

Predicting fracture network development in crystalline rocks

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Highlights

- Machine learning reveals the predictive power of fracture network characteristics in triaxial compression experiments.
- The fracture networks are more predictable in granite and monzonite than marble.
- Fracture volume, length and aperture are the most predictable of the examined characteristics, and orientation is the least predictable.

Abstract

How do rocks break? The shape and length of fractures influence whether they propagate, and whether a rock will macroscopically fail within a particular stress field. Thus, deriving equations between fracture characteristics that we can measure in the field, and the characteristics that are more difficult to measure, would be a valuable advance. We use machine learning to identify the sets of fracture characteristics that should be in these equations. We perform in situ X-ray synchrotron experiments on marble, granite and monzonite during triaxial compression that enable quantifying the evolving fracture network. The varying success of the machine learning models reveals the rock types in which fracture network development is more systematic, and thus predictable (the igneous rocks). The model success also reveals the fracture characteristic that is the least predictable (orientation), and thus highlights a fundamental application in geoscience that requires reexamination.

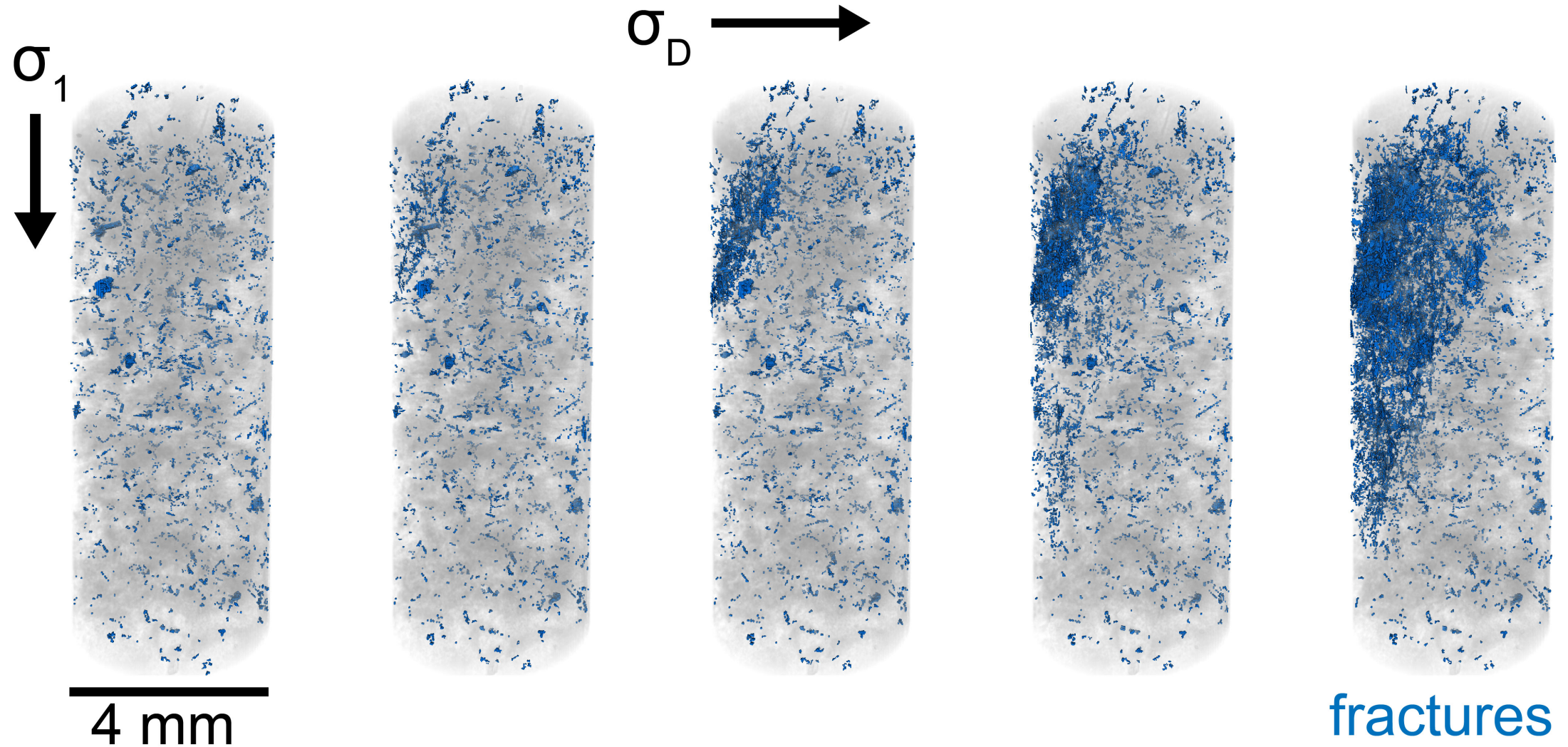


Figure 1. Example of fracture network development in an X-ray synchrotron triaxial compression experiment on granite (experiment granite #4). Fractures are shown in blue and the host rock is shown in gray. The applied differential stress, σ_D , increases from left to right. The rightmost image shows the core immediately preceding macroscopic failure.

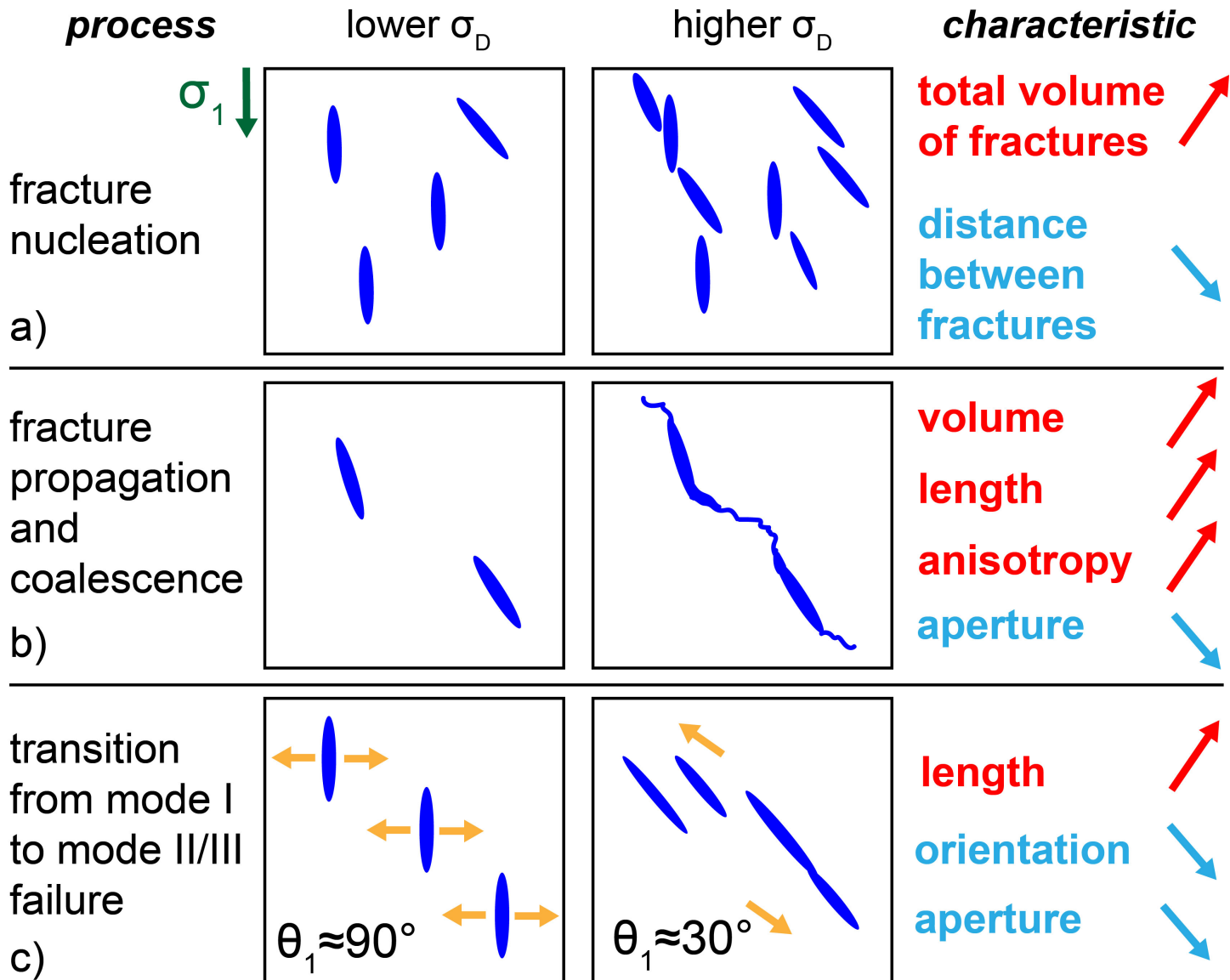


Figure 2. Expected development of fracture network characteristics in triaxial compression experiments. Based on the processes listed to the left of the figure, we expect the fracture network characteristics to increase (red), or decrease (blue) with increasing differential stress, σ_D . Fracture nucleation (a) may increase the total fracture volume and decrease the distance between fractures. Propagation and coalescence (b) may increase the volume, length and anisotropy, and decrease the aperture. The transition in failure mode (c) may decrease the aperture and orientation of the minor axis relative to the maximum compression direction, and increase the length. The three kinds of fracture development (a-c) may occur simultaneously, but here we show them separately for clarity.

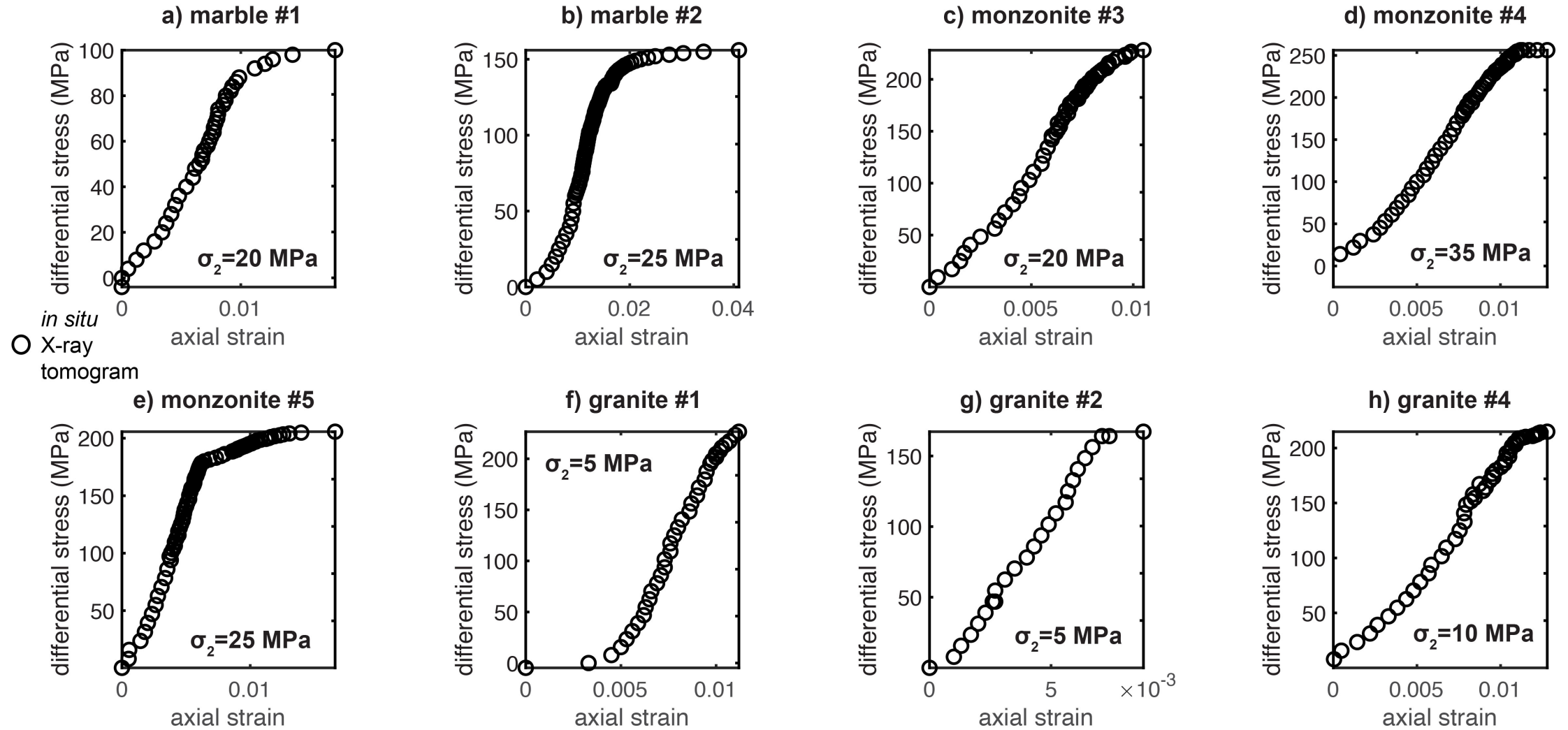


Figure 3. Differential stress and axial strain relationships for eight experiments: a) marble #1, b) marble #2, c) monzonite #3, d) monzonite #4, e) monzonite #5, f) granite #1, g) granite #2, and h) granite #4. Each black circle shows the stress and strain conditions when an X-ray tomogram was acquired. The applied confining stress, σ_2 , of each experiment is shown in the corresponding plot. All of the experiments were performed without pore fluid, except monzonite #4, which included 5 MPa of pore fluid pressure.

Figure 4. Success of predicting fracture network characteristics in all of the examined rock types (dark blue), only the igneous rocks (light blue) and only the marble rocks (orange), shown with the R^2 score. We train and test models 10 times using different divisions of training and testing data in order to account for random variations. We report the mean $\pm$ one standard deviation of the R^2 scores of the 10 models with different training and testing data sets. Thus, the orange symbol above the total volume label on the horizontal axis shows the mean $\pm$ one standard deviation of the scores for the models that predict the total volume of fractures in a subvolume. Higher R^2 indicates a stronger correlation between the predicted and observed characteristic, with $R^2 > 0.8$ indicating strong positive correlations.

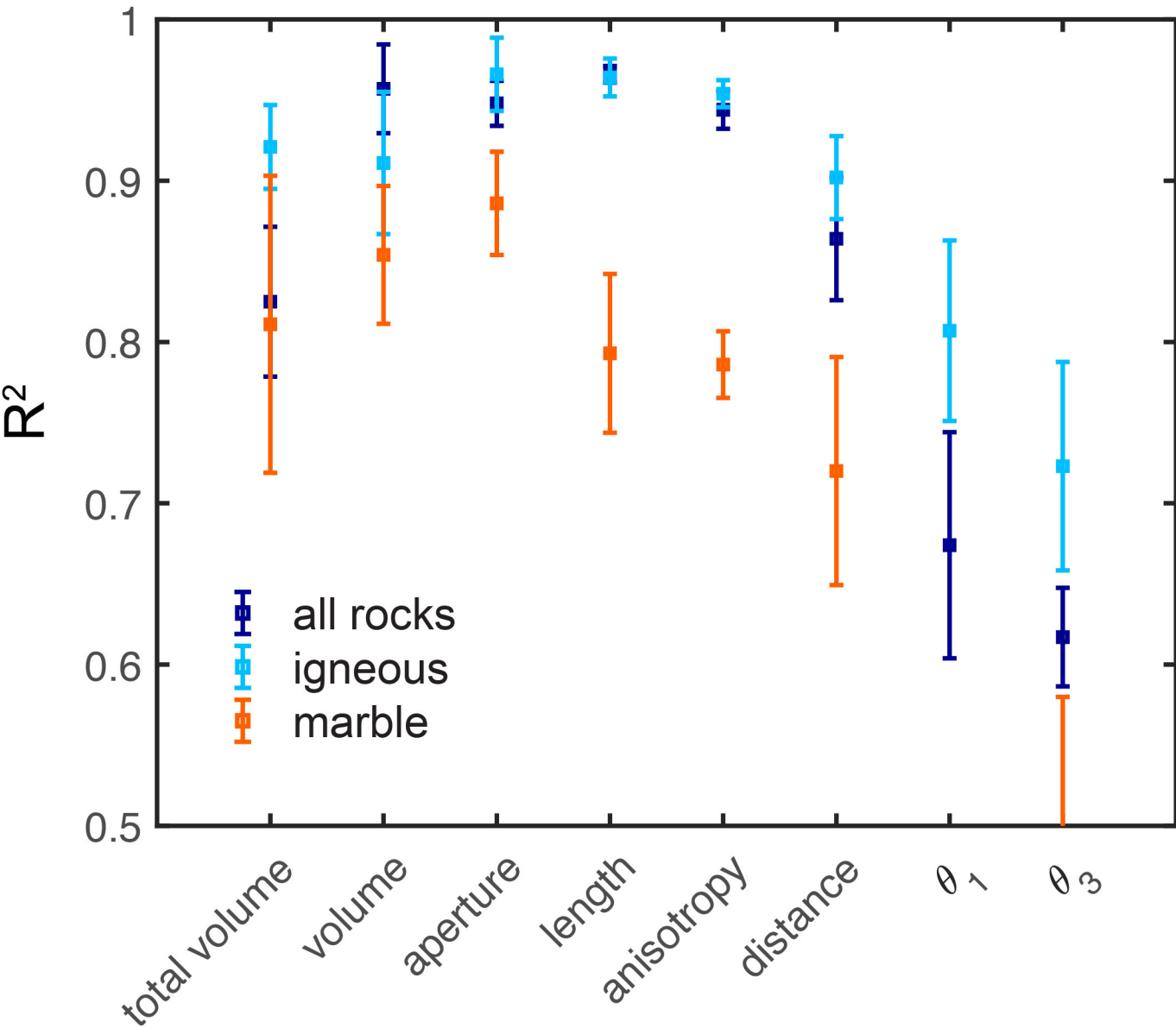
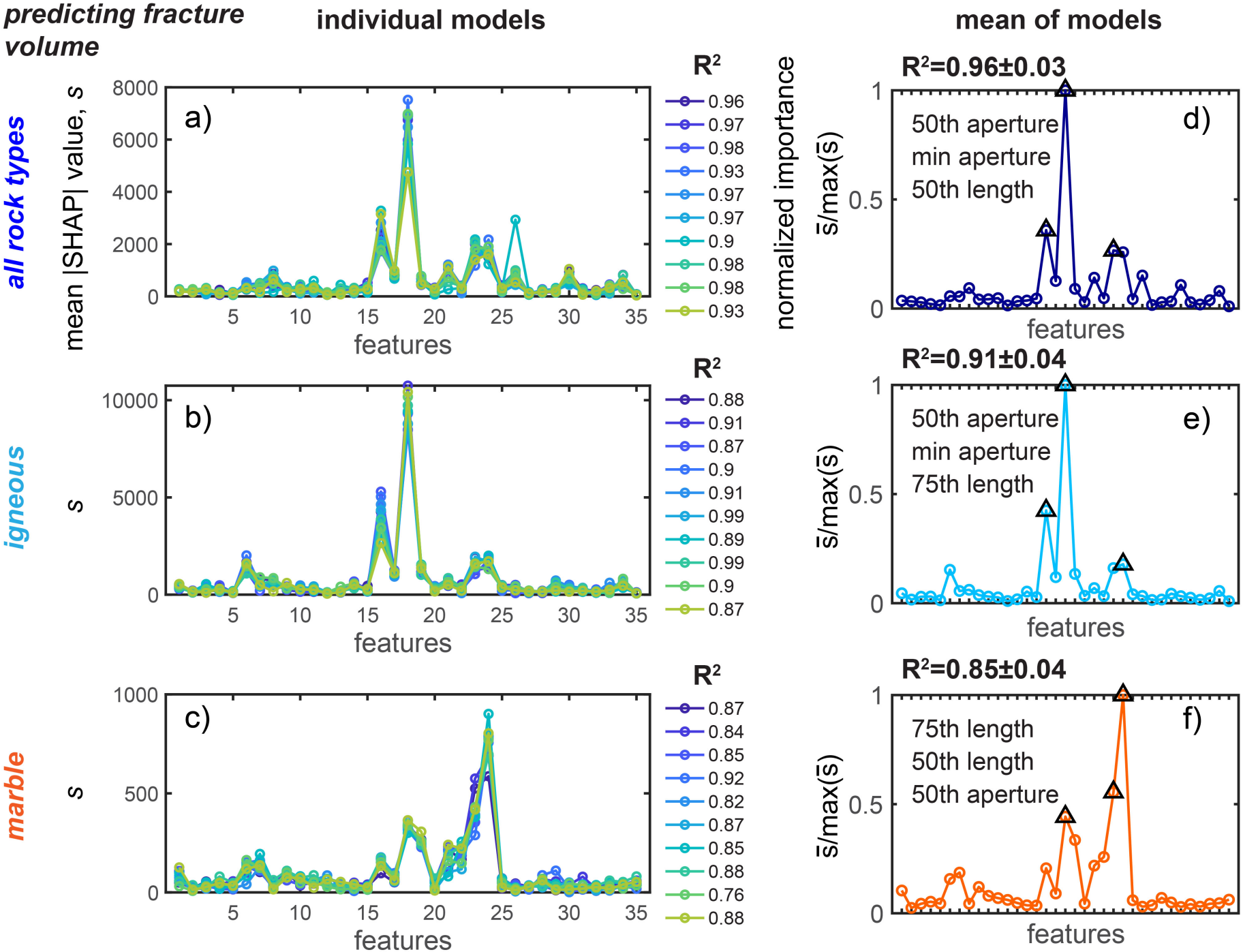


Figure 5. Example distribution of mean |SHAP| values, s , for models designed to predict the fracture volume for all rock types (a, d), igneous rocks (b, e) and marble (c, f). The first column (a-c) shows the results for each individual model and the corresponding R^2 score. The second column (d-f) shows the results as the normalized mean of each |SHAP| value returned for each feature, $\bar{s}/\max(\bar{s})$, and the top three features with the highest importance (triangles and text). The similarity of the distributions of s justifies reporting the mean s of each feature and normalizing this distribution. The features listed in the top left corner of (d-f) are the top three identified from the $\bar{s}/\max(\bar{s})$ distribution.



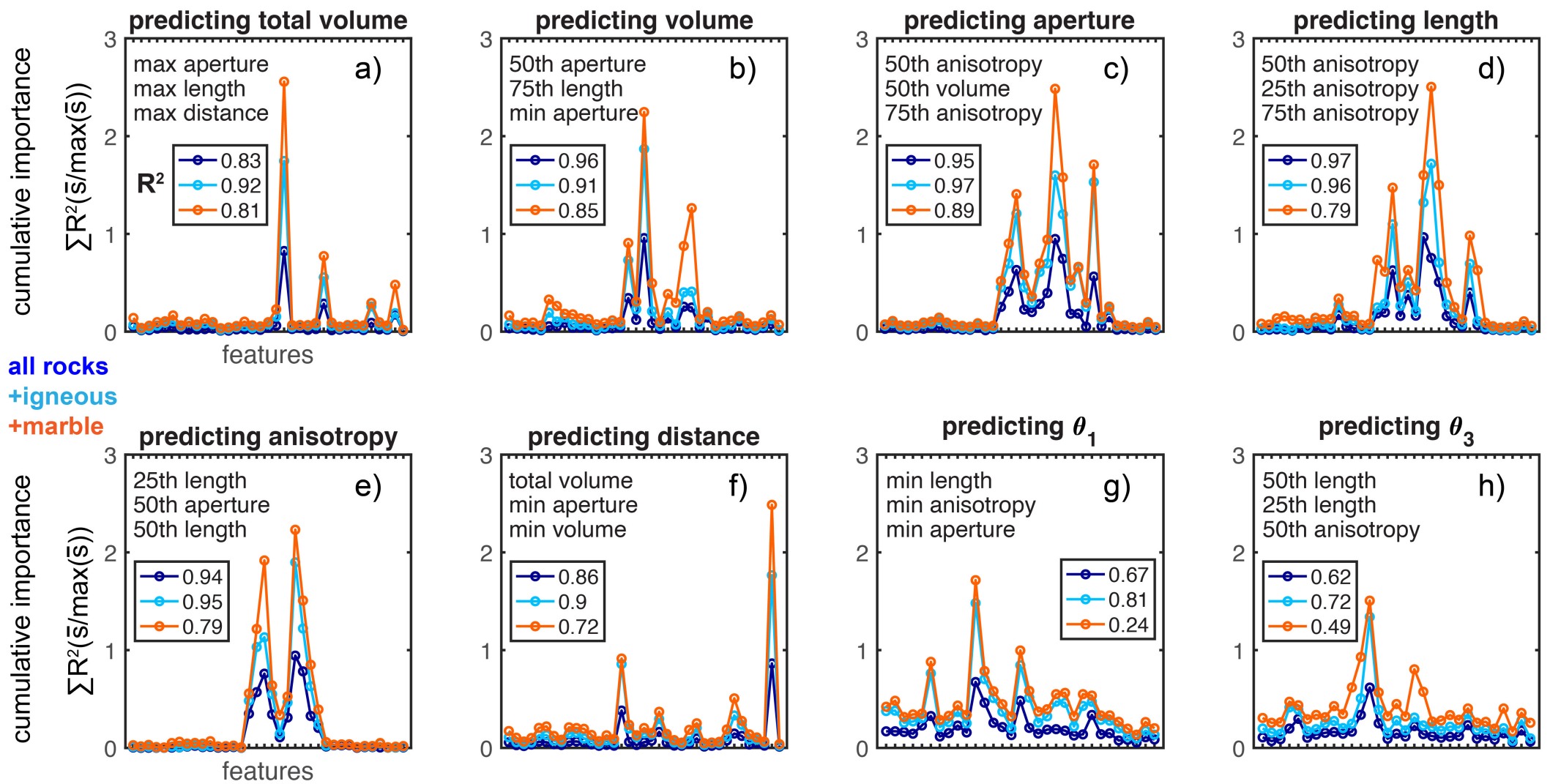


Figure 6. Cumulative importance of features for each predicted fracture characteristic: a) total volume of fractures in a subvolume, b) individual fracture volume, c) fracture aperture, d) fracture length, e) fracture shape anisotropy, f) distance between fractures in a subvolume, and orientations of the minimum eigenvector, θ_1 (g), and maximum eigenvector, θ_3 (h). Cumulative feature importance is shown as $\sum R^2(\bar{s}/\max(\bar{s}))$, where R^2 is the mean R^2 score of the ten different models of each rock type. We weight the normalized $\bar{s}$ such that more accurate models, with higher R^2 , have a greater impact on the results than less accurate models. The top three most important features are listed in the top left corner of each plot.

Table 1. Fracture characteristics of the most important features identified in models. None of the most important features rely on the orientation of the fractures.

Prediction	Important characteristics
total volume	aperture, length, distance
volume	aperture, length
aperture	volume, anisotropy
length	anisotropy
anisotropy	length, aperture
distance	volume, aperture
θ_1	length, aperture, anisotropy
θ_3	length, anisotropy

Figure 7. Success of predicting fracture network characteristics upon removal of the most important features (i.e., Table 1, Figure 5). The horizontal axis lists the features that were removed before developing each model that predicts the total volume, v , (a), individual fracture volume, v_i , (b), aperture, A , (c), length, L , (d), anisotropy, a , (e), distance between fractures, d , (f), θ_1 (g), and θ_3 (h). For example, the scores listed in the position marked v , A , L , d in (a) show the scores for models developed to predict the total volume without using features that include information about the volume, v , aperture, A , length, L , and distance, d .

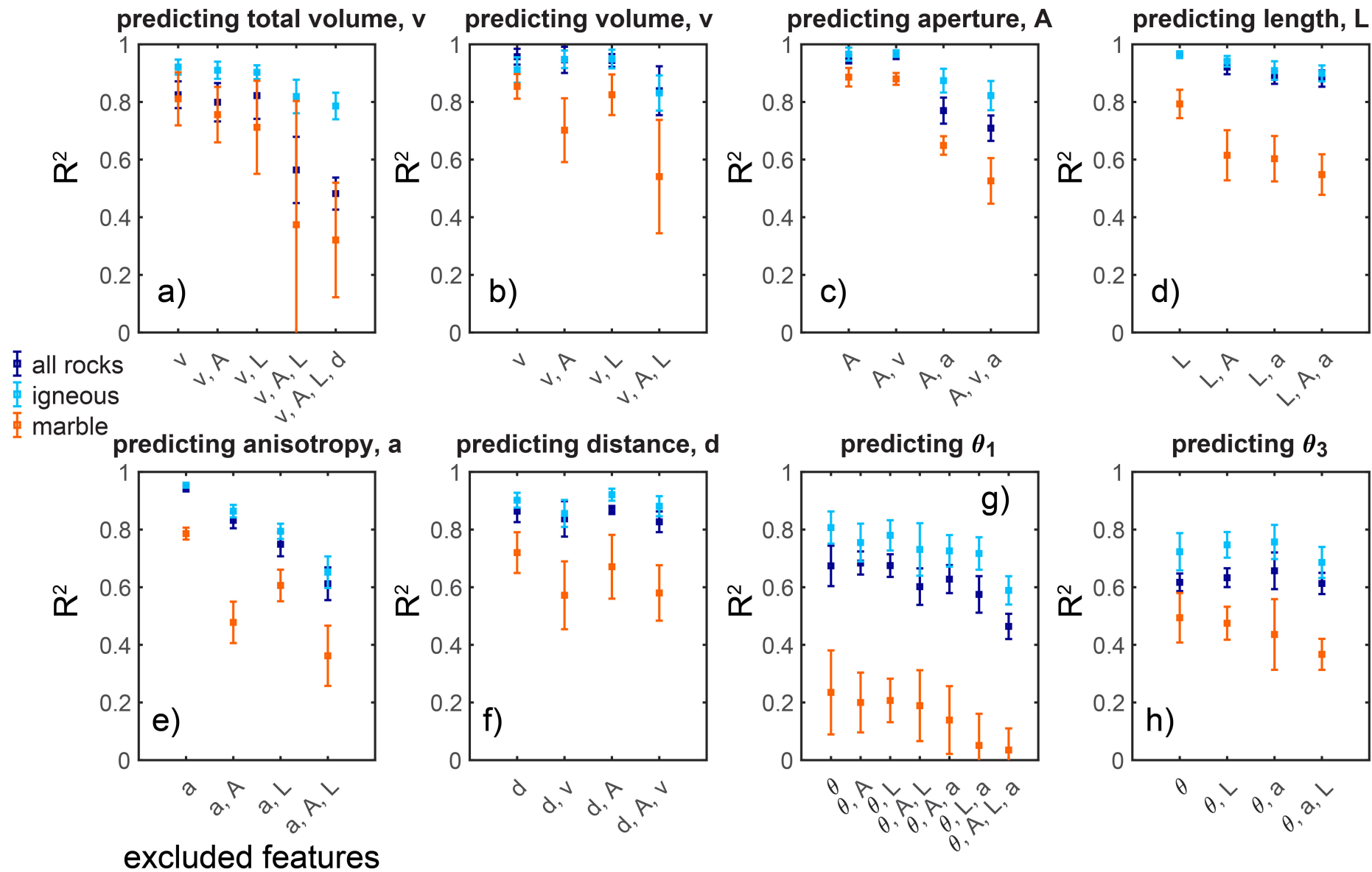


Figure 8. Difference in the mean R^2 score for models that include all of the features, R_a , and models that exclude all of the most important features, R_e , as $\Delta R^2 = R_e - R_a$ for models developed with the three groups of rock types. The decrease in R^2 is the largest for the marble models for all but one fracture characteristic, θ_1 .

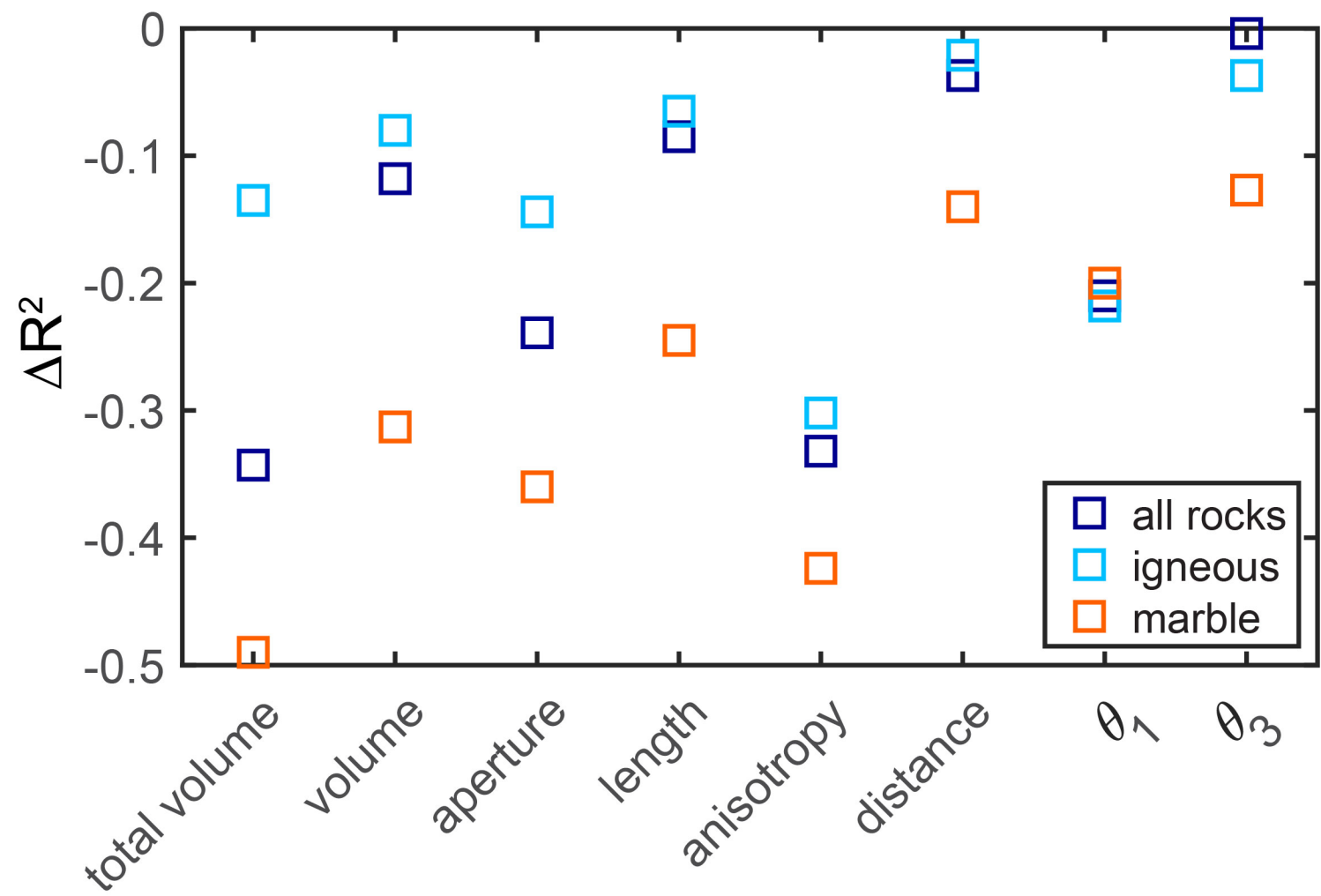


Figure 9. Cumulative importance of features for each predicted fracture characteristic: a) total volume of fractures in a subvolume, b) individual fracture volume, c) fracture aperture, d) fracture length, e) fracture shape anisotropy, and f) distance between fractures in a subvolume. Cumulative feature importance is shown as $\sum R^2(\bar{s}/\max(\bar{s}))$, where R^2 is the mean R^2 score of the 10 different models of each rock type. We weight the normalized $\bar{s}$ such that more accurate models, with higher R^2 , have a greater impact on the results than less accurate models. Left columns show the results for models developed using all of the features (except the one being predicted). Right columns show the results for models developed using a subset of the features that excludes the identified most important features (listed in the left column).

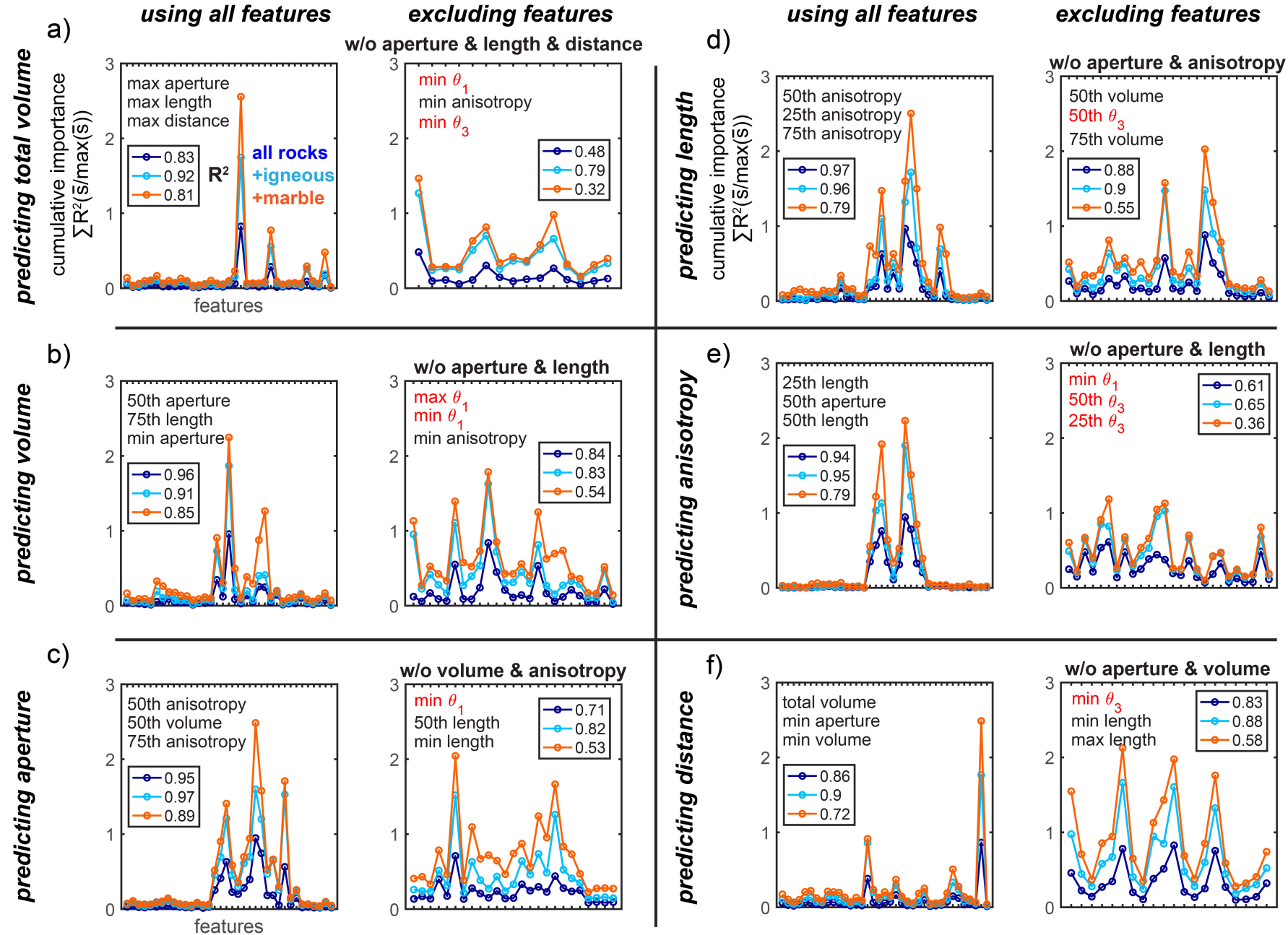


Table 2. Most important characteristics identified in models with the listed features excluded.

Prediction	Excluded features	Important characteristics
total volume	aperture, length, distance	θ_1, θ_3 , anisotropy
volume	aperture, length	θ_1 , anisotropy
aperture	volume, anisotropy	θ_1 , length
length	anisotropy, aperture	θ_3 , volume
anisotropy	length, aperture	θ_1, θ_3
distance	volume, aperture	θ_3 , length

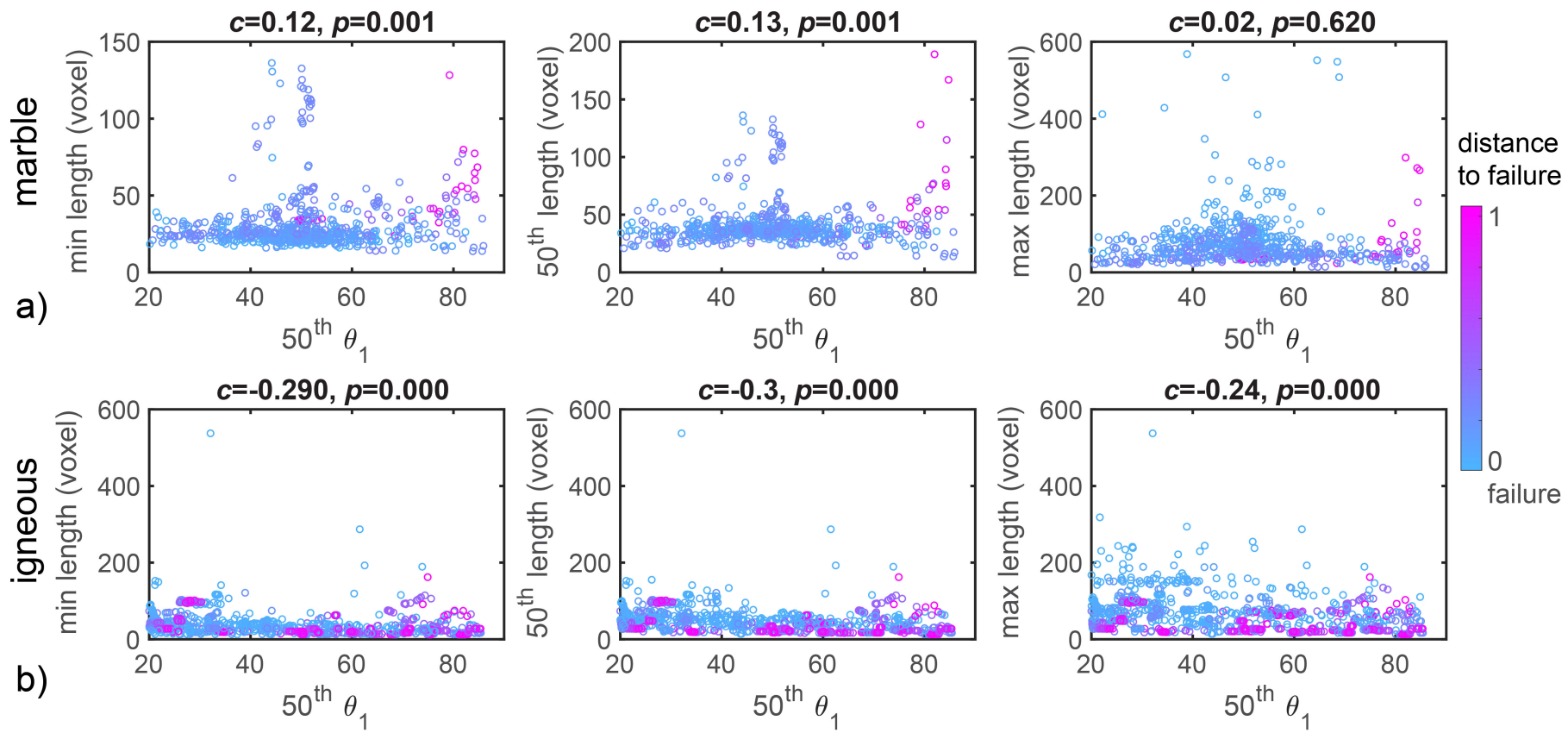


Figure 10. Relationship between the fracture orientation, θ_1 , and representative statistics of the fracture length for the a) marble and b) igneous rocks. The values at the top of each plot are the linear correlation coefficient, c , and the p-value, p , of the two fracture characteristics shown in the plot. Coefficients with $p < 0.05$ are considered significant. The color of the symbols indicates the distance to failure, $(\sigma_F - \sigma_D)/\sigma_F$, where σ_F is the differential stress at macroscopic failure, and σ_D is the differential stress when the tomogram was acquired. Zero is at macroscopic failure. There is no clear trend between the applied differential stress (i.e., distance to failure), and the fracture orientation. The low c between the orientation and length indicate that longer fractures are not more likely to attain the expected orientation oblique to σ_1 . Rather, long and short fractures have a wide range of orientations.

Figure 12. Conceptualization of fracture network development revealed by machine learning models. The fracture orientations under higher differential stress may not match the expected Coulomb criterion due to the initial configuration of the fractures, and resulting local stress perturbations.

