Geomechanical Characterization of Soft Volcanic Rock Masses in Azores Islands

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Abstract: Soft rocks, characterized by low strength, high deformability, and poor cementation, pose significant challenges in geomechanical characterization, particularly within complex volcanic environments. The Azores Islands, shaped by diverse eruptive processes and intense weathering, present volcanic rocks with substantial lithological variability and heterogeneities. Combined with active seismicity and volcanism, these factors complicate the assessment of rock mass behavior and stability. This study focuses on the geomechanical characterization of soft volcanic rock (VR) masses in the Azores using the Volcanic Rock System (VRS), an empirical classification specifically adapted for volcanic formations. By applying the VRS to an enriched database that integrates new geotechnical data from the Azores, the study refines correlations between key parameters such as uniaxial compressive strength, porosity, and deformability. The results reveal the limitations of conventional systems like RMR in capturing the complexity of volcanic formations and highlight the VRS's enhanced capability to assess rock mass quality, stability, and excavation challenges. A new subsystem within the VRS is also proposed to improve the classification of soft volcanic rocks, offering a more tailored approach for managing the unique geotechnical conditions found in the Azores

Keywords: Azores Islands; Volcanic Rocks; Soft Rocks; VRS Empirical System.

1. Introduction

The islands of the Azores Archipelago are in the middle of the North Atlantic Ocean, in a very seismically active region, where American, Euroasian and African tectonic plates meet – Azores Triple Junction. The islands are volcanic structures emerging from the Azores Platform. Since the settlement of the islands by the Portuguese, in 15th century, there are many historical records of natural catastrophes, such as destructive earthquakes, volcanic eruptions and landslides (Gaspar et al., 2007; Malheiro and Nunes, 2007).

The Azores archipelago is almost entirely characterized by volcanic rocks (Gaspar et al., 2007; Malheiro and Nunes, 2007; Jorge, 2023). These volcanic rocks are subject to various weathering processes that can result in rock masses exhibiting soft rock characteristics, with a wide range of geological features.

Typically, the soft rocks are classified as soft sedimentary rocks or weathered geological materials, but in Azores Archipelago only Santa Maria Island has sedimentary rocks, due to it age and geologic evolution (Marques et al., 2020). The other islands are composed only with volcanic materials, characterized by the alternance of subaerial explosive and non-explosive eruptions, as is common (Jorge, 2023). The geotechnical behavior of these volcanic materials differs significantly from that of other geological materials (sedimentary, intrusive magmatic and metamorphic rocks – rock masses, and soil formations), necessitating a specific approach to evaluate their geomechanical parameters.

Soft volcanic rock (VR) masses are composed of materials like tuff, pumice, volcanic ash, and certain types of lava flows, which are characterized by their relatively low strength, low density, high compressibility and expansivity and high porosity compared to harder, denser volcanic rocks. Such characteristics present engineering challenges, including instability, water absorption, limited bearing capacity, erosion and accelerated weathering (Miranda et al., 2018). According to Kanji (2014), sampling and site investigation of soft rocks are usually a challenge, and their features are too soft to be tested in rock mechanical laboratory equipment and too hard for soil mechanics laboratory equipment, what oblige to some procedure's adaptation. Kanji (2014) also highlights the significant difficulty in classifying these rocks using conventional geomechanical systems, which are primarily designed for the discontinuous media of harder rocks.

Preliminary evaluation of the geomechanically parameters of rock masses can be carried out using empirical classification systems. These systems consider key properties such as rock strength, the condition and orientation of discontinuities, groundwater presence, and in situ stress state. Each property is assigned a numerical value, which is then combined using a specific formula to calculate a final geomechanical index. The most widely used systems are the rock mass rating (RMR), Q and geological strength index (GSI) (Bieniawski, 1983; Barton, 2000; Hoek et al., 2002). For evaluating deformability, there are several analytical equations establish relationships between the deformability modulus and geomechanically indices derived from these classification systems. However, these equations should be applied with caution, considering their inherent assumptions and limitations.

Several specialized subsystems have been developed to address specific geotechnical challenges. One example is the Q_{TBM} system (Barton, 2000), an adaptation of the Q-system designed to predict key parameters for tunnel excavations using Tunnel Boring Machines (TBMs), including machine performance, support requirements, and potential ground behavior. In addition to global systems, some countries developed their own region specific empirical/classification systems like the Chinese BQ classification system (Feng and Hudson, 2011), and the MR system applied in Portugal and in Brazil (Rocha, 1975; Miranda, 2003). Efforts have additionally been made to develop classification systems specific to volcanic formations. Del Potro and Hürlimann (2008) pioneered one of the first empirical classifications for volcanic materials in the Canary Islands, focusing primarily on slope stability analysis. Sousa et al. (2022) developed a new empiric system, for volcanic rocks, by adapting RMR system. This followed the experience acquired in Brazil during the construction of a wide number of large dams in volcanic foundations (Cabrera, 1988; Herrera, 2005). The new empirical system for volcanic rocks is designated as VRS – Volcanic Rock System (Miranda et al, 2018; Sousa et al., 2021), was specifically designed to address the unique geomechanical characteristics of volcanic formations. The VRS considers six geotechnical parameters to which relative weights are attributed. The final VRS index value, which varies between 0 and 100, is obtained through the algebraic sum of these weights. With this index, it is possible to obtain strength properties, deformability modulus, and description of the rock mass quality, as well is possible to define recommendations for excavation and support needs and support loads, using correlations with other geomechanically indices.

To implement the empirical VRS, Sousa et al. (2021) built a database with volcanic rocks characteristics. The initial dataset was compiled from data of Madeira Island volcanic materials and later expanded with data from the islands of Canarias Archipelago and Mexico. Subsequently, Amaral and Malheiro (2016) contributed with more information from the volcanic materials of the Islands of São Miguel and Faial, of Azores Archipelago, regarding both VRS and RMR system, to enrich and complete the previous database (Sousa et al., 2021).

Accurate implementation of the VRS depends on high-quality geotechnical data to effectively characterize volcanic rock masses. To achieve this, detailed field investigations are fundamental to capturing the complexity and variability of volcanic formations. Geophysical surveys can be employed as a non-invasive method to gain preliminary insights into subsurface conditions but are not always utilized. More commonly, direct geological and geotechnical investigations—such as boreholes, shafts, or field exposures—serve as the primary means of collecting the essential data required for VRS classification (Wyllie and Mah, 2010; Zhigang et al., 2020).

This becomes particularly critical when dealing with soft and weathered volcanic rocks, which present unique challenges due to their intermediate strength between soils and hard rocks (Kanji, 2014). These materials are often too soft for conventional rock mechanics testing but too hard for standard soil mechanics procedures, complicating both sampling and laboratory characterization. Specialized drilling techniques, such as air drilling to minimize water-induced sample degradation or mud drilling for improved core recovery, are often necessary to ensure representative samples. Advances in sampling equipment, like those developed at SKL-GDUE in China (Zhigang et al., 2020), have further improved the quality of data collected. Recent improvements in in situ and laboratory testing methods, along with enhanced numerical models (Sousa et al., 2020a), have strengthened the evaluation of geomechanical properties in volcanic rocks. Nevertheless, the inherent heterogeneity of these materials often leads to significant data variability. Each formation has its own properties and interpolation, and extrapolation data treatment are not appropriate (data statistical treatment - multivariate statistical analyses). Geotechnical databases of volcanic materials, when analysed by Artificial Intelligence (AI) – based on Data Mining (DM) techniques, make it possible to obtain new and useful knowledge. The present paper concerns to the geomechanically characterization of volcanic rock masses in the Azores Islands, with incidence on soft rock masses. Concepts of AI are introduced, with particular incidence in DM and applied to the volcanic rock database enriched by information from rocks from Azores Islands (Faradonbeh et al., 2020).

This paper is structured into six sections. Section 1 presents the Introduction. Section 2 discusses the fundamental concepts of soft rock masses, with a focus on volcanic rock masses. Section 3 provides an overview of the geological conditions of the volcanic rock masses in the Azores Islands, highlighting specific case studies, including the slope instability at Porto Formoso, the foundation challenges during the extension of the runway at Ponta Delgada Airport on São Miguel Island, and the landslide event at Faial Island. In Section 4, the application of the VRS to the Azorean context is detailed, alongside a comparison with the RMR system. This section also explores the integration of AI techniques applied to the enriched geotechnical database. Section 5 introduces a newly developed classification subsystem tailored specifically for soft volcanic formations. Finally, Section 6 presents the concluding remarks, summarizing the key findings and implications of the study.

2. Soft Rock Mechanics - Concepts

The definition of soft rocks is connected to rock masses with low strength, large porosity and poor cementation (Rocha, 1975; ISRM, 1981; Kanji, 2014; He and Sun, 2020; Sadowsky, 2020). The uniaxial compressive strength (UCS) for soft rocks typically falls below 25 MPa. However, there is some variability in the literature, with lower limits suggested around 2 MPa and upper limits up to 20 MPa, depending on the classification criteria (Rocha, 1975; Sadowski, 2020).

Soft rock masses include sedimentary rocks of detrital or chemical origin, with weak cementation, and residual rock masses that result from weathering of the Earth's crust. The residual soft rock materials must be associated with their geological genetic heritage, so that potential geotechnical problems can be predicted. Naturally, volcanic rocks must also be included (volcanic conglomerates, breccias and lahar; basaltic breccias; pyroclastic deposits, volcanic ash, and tuff and ignimbrite; and weathering products of crystalline rocks - Sadowski, 2020) when they have low strength to uniaxial compression and great deformability. Table 1 presents typical parameters associated with soft rocks namely typical values of rock deformability, shear strength (cohesion and friction angle), and strength to uniaxial compression of the rock. In the evaluation of deformability, it is important to consider anisotropy that exists in rock masses. In soft rock masses anisotropy is mainly related with the rock anisotropy that influences the rock mass properties (Sousa et al., 2020a).

The deformability of soft rocks, if the correlation $E_r = 200 \cdot \sigma_c$, established by Rocha (1975), is accepted (Er is the deformability of the rock mass and σ_c is uniaxial compression strength of the rock), and assuming that σ_c varies between 2MPa and 25MPa, the deformability modulus of soft rocks ranges between 4GPa and 50GPa. This significant deformability poses challenges in geotechnical applications, especially when dealing with highly weathered or deeply buried rock masses. Another critical aspect of soft rock masses anisotropy is introduced by geological discontinuities and the inherent fabric of the rock. Time-dependent behaviors, such as creep and long-term deformation, are also significant in soft rocks. Rocha (1975) highlighted how soft rocks undergo large deformations at depth and experience marked porosity increases near the surface due to weathering. This weathering process leads to a degradation of mechanical properties, with a substantial increase in interaggregate pore content and only a slight increase in intra-aggregate porosity (Knopp et al., 2022).

Table 1. Geomechanically parameters of soft rocks (Adapted from Rocha, 1975).

Rock type	Elasticity modulus E (GPa)	Cohesion c (MPa)	Friction angle ϕ (˚)	Uniaxial strength σ_c (MPa)
Claystone and siltstone				
Low strength	0.4-3.0	0.5-3.0	30-35	2-12
Average strength	3.0-8.0	3.0-6.0	35-40	12-25
High strength	80.-30.0	6.0-12.0	40-55	25-80
Sandstone and conglomerate				
Low strength	0.5-4.04.0-10.0	0.5-3.0	30-40	2-12
Average strength	10.0-60.0	3.0-8.0	40-50	12-40
High strength		8.0-16.0	50-65	40-150
Limestone				
Clay	0.5-5.0	0.5-3.0	30-40	2-20
Shale	1.0-10.0	3-8	30-40	4-30
Sound	20.0-100.0	8-16	40-50	4-250
Shale				
Decomposed	0.4-2.0	0.4-2.0	30-35	1.5-8
Weathered	2.0-15.0	2.0-10.0	35-40	8-40
Sound	15.0-80.0	10.0-20.0	40-65	40-200

Regarding the strength of the rock masses, friction angle (φ) is, as a rule, between 30˚ and 45˚ and cohesion (c) presents, as a rule, low values but in general is greater than 0.4 MPa. The presence of discontinuities influences the shear strength of the rock mass; however, in soft materials with inherently low strength, the effect of these discontinuities is less pronounced (Rocha, 1975).

Construction on soft rocks presents significant challenges and often requires specialized engineering solutions (Zhigang et al., 2020). Numerous documented accidents highlight the risks associated with building on soft rock foundations, especially in regions where these materials are the predominant geological formation. Soft rocks are commonly encountered in foundations, underground structures (such as tunnels and excavations), and mining or extractive activities. Additionally, natural slope instability is a frequent concern in these materials and must be carefully managed. Given their complex and often unpredictable behavior, real-time monitoring is essential when working with soft rock formations. In China, the definition of soft rocks has been further refined, particularly in the context of controlling ground deformation in coal mining operation (He and Sun, 2020). According to He and Sun (2020), soft rocks in an engineering context are those that undergo significant deformations under stress, leading to potential structural issues. This concept is expressed mathematically as:

$$\sigma \geq [\sigma] \text{ and } U \geq [U] \quad (1)$$

where σ is the engineering stress (MPa), $[\sigma]$ is the strength of the rock mass (MPa), U is rock deformation (mm), and [U] is the deformation allowed in the practice (mm).

Tunnels and other underground projects are subject to the same geomechanical challenges posed by soft rock formations, which can lead to geological hazards if not properly addressed (Zhigang et al., 2020). All design and construction of underground infrastructure and related projects must consider the special problems of soft rock. But it is very important not forget the surficial behaviour.

One of the most critical factors influencing the stability of tunnels and other underground structures is the presence of continuous low-resistance planes within rock masses. These weak planes can act as slip surfaces, leading to rock mass movements and potential failures in underground excavations (Rocha, 1975; Pedro et al., 1975; Sousa et al., 2025). In soft rocks, where the inherent strength is already low, the presence of such discontinuities can significantly compromise tunnel stability. A notable example occurred during the excavation of a surge chamber for an underground hydroelectric project in Mozambique, where weak planes within the rock mass led to unexpected instability (Sousa et al., 2025). Similarly, a gravity dam experienced foundation issues due to an extensive sub-horizontal basaltic layer with a weak circular surface approximately 50 cm thick. Finite element modeling, as shown in Fig. 1, was used to analyze the dam's foundation, revealing that the risk of progressive failure decreased as the deformability of the weak surface increased—supporting earlier findings (Rocha, 1975; Pedro et al., 1975; Sousa et al., 2020b).

While weak planes and discontinuities present immediate risks to tunnel stability, long-term degradation due to weathering processes can further exacerbate these issues. In underground environments, weathering can continue even after excavation, particularly in soft rocks that are highly sensitive to moisture and air exposure. Hydration of clay minerals and the entrapment of air in pore spaces initiate wetting-drying cycles, leading to micro-fracturing and material expansion. These processes reduce the strength and increase the deformability of the rock mass over time (Marques et al., 2020). The presence of water is especially problematic, as it not only accelerates weathering but also weakens the rock by increasing pore pressure and reducing shear strength. In tunnels, water infiltration can lead to significant stability concerns, including roof collapses, wall failures, and floor heaving, highlighting the need for effective drainage and support systems.

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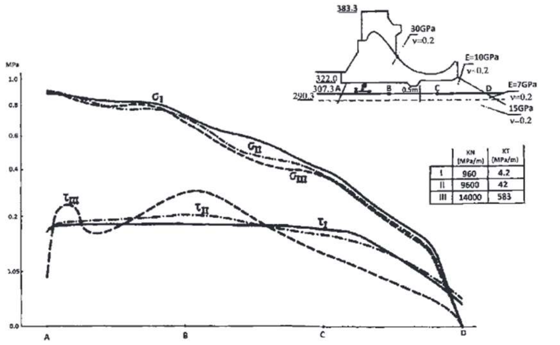

Fig. 1. Numerical results for the foundation of a gravity dam (Pedro et al., 1975; Sousa et al., 2020b).

3. Volcanic Rocks in Azores Islands

3.1 Volcanic mechanisms

Volcanic eruptive systems are highly complex and influenced by multiple factors, including the age of the system and the geological context, such as divergent or convergent continental plate margins, island arcs, and within the plates, which determine their initial characteristics. These systems may include multiple eruption centers, each with distinct geochemical compositions. The geochemical composition of the magmas, associated with the evolutionary process of magma ascent, physical variables like temperature and pressure, and interaction with surrounding rocks or other magma chambers, creates specific conditions that influence the extent, morphology, and type of volcanic activity.

More acidic magmas, such as trachyte lavas, contain high levels of silica, which gives them high viscosity, even at high temperatures and pressures. These magmas also have low gas solubility at low confining pressures, resulting in explosive and violent eruptions that generate large quantities of pyroclasts. In contrast, more basic magmas, like basaltic magma, have a lower silica content and are therefore more fluid, forming lava flows that can travel long distances and cover vast areas. These differences result in distinct geological structures: volcanoes formed by acidic magmas tend to have steeper and more mountainous shapes, with a pronounced conical structure, while basaltic volcanoes generally have broader and less inclined slopes due to the fluidity of their lavas.

Volcanic rock masses are compositional and structurally heterogeneous and anisotropic both vertically and horizontally, characterized by the alternation of strata of compact rocks and pyroclastic materials (such as volcanic ash, Lapilli, and volcanic bombs) with limited continuity. This pattern is also influenced by weathering, erosion, and sedimentation processes that occur between sequential eruptive episodes, transforming the geological structure over time. All these features contribute to the existence of zones with different mechanical and hydraulic properties, degree of weathering, and water content, among other characteristics.

Contributing to the weathering of the volcanic materials are two important processes. Hydrothermal alteration/weathering is a complex poro-chemo-mechanical process that develops in volcanic environments impacting the mechanical and petrophysical properties of rocks by changing mineralogy, texture, and fabric (e.g., Pereira et al., 2024). Also, essentially on islands, salt weathering (physical process) is particularly important because of the presence of salts, resulting from marine spray, that crystallize in and on the particulates of the volcanic materials (e.g., Alves and Figueiredo, 2018), principally in cycles of wet – drying conditions. Simultaneously, climate change, with extreme weather events, by very intense precipitation rate may contribute to the erosion of the volcanic masses or to increase the dissolution rate of some minerals, essentially associated with moderate to high temperature. These processes affect all volcanic rocks characteristics and contribute to their evolution. VR are particularly sensitive to them.

There are several areas in the world with VR, as is the case of volcanic islands, where soft rocks are dominant. The volcanic formations of Azores archipelago are a good example of the complexity mentioned above, and to the issues related to VR.

3.2 Azores Archipelago

As was mentioned in the Introduction, the Azores Archipelago is in a very active seismic zone, associated to the Central Rift of the Atlantic Ocean. The nine islands are distributed in a WNW-ESE general orientation strip, as is shown in Fig. 2. The islands are volcanic, connected with the complex local geotectonic of the oceanic crust. Detailed description of this local geotectonic context identifies the Mid-Atlantic Ridge (CMA), the East Fracture Zone (ZFEA) and the North Fracture Zone (ZFNA) of Azores and the Terceira Rift (RT) (Santos, et al., 2024). The alignments defined by the islands of S. Jorge and Faial Pico are distinguished to a limited extent (Gaspar, 1996).

The geomorphology of the islands is dominated by evidence of intense volcanic activity, with notable features such as imposing calderas—Sete Cidades, Fogo, and Furnas on São Miguel Island—alongside numerous monogenetic eruptive centers, including trachytic domes, pumice cones, slag cones, volcanic dykes, and hydrovolcanic structures (Santos et al., 2024). Each island has its own specificity, with diversified geomorphology among them. Even on the same island the geomorphology varies. These variations resulted from the type of volcanism that occurred. The islands of Pico, São Jorge and Santa Maria resulted from a marked fissural and basic volcanism. While the islands of São Miguel, Terceira, Faial, Graciosa, Corvo e Flores resulted from mixed volcanism – basic and explosive, which gave origin of lava materials with distinguishing characteristics and to pyroclastic deposits with very different compositions.

This way it is easy to understand that the volcanic formations of the Azores islands present a very important complexity, resulting from different types of volcanic activity (from the effusive Hawaiian style, to the strongly explosive Plinian style), different types of emitting volcanic structures (mono- and polygenic), the magnitude of the volcanic activity, and the erosion dynamic. This complexity is translated into main factors: at micro scale – composition and texture; and at macro scale - structure and morphology. According to Trota et al. (2011) several studies carried out on the geochemistry of the rocks of the Azores have led to the conclusion that the greatest occurrence of volcanic rocks (*l.s.*) in this archipelago is located at the extremes of the calco-alkaline series, the basalts and trachytes, with less importance given to intermediate terms.

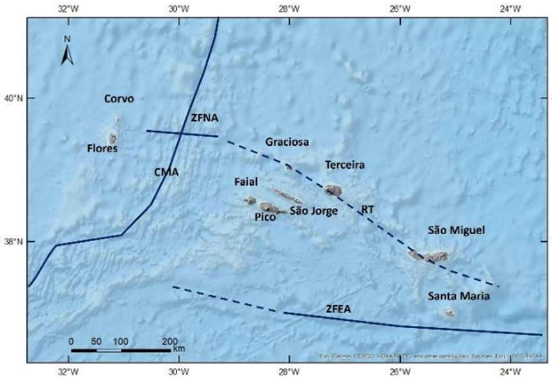

Fig. 2. Location and geotectonic framework of the Azores Archipelago (Santos et al., 2024).

3.3 Specificity of Azores rock materials

Wallenstein (1999) defined that all the volcanic materials found in the Azores archipelago belong to an igneous series of magmatic evolution known as the alkaline series. It is characterized by an evolution from the most primitive terms, the basalts (*l.s.*), to the most evolved terms of the igneous series, the trachytes (*l.s.*), and its chemical variety is explained mainly by fractional crystallization from a parental basaltic magma. This author states that the volcanic rocks of Azores islands are subdivided into two large groups: (1) rocks formed by the cooling of lava flows of basic composition (e.g., basalts (*l.s.*) and intermediate to acidic composition (e.g., trachytes (*l.s.*)); and (2) pyroclastic rocks, formed by the cooling and agglutination of constituents such as ash, lapilli and juvenile and lithic blocks, during explosive phases, whether explosive or effusive volcanism.

In the first group mentioned above, basalts (*l.s.*) appear in the least evolved phase, and in the most evolved phase appear trachytes, which are hard rocks. In the second group, the pyroclastic rocks can be divided into welded ignimbrites, welded pyroclasts of volcanic slag and surtsean tuffs, which are rocks from their genesis (formed by fragmented materials during the cooling of the products ejected by the eruptive columns, with different granulometric and textural sizes) have soft characteristics and physical and mechanical aspects that are different from more competent rocks.

The rocks of the two groups exhibit different physical and mechanical behavior, as is understandable from the previous description. The hard materials of the first group, with a higher density and greater mechanical resistance, when subject to weathering processes develop different degrees of weathering/alteration that modify their initial behavior. The materials of the second group, usually, have high porosity and low density, when compared to rocks formed by the cooling of lava flows.

Basalts (*l.s.*) can have a closed matrix (compact rock) and/or with vacuoles, because of the release of gases and to the type of lava (e.g., aa or pahoehoe). Wallenstein (1999) also adds that for characterization, the basalts were divided into vacuolar (V) and compact (C), and those with weathering greater than or equal to W3. Trachytes (Traq) and welded ignimbrites (IS) were also characterized by Wallenstein (1999). In addition to these mentioned lithotypes, there are also occasionally cemented basaltic pyroclastic deposits and surtsteyn tuffs, both of which were not characterized in this work due to their limited territorial expressiveness.

Slag cones are common on these islands as a result of subaerial basaltic eruptions. Basaltic pyroclasts are fragments projected during the most explosive phase of Hawaiian and/or Strombolian volcanic eruptions. These materials are deposited by fall and/or ballistic trajectory. Their accumulation near the eruption center gives rise to the so-called “slag cones”, which correspond to conical structures that are generally well-defined and symmetrical, with heights that rarely exceed a few hundred meters. These structures sometimes have one or more craters at the top and can take on more elongated shapes when they develop along fissures (Marques et al., 2020).

Under static conditions, in these volcanic cones the inclination of their slopes, when recent, corresponds approximately to the angle of friction of their constituents (around 33º). Over time, and due to erosion, this slope tends to decrease (Fraga, 1988). Basaltic pyroclasts take on different shapes and sizes. This results from the fact that they are often ejected while still fluid and solidified in the air. In terms of the shape, they acquire different shapes (from rounded to elongated). Regarding to the size, they vary significantly; generally, they are grouped into three categories: (1) Fine Basaltic Pyroclastic Deposits, those that present basaltic silt textures; (2) Coarse Basaltic Pyroclastic Deposits, those that present clasts of the size of gravels; (3) Undifferentiated Basaltic Pyroclastic Deposits, those that present a textural variety, although with a greater predominance for the granulometry of sands (Amaral et al., 2016).

These authors state also that it should be noted that in terms of pyroclastic deposits, the different ones have some peculiarities: in general, the black ones are found in the outer layer of the cones and are looser; while the reddish ones are found in the central area of the cones and have a greater tendency to be welded.

About mineralogy, Malheiro et al. (2010) found that the most abundant mineral in the samples analyzed was plagioclase (anorthite), followed by pyroxenes (augite) and olivines (forsterite). These authors also found that the samples corresponding to red basaltic pyroclasts showed the presence of hematite, resulting from the oxidation of iron.

Azores islands present different geological characteristics due to the volcanic nature of the rocks and the variability of its sequences of stratigraphic (Forjaz et al. 2001; Malheiro and Nunes 2007; Malheiro et al. 2018). Malheiro and Nunes (2007) presented the general stratigraphic profiles on Azores islands (Fig. 3).

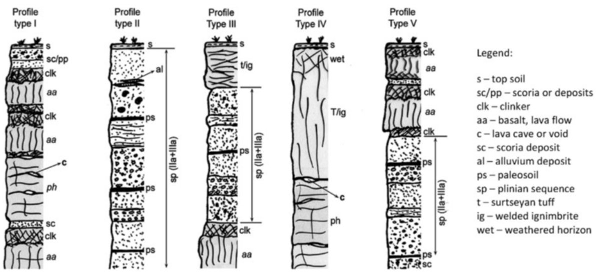

Fig. 3. Stratigraphic profiles at Azores Island (Malheiro and Nunes, 2007).

3.4 Geotechnical characteristics

Malheiro et al. (2018) conducted geomechanical characterization studies of rock materials found in the Azores archipelago to determine the ranges of variation of the different volcanic lithotypes. Various tests were carried out, including resistance to uniaxial compression (σc), density (ρ), effective porosity (p0), and propagation velocities of longitudinal seismic waves (V), among other tests. Tests on trachytes are shown in Table 2 (Malheiro et al. 2018), where γd is bulk unit weight; ρr is real density; ρb is apparent volume mass; p0 is open porosity; p is total porosity, and UCS is uniaxial compressive strength. The samples were from São Miguel, Santa Maria, Faial, and Flores Islands.

The authors obtained the correlations presented in Table 3.

Other studies were carried out on the Azores islands. Moniz et al. (2016) studied the materials on the island of São Miguel using triaxial tests and obtained the results shown in Table 4. Also, Santos et al. (2024) tested 263 samples of different volcanic materials (pomitic deposits of a trachytic nature with a fine (soil) and coarse (pumice) matrix, welded and non-welded ignimbrites, and secondary deposits such as slope deposits), for evaluation of uniaxial compression and density and the results are presented in Fig. 4.

Table 2. Summary of geotechnical information for trachytes in the Azores.

Parameters	Mean	Standard dev.	Min.	Max.	No. of tests
γd (kN/m³)	25	1	21	26	24
ρr (kg/m³)	2684	34	2660	2750	5
ρb (kg/m³)	2458	131	2080	2540	24
p_o (%)	70	4.7	4.3	21.5	24
p (%)	12.2	7.7	4.9	24	5
UCS (MPa)	136.4	49.5	40.0	204.0	22

Table 3. Equations obtained by the correlation among the different geotechnical parameters (Malheiro et al., 2018).

Independent variable	Dependent variable	Equation	correlation R^2
σ_c (MPa)	γ_d (kN/m^3)	$\sigma_c = 9E^{-05} . \gamma_d^{4.24}$	0.48
p_o (%)	γ_d (kN/m^3)	$p_o = -2.23 . \gamma_d + 69.5$	0.83
p_o (%)	σ_c (MPa)	$p_o = -12.2 . \ln(\sigma_c) + 66.1$	0.87
V_{us} (m/s)	γ_d (kN/m^3)	$V_{us} = 4.1 . \gamma_d^{2.2}$	0.82
E_d (GPa)	γ_d (kN/m^3)	$E_d = 2E^{-06} . \gamma_d^{5.4}$	0.81
V_{us} (m/s)	σ_c (MPa)	$V_{us} = 661.4 . \sigma_c^{0.47}$	0.65

Table 4. Shear strength obtained in triaxial tests of rock samples (Moniz et al., 2018).

Sample	ϕ' (°)*	c' (kPa)*	ϕ_{cu} (°)**	C_{cu} (kPa)**
DV	25.1	5.5	11.9	1.4
DPF1	37.8	0.9	23.5	20.1
DPF2	35.7	0.0	32.7	3.0
INS	37.4	15.5	29.0	4.3
IS-W5	35.2	23.7	28.3	76.3
PPI	39.2	0.0	--	--
PPII	42.1	0.0	--	--

* drained conditions
** undrained conditions
DV – Slope deposit; DPF – Fine pomitic deposit; INS – Non welded ignimbrite; IS-W5 – Weathered welded ignimbrite; PP_I – Coarse pomitic deposit (type I); PP_{II} – Coarse pomitic deposit (type II).

4. Application of VRS to Azores Islands

An empirical system was developed for the characterization of volcanic rocks and is designated as VRS. The VRS is an adaptation of the RMR system and includes a classification developed at São Paulo, for tunnels in basaltic formations (Menezes et al., 2005; Moura and Sousa, 2007).

The new empirical system is based on the consideration of six geotechnical parameters to which relative weights are attributed. The final VRS index value, which varies between 0 and 100, is obtained through the algebraic sum of these weights. The following geomechanically parameters were considered: P_1 - UCS; P_2 - Rock weathering characteristics; P_3 - Intensity of jointing; P_4 - Discontinuity conditions; P_5 - Presence of water; P_6 - Disposition of blocks. Different weights are assigned to each parameter, as illustrated in Fig. 5 (Miranda et al., 2018; Sousa et al., 2021).

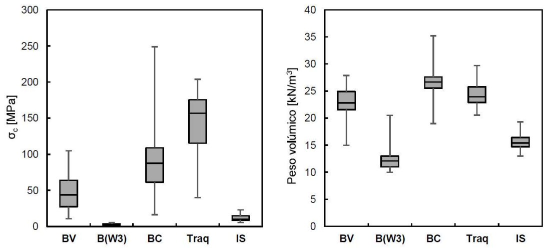

Fig. 4. Box-and-whisker plots of uniaxial compressive strengths and density values for the different lithotypes characterized (Santos et al., 2024). Note: BV - Vacuolar Basalt, B(W3) - Weathered Vacuolar Basalt, BC - Compact Basalt, Traq – Trachytes, IS - Welded Ignimbrites.

In relation to RMR empirical system, the properties were identical for P_1, P_4 and P_5, but have different weights. The parameter due to discontinuities orientation P_6, introduced by Bieniawski (1983) as an adjustment of the sum of the remaining five parameters, was difficult to assign a weight, because it depends on groundwater conditions. Instead, it was substituted by another parameter related to the disposition of blocks. This parameter is considered to evaluate block stability. Four situations were considered: blocks of very favourable, favourable, acceptable and not acceptable which refer to the stability of the geotechnical structure. The VRS system considers for P_2 the rock weathering effect, which is not considered by the RMR system, while P_3 is related to the joint intensity combining the effects of parameters RQD and discontinuity spacing considered by RMR system.

Parameter	*Properties*					
P_1	UCS (weight)	R_1 (15)	R_2 (9)	R_3 (6)	R_4 (3)	R_5 (1)
P_2	Rock weathering (weight)	A_1 (20)	A_2 (12)	A_3 (4)	-	-
P_3	Joint frequency (weight)	F_1 (25)	F_2 (20)	F_3 (15)	F_4 (10)	F_5 (5)
P_4	Joint surface conditions (weight)	B_1 (30)	B_2 (25)	B_3 (17)	B_4 (10)	B_5 (0)
P_5	Presence of water (weight)	C_1 (10)	C_2 (7)	C_3 (4)	C_4 (0)	-
P_6	Block position (weight)	D_1 (0)	D_2 (-2)	D_3 (-5)	D_4 (-10)	-

Fig. 5. VRS classification and weights for the system.

The meaning of different parameters is presented by the publications of Miranda et al. (2018) and Sousa et al. (2024). The rock mass is classified into six classes. A rock mass designated as class VI and class V has a behaviour conditioned by the rock characteristics of deformability and strength and correspond to soft rock masses. On the other hand, a formation designated as class I behaves in accordance with the characteristics of the discontinuities. For rock masses with other classes, behaviour is determined by the combination of both types of characteristics. Table 5 indicated the classification of rock masses in accordance with the value of the index VRS.

Table 5. Classification of volcanic rock masses by VRS index

Classification	*Values of VRS*
I – Excellent	100-91
II – Good	90-76
III – Reasonable	75-61
IV – Regular	60-41
V – Poor	40-21
VI – Very Poor	20-0

Three different cases of application of the empirical systems VRS and RMR were considered at São Miguel and Faial islands, from Azores archipelago.

The case 1 is related to the foundation of the extension of the runway at Ponta Delgada Airport in São Miguel Island (Fig. 6). During the construction, volcanic cavities were detected in the foundation of the landfill, which implied the geomechanical characterization of the volcanic foundation mass (Neves et al., 1986). The study carried out referred to the application of numerical and analytical models to analyze the influence of natural cavities on the landfill's foundation rock mass. To this end, six drillings were carried out, which allowed the volcanic rock mass to be characterized. Also, uniaxial compression and discontinuous sliding tests on rock specimens resulting from drilling cores were performed.

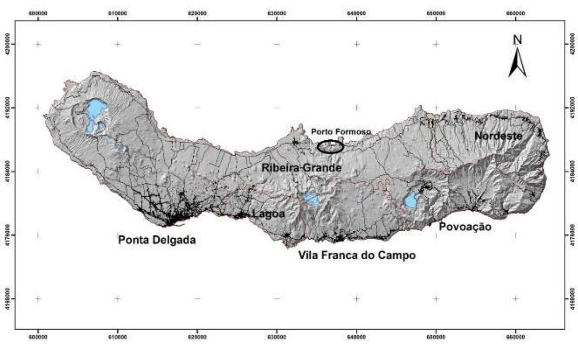

Fig. 6. São Miguel Island. Location of cases at Ponta Delgada and Porto Formoso.

Fig. 7 shows an interpretative geologic profile of several boreholes. The foundation is made up of layers of basaltic lava and volcanic clinker with interspersed volcanic tuffs. The foundation structure is very complex due to the lithological heterogeneity of the formations with marked thickness variations.

At the borehole SM1, uniaxial compression tests were done as indicated in Table 6. Also, sliding tests were also carried out on a discontinuity at the same borehole, the results of which are presented in Table 7.

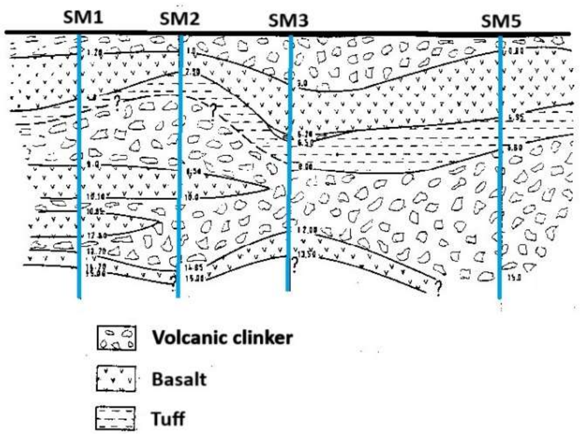

Fig. 7. Interpretive geological profile of boreholes SM1, SM2, SM3 and SM5 (Adapted from Neves et al., 1986).

Table 6. Uniaxial tests to basalt formations at the borehole SM1 (Adapted from Neves et al., 1986).

Depth (m)	E (GPa)	σ_c (MPa)	Comments
3	4.6	30.5	Basalt fractured
13.9 (A)	11.5	41.7	Basalt very porous
13.0 (B)	7.5	38.0	Basalt very porous

Table 7. Shear tests in a discontinuity in basalt (Neves et al., 1986).

Applied stresses (MPa)			KN .10^3 MPam	KT .10^3 MPam	i (°)	Coulomb Strength (*)
σ_N	Peak shear	Resid. shear				
0.1	0.21	0.26	167	2.0	11	c_p=0.08
0.3	0.50	0.49	48	1.6	15	c_r=0.12
0.6	0.90	0.85	88	2.6	16	φ_p=53.6°
0.9	1.30	1.27	80	3.1	14	φ_r=51.5°

(*) c_p – peak coesion; c_r – residual coesion; φ_p – peak friction angle; φ_r – residual friction angle.

The survey of the different volcanic formations were the following; i) the basaltic formations were hard and compact, with a high percentage of recovery (80-100%) and RQD between 50 and 100; ii) clinker settlements were very heterogeneous and with a high quantity of voids, percentage of recovery is very variable (20-80%), and null RQD values; and iii) Volcanic tuffs are soft and poorly consolidated formations, with recovery percentages very low (20-60%), and very low RQD values.

For the basaltic formations and considering the borehole SM1, the following values of VRS and RMR were obtained: i) VRS values – maximum of 61 and minimum of 37, the classification of the rocks mass was III to V; ii) RMR values – maximum of 54 and minimum of 46, the classification of the rock mass was III.

For the tuff formations and considering the borehole SM1, the following values of VRS and RMR were obtained: i) VRS values – maximum of 49 and minimum of 29, the classification of the rocks mass was IV to V; ii) RMR values – maximum of 54 and minimum of 46, the classification of the rock mass was III.

The case 2 is related to a stability hazard study, using the VRS (Fernandez et al., 2025), of a slope near Porto Formoso, also in São Miguel Island, in the municipality of Ribeira Grande, located on the north coast, as shown in Fig. 8. Fig. 6 shows a map of the Island and the location of Porto Formoso.

Fig. 8. Front view of the landslide at Porto Formoso (Fernandez et al., 2025).

The volcanic formations involved are trachytes. These rocks were obtained from lava flows with acidic composition and high percentage of silicia. The VRS and RMR empirical systems were applied for these rocks being obtained the following values: i) VRS values – maximum of 74 and minimum of 50, the classification of the rocks mass was class III (reasonable) and class IV (regular); ii) RMR values – maximum of 89 and minimum of 37, the classification was class I (rock mass very good) and class IV (bad rock mass), respectively (Fernandez et al., 2025). The comparison of the values shows an important discrepancy between both systems. This is due to the property P_6 (adjusted due to the orientation of discontinuities in slopes).

The case 3 is related to Lomba Grande landslides in the Island of Faial (Fig. 9). The Faial Island develops along an approximate WNW-ESE axis, with a maximum length and width of around 21 km and 14 km, respectively. It has an area of 170 km^2 and is made up of two central volcanoes (Pacheco et al., 2017).

Landslides occurred at Lomba Grande (Fig. 10) were triggered by the earthquake of July 1998. Five boreholes were carried out, with continuous sampling. The VRS and RMR empirical systems were applied for pyroclasts and the following values were obtained: i) VRS values – maximum of 37 and minimum of 27, the classification of the rocks mass was V; ii) RMR values – maximum of 15 and minimum of 2, the classification of the rock mass was V (Fernandez et al., 2025).

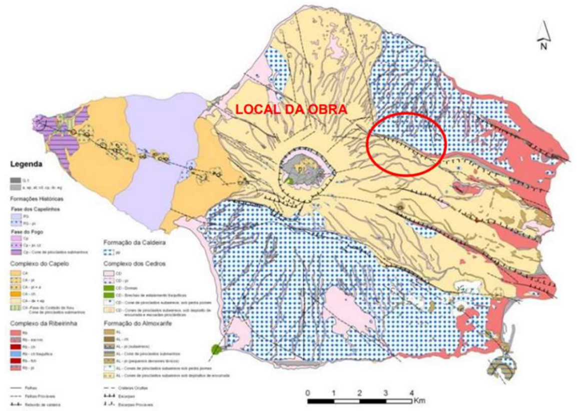

Fig. 9. Geological cartography of the Island of Faial (Serralheiro et al., 1989).

Fig. 10. Landslides occurred at Lomba Grande, Faial Island (Fernandez et al., 2025).

5. New Subsystem Developed for Soft Volcanic Formations

In this section, we leverage the adaptive learning capabilities of Machine Learning (ML) techniques to develop predictive models for the classification of VR masses. Specifically, we implement two distinct approaches to evaluate the effectiveness of ML-based classification.

a) VR Class Prediction Using a Decision Tree Algorithm with VRS System Variables: this approach employs a decision tree algorithm to classify VR masses based on key attributes derived from the VRS classification. The predictive model utilizes six primary variables (P1, P2, P3, P4, P5, and P6) capturing essential geomechanical properties of the rock mass.

b) VR Class Prediction Using a Decision Tree Algorithm with RMR System Variables: in this approach, the decision tree algorithm is applied to predict the classes of VR masses classes using the same six input variables (P1, P2, P3, P4, P5, and P6), but this time obtained from the widely recognized RMR classification system. This enables a comparative analysis between the classification frameworks and their influence on predictive accuracy.

ML techniques are powerful computational tools capable of solving complex problems and have gained increasing prominence across various scientific disciplines over the past decade. These methods have been successfully applied in diverse knowledge domains (Javadi et al., 2012; Liao et al., 2012; Garg et al., 2014), including civil engineering (Miranda et al., 2011; Miranda and Sousa, 2012; Gomes Correia et al., 2013; Tinoco et al., 2014a; 2014b; He et al., 2015; Tinoco et al., 2016). Similarly, Data Mining (DM) techniques have been utilized in the analysis and characterization of rock masses (Martins and Miranda, 2012; Miranda et al., 2013; Miranda et al., 2014), further demonstrating their applicability in geotechnical engineering.

The widespread adoption of ML for addressing real-world, complex problems underscores its potential and serves as the primary motivation for its application in this study. Notably, ML techniques have been employed in Rock Mechanics for projects such as the Venda Nova II and Bemposta II hydroelectric schemes in northern Portugal, where novel predictive models were developed to estimate the strength and deformability parameters of granite formations (Miranda and Sousa, 2012). Additionally, ML methods have been leveraged to assess new geomechanical models at the former Homestake gold mine in Lead, USA. In this case, ML algorithms were applied to widely used empirical classification systems, as RMR, Q-system, and GSI—alongside Bayesian Networks (BNs) to enhance the prediction of RMR values (Sousa et al., 2012). Another notable application is the development of rockburst indices using ML techniques, where predictive models were trained on an extensive database of laboratory rockburst tests (He et al., 2015). A more recent study by Owusu-Ansah et al. (2023) further highlights the capabilities of ML techniques in predicting rockburst conditions. This research reinforces the growing body of evidence demonstrating the effectiveness of ML-based models in assessing geomechanical hazards, providing enhanced predictive accuracy compared to traditional empirical approaches. The study underscores the potential of ML in improving rockburst risk evaluation, contributing to safer and more reliable underground construction and mining operations.

5.1 Modeling

This section provides a brief overview of the different DM algorithms utilized in this research.

A Decision Tree (DT) is a directed acyclic graph that represents a structured set of rules used to distinguish between different classes or predict values in a hierarchical manner. These rules are derived from the dataset using rule induction techniques and are expressed in an intuitive "If-Then" structure, allowing for simple yet effective conditional logic. The DT algorithm operates by recursively splitting the source data into smaller subsets based on attribute test values, progressively refining the decision process. Graphically, decision trees exhibit a characteristic branching structure composed of three main components:

1. Root Node – The topmost node of the tree, representing the entire dataset before any partitioning occurs.
2. Branches and Internal Nodes – Each internal node represents a test applied to an attribute, while the branches denote the possible outcomes of that test, directing the flow of decision-making.
3. Leaf Nodes – Terminal nodes that represent the final class labels or predicted values after all relevant attribute tests have been performed.

Once a decision tree has been trained, it can be used for classification or regression tasks by mapping new data instances through the learned tree structure. Decision trees are categorized into two primary types:

- Classification Trees – Used for predicting discrete categorical outcomes by assigning data instances to predefined classes.
- Regression Trees – Designed to predict continuous numerical values based on induced mathematical relationships.

Among the various decision tree algorithms, the Classification and Regression Trees (CART) algorithm (Berry and Linoff, 2000) is one of the most widely used methodologies for constructing decision trees. CART follows a binary tree structure, meaning that each internal node always produces exactly two child nodes. The algorithm partitions data at each step using a selected predictor, which may be applied multiple times at different hierarchical levels. The goal of each split is to maximize the homogeneity of the resulting subsets compared to the parent node, ensuring that instances within each subset share more similar characteristics.

Despite its flexibility, the binary nature of the CART algorithm can introduce certain challenges. Specifically, it can become computationally intensive when handling large and complex datasets, and its reliance on repeated splits may sometimes result in overfitting. Overfitting occurs when the tree structure captures noise or outliers in the training data, leading to an overly complex and inefficient model. To mitigate this, pruning techniques are employed to simplify the tree by removing unnecessary branches, thereby improving its generalization capability on unseen data.

One of the key advantages of decision trees, including CART, is their interpretability. They follow a “white-box” model, meaning that the decision-making process is transparent and can be easily understood by domain experts. This interpretability makes decision trees particularly useful for applications where model explainability is critical. However, as the complexity of the dataset increases, decision trees can become harder to manage due to a proliferation of branches, potentially reducing their efficiency and scalability.

All experiments were conducted using the R statistical environment (R Core Team, 2009) and were facilitated by the RMiner package (Cortez, 2010). RMiner provides a user-friendly interface for implementing various DM algorithms, including DTs. Additionally, it supports multiple validation techniques, such as cross-validation, enabling robust model assessment and performance evaluation. The use of RMiner streamlines the experimentation process by offering a structured framework for algorithm selection, model training, and validation, ensuring reliable and reproducible results.

5.2 Model assessment

To assess and compare the performance of the models, three classification metrics were employed based on the confusion matrix (Hastie et al., 2009): recall, precision, and F1-score.

- **Recall** measures the proportion of instances belonging to a given class that were correctly identified by the model. Mathematically, recall for a particular class is defined as: $\mathrm{TruePositives}/(\mathrm{TruePositives} + \mathrm{FalseNegatives})$
- **Precision** quantifies the accuracy of the model when predicting a specific class, i.e., the proportion of correctly classified instances among all instances predicted as belonging to that class. It is expressed as $\mathrm{TruePositives} + \mathrm{FalsePositives})$
- **F1-score** represents a balance between precision and recall, acting as a single performance metric that considers both false positives and false negatives. It is calculated as the harmonic mean of precision and recall: $2 \cdot \frac{precision \cdot recall}{precision + recall}$

For all three metrics, higher values indicate better predictive performance.

To ensure robust model evaluation, a 10-fold cross-validation approach (k = 10) was applied. In this technique, the dataset (P) is randomly partitioned into k mutually exclusive subsets $(P_1, P_2, \cdots, P_k)$ of equal size (Hastie et al., 2009). The training and testing process is repeated k times, with each subset used once as a test set while the remaining *k-1* subsets are used for training. The final model performance is obtained by averaging the errors across all iterations. While this method provides a reliable estimation of the model's generalization ability, it requires approximately k times more computational effort, as *k* separate models must be trained and evaluated.

Beyond model accuracy, interpretability is a critical aspect, particularly from an engineering perspective. To address this issue, Cortez and Embrechts (2013) introduced a visualization-based Sensitivity Analysis (SA) approach, which is applied in this study. SA is a post-training technique that examines model behavior by analyzing its responses to variations in input values. This allows for:

- Quantification of the relative importance of each input feature
- Understanding the average effect of each variable on the predicted outcome

In particular, the Global Sensitivity Analysis (GSA) method was implemented, which is capable of detecting interactions among input variables. This is achieved by simultaneously varying multiple input parameters, while keeping the remaining inputs fixed at a baseline value. In this study:

- The baseline value was set to the average input variable value
- The number of variation levels was set to *L = 12*, striking a balance between computational efficiency and resolution

Using GSA, various visualization techniques can be employed to analyze the model's response. A key graphical representation is the input importance bar plot, which illustrates the relative influence (R_a) of each input variable in the model. The relative influence is derived from the gradient metric (g_a) calculated for all inputs and computed as per the following equation:

$$R_a = g_a \Big/ \sum_{i=1}^{I} g_i \cdot 100(\%) \quad where, \quad g_a = \sum_{j=2}^{L} \left|\hat{y}_{a,j} - \hat{y}_{a,j-1}\right| / (L-1) \tag{2}$$

where a denotes the input variable under analysis and $\hat{y}_{a,j}$ is the sensitivity response for $x_{a,j}$.

5.3 ML results discussion and interpretation

A Hierarchical Volcanic Rock Mass Rating (HVR) system was developed using a DT algorithm, with input variables P1, P2, P3, P4, P5, and P6 derived from the VRS classification. This model, referred to as HVR, establishes a hierarchical decision framework for classifying volcanic rock masses based on these geomechanical parameters.

A similar methodology was applied to develop the Hierarchical Rock Mass Rating (HRMR) system, where the same six input variables were instead sourced from the RMR classification system. This alternative approach allows for a comparative assessment of the predictive capabilities of both classification frameworks.

Figs. 11 and 12 illustrate the decision trees generated under these two modeling strategies respectively, visually depicting the hierarchical classification rules derived from the respective datasets. Table 8 presents a comparative summary of the recall, precision, and F1-score values obtained for each class across all proposed models, offering a quantitative evaluation of their predictive performance.

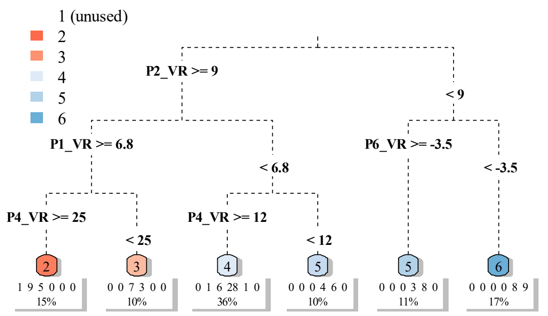

Fig. 11. Decision tree for VRS.

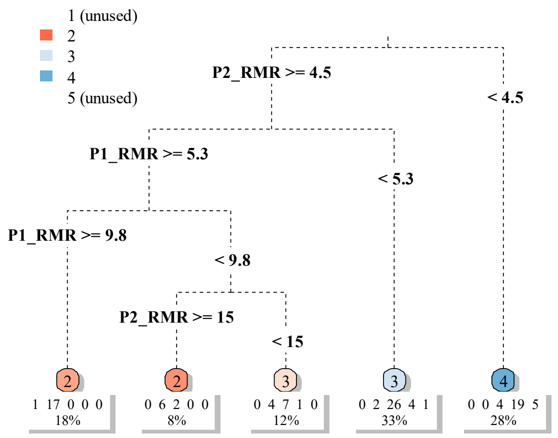

Fig. 12. Decision tree for RMR system.

Table 8. Models comparison based on recall, precision and F1-score.

Class	Recall		Precision		F1-score	
	HVR	HRMR	HVR	HRMR	HVR	HRMR
1	0.00	0.00	0.00	0.00	0.00	0.00
2	0.48	0.74	0.53	0.72	0.50	0.73
3	0.49	0.71	0.55	0.62	0.52	0.66
4	0.72	0.57	0.72	0.57	0.72	0.57
5	0.52	0.00	0.47	0.00	0.49	0.00
6	0.33	-	0.29	-	0.31	-

Figs. 13 and 14 illustrate the observed versus predicted classes for the HVR and HRMR models, respectively. In these figures, the x-axis represents the actual observed class, while the y-axis depicts the predicted class. The color of the cell represents the number of correct predictions.

Examining Fig. 13, it is evident that the HVR model struggles to correctly classify class 1, with its highest performance observed for class 4. Approximately 90% of VR instances that belong to class 1 (true condition) were misclassified as class 2, while the remaining 10% were assigned to class 3.

Similarly, the HRMR model (Fig. 14) also encounters difficulties in correctly identifying VR classes. The decision tree fails to classify both class 1 and class 5, highlighting potential limitations in the classification approach. The best performance is observed for class 2, where an F1-score of approximately 73% was achieved (Table 5). For classes 3 and 4, the model demonstrates slightly better performance but still exhibits classification challenges.

Fig. 15 presents the relative importance of each input variable for both the HVR and HRMR models.

- In the HVR-based DT model, the three most influential variables are P2, P4, and P1, each contributing approximately 30% to the classification decision.
- In contrast, the HRMR-based DT model identifies P1, P4, and P2 as the most critical variables, collectively accounting for 94% of the total influence on model predictions.

These findings suggest that while both models rely heavily on P1, P2, and P4, their respective classification frameworks may lead to differences in predictive performance and class distinguishability.

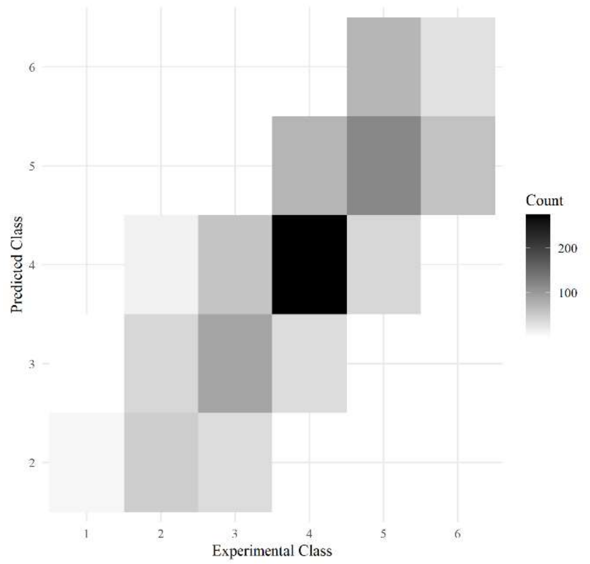

Fig. 13. HVR performance.

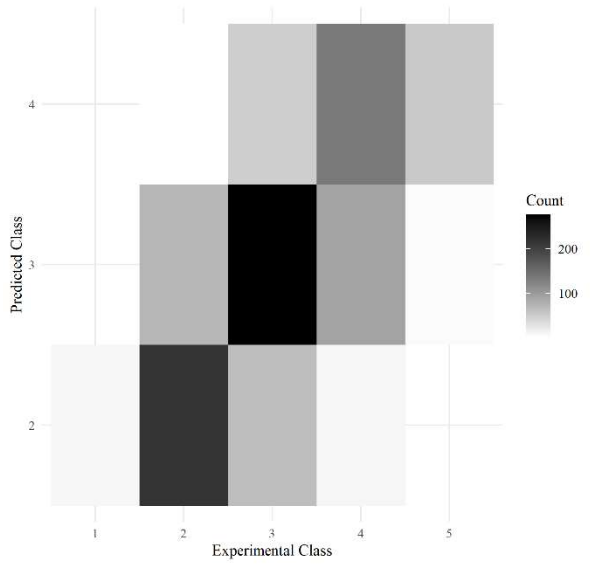

Fig. 14. HRMR performance.

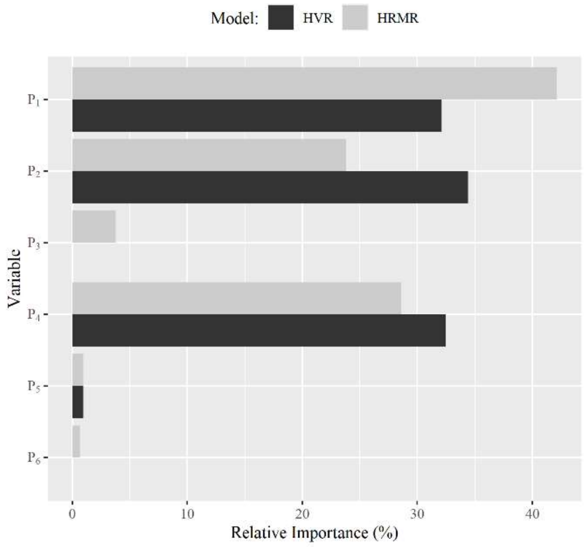

Fig. 15. HVR and HRMR relative importance.

6. Concluding Remarks

This paper presents a methodology for the geomechanical characterization of soft volcanic rock masses in the Azores archipelago based on the use of the new VRS. The islands of the archipelago are located in the Atlantic Ocean, in a highly tectonically active region, where three main tectonic plates meet. Consequently, the islands are affected by natural disasters, as earthquakes and volcanic eruptions. The nature of the volcanic materials (internal factors), associated with external factors (i.e., earthquakes and particular conditions of weathering), contributes to the occurrence of other kind of natural hazard – the landslides.

To make the use of VRS more effective and efficient, the adaptive learning capabilities of ML techniques were used to develop predictive models for the classification of soft volcanic rock masses. Similarly, DM techniques were used in the analysis and characterization of rock masses. Their use allowed to the expert to classify the soft rock masses and conclude on the correctness of the results, comparing VRS and RMR system, and their influence on predictive accuracy.

Availability of Materials and Data Declaration – The data and materials will be available by request.

Competing Interests Declaration – The authors have no conflicts of interest to declare.

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Author's Contribution – Celeste Jorge: writing, design of the paper and supervision; Joaquim Tinoco: methodology, conceptualization and data analysis; Luis Ribeiro e Sousa: supervision, conception and design of the paper, and writing; Ana Malheiro: data collection; and Rita Leal e Sousa: validation and writing.

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