

SPECIAL PROJECT PROGRESS REPORT

Progress Reports should be 2 to 10 pages in length, depending on importance of the project. All the following mandatory information needs to be provided.

Reporting year 2016

Project Title: Small-scale severe weather events: Downscaling using Harmonie

Computer Project Account: spnlster

Principal Investigator(s): Andreas Sterl

Affiliation: KNMI (Royal Netherlands Meteorological Institute)
P.O. Box 201
3730 AE De Bilt
Netherlands

Name of ECMWF scientist(s) collaborating to the project (if applicable) n/a

Start date of the project: 13 April 2016

Expected end date: 31 December 2019

Computer resources allocated/used for the current year and the previous one
(if applicable)

Please answer for all project resources

		Previous year		Current year	
		Allocated	Used	Allocated	Used
High Performance Computing Facility	(units)	25000000	25000000	25000000	0
Data storage capacity	(Gbytes)	15,000	0	15,000	0

Summary of project objectives

(10 lines max)

The non-hydrostatic Harmonie model is used in climate mode (HCLIM) to downscale climate model results. It offers the possibility to investigate the effect of climate change on small-scale phenomena like convective rainfall and wind gusts. This is not only relevant from a scientific point of view, but has many applications. For example, wind turbines suffer from night-time low level jets that are not represented well in current climate models, and convective events are only parameterized.

Summary of problems encountered (if any)

(20 lines max)

In 2016 a 10-year run was performed. During the run a bug in the surface scheme became apparent that caused a severe wet soil-moisture bias. With the remaining computing-time budget for 2016 only part of the run could be re-run. The rest will follow in 2017 using KNMI-intern resources so that no problems for the project are foreseen.

Summary of results of the current year (from July of previous year to June of current year)

This section should comprise 1 to 8 pages and can be replaced by a short summary plus an existing scientific report on the project

The aim of this project is to dynamically downscale climate model output using the non-hydrostatic Harmonie Climate (HCLIM). The model has a horizontal resolution of 2.5 km, and the model domain covers western Europe (e.g., see Fig. 1).

As explained in the “problems” section above, a first 10-years run had to be discarded. A re-run could be performed for five years (2005-2009). The model output of this five years re-run has been assessed by comparing them with ERA-Interim, E-OBS (station-based gridded data set, Haylock et al. 2008), and Dutch rain gauges.

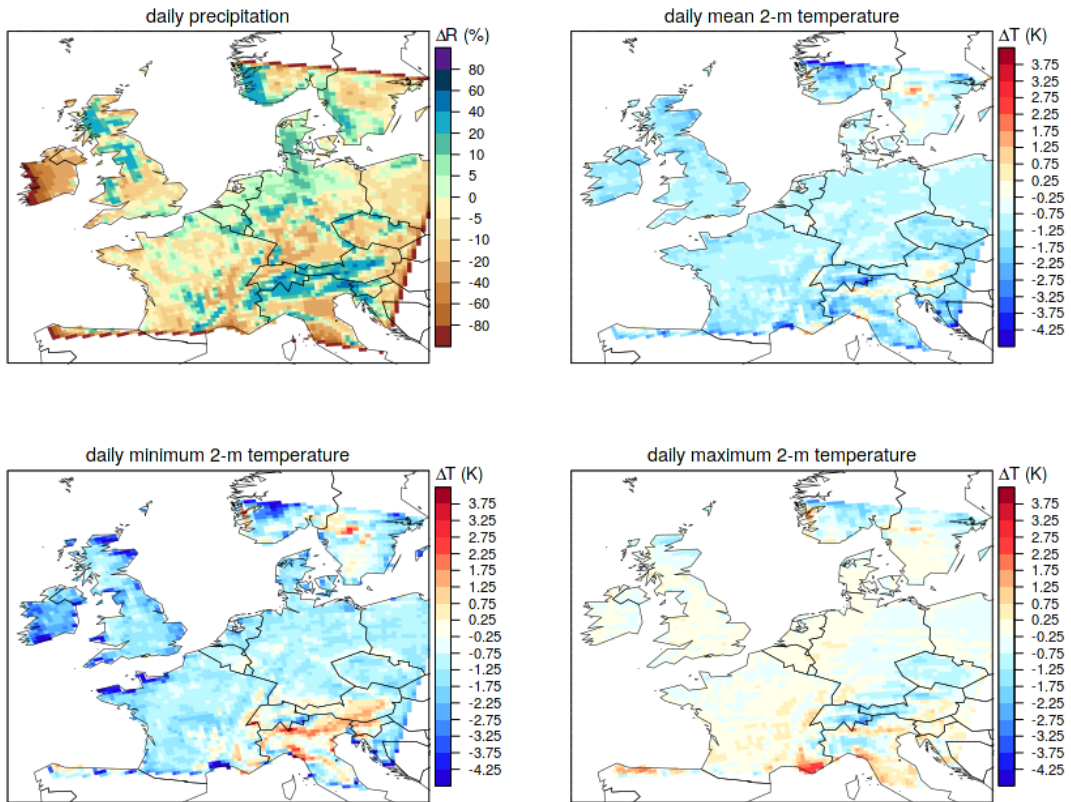
Climatology

The climatological comparison with ERA-Interim is shown in Figure 1. It reveals that HCLIM exhibits

- more precipitation over the higher-elevated regions in both seasons, less precipitation elsewhere, in particular near the W- and S- lateral boundaries (Ireland, France);
- lower daily mean temperature, everywhere in DJF and in most regions in JJA;
- lower daily minimum temperature in most regions for both seasons; in particular in coastal regions differences can be substantial. In the comparison with E-OBS, which has much finer resolution, this effect is nearly absent. It is probably caused from comparing pure land area information from HCLIM with mixed land/sea information from ERA-Interim;
- considerably higher daily maximum temperature in JJA, with the exception of the Alps (probably related to snow cover at the very high-elevated grid cells in Harmonie). As for Tmin differences are larger in coastal regions, probably for the same reason.

In addition, there is a large region in Southern France and Northern Italy where HCLIM predicts much higher Tmax than diagnosed from ERA-Interim, which we speculate is either related to anomalous soil moisture deficit or a spurious interaction with information entering from the lateral boundaries, or a combination of these effects. To sort this out requires further analysis.

DJF / 2005-2009 / Harmonie-Climate 38h1 vs ERA-Interim



JJA / 2005-2009 / Harmonie-Climate 38h1 vs ERA-Interim

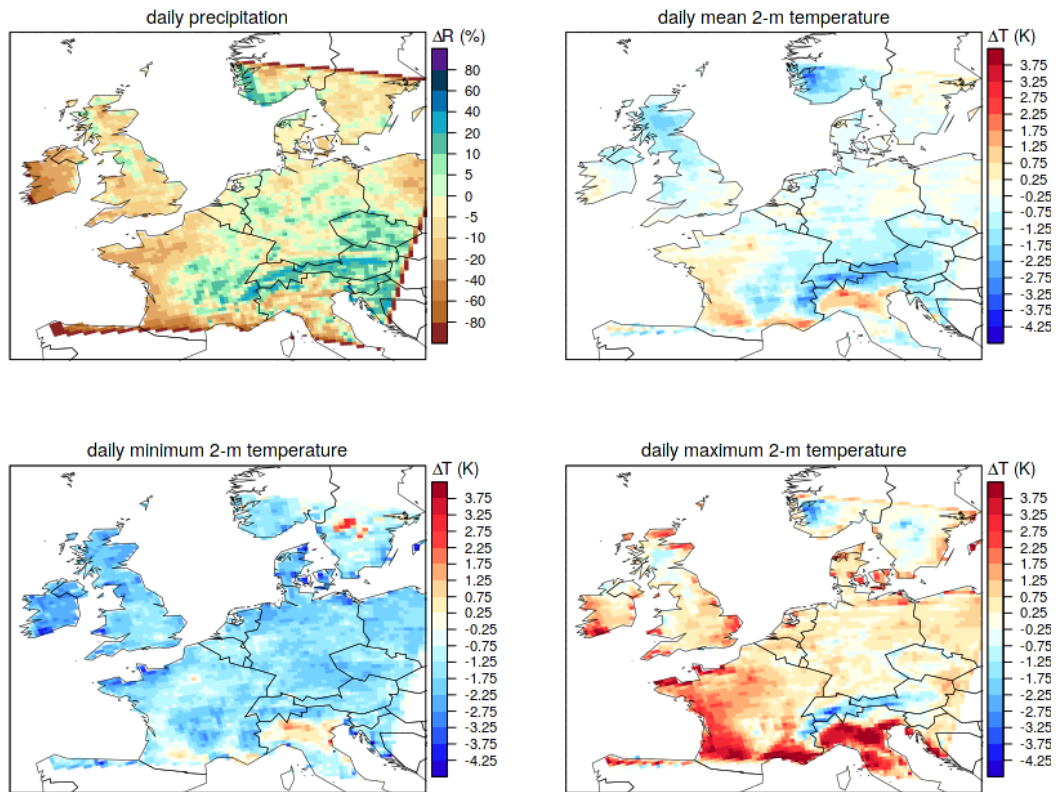


Figure 1: Difference between HCLIM (5 years) and ERA-Interim climatology for winter (DJF) and summer (JJA).

The main findings of the HCLIM-ERA-Interim comparison are confirmed by the comparison with the E-OBS data set. E-OBS is based on station observations and shows much more detail than ERA-Interim. More details of the comparison are found in Appendix 1.

Temperature patterns are well captured, but the model has a cold bias. While the cold bias is seen throughout the model domain in winter (DJF), some areas have a warm bias in summer (JJA). This happens most clearly in southern France and in a region near the eastern edge of the domain. There appears to be a clear connection with (strongly) reduced rainfall in the region, which leads likely to too dry soils and soaring temperatures. Daily maximum temperatures are strongly positively biased in the southwest of the domain (the daily-minimum temperatures are much closer to normal, even cold-biased). At the same time, precipitation is strongly underestimated, locally by more than 50%.

This negative precipitation bias is not exclusive to the southwestern part of the domain. Also Ireland and parts of the UK are too warm and too dry in summer. All these regions are close to boundaries of the model domain that are *influx* boundaries: The predominantly westerly/south-westerly circulation carries information into the model domain. Convection and subsequent rain need some time to develop, rendering areas close to the boundary too dry. We will check whether it is possible to virtually move the boundary farther outward by not applying the ERA-Interim forcing directly at the HCLIM boundaries, but to add an intermediate downscaling step using RACMO. RACMO has a lower resolution than HCLIM and can easily be run on a larger domain.

Statistics of hourly rainfall

The statistics of hourly rainfall in the Netherlands have been extensively analysed (report by G. Lenderink). We here give a short summary of the results of that assessment. The full report is attached to this Progress Report as Appendix 2.

We evaluated the statistics of hourly precipitation derived from a 5-year re-analysis driven climate integration with HARMONIE compared to ≈ 35 automatic weather stations (AWS) within the Netherlands. In general, the model produces results that are close to, or even very close to, the observations, both in term of frequency of occurrence of rainfall events and the behaviour of the extremes. Typically, the model over-predicts the number of hours with rain – wet-hour frequency – by $\approx 10\%$, except for the summer season. For that season, the number of hours with small precipitation amounts, around 1 mm hour^{-1} , is underestimated by at most 20%. In general, rainfall amounts are higher in afternoon than during the morning hours. As a consequence, the model produces a too pronounced diurnal cycle. For instance, in summer with good average precipitation rates (averaged across all hours including dry ones), but too high extremes in the afternoon, and too low average rates in the morning but realistic extremes. Nevertheless, the statistics of HARMONIE appear in general much closer to the AWS observations than the hydrostatic model RACMO, except for perhaps the mean precipitation rate where the skill of both models is generally rather equal.

The diurnal cycle of temperature and dew point temperature is realistically captured (Fig. 2), yet the model generally produces a slightly too strong diurnal cycle associated with too cold night time temperatures (approximately 0.5 to 1°C). The diurnal cycle in dew point temperature is realistic, however the model is on average too dry with an average bias in dew point temperature of almost 1°C . The bias in night temperature could be physically related to the dry model bias. The exception is spring, for which dew point temperatures during daytime are too high, likely as a result of excessive evaporation.

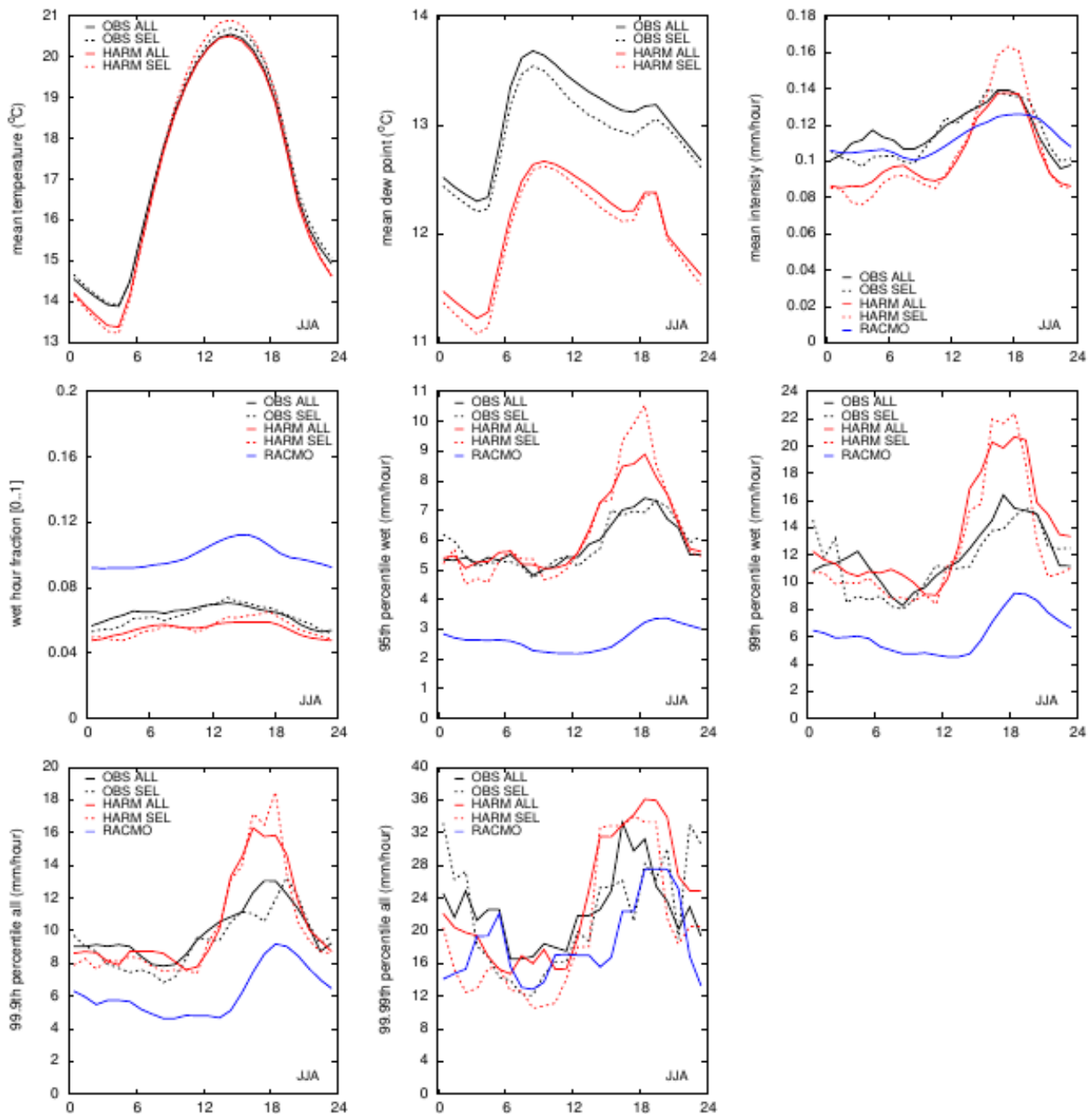


Figure 2: Statistics for the summer period as function of the hours of the day. “ALL” means all 35 AWS stations, regardless of whether the OBS has data: “SEL” means a selection of 10 stations with complete data coverage in the observations (stations: 235, 260, 270, 275, 280, 290, 310, 370, 380, 391). Wet hour fraction uses a threshold of 0.25 mm. Precipitation statistics are derived using a three hour block to decrease the noise component.

Scaling of hourly extremes intensities with dew point temperature shows that Harmonie is able to reproduce the double Clausius-Clapeyron (CC) relation – 14 % per degree – as seen in the observations for the summer period (Fig. 3). In winter, the model correctly reproduces a CC scaling, except for perhaps the highest dew point temperature range which are more sensitive in the observations. In summer and for dew point temperatures above $\approx 16^{\circ}\text{C}$ the model appears to be too active, with too many strong precipitation events. Above $\approx 20^{\circ}\text{C}$ the model reaches a maximum intensity whereas the observation appear to remain sensitive to the surface dew point temperature up to 22°C . This suggests that in the model the organisation of convective clouds into big convective clusters is (somewhat) too strong and occurs on average at too low surface humidity values (by

approximately 2 degrees). In that sense, it is noteworthy that the dry bias of the model may well have a positive impact on the statistics of extremes.

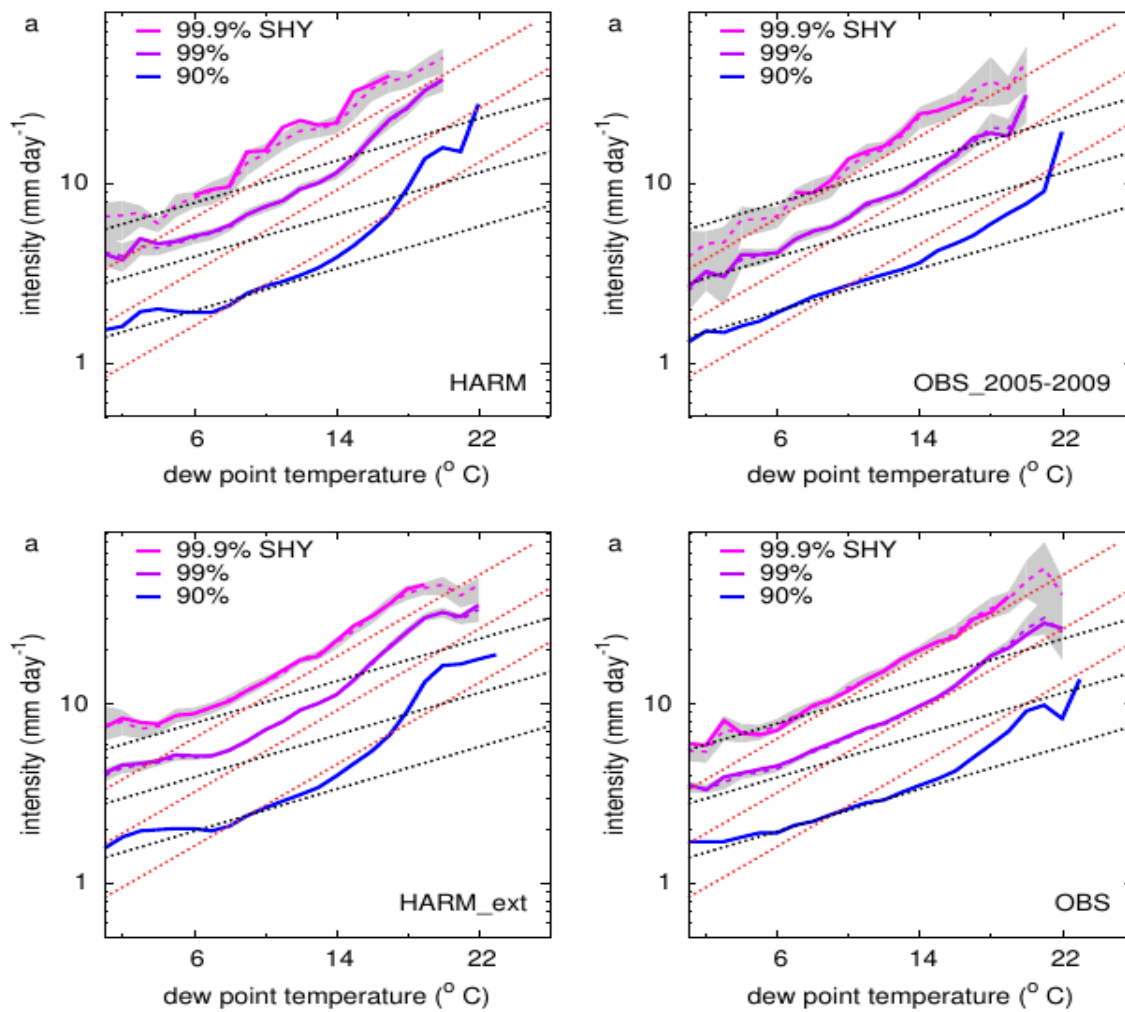


Figure 3: Scaling of hourly extremes with dew point temperature for summer half year. $P_{threshold} = 0.25 \text{ mm}$.

Speculating about the interpretation of the results, it appears that the model is slightly too active under strongly forced conditions. As an example, the biggest errors in extreme precipitation occur in spring in the afternoon, where the atmosphere is maximum unstable and with strong moisture supply (possibly enhanced by strong evaporation). On average, the model is slightly too inactive with weaker forcing from the surface, such as in the morning hours. So, when the forcing is sufficiently large and when ample moisture is available, the model produces somewhat too strong convective systems, except for spring in which case the overestimation is substantial in the afternoon. Under weaker forcing the model tends to underestimate the number of convective precipitation events, however when they occur they have about the right statistics.

List of publications/reports from the project with complete references

- Evaluation of hourly precipitation statistics in a 5-year climate integration of HARMONIE. G. Lenderink, April 2017. Internal Report.

Summary of plans for the continuation of the project

(10 lines max)

The basic idea of the project is to have three 10-years runs: (i) actual present climate, i.e., driven by ERA-Interim, (ii) model present climate (driven by EC-Earth), and (iii) future model climate. As explained in the “problems” section above, run (i) has to be repeated. This has partly been done using the remaining 2016 budget and will be finished in 2017. It is planned to start with run (ii) later this year when the new EC-Earth runs become available. However, EC-Earth development is currently behind schedule. We will decide later this year how to proceed in case the runs are not available this year. A possible alternative is to use existing results from an older version of EC-Earth. Run (iii) is planned for 2018/19. Furthermore, we will investigate whether the dry/hot bias in southern France and Ireland can be eliminated by virtually extending the model domain by adding RACMO between ERA-Interim and HCLIM.

Appendix 1: HCLIM38h1 performance over Europe (Hylke de Vries, Bert van Uft)

Appendix 2: Evaluation of hourly precipitation statistics in a 5-year climate integration of HARMONIE (Geert Lenderink)

HCLIM38h1 performance over Europe

Hylke de Vries, Bert van Ulft

Introduction

In 2016 a 10-year long climate run with HCLIM38h1 (forced by ERA-Interim) was performed for the period 2005-2014. Shortly afterwards, however, it was realized by the HCLIM community that in the development of HCLIM38h1, a few SURFEX routines had been erroneously excluded from the updating process. This “bug” of the non-updated SURFEX routines led among others to substantially lower near surface temperatures, especially in summer.

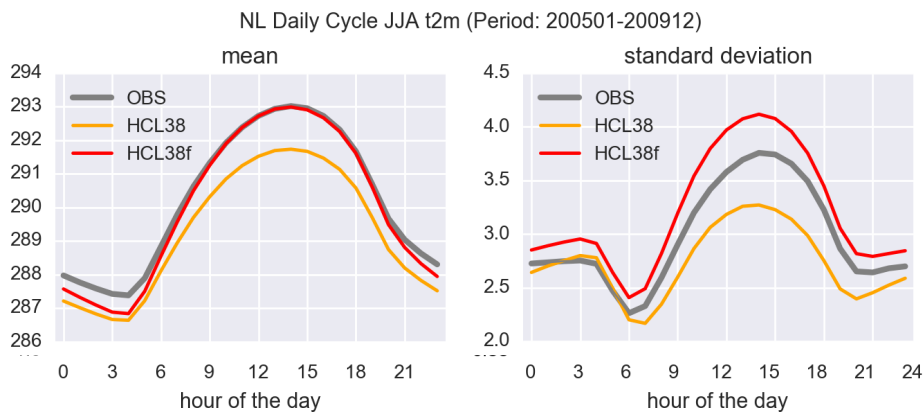


Figure 1: Diurnal cycle of 2m-temperature in summer (JJA) for HCLIM38h1 and HCLIM38h1f (after SURFEX fix), verified against synops-stations over the Netherlands. The right panel shows the standard deviation.

Figure 1 above displays the diurnal cycle of 2m-temperature over the Netherlands in summer (JJA), compared to observations from synops-stations. The red line denotes the performance of HCLIM38h1 after the fix (the orange line the performance prior). Unmistakably the mean diurnal cycle is much better represented in the updated code, with only night temperatures showing a mean negative bias. The temperature variability is also enhanced (right panel), and in fact over-estimated compared to observations.

Unfortunately, resources were at the time insufficient to carry out another full 10-year integration. A new simulation was started for the period 2005-2009. Below, results are shown from this second, shorter simulation. We focus attention on the mean and variability of 2m-temperature in winter and summer, and compare HCLIM38h1 to E-OBS and simulations with RACMO2 over the same period. RACMO2 is a hydrostatic RCM run at ~12km resolution. The simulations were done on a slightly bigger domain than that of HCLIM. Differences with respect to E-OBS are computed by regridding to the E-OBS 0.25x0.25 degree grid.

Winter temperature and temperature variability

Figure 2 shows the mean winter 2m-temperature over the simulation domain of HCLIM, the monthly standard deviation of daily-mean 2m-temperature, as well as the differences of HCLIM and RACMO with respect to E-OBS.

The basic pattern of the mean temperature is well represented, but HCLIM (and RACMO even more strongly) exhibits a negative temperature bias compared to E-OBS. The bias is stronger at night than at day. It is more pronounced in mountainous regions, where spatial representativeness of E-OBS can be questioned. A “red-spot” positive bias is seen over big lakes (e.g. in Sweden), related to a snow-on-ice issue in FLAKE, the lake-model used in HCLIM.

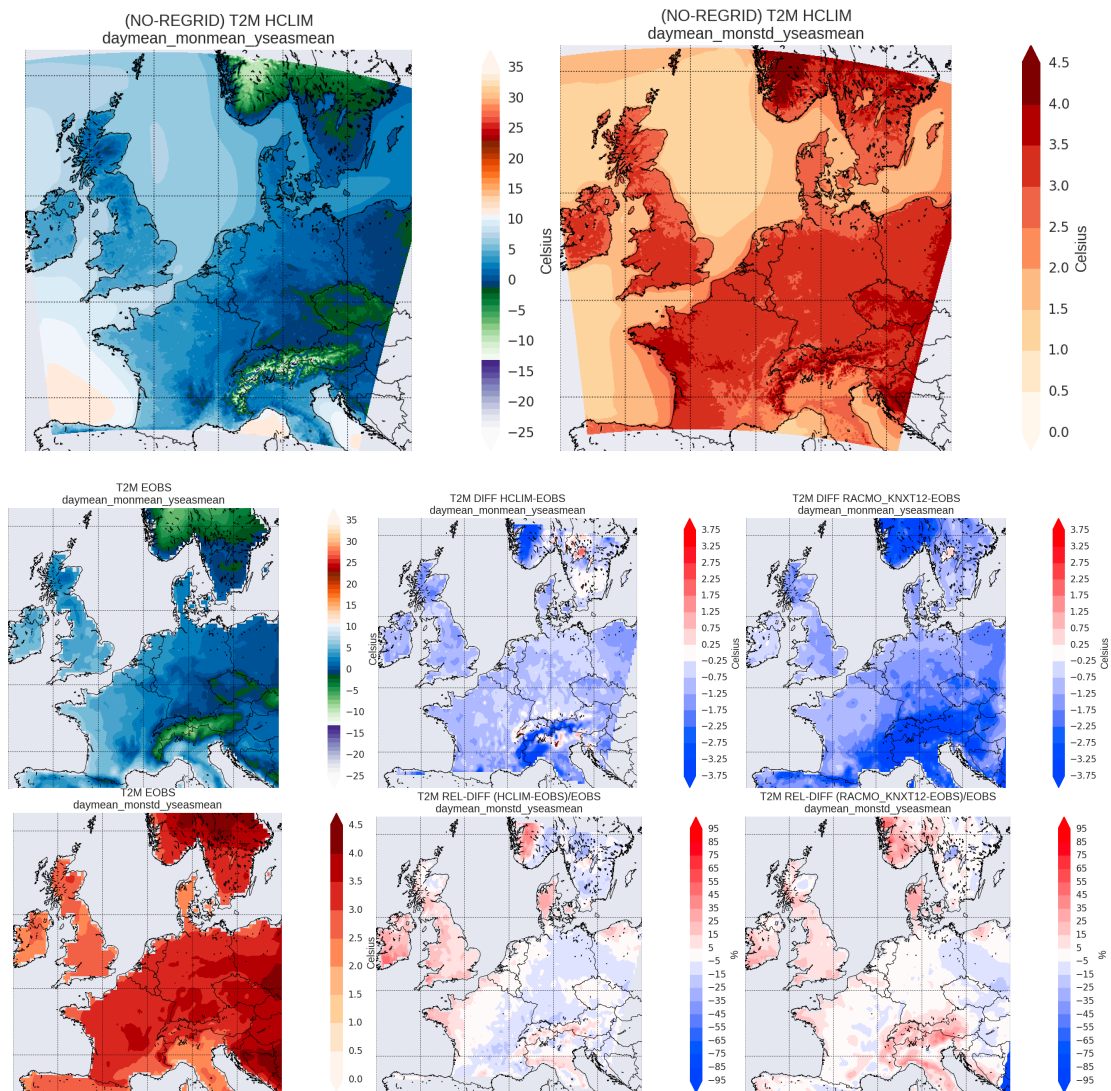


Figure 2: Winter (DJF) 2m-temperature. Top-row: HCLIM (left: daily-mean, right: monthly stdev of daily-mean). Middle row: mean (left: E-OBS, middle: diff. HCLIM and E-OBS, right: diff. RACMO and E-OBS). Bottom row: standard deviation (left: E-OBS, middle: rel.diff HCLIM and E-OBS, right: rel.diff. RACMO and E-OBS).

Daily temperature variations are also well represented. Again the level of detail presented by HCLIM is much higher than E-OBS. To the western side of the domain there is a tendency to over-estimate the temperature variability. This can be related most likely to a marked negative precipitation bias over the region.

Summer temperature and variability

Summer temperature pattern is also well captured (Figure 3), with the overall mean cold bias seen in DJF locally turning into a warm bias. This happens most clearly in southern France and in a region near the eastern edge of the domain. There appears to be a clear connection with (strongly) reduced rainfall in the region, which leads likely to too dry soils and soaring temperatures. This is also clear from the standard deviation, which is overestimated more consistently. Figure 4 makes this connection more explicit. Daily maximum temperatures are strongly positively biased in the southwest of the domain (the daily-minimum temperatures are much closer to normal, even cold-biased). At the same time, precipitation is strongly underestimated, locally by more than 50%. This negative precipitation bias is not exclusive to the southwestern part of the domain. Also Ireland and parts of the UK suffer from the near-presence of the boundary.

Clearly, for models like HCLIM one has to be careful in dimensioning the domain. It is not recommended to run HCLIM for a small domain if forcing is used from relatively coarse products

like ERA-Interim. At KNMI we are currently implementing a nesting strategy, where HCLIM is nested within RACMO. In this way we are able to present higher-resolution (both temporal and spatial) forcing at the boundaries, which hopefully alleviates the precipitation biases somewhat.

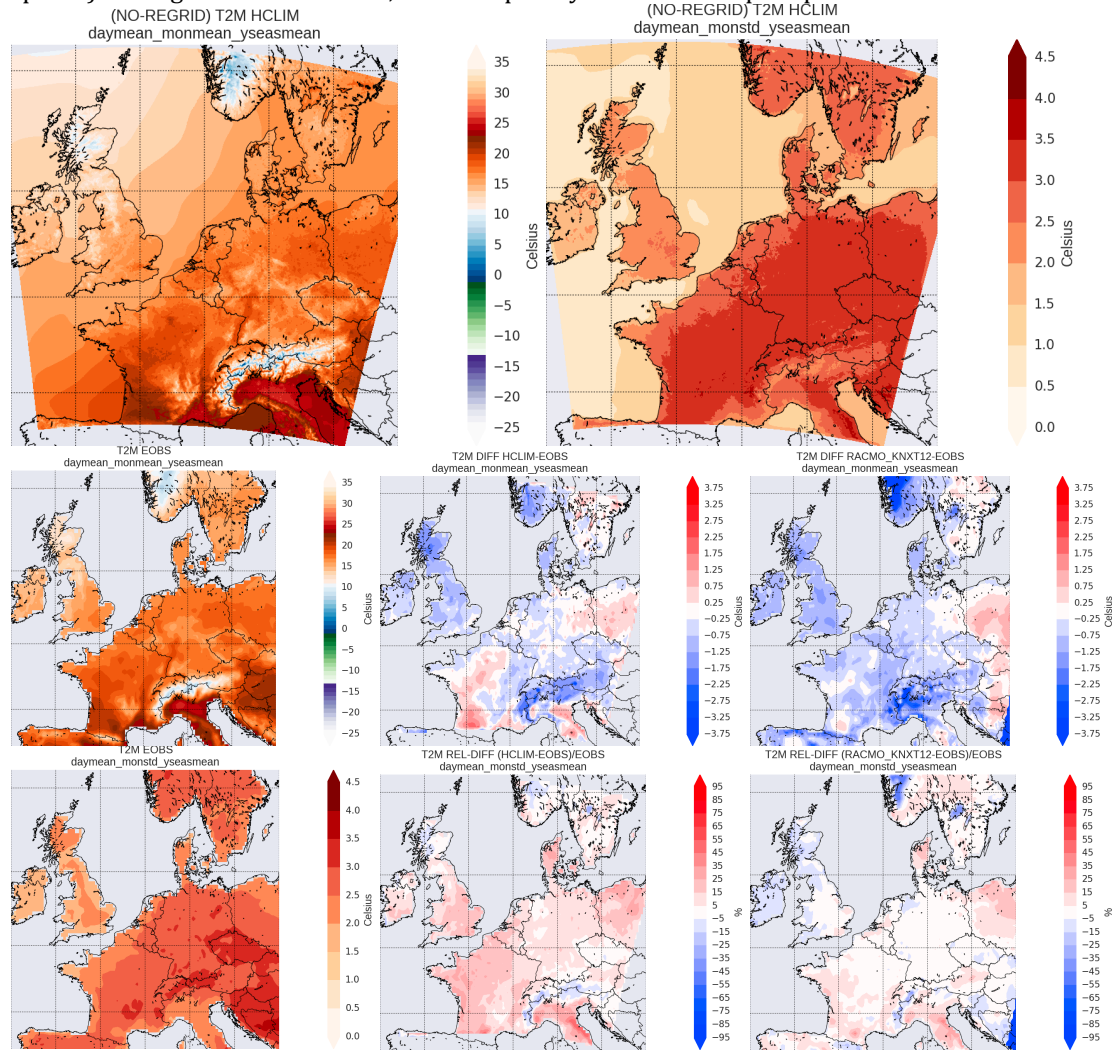


Figure 3: As in Figure 2, but for summer (JJA) 2m-temperature. Top-row: HCLIM (left: daily-mean, right: monthly stdev of daily-mean). Middle row: mean (left: E-OBS, middle: diff. HCLIM and E-OBS, right: diff. RACMO and E-OBS). Bottom row: standard deviation (left: E-OBS, middle: rel.diff HCLIM and E-OBS, right: rel.diff. RACMO and E-OBS).

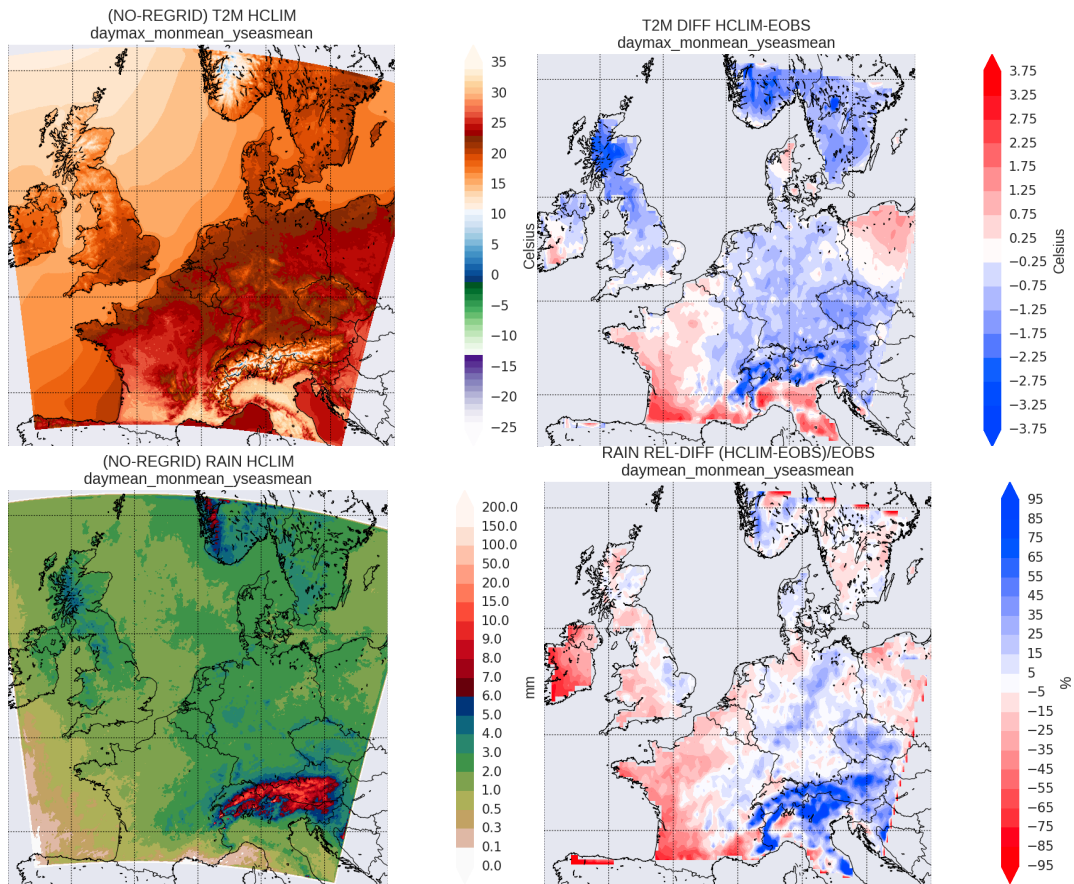


Figure 4: Summer (JJA). Top-row: mean daily-max temperature. (top-left: HCLIM, top-right: diff HCLIM and E-OBS). Bottom-row: daily-mean precipitation (bottom-left: HCLIM, bottom-right: relative difference HCLIM and E-OBS).

Evaluation of hourly precipitation statistics in a 5-year climate integration of HARMONIE

G. Lenderink, April 2017

1. Introduction

This document contains a first evaluation of hourly precipitation derived from a 5-years climate integration with HARMONIE using ERA-interim (Dee et al. 2011) as boundary conditions. The period of integration was 2005 until the end of 2009. [Details on the model setup to be added later]. Model results are compared to station observations at around 35 automatic weather stations (AWS). Some basic statistics are also compared to the output by the hydrostatic climate model RACMO2, also forced by ERA-interim boundaries, yet for a somewhat bigger domain (named KNXT12).

2. Daily cycles

Figures 1 to 4 show the diurnal cycle of temperature, dew point temperature and a number of hourly precipitation statistics for the 4 different seasons: winter (DJF), spring (MAM), summer (JJA) and autumn (SON). The precipitation measures are somewhat filtered in time by using a 3-hour block period, which allows us to obtain more robust statistics for the most extreme events.

The mean diurnal cycle of temperature is represented well. During day time modelled temperatures are close to observations, except for spring during which the model is too cold compared to the observations. Night-time temperature are on average 0.5 to 1 °C too high. The night-time bias is reasonably constant across seasons. On average the model has a negative bias in dew point temperatures, again between 0.5 and 1.0 °C. Except for spring this bias is almost constant throughout the days, and consequently the diurnal cycle is realistically simulated. In spring however during the afternoon dew point temperatures are too high. The reason for this behaviour could be excessive evaporation from still wet soil in spring, possibly related to the Leaf Area Index (LAI).

Mean hourly precipitation rates, including dry hours, are generally rather realistic for all seasons (upper right panels of Figs. 1-4). There is a small tendency to over-predict rainfall amounts during midday to afternoon in winter. We note, however, that also the observations may be biased; rainfall amount at the AWS could be ~5% lower than in reality. In spring the observations reveal a peak during late night and early morning, whereas the model peaks later during the day. This again could be related to the negative bias in humidity early on the day changing to a positive bias during the afternoon. In summer, the model underestimates mean rainfall for most parts of the day

33 by 10 to 20%. However, at the peak of precipitation in the late afternoon the model is unbiased
34 compared to the observations. Also, the timing of the peak precipitation is correctly simulated.
35 Precipitation rates in fall are realistic.

36 The lower panels of Figs. 1-4 show a number of different precipitation statistics as function of
37 hour of the day. The frequency of wet hours is computed using a threshold of $0.25 \text{ mm hour}^{-1}$.
38 In the observational data base the precipitation data are rounded to 0.1 mm. An analysis of the
39 model behaviour for low amounts is provided below. In winter and spring the wet hour frequency
40 (WHF) is generally slightly over-predicted, whereas in summer it is underestimated. In autumn
41 again it is very close to the observations. In comparison, RACMO over-predicts WHF, in particular
42 during the summer season and fall. Concerning extremes, the model is generally rather close to
43 the observation during the early part of the day, but has a tendency to produce too strong extremes
44 in the late afternoon. This is most visible in spring, but also clear for summer and autumn (and
45 even winter). The results of HARMONIE, however, are generally much closer to the observation
46 than RACMO, except for the highest intensities in summer (99.99th percentile, middle plot at the
47 bottom in Fig. 3)

48 **3. Dependencies on dew point temperature**

49 To investigate how HARMONIE responds to surface moisture, we computed the so-called pre-
50 cipitation dew-point temperature scaling (Lenderink et al. 2011; Lenderink and van Meijgaard
51 2010). This done for the winter and summer halve-year, WHF (October until March) and SHF
52 (April until September) respectively. In general scaling is derived from the wet-hours only – here
53 we again used a threshold of $0.25 \text{ mm hour}^{-1}$ – but considering the bias in frequency in wet-hour
54 frequency we also computed the percentiles based on all hours. Results are shown in Figs. 5 to 7,
55 where the upper panels show the data derived from the 35 stations, and the lower panels scaling
56 derived from a larger data set. For HARMONIE this is 184 “stations” in a regular grid over the
57 Netherlands (same 5-year period) and for the observations it is the longer data set from 1995 up to
58 2016 (same ~ 35 stations). Comparing the upper panels with the lower panels gives an indications
59 of the robustness of the results.

60 In the winter halve-year hour precipitation intensities are simulated well by the model (Figure
61 5). The model appears to slightly over-predict the 99 and 99.9th percentiles, whereas the 90th
62 percentile is spot on. The dependency is generally close to 7% per degree, which is the expectation
63 from the Clausius-Clapeyron (CC) relation. For high humidities, dew point temperature above 10
64 $^{\circ}\text{C}$ the observations suggest a somewhat steeper dependency than CC, which is not captured by
65 the model.

66 In the summer halve-year the model again produces realistic results, with intensities close to or
67 somewhat above the observed ones (Figs. 6 and 7). The model is also able to capture the 2CC
68 behaviour – 14% per degree – of the most extreme events, given by the 99.9th percentile of the wet
69 hours and the 99.99th percentiles of all hours. However, intensities of the less extreme percentiles
70 are too high for surface dew point temperatures above 15°C , and the dependency on dew point
71 temperature is too strong, larger than 2CC, in the range between 15 and 20°C . For even higher
72 dew point temperatures, precipitation intensities appear to level off, in particular well visible in
73 lower-left plots. The observations are generally closer to the 2CC lines, and level off at a higher
74 dew point temperature. The latter is difficult to see in the Dutch data, but the levelling off is very
75 clear at a dew point of 23°C in the Hong Kong data (Lenderink et al. 2011). (My interpretation at
76 the moment is the levelling off occurs at slightly lower dew point temperatures in the Dutch data,
77 and that this is related to the height of tropopause; in the data from Djakarta there is no levelling
78 off up to 27°C).

79 Finally, we looked at the wet-hour frequency (WHF) as a function of dew point temperature
80 (Figure 8). In winter the model produces too many wet hours over the whole dew point temperature
81 range. In the summer halve-year, the results are more diverse. For low dew point temperature the
82 model is practically unbiased. For intermediate dew point temperatures, between 13 and 17°C ,

83 the model has a negative bias, and above 17 °C the model produces too many rain events. A rapid
84 increase in WHF at those high dew point temperature is obtained in the model results, whereas the
85 observations only shows this increase beyond 20 °C. We note that the statistical significance is not
86 tested, and that there are not many event at dew point temperatures above 20 °C. Also, the model
87 has a mean negative bias in dew point temperatures of 1 °C.

88 Scaling results in summer suggest that HARMONIE is somewhat too active for dew points in
89 the range between ~17 and 20°C, and that the model has a tendency to simulate too many highly
90 organized convective systems producing too much rain. However, the mean bias in number of rain
91 events in summer is originating from lower dew points in the range between 13 and 17 °C, which
92 are far more common in summer, but are not very likely to lead to very extreme precipitation.

93 4. Statistics small precipitation amounts

94 In operational use of HARMONIE in short term weather prediction, it is noticed that model
95 appears to underestimate the number of small showers producing small amounts of precipitation. It
96 is not so clear whether this results from running the model in an operational forecast cycle – where
97 small-scale dynamical features generated by the model can be disturbed by the data assimilation at
98 regular intervals – or whether this is (partly) the result of the internal dynamics and physics of the
99 model. For that reason, investigating the behaviour of the model in climate mode can be revealing.

100 Comparing small precipitation amounts between the model and the observations is not trivial.
101 To start with the model stores precipitation as an accumulating field with finite precision. This
102 introduces a random error. Assuming that the model does not produce negative rain, but the time
103 series of the hourly precipitation derived from the de-accumulated fields do contain small negative
104 values, an estimate of the noise component due to the finite precision of the accumulated fields is
105 $0.02 \text{ mm hour}^{-1}$. Likewise, observations of low amounts could also be biased, for instance due to
106 evaporation of rain in the measurement instrument, but before it is actually recorded, or the finite
107 measuring precision of the instrument (e.g. a tipping bucket). According to the documentation the
108 AWS stations round precipitation to 0.1 mm, and an observation of 0.1 mm corresponds to rainfall
109 amounts between 0.05 and 0.15 mm. The observational data also contain an indication of rainfall
110 amounts below 0.05 mm. The latter, however, cannot be compared to the model results due to
111 finite precision of accumulated rain fields.

112 To compare the model with the observations we used two methods. The first method assumes
113 no error in both observations and model results, and compares 0.1 mm in the observations to
114 rainfall amounts between 0.05 and 0.15 mm, and likewise for higher precipitation amounts. The
115 second method assumes that the actual observed rainfall amounts are higher, and compares 0.1
116 mm observed precipitation with between 0.1 and 0.2 mm in the model results. We investigated
117 frequencies of precipitation amounts between 0.1 and 1.0 mm hour^{-1} , with steps of 0.1 hour^{-1} .
118 In addition, we looked at frequencies of amounts exceeding 1 and 5 hour^{-1} .

119 In winter there is no sign of a negative bias in the number of events producing small rainfall
120 amounts (Fig. 9) (Here, with events we mean hours with a certain rainfall amount, but we note
121 that these amounts can be produced not only by one shower, but also by a sequence of showers,
122 so it is not necessarily one rainfall event in physical sense.) In general, the model is producing
123 the right statistics, tending even to produce too many very small events. In spring, the situation
124 is similar (Fig. 10). For the morning hours – here defined from midnight to noon in UTC – the
125 model perhaps has a very small negative bias for precipitation exceeding 1 mm and more (see also
126 next section). This changes for summer precipitation (Fig. 11). The model has a negative bias
127 in the frequency of low precipitation amounts reaching up to 20%. This is in particular clear for

128 the morning hours, but also visible in the afternoon. In morning the negative bias also extends to
129 higher precipitation amounts, even exceeding 5 mm hour^{-1} . This is not the case for the afternoon
130 hours. Please note that the negative bias does not apply for the lowest precipitation amounts near
131 0.1 mm hour^{-1} ; it is strongest for values around 1 mm hour^{-1} . In autumn again there is no negative
132 bias, but the model tends towards a very small positive bias (Fig. 12).

5. Statistics of extremes

Finally, we look in more detail to the extreme statistics of the model. A probability of exceedance plot is produced by pooling the observations and the model results at the AWS stations. This distribution is produced for all hours, including dry ones, and for the wet-hours only (again a threshold of $0.25 \text{ mm hour}^{-1}$). The frequency of wet hours is indicated in the plot.

In winter, the model generally has very good extreme statistics (Fig. 13). For precipitation amount over 5 mm hour^{-1} , the model is generally too active, except perhaps for the highest precipitation amounts above 10 mm hour^{-1} . As we have noted before the model produces 10-20 % more precipitation events than observed.

In spring, the distribution of morning precipitation is very close to the observations (Fig. 14, middle panels). This changes in the afternoon, where the model is clearly producing too intense rain. This could be related to the higher humidities in the afternoon (see Fig. 2), or directly to the presumable overestimation of the latent heat flux. It is, however, also possible that the model is too active under strongly forced conditions from the surface, like in spring when the insulation is high and upper atmospheric temperature are still rather cold leading to large instability.

In summer, the model start to underestimate the number of wet events. However, the distribution of extremes is simulated rather well, with a small tendency of overestimation during afternoon hours (Fig. 15). Like in winter, the model appears to underestimate the very far tail of the distribution, but these only consist of a very small number of events (mostly only a few) and therefore cannot be considered statistically significant. However, it is consistent with the finding in the dew point temperature scaling that the intensities level off at too low dew point temperature ((Fig. 6). Likewise, the overestimation of the intensities mostly in the range between 20 and 40 mm hour^{-1} could well be related to the too strong dependence on dew point temperature at the high dew point temperature range.

Autumn results are close to the observation, again with the model generally overestimating the extremes, but only to a very small extend ((Fig. 16).

6. Summary

We evaluated the statistics of hourly precipitation derived from a 5-year re-analysis driven climate integration with HARMONIE compared to ~ 35 automatic weather stations (AWS) within the Netherlands. In general, the model produces results that are close to, or even very close to, the observations, both in term of frequency of occurrence of rainfall events and the behaviour of the extremes. Typically, the model over-predicts the number of hours with rain – wet-hour frequency – by $\sim 10\%$, except for the summer season. For that season, the number of hours with small precipitation amounts, around 1 mm hour^{-1} , is underestimated by at most 20% . In general, rainfall amounts are higher in afternoon than during the morning hours. As a consequence, the model produces a too pronounced diurnal cycle. For instance, in summer with good average precipitation rates (averaged across all hours including dry ones), but too high extremes in the afternoon, and too low average rates in the morning but realistic extremes. Nevertheless, the statistics of HARMONIE appear in general much closer to the AWS observations than the hydrostatic model RACMO, except for perhaps the mean precipitation rate where the skill of both models is generally rather equal.

The diurnal cycle of temperature and dew point temperature is realistically captured, yet the model generally produces a slightly too strong diurnal cycle associated with too cold night time temperatures (approximately 0.5 to $1 \text{ }^\circ\text{C}$). The diurnal cycle in dew point temperature is realistic, however the model is on average too dry with an average bias in dew point temperature of almost $1 \text{ }^\circ\text{C}$. The bias in night temperature could be physically related to the dry model bias. The exception is spring, for which dew point temperatures during daytime are too high, likely as a results of excessive evaporation.

Scaling of hourly extremes intensities with dew point temperature shows that HARMONIE is able to reproduce the double Clausius-Clapeyron (CC) relation – 14% per degree – as seen in the observations for the summer period. In winter, the model correctly reproduces a CC scaling, except for perhaps the highest dew point temperature range which are more sensitive in the observations. In summer and for dew point temperatures above $\sim 16 \text{ }^\circ\text{C}$ the model appears to be too active, with too many strong precipitation events. Above $\sim 20 \text{ }^\circ\text{C}$ the model reaches a maximum intensity whereas the observation appear to remain sensitive to the surface dew point temperature up to $22 \text{ }^\circ\text{C}$. This suggests that in the model the organisation of convective clouds into big convective clusters is (somewhat) too strong and occurs on average at too low surface humidity values (by approximately 2 degrees). In that sense, it is noteworthy that the dry bias of the model may well have a positive impact on the statistics of extremes.

Speculating about the interpretation of the results, it appears that the model is slightly too active under strongly forced conditions. As an example, the biggest errors in extreme precipitation

194 occur in spring in the afternoon, where the atmosphere is maximum unstable and with strong
195 moisture supply (possibly enhanced by strong evaporation). On average, the model is slightly
196 too inactive with weaker forcing from the surface, such as in the morning hours. So, when the
197 forcing is sufficiently large and when ample moisture is available to model produces somewhat
198 too strong convective systems, except for spring in which case the overestimation is substantial in
199 the afternoon. Under weaker forcing the model tends to underestimate the number of convective
200 precipitation events, however when they occur they have about the right statistics.

201 **References**

202 Dee, D. P., and Coauthors, 2011: The ERA-Interim reanalysis: Configuration and performance of
203 the data assimilation system. *Quarterly Journal of the Royal Meteorological Society*, **137 (656)**,
204 553–597, doi:10.1002/qj.828.

205 Lenderink, G., H. Y. Mok, T. C. Lee, and G. J. van Oldenborgh, 2011: Scaling and trends of
206 hourly precipitation extremes in two different climate zones – Hong Kong and the Netherlands.
207 *Hydrology and Earth System Sciences*, **15 (9)**, 3033–3041, doi:10.5194/hess-15-3033-2011,
208 URL <http://www.hydrol-earth-syst-sci.net/15/3033/2011/>.

209 Lenderink, G., and E. van Meijgaard, 2010: Linking increases in hourly precipitation ex-
210 tremes to atmospheric temperature and moisture changes. *Environmental Research Letters*,
211 **5 (2)**, 025 208, doi:10.1088/1748-9326/5/2/025208, URL [http://stacks.iop.org/1748-9326/5/i=](http://stacks.iop.org/1748-9326/5/i=2/a=025208?key=crossref.52c9961937d9e5364bd75303ea29738e)
212 [2/a=025208?key=crossref.52c9961937d9e5364bd75303ea29738e](http://stacks.iop.org/1748-9326/5/i=2/a=025208?key=crossref.52c9961937d9e5364bd75303ea29738e).

213 **LIST OF FIGURES**

214 **Fig. 1.** Statistics for the winter period as function of the hours of the day. “ALL” means all 35 AWS
 215 stations, irregardless of whether the OBS has data: “SEL” means a selection of 10 stations
 216 with complete data coverage in the observations (stations: 235, 260, 270, 275, 280, 290,
 217 310, 370, 380, 391). Wet hour fraction uses a threshold of 0.25 mm. Precipitation statistics
 218 are derived using a three hour block to decrease the noise component. 11

219 **Fig. 2.** Statistics for the spring period as function of the hours of the day 12

220 **Fig. 3.** Statistics for the summer period as function of the hours of the day 13

221 **Fig. 4.** Statistics for the autumn period as function of the hours of the day 14

222 **Fig. 5.** Scaling of hourly extremes with dew point temperture for winter halve year. $P_{\text{threshold}} =$
 223 0.25 mm 15

224 **Fig. 6.** Scaling of hourly extremes with dew point temperture for summer halve year. $P_{\text{threshold}} =$
 225 0.25 mm 16

226 **Fig. 7.** Scaling of hourly extremes with dew point temperture for summer halve year. including dry
 227 events 17

228 **Fig. 8.** Wet hour frequency as function of dew point temperature for winter and summer halve year
 229 Results JJA and DJF very similar 18

230 **Fig. 9.** Frequencies of small precipitation amounts, and those exceeding 1 and 5 mm. Upper panels
 231 show the absolute frequencies in the observations (black) and in HARMONIE (red). The
 232 open red symbols shows results from the second method, comparing 0.1 mm observed with
 233 modelled 0.1 to 0.2 mm hour⁻¹, and so on (see text). Lower panels show the relative errors
 234 in HARMONIE when compared to the observations. 19

235 **Fig. 10.** Frequencies of small precipitation amounts, and those exceeding 1 and 5 mm. 20

236 **Fig. 11.** Frequencies of small precipitation amounts, and those exceeding 1 and 5 mm. 21

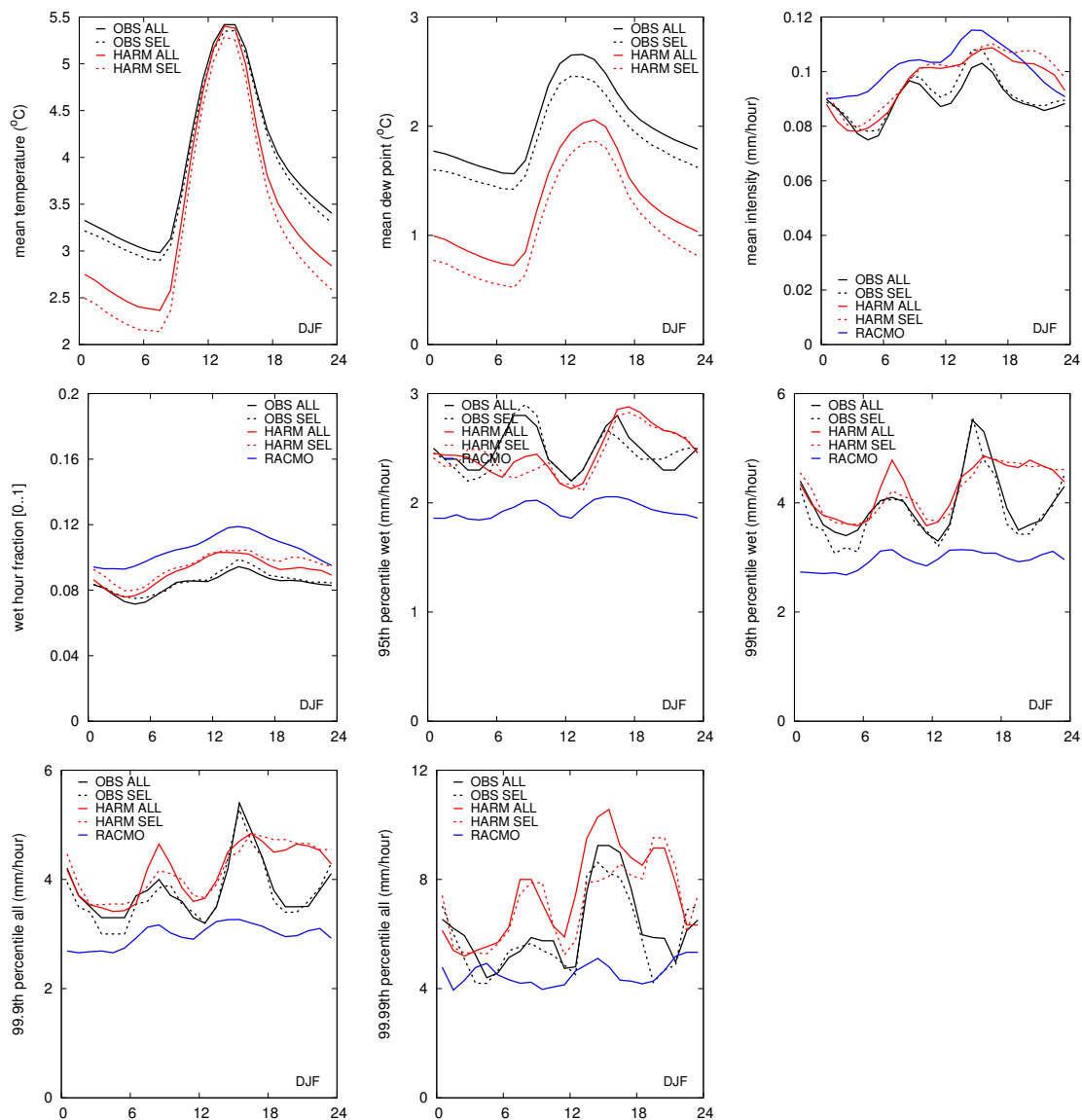
237 **Fig. 12.** Frequencies of small precipitation amounts, and those exceeding 1 and 5 mm. 22

238 **Fig. 13.** Probability of exceedance of hourly rainfall for winter. Upper panels including dry hours,
 239 lower panel only wet hours exceeding 0.25 mm (note in the observations this is 0.3 and
 240 more). 23

241 **Fig. 14.** Probability of exceedance of hourly rainfall for spring. Upper panels including dry hours,
 242 lower panel only wet hours exceeding 0.25 mm (note in the observations this is 0.3 and
 243 more). 24

244 **Fig. 15.** Probability of exceedance of hourly rainfall for summer. Upper panels including dry hours,
 245 lower panel only wet hours exceeding 0.25 mm (note in the observations this is 0.3 and
 246 more). 25

247 **Fig. 16.** Probability of exceedance of hourly rainfall for autumn. Upper panels including dry hours,
 248 lower panel only wet hours exceeding 0.25 mm (note in the observations this is 0.3 and
 249 more). 26



250 FIG. 1. Statistics for the winter period as function of the hours of the day. “ALL” means all 35 AWS stations,
 251 irregardless of whether the OBS has data: “SEL” means a selection of 10 stations with complete data coverage in
 252 the observations (stations: 235, 260, 270, 275, 280, 290, 310, 370, 380, 391). Wet hour fraction uses a threshold
 253 of 0.25 mm. Precipitation statistics are derived using a three hour block to decrease the noise component.

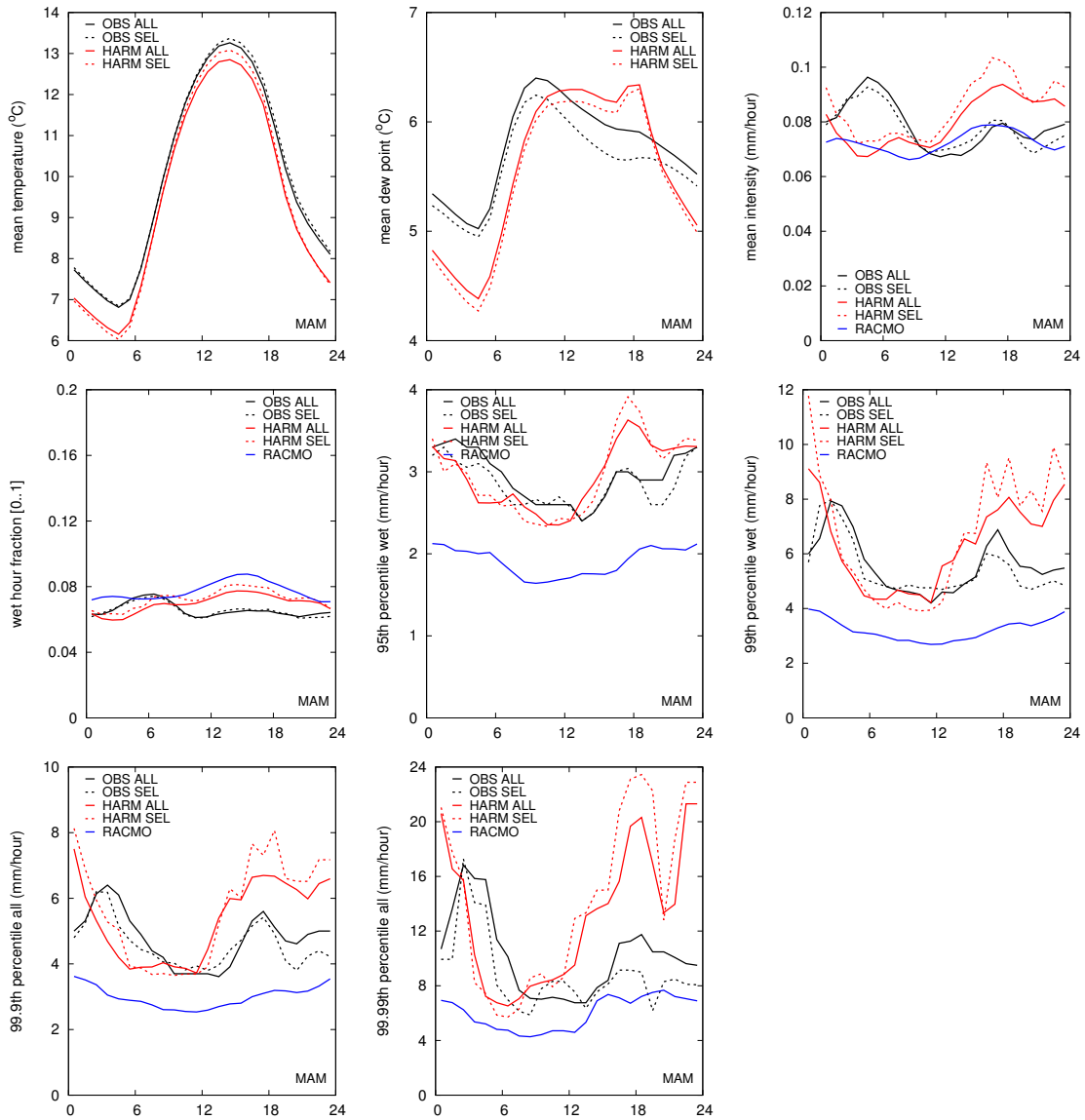


FIG. 2. Statistics for the spring period as function of the hours of the day

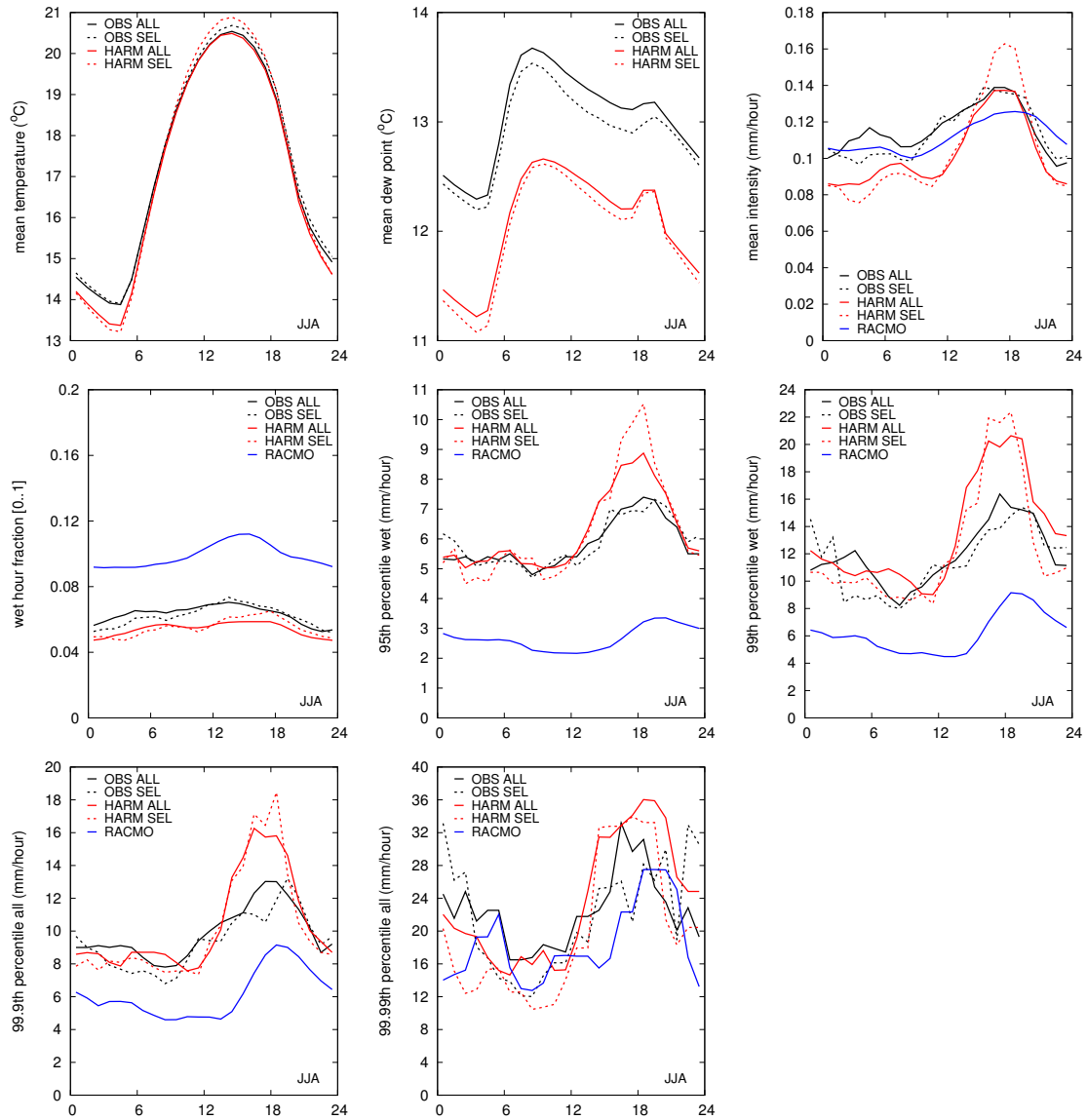


FIG. 3. Statistics for the summer period as function of the hours of the day

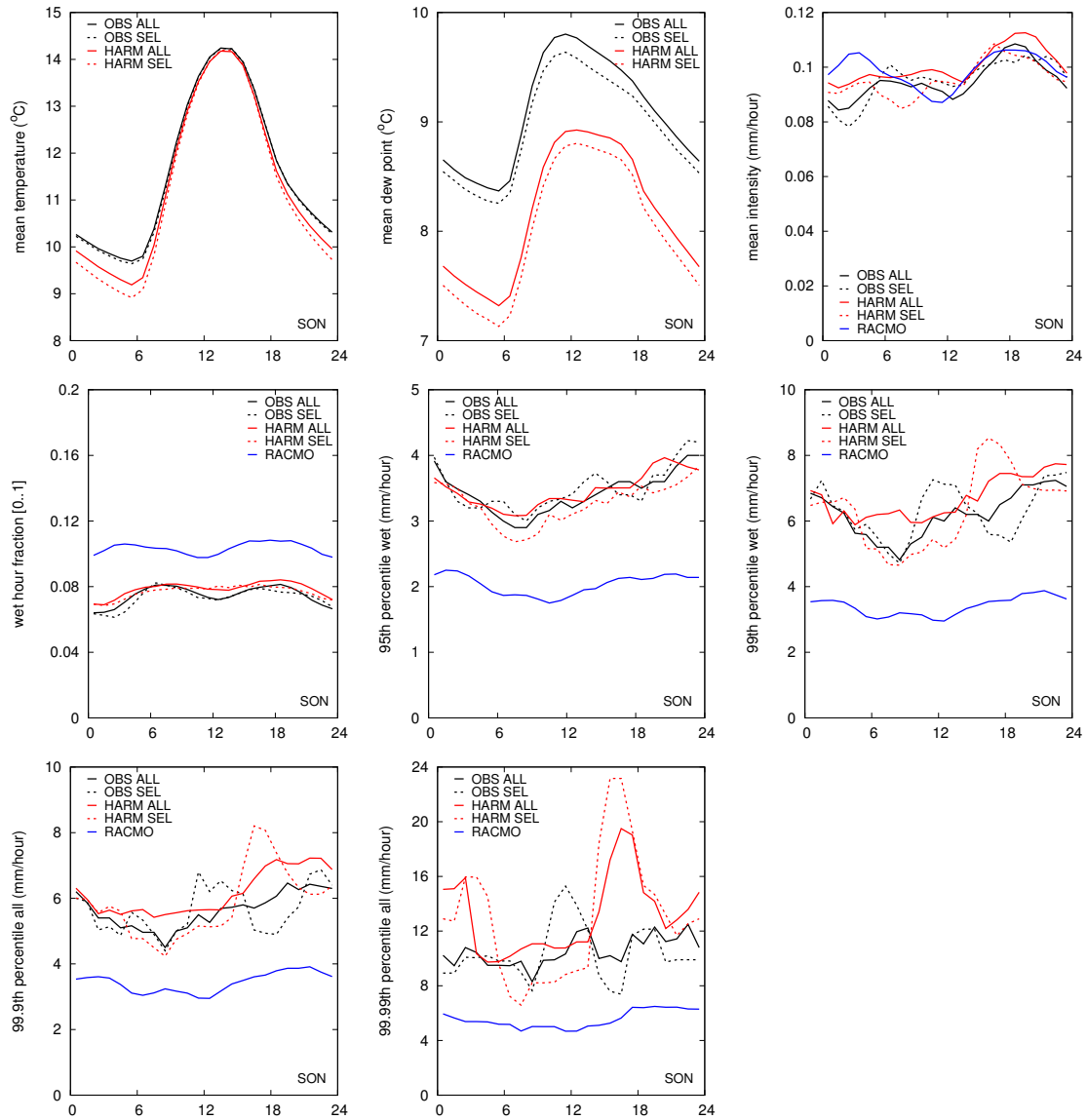


FIG. 4. Statistics for the autumn period as function of the hours of the day

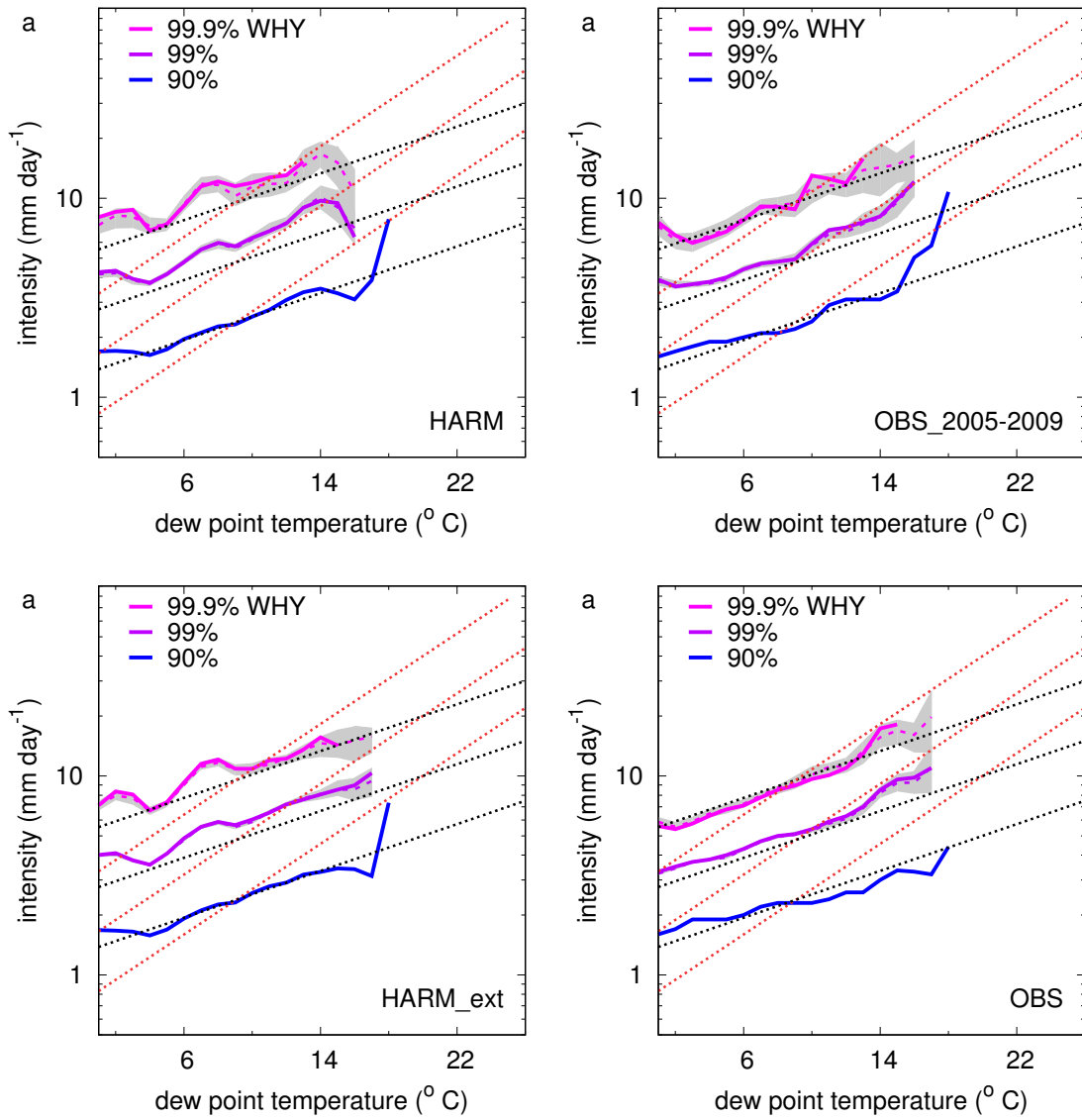


FIG. 5. Scaling of hourly extremes with dew point temperature for winter half year. $P_{\text{threshold}} = 0.25 \text{ mm}$

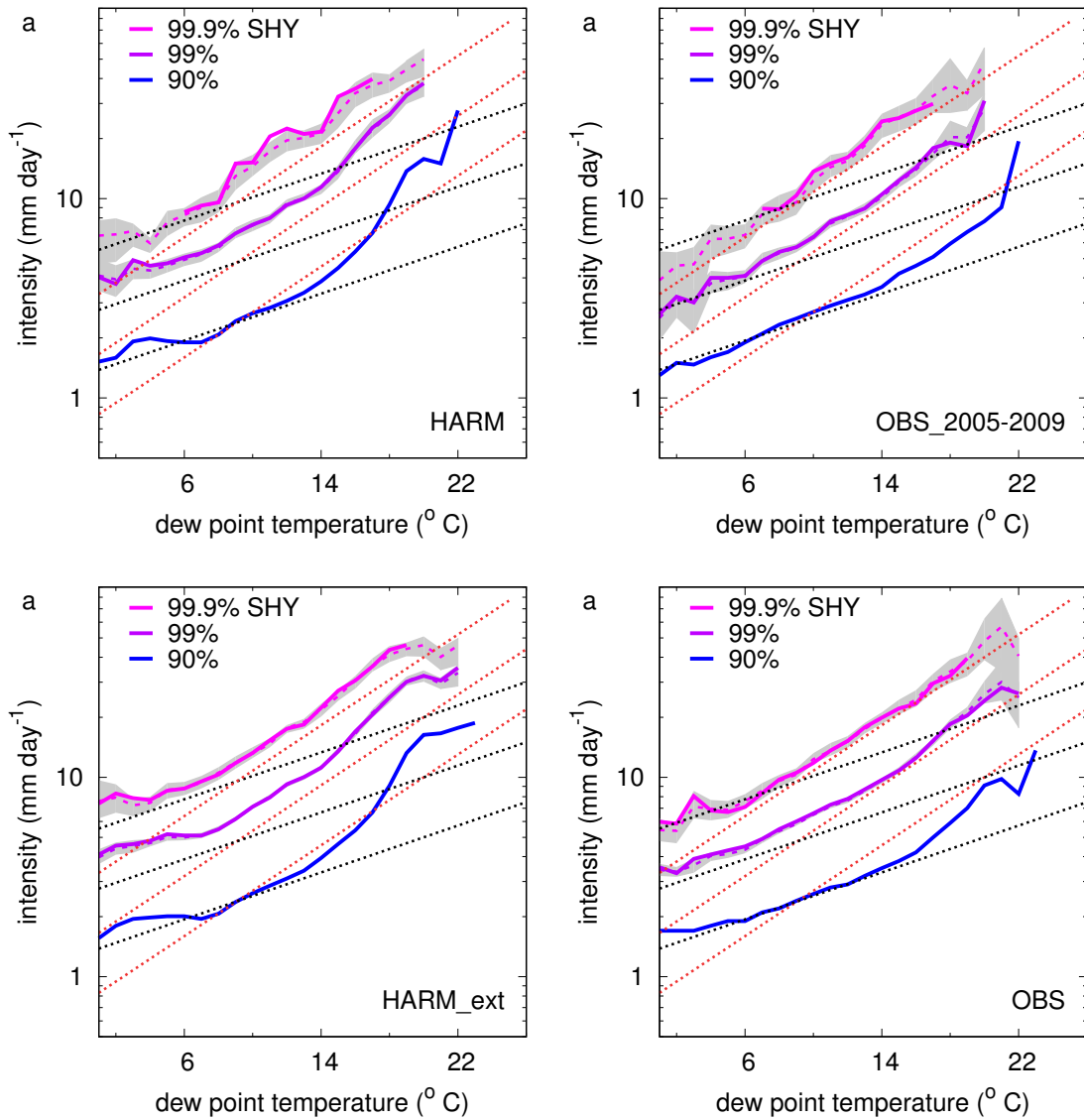


FIG. 6. Scaling of hourly extremes with dew point temperature for summer half year. $P_{\text{threshold}} = 0.25 \text{ mm}$

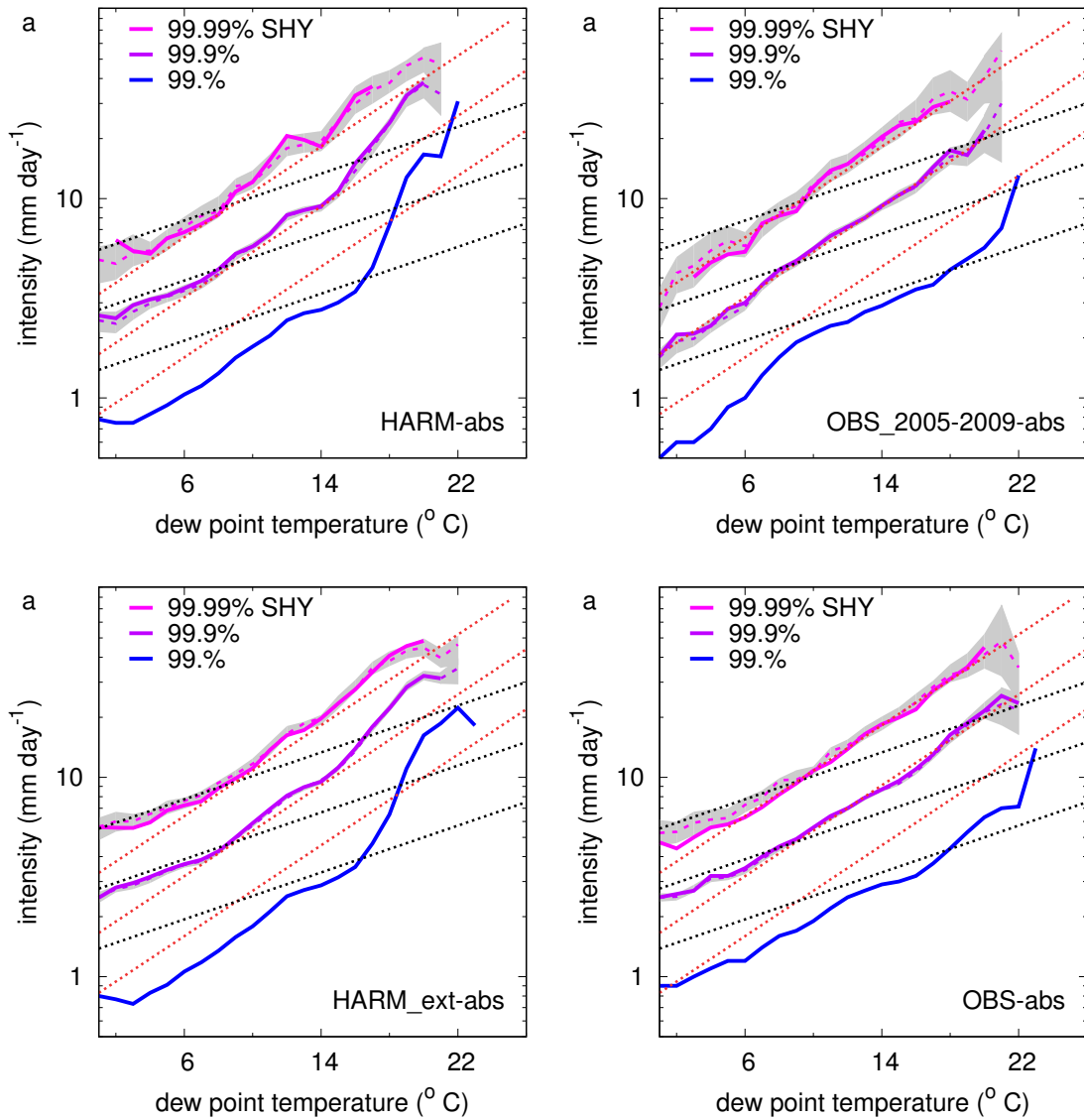
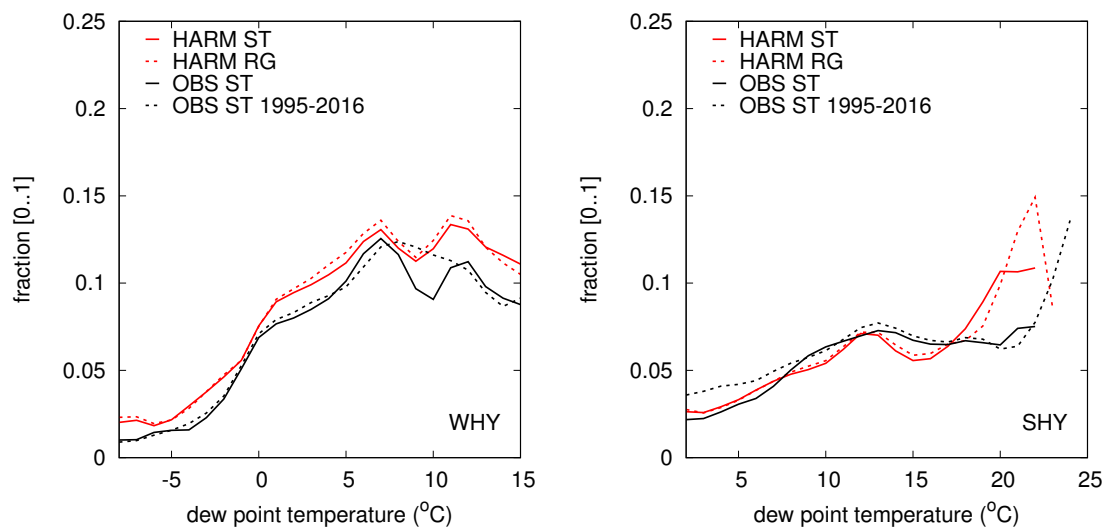
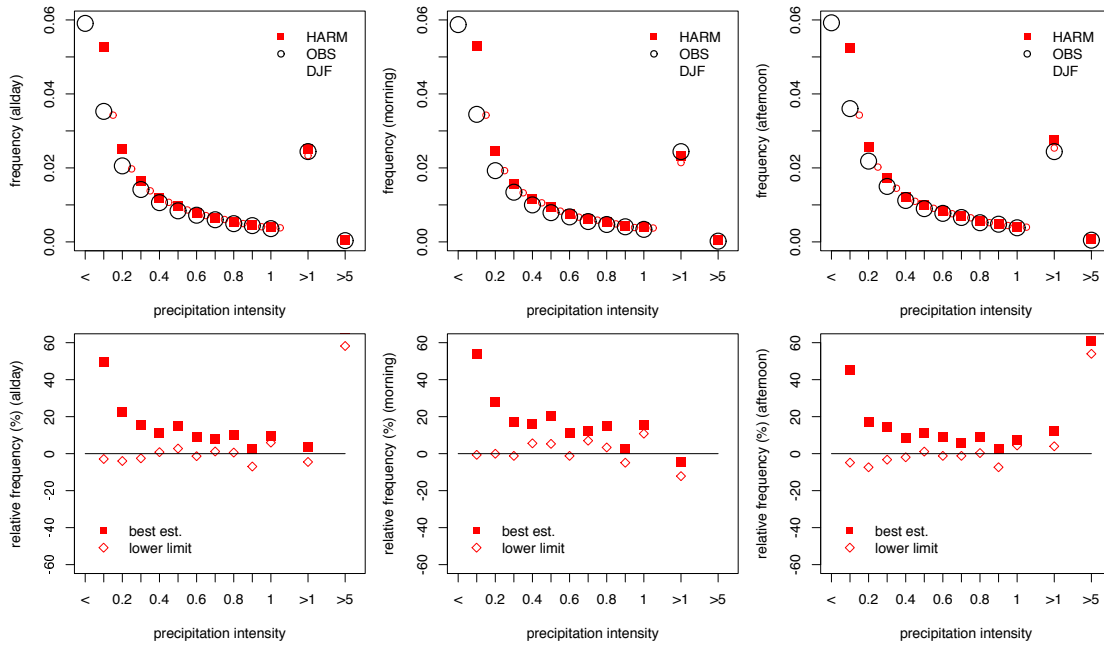


FIG. 7. Scaling of hourly extremes with dew point temperature for summer half year, including dry events



254 FIG. 8. Wet hour frequency as function of dew point temperature for winter and summer halve year Results

255 JJA and DJF very similar



256 FIG. 9. Frequencies of small precipitation amounts, and those exceeding 1 and 5 mm. Upper panels show
 257 the absolute frequencies in the observations (black) and in HARMONIE (red). The open red symbols shows
 258 results from the second method, comparing 0.1 mm observed with modelled 0.1 to 0.2 mm hour⁻¹, and so on
 259 (see text). Lower panels show the relative errors in HARMONIE when compared to the observations.

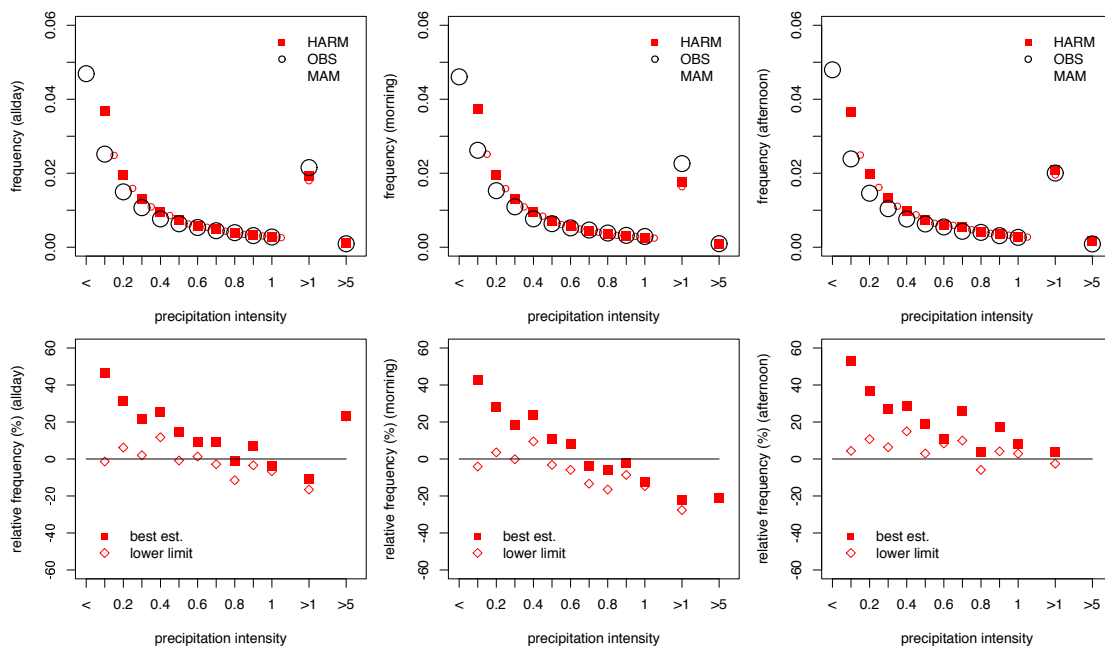


FIG. 10. Frequencies of small precipitation amounts, and those exceeding 1 and 5 mm.

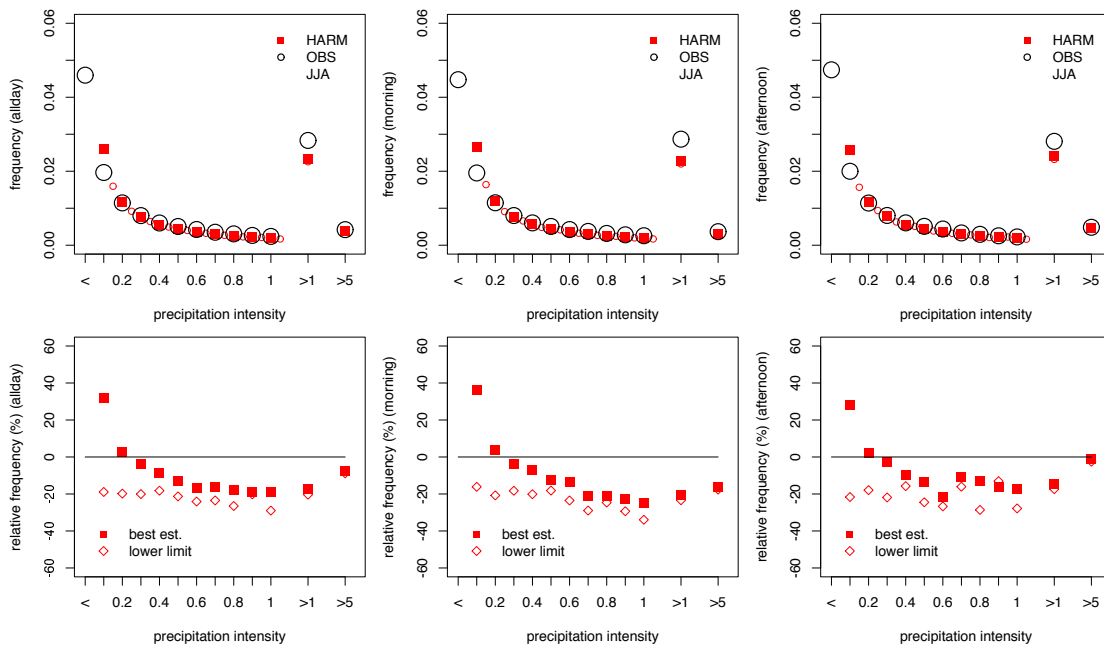


FIG. 11. Frequencies of small precipitation amounts, and those exceeding 1 and 5 mm.

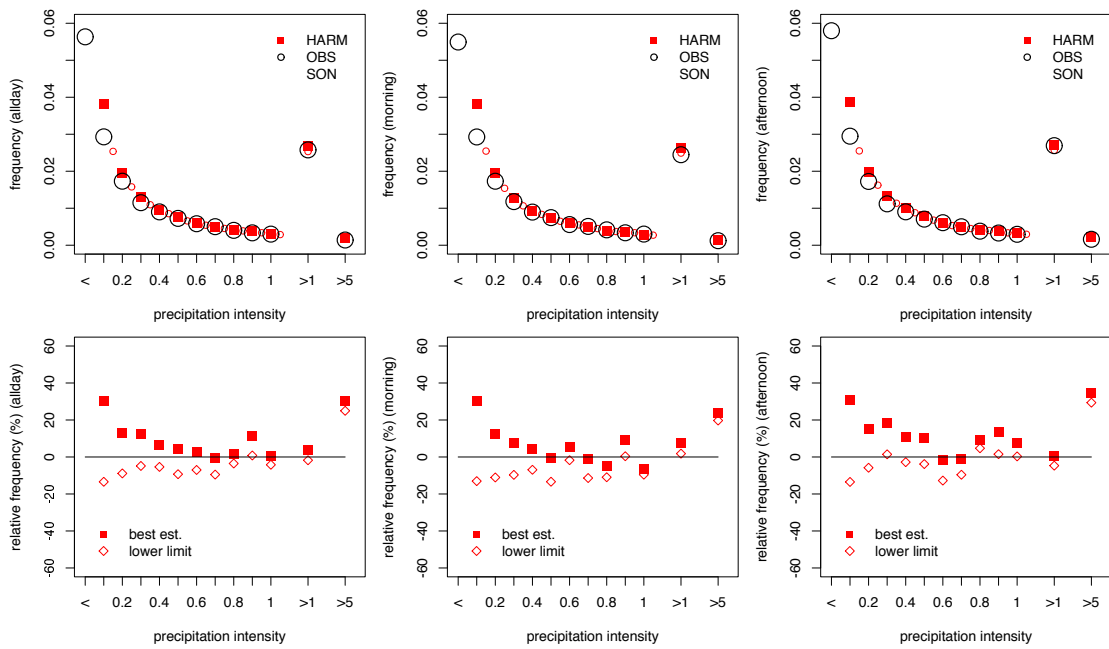
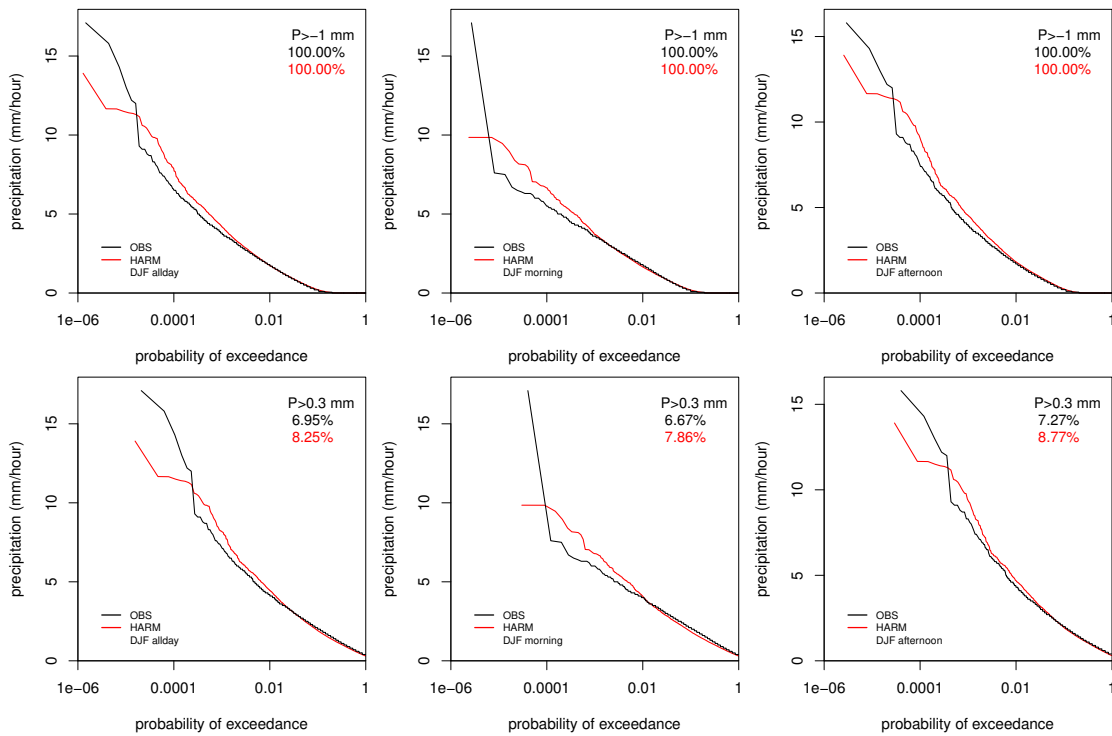
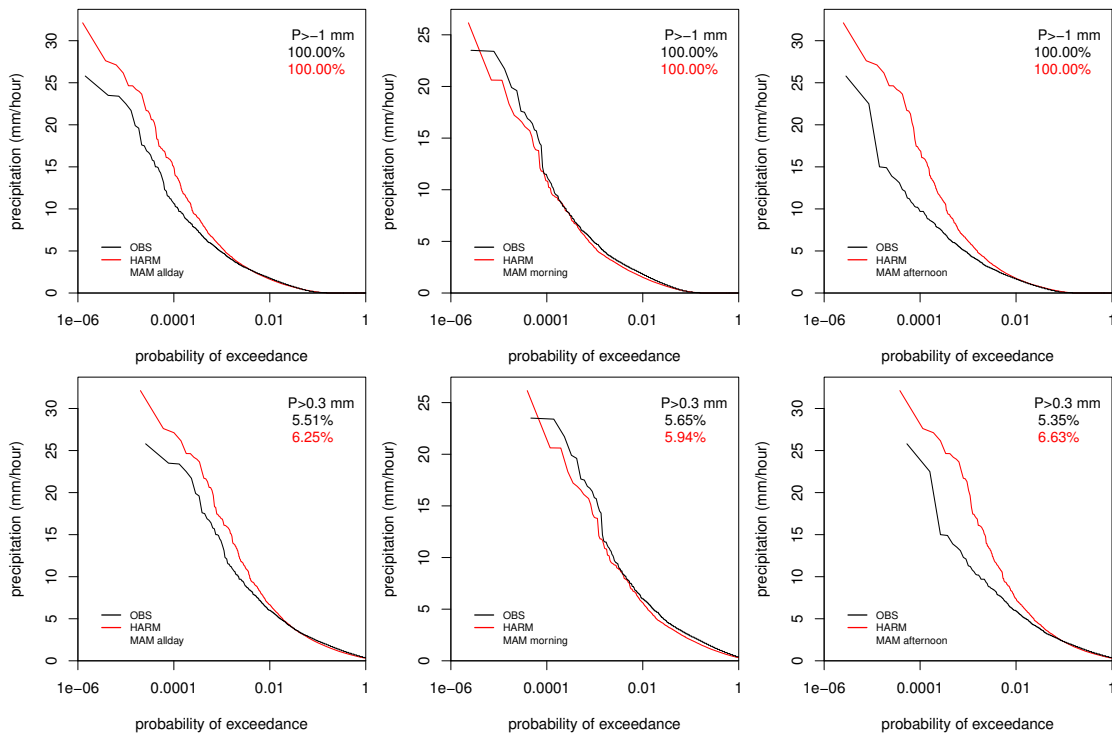


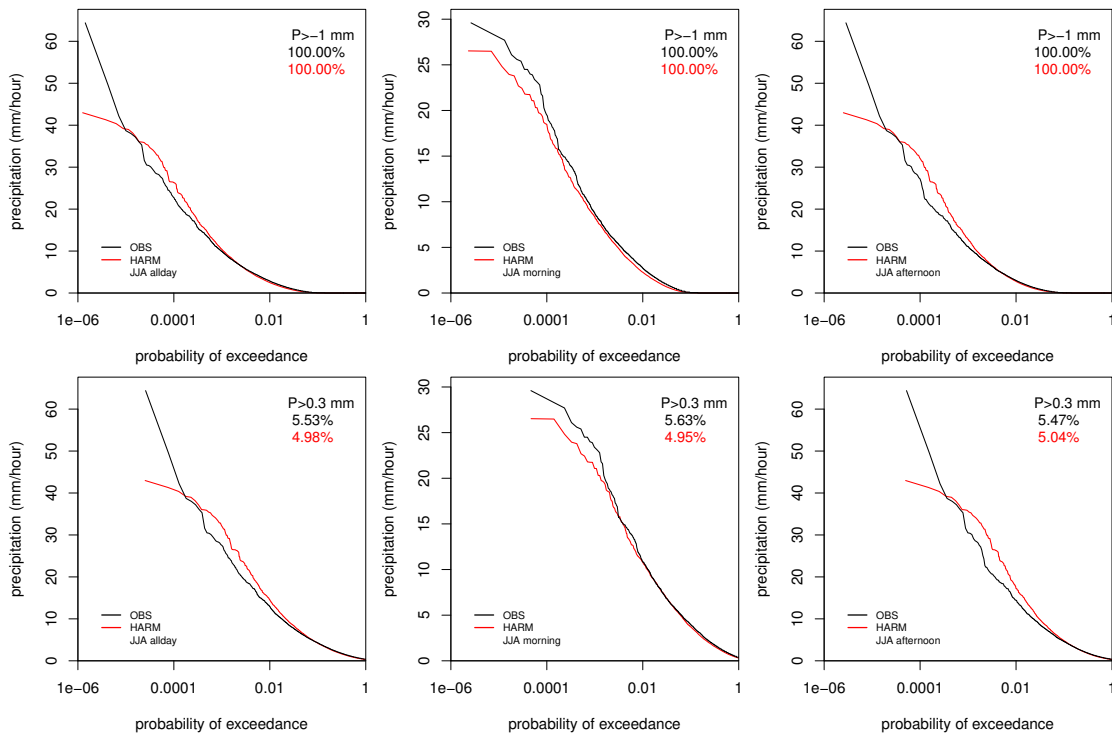
FIG. 12. Frequencies of small precipitation amounts, and those exceeding 1 and 5 mm.



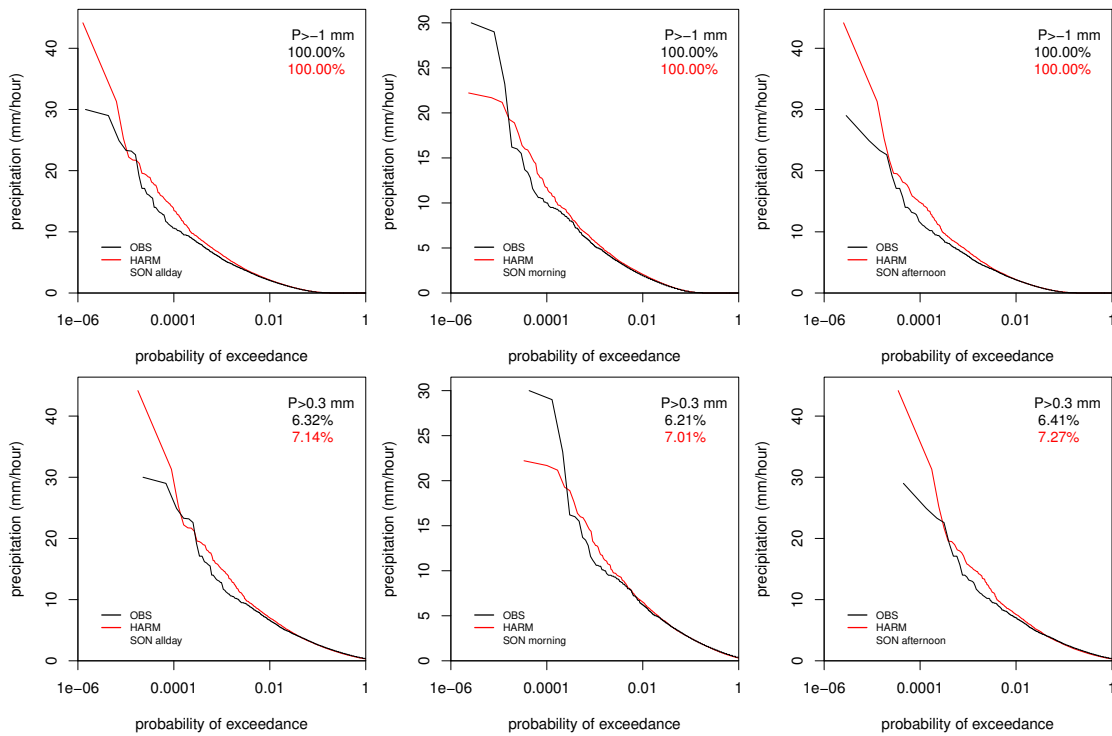
260 FIG. 13. Probability of exceedance of hourly rainfall for winter. Upper panels including dry hours, lower
 261 panel only wet hours exceeding 0.25 mm (note in the observations this is 0.3 and more).



262 FIG. 14. Probability of exceedance of hourly rainfall for spring. Upper panels including dry hours, lower
 263 panel only wet hours exceeding 0.25 mm (note in the observations this is 0.3 and more).



264 FIG. 15. Probability of exceedance of hourly rainfall for summer. Upper panels including dry hours, lower
 265 panel only wet hours exceeding 0.25 mm (note in the observations this is 0.3 and more).



266 FIG. 16. Probability of exceedance of hourly rainfall for autumn. Upper panels including dry hours, lower
 267 panel only wet hours exceeding 0.25 mm (note in the observations this is 0.3 and more).