SoftwareX 32 (2025) 102369

Contents lists available at ScienceDirect

SoftwareX

journal homepage: www.elsevier.com/locate/softx

Original Software Publication

RockDisc-Gen: A python software package for rock discontinuity generation

Yujie Su [a], Hong Gao [a], Han Meng [a], Jinming Wang [b], Gang Mei [a,*]

[a] School of Engineering and Technology, China University of Geosciences (Beijing), 100083, China
[b] CNOOC EnerTech-Drilling & Production Co, Tianjin 300452, China

ARTICLE INFO

Keywords:
Rock discontinuity generation
Deep learning
Monte Carlo method

ABSTRACT

Rock discontinuity generation possesses considerable application value in geotechnical engineering. However, current tools exhibit constraints regarding functionality, usability, and adaptability. Here, we developed a Python software package, **RockDisc-Gen**, for ease-of-use rock discontinuities generation and visualization. RockDisc-Gen incorporates four methods (i.e., the Monte Carlo method, Copula-based method, generative adversarial networks (GANs), and denoising diffusion probability model (DDPM)), for generating synthetic datasets that accurately reflect rock discontinuity orientations and sizes, derived from limited field observation data. The software package can also assess the statistical properties of generated data against the original input data, thus systematically evaluating the generation performance.

Code metadata

Current code version	1.0
Permanent link to code/repository used for this code version	https://github.com/GangMei-CUGB/RockDisc-Gen
Permanent link to Reproducible Capsule	–
Legal Code License	MIT License
Code versioning system used	git
Software code languages, tools, and services used	Python
Compilation requirements, operating environments & dependencies	Windows, Visual Studio Code
If available Link to developer documentation/manual	https://github.com/GangMei-CUGB/RockDisc-Gen
Support email for questions	gang.mei@cugb.edu.cn

1. Motivation and significance

Discontinuities in rock masses are essential geological components that govern the engineering rock mechanics behavior, hydraulic properties, and long-term stability of rock masses. The accurate delineation of their spatial distributions and geometric attributes is crucial for applications like tunnel excavation and slope stability evaluation. Conventional methods, such as field mapping, drill core logging, and 3D laser scanning, often face challenges due to data sparsity and lack of representativeness [1–5]. These methods are limited by outcrop conditions, site accessibility, and exploration costs, leading to inadequate representation of the heterogeneity and anisotropy of rock masses. Additionally, scale effects and subjective biases in human mapping, along with environmental noise in instrumental measurements, reduce data reliability [6–9].

To overcome these limitations, stochastic generation approaches have become essential for developing rock discontinuity network models. The Monte Carlo method excessively depends on predetermined probability distributions, complicating the characterization of the intrinsic nonlinear interactions [10,11]. The Copula-based method offers a more adaptable framework for the joint modeling but struggles with parameter estimation in high-dimensional data [12]. Recently, generative deep learning models like GAN and DDPM have exhibited robust capabilities in learning high-dimensional data distributions, offering new paradigms for rock discontinuity data generation without predefined distribution forms [13,14]. However, these methods are still emerging in geological engineering, requiring specialized tools for comprehensive process verification.

Mainstream commercial software for rock discontinuity generation often suffers from low transparency and limited scalability. While open-source tools facilitate user-defined modeling, they typically lack standardized generation-verification methods, particularly for 3D display and statistical validation. Consequently, developing an open-source, modular platform for rock discontinuity generation holds significant theoretical and practical value.

Recently, traditional probabilistic methods and deep learning models have been used for rock discontinuity generation. For example, the

* Corresponding author.
E-mail address: gang.mei@cugb.edu.cn (G. Mei).

https://doi.org/10.1016/j.softx.2025.102369
Received 6 July 2025; Received in revised form 1 September 2025; Accepted 14 September 2025
Available online 18 September 2025

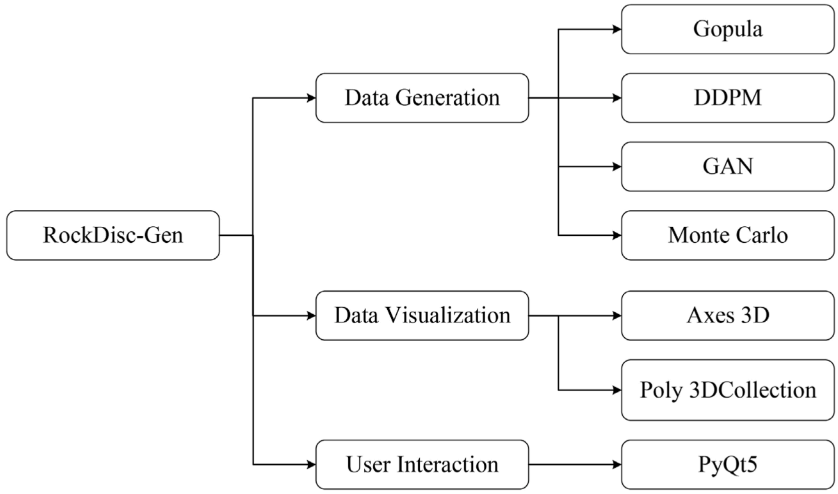

Fig. 1. Framework of the RockDisc-Gen.

Monte Carlo method enhances its computational efficiency by refining sampling strategies. The Copula-based method effectively captures nonlinear dependencies using rank correlation coefficients, circumventing the stringent assumptions of traditional geostatistical methods regarding specific marginal distribution forms. GANs enhance morphological characteristics through adversarial training, though they risk pattern collapse, mitigated by Bayesian frameworks like Bayesian GAN (Feng et al., 2022) [14]. Meng et al. (2024) applied DDPM to rock discontinuity generation, achieving superior statistical consistency in dip angle and dip direction distributions compared to conventional methods [9].

In this study, we developed an open-source software package, RockDisc-Gen, to address the constraints of current rock discontinuity generation tools regarding functional completeness, user-friendliness, variety, and data processing capabilities. This software package seeks to furnish engineers and researchers with an intuitive, comprehensive, and adaptable platform for generating rock discontinuities and addressing the practical limitations of current tools. In contrast to conventional tools, RockDisc-Gen enhances user productivity with its streamlined and straightforward interface, along with its robust integrated features. Moreover, its sophisticated data processing techniques and comprehensive visualization modules offer customers complete support throughout the process, significantly improving the engineering applicability of the produced outcomes. A comparative summary of RockDisc-Gen and other DFN tools is provided in Appendix A.

2. Software description

RockDisc-Gen is a specialized software package for rock discontinuities generation and visualization. The primary functional modules are developed in the Python programming language. The software package is fundamentally constructed using essential libraries including

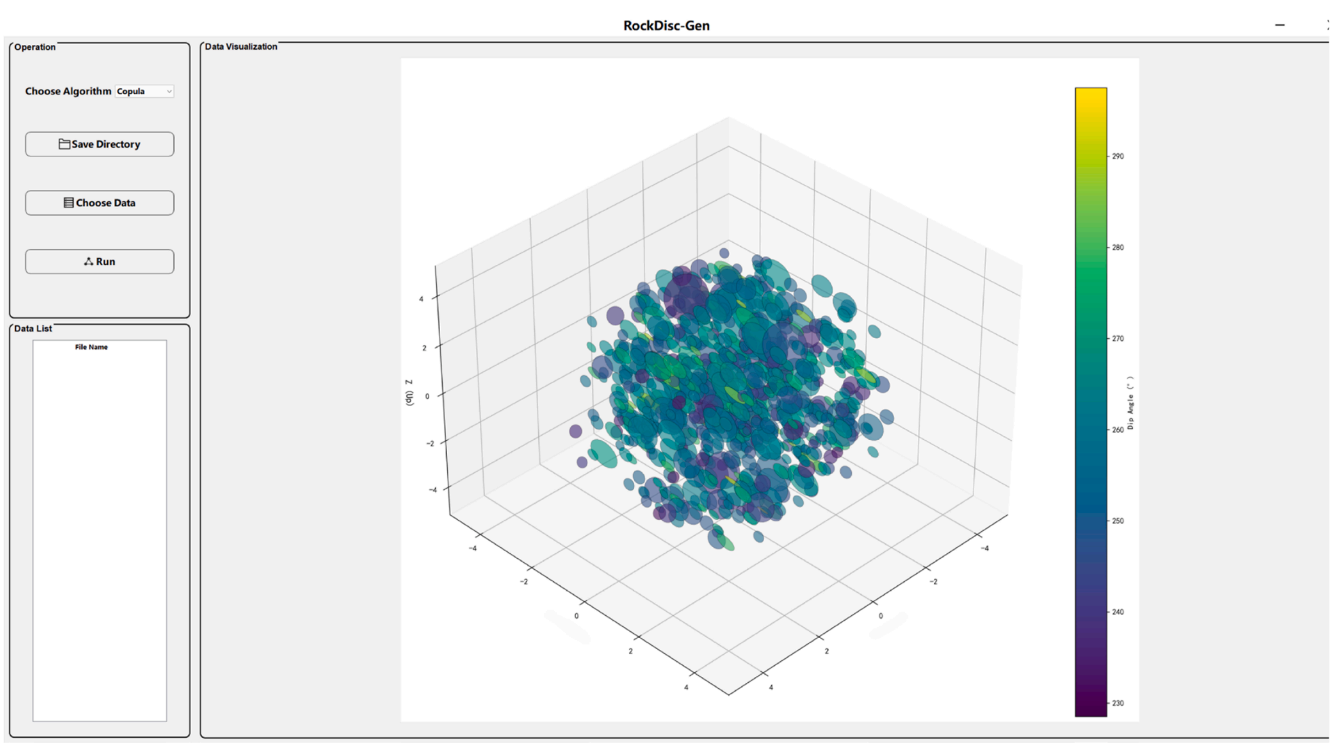

Fig. 2. The GUI of the RockDisc-Gen.

NumPy [15], Pandas [16], copulae [17], PyTorch [18], Matplotlib [19], and PyQt5 [20]. Its code is available on GitHub: https://github.com/GangMei-CUGB/RockDisc-Gen.

2.1. Software architecture

The RockDisc-Gen primarily comprises three components: (1) a data-generating module, (2) a display module, and (3) a user interaction layer. The comprehensive architecture is illustrated in Fig. 1.

The Data Generation Module functions as the key operational component of the RockDisc-Gen, having two categories of generation approaches: (1) conventional statistical methods and (2) deep learning models. It utilizes scientific computing libraries and deep learning frameworks for efficient computation. At the statistical method level, it employs NumPy for Monte Carlo generations and sampling of standard probability distributions like normal and log-normal. The Gaussian Copula model from the copulae library captures variable dependencies, ensuring correlation attributes. This module utilizes the PyTorch framework to develop GAN and DDPM, employing multi-layer perceptron architectures to discern the intrinsic distributional properties of complex data, particularly non-Gaussian or limited sample datasets. All generated data are systematically organized and saved using the Pandas library, facilitating versatile read and write operations for CSV format files.

The Visualization Module employs Matplotlib as its primary toolbox, integrating 3D spatial representation with 2D statistical analysis to facilitate multi-dimensional comparison and presentation of both generated and raw data. It employs the Poly3DCollection class from the mpl_toolkits.mplot3d sublibrary to render circular rock discontinuities, computes the spatial coordinates of these planes utilizing rotation transformation matrices, and integrates color mapping techniques, such as viridis color scales, to visually represent the distribution of critical parameters, including dip direction, dip angle and trace length [21]. This module incorporates various professional statistical chart styles for two-dimensional visualization, emphasizing the examination of critical parameters of rock discontinuities. Scatter plots visually depict the consistency of the distribution between generated and original data across two-dimensional feature combinations. Histograms and box plots, respectively, compare the distributional disparities of individual variables, such as strike length and dip angle, from the perspectives of probability density distribution patterns and statistical extremes.

The user interaction layer is built using the PyQt5 framework and incorporates parameter setting, model control, and result display functionalities. The interface, illustrated in Fig. 2, comprises a primary display window, an icon toolbar, and a class tree window. The primary display window serves as the central element of the interface, specifically designed for seeing geometric objects within the system. It can intuitively illustrate the fundamental paradigm of rock discontinuities. The icon toolbar offers interactive options for users to select the generation method, designate the data file for processing, establish the output file save destination, and initiate or terminate the software. The class tree window primarily facilitates the organization and management of data and results, enabling users to swiftly navigate the generated rock discontinuity disk diagrams and their associated statistical analysis charts. A step-by-step usage guide for operating the GUI is included in Appendix B.

2.2. Software functionalities

There are two main functionalities in the RockDisc-Gen software package, i.e., rock discontinuities generation and visualization.

2.2.1. Rock discontinuities generation

The four methods in the RockDisc-Gen software package utilize mathematical models and deep learning models to independently produce generated rock discontinuity data.

The Monte Carlo method uses statistical sampling. This method first computes the mean and variance of features, including dip direction, dip angle, and trace length from the original data, presuming that dip direction and dip angle adhere to a normal distribution while trace length conforms to a log-normal distribution. Following the aforementioned distribution types and their parameters, random sampling from a normal distribution is conducted on the dip angle and dip direction to generate data that aligns with the specified mean and standard deviation; concurrently, random sampling from a log-normal distribution is executed on the trace length to yield data that adheres to the properties of the log-normal distribution [22].

The Copula-based method employs a three-dimensional Gaussian Copula to model the statistical dependencies among dip direction, dip angle, and trace length of rock discontinuities. The method first executes a rank transformation on dip direction, dip angle and trace length of the original data, converting them into variables with marginal distributions that adhere to a uniform distribution within the [0,1] interval. Second, a joint distribution model is constructed based on the transformed data. During the model fitting phase, the method estimates the copula parameters using the transformed uniformly distributed data and develops a three-dimensional copula joint distribution model. Third, the process proceeds to the stochastic sample generation phase: a predetermined quantity of stochastic samples is drawn from the fitted Copula-based method, ensuring that these samples preserve the dependence structure of the original data within the $[0,1]^2$ unit square space. The generated samples are reverted to the distribution space of the original variables by inverse quantile transformation, producing generation results with statistical properties closely aligned with the original data.

GAN generates data via adversarial training between a generator and a discriminator. Similar to preceding methods, structural features are first normalized to [0,1]. Deep neural networks are then designed: the generator uses a fully connected network (FCN) to transform random noise vectors into synthetic samples matching real data dimensions. The discriminator employs a 7-layer FCN to distinguish real from generated samples. Through adversarial training, both networks iteratively improve—the generator produces more realistic outputs, while the discriminator enhances its discrimination capability. After training, random noise vectors are fed into the trained generator to produce batches of synthetic samples within the normalized space [23]. These samples exhibit statistical properties similar to authentic data and are finally transformed back to original dimensions via inverse normalization, yielding parameter values consistent with field measurements.

DDPM is a generative deep learning model that emulates the progressive diffusion of noise and its inverse in the feature space to facilitate high-quality data production [13]. The method first normalizes the original data, encompassing dip direction, dip angle, trace length, and additional features of rock discontinuities, thereafter mapping each feature value to the [0,1] interval. Second, a Markov chain comprising 1000 time steps is established to delineate the forward diffusion process: at each time step, the method incrementally introduces Gaussian noise to the data, regulating the addition rate via a meticulously crafted noise scheduling strategy to guarantee a smooth and controlled transition from the initial distribution to pure Gaussian noise. Third, a multi-layer perceptron is established as the fundamental architecture of the denoising model.

Both GAN and DDPM models were trained for 200 epochs with a batch size of 8 using the Adam optimizer. The GAN used distinct learning rates for the generator (1×10^{-6}) and discriminator (6×10^{-5}), while DDPM used 1×10^{-4}. Training was performed on normalized dip direction, dip angle, and trace length data. Although no separate validation set was used, training loss was monitored to ensure convergence. Small learning rates and stable configurations helped mitigate overfitting.

A comparison of the four generation methods in terms of key characteristics, strengths, limitations, and recommended scenarios is presented in Appendix C.

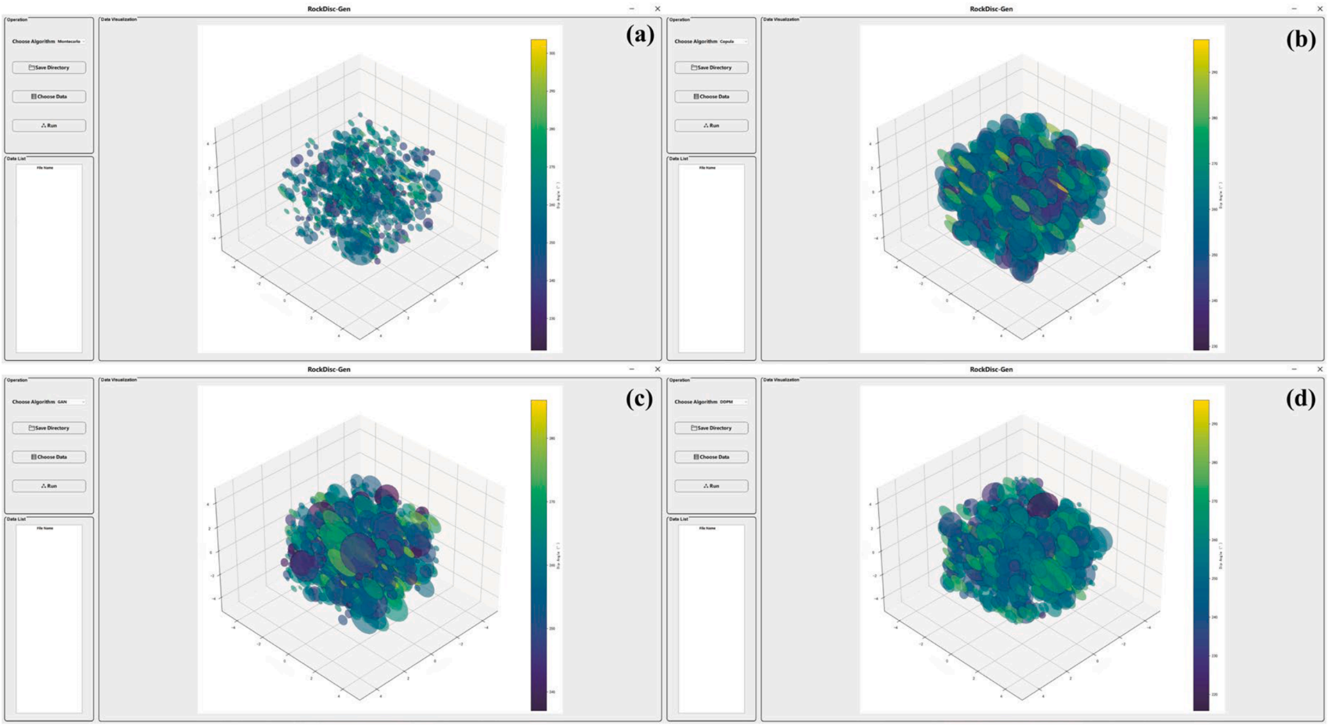

Fig. 3. Rock discontinuity generated by different methods: (a) the Monte Carlo method; (b) the Copula-based method; (c) GAN; (d) DDPM.

2.2.2. *Rock discontinuities visualization*

RockDisc-Gen has 3D visualization capabilities, illustrating the geographic distribution characteristics of rock discontinuities and presenting the validation outcomes of generated data.

This software package uses the Baecher model, using dip direction, dip angle, and trace length data of rock discontinuities to produce a 3D disk diagram that visually depicts the spatial orientation and geometric attributes of rock discontinuities [24]. The procedures are as follows. First, the generated data, including dip direction, dip angle, and trace length, are analyzed. Angular measurements are converted to radians, and trace length data are normalized to restrict values within a specified range. Second, a circular plane is generated for each rock discontinuity. A 3D rotational transformation is performed based on the dip direction and dip angle data, ensuring accurate alignment of the disk orientation with genuine geological discontinuities. The rotatable disks are randomly allocated within the 3D space, adhering to limitations that prohibit geometric overlap while ensuring adequate spatial density. Disk coloration is designated based on dip angle ranges, employing color gradients to visually differentiate distribution variances among various discontinuity sets. The final 3D visualization includes labeled coordinate axes and a color bar legend.

Histogram and Boxplot utilized to analyze disparities in the distribution of dip directions, dip angles, and trace lengths between empirical data and generated data. The procedure for constructing a histogram is as follows. First, the software computes the binning parameters for both datasets to guarantee consistency in statistical comparison. Then, it creates side-by-side histograms, employing distinct colors to differentiate and illustrate the frequency distributions of the original and generated data. To validate the distribution characteristics, the method superimposes theoretical distribution curves, derived from the mean and standard deviation of the data, onto the histogram, therefore graphically representing the distribution traits of the data. The histogram's coordinate axes, labels, and legends have been refined to enhance clarity and facilitate rapid evaluation of the statistical resemblance between the generated and original data. The box plot is generated by consolidating the two data sets: the method amalgamates the data and employs a box plot to illustrate its five-number summary (minimum value, first quartile, median, third quartile, maximum value) and outlier distribution. The fill color of the box and the color of the scatter points differentiate between real and generated data, with the scatter points gently jittered to prevent overlap. By modifying the coordinate axis range and incorporating a legend, the graph successfully emphasizes the statistical disparities between the two data sets, including median shifts and variations in dispersion.

3. Illustrative examples

3.1. *Experimental data*

The experimental data used in this investigation were sourced from the rock slope dataset supplied by Larissa Elisabeth Darvell [25]. The study area is located in Auliabotn, central-northern Norway, near the geographical coordinates 15°43′E, 67°19′N. The region is situated on the eastern shore of Straumsvatnet Lake in Nordland County. The outcrop spans 230 m down the slope, with an elevation varying from 280 m to 425 m, encompassing a gently inclined rock slope and a talus formation. The rock slope is oriented westward, with an elevation of roughly 125 m, primarily composed of granitic gneissic formation. A total of 766 rock discontinuities were delineated and documented within the study area.

3.2. *Results generated by the RockDisc-Gen*

After inputting the experimental data into the RockDisc-Gen, a set of rock discontinuities with varying dip directions, dip angles, and trace lengths is generated through the use of a designated method. To enable the comparison analysis with the measured rock discontinuities, each generation method generated a dataset comprising 766 rock discontinuities.

Fig. 3(a)-(d) illustrate the rock discontinuity distribution maps generated by the Monte Carlo method, the Copula-based method, GAN and DDPM, respectively. All four methods use dip direction, dip angle, and trace length as input parameters to generate all 766 rock discontinuities. The distribution characteristics of the rock discontinuities generated by the aforementioned four approaches closely align with the

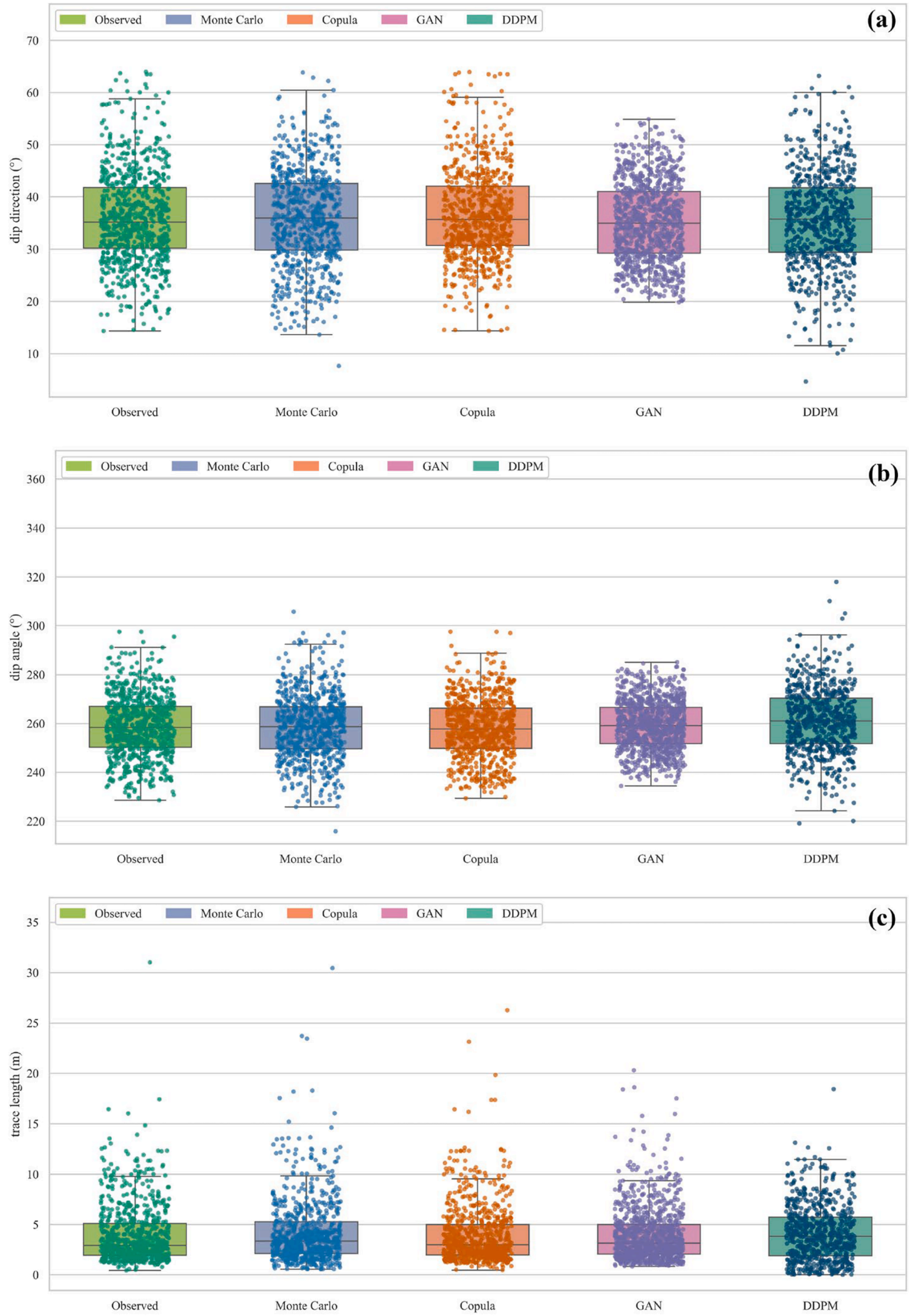

Fig. 4. The box plots of each parameter generated by the Monte Carlo method, the Copula-based method, GAN, and DDPM compared with each parameter of the measured rock discontinuities: (a) the dip direction; (b) the dip angle;(c) the trace length.

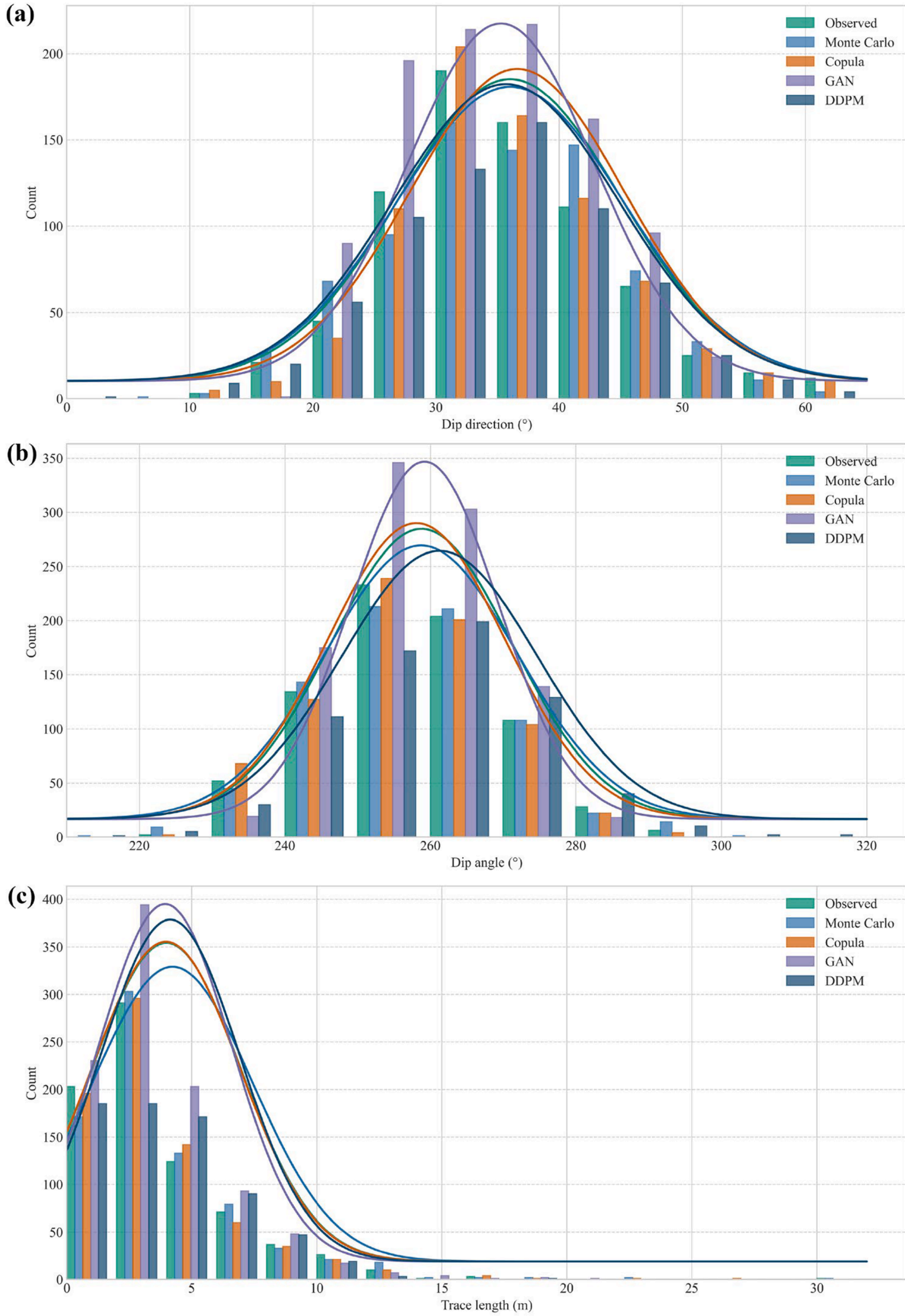

Fig. 5. Comparison of histograms of each parameter of the measured rock discontinuities and the histograms of each parameter of the generated rock discontinuities using the Monte Carlo method, the Copula-based method, GAN, and DDPM. (a) the dip direction; (b) the dip angle; (c) the trace length.

measured rock discontinuities.

Fig. 4 presents the comparative results of the rock discontinuity parameters (dip direction, dip angle, trace length) generated by the Monte Carlo method, the Copula-based method, GAN, and DDPM against the measured values, visualized using box plots. Fig. 5 presents the comparative results of the rock discontinuity parameters generated by the Monte Carlo method, the Copula-based method, GAN, and DDPM against the measured values, visualized using cumulative distribution curves. The box plot analysis reveals that the distribution patterns of each parameter, including median, interquartile range, and outlier range, closely resemble the measured data, suggesting that the created rock discontinuity well represents the actual geological properties. The cumulative distribution curve graph features the horizontal axis for parameter values and the vertical axis for cumulative probabilities, thus confirming the distribution consistency between the generated and measured data. Detailed numerical validation results are provided in Appendix D.

4. Impact

RockDisc-Gen is a software package dedicated to the generation and visualization of rock discontinuities, committed to providing researchers in the fields of geological engineering and geomechanics with efficient and flexible tools for modeling the spatial distribution characteristics of complex geological structures. The software package integrates classic statistical approaches with deep learning models to improve the diversity and accuracy of the generated data: the Monte Carlo method provides a reliable benchmark for data generation; the Copula-based method can accurately capture the nonlinear dependencies between variables; while GAN and DDPM models demonstrate satisfactory generation capabilities under small sample or non-Gaussian distribution conditions. The 3D visualization module intuitively depicts the spatial distribution patterns of rock discontinuities through disk plots, supported by multidimensional statistical analysis utilizing histograms and box plots, enabling users to efficiently assess the generated data. The user interface designed based on the PyQt5 framework is friendly and easy to use. In summary, RockDisc-Gen is a useful tool for rock discontinuities generation, and provides easy assistance for numerical modeling and risk assessment in related research domains.

5. Conclusions

This paper presents RockDisc-Gen, a Python-based software package for generating and visualizing rock discontinuities. The software integrates four core methods: the Monte Carlo method, the Copula-based method, GAN and DDPM. It comprehensively covers traditional statistical analysis and deep learning models, enabling the generation of rock discontinuity with high geological plausibility. The 3D visualization module is based on the Baecher disk model, which intuitively presents the spatial distribution characteristics of rock discontinuities. With the use of histogram and box plot multi-dimensional statistical analysis functions, it provides a powerful tool for reliable verification of the generated data. The user interaction layer design takes into account both functionality and ease-of-use, effectively adapting to the needs of different users. Currently, RockDisc-Gen has been verified in multiple practical cases and has demonstrated good application potential.

Future work will focus on (1) improving the performance of generating large amounts of rock discontinuity data and (2) enhancing the robustness of the software package under complex geological conditions, and (3) extending the geometric flexibility of the visualization module by supporting alternative representations beyond circular disks, such as polygonal or irregular fracture shapes. RockDisc-Gen is expected to significantly improve the efficiency and accuracy of rock discontinuity modeling in the field of geological engineering and become a more influential professional research tool.

Data availability

Source code is available to access in Github: https://github.com/GangMei-CUGB/RockDisc-Gen.

CRediT authorship contribution statement

Yujie Su: Writing – review & editing, Writing – original draft, Validation, Software, Formal analysis, Data curation. **Hong Gao:** Validation, Software, Formal analysis. **Han Meng:** Validation, Software, Methodology, Formal analysis. **Jinming Wang:** Validation, Software, Formal analysis. **Gang Mei:** Supervision, Resources, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Gang Mei reports financial support was provided by National Natural Science Foundation of China. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research was jointly supported by the National Natural Science Foundation of China (Grant Numbers: 42277161).

Appendix A. Comparative summary of DFN modeling tools

To supplement the main text, we provide a comparative summary of RockDisc-Gen and several representative DFN modeling tools (FracMan, dfnWorks, and 3DEC) in Table A1. This table highlights their differences in modeling techniques, validation support, interface design, and accessibility. RockDisc-Gen is the only tool among those compared that integrates both statistical methods and deep generative models, and offers built-in validation features.

Table A1
Comparison of key features between RockDisc-Gen and representative DFN tools.

Feature	FracMan	dfnWorks	3DEC	RockDisc-Gen
Deep generative models	No	No	No	Yes
Statistical methods	Partial	Partial	No	Yes
Statistical validation tools	No	Partial	No	Yes
3D visualization and GUI interface	Yes	No	Yes	Yes
Open-source and extensible	No	Yes	No	Yes
Customizability and modularity	Limited	Moderate	Moderate	High

Appendix B. Step-by-step guide for running RockDisc-Gen

To assist users in reproducing the figures and operating the software, we provide the following brief usage instructions. The GUI of RockDisc-Gen is designed for intuitive interaction. An overview of the GUI layout is shown in Fig. 2 of the main text. The left panel (titled Operation) contains four sequential steps for running the software.

First, the user selects one of the four generation methods—the Monte Carlo method, the Copula-based method, GAN, or DDPM—from the drop-down menu. Second, the output directory is specified via the Save Directory button, where all generated results—including synthetic datasets, 3D visualizations of rock discontinuities, and statistical validation plots—will be stored. Third, the user selects the input data file using the Choose Data button. Finally, by clicking Run, the software automatically performs data generation based on the selected method, creates corresponding visualizations for both the original and synthetic discontinuities, and generates boxplots and histograms for statistical comparison.

Appendix C. Method comparison and recommended usage scenarios

To assist users in selecting appropriate generation methods based on their specific data conditions and modeling needs, we provide a comparative summary of the four implemented approaches in RockDisc-Gen. Table C1 outlines the key characteristics, strengths, limitations, and recommended usage scenarios of each method implemented in RockDisc-Gen.

Table C1
Comparison of generative methods in RockDisc-Gen.

Method	Key Characteristics	Strengths	Limitations	Recommended Scenario
The Monte Carlo method	Uses predefined probability distributions	Simple, fast, interpretable	Assumes fixed distribution forms; limited for complex dependencies	Large datasets with well-characterized parametric forms
The Copula-based method	Models nonlinear dependencies using Gaussian Copula	Captures variable correlation; no need for joint distribution assumption	Sensitive to copula choice; parameter estimation may be unstable	Data with known marginal distributions and strong correlation
GAN	Adversarial training between generator and discriminator	Learns complex distributions; flexible with data shapes	May suffer from mode collapse; requires careful training	Moderate-sized datasets; distribution learning is the goal
DDPM	Diffusion-based generative model with denoising architecture	High generation quality; stable training	Computationally intensive; less intuitive to configure	Small or noisy datasets; focus on generation fidelity

Appendix D. Numerical validation of statistical consistency

To complement the visual comparisons in the main text, we conducted a quantitative evaluation of the statistical similarity between the original dataset and the generated datasets using three commonly used metrics: the Kolmogorov–Smirnov (KS) test, root mean square error (RMSE), and Kullback–Leibler (KL) divergence.

Each of the four methods was compared against the real dataset across three key features—dip direction, dip angle, and trace length. Table D1 summarizes the KS test results, Table D2 summarizes RMSE values, and Table D3 reports KL divergence values for each method and feature.

Table D1
KS test results.

Method	dip direction	dip angle	trace length
the Monte Carlo method	0.0699	0.0271	0.0999
the Copula-based method	0.0414	0.0243	0.0300
GAN	0.0528	0.0613	0.0613
DDPM	0.0442	0.1041	0.1441

Table D2
RMSE values.

Method	dip direction	dip angle	trace length
the Monte Carlo method	13.2283	17.8363	4.2667
the Copula-based method	12.4899	17.8819	4.1734
GAN	11.7702	16.0477	4.0854
DDPM	12.4499	18.2814	3.9927

Table D3
KL divergence values.

Method	dip direction	dip angle	trace length
the Monte Carlo method	0.2271	0.0533	0.1177
the Copula-based method	0.1782	0.1949	0.1605
GAN	1.0474	0.7389	0.1134
DDPM	0.3402	0.0748	0.3478

References

[1] Huang X, Li S, Jin J, Shi C. Determining digital representation and representative elementary volume size of broken rock mass using the discrete fracture network–Discrete element method coupling technique. Appl Sci 2024;14(2):606. https://doi.org/10.3390/app14020606.

[2] Ghosh, K. (2003). Characterizing fracture distribution in layered rocks using geographic information system-based techniques. https://doi.org/10.25148/etd.FI15101569.

[3] Cao W, Lei Q. Influence of landscape coverage on measuring spatial and length properties of rock fracture networks: insights from numerical simulation. Pure Appl Geophys 2018;175:2167–79. https://doi.org/10.1007/s00024-018-1774-4.

[4] Chen J, Fang Q, Zhang D, Huang H. A critical review of automated extraction of rock mass parameters using 3D point cloud data. Intell Transp Infrastruct 2023;2:liad005. https://doi.org/10.1093/iti/liad005.

[5] Fowler MJ. Structural data bias in the digital age. In: Slope Stability 2013: Proceedings of the 2013 International Symposium on Slope Stability in Open Pit Mining and Civil Engineering. Australian Centre for Geomechanics; 2013. p. 219–25. https://doi.org/10.36487/ACG_rep/1308_09_Fowler.

[6] Chicco, Jessica & Comina, Cesare & Mandrone, Giuseppe & Vacha, Damiano & Vagnon, Federico. (2023). Field surveys in heterogeneous rock masses aimed at hydraulic conductivity assessment. https://doi.org/10.1007/s42452-023-0557 8-3..

[7] Meyer T, Einstein HH. Geologic stochastic modeling and connectivity assessment of fracture systems in the boston area. Rock Mech Rock Eng 2002;35:23–44. https://doi.org/10.1007/s006030200007.

[8] Kulatilake PHSW, Chen J, Teng J, Shufang X, Pan G. Discontinuity geometry characterization in a tunnel close to the proposed permanent shiplock area of the three gorges dam site in China. Int J Rock Mech Min Sci Geomech Abstr 1996;33:255–77.

[9] Meng H, Qi X, Mei G. A deep learning approach for stochastic structural plane generation based on denoising diffusion probabilistic models. Mathematics 2024;12:1997. https://doi.org/10.3390/math12131997.

[10] Hurtado JE, Barbat AH. Monte Carlo techniques in computational stochastic mechanics. Arch Comput Methods Eng 1998;5:3–29. https://doi.org/10.1007/BF02736747.

[11] Chen X, Shen Z, Liu X. A copula-based and monte carlo sampling approach for structural dynamics model updating with interval uncertainty. Shock Vib 2018;2018:3958016. https://doi.org/10.1155/2018/3958016.

[12] Goodfellow I, Pouget-Abadie J, Mirza M, Xu B, Warde-Farley D, Ozair S, Courville A, Bengio Y. Generative adversarial networks. Commun ACM 2020;63:139–44. https://doi.org/10.1145/3422622.

[13] Ho J, Profile View, Jain A. View profile, Abbeel P, View profile. Denoising diffusion probabilistic models. In: Proceedings of the 34th International Conference on Neural Information Processing Systems; 2020. p. 6840–51. https://doi.org/10.5555/3495724.3496298.

[14] Feng R, Grana D, Mukerji T, Mosegaard K. Application of bayesian generative adversarial networks to geological facies modeling. Math Geosci 2022;54:831–55. https://doi.org/10.1007/s11004-022-09994-w.

[15] Van Der Walt S, Colbert SC, Varoquaux G. The NumPy array: a structure for efficient numerical computation. Comput Sci Eng 2011;13:22–30. https://doi.org/10.1109/MCSE.2011.37.

[16] Vaughan J., Victora C., Chowdhury A. Data processing and analysis, 2021, p. 147–59. https://doi.org/10.1093/med/9780192848741.003.0011.

[17] Größer J, Okhrin O. Copulae: an overview and recent developments. WIREs Comput Stat 2022;14:e1557. https://doi.org/10.1002/wics.1557.

[18] Imambi S, Prakash KB, Kanagachidambaresan GR. PyTorch. editors. In: Prakash KB, Kanagachidambaresan GR, editors. Programming with tensorflow. Cham: Springer International Publishing; 2021. p. 87–104. https://doi.org/10.1007/978-3-030-57077-4_10.

[19] Hunter JD. Matplotlib: a 2D graphics environment. Comput Sci Eng 2007;9:90–5. https://doi.org/10.1109/MCSE.2007.55.

[20] Willman J. Overview of pyqt5. modern pyqt. Berkeley, CA: Apress; 2021. p. 1–42. https://doi.org/10.1007/978-1-4842-6603-8_1.

[21] Pajankar A. Hands-on matplotlib: learn plotting and visualizations with python 3. Berkeley, CA: Apress; 2022. https://doi.org/10.1007/978-1-4842-7410-1.

[22] O'Connor PDT, Kleyner A. Practical reliability engineering. 1st ed. Wiley; 2011. https://doi.org/10.1002/9781119961260.

[23] Liu Z, Ma C, She W, Xie M. Biomedical image segmentation using denoising diffusion probabilistic models: a comprehensive review and analysis. Appl Sci 2024;14:632. https://doi.org/10.3390/app14020632.

[24] Baecher GB. Statistical analysis of rock mass fracturing. J Int Assoc Math Geol 1983;15:329–48. https://doi.org/10.1007/BF01036074.

[25] Darvell L. *Photogrammetric 3D-models and digitally mapped rock masses of slopes susceptible to rockfalls* [Data set]. NIRD RDA 2025. https://doi.org/10.11582/2022.00009.