Our thanks to both reviewers, which -with their comments- helped us to improve the quality of this work. Below, we provide the detailed replies (**R/.**) to each of the comments.

<u>ANONYMOUS REVIEWER #1</u>

1. The presentation of the results and the discussion that follows are rather superficial and could be substantially improved. Let's be honest! Given the large number of links, it should come as no surprise that the measurement and representativity errors constitute the major source of uncertainty. The idea of assessing the relative error associated with mapping is new but the methodology used to tackle this issue could be further improved. For example, other interpolation methods (e.g., universal kriging and splines) and network topologies (e.g., various subsets of the considered network) should be considered before drawing any hasty conclusions.

R/. In this work, the use of Ordinary Kriging (OK) enables not only a consistent comparison of our results against those presented by Overeem et. al. (2013) [*Overeem, A., Leijnse, H., and Uijlenhoet, R.: Country-wide rainfall maps from cellular communication networks, P. Natl. Acad. Sci. USA, 110, 2741–2745, doi:10.1073/pnas.1217961110, 2013*], but also a simple and straightforward way of disentangling various sources of uncertainty in rainfall maps derived from microwave link measurements. The OK approach also works as a simple interpolation technique highly suited for the geographical conditions of The Netherlands (and its climate), under the conditions further explained below in our reply to comment #15.

We realize that alternative interpolation methodologies could yield lower mapping uncertainties/errors; however, a comparison of different interpolation methods was considered beyond the scope of the current research. Such a comparison could indeed form a good starting point for future research along this line.

We agree with the reviewer that one would expect the contribution of mapping to the total uncertainty to be small given the high density of the link network in The Netherlands. We have carried out some additional analyses on the effect of the local link density on the uncertainty. See our reply to comment #9 for details.

2. The title of the paper is somewhat misleading: it gives the false impression that this is a general and exhaustive analysis of the different error sources involved in microwave link rainfall estimation. In reality, however, the authors provide a case study for the Netherlands and only consider two main sources of errors (i.e., measurement and mapping). A better phrasing that is more aligned with the content of the paper would help.

R/. The title of the paper will be changed to: “**Measurement and interpolation uncertainties in rainfall maps from cellular communication networks**”.

Our analyses involve data from an entire cellular communication network. As such, it complements our previous detailed treatment of the various physical error sources affecting rainfall estimates from individual microwave links only:

– *Leijnse, H., R. Uijlenhoet, and J.N.M. Stricker, 2008: Microwave link rainfall estimation:*

Effects of link length and frequency, temporal sampling, power resolution, and wet antenna attenuation. Adv. Water Resour., 31, 1481–1493, doi:10.1016/j.advwaterres.2008.03.004.
- *Leijnse, H., R. Uijlenhoet, and A. Berne, 2010: Errors and uncertainties in microwave link rainfall estimation explored using drop size measurements and high-resolution radar data. J. Hydrometeor., 11, 1330–1344, doi:10.1175/2010JHM1243.1.*

Note that The Netherlands and Israel are currently the only countries in the world where such data are available to the research community at a country-wide scale. In our opinion, we present more than one case study, since the analyses are based on 12 days of country-wide data.

3. There is a general confusion between "measurement" errors and "link-radar representativity" errors in the paper. Often, the term "measurement error" is used to denote both types of errors (e.g., p.3301, ll.6-7 and p.3302, ll.1-2). At other instances (e.g., p.3305, ll.3-6), the "link-radar representativity" is grouped with the mapping errors. This absolutely needs to be clarified to avoid any confusion.

R/. We agree with the reviewer that there is some confusion in the paper about representativity errors, and that this should be clarified. The aim of the paper was to separate mapping errors from the other sources of error, whereby we assume the gauge-adjusted radar rainfall fields to be the ground truth. Because our mapping methodology takes line-averaged rainfall intensities and treats these as point-scale rainrates, such errors (which could be called spatial representativity errors) are included in the mapping error. The term "measurement error" that we use throughout the paper includes all other representativity errors. We will modify the text in several places in order to clarify the issue:

- On p. 3295, lines 15-17, we will replace the sentence "In this way … or temporal sampling." by **"The simulation allows us to separate mapping errors from other errors."**.
- On p. 3296, lines 6-10, we will remove the two sentences "Radars sample a … microwave link measurements.".
- On p. 3296, line 26, we will add **"The path-average link rainfall estimates are assigned to the point at the center of the link, so that these point data can be used in the OK interpolation. This conversion from line-scale to point-scale data is part of our mapping method, and hence errors resulting from this conversion are part of the mapping uncertainty."**.
- On p. 3299, line 15 we will modify "in space and time" to **"in time".**
- On p. 3302, lines 5-10, we will modify the sentence "The remaining scatter … such as weather radars)." to **"The remaining scatter can be attributed to the interpolation methodology (including the assignment of line-average rainfall intensities to the link's center point), the spatial variability of rainfall, and the effect of other factors such as the variable and limited density of the link network (more links in urban than in rural areas)."**.
- On p. 3305, lines 3-5, we will remove the sentence "We converted our analyses … microwave link measurements.".

4. Some additional details about the variogram used to krige the rainfall fields (LINK, partSIM and fullSIM) are required. Please specify if you used a single variogram for all three cases and all time steps or if some kind of estimation/adjustment was performed. If the kriging of the link data was performed using a climatological variogram, please mention it. Also, it might be worth mentioning what happens to the interpolation in case the variogram has to be estimated from the link data.

R/. We used a single semivariogram model, namely the spherical model with parameters derived by van de Beek et al. (2011) [*van de Beek, C. Z., Leijnse, H., Torfs, P. J. J. F., and Uijlenhoet, R.: Climatology of daily rainfall semi-variance in The Netherlands, Hydrol. Earth Syst. Sci., 15, 171–183, doi:10.5194/hess-15-171-2011, 2011.*] based on rain gauge data. This is an isotropic and climatological model, which indeed was used in all the kriged rainfall fields from the LINK, partSIM and fullSIM data. No adjustment or semivariogram fitting was done for any of the three types of data.

We described and detailed the characteristics of this model in the last two paragraphs of Section 2.3 (Rainfall maps).

Below, in reply to comment # 15, we now indicate why we chose this model and not one fitted model from link data, namely because of the difficulty to systematically retrieve one consistent model for 15-min rainfall depths. In order to implement the remaining suggestions of the reviewer, the beginning of the last paragraph of Section 2.3 will be rephrased as follows: "**For the LINK, partSIM, and fullSIM datasets, 15-min rainfall maps were obtained as follows: first, the spherical semivariogram parameters were computed and downscaled for the given day of the year. Hence, a single semivariogram is applied to all 15-min time steps within that given day. The nugget was defined as 10% of the sill. Second, rainfall depths...**".

5. What about a simulation approach? If you know the variogram, you can generate artificial rainfall fields with similar spatial structures. This could be used to study the importance of the interpolation method and of the network topology.

R/. In our application of OK we have restricted our analyses to average fields (i.e. expected values). To study the effect of interpolation method and network topology we will introduce in the revised manuscript the concept of microwave link density per pixel, and compare such values against the error metrics (r^2 and CV). In that way we can assess the influence of the network topology (i.e., its density) on the OK method, as suggested by the reviewer.
Please see our detailed analysis in our reply to comment # 9.

6. What about intermittency? Is intermittency the reason why on p.3300 ll.5-6 you restrict the comparison to points with at least 0.1 mm accumulation? Please specify the underlying assumptions and comment on the effects they might have on the results (i.e., bias, CV and non-stationarity).

R/. The reason to select only those paired-rainfall depths for which the gauge-adjusted radar value (considered to be the ground-truth) exceeded 0.1 mm, was to only consider hydrologically significant rainfall depths. In other words, all radar rainfall depths below 0.1 mm were considered as no rain. This allowed us to be consistent with the inter-comparison we carried out among the three datasets we based our analyses on, namely LINK, partSIM, and fullSIM.

In page 3301, lines 19-22; we indeed gave a hint of what would happen to the metrics (more specifically to the relative bias), had the 0.1-mm threshold not been applied: "If all paired rainfall accumulations would have been used (and not only those in which at least the radar rainfall depth exceeds 0.1 mm) one would expect the relative bias to be exactly the same for all aggregation levels, because both aggregation and computation of the bias are linear operators (Eq. 1)".

As a matter of fact, had we decided not to apply such a threshold, the relative bias would have been substantially reduced (almost to an unbiased situation), the CV would have drastically increased, and the square of the correlation coefficient would have improved by 30, 16, and 10% respectively for the LINK, partSIM, and fullSIM datasets. This comparison between metrics is shown in the table below, only for the case of 15-min rainfall maps (A = 1 km^2).

	0.1 mm Threshold			NO Threshold		
	LINK	partSIM	fullSIM	LINK	partSIM	fullSIM
rBias	-14.3%	-13.0%	-9.3%	1.9%	-0.5%	0.9%
CV	1.216	0.871	0.748	3.2813	2.332	2.002
r^2	0.366	0.605	0.709	0.477	0.700	0.779

The differences between the two cases of "thresholding" are mainly attributed to the size of the sample over which the metrics are computed. When the 0.1 mm threshold was applied to the radar rainfall depths, there is a reduction in 86.1% in the number of pixels used for computing the metrics compared to the case of no threshold. If we look at the expression for CV (Eq. (2)), and assume that the bias is close to 0, then the effect of adding zeroes to both link and radar rainfall data is that the CV increases with sqrt(N). Given the 86.1% data reduction this means that the CV is expected to decrease by a factor of 2.68 if all values that are removed are indeed zero for both datasets. The fact that the reduction factor is 2.70, 2.67, and 2.68 for LINK, partSIM, and fullSIM, respectively, means that the differences in bias are caused by low rainfall intensities.

7. p.3301, ll.15-17, *We see that the biases are hardly reduced and therefore conclude that the under-estimation noted earlier must be almost entirely due to errors introduced by the* *<u>incomplete spatial sampling</u>*.

I would be more careful with this statement. The observed differences can also be the result of a sub-optimal interpolation method. In this case, the major issue is not the fact that you have incomplete sampling but the stationarity assumption behind ordinary kriging (i.e., constant mean and variance). In other words, the fact that partSIM has only a slightly lower bias than LINK may also be because ordinary kriging is not the best interpolation method in this case. The point I try to make here is that the choice of the interpolation method and the assumptions behind it matter, especially in networks with highly variable densities. Maybe if you had used another interpolation method, the differences in bias between partSIM and fullSIM would not have been that large...

R/. As we explain more in detail in our response to comment # 15, for the conditions and constraints of this work, we assumed stationarity. The fact that we only used one method of interpolation allowed us to determine the relative contribution to the global error. It seems that it can be attributed to incomplete spatial sampling. Note, however, the table in comment # 6, which shows the dependence of relative bias on the chosen threshold(s). Hence, we believe that underestimation cannot be directly attributed to incomplete spatial sampling.

On p. 3301, lines 8-17, we will remove the entire paragraph "The main question we focused... by incomplete spatial sampling.".

8. p.3303, ll.25-26, *We found that link rainfall retrieval errors themselves are the source of error that contributes most to the overall uncertainty in rainfall maps from commercial microwave link networks*.

It's more correct to say that the major error is due to the retrieval and/or the representativity error between link and radar, with no way of knowing which contributes most. Also, you forget to say that this result is based on the assumption that the variogram of the rainfall field is known a priori. If you had no radar nor gauge data, the variogram would have to be estimated directly from the (incomplete) link data, which adds another dimension to the problem.

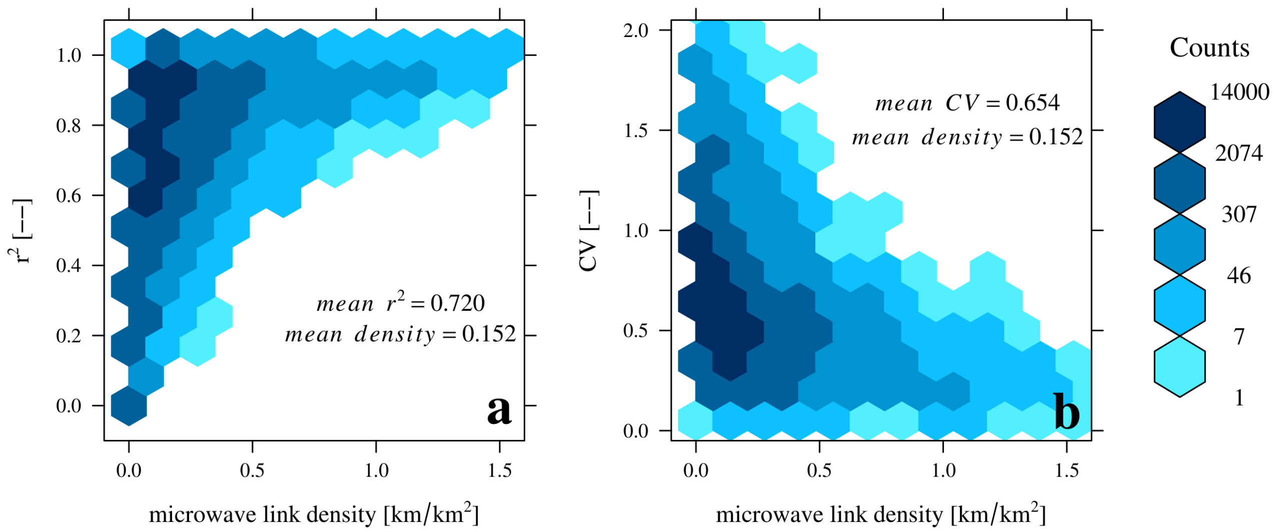
R/. In our response to comment # 15, we explain our reasons to use a model semivariogram and not an empirical (fitted) version.

We maintain that measurement errors are the source of uncertainty that contributes the most to the overall error, given our two-category classification and how we used one reference framework (radar info as ground-truth) to estimate the relative error contribution of each category: measurements and mapping. Note that the term "measurement error" that we use throughout the paper includes almost all types of representativity errors (see comment # 3).

The sentence will be rephrased as: ***"We found that measurement errors themselves are the source of error that contributes most to the overall uncertainty in rainfall maps from commercial microwave link networks."***.

9. More generally, it would be interesting to see how the relative contributions of measurement errors and mapping errors change as a function of the number of links, their density or any other characteristic related to the network's topology. Intuitively, the mapping error is going to increase with decreasing link density. I understand that this is a difficult question to answer. But at least, the authors could discuss it a little bit more.

R/. A detailed exploration of the relative contributions of measurement and mapping errors as a function of link density, as the reviewer suggests, was thought as a follow up for this work. The idea was to explore more in detail the regional contribution to the error/uncertainty distribution of areas with higher and lower link densities, i.e., cities and rural areas respectively. This was meant to be done by applying the same methodology but only using subsets of the Dutch link network (hence not the entire network). Nevertheless, as a first exploration of this suggestion in the current work, we created two more scatter density plots in which we present the dependence of the metrics r^2 and CV on the microwave link density (see figure below), for every pixel in all 15-min time steps in the 12-day data set for the fullSIM case (A = 1 km^2). We selected this data set because it is the only one in which the link network is fully operational among all 15-min time steps. The microwave link density (map) was computed for every pixel as the cumulative length of all link paths contained within a 13x13 pixel square area divided by the corresponding area size.



In the revised version of the paper, the above figures and the paragraph below will be included: **"From the figure above it can be seen that a higher density in the link network guarantees good correlation between the estimated values of rainfall and the ground-truth. From the left panel (a) it can be concluded that lower link densities also contribute (and in large**

proportion) to higher correlation coefficients. This means that without considering errors in link measurements, these latter being the largest source of uncertainty in country-wide rainfall fields, the network density and the mapping methodology considered here are, respectively, high and good enough to retrieve accurate rainfall fields at such country-wide scales (at least in The Netherlands).”.

10. Is a relative bias of 15%, a CV of 121% and a coefficient of determination of 0.37 at 15 min acceptable for practical applications in hydrology or not? If not, what could and should be done to overcome these issues and improve the overall accuracy of rainfall maps derived from microwave links?

R/. That depends on the catchment characteristics, in particular the catchment’s response time (e.g. Berne et al., 2004 - [*Berne, A., Delrieu, G., Creutin, J.D., Obled, C.: Temporal and spatial resolution of rainfall measurements required for urban hydrology, J. Hydrol., 299, 166-179, doi:10.1016/j.jhydrol.2004.08.002, 2004.*]). A detailed investigation of these issues is therefore beyond the scope of the current work and will be dealt with in future contributions.

For practical hydrological applications (distributed models) it is always better to have an unbiased rainfall input (or close to such situation) than one with no uncertainty but a large bias. This is because a bias will systematically propagate throughout the whole hydrological model. In practical applications, rainfall field inputs will also contain NO-rain values (intermittency), and their metrics would certainly be improved in comparison to the statistics cited by the reviewer, which have been obtained after applying a 0.1 mm threshold (see Table in reply to comment # 6). Although the CV increases (larger uncertainty; see the discussion in our reply to comment #6), the relative bias substantially decreases (from 15% to 2%), leading to a nearly unbiased situation ideal for hydrologic (rainfall-runoff) models.

Exploring exactly how the measurement errors in microwave link rainfall retrievals propagate through hydrological models, is beyond the scope of the current work. How link networks compare to other networks (radar, gauges, satellites) when their rainfall retrievals are used as inputs in hydrological models is ongoing work.

11. Section 3 (Results) is very short. It could easily be merged with Section 4 (Discussion).

R/. We decided to keep sections 3 and 4 (Results and Discussion) separate.

12. It would be nice to mention the main result in the abstract as well, and not just in the conclusion.

R/. We will add the following sentence at the end of the abstract: “**Errors in microwave link measurements were found to be the source that contributes most to the overall uncertainty**”.

13. p.3292, l.19 ... *that is, the physics involved in the measurements such as wet antenna attenuation, sampling interval of measurements, wet/dry period classification, drop size distribution (DSD), and multi-path propagation.*
The sampling interval and the wet/dry classification are not exactly related to the physics of the problem. It's more a sampling and signal processing issue. Please reformulate. In addition, you could include the dry weather baseline attenuation in the list of uncertainties.

R/. The “dry weather baseline attenuation” suggestion will be incorporated, and the sentence rephrased like it was originally stated in the abstract: “... **(1) those associated with the individual microwave link measurements such as wet antenna attenuation, sampling interval of measurements, wet/dry period classification, dry weather baseline attenuation, drop size distribution (DSD), and multi-path propagation;...**”.

Lines 5 to 10 in page 3303 will be also rephrased to be consistent with the change above: “**In general, these errors can be attributed to different sources like wet antenna attenuation, sampling interval of measurements, wet/dry period classification, dry weather baseline attenuation, drop size distribution (DSD), multi-path propagation, interpolation methodology and algorithm, the availability of microwave link measurements, and the variability of rainfall itself across time and space**”.

14. p.3296, ll.8-10. *Simulated rainfall depths are based on radar data; hence, they largely reduce the sampling differences between radar and microwave links measurements.*
This sentence is confusing. Are you referring to the weighted averaging of the radar data with respect to the link path? Or am I missing a crucial point here? Please clarify.

R/. The reviewer is not missing any crucial point here; indeed the related sentence refers to the problem in comparing gauge-adjusted radar rainfall measurements (i.e., measurements taken in a volume in the atmosphere at 1500 m altitude adjusted by point measurements on the ground) against microwave rainfall retrievals.

We agree with the reviewer that this sentence can cause confusion. We will therefore remove it (see also our reply to comment #3).

15. p.3296, ll.25-26, *Kriging is ideally suited for interpolation of highly irregular-spaced data points.*
This statement needs to be nuanced a little bit. Kriging is a good (linear) interpolation method that takes into account the spatial structure of the data but also comes with its own limitations. In particular, ordinary kriging assumes second-order stationarity of the process. Thus the mean and variance of the process are assumed to be constant. In reality, however, rainfall often turns out to be spatially heterogeneous and non-stationary. Typically, the stochastic relation linking the rainfall at two separate sites depends not only on the relative distance separating the two sites but also on surrounding topographic features and their location with respect to the flow of weather. By applying ordinary kriging, you assume that there are no trends and heterogeneities in the field. This should be clearly mentioned in the text as it is a strong hypothesis.

R/. We indeed assumed the anisotropy and stationarity restrictions that Ordinary Kriging (OK) implies. Still, we, like Overeem et. al. (2013), used the OK approach as a simple and straightforward interpolation technique. For the OK to be applied, we indeed made several assumptions, isotropy and stationarity included. We based these assumptions on the geographical conditions of The Netherlands. Its relative small area and flat topography allows for meteorological events (like rain) to be (statistically) homogeneously distributed across its land surface.

As suggested by the reviewer, the related sentence will be rephrased as follows: “**Kriging is ideally suited for interpolation of highly irregularly-spaced data points. Nevertheless, this method comes with its own limitations, and a number of assumptions should be made for the method to be valid, e.g., isotropy and statistical stationarity. These assumptions are further explained in Sect. 6.**”; and a new paragraph will be included in the Constraints and Recommendation section explaining more in detail the above reasoning behind these assumptions.

This is the new paragraph to be included: "**Apart from its simplicity and the 30-year rainfall dataset on which it is based, we also chose the isotropic spherical semivariogram of van de Beek et al. (2011), because a consistent semivariogram model estimated from link data was not feasible for 15-min rainfall intensities. Isotropic semivariograms assume equal spatial dependence in all possible directions. Rainfall is generally a phenomenon that exhibits anisotropy in time and space (Lepioufle et al., 2012; Velasco-Forero et al., 2012; Guillot and Lebel, 1999; Amani and Lebel, 1997). Nevertheless, it is reasonable to assume isotropy for The Netherlands given its relative small area and flat topography. OK assumes the mean to be constant and unknown within the region of interpolation. When this unknown mean presents substantial changes over short distances, the assumption of statistical stationarity is no longer valid. Universal Kriging, Kriging with External Drift, and Regression Kriging (RK) are more sophisticated interpolation techniques that incorporate trends to account for non-stationarity (e.g. Schuurmans et al., 2007). The performance of these geostatistical techniques to retrieve link rainfall maps was beyond the scope of this research.**"

16. Please reconsider the color scales in Fig 6 and Fig 7. Red is perceived as a bright color and should therefore be associated with large values (and vice-versa for green). Also, a significant fraction of the population has problems differentiating between red and green tones. Blue-red, green-purple or shades of gray are common alternatives.

R/. We are aware of the particular (and uncommon) color scale we used in Figs. 6 and 7. The departure point of this work/paper is the previous work by Overeem et. al. (2013) [Overeem, A., Leijnse, H., and Uijlenhoet, R.: Country-wide rainfall maps from cellular communication networks, P. Natl. Acad. Sci. USA, 110, 2741–2745, doi:10.1073/pnas.1217961110, 2013]. The reason we decided to implement this color scale was to bring some continuity to the plots/maps presented in Overeem et. al. (2013). Therefore, readers (especially those familiar with Overeem et. al. (2013)) would be able to visually compare the maps presented in both papers, and easily see (or perceive) the improvement in rainfall maps.

17. In general, it would be nice to have a more consistent use of color scales throughout the paper.

R/. The reviewer in his previous comment (# 16) expressed the color-blind issues that affect a significant fraction of the population. He/she also suggests blue-red, green-purple or shades of gray as common alternatives to be used in color scales. We are also aware of such issues. That is why in figures not related to any previously presented by Overeem et. al. (2013), i.e., Figs. 2 and 3, we indeed used the blue-red and green-purple color scales suggested by the reviewer.

18. p.3290, l.25 *These rainfall maps were compared against ...*
Not sure which rainfall maps you are referring to. The 3500 ones mentioned on l.23 or the simulated ones from l.24? Please clarify.

R/. "... ~3500 computed rainfall maps..." refers to maps obtained from real and simulated link rainfall depths. In the paper, the following sentence on 1.24 "Simulated link rainfall depths were obtained from radar data." indicates that the simulated link rainfall depths from which the rainfall maps were computed are based (or were obtained) from radar rainfall depths.

The related sentences will be rephrased as follows: "**Simulated link rainfall depths refer to path-**

averaged rainfall depths obtained from radar data. The ~3500 real and simulated rainfall maps were compared against quality-controlled gauge-adjusted radar rainfall fields (assumed to be the ground truth).”

19. p.3292, l.2 the reference to Messer et al., 2012 should be put into parentheses.

R/. Thanks. When the manuscript was submitted, the related reference was indeed into parentheses. The parentheses were removed during the editing process. This concern is probably related to referencing-rules (or edition standards) established by HESS/Copernicus. We will make sure this is corrected in a revised version of the manuscript.

20. p.3292, l.25 I'm not sure if the term physical errors is appropriate here. Maybe “measurement" or “sampling" would be more appropriate.

R/. The word “physical” will be replaced by “measurement” yielding: “**Only the overall effects of measurement and interpolation errors were addressed here, but not all measurement errors separately.**”

21. p.3293, l.10, The parentheses in (2011) are not really necessary.

R/. Thanks. The parentheses will be removed. The sentence will read: “**which is spread across the months of June, August and September 2011.**”

22. p.3294, l.17 *(2) there are gaps in the network, <u>without link data</u> at all ...*

R/. The sentence will be changed to: “**... (2) there are gaps in the network, because of complete absence of link data or low data availability.**”

23. p.3295, l.10 ... *the performance of the link network <u>assuming that all links provide perfect measurements</u>* ...

R/. The sentence will be changed to: “**... (1) to evaluate the performance of the link network assuming that all links provide perfect measurements of path-averaged rainfall at the 15 min interval;...**”

24. p.3300, l.21, *Figure 4a, d and g <u>show</u> the relation between the actual link...*

R/. Thanks. The sentence will be changed to: “**Figure 4a, d and g show the relation between the actual link and radar rainfall depths, for the three cases of spatiotemporal aggregation.**”

25. p.3303, ll.1-2 *In other areas, the nugget of the employed variogram has a similar effect of reduction on large errors.*
This sentence is not clear. Please reformulate.

R/. The sentence will be changed to: “**In areas with lower link densities the nugget of the**

employed variogram has a similar reducing effect on large errors.”

ANONYMOUS REVIEWER #2

While the scientific content is very good, I agree with most points Reviewer #1 raised. The paper can certainly be improved by adding a more detailed description of the sources of error listed in the introduction, and their implications on data quality.
Overall, I suggest that the paper could be published after some additions are made to the methods and discussion sections. It is currently very short and could gain in clarity this way. Also, the main findings of the study that the main source of uncertainty are the link rainfall retrievals themselves is not reported in the abstract.

R/. Most of the changes suggested by reviewer # 1 will be implemented. Thus, the suggested changes of reviewer # 2 with regard to reviewer # 1 have already been taken into account (see replies to reviewer #1).

Finally, while this is an interesting alternative to use already existing infrastructures, discussion is needed on the usefulness of these network-based rainfall data for hydrological modelling and flood forecast.
More precisely, while the study focuses on 12 days, can we foresee using link rainfall in an operational way in the future? and what are the key improvements required to reach this stage? This would make an interesting point of the applicability of this method to measures rainfall in places which may have a well-developed cellular network but lack a radar and/or an extensive gauge network.

R/. The applicability of rainfall fields from link networks as input in hydrological modeling, has been discussed in our response to comment # 10 from reviewer # 1.
To foresee their operational applicability in the near future is something really difficult to predict. Although it is true that the spatiotemporal resolution of link measurements of rainfall falls within the requirements for hydrological modeling of urban catchments (Berne. et al., 2004), the largest hurdle is to overcome the restrictions by most of the cellular providers with regard to data availability (i.e. their data sharing policies).

Below, the detailed list of the changes we implement on our manuscript.

Pag. 1.: The title of the paper was changed to: "**Measurement and interpolation uncertainties in rainfall maps from cellular communication networks**".

Pag. 2. l19.: "**dry weather baseline attenuation,**" was added.

Pag. 2. l24-26.: The sentences were rephrased as: "**Simulated link rainfall depths refer to path-averaged rainfall depths obtained from radar data. The ~3500 real and simulated rainfall maps were compared against quality-controlled gauge-adjusted radar rainfall fields (assumed to be the ground truth).**"

Pag. 3. l2.: "**Errors in microwave link measurements were found to be the source that contributes most to the overall uncertainty.**" was added.

Pag. 3. l23.: "in" was replaced by "**by using**".

Pag. 3. l27.: "1" was replaced by "**1 sec, 1 min**".

Pag. 4. l2.: As suggested by anonymous referee #1, "Messer et al., 2012" was put into parentheses "**(Messer et al., 2012)**". Please see rebuttal letter, item 19.

Pag. 4. l5.: "yet" was replaced by "**(yet)**".

Pag. 4. l18-21.: The sentence was rephrased as: "**(1) those associated with the individual microwave link measurements such as wet antenna attenuation, sampling interval of measurements, wet/dry period classification, dry weather baseline attenuation, drop size distribution (DSD), and multi-path propagation;**".

Pag. 4. l24-25.: The word "physical" was changed to "**measurement**".

Pag. 4. l24.: "were" was replaced by "**are**".

Pag. 5. l10.: "(2011)" was replaced by "**2011**".

Pag. 6. l12.: "**, wet/dry classification, and outlier removal,**" was added.

Pag. 6. l17-18.: The sentence was rephrased as: "**(2) there are gaps in the network, because of complete absence of link data or low data availability.**".

Pag. 7. l10-12.: The sentence was rephrased as: "**(1) to evaluate the performance of the link network assuming that all links provide perfect measurements of path-averaged rainfall at the 15 min interval;**".

Pag. 7. l15-17.: The sentence was rephrased as: "**The simulation allows us to separate mapping errors from other errors.**".

Pag. 8. l6-10.: The paragraph was removed.

Pag. 8. l25-26.: The sentence was rephrased as: "**Kriging is ideally suited for interpolation of highly irregularly-spaced data points. Nevertheless, this method comes with its own limitations, and a number of assumptions should be made for the method to be valid, e.g., isotropy and statistical stationarity. These assumptions are further explained in Sect. 6.**".

Pag. 8. l26.: "**The path-average link rainfall estimates are assigned to the point at the center of the link, so that these point data can be used in the OK interpolation. This conversion from line-scale to point-scale data is part of our mapping method, and hence errors resulting from this conversion are part of the mapping uncertainty.**" was added.

Pag. 9. l14-16.: The sentences were rephrased as: "**For the LINK, partSIM, and fullSIM datasets, 15-min rainfall maps were obtained as follows: first, the spherical semivariogram parameters were computed and downscaled for the given day of the year. Hence, a single semivariogram is applied to all 15-min time steps within that given day. The nugget was defined as 10% of the sill.**"

Pag. 11. l15.: "space and" was removed.

Pag. 11. l18.: "Supplement" was replaced by "**Supporting Information**".

Pag. 12. l21.: "represents" was replaced by "**show**".

Pag. 13. l8-17.: The paragraph was removed.

Pag. 13. l28.: "availability" was removed.

Pag. 14. l5.: "path-average" was replaced by "**path-averaged**".

Pag. 14. l6.: "**(including the assignment of line-average rainfall intensities to the link's centre point)**" was added.

Pag. 14. l5-9.: The sentence was rephrased as: "**The remaining scatter can be attributed to the interpolation methodology (including the assignment of line-average rainfall intensities to the link's center point), the spatial variability of rainfall, and the effect of other factors such as the variable and limited density of the link network (more links in urban than in rural areas).**"

Pag. 15. l1-2.: The sentence was rephrased as: "**In areas with lower link densities the nugget of the employed variogram has a similar reducing effect on large errors.**"

Pag. 15. l2.: "**From Fig. 6 it can be seen that a higher density in the link network guarantees good correlation between the estimated values of rainfall and the ground-truth. From the left panel (Fig. 6a) it can be concluded that lower link densities also contribute (and in large proportion) to higher correlation coefficients. This means that without considering errors in link measurements, these latter being the largest source of uncertainty in country-wide rainfall fields, the network density and the mapping methodology considered here are, respectively, high and good enough to retrieve accurate rainfall fields at such country-wide scales (at least in the Netherlands).**" was added.

Pag. 15. l5-10.: The sentence was rephrased as: "**In general, these errors can be attributed to different sources like wet antenna attenuation, sampling interval of measurements, wet/dry period classification, dry weather baseline attenuation, drop size distribution (DSD), multi-path propagation, interpolation methodology and algorithm, the availability of microwave**

link measurements, and the variability of rainfall itself across time and space.”

Pag. 15. l25-26.: The sentence was rephrased as: “**We found that measurement errors themselves are the source of error that contributes most to the overall uncertainty in rainfall maps from commercial microwave link networks.**”

Pag. 16. l13.: “**more**” was added.

Pag. 17. l3-5.: The sentence was removed.

Pag. 17. l6.: “**Apart from its simplicity and the 30 year rainfall dataset on which it is based, we also chose the isotropic spherical semivariogram of van de Beek et al. (2011), because a consistent semivariogram model estimated from link data was not feasible for 15-min rainfall intensities. Isotropic semivariograms assume equal spatial dependence in all possible directions. Rainfall is generally a phenomenon that exhibits anisotropy in time and space (Lepioufle et al., 2012; Velasco-Forero et al., 2012; Guillot and Lebel, 1999; Amani and Lebel, 1997). Nevertheless, it is reasonable to assume isotropy for The Netherlands given its relative small area and flat topography. OK assumes the mean to be constant and unknown within the region of interpolation. When this unknown mean presents substantial changes over short distances, the assumption of statistical stationarity is no longer valid. Universal Kriging, Kriging with External Drift, and Regression Kriging (RK) are more sophisticated interpolation techniques that incorporate trends to account for non-stationarity (e.g. Schuurmans et al., (2007)). The performance of these geostatistical techniques to retrieve link rainfall maps was beyond the scope of this research.**” was added.

Pag. 18. l19.: “**daily**” was added.

Pag. 19. l1.: “the” was removed.

Pag. 19-21.: The respective citation/references of **Amani and Lebel, (1997)**; **Guillot and Lebel, (1999)**; **Lepioufle et al., (2012)**; **Schuurmans et al., (2007)**; **and Velasco-Forero et al., (2012)** were added.

Pag. 27 or 28.: A new graph with its caption was added.

Pag. 28 and 29.: “row-labels” was replaced by “**row labels**” in the captions.

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~~Sources of uncertainty~~ Measurement and interpolation uncertainties in rainfall maps from cellular communication networks

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Abstract

Accurate measurements of rainfall are important in many hydrological and meteorological applications, for instance, flash-flood early-warning systems, hydraulic structures design, irrigation, weather forecasting, and climate modelling. Whenever possible, link networks measure and store the received power of the electromagnetic signal at regular intervals. The decrease in power can be converted to rainfall intensity, and is largely due to the attenuation by raindrops along the link paths. Such alternative technique fulfills the continuous strive for measurements of rainfall in time and space at higher resolutions, especially in places where traditional rain gauge networks are scarce or poorly maintained.

Rainfall maps from microwave link networks have recently been introduced at country-wide scales. Despite their potential in rainfall estimation at high spatiotemporal resolutions, the uncertainties present in rainfall maps from link networks are not yet fully comprehended. The aim of this work is to identify and quantify the sources of uncertainty present in interpolated rainfall maps from link rainfall depths. In order to disentangle these sources of uncertainty, we classified them into two categories: (1) those associated with the individual microwave link measurements, i.e., the errors involved in single-link rainfall retrievals such as wet antenna attenuation, sampling interval of measurements, wet/dry period classification, dry weather baseline attenuation, quantization of the received power, drop size distribution (DSD), and multi-path propagation; (2) those associated with mapping, i.e., the combined effect of the interpolation methodology and the spatial density of link measurements.

We computed ∼3500 rainfall maps from real and simulated link rainfall depths for 12 days for the land surface of the Netherlands. Simulated link rainfall depths ~~were~~ refer to path-averaged rainfall depths obtained from radar data. ~~These~~ The ∼3500 real and simulated rainfall maps were compared against quality-controlled gauge-adjusted radar rainfall fields (assumed to be the ground truth). Thus, we were able to not only identify and quantify the sources of uncertainty in such rainfall maps, but also to test the actual and optimal performance of one commercial microwave network from one of the cellular

providers in the Netherlands. Errors in microwave link measurements were found to be the source that contributes most to the overall uncertainty.

1 Introduction

Accurate rainfall estimates are crucial inputs for hydrological models, especially those employed for forecasting flash floods, due to the short time scales in which they develop. Rainfall rates can be retrieved from microwave links because rain droplets attenuate the electromagnetic signal between transmitter and receiver along the microwave link path. The principles behind rainfall estimates from microwave attenuation were investigated by Atlas and Ulbrich (1977). They established the nearly linear relationship between the rainfall intensity and the specific attenuation of the signal for frequencies between 10 and 35 GHz.

Messer et al. (2006) and Leijnse et al. (2007) used commercial microwave links to estimate rainfall rates. Note that networks of such links have not been designed for that purpose. In the last decade several studies have developed methods to improve rainfall estimates from microwave link measurements (Leijnse et al., 2008, 2010; Overeem et al., 2011; Schleiss et al., 2013; Chwala et al., 2014). In addition, Goldshtein et al. (2009) and Zinevich et al. (2008, 2009, 2010) proposed methods to estimate rainfall fields via commercial microwave networks. Giuli et al. (1991) had previously reconstructed rainfall fields from simulated microwave attenuation measurements. Overeem et al. (2011) developed an algorithm to estimate rainfall from minimum and maximum received signal levels over 15 min intervals, in which the wet antenna effect is corrected for, and where wet and dry spells are identified from the removal of signal losses not related to rainfall ~~in~~ by using nearby links.

Rainfall fields can generally be retrieved from commercial microwave link networks at a higher resolution than rain gauge networks. This holds not only for the spatial resolution (usually microwave links outnumber rain gauges) but also for the temporal resolution (microwave link measurements can be obtained for 1 sec, 1 min, 15 min or daily intervals at either instantaneous or minimum-and-maximum samples of Received Signal Level (RSL) measurements ~~, Messer et al., 2012~~ (Messer et al., 2012)). The massive deployment of microwave links provides a complementary network to measure rainfall, especially in countries where rain gauges are scarce or poorly maintained, and where ground-based weather radars are not ~~yet~~ (yet) deployed (Doumounia et al., 2014).

Recently, Overeem et al. (2013) obtained 15 min and daily rainfall depths from one commercial microwave link network for 12 days for the land surface of the Netherlands (∼35 000 km^2; ∼1750 links). They interpolated these rainfall depths to obtain rainfall fields to be compared against gauge-adjusted radar rainfall maps. Although the associated biases were small, the corresponding uncertainties were not. The coefficient of determination, i.e., the square of the correlation coefficient, between link-based and gauge-adjusted radar rainfall maps was 0.49 for the 15 min time scale, and 0.73 for the daily time scale. They did not explore the sources of error that impeded these correlations to reach higher values, though. Here, we address this issue with the aim to unravel and understand the sources of error (and their uncertainties) present in the methodology proposed by Overeem et al. (2013) to estimate rainfall fields. We split the overall uncertainty in rainfall maps from commercial microwave networks into two main sources of error: (1) those associated with the individual microwave link measurements ~~, that is, the physics involved in the measurements~~ such as wet antenna attenuation, sampling interval of measurements, wet/dry period classification, dry weather baseline attenuation, drop size distribution (DSD), and multi-path propagation; (2) those associated with mapping, that is, the combined effect of the interpolation methodology and the spatial density of microwave link measurements. Note that not all the links in the network continuously report data. Only the overall effects of ~~physical~~ measurement and interpolation errors ~~were~~ are addressed here, but not all ~~physical~~ measurement errors separately.

This paper is organized as follows: Sect. 2 describes the data sets and methodology developed by Overeem et al. (2013) to estimate rainfall maps, jointly with the methodologies for this work to derive rainfall maps to identify and quantify error sources. Section 3 compares the results obtained here with those presented in Overeem et al. (2013). Section 4 highlights our major findings. Finally, Sects. 5 and 6 provide a summary, conclusions and recommendations.

2 Materials and methods

2.1 Data

Two categories of data were used: link data, and radar data. These two data sets are fully independent given that each one originates from a different source: microwave link measurements, and a combination of radar and rain gauge measurements, respectively. Link and radar data contain rainfall depths from the 12-day validation period studied by Overeem et al. (2013), which is spread across the months of June, August and September ~~(2011).~~ 2011. This validation period was selected because of its large number of rainfall events. Figure 1 conceptually illustrates the steps we followed to quantify uncertainties in rainfall maps from link networks.

2.1.1 Link data (LINK)

Link data refers to rainfall depths retrieved from measurements of the attenuation of electromagnetic signals from one commercial microwave link network in the Netherlands. Overeem et al. (2011, 2013) thoroughly explain the methodology to convert measurements of the decrease in the received power to rainfall depths, with reference to a level representative of dry weather. Briefly explained, their methodology is based on four steps: (1) a link is considered to be affected by rainfall if the received power jointly decreases with that one of nearby links; (2) a reference signal level representative of dry weather, i.e., the median signal level of all dry periods in the previous 24 h is determined, and the signal subtracted from this reference level; the result is the attenuation estimate; (3) microwave links for which accumulated (over one day) specific attenuation deviates too much (from that one of nearby links) are excluded from the analysis; (4) 15 min average rainfall intensities are computed from a weighted average of minimum and maximum rainfall intensities obtained by a power-law correlation of specific attenuation (Atlas and Ulbrich, 1977). These rainfall intensities are expressed as path-averaged rainfall depths, and are assumed to be representative of the rainfall across the link path. Full details of the algorithm can be found in Overeem et al. (2011, 2013).

Data from up to 1751 link paths are available, with path lengths from 0.13 to 20.26 km, and frequencies from 12.8 to 39.4 GHz (Fig. 2). It is also clear that the network is designed such that the link frequency decreases as path length increases, mainly because low-frequency links suffer less from rain attenuation.

Figure 3 presents the spatial distribution of one commercial link network from one of the providers in the Netherlands, as well as the temporal availability for each link path. Due to data storage problems, wet/dry classification, and outlier removal, it is not feasible to have link data for all the possible link paths in the network (1751) for every time step. The temporal availability per link varies from 0.9 to 99.9 %, with a global average over the entire 12-day dataset of 83.5 %.

The spatial distribution of the network has two characteristics: (1) there is a strong contrast between urban and rural areas with regard to the spatial distribution of the network; and (2) there are gaps in the network, ~~without no link data at all or because of~~ because of complete absence of link data or low data availability. Analyses of the link path orientations show no preferred orientations, i.e., a uniform distribution (such analyses are not presented in this paper).

2.1.2 Radar data

Radar data is taken from the climatological rainfall data set[1] of two C-band Doppler weather radars operated by the Royal Netherlands Meteorological Institute (KNMI) (Overeem et al., 2009a, b, 2011). The composite image of rainfall depths has a temporal resolution of 5 min, and a spatial resolution (pixel size) of 0.92 km^2 (rounded to 1 km^2 in figures, tables, and subsequent analyses), for the entire land surface of the Netherlands (38 063 pixels). This composite image is adjusted with rainfall depths from one automatic and one manual rain gauge network (32 and 325 gauges, respectively) also operated by KNMI. The spatial and

[1]KNMI climatological rainfall data sets are freely available at the IS-ENES climate4impact portal: http://climate4impact.eu/impactportal/data/catalogbrowser.jsp?catalog=http://opendap.knmi.nl/knmi/thredds/./radarprecipclim.xml.

temporal resolution, and its accuracy, make this data set a reliable source of rainfall data. We used the same radar data set as in Overeem et al. (2013).

2.2 Simulated link rainfall depths

Simulated link rainfall depths are averages of radar data based on the topology and time-availability features of the link network. The purpose of simulated link rainfall depths is twofold: (1) to evaluate the performance of the link network ~~as if all links would~~ assuming that all links provide perfect measurements of ~~path-average rainfall in the 15min intervals they are available~~path-averaged rainfall at the 15 min interval; (2) to evaluate the performance of the link network if all links would be available all the time.

Because link data was obtained in intervals of 15 min, sets of three consecutive 5 min radar composite images were summed up on a pixel-by-pixel basis. ~~In this way only the effect of rainfall variability along the link path was considered, not the effect of measurement errorsor temporal sampling~~The simulation allows us to separate mapping errors from other errors. For detailed studies on the effects of link length and frequency, temporal sampling, power resolution, and wet antenna attenuation in link measurements see Leijnse et al. (2008, 2010). After the addition of 5 min radar composite images, the link network topology was overlaid on the 15 min radar composite image, and all pixels under every single link path were selected. Then, for every link path and its associated pixels, rainfall depths were averaged. This was a weighted average in which the weight was taken as the fraction of the total link path that overlaps one radar pixel. For instance, if a 1 km link path was located 0.6 km over one pixel and 0.4 km over a contiguous pixel, the average rainfall depth was the sum of 60 % of the first pixel's rainfall depth plus 40 % of the second pixel's rainfall depth.

Not all link data is available for all the possible link paths in the network (1751) at every time step. In addition to the performance of the actual topology of the network, the complete availability of radar data allowed us to simulate the optimal performance of the link network, i.e., the performance that could theoretically be achieved if all links (1751) would be available all the time.

~~Radars sample a volumetric space up in the air, whereas microwave link retrievals are based on attenuation measurements along the link path, tens of meters above the ground (Battan, 1973; Atlas and Ulbrich, 1977) . Simulated rainfall depths are based on radar data; hence, they largely reduce the sampling differences between radar and microwave link measurements.~~

2.3 Rainfall maps

The rainfall depths from actual link measurements and both types of simulation (actual and 100 % network availability) were spatially interpolated to obtain 15 min rainfall maps with a spatial resolution of 1 km^2. In all rainfall maps the land surface of the Netherlands was represented by 38 063 pixels. For any given time step, interpolated rainfall maps were compared on a pixel-by-pixel basis against the radar rainfall fields. Hence, 15 min rainfall maps were obtained for the 12-day validation period, i.e., 1152 rainfall maps in total for each of the four sets of rainfall maps considered (namely radar, actual links, simulated links with partial availability, and simulated links with 100 % availability). In subsequent figures and tables, these four datasets will be identified as “RADAR”, “LINK”, “partSIM”, and “fullSIM”, respectively (see Fig. 1). 15 min rainfall maps were accumulated to daily rainfall maps, i.e., 12 daily rainfall maps per data set.

Ordinary Kriging (OK) was employed to generate rainfall maps, because it is the simplest and most straightforward method that accounts for the local variability of the stochastic process, rainfall in this case (Cressie, 1990; Haining et al., 2010). Kriging is ideally suited for interpolation of highly ~~irregular-spaced~~ irregularly-spaced data points. Nevertheless, this method comes with its own limitations, and a number of assumptions should be made for the method to be valid, e.g., isotropy and statistical stationarity. These assumptions are further explained in Sect. 6. The path-averaged link rainfall estimates are assigned to the point at the center of the link, so that these point data can be used in the OK interpolation. This conversion from line-scale to point-scale data is part of our mapping method, and hence errors resulting from this conversion are part of the mapping uncertainty.

Any kriging method heavily relies on the function that describes the spatial covariance, i.e., the semivariogram. The semivariogram is a continuous function that describes how the spatial dependence of a random variable changes with distance and direction (Isaaks and Srivastava, 1989, chap. 7). Like Overeem et al. (2013), we chose the semivariogram approach of van de Beek et al. (2011) because it is a simple isotropic spherical model developed for the Netherlands on the basis of a 30-year climatological rainfall data set. van de Beek et al. (2011) concluded that the seasonality in range and sill of the semivariogram can be described by cosine-function models with the day-of-year as the independent variable. Note that they assumed the nugget to be zero. van de Beek et al. (2012) also developed two methodologies that allowed for the spherical semivariogram to be downscaled from daily to hourly time steps. We chose their second methodology, namely power-law scaling of cosine function parameters, because it was shown to perform better. This downscaling methodology was based on hourly rainfall data aggregated to 2, 3, 4, 6, 8, 12 and 24 h. Here we extended this power-law downscaling to smaller time scales, namely 0.25 h, i.e., 15 min.

For the LINK, partSIM, and fullSIM datasets, 15 min rainfall maps were obtained as follows: first, the spherical semivariogram parameters were computed and downscaled for the given day of the year. Hence, a single semivariogram is applied to all 15 min time steps within that given day. The nugget was defined as 10 % of the sill. Second, rainfall depths were assigned to the coordinates of the link paths' middle points. Third, rainfall depths were interpolated over the spatial grid of the radar data set. The interpolation algorithm always selects the closest 100 rainfall depths to the pixel for which the interpolation is carried out. This selection was established to speed up the interpolation process. 24 h rainfall maps were obtained from the aggregation of 15 min rainfall maps.

2.4 Error and uncertainty metrics

To quantify the uncertainty in rainfall maps from microwave link networks, we used three metrics: (1) the relative bias, (2) the coefficient of variation, and (3) the coefficient of determination.

The relative bias is a relative measure of the average error between the interpolated and radar rainfall fields (considered to be the ground truth):

$$\text{relative bias} = \frac{\overline{R}_{\text{res}}}{\overline{R}_{\text{radar}}} = \frac{\sum_{i=1}^{n} R_{\text{res},i}}{\sum_{i=1}^{n} R_{\text{radar},i}} \quad (1)$$

$$\text{where } R_{\text{res},i} = R_{\text{int},i} - R_{\text{radar},i}$$

In Eq. (1), n represents all possible pixels and time steps for the 12-day validation period.

The coefficient of variation is a dimensionless measure of dispersion, which is defined as the standard deviation divided by the mean (Haan, 1977). In this case we took the standard deviation of the residuals divided by the mean of the reference field, i.e., the mean of the radar rainfall field: $\text{CV} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(R_{\text{res},i} - \overline{R}_{\text{res}}\right)^2}\,\Big/\,\overline{R}_{\text{radar}}$

The coefficient of variation is a measure of uncertainty (similar to the root mean squared error). For instance, a $\text{CV} = 0$ would indicate a hypothetical case with no bias and no uncertainty, i.e. a case in which all data points would fall exactly on the $1:1$ line.

The coefficient of determination is a measure of the strength of the linear dependence between two random variables, interpolated and radar rainfall depths, in this case. It is simply defined as the square of the correlation coefficient between the interpolated and radar rainfall depths:

$$r^2 = \frac{\left[\sum_{i=1}^{n}\left(R_{\text{radar},i} - \overline{R}_{\text{radar}}\right)\cdot\left(R_{\text{int},i} - \overline{R}_{\text{int}}\right)\right]^2}{\left[\sum_{i=1}^{n}\left(R_{\text{radar},i} - \overline{R}_{\text{radar}}\right)^2\right]\cdot\left[\sum_{i=1}^{n}\left(R_{\text{int},i} - \overline{R}_{\text{int}}\right)^2\right]} \quad (2)$$

The coefficient of determination represents the fraction of the variance of the reference variable that can be explained by a linear regression. In a case of perfect linear correlation, i.e., $r^2 = 1$, all data points would fall on a straight line without any scatter. Hence, the linear regression would be able to explain $100\,\%$ of the variance of the reference variable in that case. However, perfect linearity does not imply unbiased estimation because the regression line could not necessarily coincide with the $1:1$ line, even if it captures all variability.

3 Results

From the actual and simulated link rainfall depths, rainfall maps were obtained for three cases: (1) 15 min rainfall maps from interpolation of 15 min rainfall depths; (2) 24 h rainfall maps from the sum of these 15 min rainfall maps; and (3) 15 min rainfall maps from interpolation of 15 min rainfall depths, in which each pixel (interpolated rainfall depth) was averaged with the surrounding pixels within a 9×9 pixel-square. The reason for this posterior average of the rainfall depths was to limit representativeness errors in ~~space and~~ time (Overeem et al., 2013). Incidentally, this area ($\sim$81 km^2) roughly corresponds to the spatial extent of typical water management units in the Netherlands.

Appendix 6 presents five examples of 24 h and 15 min rainfall maps. ~~Overeem et al. (2013, Supplement)~~ Overeem et al. (2013, Supporting Information) showed daily comparisons between actual link rainfall maps and radar rainfall fields for the 12-day validation period. Here, we present five of those 12 cases for reference. These comparisons are extended to both types of simulated link rainfall maps (actual and 100 % network availability) (Fig. 7). Five comparisons of 15 min rainfall maps are also presented (Fig. 8). These examples provide information on the improvement in rainfall fields when the sources of error studied here are removed.

For any given time step, interpolated rainfall maps were compared on a pixel-by-pixel basis against radar rainfall fields. This pixel-by-pixel comparison was done via scatter density plots of interpolated against radar rainfall depths (ground-truth). Figure 4 presents an array of scatter plots, for the three cases of spatiotemporal aggregation, for the actual and both types of simulated link rainfall depths (actual and 100 % network availability). Each of the scatter plots in Fig. 4 corresponds to all 15 min (or 24 h) rainfall maps within the 12-day validation period. These plots show paired rainfall depths of interpolated and radar rainfall maps, for any pair in which the radar rainfall depth is larger than 0.1 mm.

The scatter density plot of Fig. 5 corresponds to the actual and simulated link rainfall depths (actual availability) at the locations of the links, i.e., before any interpolation was applied. Only those pairs for which at least one rainfall depth exceeded 0.1 mm were plotted.

Table 1 summarizes the values of the relative bias, the coefficient of variation (of the residuals), and the coefficient of determination (i.e., the squared correlation coefficient) for the three cases of spatiotemporal aggregation, for the actual and both types of simulated link rainfall depths.

4 Discussion

From left to right and from top to bottom, the general picture that arises from Fig. 4 and Table 1 is: (1) a reduced systematic error (relative bias); (2) a smaller random error (CV); and (3) a stronger linear dependence (r^2). This suggests a general improvement of the interpolated link rainfall depths with respect to the radar rainfall depths, as more sources of error are removed from the analysis.

Figure 4a, d and g ~~represents~~ show the relation between the actual link and radar rainfall depths, for the three cases of spatiotemporal aggregation. The scatter in these plots can be attributed to all possible sources of error in rainfall maps from microwave link measurements, i.e., those associated with the link measurements themselves and those associated with the interpolation of individual measurements (mapping).

The dark blue shading close to the $1:1$ line for small rainfall depths in all panels of Fig. 4 indicates a good agreement between rainfall estimates from microwave links and radar (note that the color scale is logarithmic). Conversely, for larger rainfall depths the scatter seems to relatively increase for the actual link measurements (panels a, d, g), while it decreases for the simulated link measurements (all other panels). Such deviations must be the result of errors in individual link measurements as well as the combination of limited spatial coverage of the link network (Fig. 3) with the strong variability of rainfall in space. The relative contribution of the measurement errors to the total error hence increases with rainfall amounts.

~~The main question we focused on is whether the relative bias is due to the link rainfall retrievals themselves, or whether it can partially be attributed to the errors introduced by the link network due to the incomplete spatial sampling of the rainfall fields. To that end,~~

~~we compare the biases in the first column of Fig. 4 and Table 1 with those in the second column. These second columns represent the performance of a hypothetical link network with the same spatial density and temporal availability as the actual network, but for which the individual link measurements are perfect estimates of the true path-average rain rates. We see that the biases are hardly reduced and therefore conclude that the underestimation noted earlier must be almost entirely due to errors introduced by incomplete spatial sampling.~~

From Fig. 4 and Table 1, it is clear as well that the relative bias is most sensitive to the spatial and temporal aggregation level. If all paired rainfall accumulations would have been used (and not only those in which at least the radar rainfall depth exceeds 0.1 mm) one would expect the relative bias to be exactly the same for all aggregation levels, because both aggregation and computation of the bias are linear operators (Eq. 1).

There is a limited improvement in terms of the coefficients of variation and determination, when the scatter plots in the second column of Fig. 4 are compared to those in the third column, as well as their respective statistics in Table 1. This means that the main reduction of uncertainty is achieved when the actual link measurements are replaced with the simulated microwave link measurements, rather than to increase the actual link network availability to 100 % ~~availability~~ for all links. This implies that a significant fraction of the overall uncertainty must be due to errors and uncertainties in the link measurements themselves, rather than due to errors and uncertainties associated with mapping, at which rainfall maps are reconstructed.

Figure 4c, f, and i and the last column of Table 1 indicate the best possible performance that can be achieved with the employed link network (if all links would yield perfect measurements of ~~path-average~~ path-averaged rainfall all the time). The remaining scatter can be attributed to the interpolation methodology (including the assignment of line-average rainfall intensities to the link's centre point), the spatial variability of rainfall, and the effect of other factors such as ~~:~~ the variable and limited density of the link network (more links in urban than in rural areas)~~; and the line support of the link measurements (i.e., link rainfall~~

~~retrievals are obtained for a line segment in space rather than for a point such as rain gauges or for a volume such as weather radars)~~.

When 15 min rainfall depths at the 1 km^2 spatial scale (Fig. 4a–c) are summed to daily rainfall depths (Fig. 4g–i), the discrepancies in rainfall estimates at 15 min tend to cancel each other. This explains the sharp decrease in the coefficient of variation, and the sharp increase in the coefficient of determination between 15 min and 24 h rainfall accumulations, which implies a certain degree of independence among the errors in the 15 min accumulations.

Figure 5 compares simulated against actual link rainfall depths, before any interpolation was applied. This indicates the performance of the 1751 individual links in terms of rainfall retrieval, regardless of the errors and uncertainties introduced by interpolation (mapping). Note that the coefficient of variation is larger than that of the 1 km^2, 15 min rainfall accumulations presented in panel a of Fig. 4; and that the coefficient of determination is between those coefficients presented in panels a and d of Fig. 4. If we would assume that rainfall retrieval and mapping errors are independent, we would expect the CV in Fig. 4 to be greater than that in Fig. 5. This means that there is a clear interplay between these two type of errors, and that the assumption of independence does not hold. This may be explained by the fact that we use Kriging with a variogram that includes a nugget. In areas with a dense link network, the weight of each individual link is relatively small in the computation of the interpolated rainfall field. This reduces the effect of large errors in a given link. In ~~other areas ,~~ areas with lower link densities the nugget of the employed variogram has a ~~similar effect of reduction~~ similar reducing effect on large errors.

From Fig. 6 it can be seen that a higher density in the link network guarantees good correlation between the estimated values of rainfall and the ground-truth, and a low coefficient of variation of the residuals. From the left panel (Fig. 6a) it can be concluded that lower link densities also contribute (and in large proportion) to higher correlation coefficients. This means that without considering errors in link measurements, these latter being the largest source of uncertainty in country-wide rainfall fields, the network density and the mapping methodology considered here are, respectively, high and good enough to retrieve accurate rainfall fields at such country-wide scales (at least in the Netherlands).

5 Summary and conclusions

Our goal was to quantify the errors and uncertainties in rainfall maps from commercial microwave link networks. In general, these errors can be attributed to different sources ~~, namely the physics involved in the measurements such as~~ like wet antenna attenuation, ~~the~~ sampling interval of ~~the~~ measurements, wet/dry period classification, dry weather baseline attenuation, drop size distribution (DSD), multi-path propagation, interpolation methodology and algorithm, the availability of microwave link measurements, and the variability of rainfall itself across time and space. For the purpose of this paper we classified all possible sources of error into two categories: (1) those associated with the link measurements themselves (retrieval algorithm included), and (2) those associated with mapping. Only the overall effects of physical and interpolation errors were addressed here; not all physical errors separately.

To quantify the errors and uncertainties that can be attributed to these two categories, rainfall maps created from three sets of link rainfall depths were compared: actual link measurements, simulated link measurements with the actual network availability, and simulated link measurements with $100\,\%$ network availability assumed. Simulated link rainfall depths are not affected by errors and uncertainties attributed to actual link measurements, therefore we could estimate uncertainties attributed to mapping. Based on a pixel-by-pixel comparison, interpolated rainfall maps of the Netherlands were compared against radar rainfall fields (considered to be the ground-truth). These comparisons were carried out on the basis of scatter density plots and three metrics: relative bias, coefficient of variation (CV), and coefficient of determination (r^2).

We found that ~~link rainfall retrieval~~ measurement errors themselves are the source of error that contributes most to the overall uncertainty in rainfall maps from commercial microwave link networks.

In a standard operational framework, data from commercial microwave link networks may not be continuously available for the entire network. Such data gaps affect the accuracy of the retrieved rainfall intensities. Because we were able to simulate rainfall depths on the basis of radar composites, we could investigate the hypothetical case in which data from a commercial link network would be available for all time steps, and for all possible link paths in the network. This best-case scenario could explain an additional 10 % of the variance explained by error-free link measurements with actual network availability for the 15 min accumulation (3 % for the 24 h accumulation). Note that these percentages are particular for the region and period considered in this study. Nevertheless, even the best-case scenario showed a remaining and significant amount of uncertainty that could not be removed in rainfall maps. This means that the space–time variability of rainfall is such that it would require an even more dense and robust network of microwave links to generate more accurate rainfall maps at country-wide scales. The uncertainties in link rainfall retrievals found in this paper are partly explained by the combined effects of rainfall space variability along the link, nonlinearity of the retrieval relation, imperfect temporal sampling strategy, quantization of the received power (data stored in integer number of dBs), and wet antenna attenuation (and correction) investigated by Leijnse et al. (2008, in particular Fig. 13, upper-right panel on p. 1487). They reported a CV of ~ 1.0, which explains a significant part of the CV (1.44) given in Fig. 5. Daily rainfall maps from microwave links showed less uncertainty compared to 15 min rainfall maps, because errors present in 15 min rainfall maps tend to cancel each other when 15 min rainfall maps are aggregated.

6 Constraints and recommendations

The kriging algorithm we used was that of Pebesma (1997); Pebesma and Wesseling (1998). The interpolated maps from simulated link rainfall depths represent the outcome of a process in which a linear feature (link path) obtained from the average of volume samples (radar data) is assigned to a point (link path middle point). Each of these features (area, line, volume, point) represents what in geostatistics is referred to as support, i.e., the spatial resolution at which the random variable is analyzed (Cressie and Wikle, 2011, chap 4.1). ~~We converted our analyses to a common areal support to largely remove differences between the samples of radar and microwave link measurements.~~ The arbitrary change from line to point support introduces a source of error that is implicitly included in the errors related to mapping.

Apart from its simplicity and the 30 year rainfall dataset on which it is based, we also chose the isotropic spherical semivariogram of van de Beek et al. (2011) , because a consistent semivariogram model estimated from link data was not feasible for 15 min rainfall intensities. Isotropic semivariograms assume equal spatial dependence in all possible directions. Rainfall is generally a phenomenon that exhibits anisotropy in time and space (Lepioufle et al., 2012; Velasco-Forero et al., 2012; Guillot and Lebel, 1999; Amani and Lebel, 19 Nevertheless, it is reasonable to assume isotropy for the Netherlands given its relative small area and flat topography. OK assumes the mean to be constant and unknown within the region of interpolation. When this unknown mean presents substantial changes over short distances, the assumption of statistical stationarity is no longer valid. Universal Kriging, Kriging with External Drift, and Regression Kriging (RK) are more sophisticated interpolation techniques that incorporate trends to account for non-stationarity (e.g., Schuurmans et al. (2007)). The performance of these geostatistical techniques to retrieve link rainfall maps was beyond the scope of this research.

If a similar study were to be carried out in a country with different conditions than those present in the Netherlands, three issues should be considered: (1) the spatial and operational configuration of the link network, (2) the climatology of the region where the link network operates, and (3) the spatial scale at which the analysis is carried out.

The first issue, the spatial and operational configuration of the link network, refers to the distribution of link frequencies, lengths, and densities of link networks around the world. For instance, the commercial microwave link network used in this study has an average link-path length of 3.1 km, a mean frequency of 36.0 GHz, and a global average density of 83.5 % across the Netherlands (Figs. 2 and 3). Other regions may have more extensive urban and/or rural areas. In particular, for rural areas one expects to find longer link paths, and therefore lower microwave frequencies. Another issue related to the lower frequencies, e.g. 7 GHz, is the low sensitivity to rainfall and the non-linearity of the R–k relationship, mostly in tropical regions (Doumounia et al., 2014). This non-linearity will lead to biases in rainfall intensities in cases of large rainfall variability along the link path (positive biases at lower frequencies where the exponent of the R–k power law is smaller than 1; see Leijnse et al., 2010). Thus, the performance of the rainfall retrieval algorithm for such link networks will differ from the performance found in this study. For instance, in places where link paths are longer (tens of km) the error due to spatial variability of rainfall along the link path becomes more important (Berne and Uijlenhoet, 2007; Leijnse et al., 2008, 2010). Moreover, less dense networks with long link paths will provide less detailed information about rainfall.

The second issue, the climatology of the region refers to the local pattern of rainfall that characterizes different regions around the world. The rainfall characteristics of the Netherlands are different from the ones encountered in e.g. (sub-)tropical regions. For instance, the spherical semivariogram model applied here was derived from climatological rain gauge data for the Netherlands. Furthermore, rainfall characteristics such as raindrop size distributions or the distribution of rainfall intensities will affect the optimal values of the parameters of the retrieval algorithm. Therefore, for regions with different rainfall climatologies than the Netherlands, variations should be considered not only in the interpolation methodology but also in the algorithms and their parameters to retrieve rainfall intensities.

The third issue refers to the spatial scale at which rainfall maps are reconstructed. The analyses presented here focused on 15 min (and 24 h) maps at 1 and 81 km^2, and the differences in error characteristics are significant. For larger regions, for instance, the uncertainty attributed to mapping could play a major role in the overall error distribution. Still, the scale at which rainfall can effectively be retrieved depends greatly on the density of the underlying link network. This means that in regions with a much lower link density than in the Netherlands, the effective spatial resolution for which rainfall maps can be derived will be lower.

Appendix: Comparison of 24 h and 15 min rainfall maps

In Fig. 7, the LINK column (top and bottom rows – 20110907_08:00 and 20110819_08:00) shows how daily rainfall depths are greatly overestimated by link data, especially in places where there is intense rainfall, and the density of the network is higher. Simulated rainfall depths (actual availability) show improvement of rainfall fields with regard to link-based rainfall fields. Conversely to actual link rainfall maps, simulated rainfall fields based on the actual availability of the network present a slight underestimation of rainfall depths. Simulated link rainfall fields (actual and 100 % network availability) are similar because the effect of actual or 100 % availability among 15 min intervals is smoothed out by the sum of 15 min rainfall fields.

Figure 8 shows how accurate rainfall events are captured across the ~~the~~ Netherlands at 15 min intervals. Note how the accuracy is improved for the best-case scenario of 100 % network availability (fullSIM column).

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Table 1. Relative bias, and coefficients of variation and determination for the three cases of spatiotemporal aggregation (15 min [1 km^2], 15 min [81 km^2], 24 h [1 km^2]), for the three sets of link measurements, i.e., the actual and both types of simulated link rainfall depths (actual and 100 % network availability).

	LINK	partSIM	fullSIM
Relative bias [%]			
15 min [1 km^2]	−14.3	−13.0	−9.3
15 min [81 km^2]	−9.1	−9.1	−5.6
24 h [1 km^2]	+1.6	−0.8	+0.7
Coefficient of variation – CV			
15 min [1 km^2]	1.216	0.871	0.748
15 min [81 km^2]	0.995	0.586	0.435
24 h [1 km^2]	0.523	0.262	0.224
Coefficient of determination – r^2			
15 min [1 km^2]	0.366	0.605	0.709
15 min [81 km^2]	0.496	0.770	0.873
24 h [1 km^2]	0.720	0.903	0.928

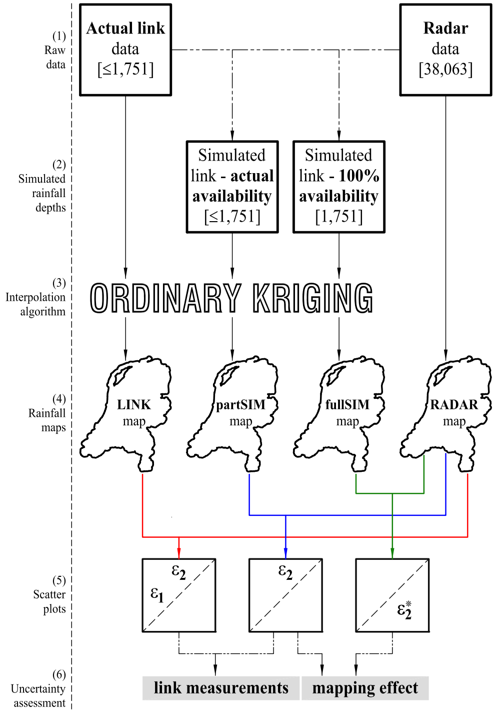

Figure 1. Flowchart to visualize the hierarchical process to identify and quantify uncertainties in rainfall maps from link networks. From top to bottom: (1–2) raw data is selected and rainfall depths simulated; (3–4) through the interpolation methodology rainfall maps are obtained; (5) from the comparison between rainfall maps scatter plots are created; and (6) from the comparison between these scatter plots (and their metrics) the error sources are quantified. ε_1 and ε_2 represent the categories in which the sources of error are classified. Specifically, ε_1 indicates the error from microwave link rainfall retrievals, and ε_2 indicates the error related to mapping. ε_2^* indicates the best-case for the mapping-related error (i.e., all links are available all of the time). The number between brackets (1–2) indicates the number of data for every single map or data set.

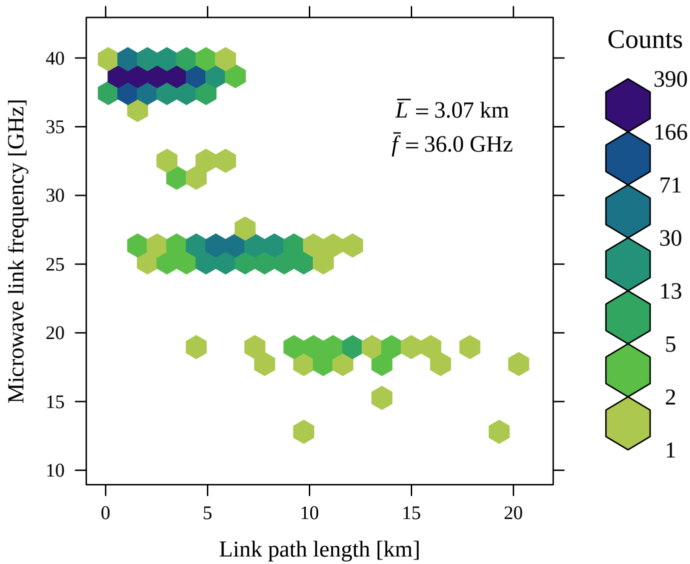

Figure 2. Scatter density plot of microwave link frequencies vs. link path lengths for the 12-day validation period. The color scale is logarithmic.

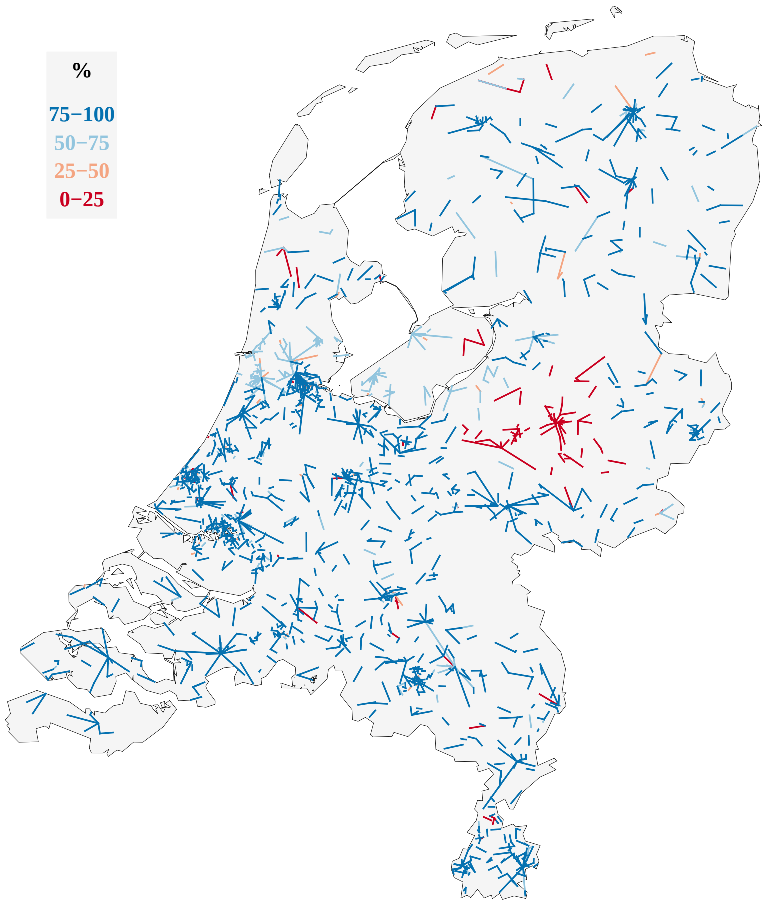

Figure 3. Topology of the T-Mobile NL microwave link network used for this study. The color scale of the microwave network represents the temporal availability of the link data for the 12-day validation period. The average availability is 83.5 %.

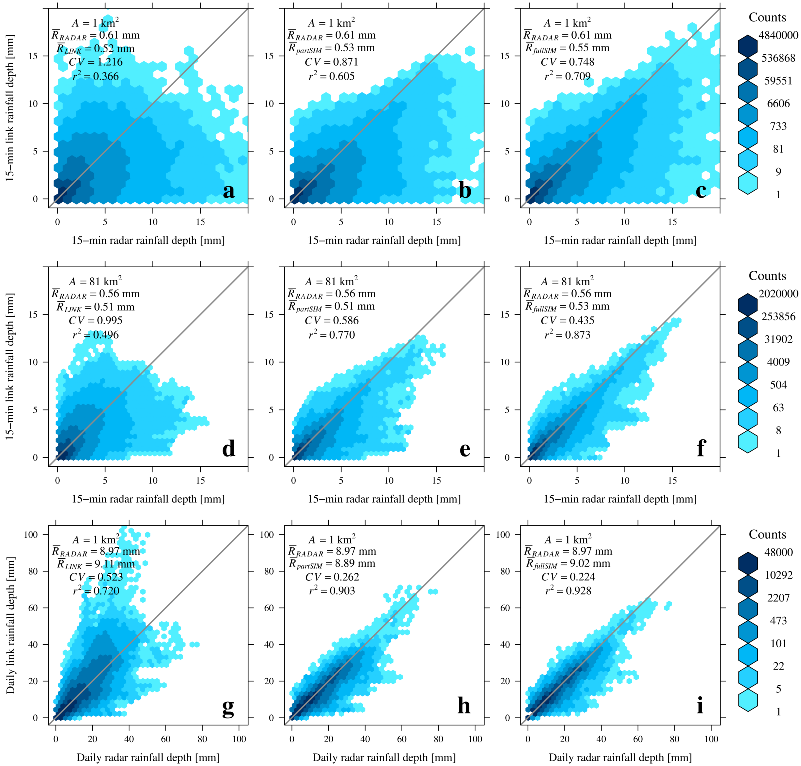

Figure 4. Scatter density plots of interpolated link rainfall depths vs. radar rainfall depths for 15 min and 24 hours. Top row **(a, b, c)**: 15 min rainfall depths; middle row **(d, e, f)**: 15 min rainfall depths averaged with the surrounding pixels within a 9×9 pixel-square; bottom row **(g, h, i)**: daily sum of 15 min rainfall depths. Left column **(a, d, g)**: actual link rainfall maps vs. radar rainfall fields; centre column **(b, e, h)**: simulated link rainfall maps (actual availability) vs. radar rainfall fields; right column **(c, f, i)**: simulated link rainfall maps (100 % availability) vs. radar rainfall maps. **(d)** and **(g)** are comparable to Overeem et al. (2013). The color scale is logarithmic.

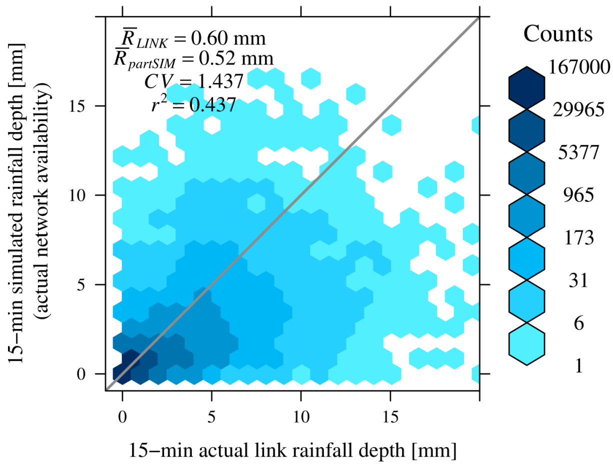

Figure 5. Scatter density plot of simulated link rainfall depths (actual availability) vs. actual link rainfall depths for all 15 min time steps in the 12-day validation period. Both simulated and actual link rainfall depths are path-averaged rainfall depths. The color scale is logarithmic.

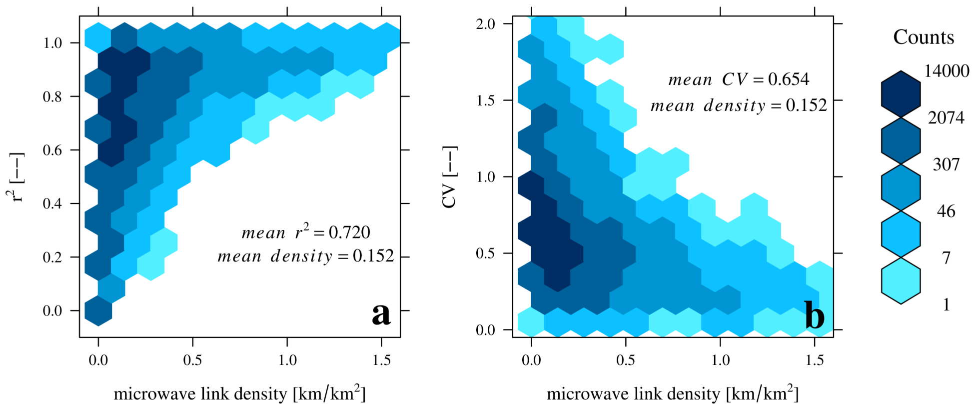

Figure 6. Scatter density plots of coefficient of determination (r^2) and coefficient of variation (CV) vs. microwave link density (averaged over 155 km^2), for the fullSIM case at 15 min and 1 km^2 spatial scale. The color scale is logarithmic.

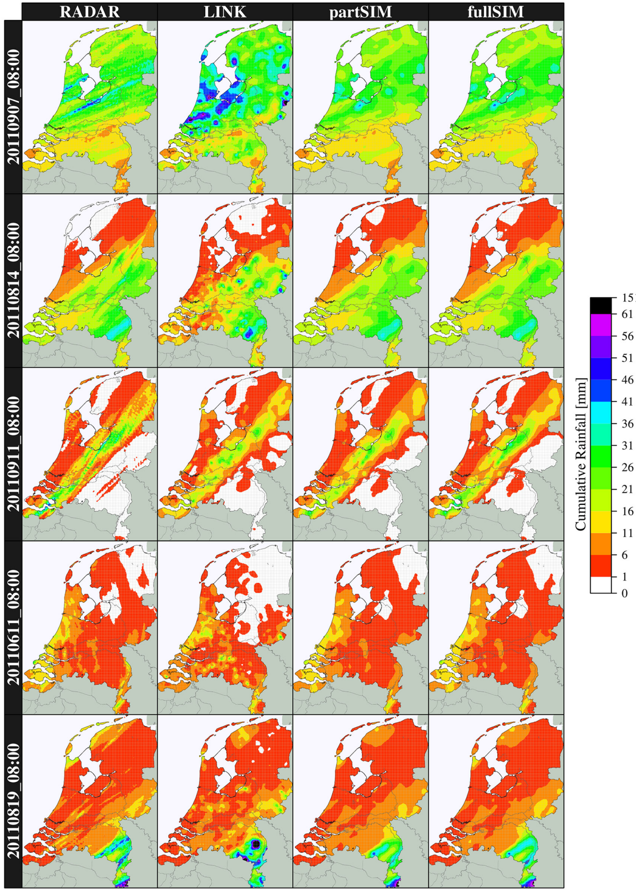

Figure 7. Comparison of daily interpolated rainfall maps with regard to radar rainfall fields (ground truth, left column). The rows show five of the 12 days of the validation period. Daily rainfall maps were aggregated from 15 min rainfall maps. The ~~row-labels~~ row labels indicate the end UTC for which the maps were obtained.

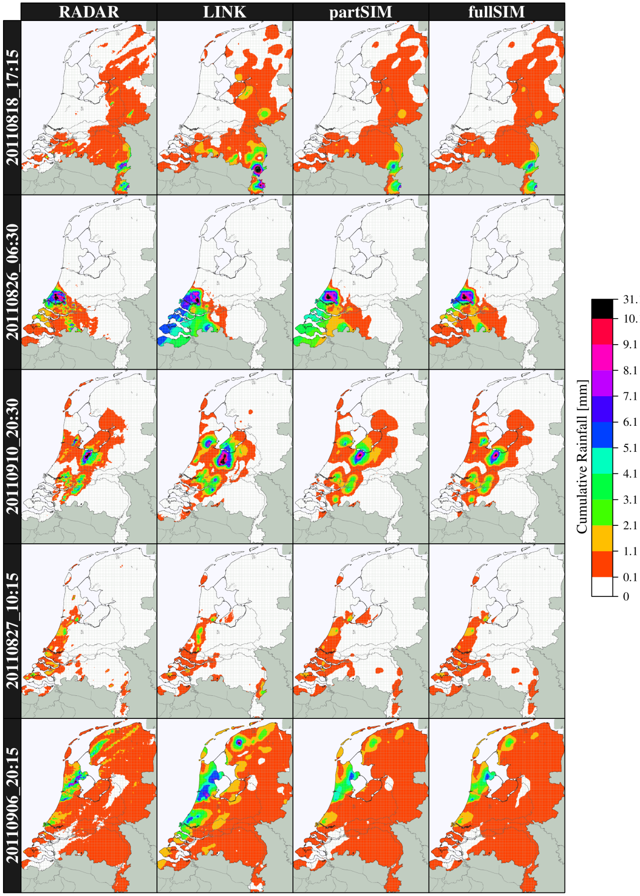

Figure 8. Comparison of 15 min interpolated rainfall maps with regard to radar rainfall fields (ground truth, left column). The rows show five of the 1152 time steps (cases) present in the 12-day validation period. The ~~row-labels~~ row labels indicate the start UTC for which the maps were obtained.