# Potential use of specific differential propagation phase delay for the retrieval of rain rates in strong convection over Switzerland

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## ABSTRACT

The presented work aims at investigating the potential of using retrieved fields of specific propagation delay ($K_{\mathrm{DP}}$) for rain rate estimation in Switzerland. This study is part of a broader project whose objective is to improve the QPE retrieval by complementing it with polarimetric data, instead of relying solely on the reflectivity. A large dataset of DSD measurements was used to derive a $R$-$K_{\mathrm{DP}}$ model specifically valid for Switzerland, which takes into account the type of air mass and the incidence angle, and also provides error estimates. This model was then tested on a selection of strong summer convective events, and was shown to provide a much better estimation of strong precipitation intensities than a simple $R$-$Z_{\mathrm{H}}$ power-law. A fusion routine was then implemented that merges the operational QPE with the $R$-$K_{\mathrm{DP}}$ model based on their respective expected errors. This scheme was tested on three years of spring and summer precipitation and was shown to give almost systematically a smaller error with respect to rain gauge measurements than when relying solely on the reflectivity.

## 1 Introduction

In 2011, MeteoSwiss has started the renewal and enlargement of its radar network: it now consists of five dual-polarization, Doppler, C-band radars. The update to dual-polarization offers wide opportunities, and the rich additional information it provides is already used operationally for the detection of hydrometeors classes from radar measurements and the identification of ground clutter.

Until now, MeteoSwiss has been using a sophisticated real-time quantitative precipitation estimation (QPE), based on a local correction with a vertical profile of reflectivity [Germann et al., 2006]. However this QPE algorithm is still based solely on the horizontal reflectivity, and does not benefit from the additional information brought by the dual-polarimetry. One particular quantity of interest for QPE is the specific differential differential propagation delay ($K_{\mathrm{DP}}$). $K_{\mathrm{DP}}$ is defined as the rate at which the difference between the phases measured using horizontal and vertical polarization changes with increasing distance from the radar. Several studies showed that $K_{\mathrm{DP}}$ is a superior estimator at high rain rate values as compared to conventional reflectivity, because it is unaffected by attenuation and more linearly related to the rain rate. Unfortunately, $K_{\mathrm{DP}}$ is not directly measured by a weather radar but needs to be numerically estimated from noisy observations of the total phase shift.

## 2 Methods and data

The derivation of QPE relations for Switzerland is based on a large dataset of more than 280’000 5-min averaged DSDs recorded by several Parsivel disdrometers during various field campaigns in the past 10 years.The DSDs have been corrected for spurious non- physical drops by filtering unrealistic fall velocities. From these DSDs the rain intensity has been estimated with the Beard [1976] terminal velocity model, which accounts for variations in terminal velocity due to altitude and temperature. The DSDs have then been used to simulate polarimetric variables at C-band at different incidence elevation angles, using the T-matrix method [Mishchenko et al., 2002], with a Gaussian canting angle distribution of 10° and the aspect-ratio model of Brandes et al. [2002]. These simulated polarimetric variables were used to estimate $R$-$K_{\mathrm{DP}}$ relations and error models for both the $R$-$K_{\mathrm{DP}}$ relations and the standard operational $R$-$Z_{\mathrm{H}}$ model. To derive the error models, the estimated rain rates have been binned into 200 quantiles, yielding around 1000 observations per class, for which an average root-mean-square error (RMSE) is computed. Power-law were then fitted for every elevation angle, both for the $R$-$K_{\mathrm{DP}}$ relations and their error models. The power-law fits were performed with non-linear fitting, using the mean absolute error (MAE) as cost function.

The proposed models were then tested on real radar data, using a dataset of 15 strong convective events, and focusing on 30 raingauges with good radar visibility around the three lower altitude radars (La Dôle, 1682 m, Albis 938 m, Monte Lema 1626 m). Restricting all measurements to relatively high intensities ($R \geq 1$ mm h$^{-1}$) gives of total of 459 gauge-hours measurements,

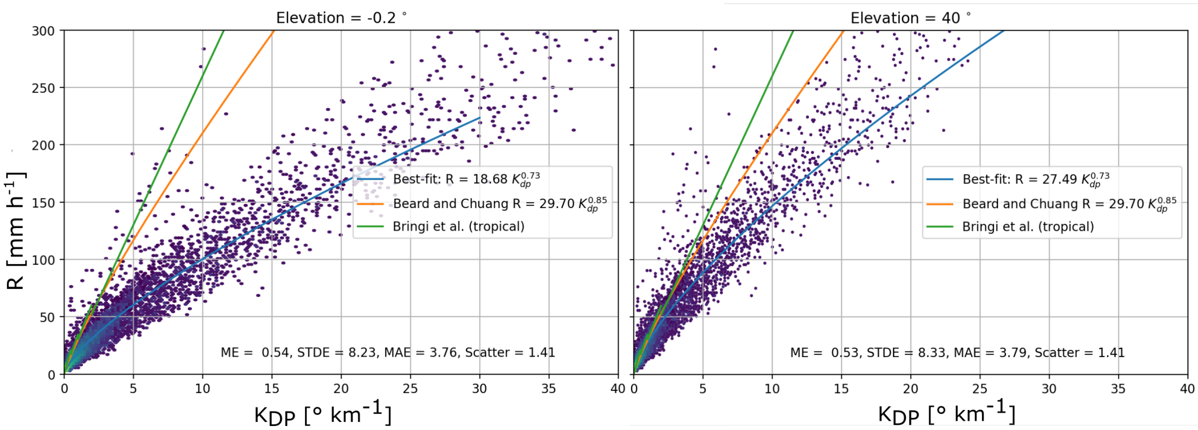


**Figure 1.** $R$-$K_{DP}$ relationships for the two extreme elevation angles used by MeteoSwiss. ME, STDE, and MAE indicate the mean error, the standard deviation of errors and the mean absolute error of the estimated R (in mm $h^{-1}$).

with an average precipitation intensity of 8.59 mm $h^{-1}$.

| Campaign | Avg. Alt. [m] | Coordinates | Period | Nb. of 5 min DSDs |
|---|---|---|---|---|
| Ardèche (France) | 300 | 44.65°N, 4.49°E | Fall 2012, 2013, 2014 | 95’085 |
| Lausanne (EPFL) | 400 | 46.52°N, 6.57°E | Jan. 2008 to Nov. 2008 | 96’624 |
| Rietholzbach | 750 | 47.38°N, 9°E | Aug. 2011 to May 2012 | 37527 |
| Zürich | 480 | 47.4°N, 8.51°E | Mar. 2011 to Sep. 2012 | 23788 |
| Davos | 2540 | 46.77°N, 9.83°E | Jan. 2010 to Jul. 2011 | 15982 |
| Payerne | 450 | 46.83°N, 6.90°E | Spring 2014 | 12451 |
| | | | | **281’620** |

**Table 1.** List of all Parsivel data from various field campaigns operated by the LTE-EPFL lab. and used in the derivation of $R$-$K_{DP}$ relationships. Note that the Ardèche dataset is located outside of Switzerland, but was found to be statistically consistent with the Swiss data.

## 3 Results of the $R$-$K_{DP}$ derivations

Figure 1 shows the two $R$-$K_{DP}$ power-laws obtained from the lowest and highest elevation angles used in the MeteoSwiss scanning strategy. One can see clearly that the $R$-$K_{DP}$ relation becomes steeper for increasing elevation angles, which is due to the fact that raindrops appear more and more spherical leading to smaller $K_{DP}$ for the same rain intensity.

In fact, the elevational trend in these power-laws was found to be well fitted with a simple linear regression, giving the generalized relations:

$$R(K_{DP}) \approx (18.638 + \alpha_{el}(\theta))\, K_{DP}^{0.73} \tag{1}$$

with $\theta \in [-0.2, 40°]$

$$\alpha_{el}(\theta) = 1.725910^{-2}\theta + 2.0054610^{-3}\theta^2 + 7.6520310^{-5}\theta^3 \tag{2}$$

Figure 1 also shows two $R$-$K_{DP}$ given in the literature, for more tropical precipitation (the Bringi et al. model was derived in Darwin, Australia [Bringi et al., 2001]), while the Beard and Chuang DSD based model was derived in Oklahoma, during a heavy storm [Sachidananda and Zrnic, 1986]. It can be observed that the Swiss observations differ quite strongly from these models, which might be due to the fact that precipitation in Switzerland is more continental and consists of fewer but larger drops. In fact a few samples (within the blue ellipse in Figure 1), seem to agree much better with these models.

Therefore, the final model takes into account $Z_{DR}$ to discriminate between more tropical (for which the Beard and Chuang $R$-$K_{DP}$ model is used) and more continental rain (for which the best fits from Parsivel data is used), as proposed by Ryzhkov et al. [2014].

$$R(K_{\mathrm{DP}}, Z_{\mathrm{DR}}) = \omega \left(18.638 + \alpha_{\mathrm{el}}(\theta)\right) K_{\mathrm{DP}}^{0.73} + (1-\omega)\left(29.7 + \alpha_{\mathrm{el}}(\theta)\right) K_{\mathrm{DP}}^{0.85} \tag{3}$$

where $\omega$ is a weight that depends on $Z_{\mathrm{DR}}$ with a sigmoid function:

$$\omega = 2.3 \frac{1}{1 + \exp\left[-(Z_{\mathrm{DR}} - 1.2)\right]} \tag{4}$$

Note that the parameters of the weighting $\omega$, have been derived by cross-validation in order to minimize the error of the final $R(K_{\mathrm{DP}}, Z_{\mathrm{DR}})$ estimate. The effect of this combined model leads to a removal of some strong outliers, while barely affecting all other points. Overall, it leads to a corresponding decrease of all additive errors (bias, standard deviation of error and mean absolute error).

Estimates of rain intensities would not be complete without an estimation of the associated incertitude. Figure 2 shows the estimated error models, for the operational $R$-$Z_{\mathrm{H}}$ relation and the proposed $R$-$K_{\mathrm{DP}}$ model (Equ. 3) for the minimal and maximal elevation angles used by MeteoSwiss.

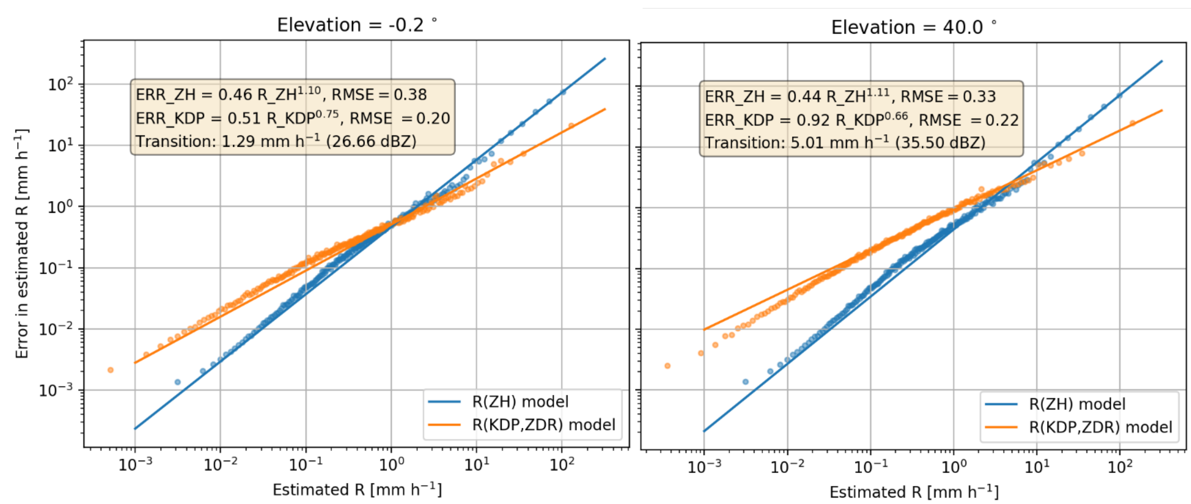


**Figure 2.** Error-models for the two extreme elevation angles used by MeteoSwiss, for the operational $R$-$Z_{\mathrm{H}}$ model (blue) and the proposed $R$-$K_{\mathrm{DP}}$ model (orange). The transition value is the limit from which the $R$-$K_{\mathrm{DP}}$ model gives a smaller error.

The transition value indicated in the plots is the estimated precipitation intensity starting from which the $R$-$K_{\mathrm{DP}}$ gives the smaller error. Obviously, at higher elevation angles, $K_{\mathrm{DP}}$ becomes less informative as it tends to decrease for a constant rain rate. It was observed that these error models could be generalized to all elevations used by MeteoSwiss with the following formulas.

$$\begin{cases} \sigma_{R-Z_{\mathrm{H}}} = 0.46\, R(Z_{\mathrm{H}})^{1.1} \\ \sigma_{R-K_{\mathrm{DP}}} = A(\theta)\, R(K_{\mathrm{DP}})^{B(\theta)} \end{cases} \tag{5}$$

where

$$\begin{cases} A(\theta) = 0.5106 - 2.79510^{-3}\theta + 3.03110^{-4}\theta^2 + 4.16510^{-7}\theta^3 \\ B(\theta) = 0.747 + 4.49310^{-3}\theta - 3.92510^{-4}\theta^2 + 5.49210^{-6}\theta^3 \end{cases} \tag{6}$$

Note that the very weak elevational dependence on the $R$-$Z_{\mathrm{H}}$ model has been neglected.

## 4 Testing the model with radar data and various $K_{\mathrm{DP}}$ estimators

In practical applications, $K_{\mathrm{DP}}$ has to be estimated numerically from noisy phase measurements, with a robust estimator. To determine the best estimators, hourly precipitation intensities retrieved with the $R$-$K_{\mathrm{DP}}$ relation with $K_{\mathrm{DP}}$ obtained from several estimators were compared with gauge measurements using the convective dataset described in Section 2.

The seven last rows in Table 2 list the scores obtained with several $K_{\mathrm{DP}}$ estimators (the Maesaka et al. [2012] method, the Vulpiani et al. [2012] method, and with a simple moving linear regression, with prior median filtering, but with different window sizes). The four first rows correspond to various estimates of $R$ based on $Z_{\mathrm{H}}$. The first is the power-law that is used operationally, the second is a polynomial relation originally derived by Ishtar Zawadzki and presented in Fabry [2015], the third

| Method name | ME | STDE | MAE | Scatter [dB] | Bias []dB[] |
|---|---|---|---|---|---|
| $Z_h = 10^{2.5}$ R$^{1.5}$ | -4.94 | 7.54 | 5.34 | 2.68 | -3.72 |
| Zawadzki Z-R | -2.52 | 8 | 5.03 | 3.17 | -1.51 |
| Operational QPE | -2.3 | 6.06 | 3.88 | 2.10 | -1.33 |
| CPC | -0.92 | 4.63 | 2.68 | 1.42 | -0.49 |
| KDP_Maesaka | -1.79 | 5.14 | 3.17 | 1.84 | -1.01 |
| KDP_Vulpiani | 7.98 | 5.92 | 8.79 | 2.43 | 2.85 |
| KDP_LS_1W_2000 | 4.91 | 8.05 | 6.68 | 2.47 | 1.96 |
| KDP_LS_1W_3000 | 2.32 | 6.57 | 4.68 | 2.10 | 1.04 |
| KDP_LS_1W_4000 | 1.04 | 5.98 | 3.87 | 1.93 | 0.5 |
| KDP_LS_1W_5000 | 0.47 | 5.64 | 3.52 | 1.90 | 0.23 |
| KDP_LS_1W_6000 | -0.07 | 5.6 | 3.33 | 1.74 | -0.04 |

**Table 2.** Scores of several $K_{\mathrm{DP}}$ estimators at hourly . ME, STDE and MAE are all in mm h$^{-1}$ and the Scatter and Bias are in dB Germann et al. [2006].

is the operational QPE that includes many additional corrections (see Germann et al. [2006]), and the last is the CombiPrecip (CPC) product, which merges radar and gauge measurements [Sideris et al., 2014].

It appears that for this particular dataset of strong convective events, the $R$-$K_{\mathrm{DP}}$ model appears to be generally superior to the $Z_{\mathrm{H}}$ based models, both in terms of additive errors (ME, STDE, MAE) and multiplicative error (Scatter). The $K_{\mathrm{DP}}$ method that provides the best results is the Maesaka et al. [2012] method, which unfortunately is valid only in the liquid phase. The next best choice is the least-squares method with a large window size (6000 m), which offers the advantage of being also valid in the solid phase, and being a very simple method. To illustrate this, Figure 3 clearly shows how closer to the 1-1 line the $R$ estimates provided by $R$-$K_{DP}$ are when compared to a simple $R$-$Z_{\mathrm{H}}$ relation. Note that the Vulpiani et al. [2012] method could benefit from a preliminary filtering of the raw phase field but this could not be tested yet.

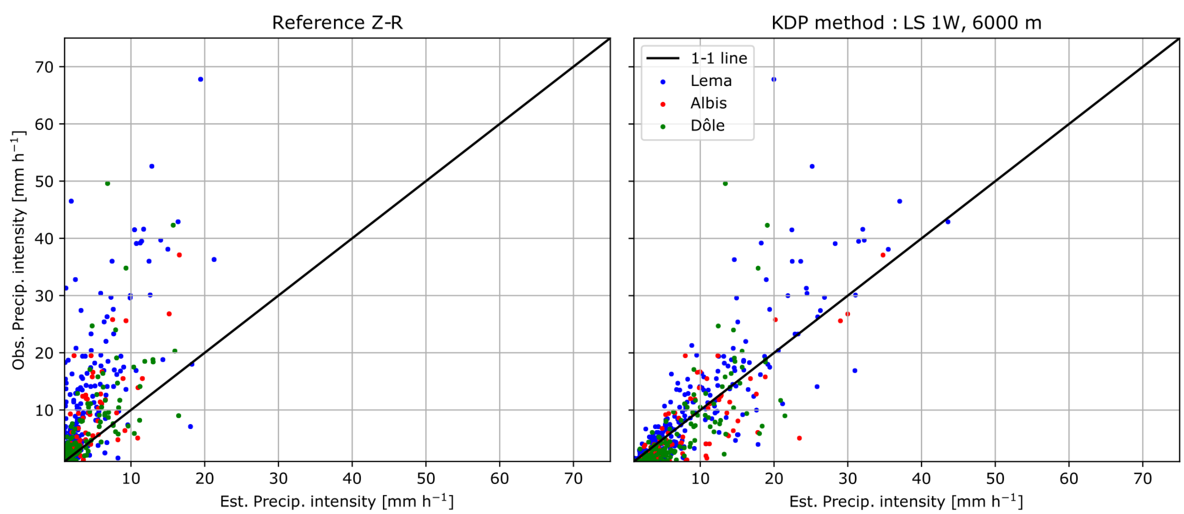


**Figure 3.** Observed versus estimated precipitation intensities, during strong convective events, for the reference $Z-R$ relation and the $K_{\mathrm{DP}}$-$R$ model, with $K_{DP}$ obtained with a moving least-square method.

The previous comparison focused on heavy precipitation and is thus naturally advantageous to the $K_{\mathrm{DP}}$ based QPE. Obviously, an operational QPE needs to perform well in low precipitation also. A very preliminary merging scheme was thus developed in which both the traditional $R$ estimate based on $Z_{\mathrm{H}}$ and the estimate based on $K_{\mathrm{DP}}$ are merged depending on their expected estimation errors (see Figure 2). Note that, according to the previous conclusions, the simple least-square method with a window size of 6000 m was used as $K_{\mathrm{DP}}$ estimation method. This scheme was then tested on 3 years of summer precipitation, for a total of more than 30'000 hours of gauge measurements with $R > 0.3$ mm h$^{-1}$, at gauges with good visibility around all Swiss radars. In fact the operational QPE includes many additional subtleties (weighting based on altitude, visibility correction, vertical profile of reflectivity correction, bias correction at the ground). These procedures were also applied to the merged

QPE, with the exception of the fusion of the estimates from the different radars (only the closest radar is used currently). The scores are shown in Table 3. Here again it is obvious that the merged QPE, which includes the $R$-$K_{\mathrm{DP}}$ model, gives a much better estimation of precipitation intensities, with a decrease in all additive errors, and a reduction of the multiplicative bias. The improvement with respect to the operational QPE is not as important, and is not consistent for all radars (for some radars, the operational QPE is better) which might be due to the positive effect of combining the different radars to derive the final precipitation estimate. Obviously, these results still require some further investigation.

| Method | ME | STDE | MAE | Scatter [dB] | Bias [dB] |
|---|---|---|---|---|---|
| Operational QPE | -0.122 | 1.85 | 0.93 | 2.85 | -0.31 |
| Research QPE, $Z_{\mathrm{H}}$ only | 0.95 | 3.74 | 1.45 | 2.85 | 1.87 |
| Research QPE, merged | 0.51 | 1.73 | 1.08 | 2.77 | 1.77 |

**Table 3.** Validation scores obtained from a comparison with hourly gauge measurements during three years (from May to October only). The research QPE is a Python implementation that includes all steps of the operational QPE, except the radar fusion part. The bias is the average ratio of the estimated intensity over the gauge measurement over estimated intensities, expressed in log scale. A positive value indicates overestimation.

## Conclusions

Specific $R$-$K_{\mathrm{DP}}$ relations were derived for Switzerland using simulations of polarimetric variables based on a large dataset of measured DSDs. A model was derived that provides estimates of rain intensity and its associate error estimates from $K_{\mathrm{DP}}$ at different incidence angles and for different types of rainfall, using $Z_{\mathrm{DR}}$ as a way to differentiate between more continental rainfall (few large drops) and more tropical rainfall (many small drops). This model was then tested on strong summer convection events, and it was found that for strong rainfall this estimation method was very promising, leading to a significant reduction of additive and multiplicative errors, with respect to an $R$-$Z_{\mathrm{H}}$ power-law, even when a simple least-square $K_{\mathrm{DP}}$ retrieval method is used. A new QPE was then tested which combines the operational QPE based on $Z_{\mathrm{H}}$ with the new estimate based on $K_{\mathrm{DP}}$, using their respective expected errors. A validation on three years of gauge measurements, shows a significant improvement of the merged model, with respect to using $Z_{\mathrm{H}}$ only, but much less improvement compared with the operational QPE, which might be due to the fact that in our simplified model, for each gauge only the closest radar was considered.

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