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Small-Sample Re-analysis and Uncertainty-Aware Modelling of Strength and Durability Relationships in Quarry-Dust and Washed-Gravel Concrete

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Abstract - This study re-analyses published experimental data for concrete produced using quarry rock dust and washed 10 mm gravel as 100% replacements for conventional fine and coarse aggregates, respectively. The objective was to develop a transparent small-sample modelling framework for 28-day characteristic compressive strength and to examine whether strength could provide a useful empirical basis for estimating other hardened properties and durability indicators. The compiled dataset comprised nine compressive-strength observations covering three nominal mix proportions and three water/cement ratios, together with three observations for elastic modulus, flexural strength, water absorption and chemical-attack mass loss at the reported optimum mixtures. Ordinary least-squares regression, alternative response-surface formulations, nonlinear fitting and leave-one-out cross-validation were used, with coefficient confidence intervals, prediction intervals, bootstrap sensitivity analysis and residual diagnostics applied to the primary strength model. A parsimonious linear model (fcu=76.71-7.054(a/c)-42.95(w/c)) provided the best cross-validated performance, with (R^2=0.90) and a leave-one-out RMSE of 4.6 MPa, compared with 9.5 MPa for the full second-order response surface. The results demonstrate the value of restricting model complexity when the calibration dataset is very small. Strength development was represented by an ACI-209-type hyperbolic relationship, while empirical relationships were also obtained for elastic modulus, flexural strength, water absorption and acid-attack mass loss. However, each downstream relationship is based on only three observations in which mix proportion, water/cement ratio and strength vary simultaneously. These relationships should therefore be regarded as exploratory rather than independently validated durability predictions. The principal methodological implication is that an uncertainty-aware strength model can be supported by the available data, whereas a strength-only durability cascade cannot yet be established. De-confounded experiments combining equal-strength mixtures with transport testing and microstructural characterisation are required to determine whether strength can adequately represent durability for this aggregate system.

Keywords: Quarry rock dust; Washed gravel; Alternative aggregates; Compressive strength prediction; Uncertainty quantification; Concrete durability; Small-sample modelling;

1. INTRODUCTION

Affordable housing and the economics of construction remain persistent concerns across sub-Saharan Africa. Aggregates constitute roughly 70% of the volume of concrete, so their cost, availability, and environmental impact are of first-order importance. In Nigeria, two pressures have sharpened interest in local, non-standard aggregates: the cost of Portland cement rose steeply through 2024, with the price of a 50 kg bag reported to have roughly doubled over the year, and the national housing deficit is variously estimated at between about 15 and 28 million units. River-sand mining faces growing environmental and regulatory constraints, while crushed-granite coarse aggregate must be imported into the low-lying riverine areas of the Niger Delta at appreciable haulage cost.

Two locally abundant materials offer a response. Washed 10 mm all-in gravel occurs in quantity in the riverine Niger Delta and is available year-round, while quarry rock dust is a crushing by-product otherwise stockpiled as waste. Used together, gravel replacing crushed granite and quarry dust replacing river sand will promise cheaper concrete while diverting a waste stream to productive use. The mechanical and durability behaviour of this specific full-replacement system was established experimentally in two companion papers [1,2], which reported that mixes of 1:2:3, 1:1½:2 and 1:1:2 (by weight) reached 28-day characteristic strengths of 18.9, 28.2

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and 38.3 N/mm² (grades C15, C25 and C35) at their respective optimum water/cement ratios, together with density, workability, static elastic modulus, flexural strength, water absorption and chemical-attack resistance.

Predicting concrete strength from mix design is a mature field, but one dominated by large datasets. Most contemporary machine-learning models are trained and benchmarked on the 1,030-instance high-performance-concrete dataset introduced by Yeh [3], and critical reviews report that ensemble and neural-network models typically achieve high accuracy on datasets of hundreds to thousands of mixes [4,5]. Such data volumes are unattainable for a local, non-standard aggregate system characterised in a single laboratory campaign. Where data are scarce, the literature instead favours designed experiments and parsimonious, interpretable surrogates: response-surface methodology is well established for concrete-mixture optimisation with only tens of runs [6], and reviews of small-sample and surrogate modelling emphasise uncertainty quantification and warn that flexible models overfit and generalise poorly when the sample is small [7,10]. Prediction models for alternative-aggregate concretes such as manufactured sand, recycled aggregate, and quarry/rock dust exist, but are comparatively few and, for quarry-dust systems in particular, largely confined to regional mixture-experiment studies [11,12].

Against this background, three gaps motivate the present study. First, the properties of the gravel/quarry-dust system were reported individually and descriptively; no unified, cross-validated model links mix design to the full suite of hardened properties. Second, the data belong to a genuinely small-sample regime with nine strength observations and three durability observations, so methods that are honest and stable with tens of points, and that report their own uncertainty, are required. Third, the durability behaviour was interpreted purely as a function of compressive strength, whereas a substantial microstructural literature holds that strength is not a sufficient indicator of durability [13,14,15], and that aggregate shape and fines content are the two defining features of this system which independently govern the interfacial transition zone (ITZ) and pore structure that control transport and deterioration.

The objectives are therefore: (i) to compile and quality-check the published data into a single analysis-ready dataset; (ii) to develop a transparent cascade framework that predicts 28-day characteristic compressive strength from mix-design variables and explores empirical relationships between strength and strength development, elastic modulus, flexural strength and durability indicators; (iii) to select model forms by out-of-sample performance and to quantify predictive uncertainty through confidence intervals, prediction intervals, bootstrap resampling and formal diagnostics; and (iv) to interpret the model, particularly its strength-only durability sub-models, against the current ITZ and pore-structure literature.

2. MATERIALS AND DATA

2.1. Source experimental programme

The experimental data re-analysed here derive from two companion studies of the same materials and mixes [1,2]. The binder was ordinary Portland cement; the coarse aggregate was washed 10 mm all-in gravel from Emoha, classified as irregular-to-rounded and smooth in texture; and the fine aggregate was quarry rock dust from a commercial crushing operation. Three nominal mix proportions (1:2:3, 1:1½:2 and 1:1:2, cement:fine:coarse by weight) were cast across water/cement (w/c) ratios from 0.40 to 0.70. Compressive strength was determined on 150 mm cubes at 7, 14, 21 and 28 days; density and slump were recorded; and the static modulus of elasticity, flexural strength, water absorption and resistance to five aggressive media ($MgSO_4$, Na_2SO_4, H_2SO_4, HCl and NaOH) were measured at each mix's optimum w/c.

2.2. Aggregate properties

The measured physical properties of the two aggregates are summarised in Table 1. Two features matter for later interpretation. The coarse aggregate is a smooth, rounded gravel with low water absorption, a shape reported to form a weaker bond with cement paste than crushed, angular rock [24,25]. The fine aggregate is very fine, with a fineness modulus of 2.66 and a particle-size distribution dominated by a 60% silt-sized fraction, a high-microfines material whose behaviour differs from that of clean manufactured sand or natural river sand. Because these properties were held constant across every mix, they act as fixed constants in the present dataset rather than as predictors, a limitation revisited in Section 5.

Table 1. Measured physical properties of the aggregates (after the source experimental programme).

Property	10 mm washed gravel (coarse)	Quarry dust (fine)	BS 882 limit
Coefficient of uniformity, C_u	5.71	8.18	≥ 4
Coefficient of curvature, C_c	3.21	1.67	1–3
Fineness modulus	4.75	2.66	–

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Property	**10 mm washed gravel (coarse)**	**Quarry dust (fine)**	**BS 882 limit**
Specific gravity	2.72	2.80	–
Water absorption (%)	1.21	0.35	≤ 2.50
Bulk density (kg/m³)	1830	1620	–
Gravel/sand/silt split (%)	30 / 60 / 10	5 / 35 / 60	–

2.3. Compiled datasets, data quality and reuse

The nine compressive-strength observations used for modelling are given in Table 2, together with the derived aggregate/cement (a/c) ratio, the standard deviation and the characteristic strength fcu = fm − 1.64σ. The three optimum-mix observations for elasticity, flexure and durability are given in Table 3. During compilation, three internal inconsistencies in the source data were identified and are reported here for transparency: two rows in which the reported characteristic strength does not equal fm − 1.64σ within rounding; slump values that differ between the main results table and the workability appendix; and an optimum w/c for the 1:1½:2 mix quoted as 0.60 in one paper and 0.55 in the other. These were resolved to a single convention before fitting, and any downstream use of the data should acknowledge them rather than treat the figures as exact.

Table 2. Compiled compressive-strength dataset (nine mix / water-cement combinations); strengths in N/mm², σ = standard deviation, $f_{cu} = f_m - 1.64σ$.

Mix	w/c	a/c	f_m 7d	f_m 14d	f_m 28d	σ	fcu (28d)	Density (kN/m³)
1:2:3	0.60	5.0	8.44	10.22	11.73	0.45	10.97	22.80
1:2:3	0.65	5.0	14.44	16.59	20.13	0.76	18.88	23.10
1:2:3	0.70	5.0	8.24	10.15	13.68	0.76	10.35	22.10
1:1½:2	0.55	3.5	19.85	22.32	30.40	1.42	28.06	24.30
1:1½:2	0.60	3.5	19.85	22.22	29.97	0.46	28.23	24.50
1:1½:2	0.65	3.5	16.96	20.22	25.91	0.80	23.93	23.00
1:1:2	0.45	3.0	28.15	33.28	40.99	1.58	38.29	24.00
1:1:2	0.50	3.0	22.67	27.58	35.28	0.47	34.51	24.40
1:1:2	0.55	3.0	20.39	25.93	28.81	0.31	28.32	23.50

This work is a secondary re-analysis of experimental data reported in two openly published companion papers [1,2] in which the author is the corresponding author for the research papers; no new specimens were cast. All measurements remain attributable to the original investigators through citation, and the present contribution is confined to data compilation, quality control, modelling, uncertainty quantification and interpretation. Individual author contributions are declared at the end of the paper.

Table 3a. Optimum-mix elasticity, flexural strength and water absorption (Ec in kN/mm², MOR in N/mm²).

Mix	w/c	fcu	Ec exp.	Ec theo.	MOR	Water abs. 9d (%)
1:2:3	0.65	18.88	14.50	24.00	2.43	7.89
1:1½:2	0.55	28.23	25.00	27.50	3.18	6.41
1:1:2	0.45	38.29	27.00	30.00	3.66	3.80

Table 3b. Optimum-mix chemical-attack resistance: mass loss (%) after immersion in five aggressive media.

Mix	fcu	$MgSO_4$	Na_2SO_4	H_2SO_4	HCl	NaOH
1:2:3	18.88	3.44	0.82	3.95	5.24	1.12

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Mix	fcu	$MgSO_4$	Na_2SO_4	H_2SO_4	HCl	NaOH
1:1½:2	28.23	1.26	0.62	1.23	2.41	0.64
1:1:2	38.29	1.11	0.59	1.17	1.55	0.40

3. MODELLING METHODOLOGY

3.1. Cascade framework

The model is organised as a cascade that mirrors the structure of the source data, in which stiffness, flexural strength and every durability measure were reported against compressive strength. Twenty-eight-day characteristic compressive strength is first predicted from mix design (a/c and w/c); strength at other ages is obtained from a development law; and the remaining hardened properties are then predicted from strength. This structure keeps each sub-model low-dimensional and essential, with only nine or three calibration points, and yields an interpretable chain from proportions to performance.

3.2. Candidate model forms

For 28-day strength, three forms were compared: a two-term linear model in a/c and w/c; the same with an added quadratic w/c term; and a full second-order response surface. Mix-wise quadratics in w/c were also fitted to locate each mix's optimum. Strength development was modelled with an ACI-209-type hyperbolic law [28], $f(t)/f(28) = t/(a + b\,t)$. The static elastic modulus was tested against a square-root form, $E_c = k\sqrt{f_{cu}}$, a linear form, and the BS 8110 expression $E_c = 20 + 0.2\,f_{cu}$ [30]. Flexural strength was modelled as $MOR = c\sqrt{f_{cu}}$. For durability, water absorption and chemical mass loss were fitted against strength using linear and exponential-decay forms.

3.3. Fitting, validation and software

Linear models were fitted by ordinary least squares and non-linear models by Levenberg–Marquardt least squares. Because the dataset is small, model selection relied on leave-one-out cross-validation (LOO): each observation was predicted from a model refitted on the remaining points, and the LOO-RMSE was the primary discriminator, alongside R^2, adjusted R^2 and in-sample RMSE. All computation used open-source Python (NumPy and SciPy); the compiled dataset and code are available so that the analysis is fully reproducible.

3.4. Uncertainty quantification and diagnostics

Reporting a fitted equation without its uncertainty would understate the effect of the small sample, so four complementary tools were applied to the primary (28-day strength) model, following established practice in materials and infrastructure modelling [7,8,9]. First, coefficient standard errors and 95 % confidence intervals were obtained from the ordinary-least-squares covariance matrix using the Student t distribution with six residual degrees of freedom. Second, 95 % prediction intervals for a new specimen and confidence intervals for the mean response were computed at the three design points. Third, a case-resampling bootstrap with 5,000 replicates was used as a sensitivity analysis to examine the stability of coefficient and model-error estimates. Because the empirical dataset contains only nine observations, the bootstrap intervals are not treated as independent evidence of precision but as a complementary assessment of sampling instability. Fourth, model assumptions were examined through residual-versus-fitted plots, a normal quantile–quantile plot, the Shapiro–Wilk test, the Durbin–Watson statistic, leverage (hat) values with the 2k/n rule, and Cook's distance with the 4/n rule. Because the durability and elasticity sub-models rest on three points and one or two residual degrees of freedom, formal intervals cannot be estimated reliably for them; they are therefore reported as indicative correlations only.

4. RESULTS

4.1. Twenty-eight-day compressive strength

The parsimonious two-term linear model gave the best out-of-sample performance:

$$f_{cu} = 76.71 - 7.054\,(a/c) - 42.95\,(w/c) \tag{1}$$

with $R^2 = 0.90$, adjusted $R^2 = 0.87$, in-sample RMSE = 2.9 MPa and LOO-RMSE = 4.6 MPa. Adding a quadratic w/c term worsened the LOO-RMSE to 5.7 MPa, and the full second-order response surface, in which six coefficients were fitted to nine points, reached an in-sample R^2 of 0.93 while its LOO-RMSE degraded to 9.5 MPa, a clear case of overfitting. Equation (1) is therefore recommended within the calibration domain (a/c 3.0–5.0; w/c 0.45–0.70). The coefficient estimates and their uncertainty are given in Table 4. The aggregate-to-cement ratio was statistically significant in the fitted model ($p = 0.01$), whereas the water-to-cement

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ratio was not significant at the 5% level ($p = 0.12$). The statistical significance of the aggregate-to-cement term should not, however, be interpreted as evidence of an independent causal effect of aggregate-to-cement ratio or cement content, because the nine observations represent three discrete mix families in which aggregate-to-cement ratio is structurally linked to mix proportion.

Equation (1) is monotonic and so does not reproduce the within-mix strength peak at an intermediate, optimum w/c, and it therefore under-predicts strength at the optimum for the leanest mix. To retain the design-relevant optima without overfitting the global model, mix-wise quadratics were fitted; the recovered optima (Table 5) reproduce the source papers' reported values closely and are recommended as the reference for design at the optimum. No continuous optimum-w/c formula is proposed, because only three optimum points exist.

Table 4. Coefficients of the two-term linear strength model (Eq. 1) with standard errors, t-based and bootstrap (B = 5,000) 95% intervals, and p-values. $R^2 = 0.90$, adjusted $R^2 = 0.87$, residual standard error = 3.5 MPa, n = 9.

Term	Estimate	Std. error	95% CI (t)	Bootstrap 95% CI	p-value
Intercept	76.71	9.48	[53.5, 99.9]	[51.9, 89.3]	< 0.001
a/c	−7.054	2.06	[−12.1, −2.0]	[−10.9, 0.4]	0.014
w/c	−42.95	23.47	[−100.4, 14.5]	[−100.1, 8.8]	0.117

4.2. Uncertainty and model diagnostics

Prediction intervals at the three design points are reported in Table 5. The intervals are wide, on the order of ±10 MPa for a single new specimen, which is the honest cost of nine calibration points and should temper any deterministic use of the model. The case-resampling bootstrap agreed with the parametric analysis: the bootstrap 95 % intervals for the coefficients were consistent with those in Table 4, and the bootstrap model error had a median of about 2 MPa. Diagnostics (Figure 1 and Table 6) were satisfactory: residuals showed no systematic pattern against fitted values, the normal quantile–quantile plot was close to linear, and the Shapiro–Wilk test did not reject normality ($p = 0.88$); the Durbin–Watson statistic (2.4) indicated no meaningful residual autocorrelation. No observation exceeded the leverage threshold; however, the two 1:2:3 points nearest the strength optimum had the largest Cook's distances. This reflects the monotonic model's inability to capture the optimum in the leanest mix, indicating a model-form limitation rather than a data error and supporting the mix-wise optima reported in Table 5.

Table 5. Mix-wise strength optima and 28-day predictions with 95% mean-response confidence intervals and 95% single-specimen prediction intervals. The global linear model (Eq. 1) under-predicts at the lean-mix optimum, where the mix-wise peak is the design reference.

Mix	a/c	Opt. w/c	Peak fcu	Pred. fcu (Eq. 1)	95% mean CI	95% prediction interval
1:2:3	5.0	0.65	18.9	13.5	[8.7, 18.4]	[3.7, 23.4]
1:1½:2	3.5	0.58	28.7	27.1	[23.9, 30.4]	[18.0, 36.3]
1:1:2	3.0	0.40	39.7	38.4	[30.0, 46.8]	[26.4, 50.4]

Table 6. Residual, leverage and influence diagnostics for the linear strength model. Leverage threshold 2k/n = 0.67; Cook's distance threshold 4/n = 0.44.

Mix	w/c	Obs.	Pred.	Residual	Std. resid.	Leverage h	Cook's D
1:2:3	0.60	10.97	15.67	−4.70	−1.86	0.481	1.072
1:2:3	0.65	18.88	13.52	5.36	1.86	0.325	0.557
1:2:3	0.70	10.35	11.37	−1.02	−0.38	0.394	0.031
1:1½:2	0.55	28.06	28.40	−0.34	−0.10	0.134	0.001
1:1½:2	0.60	28.23	26.25	1.98	0.63	0.195	0.032
1:1½:2	0.65	23.93	24.10	−0.17	−0.07	0.481	0.001
1:1:2	0.45	38.29	36.22	2.07	0.83	0.498	0.230

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Mix	w/c	Obs.	Pred.	Residual	Std. resid.	Leverage h	Cook's D
1:1:2	0.50	34.51	34.07	0.44	0.14	0.255	0.002
1:1:2	0.55	28.32	31.93	−3.61	−1.18	0.238	0.145

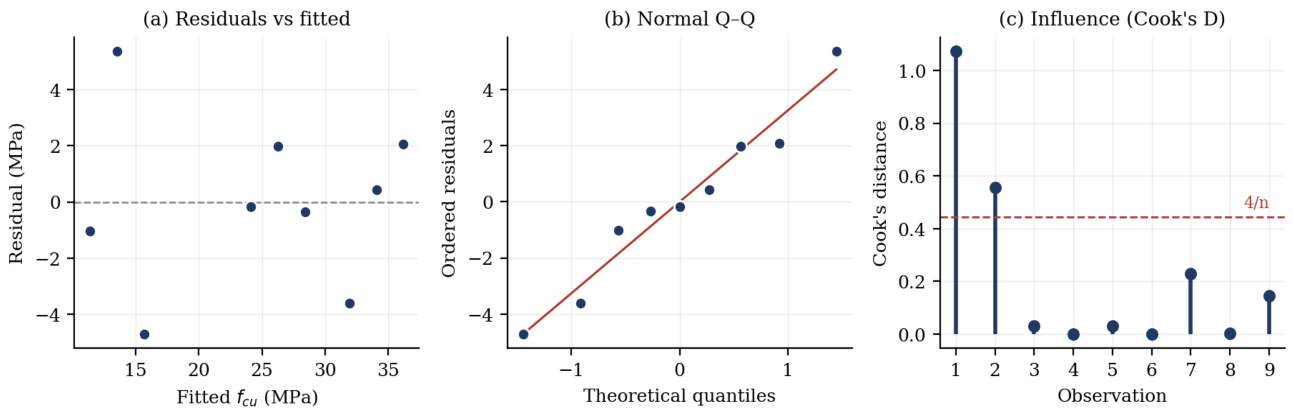

Figure 1. Diagnostics for the two-term linear strength model: (a) residuals versus fitted values; (b) normal quantile–quantile plot of residuals; (c) Cook's distance by observation, with the 4/n influence threshold.

4.3. Strength development with age

The ACI-209-type hyperbolic law fitted the age data well ($R^2 = 0.88$):

$$f(t)/f(28) = t / (4.85 + 0.847\, t) \qquad (2)$$

consistent with the empirical pattern of roughly 67 %, 80 % and 100 % of 28-day strength at 7, 14 and 28 days. Combined with Equation (1), this provides mean strength at any age within the tested window.

4.4. Static elastic modulus

A fitted linear relation described the modulus best ($R^2 = 0.85$):

$$Ec = 0.638\, fcu + 3.99 \;\; (kN/mm^2) \qquad (3)$$

outperforming the square-root form ($R^2 = 0.76$). The BS 8110 expression over-predicted the weakest (1:2:3) mix substantially (about 24 against a measured 14.5 kN/mm²), consistent with the source paper's own observation that this mix's modulus falls below the theoretical value; the smooth rounded gravel and high aggregate volume plausibly lower the composite stiffness, an effect documented for rounded relative to crushed aggregate [22,24,25]. Equation (3) rests on three points and is indicative only.

4.5. Flexural strength and durability

Flexural strength followed the classical square-root relationship with high fidelity ($R^2 = 0.98$), $MOR = 0.587\sqrt{f\_cu}$, which is preferable to a fixed modulus-of-rupture-to-strength ratio because that ratio drifts across the strength range. Both durability measures improved as strength increased. Water absorption at nine days declined approximately linearly, $Wa = 12.05 - 0.211\, fcu$ ($R^2 = 0.98$), while acid-attack mass loss was better represented by exponential decay in strength, for example $L_{HCl} = 19.79 \exp(-0.071\, fcu)$ and $L_{H2SO4} = 21.35 \exp(-0.091\, fcu)$. These correlations are calibrated on only three points at which mix proportion, w/c and strength vary together; they indicate the direction and approximate magnitude of the durability response but cannot attribute it to any single factor, and no formal intervals are reported for them.

4.6. Model Summary and Reliability Tiers

Table 7. Summary of the fitted cascade model. LOO = leave-one-out RMSE (MPa where applicable). Tier A: nine cross-validated points; Tier B: three calibration points (indicative).

Property/Model	Fitted Equation	R^2	RMSE / LOO	Tier
28-day strength (linear)	$fcu = 76.71 - 7.054(a/c) - 42.95(w/c)$	0.90	2.9 / 4.6	A

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Property/Model	Fitted Equation	R^2	RMSE / LOO	Tier
28-day strength (full RSM)	2nd-order surface (6 terms)	0.93	– / 9.5	rejected
Age development	$f(t)/f_{28} = t/(4.847 + 0.847t)$	0.88	–	A
Optimum w/c (1:2:3 / 1:1½:2 / 1:1:2)	0.65 / 0.58 / 0.40 → 18.9 / 28.7 / 39.7 MPa	–	–	A
Elastic modulus	$E_c = 0.638\ f_{cu} + 3.99$	0.85	–	B
Flexural strength	$MOR = 0.587\sqrt{f\_cu}$	0.98	–	B
Water absorption (9d)	$W_a = 12.05 - 0.2113\ f_{cu}$	0.98	–	B
HCl mass loss	$L = 19.79 \exp(-0.0711\ f_{cu})$	0.98	–	B
H_2SO_4 mass loss	$L = 21.35 \exp(-0.0907\ f_{cu})$	0.91	–	B

Table 7 collects the fitted equations with their fit statistics and a reliability tier. Tier A models (28-day strength and age development) rest on nine leave-one-out-validated points and carry the full uncertainty analysis of Section 4.2; they are suitable for prediction within the calibration domain. Tier B models (elastic modulus, flexural strength and all durability measures) rest on three points each, have one or two residual degrees of freedom, and should be used for screening and trend estimation only; their reported R^2 values are correspondingly optimistic.

5. DISCUSSION

5.1. Parsimony and honesty under data scarcity

The central methodological finding is that a deliberately simple model generalised far better than a flexible one: the full response surface achieved the highest in-sample fit yet the worst out-of-sample error, while the two-term linear model achieved a LOO-RMSE close to the scatter of the underlying cube tests. Reporting out-of-sample performance and explicit uncertainty, rather than in-sample R^2 alone, which is the more defensible practice for alternative-aggregate research in low-resource settings, where the large datasets that justify flexible machine-learning models are rarely attainable [6,7,10]. The wide coefficient and prediction intervals reported here are not a weakness of the analysis but an accurate expression of what nine points can and cannot support.

5.2. Is Compressive Strength a Sufficient Indicator of Durability?

The cascade predicts every durability property from strength alone. This is convenient and, within the present data, empirically close, but it is the assumption most in tension with the recent microstructural literature. A consistent body of work reaffirms that compressive strength is not, in itself, a reliable indicator of durability, because transport and deterioration are governed by the connectivity of the near-surface pore network and by the quality of the interfacial transition zone, neither of which strength testing captures [13,14,15]. Concretes of equal strength can differ in sorptivity, permeability, carbonation and chloride ingress when water/cement ratio, binder content, curing or aggregate characteristics vary independently.

The two defining features of this system make it a likely place for the strength–durability link to weaken. The coarse aggregate is smooth, rounded gravel, which forms a weaker, more porous interfacial transition zone than crushed rock; fracture studies report that gravel concrete has the lowest fracture toughness among common aggregates because of poor paste-to-aggregate bonding, and that the interfacial zone is the most permeable region in concrete, with a percolation threshold near an aggregate volume fraction of about 0.48 [16,17,18]. The fine aggregate is a high-microfines quarry dust: the manufactured-sand literature identifies a beneficial-filler window of roughly 5–15 % fines (optimum near 10 %) beyond which excess fines dilute hydration and coarsen the pore system [19,20]. A dust dominated by a 60 % silt-sized fraction sits well outside that window, so its effect on capillary porosity cannot be assumed benign. The present durability sub-models should therefore be read as empirical summaries of three confounded points, not as evidence that strength governs durability.

5.3. Implications for a de-confounded experimental design

The data structure and literature indicate that the appropriate approach is a designed experiment in which water–cement ratio and mix proportion are varied independently while maintaining approximately constant strength, coupled with transport tests (sorptivity, chloride migration, gas permeability, and carbonation) and pore-structure/interfacial characterization. Mercury intrusion

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porosimetry should report threshold pore diameter and connectivity, with nuclear magnetic resonance or micro-computed tomography used for corroboration and to mitigate ink-bottle artefacts [21]. Interfacial porosity should be quantified by image analysis. A practical criterion is that, if transport properties diverge by more than about a factor of two among equal-strength mixes, strength is insufficient for this system; if they track strength within scatter, the cascade is vindicated. Either outcome would provide a stronger empirical basis for evaluating the validity of the strength-only durability relationships; divergence among equal-strength mixtures would demonstrate the need for additional transport- or microstructure-related predictors, whereas close agreement would provide evidence supporting the practical adequacy of the strength-based approximation within the tested material system.

5.4. Practical use and transferability

Within the calibration domain, Equation (1) can be used as a preliminary strength-estimation tool when its prediction intervals are reported alongside the point estimate. The age-development relationship provides an indicative estimate of strength development, while the modulus, flexural-strength and durability relationships should be regarded only as exploratory screening relationships because each is based on three observations and has not been independently validated. Because the aggregate properties were fixed, the coefficients are specific to Emoha-type rounded gravel and this particular quarry dust, and gravel from other pits or dust from other parent rocks will shift them. The framework is therefore best regarded as a methodology that may be adapted for other low-resource laboratories using non-standard aggregates, subject to recalibration and independent validation with locally sourced materials rather than as a directly portable set of coefficients. Extending it to sample multiple aggregate sources, and re-fitting with aggregate descriptors as explicit predictors, would test and, if warranted, establish wider transferability. Given that substandard materials and workmanship are repeatedly implicated in building failures in Nigeria, with reported contributions varying widely across studies, from a lower bound near 10% to about half of documented collapses [26,27], durability-aware specification of these indigenous aggregate systems is a practical need rather than an academic one.

6. CONCLUSIONS

This study re-analysed published experimental data for concrete incorporating quarry rock dust and washed 10 mm gravel as 100% replacements for conventional fine and coarse aggregates. The principal findings are as follows:

- A parsimonious two-term linear model relating 28-day characteristic compressive strength to aggregate/cement and water/cement ratios provided the best performance among the evaluated strength models. It achieved (R^2=0.90) and a leave-one-out RMSE of 4.6 MPa, whereas the full second-order response surface produced a substantially larger leave-one-out RMSE of 9.5 MPa. The result indicates that increased model flexibility is not justified by the available nine-point dataset.
- The uncertainty analysis demonstrates that predictions from the strength model are imprecise, with relatively wide prediction intervals. The aggregate/cement coefficient was statistically significant, whereas the water/cement coefficient was estimated imprecisely. These results should not be interpreted as evidence that the water/cement ratio is physically unimportant, given the limited sample size and the structure of the experimental data.
- The ACI-209-type hyperbolic expression provided an adequate empirical representation of the reported strength development data. Relationships were also obtained for elastic modulus and flexural strength; however, these downstream relationships are based on only three observations and therefore provide indicative rather than independently validated predictive capability.
- Water absorption and chemical-attack mass loss decreased with increasing strength in the three optimum-mixture observations. Because strength, water/cement ratio and mix proportion vary simultaneously in these observations, the present data cannot establish whether the observed durability trends are caused by strength itself or by other correlated mixture variables.
- The strength-only durability cascade should therefore be regarded as an exploratory framework rather than a validated durability prediction model. The principal unresolved question is whether concretes having similar strength but different mixture proportions exhibit materially different transport and deterioration behaviour.
- The most appropriate next step is a de-confounded experimental programme in which water/cement ratio, mixture proportion and other relevant material variables are varied independently while comparable strength levels are achieved. Such an experiment should combine durability testing with pore-structure and interfacial characterisation to determine whether strength provides a sufficiently robust surrogate for durability in this particular aggregate system.
- The fitted strength coefficients are specific to the tested quarry dust, washed gravel, cement and experimental conditions. Application to other aggregate sources should therefore require recalibration and independent validation rather than direct transfer of the reported coefficients.

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7. LIMITATIONS AND FUTURE WORK

The analysis inherits the source data's small size and internal inconsistencies, and its durability and elasticity components rest on three points each. The aggregate properties were fixed, limiting transferability, and the durability tests were accelerated laboratory proxies rather than field exposure. Priorities for future work follow directly: a Box-Behnken or central-composite durability experiment that de-confounds w/c from strength; multi-source aggregate sampling to build and externally validate a transferable, descriptor-based cascade; microstructural characterisation (interfacial transition zone and pore structure) to test the sufficiency of the strength cascade; and a performance-normalised cost and embodied-carbon assessment of the system.

Data Availability

The compiled dataset and the model-fitting code are available from the corresponding author on reasonable request. The underlying experimental measurements are contained in the two cited source publications [1,2].

Author Contributions

The contribution of this study is not the generation of a new experimental dataset or the establishment of a universally transferable concrete-strength equation. Rather, it is the systematic re-analysis of a very small, locally specific aggregate dataset using a transparent modelling workflow that explicitly compares model complexity, out-of-sample performance and predictive uncertainty. The analysis demonstrates the extent to which a strength model can be supported by nine observations and, importantly, identifies the evidential boundary beyond which downstream durability relationships cannot be regarded as validated predictions. This distinction provides a basis for designing a subsequent de-confounded experimental programme for quarry-dust and washed-gravel concrete.

Declaration of Competing Interests

The authors declare no competing financial interests or personal relationships that could have influenced the work reported in this paper.

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