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Advancing erosion predictive capabilities through deep learning in southeast Australia

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Abstract: Influenced by both natural forces and human activities, soil erosion has become a global environmental problem. Soil erosion, a climate risk, negatively impacts soil quality, agricultural productivity, water quality and biodiversity. In areas where the rate of soil loss is greater than that of soil formation, it is critical to develop efficient erosion control practices to sustain soil condition and capability. Climate change can intensify soil erosion through increased rainfall events, especially in areas with poor land management, leading to fertile topsoil loss and reduced agricultural productivity. In recent years, there has been a growing interest in applying machine learning (ML) and deep learning (DL) techniques to model and map soil erosion susceptibility, particularly in the context of environmental management. However, whether ML and DL can provide more accurate and site-specific predictions remains uncertain, especially under global warming and rainfall patterns change.

In this study, we predict soil erosion by a Random Forest (RF) and a Convolutional Neural Network (CNN), then compare with simulations by typical empirical soil loss model (RUSLE) to explore the capacity of ML and DL technology on erosion modelling and prediction. SILO rainfall observation, soil types, topography and fractional vegetation cover were obtained to simulate erosion at a monthly base from 1986 to 2023. RF and CNN driven erosion incorporating environmental variables as above, were trained based on the historical erosion rates (90% for training, 10% for validation). February and August were selected to represent typical summer and winter rainfall patterns, highlighting high-risk areas on the New South Wales (NSW) northeast coast in February and in the Alpine region in August (Figure 1). Both RFs and CNNs offer valuable applications in climate change adaptation for soil erosion. The RF method is better at capturing extreme values, while the CNN more effectively identifies high-risk areas. This may be due to the optimization of neural networks, which can easily fall into local optimal solutions. CNNs can process large datasets and capture intricate spatial and temporal patterns, thus, enabling improved spatial and temporal resolution in soil erosion assessment, underpinning more precise conservation and management strategies.

To sum up, deep learning technologies have expressed their potential capacity in predicting soil erosion enabling the integration of climate models and historical climate data, enhancing the understanding of how climate change may impact erosion rates and patterns. These methods can enhance spatial detail and accuracy by integrating baseline estimates from the NSW and Australian Regional Climate Modelling (NARCLiM2.0). These techniques facilitate data integration and fusion, enabling comprehensive erosion risk assessments that consider multiple variables simultaneously. These applications hold promise for improving soil and land adaptive management in the face of a changing climate.

Keywords: *Extreme rainfall, Water erosion, Deep learning, Climate change, Adaptation strategy*

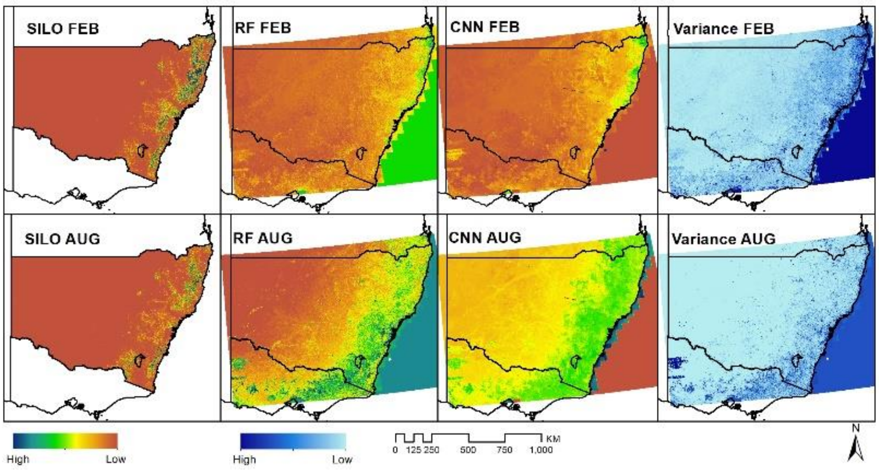

Figure. Comparative analysis of erosion predictions (bare cover) driven by observational baseline, Random Forest (RF), Convolutional Neural Networks (CNN), and their associated uncertainties for southeast Australia

