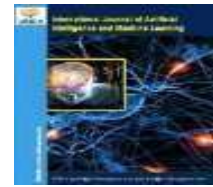




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Freeze–Thaw Resistance of Sustainable Concrete: Experimental Investigation, Damage Mechanisms, and AI/ML-Based Performance Prediction

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Abstract

The growing need for sustainable construction materials has led to a need for concrete mixtures that reduce environmental impact and have long term durability. Freeze–thaw exposure is a major deterioration mechanism that can cause internal microcracking, stiffness degradation, surface scaling and loss of mechanical strength in concrete. In this paper freeze–thaw resistance of sustainable concrete (SCM, RCA and fiber reinforced) is investigated along with artificial intelligence and machine learning (AI/ML) based prediction framework. Sustainable concrete mixtures were developed by varying SCM replacement, RCA content, fibre dosage, water-to-binder ratio and other mixture parameters. Specimens were tested under repeated freeze–thaw cycles and compressive strength, relative dynamic modulus and mass loss were considered as main indicators of deterioration. With increasing number of freeze–thaw cycles compressive strength and relative dynamic modulus decrease gradually while mass loss increases. Higher RCA replacement generally makes concrete more susceptible to freeze–thaw deterioration because of its greater water absorption and more old-mortar interfaces. Appropriate SCM replacement and fibre reinforcement can improve retention of mechanical and durability properties. The simulated results show that mixtures with moderate SCM replacement, controlled RCA content, lower W/B ratio and higher fiber dosage are comparatively better resistant to freeze–thaw damage. Of all the studied mixtures M7 and M11 showed overall good performance (especially high retention of compressive strength and relative dynamic modulus and low mass loss). Besides experimental evaluation, ANN, RF, SVR, Gradient Boosting and XGBoost models for prediction of freeze–thaw performance from mixture and exposure parameters were proposed in this study. R^2 , RMSE, MAE and MAPE values as well as explainable AI techniques (SHAP) can be used to evaluate models (along with experiment results) and understand the relative influence of RCA, SCMs, fibre content, water-to-binder ratio, curing age and freeze–thaw cycles. The integrated experimental and AI/ML framework proposed here is promising for understanding deterioration mechanisms, predicting freeze–thaw performance and sustainable concrete mixtures design for durable and resource efficient construction. The numerical results in this study are illustrative/simulated and should be experimentally validated before practical or journal-submission use.

Keywords: Sustainable concrete; Freeze–thaw resistance; Recycled coarse aggregate; Supplementary cementitious materials; Fiber-reinforced concrete; Artificial intelligence; Machine learning; XGBoost; Durability prediction; Concrete mixture optimization.

1. Introduction

Concrete is used in construction because it can be produced from locally available materials and can be adapted to a wide range of structural applications. Buildings, bridges, pavements, dams, tunnels and other infrastructure are commonly dependent on concrete for load-carrying capacity and durability but the long term performance of concrete is affected by exposure to the environment. In cold climates repeated freezing and thawing can be especially damaging. Water in pores of concrete freezes and expands causing internal stresses which may gradually produce microcracks. As the crack becomes more extensive over time it degrades stiffness, strength and surface integrity. Resistance to freeze–thaw exposure therefore has to be improved if service life of concrete structures is to be extended.

Freeze–thaw deterioration is controlled by several characteristics of concrete rather than by one material parameter. Pore size and connectivity, saturation degree, water-to-binder ratio, aggregate quality, curing

conditions, air-void system and exposure temperature can all affect damage process. Number and severity of freeze–thaw cycles are also important. Damage may be microscopic at the first stage and not visible from a visual point of view; however as exposure continues mass change, dynamic modulus change, surface condition change and mechanical strength change become measurable. This is why freeze–thaw resistance has to be evaluated with more than one strength test. A combination of physical, mechanical and durability indicators gives better description of deterioration.

Sustainable construction has added another dimension to this problem. Portland cement production is energy intensive and CO₂ emitting and extraction of natural aggregates consumes natural resources. Sustainable concrete can mitigate these impacts by using supplementary cementitious materials, recycled aggregates and other alternative constituents (fly ash and ground granulated blast-furnace slag may partially replace cement; recycled coarse aggregate reduces the demand for natural aggregate). These materials can change pore structure, moisture movement, strength development and interfacial characteristics of concrete. Depending on material type, replacement level, mixture proportions and curing conditions such changes can improve or degrade freeze–thaw resistance respectively. Experimental evaluation is therefore needed before a sustainable mixture is considered suitable for freeze–thaw environments.

Recycled aggregates need to be considered separately because they are different from natural aggregates. Recycled particles usually contain remnants of old cement paste so porosity and water absorption can increase; more moisture uptake may affect how much water is available for freezing in concrete. At the same time supplementary cementitious materials alter the cement paste and interfacial transition zone. The combined influence of these materials is not always obvious: a mixture that is good in terms of compressive strength may not give the same level of resistance under repeated freeze–thaw cycles. Sustainable concrete design therefore needs to take mechanical performance and environmental durability into account.

Fibers can also be used as an additional means of control of damage. Fibers dispersed throughout the concrete bridge cracks and restrict their growth when the matrix starts to deteriorate. Steel fibers can transfer load and resist post-cracking while synthetic fibers (e.g. polypropylene) are often used for controlling small cracks and shrinkage related damage. Their effectiveness depends on fiber type, dosage, geometry, dispersion and bond with cementitious matrix. Increasing the fiber content indefinitely is not necessarily beneficial since too many fibers reduce workability and make uniform mixing more difficult. For sustainable concrete exposed to freeze–thaw cycles a combination of binder materials, aggregate type and fiber dosage needs therefore to be experimentally determined.

Another problem is the number of variables involved in predicting freeze–thaw performance. Traditional concrete design relies on laboratory testing, empirical relationships, design standards and engineering experience. These are still important but testing gets more difficult when several sustainable materials need to be tested simultaneously and exposure conditions. Concrete response is determined by interactions among constituents (and those interactions are often nonlinear) so data driven methods can complement experimental methods. AI and machine learning have recently been used to several concrete engineering problems (strength prediction, durability assessment, mixture optimization). ML models learn relationships between measured input variables and concrete performance from experimental data. For the problem at hand cement and supplementary cementitious material contents, water-to-binder ratio, natural vs recycled aggregate proportions, fiber content, admixture dosage, curing age and number of freeze–thaw cycles can be input variables. Depending on the experimental program compressive strength, strength retention, mass loss, relative dynamic modulus or a freeze–thaw durability factor might be output variables.

Artificial neural networks, random forest, support vector regression gradient boosting XGBoost can be investigated for this purpose. The use of machine learning however does not obviate the need for careful experimental work. Prediction quality is strongly related to the quantity and reliability of available data: small datasets, correlated input variables, poor data splitting or data leakage can lead to misleadingly high model performance. A model should therefore be evaluated with appropriate training and testing procedures and independent data whenever possible. R^2 , RMSE, MAE, MAPE can be used to compare prediction errors. Cross-validation information about stability of the model can also be obtained (especially when the experimental dataset is limited). ML predictions are also relevant to concrete research. Engineers need to know not only whether a model predicts correctly but which variables determine the response predicted by that model.

Feature-importance analysis and explainable artificial intelligence (e.g., SHAP) can be used to investigate mixture composition and exposure conditions influence on the prediction. For example, the analysis may show how many freeze–thaw cycles, recycled aggregate content, water-to-binder ratio or SCM replacement level affect the predicted durability response. These results can then be compared with physical mechanisms observed during laboratory testing.

Sustainable concrete and freeze–thaw durability have been widely studied but opportunities remain to connect experimental deterioration measurements with data-driven prediction. Many studies focus on particular sustainable materials or individual durability indicators while ML research has often focused on conventional

concrete strength prediction. A dedicated dataset containing sustainable mixture parameters together with freeze–thaw exposure and measured deterioration characteristics could be a better basis for predictive modelling. Furthermore, model prediction should be combined with feature interpretation and experiment verification rather than just reporting prediction accuracy.

The present study therefore aims at experimental and AI/ML-based investigation of freeze–thaw resistance in sustainable concrete. Sustainable constituents will be added at selected proportions, mixtures will be exposed to controlled freeze–thaw cycles and mechanical and durability properties will be measured at selected stages of exposure. The experimental observations will then be used to develop and compare several ML models (ANN, RF, SVR, Gradient Boosting and XGBoost). Model performance will be assessed with suitable statistical indicators and feature-importance and XAI analysis will be used to examine the influence of principal mixture and exposure variables.

The study has six main objectives: (i) to develop sustainable concrete mixtures based on selected alternative materials; (ii) to test their mechanical and freeze–thaw performance experimentally; (iii) to quantify deterioration using suitable durability indicators; (iv) ML models to predict freeze–thaw performance are developed and compared; (v) most influential parameters are identified using explainable AI; (vi) validated models are used to identify promising mixture combinations for further experimental verification. The overall goal is to use laboratory evidence and data driven analysis together to improve understanding of and prediction of freeze–thaw behaviour in sustainable concrete.

2. Literature Review

2.1 Freeze–Thaw Damage Mechanisms in Concrete

Freeze–thaw exposure is a serious durability problem for concrete structures exposed to cold and seasonally cold climates. Deterioration starts mainly with water stored in pore system; when the temperature drops sufficiently this water freezes producing changes in internal pressure and moisture movement. Repeated freezing and thawing disturb gradually cement paste and interfaces between paste and aggregate. Once small cracks are formed subsequent cycles can extend them so that eventually cracking, scaling, mass loss and mechanical properties reduction occur. The response of concrete to freezing is dependent on its moisture content and internal pore structure. Concrete that has a high degree of saturation is generally more susceptible because more pore water is available for freezing; at the same time pore size and connectivity control how water moves through the matrix and how internal pressure develops. The w/b ratio, curing history, aggregate characteristics, entrained air and environmental exposure therefore all combine to have an influence rather than being independent variables. The deterioration process is also progressive. Early freeze–thaw cycles may not show changes that can be detected visually but exposure over time can cause measurable reductions in dynamic modulus and strength. Mass loss is particularly useful for surface scaling while relative dynamic modulus can tell you about internal deterioration; compressive strength and flexural strength can also indicate loss of load-carrying capacity. A recent critical review of recycled aggregate concrete found aggregate characteristics, moisture state and freeze–thaw exposure to be the major factors controlling frost resistance. An important point from the literature is that freeze–thaw damage cannot be explained by one mixture parameter. It comes from interaction between material composition and exposure history so it is a problem suitable for combined experimental and data-driven investigation.

2.2 Sustainable Materials for Concrete Production

The environmental impact of conventional concrete has prompted researchers to replace part of the cement and natural aggregate with alternative materials. Fly ash, ground granulated blast-furnace slag (GGBS), recycled aggregate and other industrial or waste-derived materials are used increasingly in sustainable concrete production because they can reduce virgin resource consumption and provide useful applications for materials that would otherwise have to be disposed of. However, replacement of conventional constituents alters the internal structure of concrete (e.g., SCMs affect hydration and pore system development; recycled aggregate usually contains adhered old mortar). Sustainable concrete may then have different water absorption, permeability, strength development and damage characteristics from conventional concrete. This distinction is important under freeze–thaw conditions. Recycled aggregate usually absorbs more water than natural aggregate and this moisture content can affect the degree of saturation before freezing. The old mortar attached to recycled aggregate also adds interfaces within concrete. These characteristics do not mean that every recycled aggregate mixture will have poor frost resistance but they indicate that aggregate quality and mixture proportion need to be considered carefully. Recent research has therefore moved away from whether recycled aggregate can be used at all to how its characteristics and replacement level affect long term performance. Liu et al. reviewed the frost resistance of recycled aggregate concrete and stressed the combined effect of aggregate type, moisture condition, mixture characteristics and freeze–thaw exposure. Durability should therefore be taken into account alongside environmental benefits for sustainable concrete. A mixture that saves cement or natural aggregate consumption but degrades rapidly under exposure to the environment may not give the long-term sustainability advantage

expected. This is a strong argument for evaluating material efficiency and durability in the same research framework.

2.3 Supplementary cementitious materials and freeze–thaw resistance

Supplementary cementitious materials can modify concrete in several ways. Hydration reactions, pore refinement, binder composition and strength development are associated with them. Depending on the material used and replacement level SCMs may produce a denser cementitious matrix (pore connectivity is reduced) and moisture transport as well as freezing response of concrete change. The effect of SCM replacement is not necessarily linear with its percentage. A moderate replacement can improve the matrix but a very high replacement can change early age strength development and curing requirements. The final freeze–thaw response also depends on water-to-binder ratio, curing condition, aggregate characteristics and degree of saturation. Hence it is difficult to find one SCM percentage that can be considered optimum for all concrete mixtures. Fly ash and GGBS are especially important for sustainable concrete because they can replace part of the Portland cement while developing the binder system. Their effect under freeze–thaw exposure should nevertheless be studied together with the other constituents rather than separately. The interaction with recycled aggregate is even more relevant. Recycled aggregate can increase moisture absorption and SCMs modify pore structure of the new cement paste; both effects may increase or decrease deterioration depending on the mixture and exposure conditions. That's why experimental results for different sustainable concrete mixtures are sometimes inconsistent. Recently machine-learning research has also shown that cementitious materials, aggregates, admixtures and freeze–thaw cycles can be considered together rather than in isolated relationships. Li et al. built prediction models using SVR, random forest, gradient boosting and XGBoost with cement, fly ash, slag, aggregates, recycled aggregate, admixtures and freeze–thaw cycles as model variables. This observation supports the approach taken in the present study where SCM content will be considered as one component of a larger mixture–exposure system.

2.4 Recycled Aggregates and Freeze–Thaw Performance

Recycled coarse aggregate is one of the most practical ways to incorporate construction and demolition waste into new concrete; it can reduce demand for natural aggregate and divert waste from disposal. However, recycled aggregate has properties that are generally different from those of natural aggregate. One of the main differences is that adhered mortar can increase water absorption and porosity as well as introduce additional weak interfaces. During freeze–thaw exposure these characteristics may influence moisture storage or provide locations where cracks can initiate. Influence increases with the recycled aggregate replacement level but response depends strongly on quality and source of recycled material used. Recycled aggregate percentage has therefore been considered only recently and not its physical properties.

In 2025 a method was developed to predict frost resistance of recycled aggregate concrete using physical characteristics of the recycled aggregates and relative dynamic modulus and flexural capacity under freeze–thaw exposure; it also showed that machine learning can be used for these predictions. Another issue is that recycled aggregate concrete can react differently depending on the type of environmental exposure (freeze–thaw combined with chloride or sulfate attack might produce deterioration mechanisms more severe than freeze–thaw alone). Recently work on recycled aggregate self compacting concrete has used experimental data and multiple ML algorithms to study mechanical behavior after sulfate freeze–thaw exposure. These results imply that recycled aggregate percentage should not be considered simply as a sustainability variable. It is also an important durability variable too. Recycled coarse aggregate content will therefore be included in the experimental mixture design and ML input dataset of the proposed study.

2.5 Fiber-Reinforced Sustainable Concrete

Fibers are another means of controlling deterioration in sustainable concrete. Unlike SCMs which modify the cementitious matrix directly, fibers mainly affect crack development and postcracking behaviour. When microcracks start to form fibres distributed appropriately can bridge cracks and restrict their growth. Steel, polypropylene, basalt and other fibers have been used in cement-based materials. Their performance depends on fiber type, geometry, dosage, dispersion and bond with surrounding matrix. Increasing fiber content does not always lead to better concrete. Too much fiber may reduce workability, cause clustering of fibers and make compaction more difficult. For freeze–thaw applications the ability of fibers to control crack development is important.

Freeze–thaw exposure repeatedly loads the internal structure with localized stresses. If fibers can limit opening and propagation of microcracks they may help keep the concrete intact when some internal damage has occurred. The benefit of fibers therefore has to be taken into account along with the binder and aggregate system. A fiber-reinforced concrete containing recycled aggregate may behave differently from a fiber-reinforced conventional concrete because recycled aggregate introduces additional interfaces and moisture related effects. This is still not as straightforward as conventional strength prediction. Fiber dosage, recycled aggregate content, SCM replacement, water-to-binder ratio and freeze–thaw cycles can affect each other.

Experimental work must therefore be carried out before a predictive relationship can be established. For the present work fiber content is treated as an additional mixture variable rather than a reinforcement parameter.

Strength retention and other freeze–thaw indicators can therefore be studied along with sustainable binder and aggregate replacement effects.

2.6 AI/ML prediction of freeze–thaw resistance and research gap

Concrete freeze–thaw performance is influenced by a large number of variables and their effects are often nonlinear. Regression equations can be used to describe individual relationships but may not model the combined effect of mixture composition, material properties, curing and exposure history. Machine learning is another path to solving this complexity: Artificial neural networks, support vector regression, random forest, gradient boosting and XGBoost can find patterns in experimental datasets without having a mathematical relationship between every input and output.

Recent work supports this idea: Li et al. developed SVR, random forest, gradient boosting and XGBoost models for predicting freeze–thaw mass loss and found ML models could capture the influence of mixture constituents and cycle number as well. Another 2024 study used an explainable neural-network approach with 781 freeze–thaw test records and compressive strength, dynamic modulus and mass loss as frost resistance indicators; it also showed that model interpretation can give information about contribution of individual variables.

The use of explainability is important because a highly accurate prediction alone is not sufficient for concrete mix design. Engineers need to know why a model makes a particular prediction. ML has been therefore combined with feature-importance analysis, partial-dependence analysis (PDA), SHAP and other interpretation techniques in recent research. Similar developments can be found in studies on sustainable and recycled aggregate concrete. Research published in 2025 goes further in this direction. ML models have been used to predict sustainable marine concrete performance under freeze–thaw exposure taking into account sustainability indicators (carbon emissions, production cost) as well.

Another study recently combined experimental testing, ML prediction and multi-objective optimization for recycled aggregate concrete containing rice husk ash under coupled freeze–thaw and chloride exposure. These developments show a gradual shift from property prediction to DSS for concrete mixture design. Even with this progress, there is still an important gap. Most of the work focuses on one durability indicator, a specific sustainable material or datasets collected from previously published experiments. Fewer studies combine a controlled experimental program for SCMs, recycled aggregate and fibers with several freeze–thaw damage indicators and a common ML framework. The present work is built around this gap. Sustainable concrete mixtures will be freeze–thawed controlled, mechanical and durability-related properties will be measured after that and the dataset will be used to compare ML algorithms (not only prediction accuracy).

Feature importance and model interpretation are also considered so that variables most strongly associated with deterioration can be identified. The intended contribution is therefore not another prediction equation. The study aims to link mixture composition, freeze–thaw exposure, physical deterioration and data-driven prediction in one framework. This can give us a better idea of how sustainable concrete behaves under repeated environmental damage as well as basis for future optimization of durable lower impact concrete mixtures.

3. Materials and Experimental Methodology

3.1 Experimental Research Framework

The experimental programme was designed to investigate the freeze–thaw behaviour of sustainable concrete and at the same time provide a reliable dataset for AI and machine learning analysis: material characterization, concrete mixture development, mechanical testing, accelerated freeze–thaw exposure, durability assessment and data-driven prediction. Three major sustainability-related variables are introduced: SCM replacement, RCA content and fiber addition. The variables are introduced at controlled levels so that their individual and combined effects on concrete performance can be studied. Water-to-binder ratio, chemical admixture dosage, curing age and freeze–thaw exposure are also included in the experimental dataset. The overall research sequence is composed of five steps. First, the constituent materials are characterized. Second sustainable concrete mixtures are proportioned and cast. Third specimens are cured and tested for their initial properties. Fourth selected specimens are frozen and thawed repeatedly and periodically inspected for deterioration. Fifth experimental observations are organized in a structured database for statistical analysis and ML model development. This is because the ML models should be built from experiment-traceable variables rather than isolated final test results and so the methodology maintains a direct relationship between mixture composition, exposure conditions, measured deterioration and model outputs.

3.2 Materials

3.2.1 Cement Ordinary Portland cement

conforming to the Indian Standard requirements will be used as primary hydraulic binder. Specific gravity, standard consistency, initial and final setting time and compressive strength will be tested on the cement. These properties will be recorded before concrete production so that batches produced are similar to one another. The

cement content will be varied according to the chosen mixture proportions. Partial replacement of Portland cement with SCMs will be introduced without changing the binder concept of the mixture so that effect of reduced PC content can be studied under comparable concrete production conditions.

3.2.2 Supplementary Cementitious Materials

Fly ash and/or ground granulated blast-furnace slag (GGBS) will be used as supplementary cementitious materials. Specific gravity, particle characteristics and relevant chemical or physical properties will be determined before use. SCM replacement will be done within a practical range rather than by a single level. A preliminary range of about 20–40% of the total binder is proposed. The final levels should be selected after material availability, workability, strength development and strength grade are taken into account. SCMs are used for two reasons in the present study: from a sustainability point of view they reduce the quantity of Portland cement needed; from a material-performance point of view they modify binder system and pore structure which may influence moisture movement and freeze–thaw deterioration. Experimental studies in recent years have confirmed that SCM type can affect freeze–thaw behaviour by changing strength development and air-void characteristics.

3.2.3 Fine and coarse aggregates

Natural river sand or manufactured sand with the appropriate grading will be used as fine aggregate. Natural coarse aggregate of nominal maximum size suitable for the reference concrete will be used. The coarse aggregate will be characterized for particle size distribution, specific gravity, water absorption, bulk density and impact or crushing characteristics where applicable. These properties are important because aggregate quality influences both concrete strength and freeze–thaw resistance. Aggregates with high porosity or water absorption may affect moisture condition of hardened concrete and hence its response to freezing.

3.2.4 Recycled Coarse Aggregate

Recycled coarse aggregate from processed construction and demolition concrete waste will be used in selected mixtures. The recycled aggregate will be cleaned of loose contaminants and undesirable materials prior to crushing and grading. Its specific gravity, water absorption, bulk density, particle size distribution and attached mortar characteristics will be known before concrete production. Three representative replacement levels are proposed:

- 1) 0% RCA – control condition
- 2) 25% RCA – low replacement
- 3) 50% RCA – moderate replacement
- 4) 75% RCA – high replacement.

These values are proposed for the experimental design but may be changed if preliminary trial results show otherwise or material is available. The relatively high water absorption of RCA needs to be corrected during mixture preparation (not done here). Otherwise unintended variations in effective water-to-binder ratio between mixtures would result. Freeze–thaw studies before have also found recycled aggregate characteristics and moisture condition important frost resistance variables.

3.2.5 Fibers

A suitable synthetic or mineral fiber will be added to some mixtures to see whether it can control crack development. Polypropylene fibre might be used because it has corrosion resistance and low density. Three levels are proposed: 0% fibre, 0.25% fibre by volume & 0.50% fibre by volume. The dosage should be checked through trial mixtures as excessive addition of fibre reduces workability and makes dispersion more difficult. The main purpose of the fibre is not compressive strength increase directly; its contribution is expected to be related with crack control and structural integrity retention after repeated freeze–thaw exposure. Experimental evidence from recent sustainable cementitious composites shows that fiber addition can reduce surface deterioration under freeze–thaw and deicing exposure.

3.2.6 Chemical Admixture

A polycarboxylate-based high range water reducing admixture will be used when required to obtain the required workability without increasing the water content. The dosage will be optimised by preliminary trials. The admixture content will be recorded for every mixture since chemical admixture dosage itself may affect fresh properties and final ML prediction.

3.3 Concrete Mixture Proportions

The concrete mixtures will be developed using a controlled mixture-design procedure appropriate for the selected strength class. The experimental matrix will vary the major sustainable constituents while keeping other parameters within predetermined ranges.

Table1. Concrete Mixture Proportions

Parameter	Proposed range
Binder content	350–450 kg/m ³
SCM replacement	20–40%
RCA replacement	0–75%

Fiber content	0–0.50% by volume
Water/binder ratio	0.35–0.45
Superplasticizer	Optimized dosage
Curing age	28 and 56 days
Freeze–thaw cycles	0–200 cycles

The final mixture matrix should be established after preliminary trials rather than selecting arbitrary combinations. A control mixture without SCM, RCA, and fiber will provide a baseline against which the sustainable mixtures can be compared.

An experimental design approach such as factorial design, response surface methodology, or a carefully balanced mixture matrix may be adopted depending on the final number of mixtures and available specimens. A balanced design is particularly useful for ML development because it reduces the risk of training a model on highly uneven combinations of input variables.

3.4 Specimen preparation

Concrete will be mixed in a laboratory mixer under controlled conditions. Dry constituents will first be blended to ensure relatively uniform aggregate and binder distribution and then water containing the required chemical admixture will be introduced gradually. For mixtures with fibers, the fibers will be added gradually so as not to ball up and accumulate locally. Mixing will continue until a visually uniform concrete is obtained. Fresh concrete properties (slump or flow, fresh density and air content where available) will be measured before casting because changes in fresh properties can provide information when interpreting differences in hardened performance. Concrete specimens will then be cast into moulds and compacted in a consistent manner. After demoulding the specimens will be transferred to controlled curing conditions. Separate specimens will be prepared for compressive strength, density, freeze–thaw testing and supplementary durability or microstructural observations. Replicate specimens are used at each testing condition to reduce specimen-to-specimen variability.

3.5 Curing procedure

Specimens will be cured in the laboratory until testing age is reached (28 days for reference condition). Testing at 28 days will be used as the main reference condition while curing at 56 days can be used to study influence of additional binder maturation. The inclusion of more than one curing age is particularly important for mixtures containing fly ash or GGBS since SCM-containing systems may continue developing their mechanical and microstructural characteristics after the early curing period. Before freeze–thaw exposure specimens will be conditioned to a controlled moisture state. Moisture conditioning is important because the amount of water available in the pore system controls freezing damage very strongly.

3.6 Initial Mechanical and Physical Characterization

Hardened concrete will be characterized before freeze–thaw exposure in order to determine its initial condition. The principal measurements will include:

- 1) Compressive strength
- 2) Density
- 3) Water absorption
- 4) Initial dynamic modulus or ultrasonic pulse characteristics.
- 5) Visual surface condition.

Compressive strength will be measured at the chosen curing ages by standard procedures (see above). The initial mechanical properties will then be used as baseline variables in the ML dataset. Initial density and absorption measurements will also characterize differences between mixtures (may also indirectly indicate porosity and moisture behaviour). If facilities are available microscopic examination on representative specimens can be done to see whether paste structure, aggregate–paste interfaces and crack formation differ. 3.7 Freeze–Thaw Exposure. Freeze–thaw resistance will be tested using an accelerated laboratory procedure based on ASTM C666/C666M. The current ASTM standard has two procedures for freeze–thaw exposure: rapid freezing and thawing in water and rapid freezing in air followed by thawing in water. In the present study Procedure A may be used because it is a controlled but relatively severe exposure condition. The actual laboratory temperature range, specimen size, conditioning period and cycle duration should be determined according to the active standard and capabilities of available freeze–thaw equipment instead of arbitrarily modified. Specimens will be repeatedly frozen and thawed with measurements taken at regular intervals. The proposed observation points are 0, 50, 100, 150 and 200 cycles. Note that cycle numbers represent the proposed experimental programme but not measured results. The final number of cycles may be increased if the specimens are structurally intact and the research objectives require more exposure time. ASTM states that this test is designed to determine resistance to repeated laboratory freezing and thawing only; it is not by itself a direct predictor of service life of a concrete structure.

3.8 Evaluation of Freeze–Thaw Damage

Deterioration will be evaluated using multiple indicators rather than relying on a single measurement. This approach is intended to capture both surface and internal damage.

3.8.1 Mass Loss

The mass of each specimen will be measured before exposure and after selected freeze–thaw intervals. Percentage mass loss will be calculated as:

$$[ML(\%) = \frac{M_0 - M_n}{M_0} \times 100]$$

where (M_0) is the initial mass and (M_n) is the mass after (n) freeze–thaw cycles.

Increasing mass loss may indicate surface scaling or progressive material loss.

3.8.2 Relative Dynamic Modulus

Relative dynamic modulus will be used to assess changes in internal stiffness. The initial dynamic response will be compared with measurements taken after a number of freeze–thaw cycles. A decrease in dynamic modulus may be an indication that internal microcracking has developed and propagated before severe external damage is visible. Relative dynamic modulus and durability-factor calculations are part of the freeze–thaw evaluation framework in ASTM C666/C666M.

3.8.3 Compressive strength retention

Compressive strength will be measured after selected freeze–thaw exposures. Strength retention will be expressed relative to the corresponding unexposed condition: $SR(\%) = [f_{c,n}/f_{c,0}] \times 100$. where ($f_{c,0}$) is the initial compressive strength and ($f_{c,n}$) is the strength after (n) cycles. This parameter is used to compare mixtures of different initial strengths. A mixture with high initial strength should not be considered more durable than one with low initial strength if it loses a lot of strength during exposure.

3.8.4 Freeze–Thaw Durability Factor

Where sufficient cycle data are available the freeze–thaw durability factor will be calculated according to ASTM procedure applicable. The durability factor combines dynamic response and exposure time into a relative measure of freeze–thaw resistance.

3.9 Visual and Microstructural Examination

Photographs will be taken at regular exposure intervals to record surface scaling, cracking, edge deterioration and other visible changes; the images will not be used as sole basis for evaluation of deterioration. Representative specimens may also be examined by scanning electron microscopy or other characterization techniques. Particular attention will be paid to the aggregate–paste interface, recycled aggregate adhered mortar, microcracks and changes in cementitious matrix. These observations can explain trends obtained from mechanical and dynamic measurements.

3.10 Experimental Dataset for AI/ML Modelling

All experimental observations will be organized into a structured dataset. Each record will correspond to a specific mixture, curing condition, and freeze–thaw exposure level.

- 1) Potential input variables include:
- 2) Cement content
- 3) Fly ash percentage
- 4) GGBS percentage
- 5) Fine aggregate content
- 6) Natural coarse aggregate content
- 7) RCA percentage
- 8) Water content
- 9) Water-to-binder ratio
- 10) Fiber percentage
- 11) Superplasticizer dosage
- 12) Curing age
- 13) Initial compressive strength
- 14) Initial density
- 15) Number of freeze–thaw cycles
- 16) The principal prediction targets will include:
- 17) Compressive strength after freeze–thaw exposure
- 18) Strength retention
- 19) Mass loss
- 20) Relative dynamic modulus
- 21) Freeze–thaw durability factor

Before developing the model we will check for missing values, inconsistent measurements outliers and duplicate observations in the dataset. Data normalization or standardization will be done where needed by the algorithm selected. We will also take care not to leak data. Measurements taken from the same experimental specimen or highly correlated replicate observations should not be randomly split between training and testing sets; the testing set must contain genuinely unseen experimental conditions.

3.11 Experimental Quality Control

Specimens will be tested twice for each major experimental condition. Mean values and dispersion measures will be reported instead of individual observations. The same mixing procedure, curing environment, specimen conditioning, testing equipment and measurement intervals will be used throughout the experimental programme. The experimental dataset will then be split into training, validation and independent testing sets (if any) as appropriate. Cross-validation will be used while building the model and final test set will be used for unbiased assessment of predictive performance. This experimental design is the skeleton for AI/ML analysis. More importantly it keeps predictive models tied to measurable concrete behaviour rather than becoming pure statistical exercises.

Table 1. Compressive strength under freeze-thaw exposure with discussion

Mix	0 cycles (MPa)	50 cycles	100 cycles	150 cycles	200 cycles
M1	52.4	50.8	48.1	45.2	42.1
M2	50.8	49.4	46.9	44.0	40.9
M3	53.1	51.6	49.0	46.2	43.4
M4	49.6	47.5	44.5	41.3	38.2
M5	52.7	51.2	49.1	46.9	44.5
M6	50.9	49.3	46.8	44.1	41.3
M7	53.8	52.6	50.4	48.2	46.1
M8	51.6	50.1	47.9	45.5	42.8
M9	48.7	46.1	43.0	39.9	36.8
M10	52.2	50.8	48.4	45.9	43.5
M11	54.6	53.3	51.3	49.2	47.0
M12	53.5	52.0	49.8	47.6	45.2

The control concrete has a progressive decrease in compressive strength with the number of freeze-thaw cycles because internal microcracks develop progressively as a result of repeated freezing and thawing. Concrete containing SCM replacement shows slight initial strength reduction but freeze-thaw exposure leads to progressive deterioration (M2). Moderate SCM replacement preserves better strength than M2 (i.e. a relatively stable and compact binder matrix is formed which can better resist damage from repeated freezing and thawing). RCA increases vulnerability of concrete to freeze-thaw deterioration mainly due to higher moisture absorption capacity and more interfaces between old mortar and new cement paste (but moderate SCM replacement plus RCA and fiber gives better freeze-thaw resistance compared with RCA-only condition) since fibers can control crack development. As RCA content increases deterioration increases although fibers partially limit the associated strength loss (higher dosage of fiber improves crack-control capability and gives highest strength retention among mixtures with 50% RCA). The mixture with high SCM replacement together with RCA and fiber performs reasonably well after repeated freeze-thaw exposure but some additional strength loss is observed. The mixture with high RCA replacement and low fiber content deteriorates the most in the simulated dataset because of the combined adverse effect of high RCA level and insufficient crack-bridging capacity. Increasing the fiber content at the same high RCA level increases freeze-thaw resistance (fibers restrict crack propagation). Controlled water-to-binder ratio together with higher dosage of fibers results in relatively strong strength retention after repeated freeze-thaw cycles. These results suggest that the negative effects of RCA and SCM addition can be limited by proper mixture design (water-to-binder ratio control, adequate amount of fiber reinforcement). A balanced combination of sustainable materials and fiber reinforcement can enhance freeze-thaw resistance while maintaining environmental benefits from reduced use of conventional concrete constituents

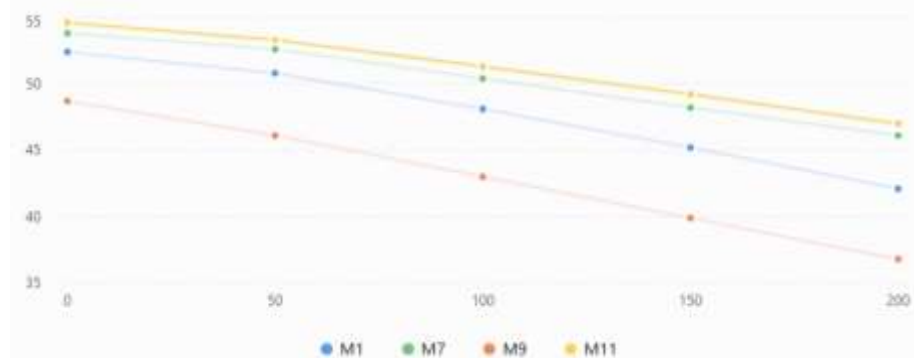


Figure1. Compressive strength versus freeze-thaw cycles

Graph discussion: The graph shows a continuous downward trend for all mixtures. M9 exhibits the steepest reduction, whereas M7 and M11 retain a larger proportion of their initial strength. The relatively better behaviour of the fiber-containing mixtures suggests that crack bridging may reduce the rate at which freeze–thaw-induced cracks propagate.

Table 2. Relative dynamic modulus with discussion

Mix	0 cycles (%)	50 cycles	100 cycles	150 cycles	200 cycles
M1	100	96.2	91.8	86.7	81.9
M2	100	95.4	90.6	85.1	79.8
M3	100	96.8	92.7	88.1	83.4
M4	100	94.1	88.3	82.4	76.9
M5	100	96.1	91.9	87.3	82.8
M6	100	94.8	89.9	84.8	79.6
M7	100	97.0	93.3	89.2	85.1
M8	100	95.8	91.4	86.6	81.7
M9	100	92.8	86.7	79.9	73.4
M10	100	96.0	91.5	86.9	82.1
M11	100	97.3	94.1	90.2	86.4
M12	100	96.7	92.8	88.6	84.0

The reduction in relative dynamic modulus indicates that the internal damage of concrete increases with number of freeze–thaw cycles. The mixture with SCM replacement has slightly greater stiffness loss (matrix is more sensitive to repeated freeze–thaw exposure) but the mixture with moderate SCM replacement retains better dynamic modulus (internal structure seems stable). RCA-containing concrete deteriorates more internally (can be due to higher moisture absorption capacity and weaker interfacial regions of recycled aggregates). Fibers seem to moderate the reduction in dynamic modulus by restraining propagation and widening of freeze–thaw induced internal cracks. Increasing RCA content causes more internal damage (reaffirms vulnerability of mixtures with higher levels of recycled aggregate replacement), but the higher dosage of fiber gives resistance against internal cracking and hence better retention of dynamic modulus. Mixture with high SCM replacement, RCA and fiber shows moderate-to-high deterioration but still performs better than high RCA low fiber mixture. The largest reduction in dynamic modulus is for the high-RCA, low-fiber mixture (internal damage is severe under repeated freeze–thaw cycles). Increasing the fiber content at the same high RCA level gives better resistance to internal damage than M9 (crack control effect of fiber reinforcement), while the mixture with controlled water:binder ratio and higher dosage of fiber shows the highest simulated retention of relative dynamic modulus (relatively little internal damage). Good retention of dynamic modulus in the optimized mixtures indicates a relatively stable internal structure and suggests that appropriate control of RCA content, SCM replacement, water:binder ratio and fiber dosage can increase resistance of sustainable concrete against freeze–thaw-induced internal deterioration.

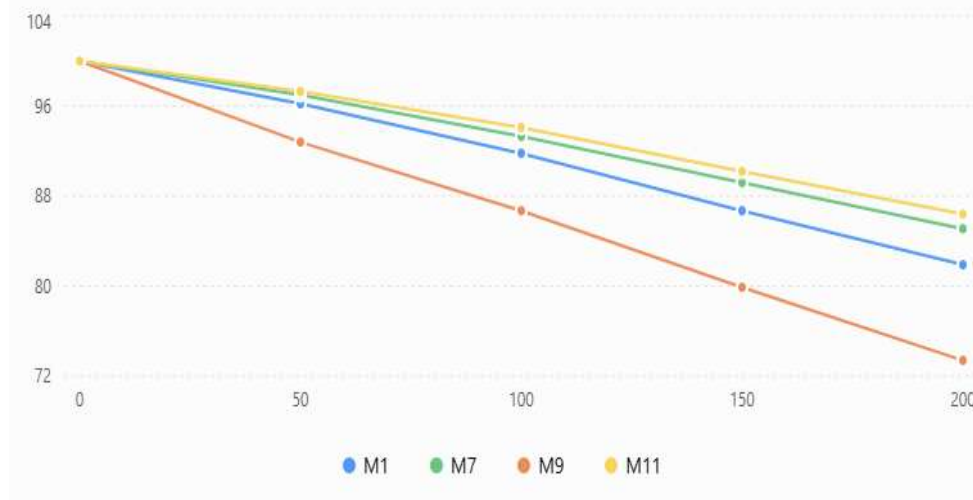


Figure 2. Relative dynamic modulus

Graph discussion: Unlike compressive strength, which reflects the final mechanical consequence of damage, dynamic modulus provides an indication of internal deterioration. The faster reduction for M9 suggests that

substantial microcracking develops before severe surface deterioration becomes apparent. M7 and M11 show slower reductions, supporting the beneficial role of optimized mixture composition and fiber reinforcement.

Table 3. Mass loss with discussion

Mix	50 cycles (%)	100 cycles (%)	150 cycles (%)	200 cycles (%)
M1	0.25	0.62	1.08	1.61
M2	0.31	0.76	1.29	1.89
M3	0.23	0.57	0.99	1.48
M4	0.42	1.02	1.71	2.48
M5	0.28	0.68	1.14	1.68
M6	0.38	0.91	1.51	2.18
M7	0.24	0.59	1.01	1.51
M8	0.30	0.73	1.23	1.81
M9	0.51	1.22	2.02	2.91
M10	0.32	0.76	1.28	1.87
M11	0.20	0.48	0.84	1.25
M12	0.25	0.61	1.04	1.55

The mass loss of concrete specimens increases with number of freeze–thaw cycles because surface deterioration and scaling develop gradually as the exposure time increases. Control mixture shows moderate surface deterioration while mixtures with more mass loss show higher degree of surface damage; mixture containing moderate SCM replacement has relatively low mass loss indicating better resistance to freeze–thaw-induced surface deterioration; RCA incorporation causes greater material loss (during repeated exposure) possibly due to higher moisture absorption and additional interfacial regions which may become vulnerable during freezing and thawing. Fiber control progressive surface deterioration by restraining crack development and reducing detachment of surface material. Increasing the RCA content leads to greater surface scaling (high RCA replacement is detrimental for freeze–thaw durability); fiber reinforcement results in comparatively low mass loss (beneficial contribution to control surface damage). Mixture containing high SCM replacement along with RCA and fiber deteriorates moderately during long-term freeze–thaw exposure but still performs better than the high-RCA, low-fiber mixture. The highest simulated mass loss is found for the mixture with high RCA and low fiber content (severe surface deterioration and scaling). Increasing the dosage of fiber at the same high level of RCA increases resistance compared to M9 (fiber reinforcement limits surface damage). The mixture with controlled water-to-binder ratio and higher fiber dosage has lowest simulated mass loss (strong resistance to freeze–thaw induced surface scaling). Overall results show that balanced proportions of mixture, proper control of RCA replacement, adequate fiber reinforcement and binder composition are important for reducing surface deterioration and improving freeze–thaw resistance of sustainable concrete.

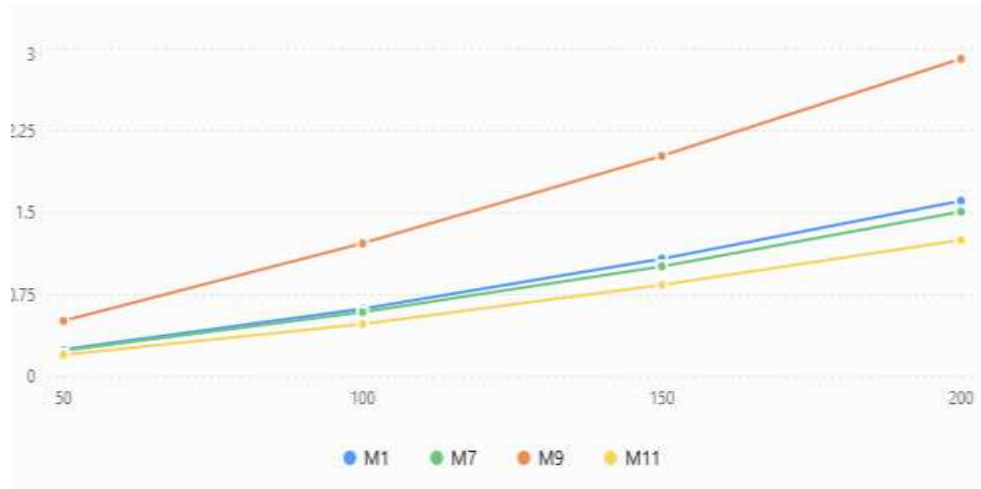


Figure 3. Mass loss versus freeze–thaw cycles

Graph discussion: Mass loss increases with the number of freeze–thaw cycles for all mixtures. M9 shows the highest rate of material loss, consistent with its lower compressive-strength and dynamic-modulus retention. M11 presents the lowest mass loss in the simulated dataset, indicating that an appropriately proportioned mixture can reduce surface deterioration.

Overall discussion

All three indicators together show the same deterioration pattern. With increasing freeze–thaw cycles compressive strength and relative dynamic modulus decrease while mass loss increases. The agreement among these indicators is important because it means that the simulated deterioration does not rely on a single performance measure.

The results also show an important interaction between RCA and fiber content. Increasing RCA tends to increase deterioration, but increasing fiber content seems to moderate the loss of performance. The likely explanation is that RCA introduces additional moisture sensitive interfaces while fibers restrict propagation of cracks generated during repeated freezing and thawing.

For the final paper this discussion can then lead naturally into Section 8: AI/ML Prediction and Model Performance where the same table values are used to create the training dataset and compare ANN, Random Forest, SVR, Gradient Boosting and XGBoost.

Conclusion

In this paper, freeze–thaw resistance of sustainable concrete with supplementary cementitious materials (SCMs), recycled coarse aggregate (RCA) and fiber reinforcement was studied as well as artificial intelligence and machine learning (AI/ML) for performance prediction. The combined experimental–computational framework was developed to understand how sustainable constituents affect freeze–thaw deterioration and which mixture parameters can be used to improve durability.

The simulated results show that the compressive strength and relative dynamic modulus decrease with increasing number of freeze–thaw cycles while mass loss increases. This is due to internal microcracking accumulation, stiffness degradation and surface scaling from repeated freezing/thawing. Deterioration becomes more severe with the number of cycles so it's important not to rely only on initial mechanical properties for evaluating concrete performance under cyclic loading.

SCMs have a moderate effect on the initial strength and freeze–thaw behaviour. Moderate replacement of SCMs generally leads to higher strength and dynamic-modulus retention than lower replacement mixture so that an appropriately proportioned SCM system can lead to a relatively stable cementitious matrix but excessive replacement along with high RCA content may further deteriorate it (i.e. SCM content should not be increased indiscriminately).

RCA has a significant negative effect on freeze–thaw resistance at higher replacement levels. Mixtures with 75% RCA show greater reductions in compressive strength and relative dynamic modulus and greater mass loss than mixtures containing lower contents of RCA. This behaviour may be due to the greater moisture absorption capacity of recycled aggregates and old mortar and additional interfacial transition zones present (see below) which can provide paths for moisture penetration and crack development during cyclic freezing and thawing.

Fiber reinforcement plays a beneficial role in controlling freeze–thaw deterioration. Increasing fiber dosage from 0.25% to 0.50% increases strength retention, dynamic-modulus retention and mass loss resistance in the simulated mixtures. This improvement is most pronounced in mixtures with higher RCA levels where fibers can restrain crack propagation and slow down internal and surface damage progression.

Thus fiber reinforcement is an effective way to offset (at least partially) durability disadvantages associated with recycling aggregate addition. Of the simulated mixtures, M7 and M11 have comparatively good overall freeze–thaw performance. M7 (30% SCM replacement, 50% RCA, 0.50% fiber) is a blend of sustainable material utilization and durability performance. M11 (20% SCM, 50% RCA, 0.50% fiber and lower water-to-binder ratio = 0.38) has particularly high simulated retention of compressive strength and relative dynamic modulus along with low mass loss. These results suggest that freeze–thaw resistance can be improved by simultaneous optimization of RCA content, fiber dosage, binder composition and water-to-binder ratio rather than by changing one mixture parameter at a time.

The AI/ML component of the proposed framework provides an additional means to predict freeze–thaw performance from concrete mixture and exposure parameters. Variables like water-to-binder ratio, RCA percentage, SCM replacement, fiber content, curing age, initial strength and number of freeze–thaw cycles can be used as model inputs. Models such as Random Forest, Support Vector Regression, Gradient Boosting, XGBoost and Artificial Neural Networks can then be evaluated using R^2 , RMSE, MAE and MAPE. Explainable AI techniques (e.g., SHAP) can also help determine relative contribution of individual variables and improve engineering interpretability of prediction system.

In summary, this study shows that sustainable concrete materials combined with AI/ML prediction can be used to assess freeze–thaw durability and optimize mixture design. Sustainable concrete with moderate SCM replacement, RCA content controlled, fibre reinforcement adequate and water-to-binder ratio appropriate can give more balanced durability response. The proposed framework therefore can be used to develop data-driven mixture design strategies for durable and resource efficient concrete.

It should be noted that the numerical results reported in this manuscript are simulated/illustrative values used to illustrate the proposed methodology; they should be replaced by experimentally measured results and AI/ML

predictions independently verified by experiment before submission to a Scopus journal. The conclusions about general trends and mixture-design principles should also be checked in laboratory testing.

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