A nowcasting technique for cumulative rainfall for the Mediterranean basin

Alessandro Mazza[1,2], Andrea Antonini[2], Samantha Melani[1,2] and Alberto Ortolani[1,2]

[1]*Institute of Biometeorology – National Research Council Via Gino Caproni 8, 50145 Florence, Italy*
[2] *LAMMA Consortium Via Madonna del Piano 10, 50019 Sesto Fiorentino (FI), Italy*
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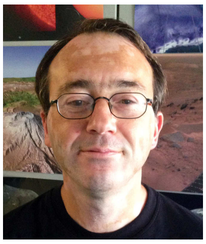

Alessandro Mazza

1 Introduction

Nowcasting of rainfall is very important for many purposes. The rainfall predictions are crucial for the management of airport and urban and extra urban traffic, the warning of severe weather and many other things. So it would be very useful to be able to accurately forecast the rainfall on each point of the territory.

The comparison between raingauge and time and space coincident radar observations [1,2], does not give satisfactory results: as there is not high correlation therefore it is not possible to make a punctual rainfall prediction using radar. The radars are not able to perform point measurements, as the backscattering signal caused by hydrometeors, is averaged over an area of approximately 1km square.

In this paper we have proposed a nowcasting technique for the prediction of average cumulative rainfall every fifteen minutes on an square area 30 km side. For a given initial instant, we have predicted the cumulative rainfall for the next fifteen minutes.

The nowcasting technique is based on the estimation of rain rate obtained by radar reflectivity measurements, measurements of brightness temperature at 10.8 μm by SEVIRI instrument aboard MSG-3 satellite and on the cumulative rainfall measures of the fifteen minutes prior to the time of nowcasting. The radars, the SEVIRI instrument and the rain gauges provide the measurements every fifteen minutes.

Nowcasting technique involves the measurements of the average of cumulative rainfall made with rain gauges and radars, and on the nature of cloudiness determined by means of the SEVIRI instrument. To evaluate the average cumulative rainfall by rain gauges, we have used the point measurements obtained with the raingauges located in the selected area. To spatialize the precipitation measured by gauge we have used the **Non Parametric Ordinary Block Kriging** (**NPOBK**) [3,4,5] that provides both a measure of the average value of the average cumulative rainfall on the area of interest and the evaluation of measurement uncertainty. Analysing a consistent data set of rainfall patterns for several seasons and years, we have decided to fix the spatial extent of the pixel in an area of 30x30 km^2: this assures a good correlation between precipitation measurements as obtained by radar and gauges. We have done the nowcasting of average cumulative rainfall by assimilating measurements of radar, satellite and raingauge and then evolving the results obtained from the assimilated data. We have obtained the time evolution of the observable by applying a time evolution operator to the initial value. The technique of data assimilation we used is the Kalman Filter [6].

2 The techniques of nowcasting

We have proposed two nowcasting techniques, the first one using radar, SEVIRI instruments and rain gauges, and the second only measurements of radar and SEVIRI instrument. The instruments make measurements every 0, 15, 30, 45 minutes of each hour. The measurements we have used consist of:

Rain rate. The radar system has provided us the radar rain rate but not the reflectivity measurement. The radar system compute the rain rate by applying the Marshall Palmer relationship for each reflectivity measurements acquired.

$$Z = aR^b \quad a=200 \quad b=1.6 \tag{2.1}$$

The rain rate is given in arbitrary units.

Cumulative rainfall. The rain gauges acquire at the instant t the cumulative rainfall of the previous fifteen minutes over an area of a few dm^2. Cumulative rainfall is measured in mm.

Brightness temperature at 10.8 μm. The SEVIRI instrument acquires the brightness temperature at 10.8 μm on a pixel of about 5X5 km^2.

To realize a nowcasting technique of cumulative rainfall using radar we must have available a faithful measurement of the observable. Since rain gauges measurements are a direct measurements of precipitation and then they represent the ground truth it is necessary that the radar measurements are consistent with the latter. Unfortunately, comparing cumulative rainfall measurements of rain gauges with those of radar we do not have a satisfactory correspondence. We can explain this

 mazza@lamma.rete.toscana.it

behaviour by observing that the rain gauges measurements are punctual while radar measurements are averaged over larger areas. Furthermore raingauges accumulate rainfall continuously throughout a selected period of time while radars measure rainfall instantaneously. Precipitation has a temporal variation significantly different from zero for time intervals of the order of few minutes, and a spatial variation significantly different from zero for points separated by few hundred of meters.

The above arguments imply that we can not use the radar measurements to estimate punctual cumulative rainfall. On the basis of these observations, we have studied the average cumulative rainfall on a square area 30 km side for a period of fifteen minutes so as to measure with two different instruments the same observable. By measuring precipitation by means of radar and rain gauges we have found comparable results, implying the goodness of radar estimates of the average cumulative rainfall.

2.1 Nowcasting by means of radar, satellite and rain gauges

We have realized nowcasting of rainfall using the scalar case of Kalman Filter [6]. The process takes place in two phases: the first one we have assimilated the data of the average cumulative rainfall obtained by radar and raingauge at time t. In a second step we have applied to the data assimilated at time t the time evolution operator to obtain the expected value at time t+15 minutes. This operator depends on the brightness temperature at 10.8 μm. We have treated all these quantities as random variables that we have to know the mean and the standard deviation.

2.1.1 Measurement of mean and variance of the observable using rain gauges

To determine the average cumulative rainfall on the selected area we have used the Kriging method. In our case, there is not reason to suppose that the random variables associated with the measurements of the cumulative rainfall differs in different points of the surface because we have not a priori information to assume that the behaviour of rainfall differs at different location. In this case the model is said **Ordinary Block Kriging** [3,4,5]. We also have made the hypothesis that the variogram is independent from the position and the direction of the lag vector h.

$$\gamma(x, \vec{h}) = \gamma(h) \tag{2.2}$$

We have evaluated the variogram nonparametrically; we have assumed that we do not know the a priori form but we evaluate it using the data acquired from the rain gauges by means of the following expression:

$$2\gamma(h) = \frac{1}{n(h)} \sum_{i=0}^{n(h)} \left[Z(X_i) - Z(X_i + h) \right]^2 \tag{2.3}$$

Where $Z(X_i)$ are the measurements of the rain gauges located on the points X_i.

Such a technique is called **Non Parametric Ordinary Block Kriging** (**NPOBK**) [3,4,5]. We have determined the mean and variance by the following expressions:

$$\psi^{gauge} = \sum_{\alpha=1}^{N} \lambda_\alpha Z_\alpha \tag{2.4}$$

$$\sigma^2_{gauge} = \sum_{\alpha=1}^{n} \lambda_\alpha \gamma_{\alpha V} - \gamma_{VV} - \mu \tag{2.5}$$

$$\gamma_{vv} = \frac{1}{|A|^2} \int_v \int_v \gamma(x, y) dxdy \qquad \gamma_{\alpha v} = \frac{1}{|A|} \int_v \gamma(x_\alpha, x) dx \tag{2.6}$$

where λ_α are the parameters determined by the **NPOBK**, Z_α the measurements values of rain gauges on the points x_α, A the area, $\gamma(x, y)$ the variogram of the pair of points x and y, μ a parameter determined by **NPBOK**.

2.1.2 Measurement of mean and standard deviation of the observable using radar

To measure the average cumulative rainfall is necessary to compute the cumulative rainfall over the pixels that compose the selected area. We have evaluated the cumulative rainfall using the expression:

$$C_{radar} = \left(R_{ini} + R_{fin}\right)/2 \tag{2.7}$$

R_{ini} and R_{fin} are the rain rate at the initial and final time of the period of accumulation.

After determining the cumulative rainfall on each pixel composing the study area we have computed the corresponding average C_{radar}. Since the reflectivity are assigned in arbitrary unit, the estimates of the average cumulative rainfall must be calibrated. For this purpose we have fitted the radar estimates versus rain gauges measurements at the same instant with a linear relation:

$$C_{radar} = A * \psi_{gauge} + B \quad (2.8)$$

We have determined the A and B coefficients by the least squares method; then we have assigned the value to the average of the cumulative rainfall. The standard deviation of the random variable C_{radar} is given by the following relation

$$\sigma_{radar} = \sqrt{\frac{1}{N-2}\sum_{i}^{N}\left(C_i^{radar} - B - A\psi_i^{gauge}\right)^2} + A\sigma_{gauge} \quad (2.9)$$

2.1.3 The Kalman Filter

We have carried out the assimilation of rain gauges and radar measurements applying the following relations [6], we have neglected the calibration coefficient B because we have shown to be negligible (sec. 3). :

$$\psi^a(t-15\min) = \frac{\psi^{gauge}(t-15\min)\frac{1}{\sigma_{gauge}^2} + \psi^{radar}(t-15\min)\frac{1}{\frac{\sigma_{radar}^2}{A^2}}}{\frac{1}{\sigma_{gauge}^2} + \frac{1}{\frac{\sigma_{radar}^2}{A^2}}} \quad (2.10)$$

Where ψ^a is the value assimilated, $\psi^{radar} = C^{radar}/A$ is the value calibrated of radar measured in mm (2.8).

The variance is equal to:

$$\sigma_a^2 = \frac{1}{\frac{1}{\sigma_{gauge}^2} + \frac{1}{\frac{\sigma_{radar}^2}{A^2}}} \quad (2.11)$$

We have performed the nowcasting by determining the temporal evolution of the observable through the following relation:

$$\psi^f(t) = G\left(T_B^{10.8}\right)\psi^a(t-15\min) \quad (2.12)$$

Where ψ^f is the nowcasting of the average cumulative rainfall at time t, G the time evolution operator, $T_B^{10.8}$ the brightness temperature at 10.8 μm. We have assumed the following form for the operator G:

$$\begin{array}{ll} G\left(T_B^{10.8}, T\right) = 1 & if\ T - T_B^{10.8} > 20\,K \\ G\left(T_B^{10.8}, T\right) = 0 & if\ T - T_B^{10.8} \leq 20\,K \end{array} \quad (2.13)$$

Where T is the thermodynamic temperature to the ground.

We have justified the form of the operator G by the following considerations. The temperature of the soil is always at least 20 degrees greater than that measured on clouds top. The brightness temperature at 10.8 μm refers with a good approximation to the thermodynamic temperature of the cloud tops or to the ground in case of clear sky. If the inequality $T - T_B^{10.8} < 20K$ is true, we have considered the sky to be clear and no precipitation occurs. Conversely, if the sky is covered by clouds, the probability of rainfall is different from zero.

We have shown the autocorrelation coefficient of the assimilated observable in Fig. 1. For time delays of 15 minutes we have observed a value greater than 0.9, then the value of the average cumulative rainfall varies very little. This is not a trivial result, that occurs only if we consider the average over a sufficiently large areas. Increasing the time delay, the autocorrelation coefficient is decreasing, which leads a unpredictability of the rainfall events.

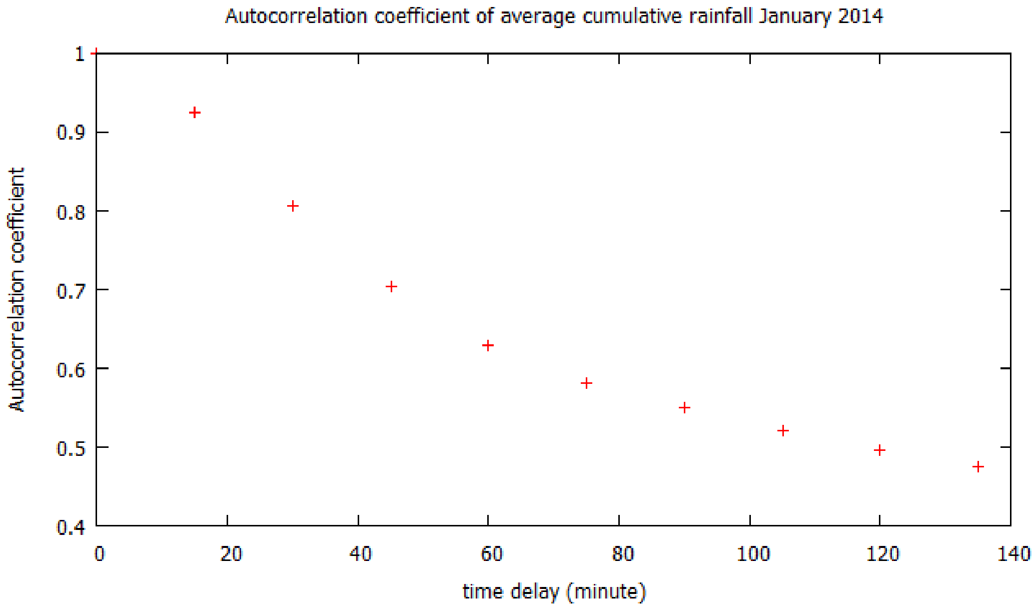

Figure 1: Autocorrelation coefficient of average cumulative rainfall for the period January 1, 2014 - February 1, 2014 for the square area of side 30 km centered on the point: lat: 43.75 lon: 11:25.

We have not to been able to estimate a priori the standard deviation of ψ^f because we could not evaluate the uncertainty introduced by the application of the operator G. We have fitted the values of ψ^f versus the values of ψ^a at the same time t with a linear relation:

$$\psi_f = C * \psi_a + D \tag{2.14}$$

We have determined the C and D coefficients by the least squares method. The standard deviation of ψ^f is given by the following relation:

$$\sigma_f = \sqrt{\frac{1}{N-2}\sum_i^N \left(\psi_i^f - D - C\psi_i^a\right)^2} + C\sigma_a \tag{2.15}$$

2.2 Nowcasting by means of radar and satellite

This technique is very similar as the one described in the previous section. In this case the only available measure is that acquired by the radar. The temporal evolution equation becomes:

$$\psi^f(t) = G\left(T_B^{10.8}\right)\psi^{radar}(t - 15\,\mathrm{min}) \tag{2.16}$$

To estimate ψ^{radar} we have used the calibration relation (2.8); we have estimated the standard deviation using eq. (2.9). Also in this case we could not estimate in advance the standard deviation of ψ^f and then we have proceeded as in the previous section, we have fitted the values of ψ^f versus the values of ψ^a at the same time t with a linear relation:

$$\psi_f = E * \psi_a + F \tag{2.17}$$

We have determined the E and F coefficients by the least squares method. The standard deviation of ψ^f is given by the following relation:

$$\sigma_f = \sqrt{\frac{1}{N-2}\sum_i^N \left(\psi_i^f - F - E\psi_i^a\right)^2} + E\sigma_a \tag{2.18}$$

3 Results

We have applied both the methods described in section 2 to a square area of 30 km by side centered on the city of Florence. The coordinates are: lat: 43.75, lon: 11.25 (in decimal degrees). The case study period is from: December 1st 2013 to 1st June 2014. We have separately analyzed measurements of each month to take into account rainfall seasonality. The validation of the method can be carried out only for those months with a sufficient number of rainfall events. We have taken into consideration only the pairs of measurements that had at least one non zero value. In the next subsection we have shown the results of months of February and March 2013, and for January and February 2014.

3.1 Validation of nowcasting by means of radar, satellite and rain gauges

Firstly, we have computed the mean (2.4) and the variance (2.5) of the observable measured by rain gauges using the **NPOBK** method [3,4,5]. The standard deviation value is almost always about 0.05 mm, so we have assumed this value for each measure of the rain gauges.

Comparing the radar and rain gauges measurements (fig. 2) we have obtained the parameter A and B of the calibration relationship (2.8) .

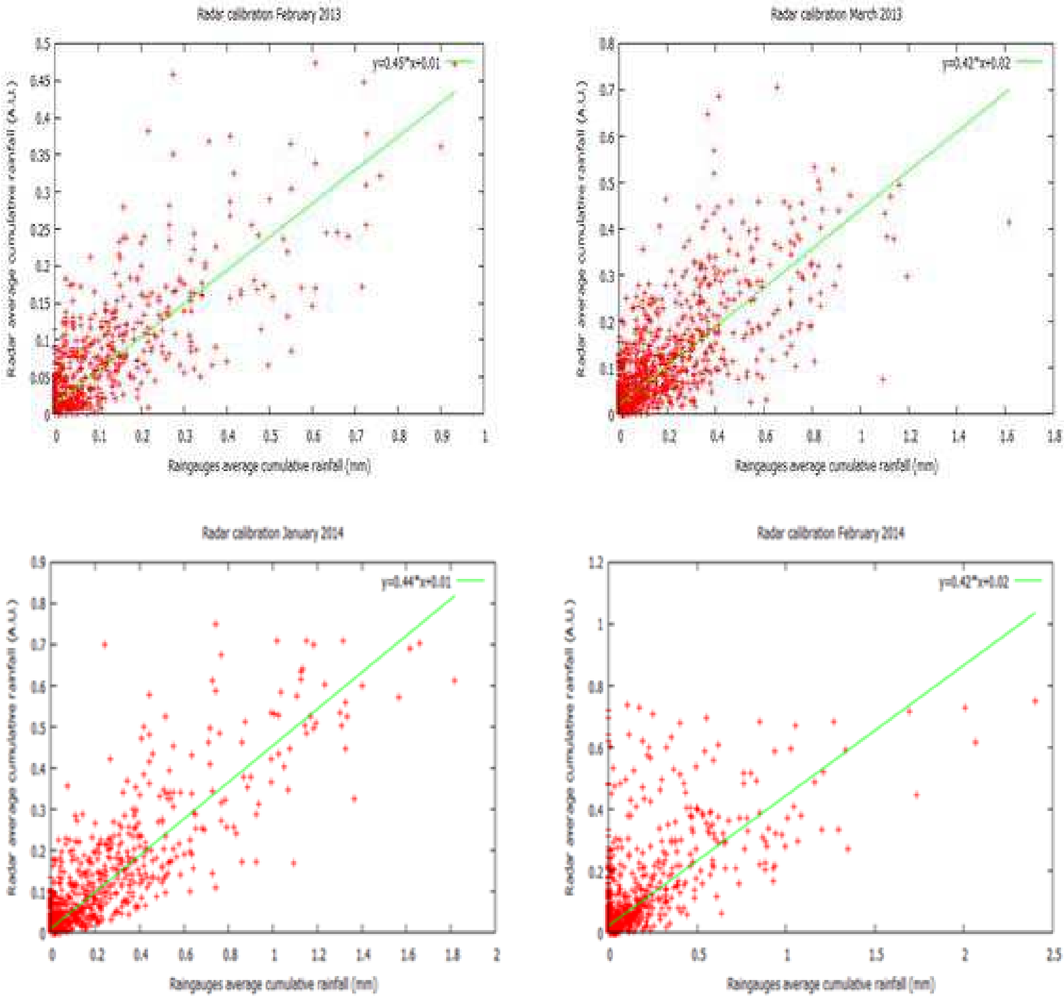

Figure 2: Scatterplot of average cumulative rainfall measured by radar and by rain gauges. Months: February 2013, March 2013, January 2014, February 2014.

Table 1: Values of the fit parameters and standard deviation of radar measurements.

Month	A	B	σ_{radar}
February 2013	0.45±0.2	0.013±0.02	0.13
March 2013	0.42±0.1	0.021±0.02	0.12
January 2014	0.44±0.1	0.010±0.02	0.08
February 2014	0.42±0.1	0.022±0.02	0.14

By means of (2.8) and (2.9) we have obtained the values of the average cumulative rainfall measured by radar in mm and the relative standard deviation. Therefore we have computed the corresponding assimilated values (2.10) and their variance (2.11).

Finally we have obtained the nowcasting of average cumulative rainfall using the relationship (2.12). To validate the results we have compared the assimilated data ψ^a with nowcasting ψ^f at the same time (fig. 3). We have obtained the parameter C e D of eq. (2.14) and the standard deviation of ψ^f (2.15).

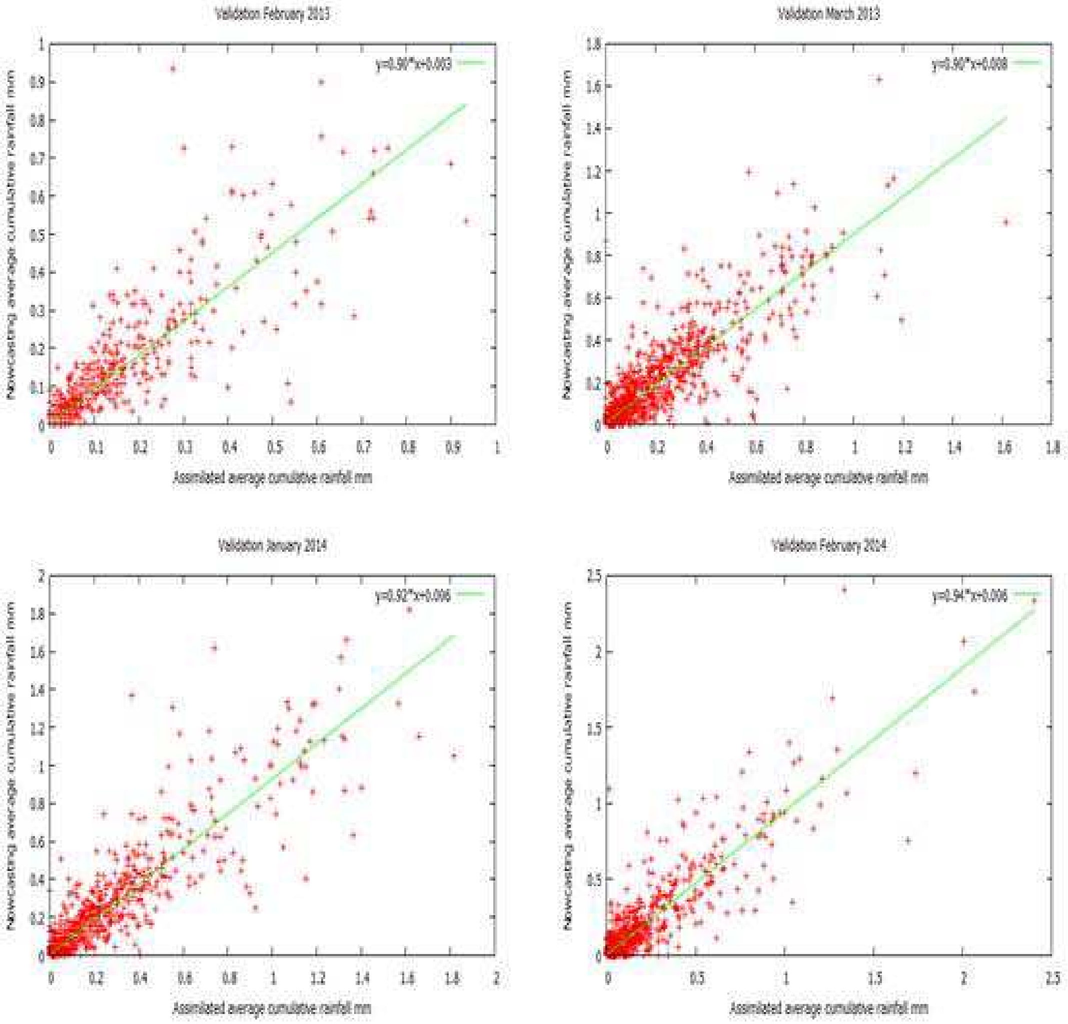

Figure 3: Scatterplot of nowcasting and assimilated value of average cumulative rainfall. Months: February 2013, March 2013, January 2014, February 2014.

Table 2: Values of the fit parameters and standard deviation of nowcasting values.

Month	C	D	σ_f
February 2013	0.90±0.2	0.003±0.02	0.049
March 2013	0.89±0.1	0.008±0.02	0.049
January 2014	0.92±0.1	0.006±0.02	0.048
February 2014	0.94±0.1	0.006±0.02	0.049

The value of D is very near to zero, and the C slope to one. These are the necessary conditions to verify the correctness of the proposed method.

3.2 Validation of nowcasting by means of radar and satellite

We have determined the average and standard deviation values of radar rainfall estimates in a similar manner to the previous case. We have performed nowcasting using the relation (2.16). Also in this case, to validate the technique we have compare the assimilated data ψ^a with nowcasting ψ^f at the same time (fig. 4). We have obtained the parameter E e F of eq. (2.17) and the standard deviation of ψ^f (2.18).

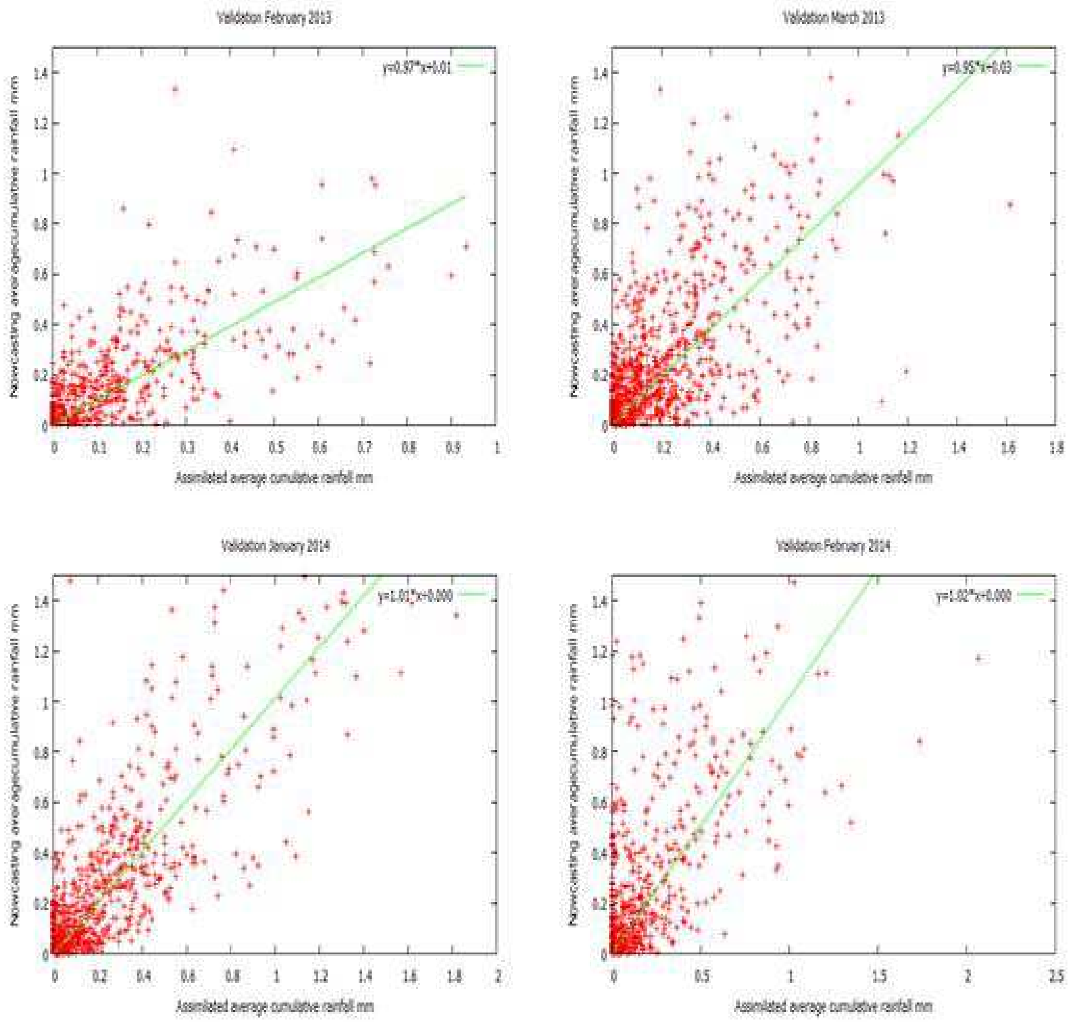

Figure 4: Scatterplot of nowcasting and assimilated value of average cumulative rainfall. Months: February 2013, March 2013, January 2014, February 2014.

Table 3: Values of the fit parameters and standard deviation of nowcasting values.

Month	F	G	σ_f
February 2013	0.97±0.4	0±0.02	0.31
March 2013	0.95±0.3	0±0.02	0.30
January 2014	1.01±0.3	0±0.02	0.21
February 2014	1.02±0.3	0±0.02	0.32

Respect to the previous described technique, data have a higher dispersion with a greater standard deviation, this technique resulting lesser accurate than that previously described.

4 Conclusions

In this work we have studied a technique for rainfall nowcasting based on radar, rain gauges and satellite sensors. We have shown the preliminary results that by means of the radar measurements we can evaluate with good accuracy the mean of the cumulative rainfall over regions of a few tens of kilometers by side.

We have shown that the average of the cumulative rainfall has slow variation over tens of minute time intervals. We have used the brightness temperature at 10.8 µm to determine the sky cloudiness and then the absence of precipitation, that allows us to define a plausible form for the time evolution operator in a Kalman filter approach.

We have applied and preliminary validated the technique over Florence area (lat: 43.75, lon: 11.25), in the future we will apply and test on the whole Tuscany. Once we have verified this technique, we will implement it and will provide nowcasting in real time. We will improve the technique using the measurements of the brightness temperature at 12 µm to eliminate cirrus contamination that are sometimes cause of false precipitations alarms [7].

We will apply the technique that involves only the use of radar measurements to areas not covered by rain gauges, such as marine areas, providing some services very precious for safety navigation. We will apply this scheme in different areas, with the only need of a proper customized data calibration.

Finally it is under study the possibility of extending the nowcasting technique for the predictability of time intervals greater than 15 minutes.

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