Evaluation of Monthly Satellite-Derived Precipitation Products over East Africa

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Abstract

East Africa experienced in the 2001–11 time period some of the worst drought events to date, culminating in the high-impact drought of 2010/11. Long-term monitoring of precipitation is thus essential, and satellite-based precipitation products can help in coping with the relatively sparse rain gauge ground networks of this area of the world. However, the complex topography and the marked geographic variability of precipitation in the region make precipitation retrieval from satellites problematic and product validation and intercomparison necessary. Six state-of-the-art monthly satellite precipitation products over East Africa during the 2001–09 time frame are evaluated. Eight areas (clusters) are identified by investigating the precipitation seasonality through the Global Precipitation Climatology Centre (GPCC) climatological gauge data. Seasonality was fully reproduced by satellite data in each of the GPCC-identified clusters. Not surprisingly, complex terrain (mountain regions in particular) represents a challenge for satellite precipitation estimates, as demonstrated by the standard deviations of the six-product ensemble. A further confirmation comes from the comparison between satellite estimates and rain gauge measurements as a function of terrain elevation. The 3B42 product performs best, although the satellite–gauge comparative analysis was not completely independent since a few of the products include a rain gauge bias correction.

1. Introduction

Multidisciplinary studies and operational applications to water cycle and water management stimulate the exploitation of satellite precipitation estimates (SPEs) thanks to the growth of long-term (10 years or longer), space-based datasets. Satellite precipitation real-time and rapid update products also enter the assimilation schemes of numerical weather prediction (NWP) models, contributing to improve short-range precipitation forecasts of extreme rainfall (Michaelides et al. 2009). Moreover, precipitation drives the accuracy of the output of hydrological models to a large extent (Thiemig et al. 2013). The high spatial and temporal resolution and the continuous, timely, and public availability of satellite datasets are essential requisites for downstream predictions with enough lead time to implement management and response actions, especially in poorly gauged basins (Serrat-Capdevila et al. 2014). In such regions applications include estimations of soil erosion, especially at the annual scale (Vrieling et al. 2010), and inundation mapping (Khan et al. 2011). Over data-rich areas, satellite-derived precipitation datasets play a considerable role in analyzing the physical processes behind extreme drought and flood events (Dong et al. 2011). Precipitation is a key variable for evaluating climate change effects at different spatial scales (Trenberth et al. 2003). Trenberth et al. (2014) have shown how the way precipitation is analyzed impacts results on drought changes under climate change. Regional climate studies on extreme event occurrences (droughts and floods) and

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their connections with other climatic features require long, homogenous, and possibly uninterrupted precipitation datasets. Not all satellite datasets can fulfill such requirements on temporal coverage, but they can satisfy the other requirements at the global scale and can be used to construct short-term climatologies for comparisons with model simulations or to evaluate precipitation trends over recent decades (Riddle and Cook 2008; Williams et al. 2012).

Satellite precipitation products can thus be a fundamental resource, especially in poorly gauged regions such as East Africa (EA; e.g., Kucera et al. 2013). This region experienced in the 2001–11 time frame some of the worst droughts to date, culminating in the high-impact drought in 2010/11 (Nicholson 2014). The frequency and impacts of these extreme events call for a continuous monitoring of precipitation for regional climatological studies and timely forecasts with important feedbacks on water management and food security assessment (Sheffield et al. 2014). However, satellite precipitation estimates over EA are inherently difficult because of the complex topography of the region. Moreover, considering the variety of precipitation retrieval methodologies, a local validation and intercomparison of satellite precipitation products is crucial. Several studies have focused on the evaluation of SPEs over EA at different temporal and spatial scales. These analyses were limited to selected areas of EA, that is, river basins such as Baro–Akobo and Juba–Shabelle (Thiemig et al. 2012), the Nile (Haile et al. 2013), and Ethiopian river basins (Romilly and Gebremichael 2011), or areas of complex topography such as the Ethiopian highlands and the Rift Valley (Hirpa et al. 2010; Dinku et al. 2007, 2008, 2011) and Uganda (Maidment et al. 2013; Asadullah et al. 2008). These studies focused on evaluating the various satellite products in hydro-meteorological applications and more generally their behavior in a region characterized by its complex terrain and by a marked seasonal and geographic variability of precipitation.

In the present work, a more systematic approach is attempted by analyzing the satellite-based precipitation variability over EA for the time period 2001–09. The analysis focuses on the monthly accumulated precipitation and examines various subareas, each characterized by a different precipitation annual cycle. Six state-of-the-art, high-resolution satellite products are considered: the Climate Prediction Center (CPC) African Rainfall Estimation (RFE), the CPC morphing technique (CMORPH), the Global Satellite Mapping of Precipitation (GSMaP), the Tropical Rainfall Measuring Mission (TRMM) Multisatellite Precipitation Analysis (TMPA) 3B42, the Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks (PERSIANN), and the Tropical Applications of Meteorology Using Satellite and Ground-Based Observations (TAMSAT) African Rainfall Climatology and Time series (TARCAT). They are representative of different methodologies, either with global coverage or tuned over Africa (TAMSAT and RFE).

Two global gauge products from the Global Precipitation Climatology Centre (GPCC) are used as reference data for the analysis of the SPEs: 1) the GPCC Climatology, version 2011 (GPCC_Clim), at 0.25° and 0.5° (Meyer-Christoffer et al. 2011a,b; Schneider et al. 2014) mean monthly global land surface precipitation for the target reference period from January 1951 to December 2000; and 2) the GPCC Full Data Reanalysis, version 6 (GPCC_FD), at 0.5° (Schneider et al. 2011; Becker et al. 2013) monthly land surface precipitation from rain gauges with a temporal coverage from January 1901 to December 2010.

In section 2, the study area is introduced together with its major topographical features and a brief description of the local climate. Details on the satellite datasets are provided in section 3, along with some indications on the analysis methodologies; section 4 deals with the geographic and seasonal variations of the precipitation annual cycles over the EA territory. In sections 5 and 6 the variability of the SPEs, quantified by evaluating the ensemble of the six satellite products, and the results of the comparisons between SPE and GPCC data are described. Finally, a summary of the main results of the analysis is provided in section 7.

2. East Africa: Topography and climate

The area examined in this work extends between 5°S and 20°N and 28° and 52°E, including southern Sudan, Eritrea, Djibouti, Ethiopia, Somalia, Kenya, Uganda, and northern Tanzania. A very complex geography characterizes a region shaped by the friction between tectonic plates, which generated the Great Rift Valley, one of Africa’s best-known geological features (Fig. 1; UNEP 2008). The Rift Valley extends over 5500 km, from the Red Sea’s junction with the Gulf of Aden, southwest toward Kenya, then south to Mozambique. While crossing the equator it divides in two branches, the Eastern and Western Rifts, enclosing the large plateau where Lake Victoria (the third largest lake in the world by area) is located. The complex geological processes associated with the Rift Valley formation are responsible for the creation of several of East Africa’s largest lakes as well as for much of its topography. A number of mountain ranges surround the Rift Valley, including the western and eastern Ethiopian highlands, with the rugged escarpments bordering the valley; the
East African highlands with the two highest African peaks, Mount Kilimanjaro (Tanzania, 5895 m; all elevations throughout the paper are meters above mean sea level (MSL)) and Mount Kenya (central Kenya, 5199 m); and Mount Elgon (4321 m) on the border between Kenya and Uganda. Other remarkable EA mountains are the Ruwenzori Mountains on the border between Uganda and the Democratic Republic of Congo reaching up to 5109 m. A relatively low-level region separating the Ethiopian highlands and the East African highlands extends from the Indian Ocean in the southeast to Sudan in the northwest: this narrow gap corresponds to the area of Lake Turkana and is usually called the “Turkana Channel” (Kinuthia 1992).

Such complex topography greatly affects the climate of the region on a local scale, having an important role in the low-level circulation and moisture transport. It makes the region an exception in terms of precipitation amount, considering that the area receives generally less precipitation with respect to other equatorial–tropical regions worldwide (Yang et al. 2015). In general, more intense precipitation is associated with mountainous regions, as in western Ethiopia and the mountainous regions along the eastern and western branch of the Rift Valley, and the Lake Victoria area, characterized by a tropical and humid tropical climate, respectively.

Three principal airstreams and three convergence zones drive the local EA climate (Nicholson 1996). The airstreams are the humid, convergent, and thermally unstable Congo airstream and the northeast and southeast monsoons associated with subsiding air that are therefore relatively dry. Two surface convergence zones, that is, the intertropical convergence zone (ITCZ) and the Congo Air Boundary, separate the airstreams. In particular, the former separates the two monsoons, and the latter separates the easterlies and westerlies. Additionally, a further convergence zone aloft separates the dry, stable, northerly flow from the Sahara and the moister, southerly flow.

3. Satellite datasets and methods

a. Satellite precipitation datasets

Six of the most used SPEs are evaluated in this work. Their main characteristics are summarized in Table 1 and briefly described hereafter.

Two products generated at CPC are selected: RFE, version 2.0 (RFE 2.0), and CMORPH, version 1.0 (v1.0), bias corrected. RFE 2.0 is devoted to the precipitation estimate over the African continent by merging daily Global Telecommunication System (GTS) rain gauge
data; passive microwave (PMW) satellite precipitation estimates from the Advanced Microwave Sounding Unit-A (AMSU-A), the Special Sensor Microwave Imager (SSM/I), and the Special Sensor Microwave Imager/Sounder (SSMIS); and GOES precipitation index (GPI) estimates based on cloud-top temperature from the geostationary Meteosat satellites (Xie and Arkin 1996). The algorithm is conceived as a two-stage approach: satellite estimates are first combined linearly using predetermined weighting coefficients and then compared with rain gauge data to remove as much bias as possible. Unlike the previous version of RFE, orographic effects are not included in RFE 2.0.

The CMORPH global technique propagates SSMIS, SSM/I, AMSU-B, Microwave Humidity Sounder (MHS), Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E), and TRMM Microwave Imager (TMI) precipitation estimates using motion vectors derived from geostationary infrared (IR) data during the time lag between two successive overpasses of PMW radiometers over a given location (Joyce et al. 2004). The shape and intensity of the precipitation systems are finally determined by a time-weighted linear interpolation between microwave-derived features propagated forward in time from the previous microwave observation and backward in time from the subsequent microwave scan, thus generating a precipitation estimate independent from IR data. This approach is referred to as “morphing” of the precipitation features. Recently, the CMORPH precipitation dataset was reprocessed using a fixed version of the “morphing” technique together with input data of CMORPH v1.0 in order to improve homogeneity with respect to the previous version of the dataset (CMORPH v0.x), in particular over the earlier years of the dataset 2003–06 (ftp://ftp.cpc.ncep.noaa.gov/precip/CMORPH_V1.0; Xie et al. 2011). CMORPH v1.0 includes three precipitation product types for the time period from 1998 to present: “raw” (satellite-only precipitation estimates), “bias corrected” (satellite-only estimates calibrated against rain gauge analysis for bias removal), and “gauge–satellite blended” (merging of CMORPH bias-corrected and gauge observations through optimum interpolation; Xie and Xiong 2011). Hereafter, the daily accumulated precipitation at 0.25° from the CMORPH v1.0 bias corrected is used, whose behavior was not evaluated over EA to date.

The GSMaP Moving Vector with Kalman Filter (GSMaP_MVK), version 5.222.1 (hereinafter GSMaP), relies on a procedure for the PMW precipitation feature propagation similar to CMORPH (Aonashi et al. 2009; Kubota et al. 2007; Okamoto et al. 2005; Ushio et al. 2009). The PMW estimates from SSMIS, SSM/I, TMI, AMSR-E, AMSU-A, AMSU-B, and MHS are temporally

### Table 1. Summary of the satellite precipitation datasets.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Description</th>
<th>Spatial resolution</th>
<th>Spatial coverage</th>
</tr>
</thead>
<tbody>
<tr>
<td>RFE, version 2.0, daily, NOAA/CPC</td>
<td>Combined product from daily GTS rain gauge data, AMSU, SSMIS, and SSM/I estimates, and GPI cloud-top IR temperature precipitation estimates.</td>
<td>0.1°</td>
<td>Africa</td>
</tr>
<tr>
<td>CMORPH, version 1.0, bias corrected, daily, NOAA/CPC</td>
<td>PMW precipitation estimates transported via spatial propagation information, which are entirely obtained from geostationary infrared (GEO IR) data. Bias in the CMORPH estimates is removed by probability density function (PDF) matching against gauge data.</td>
<td>0.25°</td>
<td>Global (60°S–60°N)</td>
</tr>
<tr>
<td>GSMaP_MVK, version 5.222.1, hourly, JAXA Earth Observation Research Center</td>
<td>Integrated PMW–GEO IR product. PMW precipitation morphed by means motion vectors derived from IR data. Estimate refinement using a Kalman filter approach.</td>
<td>0.1°</td>
<td>Global (60°S–60°N)</td>
</tr>
<tr>
<td>TMPA 3B42, version 7, daily, NASA GSFC</td>
<td>Combination of PMW precipitation estimates and PMW-adjusted merged GEO IR. GPCC data are used for the bias adjustment step.</td>
<td>0.25°</td>
<td>Global (50°S–50°N)</td>
</tr>
<tr>
<td>PERSIANN, 6 hourly, University of California, Irvine</td>
<td>Neural network approach applied to GEO IR brightness temperatures. Model parameters are regularly updated using rainfall estimates from PMW sensors.</td>
<td>0.25°</td>
<td>Global (50°S–50°N)</td>
</tr>
<tr>
<td>TAMSAT (TARCAT), version 2.0, monthly, University of Reading</td>
<td>Derived from Meteosat IR based on the recognition of convective storm clouds and calibration against ground-based rain gauge data.</td>
<td>0.0375°</td>
<td>Africa</td>
</tr>
</tbody>
</table>
propagated based on the atmospheric motion vectors derived from IR geostationary data according to the morphing technique. The resulting precipitation estimates are subsequently refined through a Kalman filter approach. GSMaP provides global precipitation estimates (60°S–60°N) at 0.1° resolution with a refresh time of 1 h.

The TMPA 3B42 precipitation estimates are generated at 0.25°, 3-hourly resolution with a global (50°S–50°N) coverage, according to a calibration-based sequential scheme for combining precipitation estimates from multiple sources: PMW estimates from polar-orbiting sensors (TMI, SSM/I–SSMIS, AMSU, MHS, and AMSR-E), IR estimates from geostationary platforms, and gauge analyses (Huffman et al. 2007). The algorithm is structured in four stages: 1) PMW precipitation estimates are calibrated and combined, 2) IR precipitation estimates are generated by calibration of IR brightness temperatures with PMW precipitation, 3) PMW and IR estimates are combined, and 4) rain gauge analyses are incorporated for bias correction. The daily 3B42, version 7, is exploited in this work, which is based on the 24-h accumulation of the 3-hourly 3B42 product.

A neural network approach applied to geostationary IR brightness temperatures is used in the PERSIANN algorithm to provide global precipitation intensities (50°S–50°N) at 0.25° spatial resolution (Hsu et al. 1997). The network parameters are recursively updated through an adaptive procedure using the instantaneous rain rate estimates from TMI (2A12 product). In the present work, the 6-h accumulated product is considered.

Like RFE, TAMSAT is a precipitation product conceived for Africa (Milford and Dugdale 1990; Grimes et al. 1999; Maidment et al. 2014; Tarnavsky et al. 2014) and adopts a different approach with respect to the other analyzed SPEs. It is based on cloud-top temperatures retrieved from Meteosat IR radiances through the cold cloud duration (CCD) concept, that is, the number of hours for which a given satellite pixel has a temperature lower than a specific threshold value over a 10-day period, which is linearly related to precipitation over the same time period. The threshold temperature and the linear relationship coefficients are estimated for a given region and time of the year (month) by means of the analysis of historic rain gauge data relative to that region and time of the year. The TAMSAT pan-African calibration archive, providing the climatological relationships (monthly but not interannually) between CCD and gauge data, is assembled using gauge data from 4300 stations between 1983 and 2010 [Tarnavsky et al. (2014), see their Fig. 1 for the location and number density of ground stations]. The dataset includes data from African national meteorological services, which are not necessarily included in the GTS network. This climatology-based calibration methodology prevents possible biases due to changes in gauge coverage. Thus, it is a viable alternative to the use of local concurrent (real time) rain gauge observations (as for the other SPE), and it is especially effective in EA, which is characterized by a sparse gauge network with an often inadequate number of stations. The key element is that substantially more gauge records are used in such a climatology-based calibration than those available for any given month in a real-time calibration process. The monthly accumulated precipitation estimates at the spatial resolution of 0.0375° are used.

The SPEs are accumulated to obtain monthly total precipitation intensities projected on common grids at 0.25° or 0.5°, as specified later in each section. Only grid cells over land are retained.

b. Methods

The nonhierarchical k-means clustering method (Hartigan and Wong 1979) was employed to identify areas (clusters) over EA characterized by similar rainfall annual cycles. The cluster analysis was applied to GPCC_Clim data at 0.25° spatial resolution, upon transforming the monthly rainfall data into empirical cumulative distribution functions over each pixel (DeGaetano 1998). Thus, the identified clusters include pixels with similar annual rainfall cycles (similar rainfall seasonality), regardless of the possible variations in the amounts of precipitation. One of the sources of subjectivity in this method is the a priori assumption on the maximum number of clusters k beyond which there is no more gain. The analysis of the sum of the squared distances between each member of a cluster and the cluster centroid is the common method to select the appropriate value for k. Nevertheless, the decision regarding the number of clusters is not a completely objective task since a degree of subjectivity is involved, based on the researchers’ experience (Gong and Richman 1995). In this study, the total within-cluster sums of squared distances were computed for k = 2, 3, 4, . . . , 15, and k = 8 was considered the optimal cluster number, because this is the value at which the rate of reduction in the sum of the squared distances slows down significantly and thus larger k values do not induce any significant decrease in the sum of the squared distances.

A set of statistical parameters was used to evaluate the SPE products versus GPCC_FD in each cluster: the linear correlation coefficient (CC), the mean error (ME), the mean absolute error (MAE), the root-mean-square error (RMSE), the efficiency coefficient (EFF), and the bias (BIAS). They are defined according to the following equations (Dinku et al. 2007):
4. Identification of the precipitation seasonality zones

Precipitation seasonality is rather complex in EA because of significant transitions across distances of tens of kilometers caused by the superimposition of large-scale climatic drivers (e.g., the ITCZ) and by regional factors such as the presence of lakes, topography, and the maritime influence. Moreover, atmospheric teleconnections between rainfall and sea surface temperatures in the tropical Pacific and Indian Oceans are thought to be responsible for precipitation interannual variability (Nicholson 1996). For this reason, the first step in the analysis of the SPEs consists of the identification of the main areas characterized by a predominant precipitation seasonality by means of climatological data. The successive step consists of the evaluation of the SPE’s capability of correctly capturing the precipitation seasonality evidenced by the climatological data. This last issue is considered as a prerequisite that the SPEs should satisfy for being used in water cycle and water management applications.

Eight areas (clusters) are identified by clustering the GPCC_Clim data at 0.25° resolution on the basis of the characteristics of the precipitation annual cycle according to the methodology discussed in section 3b. GPCC_Clim is computed by GPCC for the global land areas by means of an objective analysis of the climatological normals of about 67,200 ground stations. The method substantially reduces the shortcomings due to space and time coverage inhomogeneities and insufficient quality control of the station data typical of past climatological datasets (Schneider et al. 2014). However, EA has a nonuniform coverage of gauges because of their scarcity, especially in Somalia, eastern Ethiopia, western Kenya, and South Sudan, as shown in Fig. 2, where the monthly mean number of GPCC_Clim ground stations over EA is presented. Note that no significantly better alternatives are presently publicly available. The location of the clusters is shown in Fig. 3a. Cluster 1 encompasses rather different environments and very distant regions (an area near Lake Victoria, most of Kenya, and two distinct coastal zones of Somalia), as illustrated in Fig. 3a. Thus, a partitioning of the cluster in subareas is deemed necessary, and the four subareas (1A, 1B, 1C, and 1D) are evaluated separately in the following analyses. Figure 3b shows the GPCC_Clim mean precipitation annual cycles of each of the subareas.
of cluster 1, and Fig. 3c shows the corresponding cycles for each of the remaining clusters.

The intracluster homogeneity is checked by evaluating the correlation coefficients between each annual cycle of a cluster and its corresponding mean annual cycle (excluding the analyzed annual cycle). A highly significant correlation (confidence level >95% for 12 samples) is found for each cluster with average correlation coefficients greater than 0.8. Monomodal annual cycles (clusters 5 and 7) cover Sudan, the Ethiopian western highlands, and Eritrea. A long wet season from March to November with maximum precipitation intensities in July and August characterizes the annual cycle of cluster 5, while cluster 7, limited to an arid area of northern Sudan and the coastal areas of Eritrea, exhibits the shortest wet season, mainly concentrated in July and August with very low intensities. Clusters 2 and 4 are characterized by two contiguous wet seasons with intensity peaks in April and July–August for cluster 2 and in April–May and September–October for cluster 4. Precipitation intensity peaks are very similar in cluster 4, while in cluster 2 precipitation is more intense during the boreal summer than in the boreal spring. Cluster 2 covers mainly central Ethiopia (the Rift Valley and adjacent western and eastern Ethiopian highlands escarpments) together with smaller areas in Uganda and Kenya, while the Ethiopian eastern highlands, part of the mountainous coastal areas of Somalia (Gulf of Aden), central Uganda, and the Democratic Republic of Congo belong to cluster 4.

The other clusters (1A–D, 3, 6, and 8) exhibit annual cycles with two distinct wet seasons (generally March–June and October–December) separated by a drier period in July–September. The differences are registered in the time of the year (month) when the precipitation intensity peaks are located and in the magnitude of their associated precipitation intensities. The four subareas of cluster 1 exhibit similar seasonality, in particular 1A, 1C, and 1D. The most intense precipitation occurs during April–May and October–November with increasing intensities from the almost arid subarea 1A, then through the other coastal subarea 1D and Kenya (1C), up to the very rainy subarea 1B surrounding Lake Victoria. This latter subarea also differs in the precipitation seasonal cycle, especially during the drier season from June to September, when intensities are sharply higher (≥30 mm month$^{-1}$) than those in the dry season of the other subareas. Moreover, subarea 1B is the only region together with contiguous cluster 8 with significant precipitation in the boreal winter (November–February). Finally, cluster 6 is characterized by a smoother transition from the March–May wet season to the October–December wet season with little but significant precipitation over the southern Somalia and Kenya coasts. The areas characterized by these bimodal annual cycles cover southeastern Ethiopia, Somalia, Kenya, southern Uganda, and Tanzania. Similar results in the identification and the geographic attribution of precipitation annual cycles are found in the literature for Ethiopia (Tsìdu 2012), Uganda (Maidment et al. 2013; Asadullah et al. 2008), Somalia (Muchiri 2007), and Kenya (Nicholson 1996).

Figure 4 shows the SPE’s mean annual cycles for each cluster obtained by averaging all the annual cycles of the various grid cells (0.25° resolution) belonging to a given...
cluster for the entire 2001–09 time period. The cor-
responding GPCC_Clim mean annual cycles are reported
for each cluster in Fig. 4 as references. The comparison
of these SPE annual cycles with those from GPCC_Clim
data provides evidence that the SPEs effectively re-
produce the characteristic seasonality in each cluster,
including the wet seasons duration, the identification of
peak intensity months, and, in case of bimodal cycles,
the presence of a prevailing wet season. Coherence be-
tween the GPCC_Clim annual cycles and the SPE an-
nual cycles is quantified for each cluster by means of
the correlation coefficients. Table 2 lists the mean SPE’s
correlation coefficients computed for each cluster. Mean
correlation coefficients greater than 0.7 (confidence
level >95%, with 42 cases out of 66 having a correlation
coefficient >0.8) are found. The exceptions are cluster
1A, where values range from 0.54 to 0.64, cluster 3 for
TAMSAT and PERSIANN, and again PERSIANN for
cluster 4. The highest correlation coefficients are asso-
ciated with cluster 2 (>0.9), and 3B42 is the SPE with
the highest coefficients for all clusters, followed by
CMORPH and GSMaP.

5. Uncertainties of satellite precipitation products

A first appraisal of the SPE uncertainties stems from
the analysis of the standard deviations from the en-
semble of the six monthly SPEs at 0.25° according to the
method by Tian and Peters-Lidard (2010). The com-
posite nature of the SPE ensemble in terms of algorithm
types can induce significant differences in the SPE be-
behavior, and this methodology proved to be effective in
pinpointing situations that the precipitation retrievals from satellite rarely catch; note that this is done without using any ground-based reference dataset. The six-member ensemble means are calculated at each grid box and time step, considering over-land-only grid boxes. After having identified and removed from the ensemble the SPE that deviates most from the six-member ensemble mean, the ensemble mean and the corresponding standard deviation are computed for the remaining five members. In Table 3 the percentages of removal from the six-member ensemble of each SPE for each month in the 2001–09 time period are shown. When no member is eliminated from the ensemble because there is no outlier, the sum of the percentages relative to a given month does not reach 100%. This analysis is carried out to highlight the possible presence within the ensemble of an element with a systematic (or frequent) behavior far from the mean. Although all SPEs were in turn removed from the ensemble, PERSIANN is the SPE with the highest percentage of removal in 8 out of 12 months, followed by 3B42 and then RFE, while TAMSAT, GSMaP, and CMORPH have similar percentages. In particular, PERSIANN stands out quite differently with respect to the other products in clusters 1B, 4, and 5, as documented in Fig. 4. The 3B42 shows a similar behavior in cluster 2 and partially 1D and 6, but at the same time it is the closest product to GPCC_CLIM.

Given the marked seasonality of EA precipitation, the average (2001–09) ensemble mean and standard deviation values are computed for the four seasons, that is, December–February (DJF), March–May (MAM), June–August (JJA), and September–November (SON), and reported in Figs. 5 and 6, respectively.

Generally, the key factors regulating the SPE spread are the precipitation intensity and the topographic complexity of the region, with a clear correspondence between high-intensity precipitation patterns and increasing values of the standard deviation. The highest ensemble mean precipitation intensities (from 80 up to more than 200 mm month\(^{-1}\); Fig. 5) are associated with mountainous areas in central and western Ethiopia in JJA and, to a lower extent, in MAM and SON, and the area of stepped plateaus (average elevation 2700 m) surrounding Lake Victoria are characterized by heavy precipitation during all seasons except DJF, when rainfall is concentrated over northern Tanzania. South-eastern Sudan receives intense precipitation in all seasons except DJF, whereas intense precipitation throughout the whole year characterizes the eastern part of the Democratic Republic of Congo at the border with Uganda, where the Ruwenzori mountain range is located.

DJF are the driest months over most of EA and are characterized by mean standard deviation values lower than 5 mm month\(^{-1}\) (Fig. 6a). This confirms the lower variability of the SPE in case of light precipitation, as displayed in Figs. 7a and 7b, where the mean standard deviation is shown as a function of the average ensemble mean. Higher standard deviation values (on average, up to 30 mm month\(^{-1}\) with peak values at about 80 mm month\(^{-1}\)) are confined in the area 5\(^\circ\)S–5\(^\circ\)N and 28\(^\circ\)–40\(^\circ\)E, corresponding to more intense precipitation. The SPE spread increases during MAM (Fig. 6b), with the highest values over South Sudan and the Democratic Republic of Congo and the area around Lake Victoria. These months correspond to a wet season for almost the entire region, except for northern Sudan, characterized by very low precipitation concentrated in boreal summer months (Figs. 3b,c and 5b). Note the presence of two small areas of greater SPE variability (mean standard deviation values up to 60 mm month\(^{-1}\)) corresponding to Mt. Kenya (0\(^\circ\), 37\(^\circ\)E) and Mt. Kilimanjaro (3\(^\circ\)S, 37\(^\circ\)E; red circles in Fig. 6b). This feature is apparent

<table>
<thead>
<tr>
<th>Cluster</th>
<th>TAMSAT</th>
<th>GSMaP</th>
<th>3B42</th>
<th>PERSIANN</th>
<th>RFE</th>
<th>CMORPH</th>
</tr>
</thead>
<tbody>
<tr>
<td>1A</td>
<td>0.54</td>
<td>0.62</td>
<td>0.61</td>
<td>0.58</td>
<td>0.54</td>
<td>0.64</td>
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<td>1B</td>
<td>0.80</td>
<td>0.84</td>
<td>0.90</td>
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<td>3</td>
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Table 2. Mean SPE’s correlation coefficients for each cluster.

<table>
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<tr>
<th>Cluster</th>
<th>TAMSAT</th>
<th>GSMaP</th>
<th>3B42</th>
<th>PERSIANN</th>
<th>RFE</th>
<th>CMORPH</th>
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<tr>
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<tr>
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<td>0.90</td>
<td>0.86</td>
<td>0.83</td>
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<tr>
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<td>0.81</td>
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</tbody>
</table>

Table 3. SPE’s removal (%) from the six-member ensemble.
also in Fig. 6d for SON: these areas are characterized by two wet seasons, March–May and September–December, and the increased standard deviation can be attributed to the orography. Southern Somalia and the Kenya coast (the area corresponding to cluster 6; Fig. 3a) show a relatively low spread among the SPE values (standard deviation up to 30 mm month\(^{-1}\)) in Figs. 6b and 6d and Fig. 7c, where the mean standard deviation is shown for grid cells with ensemble mean values between 50 and 200 mm month\(^{-1}\); Figs. 5b,d).

A significant increase in SPE variability during boreal summer months is evident from Fig. 6c with the highest standard deviation values (up to 80 mm month\(^{-1}\); see also Fig. 7d, where the mean standard deviations are displayed for ensemble mean values greater than 200 mm) occurring over western Ethiopian highlands, the Ethiopian Rift Valley, and South Sudan. In SON, the SPE variability resembles that of the MAM months.

6. Comparisons between SPE and GPCC_FD datasets

An analysis of the SPE uncertainties is performed by comparing the SPE datasets with the GPCC_FD dataset at 0.5° resolution (the best spatial resolution available for GPCC_FD) for a quantitative assessment of the behavior and the reliability of the SPEs in the different clusters and to complete the evaluation carried out in the previous section. The analysis is conducted for each cluster separately only on the grid cells at 0.5° resolution that are fully contained within a single cluster. GPCC_FD is selected as reference dataset as it is the most accurate in situ precipitation reanalysis dataset of GPCC and is recommended for regional climate monitoring and
analysis of historic global precipitation (Becker et al. 2013). It is based on quality-controlled data from all available ground stations in the GPCC database, including both real-time and non-real-time data. Nevertheless, the poor local density of rain gauge stations in some EA countries needs to be considered. In Fig. 8 the number of ground stations at each 0.5° grid cell for the years 2001 (Fig. 8a) and 2009 (Fig. 8b) is shown to have an idea of the ground station availability for the GPCC products. Somalia, Eritrea, and Djibouti are completely devoid of GPCC ground stations for the period 2001–09, and since 2005 a sharp decrease in the number of available stations is evident even over Ethiopia, Uganda, and Kenya, the countries with the highest ground station density. This situation affects the GPCC_FD data over EA and in particular over clusters 3 and 6, but also the SPEs that make use of rain gauge estimates for local calibration of the algorithms or bias correction. Becker et al. (2013, see their Fig. 13) attempted a quantitative assessment of the sampling error of the GPCC products as a function of the ground station density and gridding method at the global scale by using the MAE to calculate the sampling error of arbitrarily resampled data. From their analysis an MAE value ranging from 25 to 30 mm month\(^{-1}\) was extracted by considering both the modified SPHEREMAP as gridding methodology and the lowest number of stations. This value is considered as a rough estimate of the GPCC_FD uncertainty in the following discussion because the scarce ground station density can be considered the main contribution to the GPCC_FD error over the region.

Complex orography is a recognized issue for the precipitation retrieval from both IR and PMW satellite sensors (Dinku et al. 2011). IR-based algorithms may have problems identifying warm orographic rainfall, relying only on cloud-top temperature. PMW retrievals...
in turn suffer from the moderate to low signal from ice scattering, which is the baseline of such algorithms over land, because of the scarce ice content on top of the clouds producing warm orographic rainfall. The effect of terrain elevation on precipitation intensity is illustrated in Fig. 9 for each satellite product. The monthly mean precipitation of each cluster is displayed as a function of the 0.5° grid cell elevation $H$. In general, precipitation intensity increases with elevation ($H > 200$–$500$ m) with a trend dependent on the cluster. Satellite products give similar results over grid cells with $H < 500$ m, whereas a wider spread of precipitation intensity values is found for higher $H$ values, as previously observed in terms of the SPE ensemble standard deviation in section 5. In many cases PERSIANN exhibits a sharp decline in the precipitation intensity for the highest $H$ values, often showing the lowest values. These results confirm the findings of Hirpa et al. (2010) over the Awash River basin in Ethiopia, where a similar analysis was carried out at the annual time scale for the 3B42 RT (real-time version), CMORPH (previous version without rain gauge bias correction), and PERSIANN.
The previous results suggest an evaluation of the performances of SPEs against GPCC_FD by separating cells with $H < 1000\,\text{m}$ from those with $H \geq 1000\,\text{m}$.

Clusters 2–5 prompt us to evaluate the orographic effect on precipitation products in areas characterized by different precipitation seasonality. The lowland cells of clusters 2, 4, and 5 exhibit MAE and RMSE values from about 16 to 70 mm and from 32 to 114 mm, respectively. Cluster 3 has lower values and limited variations among the products (15–18 mm for MAE and 27–34 mm for RMSE). The seasonality and intensity of precipitation in the various clusters can help explain the higher MAE and RMSE and the greater dispersion of their values in clusters 2, 4, and 5 with respect to cluster 3. Cluster 3 is characterized by substantially lower intensities, a moderate dispersion of SPEs for lowland cells (Fig. 9), and a longer dry season than clusters 2, 4, and 5 (Fig. 4). In clusters 2, 4, and 5, 3B42 is the satellite product with the best MAE (16–27 mm) and the best RMSE (29–42 mm). The MAE values are always lower than 30 mm for all SPEs except for cluster 4 and GSMaP and PERSIANN in cluster 5. Precipitation is underestimated in clusters 2 and 3 by all products except 3B42, and overestimated in clusters 4 and 5 by GSMaP and PERSIANN. The correlation with GPCC_FD increases in clusters 4 and 5, reaching values of about 0.8. Also, the EFF values increase from clusters 2 and 3 to 4 and 5 with the exception of PERSIANN, which shows negative EFF values. Considering the statistical scores for the cells with $H > 1000\,\text{m}$, it is evident that the influence of orography on the precipitation retrieval depends on clusters. An increase in the RMSE and MAE values stands out from Figs. 10d and 10h, in particular for clusters 3 and 5. Only a very moderate effect on MAE and RMSE is found in clusters 2 and 4, where the various SPEs behave similarly. In general terms, PERSIANN shows the greatest and 3B42 the lowest MAE and RMSE. Precipitation is generally underestimated in the elevated portions of these clusters, as evident from ME and BIAS negative values (Figs. 10f,j), whereas the EFF scores are not substantially affected by the elevation (Figs. 10k,l).

Other predominantly mountainous clusters are 1B and 8 encompassing the northern Tanzania region at the border with Uganda and surrounding the southern part of Lake Victoria. Cluster 1B is characterized by very high RMSE and MAE values up to 117 and 76 mm (Figs. 10d,h), whereas RMSE and MAE of cluster 8 are more consistent with the values of the previous clusters. This can be due to the higher precipitation intensities ranging from 90 to 180 mm in cluster 1B with respect to the lower values of cluster 8 (Figs. 9b,k), but also the scarce number of cells contained in cluster 1B (19) has to be considered.
FIG. 9. Mean monthly precipitation amount as a function of terrain elevation. The mean monthly precipitation was computed for each cluster, from (a) to (k) clusters 1A to 8, considering the whole time period (2001–09) and five terrain elevation bins. Each curve refers to a different SPE according to the color table reported in the legend.
Two flat and arid regions cover clusters 1A and 7, where precipitation is mainly overestimated (Fig. 10i) with RMSE ≤ 33 mm and MAE ≤ 10 mm (Figs. 10c,g). The EFF and CC score better for cluster 7 than for cluster 1A. According to Dinku et al. (2011), precipitation overestimation is a typical result in arid areas because of sub-cloud evaporation and the combination of the coarse SPE spatial resolution and the very hot background surface, especially for PMW sensors. In this case, pixels may encompass both raining areas and underlying hot surfaces, which on average may erroneously be identified as non-precipitating. However, we believe that only results over cluster 7 can be significant because of the scarce cell number of cluster 1A.

A comparison between the results obtained in inland and coastal areas with similar seasonality can be carried out considering the Somali coastal subclusters 1A and 1D against 1B (Uganda–Tanzania border) and 1C (most part of Kenya). Precipitation is overestimated in coastal subareas with poor EFF values (mainly negative; Fig. 10k). Nevertheless, these results do not agree with the statistical scores obtained in the more populated coastal cluster 6 (96 cells against the 5 and 18 cells of clusters 1A and 1D), where precipitation is markedly underestimated by all products (Fig. 10i). Low BIAS values from 0.5 to 0.8 are found in cluster 1C for all SPEs except 3B42 and CMORPH (Fig. 10i), together with MAE values near 20 mm and RMSE in the range 27–44 mm. The MAE and RMSE significantly increase in cluster 1B, as previously described. Apart from the different BIAS values from the overestimation in coastal clusters to the underestimation in the inland ones, no particular characteristic emerges to further distinguish the two cluster classes.

7. Conclusions

The results of the present evaluation indicate a potential for effective applications of SPEs at the monthly scale over EA. The satellite datasets consistently reproduce the precipitation annual cycles as identified by in situ data in terms of wet season duration, prevailing wet season (for bimodal cycles), and peak intensity months.

The comparisons between SPEs and GPCC_FD data allow for quantifying the performances of satellite products. This is true in spite of the caveat that GPCC_FD data 1) are affected by ground station poor density over EA and 2) for some satellite products (3B42 in particular) do not represent a completely independent reference dataset for validation. From these comparisons the positive EFF scores are quite encouraging indications for the use of satellite products. The only exception is represented by PERSIANN, which exhibits negative EFF values in some occasions.

From the statistical scores 3B42 stands out as the best-performing satellite product in all clusters with MAE values in the range 5–25 mm, thus within the range of uncertainty attributed to GPCC_FD data, and the best EFF values. Moreover, MAE and RMSE are only moderately affected by the orography. Note that 3B42 uses rain gauge estimates during its final processing stage by performing a monthly based rescaling of the 3-hourly 3B42 product through a monthly satellite–gauge estimate created by accumulating the 3-hourly product and combining it with GPCC rainfall estimates (Huffman et al. 2007). The resulting high-resolution satellite precipitation product takes advantage of the typically small bias of gauge analyses over land. This explains the high agreement of 3B42 with GPCC_FD, also confirmed by the high CC values (>0.8 in many cases).

CMORPH and RFE also make use of rain gauge estimates for precipitation bias correction (not the GPCC product like 3B42), but their agreement with GPCC_FD data is not as good as that of 3B42, even though quite significant (CC values in the range 0.6–0.85 mm). Both products underestimate orographic precipitation, in particular RFE. MAE values are always lower than 30 mm in the case of lowland cells except in cluster 4 (the lowland portion of cluster 1B includes only two cells, and thus results cannot be considered significant), while an increase in MAE beyond the 30-mm value characterizes the cells with $H > 1000$ m in clusters 1B, 2, 3, 4, 5, and 8.

In terms of MAE, RMSE, and EFF, RFE performances are very similar to those of TAMSAT, thus confirming the generally high skills of locally calibrated algorithms. TAMSAT also demonstrates the positive performances of an IR-based algorithm with a contribution of historic rain gauge data for calibration purposes, as described in section 3a. Lower BIAS values characterize the performances of TAMSAT: this dry bias was already recognized by Maidment et al. (2014) and attributed to the approach used in the algorithm calibration, more oriented to drought monitoring and to an accurate representation of low rainfall amounts. In the TAMSAT calibration process, a regression is performed on all rain gauge–CCD pairs, where the median rainfall value is chosen to regress against the midpoint of the corresponding CCD bin. This approach leads to an overall dry bias as median rainfall is almost always lower than the mean rainfall.

The GSMaP algorithm shares the morphing approach of PMW rainfall estimations with CMORPH, but unlike CMORPH it does not include the bias correction by means of rain gauge data. This may partially explain its relatively poorer performance with respect to CMORPH.
GSMaP has MAE values greater than CMORPH in the lowland portion of cluster 5 and in the mountainous clusters 2, 4, and 5. Underestimation of orographic precipitation is more pronounced than in CMORPH, RFE, and sometimes also in TAMSAT.

PERSIANN shows very low EFF values, even negative, and the highest MAE values. Note that the algorithm does not make use of rain gauge estimates for the artificial neural network parameter calibration or bias correction. These results seem to confirm the PERSIANN behavior as observed in section 5 (Table 3), where this product shows the highest percentage of outliers, thus demonstrating a performance that frequently deviates from the mean of the other products.

Relevant indications on the behavior of SPEs come from the analysis of the orographic effect on satellite-derived
precipitation intensity. The analysis has identified EA as a region where satellite-derived precipitation quantification is still problematic. A considerable spread in the SPEs stems from the analysis of the six-member ensemble standard deviations, with higher values associated with more intense precipitation in mountainous or topographically complex areas. These results were also confirmed by the comparisons between SPEs and GPCC_FD data, which highlight a cluster-dependent orographic effect, more marked in clusters 3 and 5 with an increase of MAE and RMSE and a general overestimation of the precipitation intensity. Thus, one more key issue to consider is the need for additional information on the dependence between SPE and elevation for the necessary improvement of the ability of the algorithms to better catch the orographic precipitation enhancement.

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REFERENCES


