On the sensitivity of oceanic precipitation to sea surface temperature

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Abstract. Our study forms the oceanic counterpart to numerous observational studies over land considering the sensitivity of extreme precipitation to a change in air temperature. We explore the sensitivity of oceanic precipitation to changing sea surface temperature (SST) by exploiting two novel datasets at high resolution. First, we use the Ocean Rainfall And Ice-phase precipitation measurement Network (OceanRAIN) as an observational along-track shipboard dataset at 1-minute resolution. Second, we exploit the most recent European Re-Analysis version 5 (ERA5) at hourly resolution on 31 km grid. Matched with each other, ERA5 vertical velocity allows the constraint of the OceanRAIN precipitation. Despite the inhomogeneous sampling along ship tracks, OceanRAIN agrees with ERA5 on the average latitudinal distribution of precipitation with fairly good seasonal sampling. However, the 99th percentile of OceanRAIN precipitation follows a super-Clausius–Clapeyron scaling with SST that exceeds 8.5 % K^{-1} while ERA5 precipitation scales with 4.5 % K^{-1}. The sensitivity decreases towards lower precipitation percentiles while OceanRAIN keeps an almost constant offset to ERA5 due to higher spatial resolution and temporal sampling. Unlike over land, we find no evidence for decreasing precipitation event duration with increasing SST. ERA5 precipitation reaches a local minimum at about 26 °C that vanishes when constraining vertical velocity to strongly rising motion and excluding areas of weak correlation between precipitation and vertical velocity. This indicates that instead of moisture limitations as over land, circulation dynamics rather limit precipitation formation over the ocean. For strongest rising motion, precipitation scaling converges to a constant value at all precipitation percentiles. Overall, high resolutions in observations and climate models are key to understand and predict the sensitivity of oceanic precipitation extremes to a change in SST.

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1 Introduction

The equilibrium water vapor pressure increases with temperature, as described by the Clausius-Clapeyron (CC) equation, by about 7 % K^{-1} (e.g., Trenberth et al., 2003; Held and Soden, 2006). The same CC-scaling of 7 % K^{-1} atmospheric moisture increase has also been found in modeling studies (Stephens and Ellis, 2008; Allan et al., 2014) and observations (Wentz and Schabel, 2000; Simmons et al., 2010; O'Gorman et al., 2012). Willett et al. (2010) report a global change of 7.3 % K^{-1}

for global humidity observations from 1973-1999. As more atmospheric moisture can lead to stronger precipitation events, a similar scaling relation for precipitation is expected; however, the actual rate of change in precipitation with warming is still uncertain which is what this study addresses over the ocean.

Despite being studied for some years, the uncertainty in the rate of change for precipitation exceeds that of the atmospheric moisture content because radiative constraints rather than moisture availability limit precipitation. Estimates for the change in global mean precipitation range between 1-3 % K^{-1} (Allen and Ingram, 2002; Arkin et al., 2010; Allan et al., 2014). Over the global land area, there is medium confidence that precipitation increased during the second half of the 20th century while high confidence is found for the Northern-hemisphere mid-latitudes (IPCC, 2014a). At regional scales and for sub-daily precipitation estimates, some studies find changes strongly exceed 10 % K^{-1} (Lenderink and van Meijgaard, 2008, 2010). How widespread such cases of super-CC scaling occur is under debate (Haerter and Berg, 2009; Lenderink et al., 2017). Hardwick Jones et al. (2010) find a positive scaling for sub-hourly precipitation rates over Australia between 20 and 26 °C while they find a negative scaling above 26 °C due to moisture limitations. Utsumi et al. (2011) reveal latitudinal differences of CC-scaling as well as marked differences between daily and sub-daily to sub-hourly precipitation rates. Accordingly, resolution plays a crucial role in the scaling of precipitation over land with surface temperature.

Unlike over land, it remains widely unknown how precipitation scales with sea surface temperature (SST) over the ocean, particularly at sub-daily resolution, though the ocean covers more than 70 % of the Earth's surface and receives 77 % of its precipitation (Schmitt, 2008). As a reason, no long-term records of precipitation exist over the ocean (IPCC, 2014b; Maggioni et al., 2016). The few existing shorter datasets are often limited by measurement quality, sparse data coverage and low temporal resolution.

Under the challenging oceanic conditions with high wind speeds of varying direction and sea state, optical disdrometers have been recommended as a reference in-situ instrument to measure precipitation (Taylor, 2000; Weller et al., 2008). Since 2010, the Ocean Rainfall And Ice-phase precipitation measurement Network (OceanRAIN; Klepp et al., 2018) provides high-quality in-situ oceanic precipitation data from optical disdrometers at 1-minute resolution. We use this dataset in combination with the most recent European Re-Analysis version 5 (ERA5) of the European Centre for Medium-Range Weather Forecasts (ECMWF) to investigate the sensitivity of oceanic precipitation to changing SSTs.

In addition to thermodynamic drivers such as SST, dynamic drivers as part of the general atmospheric circulation strongly control if and how much precipitation is formed in the atmospheric column. Emori and Brown (2005) find an overall increase of mean and extreme precipitation, mainly due to thermodynamic changes while dynamics tend to diminish precipitation, particularly in the subtropics. Changes in extreme precipitation are particularly important as they account for most of the accumulation. To shed light on observed changes in extreme precipitation with SST we constrain extreme precipitation from OceanRAIN by the circulation regime using vertical velocities from ERA5.

The manuscript starts introducing the data sets and the methods used. Then, first, we investigate the OceanRAIN sampling and how precipitation intensities change with latitude. Second, we consider the change of different precipitation percentiles with respect to a change in SST. Third, we investigate the distribution of vertical velocity in ERA5 and use it to exclude regions of low correlation between precipitation and vertical velocity. We also compare OceanRAIN with ERA5 for the same vertical-

velocity regime (lifting airmass). Fourth, we consider how the precipitation event duration changes with SST. The last chapter summarizes our findings and presents some concluding thoughts and next steps.

2 Data and methods

2.1 Data

5 **OceanRAIN**

The Ocean Rainfall And Ice-phase precipitation measurement Network (OceanRAIN; Klepp, 2015; Burdanowitz et al., 2016; Klepp et al., 2018) provides water- and energy-cycle related parameters from Jun 2010 to Apr 2017 over the global ocean, collected onboard eight research vessels (RVs). In OceanRAIN version 1.0 (OceanRAIN-W; Klepp et al., 2017), these RVs include the German RVs *Polarstern* (since Jun 2010), *Meteor* (since Mar 2014), *Maria S. Merian* (Oct 2012 to Jun 2014)
10 and *Sonne* (Sep to Oct 2012) as well as its successor *Sonne II* (since Nov 2014). The Australian RV *Investigator* (Jan to Feb 2016) and the US-American RV *Roger Revelle* (Aug to Sep 2016) contributed temporarily to OceanRAIN. Klepp et al. (2018) describe the post-processing and quality-checking of the OceanRAIN data in detail. OceanRAIN is publicly available free of charge: more information can be accessed at https://oceanrain.org/.

Precipitation as rain, snow or mixed-phase precipitation is derived from particle size distributions recorded by the optical
15 disdrometer ODM470, manufactured by the German company Eigenbrodt GmbH & Co KG. In the ODM470, a photo diode receiver detects the signal reduction of a near-infrared diode within the cross-sectional area of the optical measuring volume casued by falling hydrometeors (Lempio et al., 2007). The ODM470 was specifically designed to measure precipitation over the ocean: its cylindrically shaped measuring volume and its wind vane attached on a pivotable axis ensure high-quality precipitation measurements even under rough oceanic conditions with strong and highly varying wind speed and sea state.
20 In addition, the typical mounting height of 30 to 45 m reduces unwanted influences by wave water and sea spray.

The SST in OceanRAIN has been interpolated from the bulk water temperature that is measured in sea water inlets of the respective RV at 2 to 7 m depth. The interpolation uses the cool skin parametrization after Donlon et al. (2002). The warm-layer effect is currently neglected.

ERA5

25 The European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis version 5 (ERA5) has been developed through the Copernicus Climate Change Service (C3S; C3S, 2017). The ERA5 data assimilation system uses the current Integrated Forecasting System (IFS) version 41r2. Released in July 2017, the data provided hourly analyses and forecast fields at a spatial resolution of globally 31 km for the period of 2010 to 2016, which has been extended back to 1979 until three months to present (Hersbach and Dee, 2016). We use the following parameters from ERA5: vertical velocity (w) at the 500 hPa
30 pressure level, and sea surface temperature (*sst*) as well as total precipitation (*tp*) at the surface level. The data has been downloaded via the ECMWF Web API from the ECMWF data archive (MARS).

2.2 Methods

A standard way to calculate the sensitivity of precipitation to a change in SST is first, to bin precipitation rates in $1°C$ increments of SST. For each of the bins, percentiles of precipitation rate can be calculated. We consider the 25th, 50th, 75th, 90th and 99th percentile to mainly reflect the sensitivity of high precipitation rates for which the 99th percentile represents heavy precipitation
5 (see Tab. 1 for all names). Second, for each of the percentiles, we calculate the slope using two linear regression methods in order to derive the precipitation scaling.

Table 1. Quantitative (mm h^{-1}) and qualitative intensities for each of five percentiles of OceanRAIN precipitation rate for $5.396 \cdot 10^6$ ($0.473 \cdot 10^6$ precipitating) minutes from June 2010–April 2017).

Percentile	P [mm h^{-1}]	Intensity
25th, P_{25}	0.05	weak
50th, P_{50}	0.18	light
75th, P_{75}	0.80	medium
90th, P_{90}	2.64	strong
99th, P_{99}	14.74	heavy

Since the widely used linear regression method of ordinary least squares (OLS) has some major weaknesses when it comes to outliers and skewed distributions, we also use the Theil-Sen estimator (TSE; Theil, 1950; Sen, 1968) as a more robust method. TSE is much less susceptible to outliers (Wilcox, 2001), which is particularly needed for the much smaller sample of
10 OceanRAIN data compared to ERA5. In addition, we simulate the robustness of the fit by bootstrapping. By these means, we get a more complete picture of how susceptible precipitation is to a change in SST.

3 Results

3.1 Is the OceanRAIN sampling sufficient to study the precipitation scaling with SST?

Oceanic precipitation is driven by the global atmospheric circulation systems. The atmospheric circulation follows seasonal
15 insolation changes. Sufficient seasonal sampling of precipitation is therefore needed from all climate zones for our attempt to investigate the precipitation sensitivity to SST changes. The global-ocean operation of RVs used in OceanRAIN ($5.396 \cdot 10^6$ min in total; $0.473 \cdot 10^6$ min with precipitation) suggests sufficient spatial sampling is possible. Most oceanic regions are well sampled during all seasons (dark-blue boxes in Fig. 1a).
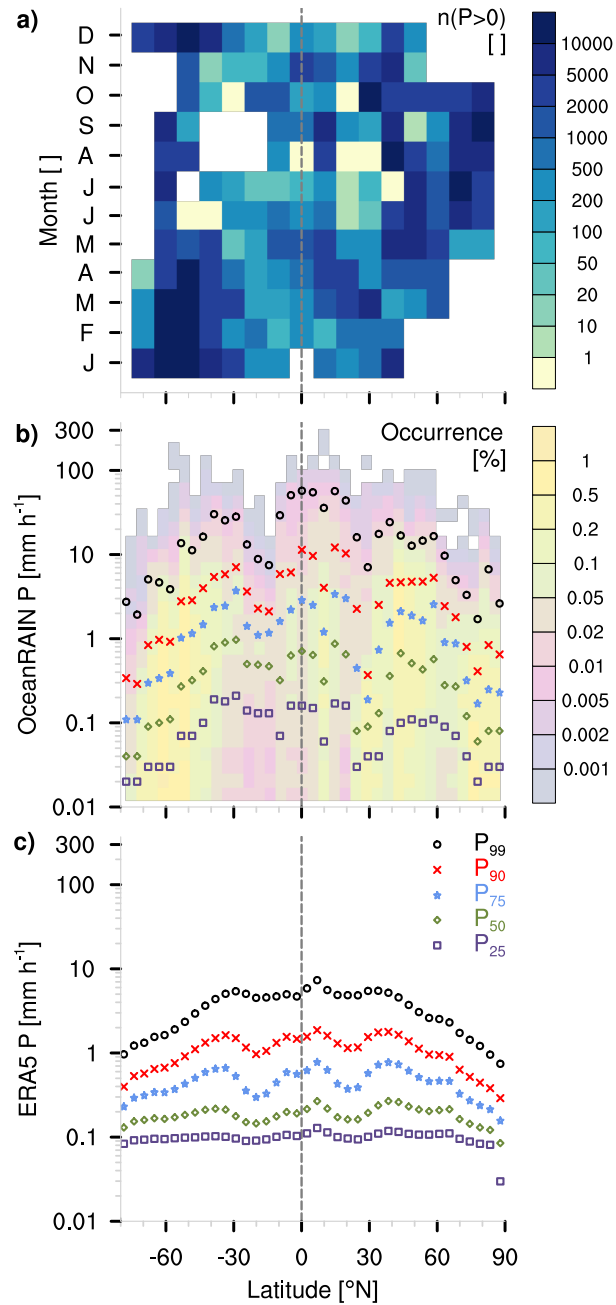
Figure 1. (a) 2D-histogram of OceanRAIN (Jun 2010–Apr 2017) precipitating minutes, $n(P > 0)$, per month as a function of latitude. Zero values (yellow boxes) indicate no precipitation sampled while white boxes were not sampled at all. **(b)** Five percentiles of OceanRAIN precipitation (mm h^{-1}) as a function of 1° latitude bands with relative occurrence (%) shown in color. **(c)** as b) but for ERA5 (Jun 2010–Dec 2016).

Some measurement gaps exist during winter of the respective high-latitude regions towards both poles due to drifting ice and rough weather conditions. The Southern Oceans around 30° S are sparsely sampled during late boreal summer as well as the northern mid-latitude regions from 50 to 70° N during late boreal winter (light-blue boxes). In some subtropical regions, no precipitation was observed during times of OceanRAIN sampling (yellow boxes). Nevertheless, we find no pronounced gaps of seasonal sampling that would introduce seasonal biases with respect to latitude in OceanRAIN.

Without obvious seasonal biases, we expect OceanRAIN to reflect the mean latitudinal precipitation distribution according to the atmospheric circulation patterns. In particular for strong-to-heavy precipitation (see Tab. 1 for classification), the highest precipitation rates occur at or close to the equator while for weak-to-medium precipitation the highest precipitation rates also occur around 30° S (Fig. 1b). Minimum precipitation rates at all intensities are found at both poles and in the subtropics at about 30° N and 15° S, respectively. The exact positions of latitudinal precipitation minima and maxima vary with intensity, likely related to sparse sampling e.g. in the dry subtropics (purple colors in Fig. 1b). Nevertheless, the OceanRAIN time period of Jun 2010–Apr 2017 reflects the expected mean precipitation distribution with respect to latitude.

Comparing the latitudinal distribution of precipitation rates from OceanRAIN to that of ERA5 reveals overall good agreement on the main climatological patterns and some major differences (Fig. 1c). One of them—the much lower amplitude of precipitation rates from ERA5—can be explained by the lower spatial and temporal resolution of ERA5 compared to Ocean-RAIN. The reduced variability for heavy precipitation in ERA5 compared to medium intensities marks a second distinction between OceanRAIN and ERA5, likely related to recurrence times of extreme precipitation events that exceed the typical OceanRAIN sampling of about 1000 min of precipitation per box mainly in the subtropics (Fig. 1a). Building on these results, a further exploration of both data sets seems plausible to investigate the sensitivity of precipitation to SST changes.

3.2 How does precipitation change with SST?

Despite a pronounced variability, precipitation shows a clear trend of increasing SST at all five P percentiles over the global ocean in OceanRAIN (Fig. 2a). The sensitivity of precipitation to SST increases for higher precipitation intensities. While weak precipitation increases by 4.5 % K^{-1} and light-to-medium precipitation increases by more than 6 % K^{-1}, heavy precipitation increases by almost 9 % K^{-1} according to TSE (Sect. 2). Here, the less robust OLS method leads to significantly lower sensitivities of 2.5 (weak) to 6 % K^{-1} (heavy), considering the median of 100-times resampled data of randomly chosen 50 % of the binned intensities.
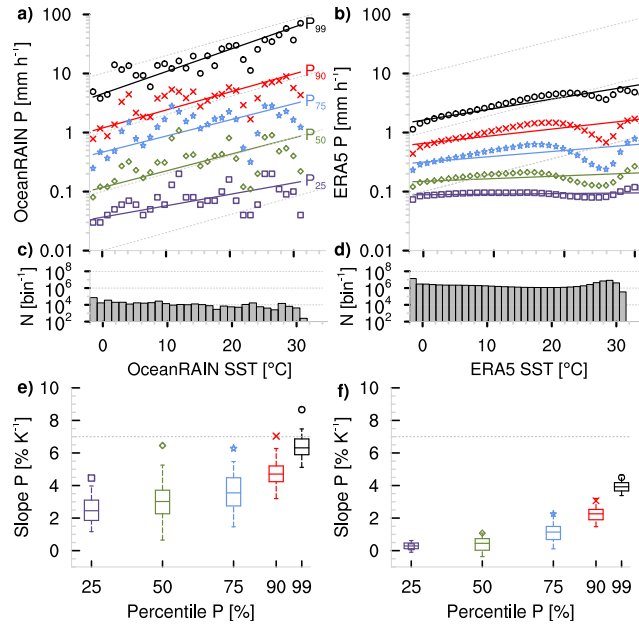
Figure 2. Five percentiles of **(a)** OceanRAIN (Jun 2010–Apr 2017) and **(b)** ERA5 (Jun 2010–Dec 2016) precipitation rate P (mm h^{-1}) as a function of bin-wise SST ($^\circ$C) shown with linear regressions from TSE calculation. Grey lines indicate 7 % K^{-1} slope. **(c),(d)** Histograms illustrate number of cases N (bin^{-1}) for all in a) and per month in (b). **(e),(f)** Slopes from TSE regressions (% K^{-1}) in (a),(b) are indicated by markers as a function of percentile. Boxes (5th–95th percentile) refer to OLS method as comparison using a 100-times resampling of the halved dataset.

The interquartile spread of 1 to 2 % K^{-1} (50 % of the sensitivity) and data samples of much less than 1000 min for some of the bins (Fig. 2c) indicate a high variability which is why we put more trust in the sensitivities calculated by the more robust TSE.

For ERA5, we find a much lower P-scaling of about 0.3 to 3.1 % K^{-1} for weak-to-strong and of 4.5 % K^{-1} for heavy precipitation with TSE (Fig. 2b,f). As these numbers rely on global ocean coverage, even the average monthly data sampling density of 10^6 bin^{-1} (Fig. 2d) strongly exceeds that of OceanRAIN, resulting in a smoother trend of the P-scaling and a lower interquartile spread of 0.4 to 0.8 % K^{-1}. As a consequence, the TSE always lies within the uncertainty of the OLS method (5th–95th percentile). Nevertheless, the question arises whether only resolution differences cause the systematically lower P-scaling in ERA5 compared to OceanRAIN.

3.3 Can vertical velocity help to understand the precipitation scaling with SST?

To enhance our understanding of different P-scalings over the ocean, we consider vertical velocity at 500 hPa from ERA5 to select cases that favor precipitation formation. As an indicator, we use the temporal correlation $r(P, \omega_{500})$ at each grid point between hourly precipitation P and hourly 500 hPa vertical velocity ω_{500} from ERA5. As in Emori and Brown (2005), we use $r(P, \omega_{500}) = -0.2$ as a threshold (note that we define positive vertical velocity as subsiding motion). The resulting areas of weak or even positive $r(P, \omega_{500})$ for a month (bluish colors in Fig. 3a) mainly comprise but are not limited
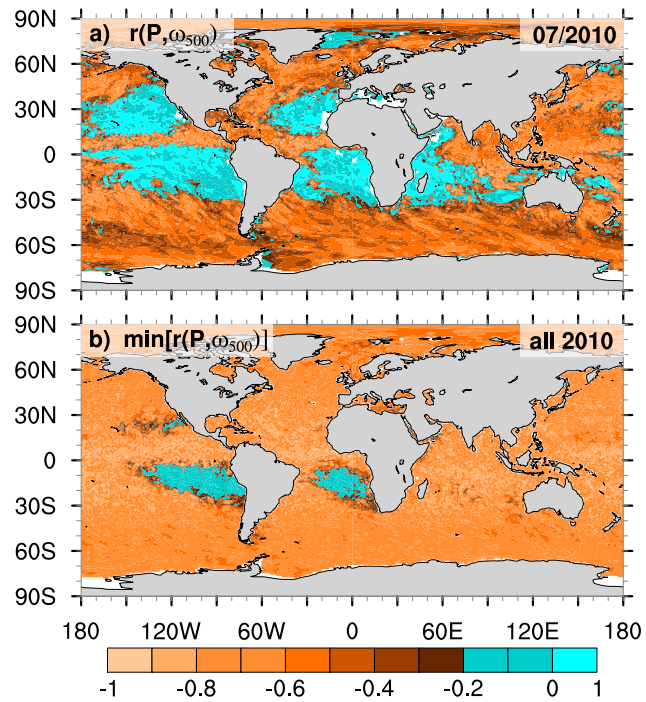
Figure 3. Maps of temporal correlation $r(P, \omega_{500})$ for each ERA5 gridbox for **a)** July 2010 and **b)** the minimum monthly correlation for the year 2010. Blue colored areas are weakly or positively correlated and are excluded from further analysis ($r > -0.2$; Emori and Brown, 2005).

to areas of subsidence and relatively low SSTs and amount to 5 % of the global ocean precipitation (see Fig. A1 for influence on ERA5). Unlike earlier studies, note that we use hourly instead of daily (e.g. Emori and Brown, 2005) or monthly timesteps (e.g. Oueslati and Bellon, 2015) for correlation but correlations are calculated per month. The high seasonal variability of $r(P, \omega_{500})$ leaves only small areas with a constantly weak $r(P, \omega_{500})$ over a whole year (e.g., minimum for each month of 2010

5 in Fig. 3b). While the size of the areas varies slightly, the Southeast-Pacific and Southeast-Atlantic areas of constantly weak correlation stay the same for the years 2010-2016 while elsewhere $r(P, \omega_{500})$ remains mostly below -0.2 (not shown).

In order to use ω_{500} to constrain OceanRAIN precipitation, we match each minute of OceanRAIN precipitation with the closest hourly ω_{500} of ERA5. Negative ω_{500} values correspond to rising motion. Almost two thirds of the global-ocean ERA5 timesteps during July 2010, as an example, have absolute vertical velocities $|\omega_{500}|$ below 100 hPa day^{-1} (Fig. 4a).
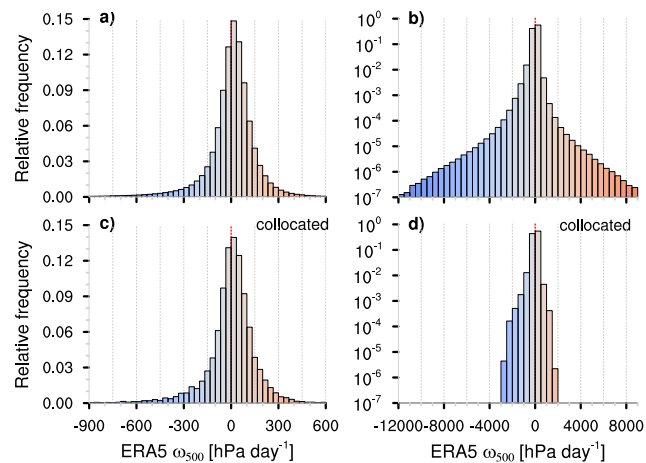
Figure 4. Histograms of relative frequency for ω_{500} (blue: rising; red: subsiding motion) of (a),(b) all ERA5 gridboxes and (c),(d) for OceanRAIN–ERA5 collocated ERA5 gridboxes with (a),(c) linear ordinate and (b),(d) logarithmic ordinate for strong motion.

The slightly left-skewed distribution of ω_{500} ($\gamma = -3.44$) has a 1st percentile of -692 hPa day^{-1}, a 99th percentile of 410 hPa day^{-1}, a mean of -1.1 hPa day^{-1} and a median of 15.5 hPa day^{-1} (Fig. 4b). When being matched to OceanRAIN, the ω_{500} distribution of ERA5 loses its extremes (1st percentile: -602 hPa day^{-1}, 99th percentile: 385 hPa day^{-1}; Fig. 4c and d with log y-axis) while the left-skewness slightly reduces ($\gamma = -2.03$). Nevertheless, the ω_{500} distribution of OceanRAIN–ERA5 matched timesteps is very similar to the overall ERA5 distribution of July 2010 (Fig. 4a and c).

The OceanRAIN–ERA5 matched timesteps enable a direct comparison between both datasets for the P-scaling. We define a range of $-1500 < \omega_{500} < -50$ hPa day^{-1} that, first, selects upward motion that generally fosters precipitation to form and, second, that provides sufficient matches per SST-bin to allow calculating the highest percentiles (Fig. 5c,d).
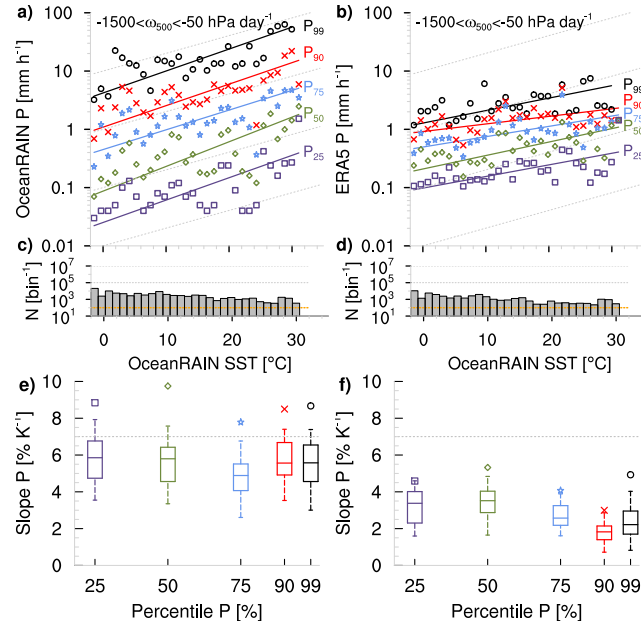
Figure 5. As Fig. 2 but for all OceanRAIN–ERA5 matched timesteps for **(a)**,**(c)**,**(e)** OceanRAIN and for **(b)**,**(d)**,**(f)** ERA5, both for rising motion ($-1500 < \omega_{500} < -50$ hPa day^{-1}) and excluding regions of $r(P, \omega_{500}) > -0.2$ from Fig. 3.

Third, we exclude grid boxes with a temporal correlation of $r(P, \omega_{500}) > -0.2$ per month, that are mainly associated with dry areas of subsidence (see Fig. 3). Its influence on the whole ERA5 dataset is shown in Appendix A (see Fig. A1). Also note that we use OceanRAIN SSTs for both data sets as the usage of ERA5 SSTs would reduce the total number of usable timesteps (437,000 without ω_{500} constraint) by 6.6 % (not shown). The resulting sub-sample of matched timesteps for ERA5

5 (hourly) and OceanRAIN (every minute) comprises about 110,000 timesteps. The relatively low number of remaining timesteps limits the statistical robustness of the sample for some of the 1°C SST-bins that contain less than 1,000 precipitation values (Fig. 5c,d). The data sparsity results in a quite scattered sensitivity distribution (Fig. 5a,b). Compared to the larger sample of OceanRAIN measurements and ERA5 data (see Fig. 2), first, particularly the weak-to-medium precipitation rates increase at a much higher rate with constrained ω_{500}. Second, all OceanRAIN precipitation percentiles scale with 7.5 to 10 % K^{-1} (ERA5:

10 3 to 5.5 % K^{-1}) according to TSE (Fig. 5e,f). This means an approximate constant sensitivity of precipitation to a change in SST, for OceanRAIN even as super-CC scaling, while the sensitivity difference remains between ERA5 and OceanRAIN.

To understand whether this about uniform sensitivity at all precipitation percentiles results from the ω_{500} constraint, from the data sparsity or is a feature of the matched sub-sample of data, we consider ERA5 with the same constraint of $-1500 < \omega_{500} < -50$ hPa day^{-1} but globally for the full ERA5 period leading to more than 1000-times more data (monthly N in Fig. 6c).
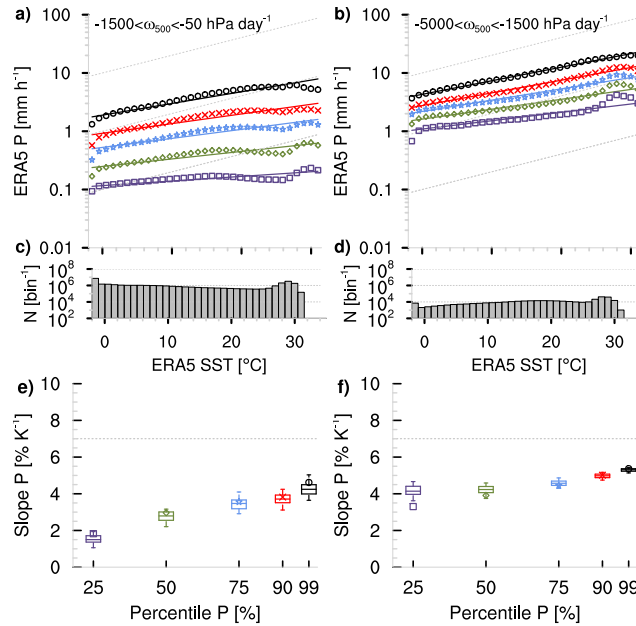
Figure 6. As Fig. 5 but for complete ERA5 period. Panels (a),(c),(e) are constrained by $-1500 < \omega_{500} < -50$ hPa day^{-1} and (b),(d),(f) by $-5000 < \omega_{500} < -1500$ hPa day^{-1}.

Compared to OceanRAIN, the P-scaling smoothens for all precipitation percentiles (Fig. 6a) while the interquartile spread reduces (Fig. 6e). Compared to Fig. 5f, mainly the P-scaling of weak precipitation decreases below 2 % K^{-1} for medium-to-heavy precipitation it remains between 3 and 5 % K^{-1}. Compared to Fig. 2e, the P-scaling increases more steeply for weak precipitation, reaches a plateau for medium-to-strong intensities before it increases again for heavy precipitation. Accordingly, the sensitivity in Fig. 5f points at the slightly increased sensitivities for low precipitation rates for the ω_{500} constraint while the picture is mainly blurred due to the small sample size.

To further investigate the influence of a constraining ω_{500}, we consider stronger rising motion between -5000 and -1500 hPa day^{-1} (Fig. 6b). Compared to somewhat weaker rising motion in ω_{500}, the weak precipitation rates increase by about an order of magnitude while heavy precipitation rates are higher by a factor of 2. The change in the P-scaling with SST smoothens while it tends towards a constant slope at all percentiles (Fig. 6f). This constant slope marks a linear increase and saturates for strongest rising motions at approximately 6 % K^{-1} in ERA5 (not shown). Accordingly, constraining lower ω_{500} (rising motion) tend to harmonize the slopes of different precipitation percentiles by mainly lifting the P-scaling at lower percentiles while high percentiles remain about constant.

3.4 Does a change in precipitation event duration with SST affect the precipitation scaling?

Over land, previous studies state a decrease in precipitation event duration with increasing air temperature that explains the drop-off in precipitation scaling at high temperatures found for sampling rates of 1 hour and above (Haerter et al., 2010; Utsumi et al., 2011). Haerter and Berg (2009) explain the decreasing event duration with a shift toward more convective precipitation events at high temperatures. To check whether this holds over the ocean we calculated the OceanRAIN precipitation event duration by counting uninterrupted periods of continuous precipitation at 1-minute sampling. The average precipitation event lasts between 6 and 11 min with an uncertainty of 1 to 2 min obtained from bootstrapping (Fig. 7a).
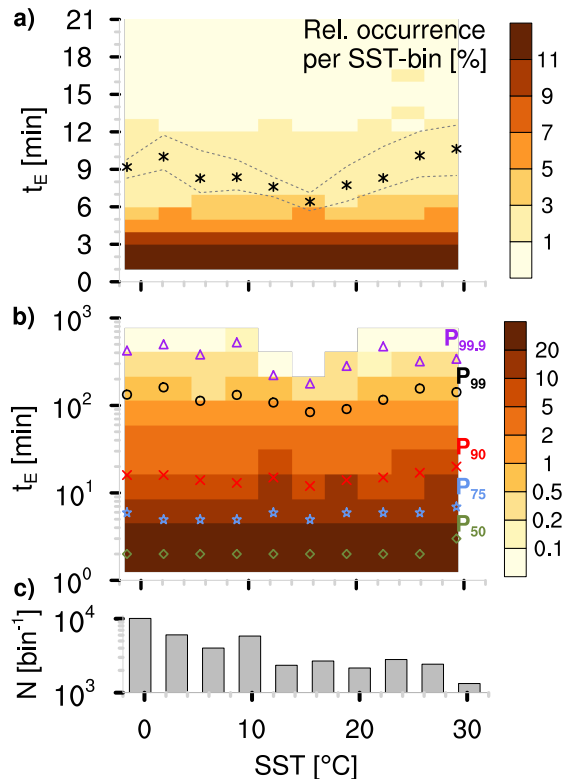
Figure 7. 2d-histogram as a function of precipitation event duration t_E (min) and OceanRAIN SST (°C) for (a) linear and (b) logarithmic ordinate. Colors indicate relative occurrence (%) per SST-bin. Markers in (a) show mean per SST-bin surrounded by minimum and maximum from 100-times resampling as a measure of uncertainty. Markers in (b) show percentiles 50, 75, 90, 99 and 99.9 of t_E. Panel (c) shows the number N of events per SST-bin.

The shortest mean precipitation event duration occurs at 15°C while the longest mean precipitation event duration occurs around 2 and above 28°C. The mean is mainly driven by the highest percentiles (99th to 99.9th exceeding 2 h) that mainly cause the minimum at 15°C but it is less pronounced for the 50th to 75th percentile where precipitation event duration remains about constant (Fig. 7b). Although the precipitation event duration tends to decrease between 2 and 16°C as over land (Haerter et al., 2010; Utsumi et al., 2011), we find no systematic decrease over the whole SST range.

The precipitation event duration as a function of temperature can be influenced by several factors. First, the heterogeneous sampling in OceanRAIN can influence the event duration. Exceeding 2000 samples per bin, the sampling density per SST-bin seems fairly good for most of the SST range; below 12°C it even exceeds 4000 samples per bin (Fig. 7c). Nevertheless, heterogeneous spatial sampling by the ships can lead to a biased picture (see Fig. 3 in Burdanowitz et al., 2018); e.g. the Eastern Atlantic has been more densely sampled compared to the Western Atlantic which might have an effect on the occurrence of very long-lasting precipitation events. Second, the ship movement relative to cloud movement can affect the retrieved event duration. However, this effect cancels out over almost 40,000 events sampled from OceanRAIN (not shown). Overall, influences by the heterogeneity of OceanRAIN on the precipitation event duration cannot be ruled out but seem rather limited according to our investigations.

4 Summary and concluding remarks

This study forms the oceanic counterpart to numerous observational studies over land that considered the sensitivity of extreme precipitation to a change in air temperature. Unlike earlier studies with mainly hourly to daily sampling calling for higher resolution (e.g., Panthou et al. 2014; Drobinski et al. 2016), we consider precipitation rate and SST at a very high sampling rate of 1 minute from OceanRAIN optical disdrometer measurements aboard global-ocean research vessels. In addition, hourly measurements of the new ERA5 reanalysis serve to compare and, additionally, constrain precipitation by large-scale vertical velocity.

OceanRAIN challenges the user with its non-uniform sampling and variable spatial resolution along ship tracks. However, at the same time, it offers a unique opportunity to study oceanic precipitation at high quality with global-ocean sampling at 1-minute temporal resolution. Additionally, we show that differences in seasonal and latitudinal sampling are small, which could otherwise affect the precipitation scaling (Schroeer and Kirchengast, 2018). Furthermore, the OceanRAIN average precipitation distribution with latitude looks similar to that in ERA5 with its homogeneous global-ocean coverage.

For OceanRAIN, the 99th percentile of 1-minute precipitation rates shows a super-CC scaling of almost 9 % K^{-1} in line with studies over land (e.g., Bürger et al. 2014; Schroeer and Kirchengast 2018) while for ERA5, the 99th percentile of the hourly ERA5 precipitation rates increases by only 4.5 % K^{-1} (linear regression using Theil-Sen estimator). The tendency of a stronger scaling with higher temporal sampling confirms findings by Utsumi et al. (2011) and Drobinski et al. (2016). This difference in CC-scaling ranges between 4 and 6 % K^{-1} for the weak-to-strong precipitation rates between OceanRAIN and ERA5. For both data sets precipitation increases with SST at all percentiles considered. Unlike over land due to moisture

limitations (Hardwick Jones et al., 2010), we find no decreasing precipitation rates over temperature ranges of more than 8 K but an increase again towards highest SSTs of about 30°C.

Nevertheless, the ERA5 precipitation rates reveal a local minimum at about 26°C. When excluding areas of weak temporal correlation of 500 hPa vertical velocity with precipitation rate, the local minimum in precipitation scaling becomes weaker. Despite the fact that the hourly vertical velocity might not necessarily be the best indicator for large-scale subsidence, the dip vanishes when constraining precipitation to rising motion below -1500 hPa day^{-1}. From this, we infer that dynamical drivers such as subtropical large-scale subsidence inhibit precipitation formation and cause the local precipitation minimum at 26°C.

The fact that the local precipitation minimum is hardly visible in OceanRAIN likely arises from the low data sampling density, specifically in precipitation-sparse regions that would need the longest sampling to be well represented. Generally, the non-uniform sampling by ships in OceanRAIN results in a more variable precipitation distribution with respect to SST. Therefore, we mainly rely on the Theil-Sen estimator (TSE) as linear regression method, which is less susceptible to outliers (Wilcox, 2001) instead of only trusting the widely known ordinary least squares (OLS) method.

Although we find a more steady precipitation scaling in OceanRAIN compared to ERA5 at high SSTs, there is no evidence that this is caused by a decreasing duration of precipitation events with temperature as indicated by studies over land (Haerter et al., 2010; Utsumi et al., 2011). Instead, we find a minimum average precipitation event duration in OceanRAIN of 7 min at about 15°C that rises beyond 10 min above 28°C. This temperature dependence remains the same for higher percentiles corresponding to longer events. As most of the precipitation events last only few minutes, this confirms our decision to use a high temporal sampling rate of 1 minute to exclude resolution artifacts from the precipitation scaling. At 1-minute resolution, we find no evidence of generally decreasing precipitation event duration with temperature.

For the OceanRAIN–ERA5 matched timesteps, we find a high uncertainty for the reduced data sample using vertical velocity in 500 hPa from ERA5 to constrain precipitation rates. The OceanRAIN precipitation scales with super-CC behavior at all precipitation percentiles (8 to 10 % K^{-1}) while ERA5 precipitation scales with 3 to 6 % K^{-1}, confirming the offset that we found between both unconstrained datasets. The offset in precipitation scaling is therefore likely attributable to the marked difference in spatial resolution that confronts the OceanRAIN along-track data with the areal ERA5 data of 31 km grid boxes. Furthermore, constraining precipitation towards strongly rising air-masses leads to a precipitation scaling that converges towards 6 % K^{-1} for all precipitation rates in ERA5. For OceanRAIN, the too-small data sample for precipitation in lifting air-masses does not allow us to derive a number for the scaling but the offset to ERA5 and the scaling with the OceanRAIN–ERA5 matched data both suggest super-CC scaling for OceanRAIN.

Two aspects should be kept in mind when interpreting our results. First, the average precipitation scaling should not be directly translated into an increase of local precipitation per degree of warming, as locally dynamic processes can strongly alter the precipitation–SST relationship. Second, in light of the projected rising global mean temperature by anthropogenic climate change, large-scale circulation changes and other side effects in the Earth system could contribute or counteract the diagnosed precipitation sensitivity to a change in SST. Therefore, care needs to be taken when interpreting our results that are valid under the present climatic conditions.

Next steps would include more local analyses at 1-minute resolution once data sampling allows to globally resolve the highest precipitation intensities. Furthermore, higher resolutions are needed in global climate models to project the hydrological sensitivity of extremes in a warming climate and its feedbacks.

Data availability. The OceanRAIN data is available through the Climate and Environmental Retrieval and Archive (CERA) of World Data Center for Climate (WDCC) via Klepp et al. (2017). The ERA5 data is available through the Climate Data Store (CDS) Application Program Interface (API) via the Copernicus Climate Change Service (C3S, 2017).

Appendix A: How circulation dynamics impact the precipitation scaling in ERA5

To shed light on the influence of circulation dynamics on the P-scaling of ERA5, we consider the temporal correlation $r(P,\omega_{500})$. According to Emori and Brown (2005), we exclude all precipitation time steps with $r > -0.2$ diminishing the influence of precipitation from very shallow convection and large-scale subsidence. The resulting precipitation distribution with respect to SST reveals a less pronounced minimum at about 26°C (Fig. A1b). This leads to a slight increase of the
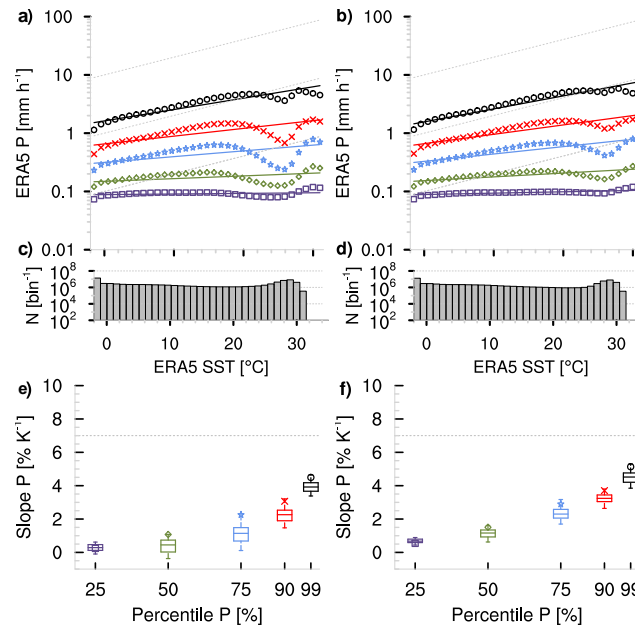
Figure A1. Left panel is same as right panel of Fig. 2. Right panel excludes regions of $r(P,\omega_{500}) > -0.2$ from Fig. 3 for complete ERA5 period.

P-scaling at all intensities (Fig. A1e-f). Accordingly, ω_{500} itself can better explain the dip at 26°C compared to areas of low correlation between ω_{500} and P.

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