5th International Earth Surface Working Group Meeting, Helsinki, Finland,
26-28 September, 2023

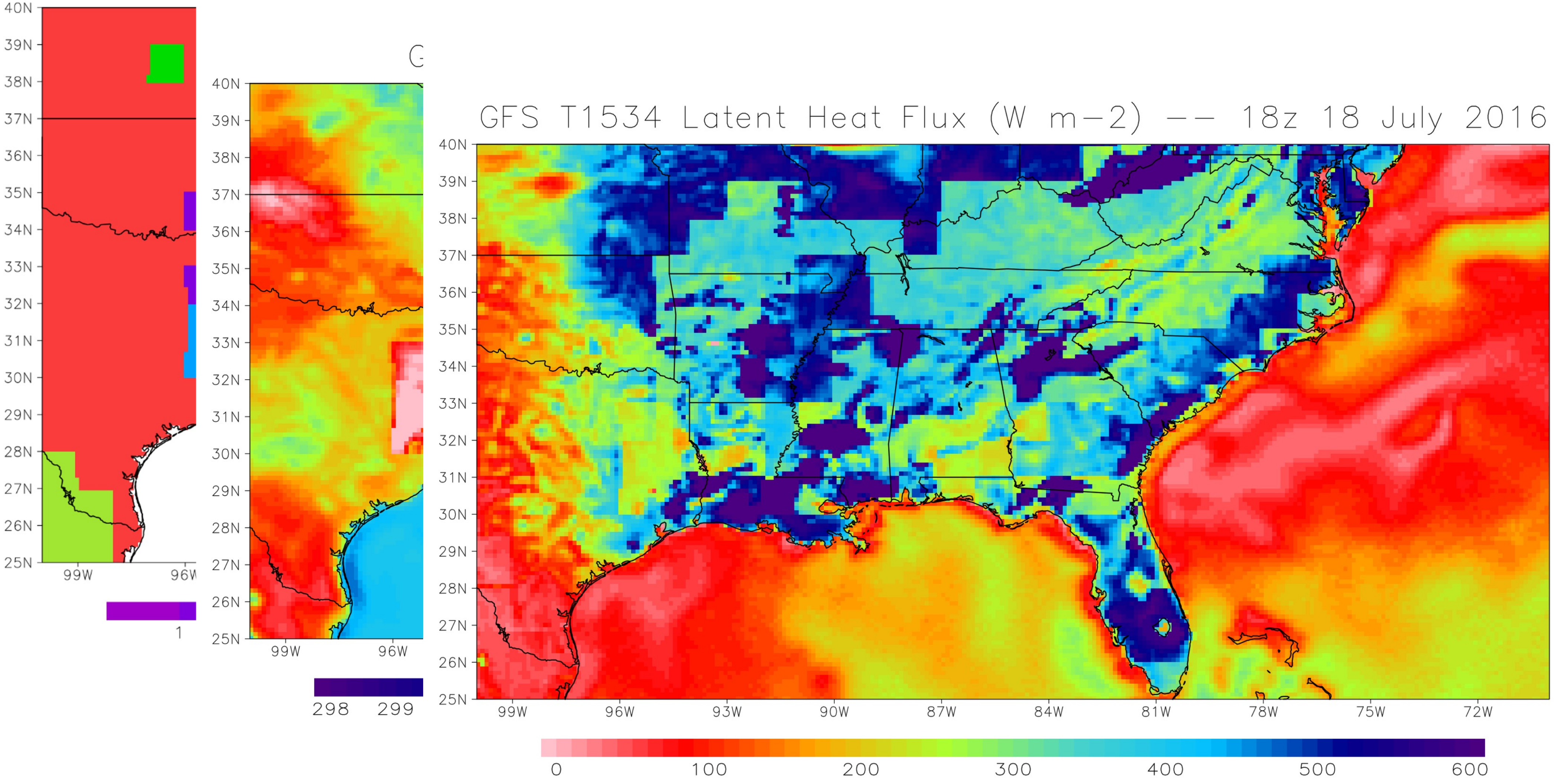
Land Surface Satellite Data Products from NOAA NESDIS for Numerical Weather and Water Prediction Models and Societal Applications

Xiwu Zhan, Chengquan Huang, Jifu Yin, Jicheng Liu, Li Fang, Wei Guo, Yan Luo, et al.

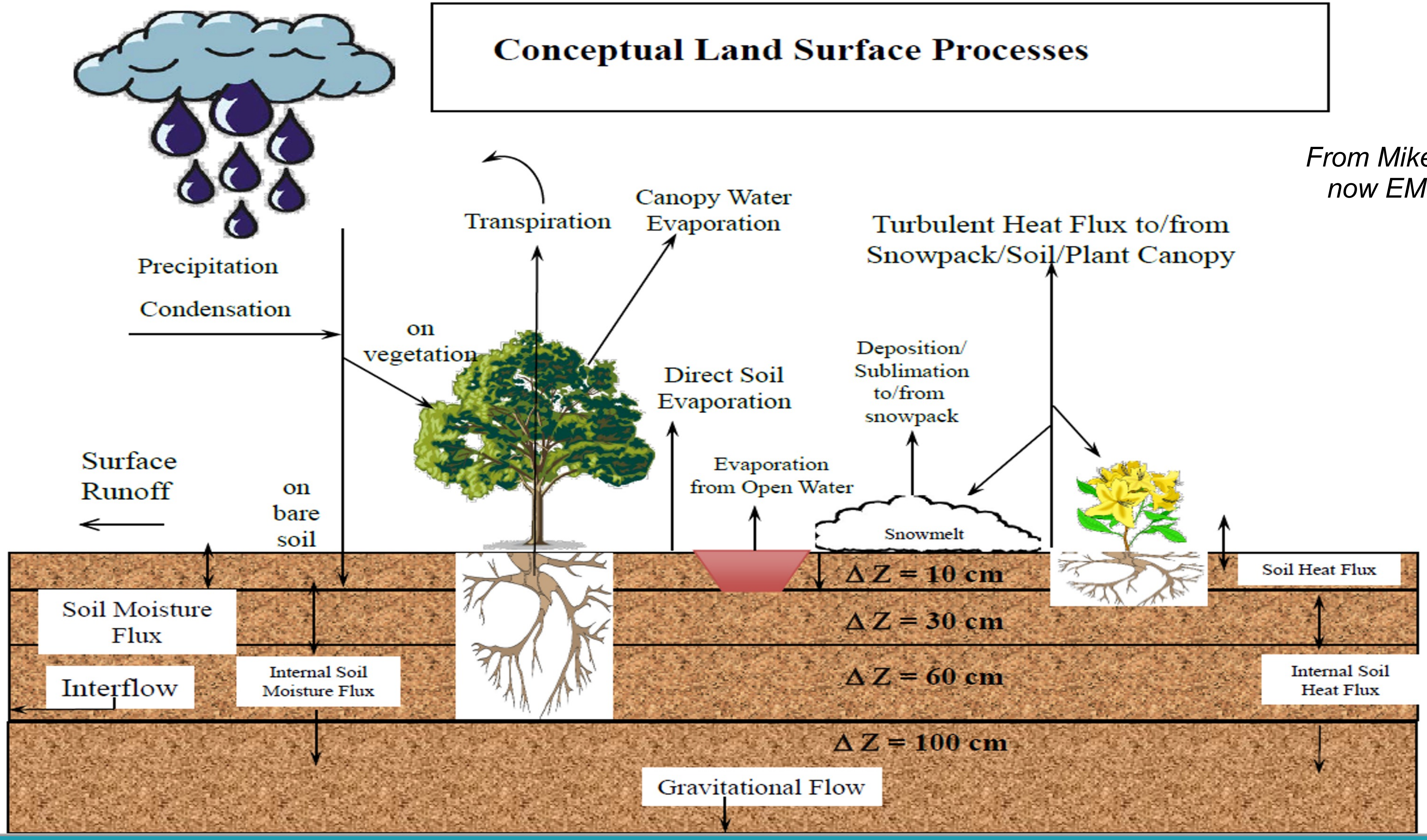
NESDIS-STAR, UMD-CISESS, IMSG

NOAA
National Satellite, Data, and Information Service (NESDIS)

A NCEP-EMC Story on Surface Type in NWP Models

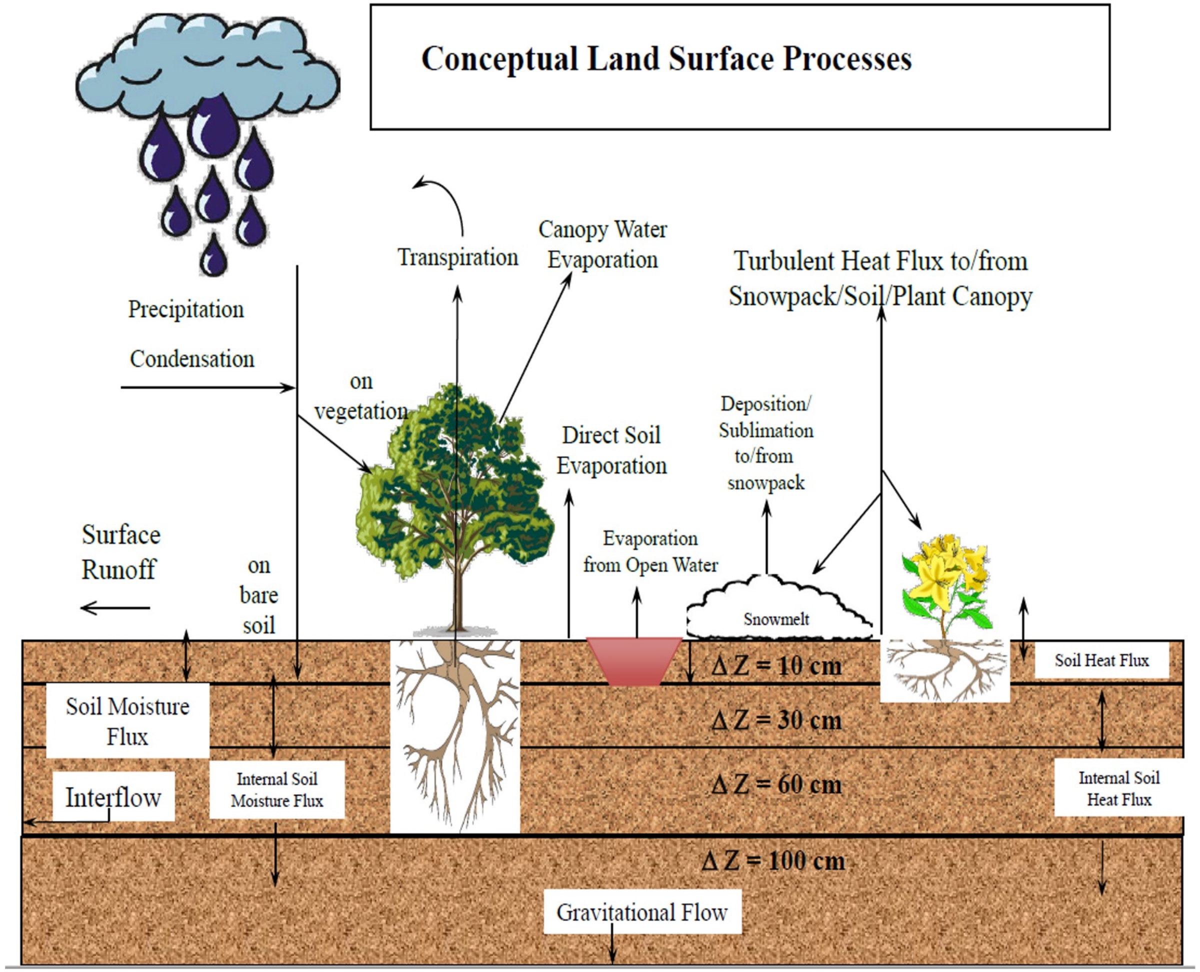


Noah/Noah-MP Land Surface Model for NWP and NWM



From Mike Barlage of NCAR, now EMC Land Team Lead

Noah/Noah-MP Land Surface Model for NWP and NWM



LSM primary inputs:

- Surface type
- Green vegetation fraction
- Leaf area index
- Albedo

LSM state variables or fluxes:

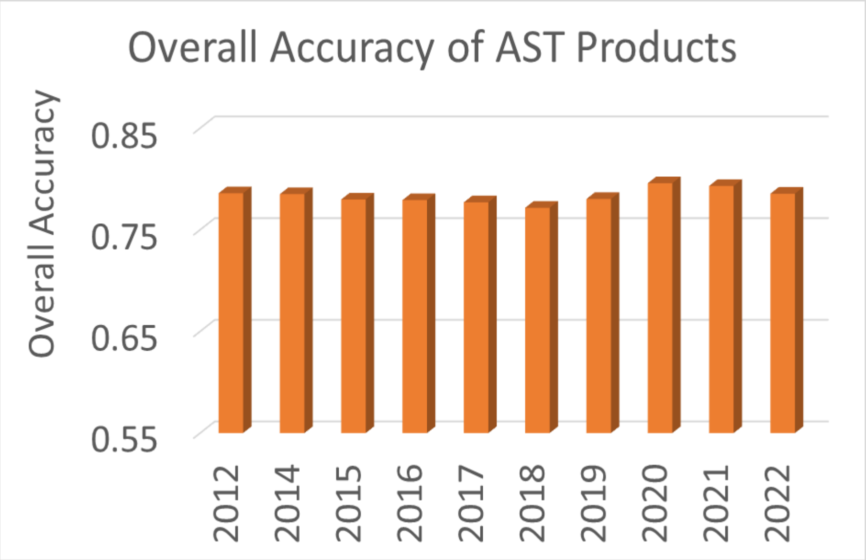
- Land surface temperature
- Soil moisture
- Evapotranspiration/Latent heat flux
- …

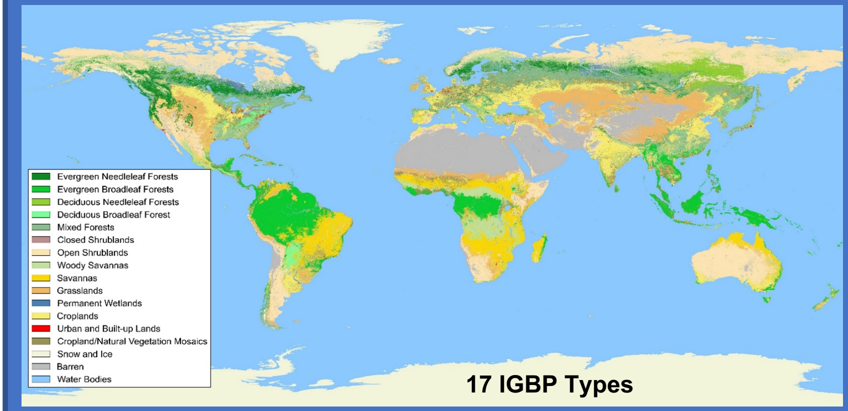
OUTLINE: NOAA Satellite Land Products and Applications

Satellite Land Products	Application Areas
Surface Type/Land cover	LSM input parameter
Surface Soil Moisture	LSM state variable Initialization, output verification, parameter calibration, and data assimilation (DA) Monitoring of drought, flooding, heat wave, etc.
Land Surface Temperature	
Land Surface Albedo	
Green Vegetation Fraction	
Leaf Area Index	
Evapotranspiration	LSM flux verification, parameter calibration, and DA, Drought monitoring, fire risk assessment
Vegetation Health Indices	Crop productivity monitoring and forecast, drought, commodity market outlook, fire risk assessment,

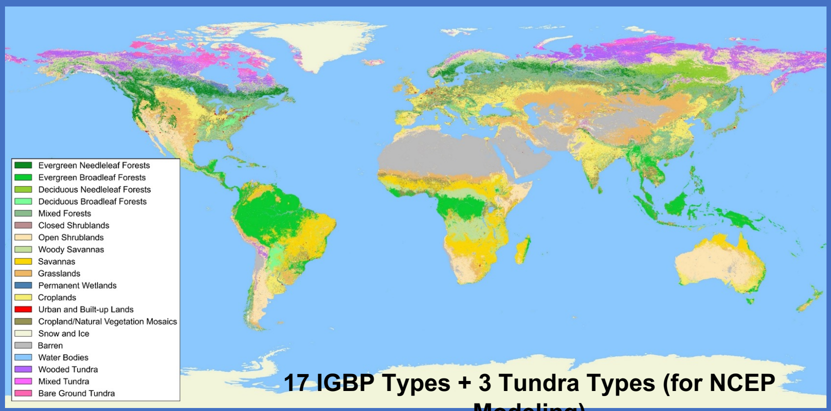
VIIRS **Annual Surface Type** Products (**AST**)

- Annual Surface Type (AST) Products (Since 2012)
  - Based on VIIRS observations acquired within one calendar year
  - Three classification legend systems
    - IGBP (17 types)
    - EMC (17 IGBP types + 3 Tundra types)
    - Biome for LAI/FPAR estimation (9 types)
  - Overall accuracies: ~78%
- Multi-Year Climatology Products
  - For use by EMC
  - Based on AST data from 2012 to 2019

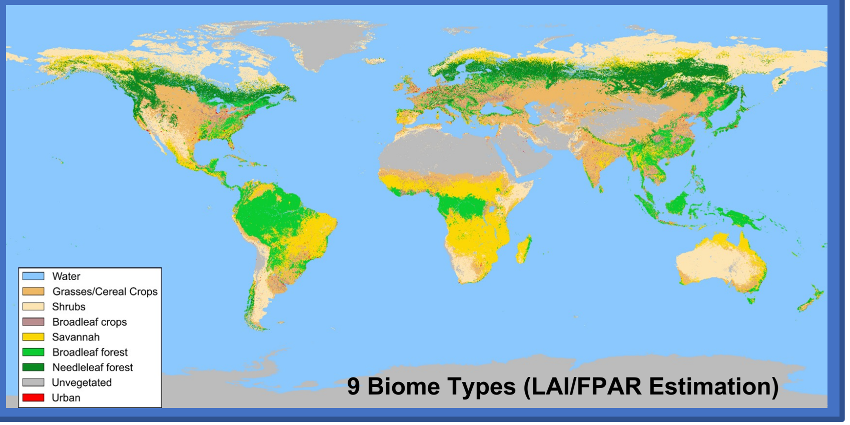




17 IGBP Types

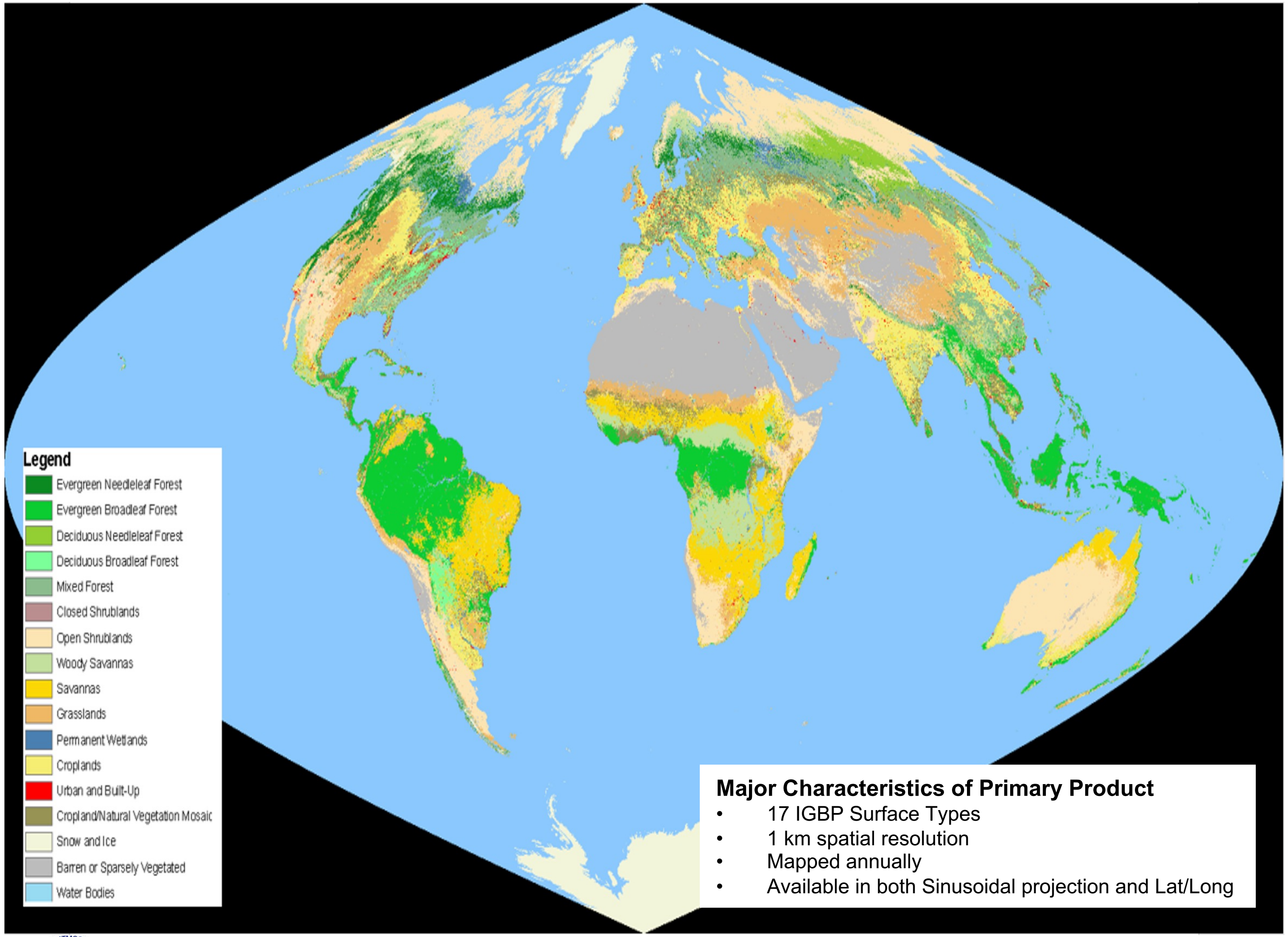


17 IGBP Types + 3 Tundra Types (for NCEP Modeling)



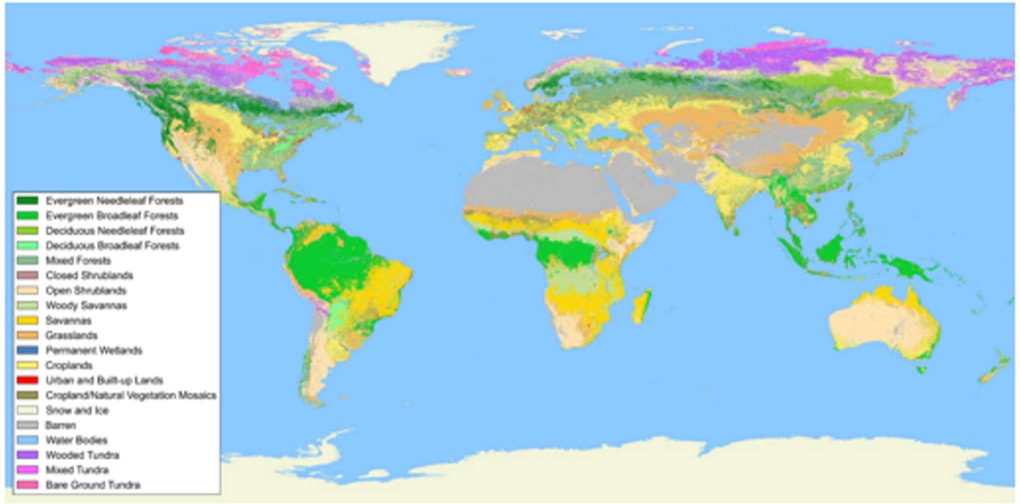
9 Biome Types (LAI/FPAR Estimation)

VIIRS **Annual Surface Type** Products (**AST**)

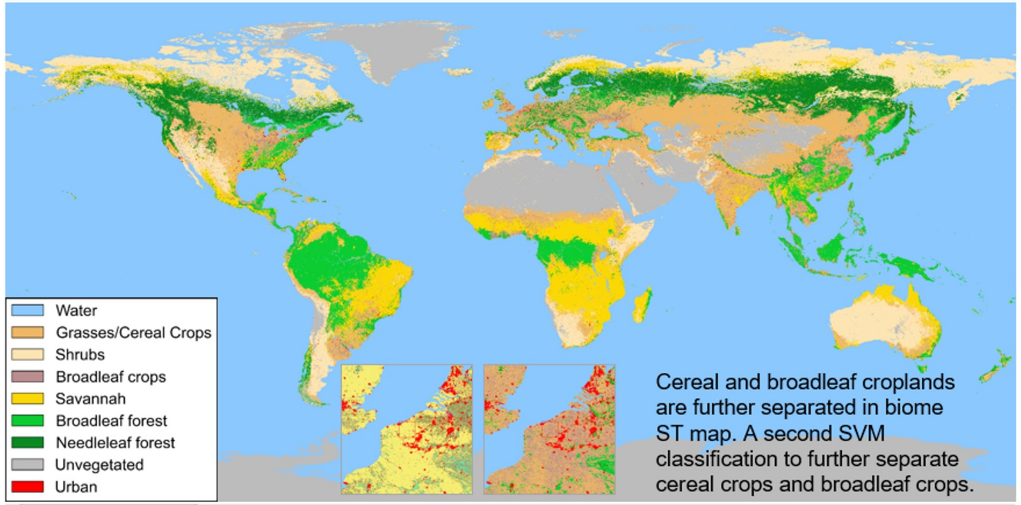


Major Characteristics of Primary Product

- 17 IGBP Surface Types
- 1 km spatial resolution
- Mapped annually
- Available in both Sinusoidal projection and Lat/Long

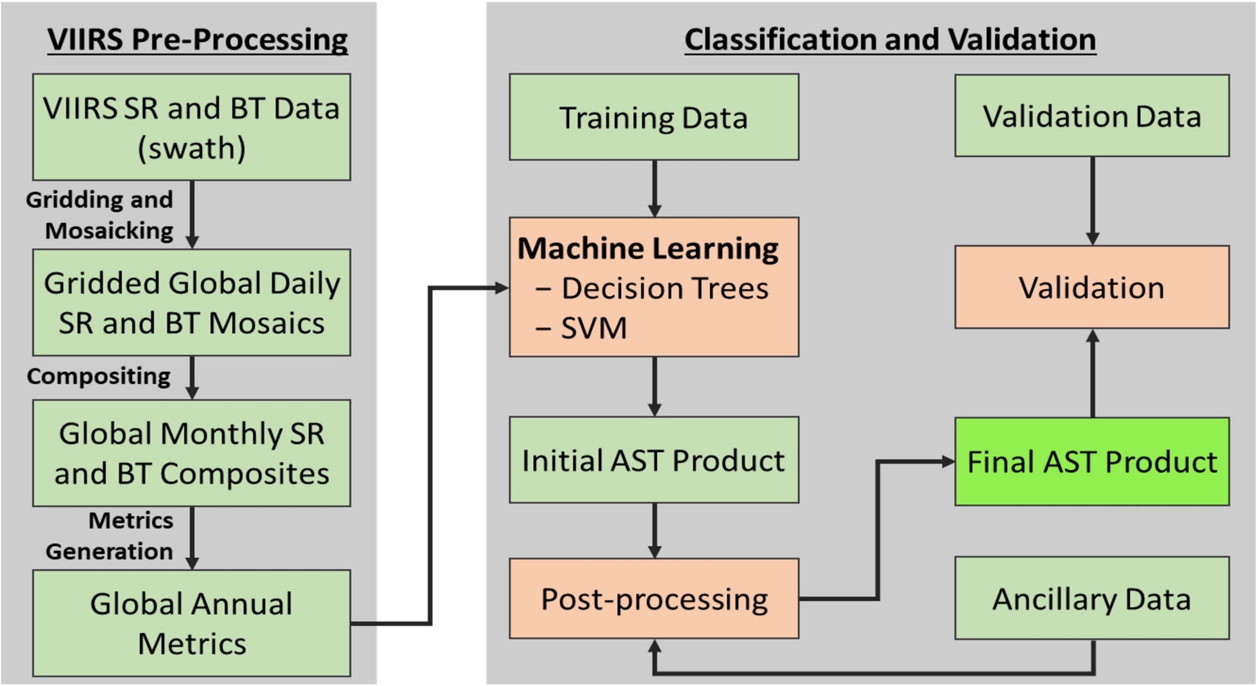


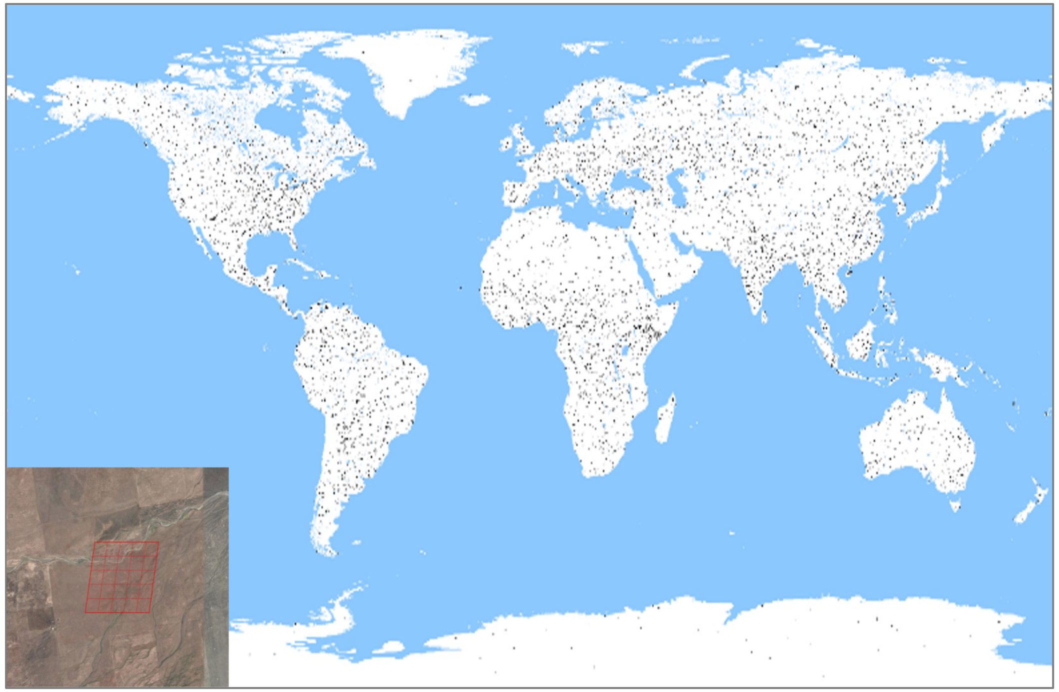
Surface Type map with classes needed to support NCEP modeling



Surface Type map with classes needed to support LAI/FPAR retrieval

AST Product Procedures and Algorithms





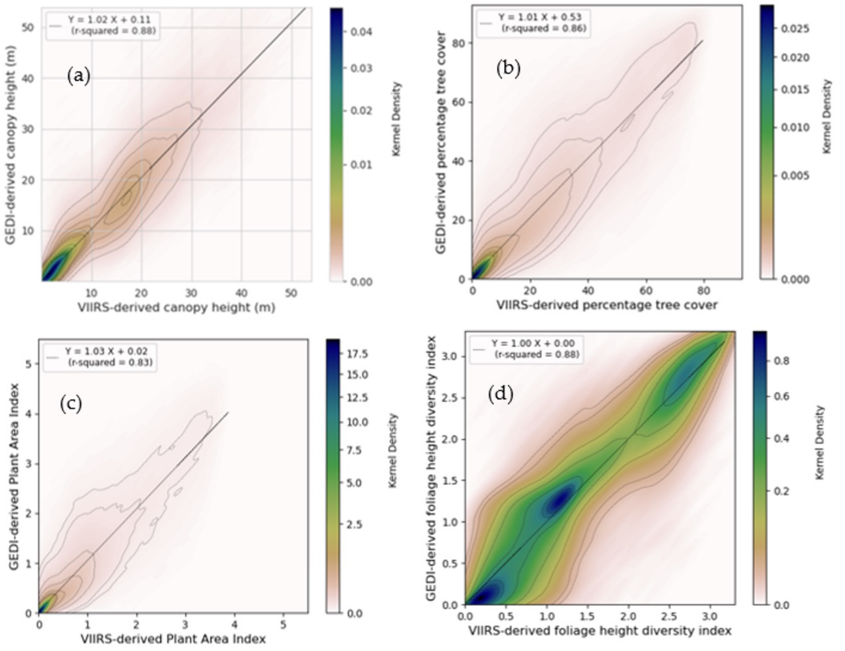
Large quantities of reference samples have been derived based on Google Earth and other available high resolution imagery

- Well distributed across the globe
- Highly reliable class labeling
- Training samples: > tens of thousands, add as needed
- Validation samples: ~6000 selected following a probability based sampling design.

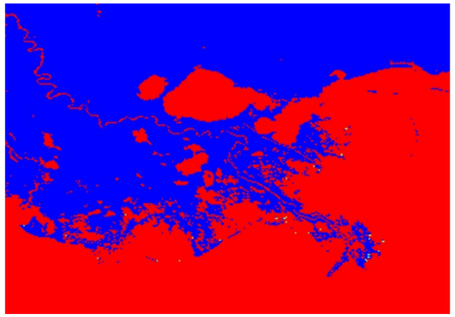
Challenges and Opportunities on **Surface Type**

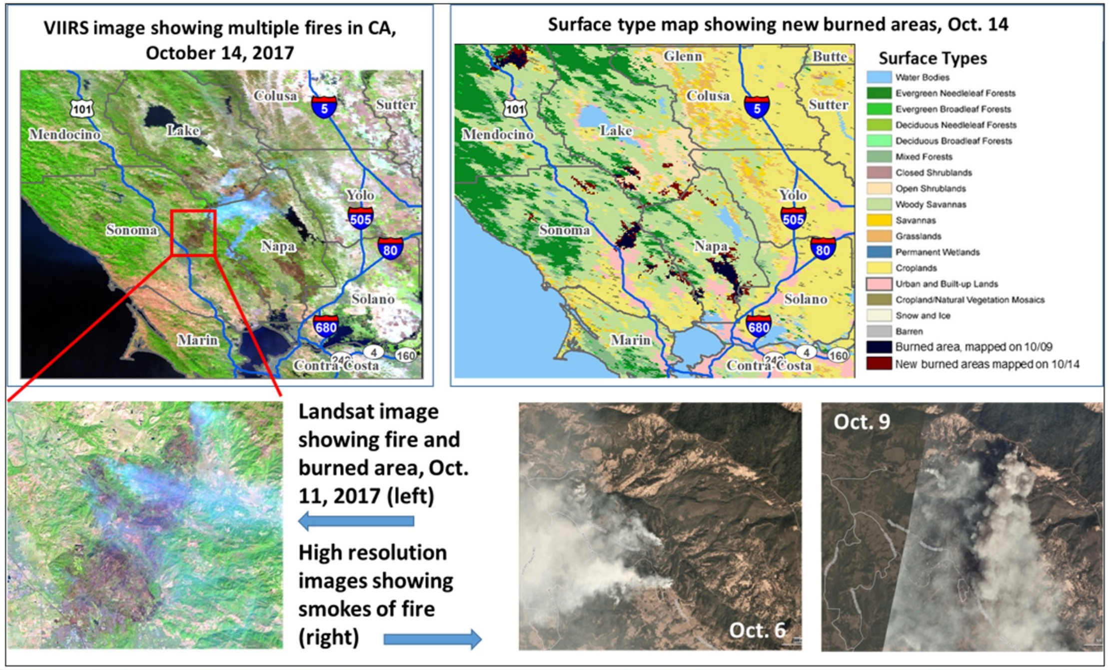
Machine Learning approaches for

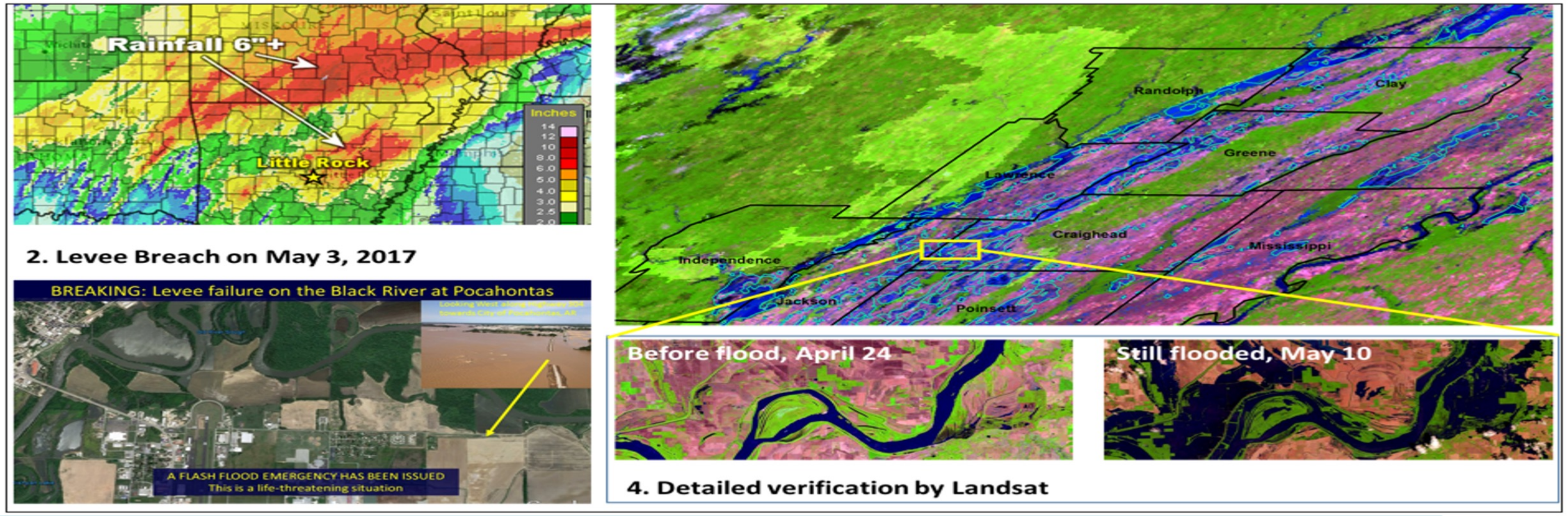
- Burned areas
- Flooded areas
- High resolution L/W, tree cover, etc.
- Vegetation structure parameters



Comparisons between VIIRS-derived and GEDI-derived: (a) canopy height; (b) canopy fraction cover; (c) plant area index; and (d) foliage height diversity



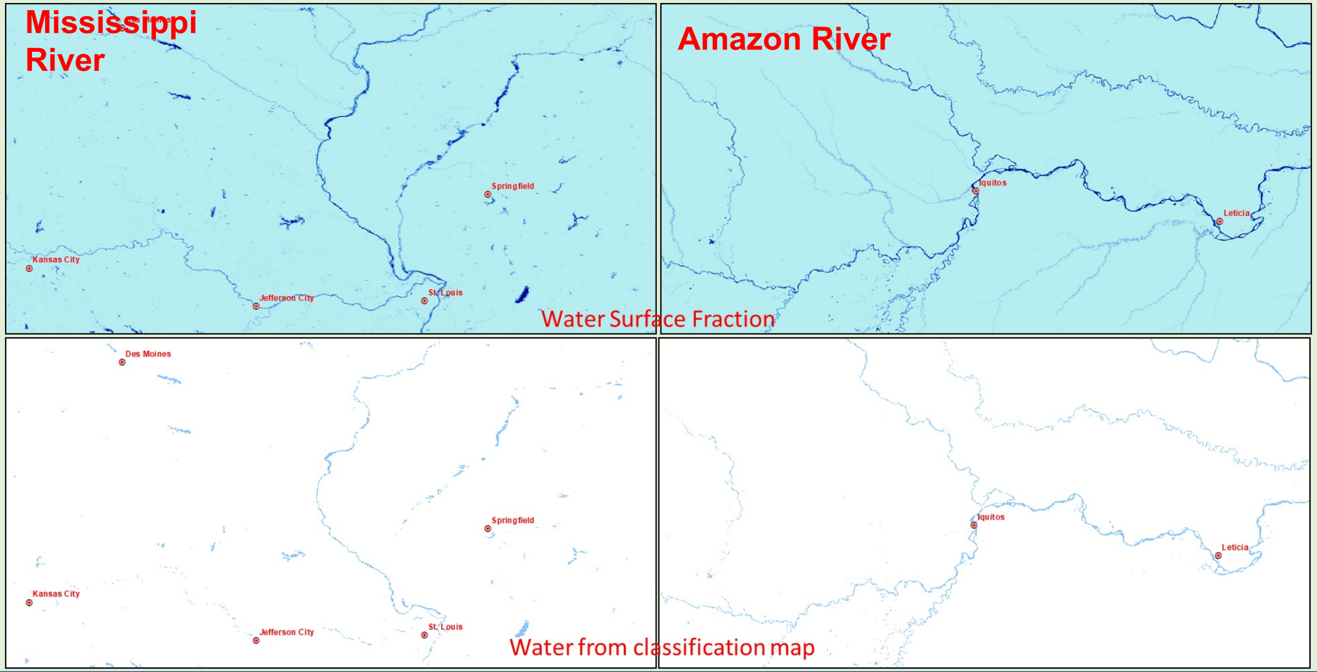




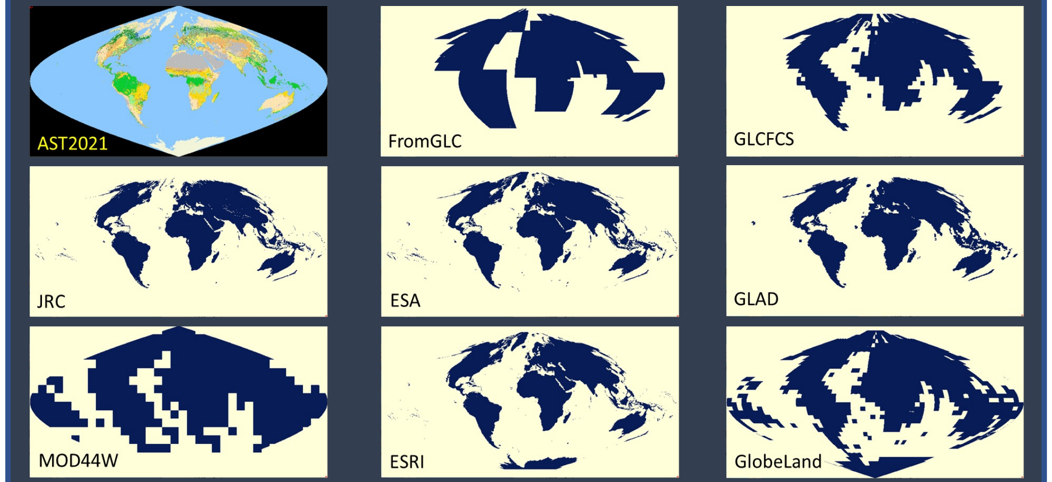
Water Surface Fraction (WSF) Product

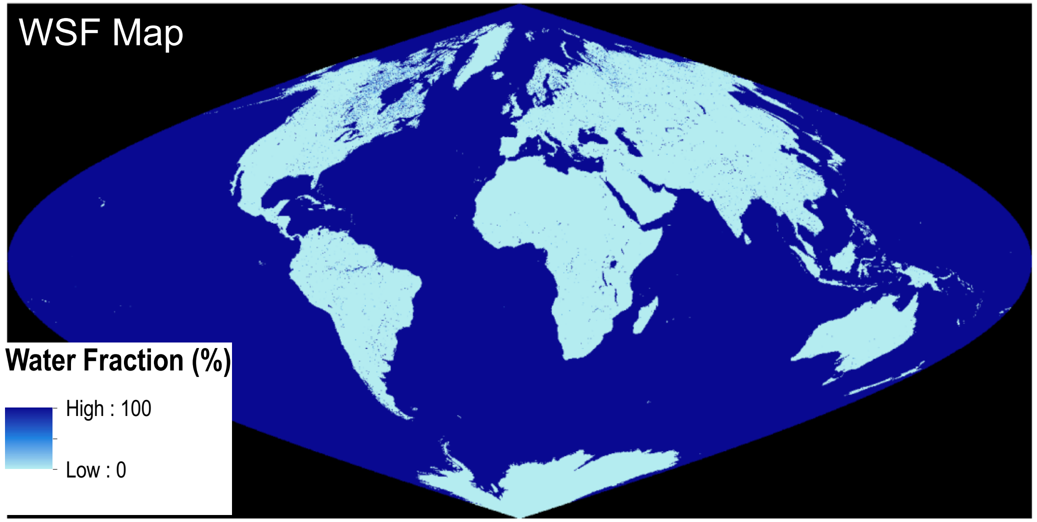
- Provide subpixel water estimates to improve the mapping of small waterbodies and narrow rivers
- Derived by synthesizing 9 circa-2020 global fine and moderate resolution land cover products
- Available at 1km and 250m resolutions

Greatly improved mapping of river channels by WSF



Inputs for deriving WSF

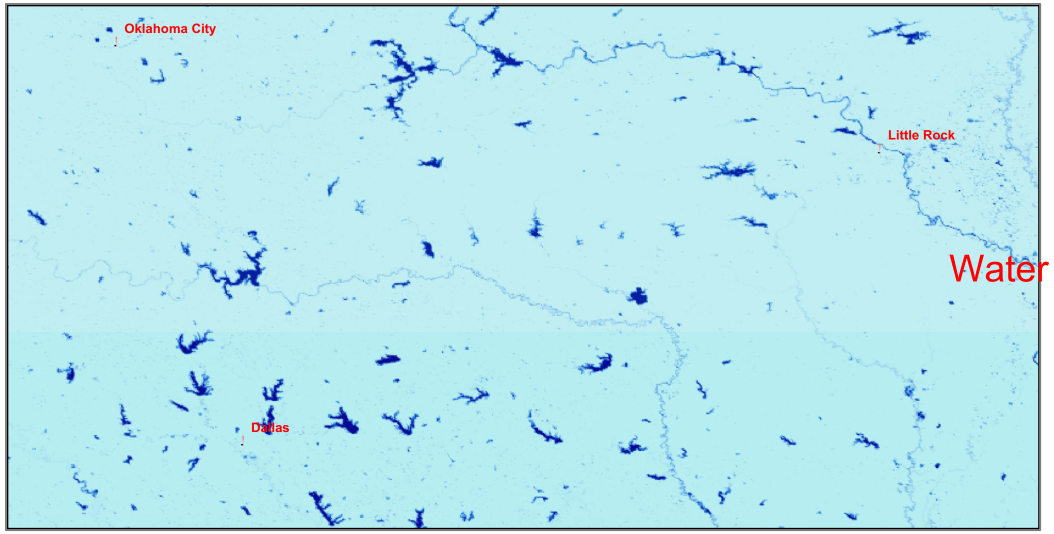


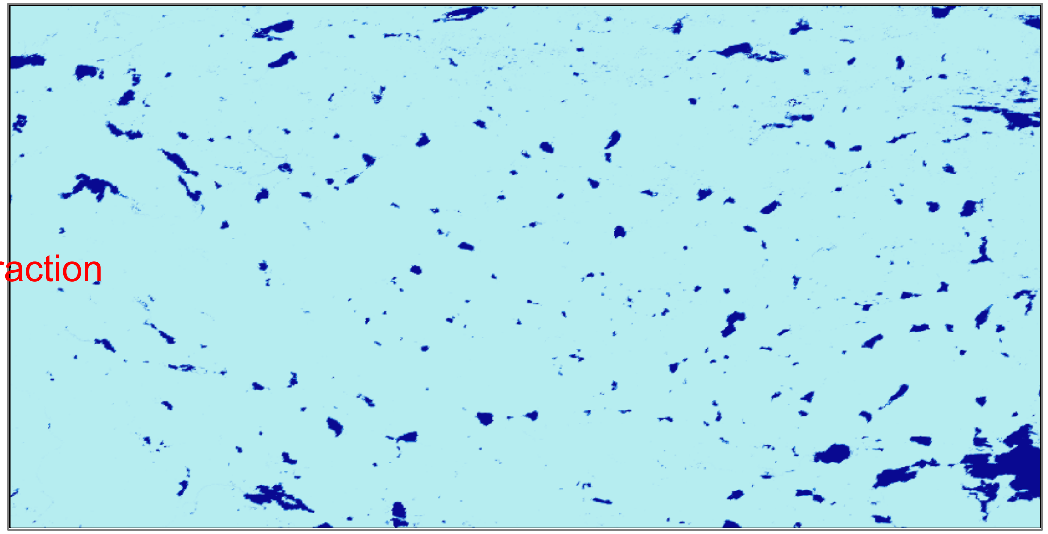


Many Small Lakes Captured by Water Surface Fraction Product

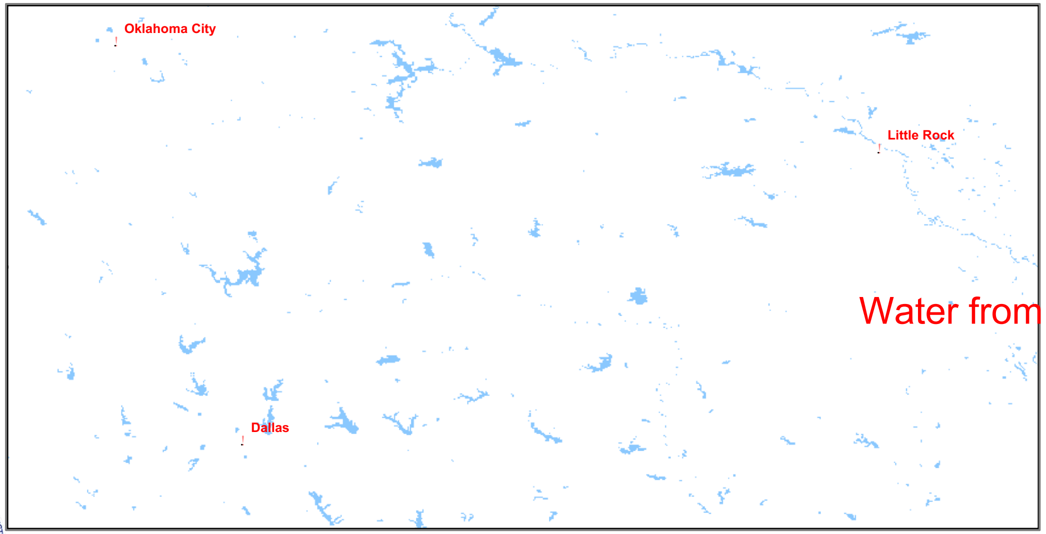
1. Lakes/Reservoirs in southern US

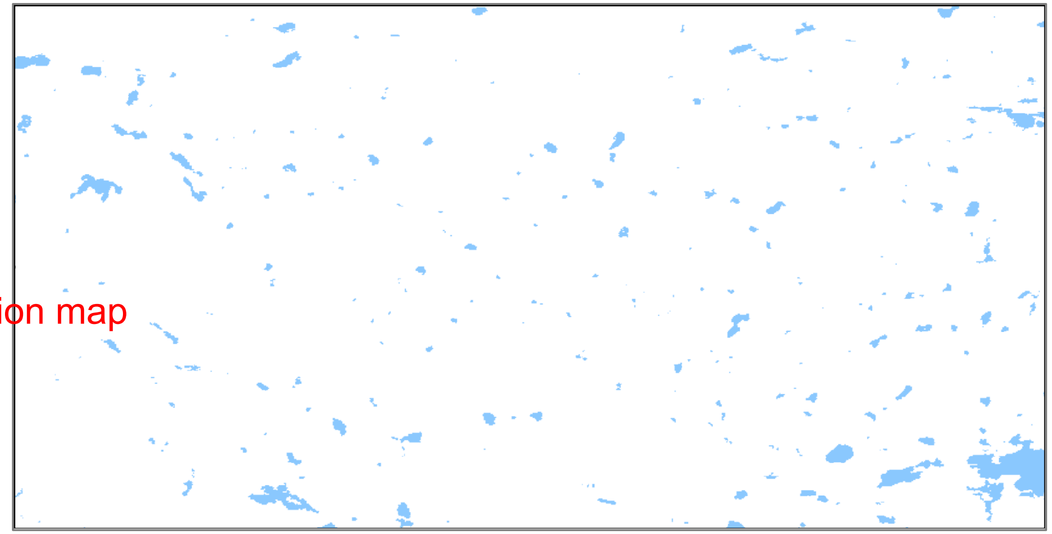
2. Tibetan Plateau





Water Surface Fraction



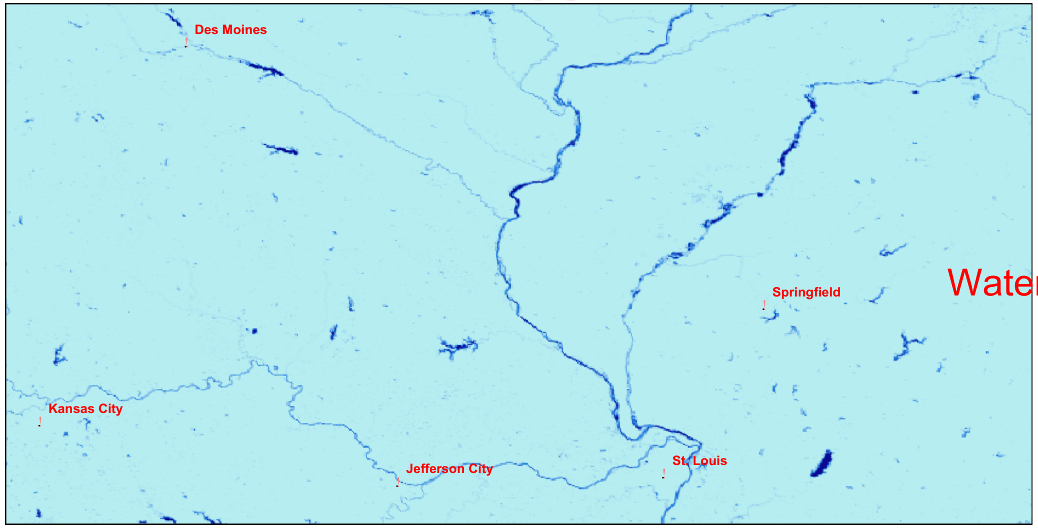


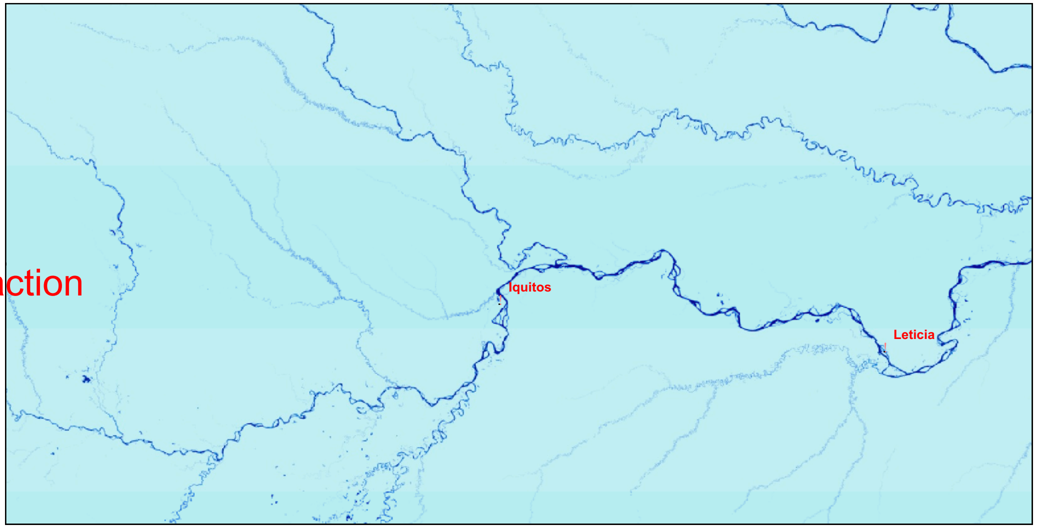
Water from classification map

Narrow River Branches Captured by Water Surface Fraction Product

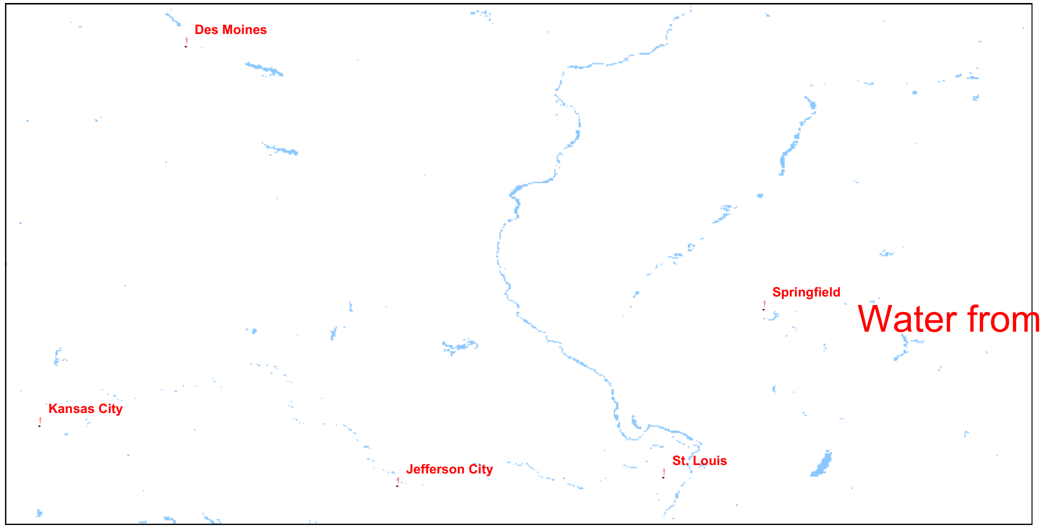
3. Mississippi River

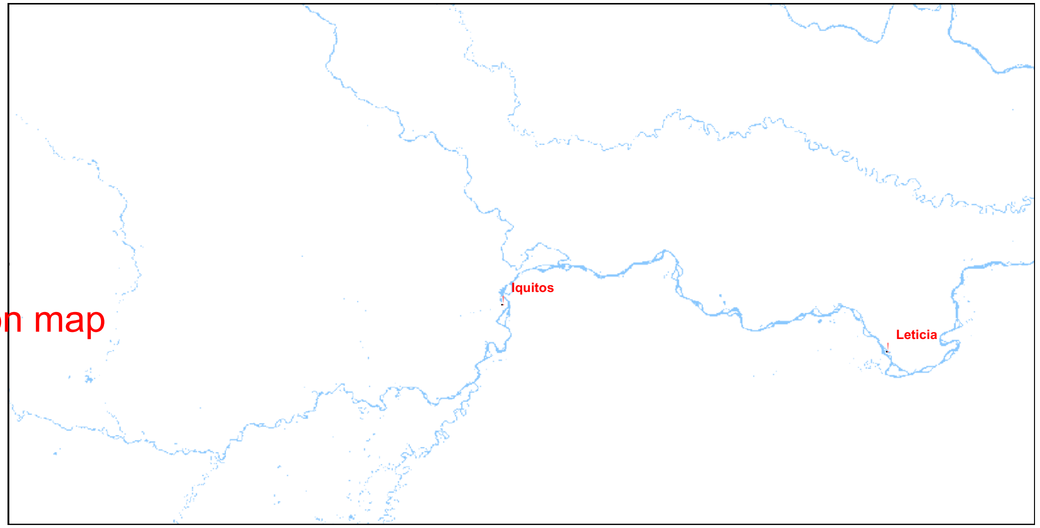
4. Amazon River





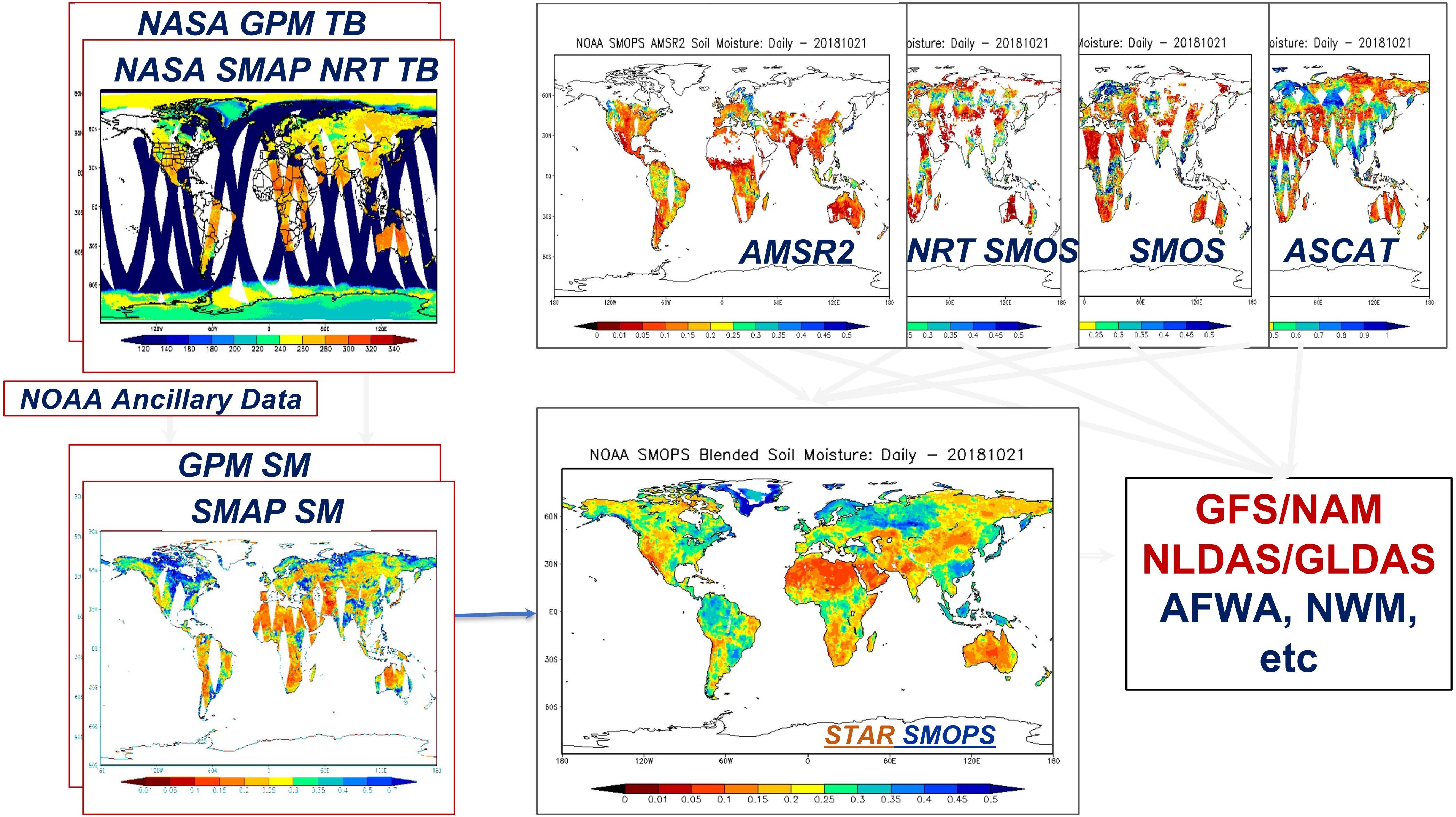
Water Surface Fraction



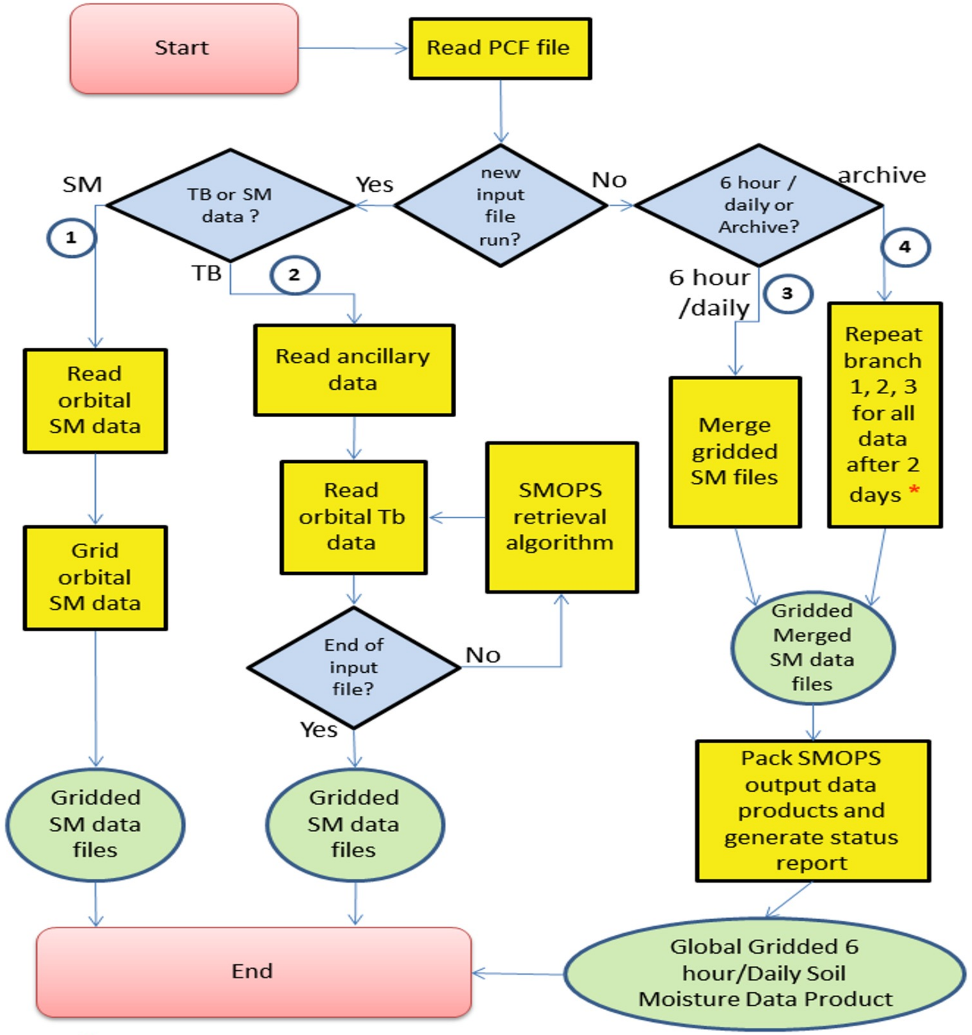


Water from classification map

SMOPS: Soil Moisture Operational Product System

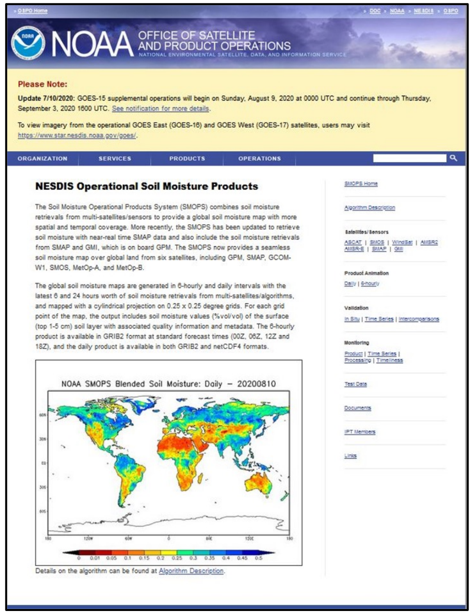


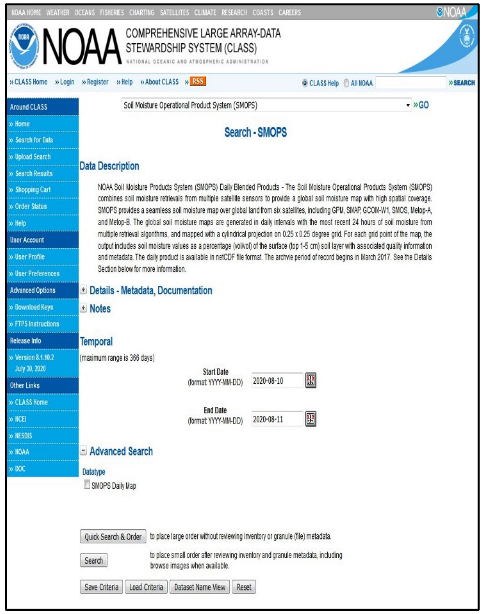
SMOPS Algorithms and Production



* *All data acquired within the 6 hour or whole day time period arrived in the past 48 hours*

1. **SM ingesting:** unify file format and projection
2. **SM retrieving:** single channel algorithm
3. **SM merging:** simple average & SD
4. **Delayed processing for archiving:** 48 hours delay





OSPO SMOPS

CLASS SMOPS

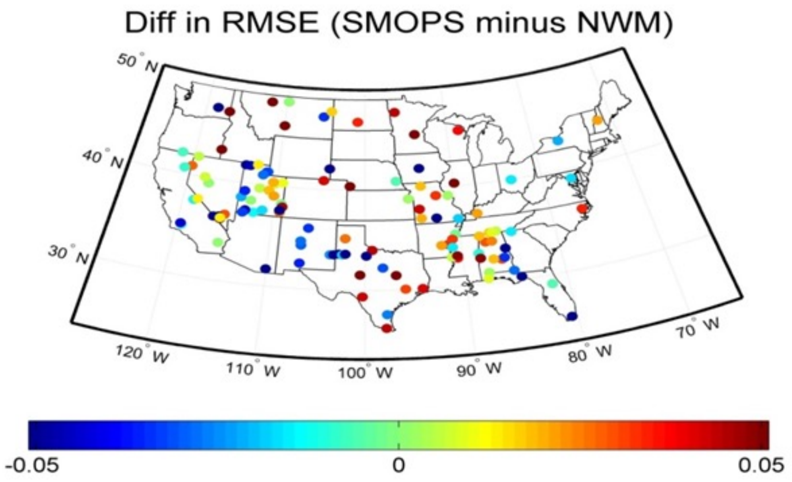
SMOPS: Data Types and Uses

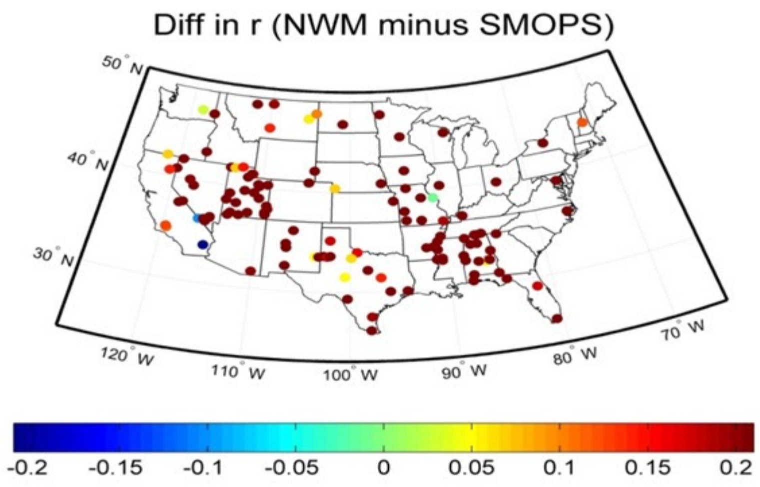
Products	Description	Data Sources	Projec tion	Spatial Coverage	Spatial Resolution	Main Purpose
SMOPS 6-Hour Products	SMOPS 6-hour Gridded Soil Moisture	GAASP SM, SMAP NRT L1B TB, SMAP NRT L2 SM, ASCAT_B&C SM, GMI TB	Lat/Long	Global	0.25 degree (720x1440)	For operational use
SMOPS Daily Products	SMOPS Daily Gridded Soil Moisture	GAASP SM, SMAP NRT L1B TB, SMAP NRT L2 SM, ASCAT_B&C SM, GMI TB	Lat/Long	Global	0.25 degree (720x1440)	For operational/research use
SMOPS Archive Products	SMOPS Daily Gridded Soil Moisture	GAASP SM, SMAP NRT L1B TB, SMAP L2 SM, ASCAT_B&C SM, GMI TB	Lat/Long	Global	0.25 degree (720x1440)	For research use

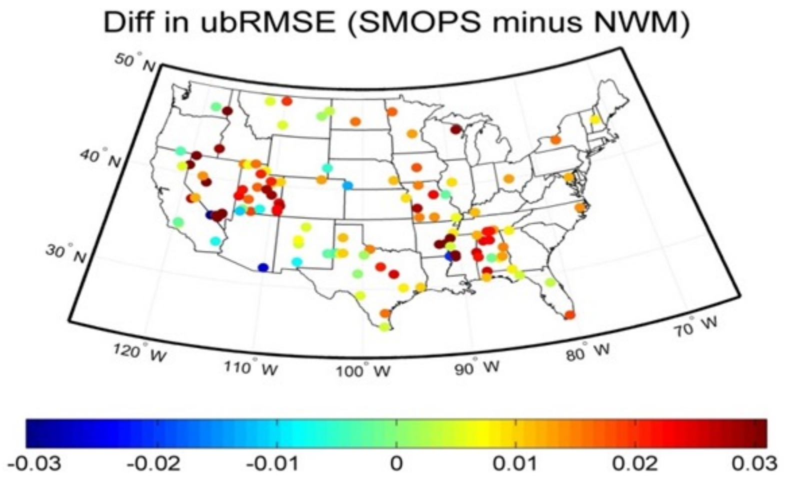
SMOPS: Data Layers and Time Coverage

Soil Moisture Product	SMOPS Version 1.3	SMOPS Version 2.0	SMOPS Version 3.0	SMOPS Version 4.0 (in AWS Cloud)
	Jan’03 - Feb’16	Mar’16 - Oct’16	Nov’16 - current	Starting from Sep’21
SMOPS Blended	√ (1)	√ (1)	√ (1)	√ (1)
NOAA AMSR-E	√ (2)	×	×	×
NOAA NRT SMOS	×	√ (2)	√ (2)	×
ESA SMOS	√ (3)	√ (3)	√ (3)	×
EUMETSAT ASCAT-A	√ (4)	√ (4)	√ (4)	×
EUMETSAT ASCAT-B	√ (5)	√ (5)	√ (5)	√ (2)
EUMETSAT ASCAT-C	×	×	×	√ (3)
NOAA WindSat	√ (6)	×	×	×
NOAA AMSR2	×	√ (6)	√ (6)	√ (4)
NOAA GMI	×	×	√ (7)	√ (5)
NOAA NRT SMAP	×	×	√ (8)	√ (6)
NASA SMAP	×	×	√ (9)	√ (7)

SMOPS: Preliminary Comparison with NWM 1.2







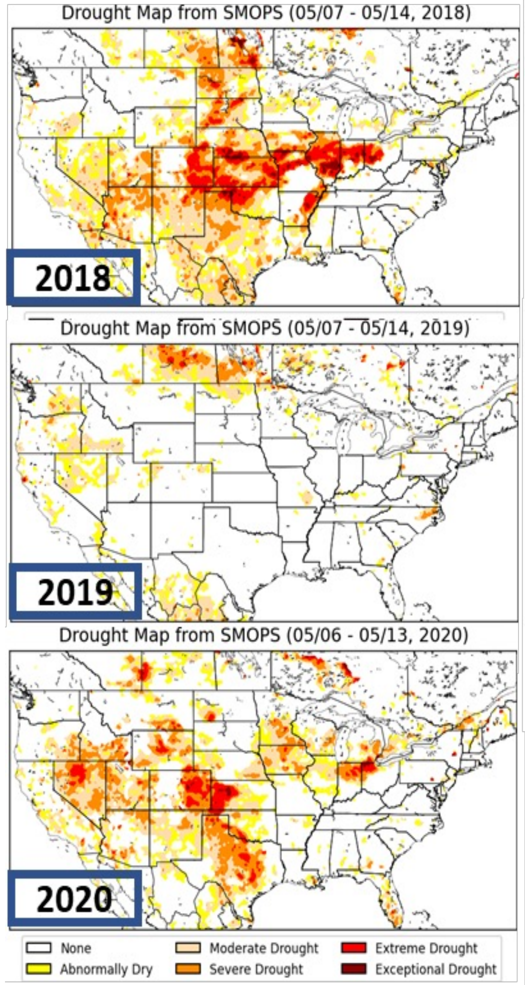
Differences in

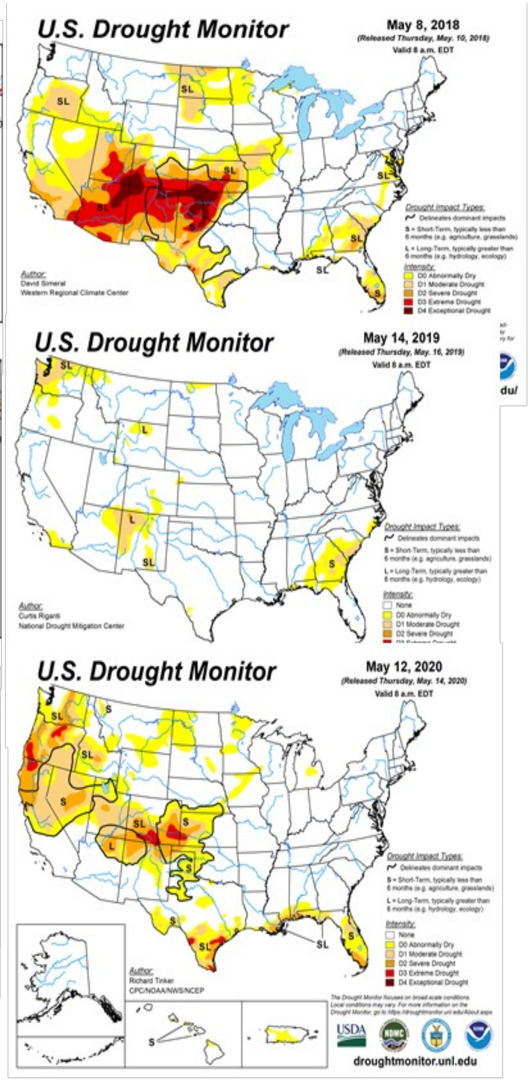
RMSE, ubRMSE & Pearson correlations (r)

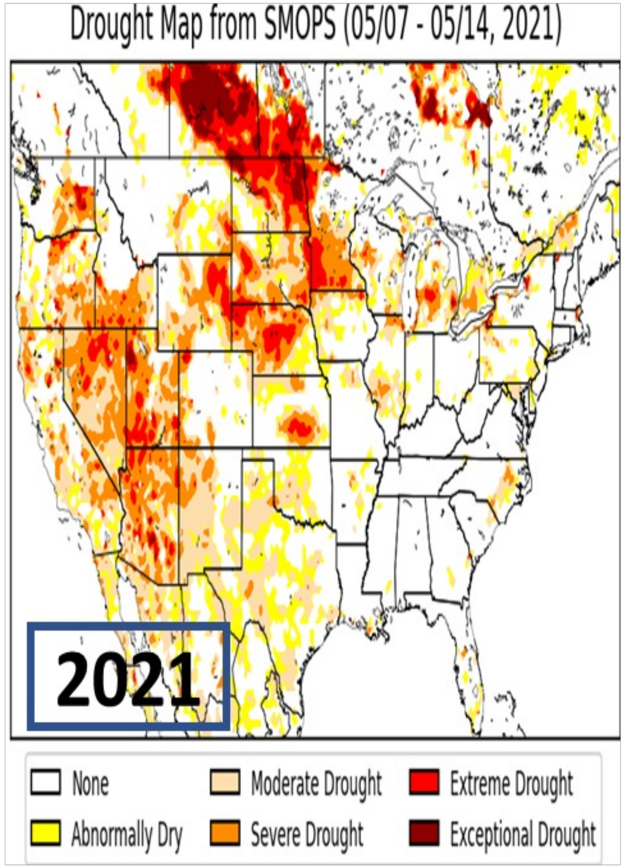
between SMOPS & NWM over 1 April 2015-30 June 2017 period with respect to the SCAN measurements.

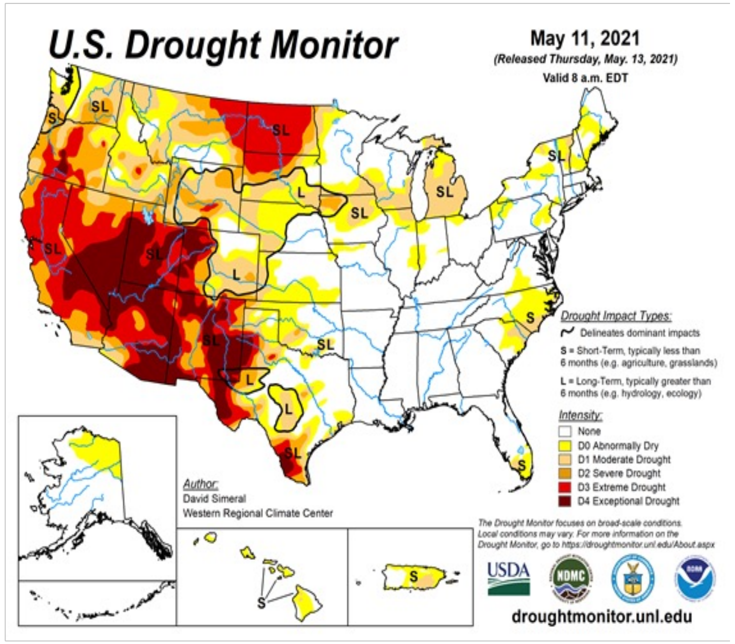
Blue: SMOPS is better
Red: NWM is better

SMOPS: Application in Drought Monitoring



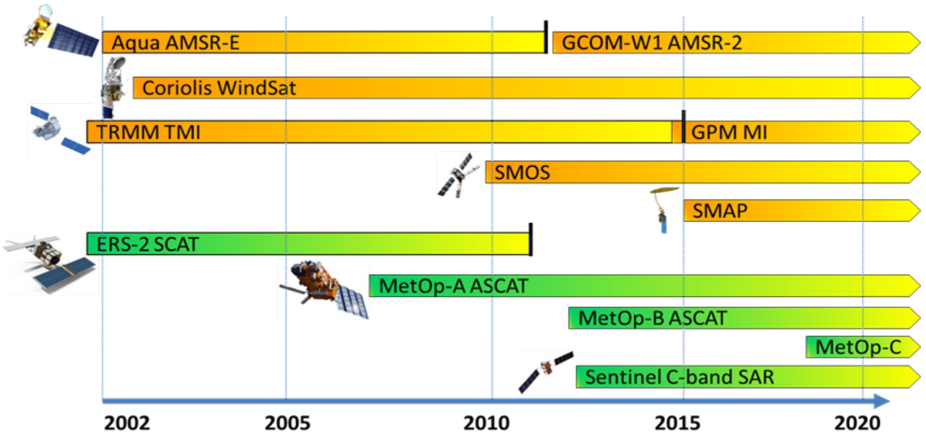




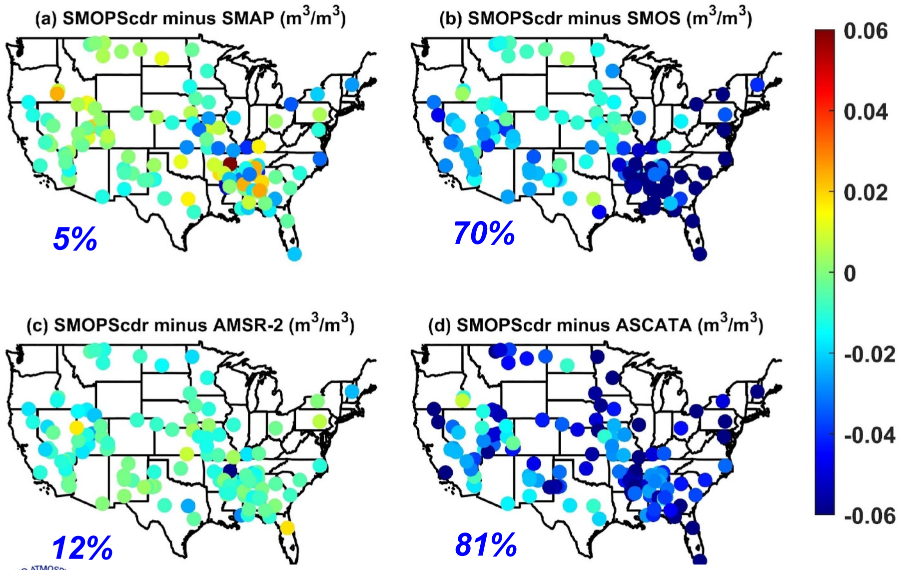


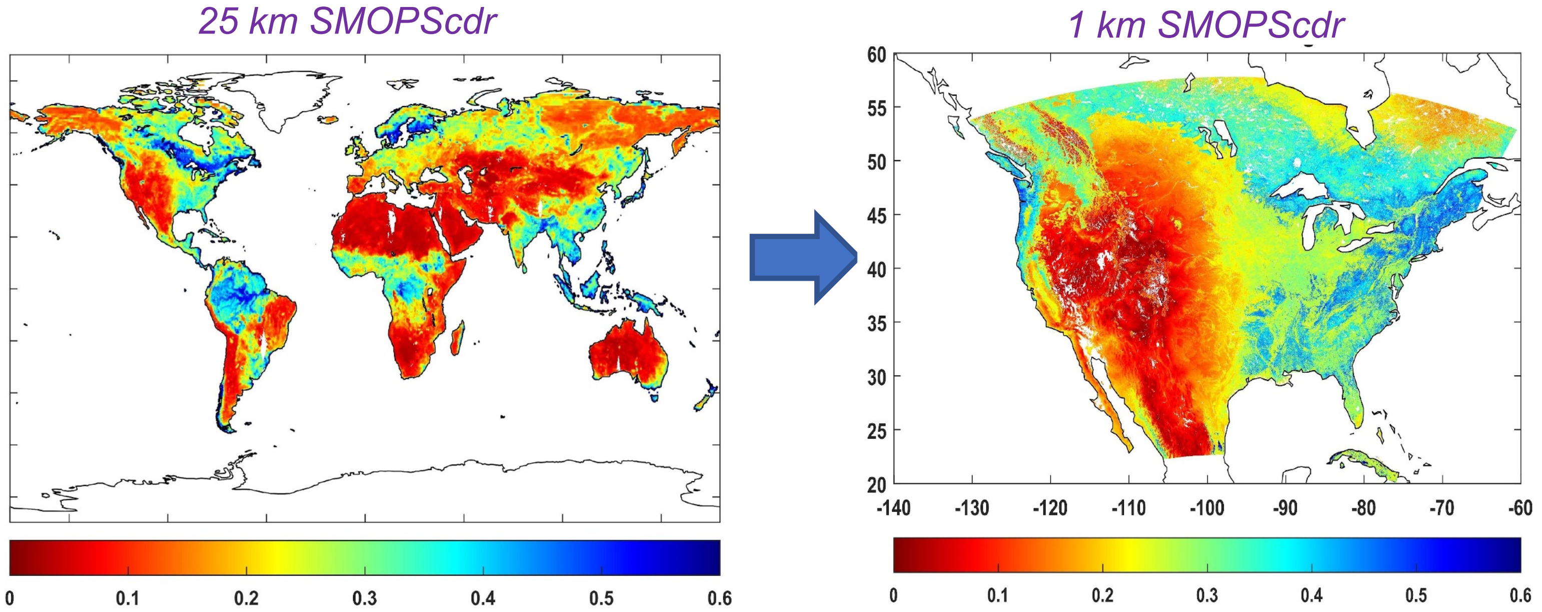
Much of the Western half of the United States is in the grip of a severe drought of historic proportions in first half of 2021.

SMOPS: Reprocessing and Downscaling



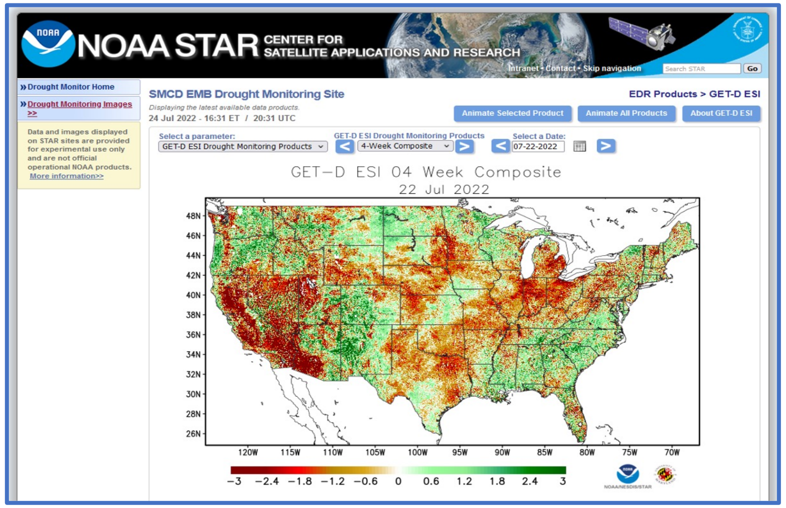
- Multi-sats calibration & reprocessing
- Downscaling to high resolution (1km)
- New satellites (NISAR, SNOOPI, etc.)
- Data assimilation in NWM and NWP models



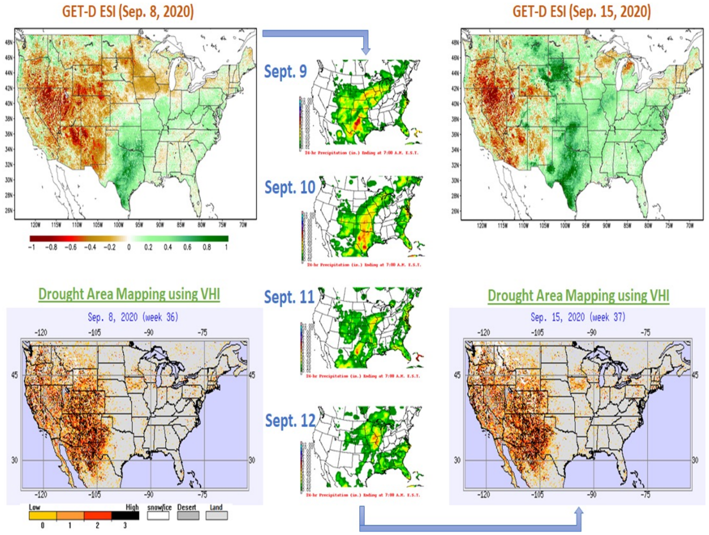


GOES ET and Drought (GET-D) Product System

- Satellite evapotranspiration (ET) data product provides validation data for NWM & NWP models and recently EMC started to use GET-D ET routinely.
- Negative temporal anomalies in ET ratio over potential ET, called Evaporative Stress Index (ESI), highlight areas with anomalously low level of crop/plant water use, i.e., drought occurrence.
- Daily ET and multi-weekly ESI at 2km are generated from NOAA GOES Advanced Baseline Image infrared (TIR) data via GET-D system using the Atmosphere-Land Exchange Inversion (ALEXI) model for CONUS.
- The GET-D system was operational for GOES-13/15 images and is upgraded for GOES-16/17 ABI. Near current time ESI composite maps of CONUS for 2, 4, 8 & 12 weeks from the new GET-D system are posted in a STAR webpage as shown on the right.



STAR GET-D

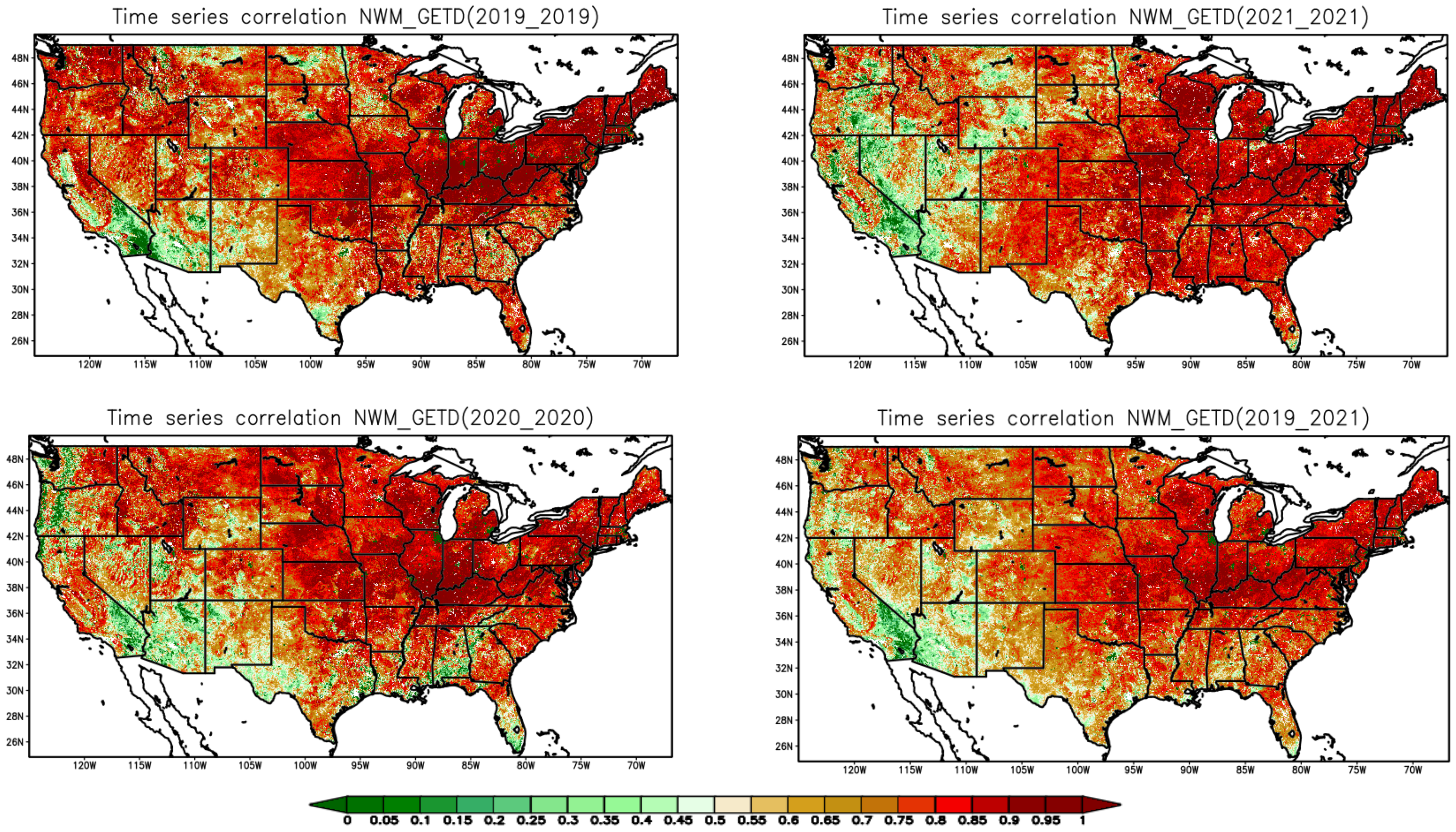


GET-D ET/ESI Provides Unique Drought Infor.

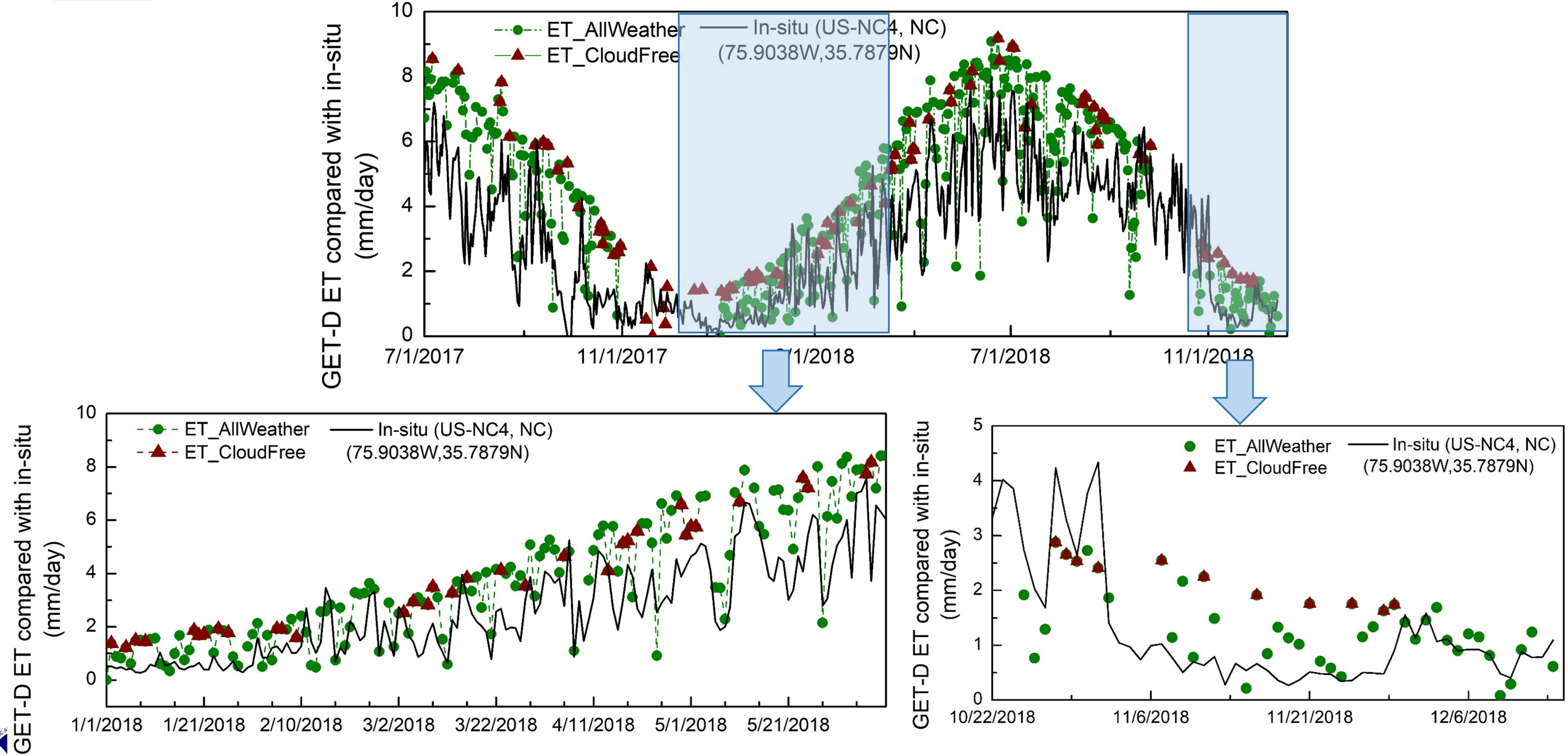
Fang et al. *Front. Big Data 5:768676*. https://doi.org/10.3389/fdata.2022.768676.

Fang et al. *Remote Sens*. 2019, 11, 2639; https://doi:10.3390/rs11222639.

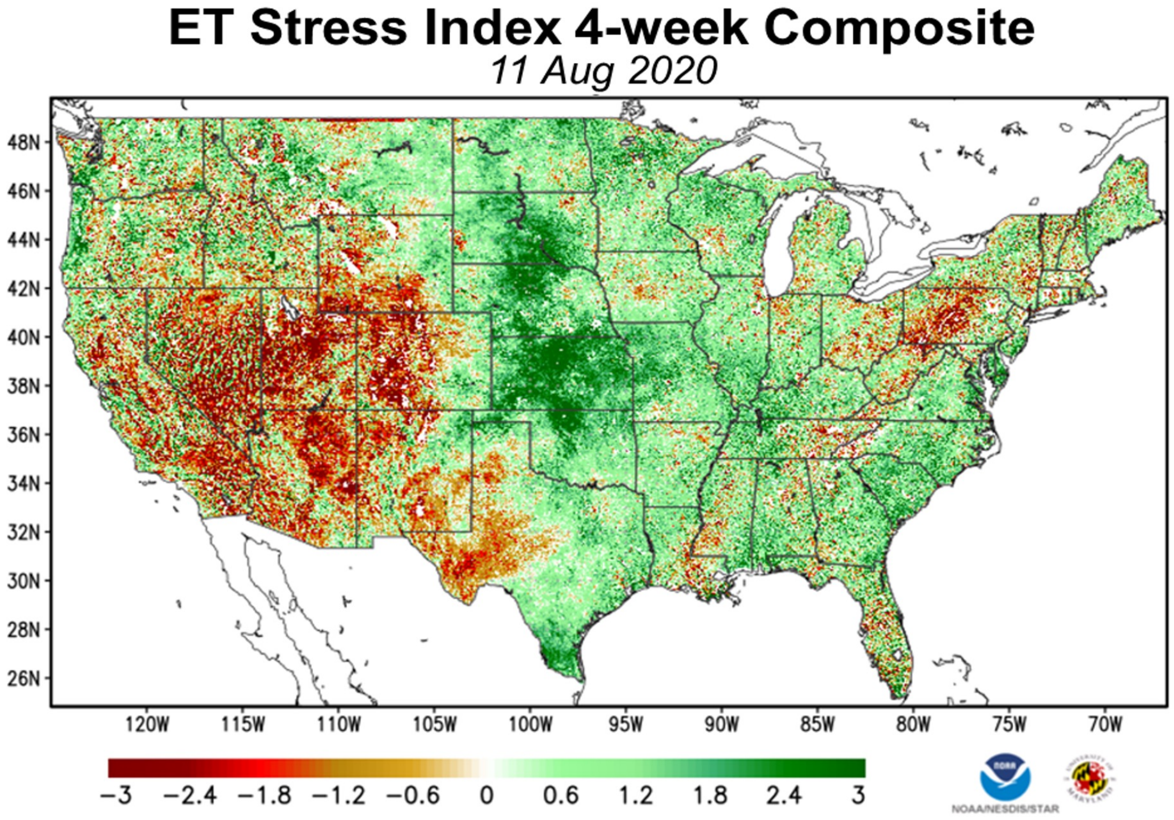
GET-D ET Compared with NWM 1.2



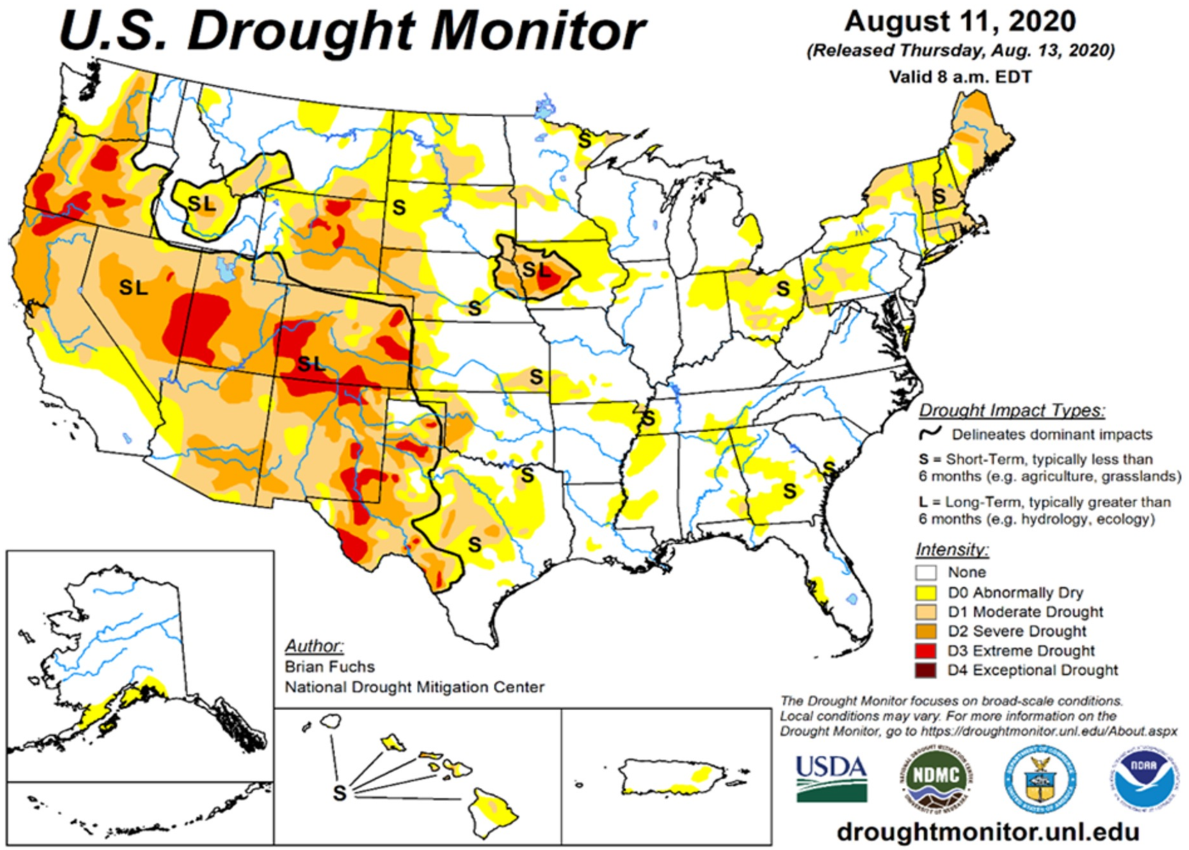
GET-D ET Compared with in situ Measurements



GET-D ESI Compared with USDM



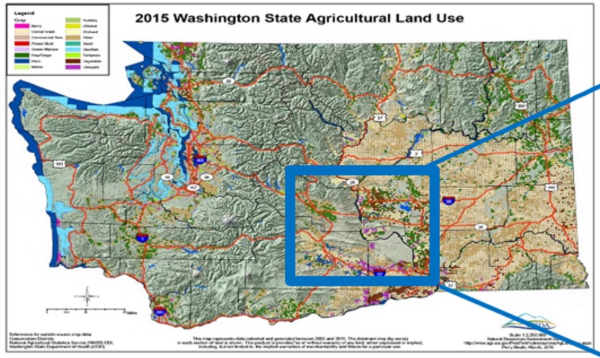
* ESI maps composited for 2, 4, 8, 12–weeks before the selected date are generated from GET–D updated for the Advanced Baseline Imagers (ABI) of GOES–16 and GOES–17 satellites.



GET-D ESI Compared with SPI for DM

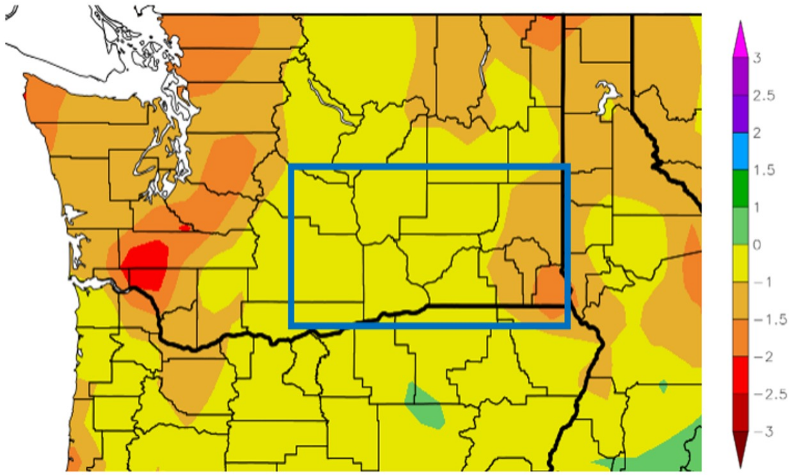
Capability of capturing irrigation activities

Daily changes of GET-D ESI over the irrigation areas in Columbia Basin, Washington from Mid-June to the end of July in 2021 (bottom-right), compared with the monthly Standardized Precipitation Index (SPI) in July 2021 (bottom-left)

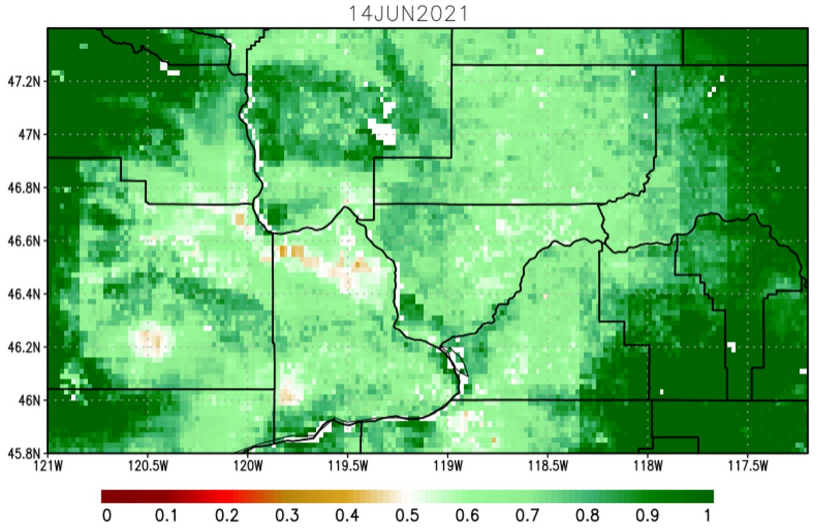


Agricultural fields in Columbia Basin, Washington

Monthly SPI (7/1/2021 – 7/31/2021, shaded)



GET-D ESI over Crop Land in Columbia Basin, Washington June 14 – July 31, 2021

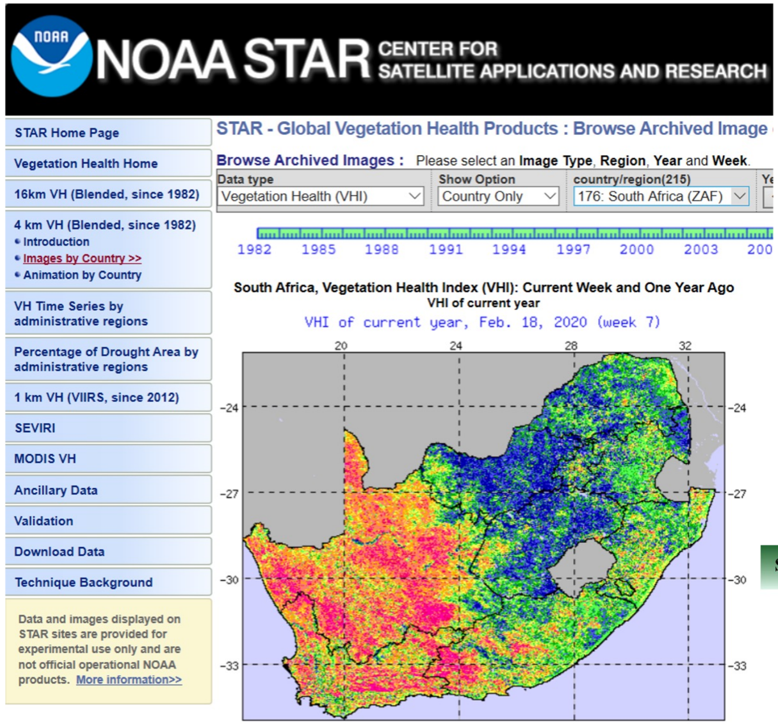


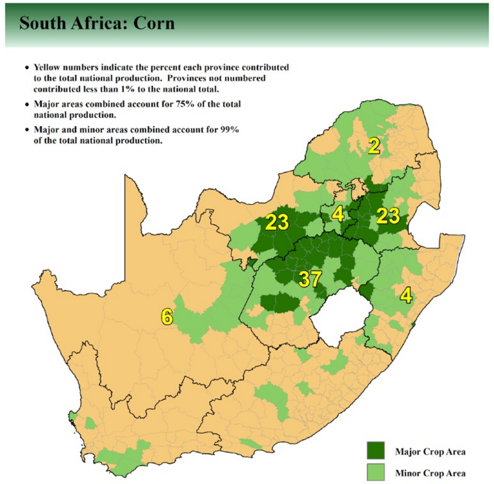
Vegetation Health Index (VHI) for Societal Welfare

Wide Use of VHI:

- Crop growth & yields
  - *USDA(NASS/FAS/WAOB), FAO, etc.*
- Drought
  - *CPC, NIDIS, etc.*
- Fire risks
  - *USFS, etc.*
- Vector disease
  - *WHO, etc.*
- …

VHI Applications at USDA – A Blossoming Success Story





From Harlan Shannon of USDA Office of the Chief Economist & World Agricultural Outlook Board

Several key aspects have facilitated success:

- **VHI data have a long track record** – support development of crop yield relationships
- **Data are available in a GeoTiff format** – user friendly and GIS compatible
- **Data are updated weekly** – when issues do arise, they are often addressed very quickly
- **Recalculated data incorporated in updates** – removes noise, improving yield forecasts
- **Well designed web site** – easy to navigate and promotes automated downloads
- **Development of cropland specific data sets** – significantly reduces USDA processing time and greatly increases operational value

You know a data set has value when the ICEC chairs request to see it!

VHI Products Algorithm and Production

$$NDVI = (R_{NIR} - R_{VIS})/(R_{NIR} + R_{VIS})$$

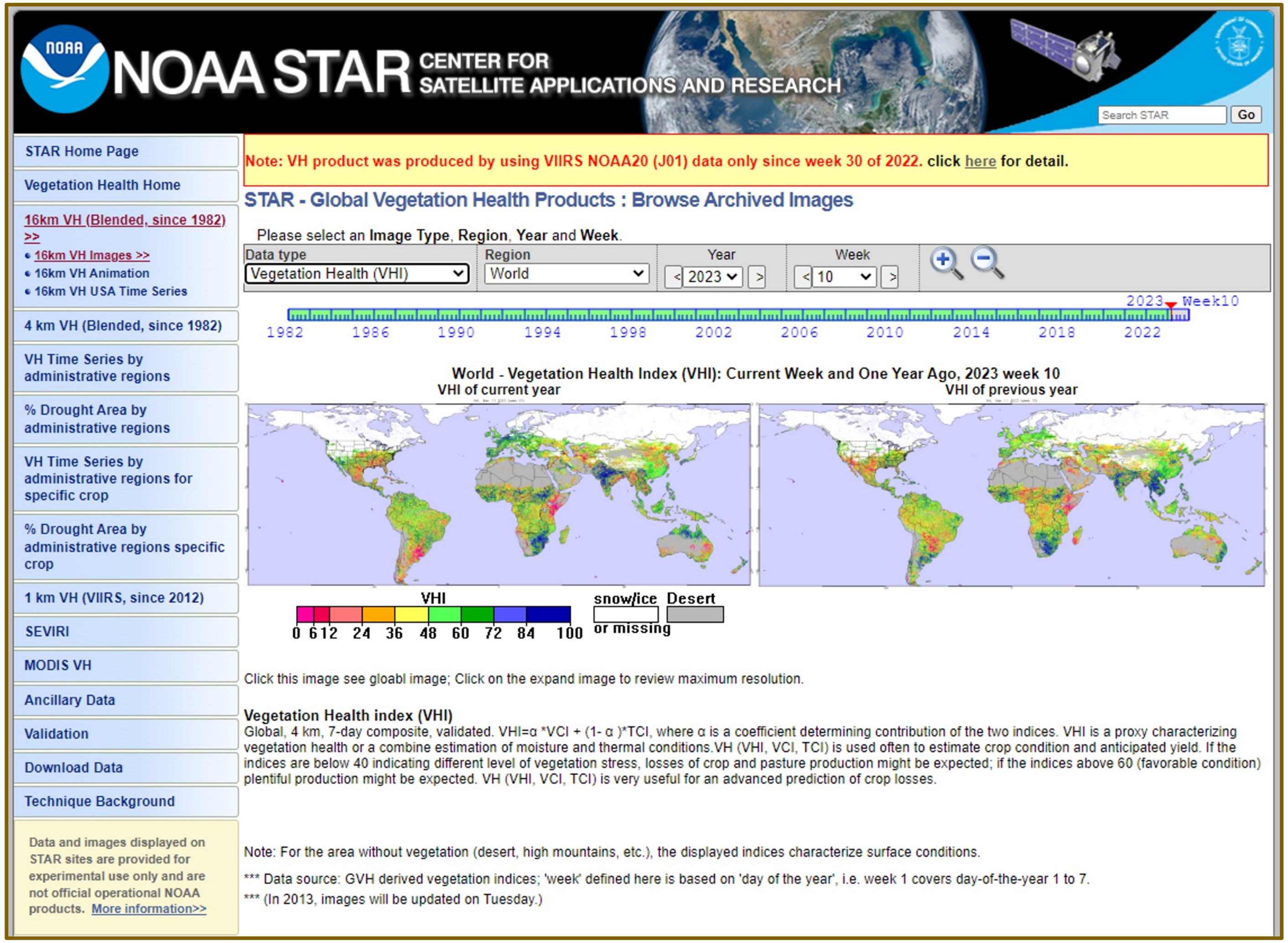
$$VCI = 100 \times (NDVI - NDVI_{min})/(NDVI_{max} - NDVI_{min})$$

$$TCI = 100 \times (BT - BT_{min})/(BT_{max} - BT_{min})$$

$$VHI = \alpha \times VCI + (1 - \alpha) \times TCI \quad (\alpha=0.5)$$

Extending AVHRR climatology to VIIRS:

$$V36 = V5 \times A36/A5$$



STAR VHI

Challenges and Opportunities on **VHI**

- AVHRR and VIIRS (S-NPP, N-20 & N-21) data integration:
  - *VIIRS 375m/500m VHI production for current users*
- Long term VHI data for climate studies:
  - *Climatology calibration for multiple sensors on multiple satellites*
- VHI relationship to yield of different crops in different regions:
  - *Adjust VHI weighting coefficients using historical data and machine learning models*

Recent Related Publications on the Products

Yin, J., **X. Zhan**, M. Barlage, J. Liu, H. Meng, R.R. Ferraro. Refinement of NOAA AMSR-2 Soil Moisture Data Product: 1. Intercomparisons of the Commonly Used Machine-Learning Models. IEEE Transactions on Geoscience and Remote Sensing, VOL. 61, 2023. https://doi.org/10.1109/TGRS.2023.3280173

Yin, J., **X. Zhan**, M. Barlage, J. Liu, H. Meng, R.R. Ferraro. Refinement of NOAA AMSR-2 Soil Moisture Data Product—Part 2: Development With the Optimal Machine Learning Model. IEEE Transactions on Geoscience and Remote Sensing, VOL. 61, 2023. https://doi.org/10.1109/TGRS.2023.3280176

Yin, J., **X. Zhan**, M. Barlage, S. Kumar, A. Fox, C. Albergel, C.R. Hain, R.R. Ferraro, J. Liu. Assimilation of Blended Satellite Soil Moisture Data Products to Further Improve Noah-MP Model Skills. Journal of Hydrology Vol. 621 2023. https://doi.org/10.1016/j.jhydrol.2023.129596.

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Rishmawi, K.; Huang, C.; **Zhan, X**. Monitoring Key Forest Structure Attributes Across the Conterminous United States by Integrating GEDI LiDAR Measurements and VIIRS Data. Remote Sens. 2021, 13, 442. https://doi.org/10.3390/rs13030442

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OUTLINE: NOAA Satellite Land Products and Applications

Satellite Land Products	Application Areas
Surface Type/Land cover	LSM input parameter
Surface Soil Moisture	LSM state variable Initialization, output verification, parameter calibration, and data assimilation (DA) Monitoring of drought, flooding, heat wave, etc.
Land Surface Temperature	
Land Surface Albedo	
Green Vegetation Fraction	
Leaf Area Index	
Evapotr	
Vegetat	

Contact: Bob Yu (yunyue.yu@noaa.gov)
STAR JPSS web site: https://www.star.nesdis.noaa.gov/jpss/
STAR GOES-R web site: https://www.star.nesdis.noaa.gov/goesr/index.php
STAR Land Products List: https://www.star.nesdis.noaa.gov/portfolio/productListings.php#tab6

Thank you!!!

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