Prediction of Fresh and Mechanical Properties of Self-Compacting Concrete Using Gaussian Process Regression

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Abstract: Self-compacting concrete (SCC) incorporating ceramic waste powder (CWP) as a partial cement replacement offers a route to reduce both landfill burden and embodied carbon in construction, but characterising the combined effect of mix design variables on the full suite of fresh and hardened properties normally demands extensive laboratory testing. This study evaluates Gaussian Process Regression (GPR) as a data-efficient surrogate modelling approach for predicting twelve fresh and mechanical properties of CWP-based SCC from three mix design inputs: cement content, CWP content, and water-to-binder (w/b) ratio. A dataset of twenty-one experimentally characterised SCC mixes, spanning slump flow, T_{500} time, V-funnel time, L-box ratio, segregation resistance, compressive strength (7, 28, and 90 days), split tensile strength (7, 28, and 90 days), and 28-day flexural strength, was modelled using independent GPR models with a Matern 5/2 kernel and white-noise term, with performance assessed exclusively through leave-one-out cross-validation (LOOCV) given the small sample size. Eleven of the twelve properties were predicted with LOOCV coefficients of determination (R^2) between 0.80 and 0.99, with the strongest performance observed for slump flow and split tensile strength ($R^2 \geq 0.96$). Twenty-eight-day flexural strength was the exception, with a negative LOOCV R^2 indicating that the three mix design inputs alone do not explain its variability in this dataset. The results demonstrate that GPR, combined with rigorous LOOCV validation and explicit predictive uncertainty, is a viable and transparent tool for mix-design-stage property prediction in small experimental SCC datasets, while also illustrating the diagnostic value of LOOCV in identifying properties that require additional explanatory variables.

Keywords: *Self-Compacting Concrete; Ceramic Waste Powder; Gaussian Process Regression; Leave-One-Out Cross-Validation; Machine Learning; Sustainable Construction Materials; SDG 9 — Industry, Innovation and Infrastructure.*

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I. INTRODUCTION

Self-compacting concrete (SCC) is a highly flowable concrete that consolidates under its own weight without mechanical vibration, first developed in Japan in the late 1980s to address defects arising from inadequate compaction in congested reinforcement [1]. Its adoption has grown steadily in modern construction because it reduces labour requirements, shortens placement time, and improves surface finish in densely reinforced or geometrically complex elements. At the same time, cement production remains one of the most carbon- and energy-intensive processes in the construction materials sector, and the concrete industry has increasingly sought supplementary cementitious materials (SCMs) derived from industrial and post-consumer waste streams to reduce clinker demand without compromising performance.

Ceramic waste powder (CWP), generated in large volumes as a by-product of tile, sanitaryware, and brick manufacturing, is one such waste stream. Ground ceramic waste exhibits pozzolanic activity due to its amorphous silica and alumina content, and its use as a partial cement replacement has been shown to be technically feasible while diverting material from landfill [2]. In SCC specifically, incorporating CWP interacts with the mix design variables that govern flowability and passing ability, so its effect must be evaluated jointly across both fresh-state and hardened-state properties rather than compressive strength alone. Characterising an SCC mix fully, however, requires a battery of standardised tests: slump flow and T_{500} time for

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filling ability, V-funnel time for viscosity, L-box ratio for passing ability, and column segregation for stability in the fresh state, together with compressive, split tensile, and flexural strength testing at multiple curing ages in the hardened state. Generating this data across a meaningful range of cement content, waste replacement level, and water-to-binder (w/b) ratio is time- and resource-intensive, which motivates the use of predictive modelling to interpolate between tested mixes and to guide the design of further experiments.

Machine learning methods, including artificial neural networks (ANN), response surface methodology (RSM), support vector regression, and Gaussian process regression (GPR), have all been applied to concrete property prediction with varying degrees of success [8, 9]. Among these, GPR is distinguished by two properties that are particularly relevant to small, expensive-to-generate experimental datasets: it is a non-parametric Bayesian method that does not require large sample sizes to fit a smooth, non-linear response surface, and it produces a full predictive distribution rather than a point estimate, allowing the model to report how confident it is in each prediction [10]. This uncertainty quantification is valuable in mix design contexts, where practitioners need to know not only the expected property value but also how reliable that estimate is, particularly at the edges of the tested design space.

This study applies GPR to a dataset of twenty-one CWP-based SCC mixes spanning three mix design inputs (cement content, CWP content, and w/b ratio) and twelve fresh and mechanical outputs. Because the dataset is small, all reported performance is based on leave-one-out cross-validation (LOOCV), which trains on twenty mixes and tests on the single held-out mix in twenty-one successive iterations, using every data point for both training and testing without ever mixing the two roles within a single evaluation [13]. The specific objectives of this work are to: (i) develop independent GPR surrogate models for each of the twelve measured properties; (ii) rigorously validate each model using LOOCV rather than a single train/test split, which would not be statistically defensible at this sample size; (iii) quantify predictive uncertainty alongside point predictions; and (iv) critically identify which properties are, and are not, well explained by the three mix design inputs considered, since a negative or weak LOOCV result is itself informative about the underlying material behaviour.

II. LITERATURE REVIEW

➢ *Self-Compacting Concrete: Fresh Property Characterisation*

The characterisation of SCC in its fresh state is standardised primarily through the guidelines issued by the European Federation of National Associations Representing producers and applicators of specialist building products (EFNARC) [1]. These guidelines define acceptance ranges for slump flow (650-800 mm), T_{500} time (2-5 s), V-funnel time (6-12 s), and L-box ratio (0.8-1.0), obtained respectively from the slump-flow, V-funnel, and L-box tests, together with segregation resistance assessed through column or sieve segregation testing. Numerous experimental studies have benchmarked SCC mixes incorporating waste-derived SCMs against these criteria, generally finding that increasing replacement of cement with fine, water-absorptive waste powders reduces flowability and increases viscosity-related test times, while the passing ability and segregation resistance response depends on the specific powder characteristics and dosage of superplasticiser used to compensate [3].

➢ *Ceramic Waste Powder as a Cement Replacement in SCC*

Several experimental investigations have specifically examined CWP as a partial cement replacement in SCC. Aly, El-Dieb, and Reda Taha [2] examined high-volume CWP replacement of cement in SCC and reported a slight reduction in slump flow accompanied by improvements in other fresh-state indicators, together with a modest reduction in compressive strength as replacement level increased. AlArab et al. [3] similarly found that combining CWP with blast furnace slag produced a pozzolanic binder system with improved thermal properties, while confirming that CWP's water absorption characteristics require the effective water content to be managed carefully to preserve workability. Khairi and Rejeb [4] evaluated combined ceramic and glass waste powders in SCC against EFNARC criteria across sixteen mixes and reported that both rheological and mechanical performance remained within acceptable limits at moderate replacement levels. A critical review by Viramgama, Vaniya, and Parikh [5] synthesised findings across multiple CWP-SCC studies, concluding that CWP generally reduces workability moderately while replacement levels below roughly 20% typically preserve compressive strength within an acceptable margin of the control mix; these findings are broadly consistent with observations for other waste powders used as fillers in SCC, including waste marble powder [6] and recycled glass powder [7], which show comparable trade-offs between flowability and strength depending on particle fineness and dosage.

Across this body of work, a recurring theme is that CWP's effect on SCC is not adequately summarised by compressive strength alone: fresh-state filling ability, passing ability, and segregation resistance are all mix-design-sensitive, and mechanical properties beyond compressive strength, notably tensile and flexural strength, do not always track compressive strength proportionally. This motivates the multi-output modelling approach adopted in the present study.

➢ *Machine Learning and Gaussian Process Regression for Concrete Property Prediction*

The application of machine learning to concrete property prediction has expanded substantially over the past decade, driven by the recognition that empirical mix-design formulae struggle to capture the non-linear, multi-factor interactions present in modern concretes containing SCMs and chemical admixtures. Artificial neural networks and RSM remain the most widely applied techniques for SCC specifically; comparative studies of RSM and ANN modelling for waste-modified concrete have found that

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RSM can outperform ANN when the available dataset is limited, attributing this to RSM's lower parameter count and correspondingly lower overfitting risk on small samples. Similarly, Ofuyatan et al. [9] applied both RSM and ANN to SCC containing silica fume and PET plastic waste and obtained comparably strong fits from both methods ($R2 \geq 0.92$), underscoring that method choice at small sample sizes should be guided by the bias-variance trade-off rather than by an a priori preference for more flexible models.

GPR has emerged as a particularly well-suited alternative for small, high-value experimental datasets in concrete research because, as a kernel-based non-parametric Bayesian method, it can represent smooth non-linear response surfaces without requiring the large sample sizes that neural networks typically need to avoid overfitting, while additionally returning a predictive variance at every query point [10]. Recent applications of GPR to concrete compressive strength prediction have consistently reported strong performance relative to competing algorithms: an enhanced GPR framework incorporating singular value decomposition and Kalman filtering for data pre-processing outperformed both ANN and standard regression for ultra-high-performance concrete, while requiring substantially less computation time than the ANN alternative [11]; and a large benchmarking study across six regression algorithms for steel-fibre-reinforced concrete found GPR to track non-linear strength trends, including a parabolic water-to-cement ratio effect, more accurately than support vector regression, random forest, extreme gradient boosting, ANN, and k-nearest neighbours [12]. GPR-based approaches have also been extended specifically to real-time compressive strength prediction in SCC [14], reflecting a growing recognition that SCC's sensitivity to mix proportioning makes it a natural candidate for surrogate modelling.

➢ *Small-Sample Modelling and Cross-Validation Practice*

A methodological issue common to nearly all experimental SCC datasets, including the present one, is that laboratory-scale mix design studies rarely exceed a few dozen mixes because of the cost and time required for full fresh- and hardened-property characterisation. Bušić et al. [8], for example, developed multivariate regression models for the mechanical properties of rubberised SCC from twenty-one experimentally tested mixes, a sample size identical to that used in this study, illustrating that meaningful predictive models can be built from datasets of this scale provided the validation strategy is chosen appropriately. The broader machine learning literature confirms that conventional single train/test splits are unreliable at small sample sizes because a single held-out subset gives a high-variance, potentially misleading estimate of generalisation performance [13]. Leave-one-out cross-validation addresses this by using every observation as a test case exactly once while training on all remaining observations, and is widely recommended specifically for small, expensive-to-collect datasets in materials science and engineering [13]. This study accordingly adopts LOOCV as the sole validation strategy, consistent with recommended practice for datasets of this size.

➢ *Research Gap*

While RSM and ANN have both been applied to SCC containing various waste-derived SCMs, and GPR has been increasingly validated for concrete compressive strength prediction in general, the literature reviewed above shows no prior application of GPR, validated through LOOCV, to the combined fresh- and mechanical-property prediction of CWP-based SCC across multiple curing ages and multiple strength measures simultaneously. This study addresses that gap by developing and rigorously validating independent GPR surrogate models for twelve fresh and mechanical properties of CWP-SCC from a compact, three-input mix design dataset, and by using the resulting LOOCV diagnostics to identify which properties are, and are not, adequately explained by cement content, CWP content, and w/b ratio alone.

III. MATERIALS AND METHODOLOGY

➢ *Dataset Description*

The dataset used in this study comprises twenty-one experimentally characterised SCC mixes in which 53-grade Ordinary Portland cement was partially replaced with ceramic waste powder (CWP) at seven replacement levels (0, 22.5, 45, 67.5, 90, 112.5, and 135 kg/m^3, corresponding to nominal replacement of 0-30% by mass of the 450 kg/m^3 total binder content) at each of three water-to-binder (w/b) ratios (0.40, 0.45, and 0.50), giving a 7 x 3 full-factorial mix design. The three inputs (cement content, CWP content, w/b ratio) are therefore not independent, since cement content and CWP content sum to a constant total binder content of 450 kg/m^3 within each w/b ratio group; this is a deliberate feature of the mix design, reflecting a like-for-like binder replacement study, and is accounted for by treating all three as joint inputs to the regression rather than assuming independence. The remaining input parameters – VMA content, coarse aggregate content and fine aggregate content are skipped from modelling as they have a constant value across all mix.

Table 1 Mix Design and Fresh-Property Dataset (n = 21)

Mix ID	Cement (kg/m^3)	CWP (kg/m^3)	w/b	Slump Flow (mm)	T_{500} (s)	V-Funnel (s)	L-Box (h2/h1)	Segregation (%)
M1	450	0	0.4	690	4.2	9.7	0.92	13
M2	427.5	22.5	0.4	700	4.1	9.2	0.94	12.2
M3	405	45	0.4	710	3.8	8.8	0.95	10.8
M4	382.5	67.5	0.4	710	3.8	8.7	0.93	10.6
M5	360	90	0.4	695	4	9.4	0.84	9.4
M6	337.5	112.5	0.4	670	4.2	10.6	0.82	8.8

M7	315	135	0.4	670	5.2	14.6	0.82	8.4
M8	450	0	0.45	755	3.5	8.3	0.94	14.8
M9	427.5	22.5	0.45	770	3.3	7.9	0.96	13.6
M10	405	45	0.45	775	2.8	7.8	0.97	11.2
M11	382.5	67.5	0.45	770	2.8	7.6	0.95	11.2
M12	360	90	0.45	765	3.3	9.2	0.85	11.2
M13	337.5	112.5	0.45	750	4	10.4	0.84	10.8
M14	315	135	0.45	740	5	12.3	0.83	10.4
M15	450	0	0.5	810	2.8	7.9	0.96	18.46
M16	427.5	22.5	0.5	820	2.5	7.7	0.98	18
M17	405	45	0.5	825	2.4	7.7	0.98	16.8
M18	382.5	67.5	0.5	830	2.3	7.3	0.99	13.6
M19	360	90	0.5	830	3.2	8.4	0.93	13
M20	337.5	112.5	0.5	800	3.6	9.8	0.87	12.6
M21	315	135	0.5	775	3.9	13.4	0.86	12.2

Twelve output properties were measured for each mix. Fresh-state properties, tested in accordance with EFNARC guidelines [1, 15], comprised slump flow (mm), T_{500} time (s), V-funnel time (s), L-box ratio (h2/h1), and segregation resistance (%). Mechanical properties comprised compressive strength at 7, 28, and 90 days (CS7, CS28, CS90, in MPa), split tensile strength at 7, 28, and 90 days (ST7, ST28, ST90, in MPa), and 28-day flexural strength (Flex28, in MPa).

Table 2 Mechanical Property Dataset (n = 21)

Mix ID	**CS7 (MPa)**	**CS28 (MPa)**	**CS90 (MPa)**	**ST7 (MPa)**	**ST28 (MPa)**	**ST90 (MPa)**	**Flex28 (MPa)**
M1	24.16	36.24	45.6	2.74	4.48	5.08	5.17
M2	23.6	38.05	50.16	2.62	4.25	4.77	5.59
M3	23.74	36.96	52.9	2.64	4.23	4.75	5.85
M4	22.9	35.08	49.25	2.55	4.25	4.77	5.07
M5	21.83	34.59	44.41	2.43	4.19	4.66	4.65
M6	20.63	33.53	43.49	2.29	4.06	4.51	4.2
M7	19.95	32.54	42.21	2.22	3.94	4.38	6.17
M8	21.64	32.46	40	2.47	3.03	3.73	5.32
M9	19.25	29.76	43.2	2.28	2.73	3.28	6.08
M10	18.98	29.66	44.4	2.3	2.72	3.21	4.97
M11	18.18	30.02	40.8	2.33	2.75	3.21	5.27
M12	17.53	28.89	37.6	2.32	2.74	3.2	4.84
M13	16.88	26.78	36.6	2.28	2.66	3.11	4.5
M14	15.58	25.32	32.8	2.21	2.59	3.02	4.17
M15	19.72	29.58	36.6	2.1	2.58	3.17	5.98
M16	15.91	25.39	34.62	1.88	2.17	2.51	5.45
M17	15.98	25.5	36.09	1.93	2.19	2.52	4.02
M18	16.36	26.11	34.73	1.97	2.23	2.58	4.8
M19	15.58	25.53	33.96	1.91	2.18	2.52	4.87
M20	15.05	23.96	33.19	1.86	2.09	2.41	4.77
M21	13.41	22.48	29.28	1.82	2.06	2.36	4.72

Table 3 Descriptive Statistics of the Mix Design Inputs and Fresh/Mechanical Output Properties (n = 21)

Variable	**Mean**	**SD**	**Min**	**Q1**	**Median**	**Q3**	**Max**
Cement (kg/m^3)	382.5	46.111	315	337.5	382.5	427.5	450
CWP (kg/m^3)	67.5	46.111	0	22.5	67.5	112.5	135
w/b ratio	0.45	0.042	0.4	0.4	0.45	0.5	0.5
Slump Flow (mm)	755.238	53.091	670	710	765	800	830
T_{500} (s)	3.557	0.792	2.3	2.8	3.6	4	5.2
V-Funnel (s)	9.367	1.972	7.3	7.9	8.8	9.8	14.6
L-Box (h2/h1)	0.911	0.059	0.82	0.85	0.93	0.96	0.99
Segregation (%)	12.431	2.753	8.4	10.8	12.2	13.6	18.46
CS7 (MPa)	18.898	3.222	13.41	15.98	18.98	21.64	24.16
CS28 (MPa)	29.925	4.623	22.48	25.53	29.66	33.53	38.05

CS90 (MPa)	40.09	6.339	29.28	34.73	40	44.4	52.9
ST7 (MPa)	2.245	0.275	1.82	1.97	2.28	2.43	2.74
ST28 (MPa)	3.053	0.873	2.06	2.23	2.73	4.06	4.48
ST90 (MPa)	3.512	0.936	2.36	2.58	3.21	4.51	5.08
Flex28 (MPa)	5.07	0.623	4.02	4.72	4.97	5.45	6.17

Prior to machine learning model development, an exploratory data analysis (EDA) was performed to evaluate the quality and statistical characteristics of the experimental dataset. The EDA included: verification of dataset completeness, descriptive statistical analysis, distribution analysis using histograms, boxplot-based outlier inspection, Pearson correlation analysis, correlation matrix visualization, and assessment of correlations between predictor and response variables. The dataset for the input and output variables are summarised in Tables 1 and 2, and no missing values were present in the dataset. Descriptive statistics, including the mean, standard deviation, minimum, maximum, and quartile values (Q1, median, Q3), were calculated for all fifteen variables (three mix design inputs and twelve fresh and mechanical output properties) to characterise the distribution, central tendency, and variability of the dataset prior to modelling. These statistics are reported in Table 3 and visualised in Figure 1, which presents grouped box plots with overlaid individual data points for each variable, organised by physical category and scale.

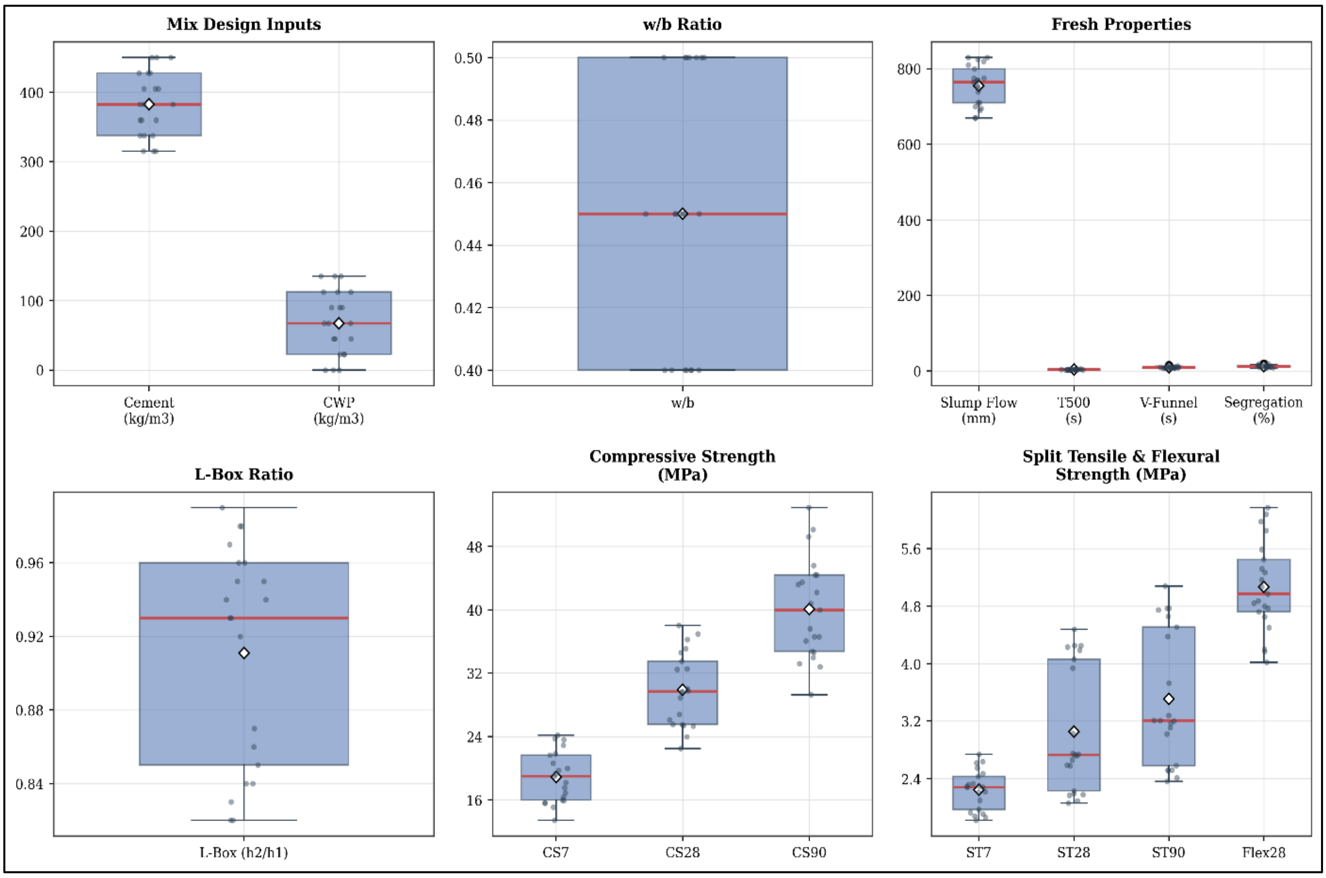

Fig 1 Distribution of the Mix Design Inputs and Fresh/Mechanical Output Properties. Box Limits Show the Interquartile Range (Q1-Q3); the Horizontal Red Line Marks the Median and the White Diamond Marks the Mean; Whiskers Extend to 1.5x the Interquartile Range; Individual Jittered Points Show all 21 Observations; Open Circles Beyond the Whiskers Denote Statistical Outliers.

The two mix design inputs, cement and CWP content, are perfectly complementary by construction (both range 0-450 kg/m^3 with equal and opposite means, since they sum to a constant 450 kg/m^3 total binder content), while w/b ratio spans a narrower, evenly distributed range of 0.40-0.50. Among the fresh properties, slump flow (mean 755 mm, SD 53 mm) and segregation resistance show the widest relative spread, while L-box ratio is comparatively tightly clustered around its median of 0.93, consistent with all mixes broadly meeting EFNARC passing-ability criteria [1]. Compressive strength shows the expected increase in both mean and absolute spread with curing age (CS7 mean 18.9 MPa, SD 3.2 MPa; CS90 mean 40.1 MPa, SD 6.3 MPa), while split tensile strength follows a similar pattern at a much smaller absolute scale. Flex28 shows the narrowest interquartile range among the mechanical properties in absolute terms (Q1 = 4.72, Q3 = 5.45 MPa) but, as discussed in Section 6, this narrow, comparatively noisy distribution is itself

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consistent with the weak explanatory relationship between Flex28 and the three mix design inputs identified later through LOOCV.

➢ *Data Pre-Processing*

The three input variables (cement content, CWP content, w/b ratio) differ substantially in scale and were therefore standardised (zero mean, unit variance) prior to model fitting. To prevent information leakage from the held-out point into the scaling transformation, the standardisation parameters were re-computed from only the training fold at each iteration of the cross-validation procedure, rather than being fixed once from the full dataset. Each output variable was likewise standardised prior to fitting its corresponding GPR model, and predictions were transformed back to the original physical units before evaluation.

IV. MODELS USED

➢ *Gaussian Process Regression*

Gaussian Process Regression (GPR) is a non-parametric, Bayesian regression method that models the target function as a distribution over functions constrained by a covariance (kernel) function [10]. Rather than fitting a fixed set of parameters as in linear or polynomial regression, GPR defines a prior distribution over possible functions relating the inputs to the output, and updates this prior using the observed training data to obtain a posterior predictive distribution at any query point. This predictive distribution is fully characterised by a mean, which serves as the point prediction, and a variance, which quantifies the model's uncertainty in that prediction; the variance is small near densely sampled regions of the input space and grows in sparsely sampled or extrapolated regions, which is a key practical advantage of GPR over deterministic methods such as standard ANN or RSM point-estimate models.

In this study, an independent GPR model was fitted for each of the twelve output properties, using the three standardised mix design variables (cement content, CWP content, w/b ratio) as inputs. A composite kernel was used, consisting of a constant (amplitude) term multiplied by a Matern kernel with smoothness parameter υ = 2.5, plus an additive white-noise kernel to absorb measurement and process noise:

$$k(x,x') = \sigma_f^2 * Matern_{2.5}(x,x';\, l) + \sigma_n^2 * \delta(x,x')$$

Where σ_f^2 is the signal variance, is a vector of automatic relevance determination (ARD) length-scales (one per input dimension, allowing the model to learn the relative sensitivity of each output to cement content, CWP content, and w/b ratio independently), is the noise variance, and δ is the Kronecker delta. The Matern 5/2-family kernel was selected over the smoother squared-exponential (RBF) kernel because it makes a less restrictive smoothness assumption, which is generally preferable when the true functional form of a physical response surface is unknown. All kernel hyperparameters (σ_f^2, l, σ_n^2) were optimised by maximising the log marginal likelihood of the training data at each cross-validation fold, using ten random restarts of the optimiser to reduce the risk of convergence to a poor local optimum.

➢ *Leave-One-Out Cross-Validation*

Given the sample size of twenty-one mixes, a conventional single train/test split was judged unsuitable, since holding out even 20% of the data (four to five mixes) as a fixed test set would leave too few points to reliably characterise generalisation performance, while also discarding data that could otherwise inform the fitted model. Leave-one-out cross-validation (LOOCV) was therefore adopted as the sole validation strategy, consistent with established practice for small experimental and materials-science datasets [13]. For each output property, the LOOCV procedure trained a GPR model on twenty of the twenty-one mixes and predicted the property value, together with its 95% confidence interval, for the single held-out mix; this was repeated twenty-one times so that every mix served as the test case exactly once, and the twenty-one out-of-fold predictions were pooled to compute the reported performance metrics. Because the input scaling and kernel hyperparameter optimisation were both re-fitted within each fold using only the training data for that fold, the reported LOOCV metrics provide an honest, leakage-free estimate of how each model would be expected to perform on a genuinely new mix within the tested design space.

➢ *Performance Metrics*

Four metrics were computed from the pooled LOOCV predictions for each output property: the coefficient of determination (R^2), the root mean squared error (RMSE), the mean absolute error (MAE), and a normalised RMSE (NRMSE), expressed as RMSE divided by the observed range of that property across the twenty-one mixes and reported as a percentage. The NRMSE metric was included specifically because the twelve output properties span very different physical scales and units (for example, L-Box ratio ranges over approximately 0.17 while CS90 ranges over approximately 24 MPa), making RMSE alone unsuitable for comparing relative model performance across properties.

V. RESULTS

Table 4 summarises the LOOCV performance of the twelve GPR models, ordered by descending R^2. Figure 2 presents the corresponding predicted-versus-actual scatter plots for all twelve properties, with error bars showing the 95% confidence interval of each GPR prediction and a dashed 1:1 line indicating perfect agreement.

Eleven of the twelve output properties were predicted with LOOCV R^2 between 0.80 and 0.99. The strongest performance was obtained for slump flow (R^2 = 0.988, NRMSE = 3.5%) and 28-day split tensile strength (R^2 = 0.988, NRMSE = 3.8%), followed closely by 90-day split tensile strength (R^2 = 0.980), 7-day split tensile strength (R^2 = 0.964), segregation resistance (R^2 = 0.956), 90-day compressive strength (R^2 = 0.955), 28-day compressive strength (R^2 = 0.951), 7-day compressive strength (R^2 = 0.930), and L-box ratio (R^2 = 0.922). T_{500} time (R^2 = 0.861)

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and V-funnel time (R^2 = 0.805) were predicted with somewhat lower, but still practically useful, accuracy; both are viscosity-related measures known to be sensitive to small variations in VMA dosage, water absorption of CWP and mixing consistency that are not captured by the three modelled inputs, which likely explains their comparatively higher NRMSE values (9.9% and 11.6% respectively).

Table 4 LOOCV Performance of GPR Models for All Twelve Output Properties

Output Property	LOOCV R2	RMSE	MAE	NRMSE (% of Range)
Slump Flow (mm)	0.988	5.59	4.49	3.5
T_{500} (s)	0.861	0.29	0.22	9.9
V-Funnel (s)	0.805	0.85	0.59	11.6
L-Box (h2/h1)	0.922	0.02	0.01	9.5
Segregation (%)	0.956	0.56	0.43	5.6
CS7 (MPa)	0.930	0.83	0.45	7.8
CS28 (MPa)	0.951	1.00	0.64	6.4
CS90 (MPa)	0.955	1.31	0.98	5.5
ST7 (MPa)	0.964	0.05	0.04	5.6
ST28 (MPa)	0.988	0.09	0.05	3.8
ST90 (MPa)	0.980	0.13	0.06	4.8
Flex28 (MPa)	-0.407	0.72	0.51	33.5

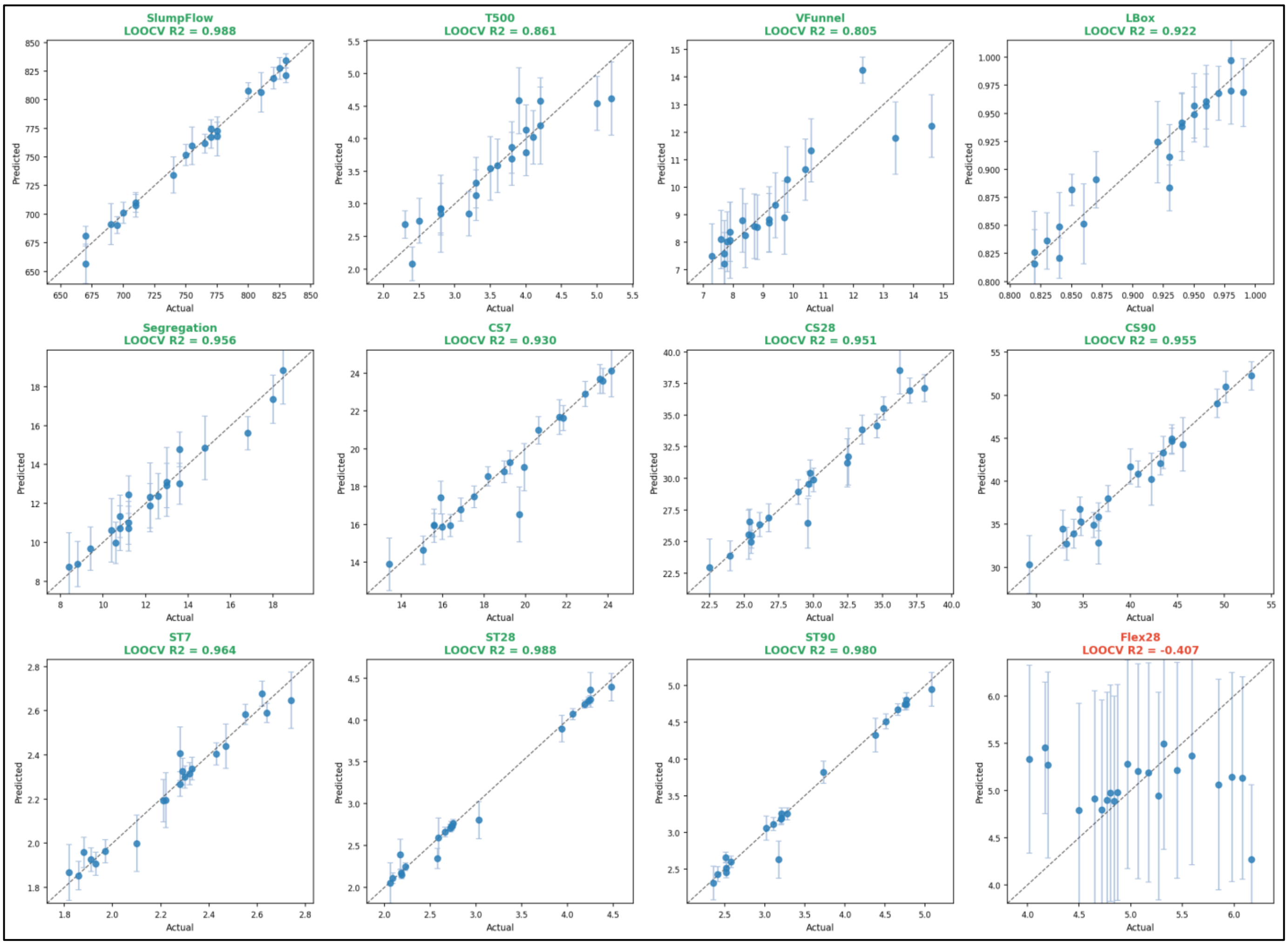

Fig 2 Predicted vs. Actual LOOCV Plots for All Twelve Output Properties. Error Bars Show the 95% Confidence Interval of the GPR Prediction; the Dashed Line Indicates Perfect Agreement (1:1).

Twenty-eight-day flexural strength (Flex28) was a clear outlier: its LOOCV R^2 was negative (-0.407), meaning the GPR model performed worse than simply predicting the sample mean for every held-out mix, and its NRMSE (33.5%) was three to ten times higher than that of every other property. Examination of the raw data shows that flexural strength correlates only weakly with cement content (Pearson r = 0.47) and CWP content (r = -0.47), and only

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weakly with 28-day compressive strength within the same dataset (r = 0.41), despite compressive and flexural strength typically being strongly correlated in concrete. Two mixes in particular deviate from the local trend suggested by neighbouring mixes: mix M7 (315 kg/m^3 cement, 135 kg/m^3 CWP, w/b = 0.40) records the highest flexural strength value in the dataset (6.17 MPa) despite having the lowest cement content among its w/b group, and mix M9 (427.5 kg/m^3 cement, 22.5 kg/m^3 CWP, w/b = 0.45) records a comparably high value (6.08 MPa) that is not matched by its compressive strength ranking. These patterns indicate that flexural strength in this dataset is governed substantially by factors outside the three modelled mix design variables, and/or reflects test variability characteristic of flexural strength measurement, which is known to be more sensitive to specimen preparation and loading configuration than compressive strength.

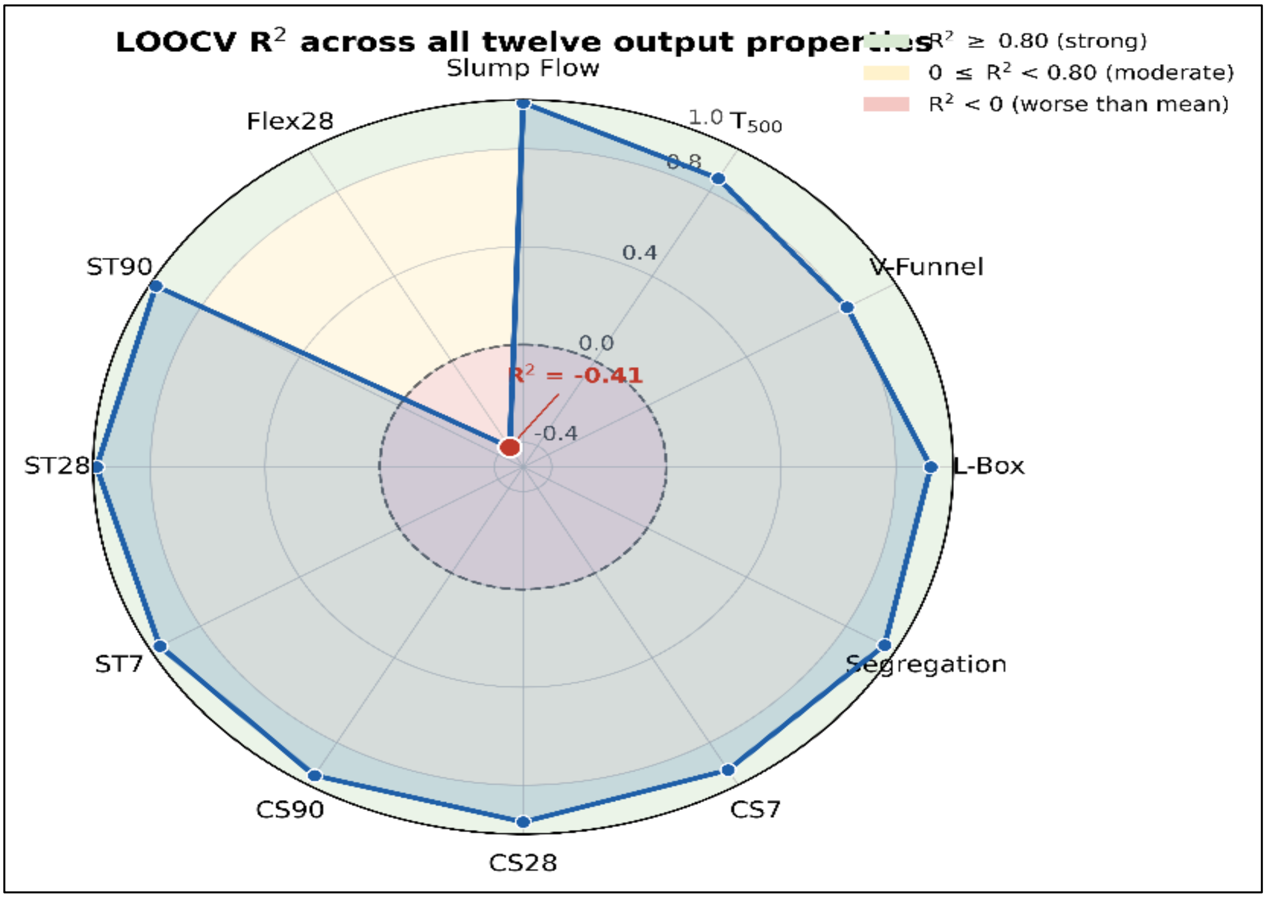

Fig 3 LOOCV R² Values Across All Properties

VI. DISCUSSION

The results demonstrate that GPR, validated through LOOCV, provides an accurate and appropriately uncertainty-aware surrogate model for the majority of fresh and mechanical properties of CWP-based SCC from a compact, three-input mix design dataset. The consistently strong performance across compressive strength at all three curing ages (R^2 = 0.93-0.96), split tensile strength at all three curing ages (R^2 = 0.96-0.99), slump flow (R^2 = 0.99), L-box ratio (R^2 = 0.92), and segregation resistance (R^2 = 0.96) indicates that cement content, CWP content, and w/b ratio jointly explain the dominant share of variability in these properties within the tested design space, consistent with the physical expectation that binder content and effective water content are the primary governing variables for both flowability and strength development in this mix family. The comparatively lower, though still acceptable, performance for T_{500} and V-funnel time is consistent with the wider concrete literature, which identifies these viscosity-related measures as more sensitive to superplasticiser/VMA dosage, mixing time, and ambient temperature than to binder proportioning alone [1, 15].

The negative LOOCV R^2 obtained for flexural strength is the most consequential finding of this study from a research-design perspective. In predictive modelling generally, a negative R^2 does not indicate a coding or fitting error but rather demonstrates that the model, even with hyperparameters optimised via marginal likelihood, cannot extract a signal from the three inputs that outperforms the trivial mean-prediction baseline. Three non-exclusive explanations are consistent with the observed data. First, flexural strength may be more strongly influenced by variables not captured in this dataset, such as aggregate interlock, fibre content (if any), curing consistency, or specimen geometry, than by cement, CWP, and w/b ratio. Second, flexural strength testing is inherently more variable than compressive strength testing because of its sensitivity to specimen surface preparation, loading rate, and support

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conditions, and this measurement noise may simply exceed the signal available from three coarse mix design variables at only twenty-one samples. Third, the two locally anomalous identified mixes (M7 and M9) may reflect either genuine non-monotonic material behaviour, for example a beneficial pozzolanic contribution from CWP to flexural performance at specific replacement levels, or data recording variability that would benefit from re-testing.

From a methodological standpoint, this outcome illustrates a broader value of LOOCV beyond simple performance reporting: because LOOCV evaluates every data point as an independent test case, it surfaces properties for which the available inputs are insufficient, which a single train/test split, or worse, an in-sample R^2 computed only on training data, could mask. Reporting only training-set fit for flexural strength would have produced a misleadingly favourable impression of predictive capability; the LOOCV diagnostic instead correctly identifies this property as requiring either additional input variables or a larger, more targeted dataset before a reliable predictive model can be built.

Compared with RSM and ANN approaches reported elsewhere for SCC containing waste-derived SCMs, which typically report R^2 in the range of 0.91-0.99 for mechanical properties when evaluated on training or single-split test data [9], the LOOCV-based R^2 values obtained here for GPR (0.80-0.99 for eleven of twelve properties) are directly comparable in magnitude while being derived from a more conservative, leakage-resistant validation scheme. This suggests that GPR is at least competitive with, and arguably more information-rich than, these more commonly applied methods for small SCC datasets, particularly because of its native predictive uncertainty, which RSM and standard ANN implementations do not provide without additional bootstrapping or ensembling.

Several limitations of this study should be acknowledged. The dataset is confined to a single ceramic waste source, a single superplasticiser system (implicitly), and a full-factorial design in which cement and CWP content are linearly dependent within each w/b group; the fitted models should therefore not be extrapolated to CWP sources with substantially different particle size distribution or pozzolanic reactivity, nor to binder contents outside the 315-450 kg/m^3 range tested. The sample size of twenty-one, while adequate for LOOCV-validated GPR modelling of most properties studied, remains small in absolute terms, and the flexural strength result in particular indicates that some properties may require additional inputs or observations before a reliable predictive model can be established. Finally, GPR with an ARD kernel provides some indication of relative input sensitivity through its fitted length-scales, but does not provide the same direct mechanistic interpretability as RSM's explicit polynomial coefficients; future work could usefully combine GPR's predictive accuracy with RSM or SHAP-based sensitivity analysis for a more complete picture of the underlying structure-property relationships.

VII. CONCLUSION

This study developed and validated Gaussian Process Regression models for twelve fresh and mechanical properties of ceramic-waste-powder self-compacting concrete, using a dataset of twenty-one experimentally characterised mixes and leave-one-out cross-validation as the sole performance evaluation strategy. The principal conclusions are as follows.

- GPR combined with a Matern 5/2 kernel and LOOCV validation successfully predicted eleven of the twelve studied properties with R^2 between 0.80 and 0.99, demonstrating that cement content, CWP content, and w/b ratio are sufficient inputs to characterise slump flow, T_{500} time, V-funnel time, L-box ratio, segregation resistance, compressive strength at 7, 28, and 90 days, and split tensile strength at 7, 28, and 90 days, within the design space tested.
- The 28-day flexural strength (Flex28) could not be reliably predicted from the same three inputs (LOOCV R2 = -0.41), indicating that this property is governed by factors outside the tested mix design variables or is subject to a level of test variability that the available sample size cannot resolve; this result is presented as a genuine finding rather than a modelling shortfall, and is attributed to the weak underlying correlation between flexural strength and the three inputs observed directly in the raw data.
- LOOCV proved essential, rather than optional, at this sample size: it provided an honest, leakage-free performance estimate for each property and, critically, was able to distinguish reliably modellable properties from Flex28, a distinction that in-sample fit metrics would likely have obscured.
- GPR's native predictive uncertainty offers a practical advantage over deterministic RSM or ANN point-estimate models for mix-design decision support, since it allows a practitioner to gauge confidence in a predicted property value, particularly when proposing new mixes near the edges of the tested design space.
- For future work, expanding the dataset with additional mixes, incorporating superplasticiser/VMA dosage and aggregate characteristics as explicit inputs, and specifically targeting additional flexural strength observations around the two anomalous mixes identified in this study, would be valuable next steps toward a fully reliable multi-output predictive framework for CWP-based SCC. Extending the comparison to include RSM and ANN under the same LOOCV protocol would also allow a direct, leakage-controlled benchmarking of predictive methods for this class of small, high-value experimental datasets.

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