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Radar-based quantitative precipitation estimation over arid, semi-arid and Mediterranean climate regimes in Israel

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1 Introduction

Accurate quantitative precipitation estimation (QPE) is one of the most important elements in meteorological and hydrologic analyses. It has been long recognized, however, that rain gauge networks are usually inadequate because of their limited distribution. During the last decades intense scientific efforts have been devoted to utilize remote sensing information for the estimation of high resolution precipitation data over large areas. Ground meteorological radar systems are the most common source of this information.

Radar-based QPE are subject to several sources of errors. Among them is the effect of topography causing ground clutter contamination and beam blockage, especially in mountainous regions, beam broadening and its increasing altitude above ground with distance, and gradients of vertical reflectivity profiles. Several methods were proposed how to combine radar and gauge data to generate precipitation estimates with reduced levels of error. The simplest approach adjusts radar estimates by removing the mean bias (e.g., Krajewski and Smith, 2000). For regions with complex terrain, Gabella et al. (2000) suggested radar-gauge adjustment using the weighted multiple regression (WMR) method.

While a considerable number of papers deal with radar-based precipitation estimation in temperate climatic regimes, few have covered semi-arid and arid regions (e.g., Morin et al., 2005). In these dry regions rainstorms are often local and highly variable while rain gauge networks are very scarce. The objective of the current study is to examine methods for radar-based QPE of storm rain depth for Israel, where the climate ranges from Mediterranean to semi-arid and arid types. This goal is achieved using radar-gauge training and validation procedures applied to a five year data record.

2 Study region

Israel is located at the southeast corner of the Mediterranean Sea between latitudes 29.5-33.5°. The rainy season is October-May. Israel is characterized by a sharp gradient of annual rainfall, from more than 1000 mm in the north to only 30 mm in the south, all within a 400 km distance. Israel climate is spread over three different regimes according to Köppen classification: Mediterranean, semi-arid and arid (Fig. 1).

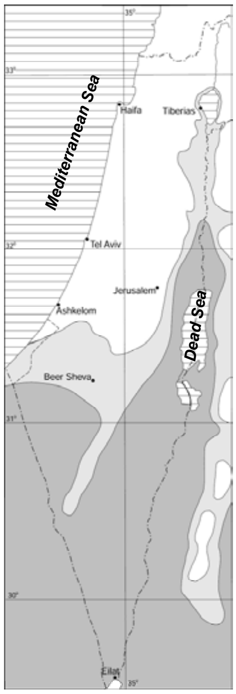

Fig. 1. Climate classification of Israel and surrounding region according to Köppen; Mediterranean in white, semi-arid in light gray and arid in gray.

3 Data and methods

3.1 Data

Radar and rain gauge data for the five hydrological years 1998/1999 – 2002/2003 were analyzed for this study. Data of the C-band radar system located at Ben-Gurion airport (central Israel) were obtained from E.M.S Mekorot (Fig. 2). Radar data resolutions are 5 minutes in time and 1.4°x1 km in space (polar coordinates) with radar scans at several elevation angles. Gauge daily rain depth data were obtained from the Israel Meteorological Service and included 274 gauges located within the radar coverage that were operating during the whole five year period (Fig. 2).

In the current study, analysis is based on storm rain depth, where storms are defined as periods of rainy days separated by at least one day with no record of rainfall in Israel. Storms with low rain depth (less than 10 mm storm depth) or with large radar data gaps (more than 50% of the storm period

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missing) were excluded from the analysis. This procedure resulted in a list of 30 storms for the study period.

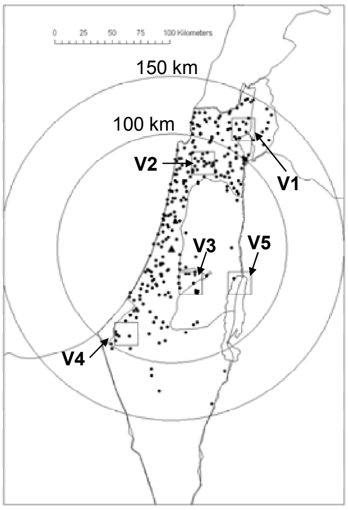

Fig. 2. Rain gauges (filled circles) and the five validation areas of 20x20 km^2 size (marked by V1-V5). Radar location is marked by a triangle and the 100 and 150 km radiuses are indicated.

3.2 Radar ground-clutter and beam blockage procedures

Two major difficulties of radar rainfall estimation in mountainous regions are signal contamination by ground clutter and radar beam blockage. In Israel the problematic regions are the mountain ridge east of the radar (Samaria and Judea Mountains) that is heavily contaminated by ground clutter and the Jordan Rift Valley east of these mountains that is blocked. Additional ground clutter areas surround the radar at a distance of 20-25 km.

The approach taken in the current study to overcome these disturbances is to use radar data from spatially-varied elevation angles such that the beam centre lays at least a whole beam width and additional 500 meters above the ground, and has a clear sight from the radar to the test point. The computation of the appropriate radar elevation angle utilizes the 3 arc sec (about 90 m) topography data of the U.S. National Oceanic and Atmospheric Administration and it assumes radiation propagation in normal atmospheric conditions.

3.3 Radar-rainfall estimation methods

Radar rainfall estimation methods examined in this study are based on an initial power law transformation as a first step and then the derivation of the storm radar-to-gauge ratios to correct the initial estimation.

The initial relation applied is

$$Z = 316R^{1.5} \quad (1)$$

where Z is the radar reflectivity data [m^{3}mm^{-6}] and R is rain intensity [mm/h]. This relationship was applied in former studies, for example Gabella et al. (2001). It should be noted that while the exponent parameter in the above relationship has some effect on the results, the multiplicative parameter is anyhow corrected with the applied factor. A lower threshold of 10 dbz (1 dbz = 10Log10Z) for noise filtering is applied and an upper threshold of 250 mm/h is applied to prevent overestimations caused by wet hail particles in the cloud. The upper threshold rain intensity value was selected based on rain intensity statistics for several rain stations in Israel. Radar rain intensities are integrated for each storm period to get initial storm depth estimations over the radar coverage.

At the second step the storm radar-to-gauge ratio is determined for locations with gauge data:

$$F = \frac{P^*}{G} \quad (2)$$

where G is the gauge storm depth and P^* is the initial radar-rainfall estimation at the radar pixel above the gauge. The different methods described below estimate the variability of F in space and its value is derived for the whole radar coverage area. The initial radar estimates are corrected by applying the derived radar-to-gauge ratios.

Three methods to estimate variability of F are examined:

1) Bulk adjustment (e.g., Krajewski and Smith, 2002): the radar-to-gauge ratio is assumed to be uniform over the whole study area. It is computed from gauge and radar storm depth data for a training data set such that the overall bias is removed:

$$F = \frac{\sum_{i=1}^{N} P^*{}_i}{\sum_{i=1}^{N} G_i} \quad (3)$$

where N is the number of storm datum.

2) Ordinary Multiple Regression – OMR: the radar-to-gauge ratio is assumed to vary in space as a function of: distance from radar, ground height and latitude. The relationships between these variables are obtained by linear regression analysis between the dependent variable F in decibels:

$$Fdb = 10Log_{10}F \quad (4)$$

and the independent variables:

a) Log of distance from radar in reference to a 60 km distance: $D = Log_{10}(d/60)$, where d is distance from the radar in km.

b) Ground height in km above see level: H.

c) Latitude in degrees with reference to the radar location of 32^{o}N: $L = l - 32$, where l is latitude in decimal degrees.

The selected reference values (60 km for distance, 0 km for ground height and 32^o for latitude) do not affect the rainfall estimations but only the derived regression coefficients.

3) Weighted Multiple Regression - WMR: Gabella et al. (2001) suggest using weighted regression instead of the standard ordinary regression to derive radar-to-gauge ratios. This method minimizes the weighted sum of square errors instead of the regular sum as in ordinary regression. The residuals are weighed according to the physical quantity of interest, i.e., rainfall amounts, in hydrological applications. There is more than one possibility: the weights can be either the radar-derived precipitation amounts or the amount of rain measured by the gauges. Furthermore, more meaningful results are obtained if the values derived from the sensor that has to be adjusted are used for weighting, since the weights act as "soft" thresholds in the regression: less importance is given to those areas where the sensor is "lacking". This fact has already been observed in similar analyses using non-linear weighted multiple regressions (Gabella et al., 2000). In Gabella et al. (2001) it was shown that the best results are obtained when radar-derived rainfall estimates serve as weights for the analysis.

3.4 Training and validation procedures

Five 20X20 km^2 validation areas were defined for the analysis (Fig. 2) representing different climate regimes as well as areas of interest for hydrological applications. The first, V1, contains 10 gauges and is located in a semi-arid/Mediterranean climate regime within the drainage area of Lake Kineret which is the main surface water reservoir in Israel. Note that from a QPE point of view this area is "far" from the radar (more than 100 km distance). The second validation area, V2, with 18 gauges is located in a region of moderate topography at about 80 km distance from the radar and within the Mediterranean climate regime. The third validation area, V3, also Mediterranean in climate, has 12 gauges but within a complex topographic area with elevations between 200-1000 m above sea level. This area is of hydrological importance because it is located within the recharge area of the mountain aquifer and therefore rainfall estimations over these areas are important for groundwater models. The fourth validation area, V4, is in a semi-arid region with annual rainfall varying between 150-300 mm. The specific location of this validation area was selected because of the relatively dense network of gauges (5 gauges within this area) as opposed to the rest of the semi-arid area. The fifth validation area, V5, is an arid region at the northern edge of the Dead Sea, with annual precipitation of 100 mm. Because of the very sparse rain gauge networks in the arid parts of Israel, only one rain gauge exists within this area. Gauges within the validation areas are excluded from the training procedure.

Training is done for each storm by computing the radar-to-gauge ratios according to the above methods based on data in the training data set, which is composed from all gauges outside the validation areas (228 gauges). Because of the ratio and logarithmic operations (see Eq. 3 and 4), only non-zero gauge and radar storm depth data are processed. The radar-to-gauge ratios obtained for the training data sets are tested for the validation data sets for the same storm. This training-validation scheme represents a situation where gauge data are available for the storm (non-real-time application). Validation results provide information on the accuracy of radar estimates in ungauged areas.

To quantify the goodness of fit between gauge storm depth, G_i, and estimated radar storm rain depth, P_i, the following scores are used:

1) Bias: $\dfrac{\sum_{i=1}^{N} P_i}{\sum_{i=1}^{N} G_i}$

2) Fractional Standard Error (FSE): $\dfrac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - G_i)^2}}{\frac{1}{N}\sum_{i=1}^{N} G_i}$

To judge the validation results a reference level of error is computed in the form of gauge-only estimation. For each gauge in the validation areas, storm rainfall is estimated by spatial interpolation of gauge data in the training data set. In this work, the Inverse Distance Weight (IDW) method is used for the interpolation. If the radar-based estimation results in better scores than the estimation based on gauge data only, then the radar estimations can be considered useful.

4 Results

4.1 Case study demonstration

We first demonstrate the analysis for one case study, the storm of 12-17/2/2000. Gauge rain depth for this storm ranged between zero to 107 mm with an average and standard deviation of 47 and 24 mm, respectively. Table 1 lists the equations derived for the storm training data set by the different estimation methods described above.

Table 1. Derived equations for the training data set of the storm of 12-17/2/2000

Method	Equation
Bulk Adj.	$Fdb = -5.91$
OMR	$Fdb = -5.53 - 10.01D - 0.83H - 3.28L$
WMR	$Fdb = -4.74 - 6.16D - 0.64H - 1.48L$

All three variables appear with negative coefficients, indicating a decrease of radar-to-gauge ratio (i.e., underestimation) with increased distance from radar, topography height and latitude. Coefficients derived using the ordinary regression method are more negative than those derived by the weighted regression method, implying lower radar-to-gauge ratios and therefore higher rainfall estimations using OMR.

Scores of fit for the training data set are presented in the first row of Table 2 (marked by T). As in previous analyses (Gabella et al. 2001 Tables 4,5 and 7; Gabella et al. 2000 Tables 5, 8b and 9), the weighted regression results in a better fit in terms of FSE relative to the other methods. However, it generally underestimates rainfall depth. The ordinary regression, on the other hand, overestimates rainfall. By definition, a perfect match between gauge data and radar estimates in terms of bias is achieved for the training data set using the bulk adjustment method.

Of more interest is the fit achieved for the validation data set (marked by V1-V5 in Table 2). In order to evaluate the derived scores, rainfall estimates based solely on gauge data were computed (IDW) and their scores of fit are provided in Table 2.

Table 2. Scores for training and validation data sets of the storm of 12-17/2/2000

	N	Score	Bulk Adj.	OMR	WMR	IDW
T	194	Bias	1.00	1.23	0.81	
		FSE	0.85	0.97	0.60	
V1	10	Bias	0.18	0.67	0.29	0.71
		FSE	0.83	0.38	0.72	0.36
V2	18	Bias	0.76	1.54	0.88	1.29
		FSE	0.39	0.74	0.33	0.71
V3	12	Bias	1.62	0.74	0.85	0.74
		FSE	1.03	0.48	0.47	0.68
V4	5	Bias	1.87	1.52	1.45	2.52
		FSE	0.99	0.63	0.56	4.56
V5	1	Bias	1.01	0.72	0.67	11.14
		FSE	0.01	0.28	0.33	10.14

As can be seen in Table 2, radar-based rainfall estimations in validation area V1 are not as good as those based on gauge data only. However, for the other four validation areas, radar estimates are better than the gauge interpolation estimates. Gauge-based interpolations in the semi-arid and arid areas (V4 and V5, respectively) were incorrect because of the sparse networks in these areas, while radar-based estimates were quite reasonable.

4.2 Five year analysis – training
The analysis was applied to the 30 storms in the five year record. In most cases coefficients of the ordinary regression method are lower than those of the weighted regression method and therefore, in general, radar rainfall estimates using the ordinary regression method are higher than the estimated based using weighted regression. The difference between the two methods results in high (low) bias for the ordinary (weighted) regression method as can be seen in the first row of Table 3. The scores in the table are the weighted averages of the thirty storm scores with storm average depth as the weighting value. For the training data set, the lower weighted score in terms of FSE is obtained for the weighted regression method.

Table 3. Weighted scores for training and validation data sets for thirty storms

	Score	Bulk Adj.	OMR	WMR	IDW
T	Bias	1.00	1.28	0.83	
	FSE	0.77	1.01	0.53	
V1	Bias	0.28	0.93	0.40	0.76
	FSE	0.75	0.55	0.63	0.39
V2	Bias	0.89	1.73	0.97	0.97
	FSE	0.34	0.93	0.34	0.40
V3	Bias	1.08	0.83	0.86	0.89
	FSE	0.66	0.49	0.46	0.62
V4	Bias	1.00	1.44	1.12	0.88
	FSE	0.21	0.53	0.26	0.73
V5	Bias	0.78	0.65	0.55	3.45
	FSE	0.36	0.49	0.52	2.46

4.3 Five year analysis – validation
Three of the validation areas are located within a Mediterranean climate regime (Fig. 2). Weighted scores for these areas are presented in Table 3 (V1-V3). As before, improvement in terms of FSE relative to gauge interpolation is achieved for validation areas V2 and V3, but such improvement cannot be shown for area V1. Most probably the reasons are the large distance of the V1 area from the radar (more than 100 km) and the sufficient gauge information to support relatively accurate spatial interpolation. For validation area V2 the weighted regression method scores the best results from the three radar-estimate methods. This method also gives minimal FSE values for validation area V3, but, in terms of bias, the bias adjustment method is somewhat better.
The improvement of rainfall estimates using radar data is most pronounced for the two dry validation areas, V4 (semi-arid) and V5 (arid), as can be seen in Table 3. The best results were obtained with the bias adjustment method. Comparison of gauge rain depth and the estimated rain depth based on the different methods is presented in Fig. 3.

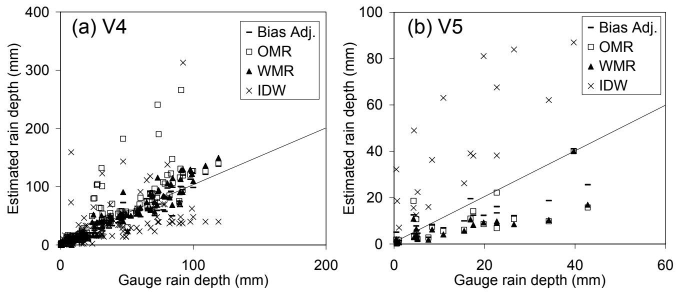

Fig. 3. Comparison of observed (gauge) and estimated (radar or gauge interpolation) storm rain depth for a) the semi-arid validation area (V4), and, b) the arid validation area (V5).

5 Summary and conclusions

The analysis presented here suggests that rainfall estimates based on radar and rain gauge data are relatively accurate as compared to estimates based on gauge interpolation. The benefits of using radar data was demonstrated for validation areas in Mediterranean, semi-arid and arid climate regimes that were less than 100 km distant from the radar system. Minimal errors, 30-50% on average, were obtained by the weighted regression method for the Mediterranean climate areas. It should be noted, however, that this method often underestimates rainfall. For the semi-arid and arid climatic regimes the standard bias adjustment method resulted in the lowest level of error, 20-30% on average. It is interesting to note that in such areas, because of a paucity rain gauge data, a high level of errors were obtained applying a gauge interpolation estimation method.
The application of the training-validation procedure used here is for situations where gauge data are available for a storm but where rainfall estimations are required for ungauged areas. A different situation is provided by real-time radar rainfall estimation, where gauge data are often not available for a current storm but only for past events. This issue is currently being investigated.

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