Monitoring and Forecasting Floods over North Africa based on Satellite data: Uncertainties and Challenges

*T. Kunhikrishnan[*1], F . Policelli[1], S. Habib[1], J. David[*1], K. Melocik[*1]*
G. Huffman[1], M. Anderson[2],
Atef B H Ali[3], S. Bacha[3], A. Er Raji[4]

[1]NASA GSFC, Greenbelt; *SSAI, Lanham; [2]USDA-ARS, Beltsville; MD, USA
[3]CRTEAN, CNCT & DGRE, Tunisia; [4]RCRS, Morocco

Motivation, Why North Africa?

- ➢ **Unique in hydrological processes due to complex meteorology, geography, and arid climate**

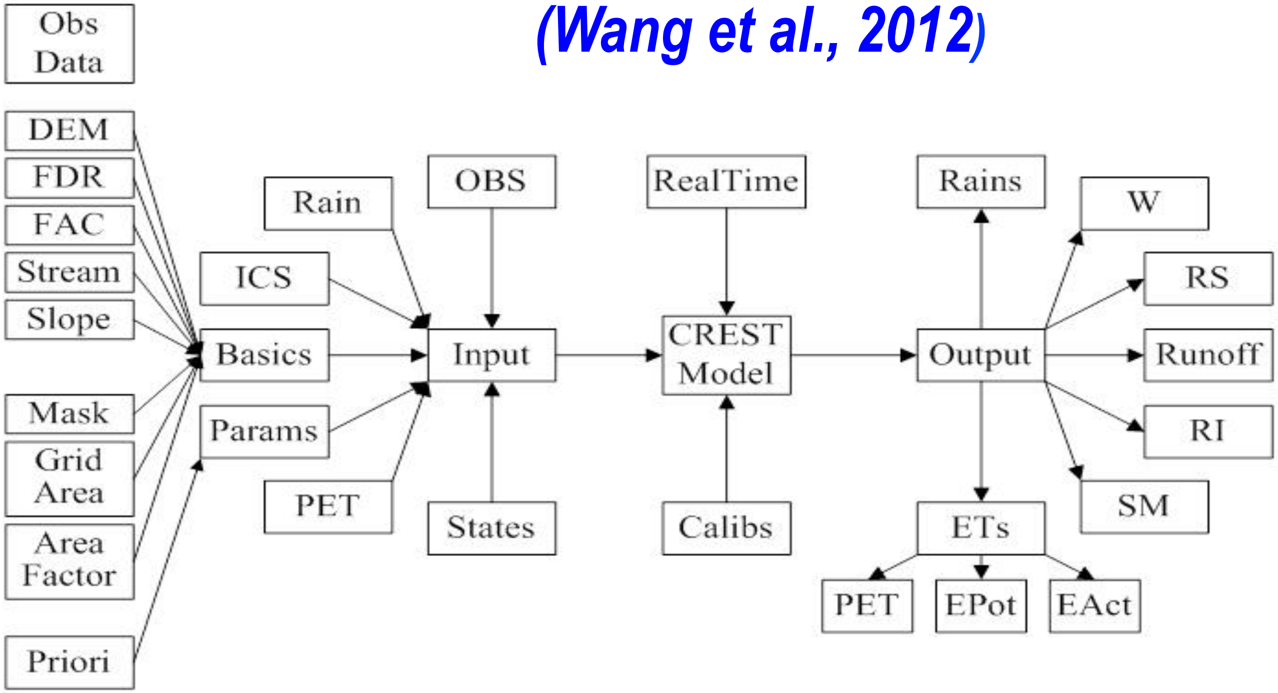
- ➢ **Limited understanding, because of lack of sufficient data**

- ➢ **Performance of multi-sensor satellite products is not very well known**

- ❑ ***Utilize satellite data for NRT flood monitoring and modeling***
- ❑ ***Better to understand the uncertainties in the model inputs, which can propagate through the flood model***

Coupled Routing and Excess Storage (CREST) model, V.2.0.

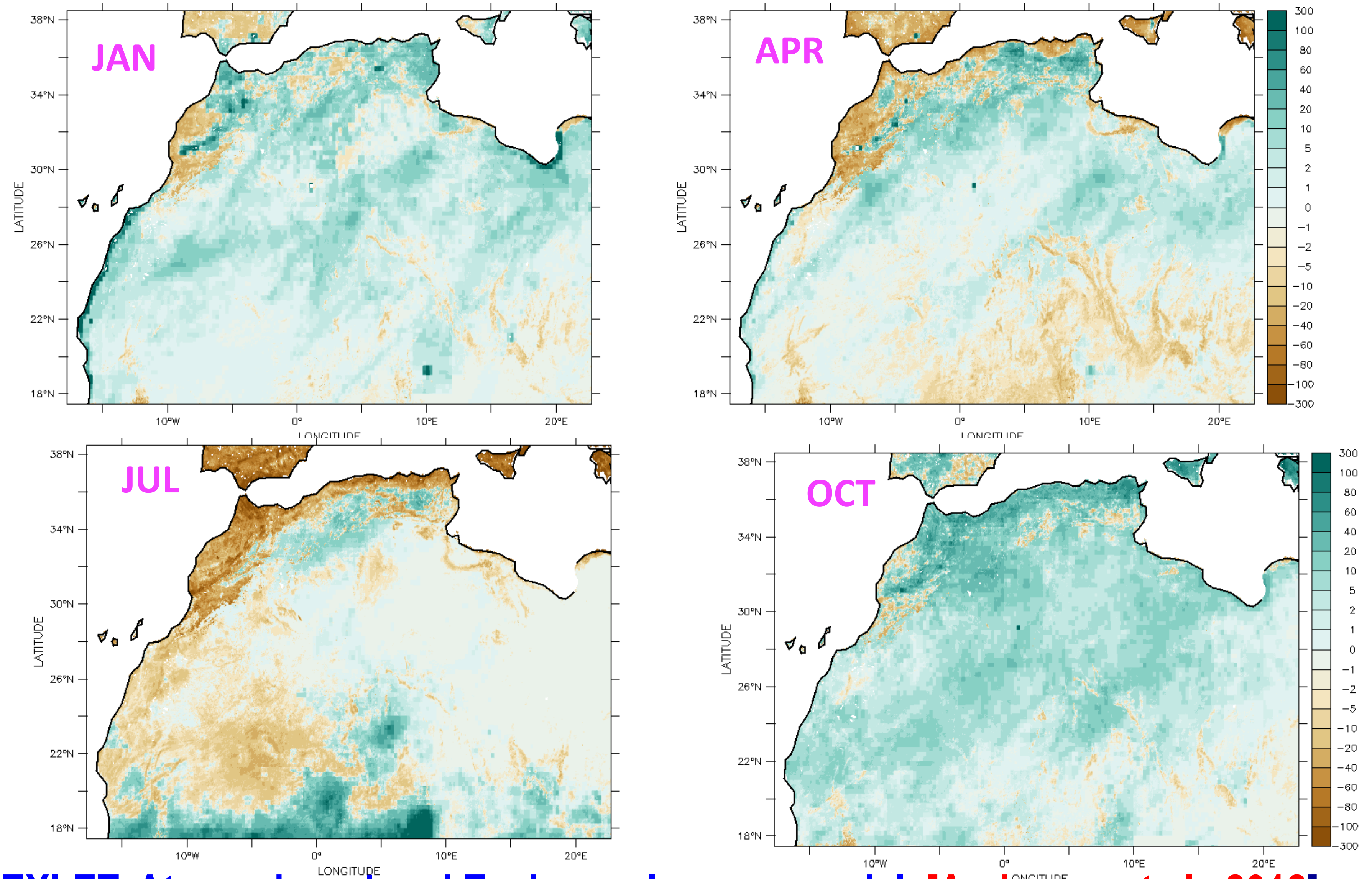
(Wang et al., 2012)



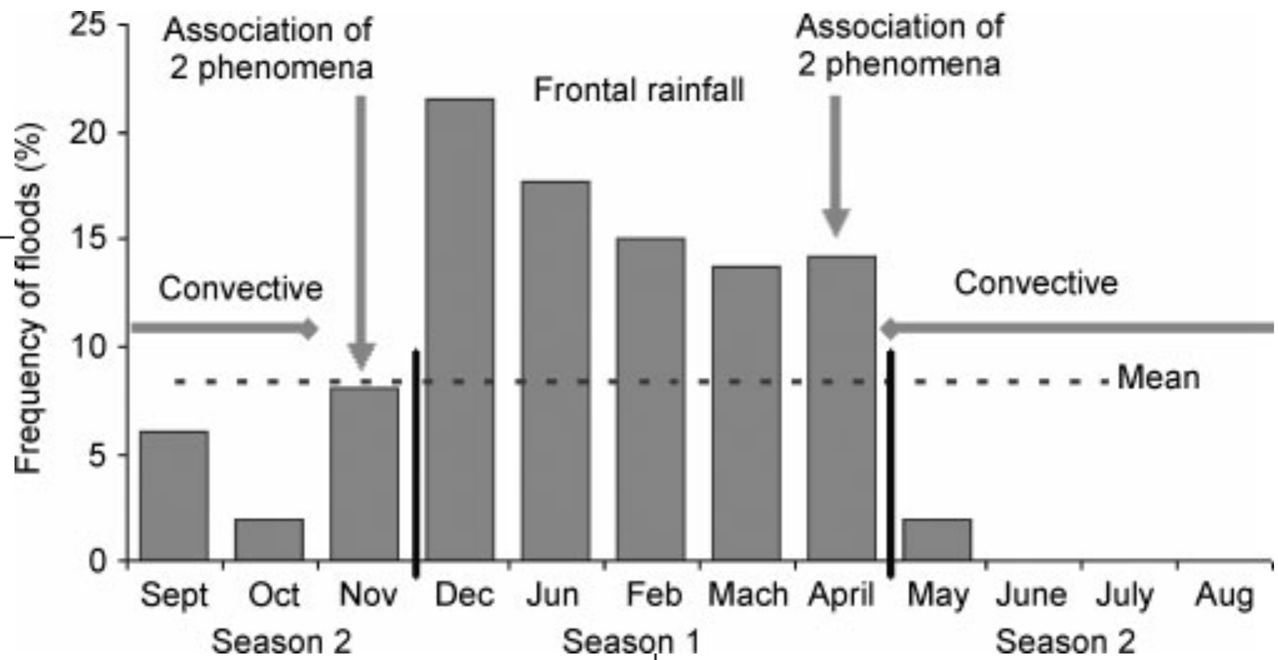
- **Forcing Data:**
  TMPA-RT: TRMM Multi-Satellites Precipitation Analysis (Huffman G et al., 2007)
  PET: Famine Early Warning Systems Network (FEWS)

- **Input Basics: Shuttle Radar Topography Mission (SRTM)-DEM and derived products FAC, FDR**

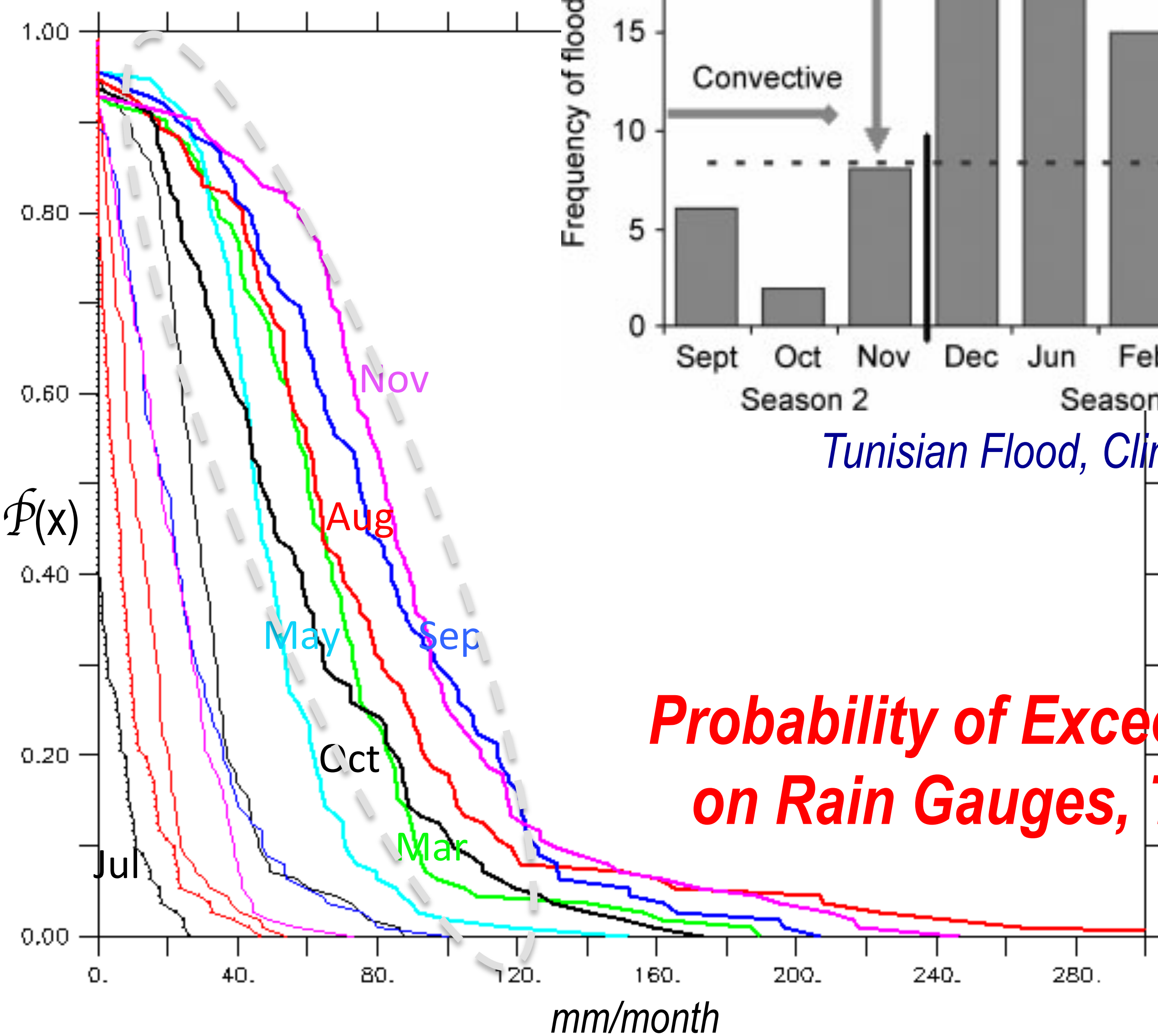
Seasonal Water Balance from Space: A first order check (P-E), TMPA-RT- ALEXI-ET, (2007-2011, climatology)



ALEXI-ET: Atmosphere-Land Exchange Inverse model, [Anderson et al., 2012],

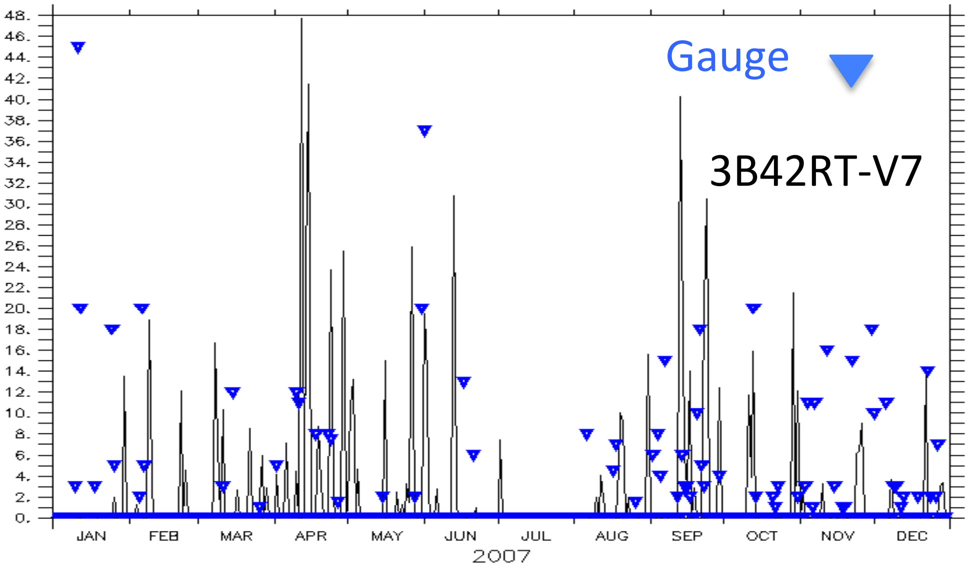


Tunisian Flood, Climatology (QJRMS, R.Met.Soc.)

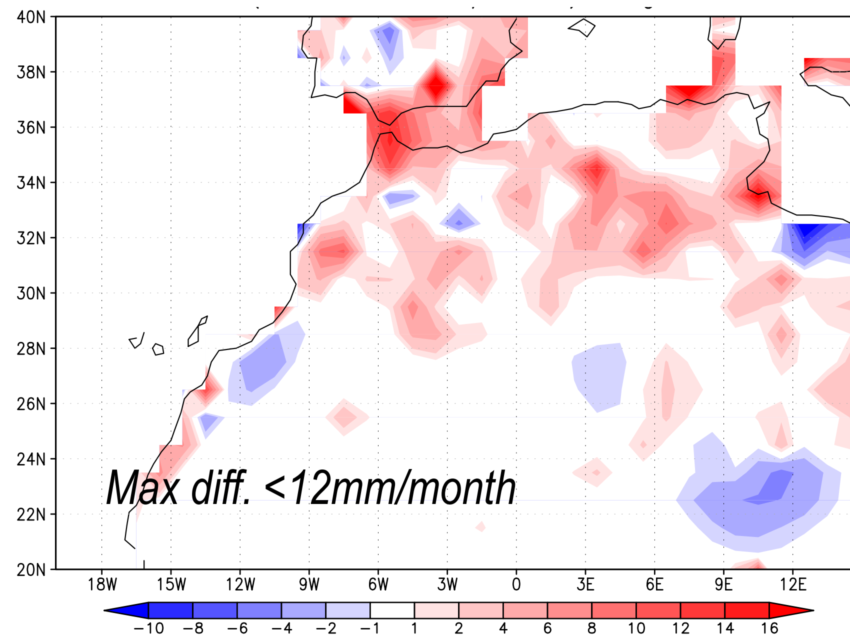


Probability of Exceedance based on Rain Gauges, Tunisia, 2007

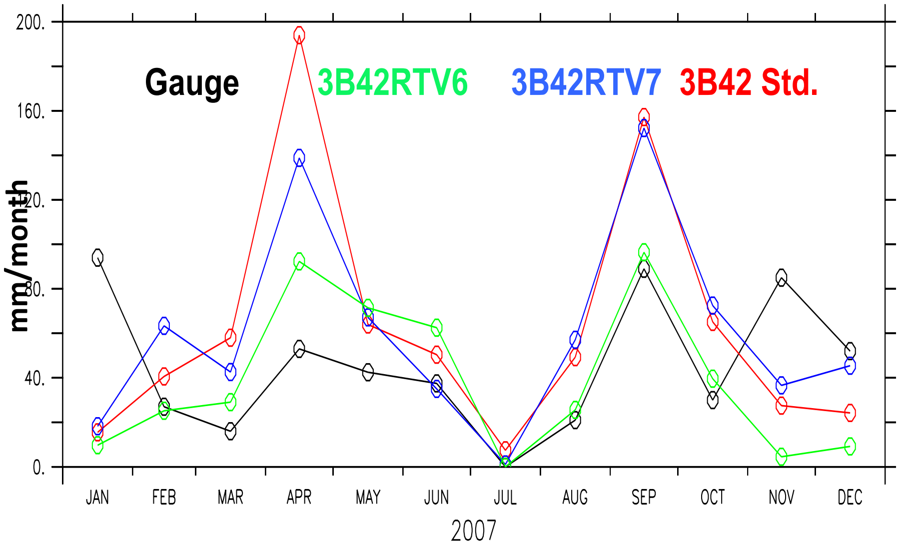
TMPA V7RT vs. Gauges-Daily



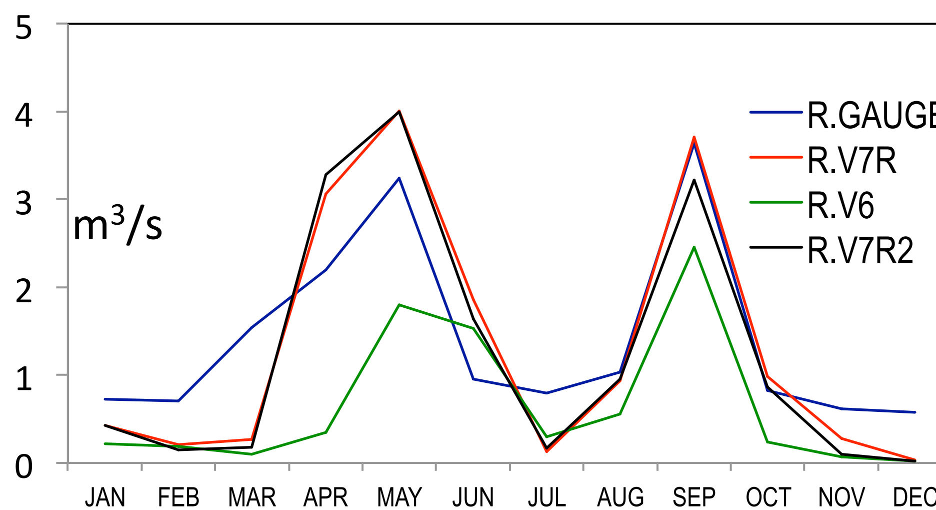
TMPA-GPCP for Jan-Feb. 2007



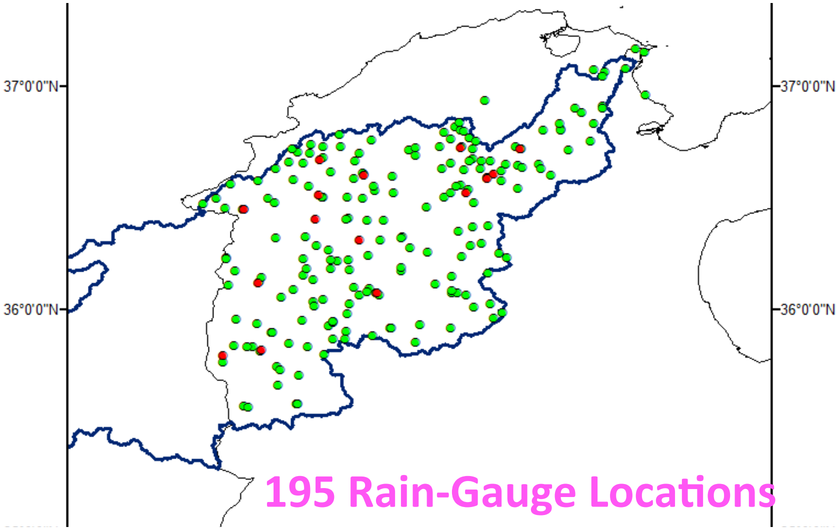
TMPA (Versions) vs. Gauges-Monthly

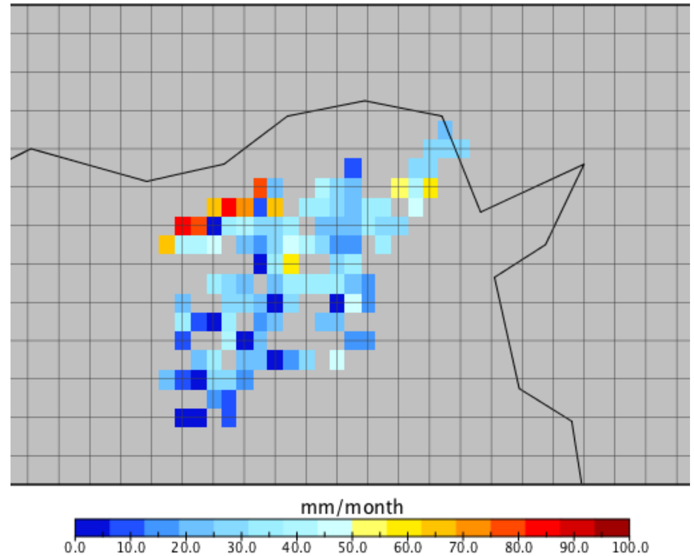


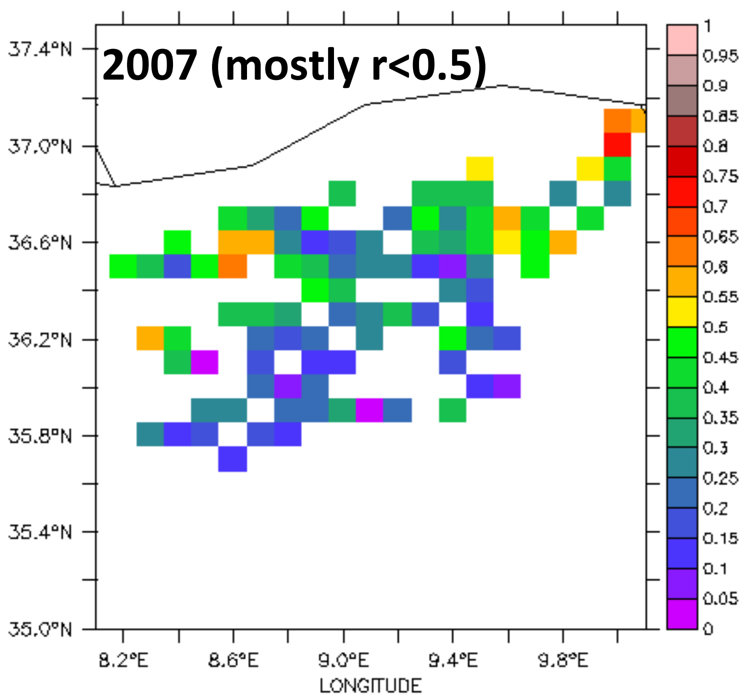
CREST model sensitivity to TMPA versions

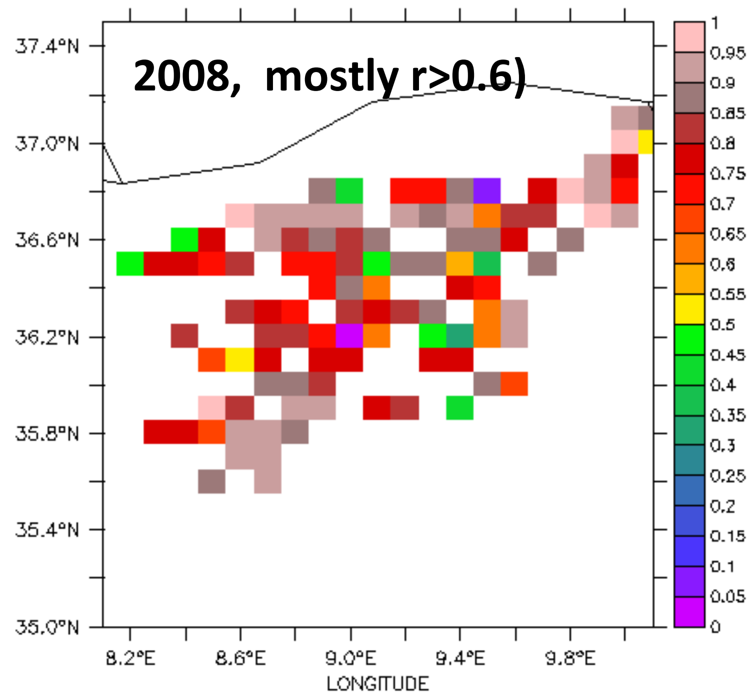


Spatial Correlation: TMPA(3B43) vs. Rain-Gauge Analysis

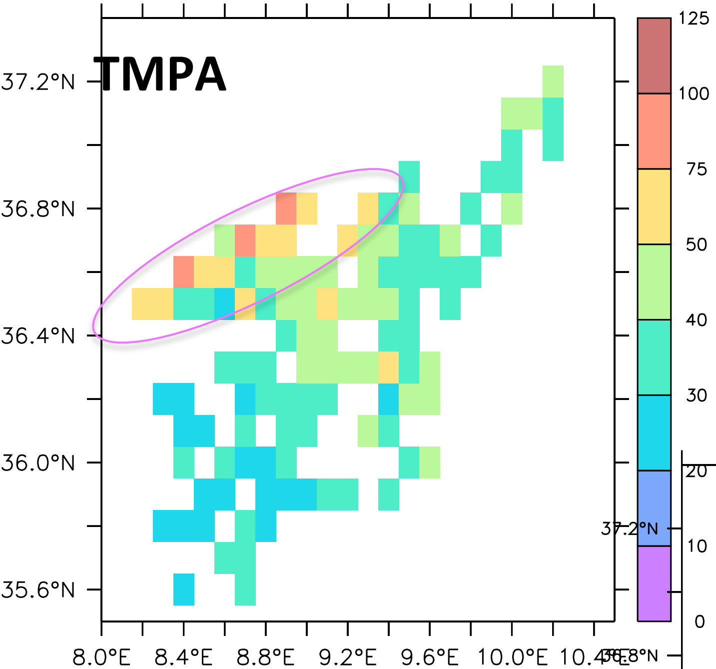




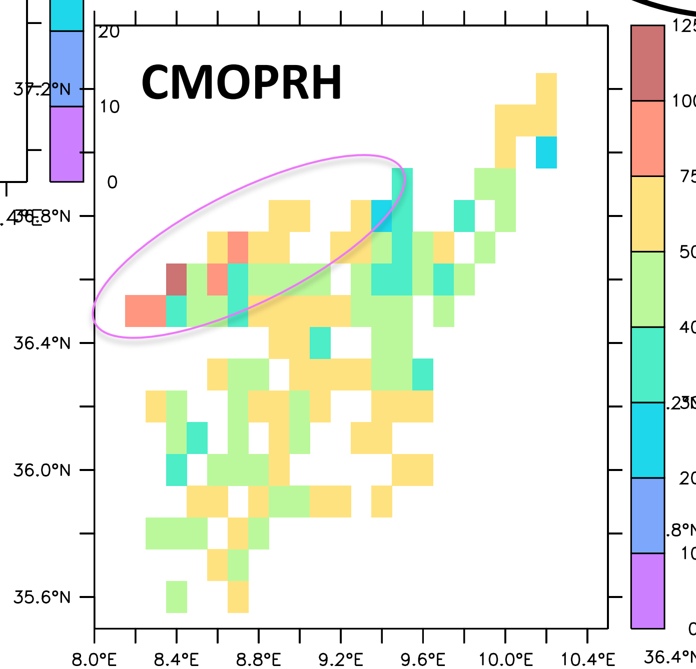




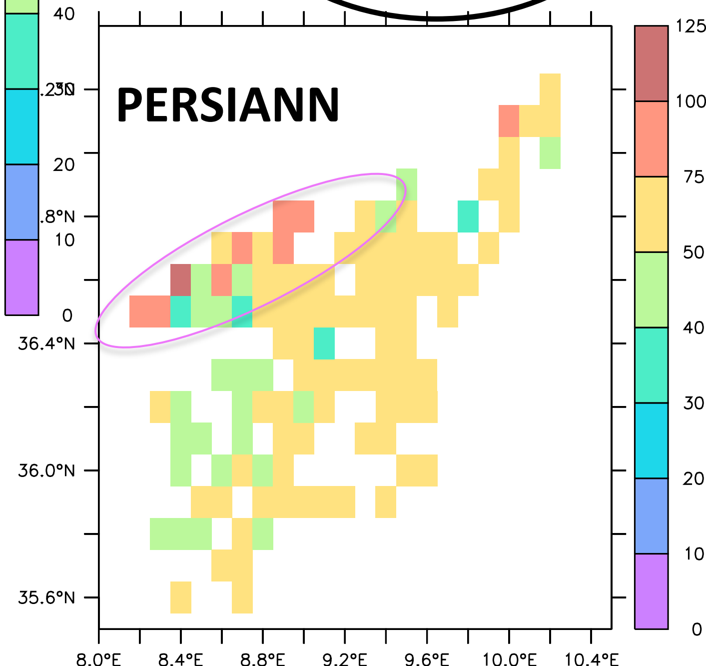
Medjerda Basin -Tunisia



Min.: 23.42
Max.: 70.91
Mean : 38.99
SD: 10.06



Min.: 28.47
Max.: 103.2
Mean: 50.9
SD: 12.1

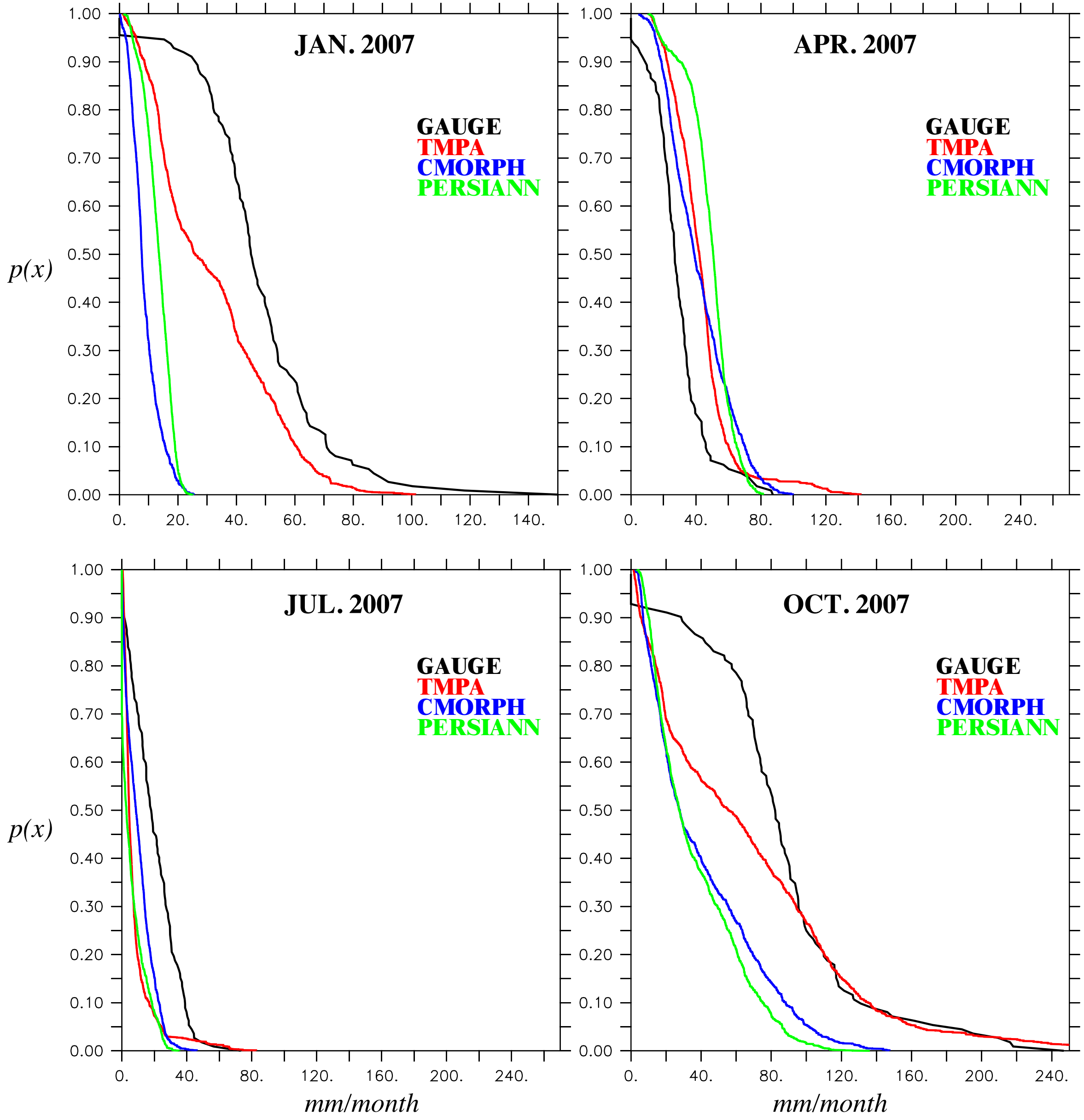


Min: 30.731
Max: 111.47
Mean: 57.447

Generally Maximum RMS errors are found to be in regions Close to Atlas mountain areas. RMS error is relatively small for TMPA (3B43)

RMS Errors (RMSE, mm/month) against Rain-Gauge Analysis for 2007

Exceedance Probability of getting extreme Rainfall based on Gauge, TMPA(3B43), CMORPH and PERSIANN

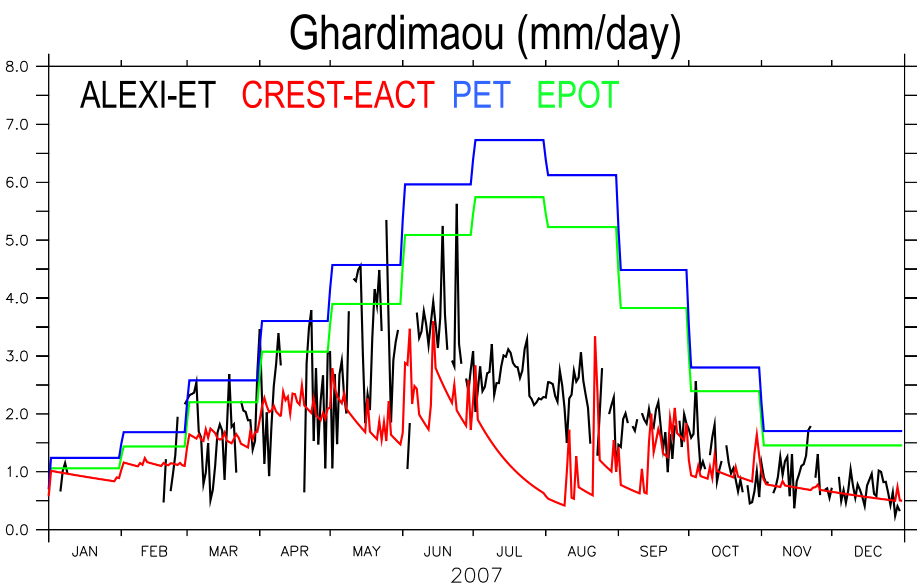


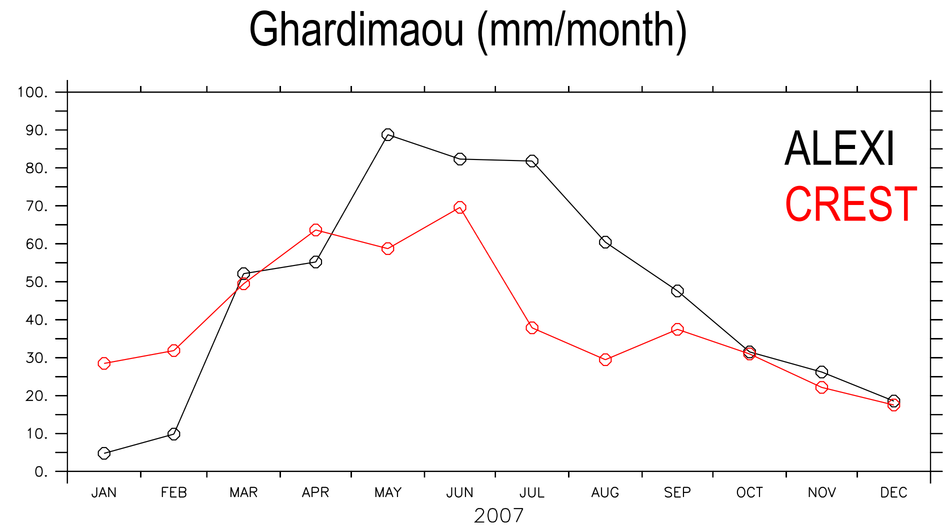
Extreme RF rates occur less frequently with a prob. of less than 0.1%, especially during extended winter

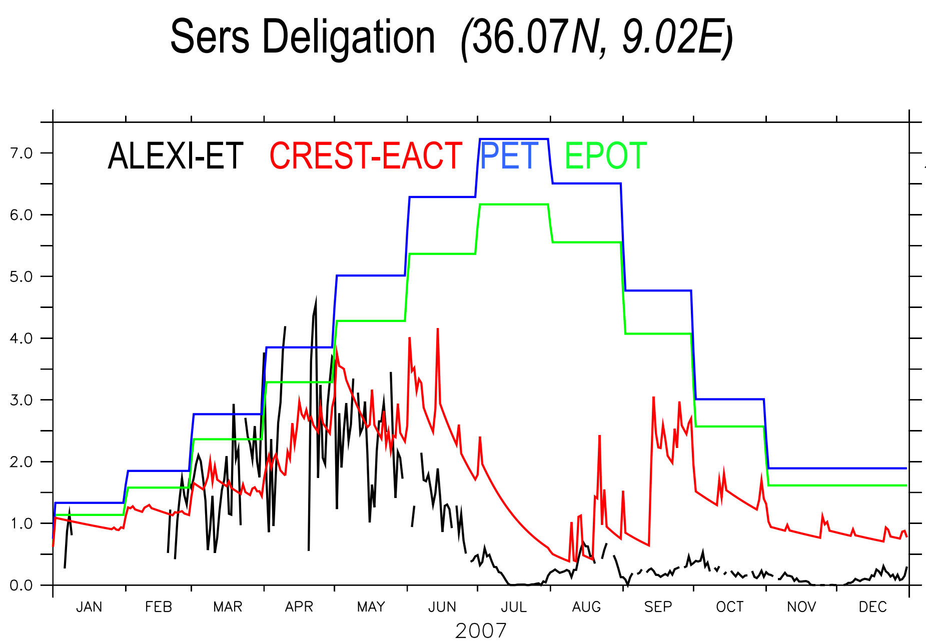
Rain fraction analysis:
Only less than 1% of rainy pixels greater than 1-2 cm/hr. rainfall

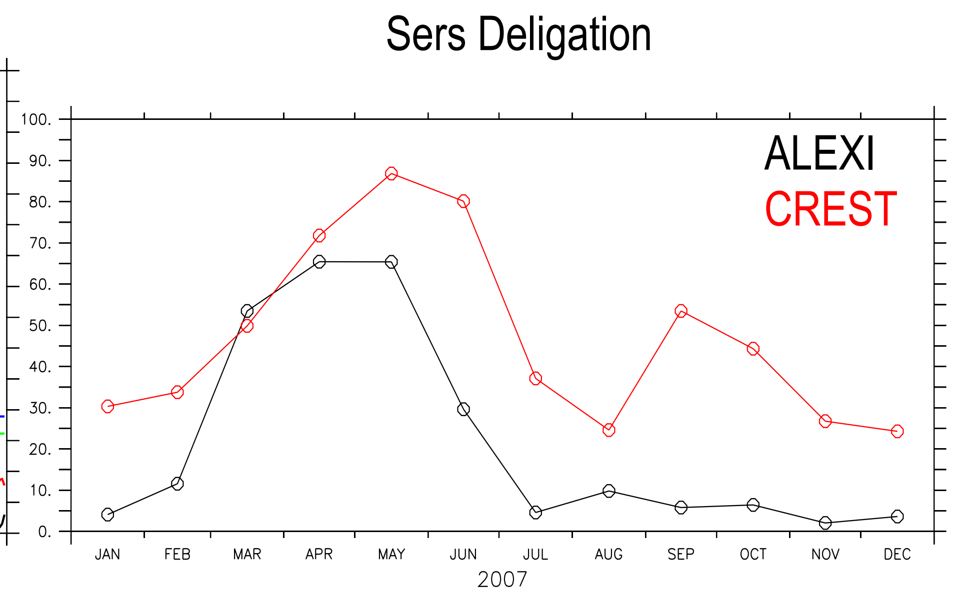
No. of rainy days in a month with 100-250mm rainfall is < 5days. Flood usually comes if the rain rate >10-20mm/hour.

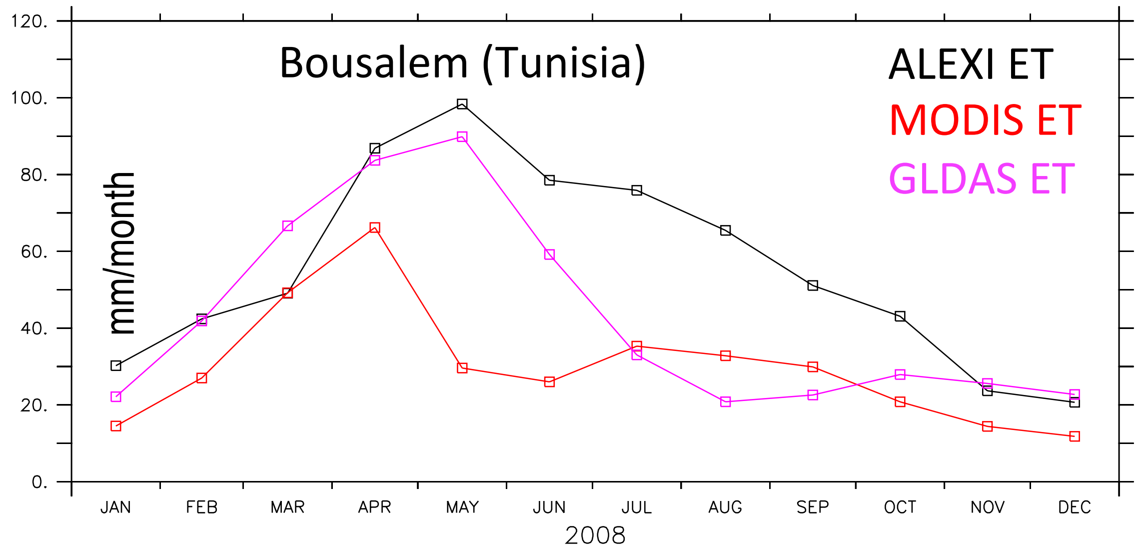
Daily and monthly ET based on CREST and ALEXI-ET



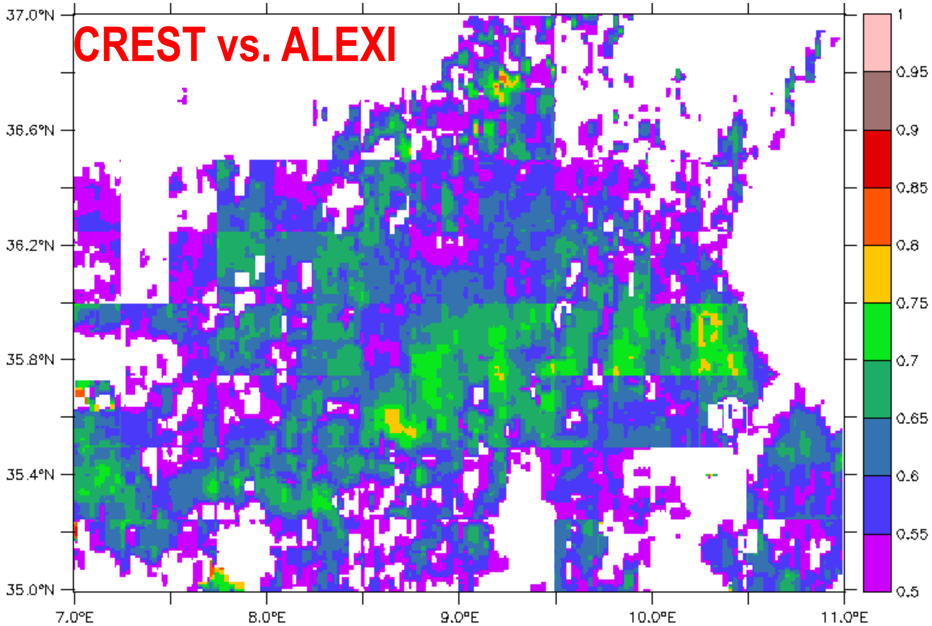




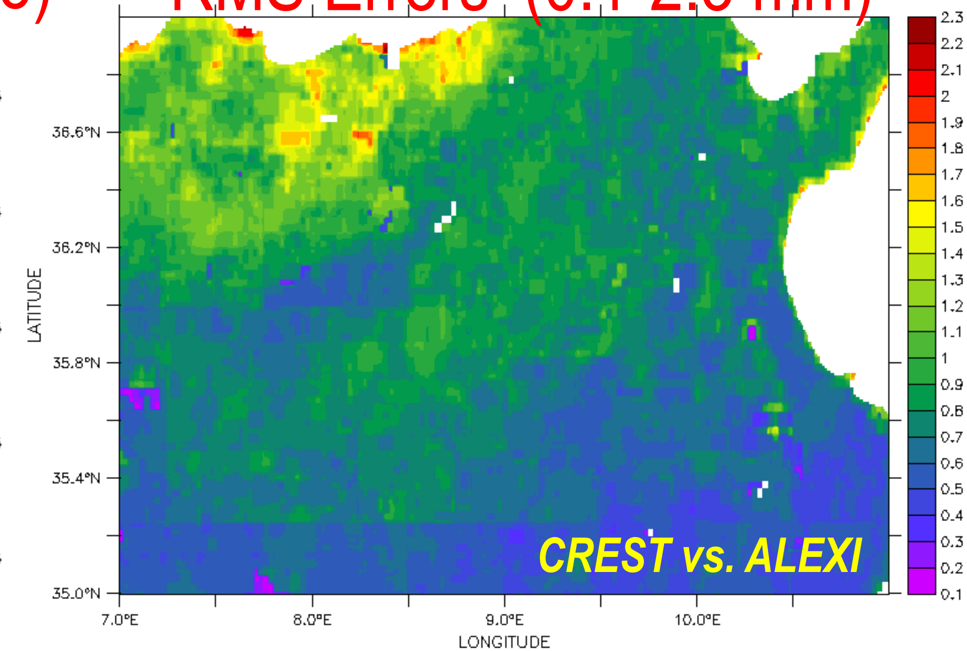


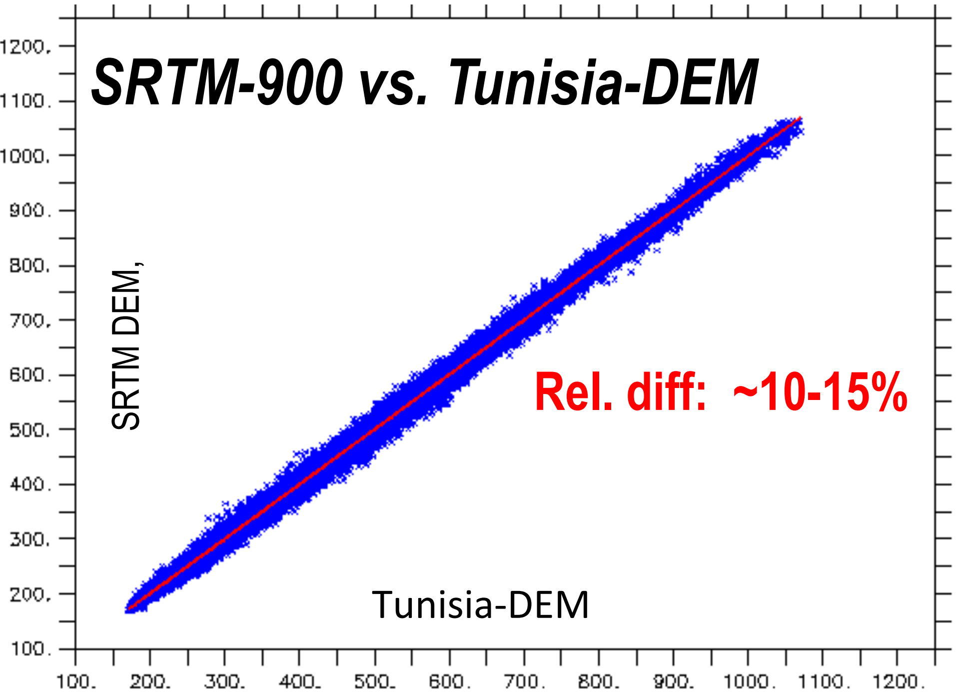


Sp.Correlation(plotted only r >0.5)

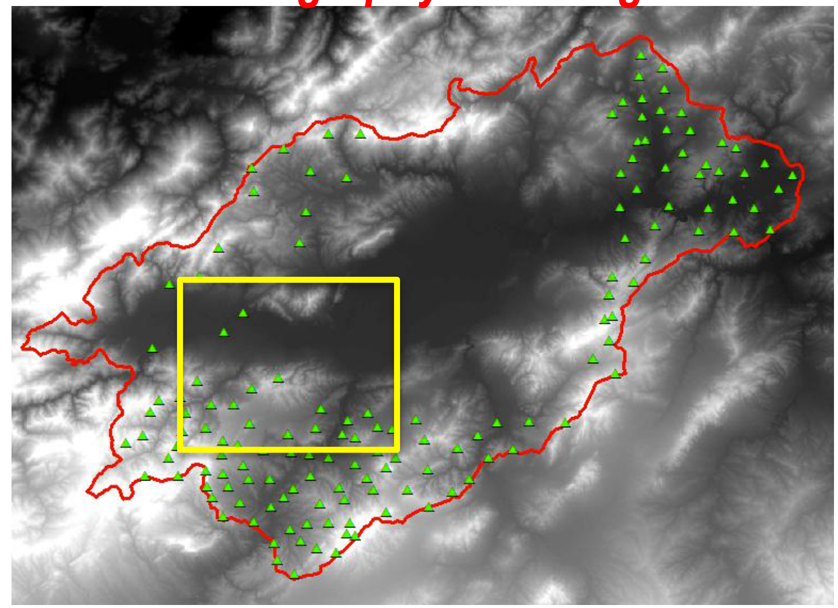


RMS Errors (0.1-2.3 mm)

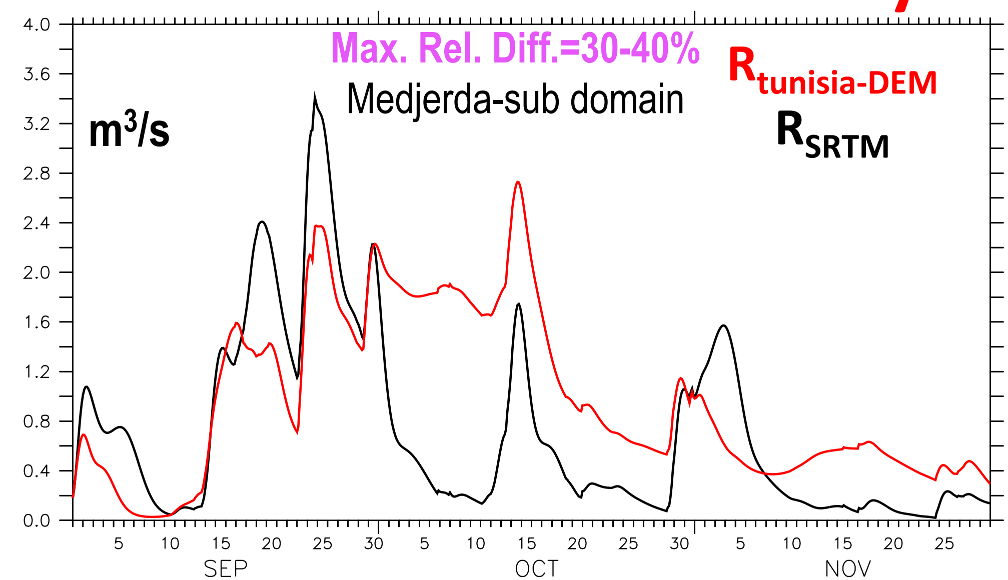


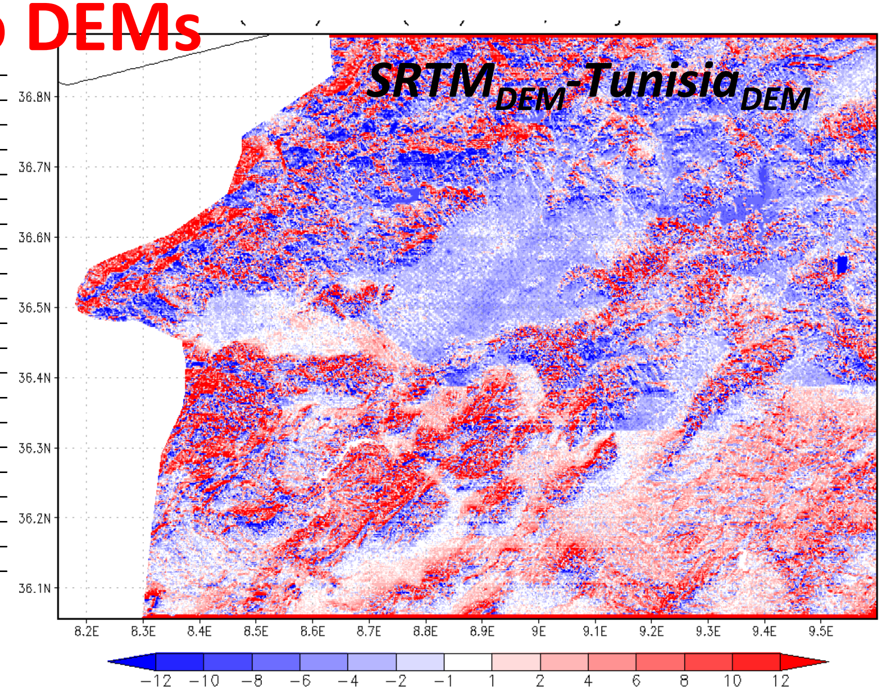


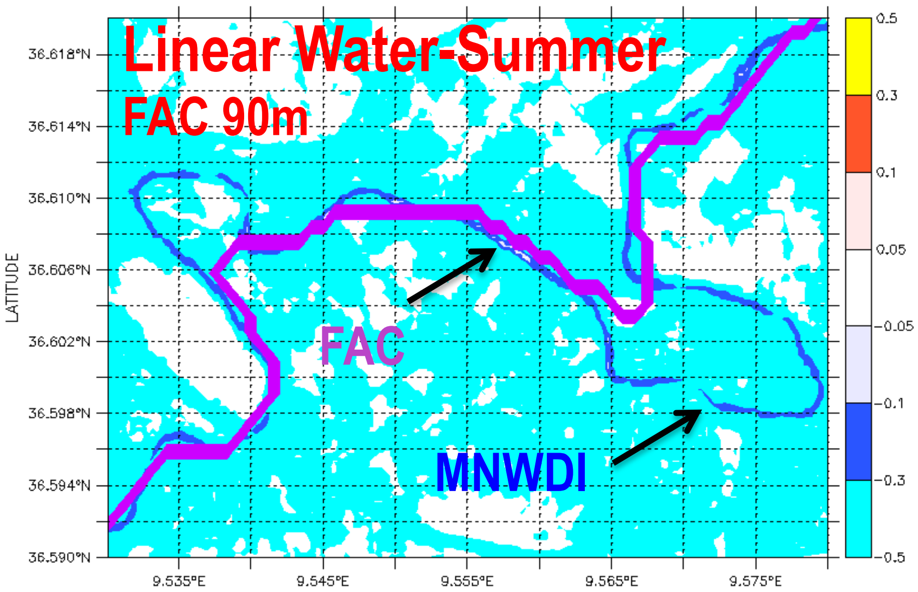
Tunisia-DEM (from Site)
Aerial Photography-aertriangulaization

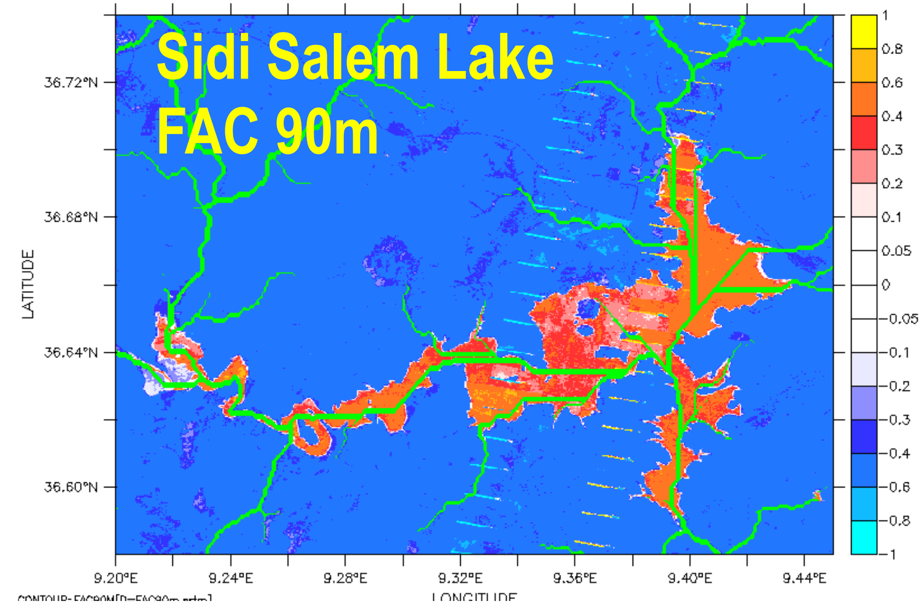


CREST simulation: Sensitivity to DEMs





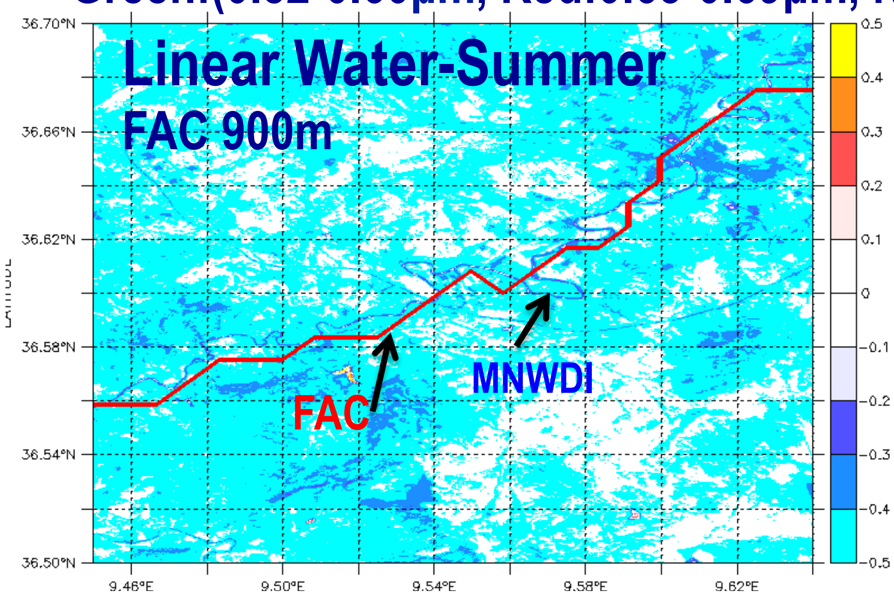


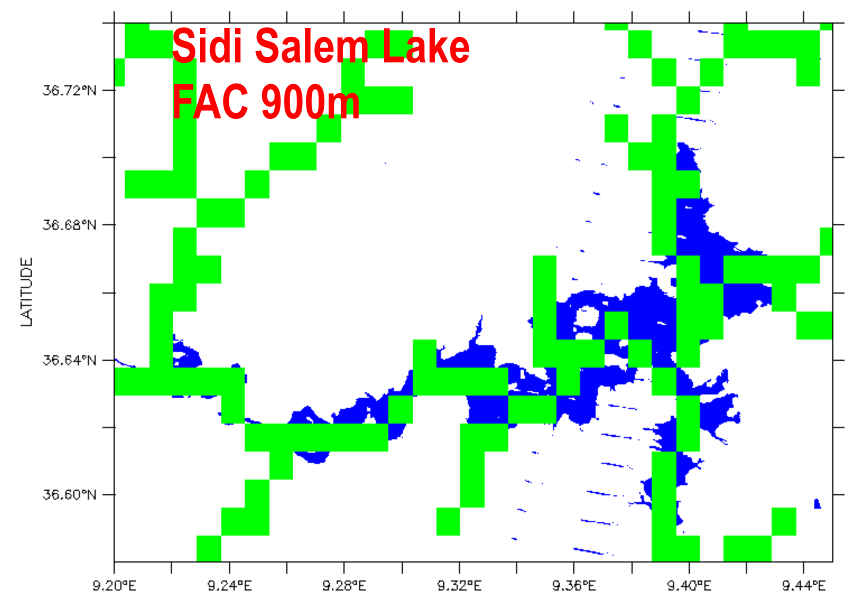


FAC versus LANDSAT derived water delineated rivers and lakes

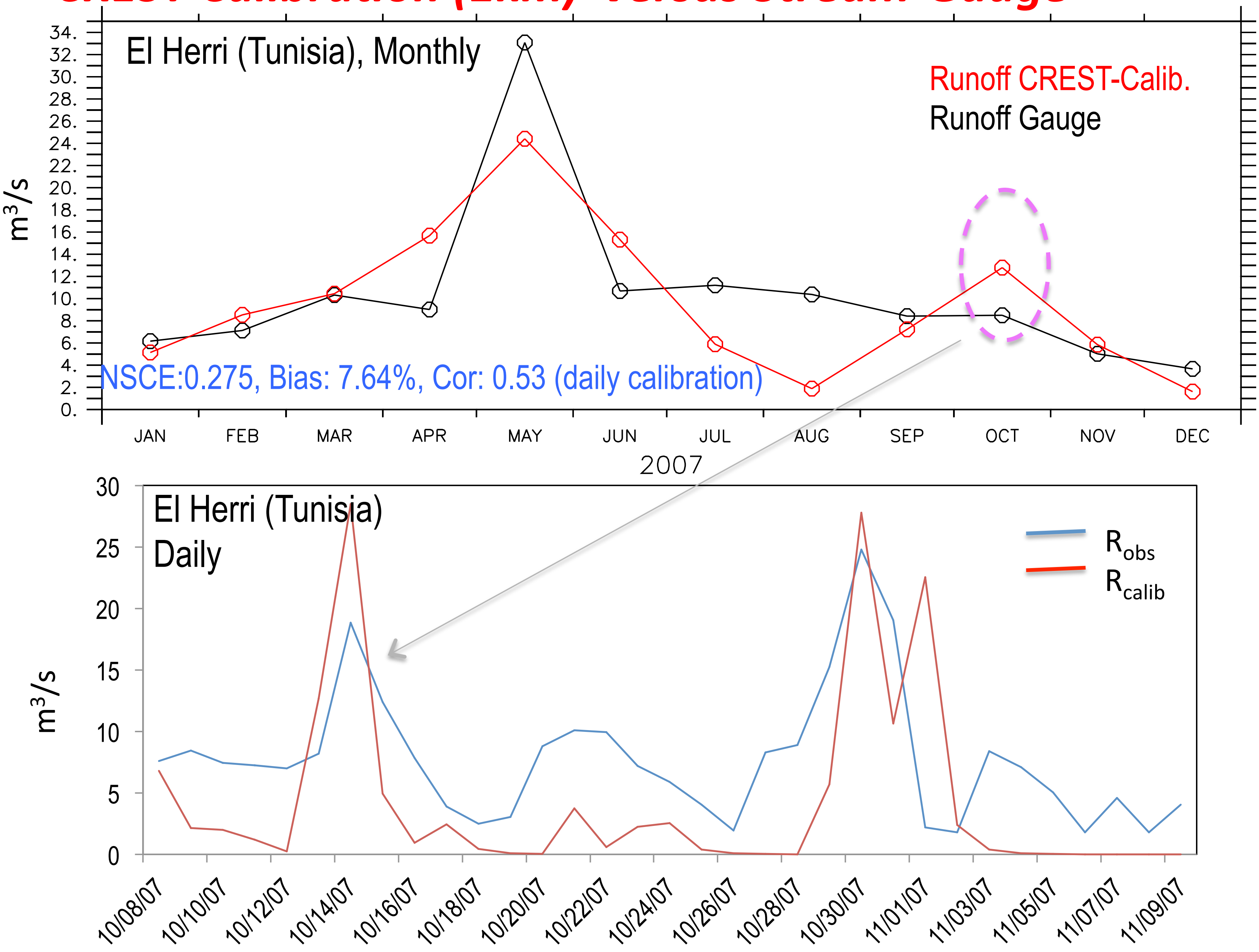
Landsat derived Index: MNWDI=(G-MIR)/(G+MIR), WRI=(G+R)/(NIR+MIR),

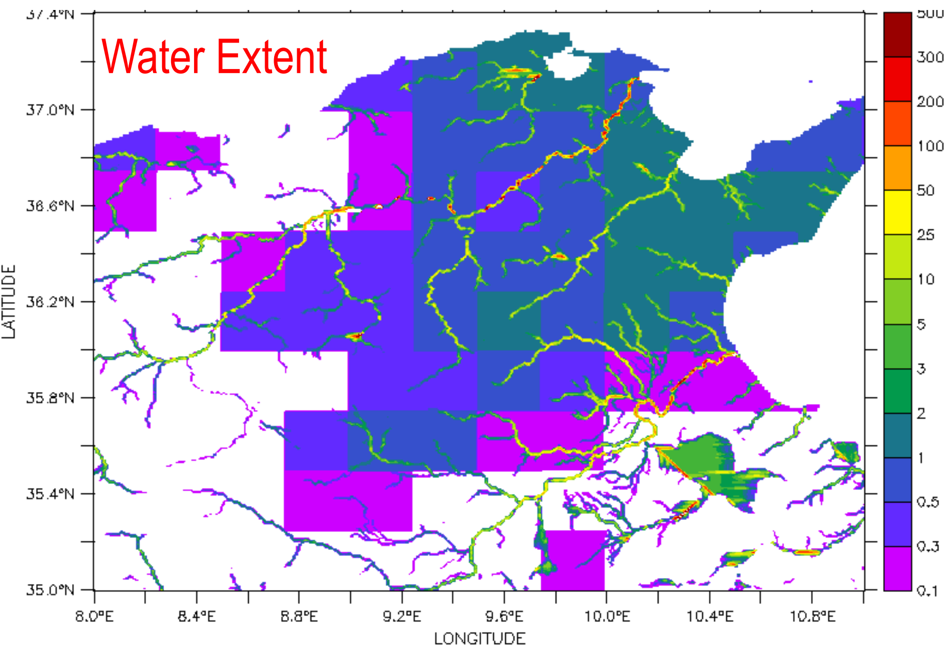
– Green:(0.52-0.60µm, Red:0.63-0.69µm, NIR :0.77-0.9µm, MIR:1.55.-1.75µm)

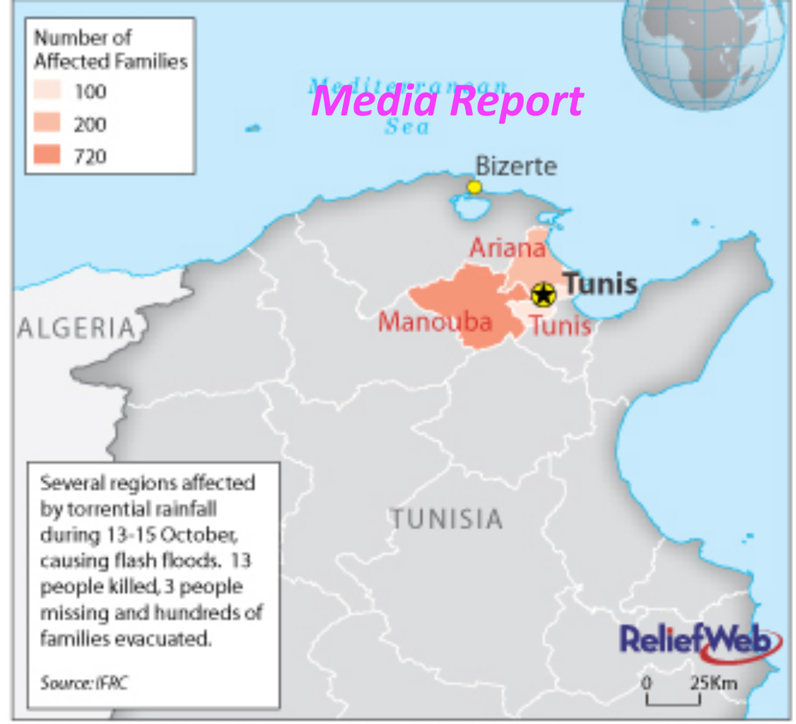




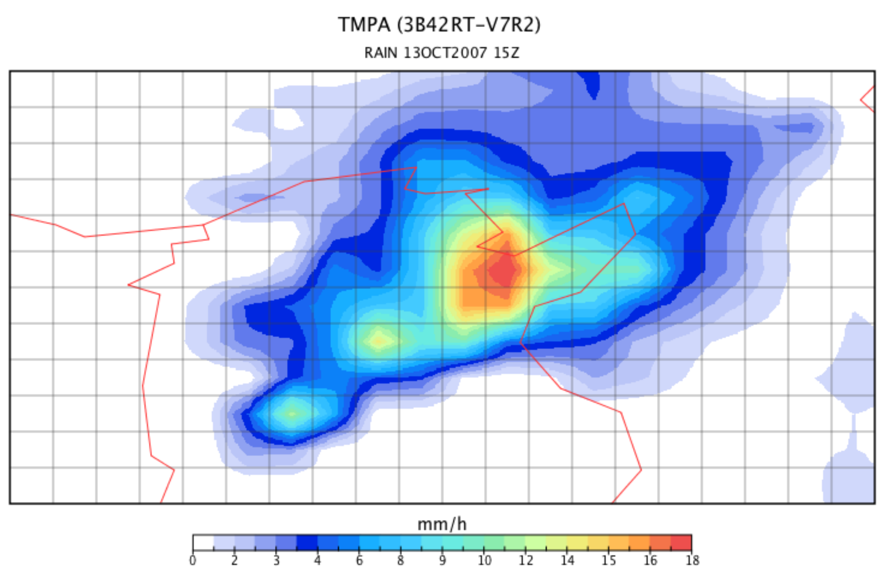
CREST Calibration (1km) versus Stream-Gauge

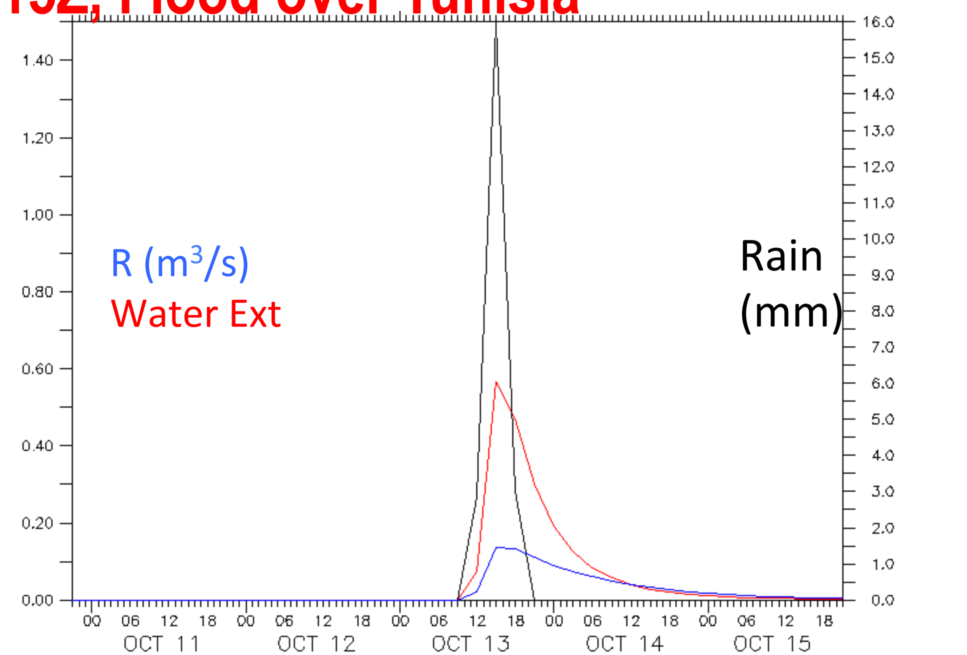






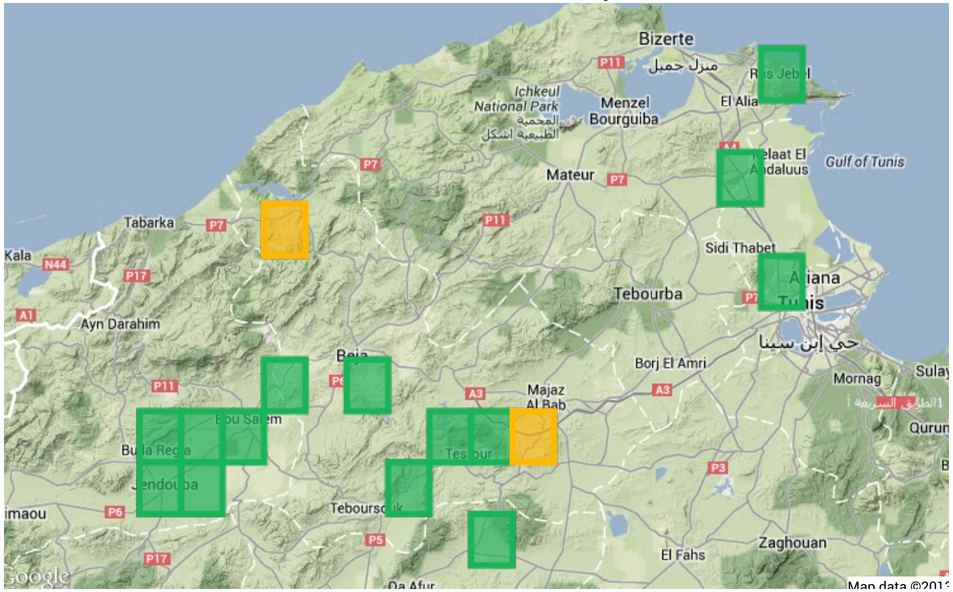
CREST Simulation: 13-17 Oct. 2007, 15Z, Flood over Tunisia





Stream Watch from Space (Space-borne sensor of Runoff)

River Watch Locations, Tunisia



Courtesy: Global Flood Detection, JRC

Signal

$$M/C = BT_{wet}/Bt_{dry}$$

Wet measurement pixel over River

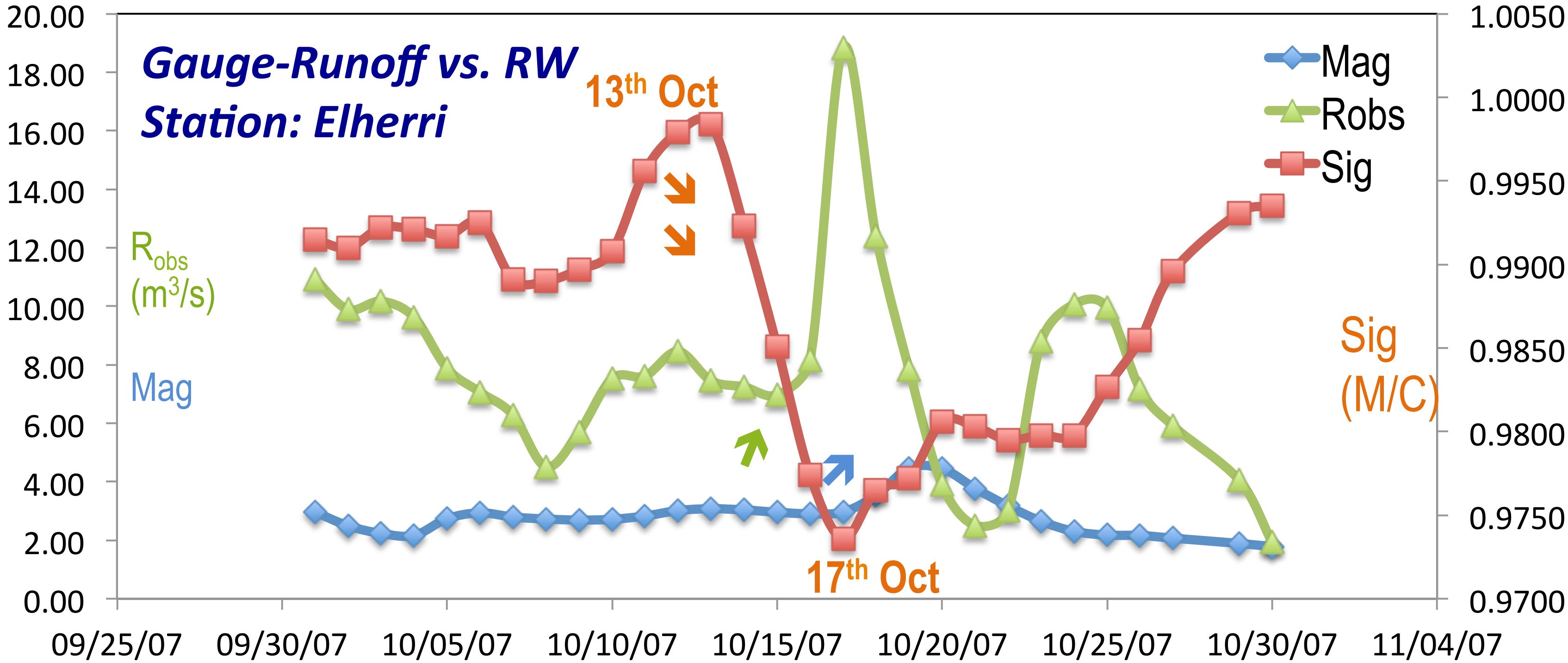
Dry pixel not affected by flooding

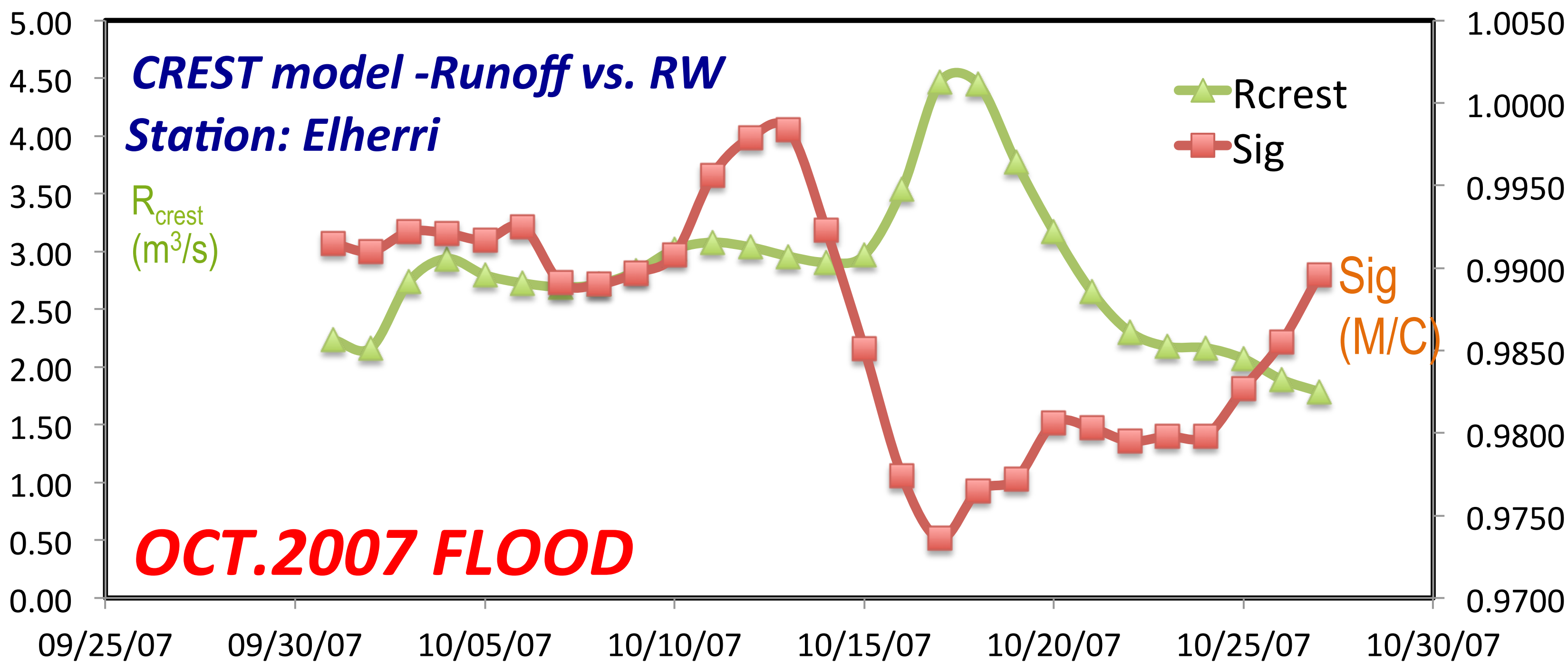
Magnitude:

Signal anomaly

(SD removed from mean)

- Uses 36GHz H-polarization band (AMSRE on NASA EOS Aqua)
- Footprint size ~ 8x12km (level 2A)
- Assumption: Wet and Dry land surfaces have same characteristics except for water surface extent


Gauge-Runoff vs. RW
Station: Elherri
13th Oct
17th Oct
Mag
Robs
Sig
R_{obs} (m^3/s)
Mag
Sig (M/C)
20.00
18.00
16.00
14.00
12.00
10.00
8.00
6.00
4.00
2.00
0.00
1.0050
1.0000
0.9950
0.9900
0.9850
0.9800
0.9750
0.9700
09/25/07
09/30/07
10/05/07
10/10/07
10/15/07
10/20/07
10/25/07
10/30/07
11/04/07


CREST model -Runoff vs. RW
Station: Elherri
Rcrest
Sig
R_{crest} (m^3/s)
Sig (M/C)
OCT.2007 FLOOD
5.00
4.50
4.00
3.50
3.00
2.50
2.00
1.50
1.00
0.50
0.00
1.0050
1.0000
0.9950
0.9900
0.9850
0.9800
0.9750
0.9700
09/25/07
09/30/07
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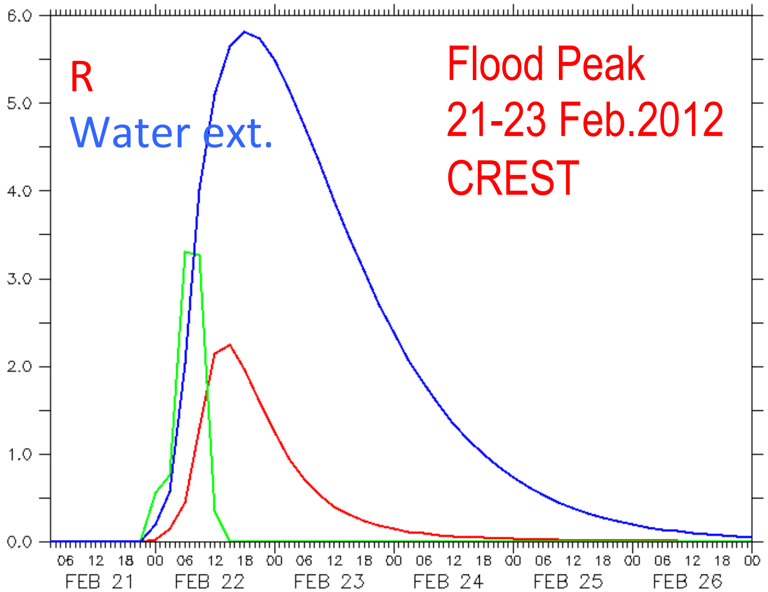
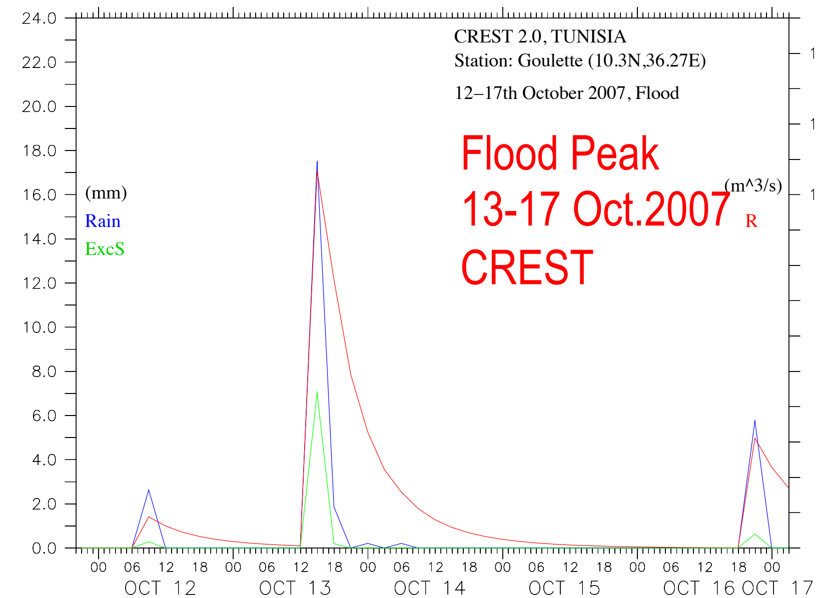
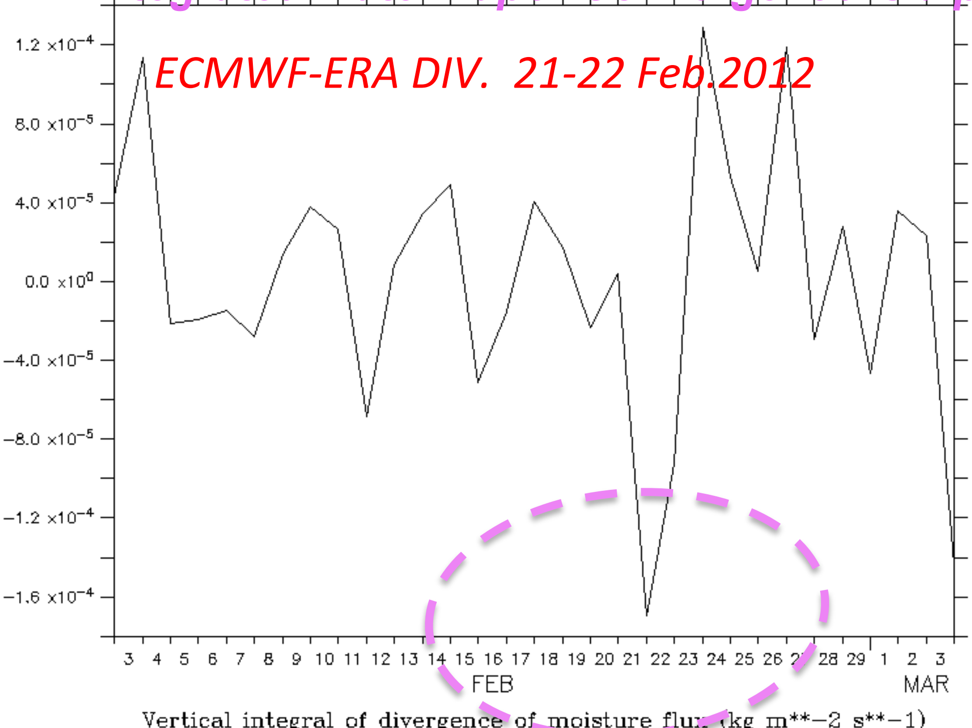
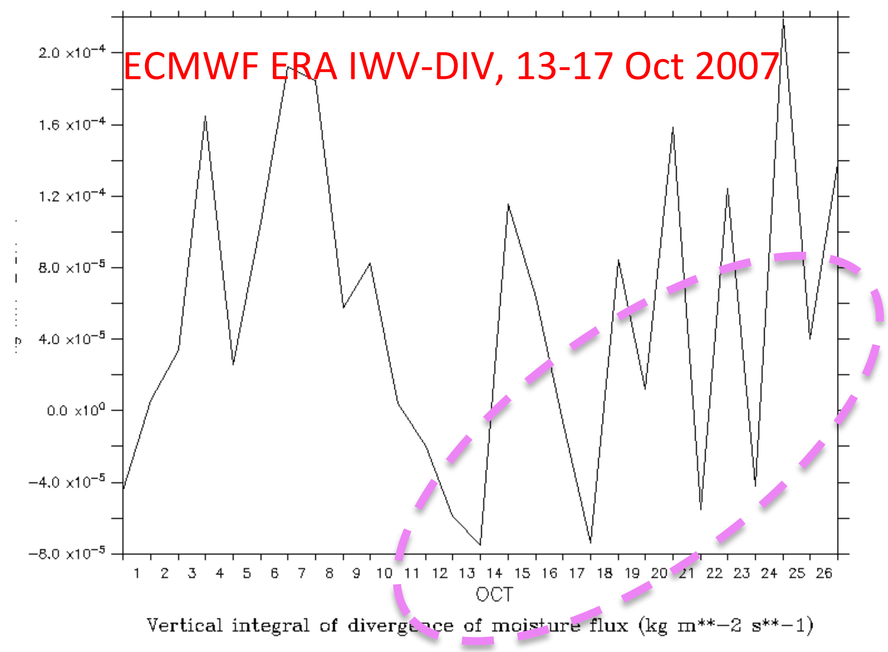
10/25/07
10/30/07





Integrated Water Vapor Convergence is a proxy for detecting the onset of floods





Concluding Remarks

- Considerable uncertainties in daily input basics (DEM, FAC) and rainfall were noted for North Africa. Overall, TMPA monthly (3B43) shows relatively better performance in comparison with Gauges.

- The model is able to simulate the episodic flood events fairly well, but underestimated as compared to Gauges.
  Model's accuracy in simulating streamflow is limited by poor calibration with small volume of available Gauge data.

- River Watch based on AMSR-E is found to be a promising tool for flood detection, monitoring, and flood model evaluation.

- ECMWF-ERA interim-vertically integrated water vapor convergence is found to be a useful proxy for detecting the onset of floods.

Flood model implementation: Uncertainties and Challenges

- **1. Model uncertainty:** modeling strategy: Conceptual + Distributed) Nonlinear conversion of RF to Runoff, hydraulic routing over steep orography etc.
- **2. Input Uncertainty:**
  (mainly hydrological model is data driven, rather than Physics/ dynamics) .
  Considerable uncertainties in input basics and forcing data.
  Satellite data correction requires reliable reference data.
  Note: Generally calibrations mask the uncertainties,
  so needs high volume data for better parameterization and convergence
- **3. Parameter Uncertainty:**
  Due to imperfect assessment of model parameters
- **4. Natural and operational uncertainty**

(i) Real-time forecasting: faces problem with data latency, dealing with different sources of information and data that need to be processed in short time during critical situations

(ii) Expert knowledge-based evaluation: how to interpret model outputs, especially when it concerns extreme conditions linked to rare events

Thank you!!!