1 **Assessment of evolving TRMM-based multi-satellite real-time precipitation**

2 **estimation methods and their impacts on hydrologic prediction in a high**

3 **latitude basin**

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Abstract

[1] The real-time availability of satellite-derived precipitation estimates provides hydrologists an opportunity to improve current hydrologic prediction capability for medium to large river basins. Due to the availability of new satellite data and upgrades to the precipitation algorithms, the Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis real-time estimates (TMPA-RT) have been undergoing several important revisions over the past ten years. In this study, the changes of the relative accuracy and hydrologic potential of TMPA-RT estimates over its three major evolving periods were evaluated and inter-compared at daily, monthly and seasonal scales in the high-latitude Laohahe basin in China. Assessment results show that the performance of TMPA-RT in terms of precipitation estimation and streamflow simulation was significantly improved after 3 February 2005. Overestimation during winter months was noteworthy and consistent, which is suggested to be a consequence from interference of snow cover to the passive microwave retrievals. Rainfall estimated by the new version 6 of TMPA-RT starting from 1 October 2008 to present has higher correlations with independent gauge observations and tends to perform better in detecting rain compared to the prior periods, although it suffers larger mean error and relative bias. After a simple bias correction, this latest dataset of TMPA-RT exhibited the best capability in capturing hydrologic response among the three tested periods. In summary, this study demonstrated that there is an increasing potential in the use of TMPA-RT in hydrologic streamflow simulations over its three algorithm upgrade periods, but still with significant challenges during the winter snowing events.

1. Introduction

[2] Precipitation is fundamental to life on Earth, and it is among the most important factors in energy and mass fluxes that dominate the weather, climate, hydrology, and ecological systems. Therefore, precipitation measurements offer essential information in understanding the balance of the global energy and water cycle exchange that drives most hydrologic models and has direct impacts on the planetary circulation of the atmosphere [*Sorooshian*, 2004; *Elizabeth et al.*, 2007]. However, accurately measuring precipitation at regional or global scales has been a challenging task due to its high small-scale variability in space and time. Conventional rain gauge and meteorological radar networks have their own limitations because their distributions are often sparse and data availability in remote regions and in complex terrain is rather limited [*Griffith et al.*, 1978; *Simpson et al.*, 1996; *Astin et al.*, 1997; *Vicente et al.*, 1998; *Huffman et al.*, 2001; *Margulis et al.*, 2001; *Maddox et al.*, 2002; *Steiner et al.*, 2003]. Thus, satellite-based precipitation estimates play an important role in detecting rainfall distribution and have been complementary to the ground-based rain gauge and radar measurements. Since the launch of the Tropical Rainfall Measuring Mission [TRMM; *Simpson et al.*, 1988 and *Kummerow et al.*, 2000] in 1997, there has been a growing number of real-time and quasi-global satellite precipitation products [*Sorooshian et al.*, 2000; *Joyce et al.*, 2004; *Hong et al.*, 2004; *Turk and Miller,* 2005; *Huffman et al.*, 2007; *Kubota et al.*, 2007] for a variety of scientific uses and natural hazard detection and warning, such as flood forecasting, drought assistance, landslide detection, and water quality monitoring. The planned Global Precipitation Measurement (GPM) mission with an approaching launch date of 14 February 2014 [*Tapiador et al.*, 2012], which will use an international constellation of microwave sensors, is anticipated to provide more accurate global precipitation products so as to improve our scientific understanding of the Earth system from

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70 space [*Smith et al.*, 2006; *Hou*, 2008]. As a prelude to GPM, the current operational TRMM

71 Multi-satellite Precipitation Analysis (TMPA) is intended to provide the best estimates of

72 quasi-global precipitation [*Huffman et al.*, 2007]. The TMPA merged data collected by two

73 different types of satellite sensors: low-Earth orbiting passive microwave (PMW) data, which

74 have a direct physical connection to the hydrometeor profiles but sparse sampling of the

75 time-space occurrence of precipitation, and geostationary infrared (IR) data with excellent

76 space-time coverage (approximately 30 min/4×4 km), but indirect physical relations with

77 precipitation. The standard TMPA products include real time (3B42 RT, hereafter referred to as

78 TMPA-RT) and post-real time research products (3B42 V6, hereafter referred to as TMPA-V6),

79 and both versions of the TMPA products have been provided for a sufficiently long time that

80 researchers have had the chances to develop and start reporting on various applications and

81 validation studies that employ one or both versions [*Huffman et al.*, 2010].

82 [3] Many prior studies have reported on the improvement of the TMPA-V6 products over

83 TMPA-RT products through bias correction using monthly rain gauge accumulations [e.g., *Tian*

84 *et al.*, 2007; *Su et al.*, 2008; *Li et al.*, 2009; *Dinku et al.*, 2010; *Gourley et al.*, 2010; *Hirpa et al.*,

85 2010; *Tobin and Bennett*, 2010; *Behrangi et al.*, 2011; *Betew and Gebremichael*, 2011; *Yong et*

86 *al.*, 2010; *Su et al.*, 2011]. However, it is the near real-time availability of the TMPA-RT products

87 and high spatial (0.25°×0.25°) and temporal (3h) resolution that has made them very attractive to

88 the water resources community, especially in developing countries, in order to provide hydrologic

89 predictions from which actions can be taken on medium to large river basins. Presently,

90 TMPA-RT products have been widely utilized in a variety of research and operational

91 applications [e.g., *Gottschalck et al.*, 2005; *Li et al.*, 2009; *Yong et al.*, 2010; *Tobin and Bennett*,

92 2010; *Behrangi et al.*, 2011; *Khan et al.*, 2011; *Romilly and Gebremichael*, 2011; *Su et al.*, 2011;

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93   *Wang et al.*, 2011]. For example, currently the global real-time flood monitoring system

94   developed by NASA TRMM group [http://trmm.gsfc.nasa.gov/; *Hong et al.*, 2007; *Wang et al.*,

95   2011; *Wu et al.*, 2012] has demonstrated the initial capability of using satellite-derived

96   precipitation data as forcing for global river forecast models.

97   [4] During the course of TMPA-RT development, precipitation estimates from new sensors on

98   various satellites were integrated and thus the real-time algorithm has undergone several updates.

99   Table 1 summarizes all precipitation-sensing microwave satellites/sensors that were introduced

100   into the TMPA processing at different historical periods. Generally speaking, the evolution of

101   TMPA-RT can be separated into the following three main development periods: 29 January 2002

102   to 3 February 2005 (Period I), 3 February 2005 to 1 October 2008 (Period II), and 1 October 2008

103   to present (Period III). Specific details regarding the sensors used, nominal coverage, and

104   algorithmic changes are provided in Appendix A.

105   **Insert Table 1 here**

106   [5] Given the dynamical evolution of the TMPA-RT algorithm by the Appendix A, a thorough

107   understanding to the above-mentioned major upgrades is critical to physically analyzing the

108   changes of data accuracy and hydrologic potential of the real-time TMPA products across the

109   three different developing periods. Many efforts have been made in prior studies to evaluate the

110   hydrologic utility of TMPA-RT for different basins throughout the globe [e.g., *Li et al.*, 2009;

111   *Dinku et al.*, 2010; *Hirpa et al.*, 2010; *Betew and Gebremichael*, 2011; *Khan et al.*, 2011; *Su et al.*,

112   2011]. Yet, their study areas are rarely located at the high latitude bands beyond the current

113   TMI/PR orbiting regions. Below, we highlight a number of questions about the TMPA-RT

114   algorithm evolution with the intention of addressing them in this study:

115   (1) Have the TMPA-RT estimates been significantly improved over the three major evolution

116   periods?

117   (2) TMI and TCI, the calibrators of TMPA-RT, provide coverage from 40˚N-S. Thus, do the

118   data of TMPA-RT that cover higher latitude bands beyond 40˚suffer from large bias, especially in

119   basins with snow-covered land surfaces?

120   (3) Are the latest TMPA-RT products (i.e., 3B42RT-Version6) much more similar to the

121   gauge-adjusted TMPA-V6 estimates than the previous two periods as suggested by the developers,

122   particularly in high-latitude basins?

123   (4) Finally, how did changes in input data and algorithm design for TMPA-RT over the three

124   different periods impact hydrologic prediction skill?

125   [6] *Yong et al.* [2010] evaluated the data accuracy and hydrological potential of TMPA-RT and

126   TMPA-V6 in the Laohahe Basin, China within the TMPA latitude band (50˚NS) but beyond the

127   latitude band of the TMPA calibrator (40˚N-S). In this study, we extend the work of *Yong et al.*

128   [2010] by specifically addressing the above questions through evaluation of TMPA-RT

129   precipitation products using independent gauge reports and examination of TMPA-RT estimates

130   on hydrologic simulation using the three-layer Variable Infiltration Capacity (VIC-3L) Model

131   [*Liang et al.*, 1994, 1996]. Section 2 describes the Laohahe basin, the datasets used, and the

132   statistics used to evaluate TMPA precipitation estimates and resulting hydrologic simulations.

133   The precipitation evaluation is divided into daily, monthly, and seasonal analyses in section 3;

134   this section also evaluates the similarity between TMPA-RT to TMPA-V6. The impact of the

135   algorithmic changes on hydrologic simulation is evaluated in section 4, and the paper is closed in

136   section 5 with conclusions and future recommendations.

137   ## 2. Study Basin, Observed Data and Methodology

138   [7] The Laohahe basin, of which a detailed description is provided in *Yong et al.* [2010], is

139   located within the Chinese typical arid and semi-arid regions. Accurate precipitation estimates at

140   high spatio-temporal scale is of particular importance for such drought-prone basins with

141   heterogeneous distributions of surface water resources. Compared to other basins in the northern

142   part of China, the Laohahe basin has a remarkably dense observation network that can offer

143   detailed ground verification for the satellite-derived precipitation estimates (Figure 1). There are

144   52 rain gauges evenly distributed within this 18,112 km^2 basin and a streamflow station of

145   Xinlongpo located at the watershed outlet to record observations of daily precipitation and

146   streamflow continuously from January 1990 to September 2010. Both the China Meteorological

147   Administration (CMA) and the Chinese Ministry of Water Resources (CMWR) operate all rain

148   gauge networks over mainland China. In practice, the local workers record the precipitation using

149   two approaches (i.e., tipping-bucket raingauge and manual traditional ombrometer). Then these

150   two types of recorded data are crosschecked and the final errors have to be controlled within 4%

151   for daily rainfall observation according to the ministerial standard. Hence, the Laohahe basin

152   gauge network is of high quality and is independent from what *Huffman et al.* [2007] used for the

153   gauge correction of TMPA post-real-time products. With respect to snow observations, they

154   introduced a known volume of warm water to thaw the snow in the standard vessel. So the liquid

155   equivalency of the snow is computed as the total water volume minus the input warm water

156   volume. The observers make a particular mark after the snow water equivalent digit in order to

157   distinguish snow or rainfall as the precipitation type. Such manual but effective recording

158   techniques can ensure the data quality and information of observed snow for our study. Ultimately,

159   these precipitation data will be collected and edited in the Chinese Hydrology Almanac at the end

160   of every year.

161   **Insert Figure 1 here**

162 [8] Daily maximum and minimum temperature and daily average wind speed from 1990 to

163 2010 were gathered from four meteorological stations to force the hydrologic model (see Figure.

164 1). Other data sources such as a digital elevation model (DEM), soil surveys, and vegetation,

165 which are needed to run the VIC-3L model, were taken from *Yong et al.* [2010]. The grid mesh

166 size of the hydrologic model used in this study is $\frac{1}{16}^{\circ} \times \frac{1}{16}^{\circ}$. To quantify the accuracy of

167 satellite-derived precipitation estimates, we used three types of statistical indices including

168 Pearson linear correlation coefficient (CC), mean error (ME), root mean squared error (RMSE),

169 relative bias (BIAS), and contingency table-based detection of rainy events (i.e., probability of

170 detection (POD), false alarm rate (FAR), and critical success index (CSI)). In addition,

171 Nash-Sutcliffe Coefficient of Efficiency (NSCE) was used to assess the hydrologic model fit

172 between simulated and observed streamflow. The interested reader can refer to all above

173 statistical indices for their corresponding formulae and meaning in Table 1 in *Yong et al.* [2010].

3. Evaluation and Comparison of Satellite Precipitation Estimates

175 [9] Our evaluation and comparison were performed over three domains including two selected

176 0.25°×0.25° grids (hereafter labeled as "Grid0501" and "Grid0401", see Figure 1) corresponding

177 to TRMM pixel resolution as well as the basin-averaged analysis (hereafter referred to as "Basin

178 Average"). The two, nested grid locations were chosen because they contain 4-5 rain gauges

179 within them and provide an analysis at the fine, TRMM pixel scale. Furthermore, there are

180 significant differences in terrain and land cover between these two grids though they are adjacent

181 to each other. Almost 80% of Grid0401 is at high elevation (>1000 m) with evergreen broadleaf

182 or coniferous trees, while most regions within Grid0501 are considered flat croplands and

183 lowlands (elevations < 1000 m) and are predominately covered by sparse grassland and shrubs.

184　The rain gauge accumulations from each gauge are averaged within each TRMM pixel so that

185　they can be compared to the TMPA estimates. The objective aims to investigate the evolution of

186　the performance of TMPA-RT during the three periods at daily, monthly, and seasonal time scale.

187　Algorithm skill in estimating rainfall amounts is compared to that obtained with TMPA-V6 in

188　order to assess whether TMPA-RT is approaching the skill of TMPA-V6 following the critical

189　algorithm updates. Considering both the major upgrade periods of TMPA-RT and the time span

190　of available observation data in the Laohahe basin, we separated the comparison periods of this

191　study into three parts: Period I (1 February 2002 – 1 January 2005), Period II (1 February 2005 –

192　30 September 2008), and Period III (1 October 2008 – 30 September 2010). The different sensors,

193　data inputs, and algorithm changes during these three time periods are summarized in Table 1 and

194　the details are available in the Appendix A.

195　**3.1 Daily Comparison**

196　　[10] We start with the evaluation of daily TMPA-RT against averaged rain gauge observations

197　over Grid0501, Grid0401, and Basin Average across Periods I, II, III, respectively (Figure 2 and

198　3). There is a gradually increasing CC between TMPA-RT and observed precipitation from

199　Period I to III for all three domains (Figure 3a). Taking the domain of Basin Average for example,

200　the CC value increases from 0.46 in Period I to 0.75 in Period III (increasing by approximately

201　63%). With respect to ME and BIAS, TMPA-RT during Period III, however, didn't perform as

202　well as expected, and was even worse than Period I for Grid 0501 and Basin Average (Figures 3c

203　and 3e). But, it is worth noting that TMPA-RT exhibits a significant improvement in the skill of

204　detecting rain events. The indices of POD and CSI are substantially increased throughout the

205　three evolving periods (Figure 2 and Figure 3g), while the FAR has an obvious decreasing

206　tendency (Figure 3i). The results suggest that the new algorithm adjustments to

207　3B42RT-Version6 (i.e., TMPA-RT during Period III) do not always reduce the error and bias of

9

208   the 3B42RT estimates, but they apparently provide higher correlation with gauge observations

209   and better detection for precipitation events in high-latitude basins, which are potentially

210   favorable factors for improving the hydrologic potential of TMPA-RT. On the other hand,

211   statistics describing TMPA-V6 performance don't reflect the same tendencies noted with

212   TMPA-RT over the three periods, though it has relatively low ME and BIAS (see the right

213   column of Figure 3). Lastly, scatterplots in Figure 2 reveal an interesting phenomenon in that

214   TMPA-RT has a slight tendency to overestimate lower rainfall rates and underestimate higher

215   ones, which is a similar finding in an evaluation of GOES-based rainfall estimates from *Vicente et*

216   *al.* [1998].

217   **Insert Figure 2 here**

218   **Insert Figure 3 here**

219   **3.2 Monthly Comparison**

220   [11] To directly assess the skill of the TMPA products in tracking the monthly variation of

221   precipitation over the three tested periods, we compare the time series of TMPA-RT, TMPA-V6,

222   and gauge observations over Grid 0501, Grid 0401, and Basin Average in Figure 4. Similar to the

223   daily results, the purely satellite-derived TMPA-RT demonstrated a relatively poor performance

224   in tracing the monthly variations of precipitation during Period I, while substantial improvements

225   were realized after 2005. This result confirms the assertion of *Huffman et al.*, [2010] that all

226   TMPA-RT datasets produced before 3 February 2005 should not be used. However, at least in

227   this high-latitude study basin, the TMPA-RT estimates after 2005 still overestimate precipitation

228   compared to gauges, especially during the winter and summer months. The BIAS of TMPA-RT

229   during Period III is even larger than that during Period II. But the monthly CC of Period III looks

230   better than the prior two periods. We further analyzed the TMPA-RT estimates for two largest

231   snowfall events in the winter of 2010 and two heavy rainstorms in the summer of 2010 (see

10

232 Figure 5). TMPA-RT significantly overestimates precipitation during all these extreme weather

233 events. For example, for the snowfall event that occurred on 26th February 2010, TMPA-RT

234 dramatically overestimated gauge observations over the whole basin by approximately 2000%

235 (i.e., 62.24 mm for TMPA-RT versus 2.96 mm by gauges for Basin Average). Similarly, for the

236 largest rainstorm in 2010, the cumulative gauge precipitation from the 23rd to 31st July is

237 70.81mm for Basin Average, while the corresponding estimation of TMPA-RT is 198.81mm,

238 indicating overestimation of 180%. In contrast, precipitation from TMPA-V6 remains in good

239 agreement with gauge precipitation throughout all the periods (see Figure 4 and 5).

240 **Insert Figure 4 here**

241 **Insert Figure 5 here**

242 [12] Next, we selected three statistical indices, CC, ME, and BIAS to illustrate the evolution of

243 monthly error characteristics of TMPA-RT and TMPA-V6. The values of CC improve throughout

244 all three tested periods, while relatively large values of ME and BIAS were still found for Period

245 III (see Figure 6). Above analyses suggest that the incorporation of AMSU-B and AMSR-E on

246 February 2005, which provides more passive microwave data covering high-latitude bands,

247 significantly improved the accuracy of TMPA-RT precipitation estimates. Another important

248 factor might be that the microwave-calibrated IR coefficients were updated every 3hr instead of

249 each pentad, and thus the IR-based scheme for filling PMW coverage gaps was substantially

250 changed at higher latitudes. Relative to the prior two periods, the latest upgrades of TMPA-RT

251 greatly helped it to improve its correlation with observed precipitation and improve the skill of

252 detecting rainy events, but the incorporation of PMW and IR data did little to reduce ME and

253 BIAS. We speculate that the causes for such large bias of the current TMPA-RT version come

254 from two sources: 1) The PMW data for TMPA are first calibrated by the TRMM Combined

255 Instrument (TCI) estimate, which combines data from TMI and PR. However, the coverage of

256　both TMI and PR is limited within the latitude bands between 40˚N-S. 2) Likewise, the TMI-TCI

257　used as the climatological monthly calibrator in 3B42RT-Version6 also cannot cover latitude

258　bands beyond 40˚. Thus, the IR-based schemes are poorly calibrated for higher latitudes to the

259　passive microwave, especially during the cool season. Therefore, the upgrades to the TMPA

260　algorithm had little impact on ME and BIAS. The monthly TMPA-V6 data didn't reveal any clear

261　trends in error characteristics over the three periods, thus the relatively higher CC and lower ME

262　can mostly be attributed to the monthly gauge adjustments yielding the post-real-time products

263　[*Su et al.*, 2008; *Yong et al.*, 2010].

264　　　　　　　　　　　　　　　　**Insert Figure 6 here**

265　**3.3 Seasonal Comparison**

266　　[13] Table 2 lists the statistical summary of seasonal comparisons including spring

267　[March-May (MAM)], summer [June-August (JJA)], autumn [September-November (SON)], and

268　winter [December-February (DJF)]. We also specifically computed the statistics during winter by

269　separating snow vs. rain events in order to assess the impact of precipitation phase on TMPA-RT.

270　Generally, there are strong seasonal variations in the computed statistics during the three tested

271　periods. All evaluations over Grid0501, Grid0401, and Basin Average show higher CC, POD, and

272　CSI and lower FAR in the summer compared to other seasons, while the worst performance

273　occurs in winter. In terms of the first four indicators, all seasons tended to experience better

274　precipitation estimates during the three evolving periods of TMPA-RT. For example, the CC

275　value of Basin Average in summer rises from 0.48 in Period I to 0.68 in Period II, and finally

276　reaches 0.85 in Period III. For random error and bias there are the largest values of ME and

277　RMSE in summer months because both the amount and frequency of precipitation are highest in

278　this season. By analyzing all values of ME, RMSE, and BIAS for different seasons throughout the

279 three different periods, we can conclude that the errors in Period III found in the daily and

280 monthly comparisons (Figure 3 and 6) are primarily attributed to the overestimation of the

281 3B42RT-Version6 algorithm for summer rainstorms. In addition, it is worth noting that the largest

282 relative biases occur in winter in estimating the water equivalent with snowing events. After

283 excluding these snowing days, we found that the CC evidently increased from Period I to III,

284 meanwhile ME, RMSE, and BIAS improved significantly in winter. Moreover, the detection of

285 precipitating events also performs slightly better for rainy days. In general, approximately 45% of

286 the total annual errors come from heavy rainfall events in summer, while the proportion during

287 winter is only 15%.

288 **Insert Table 2 here**

289 [14] To help developers diagnose the impact of snow on TMPA estimates in high-latitude

290 basins, we calculated the number of snowing days, cumulative snow water equivalent, and four

291 representative statistical indices (i.e., CC, ME, RMSE, and BIAS) of TMPA-RT and TMPA-V6

292 vs. Gauge for the winters from 2005 to 2010 in the Laohahe basin (see Table 3). It is notable that

293 TMPA-RT has relatively better cool season performance during the years with the least number

294 of snowing days. For example, the best performance occurred in the winter of 2009, which only

295 has two snowing days and 2.35 mm of snowmelt for the whole basin. In contrast, the worst

296 performance is found in the winter of 2010 with the maximum of snowing days (5 days) and

297 water-equivalent cumulative snowmelt (10.54 mm). The overestimation with TMPA-RT during

298 winter months in the Laohahe basin was especially remarkable and consistent, which might be

299 attributed to two major reasons: 1) The IR-based retrievals with high space-time coverage, but

300 poor correlation with rainfall (or snow water equivalent), are the main inputs of the TMPA system

301 in high-latitude areas. Unfortunately, IR-based estimates with warm-top stratiform cloud systems

302 perform rather poorly during the cold seasons [*Vicente et al.*, 1998; *Tian et al.*, 2007]. 2) As

303   another confounding factor, the snow cover in winter very likely interferes with the PMW-based

304   retrievals [*Grody*, 1991; *Ferraro et al.*, 1998], such as these two important microwave sensors of

305   AMSR-E and AMSU-B that can cover higher-latitude bands (beyond 40°N-S). In particular, the

306   high frequency channels (89 and 150-GHz) of AMSU-B might detect more scattering associated

307   with precipitation sized ice particles in the winter atmosphere, which indirectly raises its retrieval

308   precipitation rate [*Vila et al.*, 2007]. Thus, the available PMW-based calibrations of IR and the

309   PMW data themselves covering high-latitude regions cannot offer accurate retrievals with snow

310   events. As a result, the TMPA estimates suffer serious bias during the cool seasons.

311   **Insert Table 3 here**

312   **3.4 Detection of Similarity between TMPA-RT and TMPA-V6**

313   [15] Some previous studies have verified that TMPA-V6 showed better performance in

314   hydrologic simulation than TMPA-RT in many basins over the globe [*Su et al.*, 2008; *Stisen and*

315   *Sandlholt*, 2010; *Yong et al.*, 2010; *Betew and Gebremichael*, 2011]. Meanwhile, the TMPA

316   producers also suggested that the real-time datasets were made to be similar to the research

317   products as much as possible. Therefore, we specifically address the following question that

318   naturally arises amongst data users: Did the latest upgrades make TMPA-RT closer to TMPA-V6

319   than before? To address this issue, we first plotted the annual statistical indices of TMPA-RT vs.

320   TMPA-V6 over Grid0501, Grid0401, and Basin Average during 2002-2010 (Figure 7). The

321   results of annual statistics show that the TMPA-RT estimates after 2005 generally have higher

322   correlation, lower errors, and better rain detection against TMPA-V6 than before. However,

323   TMPA-RT of Period III doesn't continue the tendency of approaching the skill of TMPA-V6 like

324   that from Period I to Period II. Four statistics (i.e., CC, POD, FAR, and CSI) of Period III show

325   no clear significant improvements compared with Period II. The indices of error and bias (i.e.,

326   ME, RMSE, and BIAS) are even larger than those of Period II.

327   **Insert Figure 7 here**

328   [16] Considering the strong seasonality within satellite-based precipitation estimates, we

329   further investigated the seasonal statistics of TMPA-RT vs. TMPA-V6 for more insightful

330   understanding. Figure 8a and 8c show that there are gradually increasing CC, POD, and CSI

331   between TMPA-RT and TMPA-V6 from Period I to III during the spring and autumn seasons.

332   Interestingly, the values of error and bias (ME, RMSE, and BIAS) and false alarm ratio (FAR)

333   have a significant decreasing tendency for these two seasons, which is different from the annual

334   statistics. However, such variations expected by the TMPA producers were not found in the

335   seasons of summer and winter (Figure 8b and 8d). For instance, the values of ME, RMSE, and

336   BIAS in Period III are higher than those values in Period II during the summer months. For winter,

337   besides similar overestimation of error and bias, the POD values of three domains even show

338   anomalous fluctuations. Therefore, it can be concluded that relative to the prior two periods, the

339   larger bias and error between TMPA-RT and TMPA-V6 during Period III are chiefly attributed to

340   the remarkable overestimation of the TMPA-RT algorithm for the summer rainstorms and the

341   winter snowfall over our high-latitude basin.

342   **Insert Figure 8 here**

343   **4. Evaluation and Comparison of Hydrologic Streamflow Simulations**

344   [17] Up to this point, we have directly evaluated the precipitation estimates from TMPA-RT

345   and TMPA-V6. The purpose of this section is to assess the impacts of the TMPA-RT's upgrades

346   over the three evolving periods from the hydrologic perspective after applying the estimates as

347   forcing to the VIC-3L hydrologic model. The VIC-3L model was calibrated using monthly rain

348   gauge and streamflow observations on the Laohahe basin for the period 1990-1999 by *Yong et al.*,

349   [2010]. Figure 9a shows the monthly series of observed and VIC-simulated streamflow using rain

350   gauge inputs from 1990-2010. The plots of cumulative annual precipitation and streamflow

351   indicate that the annual rainfall of the Laohahe basin hardly changed during the last twenty years

352   (Figure 9b). However, there is a dramatic decreasing tendency with the observed discharge after

353   2000 (Figure 9c). *Yong et al.* [2010] concluded that human activities such as increased water

354   diversions for irrigation, newly built reservoirs and dams, rapid development of water-consuming

355   industries, and growth of local economies have substantially altered the natural hydrologic system.

356   Here, we emphasize that the streamflow after 2000 cannot be used as a standard reference for

357   assessing TMPA's hydrologic potential provided that the model parameters were estimated prior

358   to 2000 due to the tremendous human impacts in this basin. Therefore, as recommended by some

359   previous studies [e.g., *Wang et al.,* 2010; *Yong et al.,* 2010], we adopted the streamflow

360   reconstructed with gauge-observed precipitation input to the hydrologic model as the surrogate

361   for the observed streamflow during 2000-2010 (i.e., reconstruction period) in following

362   hydrologic evaluations.

363   **Insert Figure 9 here**

364   [18] We designed three simulation schemes (i.e., validation, bias-correction, and recalibration)

365   to assess and inter-compare the hydrologic potential of TMPA-RT over the three evolving periods

366   using the reconstructed streamflow as the reference. First, we kept the same calibrated parameters

367   optimized during the calibration period 1990-1999 unchanged and used the $\frac{1}{16}^{\circ} \times \frac{1}{16}^{\circ}$ gridded

368   TMPA-RT and TMPA-V6 data to directly force the VIC-3L model for hydrologic simulation.

369   Figure 10 shows that simulations using TMPA-RT significantly overestimates streamflow in the

370   Laohahe basin mostly due to its unrealistically high precipitation estimates as presented in section

371   3. However, it is worth noting that there is a gradually increasing tendency in the correlation

16

372   between TMPA-RT-derived and reconstructed streamflow during the three periods. For example,

373   CC of daily streamflow in Period I is 0.02, while this value rises to 0.24 in Period II and to 0.45 in

374   Period III. With respect to monthly simulation, the values of CC are -0.11, 0.49, and 0.61 for the

375   three periods, respectively. On the other hand, TMPA-V6 exhibits very good performance in

376   simulating the daily and monthly variations of reconstructed streamflow, compared with

377   TMPA-RT. Moreover, the streamflow driven by TMPA-V6 even agrees with the reconstructed

378   reference runoff more than the observed streamflow due to the significance of land use changes

379   and human infrastructure impacts on streamflow in the Laohahe basin. In other words,

380   satellite-derived precipitation estimates should have greater potential applications in simulating

381   natural hydrologic processes for typical ungauged basins which experience much lower human

382   impacts.

383   **Insert Figure 10 here**

384   [19] The hydrologic validation in Figure 10 suggests that there exists a high system bias in the

385   TMPA-RT estimates for our study basin. We speculate that similar results might be prevailing

386   with other high-latitude basins. Therefore, next we adopted a simple bias reduction method to

387   potentially improve streamflow prediction using TMPA-RT at basin scale. In the proposed

388   approach, we defined a ratio bias correction factor (rr) as:

389   $$rr = \frac{1}{1+ \mathrm{BIA}} \tag{1}$$

390   where the relative bias (BIAS) is defined as following:

391   $$\mathrm{BIAS} = \frac{\sum_{i=1}^{n}(S_i - G_i)}{\sum_{i=1}^{n}G_i} \times 100\% \tag{2}$$

392   In (2), S_i is the daily or monthly precipitation of TMPA-RT at the ith time step, G_i is the

393   corresponding gauge precipitation, and *n* is the number of time steps.

394   [20] Next, the bias correction factor (*rr*) was applied to the satellite precipitation retrievals

395   (i.e., $rr \times \text{TMPA}$) for each of the three tested periods (*rr* was 0.5622 for Period I, 0.6038 for

396   Period II, and 0.4918 for Period III). We kept the calibrated model parameters the same and

397   merely replaced the original TMPA-RT estimates with the bias-corrected inputs to drive the

398   VIC-3L hydrologic model. As we anticipated, the simple approach of bias-correction remarkably

399   improved the application of TMPA-RT estimates to streamflow simulation (Figure 11). The

400   TMPA-RT-driven simulation agrees well with the reconstructed streamflow especially after 2005.

401   The best hydrological performance was found in Period III (NSCE of 0.39 and 0.67, CC of 0.63

402   and 0.85 for daily and monthly streamflow prediction, respectively) despite some overestimates

403   during the summer and winter months of 2010. Apparently, it was the higher CC and better

404   rainfall detection skill (POD, FAR, and CSI) of TMPA-RT precipitation with rain gauges during

405   Period III compared to the prior two periods that drastically improved its hydrologic capability.

406   Following the simple procedure of bias-correction, the TMPA-RT was closer to observed

407   precipitation and its potential for capturing the hydrological features of the basin was significantly

408   enhanced for our study basin, though it still cannot achieve the simulation accuracy as in medium-

409   or low-latitude basins (e.g. those reported by *Behrangi et al.* [2011], *Betew and Gebremichael*

410   [2011], and *Su et al.* [2011]).

411   **Insert Figure 11 here**

412   [21] Presently, there is an increasing realization that many hydrologic models are sensitive to

413   the meteorological forcing data, in particular precipitation [*Wilk et al.*, 2006]. If the error

414   characteristics of input precipitation change dramatically, then it is likely that sensitive model

415   parameters, such as soil infiltration parameters and baseflow parameters will need to change

416   accordingly in order to achieve accurate streamflow simulations [*Su et al.*, 2005; *Yong et al.*,

2010]. Although bias correction to the forcing data is the preferred approach, these error characteristics may only be known after a given algorithm was implemented and evaluated after a significant passage of time. In other words, the identification of bias may not be readily available for a recently implemented precipitation algorithm or in locations where there are scarce or nonexistent gauge networks. In the third experiment, we recalibrated the sensitive parameters of VIC-3L for the whole period of February 2002 – September 2010 by using the original TMPA-RT precipitation estimates as forcing data. Table 4 lists the calibrated and recalibrated values of the seven sensitive parameters in the VIC-3L model. These parameters are briefly depicted as follows: 1) the infiltration parameter (b) which controls the amount of water that can infiltrate into the soil; 2) the three soil layer thicknesses (d_1, d_2, d_3) which affect the maximum storage available in the soil layers and consequently the water available for transpiration; 3) three baseflow parameters including the maximum velocity of baseflow (D_m), the fraction of maximum baseflow (D_s), and the fraction of maximum soil moisture (W_s), which jointly determine how quickly the water stored in the third layer is withdrawn [*Liang et al.*, 1996; *Su et al.*, 2005]. Among them, the most intensive parameters are the infiltration parameter (b) and the second soil layer thicknesses (d_2), which were targeted for intensive calibration/recalibration. Similar to Figure 11, the recalibrated simulations also show that the TMPA-RT after 2005 performed much better than prior periods for hydrologic simulation (see Figure 12). From the values of NSCE and CC, it can be seen that the best performance still occurred in Period III. The recalibrated results suggest again that hydrologic potential of TMPA-RT tends to gradually increase during its three evolving periods. However, the recalibration approach compromised the model's parameterized representation of real-world physical processes. For example, the recalibrated parameter, b, is 0.0055 (see Table 4), which almost reaches its minimum value of zero. The other sensitive parameter, d_2, has an optimized value of 5.7 m that substantially exceeded the upper limit of its

19

441　　normal physical range (0.1-2.0 m). Thus, it can be seen that the bias of TMPA-RT overestimation

442　　was mitigated at the cost of comprising the physical representativeness of hydraulic properties of

443　　the basin, which seriously alters the basin response under varying wetness conditions. Although

444　　the recalibration may not be a physically consistent approach for modeling the hydrologic

445　　response of real basins, it certainly helps us to confirm two facts: 1) the errors in simulating

446　　streamflow forced by TMPA-RT are mostly due to the unrealistically high precipitation

447　　estimation, and 2) there is an increasing hydrologic potential for TMPA-RT in streamflow

448　　simulations over its three historic development periods. However, we did not intend to advocate

449　　the recalibration as the norm for the satellite QPE-hydrology community, rather than an

450　　investigation tactic in this study.

451　　　　　　　　　　　　　　　　**Insert Figure 12 here**

452　　　　　　　　　　　　　　　　**Insert Table 4 here**

453　　　　[22] *Hossain and Lattenmaier* [2006] have argued that a shift in paradigm is needed to properly

454　　assess estimates of rainfall from satellite sensors for modeling dynamic hydrologic processes such

455　　as the rainfall-runoff transformation and associated energy and moisture fluxes. To better

456　　understand how error characteristics of input precipitation affect hydrologic model results, we

457　　compared the error propagation of TMPA-RT through VIC-3L rainfall-runoff processes at daily

458　　and monthly scale for the above three types of simulation schemes. For NSCE and CC, Table 5

459　　shows that the hydrological simulations of scheme 2 (bias-correction) and 3 (recalibration)

460　　performed much better than those of scheme 1 (validation). This suggests that both

461　　bias-correction and model-parameter adjustment can effectively remove the system bias of

462　　TMPA-RT through the VIC-3L model and then improve the hydrologic potential of satellite

463　　precipitation in this specific basin. NSCE and CC of TMPA-RT-driven streamflow in scheme 2

464　　and 3 exhibit an apparent upward trend over the three tested periods (e.g., NSCE of -1.44, 0.47,

465 and 0.67; CC of 0.18, 0.71, and 0.85 for the monthly streamflow simulation in scheme 2,

466 respectively), which is closely corresponding to the trend in CC between satellite precipitation

467 inputs and observations (e.g., CC of 0.67, 0.80, and 0.91 for the monthly rainfall in scheme 2).

468 Among the three tested periods, the best performance is in Period III. This implies that the

469 upgraded algorithm using climatological monthly calibration that increased the CC, POD, CSI

470 and decreased the FAR between satellite precipitation and gauged observations potentially

471 improved the hydrologic application of TMPA-RT. In terms of BIAS and RMSE, it is shown that

472 the VIC-3L model significantly amplified the errors propagated from original satellite rainfall to

473 the TMPA-RT-driven simulations (refer to the statistics of scheme 1 in Table 5). However,

474 following precipitation bias-correction or model-parameter adjustment, both procedures having

475 the same effect on hydrologic simulation, this situation was remarkably improved. Overall, the

476 results of rainfall-runoff error propagation suggest that the hydrological potential of TMPA-RT

477 tends to become better and better during its evolving periods even in high-latitude regions. The

478 authors argue that such improvements of hydrologic prediction are closely related to the inclusion

479 of new satellite data sources and upgrades to the precipitation algorithms in the TMPA real-time

480 precipitation systems. Additionally, the error in rainfall versus error in runoff presented in Table 5

481 indicates that the hydrologic propagation of satellite rainfall error through the VIC model exhibits

482 a quasi-linear behavior due to the large basin scale (18,112 km^2) and longer time scales (daily or

483 monthly) in this study. While previous studies [*Nikolopoulos et al.*, 2010; *Serpetzoglou et al.*,

484 2010] have indicated that a strong non-linearity exists in the rainfall-runoff error transformation,

485 those results are generally for hourly flood simulations on smaller-scale basins (<600 km^2).

486 Clearly, our results demonstrate that there is a dependence of satellite rainfall error propagation

487 on basin scale.

488 **Insert Table 5 here**

5. Conclusions and Recommendations

[23] In this study, we have evaluated and inter-compared the TMPA-RT precipitation estimates over three major evolution periods at daily, monthly and seasonal time scales using an independent, high-quality rain gauge network in a high-latitude basin in China. Then, we investigated whether the latest updates within Period III made the TMPA-RT data more similar to the gauge-adjusted TMPA-V6 estimates as intended by the algorithm developers. Lastly, we designed three types of streamflow simulation experiments using the VIC-3L model forced by TMPA-RT precipitation estimates in order to explore their hydrologic potential throughout the three evaluation periods. Results drawn from the above analyses may be specific to the Laohahe basin but are likely to be more generally applicable to basins situated in 40˚-50˚ latitude bands; they are summarized as follows:

(1) TMPA-RT estimates were least accurate and had the poorest hydrologic performance prior to February 2005 (in Period I), while substantial improvements by use of AMSR-E and AMSU-B data occurred thereafter as the developers have documented. Our results support their recommendation that users of TMPA precipitation should not utilize the real-time datasets before February 2005 for application to or feasibility studies involving hydrologic prediction or other natural hazard studies (e.g., landslides). The post-real-time research products (i.e., TMPA-V6) can be regarded as a reliable substitute to use prior to February 2005.

(2) Compared to the two prior periods before October 2008 (Periods I and II), the most recent version of TMPA-RT (i.e., 3B42RT-Version6 for Period III in this study) has higher CC, POD, and CSI and lower FAR compared to rain gauge observations. However, it was noted that it also has larger ME, RMSE and BIAS in our study basin. This implied that the latest

512   algorithm upgrades to TMPA-RT tended to increase its correlation with independent rain

513   gauge observations and improve the skill of detecting rainy events, but was not capable of

514   systematically reducing bias. Therefore, caution must be exercised when using the current

515   version 6 of TMPA-RT as inputs for flood forecasting models due to its propensity to

516   overestimate precipitation in higher-latitude basins.

517 (3) The latest upgrades to TMPA-RT during Period III made it more statistically similar to

518   TMPA-V6 than the real-time algorithm running in Period II during the spring and autumn

519   seasons. However, such improved performance anticipated by both the TMPA produced and

520   data users was not found in the summer and winter seasons due to the remarkable

521   overestimation of the current 3B42RT-Version6 algorithm in detecting the summer

522   rainstorms and the winter snowfall over this high-latitude basin.

523 (4) In the present version of TMPA-RT, one of the most serious issues was its notably poor

524   performance (i.e., BIAS > 1000%) during winter months, in particular with snowy events.

525   Apparently, satellite-based precipitation estimates in high latitudes during cold seasons still

526   present significant challenges. Snow-covered surfaces present problems for passive

527   microwave retrievals, which are infrequent at high latitudes. It is also possible that IR-based

528   schemes are poorly calibrated for high-latitude, cool season precipitation estimates.

529 (5) Prior to performing a hydrologic evaluation, streamflow was reconstructed on the Laohahe

530   basin using rain gauge inputs to the calibrated VIC-3L model. This reconstruction step was

531   needed in order to account for the tremendous, unnatural and difficult-to-model reductions to

532   streamflow caused by human impacts after 2000. The first experiment directly input

533   TMPA-RT estimates to the calibrated VIC-3L model and compared simulations with the

534   reconstructed streamflow. Not surprisingly, the TMPA-RT-driven model simulation

535   significantly overestimated the daily and monthly hydrographs for the entire period from

2002 to 2010. The second experiment applied a mean bias correction factor to the TMPA-RT estimates for each of the three periods and evaluated them as inputs to the calibrated VIC-3L hydrologic model. In this hydrologic evaluation, the TMPA-RT datasets revealed improvements throughout the three evolving periods. The third, naive experiment incorporated no information about TMPA-RT precipitation bias, which will be the case in basins lacking rain gauge networks, and recalibrated model parameters to the uncorrected, biased TMPA-RT estimates. The hydrologic skill in this latter experiment was essentially the same as that achieved in the second experiment. This indicates the model parameters can be estimated in a manner to effectively remove precipitation bias. However, it is noted that model parameter estimation procedures require a long, multi-year dataset, over which the error characteristics of precipitation might change especially following algorithm updates. Furthermore, the recalibrated parameters didn't always represent the realistic changes of hydraulic properties for real basins. Thus, it is recommended that the best procedure to increase the hydrologic use of TMPA-RT precipitation estimates is to improve their accuracy as much as possible and be cognizant of potential biases.

[24] Looking to the future, *Huffman et al.* [2010] suggested that more work is needed to extend TMPA precipitation estimates to higher latitudes and further evaluate the effectiveness of ongoing algorithm upgrades. Compared to the post-real-time research products, TMPA-RT data have attracted the attention of hydrologists who are engaging in studies of flood forecasting and landslide warning over vast regions due to the availability of the data in near-real time over most parts of the globe. We expect the results reported here will both provide the retrieval developers with some valuable references and offer hydrologic users of TMPA-RT data a better understanding of their error characteristics and potential utilization for various operational hydrological applications in high-latitude basins. In summary, this study demonstrated that there

560   is an increasing potential in the use of TMPA-RT in hydrologic streamflow simulations over its

561   evolving periods. But, accurate detection and estimation of precipitation during the winter months

562   (especially for snowing events) is still a challenging task for the satellite-based precipitation

563   estimates. We also note that the evaluation of TMPA-RT across the time history of algorithm

564   development presented herein potentially mixes effects due to varying storm or snowfall

565   characteristics during various years and the changes in the retrieval algorithms themselves.

566   Therefore, a more fair comparison could be accomplished by applying the different algorithmic

567   versions on the same data period, a topic inviting future research. Additionally, the results shown

568   in this study are only from a representative, semi-arid, high-latitude basin in China, so future

569   work should extend to different hydroclimatic basins located in different latitude bands. Moreover,

570   the evaluation framework developed herein can apply to new satellite precipitation products such

571   as the forthcoming 3B42RT Version 7 datasets and future GPM-era products.

572

573   Appendix A: Major Upgrades of TMPA-RT During Its Three Evolving

574   Periods

575   [25] (1) 29 January 2002 to 3 February 2005 (Period I): Only the observations from two

576   multi-channel passive microwave radiometers, i.e. the TRMM Microwave Imager (TMI) and the

577   Special Sensor Microwave/Imager (SSM/I) on Defense Meteorological Satellite Program (DMSP)

578   platforms, are converted to the merged microwave (3B40RT, or HQ product) precipitation

579   estimates with sensor-specific versions of the Goddard Profiling Algorithm [GPROF; *Kummerow*

580   *et al.*, 1996; *Olson et al.*, 1999]. During this initial period, the microwave HQ product, merged

581   from TMI, PR (precipitation radar, TRMM product 2B31) and SSM/I, was used to calibrate the

582 IR inputs collected from a variety of sensors flying on several geosynchronous Meteorological

583 satellites (refer to the note of Table 1).

584   [26] (2) 3 February 2005 to 1 October 2008 (Period II): Several important upgrades occurred

585 at the beginning of this period for improving the data accuracy and algorithm stability of TMPA.

586 First, Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E) on

587 Aqua and 3 Advanced Microwave Sounding Unit-B (AMSU-B) sensors onboard NOAA-series

588 satellites were included into the PMW mosaics to further calibrate the TMPA-RT algorithm,

589 which nearly doubles the typical combined microwave coverage in the latitude band 50°N-S from

590 ~45% to nearly 80% [*Huffman et al.*, 2007]. The polar orbits of AMSR-E and AMSU-B provide

591 broader nominal coverage (see Table 1). Especially, the use of AMSU-B offers an excellent

592 opportunity to reduce the errors associated with the inadequate samples by combining PMW

593 information from three NOAA POES satellites spaced approximately 4 h apart with a spatial

594 resolution of 16 km at nadir and a wider swath than prior SSMI (2200 km) [*Vila et al.*, 2007].

595 However, both AMSU-B and AMSR-E still have some limitations in their retrieval techniques

596 which prevent useful precipitation estimates over many land surfaces or sea ice. Second, the

597 Microwave Humidity Sounder (MHS) on NOAA-18 was incorporated in TMPA-RT to replace

598 the AMSU-B on board NOAA-17 since 27 November 2007. Similar to AMSU-B, the MHS

599 contains 5 channels and maintains almost same algorithm-wise within TMPA-RT. But it was an

600 afternoon sounder with a 1330 equator-crossing time, while the previous AMSU-B on NOAA-17

601 has a morning equator-crossing time of around 1030 local time [*Labow et al.*, 2011]. According to

602 *Turk et al.* [2010], the local crossing time of the AMSU-like sounders did have an impact upon

603 the soil moisture simulated with two land surface models. So presumably they might also affect

604 the hydrologic performance of the TRMM-based precipitation estimation. Third, inter-satellite

605   calibration in the HQ product is climatological, which reduced the real-time computational load

606   and prepared for the eventual decommissioning of TRMM. Finally, the microwave-calibrated IR

607   coefficients are recomputed every three hr to better control unrealistically high estimates

608   associated to unusually cold IR background temperatures (Tb's) but with low rainfall rates, such

609   as with high-level cirrus clouds (ftp://trmmopen.gsfc.nasa.gov/pub/merged/3B4XRT_doc.pdf).

610   [27] (3) 1 October 2008 to present (Period III): The last major upgrades for the TMPA

611   real-time system occurred on 17 February 2009. The datasets of the new Version 6 of the

612   TMPA-RT (hereafter "3B42RT-Version6"; note that this should not to be confused with TMPA

613   post-real time product "3B42V6") starting from 1 October 2008 were released so as to provide

614   the users a backlog for validation and application activities with the new data. Once the new

615   system is stable, the algorithm developers will seriously consider that the entire data record of

616   TMPA-RT might be reprocessed by the 3B42RT-Version6 scheme. The primary goal of the new

617   design of this algorithm and input data is to enable the real-time TMPA-RT and the post real-time

618   gauge-adjusted products TMPA-V6 systems to be as similar as possible for ensuring consistency

619   between these two datasets [*Huffman et al.*, 2010]. One important difference between them is the

620   calibrator of TMPA-V6, TRMM Combined Instrument (TCI) that combines data from both TMI

621   and PR, is not available in real time. Therefore, the developers first determined a matched

622   histogram calibration of TMI to the TCI, computed from 10 years of coincident data to establish

623   the climatology for each calendar month. Then, a climatological monthly calibration of TCI to

624   3B43 V6 (another TRMM product computed at monthly time intervals; not to be confused with

625   aforementioned "3B42V6" and "3B42RT-Version6") is calculated as a simple ratio on a $1°×1°$

626   grid, aggregated to an overlapping $3°×3°$ template, and using 10 years of data. Finally, the

627   TMI-TCI and TCI-3B43 calibrations are successively applied to the preliminary real-time

products to create the 3B42RT-Version 6 products. One of the main purposes of this algorithm upgrade is to reduce the bias of TMPA-RT over land. In addition, the AMSU-B sensor on NOAA-17 was inactive on 12 December 2009 and it was replaced by the MHS sensor on the European Operational Meteorological (MetOp) satellite since 27 March 2009 (Table 1). Later enhancements to the TMPA standard products mainly include improving error quantification and more importantly, extension to higher latitudes.

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814 **Table 1.** Time History of Major Upgrades of Microwave Satellites/Sensors Introduced into the

815 TMPA Processing[a]

Period	Satellites	Sensors	Period of Record	nominal coverage	Current Status
Period I	TRMM	TMI	8 Dec. 1997 – Current	40° N-S	Active
	TRMM	PR	8 Dec. 1997 – Current	38° N-S	Active
	DMSP-F13	SSM/I	29 Jan. 2002 – 18 Nov. 2009	85° N-S	Inactive
	DMSP-F14	SSM/I	29 Jan. 2002 – 23 Aug. 2008	85° N-S	Inactive
	DMSP-F15	SSM/I	29 Jan. 2002 – 14 Aug. 2006	85° N-S	Active, but unusable
Period II	Aqua	AMSR-E	3 Feb. 2005 – Current	85° N-S	Active
	NOAA-15	AMSU-B	3 Feb. 2005 – Current	Global	Active
	NOAA-16	AMSU-B	3 Feb. 2005 – Current	Global	Active
	NOAA-17	AMSU-B	3 Feb. 2005 – 17 Dec. 2009	Global	Inactive
	NOAA-18	MHS	27 Nov. 2007 – Current	Global	Active
Period III	MetOP-1	MHS	27 Mar. 2009 – Current	Global	Active
	DMSP-F16	SSMIS	Being incorporated into TMPA	85° N-S	Active
	DMSP-F17	SSMIS	Being incorporated into TMPA	85° N-S	Active

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817 [a]Notation. Except for above microwave satellites/sensors, the international constellation of geosynchronous-orbit

818 meteorological satellites including the Geosynchronous Operational Environmental Satellites (GOES, United

819 States), the Geosynchronous Meteorological Satellite (GMS, Japan), and the Meteorological Satellite (Meteosat,

820 European Community) provide the infrared (IR) data on a 4 km-equivalent grid over the latitude band 60° N-S for

821 TMPA-RT.

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330   **Table 2.** Statistical Summary of the Seasonal Comparison of Daily TMPA-RT vs. Gauge at Three Evolving Periods[a]

Index	Evaluating domains	Spring			Summer			Autumn			Winter [Winter but excluding snowing days]		
		Period I	Period II	Period III	Period I	Period II	Period III	Period I	Period II	Period III	Period I	Period II	Period III
CC	Grid 0501	0.16	0.47	0.63	0.36	0.47	0.68	0.36	0.39	0.53	0.02 [0.03]	0.03 [0.08]	0.15 [0.45]
	Grid 0401	0.16	0.49	0.65	0.36	0.48	0.72	0.36	0.49	0.56	0.003 [0.02]	0.08 [0.15]	0.12 [0.47]
	Basin Average	0.16	0.60	0.69	0.39	0.68	0.85	0.39	0.65	0.86	0.05 [0.08]	0.14 [0.23]	0.15 [0.49]
ME (mm)	Grid 0501	1.05	1.38	0.90	1.77	1.29	3.51	1.77	0.97	0.31	1.19 [0.55]	0.64 [0.35]	1.39 [0.41]
	Grid 0401	1.00	1.04	0.59	1.04	0.84	2.47	1.04	0.75	0.18	1.09 [0.53]	0.55 [0.39]	1.24 [0.38]
	Basin Average	0.62	0.76	0.51	1.39	1.07	2.33	1.39	0.60	0.82	1.24 [0.56]	0.44 [0.30]	1.29 [0.45]
RMSE (mm)	Grid 0501	6.00	4.39	4.28	7.77	7.79	11.89	7.77	3.72	3.45	3.98 [1.89]	2.13 [1.28]	5.80 [1.64]
	Grid 0401	6.14	4.07	4.33	5.94	7.70	9.90	5.94	3.49	3.66	3.90 [2.09]	1.83 [1.25]	5.70 [1.60]
	Basin Average	4.60	2.38	2.65	5.45	4.99	6.59	5.45	1.83	2.72	4.11 [1.85]	1.40 [0.83]	5.60 [1.66]
BIAS (%)	Grid 0501	130.19	173.76	109.54	169.90	44.95	175.56	169.90	199.43	35.29	2104.65 [1086.49]	1399.94 [751.89]	1230.79 [341.39]
	Grid 0401	134.89	133.91	66.29	84.60	26.61	108.80	84.60	141.65	18.61	1640.58 [844.06]	1357.14 [1070.02]	1096.01 [317.32]
	Basin Average	85.39	106.35	59.09	135.06	36.71	106.58	135.06	118.10	35.89	1742.62 [835.71]	940.51 [707.14]	1300.39 [449.65]
POD	Grid 0501	0.54	0.69	0.57	0.88	0.72	0.79	0.88	0.54	0.54	0.36 [0.37]	0.33 [0.33]	0.20 [0.20]
	Grid 0401	0.50	0.61	0.54	0.74	0.71	0.81	0.74	0.60	0.64	0.20 [0.21]	0.25 [0.33]	0.50 [0.50]
	Basin Average	0.56	0.77	0.64	0.84	0.86	0.92	0.84	0.83	0.90	0.50 [0.33]	0.33 [0.50]	0.33 [0.33]
FAR	Grid 0501	0.84	0.82	0.69	0.60	0.38	0.37	0.60	0.69	0.68	0.94 [0.95]	0.98 [0.96]	0.97 [0.95]
	Grid 0401	0.75	0.75	0.55	0.55	0.30	0.44	0.55	0.59	0.64	0.98 [0.98]	0.97 [0.97]	0.89 [0.85]
	Basin Average	0.75	0.63	0.55	0.54	0.21	0.23	0.54	0.54	0.60	0.96 [0.97]	0.97 [0.96]	0.97 [0.95]
CSI	Grid 0501	0.14	0.16	0.25	0.38	0.50	0.54	0.38	0.24	0.25	0.06 [0.05]	0.02 [0.03]	0.03 [0.04]
	Grid 0401	0.20	0.22	0.33	0.39	0.55	0.49	0.39	0.32	0.30	0.02 [0.02]	0.03 [0.03]	0.10 [0.15]
	Basin Average	0.21	0.33	0.36	0.43	0.70	0.72	0.43	0.42	0.38	0.04 [0.03]	0.03 [0.04]	0.03 [0.04]
Error Contribution (EC)		20.73%			45.28%			18.94%			15.05%		

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333   aNotation. The seasonal comparison includes five cases: spring [March-May (MAM)], summer [June-August (JJA)], autumn [September-November (SON)], winter

334   [December-February (DJF)], and winter but excluding snowing days. The computing equation of Error Contribution (EC) is defined as:

$$EC = \frac{\sum_{i=1}^{n}|S_i - G_i|}{\sum_{j=1}^{m}|S_j - G_j|} \times 100\%,$$

335   among which S_i and G_i are satellite precipitation and gauged observation, and n and m represent the number of a certain season and all season days,

336   respectively.

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Table 3. Number of Snowing Days, Observed Cumulative Snowmelt, and Statistical Indices (CC, ME, RMSE, and BIAS) of Daily TMPA-RT and TMPA-V6 vs. Gauge for Every Winter from 2005 to 2010 in Laohahe Basin[a]

Phases	Year	Number of snowing days	Observed cumulative snowmelt	TMPA-RT vs. Gauge				TMPA-V6 vs.Gauge				Performance Level
				CC	ME	RMSE	BIAS	CC	ME	RMSE	BIAS	
	2005	4	5.434	0.086	1.153	3.825	1909.40%	0.120	0.052	0.443	85.63%	Poor
Period II	2006	4	4.766	-0.042	0.537	1.593	1013.50%	-0.009	0.014	0.381	26.56%	Average
	2007	2	3.400	0.249	0.388	1.232	1023.75%	0.539	0.029	0.273	75.19%	Average
	2008	3	3.480	0.237	0.409	1.319	1497.97%	0.218	0.061	0.393	221.84%	Average
Period III	2009	2	2.350	0.773	0.489	1.679	597.42%	0.888	0.085	0.313	104.31%	Good
	2010	5	10.540	-0.042	2.099	7.733	1791.94%	-0.045	0.076	0.857	64.99%	Poor

[a]Notation. If the snowing observations of more than half rain gauges distributed within the whole basin exceed the threshold of 0.1mm, this day will be labeled as a "snowing day".

861   **Table 4.** Comparison of Calibrated and Recalibrated Parameter Values in VIC-3L Hydrologic

862   Model for TMPA-RT-driven Streamflow Simulations[a]

Parameter	Unit	Typical Range	Calibrated values with gauge precipitation	Recalibrated values for TMPA-RT
b	N/A	0~0.5	0.01	0.0055
d_2	m	0.1~2.0	1.2	5.7
D_s	Fraction	0~1.0	0.004	0.0025
D_m	mm/day	0~30.0	8.0	7.3
W_s	Fraction	0~1.0	0.98	0.98
d_1	m	0~0.1	0.05	0.05
d_3	m	0.1~2.0	1.5	2.0

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864   [a]Notation. In this study, the calibration period is Jan. 1990 - Dec. 1999 and the recalibration period is Feb. 2002 –

865   Sep. 2010.

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Table 5. Comparison Results of Rainfall-Runoff Error Propagation for Three Simulation Schemes, i.e., Validation, Bias-correction, and

Recalibration through VIC-3L Hydrologic Model at Daily and Monthly Scales, Respectively

Item	Index	Daily scale						Monthly scale					
		Period I		Period II		Period III		Period I		Period II		Period III	
		Rainfall	Streamflow	Rainfall	Streamflow	Rainfall	Streamflow	Rainfall	Streamflow	Rainfall	Streamflow	Rainfall	Streamflow
Scheme 1: Validation	NSCE	-1.14	-161.62	0.01	-275.78	-2.05	-94.29	-0.35	-298.74	0.03	-348.21	-0.91	-205.08
	CC	0.46	0.02	0.70	0.24	0.75	0.45	0.67	-0.11	0.80	0.49	0.91	0.61
	BIAS (%)	77.86	609.95	65.61	853.20	103.34	565.77	77.86	609.79	65.46	853.45	103.57	565.62
	RMSE(mm)	5.29	385.27	3.10	482.12	4.72	298.07	46.95	48.09	30.19	59.90	51.50	38.33
Scheme 2: Bias-correction	NSCE	0.02	-1.33	0.48	0.29	0.59	0.39	0.44	-1.44	0.62	0.47	0.79	0.67
	CC	0.46	0.23	0.70	0.55	0.75	0.63	0.67	0.18	0.80	0.71	0.91	0.85
	BIAS (%)	0.00	23.78	0.00	13.60	0.00	5.75	0.00	23.76	0.00	13.60	0.00	5.78
	RMSE(mm)	3.57	46.05	2.26	22.93	1.92	25.14	30.18	4.34	23.04	2.34	18.30	1.53
Scheme 3: Recalibration	NSCE	-1.14	-0.45	0.01	0.32	-2.05	0.37	-0.35	-0.50	0.03	0.52	-0.91	0.61
	CC	0.46	0.34	0.70	0.57	0.75	0.66	0.67	0.32	0.80	0.76	0.91	0.85
	BIAS (%)	77.86	-14.66	65.61	-6.30	103.34	7.52	77.86	-14.62	65.46	-6.33	103.57	7.58
	RMSE(mm)	5.29	36.38	3.10	22.72	4.72	25.67	46.95	3.40	30.19	2.08	51.50	1.67

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FIGURE CAPTIONS

888 **Figure 1.** Map of Laohahe Basin situated beyond the TMI/PR orbiting bands (40°NS) and

889 locations of rain gauges, meteorological stations, and streamflow station included in the study.

890 Hydrologic evaluation of TMPA-RT during three major evolving periods was performed over the

891 whole basin (i.e., Basin Average) and two selected 0.25°×0.25°grids with black squares (i.e.,

892 Grid0501 and Grid0401), which contain 5 and 4 rain gauges, respectively.

893 **Figure 2.** Scatterplots of the daily TMPA-RT vs. gauge observation for (1st row) Grid 0501, (2nd

894 row) Grid 0401, and (3rd row) Basin Average at (left column) period I, (middle column) period II,

895 and (right column) period III.

896 **Figure 3.** Comparisons of statistical indices of the daily (left) TMPA-RT and (right) TMPA-V6

897 vs. gauge observation at three evolving periods (I-III): (a and b) correlation coefficient, (c and d)

898 mean error, and (e and f) relative bias, (g and h) probability of detection, (i and j) false alarm

899 ratio.

900 **Figure 4.** Monthly variations of gauged precipitation, TMPA-RT, and TMPA-V6 during three

901 evolving periods, i.e. Period I (Feb. 2002 – Jan. 2005), Period II (Feb. 2005 – Sep. 2008), and

902 Period III (Oct. 2008 – Sep. 2010): (a) Grid 0501, (b) Grid 0401, and (c) Basin Average.

903 **Figure 5.** Comparisons of gauge observation, TMPA-RT, and TMPA-V6 for two largest snowfall

904 events (i.e., 3 Jan. and 26 Feb.) in the winter of 2010 and two heavy rainstorms (i.e., 23-31 Jul.

905 and 17-22 Aug.) in the summer of 2010: (a and b) Grid 0501, (c and d) Grid 0401, and (e and f)

906 Basin Average.

907 **Figure 6.** Same as Figure 3 but for monthly precipitation: (a and b) correlation coefficient, (c and

908 d) mean error, and (e and f) relative bias.

909   **Figure 7.** Annual variations of statistical indices for daily TMPA-RT vs. TMPA-V6 over Grid

910   0501, Grid 0401, and Basin Average, respectively.

911   **Figure 8.** Same as Figure 7 but for seasonal statistics: (a) Spring [March-May (MAM)], (b)

912   Summer [June-August (JJA)], (c) Autumn [September-November (SON)], (d) Winter

913   [December-February (DJF)].

914   **Figure 9.** (a) Observed and gauge-driven VIC-simulated monthly streamflow for calibration

915   period (1990-1999) and reconstruction period (2000-2010), (b) Cumulative annual precipitation

916   from 1990 to 2010 for the Laohahe basin, (c) same as (b) but for streamflow.

917   **Figure 10.** Hydrologic simulation scheme 1: validation for TMPA-RT and TMPA-V6. VIC-3L

918   reconstructed streamflow with the observed gauge precipitation and VIC-3L simulated

919   streamflow directly forced by TMPA-RT and TMPA-V6 during three evolving periods: (a) daily

920   scale and (b) monthly scale.

921   **Figure 11.** Hydrologic simulation scheme 2: Simulation forced with bias-adjusted TMPA-RT.

922   Simulated streamflow with bias-adjusted TMPA-RT referenced by the reconstructed streamflow

923   with the gauged precipitation during three evolving periods: (a) daily scale and (b) monthly scale.

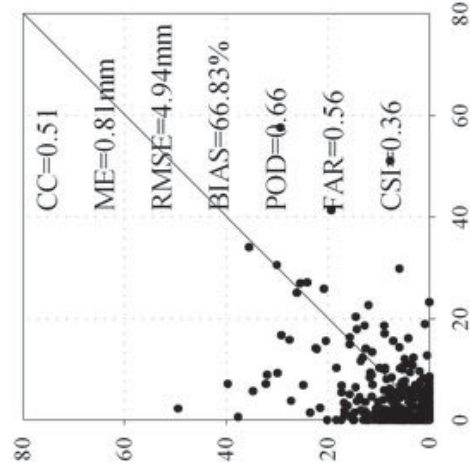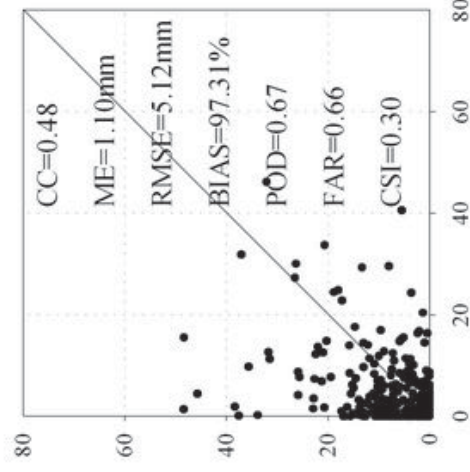924   **Figure 12.** Hydrologic simulation scheme 3: recalibration for TMPA-RT. Recalibrated

925   streamflow with TMPA-RT (recalibrated model parameter values listed in Table 4) referenced by

926   the reconstructed streamflow with the gauged precipitation during three evolving periods: (a)
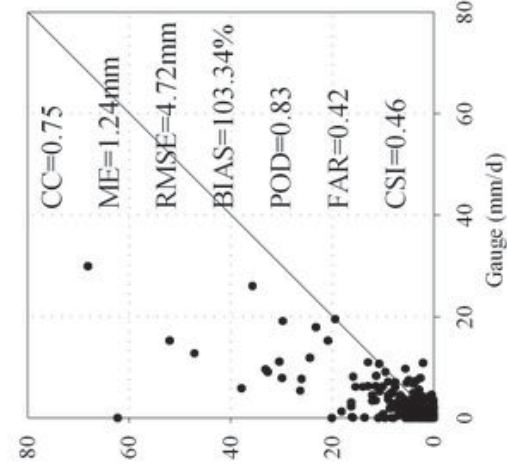
927   daily scale and (b) monthly scale.

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Laohahe Basin

Period I   Period II   Period III

Grid 0501

CC=0.56
ME=1.53mm
RMSE=7.18mm
BIAS=160.48%
POD=0.71
FAR=0.62
CSI=0.32

CC=0.48
ME=1.10mm
RMSE=5.12mm
BIAS=97.31%
POD=0.67
FAR=0.66
CSI=0.30

CC=0.41
ME=1.37mm
RMSE=8.12mm
BIAS=111.47%
POD=0.65
FAR=0.66
CSI=0.29

Grid 0401

CC=0.64
ME=0.88mm
RMSE=5.75mm
BIAS=82.58%
POD=0.70
FAR=0.54
CSI=0.39

CC=0.51
ME=0.81mm
RMSE=4.94mm
BIAS=66.83%
POD=0.66
FAR=0.56
CSI=0.36

CC=0.41
ME=1.15mm
RMSE=7.37mm
BIAS=90.32%
POD=0.60
FAR=0.61
CSI=0.31

Basin Average

CC=0.75
ME=1.24mm
RMSE=4.72mm
BIAS=103.34%
POD=0.83
FAR=0.42
CSI=0.46

CC=0.70
ME=0.74mm
RMSE=3.10mm
BIAS=65.61%
POD=0.83
FAR=0.45
CSI=0.49

CC=0.46
ME=0.93mm
RMSE=5.29mm
BIAS=77.86%
POD=0.68
FAR=0.59
CSI=0.35

Gauge (mm/d)

TMPA-RT (mm/d)

TMPA-RT vs. Gauge   TMPA-V6 vs. Gauge

Period I · Period II · Period III

(a) Grid 0501

Legend:
— ● — Gauged Precipitation
···○··· TMPA-RT Precipitation
– △ – TMPA-V6 Precipitation

(b) Grid 0401

Legend:
— ● — Gauged Precipitation
···○··· TMPA-RT Precipitation
– △ – TMPA-V6 Precipitation

(c) Basin Average

Legend:
— ● — Gauged Precipitation
···○··· TMPA-RT Precipitation
– △ – TMPA-V6 Precipitation

Precipitation (mm/month)

Jan 2002 · Jul · Jan 2003 · Jul · Jan 2004 · Jul · Jan 2005 · Jul · Jan 2006 · Jul · Jan 2007 · Jul · Jan 2008 · Jul · Jan 2009 · Jul · Jan 2010 · Jul

Two Largest Snowfall Events

Two Largest Rainstorm Events

Period I   Period II   Period III

(a) CC

(b) ME

(c) RMSE

(d) BIAS

(e) POD

(f) FAR

(g) CSI

mm
mm
%

2002 2003 2004 2005 2006 2007 2008 2009 2010

Grid 0501
Grid 0401
Basin Average

(a)

Period I

$CC_{RT\_I} = 0.02$

Period II

$CC_{RT\_II} = 0.24$

Period III

$CC_{RT\_III} = 0.45$

(b)

Period I

$CC_{RT\_I} = -0.11$

Period II

$CC_{RT\_II} = 0.49$

Period III

$CC_{RT\_III} = 0.61$

Observed Streamflow

Simulated with TMPA-RT

Reconstructed with Gauged Data

Simulated with TMPA-V6

Figure. Streamflow time series comparison between reconstructed with gauged data, simulated with bias-corrected TMPA-RT, and observed streamflow across Period I, Period II, and Period III.

(a) Time Series (day), Streamflow (m³/s)

- Period I: rr = 0.5622, RT$_{NSCE}$ = -1.33, RT$_{CC}$ = 0.23
- Period II: rr = 0.6038, RT$_{NSCE}$ = 0.29, RT$_{CC}$ = 0.55
- Period III: rr = 0.4918, RT$_{NSCE}$ = 0.39, RT$_{CC}$ = 0.63

(b) Time Series (month), Streamflow (mm)

- Period I: rr = 0.5622, RT$_{NSCE}$ = -1.44, RT$_{CC}$ = 0.18
- Period II: rr = 0.6038, RT$_{NSCE}$ = 0.47, RT$_{CC}$ = 0.71
- Period III: rr = 0.4918, RT$_{NSCE}$ = 0.67, RT$_{CC}$ = 0.85

Legend:
- Reconstructed with Gauged Data
- Simulated with Bias-corrected TMPA-RT
- Observed Streamflow

(a) Period I $RT_{NSCE} = -0.45$ $RT_{CC} = 0.34$ — Period II $RT_{NSCE} = 0.32$ $RT_{CC} = 0.57$ — Period III $RT_{NSCE} = 0.37$ $RT_{CC} = 0.66$; Streamflow (m^3/s); Time Series (day)

(b) Period I $RT_{NSCE} = -0.50$ $RT_{CC} = 0.32$ — Period II $RT_{NSCE} = 0.52$ $RT_{CC} = 0.76$ — Period III $RT_{NSCE} = 0.61$ $RT_{CC} = 0.85$; Streamflow (mm); Time Series (month)

— Reconstructed with Gauged Data
— — Recalibrated with TMPA-RT
Observed Streamflow