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3 **The Predictability of Precipitation Episodes during**
4 **the West African Dry Season**

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21 **Abstract**

22 Precipitation episodes in tropical West Africa (7–15°N, 10°W–10°E) during the dry
23 season from November to March are rare, but can have significant impacts on human
24 activities reaching from greening of pastures to spoiling harvests and health implications.
25 Previous work has shown a link between these unseasonal rainfalls and extratropical
26 disturbances via a decrease of surface pressure over the Sahara/Sahel and a subsequent
27 inflow of moist air from the Gulf of Guinea. This paper supports the previously stated
28 hypothesis that the extratropical influence leads to a high rainfall predictability through a
29 careful analysis of operational 5-day forecasts from the European Centre for Medium-
30 Range Weather Forecasts (ECMWF) Ensemble Prediction System (EPS), which are
31 evaluated using Global Precipitation Climatology Project (GPCP) and Tropical Rainfall
32 Measuring Mission (TRMM) precipitation estimates for the 11 dry seasons 1998/99–
33 2008/09. The long-term regional average of ensemble-mean precipitation lies between the
34 two observational datasets with GPCP being considerably wetter. Temporal correlations
35 between the ensemble mean and observations are 0.8. Standard probabilistic evaluation
36 methods such as reliability and relative operating characteristic (ROC) diagrams indicate
37 remarkably good reliability, sharpness and skill across a range of precipitation thresholds.
38 However, a categorical verification focusing on the most extreme ensemble mean values
39 indicates too many false alarms. Despite the considerable observational uncertainty the
40 results show that the ECMWF EPS is capable of predicting winter rainfall events in
41 tropical West Africa with good accuracy, at least on regional spatial and synoptic time
42 scales, which should encourage West African weather services to capitalize more on the
43 valuable information provided by ensemble prediction systems during the dry season.

44 **1. Introduction**

45 Tropical West Africa is characterized by a monsoon climate with the largest portion
46 of the annual precipitation falling in the boreal summer months (Hastenrath, 1991;
47 Buckle, 1996). The period from around the start of November to the end of March is
48 dominated by the dry and often-dusty northeasterly Harmattan winds and very sporadic
49 rainfall events, which contribute little to the annual total on average. Nevertheless,
50 impacts of these events on the local population can be manifold and include: (A) Harvests
51 such as cotton are often stored to dry outdoors and unexpected rain can cause them to rot
52 (Buckle, 1996; Knippertz and Fink, 2008; 2009). (B) If damp, staple foods such as
53 groundnut and maize can become contaminated by aflatoxins, fungal metabolites that can
54 cause sickness or death in humans and animals (Hell and Mutegi, 2011). (C) Unseasonal
55 rains can significantly improve grazing conditions, e.g. for the herds of kettle nomads,
56 and facilitate agricultural work such as ploughing or building moulds for yam due to
57 enhanced soil moisture. (D) Anomalously moist periods during the dry-season can help to
58 prevent epidemics of meningococcal meningitis, which is widespread in West Africa
59 (Sultan *et al.*, 2005; Thomson *et al.*, 2006). These examples show that reliable predictions
60 of dry-season rainfall events in tropical West Africa on synoptic timescales have the
61 potential to support decision-making processes for a wide range of mitigating actions.
62 Particularly points (A) and (B) above would clearly benefit from the establishment of an
63 early-warning system up to a week ahead.

64 Given the predominance of summer rainfalls for the annual totals, rather little work
65 has been dedicated to the dynamics and climatology of precipitation during the dry
66 season, mostly in the form of case studies of extreme events (e.g. Knippertz and Martin,

67 2005; Fall *et al.*, 2007; Knippertz and Fink, 2008; Meier and Knippertz, 2009). Most of
68 these cases occurred over the western parts of tropical and subtropical West Africa,
69 which are occasionally affected directly by very deep upper-level disturbances over the
70 Atlantic Ocean (Fröhlich and Knippertz, 2008). Knippertz and Fink (2008; KF08
71 hereafter) were among the first to analyze the dynamics of extreme unseasonal rainfall in
72 southern West Africa. The mechanism they proposed is schematically depicted in Figure
73 1. The presence of a pronounced, positively tilted upper-level trough over northwestern
74 Africa leads to a shift of the subtropical jet (STJ) and a decrease of surface pressure over
75 the Sahara and Sahel. In the particular case KF08 investigated, two low-pressure centres
76 formed, one close to the base of the trough over Algeria associated with unusual
77 precipitation over the northern Sahara and one over tropical West Africa. The latter can
78 be regarded as an intensified and northward shifted wintertime continental heat low. This
79 pressure configuration leads to a significant break in the Harmattan winds and the inflow
80 of moist southerlies from the Gulf of Guinea, which shifts the Intertropical Discontinuity
81 (ITD), the surface boundary between moist maritime and dry continental air, northwards
82 and feeds the unseasonal rainfalls.

83 A follow-up study by Knippertz and Fink (2009; KF09 hereafter) contains the first-
84 ever statistical analysis of dry-season rainfall events over southern West Africa (7–15°N,
85 10°W–10°E), based on pentad precipitation from the Global Precipitation Climatology
86 Project (GPCP) and 5-day forecasts made as part of the European Centre for Medium-
87 Range Weather Forecasts (ECMWF) ERA-40 re-analysis project (Uppala *et al.*, 2005) for
88 the period 1979/80–2001/02. The main conclusions from this work are that (A) the
89 schematic shown in Figure 1 is representative for many of the identified events, (B) the

90 ECMWF model shows skill in predicting event occurrence on a regional scale up to a
91 week ahead and (C) predictability appears to be enhanced in cases of a clear connection
92 to the extratropics. The latter is typically manifested through a well-defined and persistent
93 upper-level trough or the succession of two troughs, accompanied by an elongated
94 southwest–northeast oriented band of upper- and midlevel clouds stretching from the
95 Tropics to the subtropics along the equatorward side of the STJ. Such bands are often
96 referred to as “Tropical Plumes” (see Knippertz, 2005 and references therein).

97 This study builds on those by KF08 and KF09, and expands them in the following
98 ways: (A) In order to test the hypothesis of enhanced predictability formulated in KF09,
99 operational ensemble predictions from ECMWF are investigated instead of ERA-40 data.
100 This allows a combination of conventional and probabilistic verification measures to be
101 used. (B) KF09 amongst other authors have demonstrated problems with the old pentad
102 product of the GPCP (Xie *et al.*, 2003) over data-sparse West Africa. The present study
103 uses a new daily version of GPCP (1DD) together with rainfall estimates from the
104 Tropical Rainfall Measuring Mission (TRMM), which includes information from space-
105 born rainfall radar, to assess aspects of observational uncertainty. These improvements in
106 the data quality come at the expense of reduced data availability, which limits this
107 analysis to the 11 dry seasons 1998/99–2008/09. Section 2 provides more information on
108 the datasets used in this study. The results are presented in sections 3 and 4 focussing on
109 evaluation of the ensemble mean and probabilistic analysis, respectively. Section 5
110 provides a short discussion of the results and gives the main conclusions.

111

112

113 **2. Data**

114 Most analyses presented in this paper are based on gridded datasets of estimated
115 and forecast precipitation, respectively, as detailed in the following sections 2.1 and 2.2.
116 Following KF09, these fields are averaged spatially over 7–15°N, 10°W–10°E and
117 accumulated over 5 days to give a regional precipitation index. As shown in KF09, the
118 ECMWF model is generally capable of forecasting accurately at much finer scales, but a
119 grid-point based verification of the predominantly convective rainfalls is generally
120 difficult, which has motivated several authors to develop object-based methods, all with
121 their different advantages and problems (e.g. Wernli *et al.*, 2008). Such an approach is
122 beyond the scope of this paper. Instead this study focuses on the question whether the
123 ECMWF model can accurately predict moist episodes during the dry-season on a regional
124 scale, which in our view is sufficient for many of the applications discussed in the
125 Introduction, particularly for early-warning systems. The time period covered is the entire
126 dry-season from 1 November to 31 March.

127

128 *2.1 Observational data*

129 Daily precipitation estimates used in this paper are from the GPCP 1DD and
130 TRMM 3B 42 Version 6 datasets. The former is largely based on a monthly combined
131 satellite-gauge product, which is used to calibrate daily estimates derived from
132 geostationary and polar-orbiting infrared sensors (Huffman *et al.*, 2001; Roca *et al.*,
133 2010). Microwave and gauge estimates are not used explicitly owing to sampling
134 limitations. It is provided with a spatial resolution of one degree. The TRMM daily
135 product is derived from a combination of TRMM microwave imager, radar and visible-

136 infrared scanner data and other satellite infrared observations (e.g. Meteosat; see
137 Huffman *et al.*, 2007). Among other things, the TRMM data are used to produce monthly
138 infrared calibration parameters, which are then applied to 3-hourly precipitation estimates
139 from the other satellite infrared datasets. The daily totals are estimated from the 3-hourly
140 precipitation data between 00Z and 21Z. Finally the daily totals are scaled so that the
141 monthly total matches that of the satellite-gauge TRMM Combination 3B 43 Version 6.
142 These data have a spatial resolution of 0.25 degrees. Both datasets are averaged
143 regionally as explained above and accumulated over five days starting at 0000 UTC each
144 day. This results in 147 pentads for one entire dry season with the first ranging from 1–5
145 November, the second from 2–6 November and so on, the last covering 27–31 March.
146 This gives 1617 pentads for the 11 dry seasons under study here. Note that for the sake of
147 simplicity, 29 February was ignored for the leap years during the study period 1998/99–
148 2008/09.

149 A scatter plot of all GPCP pentad precipitation values against their TRMM
150 counterparts (Figure 2) shows a clear positive bias in the GPCP data. Such discrepancies
151 between rainfall estimates illustrate the challenge in evaluating short-term forecasts in the
152 light of large observational uncertainties. Intercomparison studies at 10-day and monthly
153 scales over West Africa (Nicholson *et al.*, 2003a, b; Ali *et al.*, 2005; Lamptey, 2008;
154 Jobard *et al.*, 2011; Paeth *et al.*, 2011) have also found substantial differences between
155 the two datasets. For more details, see the recent comprehensive review by Parker *et al.*
156 (2011), which also includes daily products. Despite the bias, the correlation between
157 TRMM and GPCP is 0.92. In interpreting this value, however, it should be kept in mind
158 the data points in Figure 2 are not independent due to the overlap of adjacent pentads.

159 In addition to the precipitation data discussed above, ECMWF ERA-Interim re-
160 analysis (Dee *et al.*, 2011) and Meteosat infrared satellite images are used in section 3 for
161 the discussion of example case studies (e.g. Figure 8).

162

163 *2.2 Ensemble predictions*

164 The forecast dataset under investigation comes from the operational ECMWF
165 ensemble prediction system (EPS; Buizza *et al.*, 1997; 2007). It was designed to cope
166 with uncertainty in initial conditions and is now also taking into account uncertainties in
167 model physics (Buizza *et al.*, 1999). The EPS became operational in 1992 and has had 50
168 members since 1996. As a fully operational system, it went through a number of model
169 and configuration changes in the course of our investigation period 1998–2009, so that
170 the forecasts studied here are not a homogeneous dataset in the strictest sense. It is,
171 however, one of the longest and arguably best available EPS datasets to study
172 predictability today. The EPS is currently run twice daily at 0000 and 1200 UTC, but as
173 this was not the case during the first part of our study period, we restrict the analysis to
174 the latter time only. In order to match the TRMM and GPCP pentad data, differences
175 between total precipitation accumulations (convective plus large-scale) at +132h and
176 +12h are considered for each day and then averaged over 7–15°N, 10°W–10°E.

177

178 **3. Analysis of the ensemble mean**

179 It has been shown that for forecast ranges beyond three days predictions based on
180 the mean of a well-calibrated EPS outperforms a deterministic forecast with the same
181 model after about 3 days (e.g. Buizza *et al.*, 1997). Therefore, this section concentrates on

182 assessing forecast quality based on the ensemble mean only, while section 4 will focus on
183 probabilistic measures. Section 3.1 analyzes the mean seasonal cycle and correlations
184 between the observational and EPS data, while section 3.2 focuses on an event-based
185 verification. Finally, section 3.3 discussed exemplary cases of subjectively selected
186 successful and unsuccessful forecasts.

187

188 *3.1. Mean seasonal cycle and correlations*

189 Figure 3 shows the seasonal cycle for the EPS, TRMM and GPCP datasets
190 averaged over the 11 dry-seasons 1998/99 to 2008/09. All three datasets show the
191 characteristic decrease from above 2 mm per pentad in early November to very small
192 values in late December and then a gradual increase to values above 3 mm per pentad at
193 the end of the period in late March. Although the overlapping pentad accumulation
194 causes a smoothing of the curves, single significant events still stand out from the 11-year
195 background as for example a period in mid-February. Overall, GPCP shows considerably
196 higher values (on the order of 50%) during the early and late parts of the dry season,
197 while agreement with the other two datasets is better during the middle part. TRMM
198 agrees remarkably well with EPS during the first half of the dry season and shows some
199 tendency for lower values than EPS later on. Averaged over the entire dry season and all
200 years, differences between EPS and TRMM (GPCP) are 0.12 mm (−0.41 mm) per pentad.
201 An analysis of the reasons for these discrepancies is beyond the scope of this paper. They
202 show, however, that there is a considerable uncertainty in the observations, which pose a
203 significant problem to evaluation and model development. Part of this problem is

204 certainly related to the sparse network of surface stations that hampers the calibration and
205 evaluation of satellite retrievals (see also the discussion at the end of section 2.1).

206 Despite the biases discussed above, the temporal behaviour found in the
207 observational datasets is overall well reproduced by the EPS with linear correlation
208 coefficients reaching a remarkable 0.80 for both observational datasets (Figure 4). Part of
209 this strong relation is certainly associated with the general moistening in February/March
210 (Figure 3), but as we will show below there are significant events that stand out well from
211 the background during all parts of the dry season, which are mostly well reproduced by
212 the ensemble mean. Correlations with positive and negative lags show consistently lower
213 values, indicating that the model does not tend to trigger precipitation too late or too early
214 in a systematic way. It is interesting to note that the regression lines in both panels of
215 Figure 4 are below the diagonal despite the slightly lower mean values in TRMM. This
216 indicates that the EPS shows a general tendency to underestimate the wettest events and
217 overestimate low-intensity events. This finding is consistent with results by KF09 using
218 ERA-40 data.

219

220 *3.2 Event-based verification*

221 Given the strong seasonal cycle displayed in Figure 3, an event definition based on
222 absolute values (either total or anomaly thresholds) is problematic. To circumvent this
223 problem, KF09 defined events as anomalies of more than 200% relative to the mean
224 seasonal cycle. This method biases the event identification to the driest part of the season
225 when such large values are reached with much smaller absolute precipitation amounts. To

226 avoid this effect, a new approach is proposed here that involves a moving block of 10
227 pentads in the following way:

- 228 • Identify the maximum of the first 10 pentad accumulations of the season (1–5
229 November, 2–6 November, 3–7 November, and so on until 10–14 November) of all 11
230 dry-seasons (110 values in total).
- 231 • Shift by 5 days and identify maximum of the 110 pentads 6–10 November, 7–11
232 November, 8–12 November and so on until 15–19 November of all dry-seasons.
- 233 • Repeat shift by 5 days 26 times until the end of the dry-season. The last 10-pentad
234 block contains 16–20 March, 17–21 March, 18–22 March and so on until 25–29
235 March. This way the last two days, 30 and 31 March, cannot be considered.

236 In principle this procedure finds 28 maxima evenly distributed across the dry
237 season. However, the overlap between the 10-pentad blocks used to find maxima leads to
238 double counting, giving 20 actual maxima in TRMM and 21 in GPCP and EPS. In
239 addition, if identified maxima are four days or less apart from each other in time, they are
240 considered part of the same meteorological event and only the pentad with the larger
241 precipitation value is retained. This reduces the final numbers of events to 16 (TRMM)
242 and 17 (GPCP and EPS), thus about one and a half event per dry-season (results are listed
243 in Table I). The two dry-seasons 2000/01 and 2004/05 stand out as the ones without any
244 events in any of the datasets. Remarkably, TRMM and GPCP only agree on 12 events
245 (75% and 71% of all, respectively), underlining the substantial observational uncertainty.

246 The definition of events as explained above enables the identification of forecast
247 hits, missed events and false alarms. In matching events from two different datasets, a
248 time shift of 1 or 2 days was tolerated. Table II gives the results of this analysis. 7 events

249 were found with all three datasets matching, while additional 2 had at least a match
250 between EPS and TRMM (see shadings in Table I). Given the observational uncertainty,
251 these can be regarded as 9 hits. 5 events are identified in both TRMM and GPCP, but not
252 in the EPS data and therefore qualify as missed events. Interestingly these are
253 predominantly during the early part of the study period (1998/99, 1999/2000, 2 in
254 2001/02, 2008/09). It may indicate that improvements to the operational system in the
255 course of the study period have led to a reduction of misforecasts. There are 7 situations
256 in which only one of the two observational datasets shows an event. These could be
257 interpreted as partial misses, but we would argue that they should be considered correct
258 negatives in the light of the observational uncertainty. The biggest problem with the event
259 forecasts is the high number of false alarms (8 during the 11 seasons). Some of these
260 clearly stand out as significant outliers in Figure 4. Given the impacts of dry-season
261 rainfalls as discussed in the introduction, it is probably tolerable to have more false
262 alarms than missed events, but such a high number points to some fundamental problem
263 in terms of predicting rainfall quantities.

264 Given the relatively small number of events and the particular nature of the
265 identification routine that is designed to give fairly equal numbers for each datasets, the
266 authors decided not to take this analysis any further by computing standard verification
267 measures such as frequency bias, hit rate, false-alarm ratio etc. However, it is interesting
268 to view the results for the categorical evaluation of the ensemble mean in a more
269 probabilistic sense. To do this, it is necessary to see to what extent the false alarms and
270 missed events discussed above are consistent with the ensemble spread for the given
271 period. Situations where the observations lie outside of the spread are undesirable and

272 should occur rarely for a well-tuned EPS. Results show that four out of five missed
273 events (all but that in 1998/99) fall inside of the ensemble spread with one even inside the
274 interquartile range. This suggests that most of these cases are only ‘missed’ in the sense
275 of the event definition based on the ensemble mean, but that they can still be considered
276 successful forecasts in a probabilistic sense. Five of the eight false alarms fall inside of
277 the spread with three inside the interquartile range. The remaining three can be
278 considered as misforecasts. This simple analysis suggests that probabilistic measures as
279 discussed in section 4 will most likely evaluate the performance of the EPS more
280 positively than the event-based one presented here.

281

282 *3.3 Example cases*

283 To illustrate this further, Figure 5 shows time series of the three considered datasets
284 for four selected example dry seasons. TRMM and GPCP data are plotted as lines with
285 crosses; the EPS data is depicted with box-and-whiskers plots (see caption for more
286 details). Identified events are marked with bold horizontal lines. There is a generally very
287 low ensemble spread during many observed dry periods, which could be capitalized on in
288 terms of impacts.

289 The first season 2001/02 shows four conspicuous rainfall periods (Figure 5a):

- 290 • The event in mid-November qualifies as a miss, but at least the EPS forecasts
291 unseasonal rainfall around the right time with all members above 2 mm per pentad and
292 TRMM estimates well within the ensemble spread. The quantitative disagreement
293 between GPCP and TRMM is remarkable.

- 294 • The weaker event in late November is only flagged by GPCP, while TRMM is well
295 within the interquartile range of the EPS, which starts precipitation too early in this
296 case, possibly related to problems with representing shallow stable layers (see KF09).
- 297 • The event in early January is a clear hit with remarkable agreement between the three
298 datasets. This case brought heavy rainfall across large parts of West Africa and severe
299 flooding in Senegal and Mauritania (outside of our study region; see Knippertz and
300 Martin, 2005; Fall *et al.*, 2007). Figure 6 shows the horizontal distribution of rainfall
301 for the three datasets. The overall spatial agreement is good, but GPCP tends to extend
302 very light rainfall far into the Sahel and Sahara and smears out the localized maximum
303 over the Ivory Coast (Figure 6b). The ensemble-mean forecast (Figure 6c) is
304 expectedly rather smooth and shows the advance of the rainfalls into the southwestern
305 part of the domain very clearly. Meier and Knippertz (2009) also noted the high
306 predictability of this case in their model sensitivity experiments.
- 307 • The event in the first half of March qualifies as a miss. This event brought unusual
308 early rains in central Benin between 9 and 11°N (Fink *et al.*, 2006). Again, there is a
309 large disagreement between GPCP and TRMM, which falls just inside the interquartile
310 range of the EPS. An underestimation of March rainfalls is not observed for most
311 other years, which might be connected to a soil moisture or vegetation bias after the
312 unusual rainfalls in January.

313 The dry season 2003/04 had four wet events (Figure 5b). The first (early
314 November), third (late January) and fourth (early March) are classified as hits, despite a
315 significant underestimation for the former two (recall that event identification occurs
316 relative to each dataset). This is clearly a disadvantage of the event identification

317 proposed here, suggesting that it should only be used in combination with other, more
318 continuous measures. The event in mid-January (Figure 7) is the case discussed in detail
319 in KF08, which first instigated research into this phenomenon. TRMM clearly shows
320 very unusual, heavy precipitation reaching from Ivory Coast into Nigeria (Figure 7a).
321 GPCP shows a coarse-grained and somewhat weaker pattern, again with light rains
322 spreading far away from the main rainfall event (Figure 7b). The ensemble mean gives a
323 clear indication of a general northward shift of the rain zone, but fails to reflect the full
324 detail and magnitude (Figure 7c), largely consistent with the ERA-40 forecasts in KF08.
325 The event in mid-November 2003 (Figure 5b) and the very last pentad of this dry season
326 (not identified as an event) show a remarkable disagreement between GPCP and the other
327 two datasets..

328 The dry season 2005/06 (Figure 5c) again shows large disagreement between the
329 two observational datasets over longer periods, particularly in November, December and
330 March. The first event in late January is remarkably well forecast, but the second one in
331 mid-February is the most significant false alarm of the study period with both
332 observational datasets well below the driest ensemble members. The synoptic situation
333 during this event was characterised by a very pronounced, strongly tilted upper-level
334 trough located over northwestern Africa and the adjacent Atlantic Ocean, which is
335 associated with an area of low surface pressure reaching from Burkina Faso to
336 southwestern Algeria (Figure 8a). As a consequence the ITD shifts northward (thick line
337 in Figure 8a). The satellite image on 17 February 2006 (Figure 8b) shows a subtropical
338 cyclone-like cloud structure over the Sahara with some patchy convection to the south of
339 it in the Tropics, which locally brought precipitation exceeding 50 mm (e.g. on 15

340 February 2006 around 9.5°N, 2°E; Pospichal et al., 2010). According to TRMM there are
341 two separated areas of rainfall of moderate intensity: one associated with the cyclonic
342 feature (mostly outside the study area) and one associated with the northward shifted ITD
343 (Figure 8c). GPCP shows a coarse-grained version of this with very widespread light
344 precipitation over the Sahel and Sahara (Figure 8d). Surprisingly, the main band over the
345 Sahara is shifted eastwards in the GPCP data with respect to TRMM. In the EPS mean
346 the two precipitation areas are connected, leading to too much and too widespread
347 precipitation (Figure 8e). It appears that the model triggers convection too easily in this
348 situation of enhanced low-level moisture and supposedly upper-level forcing for uplift. It
349 is also conceivable that evaporation of precipitation in the dry desert air is not handled
350 well in the model. The frequent occurrence of false alarms suggests that these problems
351 are potentially systematic.

352 The last example, the dry season 2008/09, was one of the most active seasons with
353 5 identified events (3 hits, one missed event and one false alarm; Figure 5c). The latter
354 underlines again the problems with the event definition, which can indicate a misforecast,
355 although the absolute precipitation amounts agree rather well with each other. The most
356 remarkable event in this season is the heavy rainfall in mid February 2009 (see Waliser *et*
357 *al.* 2012). Other events mentioned in that paper are 5–6 December 2008 and 8–9 January
358 2009.

359

360 **4. Probabilistic analysis**

361 In this section the full probabilistic information content from the EPS is explored
362 with two standard evaluation methods, using the available TRMM and GPCP data for the

363 11 dry seasons 1998/99 to 2008/09 (as described in section 2.1) as the observed ‘truth’.
364 This analysis complements the categorical evaluation based on extreme values in the
365 ensemble mean presented in section 3. It is assumed here that each ensemble member
366 carries the same probability of occurrence.

367 The first method is the relative operating characteristic (ROC) diagram (e.g. Joliffe
368 and Stephenson, 2003). It is constructed using a set of simple four-cell contingency
369 tables. For the observations an event is defined through exceedance of a certain
370 precipitation threshold. For the EPS, the event/no event decision is made based on a
371 given forecast probability threshold (here 2, 20, 40, 60, 80 and 98%) for the chosen
372 precipitation amount. The hit rate, H , is then defined as the ratio of the number of correct
373 forecasts divided by the total number of observed events. The false alarm rate, F , is
374 defined as the ratio of the number of false alarms divided by the total number of non-
375 events in the observations. In this way, a single point can be plotted on a graph of H
376 against F . Plotting this for a set of probability thresholds creates a ROC curve, which has
377 several important characteristics. The bottom left corner represents a situation of no
378 warnings at all and therefore $H = F = 0$. The top right corner describes a situation of
379 always warnings and therefore $H = F = 1$. Typically the area underneath the ROC curve
380 is taken as a measure of skill (Buizza *et al.*, 1999). A perfect forecast will have $H = 1$ and
381 $F = 0$ and therefore a ROC area of 1.

382 The reliability of an EPS is its ability to forecast accurate probabilities (Palmer,
383 1999). This can be simply tested by plotting forecast probability against observed
384 frequency, again for a given precipitation threshold. The diagonal in this diagram
385 indicates perfect reliability. Circles of varying sizes represent the frequency of forecast

386 probabilities. Largest circles in the centre of the diagram indicate clustering around the
387 climatological average and therefore low predictability. The property of an EPS to spread
388 away from the climatological average is called “sharpness”.

389 Examples of ROC and reliability diagrams for different thresholds are shown in
390 Figure 9 for both TRMM and GPCP observations. For a threshold of 0.5 mm per pentad
391 both datasets are relatively close to the diagonal indicating good reliability (Figure 9a).
392 There is a general tendency to underestimate observed frequencies for low forecast
393 probability, particularly in GPCP. This could be partly related to the spurious widespread
394 low-intensity rainfall evident from Figures 6b, 7b and 8d. On the other hand observed
395 frequencies are overestimated for high forecast probability. This might be a reflection of
396 the EPS triggering convection too easily if the general conditions are favourable
397 consistent with the high number of false alarms discussed in the previous section. The
398 positive bias of GPCP with respect to TRMM leads to a general upward shift to higher
399 observed frequencies in the diagram. The differences in behaviour between low and high
400 observed frequencies do not make it possible to improve reliability greatly through a
401 general bias correction. The distribution has good sharpness with largest circles in the top
402 right corner, representing situations of successful forecasts where all ensemble members
403 exceed the threshold. The corresponding ROC diagram (Figure 9b) shows good skill for
404 both observational datasets with ROC areas of 0.90 (TRMM) and 0.91 (GPCP), with
405 differences again reflecting the different biases as discussed previously.

406 Figures 9c and 9d show the corresponding analyses for a precipitation threshold of
407 1 mm per pentad. Overall the results are very stable with only a slight shift to more
408 frequent events of low forecast probability as expected for a higher precipitation

409 threshold. This general behaviour continues for higher thresholds, so that for 3 mm per
410 pentad only few events in the top right corner of the reliability diagram are recorded
411 (Figure 9e). However, ROC scores continue to remain above 0.9, even for these relatively
412 extreme events (Figure 9f). Overall this analysis shows that EPS forecast of dry-season
413 precipitation are in fact of high quality and usefulness.

414

415 **5 Discussion and conclusions**

416 Dry-season precipitation events in tropical West Africa are rare, but have important
417 ramifications for the local population. This work extended previous studies on this
418 subject by KF08 and KF09 in two ways: (A) Forecasts of these events considered here
419 are from operational ECMWF ensemble predictions that allow an assessment of
420 predictability. (B) More recent and high-resolution precipitation datasets are used for
421 evaluation. The study region corresponds to that of KF09 and spans 7–15°N, 10°W–
422 10°E. The 11 dry seasons (November–March) 1998/99–2008/09 were investigated. EPS
423 forecasts and observations were compared on the basis of pentads, using +132h minus
424 +12h predictions. Evaluations are done both for the ensemble mean and using
425 probabilistic methods. The most important conclusions from this work are:

- 426 • There is a considerable observational uncertainty for this region during this time of
427 year. GPCP has a substantial positive bias with respect to TRMM and tends to show
428 widespread low-intensity rainfall. Although the overall temporal correlation is 0.92,
429 deviations during single events can be remarkably high, practically impeding a
430 forecast evaluation for some individual cases.

431 • The agreement of EPS is generally better with TRMM than with GPCP. This holds for
432 the mean seasonal cycle, temporal correlations, event evaluation and ROC scores.

433 • Temporal correlations between EPS mean and the observational datasets reach 0.8.

434 • ROC scores are on the order of 0.9. Sharpness and reliability are satisfactory with a
435 general tendency of too high (low) forecast probabilities for high (low) observed
436 frequencies.

437 • Categorical evaluation of extreme events identified from the ensemble mean is much
438 more sensitive to small variations in precipitation amounts and therefore indicates less
439 skill. There is a moderate number of missed events, but the biggest problems are too
440 many false alarms and a tendency of the EPS to start precipitation too early. Both may
441 indicate that convection is triggered too easily in the typical dry-season rainfall
442 situation with upper-level forcing and high low-level moisture.

443 Overall the results presented here indicate a general ability of the ECMWF EPS to
444 provide reliably forecast information of dry-season rain events in tropical West Africa on
445 the pentad timescale. It would be interesting to explore whether there is also some
446 seasonal predictability, for example related to the influence of El Niño on upper-level
447 troughs and tropical plumes over the eastern North Atlantic (Luise Fröhlich, University of
448 Cologne, pers. comm., 2012). One of the important limitations of this study is the large
449 observational uncertainty related to the disagreement of different precipitation products
450 on daily timescales (see Parker et al., 2011). The evaluation of rainfall products is
451 generally focused on the rainy season, such that biases during the dry season are
452 particularly large (Adeyewa and Nakamura, 2003). More targeted efforts are needed to
453 understand the origin of such biases and to explore retrievals designed for precipitation

454 outside of the main rainy season. Other research in the future should explore how the
455 predictability found in this study can be used to inform decision makers in West Africa,
456 particularly in the health, agriculture and water sectors. This will most likely require
457 investigations on finer spatial scales than used in this study and include the identification
458 of optimal forms of communicating uncertainty in ensemble predictions to a given end-
459 user community.

460

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465 Met Office for providing access to the ECMWF archive and the Dundee Satellite
466 Receiving Station for providing access to Meteosat imagery. We are grateful to two
467 anonymous reviewers whose comments helped to substantially improve an earlier version
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562 **Tables**

563 Table I: List of identified extreme pentads in the three datasets considered. Light shading
 564 indicates agreement between TRMM and GPCP, intermediate shading between EPS and
 565 TRMM and dark shading between all three datasets.

EPS	TRMM	GPCP
14–18 MAR 1999	06–10 DEC 1998	05–09 DEC 1998
17–21 NOV 1999	15–19 FEB 1999	30 DEC 1999–03 JAN 2000
23–27 NOV 1999	25–29 NOV 1999	16–20 MAR 2000
01–05 JAN 2000	31 DEC 1999–04 JAN 2000	11–15 NOV 2001
05–09 JAN 2002	16–20 MAR 2000	23–27 NOV 2001
03–07 NOV 2002	11–15 NOV 2001	06–10 JAN 2002
06–10 DEC 2002	06–10 JAN 2002	07–11 MAR 2002
07–11 NOV 2003	07–11 MAR 2002	13–17 FEB 2003
19–23 JAN 2004	05–09 NOV 2003	05–09 NOV 2003
01–05 MAR 2004	19–23 JAN 2004	16–20 NOV 2003
26–30 JAN 2006	27 FEB–03 MAR 2004	19–23 JAN 2004
13–17 FEB 2006	26–30 JAN 2006	26 FEB–02 MAR 2004
07–11 FEB 2007	01–05 DEC 2008	22–26 DEC 2004
03–07 DEC 2008	14–18 DEC 2008	26–30 JAN 2006
15–19 DEC 2008	02–06 FEB 2009	20–24 MAR 2008
16–20 FEB 2009	25–29 MAR 2009	13–17 DEC 2008
16–20 MAR 2009		01–05 FEB 2009

566

567

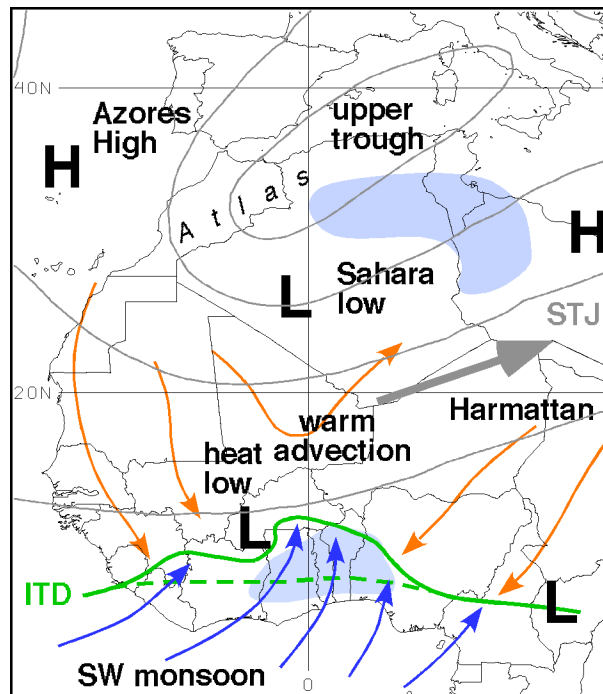
568 Table II: Results from the event-based evaluation. Situations where the two observational
 569 datasets disagree can be interpreted in two different ways. For more details see section
 570 3.2.

Event in	All three	EPS TRMM	EPS GPCP	EPS	TRMM GPCP	TRMM	GPCP
Number	7	2	0	8	5	2	5
Interpretation	hit	hit / false alarm		false alarm	miss	miss / correct neg.	

571

572 **Figures**

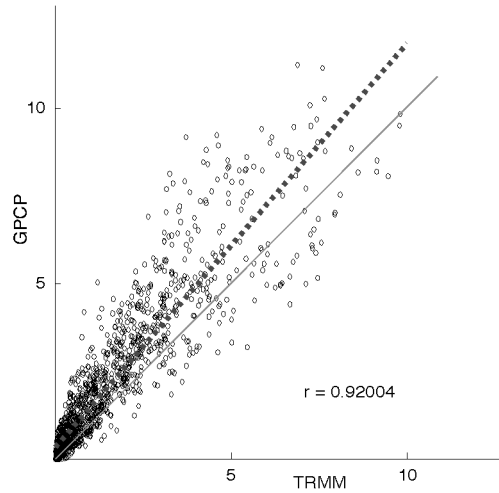
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575

576 **Figure 1.** Schematic depiction of the mechanism of tropical-extratropical interaction
577 responsible for many dry-season precipitation events (modified version of Figure 14 in
578 KF08). Thin solid lines depict upper-level geopotential height with the subtropical jet
579 (STJ) marked with a thick arrow. Thin arrows depict the predominantly northerly
580 (southerly) low-level flow of dry Saharan (moist tropical) air masses. 'H' and 'L' mark
581 high- and low-pressure centres, respectively. The thick dashed and solid lines show the
582 climatological and the actual positions of the Intertropical Discontinuity (ITD). Areas of
583 precipitation are shaded.



584

585 **Figure 2.** Comparison between GPCP and TRMM rainfall estimates. The scatter diagram
586 shows pentad precipitation (mm) for each day during the 11 dry seasons (November–
587 March) 1998/99–2008/09 averaged over the study area (7–15°N, 10°W–10°E). The linear
588 regression line (thick dashed), the diagonal (thin solid) and the linear correlation
589 coefficient are also given in the plot.

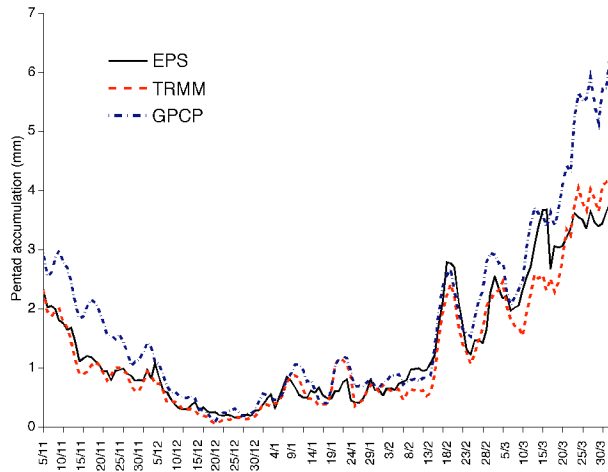
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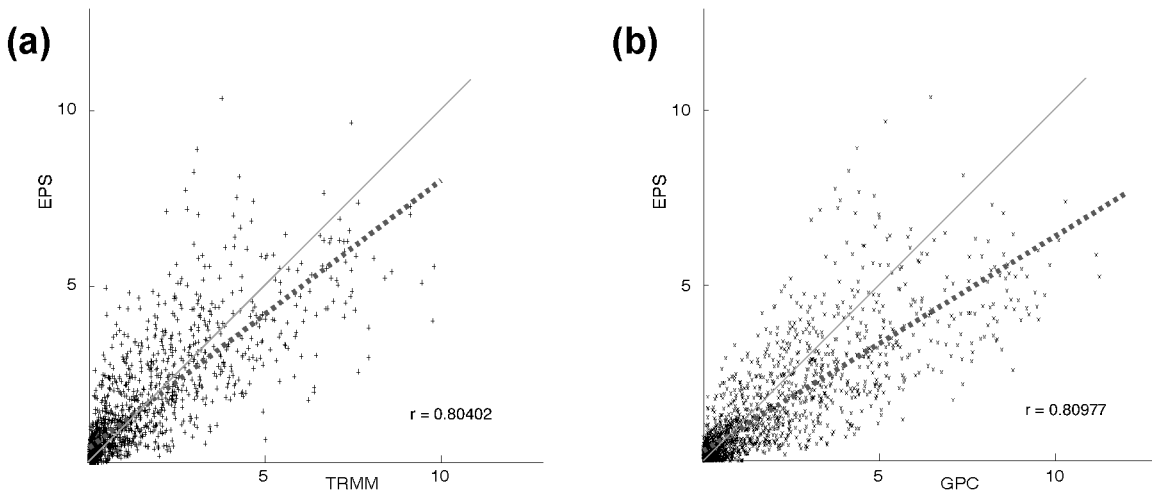


595

596 **Figure 3.** Mean seasonal cycle in EPS ensemble means, TRMM and GPCP data. Shown
 597 are pentad precipitation values for each dry-season day (November–March) averaged
 598 temporally over 1998/99–2008/09 and spatially over the study area (7–15°N, 10°W–
 599 10°E). The dates underneath the x-axis give the end date of the respective pentad.

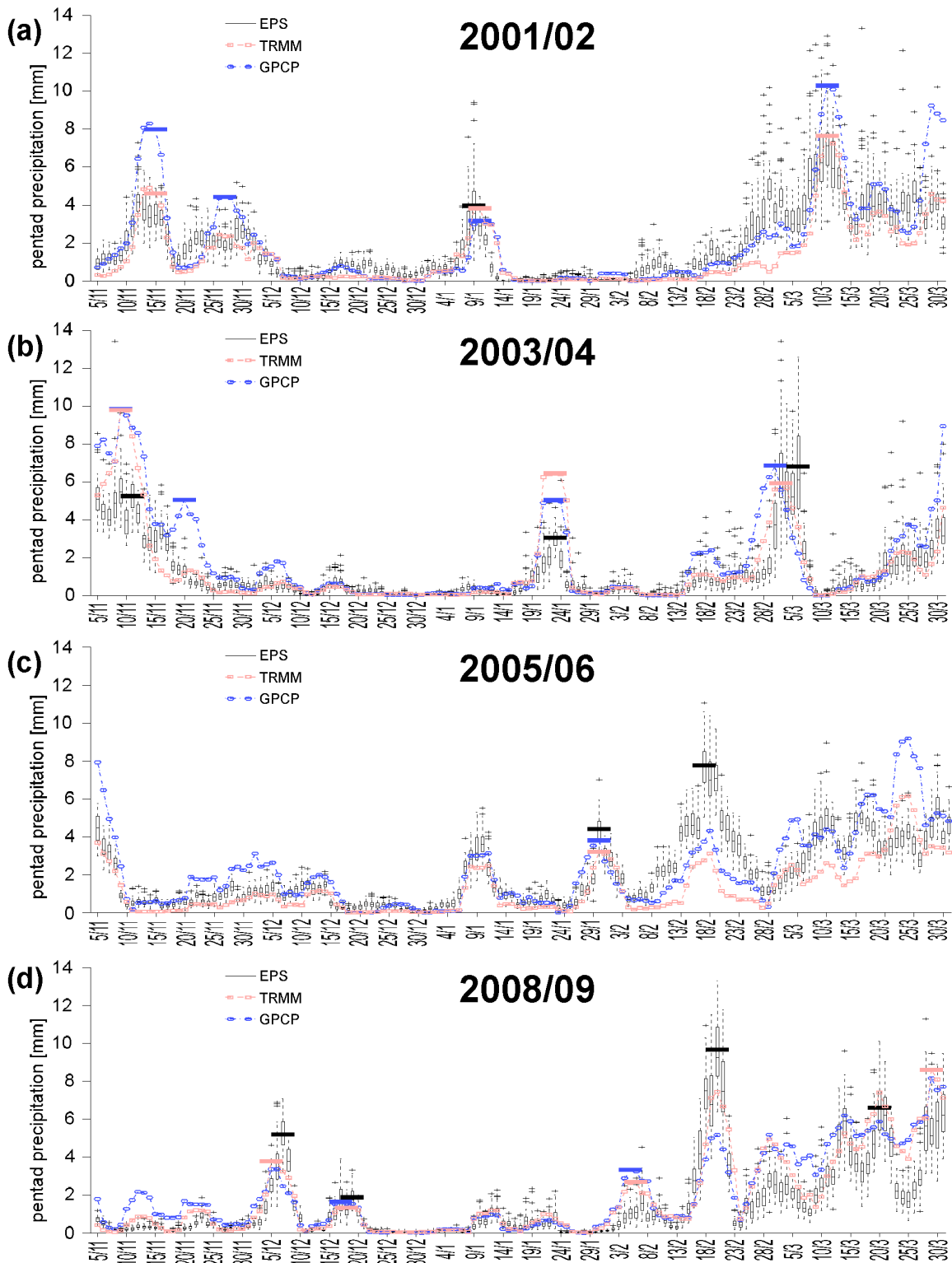
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602

603 **Figure 4.** As Figure 2 but for EPS ensemble mean precipitation forecasts and (a) TRMM
 604 and (b) GPCP.

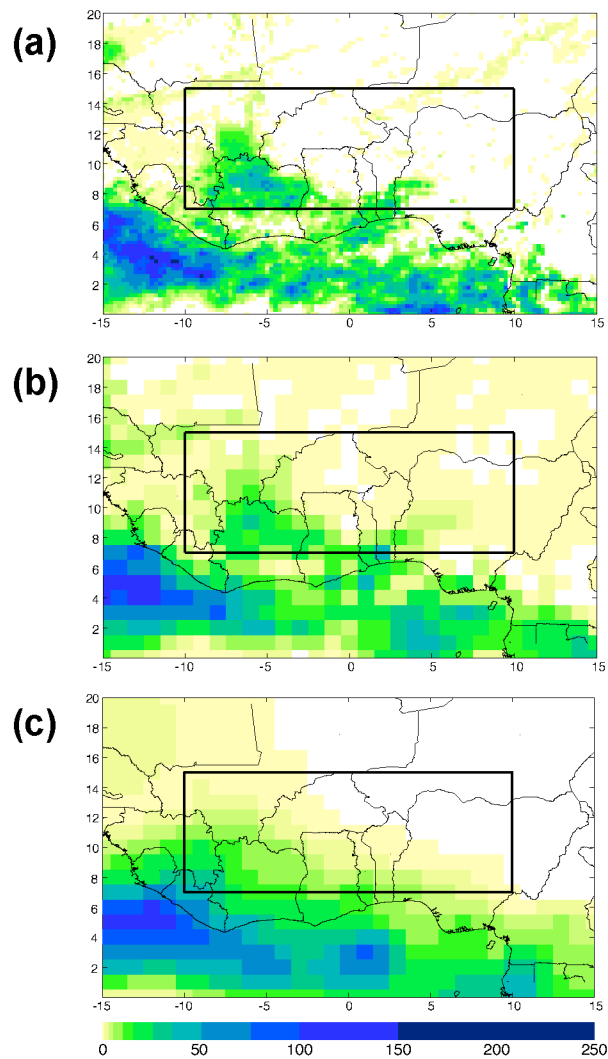


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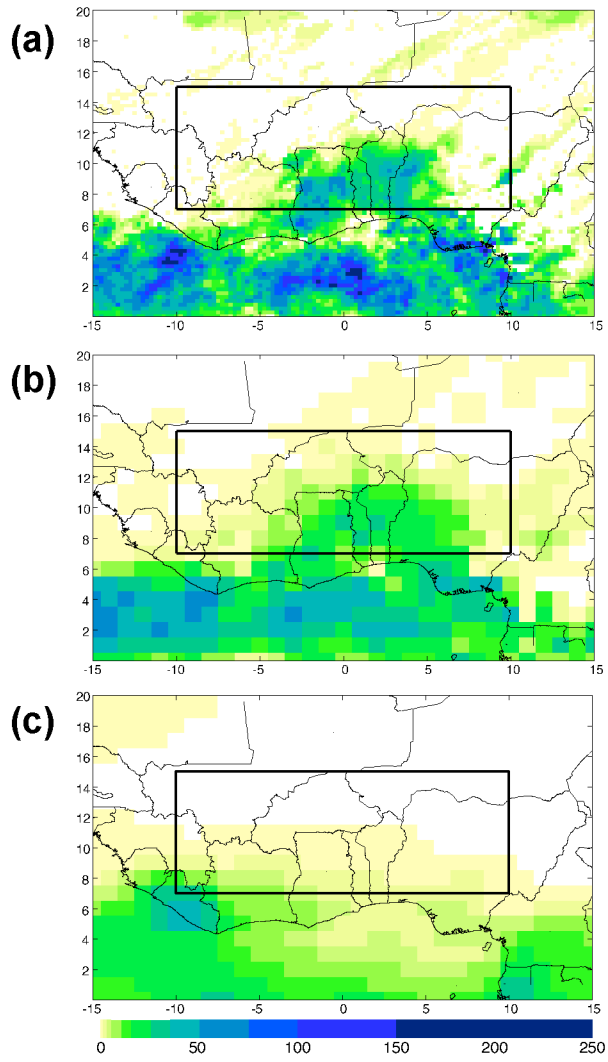
606 **Figure 5.** Time series of selected dry seasons (November–March): (a) 2001/02, (b)

607 2003/04, (c) 2005/06 and (d) 2008/09. Shown are daily pentad precipitation values

608 averaged over the study area (7–15°N, 10°W–10°E) with the end dates given underneath
609 the x-axis. EPS forecasts are depicted as box-and-whisker plots (the box indicates the
610 interquartile range, the central line is the median, and ‘+’ represent outliers). Ellipses
611 (rectangles) represent GPCP (TRMM) observations. The heavy horizontal lines represent
612 pentad rainfall for extreme events, as further detailed in section 3.2.
613

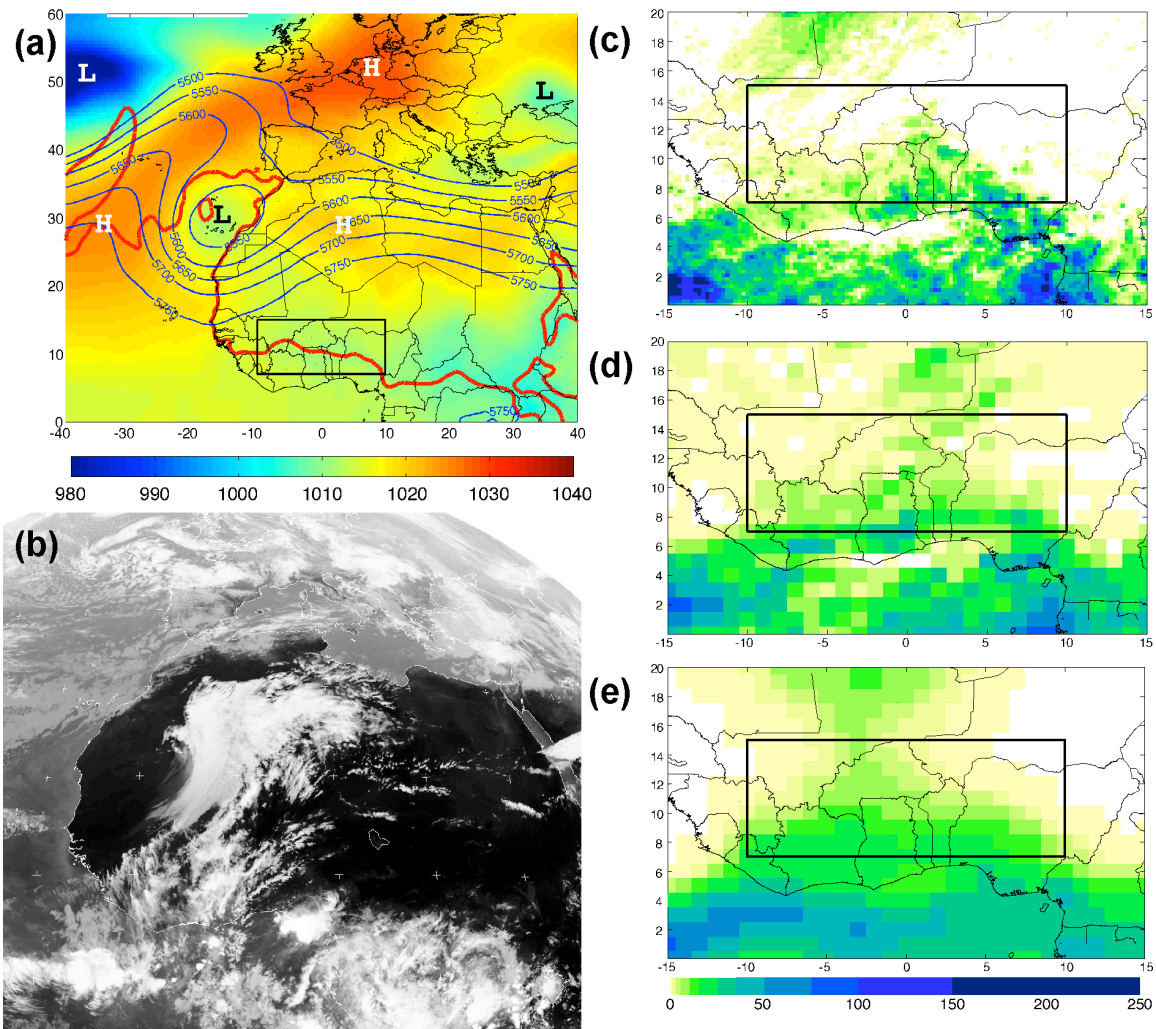


614
615 **Figure 6.** Example case I. Pentad precipitation (mm) for 5–9 January 2002 showing
616 (a) TRMM, (b) GPCP and (c) EPS mean. The black boxes indicate the study area used
617 for averaging in Figures 2–5.



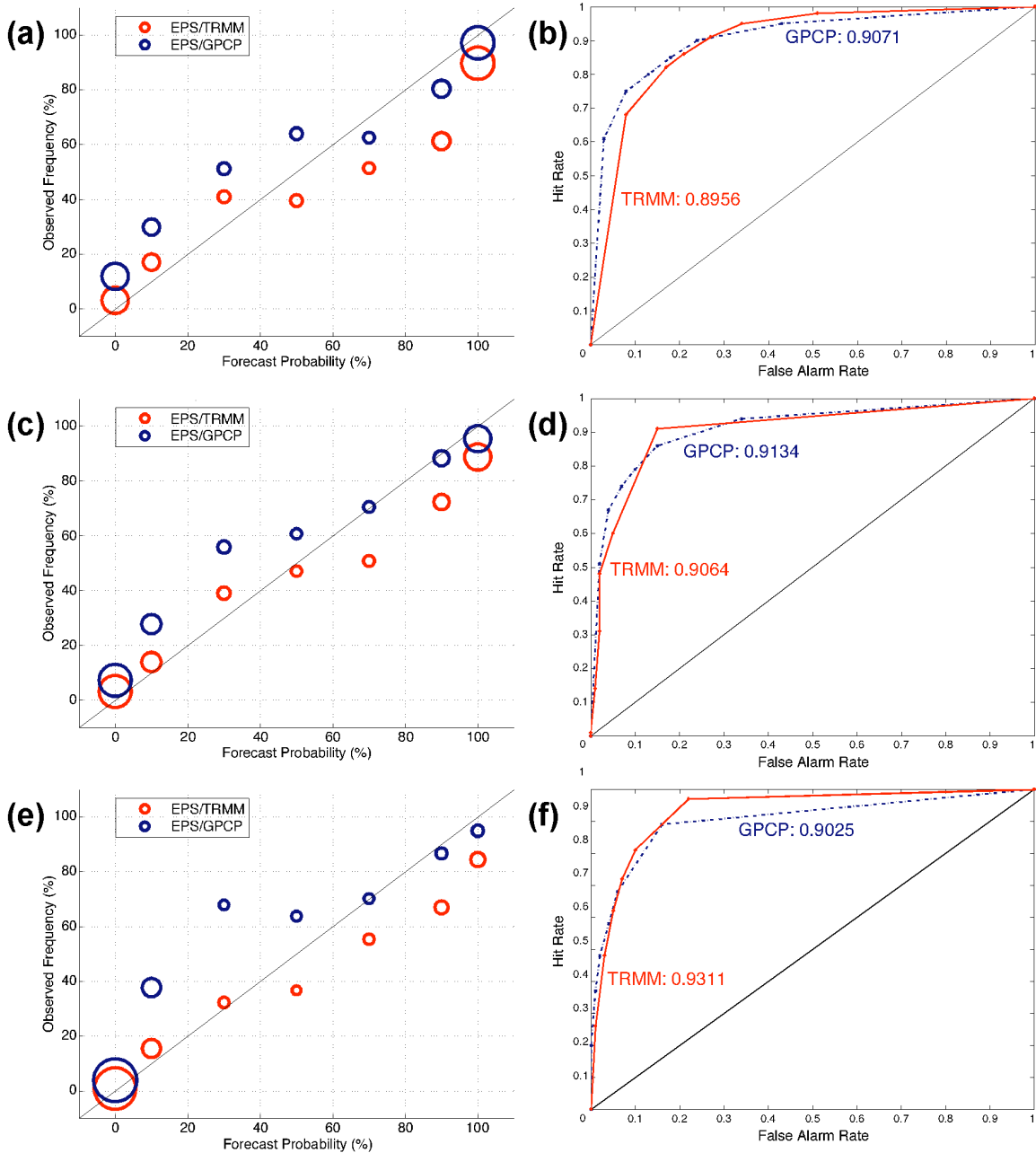
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619 **Figure 7.** Example case II. As Figure 6 but for 19–23 January 2004.



620

621 **Figure 8.** Example case III. (a) Geopotential height at 500 hPa (contours every 50m),
 622 mean sea-level pressure (hPa, shading) and the position of the ITD as indicated by the
 623 14°C contour of the 2m dewpoint (dashed line) at 0000 UTC 15 February 2006. ‘H’ and
 624 ‘L’ mark high- and low-pressure centres, respectively. (b) Meteosat infrared satellite
 625 image at 1200 UTC 17 February 2006. (c)–(d) as in Figure 6 but for 13–17 February
 626 2006.



627

628 Figure 9: Probabilistic forecast evaluation. Reliability (left) and ROC (right) diagrams for

629 TRMM and GPCP pentad precipitation values averaged over the study area (7–15°N,

630 10°W–10°E) for the 11 dry seasons 1998/98–2008/09. Thresholds are (a), (b) 0.5 mm,

631 (c), (d) 1 mm and (e), (f) 3 mm. The size of the circles in the reliability diagrams

632 indicates the number of cases in each bin (e.g. 1088 for the largest circles in Fig. 9e).

633 ROC areas are also given in the plots.