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Machine Learning in Geohazard Risk Prediction and Assessment: From
Microscale Analysis to Regional Mapping presents an overview of the
most recent developments in machine learning techniques that have
reshaped our understanding of geo-materials and management
protocols of geo-risk.
