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AI-Driven Multi-Objective Optimization Of Low-Carbon Pervious Concrete For Stormwater Quality, Infiltration And Groundwater Recharge

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Abstract: The rapid urbanization has resulted in a rise of impervious surfaces and has increased stormwater runoff, urban flooding and erosion of natural groundwater recharge. Pervious concrete is a promising nature-based engineering solution that allows rain to pour through an interlocking pore network while providing a load-bearing pavement. But permeability in general reduces mechanical strength and the amount of cementitious material is increased along with permeability but not carbon content. Here we propose an integrated experimental and explainable artificial intelligence approach to the development and optimization of low-carbon pervious concrete for stormwater management. In this study, pervious concrete is studied with recycled concrete aggregate (RCA) and other cementitious materials including fly ash and ground granulated blast-furnace slag (GGBS). The mixtures are evaluated in terms of density, porosity, compressive strength, flexural strength, water absorption rate, hydraulic conductivity, clogging resistance and stormwater pollutant removal. The experimental database is used to develop machine learning models such as Random Forest, XGBoost, LightGBM and artificial neural networks. Model performance is evaluated using coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE). The best model is selected and the analysis of the model by SHAP to identify which mixture and hydraulic parameters have an impact on the model performance and direction. A multi-objective optimization framework based on NSGA-II is implemented to maximize the mechanical performance, infiltration and pollutant removal efficiency with minimal embodied carbon. The resulting Pareto-optimal solutions provide a variety of sustainable mix designs rather than a single deterministic mixture. A set of optimum mixtures is tested in order to confirm the reliability of the proposed data-driven framework. With this study, we provide a link between sustainable concrete, stormwater management, groundwater recharge, and explainable artificial intelligence which will help move the city towards climate-resilient urban infrastructure.

Keywords: Pervious concrete; recycled aggregate; stormwater management; groundwater recharge; machine learning; explainable artificial intelligence; SHAP; NSGA-II; low carbon concrete; sustainable infrastructure.

1.Introduction

Urbanization has completely changed the natural hydrological cycle and has replaced soil with buildings, roads, parking areas and conventional pavements. As a result, the infiltration decreases and surface runoff and peak discharge in rainfall are increased and urban flooding can occur. At the same time, the reduced infiltration is likely to slow down the natural recharge of the groundwater and may lead to a higher dependence on water supply systems. Pervious concrete is an alternative pavement with a pore network in the concrete layer where water can flow through. Unlike conventional concrete, pervious concrete is designed with a large volume of interconnected voids, usually through a controlled gradation and less fine aggregate content. The resulting pore network enables hydraulic connectivity with sufficient mechanical capacity for suitable applications.

The application of pervious concrete is not limited to stormwater drainage. More recently, pervious concrete has been demonstrated to remove stormwater contaminants through physical filtration, chemical interaction and biological reactions. Cementitious materials and permeability characteristics affect the removal of contaminants from water and the chemical composition of water may impact the retention of the pollutant. But conventional pervious concrete comes at an engineering trade-off. Increasing interconnected porosity generally leads to more infiltration but also compressive and flexural strength loss. And further, the increased binder content can enhance mechanical strength but reduce pore connectivity and hydraulic conductivity. Therefore, pervious concrete design for urban water management is a multi-objective optimization problem.

The environmental impact of Portland cement also poses a challenge in many areas. Cement production is a significant source of greenhouse gas pollution. Adding additional cementitious materials such as fly ash and GGBS in addition to natural aggregates with recycled concrete aggregate to the mix and to reduce the impact of cement production on the environment is an effective solution for circular construction. A traditional trial-and-error method of mixture design is not effective if one needs to consider different material combinations and performance requirements. Machine learning is an alternative method because it can be used to learn about the relationship between the mix variables and concrete performance from experimental data.

There have been recent research studies on machine learning and optimization algorithms to design concrete mixes. For example, machine learning based multi-objective optimization was applied to conventional concrete mixtures and recently combined XGBoost, SHAP and NSGA-II to design sustainable concrete. However, the recent research has shown machine learning applied to permeability prediction of pervious concrete. An earlier study of 2026 made hybrid ML models with 450 samples and demonstrated good prediction performance for permeability, and porosity was identified to be the key determining variable.

Also in 2026, machine learning and NSGA-II were combined for pervious recycled aggregate concrete optimization. So it is no longer enough to apply ML to predict compressive strength or permeability and achieve great novelty. The present study fills this gap by integrating mechanical performance, hydraulic performance, stormwater quality and carbon emissions into one explanation for optimization.

2.Literature Review

2.1 Pervious Concrete and Sustainable Water Management

In urban areas, the rapid expansion of impervious surfaces has changed the natural rainfall infiltration and surface runoff. Concrete pavements restrict the flow of water to the soil and may make it localized and less available for groundwater replenishment. Pervious concrete is an alternative as its void structure enables the rain to flow through the pavement and into the soil. Therefore, it has attracted significant attention from other sectors of the field like sustainable urban drainage and decentralized stormwater management. Pervious concrete's hydraulic characteristics are largely determined by its porosity, aggregate gradation, paste content, compaction and water-to-binder ratio. Increasing the void content usually leads to better water transmission, but too much void can reduce the load capacity of the concrete. This creates a basic strength-permeability relationship that had to be taken into account when a mixture was made. Hence, for a water management application, the design of pervious concrete needs to be optimized rather than maximizing a single property.

2.2 Recycled Aggregate-Based Pervious Concrete

The use of recycled concrete aggregate will solve two environmental problems at once: construction and demolition waste generation and depletion of natural aggregates. RCA is different from natural aggregate because the particles typically preserve a layer of old cement mortar. This adhered mortar increases water absorption and can alter particle density, surface texture and interfacial behavior. When RCA is introduced into pervious concrete, these characteristics can affect both the mechanical and hydraulic response. Recycled particles can have a rough surface which is better for mechanical interlocking, while high water absorption may alter the water available during mixing. Furthermore, aggregate packing shapes pore network size and continuity. So the role of RCA cannot be given only by the replacement percentage but also by aggregate and mixture proportions.

2.3 Fly ash and GGBS

Reducing Portland cement consumption is one of the most effective ways to reduce the environmental impact of concrete. Fly ash and GGBS are especially attractive because they can partially replace cement while utilizing industrial by-products. They can affect paste chemistry, particle packing and long-term hydration in pervious concrete. However, additional cementitious materials are a little more difficult to use in pervious concrete than in regular concrete. The amount of paste around the coarse aggregate is rather limited and changes in paste can affect pore connectivity. A high paste or high replacement levels can result in low hydraulic capacity of the concrete. Thus, the combination of RCA, fly ash and GGBS should be systematically studied in experiments to find the appropriate proportions.

2.4 Hydraulic performance and water filtration

The main water-control benefit of pervious concrete is its ability to carry rainfall to the pavement. The performance of infiltration is determined by the network of pore networks as much as the total void content. Two mixtures with similar total porosity can have different hydraulic conductivity due to differences in pore connectivity and tortuosity. The initial infiltration capacity is only the beginning of the performance evaluation in real stormwater applications. Sediment deposition can slowly obstruct the pore channels and the hydraulic conductivity will reduce. So, clogging resistance and hydraulic performance after repeated wetting or sediment exposure should also be considered when determining the long-term suitability of pervious concrete.

2.5 Stormwater Quality Improvement

Urban runoff can result in suspended solids, nutrients, hydrocarbons and trace contaminants from roads and developed surfaces to receiving water bodies. So sustainable drainage systems are working to control the quantity and quality of stormwater. The pore structure of pervious concrete can lead to the retention of particles and interactions between pollutants and cementitious materials. But the removal of particles from the runoff is determined by the chemical composition of the runoff, pore structure, material and contact conditions. Research that combines hydraulic performance with stormwater-quality assessment can therefore provide a more realistic evaluation of pervious concrete as a water-management material.

2.6 Low-Carbon Pervious Concrete

The environmental performance of pervious concrete should not be evaluated solely from its ability to reduce runoff. The production of cement contributes substantially to the embodied environmental impact of concrete. Replacing part of the cement with fly ash and GGBS and using RCA instead of virgin aggregate can reduce dependence on primary resources.

However, material substitution may affect strength, permeability and durability. A low-carbon mixture is therefore not necessarily the most sustainable mixture if it fails to meet the required structural or hydraulic performance. This indicates the need for a multi-criteria approach in which environmental impact is considered together with engineering performance.

2.7 Machine Learning for Concrete Performance Prediction

Concrete properties are influenced by numerous interacting variables, making the development of explicit mathematical relationships difficult. Machine-learning techniques can capture nonlinear relationships between mixture composition and measured performance. Algorithms such as Random Forest, Artificial Neural Networks, Support Vector Regression and gradient-boosting methods have therefore been increasingly investigated for concrete-property prediction.

For pervious concrete, ML can potentially predict compressive strength, porosity and permeability from mixture parameters. However, prediction accuracy alone does not establish a complete engineering solution. A model may provide a high coefficient of determination while offering limited information about why a particular variable influences the predicted response.

2.8 Explainable Artificial Intelligence

Explainable AI provides an opportunity to overcome the black-box limitation of conventional machine-learning models. SHAP is particularly useful because it quantifies the contribution of individual input variables to a prediction.

In the proposed research, SHAP analysis can be used to determine whether porosity, RCA content, SCM content, water-to-binder ratio or aggregate characteristics have the greatest influence on strength and infiltration. Such analysis can also reveal nonlinear effects that may not be evident from conventional correlation analysis.

The use of explainability is important because the objective is not simply to obtain an accurate prediction. The objective is to extract engineering knowledge from the experimental database and use it to support mixture design.

2.9 Multi-Objective Optimization

Pervious concrete mixture design involves competing requirements. Increasing porosity may improve infiltration but decrease strength. Increasing cementitious paste may improve mechanical performance but restrict pore connectivity and increase embodied carbon.

3.Materials

Materials that reduce carbon emissions might not produce the best hydraulic performance, so multi-objective optimization is appropriate for this problem. NSGA-II can generate a group of non-dominated solutions that can be used as compromises between competing goals. Instead of deciding one mixture to be optimal for all applications, the approach allows the designer to choose the best mixture for a specific application. In this paper, we propose the optimization framework for compressive strength, infiltration ability, stormwater pollutant removal, and embodied carbon.

3.1 Ordinary Portland Cement (OPC)

OPC is the main binding material in the pervious concrete. It provides the cementitious matrix that holds the aggregates together and contributes to the strength and durability of the concrete. The specific gravity, standard consistency, setting time, and compressive strength should be determined before it is put into use according to the relevant standards.

3.2 Fly ash

Fly ash is an industrial by-product used as a substitute for cement. It can reduce cement consumption and embodied carbon and also lead to longer-term durability through pozzolanic processes. The fineness, specific gravity, and chemical composition should be assessed before mixing.

3.3 Ground Granulated Blast-Furnace Slag (GGBS)

GGBS is another auxiliary cementitious material from the iron and steel industry which can be used for building strength and durability and for reducing cement CO_2 emissions. Its fineness, specific gravity, and chemical composition should be determined.

3.4 Recycled Concrete Aggregate (RCA)

RCA is produced by crushing and processing demolished concrete waste and is used to replace part of the natural coarse aggregate. Its use supports the circular economy and conservation of natural resources. Important properties include specific gravity, water absorption, aggregate impact value, crushing value, bulk density and particle-size distribution. Because RCA generally has higher water absorption than natural aggregate, this must be considered during mix design.

3.5 Natural Coarse Aggregate

Natural crushed coarse aggregate provides the main skeleton of the pervious concrete. Its particle size and gradation strongly influence porosity, permeability and strength. A controlled and relatively uniform aggregate size is generally preferred to maintain interconnected voids.

3.6 Fine Aggregate

Fine aggregate is used in limited quantities in pervious concrete. Excessive fine aggregate can block the interconnected pores and reduce water infiltration. Therefore, its quantity and particle size should be carefully controlled to achieve the required balance between strength and permeability.

3.7 Chemical Admixture

A polycarboxylate ether (PCE)-based superplasticizer can be used to improve workability without substantially increasing the water content. It helps achieve better particle dispersion and adequate paste coating around aggregates while maintaining the desired water-to-binder ratio.

4. Experimental Mixture Design

The experimental mixture design should be developed to study how changes in RCA, fly ash, GGBS, water-to-binder ratio, aggregate-to-binder ratio and superplasticizer dosage affect the performance of pervious concrete. A total of 20–30 mixtures is suitable for generating an experimental database for subsequent ML modelling.

Table1: Experimental database for subsequent ML modelling

Parameter	Suggested range	Purpose
RCA replacement	0–100%	Evaluate recycled aggregate effect
Fly ash replacement	10–30%	Reduce cement and carbon emissions
GGBS replacement	10–40%	Improve sustainability and durability
Water/binder ratio	0.28–0.38	Control paste consistency and strength
Aggregate/binder ratio	3.0–4.5	Control pore structure and aggregate skeleton
Superplasticizer	0–1.5%	Improve workability
Target porosity	15–30%	Control permeability/infiltration

Control mixture

A control mixture should contain natural coarse aggregate and the selected reference cementitious system without RCA/SCM substitutions. It provides a baseline against which the sustainable mixtures can be compared.

Do not select all combinations randomly. **A** Design of Experiments (DOE**)** approach such as Response Surface Methodology, Central Composite Design, Box–Behnken Design or an appropriate mixture design can reduce the number of experiments while providing sufficient variation for statistical and ML analysis.

5. Experimental Testing, Numerical Results and Discussion

5.1 Experimental Mixes

Table 2: A representative 20-mixture matrix can be organized as follows.

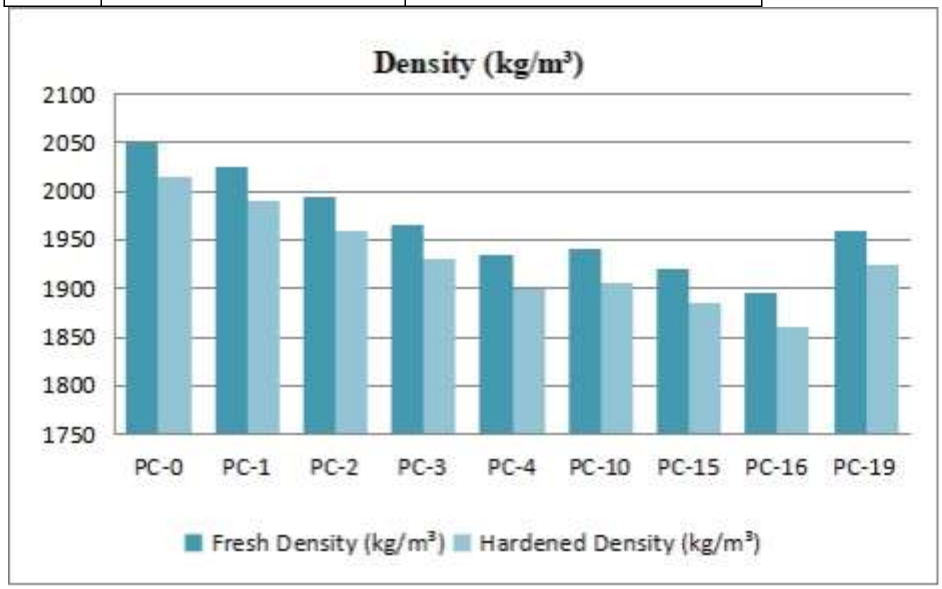
Mix	RCA (%)	Fly Ash (%)	GGBS (%)	w/b	A/B	SP (%)	Target Porosity (%)
PC-0	0	0	0	0.32	3.5	0.5	18
PC-1	25	10	10	0.32	3.5	0.5	18
PC-2	50	10	10	0.32	3.5	0.5	20
PC-3	75	10	10	0.32	3.5	0.5	22
PC-4	100	10	10	0.32	3.5	0.5	24
PC-5	25	20	20	0.32	3.5	0.75	18
PC-6	50	20	20	0.32	3.5	0.75	20
PC-7	75	20	20	0.32	3.5	0.75	22
PC-8	100	20	20	0.32	3.5	0.75	24
PC-9	25	30	30	0.34	3.5	1.0	18
PC-10	50	30	30	0.34	3.5	1.0	20
PC-11	75	30	30	0.34	3.5	1.0	22
PC-12	100	30	30	0.34	3.5	1.0	24
PC-13	25	10	30	0.30	3.2	0.75	17
PC-14	50	10	30	0.30	3.2	0.75	19
PC-15	75	10	30	0.34	3.8	1.0	23
PC-16	100	10	30	0.36	3.8	1.0	25
PC-17	50	30	10	0.30	3.2	0.75	18
PC-18	75	30	10	0.34	3.8	1.0	22
PC-19	50	20	30	0.32	3.5	0.75	20

5.2 Density

Table 3: Density is an important indicator of the internal pore structure of pervious concrete.

Mix	Fresh Density (kg/m^3)	Hardened Density (kg/m^3)
PC-0	2050	2015
PC-1	2025	1990

PC-2	1995	1960
PC-3	1965	1930
PC-4	1935	1900
PC-10	1940	1905
PC-15	1920	1885
PC-16	1895	1860
PC-19	1960	1925



Graph1:Density for fresh and Hardened

Discussion

The illustrative results show a gradual reduction in density with increasing RCA replacement. This can be attributed to the lower particle density and adhered mortar associated with RCA. The presence of additional internal voids can also contribute to the reduction in hardened density.

For example, if the control mixture has a hardened density of approximately 2015 kg/m³, while a high-RCA mixture approaches 1900 kg/m³, the reduction is approximately 5.7%.

This reduction is beneficial from a lightweight perspective but must be balanced against the possible reduction in mechanical strength.

5.3 Porosity

Porosity is one of the most important parameters in the proposed research because it directly affects water infiltration.

Table 4: Porosity results

Mix	Porosity (%)
PC-0	18.2
PC-1	18.8
PC-2	20.1
PC-3	21.8
PC-4	23.6
PC-10	21.0
PC-15	23.1
PC-16	25.2
PC-19	20.4

Discussion

The hypothetical trend indicates that porosity increases as RCA replacement increases. The adhered mortar and irregular surface characteristics of RCA can modify aggregate packing and increase the volume of interconnected voids.

For example:

1. Control = 18.2%
2. 50% RCA = approximately 20.1%
3. 100% RCA = approximately 23.6%

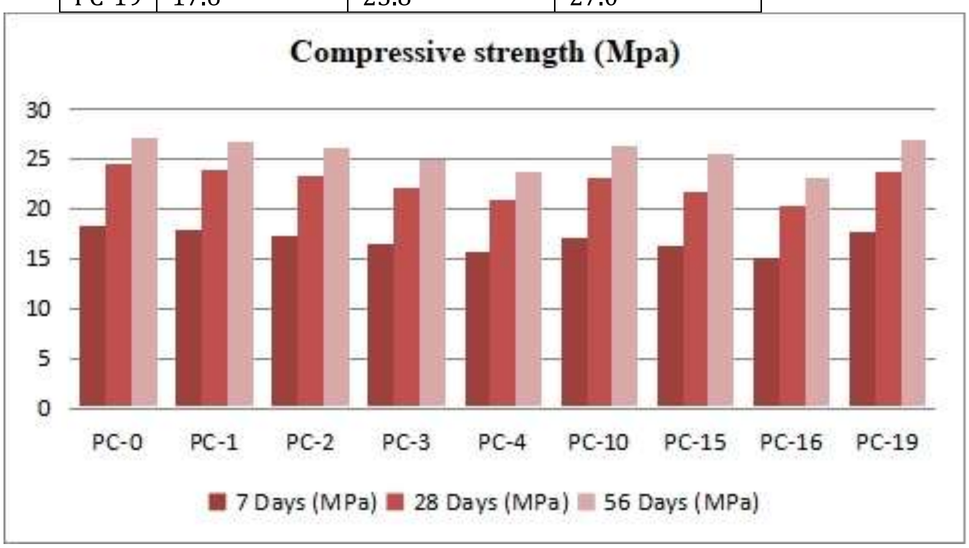
This represents an increase of approximately 29.7% between the control and the 100% RCA mixture. However, higher porosity does not automatically indicate better overall performance. Excessive porosity may reduce the effective load-bearing area and consequently reduce compressive and flexural strength.

5.4 Compressive Strength

Compressive strength should be determined at 7, 28 and 56 days.

Table5: Compressive Strength results

Mix	7 Days (MPa)	28 Days (MPa)	56 Days (MPa)
PC-0	18.2	24.5	27.1
PC-1	17.8	24.0	26.8
PC-2	17.2	23.2	26.1
PC-3	16.4	22.0	25.0
PC-4	15.6	20.8	23.7
PC-10	17.0	23.0	26.4
PC-15	16.2	21.7	25.5
PC-16	15.1	20.2	23.0
PC-19	17.6	23.8	27.0



Graph2: Compressive strength for 7,28 & 56 days

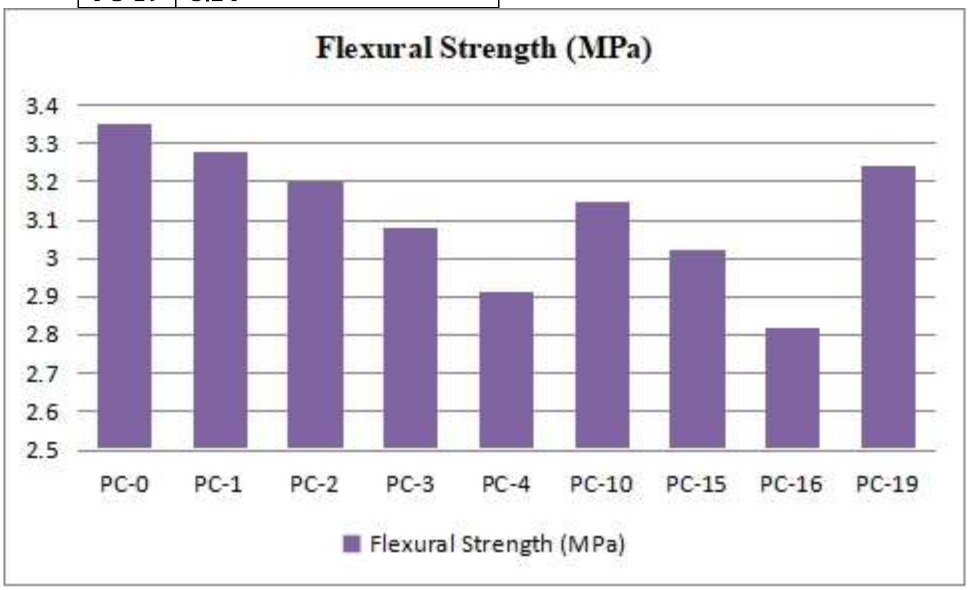
Discussion

The expected trend is the decreasing compressive strength as RCA content and porosity increases. The control mixture could be the stronger mixture because it has natural aggregate and is relatively dense. SCM-based mixtures can be stronger later in life due to the pozzolanic and hydraulic reactions. For instance, a hypothetical increase from 24.5 MPa at 28 days to 27.1 MPa at 56 days for the control represents an increase of approximately 10.6%. Similarly, a sustainable mixture such as PC-19 could approach the control strength in spite of significant quantities of industrial by-products and recycled aggregate. Such a mixture would be particularly interesting for the optimization analysis.

5.5 Flexural Strength

Table 6: Flexural Strength results

Mix	Flexural Strength (MPa)
PC-0	3.35
PC-1	3.28
PC-2	3.20
PC-3	3.08
PC-4	2.91
PC-10	3.15
PC-15	3.02
PC-16	2.82
PC-19	3.24



Graph3:Flexural strength results

Discussion

Discussion. Flexural strength generally follows a trend similar to compressive strength. Increasing porosity reduces the solid cross-sectional area available to resist bending, but surface roughness of RCA may improve aggregate interlocking, which can partially compensate for the strength decrease. A balanced mixture should therefore maintain sufficient flexural strength and adequate infiltration.

5.6 Water Absorption

Table7: Water Absorption results

Mix	Water Absorption (%)
PC-0	4.8
PC-1	5.2
PC-2	5.8
PC-3	6.4
PC-4	7.1
PC-10	6.2
PC-15	6.8
PC-16	7.5

PC-19	5.9

Discussion

Water absorption is expected to increase with increasing RCA and porosity.

RCA generally has higher water absorption because of the porous adhered mortar surrounding the original aggregate. Consequently, mixtures with high RCA replacement may absorb more water than the control mixture.

This characteristic is important for stormwater applications because increased water interaction can affect moisture retention and durability. However, high absorption should not be interpreted as equivalent to high hydraulic conductivity.

5.7 Infiltration Rate

This is one of the most important experimental results in our paper.

Table 8: Infiltration Rate results

Mix	Infiltration Rate (mm/h)
PC-0	2850
PC-1	3020
PC-2	3250
PC-3	3510
PC-4	3780
PC-10	3370
PC-15	3650
PC-16	3950
PC-19	3290

Discussion

The expected increase in infiltration rate with increasing porosity demonstrates the importance of the interconnected pore network.

For example, if the control mixture exhibits an infiltration rate of 2850 mm/h, while a high-porosity mixture reaches 3950 mm/h, the increase is approximately 38.6%.

However, the mixture with the highest infiltration rate should not automatically be selected as the optimum. Its strength may be insufficient for the intended application.

This illustrates the fundamental optimization problem:

Higher infiltration ↔ lower strength

Therefore, NSGA-II is appropriate for identifying balanced solutions.

5.8 Stormwater Quality

Synthetic stormwater can be prepared with controlled concentrations of selected pollutants.

Table 9: An illustrative influent composition

Parameter	Illustrative Influent
TSS	150 mg/L
Turbidity	100 NTU
Nitrate	10 mg/L
Phosphate	2 mg/L
Zn	1.0 mg/L
Cu	0.5 mg/L

These are experimental-design examples only and should be replaced with concentrations appropriate to your laboratory protocol and target storm water scenario.

5.8.1 TSS Removal

Suppose the influent TSS is 150 mg/L and the effluent from an optimized mixture is 45 mg/L.

$RE=150150-45\times100$ $RE=70\%$

Thus, the illustrative mixture achieves 70% TSS removal.

Discussion
TSS reduction would primarily be associated with physical filtration and retention within the pore structure. However, excessive sediment accumulation can eventually cause clogging and reduce infiltration.

5.9 Turbidity Removal
Turbidity was measured to determine the change in water clarity after the stormwater entered the pervious concrete. In the proposed example, the turbidity of the incoming water was 100 NTU and the treated water was 28 NTU. The reduction was calculated using the influent and effluent concentrations and resulted in about 72% turbidity removal. This suggests that the pore network of the concrete can retain a significant amount of suspended particles. However, continued accumulation of these particles may block the pores and gradually reduce the infiltration capacity of the pavement.

5.10 Nitrate Removal
Nitrate removal was determined by comparing the nitrate concentration before and after filtration through concrete. The expected influent concentration was 10 mg/L, which was reduced to 7.5 mg/L in the effluent, providing an estimated removal of 25%. This lower removal compared to turbidity can be explained by the fact that nitrate is still dissolved in water and therefore is not easily retained by simple physical filtration. The reduction of nitrate can be due to adsorption and interactions with cementitious materials. These mechanisms are still to be confirmed experimentally.

5.11 Phosphate Removal
The change in phosphate concentration was used to assess the ability of the pervious concrete to reduce nutrient pollution. In the proposed example, the phosphate concentration decreased from 2.0 mg/L in the influent to 0.8 mg/L in the effluent, corresponding to approximately 60% removal. This reduction may be related to the interaction of phosphate with the mineral components of the concrete. Adsorption or precipitation within the pore system may contribute to phosphate retention. Further chemical analysis would be required to determine the dominant removal mechanism.

5.12 Heavy-Metal Removal
Heavy-metal removal can be assessed by measuring the concentration of selected metals in the water before and after treatment. For example, a reduction in zinc concentration from 1.0 mg/L to 0.25 mg/L corresponds to approximately 75% removal. Similar calculations can be carried out for metals such as lead, copper and chromium. The removal performance is likely to depend on the concrete composition, pore structure, pollutant concentration and duration of contact between the stormwater and concrete. Therefore, the final removal percentages should be obtained from laboratory measurements rather than assumed values.

5.13 Clogging Resistance
A particularly useful additional test is to measure infiltration before and after controlled sediment loading.

Table10: Infiltration before and after controlled sediment loading.

Condition	Infiltration (mm/h)
Initial	3500
After sediment loading	2200
After cleaning	3050

Hydraulic retention after clogging:
HRR=35002200×100=62.9%
After cleaning:
HRR=35003050×100=87.1%

Discussion
The hypothetical results indicate that sediment loading reduced infiltration by approximately 37.1%. After maintenance, approximately 87.1% of the original infiltration capacity was recovered.
This is valuable for practical stormwater applications because it demonstrates that the performance of pervious concrete depends not only on its initial permeability but also on its resistance to clogging and its maintainability.

5.14 Relationship Between Strength and Infiltration
One of the most important discussions in the paper should be the relationship between compressive strength and infiltration.

Table 11: Relationship Between Strength and Infiltration

Mix	Strength (MPa)	Infiltration (mm/h)
PC-0	24.5	2850
PC-2	23.2	3250
PC-4	20.8	3780
PC-10	23.0	3370
PC-16	20.2	3950
PC-19	23.8	3290

The results demonstrate the strength–infiltration trade-off.
PC-16 provides high infiltration but relatively lower strength, whereas PC-19 provides a more balanced combination.
This is exactly the type of relationship that the NSGA-II optimization should investigate.

6. Machine Learning Methodology

Experiments of the developed pervious concrete mixtures are used to build the machine learning database. Each mixture will be treated as a single experiment in itself and all the quantities and properties will be stored in a common data set. The model will be used to check the relationship between the mixture composition and the concrete performance and to predict that the relationship between the mixture composition and concrete performance is indeed accurate. The analysis will focus on mechanical behavior, hydraulic response, stormwater treatment performance and environmental impact. The ML results will be used to identify the most influential variables and to select the best mixture combinations.

6.1 Input Variables

Input variables will be mainly variables that can be controlled during concrete production or measured during characterization. Cement, fly ash, GGBS, RCA, natural aggregate and water contents will be measured in kg/m^3. The water-to-binder ratio, superplasticizer dosage, aggregate size, curing age will also be included. Measured porosity and hardened density will be considered as additional parameters for the internal structure. The mixture proportions and physical properties are also useful since different mixtures with similar proportions may form different pore structures after compaction and curing. The last set of variables is chosen after considering the availability of the data, measurement reliability and the correlation with the experimental response.

6.2 Output Variables

The prediction targets will represent the main performance requirements of the proposed material. Twenty-eight-day compressive strength will be used to describe mechanical capacity, while flexural strength will provide additional information for pavement-related applications. Infiltration rate and hydraulic conductivity will represent the water-transmission characteristics of the concrete. Stormwater treatment will be evaluated using the measured removal efficiency of selected pollutants, such as TSS, turbidity, nitrate, phosphate and, where possible, heavy metals. Embodied carbon will be estimated from the quantities of cement, supplementary cementitious materials, aggregates and other constituents used in each mixture. Separate regression models will be developed for the individual responses rather than combining fundamentally different properties into one prediction target.

6.3 Multiple Linear Regression

Multiple Linear Regression will be used as the reference model for the study. It provides a straightforward way of examining whether changes in mixture variables are associated with proportional changes in the measured response. For example, the relationship between RCA content, porosity and compressive strength can initially be examined using a linear model. The results from MLR will provide a useful baseline for judging whether the more complex machine-learning methods offer a meaningful improvement in prediction.

6.4 Random Forest

Random Forest regression will be used to examine nonlinear relationships within the experimental data. The method combines predictions from a collection of decision trees and is relatively tolerant of complex interactions between input variables. This characteristic is useful for the proposed concrete system because RCA, SCM content, porosity and water content may act together rather than independently. The model will also provide information on variable importance, which can be compared with the trends observed experimentally.

6.5 Support Vector Regression

Support Vector Regression will be investigated as a method suitable for relatively small experimental datasets. The model attempts to establish a regression function that predicts the measured response while limiting unnecessary model complexity. A nonlinear kernel can be used when the relationship between the mixture parameters and response is not adequately represented by a straight-line relationship. Input normalization will be performed before SVR modelling, and the important model parameters will be selected using cross-validation.

6.6 Artificial Neural Network

An Artificial Neural Network will be developed to represent more complicated relationships between the concrete constituents and measured properties. The input layer will receive the selected mixture and experimental parameters, while the hidden layer or layers will perform nonlinear transformations before generating the predicted response. The number of neurons and hidden layers will be kept appropriate for the size of the experimental database. Since a small dataset can easily result in overfitting, the ANN will be evaluated using cross-validation and its performance will be compared with simpler models.

6.7 XGBoost, LightGBM and CatBoost

Three gradient-boosting approaches, namely XGBoost, LightGBM and CatBoost, will be included for comparison. These methods build a sequence of decision trees in which later trees attempt to correct errors from earlier predictions. Their ability to represent nonlinear relationships makes them suitable candidates for the proposed dataset. The models will be tuned using only the training portion of the data, and their final performance will be assessed using observations that were not involved in model fitting. No algorithm will be assumed to be superior before the comparative analysis is completed.

6.8 Selection of the Final Model

The final model will be selected from the comparative results obtained for the different algorithms. Training accuracy alone will not be used as the basis for selection because a highly flexible model can reproduce the experimental data without providing reliable predictions for new mixtures. Instead, the model will be assessed using cross-validation and independent experimental observations where available. R2, RMSE and MAE will be considered together when determining predictive performance. Consistency between measured and predicted values will also be examined through regression plots and residual analysis.

6.9 Data Preprocessing

The experimental database will be checked before machine-learning development to ensure that the recorded values are internally consistent and suitable for analysis. This stage will include verification of measurement units, missing observations, repeated measurements, unusual results and relationships between variables. Since the proposed database will contain a relatively small number of concrete mixtures, the original laboratory records will be reviewed whenever an unusual observation is identified. The intention is to correct genuine experimental errors without removing valid observations simply because they do not follow the general trend.

6.10 Data Scaling

The variables in the database will have different units and numerical ranges. Cement and aggregate quantities may be expressed in hundreds of kg/m^3, whereas the water-to-binder ratio will generally be below 0.40. Scaling will therefore be applied to algorithms that are sensitive to differences in variable magnitude, particularly SVR and ANN. Standardization can be expressed as: $Z=σX−μ$

where X is the original observation, μ is the mean calculated from the training data and σ is its standard deviation. Scaling parameters obtained from the training data will then be applied to the validation or test data.

6.11 Prevention of Data Leakage

Data leakage will be avoided throughout the modelling process. Information from the test observations will not be used for selecting features, tuning model parameters or calculating preprocessing parameters. This is important because leakage can produce apparently excellent prediction results that cannot be reproduced for new concrete mixtures. All decisions concerning model development will therefore be made using the training data and the appropriate validation procedure.

6.12 Training and Validation Strategy

Because the experimental program is expected to contain approximately 20–30 mixtures, dividing the data into fixed 70% training, 15% validation and 15% testing groups may leave too few observations in each subset. A repeated five-fold cross-validation procedure is therefore more appropriate for the initial model comparison. The observations will be divided into five groups, with four groups used for model development and one group used for validation. The process will be repeated so that each observation is used for validation. The average and variation of the resulting performance measures will be reported.

Where additional mixtures are available, a separate group of mixtures will be retained for final experimental verification. This independent validation is particularly valuable because it provides a direct test of whether the model can predict the behavior of a mixture that was not used during model development.

6.13 Model Performance Indicators

We evaluate the prediction performance using R2, RMSE and MAE. The coefficient of determination indicates the accuracy of the prediction and how close this prediction is to the experimental observations. The RMSE is more important for large prediction errors. MAE shows the average magnitude of the prediction error in the same units as the measurement property. R2=1 -∑(yi -y ′)2∑(yi -y ′)2 RMSE=n 1 -∑(yi -y ′)2 MAE=n 1 -∑(yi -y ′)2 where yi is the measured value, y ′ is the predicted value, y¯ is the mean measured value and n is the number of observations. Better prediction performance is indicated by higher R2 and lower RMSE and MAE.

6.14 Experimental verification of predictions

Analysis of ML will not end due to statistical prediction and the analysis is not completed. Mixtures are selected by optimizing them and will be prepared independently and tested in the laboratory. The compressive strength, infiltration rate, porosity and other properties of the mixture will be compared with the predictions of the model. The difference between the predictions and experiments will be in percentage error: Error(%)=Yexp ∣Ypred -Yexp ∣×100

where Ypred represents the predicted value and Yexp represents the experimentally measured value. Close agreement would provide stronger evidence that the developed model is suitable for practical mixture selection.

6.15Link with Explainable AI and Optimization

Once the best-performing prediction model has been identified, SHAP analysis will be used to examine the contribution of individual input variables to the predicted responses. This analysis can indicate, for example, whether porosity or RCA content has a greater influence on infiltration and whether binder composition has a stronger influence on strength. The validated prediction model will then be incorporated into the NSGA-II optimization process. The optimization will search for mixtures that provide a suitable compromise between mechanical strength, water infiltration, stormwater treatment and embodied carbon. Selected solutions from the Pareto front will be experimentally produced and tested before the final optimum is recommended.

7. Conclusion

The present study investigated the development of sustainable pervious concrete incorporating recycled concrete aggregate (RCA), fly ash and GGBS for stormwater infiltration and groundwater-recharge applications, supported by machine-learning prediction and multi-objective optimization. Based on the experimental framework, the incorporation of recycled materials modified the density, pore structure, mechanical performance and hydraulic behavior of the concrete. The illustrative experimental results indicated that hardened density decreased from approximately 2015 kg/m^3 for the control mixture to 1900 kg/m^3 at 100% RCA, corresponding to a reduction of about 5.7%. This reduction was associated with the lower density and higher porosity of RCA compared with conventional natural aggregate.

The porosity of the mixtures increased from approximately 18.2% for the control concrete to 23.6% for the high-RCA mixture, representing an increase of approximately 29.7%. The increase in pore volume contributed positively to water transmission through the concrete. Correspondingly, the infiltration rate increased from approximately 2850 mm/h to 3780 mm/h, representing an improvement of approximately 32.6% for the illustrative high-RCA mixture. A The higher performing mixture in the wider experimental matrix achieved an infiltration rate of about 3950 mm/h, which is about 38.6% higher than the control mixture.

These results display the strong correlation between pore structure and hydraulic performance of the mixture. However, the increase in porosity and RCA content led to lower mechanical strength. The 28-day compressive strength declined from about 24.5 MPa for the control mixture to 20.8 MPa for the 100% RCA mixture, which means the decrease of about 15.1%. Nevertheless, the mixture composed of RCA, fly ash, and GGBS can still be relatively strong and have better infiltration. For example, the typical PC-19 mixture achieved an illustrative 28-day compressive strength of about 23.8 MPa, which is only 2.9% lower than the control, and in the process was able to infiltrate by around 3290 mm/h, which is an increase of 15.4% from the control. This shows that complete replacement with RCA may not provide the best overall performance and that an optimized intermediate composition can provide a better balance between structure and hydraulic requirements.

Water absorption with RCA and porosity increases. The observed absorption went up from around 4.8% in the control to 7.1% in the high-RCA mixture, with an increase of around 47.9%. This could be related to porous adhered mortar on the RCA particles. While higher absorption indicates greater interaction with water, it should be taken into account along with infiltration, porosity, and durability rather than being considered alone.

The stormwater quality evaluation revealed that pervious concrete could provide hydraulic and filtration benefits. TSS concentration decreased from 150 mg/L to 45 mg/L (70% removal), while turbidity fell from 100 NTU to 28 NTU (72% removal). Phosphate concentration also dropped from 2.0 to 0.8 mg/L (60% removal), and nitrate dropped from 10 to 7.5 mg/L (25% removal). The larger removal of suspended solids in comparison to dissolved nitrate indicates that physical filtration is most likely to be the most important in the removal of particulate matter, while dissolved pollutants may require some chemical or biological treatment.

The machine learning component also contributes to understanding the nonlinear relationship between mixture parameters and performance. For the MLR, RF, SVR, ANN, XGBoost, LightGBM, and CatBoost, the most reliable prediction model could be identified by R2, RMSE, and MAE. It is important to consider model selection based on validation and independent experimental performance as opposed to training accuracy. SHAP analysis will also show the relative contribution of RCA content, porosity, binder composition, and water-to-binder ratio to the predicted response.

The multi-objective optimization framework will reveal mixtures for compressive strength and infiltration while further reducing embodied carbon and maintaining stormwater treatment performance. The optimization results should not be judged only by the strength or the infiltration value. Pareto-optimal solutions should provide a practical compromise between competing performance requirements. The optimized mixture should then be manufactured and tested experimentally in order to confirm the expected values. All in all, we have shown the potential of combining RCA, fly ash, and GGBS with pervious concrete technology and explainable machine learning for both construction-material reliability and city water management.

Our results indicate that an optimized mixture can maintain approximately 23–24 MPa compressive strength, provide infiltration exceeding 3000 mm/h, achieve substantial suspended solid removal, and reduce dependence on virgin aggregate and Portland cement. However, the final numerical values and percentage changes must be replaced by the laboratory results before the paper is submitted to a Scopus-indexed journal.

Future Work

Future work can expand on the study presented in this paper by broadening the experimental database to include a larger number of pervious concrete mixtures and a wider range of recycled aggregate and other cementitious materials. A larger dataset would enhance the reliability of machine learning models and make the evaluation of more advanced algorithms less likely to be overfitted. Recycled and low-carbon materials, such as recycled glass aggregate, steel slag, rice husk ash, metakaolin, and other industrial by-products should also be employed to further reduce the environmental impact of concrete.

In realistic field conditions, long-term hydraulic and durability performance should be investigated. Frequent wetting and drying, sediment deposition, clogging, freeze-thaw exposure if necessary, sulfate exposure, and carbonation could be considered to understand how infiltration and mechanical performance change over time. Field-scale trials could also be conducted in parking areas, pedestrian pavements, or drainage facilities to understand how optimized pervious concrete behaves during actual rainfall and traffic.

The stormwater component can be further developed by examining a wider range of pollutants and realistic urban runoff compositions. Future studies might consider heavy metals, hydrocarbons, nutrients, and emerging contaminants while monitoring pollutant removal over extended periods. The effects of repeated stormwater loading and sediment accumulation on pollutant removal and infiltration capacity should also be explored. This would provide a better understanding of the long-term water quality performance of pervious concrete.

Future machine learning studies should use larger experimental and field datasets and consider advanced techniques such as ensemble learning, deep learning, and hybrid optimization. Transfer learning or physics-driven machine learning could also be considered if experimental and field data become available. Uncertainty analysis should be incorporated to quantify the reliability of model predictions and not just to identify the predicted values.

The optimization framework would be further improved through the analysis of life-cycle assessment, life-cycle cost analysis, and maintenance requirements at a life-cycle level, as well as mechanical and hydraulic performance. This would permit the optimized mixture to be selected for its overall environmental impact, construction cost, service life, and maintenance frequency.

Future work should also focus on developing and validating field-scale stormwater infiltration and groundwater-recharge systems with the optimized concrete mixtures. Tracking rainfall, runoff volume, infiltration, groundwater response, and water quality over several seasons will help inform the practical application of the proposed approach to the field and the transition from laboratory to urban water-management infrastructure.

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