Dynamic factor process convolution models for multivariate space-time data with application to air quality assessment

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Abstract

We propose a Bayesian dynamic factor process convolution model for multivariate spatial temporal processes and illustrate the utility of this approach in modeling large air quality monitoring data. Key advantages of this modeling framework are a descriptive parametrization of the cross-covariance structure of the space-time processes and dimension reduction features that allow full Bayesian inference procedures to remain computationally tractable for large data sets. These features result from modeling space-time data as realizations of linear combinations of underlying space-time fields. The underlying latent components are constructed by convolving temporally-evolving processes defined on a grid covering the spatial domain and include both trend and cyclical components. We argue that mixtures of such components can realistically describe a variety of space-time environmental processes and are especially applicable to air pollution processes that have complex space-time dependencies. In addition to computational benefits that arise from the dimension reduction features of the model, the process convolution structure permits misaligned and missing data without the need for imputation when fitting the model. This advantage is especially useful when constructing models for data collected at monitoring stations that have misaligned sampling schedules and that are frequently out of service for long stretches of time. We illustrate the modeling approach using a multivariate pollution dataset taken from the EPA's CASTNet database.