Royal Netherlands
Meteorological Institute
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Drought trends in the Rhine and Meuse basins - Extension of the study "Regional differentiation in climate change induced drought trends in the Netherlands"

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Content

Nederlandse samenvatting

In dit rapport zijn trends in lage rivierafvoeren in de Rijn en Maas en verschillende factoren die invloed hebben op rivierafvoeren onderzocht. De extreem droge condities die zich in 2018 in Nederland voordeden vormen de motivatie voor deze studie. Voor drie droogte-gerelateerde variabelen die rivierafvoer beïnvloeden (neerslag, temperatuur en potentiële verdamping) zijn voor de Rijn- en Maas-stroomgebieden de verandering in intensiteit tussen 1900 en 2018 geanalyseerd. Hiervoor zijn meerdere observationele en model datasets gebruikt, waarbij gemiddeld is over het zomerhalfjaar april-september.

Observationele en modelresultaten samen laten geen significante verandering zien in neerslagintensiteit. Beide stroomgebieden laten hierbij een vergelijkbaar betrouwbaarheidsinterval zien.
Voor temperatuur resulteert dit voor zowel het Rijn- als het Maasstroomgebied in een significante positieve trend met beste schatting tussen +1.5 en +2 K.
Voor potentiële verdamping liggen de schattingen van observaties en modellen uit elkaar en geven ze geen eenduidige trend voor de attributie aan klimaatverandering. Zowel observaties als modellen laten echter wel een toename in intensiteit zien, voor modellen is de toename minstens 3%.

Observaties van rivierafvoeren laten een afname zien voor de Rijn (Lobith) van -9% (95% betrouwbaarheidsinterval (CI) -19 to 3%), wat alleen significant is voor p=0.1. Voor de Maas (Monsin/Eijsden) is de afname significant voor p=0.05, met -30% (95% CI -45 to -13%). Deze waargenomen rivierafvoeren zijn echter ook onderhevig aan veranderingen die niet gerelateerd zijn aan klimaatverandering.

Deze studie houdt verband met een publicatie uit 2020 waarbij de focus lag op droogte-gerelateerde trends in Nederland.

Abstract

Motivated by the extreme drought conditions experienced in the Netherlands in 2018, trends in low discharge events for both the Rhine and Meuse rivers are explored, as well as drivers influencing discharge. The change in intensity between 1900 and 2018 of three drought-related variables that influence discharge (precipitation, temperature and potential evaporation) is studied using multiple

observational and model data sets, with quantities averaged over April to September for the Rhine and Meuse basins.

Synthesizing observational and model results, no significant change in precipitation intensity is found, with comparable outcome and confidence range for both basins. For temperature, a significant positive intensification results, with a best estimate lying between +1.5 and +2 K, for both the Rhine and the Meuse. For potential evaporation, observational and model estimates do not overlap and therefore no synthesized value for the attribution to climate change is given. However, both types of data point to an increase in intensity, with models indicating an intensity change of at least 3%.

Observed trends in discharge show a decrease for the Rhine (Lobith) of -9% (95% confidence interval, CI, of -19 to 3%) which is significant at p=0.1. For the Meuse (Monsin/Eijsden) we find a negative trend of -30% (95% CI -45 to -13%), which is significant at p=0.05. However, these observed discharge series are also subject to local changes not related to climate change.

The study is related to a 2020 publication that focussed on drought-related trends in the Netherlands alone.

Introduction

In recent work Philip et al. (2020) investigated drought-related trends in the Netherlands. For this study, the Netherlands was divided into two regions: coastal and inland. Four drought-related variables averaged over Apr-Sep were studied: precipitation, temperature, potential evaporation (PET) and soil moisture. A trend detection analysis was performed on the coastal region, and both trend detection and attribution analyses were performed on the inland region. It was concluded that, in the coastal region, a positive trend in precipitation counteracts the effect of rising temperatures and increasing global radiation (total downward shortwave radiation) at the surface on drought. In the inland area, observations and models showed a trend towards more or stronger agricultural droughts, driven by somewhat stronger trends in temperature and global radiation combined with no trend in precipitation.

The analyses of precipitation, temperature, PET and soil moisture were accompanied by an analysis of Apr-Sep averaged discharge measurements of the Rhine at Lobith and E-OBS (Cornes et al. 2018) precipitation over the Rhine catchment upstream of Lobith. A trend towards less precipitation over the Rhine catchment was found. For discharge, only a non-significant trend towards lower Apr-Sep discharge averages at Lobith was found, in part due to large variability.

The volume of river water that enters the Netherlands via the Rhine and the Meuse, and that is available for irrigation of the low-lying parts of the country, depends on what happens in the Rhine and Meuse catchments. In this study, within the context of the KNMI Klimaatscenarios, we extend the analyses of the Dutch drought (Philip et al., 2020) with attribution analyses for the Rhine and Meuse catchments. This gives a better indication of what may be expected for Apr-Sep mean discharge in both rivers. Furthermore, we analyse Apr-Sep mean discharge measurements at both Lobith (Rhine) and Monsin/Eijsden (Meuse). The Monsin/Eijsden time series is the Eijsden time series extended with the Monsin time series.

We investigate the change in characteristics associated with the low discharge event in 2018 caused by low precipitation as well as high temperatures resulting in higher evaporation and increased water demand. The results, however, are not very sensitive to that specific event so the study can also be seen as a trend analysis rather than an event attribution study.

In this report we present the results of the attribution analyses of the 2018 drought event in the Rhine and Meuse catchments. As the study directly builds upon the results of Philip et al. (2020), we refer the reader to that paper for extensive descriptions of the data, methods and assumptions.

1 Region, data and methods

There are only a few minor changes in the use of data and methods compared to Philip et al. (2020). These are listed in the sections below.

1.1 Region

We report results for two regions: the Rhine catchment upstream of Lobith and the Meuse catchment upstream of Monsin/Eijsden. The basins are plotted in Figure 1. The Rhine catchment is the same as that used in Philip et al. (2020). For the Meuse basin we used the Meuse catchment south of 50.8N. Most models used here, and especially the GCMs, are however too coarse to distinguish this exact boundary.

The only exception made to the region definitions is that for the GFDL model we use the grid box just west of the Meuse basin (48.5N-50.5N; 5E-7.5E). This avoids duplication of the same region/grid box in both the Rhine and the Meuse analyses.

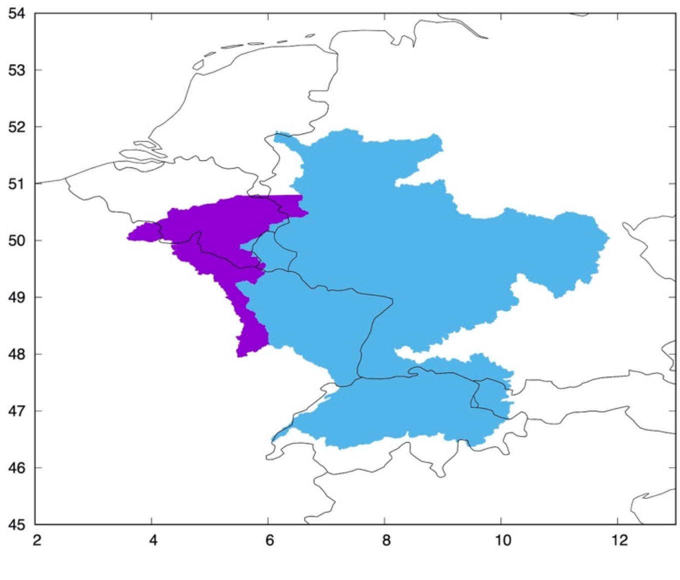


Figure 1. Outline of the Rhine (blue) and Meuse (purple) catchments investigated in this study.

1.2 Data

To keep the methods used here as close as possible to the study by Philip et al. (2020) which we used as a basis, we use mostly the same observational and reanalysis datasets, the same hydrological models of the ISIMIP ensemble driven by CMIP5 models and the same CMIP5 models. The differences between data used in Philip et al. (2020) and the current study are outlined in the list below.

1. We only analyse temperature, precipitation and PET for the Rhine and Meuse basins. We restrict the analyses to meteorological variables because for the Netherlands, results for soil moisture did not point to a clear picture of trends and contain large uncertainties. Furthermore, the uncertainties in soil moisture results are larger than models indicate because irrigation plays an important role and this is not captured well in the hydrological models used here. Although low soil moisture levels in the Rhine and Meuse basins influence river discharge, PET and precipitation, possibly supplemented by irrigation, in principle control the water balance and the state of the soil. As there are no long time series from direct soil moisture measurements, we choose not to analyse soil moisture in this study.
2. For PET, instead of ERA-I we now use ERA5 (Hersbach et al., 2020), which is at present available for the years 1979-2020.
3. We use MIROC results and ISIMIP results that are driven by the MIROC model for 1880-2020 rather than for 1850-2020. This is because there are indications that the model has a starting up problem before 1880, which results in unrealistically low trends, especially in temperature.
4. For precipitation we additionally use the GPCC (1891-now, Schneider et al., 2018) and CRU TS4.04 (1901-now, Harris et al., 2020) datasets. These datasets extend further back in time than the E-OBS dataset, which influences the results (see Results section).
5. For temperature we additionally use the CRU TS4.04 (1901-now) dataset.

1.3 Methods

For precipitation, temperature and discharge we calculate the trends in the occurrence of events like 2018. The return periods for the 2018 summer half year precipitation are 35 years in the Rhine basin and 20 years in the Meuse basin. For the PET analysis we use the same return periods as for the precipitation analysis. The return period for the 2018 temperature event is about 90 years in the Rhine basin and about 140 years in the Meuse basin. In general, the results do not strongly depend on the exact value of the return period. We include the year 2018 in the fits, because the regions were pre-defined, and because we have data extending beyond 2018 up to 2019 or 2020.

All trends are given for 2018 compared to 1900. Note that in Philip et al. (2020) this was for 2018 compared to 1950. For the results, the effect of this choice is very small, as the bulk of global warming took place after 1950.

2 Results attribution

All models were subjected to validation tests, as detailed in Philip et al. (2020). Tabulated results of these tests can be found in the Appendix. The results of the attribution are presented in synthesis figures, displaying intensity change between 1900 and 2018 (equivalent to trend; see caption for details), for each studied variable in turn. Only the models that passed the validation tests are included in these figures and resulting statements.

2.1 Precipitation

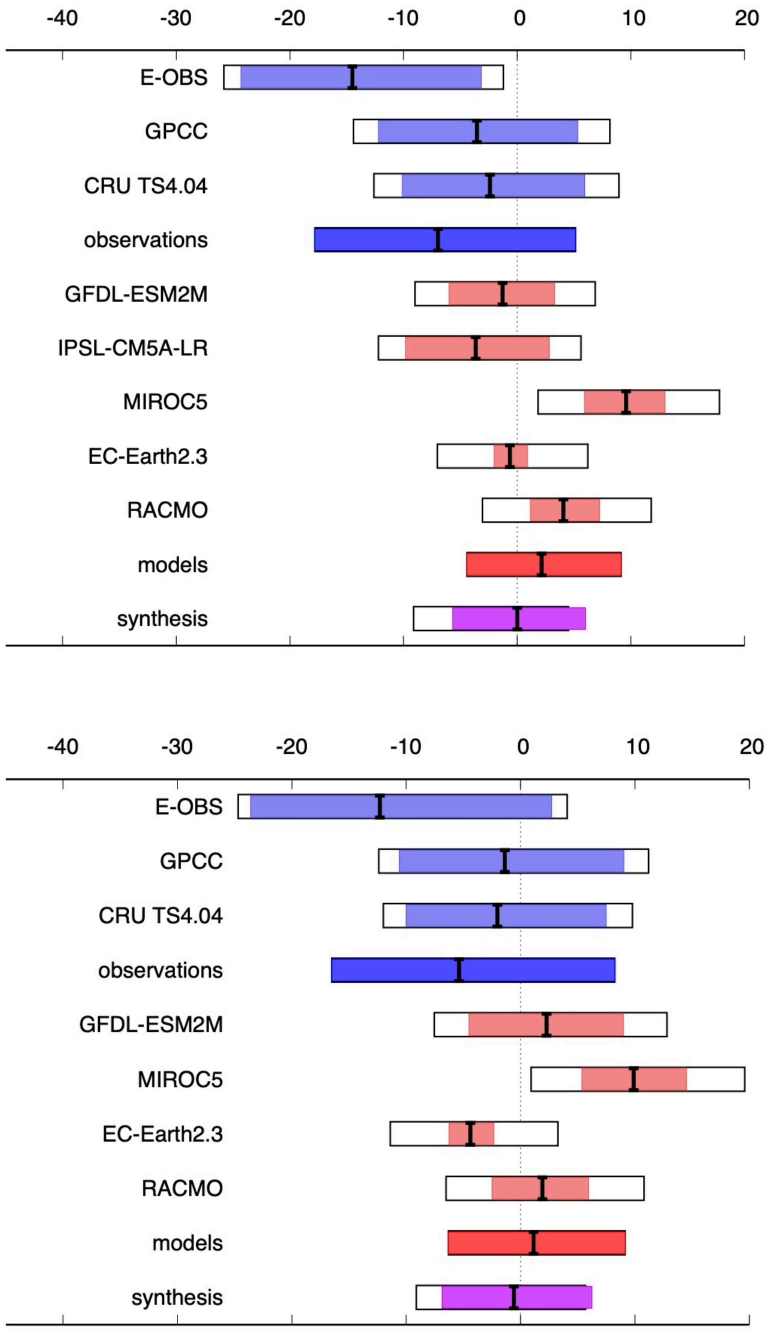


Figure 2. Synthesized values of trends for precipitation [percentage change] for the Rhine catchment (top) and the Meuse catchment (bottom). Vertical black markers are the average trends, colored bars denote the 95% CI. Blue represents observations and reanalyses, red represents models. Coloured bars denote natural variability, white bars also take representativity or model errors into account (only if applicable). In the synthesis, the magenta bar denotes the weighted average (weighted with the inverse total variances) of observations and models and the white bar denotes the unweighted average.

In both the Rhine and Meuse basin we see no significant trend in precipitation (Figure 2).
Considering trend detection (observations only), the trend in E-OBS is stronger in a negative direction than the trends in the GPCC and CRU TS4.04 data. This is partly because of the difference in the years used to compute the trend: the trend in GPCC and CRU TS4.04 becomes increasingly negative as well when using only data from 1950 onwards. However, even when using the same, shorter period, the trend in E-OBS is more pronounced than the trend in GPCC and CRU TS4.04. For the synthesis we use as much data as available. Each bar can be viewed as representing the result for each data set individually, as would be reported by a study using that data set alone.

The E-OBS dataset was recently extended back to 1920. As an additional test, we used the new extended data set to calculate the trend with E-OBS data for the years 1920-2019. This gives a trend of -15 % (95% confidence interval, CI, -24 to -6 %) compared to -14% (95% CI -24 to -3 %) for 1950-2019 data, i.e., basically unchanged. For the Meuse basin using years 1920-2019 gives a trend of -6 % (-16 to 8 %) compared to -12 % (95% CI -24 to 3 %) for the shorter time series, which is still more negative than the trend in the GPCC and CRU datasets. Note that the previous version of E-OBS (data starting in 1950) is used for the synthesis since that is the same dataset as was used in Philip et al. (2020). The conclusions drawn from the synthesis with E-OBS 1950-2020 are still valid.

Models show a mixed picture for the trend in precipitation in both basins, ranging from a small negative to a small positive trend. On average we see no significant trend in models, taking a measure of model spread into account (the white extensions of the bars). Synthesizing observational and model results together we conclude that there is no significant trend in precipitation over the Rhine and Meuse basins.

Extending the precipitation analysis to the future, we do not see large differences between the analysis of past model runs and runs up to 2050.

2.2 Temperature

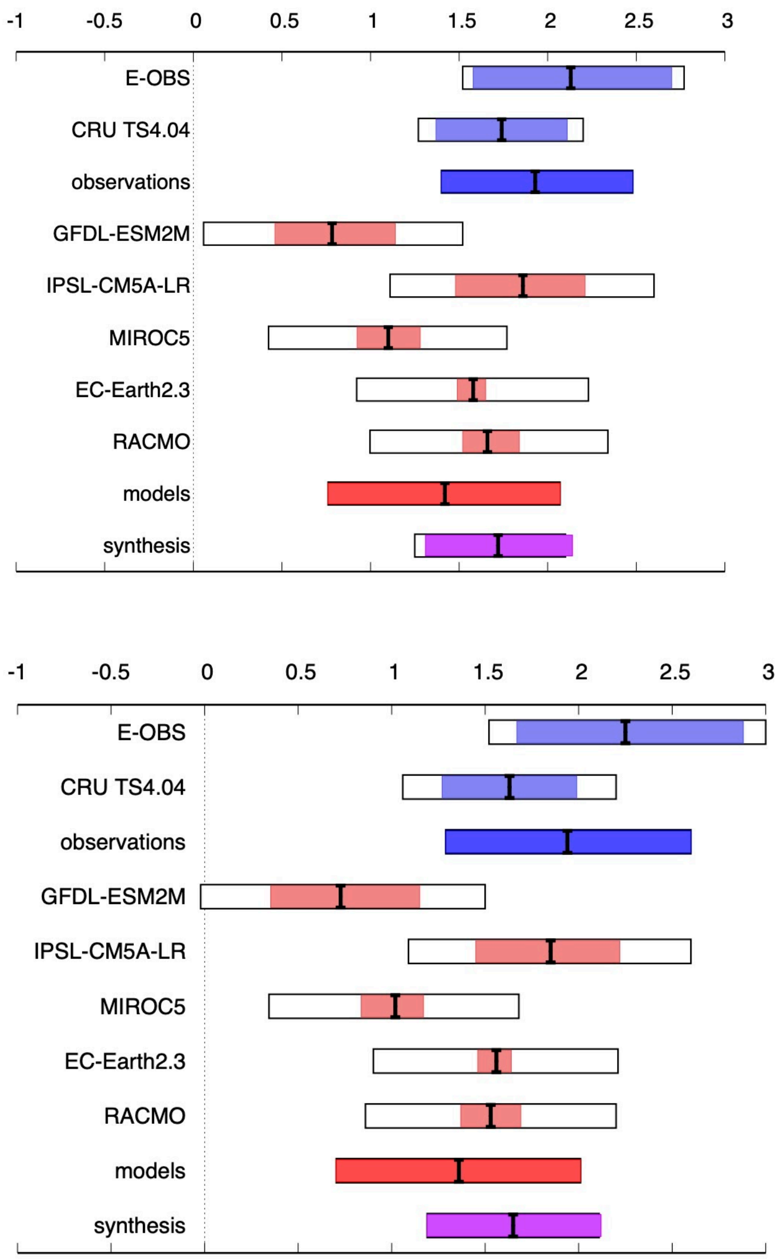


Figure 3. Similar to Figure 2 but for synthesized values of change in temperature [absolute change in K] for the Rhine catchment (top) and the Meuse catchment (bottom).

Results for temperature are summarised in Figure 3. Two observational data sets were used to assess observed trends in temperature. The years included in the assessment influence the result. If the years included in CRU are restricted to start in 1950 (to be the same as for E-OBS), then the CRU and E-OBS trend becomes comparable. Similarly, using the recently extended version of E-OBS starting in 1920, the E-OBS trends for the Rhine and Meuse basins approach that of CRU (starting 1901). This implies that our trend measure, a regression on the smoothed global mean surface temperature (GMST), is less invariant under the start date then for summer half year temperatures in the Netherlands inland region, see Table 1.

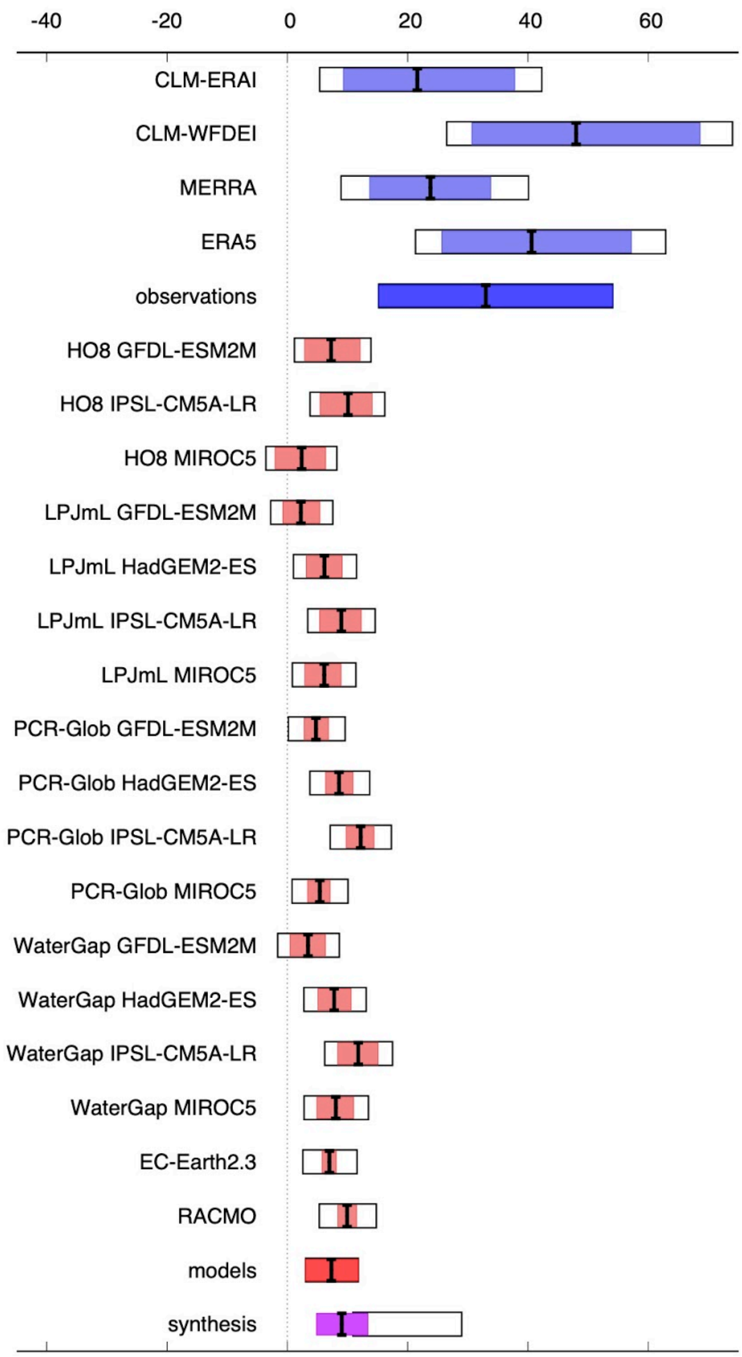
Table 1. Change in temperature over 1900-2018 [absolute change in K] for E-OBS data with different starting years.

Region	E-OBS 1950-2019	E-OBS 1920-2019	CRU TS4.04 1901-2019
Netherlands inland	2.0 (1.5 … 2.6)	1.7 (1.3 … 2.1)	1.4 (1.1 … 1.8)
Rhine	2.1 (1.6 … 2.7)	1.5 (1.1 … 2.0)	1.7 (1.4 … 2.1)
Meuse	2.3 (1.7 … 2.9)	1.5 (1.0 … 1.9)	1.6 (2.3 … 2.0)

Of the model data analysed, the GFDL model is a low outlier, which holds also if only using the years from 1950. MIROC has a best estimate significantly lower than observed, but becomes closer to observations when data starting from 1950 is used. These two modes pull the model synthesis towards slightly lower trends compared with observations. The other three models analyzed, IPSL, EC-Earth and RACMO, show comparable values to the observed values. Note that although RACMO is downscaled from EC-Earth, both are included because the results show slightly different behaviour.

As the modelled and observed trends agree we combine them to a single synthesis statement. The purple bar, a weighted average of the synthesized observations (bright blue) and models (bright red) gives the overall result, which is a significant positive trend with a best estimate lying between 1.5 and 2 K, for both the Rhine and the Meuse. As 6-month averaged temperature has a large decorrelation length, it is not surprising that these results for the Rhine and Meuse are so similar.

2.3 PET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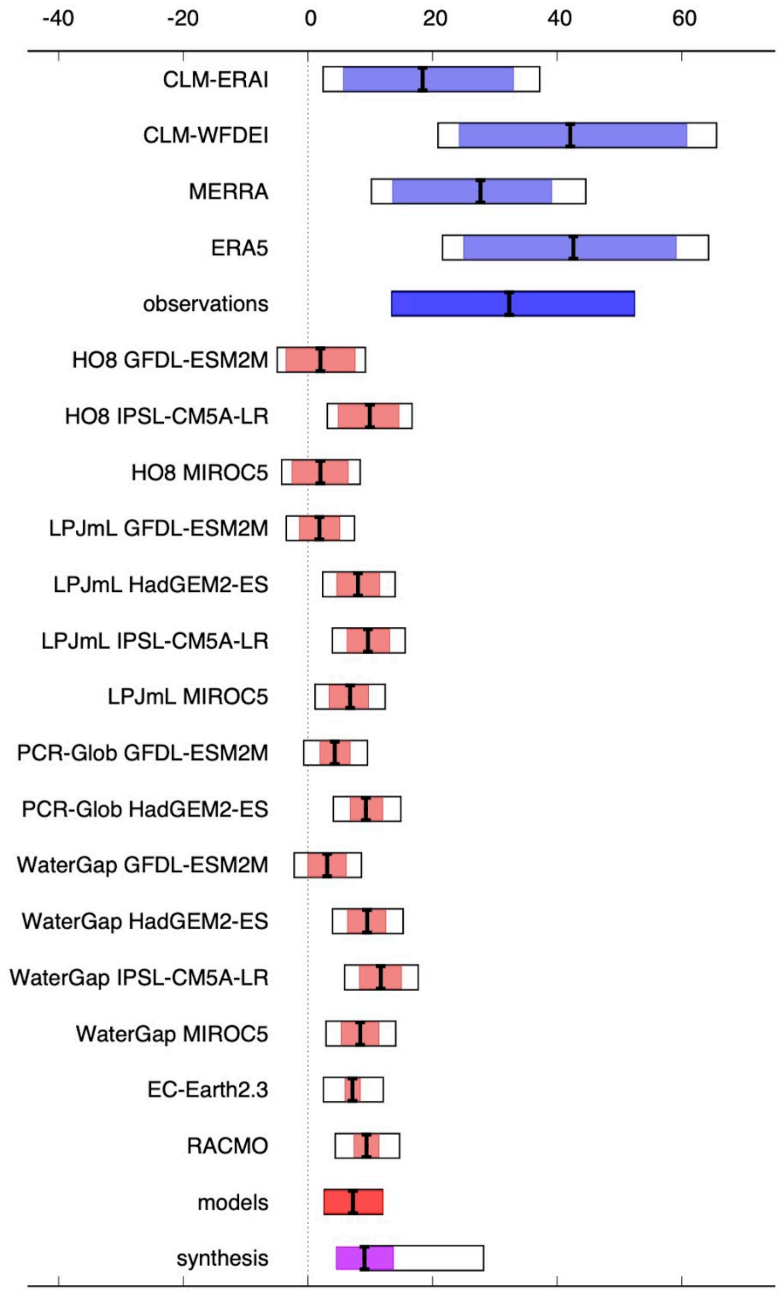


Figure 4. Similar to Figure 2 but for synthesized values of change in PET [percentage change] for the Rhine catchment (top) and the Meuse catchment (bottom).

In contrast to the other variables studied, for trends in PET there is no agreement between observations and models (see Figure 4). Several possible reasons or factors contributing to this mismatch are:

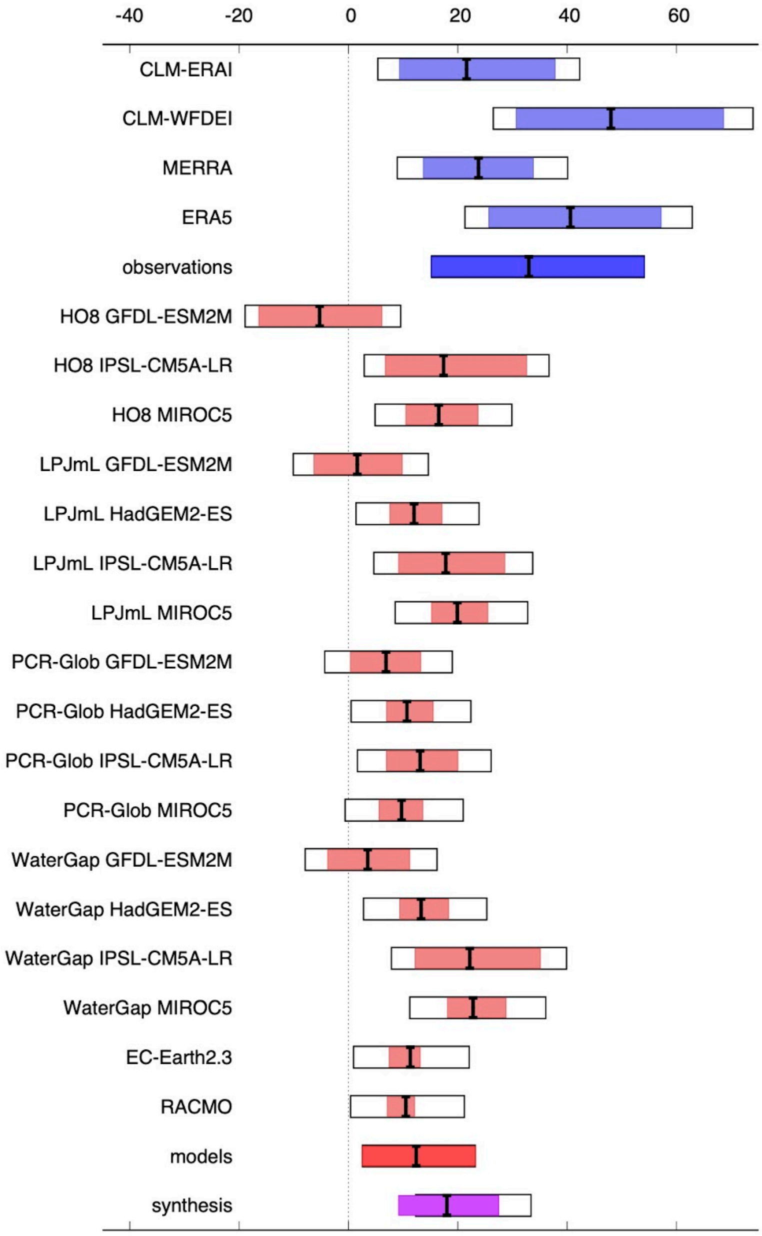
- The short observational time series and the much longer model runs. As shown for the other variables, differences in the time period analysed can affect the trend. Reliable real-world data for PET, in this case from reanalyses, only starts in 1979, which is later than for the other two variables, whereas many model runs start around 1860.

- The influence of differences in the trend in temperature on PET values. Some modelled temperature trends are lower than observed temperature trends, and the same holds for PET. Models GFDL and MIROC have the lowest trends for both PET and temperature results.
- The influence of the differences in the trend in incoming surface solar radiation on PET values. This variable shows an increasing trend on two time scales. There is an increase from the 1980's to now due to decreasing aerosol concentrations, this is evident in the observed trend over 1979-now. Models that include realistic aerosol concentrations show decreasing global radiation up to around 1980 and an increase thereafter. Averaged over a long period, the modelled trend is resultantly lower than for the subset 1979-now.

Beside these differences there is a trend towards more radiation in the summer half year in both models and observations thought to be due to decreasing cloud cover.

Analysing only data between 1979-2020 for models we obtain on average higher positive PET trends, with larger error margins due to the shorter series, see Figure 5. The syntheses of model data for PET gives a range for the 95% CI of 3% to 23% for recent years and 3% to 12% for all data for the Rhine catchment, and 5% to 24% for recent years and 3% to 12% for all data for the Meuse. This indicates that part of the discrepancy between models and observations is indeed related to the short observational time series. We conclude that both the difference in temporal extent of the data sets and the relatively low trend in temperature in some models contribute to the large difference between modelled and observed PET trends.

Summarising, we conclude that there is a trend towards higher PET, although we cannot quantify the trend in detail. Therefore we restrict ourselves to providing an estimate of the lower bound of this trend. The synthesis of model-only results indicates a change of at least 3%, whereas the observational analysis over a relatively short period indicates a percentage change of at least 14%. However, this observational value is specific to the period 1979-2020 and it is inflated by the decrease in air pollution and hence is not representative for the influence of climate change since 1900.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PCR-Glob MIROC5
WaterGap GFDL-ESM2M
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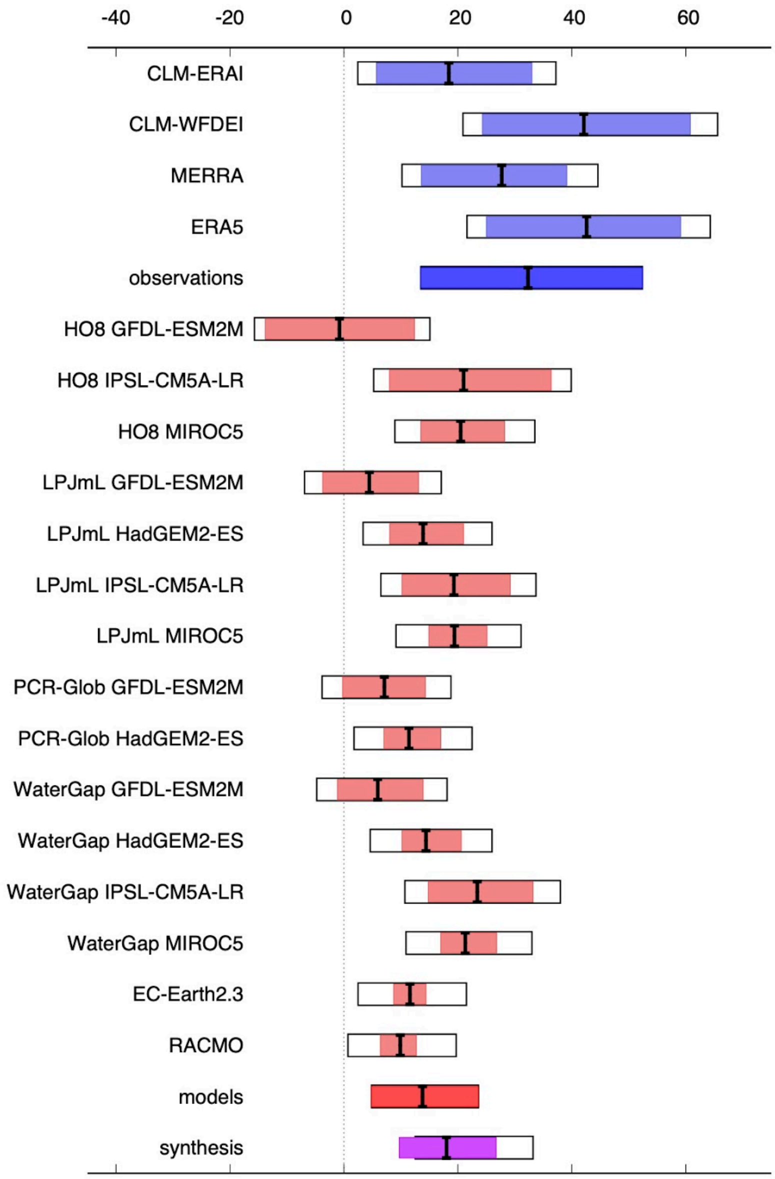

Figure 5. Similar to Figure 4 but only considering data for the period 1979-2020 for the Rhine catchment (top) and the Meuse catchment (bottom).

3 Discharge trend detection

For discharge, trend detection was performed on Apr-Sep averaged discharge only. This time scale compares well to the analyses of other variables in this study over the Rhine and Meuse basins. The Apr-Sep averaged discharge time series are shown in Figure 6. For the Rhine, the trend is -9% (95% CI -19 to 3%) which is significant at p=0.1. For the Meuse we find a negative trend of -30% (95% CI -45 to -13%), which is significant at p=0.05.

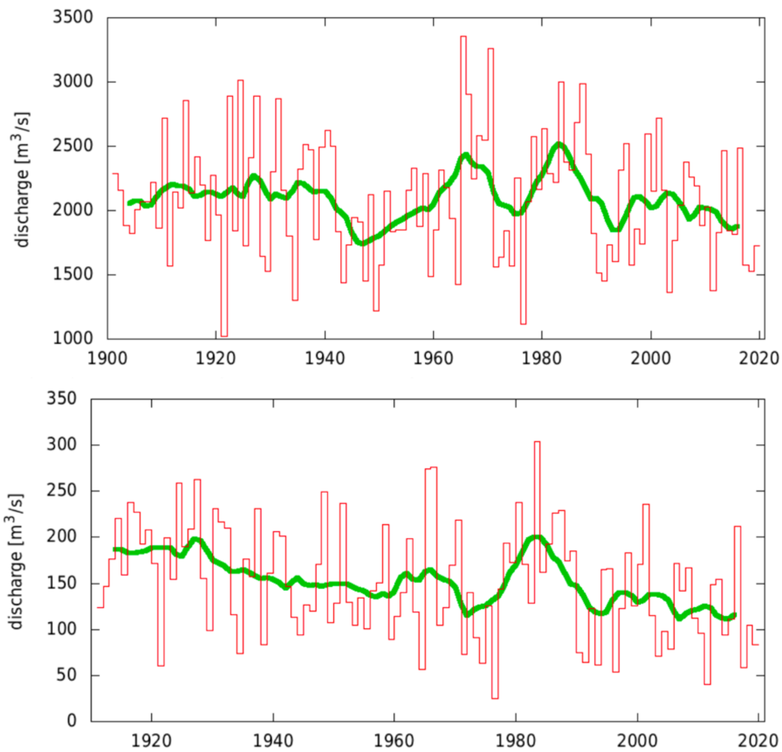

Figure 6. Apr-Sep averaged discharge [m^3/s] over the Rhine (top) and Meuse (bottom) basins. Green lines show the 10-year running average.

The trends in discharge are influenced by many factors. Given that we did not find a significant trend appearing above natural variability in precipitation, it is not likely that changes in precipitation are the main driver of the trend in discharge. If potential evaporation is representative for actual evaporation, the trend towards higher temperature and PET logically would result in lower discharge rates. However, we did not investigate the influence of human activities other than those via GMST. It is well possible that factors other than human induced climate change, e.g., the operation of reservoirs or the abstraction of water for irrigation or other purposes, have changed the discharge at Lobith and

Monsin/Eijsden. These conclusions on the origin of a possible trend agree with those drawn by Kramer (2018) on discharge over 1901-2015 (Rhine) and 1911-2014 (Meuse), although they did not (yet) find significant trends for Lobith and Monsin discharge. Note that they used Monsin (1911-2016) rather than Eijsden/Monsin.

4 Conclusions

Precipitation
Using observations and model data we do not find a significant trend in precipitation over the Rhine or Meuse basin. Best estimates of the synthesized 1900-2018 percentage change in intensity are close to zero.

Temperature
For temperature, the modelled and observed trends agree, and we find significant positive changes in both the Rhine and Meuse basin. Best estimates of the increase between 1900 and 2018 lie between +1.5 and +2 K.

PET
Modelled PET trends are lower than observed PET tends, but both indicate a significant positive trend. The synthesis of model-only results indicates a change of at least 3% between 1900 and 2018.

Discharge
The observed discharge time series for Lobith (Rhine) and Monsin/Eijsden (Meuse) indicate a negative trend, however, the observed discharge series are also subject to human induced changes not related to climate change. Using observations alone we cannot determine to what extent the trend is attributable to climate change.

Acknowledgements

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Appendix. Model validation

In this Appendix we show all model validation results including the final decision about inclusion or exclusion of the model from the analysis. For the check on the pattern and seasonal cycle this an expert-judged categorical check. For PET the pattern check is considered lower priority and not included, as the GCMs passed the pattern check for temperature and precipitation already.

Table A1. Model validation over 1950-2020 of the precipitation for the Rhine basin, showing the mean precipitation over Apr-Sep over the Rhine basin [mm/day], a check on the average precipitation pattern and seasonal cycle [okay, reasonable, bad], the fit parameters of a Gaussian fit which scales with GMST (including 95% Confidence Intervals) and the final decision on the validation.

dataset	mean	pattern	seasonal cycle	sigma/mu (95% CI)	decision
E-OBS	2.637			-0.142 (-0.164... -0.115)	
GPCC	2.759			-0.137 (-0.158... -0.109)	
CRU TS4.04	2.799			-0.128 (-0.147... -0.104)	
GFDL-ESM2M	3.772	ok/reas	ok/reas	-0.126 (-0.151... -0.098)	yes
HadGEM2-ES	2.920	ok	reas/bad	-0.174 (-0.190... -0.156)	No: only overlap and seasonal cycle reas/bad.
IPSL-CM5A-LR	2.742	ok/reas	ok/reas	-0.132 (-0.147... -0.111)	yes
MIROC5	3.664	ok	ok	-0.130 (-0.143... -0.116)	yes
EC-Earth2.3	3.298	ok	ok	-0.121 (-0.125... -0.115)	yes
RACMO	2.745	ok	ok	-0.138 (-0.143... -0.132)	yes

Table A2. Similar to Table A1 but for the Meuse basin.

dataset	mean	pattern	seasonal cycle	sigma/mu (95% CI)	decision

E-OBS	2.298			-0.163 (-0.192... -0.132)	
GPCC	2.328			-0.160 (-0.191... -0.130)	
CRU	2.518			-0.154 (-0.183... -0.121)	
GFDL-ESM2M	3.086	ok/reas	ok	-0.159 (-0.182... -0.129)	yes
HadGEM2-ES	1.973	ok	bad	-0.221 (-0.240... -0.199)	no: no overlap, bad seasonal cycle.
IPSL-CM5A-LR	1.834	ok/reas	reas/bad	-0.213 (-0.250... -0.168)	No: only reas fit parameters, and reas/bad seasonal cycle.
MIROC5	3.180	ok	ok	-0.161 (-0.175... -0.146)	yes
EC-Earth2.3	2.983	ok	ok	-0.156 (-0.162... -0.150)	yes
RACMO	2.535	ok	ok	-0.169 (-0.176... -0.162)	yes

Table A3. Model validation over 1950-2020 of the temperature for the Rhine basin, showing the mean temperature over Apr-Sep over the Rhine basin [°C], a check on the average temperature pattern and seasonal cycle, the fit parameters of a Gaussian fit which shifts with GMST (including 95% Confidence Intervals) and the final decision on the validation.

dataset	**mean**	**pattern**	**seasonal cycle**	**sigma (95% CI)**	**decision**
E-OBS	13.73			0.641 (0.531... 0.731)	
CRU TS4.04	14.15			0.611(0.503... 0.692)	
GFDL-ESM2M	12.37	reas	ok	0.645 (0.508... 0.755)	yes
HadGEM2-ES	15.25	ok	ok	0.890 (0.793... 0.973)	no, sigma too high
IPSL-CM5A-LR	12.90	ok	ok	0.719 (0.606... 0.809)	yes

MIROC5	15.62	ok	ok	0.587 (0.528... 0.636)	yes
EC-Earth2.3	11.72	ok	ok	0.619 (0.594... 0.646)	yes
RACMO	11.13	ok	ok	0.675 (0.648... 0.705)	yes

Table A4. Similar to Table A3 but for the Meuse basin.

dataset	mean	pattern	seasonal cycle	sigma (95% CI)	decision
E-OBS	13.95			0.660 (0.552... 0.746)	
CRU TS4.04	14.57			0.611 (0.507... 0.690)	
GFDL-ESM2M	14.32	reas	ok	0.719 (0.586... 0.811)	yes
HadGEM2-ES	16.78	ok	ok	0.987 (0.887... 1.082)	no, sd too high
IPSL-CM5A-LR	14.56	ok	ok	0.746 (0.626... 0.835)	yes
MIROC5	17.18	ok	ok	0.595 (0.542... 0.646)	yes
EC-Earth2.3	12.96	ok	ok	0.655 (0.624... 0.682)	yes
RACMO	11.80	ok	ok	0.691 (0.660... 0.721)	yes

Table A5. Model validation over 1979-2020 of PET for the Rhine basin, showing the mean precipitation over Apr-Sep over the Rhine basin [mm/day], a check on the average precipitation pattern and seasonal cycle, the fit parameters of a Gaussian fit which scales with GMST (including 95% Confidence Intervals) and the final decision on the validation.

dataset (Reanalysis or GCM)	dataset (Hydrological model)	mean	seasonal cycle	sigma/mu (95% CI)	decision
CLM-ERAi		2.748		0.057 (0.041... 0.071)	
CLM-WFDEI		2.605		0.054 (0.040... 0.065)	

MERRA		3.092		0.051 (0.036… 0.062)	
ERA5		3.246		0.070 (0.048… 0.088)	
HO8	GFDL-ESM2M	3.452	ok	0.078 (0.059… 0.091)	yes
	HadGEM2-ES	3.707	ok	0.118 (0.089… 0.139)	no
	IPSL-CM5A-LR	3.612	ok	0.071 (0.056… 0.082)	yes
	MIROC5	3.594	ok	0.073 (0.054… 0.089)	yes
LPJmL	GFDL-ESM2M	3.675	ok	0.054 (0.040… 0.064)	
	HadGEM2-ES	3.788	ok	0.063 (0.050… 0.073)	
	IPSL-CM5A-LR	3.830	ok	0.054 (0.042… 0.063)	
	MIROC5	3.786	ok	0.049 (0.035… 0.062)	
PCR-Glob	GFDL-ESM2M	2.592	ok	0.043 (0.031… 0.053)	
	HadGEM2-ES	2.634	ok	0.052 (0.039… 0.063)	
	IPSL-CM5A-LR	2.631	ok	0.036 (0.028… 0.043)	yes
	MIROC5	2.618	ok	0.038 (0.029… 0.045)	yes
WaterGap	GFDL-ESM2M	2.738	ok	0.053 (0.040… 0.062)	

	HadGEM2-ES	2.822	ok	0.059 (0.045… 0.068)	
	IPSL-CM5A-LR	2.860	ok	0.054 (0.041… 0.063)	
	MIROC5	2.827	ok	0.049 (0.035… 0.061)	
EC-Earth2.3		3.115	ok	0.065 (0.061… 0.070)	
RACMO		2.680	ok	0.060 (0.057… 0.063)	

Table A6. Similar to Table A5 but for the Meuse basin.

dataset (Reanalysis or GCM)	**dataset (Hydrological model)**	**mean**	**seasonal cycle**	**sigma/mu (95% CI)**	**decision**
CLM-ERAi		2.694		0.060 (0.044… 0.071)	
CLM-WFDEI		2.609		0.059 (0.045… 0.070)	
MERRA		2.931		0.063 (0.049… 0.073)	
ERA5		3.066		0.072 (0.055… 0.085)	
HO8	GFDL-ESM2M	3.813	ok	0.093 (0.072… 0.105)	yes
	HadGEM2-ES	4.067	ok	0.152 (0.117… 0.175)	no, too high sigma/mu
	IPSL-CM5A-LR	4.004	ok	0.086 (0.066… 0.101)	
	MIROC5	3.946	ok	0.081 (0.059… 0.098)	

LPJmL	GFDL-ESM2M	3.633	ok	0.055 (0.041… 0.062)	
	HadGEM2-ES	3.736	ok	0.075 (0.059… 0.086)	
	IPSL-CM5A-LR	3.789	ok	0.051 (0.040… 0.059)	
	MIROC5	3.720	ok	0.051 (0.037… 0.062)	
PCR-Glob	GFDL-ESM2M	2.637	ok	0.047 (0.035… 0.056)	yes
	HadGEM2-ES	2.680	ok	0.062 (0.047… 0.074)	
	IPSL-CM5A-LR	2.673	ok	0.038 (0.031… 0.043)	no, too low sigma/mu
	MIROC5	2.658	ok	0.041 (0.031… 0.048)	no, too low sigma/mu
WaterGap	GFDL-ESM2M	2.742	ok	0.051 (0.039… 0.059)	
	HadGEM2-ES	2.826	ok	0.065 (0.051… 0.076)	
	IPSL-CM5A-LR	2.873	ok	0.047 (0.037… 0.055)	yes
	MIROC5	2.820	ok	0.046 (0.033… 0.057)	yes
EC-Earth2.3		3.178	ok	0.068 (0.064… 0.072)	
RACMO		2.504	ok	0.075 (0.070… 0.078)	

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