Sustainable Reservoir Operation and Control Using a Deep Reinforcement Learning Policy Gradient Method

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Reservoir Operation Problem and Complexities

Reservoir Operation Problem

- Specify the optimal amount of water to be released from the reservoir at any time

Problem Complexities

- High degrees of short- and long-term hydrologic variabilities
- Multipurpose operating complexities
- Stochasticity
- Nonconvexity
- Nonlinearity
- Dimensionality

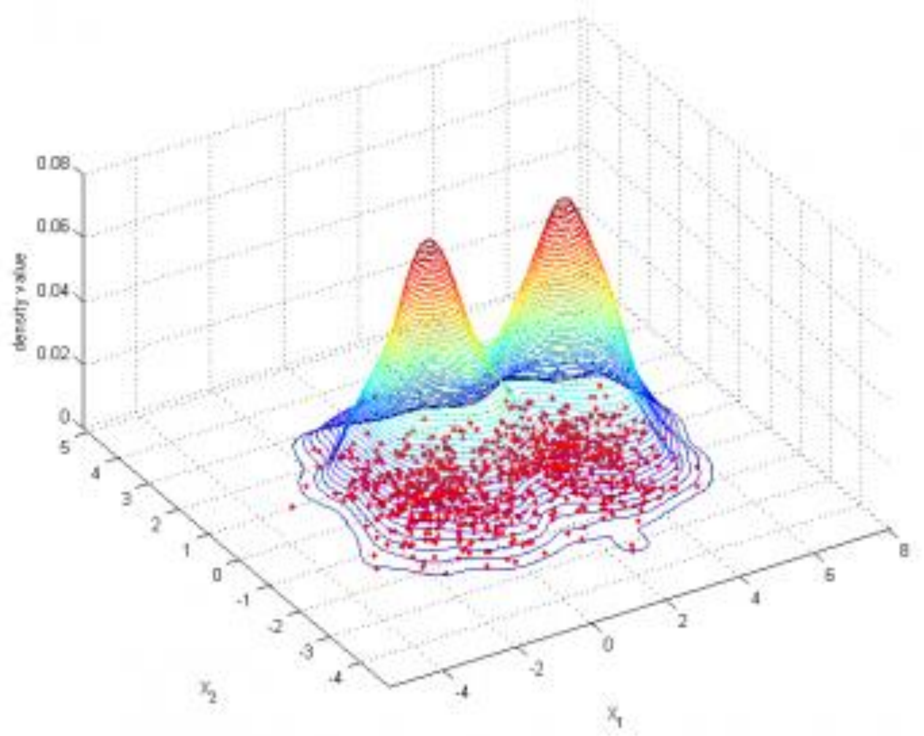
Folsom Reservoir, CA, US.

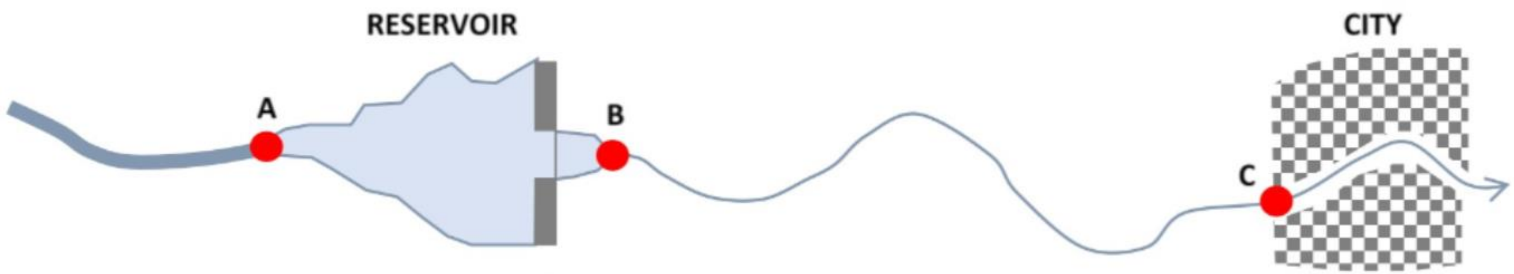
Well-known techniques to Solve Reservoir Operation Problem

- ➢ Dynamic Programming (DP)
- ➢ Stochastic DP (SDP)

Issues

- Curse of Modeling
- Curse of Dimensionality





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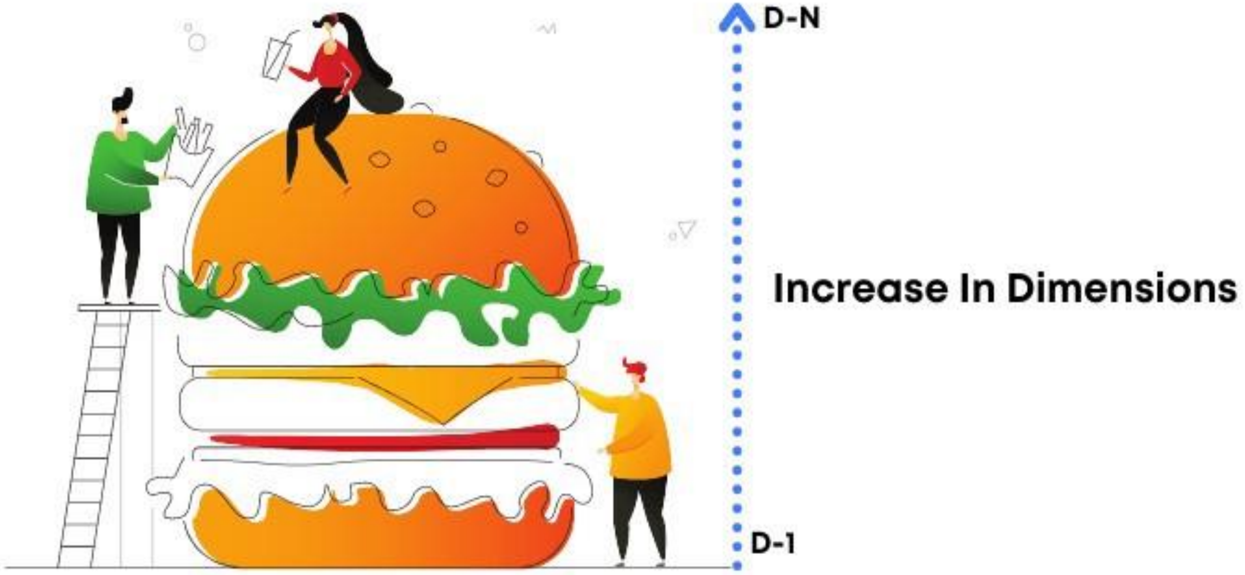
Traditional Solutions to Overcome Curse of Dimensionality

- ➢ Successive Approximations DP
- ➢ Incremental DP
- ➢ Differential DP
- ➢ Problem-specific heuristics



Issue

- Designed primarily for deterministic problems

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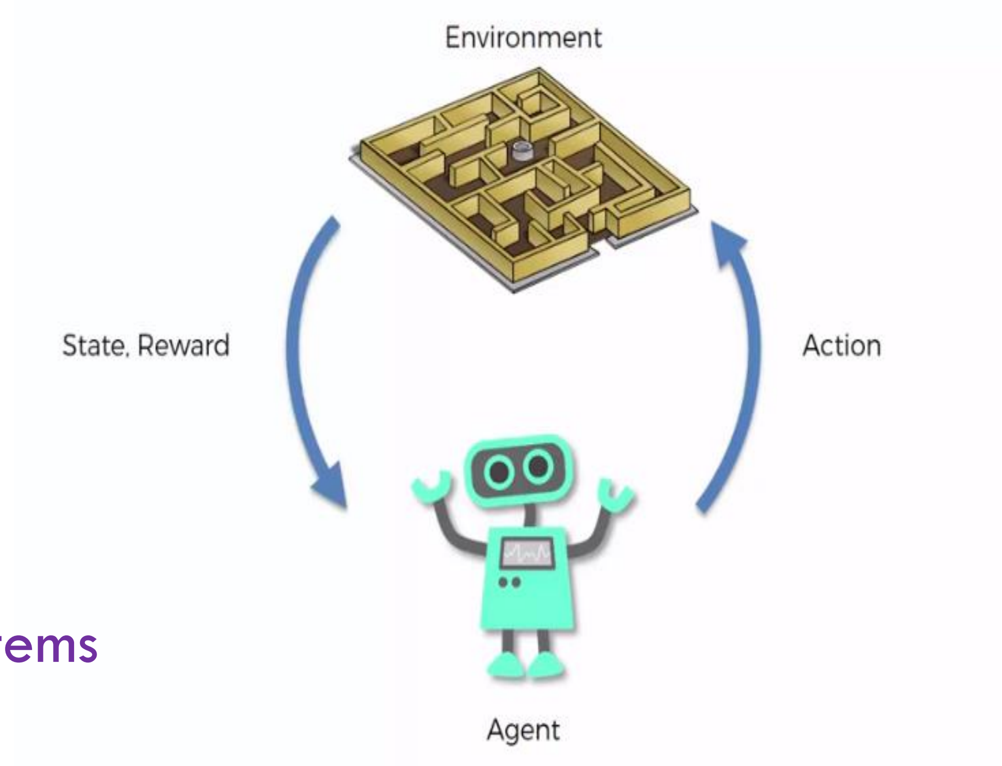
Deep Reinforcement Learning



➢ Deep Reinforcement Learning

- Leveraging deep neural networks (DNNs) for function approximation

➢ Benefits

- No need for discretizing state and action spaces
- Addressed well the curse of dimensionality
- Potential to capture hard-to-model dynamics systems due to its model-free nature
- Able to make sequential decisions in an uncertain environment

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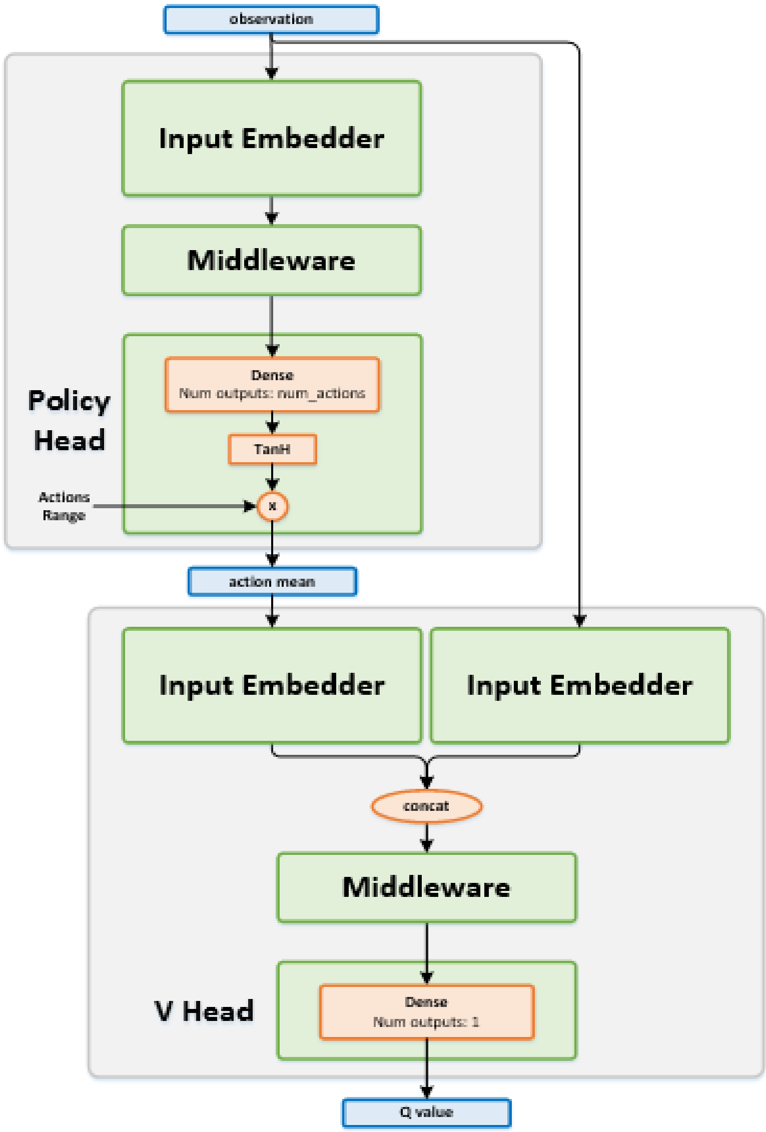
Deep Deterministic Policy Gradient (DDPG)

- Developed by Lillicrap et al., (2015)
- Resulted from coupling DPG and DQN algorithms
- Model free
- Off policy
- Actor-critic
- Deterministic policy
- Experience replay buffer
- Continuous action space
- Reduced computation cost
- DNNs as non-linear function approximators

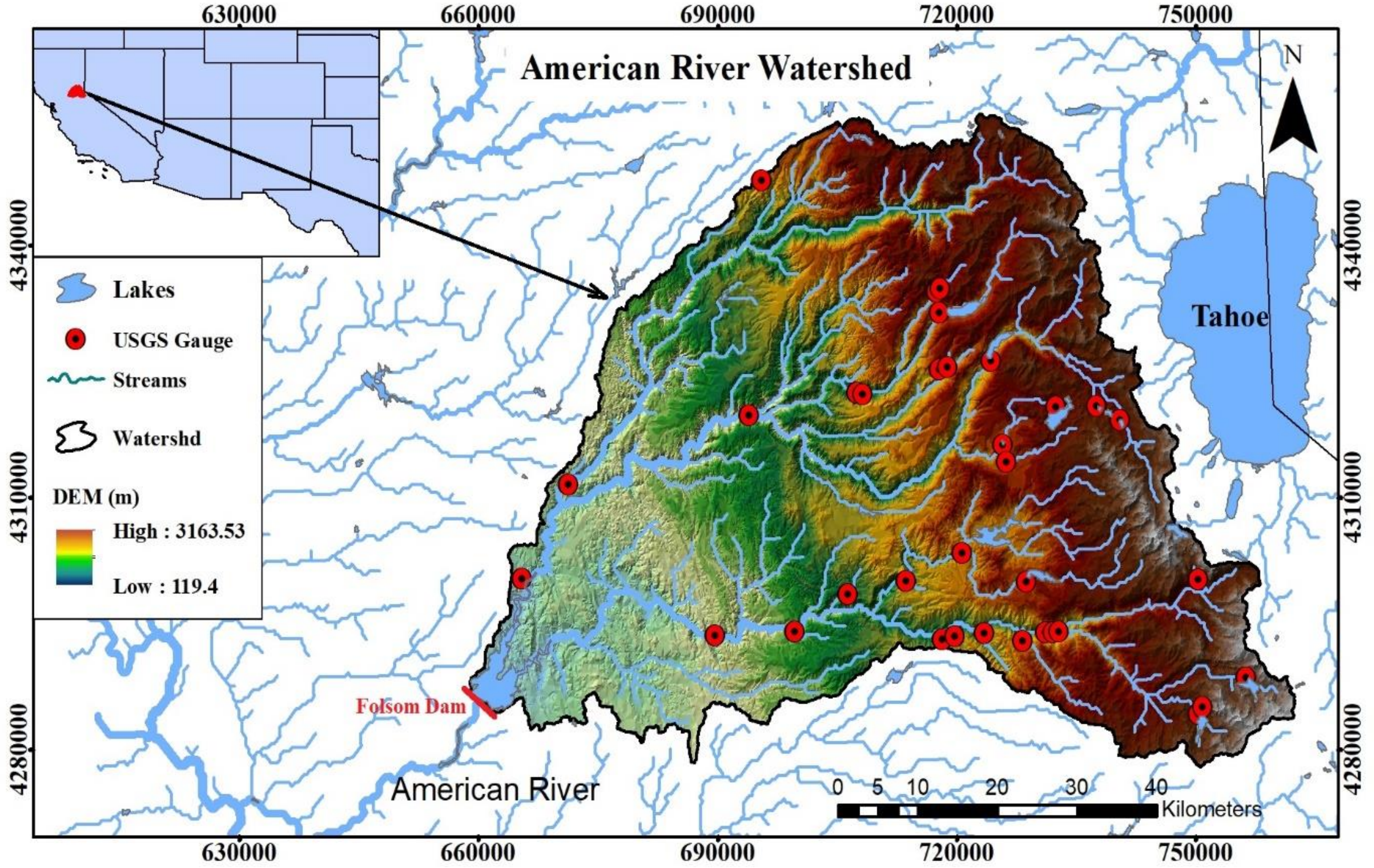
- Drawback: tendency to overestimate the value function



Reservoir Operation Problem

- **Water balance equation:** $S_{t+1} = S_t + Q_t - E_t - R_t - Spill_t$
- **Power production:** $HP_t = \eta g \gamma_w \overline{h_t} R_t^{Turb} \times 10^{-6}$
- **Storage constraint:** $S^{\min} \leq S_t \leq S_t^{\max}$
- **Release constraint:** $R^{\min} \leq R_t \leq R^{\max}$
- **Maximum turbine release capacity:** $R_t^{Turb} \leq R_{\max}^{Turb}$

Folsom Lake and the American River Basin location



Folsom Reservoir properties

- Capacity: 966 thousand acre-feet (1.19 cubic kilometers)

- Design purposes

(i) Supplying agricultural and municipal demands
(ii) Flood control and protection
(iii) Hydropower
(iv) Environmental flows

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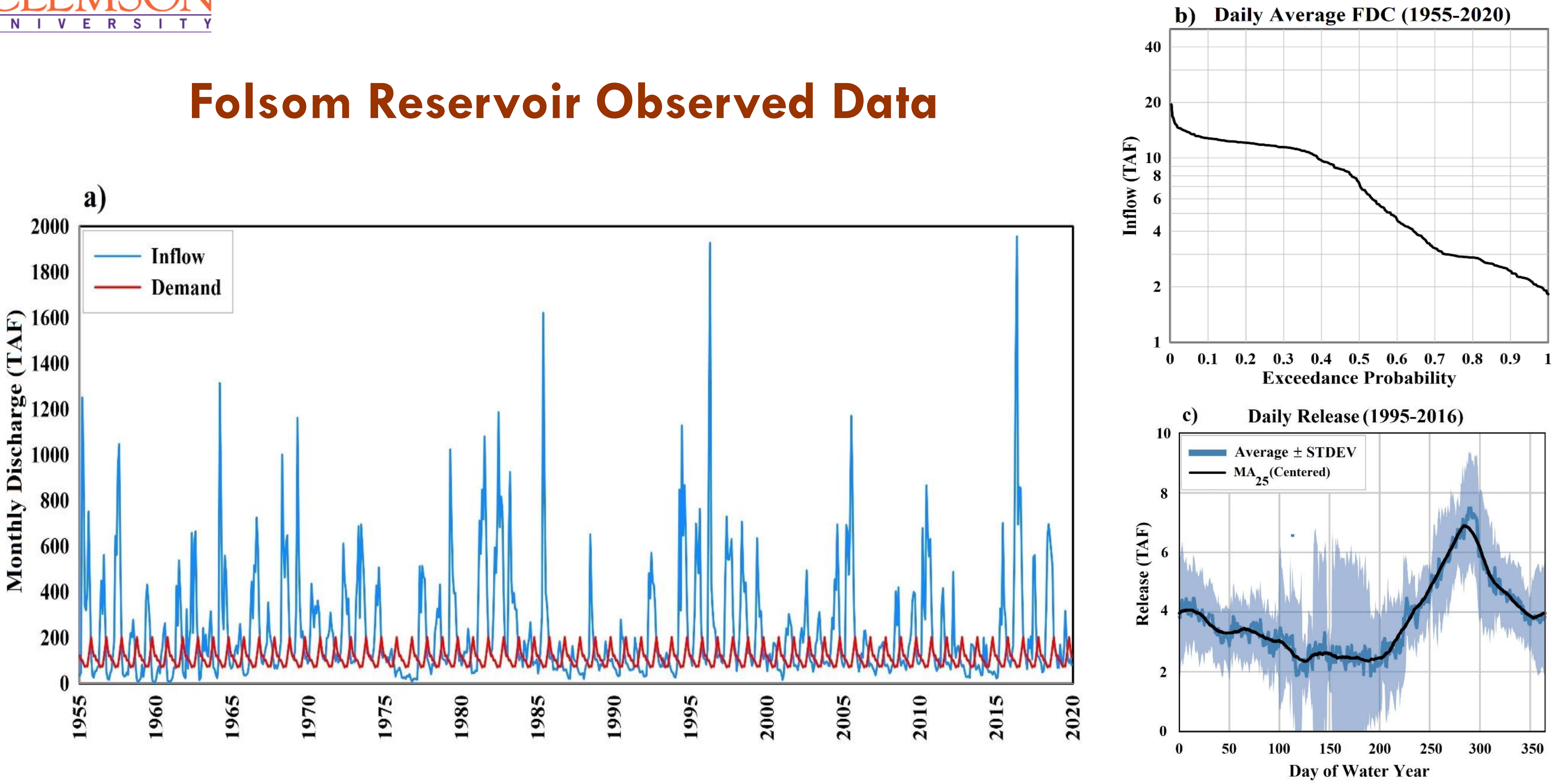
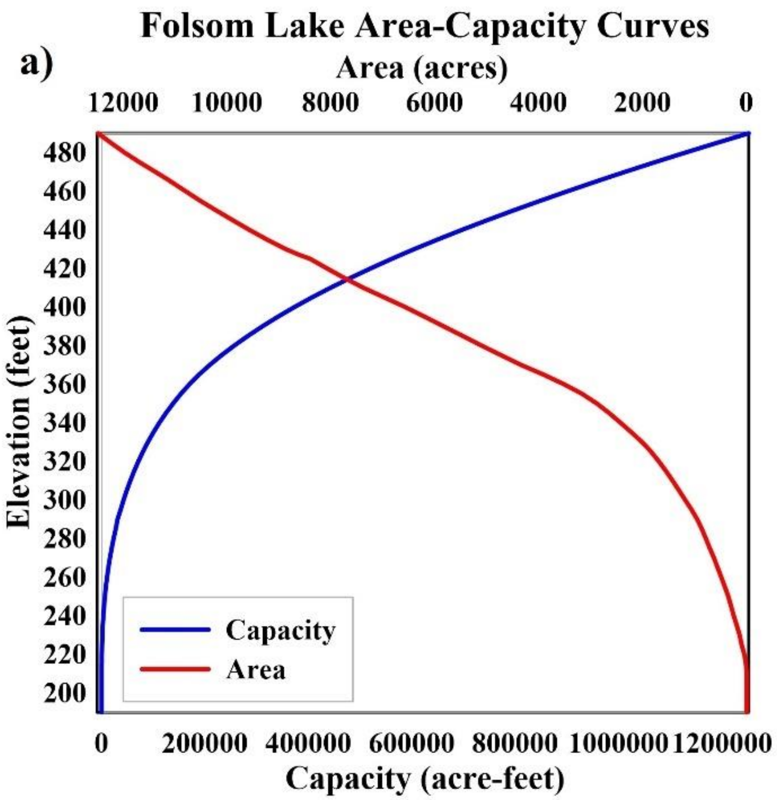
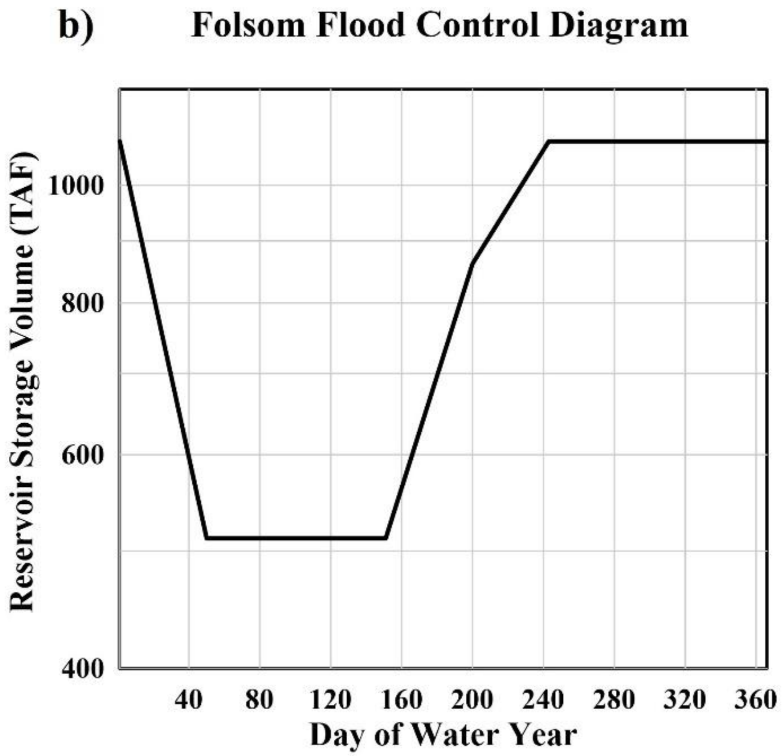
Folsom Reservoir Observed Data



Folsom Reservoir Observed Data - continued





Month	Evaporation (in)	Month	Evaporation (in)	Month	Evaporation (in)
January	0.91	May	8.07	September	7.64
February	1.61	June	10.08	October	5.00
March	3.50	July	11.50	November	2.05
April	3.50	August	10.20	December	0.91

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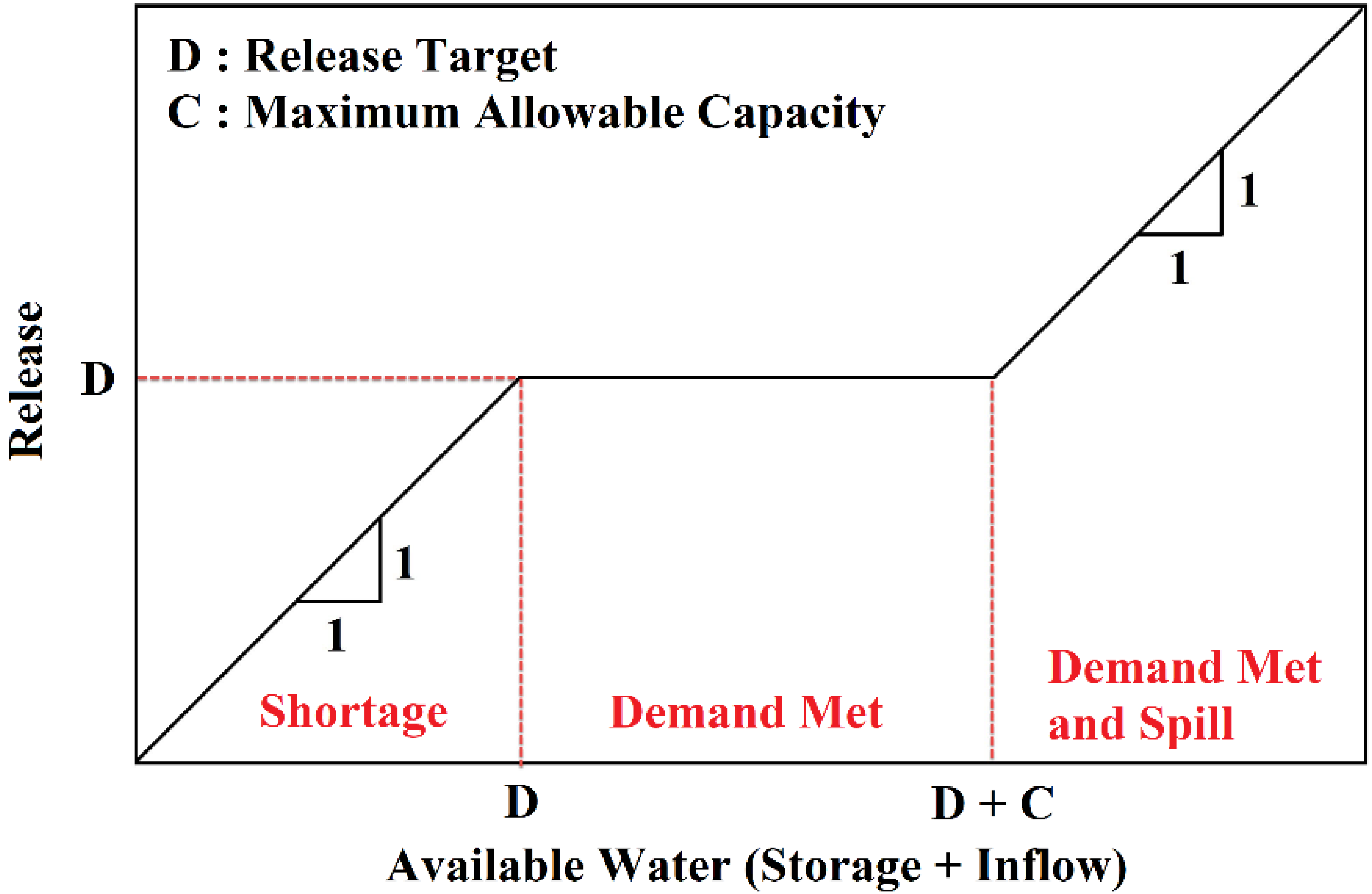
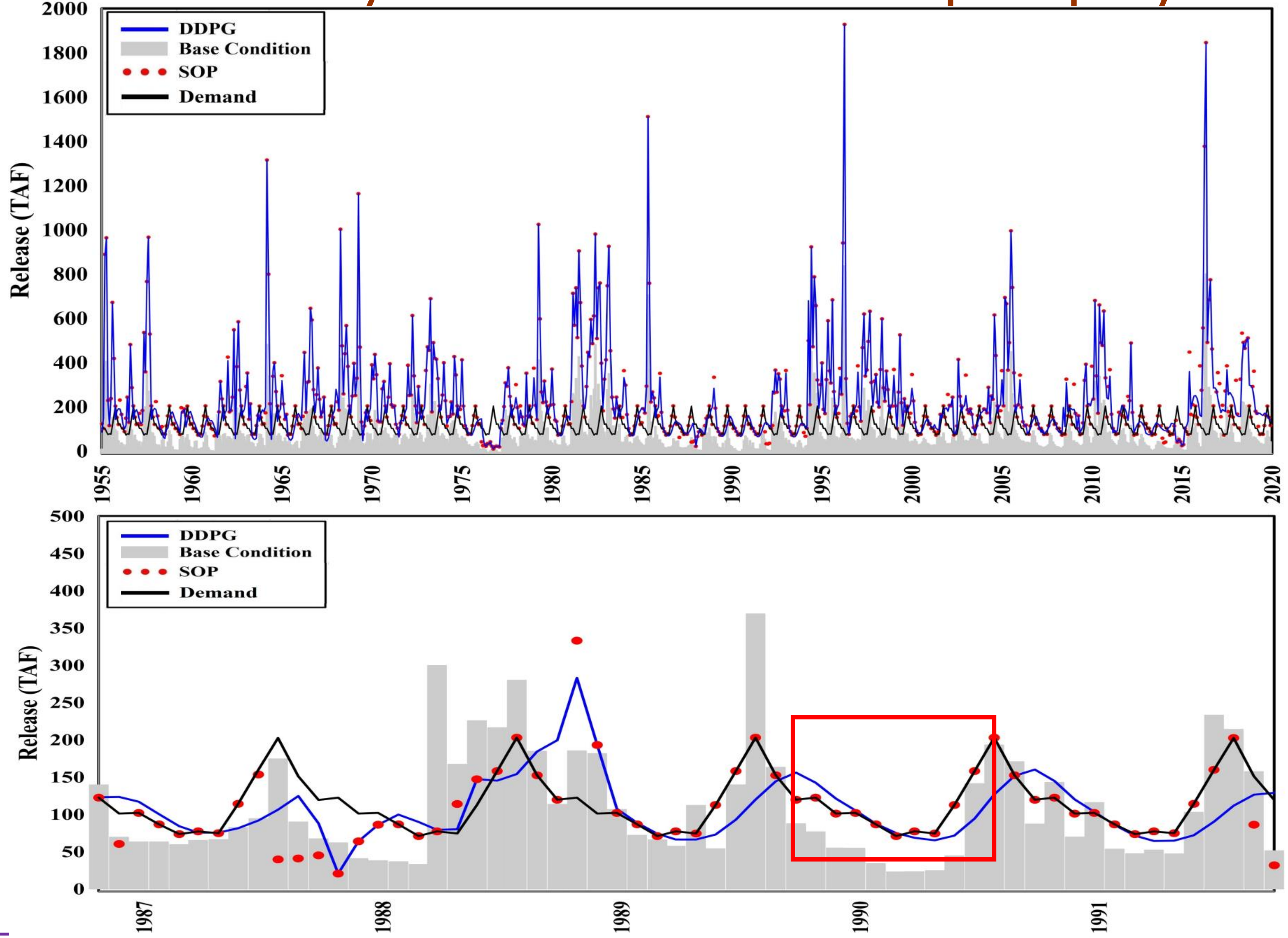
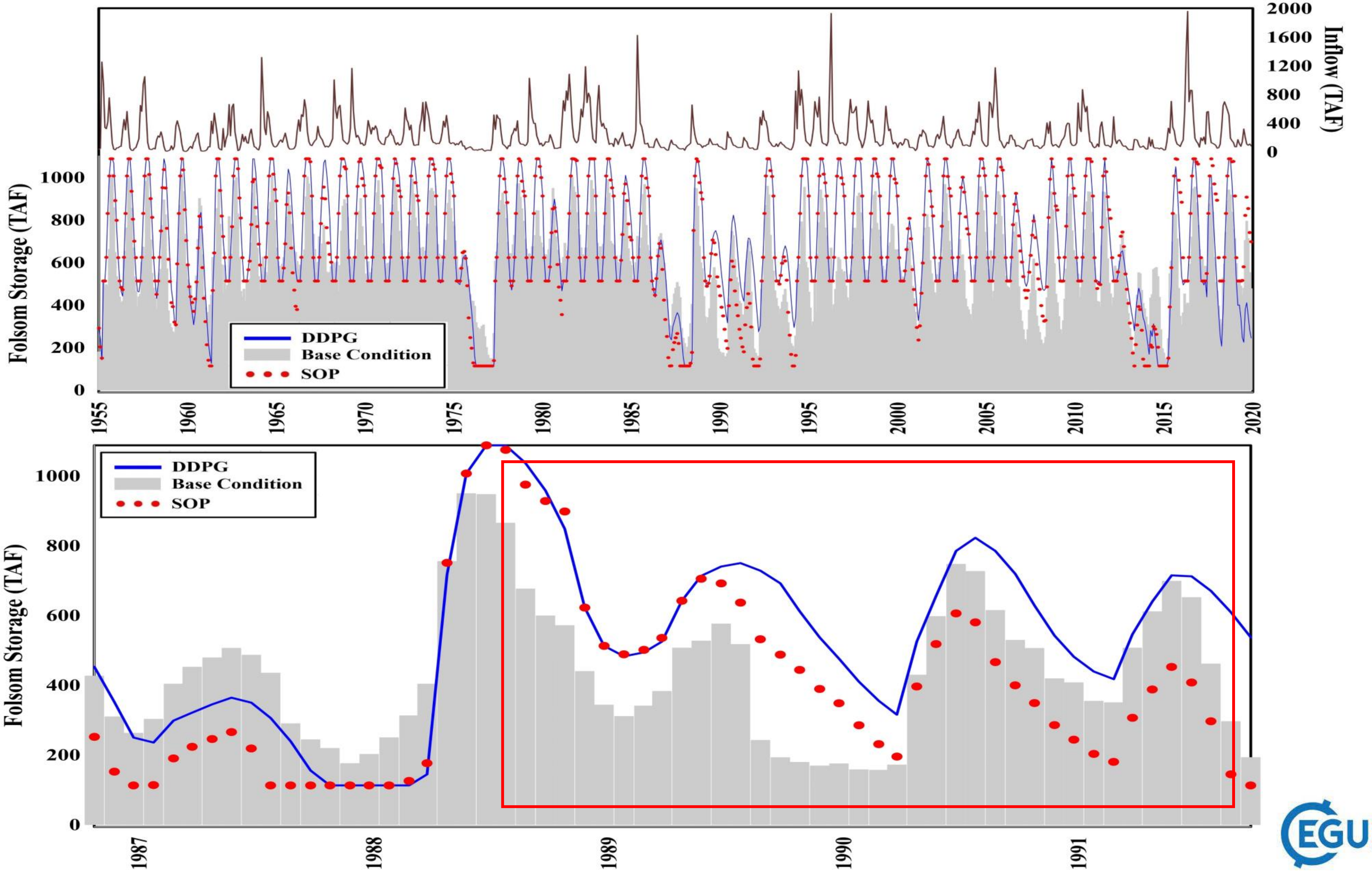
Standard Operating Policy (SOP)



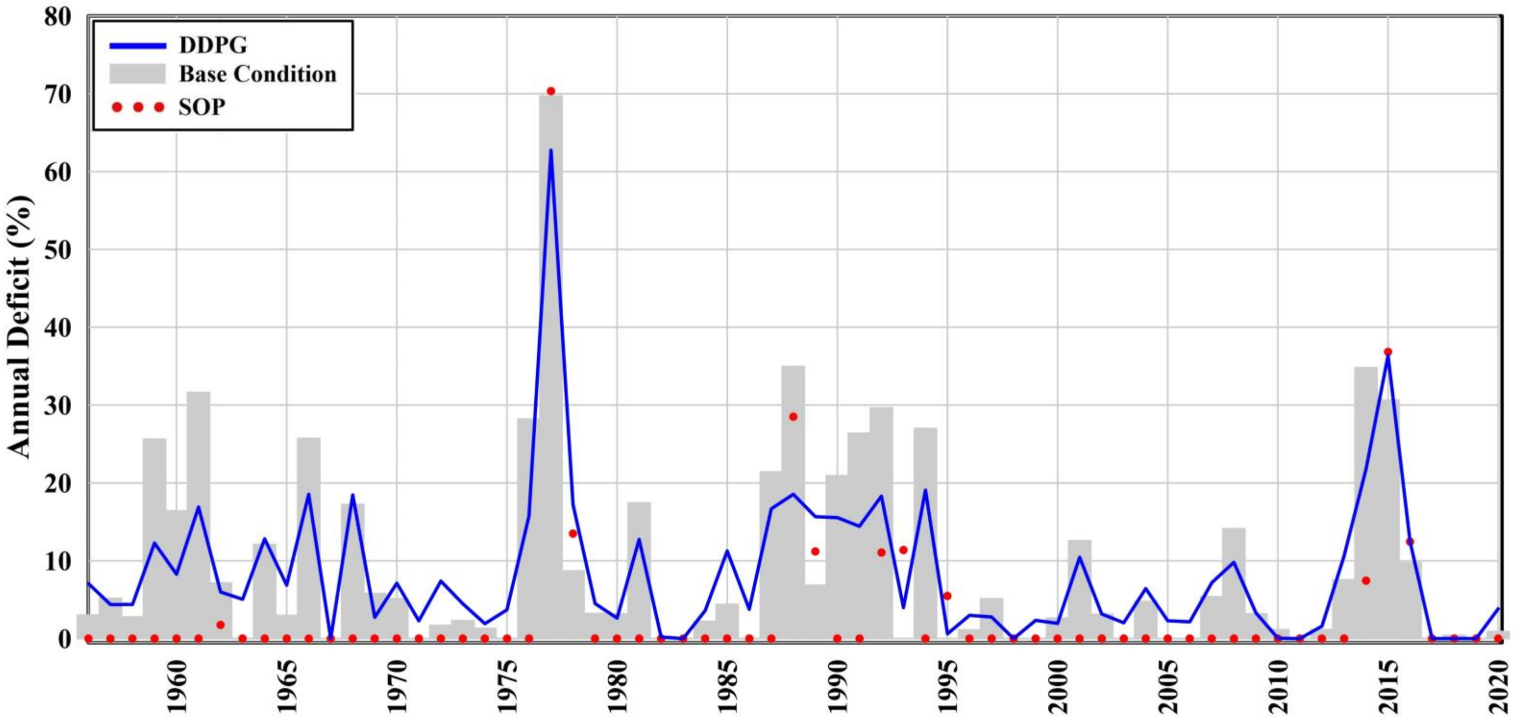
Monthly release values obtained from optimal policy actions



Folsom monthly storage amounts identified by different methods



Annual deficit based on the suggested operating policies and performance metrics



Method	Reliability (Volume)	Resilience	Vulnerability	Max Annual Deficit (%)	Sustainability Index	Ave. Annual Power Production (GWh)
DDPG	0.91	0.39	5.18E-04	0.76	0.54	683.60
SOP	**0.97**	0.23	8.09E-04	0.71	0.50	700.46
Baseline	0.90	0.27	3.96E-04	0.70	0.56	620.00

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What we have learned?!

- ✓ DRL-based techniques with continuous state and action spaces were able to deal with dimensionality problem without any simplification and approximation.
- ✓ The results from the employed method were consistent and reflect our intuitive knowledge of reservoir operation.
- ✓ DDPG effectively focused on mitigating water supply deficiency, more specifically during drought periods and on the other hand flood management and control during wet seasons as well as increasing annual hydropower production.
- ✓ The proposed framework is flexible to any user-defined reward function, different time scales or extended with additional constraints.

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Thanks for your attention!

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Performance Assessment and Sustainability Metrics

$$D_t = \begin{cases} X_t^T - X_t^S, & \text{if} X_t^T > X_t^S \\ 0, & \text{if} X_t^T \leq X_t^S \end{cases}$$

$$Rel = \frac{\sum_{t=1}^{t=n} X_t^S}{\sum_{t=1}^{t=n} X_t^T}$$

$$Res = \frac{No.of times D_t = 0 follows D_t > 0}{No.of times D_t > \ 0 \ \ ocurred}$$

$$Max.Deficit = \frac{\max(D^i_{annual})}{X^T_{annual}}$$

$$Vul = \frac{\left(\frac{\sum_{t=1}^{t=n} D_t}{No.of times D_t > 0 ocurred} \right)}{\sum_{t=1}^{t=n} X_t^T}$$

$$SI = [Rel \times Res \times (1 - Vul) \times (1 - Max.Deficit)]^{1/4}$$

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