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To cite this article: Wenhao Wang, Jingguo Cao, Ming Zeng & Yongxiang Qiao (2024) A comprehensive literature mining and machine learning to decipher and predict effects of concrete materials on concrete corrosion of sewer pipe, Urban Water Journal, 21:6, 727-744, DOI: [10.1080/1573062X.2024.2352599](https://doi.org/10.1080/1573062X.2024.2352599)

To link to this article: <https://doi.org/10.1080/1573062X.2024.2352599>



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A comprehensive literature mining and machine learning to decipher and predict effects of concrete materials on concrete corrosion of sewer pipe

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ABSTRACT

The concrete composition of different pipelines varies greatly, and a comprehensive analysis of the impact of concrete design on pipeline corrosion is required. Developed an integrated model based on Scikit-Optimize, XGBoost and SHAP to analyze concrete's carbonation and sulfuric acid resistance from five aspects: binder type, supplementary cementitious material (SCM's), aggregate, admixture and w/b. Choose Scikit-Optimize for parameter optimization. As an explanation model, the SHAP model can perform analysis well and explain the analysis basis of the XGBoost training model. The established model can accurately predict the corrosion effect ($R^2 > 0.987$) without overfitting. Binder should be maintained at 380 to 400 (kg/m^3). Water/binder and coarse aggregate/binder are the two main factors that influence the binder, and they should be maintained at a ratio of around 0.4 to 0.6 and 2.5, respectively. Fly ash (FA) should be SCM's used as at a range of 300 to 350 (kg/m^3) to improve corrosion resistance.

ARTICLE HISTORY

Received 22 November 2023
Accepted 30 April 2024

KEYWORDS

Sewer corrosion; concrete; workability; machine learning; acid corrosion

1. Introduction

Concrete is currently the most widely used piping material in sewage systems. Corrosion of sewer pipes, however, has always been a serious problem, and the cost of protecting them can skyrocket as sewers age. This problem occurs all over the world such as China (Wu et al. 2020), the United States (Sabour, Dezvareh, and Bazzazzadeh 2019), Australia (Wells and Melchers 2016), and Germany (Sand 1997), resulting in high maintenance costs of up to £450 million per year. Microbial-induced concrete corrosion has been proven to be the main process of concrete degradation, which is mostly studied has been simulated by sulfuric acid immersion.

Test methods for studying corrosion of concrete can be divided into several types. One of the most important characteristics is the nature of the environment in which the concrete specimen will be exposed to accelerated corrosion. The most important testing methods are: laboratory chemistry, laboratory microbiology and in situ (Madraszewski et al. 2022). The in situ method has a major disadvantage: it takes a long time, often months or even years (Wells and Melchers 2014, 2015). Moreover, because the environment variable is dynamic and uncontrollable, it cannot be repeated, which is only suitable for verification experiments (Grenng et al. 2015; Sun et al. 2014). Disparities in the selection of microorganisms for laboratory microbiological methods can be a critical factor, and laboratory microbiological methods that involve inoculating bacteria but do not provide studies of other corrosion components, such as cyclic wear, cannot fully simulate MICC (Madraszewski et al. 2022). The chemical test mainly tests the carbonation rate of

concrete or mortar samples and the resistance to chemical corrosion. Although the chemical method cannot accurately measure the MICC process, it can easily evaluate the carbonation resistance and acidity of the material compared with the first two methods (De Belie et al. 2004). Exposure of concrete to carbon dioxide and immersion in acidic solutions enables testing of the resistance of concrete or mortar to typical chemical attack (Khan et al. 2019). Long-term exposure to highly acidic conditions causes the hydrated Portland cement to be eroded and degraded (Jiang, Keller, and Bond 2014; Valencia-Saavedra, Mejía de Gutiérrez, and Puertas 2020). The sulfuric acid produced by SOB will react with cement hydrate, usually calcium silicate hydrate (C-S-H), to generate sulfate such as gypsum, and the reaction between gypsum and aluminate to form ettringite will cause the internal structure of concrete to be unstable and form cracks (De Belie et al. 2004; Monteny et al. 2000).

According to the five aspects of relevant binder types, SCM's, aggregates, admixtures, and w/b, different types and dosage combinations vary greatly (Hafez et al. 2022). Manufacturing test concrete mixes, chemical testing and multiple performance tests are time-consuming and can only be done on a case-by-case basis (Al-Jamimi et al. 2022). There are essential differences in the impact of the relevant cement types on the performance of concrete, with cement like CAC and geopolymers having a better ability to neutralize acids and contain corrosion into its final stages than conventional OPC (Menéndez et al. 2013). Supplementary cementitious materials (SCM's) have been

extensively studied for resistance to acid corrosion, such as ground granulated blast-furnace slag (GGBS), fly ash (FA), silica fume (SF), Lime powder (LP), calcined clay (CC), metakaolin (MK). The performance of SCM's added to the concrete is positively affected by the reduction of porosity and permeability in the sulfuric acid test. The addition of aggregate has been well proven to reduce the corrosion rate under exposure conditions, and when the proportion of aggregate is large, its high alkalinity can well neutralize biological acid (Wu et al. 2020). The reduction of w/b and the addition of SP will reduce the permeability of the pipeline in resisting corrosion (Tripathi et al. 2020). In a recent study, adding sodium hydroxide and sodium silicate solutions obtained lower mass loss during acid attack (Van Jaarsveld, Van Deventer, and Lorenzen 1997).

However, finding the optimal parameters is difficult, and the machine learning model can use existing data for analysis and prediction. Compared with traditional machine learning models, XGBoost can better capture data patterns in prediction and provide related methods to prevent model overfitting (Y. Wang et al. 2022). In order to make the model have better accuracy and to prevent overfitting and waste of computing resources, this study chose Scikit-Optimize for parameter optimization. As an explanation model, the SHAP model can be analyzed very well, and it can well explain the analysis basis of the XGBoost training model.

In this paper, an integrated model based on Scikit-Optimize, XGBoost, and SHAP was developed to analyze the carbonation and sulfuric acid resistance of concrete according to five aspects relevant binder types, SCM's, aggregates, admixtures and w/b. The structure of this paper is as follows: Section 2 mainly introduces the literature related to concrete manufacturing; Section 3 describes the acquisition of data and the realization of the model; Section 4 realizes the predictive analysis results of the model; Section 5 summarizes the paper.

2. Materials and methods

2.1. Datasets collection

To comprehensively assess the performance of concrete of sewer pipes, a statistically plausible database of relevant 4 functional properties was extracted from published articles and 2576 data points were collected from published papers (Alhassan, Ballim, and Research 2017; Angulo-Ramirez et al. 2019; Arora, Singh, and Patel 2019; Atiş 2003; Boudjehm et al. 2022; Bucher et al. 2017; Burden 2006; Buss 2013; Chang et al. 2005; Collepardi et al. 2004; Czarnecki, Woyciechowski, and Adamczewski 2018; De Belie et al. 2004; De Muynck, De Belie, and Verstraete 2009; Divsholi, Lim, and Teng 2014; Duran-Herrera et al. 2015; García-Segura, Yepes, and Alcalá 2014; Gettu et al. 2018; Gu, Bennett, and Visintin 2019; Hafez et al. 2022; Harrison et al. 2012; E. H. Hewayde 2006; E. Hewayde et al. 2007; Higuchi et al. 2014; Holt et al. 2010; House 2013; Kaewmanee and Tangtermsirikul 2014; Khan, Yasir, and Castel 2022; Khan et al. 2019; Khunthongkeaw, Tangtermsirikul, and Leelawat 2006; Lee, Park, and Lee 2013; Leemann et al. 2015; Löfgren, Esping, and Lindvall 2016; Marques, Chastre, and Nunes 2013; McNally and Sheils 2012; Okoye, Prakash, and Singh 2017; Quan and Kasami 2014; Rathnarajan et al. 2017; Roziere, Loukili, and Cussigh 2009; Ruixia 2010; San Nicolas, Cyr, and Escadeillas 2014; Sanjuán, Andrade, and Cheyrez 2003; Sisomphon and Franke 2007; Soja 2019; Valencia-Saavedra, Mejía de Gutiérrez, and Puertas 2020; X-Y. J. C. Wang 2019; Woyciechowski, Woliński, and Adamczewski 2019; Younsi et al. 2011, 2013; Zhang et al. 2013; Zhao et al. 2015) and present them in Figure 1. The composition and classification of mixture databases extracted from 49 journal articles are summarized in supplementary material II published between 1997 and 2022.

A total of 29 input variables were selected to predict concrete properties. In addition to the variables shown in Figure 3, mixture/binder was added to explore whether mixture weight per cubic meter or mixture/binder had more influence on

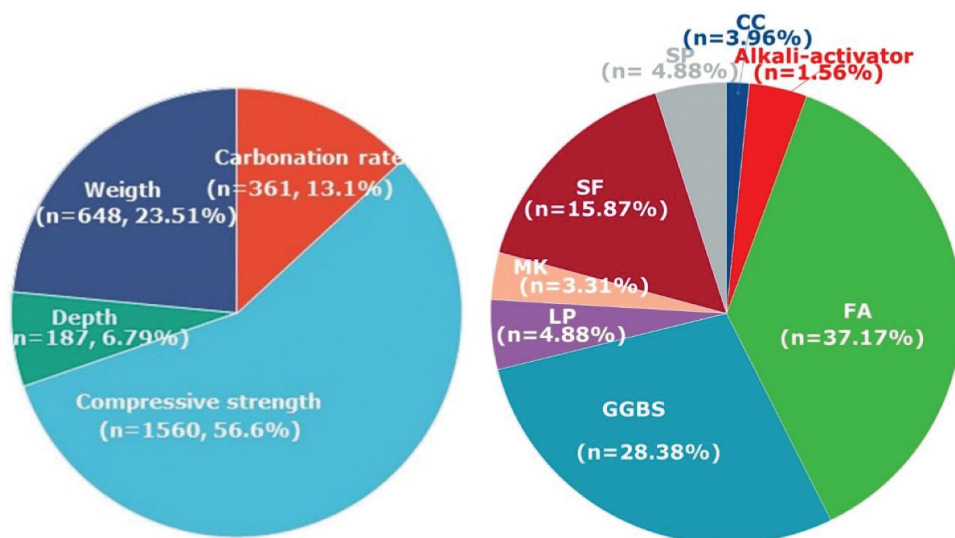


Figure 1. Data points for the estimated parameters (left) and for the mixture components such as ground granulated blast-furnace slag (GGBS), fly ash (FA), silica fume (SF), Lime powder (LP), calcined clay (CC), metakaolin (MK) (right).

concrete properties. If the original source is not differentiated, it is calculated according to CEM I-42.5.

As shown in Figure 3, the concrete is evaluated from five aspects of the inclusions, e.g. relevant binder types, SCM's, aggregates, water, admixtures. Concrete manufacturing is mainly divided into five factors: relevant binder types, SCM's, aggregates, admixtures, water (Herisson et al. 2013, 2016). The categories of cement are mainly divided into CEM I-42.5 and CEM I-52.5 with ordinary Portland cement (OPC) as the main binder material (De Muynck, De Belie, and Verstraete 2009). Following the same approach as in the literature, the cement content was subdivided into two sub variables representing cement strength (CEM I-42.5 and CEM I-52.5). Since hydrogen sulfide is oxidized by SOM, the final product is sulfuric acid, and the chemical composition of OPC makes most concrete easily degrade when exposed to acidic conditions (Yang et al. 2021). Since cementitious materials as a substitute for cement can better inhibit corrosion when exposed to inorganic acids, as a substitute for cement, SCM's can better inhibit corrosion when exposed to inorganic acids, so it is very important to understand the mechanism of cementitious materials such as FA, GGBS, and SF in acid attack (E. H. Hewayde 2006; Valencia-Saavedra, Mejía de Gutiérrez, and Puertas 2020). Aggregates is mainly divided into coarse aggregate and fine aggregate, among which coarse aggregate has a significant effect on the resistance to microbial corrosion (O'Connell, McNally, and Richardson 2010). Admixtures mainly include plasticizers and alkaline activators. Alkali-activated concrete (AAC) has been used as a substitute for OPC in recent years due to its better acid resistance (Ren, Zhang, and San Nicolas 2021). Superplasticizer can provide flowable concrete with reduced water demand, and its main component is polycarboxy ether polymer, which can have better anti-permeability, and its normal recommended dosage rate is 0.8–2.5 L/100 kg binder (Boudjehm et al. 2022).

Due to the strong alkaline conditions in the concrete, microbial occurrence at this stage is limited. Diffusion of sulfate-rich pore fluids initiates initial leaching of calcium hydroxide-rich and isochronous precipitation of expanding sulfate salts such as gypsum or sulfate, especially in the transition zone near the cement-rich interface of the aggregate. The compressive strength of the concrete mix is the most representative mechanical performance index, and the concrete that has been cured for 28 days is usually used for testing. There are great differences in the corrosion depth in different environments, mainly due to the differences in test conditions, exposure to different concentrations of H_2SO_4 solutions. The most important parameters for evaluating concrete corrosion include weight change.

2.2. Correlation analysis

This study chose Pearson analysis mainly to initially understand the impact of factors on the target variables and primarily used statistical analysis methods for qualitative analysis. In this paper, Pearson analysis is used to preliminarily understand the effect of dopant on carbonation rate, compressive strength, corrosion depth and weight of

concrete in carbonation and acid corrosion. The correlation coefficient of Pearson analysis is between $[-1, 1]$. The closer to 0, the lower the correlation; the closer to red, the positive correlation, and the closer to blue, the negative correlation.

2.3. Model development details

2.3.1. XGBoost model

XGBoost is the most representative gradient boosting tree model. The default is gbtrees, also known as Classification and Regression Trees, and it can also be a linear weak learner (Y. Wang et al. 2022). This study only uses Eq. (2) shows that XGBoost uses the expansion of the second-order Taylor formula as Eq. (3), where T represents the number of training trees, and n represents the number of samples. And g_i and h_i are the first and second derivatives, respectively. y_i represents the prediction result after the t th iteration, $\hat{y}^{(t-1)}$ represents the prediction result of the previous tree, and Obj represents the objective function. Adds a regularization Ω to the objective function, which controls the complexity of the tree and prevents overfitting. (As Eq. (6))

$$Obj^{(t)} = \sum_{i=1}^n l(y_i, \hat{y}^{(t-1)} + f_t(x_i)) + \Omega(f_t) + const \quad (1)$$

$$Obj^{(t)} \cong \sum_{i=1}^n \left[l(y_i, \hat{y}^{(t-1)}) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right] + \Omega(f_t) + const \quad (2)$$

$$g_i = \partial_{\hat{y}^{(t-1)}} l(y_i, \hat{y}^{(t-1)}) \quad (3)$$

$$h_i = \partial_{\hat{y}^{(t-1)}}^2 l(y_i, \hat{y}^{(t-1)}) \quad (4)$$

$$\Omega(f_t) = \gamma T + \lambda \frac{1}{2} \sum_{j=1}^T \omega_j^2 \quad (5)$$

Since the residual $L()$ has little effect on the change of the objective function, it can be simplified to Eq. (9) after adding the regular term.

$$Obj^{(t)} \cong \sum_{i=1}^n \left[g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right] + \Omega(f_t) \quad (6)$$

$$= \sum_{i=1}^n \left[g_i \omega_q(x_i) + \frac{1}{2} h_i \omega_q^2(x_i) \right] + \gamma T + \lambda \frac{1}{2} \sum_{j=1}^T \omega_j^2 \quad (7)$$

$$= \sum_{j=1}^T \left[\left(\sum_{i \in I_j} g_i \right) \omega_j + \frac{1}{2} \left(\sum_{i \in I_j} h_i + \lambda \right) \omega_j^2 \right] + \gamma T \quad (8)$$

Eq. (10) is the derivative of the objective function is equal to zero, and the minimum weight is obtained Eq. (11).

$$\omega_j^* = -\frac{G_j}{H_j + \lambda} \quad (9)$$

$$Obj = -\frac{1}{2} \sum_{j=1}^T \frac{G_j^2}{H_j + \lambda} + \gamma T \quad (10)$$

The first part is the objective function of the right cotyledon after feature splitting, the second part is the objective function of the right cotyledon after feature splitting, the next is the objective function of the original leaf before feature splitting, and the last is the regularization coefficient after feature splitting, which can be used Eq. 6 expression.

$$Gain = \frac{1}{2} \left[\frac{G_L^2}{H_L + \lambda} + \frac{G_R^2}{H_R + \lambda} - \frac{(G_L + G_R)^2}{H_L + H_R + \lambda} \right] - \lambda \quad (11)$$

2.3.2. Model training and hyperparameter optimization

Finding the optimal parameters of the model usually relies on empirical tuning, which is a time-consuming and inaccurate method. Automatic parameter tuning algorithms can achieve better results than empirical parameter tuning. At present, the more commonly used automatic parameter tuning algorithms are Grid Search and Bayesian Optimization. Scikit-Optimize is an alternative to GridSearchCV that uses Bayesian optimization, a predictive model 'surrogate' to model the search space and is used to get a good combination of parameter values as quickly as possible. The 'estimators' can be tuned by observing that each iteration shows the best results. And by defining ranges for model parameters, gain an intuition about the fractional sensitivities associated with hyperparameters. It is possible to decide which parts of the space may require a more fine-grained search, and which hyperparameters barely affect the score and may be dropped from the search.

The parameters of the four models are shown in Table 1. The optimization process is shown in Figure 3. The input variables selected for the training model are the concrete mixture and the ratio of the binder to a total of 29. Then, the data set is randomly divided into training set and test set at a ratio of 80% and 20%. The next step is to optimize and search the hyperparameters of CART. The parameters to be adjusted mainly include max_depth, eta, min_child_weight, subsample, comsample_bytree, gamma, lambda, and n_estimators. n_estimators take an integer value to count the number of trees. First of all, choose the appropriate value of n_estimators. Although the larger the value, the stronger the learning ability of the model, but to a certain extent, it will not only waste computing resources, but also cause overfitting. The parameter max_depth and lambda are used to avoid overfitting, and the model can effectively avoid learning singular values from samples. The role of the parameter subsample is random sampling. In the iteration, there must be put back to extract a new training sample set. The range of this parameter is (0,1]. The role of the parameter subsample is random sampling.

In the iteration, there must be put back to extract a new training sample set. The range of this parameter is (0,1]. The step size of the representative model training is eta. The larger the step size, the faster the training speed, but it is not conducive to finding the optimal value. The sub-sampling rate of columns when constructing each tree is expressed by colsample_bytree. Weight threshold of the smallest node is min_child_weight, and gamma represents the minimum threshold of loss caused by node splitting.

2.3.3. SHapley Additive exPlanations (SHAP)

The SHAP model is to help understand the XGBoost black box model to judge the prediction of the final result from known conditions. SHAP is used to analyze the trained model. The core idea is to calculate the marginal contribution of features to the model output, and then explain the 'black box model' from the global and local levels. This study mainly used summary plot, feature importance and dependency scatter plots in the SHAP model to analyze the model and data. SHAP summary plot was used to analyze the influence of the sample point size on the SHAP value, and it was also an array of feature importance. Compared with SHAP summary plot, SHAP feature importance can intuitively reflect the influence of the feature value on the result mean(|SHAP value|). SHAP dependency scatter plots can observe the sample distribution and whether the samples with the same value are similar to the SHAP value, and also the changing trend of the data can be found to find the critical point.

3. Results and discussion

3.1. Correlation of concrete composition and corrosion parameters

In this section, the key concrete composition parameters are selected, and the four properties and their corresponding concrete composition parameters are calculated respectively. Figure 2 shows the correlation diagram of carbonization rate, compressive strength, depth, weight change, and the Pearson correlation coefficient of any two variables, respectively.

As shown in Figure 2(a), the relative mass composition of the components and the component/binder effects on the carbonization rate are slightly different. It could be observed that with the increase of binder, SP and cement content in concrete, the carbonation rate would be inhibited. Consistent with Hewayde (2006), the increase of aggregate, water and FA will accelerate the carbonation rate of concrete.

Figure 2(b–c) show the changes of the three properties of concrete with different components in acidic solution. CEM I-42.5 and CEM I-52.5 showed similar corrosion depth and compressive strength characteristics during acid attack, CEM I-42.5 was more resistant to acid attack than CEM I-52.5, and the alkaline concrete after adding alkaline activator reduced compressive strength. While the addition of SCM's had a more limited effect on

Table 1. Parameter selection for XGBoost model.

Variable	max_depth	eta	min_child_weight	subsample	Comsample_bytree	gamma	lambda	n_estimators
Carbonation rate	6	0.18	0	0.72	0.90	0.5	1	210
Compressive strength	11	0.13	1	0.7	0.52	0.8	4	120
Depth	5	0.18	2	0.68	1	0	0	100
Weight change	8	0.18	4	0.6	0.98	0	0	70

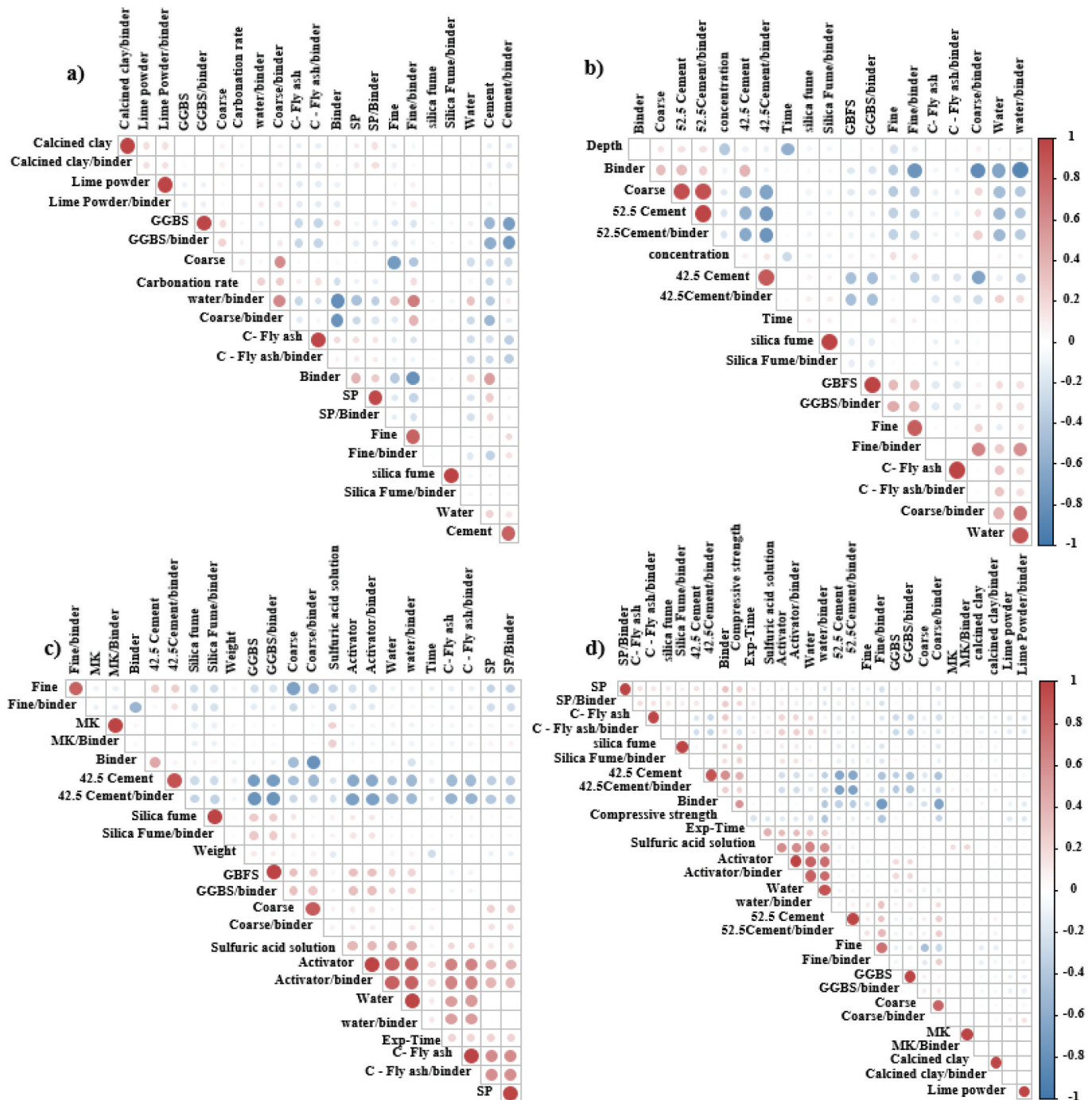


Figure 2. Heat map of effect of concrete composite factors on carbonation rate (a) corrosion depth (b), weight change (c) and compressive strength (d).

corrosion depth and mass loss, it could be found to play an important role in compressive strength. FA and SF increased the compressive strength of concrete, while LP reduced the compressive strength. The addition of fine aggregate inhibited corrosion progression, but also slashed compressive strength, while the behavior of coarse aggregate was opposite. SP as admixtures could improve the compressive strength, but may also lead to accelerated loss of concrete weight.

3.2. Model parameter optimization

The parameter optimization process of the carbonization prediction model is shown in Figure 4 and Fig. A.1, and the optimization process of the remaining three models is given in the supplementary material. The judgment criteria of parameters are mainly based on the red dot combination of Scikit-Optimize. This set of parameters can optimize the prediction performance of the model and prevent over-fitting of the

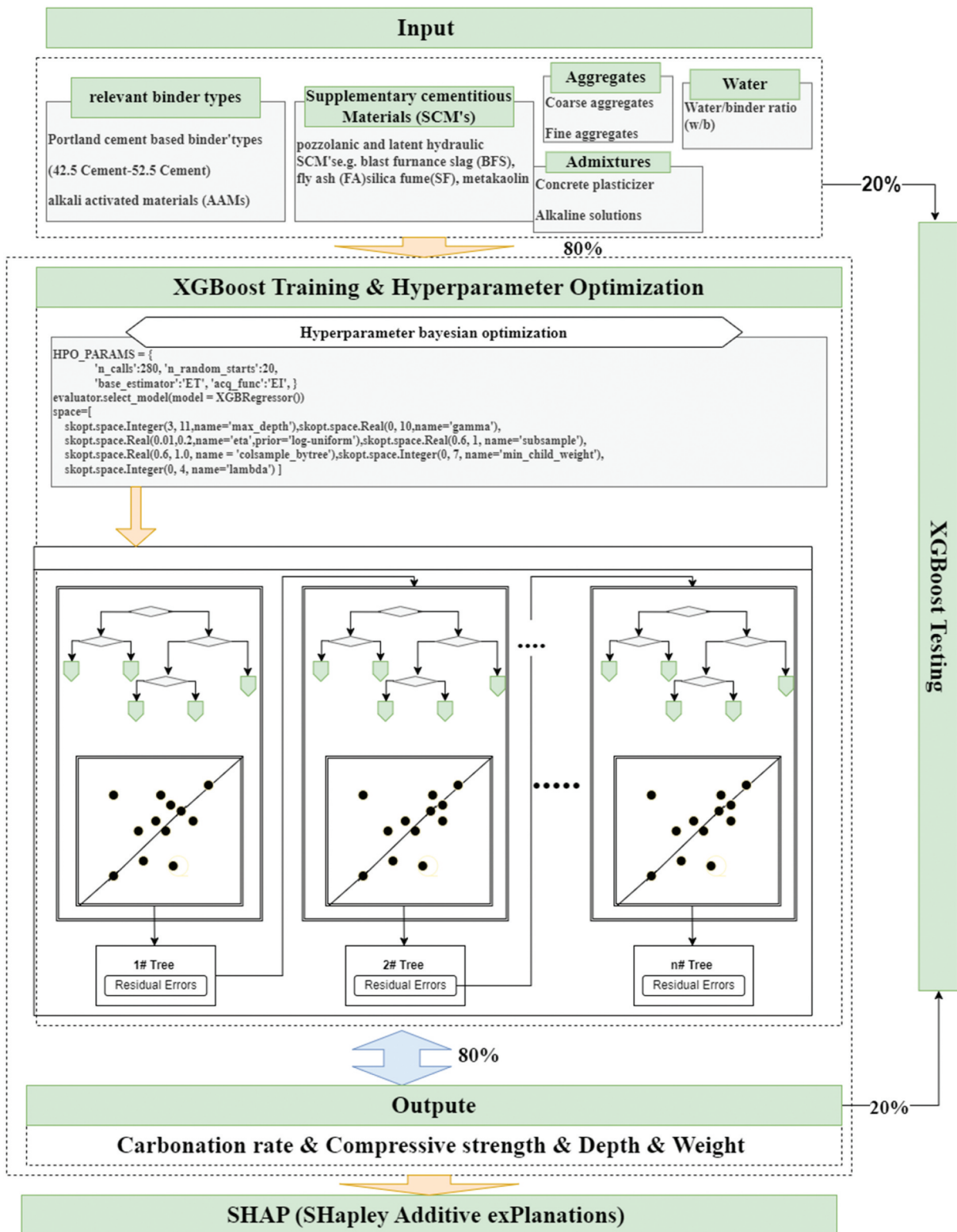


Figure 3. The process of the model realization.

model. Due to the differences in prediction data, the complexity of prediction is also different, so different optimization parameters are selected for different concrete properties, and list the parameters in Table 1.

The parameter optimization of the carbonization prediction rate model $n_{\text{estimators}}$ is shown in Fig. A.1. It converges when

iterating about 200 times. If the number of iterations increases, overfitting may occur. So chose $n_{\text{estimators}} = 210$, as was the choice of $n_{\text{estimators}}$ for the other three models (Table 1).

The search of the model parameters in the Bayesian optimization process is shown in Figure 4. The black dots represent the sampling points for each search, while the red dots

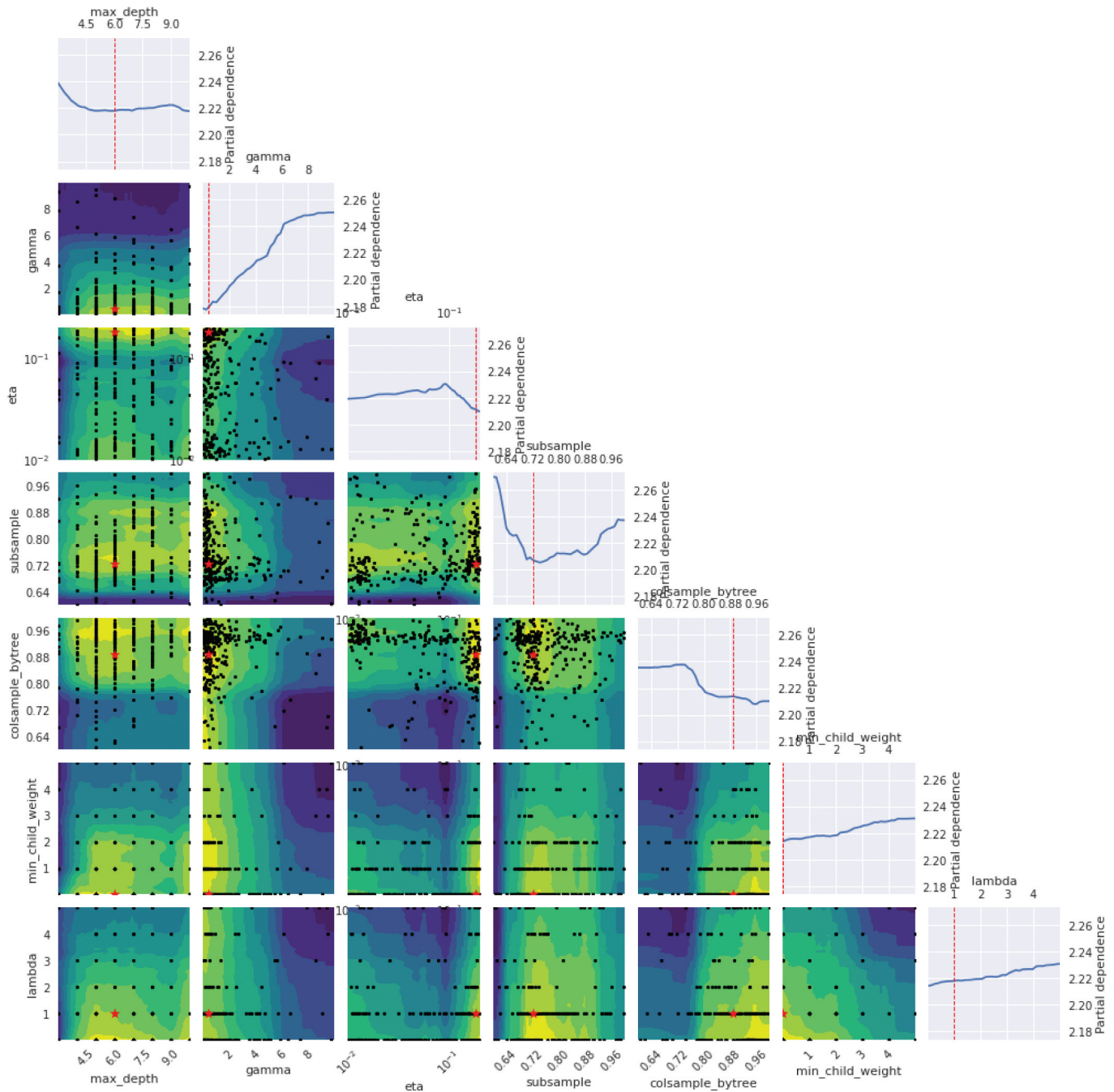


Figure 4. An interactive plot of 1D and 2D partial dependence of hyperparameter searching with scikit-optimize.

Table 2. Performance indices values of XGBoost models.

Variable	Training Size	Test Size	Train_RMSE	Test_RMSE	Train_R ²	Test_R ²
Carbonation rate	289	72	0.327	0.226	0.994	0.993
Compressive strength	1248	312	1.382	1.357	0.994	0.994
Depth	150	37	0.116	0.101	0.998	0.999
Weight change	518	130	1.443	0.988	0.973	0.989

represent the optimal parameter values. This set of parameter values is selected based on the minimum RMSE. Figure 4 showed max_depth = 6, eta = 0.18, min_child_weight = 0, subsample = 0.72, colsample_bytree = 0.90, gamma = 0.5, lambda = 1.

3.3. Predicting corrosion effect under different concrete properties

Use the above four models with adjusted parameters to make predictions respectively. Table 2 lists the size of the training set and test set and the prediction performance of the

corresponding model on the training and test sets. The four models have relatively good performance in predicting different properties of concrete, and the R^2 values are 0.993, 0.994, 0.999, and 0.989, respectively. The representation model can better capture the contribution of the data to the prediction results, and also provide a reasonable basis for the subsequent SHAP analysis.

As shown in Figure 5, in order to better demonstrate the prediction performance of the model, the prediction effect of the model on global variables was tested. It is observed that the trained models show better performance in actual prediction. Only weight change has biased predictions for individual variables, possibly due to singular values in the data.

3.4. Importance analysis of components and operating conditions

Figure 6 lists the top 20 global importance feature maps for the four models using SHAP feature importance. It is to take the absolute value and average the SHAP value of each data point of the entire data set, and sort according to the impact from high to low. In terms of relevant binder types, the cement content has a more significant impact on each attribute than cement/binder, and the impact on each attribute is more

obvious. The differences in the effect of different SCM's on concrete properties are also well represented. For example, addition of FA significantly affects carbonation and compressive strength, and addition of MK results in changes in concrete quality. Coarse aggregate, water content and Admixtures also play non-negligible elements in carbonation and acid corrosion.

As shown in Figure 7, Each data has a corresponding point on the feature, so the total number of points on each feature is fixed. The abscissa represents the SHAP value, and the size of the feature value is represented by color from blue to red. From the analysis related binder types, the carbonation rate was suppressed with increasing cement content. In contrast, although the |SHAP value| of cement/binder is large but irregular, the content of concrete is more informative in carbonation rate. Compared with CEM I-42.5, CEM I-52.5 could obviously improve the compressive strength of concrete, but the influence of both on the corrosion depth is relatively limited. Increasing the content of CEM I-42.5 accelerated the weight loss, but no direct relationship with the ratio was observed.

High FA, GGBS, and CC contents would accelerate the carbonization rate, so the addition of SCMs could not resist carbonization well. With the increase of FA, LM and SF content, the compressive strength of concrete was also reduced. The effect of

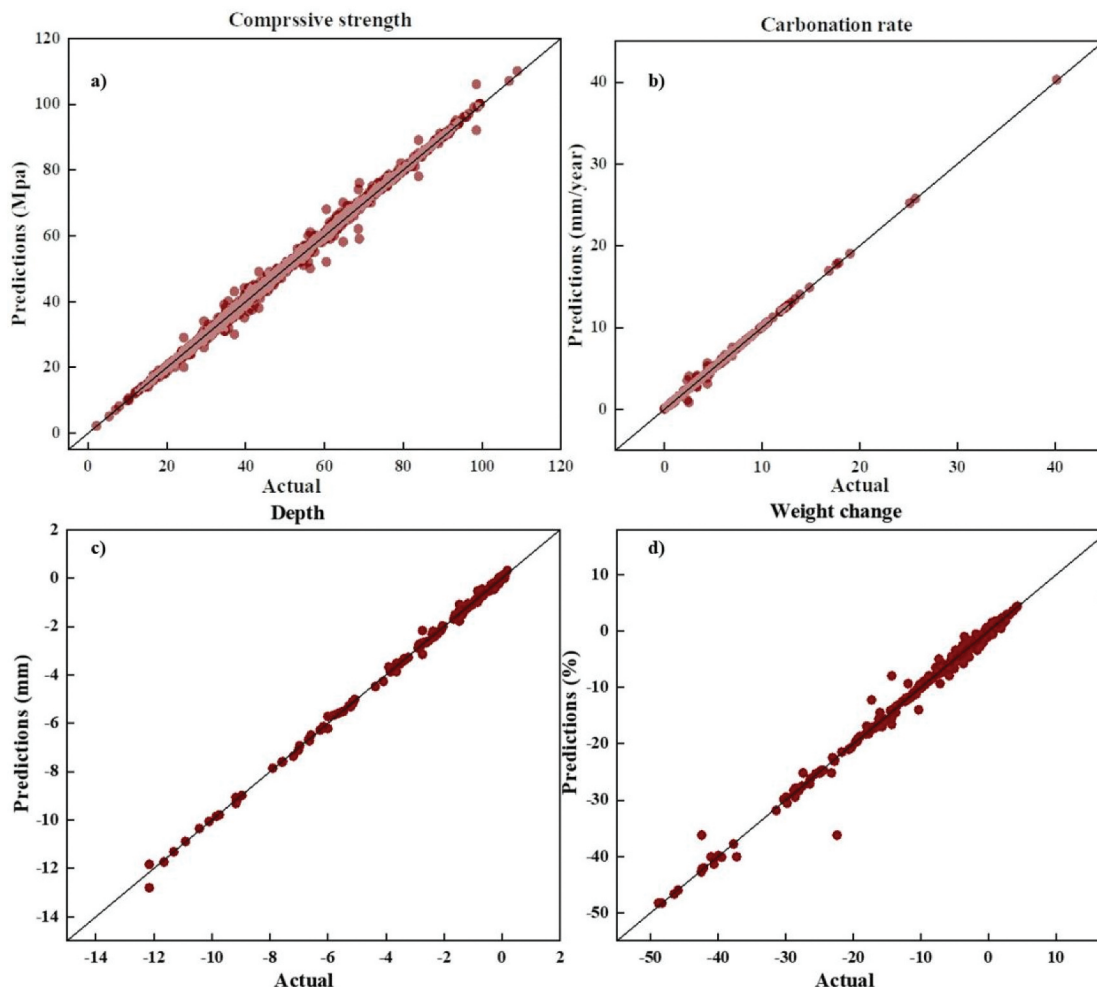


Figure 5. Predicted vs actual values of the testing sample: carbonation rate (a) corrosion depth (b), weight change (c) and compressive strength (d).

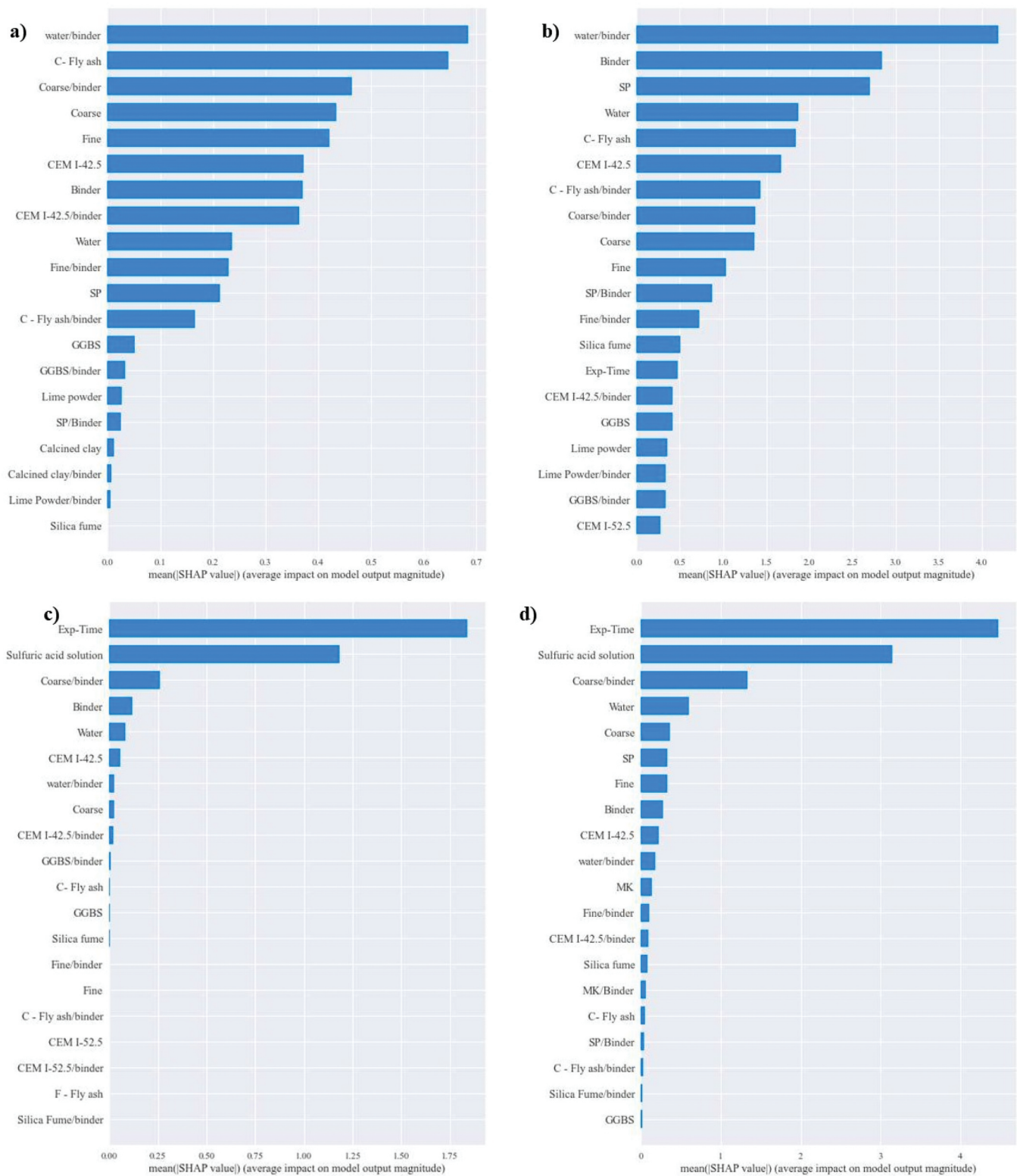


Figure 6. Global interpretations of XGBoost model by SHAP feature importance: carbonation rate (a) corrosion depth (b), weight change (c) and compressive strength (d).

SCM's was more limited in terms of corrosion depth. High content of MK, low content of FA, SF and GGBS would alleviate the weight loss.

High coarse aggregate/binder accelerated the carbonization rate, while the increase of coarse aggregate content inhibited the corrosion rate, which would be analyzed in detail later. High

content of fine aggregate and a low proportion of coarse aggregate would increase the compressive strength. The effects of water and SP are diametrically opposite in the four properties. The increase of binder content not only slowed down the carbonization rate and increases the compressive strength, but also deepened the corrosion depth. It could be observed that the

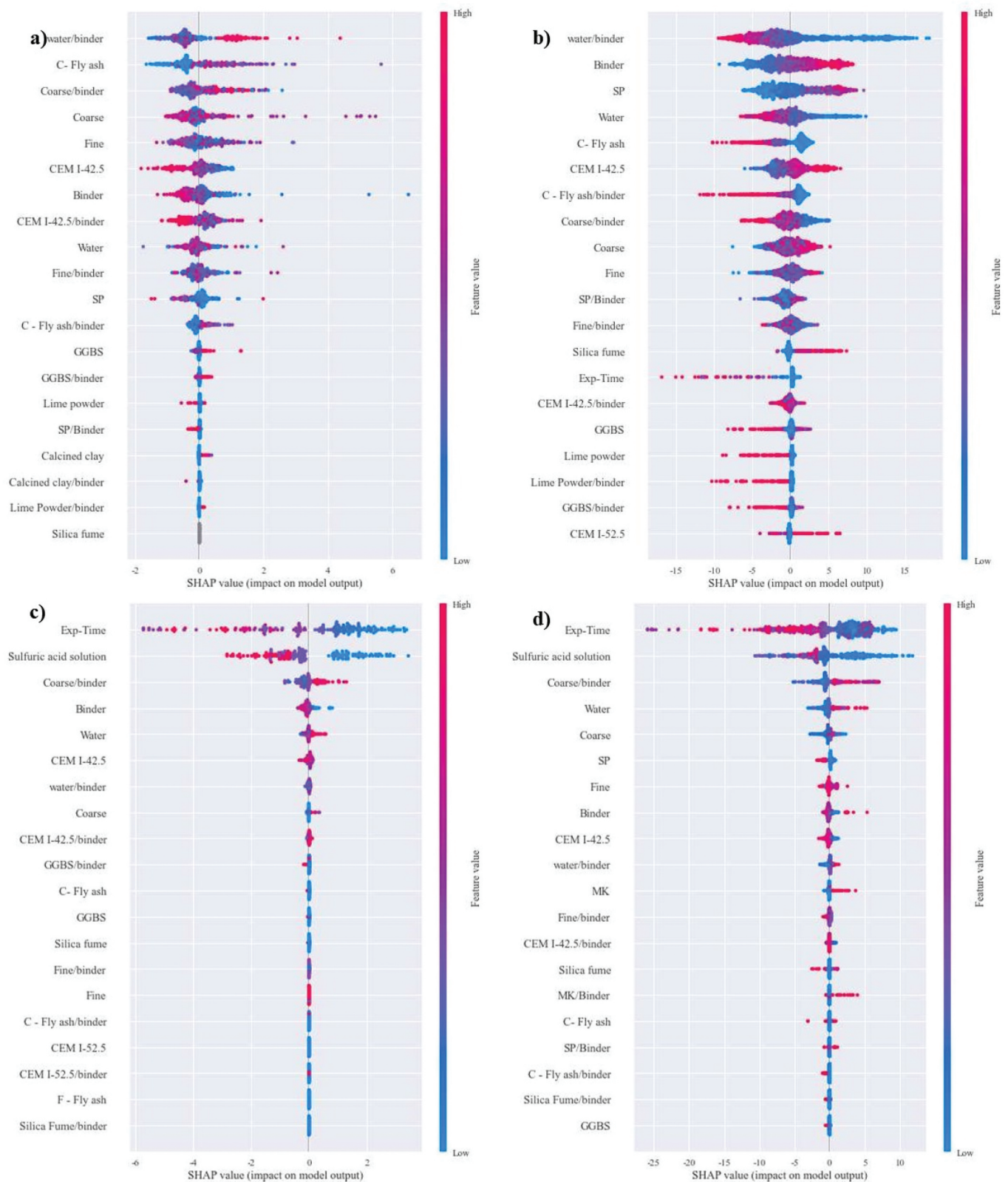


Figure 7. Global interpretations of XGBoost model by SHAP summary plot: carbonation rate (a) corrosion depth (b), weight change (c) and compressive strength (d).

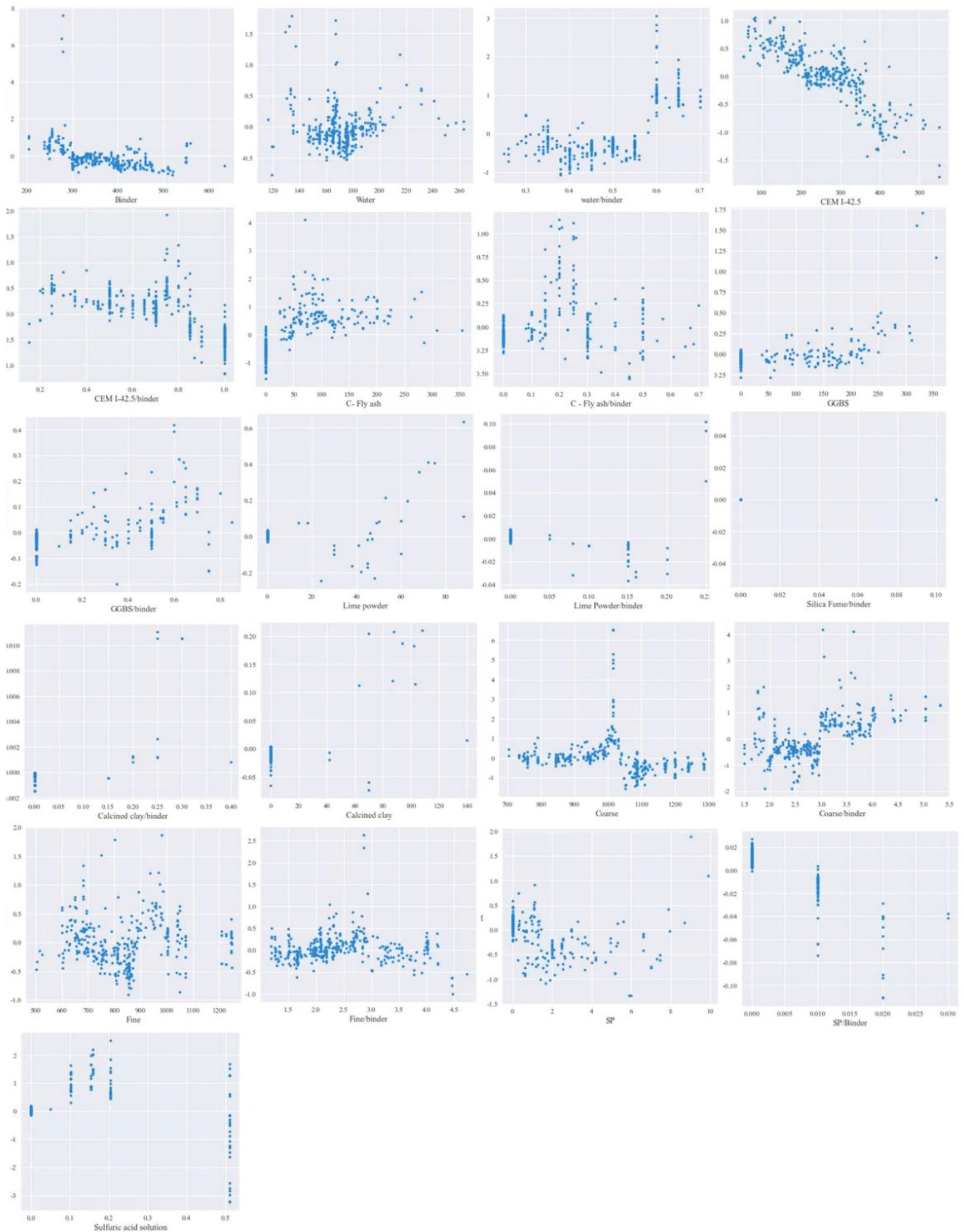


Figure 8. Feature dependence plots of carbonation rate.

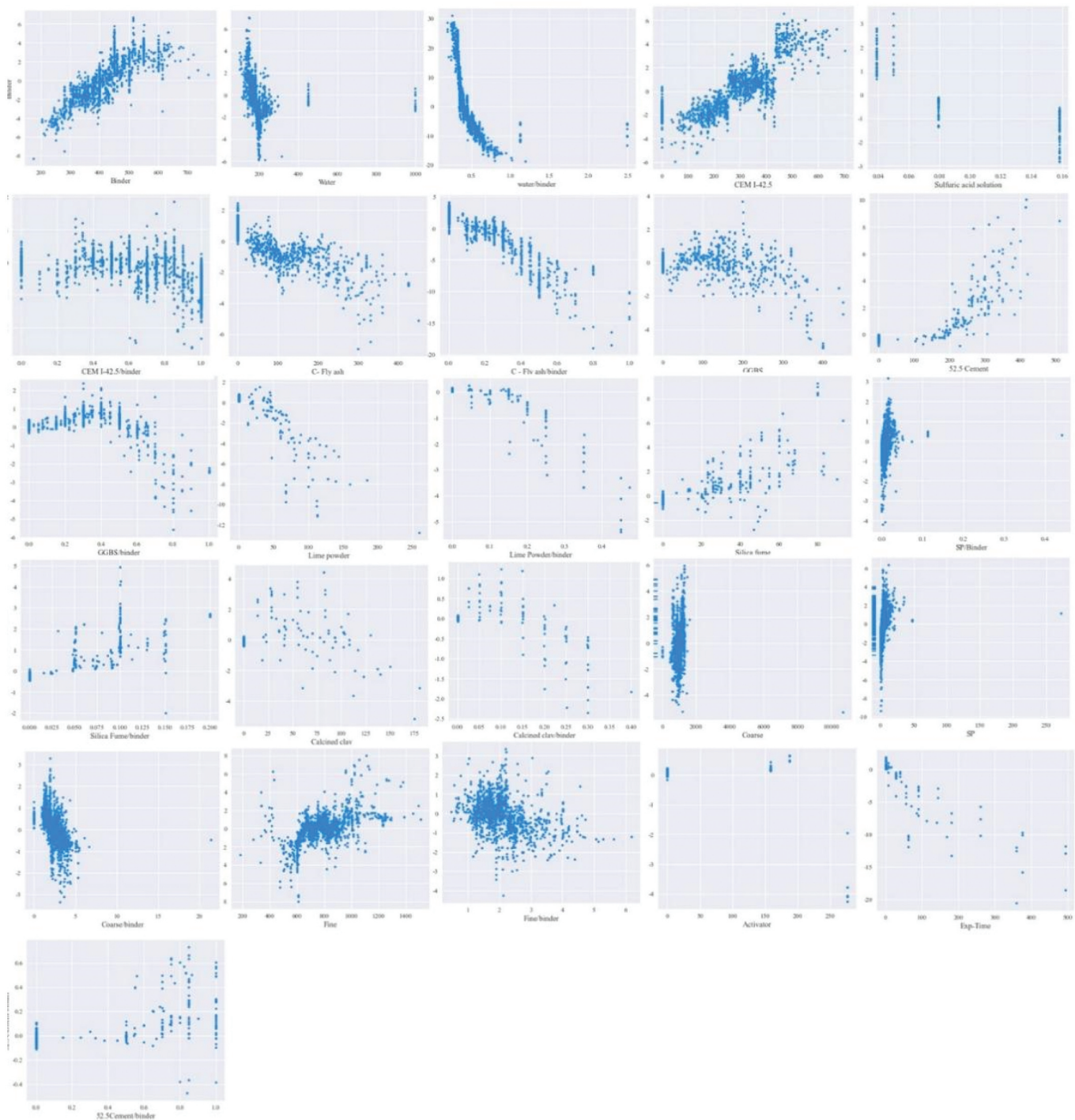


Figure 9. Feature dependence plots of compressive strength.

high proportion of coarse aggregate slows down the weight loss and corrosion depth simultaneously. However, the increase of fine aggregate content accelerated the weight loss and had no significant effect on the corrosion depth.

3.5. Individual interpretation based on the partial dependency plots

Compared with the summary diagram, the partial dependence diagram uses the scatter diagram to reflect the variable's non-

linear |SHAP value| change trend, and the influence of each input variable on the evaluation parameter is shown in Figures 8–11.

When the cement content exceeded about 200 (kg/m³), or the cement ratio exceeded about 0.85, the SHAP value stood less than 0 and inhibited the carbonation rate. CEM I-42.5 rises linearly around [0, 380], SHAP value breaks through 0 around 380 and continues to rise after CEM I-42.5 > 380(kg/m³), so CEM I-42.5 should be > 380(kg/m³). Also, raising the proportion of CEM I-42.5 would boost the SHAP value and weaken the

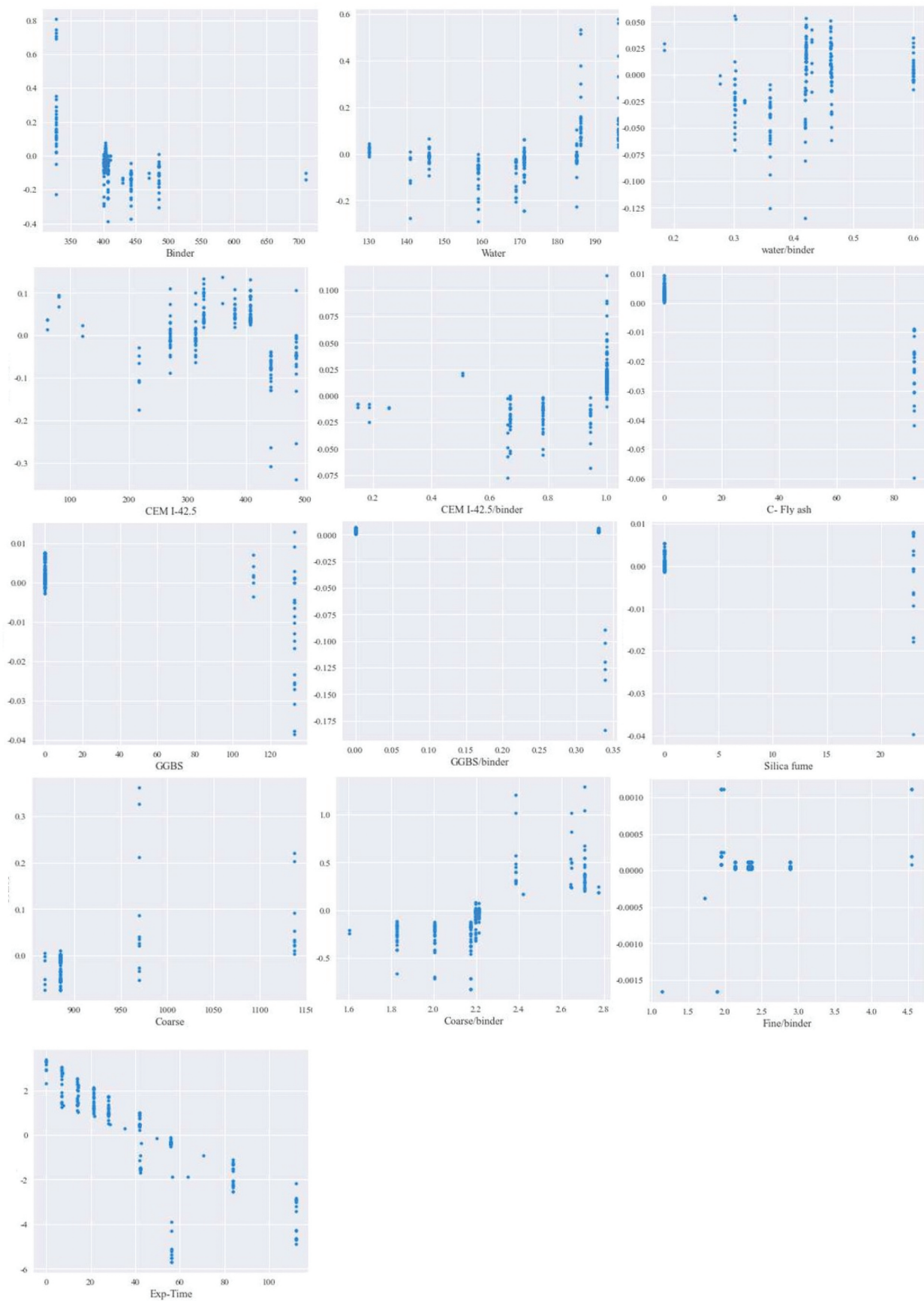


Figure 10. Feature dependence plots of depth.



Figure 11. Feature dependence plots of weight change.

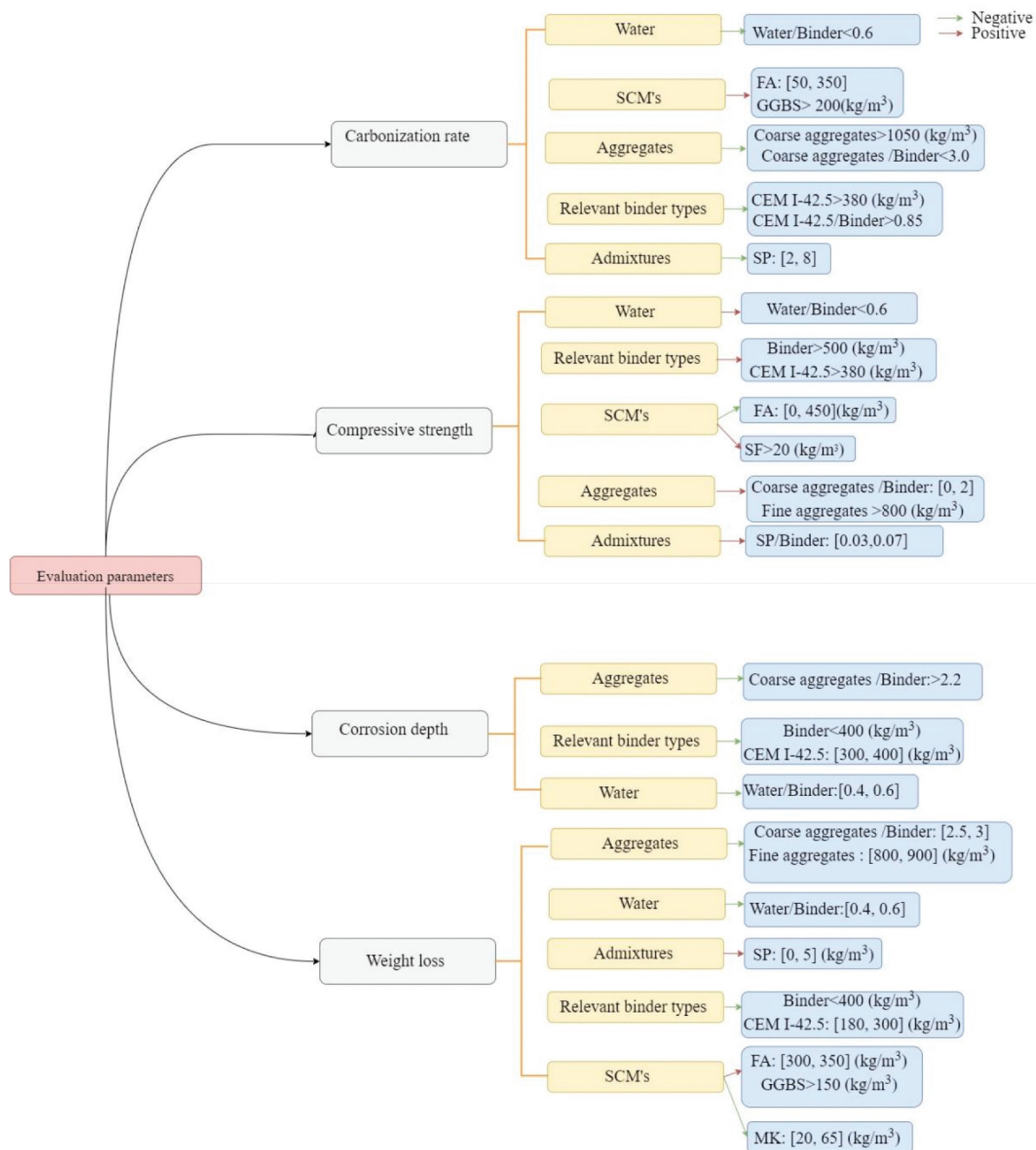


Figure 12. Comprehensive analysis of the influence of concrete composition on corrosion.

negative impact on the compressive strength. Compared with CEM I-42.5, the increase in compressive strength of CEM I-52.5 was significant, showing a rising trend with the upsurge in content, and the SHAP value reached 10. Neither CEM I-42.5 nor CEM I-52.5 had a significant effect on corrosion depth. Combined with CEM I-42.5 content and cement CEM I-42.5/binder, added SCM's to cement with a higher content of cement could slow down the weight loss, where the critical point was cement content 400 (kg/m³), and CEM I-42.5/binder was 0.6.

The influence of SCM's on the carbonization rate is limited, except for FA, which fluctuates between [−0.5, 0.5]. The exaltation of FA content accelerated the

carbonization rate, while GGBS could inhibit the carbonization rate but the effect was relatively limited. When the coarse aggregate content was more significant than about 1050 (kg/m³) and the specific gravity of the binder was less than 3.0, the SHAP value was positive, so the binder content should be controlled above 380 (kg/m³). No response to carbonization rate was observed for fine aggregates. The amount of water added had little effect on the properties of the concrete. When the w/b was lower than 0.6 would suppress the carbonization rate, and the increase of SP/binder would also be suppressed. The SHAP values of the FA addition amount of [100, 400] (kg/m³) and FA/binder of [0, 1] were negative numbers, adding FA reduced the

compressive strength. GGBS/binder could clearly express the impact on compressive strength, and the SHAP value corresponding to the GGBS content of about 0.5 was about 0. Therefore, the amount of GGBS/binder added to the binder was controlled at less than 0.5, and the specific content was about 200. LM had a similar trend to FA regarding compressive strength but had a somewhat more significant effect. SF was the only one in SCM's that had increased the compressive strength, and it was the highest at around 80 (kg/m³). According to the analysis, the influence of SCM's on the corrosion depth was relatively limited. SCM's had a significant effect on weight loss compared to corrosion depth. When FA/binder was around 0.8 and GGBS content was above 300 (kg/m³), the weight loss of concrete was accelerated, while MK had the opposite effect. However, SF could not see the impact on weight loss.

The increase in binder improved the compressive strength and inhibited the corrosion depth and quality loss. Coarse aggregate content and coarse aggregate/binder showed no regularity in compressive strength, but coarse aggregate/binder in the range of [0, 2] and fine aggregate above 1000 (kg/m³) could increase the compressive strength. When the coarse aggregate/binder agent was about 2.4, it began to have an apparent inhibitory effect on the corrosion depth and weight loss. The fine aggregate was 850 (kg/m³) in the density of concrete, which could help reduce weight loss, and more fine aggregate will accelerate weight loss. The amount of water added had little effect on the properties of the concrete.

Due to the nature of SP dehydration, reducing the addition of water or increasing the proportion of SP in the concrete manufacturing stage could also effectively inhibit the carbonation rate. When the w/b was about 0.2, the impact on the compressive strength of concrete was the most significant, and the SHAP value was as high as 30. Increasing SP/binder could also improve compressive strength to a certain extent. However, the effects of SP/binder and w/b on corrosion depth were relatively limited. The addition of water/binder would reduce weight loss, and alkaline-activator can resist acid corrosion.

The effect of exposure time on the loss of compressive strength and weight lessened as the concrete was exposed to sulfuric acid over time, while the impact on corrosion depth grew linearly with time (Wells and Melchers 2016). Consistent with previous studies, SHAP values for both corrosion depth and weight change were positive for the first 50 days of exposure time due to surface sulfate formation (Ling 2013). The optimized concrete parameter ratio is shown in Figure 12.

4. Conclusions

- (1) The developed interpretable model based on Scikit-Optimize-XGBoost-SHAP is the first one based on relevant binder types, SCM's, aggregates, admixtures, water to comprehensively predict and analyze

the carbonation rate of sewage pipe materials, Models for compressive strength, corrosion depth, and weight change.

- (2) This research Uses Scikit-Optimize technology to find the optimal parameters while preventing the model from overfitting and listed the parameters for predicting the four properties of concrete pipes.
- (3) The model has good prediction accuracy ($R^2 > 0.989$) to ensure reliable results of SHAP analysis to analyze the durability of concrete components in chemical corrosion.
- (4) Considering the corrosion resistance of drainage pipe materials, the ratio was optimized from five aspects: related binder type, SCM's, aggregate, admixture, and water.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability statement

All data presented herein will be provided upon reasonable request.

Author's contribution statement

Wenhao Wang: Investigation, Methodology, Writing. Jingguo Cao: Supervision, Project administration; Ming Zeng: Supervision, Methodology, Yongxiang Qiao: Concepts.

References

- Alhassan, Y., Y. Ballim, and T. Research. 2017. "An Experimental Study on Carbonation of Plain and Blended Cement Concrete." *International Journal of Scientific & Technology Research* 6 (8): 436–443.
- Al-Jamimi, H. A., W. A. Al-Kutti, S. Alwahaishi, and K. S. Alotaibi. 2022. "Prediction of Compressive Strength in Plain and Blended Cement Concretes Using a Hybrid Artificial Intelligence Model." *Case Studies in Construction Materials* 17:e01238. <https://doi.org/10.1016/j.cscm.2022.e01238>.
- Angulo-Ramirez, D., R. M. de Gutiérrez, W. Valencia-Saavedra, M. De Medeiros, and J. Hoppe-Filho. 2019. "Carbonation of Hybrid Concrete with High Blast Furnace Slag Content and its Impact on Structural Steel Corrosion." *Materiales de Construcción* 69 (333): e182–e182. <https://doi.org/10.3989/mc.2019.05418>.
- Arora, V., B. Singh, and V. Patel. 2019. "Durability and Corrosion Studies in Prestressed Concrete Made with Blended Cement." *Journal of Asian Concrete Federation* 5 (1): 15–24. <https://doi.org/10.18702/acf.2019.06.30.15>.
- Atiş, C. D. J. C. 2003. "Accelerated Carbonation and Testing of Concrete Made with Fly Ash." *Construction and Building Materials* 17 (3): 147–152. [https://doi.org/10.1016/S0950-0618\(02\)00116-2](https://doi.org/10.1016/S0950-0618(02)00116-2).
- Boudjehm, H., F. Bouteldja, Z. Nafa, and R. Bendjaiche. 2022. "Hardened Properties of Pre-Cracked Concrete Incorporating Metakaolin and Crushed Blast Furnace Slag as an Additional Blend Material." *Construction and Building Materials* 352:129009. <https://doi.org/10.1016/j.conbuildmat.2022.129009>.

- Bucher, R., P. Diederich, G. Escadeillas, and M. J. C. Cyr. 2017. "Service Life of Metakaolin-Based Concrete Exposed to Carbonation: Comparison with Blended Cement Containing Fly Ash, Blast Furnace Slag and Limestone Filler." *Cement and Concrete Research* 99:18–29. <https://doi.org/10.1016/j.cemconres.2017.04.013>.
- Burden, D. 2006. *The Durability of Concrete Containing High Levels of Fly Ash*. University of New Brunswick, Department of Civil Engineering.
- Buss, K. 2013. "Ternary Combination Concretes Using GGBS, Fly Ash & limestone." PhD Thesis, Dundee, UK: University of Dundee.
- Chang, Z.-T., X.-J. Song, R. Munn, and M. Marosszeky. 2005. "Using Limestone Aggregates and Different Cements for Enhancing Resistance of Concrete to Sulphuric Acid Attack." *Cement and Concrete Research* 35 (8): 1486–1494. <https://doi.org/10.1016/j.cemconres.2005.03.006>.
- Collepardi, M., S. Collepardi, J. O. Olagot, and F. Simonelli. 2004. "The Influence of Slag and Fly Ash on the Carbonation of Concrete." *Proceedings Eighth CANMET/ACI Int. Conf. on fly ash, silica fume, slag, and natural pozzolans in concrete. Proceedings ACI SP-221-29*, 23–29. Las Vegas, Nevada, USA.
- Czarnecki, L., P. Woyciechowski, and G. Adamczewski. 2018. "Risk of Concrete Carbonation with Mineral Industrial By-Products." *KSCE Journal of Civil Engineering* 22 (2): 755–764. <https://doi.org/10.1007/s12205-017-1623-5>.
- De Belie, N., J. Monteny, A. Beeldens, E. Vincke, D. Van Gemert, and W. Verstraete. 2004. "Experimental Research and Prediction of the Effect of Chemical and Biogenic Sulfuric Acid on Different Types of Commercially Produced Concrete Sewer Pipes." *Cement and Concrete Research* 34 (12): 2223–2236. <https://doi.org/10.1016/j.cemconres.2004.02.015>.
- De Muynck, W., N. De Belie, and W. Verstraete. 2009. "Effectiveness of Admixtures, Surface Treatments and Antimicrobial Compounds Against Biogenic Sulfuric Acid Corrosion of Concrete." *Cement and Concrete Composites* 31 (3): 163–170. <https://doi.org/10.1016/j.cemconcomp.2008.12.004>.
- Divsholi, B. S., T. Y. D. Lim, and S. Teng. 2014. "Durability Properties and Microstructure of Ground Granulated Blast Furnace Slag Cement Concrete." *International Journal of Concrete Structures and Materials* 8 (2): 157–164. <https://doi.org/10.1007/s40069-013-0063-y>.
- Duran-Herrera, A., J. M. Mendoza-Rangel, E. De-Los-Santos, F. Vazquez, P. Valdez, and D. P. J. M. Bentz. 2015. "Accelerated and Natural Carbonation of Concretes with Internal Curing and Shrinkage/Viscosity Modifiers." *Materials and Structures* 48 (4): 1207–1214. <https://doi.org/10.1617/s11527-013-0226-y>.
- García-Segura, T., V. Yepes, and J. Alcalá. 2014. "Life Cycle Greenhouse Gas Emissions of Blended Cement Concrete Including Carbonation and Durability." *The International Journal of Life Cycle Assessment* 19 (1): 3–12. <https://doi.org/10.1007/s11367-013-0614-0>.
- Gettu, R., R. G. Pillai, M. Santhanam, A. S. Basavaraj, S. Rathnarajan, and B. S. Dhanya. 2018. "Sustainability-Based Decision Support Framework for Choosing Concrete Mixture Proportions." *Materials and Structures* 51 (6): 1–16. <https://doi.org/10.1617/s11527-018-1291-z>.
- Grengg, C., F. Mittermayr, A. Baldermann, M. E. Böttcher, A. Leis, G. Koraimann, P. Grunert, and M. Dietzel. 2015. "Microbiologically Induced Concrete Corrosion: A Case Study from a Combined Sewer Network." *Cement and Concrete Research* 77:16–25. <https://doi.org/10.1016/j.cemconres.2015.06.011>.
- Gu, L., T. Bennett, and P. Visintin. 2019. "Sulphuric Acid Exposure of Conventional Concrete and Alkali-Activated Concrete: Assessment of Test Methodologies." *Construction and Building Materials* 197:681–692. <https://doi.org/10.1016/j.conbuildmat.2018.11.166>.
- Hafez, H., A. Teirelbar, R. Kurda, N. Tošić, and A. de la Fuente. 2022. "Pre-Bcc: A Novel Integrated Machine Learning Framework for Predicting Mechanical and Durability Properties of Blended Cement Concrete." *Construction and Building Materials* 352:129019. <https://doi.org/10.1016/j.conbuildmat.2022.129019>.
- Harrison, T. A., M. R. Jones, M. D. Newlands, S. Kandasami, and G. Khanna. 2012. "Experience of Using the PrTS 12390-12 Accelerated Carbonation Test to Assess the Relative Performance of Concrete." *Magazine of Concrete Research* 64 (8): 737–747. <https://doi.org/10.1680/macr.11.00162>.
- Herisson, J., M. Guéguen-Minerbe, E. D. van Hullebusch, and T. Chaussadent. 2016. "Influence of the Binder on the Behaviour of Mortars Exposed to H₂S in Sewer Networks: A Long-Term Durability Study." *Materials and Structures* 50 (1). <https://doi.org/10.1617/s11527-016-0919-0>.
- Herisson, J., E. D. van Hullebusch, M. Moletta-Denat, P. Taquet, and T. Chaussadent. 2013. "Toward an Accelerated Biodeterioration Test to Understand the Behavior of Portland and Calcium Aluminate Cementitious Materials in Sewer Networks." *International Biodeterioration & Biodegradation* 84:236–243. <https://doi.org/10.1016/j.ibiod.2012.03.007>.
- Hewayde, E. H. 2006. *Investigation on Degradation of Concrete Sewer Pipes by Sulfuric Acid Attack*.
- Hewayde, E., M. L. Nehdi, E. Allouche, and G. Nakhla. 2007. "Using Concrete Admixtures for Sulphuric Acid Resistance." *Proceedings of the Institution of Civil Engineers - Construction Materials* 160 (1): 25–35. <https://doi.org/10.1680/coma.2007.160.1.25>.
- Higuchi, T., M. Eguchi, M. Morioka, and E. J. C. Sakai. 2014. "Hydration and Properties of Expansive Additive Treated High Temperature Carbonation." *Cement and Concrete Research* 64:11–16. <https://doi.org/10.1016/j.cemconres.2014.06.001>.
- Holt, E., H. Kuosa, M. Leivo, F. Al-Neshawy, J. Piironen, and E. Sistonen. 2010. "Accounting for Coupled Deterioration Mechanisms for Durable Concrete Containing Mineral By-Products." *Proceedings of the 2nd International Conference on Sustainable Construction Materials and Technologies*, 1631–1643. Ancona, Italy.
- House, M. W. 2013. *Using Biological and Physico-Chemical Test Methods to Assess the Role of Concrete Mixture Design in Resistance to Microbially Induced Corrosion*. Purdue University.
- Jiang, G., J. Keller, and P. L. Bond. 2014. "Determining the Long-Term Effects of H₂S Concentration, Relative Humidity and Air Temperature on Concrete Sewer Corrosion." *Water Research* 65:157–169. <https://doi.org/10.1016/j.watres.2014.07.026>.
- Kaewmanee, K., and S. Tangtermsirikul. 2014. "Properties of Binder Systems Containing Cement, Fly Ash, and Limestone Powder." *Songklanakarinn Journal of Science & Technology* 36 (5): 569–576. <https://www.thaiscience.info/Journals/Article/SONG/10968346.pdf>.
- Khan, H. A., A. Castel, M. S. H. Khan, and A. H. Mahmood. 2019. "Durability of Calcium Aluminate and Sulphate Resistant Portland Cement Based Mortars in Aggressive Sewer Environment and Sulphuric Acid." *Cement and Concrete Research* 124:124. <https://doi.org/10.1016/j.cemconres.2019.105852>.
- Khan, H. A., M. Yasir, and A. Castel. 2022. "Performance of Cementitious and Alkali-Activated Mortars Exposed to Laboratory Simulated Microbially Induced Corrosion Test." *Cement and Concrete Composites* 128:128. <https://doi.org/10.1016/j.cemconcomp.2022.104445>.
- Khunthongkeaw, J., S. Tangtermsirikul, and T. J. C. Leelawat. 2006. "A Study on Carbonation Depth Prediction for Fly Ash Concrete." *Construction and Building Materials* 20 (9): 744–753. <https://doi.org/10.1016/j.conbuildmat.2005.01.052>.
- Leemann, A., P. Nygaard, J. Kaufmann, and R. J. C. Loser. 2015. "Relation Between Carbonation Resistance, Mix Design and Exposure of Mortar and Concrete." *Cement and Concrete Composites* 62:33–43. <https://doi.org/10.1016/j.cemconcomp.2015.04.020>.
- Lee, S., W. Park, and H. J. E. Lee. 2013. "Life Cycle CO₂ Assessment Method for Concrete Using CO₂ Balance and Suggestion to Decrease LCCO₂ of Concrete in South-Korean Apartment." *Energy & Buildings* 58:93–102. <https://doi.org/10.1016/j.enbuild.2012.11.034>.
- Ling, A. L. 2013. *Characterization and Control of Microbially Induced Concrete Corrosion*. University of Colorado at Boulder.
- Löfgren, I., O. Esping, and A. Lindvall. 2016. "The Influence of Carbonation and Age on Salt Frost Scaling of Concrete with Mineral Additions." *Materials, Systems and Structures in Civil Engineering* 2016:91–100. <https://core.ac.uk/download/pdf/70617924.pdf>.
- Madraszewski, S., F. Dehn, J. Gerlach, and D. Stephan. 2022. "Experimentally Driven Evaluation Methods of Concrete Sewers Biodeterioration on Laboratory-Scale: A Critical Review." *Construction and Building Materials* 320:126236. <https://doi.org/10.1016/j.conbuildmat.2021.126236>.
- Marques, P. F., C. Chastre, and Á. J. C. Nunes. 2013. "Carbonation Service Life Modelling of RC Structures for Concrete with Portland and Blended

- Cements." *Cement and Concrete Composites* 37:171–184. <https://doi.org/10.1016/j.cemconcomp.2012.10.007>.
- McNally, C., and E. J. C. Sheils. 2012. "Probability-Based Assessment of the Durability Characteristics of Concretes Manufactured Using CEM II and GGBS Binders." *Construction and Building Materials* 30:22–29. <https://doi.org/10.1016/j.conbuildmat.2011.11.029>.
- Menéndez, E., T. Matschei, F. Glasser, and RILEM TC 211-PAE. 2013. *Sulfate Attack of Concrete*. 7–74.
- Monteny, J., E. Vincke, A. Beeldens, N. De Belie, L. Taerwe, D. Van Gemert, and W. Verstraete. 2000. "Chemical, Microbiological, and in situ Test Methods for Biogenic Sulfuric Acid Corrosion of Concrete." *Cement and Concrete Research* 30 (4): 623–634. [https://doi.org/10.1016/S0008-8846\(00\)00219-2](https://doi.org/10.1016/S0008-8846(00)00219-2).
- O'Connell, M., C. McNally, and M. G. Richardson. 2010. "Biochemical Attack on Concrete in Wastewater Applications: A State of the Art Review." *Cement and Concrete Composites* 32 (7): 479–485. <https://doi.org/10.1016/j.cemconcomp.2010.05.001>.
- Okoye, F. N., S. Prakash, and N. B. Singh. 2017. "Durability of Fly Ash Based Geopolymer Concrete in the Presence of Silica Fume." *Journal of Cleaner Production* 149:1062–1067. <https://doi.org/10.1016/j.jclepro.2017.02.176>.
- Quan, H.-z., and H. Kasami. 2014. "Experimental Study on Durability Improvement of Fly Ash Concrete with Durability Improving Admixture." *Scientific World Journal* 2014:1–11. <https://doi.org/10.1155/2014/818103>.
- Rathnarajan, S., N. P. Vaddey, R. G. Pillai, R. Gettu, and M. Santhanam. 2017. "Modelling Carbonation Rates in Concretes with Similar Strength and with and without Slag." *Proceedings Conference: ICACMS 2017*, Chennai, India.
- Ren, J., L. Zhang, and R. San Nicolas. 2021. "Degradation of Alkali-Activated Slag and Fly Ash Mortars Under Different Aggressive Acid Conditions." *Journal of Materials in Civil Engineering* 33 (7). [https://doi.org/10.1061/\(ASCE\)MT.1943-5533.0003713](https://doi.org/10.1061/(ASCE)MT.1943-5533.0003713).
- Roziere, E., A. Loukili, and F. J. C. Cussigh. 2009. "A Performance Based Approach for Durability of Concrete Exposed to Carbonation." *Construction and Building Materials* 23 (1): 190–199. <https://doi.org/10.1016/j.conbuildmat.2008.01.006>.
- Ruixia, H. 2010. "A Study on Carbonation for Low Calcium Fly Ash Concrete Under Different Temperature and Relative Humidity." *The Electronic Journal of Geotechnical Engineering (EJGE)* 15:1871–1877. https://web.archive.org/web/20180423213748id_/http://www.ejge.com/2010/Ppr10.137.pdf.
- Sabour, M., G. Dezvareh, and R. Bazzazzadeh. 2019. "Corrosion Prediction Using the Weight Loss Model in the Sewer Pipes Made from Sulfur and Cement Concretes and Response Surface Methodology (RSM)." *Construction and Building Materials* 199:40–49. <https://doi.org/10.1016/j.conbuildmat.2018.11.283>.
- Sand, W. 1997. "Microbial Mechanisms of Deterioration of Inorganic Substrates—A General Mechanistic Overview." *International Biodeterioration & Biodegradation* 40 (2–4): 183–190. [https://doi.org/10.1016/S0964-8305\(97\)00048-6](https://doi.org/10.1016/S0964-8305(97)00048-6).
- Sanjuán, M., C. Andrade, and M. Cheyrez. 2003. "Concrete Carbonation Tests in Natural and Accelerated Conditions." *Advances in Cement Research* 15 (4): 171–180. <https://doi.org/10.1680/adcr.2003.15.4.171>.
- San Nicolas, R., M. Cyr, and G. J. C. Escadeillas. 2014. "Performance-Based Approach to Durability of Concrete Containing Flash-Calcined Metakaolin as Cement Replacement." *Construction and Building Materials* 55:313–322. <https://doi.org/10.1016/j.conbuildmat.2014.01.063>.
- Sisomphon, K., and L. J. C. Franke. 2007. "Carbonation Rates of Concretes Containing High Volume of Pozzolanic Materials." *Cement and Concrete Research* 37 (12): 1647–1653. <https://doi.org/10.1016/j.cemconres.2007.08.014>.
- Soja, W. 2019. *Carbonation of Low Carbon Binders*. EPFL.
- Sun, X., G. Jiang, P. L. Bond, T. Wells, and J. Keller. 2014. "A Rapid, Non-Destructive Methodology to Monitor Activity of Sulfide-Induced Corrosion of Concrete Based on H₂S Uptake Rate." *Water Research* 59:229–238. <https://doi.org/10.1016/j.watres.2014.04.016>.
- Tripathi, D., R. Kumar, P. K. Mehta, and A. Singh. 2020. "Silica Fume Mixed Concrete in Acidic Environment." *Materials Today: Proceedings* 27:1001–1005. <https://doi.org/10.1016/j.matpr.2020.01.311>.
- Valencia-Saavedra, W. G., R. Mejía de Gutiérrez, and F. Puertas. 2020. "Performance of FA-Based Geopolymer Concretes Exposed to Acetic and Sulfuric Acids." *Construction and Building Materials* 257:119503. <https://doi.org/10.1016/j.conbuildmat.2020.119503>.
- Van Jaarsveld, J. G. S., J. S. J. Van Deventer, and L. Lorenzen. 1997. "The Potential Use of Geopolymeric Materials to Immobilise Toxic Metals: Part I. Theory and Applications." *Minerals Engineering* 10 (7): 659–669. [https://doi.org/10.1016/S0892-6875\(97\)00046-0](https://doi.org/10.1016/S0892-6875(97)00046-0).
- Wang, X.-Y. J. C. 2019. "Simulation for Optimal Mixture Design of Low-CO₂ High-Volume Fly Ash Concrete Considering Climate Change and CO₂ Uptake." *Cement and Concrete Composites* 104:103408. <https://doi.org/10.1016/j.cemconcomp.2019.103408>.
- Wang, Y., F. Su, Y. Guo, H. Yang, Z. Ye, and L. Wang. 2022. "Predicting the Microbiologically Induced Concrete Corrosion in Sewer Based on XGBoost Algorithm." *Case Studies in Construction Materials* 17:17. <https://doi.org/10.1016/j.cscm.2022.e01649>.
- Wells, T., and R. Melchers. 2016. *Concrete Sewer Pipe Corrosion—Findings from an Australia Field Study*.
- Wells, T., and R. E. Melchers. 2014. "An Observation-Based Model for Corrosion of Concrete Sewers Under Aggressive Conditions." *Cement and Concrete Research* 61–62:1–10. <https://doi.org/10.1016/j.cemconres.2014.03.013>.
- Wells, T., and R. E. Melchers. 2015. "Modelling Concrete Deterioration in Sewers Using Theory and Field Observations." *Cement and Concrete Research* 77:82–96. <https://doi.org/10.1016/j.cemconres.2015.07.003>.
- Woyciechowski, P., P. Woliński, and G. J. M. Adamczewski. 2019. "Prediction of Carbonation Progress in Concrete Containing Calcareous Fly Ash Co-Binder." *Materials* 12 (17): 2665. <https://doi.org/10.3390/ma12172665>.
- Wu, M., T. Wang, K. Wu, and L. Kan. 2020. "Microbiologically Induced Corrosion of Concrete in Sewer Structures: A Review of the Mechanisms and Phenomena." *Construction and Building Materials* 239:117813. <https://doi.org/10.1016/j.conbuildmat.2019.117813>.
- Yang, F., T. B. Pluth, X. Fang, K. B. Francq, M. Jurjovec, and Y. Tang. 2021. "Advanced Machine Learning Application for Odor and Corrosion Control at a Water Resource Recovery Facility." *Water Environment Research* 93 (11): 2346–2359. <https://doi.org/10.1002/wer.1618>.
- Younsi, A., P. Turcry, A. Ait-Mokhtar, and S. J. C. Staquet. 2013. "Accelerated Carbonation of Concrete with High Content of Mineral Additions: Effect of Interactions Between Hydration and Drying." *Cement and Concrete Research* 43:25–33. <https://doi.org/10.1016/j.cemconres.2012.10.008>.
- Younsi, A., P. Turcry, E. Rozière, A. Ait-Mokhtar, and A. J. C. Loukili. 2011. "Performance-Based Design and Carbonation of Concrete with High Fly Ash Content." *Cement and Concrete Composites* 33 (10): 993–1000. <https://doi.org/10.1016/j.cemconcomp.2011.07.005>.
- Zhang, X., X. Zhou, H. Zhou, K. Gao, and Z. J. A. C. S. Wang. 2013. "Studies on Forecasting of Carbonation Depth of Slag High Performance Concrete Considering Gas Permeability." *Applied Clay Science* 79:36–40. <https://doi.org/10.1016/j.clay.2013.02.020>.
- Zhao, H., W. Sun, X. Wu, and B. Gao. 2015. "The Properties of the Self-Compacting Concrete with Fly Ash and Ground Granulated Blast Furnace Slag Mineral Admixtures." *Journal of Cleaner Production* 95:66–74. <https://doi.org/10.1016/j.jclepro.2015.02.050>.