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Predicting Long-Term Durability of Rock Material for Breakwater Design with Machine Learning Algorithms

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Abstract

Predicting the long-term durability of rock in the construction of breakwaters is crucial for their safe and economic operation, but remains challenging. Here, we report on the application of Machine Learning models to such prediction. We developed a database of physical and mechanical properties of rocks from 35 rubble mound breakwaters on the Caspian Sea, Oman Sea and Persian Gulf coastlines of Iran. Properties include uniaxial compressive strength, point load strength, Brazilian tensile strength, aggregate impact and aggregate crushing values, Los Angeles abrasion, porosity, ultrasonic wave velocity, density, sodium sulfate soundness and slake durability index, together with petrophysical data. These data were analysed using the four supervised machine learning (ML) models of random forest (RF), support vector (SV) machine, gradient boost (GB) and k-nearest (KN) neighbour. Model performance was assessed using RMSE computed using predicted and measured values of slake durability, and R2 of the linear regression of the predicted and measured slake durability values. The results indicate that the random forest (RF) models perform best, especially for igneous rocks: for both saturated and oven-dry igneous rocks the RF model produced prediction errors of under ±0.6%, and R2 was unity to five significant figures. We conclude that ML techniques are robust methods for predicting the slake durability resistance of rock material used in the construction of breakwaters.

Keywords: *Breakwaters, long-term durability resistance, rock property database, supervised machine learning, random forest model.*

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1. Introduction

Understanding the complexities of rock engineering behaviour is critical for reliable rock engineering design, particularly when utilizing rock as an engineering material for construction. Given the local availability of quarries, the optimal construction approach for coastal protection structures is often rubble mound breakwaters. Considering the extensive coastlines of northern and southern Iran, spanning over 3000 km across the Persian Gulf, Oman, and Caspian seas, the construction of large protective structures is imperative for the development of the country's safe marine transportation.

A wide range of climatic and environmental conditions exist around the coastline of Iran. While rock materials have traditionally been utilized in breakwater construction worldwide, the lack of suitable standards appropriate for these conditions has restricted their widespread application in Iran. A particular challenge in breakwater construction is predicting the long-term engineering behaviour of rock material in the marine environment. This is most acute for rock used as armourstone in rubble mound breakwaters. Poor long-term performance of breakwater and coastal protection materials has been widely observed southern and northern Iran, with deterioration of the rock from which they are constructed (i.e., lack of durability) being identified as the primary failure mechanism. Consequently, effective prediction of factors affecting the durability of armourstone, as well as the criteria needed for material selection, can significantly reduce risks, enhance safety, and improve long-term reliability. This paper examines the use of machine learning (ML) algorithms to predict the long-term durability and performance of such rock materials. The main objective of this paper is to understand how the predictability of rock material durability in breakwater armourstone selection during the design process can be improved.

Rubble mound structures have been used for over 100 years, with extensive use being made of rock materials. Early work on the design process of such marine structures (e.g., Wakeling 1977; Gravesen & Sorensen 1977; US Army Corps of Engineers, 2002) did not concentrate on the significance of the durability of rock materials, particularly in relation to deterioration mechanisms over time. This situation began to change in the 1980s as researchers began to investigate factors and mechanisms affecting long term durability, using both laboratory testing and field monitoring.

Rock used in breakwater construction is required to have physical and chemical characteristics that can endure the marine conditions within the specific section of the structure where it is employed. Durability of rock material is its ability to continue performing adequately in a specific working environment (Latham et al., 2006) and is known to be a function of mineralogical composition, texture, grain size, and geological weathering (Poole, 1991). Predicting rock behaviour and its durability in a marine environment therefore requires consideration of physical, mechanical and petrophysical properties, marine environmental factors, and the specific placement of rock material in the structure. Similarly, Dibb et al., (1983) reported on in-service resistance and deterioration of rock material used in breakwaters, and discussed how factors such as rock type, rock engineering properties and strength, salt and sodium sulfate solutions in the marine environment, and their interactions affect the process of deterioration and degradation. Such properties should be determined during material selection and the design process of breakwaters (Latham et al., 1988). A review of the literature shows that a variety of engineering and laboratory tests are used to measure and understand the process of degradation and material weight loss in rubble mound structures and breakwaters. These include abrasion tests (Latham & Poole 1988), sodium or magnesium sulfate soundness tests (Dibb et al., 1983), and material durability evaluations and the quality of armourstone in breakwater structures (Latham & Poole 1986; Latham & Poole 1988; Latham 1991; Poole 1991; Lienhart 1998; Gökceoğlu et al., 2000; Latham et al., 2006; Ozden & Topal 2009; Latham 1998; Karandagh et al., 2019). According to Rosa et al., (1991), petrographical characteristics and physical properties such as void spaces associated with water absorption influence the durability of rock materials and are the most significant factors controlling their longevity. This comprehensive overview also makes clear the intricate relation between rock properties and deterioration factors.

Various researchers have studied specific quarries as sources of armourstone material. For example, Ozden & Topal (2009), examined rock from an andesite quarry for use in the Hisarönü rubble mound breakwater. Using laboratory and field measurements, Ertas & Topal (2007) compared site performance, material durability and the mass properties of armourstone. In other work, Ozden & Topal (2007), determined the long-term quality and durability of armourstone through field and laboratory studies. Such work provides insights into the geological characteristics and suitability of armourstone sources, thereby contributing to informed decisions in breakwater construction (Topal & Acir 2004).

Most design and construction standards for coastal and marine structures, such as CIRIA/CUR (2007), classify the quality of rock material based on experimental results obtained through laboratory testing procedures such as this referred to above. However, many of these procedures tend to be costly and time-consuming. Additionally, measurement methods primarily focus on quantitative engineering properties independently and are mostly unable to represent the complexities of rock engineering behaviour where many properties combine to confound overall performance. Consequently, the intricate correlations of parameters and the pattern of effects between them are difficult to detect through typical laboratory testing. As we show below in Section 3, machine learning techniques seem to offer a means of overcoming these difficulties.

2. Methodology

2.1. Establishing a rock property database

The basis of this research is a comprehensive database of rock properties developed by the principal author from laboratory testing of rocks materials taken from different quarry sites and utilized as construction material of 35 rubble mound breakwater in southern and northern coastlines of Iran, including the Caspian Sea, Oman Sea, and Persian Gulf, and encompass sedimentary (sandstone, limestone and carbonate) and igneous (basalt, andesite, rhyolite, and granite) rock types (Hamidi, 2024).

Figures 1, 2 and 3 indicate the sample locations, and Table 1 gives sample locations and rock types. Table 1 is ordered by increasing UTM easting to allow easy correspondence with Figures 2 and 3. Complete details of the sample locations and geology is presented in Hamidi, 2024.

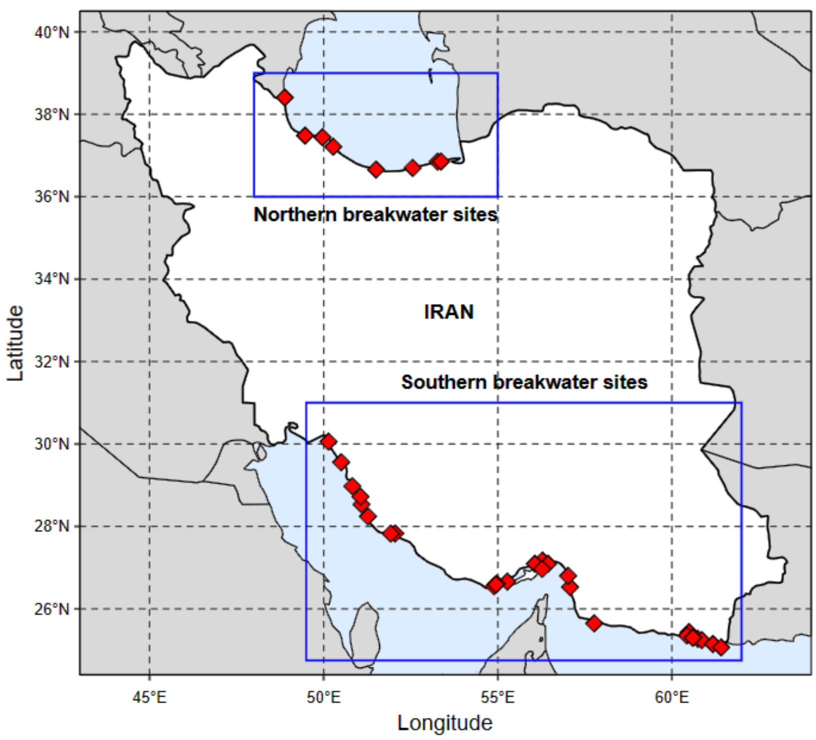

Figure 1. Regional location map.

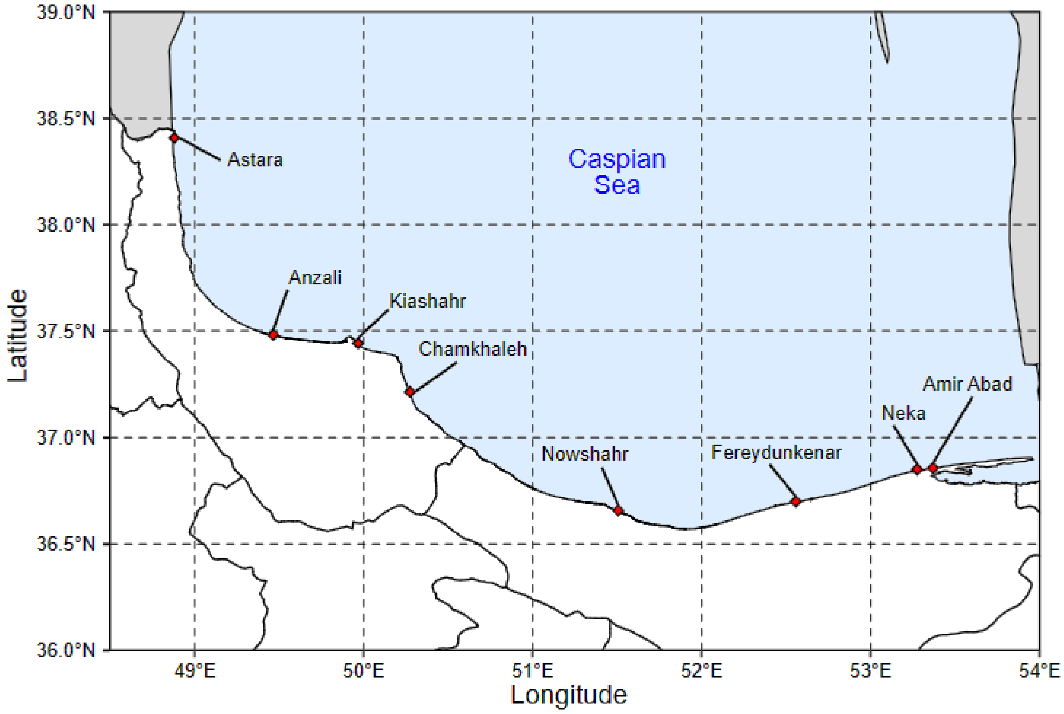

Figure 2. Northern breakwater sites.

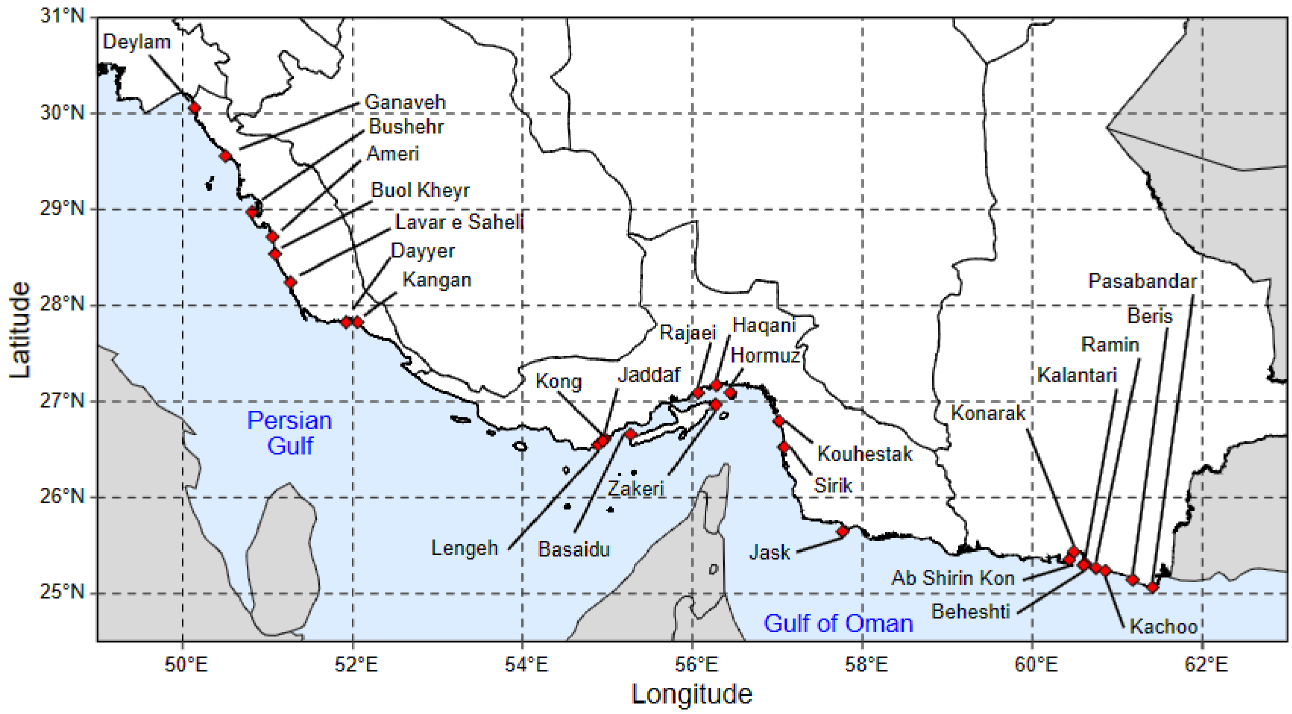

Figure 3. Southern breakwater sites.

Table 1. Site locations and rock types (after Hamidi, 2024)

Breakwater	Province	UTM zone	UTM east	UTM north	Material	XRD mineral identification
Deylam	Bushehr	39	417196	3325598	Limestone; sandstone; calcareous conglomerate; lomashell	Calcite; dolomite; quartz
Ganaveh	Bushehr	39	451809	3269776	Sandstone; lomashell	Calcite; quartz; dolomite; gypsum
Bushehr	Bushehr	39	482548	3205053	Limestone; lomashell	Calcite; dolomite
Shahid Ameri	Bushehr	39	505523	3176710	Limestone; lomashell; mudstone	Calcite
Buol Kheyr	Bushehr	39	508608	3156566	Crystallized limestone; marly limestone; mudstone; lomashell	Calcite; dolomite; quartz; halite (minor)
Lavar e Saheli	Bushehr	39	526636	3124207	Limestone; siltstone; lomashell; calcareous conglomerate	Calcite; dolomite; feldspar
Dayyer	Bushehr	39	591309	3078513	Limestone; lomashell	Calcite; dolomite; quartz (minor)
Kangan	Bushehr	39	604123	3078768	Limestone; lomashell, mudstone	Calcite; dolomite
Lengeh	Hormozgan	40	289717	2938250	Lomashell; limestone; basalt	Calcite; quartz; feldspar; zircon
Kong	Hormozgan	40	295365	2942746	Lomashell; limestone conglomerate	Calcite
Jaddaf	Hormozgan	40	297593	2945289	Gabbro; basalt	—
Basaidu	Hormozgan	40	327824	2950036	Lomashell; limestone	Calcite; rutile
Shahid Rajaei	Hormozgan	40	407430	2997026	Granite; diorite; andesite; basalt; rhyolite; gabbro	Quartz; calcite; feldspar; anatase; clay minerals (minor)
Zakeri	Hormozgan	40	427744	2983069	Lomashell; limestone;	Calcite
Shahid Haqani (Haghani)	Hormozgan	40	428785	3005743	Agglomerate; gabbro	Quartz; feldspar; calcite; kaolinite
Hormuz	Hormozgan	40	444816	2996894	Basalt; gabbro; lomashell; conglomerate; sandstone	Quartz; kaolinite; illite
Kouhestak	Hormozgan	40	502043	2664235	Sandstone; lomashell	Calcite; quartz (minor); feldspar (minor)
Sirik	Hormozgan	40	507474	2933936	Lomashell; limestone conglomerate	Calcite; quartz; feldspar (minor)
Jask	Hormozgan	40	577016	2836900	Sandstone; lomashell	Calcite; feldspar
Ab Shirin Kon	Sistan & Balouchestan	41	247296	2815655	Lomashell	Calcite
Konarak	Sistan & Balouchestan	41	241585	2806795	Lomashell	—
Shahid Beheshti	Sistan & Balouchestan	41	258431	2800285	Lomashell	Calcite; quartz
Shahid Kalantari	Sistan & Balouchestan	41	260276	2801793	Sandstone; lomashell; limestone	Quartz; feldspar; calcite; kaolinite
Ramin	Sistan & Balouchestan	41	272979	2796692	Lomashell	Calcite; quartz; rutile
Kachoo	Sistan & Balouchestan	41	284132	2793127	Lomashell	—
Beris	Sistan & Balouchestan	41	316324	2782321	Lomashell	Calcite; quartz
Pasabandar	Sistan & Balouchestan	41	339804	2773192	Lomashell	Calcite; quartz
Astara	Gilan	39	315004	4253122	Andesite; sandstone	—
Anzali	Gilan	39	364384	4149475	Igneous	Calcite; quartz
Kiashahr	Gilan	39	408686	4144500	Igneous, sedimentary	Feldspar; geothite
Chamkhaleh	Gilan	39	435670	4118964	Dacite; diorite; andesite; granite; agglomerate	Quartz; calcite; feldspar; kaolinite
Nowshahr	Mazandaran	39	545338	4056963	Limestone; sandstone; granite	Calcite

Fereydunkenar	Mazandaran	39	639092	4062642	Limestone; sandstone; syenite; dacite; slate	Calcite; quartz (minor)
Neka	Mazandaran	39	702886	4080657	Limestone; sandstone; diorite; agglomerate; slate; schist	Calcite; quartz
Amir Abad	Mazandaran	39	711240	4081488	Limestone; sandstone; limestone conglomerate	Calcite

To examine the performance of quarried rock used in the construction of breakwaters, an extensive research project was conducted in conjunction with the Ports and Maritime Organization and the Road, Housing and Urban Development Research Center (BHRC). This project involved sampling of the rocks used at multiple breakwater sites, followed by various tests conducted in the laboratories of Ferdowsi University of Mashhad (FUM) and BHRC.

The general geology of the southern quarries (i.e., those that supplied the material for the southern breakwaters) fall within the structural units of the Iranian Plateau, specifically the Folded Zagros, Makran, and the sedimentary-structural zone of Alborz (Aghanabati, 2004). The Folded Zagros comprises a thick sedimentary sequence from the Mesozoic and Cenozoic eras, featuring stratigraphic gaps from various orogenic phases and diverse lithologies, including alternating carbonate rocks (limestone, dolomite), evaporitic rocks (marl), and clastic rocks (sandstone, siltstone). This sequence includes formations such as the Hormuz Series, Khami Group, Asmari, Jahrum, Mishan, Gachsaran, and Bakhtiari formations. Volcanic activities are generally absent, except for intrusive volcanic rocks in salt domes from the Late Precambrian (Khosrotehrani, 1998). The southeastern coastal strip in the Chabahar region lies within the Makran structural zone, specifically the coastal Makran part.

In the northern regions, quarries for the construction of northern breakwaters are situated within the sedimentary-structural zones of the Alborz range, Caspian subsidence, and southern Caspian margin. The Alborz range forms a composite anticline extending from Azerbaijan to Khorasan. The northern border coincides with Tertiary deposits and the Caspian coastal plain. Geologically, the northern boundary of Alborz is defined by the Tethys suture zone, formed by the collision of the Alborz continental lithosphere with the Turan continent in the Late Triassic (Aghanabati, 2004). Sedimentary sequences south of the Caspian Sea, from Gonbad Kavus to the Moghan plain, indicate Middle Miocene deposits onwards.

The rock property data were obtained from 210 blocks, each with dimensions greater than 30×30×30 cm, taken from the armor layer at the mentioned 35 breakwater locations. These blocks were transported to the Geotechnical Engineering Department of BHRC. Test samples were prepared by the first author to conduct laboratory experiments, investigate rock sample properties, and develop the database. All tests were conducted in the laboratories of FUM and BHRC. The database contains physical, mechanical, petrophysical and petrographical properties, as well as durability indicators through simulation tests, as recommended in design standards and the literature for the use of rock in marine structures (Dibb et al., 1983; Latham & Poole 1988; Fookes 1991; Poole 1991; CUR/CIRIA 2007; Latham et al., 2006). Additionally, the procedures align with the Iranian Ports and Marine Structures Design Code (Iran Planning and Management Organization 2007) for engineering tests required for determining the properties of the rock material used in the armour layer and underlying units.

Properties determined include rock type, petrographical data (e.g., mineralogy, textural features), uniaxial compression strength (UCS), point load strength (PLT), Brazilian tensile strength (BTS), aggregate impact value (AIV), aggregate crushing value (ACV), Los Angeles abrasion (LAA), porosity, ultrasonic velocity (Vp), density, sodium sulfate soundness after 5, 10 and 15 cycles (SN05, SN10 and SN15), and slake durability index after 5, 10 and 15 cycles (ID05, ID10 and ID15). LAA, slake durability and sodium sulfate soundness were used as potential indicators of long-term durability. The decision to subject the igneous rocks to slake durability determination was based on the observation that XRD results Table 1 (not reported here for brevity but presented in Hamidi (2024)) indicated that they contained clay minerals; the deleterious effect of such minerals on long-term durability of rocks when in service as breakwater materials is well known. All determinations were conducted based on standard methods including ISRM, ASTM and BS procedures, as indicated in Table 2 (Fookes et al, 1988). Example photographs of various laboratory tests are provided in Appendix A. In all, the database is considered to offer a comprehensive evaluation of quality, integrity, soundness, and porosity. Summaries of the data are given in Table 3 and Table 4. Given the numerous factors that contribute to durability – including physical and mechanical properties, as well as environmental factors which are assessed in simulation test procedures – the dataset has much larger dimensions than would usually be used in multivariate regression.

Table 2. Test method standards and procedures

Physical Tests	Mechanical tests	Simulation Tests	Petrographic Tests
Specific gravity Water absorption (BS 812)	Unconfined compressive strength (ISRM) Point load strength (ISRM 1985) (apparent, oven- dried, saturated surface dry) -10% fines value (BS 812) Schmidt rebound number (Duncan, 1969) Aggregate impact value (AIV) (BS 812) Aggregate abrasion value (BS 812) Aggregate crushing value (ACV) (BS 812)	Modified aggregate impact value (Husking & Tubi, 1969) Los Angeles abrasion (ASTM C535) Washington degradation test (DMR T214) Wetting and drying Magnesium/sodium sulphate soundness test (ASTM C88) Freeze-thaw durability test (AASHTO T103-78) Slake durability index (ASTM D4644)	Petrographic examination (ASTMC 295) Thin Section Clay mineral analysis (XRD, DTA, methylene blue absorption) Blue Absorption Ethyl Glycol (XRD)

Table 3. Summary of experimental database (sedimentary)

			Saturated					Oven dried				
No.	Property	Units	count	max	min	mean	sdev	count	max	min	mean	sdev
1	UCS	MPa	348	86.22	0.51	18.54	17.33	378	142.09	1.90	26.62	24.37
2	PLT	MPa	237	9.76	0.31	2.07	1.45	232	16.19	0.58	2.94	2.29
3	BTS	MPa	214	16.39	0.22	3.03	2.33	208	24.20	0.73	4.32	2.95
4	AIV	%	196	65.66	10.31	31.17	15.87	196	65.66	10.31	31.17	15.87
5	ACV	%	196	91.31	17.09	46.35	22.46	196	91.31	17.09	46.35	22.46
6	LAA	%	197	90.84	11.65	49.62	22.46	188	90.84	11.65	49.84	22.28
7	e	%	290	28.32	0.20	10.31	5.50	290	28.32	0.20	10.31	5.50
8	Vp	m/s	244	10000	604.2	3995	1389	199	12730	34.80	3920	1685
9	γ	g/cm^3	290	2.86	1.25	2.20	0.30	290	2.82	1.17	2.10	0.33
10	SN05	%	202	61.69	-0.37	8.21	11.59	200	61.69	-0.37	8.01	11.49
11	SN10	%	202	79.88	0.47	20.73	20.70	200	79.88	0.47	20.28	20.48
12	SN15	%	202	88.69	0.54	28.54	24.12	200	88.69	0.54	28.07	24.12
13	ID05	%	137	103.68	71.82	92.29	7.04	122	103.68	71.82	90.65	7.13
14	ID10	%	137	102.75	58.00	87.44	10.53	122	102.75	58.00	85.37	10.62
15	ID15	%	137	100.63	46.26	84.23	12.46	122	100.63	46.26	81.35	13.19

Property abbreviations

UCS: unconfined compressive stress. PLT: point load strength. BTS: Brazilian tensile strength. AIV: aggregate impact value. ACV: aggregate crushing value. LAA: Los Angeles abrasion. *e*: porosity. Vp: *p*-wave ultrasonic velocity. γ: mass density. SN05, SN10, SN15: soundness (5, 10 and 15 cycles, respectively). ID05, ID10, ID15: durability (5, 10 and 15 cycles, respectively).

Table 4. Summary of experimental database (igneous)

			Saturated					Oven dried				
No.	Property	Units	count	max	min	mean	sdev	count	max	min	mean	sdev
1	UCS	MPa	119	119.12	0.67	46.44	28.14	111	152.00	4.09	56.26	41.05
2	PLT	MPa	54	9.40	0.61	5.22	2.52	54	12.86	0.65	6.55	2.94
3	BTS	MPa	45	13.40	0.74	7.15	3.29	45	32.34	1.18	10.15	5.96
4	AIV	%	58	31.56	6.26	15.03	7.74	58	31.56	6.26	15.03	7.74
5	ACV	%	58	68.73	8.38	26.87	19.21	58	68.73	8.38	26.87	19.21
6	LAA	%	57	43.00	9.76	19.67	10.20	50	43.00	9.76	20.51	10.49
7	e	%	70	22.81	0.52	7.28	5.77	70	22.81	0.52	7.28	5.77
8	Vp	m/s	75	7938	1463	4250	1370	68	7147	1461	4260	1134
9	γ	g/cm^3	70	2.79	1.76	2.39	0.16	70	2.77	1.64	2.32	0.21
10	SN05	%	49	24.45	-0.80	5.04	8.32	39	24.45	-0.80	6.13	8.90
11	SN10	%	49	42.26	0.01	10.95	14.69	39	42.26	0.01	13.31	15.37
12	SN15	%	49	47.96	0.10	13.57	17.36	39	47.96	0.10	16.46	18.08
13	ID05	%	40	99.17	90.65	96.62	3.35	31	99.17	90.65	96.07	3.56
14	ID10	%	40	98.49	85.02	94.61	5.37	31	98.49	85.02	93.71	5.68
15	ID15	%	40	98.12	81.59	93.30	6.57	31	98.12	81.59	92.18	6.94

Property abbreviations

UCS: unconfined compressive stress. PLT: point load strength. BTS: Brazilian tensile strength. AIV: aggregate impact value. ACV: aggregate crushing value. LAA: Los Angeles abrasion. *e*: porosity. Vp: *p*-wave ultrasonic velocity. γ: mass density. SN05, SN10, SN15: soundness (5, 10 and 15 cycles, respectively). ID05, ID10, ID15: durability (5, 10 and 15 cycles, respectively).

The complete database contains 467 records, comprising 119 igneous and 348 sedimentary records. No further separation beyond igneous and sedimentary was performed; an effect of this is considered further in Section 4. As Table 3 and Table 4 show, the count of test numbers is less than that of the record count. This means that many records contained missing data, which has ramifications for the machine learning process. This is discussed below. The rock property database is arranged as four groups, one for each of saturated sedimentary rock (SS), saturated igneous rock (IS), oven dry sedimentary rock (SD) and oven dry igneous rock (ID). ML was applied separately to each of these groups.

2.2. Supervised machine learning for durability prediction

As the rationale for the application of machine learning (ML), it is emerging as a dominant approach in the application of artificial intelligence. ML can be categorized into supervised and unsupervised learning. Supervised learning in machine learning (ML) primarily concentrates on addressing regression and classification issues (El Mrabet et al., 2021). Supervised ML models construct non-linear mappings between input and output variables, exhibit a robust capacity to extract valuable information from a complex dataset, and are adept at handling multivariate relations in high-dimensional data (Yu et al., 2022). Rock material often exhibits significant heterogeneity, leading to the requirement for extensive laboratory experimental campaigns in order to obtain comprehensive characterisation. These are time consuming and costly. Furthermore, the empirical correlations that are inevitably required in order to predict engineering behaviour often fail to achieve the necessary accuracy required for addressing problems and challenges in rock engineering applications. Machine learning algorithms are being used in the field of rock mechanics to address these challenges, encompassing tasks such as clustering, prediction, and classification (Abdelhedi et al., 2023).

Rock mechanics applications of supervised ML algorithms are many and varied. Examples include: correlating uniaxial compressive strength (UCS) of sandstone with Los Angeles abrasion (Liu et al., 2022); addressing inaccuracy in UCS assessments caused by small sample sizes (Abdelhedi et al., 2023); predicting UCS and elastic modulus of rock (Ghasemi et al., 2018); predicting elastic modulus (Ceryan et al., 2021); analysing rock strength and its related variables (Miah et al., 2020; Barzegar et al., 2020; Mahmoodzadeh et al., 2022); and, analysing borehole breakout (Yang et al., 2022). We have found no reports of ML being used to predict long-term performance of rock for use in breakwaters in a marine environment, and thus consider our work to be a novel contribution.

In this work, four supervised ML algorithms have been applied to develop models and predict the long-term performance of rock materials when they are utilized in armourstone and breakwater construction. The four techniques used are: support vector machines (SV); K-nearest neighbours (KN), random forest (RF), and gradient boosting (GB). Each algorithm has been used to predict the durability of rock material after 5, 10, and 15 cycles of slake durability tests.

The support vector machine is primarily used for classification and regression tasks, addressing various classification problems, and as a classifier based on statistical learning theory (Tang & Na 2021). SV machines attempt to identify the optimal hyperplane that fits to a multidimensional dataset; the points closest to the hyperplane are termed support vectors. The SV machine demonstrates effectiveness in high-dimensional spaces and is particularly valuable when a clear margin of separation exists between classes (Ebid 2021; Abdelhedi et al., 2023; Aram et al., 2023), conditions that are thought to exist in the rock property database.

K-nearest neighbours is applicable to both classification and regression problems. In regression it produces real number outputs, while in classification it provides discrete values. The method assumes that similar items are close to each other in multidimensional space and employs measures like Euclidean and Manhattan distance metrics to assess the proximity of items. The choice of distance measure significantly influences the performance of the KN classifier (Aram et al., 2023). For this work, as the data values are numeric quantities, the Euclidean distance is appropriate.

Random forest is an ensemble learning method that creates a collection, or "forest" of decision trees, and is applicable to both classification and regression tasks (Aram et al., 2023). RF does not require hyperparameter tuning and avoids overfitting through the inclusion of a comprehensive array of decision trees in the decision-making process ((Breiman, 2001; Abdelhedi et al., 2023). Notably, during the tree-splitting process, RF identifies the best feature within a random subset of features, thereby enhancing model performance (Aram et al., 2023). We consider that such feature identification is crucial for durability prediction. RF builds a number of random decision trees that are uncorrelated, and then aggregates them by majority frequency of occurrence to yield the predicted class.

The gradient boosting algorithm is applicable to both classification and regression tasks. GB forms an ensemble of weak models, typically decision trees, with the goal of minimizing loss by iteratively correcting errors from previous iterations. The algorithm excels at handling complex, non-linear data relationships, producing highly accurate models (Aram et al., 2023). Again, these are conditions that are thought to exist in the rock property database.

Two statistical indices were calculated to assess model performance: the root mean square error (RMSE) of the predictions versus the observed values of slake durability, and the correlation coefficient R2 associated with regression of the predictions against the observed values of slake durability.

3. Analysis results

Overall, the analysis procedure comprised the two elements of data preprocessing and data processing, with each of these elements containing a number of other procedures. This is shown in the flowchart presented in Figure 4. The following sub-sections discuss these two elements.

3.1. Data visualization and pre-processing

Before embarking on any campaign to fit predictive models to data it is critical to identify those features that contribute most to the prediction, as the effectiveness of models is greatly influenced by the adequacy of the observed data in terms of quality and quantity. When dealing with an excess of inputs, it becomes essential to carefully choose a pertinent set of inputs to minimize the impact of unnecessary data, thereby reducing noise. Through the utilization of appropriate inputs, not only is the interpretation of a model enhanced, but its predictive capabilities also see an improvement (Ceryan, 2014). To this end, analysis began with calculating the pairwise correlation matrix associated with the data variables, and then visualizing these as heatmaps. Pairwise correlation is required in order to correctly handle the missing data in the rock property records. Figure 5 presents the heatmap for 15 durability cycles. The heatmaps use a diverging sequential colour scheme comprising 11 colours generated by ColorBrewer (www.colorbrewer2.org) interpolated to a total of 31 colours. The diverging scheme uses deep blue for correlations of -1, white for correlations of zero and deep red for correlations of +1. The entries on the leading diagonal have values of unity, and as these are meaningless the entries have been replaced by letter codes labelling the rock property to which the row and column belong. The entries in the heatmaps are arranged in groups: A to F represent strength assessments, G to L petrophysical properties, and N to Q slake durability index.

The four heatmaps in Figure 5 are striking. Firstly, we note that the heatmaps for sedimentary rocks are clearly different from those for igneous rocks. In the former case the correlations are generally smaller in absolute magnitude than in the latter. In particular, sodium sulfate soundness (entries K to M) shows very little correlation with any other properties for the case of sedimentary rocks, whereas strong positive and negative correlations are seen for the igneous rocks. For sedimentary rocks this suggests that the factors most strongly influencing durability are their mechanical properties, rather than resistance to environmental factors such as the presence of aqueous solutions of salts.

Physical and mechanical characteristics of rock material depend on mineral composition, grain shape and size, pore expansion, and mineral particle connections. Petrographic features like contact type, grain attributes, and rock fragment density significantly influence rock engineering properties, and reactions between rocks and weathering agents are categorized into internal (e.g., mineralogical composition, texture) and external factors (e.g., pressure, humidity, and temperature) (Ulusay et al., 1994). Thus, as the filling material between particles and pore spaces in sedimentary rocks is a matrix of various cements, the properties of these cements significantly affect the chemical behaviour of sedimentary rock, especially if they contain clay minerals.

The type and pattern of cementation affects the strength and mechanical properties of sedimentary rock (Al-Tahini, 2006), but this is less important for igneous rocks as these are composed of a mixture of mineral crystals of various sizes. Thus, we see that in general both positive and negative correlations are stronger for igneous rocks than for sedimentary, indicating distinctly different behaviours between these materials. Finally, the differences between saturated and oven dry responses are much less marked than between rock types, suggesting that, in general, there is perhaps no need to prefer testing in one of oven dry or saturated conditions over the other.

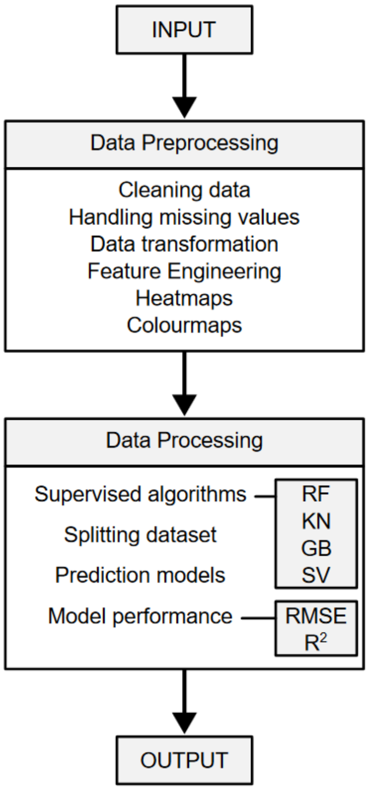

Figure 4. Flowchart of overall analysis procedure.

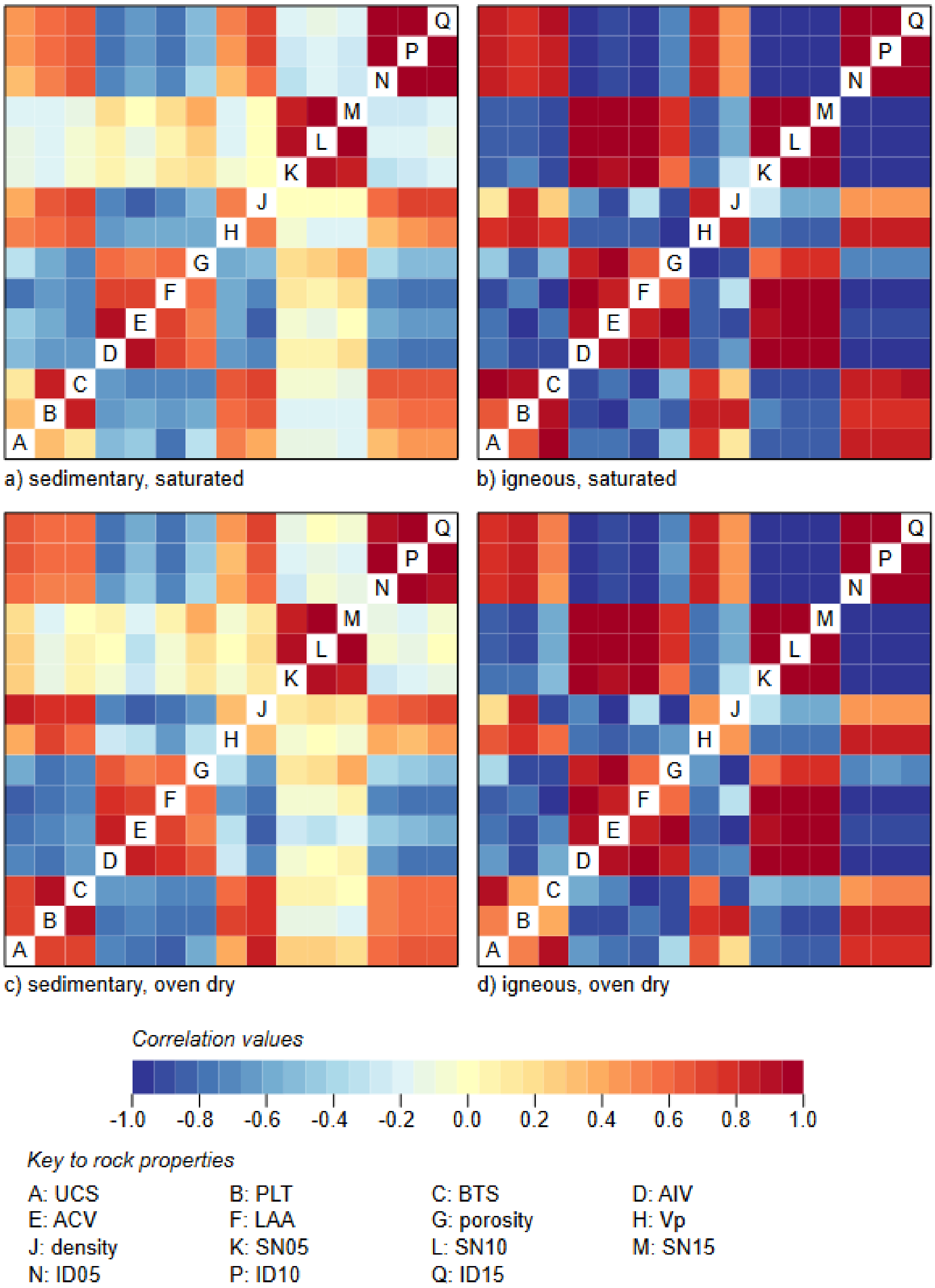

Figure 5. Correlation matrix heatmaps for 15 durability cycles.

Importantly, the heatmaps overall suggest that there is no one clear correlation pattern between the four cases, indicating that correlation-based approaches to durability prediction (e.g., through application of multivariate regression) will require different regression models for each situation. Similarly, the high (positive or negative) correlations indicate that a regression model would need to account for these and thus would be complex and cumbersome to use. This supports our investigation of ML techniques to the prediction of durability.

The four ML models used here require all data records to be free from missing values. As noted above, many records contained missing data and following standard ML practice, these were replaced with either the mean or the median of the values present (Yang et al., 2023). Thus, UCS, PLT, BTS, Vp, porosity, density, AIV and ACV were supplemented with mean values, and LA abrasion was supplemented with the median. Finally, as the data are of significantly different ranges, data normalization and standardization using a standard scaler was performed. This is to improve the performance of ML algorithms, as these are known to be sensitive to differences in scale and distribution of the input data. The outcome of these procedures was to produce a clean dataset to which ML could be applied.

3.2. ML results and discussion

The ML models applied here are supervised predictive algorithms, meaning that they have been trained on a dataset for which the result (in this case, slake durability) is known. The models were trained using a random selection of 80% of the records in the cleaned data, and then applied to the remaining 20% of the data in order to make predictions of slake durability. Table 5 gives the number of data used in each analysis, and indicates that the data set comprises 12 independent variables and one dependent variable, namely slake durability, giving a total of 13 dimensions.

Table 5. ML data set sizes

	Sedimentary, saturated	Igneous, saturated	Sedimentary, oven dry	Igneous, oven dry
complete data set	137	40	122	31
training set	109	32	97	24
prediction set	28	8	25	7

Tables 6 and 7 summarise the RMSE values for all analyses and ML models. These tables also include the R^2 values of the linear regression between the predicted and actual values of slake durability. For all cases the R^2 values are very close to unity, indicating that in general the ML approach to predicting slake durability is efficacious.
Figure 6 presents RMSE prediction error for all four ML models at 5, 10 and 15 cycles of slake durability test, and for the four rock sample conditions, combinations of sedimentary saturated, igneous saturated, sedimentary oven dry and igneous oven dry. All three plots show that, in terms of RMSE, for all cases the performance order of the ML models is the same: RF performs best, SV performs worst, and KN and GB lie between these. For the case of oven dry sedimentary rocks, RMSE for the SV model is almost 14%. Limiting our attention to the predictions at 15 slake durability cycles, we see that the RMSE associated with RF is almost zero for igneous rocks and rises to about 13% for oven dry sedimentary rocks. As predictions at 15 slake durability cycles are most representative of long-term durability, these results indicate that the RF model is most suitable for this making this prediction.

Table 6. Model performance, sedimentary

		Saturated				Oven dry			
		RF	SV	GB	KN	RF	SV	GB	KN
ID05	RMSE	3.03	5.95	4.30	5.15	2.75	6.05	3.94	4.82
	R^2	0.9990	0.9961	0.9979	0.9970	0.9991	0.9958	0.9982	0.9973
ID10	RMSE	3.03	5.95	4.30	5.15	3.38	9.30	5.70	6.82
	R^2	0.9990	0.9961	0.9979	0.9970	0.9985	0.9891	0.9958	0.9942
ID15	RMSE	3.03	5.95	4.30	5.15	4.19	12.90	6.20	8.12
	R^2	0.9990	0.9961	0.9979	0.9970	0.9976	0.9778	0.9945	0.9911

Table 7. Model performance, igneous

		Saturated				Oven dry			
		RF	SV	GB	KN	RF	SV	GB	KN
ID05	RMSE	0.05	2.80	0.93	0.19	0.27	1.90	0.93	0.51
	R^2	1.0000	0.9993	0.9999	1.0000	1.0000	0.9997	0.9999	1.0000
ID10	RMSE	0.15	5.24	1.47	0.19	0.23	4.17	1.31	0.35
	R^2	1.0000	0.9974	0.9998	1.0000	1.0000	0.9984	0.9998	1.0000
ID15	RMSE	0.11	6.70	1.79	0.25	0.33	5.58	1.63	0.41
	R^2	1.0000	0.9957	0.9997	1.0000	1.0000	0.9970	0.9997	1.0000

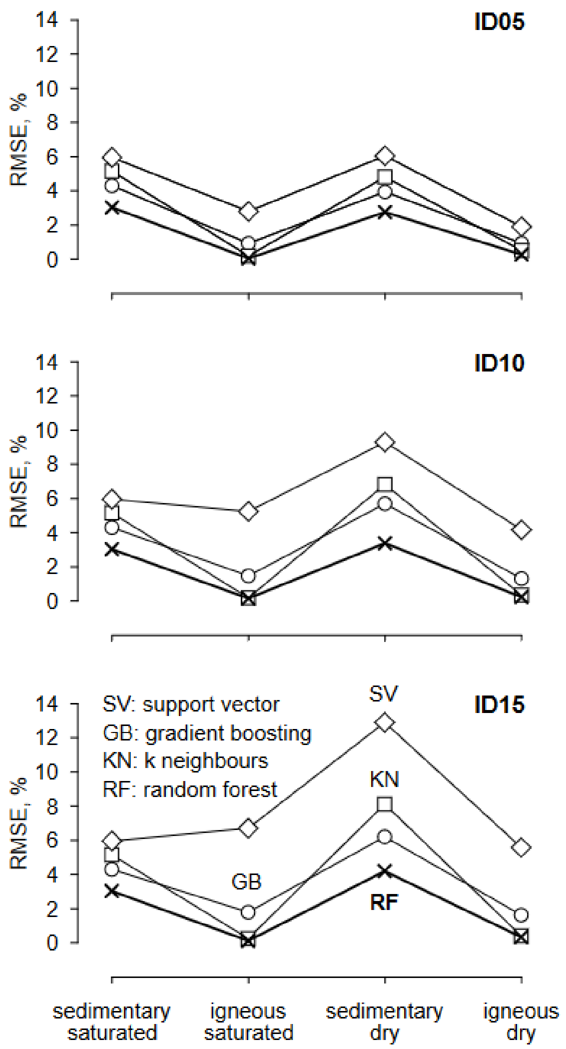

Figure 6. RMSE prediction error for four ML models after 5, 10 and 15 cycles of durability test

Figure 7 shows the individual prediction errors resulting from application of the RF model to 15-cycle slake durability results. It is clear from this figure that RF performs very well when predicting the performance of igneous materials: indeed, the maximum prediction errors range between -0.5% and +0.6%. This suggests that the RF model, when applied to the rock property data used in the database created here, can be confidently used to predict long-term durability of igneous rocks in marine environments. The prediction results for sedimentary rocks show significantly greater errors, generally within about ±10%. Particularly noteworthy are the oven dry results for those two tests with an actual slake durability of about 45%, as these display prediction errors of about 25%. A positive error indicates that the model predicts greater durability than the actual value, and using this model would therefore lead to designs that would suffer premature failure. It is not clear why the errors are so large for sedimentary rocks, but it may be a result of combining many different rock types into the one class. Further investigations are necessary to examine this, and it may be necessary to train models on more specific rock types (e.g., sandstone and carbonates will need to be trained separately). As the two greatest errors occur at slake durability values of less than 50%, this may suggest that the properties in the database and insufficient to predict the behaviour of low durability materials. Again, further investigations are needed to resolve this. Of course, although such low durability rocks are unlikely to be used in shore protection it is nonetheless essential that their durability is not overestimated.

4. Discussion on Model Performance

It is clear from Tables 5 and 6, and Figures 5 and 6, that the four ML models are able to predict slake durability index after 15 cycles (i.e., ID15), although with markedly different prediction errors. Overall, these results indicate that the RF model produces slake durability predictions more accurately than the other ML models, suggesting that it has a strong decision-making capability for material selection applications.

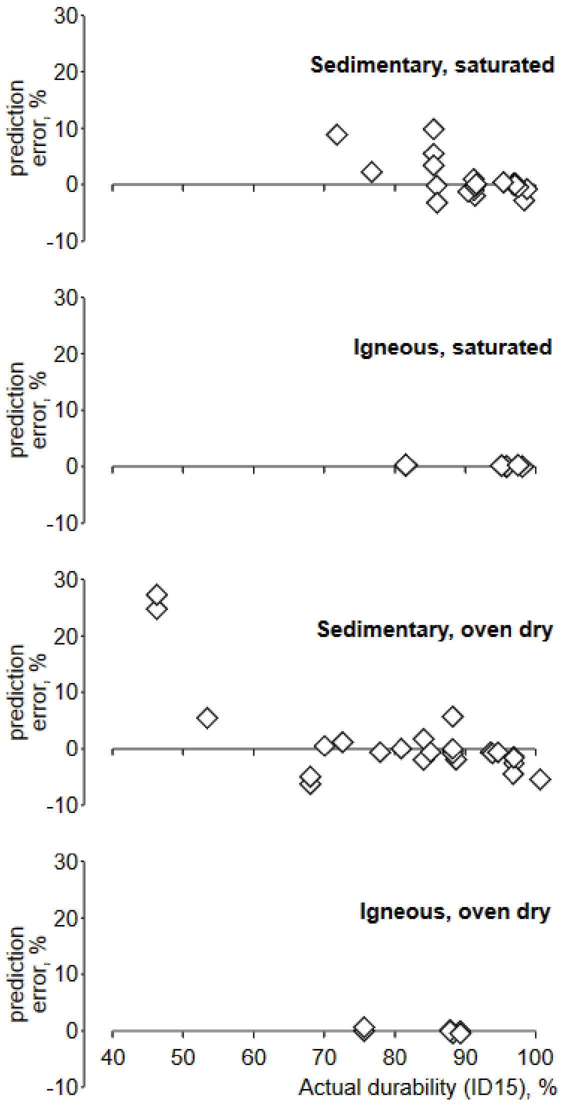

Figure 7. Individual prediction errors for the random

We consider that several factors contribute to the superior performance of the RF model. Depending on the dataset characteristics, the RF algorithm, as an ensemble method, is robust to noisy data and outliers. The database used here contains numerous rock types from a wide range of geological settings, and so displays significant variability in properties; this is apparent from the ranges and standard deviation values shown in Tables 2 and 3. The SV model is sensitive to high variation and noisy data (Li et al., 2013), and we believe this is why it does not perform well with this database.

RF is less prone to overfitting when the number of parameters is small, and there are multiple variables. Also, being a non-linear model by design, RF performs better here, where the relationship between rock properties and long-term durability is complex and non-linear. It is an ensemble method that combines multiple decision trees to make predictions, reducing variance and improving predictive accuracy compared to other supervised ML predictive algorithms, which mostly rely on a single decision boundary. Finally, the RF model is capable of handling a wide range of features without requiring feature scaling (Breiman, 2001), and this a powerful advantage when dealing with diverse geological and rock property features.

In machine learning algorithms the performance of models is highly dependent on hyperparameter settings, and thus if hyperparameters for a predictive model, such as the SV model, are not chosen correctly, suboptimal performance can result. RF has fewer hyperparameters to tune compared to other predictive regression algorithms, and we believe this is another reason for its superior performance with this database.

The RF model has performed exceptionally well in predicting the performance of the igneous rocks. We believe this is due to an inherent behavioural homogeneity in such materials, but further investigations are needed to confirm this. This conjecture is supported by the poor performance of all models with the sedimentary rocks. As noted earlier, although the database contains properties of sandstone, limestone and carbonate rocks, these were grouped as one rock type. Geological considerations indicate that there is a large range of rock types within these categories, which undoubtedly will lead to behavioural heterogeneity: such inherent differences in their engineering properties are a result of their initial sedimentation and formation environments. On the basis of our findings, we conclude that sedimentary rocks cannot be considered as a single entity and must be separated. Further investigations are needed to determine appropriate ways of doing this.

5. Summary and Conclusions

We have employed four supervised machine learning predictive models – random forest (RF), gradient boost (GB), support vector (SV) machine, and *k*-nearest (KN) neighbour – to analyse experimental data and forecast long-term durability of rock used in rubble mound breakwaters. The models operated on a comprehensive rock property database containing 467 records, consisting of 119 igneous (basalt, andesite, rhyolite, and granite) and 348 sedimentary records (sandstone, limestone and carbonate), and comprising a suite of physical, mechanical, petrophysical and petrographical properties, as well as durability characteristics determined through simulation tests. The rock properties included Vp, UCS, BTS, PLT, soundness, porosity, density, LA, AIV, and ACV. The database includes both saturated and oven-dry properties. The data were obtained by laboratory testing of rock materials taken from different quarry sites and utilized as construction material of 35 rubble mound breakwater in southern and northern coastlines of Iran (Hamidi, 2024). The data correspond to 210 block samples with dimensions greater than 30×30×30 cm.

Following initial pre-processing of the data to remove incomplete records, correlation matrices were calculated and visualized using sequential colour heatmaps. These heatmaps indicated no obvious and consistent correlations between rock properties and across rock types and saturation conditions.

The ML models were used to make predictions of slake durability after 15 cycles of slake durability index testing. The models were trained on 80% of the available data, with the remaining 20% being used for prediction. Evaluation metrics of RMSE and R^2 were computed to gauge the performance of each model. RMSE was computed using predicted and measured values of slake durability, and R^2 was determined from linear regression of the predicted and measured slake durability values.

Based on calculation of RMSE, the RF model was found to be most accurate with errors of under 4% across all rock types and saturation conditions. For both saturated and oven-dry igneous rocks the RF model produced prediction errors of under ±0.6%. For sedimentary rocks the errors were greater, up to ±10%. The limited data with measured slake durability values of under 50% showed errors of more than 20%, but this may be indicative of insufficient data on which to train the model. For the RF model the lowest value of R^2 was 0.9976 for the case of oven-dry sedimentary rocks; for all igneous rocks the value of R^2 was unity to five significant figures.

We conclude that ML, and particularly the RF model, is suitable for predicting the durability of igneous rock used in breakwater construction, but that further investigations are required to determine the applicability of ML to sedimentary rocks.

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Appendix A. Photographs

Example photographs of various laboratory tests.

(a) Aggregate impact value specimen & equipment

(b) Los Angeles abrasion test specimens

(c) Point load test specimens & equipment

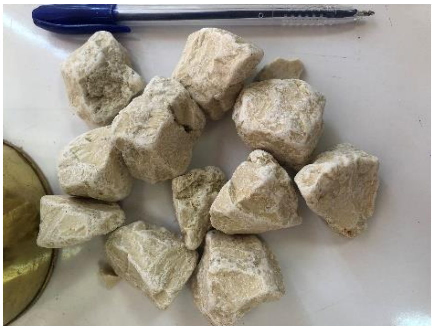
(d) Various core specimens

(e) UCS test specimen

(f) Brazilian tensile strength test

(g) Ultrasonic test specimen & equipment

(h) Sodium sulphate soundness test specimens



(j) Slake durability test specimen

(k) Slake durability test arrangement