Response to the comments of Anonymous Referee #1

We would like to thank anonymous referee#1 for the constructive feedback on our manuscript.

Our responses to the comments are shown below.

The comments of anonymous referee #1 are shown in black. Authors' responses are shown in blue.

I've read the manuscript "Degradation of commercially available digital camera images due to variation of rainfall intensity in outdoor conditions" with interest. I find it an in-depth study that is well written. I do have a couple of suggestions though to improve (the readability) of the manuscript.

< Comment 1 >

- In my opinion, the title sounds a bit negative and not entirely fits the purpose of this manuscript. I suggest to rewrite the title emphasizing rainfall intensity estimation from the degradation of camera images.

Response:

We will revise the title as follows.

  "Rainfall intensity estimations based on degradation characteristics of images taken with commercial cameras"

< Comment 2 >

- Introduction: I think this method can be considered opportunistic sensing, which includes crowdsourcing, but the term crowdsourcing seems a bit too specific, since it does not really involve the crowd. I suggest to use the term opportunistic sensing, and to use it consistently throughout the introduction.

Response:

We will revise L. 38 through 42 as follows.

"As an initiative to overcome the issues mentioned above, techniques have been proposed to build sensors using low-cost equipment not used for its intended use and to combine a variety of not fully utilized technologies to make opportunistic observation (Tauro et al., 2018)."

And we will remove L. 96 through 97 and L. 914 through 916.

< Comment 3 >

- L. 50: rainfall estimation employing commercial microwave links does not use "cellular phones", although the network is used by these phones. So, remove "of cellular phones".

Response:

We will remove "of cellular phones" in this sentence.

< Comment 4 >

- Introduction: Give a (more) clear definition of static and dynamic weather effects. In L. 99 rain streaks may appear as fog, but the process itself is still dynamic, but considered static. This can be explained a bit more.

Response:

We will revise L. 98 through 100 as follows.

"On the other hand, even if the absolute size of raindrops is constant within the camera's angle of view, the size of raindrops in the image varies with their distance from the camera. In particular, raindrops over a certain distance from the camera induce a visual effect as if they were in static weather conditions, because their fall distance within the camera's exposure time is sufficiently small compared to the pixel size that the camera's sensor cannot detect individual raindrops. In fact, it has been pointed out that rain streaks over a certain distance from the camera accumulate on the image and appear as fog (Garg and Nayar, 2007; Li et al. 2018; Li et al., 2019)."

< Comment 5 >

- L. 100: define the background. Should this be seen as those cameras capturing a relatively "undisturbed" 2D image? E.g., without persons, animals and traffic moving around? So, just the river, scenery, trees? So the background is just the quite static image that is captured.

Response:

We will add and revise the following text in L. 100 through 102.

"Such raindrops over a certain distance from the camera are likely to induce static weather effects when the camera is mainly capturing a relatively undisturbed background such as rivers, scenery, trees. On the other hand, in the case of a disturbed background with people, animals, or traffic moving around, the static weather effects of raindrops may be difficult to discern because the original background may be disturbed by their movement. Thus, in an outdoor photography system that captures a relatively undisturbed background over a certain distance, not only the dynamic weather effects caused by rain but also the static weather effects caused by rain may be apparent in the images."

< Comment 6 >

- Section 2: despite attempts to explain "direct attenuation" and "airlight", it would help to visualize these two effects or explain them more clearly. The first seems to suggest the light going from the background to the camera, whereas the second seems direct & diffuse radiation from the sun interacting with the atmosphere (but not the background) before reaching the lens.

Response:

We will revise L. 126 through 131 as follows.

""Effects of static weather are mainly caused by two scattering phenomena: "direct attenuation" and "airlight" (Fattal, 2008; He et al., 2011; Narasimhan & Nayar, 2002, 2003; Tan, 2008). "Direct attenuation" is the attenuated light received by the camera from the background along the line of sight, caused by the scattering of light by particles such as water droplets in the atmosphere. "Direct attenuation" reduces the contrast of a scene (Tripathi & Mukhopadhyay, 2014). "Airlight" is the total amount of environmental illumination reflected into the line of sight by atmospheric particles, typically direct and diffuse radiation from the sun interacting with the atmosphere in the case of daytime outdoors. "Airlight" results in a shift in color (Tripathi & Mukhopadhyay, 2014). ""

< Comment 7 >

- L. 196: replace "chapters" by "sections".

Response:

We will replace "chapters" by "sections".

< Comment 8 >

- Section 3.1: what is the typical temporal resolution, or feasible temporal resolution, especially given rainfall retrieval processing time?

Response:

We will add the following text in L. 216.

"In estimating rainfall intensity based on camera images, it is essential to consider the instantaneous intensity at the time of shooting. In contrast, when observing rainfall using a traditional tipping bucket, it is not possible to measure rainfall until it reaches the capacity of one tipping bucket. In other words, it is difficult to measure instantaneous values with a tipping bucket rain gauge with sufficient precision. However, in this study, to validate the accuracy of rainfall intensity estimated based on camera images, we decided to obtain data from a tipping bucket rain gauge with as fine a resolution as possible (one minute)."

This method is relatively computationally inexpensive and can be processed in as little as one minute per image.　This means that the proposed method enables the acquisition of instantaneous rainfall intensity in real time for time intervals of one minute or less. As shown in our response to Comment 9, we will add the following text in 5.4.2.

"On the other hand, data processing time may be an issue in utilizing the data for real-time observations. However, the proposed method is extremely simple, requiring less than one minute to process one image using a typical commercial computer. Although we used the computer having specifications of 80 GB RAM and Intel core i7-10700 @2.90 GHz CPU in this study, such RAM capacity is not necessary for this process. In other words, it is considered that instantaneous rainfall intensity can be estimated with a time resolution of one minute or less using a typical commercial computer."

< Comment 9 >

- L. 210: this is an important limitation that should be mentioned in the outlook part of the conclusions.

Response:

We will add the following text in L. 679.

"Moreover, this method is not applicable to nighttime images because it was difficult to distinguish rainfall. Therefore, rainfall estimation methods using nighttime images should be also considered separately."

Furthermore, in relation to the limitation of this method, we will remove L. 611 through 626, and add a new discussion section "5. 4 Ways of forwards" as follows to clearly show the limitation, and add related paper to references.

"5. 4 Ways forwards

5. 4. 1 Limitation of the proposed method

　　　　There are still several technical problems that need to be solved in the method of this study. The first problem is how to select an appropriate background for rainfall intensity estimation (i.e., the analysis area to be used for rainfall intensity estimation). As shown in Table 4, the accuracy of rainfall intensity estimation varies greatly depending on the background patch selected. Therefore, background patches with the highest estimation accuracy possible should be selected. One solution to this problem is to select patches with a scene depth of more than 100 m. As shown in Table 4, selecting analysis regions from patches with scene depth of more than 100 m is more accurate overall than selecting analysis regions from all background patches. On the other hand, it may also be important that the scene depth is not too large because even relatively small rainfall

intensity may cause the transmission to reach the lower limit as shown in Figure 7. It is necessary to further study in detail what scene depth is appropriate for rainfall intensity estimation. In addition, in terms of background objects, a relatively undisturbed background is desirable for the analysis area. Therefore, it is preferable to choose a static background such as building walls, tree canopies, and ground surface without people or vehicles, especially when applying this method in urban areas. However, at this time, the selection of appropriate backgrounds has not been analyzed in detail, and further study is needed on the effects of scene depth, background texture, and dynamic subject exposure on estimation accuracy.

The second problem is how to remove the effects of dew formation and raindrops on the camera lens itself from the image. Dew formation and raindrops on the camera lens itself could cause significant blurring of the image and affect the rainfall estimation results, but this effect has not been analyzed at this time. Therefore, it is necessary to consider how to physically protect the camera lens (e.g., by covering the camera with a cover) and how to remove the effect from the image if dew or raindrops get on the lens.

The third problem is the identification of fog and precipitation types (e.g., rain, snow). Figure 12 shows that the variation of the estimated rainfall intensity of Camera 2 around 6:30 on October 13 was different from that of the observed rainfall intensity. The images from Camera 2 during this period were validated to be foggy in the selected patches. Therefore, the variation in the estimated rainfall intensity for Camera 2 can be attributed to the whitening of the background due to fog. Since this method estimates rainfall intensity from image whiteness, image whiteness caused by fog is misidentified as the effect of rainfall. At present, however, there is no method to determine whether it is fog or rain. Therefore, as a further study, it is necessary to investigate a method to determine whether the whiteness in the image under bad weather conditions is caused by rain or fog.

Finally, the fourth problem is the development of a nighttime rainfall estimation method. The method of this study is not applicable to nighttime images because it was difficult to distinguish rainfall. Therefore, rainfall estimation methods using nighttime images should be also considered separately. An idea for a rainfall estimation method using nighttime images is to use dynamic weather effects, such as counting the number of rain streaks that appear around the light source or near the lens, if the image is illuminated at night. Furthermore, recently, methods using infrared and near-infrared cameras to estimate rainfall intensity at night have also been proposed, and such methods can be utilized (Lee, 2023; Wang, 2023).

Thus, there are still several technical problems in the method of this study.

5. 4. 2 Possibility for practical use

The camera used in this study was a relatively inexpensive commercially available outdoor camera (approximately 300 US dollars per unit at the time of purchase), and cameras with similar performance have become even less expensive in recent years. Although the durability of the camera needs to be validated in the future, it is expected that data acquisition will be possible at the same level or lower cost than that of a traditional tipping bucket rain gauge. Furthermore, cameras have already been installed outdoors for various purposes other than rainfall observation. The proposed method in this study can utilize images even without a special installation environment for rainfall observation purposes if there is a certain distance to the background and the background is relatively undisturbed. In other words, it is expected that by effectively utilizing images from existing cameras, it will be possible to acquire a vast amount of rainfall data on the ground surface. Therefore, this technique potentially become a gap filler for areas in lacking surface rainfall observations. Moreover, if past images have been accumulated, it may be possible to go back in time and recover surface rainfall data. On the other hand, data processing time may be an issue in utilizing the data for real-time observations. However, the proposed method is extremely simple, requiring less than one minute to process one image using a typical commercial computer. Although we use the computer having specifications of 80 GB RAM and Intel core i7-10700 @2.90 GHz CPU in this study, such RAM capacity is not necessary for this process. In other words, it is considered that instantaneous rainfall intensity can be estimated with a time

resolution of one minute or less using a typical commercial computer. Therefore, there is potential for various fields where rainfall observation can be effectively utilized, such as countermeasures against flash flood and debris flow, flood forecasting, and irrigation system operation, from a cost perspective. However, there are still several technical problems to be addressed to take advantage of this technique, as indicated in 5.4.1. Furthermore, there are concerns about privacy issues in the actual use of this method. In many outdoor surveillance cameras, it may be inevitable that persons will be captured. Therefore, when making data public, it is necessary to pay careful attention to privacy issues. Thus, it is important to understand that there are technical problems and privacy issues before practically using this method."

[Related papers to add to the references]
- Lee, J., Byun, J., Baik, J., Jun, C., and Kim, H. J.: Estimation of raindrop size distribution and rain rate with infrared surveillance camera in dark conditions, Atmos. Meas. Tech., 16, 707–725, https://doi.org/10.5194/amt-16-707-2023, 2023.
- Wang, X., Wang, M., Liu, X., Zhu, L., Shi, S., Glade, T., Chen, M., Xie, Y., Wu, Y., and He, Y.: Near-infrared surveillance video-based rain gauge, J. Hydrol., 618, 129173, https://doi.org/10.1016/j.jhydrol.2023.129173, 2023.

< Comment 10 >

- L. 233: why not the entire image is used, as can also be seen in Figure 2?

Response:

The calculation process of this method uses scene depth. If the entire image is used, the variation in scene depth become large. Therefore, we set an analysis region large enough to determine the scene depth. Thus, we will add following text in L. 234.

"The degradation magnitudes of the image should be related to the scene depth. If a relatively wide area is analyzed, the scene depth should vary considerably. Therefore, the limited number of pixels are set as analysis patches for each area."

< Comment 11 >

- Figure 3 is really helpful in clarifying and summarizing the processing chain.
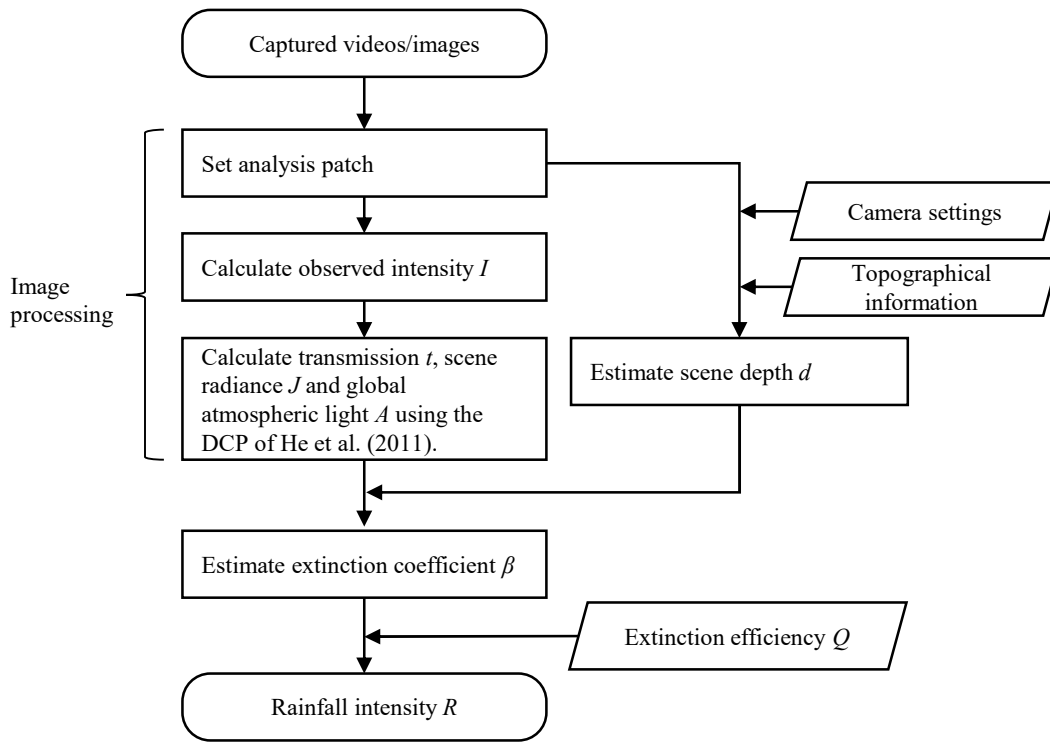
Response:

We will revise Figure 3 as follows.

Figure 3. The flowchart of estimating rainfall intensity from image information.

< Comment 12 >

- L. 269: how do you recognize the "sky background"?

Response:

We did not recognize the "sky background", but we just recognize patches where the appropriate scene depth could not be calculated. Therefore, we will revise L. 269 through 271 as follows.

"Patches where the appropriate scene depth could not be calculated due to the presence of sky background and the application of geometric corrections in the image registration process, such as the upper and rightmost patch of Camera 1, were excluded from the analysis."

< Comment 13 >

- L. 275: "rainfall intensity and rainfall intensity" seems a typo.

Response:

We will remove "shown for each rainfall intensity" in L. 275.

< Comment 14 >

- Caption Figures 4-7: mention that rainfall intensity is observed by a rain gauge.

Response:

We will add the following sentence in Caption Figures 4-7.

"Rainfall intensity is observed by the rain gauge."

< Comment 15 >

- Figures 4, 5, 7 & Table 2: this is a lot of information and I find the figures quite difficult to read. Perhaps the figures could be enlarged and put on two pages per figure (and perhaps move to an appendix).

Response:

We will revise Figures 4, 5, 7 as follows. The revised figures show the top three patches of scene depth for each camera. We will move Figures which include all patches to an appendix. Furthermore, we will remove Table 2 and add the information in Table 2 to Figure 4, 5, 7. We will also revise Figure 6 to have the same description.
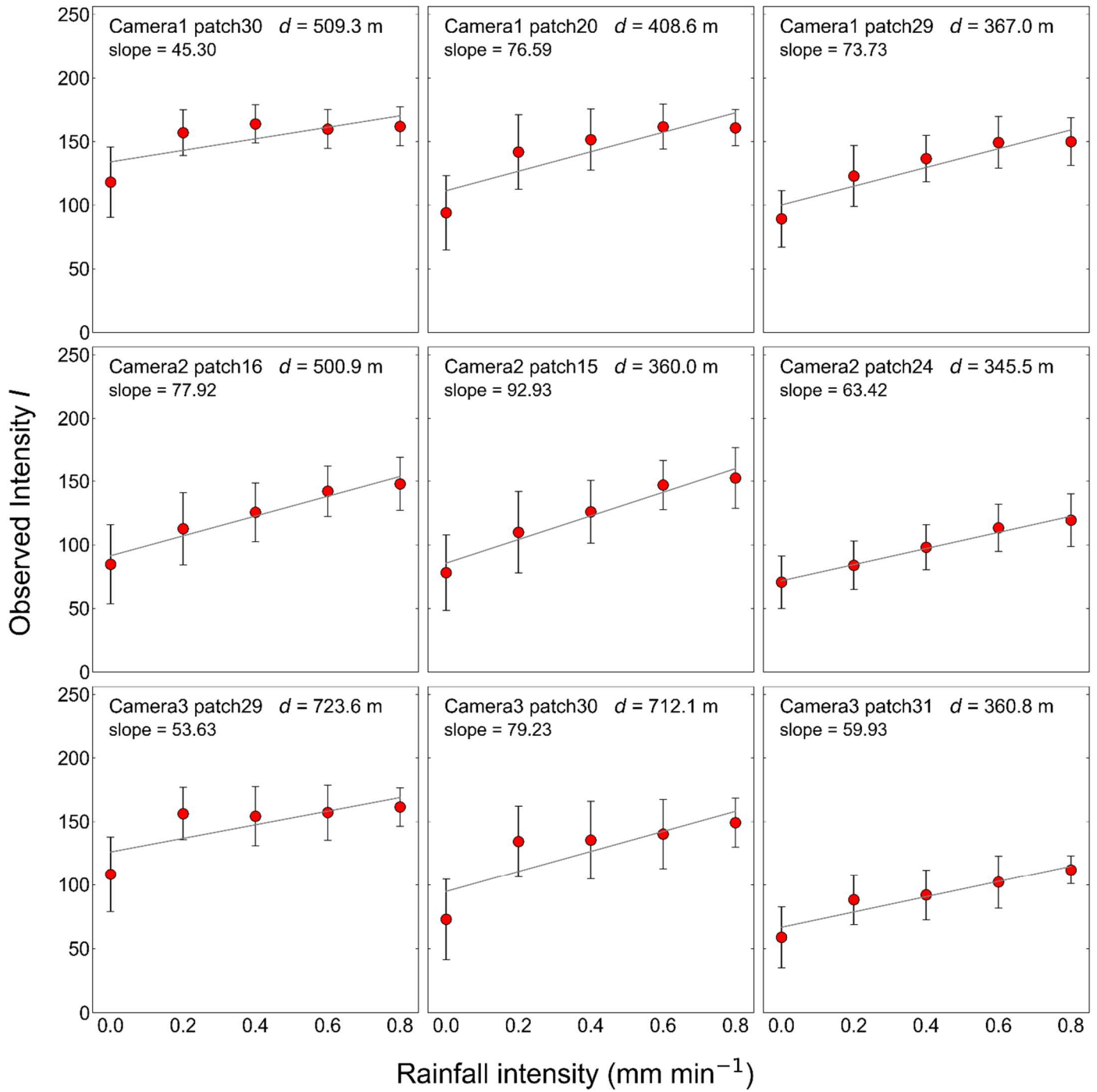
Figure 4. Distribution of observed intensity *I* by rainfall intensity. Figures show the top three patches of scene depth for each camera. Figures which include all patches are shown in Appendix C-1. Each figure is marked with a camera name, patch number, scene depth and slope of the linear regression line for the relationship between rainfall intensity and observed intensity *I*. The upper three figures are Camera 1, the middle three figures are Camera 2, and the lower three figures are Camera 3. The plots and error bars show the mean value and standard deviation of all data during the observation period. The straight lines show linear regression line for the relationship between rainfall intensity and observed intensity *I*. Rainfall intensity is observed by the rain gauge.
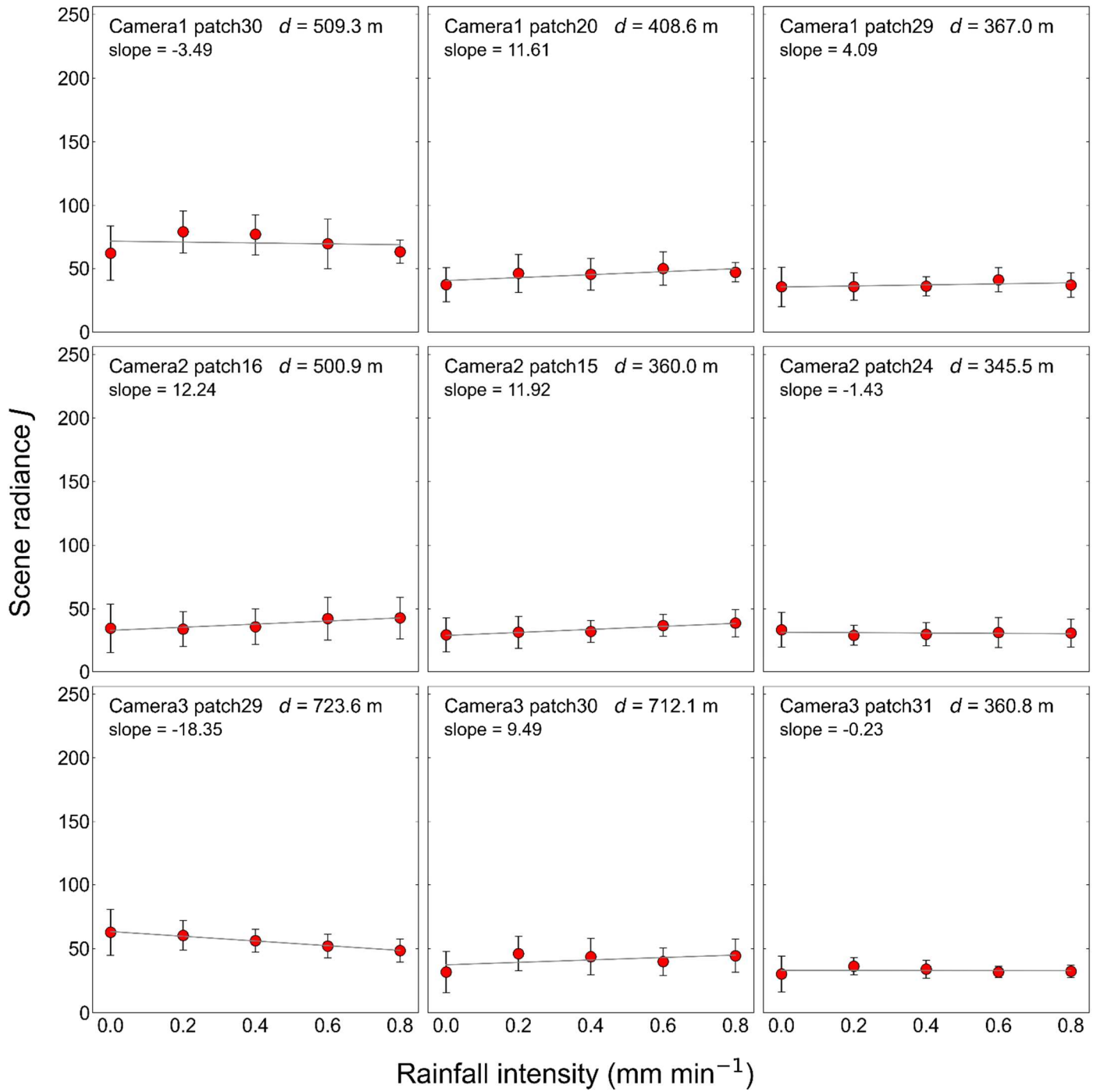
Figure 5. Distribution of scene radiance J by rainfall intensity. Figures show the top three patches of scene depth for each camera. Figures which include all patches are shown in Appendix C-2. Each figure is marked with a camera name, patch number, scene depth and slope of the linear regression line for the relationship between rainfall intensity and scene radiance J. The upper three figures are Camera 1, the middle three figures are Camera 2, and the lower three figures are Camera 3. The plots and error bars show the mean value and standard deviation of all data during the observation period. The straight lines show linear regression line for the relationship between rainfall intensity and scene radiance J. Rainfall intensity is observed by the rain gauge.
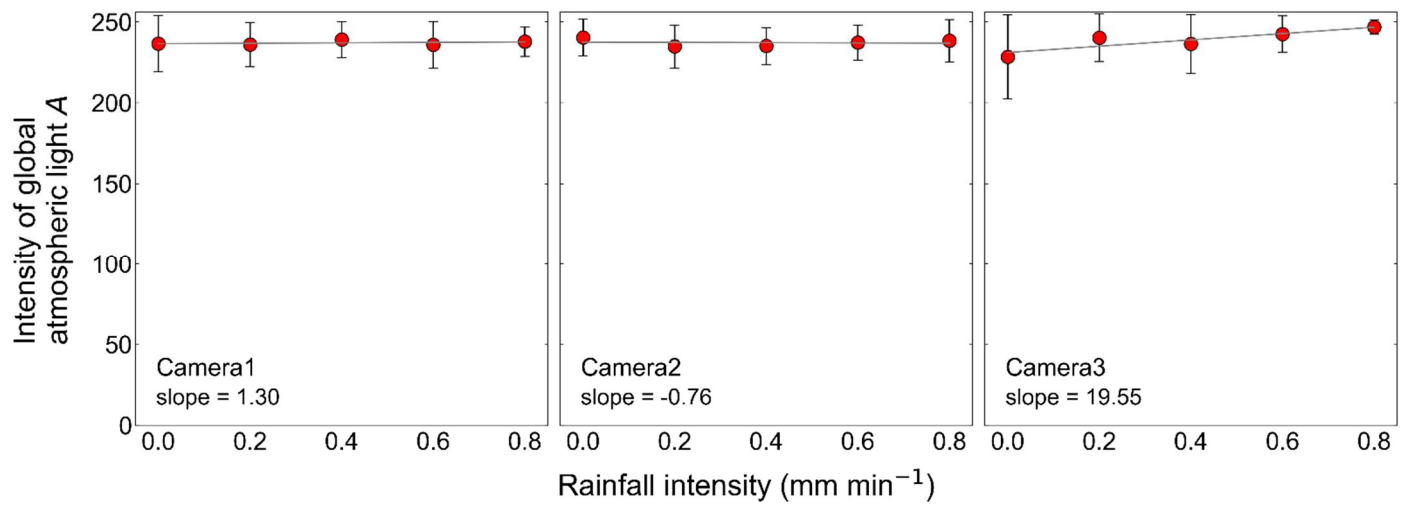
Figure 6. Distribution of global atmospheric light A by rainfall intensity. Each figure is marked with a camera name and slope of the linear regression line for the relationship between rainfall intensity and global atmospheric light A. The left figure is Camera 1, the center figure is Camera 2, and the right figure is Camera 3. The plots and error bars show the mean value and standard deviation of all data during the observation period. The straight lines show linear regression line for the relationship between rainfall intensity and global atmospheric light A. Rainfall intensity is observed by the rain gauge.
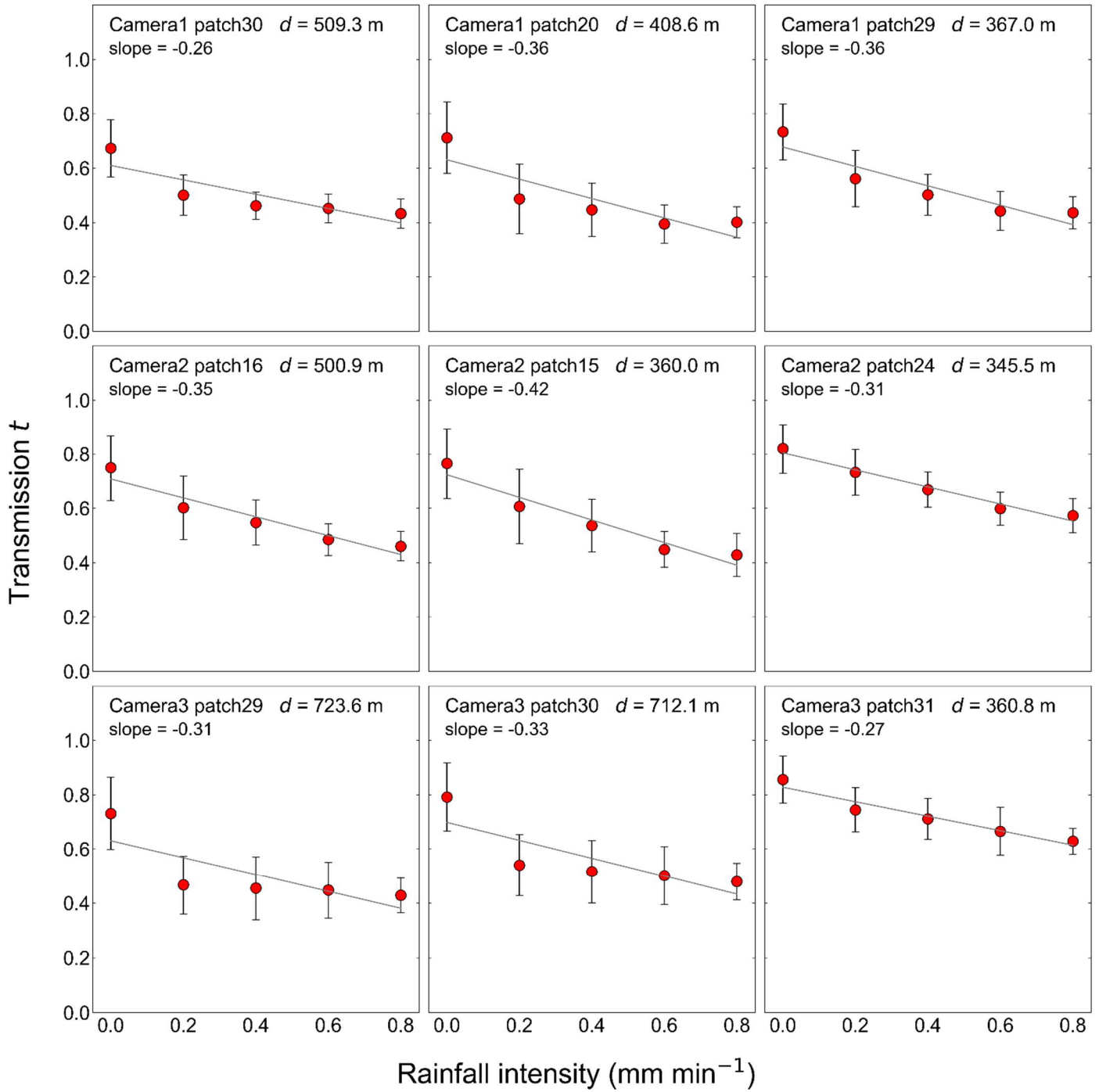
Figure 7. Distribution of transmission *t* by rainfall intensity. Figures show the top three patches of scene depth for each camera. Figures which include all patches are shown in Appendix C-3. Each figure is marked with a camera name, patch number, scene depth and slope of the linear regression line for the relationship between rainfall intensity and transmission *t*. The upper three figures are Camera 1, the middle three figures are Camera 2, and the lower three figures are Camera 3. The plots and error bars show the mean value and standard deviation of all data during the observation period. The straight lines show linear regression line for the relationship between rainfall intensity and transmission *t*. Rainfall intensity is observed by the rain gauge.

Appendix C-1: Figures including all patches showing the distribution of observed intensity *I* by rainfall intensity. Figure C-1-a, Figure C-1-b and Figure C-1-c show the distribution of observed intensity *I* by rainfall intensity of Camera 1, Camera 2 and Camera 3, respectively. Each figure is marked with a camera name, patch number, scene depth and slope of the linear regression line for the relationship between rainfall intensity and observed intensity *I*. The plots and error bars show the mean value and standard deviation of all data during the observation period. The straight lines show linear regression line for the relationship between rainfall intensity and observed intensity *I*. Rainfall intensity is observed by the rain gauge. Patches hatched in gray are patches where the appropriate scene depth could not be obtained due to the presence of sky background and the application of geometric corrections in the image registration process.
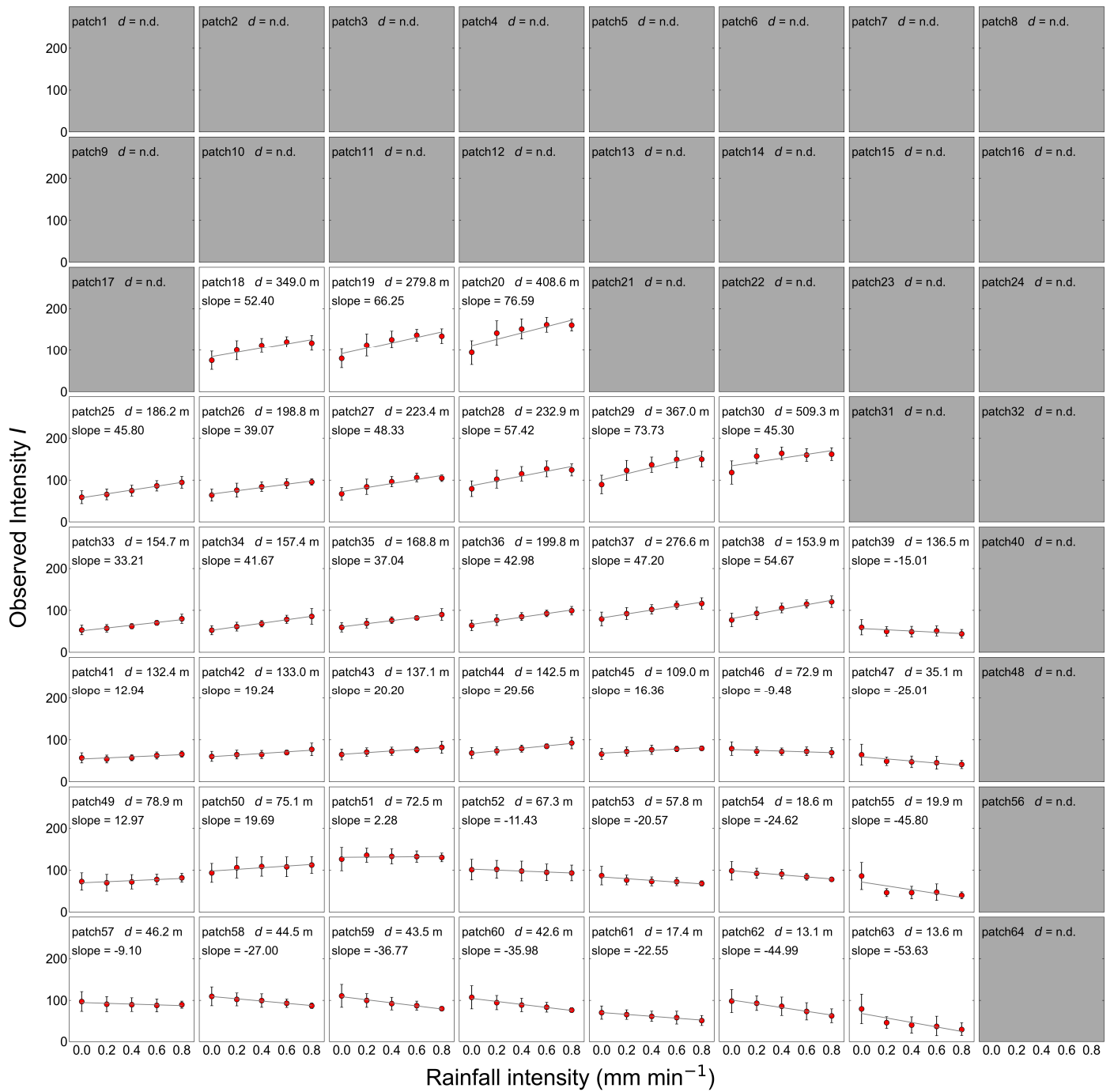

Figure C-1-a. Distribution of observed intensity *I* by rainfall intensity of Camera 1.
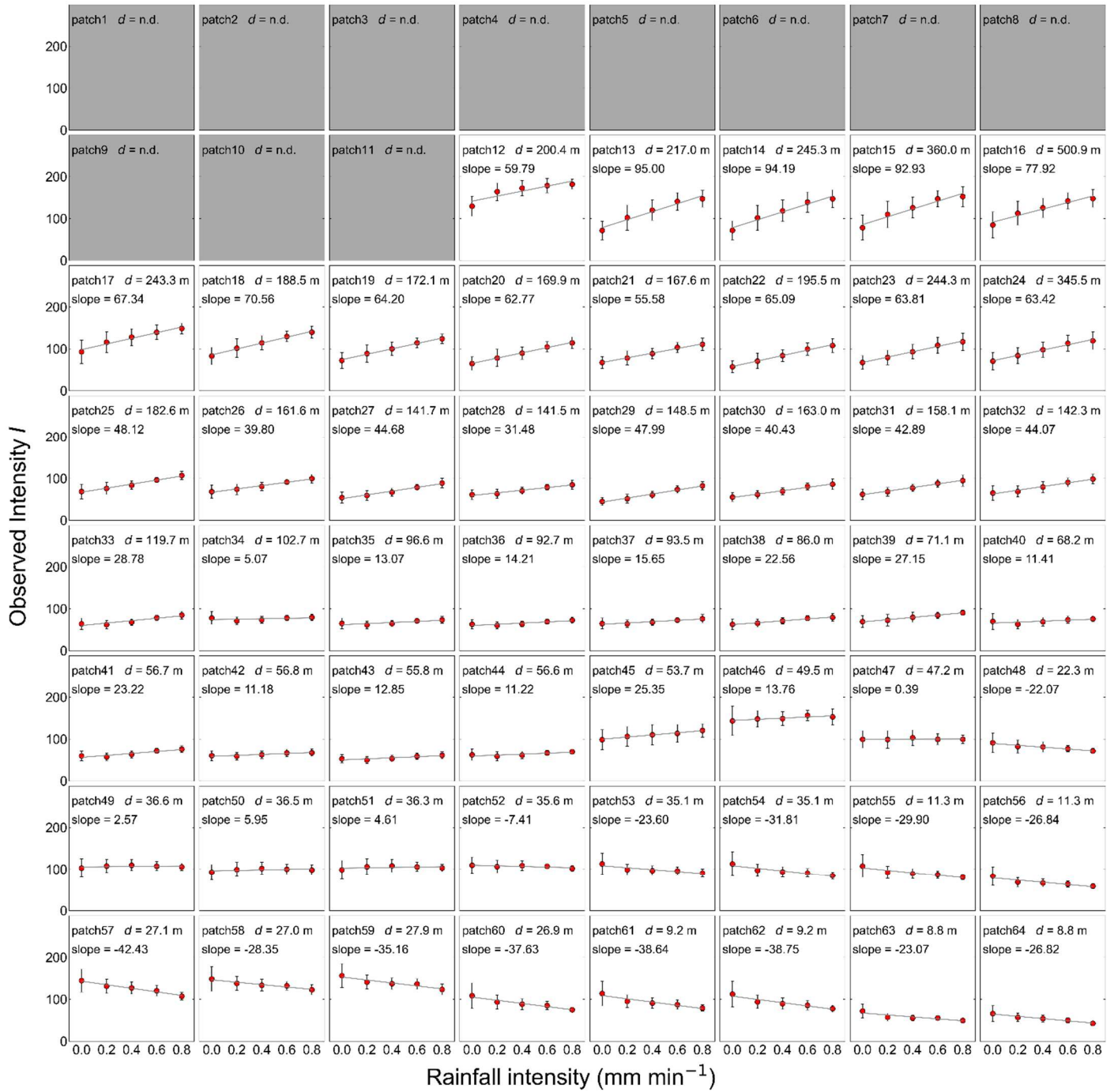
Figure C-1-b. Distribution of observed intensity *I* by rainfall intensity of Camera 2.
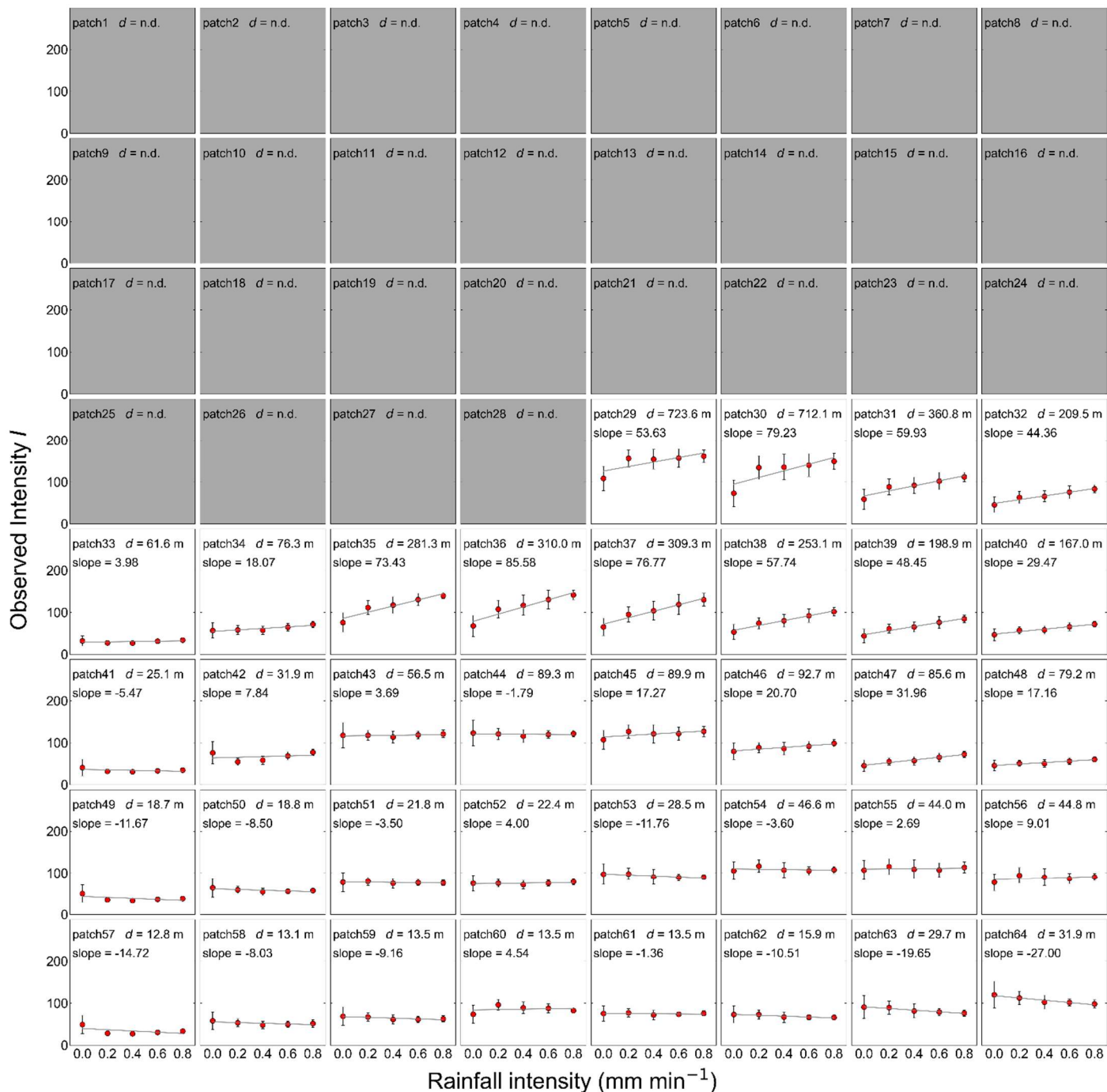
Figure C-1-c. Distribution of observed intensity *I* by rainfall intensity of Camera 3.

Appendix C-2: Figures including all patches showing the distribution of scene radiance *J* by rainfall intensity. Figure C-2-a, Figure C-2-b and Figure C-2-c show the distribution of scene radiance *J* by rainfall intensity of Camera 1, Camera 2 and Camera 3, respectively. Each figure is marked with a camera name, patch number, scene depth and slope of the linear regression line for the relationship between rainfall intensity and scene radiance *J*. The plots and error bars show the mean value and standard deviation of all data during the observation period. The straight lines show linear regression line for the relationship between rainfall intensity and scene radiance *J*. Rainfall intensity is observed by the rain gauge. Patches hatched in gray are patches where the appropriate scene depth could not be obtained due to the presence of sky background and the application of geometric corrections in the image registration process.
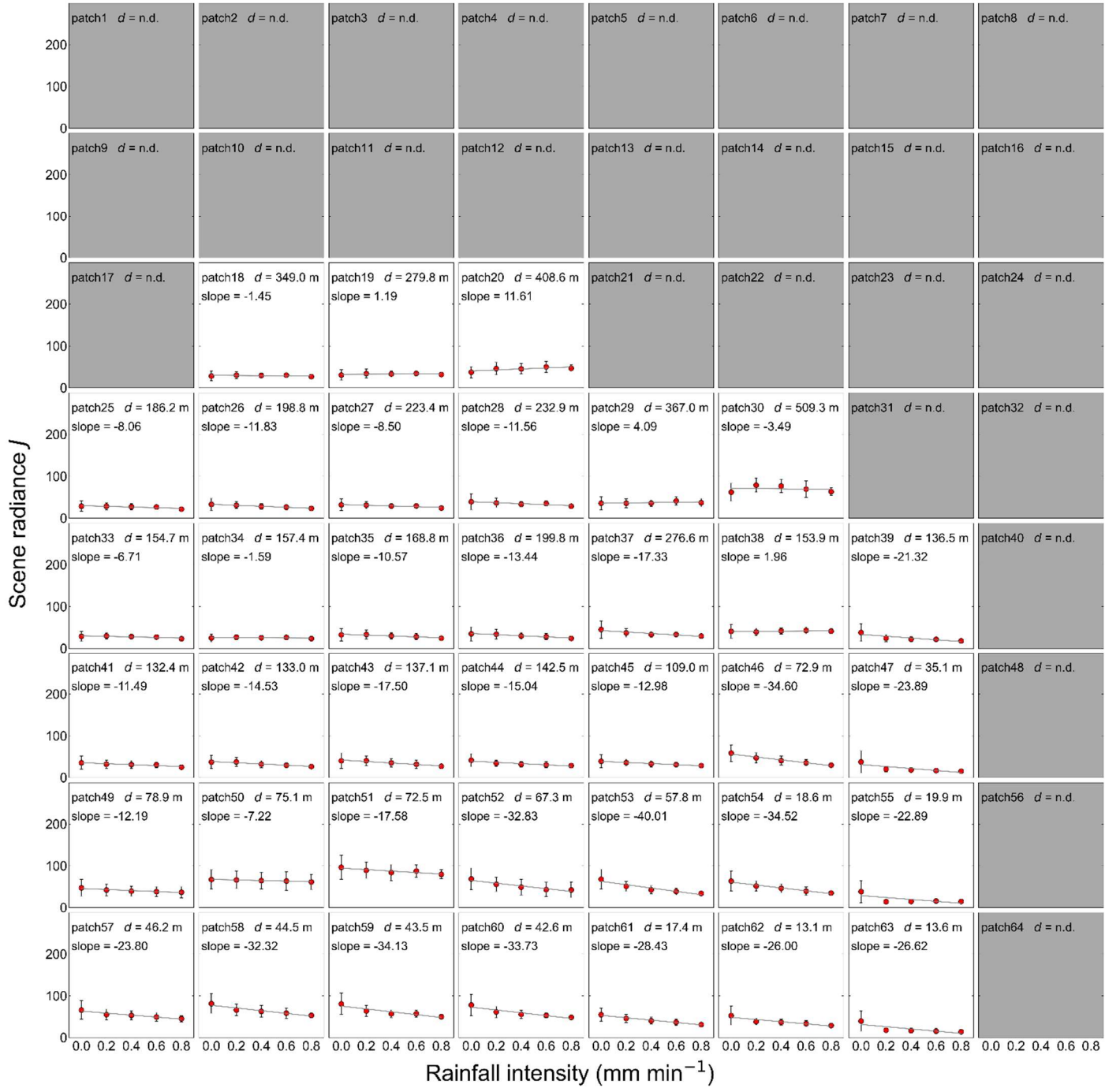

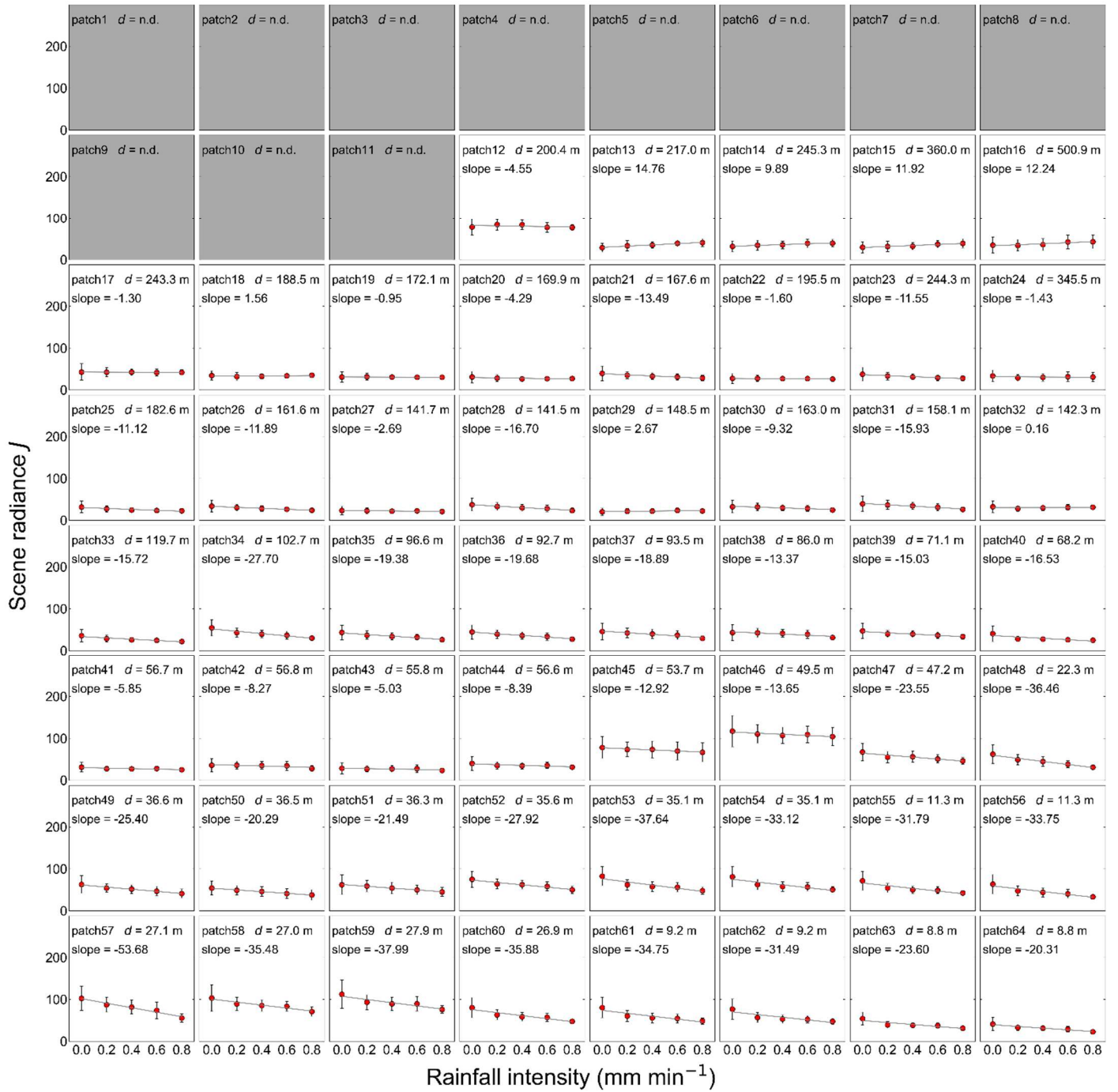Figure C-2-a. Distribution of scene radiance *J* by rainfall intensity of Camera 1.

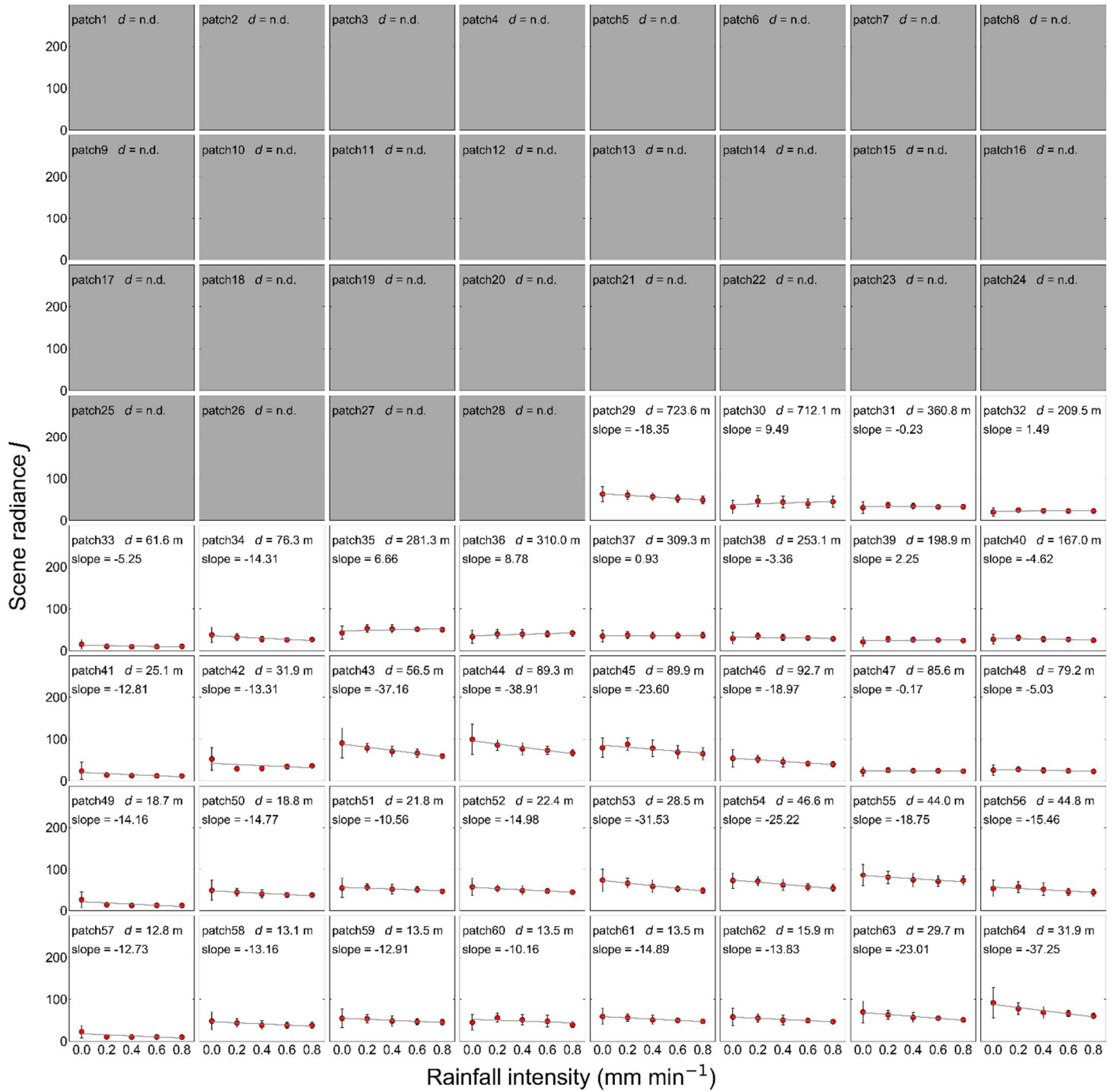Figure C-2-b. Distribution of scene radiance *J* by rainfall intensity of Camera 2.

Figure C-2-c. Distribution of scene radiance *J* by rainfall intensity of Camera 3.

Appendix C-3: Figures including all patches showing the distribution of transmission t by rainfall intensity. Figure C-3-a, Figure C-3-b and Figure C-3-c show the distribution of transmission t by rainfall intensity of Camera 1, Camera 2 and Camera 3, respectively. Each figure is marked with a camera name, patch number, scene depth and slope of the linear regression line for the relationship between rainfall intensity and transmission t. The plots and error bars show the mean value and standard deviation of all data during the observation period. The straight lines show linear regression line for the relationship between rainfall intensity and transmission t. Rainfall intensity is observed by the rain gauge. Patches hatched in gray are patches where the appropriate scene depth could not be obtained due to the presence of sky background and the application of geometric corrections in the image registration process.

Figure C-3-a. Distribution of transmission t by rainfall intensity of Camera 1.

Figure C-3-b. Distribution of transmission *t* by rainfall intensity of Camera 2.

Figure C-3-c. Distribution of transmission t by rainfall intensity of Camera 3.

< Comment 16 >

- Figures 4 - 7: what classes do the rainfall intensity values on the horizontal axis represent? E.g., 0.2 is 0 - 0.2 mm/min? And do higher values than 0.8 mm/min not occur (since the scale ends at 0.8 mm/min). In Figure 11 the scale ends at 1 mm/min.

Response:

The rainfall intensity values on the horizontal axis are the observed values from the tipping rain gauge used with a resolution of 0.2 mm as shown L. 216 through 217. During the observation period, the maximum one-minute rainfall intensity was 0.8 mm min^{-1} as shown L.222. We will revise the scale ends in Figure 11.

< Comment 17 >

- Figure 11: using square plots would make it easier to spot correspondence and deviation between estimated and observed rainfall intensity.

Response:

We will use square plots and revise Figure 11 as follows.

Figure 11-a. Relationship between observed rainfall intensity and estimated rainfall intensity of Camera 1. Each figure is marked with a patch number, scene depth and two MAPE values of rainfall intensity estimates throughout the observation period. $M_{>0.2}$ means MAPE value in cases using data with observed rainfall intensity of 0.2 mm min^{-1} or greater and $M_{>0.4}$ means MAPE value in cases using data with observed rainfall intensity of 0.4 mm min^{-1} or greater. The plots and error bars show the mean value and standard deviation of all data during the observation period. Patches hatched in yellow indicate patches with scene depth of less than 100 m. Patches hatched in gray are patches where the appropriate scene depth could not be obtained due to the presence of sky background and the application of geometric corrections in the image registration process.
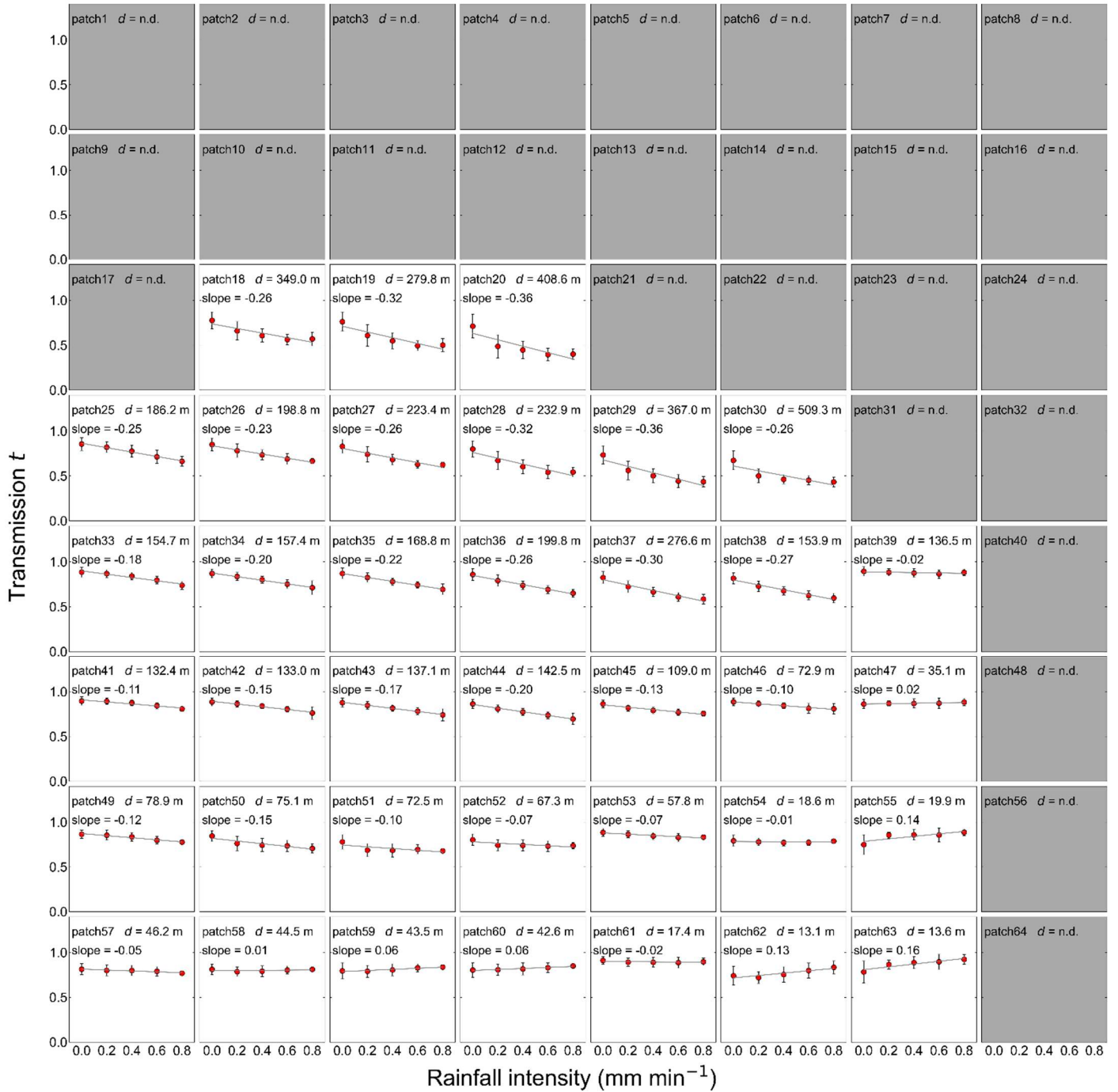
Figure 11-b. Relationship between observed rainfall intensity and estimated rainfall intensity of Camera 2. Each figure is marked with a patch number, scene depth and two MAPE values of rainfall intensity estimates throughout the observation period. $M_{>0.2}$ means MAPE value in cases using data with observed rainfall intensity of 0.2 mm min^{-1} or greater and $M_{>0.4}$ means MAPE value in cases using data with observed rainfall intensity of 0.4 mm min^{-1} or greater. The plots and error bars show the mean value and standard deviation of all data during the observation period. Patches hatched in yellow indicate patches with scene depth of less than 100 m. Patches hatched in gray are patches where the appropriate scene depth could not be obtained due to the presence of sky background and the application of geometric corrections in the image registration process.
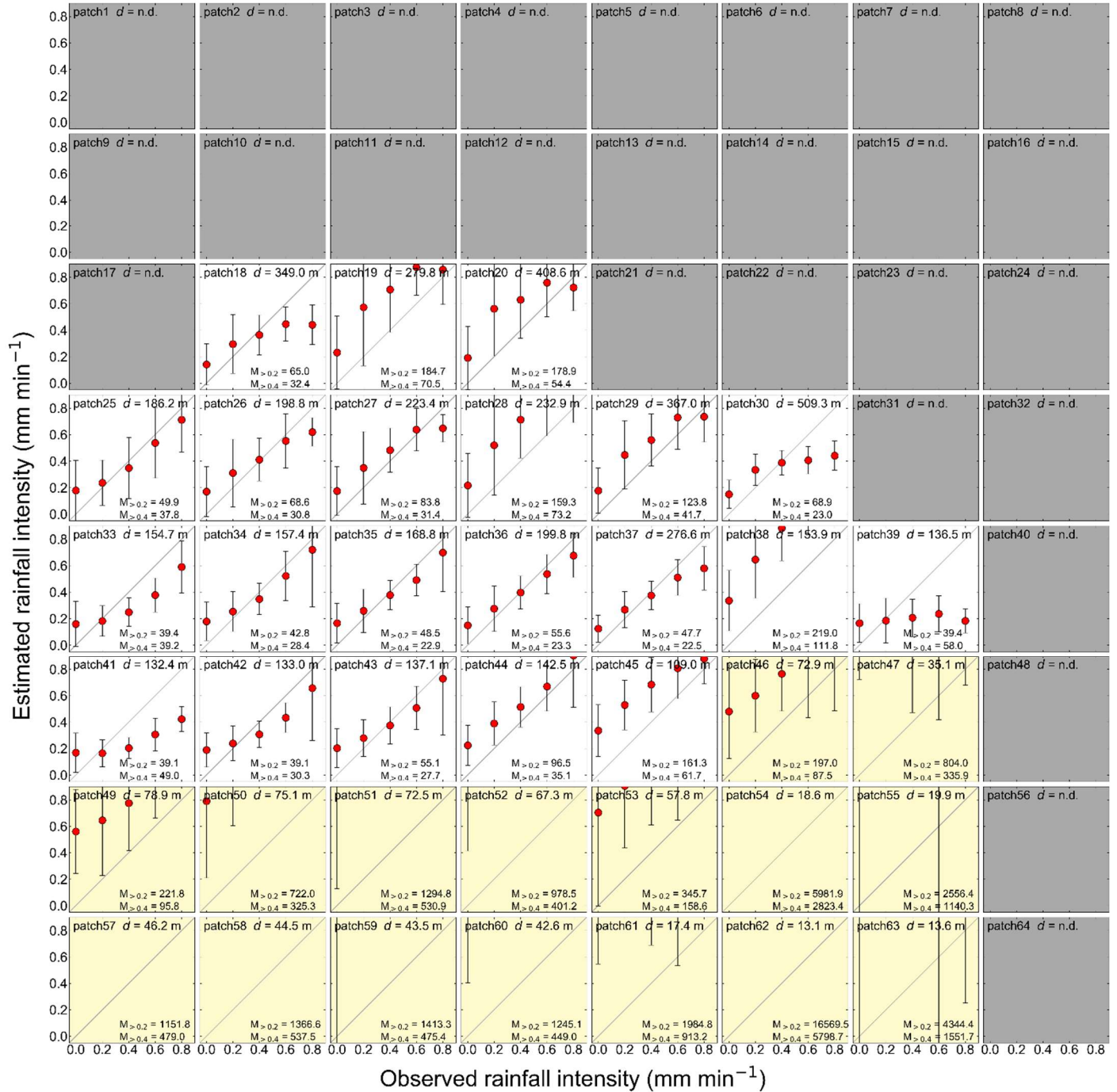
Figure 11-c. Relationship between observed rainfall intensity and estimated rainfall intensity of Camera 3. Each figure is marked with a patch number, scene depth and two MAPE values of rainfall intensity estimates throughout the observation period. $M_{>0.2}$ means MAPE value in cases using data with observed rainfall intensity of 0.2 mm min^{-1} or greater and $M_{>0.4}$ means MAPE value in cases using data with observed rainfall intensity of 0.4 mm min^{-1} or greater. The plots and error bars show the mean value and standard deviation of all data during the observation period. Patches hatched in yellow indicate patches with scene depth of less than 100 m. Patches hatched in gray are patches where the appropriate scene depth could not be obtained due to the presence of sky background and the application of geometric corrections in the image registration process.
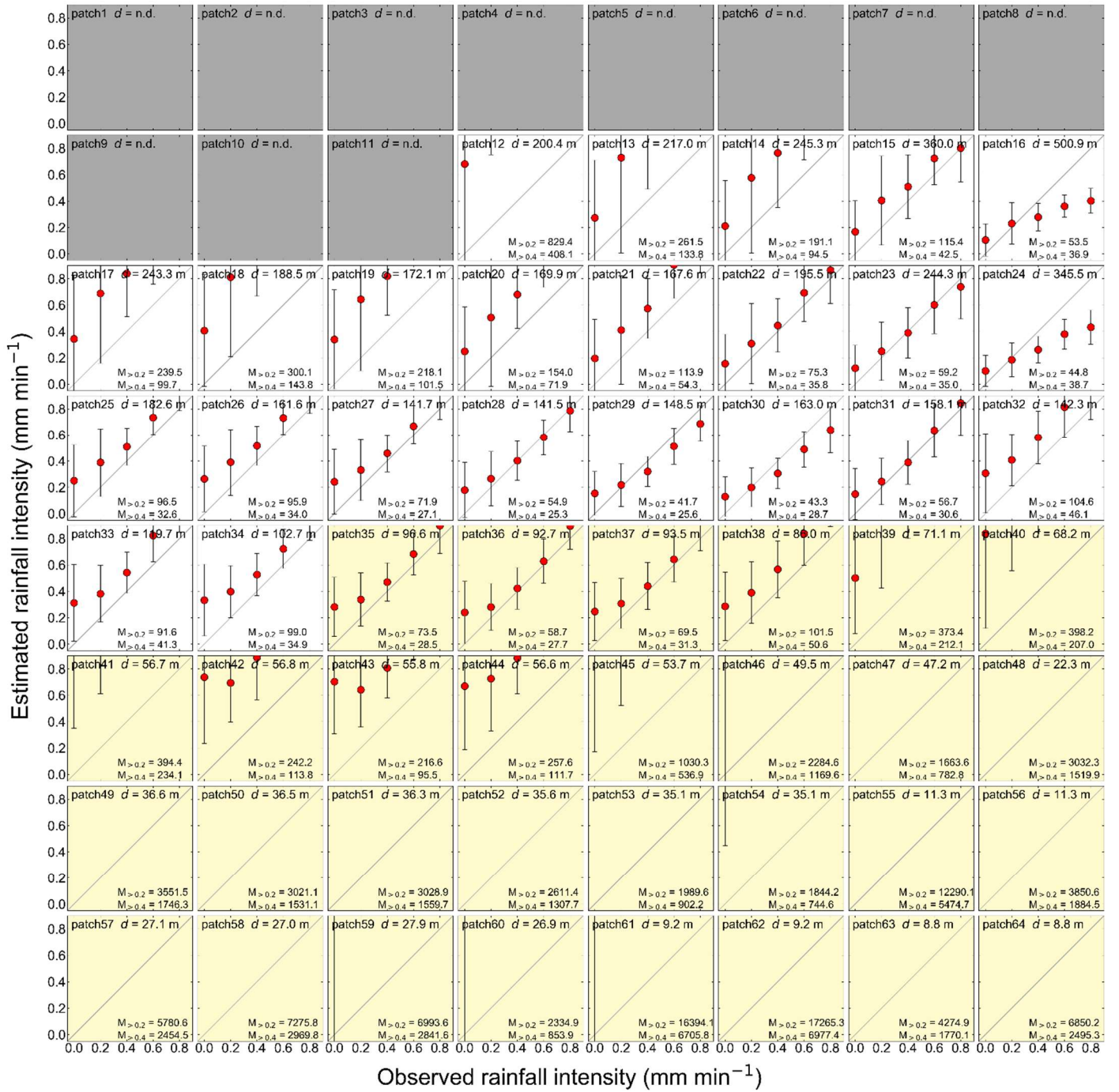
< Comment 18 >

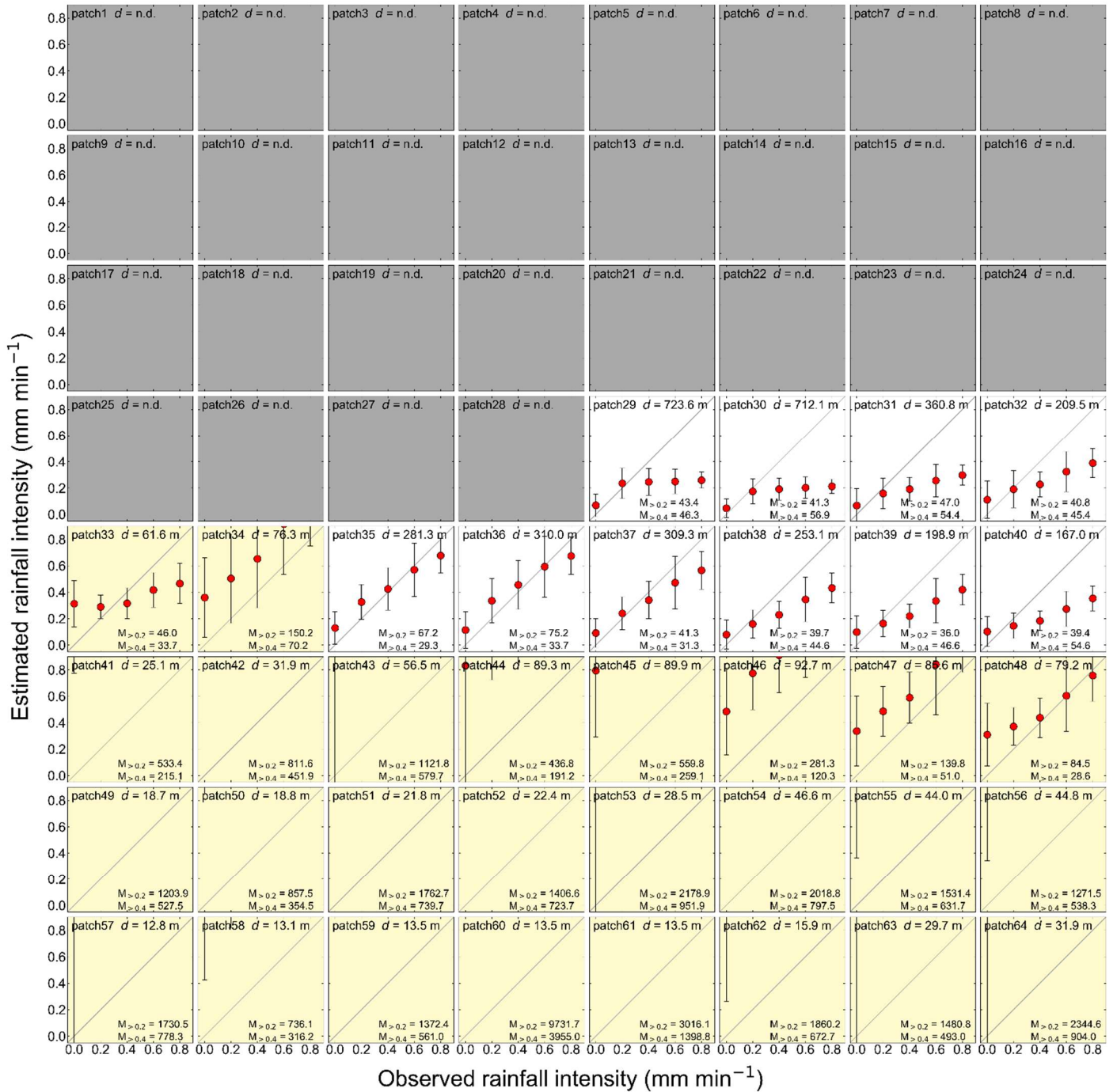- Adding a scatter density plot with metrics, or tables with metrics, such as relative bias in the mean and Pearson correlation coefficient (e.g., by expanding Table 4), would provide more insight into the performance of camera-based rainfall estimation.

A lot of time and figures are spend on the underlying relationships (e.g., Figures 4-7), and relatively little space is reserved for the evaluation of the ultimate goal: rainfall estimation.

Response:

We will revise Table 4 as follows.

The revised Table 4 shows mean, maximum, 75 percentile, median, 25 percentile and minimum values of MAPE over all patches and patches with scene depth of more than 100 m. Furthermore, we will also add MAPE value to Figure 11 for each patch. We will explain these results in response to Comment 21.

Table 4. Comparison of accuracy between five previous studies and this study: The "City, Country" row indicates the city and country where each study was conducted, and the "Köppen climate classification" row indicates the Köppen climate classification of the city. In the "Used data" row, "> 0.2 mm min^{-1}" means that data with observed rainfall intensity of 0.2 mm min^{-1} or greater were used, and "> 0.4 mm min^{-1}" means that data with observed rainfall intensity of 0.4 mm min^{-1} or greater were used. The "Observed rainfall intensity" row indicates the mean, maximum and minimum rainfall intensity during the observation period for each study. The range of "Observed rainfall intensity" indicates the range due to multiple rainfall events in each study. The rainfall intensity of Jiang et al. (2019) was converted from the duration and the accumulated rainfall of the rainfall event. MAPE is the mean absolute percentage error, and data with observed rainfall intensity of 0 mm min^{-1} were excluded by the definition of MAPE. MAPE values are shown for the case where all patches were used and for the case where only patches with a scene depth of more than 100 m were used. The number of patches used for each camera is shown in parentheses. In the column of the minimum MAPE, the patch number indicating the minimum value is shown in parentheses.

		This study						Allamano et al. (2015)	Dong et al. (2017)	Jiang et al. (2019)	Yin et al. (2023)	Zheng et al. (2023)
City, Country		Yamanashi, Japan						Torino, Italy	Nanjing, China	Shenzhen, China	Hangzhou, China	Hangzhou, China
Köppen climate classification		Humid subtropical climate (Cfa)						Humid subtropical climate (Cfa)	Humid subtropical climate (Cfa)	Monsoon influenced humid subtropical climate (Cwa)	Humid subtropical climate (Cfa)	Humid subtropical climate (Cfa)
Used data		> 0.2 mm min^{-1}			> 0.4 mm min^{-1}			-	-	-	-	-
Camera name		Camera 1	Camera 2	Camera 3	Camera 1	Camera 2	Camera 3	-	-	-	-	-
Data size for validation: Video length (min)		3261	3015	3261	120	107	120	104	9	403	170	357
Observed rainfall intensity (mm h^{-1})	Mean	12.6	12.6	12.6	28.5	28.9	28.5	2.8 - 9.3	1.1 - 6.5	4.1 - 29.5	11.0 - 23.6	9.7 - 39.3
	Maximum	48.0	48.0	48.0	48.0	48.0	48.0	6.0 - 38.2	-	-	36.0 - 66.0	24.0 -156.0
	Minimum	12.0	12.0	12.0	24.0	24.0	24.0	1.3 - 3.2	-	-	-	-
Accuracy: MAPE (%) — All patches (Camera 1: 37 patches, Camera 2: 53 patches, Camera 3: 36 patches)	Mean	1163.4	2131.4	1087.2	459.7	923.8	466.3	26.0	31.8	21.8	13.5 - 21.9	10.4 - 18.0
	Maximum	5981.9	12290.1	2178.9	2823.4	5474.7	951.9					
	75 percentile	783.5	1989.6	1296.7	333.2	853.9	565.7					
	Median	170.1	242.2	546.6	66.1	111.7	237.1					
	25 percentile	55.6	95.9	62.2	32.4	36.9	49.9					
	Minimum	39.1 (patch 42)	41.7 (patch 29)	36.0 (patch 39)	22.5 (patch 37)	25.3 (patch 28)	28.6 (patch 48)					
Accuracy: MAPE (%) — Patches with scene depth of more than 100 m (Camera 1: 21 patches, Camera 2: 23 patches, Camera 3: 10 patches)	Mean	88.9	148.3	47.1	43.1	70.6	44.3					
	Maximum	219.0	829.4	75.2	111.8	408.1	56.9					
	75 percentile	123.8	172.5	46.1	54.4	83.2	52.5					
	Median	65.0	96.5	41.3	35.1	38.7	45.9					
	25 percentile	47.7	58.0	40.0	28.4	33.3	36.4					
	Minimum	39.1 (patch 42)	41.7 (patch 29)	36.0 (patch 39)	22.5 (patch 37)	25.3 (patch 28)	29.3 (patch 35)					

< Comment 19 >

- Table 4 and discussion of other studies: are metrics computed in the same way across all these studies, i.e., with the same or no threshold? And are there differences in climatology that may lead to differences between studies?

Response:

As shown in our response to Comment 18, we will revise Table 4. The revised Table 4 shows the city and country where each study was conducted, the Köppen climate classification of the city, and the mean, maximum and minimum rainfall intensity during the observation period for each study. Table 4 shows that although only Jiang et al. (2019) was conducted in Monsoon influenced humid subtropical climate, this study and all five previous studies were conducted in a humid subtropical climate, and that there are no significant climatic differences. Furthermore, regarding the mean rainfall intensity during the observation period, the mean rainfall intensities of Allamano et al. (2015) and Dong et al. (2017) were lower than those in this study, while the mean rainfall intensities of Jiang et al. (2019), Yin et al. (2023), and Zheng et al. (2023) were comparable to this study. Overall, there is no significant difference in mean rainfall intensity between this study and the five previous studies. Moreover, in all studies, MAPE, a metrics of model performance, was calculated from observed values and model prediction. Given these facts, it seems reasonable to compare this study with five previous studies.

Therefore, we will add the following text in L. 603.

"Table 4 shows that although only Jiang et al. (2019) was conducted in Monsoon influenced humid subtropical climate, this study and all five previous studies were conducted in a humid subtropical climate, and that there are no significant climatic differences. Furthermore, regarding the mean rainfall intensity during the observation period, the mean rainfall intensities of Allamano et al. (2015) and Dong et al. (2017) were slightly lower than those in this study, while the mean rainfall intensities of Jiang et al. (2019), Yin et al. (2023), and Zheng et al. (2023) were comparable to this study. Overall, there is no significant difference in mean rainfall intensity between this study and the five previous studies. Moreover, in all studies, MAPE, a metrics of model performance, was calculated from observed values and model prediction. Given these facts, it seems reasonable to compare this study with five previous studies."

< Comment 20 >

- Table 4: From the data size I conclude that your study encompasses a much longer dataset. That could be emphasized in the introduction, since this stands out.

Response:

We will add the following sentence in L. 119.

"The estimation of rainfall intensity used over 3,000 images from rainfall events, and this data size is a unique aspect of this study."

< Comment 21 >

- Table 4: You honestly describe that you selected the values for the path with the lowest MAPE for each camera. What is the performance when the MAPE values over all patches are used? You could, e.g., provide the median and mean values found for MAPE, or just compute the MAPE over all patches. And did the other studies also select the patches with the highest performance?

Response:

As shown in our response to Comment 18, we will revise Table 4. And we will revise L. 603 through 607 as follows.

"All five of these studies did not separate the patches. This is because these previous studies focused on the dynamic weather effects and scene depth was not relevant. As shown in Table 4, the mean value of MAPE using data with observed rainfall intensity of 0.2 mm min^{-1} or greater for all patches was 1163.4 %, 2131.4 %, and 1087.2 % for Camera 1, Camera 2, and Camera 3, respectively, and the median value of MAPE using data with observed rainfall intensity of 0.2 mm min^{-1} or greater

for all patches was 170.1 %, 242.2 %, and 546.6 % for Camera 1, Camera 2, and Camera 3, respectively. The mean value of MAPE was considerably larger than the median value of MAPE, because it was heavily influenced by larger values such as the maximum value of MAPE. On the other hand, the mean value of MAPE using data with observed rainfall intensity of 0.2 mm min^{-1} or greater for patches with scene depth of more than 100 m was 88.9 %, 148.3 %, and 47.1 % for Camera 1, Camera 2, and Camera 3, respectively, and the median value of MAPE using data with observed rainfall intensity of 0.2 mm min^{-1} or greater for all patches was 65.0 %, 96.5 %, and 41.3 % for Camera 1, Camera 2, and Camera 3, respectively. Thus, the results indicate that the accuracy of rainfall intensity estimation can be improved by restricting the data to patches with scene depth of more than 100 m. Therefore, it is important to select patches with a scene depth of more than 100 m for rainfall intensity estimation. Next, we compare results of patches with scene depth of more than 100 m in this study with results of five previous studies. The median, 25th percentile, and minimum value of MAPE using data with observed rainfall intensity of 0.2 mm min^{-1} or greater for patches with scene depth of more than 100 m was higher than the MAPE value in the five previous studies. In contrast, the median value of MAPE using data with observed rainfall intensity of 0.4 mm min^{-1} or greater for patches with scene depth of more than 100 m was slightly higher than the MAPE value in the five previous studies, but the 25th percentile and minimum value of MAPE using data with observed rainfall intensity of 0.4 mm min^{-1} or greater for patches with scene depth of more than 100 m was similar to those of the five studies. Therefore, the proposed method in this study is considered to have a certain degree of effectiveness as a rainfall intensity estimation method, although there may be some error when the rainfall intensity is small."

< Comment 22 >

- Particle size distribution is known to vary between rainfall types, and hence between climates. How representative is the used distribution for your study? What do you expect from the suitability of your method for other climates, e.g., tropical climates in the Global South, where often few ground-based observations are available?

Response:

As shown in L. 706 through 709, the particle size distribution we used is the Marshall and Palmer distribution. We are thinking that the Marshall and Palmer distribution is a very good approximation to the raindrop size distribution referred to natural rainfall and widely used for describing the midlatitude particle size distribution that are characterized by low to moderate intensity (e.g., Serio et al. (2019)). However, when using the particle size distribution different from the Marshall and Palmer distribution, the change of the value of N_0 and λ may lead to the change in the value of extinction coefficient β, resulting in an overestimation or underestimation of rainfall intensity estimate.

Therefore, we will add following text in L. 180.

"As shown in Appendix A, the particle size distribution of raindrops used in this study is that presented by Marshall and Palmer (1948), hereafter referred to as the M-P distribution. The M-P distribution is a very good approximation to the raindrop size distribution referred to natural rainfall and widely used for describing the midlatitude particle size distribution that are characterized by low to moderate intensity (e.g., Serio et al., 2019). However, particle size distribution is known to vary between rainfall types and climates. Therefore, it should be noted that when using the particle size distribution different from the M-P distribution, the change of the value of N_0 and λ may lead to the change in the value of extinction coefficient β, resulting in an overestimation or underestimation of rainfall intensity estimate."

Also, we will add following paper to references.
- Serio, M. A., Carollo, F. G., and Ferro, V.: Raindrop size distribution and terminal velocity for rainfall erosivity studies. A review, J. Hydrol., 576, 210–228, https://doi.org/10.1016/j.jhydrol.2019.06.040, 2019.

< Comment 23 >

- L. 613: How to select an appropriate background in urban areas? Any suggestions, e.g., buildings?

Response:

We will revise L. 613 through 614 as follows and also refer to in our response to comment 9.

"Therefore, it is preferable to choose a static background such as building walls, tree canopies, and ground surface without people or vehicles, especially when applying this method in urban areas."

< Comment 24 >

- L. 670: Would this method be generally applicable to the abundant webcam or video images around the globe? Would it in principle be possible to obtain all the necessary data by simply downloading images from public websites? And could this technique potentially become a gap filler for (tropical) areas in the Global South lacking surface rainfall observations?

Response:

As shown in L. 671 through 675, this method only uses the camera image taken of the background over a certain distance and background scene depth information. Therefore, if they are available, it would be generally applicable to the abundant webcam or video images around the globe. As shown in L. 674 through 675, it would be possible to obtain the scene depth information measuring distances in a GIS. Of course, this means that this technique potentially becomes a gap filler for areas in the Global South lacking surface rainfall observations. Therefore, we will add the following sentence in L. 675 and in 5.4.2. as shown in our response to Comment 9.

"Therefore, this technique potentially become a gap filler for areas in lacking surface rainfall observations."

< Comment 25 >

- L. 670 & L. 678: what is the difference between "a single static image" and "a single individual image"? I find it a bit confusing to read that the method cannot be applied to a single individual image, but is applied to a single static image. Do you mean that the method can be applied to a single image, but that a sequence of images is needed to perform all necessary processing?

Response:

This method can be applied to a single individual static image. But the text in L. 677-679 was not well expressed. This text was intended to say that the overall trend in the applicability of the method was analyzed in this study, but the specific causes of the errors in each individual image were not validated. Therefore, we will revise L. 677-679 as follows. Note that this revision also includes a response to comment 26.

"Furthermore, this study examined the overall trend in the applicability of the method across the entire data set, but the specific causes of the errors in each individual image were not validated. For example, the presence of dew formation and raindrops on the camera lens itself could cause significant blurriness on the image and affect the rainfall estimation results, but this was not validated in this study. Therefore, validation of the specific causes of the errors when the proposed method is applied to each individual image is an issue to be addressed in the future."

< Comment 26 >

- What about dew formation (could be due to fog) and rain drops on the camera lens itself? Couldn't this cause significant blurriness, which could be interpreted as extinction? Or is the lens protected to rain drops by some cover above the lens? This could be mentioned around L. 677 or discussed in the Discussion section.

Response:

Dew formation and raindrops on the camera lens itself could cause significant blurring of the image and affect the rainfall estimation results. Therefore, we have included a revised version in our response to Comment 9 and 25.

< Comment 27 >

- You end the conclusions with the prospect of upscaling this technique. Would privacy issues, e.g., persons on the image, pose an obstacle for this rainfall estimation technique?

Response:

In many outdoor surveillance cameras, it may be inevitable that persons will be captured. Therefore, when making data public, it is necessary to pay careful attention to privacy issues.

We will add the following text in 5.4.2. as shown in our response to Comment 9.

"Furthermore, there are concerns about privacy issues in the actual use of this method. In many outdoor surveillance cameras, it may be inevitable that persons will be captured. Therefore, when making data public, it is necessary to pay careful attention to privacy issues."

< Comment 28 >

- What are the prospects for differentiating between precipitation types (e.g., rain, snow) and fog? This entails knowing which precipitation type (or fog) occurs, which can be highly relevant for early warnings (i.e., not focussed on intensity but only on type), but also improving rainfall estimates, by not taking into account other precipitation types and fog.

Response:

As you have pointed out, we consider differentiating between rain and fog a very important problem. At present, however, there is no method to determine whether it is rain or fog. Therefore, as a further study, it is necessary to investigate a method to determine whether the whiteness in the image under bad weather conditions is caused by rain or fog.

We will add the following text in 5.4.1. as shown in our response to Comment 9.

"Since this method estimates rainfall intensity from image whiteness, image whiteness caused by fog is misidentified as the effect of rainfall. At present, however, there is no method to determine whether it is fog or rain. Therefore, as a further study, it is necessary to investigate a method to determine whether the whiteness in the image under bad weather conditions is caused by rain or fog."