UCDAVIS
CENTER FOR
WATERSHED SCIENCES

PyVIN

Spring 2017 PyVIN Shortcourse & Hands-on Tutorial

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Agenda

- CALVIN theory & model introduction
  - **break**
- HOBBES database
- Data flow overview
  - **Break (lunch)**
- PyVIN updates & model architecture
  - **break**
- First PyVIN run
- Postprocessing results

CALVIN Theory & Model Introduction

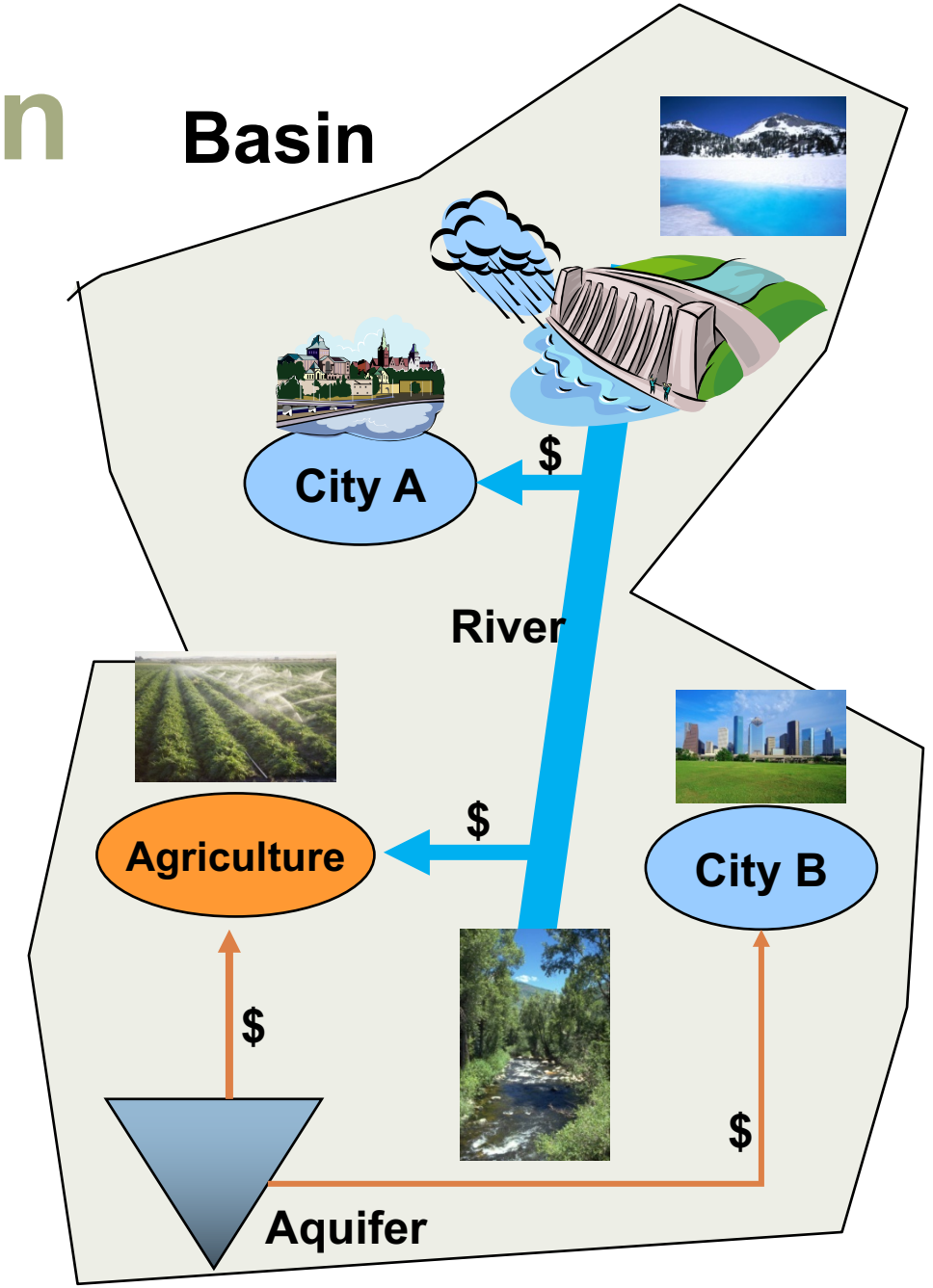
CALifornia Value Integrated Network

- Hydroeconomic optimization model
- Represents California's water operations
- Optimizes water deliveries to users
- Surface and groundwater representation
- Historical monthly hydrology (from Oct 1921 to Sep 2003)
- 2050 agricultural and urban demands

CALVIN is a planning and management model, not operating!

Water Allocation

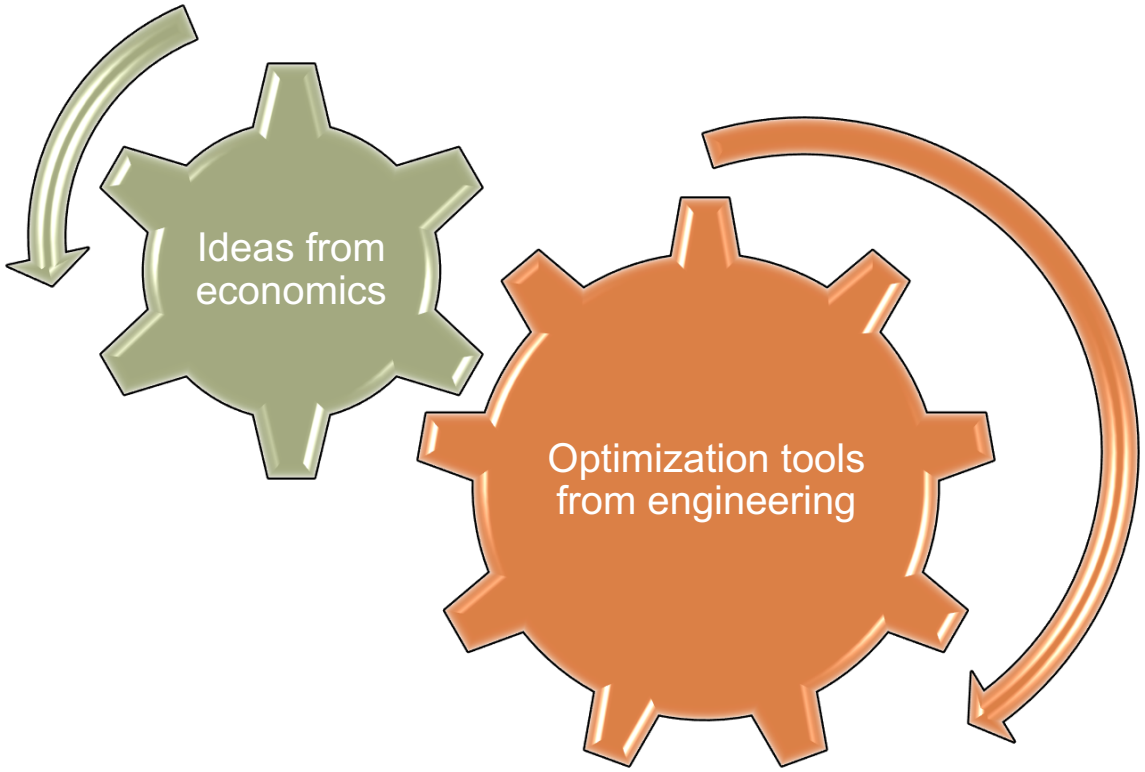
- Economic values for agricultural, urban and hydropower uses
- Constraints for capacity limitations and regulatory requirements
- 82-year hydrology and operations
- Monthly time-step



CALVIN

- Forces quantitative understanding of integrated water and economic system

- Provides insights into regional and statewide water planning and management

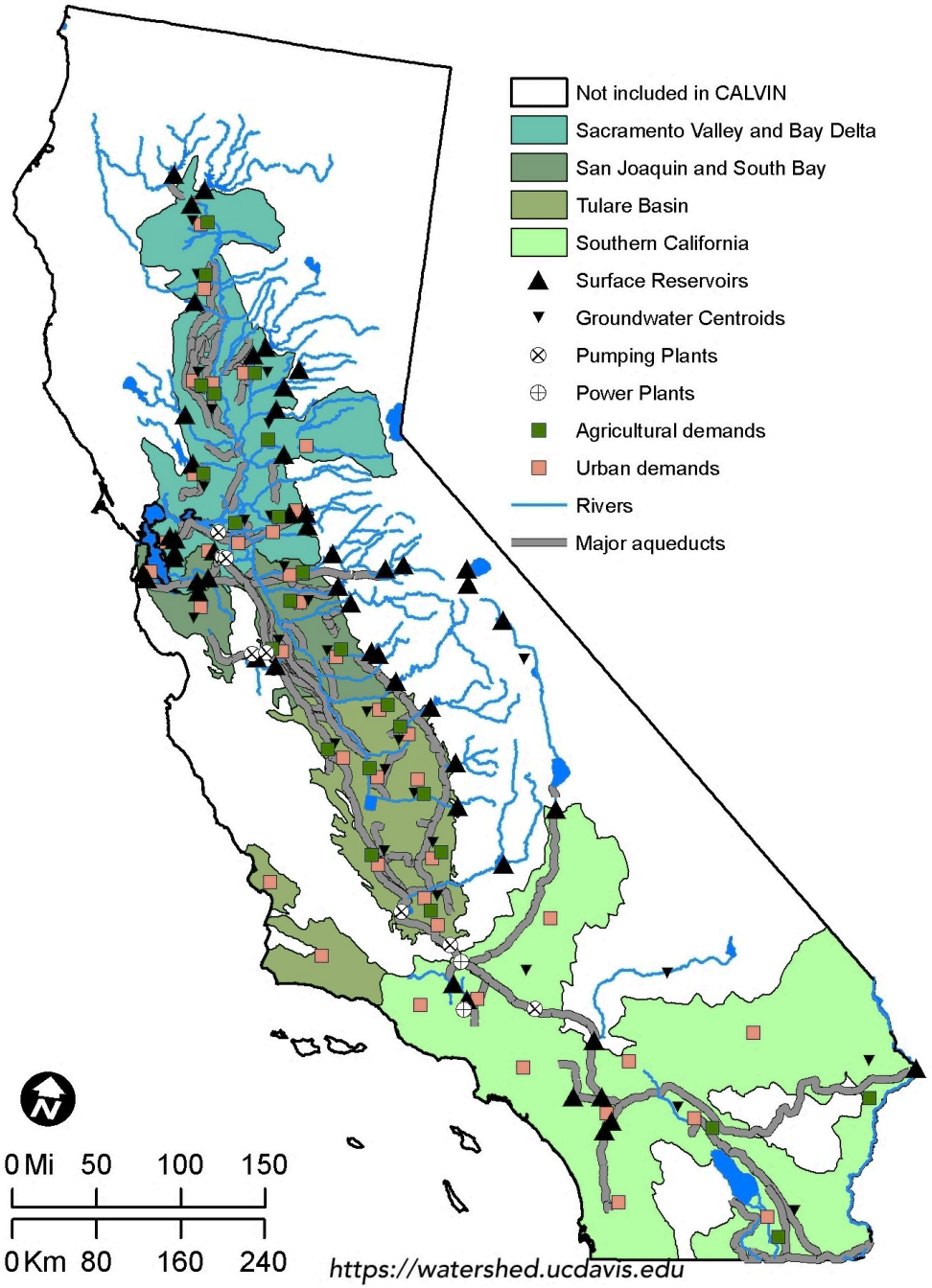


Motivation

- Make better sense of integrated system and operations
- Seek ways to improve system management
- Quantifying user willingness to pay for additional water
- Find insights into changes in physical capacities and policies

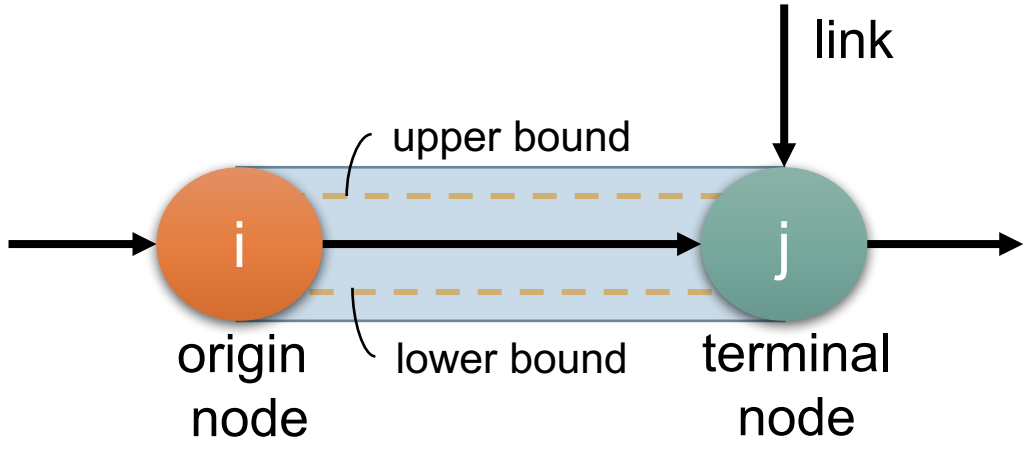
Model Coverage

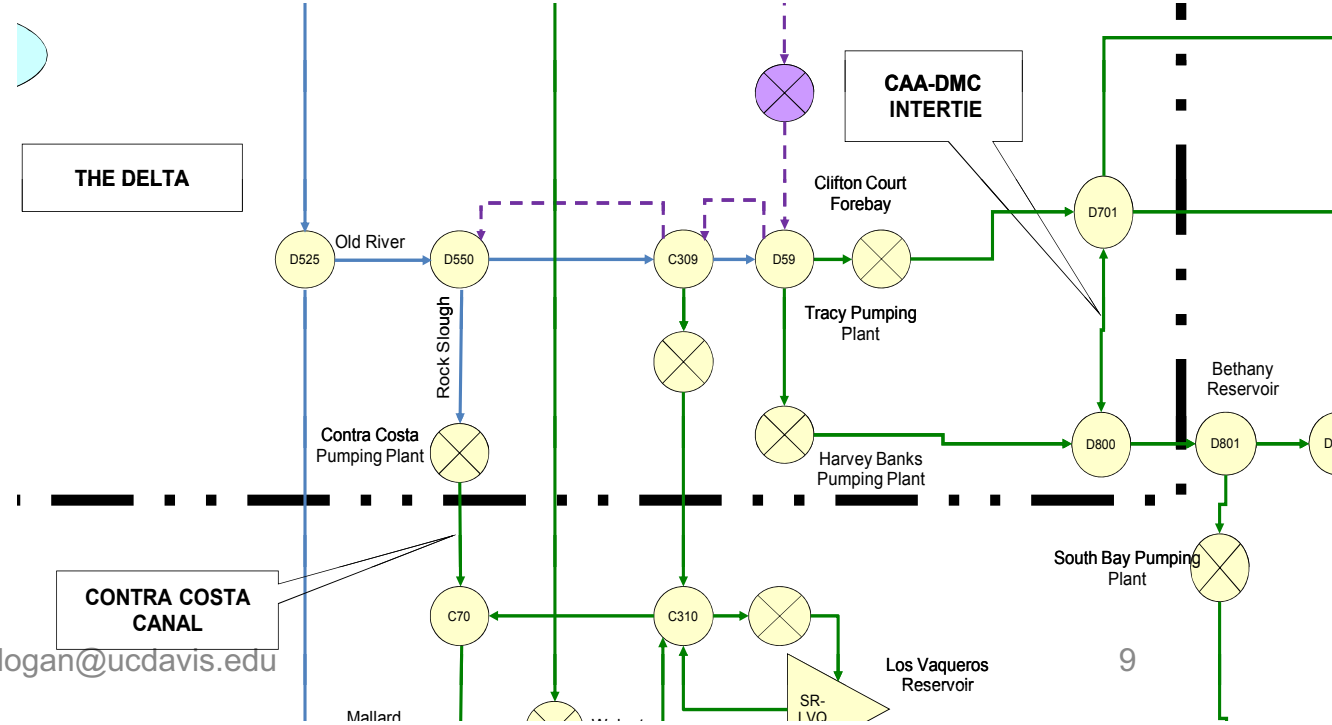
- Most agricultural activities and urban population
- Major conveyance systems (CAA, DMC, CRA)
- CVP and SWP operations
- Surface and groundwater reservoirs



Network-Flow Structure

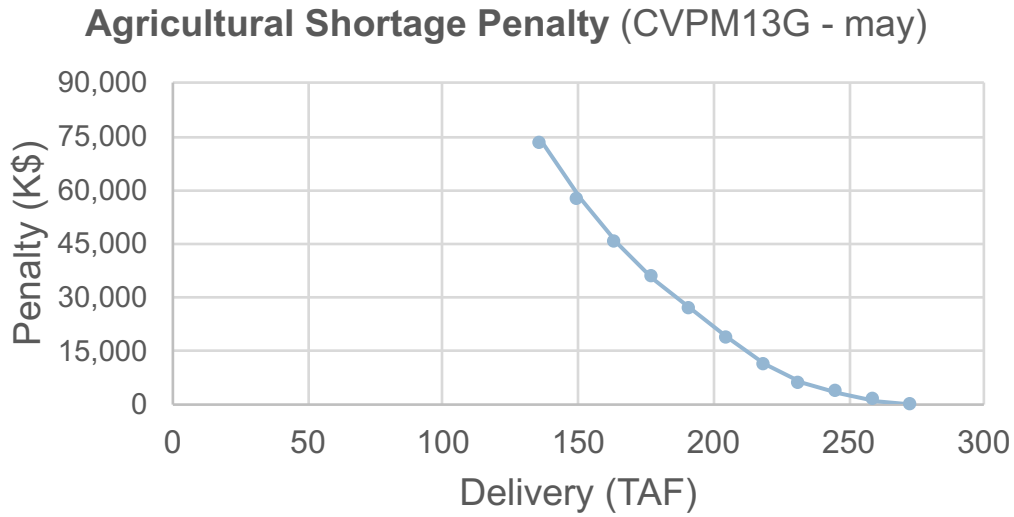
- Nodes
  - Reservoirs, plants, demand areas
- Links
  - Capacity (upper bound), minimum flow (lower bound), loss (amplitude), cost
- CALVIN network schematic

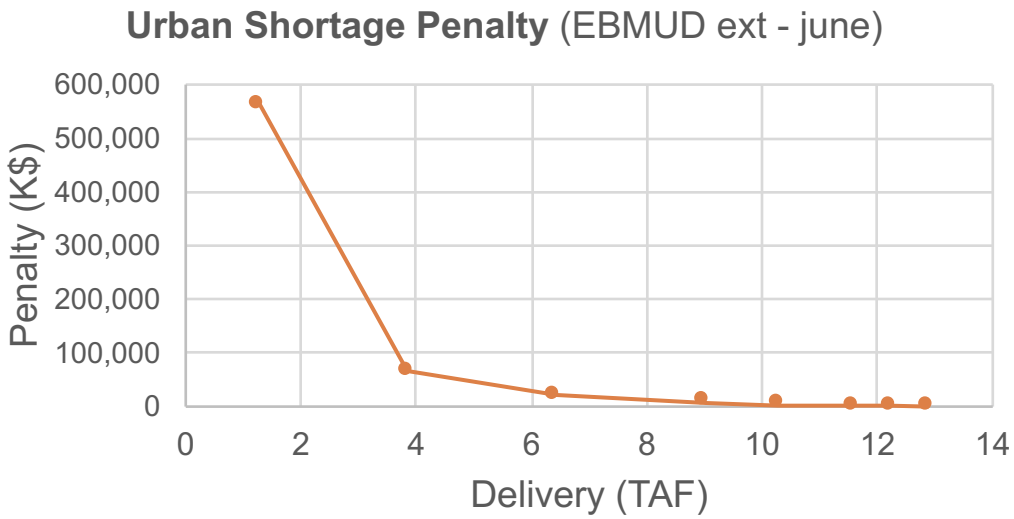




Water Users: Demand Areas

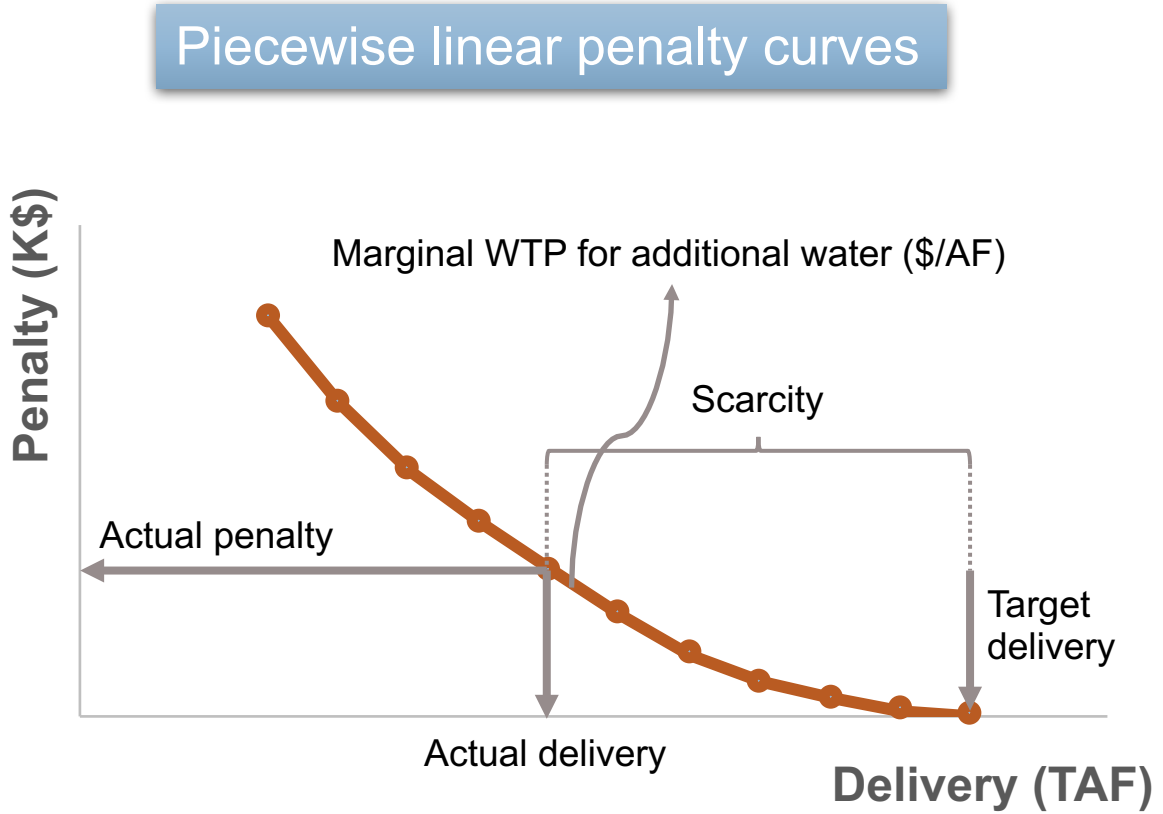
- Users
  - Agricultural
  - Urban
  - Environmental
- Economic representation for ag and urban
  - Penalty for not delivering water
  - Urban users with higher WTP
- Constrained (fixed) deliveries for environment (wildlife refuges)





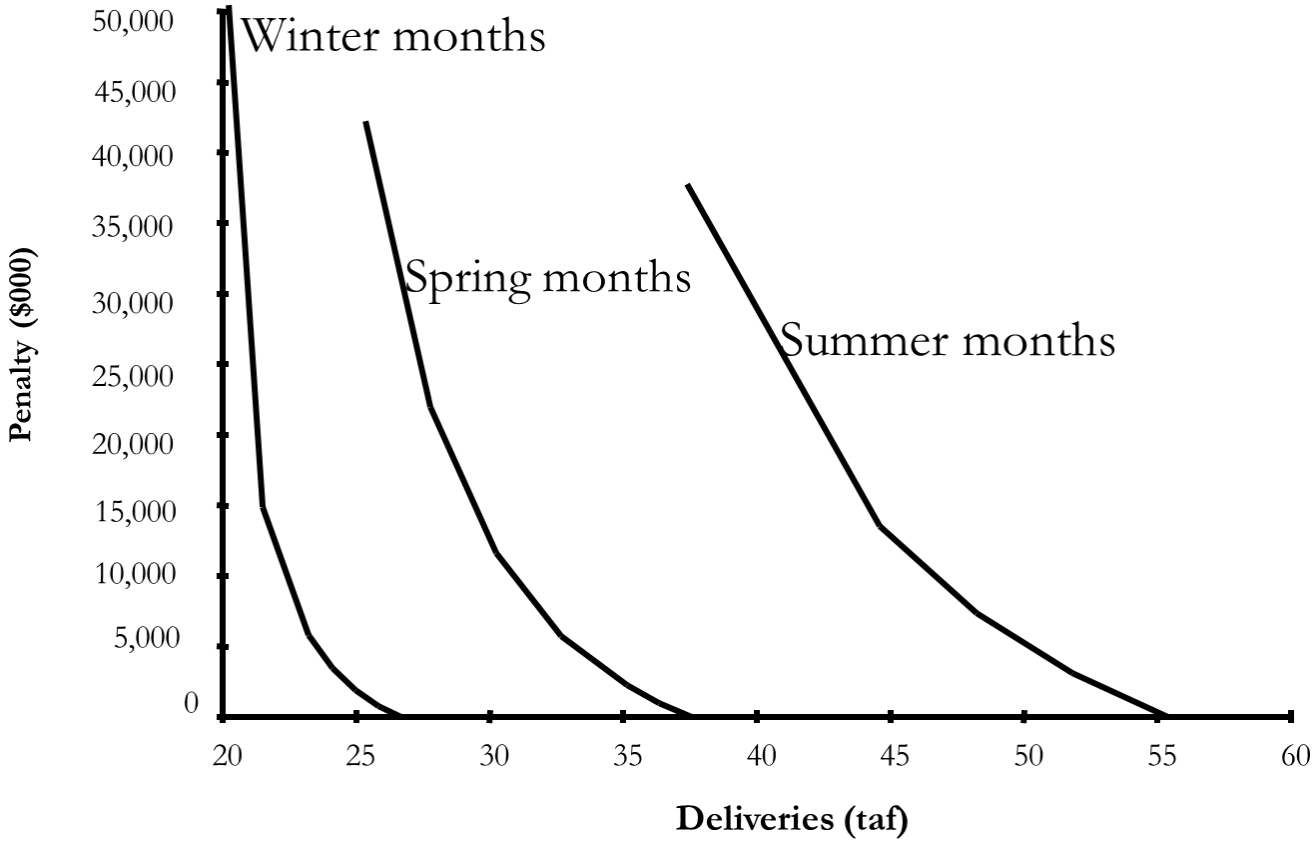
Demand Area Penalty Curves

- Penalty for not delivering water (and economic loss)
- No penalty at the target delivery
- Piecewise linear curves (linear programming model)
- User's willingness to pay (WTP) for water
- Convex: the more delivery the less penalty



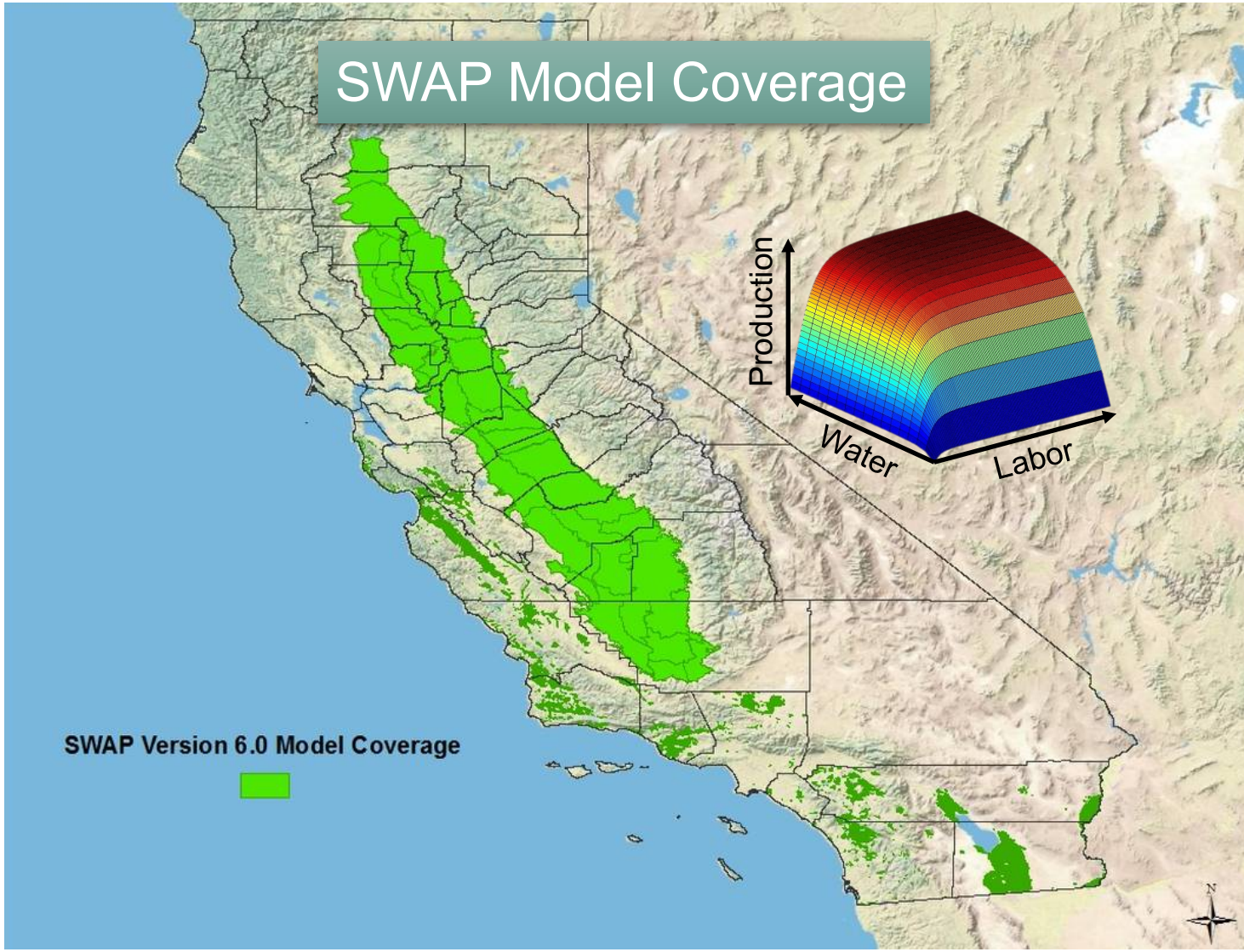
Monthly Varying Demand Curves

- Demand curves vary by month (no annual variation)
- Higher target demand in summer months
- Less price elasticity (steeper slope) in winter months



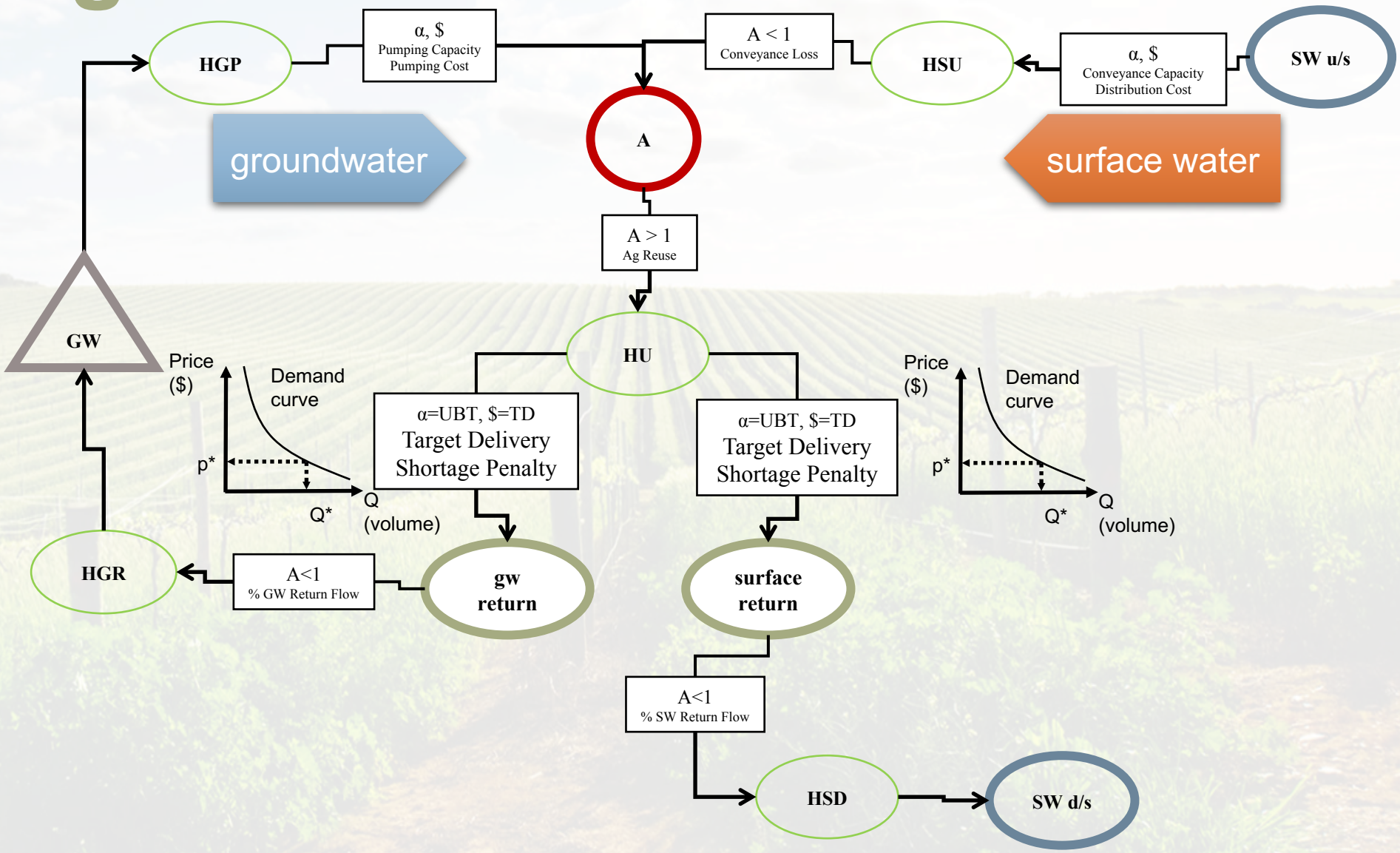
Agricultural Representation

- Results from Statewide Agricultural Production (SWAP) model
- SWAP simulates farmers decision in California
- Profit maximization model
- 35 aggregated subbasins
- SWAP results are used to create ag penalties in CALVIN (& PyVIN)



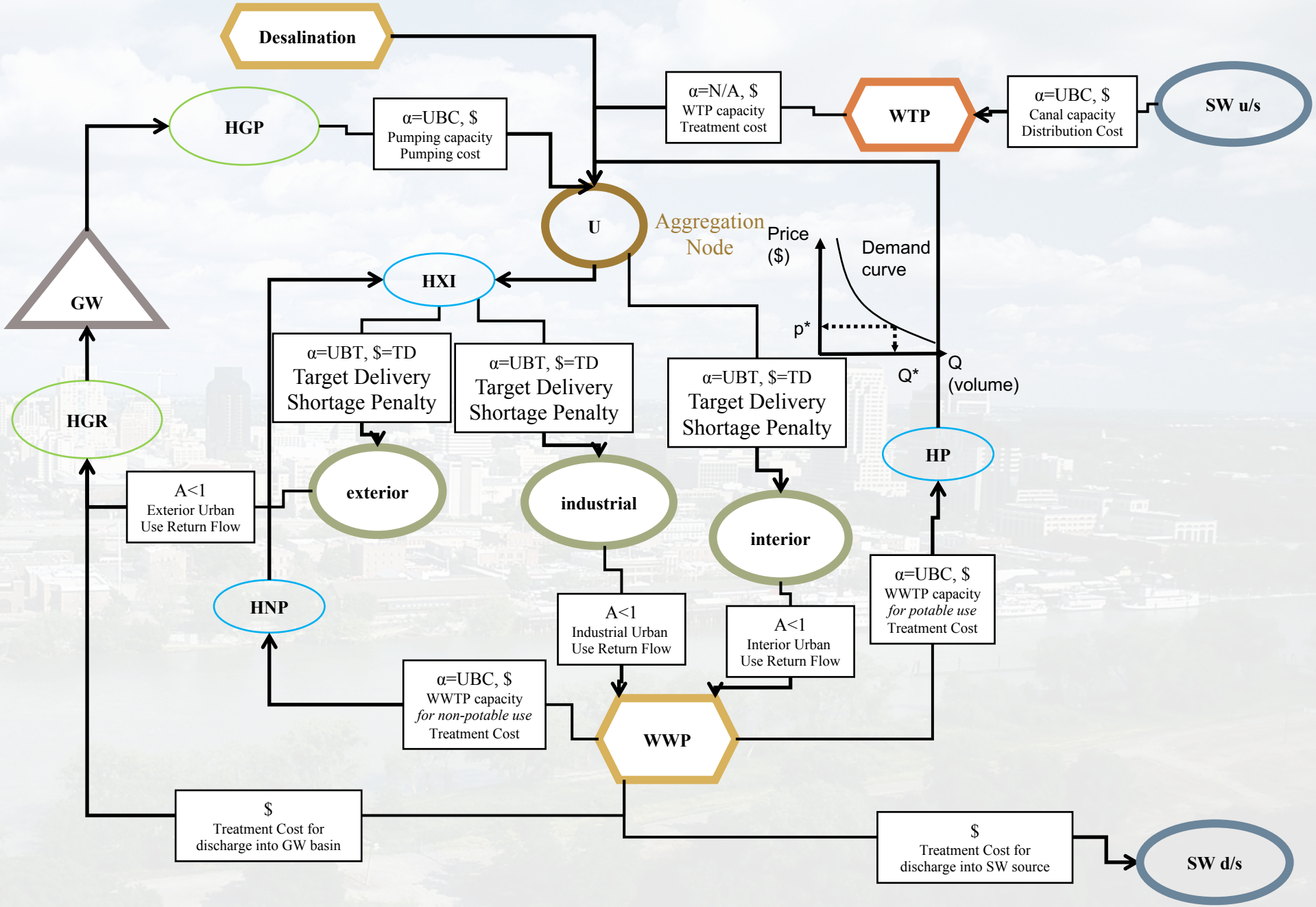
Agricultural Demand

- Standardized representation
- Supply sources:
  - Groundwater
  - Surface water
- Split into two parts depending on return flows



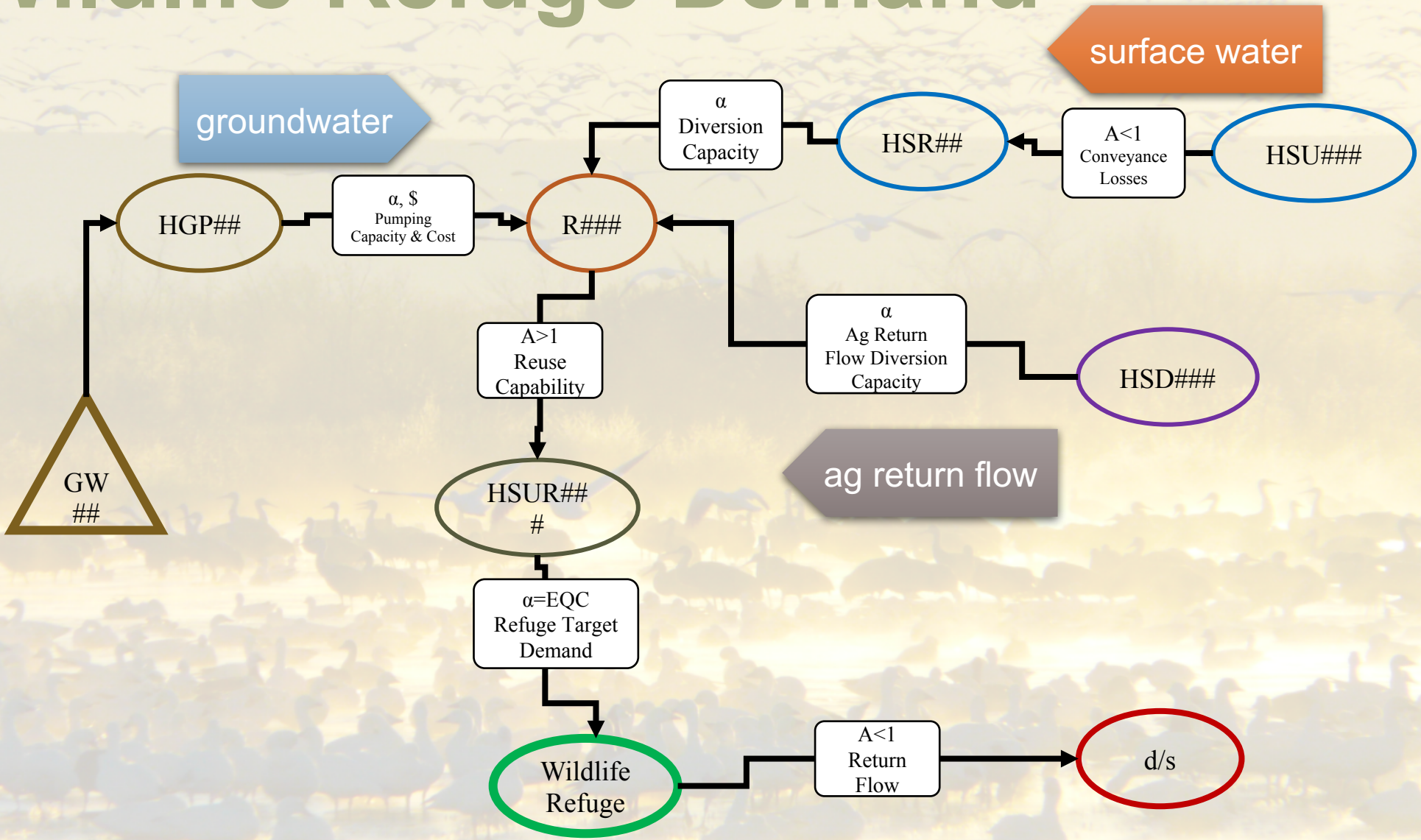
Urban Demand

- Supply sources:
  - Groundwater
  - Surface water
  - Desalination
  - Potable & nonpotable recycled
- Split into three parts
  - Exterior
  - Interior
  - Industrial



Wildlife Refuge Demand

- Supply sources:
  - Groundwater
  - Surface water
  - Ag return flow
- Constrained (fixed) flow deliveries



Advantages

- Integrated model (surface and groundwater)
- Unique combination of economics and engineering principles
- Well-documented model (reports, articles, website and theses)

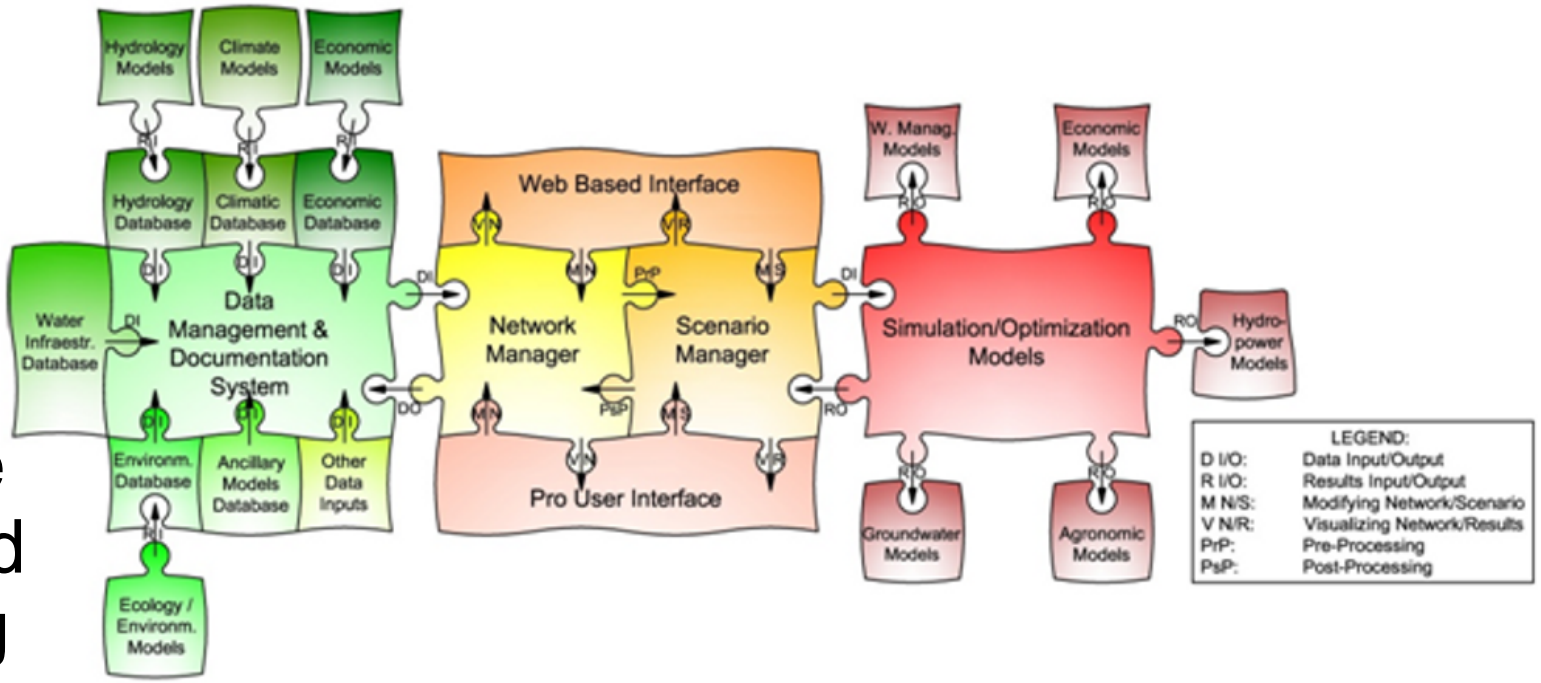
Limitations

- Perfect hydrologic foresight
  - The model knows all hydrologic events in its operating period
  - Scarcity costs are less than actual
- Simplified reservoir and Delta operations
- Piecewise linearization
- Simplified hydropower representation

HOBBES Database

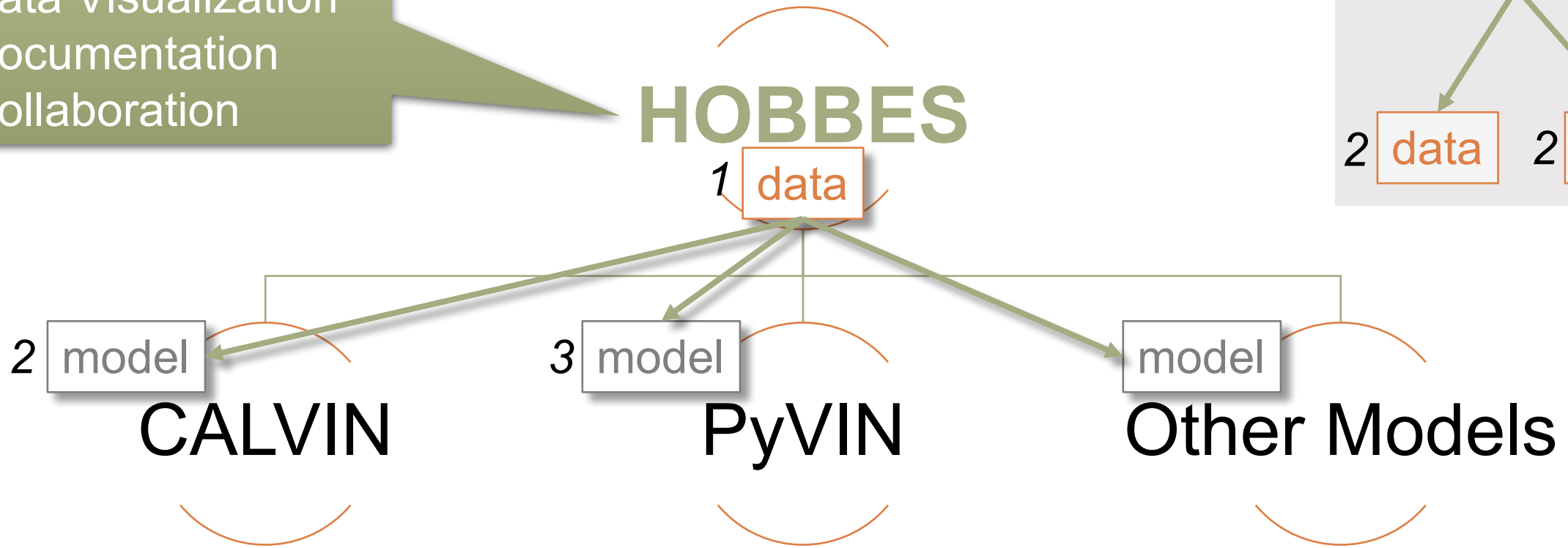
HOBBES

- A bottom up approach to improve and organize data
- Venue for modelers to create an open, organized and documented water representation
- Geocoded elements can be converted into networks and solved by multiple modeling platforms (PyVIN)

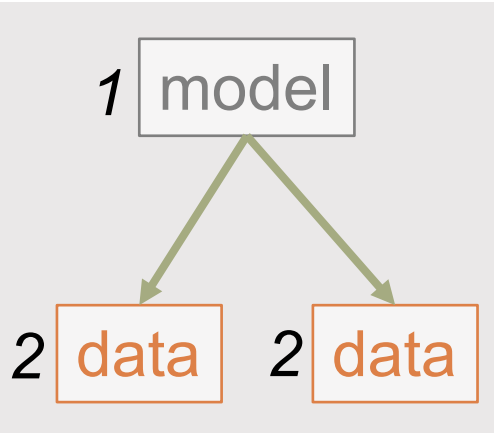


Modeling with HOBBES

- Online Database
- Version Control
- Data Visualization
- Documentation
- Collaboration



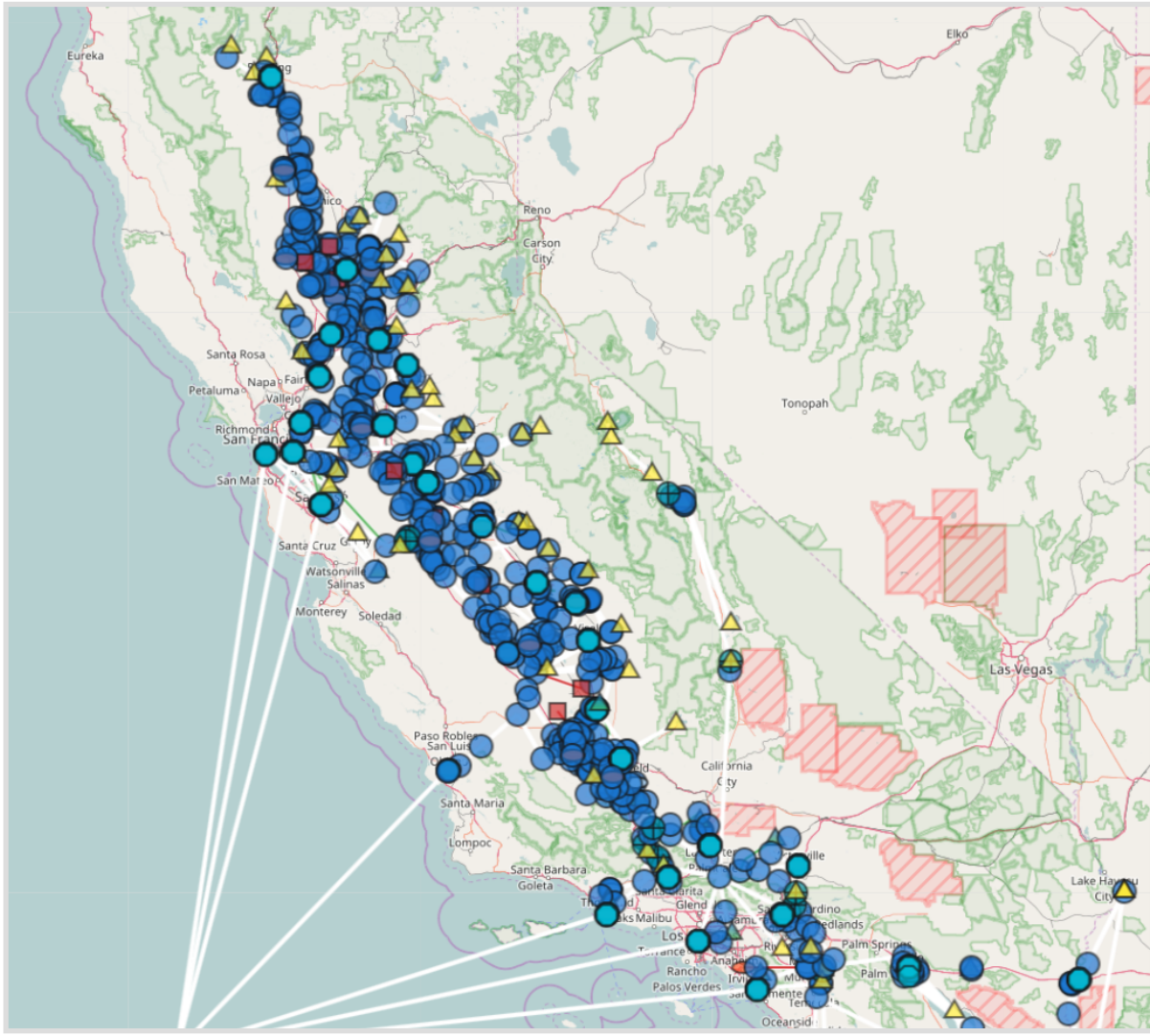
Classical Approach



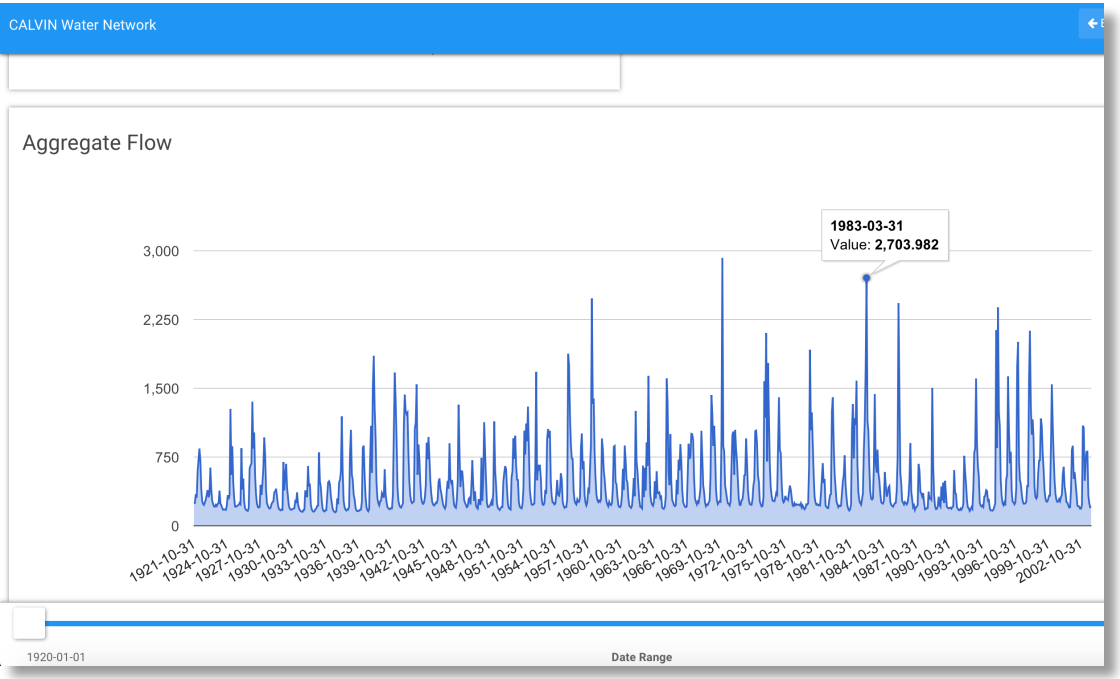
HOBBES Website

https://cwn.casil.ucdavis.edu

- California water network
- Geocoded network elements
- Layered based on hydrologic regions and subregions
- Data visualization
- Animation tool

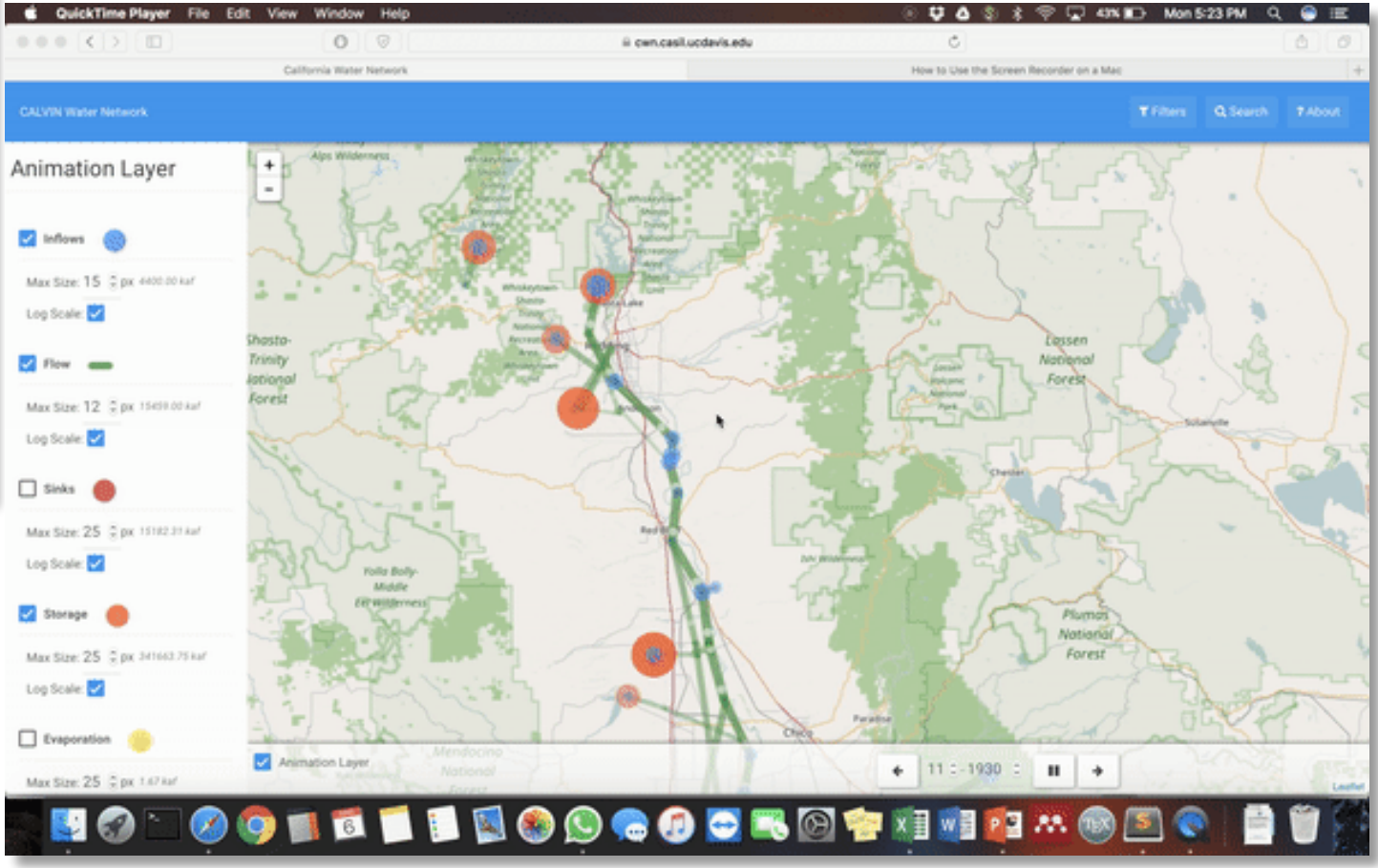


Data Visualization

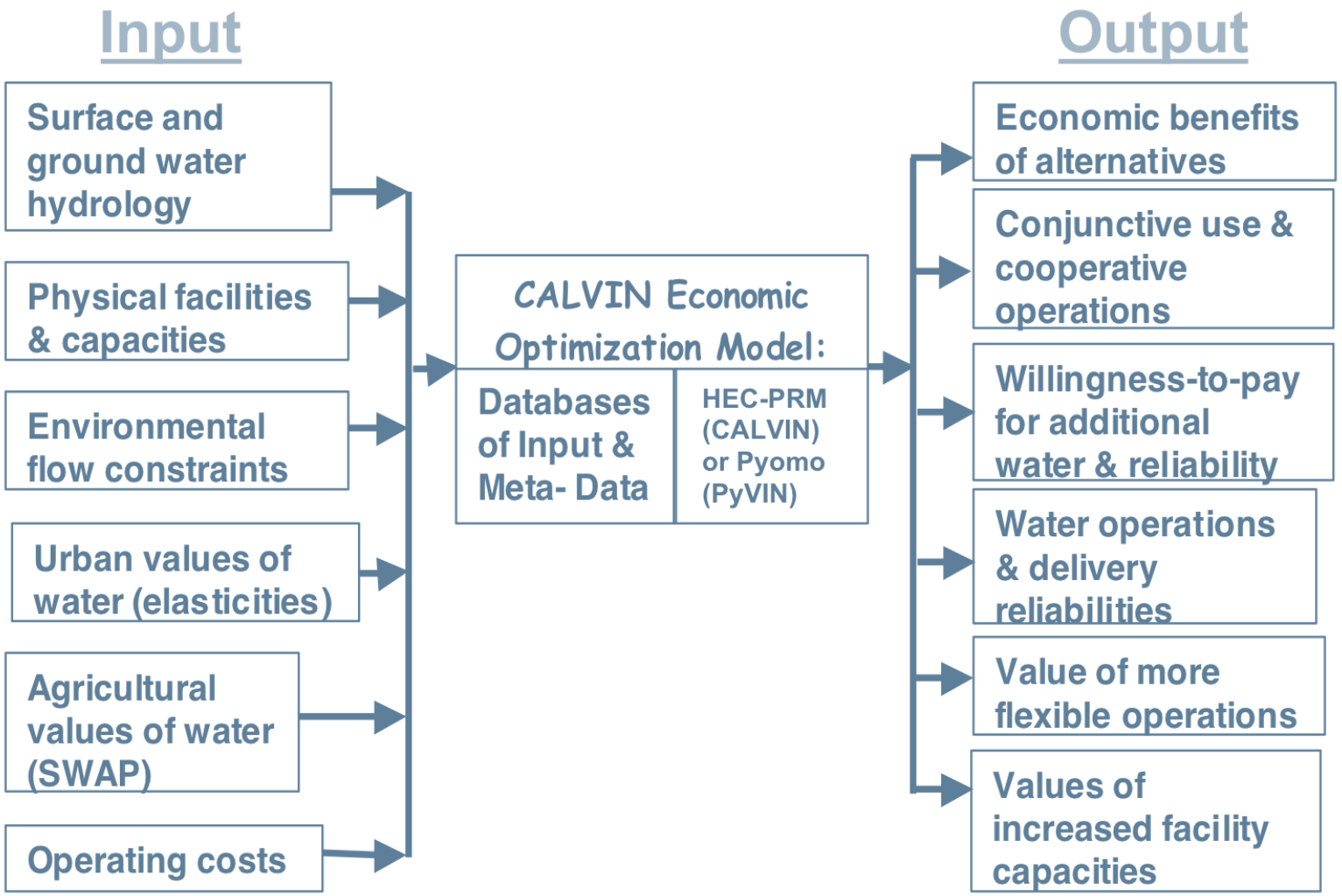


- Graph flow and storage results
- Select time-period

- Animation tool
- Inflow, flow, storage, evaporation



Data Flow Overview



Hydrology

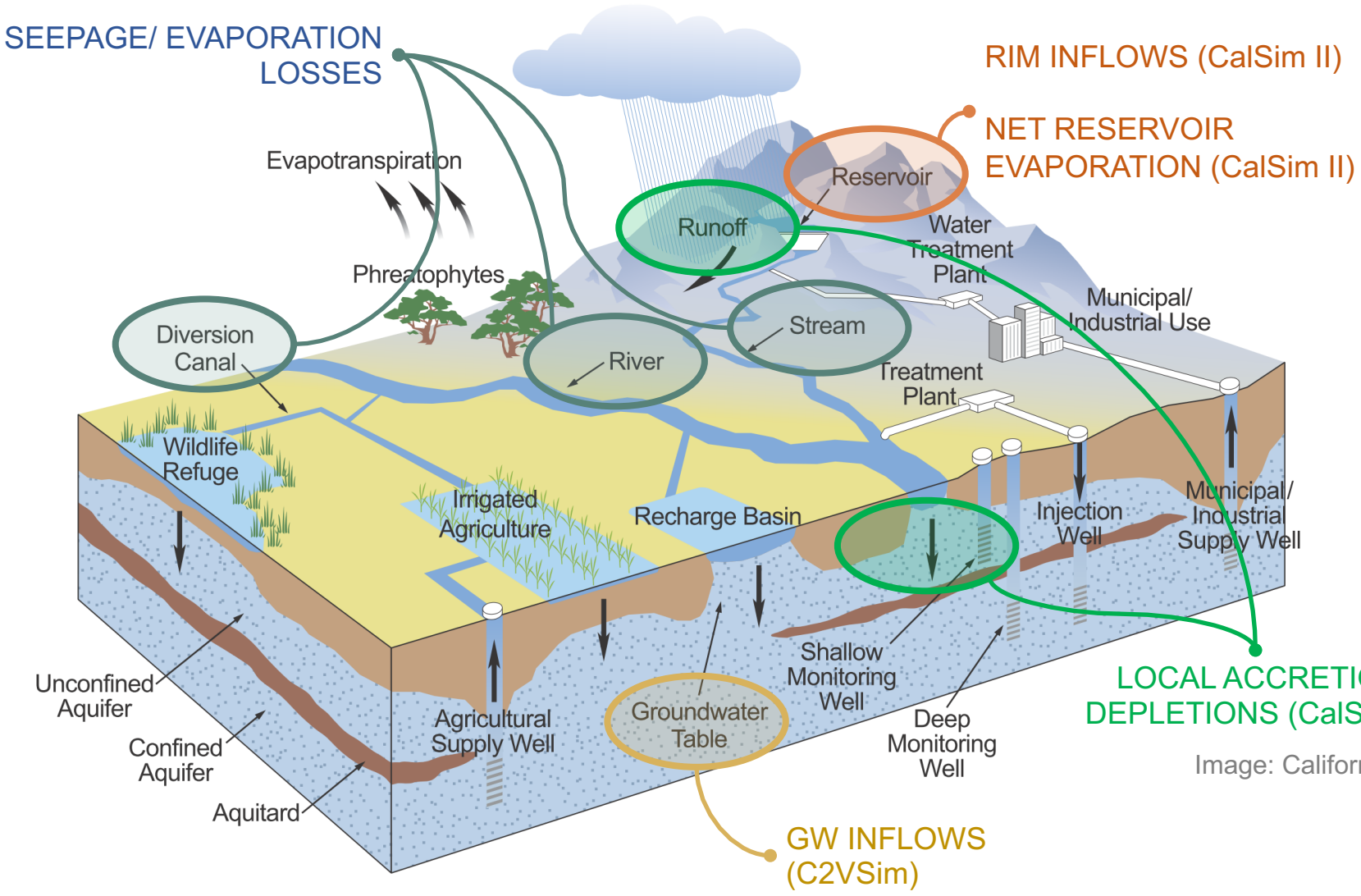


Image: California Water Plan Update 2013

Operating Cost

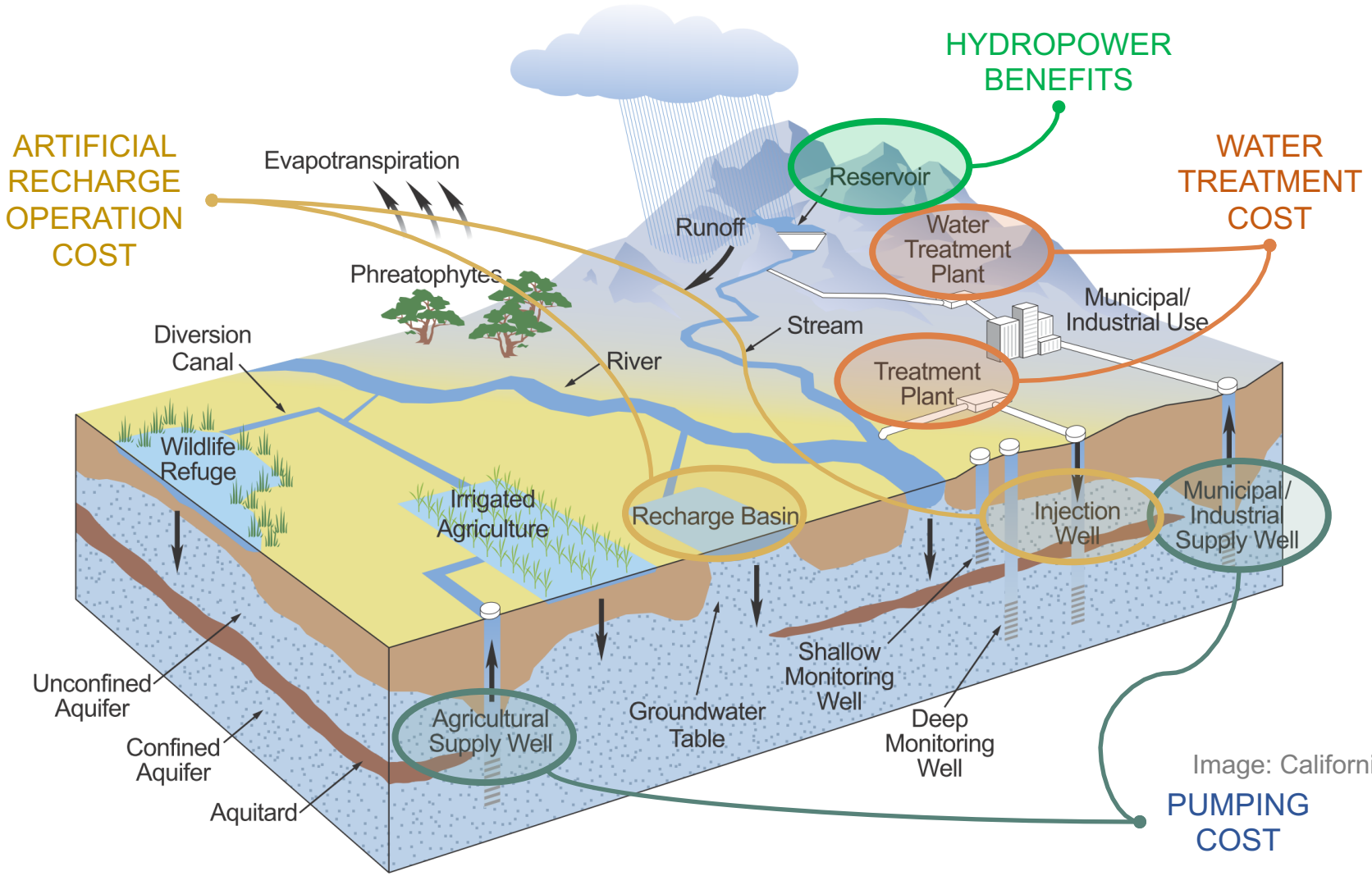
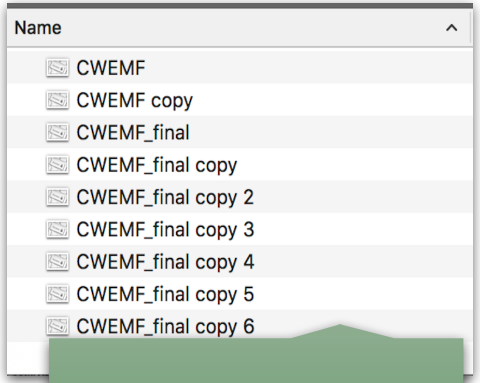


Image: California Water Plan Update 2013

PyVIN Model

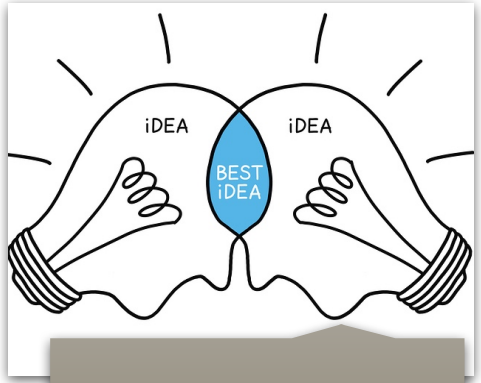
Goals

data transparency



version control

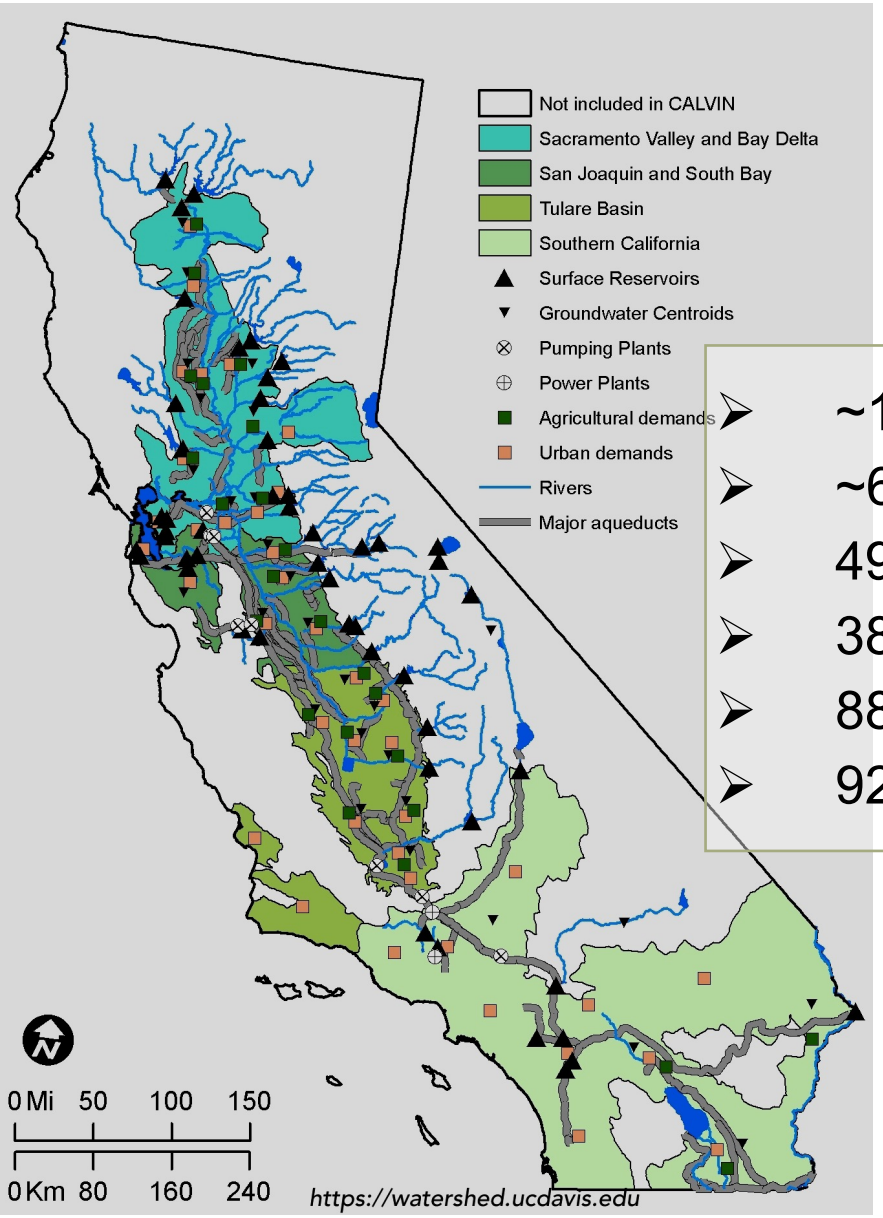
documentation



collaboration

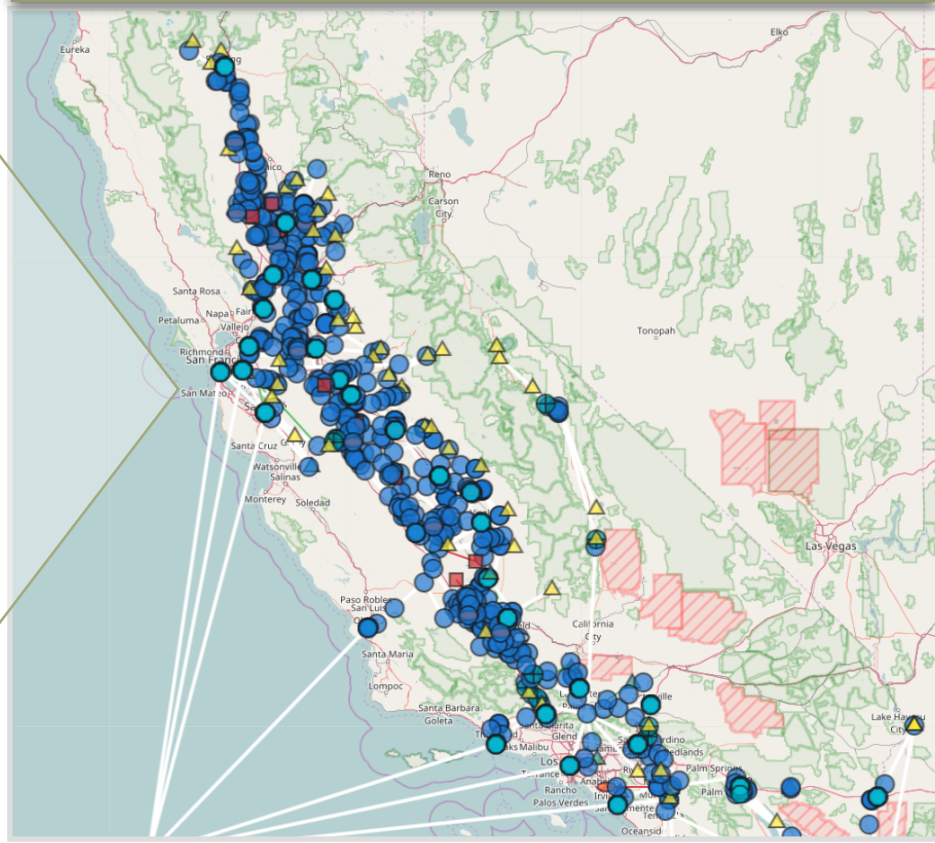
run speed

CALVIN



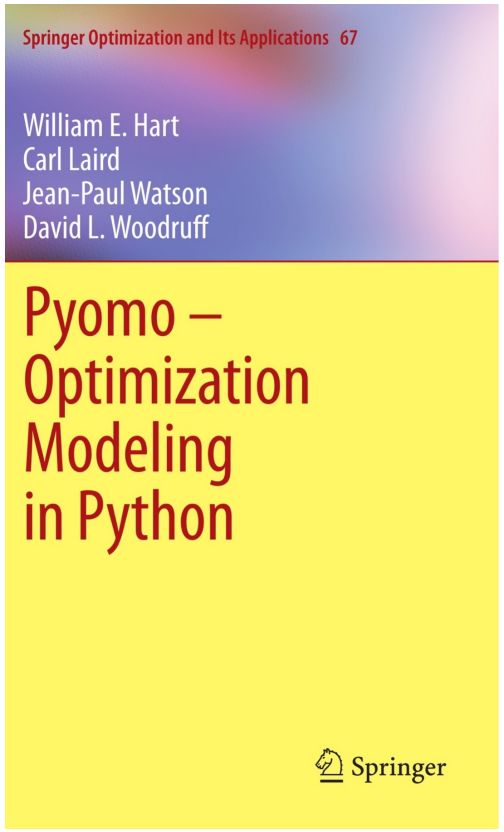
- ~1250 nodes
- ~600 conveyance links
- 49 surface reservoirs
- 38 groundwater reservoirs
- 88% of CA's irrigated acreage
- 92% of CA's urban population

HOBBES Database



https://cwn.casil.ucdavis.edu

Modeling Environment

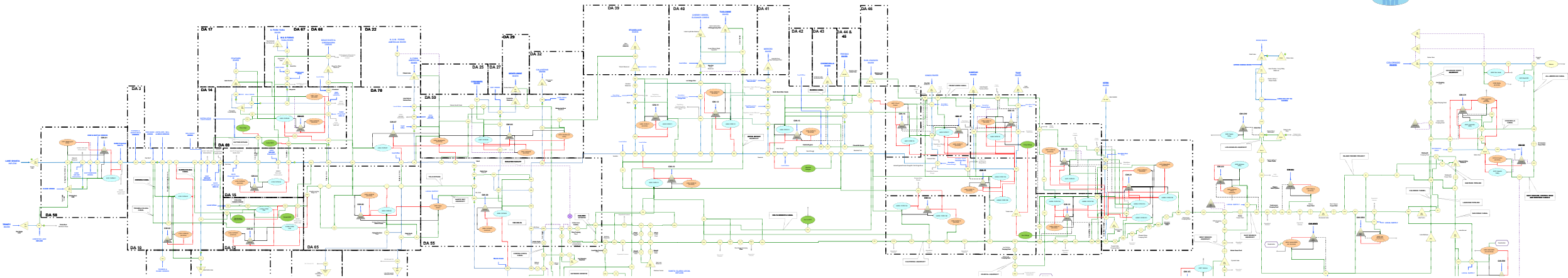


http://www.pyomo.org/documentation

- Pyomo is a Python-based, open-source optimization modeling language
- Algebraic language similar to GAMS, AMPL
- Easy to install: `"conda install -c cachemeorg pyomo"`
- User defined solvers:
  - `CPLEX`[1]
  - `GUROBI`[1]
  - `CBC`[2]
  - `GLPK`[2]

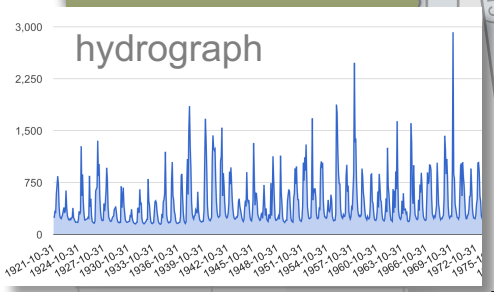
([1] free for academic purposes only, [2] open source)

CALVIN v.1	PyVIN v.2
Large-scale hydroeconomic model	
Optimize water allocation to agricultural and urban users	
Minimize statewide water scarcity and operating costs	
HEC-PRM and VBA based	Pyomo and Python based
Less flexible (limited to HEC-PRM)	More flexible (full LP)
Solver runtime: ~16 hr (depending on initial solution)	Solver runtime: ~1 min (depending on solver)
Requires 32 bit Windows PC	Any computer
HEC-DSS database	Open source: data and source code



HOBBES Matrix Creator

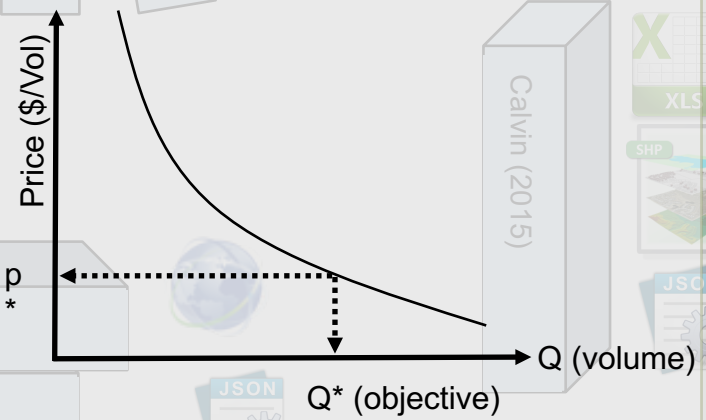
Time-series



Date	D94-SR-WHI
10/31/1921	203.00
11/30/1921	116.74
12/31/1921	53.68
01/31/1922	0.00
02/28/1922	0.00
03/31/1922	0.00
04/30/1922	0.00
05/31/1922	0.00
06/30/1922	0.00
07/31/1922	15.92
08/31/1922	0.00
09/30/1922	0.00
10/31/1922	0.00

+

Demand Curves



Data Matrix (PyVIN input)

i	j	k	cost	amplitude	lower_bound	upper_bound
HU402A.1965-05-31	CVPM14AG.1965-05-31	0	-1760	1	0	32.83
HU402A.1965-05-31	CVPM14AG.1965-05-31	1	-1619	1	0	2.98
HU402A.1965-05-31	CVPM14AG.1965-05-31	2	-1450	1	0	2.98
HU402A.1965-05-31	CVPM14AG.1965-05-31	3	-1199	1	0	2.99
HU402A.1965-05-31	CVPM14AG.1965-05-31	4	-927.5	1	0	2.98
HU402A.1965-05-31	CVPM14AG.1965-05-31	5	-782.2	1	0	2.99
HU402A.1965-05-31	CVPM14AG.1965-05-31	6	-720.7	1	0	2.98
HU402A.1965-05-31	CVPM14AG.1965-05-31	7	-614.8	1	0	2.99
HU402A.1965-05-31	CVPM14AG.1965-05-31	8	-500.4	1	0	2.98
HU402A.1965-05-31	CVPM14AG.1965-05-31	9	-224.2	1	0	2.98
HU402A.1965-06-30	CVPM14AG.1965-06-30	0	-1764	1	0	53.70
HU402A.1965-06-30	CVPM14AG.1965-06-30	1	-1618	1	0	4.88
HU402A.1965-06-30	CVPM14AG.1965-06-30	2	-1446	1	0	4.89
HU402A.1965-06-30	CVPM14AG.1965-06-30	3	-1202	1	0	4.88
HU402A.1965-06-30	CVPM14AG.1965-06-30	4	-926.6	1	0	4.88
HU402A.1965-06-30	CVPM14AG.1965-06-30	5	-784	1	0	4.88
HU402A.1965-06-30	CVPM14AG.1965-06-30	6	-719.9	1	0	4.88
HU402A.1965-06-30	CVPM14AG.1965-06-30	7	-615	1	0	4.89
HU402A.1965-06-30	CVPM14AG.1965-06-30	8	-499.9	1	0	4.88
HU402A.1965-06-30	CVPM14AG.1965-06-30	9	-223.9	1	0	4.88
HU402A.1965-07-31	CVPM14AG.1965-07-31	0	-1763	1	0	54.33

PyVIN Model Structure

1 Linear Programming Model with Gains & Losses

objective

$$\text{minimize } Z = \sum_i \sum_j \sum_k c_{ijk} \cdot X_{ijk}$$

mass balance

$$\sum_i \sum_j X_{ijk} = \sum_i \sum_j a_{ijk} \cdot X_{ijk} + b_j$$

upper bound

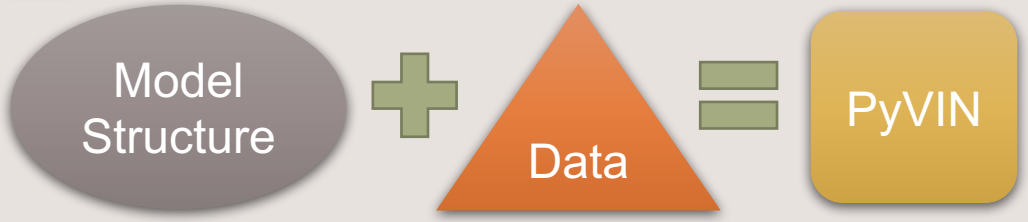
$$X_{ijk} \leq u_{ijk}$$

lower bound

$$X_{ijk} \geq l_{ijk}$$

where
Z: total cost
X: flow on the arc
c: unit cost (or penalty)
b: external flow
a: amplitude
l: lower bound
u: upper bound

2 Abstract Model in Pyomo



Separate data and model structure

3 Freely Available Solvers

- CPLEX
- CBC
- GUROBI
- GLPK

User installed and defined solvers
No dependency on any solver

PyVIN Run Process

HOBBES
- Input Data
  - Network matrix

Pyomo
- Model Run
  - Specify data file and solver

Python
- Postprocess Results
  - Analyze results stored in `*.csv` files

HOBBES
- Data Visualization
  - Time-series plots & animation

```
model = AbstractModel()

# Nodes in the network
model.N = Set()

# Network arcs
model.k = Set()
model.A = Set(within=model.N*model.N*model.k)

# Source node
model.source = Param(within=model.N)
# Sink node
model.sink = Param(within=model.N)
# Flow capacity limits
model.u = Param(model.A)
# Flow lower bound
model.l = Param(model.A)
# Link amplitude (gain/loss)
model.a = Param(model.A)
# Link cost
model.c = Param(model.A)

# The flow over each arc
model.X = Var(model.A, within=Reals)

# Minimize total cost
def total_rule(model):
    return sum(model.c[i,j,k]*model.X[i,j,k] for (i,j,k) in model.A)
model.total = Objective(rule=total_rule, sense=minimize)

# Enforce an upper bound limit on the flow across each arc
def limit_rule_upper(model, i, j, k):
    return model.X[i,j,k] <= model.u[i,j,k]
model.limit_upper = Constraint(model.A, rule=limit_rule_upper)

# Enforce a lower bound limit on the flow across each arc
def limit_rule_lower(model, i, j, k):
    return model.X[i,j,k] >= model.l[i,j,k]
model.limit_lower = Constraint(model.A, rule=limit_rule_lower)
```

PyVIN

Input

```
model = AbstractModel()

# Nodes in the network
model.N = Set()

# Network arcs
model.k = Set()
model.A = Set(within=model.N*model.N*model.k)

# Source node
model.source = Param(within=model.N)
# Sink node
model.sink = Param(within=model.N)
# Flow capacity limits
model.u = Param(model.A)
# Flow lower bound
model.l = Param(model.A)
# Link amplitude (gain/loss)
model.a = Param(model.A)
# Link cost
model.c = Param(model.A)

# The flow over each arc
model.X = Var(model.A, within=Reals)

# Minimize total cost
def total_rule(model):
    return sum(model.c[i,j,k]*model.X[i,j,k] for (i,j,k) in model.A)
model.total = Objective(rule=total_rule, sense=minimize)
```

pyvin.py

i	j	k	cost	amplitude	lower_bound	upper_bound
A101.2002-10-31	HU101.2002-	0	0	1	0	1E+12
A101.2002-11-30	HU101.2002-	0	0	1	0	1E+12
A101.2002-12-31	HU101.2002-	0	0	1	0	1E+12
A101.2003-01-31	HU101.2003-	0	0	1	0	1E+12
A101.2003-02-28	HU101.2003-	0	0	1	0	1E+12
A101.2003-03-31	HU101.2003-	0	0	1	0	1E+12
A101.2003-04-30	HU101.2003-	0	0	1	0	1E+12
A101.2003-05-31	HU101.2003-	0	0	1	0	1E+12
A101.2003-06-30	HU101.2003-	0	0	1	0	1E+12
A101.2003-07-31	HU101.2003-	0	0	1	0	1E+12
A101.2003-08-31	HU101.2003-	0	0	1	0	1E+12
A101.2003-09-30	HU101.2003-	0	0	1	0	1E+12
A102.2002-10-31	HU102.2002-	0	0	1	0	1E+12
A102.2002-11-30	HU102.2002-	0	0	1	0	1E+12
A102.2002-12-31	HU102.2002-	0	0	1	0	1E+12
A102.2003-01-31	HU102.2003-	0	0	1	0	1E+12
A102.2003-02-28	HU102.2003-	0	0	1	0	1E+12
A102.2003-03-31	HU102.2003-	0	0	1	0	1E+12
A102.2003-04-30						
A102.2003-05-31						

data.dat

Output

- water deliveries to users

flow.csv

- surface and groundwater storage

storage.csv

- cost of shortage to users and WTP for additional water

shortage cost.csv

- shadow prices of environmental flows

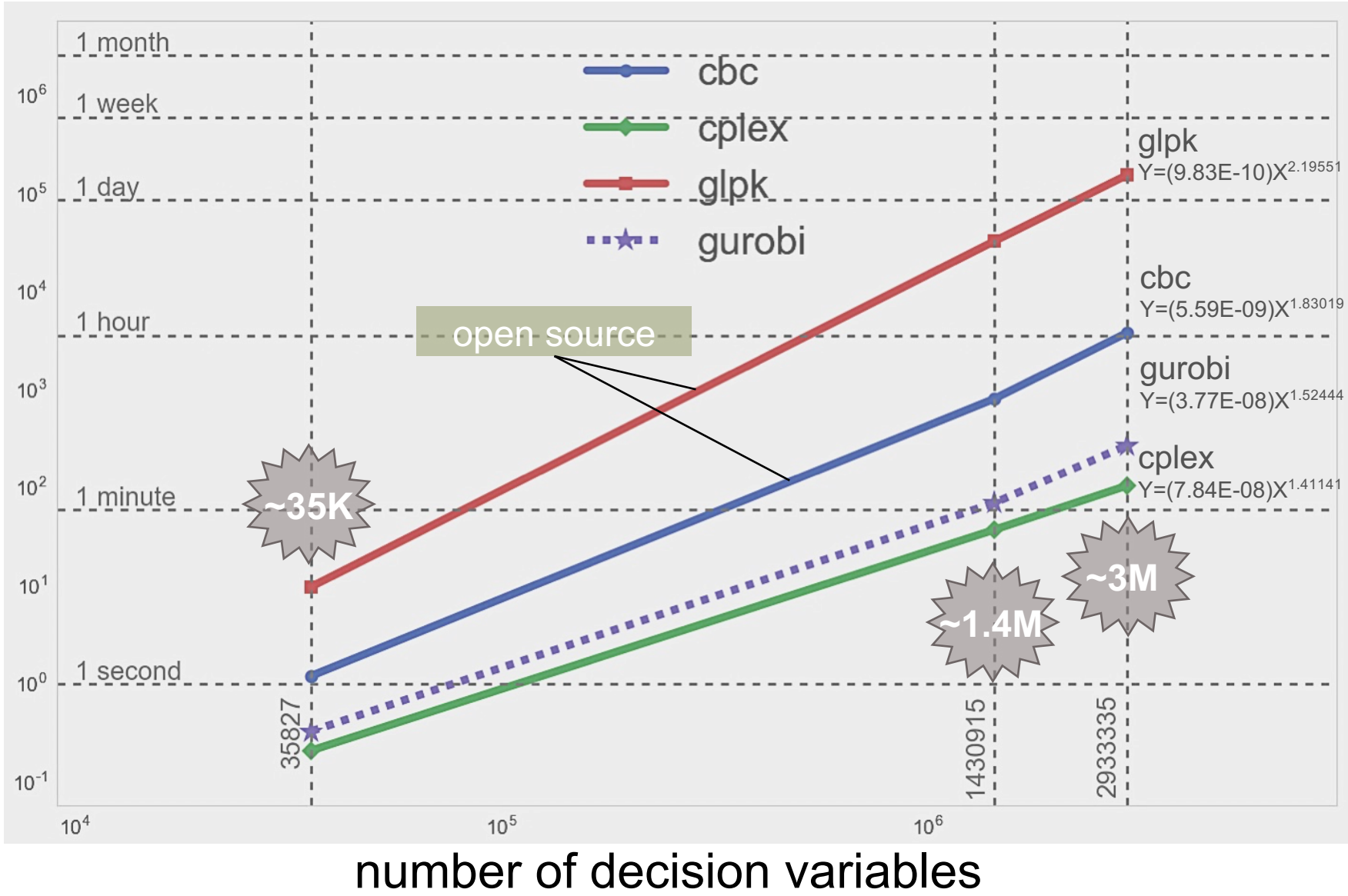
dual - lower bound.csv

- benefits of capacity expansion

dual - upper bound.csv

Solver Time

- Runs are performed on UC Davis College of Engineering's HPC1 (High Performance Computer)
- `cbc`, `cplex` and `gurobi` are run in parallel, and `glpk` is run in serial

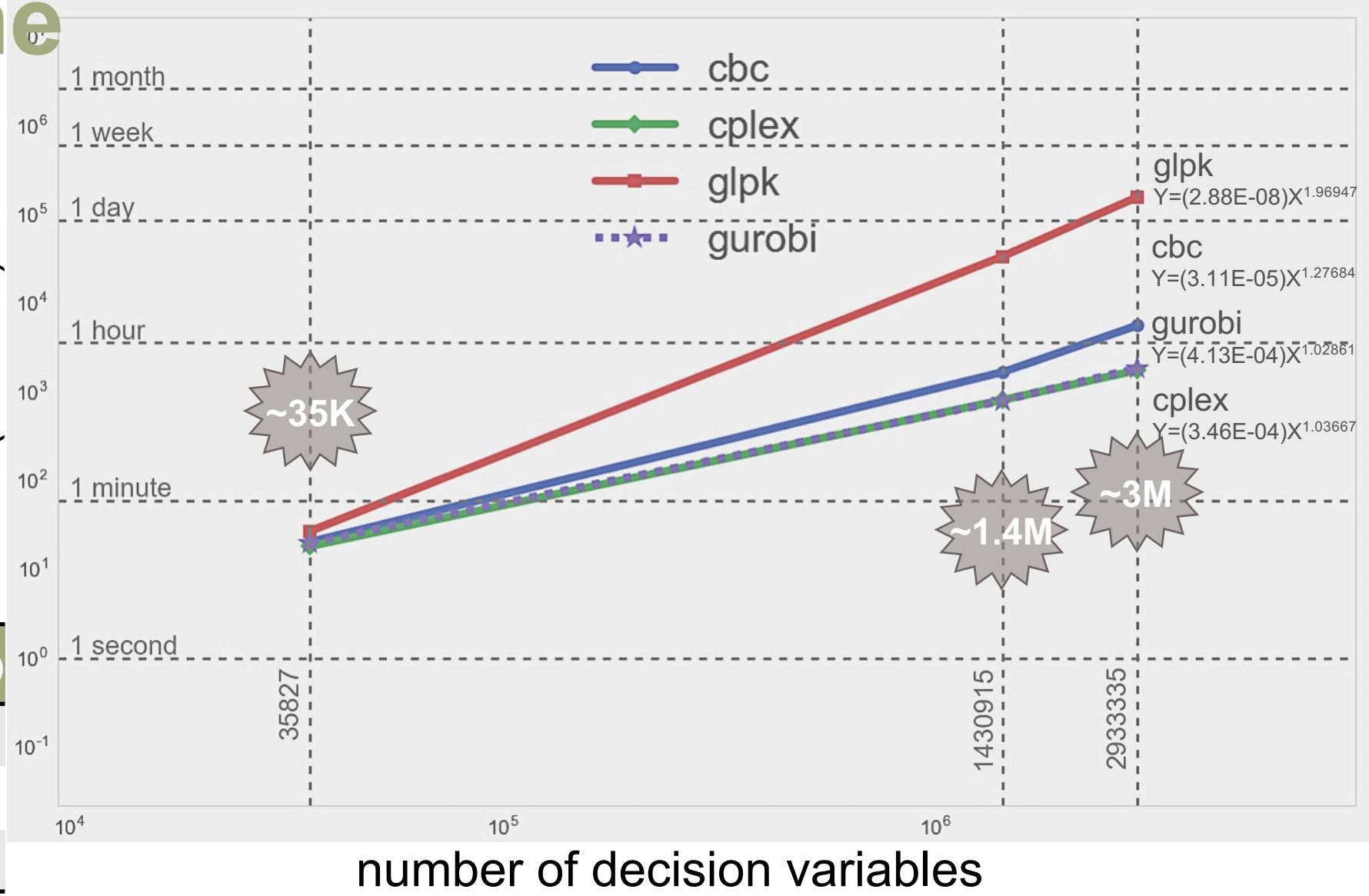


Total Runtime

Pyomo builds the model → Solver finds a solution → Pyomo writes results

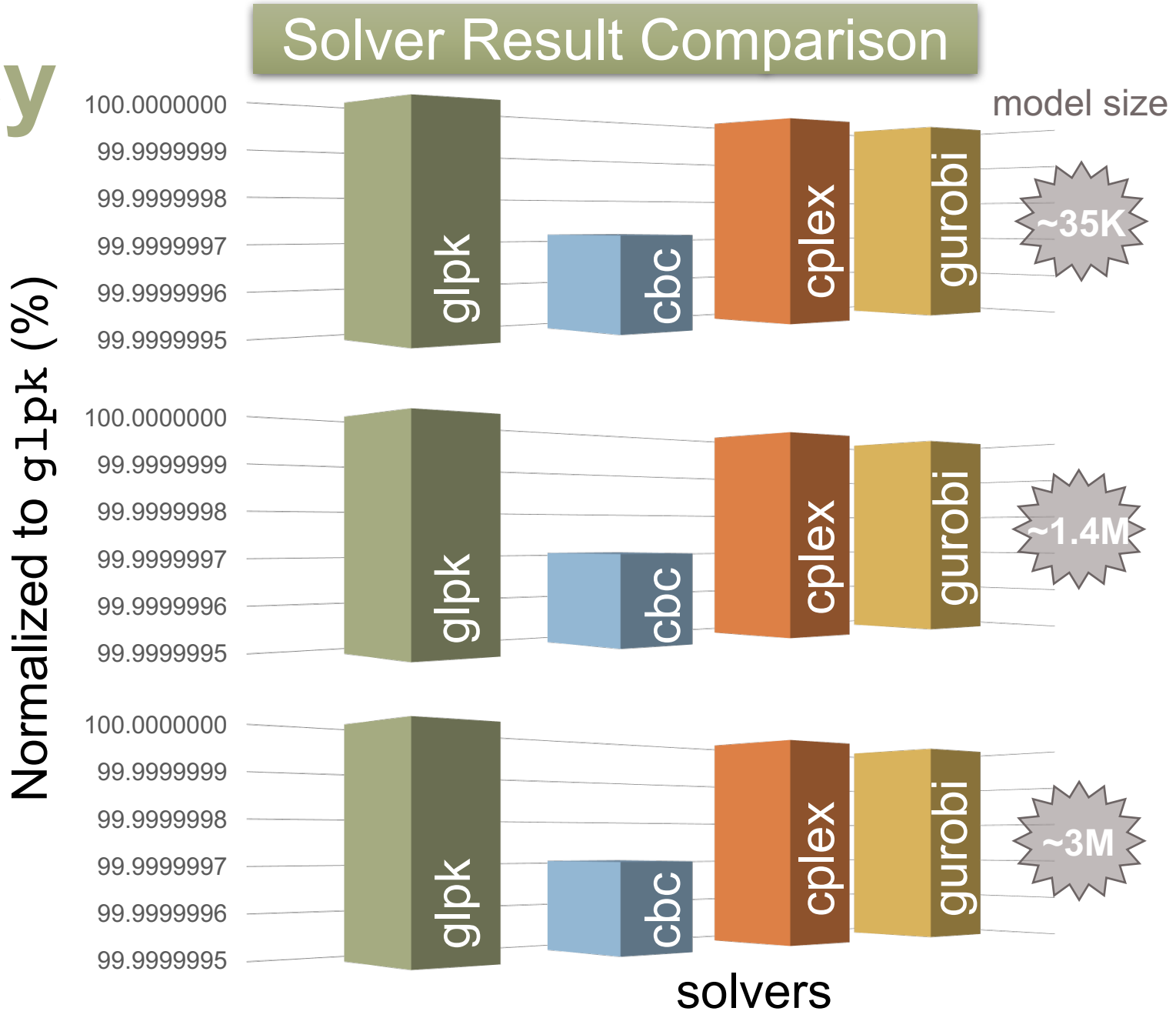
- Differences get bigger as model size increases
- `cplex` and `gurobi` have similar total runtime

# of decision variables	output file size (json)
35,827	~7.5 MB
1,430,915	~300 MB
2,933,335	~602 MB

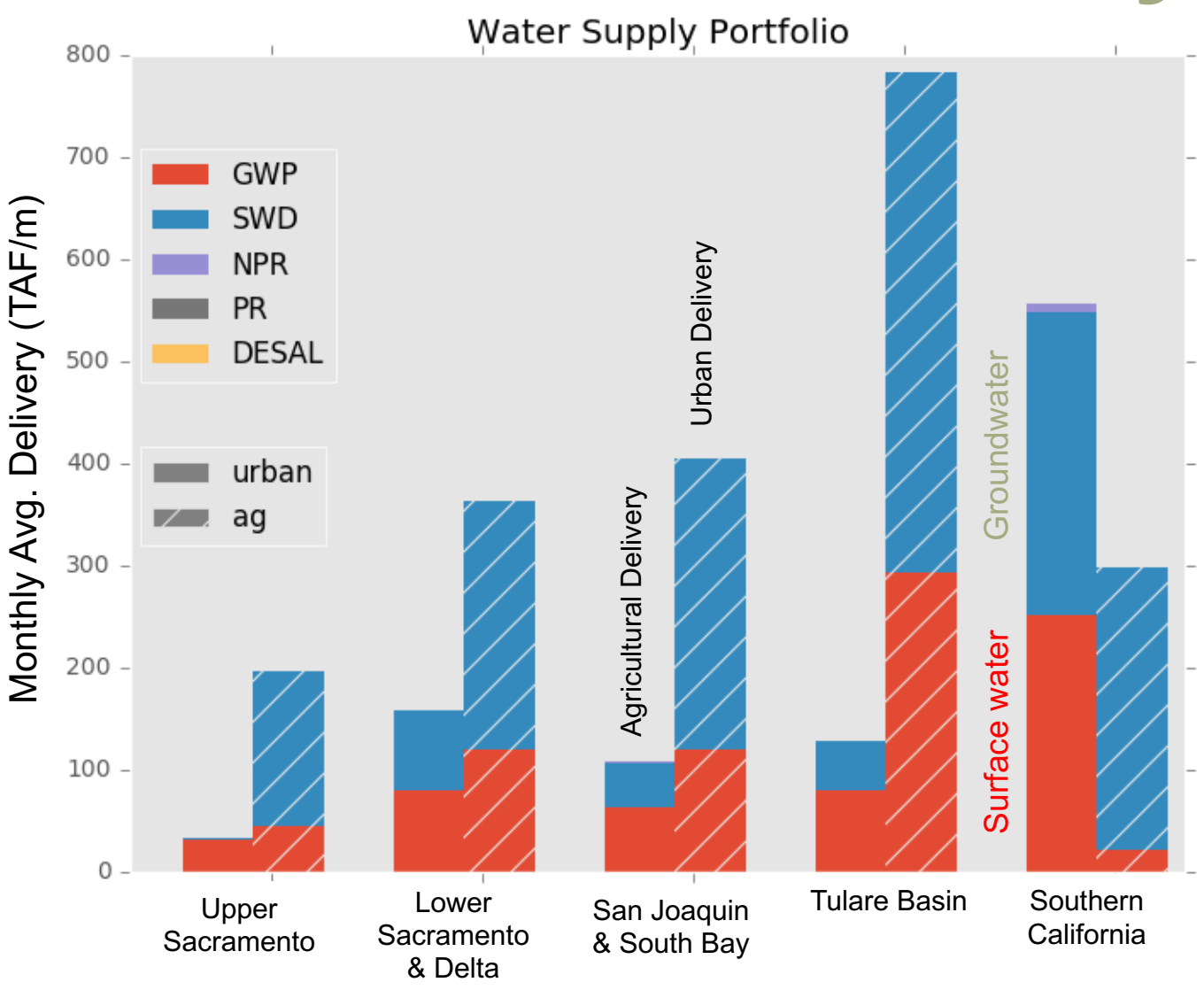


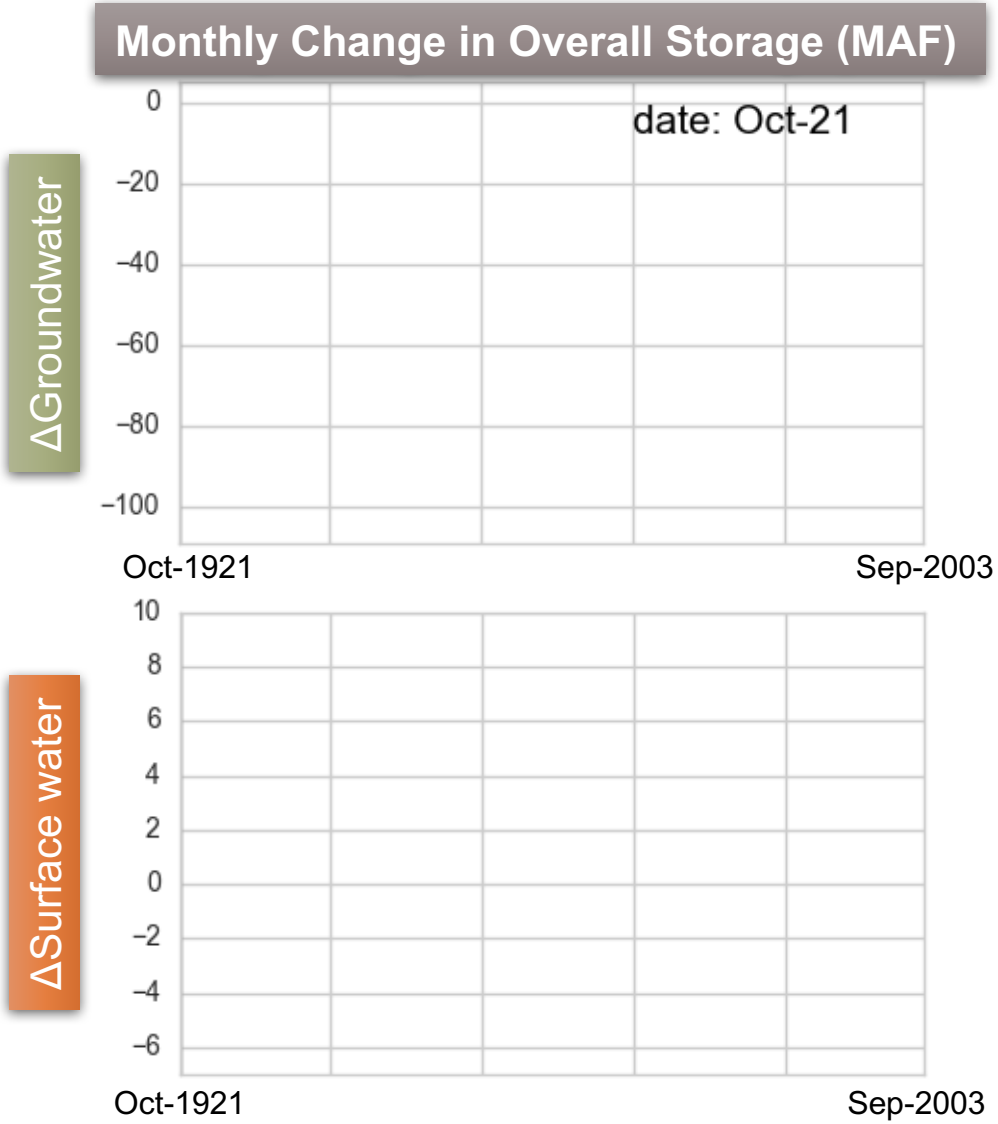
Solver Accuracy

- Objective value normalized to `glpk` results
- `cbc` results slightly lower
- Overall consistent solver results



Preliminary Results





Limitations & Improvements

- Perfect foresight
  - Run year-by-year to prevent perfect hydrologic foresight
- Groundwater representation
  - Implement SGMA constraints on groundwater basins
- Water rights
  - Represent water rights in system operations

Software Installation & Your 1st PyVIN run

- Anaconda3 or miniconda3 installed?
- Command line knowledge?
- GitHub account?

Structure File: `pyvin.py`

```
# Minimize total cost
def total rule(model):
        return sum(model.c[i ,j ,k]*model.X[i ,j ,k] for (i ,j ,k) in model.A)
model. total = Objective(rule=total rule , sense=minimize)
# Enforce an upper bound limit on the flow across each arc
def limit rule upper(model, i , j , k):
        return model.X[i ,j ,k] <= model.u[i ,j ,k]
model.limit upper = Constraint(model.A, rule=limit rule upper)
# Enforce a lower bound limit on the flow across each arc
def limit rule lower(model, i, j, k):
        return model.X[i,j,k] >= model.l[i,j,k]
model.limit lower = Constraint(model.A, rule=limit rule lower)
# Enforce flow through each node (mass balance)
        def flow rule(model, node):
        if node in [value(model.source), value(model.sink)]:
        return Constraint . Skip
        outflow = sum(model.X[i ,j ,k]/model.a[i ,j ,k] for i ,j ,k in model.A)
        inflow = sum(model.X[i,j,k] for i,j,k in model.A)
        return inflow == outflow
model.flow = Constraint(model.N, rule=flow rule)
```

objective

$$\text{minimize } Z = \sum_i \sum_j \sum_k c_{ijk} \cdot X_{ijk}$$

upper bound

$$X_{ijk} \leq u_{ijk}$$

lower bound

$$X_{ijk} \geq l_{ijk}$$

mass balance

$$\sum_i \sum_j X_{ijk} = \sum_i \sum_j a_{ijk} \cdot X_{ijk} + b_j$$

outflow inflow

Data File: `data.dat`

```
set N :=
INITIAL SR SHA.1983−10−31 SR SHA.1983−11−30
FINAL
INFLOW.1983−10−31
INFLOW.1983−11−30;

set k := 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15;

param source := SOURCE; param sink := SINK;

param: A: c a l u :=
SOURCE INITIAL 0 0 1 0 10000000
INITIAL SR SHA.1983−10−31 0 0 1 3686.84 3686.84
SR SHA.1983−10−31 SR SHA.1983−11−30 0 −7.003 0.997
SR SHA.1983−10−31 SR SHA.1983−11−30 1 −2.974 0.997
SR SHA.1983−10−31 SR SHA.1983−11−30 2 −1.466 0.997
SR SHA.1983−11−30 SR SHA.1983−12−31 0 −6.972 0.999
SR SHA.1983−11−30 SR SHA.1983−12−31 1 −3.056 0.999
SR SHA.1983−11−30 SR SHA.1983−12−31 2 −1.479 0.999
```

List of nodes

Number of piecewise pieces

Identify `SOURCE` and `SINK` (no mass balance calculation)

- Links with parameters
- TAB separated
- Order:

`i j k cost amplitude lower_bound upper_bound`

Historical Case Example Run

- Go to folder "`/CALVIN-PyVIN Shortcourse/Run Folder/base case/`"
- Take a look at `pyvin.py` (right click, don't run) and `data.dat`
- Open command line and change directory to run folder

```
cd \path\to\folder
```

- `Run the model command:`

```
pyomo solve --solver=glpk --solver-suffix=dual pyvin.py
data.dat -- stream-solver --report-timing --json
```

Postprocessing Results

Running Postprocessors

- Copy all postprocessors to run folder (where `results.json` is generated)
- Run `postprocess.py`
- Run `aggregate_regions.py`
- Run `supply portfolio hatchedbarplot.py`
- Should you have any problem with running postprocessors, results are saved under ”`output`” folder.