Dear Prof. András Bárdossy (Reviewer#2),

Thank you for your detailed comments about our manuscript. All your suggestions have been considered, and we propose the following changes to address the questions you raised in your review.

In the following point-by-point responses, RC denotes a referee comment (in black), AR denotes the author response (in blue), and PM denotes the proposed modifications (in green).

Hoping that the proposed improvements will fulfill your expectations,

Best regards,

Lionel Benoit, Mathieu Vrac and Gregoire Mariethoz.

RC: Radar images are notoriously weak in quantifying precipitation amounts, which can lead to mismatches. Are the on ground rainfall characteristics really related to these types?

AR: This is correct that radar images are weak in quantifying precipitation amount; this is why we propose here to use them as a proxy of rain storm behavior, hence the concept of rain types. In case ground rainfall characteristics are the main focus of the application at hand, a stochastic rainfall model should therefore be calibrated (conditional to rain types) using more relevant rain estimates, e.g. in-situ observations or gauge-adjusted radar images. When combined with a properly set-up stochastic rainfall model, rain types have been shown to improve simulation results (Benoit et al, 2018). Ground rainfall characteristics are therefore related to rain types derived from radar images, but a second step of rain intensity simulation is needed to quantify the actual rain intensity at the ground level. To better explain the use of rain type simulation within the framework of stochastic rainfall simulation the last paragraph of the introduction will be improved as follows, with the addition of a new figure.

PM: "*In this context, the main goal of this paper is to propose a new approach to leverage the use of rain types for encoding rain non-stationarity in the framework of stochastic weather generators. However, the finality differs from that of classical weather generators (Richardson, 1981; Wilks and Wilby, 1999; Peleg et al., 2017) since we aim at simulating rainfall conditional to already known meteorological covariates, instead of simulating jointly the whole weather (i.e., all variables). More precisely, we develop a method for stochastic simulation of rain type time series conditional to the current state of the atmosphere, i.e. conditional to meteorological variables such as pressure, temperature, humidity or wind (Fig 1a). These meteorological covariates are assumed to be known beforehand, either from observations, numerical weather model outputs, or from other stochastic simulations. The advantage of the proposed approach is twofold: firstly, using a stochastic simulation to generate rain types allows to properly reproduce the natural variability of rain type occurrence, and thereby to indirectly model the non-stationarity of rain statistics observed in historical datasets. Secondly, the conditioning of the stochastic rain type model to the state of the atmosphere preserves the relationships between rain type occurrence and climatological drivers. Once realistic rain type time series have been simulated (i.e. the core of this study, Fig 1a), high-resolution rain fields can be simulated conditional to rain types using any high-resolution stochastic rainfall generator (e.g., Vischel et al., 2011; Leblois and Creutin, 2013; Paschalis et al., 2013; Nerini et al., 2017; Benoit et al., 2018a) as illustrated in Fig 1b. Using rain types to guide the stochastic generation of synthetic rains has been shown to improve the realism of the resulting high-resolution space-time simulations (Benoit et al., 2018b).*

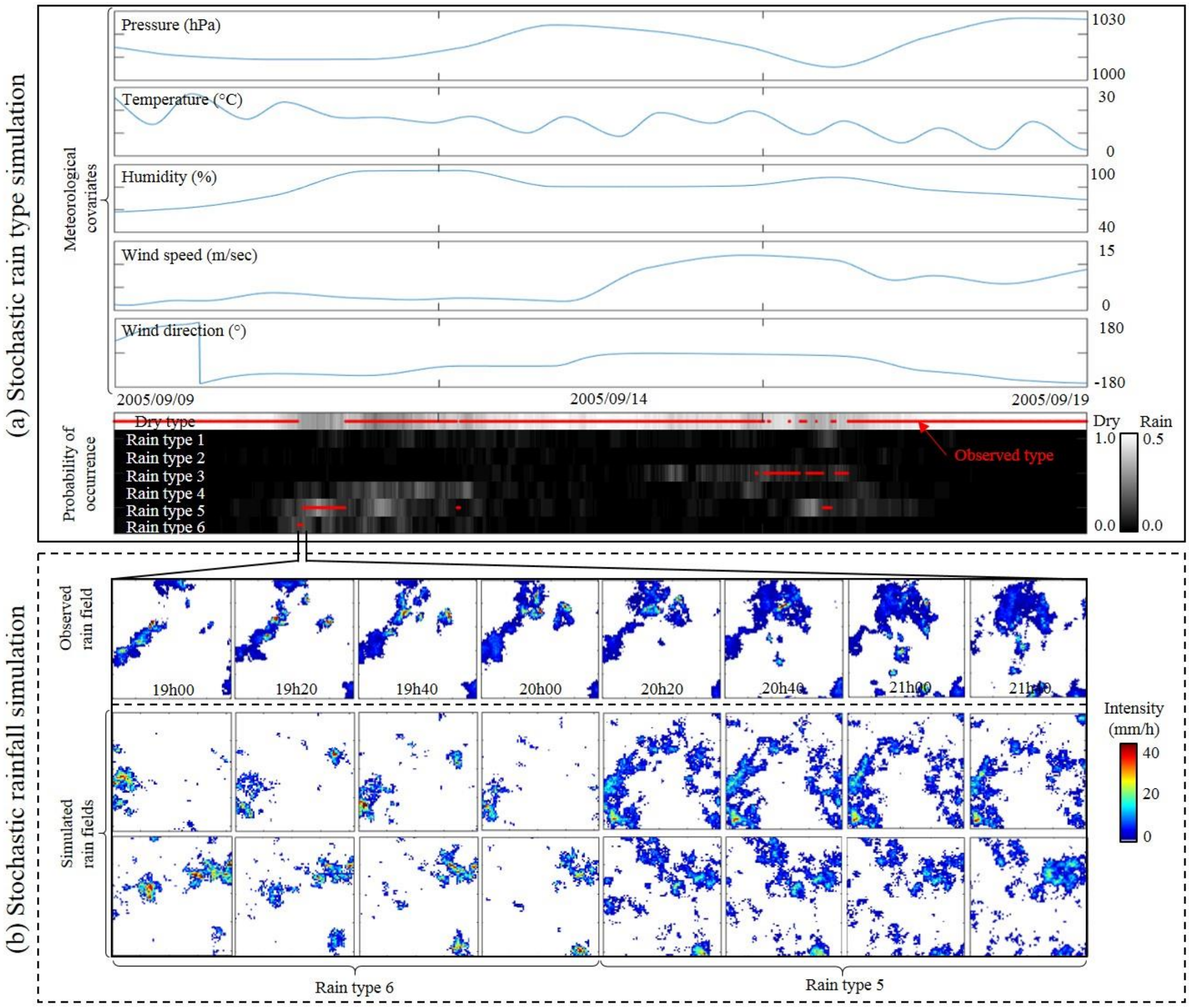


Figure 1. Overview of stochastic rain type generation (core of this study), and its application to simulate high-resolution synthetic rain fields whose statistical properties depend on meteorological conditions. (a) Rain type simulation framework developed in this study. (b) Illustration of stochastic rainfall simulation conditioned to changing rain types. In the bottom line of (a), the observed rain types are in red, and the gray shaded background denotes the probability of rain type occurrence derived from stochastic rain type simulations conditioned to the meteorological covariates displayed in the 4 top lines. In (b), the upper row displays actual rain fields observed by radar imagery, and the two bottom rows display two stochastic simulations of synthetic rain fields for the same period (Benoit et al., 2018a)."

RC: The 10 % wet pixels for the rain classifications means that the beginning and the end of the events are neglected. This leads to a reduction of the durations.

AR [Same answer than the reply to Reviewer#1. We repeat it here for easier readability]: The threshold of 10% is indeed pretty high, and leads to classify around one third of rainy images in the dry type. To deal with this 'dry bias', the typing method we use to classify radar images actually incorporates a second step (Benoit et al, 2018). It aims at assigning to images with less than 10% rain coverage the type of the closest (along the time axis) classified image. Therefore we do not define a distinct rain type for images with a small coverage area (<10%), but rather consider that this 'pseudo-type' due to a transient behavior of rainfall at the onset and at the end of rain storms.

This point was overlooked in the early version of our manuscript, and we will therefore address it in details in the revised manuscript. In particular, a paragraph will be added in the main text to discuss how we deal with images with rain coverage <10%. And an appendix will be added to show that the performance of the proposed rain type simulation method is not degraded when images with less than 10% rain coverage are considered as dry.

PM:

New paragraph in section 2.1:

"*Using only radar images with more than 10% wet pixels to define rain types ensures a reliable classification, but at the cost of a dry bias (in the present dataset, 32% of the images measuring some rain have a rain fraction under 10%, and are therefore assigned to the dry type). To deal with images with less than 10% wet pixels, Benoit et al. (2018b) proposed to classify images with a small rain fraction (i.e. 0% < rain fraction < 10<%) in a second step by assigning them the type of the closest classified image (i.e. nearest neighbor interpolation in time). This post-processing scheme is not directly transferable to the context of simulation because no information about the previously misclassified images is available in simulation outputs. Two options can be considered to alleviate this problem. First, the rain type model defined in Sect 3 can be calibrated on the final classification (i.e. including images with low rain coverage), which results in simulations that preserve the actual rain proportion. However, using a classification that includes the beginning and the end of rain storms leads to less clear relationships between climate covariates and rain type occurrence, which may degrade simulation results. Hence the second option, which we follow in this paper that consists in (1) calibrating and running the rain type model for rain types defined only from radar images with more than 10% rain coverage, and next (2) re-adjusting the wet/dry balance by post-processing. The dry bias is corrected assuming the ratio R = Ns/Nl between the number Ns of images with small rain coverage and the number Nl of images with large rain coverage as constant in observations and simulations. Subsequently, the number of epochs for which rain is simulated is increased by propagating the closest rain type to the RxNl dry epochs located at the beginning and at the end of rain storms. Appendix A shows that such post-processing performs well to mitigate the dry bias originating from the use of a 10% rain coverage threshold to define a wet image. However, since the present study focuses on climate - rain type relationships, which are better defined when considering only the first step of the classification, the aforementioned post-processing is not applied in the remainder of this paper. Hence, one should keep in mind that in the following the dry type also includes epochs with a small rain coverage (under 10%), and that a post-processing is required if the end-use is an application that involves the stochastic simulation of actual rain fields.*"

New appendix:

"*Appendix A: Cross-validation when accounting for small rain coverage.*

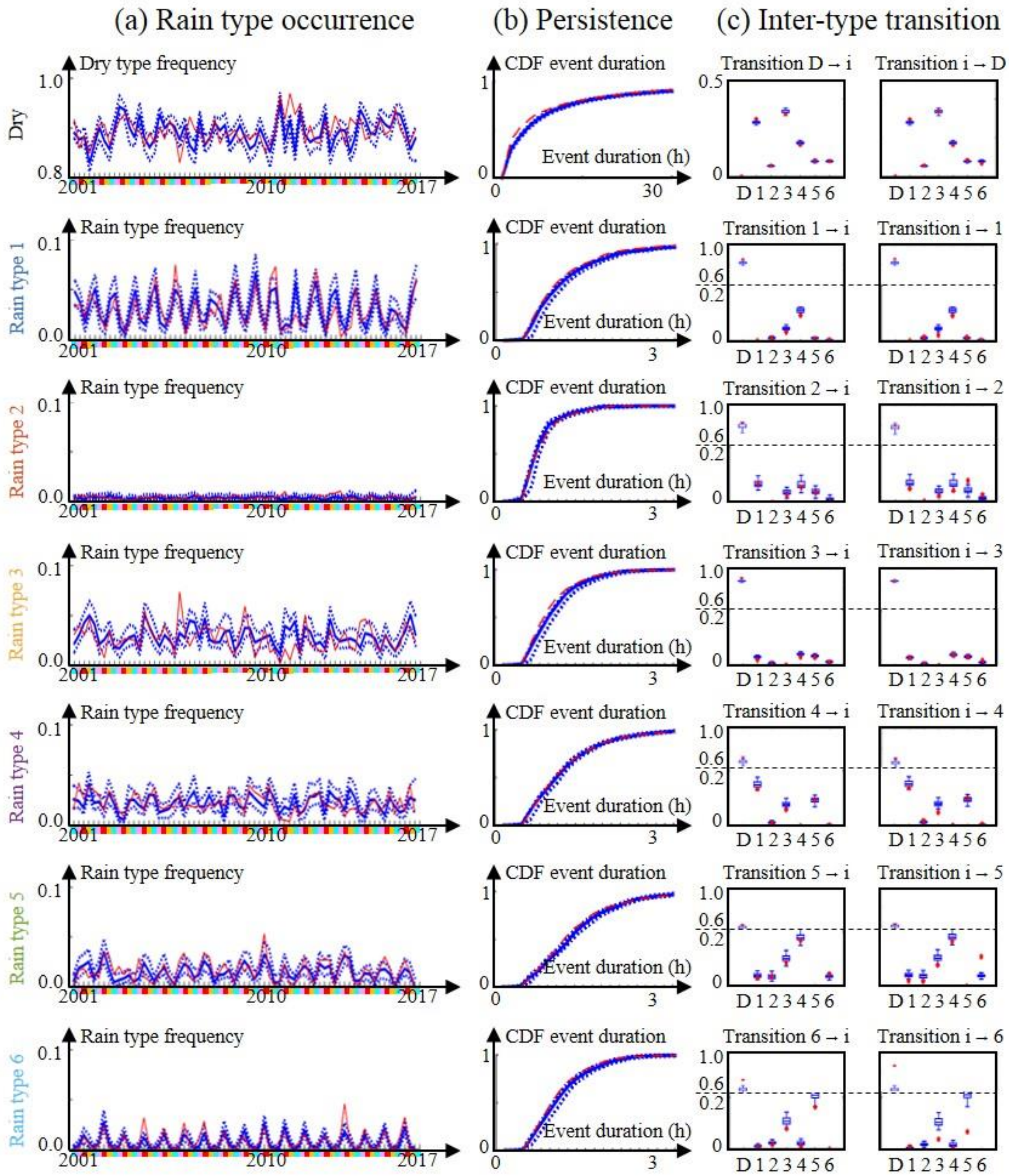


Figure A1. Results of the cross-validation experiment when images with low rain coverage (rain fraction between 5% and 10%) are regarded as wet. (a) Seasonality of rain (and dry) type occurrence (Seasons are DJF (light blue), MAM (pink), JJA (red) and SON (yellow)), (b) rain type persistence, and (c) probability of transition between rain types. Observations are in red and are obtained by assigning the type of the closest classified image to epochs with rain fraction between 5% and 10%. Simulations are in blue and are obtained by propagating the closest rain type to the beginning and to the end of each rain event. In simulations, continuous lines represent the median of the simulated ensembles (50 realizations), and dashed lines represent the Q10 and Q90 quantiles.”

RC: Wouldn’t it be reasonable to apply a space-time classification?

AR: The present classification already resorts to space-time statistics to define rain types, and is therefore implicitly a space-time classification. We will add a sentence in the description of the classification method to better explain this point. However, the whole area of interest is always considered as covered by statistically homogeneous rain fields (i.e. constant rain type in space), which is indeed a strong assumption. Nevertheless, also considering non-stationarity of rain types in space would make the classification very difficult. In particular, moving neighborhoods would have to be defined to assess the spatial statistics over sub-domains. We therefore restrict our present work to a temporal classification of space-time statistics, hence assuming that the study area is small enough to assume spatially stationary rain fields at each time step. This is obviously a simplifying assumption, and one should keep in mind that this can generate abrupt changes in simulated rain fields as shown in the new Fig 1 displayed above. This restricts the use of our method to areas of limited extend to ensure as much spatial stationarity as possible, as specified in section 2 *("We focus hereafter on a 100 km x 100 km squared area centered on the city of Jena in the Land of Thüringen, Germany (Fig. 2a). This area has been chosen because its flat topography and its location far from coastlines or major topographic barriers ensure spatially homogeneous rain fields, allowing to focus on the temporal component of rainfall non-stationarity.")*. In case of large areas, or areas where a strong non-stationarity of rainfall in space is suspected (e.g. mountains or coastlines), a truly space-time classification should be considered.

RC: The choice of the meteorological covariates is not convincing. The seven variables seem to have weak relationships with the rain types. Are these variables really better if they are combined? A scatterplot of the variables with the indication of the rain types would be necessary to see if the variables are likely to explain the occurrence of the different rain types. Would not a similar typing of the spatial patterns of these variables be a better alternative to find a relationship?

AR: A new dedicated sub-section will be created to address the concerns raised above and to better emphasize on the importance of the chosen meteorological covariates (Sect 2.1: Meteorological covariates). In this section, we follow the advice of Reviewer#2 and therefore study the joint influence of meteorological covariates on rain type occurrence (Figure B3 will be added in Appendix). From the new figure B3, it appears that if combined, the proposed covariates explain pretty well rain type occurrence. This is further reinforced by the ability of the proposed approach to capture the inter-annual variability of rain type occurrence, as highlighted for instance in the revised figure A1 above. Finally, the use of weather types instead of a set of pointwise covariates will be discussed in the new Appendix B: selection of meteorological covariates, as detailed in the reply to the next comment.

PM: "*Figure 4 displays the relationships between meteorological covariates and rain type occurrence, and confirms the strong influence of temperature and wind speed on rain types. Indeed, stratiform rain types 1 and 4 occur at lower temperatures than convective types 5 and 6, and co-occur with stronger winds. The frontal rain type 3 is characterized by strong westerlies, but occurs for a broad range of temperatures. In contrast to temperature and wind speed, the standalone knowledge of pressure, relative humidity or wind direction does not allow to discriminate between all rain types. However, when considered jointly (Appendix B, Fig. B3), all meteorological covariates bring information about rain type occurrence. In particular, pressure and humidity are key drivers for rain occurrence (no matter the type) and are therefore useful to predict dry and wet spells. Furthermore, wind direction informs the occurrence of rain type 3 and helps discriminating between rain types 5 and 6.*

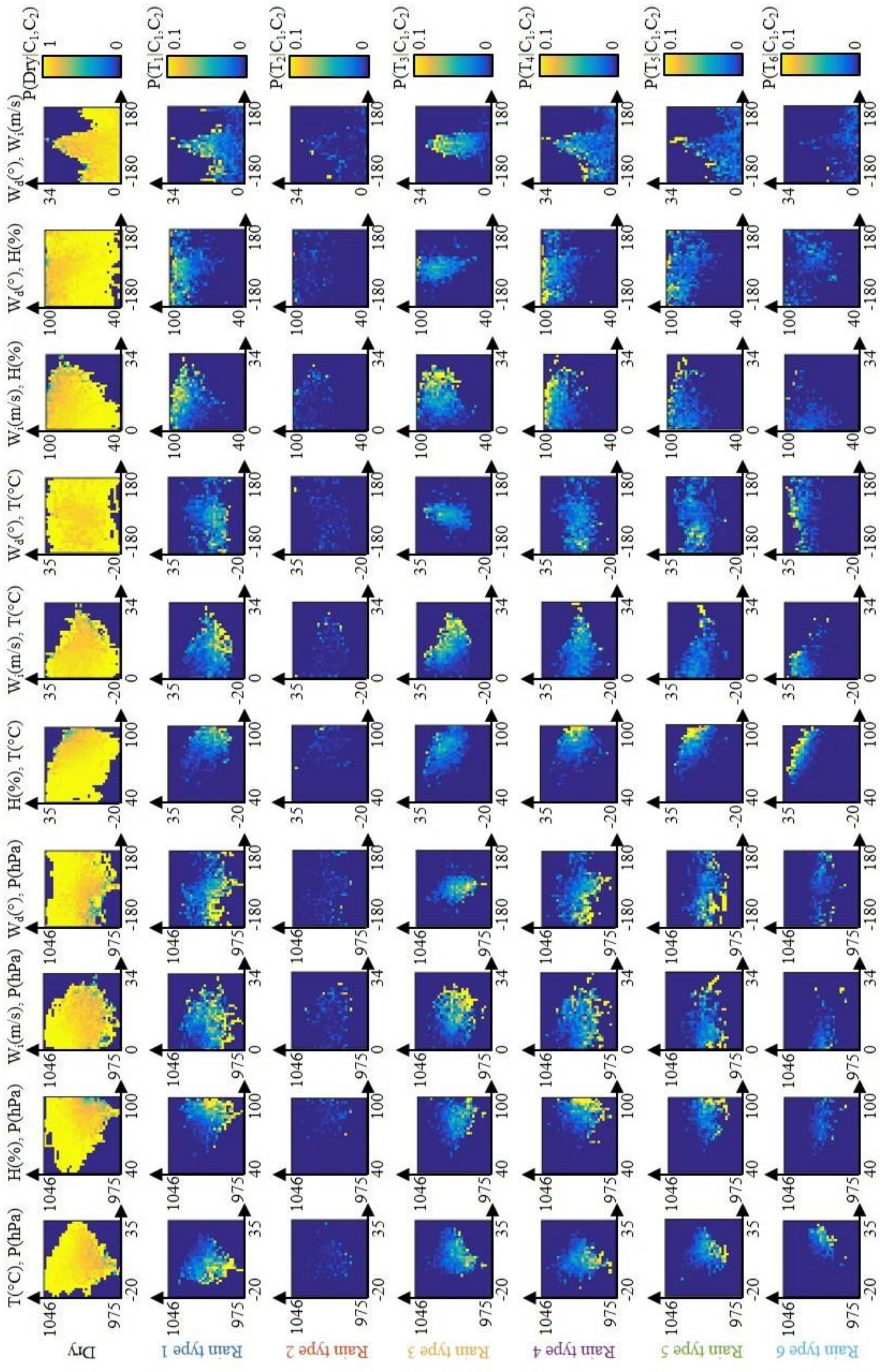


Figure B3. Joint probability of rain type occurrence conditional to pairs of meteorological covariates. Rows correspond to different rain types, and columns correspond to different pairs of meteorological covariates. The title of the rows indicates the pair of covariates of interest; the first covariate defines the abscissa axis, and the second the ordinate axis. T denotes temperature, P is pressure, H is relative humidity, Wi is wind intensity and Wd is wind direction. In each graph, the probability of rain type occurrence is coded by the color-scale."

RC: Another specific problem here is the use of daily covariates. Rainfall is often related to short time changes in temperature and air pressure. The suggested disaggregation procedure cannot cope with this and practically relates 10 min precipitation types to daily covariates through a pre-defined daily cycle. This of course reduces the possible influence of the covariates. Present observations could be used to see whether the covariates are better if available on higher resolution. The variable with the clearest signal is temperature, which may be the only reason why changes are detected in the RCM scenarios.

AR: We agree that rainfall is often related to short time changes in temperature and air pressure, and that the disaggregation procedure applied to meteorological covariates is therefore important to ensure high quality rain type simulations. As proposed by Reviewer#2, we compared our disaggregated covariates with their counterparts observed in-situ at high resolution by a weather station located within the area of interest. In addition, we compared the performance of our rain type model when forced by (1) disaggregated covariates and (2) in-situ observations of the covariates. The results of this experiment will be added in the new Appendix B and mentioned in the main text. These results show that the proposed disaggregation method performs well to capture sub-daily variations of the covariates. In addition, rain type simulations driven by the two covariate datasets (disaggregated vs high resolution in-situ) give very similar results. Consequently, we choose to keep the disaggregation of daily covariates to drive rain type simulations because this approach fits better with the illustration study considered in this paper.

PM: "*Appendix B: Selection of meteorological covariates.*

The stochastic rain type generator developed in this paper requires meteorological covariates in order to (1) ensure the climatological coherence of the simulations, and (2) reproduce the annual cycle as well as the inter-annual variability of rain type occurrence. As mentioned in Sect. 2.2 we focus on meteorological parameters that are known to influence the triggering and the behavior of rain storms (Vrac et al., 2007; Willems, 2001; Rust et al., 2013), namely: pressure, temperature, relative humidity, and wind direction and intensity. Here we choose to use the actual values of the covariates rather than weather types defined by classification of the spatial patterns of one or several of these covariates (Vrac et al., 2007; Rust et al., 2013; Milrad et al., 2014). There are two main reasons for this: First, in case of weather types derived from several covariates, each weather type combines in an intractable manner the influence of the different meteorological parameters, thus making the identification of the climatological drivers of rain type occurrence difficult. Second, the use of weather types drastically reduces the dimensionality of the covariate space, which allows fewer nuances in the links between meteorological conditions and rain types.

Rain type data and simulations are used at 10-min resolution, and therefore the meteorological covariates must be provided at the same resolution. In addition, rainfall is often related to short time changes in meteorological conditions (in particular temperature and air pressure), and high resolution covariates are therefore expected to better explain rain types. However, one of the two foreseen applications of the proposed stochastic rain type generator is the stochastic downscaling of regional climate model projections, which are most of the time available only at daily resolution. Hence the hybrid solution adopted in this study, which uses daily resolution meteorological covariates and disaggregates them to a 10-min resolution as described in Sect. 2.2.

Figure B1 compares disaggregated data derived from the ERA5 reanalysis with in-situ observations carried out by a weather station (located within the study area) at high resolution (10-min for pressure, temperature and relative humidity, and 6h for wind). Results show that pressure and temperature have similar behaviors in the two datasets, while relative humidity and wind present significant dissimilarities. Regarding relative humidity, the observed dissimilarities are mostly caused by the influence of the daily temperature cycle in the high resolution dataset. When replacing relative humidity by vapor pressure, which is not correlated with temperature, it appears that the differences between the two datasets are considerably reduced. Hence, the independent information (i.e. not correlated with *other covariates) carried by the relative humidity does not drastically differ between the two datasets. Regarding wind-related covariates (here the Eastward and Northward components of the wind vector are assessed), it is interesting to note that the dataset derived from the reanalysis carries more signal than the in-situ observations. This is because in-situ observations refer to low altitude winds, which are much more variable than the wind at 850hPa extracted from the reanalysis. Hence, the signal-to-noise ratio of the weather station dataset is lower than the one derived from ERA5. All in all, the proposed disaggregation method performs well to capture sub-daily variations of meteorological conditions, despite some mismatches during stormy periods.*

However, to ensure that the small fluctuations of the meteorological covariates that are missed by the disaggregated dataset do not negatively affect the simulation of rain types, we performed an additional cross-validation experiment where the rain type simulation is forced by the two datasets of covariates described above, namely: (1) ERA5 data disaggregated at 10 min resolution (i.e. the dataset used throughout the paper) and (2) in-situ observations from a weather station located within the study area. Fig. B2 summarizes the results of this experiment and shows very little differences between the two simulations. The almost similar performance when using the two sets of covariates can on the one hand be explained by the fact that the additional signal embedded into in-situ observations hardly emerges from the measurement noise, and on the other hand by the fact that the additional information brought by the wind data in the reanalysis dataset compensates for the uncertainties related to the 10-minute reconstruction of pressure, temperature and relative humidity data. Finally, since both sets of covariates lead to similar performances, we favor the disaggregation of daily data because it is compatible with the targeted application of regional climate model downscaling.

After disaggregation, the meteorological covariates can be used to investigate how weather conditions influence rain type occurrence. To this end, Fig. B3 displays the impact of pairs of covariates on rain type occurrence. It shows that although temperature and wind intensity are the main drivers for rain type occurrence, the joint knowledge of all covariates is important to assess rain type distribution.

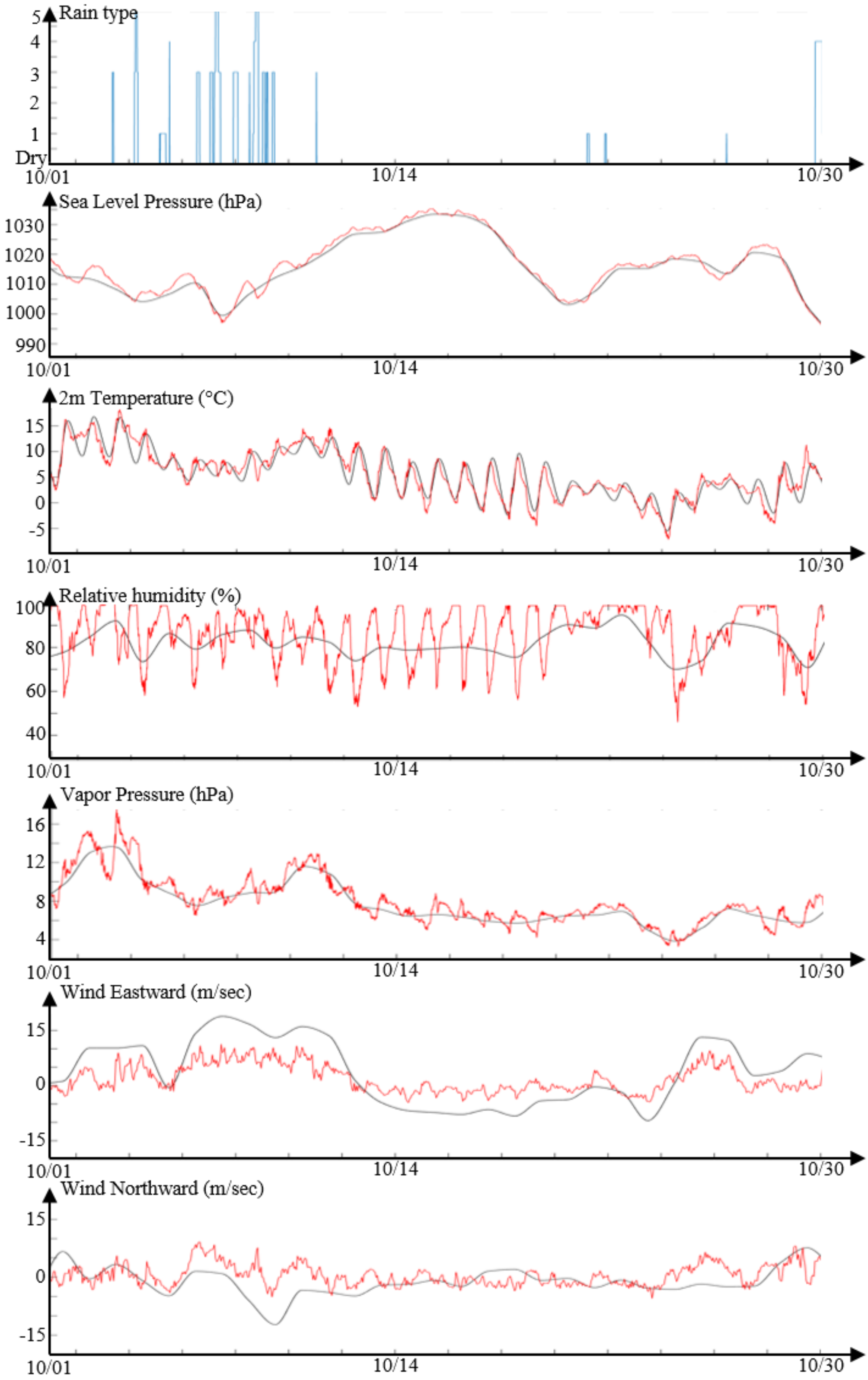


Figure B1. Comparison between in-situ observations (red) and disaggregated ERA5 reanalysis (black) of the meteorological covariates considered in this study. Period of interest: October 2003. From top to bottom: observed rain types (derived from radar images, cf Sect 2.1), pressure, temperature, relative humidity, vapor pressure, Eastward wind component, Northward wind component.

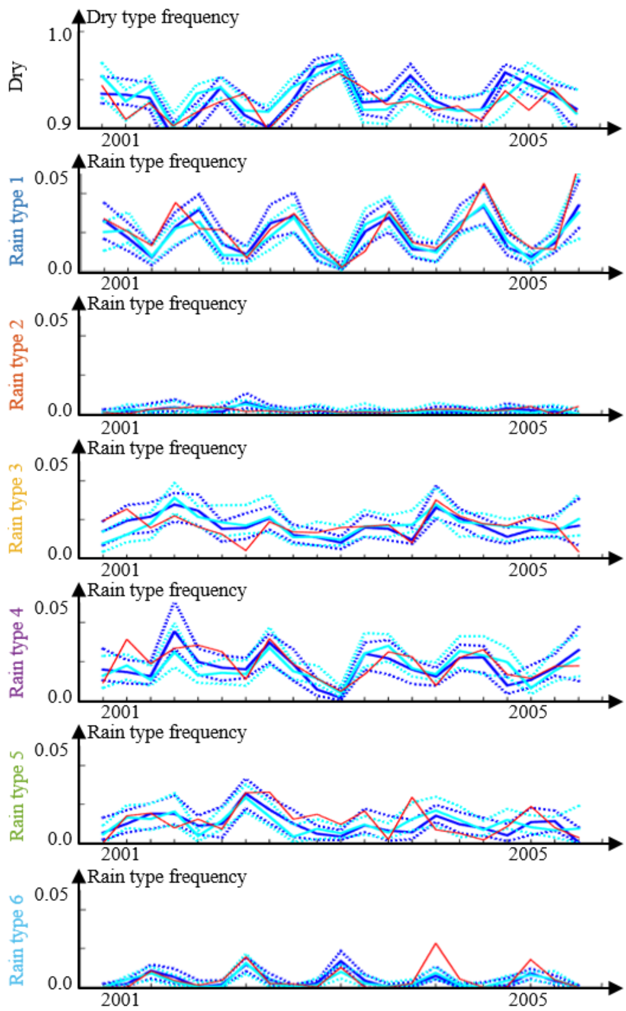


Figure B2. Cross-validation using the leave-one-year out method described in Sect. 4.1 applied to the 2001-2005 period and two different sets of covariates. Observations are in red, simulations using the disaggregated ERA5 covariates are in dark blue, and simulations using in-situ observations of covariates are in light blue. Continuous lines represent the median of the simulated ensembles (30 realizations), and dashed lines represent the Q10 and Q90 quantiles.

Figure B3. [For conciseness we do not repeat the new Figure B3; see above for this figure]."

RC: Simple year by year cross validation is not enough to show the applicability of the model for climate model downscaling. Instead a split sampling into dry and wet years and warm and cold years could help to know if the model is likely to handle climatic signals reasonably.

AR: We agree. A split-sampling will be added to the validation section. To this end we propose to add the new sub-section '4.2: Sensitivity to climate variability', as described hereafter. The results of this split-sampling test show that our model properly captures the impact of the climatic signal on rain types.

PM:

"*4.2: Sensitivity to climate variability*

To ensure that the proposed rain type model is able to capture the impact of climatic signals on rain type occurrence, the results of the cross-validation procedure are stratified according to annual climatic signatures. To this end, Fig. 7 compares simulated and observed rain type occurrences at the monthly scale for four sub-datasets: the 5 coldest years of the 2001-2017 period (Fig. 7a), the 5 warmest years

(Fig. 7b), the 5 driest years (Fig. 7c), and finally the 5 wettest years (Fig. 7d). Observations (red curves in Fig. 7) show that years with different climatic signatures indeed develop distinct dry/wet ratios and rain type distributions. Simulation results (blue curves in Fig. 7) show that the proposed model properly reproduces these climatically driven differences in rain type distribution.

Figure 7 therefore allows for a detailed investigation of the impact of climatic signals on local rain type distribution over central Germany. Comparing first cold and warm years (Fig. 7a-b), one can notice that warm years tend to be drier, in particular in late winter and spring. This is mostly caused by a deficit of type 1 precipitations during warm years, which correspond to less snow (type 1 occurs mostly at negative temperatures, cf Fig. 4). Drier springs during warm years are also caused by a deficit of type 5 (slightly convective), which probably correspond for this time of the year to rain and sleet showers. Finally, one can notice an increased occurrence of type 6 (strongly convective) during warm years, which is captured by the model despite a slight underestimation of this type for both cold and warm years. Comparing next dry and wet years (Fig. 7c-d), one can notice that all months contribute to the rain imbalance, but that the rain deficit is more pronounced in spring and autumn. In terms of rain type distribution, this is mostly caused by a deficit of rain types 1 and 4 (stratiform) as well as 5 (slightly convective) during dry years. It is also worth noting that rain type 3 (frontal) tends to be slightly more common during rainy years, but in contrast to other types its increased occurrence is spread along the whole year.

Overall, the proposed approach properly captures the impact of climatic signals on rain type occurrence. This property is essential to preserve the climatological coherence in the context of stochastic weather generation, and paves the way to RCM precipitation downscaling.

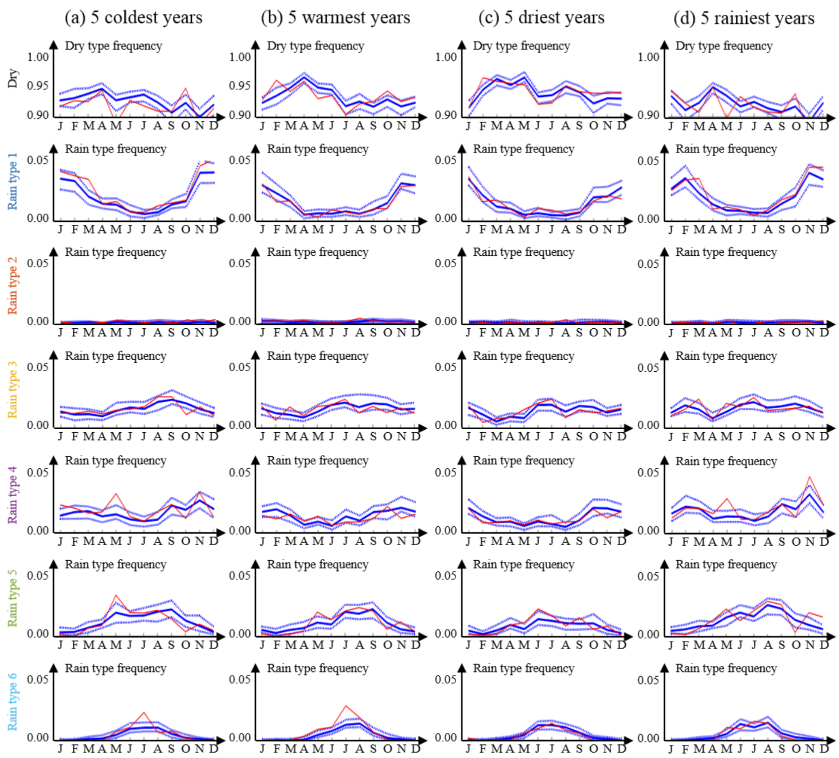


Figure 7. Monthly rain type occurrence stratified according to climate forcing: (a) 5 coldest years of the 2001-2017 period (2001, 2004, 2005, 2010, 2013), (b) 5 warmest years (2007, 2011, 2014, 2015, 2017), (c) 5 driest years (2003, 2011, 2012, 2015, 2016), and (d) 5 wettest years (2001, 2002, 2007, 2009, 2010). Observations are in red and simulations in blue. In simulations, continuous lines represent the median of the simulated ensembles (50 realizations), and dashed lines represent the Q10 and Q90 quantiles."

RC: In my opinion the systematic bias of the parametric model indicates that it was not set up properly. Therefore, it would be important to modify it and remove the bias. I would certainly not try to apply a model which is biased.

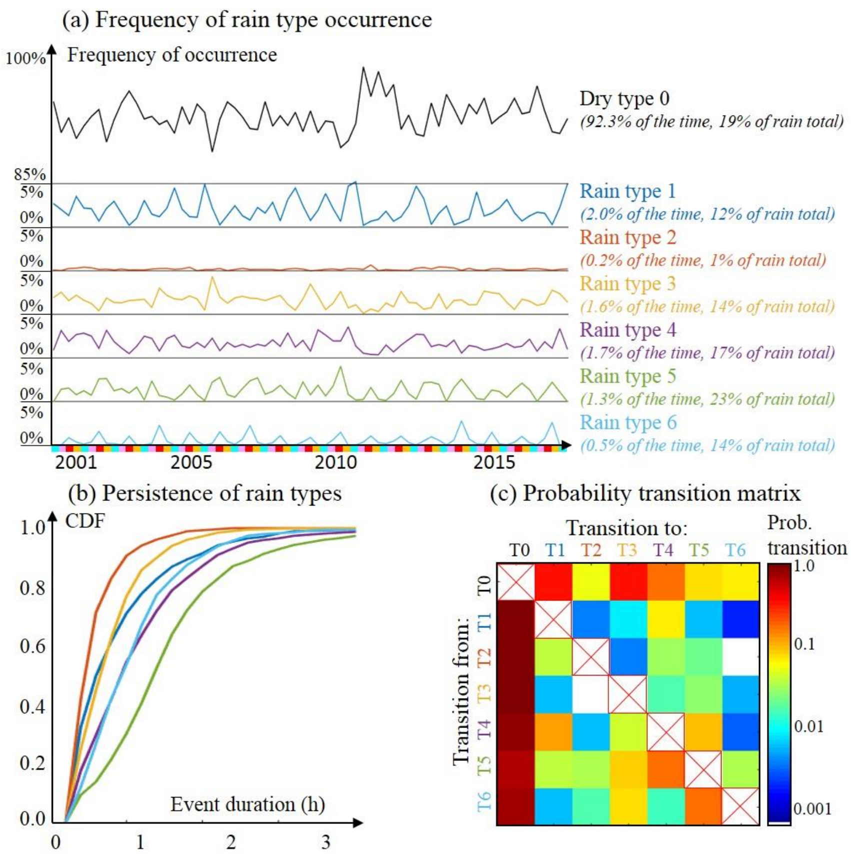
AR: We agree that we should not apply a biased model, but we believe that the poor performance of the parametric model is not due to a wrong setting but rather to the inherent difficulty to condition a semi-Markov model to continuous-time covariates. This will be clearly stated in the revised manuscript. To avoid using a biased model, the parametric model will be removed from the main text and moved in appendix. It will only be mentioned as a benchmark, and the main paper will focus only on the non-parametric model.

PM: The description and the assessment of the parametric model will be moved in appendix (new appendix C).

RC: Figure 2 upper panel: One cannot guess the fluctuations of the frequencies of the individual rain types except for type 1. I suggest to show individual lines instead.

AR: The figure will be revised accordingly.

PM:

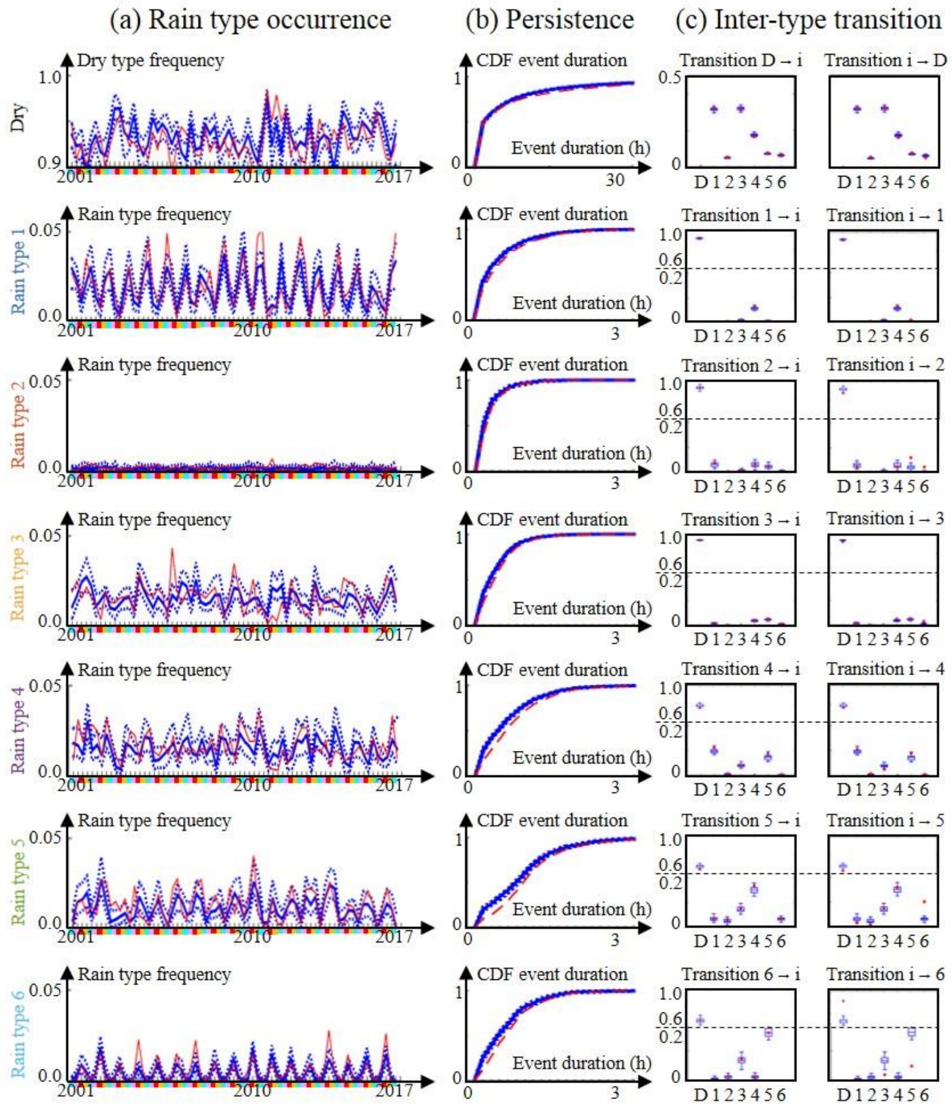


"*Figure 3. Main features of a rain type time series (2000-2017) observed over central Germany. (a) Frequency of rain type occurrence computed at a seasonal basis (Seasons are DJF (light blue), MAM (pink), JJA (red) and SON (yellow)). (b) CDF of event duration stratified by rain type. (c) Empirical matrix of transition probability between rain types.*"

RC: Figure 7 (c): due to the very high dry transition probabilities the other transitions cannot be judged from this presentation.

AR: The figure will be revised accordingly (in the revised manuscript it will be figure 6).

PM:



"*Figure 6. Results of the cross-validation experiment. (a) Seasonality of rain (and dry) type occurrence (Seasons are DJF (light blue), MAM (pink), JJA (red) and SON (yellow)), (b) rain type persistence, and (c) probability of transition between rain types. Observations are in red and simulations in blue. In simulations, continuous lines represent the median of the simulated ensembles (50 realizations), and dashed lines represent the Q10 and Q90 quantiles.*"

References:

Benoit, L., Vrac, M. and Mariethoz, G.: Dealing with non-stationarity in sub-daily stochastic rainfall models, Hydrology and Earth System Sciences, 22, 5919-5933, doi:10.5194/hess-22-5919-2018, 2018.