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Article

Rainfall Estimation with a Geosensor Network of Cars – Theoretical Considerations and First Results

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Summary: Areal rainfall information is one of the most important inputs to hydrological models. This paper presents some theoretical considerations and initial results on the idea of using a geosensor network of cars as a data source for areal rainfall estimations. The types of car sensors and different calibration schemes for the rainfall estimation functions (W-R functions) in the cars are presented. A special focus is given to the decentralized online calibration of these functions in the network by communicating measurements between measuring units. This would allow the dynamic adaptation of the functions to different situations such as different drivers, the current car environment or the current wind speed and direction. Then, results from laboratory and field experiments are presented.

Zusammenfassung: *Niederschlagsschätzungen mit einem Geosensornetz von Autos – Konzepte und erste Ergebnisse.* Schätzungen der räumlichen Niederschlagsverteilung sind eine wichtige Datengrundlage für hydrologische Modelle. Dieser Beitrag beschreibt grundlegende Konzepte der Regenschätzung mit einem Geosensornetz von Autos. Es werden sowohl die verwendeten Sensoren beschrieben, als auch die Möglichkeiten ihrer Kalibrierung. Dabei wird ein besonderer Fokus auf die dezentrale Online-Kalibrierung gelegt, die es ermöglicht, die Schätzfunktionen dynamisch anzupassen und so beispielsweise Faktoren wie Fahrer, Autoumgebung oder Windgeschwindigkeit und -richtung zu berücksichtigen. Im Anschluss daran werden erste Ergebnisse aus Labor- und Feldexperimenten zur Bestimmung der Schätzfunktionen präsentiert.

1 Introduction and Overview

Areal rainfall, representing a good estimation of the spatial variability and of the mean value over specific areas, is one of the most important inputs to hydrological models. Especially models used for reanalysis and forecasting of highly dynamic processes like floods and erosion have high requirements regarding the rainfall input. Furthermore, if predictions are required for small catchments or urban areas, the processes are very fast. However, estimating areal rainfall, especially for short time steps, is still a challenging task: In general, the density of recording rain gauges is low; further, weather radar suffers from large space-time biases and the general problem that rainfall is not measured, but estimated from the measured reflectivity values.

The idea of estimating rainfall with cars originates from Haberlandt & Sester (2010). There, computer simulations for a river catchment supported the assumption that areal rainfall estimations with cars might be superior compared to an existing network of stationary rain gauges. Haberlandt & Sester (2010) concluded that estimating areal rainfall with cars is theoretically feasible and that the accuracy depends on the number of cars equipped with sensors.

A possible application of this idea would be operational flood forecasting where real-time measurement and prediction of precipitation is required. Another possible application in a different field is car navigation, where real-time predictions of rainfall are needed for the online speed estimation for shortest path calculation (Thakuriah & Tilahun 2013). As cars

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cannot measure rainfall directly, their original raw measurements, e. g. wiper frequency, have to be calibrated. This calibration has to take additional factors into account, such as speed and the local environment the car drives through. A realization of a system would require that the calibration has to be performed for each car, using data from each of its measurements. In a centralized calculation, all cars would communicate their measurements to a central server. If many cars participate in such a system, this leads to scalability problems, as well as a high amount of data to be communicated to the central server. Therefore, the idea is to use the measurement and processing capabilities of the car itself to conduct the calibration in a decentralized way, i. e. take the cars as a distributed geosensor network (Duckham 2012). Such an approach not only solves the scalability problem, but also enables analyses beyond the calibration: the cars can collaborate in order to determine the rainfall pattern and detect homogeneities or heterogeneities; furthermore, the locally determined rainfall estimates can be used for other purposes such as risk warnings (aquaplaning) or real-time speed estimation.

Schulze et al. (2010) investigated this idea of calibrating the rainfall estimation functions in the cars while driving, subsequently called online calibration. Both earlier works relied entirely on computer simulations of either car measurements, rainfall or both. In Fitzner et al. (2012), online calibration of the estimation functions was investigated using real data from a car equipped with a wiper frequency sensor. The work analysed different online calibration schemes and sensor communication ranges. It concluded that, if the communication range (distance) is adequately short, the online calibration could improve rainfall estimation even under significant a priori training. However, not all influencing parameters such as car speed have been modelled yet in Fitzner et al. (2012) and no sound statistical model for the online calibration has been provided. Therefore, additional investigations are required, which can be summarized as follows:

a) Robust models for estimating rainfall from the sensor readings have to be derived from experiments.
b) A statistically sound model for the online calibration has to be developed.
c) Both, the feasibility as well as the advantages of online calibration have to be proven by experimental data and computer simulations.

This paper gives initial results for a) and discusses requirements for b). After a brief review of related works, the types of car sensors are introduced in section 3. Then, in section 4, the calibration of the car sensors in laboratory and field are discussed with a special focus on the decentralized online calibration. Section 5 gives first empirical results of the laboratory and field experiments and section 6 concludes.

2 Related Work

Information about rainfall is essential for hydrological predictions and water resources management (Beven 2001, Chow et al. 1988). Due to its high variability in space and time, areal estimation of rainfall is still a challenging task. There are several methods for measuring rainfall: non-recording rain gauges are available in a high density, however they do only provide aggregates of the amount of precipitation over a whole day. Recording rain gauges would be required, however, even in Germany, the network density is only approximately one station per 1,800 km². Weather radar also is an indicator for rainfall, however, it does not measure rainfall directly, but reflections, which have to be transferred to rainfall using calibration – for which a sufficiently dense point precipitation network is needed (Smith et al. 2007, Krajewski & Smith 2002). Other special and innovative methods for rainfall observation use satellites (Grimes & 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 & Parker 2001). Utilising rainfall information from different sources together and applying sophisticated interpolation or merging methods can further improve precipitation estimation for hydrological applications (Goudenhoofdt & Delobbe 2009, Chiang et al. 2007, Goovaerts 2000, Haberlandt 2007, Ehret et al. 2008). In a recent study the inclusion of distributed low cost and low accuracy measurement devices for the improvement of radar rainfall was investigated (Hill & Farzan 2012).

3 Car Sensors

Different types of sensors for estimating rainfall with cars have been used in the experiments. These include sensors for measuring the wiper frequency of a car as well as optical sensors that are typically installed in cars with automated wiper control.

A wiper frequency sensor has been developed in the course of the project which is based on a microcontroller connected to a GPS-receiver and a magnetic sensor. The magnetic sensor is placed behind the windscreen and triggers each time a magnet attached to the windscreen wipers passes, which occurs two times for each single wipe. Then an NMEA String, i. e. position, time and additional information, is recorded in an ASCII text file on an SD-card. The wiper frequency sensors are installed in cars with both manual and automatic wiper control. Cars with manual wiper control have discrete wiper frequency classes to be manually adjusted by the driver. In addition to the manual option, some cars have an automatic wiper system. When automatic wiping is switched on, an optical sensor attached to the windscreen detects raindrops on the windscreen surface and triggers the wipers. Also in this case, however, the wiper frequency is not determined completely automatic but depends on a manually controlled sensitivity setting.

Fig. 1: Xanonex (left) and Hydroeon (right) (Xanonex 2013, Rainsensors 2013).

Two other sensors are used, which measure rainfall in an optical way via transmitted and sensed infrared (Xanonex and Hydroeon) (Fig. 1).

4 Sensor Calibration – Derivation of the W-R-Relationship

In order to estimate rainfall with the sensors, a functional relationship between the sensor readings and rainfall needs to be established, termed Wiper-Rainfall (W-R) relationship or W-R function. The nature of such a relationship ranges from a simple linear regression with a single predictor variable, e. g. wiper frequency, to more complex non-linear models with multiple parameters. Calibration can either be performed in an off-line fashion in a controlled environment in a laboratory or also "in the field", by equipping cars on the road with sensors. The latter can also be organized in an online way, taking advantage of the fact that cars can continuously measure wiper frequencies and compare it with given rainfall measurements of stations and other cars in their vicinity.

In the following the different calibration strategies are described. Whereas the major

Tab. 1: Influencing factors and their consideration in the current experiments.

Factor	Lab Experiments		Field Experiments
	Wiper Frequency	Optical Sensor	
Car speed	No	Yes	Yes
Windscreen angle	Yes	Yes	Yes
Car environment	No	No	Yes
Wind speed / wind direction	No	No	No
Drivers	No	No	Yes
Road type (and road surface), spray	No	No	Yes

parameters for the determination of the rainfall are the sensor readings, there are additional factors which can influence the calculation of the rainfall, such as car speed and preferences of the driver (Tab. 1). Some of the factors influence the rainfall as such, e. g. wind, car environment such as buildings, trees, others influence the measurement of the rainfall, e. g. speed, driver. The details are explained in section 4.1.

The calibration data for the sensors is collected in the laboratory or field and used for estimating the W-R function coefficients. This can be done e. g. by executing a least squares algorithm such as ordinary least squares (OLS). Once the coefficients are determined, they can be implemented in the cars to be used for calculating rainfall during subsequent rainfall events. The offline calibration in a laboratory and field setting is summarized in 4.1. The online calibration within the geosensor network of cars is described in 4.2. First calibration results are given in section 5.

4.1 *Derivation of a Base Calibration in Lab and Field*

A basic W-R relationship can be derived in laboratory and field experiments. For the laboratory experiments, a sprinkler system has been designed and built (Fig. 2).

In order to produce different rainfall intensities, the system allows different combination of nozzles as well as different pressures on the two layers. The size of the simulator is sufficient for creating a homogeneous rainfield for a single car and all sensors under consideration at the same time. Rainfall intensities between 9 mm/h and 100 mm/h can be produced. As a reference for the car sensors, i. e. "ground truth", both, a recording rain gauge with a tipping bucket sensor and a disdrometer are used. Tipping bucket sensors are widely used to provide point-rainfall measurements. Disdrometers give valuable additional information of the rainfall characteristics such as the rain droplet distribution or its falling speed. In order to investigate the effect of car speed on the optical devices, the two optical sensors are placed on a rotating machine. The Xanonex sensor is placed with an angle of 45° in rotating direction, in order to simulate an average windscreen angle. Due to minor variations in the rain intensity for each individual run during the experiments, each of the dynamic sensors is compared with a static one of the same type within a particular run. Currently, speeds of up to 45 km/h can be generated.

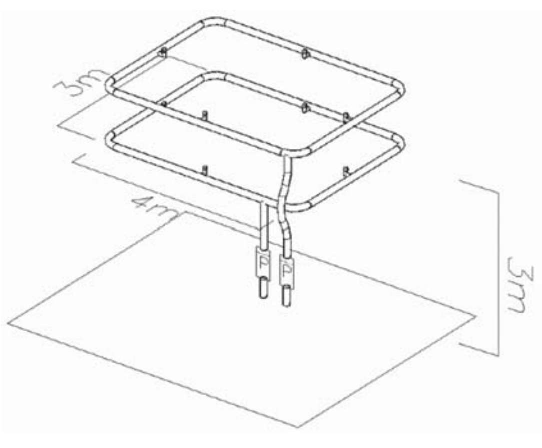


Fig. 2: Sprinkler system for the laboratory experiments.

W-R functions can also be established in a real-world setting by using cars equipped with sensors for recording wiper activity, position and time with a particular sampling rate (Fig. 3). In this way, it is possible to investigate influencing factors that are not easily testable in the laboratory, such as wind speed or local environment. The main problem in deriving accurate W-R relationships from the field experiments is the availability of suitable and correct "ground truth"-data, i. e. reference rainfall at the car positions. Currently, data from the 11 stationary rain gauges in the Hannover area are used as reference, with an inverse distance weighted (IDW) interpolation to derive rainfall estimations at the car position. As the stationary rain gauges provide measurement every minute, the sensor readings of the cars (and the car positions) have been averaged over a minute as well. Currently, 10 cars are equipped with the wiper frequency sensor, among them 6 from a taxi fleet.

4.2 *Geosensor Network of Cars*

Instead of storing the sensor readings and evaluating them in a postprocessing or at a central server, a W-R function could be directly applied to estimate rainfall while the car is driving, with the advantages as described in section 1. In addition, taking advantage of technologies of wireless sensor networks for vehicular networks, there is the possibility for the cars to exchange information with each other (Car2Car) or with stationary rain gauges equipped with communication facilities (Car2Station). Besides the general benefit of scalability described in section 1, this information exchange has two main advantages:

a) Each car iteratively calibrates a W-R relationship that takes car specific factors into account that cannot be calibrated in advance, e. g. a particular windscreen angle or driver type.
b) When exterior situations change, which are not (yet) respected in the W-R function, e. g. the current local wind speed and direction, the deviations from the estimation can be corrected on-the-fly and the model can be adjusted to the current situation.

As soon as a car enters the communication range of a stationary rain gauge (Car 1 in Fig. 3), a data exchange is established and the stationary rain gauge transmits its current rainfall measurement to the car. This results in a (*sensor readings, rainfall*)-sample that can be used to update the current W-R function. When the car enters the communication range of another car (measurement 7 of Car 1), both cars exchange measurements (Car2Car) and improve their W-R function. The accuracy of the update samples is a function of:

a) the original accuracy of the measurement or estimation at the location of the sending unit. Stationary rain gauges can be expected to provide higher accuracies compared to cars,
b) the spatial distance of the sending and receiving unit and the temporal lag between the time, the received measurement has been taken and the time, the receiver measured the predictor variables, e. g. the wiper frequency,
c) the spatio-temporal variability of the current rainfall field.

While it is possible to determine a) and b), the estimation of c) is more difficult and subject to future work. For example radar estimations or the geosensor network of cars could be employed. The update accuracies can be taken into account; e. g. by methods such as weighted least squares (Rawlings et al. 1998).

The factors influencing W-R function estimations from Tab. 1 can be categorized as shown in Tab. 2. Here, the term "dynamic" re-

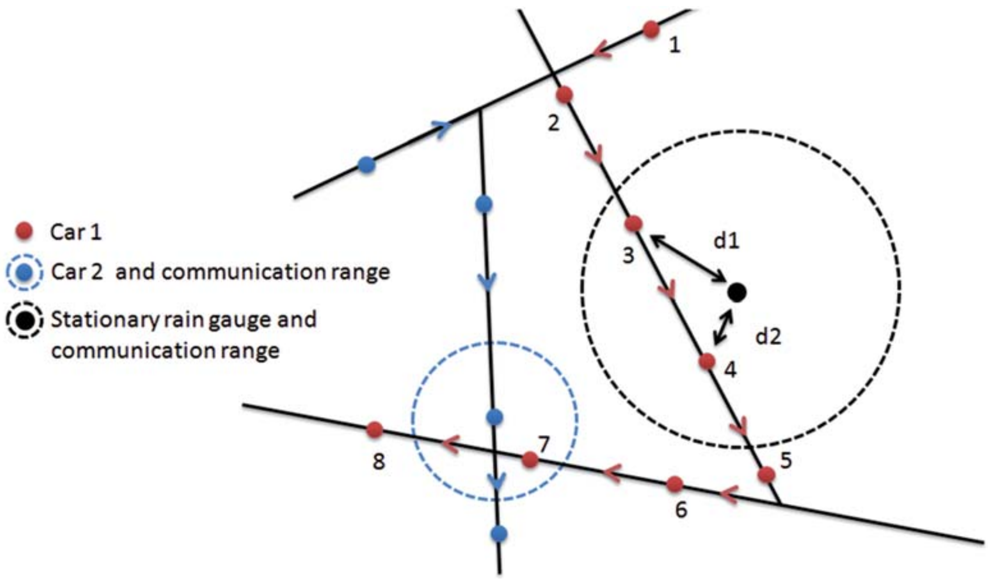


Fig. 3: Car2Car and Car2Station communication.

Tab. 2: Categorisation of influencing factors.

	Constant	Dynamic
Measured	-	Car speed, wiper frequency
Not (yet) Measured	Sensor system, windscreen angle (driver)	Wind direction and speed, local car environment, e. g. landuse

fers to factors that can change for a particular car while driving.

Factors that are measured by a car can function as parameters of the W-R function and hence their influence, i. e. coefficients, can be calibrated. This means, when the car receives a rainfall estimation from a neighbouring sensor (other car or station), it has typically a value for each measured parameter such as car speed or wiper frequency available. Therefore, an update results e. g. in a *(wiper frequency, car speed, received rainfall)*-sample that can be used to calibrate the model.

Some other factors, such as a specific sensor type or windscreen angle, remain constant for a particular car. This means, the calibration samples (*sensor readings*, *rainfall*) do not contain a reading for that particular factor, e. g. a particular value for a windscreen angle. However, with the online updates, the model is still implicitly adjusted to account for such constant factors. With a sufficiently large set of calibration samples collected over time, it can be expected that a specific car will generate a model that will work best on average for its car specific constant factors. Some influencing factors, such as the driver, change less frequently or sometimes even remain constant for a particular car and hence, cannot easily be categorized into constant or dynamic.

The calibration and application of a W-R function for online measurements requires that all factors are either:

a) **dynamic** and **measured** by a car, a model parameter, e. g. car speed, or
b) **static** for a particular car, e. g. windscreen angle, and **not necessarily measured**

Factors that are neither static nor measurable cannot be calibrated. This means, a particular car cannot learn the influence of a particular dynamic factor that it cannot measure. Since there will most likely always be unknown factors, the online estimations of rainfall by the W-R functions will most likely always deviate from the true rainfall.

Even a W-R function perfectly calibrated for a set of predictors does not imply accurate individual rainfall estimations, it just estimates best on average given the available predictors. For example, in an area where the car is covered by obstacles preventing the rain at least partly to reach the car sensor, it is likely that any W-R function will underestimate rainfall. E. g. a wiper frequency of 30 wipes/min measured under normal conditions in open space will deliver a quite accurate rainfall estimation, i. e. the estimated rainfall for that wiper frequency will be close to the true rainfall. The same model and the same wiper frequency will lead to a significant underestimation of rainfall when the car is placed in an area such as a dense forest, where obstacles, e. g. trees, prevent the rain from reaching the windscreen.

These dynamic and not measureable factors include the car environment, the wind speed and the direction or the erratic wiper operation by the driver. As these factors are often spatially, e. g. car environment, temporally, e. g. current driver, or spatio-temporally correlated, e. g. wind speed and direction, they result in autocorrelated deviations of the W-R function estimations from the true (but unobservable) rainfall values. These deviations e. g. appear as autocorrelated residuals in the analyses (Fig. 7a). For example, if a car is travelling through a dense forest and hence underestimates the rainfall, it is quite likely that at a subsequent measurement, the car is still travelling under similar conditions and still underestimates. This can also be considered as the problem of dynamic model coefficients. Model fitting approaches that take this into account are e. g. rolling regression models or the Kalman filter (Kalman 1960).

5 Experimental Results

In the following the results of the lab and field experiments will be presented.

5.1 *Laboratory Calibration Results*

The red points in Fig. 4 show the relationships between wiper frequency (x-axis) and reference rainfall measured by a tipping bucket (y-axis) in the laboratory, averaged over a minute, and a linear function fitted with OLS. Fig. 4a shows the results for the W-R relationship of a car with automatic wiper option. Fig. 4b shows the result for the wipers of the same car being adjusted completely manually. This means, a single human operator initiated a single wipe each time, his visibility was impaired. The dashed lines in both figures illustrate the 95% prediction interval.

The figures demonstrate that there is a significant correlation between wiper frequency and rainfall. It can be observed that the manually operated wipers lead to higher coefficients of determination than the automatic wipers. The conclusion drawn from this is that wiper actions triggered by the desire for a clear visibility indeed is an indication for the rainfall. Thus, the better a person or an automatic system fulfils this desire, the better the correlation with rainfall is.

In this way, the laboratory experiments support the projects' underlying assumption that there is, indeed, a relationship between visibility and rainfall intensity. Additional experiments have been conducted to investigate the influence of speed. There are different factors effecting the general overestimation of the rainfall when the sensor is moving:

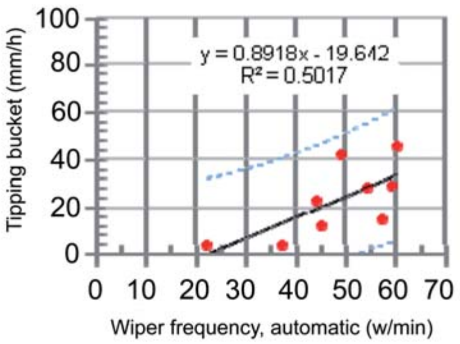
a) the sensor speed,
b) the shape and angle of the optical sensor,
c) the rainfall type, e. g. heavy rain, light rain, etc., corresponding to droplet falling speed.

Theoretically, there is a positive linear relationship between the velocity of an object in rain and the water mass hitting the object (Bocci 2012). The slope of the relationship is a function of the rainfall type and windscreen angle. The red and blue lines in Fig. 5 illustrate the theoretical relationships according to Bocci (2012) for two droplet falling speeds of 2 m/s and 5 m/s, respectively and a flat sensor placed 45° towards the direction of movement.

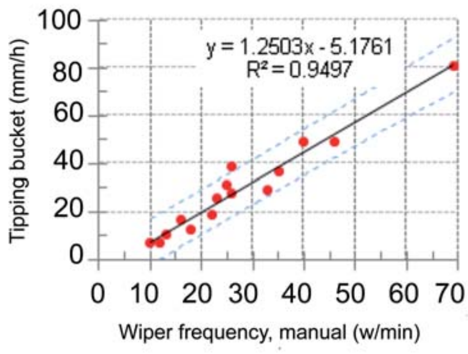
The green line in Fig. 5 illustrates the empirical result. It shows the ratio, dynamic divided by static sensor readings, between a dynamic sensor and a static one of the same type (Xanonex), averaged over different rain intensities. In contrast to the theoretical curves, the result is not a linear increment but becomes static at approximately 20 km/h. Possible reasons are a) the amount of drops remaining on the sensor surface which changes with increasing speed and b) the centrifugal force on the drops, originating from the rotation of the sensor.

5.2 *Field Calibration Results*

A set of 6 cars with manually operated wipers has been equipped with frequency measurement sensors. In total, around 36 hours of car data with substantial wiping activity has been collected (~2200 wiper frequency measure-



(a) W-R relationship for wiper frequency of automatic wipers



(b) W-R relationship for completely manual initiation of single wipes

Fig. 4: W-R (wiper-rainfall) functions determined in laboratory experiments.

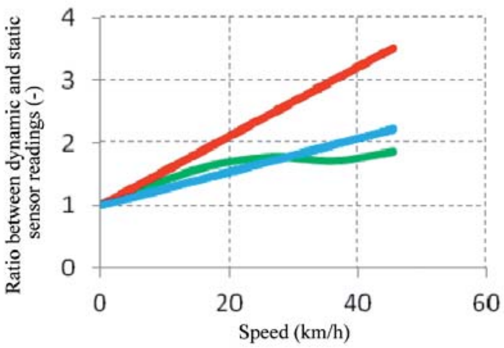


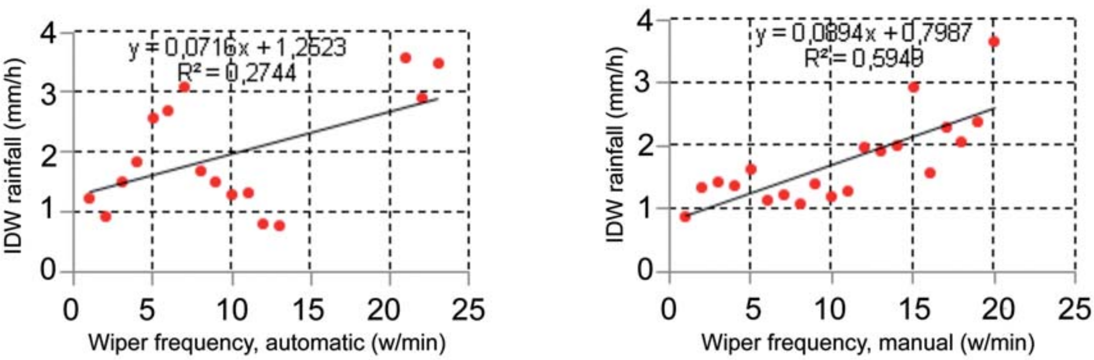
Fig. 5: Influence of speed on optical sensor readings.

ments with a sampling rate of 1 min). 4 cars with automatically controlled wipers have been equipped with frequency sensors, resulting in 30 hours of wiper frequency measurements with one minute resolution (~1800 min). This sample has been preprocessed in order to produce specific selection sets, which allow for a separate investigation of influencing factors. Further, only car measurements have been selected, where the distance to a rain gauge is lower than a given maximum. For the first experiments, the distance has been set to 4000 m, since it seemed to provide a good trade-off between the number of samples and the interpolation accuracy. In order to further reduce errors in the car measurements, e. g. due to windscreen cleaning, only those car trajectories have been evaluated with a substantial and long wiping activity.

Whereas this dataset allows for first analyses presented in the following, the number of data points is too low to perform reliable fine-grained analysis of additional factors such as the influence of different car installations (car types, drivers) on the W-R function.

For the analyses, the mean IDW rainfall for each measured wiper frequency is calculated, i.e. the rainfall conditioned on the wiper frequency. In this way, the set of samples for model fitting is reduced such that there is a single sample for each wiper frequency, represented by the individual red points in Fig. 6. A linear regression is fitted to the data, representing the W-R function for automatically (a) and manually controlled wipers (b). Here, manually refers to the manual selection and adjustment of the discrete wiper classes (e. g. slow, medium, fast) in cars without a rain sensor controlling the wiper frequency. As the conditional mean values are plotted, no confidence or prediction intervals are provided. In contrast to the laboratory experiments, the R^2 values are lower – and they are even significantly lower when all samples are plotted. The major reason for this is that influencing factors are contributing to the function, which are not yet respected. Furthermore, the quality of the interpolated rainfall is not yet known. Although the distance to the stations is limited to 4000 m, this distance still might be too large.

The analysed car data shows a clear indication of multicollinearity, i. e. a linear relationship between the predictor variables wiper frequency and speed (Rawlings et al. 1998). This can be explained by the way, in which the wiper frequency adjustment in cars works. For periodic wiping, i.e. wiping with intervals



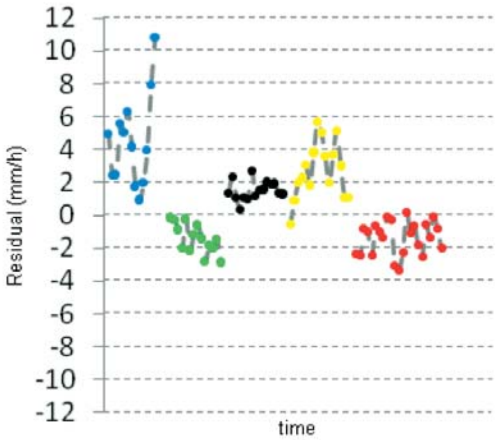
(a) Conditional mean values and fitted linear W-R relationship for a car with automatically operated wipers

(b) Conditional mean values and fitted linear W-R relationship for a car with manually operated wipers

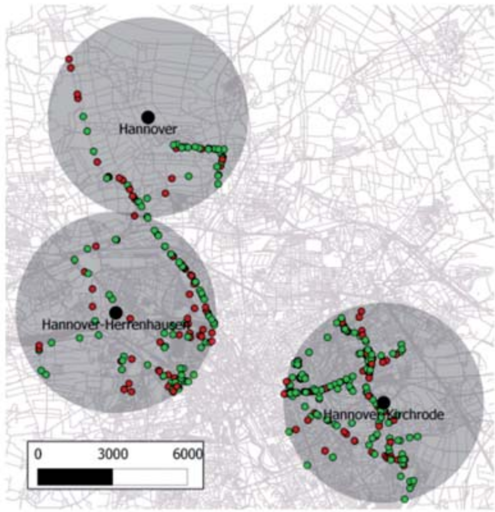
Fig. 6: W-R functions determined in field experiments.

of no wiping in between the single wipes, the wiper frequency increases with increasing car speed, i.e. the interval in between single wipes get shorter. Therefore, certain wiper frequencies occur preferably or even only at certain car speeds. This makes a fine-grained analysis of the correlated predictor variables difficult. In addition, it seriously affects the reliability of the ordinary least squares estimates. This has to be investigated further. This dependence between car speed and wiper frequency also provides the explanation why in Fig. 6b are no discrete frequency classes, e. g. fixed frequencies corresponding to slow, medium and fast.

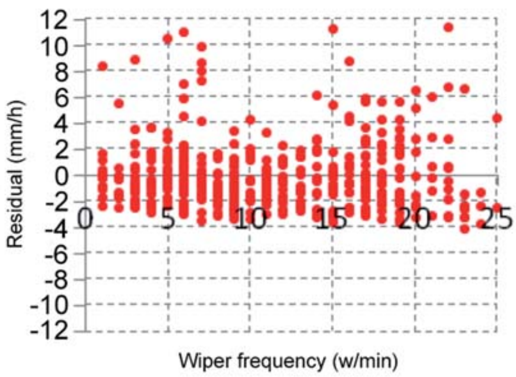
Fig. 7a shows the residuals, assumed true rainfall – estimated rainfall, against the time for a single car with manually operated wipers and a linear model fitted to all samples using OLS with the two predictor variables wiper frequency and car speed. Different colours indicate different time periods. Residuals within a time period are separated by 1 min. Residuals of different time periods are separated by an arbitrary time, e. g. hours, days or weeks. The residual autocorrelation can be clear-



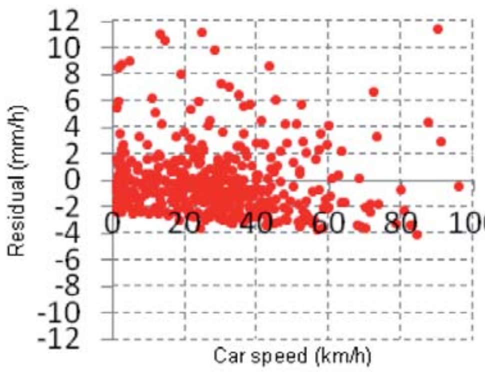
(a) Time ordered (left to right) residuals for a single car with manually controlled wipers and a fitted linear model with predictors speed and wiper frequency. Serial correlation in the residuals that are separated by 1 minute (connected by grey lines) can be recognized.



(b) Positive residuals (red), corresponding to a rainfall underestimation by the W-R functions, and negative residuals (green), corresponding to a rainfall overestimation by the W-R functions. The data of all cars served as a basis with W-R functions established for each car individually. No spatial pattern can be recognized.



(c) Residuals vs. wiper frequency for all cars. No pattern can be recognized.



(d) Residuals vs. car speed for all cars. No pattern can be recognized.

Fig. 7: Analyses of data collected in the field.

ly recognized and is confirmed by a Durbin Watson test (Durbin & Watson 1951). As described in section 4.2, identifying the reasons for this residual autocorrelation is difficult. They can be related to the car environment, the current wiper operation by the driver or dynamic factors such as wind speed and direction. In the case, that the car environment is the reason, it can be expected that the deviations will highly correlate with the spatial location where a particular car collected the sample. Fig. 7b shows over- and underestimations of the W-R functions of all cars distributed over the area. However, in this area (city environment) no spatial pattern can be recognized, thus static spatial factors, such as a particular car environment are unlikely to be the reason for the deviations.

Another possible source for autocorrelated residuals are wrongly specified models, i.e. wrong functional forms of the estimation functions (Rawlings et al. 1998). This can be analyzed in plots of the relationship between the residuals and the predictor variables. Figs. 7c and 7d show the relationship between residuals and wiper frequency, respectively the car speed. As no clear pattern can be recognized, the linear model is currently considered as suitable. However, further experiments are required, especially since the residuals also show a clear indication of deviation from normality.

6 Summary and Outlook

This paper presents investigations on rainfall estimation with cars. Laboratory and field experiments are presented and different possibilities for calibration are discussed. Initial calibration results of the estimation functions are given.

There are several issues which need further research. Currently, the W-R functions are assumed to be linear. Especially with the introduction of new predictor variables into the W-R functions, it might turn out that this assumption will be not valid anymore and that other functional forms, e. g. non-linear models, will be required. In addition to the analyses presented here, experiments with different function estimation techniques will be carried out. For example, different weights could be chosen for the samples, depending on the proximity to the next stationary rain gauge. In addition, other interpolators and the quality of the interpolations will be investigated.

Further, computer simulations including also real car trajectory data will have to prove that the online calibration indeed provides improved rainfall estimations by the cars. For these experiments, different models, such as autoregressive schemes or the Kalman filter, will be investigated and a rigorous model for the data will be developed. Further, it might turn out that an interpolated rainfield is not sufficient for assessing the benefit of the online adjustment, due to the smoothing effect. A different ground truth, such as radar data, might be considered.

Another topic is the determination of suitable communication ranges between the sensors. The communication ranges are determined by the devices, however, the inclusion of a measured value has to be restricted by the homogeneity of the current rainfield. An idea is to quantify this homogeneity and in general to detect patterns in the precipitation fields in the geosensor network itself (Sester 2009).

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