



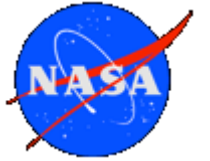
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A Benchmark Dataset of Water Levels and Waves for SWOT Validation: Insights from the St. Lawrence Estuary and Saguenay Fjord

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⁹ Department of Civil Engineering and Building, University of Sherbrooke, Sherbrooke, QC, Canada

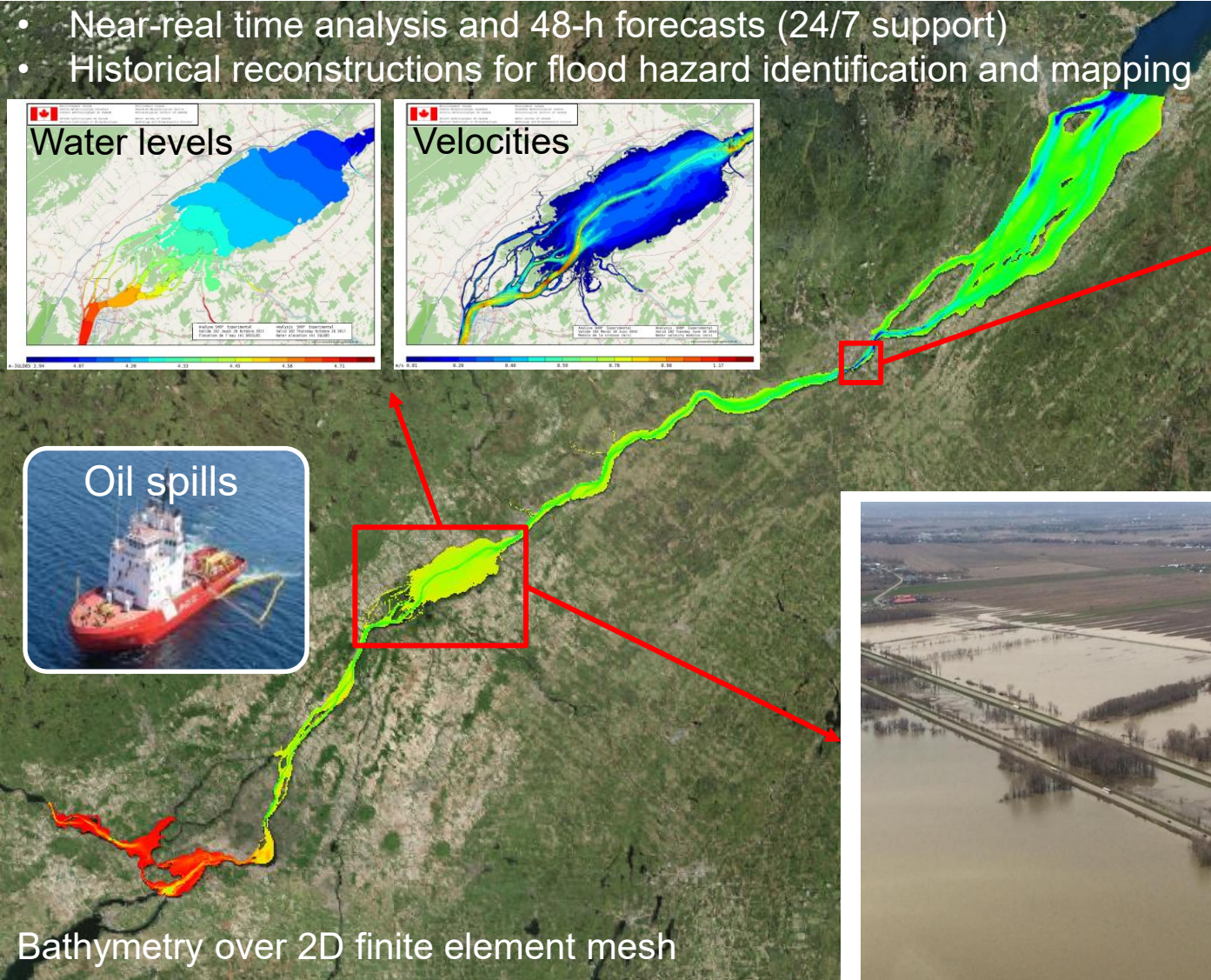
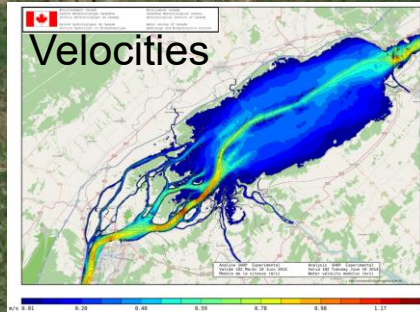
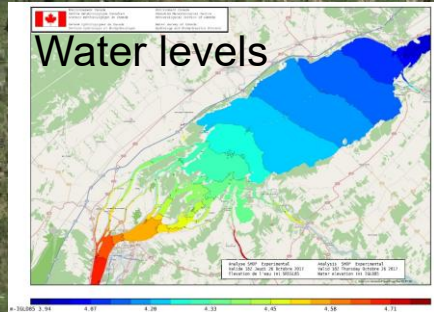
2025 SWOT Science Team Meeting
14-17 October 2025, Arcachon, France



Canada 

2D HYDRODYNAMIC PREDICTION SYSTEM OF THE ST. LAWRENCE RIVER

- Near-real time analysis and 48-h forecasts (24/7 support)
- Historical reconstructions for flood hazard identification and mapping

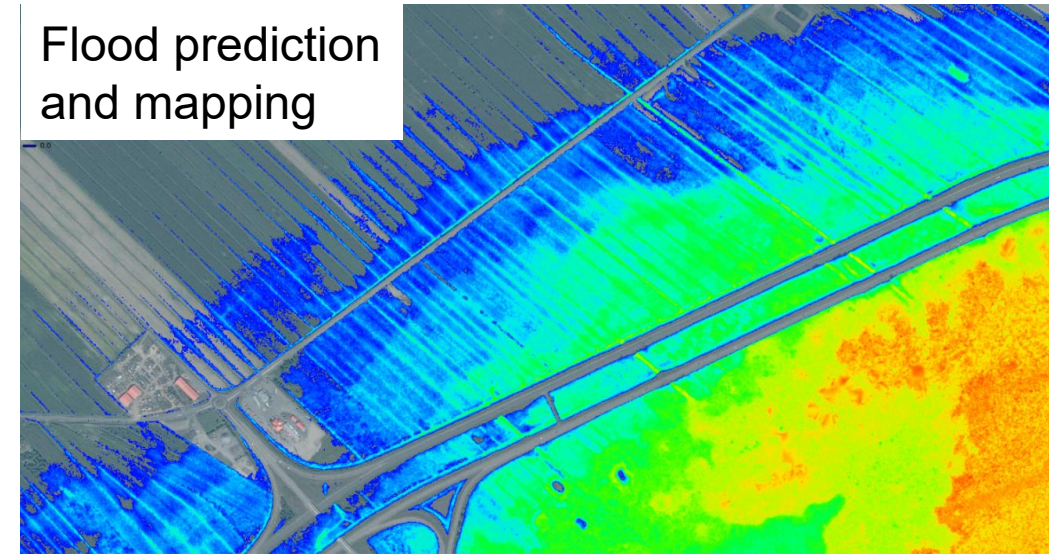


Electronic navigation



IHO designated the St. Lawrence River as an international S-100 sea trial area starting in June 2025

Flood prediction and mapping



OUR MOTIVATION TO USE SWOT

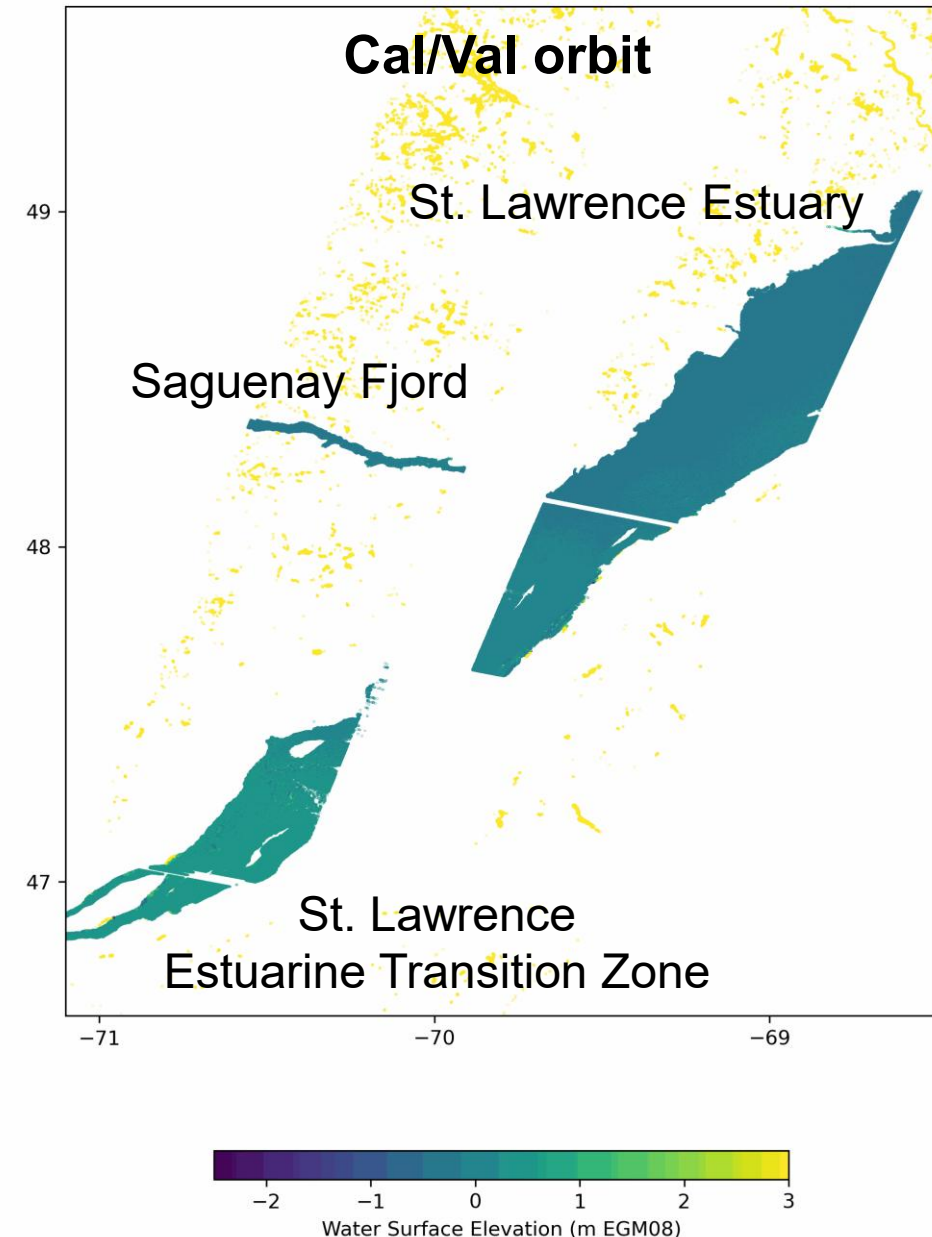
Research questions:

- How good is the SWOT data and can it help improve ECCC's numerical prediction models?
- Can SWOT enhance the mapping of extreme water levels?

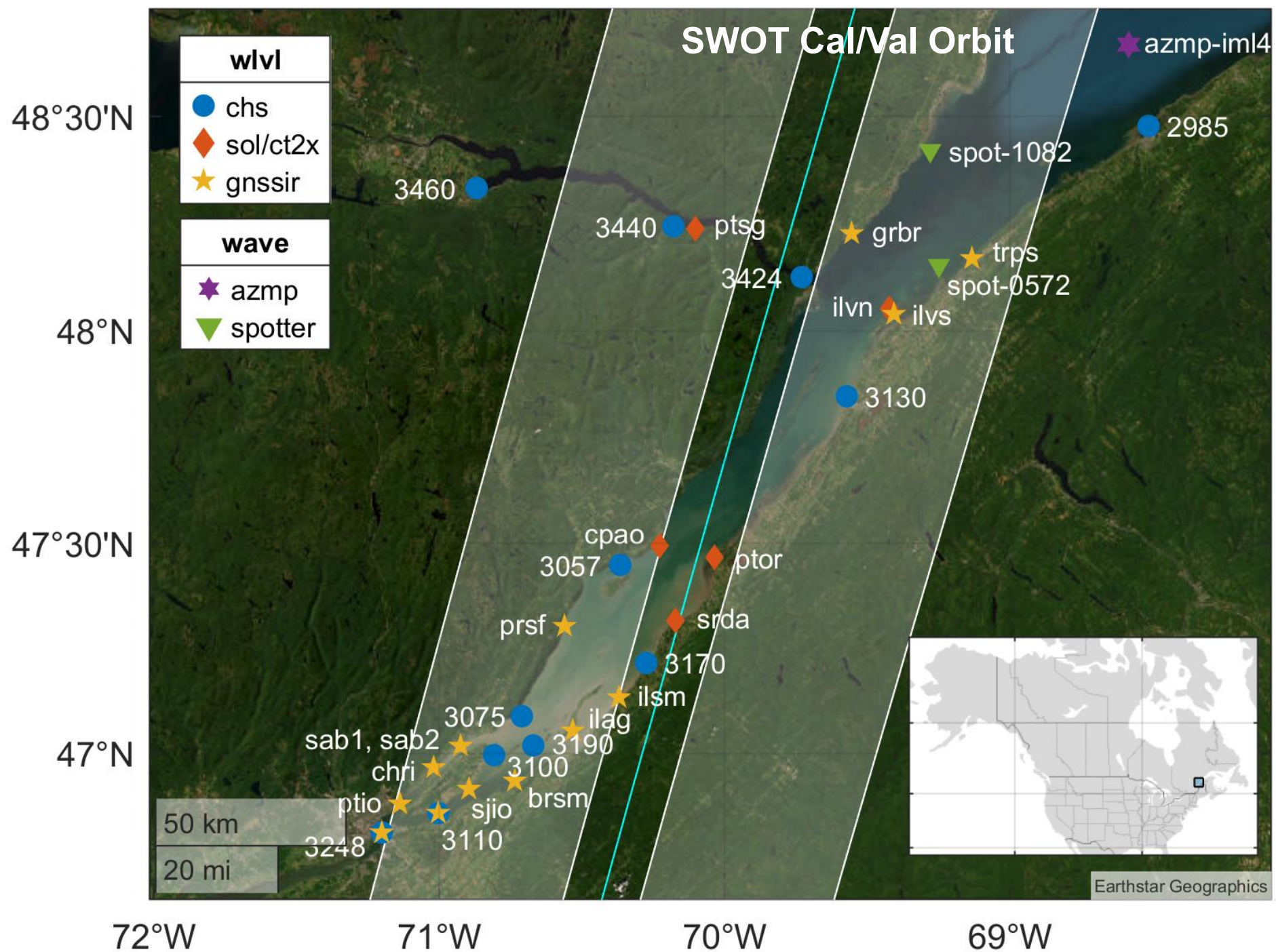
Outline of this presentation:

- Benchmark dataset of the St. Lawrence Estuary and Saguenay Fjord
- SWOT validation results
- Lag regression (gauge-constrained) method for SWOT reconstruction
- SWOT applications and highlights
 - Confronting ECCC's model and SWOT
 - Water level and tide reconstructions
 - Storm surge level analysis

SWOT_L2_HR_Raster_100m @ 20230331 05:11:54



SWOT Cal/Val Orbit



DATASET

MAIN DATASET

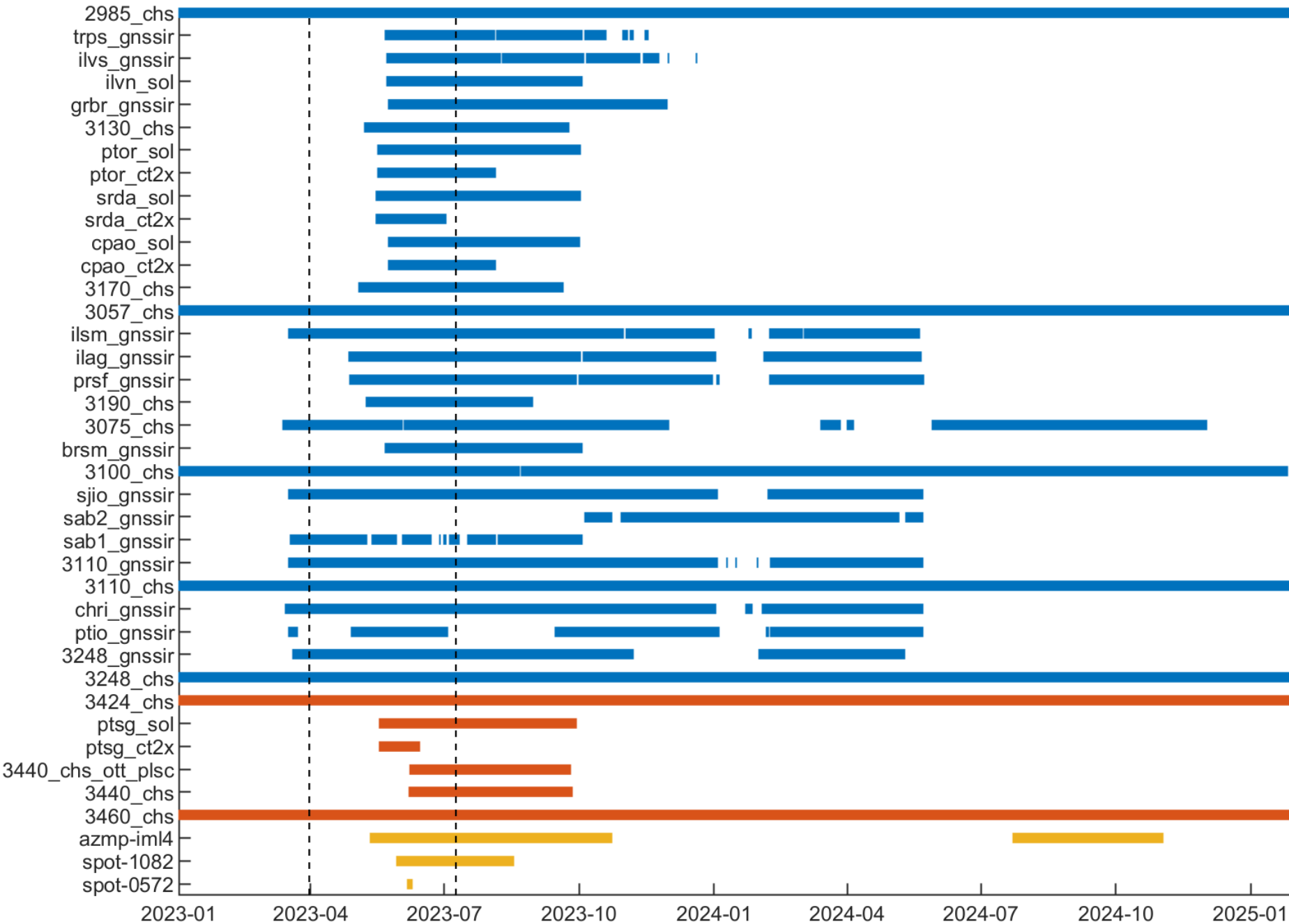
- 12 tide gauges
- 5 pressure transducers
- 13 GNSS-IR
- 3 wave buoys

AUXILIARY DATA

- 4 cameras
- 2 HF radars
- 1 fixed H-ADCP
- 4 ADCP boat surveys
- 4 AirSWOT flights (22,23,29,31 Aug 2023)
- RADARSAT Constellation Mission (RCM)
- Sentinel-1



Cal/Val



DATASET

MAIN DATASET

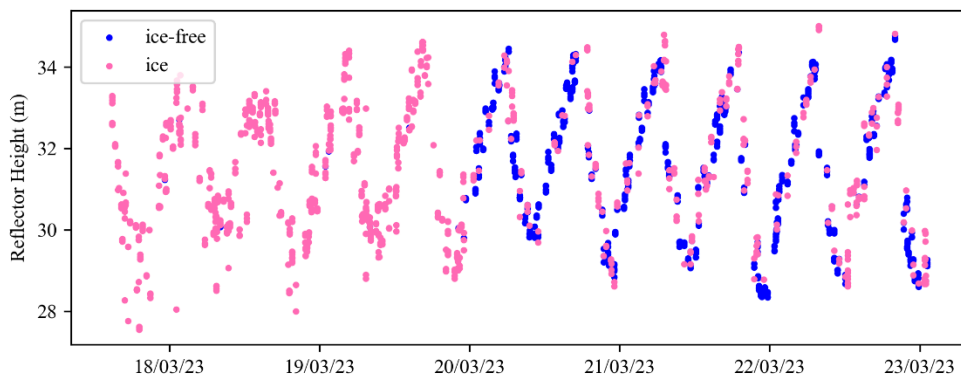
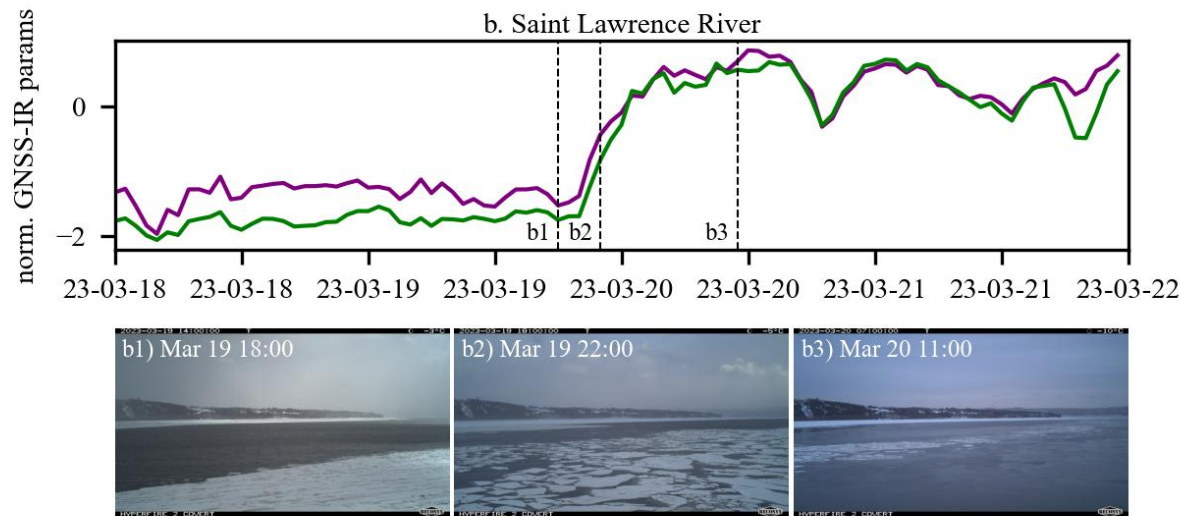
- 12 tide gauges
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AUXILIARY DATA

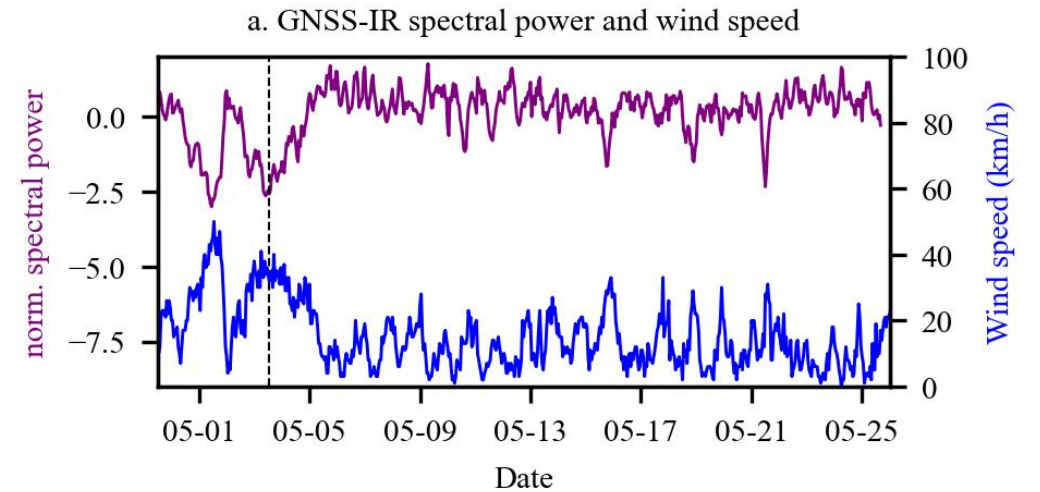
- 4 cameras
- 2 HF radars
- 1 fixed H-ADCP
- 4 ADCP boat surveys
- 4 AirSWOT flights
(22,23,29,31 Aug 2023)
- RADARSAT Constellation Mission (RCM)
- Sentinel-1

A FEW HIGHLIGHTS FROM THE DATASET

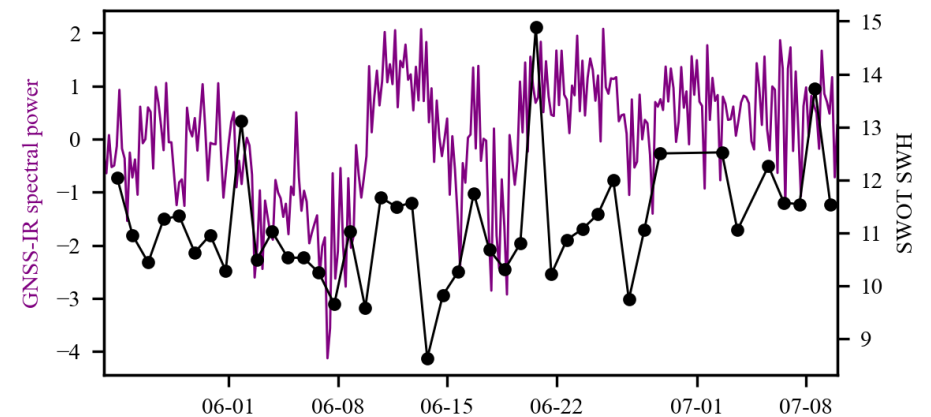
GNSS-IR and ice detection



GNSS-IR and wind/waves

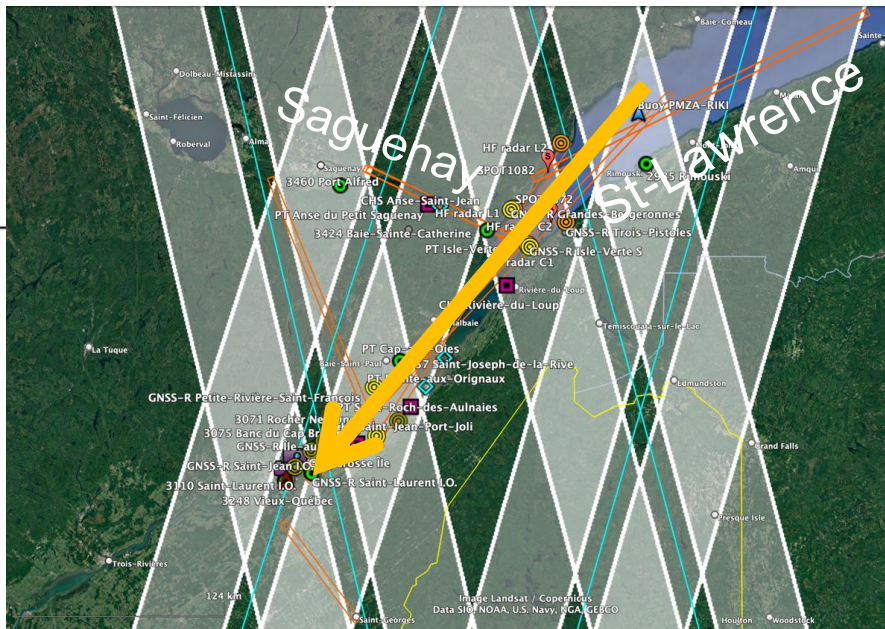


SWOT SWH

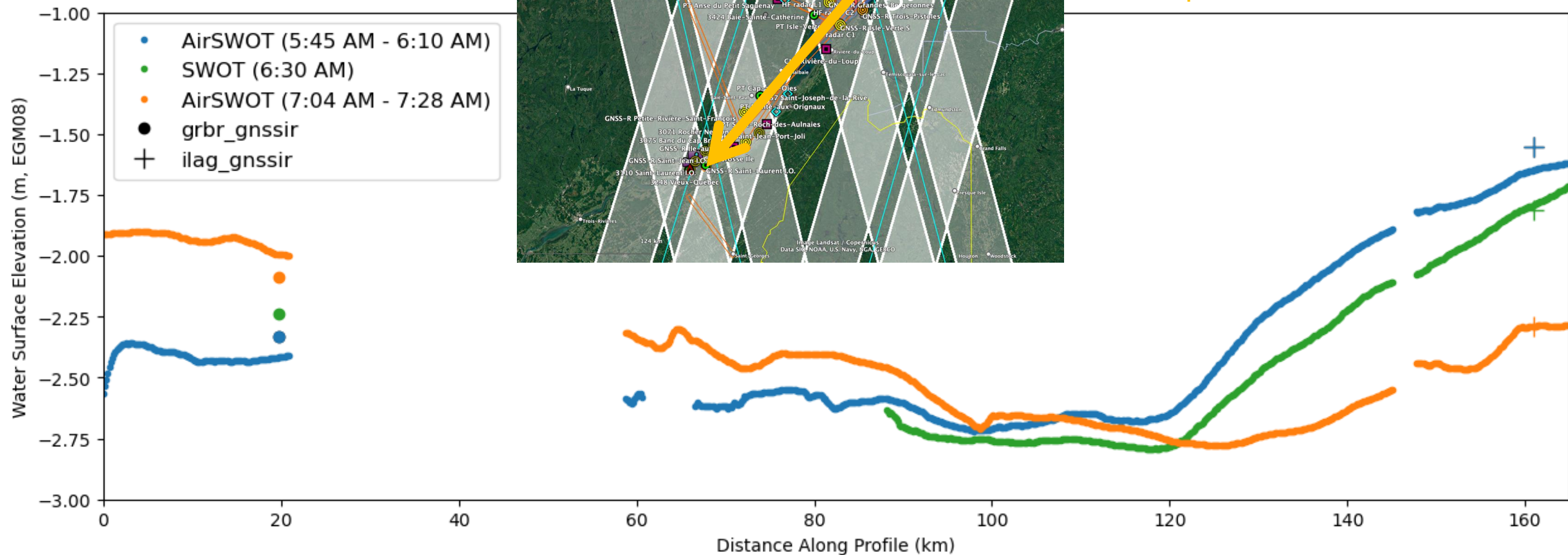


A FEW HIGHLIGHTS FROM THE DATASET

AirSWOT vs SWOT



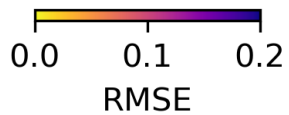
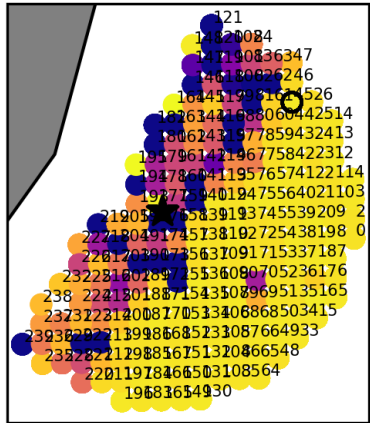
AirSWOT flights
in the upstream direction



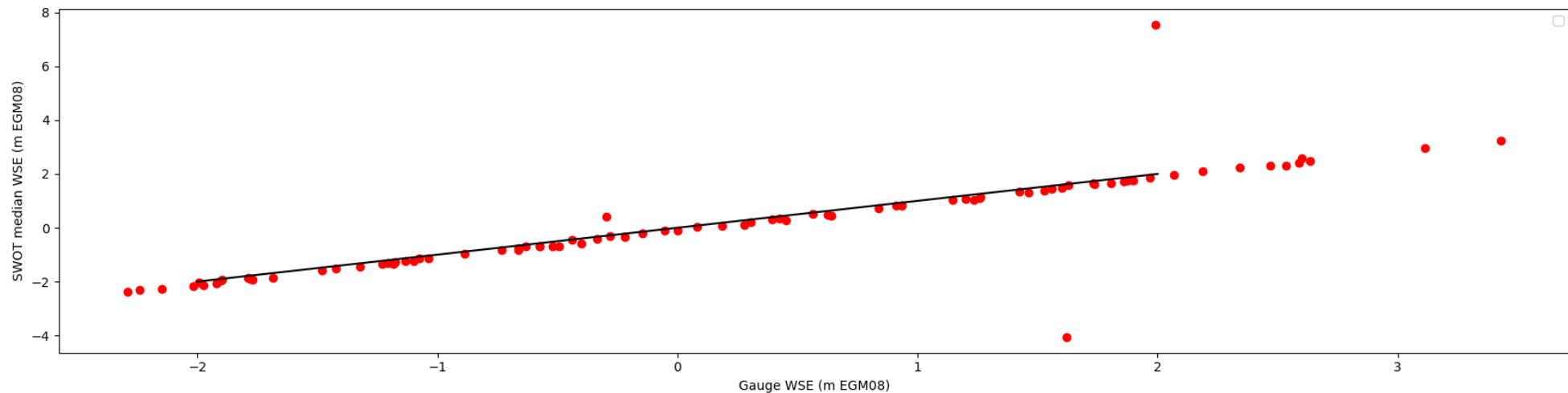
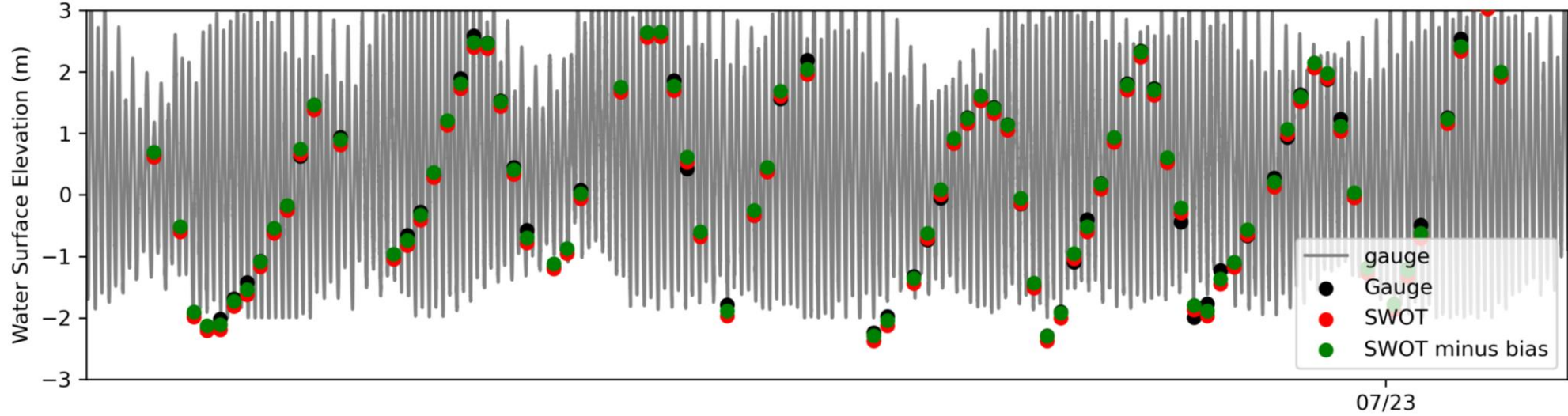
SWOT VALIDATION RESULTS

Example from Saint-François I.O.

3100_chs: SWOT_L2_HR_Raster_100m
Frame: 009_119F



Best Pixel = 45 RMSE = 0.014m
Mean bias = -0.081m when removed RMSE=0.007m



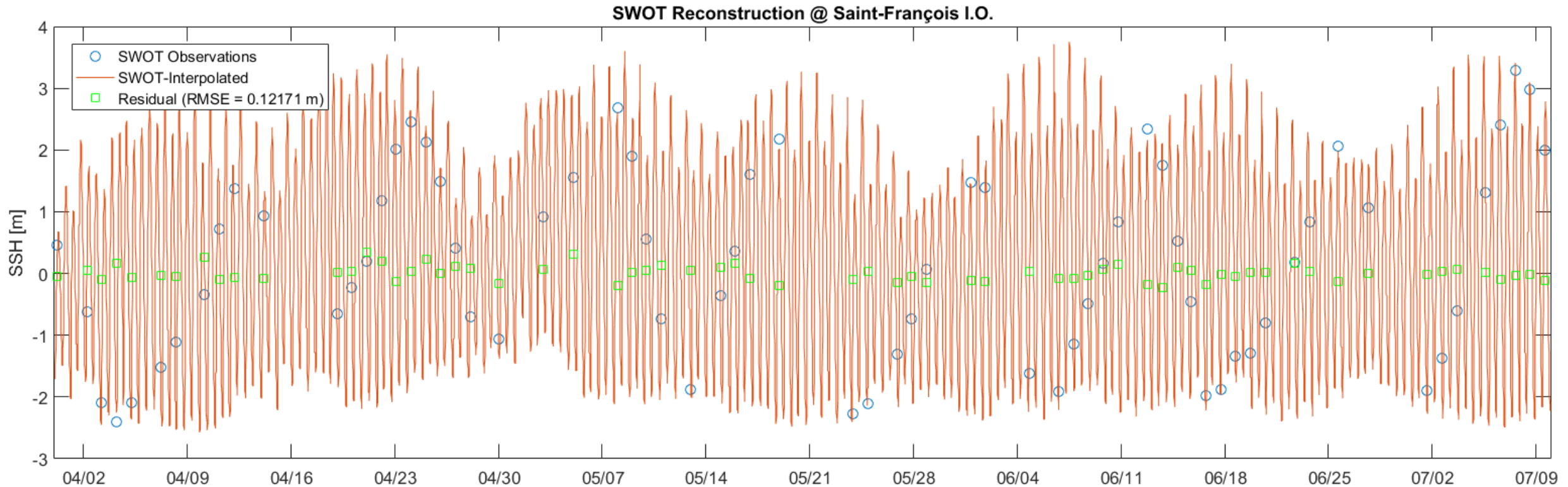
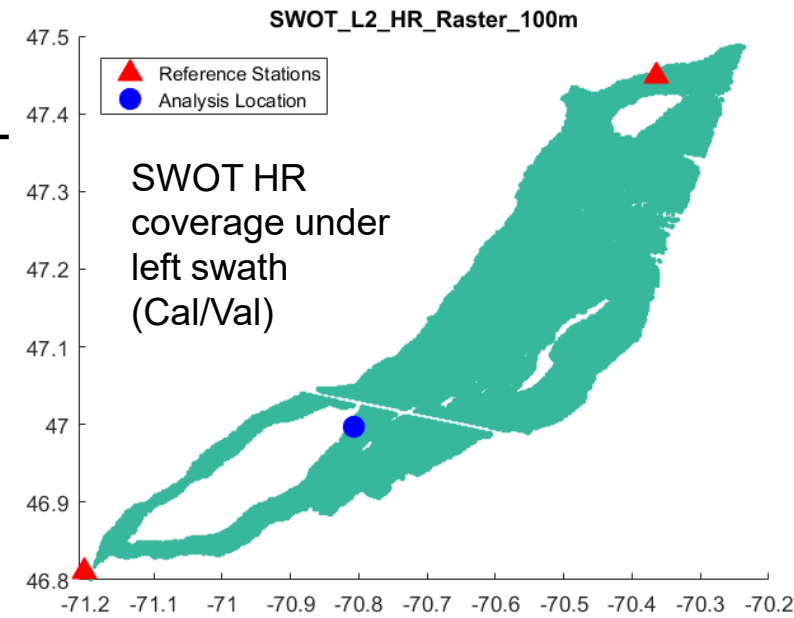
gauge_name	lat	lon	start_date	end_date	frame	rmse	bias	unbiased rmse
3248_chs	46,811	-71,202	2023-04-27	2023-07-09	009_119F	0,016	-0,089	0,008
3248_gnssir	46,811	-71,202	2023-04-27	2023-07-09	009_119F	0,014	-0,059	0,010
ptio_gnssir	46,880	-71,138	2023-04-30	2023-07-03	009_119F	0,022	0,077	0,016
chri_gnssir	46,967	-71,020	2023-03-31	2023-07-09	009_119F	0,095	-0,187	0,060
sab1_gnssir	47,018	-70,926	2023-03-31	2023-07-06	009_119F	0,010	-0,014	0,010
3110_chs	46,858	-71,003	2023-03-31	2023-07-09	009_119F	0,005	-0,057	0,002
3110_gnssir	46,858	-71,004	2023-03-31	2023-07-09	009_119F	0,007	-0,041	0,005
sjio_gnssir	46,916	-70,896	2023-03-31	2023-07-09	009_119F	0,009	-0,045	0,007
3100_chs	46,997	-70,808	2023-03-31	2023-07-09	009_119F	0,010	-0,091	0,002
brsm_gnssir	46,935	-70,736	2023-05-23	2023-07-09	009_119F	0,008	-0,043	0,006
3190_chs	47,020	-70,671	2023-05-10	2023-07-09	009_119F	0,007	-0,053	0,004
3075_chs	47,090	-70,711	2023-03-31	2023-07-09	009_119F	0,022	-0,126	0,006
ilag_gnssir	47,055	-70,532	2023-04-28	2023-07-08	009_119F	0,092	-0,184	0,059
ilsm_gnssir	47,134	-70,370	2023-03-31	2023-07-05	009_119F	0,304	0,121	0,289
prsf_gnssir	47,304	-70,561	2023-04-30	2023-07-09	009_119F	0,015	-0,047	0,013
3057_chs	47,449	-70,366	2023-03-31	2023-07-09	009_119F	0,133	0,010	0,133
cpao_sol	47,494	-70,229	2023-06-13	2023-06-17	009_119F	0,040	-0,018	0,040
cpao_ct2x	47,494	-70,229	2023-06-13	2023-06-17	009_119F	0,020	-0,012	0,020
3440_chs	48,245	-70,180	2023-06-08	2023-07-09	009_120F	0,004	-0,045	0,002
ptsg_sol	48,239	-70,102	2023-05-23	2023-07-08	009_120F	0,004	-0,034	0,003
ptsg_ct2x	48,239	-70,102	2023-05-23	2023-06-13	009_120F	0,015	0,105	0,004
3130_chs	47,847	-69,572	2023-05-09	2023-07-09	009_120F	13,443	-0,588	13,097
ilvs_gnssir	48,040	-69,406	2023-05-24	2023-07-09	009_120F	0,020	-0,072	0,015
ilvn_sol	48,053	-69,423	2023-05-24	2023-07-09	009_120F	0,023	-0,111	0,011
grbr_gnssir	48,228	-69,554	2023-05-26	2023-07-09	009_120F	0,021	0,007	0,021
trps_gnssir	48,170	-69,133	2023-05-23	2023-07-09	009_120F	0,035	-0,144	0,014

LAG REGRESSION METHOD

Lag regression reconstructs continuous SSH signals from sparse SWOT observations, using SSH observations from n reference gauges:

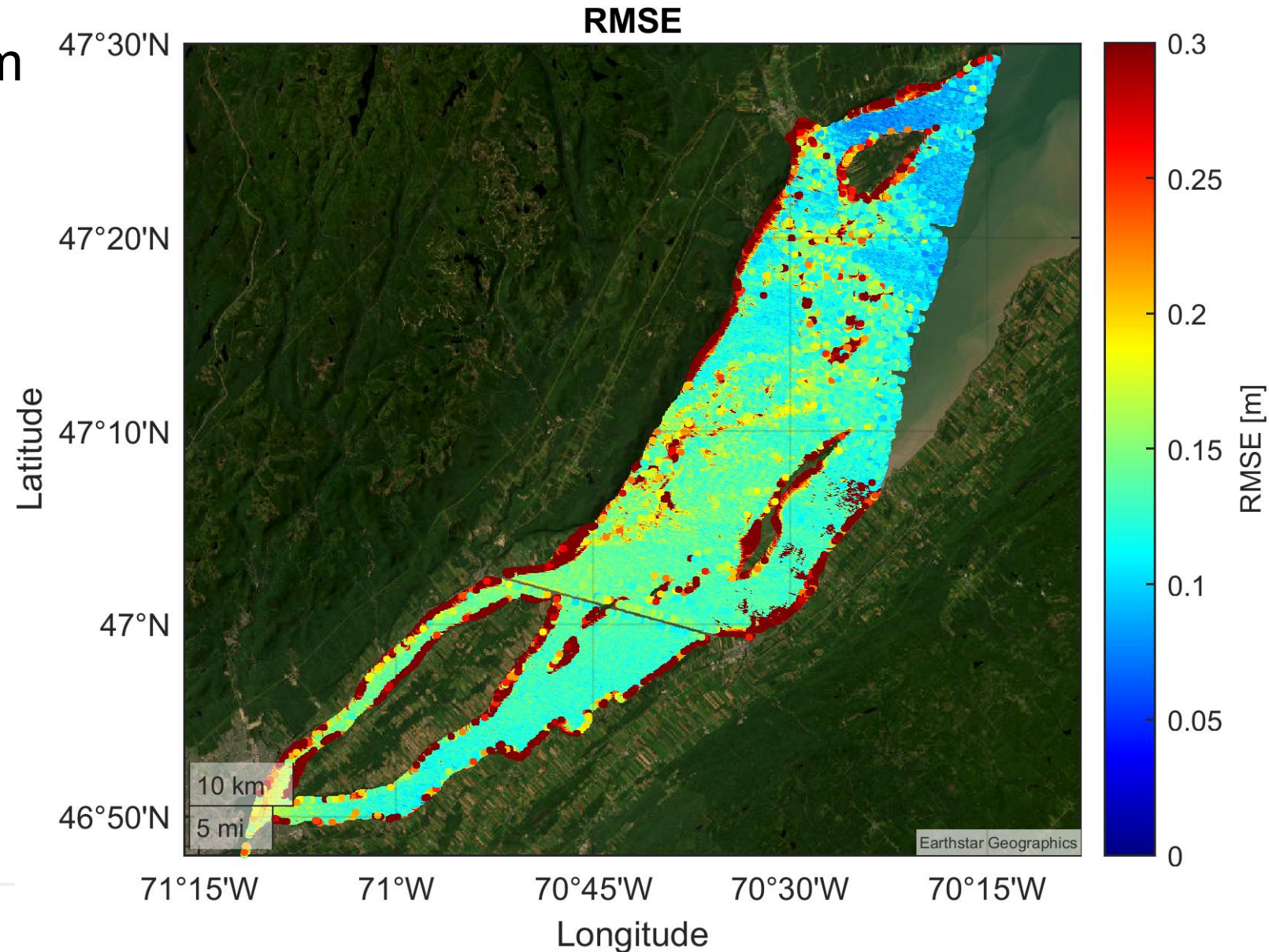
$$h_{\text{SWOT}}(t) = \beta_0 + \sum_{i=1}^n \beta_i h_{\text{ref},i}(t - \tau_i) + \varepsilon$$

where t is the SWOT observation times, τ_i are optimal lags for the reference stations, determined by cross-correlation, and β_0 and β_i are regression coefficients, with positive weights β .



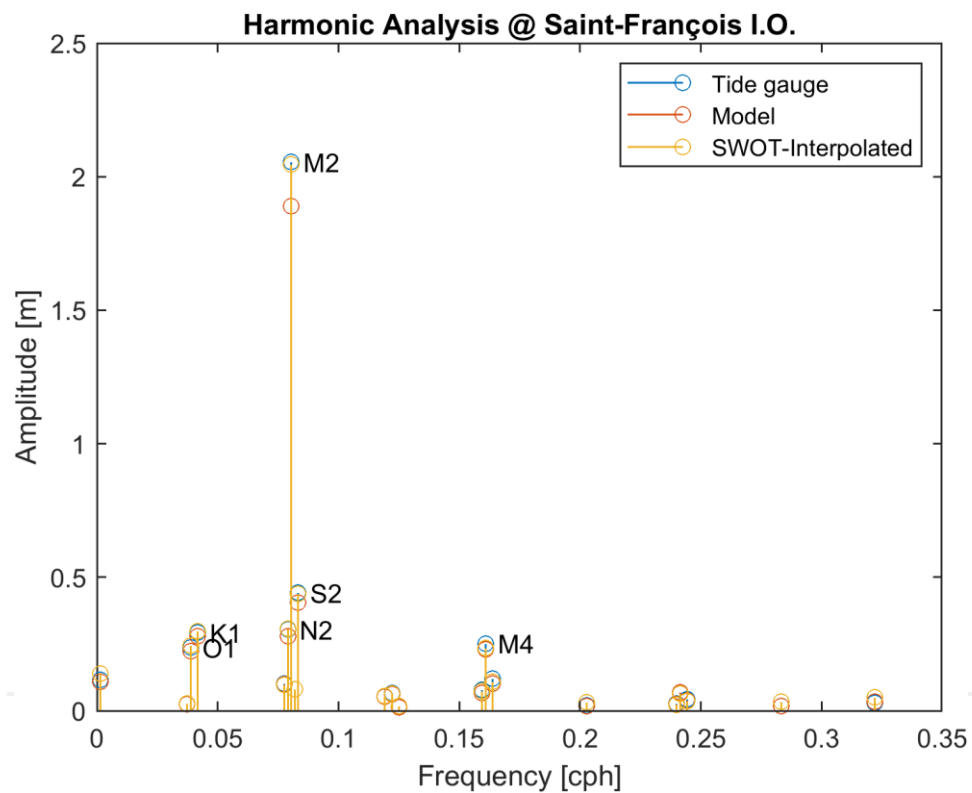
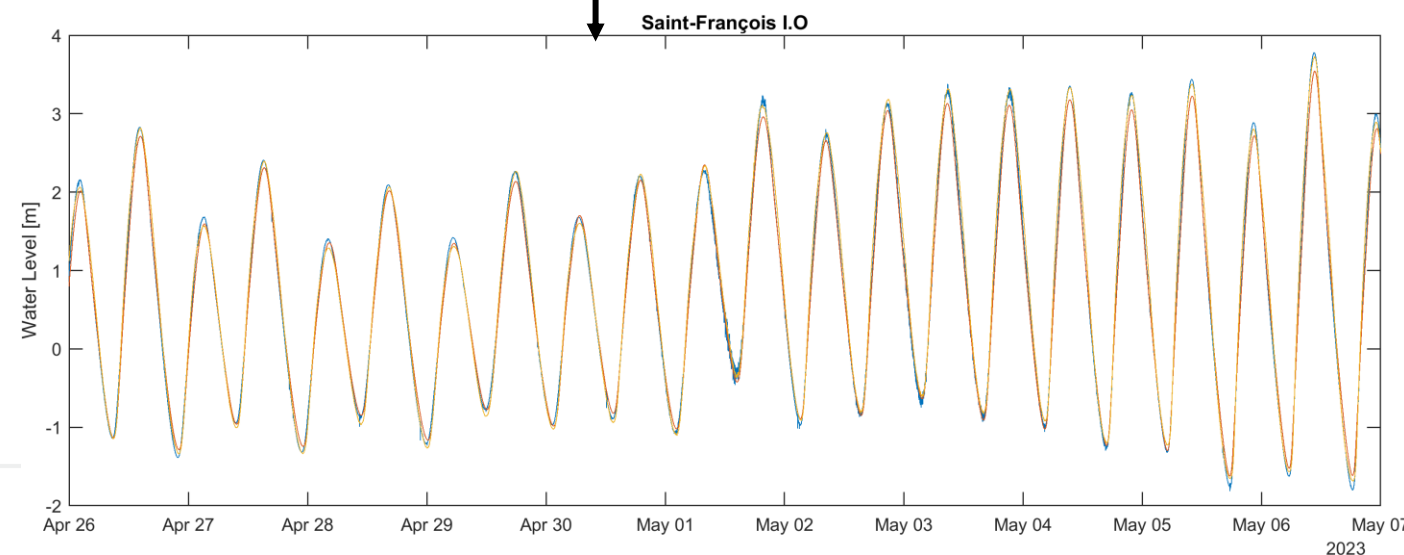
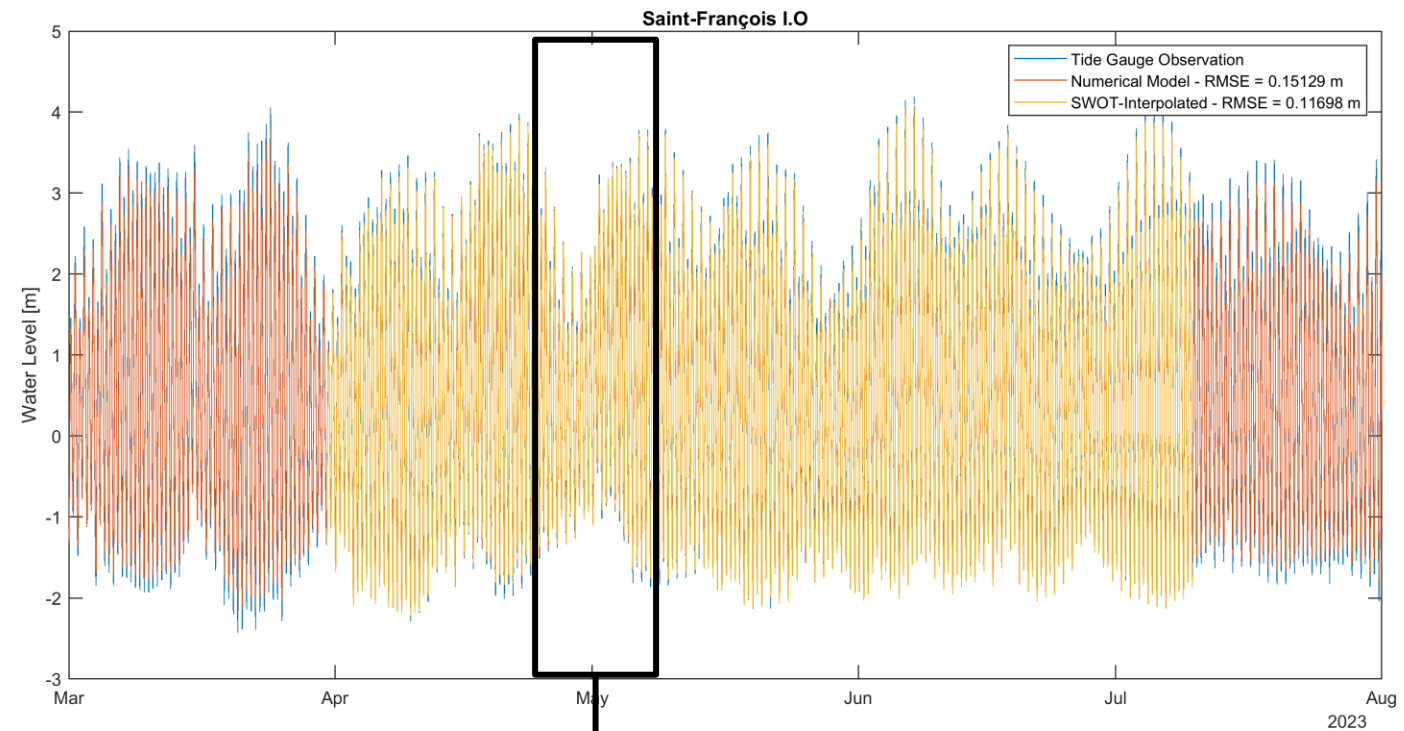
RECONSTRUCTION PERFORMANCE

- SWOT L2 HR Raster 100m
- Median RMSE is 0.135m
- Includes SWOT and regression errors
- Many areas with $RMSE > 0.3m$ correspond to intertidal flats



CONFRONTING ECCC'S MODEL AND SWOT

- SWOT reconstructions by lag regression outperform numerical model solutions (RMSE: 0.117m vs. 0.151m)
- Non-stationarity (by discharge and/or storm surge) is well captured
- Model underestimates M2 by 16cm at Saint-François I.O.
- SWOT-reconstructed amplitude errors are <1cm for all constituents



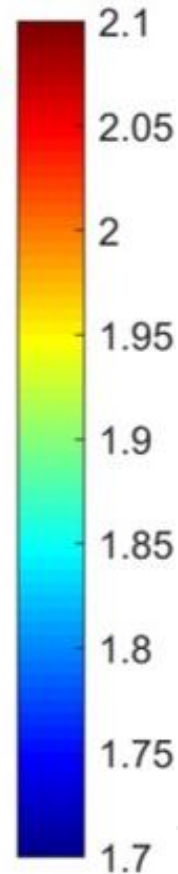
SWOT CAN HELP IMPROVE NUMERICAL MODELS

- 2D hydrodynamic model has limitations:
 - B.C. definition, bathymetry, 2D approx. (no stratification), mesh resolution, calibration
- SWOT can help identify inaccuracies in models

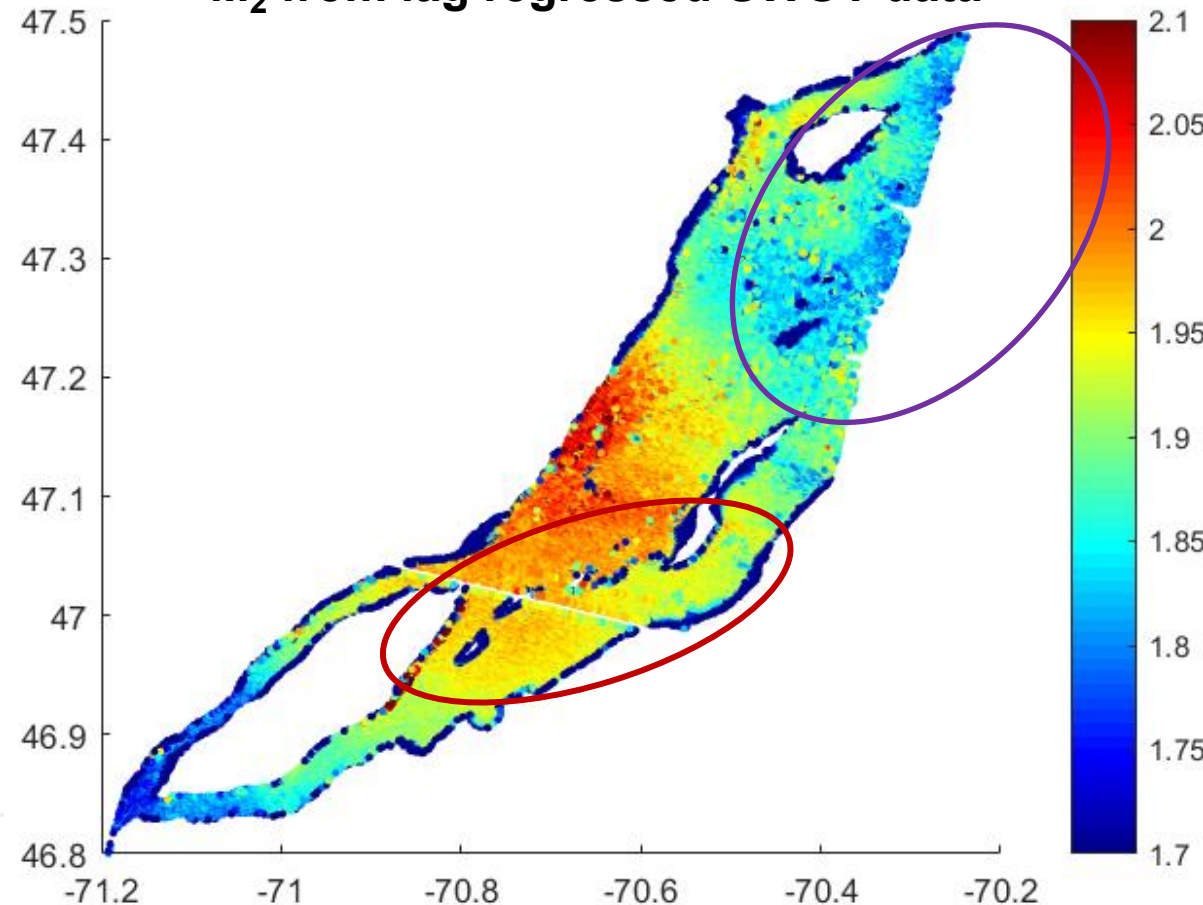
M₂ from numerical model

Poorly defined (laterally uniform) B.C. leading to overestimated tidal amplitudes

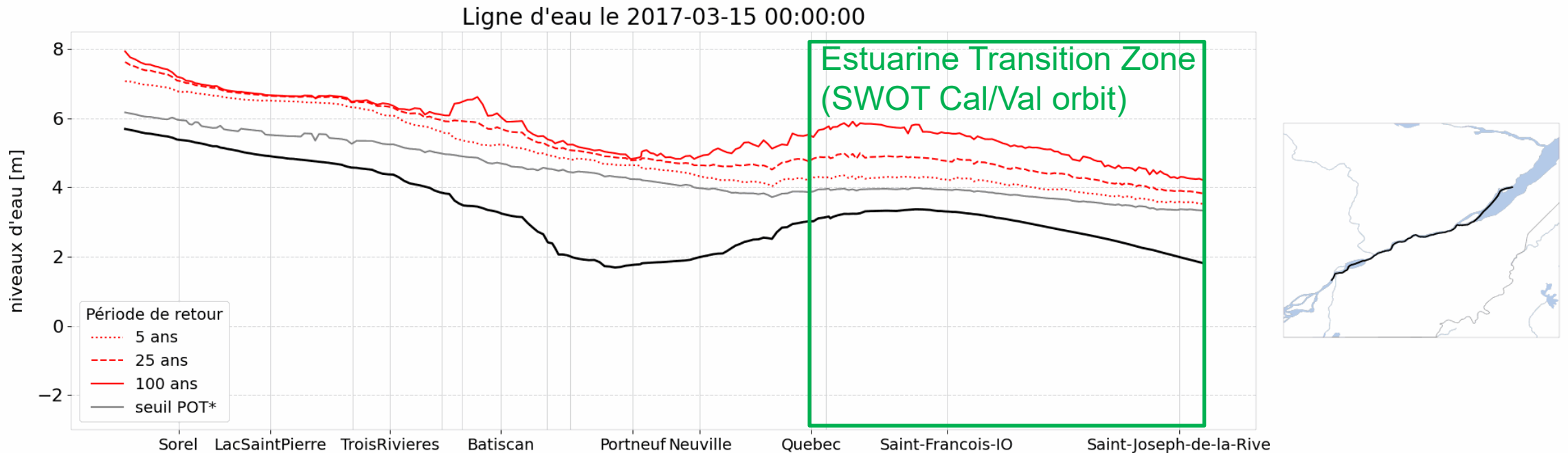
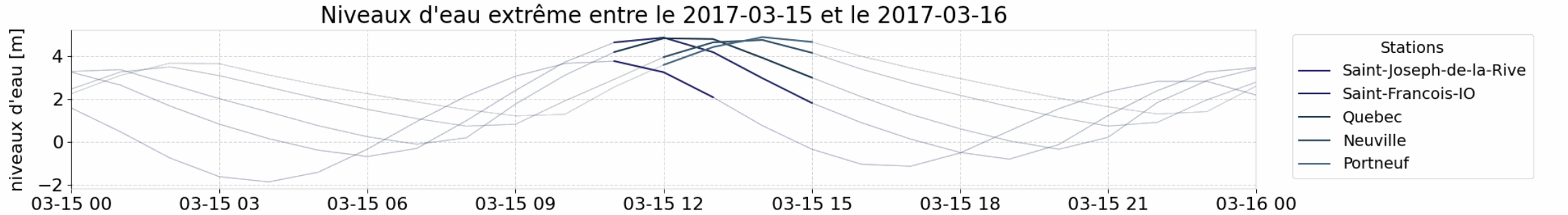
Imprecise bathymetry and too coarse mesh resolution around islands



M₂ from lag regressed SWOT data



STORM SURGE EVENTS IN THE ST. LAWRENCE: CAN WE MAP WSE EXTREMES FROM SWOT SPARSE OBSERVATIONS?

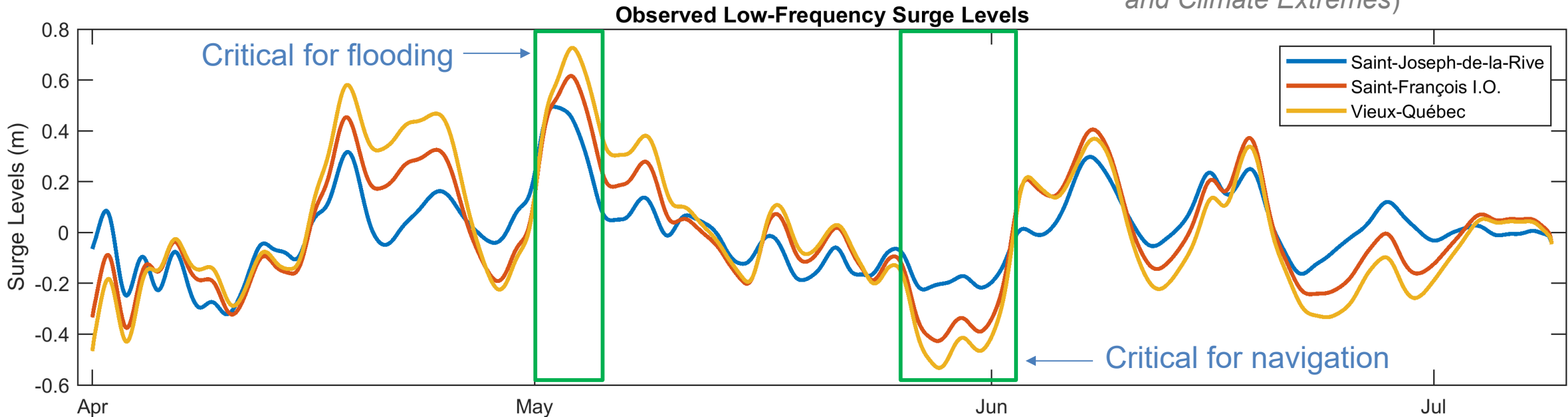


*POT: *Peak Over Threshold*

LOW-FREQUENCY STORM SURGE LEVELS: EVENTS IDENTIFICATION DURING SWOT CAL/VAL

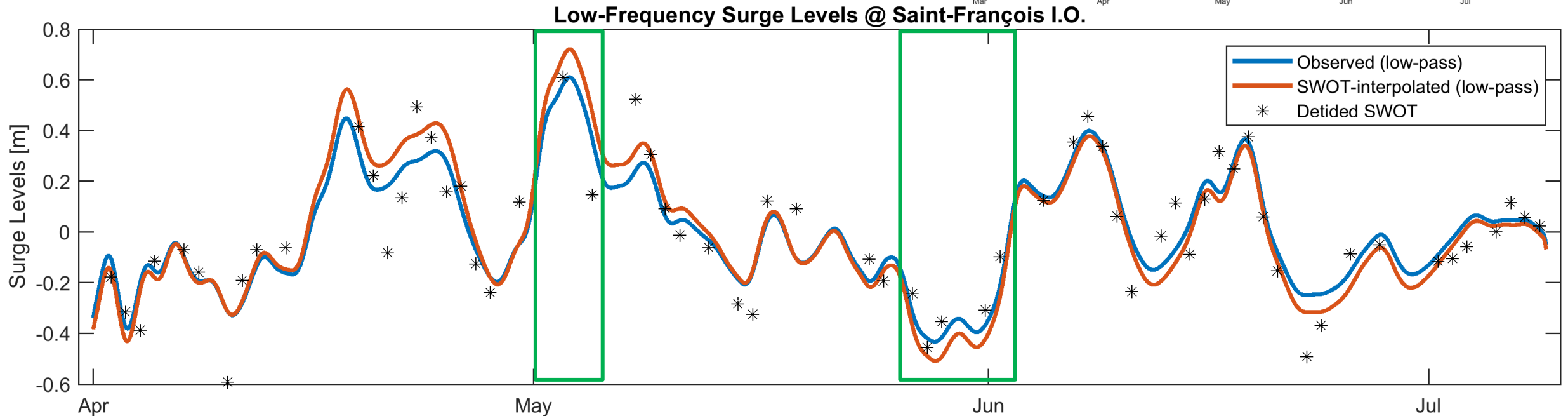
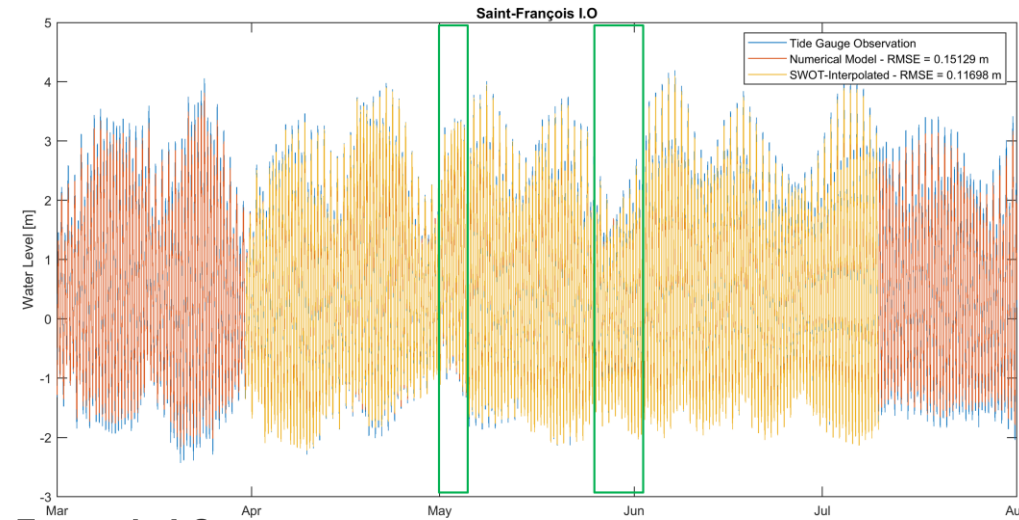
- Low-passed observations at 3 stations (Godin's filter)
- 2 events selected during SWOT Cal/Val:
 - 1 positive surge (May 1 – May 6, 2023)
 - 1 negative surge (May 25 – June 2, 2023)

Events selection approach following Innocenti et al. (submitted to *Weather and Climate Extremes*)



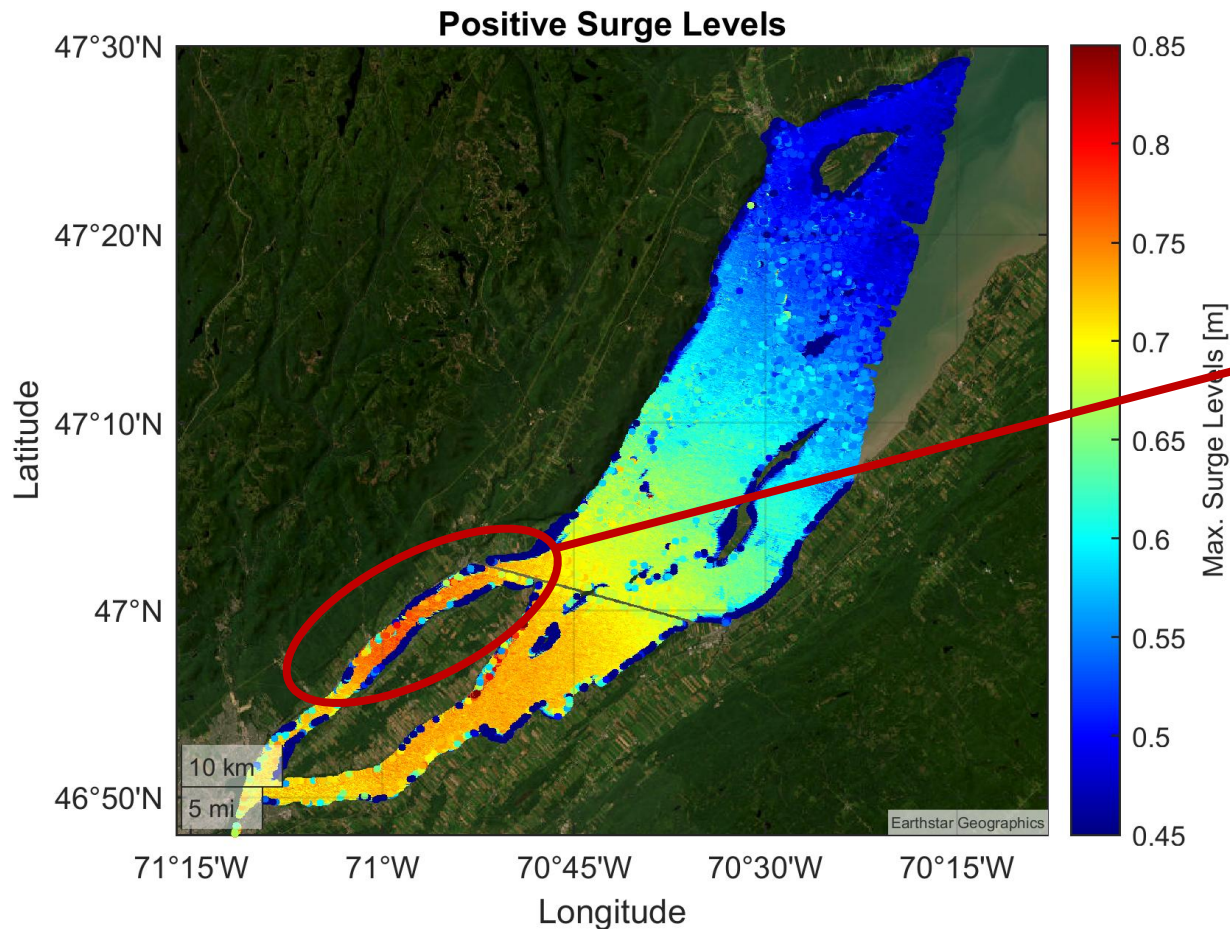
LOW-FREQUENCY STORM SURGE LEVELS: SWOT RECONSTRUCTIONS OF EXTREME EVENTS

- Low-passed SWOT reconstructions (from lag regression) closely match low-passed observations at Saint-François
- Nonstationary detiding of SWOT data using high-passed SWOT reconstructions



POSITIVE STORM SURGE MAXIMUM LEVELS

- 2D map of **positive** storm surge extrema from SWOT reconstructions
- Areas prone to flooding can be identified



CONCLUSION

Comprehensive dataset composed on *in situ*, airborne and satellite observations

- Dense station network during SWOT Cal/Val and extending into the Science phase
- SSH / tides, waves, ice, velocities
- Used for continued SWOT validation
- Data repository and accompanying paper soon to be submitted

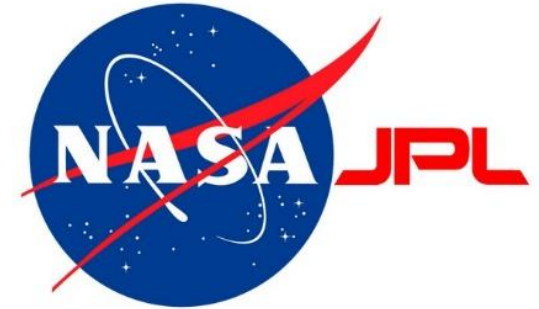
SWOT data highlights

- New spatial details revealed that could not be captured with point measurements
 - Accuracy surpasses expectations: cm-level errors (unbiased RMSE) at most stations
 - Super-resolution of tides is made possible by blending tide gauges with SWOT
 - SWOT-based model evaluation reveals potential areas for improvements in the model
 - Non-stationary detiding reveals upstream amplification of low-frequency storm surges
-

THANK YOU!



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