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Machine learning-based downscaling of coarse resolution temperature and its application for potential frost identification over complex terrain.

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The precise representation of spatial temperature is important for practical applications like agriculture where they require local information at very high resolution for managing agricultural activities. In recent times, statistical downscaling methods, specifically those utilizing machine learning methods are gaining importance due to their computational of time efficiency over dynamic downscaling.

This study focuses on enhancing the downscaling of spatial temperature over complex terrain using machine learning algorithms, particularly Random Forest (RF), Artificial Neural Networks (ANN), and Convolutional Neural Networks (CNN). The primary aim of this study is to identify the most promising machine learning model for downscaling gridded temperature at 2 meters from 9 km to 1 km over Non and Adige valleys. Additionally, we aim to apply these models for potential frost identification for the months of March, April, and May. We used static predictors such as Shutter Radar Topography Mission (SRTM) elevation which plays an important role in complex terrains to improve the performance of models. In addition to that, dynamic predictors such as zonal and meridional winds (U, V), windspeed, surface pressure (SP), etc. are used as auxiliary inputs. The study's methodology includes training and evaluating the performance of three machine learning models using statistical metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), R square (R^2), and Mean Bias Error (MBE). Furthermore, we used other metrics such as recall, precision, and F1 score for assessing model performance for frost identification.

Our results show CNN models outperform other models across all the seasons with the best performance in summer (RMSE=1, MAE= 0.78, R^2=0.94) and the least in winter (RMSE=1.3, MAE=1, R^2=0.87). All These models exhibit a consistent pattern of having good performance in summer and least in winter. The superiority of the CNN model can be attributed to its ability to capture spatial patterns in temperature data which makes it more reliable for complex terrains. Additionally, for frost identification, CNN models show better performance with the highest F1 score across March, April, and May.