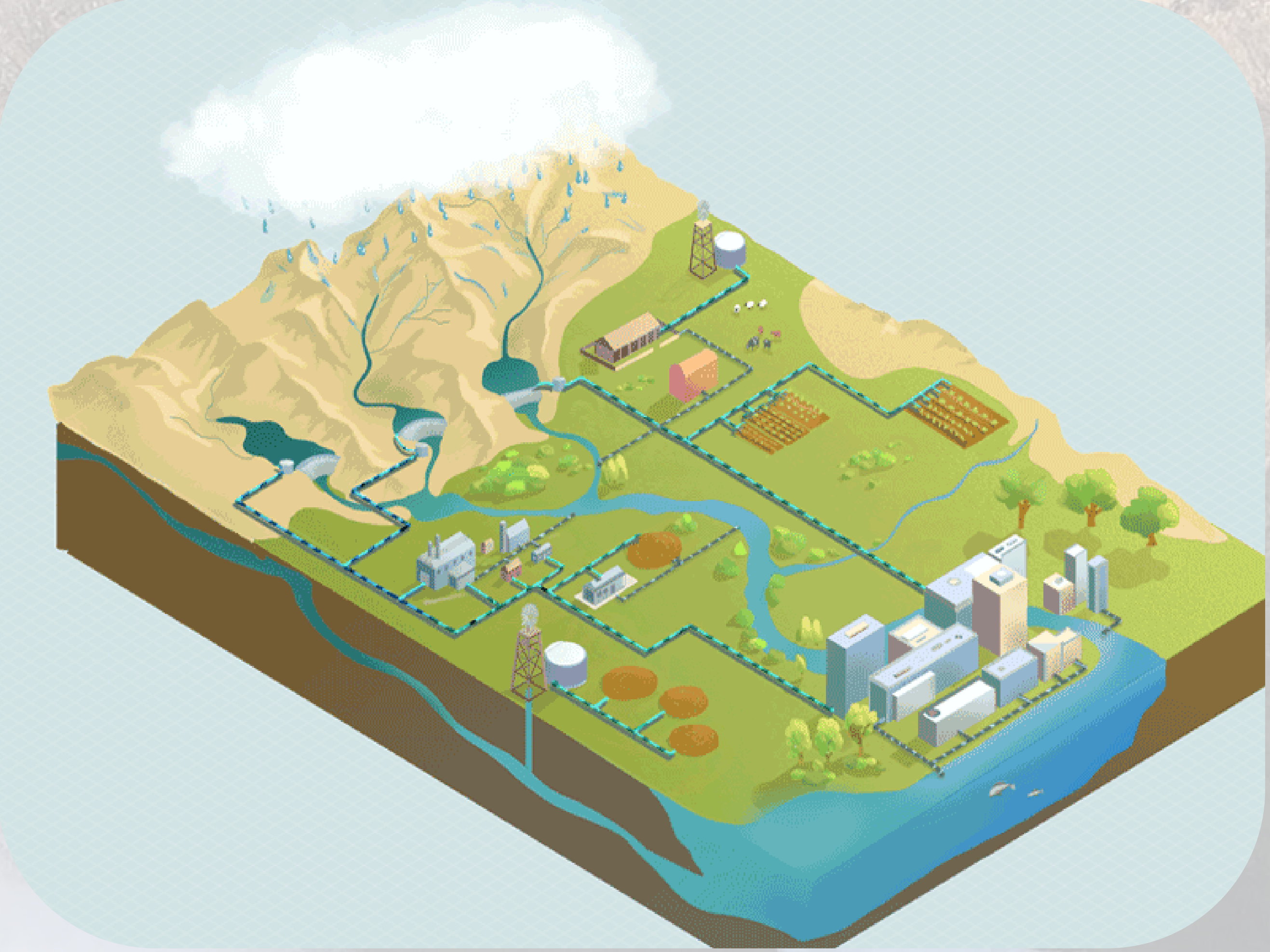
Advancing Hydrological Modeling and Water Resources Management with Machine Learning

Dr. Ryan Johnson
Research Scientist
The University of Alabama



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College of Engineering
Civil, Construction and Environmental Engineering

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Presentation Outline

- Introduction
- Research Background
- Previous Accomplishments
- Active Areas of Research
- Research Program at the University
- Teaching Goals, Philosophy, Ideas

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Dr. Ryan Johnson

Academic Background
- Environmental Sciences
- Earth System Science
- Civil and Environmental Engineering
- Water Resources

“The richness I achieve comes from Nature, the source of my inspiration” – Claude Monet

SADDLEBACK COLLEGE

Water Quality

Climate Change

Urban Water Systems

Water Resources

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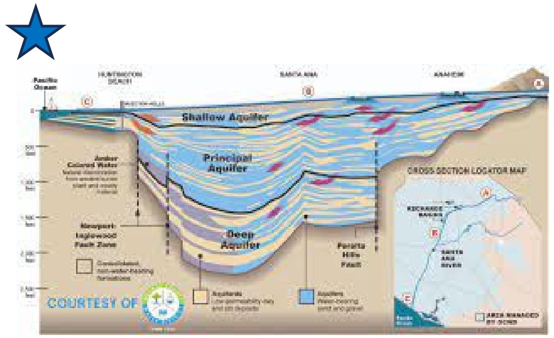
Background: Drivers of Water Research

Environmental Degradation and Social Inequality

Water Quality



Enhancing Water Resources

Environmental Management

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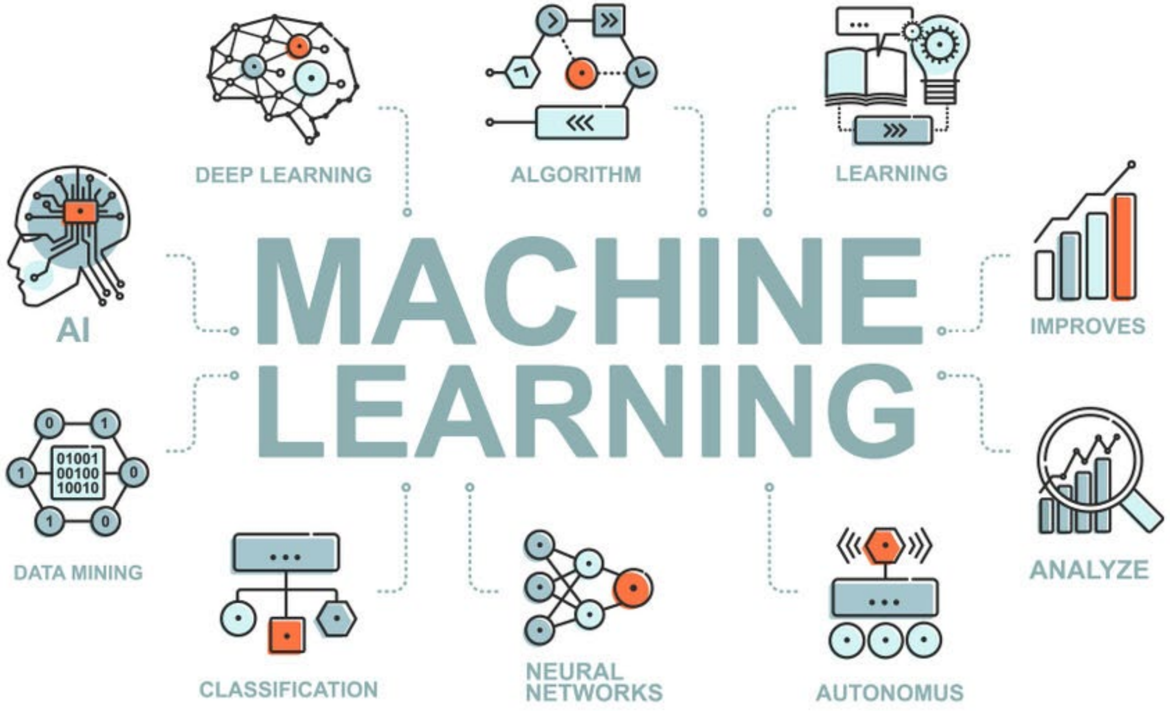
My Water Research



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Previous Research

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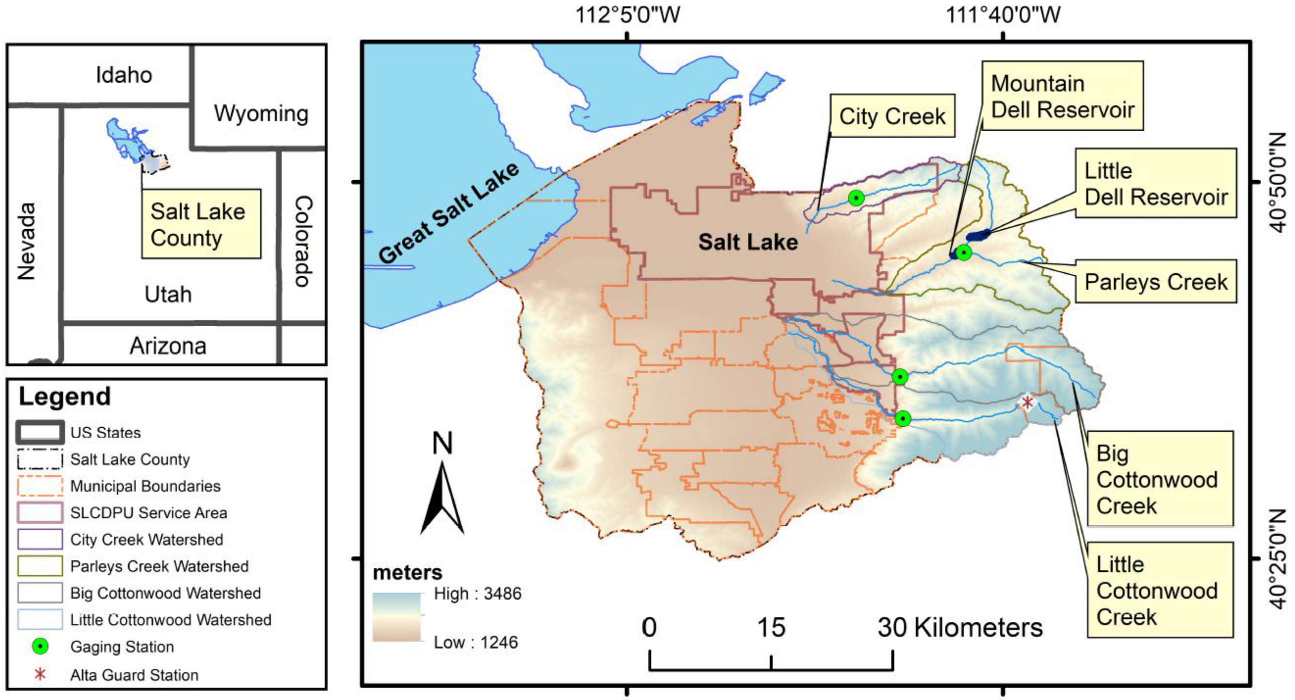
Urban Water System Modeling

Urban Water System Modeling

- ML to model water demand
- Climate influences on water system performance
- ML for water system modeling



Objective: Advance the science in water system planning in a dynamic and arid climate.

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Machine Learning for Water System Modeling

Research Question: Many utilities do not have the resources or personnel to develop a representative water system model to support planning and management activities. Can machine learning accurately model water system interactions and performance across different supply and demand scenarios?

Objective: Use simulated water system data to train machine learning models to predict daily to seasonal groundwater, reservoir levels, and imported water. Compare model skill to simulated targets.

Journal of Hydroinformatics

IAHR AIRH International Association for Hydro-Environment Engineering and Research

IAHS AISH

IWA PUBLISHING

Journal of Hydroinformatics Vol 25 No 5, 1584 doi: 10.2166/hydro.2023.170

Data-driven modeling of municipal water system responses to hydroclimate extremes

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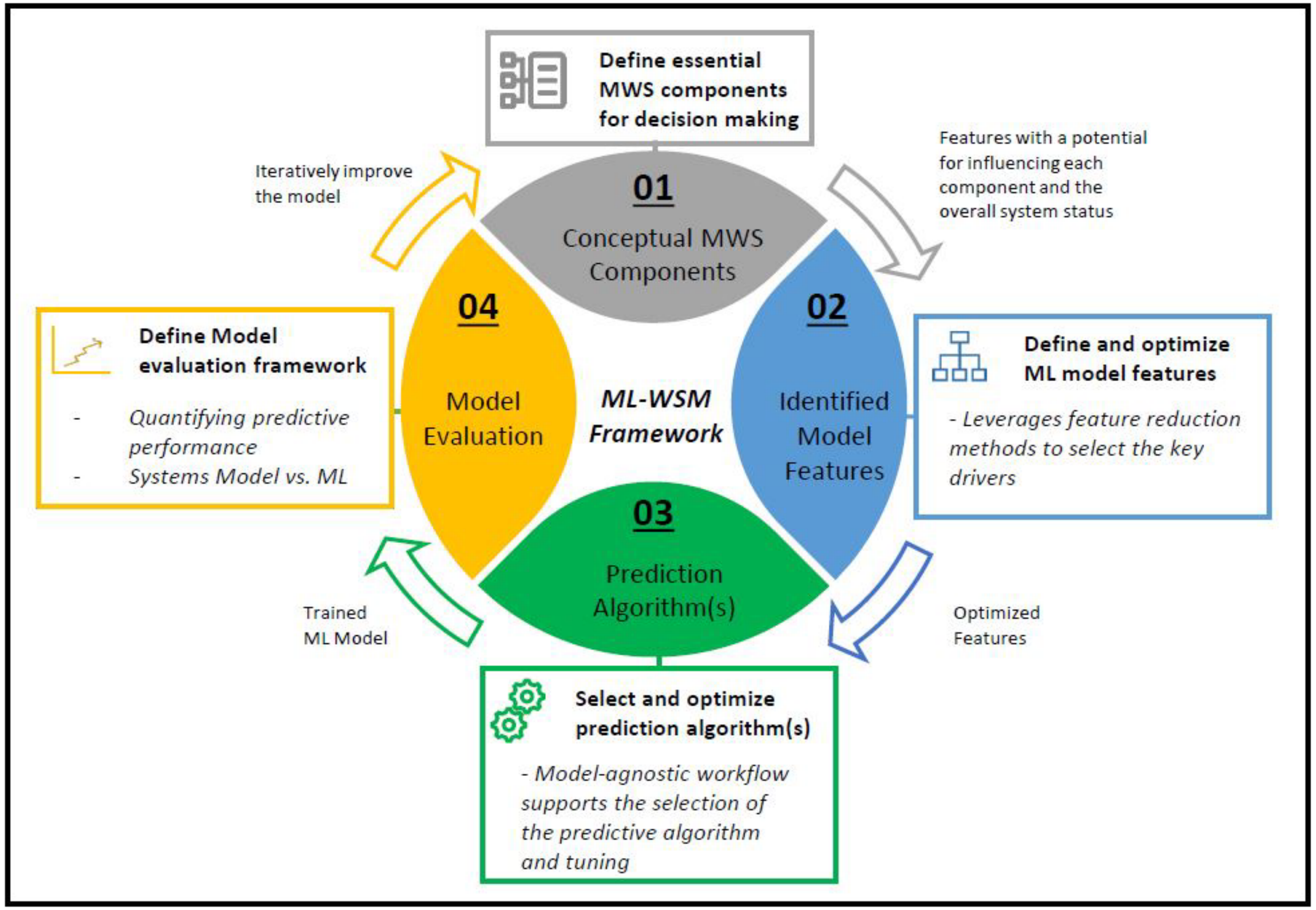
Machine Learning for Water System Modeling

Methods:
- Model key features of water system
- Incorporate serial correlation
- Model agnostic workflow
- System agnostic
- Dry, wet, average scenarios

Results:
- High model skill during critical conditions
- Representative vulnerability metrics

Impact:
- Demonstration of ML algorithms for modeling water system interactions
- Expeditious development
- Applicable to smaller water systems and/or complementary to others



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Research Impact

Advanced Water Resources Planning and Management

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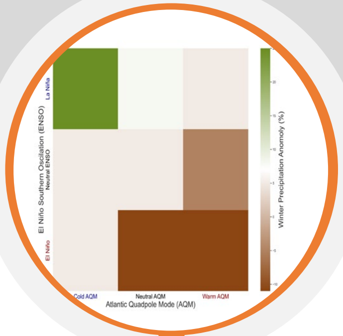
MINES AND EARTH SCIENCES | THE UNIVERSITY OF UTAH

THE UNIVERSITY OF UTAH
COLLEGE OF SOCIAL AND BEHAVIORAL SCIENCE
Department of Geography

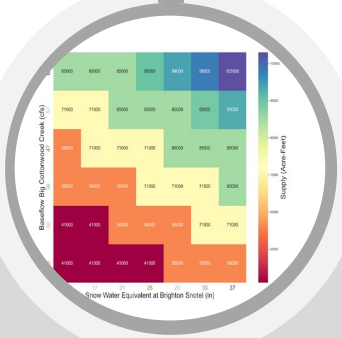


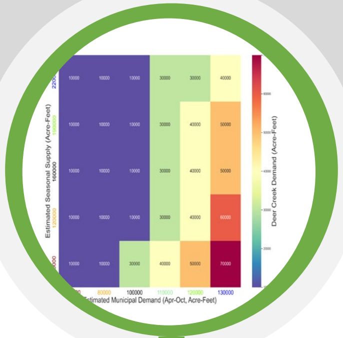
October

Winter precipitation estimates

Prelim estimates of streamflow yield

January



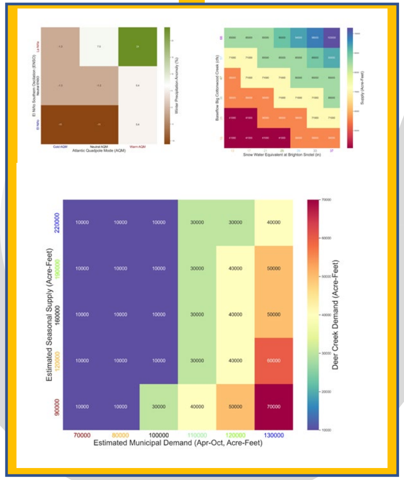


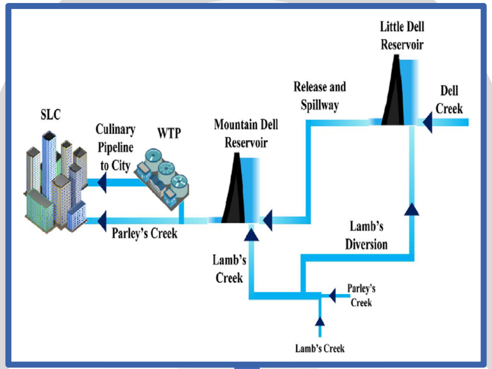
February

Seasonal water system projections

Summer precip & temp outlook
Refined estimates of surface water yield
Refined estimates of system vulnerabilities
Begin formulating management decisions

March





April-June

Assess system status
Revise/Initiate operational decisions

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Current Research Activities

Cooperative Institute for Research to Operations in Hydrology (CIROH)

- Advancing CONUS-Scale Operational Snow Modeling Capabilities
  - Snow Water Equivalent Machine Learning (SWEML)
- Community Streamflow Evaluation System (CSES)
- Enhancing Supply Forecasting for Systems Management
  - National Water Model Season-to-Season Water Supply Forecasting
- Advancing Snow Observation Systems to Improve Operational Streamflow Prediction Capabilities
  - Low-Cost Low-Power Snow Observing Systems

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Advancing CONUS-Scale Operational Snow Modeling Capabilities

PI: Ryan Johnson, PHD – University of Alabama

Co-PI: Andy Wood , PHD – Colorado School of Mines

Co-PI: Katherine Hale , PHD - University of Vermont

Co-PI: McKenzie Skiles , PHD - University of Utah

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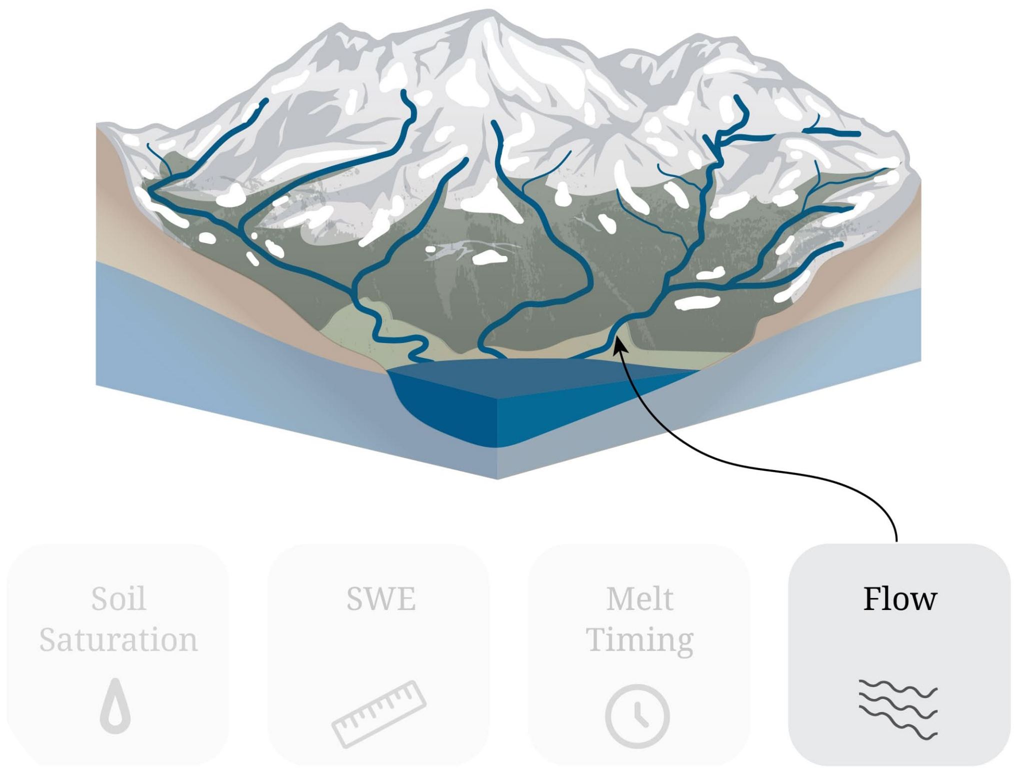
Snow Water Equivalent Machine Learning (SWEML)

Spatially continuous near-real-time SWE estimates



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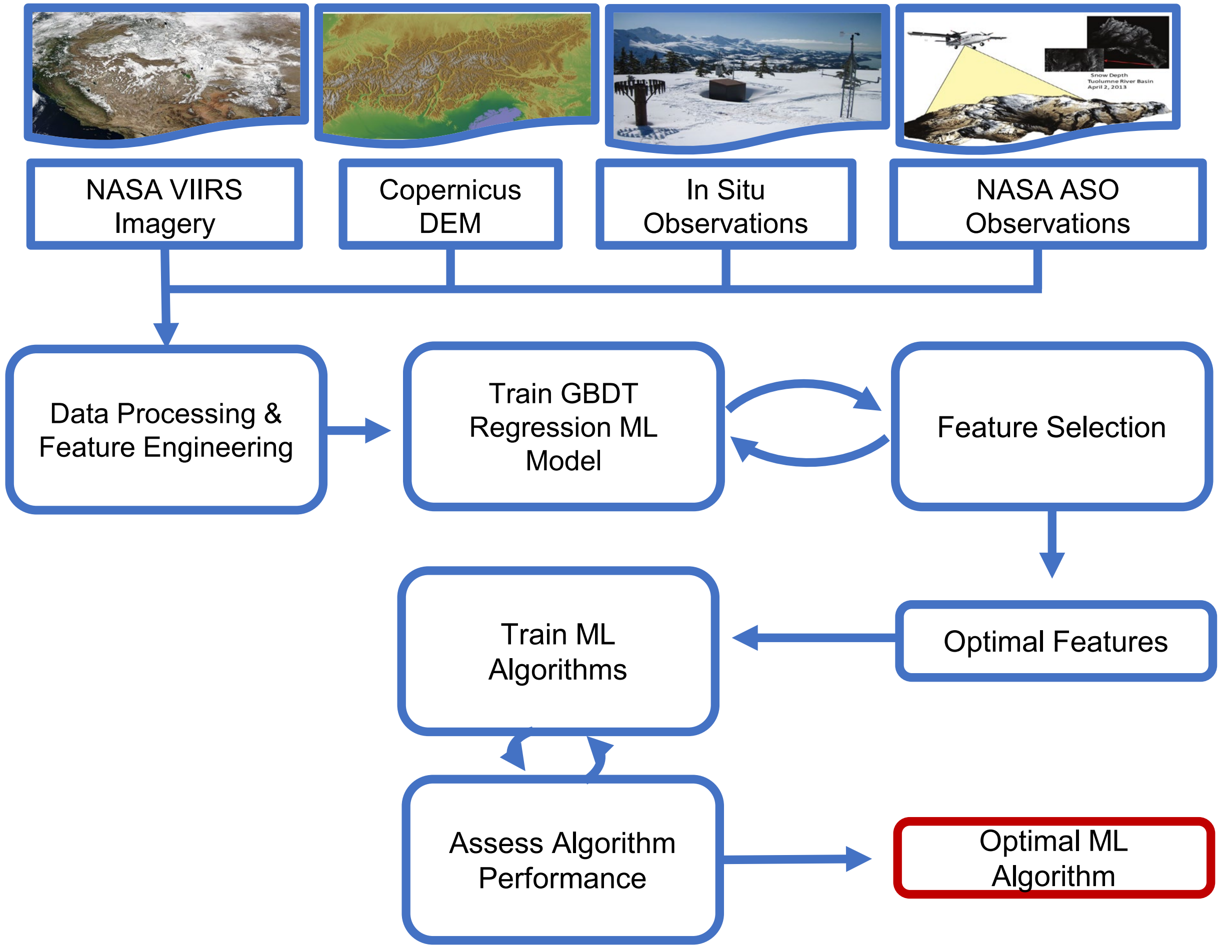
Snow Water Equivalent Machine Learning (SWEML)

Model Development

- Airborne Snow Observatory and snow course observations
- 1km spatial resolution
- Regionalization via Sturm's classification
- Multiple ML algorithms explored
- 3 feature selection method examined



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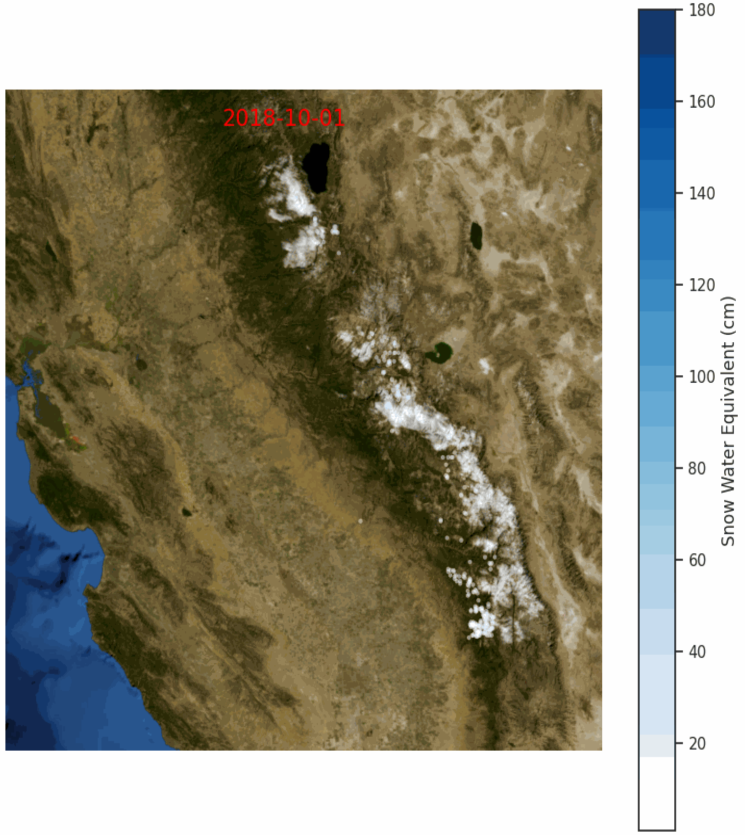
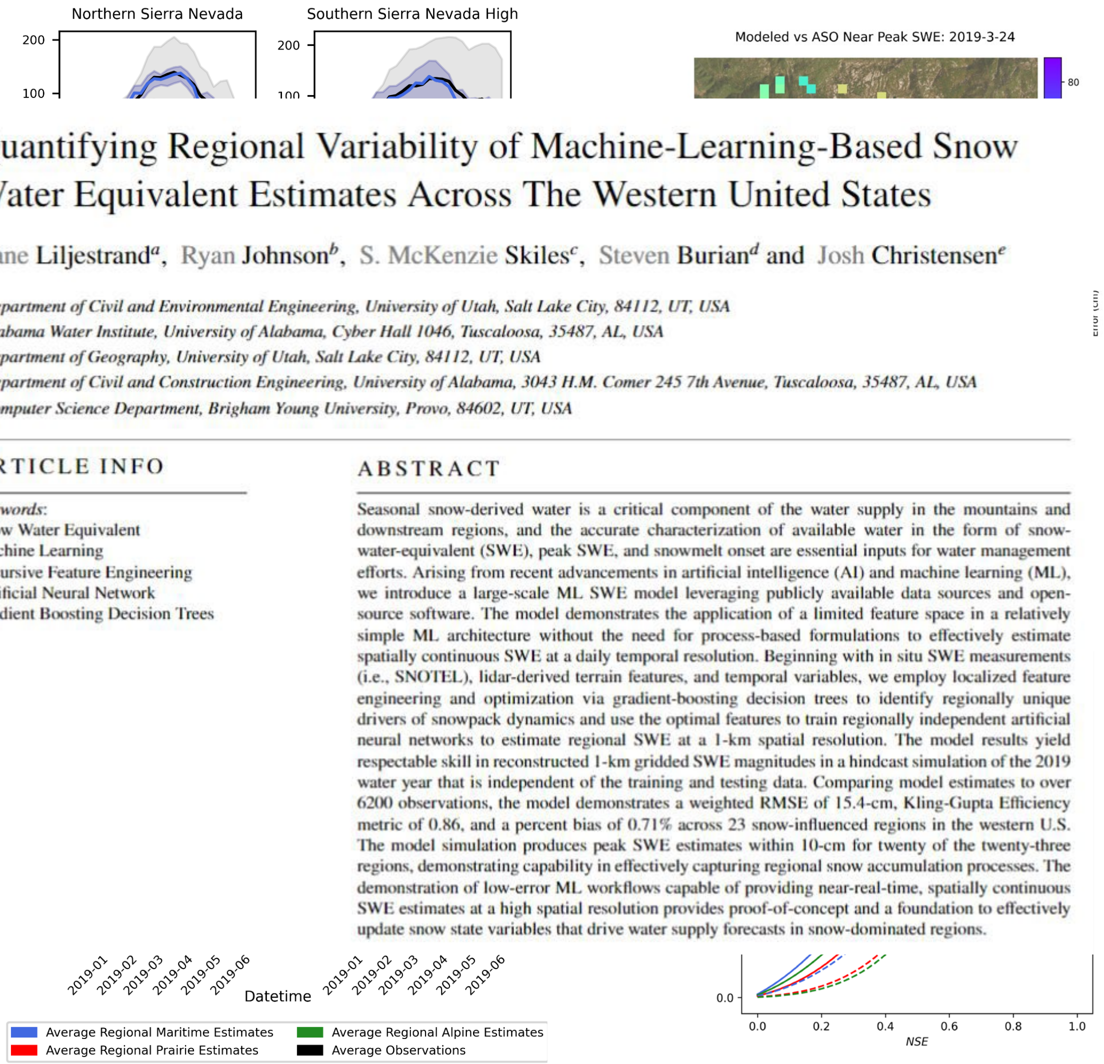
Snow Water Equivalent Machine Learning (SWEML)





Quantifying Regional Variability of Machine-Learning-Based Snow Water Equivalent Estimates Across The Western United States

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ARTICLE INFO

Keywords:
Snow Water Equivalent
Machine Learning
Recursive Feature Engineering
Artificial Neural Network
Gradient Boosting Decision Trees

ABSTRACT

Seasonal snow-derived water is a critical component of the water supply in the mountains and downstream regions, and the accurate characterization of available water in the form of snow-water-equivalent (SWE), peak SWE, and snowmelt onset are essential inputs for water management efforts. Arising from recent advancements in artificial intelligence (AI) and machine learning (ML), we introduce a large-scale ML SWE model leveraging publicly available data sources and open-source software. The model demonstrates the application of a limited feature space in a relatively simple ML architecture without the need for process-based formulations to effectively estimate spatially continuous SWE at a daily temporal resolution. Beginning with in situ SWE measurements (i.e., SNOTEL), lidar-derived terrain features, and temporal variables, we employ localized feature engineering and optimization via gradient-boosting decision trees to identify regionally unique drivers of snowpack dynamics and use the optimal features to train regionally independent artificial neural networks to estimate regional SWE at a 1-km spatial resolution. The model results yield respectable skill in reconstructed 1-km gridded SWE magnitudes in a hindcast simulation of the 2019 water year that is independent of the training and testing data. Comparing model estimates to over 6200 observations, the model demonstrates a weighted RMSE of 15.4-cm, Kling-Gupta Efficiency metric of 0.86, and a percent bias of 0.71% across 23 snow-influenced regions in the western U.S. The model simulation produces peak SWE estimates within 10-cm for twenty of the twenty-three regions, demonstrating capability in effectively capturing regional snow accumulation processes. The demonstration of low-error ML workflows capable of providing near-real-time, spatially continuous SWE estimates at a high spatial resolution provides proof-of-concept and a foundation to effectively update snow state variables that drive water supply forecasts in snow-dominated regions.

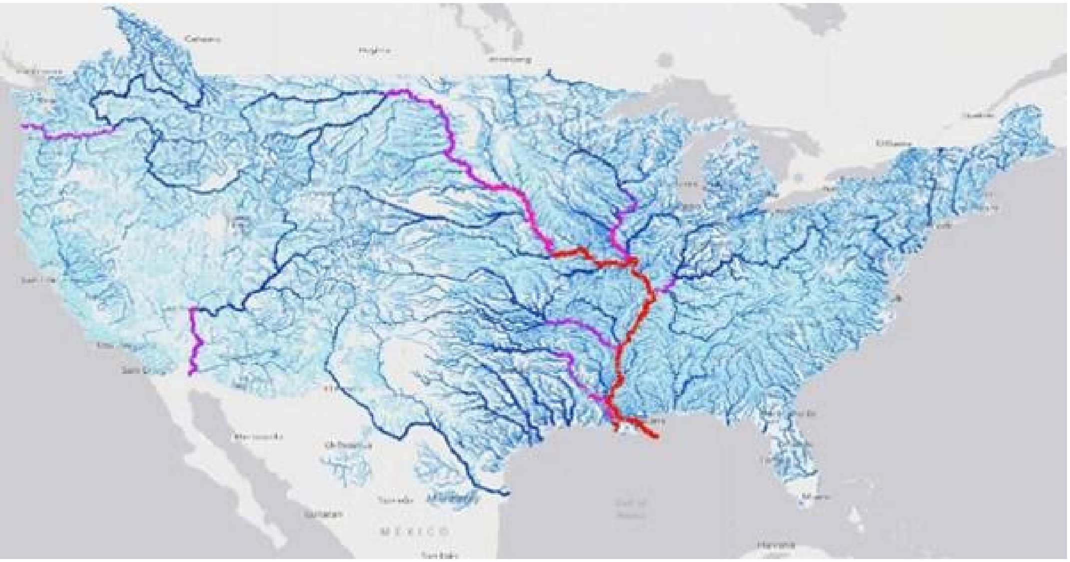
Community Streamflow Evaluation System: CSES

PI: Shahabul Alam, PHD

CO-PI: Ryan Johnson, PHD

Support:

- Nathan Swain, PHD
- Giovanni Romero



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Community Streamflow Evaluation System: CSES

Tethys web-based platform

Jupyter-based platform

Tethys Platform

jupyter

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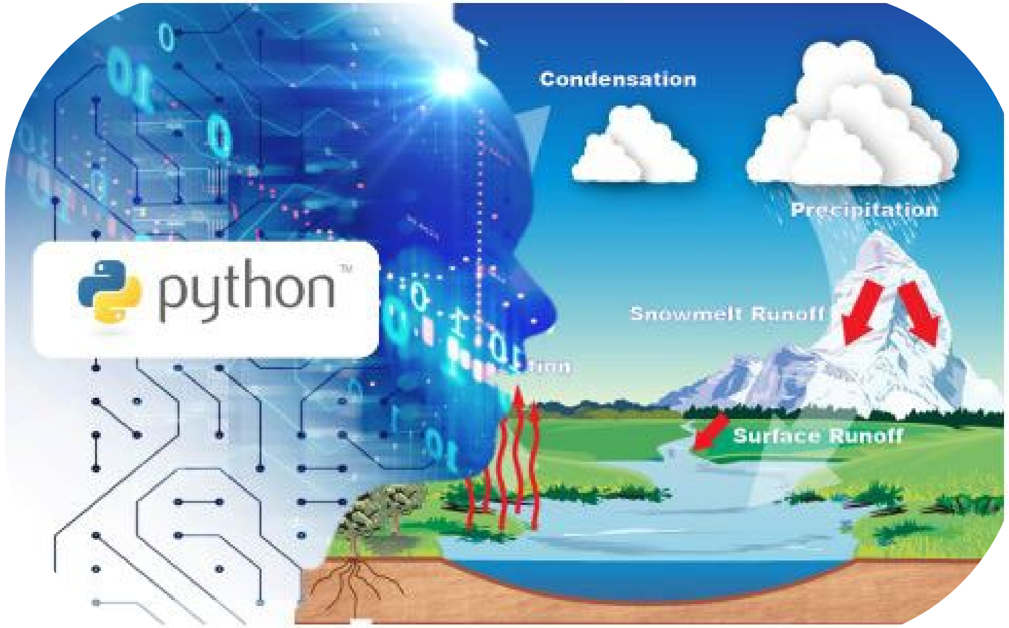
Enhancing Water Supply Forecasting for Systems Management

PI: Steven Burian, PHD

CO-PI: Ryan Johnson, PHD

Researchers:

- Shahabul Alam, PHD
- Savalan Neisary, PHD Student



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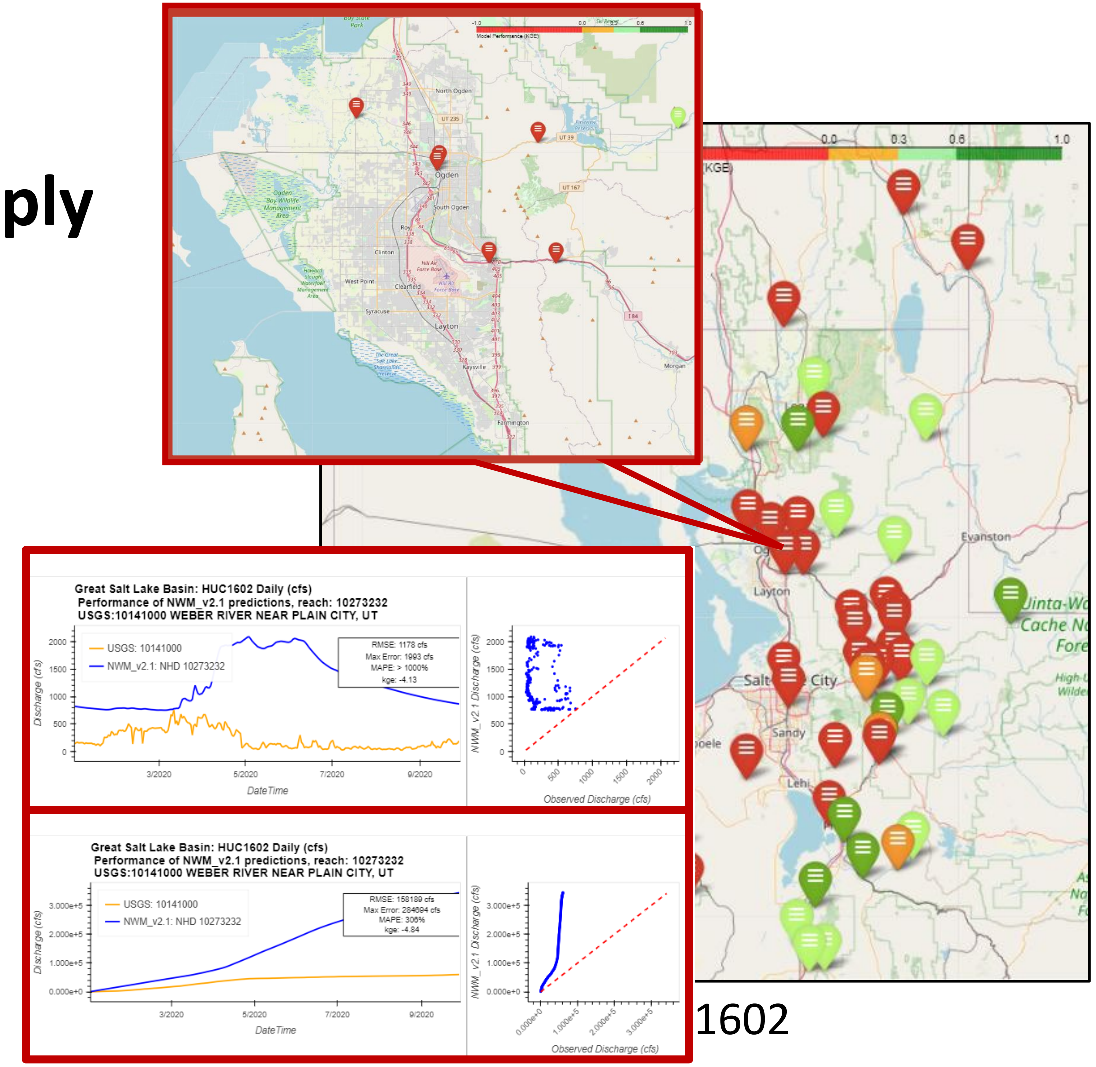
National Water Model Season-to-Season Water Supply Forecasting

Improved Season-to-Season water supply forecasting needed in Western US.

- Ecosystem Management
- Power Generation (Hydro)
- Environmental Management
- Water Supply
- Recreation

Leverage National Water Model



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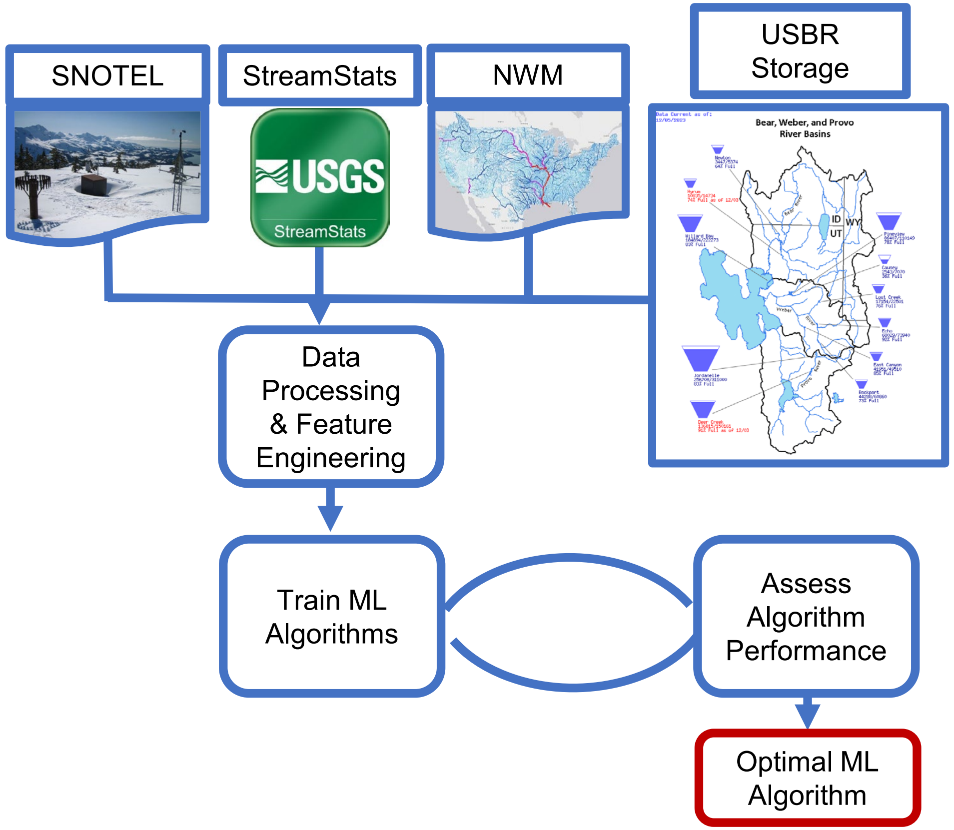
National Water Model Season-to-Season Water Supply Forecasting

Season-to-Season water supply estimates for up to 2.7 million stream segments.

- Post-processing NWM streamflow
- Catchment frozen water storage
- Catchment characteristics
- Catchment reservoir storage
- Machine Learning



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National Water Model Season-to-Season Water Supply Forecasting

USGSid	NHDPlusid	NWM RMSE (Mm^3)	NWM-ML RMSE (Mm^3)	NWM Pbias (%)	NWM-ML Pbias (%)	NWM kge	NWM-ML kge
10126000	4605050	437	133	-62	26	-0.73	0.62
10130500	10092262	78	17	-132	19	-0.77	0.59
10134500	10277268	46	7	-158	20	-1.18	0.70
10136500	10274616	248	34	-164	16	-1.50	0.63
10137500	10274270	18	16	38	33	0.56	0.58
10141000	10273232	457	19	-461	-20	-7.83	0.75
10155000	10373622	72	77	42	44	0.46	0.40
10164500	10329013	40	1	-237	0	-2.38	0.98
10171000	10390290	1339	29	-2329	-52	-30.38	0.38

National Water Model for Water Resources Management: Post-Processing with Machine Learning in Controlled Basins.

Savalan Neisary[a], Ryan C. Johnson[b], Md Shahabul Alam[b] and Steven J. Burian[a,b]

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ARTICLE INFO

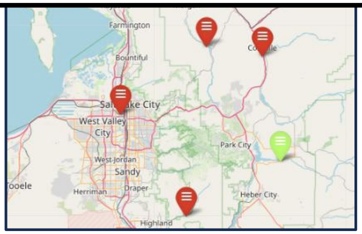
Keywords:
Machine Learning
Decision Trees
Water Supply Forecasting
Water Resources Management
Great Salt Lake

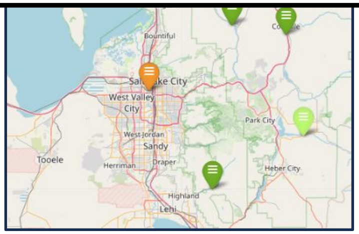
ABSTRACT

Accurate streamflow prediction is critical for water resources management in the western United States (US), especially in balancing the beneficial uses of multiyear reservoir carryover, ecological interests, irrigation, and recreational use. With Great Salt Lake (GSL) in Utah, US facing decreasing lake levels and potential environmental disaster, we investigate the utility of the National Water Model (NWM) as a water resources management tool. Using the NWM retrospective v2.1 simulations and comparing daily and seasonal flow volumes to 48 USGS gauge stations, the NWM demonstrated decreasing model performance at locations closer to the GSL where there is extensive water resources infrastructure. Given the reaches closest to the GSL are critical for lake-level management, we explored XGBoost, Random Forest, Long Short-Term Memory, and Convolutional Neural Network Machine Learning (ML) algorithms to post-process the outputs of the NWM to account for the impacts of large-scale water resources infrastructure. Using upstream reservoir storage percentage of full capacity, the seasonality index, Snow Telemetry (SNOTEL) snow water equivalent (SWE) catchment observations, and NWM outputs as inputs into the ML pipeline, we observed significant improvement in the estimated daily flow (cms) and seasonal accumulated flow volumes (mm3). The overall Kling-Gupta Efficiency (KGE), Nash–Sutcliffe (NSE), Percent Bias (PBIAS), and Root Mean Square Error (RMSE) for the GSL basin increased by x, y, and z, respectively. The results of the study demonstrate that water resources infrastructure may be the single greatest challenge in hydrological modeling, being the dominant regional hydrological process, and novel ML methods can account for the impacts of the infrastructure on regional streamflow without explicitly adding infrastructure rulesets.

NWM-ML Post Processing:

- Accounts for reservoir operations w/o explicit p
- Works in controlled and natural basins
- ML “learns” hydrological processes
- Monthly to Annual flow estimates
- Leverages NWM-Retrospective products (flow + climate)





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Research Program at the University of Alabama

College of Engineering
Civil, Construction and Environmental Engineering

Data Science and Machine Learning in Hydrology

- Machine Learning and Snow Modeling
- Season-to-Season Water Supply Forecasting
- Orographic Precipitation Gradient Downscaling

Programs for Empowering the Next-Generation of Hydrologists

U.S. National Science Foundation

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Research Vision: ML in Hydrology

College of Engineering
Civil, Construction and Environmental Engineering

Hydrologic Sciences: Advancing research in Geosciences using Ai/ML

Engineering Directorate: Environmental Sustainability

Contact: Hendratta Ali

Machine Learning for Snow Modeling

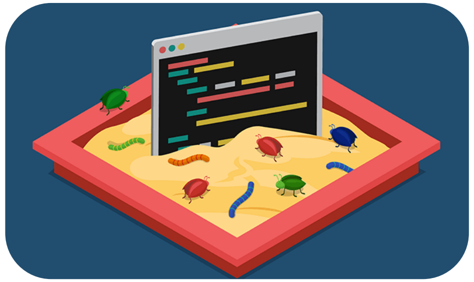
College of Engineering
Civil, Construction and Environmental Engineering

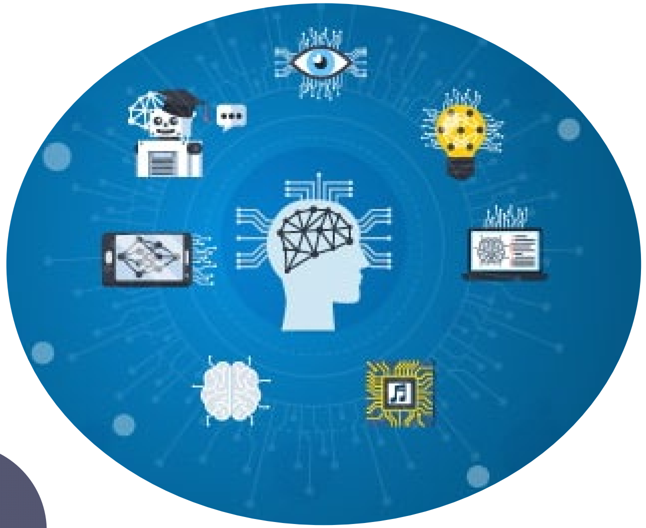
Themes:

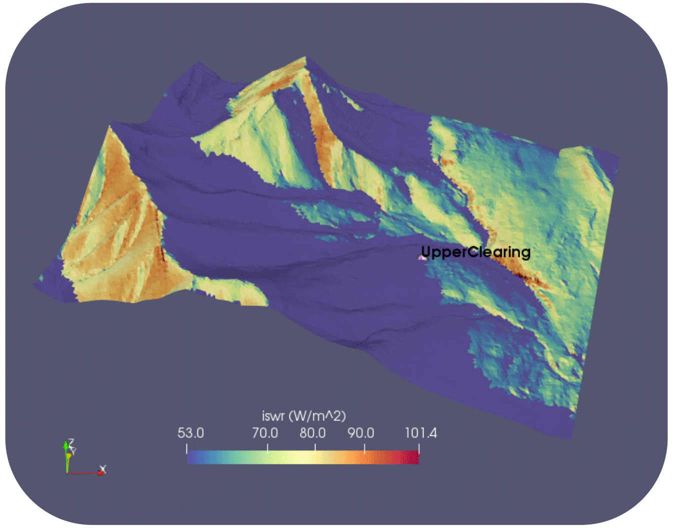
- Redefining Snow Modeling Evaluation
- Snow/No-Snow Future
- Physical/ML hybridization
- Inter-model/method comparisons
- Catchment sensing deployment

Research Activities:

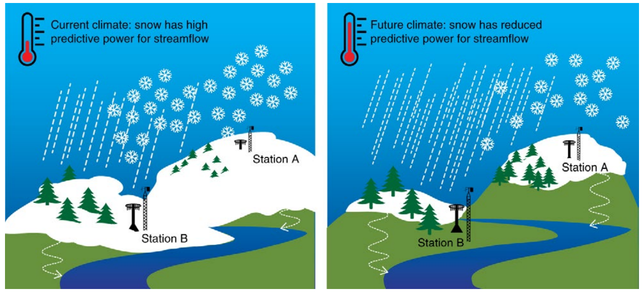
- Cyber-sand box
- Datasets, products, and visualization
- Data collection
- Algorithm Exploration
- Regional/Spatial/Meshing optimization







Marsh et al., 2020



Livneh et al., 2020

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Orographic Precipitation Gradient Downscaling

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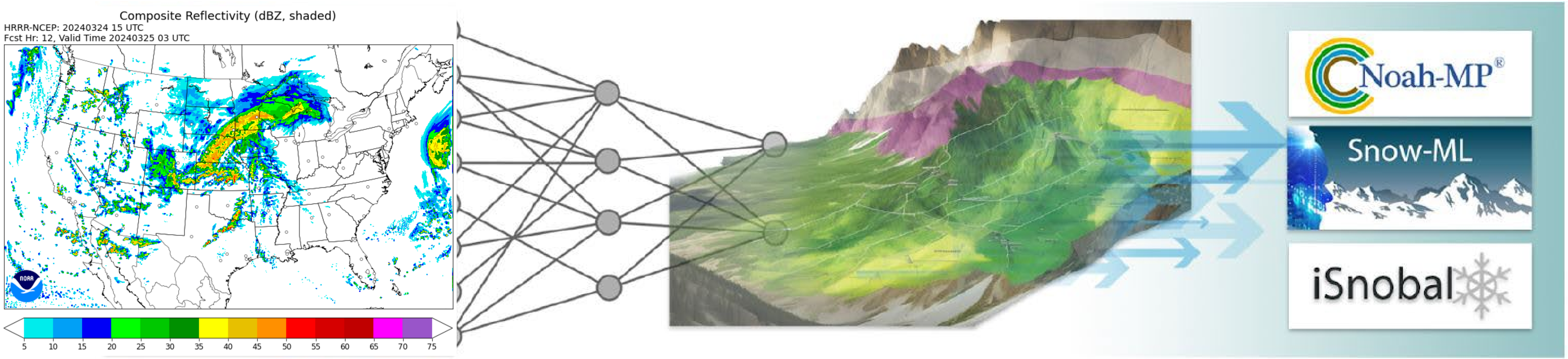

Themes:
- Optimal spatial resolution for precipitation products
- Physical/ML hybridization
- Impacts on snowpack evolution
- Phase partitioning
- Capabilities and applications of ML for downscaling

Research Activities:
- CNNs, other algorithm explorations
- Datasets, products, and visualization
- Citizen Science
- Snow model coupling
- Climate impacts on precipitation quantity and phase

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Season-to-Season Water Supply Forecasting

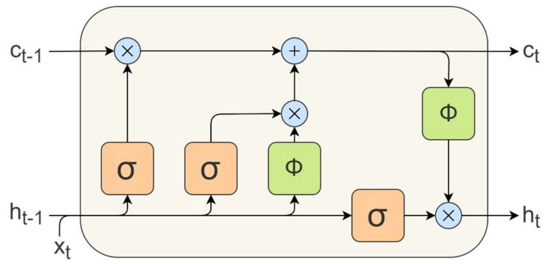
Themes:

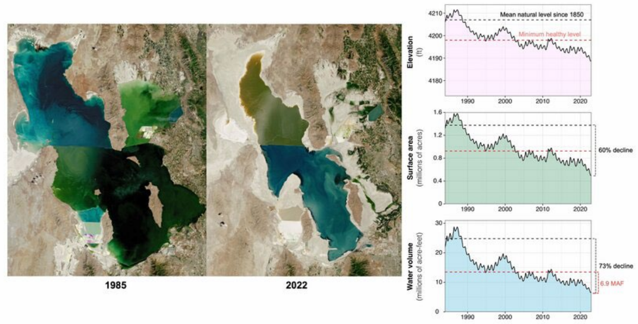
- Physics-Informed ML for S2S Forecasting
- Modeling controlled basins
- Water resources management
- Urban Water Systems
- Reservoir operations

Research Activities:

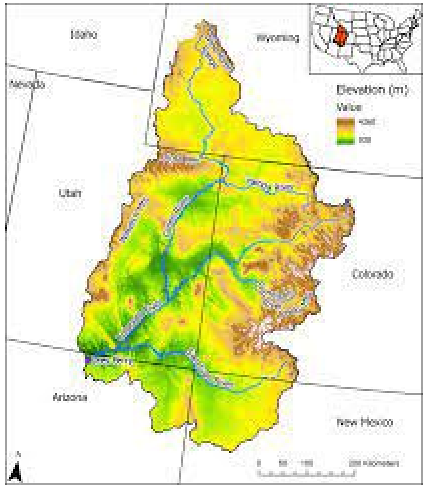
- Explore and optimize ML Algorithms
- Scale modeling efforts to the Upper Colorado
- Great Salt Lake Management
- Coupled Snow-Streamflow-Management workflows
- Cyber-sand box

LSTM





Abbot et al., 2023



Miller et al., 2021

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Programs for Empowering the Next-Generation of Hydrologists

- Networking
- Hands on connections to research
- Leadership
- Hackweeks
- Diversity, Inclusion, Equity

Location: Antelope Island State Park

2023 GeoSMART Hackweet at the University of Washington

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Other Research Interests

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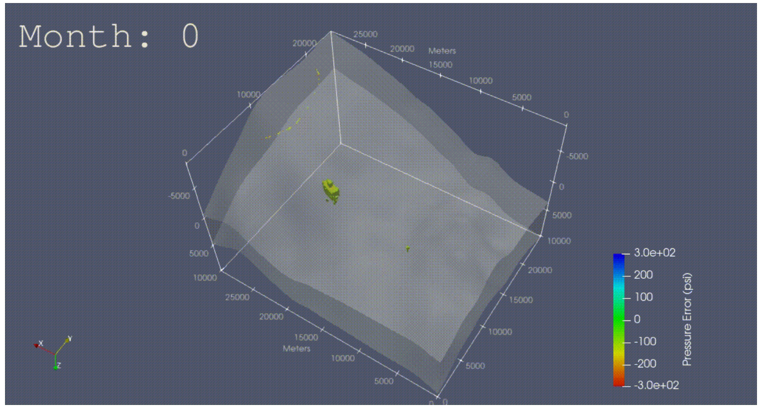

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Teaching Goals, Philosophy, and Ideas

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Teaching Goals

Capable, **confident**, and **successful** students are the product of a University.

1. Intrinsic motivation to learn
2. Fundamental Positive Action principles into students' cognitive, affective, and behavioral learning domains
3. Enhance critical thinking and analytic skills
4. Foster student development and personal growth
5. Be a role model

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Teaching Goals

College of Engineering
Civil, Construction and Environmental Engineering

- Develop a lifelong love of learning
- Apply principles, concepts, theories, and generalizations to new problems and situations
- Analytic and problem-solving skills
- Draw reasonable inferences from observations
- Synthesize and integrate information and ideas
- Think holistically: to see the whole as well as the parts
- Think creatively
- Enhance concentration, listening, speaking and writing skills

- Develop appropriate study skills, strategies, and habits
- Learn techniques and methods used to gain new knowledge
- Informed understanding of the role of science and technology
- work productively with others
- Grow management and leadership skills
- Commitment to organization, efficiency, skillful, and accurate work
- Improve ability to follow directions, instructions, and plans
- Commitment to personal achievement
- Improve self-esteem/self-confidence

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Motivation to Teach and Teaching Philosophy

Fundamentals of success learning

- Diagnose problems (topic knowledge)
- Formulate solutions (hypothesis)
- Execute a plan (methodology)
- Confront adversity and critically evaluate

Philosophy

- Inspire
- Strive for excellence
- Nurture critical thinking
- Passion for the learner
- Empathy
- Strong work ethic
- Treat everyone with respect and as friends

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Teaching Philosophy

College of Engineering
Civil, Construction and Environmental Engineering

Creating a stimulating learning environment

- Interactive lectures
- Thought provoking activities
- Active learning examples and demonstrations
- Creative and collaborative working sessions
- Project-based learning

Engaging classroom experience

- Defined learning objectives
- Frequent assessments to identify gaps in student learning
- Encourage questions
- Share views, ideas, challenges
- Peer learning and shared experiences

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Teaching at the University of Alabama

College of Engineering
Civil, Construction and Environmental Engineering

Applications of Machine Learning in Environmental Engineering

- Data Science in Civil Engineering
- Data acquisition and processing
- Machine Learning

HYDROLEARN

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Teaching at the University of Alabama

College of Engineering
Civil, Construction and Environmental Engineering

HydroInformatics

- Python
- Data Visualization
- Data Processing
- HydroShare
- AWS
- Cloud Computing

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Teaching at the University of Alabama

College of Engineering
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Field and Lab Methods in Environmental Practices

- Arduino IDE
- Environmental sensors and programming
- Field trips

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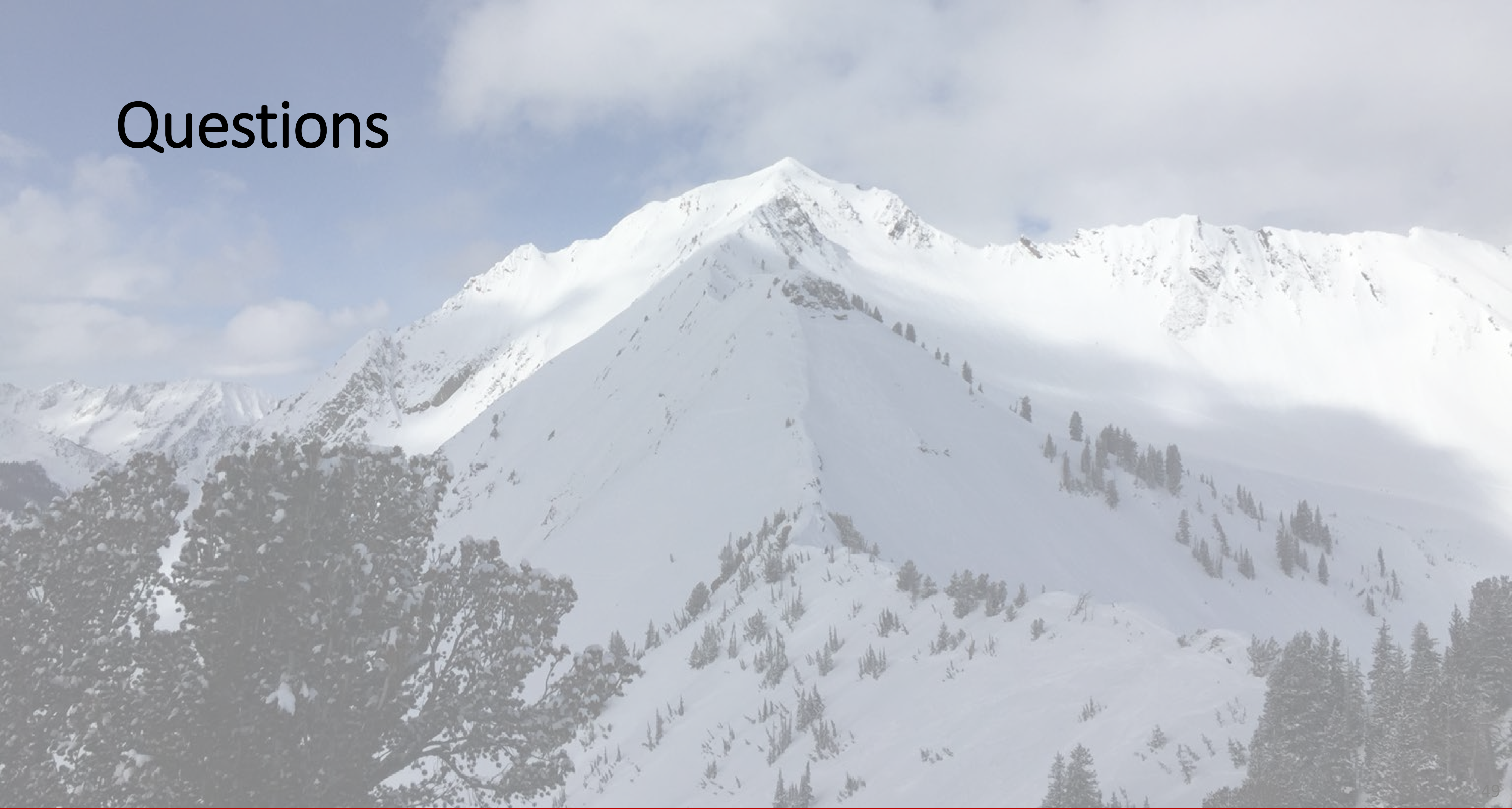
Questions



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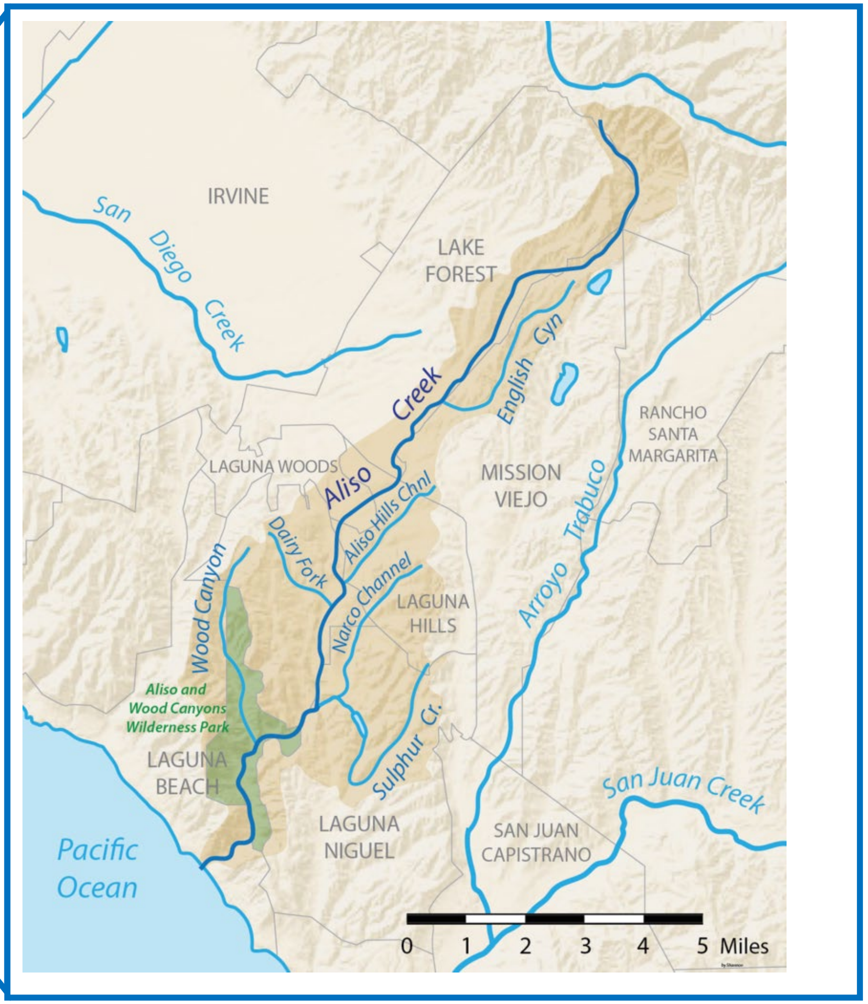
Aliso Creek Water Quality

- Water quality (nitrates) increased in the urban water system, likely from landscaping runoff.
- Water quality improved as the stream traveled through natural riparian habitat (Aliso Wilderness Park).
- Water treatment facility effluent reduced water quality.
- Golf course reduced water quality.
- Beach closures due to poor water quality.



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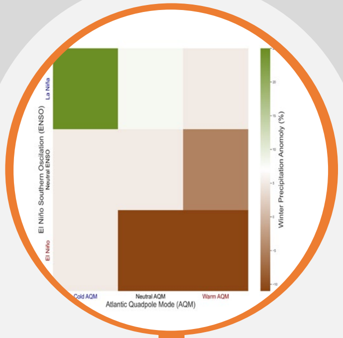
Operational Decision Timeline

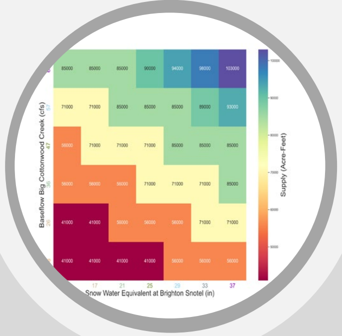


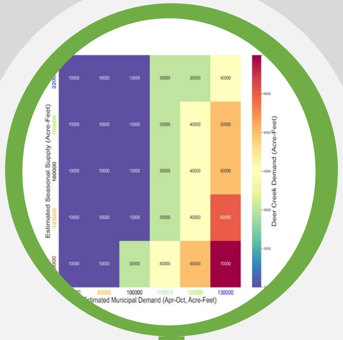
October

Climate
Winter precipitation estimates

Hydrology
Prelim estimates of streamflow yield

January



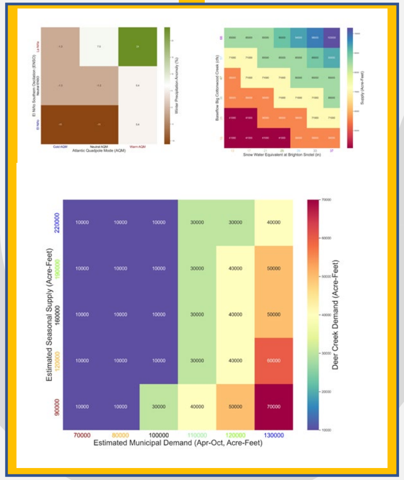


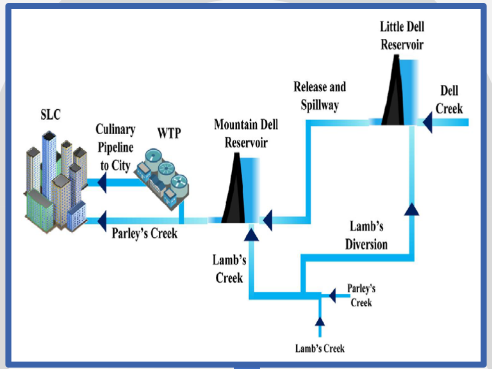
February

Engineering
Seasonal water system projections

Climate
Summer precip & temp outlook
Hydrology
Refined estimates of surface water yield
Engineering
Refined estimates of system vulnerabilities
SLC
Begin formulating management decisions

March





April-June

All
Assess system status
Revise/Initiate operational decisions

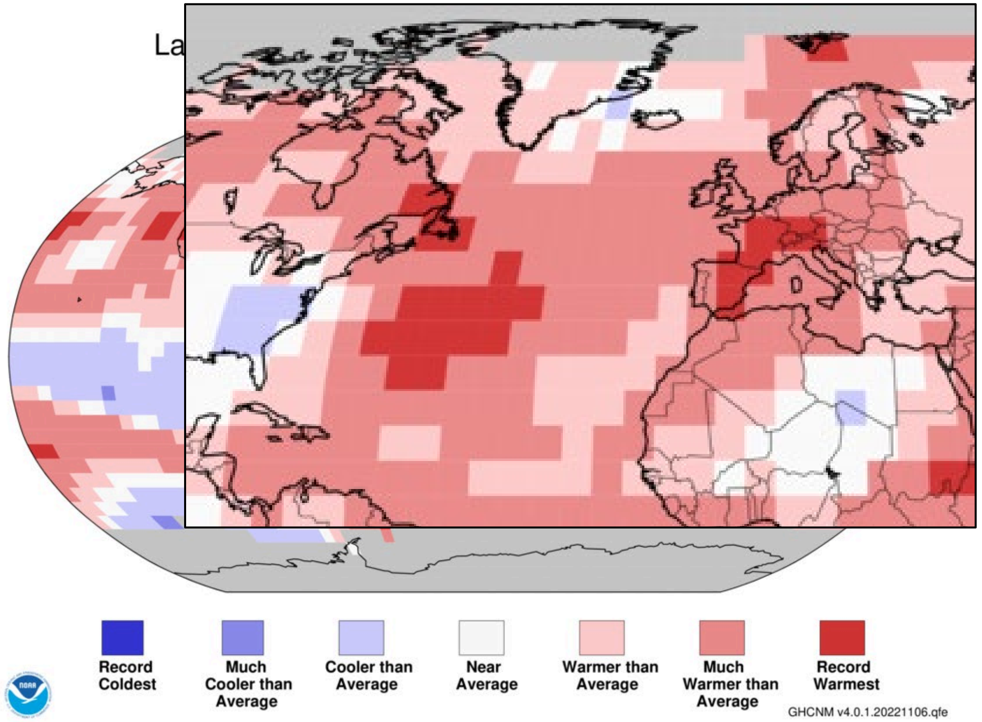
Precipitation Estimates (October)

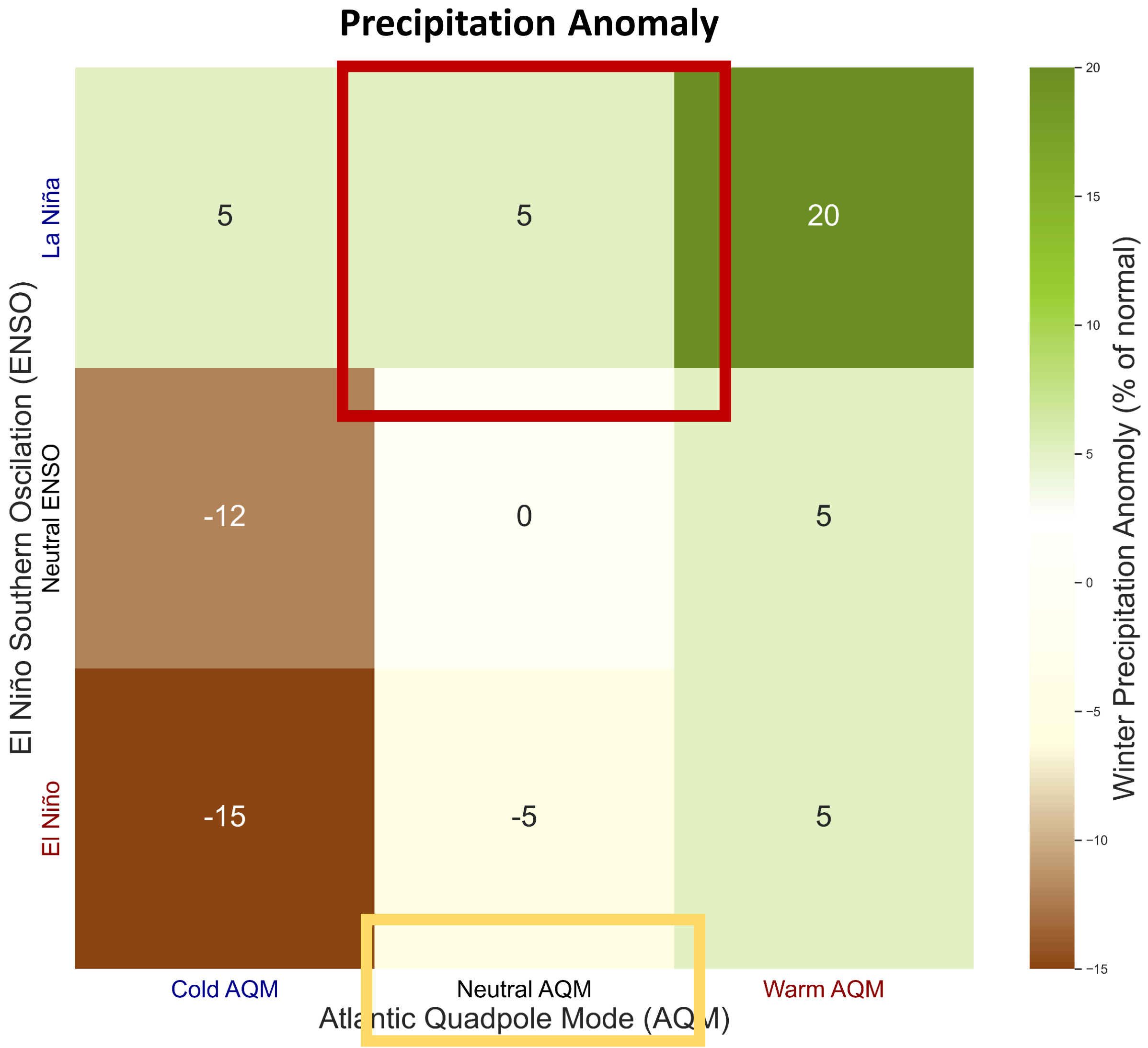
CURRENT STATUS:

LA NIÑA ADVISORY

OCTOBER 13, 2022

Forecasts indicate a 75 percent chance that La Niña—the cool phase of the ENSO climate pattern—will persist across the tropical Pacific for the third winter in a row. The map at left shows the broad swath of cooler-than-average water (blue) across the Pacific at the equator, one of the hallmarks of La Niña. Scroll down to learn about La Niña's influence on global and U.S. seasonal climate.

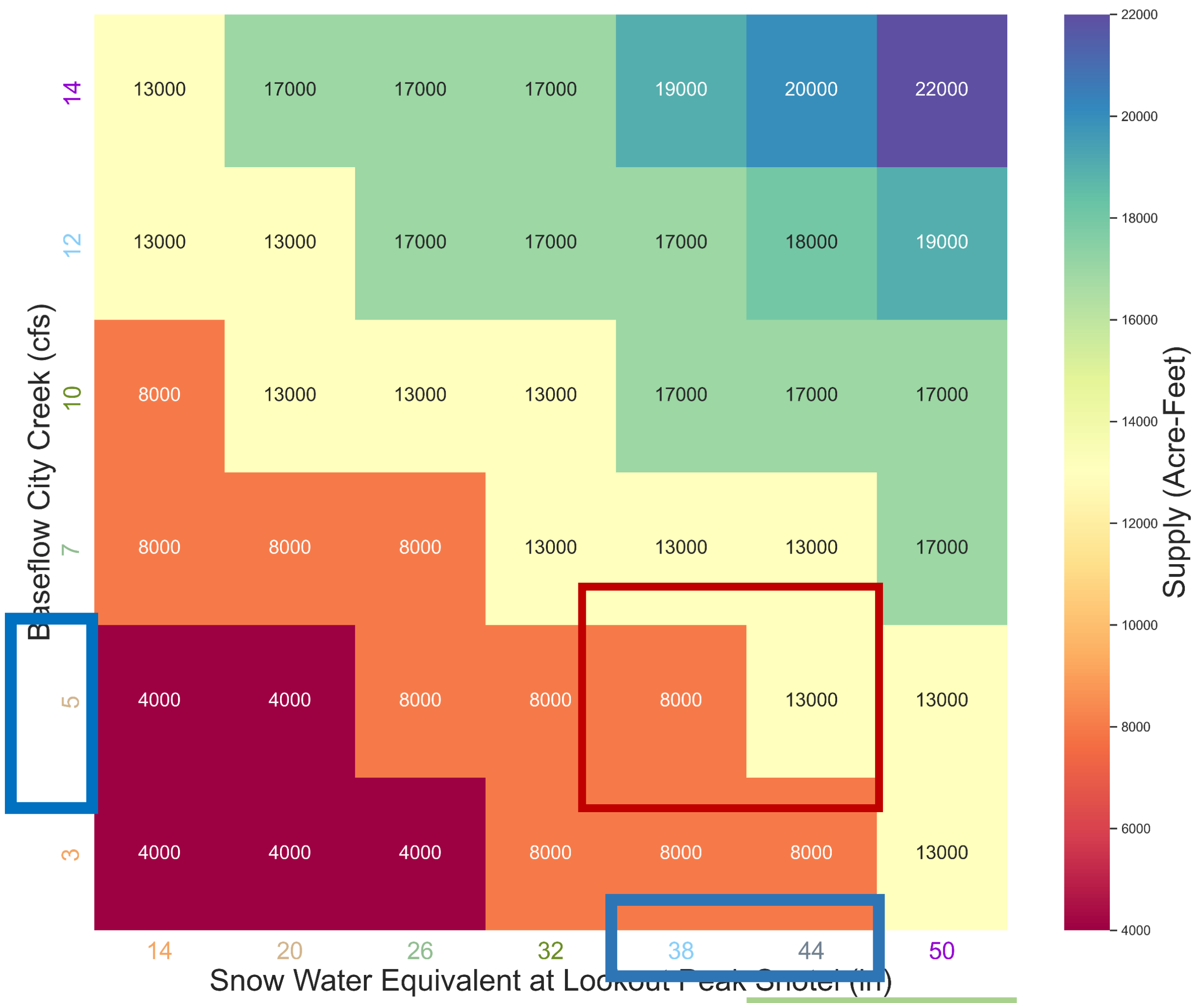




Surface Supply Yield (February)

- Use precipitation prediction to determine total max SWE.
- Average annual winter baseflow.
- Reduce uncertainty in supply. estimate.

Expected Streamflow



Below Average

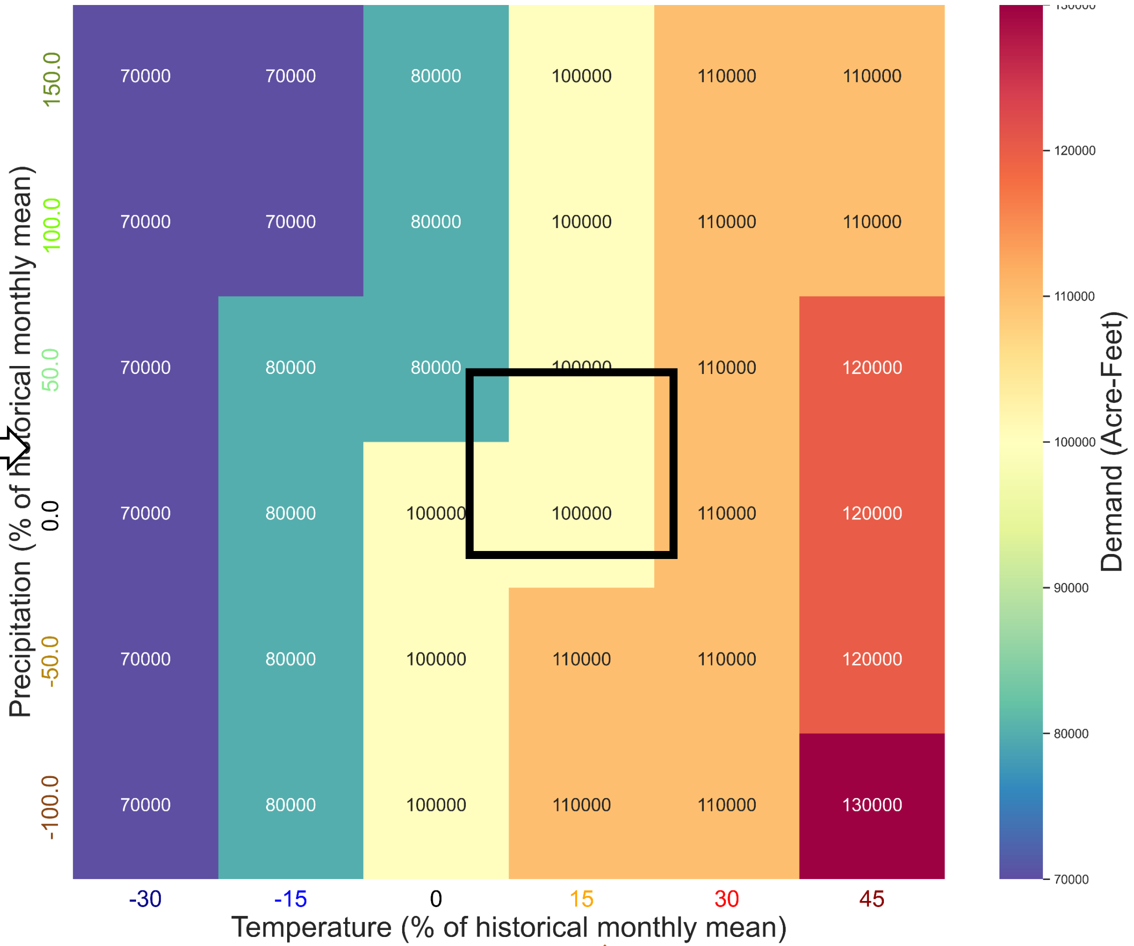
Average

Above Average

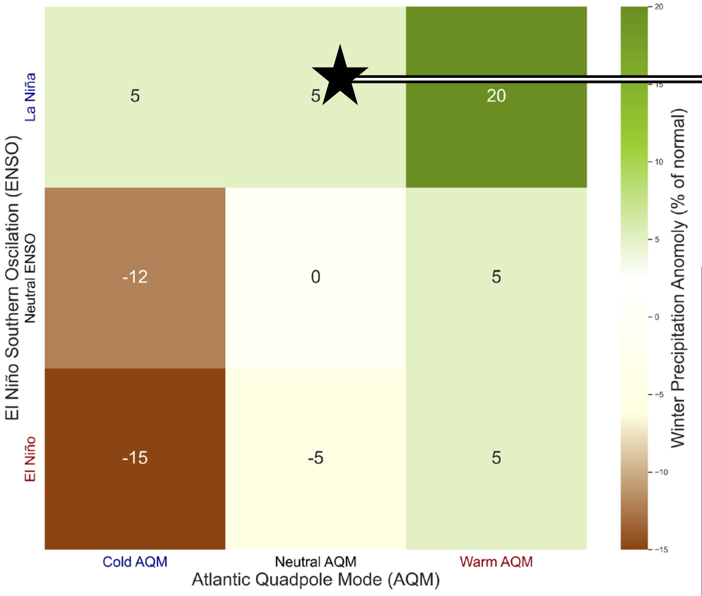
Municipal Demand Estimates (February - April)

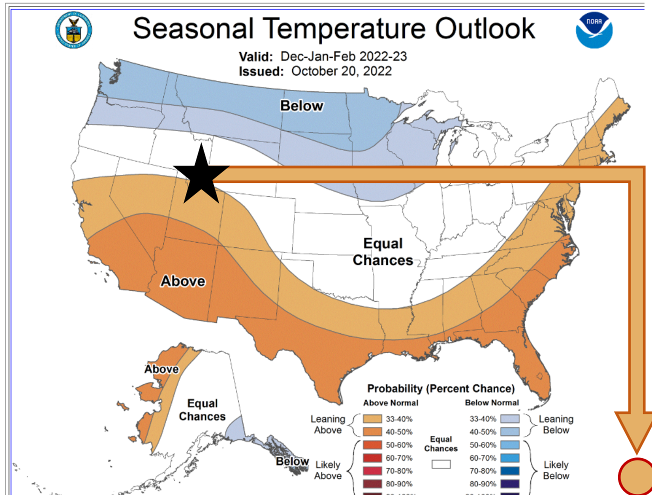
Use climate prediction (e.g., spring NOAA outlook and/or Climate Matrix) to determine expected monthly temperature and precipitation

Total Production Demand



Precipitation Anomaly

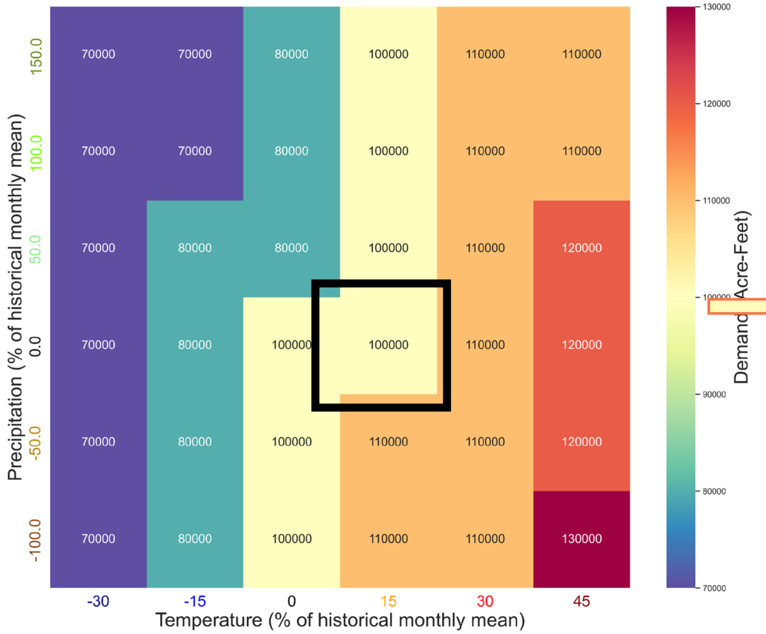




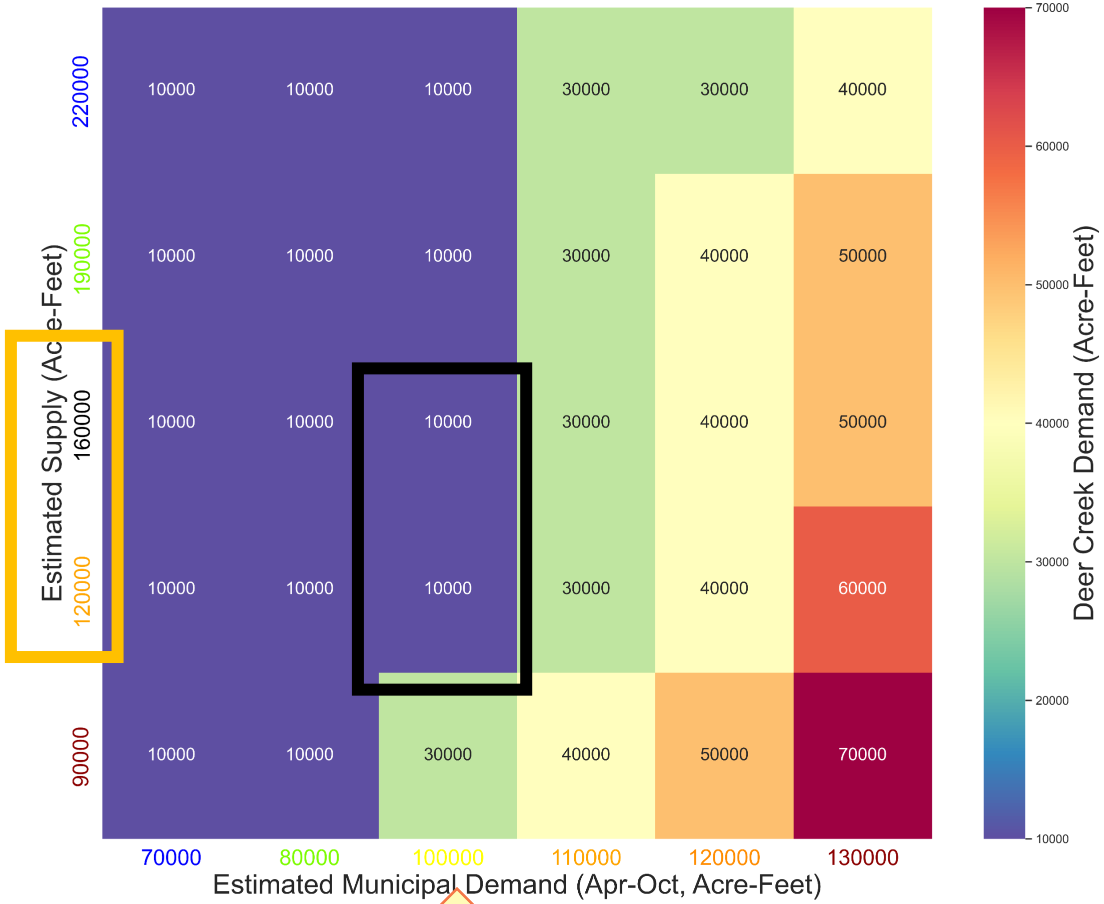
Water System Performance (February - April)

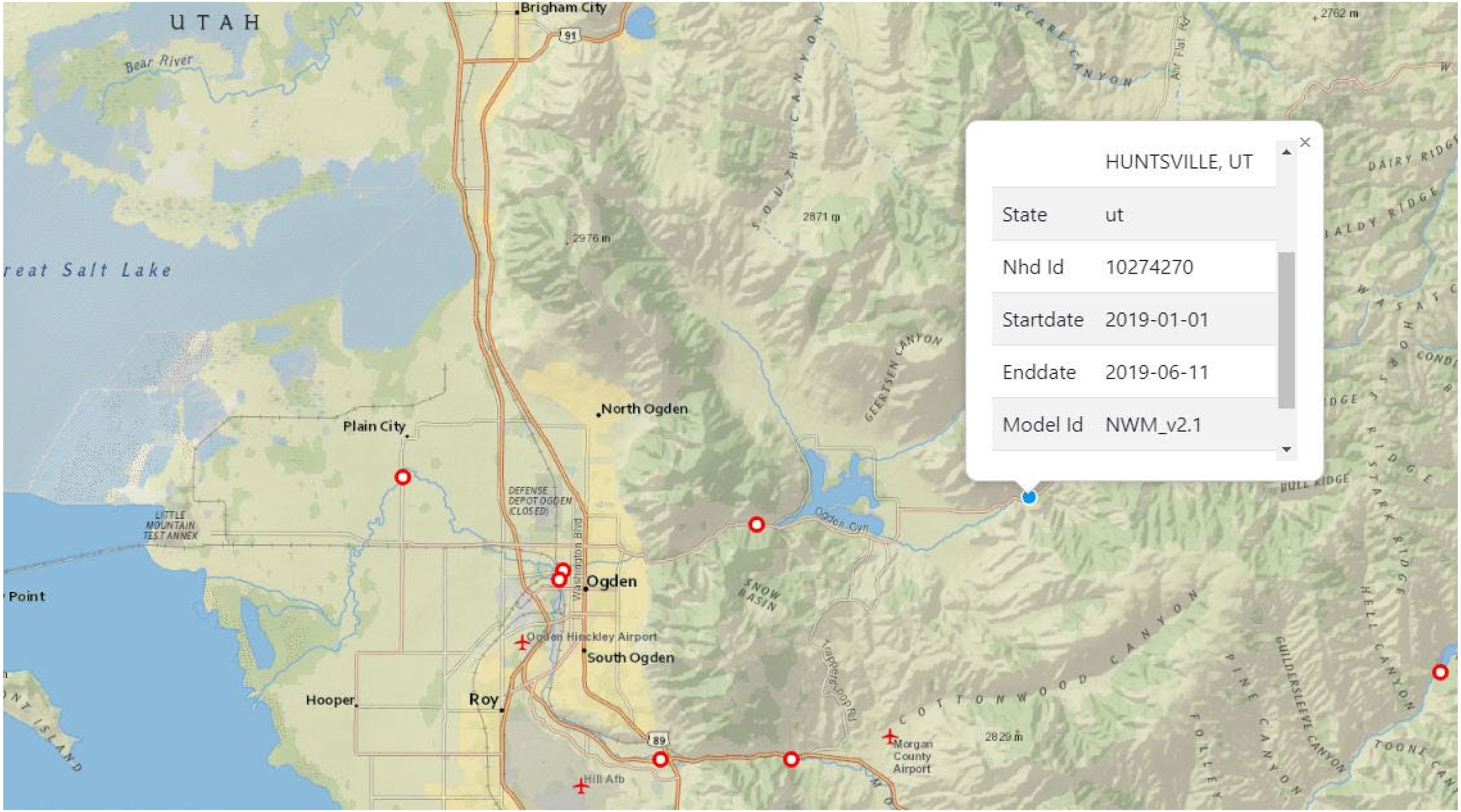
- Using supply tools, estimate 120,000 to 160,000 acre-feet.
- From NOAA climate outlook, demand should range between 80,000 to 110,000 acre-feet (mean 100,000 acre-feet).
- Estimated Deer Creek needs: 10,000 to 40,000 acre-feet.

Production Demand



Expected Deer Creek Reservoir Water Needs

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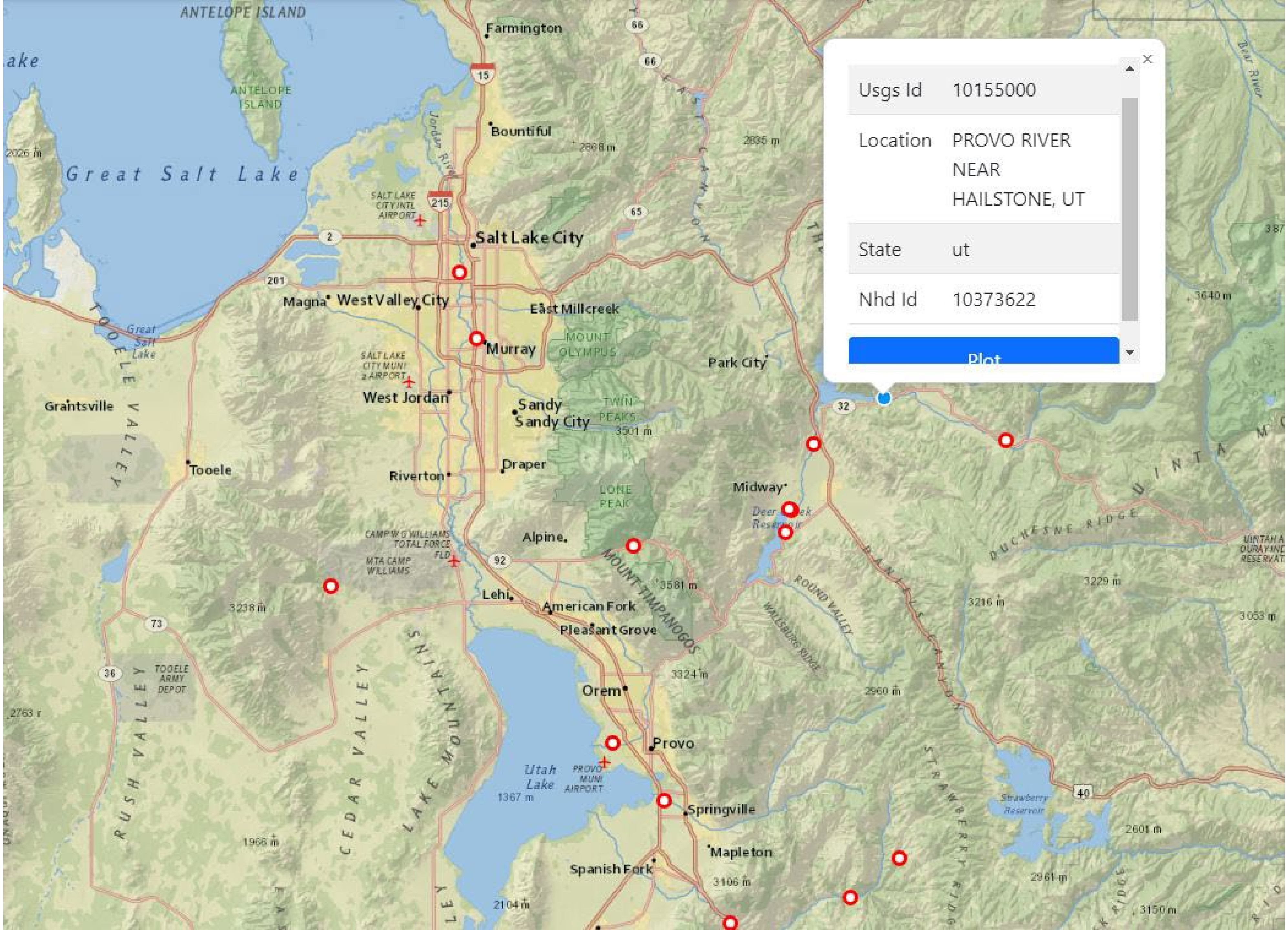
State ut
Nhd Id 10274270
Startdate 2019-01-01
Enddate 2019-06-11
Model Id NWM_v2.1
UTAH
Brigham City
Bear River
Great Salt Lake
North Ogden
Plain City
Ogden
South Ogden
Ogden Hinckley Airport
Hooper
Roy
Hill Afb
Morgan County Airport
Snow Basin
Cottonwood Canyon
South Fork Canyon
2976 m
2871 m
2829 m
2762 m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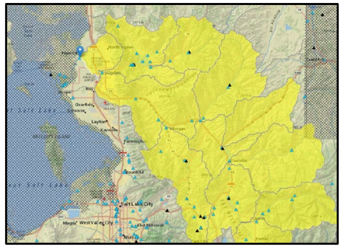
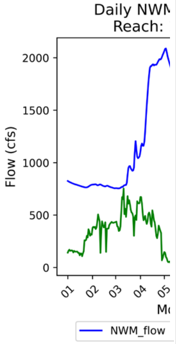
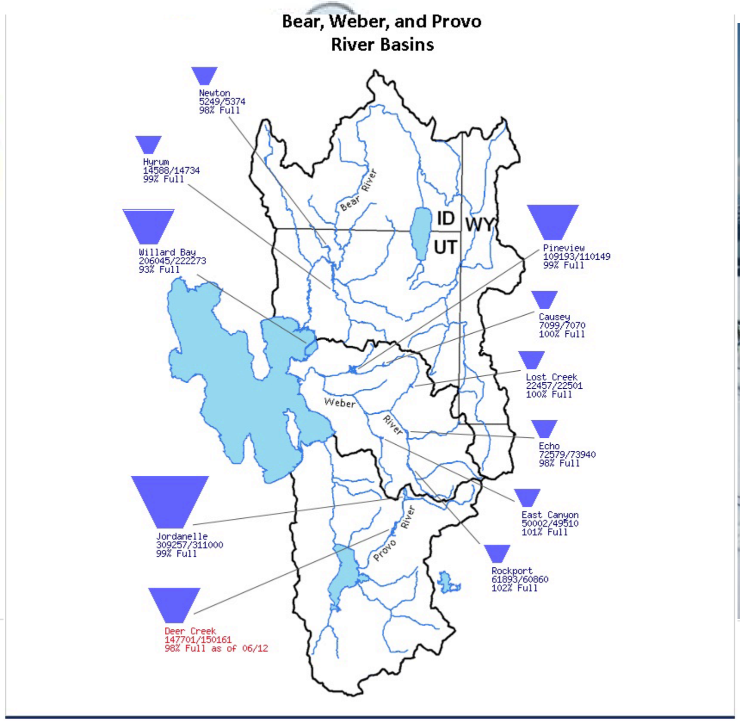
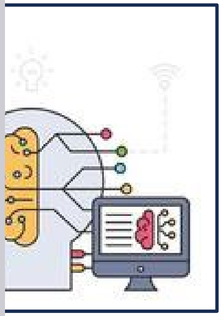
Location
PROVO RIVER NEAR HAILSTONE, UT
State
ut
Nhd Id
10373622
Plot
Great Salt Lake
Salt Lake City
West Valley City
Murray
East Millcreek
West Jordan
Sandy
Sandy City
Park City
Midway
Draper
Riverton
Alpine
Lehi
American Fork
Pleasant Grove
Orem
Provo
Springville
Mapleton
Spanish Fork
Tooele
Grantsville
Magna
Farmington
Bountiful
Utah Lake
Deer Creek Reservoir
Strawberry Reservoir
Antelope Island

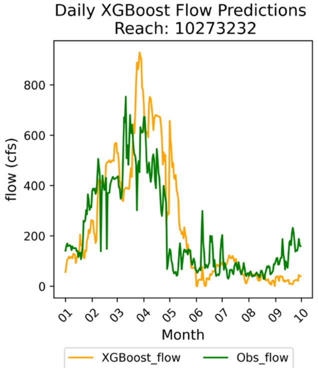
National Water Model Season-to-Season Water Supply Forecasting











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Advancing Research in Geosciences using AI/ML

U.S. National Science Foundation

Summary: Connections with snow and streamflow AI/ML methods to advance the understanding of geosciences using AI/ML methods.
- Advance core geosciences program goals and use AI/ML methods for addressing scientific problems. Build the capacity of AI/ML to explore and/or emulate physically based models.

Core geoscience goal: Advance the representation of snow on the earth's surface to support water supply forecasting and explore the impacts of a changing climate.

Broader impacts: developing AI/ML training datasets, python-based tools (evaluation), open source software, supporting workforce development. Supporting the greater hydro-meteorological practioning and research community.

U.S. National Science Foundation

Environmental Engineering

Summary: Investigation of a no-snow future within the western US, beginning with the Great Salt Lake using SNOTEL to investigate precipitation phase during the snow season (October to July).

Research questions: how has precipitation phase changed in the past half century and what can we expect in a changing climate in montane, high elevation watersheds. Most studies relate a no snow future to the impacts of temperature on snow melt, investigation peak SWE and the duration of snow. However, snowmelt is primarily driven by the energy from SW radiation.

Applications benefits: connect newfound knowledge related to precipitation phase (or at least the temperature when precip is occurring) to naturalized and managed water systems. How much snow can we expect to occur in the future and relate it to the quantity of melt to fill reservoirs/GW recharge,

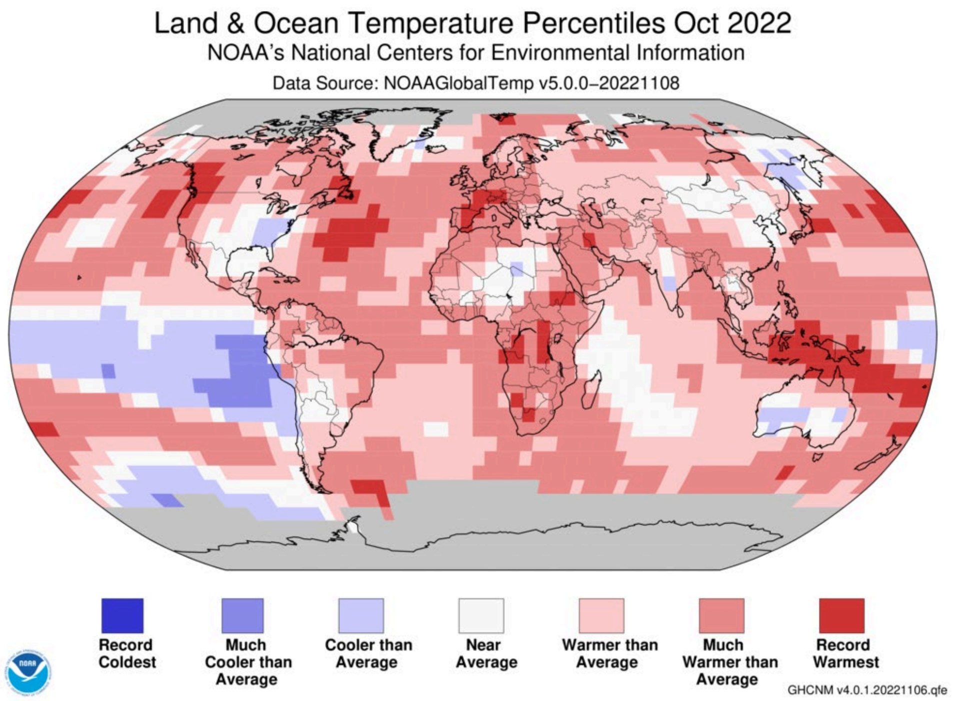
Environmental Sustainability: GSL sustainability, no snow future, climate change/scenarios/impact of scenarios on water resources management.

NIDIS: future drought risk across the West and in the context of a changing climate

- Drought vulnerability assessments
- Developing drought plans and communication plans
- Identifying primary drought impacts
- Optimal drought indicators and/or triggers and improving monitoring
- Developing drought dashboards with relevant tools and information and demonstrating the application of drought data to enhance decision-making

CVP – Advancing the Understanding of multi-year to decadal climate variability and predictability for US climate predictions

- Data analysis and investigation focused on mechanisms that govern the variability of the coupled climate systems and its predictability on the multi-year to decadal timescale with long-term observation data and or model data.
- Investigation of the relationship between the Atlantic meridional overturning circulation (AMOC) and impacts on the cryosphere and hydroclimate in the Western US



Positive Action Principles

1. Positive actions for your mind
2. Responsible self-management
3. Continuous Improvement