Capstone 2

Final Presentation

Recap of The Project and Final Outcomes

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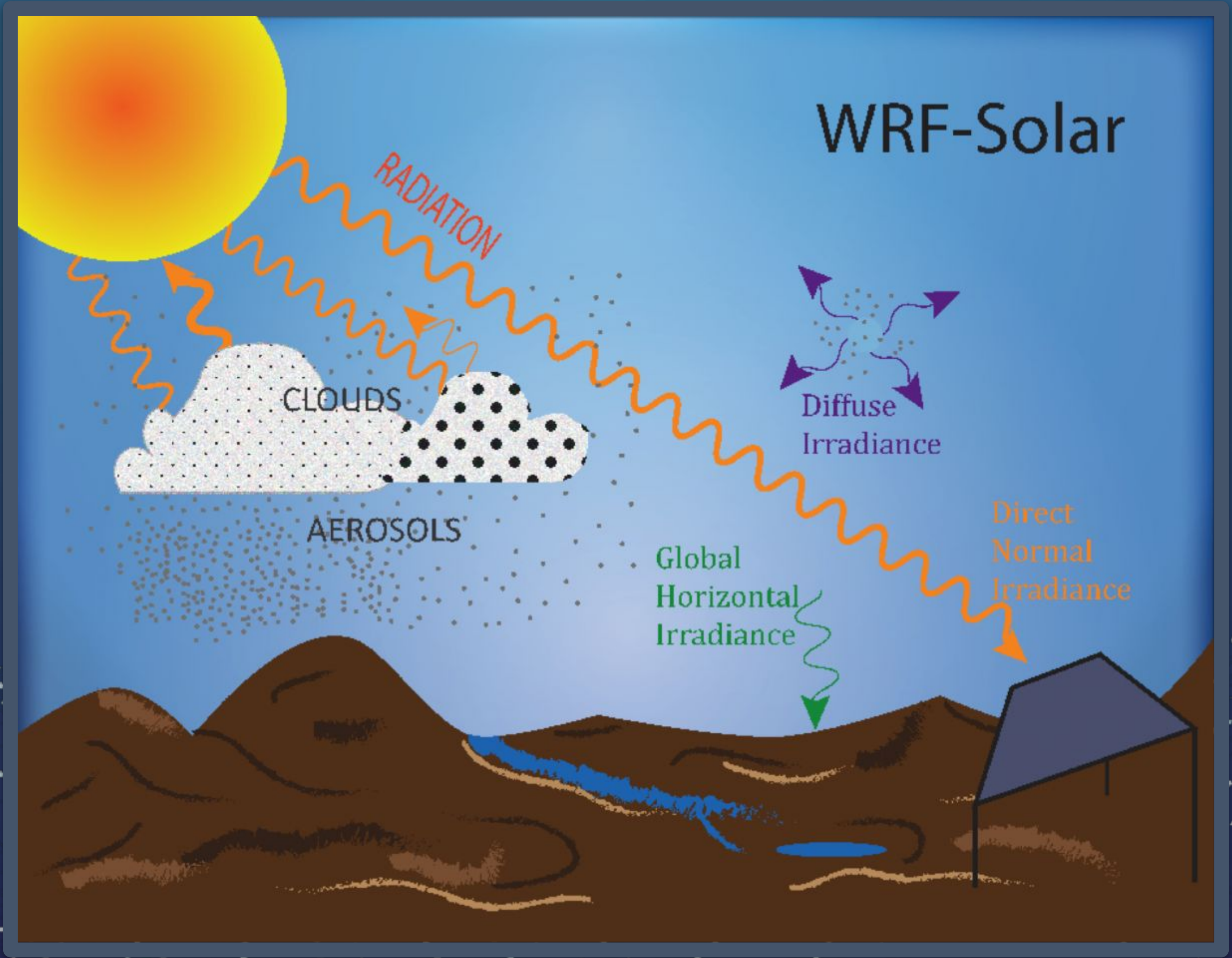
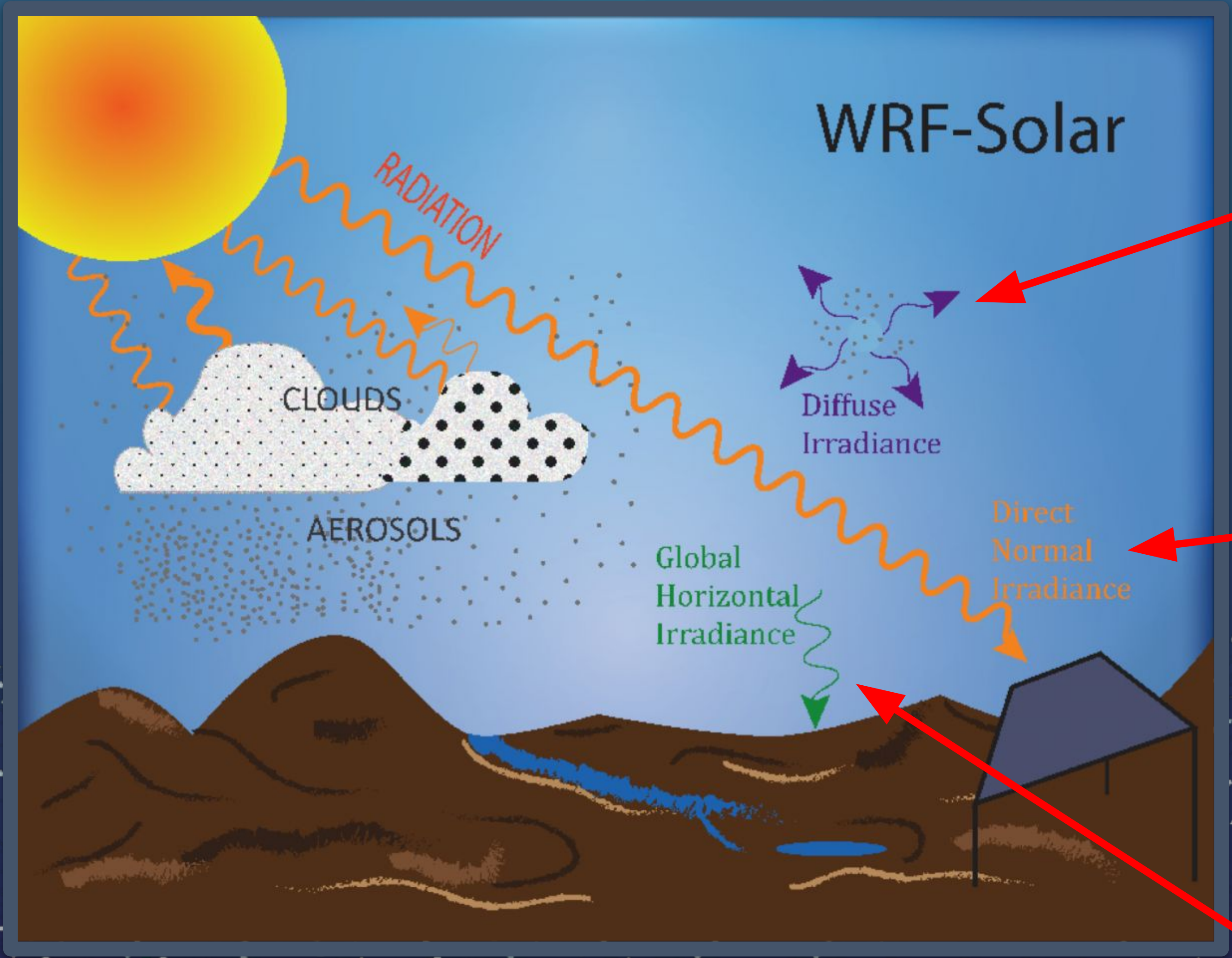
Contents

01. Background



01. Background - Three types of Irradiance:



solar radiation scattered in the atmosphere

+

solar radiation received directly from the sun, per unit area, on a surface perpendicular (normal) to the sun's rays

$\times \; sin(\theta_z)$

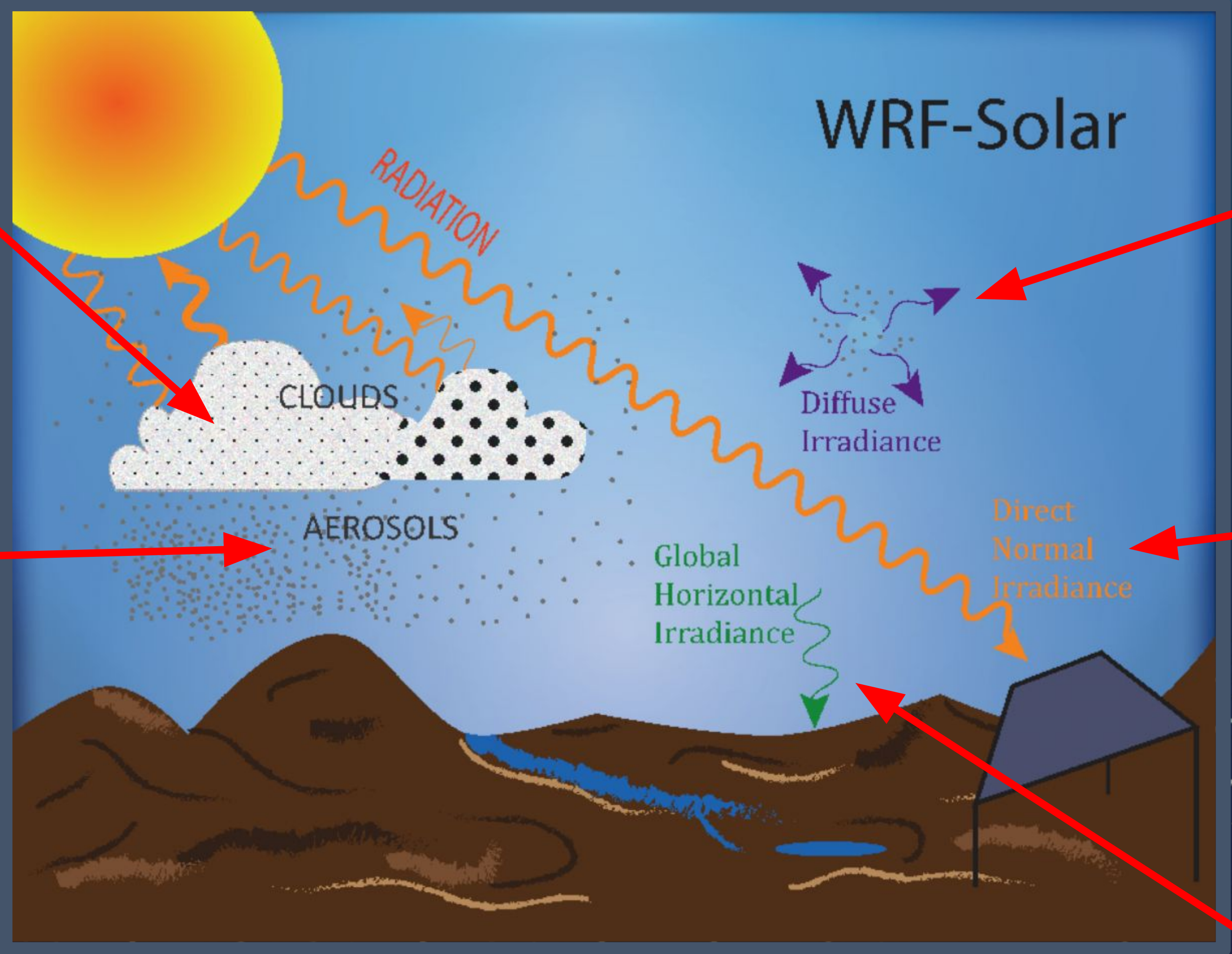
=

SWDOWN (shortwave downward radiation at the surface)

01. Background - Parameters:

beta_con: condensation rate constant. microphysics of cloud formation

vdis: relative dispersion. controls how radiation is diffused and scattered by aerosols and cloud particles



solar radiation scattered in the atmosphere

$+$

solar radiation received directly from the sun, per unit area, on a surface perpendicular (normal) to the sun's rays

$\times \; sin(\theta_z)$

$=$

SWDOWN (shortwave downward radiation at the surface)

02. Objective

- Use Bayesian Optimization (BO), Reinforcement Learning (RL), and Stochastic Approximation (SA) to optimize parameters (beta_con & vdis) in the WRF-Solar model.
- Focus on improving the accuracy and efficiency of parameter tuning in climate modeling using the above algorithms.
- Minimize Mean Squared Error (MSE) between simulated and ground truth irradiance data

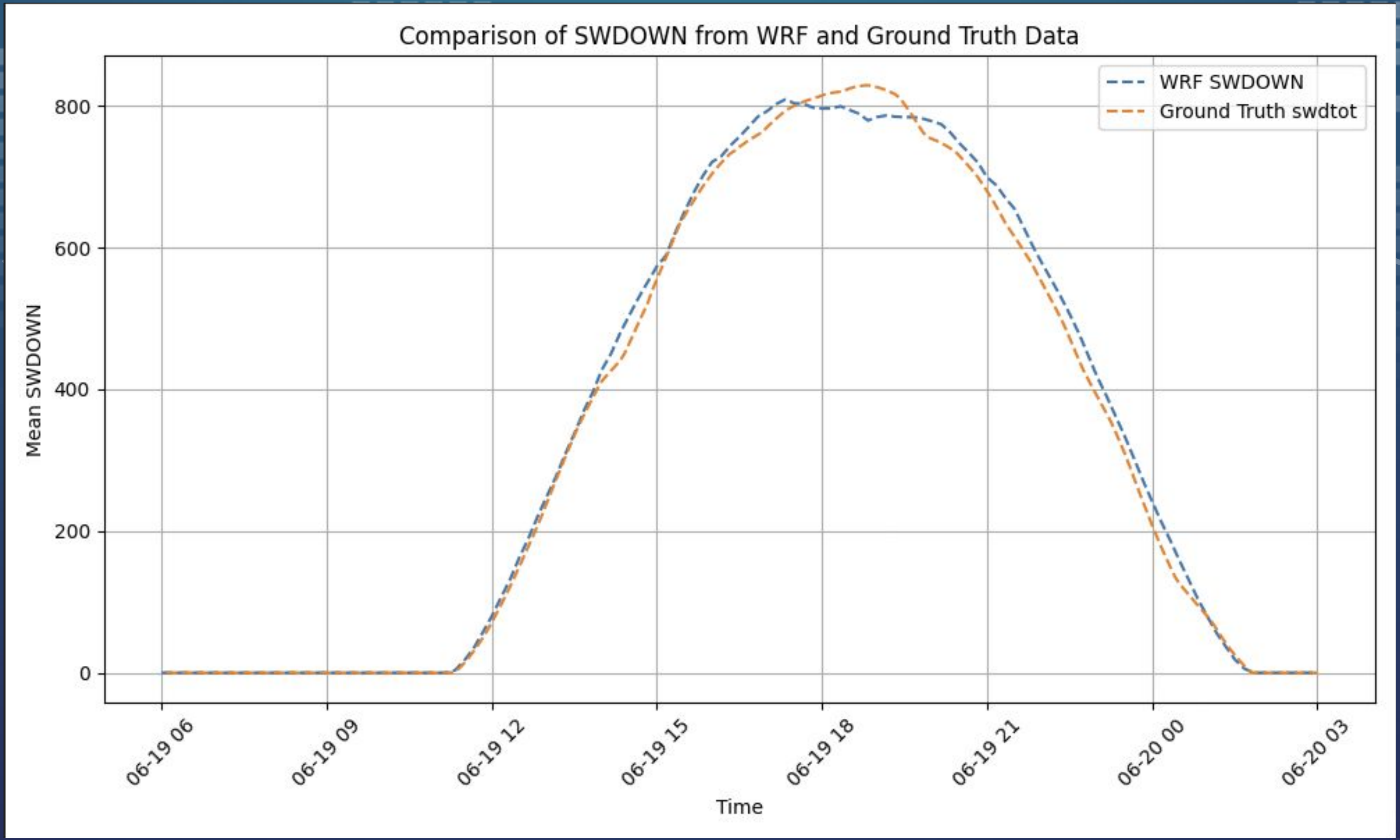
03. Brief Research Approach

- Extract ground truth solar irradiance data for comparison.
- Implement Bayesian Optimization + MSE
- Implement Double Deep Q-Network (D3QN) + MSE
- Implement Stochastic Approximation + MSE
- Evaluate performance based on MSE.

Core Parameters:

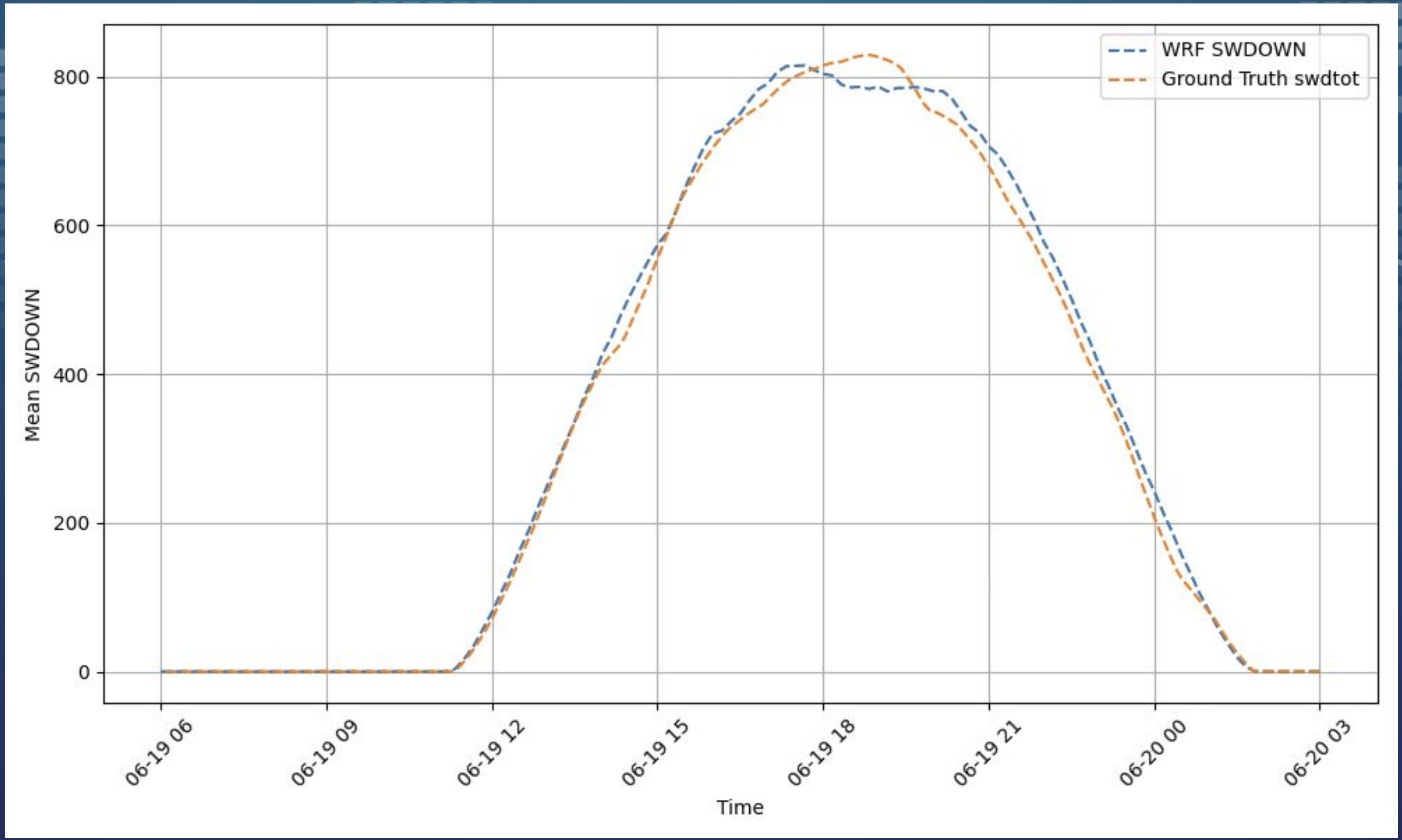
- **beta_con**: Impacts condensation rate and cloud density, influencing radiation scattering.
- **vdis**: Affects relative dispersion of cloud droplets, modulating diffuse and direct irradiance.

04a. Key Results - BO



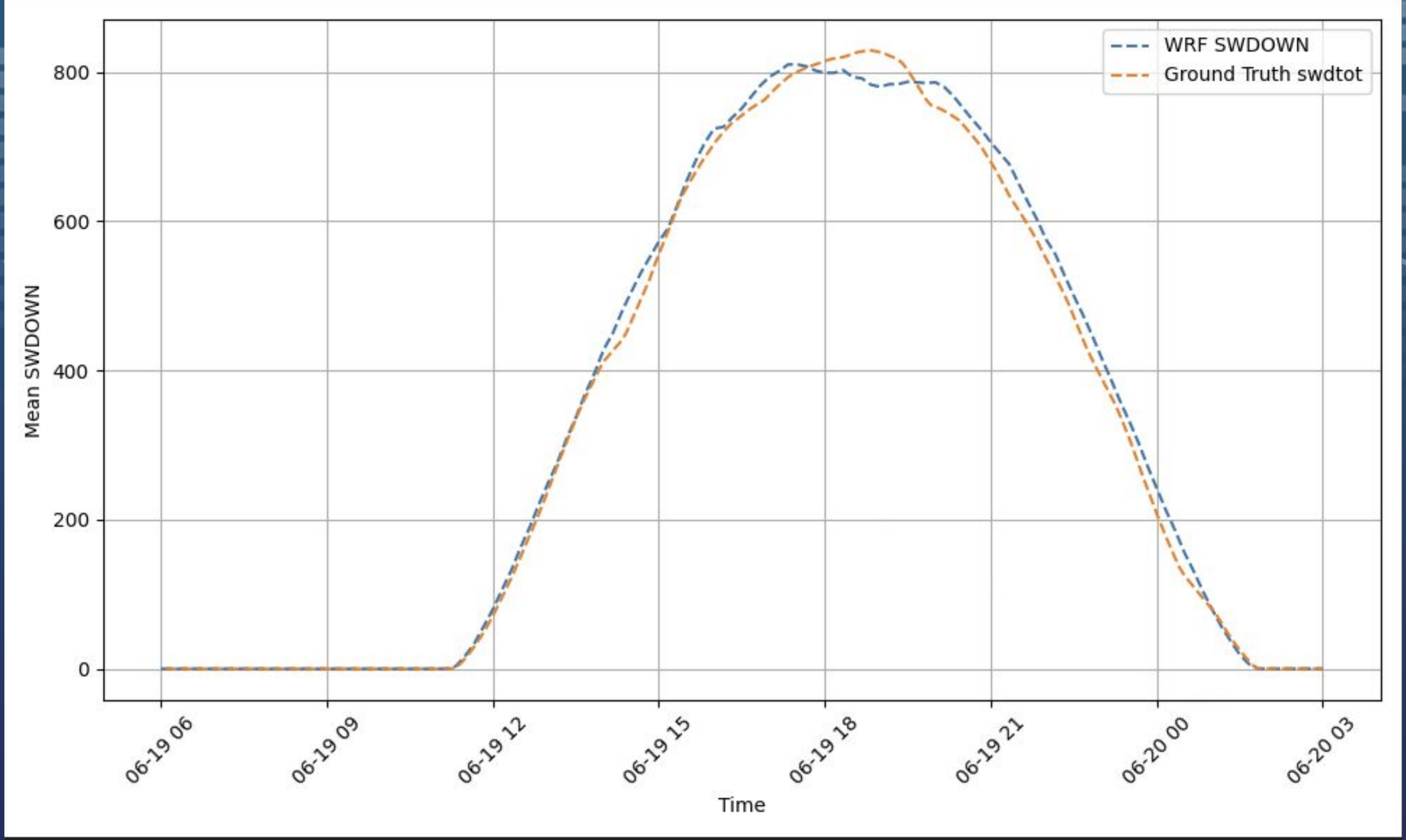
beta_con: 1e+20 | vdis: 0.0112 | MSE: 358

04b. Key Results - D3QN



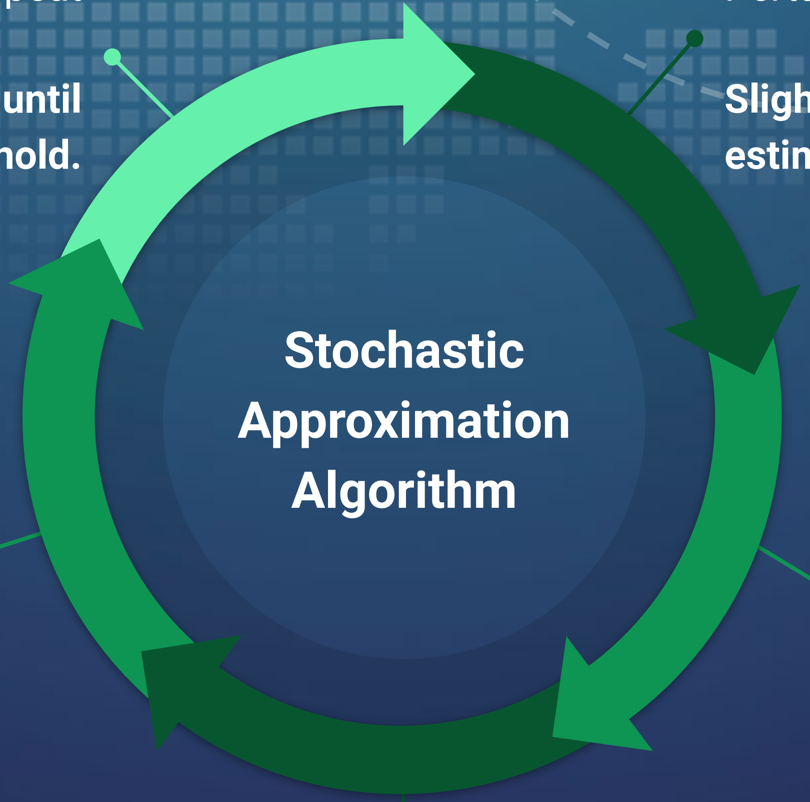
beta_con: 4.91e+23 | vdis: 0.0472 | MSE: 355

04c. Key Results - SA



beta_con: 5.03e+23 | vdis: 0.0182 | MSE: 361

04c. Key Results - SA Algorithm



Initialize

Randomly set beta_con, vdis.

Perturb

Slightly change parameters to estimate MSE changes.

Run Simulation

Run WRF model, calculate MSE using ground truth.

Compute Gradient

Use perturbation to approximate gradient for parameter update.

Update

Adjust beta_con, vdis using stochastic approximation.

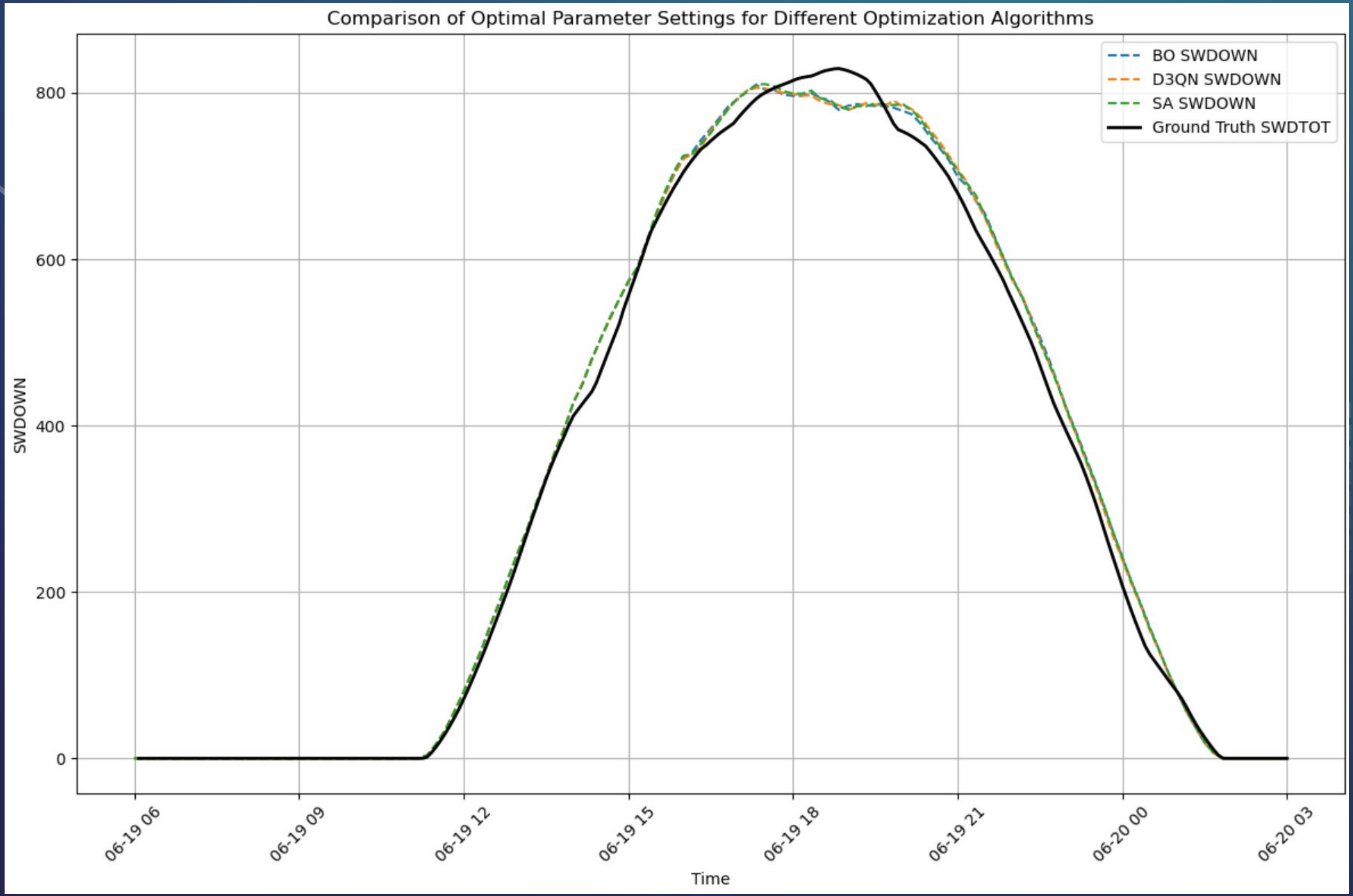
Repeat

Iterate over multiple episodes until MSE meets the threshold.

Simultaneous Perturbation Stochastic Approximation (SPSA) algorithm

- Estimates gradients using simultaneous perturbations in all parameters, rather than one-by-one updates
- Key Features:
  - **Efficient Gradient Estimation:** Requires only two evaluations of the objective function per iteration, regardless of the number of parameters.
  - **Scalable:** Ideal for high-dimensional optimization problems.
  - **Noise Resilience:** Handles noisy objective functions effectively.
- Steps in SPSA:
  - Perturb all parameters simultaneously using random directions.
  - Compute gradient estimate: $g \approx \frac{f(\theta+\Delta) - f(\theta-\Delta)}{2\Delta}$
  - Update parameters: $\theta \leftarrow \theta - \alpha \times g$
- Advantages over Standard SA:
  - Faster convergence.
  - Reduces computational cost significantly.
  - Maintains performance in noisy settings, like WRF model optimization.

04d. Overlaid Graph of all Algorithm Results



	BO	D3QN	SA
beta_con	1e+20	4.91e+23	5.03e+23
vdis	0.0112	0.0472	0.0182
MSE	358	355	361

05. Challenges and Limitations Faced

- Handling large parameter spaces
- Computational time constraints limiting iterations

06. Areas of Future Work

- **Algorithm Improvements:**
  - Hybrid models combining BO and RL and SA.
- **Dataset Expansion:**
  - Use larger and more diverse datasets.
- **Scalability:**
  - Test models on larger systems with more parameters.

Thanks