



Spatiotemporal monthly rainfall forecasting for south-eastern and eastern Australia using climatic indices

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Knowledge about future rainfall would significantly benefit land, water resources and agriculture management, as this assists with planning and management decisions. Forecasting spatiotemporal monthly rainfall is difficult, especially in Australia where there is a complex interaction between topography and the effect of Indian and Pacific Ocean.

This study describes a method for spatiotemporal monthly rainfall forecasting in south-eastern and eastern part of Australia using climatic and non-climatic variables. Rainfall data were obtained from Bureau of Meteorology (BoM) from 136 high quality weather stations from the south-eastern and eastern part of Australia with monthly rainfall records from 1879 to 2012. To reduce spatial complexity of the area and improve model accuracy, spatial classification (regionalization) was considered as first step. Significant predictors for each sub-region among lagged climatic input variables were selected using Fuzzy Ranking Algorithm (FRA). Climate classification: 1) discovered homogenous sub-regions with a similar rainfall patterns and investigated spatiotemporal rainfall variations in the area, 2) allowed selection of significant predictors with a fine resolution for each area, 3) improved the prediction model and increased model accuracy.

PCA was used to reduce the dimensions of the dataset and to remove the rainfall time series correlation. K-means clustering was used on the loadings of PCs describing 93% of long-term monthly rainfall variations. The analysis was repeated for different numbers of sub-regions (3 – 8) to identify the best number of clusters to improve the forecast model performance. Subsequently, a Fuzzy Ranking Algorithm (FRA) was applied to the lagged climatic predictors and monthly rainfall in each sub-region to identify the best predictors. After these two stages of pre-processing, a Neural Network model was developed and optimized for each of the sub-regions as well as for the entire area. It is concluded from the result of this study that climate classification can improve the result of monthly spatiotemporal rainfall forecast models in South-eastern and eastern Australia. Also, the number of sub-regions is one of the important parameters in ranking predictors at the modeling stage, and allows elucidation of climate influences for different sub regions. Classification of stations helps FRA to capture variations in Australian rainfall in space without influence of the rainfall seasonal cycle and regimes.