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Radar Rainfall Estimation at Ground Level

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1 Introduction and Summary

A technique has been developed to provide an estimate of the rainfall reaching the earth's surface by extrapolating radar data contained aloft to ground level, simultaneously estimating unknown data in the radar volume scan. It has been developed to be computationally fast, to work in real time and comprises the following steps. A rainfall classification algorithm is applied to separate the reflectivity bins (1 km cubes) into two separate types: convective and stratiform rainfall. Climatological semivariograms based on the rainfall type are then defined, which result in a fast and effective means of determining the semivariograms parameters anywhere in the radar volume scan. Extrapolations to ground level are computed by utilising 3D Universal and Ordinary Cascade Kriging; computational efficiency and stability in Kriging are ensured by using a nearest neighbours approach and a Singular Value Decomposition (SVD) matrix rank reduction technique. To validate the proposed technique, a statistical comparison between the temporally accumulated radar estimates and the Block Kriged raingauge estimates is carried out over matching areas, for selected rainfall events, to determine the quality of the rainfall estimates at ground level. A fuller exposition of these ideas appears in Wesson and Pegram (2006).

2 Rainfall Classification and Semivariograms

After checking several classification schemes (Mittermaier, 1999; Sempere-Torres et al, 2000; Steiner, 1995) and consulting the South African Weather Services, it was decided to ignore pixels with reflectivities below 18 dBz, to classify as stratiform those bins where 18< dBz <34 and as convective those bins where 35 < dBz.

The Robust Variogram, proposed by Cressie and Hawkins (1980) was the appropriate model fit the two types of data and is given by Eqn. (1) where $N(h)$ is the count of data h apart:

$$2\cdot\bar{\gamma}(h)=\left\{\frac{1}{|N(h)|}\sum_{N(h)}\left|Z(s_i)-Z(s_j)\right|^{1/2}\right\}^4 \Bigg/ \left(0.457+\frac{0.494}{|N(h)|}\right) \qquad (1)$$

By computing the sum of the absolute difference of the pairs of data points, $Z(s_i)$ and $Z(s_j)$ (values of dBz at points s_i and s_j a distance h apart) in the square root domain and then raising the result to the power of four dramatically reduces the effect of uncharacteristic observations. Computing the empirical semivariogram using the classical estimator would result in an underestimation of the correlation length L and overestimation of the exponent α in the generalized exponential model $g(h)$ of the semivariogram $\gamma(h)$ in Eqn. (2)

$$g(h)=1-\exp[-(h/L)^{\alpha}] \qquad (2)$$

Four semivariograms' parameters were fitted to stratiform and convective rainfall types in the horizontal and vertical directions as given in Table 1.

Table 1: Semivariogram parameter values in the horizontal and vertical directions for stratiform and convective rainfall.

	Horizontal		Vertical	
	α_H	L_H (km)	α_V	L_V (km)
Stratiform	1.53	8.40	1.33	2.56
Convective	1.85	3.38	1.71	4.11

For two points at horizontal and vertical separations of r and z where the corresponding correlation lengths are r_0 and z_0 the hybrid semivariogram becomes (Seed and Pegram, 2001):

$$\gamma(h)=\sigma^2\cdot\left[1-\exp\left(-h^{\alpha}\right)\right] \qquad (3)$$

where: $h^2=\left(r/r_0\right)^2+\left(z/z_0\right)^2$

3 Cascade Kriging using Nearest Neighbours

The radar-rainfall data in South Africa are processed immediately on capture into a stack of 18 levels at 1 km spacing above the radar, at 1 km horizontal resolution in a cylinder of 400 km radius, forming a Constant Altitude Plan Position Indicator (CAPPI). For hydrological purposes, the precipitation falling on the ground is of major interest. Difficulties arise from the numerical edge effects caused by the base scan limiting the range at lower levels in the CAPPI.

In addition, the influence of ground clutter can be detected up to 5 km above the radar in the vicinity of some mountains. Thus there is thus a large number of bins to be infilled in every CAPPI, each of which is collected at intervals of 5 minutes.

Efficient and robust calculation methods must thus be used for the infilling and extrapolation of the data. Four schemes were explored and employed:

- Cascade Kriging,
- Nearest Neighbour Kriging,
- Universal Kriging with rain-type as indicator variable
- Stability control in solving Kriging equations

Cascade Kriging borrows its ideas from the EM algorithm of Dempster et al (1977), where one uses data already infilled as the basis of the next infilling task. In Cascade Kriging, the two topmost layers of the CAPPI are used to infill the target bins in the next lower layer (including any available data at the altitude of the target), then all subsequent layers are infilled successively until the radar level (nominal ground level) is reached.

Nearest Neighbour Kriging was explored by Seed and Pegram (2001) and carefully studied as a precursor to this work (Wesson and Pegram, 2004). It was found that the optimum number of nearest neighbour bins (as controls around a target to be infilled) was 25. This invariably involved bins lying in the target level and no more than 2 layers above the target. The method of Ordinary Kriging was used successfully in cases where the controls were all of one type (stratiform or convective).

In mixed cases, another scheme was used: Universal (or External Drift) Kriging (Hengl et al, 2003). Environmental variables associated with each bin could be altitude etc (expressed as parameters of polynomials of order 1 or more) etc. These were explored but were found ineffective. The choice of rainfall type was found to add value to the Kriging. In Fig. 1 appear the results of infilling a layer whose data are hidden, first with Ordinary Kriging then with Universal Kriging. The improvement is dramatic.

Stability control of the computation was found to be necessary, especially with convective rain where the semivariogram model's exponential parameter approaches 2 (near Gaussian). In such cases, the coefficient matrix in the Kriging equations becomes badly ill-conditioned. In such cases, the matrix inversion is performed using Singular Value Decomposition and the relatively small singular values are set to zero, with considerable savings in computation and increase in stability (Wesson and Pegram, 2004)

4 Validation of methodology at Ground level using gauges.

To test the methodology at ground level, the rainfall data from an array of tipping-bucket raingauges sited under the radar were used. These data were accumulated over periods of 6, 12 and 24 hours on two different rain days – one with mostly convective, the other with mostly stratiform rainfall.

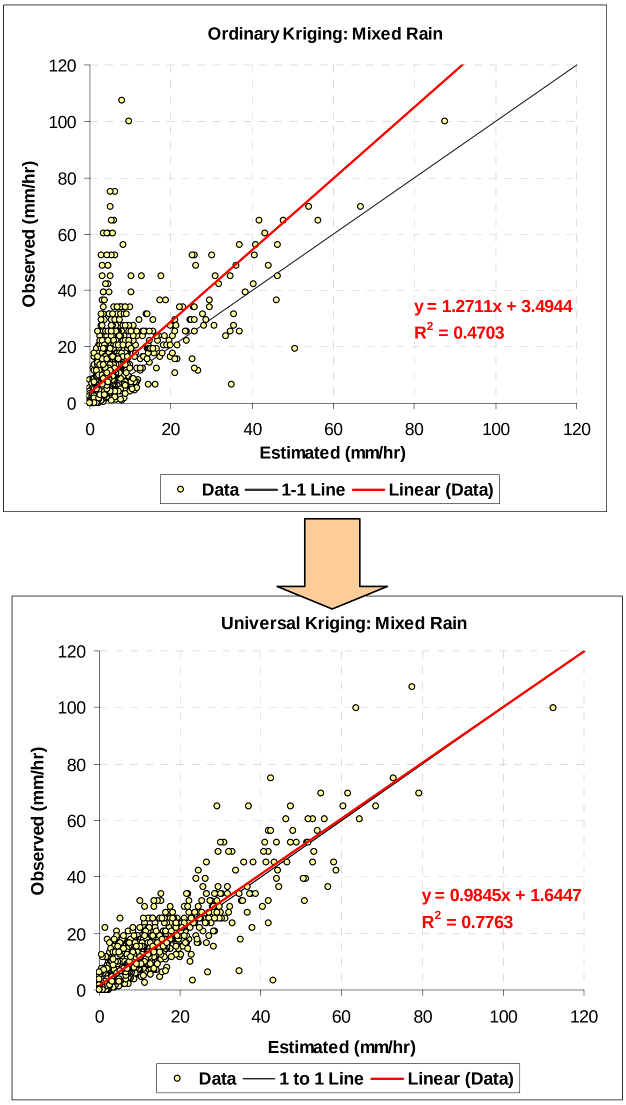

Fig.1. Scatter plot of observed and estimated rain rates at individual pixel points for mixed rainfall for a instantaneous image from the Bethlehem (South Africa) weather radar, 24 January 2002; the number of pixels estimated was 2628.

The raingauge data were block Kriged over the 9 pixels corresponding to the radar data surrounding the central gauge using the appropriate semivariogram as deduced from the radar data. Data from those raingauges within two correlation lengths of the centre of the 3 by 3 block of pixels were used to perform the Kriging. The Block Kriged raingauge data were then compared with the estimates of radar-rainfall at the ground obtained by the Cascade Kriging method.

An example of the fit appears in Figs. 2 and 3, respectively a scatter plot and a comparison of the cumulative distribution functions for the radar and the gauge data. The statistical results are summarised in Table 2.

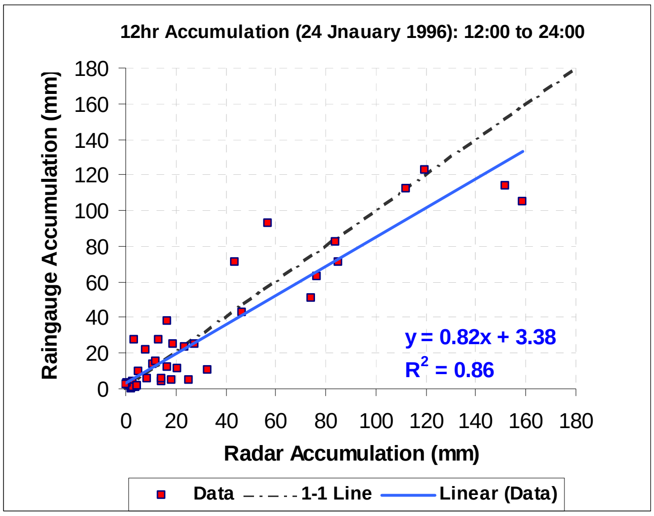

Fig. 2. Scatter plot of radar and raingauge rainfall depths for a 12-hour accumulation period for the 24 January 1996 rain event.

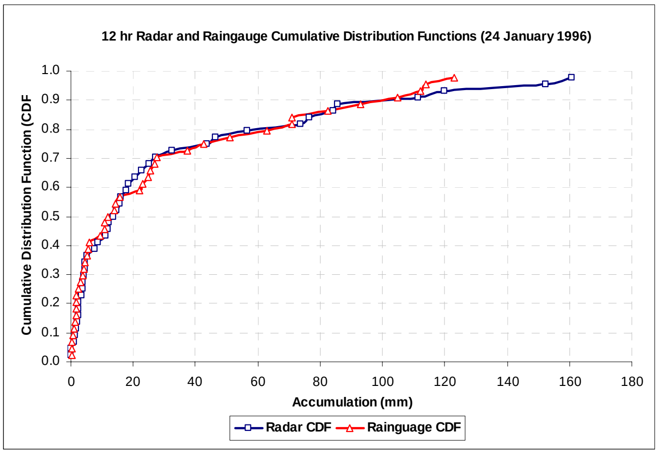

Fig. 3. Cumulative Distribution Functions for the data shown in Fig. 2. The distributions of the accumulations for the radar and raingauges are not dissimilar at a significance level of 5%.

This relatively heavy rainfall event produced pleasing results. Lighter rainfall events were not as convincing. This conclusion is supported by the middle part of Table 2 where the test rejects the Hypothesis of similar distributions, even though the means (and to a lesser extent the standard deviations) of the data are within reasonable distance of each other (from a hydrological perspective).

5 Conclusion

The methodology of infilling and extrapolation of radar-rainfall data to ground level using variants of the Kriging technique show promise in the context of the South African hydrometeorological environment, where there is little snow and where the preponderance of the country experiences summer rainfall. The methods presented here were devised to treat the data which are collected in CAPPI form. They may still be useful where the data appear in their original spherical coordinates.

Table 2: Summary of statistical results for different accumulation periods for 24 January 1996 rain event for radar and raingauge data.

	12hr accumulation (12:00 to 24:00)		**6 hr accumulation (12:00 to 18:00)**		**6 hr accumulation (18:00 to 24:00)**	
	Mean	**Stdev**	**Mean**	**Stdev**	**Mean**	**Stdev**
Radar	30.3	41.3	3.6	5.1	26.7	40.8
Gauge	29.4	36.8	4.0	7.1	25.4	38.3
Accept / reject H_0	Accept	Accept	Accept	**Reject**	Accept	Accept
R^2	0.86		0.08		0.88	
K-S test	Accept		**Reject**		Accept	

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