Stochastic Environmental Research and Risk Assessment (2020) 34:1285–1287
https://doi.org/10.1007/s00477-020-01830-z

EDITORIAL

Space–time models for hydrological and environmental applications

Dionissios T. Hristopulos[1] · Emmanouil A. Varouchakis[2] · Jon Olav Skøien[3] · Dimitri Solomatine[4]

Published online: 4 July 2020

Methods of spatial statistics and geostatistics in particular are commonly applied in environmental and hydrological problems to quantify spatial variation, to produce interpolated maps with quantified uncertainty, to simulate different probable scenarios (Lantuéjoul 2013), and to optimize spatial sampling designs (Cressie 1993; Chiles and Delfiner 2009; Olea 2012). Extensions of spatial statistics methods (Cressie 1993; Ripley 2005) in the space–time domain are also becoming widespread (Cressie and Wikle 2015; Christakos 2017). Such space–time methods allow for a better understanding of dynamic changes over various time scales of interest. As a result of technological advances that led to an abundance of new data sources from remote sensing and other proximal sensor techniques, big data analysis and data fusion for environmental problems are becoming a major focus of research (Hsieh 2009; Leuenberger and Kanevski 2015). Furthermore, methodological advances in time series analysis, space–time statistics and machine learning, as well as the incorporation of ideas from statistical physics and applied mathematics are continuing to enrich the modelling approaches used in geostatistics (Corzo and Varouchakis 2019; Hristopulos 2020).

Environmental datasets have spatial and temporal features that contain important information about the underlying processes. The analysis of environmental data and the design of proper mitigation measures for environmental risks require advanced spatial and space–time methods (Kanevski 2013; Webster and Oliver 2007; Cressie and Wikle 2015; Christakos 2017; Hristopulos 2020). Such methods should provide accurate predictive tools, including the estimation of probability levels for the occurrence of undesired events (e.g., drought, flooding) and the associated risk. Development and application of innovative space–time geostatistical methods helps to better model and predict the relationship between the magnitude and the probability of occurrence of such events of hydrological interest (Abrahart et al. 2008; Skøien and Blöschl 2007; Davison and Gholamrezaee 2012).

Motivated by the extensive research on spatiotemporal models for hydrological and environmental applications, we organized this special issue as a focal point for modern applications of space–time geostatistics. Below, we briefly introduce the papers of this special issue:

Diederen and Liu address the topic of generating synthetic precipitation fields in the framework of event-based, dynamic spatio-temporal probabilistic analysis. Their stochastic weather generator uses a classification method based on self-organising maps to derive different event types. They then fit each class to a multivariate mixture model. Using a set of synthetic descriptors they generate synthetic fields, which are subsequently used to reconstruct gridded, hourly precipitation fields of longer duration than the original dataset. The proposed methodology significantly improves the spatial coherence of the precipitation extremes.

Fischer and Schuman study different types of flood events based on the peak-volume relationship. These authors investigate changes in the frequency of the flood event types occurrence, their spatial patterns, and the consequences for estimating extreme events. Temporal changes and spatial patterns are detected for the resulting flood types, and they are connected with the generating processes as well as the specific catchment characteristics. Finally, a seasonal mixture model of partial-duration time

✉ Dionissios T. Hristopulos
dionisi@mred.tuc.gr

Emmanouil A. Varouchakis
varuhaki@mred.tuc.gr

1 Geostatistics Laboratory, School of Mineral Resources Engineering, Technical University of Crete, 73100 Chania, Greece

2 School of Environmental Engineering, Technical University of Crete, 73100 Chania, Greece

3 Joint Research Centre, European Commission, 21020 Ispra, Italy

4 Chair Group of Hydroinformatics, Department of Integrated Water Systems and Governance, IHE Delft Institute for Water Education, Westvest 7, 2611 AX Delft, The Netherlands

series is investigated, which treats event types and seasons separately and eventually combines them in an integrated annual model.

Khedhaouiria, Mailhot and Favre investigate the post-processing of reanalysis precipitation data aiming to correct biases and scale mismatch with observations. They employ a Stochastic Model Output Statistical approach combined with meta-Gaussian spatiotemporal random fields, calibrated at measurement sites, to post-process the Climate Forecast System Reanalysis (CFSR) precipitation data. The post-processed data, characterized by local parameters, are then mapped across the Great Lakes region (Canada) using two different approaches: (1) kriging, and (2) the Vector Generalized Additive Model (VGAM) with spatial covariates. Both approaches demonstrate significant improvement of statistical validation measures compared to those of CFSR without post-processing.

Naranjo-Fernandez et al. focus on the relation between rainfall and groundwater recharge. They apply spatio-temporal kriging to improve the reconstruction of the spatio-temporal rainfall variability for the period 1975–2016 at variable time scales in Donana National Park, Spain. This work presents the results of an in-depth study concerning groundwater recharge behavior over the studied period. The authors find a strong dependence between recharge and spatial variability. One of the main findings is that the spatial scale and the temporal step used to estimate groundwater recharge are critical parameters that must be considered in groundwater resources management.

Wang et al. focus on the problem of segmenting multivariate hydrometeorological time series. They propose an adaptive Gath–Geva clustering method for the fuzzy segmentation of multivariate time series. The algorithm is capable of segmenting multivariate time series which lack abrupt changes. First, Kernel Principal Component Analysis (KPCA) is used to extract principal components of multivariate time series and remove the impact of redundant variables. Then, the segmentation of the principal components of multivariate time series is achieved by combining adaptive G–G fuzzy clustering with the modified Davies–Bouldin Index (MDBI). The proposed method can effectively reduce the computational complexity and improves the segmentation accuracy of hydrometeorological series.

Yang, Yang and Wu focus on a geostatistical analysis of annual rainfall (AP) in Huanghuaihai basin in China during the time period 1956–2016. These authors apply spatiotemporal ordinary kriging (STOK) to obtain the space–time distribution of annual precipitation based on the data collected at 961 meteorological monitoring stations. Then, stochastic site indicators are used for quantitative assessment of space–time uncertainties. The study reports space–time trends for the annual precipitation; an important conclusion is that based on the space–time model, the probability for concurrent high precipitation at two different locations is extremely low. Furthermore, the authors conduct a data-driven exploration of potential relationships between precipitation and other environmental factors.

Zhu et al. address the problem of streamflow forecasting. They propose a probabilistic Long Short-Term Memory (LSTM) network coupled with the heteroskedastic Gaussian process (GP) for daily streamflow forecasting. The heteroscedastic Gaussian process is adopted to allow variations in the predictive intervals which can account for the temporal variations of the mean and variance which are common in the daily streamflow time series. The proposed method encapsulates the inductive biases of the LSTM recurrent network and retains the non-parametric, probabilistic property of Gaussian processes. The daily predictions of streamflow time series obtained with the new model are shown to favorably compare against the generalized linear model and the three other machine learning methods.

Our expectation is that the articles contained in this special issue will further stimulate the exchange of ideas on the applications of space–time methods to hydrological problems in particular and more generally to environmental problems. We would like to thank all the authors for contributing their work, the reviewers for their thorough evaluations which provided valuable comments and advice for improving the papers, the Editor-in-Chief, George Christakos, for his involvement in the editorial process, and the editorial staff for their help in the production of this issue.

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