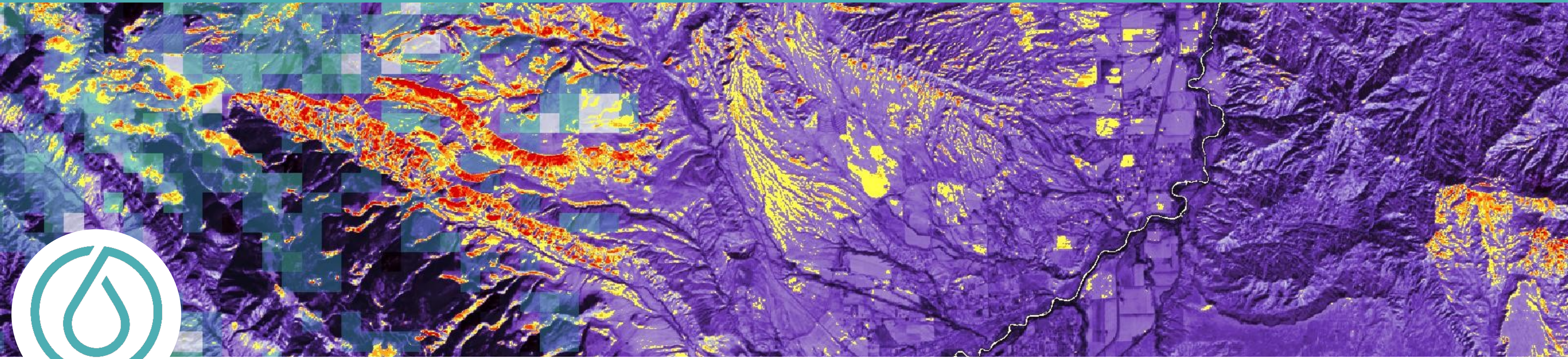


Shoshone River Water Resources II

Quantifying Sediment Input in the Shoshone River in Wyoming using the Soil and Water Assessment Tool for Enhanced Water Quality Monitoring

Christian Bitzas ⌅ Jillian Greene ⌅ Robyn Holmes ⌅ Isabella St John

25TH DEVELOP ANNIVERSARY

Pop-Up Project | Spring 2023

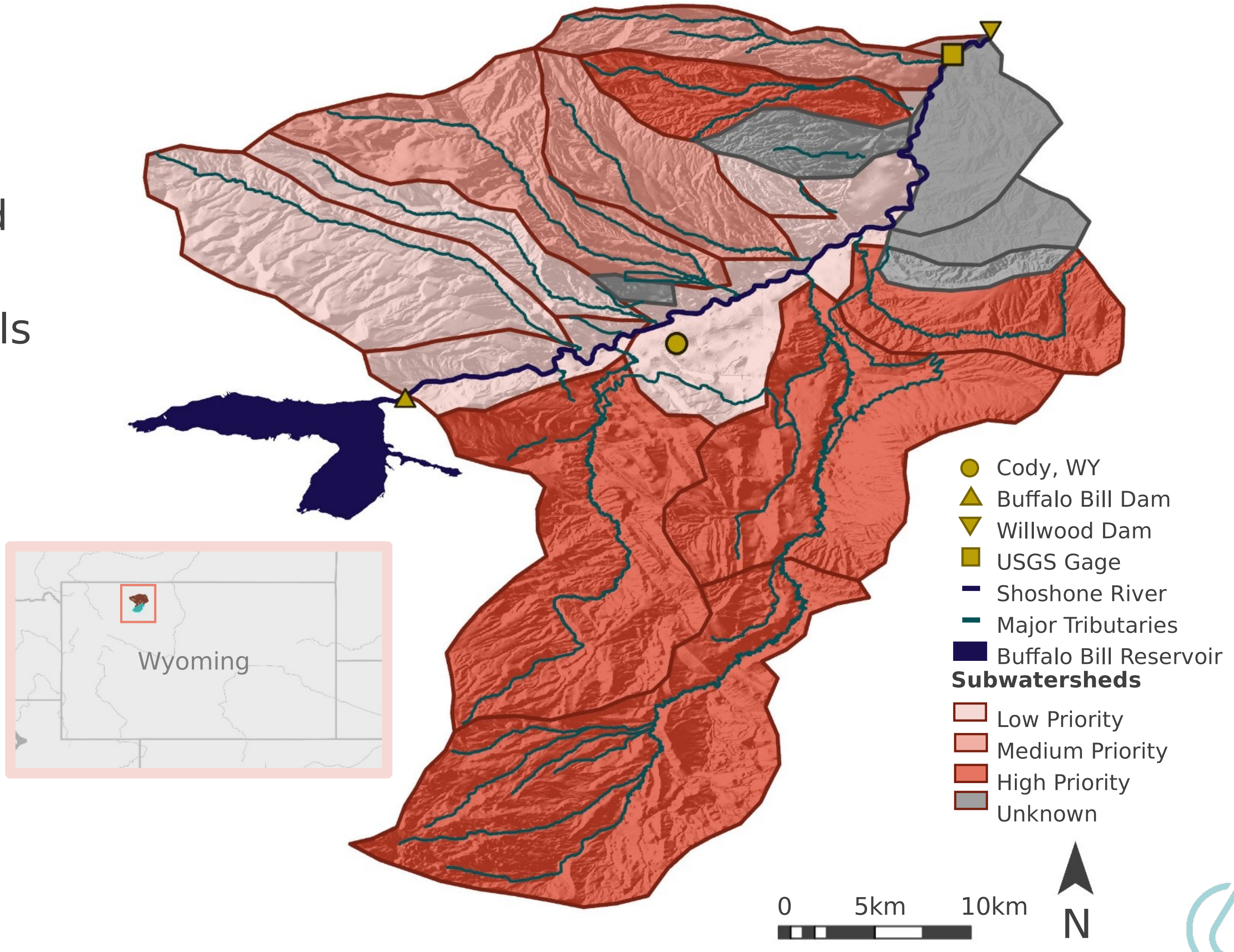
STUDY AREA

Study Area

- Shoshone River Watershed
  - Buffalo Bill Dam to Willwood Dam
  - Tributaries & irrigation canals feed into the river
- Surrounded by mountains
- Annual precipitation: 10.5in

Study Period

- Jan. 2019 – Oct. 2021
  - USGS operated water monitoring station



OBJECTIVES

Image Credit: Caroline Williams

Increase understanding of sediment sources through:

- Conduct Soil and Water Assessment Tool **(SWAT) analysis**
- Improve **plume detection** via turbidity remote sensing
- Conduct **snow cover analysis**

PARTNERS

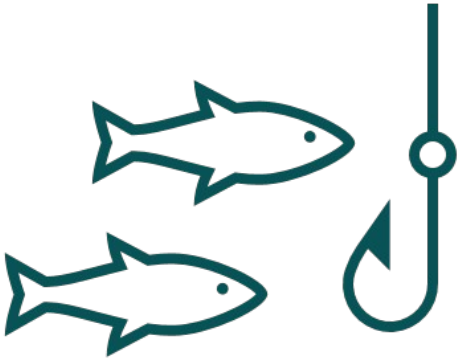
WY Department of Environmenta l Quality

Shoshone River Partners

USGS WY-MT Water Science Center

Images: Carmen McIntyre & Robyn Holmes

COMMUNITY CONCERNS

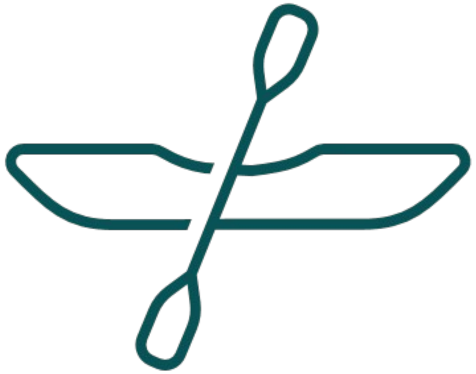


Ecological

- Impaired fish spawning habitat
- Aquatic insects

Economic

- Rafting, angling, tourist recreation
- Irrigated agriculture



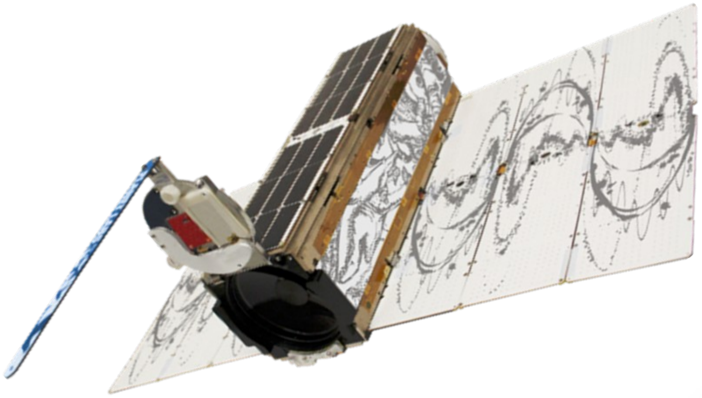
Quality of Life

- Community member recreation

SATELLITES

PlanetScope

- 4 band (RGBn) imagery
- 3m resolution
- Daily



Suomi NPP

- Visible Infrared Imaging Radiometer Suite (VIIRS)
- 375m resolution
- Daily

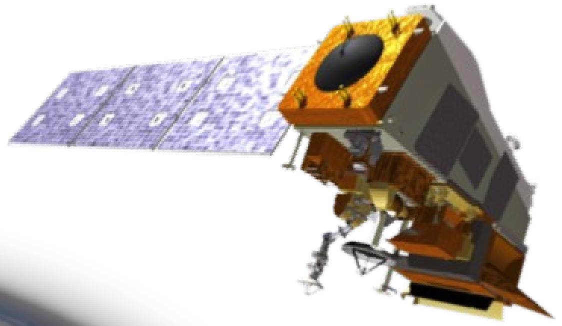
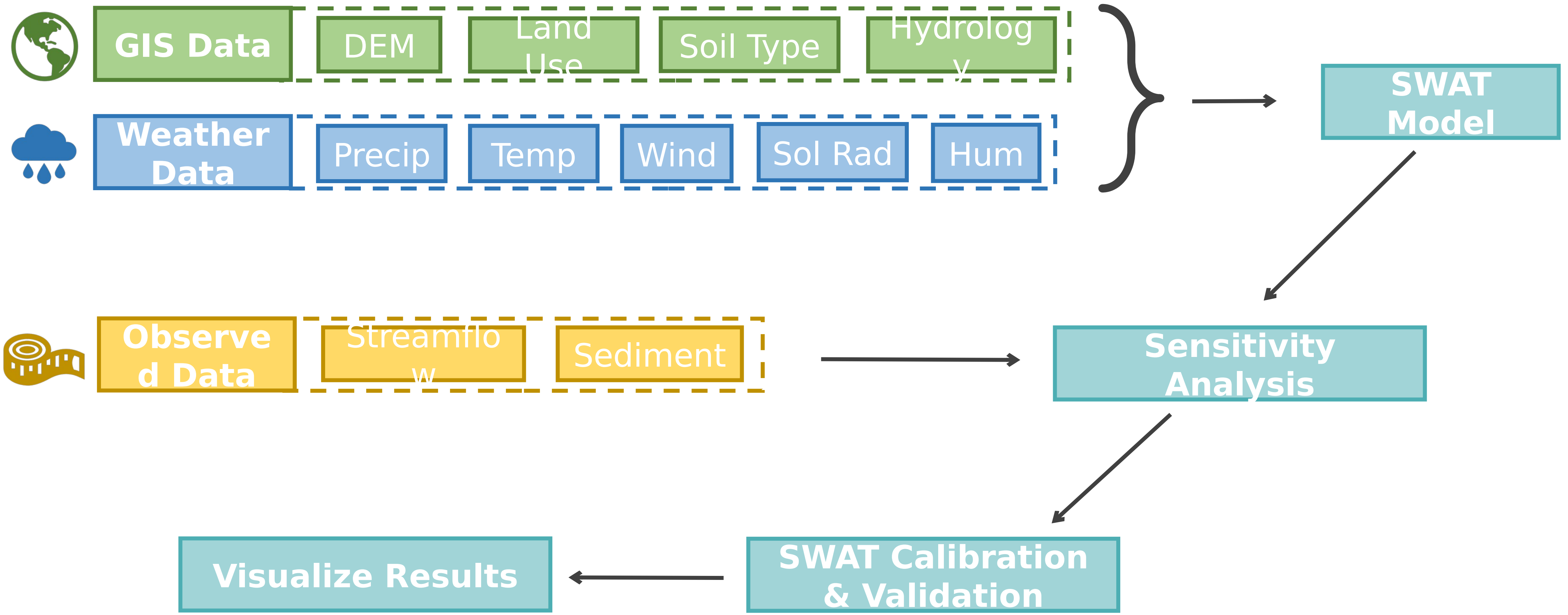


Image Credit: NASA, Planet Labs PBC

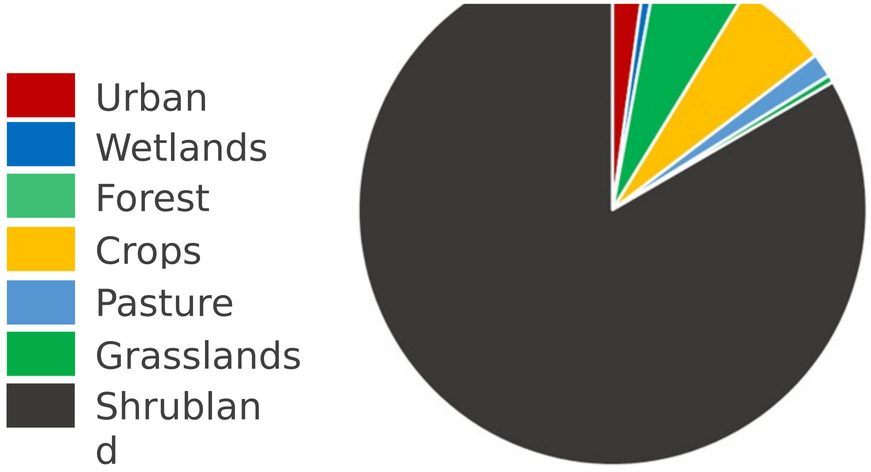
METHODS: SWAT



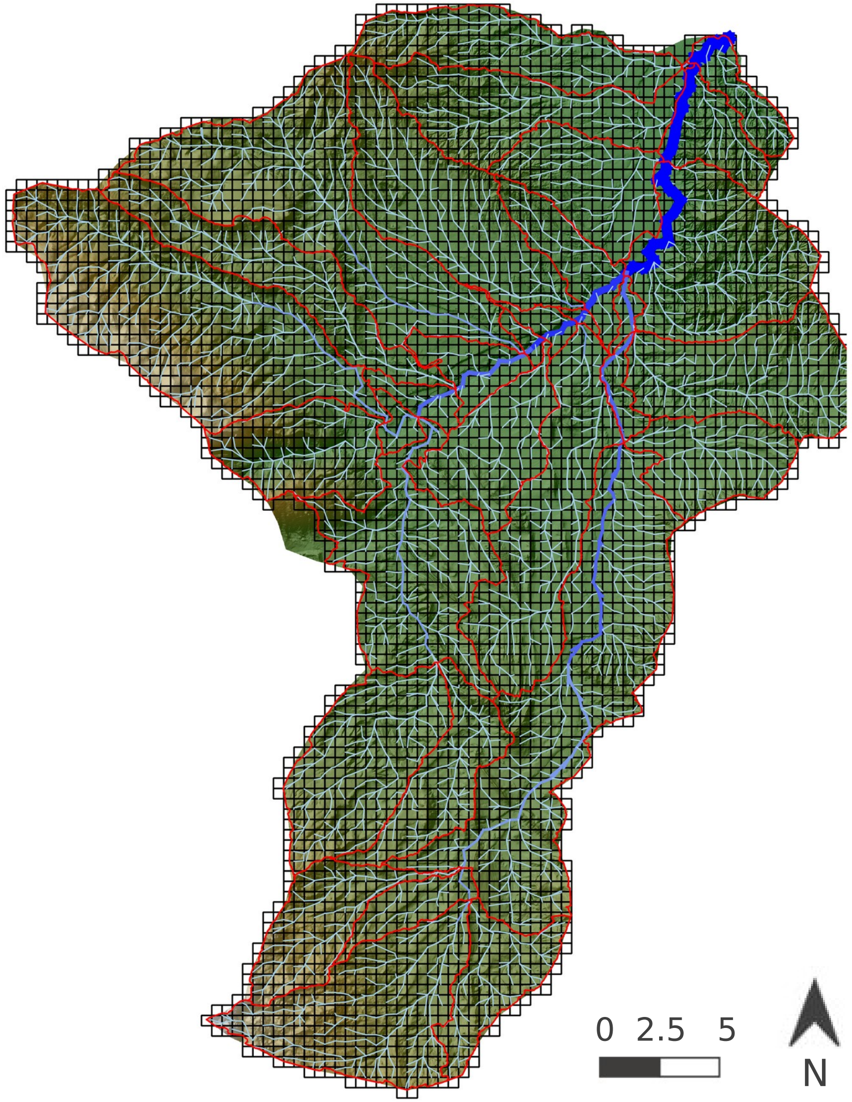
METHODS: SWAT

- 500m grid cells
- 4636 subbasins
- 7467 hydrological response units

Land Use Area

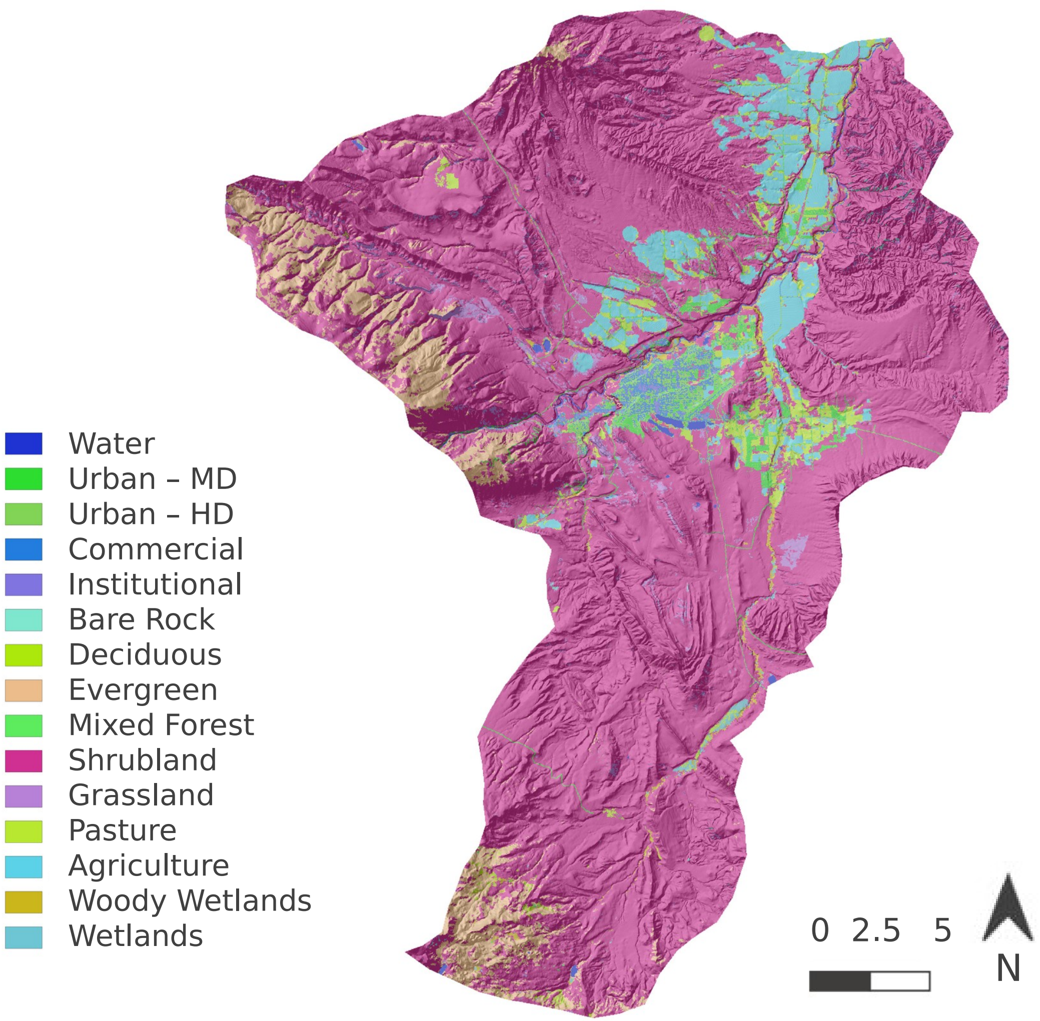


SWAT Grid Model



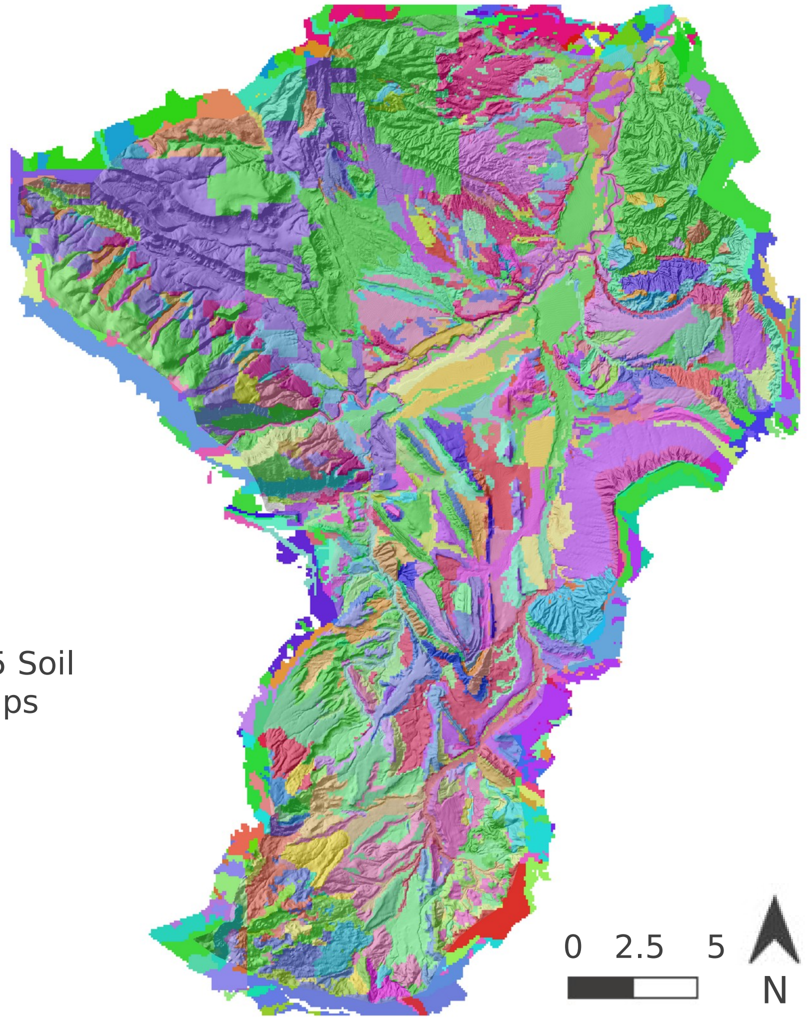
METHODS: SWAT

SWAT Land Use Map

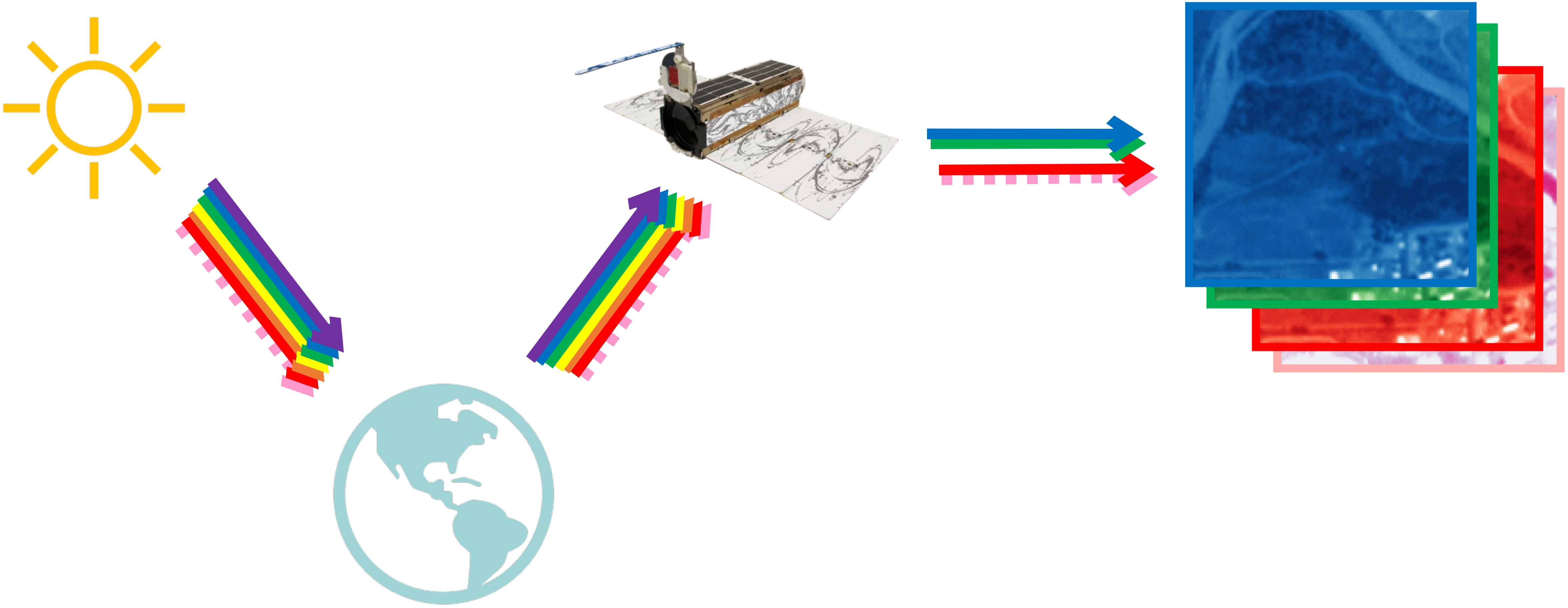


SWAT Soil Map

2055 Soil Groups



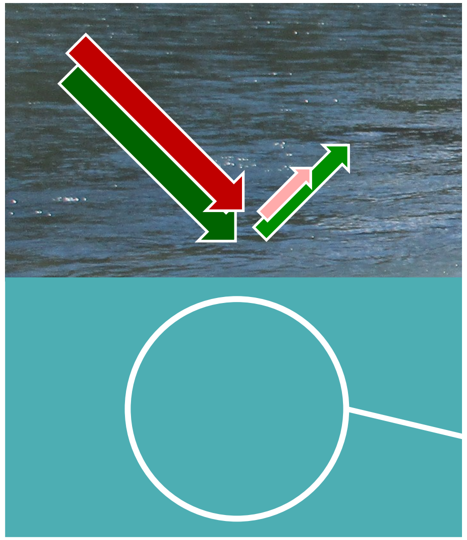
METHODS: Remote Sensing (RS) Basis



Images: PowerPoint, Planet Labs PBC

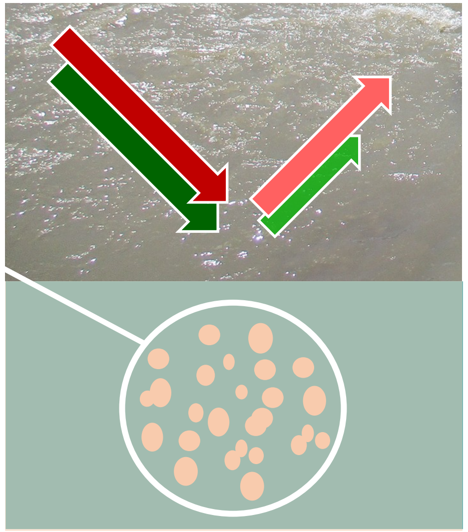
METHODS: Sediment RS

Low Turbidity:



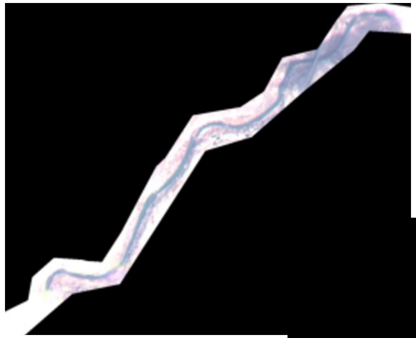
Sulphur Creek Sediment Plume

High Turbidity:



Images: Google Earth, Carmen McIntyre

METHODS: Sediment RS

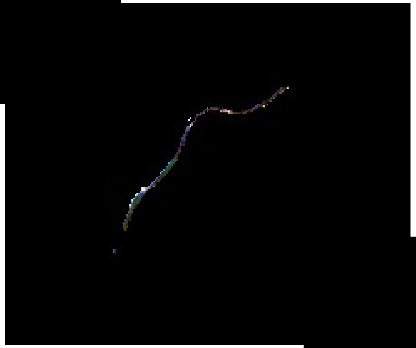


Merge Raw PlanetScope Images

- Orthotile Analytic, Top of Atmosphere Radiance

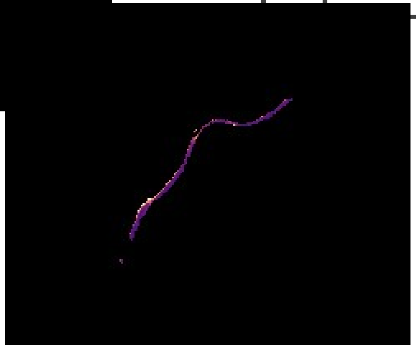
Apply Atmospheric Corrections

- ACOLITE software, Dark Spectrum Fitting algorithm



Mask Clouds, Low Conf. Pixels, & Land

- Planet’s UDM2 layer, Normalized Difference Water Index + Otsu’s method thresholding, clip to shapefile



Calculate Turbidity

- Equation calibration or machine learning

Images: PlanetScope

METHODS: Sediment RS

Date	Blue	Green	Red	NIR
2019-03-18 17:50:45	6.5E-06	8.41E-06	9.03E-06	1.03E-05
2019-05-30 17:59:25	5.62E-06	9.49E-06	1.2E-05	9.73E-06
…	…	…	…	…

Date	Streamflow (cfs)	Turbidity (FNU)
2018-10-01 07:00:00	707.6406	13.7
2018-10-01 07:15:00	708.026	18.2
…	…	…

Equation Calibration

(scipy.optimize.basin_hopping)

Machine Learning

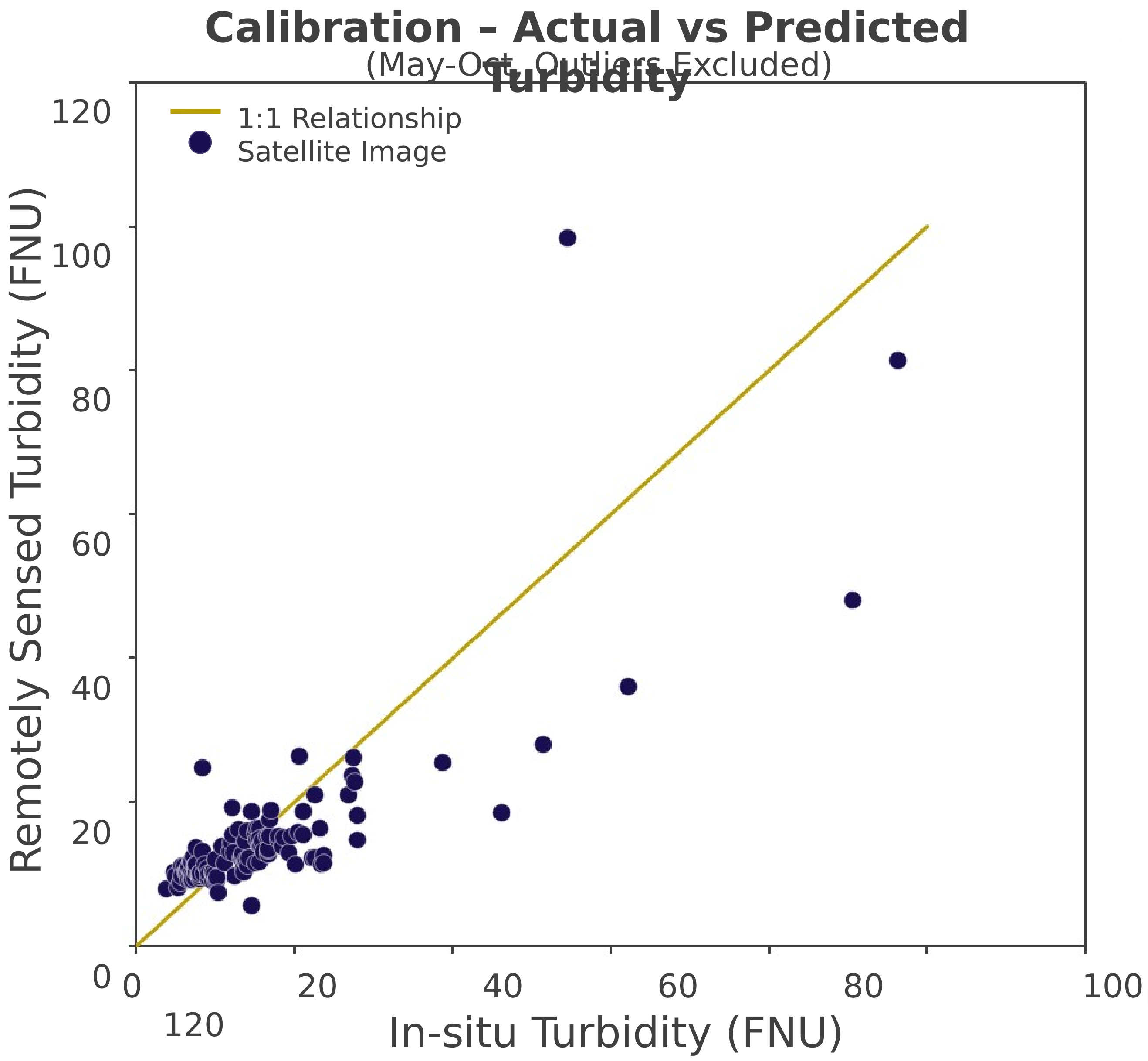
(sklearn.ensemble.RandomForestClassifier)

Image Credits: Google Earth, Jason Alexander

METHODS: Sediment RS – Eqn. Optimization

a = 277811.5
b = 1.410944

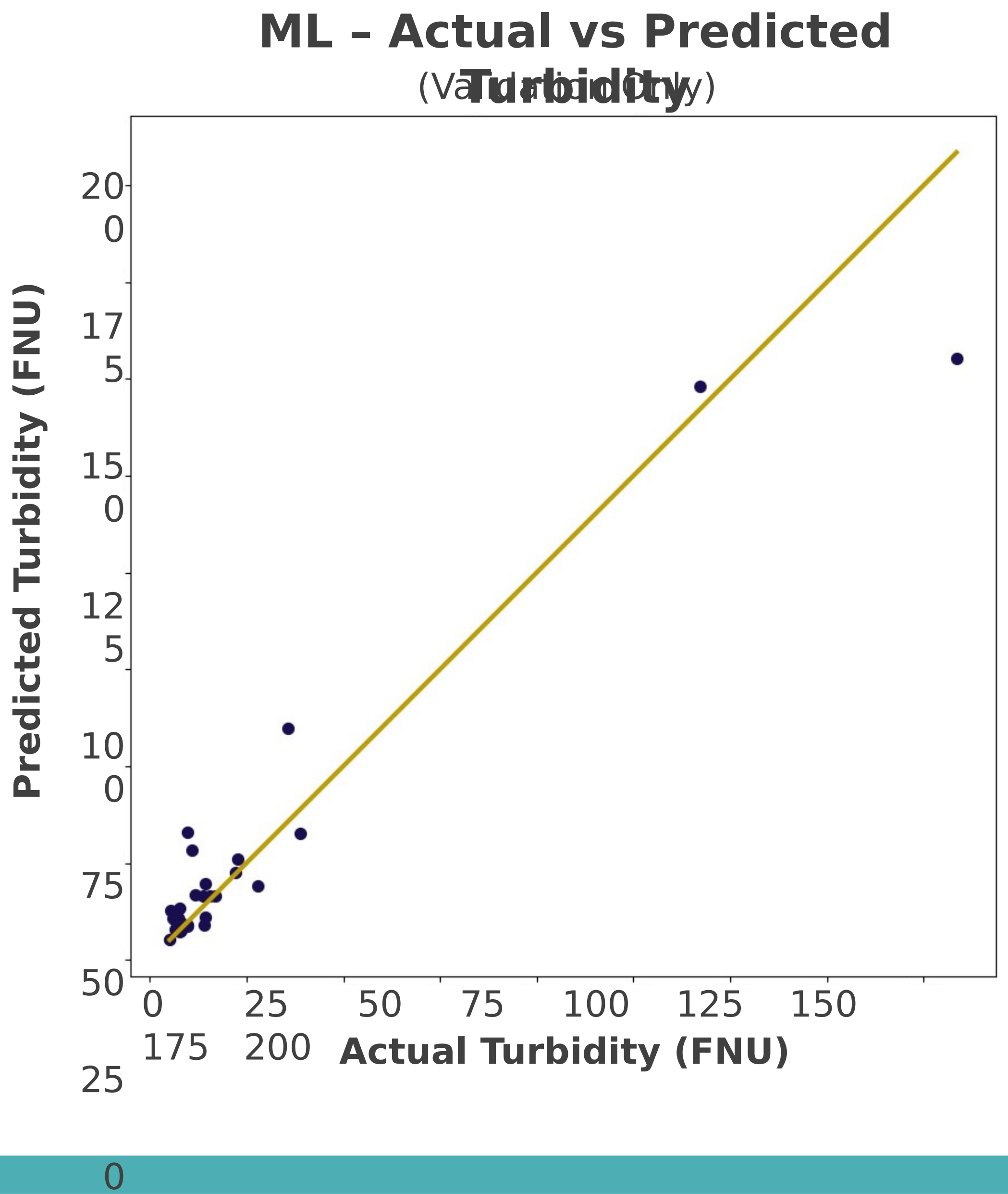
Statistic	Value
R^2	0.808
NSE	0.803
KGE	0.801



METHODS: Sediment RS – Machine Learning

Statistic	Value
R^2 (Validation)	.929

Band	Relative Importance
Red	38%
Green	20%
Blue	13%
NIR	29%



METHODS: Sediment RS – Auto Plume Detection

1

Interpolate ML Data

Remove no data (0) values.

2

Apply Savitzky-Golay Filter

Reconstruct data using 3rd order polynomials to drastically reduce noise.

3

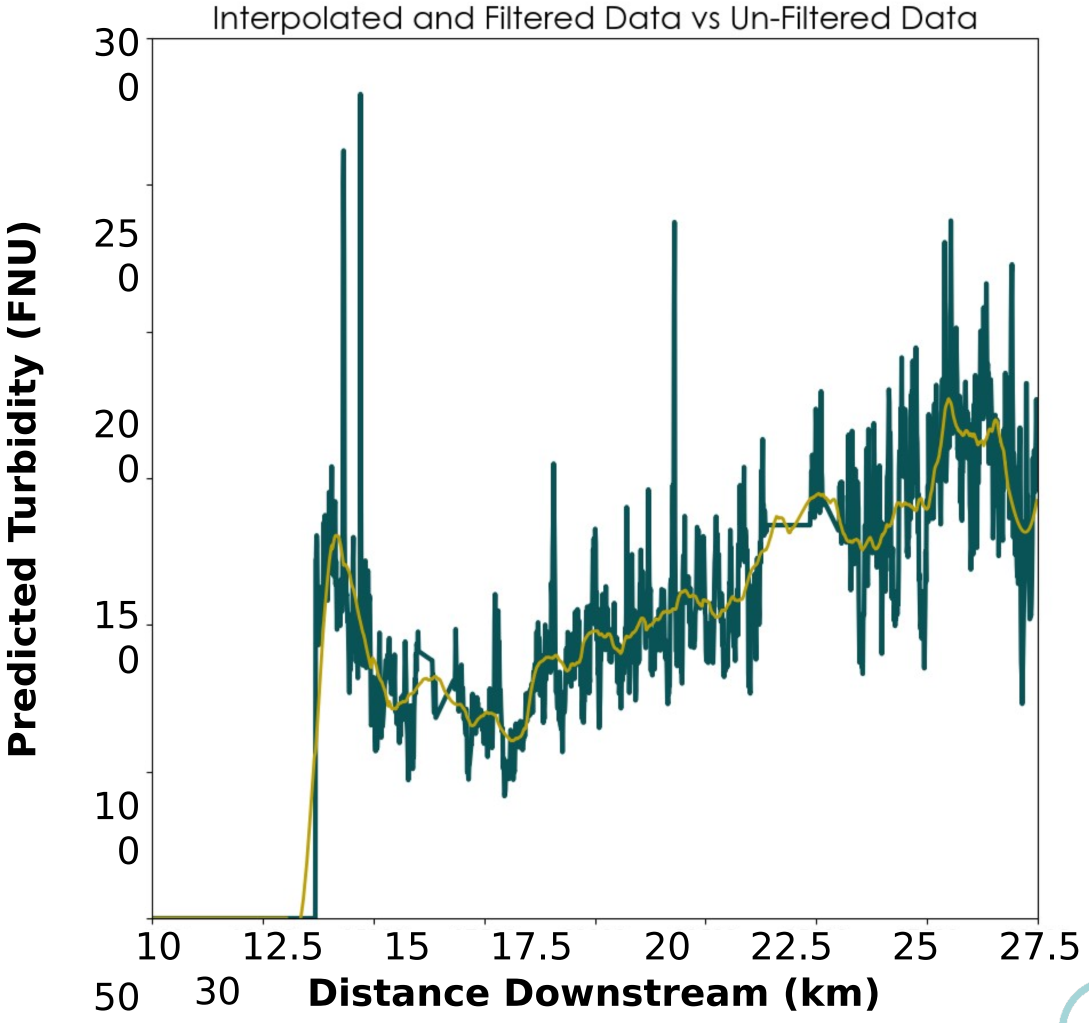
Plot Segmented Trendlines

Plot trendline of length 1KM at the start of each tributary of interest.

4

Determine Possible Plume Events

Name streams that exceed 50 FNU per 1KM increase and mark as possible event.



0

METHODS: Snow

1. Snow cover extent values
2. Time series analysis of % snow cover values and hydrologic variables

Download Suomi NPP VIIRS VNP10A1F Images & Climate/Stream data for entire study period (1035 days)

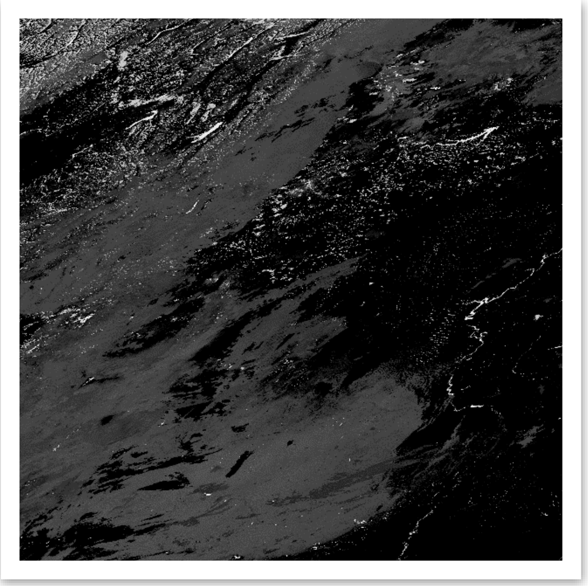
Isolate extent of watershed for VNP10A1F images from shapefile

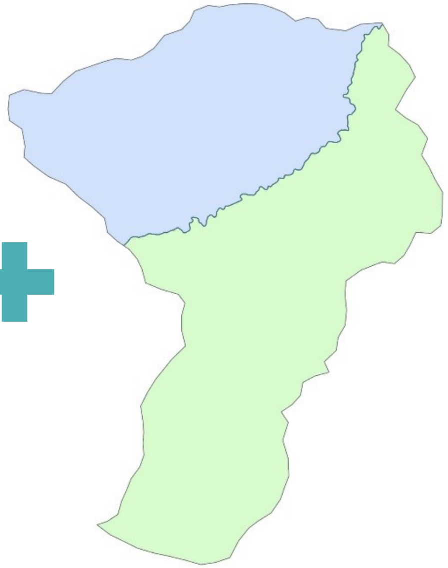
Reclassify pixel values for clipped images

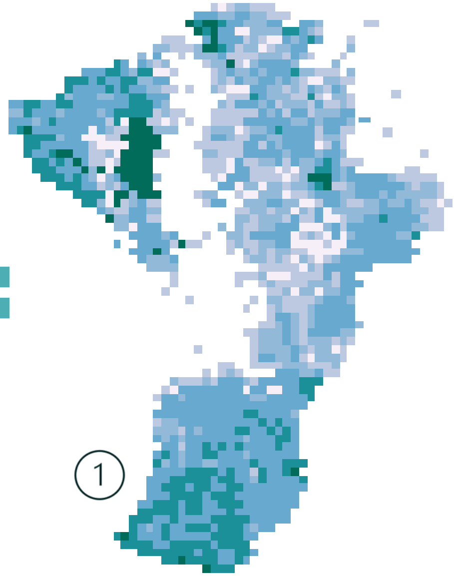
Export % Snow-Covered Pixels values to table

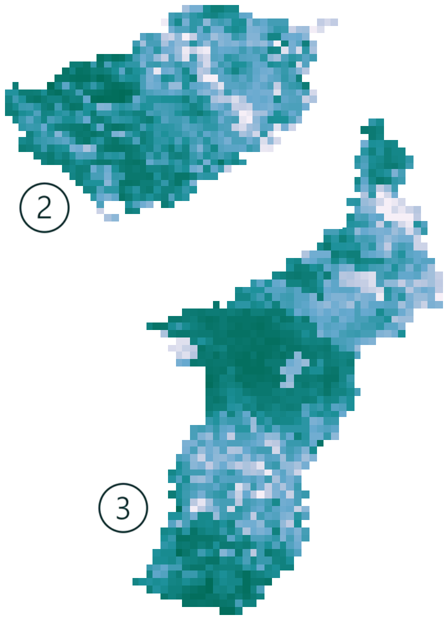
Graph snow cover % values and stream/climate data in time series

METHODS: Snow – Snow Cover Extent





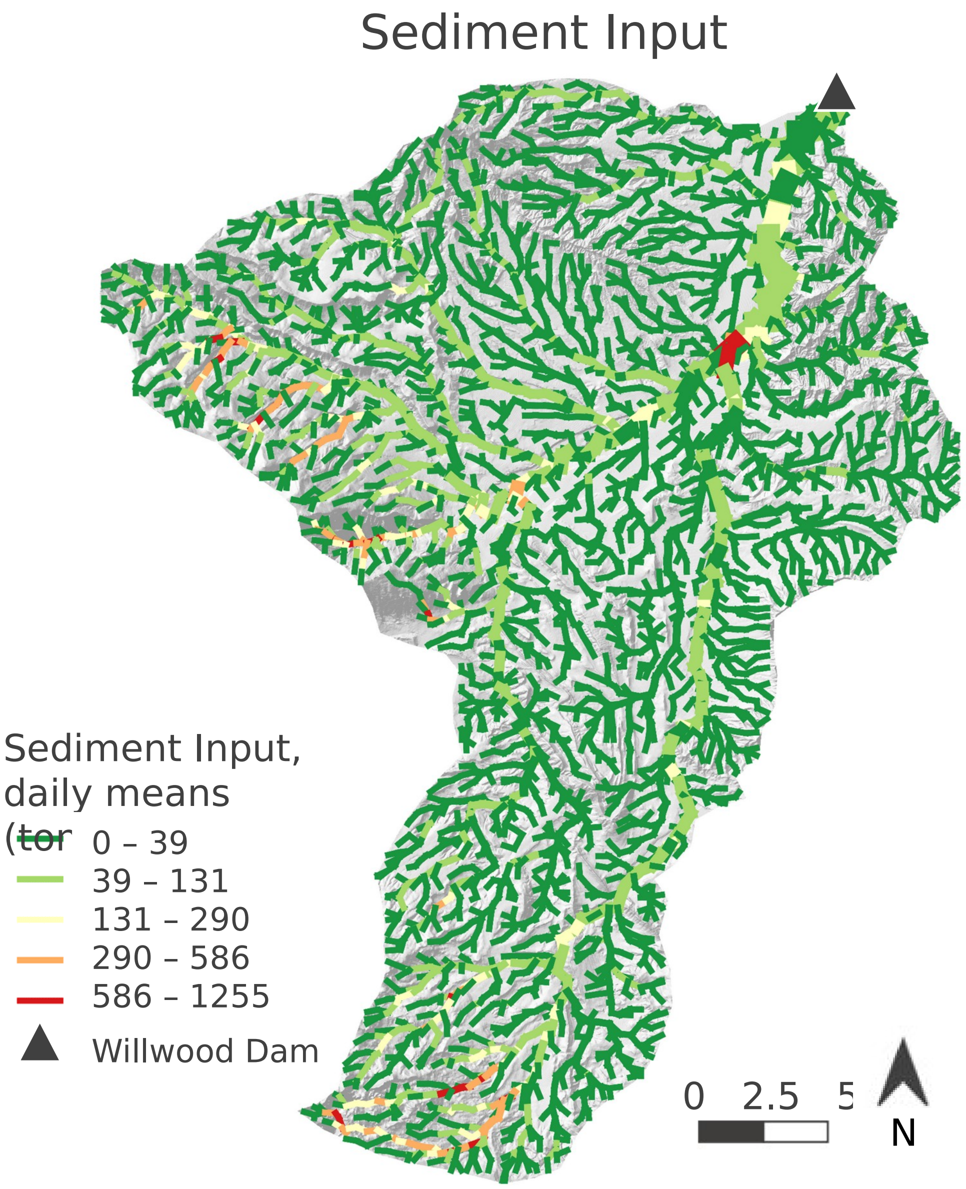


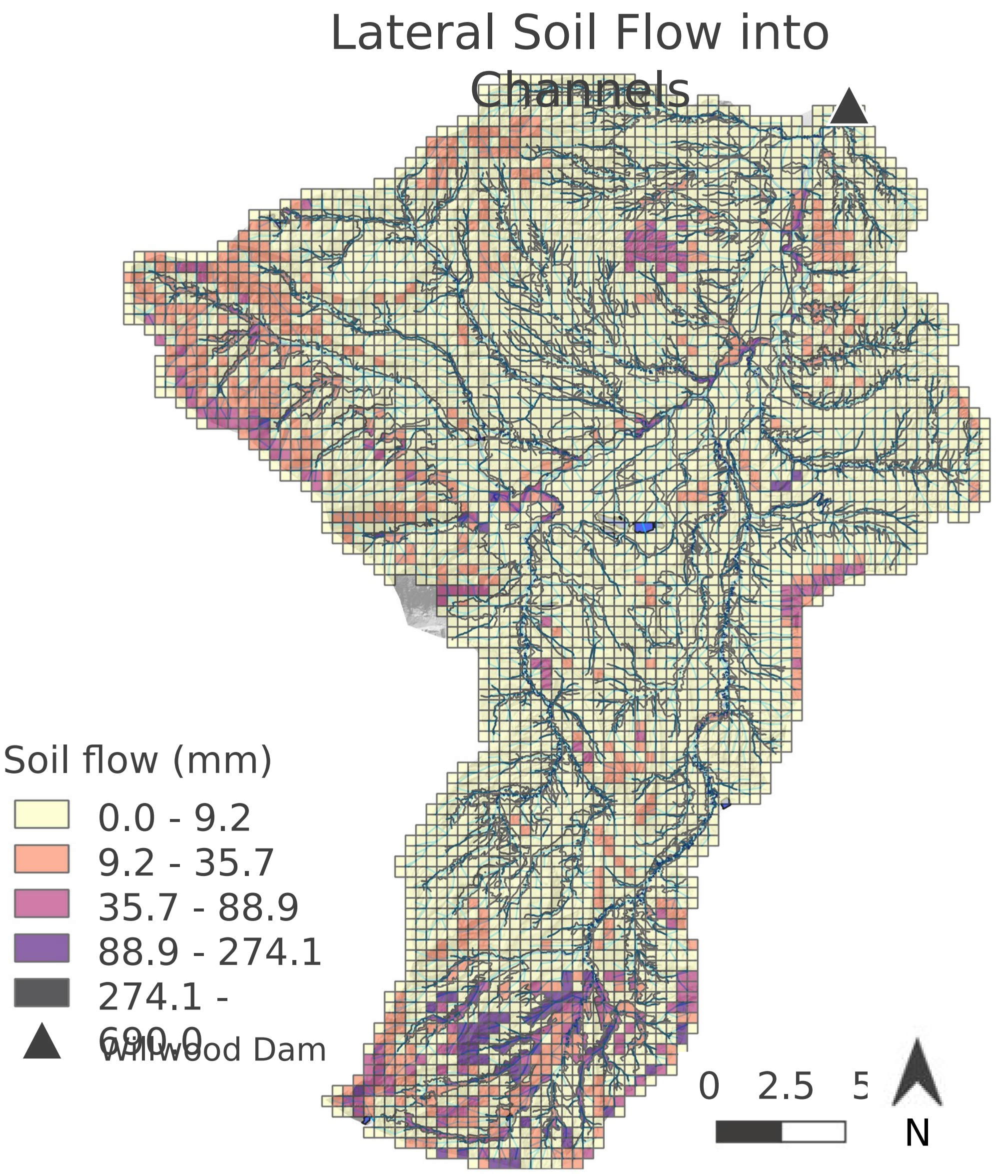


- Imagery from Suomi NPP VIIRS snow cover product VNP10A1F
  - Preprocessed using NDSI (Normalized Difference Snow Index)
- Satellite image clipped to watershed extent
  - 1: Full extent
  - 2 & 3: Division of watershed at Shoshone River
- % of pixels with a value between 10 – 100 out of total pixels in image

0-10	No Snow
10-100	Snow
>201	No Decision

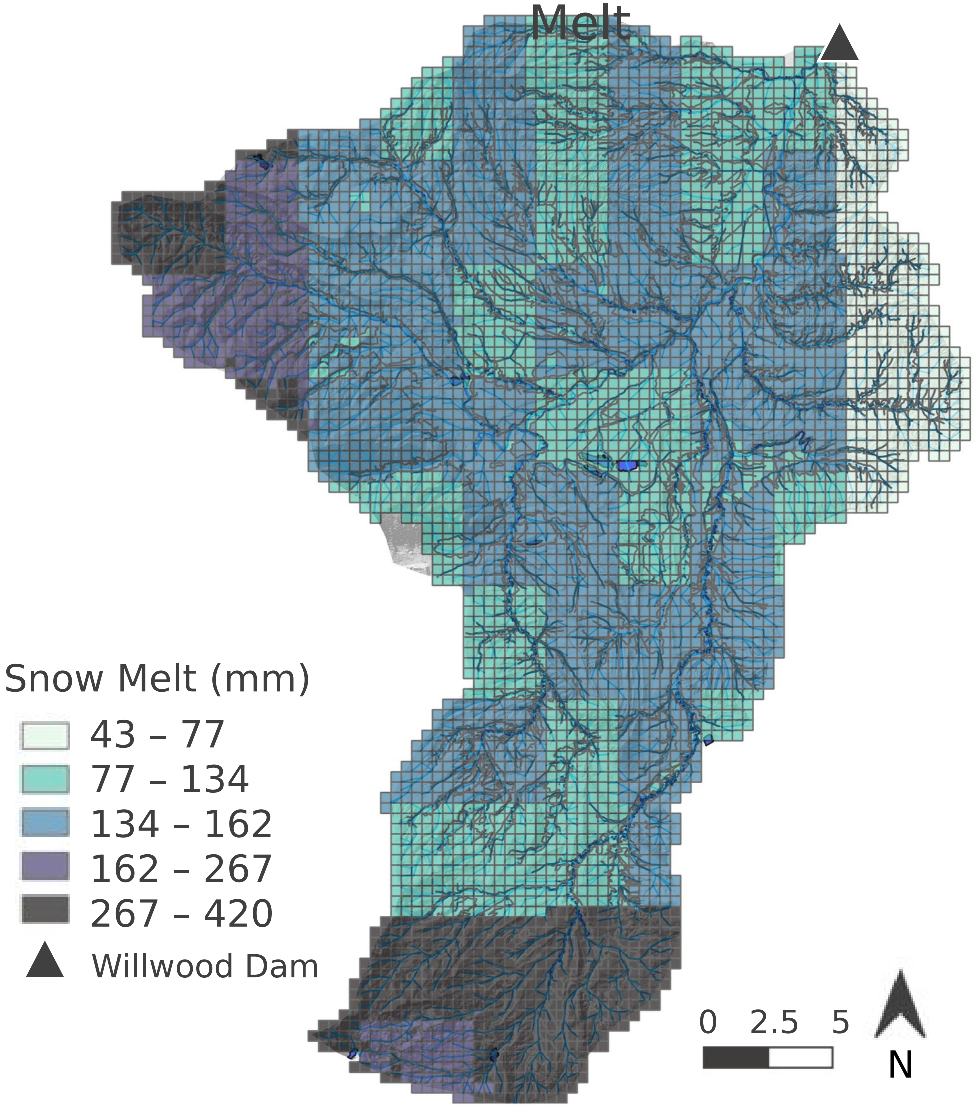
RESULTS: SWAT Soil



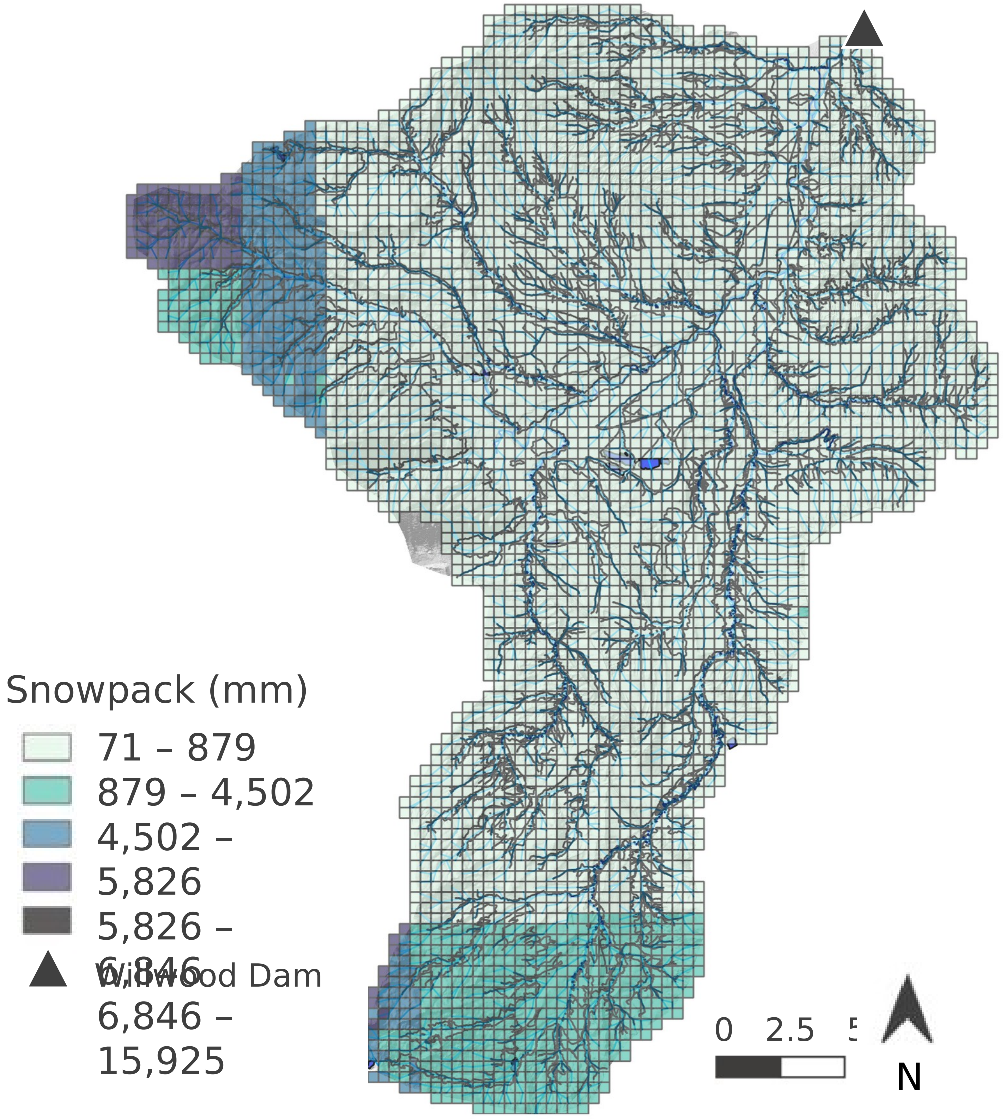


RESULTS: SWAT Snow

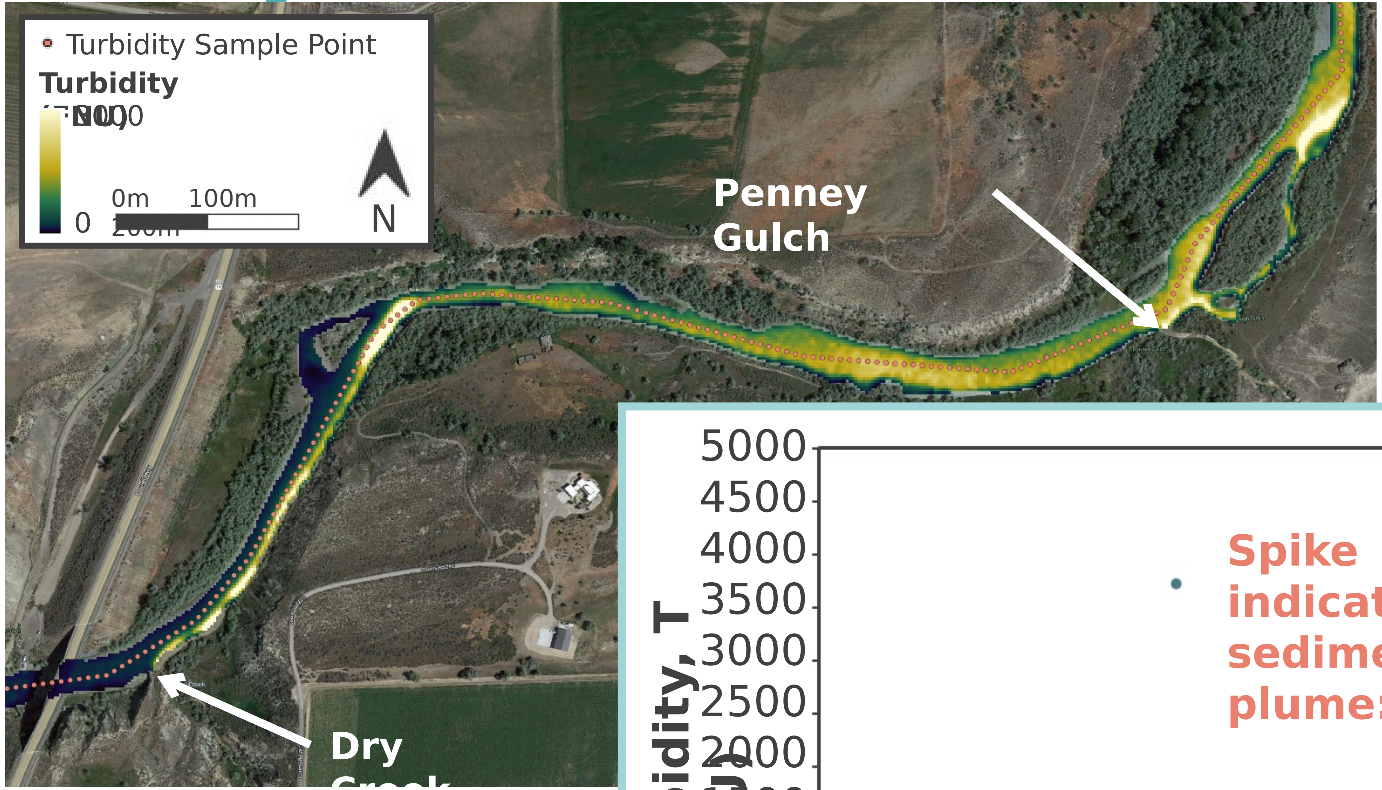
Mean Annual Snow or Ice Melt



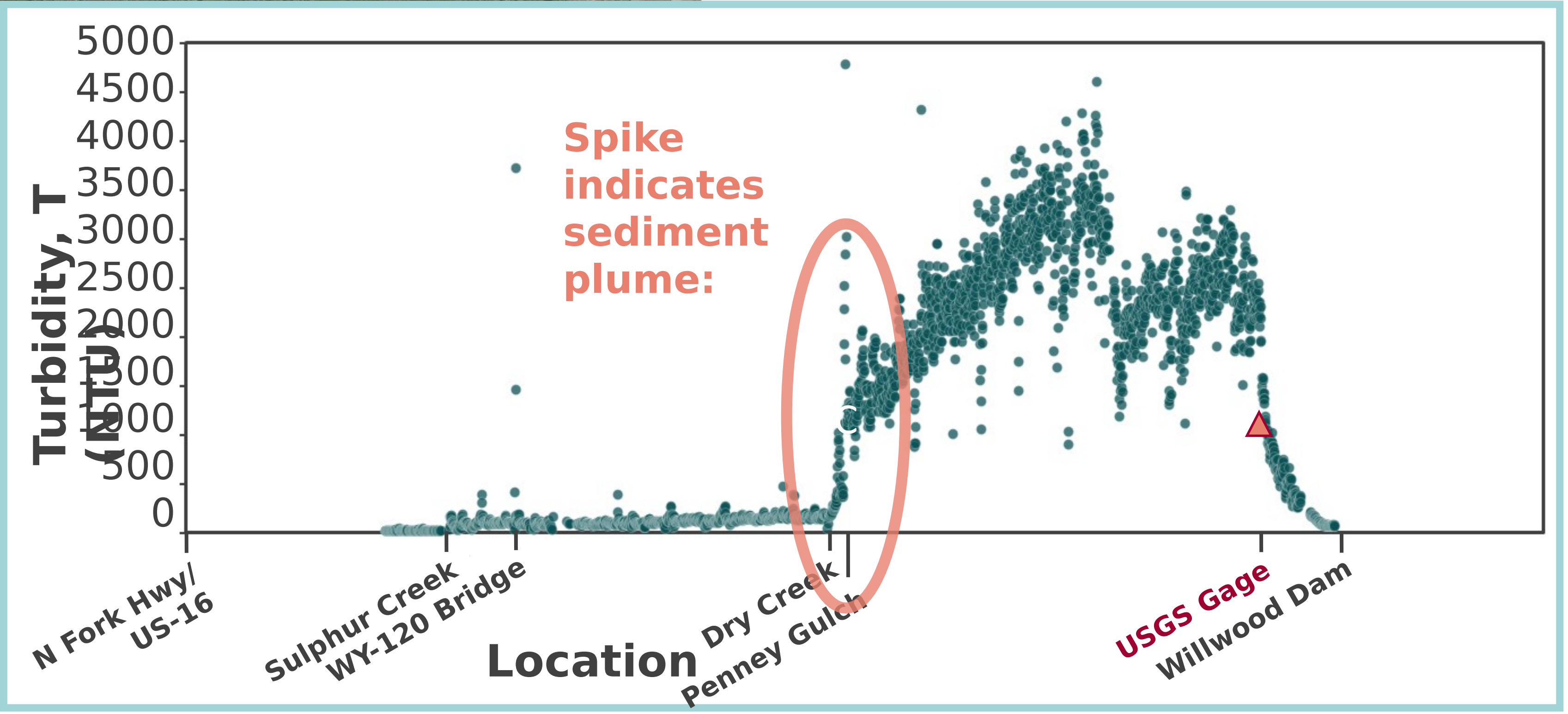
Mean Annual Water Equivalent in Snowpack



RESULTS: Sediment RS – Spatial Analysis

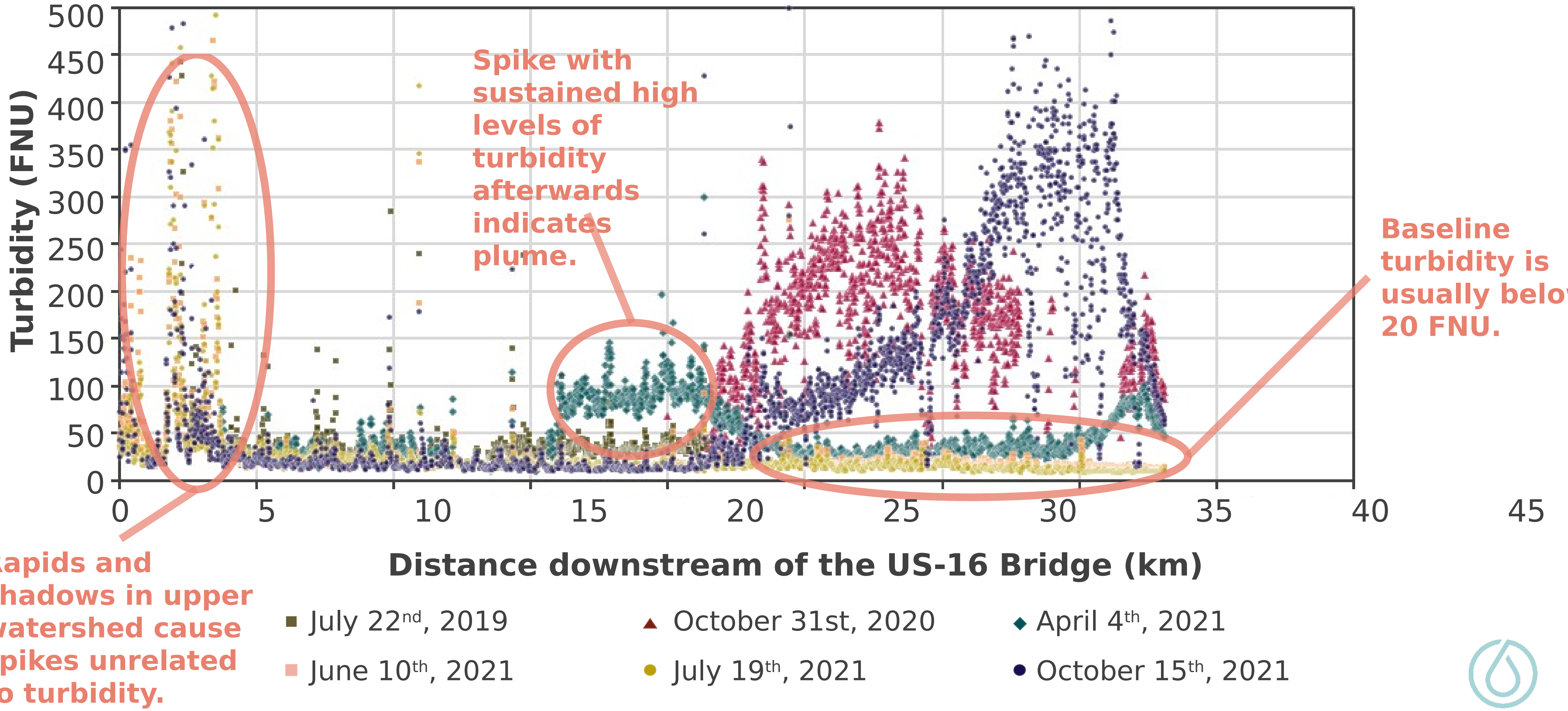


Sampling turbidity values along the river centerline allows us to locate sediment plumes.



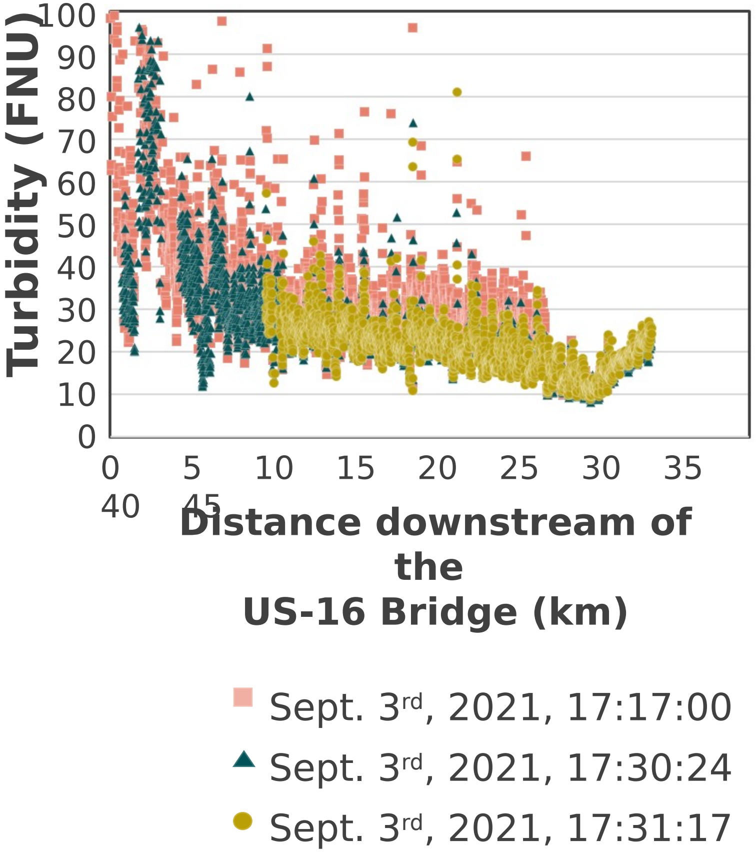
Images: Google, PlanetScope

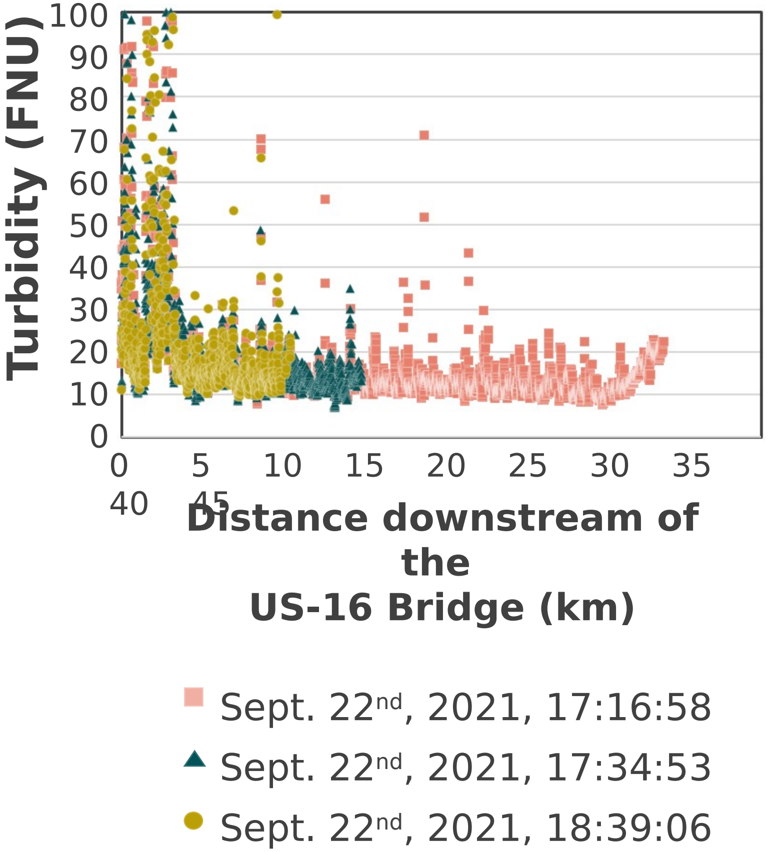
RESULTS: Sediment RS – Spatial Analysis

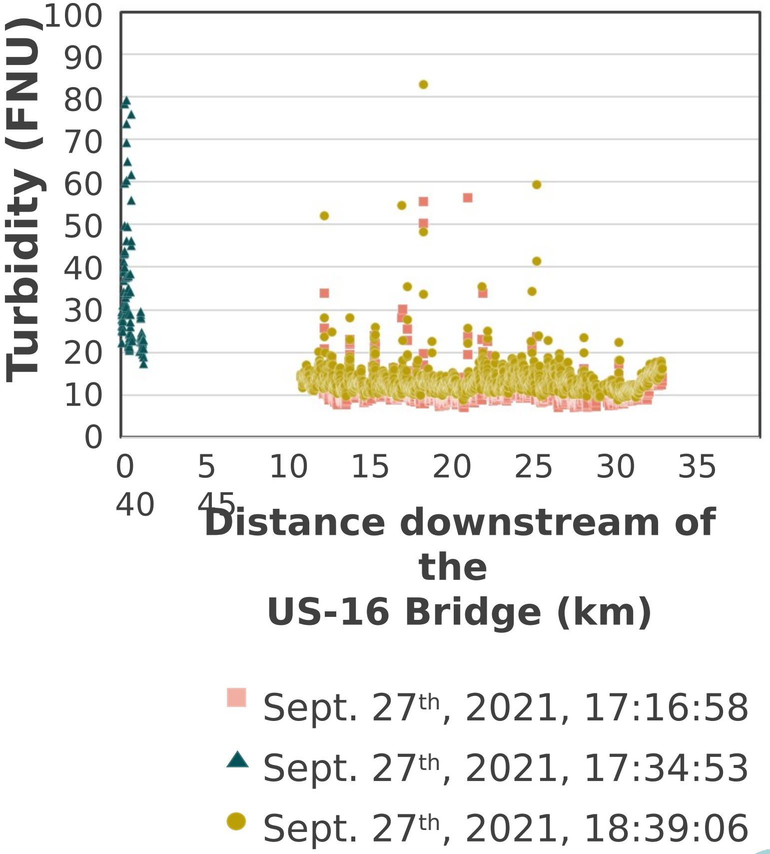


METHODS: Sediment RS

Turbidity tracks well between multiple images taken on the same day:

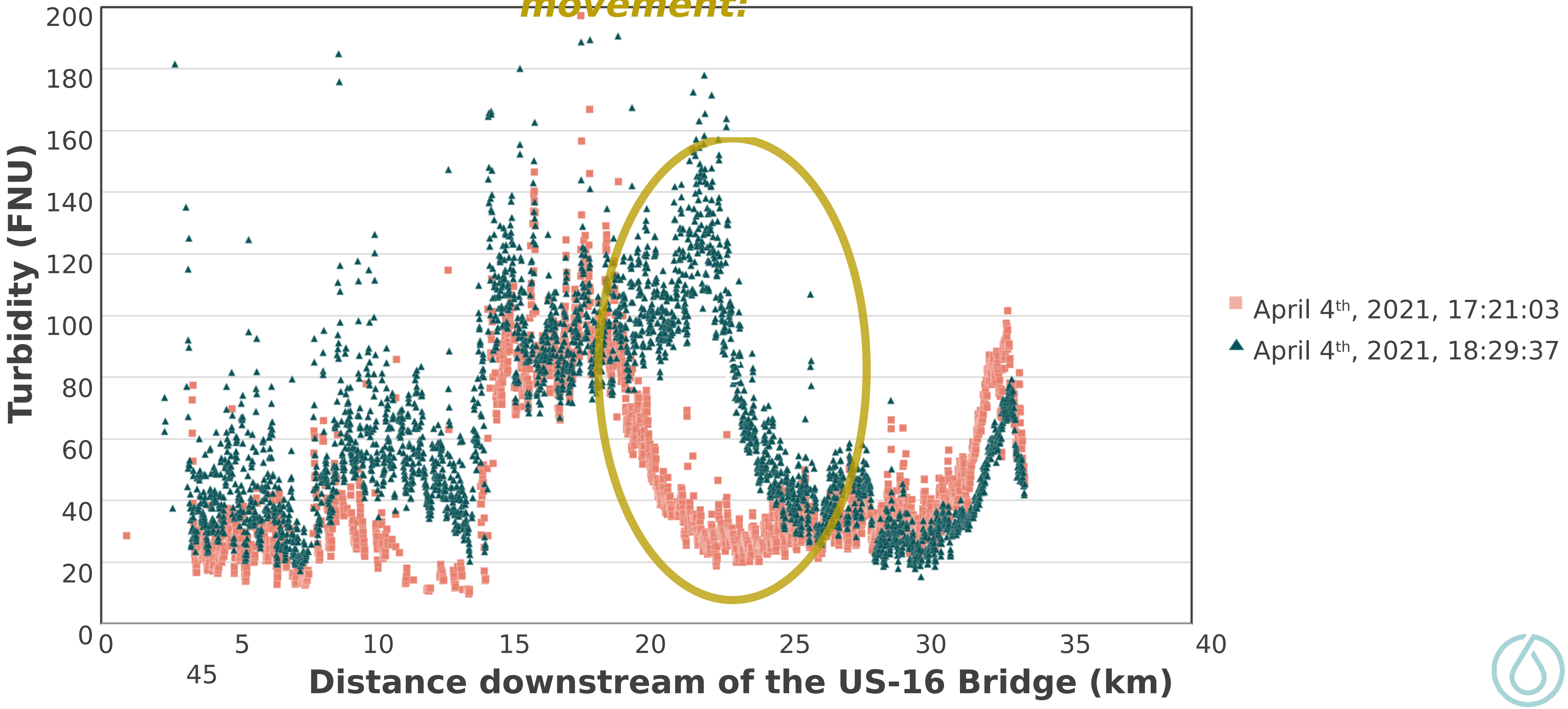






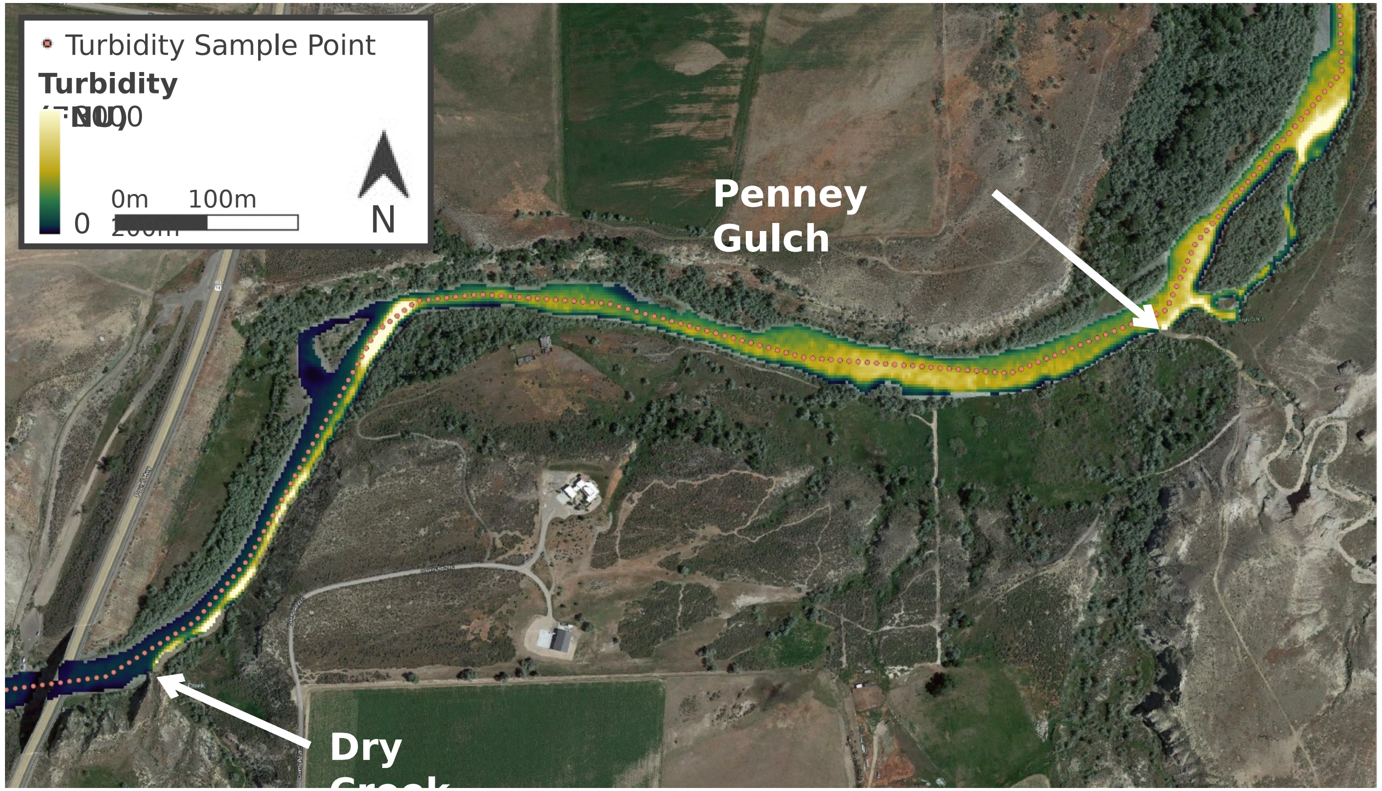
RESULTS: Sediment RS

Two images taken 68 minutes apart capture sediment plume movement:



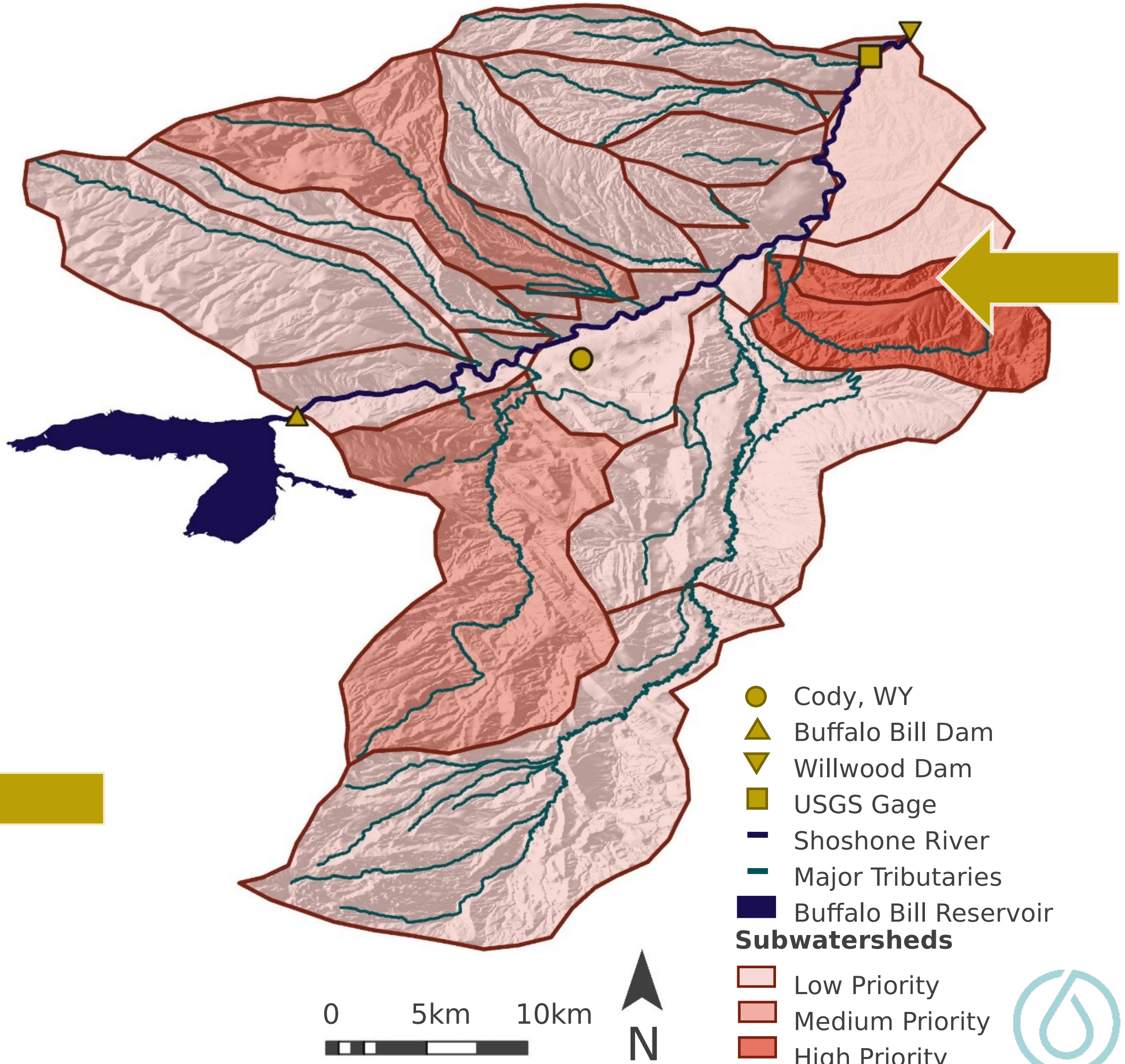
RESULTS: Sediment RS

- **Penney Gulch** and **Dry Creek** had the highest turbidity plumes with **turbidity over 200 FNU** on multiple days
- **Sulphur Creek** also had relatively frequent and significant plumes but less concentrated



RESULTS: Sediment RS

#	Stream Name	# RS Events	Prior Concern Level
1	Sulphur Creek	Medium	High
2	Cottonwood Creek	Low	Medium
3	Sage Creek	Low	High
4	Idaho Creek	Low	Medium
5	Dry Creek/ Homesteader Creek	High	High
6	Penney Gulch	High	Unknown

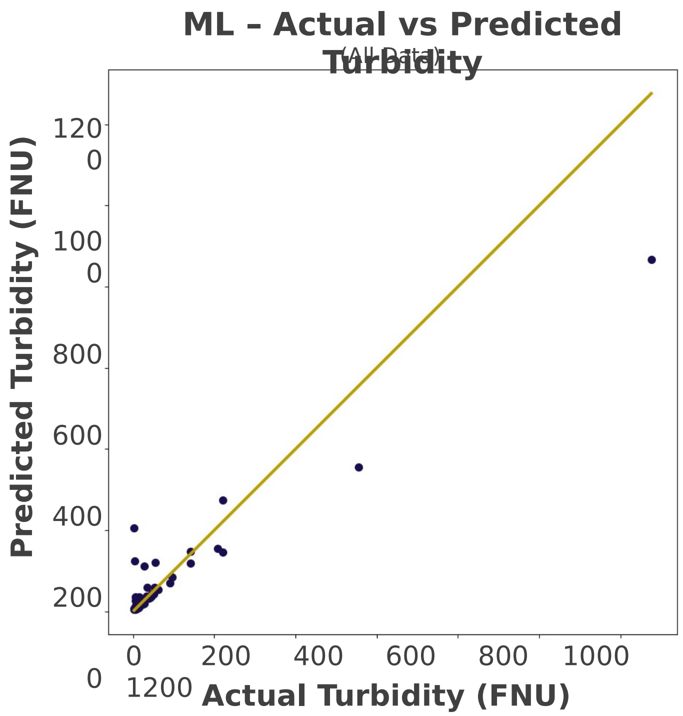


RESULTS: Sediment RS – Comparing Methods

Machine Learning

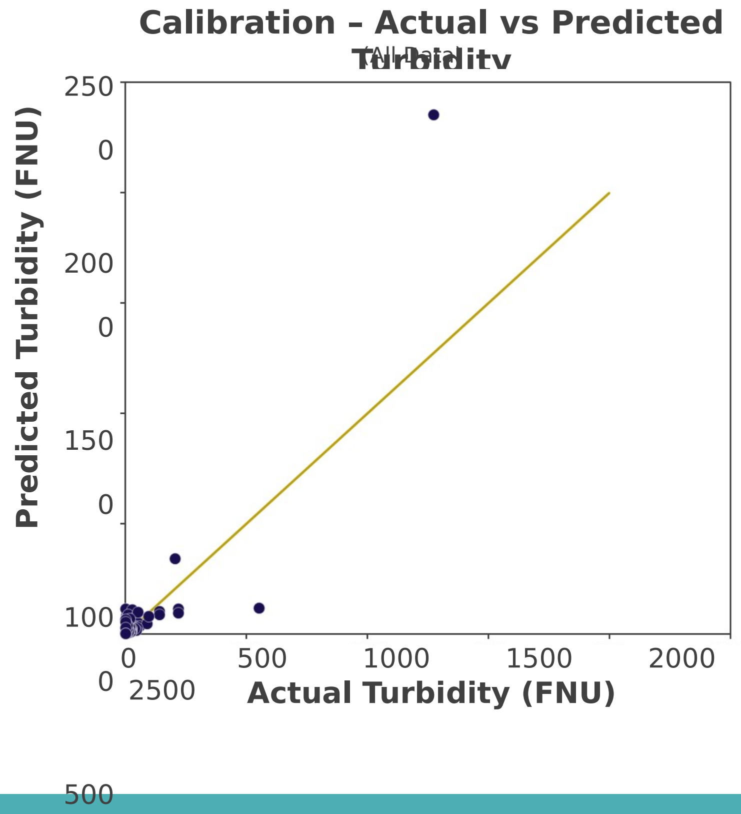
Validation Data R^2 = 0.93

All Data R^2 = 0.92



Calibration Equation

All Data R^2 = 0.80

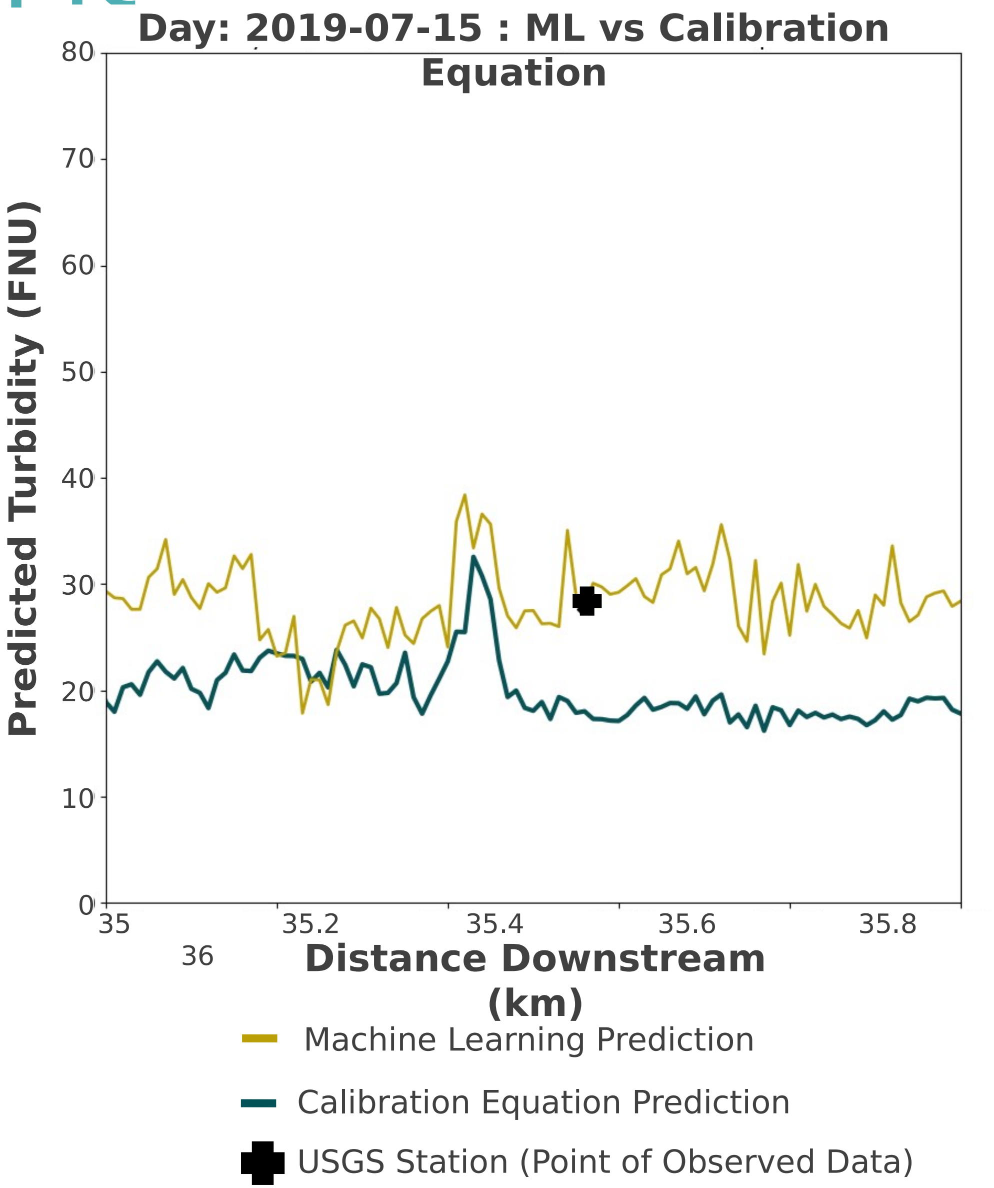


The machine learning co-efficient of determination (R^2) is higher (better) than the calibration equation.

Observed VS Predicted Turbidity

1:1 (Observed = Predicted) Line

RESULTS: Sediment RS – Comparing Methods



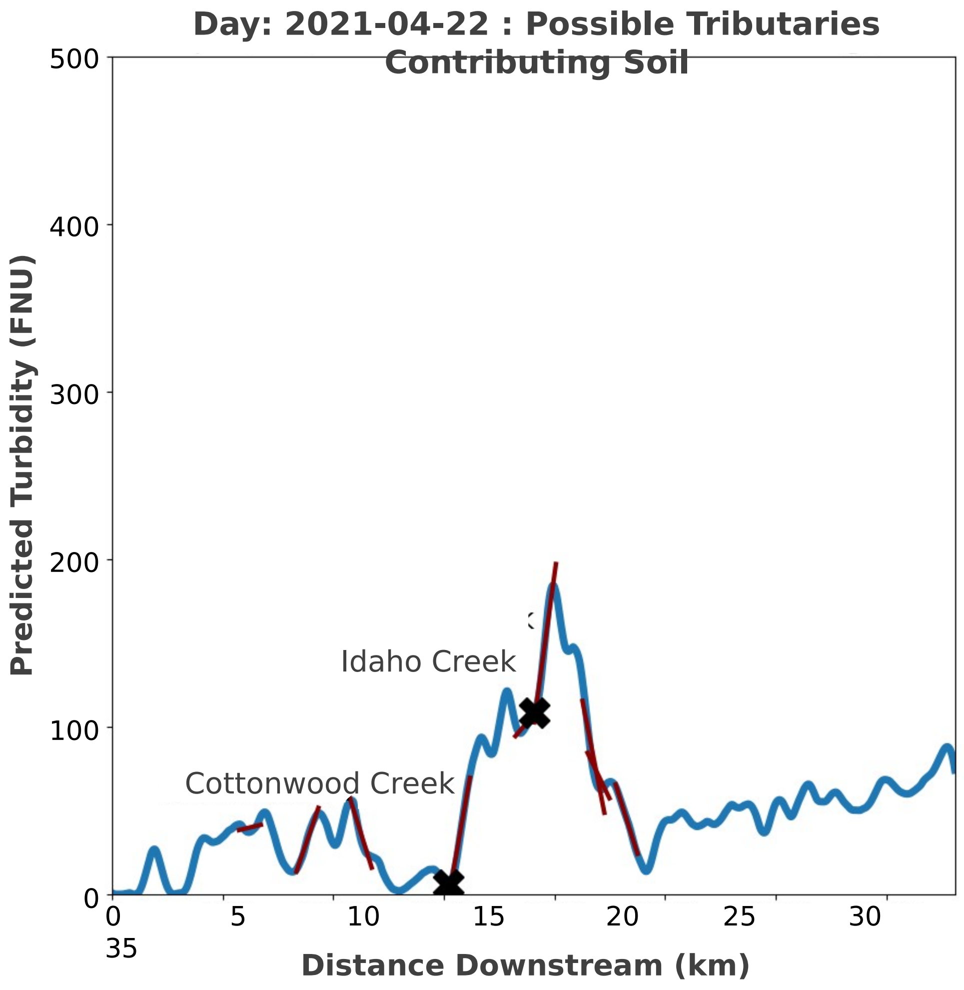
Initial analysis seems to point at the method of machine learning out-predicting the calibration equation method.

Out of **33 comparisons** between predicted and observed points:

The Machine learning Method was closer to the observed point **24 times (72.7%)**

The Calibration Equation Method was closer to the observed point **9 times (27.3%)**

RESULTS: Sediment RS – Auto Plume Detection



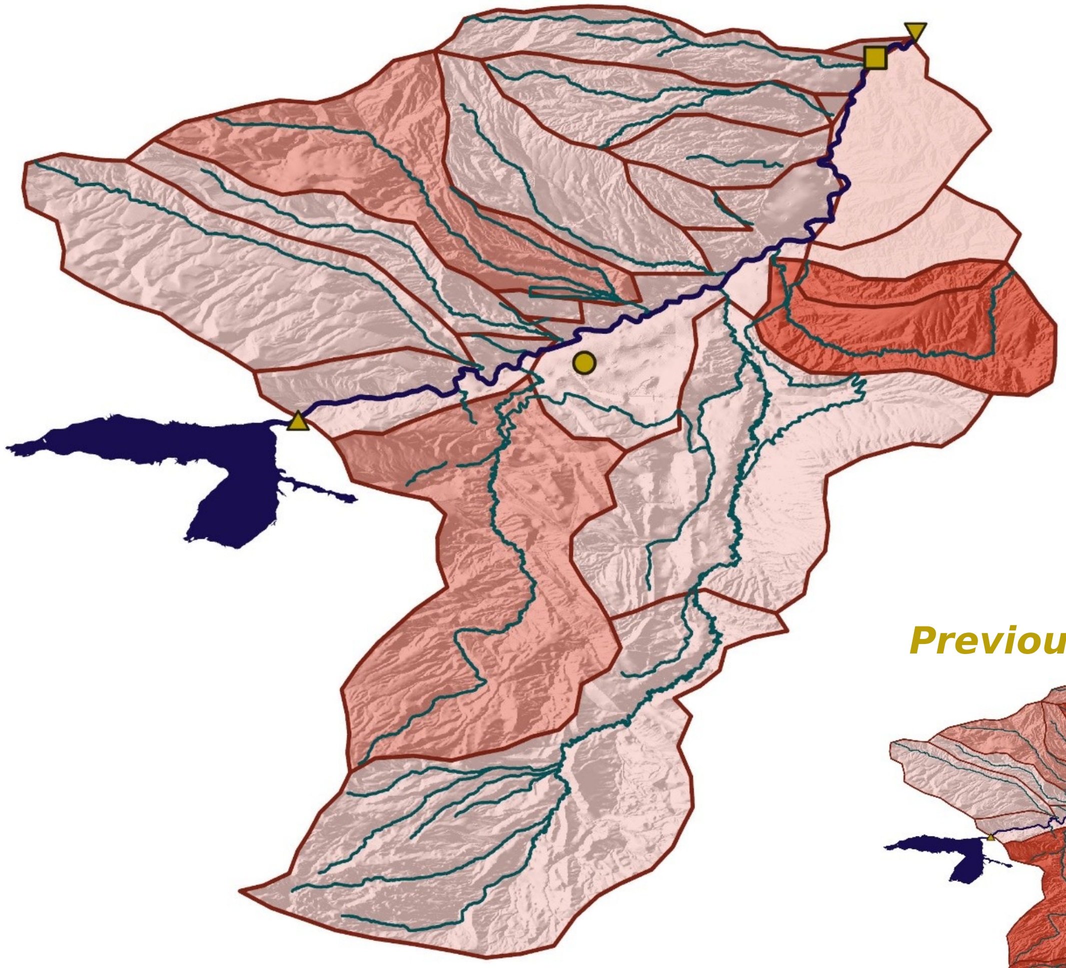
Out of **397 days** analyzed:

- **20 days** had *possible plumes*.
- **31 total** *possible plume events* were detected.

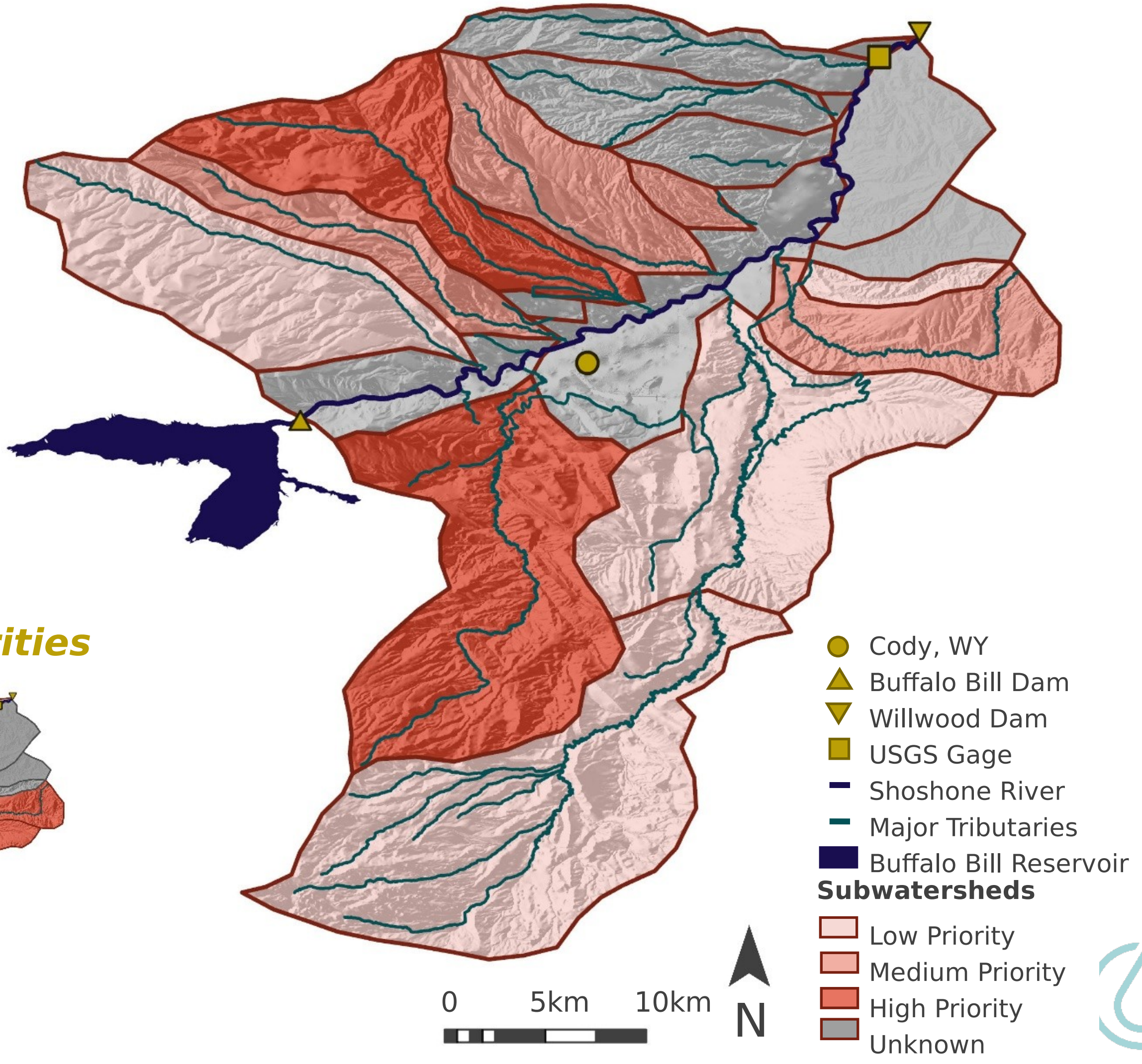
Stream Name	# RS Events	Prior Concern Level
Sulphur Creek	**7**	High Priority
Cottonwood Creek	**7**	Medium Priority
Idaho Creek	**4**	Medium Priority
Dry Creek/Homesteader Creek	**3**	High Priority
Dry Creek	**3**	Low Priority
Dry Gulch	**3**	Low Priority
Penney Gulch	**2**	Unknown
Sage Creek	**1**	High Priority
Trail Creek	**1**	Low Priority

RESULTS: Sediment RS – Comparing Methods

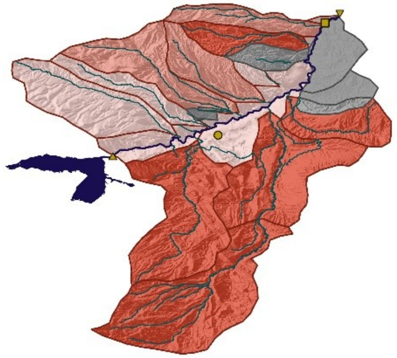
Manual Event Interpretation



Automated Event Interpretation



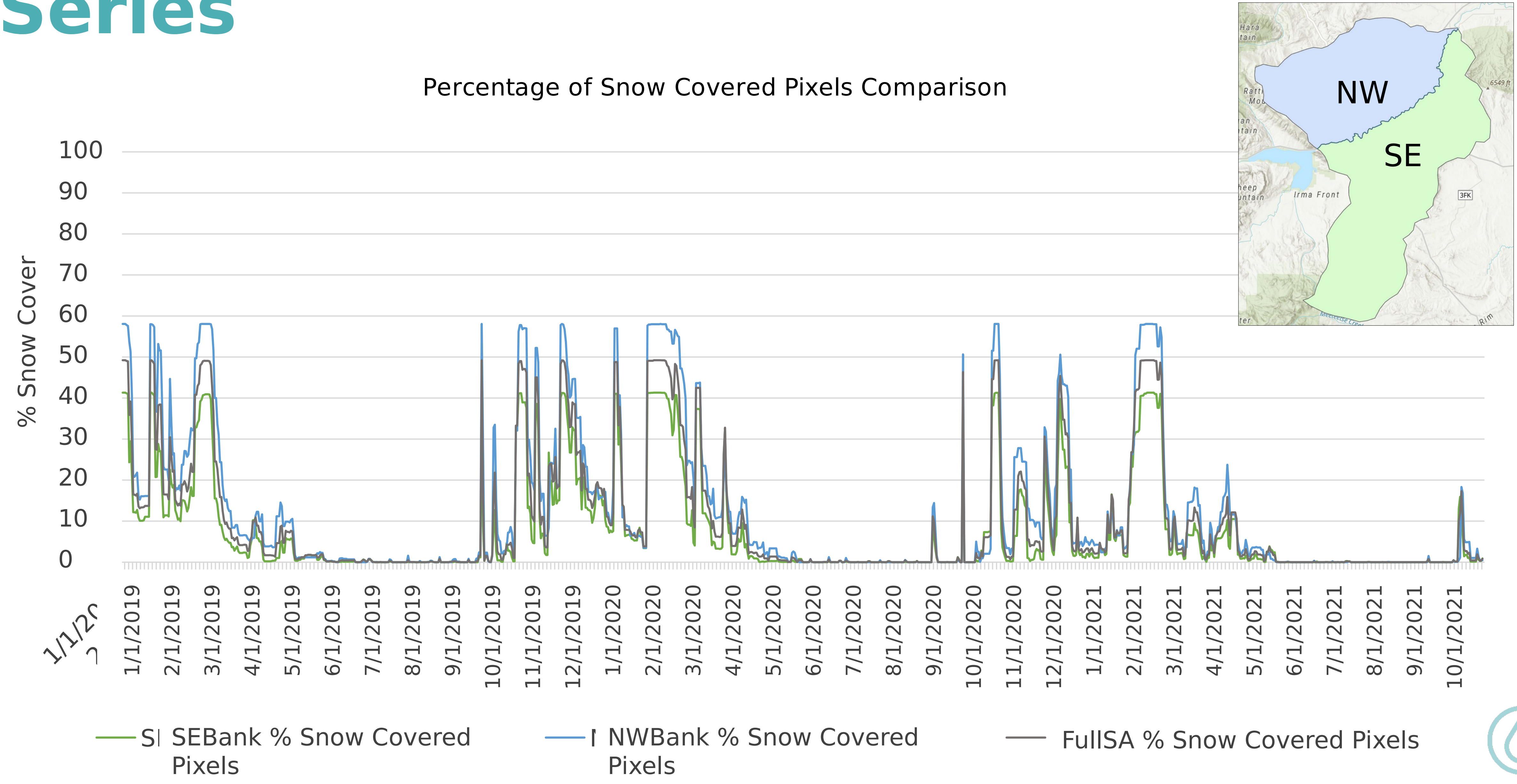
Previous Priorities



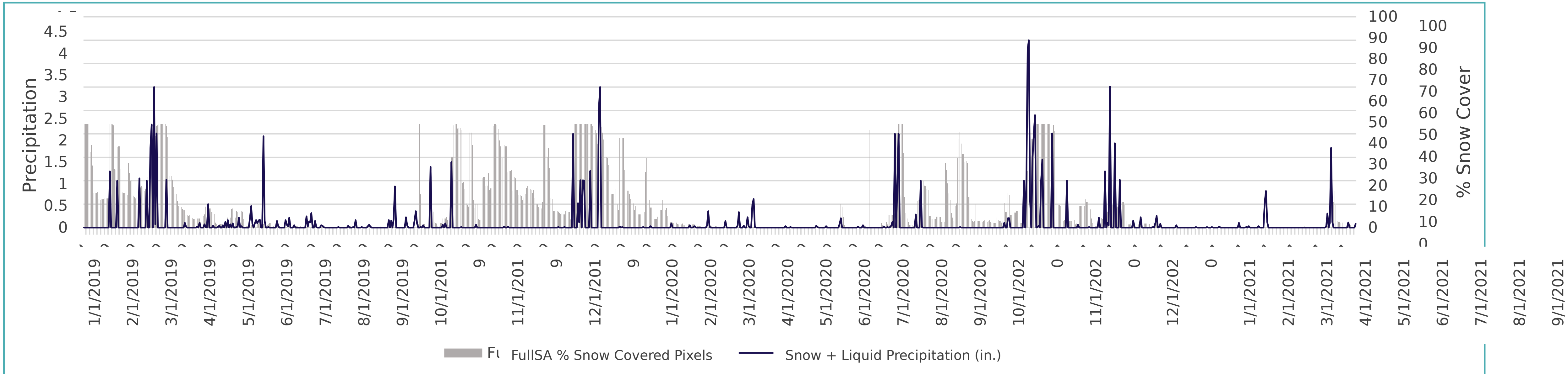
RESULTS: Sediment RS – Comparing Methods

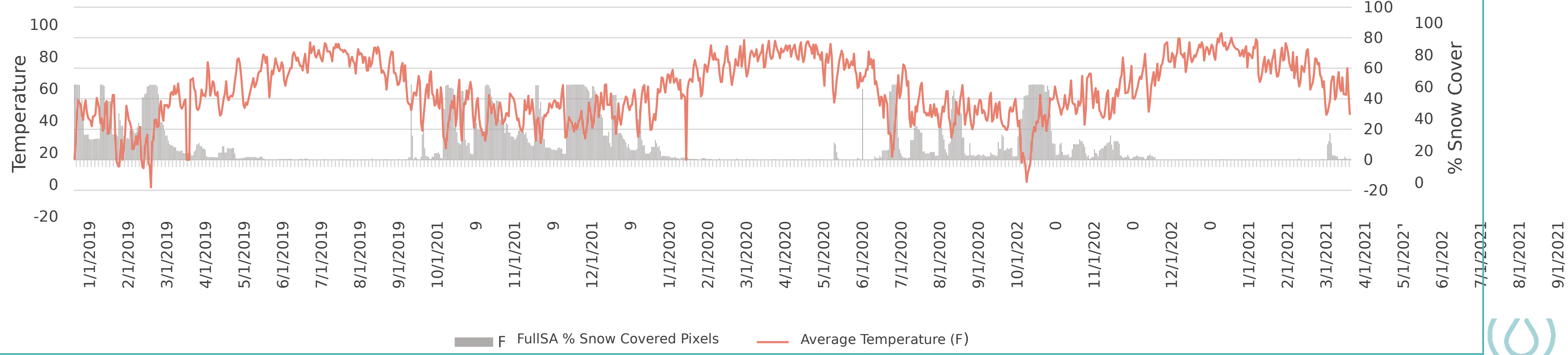
	Pros	Cons
Machine Learning	• Automatically & easily determines patterns to represent data (may be better with more complex band interactions) • Outputs relative importance of bands. • Seems to predict winter month inconsistences well.	• Long image Processing time (~10min / image) • Very complex to prove “how” the model calculated the output.
Calibration	• Faster to run image processing. • You know exactly what the equation/relationship used was.	• Need user input to choose equation. • May struggle with complex relationships or take data preprocessing (ie. had to figure we needed to give it ln(T)).

RESULTS: Snow Cover Time Series

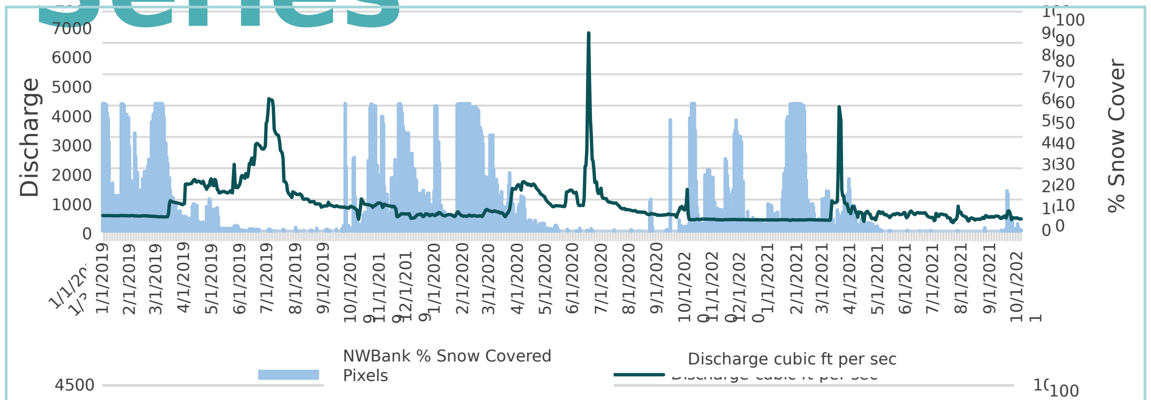


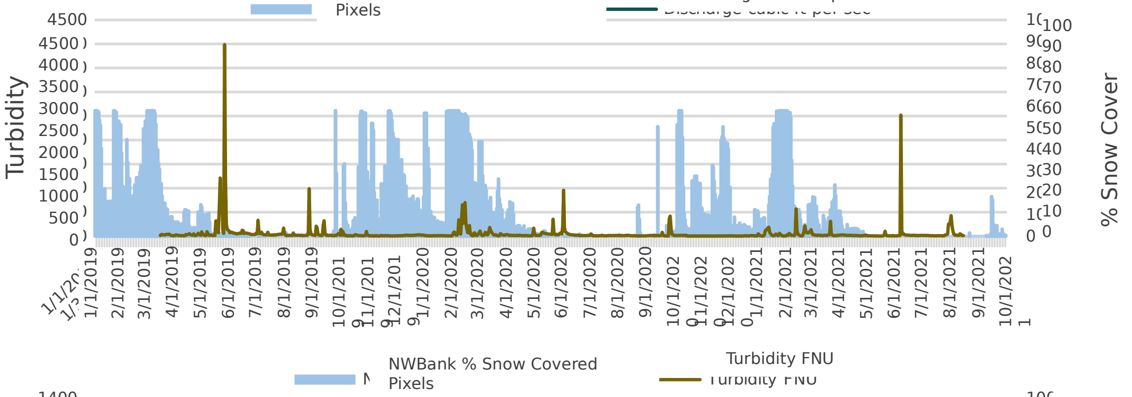
RESULTS: Snow Cover Time Series

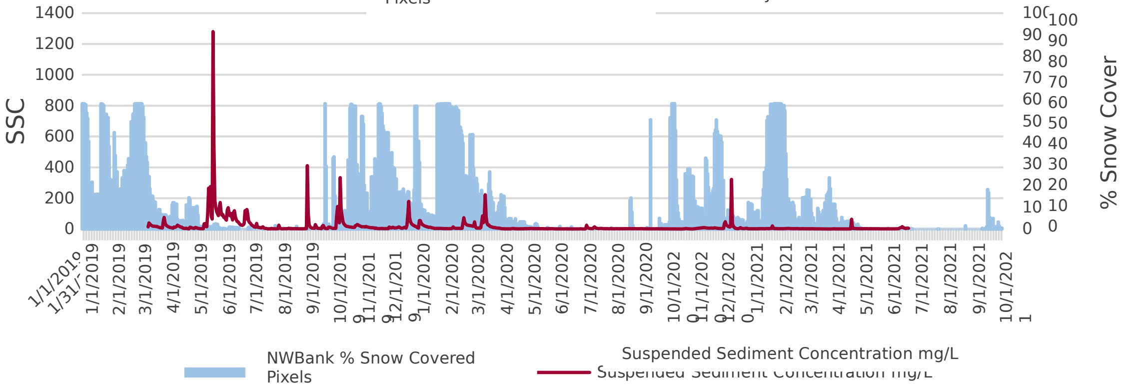




RESULTS: Snow Cover Time Series





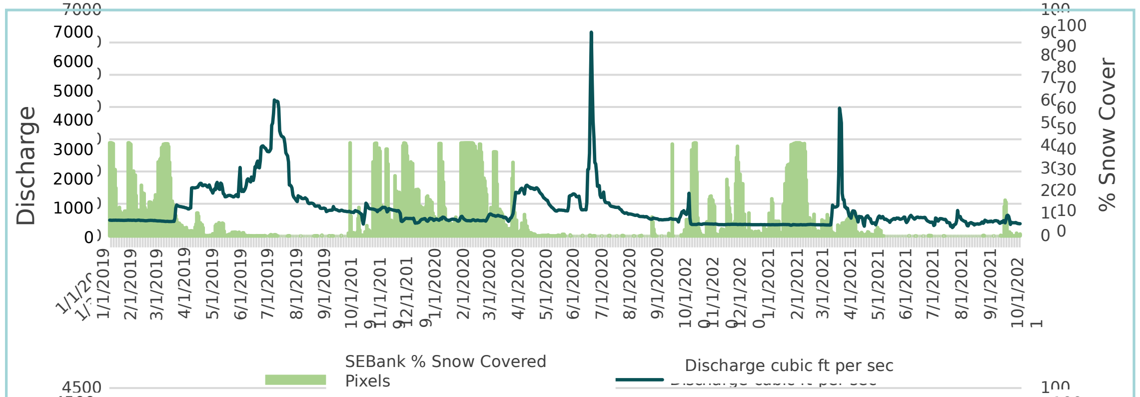


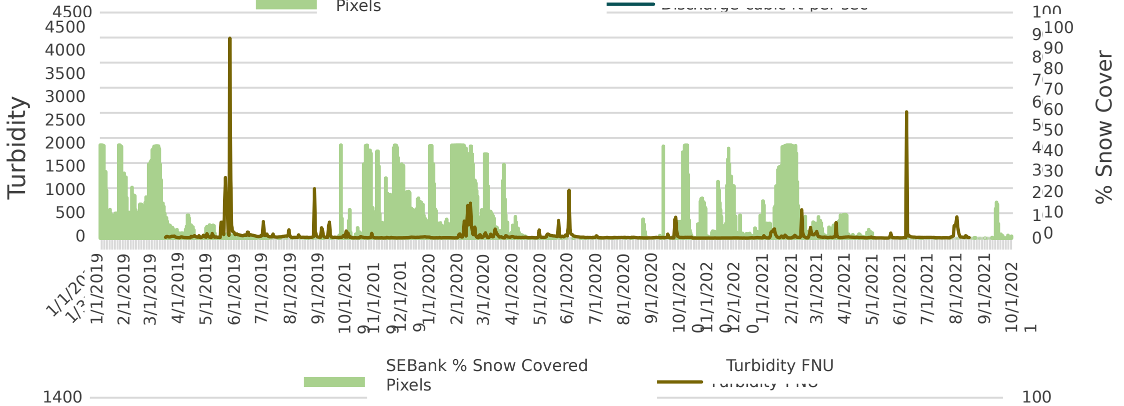
NW Watershed

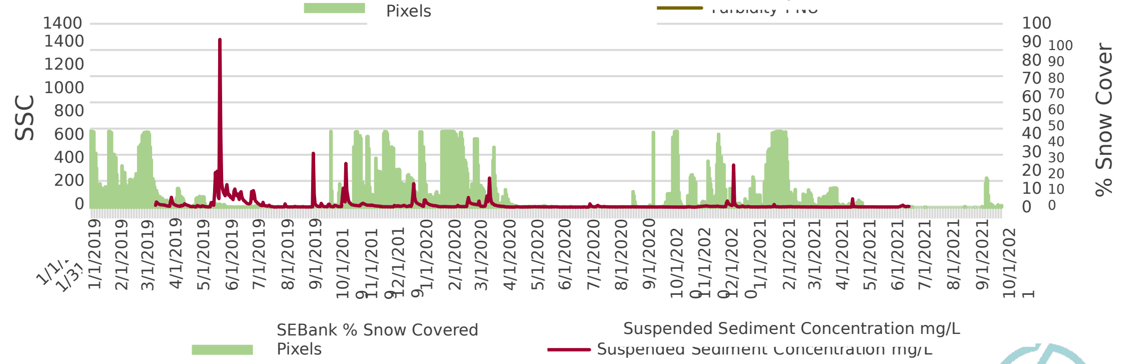
Discharge

Turbidity

Suspended Sediment Concentration

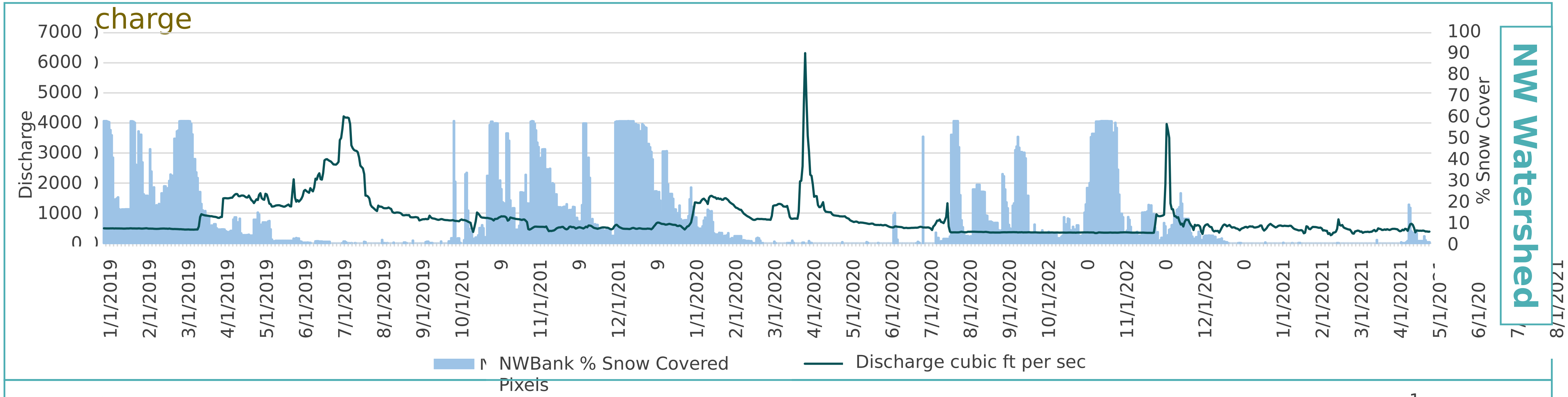


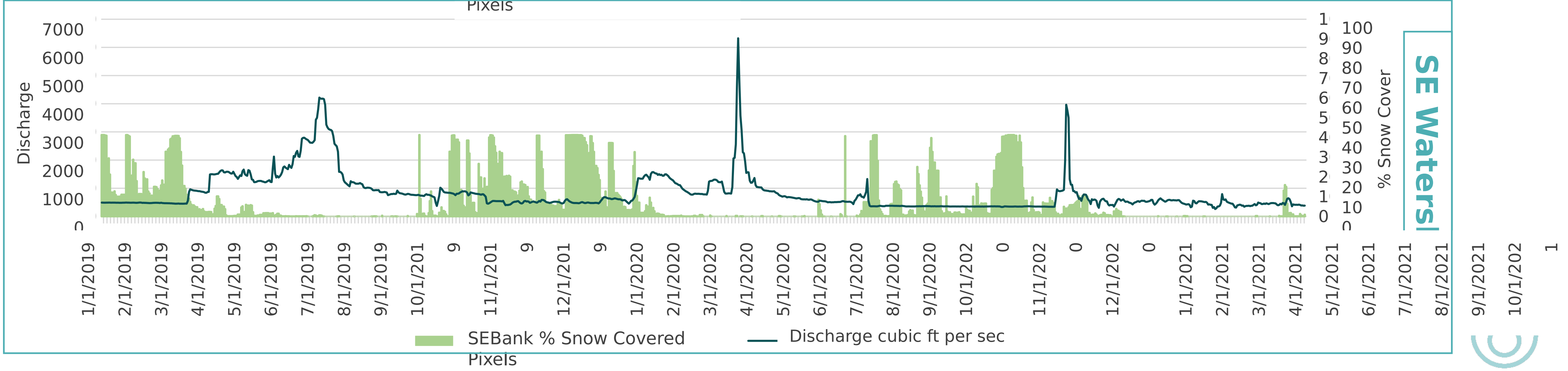




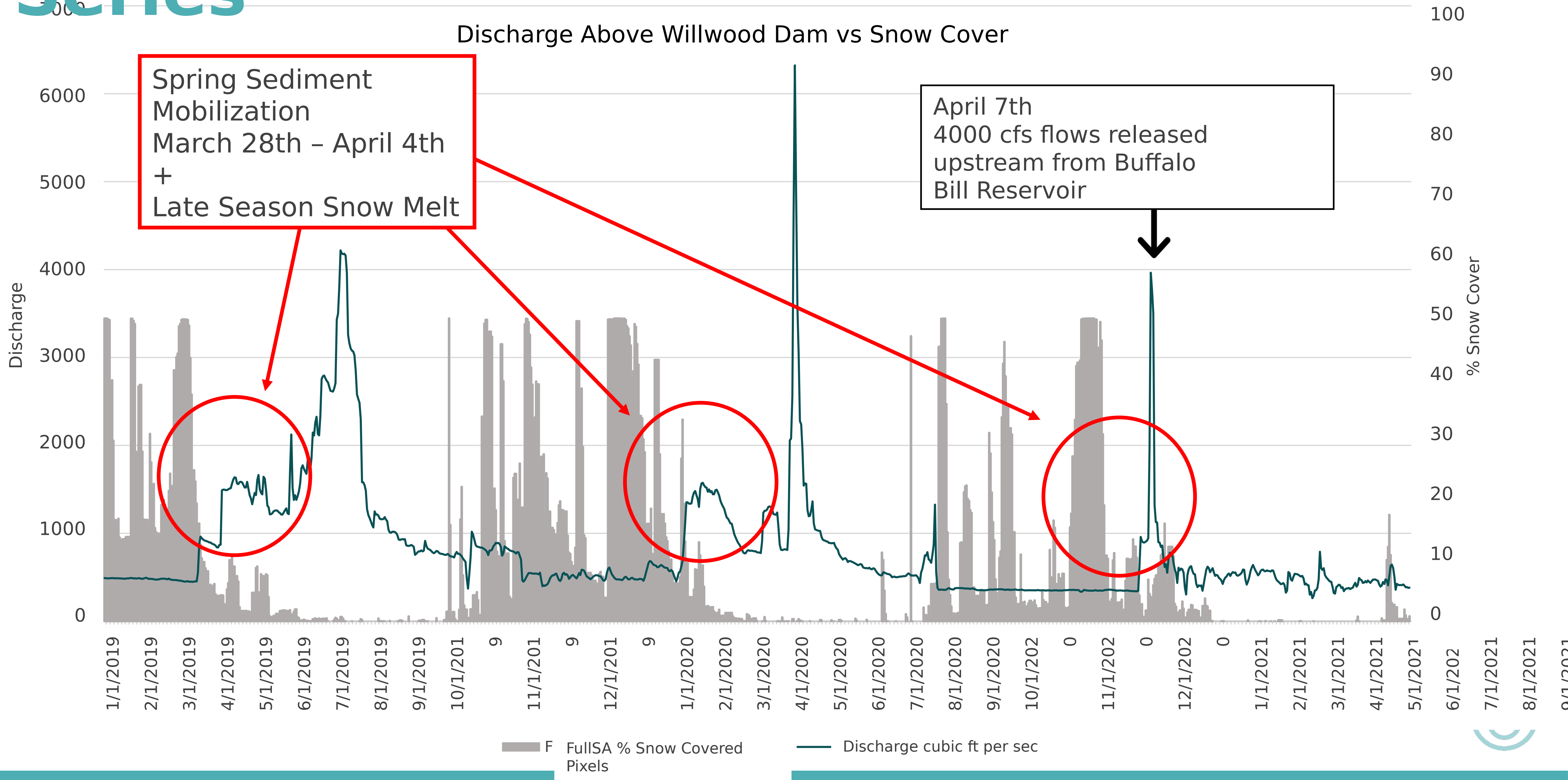
SE Watershed

RESULTS: Snow Cover Time Series

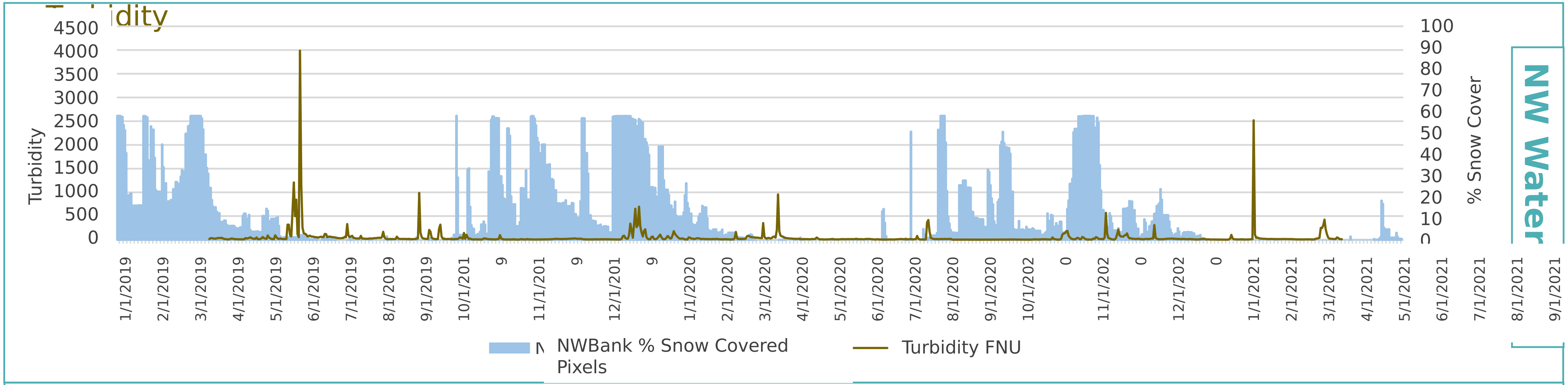


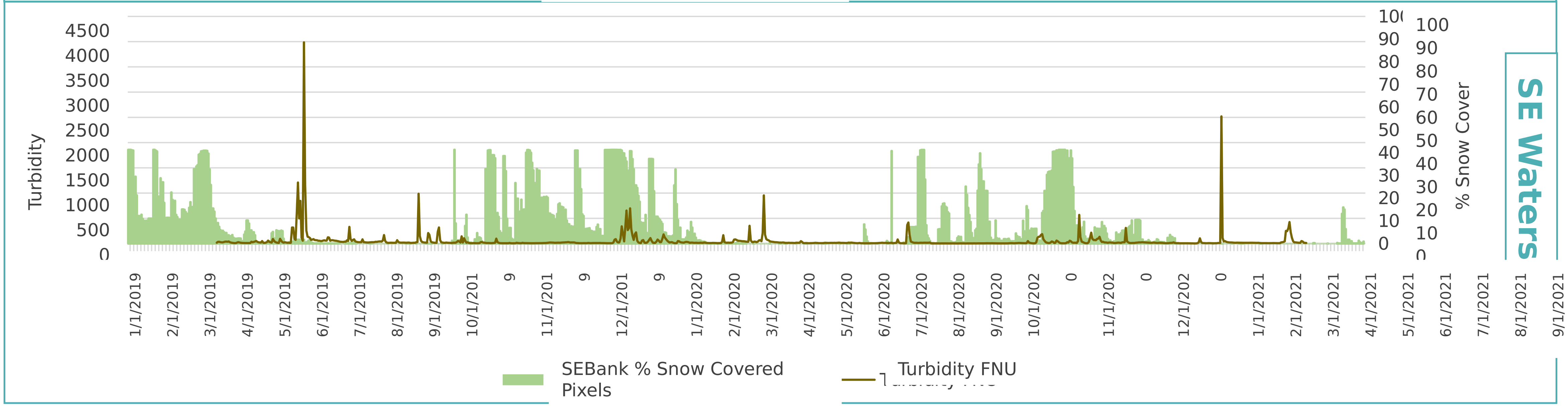


RESULTS: Snow Cover Time Series



RESULTS: Snow Cover Time Series





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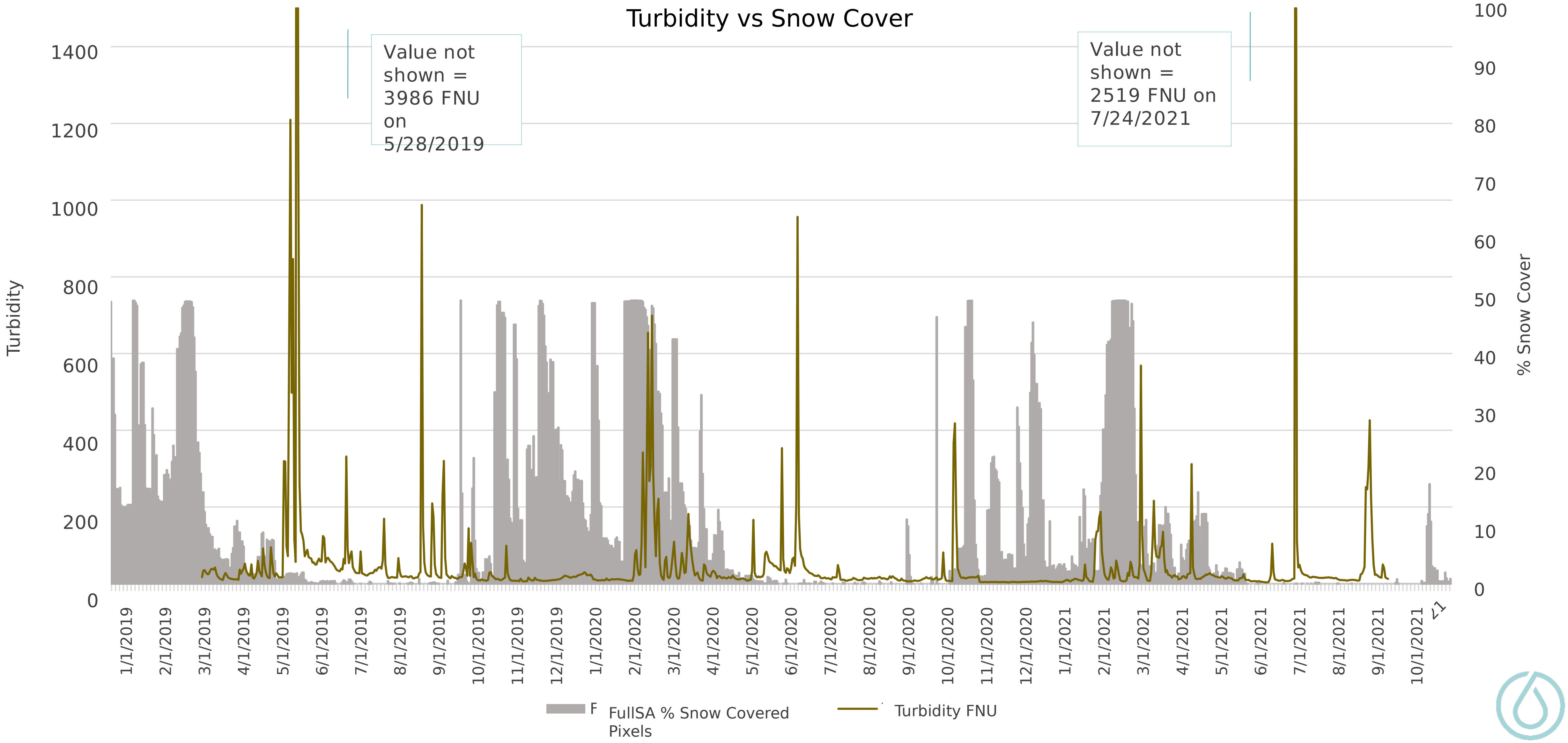

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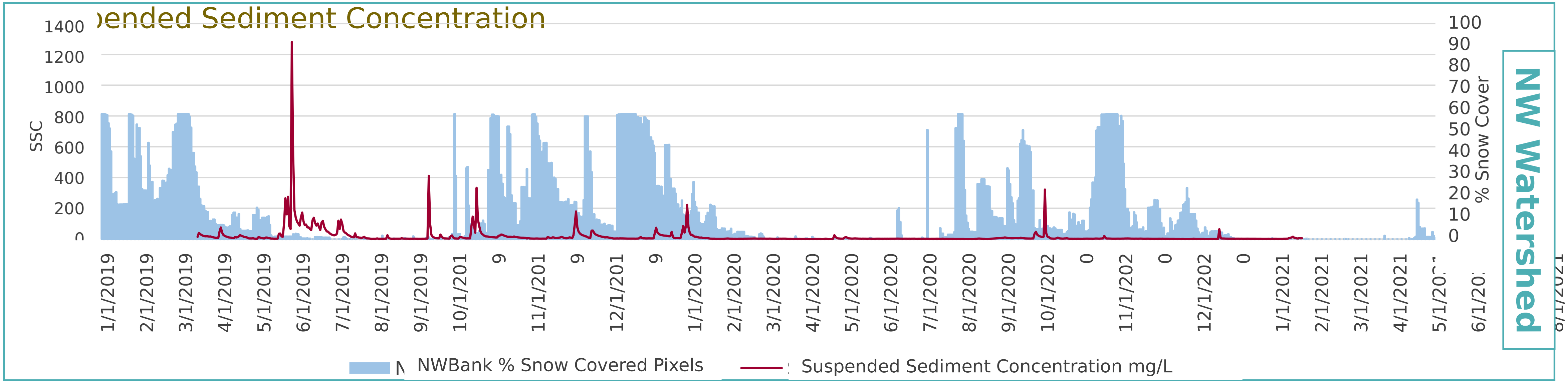

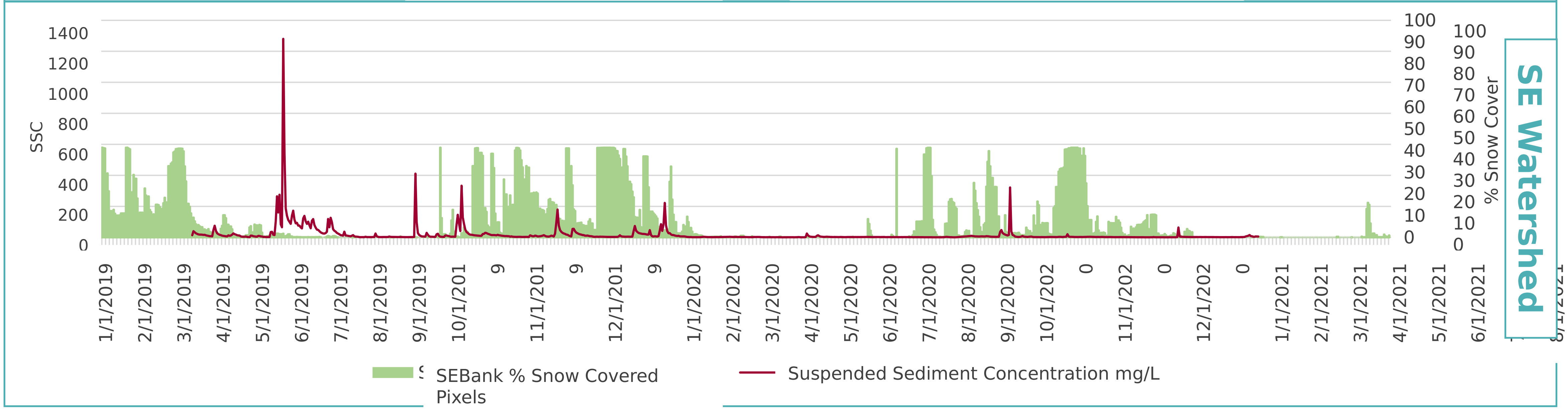

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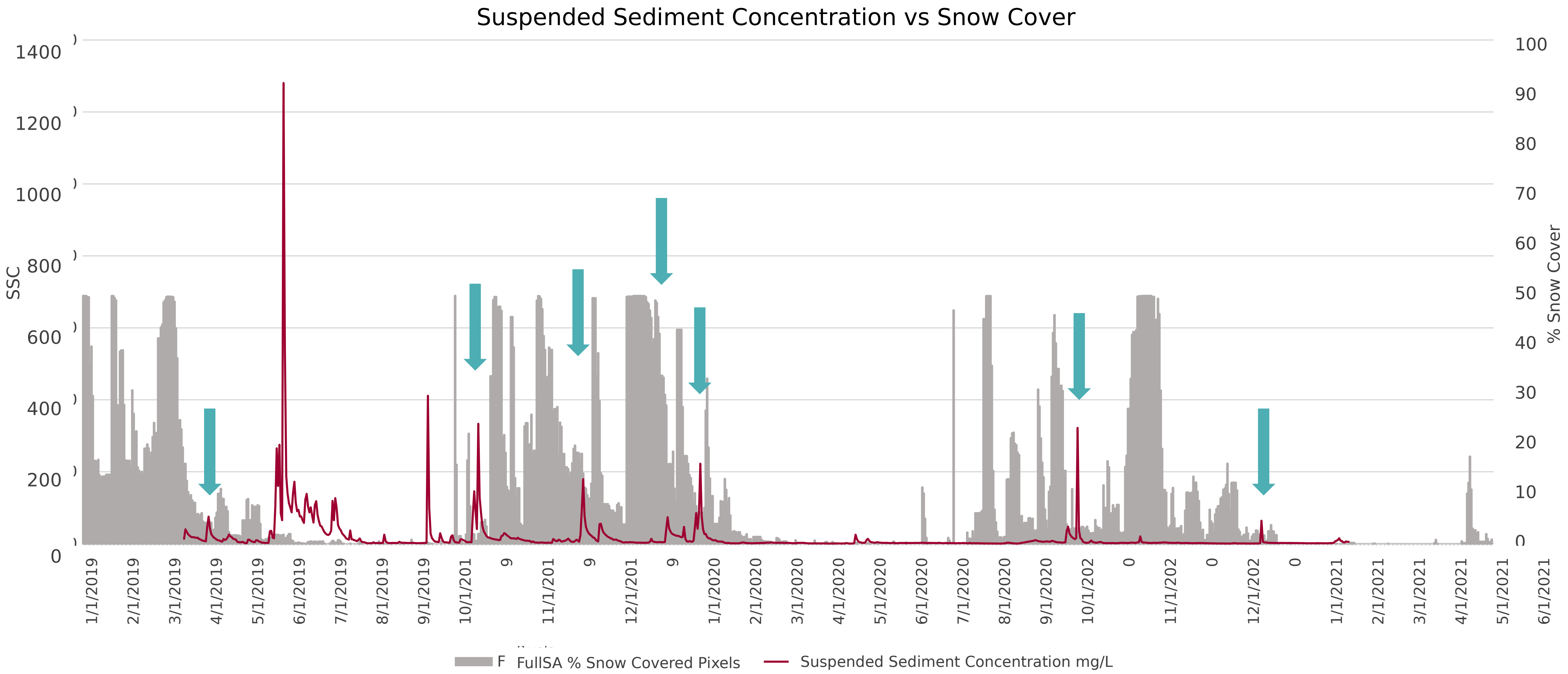


= Decrease in snow cover + increase in SSC

ERRORS/UNCERTAINTIES

SWAT Model

- 266 unknown soil types coerced to most common type
- Limited observed data
- Does not account for irrigation or reservoir releases

Sediment RS

- Winter = high variability in reflectance
- Clouds limit imagery dates, may bias results
- Difficult to distinguish small plumes downstream of other plumes
- Shallow areas, rapids, sand bars, unclipped land, & aquatic vegetation

Snow Cover TS

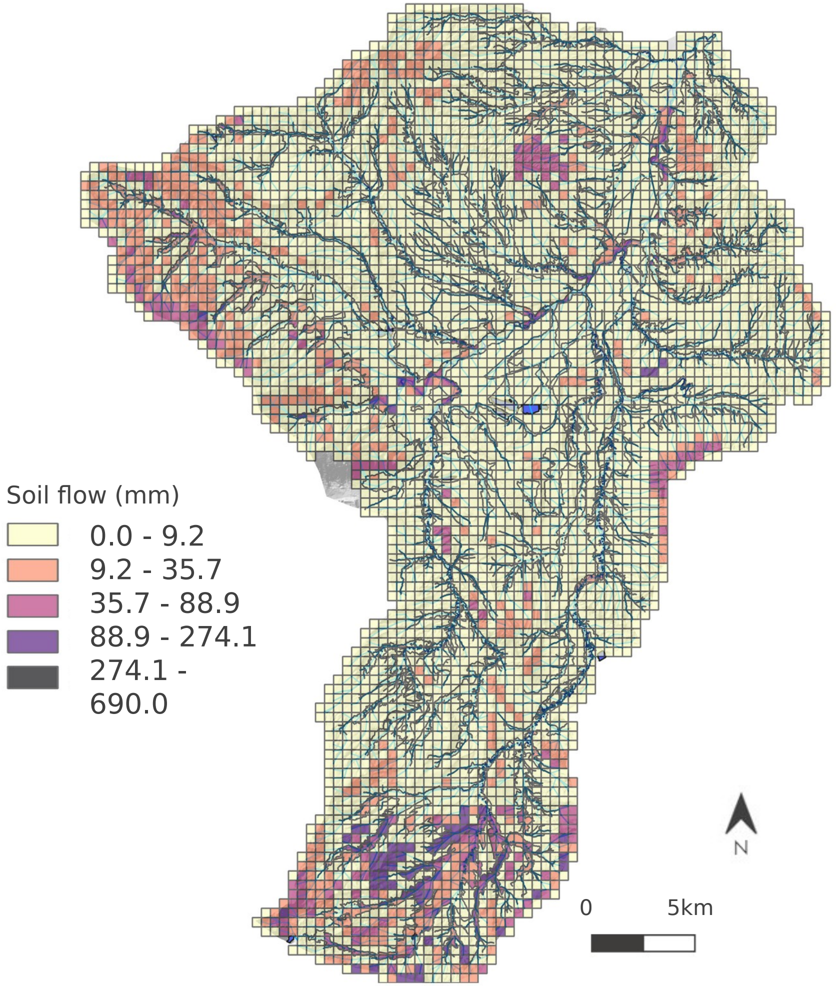
- Snow/cloud reflectance interference
- Spatial vs temporal resolution tradeoff

Image: Carmen McIntyre

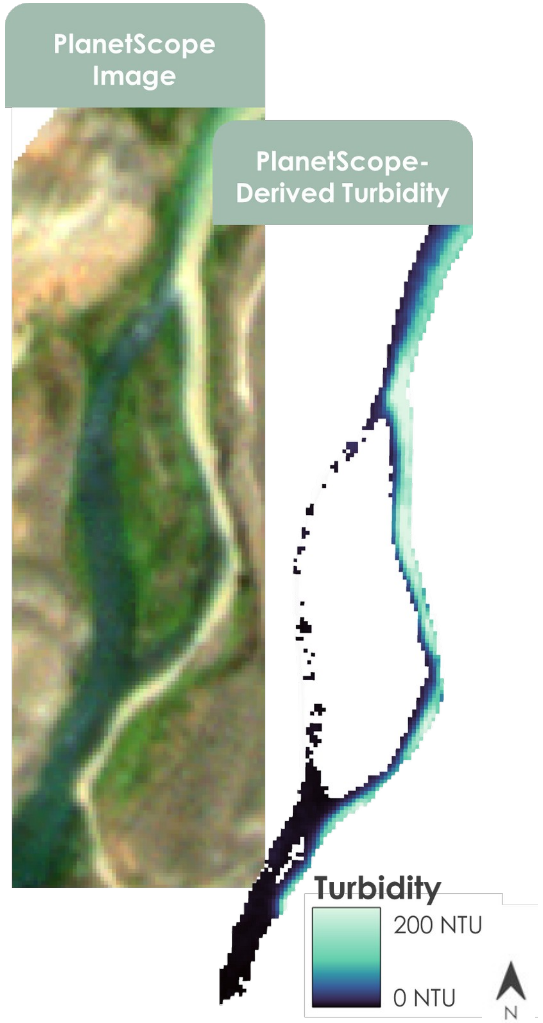
CONCLUSIONS

SWAT+

- The model provides **high resolution analysis** with limited gauge data
- Visualizes **sediment flow** and identifies specific regions of issue
- Lack of sufficient observed data resulted in model uncertainties



CONCLUSIONS



Sediment RS

- Remote sensing provides **reliable spatial turbidity measurements** for the Shoshone River
- **Penney Gulch, Sulphur Creek** and **Dry Creek** had the largest plumes
- Both machine learning and Calibration perform well but **ML perform slightly better than calibration**

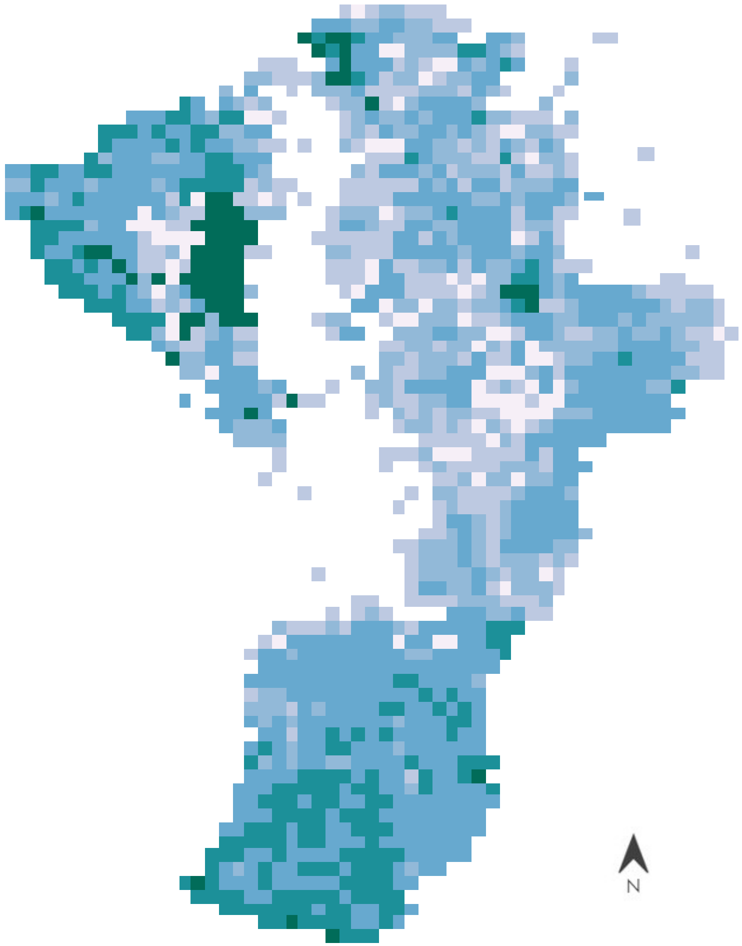
CONCLUSIONS

Snow Cover TS

- Provides visual representation of **relationships between hydrologic variables**, including the influence of snow cover/snow melt

- Correlation between trends in snow cover with other factors that **influence sediment transport**

- Use of remote sensing to **quantify snow cover extent**



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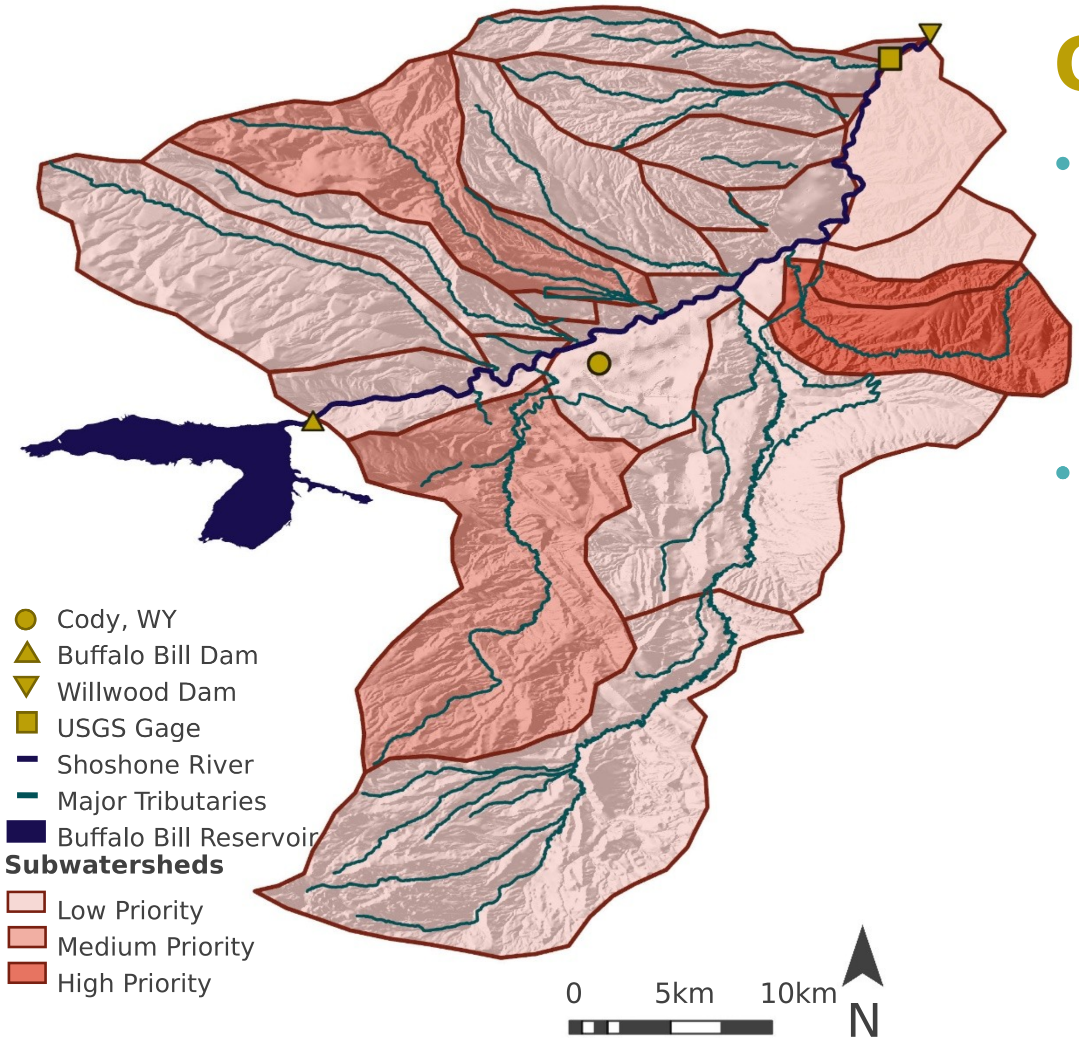


Overall

- Analysis resulted in the **identification of sediment sources** contributing to sediment accumulation behind Willwood Dam
- Coupling environmental modeling and remote sensing provides effective and accessible **results to direct management practices**

FUTURE WORK

SWAT Model

- Continue to refine SWAT+ model with observed data

Sediment RS

- Sediment transport estimations based on plume size, concentration, and streamflow could be explored

Snow Cover TS

- Methods for snow cover analysis are scalable and can be applied to specific sub-watersheds

Image: Carmen McIntyre

ACKNOWLEDGEMENTS

Special thank you to our Science Advisor and Fellow:

- Austin Madson (University of Wyoming, Assistant Professor)
- Caroline Williams (NASA DEVELOP, Fellow)

We would also like to thank our project partners for their input and guidance:

- David Waterstreet (WYDEQ)
- Carmen McIntyre (WYDEQ, Shoshone River Partners)
- Jason Alexander (USGS)

Finally, the previous project contributors:

- Cassie Ferrante
- Nelson Lemnyuy
- Will Campbell

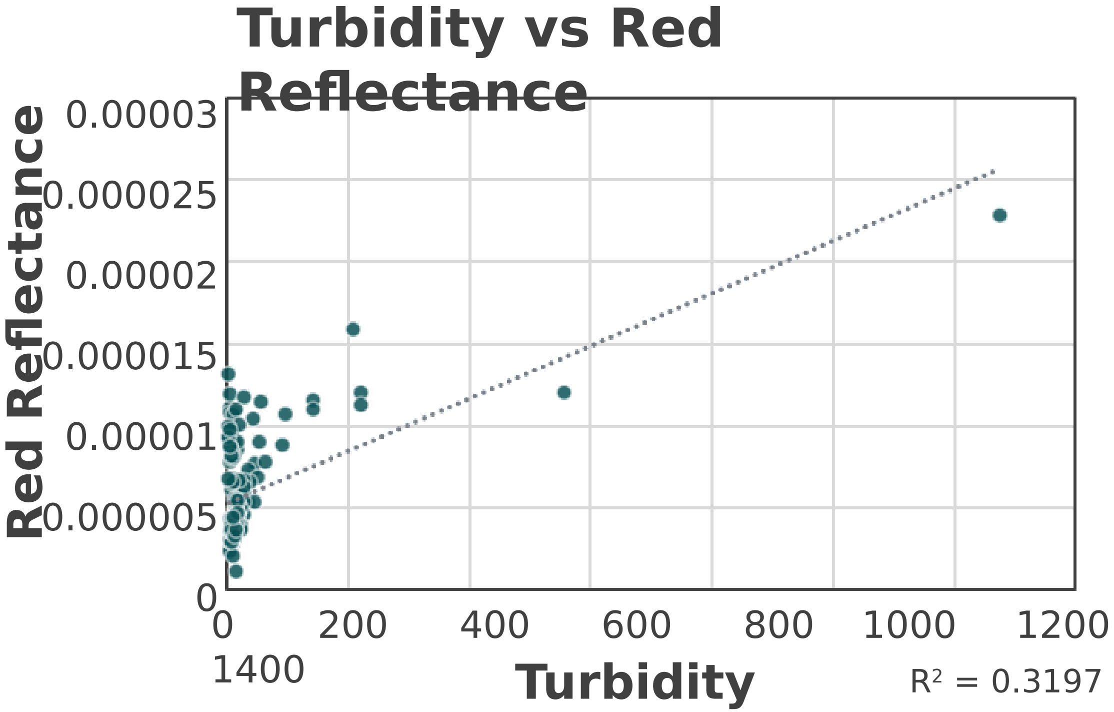
Thank you to the WyGISC department for hosting us!

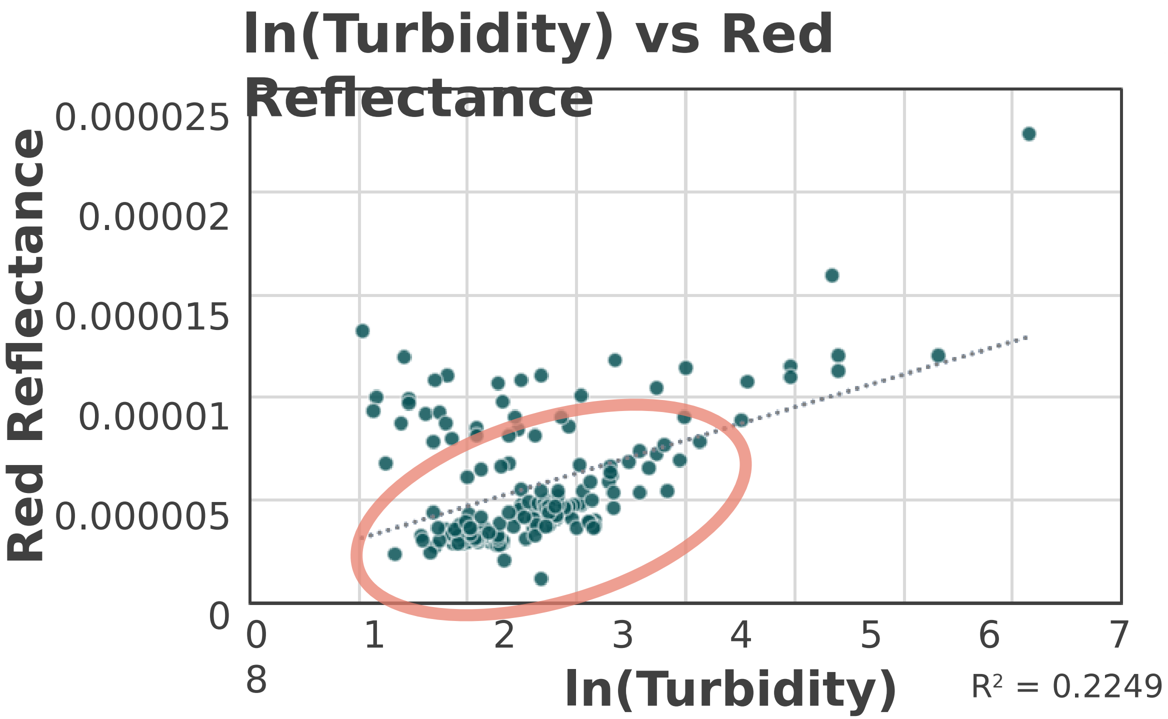
This material is based upon work supported by NASA through contract NNL16AA05C. Any mention of a commercial product, service, or activity in this material does not constitute NASA endorsement. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Aeronautics and Space Administration and partner organizations.

EXTRA SLIDES

METHODS: Sediment RS

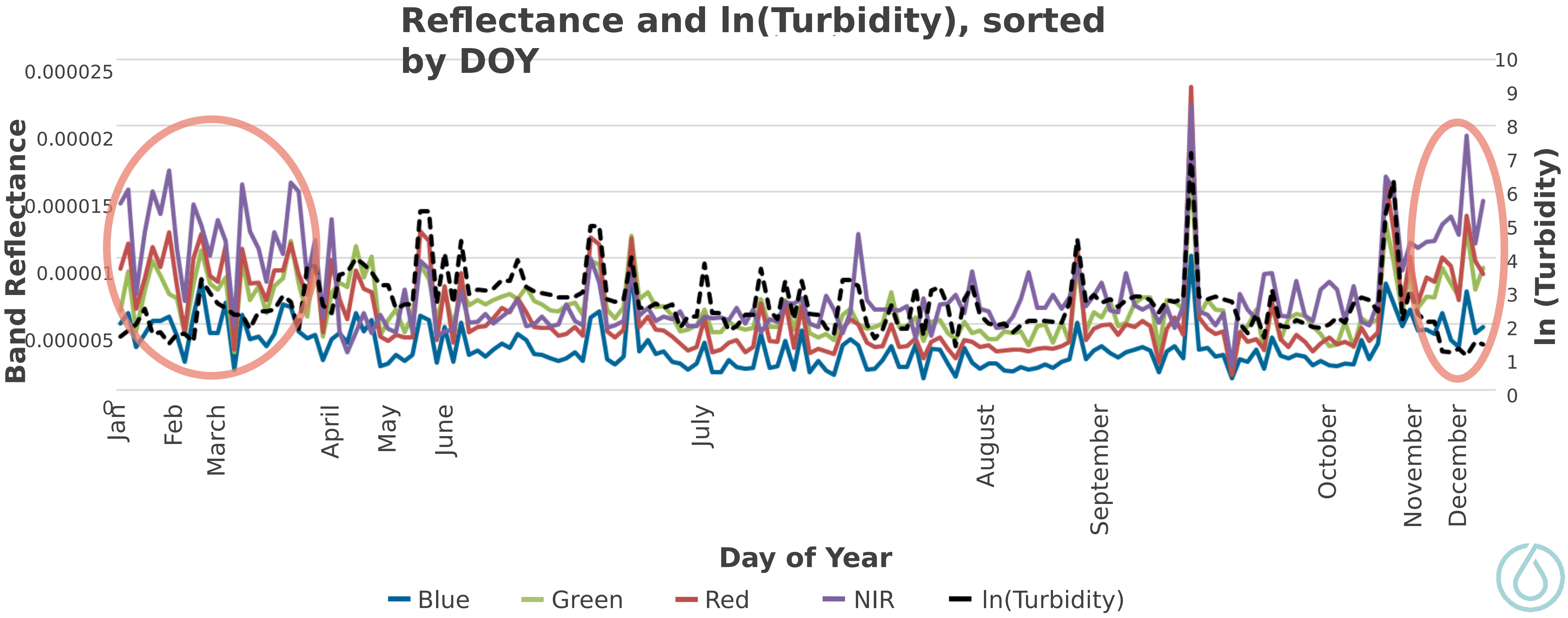
Log transforming turbidity makes the reflectance relationship more linear:





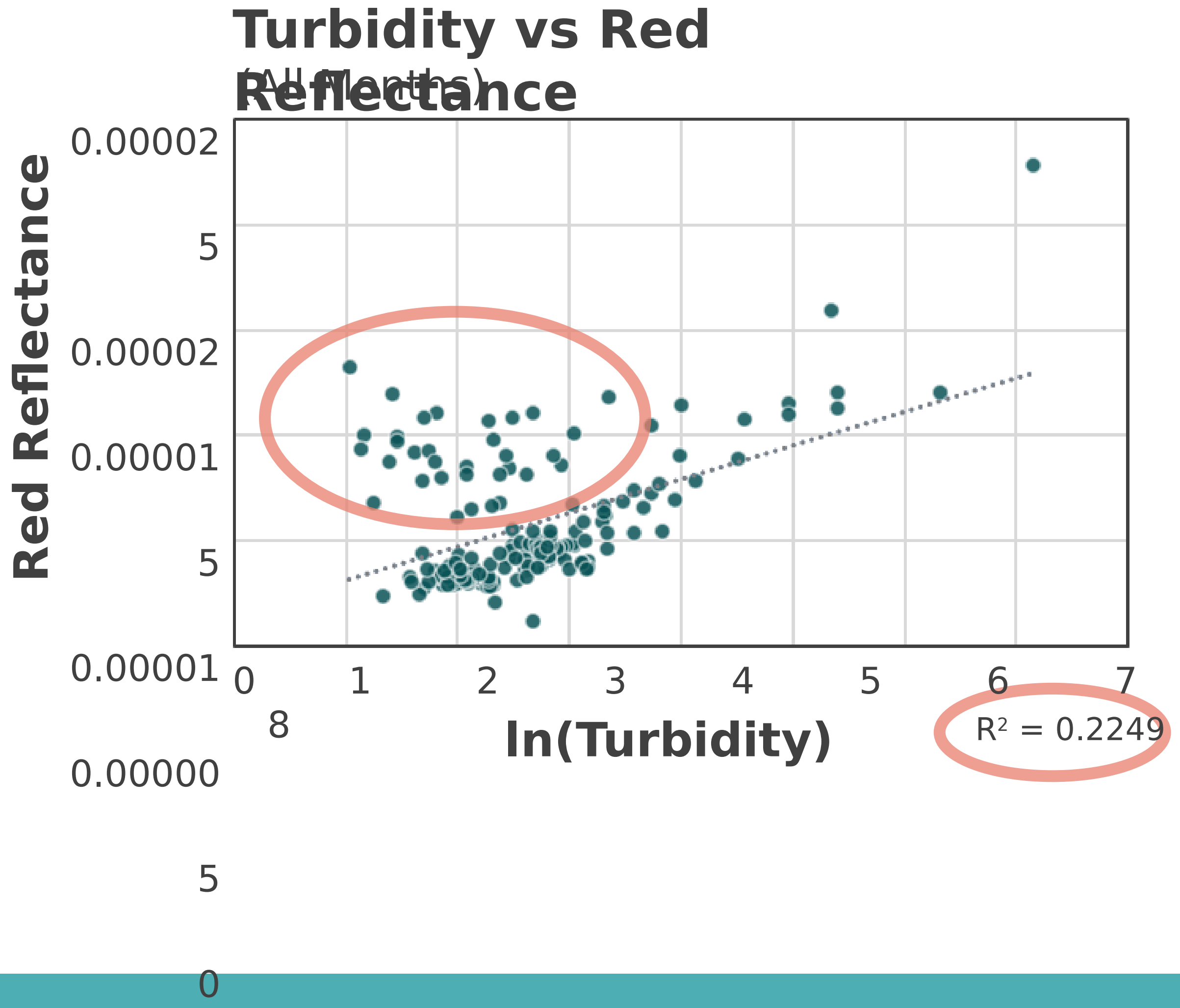
METHODS: Sediment RS

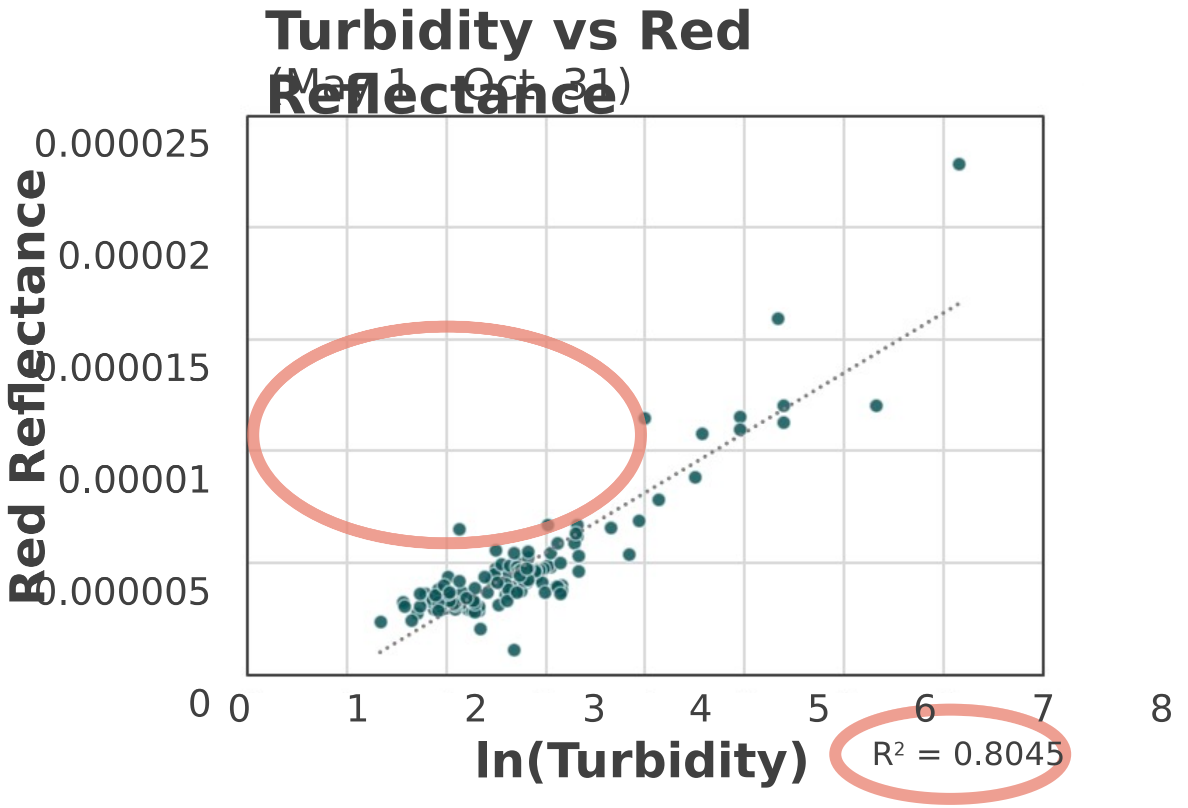
Plotting turbidity and reflectance by day of year reveals a different relationship in the winter:



METHODS: Sediment RS

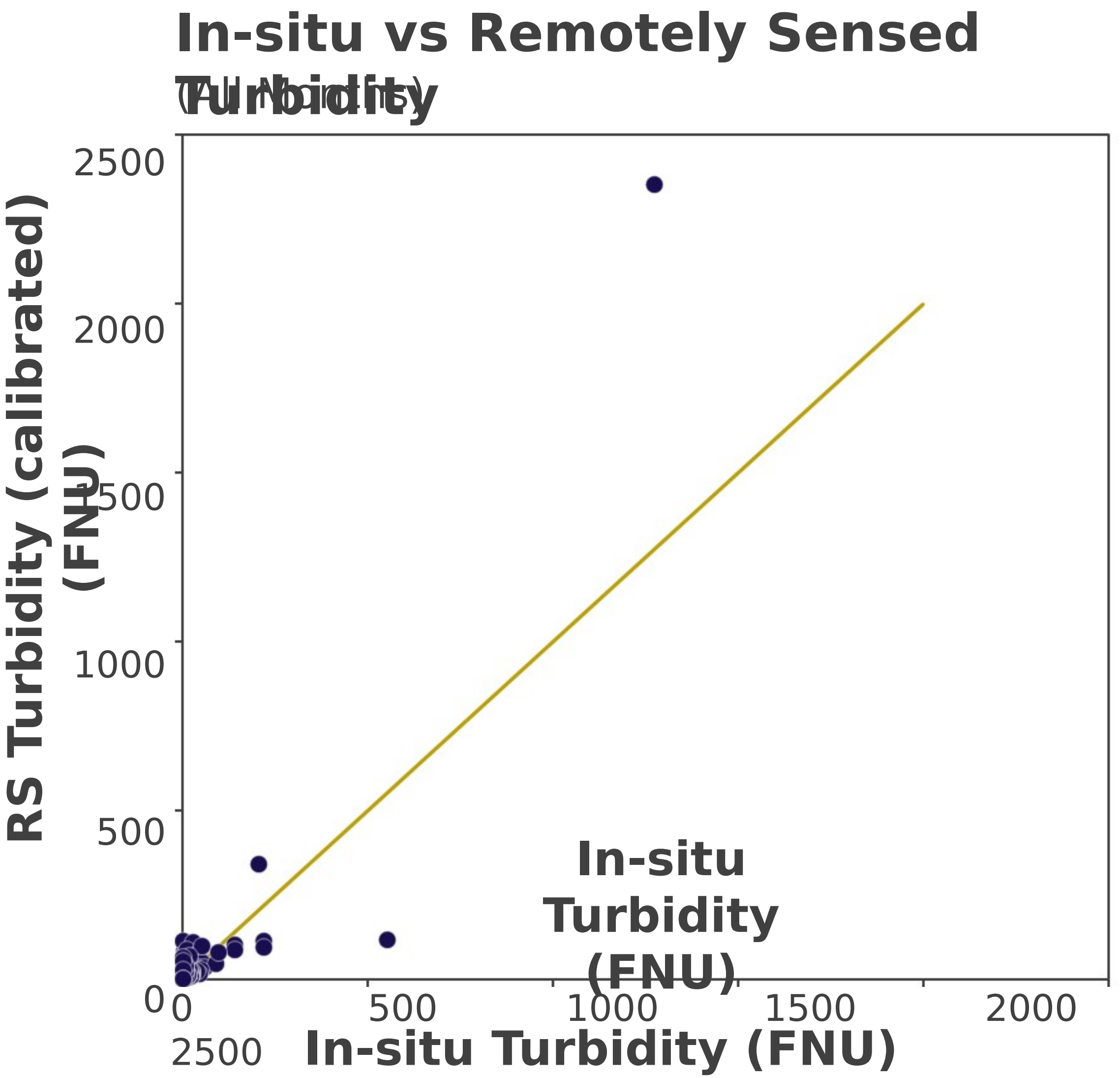
Removing Nov-April greatly improves the relationship:

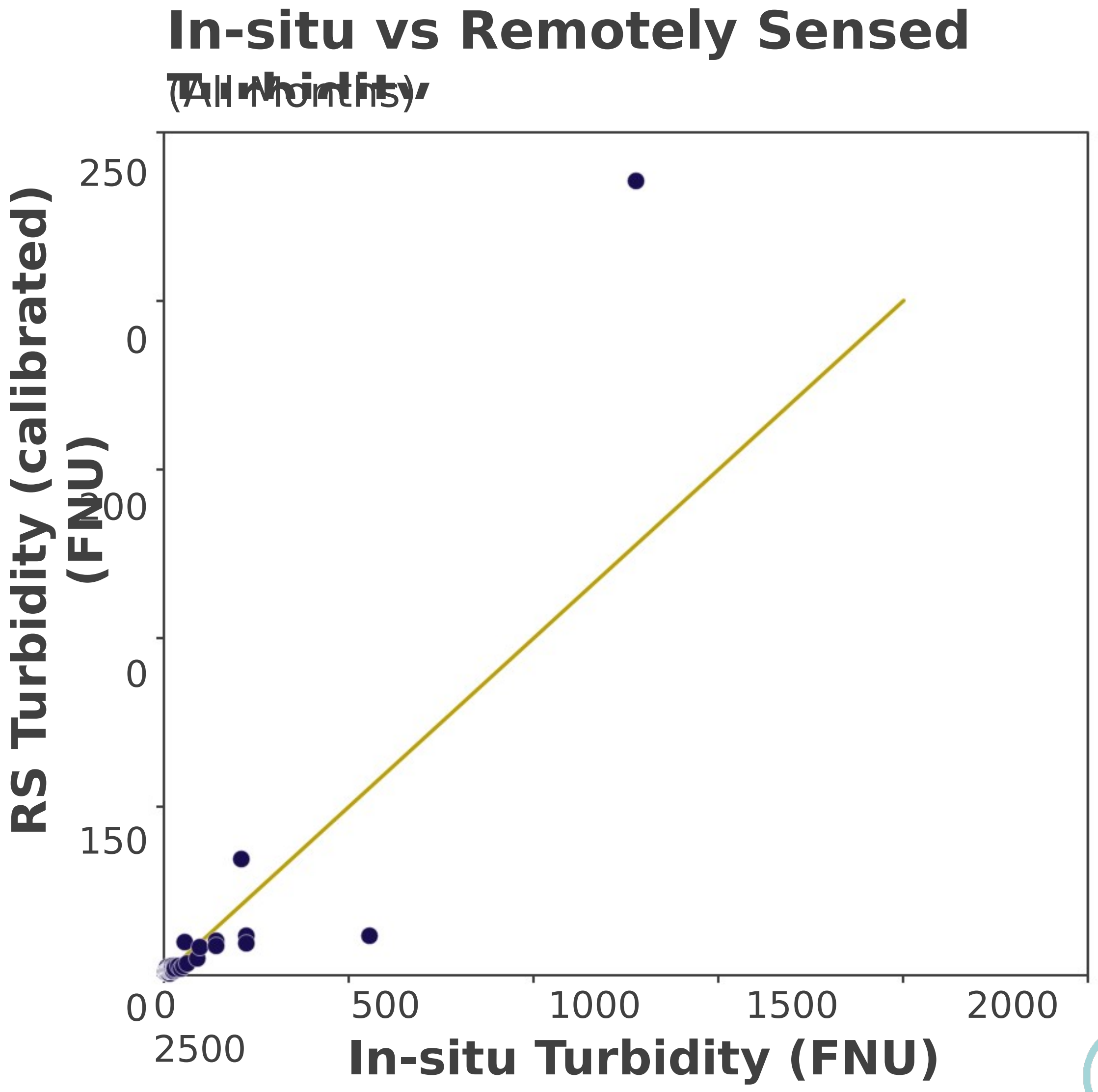




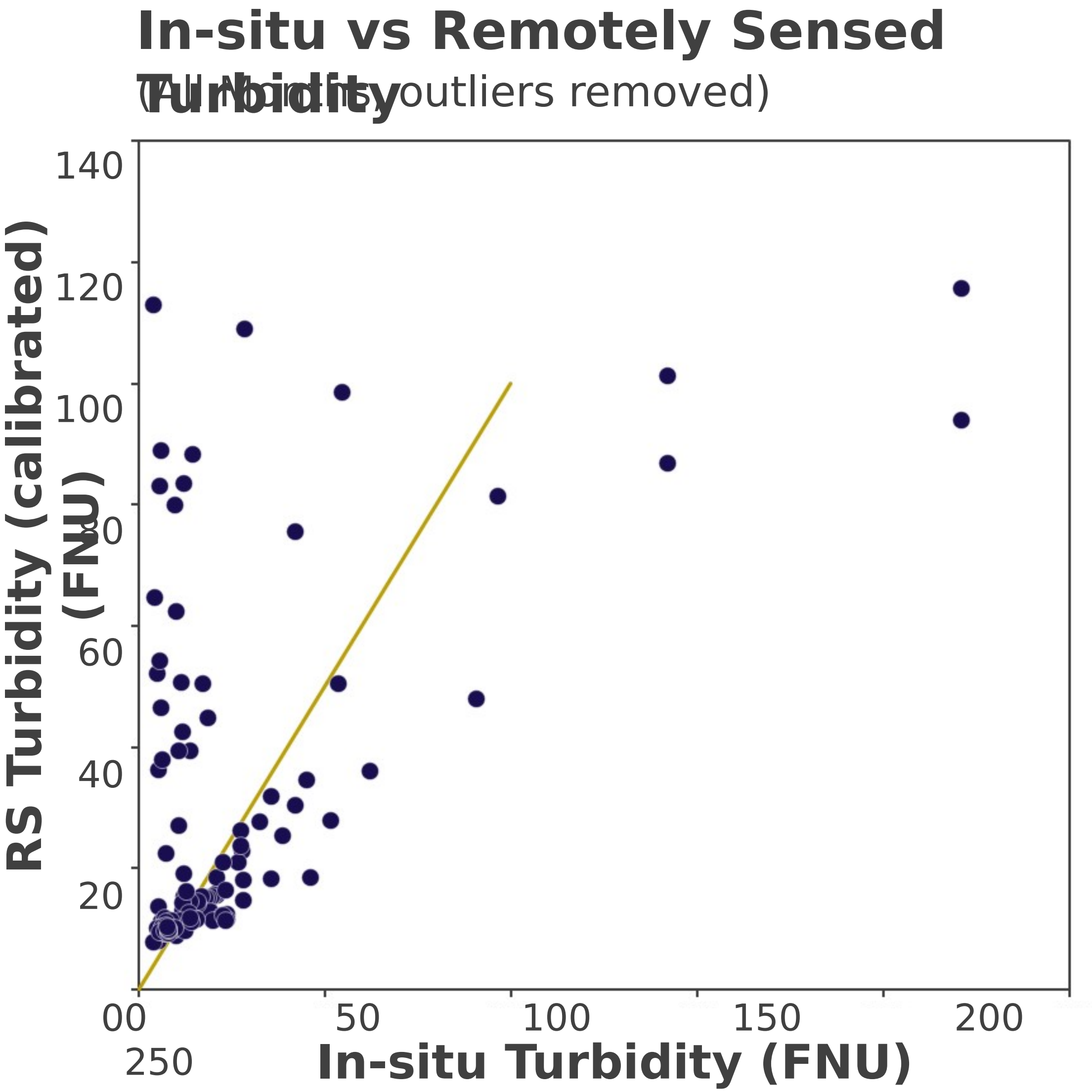
METHODS: Sediment RS

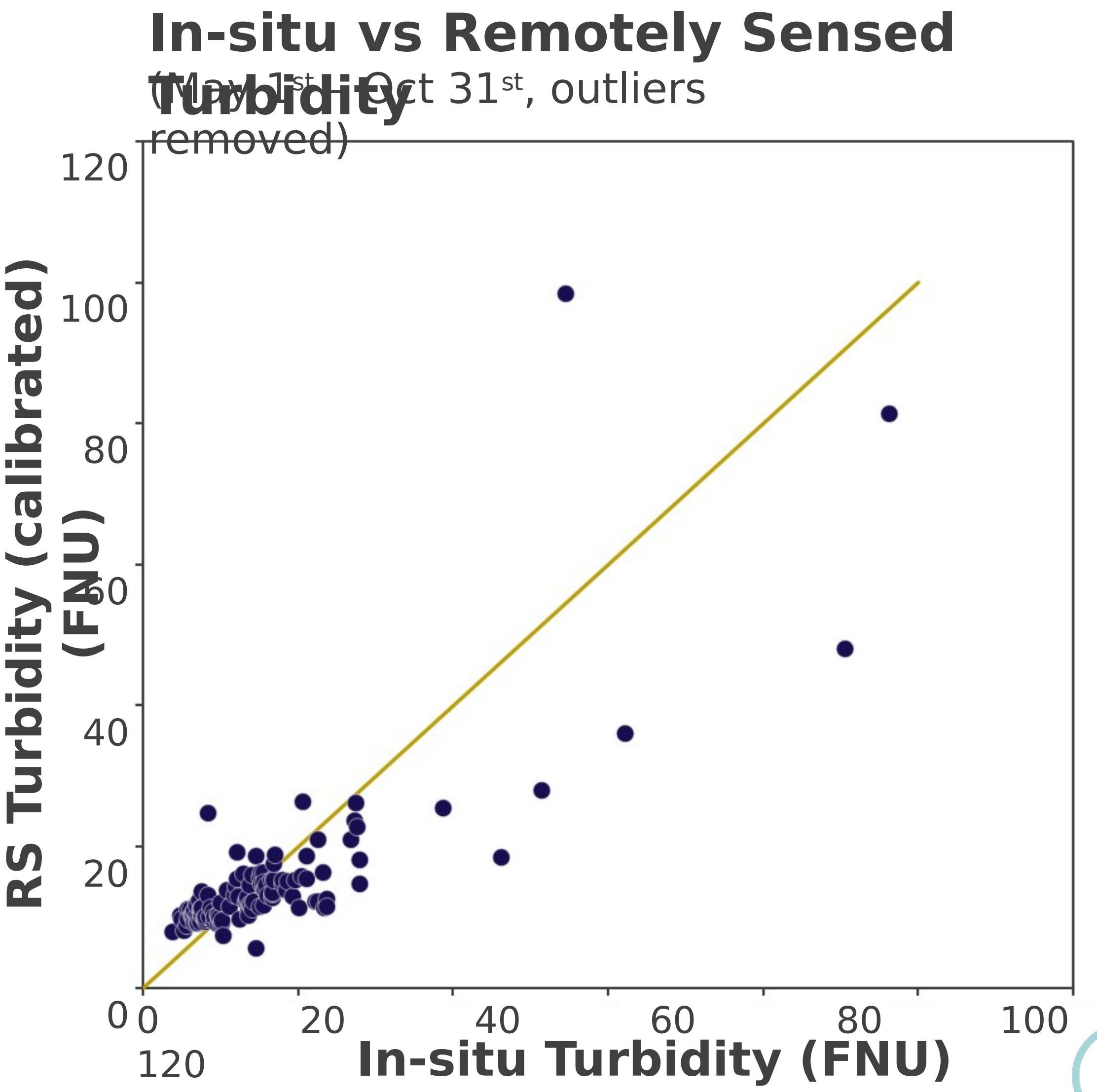
● Observed VS Predicted Turbidity
1:1 (Observed = Predicted) Line





METHODS: Sediment RS





METHODS: Sediment RS

Equations tested during calibration:

Single Band

Linear: $\ln(T) = a * Band + b$

Exponential: $\ln(T) = a * e^{b * Band}$

Polynomial: $\ln(T) = a * Band^2 + b$

Log: $\ln(T) = a + b * \log(Band)$

Double Band

DB1: $\ln(T) = a * Band1 + b * Band2^2$

DB2: $\ln(T) = \frac{Band1}{a + b * Band2}$

DB3: $\ln(T) = \frac{Band1}{a + b * Band2^2}$

DB4: $\ln(T) = a * Band1^{b * Band2}$

METHODS: Sediment RS

Single band calibration output:

	funtion	band	RMSE_ca	a_fitted	b_fitted	RMSE_va	R2_all	NSE_all	KGE_all	RMSE_all
0	linear	red	0.41069	277811.46	1.41094	0.35711	0.80756	0.80276	0.80176	0.38506
1	expo	red	0.49883	2.0204371	59786.6	0.47475	0.70546	0.68445	0.65552	0.48704
2	poly2	red	0.8715	540917.24	486577	0.61482	0.80756	0.24125	0.50804	0.75524
3	log	red	0.50215	25.764796	1.8618	0.35663	0.74861	0.74698	0.79241	0.43613
4	linear	green	0.52786	357974.89	0.68561	0.47121	0.67034	0.66666	0.69882	0.50058
5	expo	green	0.74721	2.2285033	38306.8	0.65817	0.67336	0.33981	0.22659	0.70448
6	poly2	green	0.58277	-1741403.4	462843	0.45489	0.67033	0.63573	0.81562	0.5233
7	log	green	0.67784	25.777721	1.89919	0.52949	0.51332	0.5069	0.5535	0.60884
8	linear	blue	0.50463	495357.23	1.35623	0.39378	0.73201	0.72693	0.7409	0.45308
9	expo	blue	0.54764	1.8951573	123930	0.46577	0.67343	0.65576	0.64047	0.5087
10	poly2	blue	0.85042	1291543.6	858798	0.58471	0.73201	0.28941	0.58748	0.73087
11	log	blue	0.5714	24.047046	1.65071	0.44608	0.65052	0.64976	0.72403	0.51312
12	linear	nir	0.75058	243359.8	1.18746	0.74768	0.25752	0.25344	0.34595	0.74914
13	expo	nir	0.93583	2.66587	4351.26	0.7643	0.26107	0.02731	-0.0878	0.85511
14	poly2	nir	0.85938	-85215.644	406900	0.86165	0.25752	0.015	0.50061	0.8605
15	log	nir	0.84896	20.318699	1.46364	0.75827	0.14246	0.13737	0.16841	0.80528

Used this one.

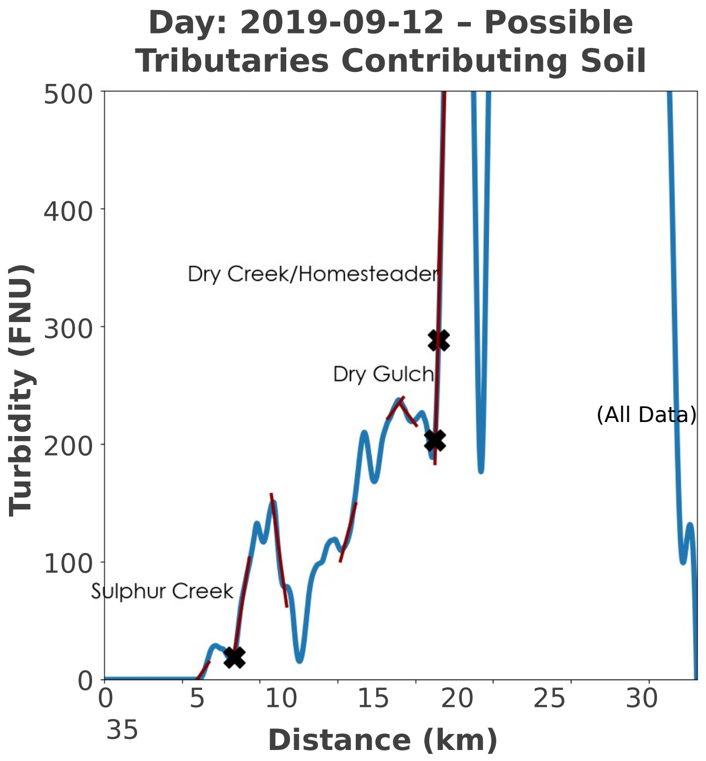
METHODS: Sediment RS

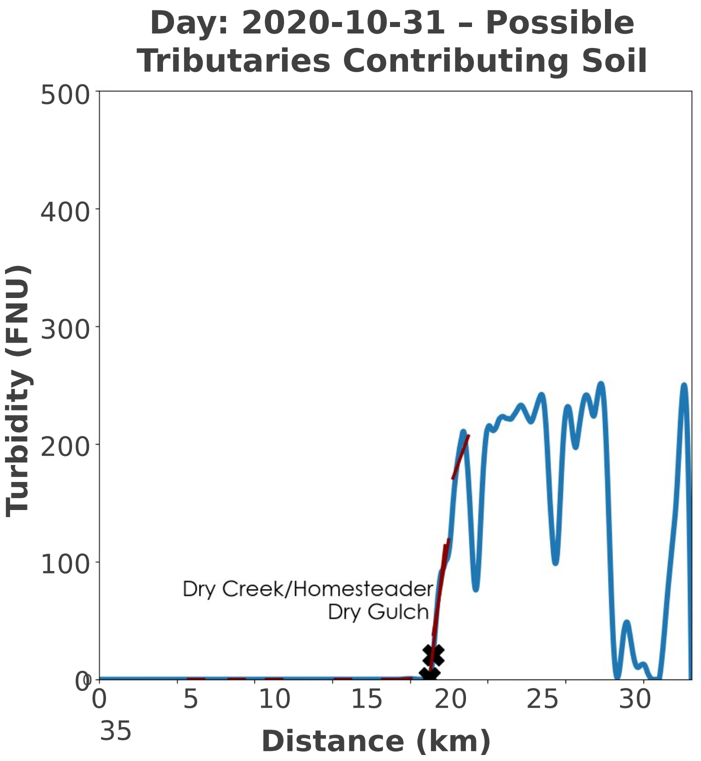
Double band calibration output:

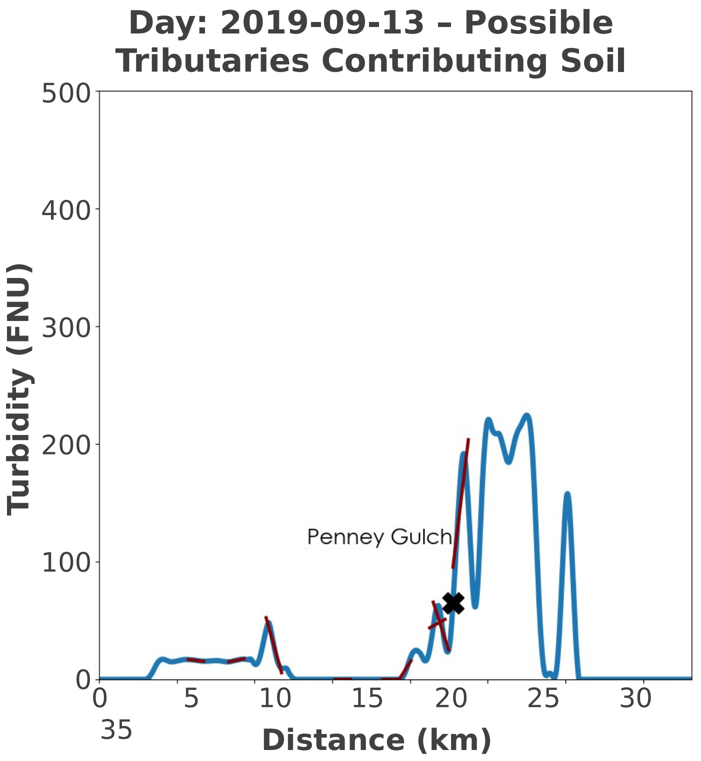
	funtion	band	RMSE_ca	a_fitted	b_fitted	RMSE_va	R2_all	NSE_all	KGE_all	RMSE_all
0	db1	red-gree	0.87143	486266	-3460136.6	0.61573	0.80756	0.24058	0.50883	0.75557
1	db2	red-gree	2.89631	1	1	2.79859	0.80756	-9.7919	-0.4178	2.84829
2	db3	red-gree	2.89631	1	1	2.79859	0.80756	-9.7919	-0.4178	2.84829
3	db4	red-gree	0.54437	1.40836	-9127.4804	0.51963	0.63195	0.62316	0.63762	0.53225
4	db1	green-re	0.58277	462274	227459.25	0.45538	0.67034	0.63544	0.81533	0.52351
5	db2	green-re	2.89631	1	1	2.79859	0.67033	-9.7919	-0.4258	2.84829
6	db3	green-re	2.89631	1	1	2.79859	0.67034	-9.7919	-0.4258	2.84829
7	db4	green-re	0.48566	1.95358	-5575.2421	0.45827	0.7231	0.70329	0.67332	0.47228
8	db1	red-nir	0.8715	485503	1392761.9	0.61771	0.80755	0.23889	0.51036	0.75641
9	db2	red-nir	2.89631	1	1	2.79859	0.80756	-9.7919	-0.4178	2.84829
10	db3	red-nir	2.89631	1	1	2.79859	0.80756	-9.7919	-0.4178	2.84829
11	db4	red-nir	0.76548	1.66454	-6147.0268	0.76997	0.22339	0.21598	0.31011	0.76771
12	db1	nir-red	0.85939	406476	1071170.8	0.86198	0.25754	0.01461	0.50042	0.86067
13	db2	nir-red	2.89631	1	1	2.79859	0.25751	-9.7919	-0.4975	2.84829
14	db3	nir-red	2.89631	1	1	2.79859	0.25752	-9.7919	-0.4975	2.84829
15	db4	nir-red	0.47304	1.93991	-5717.6522	0.44205	0.74008	0.72103	0.68911	0.45794
16	db1	green-ni	0.58276	462355	-978815.2	0.45532	0.67033	0.63547	0.81536	0.52348
17	db2	green-ni	2.89631	1	1	2.79859	0.67033	-9.7919	-0.4258	2.84829
18	db3	green-ni	2.89631	1	1	2.79859	0.67034	-9.7919	-0.4258	2.84829
19	db4	green-ni	0.75244	1.70354	-5946.557	0.7563	0.24781	0.24302	0.33407	0.75435
20	db1	nir-greer	0.85937	407358	3093631.4	0.86121	0.25757	0.0155	0.50092	0.86028
21	db2	nir-greer	2.89631	1	1	2.79859	0.25751	-9.7919	-0.4975	2.84829
22	db3	nir-greer	2.89631	1	1	2.79859	0.25752	-9.7919	-0.4975	2.84829
23	db4	nir-greer	0.5287	1.44992	-8892.6597	0.49575	0.65919	0.65042	0.66124	0.51263

	funtion	band	RMSE_ca	a_fitted	b_fitted	RMSE_va	R2_all	NSE_all	KGE_all	RMSE_all
24	db1	blue-red	0.85039	857977	-832966.66	2.84437	0.73201	0.2885	0.58839	0.73134
25	db2	blue-red	2.89631	1	1	2.79859	0.73201	-9.7919	-0.4216	2.84829
26	db3	blue-red	2.89631	1	1	2.79859	0.73201	-9.7919	-0.4216	2.84829
27	db4	blue-red	0.49011	1.94416	-5347.87	0.59822	0.71736	0.69736	0.66816	0.47698
28	db1	red-blue	0.87146	486550	-2365111	1.45212	0.80756	0.24122	0.50815	0.75525
29	db2	red-blue	2.89631	1	1	2.79859	0.80756	-9.7919	-0.4178	2.84829
30	db3	red-blue	2.89631	1	1	2.79859	0.80756	-9.7919	-0.4178	2.84829
31	db4	red-blue	0.56152	1.81283	-11529.625	1.25135	0.6642	0.64688	0.63367	0.51522
32	db1	blue-nir	0.85041	858486	1033331.3	1.59686	0.73202	0.28909	0.5878	0.73104
33	db2	blue-nir	2.89631	1	1	2.79859	0.73201	-9.7919	-0.4216	2.84829
34	db3	blue-nir	2.89631	1	1	2.79859	0.73201	-9.7919	-0.4216	2.84829
35	db4	blue-nir	0.7649	1.69655	-5647.0903	0.9169	0.22751	0.22154	0.31032	0.76498
36	db1	nir-blue	0.85938	407150	1335446.4	1.66677	0.25753	0.01524	0.50076	0.8604
37	db2	nir-blue	2.89631	1	1	2.79859	0.25751	-9.7919	-0.4975	2.84829
38	db3	nir-blue	2.89631	1	1	2.79859	0.25752	-9.7919	-0.4975	2.84829
39	db4	nir-blue	0.55932	1.84691	-11186.684	2.21561	0.6732	0.65548	0.63975	0.50891
40	db1	blue-gre	0.85039	858438	-2395436.4	2.84713	0.73201	0.289	0.58793	0.73109
41	db2	blue-gre	2.89631	1	1	2.79859	0.73201	-9.7919	-0.4216	2.84829
42	db3	blue-gre	2.89631	1	1	2.79859	0.73201	-9.7919	-0.4216	2.84829
43	db4	blue-gre	0.54012	1.43927	-8457.9356	0.98984	0.63593	0.62618	0.63698	0.53011
44	db1	green-b	0.58277	462514	-1043371.4	1.51673	0.67033	0.63556	0.81545	0.52342
45	db2	green-b	2.89631	1	1	2.79859	0.67033	-9.7919	-0.4258	2.84829
46	db3	green-b	2.89631	1	1	2.79859	0.67034	-9.7919	-0.4258	2.84829
47	db4	green-b	0.54869	1.83293	-11349.237	1.63107	0.6777	0.6607	0.6461	0.50504

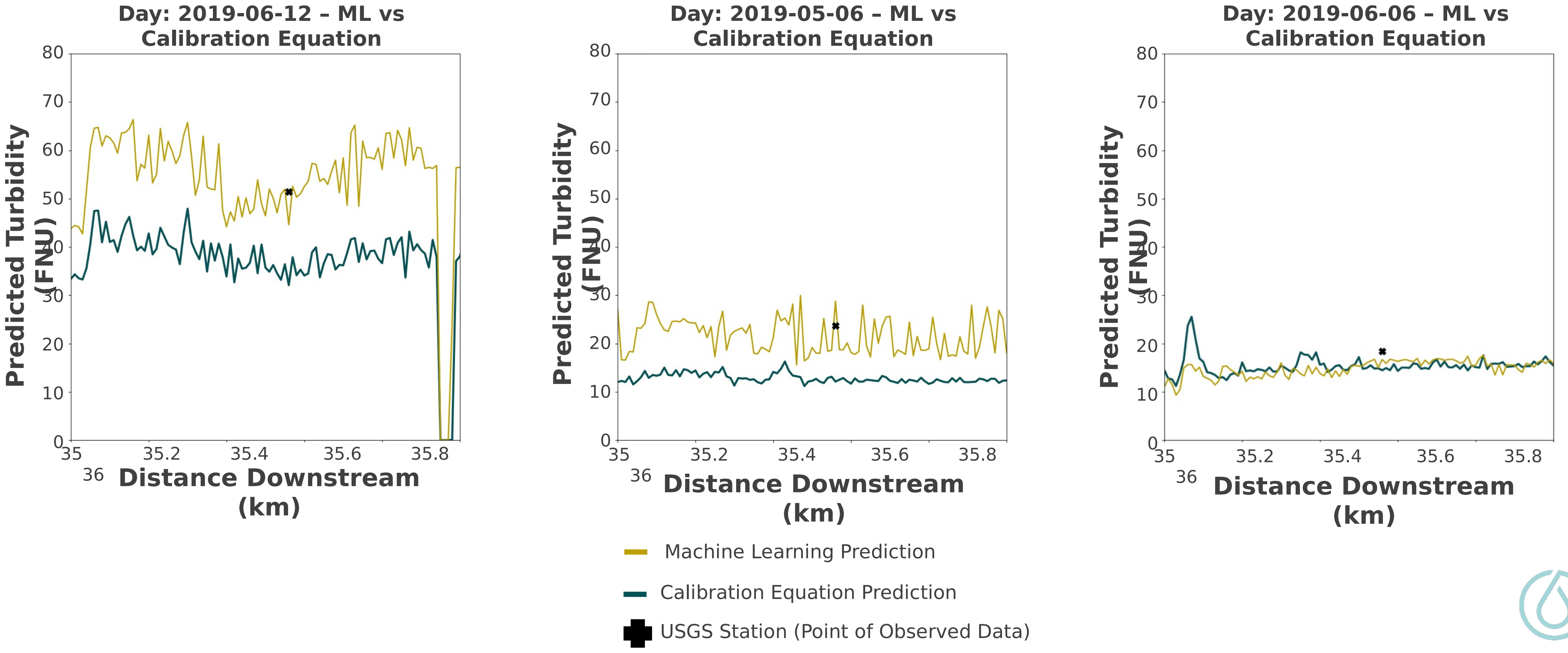
Results: Automatic Plume Detection



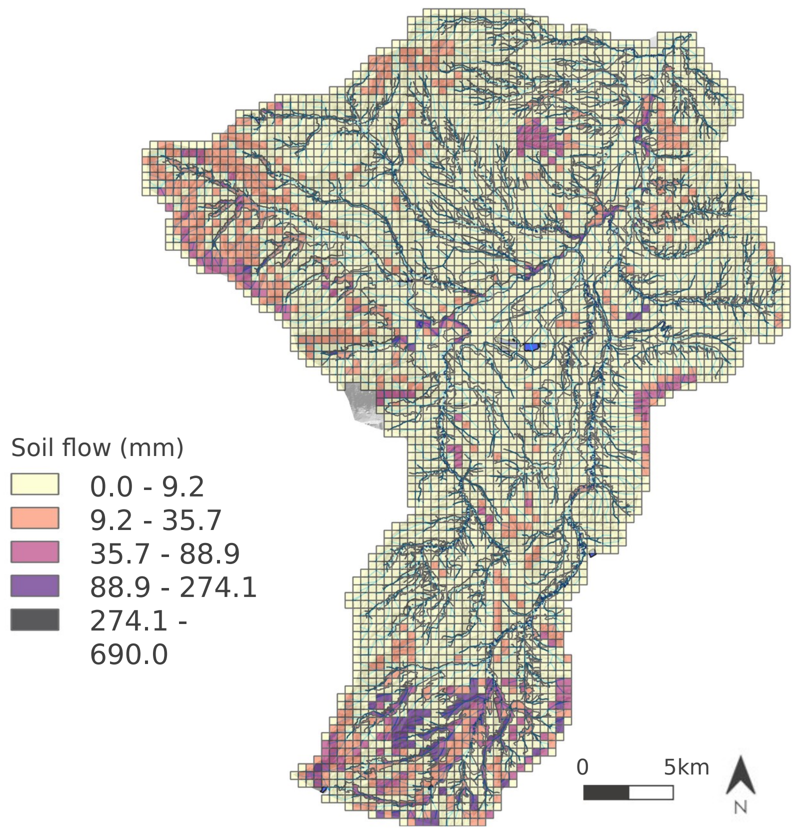




RESULTS: Machine Learning VS Cal. Eq.



CONCLUSIONS



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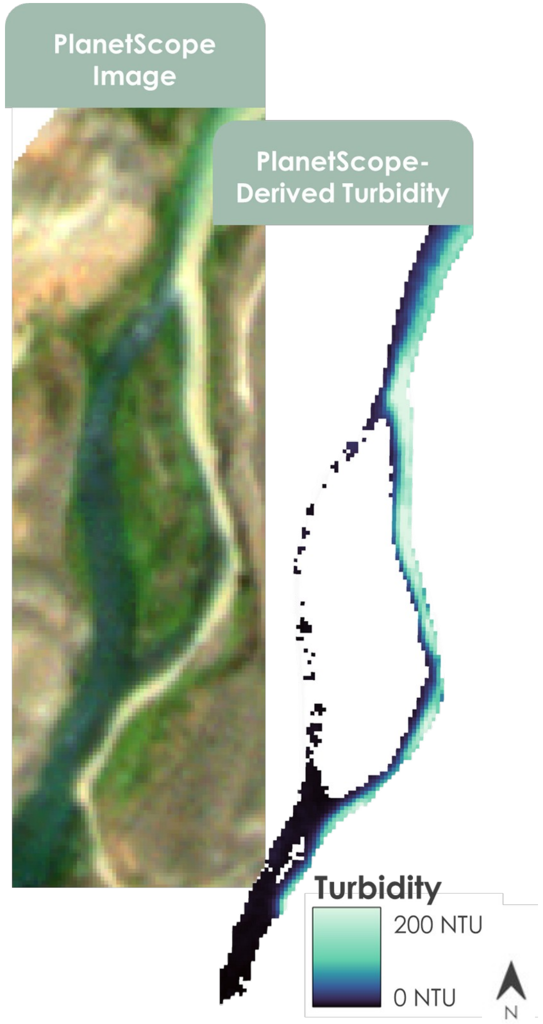

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Overall

Coupling environmental modeling and remote sensing provides effective and accessible results to direct management practices.