

1 **Evaluation of TRMM 3B42 precipitation estimates and WRF retrospective**  
2 **precipitation simulation over the Pacific-Andean region of Ecuador and**  
3 **Peru**

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14 **Abstract**

15 The Pacific-Andean region in western South-America suffers from rainfall data scarcity, as is the case  
16 for many regions in the south. An important research question is whether the latest satellite-based and  
17 Numerical Weather Prediction (NWP) model outputs capture well the temporal and spatial patterns of  
18 rainfall over the region, hence have the potential to compensate for the data scarcity. Based on an  
19 interpolated gauge-based rainfall dataset, the performance of the Tropical Rainfall Measuring Mission  
20 (TRMM) 3B42V7 and its predecessor V6, and the North Western South America Retrospective  
21 Simulation (OA-NOSA30) are evaluated over 21 sub-catchments in the Pacific-Andean region of  
22 Ecuador and Peru (PAEP).

23 In general, precipitation estimates from TRMM and OA-NOSA30 capture the seasonal features of  
24 precipitation in the study area. Quantitatively, only the Southern sub-catchments of Ecuador and  
25 Northern Peru (3.6-6°S) are relatively well estimated by both products. The accuracy is considerably  
26 less in the northern and central basins of Ecuador (0-3.6°S). It is shown that the probability of  
27 detection (POD) is better for light precipitation (POD decreases from 0.6 for rates less than 5 mm day<sup>-1</sup>  
28 <sup>1</sup> to 0.2 for rates higher than 20 mm day<sup>-1</sup>). Compared to its predecessor 3B42V7 shows modest  
29 region-wide improvements in reducing biases. The improvement is specific to the coastal and open  
30 ocean sub-catchments. In view of hydrological applications, the correlation of TRMM and OA-  
31 NOSA30 estimates with observations increases with time aggregation. The correlation is higher for the  
32 monthly time aggregation in comparison with the daily, weekly and 15-daily time scales. Furthermore,  
33 it is found that TRMM performs better than OA-NOSA30 in generating the spatial distribution of  
34 mean annual precipitation.

35 Keywords: TRMM, WRF, KED, PAEP, Ecuador, Peru.

## 36 **1 Introduction**

37 Precipitation is the primary driver of the hydrologic cycle and the main input of most  
38 hydrologic studies. Accurate estimation of precipitation is therefore essential. The availability  
39 of rainfall data, in particular in developing countries, is hampered by the scarcity of accurate  
40 high-resolution precipitation. Since its inception, rainfall measurement principles remained  
41 unchanged; non-recording and recording rain gauges are still the standard equipment for  
42 ground-based measuring precipitation notwithstanding that they only provide point  
43 measurements. Rainfall amounts measured at different locations are traditionally extrapolated  
44 to obtain areal averaged rainfall estimates. These estimates from point gauge measurements  
45 will only improve, if over time the rain gauge network density increases. The latter is not  
46 always the case in developing countries. In fact, in many regions gauge densities are  
47 decreasing (Becker et al. 2013). One potential way to overcome the limitations of rain gauge  
48 based networks and weather radar systems in estimating areal rainfall is by using satellite-  
49 based global climate information and Numerical Weather Prediction (NWP) products.  
50 Compared with rain gauge observations satellite rainfall data provide observations in  
51 otherwise data sparse areas but their disadvantage is that they are indirect estimates of rainfall.  
52 On the other hand, increased computational power and improvement of NWP models have  
53 resulted into a considerable advancement in the ability to estimate rainfall. However, the main  
54 limitation for NWP models is that they cannot resolve weather features that occur within a  
55 single model grid box. To improve the accuracy of satellite rainfall estimation and NWP  
56 models, and facilitate their intake over data sparse areas, the evaluation of both products  
57 needs to be region specific and user-oriented.

58 A wide range of satellite derived precipitation products emerged the last decade and their  
59 performance over different regions of the world has been evaluated. Several studies have been  
60 conducted to assess the accuracy of three of the most widely used satellite based methods  
61 producing global precipitation estimates, such as the Climate Prediction Centre morphing  
62 method (CMORPH), Precipitation Estimation from Remotely Sensed Information Using  
63 Neural Networks (PERSIANN) and the Tropical Rainfall Measuring Mission (TRMM)  
64 Multisatellite Precipitation Analysis (TMPA) 3B42 (Romilly and Gebremichael, 2011).  
65 TMPA 3B42V6 version performance has been evaluated over the tropical Andes of South  
66 America at high-altitude regions ( $> 3000$  m a.s.l.) by Scheel et al. (2011) with focus on the  
67 Cuzco and La Paz regions in the Central Andes. Ward et al. (2011) conducted similar  
68 investigation in the Paute region ( $> 1684$  m a.s.l.) situated in the southern Ecuadorian Andes

69 and Arias-Hidalgo et al. (2013) explored its applicability as input for hydrologic studies on a  
70 catchment in the Pacific-Andean region in central Ecuador. They all concluded that  
71 disregarding the limitations at small temporal scale (daily) the performance of this product  
72 increases with time aggregation and highlighted the potential to use TMPA 3B42V6 at large-  
73 scale basins. Dinku et al. (2010) conducted a wider evaluation covering different  
74 climatological regions and altitudinal ranges of the Colombian territory. Results showed good  
75 performance when the temporal scale increases (10-days), however they are region distinct  
76 yielding the best performance over the eastern Colombian plain. The availability of the  
77 improved version, the TMPA 3B42V7, opens a new question concerning its usefulness on  
78 South-American regions. Recently, Zulkafli et al. (2014) assessed the improvement of the V7  
79 over the V6 and reported a lower bias and an improved representation of the rainfall  
80 distribution over the northern Peruvian Andes and the Amazon watershed. The diversity of  
81 South-American environments demands new comparisons over regions with different  
82 precipitation regimens and mechanisms.

83 On the other hand, NWP models capabilities keep evolving and providing precipitation fields  
84 at high spatio-temporal resolutions. In general, NWP models are not only valuable tools for  
85 weather forecasting but also for climate reconstruction. NWP can be initialized and bounded  
86 by assimilated observational data describing the large-scale atmospheric conditions  
87 throughout the reconstructed period. Periods of years to decades can be retrieved using NWP  
88 models, commonly known as “regional atmospheric reanalysis”. Although, this technique is  
89 still in its early stages, in tropical South America, some NWP model applications were  
90 conducted by Muñoz et al. (2010). Their study follows a three-level hierarchical approach.  
91 Global-scale analysis and/or GCM outputs are generated and then used as boundary  
92 conditions for the meso-scale meteorological models, which in turn provide information for  
93 tailored applications. In a “regional atmospheric reanalysis” setting, the Weather Research  
94 and Forecasting model (WRF, Skamarock et al., 2005) was forced by applying boundary  
95 conditions of the NCEP/NCAR Reanalysis project (NNRP, Kistler et al., 2001) to retrieve for  
96 the first time meteorological data for North Western South America in the so-called OA-  
97 NOSA30 product. The aim of the retrospective simulation was to provide input data for  
98 hydrologic and health-epidemiological models with the hypothesis that the WRF retrospective  
99 simulation may add skill to GCMs in countries where the Andes provides complex  
100 disturbances that global models cannot solve.

101 The westernmost N-S axis of South America, which embraces the Pacific-Andean region of  
102 Ecuador and northern Peru (PAEP), is a region with below average density and unevenly  
103 distribution of meteorological stations. Because of its location, contrasting landscapes and  
104 complex topography, that includes humid regions of the western Andean foothills and arid  
105 areas offshore the coastal line. The PAEP region provides a unique case to evaluate the  
106 potentials and drawbacks of satellite and numerical model rainfall estimates. In consequence,  
107 the objective of this study is to provide an evaluation of the performance of the TMPA V7  
108 and its predecessor the TMPAV6 version and the OA-NOSA30 products versus regionalized  
109 ground data over the PAEP region. Specifically, emphasis is given to determine whether there  
110 are regions and time aggregation scales on which precipitation estimates may be considered  
111 as an alternative and/or complementary information source for poorly gauged basins.

112

## 113 **2 Materials and Methods**

114

### 115 **2.1 Study area**

116 The western coast of South America is a region with contrasting landscapes and a rather  
117 complex orography. Near to the equator the coastal area of Ecuador is characterized by a high  
118 precipitation regimen and supports dense vegetation down to the shore. However, at the  
119 southern margin and along the northern Peruvian littoral, the coast is almost devoid of  
120 vegetation. The PAEP region (ca. 100800 km<sup>2</sup>) is located along the N-S axis between 0°-6°S  
121 and drains the westernmost slope of the Andes Cordillera (Figure 1a). The various steep  
122 Andean ridges down to the coast together with the Cordillera ‘Costanera’ shapes thirteen  
123 Pacific-Andean valleys from north to south: Chone (1), Portoviejo (2), Guayas (3), Taura (4),  
124 Cañar (5), Naranjal-Pagua (6), Jubones (7), Santa Rosa (8), Arenillas (9), Zarumilla (10),  
125 Puyango-Tumbes (11), Catamayo-Chira (12), and Piura (13) (Figure 1b) each one with  
126 particular geomorphological and climatological features. The proximity of the Andes to the  
127 coastal line is the main influence on the basin’s relief and climatology. Short and steep basins,  
128 i.e. Puyango (10), descend from nearly 4000 meters of altitude in less than 240 km of river  
129 length. On the other hand, large basins host the largest plains and low land valleys in the  
130 Ecuadorian littoral with roughly 70% of its area below an elevation of 200 m. The Guayas (3),  
131 which is one the most important fluvial system in the western coast of South America, is such  
132 large basin.

## 134 **2.2 Climate**

135 The coastal region of Ecuador has a seasonal rainfall distribution characterized by a single  
136 rainy period, with 75-90% of the rainfall occurring between December and May. Overall, in  
137 the PAEP region the rainy season starts around late November and ends in June, with a peak  
138 between February and March. Over the humid Andean foothills in the coastal plain a 2-3  
139 month dry period separates the rainy seasons. On top of this seasonal rainfall pattern the  
140 distribution of precipitation is affected by the seasonal latitudinal migration of the Inter-  
141 Tropical Convergence Zone (ITCZ) and eastern tropical Pacific Sea Surface Temperature  
142 (SST) variations. The north-southern seasonal ITCZ displacement and SST variations bring to  
143 the area air masses of different humidity and temperature. When the ITCZ and the equatorial  
144 front are in their southernmost position near the equator, Ecuador's coastal regions are under  
145 the influence of warm moist air masses, originating from the northwest, bringing significant  
146 rainfall and rising air temperatures. The latter mainly defines the rainy season. Inversely, the  
147 northernmost ITCZ displacement and the equatorial front result in the presence of cooler and  
148 dryer air masses descending from upwelling regions in the south-west, influencing the dry  
149 season (Rossel and Cadier, 2009).

150 The most important feature of the rainfall variability in the PAEP region is the occurrence of  
151 inter-annual anomalies as related to the large-scale circulation phenomena such as El Niño-  
152 Southern Oscillation (ENSO). The PAEP region is bounded by the limit of the strong ENSO  
153 influence defined by Rossel et al. (1999) as the region where the increase in mean annual  
154 precipitation is greater than 40%. Therefore, in ENSO years abrupt changes in the mean  
155 annual rainfall conditions are considerable with a coefficient of variation reaching 0.40  
156 (Rossel and Cadier, 2009). Such increase is not region-wide uniform, there are important  
157 regional differences in heavy rainfall formation during El Niño (EN) events (Bendix and  
158 Bendix, 2006) and the EN influence on rainfall variability may change substantially in short  
159 distances in the same Pacific-Andean hydrological unit (Pineda et al., 2013). Furthermore,  
160 since 2000 an atypical meteorological response to EN and La Niña (LN) conditions is  
161 reported over the coastal plains and the western Andean highlands (Bendix et al., 2011). All  
162 this results in a very complex spatio-temporal distribution of rainfall patterns during ENSO  
163 and non ENSO years. These considerations are of paramount interest when dealing with data  
164 quality control of unevenly distributed rain gauges in the PAEP region.

165

## 166 **2.3 Data**

### 167 **2.3.1 Rain gauge data**

168 A ground precipitation network of 131 rain gauges with daily data (~1964-2010) in the PAEP  
169 region was provided by the Ecuadorian and Peruvian Meteorological and Hydrological  
170 Services, INAMHI and SENAMHI, respectively (Figure 1b). Records with gaps higher than  
171 20% were excluded resulting in 107 locations with long-term daily rainfall time series.

172 In a first step, a regionalization analysis was conducted on the long-term records to group  
173 spatially homogeneous stations. A station was considered as spatially homogenous if it  
174 showed proportionality in the cumulative monthly volumes as referred to a control station in  
175 the same sub-catchment. The most reliable records were identified by selecting records with  
176 no changes in location and instrument type and then set as control stations for a double mass  
177 analysis (Wilson, 1983). In the double mass analysis, the hierarchical criteria to check  
178 proportionality between the control and the candidate station involves: i) neighbouring, ii)  
179 similarity in altitude, and iii) exposure to the same meso/synoptic climatological feature (e.g.  
180 ENSO).

181 Next, the temporal homogeneity of each record was checked against error measurements. A  
182 record was considered as temporally homogenous if the record showed no step changes (shifts  
183 in the means) or if the detected step changes were attributed only to climatic processes. The  
184 R-based RHtests\_dlyPrpc software package, developed by the Climate Research Division of  
185 the Meteorological Service of Canada and which is available from the Expert Team on  
186 Climate Change Detection, Monitoring and Indices (ETCCDMI) website (Wang and Feng,  
187 2012), was used to identify multiple step changes at documented or undocumented change  
188 points. It is based on the integration of a Box-Cox power transformation into a common trend  
189 two-phase regression model suitable for non-Gaussians series such as non-zero daily  
190 precipitation (Wang et al., 2010). Documented changes (EN driven) are referred as those  
191 defined by Rossel and Cadier (2009) and are the sequence of at least three consecutive  
192 months where the monthly SST anomalies are above 23°C and exhibit a positive anomaly  
193 equal or greater than 1°C. Such events occurred in the years 1965, 1972-1973, 1976, 1982-  
194 1983, 1987, 1992 and 1997-1998. For LN driven-changes the year 2008 was also considered.  
195 Non-homogeneous periods were considered as modifications in the field during data

196 collection and set as Not Available (NA) and then retested to verify whether they are  
197 homogeneous with the disregarded period(s).

### 198 **2.3.2 Gridded rainfall dataset**

199 In this study we compare basin station-gridded precipitation fields against basin averaged  
200 precipitation products. Rather than rescaling the products to an arbitrary resolution the  
201 products were evaluated at sub-catchment scale identified during the regionalization analysis.  
202 Namely, instead of a punctual comparison, spatial averages were calculated for the  
203 precipitation products using the proportional coverage of each grid cell. The analysis was  
204 performed for the 1998-2008 11yr period. This period was chosen as common between the  
205 TMPA products and the WRF retrospective simulation. All data-quality checked records were  
206 interpolated to obtain spatial averages in each sub-catchment, except the few whose data is  
207 available through the Global Telecommunication System (GTS). Data from these stations  
208 may have been used for adjusting TRMM estimates. Three GTS stations were identified in  
209 our dataset and excluded. The locations of the GTS stations (five) are shown in Figure 1b.

210 Using the kriging approach for spatial interpolation of daily rainfall over complex terrains, the  
211 incorporation of correlation with topography/altitude has been suggested to improve  
212 performance; see Buytaert et al. (2006) for highlands ~3500 m a.s.l. and Cedeño and Cornejo  
213 (2008) for the coastal region below 1350 masl in Ecuador. Also, in a climatological study for  
214 Ecuador and North Peru, Bendix and Bendix (1998) showed that the inclusion of the altitude  
215 increases significantly the performance of kriging.

216 In parallel, several interpolation techniques of increasing complexity have been developed  
217 and evaluated using the gstat R package (Edzer Pebesma, 2011). Inverse distance weighting  
218 (IDW) and ordinary kriging (OK) are fairly similar; both take into account the distance  
219 between stations, but OK has a more complex formulation and therefore expected to be more  
220 accurate. Linear regression (LR) is supposed to perform similar to kriging with external drift  
221 (KED) since they both implement regression with altitude. KED is, however, more accurate  
222 accounting for kriging of residuals, which means that distance between stations influences  
223 interpolation as well. KED was applied on daily basis, the variogram analysis was performed  
224 at each time step to determine the spatial variability function of precipitation, then,  
225 parameters were estimated from regression residuals for each time step (zero values were  
226 included in the semi-variogram fitting). To discern among different interpolation techniques  
227 Li and Heap (2008) recommends assessing the performance by cross validation methods.

228 A key issue in this study is whether the change of spatial support provides a sound reference  
229 for comparison with TMPA's and WRF products. In general, errors and uncertainty in a  
230 gridded dataset arise from many sources, including errors in the different steps of the data  
231 supply chain (measurements, collection, homogeneity) and in the interpolation technique. It  
232 would be ideal to split and quantify all of them. This is, however, not possible without the  
233 possibility to track them back. Kriging provides a measure of the expected mean value and its  
234 variance at an interpolated point. Several climate studies have used the kriging variance as a  
235 proxy of uncertainty. However, it is acknowledged that kriging variance is not a true estimate  
236 of uncertainty (Yamamoto, 2000 and Haylock et al., 2008). A solution would be to perform  
237 an ensemble of stochastic simulations from which uncertainty can be estimated at the expense  
238 of highly computational resources. Such detailed analysis is out of the scope of this work.

239 We therefore adopted the alternative method by Yamamoto (2000) for assessing kriging  
240 uncertainty using just the data provided by a single realization. We quantify the total residual  
241 variance and split it up in its main contributing residual variance sources (input (data) and  
242 kriging interpolation (geo-statistical model)) based on a variance decomposition technique  
243 (Willems, 2008, 2012) in order to estimate the fraction of each contributing source. The total  
244 residual variance is assessed based on statistical analysis of the residuals between each  
245 precipitation product ( $Y_{PP}$ ) and KED estimates ( $Y_{KED}$ ). The underlying assumption of the  
246 variance decomposition is that the (causes of the) errors on the  $Y_{PP}$  and  $Y_{KED}$  precipitation  
247 estimates are highly different, hence that they can be assumed independent. The residuals are  
248 converted into homoscedastic residuals by means of a Box-Cox (BC) transformation (Box &  
249 Cox, 1964). After this conversion, the total  $Y_{PP}$  residual variance ( $S_{BC(Y_{PP,Residual})}^2$ ) is  
250 decomposed into the precipitation product error variance, hereafter called model error  
251 variance ( $S_{BC(Y_{PP,Model})}^2$ ), and the KED error variance ( $S_{BC(KED)}^2$ ) (Equation 1).

252 The KED uncertainty is evaluated using just the random field provided by a single realization  
253 with prescribed parameters (i.e. mean structure, residual variogram) (Yamamoto, 2000). We  
254 estimate the total ( $Y_{PP}$ ) residual variance at every tile ( $_{PP-KED}$ ). By subtracting the KED error  
255 variance from the total residual variance of  $Y_{PP}$  based on Equation (1), we obtain indirect  
256 estimates of the model error variance and map its spatial distribution.

$$257 \quad S_{BC(Y_{PP,Residual})}^2 = S_{BC(Y_{PP,Model})}^2 + S_{BC(KED)}^2 \quad (1)$$

258



### 259 **2.3.3 TMPA TRMM 3B42 products**

260 The TMPA 3B42 V7 and its predecessor version V6 version are used in this study. The  
261 TMPA 3B42V6 consists of hourly rainfall rates ( $\text{mm h}^{-1}$ ) at surface level with a global  
262 coverage between  $50^\circ$  N and S since 1998. This method combined precipitation estimates of  
263 four passive microwave (PMW) sensors, namely TRMM Microwave Imager (TMI), Special  
264 Sensor Microwave/Imager (SSM/I) F13, F14 and F15, Advanced Microwave Scanning  
265 Radiometer-EOS (AMSR-E) and Advanced Microwave Sounding Unit-B (AMSU-B). The  
266 TMPA V6 algorithm is described in Huffman et al. (2007). The improved version, the 3B42  
267 V7, includes consistently reprocessed versions for the data sources used in 3B42V6 and  
268 introduces additional datasets, including the Special Sensor Microwave Imager/Sounder  
269 (SSMIS) F16-17 and Microwave Humidity Sounder (MHS) (N18 and N19), the  
270 Meteorological Operational satellite programme (MetOp) and the  $0.07^\circ$  Grisat-B1 infrared  
271 data. The changes in the V7 algorithm at various processing levels are described in Huffman  
272 et al. (2010) and Huffman and Bolvin (2012).

273 It is useful to review some of the efforts in validating TMPA V6 and/or comparing V6 and V7  
274 at low and high altitudes in the tropical Pacific because it has a bearing on the choice of the  
275 satellite products used in our study. While evaluating several precipitation products, Dinku et  
276 al. (2010) reported that V6 outperforms other satellite products (i.e. CMORPH) at 10-daily  
277 accumulation over the dry northern Colombian littoral. The converse was found over the wet  
278 western Pacific coast where CMORPH was slightly better especially at daily scale. In an  
279 evaluation of V7 daily rainfall estimates to analyze tropical cyclone rainfall, Cheng et al.  
280 (2013) found improved skill scores over coastal and island sites in the tropical Pacific. Also,  
281 Zulkafli et al. (2014) reported that the improvement of V7 against V6 is a reduction of the  
282 bias especially in the Peruvian Pacific lowlands. To assess whether such improvements are  
283 seen in the PAEP region, we use both TMPA versions. TMPA 3B42V6 and 3B42V7  
284 precipitation estimates having 3-hourly,  $0.25 \times 0.25$  degrees resolution were aggregated to  
285 daily data for the 11yr period.

286

### 287 **2.3.4 WRF retrospective simulation**

288 The Scientific Modelling Centre from Venezuela (CMC) and the National Institute of  
289 Hydrology and Meteorology from Ecuador (INAMHI) developed a North Western South  
290 America Retrospective simulation. The dataset, called OA-NOSA30, is available online at the

291 International Research Institute for Climate and Society (IRI) web page (Muñoz and Recalde,  
 292 2010). The simulation provides numerous climate variables with a 30 km spatial and 6-hour  
 293 temporal resolution for the period January 1996 to December 2008 and a global coverage  
 294 between 11°S to 17°N and 98°W to 50°E. The accumulated precipitation was extracted on a  
 295 daily basis for the 11-year common period.

296 OA-NOSA30 is the simulation result from the Weather Research and Forecasting (WRF)  
 297 model, a Regional Climate Model (RCM) herein used to downscale the meteorological data  
 298 from the NCEP/NCAR Reanalysis Project (NNRP or R1, details at Kistler et al., 2001).  
 299 NNRP stands for the combination of global climate model outputs and observations. The  
 300 WRF configuration for the Microphysics Parameterization, governing the outputs, was  
 301 applied. Muñoz and Recalde (2010) explained that the microphysics were modelled by the  
 302 Kessler scheme (RRTM), the Dudhia schemes were used for the modelling of the longwave  
 303 and shortwave radiation, respectively; the Monin-Obukhov (Janjic) scheme for modelling of  
 304 the surface-layer; and the thermal diffusion with 5 soil levels for modelling the land-surface  
 305 physics. Finally the Mellor-Yamada-Janjic TKE scheme was applied for describing the  
 306 boundary-layer option, in which the SST update option was selected.

307

## 308 **2.4 Rainfall products evaluation**

309 Bias, root mean square error (RMSE) and Pearson's correlation ( $\gamma_{xy}$ ) were applied to analyse  
 310 the accuracy of the TMPA's and OA-NOSA30 estimates comparing them with rain-gauge  
 311 interpolated estimates at sub-catchment scale (Equations 1 to 3). RMSE includes both  
 312 systematic (bias) and non-systematic (random) errors.

$$313 \quad BIAS = \frac{1}{n} \sum_{i=1}^n (P_{xi}^{PP} - P_{xi}^{gauge}) \quad (2)$$

$$314 \quad RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (P_{xi}^{PP} - P_{xi}^{gauge})^2} \quad (3)$$

$$315 \quad \gamma_{xy} = \frac{Cov(P^{PP}, P^{gauge})}{\sqrt{Var(P^{PP})} \times \sqrt{Var(P^{gauge})}} \quad (4)$$

316

317 Where,  $P^{PP}$  is the precipitation products value,  $P^{gauge}$  the interpolation estimate from rain  
 318 gauge values, and n the number of observations.

319 Additionally, skill scores were calculated to quantify the products accuracy in detecting daily  
 320 accumulation at different precipitation thresholds and they were calculated based on average

321 sub-catchment precipitation. The Probability of Detection (POD) gives the fraction of rain  
322 occurrences that were correctly detected; it ranges from 0 to a perfect score of 1. The  
323 Equitable Threat Score (ETS) measures the fraction of observed and/or detected rain that was  
324 correctly detected and adjusted for the number of hits that could be expected due purely to  
325 random chance. A perfect score for the ETS is 1. The Frequency Bias Index (FBI) is the ratio  
326 of the number of estimated to observed rain events; it can indicate whether there is a tendency  
327 to underestimate or overestimate rainy events. It ranges from 0 to infinity with a perfect score  
328 of 1. The False Alarm Rate (FAR) measures the fraction of rain detections that were actually  
329 false alarms. It ranges from 0 to 1 with a perfect score of 0 (Su et al., 2008).

330 The ETS is commonly used as an overall skill measure by the numerical weather prediction  
331 community, whereas the FBI, FAR, and POD provide complementary information about bias,  
332 false alarms, and misses. To evaluate the performance of the products for light and heavy  
333 precipitation events they were calculated for each sub-catchment and for several thresholds:  
334 0.1, 0.5, 1, 2, 5, 10, and 20 mm day<sup>-1</sup> (Schaefer, 1990; Su et al., 2008).

335 Seasonality accuracy at sub-catchment level was evaluated confronting precipitation estimates  
336 against interpolated average monthly rainfall depths. Furthermore, in order to evaluate  
337 precipitation products on increasing time scales, daily, weekly, 15-daily and monthly  
338 estimates were accumulated deriving Pearson's correlation (Equation 3) and relative bias. The  
339 relative bias was calculated for daily/weekly/15days/monthly time aggregations by  
340 normalizing the Bias (Equation 1) in order to compare different time resolutions. Finally,  
341 annual mean precipitation was calculated for interpolated rain gauges and precipitation  
342 products and depicted spatially.

343

## 344 **3 Results**

### 345 **3.1 Data quality verification, interpolation and uncertainty**

346 The double mass analysis discriminated 21 sub-catchments within which rainfall is spatially  
347 correlated. The proportionality is strong in the coastal areas where the altitude range is narrow  
348 but is less marked at higher altitudes. Four stations do not have significant correlation with  
349 any other station, and the sub-catchments in which they are situated were ranked as  
350 independent.

351 The temporal homogeneity check for each station reported several change-points, with a  
352 statistical significance of 5%. However, most of them were attributed to EN regional

353 variations and therefore rejected as artificial change-points. Besides the documented changes,  
354 several change-points appeared repeatedly in nearby locations. They were interpreted as a  
355 common modification in the local climate and therefore disregarded as change-points. Despite  
356 of these considerations, non-homogeneous periods significant at 5% were found in 30  
357 stations. Those periods were discarded and the stations tested again for homogeneity. Nine  
358 stations did not pass the test. Therefore they were no longer taken into account, resulting into  
359 a quality checked set of 98 time series. From this dataset the 11yr period, January 1998 to  
360 December 2008, was taken for the comparison between OA-NOSA30 and the TMPA's  
361 estimates, and rain gauge precipitation data. The 98 homogeneous stations together with the  
362 21 homogenous sub-catchments are shown in Figure 1b. The area and the density of the rain  
363 gauge stations per sub-catchment are listed in Table 1. The highest density is found in Quiroz,  
364 Upper Guayas, Alamor, Chipillico and the lowest in Naranjal-Pagua, Lower Guayas and Piura  
365 and Tumbes.

366 Table 2 reports the mean cross validation results of the four investigated techniques to grid  
367 daily precipitation in the period 1998-2008. Correlation for KED (0.49) is twice the value  
368 than for IDW, LR, and OK techniques (0.26, 0.28, and 0.21, respectively). Not only its mean  
369 is higher but correlation on almost every day was better than for any other technique. The  
370 Mean Square Error (MSE) for KED is less than for LR and slightly less for OK. The  
371 performance values explain how well the technique represents the variability of the  
372 precipitation assessed by the squared of the residuals and it was found better for KED.  
373 Overall, KED performed better in all statistics and LR was the second best. Finally, the KED  
374 technique, which includes variogram analysis and the use of a 92x92m Digital Elevation  
375 Model (DEM) from the Shuttle Radar Topography Mission (SRTM) as external drift, was  
376 chosen to interpolate station precipitation. The result is a daily gridded dataset (4018 time  
377 steps) with 92x92m resolution, which captures the horizontal and vertical gradients as well as  
378 the most prominent orographic features. We first discuss the gridded dataset constraints and  
379 related uncertainty when applying this dataset for comparison with the precipitation products.

380 Figure 2a, 2b and 2c present results of the uncertainty analysis for the comparison of OA-  
381 NOSA30, TMPAV6 and V7 with KED estimates, based on the variance decomposition  
382 technique of one-day single random realization. Figure 2a shows that the OA-NOSA30  
383 estimates are subject to the largest model residual variance, which strongly correlates with the  
384 high topographic precipitation gradients as seen over the inner-sierra foothills (i.e. Upper-  
385 Guayas (5), Cañar (7) and Jubones (9)), and to a lesser extent over the moderate slopes of the

386 Cordillera Costanera (i.e. Chone (1)). The KED uncertainty has the highest contribution to the  
387 total residual variance in these regions whereas in the remaining stations the contribution of  
388 the KED uncertainty is more or less proportional to the total residual variance. In the  
389 comparison of TMPAV6-V7 (Figures 2b and 2c) with KED estimates the spatial trends are  
390 less evident. Correlation with elevation still takes place in the V6 analysis but the largest total  
391 residual variance does not show clear distinction between middle (~500 masl) and high  
392 altitudes (~3000 masl). For the V7 analysis the uncertainty mapping shows a more scattered  
393 distribution with almost no spatial trends. In both the V6 and V7 cases, the KED contribution  
394 to the total uncertainty remains slightly larger than the precipitation product error variance.  
395 All results together suggests that when comparing precipitation products against KED  
396 estimates, the TMPAV7 based product, in the first place, followed by the V6 product, offer  
397 the best precipitation estimates since the precipitation uncertainty is less affected by the  
398 topographic setting that provides the basis for our proposed gridded dataset. The largest  
399 errors are encountered in the comparison between OA-NOSA30 and KED estimates at high  
400 altitudes. This has implications for our catchment-averaged analysis. These limitations are  
401 relevant for the results presented in the following sections.

402

### 403 **3.2 Daily verification**

404 Figure 3a, 3b, 3c shows the bias, RMSE and Pearson's correlation between precipitation  
405 products and daily KED estimates accumulated over each sub-catchment unit and ranked  
406 from N-S within the period 1998-2008. These statistics reveal a strong spatial variation; for  
407 3B42V6 and OA-NOSA30 bias and RMSE decrease from North to South while correlation  
408 increases, whereas for TMPA V7 significant bias reduction and increase in correlation seems  
409 sub-catchment and precipitation regimen dependent.

410 TMPA V7 and V6 overestimate precipitation in all sub-catchments, with an average range  
411 between 0 to ~2 mm day<sup>-1</sup>. Conversely, OA-NOSA30 underestimates precipitation, except in  
412 Quiroz (17) and Chipillico (19), the range of over/under estimation is within ~0.5 to -1.5 mm  
413 day<sup>-1</sup> (Figure 3a). The RMSE ranges from 4 to 9 mm day<sup>-1</sup> for both TMPA estimates. The  
414 RMSE gives more weight to the extremes because residuals are squared and they are typically  
415 higher for precipitation extremes. Given that, particularly for TMPA V6, the bias is very high  
416 in wet seasons RMSE values are higher for TMPA V6 estimates than for OA-NOSA30  
417 (Figure 3b).

418 Figure 3c shows that the Pearson correlation is very similar between TMPA V6 and OA-  
419 NOSA30 oscillating between 0.3 and 0.6 except in Arenillas (11) where OA-NOSA30's  
420 detection fails. In the Northern region the highest correlation (0.5) is found at Lower/ Middle  
421 Guayas (3)/(4) and the rest of the northern sub-catchments record correlations  $\sim 0.3$ . In the  
422 Central region, average correlation is about 0.35. In the southern region, correlation  
423 consistently rises to 0.5 in a large area (Catamayo-Chira and Piura catchments). TMPA V7  
424 shows a very modest region-wide improvement over TMPA V6 only with a notable  
425 correlation increase on Chone (1), Upper Guayas (5), Taura (6), Jubones (9) and Zarumilla  
426 (12).

427 OA-NOSA30 presents almost no region-wide bias on precipitation rates less than  $1 \text{ mm day}^{-1}$ .  
428 For the southern sub-catchment: Alamor (15), Macará (16), Quiroz (17), Chira (18) and Piura  
429 (21) this is up to  $10 \text{ mm day}^{-1}$ ; over such a threshold precipitation is systematically  
430 underestimated. TMPA V7 and V6 overestimate precipitation amounts smaller than  $10 \text{ mm}$   
431  $\text{day}^{-1}$  in sub-catchments in the central and southern regions. For lowland areas in the north this  
432 threshold changes to  $20 \text{ mm day}^{-1}$ . As well as for OA-NOSA30, precipitations over  $20 \text{ mm}$   
433  $\text{day}^{-1}$  are systematically underestimated.

434 Figure 4a, 4b and 4c shows categorical scores POD, ETS, FBI and FAR for representative  
435 sub-catchments distributed in the Northern, Central and Southern region corresponding to the  
436 TMPA V7, V6 and OA-NOSA30 estimates. The four sub-catchments shown in Figure 3 were  
437 chosen as representative according to their location and dominant precipitation regime. In the  
438 humid northern part, Chone (1), a coastal and ocean exposed sub-catchment, and Middle  
439 Guayas (4) in the inner core and greatly influenced by the continental climate divide, were  
440 selected. In the Central region, Jubones (9) with a pronounced leeward effect; and Chira (18)  
441 in the southern arid coast, were considered. Their indexes lead to conclusions which can also  
442 describe the situation of the surrounding sub-catchments in each region. The difference  
443 between scores of TMPA V7 (4a) and V6 (4b) is almost undistinguished, both estimates  
444 shows a POD value of 0.6, on average, for precipitation rates less than  $5 \text{ mm day}^{-1}$ . It  
445 gradually decreases to  $\sim 0.2$  when the threshold is higher than  $20 \text{ mm day}^{-1}$ . A close inspection  
446 reveals a marginal improvement of V7 over V6 only evident in Middle Guayas (4) at higher  
447 thresholds. ETS scores, for precipitation estimates equal or lower than  $5 \text{ mm day}^{-1}$ , are on  
448 average 0.25. ETS, a summary score that penalizes for hits that could occur due to  
449 randomness, can be used to compare performance across regimes. A slight improvement of  
450 V7 across all threshold is restricted to Chone (1). FAR and FBI increase with higher

451 thresholds. This means that overestimation exists over 1 or 2 mm day<sup>-1</sup> and false alarms are  
452 then also present. In general, TMPA products detect amounts of precipitation higher than 5  
453 mm day<sup>-1</sup> but it overestimates them; while amounts of precipitation less than 2 mm day<sup>-1</sup> are  
454 detected with a low fraction of FAR, although bias is present. TMPA's scores are better in the  
455 Southern region, Chira (1).

456 Figure 4c show the same categorical scores for OA-NOSA30. In all sub-catchment, POD  
457 decreases when the threshold increases, indicating that the NWP estimates better small  
458 precipitation events. POD decreases abruptly to 0 when considering thresholds of 5 and 10  
459 mm day<sup>-1</sup> thresholds. The behaviour of ETS scores is the same as for POD but the average  
460 scores are half the amount of POD. For small amounts of precipitation, i.e. less than 3 mm  
461 day<sup>-1</sup>, OA-NOSA30's POD scores are around 0.6 while ETS scores are 0.3. The FBI plot  
462 shows underestimation. False alarms increase with higher thresholds with FAR values  
463 typically in the range 0.2 to 0.5. There are no FAR values given for thresholds over 5- 10 mm  
464 day<sup>-1</sup> since the POD of OA-NOSA30 is zero for those precipitation depths. Spatially, POD  
465 and ETS show a better probability of detection in the Southern region and FBI shows lower  
466 bias in that region compared to the Northern and Central regions; however FAR is lower in  
467 the Northern region Middle Guayas (4).

468

### 469 **3.3 Monthly verification**

470 Although Figure 5a, 5b and 5c shows the mean monthly precipitation within the period 1998-  
471 2008 for KED estimates against TMPA V7, V6 and OA-NOSA30 for the four selected sub-  
472 catchments, the analysis below corresponds to all 21 sub-catchments. In general, Figure 5c  
473 reveals that the three approaches yield comparable results for the Southern region, which  
474 includes the sub-catchments Alamor (15), Macará (16), Quiroz (17), Chira (18), and  
475 Chipillico (19). In most of the sub-catchments, all datasets depict well seasonality showing  
476 wet conditions within the period January-May. In the Northern and Central regions, during  
477 the wet season, TMPA V7 and V6 overestimate while OA-NOSA30 underestimates  
478 precipitation (Figures 5a, 5b). The pattern of over- and underestimation is not that clear in all  
479 datasets during the dry season. Maussion et al. (2011) showed that the WRF and TRMM well  
480 estimated the precipitation distribution, but depths and positions of maxima do not match.  
481 Additionally, they showed that WRF usually predicts more rainfall over larger areas,  
482 notwithstanding WRF may be closer to reality than TRMM.

483 The density of rain gauges in the Catamayo-Chira catchment is higher and also the quality of  
484 data is better (fewer missing gaps and change-points). This might indicate that KED estimates  
485 are better for this area. However, in most of the Southern region TMPA and OA-NOSA30  
486 estimates are similar to KED estimates even in the high altitude sub-catchment i.e. Quiroz  
487 (17), which is not the case for the rest of the sub-catchments. Also, there are other sub-  
488 catchments such as Catamayo (14) and Upper Guayas (5) where the precipitation estimates  
489 are neither similar between them nor to KED estimates, despite the high quality of data. Thus,  
490 KED estimates prove to be a good reference and the dependence of the interpolation  
491 technique on the rain-gauge density (Table 1) as well as the error seen at high altitudes when  
492 comparing OA-NOS30 and KED is not affecting substantially the analysis. This is a very  
493 important issue, given that the density of rain gauges is relatively low and building up a  
494 gridded rainfall dataset that is the least influenced by this fact is crucial. Notice that the  
495 success of KED technique may differ for areas with lower gauge densities, which was not  
496 tested in this study. TMPA's overestimation occurs for any precipitation amount when  
497 aggregated per month (Figure 5); unlike daily aggregation where over-underestimation occurs  
498 according to the amount of precipitation (see FBI scores in the Figures 4a and 4b).

499

### 500 **3.4 Verification on multi-temporal resolutions**

501 The Pearson correlation (Figure 6a) and bias (Figure 6b) were calculated on daily, weekly,  
502 15-daily and monthly time scales for TMPAV7, V6 and OA-NOSA30. In general, correlation  
503 increases with time scale, and is higher for monthly than 15-daily and weekly time aggregated  
504 periods. Bias seems to accumulate when time aggregation increases as found for WRF in  
505 other regions (Cheng and Steenburgh, 2005; Ruiz et al., 2010). The purpose of finding the  
506 relative bias in the estimates is to quantify respectively the over-underestimation of the  
507 precipitation depth. The relative bias is consistent with the correlation coefficient, decreasing  
508 as the time aggregation increases. Although the daily bias is high in Jubones (9) (~1000% for  
509 V7 and ~1200% for V6) and in Middle Guayas (4), higher for V7 than V6; on a weekly to  
510 monthly scale the bias percentage decreases. The worst performance of both TMPA estimates  
511 was found in Jubones, where correlation is lowest and bias percentage is highest. For OA-  
512 NOSA30 that is the case for Chone (1) and Jubones (9). The results found for TMPA, i.e. that  
513 correlation increases and bias reduces as time aggregation increases, are in agreement with  
514 previous studies (Scheel et al., 2011; Habib et al., 2009; among others).



515 Aggregation of the mean annual rainfall was performed to compare the spatial performance of  
516 the three approaches (OA-NOSA30, TMPAV6 and V7) against KED estimates in the study  
517 area (Figure 7). Comparison shows that the TMPA estimates are closer to the spatial pattern  
518 of the mean annual rainfall, though mean annual rainfall in the north and south-east are  
519 overestimated. OA-NOSA30 presents a huge underestimation and does not reflect spatial  
520 variability, except over the Southern region. Over the latter region, OA-NOSA30 bias is small  
521 enough to represent a spatial pattern approaching the one based on TMPA estimates.

## 522 **4 Discussion**

523 Our analysis shows that both TMPA products overestimate precipitation in the 21-  
524 subcatchments of the heterogeneous PAEP region. Key challenges in the estimation of  
525 precipitation from satellite estimates arise from the processing scheme for MW and IR data.  
526 The problem with IR data processing is that global algorithms do not consider the altitude of  
527 the hydrometeor. Dinku et al. (2011) suggest that overestimation over dry areas may be  
528 attributed to sub-cloud evaporation. While this mechanism may have implications on the  
529 overestimation of TMPA onshore the coastal plain, especially in the arid Peruvian littoral  
530 where a dry low-atmosphere is common all year-round; the attribution of TMPA  
531 overestimation to sub-cloud evaporation on the middle/high altitude sub-catchments is  
532 inconclusive. Bendix et al. (2006) showed that, over the Ecuadorian territory and  
533 surroundings, average cloud-top height increases from W-E showing a more stratiform cloud  
534 dynamics in the Pacific area and the coastal plains, and, that the western Cordillera is a true  
535 division for the Pacific influence. These authors describe the seasonal spatial pattern of  
536 cloud-top height distribution within December-May (wet season), possessing a well-defined  
537 blocking height ( $\sim 4.5 < 5.0$  km) between  $0-3^{\circ}\text{S}$ , but less marked southward. Given that IR  
538 data processing scheme infers precipitation from the IR brightness temperature at the cloud  
539 top (implicitly cloud height) it would be expected that overestimation follows the same spatial  
540 pattern. However, our analysis showed that even though TMPA overestimation matches the  
541 increasing W-E cloud-top gradient it does not explain the large overestimation in the Northern  
542 bottom valleys (i.e. Lower Guayas and Chone catchment). The regional differences in cloud  
543 properties between the Northern and Southern catchments help to explain the differences in  
544 TMPA overestimation. Over the northern region  $\sim 0^{\circ}$  (Quito-transect), (Bendix et al. 2006),  
545 cloud frequency is substantially higher than the reduced cloudiness at  $\sim 4^{\circ}\text{S}$  (Loja-transect).  
546 To illustrate these differences Figure 8a, 8b, 8c show cloud density patterns using anomalies  
547 of interpolated Outgoing Longwave Radiation (OLR) (Liebmann and Smith, 1996) as proxy

548 for cloudiness (negative anomalies imply increased cloudiness) during the rainy season within  
549 1998-2008. During December-January (8a) symmetrical patterns of cloudiness are observed  
550 over northern and southern sub-catchment, followed by increased cloudiness which  
551 concentrates over the north-western edge during January February (8b). Then, cloudiness  
552 exhibits a marked north-southeast gradient in April-May (8c). This suggests that in addition to  
553 the error introduced by the estimation of the cloud-top, the TMPA overestimation on the  
554 Northern catchments may also be influenced by frequent occurrence of low stratiform clouds  
555 (typical on the coastal area) which under stable conditions are detached from precipitation  
556 patterns (Bendix, et al., 2006). This high density of non-rain producing clouds would affect  
557 the IR data retrieval resulting into overestimation.

558 The largest deficiencies of TMPA's estimates are encountered in separating the  
559 windward/leeward effect of the Andean ridges on orographic rainfall which is particularly  
560 witnessed in Jubones where the leeward effect is dominant. West of the climate divide there  
561 is no typical precipitation gradient. Through blocking at the ridges and through re-  
562 evaporation, rainfall of any origin affects more frequently higher elevations than valley floors  
563 (Emck, 2007).

564 TMPA V7 and V6 estimates show different region-wide skills on daily basis but they yield  
565 comparable results particularly in the Southern region (3.6-6°S) in weekly to monthly time  
566 aggregations. TMPA V7 shows localized skill that is higher than V6 on short-steep coastal  
567 and ocean exposed sub-catchments but similar or lower skills on large inland basins. The  
568 improvement is seen in the detection capacity of light orographic precipitation on coastal  
569 ocean exposed sub-catchments, where the spatial sampling seems to capture small  
570 precipitation gradients. Over coastal areas the orographic enhancement is a small spatial scale  
571 event (Minder et al., 2008, Cheng et al., 2013). In the inner-most sub-catchments where  
572 gradients on annual precipitation may reach i.e.700 mm / 100 m at 3400 masl (Emck, 2007)  
573 the temporal sampling of V7 cannot capture the rapid evolution of orographic rainfall and the  
574 overestimation is similar to that of the V6 version. Notice that inland the total residual variance  
575 and the KED uncertainty increase with elevation (especially for V6). This could influence the  
576 apparent decrease of the V6 performance seen on the inner-most sub-catchments. This is,  
577 however, restricted to very few sub-catchments where the spatial average is dominated by the  
578 weight of high altitude stations.

579 OA-NOSA30 product only shows reasonable skills in the Southern region (3.6-6°S) where  
580 amount and occurrence are relatively well represented. The greatest NWP limitations are

581 encountered in representing the fast enhancement of rain rates due to the effect of the coastal  
582 mountains as premier barrier for moisture transport in short-steep coastal sub-catchments (3-  
583 3.6 °S). The nearly null NWP detection capability is likely related to the unique rainfall rates  
584 that occur on the ocean facing foothills of the Cordillera “Costanera”. Unlike in most tropical  
585 mountains where convective rainfall dominates in Southeast Ecuador  
586 vigorous advection shape a monotonic increasing precipitation gradient with altitude. In the  
587 core of the southern region, Emck (2007) reported that rainfall originates from an equal-  
588 balance of advective-topographic (light) and convective (heavier) genesis. Such a  
589 characteristic, over the Southern region, suggests that the NWP parameterization for OA-  
590 NOSA30 is particularly suited to solve this type of precipitation. For the Northern regions,  
591 which are more affected by the annual movement of the ITCZ, the influence of the continental  
592 climate divide and the occurrence of more stratiform cloud, deep convection (likely the  
593 dominant mechanism) is not emulated by the NWP model. A complete description of the  
594 errors in the NWP implementation is out of the scope of this study, we therefore only  
595 highlight some of the major sources. The lateral boundary conditions (reanalysis dataset) have  
596 presumably a major role on the degradation of WRF product quality. The poor representation  
597 of the Andes in the reanalysis model has showed to contribute to a modest simulation of  
598 meteorological fields such as wind (Schafer et al., 2003). Maussion et al. (2011) found that  
599 some undesired numerical effects and, eventually, inadequate input data can affect the  
600 operational output of the WRF model, in particular for extreme events; probably by  
601 overstressing certain physical processes. Jankov et al. (2005) found that the greatest  
602 variability in rainfall estimates from the WRF model originates from changes in the choice of  
603 the convective scheme, although notable impacts were observed from changes in the  
604 microphysics and planetary boundary layer (PBL) schemes. However, Ruiz et al. (2010)  
605 found that rainfall estimates only vary slightly among different configurations, but biases  
606 increase with time aggregation. Those findings agree with previous studies (Blázquez and  
607 Nuñez, 2009; Pessacg, 2008) and suggest that there is a common deficiency in the convective  
608 schemes used for this model.

609

## 610 **5 Conclusions**

611 In general, TRMM V7, V6 and OA-NOSA30 estimates capture the most prominent seasonal  
612 features of precipitation in the study area. Quantitatively, only the Southern sub-catchments of

613 Ecuador and Northern Peru are well estimated by both satellite and NWP estimates. There is  
614 low accuracy of both approaches in the Northern and Central regions where TMPA V7 and  
615 V6 overestimate while OA-NOSA30 systematically underestimates precipitation. The  
616 improvement of V7 over V6 is not evident region-wide. It appears that V7 detects better light  
617 precipitation rates on coastal and ocean exposed basins. Inland the differences of the two  
618 versions of TRMM 3B42 are almost unnoticeable. The separation of the windward/leeward  
619 Andean effect on orographic precipitation appears as the main challenge for TMPA  
620 algorithms. It was found that the detection probability is better for small rainfall depths (less  
621 than 5 mm day<sup>-1</sup>) than for high amounts of precipitation. OA-NOSA30 showed the best skills  
622 in detecting a balanced advective/convective regime of precipitation in the Southern region.

623 Analysis of daily, weekly, 15-daily and monthly time series revealed that the correlation with  
624 station observations increases and bias decreases with the time aggregation. Differences are  
625 considerably larger for daily than weekly aggregation. The correlation and bias values are  
626 similar in the Northern and Southern region but in the Central region correlation is smaller  
627 and bias is higher for all time aggregations. TMPA V7, V6 and OA-NOSA30 are able to  
628 capture relatively well the spatial pattern in the Southern region of the study area, but the  
629 performance of both approaches reduces in the Northern and Central region. In general the  
630 two TMPA versions perform better than OA-NOSA30.

631 In view of hydrological and water resources management applications, it has been  
632 demonstrated that the potential intake of both satellite and NWP estimates in the PAEP region  
633 differs among catchments and precipitation regimes. Our analysis has shown that both  
634 approaches capture the mean spatial and temporal features of precipitation at weekly to  
635 monthly accumulations over a particular region of Southern Ecuador-Northern Peru. These  
636 findings are relevant for these poorly gauged regions where there is growing pool of  
637 modelling work that rely on the use of satellite-based rainfall estimates as forcing data. Also  
638 dynamical weather prediction becomes more frequently applied, but this prediction is still in  
639 an experimental stage. However, for operational applications such as flood warning, which  
640 demand high temporal resolution rainfall data, accurate depth and storm location estimates are  
641 mandatory. The usefulness of both estimates is less promising.

642

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650

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797 Table 1. Description of sub-catchments and rain gauge density of homogeneous stations

Code	Sub-catchments	Catchment	Altitudinal range (m)	Area (km <sup>2</sup> )	Stations density*
1	Chone	Chone	0 - 350	3259	0.80
2	Portoviejo	Portoviejo	0 - 600	3548	1.00
3	Lower Guayas	Guayas	0 - 680	14641	0.30
4	Middle Guayas		0 - 4100	21423	0.70
5	Upper Guayas		300 - 4000	3642	2.50
6	Taura	Taura	0 - 2600	2449	0.40
7	Cañar	Cañar	0 - 4300	2412	1.50
8	Naranjal-Pagua	Naranjal-Pagua	0 - 4000	3387	0.01
9	Jubones	Jubones	0 - 4000	4361	1.20
10	Santa Rosa	Santa Rosa	0 - 2200	1062	0.80
11	Arenillas	Arenillas	0 - 1400	653	1.40
12	Zarumilla	Zarumilla	0 - 800	810	1.10
13	Puyango	Puyango - Tumbes	300 - 3500	3662	0.50
14	Catamayo	Catamayo - Chira	300 - 3500	4173	1.70
15	Alamor		200 - 2300	1182	2.30
16	Macará		150 - 3600	3166	2.00
17	Quiroz		150 - 3500	3137	3.70
18	Chira		0 - 800	4931	0.70
19	Chipillico		100 - 3200	1179	2.30
20	Tumbes	Puyango - Tumbes	0 - 1200	8200	0.30
21	Piura	Piura	0 - 2500	9472	0.30
Total				100745	

\* Stations per precipitation products grid cell (~900 km<sup>2</sup>)

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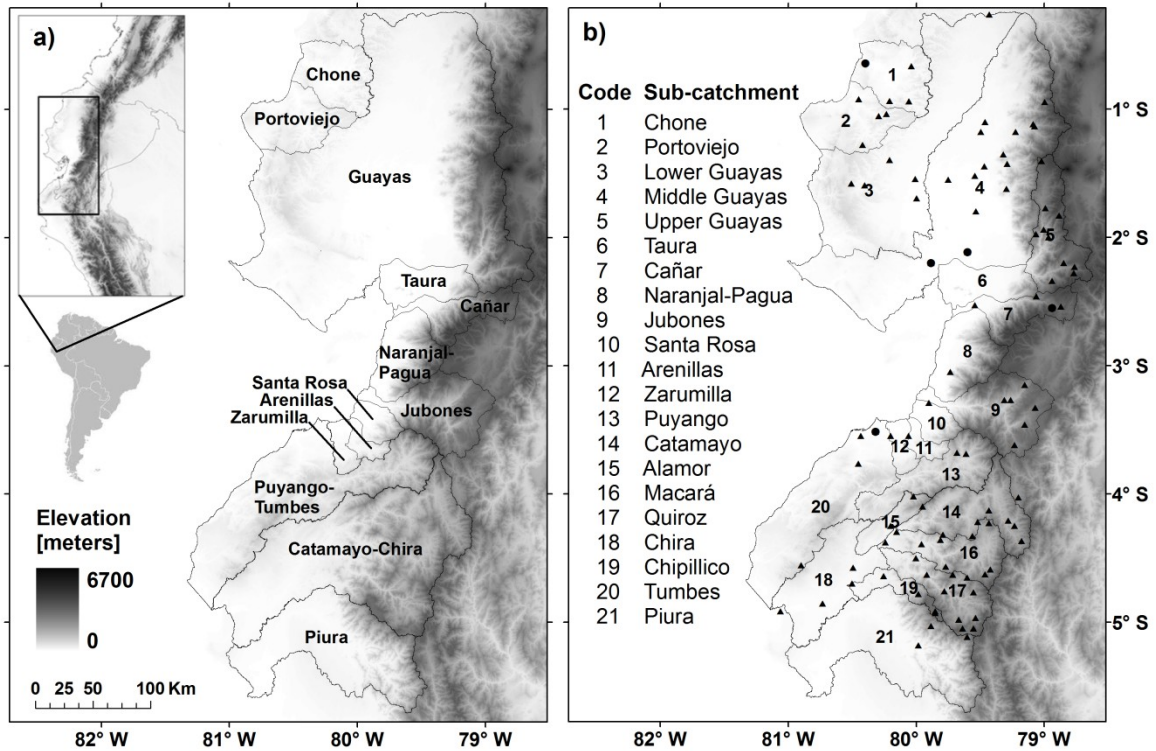
799 Table 2. Cross-validation results of daily rainfall interpolation for all stations over the period  
800 1998-2008 using inverse distance weighting (IDW), linear regression with altitude (LR),  
801 ordinary kriging (OK), and kriging with external drift (KED) techniques

Method	Correlation	MSE	Performance
IDW	0.260	65.33	0.012
LR	0.275	0.656	0.881
OK	0.210	0.550	0.865
KED	0.484	0.510	0.885

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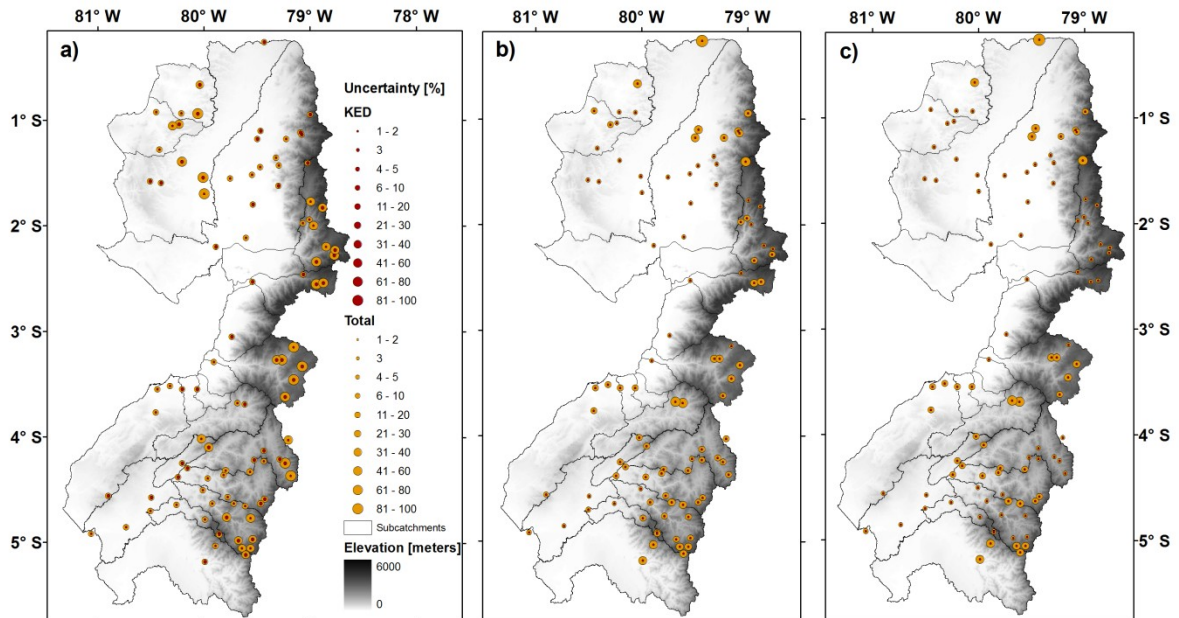
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Figure 1. (a) Location of the study area. Topography and boundaries of the catchments (grey line) in the Pacific-Andean region of Ecuador and Peru. (b) Sub-catchment boundaries (grey line) and rain gauge stations (triangles) used for the evaluation. Dots indicate GTS stations.



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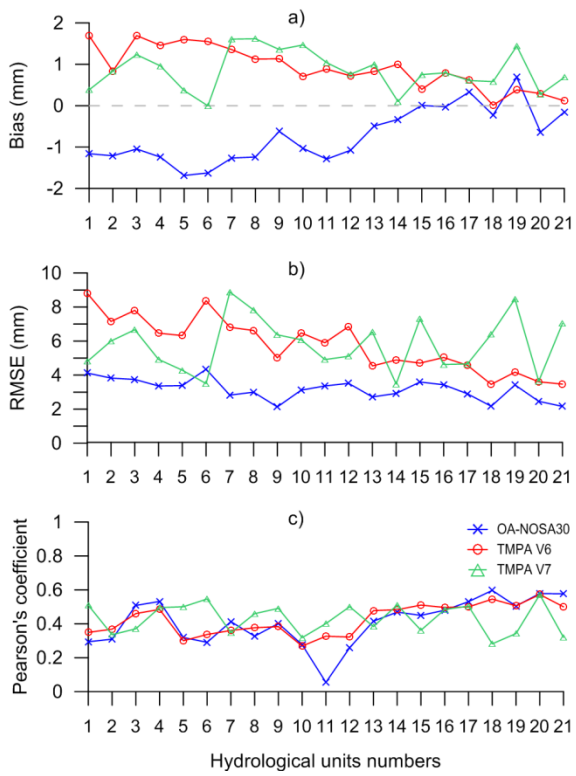
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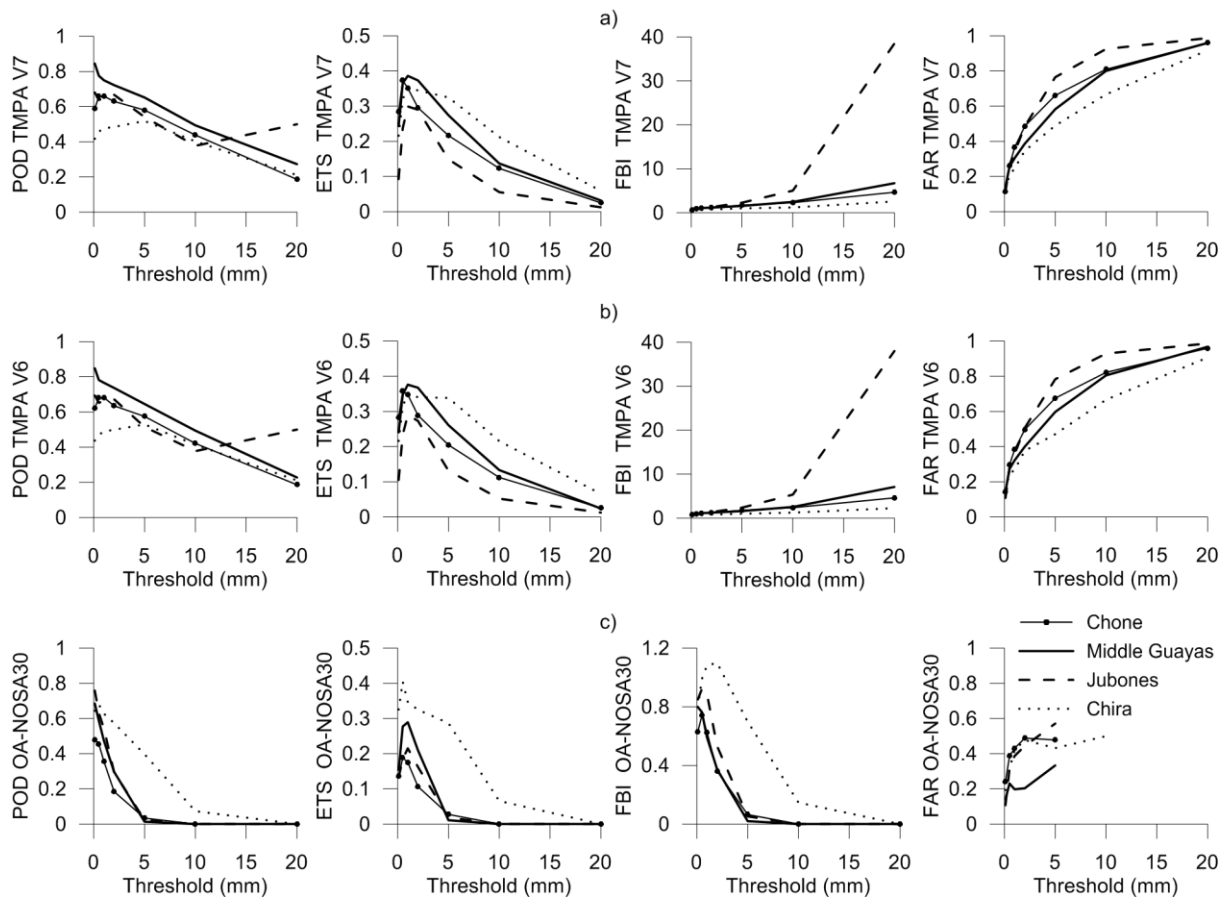
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Figure 2. Spatial distribution of the total residual variance (graded orange circles) and the fractional contribution of the KED uncertainty in the total residual variance (graded red circles) based on the comparison of one-single day random KED simulation against (a) OANOSA-30, (b) TMPA V6 and (c) TMPA V7. The size of the circles is proportional to the variance value.



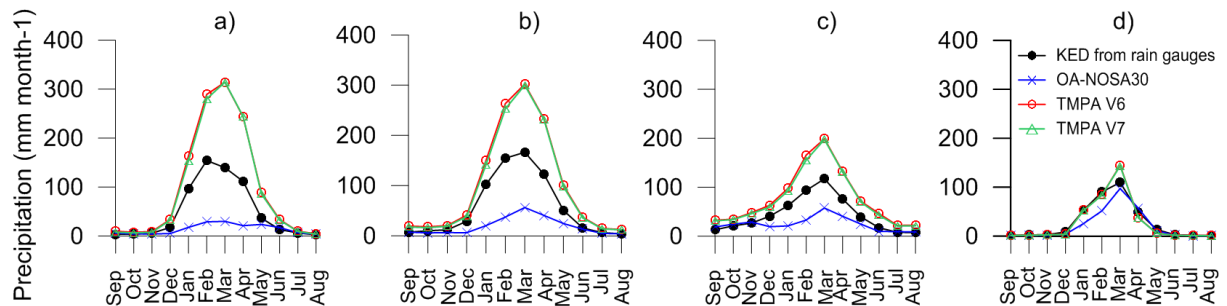
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815 Figure 3. Overall performance of the daily analysis for TMPA V7, V6 and OA-NOSA30 and  
 816 precipitation estimates per sub-catchment, averaged over the period 1998-2008. Names of sub-  
 817 catchments corresponding to the numbers are detailed in Table 1. a) Bias b) RMSE and c) Pearson's  
 818 correlation coefficient.



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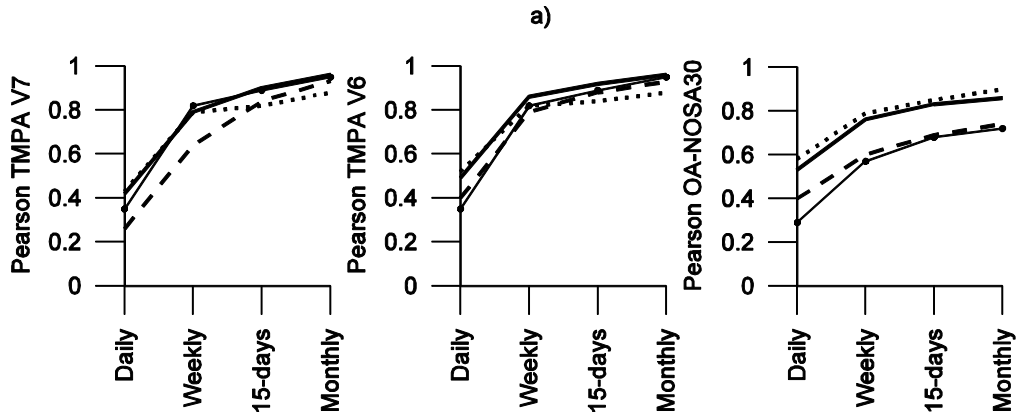
821 Figure 4. Categorical scores (POD, ETS, FBI, and FAR) of daily rainfall average for a) TMPA V7, b)  
822 V6 and c) OA-NOSA30 outputs against KED interpolated station data averaged over the period 1998-  
823 2008, applying different thresholds as precipitation upper limit.



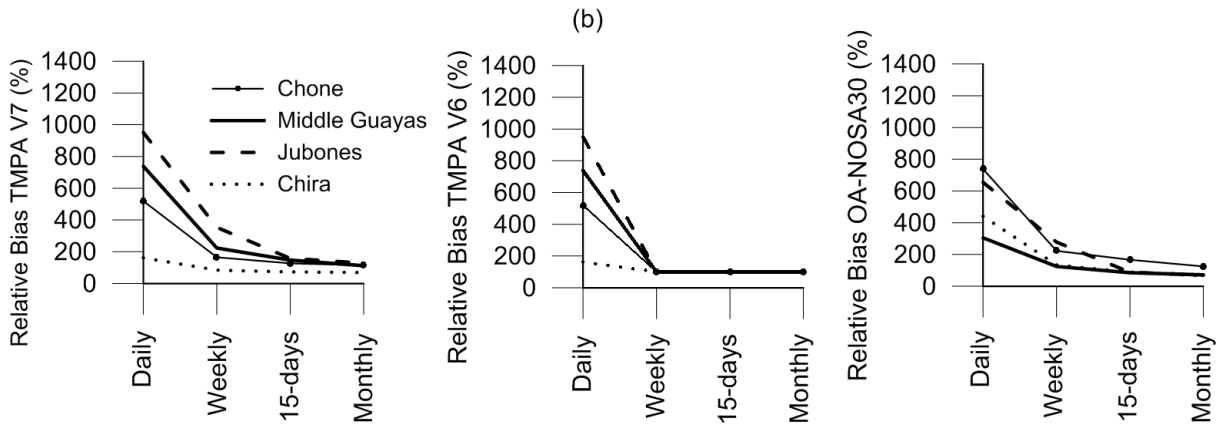
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825 Figure 5. Mean monthly precipitation in sub-catchments from North to South: (a) Chone, (b) Middle  
826 Guayas, (c) Jubones, and (d) Chira over the period 1998-2008.

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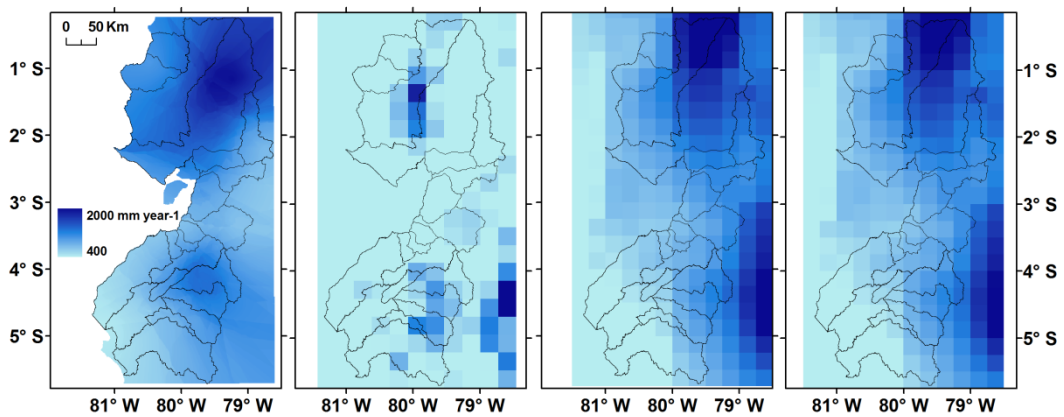


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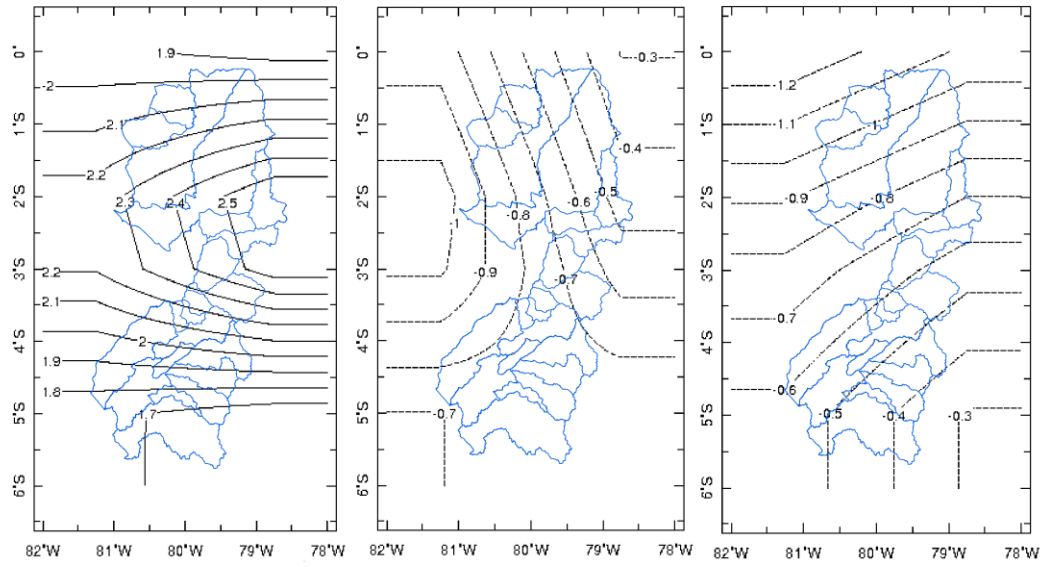


829 Figure 6. Overall performance analysis considered for daily, weekly, 15-daily and monthly time  
830 aggregations over the period 1998-2008. a) Pearson's correlation coefficient and b) relative bias (%)  
831 for TMPA V7, V6 and OANOSA-30 products calculated for a representative sub-catchment in the  
832 north, centre and south.

833



834 Figure 7. Spatial distribution of mean annual precipitation over the period 1998-2008 according to the  
835 KED interpolation of 98 rain gauges (a), OANOSA30 (b), TMPA V6 (c) and TMPA V7 (d).



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 837 Figure 8. Monthly anomalies of OLR ( $\text{Watts/m}^2$ ) during 1998-2008 within the rainy season  
 838 December-January (left), February-March (centre), April-May (right).  
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