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Predicting spatio-temporal man-made slope failures induced by rainfall in Hong Kong using machine learning techniques

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Abstract

Rain-induced man-made slope failures pose great threats to public safety as most man-made slopes are formed in densely populated areas. A critical step in managing landslide risks is to predict the time, locations and consequences of slope failures in future rainstorms. Based on comprehensive databases of in-service man-made slopes, rainstorms and landslides in Hong Kong during the past 35 years, a spatiotemporal landslide forecasting model for man-made slopes is developed in this study within a unified machine learning framework. The machine learning-based landslide forecasting model is validated against historical landslide incidents both temporally and spatially and through a case study of the June 2008 storm; the model significantly outperforms the prevailing statistical rainfall-landslide correlations in terms of prediction accuracy. The model can predict the real-time evolution of probabilities, scales and spatial distribution of landslides during the progression of a rainstorm, which can never be achieved by statistical methods. It can serve as an essential module for state-of-the-art landslide risk assessment and early warning.

Significance and Impact

- Rapid prediction of the spatio-temporal evolution of landslides in a future storm is critical for real-time decision-making in landslide early warning and risk management (**Fig. 1**).
- Machine learning would be a powerful and smooth alternative to the statistical methods widely used in the existing landslide early warning systems.

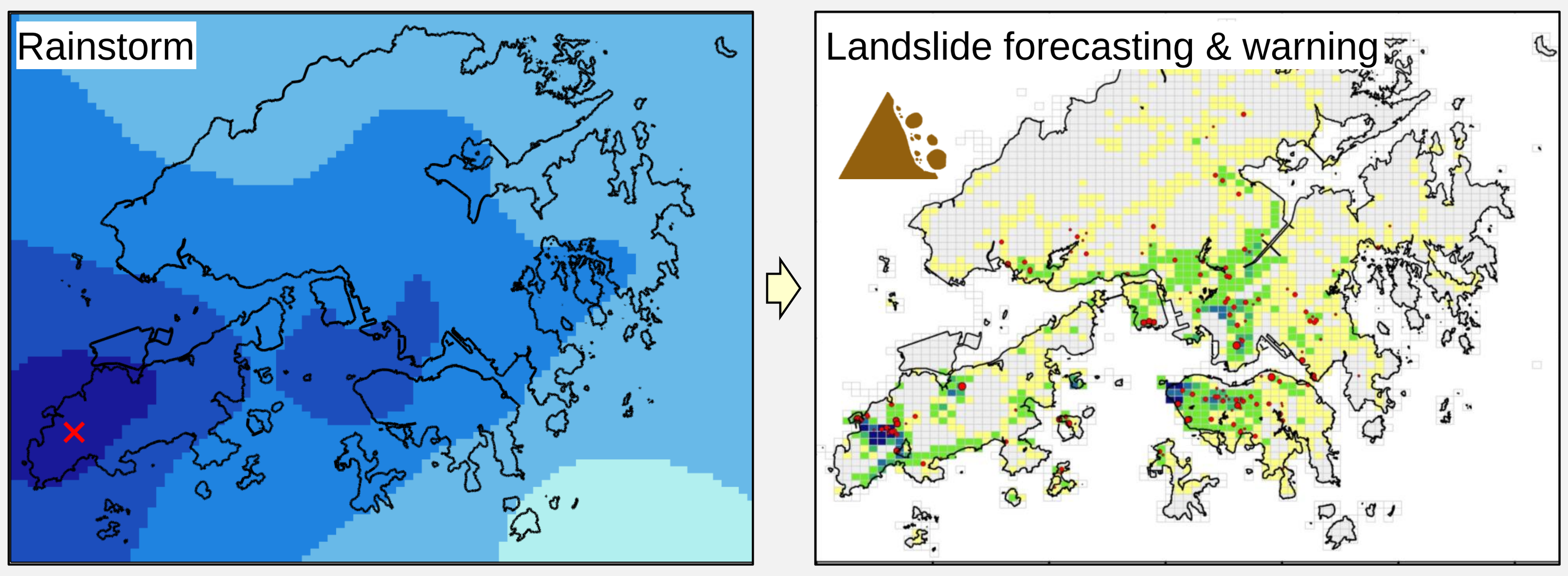

Fig. 1. City-scale spatio-temporal landslide forecasting

Methods and Materials

- Comprehensive databases are established for Hong Kong, including 60,000 registered man-made slopes, 400 major rainstorms, and 2000 landslide records in 1984−2017. A total of 29 static features and 15 dynamic features are extracted for machine learning.
- A machine learning framework (**Fig. 2**) is proposed for spatio-temporal landslide forecasting, featured with (a) storm-based data integration to incorporate landslide times, (b) a multiclass classifier to assess landslide consequences, and (c) simultaneous prediction of probabilities, locations and consequences of landslides over the time.

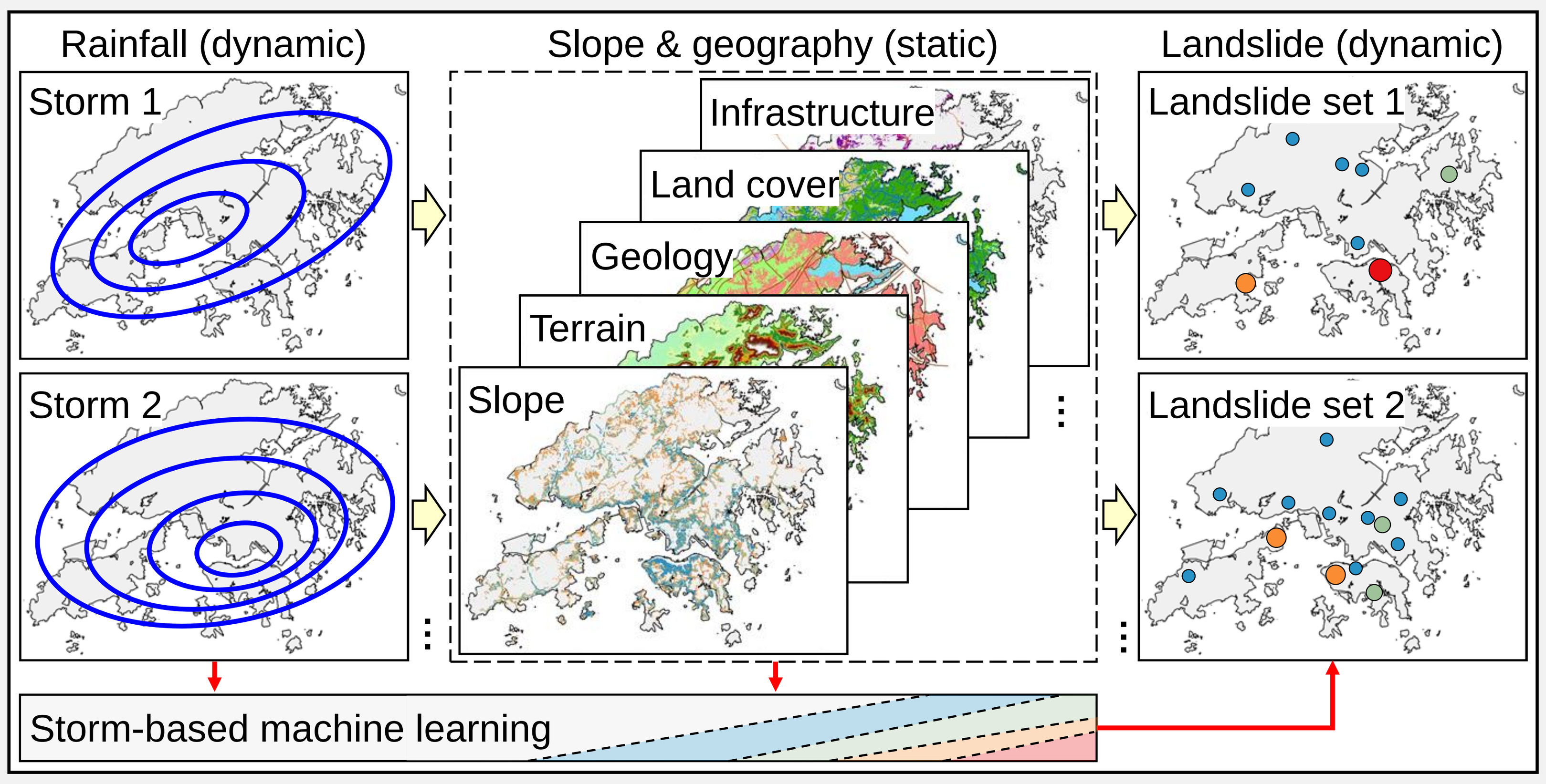

Fig. 2. Machine learning framework

Results and Discussion

- Validated against historical landslide incidents both temporally and spatially (**Fig. 3**), the machine learning-based landslide forecasting model demonstrates excellent performance in landslide forecasting and outperforms the statistical rainfall-landslide correlations.
- A case study of the June 2008 storm is investigated. The machine learning model can accurately predict the spatio-temporal evolution of landslides in real time.
- The dynamic rolling rainfall features (e.g., maximum rolling 24-h rainfall) are far more critical than slope property features and antecedent rainfall features. Both short-duration and long-duration rainfall features facilitate landslide forecasting.
- The spatial location of slopes and the failure time of landslides are the top two critical data in developing a spatio-temporal landslide forecasting model.

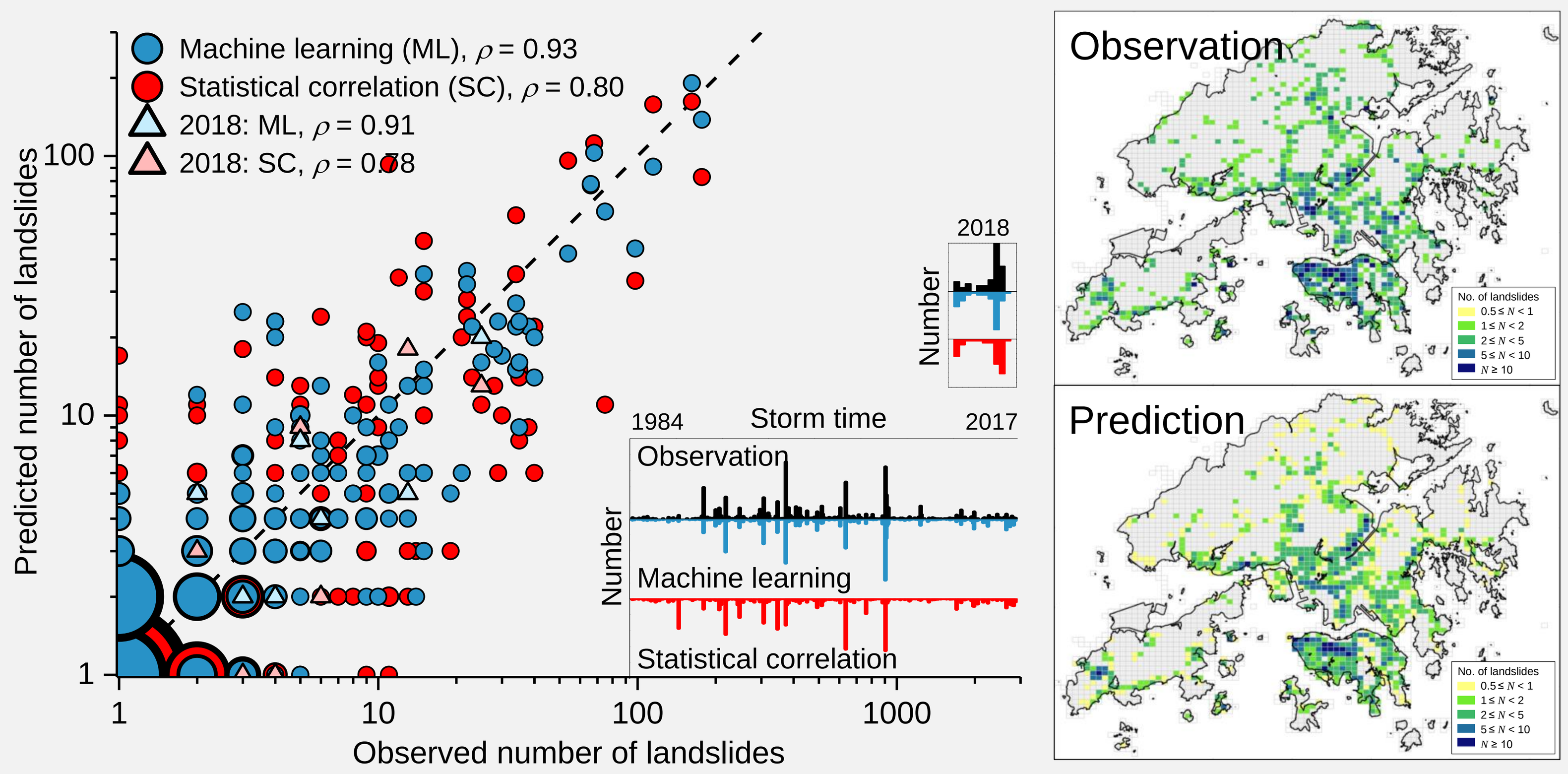

Fig. 3. Spatio-temporal model comparison and validation

Conclusion/Remarks

- The machine learning model incorporates landslide time and consequences into conventional landslide susceptibility mapping to achieve spatio-temporal landslide forecasting.
- The machine learning model significantly outperforms the statistical rainfall-landslide correlations, not only in the prediction accuracy but also in the ability to predict both landslide locations and consequences.
- The rolling rainfall features are critical factors governing slope stability. It is necessary to utilise both short- and long-duration rainfall features to consider different failure mechanisms of man-made slopes.

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