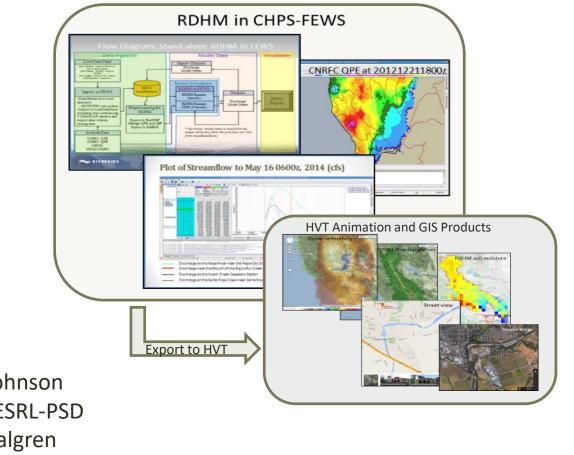
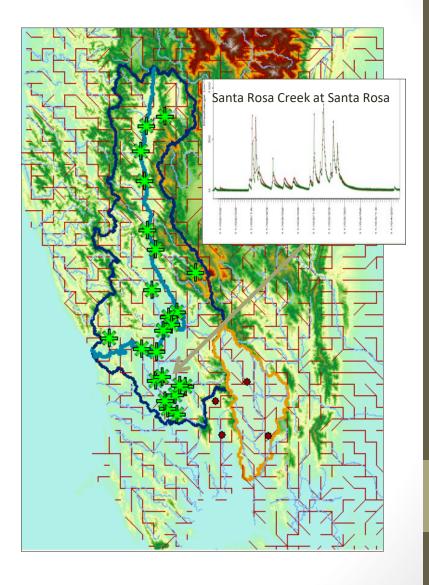
Distributed Hydrological Modeling for NWS Flash Flood Operations



Lynn E. Johnson CSU-CIRA, ESRL-PSD James Halgren RTI-International Tim Coleman CU-CIRES, ESRL-PSD

Russian-Napa Basins 2-D Model

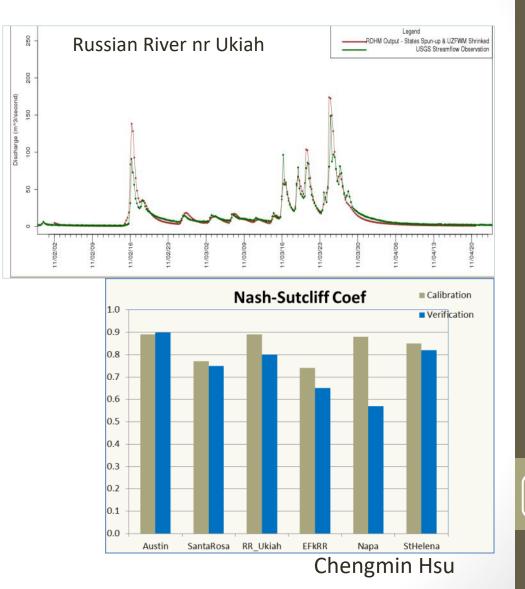
- Purpose:
 - Account for spatial distribution of rain, topography, soils, land use and runoff
 - Tool to assess QPE/QPF products
- Research Distributed Hydrologic Model (RDHM)
 - Developed by NWS-OHD
 - 2-D using HRAP grid (~4.1 km side; ~1 km also)
 - Gridded precipitation and surface temperature
 - Sacramento Soil Moisture Accounting Model (SAC-SMA) in each grid cell
 - Connectivity derived from DEM
 - Runoff (overland and channel) routed by kinematic wave equations
 - Soils parameters based on SSURGO
 - Channel routing based on USGS field measurements
- Report link: <u>http://dx.doi.org/10.7289/V5M32SS9</u>



2

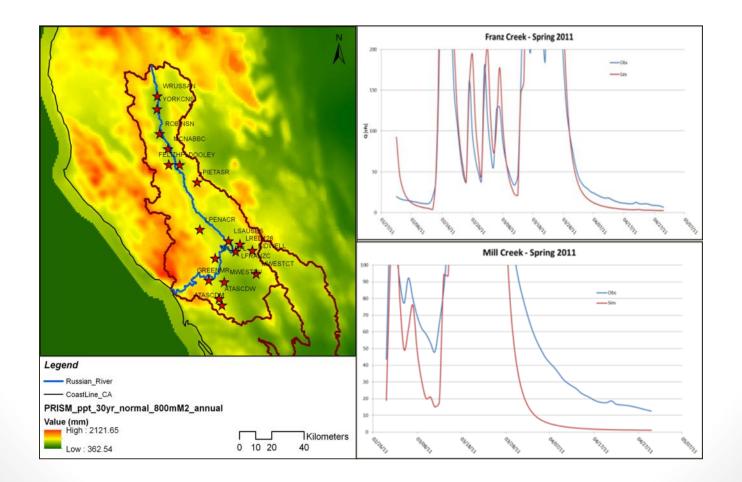
RDHM Calibration/Verification

- Calibration Period
 - 2/1/11 3/12/12
 - N-S(average) = 0.84
- Verification Period
 - 3/13/12 3/31/12
 - N-S(average) = 0.75
- Generally characterize as "Good" when N-S > 0.7
- In general, RDHM model does "OK" in reproducing flood peaks and flow recessions
 - Concern with 1st storm of season
 - Storm precipitation tracking an issue for some events (amount and timing)
- Water management influences (reservoirs, diversions and return flows) not represented

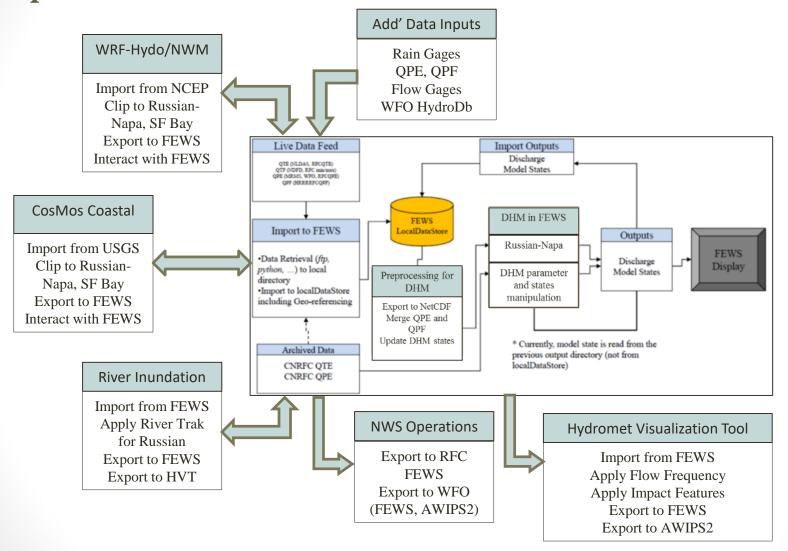


Low Flow Verification

- 15 tributary sites gaged for low flows by NMFS basis for verification
- Verification of lows flows range from "good" to "poor"
- RDHM has low flow predictability of 0.76 cfsm using the OHD default parameters (uncalibrated); this improves to 0.11 cfsm when calibrated.

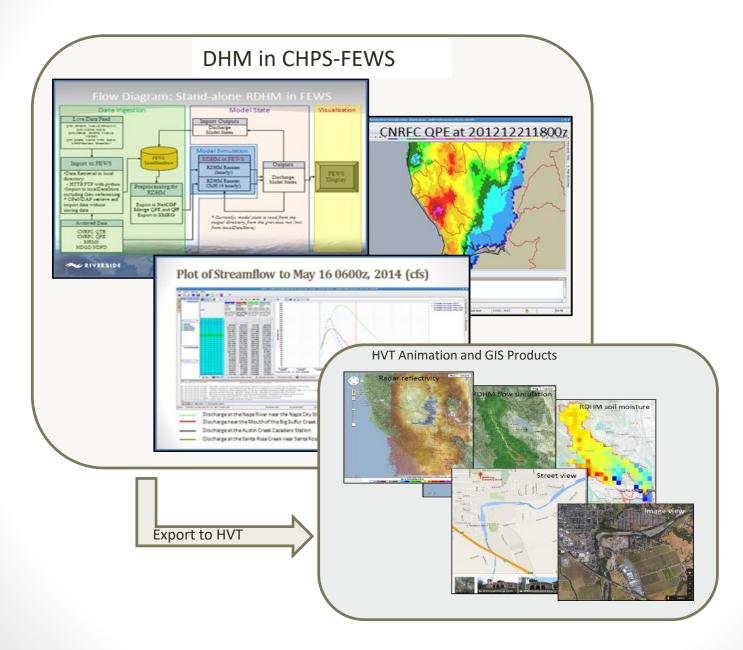


DHM with CHPS-FEWS – Extensions for Operations

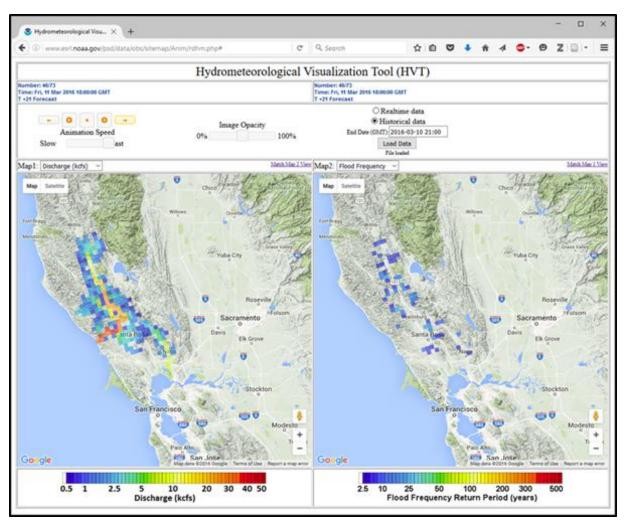


James Halgren

Hydrometeorological Visualization Tool (HVT)

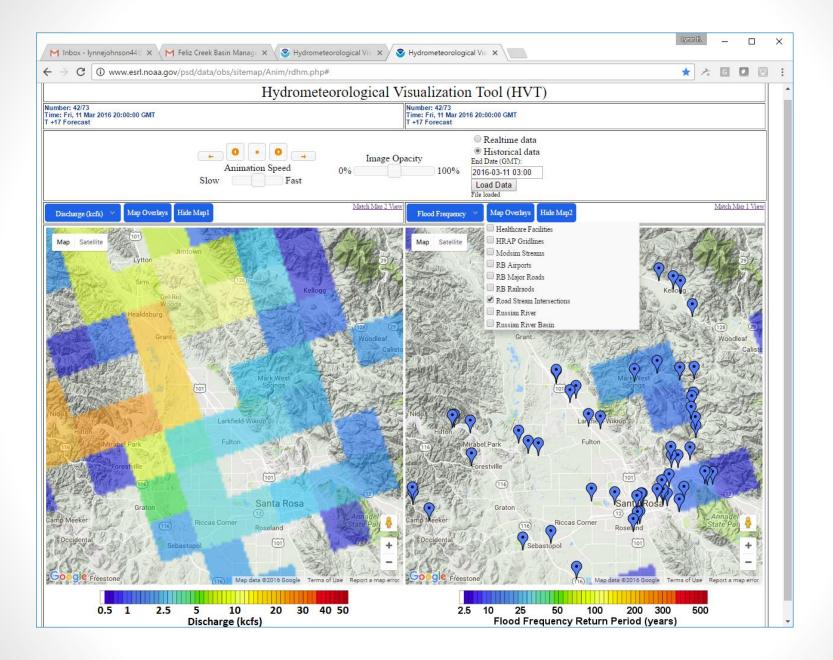


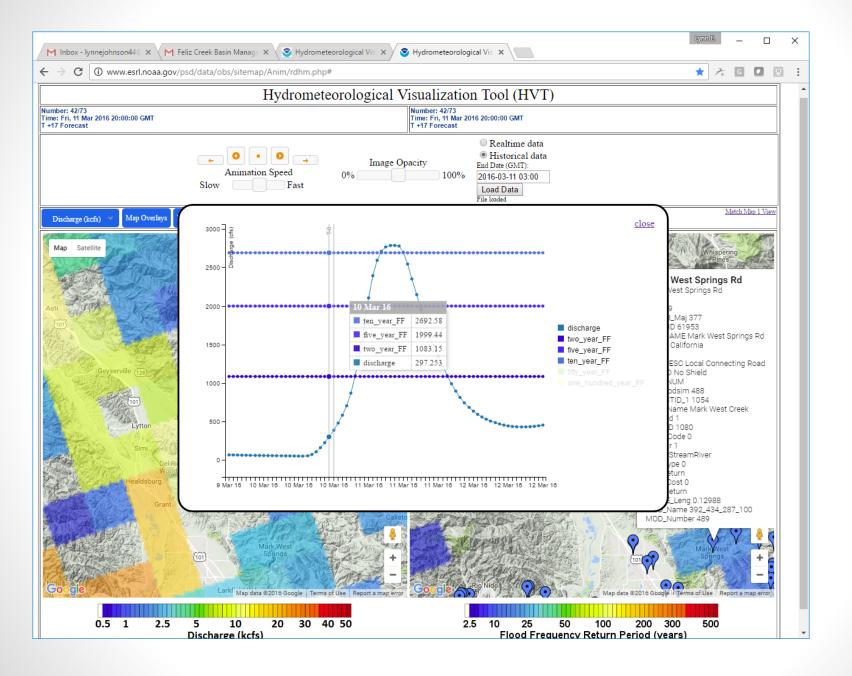
HVT displays animations of (a) grid surface flows, and (b) flood flow frequency equivalent

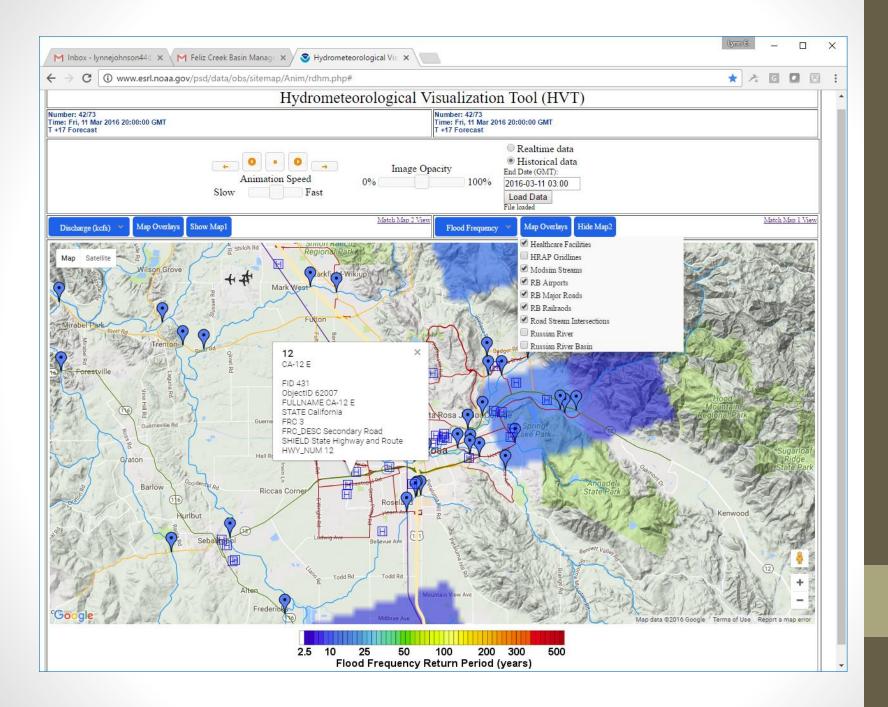


http://www.esrl.noaa.gov/psd/data/obs/sitemap/Anim/rdhm.php

Tim Coleman





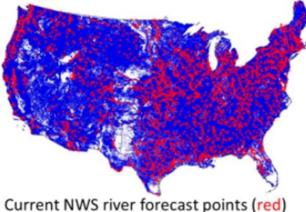


National Water Model

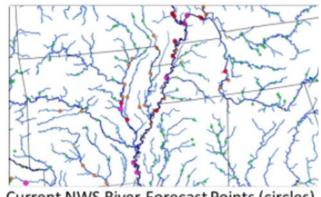
WRF-HYDRO IOC PRODUCTS

- Hydrologic Output
 - River channel discharge and velocity at 2.6 million river reaches
 - Surface water depth and subsurface flow (250 m CONUS+ grid)
- Land Surface Output
 - 1km CONUS+ grid
 - Soil and snow pack states
 - Energy and water fluxes
- Direct-output and value-added geointelligence products





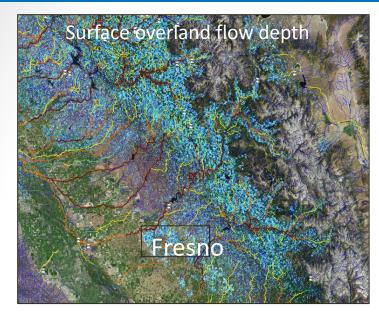
WRF-Hydro forecast points (blue)

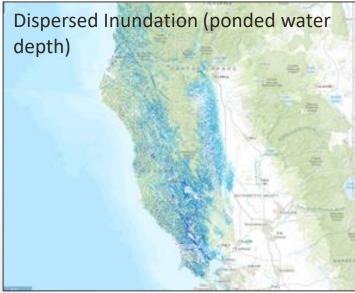


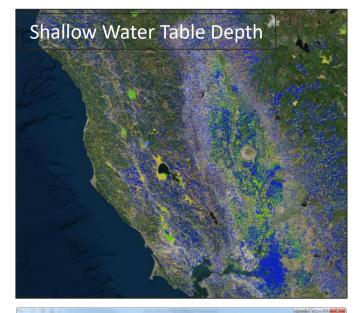
Current NWS River Forecast Points (circles) Overlaid with WRF-Hydro Stream Reaches

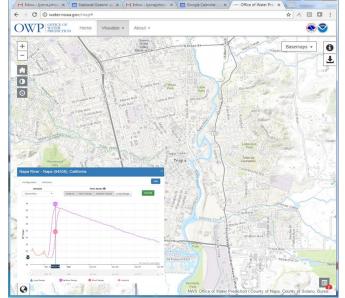
Dave Gochis, NCAR ¹⁹

National Water Model Products





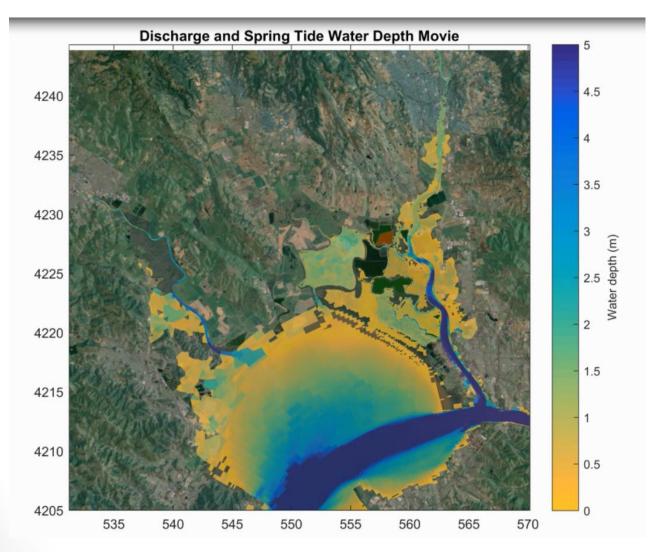




Cover

Dave Gochis, NCAR

<u>**Co</u>astal <u>S</u>torm <u>Mo</u>deling <u>S</u>ystem</u>**





Application of Stochastic Dynamic Programming and HEC-ResSim for Development of Forecast-based Operational Rules for Lake Mendocino in the Russian River Basin, California

Matthew Peacock

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John Labadie

Professor, Department of Civil and Environmental Engineering, Colorado State University, Fort Collins, CO

Lynn Johnson Senior Research Hydrologist, Physical Sciences Division, NOAA Earth System Research Laboratory, Boulder, CO

Problem Overview

- Focus is on the upper Russian River Basin
- Three criteria:
 - 1. Flood control
 - 2. Water Supply
 - 3. Environmental Flows
- Currently a desire to modify operations

- Operations Factors

 Physical constraints
 Water supply demand
 Max release constraints
 Hydrologic index
 Potter Valley Project
 Downstream maximum flows
- Efforts are underway to develop forecast informed reservoir operation plan (FIRO)

Current Operations

- USACE controls releases above the guide curve
- SCWA makes recommendations on releases below the guide curve
- Releases must comply with the Hydrologic Index

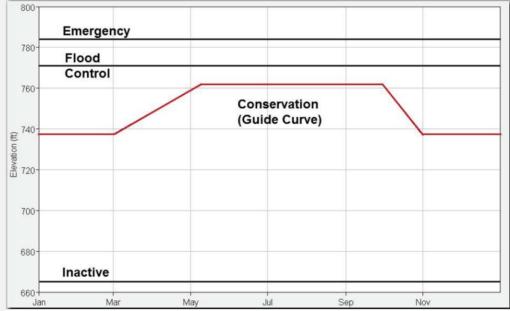
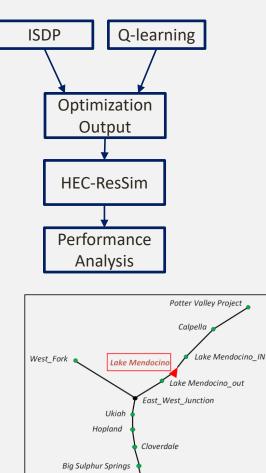


Figure 5. Lake Mendocino Seasonal Guide Curve.

Source: Determination of a Hydrologic Index for the Russian River Watershed using HEC-ResSim, USACE

Optimization Approach

- First consider the problem without forecasts
- Can we use dynamic programing (DP) methods to improve current operations
- Explore implicit and explicit DP
- Implement rules in simulation model
- Apply machine learning techniques in the future
 Incorporate forecasts
 Represent Ensemble Forecast
 Operations

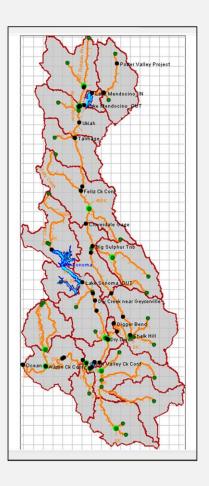


Geyserville

To Dry Creek

Cloverdale Diversion

Healdsburg



Challenges

Hydrology

Rapid flow changes Low sesason-to-season correlation Storm volume

Wet season ends abruptly

Multiple Objectives

Flood control Water supply

Environmental flows

Explicit DP not pursued

Low transition probabilities Additional random variables (e.g Potter Valley)

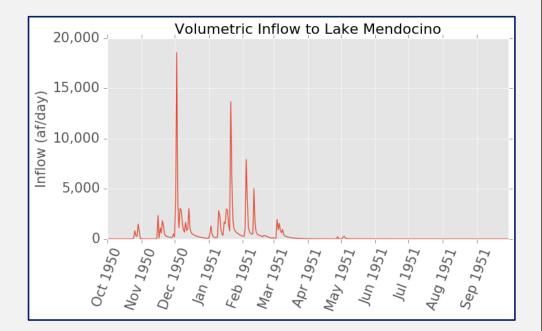
 Implicit Stochastic DP model created

Weekly time step

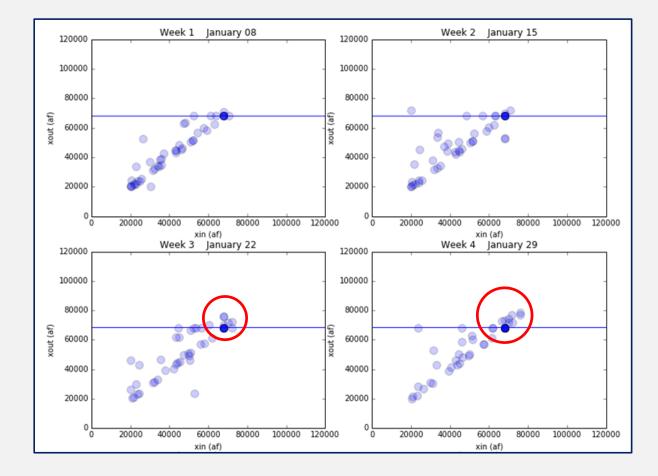
Based on utility functions for each criteria

Run deterministic DP, then infer operating rules

Used 1950-1999 as training data

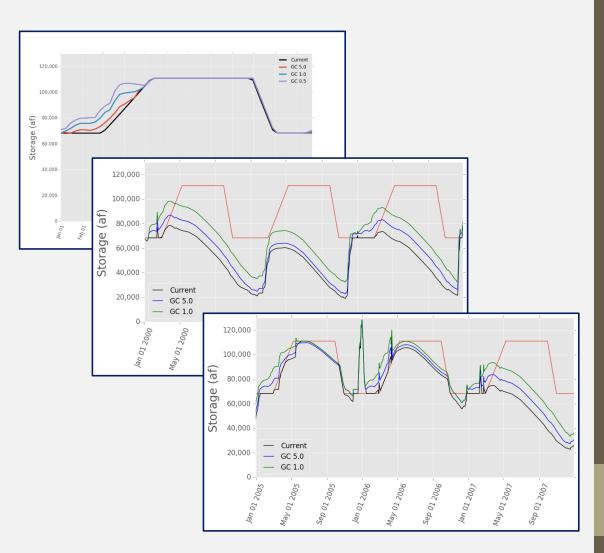


Implicit Stochastic DP



Guide curves generated through ISDP analysis

- A) Selected the higher of values from original curve and the ISDP value
- B) Storage graph from HEC-ResSim using alternate guide curves 2000-2002
- C) Storage graph from HEC-ResSim using alternate guide curves 2005-2007

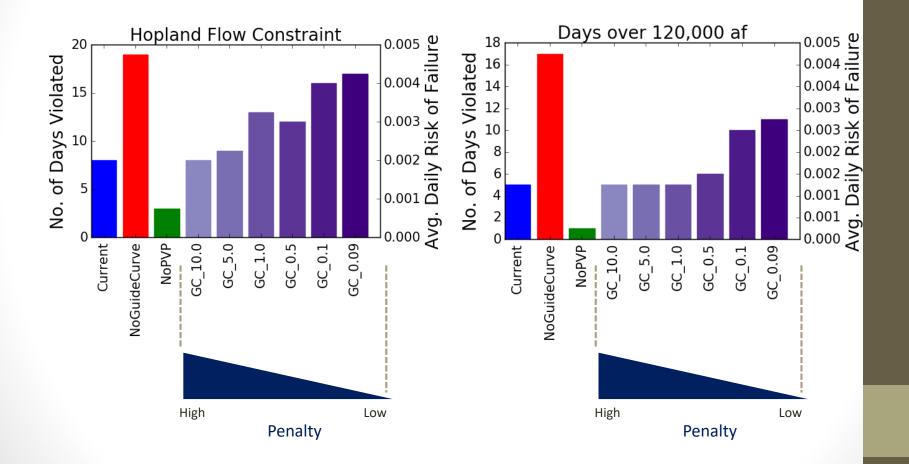


Implicit Stochastic DP – Performance Measures

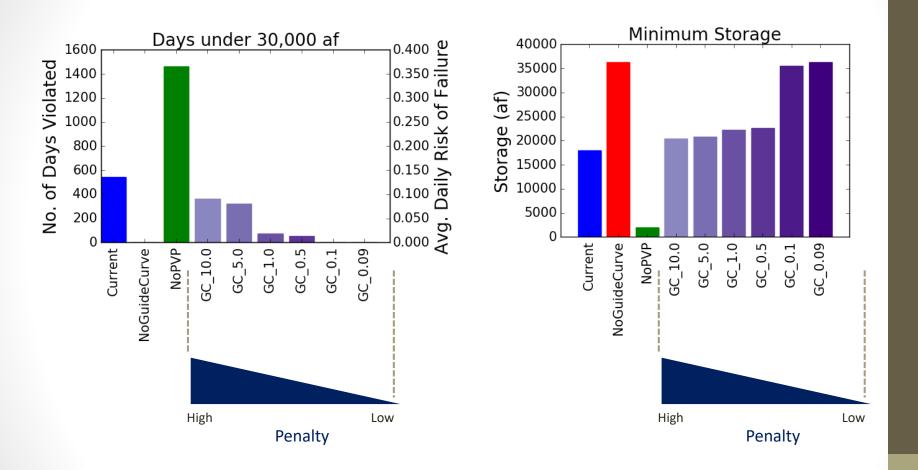
Performance Measure Title	Related Criterion
Hopland Flow	Flood Control
Days over 120,000 af	
Healdsburg Env Flow	Environmental
Days under 30,000 af	Water Supply
Minimum Storage	

Title of	Description	
Alternative		
Current	Current operating rules	
NoGuideCurv	No guide curve (constant 110,000 af) –	
	Represents preference for water supply and	
е	environmental flows	
NoPVP	No PVP flows – Represents water stressed	
	situation	
GC_10.0	Results from running ISDP model with guide	
	curve penalty of 10.0	
GC_5.0	Results from running ISDP model with guide	
	curve penalty of 5.0	
GC_1.0	Results from running ISDP model with guide	
	curve penalty of 1.0	
GC_0.5	Results from running ISDP model with guide	
	curve penalty of 0.5	
GC_0.1	Results from running ISDP model with guide	
	curve penalty of 0.1	
GC_0.09	Results from running ISDP model with guide	
	curve penalty of 0.09	

ISDP – Flood Control Measures



ISDP – Water Supply Measures



ISDP - Conclusions

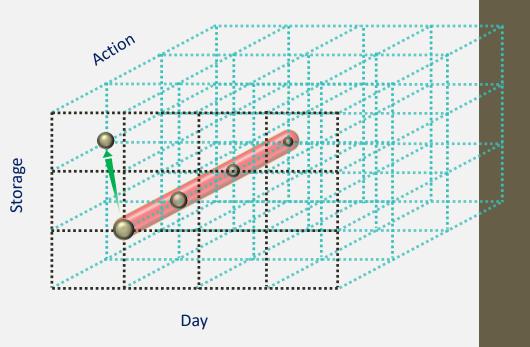
- Optimization techniques can provide information for a tradeoff analysis between flood control, water supply and environmental flows
- Able to implement results in current HEC-ResSim model
- New curves suggest additional storage at the end of the wet season provides benefit to environmental flows and water supply

Reinforcement Learning (RL)

- Learning best actions through an iterative process
- Q-learning algorithm is well suited to this problem
- No probability distributions needed
- Learning process removes the need for inference

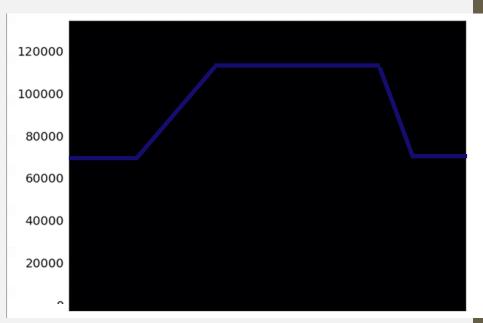
Q-learning

- Discretize the state space
- Add a dimension for all of the discretize actions that can be taken at each possible state
- Consider the system starting in a particular state, then use a long series of single day inflows
- Algorithm chooses an action based on an explore/exploit parameter that we program, and ends up in a new state
- Algorithm looks at the value that is possible for all actions that can be taken at that next state



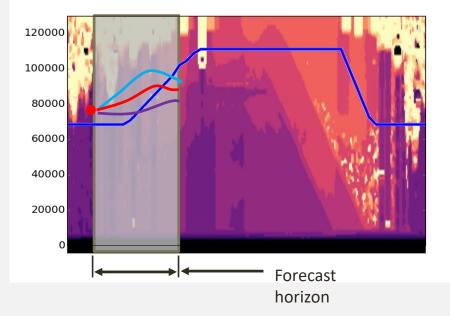
Q-learning

- Here is a video of the learning process in action projected into 2dimensions.
- This is a very rough prototype that Matt created.
- In this video we are just looking at the action that provides the highest benefit for each state.
- The brighter colors indicate higher releases.
- Eventually we want the algorithm to converge to a steady state of values for each state location in this array.



Q-learning

- This will give us what we need to begin using the forecast information.
- When you are using forecasts to make operational decisions you want to look at decisions that will give you the most benefit over the forecast horizon, and allow you to arrive in a state at the end of the forecast horizon that will provide benefit in the future.
- Considering both of these factors prevents making greedy decisions.



Conclusions

- RL is a powerful method for learning best actions in a highly non-linear, stochastic environment
- Provides the basis for extending analysis to include ensemble forecasts
- Flexible for incorporating stakeholder input into reward function
- Challenges ahead include:
 - 1. Implementation in code
 - 2. Inclusion of routing and additional reservoir
 - 3. Development of synthetic data
 - 4. MCDA/Robustness analysis for operating decisions
- Suggest more detailed review using webinar.

Acknowledgments

- NOAA-ESRL Physical Sciences Division
- NOAA-OAR Office of Weather and Air Quality -Hydrometeorology Testbed
- Sonoma County Water Agency
- United States Army Corps of Engineers Hydrologic Engineering Center