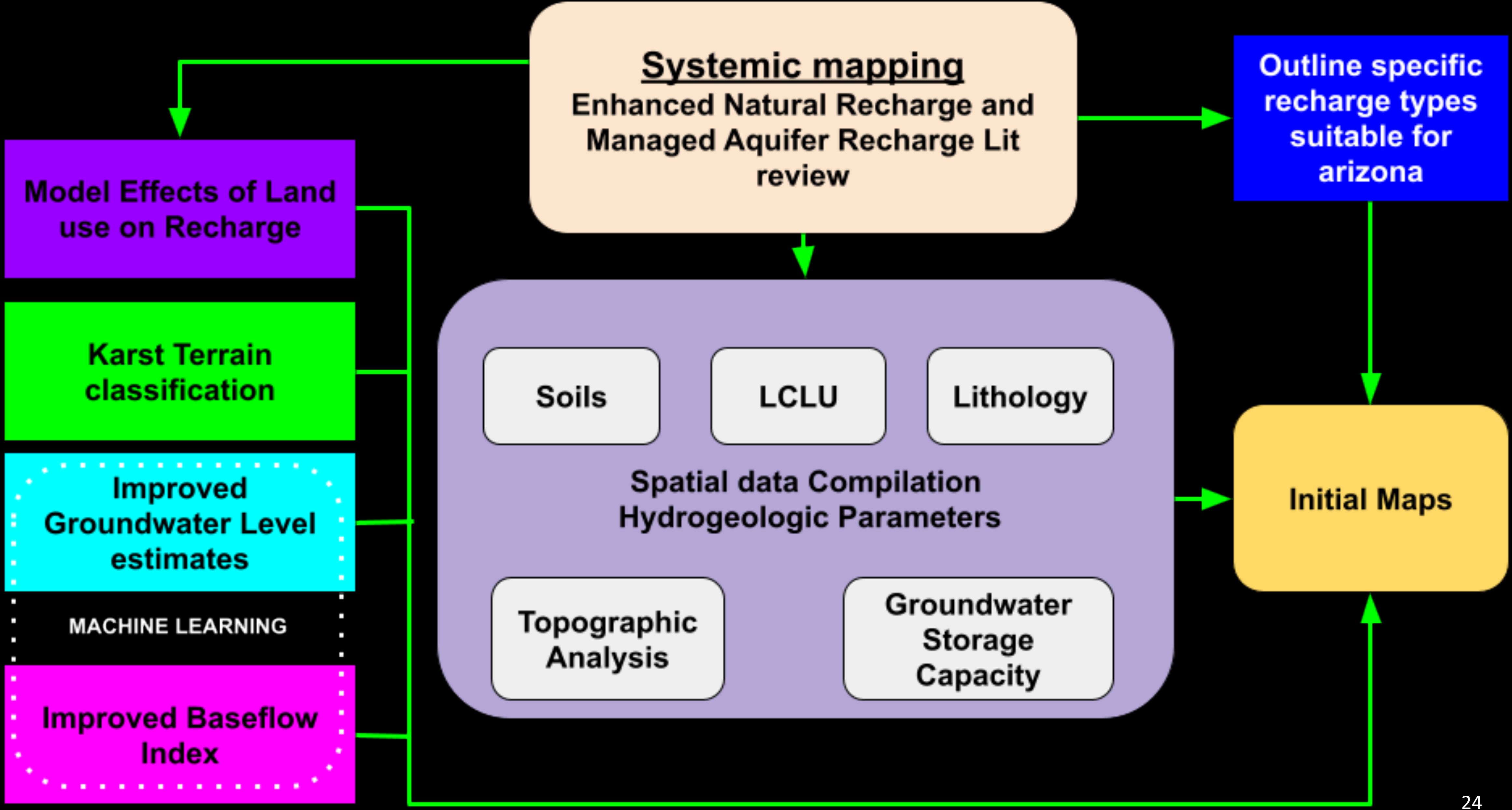
Alternative Recharge Approaches, Recharge Suitability and Baseflow

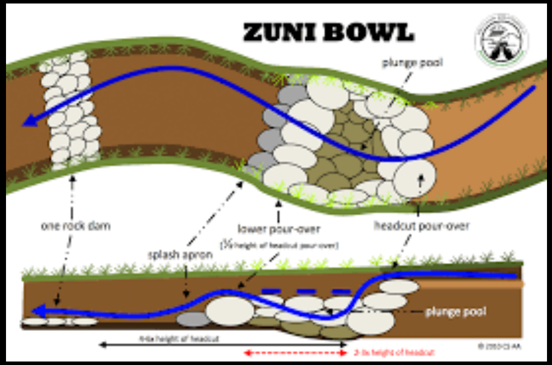
Hector Venegas-Quinones, University of Arizona

Ryan Lima, Northern Arizona University

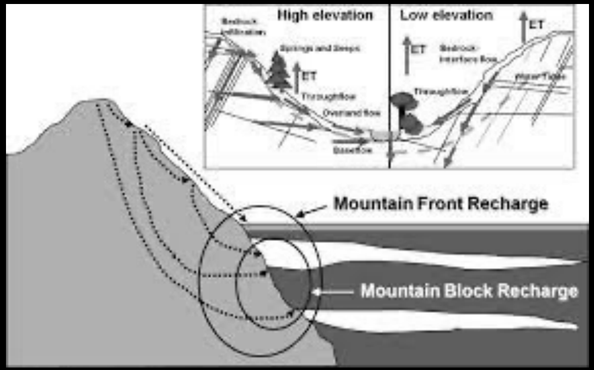
Recharge Team Overview



- Systematic Mapping
  - What has been done & where
  - Broad in scope
  - Catalog evidence
  - Map concepts

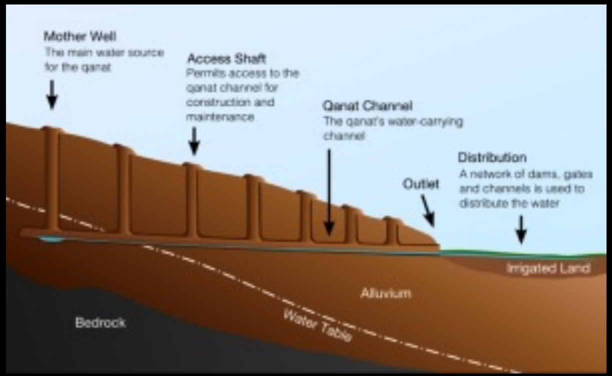


In-channel structures enhancing recharge (https://www.milkwood.net/2011/11/04/making-a-zuni-bowl-let-the-water-do-the-work/)



Mountain Front Recharge Aishlin and McNamara, 2011

- Compile a list of suitable recharge types
  - Enhanced Urban Recharge
  - Enhanced in Channel recharge
  - Enhanced Upland Recharge
  - Mountain front or alluvial fan recharge
  - Enhanced focused recharge



AHS.org - Qanats

Managed Aquifer Recharge
MAR

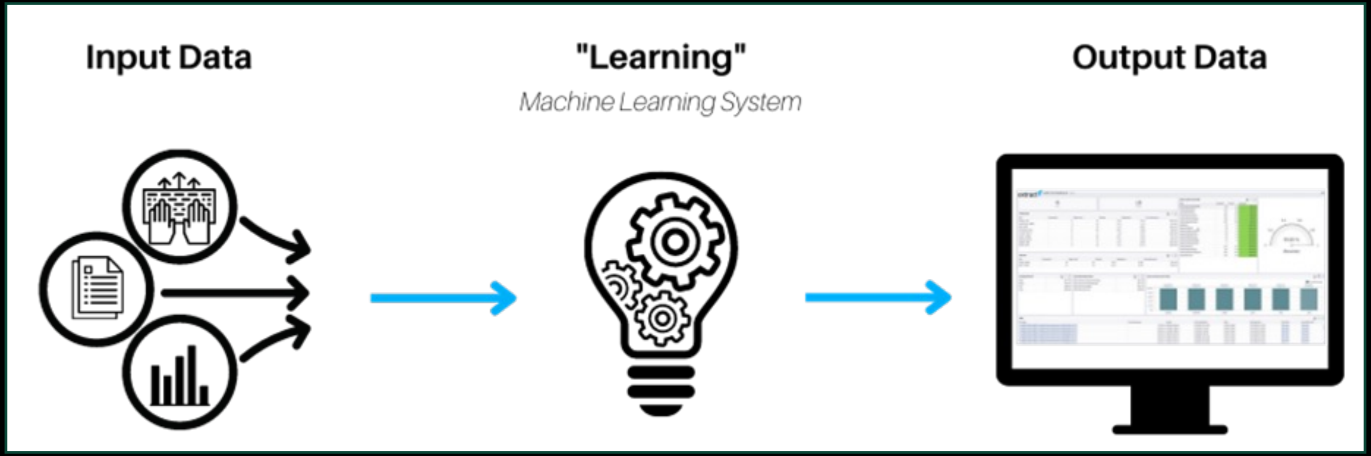
- Recharge and Recovery High Priority
- Designed with specific method of recharge
- Recharge quantified
- Subject to state and federal regulations
- Site specific, often smaller in scale

Enhanced Natural/Incidental Recharge
ENR

- Recharge often not the number one priority, added benefit
- Not as engineered
- Not explicitly managed, often not subject to the same regulation
- Often broader including small changes to forest restoration prescriptions, or flood/sediment mitigation to increase recharge

Employ Machine Learning to enhance our understanding of groundwater dynamics state-wide

“Machine learning is a data analysis method that includes statistical data analysis to create desired prediction output without the use of explicit programming. It uses a sequence of algorithms to comprehend the link between input and output to produce the desired result”. – Vijay Kanade



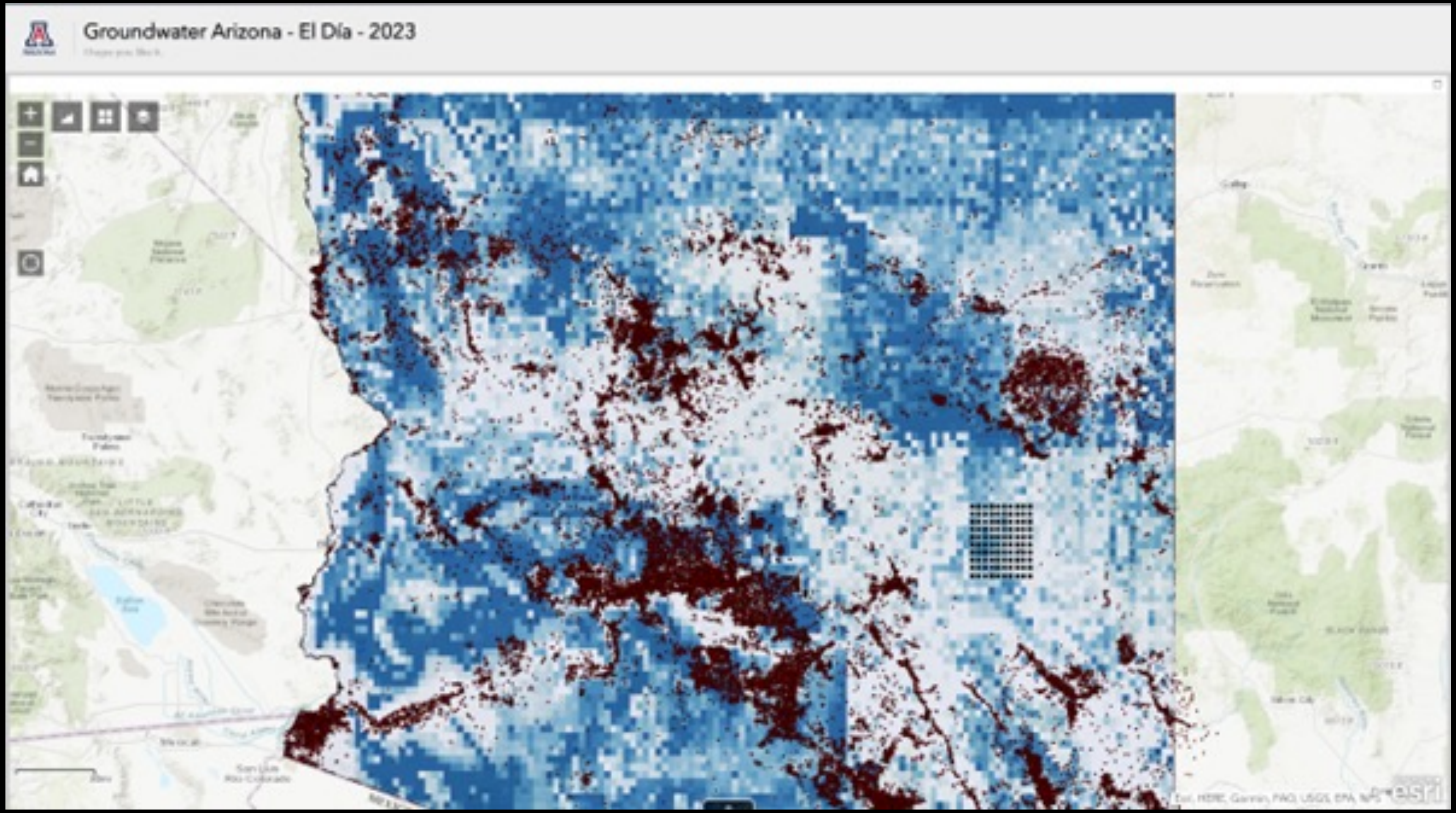
Feed ‘Learner’ Data

Align Learning System Type

Present Results

Spatial and Temporal Coverage of Groundwater Levels using Machine Learning and Remote Sensing Data

Our study highlights the potential of using machine learning as an interpolation method for hydrologic applications. In this study, the Random Forest algorithm is used to infer the monthly groundwater level. We consider monthly groundwater levels extracted from these two sources from 1982 to 2022, resulting in 144,079 records.



TERRA CLIMATE

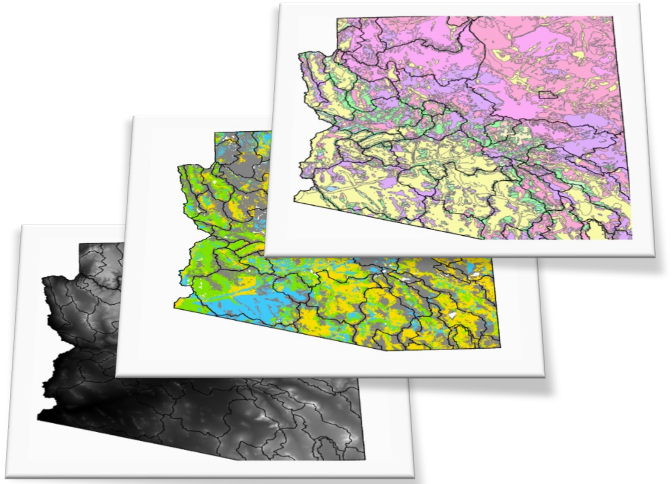
Topography

EARTHDATA

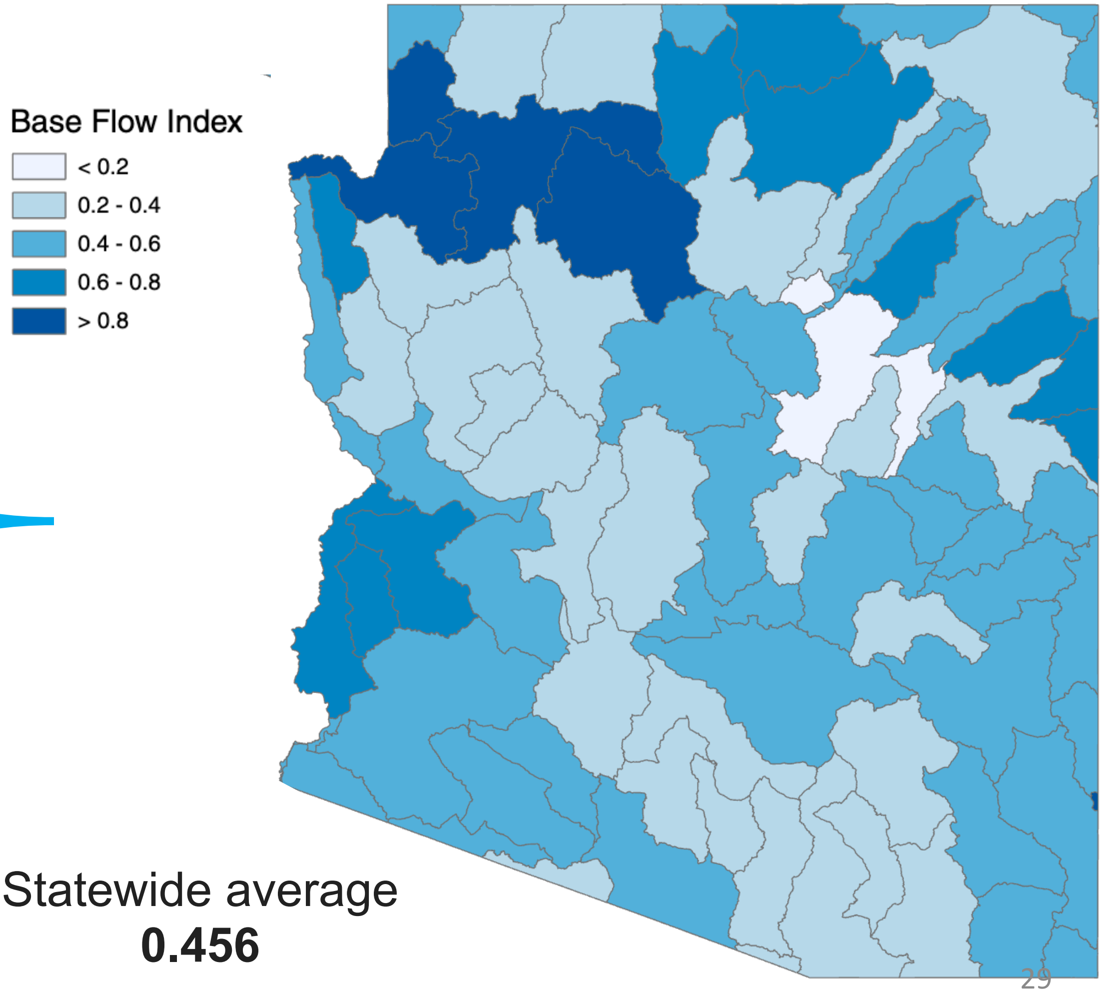
ERA5

GRACE FOLLOW-ON

Basin-average BFI from **1991-2020** is predicted using a machine learning algorithm trained on geospatial and hydroclimate variables



Variable Type	Predictors
Hydroclimate	Precipitation, Temperature, ET
Geospatial	Land Cover, Geology, Slope, Area, Elevation, Aspect



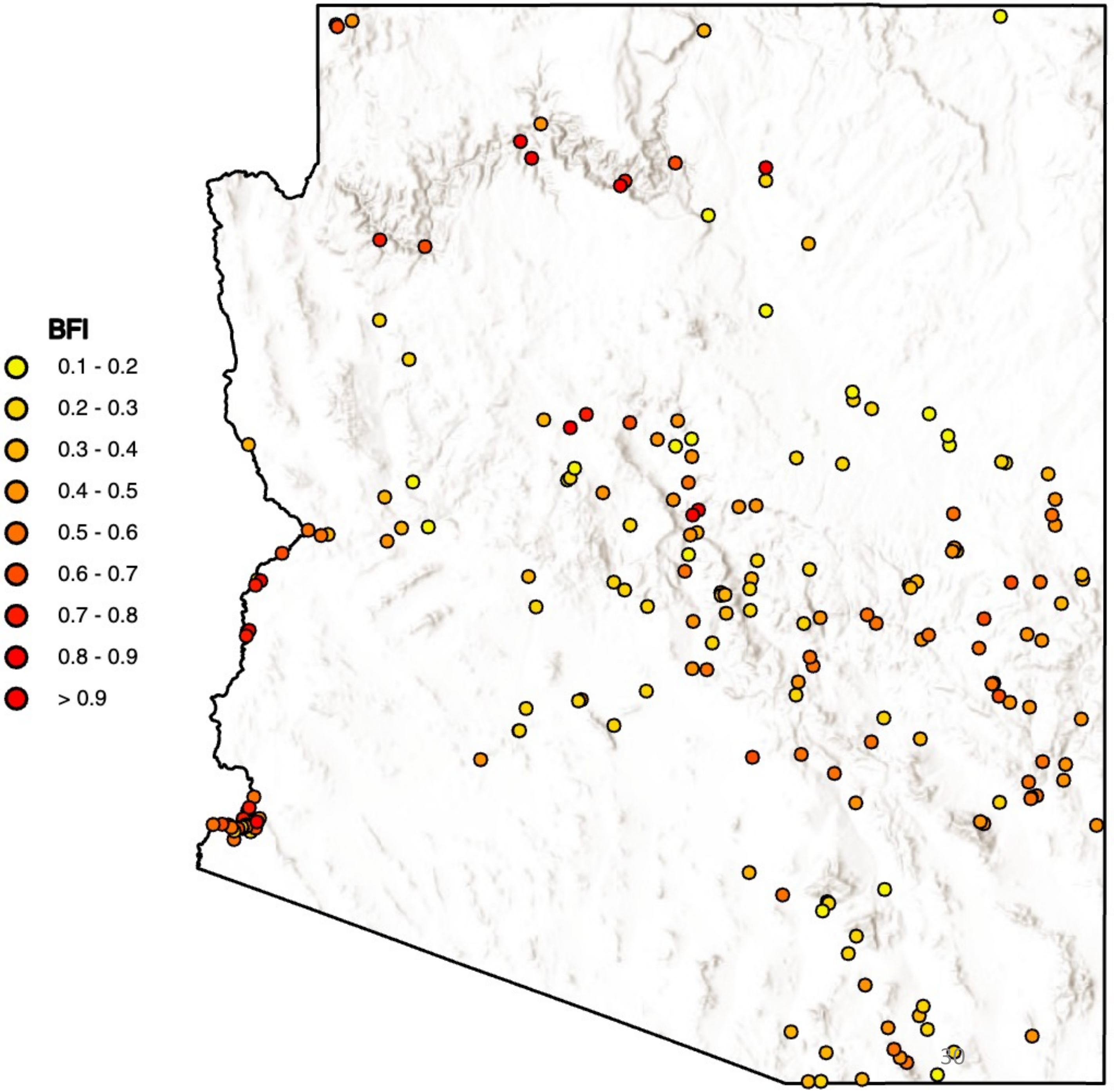
Statewide average
0.456

Why Base Flow?

- Consistent streamflow contribution from groundwater and other delayed sources
- Proxy to estimate streambed/focused recharge

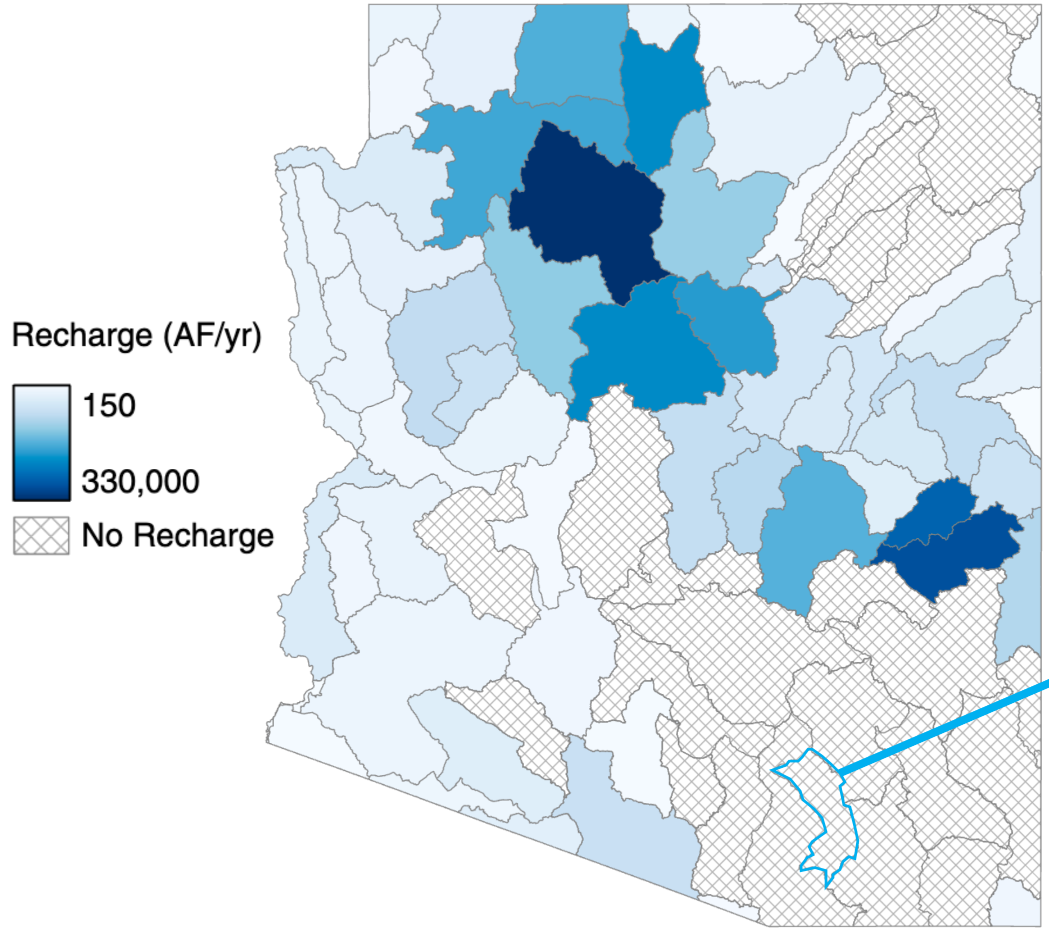
Base-Flow Index (BFI)

- Ratio of long-term mean baseflow to total flow



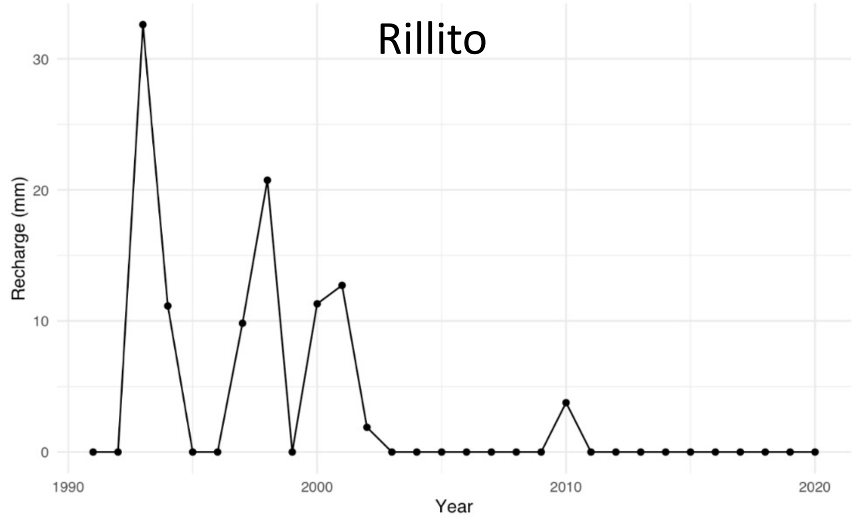
Using predicted BFI and an areal water balance, focused recharge estimates are calculated

Mean annual recharge (1991-2020)



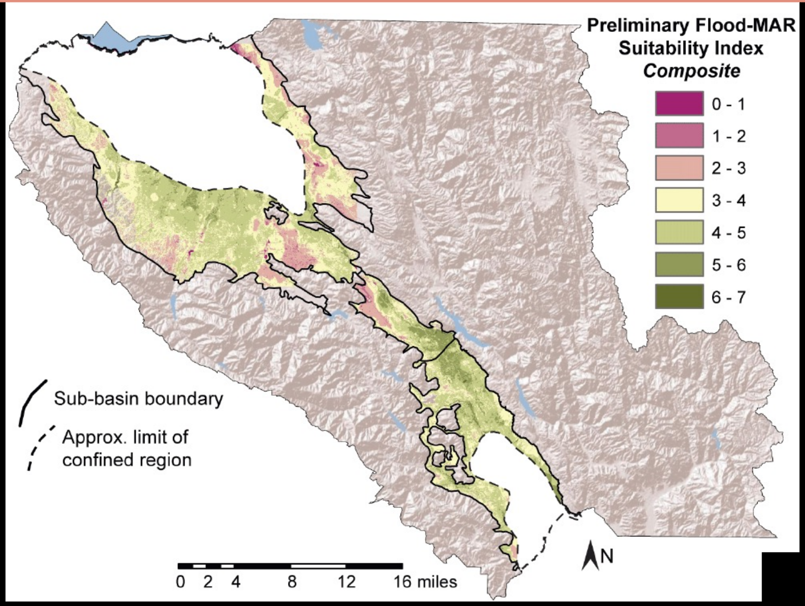
Statewide - **2.2 million** AF/yr

Average recharge over period of record doesn't capture annual recharge events in SE AZ

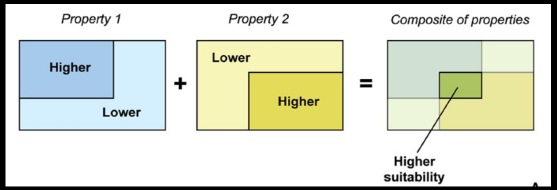


Flood-MAR – Suitability Index – *In a nutshell*

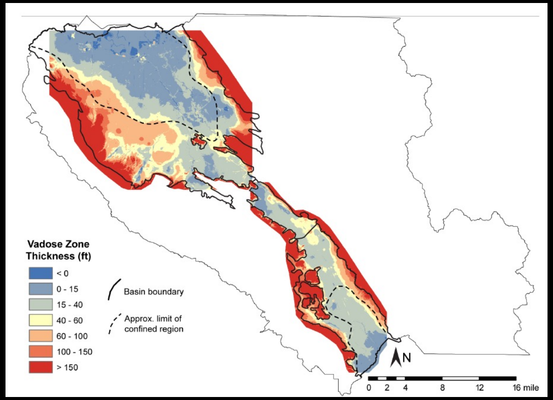
$$SI = (0.2 \cdot IC) + (0.2 \cdot LULC) + (0.2 \cdot Geol) + (0.2 \cdot VZ) + (0.2 \cdot CS)$$



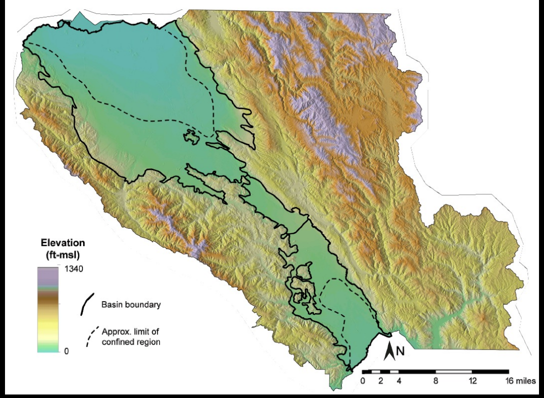
IC	Soil Infiltration Capacity
LULC	Land Use / Land Cover
Geol	Geology rating
VZ	Vadose Zone Thickness
CS	Climate Sensivity of groundwater level



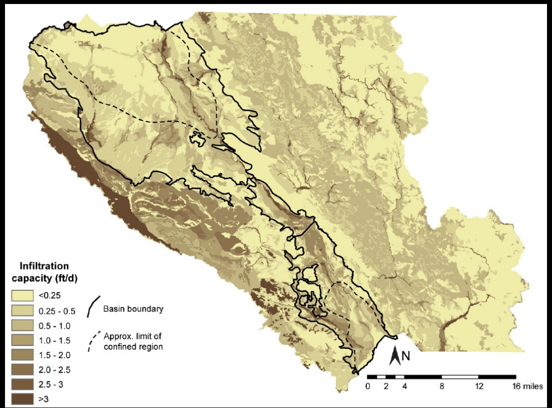
Vadose Zone Thickness (ft)



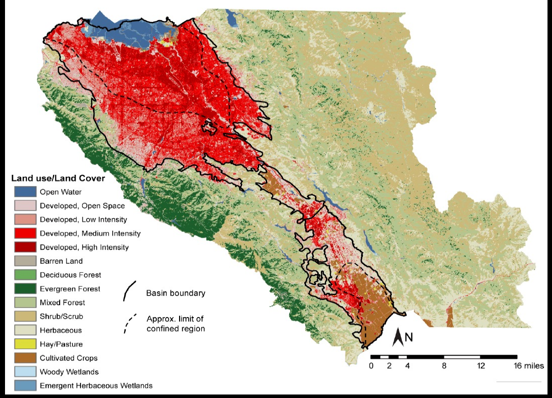
Elevation



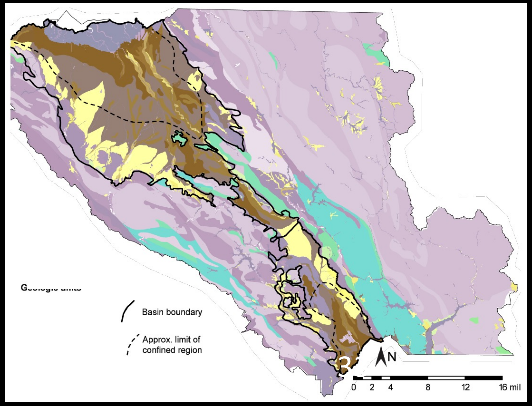
Infiltration



Land Cover



Geologic Units



Recharge Team Summary

- Systemic mapping of groundwater recharge potential state-wide
- compiling geospatial data of hydrogeologic parameters that are relevant to suitability for MAR and ENR
- Estimating groundwater levels by using Machine Learning
- Calculating Base-flow contribution to streamflow using Machine Learning

In process

- Mapping losing and gaining streams statewide
- Mapping high recharge potential karst landscape features