Spatio-temporal generation of precipitations using a hidden Markov Model with correlated emissions

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Abstract

Accurate spatio-temporal rainfall simulation is critical for hydrological risk assessment or climate studies. This study proposes a spatio-temporal weather generator for precipitation across multiple stations, extending the classical multivariate hidden Markov model used in weather generation to a spatial framework for both occurrence and intensity.
Usually, rain occurrence at each site are modelled independently, conditioned on a shared hidden state representing a weather type. In our approach, the spatial rain occurrence is modelled using a Gaussian field with a Matérn covariance, thresholded at each location into a Bernoulli variable based on the local rain probability. We incorporate this spatial model in the hidden Markov framework, with the aim of identifying interpretable states, such as those characterized by lower rain probability or higher spatial correlation.

The rain amounts are modelled with Extended Generalized Pareto Distributions (EGPD) in each weather states. The spatio-temporal link between occurrence and intensity is captured by a censored Gaussian process on normalized variables, conditioned on the occurrence process. By separating occurrence and intensity, we can represent their dependencies with different spatial and temporal scales. This is not possible with a single censored Gaussian model. Seasonal variability is accounted for by periodic parameterizations rather than fitting separate monthly models.

Model parameters are estimated using composite pairwise likelihood and the EM algorithm for the occurrence process, then with marginal and pairwise likelihood for the intensity process. Simulations are evaluated against observed data using several spatio-temporal metrics. These include the rain occurrence ratio (ROR), the daily proportion of stations with rainfall, and quantile exceedance ratios (QERs), which measure the proportion of stations above a rainfall quantile.

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The methodology is applied to 37 weather stations in France, using 51 years of daily precipitation data. The hidden Markov model identifies four distinct states that align with known weather types. The most likely sequence of states is also consistent with meteorological patterns. Using the censored Gaussian framework, we are able to condition the spatial-temporal generation of the non-zero precipitation to the realization of the occurrence process. This approach preserves spatio-temporal continuity between dry and wet conditions, which, to our knowledge, has not been achieved before. We find that the chosen indicators are well-reproduced. This framework enables realistic simulation of droughts and rain events over large spatial and temporal scales, with potential applications in climate impact assessment and hydrological modelling.

Keywords: Meta, Gaussian, Precipitation, Spatio, temporal, Hidden Markov Model, Conditional simulation