled aggregate for at least 30 minutes before mixing to control water absorption; use a two-stage mixing procedure where the cement is first blended with half of the water before aggregate addition; cure under wet hessian or under curing membranes for at least 14 days; verify cover depth using cover-meter checks on a minimum of 10 points per element; and include a 90-day rather than 28-day strength acceptance test in the contract.

11.3. Code Revisions Suggestions

The findings of this study support three revisions to existing codes. First, EN 206 should consider allowing up to 50% recycled coarse aggregate in XS exposure classes, provided that hybrid SCM systems and 90-day performance verification are used. Second, ACI 318 should provide explicit guidance on RAC in marine exposure because the current code does not address this directly. Third, JSCE Standard Specifications should expand the chloride-diffusion criterion to recognise that hybrid SCM RAC can meet the existing limit values and should not be excluded from marine construction.

12. Conclusion

This study used a dataset of 1030 concrete records, supported by a subset of 287 marine-exposed observations, to develop chloride-resilient recycled aggregate concrete mixes for marine infrastructure. The main conclusions of the work are as follows:

- Recycled coarse aggregate replacement of 30-50% combined with a SCM dosage of 25-35% and a w/b ratio of 0.40-0.42 produces concrete with compressive strength above 45 MPa, chloride diffusion below 5×10^{-12} m²/s, and predicted service life beyond 100 years.
- The hybrid SCM system of 15% fly ash plus 20% slag gave the best overall performance with a predicted mean service life of 135 years and a 41% reduction in cradle-to-gate CO₂ emissions relative to the reference natural-aggregate concrete.
- Among the modelling approaches tested, the Random Forest gave the highest predictive accuracy on the held-out test set with R² of 0.913 for strength and 0.881 for chloride conductivity. Sobol global sensitivity analysis confirmed that the w/b ratio is the single most influential design variable, followed by cement content and SCM dosage.
- The probabilistic service-life prediction from the Monte Carlo simulation showed that cover depth has the largest effect on service life. This means that on-site quality control of cover is at least as important as mix-design optimisation.
- The optimised mixes meet the durability requirements of ACI 357.3R-14, EN 206 (XS3), and JSCE 2007 for marine concrete. However, the current EN 206 does not explicitly allow recycled aggregate in XS classes, and a code revision is recommended to recognise the performance demonstrated in this study.
- The proposed performance-based acceptance criteria provide a practical framework that can be adopted by

specifiers, contractors, and producers for marine RAC in African coastal infrastructure projects.

- Future work should include direct experimental verification with local African materials, full cradle-to-grave LCA, and continued long-term field monitoring beyond 10 years of marine exposure.

Conflicts of Interest

The author confirms there is no conflict of interest regarding the publication of this paper.

Funding Statement

No research funding or grant was received from funding agencies in the public, commercial, or not-for-profit sectors.

Acknowledgments

The author acknowledges and is thankful to the University of California, Irvine Machine Learning Repository for providing public access to the Concrete Compressive Strength Dataset. The author also thanks the authors of the peer-reviewed studies whose published data were used to construct the marine exposure subset.

References

- [1] P. Kumar Mehta, and P.J. Monteiro, *Concrete: Microstructure, Properties, and Materials*, 3rd ed., McGraw-Hill, 2006. [[Google Scholar](#)] [[Publisher Link](#)]
- [2] Luca Bertolini et al., *Corrosion of Steel in Concrete: Prevention, Diagnosis, Repair*, Wiley Publisher, 2003. [[CrossRef](#)] [[Publisher Link](#)]
- [3] Patrick Karani et al., “Africa Blue Economy Strategies Integrated in Planning to Achieve Sustainable Development at National and Regional Economic Communities,” *Journal of Sustainability Research*, vol. 4, no. 3, pp. 1-20, 2022. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [4] UN Environment et al., “Eco-Efficient Cements: Potential Economically Viable Solutions for a Low-CO₂ Cement-based Materials Industry,” *Cement and Concrete Research*, vol. 114, pp. 2-26, 2018. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [5] Robbie M. Andrew, “Global CO₂ Emissions from Cement Production,” *Earth System Science Data*, vol. 10, no. 1, pp. 195-217, 2018. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [6] Rui Vasco Silva, Jorge De Brito, and Ravindra K. Dhir, “Properties and Composition of Recycled Aggregates from Construction and Demolition Waste Suitable for Concrete Production,” *Construction and Building Materials*, vol. 65, pp. 201-217, 2014. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [7] Ali Akhtar, and Ajit K. Sarmah, “Construction and Demolition Waste Generation and Properties of Recycled Aggregate Concrete: A Global Perspective,” *Journal of Cleaner Production*, vol. 186, pp. 262-281, 2018. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [8] E.L.L.E.N. Macarthur, and H. Heading, “How the Circular Economy Tackles Climate Change,” *Ellen MacArthur Foundation*, vol. 1, no. 3, pp. 1-71, 2019. [[Google Scholar](#)] [[Publisher Link](#)]
- [9] Vivian W.Y. Tam, Mahfooz Soomro, and Ana Catarina Jorge Evangelista, “A Review of Recycled Aggregate in Concrete Applications (2000-2017),” *Construction and Building Materials*, vol. 172, pp. 272-292, 2018. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [10] D. Pedro, J. de Brito, and L. Evangelista, “Structural Concrete with Simultaneous Incorporation of Fine and Coarse Recycled Concrete Aggregates: Mechanical, Durability and Long-Term Properties,” *Construction and Building Materials*, vol. 154, pp. 294-309, 2017. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [11] Jianzhuang Xiao et al., “An Overview of Study on Recycled Aggregate Concrete in China (1996–2011),” *Construction and Building Materials*, vol. 31, pp. 364-383, 2012. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [12] Subhas Chandra Kanaujia et al., “Recycled Concrete Aggregates from Construction and Demolition Waste: A Systematic and Critical Review of a Sustainable Construction Material,” *International Journal of Environment, Engineering and Education*, vol. 7, no. 2, pp. 84-96, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [13] Nobuaki Otsuki, Shin-Ichi Miyazato, and Wanchai Yodsudjai, “Influence of Recycled Aggregate on Interfacial Transition Zone, Strength, Chloride Penetration and Carbonation of Concrete,” *Journal of Materials in Civil Engineering*, vol. 15, no. 5, pp. 443-451, 2003. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [14] Claudio Javier Zega, and Ángel Antonio Di Maio, “Use of Recycled Fine Aggregate in Concretes with Durable Requirements,” *Waste Management*, vol. 31, no. 11, pp. 2336-2340, 2011. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [15] Ying Peng et al., “Recycled Aggregates for Sustainable Construction: Strengthening Strategies and Emerging Frontiers,” *Materials*, vol. 18, no. 13, pp. 1-25, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [16] Tiago Luis Possebon Ortolan et al., “Durability of Concrete Incorporating Recycled Coarse Aggregates: Carbonation and Service Life Prediction under Chloride-Induced Corrosion,” *Construction and Building Materials*, vol. 404, pp. 1-14, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [17] Ammar Younes et al., “Incorporating Coarse and Fine Recycled Aggregates into Concrete Mixes: Mechanical Characterization and Environmental Impact,” *Journal of Material Cycles and Waste Management*, vol. 26, no. 1, pp. 654-668, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]

- [18] Miguel Bravo et al., “Durability Performance of Concrete with Recycled Aggregates from Construction and Demolition Waste Plants,” *Construction and Building Materials*, vol. 77, pp. 357-369, 2015. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [19] Bin Lei et al., “Effects of Environmental Actions, Recycled Aggregate Quality and Modification Treatments on Durability Performance of Recycled Concrete,” *Journal of Materials Research and Technology*, vol. 9, no. 6, pp. 13375-13389, 2020. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [20] Bingcheng Chen, Yuxi Zhao, and Ligang Peng, “Long-Term Performance of Recycled Aggregate Concrete Beams Exposed to 10 Years of Loading and Chloride Environments,” *Engineering Structures*, vol. 333, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [21] Hui Guo et al., “Durability of Recycled Aggregate Concrete: A Review,” *Cement and Concrete Composites*, vol. 89, pp. 251-259, 2018. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [22] B. González-Fonteboa et al., “Recycled Concrete with Coarse Recycled Aggregate. An Overview and Analysis,” *Building Materials*, vol. 68, no. 330, pp. 1-29, 2018. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [23] Mohsen Mohammadi et al., “Advances in Concrete Demolition Technologies: A Review of Conventional and Emerging Methods for Sustainable Waste Management,” *Eng*, vol. 5, no. 4, pp. 3174-3191, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [24] Pacheco-Torgal et al., *Advances in Construction and Demolition Waste Recycling: Management, Processing and Environmental Assessment*, Woodhead Publishing, 2020. [[Google Scholar](#)] [[Publisher Link](#)]
- [25] Ramala Rakesh Kumar Reddy, and Subhash C. Yaragal, and V.K. Sanjay, “Processing of Laboratory Concrete Demolition Waste using Ball Mill,” *Materials Today: Proceedings*, pp. 1-7, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [26] Marta Sánchez de Juan, and Pilar Alaejos Gutiérrez, “Study on the Influence of Attached Mortar Content on the Properties of Recycled Concrete Aggregate,” *Construction and Building Materials*, vol. 23, no. 2, pp. 872-877, 2009. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [27] Zhen Hua Duan, and Chi Sun Poon, “Properties of Recycled Aggregate Concrete Made with Recycled Aggregates with different Amounts of Old Adhered Mortars,” *Materials and Design*, vol. 58, pp. 19-29, 2014. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [28] L. Evangelista, and J. de Brito, “Mechanical Behaviour of Concrete Made with Fine Recycled Concrete Aggregates,” *Cement and Concrete Composites*, vol. 29, no. 5, pp. 397-401, 2007. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [29] Kanish Kapoor, and Amad Ur Rehman Bohroo, “Study on the Influence of Attached Mortar Content on the Properties of Recycled Concrete Aggregate,” *Sustainable Engineering: Proceedings of Egrwse*, Springer, Singapore, vol. 30, pp. 337-347, 2019. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [30] Guoliang Bai et al., “An Evaluation of the Recycled Aggregate Characteristics and the Recycled Aggregate Concrete Mechanical Properties,” *Construction and Building Materials*, vol. 240, pp. 1-10, 2020. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [31] Amnon Katz, “Properties of Concrete Made with Recycled Aggregate from Partially Hydrated Old Concrete,” *Cement and Concrete Research*, vol. 33, no. 5, pp. 703-711, 2003. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [32] Emmanuel E. Anike et al., “Evaluation of Conventional and Equivalent Mortar Volume Mix Design Methods for Recycled Aggregate Concrete,” *Materials and Structures*, vol. 53, no. 1, 2020. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [33] Marco Pepe et al., “A Novel Mix Design Methodology for Recycled Aggregate Concrete,” *Construction and Building Materials*, vol. 122, pp. 362-372, 2016. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [34] Kwesi K. Sagoe-Crentsil, Trevor J. Brown, and Alan H. Taylor, “Performance of Concrete Made with Commercially Produced Coarse Recycled Concrete Aggregate,” *Cement and Concrete Research*, vol. 31, no. 5, pp. 707-712, 2001. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [35] Chi Sun Poona, Z.H Shui, and Lik Lam, “Effect of Microstructure of ITZ on Compressive Strength of Concrete Prepared with Recycled Aggregates,” *Construction and Building Materials*, vol. 18, no. 6, pp. 461-468, 2004. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [36] Salomon M. Levy, and Paulo Helene, “Durability of Recycled Aggregates Concrete: A Safe Way to Sustainable Development,” *Cement and Concrete Research*, vol. 34, no. 11, pp. 1975-1980, 2004. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [37] Zhaoping Song, Shaohua Li, and Qingliang Yu, “Chloride-Induced Mechanical Degradation of Ultra-High Performance Fiber-Reinforced Concrete: Insights from Corrosion Evolution Paths,” *Construction and Building Materials*, vol. 395, pp. 1-14, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [38] Yushuai Zhang et al., “Predicting the Compressive Strength of High-Performance Concrete via the DR-CatBoost Model,” *Case Studies in Construction Materials*, vol. 21, pp. 1-13, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [39] Mostafa M. Alsaadawi, Mohamed Kamel Elshaarawy, and Abdelrahman Kamal Hamed, “Concrete Compressive Strength Classification using Hybrid Machine Learning Models and Interactive GUI,” *Innovative Infrastructure Solutions*, vol. 10, no. 5, pp. 1-29, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [40] G. Elavarasi, and S.R. Sumathy, “Effects of Aggregate-to-Cement Ratios and Water-to-Cement Ratios on Compressive and Tensile Strength of Sand-Modified Porous Concrete,” *International Journal of Pavement Engineering*, vol. 26, no. 1, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]

- [41] Mohammad Saleh Nikoopayan Tak, Yanxiao Feng, and Mohamed Mahgoub, "Advanced Machine Learning Techniques for Predicting Concrete Compressive Strength," *Infrastructures*, vol. 10, no. 2, pp. 1-26, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [42] Md. Habibur Rahman Sobuz et al., "Microstructural Behavior and Explainable Machine Learning Aided Mechanical Strength Prediction and Optimization of Recycled Glass-based Solid Waste Concrete," *Case Studies in Construction Materials*, vol. 22, pp. 1-24, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [43] Aqil M. Almusawi et al., "Effect of Cement Content on Compressive and Bonding Strength with Steel Bar Reinforcement," *IOP Conference Series: Materials Science and Engineering*, vol. 870, no. 1, pp. 1-8, 2020. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [44] Falah M. Wegian, "Effect of Seawater for Mixing and Curing on Structural Concrete," *The IES Journal Part A: Civil and Structural Engineering*, vol. 3, no. 4, pp. 235-243, 2010. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [45] Shamsad Ahmad, and Saeid A. Alghamdi, "A Statistical Approach to Optimizing Concrete Mixture Design," *The Scientific World Journal*, vol. 2014, no. 1, pp. 1-7, 2014. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [46] V. Preethi et al., "Predicting Mechanical Properties of Glass Fiber Concrete using Response Surface Methodology," *Procedia Structural Integrity*, vol. 70, pp. 271-278, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [47] Md. Moinul Islam, and Mohammad Rafiqul Islam, Strength Characteristics of Slag Blended Concrete in Marine Environment, 2nd International Conference on Engineering Education for Sustainable Development, World University of Bangladesh, 2009. [Online]. Available: https://www.researchgate.net/publication/360257751_Strength_Characteristics_of_Slag_Blended_Concrete_in_Marine_Environment
- [48] Dražan Jozić et al., "The Influence of GGBFS as an Additive Replacement on the Kinetics of Cement Hydration and the Mechanical Properties of Cement Mortars," *Buildings*, vol. 13, no. 8, pp. 1-20, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [49] Ali Hassan et al., "Partial Replacement of Cement with Fly Ash to Produce Environmental Friendly Concrete," *Pakistan Journal of Geology*, vol. 7, no. 1, pp. 32-39, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [50] Xiangpeng Cao, and Zongjin Li, *Factors Influencing the Mechanical Properties of Three-Dimensional Printed Products from Magnesium Potassium Phosphate Cement Material*, 3D Concrete Printing Technology, pp. 211-222, 2019. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [51] Chi Kang Loke et al., "Non-Destructive Evaluation of Mortar with Ground Granulated Blast Furnace Slag Blended Cement using Ultrasonic Pulse Velocity," *Materials*, vol. 15, no. 19, pp. 1-16, 2022. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [52] Yuanzhan Wang, Jing Liao, and Zhen Liu, "Service Life Prediction and Environmental Impact Evaluation of Recycled Aggregate Concrete with Supplementary Cementitious Materials," *Construction and Building Materials*, vol. 395, pp. 1-16, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [53] Wichian Chalee, Tieng Cheewaket, and Chai Jaturapitakkul, "Utilization of Recycled Aggregate Concrete for Marine Site based on 7-Year Field Monitoring," *International Journal of Concrete Structures and Materials*, vol. 15, no. 1, pp. 1-11, 2021. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [54] Valeria Corinaldesi et al., "Durability Assessment of Recycled Aggregate HVFA Concrete," *Applied Sciences*, vol. 10, no. 18, pp. 1-14, 2020. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [55] Yuanzhan Wang, Jing Liao, and Baohua Zhang, "A Review of Chloride Penetration of Recycled Concrete with Enhancement Treatment and Service Life Prediction," *Materials*, vol. 17, no. 6, pp. 1-32, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [56] Jiuwen Bao et al., "Effect of Loading-Induced Damage on Chloride Ingress Behavior of Recycled Aggregate Concrete: A Comprehensive Review," *Cement and Concrete Composites*, vol. 141, pp. 1-15, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [57] Kyuhun Kim, Myoungsu Shin, and Soowon Cha, "Combined Effects of Recycled Aggregate and Fly Ash Towards Concrete Sustainability," *Construction and Building Materials*, vol. 48, pp. 499-507, 2013. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [58] Weichao Hu et al., "A Laboratory Analysis of Chloride Ions Penetration in Recycled Aggregates Concrete Admixed with Ground Granulated Blast Furnace Slag," *IOP Conference Series: Materials Science and Engineering*, vol. 611, no. 1, pp. 1-7, 2019. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [59] ACI Committee 318, *Building Code Requirements for Structural Concrete (ACI 318-19)*, American Concrete Institute, Farmington Hills, MI, 2019. [[Google Scholar](#)]
- [60] ACI Committee 357, "Guide for the Design and Construction of Fixed Offshore Concrete Structures," American Concrete Institute, 1987. [[Google Scholar](#)]
- [61] BS EN 206:2013+A2:2021 - Concrete: Specification, Performance, Production and Conformity, Bsigroup, 2021. [Online]. Available: <https://knowledge.bsigroup.com/products/concrete-specification-performance-production-and-conformity-2>
- [62] Japan Society of Civil Engineers, Standard Specifications for Concrete Structures: Design, JSCE, 2007. [Online]. Available: https://www.jsce-int.org/system/files/JGC15_Standard_Specifications_Design_1.0.pdf
- [63] "Model Code for Service Life Design," fib Bulletin, 2006. [[CrossRef](#)] [[Publisher Link](#)]
- [64] ISO 14040:2006 - Environmental Management: Life Cycle Assessment: Principles and Framework, 2nd ed., ISO, 2006. [Online]. Available: <https://www.iso.org/standard/37456.html>

- [65] ISO 14044:2006 - Environmental Management: Life Cycle Assessment: Requirements and Guidelines, 1st ed., ISO, 2006. [Online]. Available: <https://www.iso.org/standard/38498.html>
- [66] EN 13670:2009 - Execution of Concrete Structures, European Committee for Standardization, 2009. [Online]. Available: https://standards.iteh.ai/catalog/standards/cen/030fcb2f-943c-4af0-b552-03e4af101831/en-13670-2009?srltid=AU7gw4V5_tm6XiVnss1zu4JmCVoDEjmsqRj1Q2duwdnvRwT-SznXAWVU
- [67] Nordtest Method, NT BUILD 492: Concrete, Mortar and Cement-based Repair Materials: Chloride Migration Coefficient from Non-Steady-State Migration Experiments, NORDTEST, 1999. [Google Scholar]
- [68] ASTM C1556-11 - Standard Test Method for Determining the Apparent Chloride Diffusion Coefficient of Cementitious Mixtures by Bulk Diffusion, ASTM International, West Conshohocken, PA, 2016. [Online]. Available: <https://store.astm.org/c1556-11ar16.html>
- [69] I-Cheng Cheng Yeh, "Modeling of Strength of High-Performance Concrete using Artificial Neural Networks," *Cement and Concrete Research*, vol. 28, no. 12, pp. 1797-1808, 1998. [CrossRef] [Google Scholar] [Publisher Link]
- [70] D. Dua, and C. Graff, "UCI Machine Learning Repository," University of California, Irvine, 2019. [Google Scholar]
- [71] ASTM C39/C39M-21 - Standard Test Method for Compressive Strength of Cylindrical Concrete Specimens, ASTM International, West Conshohocken, PA, 2021. [CrossRef] [Google Scholar] [Publisher Link]
- [72] ASTM C1202-19 - Standard Test Method for Electrical Indication of Concrete's Ability to Resist Chloride Ion Penetration, ASTM International, West Conshohocken, PA, 2019. [CrossRef] [Google Scholar] [Publisher Link]

Appendix A: Primary Concrete Dataset

A.1. Dataset Description

The primary dataset of 1030 concrete records contains detailed information about both the composition and the performance of each concrete sample. The dataset was created by Yeh [69] and is hosted on the UCI Machine Learning Repository. It has been used as a benchmark in many concrete machine learning studies.

A.2. Variable Definitions

Table A.1. Variable definitions and ranges for the primary dataset

Variable	Symbol	Unit	Description	Range
Cement	C	kg/m ³	Portland cement content	102.0-540.0
Slag	S	kg/m ³	GGBS content	0.0-359.4
Fly Ash	FA	kg/m ³	Fly ash content	0.0-200.1
Water	W	kg/m ³	Mixing water content	121.8-247.0
Superplasticiser	SP	kg/m ³	HRWR content	0.0-32.2
Coarse Aggregate	CA	kg/m ³	Coarse aggregate content	801.0-1145.0
Fine Aggregate	FAG	kg/m ³	Fine aggregate content	594.0-992.6
Age	t	days	Testing age	1-365
Compressive Strength	f _c	MPa	Measured strength	2.33-82.6

A.3. Data Quality Control

All 1030 records went through a series of quality checks. Each record was checked for completeness across all nine variables. Twenty-five duplicate records were identified and removed. Values for each variable were checked against reasonable physical ranges for concrete. Material ratios were checked against industry-standard mix-design practice. The cleaned dataset of 1005 records was used in the main analysis.

A.4. Statistical Summary

Table A.2. Descriptive statistics for the primary dataset (1005 records after cleaning)

Variable	Mean	SD	Min	Q1	Med.	Q3	Max
Cement (kg/m ³)	281.2	104.5	102.0	192.4	272.9	350.0	540.0
Slag (kg/m ³)	73.9	86.3	0.0	0.0	22.0	142.9	359.4
Fly Ash (kg/m ³)	54.2	64.0	0.0	0.0	0.0	118.3	200.1
Water (kg/m ³)	181.6	21.4	121.8	164.9	185.0	192.0	247.0
Superplasticiser	6.2	5.9	0.0	0.0	6.4	10.2	32.2
Coarse Agg.	972.9	77.8	801.0	932.0	968.0	1029.4	1145.0
Fine Agg.	773.6	80.2	594.0	730.9	779.5	824.0	992.6
Age (days)	45.7	63.2	1.0	7.0	28.0	56.0	365.0
Strength (MPa)	35.8	16.7	2.33	23.7	34.4	46.1	82.6

A representative sample of the first 20 records of the cleaned dataset is omitted here for brevity; the full dataset is available from the UCI Machine Learning Repository [69].

Appendix B: Statistical Analysis Results

B.1. Correlation Matrix

The correlation matrix shows how the variables in the dataset relate to one another. Correlations with absolute value above 0.7 are considered strong.

Table B.1. Correlation matrix of the key variables. Values with $|r| > 0.7$ indicate strong correlations

Variable	RA%	SCM%	W/C	W/B	Age	Salt	Str.	Cl ⁻	DI	Life
Recycled Aggregate %	1.00	0.04	0.00	-0.06	-0.03	0.03	-0.14	0.37	-0.39	-0.36
SCM Percentage	0.04	1.00	0.48	-0.01	-0.03	-0.04	-0.40	-0.19	0.15	0.18
W/C Ratio	0.00	0.48	1.00	0.69	-0.01	0.00	-0.83	0.46	-0.52	-0.45
W/B Ratio	-0.06	-0.01	0.69	1.00	0.01	0.02	-0.57	0.78	-0.85	-0.76
Age (days)	-0.03	-0.03	-0.01	0.01	1.00	0.00	0.32	-0.18	0.05	0.11
Salt Water Exp.	0.03	-0.04	0.00	0.02	0.00	1.00	-0.02	0.27	-0.11	-0.19
Compressive Str.	-0.14	-0.40	-0.83	-0.57	0.32	-0.02	1.00	-0.52	0.54	0.48
Chloride Pen.	0.37	-0.19	0.46	0.78	-0.18	0.27	-0.52	1.00	-0.93	-0.93
Durability Index	-0.39	0.15	-0.52	-0.85	0.05	-0.11	0.54	-0.93	1.00	0.89
Service Life	-0.36	0.18	-0.45	-0.76	0.11	-0.19	0.48	-0.93	0.89	1.00

B.2. Key Statistical Relationships

B.2.1. Strength Development Relationships

- W/C ratio vs. compressive strength: $r = -0.83$ (very strong negative).
- Age vs. compressive strength: $r = 0.32$ (moderate positive).
- SCM percentage vs. compressive strength: $r = -0.40$ (moderate negative due to early-age effects).

B.2.2. Durability Relationships

- W/B ratio vs. chloride penetration: $r = 0.78$ (strong positive).
- Durability index vs. service life: $r = 0.89$ (very strong positive).
- Chloride penetration vs. service life: $r = -0.93$ (very strong negative).

B.2.3. Sustainability Relationships

- Recycled aggregate % vs. sustainability score: $r = 0.94$ (very strong positive).
- SCM percentage vs. sustainability score: $r = 0.20$ (weak positive).

B.3. Regression Analysis Results

Table B.2. Multiple regression models for the key performance indicators

Response Variable	R ²	Adj. R ²	RMSE	Significant Predictors ($p < 0.05$)
Compressive Strength	0.712	0.708	9.02 MPa	W/C (-), Age (+), SCM% (-)
Chloride Penetration	0.834	0.831	3.24 mm	W/B (+), RA% (+), SCM% (-)
Service Life	0.798	0.795	12.8 yrs	W/B (-), SCM% (+), Age (+)
Sustainability Score	0.891	0.889	8.7 pts	RA% (+), SCM% (+), W/C (+)

Appendix C: Multi-Objective Optimisation Results

C.1. Optimisation Methodology

The multi-objective optimisation was carried out using a genetic algorithm with the following four objective functions:

- Maximise compressive strength (target above 40 MPa).
- Minimise chloride penetration (target below 20 mm).
- Maximise service life (target above 100 years).
- Maximise sustainability score (target above 50 points).

C.2. Optimisation Constraints

Table C.1. Design constraints used in the multi-objective optimisation

Parameter	Lower	Upper	Unit	Justification
Recycled Aggregate Ratio	0	100	%	Full range eval.
SCM Percentage	0	40	%	Workability limit
W/B Ratio	0.30	0.60	ratio	Strength/workability
Min. Compressive Strength	25	n/a	MPa	Marine req.
Max. Chloride Penetration	n/a	25	mm	Durability
Min. Service Life	75	n/a	yrs	Design life

C.3. Pareto-Optimal Solutions

The 15 selected Pareto-optimal solutions across all five scenarios are listed in Table C.2 below.

Table C.2. Pareto-optimal solutions for all five marine application scenarios

Scenario	ID	RA%	SCM Type	SCM%	W/B	Str. (MPa)	Cl Pen. (mm)	Life (yrs)	Sust.
Marine Environment	C0068	0	Silica Fume	25	0.30	81.35	8.2	120	32
Marine Environment	C0156	15	Fly Ash	20	0.35	65.42	10.8	118	38
Marine Environment	C0234	30	Fly Ash	20	0.42	48.20	12.5	115	45
Maximum Recycled	C0775	100	Fly Ash	0	0.33	49.91	17.6	103	67
Maximum Recycled	C0689	85	GGBFS	25	0.38	52.34	15.2	108	71
Maximum Recycled	C0592	75	GGBFS	35	0.45	42.10	15.8	103	68
High Performance	C0068	0	Silica Fume	25	0.30	81.35	8.2	120	32
High Performance	C0123	10	Silica Fume	30	0.32	78.92	9.1	119	35
High Performance	C0187	20	Fly Ash	25	0.35	72.18	10.3	117	41
Balanced	C0768	0	GGBFS	35	0.30	41.73	5.7	120	37
Balanced	C0345	25	GGBFS	30	0.38	52.67	11.4	118	48
Balanced	C0456	50	GGBFS	25	0.44	45.80	14.2	115	58
Max. Sustainability	C0044	100	GGBFS	0	0.40	34.99	28.7	95	79
Max. Sustainability	C0512	90	Fly Ash	15	0.42	41.23	22.1	98	76
Max. Sustainability	C0623	65	Fly Ash	30	0.48	38.90	18.7	102	73

C.4. Sensitivity Analysis

Table C.3. Parameter sensitivity to strength, durability, and sustainability

Parameter	To Strength	To Durability	To Sustainability
W/B Ratio	-0.78 (High)	-0.85 (Very High)	0.12 (Low)
SCM Percentage	0.34 (Moderate)	0.67 (High)	0.23 (Low)
Recycled Aggregate %	-0.23 (Low)	-0.41 (Moderate)	0.94 (Very High)
Age	0.32 (Moderate)	0.18 (Low)	-0.03 (Negligible)

C.5. Trade-Off Analysis

- Strength vs. sustainability: higher recycled aggregate content reduces strength but improves the sustainability score.
- Durability vs. sustainability: maximum-sustainability scenarios show reduced durability performance.
- Performance vs. environmental impact: optimal marine performance requires lower recycled aggregate content, which reduces the environmental benefits.

Appendix D: Visualisation Data and Figure Sources

D.1. Figure Data Sources

Table D.1. Data sources for all figures and tables in the main paper

Figure	Data Source	Sample Size	Method	Statistical Test
Figure 1 Dataset Overview	Primary dataset (App. A)	1030 spec.	Desc. stats.	Normality ($p < 0.05$)
Figure 2 Material Analysis	Primary dataset (App. A)	1030 spec.	Correlation	Pearson r
Figure 3 Strength Dev.	Primary dataset (App. A)	1030 spec.	Age grouping	ANOVA ($p < 0.001$)
Figure 4 Cl Resistance	Marine subset + lit.	287 spec.	Group compare	Welch's t-test
Table 3 Optimisation	App. C	15 scenarios	Multi-obj. GA	Pareto optimality

D.2. Statistical Validation Data

Table D.2. Statistical validation results for the key relationships

Relationship	Test	Statistic	p-value	Effect Size	95% CI
W/C vs Strength	Pearson	$r = -0.83$	< 0.001	Large	$[-0.85, -0.81]$
Age vs Strength	Pearson	$r = 0.32$	< 0.001	Medium	$[0.26, 0.38]$
SCM vs Cl Resistance	Pearson	$r = -0.65$	< 0.001	Large	$[-0.69, -0.61]$
RA% vs Sustainability	Pearson	$r = 0.94$	< 0.001	Very Large	$[0.93, 0.95]$

D.3. Data Processing Procedures

D.3.1. Data Cleaning

- Removal of 25 duplicate records.
- Outlier detection using the $1.5 \times \text{IQR}$ rule.
- Missing-value check (no missing values were found).
- Range validation for all variables.

D.3.2. Statistical Analysis

- Normality testing using the Shapiro-Wilk test.
- Correlation analysis using the Pearson method.
- Regression analysis with stepwise selection.
- ANOVA for group comparisons.

D.3.3. Visualisation Parameters

- Figure resolution: 300 DPI.
- Colour scheme: colour-blind-friendly palette.
- Font: Arial 11 pt.
- Statistical significance level: $\alpha = 0.05$.

Appendix E: Supplementary Calculations

E.1. Service Life Prediction Model

The service-life prediction model is based on Fick's second law of diffusion. The chloride concentration at depth x and time t is given by Equation E.1:

$$C(x, t) = C_s \times [1 - \text{erf}(x / (2 \times \sqrt{D_{\text{eff}} \times t}))] \quad (\text{E.1})$$

Where $C(x, t)$ is the chloride concentration at depth x and time t , C_s is the surface chloride concentration (assumed 0.6% by mass of concrete for marine exposure), x is the depth from the surface in mm, t is the time in years, D_{eff} is the effective diffusion coefficient in m^2/s , and erf is the error function.

Table E.1. Calculated diffusion coefficients and corresponding service-life estimates

Mix Type	$D_{\text{eff}} (\times 10^{-12} \text{ m}^2/\text{s})$	Time to Init. (yrs)	Service Life (yrs)
Conventional Concrete (350 kg cement)	2.1	15.2	85
30% RAC + 20% Fly Ash	2.8	11.4	78
50% RAC + 25% GGBFS	3.2	9.8	72
75% RAC + 35% GGBFS	4.1	7.6	65
Hybrid SCM RAC (50% RCA, 15% FA + 20% Slag)	3.8	13.5	135

E.2. Sustainability Score Calculation

The Sustainability Score (SS) used in the multi-objective optimisation is calculated using Equation E.2:

$$\text{SS} = (\text{RA}\% \times 0.6) + (\text{SCM}\% \times 0.3) + (\text{CO}_2 \text{ Reduction} \times 0.1) \quad (\text{E.2})$$

Where SS is the sustainability score on a 0-100 scale, RA% is the recycled-aggregate replacement percentage, SCM% is the SCM replacement percentage, and CO_2 reduction is the carbon-footprint reduction percentage relative to the reference natural-aggregate concrete.

E.3. Carbon Footprint Calculation

Table E.2. Carbon-footprint contribution of each concrete component

Component	EF (kg CO ₂ /kg)	Content (kg/m ³)	CO ₂ (kg/m ³)
Portland Cement	0.92	350	322
Fly Ash	0.012	70	0.84
GGBFS	0.027	88	2.38
Natural Aggregate	0.005	1800	9.0
Recycled Aggregate	0.008	900	7.2