A dynamical-statistical weather generator for past and future climate

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Abstract

Data from global and regional climate models usually refer to grid cells and are, hence, basically different from station data. This particularly holds for variables with enhanced spatio-temporal variability like precipitation. On the other hand, hydrological models require atmospheric data with the statistical characteristics of station data in order to simulate a realistic hydrological cycle as well as other soil and surface processes like for instance erosion rates. Here, we present a dynamical-statistical tool to construct virtual station data based on regional climate model output in tropical West Africa. This weather generator (WEGE) incorporates daily gridded rainfall from the model, an orographic term and a stochastic term, accounting for the chaotic spatial distribution of local rain events within the model grid box. Total sums and the probability density function (PDF) of daily precipitation are adjusted to available station data in Benin. It is also assured that the generated data are still consistent with other model parameters like cloudiness and atmospheric circulation. The resulting virtual station data are in excellent agreement with various observed characteristics, which are not explicitly addressed by the WEGE algorithm. This holds for the mean daily rainfall intensity and variability, the relative number of rainless days and the scaling of precipitation over different time scales.

The WEGE is once applied to a recent 25-year simulation period and once to time slices of future African climate, assuming enhanced greenhouse conditions and ongoing land degradation until 2025. Besides precipitation, other variables like temperature, wind velocity and relative humidity are adjusted to the location of the rain gauge stations in Benin. The combined forcing scenario causes a reduction in total rainfall amount and an increase in near-surface temperature at all stations in Benin. The virtual present-day and future station data are finally used as input for the SWAT2003 (soil water assessment tool) model in order to evaluate the usability of the presented WEGE for hydrological applications. RESULTS SWAT2003 ...

1 Introduction

Freshwater resources represent a socio-economic factor of rising importance (Houghton et al. 2001). This is particularly true for regions with sparse water availability and increasing demand. Tropical and subtropical Africa is a paradigm for present-day and anticipated water conflicts (Giertz et al. 2006) given the Earth's highest rate of population growth and urbanization (Gaebe 1994; Schulz 2001). In addition, the subcontinent has been subject to enhanced drought conditions since the 1960s (Nicholson et al. 2001). This has led to dramatic economic loss (Benson and Clay 1998) and large-scale partly irreversible migrations from the central Sahel towards the Guinean coast region (Findley 1994). As a consequence, it is required to improve our understanding of the hydrological processes in the atmosphere and in the basement as well as to investigate changes in the hydrological cycle in Africa due to anthropogenic impact factors, especially by conducting detailed model studies (Desanker and Justice 2001; Jenkins et al. 2002). The German interdisciplinary project IMPETUS is dedicated to the efficient management of scarce water resources in West Africa (Christoph et al. 2004). It aims at developing management tools based on extensive field campaigns and modelling approaches in two river catchments in Morocco and Benin. This study is focussed on Benin, describing an algorithm to postprocess data from a regional climate model for use in hydrological models since the assessment of the hydrological cycle requires an interdisciplinary approach including atmospheric and soil processes. This so-called weather generator (WEGE) is applied to present-day and future climate simulation periods, since it is especially relevant to periods for which observational data is not available. The resulting data are used as input for follow-up modelling studies with the SWAT2003 soil water assessment tool (Arnold and Allen 1993; Arnold and Fohrer 2005).

Many studies have addressed the key factors in African climate variability and change (Paeth 2004 and references cited therein). It appears that sea surface temperatures (SSTs) in the tropical oceans play a major role in West African rainfall variability with a degrading influence from the Guinean coast towards the Sahel Zone (Paeth and Friederichs 2004; Paeth and Hense 2004). Other authors point to the crucial importance of changes in the land surface conditions, including vegetation cover, soil moisture and albedo (Bounoua et al. 2000; Clark et al. 2001; Douville et al. 2001) because the exchange of water and energy between surface and atmosphere is a key component in the monsoon climate (Xue et al. 2004). Meanwhile, there is some consensus that changes in the hydrological cycle over Africa are primarily initiated by variations in the large-scale circulation and SST patterns and secondarily enhanced by local feedbacks with the land surface (Long et al. 2000; Nicholson 2001). Therefore, land use changes and radiative forcing need to be considered simultaneously when simulating the human impact on African climate (Douville et al. 2000). While model experiments with prescribed deforestation generally lead to reduced precipitation amount in entire tropical Africa (Semazzi and Song 2001) and a delayed summer monsoon onset (Taylor et al. 2002), simulations with enhanced greenhouse-gas (GHG) concentrations predict more abundant rainfall near the Guinean coast (Paeth and Hense 2004) but dryer conditions in the Sahel Zone (Hulme et al. 2001). Combining both impact factors, Feddema and Freire (2001) as well as Zhao and Pitman (2002) conclude that vegetation and soil degradation basically reinforces the effect of rising CO_2. Maynard and Royer (2004a) find a dominating impact of the radiative forcing compared with land use changes in Africa until 2050. Here, we consider regional climate model projections for Africa which account for both, land degradation and enhanced greenhouse conditions.

Studies on soil properties and hydrology have also been realized for Benin. Given the remarkable recent and projected changes in the imprint of land cover in Benin (Thamm et al. 2005), Giertz et al. (2005) have highlighted the effect of land use changes on hydrological processes in the upper Ouémé catchment. Based on measurements at different sites, they report enhanced surface runoff and erosion in agricultural areas compared with natural forest and savanna. Regional climate model data and hydrological models have been coupled by Giertz et al. (2006) in an interdisciplinary scenario approach. Assuming ongoing land degradation and enhanced GHG concentration, they conclude that water availability for agriculture and households is continuously decreasing. This trend is confronted with rising water demand due to population growth as revealed by a detailed survey in Benin.

When using climate model data as input for hydrological models, two major problems occur: (1) Climate models are subject to various systematic deficiencies like uncertainties in the parameterization of cloud and convection processes or even in the large-scale circulation (Errico et al. 2002; Lebel et al. 2000). (2) The spatial scale of the precipitation fields and systems is badly represented, especially in coarse-grid global climate models. Anyway, even in high-resolution regional climate models, the output still refers to a regional mean rather than to a local station value. This effect is particularly relevant for atmospheric variables of high spatio-temporal variability like for instance convective precipitation. Benin is mainly subject to convective rain events, which arise from meso-scale systems like meso-cyclones and squall lines (Fink and Reiner 2003; Redelsperger et al. 2002, Saha and Saha 2002) and account for partly up to 90 % of total precipitation amount in the central Sahel Zone (Lebel et al. 2000). This implies that the statistical characteristics of simulated precipitation are basically different from the properties of station data. However, hydrological models are mostly designed for the latters. Taking the original climate models fields as input results in unrealistically low surface runoff and erosion rates. This is due to the fact that climate models produce an exaggerated number of weak daily rain events according to the grid point presentation, while local extremes are largely underestimated (Zolina et al. 2004). This in turn prevents the hydrological model from translating abundant local preciptiation – and hence situations with highest socio-economic relevance (Changnon 2003) – to extreme runoff and erosion.

On the other hand, reliable station data are quite sparse in Africa (Funk et al. 2003) and gridded data sets do not meet the claims of hydrological models with respect to the spatio-temporal resolution (cf. GPCP 2.5°×2.5° monthly, Adler et al. 2003; CRU 0.5°×0.5° monthly, New et al. 2000; GPCC 1°×1° monthly, Rudolph 1995). Therefore, the use of regional climate model data is still one of the most promising approaches in hydrological modelling, especially for the assessment of future changes, provided that the problems mentioned above can be handled. (1) The aspect of systematic model errors can be dealt with by a statistical postprocessing. This approach consists of an adjustment of the model fields to the known characteristics of available observational data by univariate (Bartman et al. 2003; Hansen and Emanuel 2003) or multi-variate (Kang et al. 2004; Tippett et al. 2003) methods or neural networks (Coulibali et al. 2005). Here, model output statistics (MOS) are used prior to applying the WEGE in order to adjust the climate model data at the synoptic scale (Paeth 2006). (2) The problem of gridded versus local rainfall data is tackled by an extended WEGE, which performs virtual station data derived from simulated present-day and future precipitation in the corresponding grid box plus an orographic term plus a stochastic term. The use of daily data and the consideration of stochastically distributed rain events within the model grid box represent an improvement compared with former approaches by Salathé (2003, 2005). Finally, the virtual present-day and future station data are used as input for the SWAT2003 model in order to judge whether the WEGE leads to more realistic hydrological model results and to evaluate changes in the soil processes due to predicted climate conditions until 2025.

The following section gives an overview on the considered models and data. Section 3 highlights the major inconsistencies between gridded simulated and local observed precipitation data. The design of the WEGE is described in section 4, while the resulting virtual station data are evaluated in section 5. The results of the SWAT2003 model are presented in section 6 and conclusions are drawn in section 7.

2 Data and models

The statistical characteristics of observed local rainfall are inferred from the BDMET data set (Le Barbé et al. 2002). This data set comprises 131 station time series of daily precipitation. The rain gauge stations cover most parts of Benin but with higher density in the central than in the southern and northern part (Fig. 1). The time series are fairly homogeneous and cover different time windows between 1921 and 2004. Some stations are almost complete during this period, others only span a few years. The long-term climatology of precipitation amount in Benin is taken from the CRU data set which consists of gridded monthly rainfall over all land masses except Antarctica in 0.5° resolution during the period 1901-1998 (New et al. 2000). This product is based on all available station data interpolated onto a regular grid. Poccard et al. (2000) have demonstrated that the CRU data provides a more realistic description of precipitation features over Africa than reanalyses. For the orographic term of the WEGE, a high-resolution orography is required. This is derived from the digital elevation model (DEM) of the United States Geological Society (http://srtm.usgs.gov, Giertz et al. 2006). The topography of Benin in 90 m resolution is illustrated in Fig. 1. Orographic shaping mainly prevails in central Benin with highest elevations reaching up to 1000 m above surface in the Atakora region at the western boundary, while the southern and northern parts are rather flat. The fine-scale structure of rivers and streams is visible as well.

The considered regional climate model is the hydrostatic model REMO, which is designed to simulate the synoptic-scale atmospheric processes (Jacob 2001). The basic model equations are derived from the former operational weather forecast model *Europamodell* of the German Weather Service (Majewski 1991) and have been further developed at the Max-Planck Institute for Meteorology. Physical parameterizations are taken from the global climate model ECHAM4 (Roeckner et al. 1996) and adjusted to the scale of REMO. The mass flux parameterization scheme by Tiedtke (1989) represents the processes of moist convection. Soil processes are computed by a 5-layer one-dimensional soil model. A more detailed description of the model design is given by Jacob et al. (2001). In the present version, the model is run in a 0.5° resolution with 20 terrain-following vertical levels. The model domain covers tropical and subtropical northern Africa as well as the Mediterranean Basin within the sector 30°W to 60°E and 15°S to 45°N. REMO is driven in the uncoupled climate mode and nested in global atmospheric and oceanic data sets. For present-day climate, the European Centre for Medium-range Weather Forecast (ECMWF) reanalyses and analyses data (Gibson et al. 1997) are used during the 1979-2003 period. For future climate change, several time slices (2005, 2010, 2015, 2020, 2025) are performed, taking global climate model data from ECHAM4/OPYC. Land surface parameters like vegetation, albedo, orography etc. are taken from the GTOPO30 and NOAA (National Oceanic and Atmospheric Administration) data sets (Hagemann et al. 1999). Some parameters like vegetation cover, LAI and surface albedo follow an idealized seasonal cycle.

The 1979-2003 present-day experiment has been validated in all detail by Paeth et al. (2005). It is found that REMO reproduces all major features of the observed African climate, including the monsoon circulation, the tropospheric jetstreams, the spatial distribution of near-surface climatic variables and some specific characteristics of the West African monsoon climate such as the bifurcated intertropical convergence zone and the African Easterly Waves (AEWs). However, a major deficiency consists in the noticeable underestimation of Subsaharan rainfall, which appears to be a peculiarity of regional climate models in tropical Africa (cf. Gallée et al. 2004; Vizy and Cook 2002). It probably goes back to an enhanced sensitivity of the Tiedtke convection scheme in the vicinity of warm SSTs and abrupt orographic elevation along the Guinean coast. As this underestimation is of systematic nature, it can be corrected by a statistical model. For this purpose, a multiple regression model has been set up in order to adjust the monthly sums of precipitation to the observed values according to the CRU data set (Paeth 2006). In addition, daily rainfall intensity within the model grid box is corrected by comparing distribution functions of simulated and observed daily precipitation. The resulting corrected data set is only derived from REMO output, using the original rainfall and additional dynamical variables. Thus, it is still consistent with the other model processes. Moreover, the postprocessing can also be applied to time periods for which observational data are not available. The 1979 to 1998 rainfall climatology over Benin is displayed in Fig. 2, left panels. The postprocessed data from REMO are in excellent agreement with the gridded CRU data (cf. Saha and Saha 2001), implying that the model data represent a reliable basis for the WEGE. There is a distinct meridional gradient in annual precipitation amount ranging from around 1200 mm near the coast to less than 700 mm in the north. Furthermore, precipitation increases towards the east and west, a phenomenon which is commonly known as the Dahomey gap (Chatelain et al. 1996). The right panel in Fig. 2 highlights the dominant role of convective rainfall in Benin accounting for 50 to 75 % of total precipitation (cf. Fink and Reiner 2003; Redelsperger 2002), except in the southern part where the summer monsoon is responsible for large-scale precipitation fields.

Motivated by a number of previous sensitivity studies with REMO (Paeth 2004), the future time slices between 2005 and 2025 are subject to rather complex scenarios of African climate change (Paeth and Thamm 2006). The REMO simulations are nested in global ECHAM4/OPYC experiments with enhanced greenhouse conditions according to IPCC scenario B2 (Houghton et al. 2001). The same GHG scenario is prescribed within the REMO domain. In addition, ongoing land use changes are assumed based on estimates of UNEP (2003) which in turn relate to projections of future population growth (CIESIN 1996) and forest cover until 2025 (Pahari and Murai 1997). A random pattern of spatial vegation changes at grid-box level is produced with some additonal assumptions, like for instance that the vegetation loss is more (less) pronounced in the transition zone between Sahara and Sahel (in the inner core of the tropical rain forests). Besides vegetation cover, additional surface parameters like leaf area index, forest fraction, roughness length and surface albedo have been modified in order to construct a realistic process of land degradation (cf. Maynard and Royer 2004b). Finally, several soil parameters, governing the ratio between infiltration and evaporation on the one hand and surface runoff and drainage on the other hand, have been changed in order to complete the scenario of land degradation. Given this extensive scenario setup, it is argued that the resulting climate projections are fairly realistic, although local feedbacks with vegetation cover as suggested by Wang and Eltahir (2000) are not accounted for. Here, the future time slices are only used to construct virtual station data which serve as input for SWAT2003. A detailed description of the resulting climate change signals in terms of various African climate features is given by Paeth and Thamm (2006).

The SWAT2003 model was first developed by Arnold and Allen (1993) and further improved by Arnold and Fohrer (2005). It simulates the hydrological cycle, erosion processes and various fluxes of chemical constituents in the basement. The model equations are solved on spatial units according to the resolution of the DEM (90 m) within the river catchment. A large number of input data is required, including for instance soil characteristics, land cover conditions, topographic information and climate data. The latters comprise precipitation amount, 2 m temperature, minimum and maximum temperature, relative humidity, heat flux into the soil, solar irradiation and wind velocitiy in 1.7 m height, all at daily resolution. These climatic variables have to dealt with when constructing the virtual station time series from the REMO data.

3 Inconsistencies between model and station data

A basic requirement of hydrological models is that the distribution of local daily rainfall amount is correctly represented (Lebel et al. 2000). This distribution is illustrated by fitting gamma (Γ) functions to the time series of daily precipitation. Here, the method of L-moments is used to estimate the two parameters of the Γ distribution because L-moments are less sensitive to outliers in finite samples (Hosking 1990). A selection of 14 stations all over Benin is shown in Fig. 3. The dashed black line denotes the observed station data derived from BDMET, while the solid black line represents the corresponding REMO grid cell. The grey line will be discussed in section 5. It is obvious that the observed and simulated Γ distributions differ considerably from each other at all stations: the regional model produces too much low rain events and strongly underestimates the observed extremes (cf. Mearns et al. 1995; Zolina et al. 2004). This can be explained with the grid box presentation of simulated rainfall since averaged over a $0.5° \times 0.5°$ area the occurrence of precipitation is more frequent than at a single station. On the other hand, a local extreme does usually not hold for the entire region. Note that systematic errors in REMO have been suppressed before by adjusting daily rainfall to observed regional-mean precipitation (Paeth 2006). The comparison of the distribution functions visualizes a basic problem when using climate model data for hydrological modelling or related applications: extreme weather situations are not accounted for, leading to an underestimation of maximum surface runoff, streamflow, flooding and erosion (Lebel et al. 2000; Salathé 2003, 2005).

This is also reflected by the comparison of mean daily precipitation intensity in Fig. 4. While the regional model produces a typical rainfall amount between 5 and 7 mm per day, the observations reveal 12 to 22 mm per day. At the same time, the relative number of rainless days is systematically underestimated (Fig. 5) by REMO. In the real climate system, 70 to 90 % of all available local daily observations during the 20th century do not exhibit any rainfall. In the model, this portion amounts to 45 to 65 % but referring to the entire grid box. This has a serious implication for hydrological models: when weak rain events are occurring too regularly, the soil is steadily moistened and, hence, less sensitive to strong surface runoff. As a consequence, erosions rates are unrealistically low. This problem is enhanced by the fact that extreme weather situations are too unfrequent and/or too weak (Figs. 3+4). According to these findings, the daily variability of precipitation is underestimated as well (Fig. 6). At some stations, the observed standard deviation is remarkable amounting to more than 20 mm, whereas in REMO 10 mm are not exceeded. It is obvious that this reduced atmospheric variability would directly be translated to unrealistically low fluctuations in the soil and surface processes simulated by a hydrological model.

It has to be pointed out explicitly that the different characteristics of simulated and observed precipitation do not necessarily indicate a deficiency of the climate model. Actually, this is exactly not the case because Paeth (2006) has shown that REMO meets all properties of regional-mean observed rainfall. Rather the differences arise from the grid-box versus local reference of the compared data. Therefore, the model data have to be transformed to virtual station data prior to their use in hydrological models (Salathé 2003, 2005; Wilks 1999; Xu et al. 1999).

4 Weather generator

Compared with previous attempts, our WEGE combines the physical correction by Salathé (2005), the orographic term by Funk et al. (2003), the the stochastic term by Wilks (1999) and the statistical model by Helmer and Ruefenacht (2005). In addition, it applies to daily instead of monthly model data (cf. Salathé 2003, 2005) such that temporal sampling errors are avoided. The main challenge is to translate gridded precipitation to local station information. As a preparatory work, the statistical relationship between the amount of daily rainfall and orographic effects is carried out by linear regression (cf. Goldberg and Bernhofer 2000). For this purpose, the BDMET station data are area-averaged within the corresponding model grid cells in Benin and the anomalies $\dot{p}_j^s(t)$ of each station value at day t from the observed gridded mean is computed. From the high-resolution topographic data (DEM, see Fig. 1) the orographic gradient in zonal (g_x) and meridional (g_y) direction is determined within a spatial sector of 1 km around each station j. The anomalies of these station-related gradient vectors $\vec{g}_j^s$ from the respective grid-box mean gradient vector $\vec{g}_i^m$ are determined. Note that the subscript j refers to the stations, whereas i stands for the model grid cells. Daily wind vectors $\vec{v}_i^e(t)$ are taken from the ERA40 reanalyses during the 1958-2001 period (Uppala et al. 2005) and interpolated to the 0.5 REMO grid over Benin. The scalar product

$$c_j^s = \vec{v}_i^e(t) \cdot \dot{\vec{g}}_j^s \tag{1}$$

is a measure of the wind-ward and lee effects at each station (Funk et al. 2003; Salathé 2003) as a departure from the synoptic-scale regional-mean wind-ward and lee effects the climate model is aware of. Finally, the rainfall anomalies $\dot{p}_j^s(t)$ are regressed upon this scalar product, resulting in a linear regression coefficient of $b = 0.45$. Thus, a positive scalar product between wind field and orographic gradient – equivalent to a wind-ward situation – leads to enhanced precipitation at a given station relative to the regional-mean within the REMO grid cell. Note that the regression is confined to grid cells and days, which contain at least 13 values from the BDMET data in order to rely on robust regional means. This still comprises 330 data pairs in Benin over the considered 20th-century time window. Most considered regions are located in central Benin where the station density is highest (see Fig. 1). Thus, due to the limited data availability in other parts of Benin, this approach cannot account for regional differences in the orographic effect, like for instance between the coastal plain and the Atakora mountains. The correlation coefficient between $\dot{p}_j^s(t)$ and $\vec{v}_i^e(t) \cdot \vec{g}_j^s$ amounts to $r = 0.2$, which is statistically significant at the 1 % level but only accounts for 4 % of the variance. This is not astonishing given the low orographic variance in Benin (see Fig. 1). The remaining part is related to other factors we are not aware of or simply to spatial noise (cf. Wilks 1999). The statistical properties of the residual of the regression analysis is used to sample the stochastic term of the WEGE: the typical spatial rainfall variability from station to station within a model grid box in Benin amounts to 11 mm. Therefore, normally distributed random numbers $\varepsilon_j^s(t)$ are drawn with $\mu = 0$ and $\sigma = 11$ which serve as a stochastic spatial departure of local rainfall from the given regional-mean value.

Now, the WEGE for daily precipitation consist of three steps: (1) Given a simulated value $p_i^m(t)$ in model grid box i, the preliminary virtual station data $\hat{p}_j^s(t)$ at day t and at the location of BDMET station j is given by

$$\hat{p}_j^s(t) = p_i^m(t) + b \cdot \vec{v}_i^m(t) \cdot \vec{g}_j^s + \varepsilon_j^s(t) \tag{2}$$

with $\vec{v}_i^m(t)$ denoting the simulated wind field from REMO. This equation combines the large-scale rainfall information from the nonlinear dynamical climate model, the orographic effect, which is generally weak in Benin, and the stochastic spatial variability.

(2) The resulting virtual station data $\hat{p}_j^s(t)$ still does not meet the distribution function of the observed station time series. Therefore, a so called probability matching is carried out. This method is a standard tool for the postprocessing of remote sensing data, for instance when transforming optical satellite imagery to precipitation amount (Helmer and Ruefenacht 2005). Here, it is used to transfer the simulated rainfall data $\hat{p}_j^s(t)$ with distribution function $F_x(x)$ to a new sample of virtual data which fit the observed distribution function $F_y(y)$. We have fitted Γ functions to daily precipitation (cf. Dunn 2004). A Kolmogorov-Smirnov goodness-of-fit test (von Storch and Zwiers 1999) has been applied in order to ensure that the Γ distribution is an appropriate description of the data. Indeed, the Nullhypothesis, saying that the emperical and theoretical distribution functions do not comply with each other, is rejected at most stations in Benin. Given $x = \hat{p}_j^s(t)$,

$$u = F_x(x) \tag{3}$$

denotes the respective value of the cumulative distribution function derived from all values of the virtual station time series $\hat{p}_j^s(t)$ with $t = 1..n$ days. Then, the probability matching leads to the new virtual station data $\tilde{p}_j^s(t)$ which meet the observed distribution function $F_y(y)$:

$$\tilde{p}_j^s(t) = F_y^{-1}(u). \tag{4}$$

(3) Finally, the total sums of precipitation have to be adjusted to the observed values because the probability matching implies that the resulting time series do not necessarily correspond to the original total amount. For the case

$$\sum_{t=1}^{n} \tilde{p}_j^s(t) > \sum_{t=1}^{n} \hat{p}_j^s(t) \tag{5}$$

a certain number of rainy days is transformed to rainless days, using a random selection within $t = 1..n$, until the totals are correct. These additonal rainy days are drawn from the distribution function $F_y(y)$ in order to be in agreement with the fitted observed Γ distribution. In the opposite case, randomly chosen rainy days are enhanced at the respective station until the total enhancement equals the missing rainfall amount. It is taken care that no rainless days are modified in order to maintain the consistency with the model dynamics. The same holds for the procedures in Eqs. 2-4: if REMO does not produce rainfall within the grid box, the virtual station value is also equal to zero. This leads to the final virtual station data $\ddot{s}_j^p(t)$ for daily precipitation (p) at day t and station j in Benin. These data are supposed to meet all required statistical characteristics of the observed station time series but are directly derived from the model output. This holds the prospect of applying the WEGE to time periods, for instance in the future, for which observations are not available. Therefore, the method is first carried out for the 1979-2003 present-day REMO simulation to evaluate the usefulness of the data with respect to known station data in Benin. Then, the WEGE is applied to the time slices of future climate change until 2025 in order to assess future climate and hydrological changes at the local scale.

Besides precipitation, SWAT2003 requires additional atmospheric variables at the local scale (see section 2). First of all, 2 m temperature is corrected by the departures of orographic height Δz_j at each station j from the mean orographic height in the corresponding REMO grid cell. In the model equation of REMO the threshold for saturation within the grid box is set to $f = 70\%$ with f denoting the relative humidity. Therefore, the orographic correction of 2 m temperature is differentiated, depending on whether the adiabatic process is dry or moist, according to

$$\ddot{s}_j^t(t) = t_i^m(t) + 0.98°C\frac{\Delta z_j}{100m} \quad , \quad f < 70\% \tag{6}$$

$$\ddot{s}_j^t(t) = t_i^m(t) + \alpha\frac{\Delta z_j}{100m} \quad , \quad f \geq 70\% \tag{7}$$

where $t_i^m(t)$ denotes the simulated 2 m temperature in the 0.5° grid cell, $\ddot{s}_j^t(t)$ is the resulting virtual station value for 2 m temperature and alpha represents the moist adiabatic temperature gradient as a function of the background temperature. It ranges between 0.65°C per 100 m (0°C) and 0.36°C per 100 m (30°C). Relative humidity is then adjusted according to the modified 2 m temperature. Note that specific humidity is not changed with respect to the grid box value simulated by REMO because appropriate reference data are not available at the local scale and no simple statistical transfer function is found for this variable. The same holds for solar irradiation, minimum and maximum temperature as well as heat flux into the soil. The virtual station time series are retained unchanged from the REMO output. Sensitivity studies with SWAT2003 have revealed that this model is barely sensitive to minor errors in these input variables compared with the crucial role of daily precipitation (not shown).

Finally, the hydrological model requires wind velocity in 1.7 m height above ground, whereas the standard output from REMO is in 10 m. The conversion is done using the Monin-Obukhov theory for wind profiles in the Prandtl layer (Majewski 1991). The wind velocity $v(z)$ in $z = 1,7m$ is given by

$$v(z) = v_{KE}\left[\frac{z}{h} + \frac{\sqrt{c_d}}{\kappa}\left(\ln\left(\frac{z+z_0}{z_0}\right) - \frac{z}{h}\ln\left(\frac{h+z_0}{z_0}\right)\right)\right] \tag{8}$$

where v_{KE} denotes the simulated wind velocity in the nearest model level, in this case the 10 m wind with $h = 10m$. The von Kármán constant κ is dimension-less and amounts to $\kappa = 0.4$. The wind profile further depends on the roughness length of the land surface z_0. This implies the possibility to account for local differences from station to station: at each station j the orographic roughness length is determined by

$$z_0^j = 0.8 \frac{\bar{R}_s^j}{L_R} \tag{9}$$

with the orographic variance $\bar{R}_s^j$ derived from the 90 m topographic data within a perimeter of 1 km by 1 km around the station and the typical wave length of the resolved orography which is set to 55 km according to the original resolution of the REMO grid (Majewski 1991). Finally, the shear stress coefficient c_d is adjusted such that averaged over the REMO grid box, Eq. 8 fulfills the classical formula by Haltiner and Martin (1957):

$$v(z) = v_{KE} \left(\frac{z}{h}\right)^{0.2} . \tag{10}$$

Thus, c_d does not account for local changes within the model grid cell but the entire conversion in Eq. 8 does via the local orographic variance. In summary, the WEGE presented here yields virtual daily station time series $\ddot{s}_j^{\nu}(t)$ with variables $\nu \epsilon \{p, t, f, w, x, n, h, q\}$ (precipitation, 2 m temperature, relative humidity, wind velocity in 1.7 m, maximum temperature, minimum temperature, heat flux into the soil, solar irradiation) and days t during the simulated years $\{1979..2003, 2005, 2010, 2015, 2020, 2025\}$. This data set can be used for follow-up hydrological modelling under present-day and future climate conditions.

5 Validation

Prior to using the data for SWAT2003, some statistical characteristics of daily rainfall, which are not explicitly accounted for by the WEGE, are compared with the BDMET observations in order to ensure that the virtual station data draw a realistic picture of local precipitation. The Γ distributions fitted to $\ddot{s}_j^{p}(t)$ are shown in Fig. 3 for 14 selected stations in Benin. Compared with the original REMO output, a striking improvement is found: the Γ functions from BDMET and WEGE are almost identical, especially in the northern part. Obviously, the WEGE has reduced the number of weak rain events, whereas the extremes are enhanced relative to the original REMO data. An excellent agreement is also found for the mean daily rainfall intensity (Fig. 4), the relative number of rainless days (Fig. 5) and the day-to-day variability (Fig. 6). In terms of all characteristics, the WEGE has produced highly realistic station data derived from gridded simulated precipitation. It has to be emphasized that none of these rainfall properties, except the Γ functions, is explicitly dealt with by the algorithm described in section 4 since only the daily distribution functions and the total sums have been adjusted. Thus, these positive results represent meaningful validation criteria for the WEGE.

Another well-known characteristic of local precipitation is its typical scaling over various time scales. Hense and Friederichs (2006) have shown that the extremes of accumulated precipitation scale with $M^{\frac{1}{2}}$ over several orders of magnitude from 1 day up to 10 years and longer. In terms of the virtual station data, the maximum intensity of accumulated rainfall is determined for increasing accumulation times between 1 day and 100 days within the simulation period 1979 to 2003. In Fig. 7, the resulting spectrum is displayed in the upper panel (solid line) for one exemplary station (Kandi, northeastern Benin). Starting from the absolute daily maximum of 210 mm, the extreme precipitation intensity sharply drops down between 1 and 10 days and then asymptotically runs out for longer accumulation times. In log-log presentation this behaviour can be fitted by a linear trend (dashed line in the upper panel of Fig. 7). Analogous to Hense and Friederichs (2006), it is expected that this linear trend amounts to -0.5 and the scaling is $M^{-\frac{1}{2}}$, respectively. Note that the sign of the scaling is reversed because we consider maximum rainfall intensity, whereas Hense and Friederichs (2006) use maximum accumulated precipitation. It is obvious that all 131 virtual station time series in Benin approxinately obey this observed scaling behaviour (bottom panel in Fig. 7). The slightly enhanced decrease can be explained by the fact that strictly speaking the scaling in time is only valid for convective precipitation whereas the virtual station data are based on total rainfall which is to a certain part composed of large-scale precipitation (see Fig. 2, right panel). Therefore, the results in Fig. 7 further substantiate the quality of the virtual station data.

In order to illustrate the orographic effect on rainfall in Benin, the mean annual values before (pixels) and after (circles) the WEGE algorithm are compared in Fig. 8. The differences only arise from the orographic term in Eq. 2 because by definition the random numbers $\varepsilon_j^s(t)$ sum up to zero over all days $t = 1..n$. This means that a station is subject to more (less) annual precipitation amount than the regional-mean, if it is more frequently exposed at the wind-ward (lee) side with respect to the typical wind field, i.e. primarily the southwestern summer monsoon and the northeastern winter monsoon (Saha and Saha 2001). As a consequence, the differences between pixels and circles are minor in regions with low orographic variance like in southern and northern Benin. On the other hand, there are noticeable differences in the Atakora region and central Benin, basically reflecting the wind-ward and lee effects of the meridionally oriented Atakora mountain ridge.

An exemplary time window of daily precipitation from REMO, WEGE and BDMET is shown in Fig. 9 in order to visualize the functionality of the WEGE. During the 2000-2001 period, the seasonal cycle of rainfall in northeastern Benin is clearly visible: the occurrence of rainfall is strictly confined to the summer monsoon season between May and October. This holds for all three data sets. However, the original REMO time series is composed of almost continuous rainy days with low total amount. This is in contrast to the observed time series which is subject to a much larger number of rainless days within the rainy season and more pronounced extreme events. The observed behaviour is well reproduced by the virtual station data. Thus, in addition to the statistical characteristics of the observed station time series (Fig. 3-7), the virtual station data also draw a realistic picture of the temporal sequence of rain events in Benin. Nonetheless, it has to be noted that the virtual and observed station time series are not in phase with each other. This can hardly be achieved and is not the aim of the WEGE because due to the large model area the regional model does not produce precipitation events exactly at the same day and location as observed (cf. Paeth et al. 2005).

Finally, the longterm changes in monthly rainfall and 2m temperature are displayed in Fig. 10 for three exemplary stations in northern (Karimama), central (Dogué) and southern (Cotonou) Benin. The time series are based on the virtual station data. At first sight, the seasonal cycle of preciptiation and temperature is prevailing. There is large interannual variability in terms of rainfall and low year-to-year variations in temperature during the 1979-2003 period. Precipitation amount is decreasing from south to north. The opposite is true for the mean, variability and seasonality of near-surface temperature. All these features are likewise found in the observations (Saha and Saha 2001). The future time slices reveal a clear reduction in total rainfall amount and a warming trend until 2025 due to ongoing land degradation and increasing GHG concentrations. These tendencies at the local scale agree with the large-scale climate change signals (Paeth and Thamm 2006) but, in contrast to the original REMO data, the time series in Fig. 10 are adjusted to the statistical characteristics of the observed station time series and are, hence, more appropriate for various follow-up studies. When applying the WEGE to future simulation periods, it is possible and admissable that the total sums as well as the distribution of daily precpitation may change under some kind of external forcing. Thus, climate change signals are not only accounted for in the first but also in higher moments. As a consequence, the observed properties of daily rainfall in Figs. 3-6 are not equally well reproduced by the future station data compared with the present-day station data (not shown) simply because the frequency and intensity of precipitation in Benin may continuously decrease until 2025 (cf. Paeth and Thamm 2006). These validation results suggest that our WEGE is an appropriate tool not only for present-day but also for future periods. This is a basic requirement because the main potential of the WEGE is that it can be applied to periods for which observations are not at hand, i.e. during data gaps and for future climate model projections.

6 Application

In the last step of this analysis, the virtual station time series are used as input data for the SWAT2003 model in order to evaluate the usability of the WEGE and to assess future changes in the soil hydrology and erosion. RESUTLS SWAT2003 ...

7 Conclusions

Motivated by an interdisciplinary modelling approach of the hydrological cycle in tropical Africa, this study deals with an improved weather generator for climate model data (cf. Funk et al. 2003; Salathé 2003, 2005; Wiks 1999). The idea is to construct virtual station time series directly from the gridded model output. The WEGE algorithm for daily precipitation is based on the dynamical information from the regional climate model REMO, an orographic term and a stochastic term. The distribution function is adjusted by probability matching and the total sums are corrected by drawing or withdrawing individual values of the new sample. Prior to applying the WEGE, the climate model output is postprocessed by a statistical model such that systematic model errors at the synoptic scale are fairly suppressed (Paeth 2006). The WEGE is once applied to a present-day period in order to evaluate its usability, and once to several future time slices under enhanced greenhouse conditions and land degradation until 2025 in order to assess future climate changes at the local scale. During the period 1979 to 2003, the resulting virtual station data are in excellent agreement with the statistical characteristics of observed local rainfall in Benin. A major improvement is achieved with respect to the original data from REMO. This holds for the distribution function of daily precipitation, the mean intensity, the portion of rainless days, the day-to-day variability and the general scaling of rainfall in time. The typical chronology of rainy and rainless days during the West African summer monsoon is reproduced as well by the WEGE. Applied to future periods, it also accounts for changes in the first and higher moments of daily precipitation. Under the considered climate change scenario, rainfall amount is decreasing all over Benin while near-surface temperature is warming up (cf. Paeth and Thamm 2006). Besides rainfall, other atmospheric variables are transformed from the gridded model output to virtual station time series, although the respective algorithms are less complex than for precipitation. In order to test the usefulness of the virtual station data for hydrological models, they are used as input for the SWAT2003 model. RESULTS SWAT2003 ...

Given the positive validation results and the realistic follow-up modelling of soil hydrology and erosion, it is concluded that the decribed WEGE is an appropriate interface between climate and hydrological models, at least in the presence of relatively high station density like in Benin. The advantage of the WEGE is that it produces realistic station time series without gaps and that it can be applied to past and future periods for which model data are available but observations are not. The virtual station data meet all required statistical properties of the observational time series but are not in phase with the latters. This principly cannot be achieved because REMO, like all large-scale climate models, does not exactly reproduce the observed daily rain events at the local scale.

A peculiarity of the WEGE algorithm in Benin is that the orographic effect accounts for only 4 % of the total spatial precipitation variability. This is due to the low orographic variance in large parts of the country except in the western Atakora region. It is conceivable that this deterministic orographic component of the WEGE is considerably larger in mountainous regions like for instance in Morocco. This will be tested in the next step. Furthermore, there may be other statistical transfer functions between gridded and local rainfall we were not yet aware of. Such additional deterministic factors will now be investigated in more detail.

In the interdiscplinary IMPETUS project many applications for the virtual station data are planned beside hydrological modelling (cf. Christoph et al. 2004). This includes biological and agro-economic models as well as medical and demographic issues. It will be interesting to find out whether the virtual data set is appropriate for all these different follow-up studies. The time slices of future climate change will soon be completed by transient ensemble simulations with the regional climate model REMO, covering the period 1960 to 2050. The WEGE will also be applied to these model data and the resulting virtual station time series are then provided for the various applications in IMPETUS. Thus, our WEGE is an important element of the integrative research work in tropical Africa.

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Figure Captions

Fig. 1: Topography in Benin in m above sea level and geographical location of the BDMET rain gauge stations.

Fig. 2: Mean total annual precipitation in mm over Benin during 1979-1998 from observational (CRU) and regional climate model (REMO) data as well as the portion of convective precipitation in % with respect to total precipitation from REMO.

Fig. 3: Γ distributions of daily precipitation at selected locations in Benin from observational data (BDMET), virtual station data (WEGE) and corresponding REMO grid boxes.

Fig. 4: Mean daily precipitation intensity in mm at selected locations in Benin from observational data (BDMET), virtual station data (WEGE) and corresponding REMO grid boxes.

Fig. 5: Percentage of rainless days in % at selected locations in Benin from observational data (BDMET), virtual station data (WEGE) and corresponding REMO grid boxes.

Fig. 6: Mean daily precipitation variability in mm at selected locations in Benin from observational data (BDMET), virtual station data (WEGE) and corresponding REMO grid boxes.

Fig. 7: Relationship between mean daily precipitation intensity and aggregation time from the virtual station data, once in normal (solid black line), once in log-log (dashed black line) presentation at station Kandi (11.1°N, 2.9°E) (**top panel**), and linear trend in log-log presentation at all 131 BDMET stations in Benin (**bottom panel**).

Fig. 8: Mean total annual precipitation in mm over Benin during 1979-2003 from REMO grid boxes (pixels) and virtual station data (circles).

Fig. 9: Daily precipitation in mm at station Kandi (11.1°N, 2.9°E) during the period 01.01.2000 to 31.12.2001 from observational data (BDMET, no gaps), REMO grid box and virtual station data (WEGE).

Fig. 10: Time series of total monthly precipitation in mm (**top panels**) and monthly 2m temperature (**bottom panels**) in °C at three selected locations in Benin from the virtual station data during the 1979-2003 period and the future time slices.

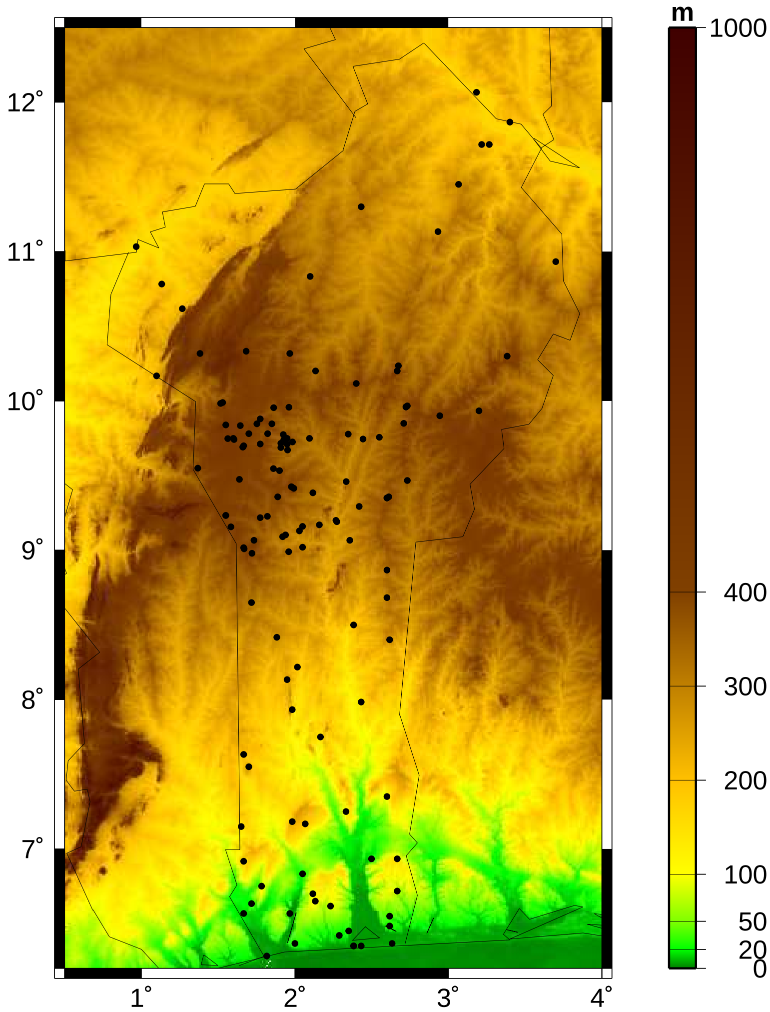

Figure 1

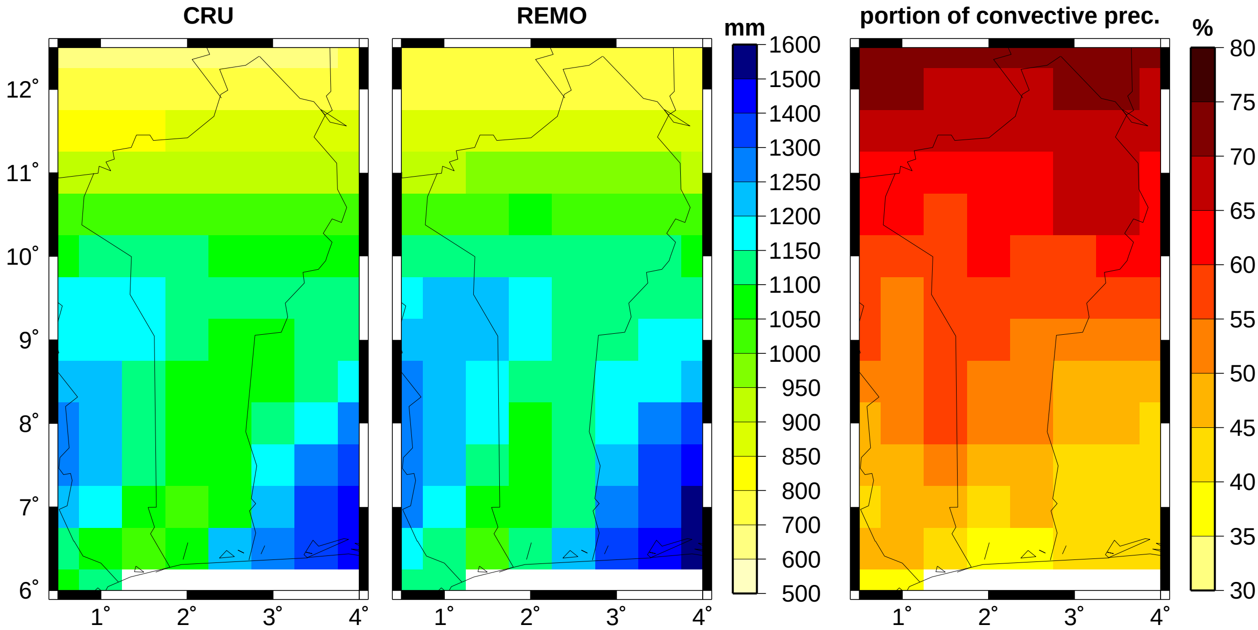
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Figure 2

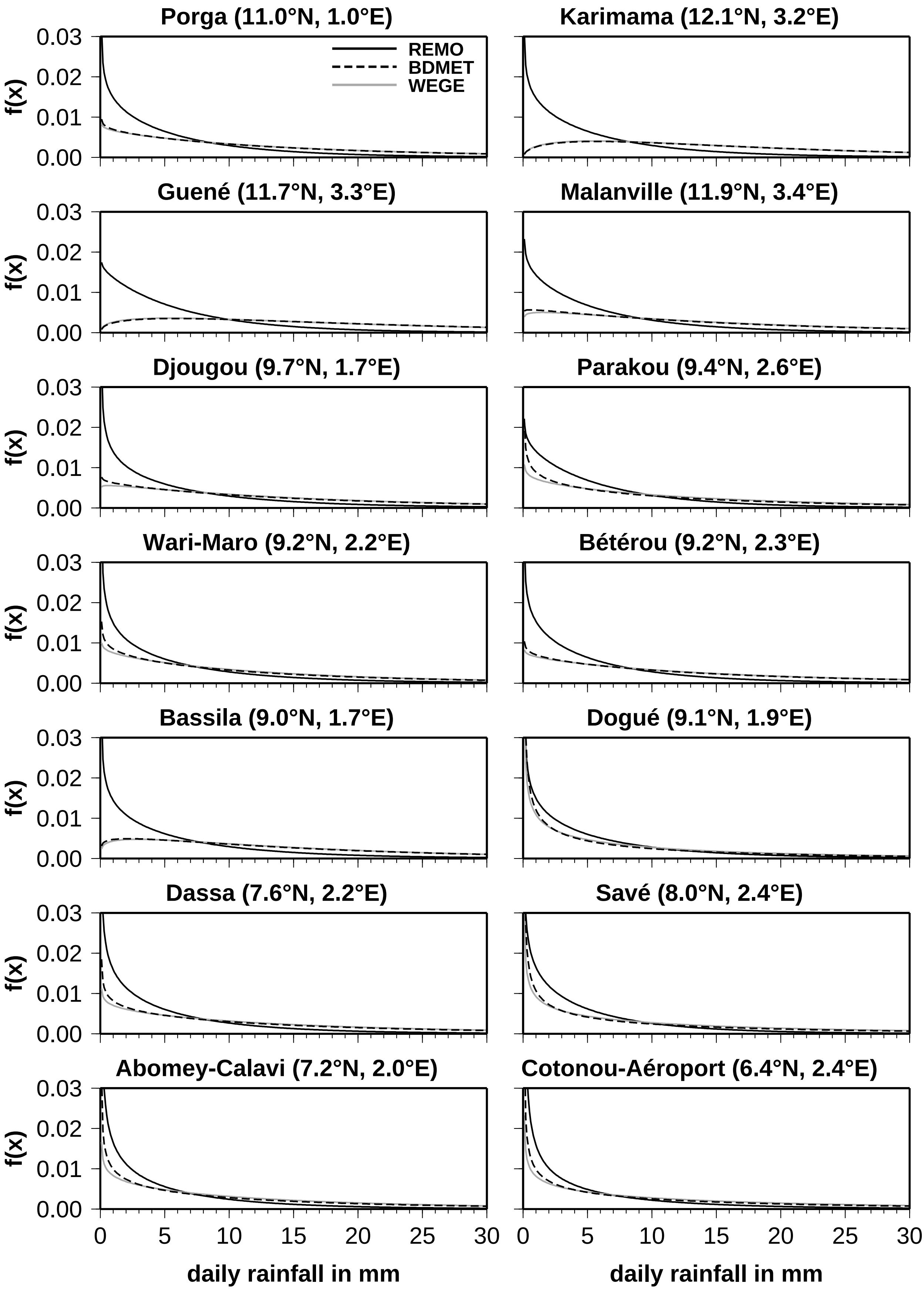

Porga (11.0°N, 1.0°E)
Karimama (12.1°N, 3.2°E)
Guené (11.7°N, 3.3°E)
Malanville (11.9°N, 3.4°E)
Djougou (9.7°N, 1.7°E)
Parakou (9.4°N, 2.6°E)
Wari-Maro (9.2°N, 2.2°E)
Bétérou (9.2°N, 2.3°E)
Bassila (9.0°N, 1.7°E)
Dogué (9.1°N, 1.9°E)
Dassa (7.6°N, 2.2°E)
Savé (8.0°N, 2.4°E)
Abomey-Calavi (7.2°N, 2.0°E)
Cotonou-Aéroport (6.4°N, 2.4°E)
REMO
BDMET
WEGE
f(x)
0.00
0.01
0.02
0.03
0
5
10
15
20
25
30
daily rainfall in mm

Figure 3

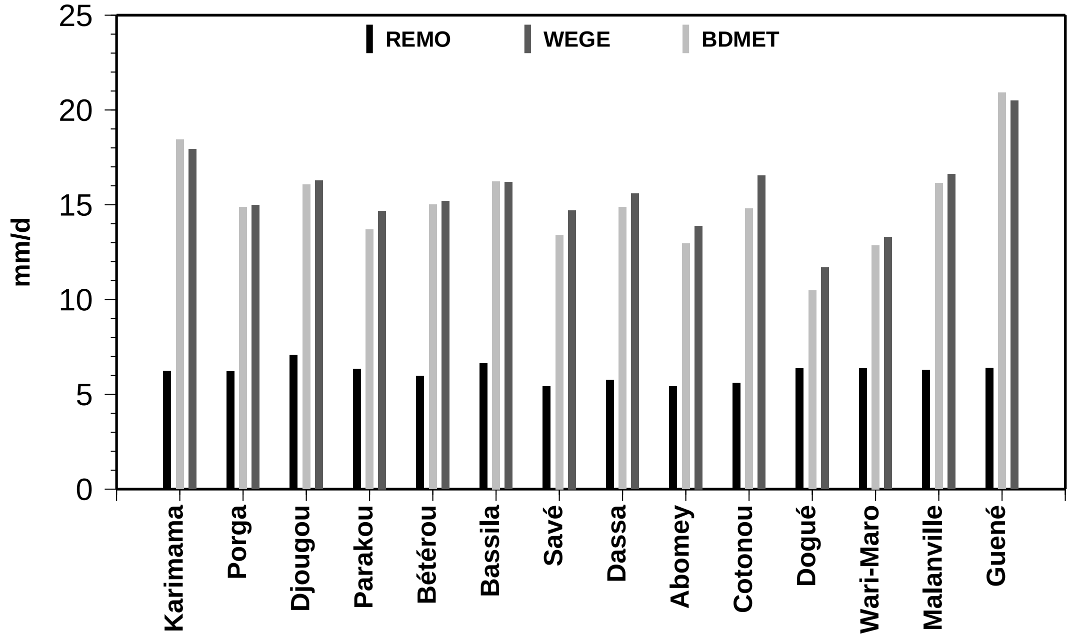
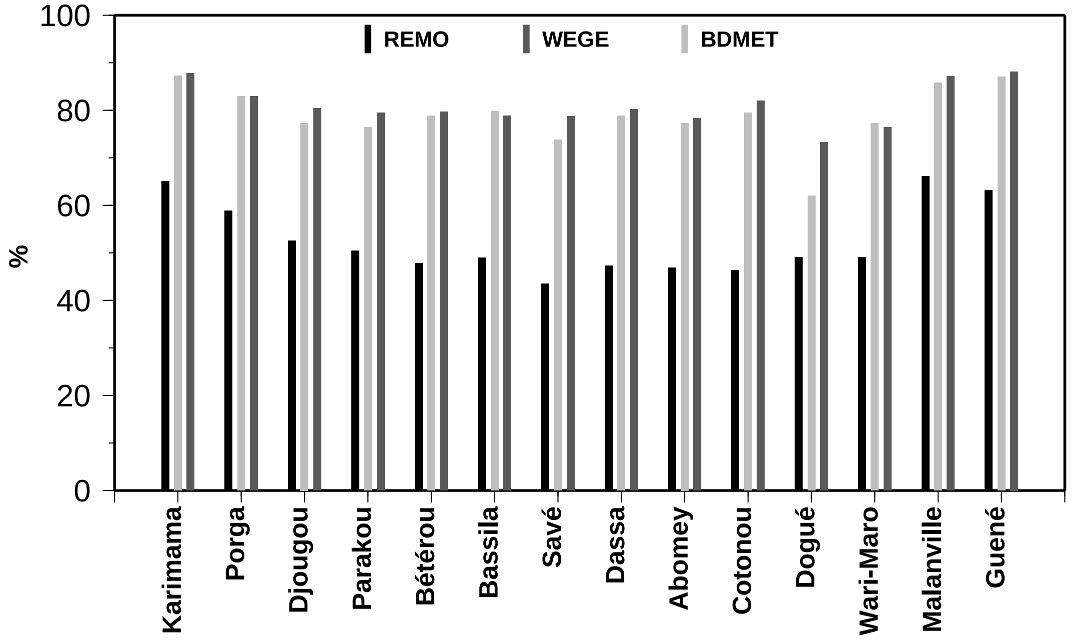

25
20
15
10
5
0
mm/d
REMO
WEGE
BDMET
Karimama
Porga
Djougou
Parakou
Bétérou
Bassila
Savé
Dassa
Abomey
Cotonou
Dogué
Wari-Maro
Malanville
Guené

Figure 4



100
80
60
40
20
0
%
REMO
WEGE
BDMET
Karimama
Porga
Djougou
Parakou
Bétérou
Bassila
Savé
Dassa
Abomey
Cotonou
Dogué
Wari-Maro
Malanville
Guené

Figure 5

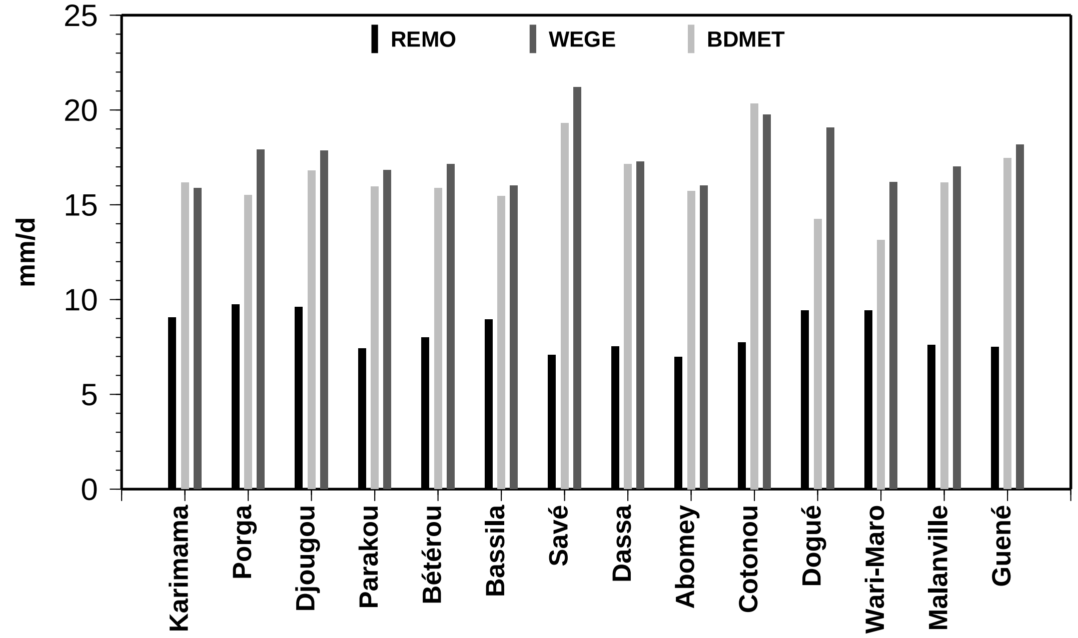
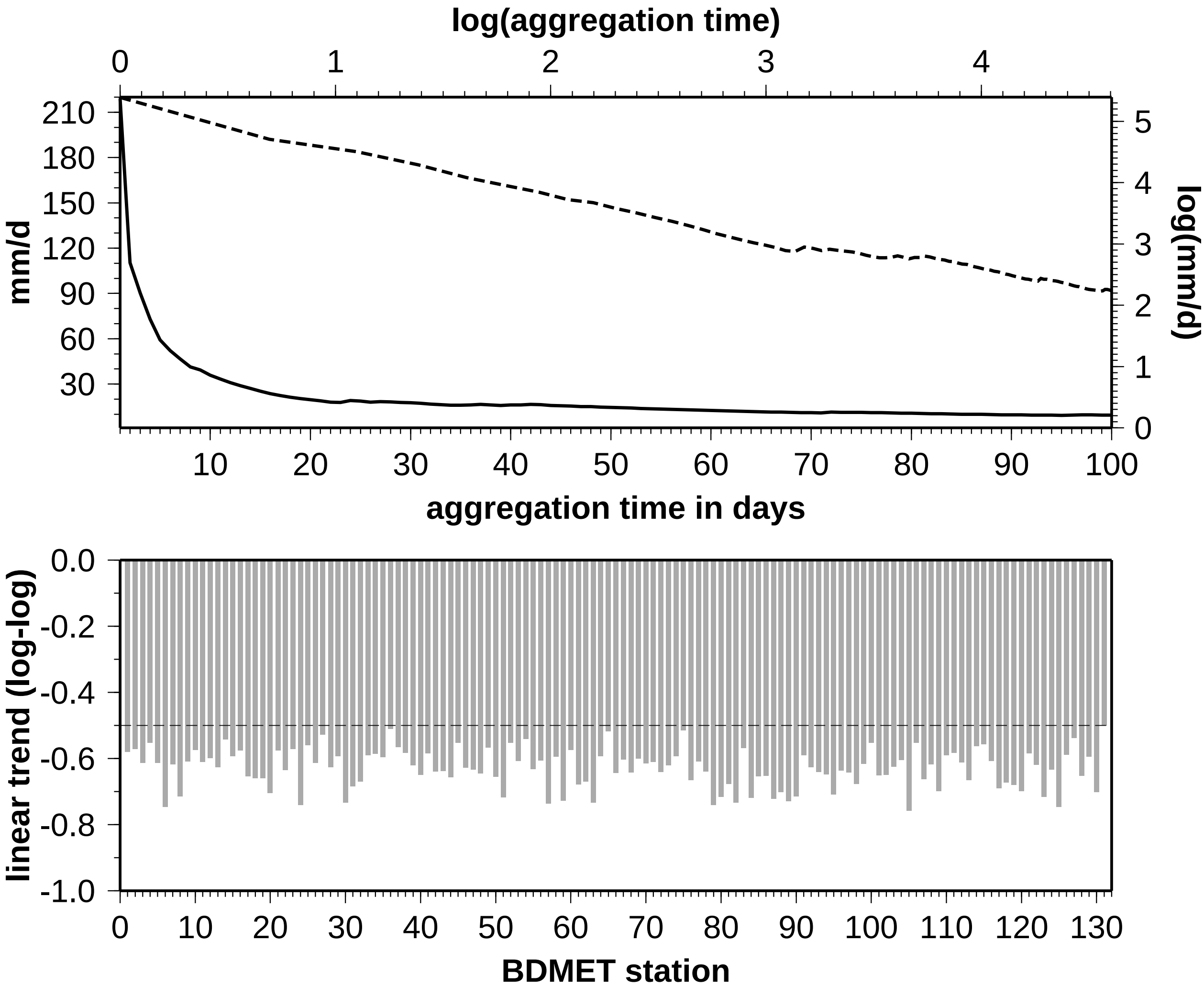

25
20
15
10
5
0
mm/d
REMO
WEGE
BDMET
Karimama
Porga
Djougou
Parakou
Bétérou
Bassila
Savé
Dassa
Abomey
Cotonou
Dogué
Wari-Maro
Malanville
Guené

Figure 6



log(aggregation time)
0
1
2
3
4
210
180
150
120
90
60
30
mm/d
5
4
3
2
1
0
log(mm/d)
10
20
30
40
50
60
70
80
90
100
aggregation time in days
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
linear trend (log-log)
0
10
20
30
40
50
60
70
80
90
100
110
120
130
BDMET station

Figure 7

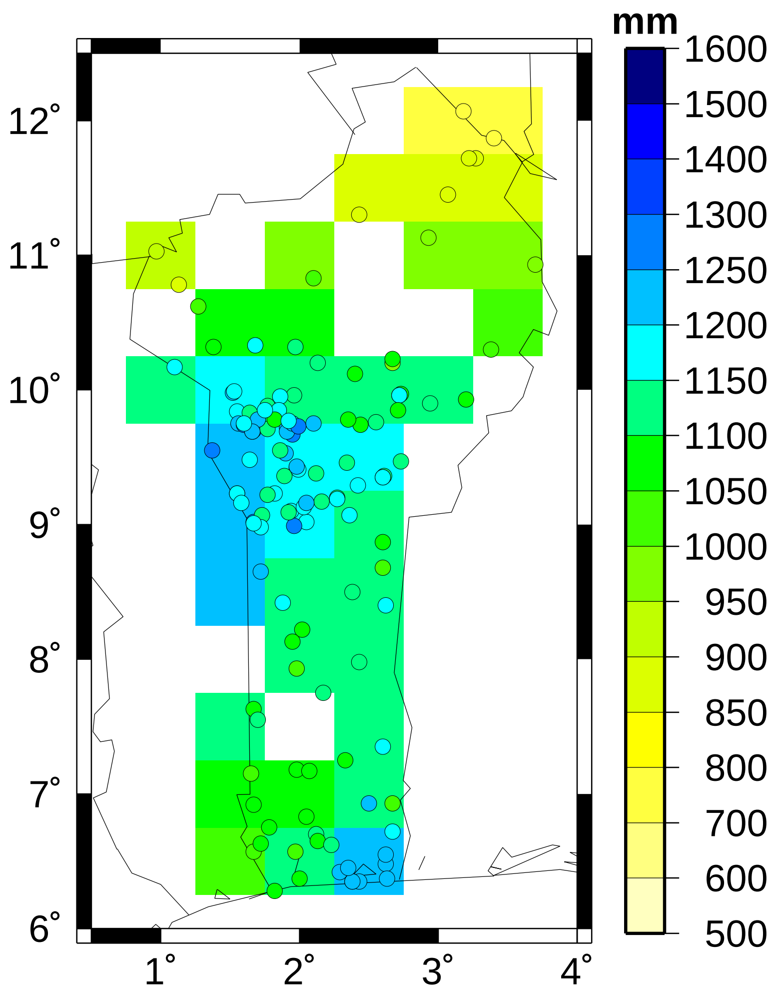

mm
1600
1500
1400
1300
1250
1200
1150
1100
1050
1000
950
900
850
800
700
600
500
12°
11°
10°
9°
8°
7°
6°
1°
2°
3°
4°

Figure 8

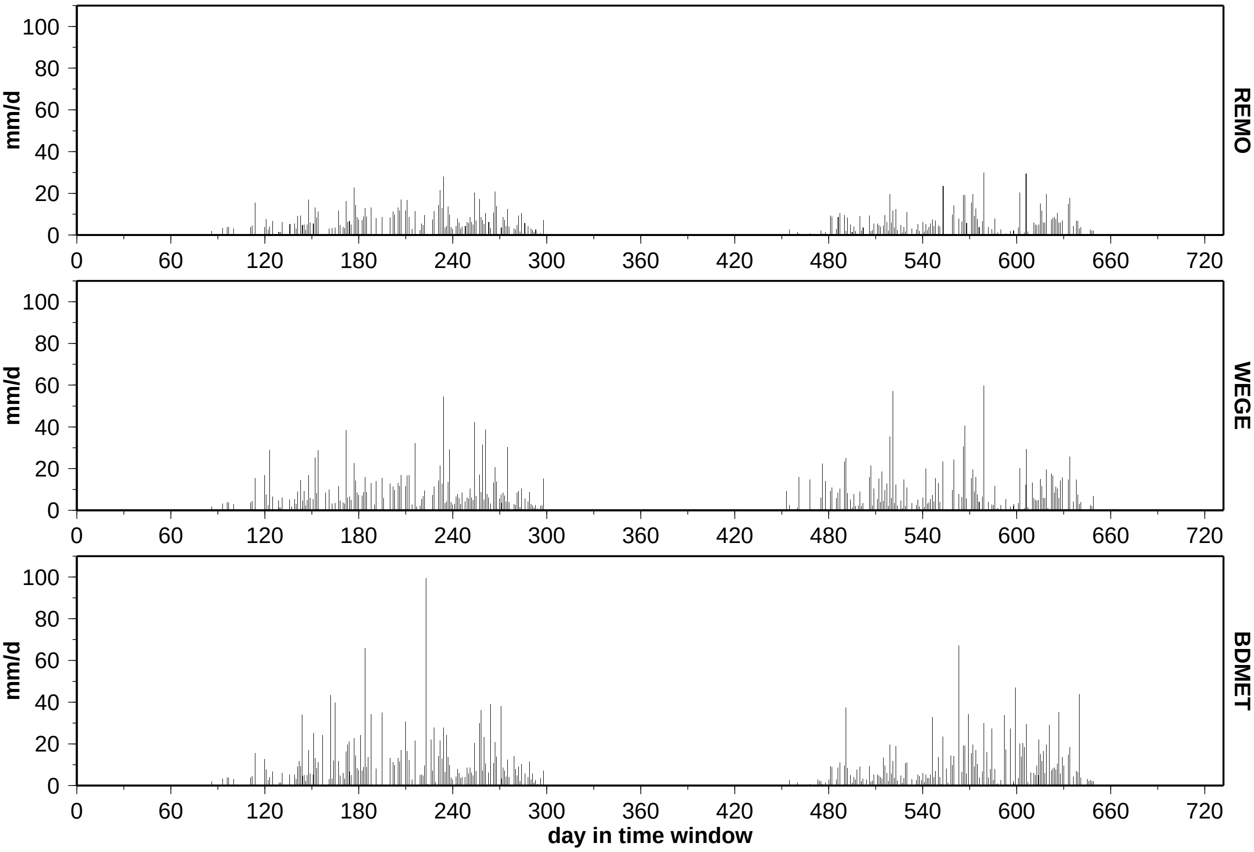

mm/d
REMO
WEGE
BDMET
0
20
40
60
80
100
0
60
120
180
240
300
360
420
480
540
600
660
720
day in time window

Figure 9

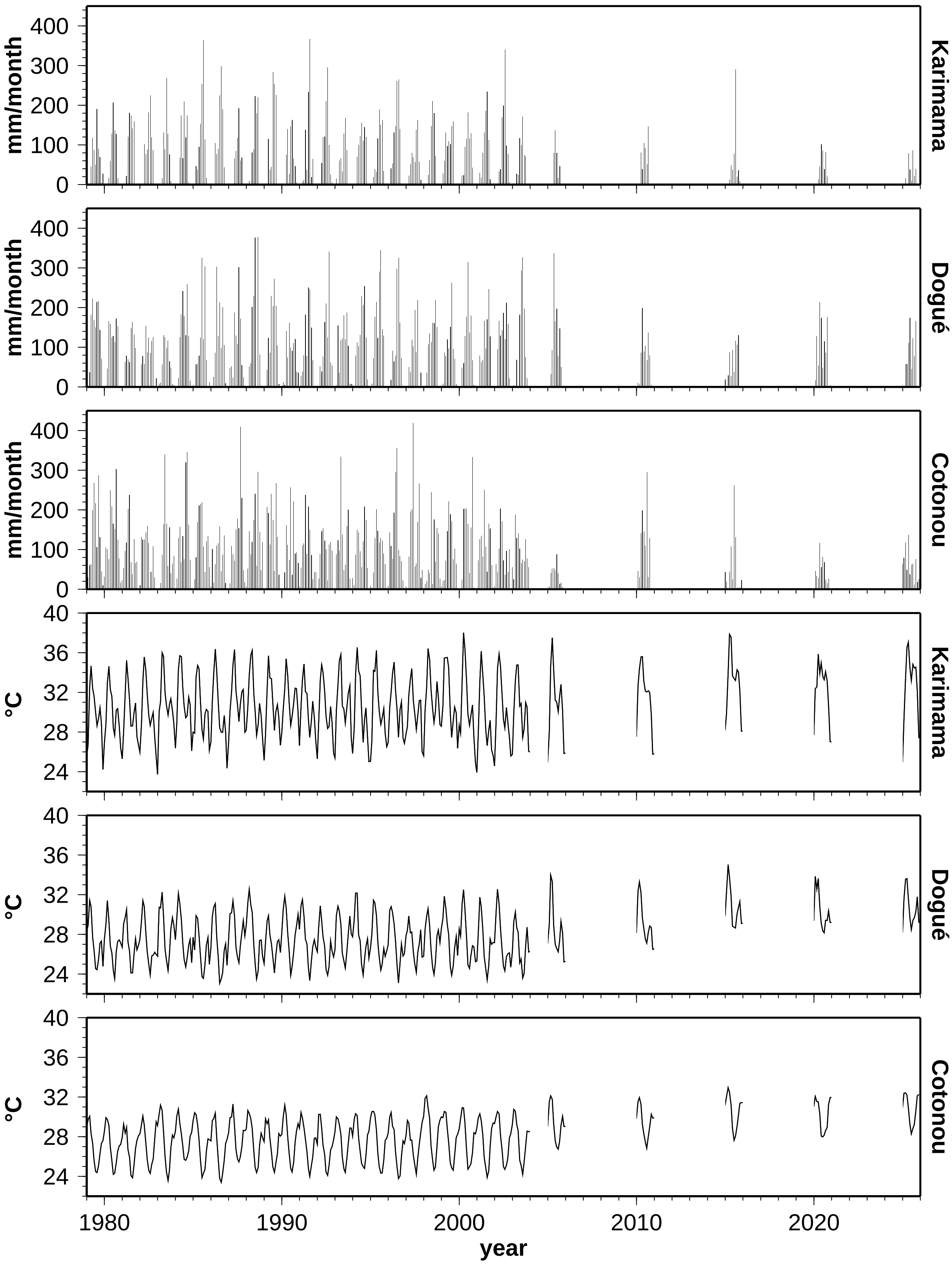

mm/month
400
300
200
100
0
Karimama
Dogué
Cotonou
°C
40
36
32
28
24
1980
1990
2000
2010
2020
year

Figure 10