

A TECHNIQUE TO DERIVE THE SPATIAL DISTRIBUTION OF RAIN INTENSITY FROM NWP DATA

Carlo Capsoni and Lorenzo Luini

Dipartimento di Elettronica e Informazione – IEIIT/CNR, Politecnico di Milano,
Piazza L. da Vinci 32, 20133 - Milano (Italy), email: capsoni@elet.polimi.it

1. ABSTRACT

Numerical Weather Predictions (NWP) provided by world meteorological organizations like ECMWF (European Centre of Medium-Range Weather Forecast) are a unique source of valuable information of the meteorological situation on a global scale [1]. Their use is becoming more and more spread, spanning from the classical weather forecast to telecommunication applications.

Unfortunately, the temporal and spatial detail of NWP data is relatively limited for some applications. Much better resolution can be achieved with Limited Area Models (LAM), although at the cost of a reduced spatial coverage [2].

Among the different quantities provided by the NWP, we focused our attention on rain precipitation, which is parameterized in terms of total rain amount, M_t , and convective rain amount, M_c , both cumulated in the reference period (3, 6 or 12 hours) and over the reference area (at the moment, the finest available resolution is 25×25 km² from the forecasting products): our goal is, in fact, to derive a more detailed information that is inherently embedded in such cumulative parameters. In particular, this contribution presents a technique to derive the spatial cumulative distribution function of point rain rate, hereinafter indicated as $P(R)$, over the reference area and relative to the reference time period: in other words, the proposed methodology allows to deduce from M_t and M_c the percentage of the reference area affected by rain and the percentages of area where the rain intensity exceeds given thresholds.

The technique was originally developed for radio propagation purposes, due to the need to know the actual temporal variation of the $P(R)$ over the area (e.g. Europe) served by a multimedia satellite system equipped with an on-board reconfigurable antenna [3], but it can be easily extended and used in other applications where the knowledge of details about the precipitation over a given area is of importance such as in hydrology, weather now casting and so on.

The rationale of this technique relies on the ergodicity principle according to which in a stochastic process the mean statistical value is equal to the mean temporal value. As a consequence, a stochastic ergodic process is stationary. This principle applies also to rain fields (although, strictly speaking, the rain process is not stationary) as it is widely accepted in the radarmeteorology community [4]. As a consequence, the $P(R)$ collected at a site in a given period of time (e.g. for one year by a raingauge) is similar in shape to the $P(R)$ obtainable at a given time over the area surrounding that site (each point can be interpreted as a raingauge): in other words, when dealing with the rainfall process, space and time can be interchanged. We have already successfully tested this principle by analysing a very large database of radar images of precipitation collected over an area of 100×100 km² around the experimental station of Spino d'Adda sited in the centre of the Padana valley - northern part of Italy - and the results have been presented in [5].

This paper introduces the algorithm to generate the $P(R)$ from the simple knowledge of the total rain amount M_t and the ratio between convective and total rain amounts, also usually referred to as $\beta = M_c/M_t$, and shows its performance, by making use of the above mentioned radar database from which both the input to the algorithm and the desired output can be derived. Namely, a set of subsequent radar images are grouped together so as to reproduce the precipitation field in the selected (e.g. 6 hour) time period. From this set of images, we have firstly derived the total cumulated rain by averaging the rain intensity values relative to the pixels of all the images (analogous to the M_t value provided by NWP); as a second step, a rain threshold of 8 mm/h is applied to isolate convective rain: similarly to how M_t is calculated, the average of such rain intensity values provides M_c and, hence, β . As a result, from the set of radar images, both M_t and β are derived, which are the input of the proposed technique. As a final step, the actual $P(R)$ is computed by evaluating the number of rain intensity values exceeding different rain rate thresholds: this is the $P(R)$ to be estimated by the proposed method and the reference curve against which its performance can be evaluated.

The procedure assumes an analytical expression for the $P(R)$ of the following type:

$$P(R) = P_0 \left[\ln \left(\frac{R_{asint} + R_{low}}{R + R_{low}} \right) \right]^n \quad (1)$$

that has proven to fit very satisfactorily the local $P(R)$ s, worldwide [6]. The proposed technique identifies three out of the four unknowns of (1) (R_{low} is fixed to 1 mm/h for convenience) based on the two input data (M_t and β) and on a statistical relationship existing between n and R_{asint} .

The results of the comparison between the radar derived $P(R)$ and the one estimated from the proposed procedure (an example of which is illustrated in Figure 1) are quite convincing: when radar images are grouped in 6-hour time periods (large averaging) the root mean square of the discrepancy between the radar and the estimated $P(R)$ is around 22%, whereas this value increases up to approximately 27% if no time averaging is considered, i.e. if the technique is applied to estimate the $P(R)$ of a single image. These tests guarantee that this procedure can be applied successfully to the data provided by NWP in order to properly estimate the $P(R)$ relative to each pixel of the grid and to a reference time slot. In practice, since spatial $P(R)$ s are concerned, the value $P(0)$ represents the percentage of the image area interested by rain, while the percentage probability for which a given value of point rain rate is exceeded (any other value of the $P(R)$ for $R > 0$ mm/h) represents the percentage of the image area with rain intensity greater than that the given value. Obviously, the proposed technique cannot provide any estimate of the actual position of the rain intensity values.

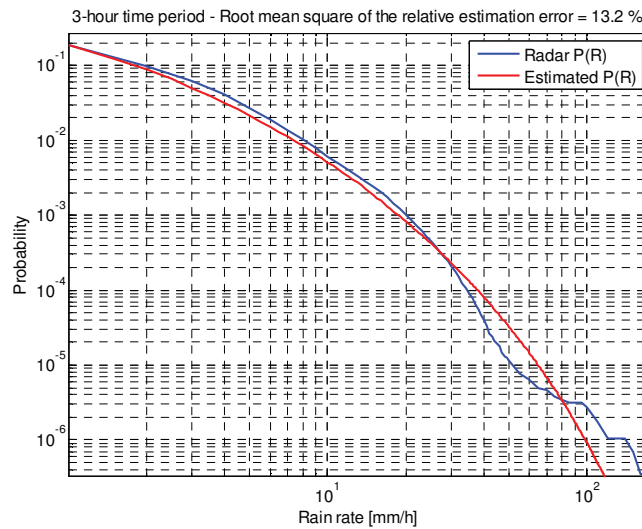


Figure 1. Example of the $P(R)$ estimated by the proposed technique (3-hour time period)

2. REFERENCES

- [1] <http://www.ecmwf.int/>, January, 2008.
- [2] <http://www.emc.ncep.noaa.gov/modelinfo/>, January 2008.
- [3] A. Paraboni *et al.*, "Reconfigurable Ka band antenna front end for active rain fad compensation," ESA ESTEC Contract n. 17877/04/NL/JA.
- [4] J. Goldhirsh, "Spatial variability of rain rate and slant path attenuation distributions at 28 GHz in the mid-Atlantic coast region of the United States," *IEEE Transactions on Antennas and Propagation*, Vol. 38, Issue 10, Page(s):1711-1716, Oct. 1990.
- [5] C. Capsoni *et al.*, "A time varying rain field generator," *14 Ka and broadband Utilization Conference*, 24-26 Sept. 2008, Matera, Italy.
- [6] C. Capsoni, L. Luini, A. Paraboni, C. Riva, "Stratiform and convective discrimination deduced from local $P(R)$ ", *IEEE Transactions on Antennas and Propagation*, vol. 54, issue 11, pp. 3566-3569, Nov. 2006.