Stochastic Simulation of Daily Rainfall Fields Conditioned on Atmospheric Circulation Patterns and Orographic Effects.

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Abstract The objective of the current work is to present a methodology for simulation of stochastic spatial distributed rainfall fields at the daily time step. For this purpose, we develop a geo-stochastic rainfall generating process (SRGP) to generate spatially distributed rainfall fields at daily time scale, that respect the spatial correlation structure of historically observed precipitation, while taking into account important factors that influence the development of observed spatial patterns. For each day, a spatially distributed rainfall field is generated from a pre-specified SRGP, selected based on atmospheric synoptic conditions relevant for that day. Each SRGP is simulated by applying the concept of double kriging, as the product of the spatial amount of rainfall and the spatial occurrence of rainfall by sequential simulation (sequential Gaussian simulation and sequential indicator simulation respectively). The SRGP can account for spatial rainfall non-stationarity related to orographic effects, and can be incorporated as part of a downscaling technique in the context of climate change impact studies. A case study for the Upper Guadiana basin (Spain) is presented that shows the ability of the method to reproduce various spatio-temporal characteristics of precipitation.

Introduction

Hydrological studies at the basin scale require precipitation at high spatio-temporal resolution as an input variable for the study of such processes as local-scale spatially-distributed runoff generation and groundwater recharge, among many others.

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Here we present a basin-extent, sub-basin-scale stochastic rainfall model that can be used to generate spatially distributed daily rainfall intensity fields having appropriate spatial correlation structure and correspondence with local factors such as topography (orographic effect). Our method acknowledges the fact that the stochastic space-time properties of daily rainfall intensity fields are known (observed) to vary with time (i.e. can be different on different days). The causes for this non-stationarity included factors such as direction of wind, type of atmospheric circulation pattern (ACP), interactions with topography and landscape, regional and local temperature patterns, source areas of moisture, etc, which vary from day to day and by season. Our approach is to approximate this variability by classifying days into different categories, in terms of: a) ACP and time of the year (e.g. Season-ACP or Month-ACP), and b) occurrence or not rainfall of anywhere within the basin, and by assuming that the continuous SRGP can be reproduced well enough as a sequence of discrete SRGP's, each of which is time-stationary.

Methodology

To construct a stochastic model of rainfall, which allow us to approximate the spatio-temporal non stationarity of the rainfall generating process, we have to make assumptions regarding the: 1) temporal non-stationarity of the rainfall generating process; 2) spatial non-stationarity of daily rainfall amount; 3) form of the probability distribution of rainfall amount; 4) spatial occurrence process; and 6) spatial covariance structure.

The major cause of temporal non-stationarity of the rainfall generating process is its dependence on climatic conditions (e.g. seasons), on synoptic scale atmospheric factors (e.g., circulation patterns; e.g., (Bardossy & Plate, 1992)), and their interactions with local factors such as topography. To simplify this dependence, we assume that the daily rainfall *Z(u) has a* probability distribution $P_A(Z(u),u)$ which can be approximated by a set of N SRGP's $\{P_A^1(Z(u),u), \dots, P_A^N(Z(u),u)\}$ where each time t (daily scale) belongs to the set *j* = {*1,…,N*} and each member $P_A^j(Z(u),u)$ is assumed to be time-invariant but may be non-stationary in space.

Having decomposed the space-time problem into a temporal sequence of {*1,…,N*} different SRGP's, we next represent the spatial intermittence of rainfall. For this, we assume that $P_A^j(Z(u),u)\ \forall j$ can be approximated by the product of two independent random fields, so that,

$$P_A^j(Z(u),u) = Pm_A^j(M(u),u) \cdot Pi_A^j(I(u),u)$$

$$Z(u) = M(u) \cdot I(u)$$

where $Pm_A^j(M(u),u)$ defines the spatial process of rainfall amounts $M(u)$ and $Pi_A^j(I(u),u)$ defines the spatial process of rainfall intermittence $I(u)$. This assumption is common in the application of geostatistics to rainfall estimation and rain radar uncertainty quantification, and was first introduced by (Barancourt, Creutin, & Rivoirard, 1992) and recently reviewed by (Grimes & Pardo-Igúzquiza, 2010).

To represent the spatial non-stationarity of rainfall amount, we follow a residual approach that estimates the trend component for each $j = \{1,\ldots,N\}$ from available data, and subtracts it from the observed rainfall amount.

Then a normal score transformation over the residual for each $j = \{1,\ldots,N\}$ is made to allow us to work with Gaussian distributions.

The spatial occurrence process is defined by transforming the rain into an Indicator variable (that takes the value 1 if it is raining, and is otherwise 0). We assume that the indicator variable is intrinsic stationary and that the trend component can be sampled from the pdf of the spatial probability of proportion of rain. This probability is estimated for each $j = \{1,\ldots,N\}$.

The spatial correlation structure for the amount and intermittence process are estimated for each $j = \{1,\ldots,N\}$ from the data available as the averaged variogram for all the days that belong to the same SRGP category j.

The atmospheric ACP classification method we use is based on an automated version of the Lamb Weather Types classification scheme (Jenkinson & Collison, 1977). In this work, we have followed the approach presented by (Goodess & Palutikof, 1998) to obtain the final ACP classification. While their approach identifies 14 basic circulation types, we have regrouped these into 8 types, including three directional types, as shown in Table 1.
Further, due the strong seasonality of climate experienced in Spain, we disaggregate each ACP into 4 seasons, resulting in a total of 4x8=32 SRGP categories, one for each "Season-ACP".

Table 1. The atmospheric circulation pattern classification types.

ACP Type	Description
C	Cyclonic
HYC	Hybrid cyclonic
UC	Unclassified/light flow cyclonic
A/HYA	Anticyclonic/ hybrid-anticyclonic
UA	Unclassified/light flow-anticyclonic
W/NW/SW/N	Westerly/northwesterly/southwesterly/northerly
E/NE	Easterly/northeasterly
S/SE	Southerly/southeasterly

Application

We apply the methodology described above to the Upper Guadiana basin (UppG) in Spain. The UppG basin has a typical continental, semi-arid, Mediterranean climate. In term of precipitation it experiences considerable space-time variability due to the combined influences of the Atlantic and Mediterranean climates, and due to the orographic effects triggered by interaction between the synoptic scale circulations and the landscape. The total annual precipitation on average is nearly around 450 mm and exhibits strong seasonality

We use two types of data to estimate the parameters needed for SRGP model. Point scale data are available, characterized by daily time scale observations from 151 rain gauges for the period 1959 to 2007. A larger scale gridded reanalysis data set is available from the NCEP (Kalnay et al., 1996), from which we use the mean sea level pressures at specific locations to classify the type of atmospheric circulation pattern for each day.

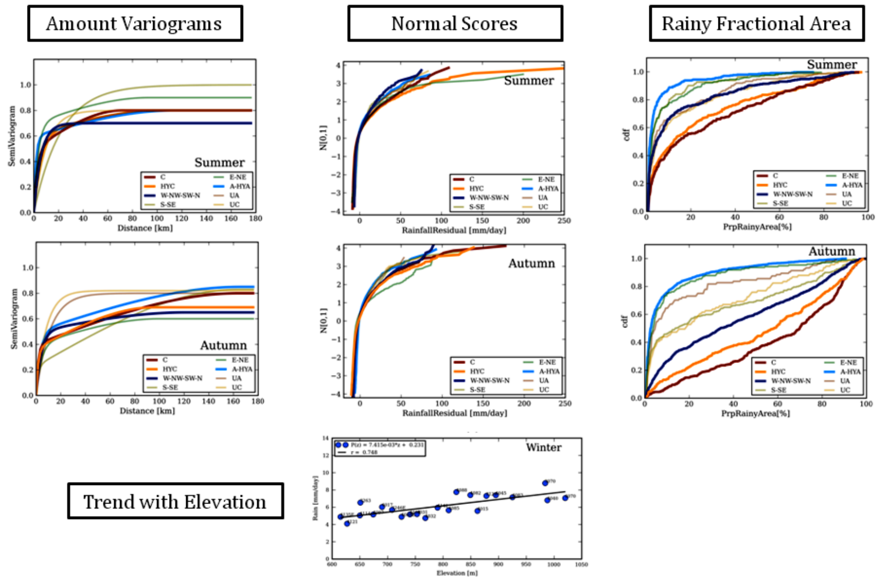

Figure 1. Some of the attributes needed to characterize the SRGP model. (Left side) The model variograms of the transformed residual amounts of rainfall; (center side) the normal score transformation of rainfall after removing the trend component; (right side) cumulative distribution functions of rainy fractional area. In the bottom center side the rainfall elevation trend with the topography is also shown.

Results

To evaluate the methodology over a historical period (1959-2001) we provide the observed daily sequence of temporal intermittence of rain (a day is defined as rainy if precipitation is registered in at least one of the rain gages) and the observed daily sequence of ACP (extracted from the NCEP reanalysis data). We compare two SRGP disaggregation models; in the first we disaggregate by Season-ACP (8x4 classes) and in the second by Month-ACP (8x12 classes). For each SRGP model type, we ran 100 precipitation field realizations and computed statistics from the ensemble of the realizations. To obtain a benchmark case, corresponding to our best available estimate of the properties of the "actual rainfall field" we use simulations generated by the Season-ACP-Drift-GC model type conditioned on the available rain gage information (by design this simulation reproduces the historical observed values at every raingage). The results are compared against this benchmark case.

We evaluate the performance of our SRGP model in terms of its ability to reproduce a) the climatological spatial average of rainfall and the climatological variability (Figure 2), and b) the probability distribution function of rainfall amount at rain gauge locations. We also examine the benefits realized by incorporating the elevation drift, by examining the climatologic spatial distribution of rain (Figure 3).

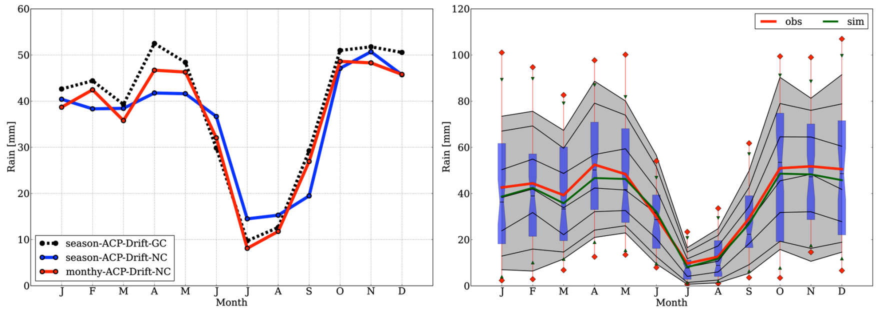

Figure 2. Left. The spatial average climatologic rainfall. Right. The spatial average climatologic variability.

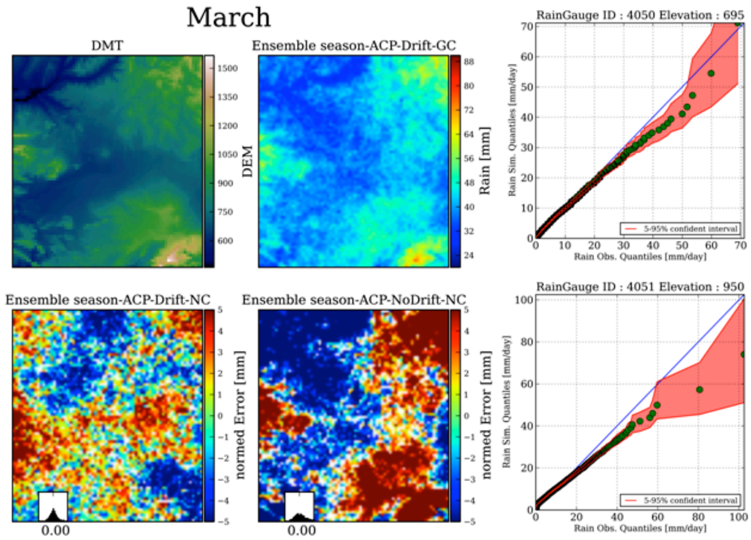

Figure 3. Left. The climatologic spatial distribution rainfall. Comparing the benefit to incorporate the elevation drift. Right. The quantile-quantile plot for the daily rainfall at two gauge locations.

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