

1. Introduction

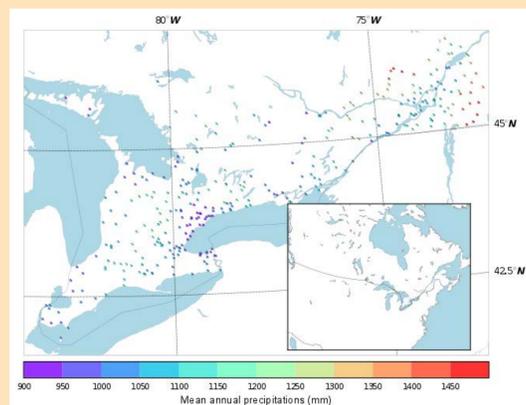
- Precipitation information at the local scale are needed for many fields, e.g. design of hydraulic infrastructures.
- Reanalysis datasets are an attractive alternative: the past state of the atmosphere is reconstructed using Numerical Weather Prediction (NWP) models assimilating past observations.
- Reanalysis datasets cover continuously past period across the earth with a relatively high temporal and spatial resolution for several climate variable as precipitation.
- However, reanalysis datasets cannot be directly used due to, among others, resolution mismatch and model bias. Therefore, reanalysis needs to be post-processed before they can be used.
- In this study, precipitation products are from one reanalysis: The Climate Forecast System Reanalysis (CFSR)

2. Objectives

- Apply stochastic downscaling approaches combined with meta-Gaussian latent field on CFSR precipitation in order to generate random daily sequences with local properties (as opposed to gridded value) and with spatio-temporal consistency.
- Regionalize the at-site downscaling parameters. As CFSR covers the whole territory, it will be then possible to generate daily precipitation datasets (not developed here).

3. Data

- Great Lakes region defined by Plummer et al. (2006)
- CFSR (Saha et al. 2010)
 - Hourly datasets aggregated to daily
 - Period: 1979-2009
 - Resolution: ~ 38 km
 - Coupled model: Ocean-Atmosphere-Land
- Observation network
 - 331 stations:
 - Each year: less than 90% missing values
 - Each station cover at least 10 years of the 1979-2009 period



4. Method

4.1 Stochastic post-treatments of precipitation (Wong et al. 2014)

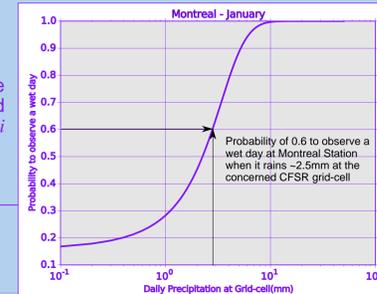
4.1.a. Logistic Regression (LR) is used to estimate local precipitation occurrence probabilities

- LR aims at modelling the pattern of dry and wet days at sites

$$\log\left(\frac{p_i}{1-p_i}\right) = \alpha_0 + \alpha_1 \log(x_i+1) + \dots + \alpha_2 \cos(2\pi d/T) + \alpha_3 \sin(2\pi d/T)$$

probability of rain at a given site conditional on the intensity estimated by the reanalysis x_i for the same day i

- α_k are estimated by the maximum-likelihood method

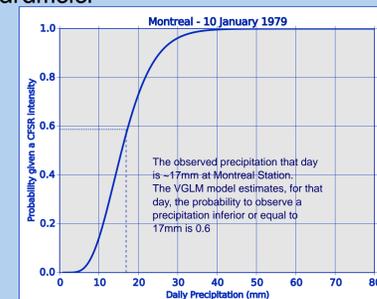


4.1.b. Vector Generalized Linear Model (VGLM) is used to estimate the precipitation intensity

- Daily precipitation distribution is represented by a two-parameter Gamma distribution (μ, γ), [position and shape]
- VGLM models allow the daily precipitation parameters at sites to be functions of daily precipitations estimated by CFSR through the following expression:

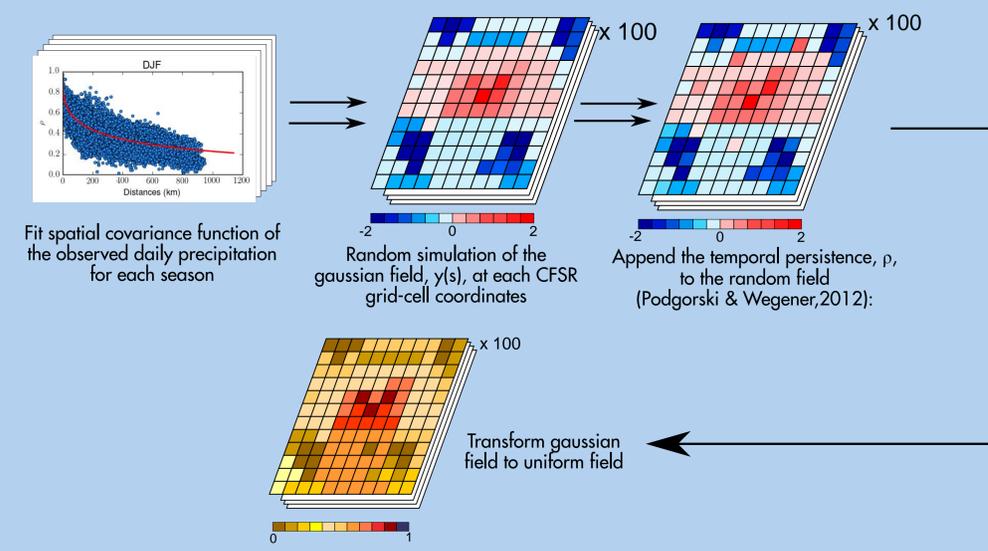
$$\begin{cases} \mu_i = \mu_0 + \mu_1 \log(1+x_i) + \mu_2 \cos(2\pi d/T) + \mu_3 \sin(2\pi d/T) \\ \gamma_i = \gamma_0 + \gamma_1 \log(1+x_i) \end{cases}$$

Daily local gamma distribution conditional, where z_i is local daily precipitation, to the simulated intensity x_i



- μ_k, γ_m are estimated by the maximum-likelihood method

4.2. Random meta-Gaussian latent field definition (Serinaldi et al. 2014)

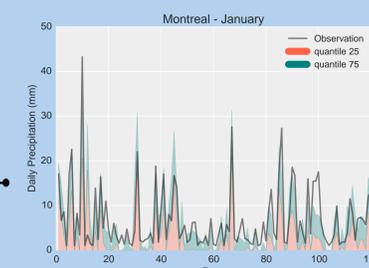


4.3. Daily precipitation at sites

- Combine the probability of occurrence and intensity to define the local daily precipitation distribution:

$$\Pr(Z \leq z_i) = p_i F\Gamma(\mu_i, \gamma_i; x_i) + (1-p_i)$$

- Generate from that distribution with the uniform random field obtained by the meta-gaussian definition



5. Evaluation

Metrics to be evaluated

Climate evaluation of the daily precipitation

- Mean, mean on wet days, number of wet days, 95th percentile

Spatial evaluation

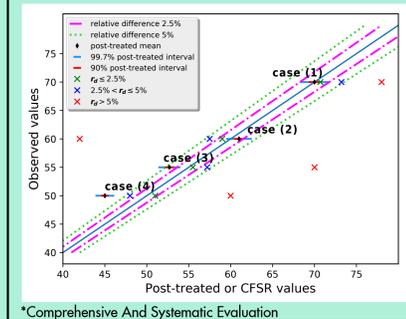
- Spatial correlation of the the daily precipitation at the pair of sites

Annual evaluation

- Climate indices from the ETCCDI indices (World Meteorological Organization's Expert Team on Climate Change Detection and Indices)

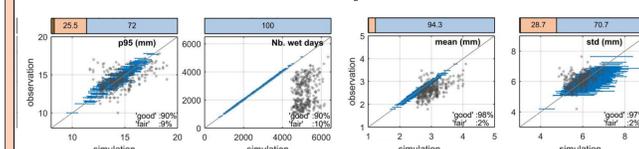
Annual cycle of the precipitation

CASE* framework evaluation



6. Results

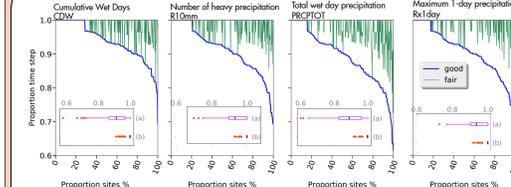
Climate evaluation of the daily statistics



The generated series displayed good climate characteristics (good representation of the marginals: occurrence and intensity)

Noticeable improvement compared to CFSR

Annual evaluation

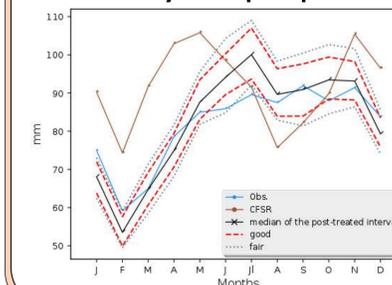


Around 30% of sites had 100% of their annual index series in the good category

For the remaining sites, this percentage dropped between 60 to 90% and for the same series, while the remaining years fell in the fair category

Here again, post-processed CFSR showed for the majority of sites and index, better estimates than CFSR

Annual cycle of precipitation



Annual cycles estimated from regionally-averaged daily precipitation

Post-processed series enabled the simulation of the regional annual cycle of the precipitation

Good or fair estimates of regional month amounts were generally obtained in post-processed series

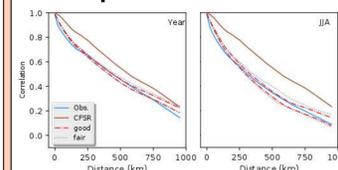
CFSR cycle was not concordant with the observed cycle

7. Conclusion

- The stochastic post-treatment is used to correct and downscale CFSR precipitation
- Post-processing of reanalysis series is achieved in two steps : one for the precipitation occurrence (LR model) and one for the precipitation intensity (VGLM model)
- Post-processing approach demonstrated high potential for providing precipitation that reproduce at-site statistics, indices, and the specific annual cycle of the Great-Lake region

- The meta-Gaussian latent field can be used to generate spatially consistent precipitation series with adequate temporal persistence
- The next step is to interpolate (e.g. kriging) the LR and the VGLM parameters to post-process reanalysis series at sites without historical records

Spatial evaluation



The meta-Gaussian field enabled the generation accurate spatial correlation even at the season scale

CFSR overestimated the spatial correlations of the daily precipitation

References

- Bennett, B., M. Thyer, M. Leonard, M. Lambert, B. Bates, 2017: A comprehensive and systematic evaluation framework for a parsimonious daily rainfall field model. *J. Hydrol.*
- Podgorski, K., Wegener, J. (2012). Velocities of a spatial-temporal stochastic field with embedded dynamics. *Environmetrics*, 23(3), 238-252.
- Plummer, D. A. et al. 2006: Climate and climate change over North America as simulated by the Canadian RCM. *Journal of Climate*, 19 (13),
- Serinaldi, F., C. G. Kilsby, 2014: Simulating daily rainfall fields over large areas for collective risk estimation. *J. Hydrol.*, 512, 285-302
- Saha S., Moorthi S., et al. (2010). The NCEP Climate Forecast System Reanalysis. *Bulletin of the American Meteorological Society*, 91(8), 1015-1057.
- Wong G., Maraun D., Vrac M., Widmann M., Eden J.M., Kent T. (2014). Stochastic model output statistics for bias correcting and downscaling precipitation including extremes. *Journal of Climate*, 27(18), 6940-6959.