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Precipitation Uncertainty and its Impacts on Hydrologic Modelling and Flood Prediction: An Investigation in IFloodS Focal Basins

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1. Introduction

A real-time Global Flood Monitoring System (GFMS) has been developed by coupling a widely used Land Surface Model, i.e. the Variable Infiltration Capacity (VIC) model (U. of Washington/Princeton U.) with a physically based Dominant River Tracing-based runoff-Routing (DRTR) model (Wu et al., 2011, 2012a,b, 2014). The coupled model is named as the Dominant river tracing-Routing Integrated with VIC Environment (DRIVE) model. The GFMS driven by Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA) rainfall products is operating routinely and producing flood detection and intensity results at (http://flood.umd.edu/) and TRMM website http://trmm.gsfc.nasa.gov (Fig. 1).

Global Flood Monitoring System (GFMS)

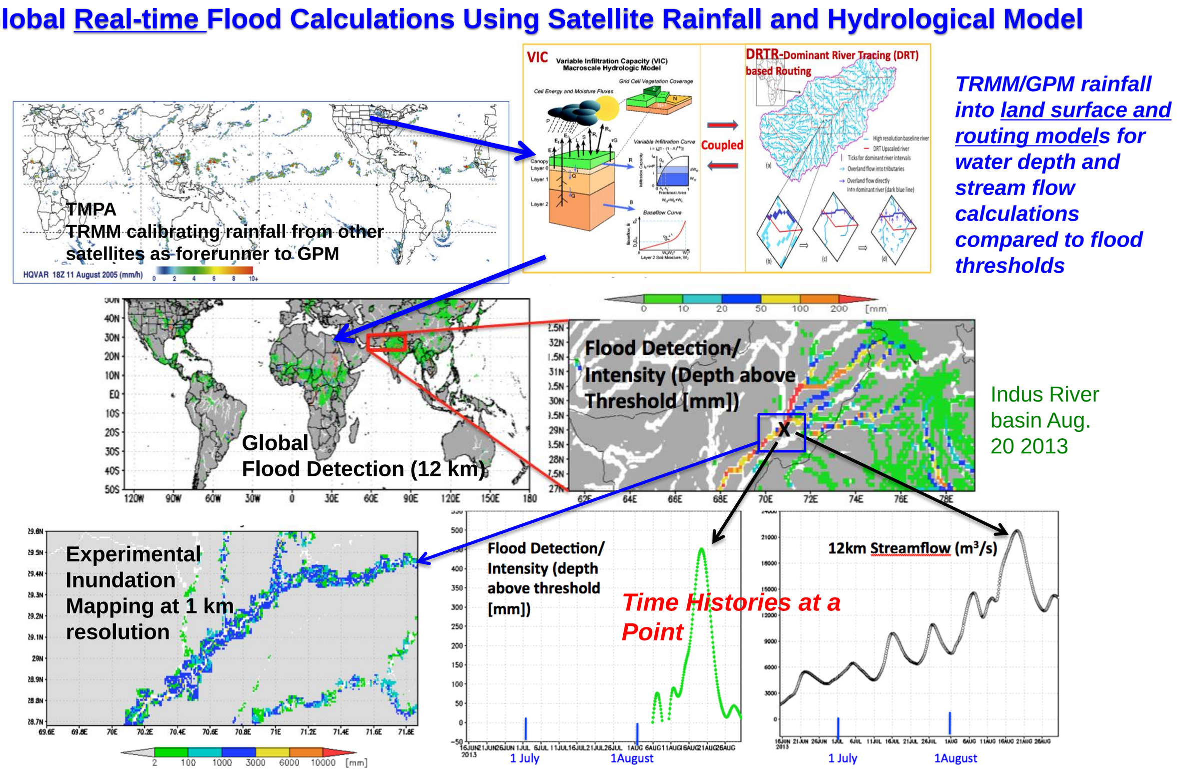

Fig. 1 Example of global to regional flood calculation by the GFMS with the DRIVE model.

The purpose of this study is to investigate the precipitation uncertainty and understand its impact on flood estimation, toward to further improve the accuracy of the real-time GFMS.

2. Experimental hydrological modelling with a set of

In this study, we investigate the precipitation uncertainty impacts on streamflow calculations through the DRIVE model with a set of real precipitation products. These precipitation products include satellite-based, ground radar based and gauge-based and reanalysis (with gauge data) based precipitation estimations (Fig. 2). We performed the hydrological simulations using these precipitation products while keeping all the rest model inputs the same, for both long-term (2002-2013) and IFloodS periods (Apr. 1-June 30, 2013). All simulations are at 1/8[th] degree spatial resolution and 3-hour time steps. To be consistent to the GFMS, all precipitation inputs are prepared to feed the DRIVE model at 1/8th degree resolution.

There are significant differences in the mean annual (Fig.2a), seasonal (Fig.2b-c), and IFloodS (Fig. 3) period precipitation estimation among the existing precipitation products.

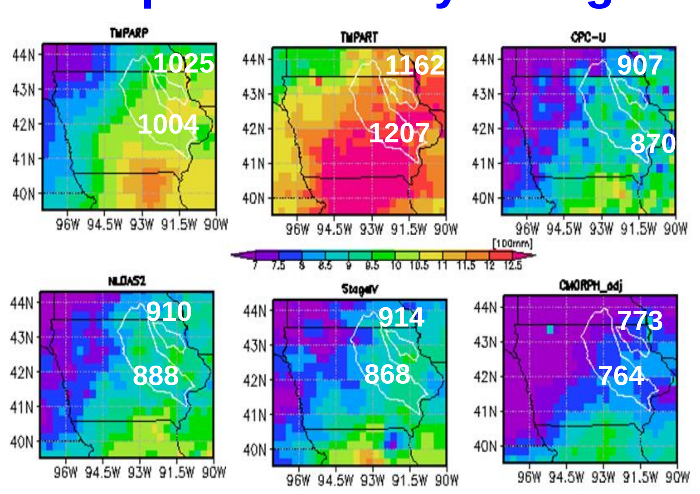

Fig. 2a Mean Annual precipitation (mm)

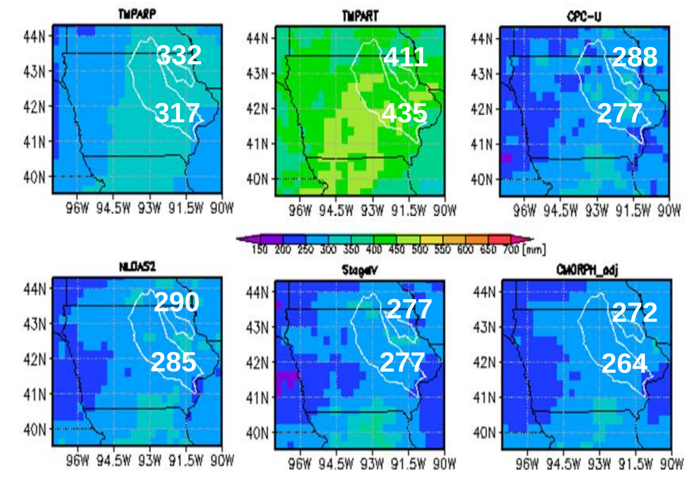

Fig. 2b Mean summer (JJA) precipitation (mm)

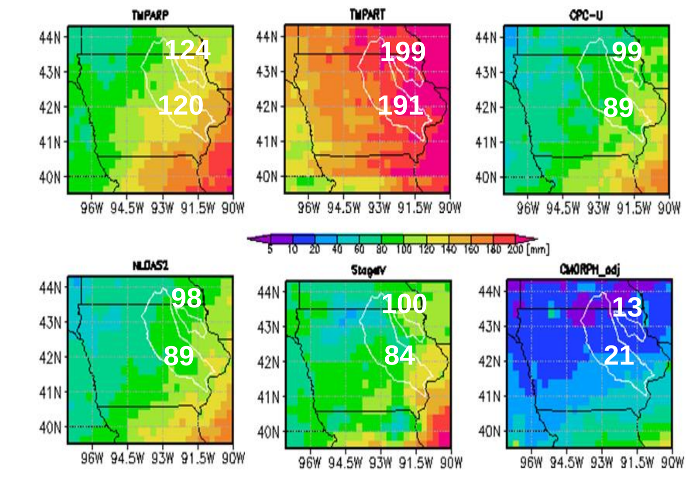

Fig. 2c Mean winter (DJF) precipitation (mm)

Fig. 2. Mean annual, seasonal precipitation estimation by the six existing precipitation products investigated in this study, with the common time period from 2002-2013. Numbers are the river basin (white shape) area averaged precipitation (mm).

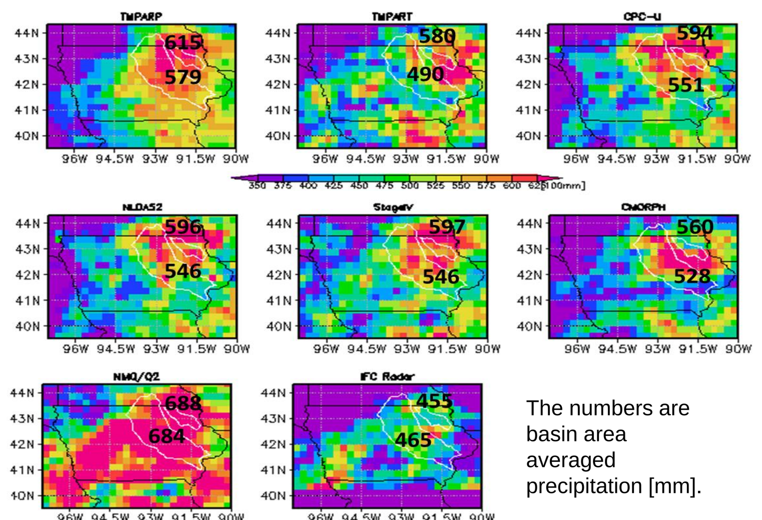

Fig. 3 Accumulated precipitation estimation [mm] during IFloodS period (April 1-June 30, 2013) according to different precipitation products.

3. Model performance vs. precipitation bias

3. 1 Nash–Sutcliffe model efficiency Coefficient (NSC)

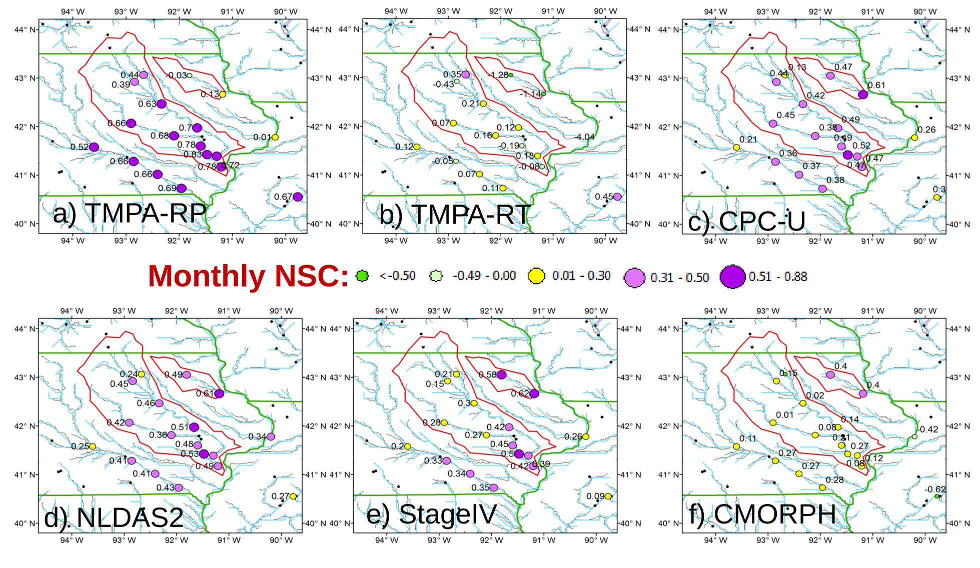

Fig. 4 Monthly NSC according to USGS gauge flow observations for the 12-year (2002-2013) simulations.

- The DRIVE model driven by CPC-U, StageIV, and NLDAS-2, showed more spatially consistent performance than the model when uses satellite-based precipitation inputs. However, the TMPA-RP (with gauge adjustment at monthly scale) showed the best model performance at both monthly and daily scale for Iowa-Cedar River Basin.
- Satellite-based results tend to be better for downstream gauge locations with larger upstream basin areas, while CPC-U, StageIV and NLDAS-2 resulted in more consistent DRIVE model performance within the river basin.
- The DRIVE model using CPC-U, NLDAS2 and StageIV precipitation products also showed more consistency of the performance of reproducing the streamflow between monthly and daily scales than the runs using TMPA products.

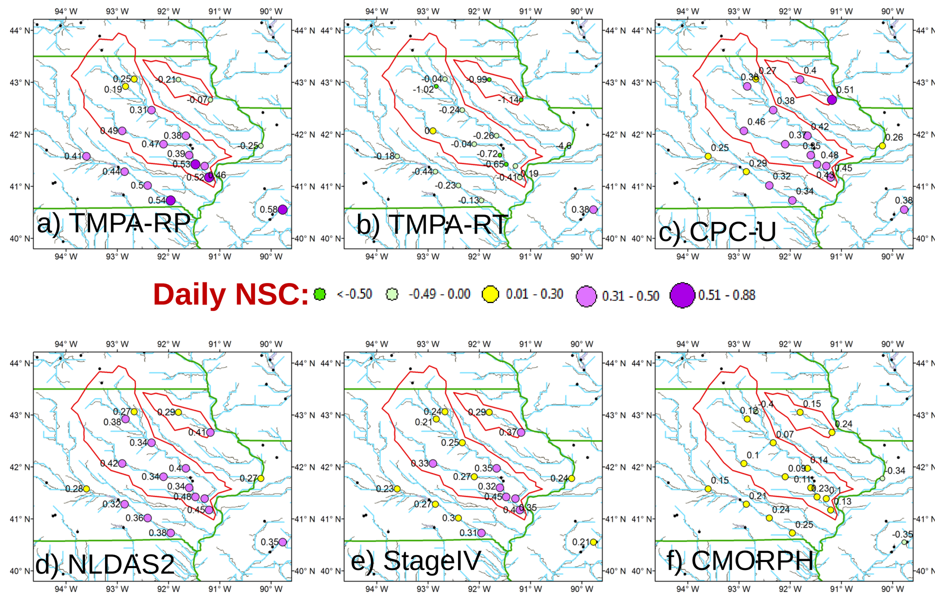

Fig. 5 Daily NSC according to USGS gauge flow observations for the 12-year (2002-2013) simulations.

3. 2 Model performance vs. precipitation bias according to the "reference" precipitation

- ***The "reference" precipitation:*** To estimate the bias in each precipitation products, a "reference" for mean annual precipitation was created based on the multiple-year (2002-2013) USGS streamflow observations and a satellite remote sensing based evapotranspiration (ET) product (U of Montana). The "reference" mean annual precipitation [mm] is defined as the sum of the mean annual streamflow (divided by basin area) and ET (Table 1).

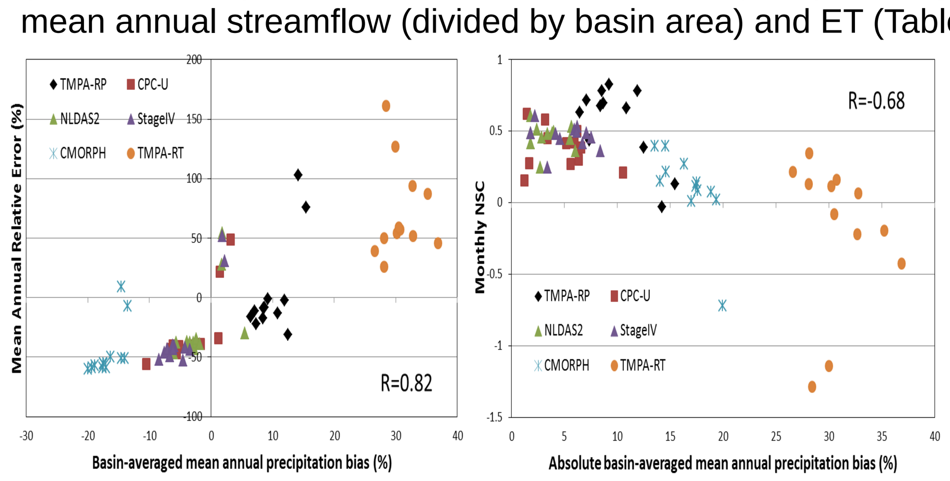

Fig. 6 Model performance vs. precipitation bias according to 2002-2013 retrospective simulations.

Model performance in streamflow simulation is controlled by precipitation bias. A total 72 simulated monthly streamflow time series (or hydrographs) were derived for the 12 locations where there are USGS gauges and when

Table 1. Mean annual water budget [mm] for Iowa-Cedar River Basin (USGS 05465500, close to basin outlet)

	Reference	TMPA-RP	TMPA-RT	CPC-U	NLDAS2	StageIV	CMORPH
Precipitation	**925**	1004 (8.5%)	1207 (30.5%)	870 (-5.9%)	888 (-4%)	868 (-6.2%)	764 (-17.4%)
ET	**627 (RS ET)**	730	739	695	710	703	682
Runoff	**298 (USGS)**	273	432	166	177	164	127
Monthly NSC	**-**	0.78	-0.08	0.47	0.50	0.42	0.12
MARE	**-**	-9%	59%	-43%	-39%	-43%	-56%

The model was driven by the six precipitation products. At each location, the simulated streamflow was compared to the observation, while the upstream basin-area-averaged mean annual precipitation was derived to compare with the "reference" precipitation. The comparisons show the simulated streamflow tend to be closer to the observations, with less bias and higher NSC scores, when the precipitation bias is smaller (Fig. 6). The similar relation between the model performance and the precipitation bias also exists in the simulations over the IFloodS period (Fig. 7).

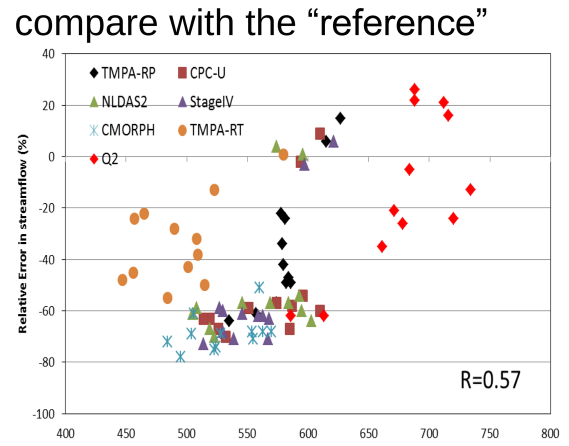

Fig. 7 Model performance vs. precipitation bias according to the retrospective simulations over the IFloodS period.

4. Monthly streamflow and precipitation over the multiple years

Conventional precipitation products resulted in more consistent model performance for both river basins than satellite-based products, with better performance for the Turkey River Basin. TMPA-RP leaded to the best performance in Iowa-Cedar River Basin. The TMPA-RT driven model generally well captured most of the peaks, but significantly overestimated the two flood peaks in 2007 and 2010, which contributed largely to decrease the NSC and MARE scores (Fig. 8).

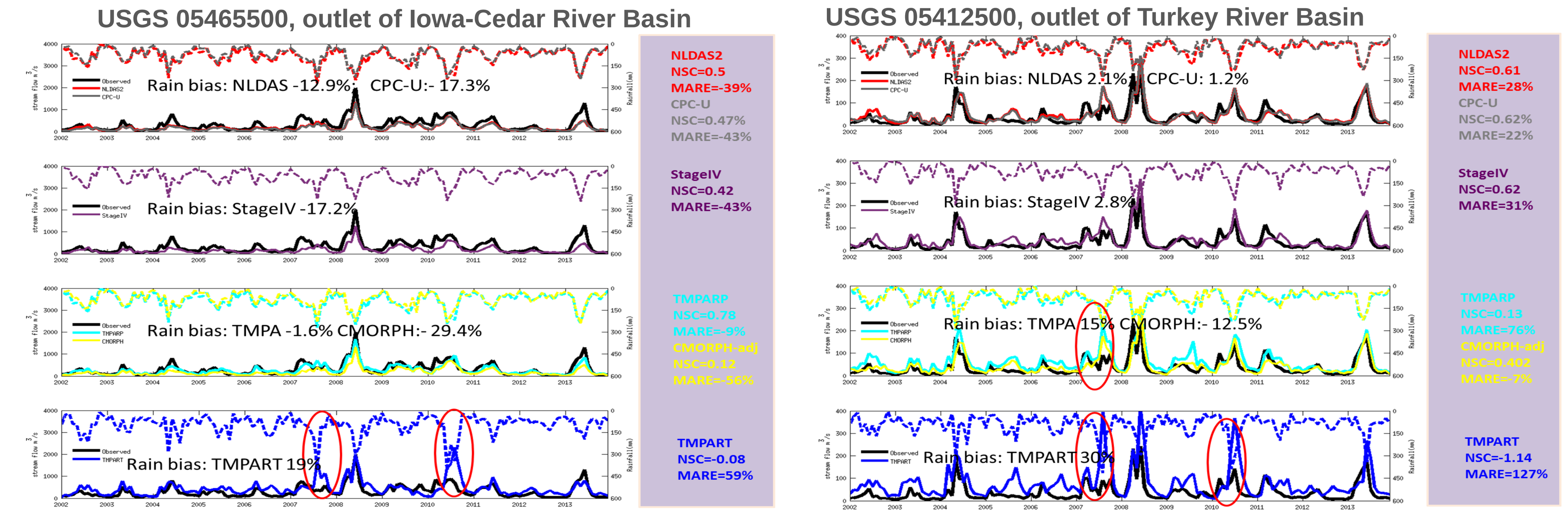

Fig. 8 Simulated vs. observed monthly hydrographs at the outlets for the two IFloodS focal basins, with river basin averaged monthly precipitation.

5. Daily streamflow and precipitation over the IFloodS period

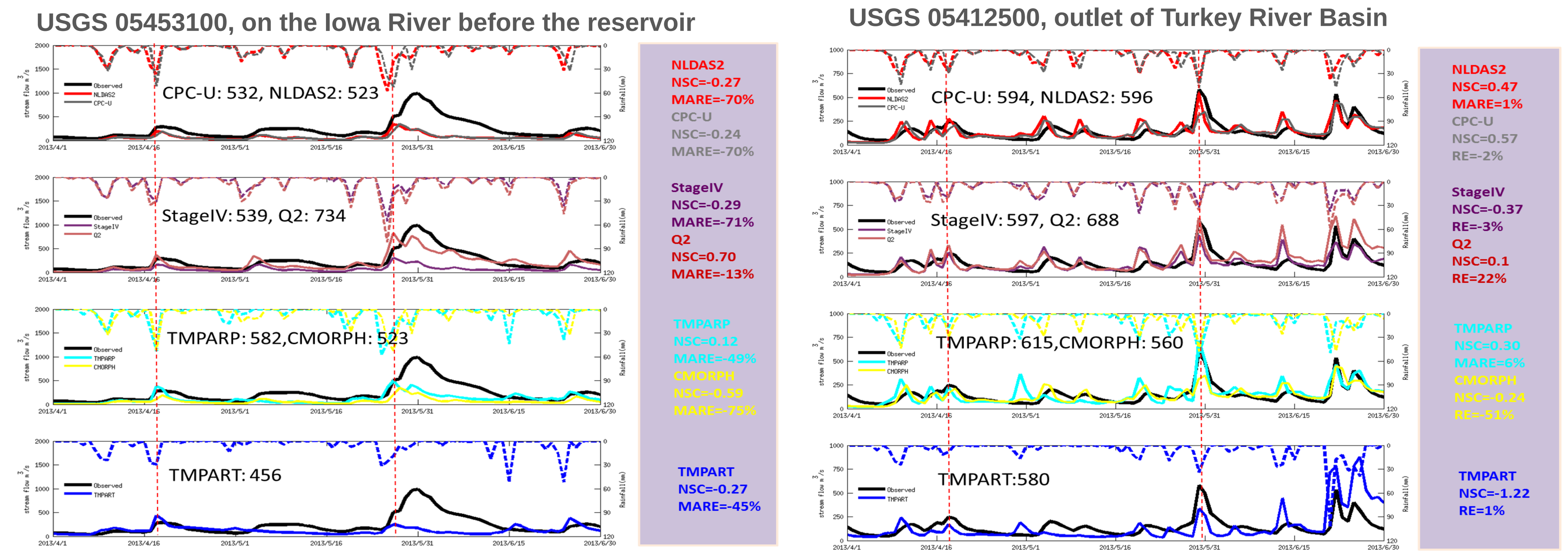

Fig. 9 Simulated vs. observed daily hydrographs at two locations of the two IFloodS focal basins, with upstream river basin averaged daily precipitation

All precipitation products underestimated the flood magnitude for the Iowa river during the IFloodS period, while the NMQ/Q2 shows the best results and TMPA products tend to be slightly better than others. CPC-U and NLDAS 2 showed the best performance for Turkey river with very small bias in streamflow calculation.

6. Simulated and observed daily hydrographs for locations along the major rivers (upstream to downstream) over the IFloodS period

The underestimation of streamflow is consistently along the Cedar River from upstream to downstream over the IFloodS period , which indicates a general consistent underestimation of precipitation over the river basin.

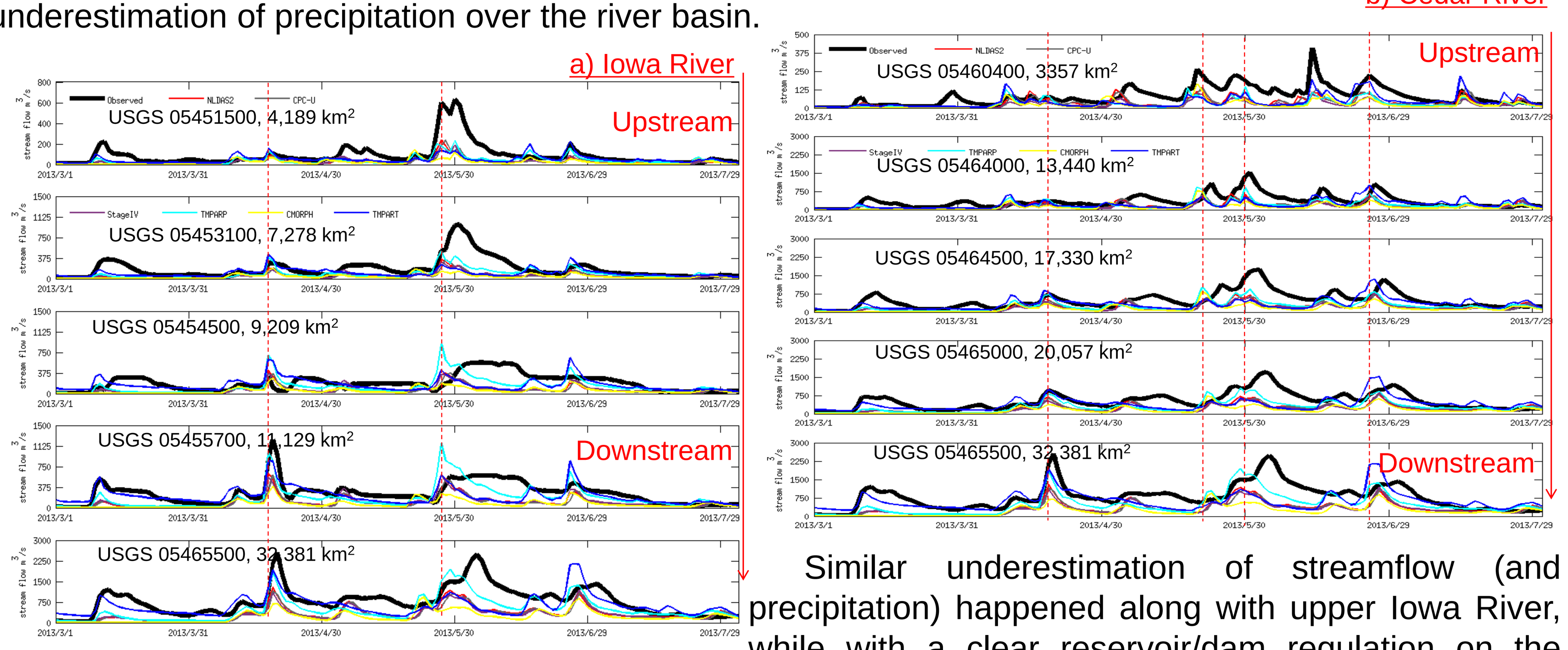

Fig. 10 Observed and simulated daily streamflow along the major rivers over the IFloodS period.

Similar underestimation of streamflow (and precipitation) happened along with upper Iowa River, while with a clear reservoir/dam regulation on the streamflow of the river.

Relative larger bias in estimation of peak time are showed in downstream rivers and larger flood events.

7. Conclusion

1. The sensitivity of the DRIVE model performance in reproducing streamflow to precipitation inputs, clearly showed that better precipitation inputs (with less bias) tend to result in better streamflow simulations, in terms of NSC and MARE. This indicates better accuracy of the GFMS is expected when improved satellite-based real-time precipitation products are available through the GPM in near future.
2. Real-time Satellite-based precipitation resulted in overall lower model performance scores than the conventional precipitation products and gauge-based remote sensing precipitation estimations. However, the lower scores are mainly attributed to the inconsistency of precipitation estimation in some extreme events. At event level, it can be better than conventional products some cases.
3. While precipitation bias mainly contributes to the over/underestimation of the flood magnitude, the DRIVE model tends to lead to faster flood waves, particularly for relatively larger floods in downstream part of the Iowa and Cedar river basin. Model calibration or a better representation of the overbank flow (for floodplain) is expected to further improve the flood timing estimation.

8. References

Wu, H., R. F. Adler, Y. Tian, G. J. Huffman, H. Li, and J. Wang (2014), Real-time global flood estimation using satellite-based precipitation and a coupled land surface and routing model, Water Resour. Res., 50, 2693–2717, doi:10.1002/2013WR014710.

Wu H., R. F. Adler, Y. Hong, Y. Tian, and F. Policelli (2012a), Evaluation of Global Flood Detection Using Satellite-Based Rainfall and a Hydrologic Model. J. Hydrometeor, 13, 1268–1284. doi: http://dx.doi.org/10.1175/JHM-D-11-087.1

Wu H., J. S. Kimball, H. Li, M. Huang, L. R. Leung, R. F. Adler (2012b), A new global river network database for macroscale hydrologic modeling, Water Resour. Res., 48, W09701, doi:10.1029/2012WR012313.

Wu, H., J. S. Kimball, N. Mantua, and J. Stanford (2011), Automated upscaling of river networks for macroscale hydrological modeling, Water Resour. Res., 47, W03517, doi:10.1029/2009WR008871.