

Seasonal to Inter-Annual Streamflow Simulation and Forecasting on the Upper Colorado River Basin and Implications for Water Resources Management

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M.S. Candidate

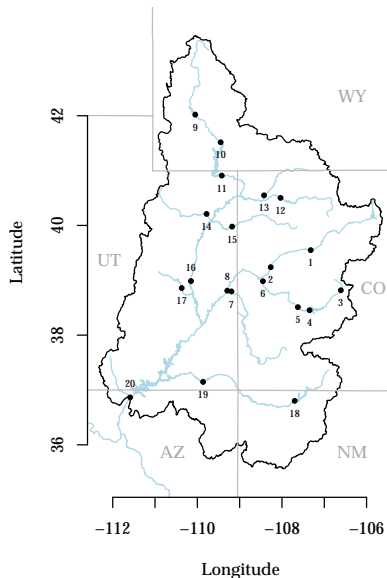
Advised by Prof. Balaji Rajagopalan and Prof. Edith Zagona

September 21, 2011

OUTLINE

- ▶ Intro and Background
- ▶ Seasonal Forecasts
- ▶ Hidden Markov Models
 - ▶ Annual Simulations
 - ▶ Two Year Forecasts
- ▶ Stochastic Reservoir Ops Model

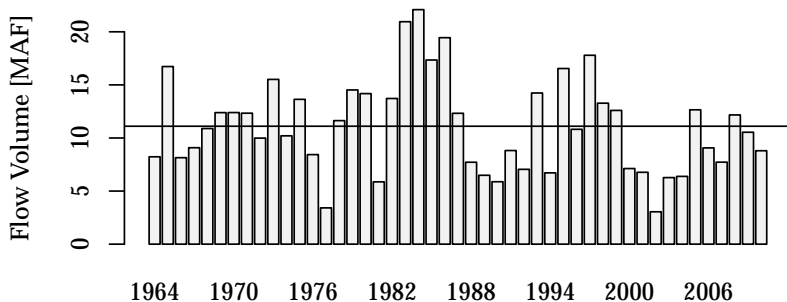
STUDY AREA



- ▶ Parts of five states with an area of 279,300 mi².
- ▶ Elevations ranging from 4000 to 14,200 ft.
- ▶ Nearly 80% of the streamflow in the UCRB is due to snowmelt during the Apr-July period.
- ▶ 19 important gages in the Upper Colorado River Basin.
 - ▶ Lees Ferry and three main tributaries

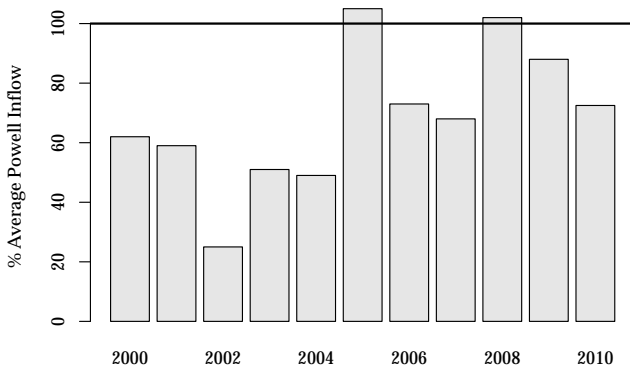
MOTIVATION

- ▶ The recent dry period (2000-2010) in the Upper Colorado River Basin (UCRB).
- ▶ Lowest inflows in Lake Powell since filling.



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WHY IS SKILLFUL LONG LEAD FORECASTING IMPORTANT?

- ▶ Flood control
- ▶ Drought mitigation
- ▶ Municipal and agricultural water supply
- ▶ Recreation
- ▶ Trans-basin diversions
- ▶ Hydropower
- ▶ E-flows
- ▶ ...

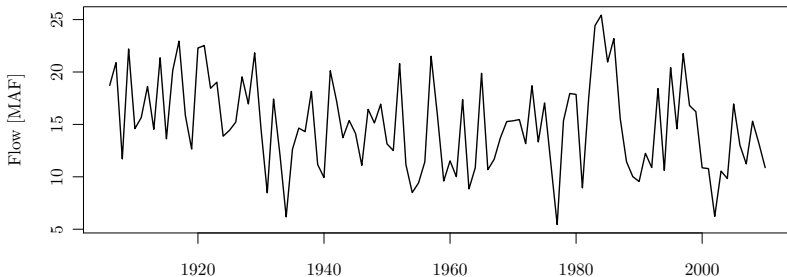
SECOND YEAR

- ▶ Decisions for Powell are made annually
- ▶ Annual Operating Plan, August
- ▶ Project Equalization

| Lake Powell | | |
|--------------------------|--|--------------------------|
| Elevation (feet) | Operation According to the Interim Guidelines | Live Storage (maf) |
| 3,700 | Equalization Tier Equalize, avoid spills or release 8.23 maf  | 24.3 |
| 3,646.26 | | 16.75 |
| 1/1/12 Projection | Upper Elevation Balancing Tier² Release 8.23 maf; if Lake Mead < 1,075 feet, balance contents with a min/max release of 7.0 and 9.0 maf | 1/1/12 Projection |
| 3,575 | Mid-Elevation Release Tier Release 7.48 maf; if Lake Mead < 1,025 feet, release 8.23 maf | 9.5 |
| 3,525 | Lower Elevation Balancing Tier Balance contents with a min/max release of 7.0 and 9.5 maf | 5.9 |
| 3,490 | | 4.0 |
| 3,370 | | 0 |

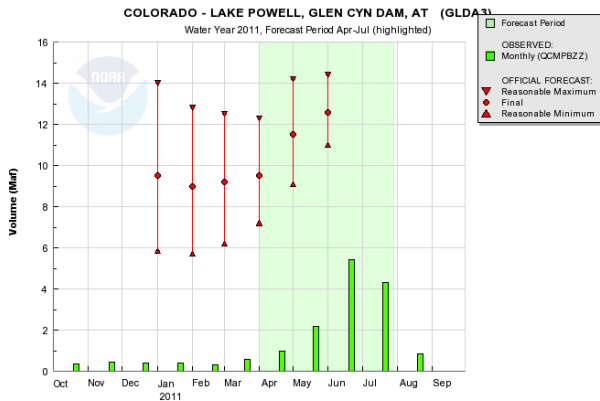
WHY IS SKILLFUL LONG LEAD FORECASTING DIFFICULT?

- ▶ Highly variable
 - ▶ Low autocorrelation
- ▶ Highly seasonal/ Very dependent on snowpack
 - ▶ Nearly 80% of flow occurs in April-July.
- ▶ Very dependent on snowpack



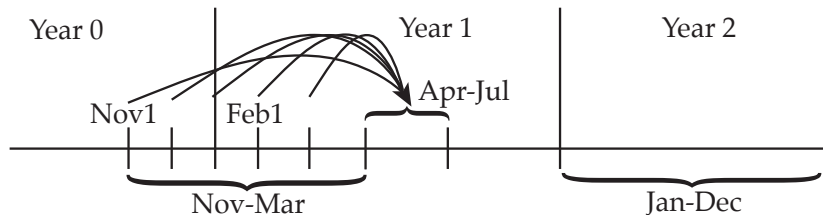
CURRENT FORECASTING

- ▶ Current forecasts are made using snowpack and soil conditions (and some climate information).
 - ▶ ESP + SWS + expertise = Coordinated Forecast
 - ▶ First peak season forecasts made starting in January
 - ▶ No second year forecast



FORECASTING GOALS

- ▶ Skillful Seasonal Flow forecasts
- ▶ Skillful Second year forecasts
- ▶ Earlier lead times than current operational forecast
- ▶ Ensemble Forecasts



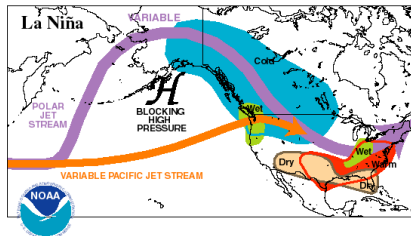
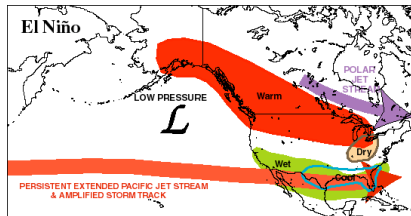
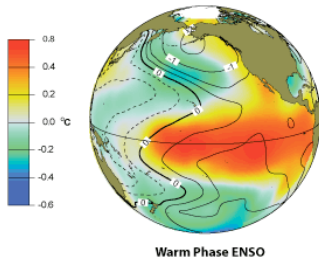
LARGE-SCALE CLIMATE INFLUENCE ON BASIN-SCALE HYDROLOGY

How can skillful predictions be made
in the earlier in the winter/spring
season when snowpack data is
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LARGE-SCALE CLIMATE INFLUENCE ON BASIN-SCALE HYDROLOGY

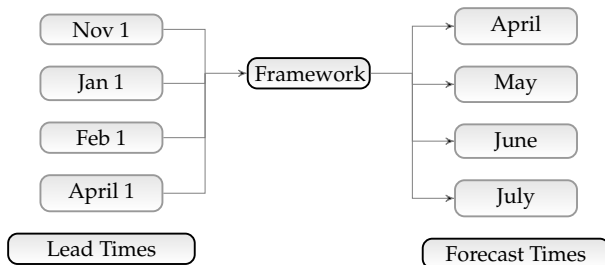
How can skillful predictions be made in the earlier in the winter/spring season when snowpack data is unavailable or incomplete?

Large-scale climate variables can be used as predictors of peak season streamflow [Grantz et. al. 2005]
[Regonda et. al. 2006].



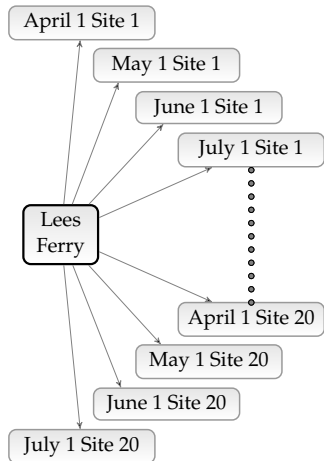
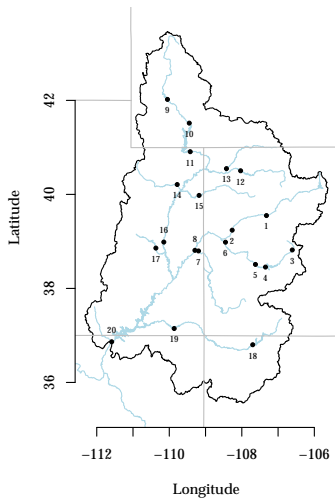
ORIGINAL STUDY

Bracken et al. 2010 demonstrated the feasibility of simultaneously forecast many spatial locations while preserving spatial dependencies.



- Predictors are: PDSI, SST, Zonal/Meridional Winds, Geopotential Height, SWE

DISAGGREGATION

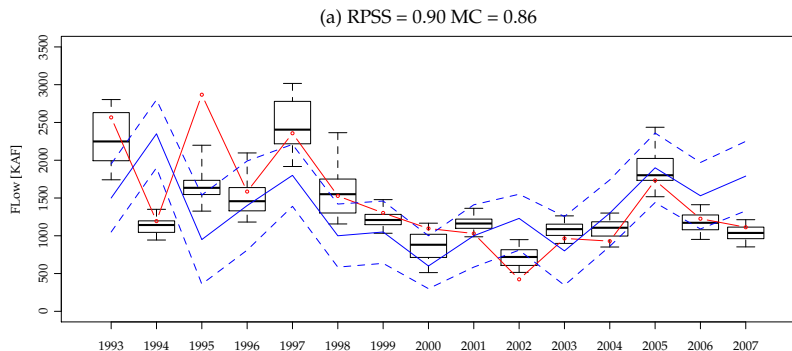


Useful for input to other models

SEASONAL FORECAST RESULTS: CROSS-VALIDATION

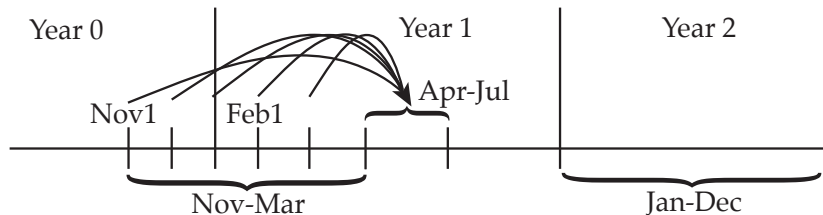
| Validation mode | apr1 | feb1 | jan1 | nov1 |
|-----------------|------|------|------|------|
| Leave-one | 0.85 | 0.74 | 0.49 | 0.30 |
| Retroactive | 0.62 | 0.58 | 0.55 | 0.52 |

Table: Lees Ferry total flow forecast skills



TWO YEAR FORECASTS

1. Poor/missing climate/snowpack information
2. A logical step is to use time series methods, ARMA, KNN, MC, frequency Domain Methods
3. Goal to make predictions of the following (second) year seasonal flow.



TWO YEAR FORECASTS

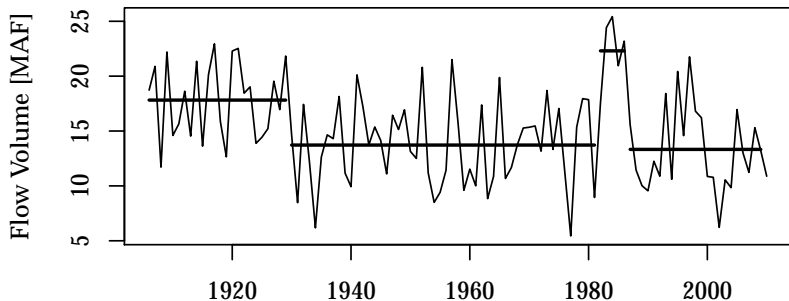
“Lees Ferry (Natural Flow) series is a time series modeler’s nightmare”

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TWO YEAR FORECASTS

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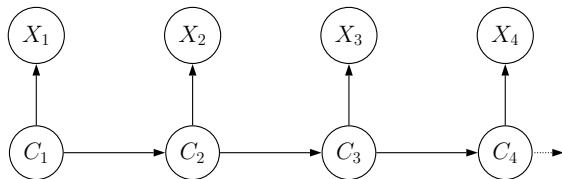
Regime switching behavior.

HIDDEN MARKOV MODELS

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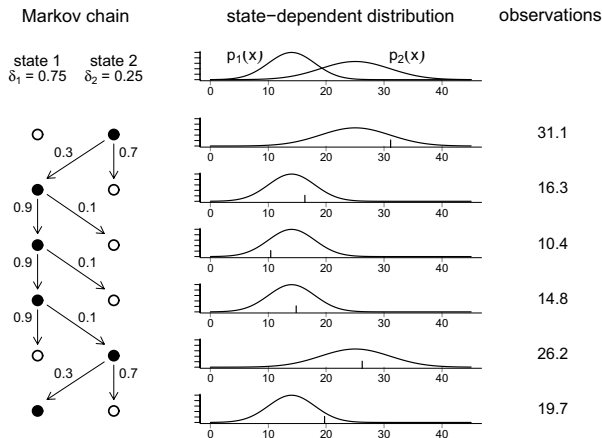
$$\Pr(C_t | \mathbf{C}^{(t-1)}) = \Pr(C_t | C_{t-1}), t = 2, 3, \dots$$

$$\Pr(X_t | \mathbf{X}^{(t-1)}, \mathbf{C}^{(t)}) = \Pr(X_t | C_t), t \in \mathbb{N}$$



1. General time series model
2. Markov process determines 'hidden' state, state dictates component distribution
3. A model that includes discrete states makes intuitive sense given the concept of climate regimes (such as El Niño)

HIDDEN MARKOV MODELS



Flexibility over explicit MC states.

PARAMETERS

Model Order

 m

Distribution parameters

Gamma- β_i, k_i Normal - μ_i, σ_i

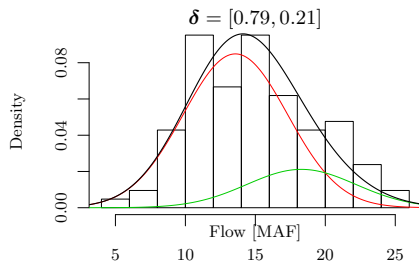
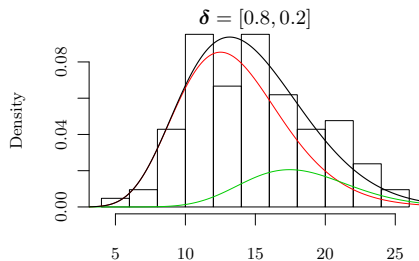
Transition Probabilities

$$\Gamma = \begin{bmatrix} \gamma_{11} & \cdots & \gamma_{1m} \\ \vdots & \ddots & \vdots \\ \gamma_{m1} & \cdots & \gamma_{mm} \end{bmatrix}$$

Stationary Distribution

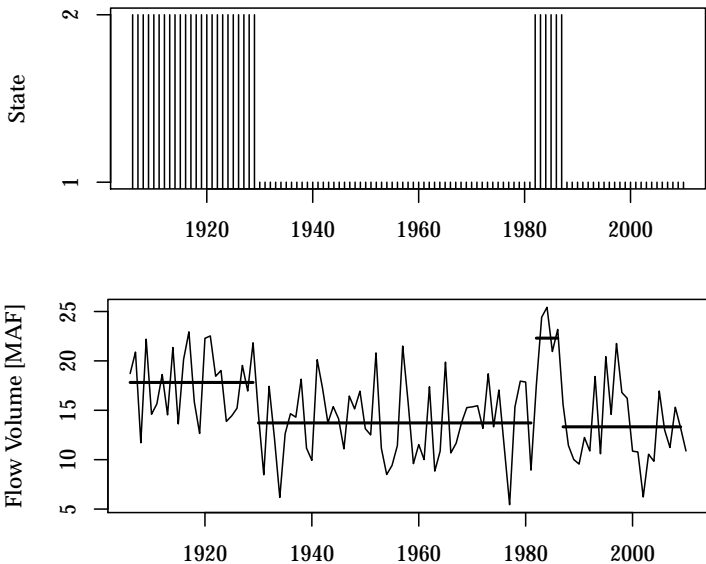
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LEES FERRY HMM



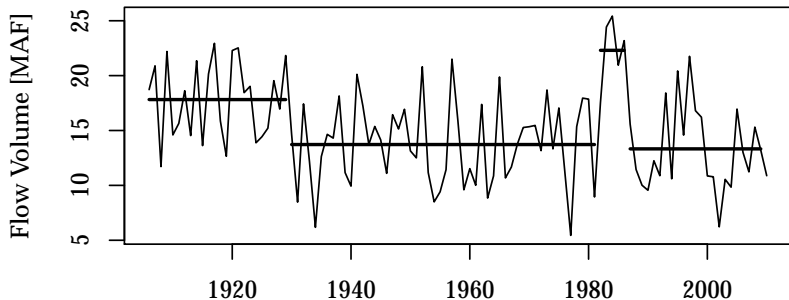
| Model | BIC | AIC |
|-------|--------|--------|
| HM2G | 621.34 | 605.42 |
| HM2N | 620.91 | 604.98 |
| HM3G | 647.26 | 615.42 |
| HM3N | 643.73 | 611.89 |

GLOBAL DECODING

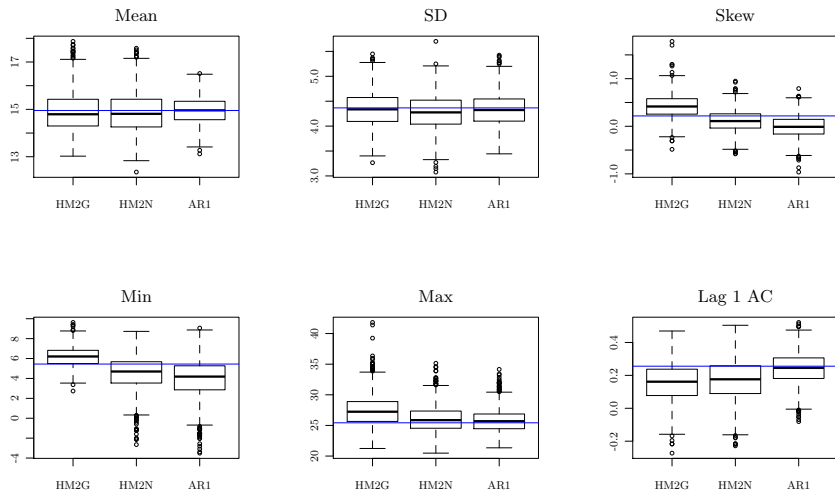


HIDDEN MARKOV MODELS FOR SIMULATION

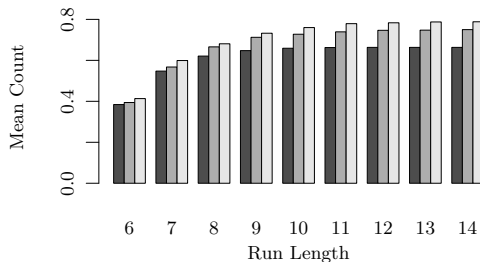
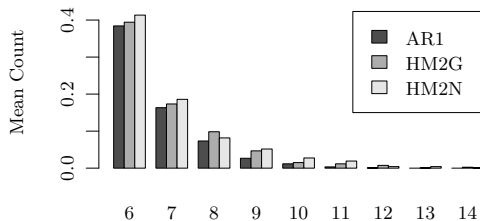
- ▶ HMMs are also useful for simulation (used in risk analysis).
- ▶ Alternative to AR simulations
- ▶ Can we capture longer period variability?



SIMULATION STATISTICS



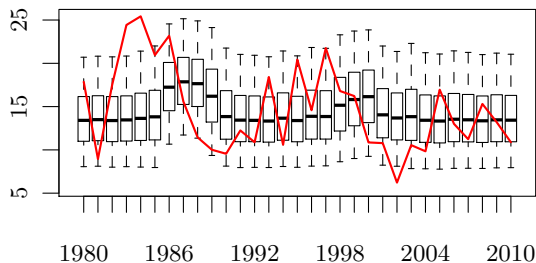
SIMULATED SPELL LENGTHS



HMMs can capture longer spells than AR models.

HMM FORECASTING

| Model | MC | RPSS | Dry RPSS | Ave RPSS | Wet RPSS |
|-------|------|-------|----------|----------|----------|
| HM2G | 0.31 | 0.21 | 0.26 | -0.11 | 0.05 |
| HM2N | 0.24 | 0.17 | 0.20 | 0.11 | 0.08 |
| AR1 | 0.07 | -0.03 | 0.07 | -0.03 | -0.25 |



DECISION-SUPPORT MODEL

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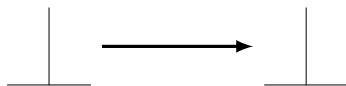
- ▶ A forecast is only as good as the decisions it is used to make
- ▶ Decision support models aid in the decision making process

CURRENT OPERATIONAL MODELING

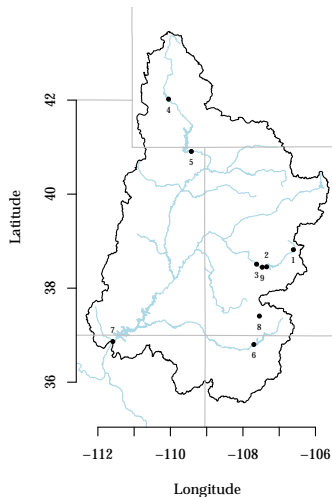
9 Upper Basin Reservoirs

The 24 Month Study

- ▶ Single trace
- ▶ Outflows are input
- ▶ Deterministic output



- ▶ Run monthly since late 90's

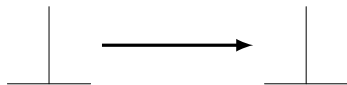


CURRENT OPERATIONAL MODELING

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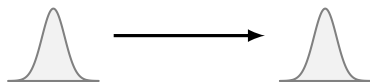
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Midterm Operations Model

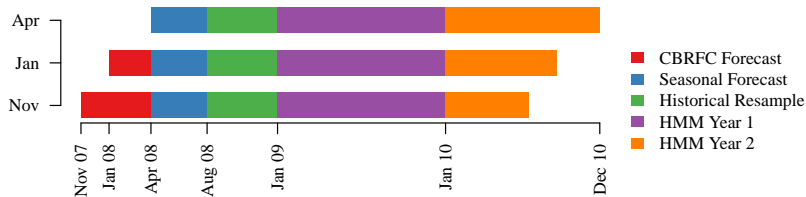
- ▶ Arbitrary number of traces
- ▶ Outflows computed on-the-fly
- ▶ Probabilistic output



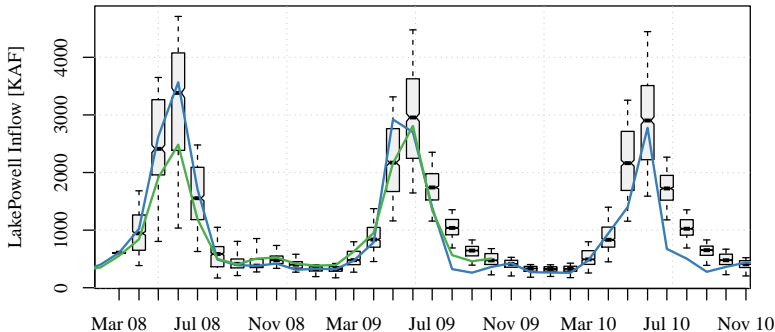
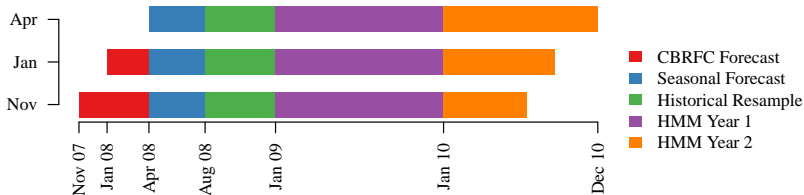
- ▶ In development since Early 2009

EXPERIMENTAL SETUP

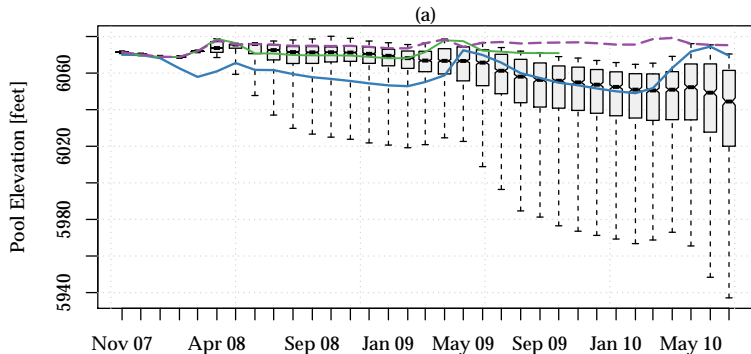
- ▶ Combine seasonal and two year forecasts
- ▶ Must run at a recent time because operations change
- ▶ Three lead times



EXPERIMENTAL SETUP



SAMPLE RESULTS - NAVAJO POOL ELEVATION



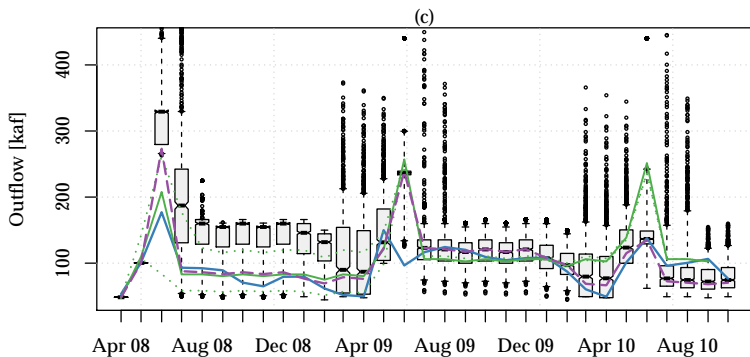
Blue - Observed

Green - 24MS

Purple - Control Run

Boxplots - Midterm Model

SAMPLE RESULTS - FLAMING GORGE OUTFLOW



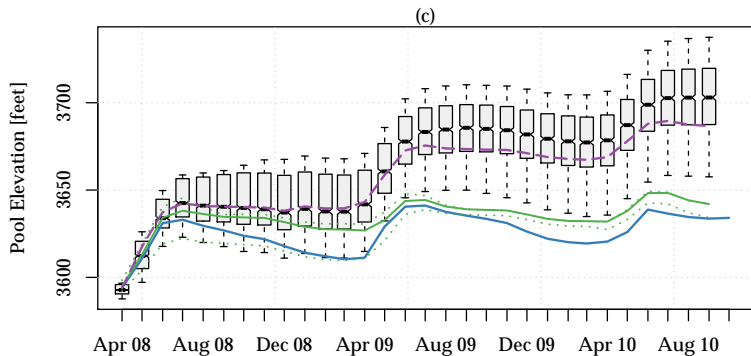
Blue - Observed

Green - 24MS

Purple - Control Run

Boxplots - Midterm Model

SAMPLE RESULTS - POWELL POOL ELEVATION



Blue - Observed

Green - 24MS

Purple - Control Run

Boxplots - Midterm Model

CONCLUSIONS

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- ▶ Long lead seasonal forecast model using large scale climate info
- ▶ Hidden Markov model for simulation and second year forecasts
 - ▶ Persistence is not the same as autocorrelation
- ▶ Forecasts combined as input to a new probabilistic operations model for the Colorado River Basin