https://doi.org/10.5194/egusphere-2026-351
Preprint. Discussion started: 10 February 2026

A simple weather generator that converts statistical information from downscaled global climate models to 24-hr precipitation input for hydrological models

Rasmus E. Benestad[1]

[1]The Norwegian Meteorological Institute, Henrik Mohns plass 1, Oslo, Norway

Correspondence: Rasmus Benestad (rasmus.benestad@met.no)

Abstract. A weather generator can provide a link between downscaled precipitation or temperature statistics on the one hand, and impact models that require daily data as input on the other. A simple design for a weather generator for daily precipitation is described together with results from an evaluation against rain gauge observations from Norway, Ghana and Romania. The results from the evaluation indicate that it gives a close approximation of the observed characteristics for daily precipitation in different climatological settings. A simple weather generator for daily temperature is also presented, and an assessment of its performance also suggests a reasonable skill level. These weather generators are part of the free and open-access R-package 'esd'.

1 Introduction

Global climate models (GCMs) are the most important tool for simulating future climatic conditions, such as World Climate Research Programme's (WCRP) Coupled Model Intercomparison Project (CMIP) phase 5 and 6 (Meehl et al., 2014; Eyring et al., 2015; IPCC, 2021). Numerical experiments have revealed that a single GCM starting with different initial conditions can produce different regional outlooks due to inherent chaotic (non-deterministic) decadal variability (Deser et al., 2012, 2020), and an important consideration for robust information about a future climate is to involve large GCM ensembles. Furthermore, the GCMs are only designed to reproduce large-scale processes, phenomena and conditions with skill, and are known to have a minimum skilful scale (Takayabu et al., 2015). However, detailed small-scale information is needed for inferring local consequences of climate change, such as impact on nature or for risk analysis to inform climate change adaptation (IPCC, 2023). For instance, hydrological models often require sequences of hourly or daily local rainfall and temperature, and are often calibrated with in-situ historical rain gauge measurements (Engeland and Alfredsen, 2020). When such models are used for assessing future consequences of a continued global warming, they need new input data which both represent the same type of basic situation as in the past but also account for a shift in the weather statistics associated with climate change.

Skilfully reproduced large-scale information distilled from GCM simulations can be combined with information about how local details depend on the large scales in what is known as *downscaling*, for which there traditionally have been two main approaches: (1) dynamical, performed with regional climate models (RCMs), and (2) empirical-statistical downscaling (ESD). Downscaling with RCMs and ESD are based on different assumptions and have different strengths and weaknesses. RCMs use

https://doi.org/10.5194/egusphere-2026-351
Preprint. Discussion started: 10 February 2026

physics-based equations to compute weather information with a higher resolution than GCMs, with model time steps on the order of a few minutes for typically hundreds of variables for each grid cell within a regional domain. This is computationally very expensive, limiting the number of GCM runs that can be downscaled dynamically.

ESD, on the other hand, determines statistical relationships between large scale structures provided by global models and local climatic conditions, and is typically carried out for one or two variables. This makes ESD computationally cheap and enables it to be applied to large multi-model ensembles of GCM simulations (Schuler et al., 2025; Benestad et al., 2025). It is best suited for downscaling large multi-model ensemble when ESD involves the estimation of statistical parameters describing the shape of mathematical curves ("downscaling climate"), as opposed to estimating each individual data point ("downscaling weather"). Moreover, the wet-day frequency f_w and wet-day mean precipitation μ are two key parameters for 24-hr precipitation which are found to change with a global warming (Benestad et al., 2019, 2025). However, this information can only be utilised in subsequent hydrological models if it can be unfolded as a sequence of daily precipitation amounts through a conditional weather generator (WG).

A WG can be described as a 'weather dice' that produces random (stochastic) data with prescribed statistical properties and structure. There are numerous types of WGs (Wilks, 1992; Wilks and Wilby, 1999; Mezghani and Hingray, 2009; Semenov and Barrow, 1997; Semenov and Brooks, 1999), however, none have been designed specifically to connect ESD, for which the output are the key parameters f_w and μ, to impact models that require daily precipitation as input data. In the SPRINGS project[1] the WG is part of a modelling chain that links the dispersion of waterborne pathogens to climate change, and ultimately outbreak of diarrhoea in Ghana and Romania. In other words, the WG facilitates a link that passes information from downscaling of GCMs on to hydrological models, and hence involves the generation of appropriate input data for hydrological models. Figure 1 shows a schematic of the simple WG, which in this case is designed to translate the downscaled key precipitation parameters f_w and μ to appropriate input data for hydrological models that need chronological sequences of daily rainfall from a single site.

2 Design of the simple weather generator for daily precipitation

One requirement of the WG in a model chain from global climate models to local hydrology is that it must be able to simulate changed rainfall due to changes in the wet-day frequency f_w and wet-day mean precipitation μ. In addition, it must provide a realistic representation of the rainy seasons, and this differs with traditional WGs based on a Markov-chain process, where the probability of a wet day depends on the previous day. Markov-chains are not defined for reproducing rainy seasons unless the probabilities vary with the seasons. Furthermore, the WG was designed to ensure that the number of rainy days and intensities are consistent with prescribed f_w and μ in addition to preserving their climatological properties in both f_w and μ. Since the mean precipitation is approximately the product of the two $\overline{x} \approx f_w \mu$ (not exact because of a cut-off threshold of 1 mm/day to distinguish between 'dry' and 'wet' days), the traditional rainfall climatology is expected to be representative if the climatologies for both f_w and μ are realistic.

[1] https://www.springsproject.eu/

https://doi.org/10.5194/egusphere-2026-351
Preprint. Discussion started: 10 February 2026

Simulations with the simple WG involve a process which loops over individual years, and for each year in the loop, it starts with estimating the total number of wet days based on the annual wet-day frequency for the respective year ($n_{wet} = 365.25 f_w$). The following step is then to distribute n_{wet} wet days over the year based on a climatological profile of f_w, which is used as a representation of the probabilities of a wet day on a given Julian day $p_{t,wet}$. To get an annual number of wet days that approximately is the same as n_{wet}, the entire curve describing the climatological profile is scaled so that the its mean value is equivalent to the annual wet-day frequency. Here $p_{t,wet}$ is the probability of a wet day for the Julian day $t \in [1, n_y]$ of the respective year, where n_y is 365 days for normal years and 366 days for leap years. A random number generator with a uniform distribution $W_t \in [0,1]$ is subsequently used to determine whether the individual Julian days are dry or wet according to $wet \Leftarrow W_t < p_{t,wet}$. The total number of wet days is then compared with n_{wet}, and a subsequent process removes or adds random wet days so that the final number matches the expected number n_{wet} associated with the annual wet-day frequency.

Once all the wet days have been dealt out throughout the year, they are given a daily rainfall amount. The simulation of the 24-hr amounts is based on an approximation by the exponential distribution $X \sim \exp(1/\mu)$ and subsequently adjusted by a scaling factor based on its return value $\beta' = 1.256 + 0.064 \ln(\tau)$, where τ is the return interval in terms of years (Benestad et al., 2019). In other words, the amounts are derived by a random number generator that produce n_{wet} numbers with an exponential distribution that subsequently are scaled by matching their probabilities according to prescribed distribution with the with the return interval $p = (365.25 * \tau)^{-1}$. In order to ensure a typical climatological profile in the intensity, both the wet-day mean precipitation μ climatology and the random daily amounts X_t are ranked, however, a noise term (a "smudge" factor) is introduced to the ranking of the climatology to avoid an unnaturally sharp peak in the climatology and avoid piling up the greatest precipitation amount on one particular day in the year. The default smudge factor is set to $\sigma_{\mu_{clim}} \overline{\mu_{clim}}/2$.

The WG is part of the free and open-source R-package `esd` (Benestad et al., 2015) 1.11.17 or later versions, and is available from https://github.com/metno/esd. The R-package provides documentation on its usage as well as some examples of use. It is designed with a flexibility in how it can be applied that is controlled by its arguments, and by default it uses daily rain gauge data from Bjørnholt, Oslo, Norway provided by the R-package, but this data can be replaced with data from any other location. For the use in Ghana with its rainy season, for instance, it needs local rain gauge data with a representative climatology. Unless prescribed, the annual wet-day frequency f_w and wet-day mean precipitation μ are estimated from the training rain gauge series, but their chronology is scrambled while keeping the temporal structure. The scrambling procedure involves a Fourier transform $F(y) = \sum_i a_i \cos(w_i t) + b_i \sin(w_i t)$, where the coefficient a_i and b_i determine the spectral power ($a_i^2 + b_i^2$), and involves changing these coefficients in a conservative way so that the spectral power is the same as in the original data. This is equivalent to introducing random phase shifts to all spectral components. If prescribed, on the other hand, the input of the WG may be (1) downscaled annual f_w and μ, or (2) the arguments may be single numbers which it will add to the scrambled annual f_w and μ derived from the training data. Some examples of how the WG can be used are provided in Algorithms 1–2 in the appendix.

https://doi.org/10.5194/egusphere-2026-351
Preprint. Discussion started: 10 February 2026

2.1 Evaluation of the weather generator for daily rainfall

The WG was tested and evaluated against daily rain gauge data from Norway, Ghana and Romania, and involved a comparison between observed and predicted daily amounts as well as wet/dry spell duration and climatology. Figure 2 shows the test results for Bjørnholt, Oslo, Norway, and a quantile-quantile plot (upper left) shows a good agreement between the daily precipitation amounts from the rain gauge measurements and the output of the WG. There are modest deviations in the upper quantiles, but this is also expected due to random sampling fluctuations. The lower left panel shows a comparison between the annual number of wet days (based on f_w), and the WG does not indicate the same modest trend as the observations since the annual precipitation statistics are randomly scrambled through a Fourier transform with scrambled phases. The right panels show a comparison between dry-spell and wet-spell durations, and the test indicated that the WG has a tendency to generate too many short wet spells as well as too many short dry spells. In this case, the spell durations had not been considered other than being a result of probabilities connected to the f_w climatology, but this aspect can be improved through a subsequent step where single wet days are moved to the nearest cluster of wet days.

Figure 3 shows further diagnostics of the WG, and the upper left panel compares the sum of total annual precipitation. The WG produced results which are comparable to the observations in terms of mean level and annual spikes. Furthermore, it reproduced the climatologies in terms of total precipitation (lower left), wet-day frequency (upper right) and wet-day mean precipitation (lower right) reasonably well.

Figures 4–5 show results from a similar evaluation for Akosombo in Ghana which also indicate a reasonable reproduction of the daily data. In this case, the data source was from Ghana Meteorological Agency that were shared within the SPRINGS project. A similar assessment was carried out for daily precipitation from Cluj-Napoca in Romania using rain gauge data from ECA&D (Klein Tank et al., 2002), and the results of the evaluation for Romania are presented in Figures 6–7. In sum, the evaluation of the simple WG for daily precipitation suggests that is gives an approximate description of various aspects of precipitation except for the statistics of dry and wet spell duration.

3 A simple weather generator for daily temperature

A WG simulating temperature has to deal with different considerations than a WG simulating precipitation, as the temperature is a continuous function in time as opposed to intermittent precipitation. Hence, there is no need to split the days into two categories for temperature, such as as 'dry' and 'wet' days for precipitation. Furthermore, daily temperature can be approximated by the normal distribution $T_{2m} \sim \mathcal{N}(\mu, \sigma^2)$, and hence the WG for daily temperature uses the mean and standard deviation as two input parameter. The WG for temperature also uses a phase-scrambled Fourier series, but uses it on the daily data in order to preserve time structures such as auto-correlations. The scrambled data then provide probability estimates, given its mean value and standard deviation. It is subsequently subject to a transform $\mathcal{N}(\mu_0, \sigma_0^2) \rightarrow \mathcal{N}(\mu_x, \sigma_x^2)$ where μ_x and σ_x are new mean and standard deviations. Some test results are shown in Figure 8 in the shape of a quantile-quantile plot, and they indicate a reasonably good reproduction of the temperatures. The time structure of the time series is designed to mimic that of observations by the use of scrambled Fourier series.

https://doi.org/10.5194/egusphere-2026-351
Preprint. Discussion started: 10 February 2026

4 Discussion

One interesting question is why there is such an underestimation of dry and wet spell durations in the data from the WG, at least for Bjørnholt, and one explanation may be that when the wet-day frequency climatology is flat ($f_w \in [0.29, 0.42]$) then the wet days tend to spread more out during a year, as opposed to when they are concentrated into more distinct rainy seasons. However, it may also be possible to shift some of the wet days simulated by the WG so that they also improve the spell length statistics, e.g. by moving single days to the closest group of consecutive wet days.

The respective simple WGs for precipitation and temperature have been designed for single series, and while they take annual statistics as input, which may correlate between nearby sites, they don't take into account possible daily systematic overlap between adjacent sites associated with precipitation or temperature with large spatial extent. Nor do they take into account potential correlation between daily precipitation and temperature. In some cases, there is no clear correlation between the two, such as in Akosombo (Figure 9), so that the different variables may be generated by different WG simulations. Furthermore, many sites only measure rainfall or temperature and not both. The covariance between daily temperature and precipitation may also be a problem with RCMs which also reproduce biased bi-variate statistical distributions (Benestad and Haugen, 2007).

Some variables may not change much or may be associated with a weak response in the impact model, and in this case, they may be represented by surrogate noise. For instance, Mtongori et al. (2015) used a crop model to evaluate the effect of either changed temperature or rainfall on maize crops, and found the model to be more sensitive to temperature change. There are other elements such as wind and short-wave radiation (sunlight) which may affect local hydrology, but there is no clear evidence that wind speed and direction are expected to change substantially. Short-wave radiation is affected by cloudiness and aerosols, and is not expected to change as a direct consequence of an increased greenhouse effect (but may nevertheless be affected by altered anthropogenic emissions of for example sulphur and soot).

The simple WGs presented herein were not designed to simulate changes in climatological profiles, and when annual statistics is used as input, it is also assumed that the climatology is stationary. However, a more advanced strategy is to use monthly statistics as input that may make it possible to simulate changes to the climatological profiles, e.g. based on downscaled monthly estimates of f_w and μ.

5 Conclusions

In summary, a simple weather generator developed for the SPRINGS project facilitates a link between the downscaled precipitation statistics from global climate models and hydrological models that require daily rainfall as input. It can take single numbers for f_w and μ as arguments, for instance from gridded maps, and simulate daily precipitation with a change to those parameters. The weather generator can also take annual statistics as arguments for f_w and μ, and use them rather than aggregated statistics from the training data. Hence, it facilitates a link between downscaled output from ensembles of global climate models and impact models. A weather generator for daily temperature uses annual mean temperature as well as standard deviation as input, and an evaluation of both WG types indicates that they give a reasonable reproduction of the observations.

https://doi.org/10.5194/egusphere-2026-351
Preprint. Discussion started: 10 February 2026

Code and data availability. Code for the WGs is available as part of the open-source R-package 'esd' version 1.11.21 from FigShare DOI:10.6084/m9.figshare.1160493.v18 (Benestad and Mezghani, 2026). Some of the data is provided as a part of the R-package, except for the rain gauge data from Ghana. The ECA&D data is public and available from https://www.ecad.eu/dailydata/.

Acknowledgements. This work has been supported by the project EU-SPRINGS (grant number is 101137255). I'm grateful for input and comments by Oskar A. Landgren.

https://doi.org/10.5194/egusphere-2026-351
Preprint. Discussion started: 10 February 2026

References

Benestad, R. and Mezghani, A.: esd for Windows, Mac \& Linux, https://doi.org/10.6084/M9.FIGSHARE.1160493.V18, 2026.

Benestad, R. E. and Haugen, J. E.: On Complex Extremes: Flood hazards and combined high spring-time precipitation and temperature in Norway, Climatic Change, 85, 381 – 406, 2007.

Benestad, R. E., Mezghani, A., and Parding, K. M.: esd V1.0, http://dx.doi.org/10.5281/zenodo.29385, 2015.

Benestad, R. E., Parding, K. M., Erlandsen, H. B., and Mezghani, A.: A simple equation to study changes in rainfall statistics, Environmental Research Letters, 14, 084 017, https://doi.org/10.1088/1748-9326/ab2bb2, 2019.

Benestad, R. E., Parding, K. M., and Dobler, A.: Downscaling the probability of heavy rainfall over the Nordic countries, Hydrology and Earth System Sciences, 29, 45–65, https://doi.org/10.5194/hess-29-45-2025, 2025.

Deser, C., Knutti, R., Solomon, S., and Phillips, A. S.: Communication of the role of natural variability in future North American climate, Nature Climate Change, 2, 775–779, https://doi.org/doi:10.1038/nclimate1562, 2012.

Deser, C., Lehner, F., Rodgers, K. B., Ault, T., Delworth, T. L., DiNezio, P. N., Fiore, A., Frankignoul, C., Fyfe, J. C., Horton, D. E., Kay, J. E., Knutti, R., Lovenduski, N. S., Marotzke, J., McKinnon, K. A., Minobe, S., Randerson, J., Screen, J. A., Simpson, I. R., and Ting, M.: Insights from Earth system model initial-condition large ensembles and future prospects, Nature Climate Change, 10, 277–286, https://doi.org/10.1038/s41558-020-0731-2, 2020.

Engeland, K. and Alfredsen, K.: Hydrology and water resources management in a changing world, Hydrology Research, 51, 143–145, https://doi.org/10.2166/nh.2020.000, 2020.

Eyring, V., Bony, S., Meehl, G. A., Senior, C., Stevens, B., Stouffer, R. J., and Taylor, K. E.: Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organisation, Geoscientific Model Development Discussions, 8, 10 539–10 583, https://doi.org/10.5194/gmdd-8-10539-2015, 2015.

IPCC: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, Tech. rep., Cambridge University Press, 2021.

IPCC: Climate Change 2022 – Impacts, Adaptation and Vulnerability: Working Group II Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, 1 edn., https://doi.org/10.1017/9781009325844, 2023.

Klein Tank, A. J. B. W., Konnen, G. P., Böhm, R., Demarée, G., Gocheva, A., Mileta, M., Pashiardis, S., Hejkrlik, L., Kern-Hansen, C., Heino, R., Bessemoulin, P., Müller-Westermeier, G., Tzanakou, M., Szalai, S., Pálsdóttir, T., Fitzgerald, D., Rubin, S., Capaldo, M., Maugeri, M., Leitass, A., Bukantis, A., Aberfeld, R., Engelen, A. F. V. v., Førland, E., Mietus, M., Coelho, F., Mares, C., Razuvaev, V., Nieplova, E., Cegnar, T., López, J. A., Dahlström, B., Moberg, A., Kirchhofer, W., Ceylan, A., Pachaliuk, O., Alexander, L. V., and Petrovic, P.: Daily dataset of 20th-century surface air temperature and precipitation series for the European Climate Assessment, International Journal of Climatology, 22, 1441–1453, https://doi.org/https://doi.org/10.1002/joc.773, 2002.

Meehl, G. A., Moss, R., Taylor, K. E., Eyring, V., Stouffer, R. J., Bony, S., and Stevens, B.: Climate Model Intercomparisons: Preparing for the Next Phase, Eos, Transactions American Geophysical Union, 95, 77–78, https://doi.org/10.1002/2014EO090001, 2014.

Mezghani, A. and Hingray, B.: A combined downscaling-disaggregation weather generator for stochastic generation of multisite hourly weather variables over complex terrain: Development and multi-scale validation for the Upper Rhone River basin, J. Hydrol., 377, 245–260, https://doi.org/10.1016/j.jhydrol.2009.08.033, 2009.

Mtongori, H., Stordal, F., Benestad, R., Mourice, S., Pereira-Flores, M., and Justino, F.: Impacts of climate and farming management on maize yield in southernTanzania, African Crop Science Journal, 23, 399, https://doi.org/10.4314/acsj.v23i4.9, 2015.

https://doi.org/10.5194/egusphere-2026-351
Preprint. Discussion started: 10 February 2026

Schuler, T. V., Benestad, R. E., Isaksen, K., Kierulf, H. P., Kohler, J., Moholdt, G., and Schmidt, L. S.: Svalbard's 2024 record summer: An early view of Arctic glacier meltdown?, Proceedings of the National Academy of Sciences, 122, e2503806 122, https://doi.org/10.1073/pnas.2503806122, 2025.

Semenov, M. and Barrow, E. M.: Use of a stochastic weather generator in the development of climate change scenarios, Climate Change, 35, 397–414, 1997.

Semenov, M. and Brooks, R. J.: Spatial interpolation of the LARS-WG stochastic weather generator in Great Britain., Climate Research, 11, 137–148, 1999.

Takayabu, I., Kanamaru, H., Dairaku, K., Benestad, R., Storch, H. v., and Christensen, J. H.: Reconsidering the quality and utility of downscaling, Journal of the Meteorological Society of Japan, 94A, 31–45, https://doi.org/10.2151/jmsj.2015-042, 2015.

Wilks, D.: Adapting stochastic weather generation algorithms for climate change studies, Climatic Change, 22, 67–84, 1992.

Wilks, D. S. and Wilby, R. L.: The weather generation game: a review of stochastic weather models, Progress in Physical Geography, 23, 329–357, https://doi.org/10.1177/030913339902300302, 1999.

https://doi.org/10.5194/egusphere-2026-351
Preprint. Discussion started: 10 February 2026

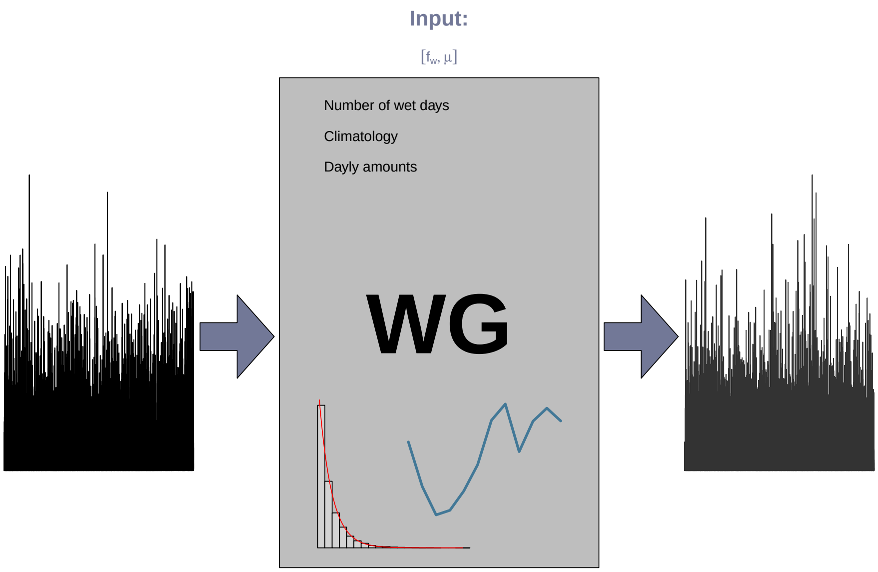

Figure 1. A schematic presentation of the WG which takes a sample station series for training and takes f_w and μ as input for simulating a sequence of 24-hr precipitation. It uses a sample rain gauge sequence for determining the climatologies in wet-day frequencies f_w and wet-day mean precipitation μ and hence how the number of wet days vary throughout the year (rainy seasons) as well as the intensity of the precipitation. If annual f_w and μ are not provided, it will estimate them from the sample data but shuffle the years by scrambling the Fourier Series phases.

https://doi.org/10.5194/egusphere-2026-351
Preprint. Discussion started: 10 February 2026

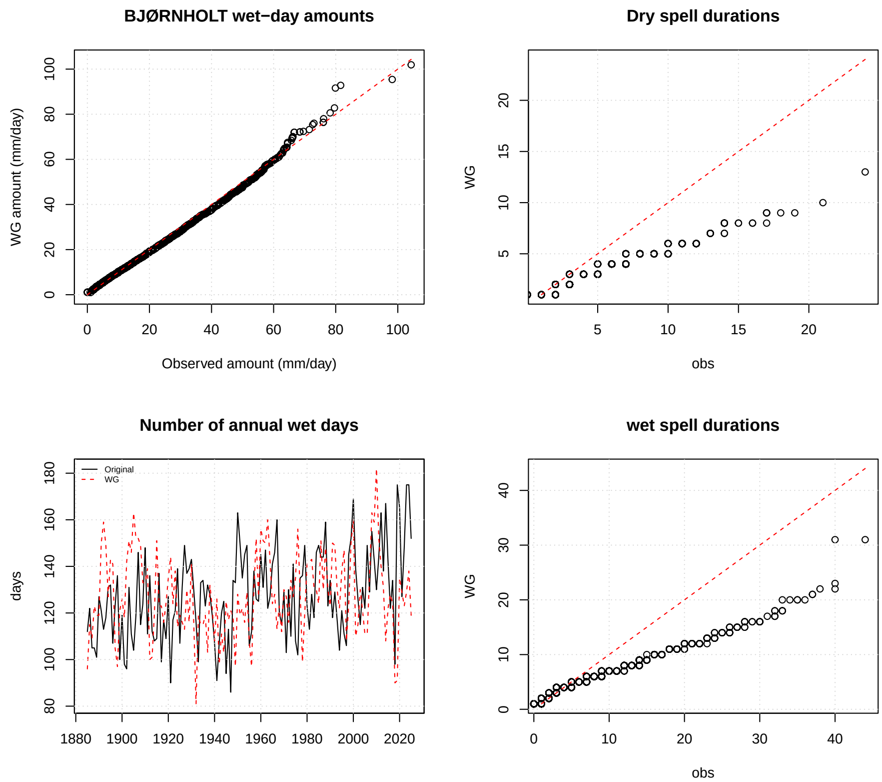

Figure 2. Test results for the WG applied to Bjørnholt rain gauge measurements north of Oslo, Norway. Upper left shows a quantile-quantile plot of the observed as opposed to simulated daily rainfall amounts; Lower left panel compares the number of annual wet days; upper right panel shows a quantile-quantile plot that compares the observed and simulated dry spell durations; and lower right shows a comparison between observed and simulated dry-spell durations. Data source: Norwegian Meteorological Institute (https://frost.met.no/index.html).

https://doi.org/10.5194/egusphere-2026-351
Preprint. Discussion started: 10 February 2026

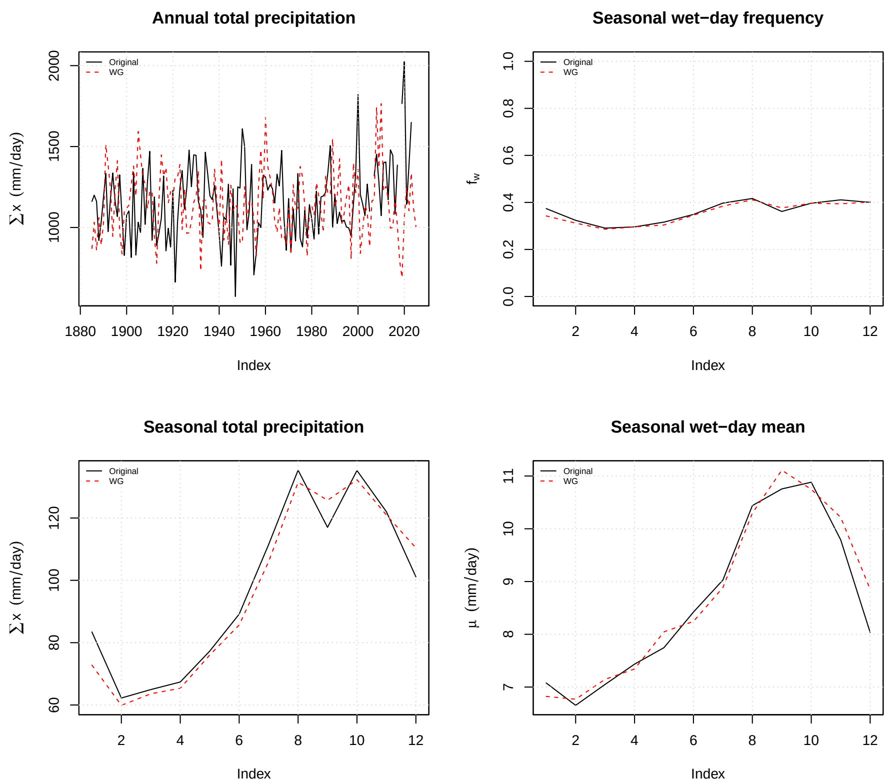

Figure 3. Test results which show a comparison between observed and simulated annual total precipitation (upper left), total rainfall distributed over the year (lower left), the climatology in f_w (upper right) and the climatology in μ (lower right). Data source: Norwegian Meteorological Institute

https://doi.org/10.5194/egusphere-2026-351
Preprint. Discussion started: 10 February 2026

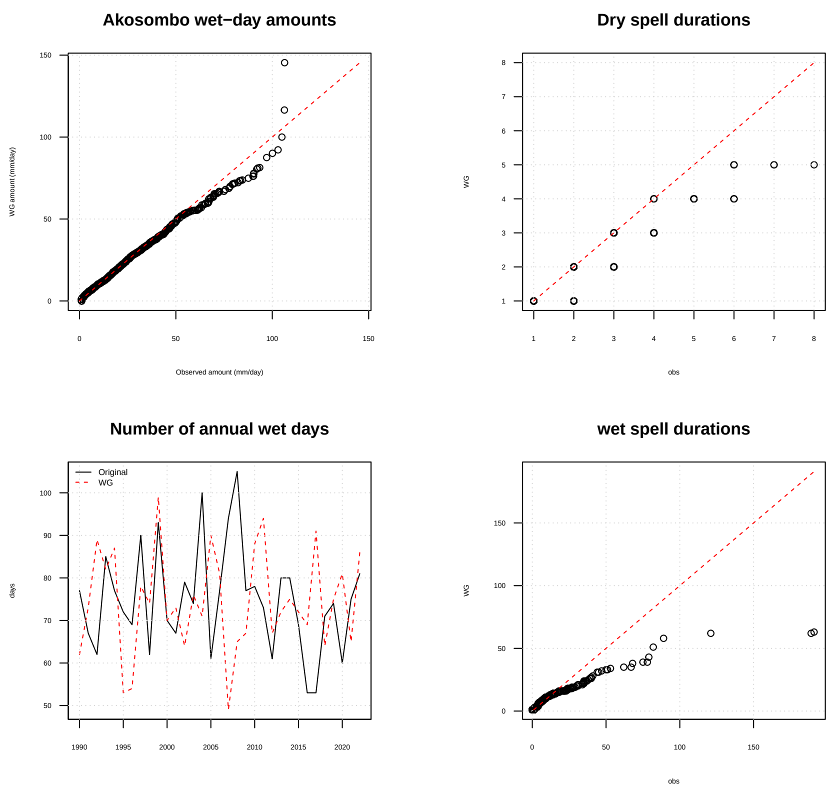

Figure 4. Same as Fig.1 but for Akosombo in Ghana. The data source is the Ghana Meteorological Agency.

https://doi.org/10.5194/egusphere-2026-351
Preprint. Discussion started: 10 February 2026

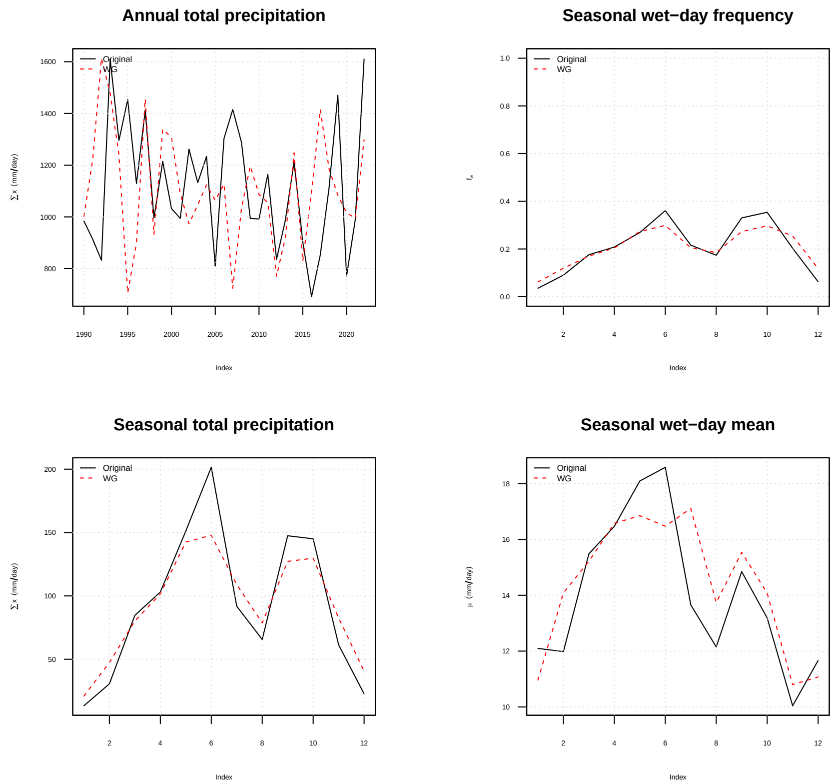

Figure 5. Same as Fig. 2. but for Akosombo in Ghana. The data source is the Ghana Meteorological Agency.

https://doi.org/10.5194/egusphere-2026-351
Preprint. Discussion started: 10 February 2026

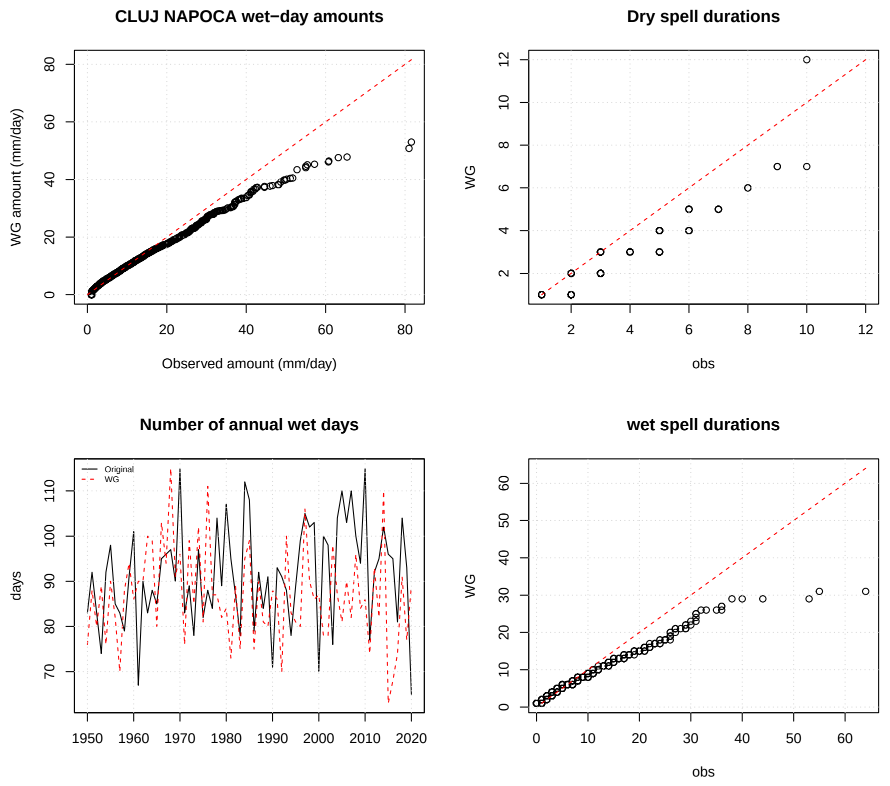

Figure 6. Same as Fig.1 but for Cluj Napoca in Romania. The data source is ECA&D.

https://doi.org/10.5194/egusphere-2026-351
Preprint. Discussion started: 10 February 2026

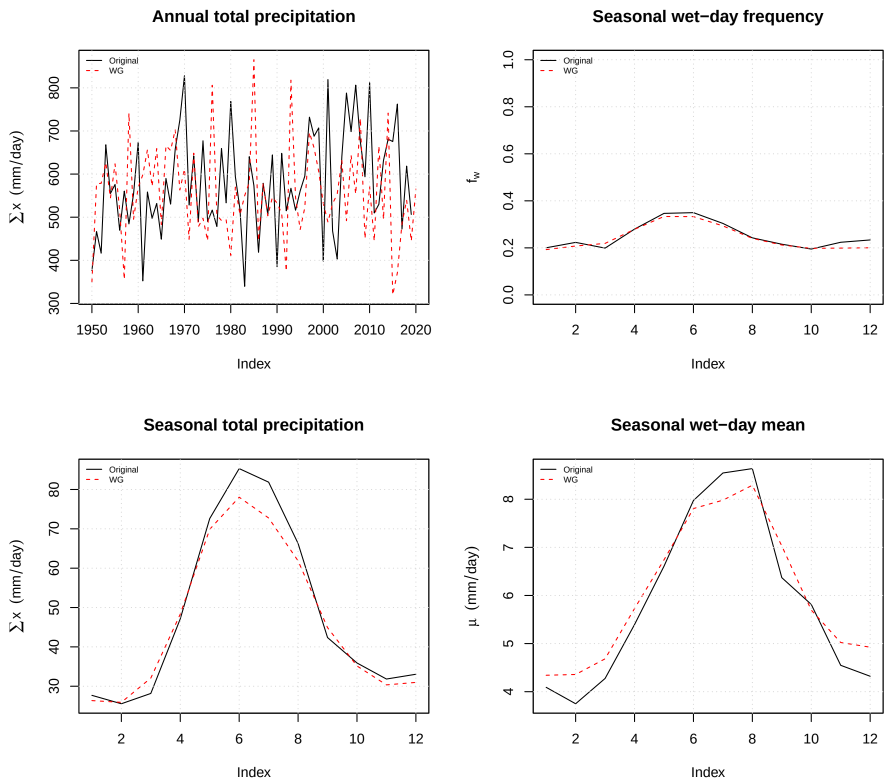

Figure 7. Same as Fig. 2. but for Cluj Napoca in Romania. The data source is ECA&D.

https://doi.org/10.5194/egusphere-2026-351
Preprint. Discussion started: 10 February 2026

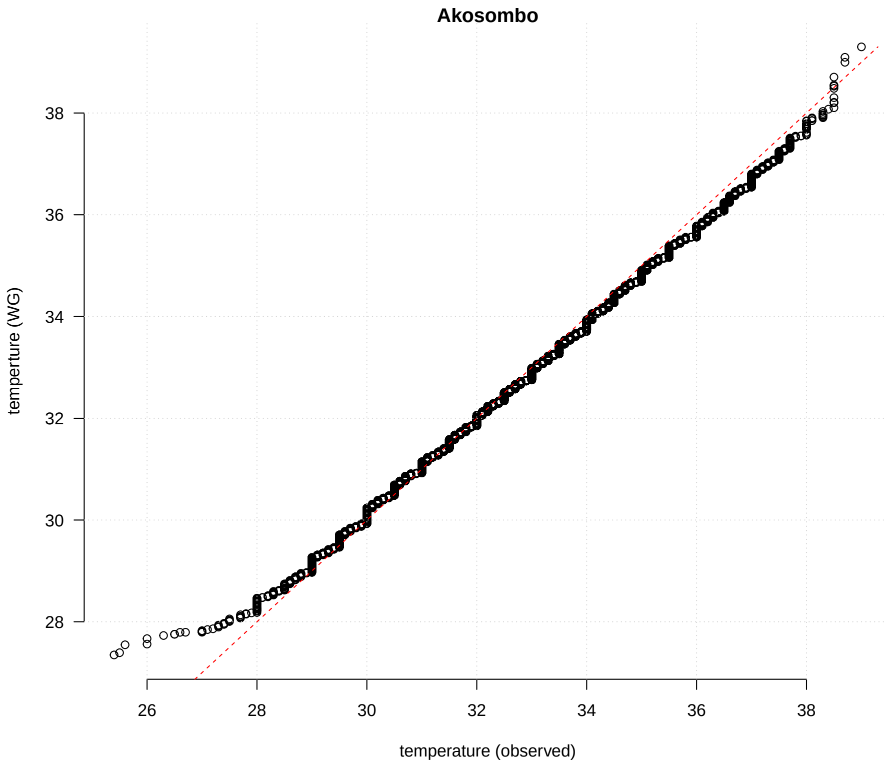

Figure 8. A quantile-quantile plot presenting test results for the simple WG for daily maximum temperature at Akosombo in Ghana. There was a some discrepancy in the lowest temperatures, but otherwise a good match with the observations.

https://doi.org/10.5194/egusphere-2026-351
Preprint. Discussion started: 10 February 2026

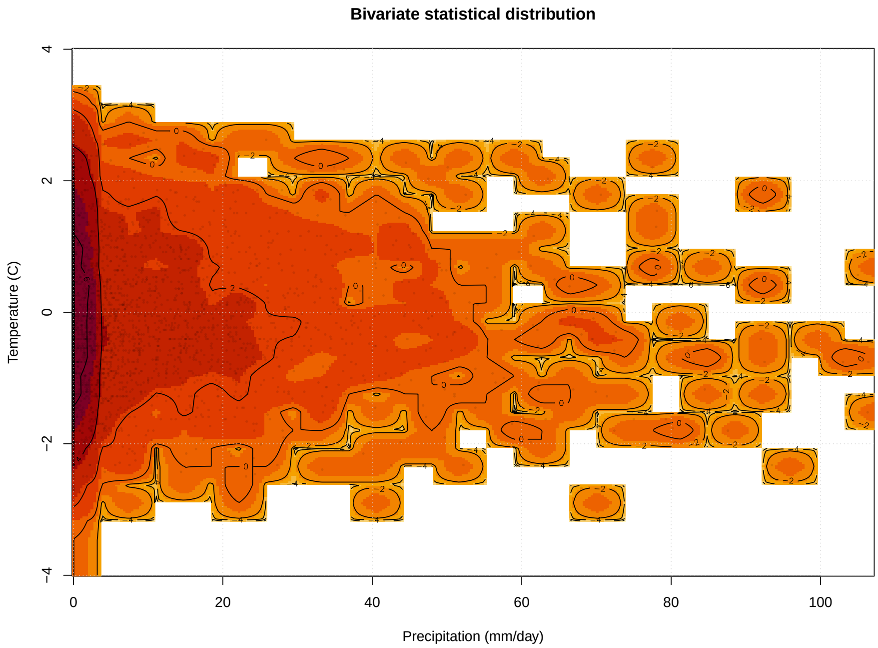

Figure 9. A bivariate statistical distribution or daily rainfall and daily mean temperature at Akosombo in Ghana shows that there is little covariance between the two variables.

https://doi.org/10.5194/egusphere-2026-351
Preprint. Discussion started: 10 February 2026

Algorithm 1 A simple demonstration of the use of the WG.

```
## The WG is a part of the R-package 'esd' and this chunk installs the esd package if it's not already
installed:

install.esd <- ("esd" %in% rownames(installed.packages()) == FALSE)
if (install.esd) {
  ## Install esd from GitHub:
  install.devtools <- ("devtools" %in% rownames(installed.packages()) == FALSE)
  if (install.devtools) {
    print('Need to install the devtools package')
    ## You need online access.
    install.packages('devtools', dependencies = TRUE)
  }
  library(devtools)
  ## Need the R-packages zoo and ncdf4
  install.zoo <- ("zoo" %in% rownames(installed.packages()) == FALSE)
  if (install.zoo) install.packages('devtools', dependencies = TRUE)
  install.ncdf4 <- ("ncdf4" %in% rownames(installed.packages()) == FALSE)
  if (install.ncdf4) install.packages('ncdf4', dependencies = TRUE)
  library(devtools)
  print('Now install the esd package')
  ## You need online access.
  install_github('metno/esd')
}

## activate the esd-package
library(esd)
## Get the WG help page with examples - also use '?WG' for help pages on WG()
data(bjornholt)
## Demo run
z <- WG(bjornholt)
## simulate a hypothetical climate with fewer but more intensive rainy days
x <- WG(bjornholt,fw=wetfreq(z) - 0.1,mu=wetmean(z) + 2)
index(x) <- index(x) - index(x)[1] + as.Date('2050-01-01')
plot(zoo(combine.stations(z,x)),plot.type='single',col=c('black','grey'))
```

https://doi.org/10.5194/egusphere-2026-351
Preprint. Discussion started: 10 February 2026

Algorithm 2 More advanced demonstration of the use of the WG.

```
## Retrieve gridded key annual rainfall statistics for the Nordic countries from thredds/OpenDap
url <- 'https://thredds.met.no/thredds/dodsC/metusers/rasmusb/'
mMU <- retrieve(file.path(url,'mu_Ayear_DSEns_Nordics_1850-2100_ssp370_.nc'))
mFW <- retrieve(file.path(url,'fw_Ayear_DSEns_Nordics_1850-2100_ssp370_.nc'))
sMU <- retrieve(param='ens_sd_mu',file.path(url,'mu_Ayear_DSEns_Nordics_1850-2100_ssp370_.nc'))
sFW <- retrieve(param='ens_sd_fw',file.path(url,'fw_Ayear_DSEns_Nordics_1850-2100_ssp370_.nc'))
## Use bjornholt (near Oslo, Norway) as an example
data(bjornholt)
## There is a difference in precipitation measured at Oslo-Blindern and Bjørnholt
# > c(wetfreq(Oslo.Blindern),wetfreq(bjornholt)):  0.3139275 0.3717596; diff= 0.06
## > c(wetmean(Oslo.Blindern),wetmean(bjornholt)): 6.804407 8.778730; diff= 1.97
## Extract daily annual statistics for the coordinates corresponding to selected site
## using bi-linear interpolation: the ensemble mean. The 8 km resolution of the gridded
## data but the distance between thetwo sites is 13 km.
mmu <- regrid(mMU,is=bjornholt)
mfw <- regrid(mFW,is=bjornholt)
## There was some missing data in fw
ok <- is.finite(mfw)
coredata(mfw) <- approx(year(mfw[ok]),coredata(mfw)[ok],xout = year(mfw))$y
## The ensemble spread
smu <- regrid(sMU,is=bjornholt)
sfw <- regrid(sFW,is=bjornholt)
ok <- is.finite(sfw)
coredata(sfw) <- approx(year(sfw[ok]),coredata(sfw)[ok],xout = year(sfw))$y
## Create annual statistics based on mean and standard deviation
mu <- zoo(rnorm(length(mmu),mean=mmu,sd=smu),order.by=year(mmu)) + 1.97
fw <- zoo(rnorm(length(mfw),mean=mfw,sd=sfw),order.by=year(mfw)) + 0.06
## Here - the difference between Bjørnholt and Oslo-Blindern is accounted for.
z <- WG(bjornholt,mu=mu,fw=fw)
yz <- combine.stations(bjornholt,z)
plot(yz)
```