Hydro Splinter Key Results

SWOT Data Assimilation and Hydrologic Modeling

Patrick Le Moigne and Ed Beighley

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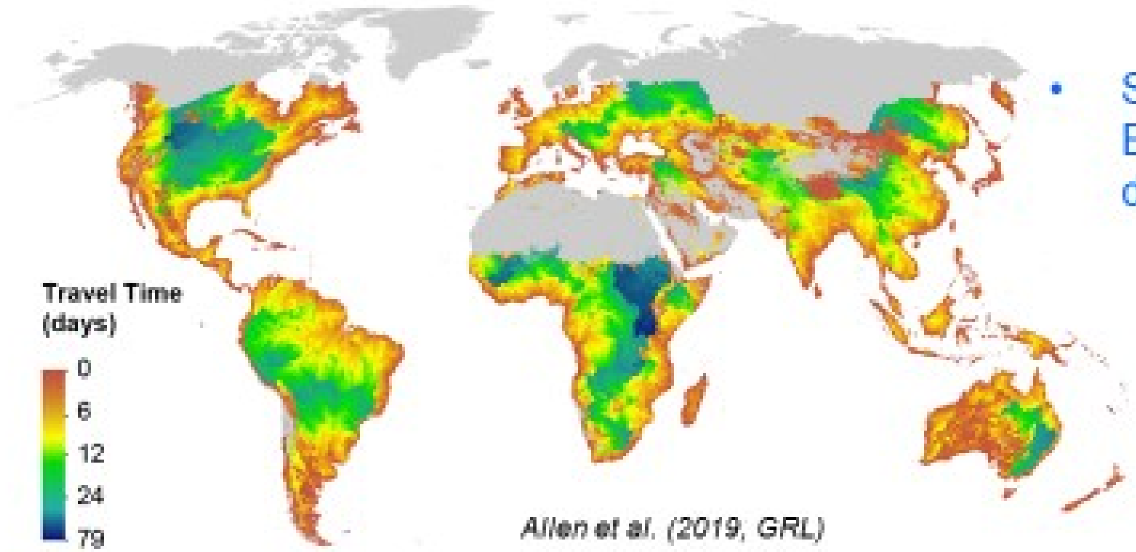
National Aeronautics and Space Administration
Jet Propulsion Laboratory
California Institute of Technology

Satellite Latency Requirements for Rivers

Cédric H. David (JPL/Caltech) and colleagues



Allen et al. (2019, GRL)

- Study of how fast flow waves move on Earth's continent help justify shorter data latency for SWOT hydrology data

Global flood wave (i.e. flow wave) travel times to basin outlets. The majority of flood waves reach their basin outlet within a week.

Current Plan

Data Latencies and the Corresponding Probability That an Observed Flow Wave Will not Have Reached its Basin Outlet, the Next Downstream City, and Next Downstream Dam

	All rivers			SWOT-observable rivers		
Latency	Basin outlet	City	Dam	Basin outlet	City	Dam
1 day	$82^{+1}_{-1}\%$	$87^{+2}_{-3}\%$	$78^{+3}_{-3}\%$	$85^{+2}_{-2}\%$	$80^{+4}_{-4}\%$	$73^{+4}_{-6}\%$
2 days	$72^{+3}_{-2}\%$	$73^{+3}_{-3}\%$	$62^{+4}_{-4}\%$	$75^{+3}_{-3}\%$	$63^{+4}_{-4}\%$	$53^{+5}_{-5}\%$
3 days	$64^{+2}_{-2}\%$	$60^{+5}_{-5}\%$	$49^{+4}_{-4}\%$	$67^{+3}_{-4}\%$	$50^{+4}_{-4}\%$	$40^{+6}_{-6}\%$
4 days	$58^{+3}_{-3}\%$	$50^{+4}_{-4}\%$	$40^{+5}_{-4}\%$	$60^{+5}_{-5}\%$	$40^{+7}_{-5}\%$	$32^{+5}_{-5}\%$
5 days	$52^{+3}_{-3}\%$	$42^{+5}_{-5}\%$	$33^{+4}_{-4}\%$	$54^{+4}_{-5}\%$	$31^{+6}_{-5}\%$	$25^{+5}_{-5}\%$
10 days	$32^{+5}_{-4}\%$	$16^{+3}_{-3}\%$	$16^{+3}_{-2}\%$	$30^{+5}_{-5}\%$	$10^{+4}_{-3}\%$	$10^{+3}_{-3}\%$
45 days	$1^{+1}_{-1}\%$	$0^{+5}_{-0}\%$	$0^{+5}_{-0}\%$	$1^{+1}_{-1}\%$	$0^{+8}_{-0}\%$	$0^{+5}_{-0}\%$

Note. The SWOT percentages do not correspond to the likelihood that SWOT will observe a flow wave, but rather the likelihood that if a flow wave is observed, SWOT observations will be available before the wave reaches the given point of interest.

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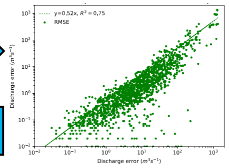
Uncertainty Quantification and Data Assimilation for River Discharge

Cédric H. David (JPL/Caltech) and colleagues

Newly-developed equation

Validated

First-ever estimates of runoff errors



David et al. (2019, GRL)

New Data Assimilation

Emery et al. (in rev. JHM)

Key Advancements

New Approach to Quantify Runoff Uncertainty and Propagate into River Discharge Uncertainty

New River Data Assimilation Approach

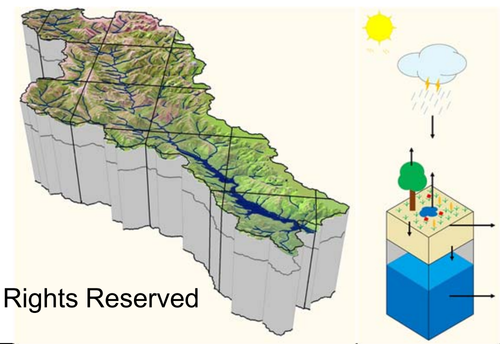
Estimated errors in runoff (from land surface model)

Estimated errors in river flow (from river model)

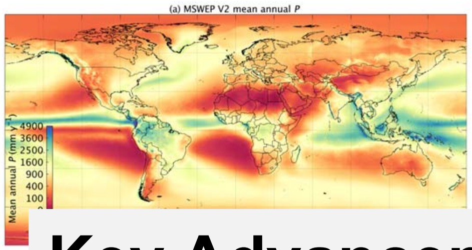
Actual errors in river flow (from observations)

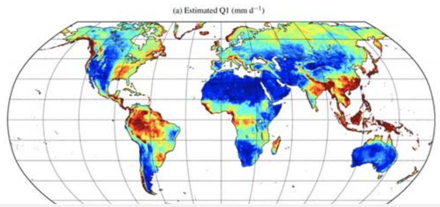
Data assimilation enabled by knowledge of model uncertainty

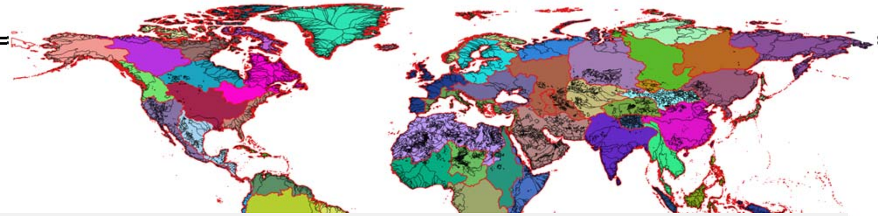
- New description of error propagation from land to rivers
- Better knowledge of river flow errors
- First estimates of land runoff errors
- Revealed critical error covariances
- New river data assimilation



Global Best-quality High-res River Modeling (PI: Wood/Pan, Princeton)





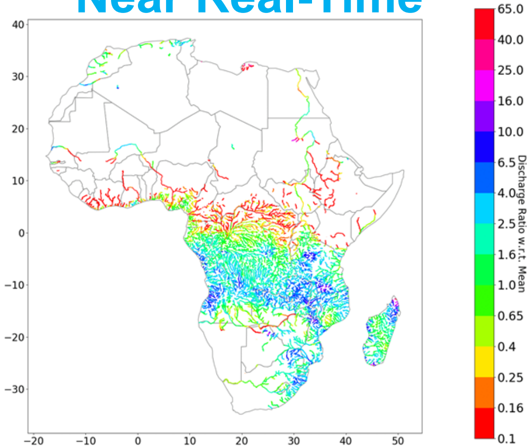


Key Advancements

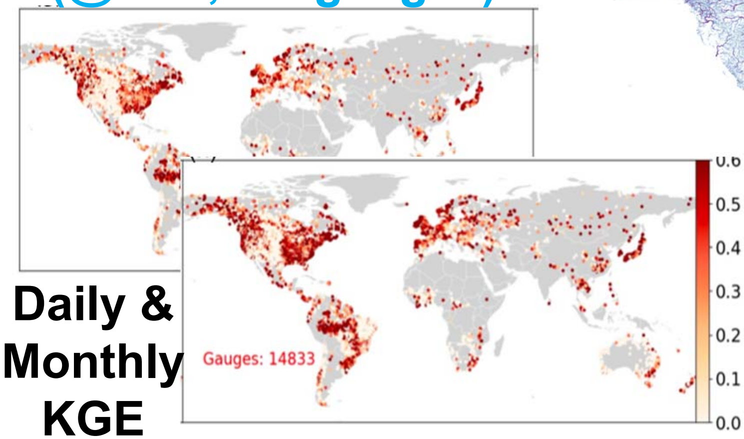
Global River Network Based on MERIT DEM

New Global High-Resolution River Discharge Model to Assess, Use or Improve SWOT Discharges

Potential for Near Real-Time

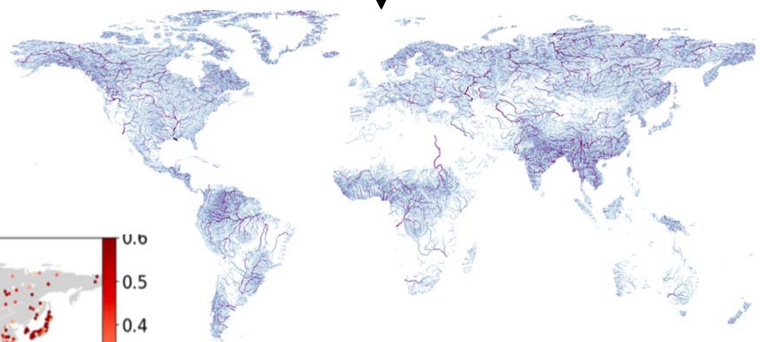


Quality Assessment (@ >14,000 gauges)



Daily & Monthly KGE

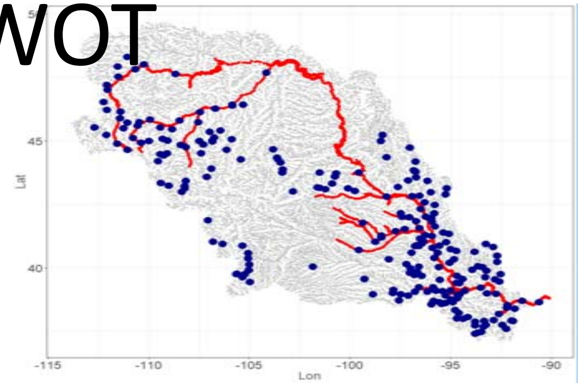
Discharge (1979 – present)



Using Landsat as a template for SWOT

Gleason et al.

“Missouri River Application”

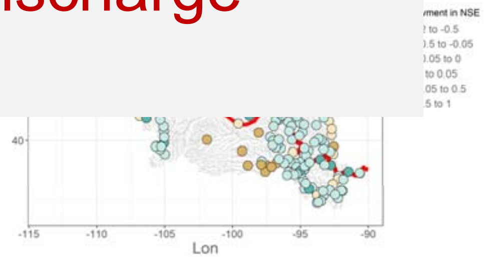


Princeton discharge

Key Advancements

SWOT-like River Discharge Algorithm Based on LandSat

New SWOT-like Discharge Assimilation Approach Provides Network-Wide Discharges and Improves River Discharge Estimates



Orbit geometry issues
Cloud/environmental issues
Most rivers too small to see
Mass conservation issues

Mean improvement in NSE is 0.1

Validated across 403 gauges, daily, for 2002-2010

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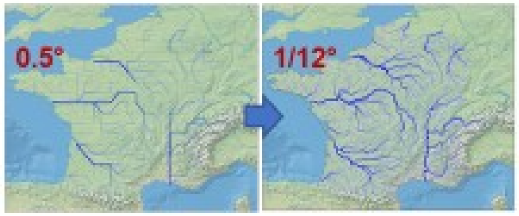
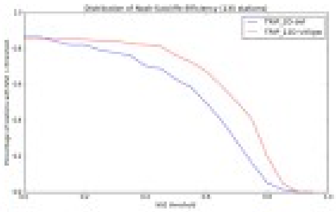
Recent Advances in Global Hydrology Modeling at CNRM, Météo-France

S. Munier, M. Lesaffre, S. Saysset, T. Guinaldo, A. Boone, P. Le Moigne (CNRM - Météo-France, CNRS)

1. River routing

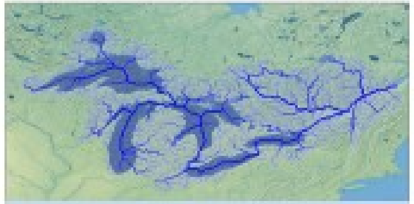
Development of **CTRIP-12D**, river routing model @ 1/12° to simulate river discharge, flood dynamics, and water storage changes in aquifers



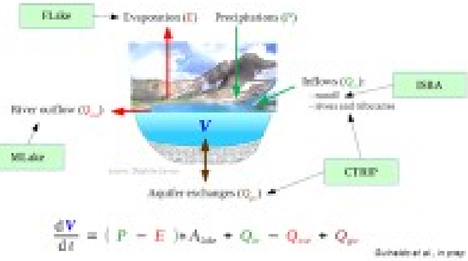


2. Lakes water mass balance

Development of a water mass balance in lakes (**MLake**) to represent water dynamics of lakes at the global scale

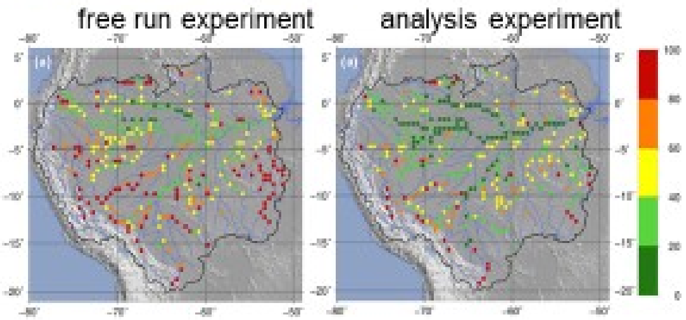


Lake mask from ECOCLIMAP-II clipped on the CTRIP-12D river network



3. Assimilation of altimetry data

Into river routing model, based on the work of Emery et al., 2018: assimilation of water levels from ENVISAT and JASON-2 data into CTRIP over the Amazon basin.



4. Dam reservoirs and water resource management

To assess the impact of dam operations on discharge propagation into the routing network.

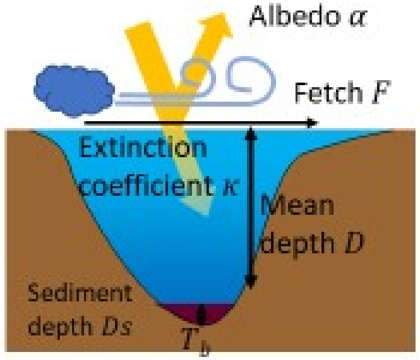
Will benefit from **CTRIP-12D** and **MLake** models to develop a dam-reservoirs model. A PhD (funded by CNES) next Autumn to improve river flow modeling with integration of dam-reservoirs model and the **assimilation** of altimetry data (SWOT)

Variance based sensitivity analysis of FLake lake model for global land surface modeling

A. Bernus, C. Ottlé, LSCE-IPSL, France

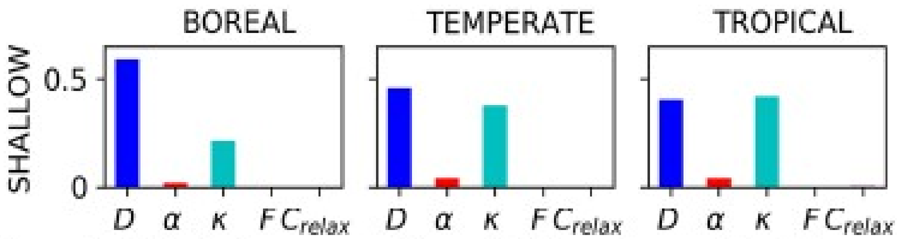
Objective: Develop a representation of lakes in the **ORCHIDEE-LMDZ climate model** constrained by SWOT observations
First step: Representation of the **energy budgets**

Approach:
- Coupling with **FLake** lake model to calculate **surface temperature and fluxes (evaporation)**
- Inventory of **lake databases** to characterize lakes at global scales
- Perform model **global sensitivity analysis (SA)** to identify dominant parameters and their time variability
- Develop data assimilation strategies to **calibrate/constrain model parameters**



7 parameters: depth, albedo, extinction coeff., fetch, relaxation coeff., sediment layer depth and bottom temperature

SA results:
- **Depth** and **Extinction coeff.** dominant parameters for **shallow lakes**
- **Albedo** and **Relaxation coeff.** dominant for **deeper lakes**



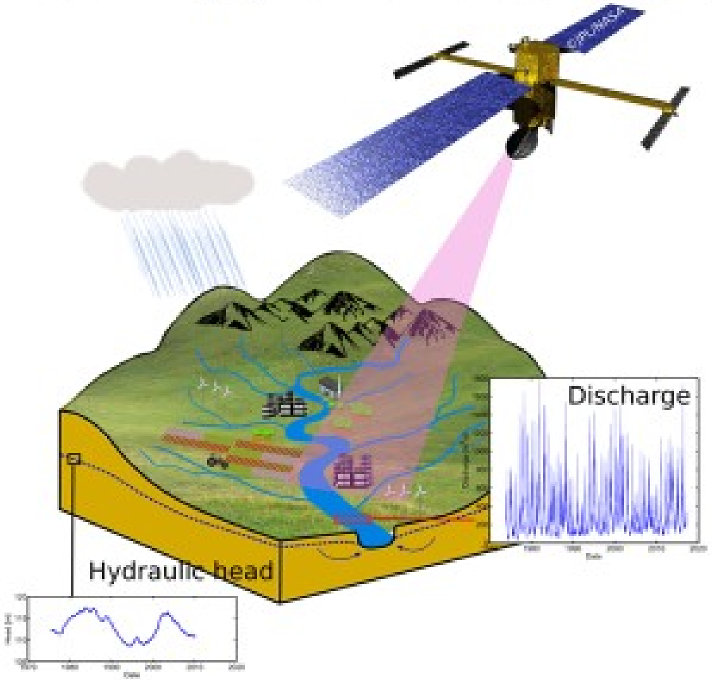
Generalized Sobol indices measure T_s sensitivity to each parameter during one year

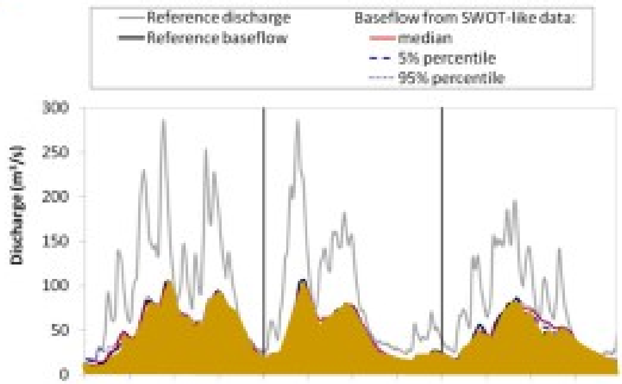
Sensitivity of depth/radiative parameters vary with incoming radiative forcing (the larger the radiation, the larger the sensitivity of albedo/extinction parameters)

→ **Results** will drive the **choice of both data assimilation method** and **time periods** used in the **optimization process**

Retrieving baseflow of large rivers from space with the future SWOT mission

Nicolas Flipo, Fulvia Baratelli, Sylvain Biancamaria, Agnès Rivière





- SWOT will provide uncertain river discharge at global scale
- Baseflow is retrieved by filtering SWOT-like river discharge: good accuracy over Seine basin
- Uncertainties on baseflow estimates are always slightly lower than those on discharge
- SWOT will potentially provide baseflow estimates with unprecedented global coverage