Quantitative Precipitation Forecast and Stochastic Rainfall Downscaling

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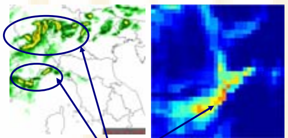
ABSTRACT. In this work we present a method for stochastic rainfall downscaling which can be easily applied to the precipitation forecasts provided by meteorological models. Our approach, called the RainFARM, Rainfall Filtered Autoregressive Model, is based on the nonlinear transformation of a Gaussian random field and it conserves the information present in the rainfall fields at larger scales. Here we test the procedure on a radar-measured intense rainfall event at mid-latitude and we show that the synthetic fields generated by the RainFARM have small-scale statistical properties which are consistent with those of the measured precipitation fields.

The problem

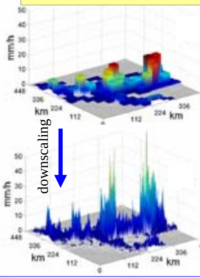


Often the position of rainfall structures is influenced by the orography…

The downscaling procedures currently available for operational purposes usually account only for the total precipitation predicted by a meteorological model over an area and during an interval of time. Some of these procedures do not provide enough information on the spatial and temporal structure of the rainfall field for reliably predicting sudden floods in small mountain catchments and urban areas. Two of the most important features needed to generate reliable stochastic rainfall downscaling are the correlation structure and the position of rainfall patterns. These features become essential in the downscaling of fields predicted by a non-hydrostatic Limited Area meteorological Model (LAM).

Another major concern in rainfall downscaling is parameter estimation. An operational downscaling procedure should indeed be linked in a straightforward way, and in real time, to the predicted large scale fields.

Rain FARM



The model presented here is based on a non-linear transformation of a linearly-correlated random field [1][2][3][4][6] and it has been designed to:

- Conserve the total amount of precipitation predicted by the meteorological model.
- Take into account anisotropy between space and time (if any).
- Conserve the correlations of meteorological rainfall fields both in space and time.
- Conserve the position of the large rainfall structures, to take into account the effects of orography.

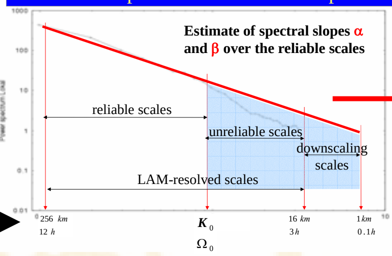
The features of the model are tailored to satisfy the operational requirements highlighted above. In the following, we discuss the procedure and an example of validation on rainfall radar estimates.

The Rain FARM procedure step by step

1. Fourier Transform of the LAM field

$$\hat{P}(K_X,K_Y,\Omega) = \int_{-\infty}^{+\infty} P(X,Y,T)\, e^{iK_X X + iK_Y Y + i\Omega T}\, dX dY dT = \left|\hat{P}(K_X,K_Y,\Omega)\right| e^{i\phi(K_X,K_Y,\Omega)}$$

2. Extrapolation of the Fourier spectrum



3. Generation of high resolution Fourier spectrum, Fourier anti-transform and generation of high-resolution gaussian field

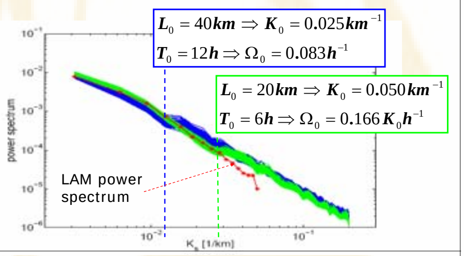
Power spectrum

$$\left|\hat{g}(k_x,k_y,\omega)\right|^2 = \frac{1}{\left(k_x^2+k_y^2\right)^{\alpha/2}\cdot\omega^{\beta}}$$

Phases

$$\phi(k_x,k_y,\omega) = rnd(0:2\pi]$$

Example of power spectra for two reliable scales



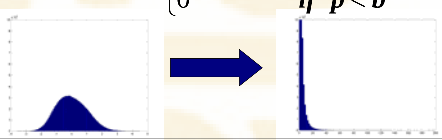
Fourier spectrum inversion

$$g(x,y,t) = \int_{-\infty}^{+\infty} \hat{g}(k_x,k_y,\omega)\, e^{-ik_x x - ik_y y - i\omega t}\, dk_x dk_y d\omega = \int_{-\infty}^{+\infty} \left[\left|\hat{g}(k_x,k_y,\omega)\right| e^{i\phi(k_x,k_y,\omega)}\right] e^{-ik_x x - ik_y y - i\omega t}\, dk_x dk_y d\omega$$

1. We estimate the space-time power spectrum $P(K_X,K_Y,\Omega)^2$ of the field P. Here, K_X and K_Y are the wavenumbers in the X and Y directions and Ω is the angular frequency. Clearly, $(K_X,K_Y) \le \pi/L_0$ and $\Omega \le \pi/T_0$, where $p/L0$ is the Nyquist wavenumber and π/T_0 is the Nyquist frequency of the field to be downscaled.
2. We extrapolate the power spectrum to small scales. To do so, we assume the power spectrum of the rainfall field to have an approximate power-law behavior. From the original field, we estimate the spatial and temporal logarithmic slopes of the power spectrum P^, which we call α and β respectively. For simplicity, we assume isotropy in the two spatial directions.
3. We generate a Fourier spectrum $g(k_x, k_y,\omega)$ that ranges from $2\pi/L_{max}$ to π/λ_0 in wavenumber and from $2\pi/T_{max}$ to π/τ_0 in frequency. By inverting the Fourier spectrum, we obtain a Gaussian field $g(x, y, t)$ defined on the whole range of scales $\lambda_0 \le (x, y) \le L_{max}$, $\tau_0 \le t \le T_{max}$, which we normalize to unit variance.
4. We generate a synthetic precipitation field $\tilde{r}(x, y, t)$ by taking a nonlinear transformation of the Gaussian field g
5. We force the synthetic field to be equal to the original field P when aggregated on the scales (L_0, T_0).

4. Non-linear transformation of the gaussian field

$$\tilde{r}(x,y,t) = \begin{cases} e^{g(x,y,t)} & \text{if } p > b \\ 0 & \text{if } p < b \end{cases}$$

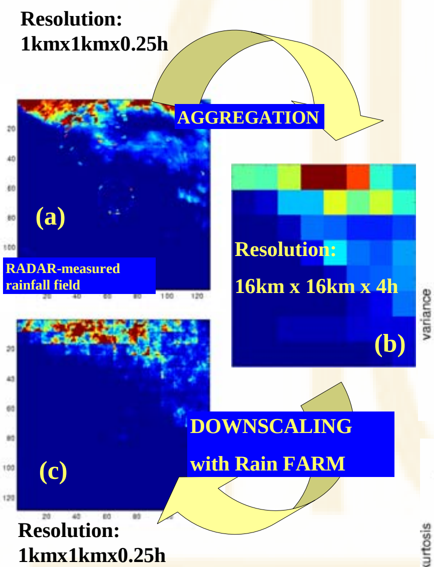


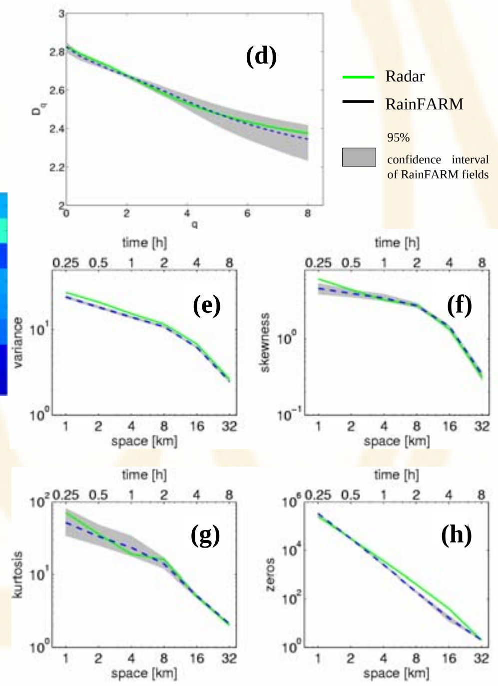
5. Non-linear transformation of the gaussian field

$$r(x,y,t) = \tilde{r}(x,y,t)\,\frac{P(X,Y,T)}{\tilde{R}(X,Y,T)}$$

R(X,Y,T) is the coarse-grained synthetic field obtained by aggregating the small-scale field r on the scale (L_0,T_0)

Rain FARM validation





This is an example of validation of the RainFARM model. A large-scale spatial-temporal field (b) obtained by aggregating a radar-measured rainfall field (a) is downscaled to the original small scale (c) by the procedure described above. In this way we test how performs the model starting from a large scale prediction. The multifractal spectrum of the downscaled signal is very close to that of the original dataset (d). Other scale properties of the rainfall fields, such as the scaling of variance (e) , skewness (f), kurtosis (g) and number of zeros (h) also display a very good agreement between the the radar-measured rainfall fields and those produced by the RainFARM model.

CONCLUSIONS

The procedure proposed here is suitable for operational purposes for two reasons:

1. with this approach, we may take into account both the correlation and the position of large scale rainfall patterns.
2. The model parameters are easily estimated, in real time, from the large scale rain fields. In this way the model is (self-)consistent and it does not need calibration.

This approach seems to be a significant improvement over the available operational downscaling procedures. Some of the hypotheses made to extrapolate the information at small scale have to be verified. These are:

1. The 3D power spectrum has a power-law shape.
2. The nonlinear transformation is exponential.

References

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