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# Areal rainfall estimation using moving cars as rain gauges – a modelling study

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## Abstract

Optimal spatial assessment of short-time step precipitation for hydrological modelling is still an important research question considering the poor observation networks for high time resolution data. The main objective of this paper is to present a new approach for rainfall observation. The idea is to consider motorcars as moving rain gauges with windscreen wipers as sensors to detect precipitation. This idea is easily technically feasible if the cars are provided with GPS and a small memory chip for recording the coordinates, car speed and wiper frequency. This study explores theoretically the benefits of such an approach. For that a valid relationship between wiper speed and rainfall rate considering uncertainty was assumed here. A simple traffic model is applied to generate motorcars on roads in a river basin. Radar data are used as reference truth rainfall fields. Rainfall from these fields is sampled with a conventional rain gauge network and with several dynamic networks consisting of moving motorcars. Those observed point rainfall data from the different networks are then used to calculate areal rainfall for different scales. Ordinary kriging and indicator kriging are applied for interpolation of the point data with the latter considering uncertain rainfall observation by cars e.g. according to a discrete number of windscreen wiper operation classes. The results are compared with the true values from the radar observations. The study is carried out for the 3300 km<sup>2</sup> Bode river basin located in the Harz Mountains in Northern Germany. The results show, that the idea is theoretically feasible. Only a small portion of the cars needed to be equipped with sensors for sufficient areal rainfall estimation. Regarding the required sensitivity of the potential rain sensors in cars it could be shown, that often a few classes for rainfall observation are enough for satisfactory areal rainfall estimation. The findings of the study suggest also a revisiting of the rain gauge network optimisation problem.

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# 1 Introduction

Rainfall is the most important input information for hydrological planning and water resources management. Especially the modelling of highly dynamic and nonlinear processes like floods, erosion or wash out of pollutants relies heavily on good information about precipitation. Due to its high variability in space and time observation of rainfall is still a challenging task. While the classical networks of non-recording rain gauges with a daily observation interval have reached a sufficient density and a good standard, the availability and density of recording rain gauges for the observation of short time step rainfall is still inadequate. Even for developed European countries like Germany the network density of recording rain gauges considering stations with longer records from the German Weather Service (DWD, MI network) is only about one station per 1800 km<sup>2</sup> compared to a density of about one station per 90 km<sup>2</sup> for non-recording rain gauges. Weather radar is a very important new data source for measuring rainfall. However, despite the high spatial resolution of radar data there is often a large space-time variable bias in radar rainfall estimates (Krajewski and Smith, 2002; Smith et al., 2007). So, a sufficient point precipitation network is still needed for calibration. Other special and innovative methods for rainfall observation use satellites (Grimes and Diop, 2003; Wardah et al., 2008), microwave links (Leijnse et al., 2007; Messer et al., 2006) or rain gauges aboard moving ships to measure rainfall at sea (Hasse et al., 1998; Yuter and Parker, 2001). Utilising rainfall information from different sources together and applying sophisticated interpolation or merging methods can further improve precipitation estimation for hydrological applications (Chiang et al., 2007; Ehret et al., 2008; Goovaerts, 2000; Goudenhoofd and Delobbe, 2009; Haberlandt, 2007).

The main objective of this paper is to present a new idea for measuring precipitation using moving cars as rain gauges with windscreen wipers as sensors to detect precipitation. This idea would easily be technically feasible if the cars were provided with a GPS and a small memory chip for recording time, car velocity and wiper frequency. Alternatively, also an online transmission of the sensed information via mobile phones

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could be realized. The potential of such a concept becomes immediately clear considering the high and ever increasing traffic density worldwide with a huge number of cars; e.g. in Germany exist more than 40 million cars (EUROSTAT, 2009).

This study explores theoretically the benefits of such an approach. A simple statistical traffic model is applied to generate car traffic on main roads in a river basin. Radar rainfall data are used as reference truth rainfall fields. Rainfall from these fields is sampled with a conventional rain gauge network and with a dynamic network consisting of moving motorcars. Those observed point rainfall data from the two networks are then used to calculate areal rainfall for different scales. Ordinary kriging and indicator kriging are applied for interpolation with the latter considering discrete rainfall ranges according to a likely number of windscreen wiper operation classes. The results are compared with the true values from radar observations. The paper is organised as follows. In Sect. 2 the methodologies for traffic generation and rainfall estimation are introduced. Section 3 presents the study region and the data. Areal rainfall estimation is carried out and the results are discussed in Sect. 4. Finally, in Sect. 5 a summary, conclusions and an outlook are given.

## 2 Methodology

### 2.1 Traffic generation model

The traffic flow of the moving cars is determined in a simple stochastic simulation process. The necessary data for the traffic flow model is geometric information about roads with associated information about traffic density at different times of the day. Furthermore, assumptions about the relative number of cars that is equipped with a rain sensor are needed. Finally, a factor determines the sampling rate, i.e. the frequency of measurements in time.

Based on these assumptions, cars are randomly generated for each road segment. From their starting position, the cars virtually drive with the given velocity towards the

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end-node of the road segment. Their position is interpolated according to the given sampling rate, here in intervals of 5 min. This leads to a collection of car positions on the roads in the form:  $x$ ,  $y$  and time. Subsequently, rainfall observations are assigned to the car positions and areal rainfall is estimated using interpolation (see below).

## 2.2 Rainfall observation by cars

Rainfall observation by cars could be realised using the windscreen wipers as sensors. The cars need to be equipped with a GPS system to obtain the geographical position. In addition a memory chip is necessary to register time, location, car speed and wiper frequency. A crucial task for this system to work is the derivation of a relationship between wiper speed and rainfall intensity. In general the rainfall intensity to be estimated depends on the wipers frequency, the car speed, the specific properties of the car and the driver's preferences operating the car. The influence of the latter could be avoided if photocell rain detectors installed in modern cars for automatic set up of wiper speed are used directly as sensors. In order to establish a relationship between rainfall rate and wiper frequency calibration is required, which could be achieved in the following ways:

- a) The system is calibrated a priori in a laboratory. Because of the many different car types and wiper systems this method is only practical considering a set of unique or similar car types. One idea would be to make use of public traffic like buses as rain gauges which are operated by one owner and have similar features, which would allow a laboratory calibration with acceptable effort.
- b) The relationships are calibrated by comparison of observed rainfall from conventional rain gauges and observed wiper frequencies in a re-analysis mode. For this method rainfall has to be interpolated from the rain gauges to the car locations considering distance and spatial variability. Also radar data could be used as additional information for calibration.

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c) The relationships are derived by on-line calibration using rainfall rates obtained from nearby automatic rain gauges with remote transmission capabilities. This would allow a dynamic updating of the transformation functions and an adaptation to different conditions like different drivers of the cars. Such a system could be further improved by allowing a communication between the cars propagating such information through the whole “sensor network” (Stefanidis and Nittel, 2004).

The calibration of the relationships between wiper frequency and rainfall rate using observed data from rain gauges would have some similarities to the procedure for calibration of radar data using the  $Z-R$  relationship. However, additional difficulties arise from the fact, that each car has its own specific features and is moving in space. Investigations for establishing valid relationships between wiper frequency and rain rate are beyond the scope of this pilot study and need quite an amount of further research. Here, it will be assumed, that such relationships exist, which allow the derivation of rainfall from the cars with uncertainty. This uncertainty will be considered by using only a few discrete classes for the rainfall rates obtained from the cars (see also Sects. 2.3 and 4.2).

### 2.3 Areal rainfall assessment

Rainfall interpolation is required to estimate raster based continuous rainfall fields in space from point observations and to calculate areal rainfall for regions or catchments. For rainfall interpolation two geostatistical methods ordinary kriging (OK) and indicator kriging (IK) are employed. OK is used for the interpolation of rainfall from the stationary gauge network and as reference method assuming continuous observation ability of the moving rain gauges. IK is used for the interpolation of rainfall measured by the cars considering their discrete observation ability in practice. It is assumed, that using the moving cars as rain gauges only a limited accuracy is possible providing rainfall observations in discrete classes. In the following a brief overview of the interpolation methods OK and IK and their implementation for this investigation is given. A more

detailed description about the theory of the methods can be found in geostatistical textbooks (e.g. Goovaerts, 1997; Isaaks and Srivastava, 1989).

Ordinary Kriging (OK) is the best known and most used geostatistical interpolation method (Matheron, 1971). For using OK the requirements of the intrinsic hypothesis have to be met. That means, first, the expected value of the variable  $Z$  is constant in the whole domain

$$E[Z(u)] = m \quad \text{for all } u \in D \quad (1)$$

and, second, the variance of the differences  $[Z(u+h)-Z(u)]$  between two points depends only on the distance vector  $h$  and not on the locations  $u$  and  $u+h$

$$\gamma(h) = \frac{1}{2} \text{Var}[Z(u+h) - Z(u)] \quad u \in D. \quad (2)$$

The function  $\gamma(h)$  is called here variogram (exact semivariogram), characterising the spatial variability of the target variable. The linear estimator for the unknown point  $u_0$  is a weighted sum of the observations from the  $n$  surrounding points  $u_i$ :

$$Z^*(u_0) = \sum_{i=1}^n \lambda_i Z(u_i). \quad (3)$$

The weights  $\lambda$  are calculated using the OK kriging system

$$\sum_{j=1}^n \lambda_j \gamma(u_i - u_j) + \mu = \gamma(u_i - u) \quad i = 1, \dots, n$$

$$\sum_{j=1}^n \lambda_j = 1, \quad (4)$$

where  $\lambda$  are the variogram values and  $\mu$  is a Lagrange parameter. Considering that time series of precipitation need to be processed a variance weighted average experimental

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variogram is calculated assuming isotropy

$$\bar{\gamma}^*(\mathbf{h}) = \frac{1}{m \cdot 2n(\mathbf{h})} \sum_{t=1}^m \frac{1}{s_t^2(Z)} \sum_{i=1}^{n(\mathbf{h})} [Z(u_i, t) - Z(u_{i+\mathbf{h}}, t)]^2, \quad (5)$$

where  $m$  is the number of time steps  $t$  and  $s_t^2$  is the variance for each time step. In this case only one experimental variogram is obtained, for which the fitting of the theoretical model can be done manually. The combination of a nugget effect with an exponential model is used here uniformly as theoretical variogram model:

$$\gamma(\mathbf{h}) = c_0 + c \cdot \left[ 1 - \exp\left(-\frac{3\mathbf{h}}{a_e}\right) \right], \quad (6)$$

where  $a_e$  is the effective range,  $c$  is the partial sill and  $c_0$  is the nugget variance.

For indicator kriging (IK) (Journel, 1983) the observed variable  $Z(u)$  is first transformed into a binary indicator variable  $I_\alpha$  according to

$$I_\alpha = \begin{cases} 1 & \text{if } Z(u) \leq \alpha \\ 0 & \text{otherwise} \end{cases}. \quad (7)$$

Using several thresholds  $\alpha_k$  with  $k=1, \dots, K$  gives a vector of indicator variables  $I_{\alpha,k}$ . Variograms have to be inferred for all indicator variables separately. Considering ordinary indicator kriging the interpolation is done for each indicator using the OK framework, which gives in the end an estimation of the cumulative distribution function (cdf) of  $Z(u)$ . Order relation deviations are corrected a posteriori following the approach of Deutsch and Journel (1992, p. 81). The mean of the cdf approximated by its discrete sum provides then an estimate for the observed variable:

$$Z^*(u) = I_{\alpha_0}(u)\alpha_0 + \sum_{k=0}^K \left[ I_{\alpha_{k+1}}^*(u) - I_{\alpha_k}^*(u) \right] \cdot \frac{\alpha_{k+1} - \alpha_k}{2}, \quad (8)$$

where  $\alpha_0$  and  $\alpha_{k+1}$  are the minimum the maximum values of the  $Z$ -range, respectively.

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## 2.4 Performance assessment

To evaluate the performance of the moving car network for estimation of areal precipitation reference “truth” rainfall fields derived from weather radar are used. Areal rainfall estimates based on moving car networks and based on a stationary gauge network are compared against “true” areal rainfall calculated from the reference radar data. Precipitation from both networks is interpolated on a regular raster for each time step using the methods described in Sect. 2.2 and then aggregated to areal averages  $Z_A^*(t)$  considering different spatial scales

$$Z_A^*(t) = \frac{1}{N} \sum_{i=1}^N Z^*(t, u_i), \quad (9)$$

where  $N$  is the number of raster cells within the area and  $t$  is the time step. For evaluation of the areal precipitation estimates the following performance criteria are used:

the total bias

$$\text{Bias} = \sum_{t=1}^m [Z_A^*(t) - Z_A(t)], \quad (10)$$

the relative standard error normalised with the average of the true areal value

$$\text{RSE} = \frac{1}{\bar{Z}_A} \cdot \sqrt{\frac{1}{m} \sum_{t=1}^m [Z_A^*(t) - Z_A(t)]^2} \quad (11)$$

and the coefficient of correlation

$$\text{Cor} = \frac{\text{Cov} [Z_A(t), Z_A^*(t)]}{\sqrt{\text{Var}[Z_A(t)] \cdot \text{Var} [Z_A^*(t)]}}, \quad (12)$$

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where  $Z_A^*$  is the estimated areal precipitation,  $Z_A$  the true areal precipitation and  $m$  the number of time steps considered for error calculation.

The performance of the areal rainfall estimation depends on the network density. To quantify the density of the station network and the car network the following kernel density estimator is applied to all cells  $i=1, \dots, N$  of the 1 km×1 km grid (Silverman, 1986):

$$D_i = \frac{1}{\pi r^2} \sum_{j=1}^n k_j \quad \text{with} \quad k_j = \begin{cases} 3 \left(1 - \left(\frac{d}{r}\right)^2\right)^2 & \text{for } d \leq r \\ 0 & \text{for } d > r \end{cases}, \quad (13)$$

where  $n$  is the number of stations within the search radius  $r$  and  $k$  is a quartic kernel weighting the stations according to their distance  $d$  from the cell centre. The total network density for one specific area or subbasin  $D_{\text{sub}}$  is then calculated by averaging  $D_i$  over all raster cells within the considered catchment. The kernel density is chosen here as estimator to consider all appropriate stations, also those located outside the catchment boundaries and to weigh the individual stations differently according to their distance from the subbasin.

### 3 Study region and data

#### 3.1 Study region

The study is carried out for the 3300 km<sup>2</sup> Bode river basin located in the Harz Mountains in Northern Germany (Fig. 1). The considered Bode region has elevations between 1140 m a.s.l. at the top of the Brocken Mountain and about 80 m a.s.l. Mean annual rainfall varies between 1700 mm/yr and 500 mm/yr. Four mesoscale catchments of different sizes are selected for areal rainfall estimation, which comprise the Trautenstein (40 km<sup>2</sup>), the Selke (102 km<sup>2</sup>), the Holtemme (167 km<sup>2</sup>) and the Gr. Graben (812 km<sup>2</sup>) catchments. The stationary rainfall observation network consists of 14

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recording rain gauges with 6 stations operated all year and 8 stations operated only during the summer time. The all year station network represents a typical recording rain gauge network density in Germany. In addition, a weather radar station is located at Ummendorf covering the whole area within its observation range.

5 For the car networks road data from the topographic information system (here, the German ATKIS) are used, where the roads are given according to different road categories ranging from highways to side roads. In order to make conservative estimations, only the highest road categories, namely highways and federal roads are considered here (see Fig. 1).

## 10 3.2 Traffic data

Traffic statistics were taken from a study related to noise propagation (R.-D. Mummen-  
they, Trade Office Hildesheim, personal communication, September 2008). Table 1  
shows the traffic data which are used in this study. Assumed average speed of the  
cars on major roads is 80 km/h. Three different classes of traffic density with respect  
15 to different times of the day are used. For simplification all traffic statistical data are  
applied uniformly within the whole study area. Only a certain fraction of all cars will  
be prepared to measure precipitation. For that four different sensor equipment rates  
between 0.5% and 4% are assumed here (see Table 1). The windscreen wipers are  
used as sensors to detect and measure precipitation. The rainfall intensity can be de-  
20 rived from the wipers frequency. As currently there is no known relationship between  
the wiper frequency and the rainfall intensity simple assumptions are made. The first  
one is to have an exact observation of the rainfall intensity as reference for potential  
maximum accuracy. The other assumptions are to use different rainfall observation  
classes, e.g. corresponding to the wiper frequency intervals that can be manually set  
25 in the cars (see also Sect. 4.2).

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### 3.3 Rainfall data

To provide reference rainfall fields for the simulation experiments radar data from the C-band instrument at Ummendorf are utilised. The data were provided by the German Weather Service (DWD) as raw reflectivities with a spatial polar resolution of  $1 \text{ km} \times 1^\circ$  and a time discretisation of 5 min. The reflectivities are converted into rainfall intensities applying the Marshall-Palmer  $Z-R$  relationship (Marshall and Palmer, 1948)

$$Z = 200 \cdot R^{1.60}, \quad (14)$$

where  $Z$  is the reflectivity in  $\text{mm}^6/\text{m}^3$  and  $R$  the rainfall intensity in  $\text{mm}/\text{h}$ . The rainfall intensities are interpolated to a  $1 \text{ km} \times 1 \text{ km}$  rectangular grid. Here a simple a nearest neighbour approach is used for those raster cells containing no more than one radar point; otherwise the mean value from all available radar points with a raster cell is taken. The radar data have been corrected for attenuation and clutter errors (Krämer, 2008), although this was not really necessary for this exercise. A bias correction of the radar data e.g. using the observations has not been applied here.

The heavy summer storm lasting from 16 July 2002 to 19 July 2002 has been selected for this analysis. It is characterised by high temporal and spatial rainfall variability with “observed” rainfall sums over the four days between 31 mm and 125 mm sampled at the 14 rainfall station locations from the radar fields. Rainfall data are used at a temporal resolution of 5 min for this analysis. Figures 2 and 3 illustrate the spatial and temporal variability of the event based on the radar precipitation data. Most rainfall occurs at the second day of the event, however with a high temporal variability. Note also that there are quite pronounced differences between the time series of areal rainfall for the four selected catchments. For further analyses only the time steps from 51 to 700 of the event are considered (see Fig. 3), which cover the most significant rainfall period.

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## 4 Analysis and results

For the analysis the following steps are carried out:

1. Areal reference rainfall time series are calculated for the selected catchments from the 5 min radar rainfall fields (cp. Fig. 3).
2. Point precipitation time series are extracted for the stationary rainfall gauge network from the 5 min radar rainfall fields.
3. Cars are randomly generated on highways and federal roads according to traffic density statistics and sensor equipment rates (cp. Table 1).
4. Point precipitation time series are extracted for the moving car networks from the 5 min radar rainfall fields considering the discrete observation ability of the car sensors.
5. The point rainfall time series from the gauge network are interpolated using ordinary kriging (OK) on a 1 km×1 km raster for the whole Bode river basin and are subsequently aggregated over the selected catchments to areal rainfall time series.
6. The point rainfall time series from the different car networks are interpolated using ordinary kriging (OK), indicator kriging with 4 rainfall classes (IK4) and indicator kriging with 10 rainfall classes (IK10) on a 1 km×1 km raster each. Then they are subsequently aggregated over the selected catchments to areal rainfall time series.
7. Error statistics are calculated by comparisons of the areal rainfall time series from gauge and car networks each with the reference areal radar rainfall time series for the four selected catchments.

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## 4.1 Car networks

Figure 4 shows examples of the distribution of cars considering a sensor equipment rate of 1% during day and night at one time step and accumulated over 1 h, respectively. The different car densities between day and night time are clearly visible. The figure also suggests that with a dynamic network the number of observation points in space can be virtually increased if measurements are integrated over time. Assuming that the change of the car locations with time (i.e. the speed of the cars) is greater than the change of the rainfall intensity with time at one location a moving network would provide advantages compared to a stationary network of the same density. In fact one car could measure rainfall at several locations before the rainfall intensity changes.

If the roads are now travelled by cars equipped with rain sensors at a rate of 1% and rainfall is sampled every 5 min, the absolute car densities for the Bode river basin can be calculated as given in Table 2. For different equipment rates the values in Table 2 have to be multiplied with these rates. Only the highways and federal roads having a total length of about 1300 km within the Bode river basin are used in this study. To the minor roads, which are not considered here, belong the state and district roads with a total length of 3100 km as well as the side roads with a total length of 10 300 km. Those figures give an impression what potential would be available additionally for measuring rainfall with car networks in this region.

## 4.2 Rainfall sampling and variogram inference

Rainfall for the stationary gauge and moving car networks is sampled every 5 min from the reference radar field from those raster cells where rain gauges and cars, respectively, are located (cp. Figs. 1 and 4). For the stationary gauges an exact rainfall measurement without errors is postulated. For rainfall observations by cars imprecision is assumed, which is related to various factors e.g. a restricted number of windscreen wiper frequency classes, non-unique features for different car types, calibration uncertainties etc. This is taken into account by a limited number of rainfall classes for which the sam-

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pling can be made. Rainfall observations based on 4 classes, corresponding to less accurate measurements (“more old fashioned cars”) and 10 classes, corresponding to rather precise measurements (“more modern cars”) are analysed here. The definition of the rainfall intervals has been done here quite subjectively based on simple assumptions about wiper frequencies and a rough examination of several observed storms in the Bode region. Table 3 lists the assumed rainfall ranges for the two classification schemes.

Prior to the application of the geostatistical interpolation methods variograms have to be estimated, which characterise the spatial variability of the rainfall fields. The variograms are inferred here a priori from the radar data. This is a certain simplification as the radar data represent the truth, which is usually not known. However, since the focus of the analysis is on relative comparisons of the performance between the stationary gauge network and different dynamic car networks and the variograms are used uniquely for both networks this is tolerable.

Average experimental variograms are calculated based on Eq. (5) for rainfall as continuous variable  $Z(u)$  and for different rainfall indicator variables  $I_{\alpha k}(u)$  with  $k=1, \dots, K$ . For the estimation of the indicator variograms radar rainfall is discretised into seven classes taking into account the predefined rainfall observation intervals. The combination of a nugget effect with an exponential model is fitted manually to all experimental variograms. Figure 5 shows the experimental and fitted theoretical variograms for  $Z(u)$  and  $I_{\alpha k}(u)$  for all selected thresholds. Table 3 lists the estimated variogram parameters and indicates which variograms are used for OK and for IK considering either 4 classes or 10 classes. Comparing the indicator variograms it can be seen that the range but also the sill decrease with increasing rainfall thresholds. Larger rainfall intensities have smaller extent which explains the decreasing range. For the highest thresholds there are only a few observed values beyond the threshold, which explains the low variance. For that reason variograms with higher thresholds than  $\alpha=2.0$  mm/5 min are not estimated. For interpolation of indicator variables with higher thresholds the last estimated indicator variogram is then applied (see Table 3).

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### 4.3 Comparisons of areal rainfall estimation

Figures 6 and 7 show exemplarily areal rainfall time series for the Gr. Graben and the Holtemme catchments estimated from the rain gauge network and the car network with 4% sensor equipment rate. For the 800 km<sup>2</sup> large Gr. Graben catchment the areal rainfall estimation using the stationary rain gauge network is poor. All approaches employing the car network provide significantly better areal rainfall estimation. This is not surprising considering that no stationary gauges are available within the basin boundaries for that catchment. For the Holtemme catchment areal rainfall estimation from the car network using IK4 provides slightly better results compared to the estimation from the rain gauge network. Using IK10 however improves significantly the areal rainfall estimation. OK used as reference method assuming no errors in rainfall observation from car observatories gives here only an additional rather small improvement.

In Table 4 all calculated performance measures for areal rainfall estimation are listed considering the four catchments, the different car sensor equipment rates and interpolation methods. Table 5 shows the corresponding kernel density calculations of the networks. In addition, a visual comparison of the relative standard errors for areal rainfall estimation and the associated network densities is given in Fig. 8. For the largest test catchment Gr. Graben all car networks perform significantly better compared to the station network no matter what sensor equipment rate or interpolation approach is used. The error from the station network is highest (RSE=0.66) and the station density is lowest ( $D_{\text{sub}}=0.6$ ) compared to the other catchments. For the smallest catchment Trautenstein the error from the station network (RSE=0.6) is still almost always higher than the errors from the car networks, which is also related to a very low station density ( $D_{\text{sub}}=1.5$ ). For the Holtemme catchment the error from the station network is smaller (RSE=0.34) as consequence of a higher rain gauge density ( $D_{\text{sub}}=7.7$ ). For that catchment, the car networks perform better only for the larger sensor equipment rates of 2% and 4% although the car network density is always superior compared to the station density. The car network for the Selke catchment can hardly do better than the tra-

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ditional rain gauge network although the average car density is higher for all sensor equipment rates which are greater or equal to 1%. One reason for that could be that the locations of the rain gauges in the Selke basin are optimal compared to the locations of the cars, which are forced on roads with possibly disadvantageous positions e.g. in valleys.

From Table 4 it can be seen, that the bias for the indicator approaches is usually higher compared to OK. This comes likely from the suboptimal rainfall classification, required by the fixed rainfall observation classes e.g. according to the wiper frequencies. This rainfall discretisation does neither guarantee an equal number of values per class nor an equal distribution of the values within the classes. Especially the maximum limit of the highest interval is a critical assumption (cp. Table 3). All this leads to a biased estimation of the mean value from the cumulative distribution function, which has been obtained from the interpolation of the indicators using Eq. (8). This bias decreases usually with increasing number of classes (cp. results for IK4 and IK10 in Table 4).

To test the above stated hypothesis of the disadvantageous location of roads to observe rainfall a further computer experiment is carried out redistributing the number of generated car positions randomly within the basins anywhere neglecting roadways. The results are shown exemplarily for two sensor equipment rates in Fig. 9. It becomes clear, that a random positioning of the cars within the catchments does not improve the estimation performance for areal rainfall. For the Selke basin even the opposite seems true. For those four catchments it can be concluded that using the roadways for measuring rainfall is not suboptimal compared to a pure random network of the same density. Still, this does not disprove the possibility that the existent station locations are optimal compared to a random distribution of gauges.

The error for areal rainfall estimation from the car networks seems not strongly related to the catchment size at least for considering the interpolation approaches IK10 and OK. The interpolation based on only 4 rainfall intervals using IK4, however, tends to give smaller estimation errors for the two larger catchments, Gr. Graben and Holtemme, compared to the two smaller ones, Selke and Trautenstein. Although for the largest

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basin (Gr. Graben) IK4 produces higher errors compared to the second largest basin (Holtemme).

Figure 10 shows the absolute number of cars together with observed and estimated areal rainfall time series for the Selke basin. It becomes clear, that there is a high variability in the car network density with changing levels for day, evening and night times. The figure shows also, that the car network density is poor for the largest peak of the event (during night time) which leads to a significant underestimation of rainfall. This could also contribute to the superiority of the actual station network in this catchment.

## 5 Summary and conclusions

The main objective of this paper was to present a new approach for rainfall observation. The idea was to consider motorcars as moving rain gauges with windscreen wipers as sensors to detect precipitation. This study has explored theoretically the benefits of such an approach. A simple traffic model was applied to generate motorcars on roads in the 3300 km<sup>2</sup> Bode river basin. Rainfall from radar data fields were sampled with a conventional rain gauge network and with several dynamic networks consisting of moving motorcars. Calculated areal rainfall for four different catchments using ordinary kriging and indicator kriging was compared against the true values from radar observations. The main results can be summarised as follows:

1. In general, the idea of using cars as rain gauges is theoretically feasible and would improve the assessment of areal rainfall compared to stationary gauge networks.
2. The error for areal rainfall estimation depends on the network density and decreases with growing number of cars. Considering the current traffic density obtained from statistical data a small sensor equipment rate between 0.5 and 4% was sufficient for areal rainfall estimation in the selected mesoscale catchments of the Bode river basin.

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3. The imprecision in rainfall observation by the cars can be considered in areal estimation using indicator kriging based on rainfall classes. For the Gr. Graben and the Trautenstein catchments even 4 intervals for rainfall observation provide better areal rainfall estimation than the stationary gauge network. Using 10 rainfall intervals gives often almost as good results as with assumed continuous rainfall observation by the car network.
4. A problem with the imprecision of rainfall observation using cars is the prior definition of suitable rainfall intervals according to the expected range of the event. This leads likely to an additional bias in rainfall estimation.
5. A simulation study has shown that locations of the main roads have no disadvantageous effect on the position of cars regarding rainfall observation compared to a theoretical random distribution of cars in space with the same network density.
6. The results for the Selke catchment indicate that there might be optimal positions for rain gauges which reduce the required network density significantly compared to an arbitrary location of the gauges.

The results of this initial study are based on one region with four considered catchments of different size and one rainfall event. A valid relationship between wiper speed and rainfall rate considering uncertainty was assumed. Additional research is needed to investigate possibilities for the derivation of such relationships. Future investigations should also consider different rainfall events, other regions and complete road networks to further test the presented ideas. Especially higher sampling rates for the cars and the integration of observations over time need to be explored. The findings also suggest a revisiting of the rain gauge network optimisation problem. Future research might also consider a merging of rainfall information from the three sources radar, stations and cars. Eventually, practical feasibility studies are required to answer questions about applicability of the ideas in praxis.

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**Table 1.** Traffic data used for car generation.

Road types	Highways, Federal Roads		
Velocity	80 km/h		
Density	Day (6:00 am–5:00 pm) 1100 cars/h	Evening (5:00 pm–10:00 pm) 700 cars/h	Night (10:00 pm–6:00 am) 180 cars/h
Sampling rate	5 min		
Sensor equipment rates	0.5%, 1%, 2%, 4%		

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**Table 2.** Number of cars per hour for the whole Bode river basin considering highways and federal roads and a sensor equipment rate of 1%.

Time of day	Absolute number of cars [ $\text{h}^{-1}$ ]	Specific number of cars [ $\text{h}^{-1} \text{km}^{-2}$ ]
Day (6 a.m.–5 p.m.)	2174	0.66
Evening (5 p.m.–10 p.m.)	1423	0.43
Night (10 p.m.–6 a.m.)	360	0.11

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**Table 3.** Rainfall discretisation into classes, thresholds used for interpolation with indicator kriging (IK) and corresponding variogram parameters. For ordinary kriging (OK) the variogram No. 0 without threshold is applied. The upper bounds are included in the classes.

No	Classes for IK with 10 intervals [mm/5min]	Classes for IK with 4 intervals [mm/5min]	Threshold [mm/5min]	Nugget [-]	Sill [-]	Effective range [km]
0	–	–	None	0.0	1.1	30
1	0.0	0.0	0.0	0.1	0.9	60
2	0.0–0.1	–	0.1	0.1	0.9	30
3	0.1–0.3	–	0.3	0.1	0.95	20
4	0.3–0.5	0–0.5	0.5	0.1	0.9	12
5	0.5–1.0	–	1.0	0.1	0.8	8
6	1.0–1.5	–	1.5	0.1	0.65	6
7	1.5–2.0	0.5–2.0	2.0	0.1	0.35	5
8	2.0–3.0	2.0–5.0				
9	3.0–4.0					
10	4.0–5.0					

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**Table 4.** Performance of areal rainfall estimation based on the rain gauge network (Stations) and the car networks (Cars) with different sensor equipment rates (SER) in comparison with the radar reference rainfall. For interpolation ordinary kriging (OK) and indicator kriging (IK) with 4 and 10 rainfall classes are used. All values between time steps 51 and 700 with reference rainfall intensity greater or equal to 0.1 mm/5min are considered for error calculations.

SER [%]	Stations OK			Cars IK4			Cars IK10			Cars OK		
	Bias [mm]	RSE [-]	Cor [-]	Bias [mm]	RSE [-]	Cor [-]	Bias [mm]	RSE [-]	Cor [-]	Bias [mm]	RSE [-]	Cor [-]
Catchment Trautenstein (39 km <sup>2</sup> )												
4	-6.7	0.60	0.58	15.1	0.49	0.87	-5.9	0.22	0.96	0.0	0.15	0.98
2	-6.7	0.60	0.58	12.1	0.50	0.80	-7.7	0.34	0.90	-1.4	0.30	0.91
1	-6.7	0.60	0.58	13.5	0.56	0.78	-6.0	0.37	0.87	-0.7	0.35	0.87
0.5	-6.7	0.60	0.58	12.0	0.63	0.69	-6.7	0.46	0.80	-3.2	0.44	0.81
Catchment Selke (102 km <sup>2</sup> )												
4	0.1	0.23	0.95	16.9	0.46	0.90	-4.7	0.22	0.96	-0.9	0.15	0.98
2	0.1	0.23	0.95	17.1	0.56	0.80	-4.8	0.35	0.88	-0.9	0.33	0.89
1	0.1	0.23	0.95	14.5	0.54	0.78	-4.5	0.38	0.86	0.4	0.30	0.90
0.5	0.1	0.23	0.95	15.8	0.60	0.76	-3.1	0.42	0.81	0.4	0.44	0.81
Catchment Holtemme (167 km <sup>2</sup> )												
4	-15.8	0.34	0.86	17.5	0.28	0.95	-10.3	0.18	0.97	-1.6	0.16	0.97
2	-15.8	0.34	0.86	12.6	0.29	0.92	-15.2	0.25	0.94	-4.9	0.24	0.93
1	-15.8	0.34	0.86	4.4	0.34	0.88	-20.2	0.34	0.89	-8.1	0.34	0.87
0.5	-15.8	0.34	0.86	-6.6	0.40	0.79	-28.1	0.44	0.82	-15.7	0.43	0.78
Catchment Gr. Graben (812 km <sup>2</sup> )												
4	-4.1	0.66	0.16	12.9	0.30	0.91	-6.9	0.18	0.95	-1.1	0.14	0.95
2	-4.1	0.66	0.16	12.3	0.33	0.84	-7.2	0.23	0.89	-1.2	0.19	0.90
1	-4.1	0.66	0.16	7.7	0.34	0.75	-10.7	0.32	0.80	-4.1	0.24	0.86
0.5	-4.1	0.66	0.16	3.4	0.45	0.50	-13.3	0.47	0.52	-6.2	0.45	0.53

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**Table 5.** Kernel network densities  $D_{\text{sub}}$  for the stationary rain gauge network (Stations) and averaged over time for the dynamic car networks (Cars) for the four selected catchments considering different sensor equipment rates (SER).

Catchment	$D_{\text{sub}}$ Stations [ $10^{-3} \text{ km}^{-2}$ ]	$D_{\text{sub}}$ Cars with SER of [ $10^{-3} \text{ km}^{-2}$ ]			
		4%	2%	1%	0.5%
Trautenstein	1.5	107.3	53.9	28.4	13.3
Selke	20.1	127.6	64.4	31.5	17.1
Holtemme	7.7	153.1	77.3	38.3	19.3
Gr. Graben	0.6	124.7	62.0	31.0	15.4

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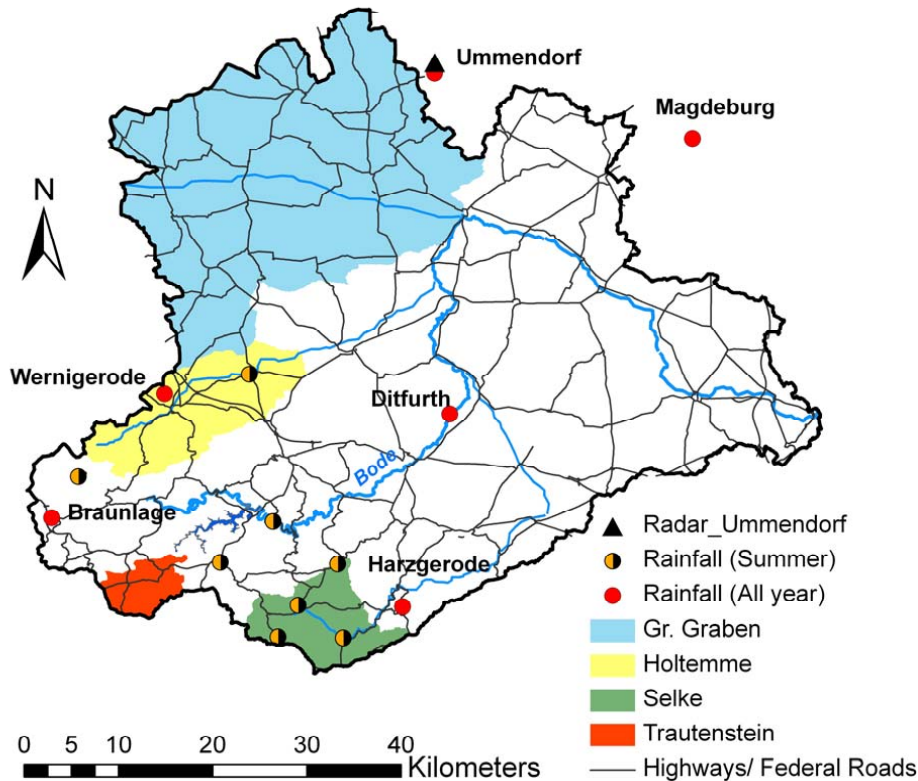
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**Fig. 1.** Study region showing the selected four catchments for the estimation of areal rainfall, the stationary rain gauge network and the location of highways and freeways used for the simulation of the car network.

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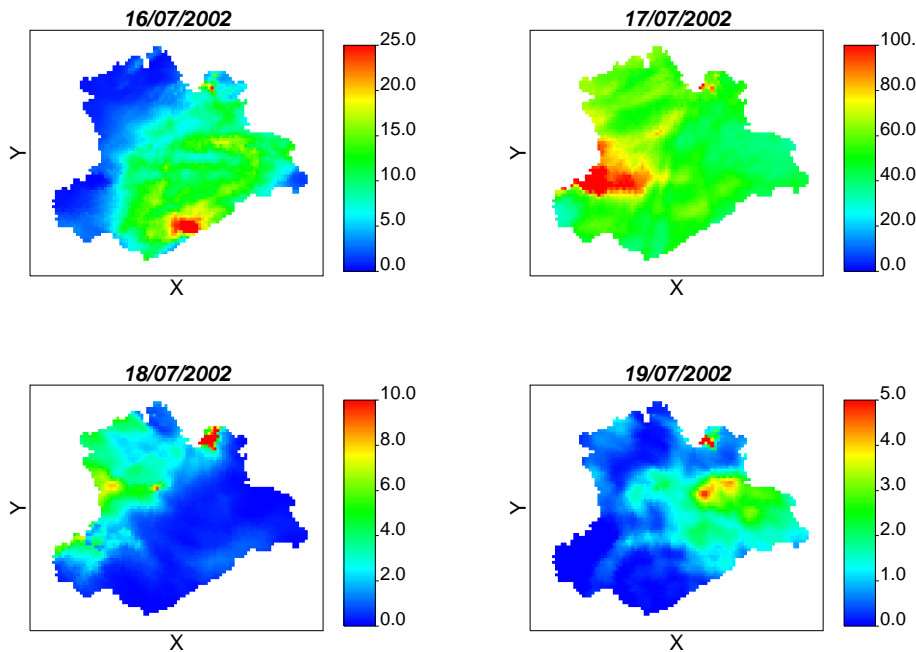
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**Fig. 2.** Spatial distribution of the reference radar rainfall in mm/d for the Bode river basin accumulated over the four days of the storm event.

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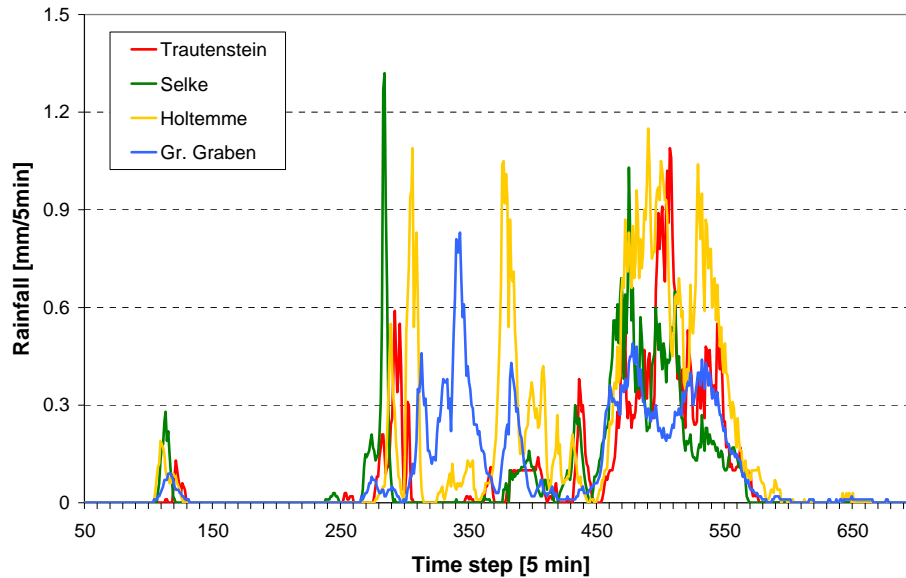
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**Fig. 3.** Time series of areal rainfall derived from the reference radar fields for the selected four catchments considering only the time period of the event with significant rainfall over the particular catchments between time steps 51 and 700.

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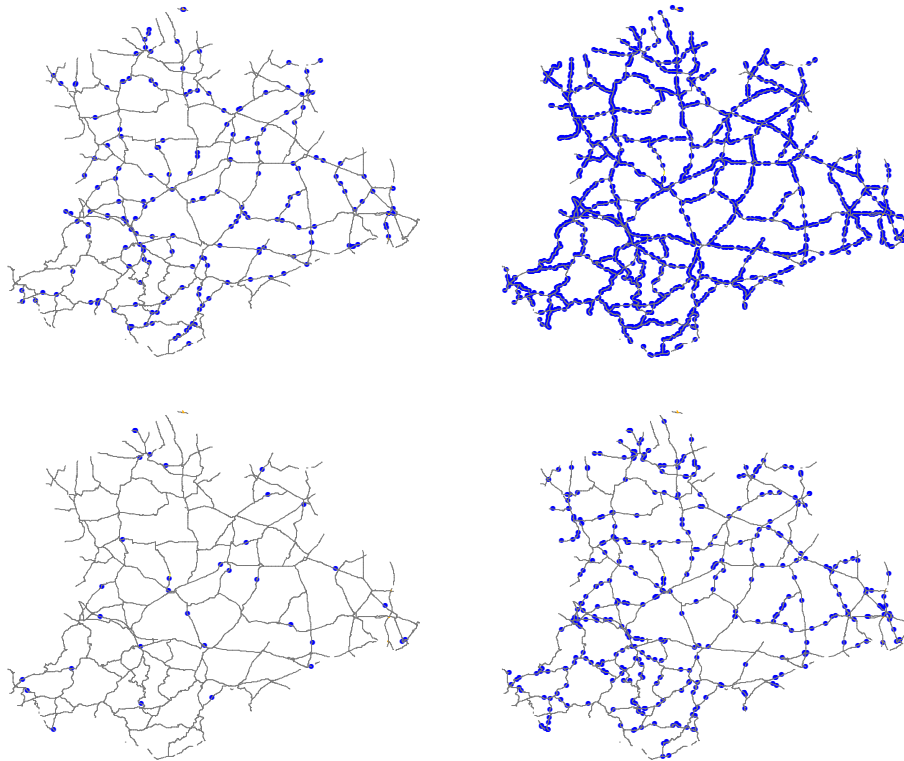
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**Fig. 4.** Example for car distributions considering traffic with a sensor equipment rate of 1% on the road network during day (upper row) and night (lower row). On the left is the situation at one particular sampling time (5 min time step), on the right is the information of an accumulated sampling result of 1 h.

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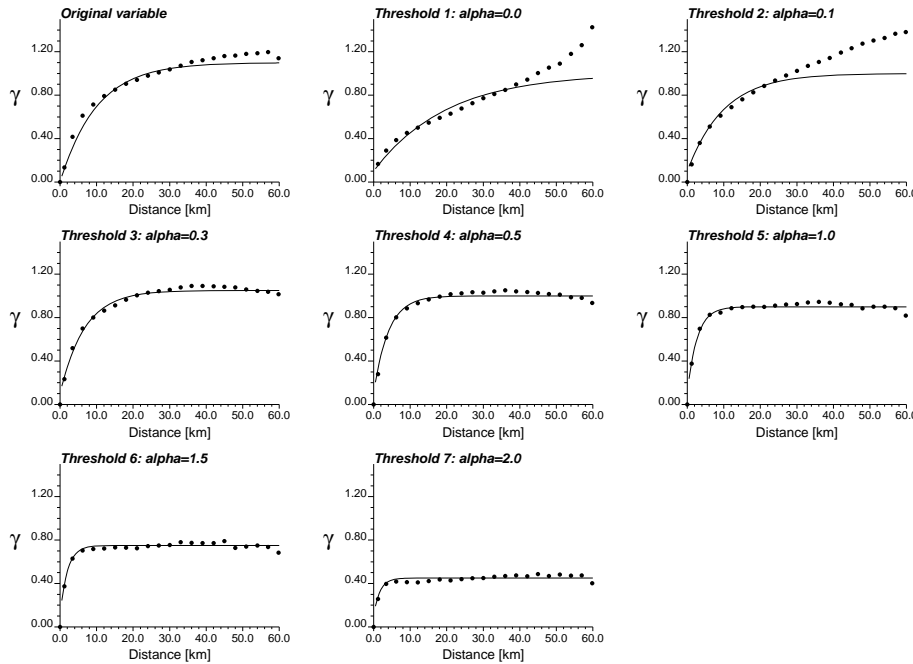
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**Fig. 5.** Average standardized variogram of the original variable rainfall and indicator variograms for 7 rainfall thresholds given in mm/5 min estimated from observed radar data.

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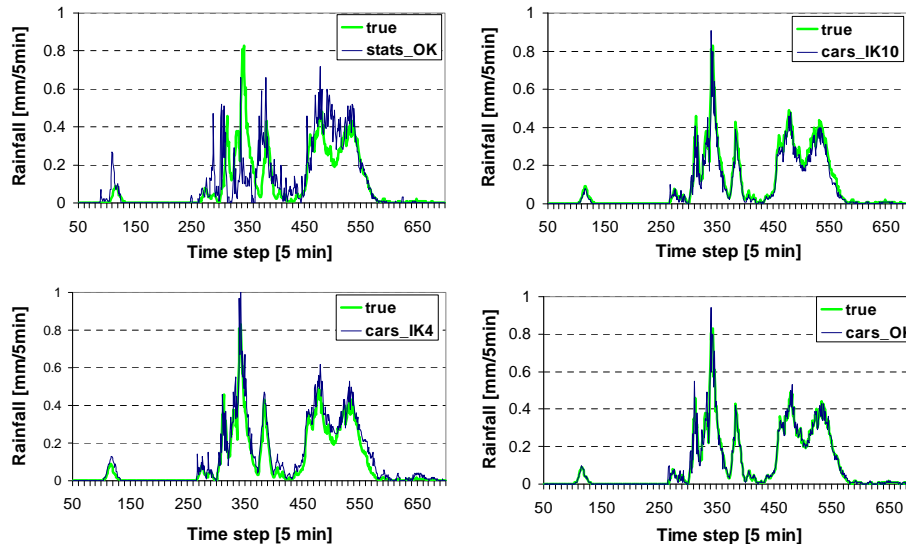
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**Fig. 6.** Areal rainfall time series for the Gr. Graben catchment estimated from the stationary gauge network using ordinary kriging (stats\_OK) and estimated from the car network with 4% sensor equipment rate using indicator kriging with 4 rainfall classes (cars\_IK4), using IK with 10 rainfall classes (cars\_IK10) and using OK without rainfall classification (cars\_OK). Reference areal rainfall is from radar data (true).

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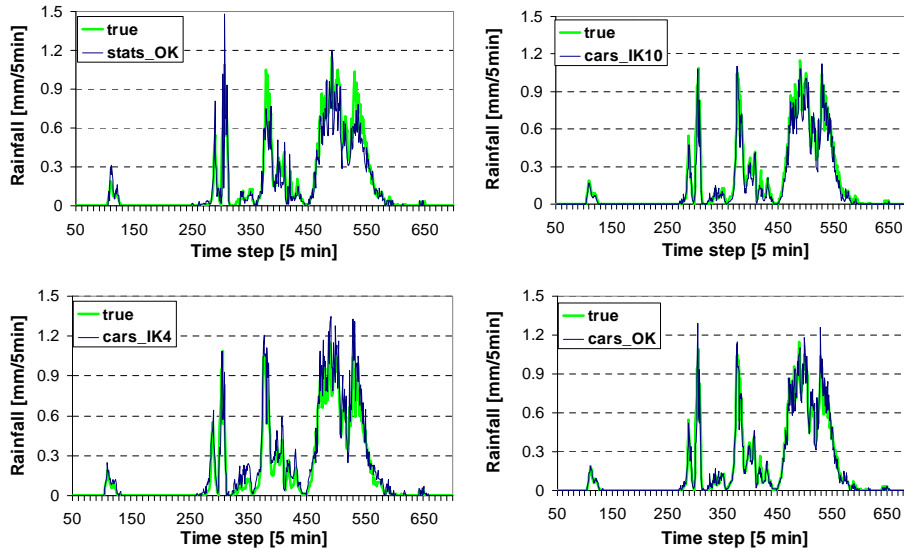
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**Fig. 7.** Areal rainfall time series for the Holtemme catchment estimated from the stationary gauge network using ordinary kriging (stats\_OK) and estimated from the car network with 4% sensor equipment rate using indicator kriging with 4 rainfall classes (cars\_IK4), using IK with 10 rainfall classes (cars\_IK10) and using OK without rainfall classification (cars\_OK). Reference areal rainfall is from radar data (true).

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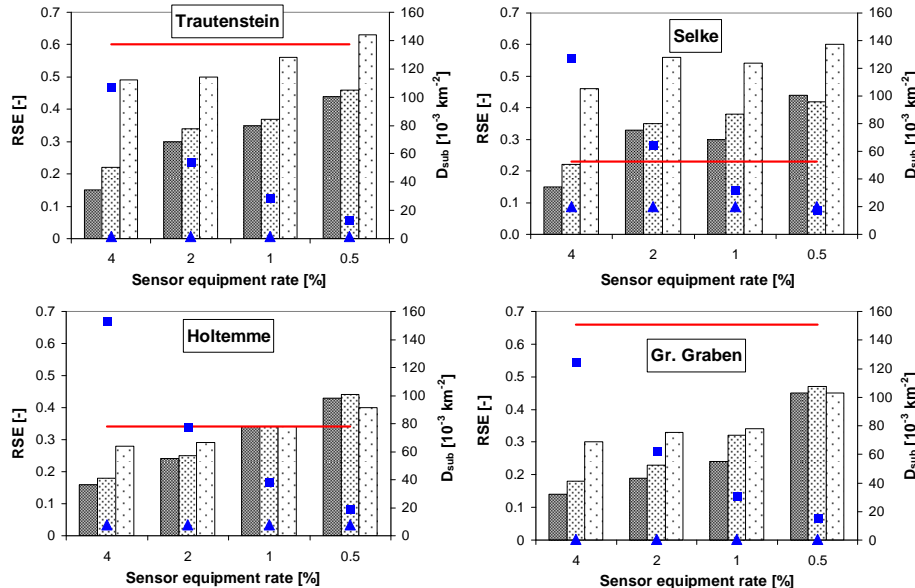
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**Fig. 8.** Performance of areal rainfall estimation from the rain gauge network (horizontal red line) and from the 4 car networks with different sensor equipment rates (bars). For interpolation of the car rainfall observations IK4 (heavy dotted bars), IK10 (medium dotted bars) and OK (light dotted bars) are used. In addition the average network densities  $D_{\text{sub}}$  for the station network (blue triangles) and the car networks (blue squares) for each subbasin are provided.

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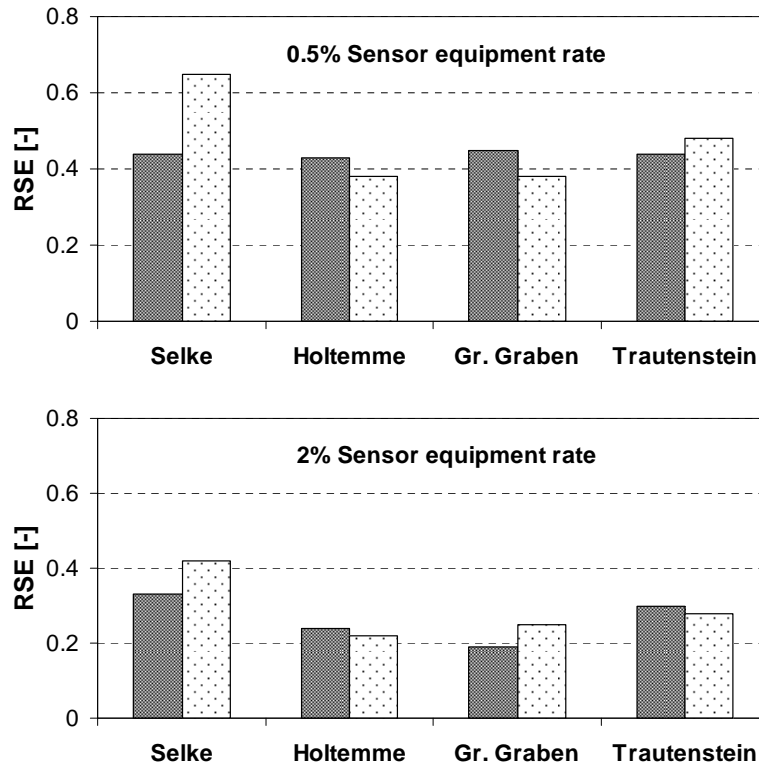
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**Fig. 9.** Relative standard errors for areal rainfall estimation using OK interpolation with regular moving cars on roads (heavy dotted) and randomly redistributed cars (light dotted) for two sensor equipment rates.

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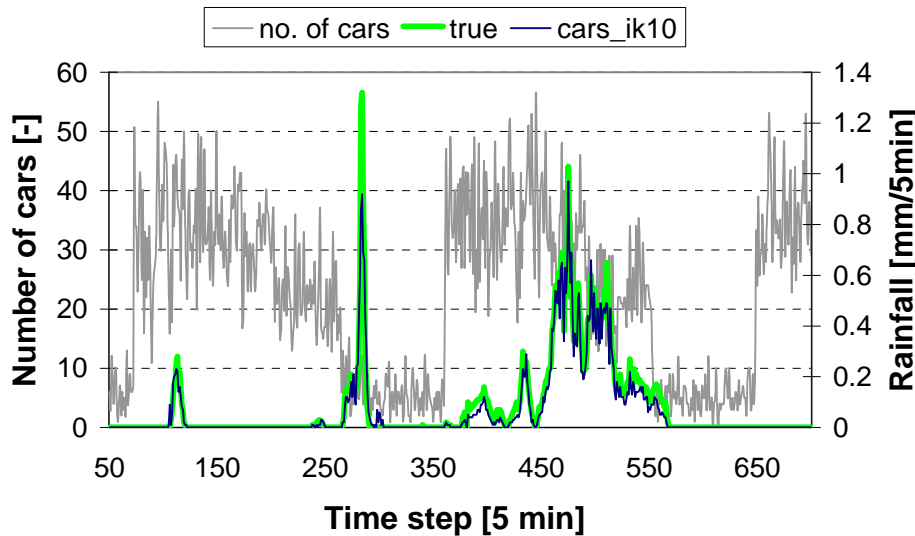
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**Fig. 10.** Absolute number of cars (No. of cars) generated on roads in the Selke catchment with 4% sensor equipment rate in comparison with time series of observed (true) and estimated areal rainfall (cars\_ik10).

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