THE ERA OF DATA RICH HYDROLOGY

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CREATING THE NEXT®

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COLOMBELLA, ITALY

ADVANCES IN HYDROLOGICAL MODELING

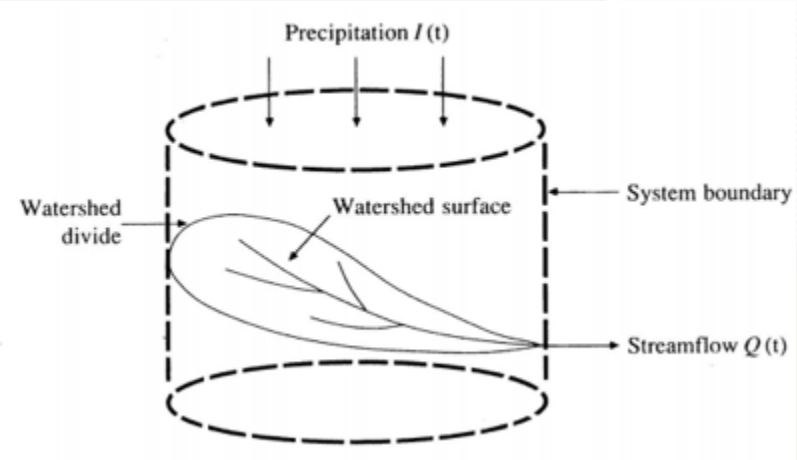
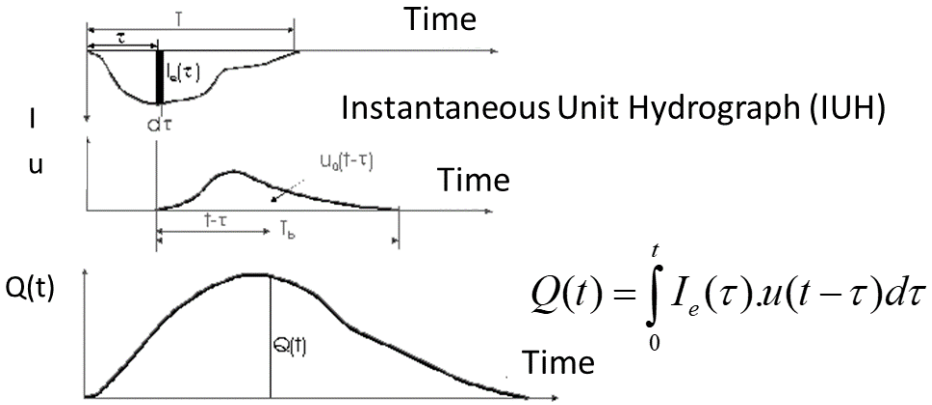


Fig: Watershed as Hydrological system (Chow et al 1998)



$$Q(t) = \int_0^t I_e(\tau).u(t-\tau)d\tau$$

Physical interpretation of catchment response

1960s

Interconnected conceptual elements

Sacramento
HBV
Xinanjiang
NAM
HySIM
TANK
ARNO
GR4J
SWM

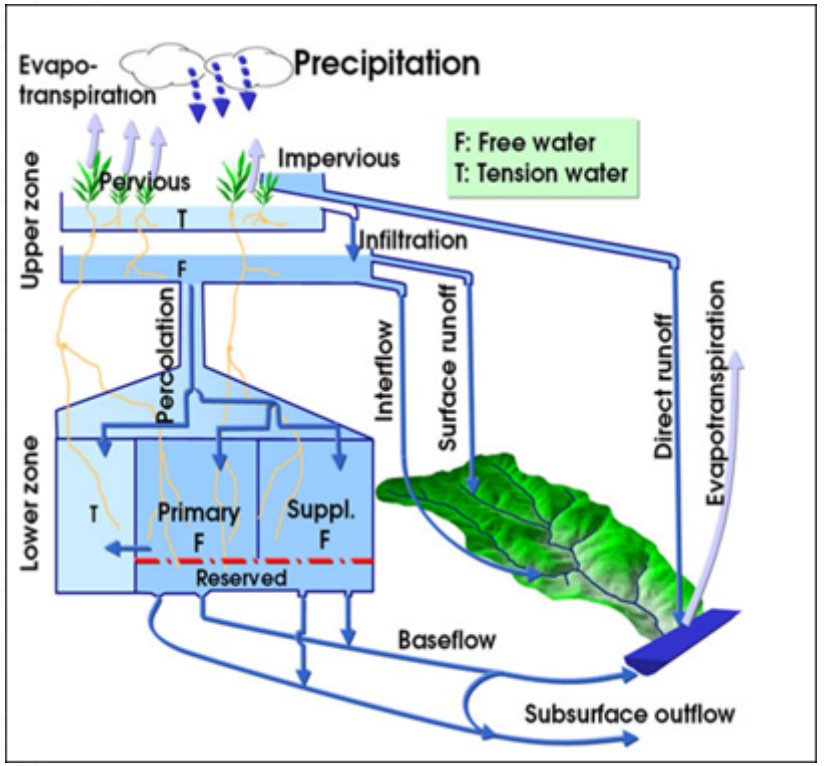
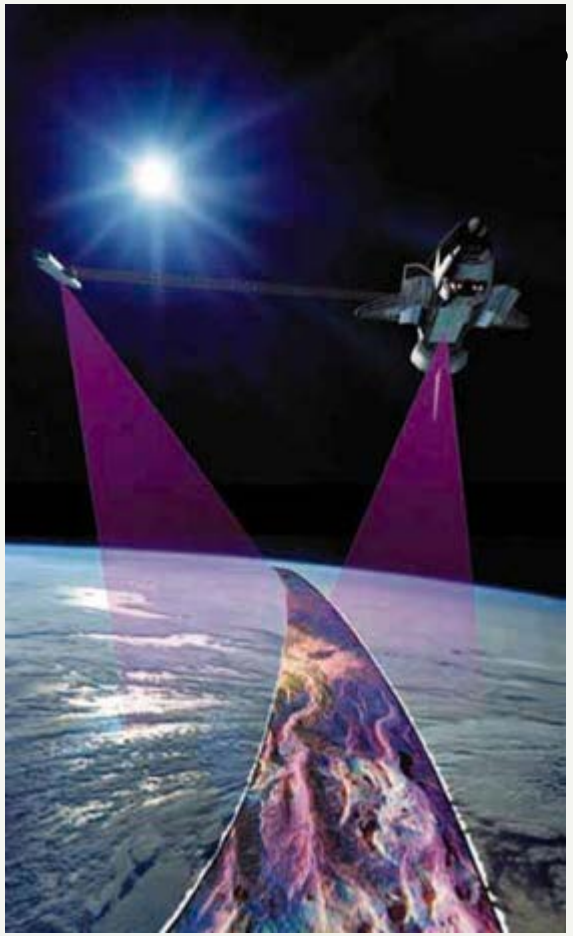


Image: mrcc.isws.illinois.edu

Geomorphological UH; Nonlinear UH; Regionalization of UH

ADVANCEMENT IN GEOSPATIAL DATA: TOPOGRAPHY

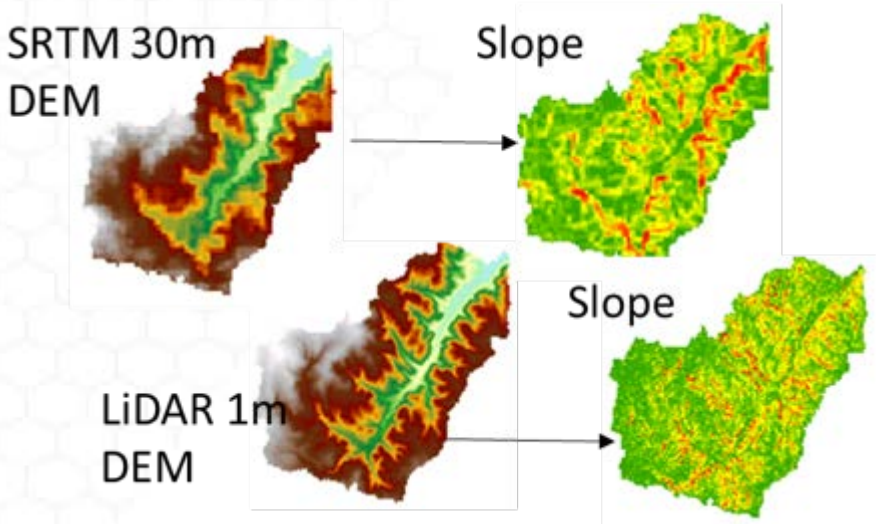


Shuttle Radar Topography Mission
C-band interferometric synthetic aperture radar technique, Covers 80% of globe at 30m*30m
(Source: Shuttle Radar Topographic Mission (SRTM) Illustration.jpg)

Rapid development in acquisition of elevation data have resulted in increased availability of data and Improvement in the digital representation of terrain.

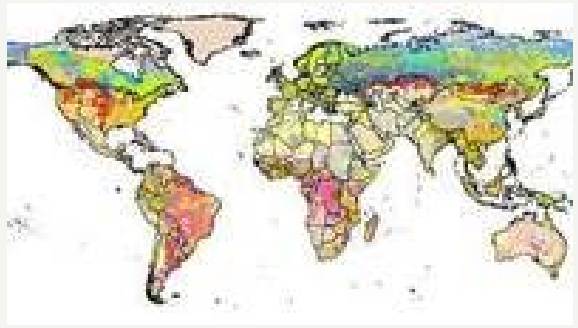
Existing Digital Elevation Models (DEM)

- Global 1-km digital raster (GTOPO30, 1996)
- Shuttle Radar Topography Mission (**SRTM,** 2000) (National) (30m)
- National Elevation Data Set **(NED)** by USGS (National) (5m)
- LiDAR based Digital elevation models (landscape scale) (1m)



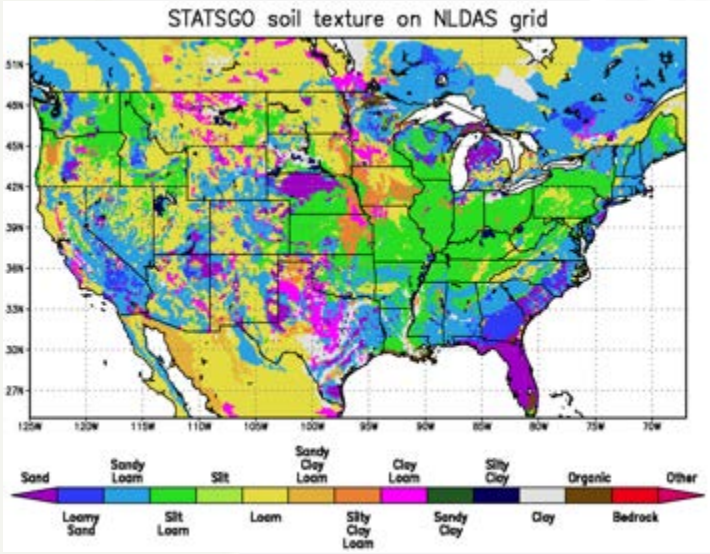
ADVANCEMENT IN GEOSPATIAL DATA: SOIL

Harmonized World Soil Database v 1.2

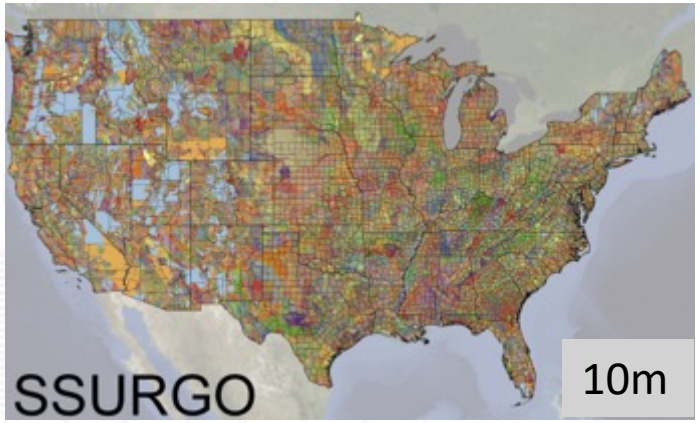


50km

STATSGO



Regional/watershed scale (general soil map) (1km)

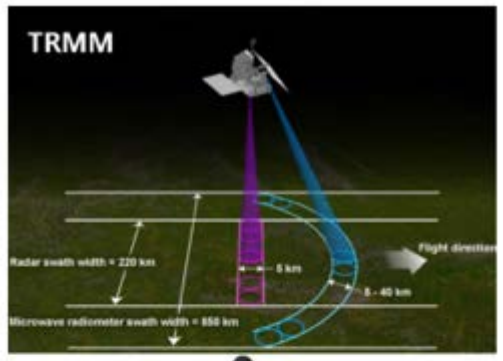


County and field scale (Detailed soil map)

State Soil Geographic (STATSGO) and Soil Survey Geographic (SSURGO) are the two most used soil database

ADVANCES IN SATELLITE RETRIEVAL : PRECIPITATION AND SOIL MOISTURE

Precipitation



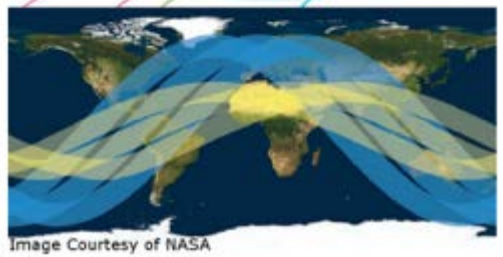


Image Courtesy of NASA

SMOS

SMAP

TRMM

GPM

CURRENT TIME

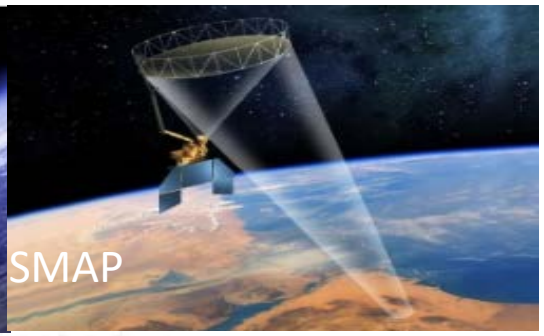


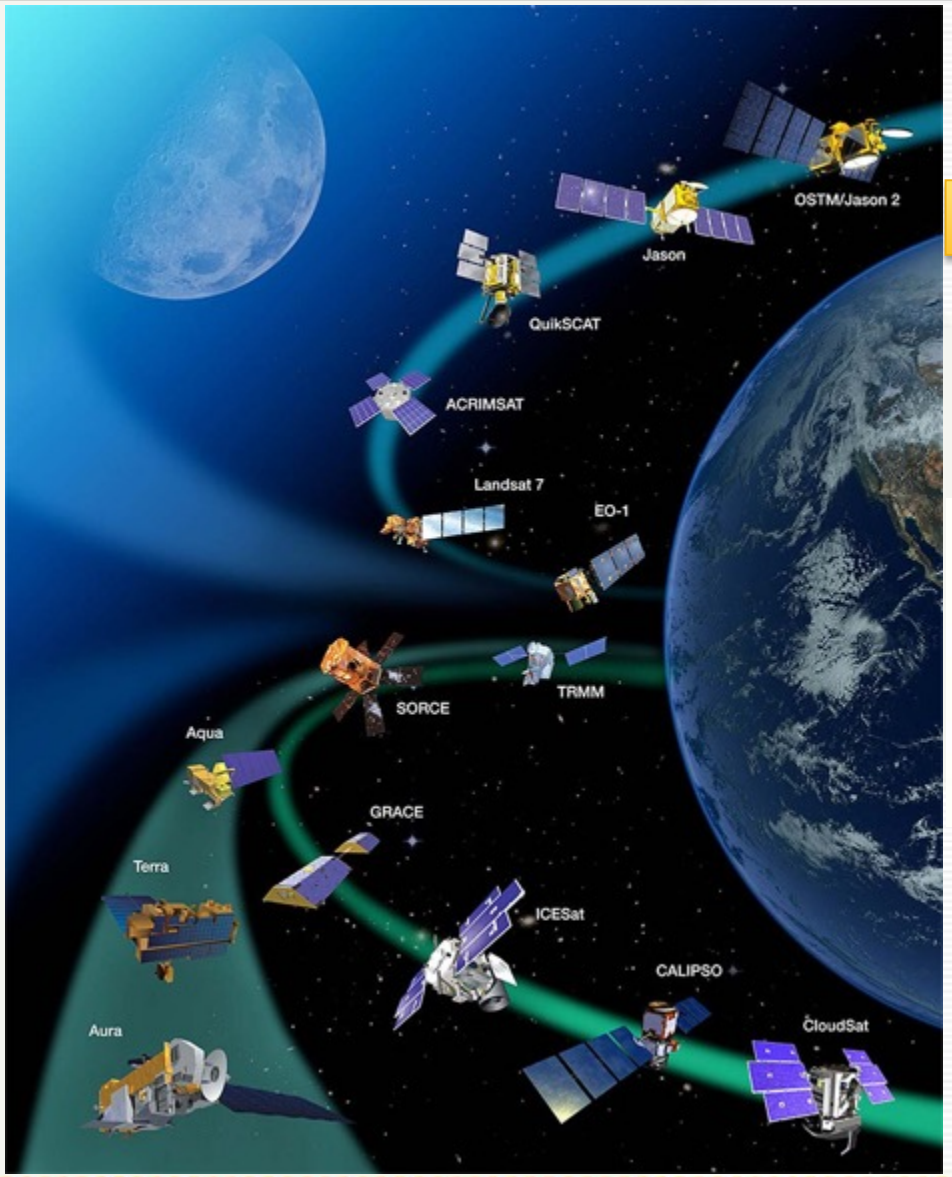
Image: NASA

Soil Moisture

	Variables	Space Resolution	Time Resolution
SMOS (2009-Present)	Top 5-cm soil moisture	~36 km	1-2 days
SMAP (2015-present)	Top 5-cm soil moisture	~36 km	1-2 days
TRMM 3B42 (1997-2015)	Precipitation	0.25 degree	3 hours
GPM IMERG (2014-Present)	Precipitation	0.1 degree	0.5 hour

Issues: measurement error/bias, coarse time-space resolutions, no deeper layer soil moisture

BIG DATA APPROACH IN HYDROLOGY

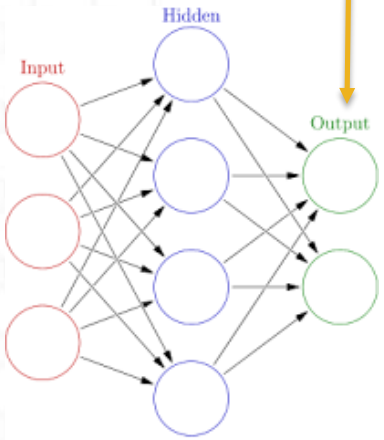


AVHRR/MODIS /Landsat

SMOS, TRMM, GPM, SMAP

Evolution of big data approach in Hydrology

Spatially distributed physically based models (e.g., tRIBS, MIKE SHE)

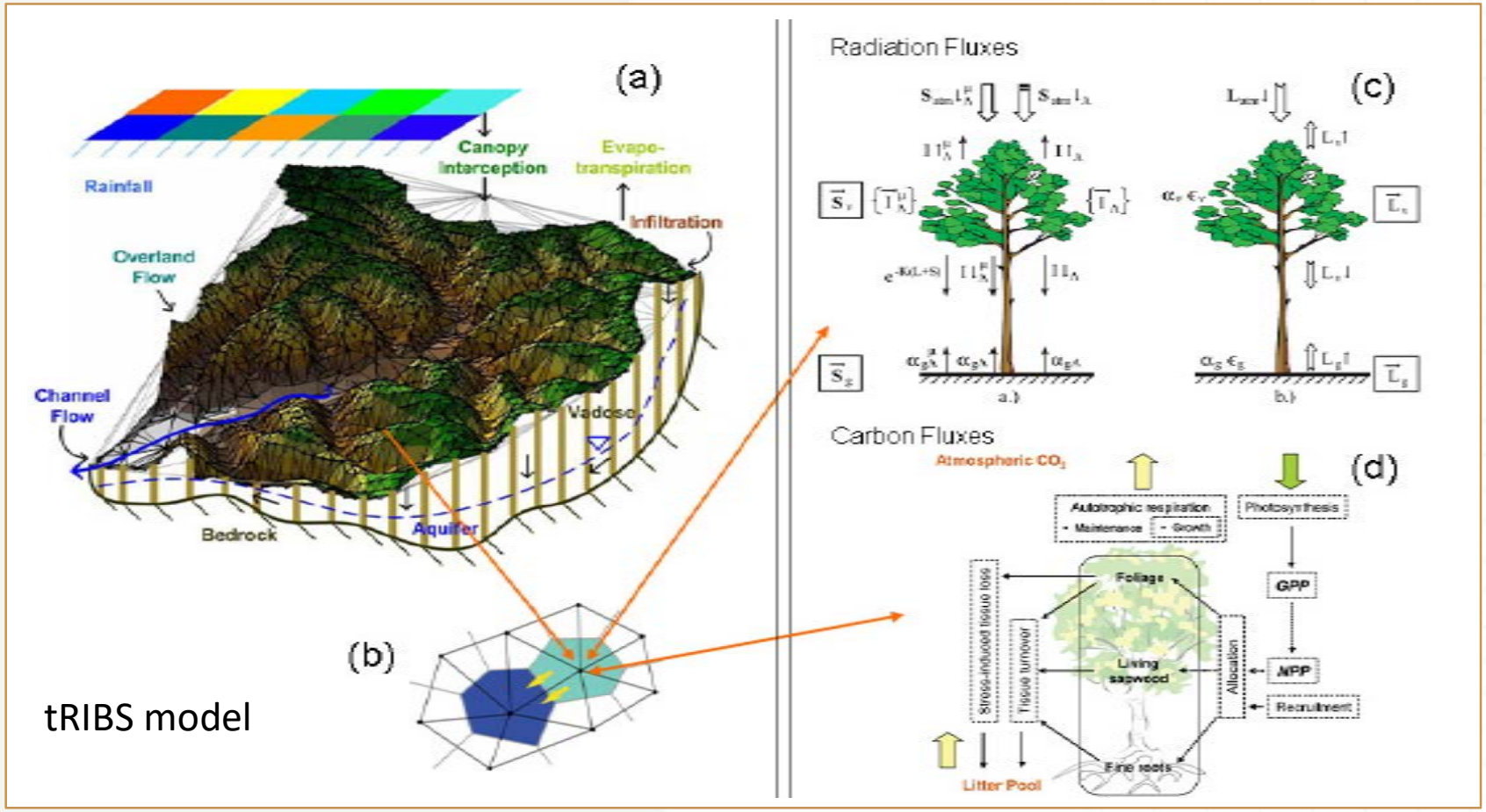


Machine/deep learning (Super resolution for downscaling)

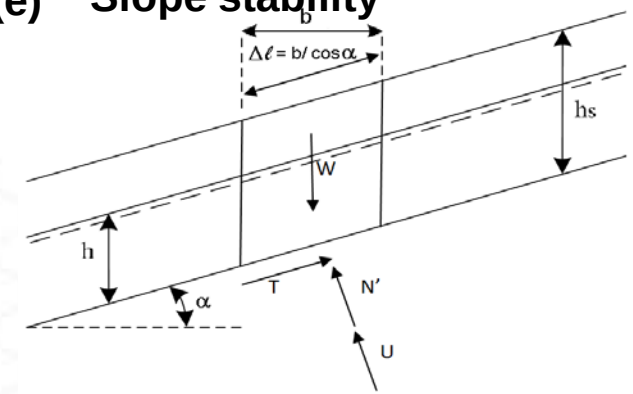
Reliable estimation of geospatial data, model forcing, parameter estimation, state estimation (**data assimilation**)

Hybrid Analytics (Combining machine learning with physically based models)

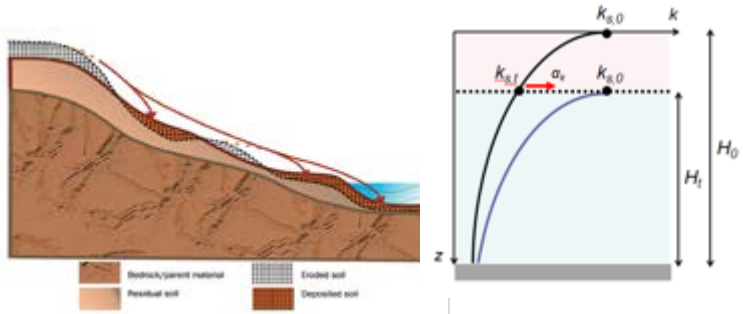
BIG DATA APPROACH: ADVANCES IN HYDROLOGICAL MODELING



(e) Slope stability



(f) Soil Organic carbon mass balance equation



(g) Soil carbon and nitrogen cycle

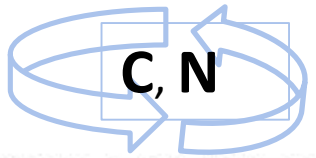


Figure The coupled tRIBS (a-c) and plant physiology model, VEGGIE, (d) is the eco-hydrological framework with additional modules (e) Slope stability sub model, (f) SOC mass balance sub model, (g) Carbon Nitrogen cycle (Lepore et al., 2013)

IMPACT OF DEM RESOLUTION: PHYSICALLY BASED SLOPE STABILITY MODEL

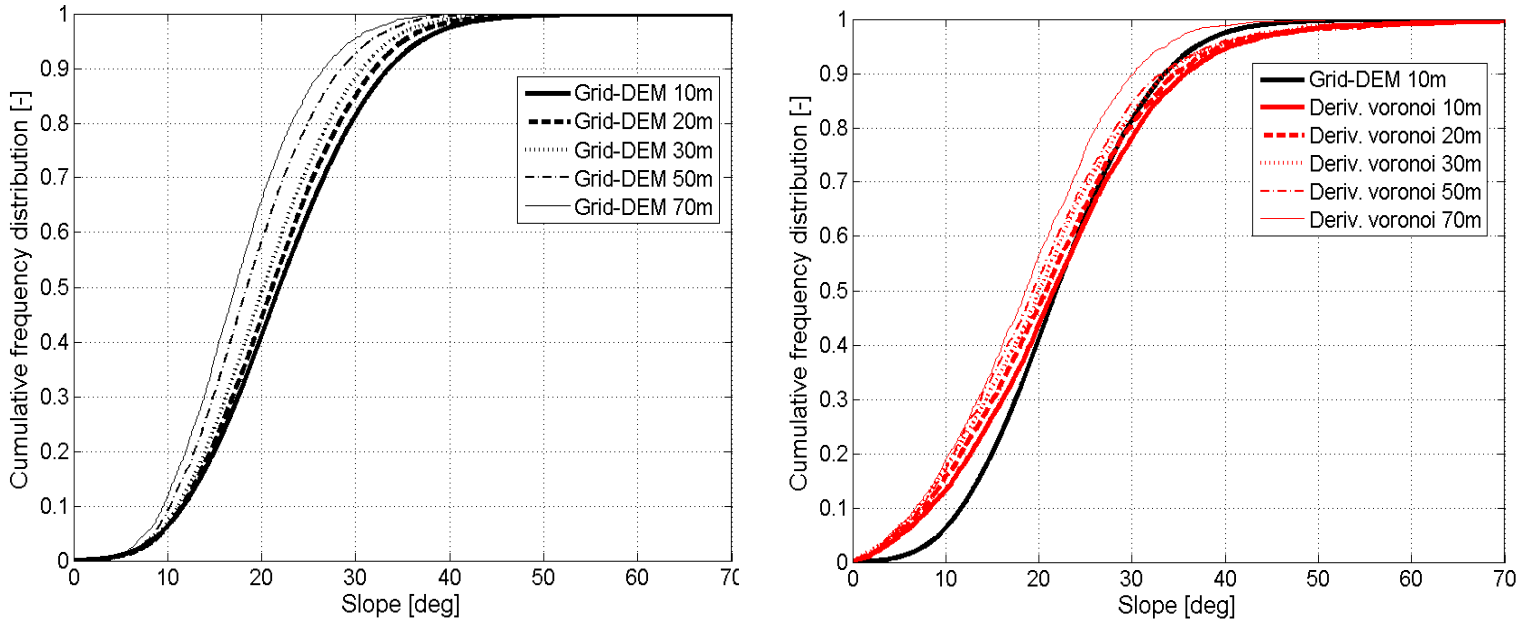
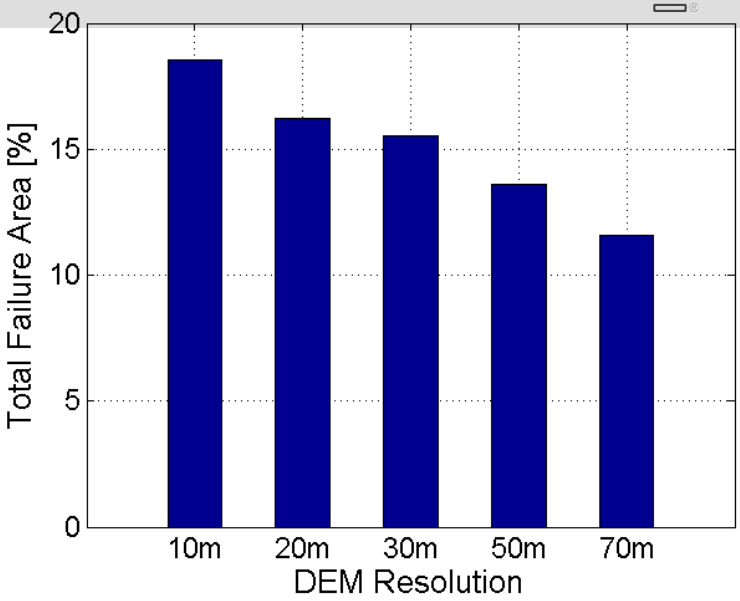


Figure: Effect of DEM resolution on cumulative distribution of slope a) Grid-DEM resolution, b)Irregular mesh



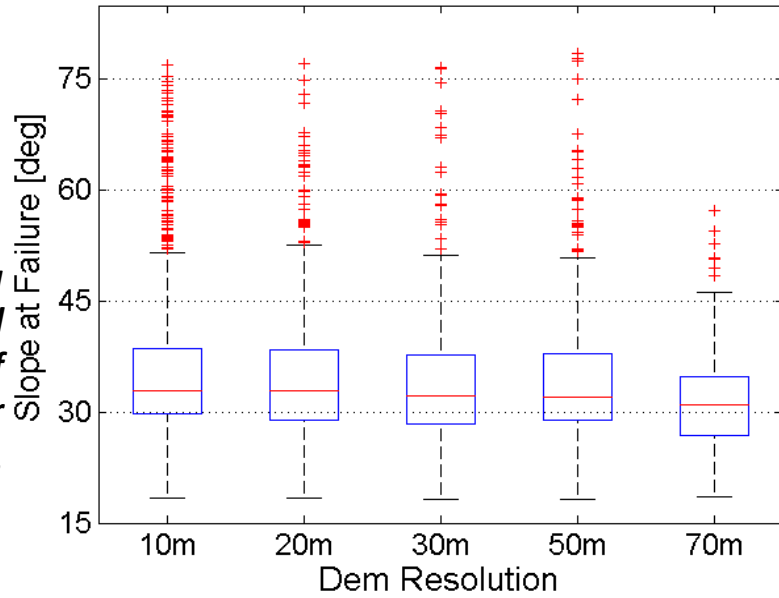
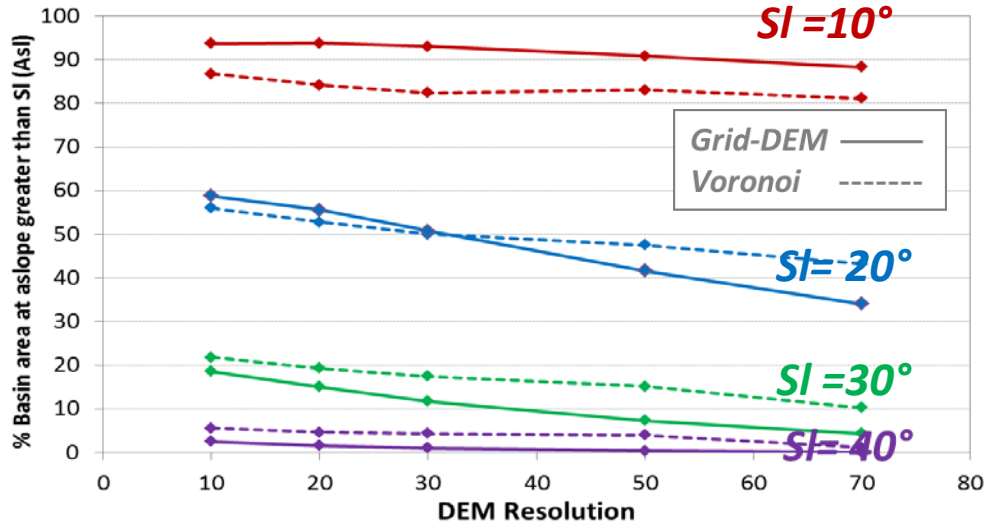
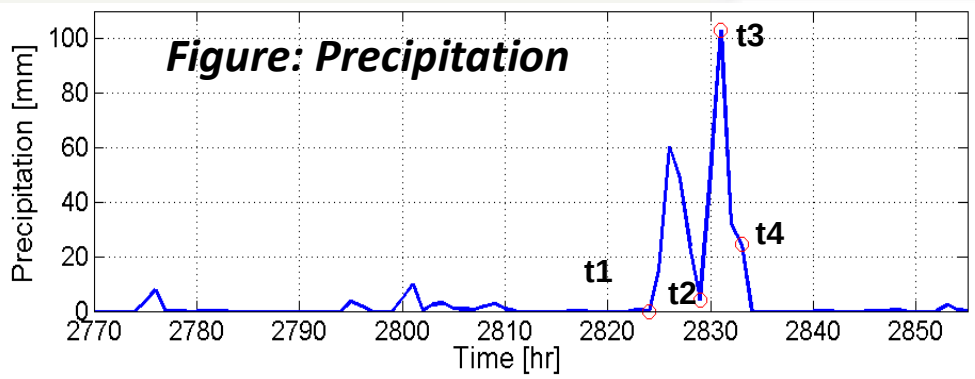


Figure: a) Total failing area at different model resolutions, b) Box plots of slope values at failure for the five resolutions.

Figure: % of Basin area at slope greater than SI



IMPACT OF DEM RESOLUTION ON SIMULATED SOIL MOISTURE



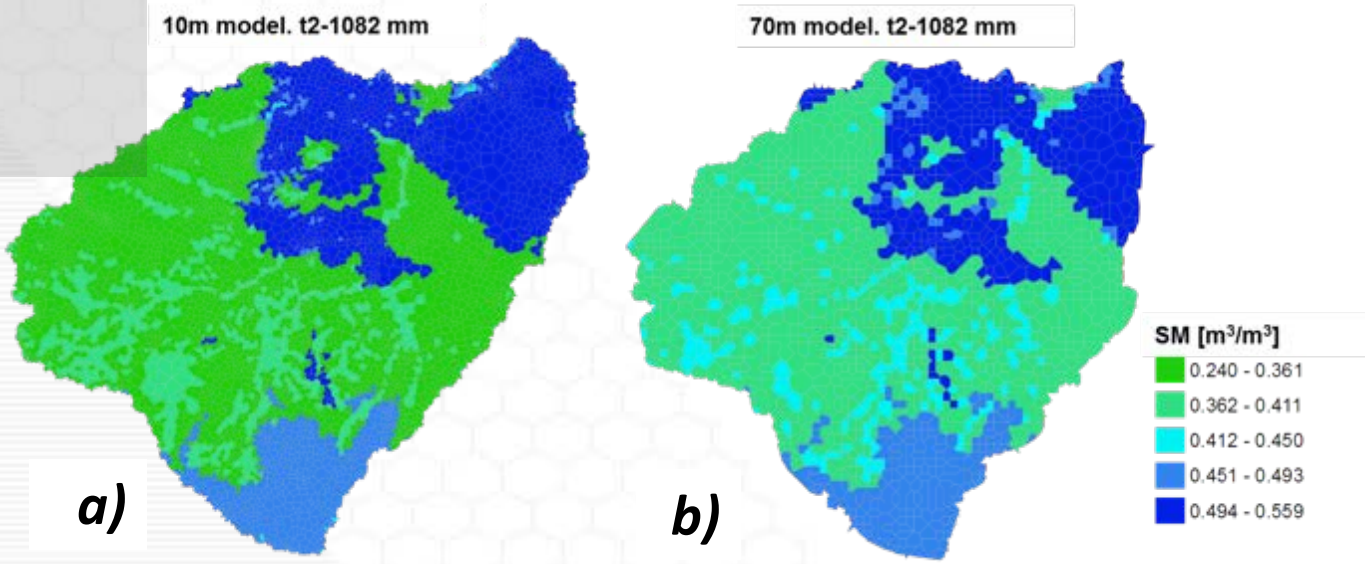


Figure: simulated SM at t2-1082mm for a)10m DEM and b) 70m DEM

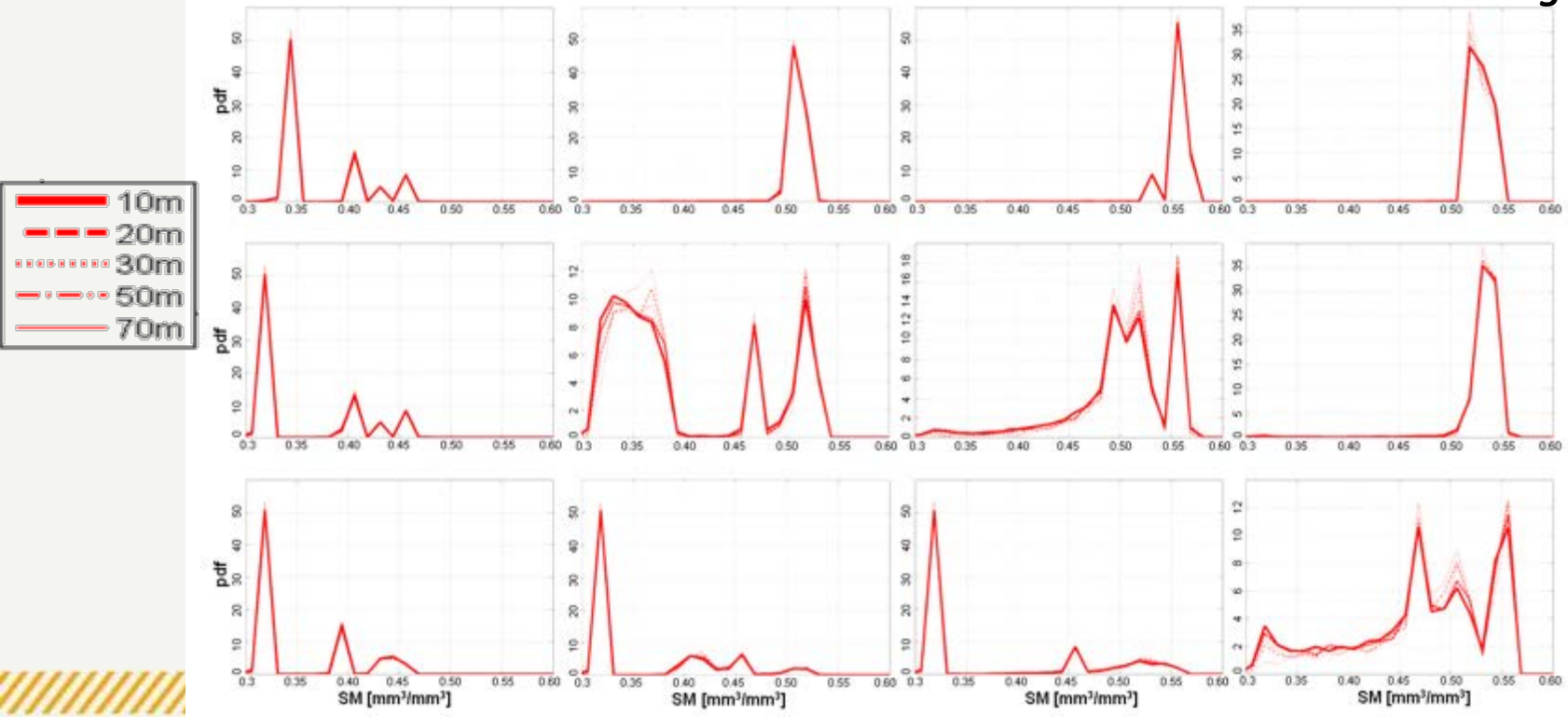
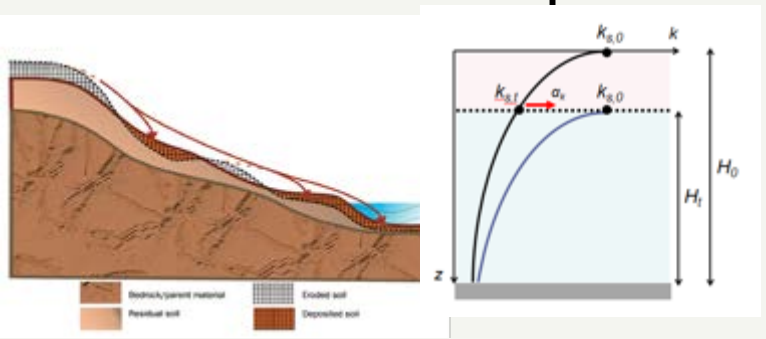


Figure: SM probability density functions at four time steps and three depths for the five resolutions. Differences are pronounced at t2-1082mm, t3-1082mm, t4-1512mm.

BIG DATA APPROACH: TERRESTRIAL SEDIMENTATION AND CARBON CYCLE

SOC mass balance equation



tRIBS-ECO

Erosion
Carbon
Oxidation

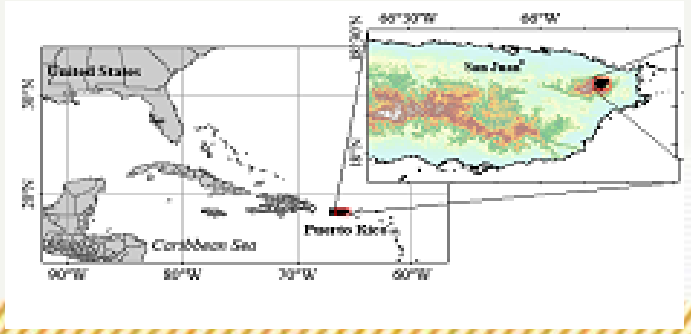
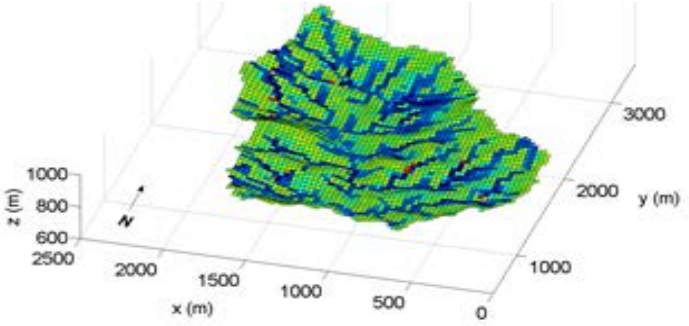
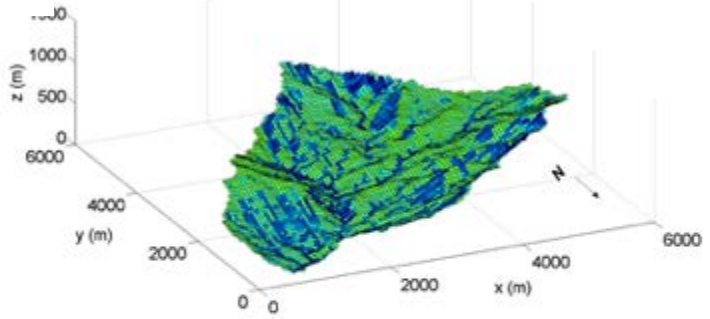


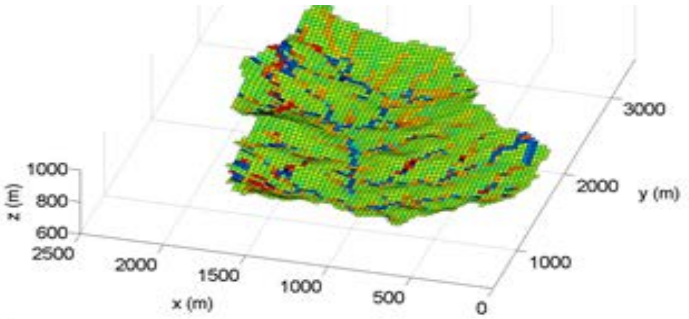
Fig Watersheds from Luquillo CZO

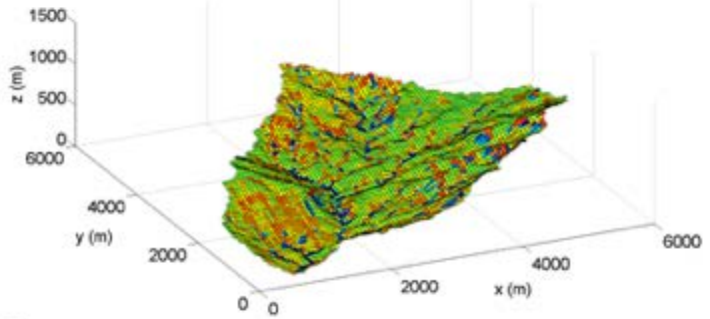
a) Maximum sink scenario



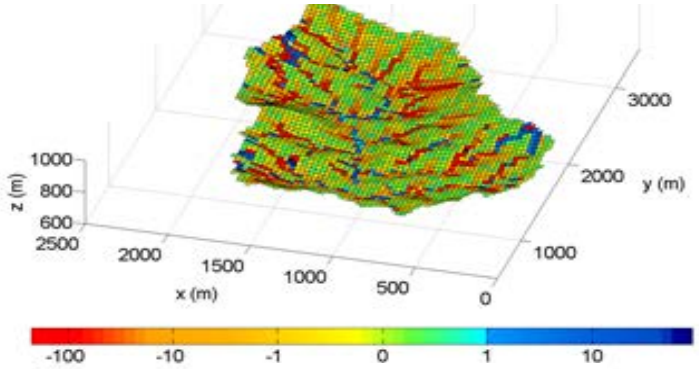


b) Maximum source scenario

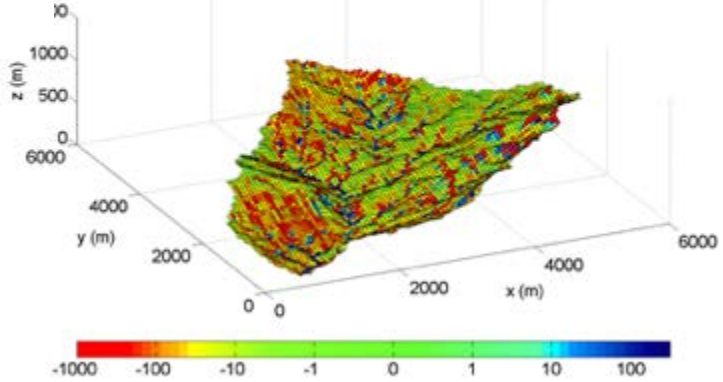




c) Intermediate source scenario

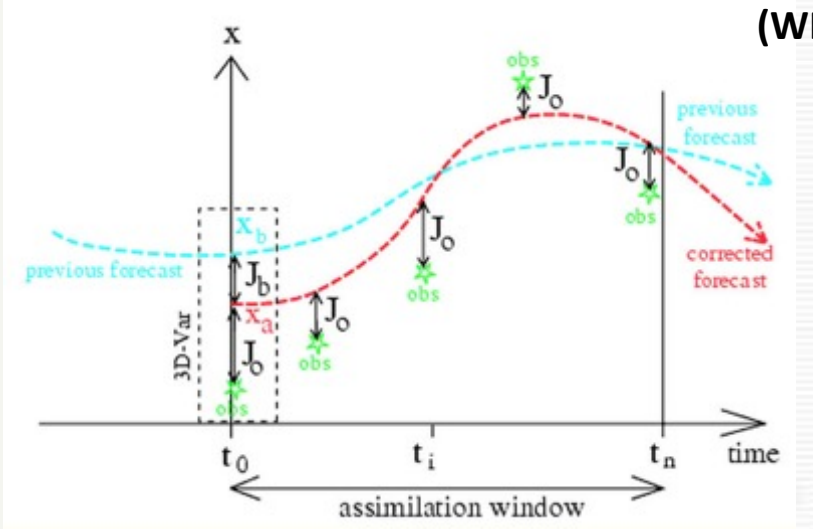


ΔSOC (g m^{-2} yr^{-1})



ΔSOC (g m^{-2} yr^{-1})

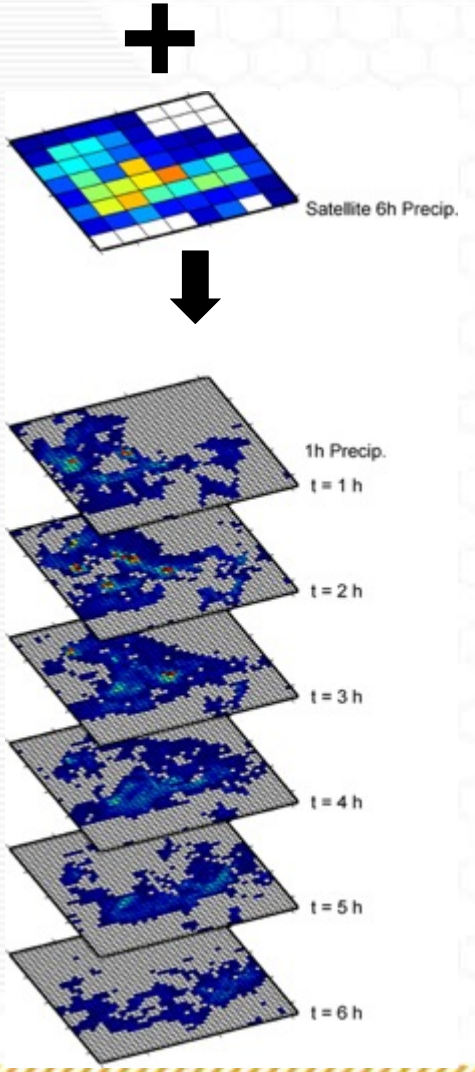
BIG DATA APPROACH: ASSIMILATION OF PRECIPITATION AND SOIL MOISTURE INTO WRF-NOAH MODEL



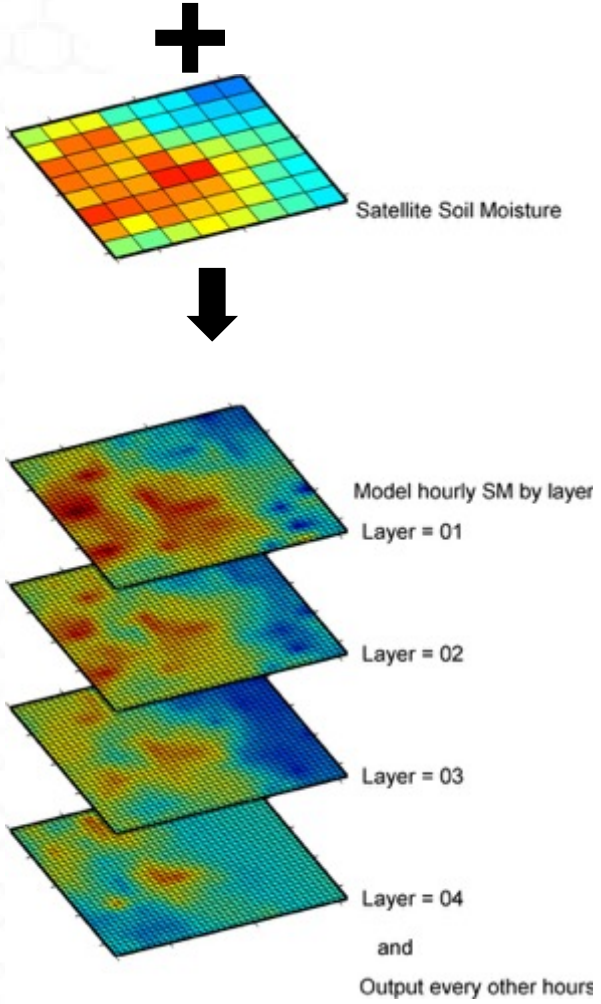
Three- and four-dimensional Variational data assimilation (3D- & 4D-Var:

- Control state: $\mathbf{x}$
- Model background: $\mathbf{x}^b$
- Cost of background part: J_b
- Cost of observation part: J_o

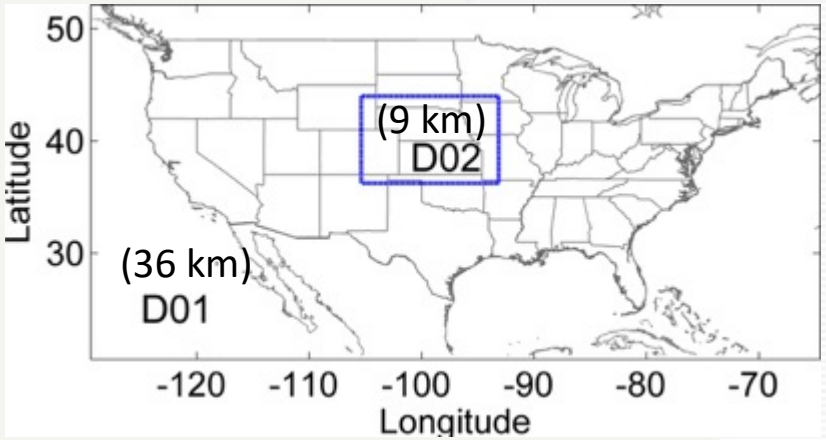
Weather Research and Forecasting (WRF) Model and 4D-Var



Noah land surface model and 1D-Var

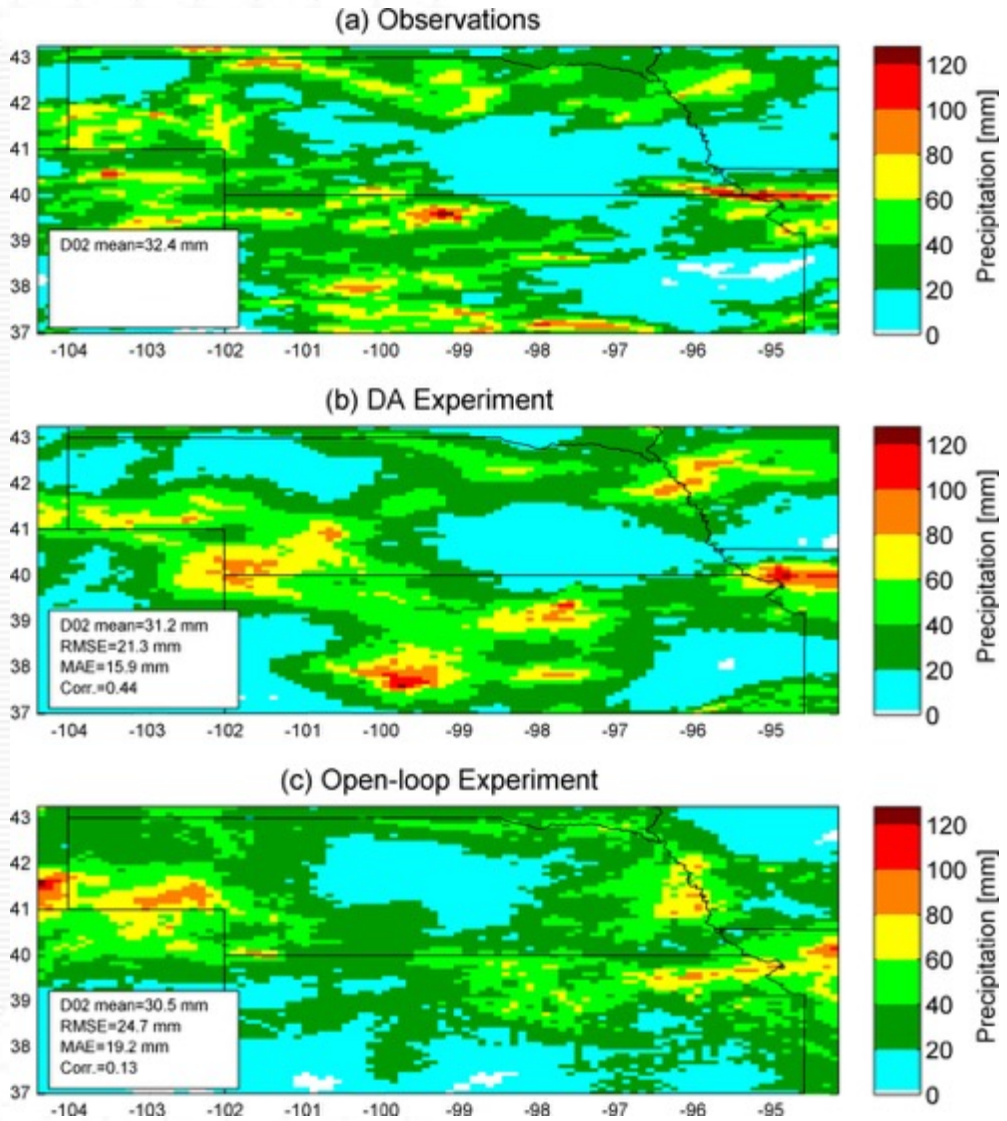


BIG DATA APPROACH: ASSIMILATION OF PRECIPITATION

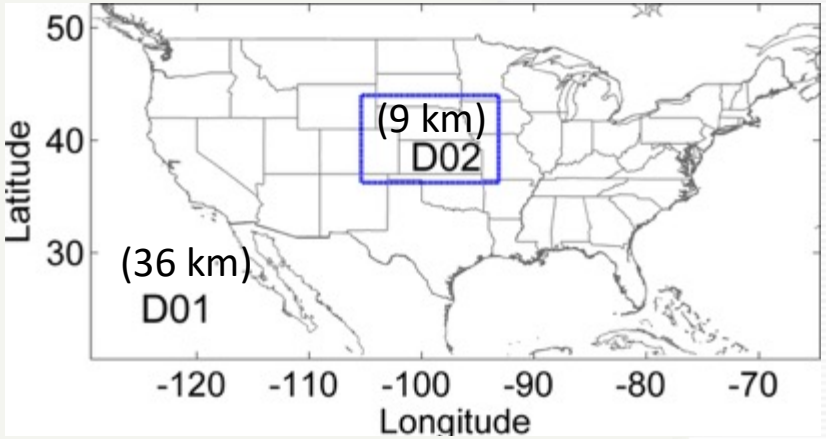


- Assimilating upscaled 6-h 20-km NCEP Stage IV precipitation in the WRF domain D01.
- Verifying the model precipitation at domain D02 against fine-scale NCEP Stage IV precipitation.

Lin et al. (2015) in JHM



BIG DATA APPROACH: ASSIMILATION OF PRECIPITATION



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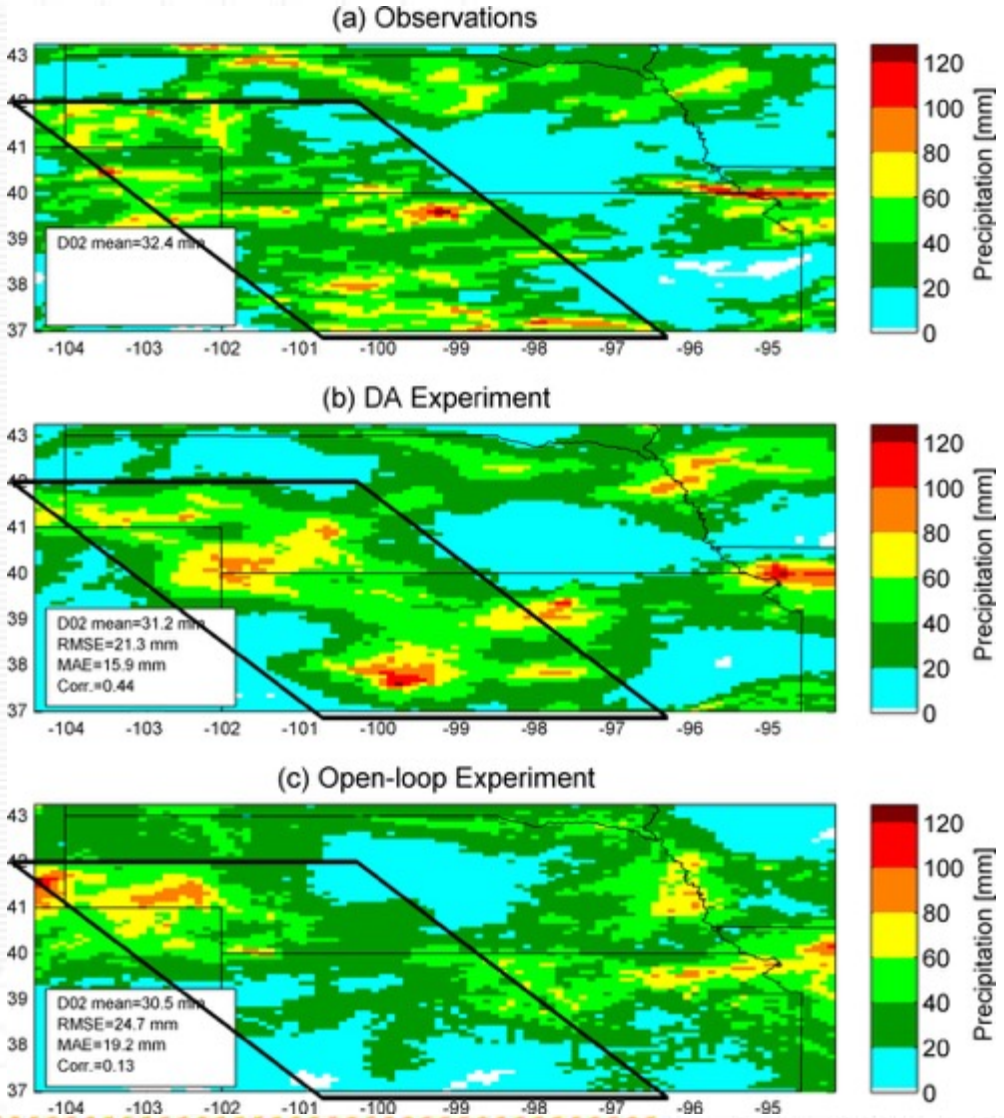
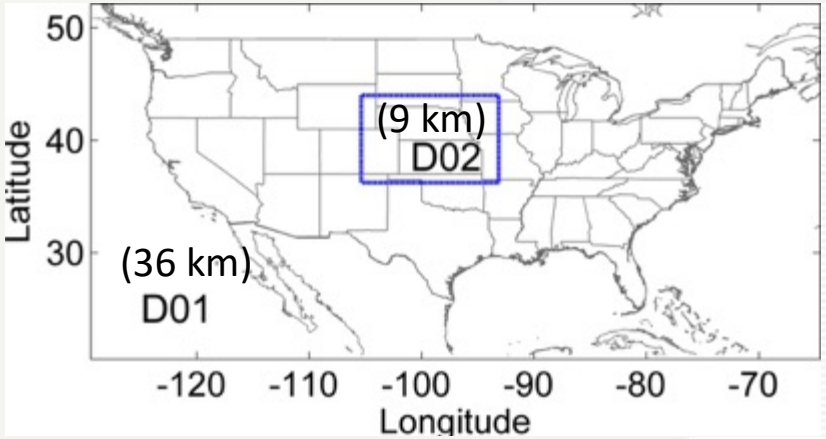


Lin et al. (2015) in JHM

BIG DATA APPROACH: ASSIMILATION OF PRECIPITATION



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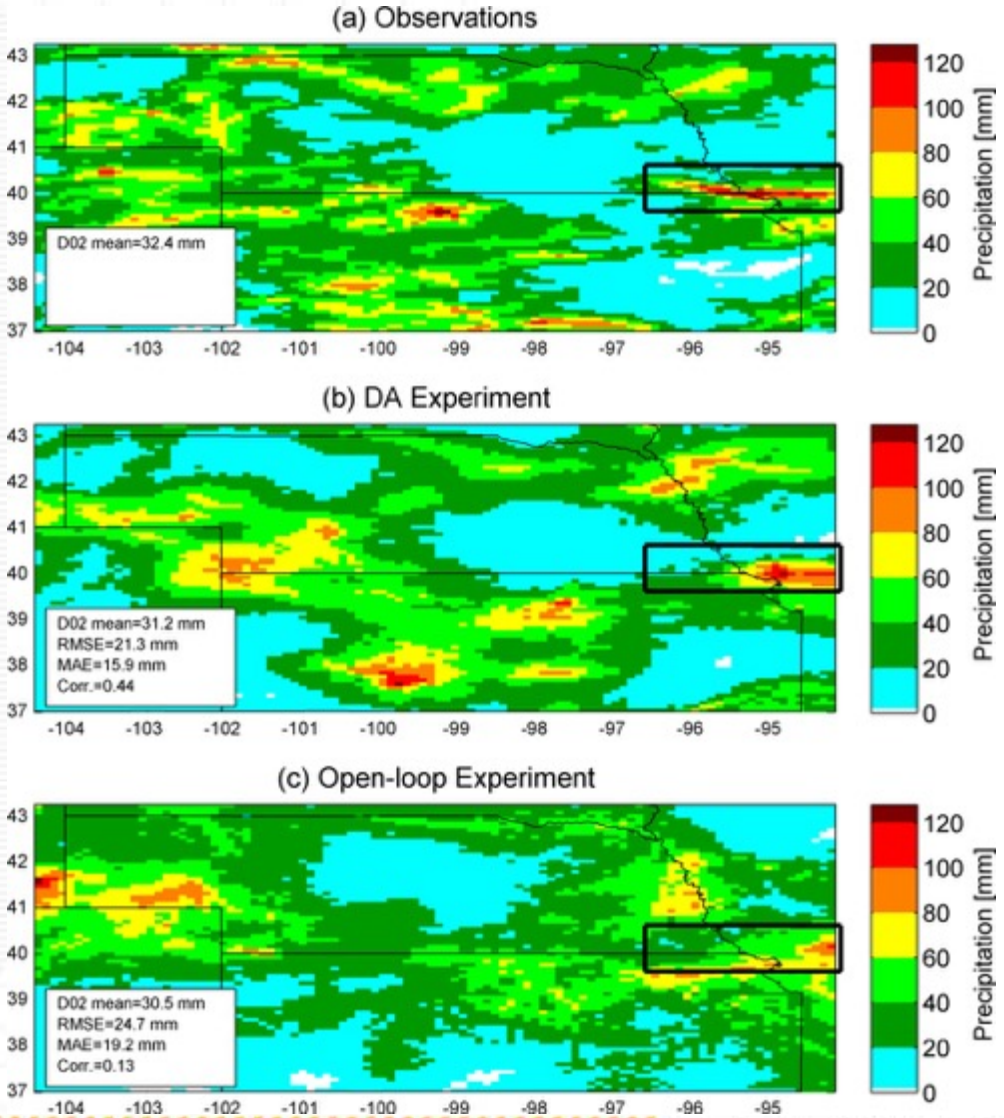
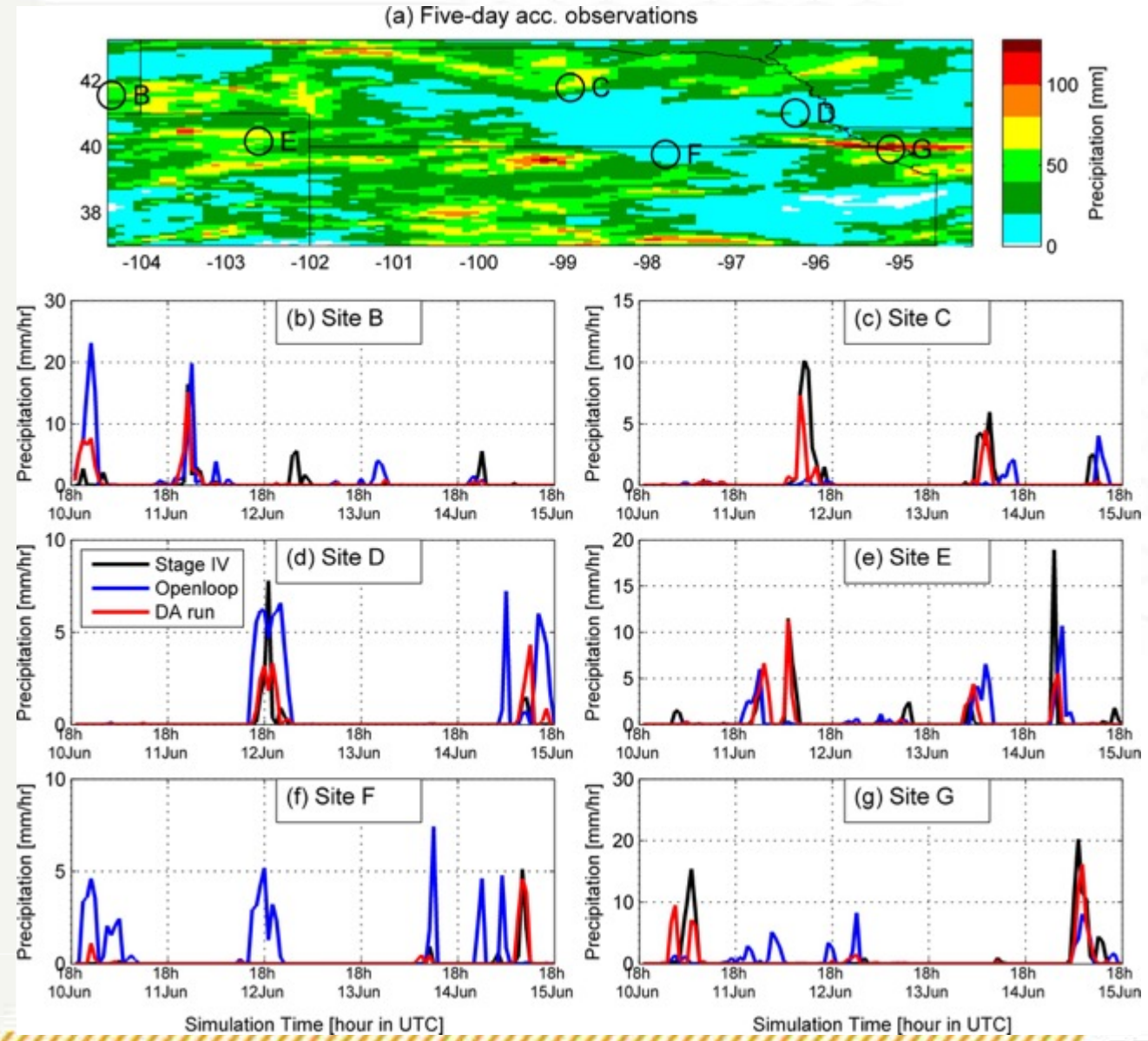


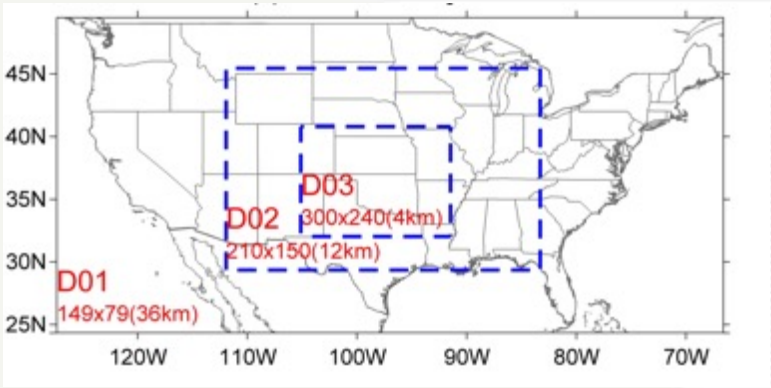
Lin et al. (2015) in JHM

BIG DATA APPROACH: ASSIMILATION OF PRECIPITATION
SELECTED HOURLY TIME SERIES

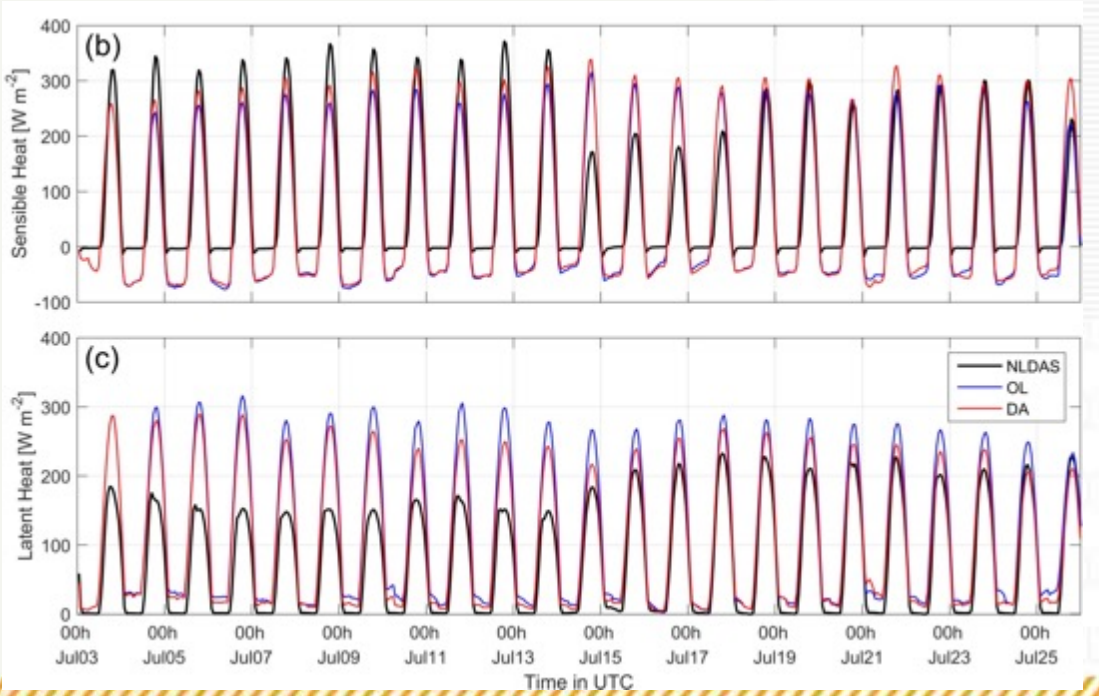


Lin et al. (2015) in JHM

BIG DATA APPROACH: ASSIMILATION OF SATELLITE SOIL MOISTURE DATA



- Assimilating SMOS soil moisture into the Noah LSM domain D01 in July 2013
- Verifying the hourly gridded model soil moisture at domain D03 against the Soil Climate Analysis Network gauge data
- Verifying the heat flux simulation against NLDAS



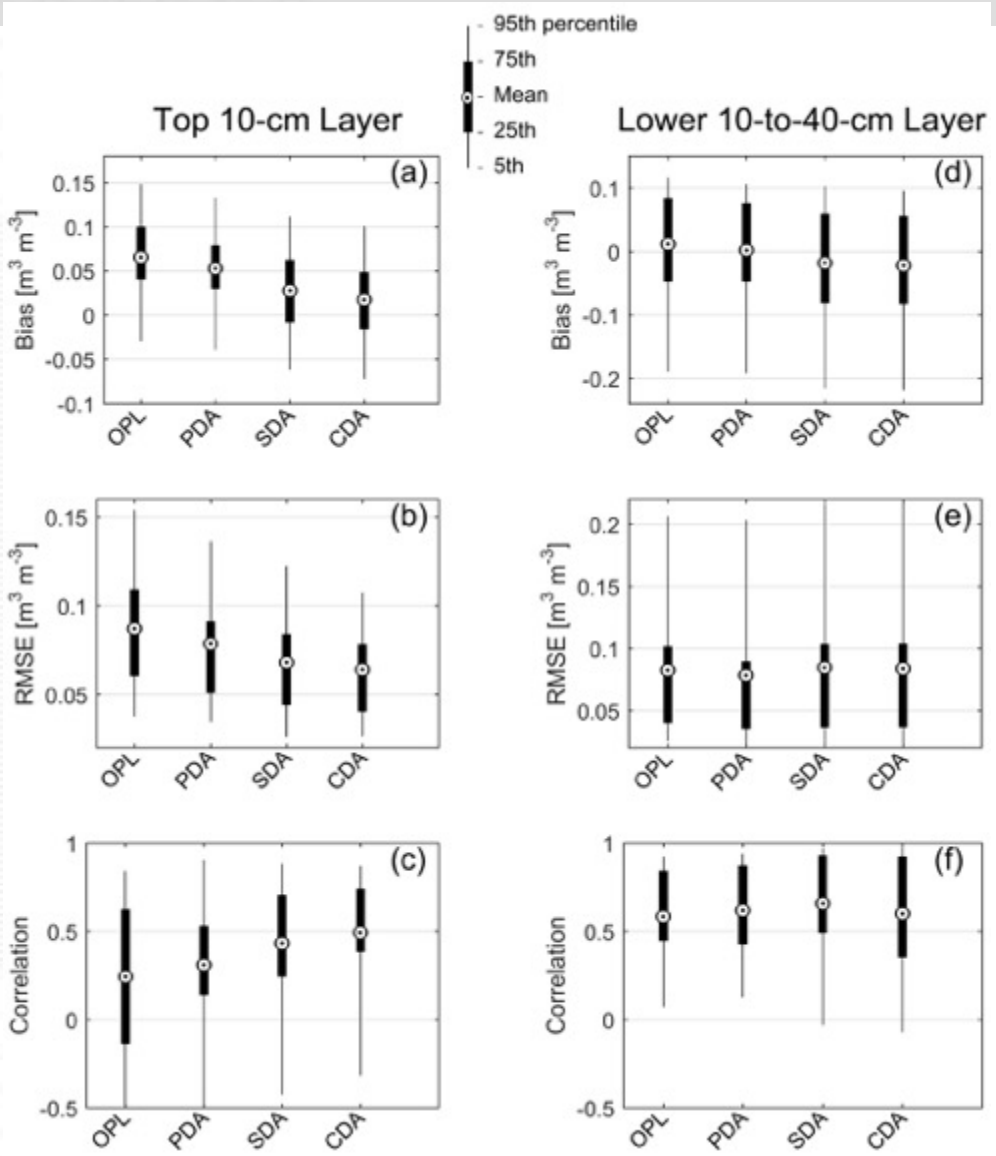
Improvement relative to Open loop (no DA)	Top 10-cm SM	10-to-40-cm SM
MAE	35%	9%
RMSE	33%	8%
Correlation	19%	25%

Lin et al. (2017) in WRR

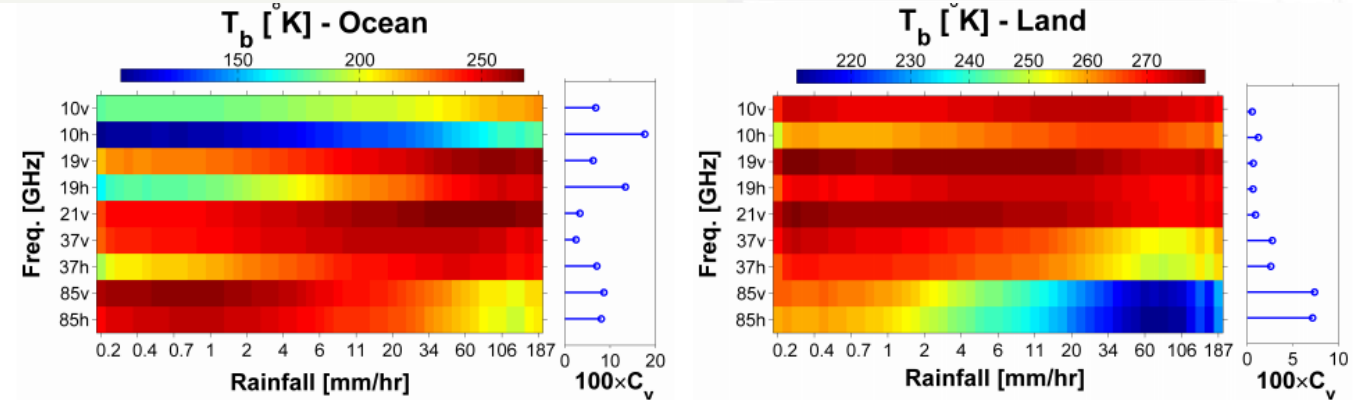
BIG DATA APPROACH: COMBINED ASSIMILATION OF PRECIPITATION AND SOIL MOISTURE

- Assimilation of TRMM 3B42 precipitation and SMOS soil moisture
- Verification of model soil moisture in the blue box against the hourly soil moisture gauge data in July 2013.

Lin et al. (2017) in MWR

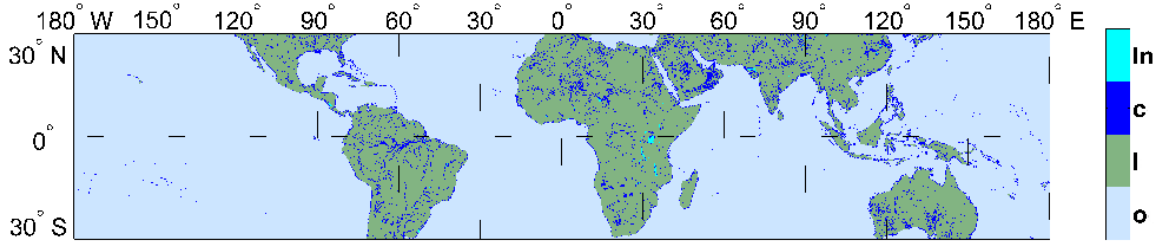


PRECIPITATION RETRIEVAL: DICTIONARY BASED SHARP ALGORITHM

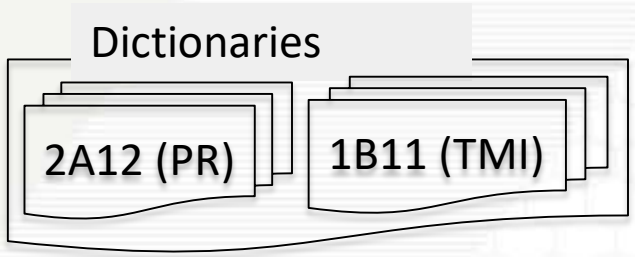


Expected values of the spectral brightness temperatures for different intervals of the surface rainfall intensity over ocean (left panel) and land (right panel)

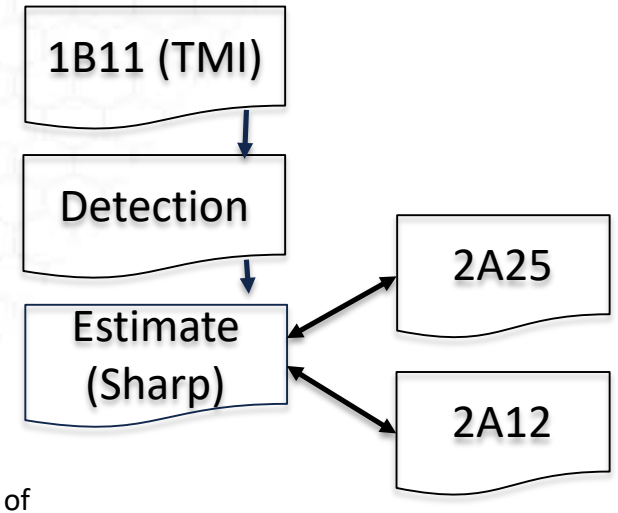
Surface class map



Different earth surface classes used in the current version of the ShARP, namely inland water body (In), coastal zone (c), land (l) and ocean (o). The classification is adopted based on the available data (version 7) of the PR-1C21 product, which are mapped onto a 0.05-degree regular grid

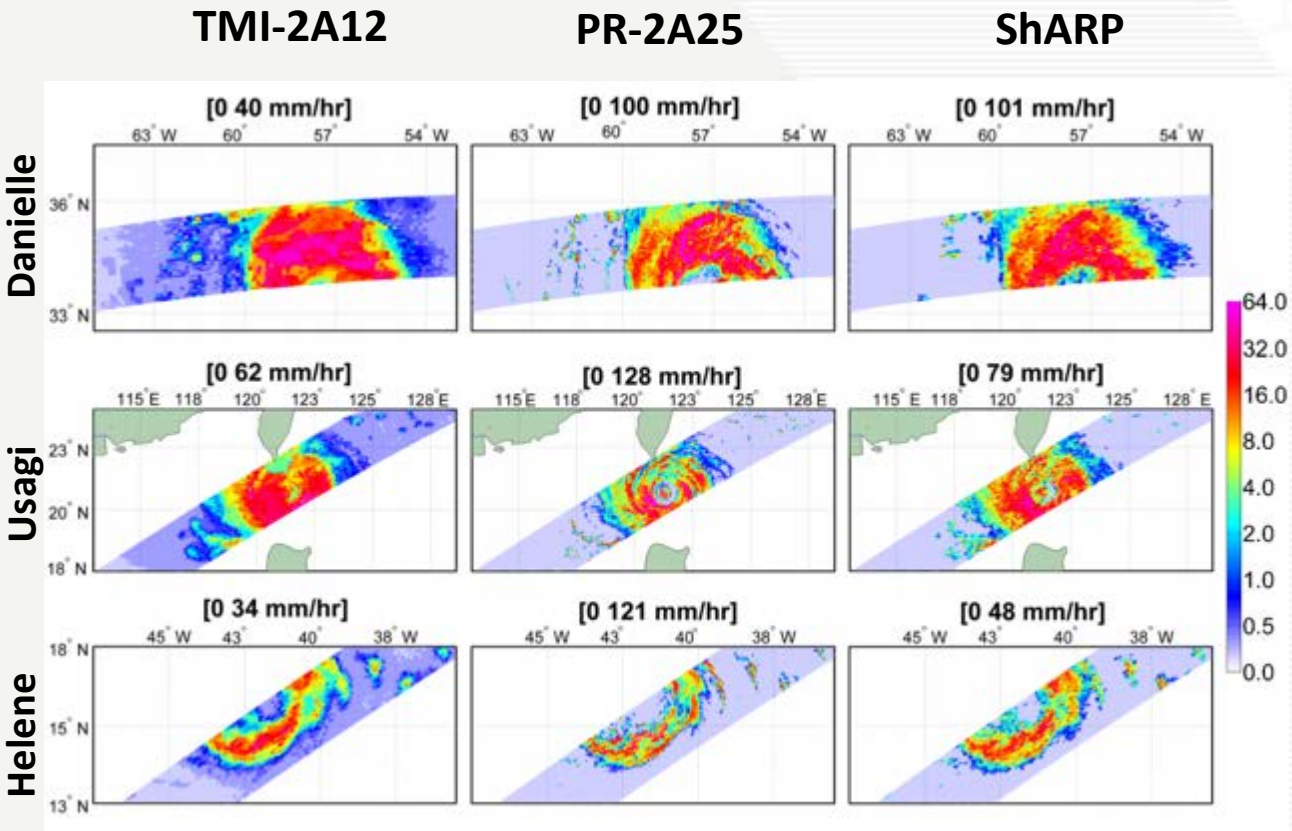


Dictionaries for 4 land classes (In, C, I, and O)

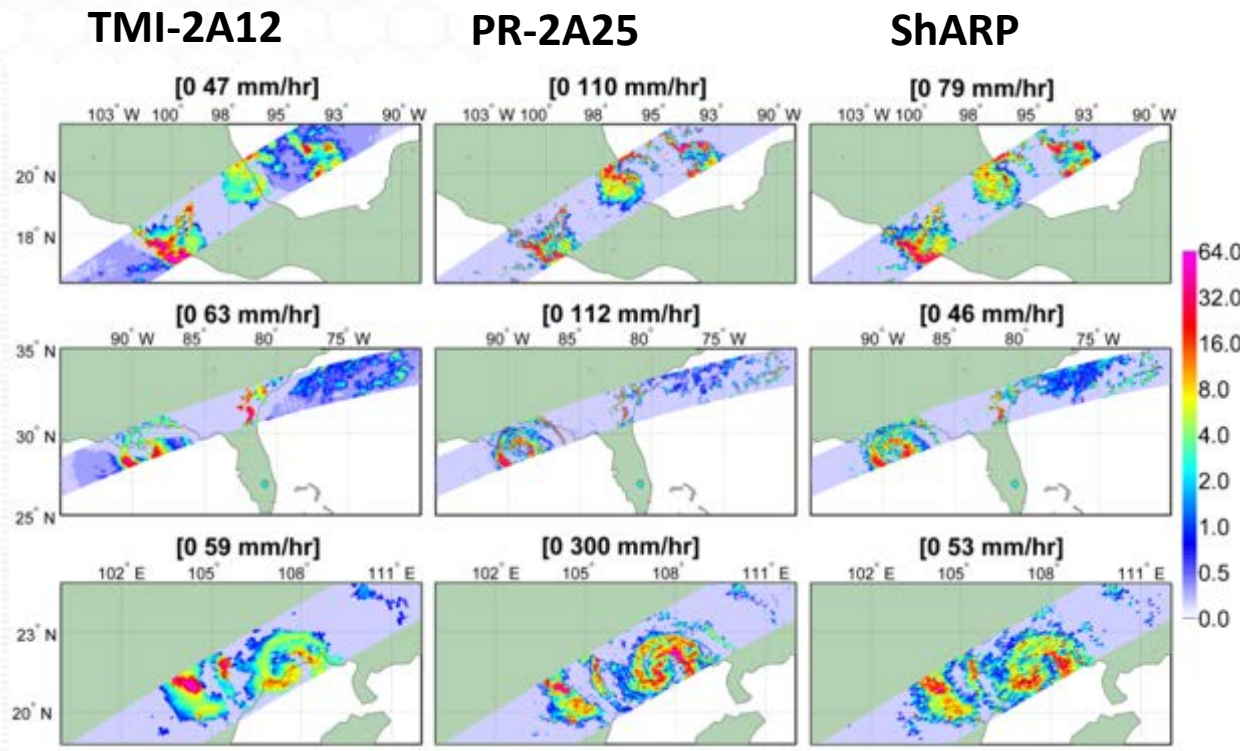


Ardeshir M. Ebtehaj, Rafael L. Bras, Efi Foufoula-Georgiou (2014) Shrunken Locally Linear Embedding for Passive Microwave Retrieval of Precipitation

PRECIPITATION RETRIEVAL : DICTIONARY BASED SHARP ALGORITHM



From left to right: TMI-2A12, PR-2A25 and ShARP retrievals. Top to bottom panels: hurricane Danielle in 08/29/2010 (orbit No. 72840) at 09:48 UTC; super typhoon Usagi in 09/21/2013 (orbit No. 90277) at 02:09 UTC; and tropical storm Helene in 09/15/2006 (orbit No. 50338) at 14:34 UTC.



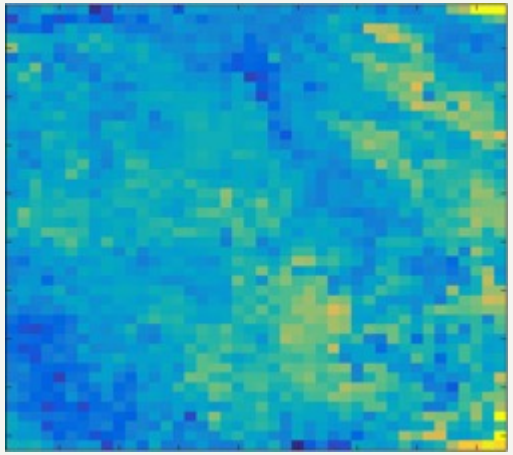
From left to right: TMI-2A12, PR-2A25 and ShARP retrievals. Top to bottom panels: tropical storm Fernand in 08/26/2013 (orbit No. 89874) at 05:30 UTC, hurricane Isaac in 28/08/2012 (orbit No. 84227) at 22:12 UTC and typhoon Kai-takin 08/17/2012 (orbit No. 84050) at 13:35 UTC.

SOIL MOISTURE ACTIVE PASSIVE (SMAP)

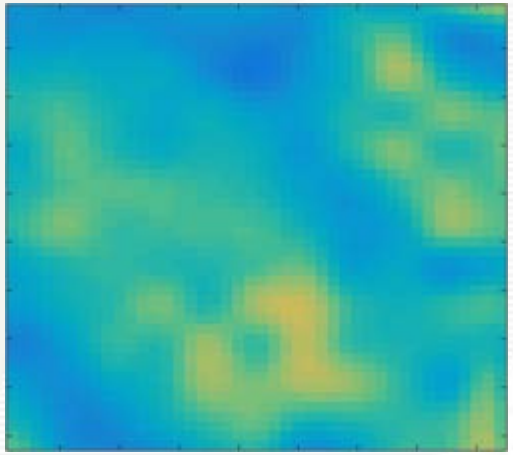
Active Radar: 3 km
Passive Radiometer: 40 km
Combined: 10 km

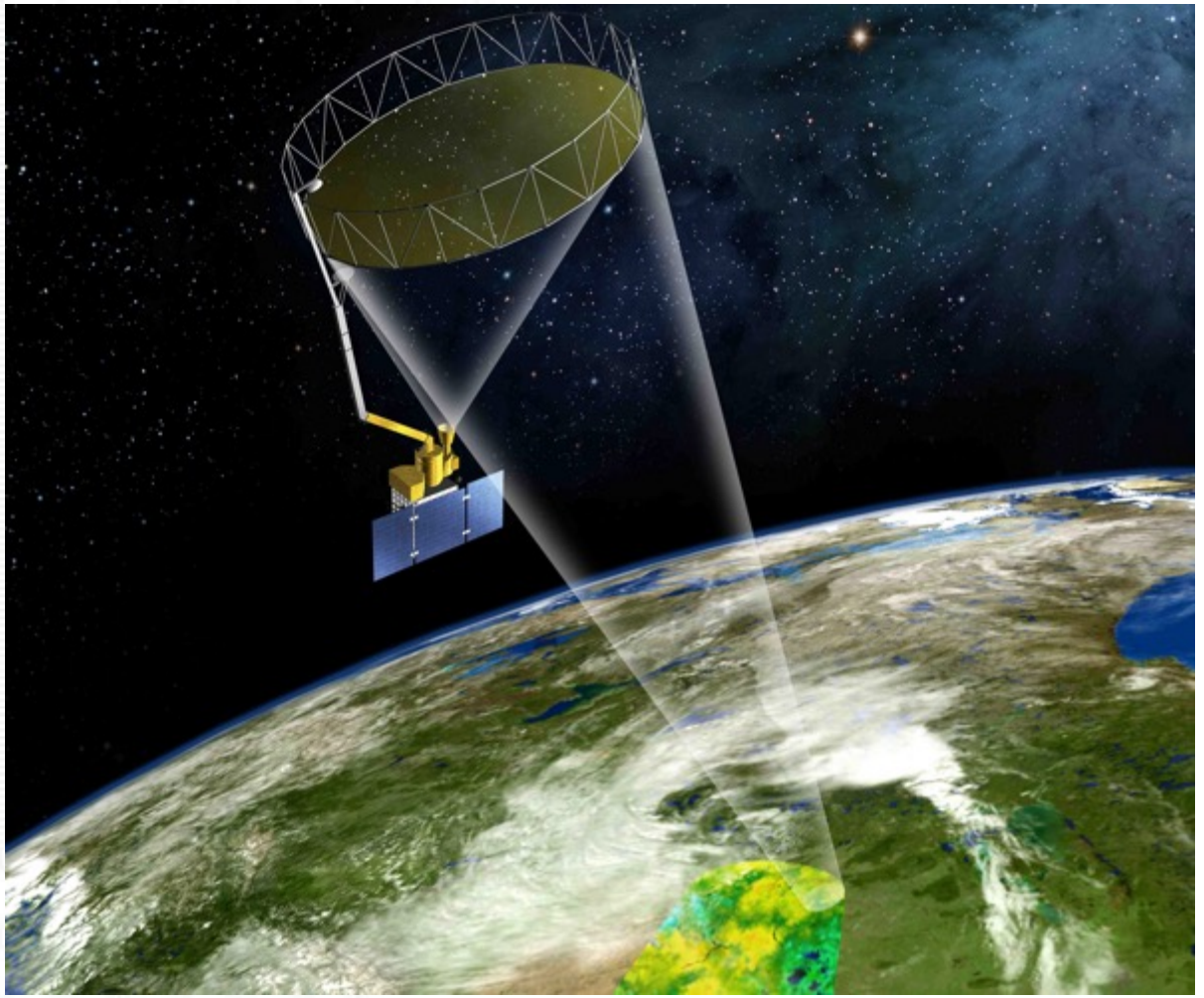
Resolution loss with radar failure:

Radiometer + Radar



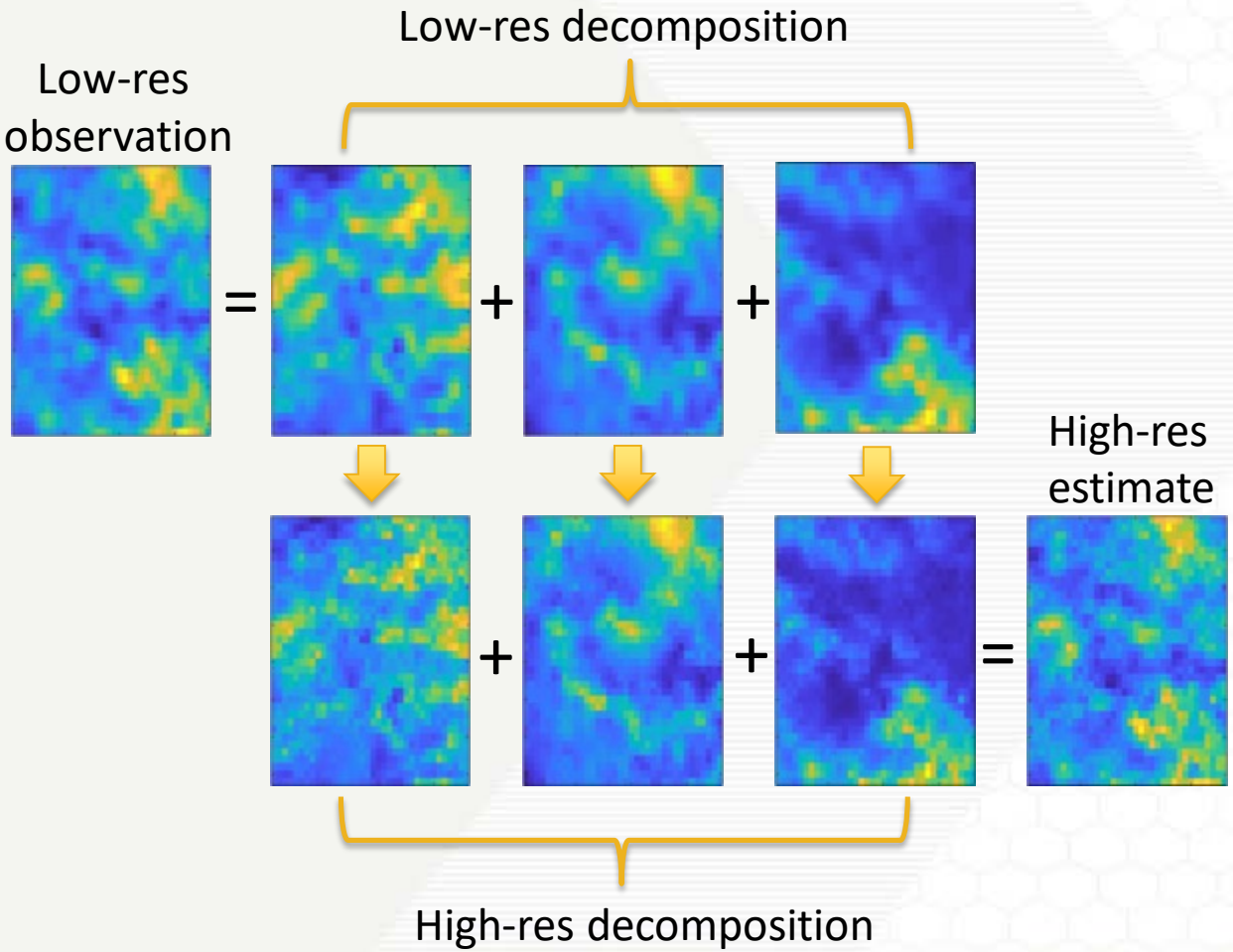
Radiometer Only



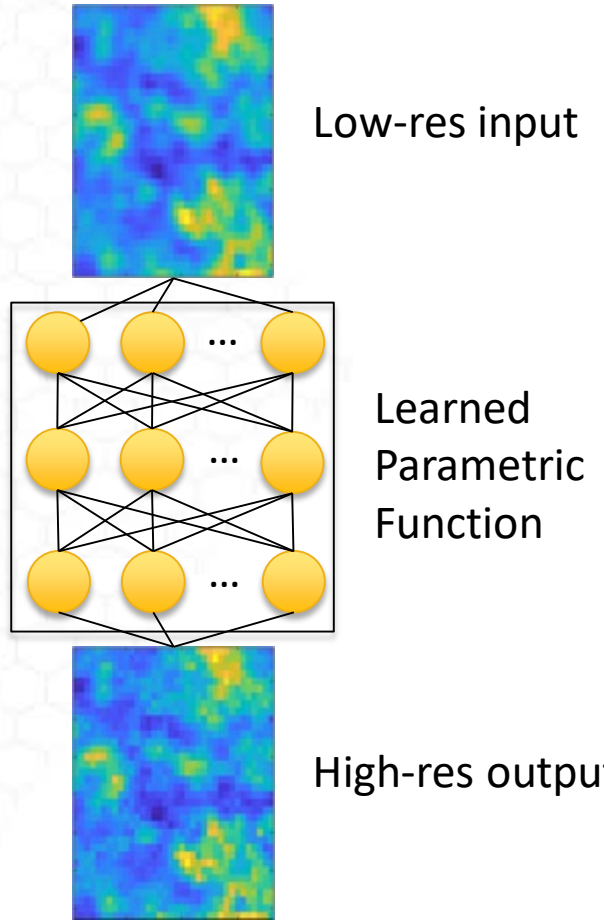


BLACK BOX SUPER-RESOLUTION METHODS

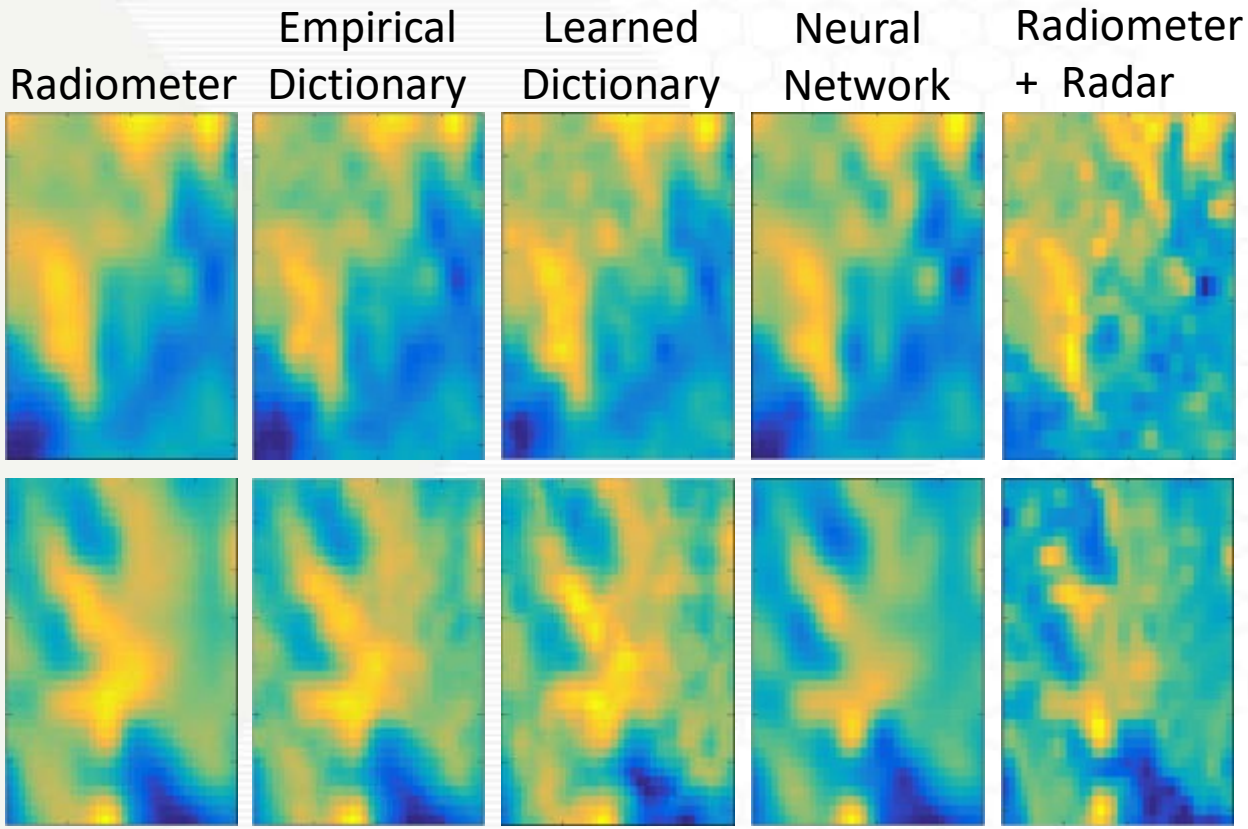
Dictionary Methods



Convolutional Neural Network



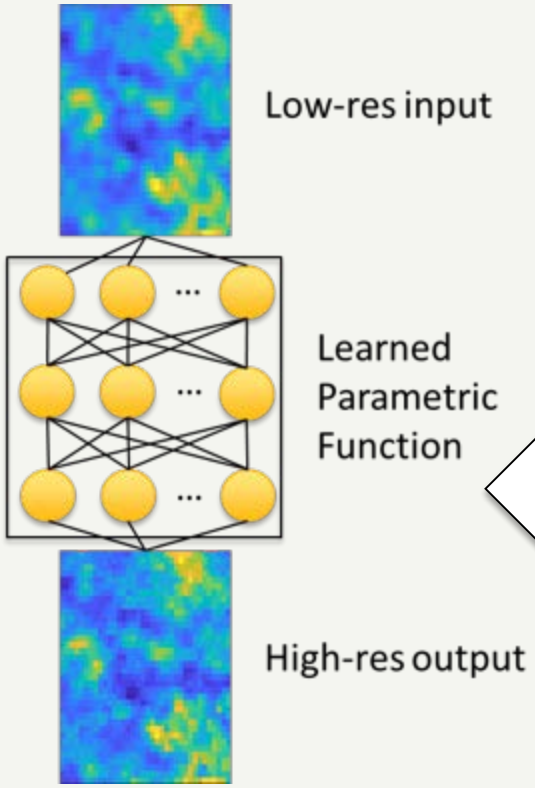
BLACK BOX SUPER-RESOLUTION OF SMAP



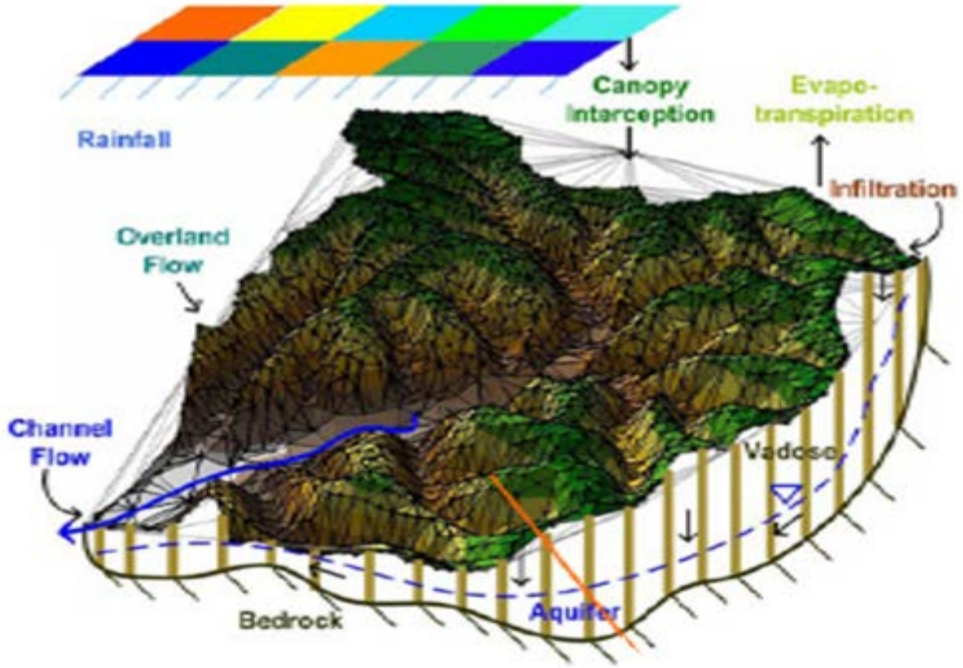
Training on all “complete” patches

Average ~1% improvement in MSE

HYBRID DATA ANALYTICS METHOD



Guide/Teach ML on how physical system behave



Machine learning (ML) models:
Based on historical information

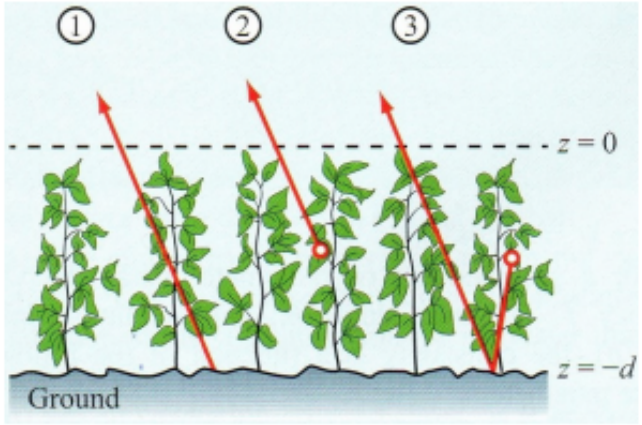
Physical models (e.g., tRIBS): Account of the soil's hydrological conditions, includes climatic variables to model terrestrial water balance

SOIL MOISTURE RETRIEVAL ALGORITHM

Soil moisture retrieval using Inversion of τ-ω model

The τ-ω model at L-Band:

① Emission by the soil surface: $(1 - r_p)\gamma T_s$
② Emission by the vegetation: $(1 - \omega)(1 - \gamma)T_c$
③ Emission by the vegetation followed by soil reflection: $r_p(1 - \omega)(1 - \gamma)\gamma T_c$



$$Tb_p = (1 - r_p)\gamma T_s + (1 - \omega)(1 - \gamma)T_c + r_p(1 - \omega)(1 - \gamma)\gamma T_c$$

T_s and T_c: soil and canopy temperature [K]

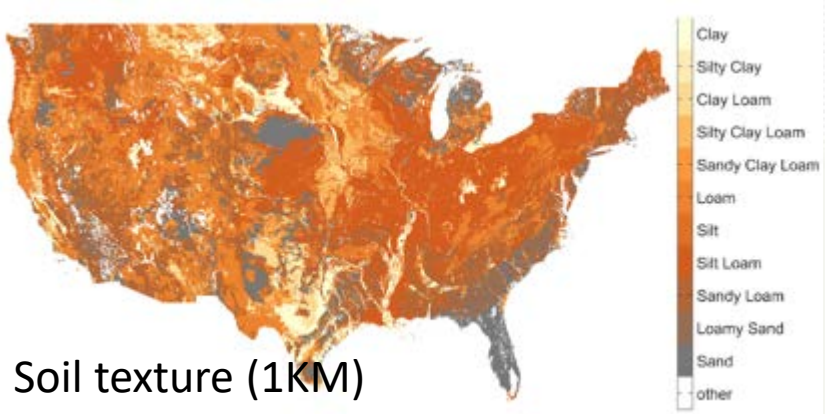
r_p (soil reflectivity), γ (vegetation transmissivity), ω (single scattering albedo)

- **Single channel algorithm(SCA)**
- Double channel algorithm (LS inversion)(DCA)
- **Constrained multichannel algorithm (CMCA)**

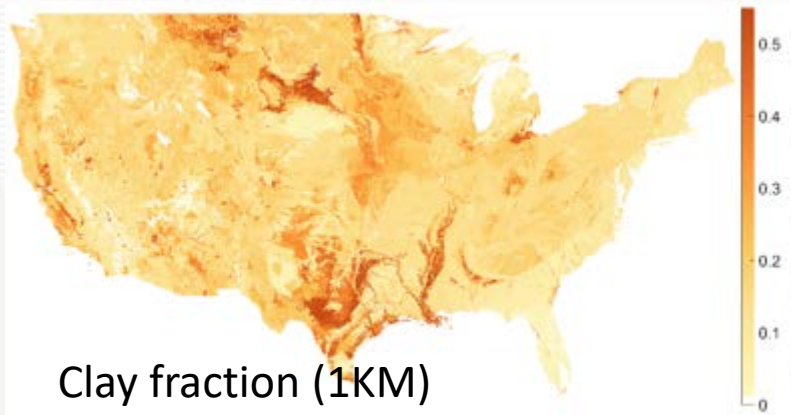
Example: Single channel algorithm

1. ω in constant and ϒ is estimated from NDVI climatology
2. Estimate r_p and infer soil moisture from Fresnel equation and a soil dielectric model

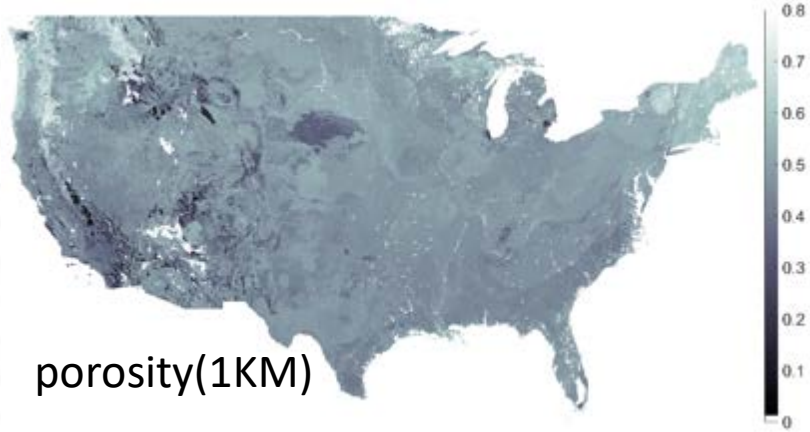
CONSTRAINED MULTICHANNEL RETRIEVAL ALGORITHM (CMCA): INVERSION PHYSICAL BOUNDS



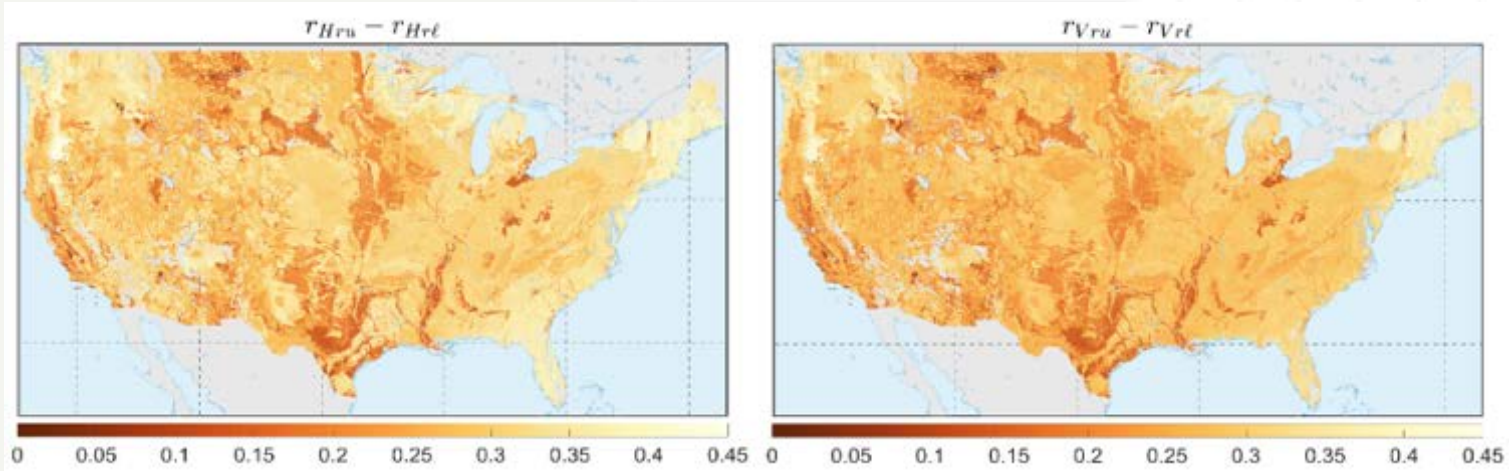
Soil texture (1KM)



Clay fraction (1KM)



porosity(1KM)



Soil reflectivity (1KM, f=1.6 GHz)

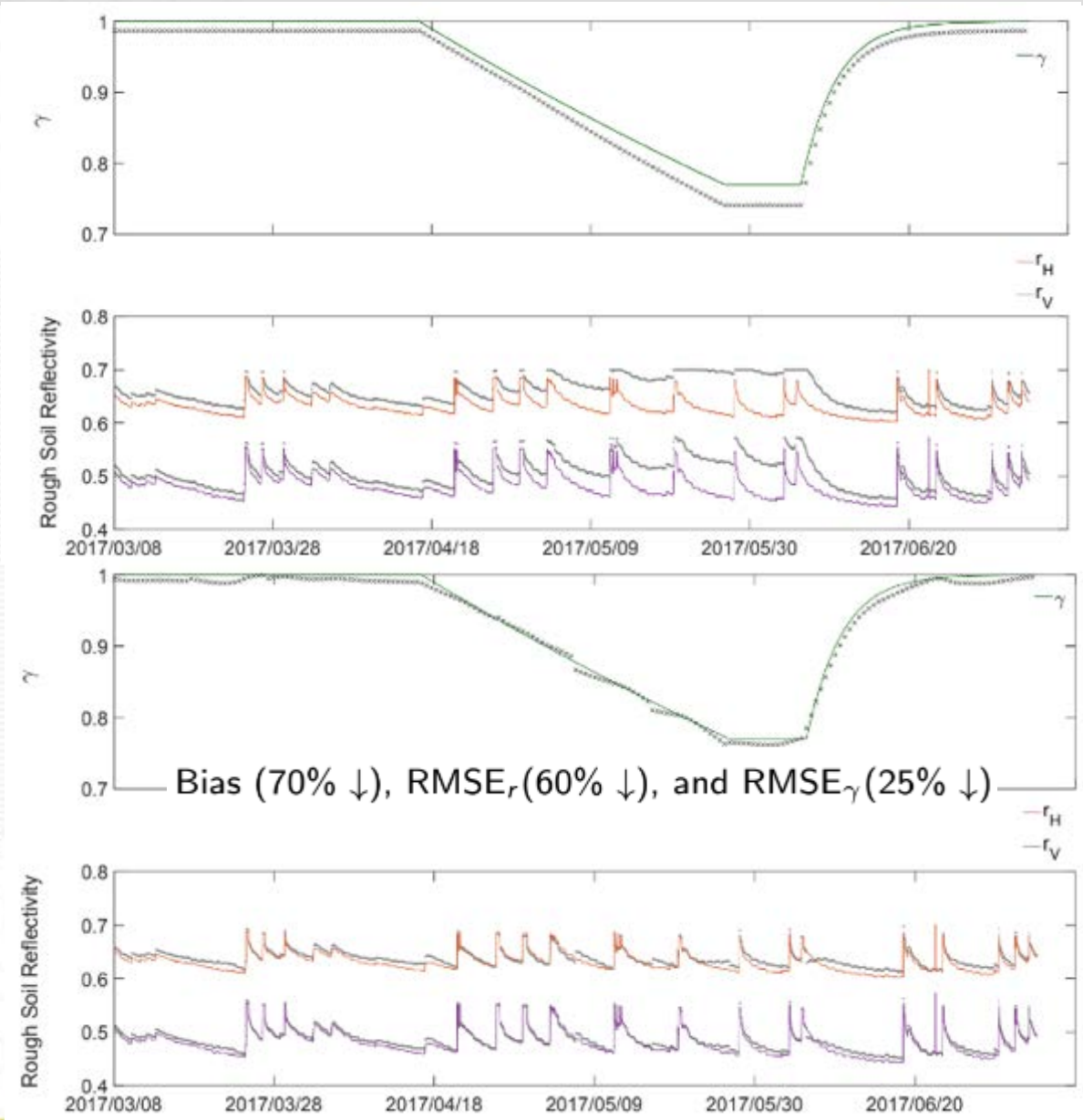
(Miller and White, 1998)

TIME SERIES EXPERIMENT: RETRIEVAL WITH AND WITHOUT PHYSICAL CONSTRAIN

Soil Climate Analysis Network gauge station in Arkansas, US

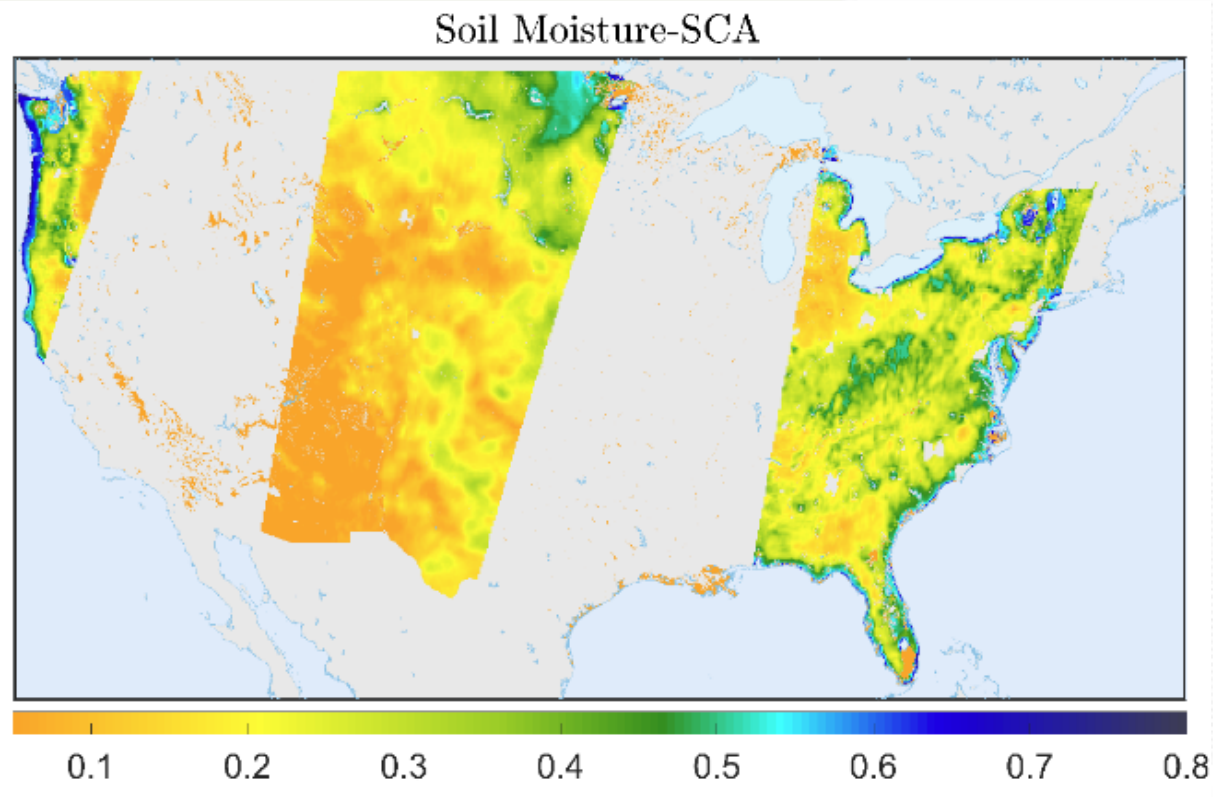
Soil moisture retrieval → Without physical constrain

With physical constrain

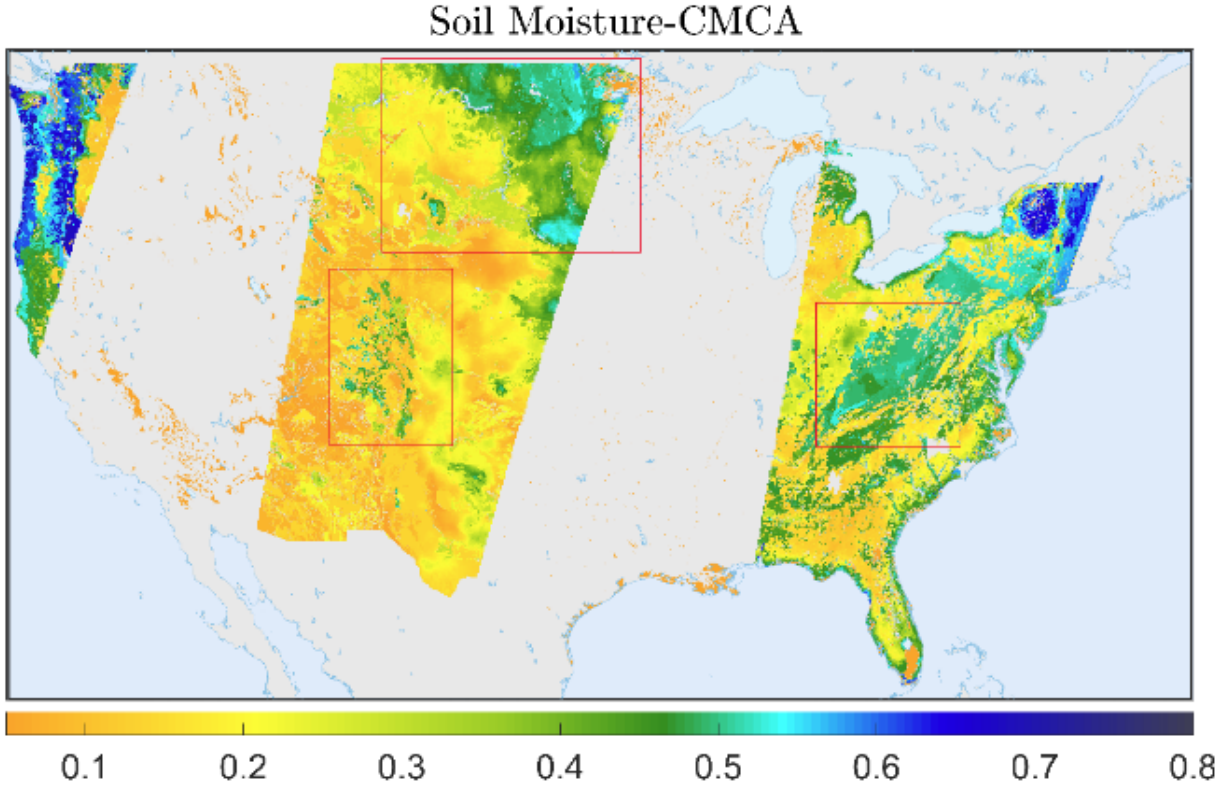


SOIL MOISTURE RETRIEVAL: IMPLEMENTATION FOR SMAP DATA

SMAP overpass on 06/01/2016-SCA official NASA product at 9km

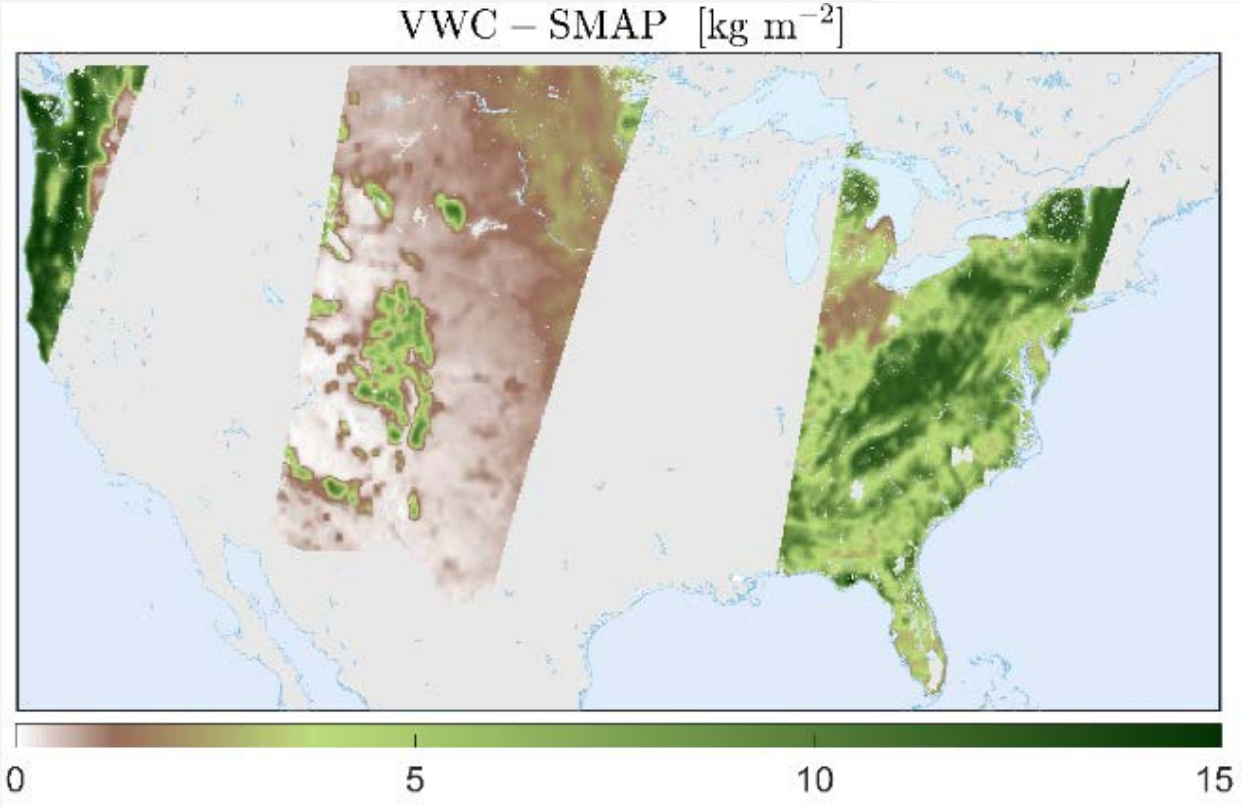


SMAP overpass on 06/01/2016-CMCA at 1km

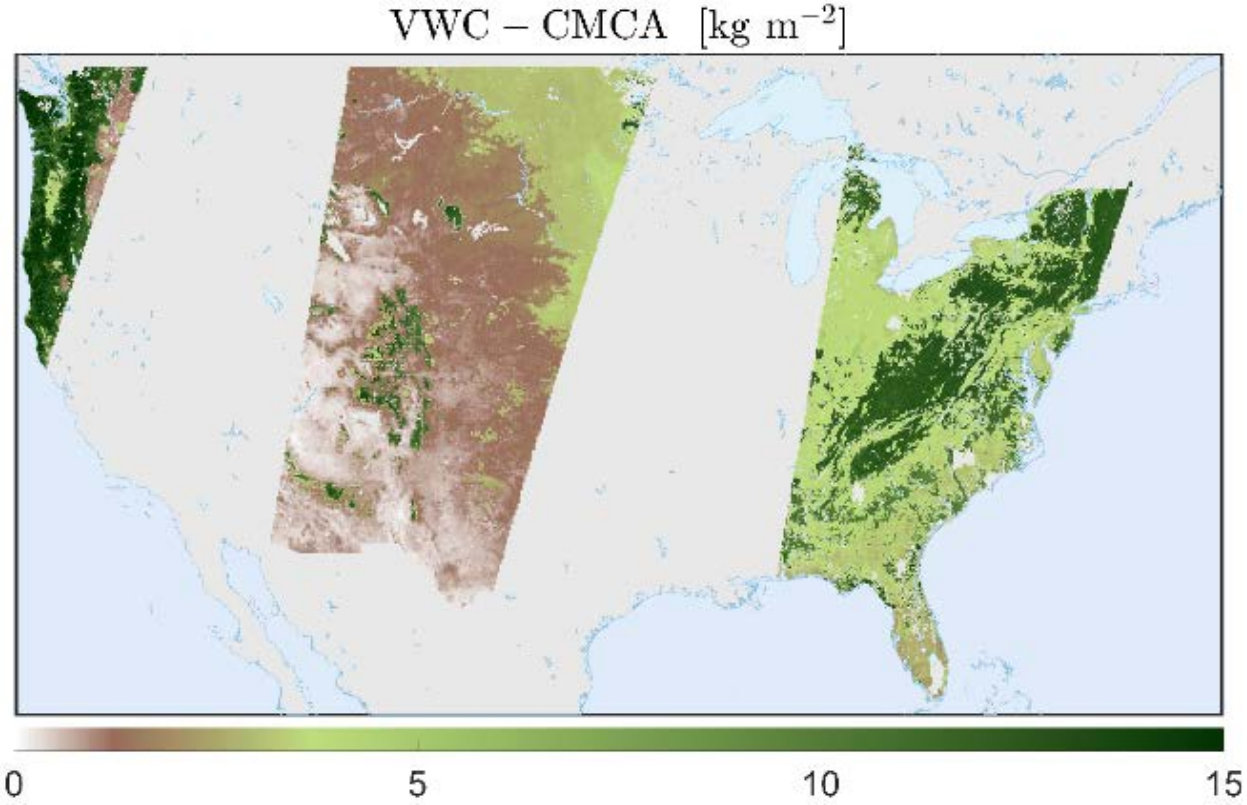


VWC RETRIEVAL: IMPLEMENTATION FOR SMAP DATA

SMAP overpass on 06/01/2016-SCA official NASA product at 9km

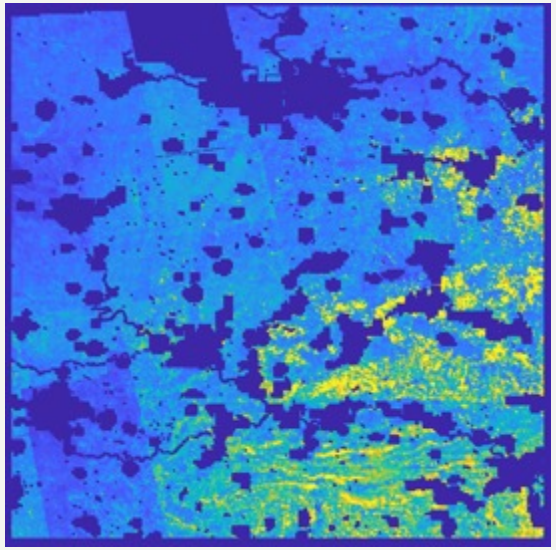


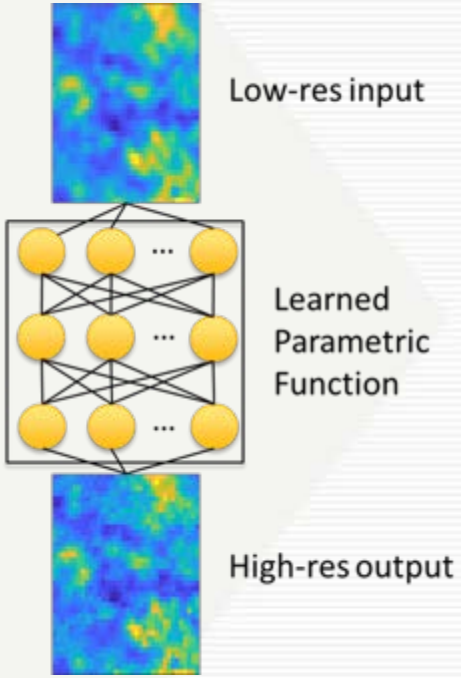
SMAP overpass on 06/01/2016-CMCA at 1km



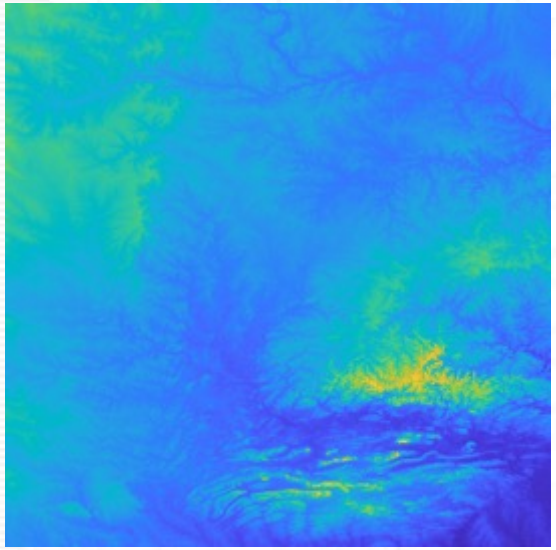
PHYSICALLY RELEVANT FEATURES

Soil Moisture

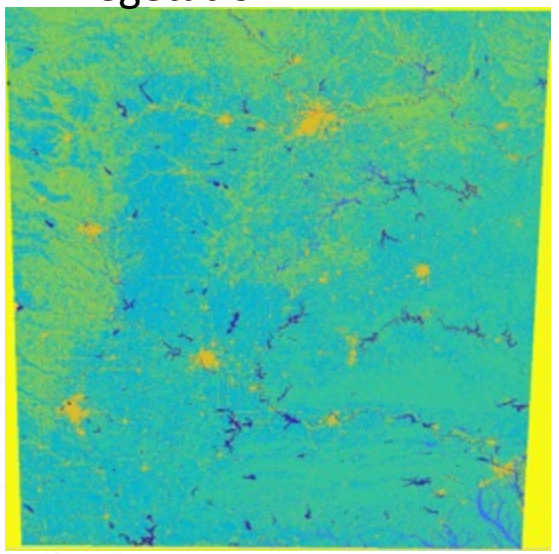




Topography



Vegetation



Soil Features

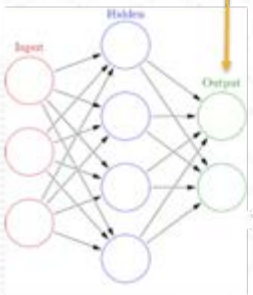
Era of Data Rich Hydrology

AVHRR/MODIS /Landsat

SMOS, TRMM, GPM, SMAP

Evolution of big data approach in Hydrology

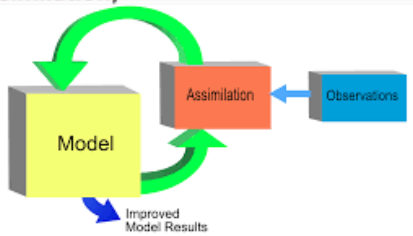
Spatially distributed physically based models (e.g., tRIBS, MIKE SHE)

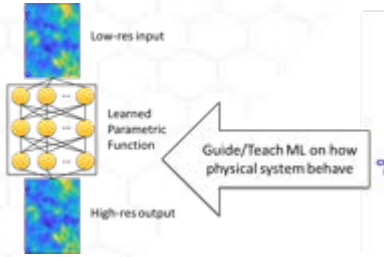


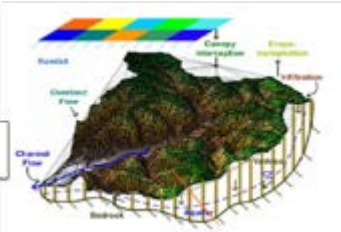
Machine/deep learning (Super resolution for downscaling)

Hybrid Analytics (Combining machine learning with physically based models)

Reliable estimation of geospatial data, model forcing, parameter estimation, state estimation (**data assimilation**)







Thank you!