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Probabilistic Cloud Optimized Day-Ahead Forecasting System Based on WRF-Solar

Award # DE-EE00033503

Solar Forecasting 2 Annual Review and Workshop

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Objectives

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Develop Solar Forecasting System based on WRF-Solar that-

- Provides probabilistic forecasts for the grid.
- Ensemble members tailored for solar forecasts.
- Optimized to operate with few ensemble members.
- Calibrated to remove bias in forecasts and has meaningful quantification of the uncertainties.
- Improves the current-state-of-art solar forecasts and reduces uncertainty by 50% from current levels.
- Improves both average irradiance and ramp forecasts.

Project Overview

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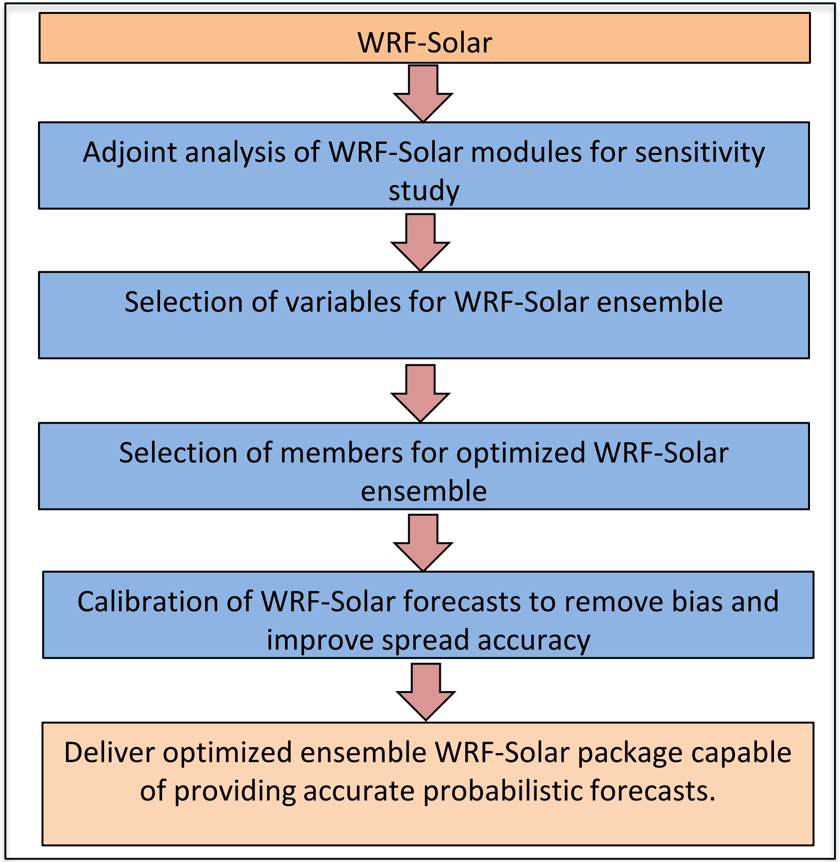
•Identify variables that significantly influence the formation and dissipation of clouds and solar radiation through an **adjoint analysis** of WRF-Solar modules that influence cloud processes.

•Consolidate the variables identified in step (a) to develop the **WRF-Solar ensemble** forecasting system.

•**Calibrate the WRF-Solar ensemble system** using measurements to ensure that the forecasts' trajectories are unbiased and provide accurate estimates of forecast uncertainties under a wide range of meteorological regimes.

•**Demonstrate the improvements** delivered by the probabilistic forecasts for the regions and locations identified by Topic Area 1.

•Develop and deliver an **open-source probabilistic WRF-Solar system** for the solar energy community.



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Framework for Sensitivity Study of WRF-Solar

WRF-Solar (version 1)

Develop a standalone version of each WRF-Solar module

- FARMS radiation scheme
- NOAH LSM
- Thompson microphysics parameterization
- MYNN boundary layer parameterization
- Deng shallow cumulus scheme
- Unresolved cloud fraction scheme (additional module)

Generate Tangent linear codes using TAF

Linearity test (code validation)

Sensitivity study for input variables of each module

Theory of Tangent Linear

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Tangent linear model (TLM)

- Derived from the forward model

$$\mathbf{Y} = \mathbf{M}(\mathbf{X})$$

$\mathbf{M}$: nonlinear model

$\mathbf{Y}$: vector of output variables

$\mathbf{X}$: matrix of input variables

- Tangent linear operator (**L**) gives the derivative of the forward model with respect to the independent variable

$$\mathrm{d}\mathbf{Y} = \mathbf{L}\mathrm{d}\mathbf{X}$$

$\mathrm{d}\mathbf{Y}$: tangent linear output

$\mathrm{d}\mathbf{X}$: tangent linear input

$$\mathbf{L} = \frac{\partial \mathbf{Y}}{\partial \mathbf{X}}$$

$\mathbf{L}$: matrix of the partial derivatives of $\mathbf{Y}$ with respect to $\mathbf{X}$ (tangent linear operator or Jacobian-matrix)

Validation of Linear Approximation

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Purpose: Validation of TL codes for linear approximation of physics modules.

Metric of linearity test

$$\emptyset(\beta) = \frac{\|F(\boldsymbol{X}+\beta d\boldsymbol{X})-F(\boldsymbol{X})\|}{\|\beta d\boldsymbol{X}F\prime(\boldsymbol{X})\|}, \lim_{d\boldsymbol{X}\to 0} \frac{\|F(\boldsymbol{X}+\beta d\boldsymbol{X})-F(\boldsymbol{X})\|}{\|\beta d\boldsymbol{X}F\prime(\boldsymbol{X})\|} = \mathbf{1.0}$$

$d\boldsymbol{X}F'(\boldsymbol{X})$: TLM output
$F(\boldsymbol{X} + \beta d\boldsymbol{X})$: perturbed Forward model acting on $\boldsymbol{X} + \beta d\boldsymbol{X}$
$\|\cdot\|$: norm of the vector

Linearity Test for WRF-Solar Modules

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Linearity test results for perturbing all input variables

(the other modules were also strictly verified)

Perturbation	FARMS	Thompson microphysics	Noah LSM
0.10000000000000000	0.00324914467627453	0.42427919061132591	1.48208928881112615
0.01000000000000000	0.00345786558440380	0.43104661976178825	1.12911502161288928
0.00100000000000000	0.00367974446810941	11.40401429679720438	0.98502741052100296
0.00010000000000000	0.00973564692016131	35.23940378673465797	0.99838789495678642
0.00001000000000000	0.05275784331725234	3.56290634414201912	0.99983757392919007
0.00000100000000000	0.34844160934770783	0.01291187993429278	0.99998374516616426
0.00000010000000000	1.00012306741732932	0.03298445036067341	0.99999837439428294
0.00000001000000000	1.00001231128564923	0.15334943930173276	0.99999983743821047
0.00000000100000000	1.00000123117398802	0.42587365386192595	0.99999998374381445
0.00000000010000000	1.00000012311785302	0.79116387355133460	0.99999999837438696
0.00000000001000000	1.00000001231178984	0.96716991951061555	0.99999999983744433
0.00000000000100000	1.00000000123117903	0.99647900764965165	0.99999999998375007
0.00000000000010000	1.00000000012311790	0.99964525412426410	0.99999999999838065
0.00000000000001000	1.00000000001231179	0.99996449863950471	0.99999999999984370
0.00000000000000100	1.00000000000123118	0.99999644959590942	0.99999999999999001
0.00000000000000010	1.00000000000012312	0.99999964495691022	1.00000000000000464
0.00000000000000001	**1.00000000000001231**	**0.99999996449566421**	**1.00000000000000609**

- **Even if all the variables are perturbed at once, the metric converges to 1 with sequentially reduced perturbations.**
- **The TL version of each WRF-Solar module approximates well the derivative of the nonlinear model solution.**
- **The linearity test was also strictly performed for each input variable of each module.**

(Performed with 128-bit precision)

Normalization of Sensitivity

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Use an estimated error of each input variable to normalize the sensitivity results.

FARMS (including only 2D variables):

$$\Delta y = \boxed{\Delta x} \times \frac{dy}{dx}$$

Error of input variable

$$e.g.\ \Delta GHI = \Delta AOD \times \frac{dGHI}{dAOD}$$

The error of each input variable can be estimated based on our experience of NSRDB, measurement, and the WRF model simulations.

Example of input errors for FARMS:

$\Delta pressure: 10hPa$
$\Delta albedo: 0.1$
$\Delta asym.: 0.1$
$\Delta CosZ: 0.001$
$\Delta total\ precipitable\ water: 10mm$

Normalization of Sensitivity

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Modules including vertical profiles (e.g. Thompson microphysics, Noah LSM, MYNN PBL):

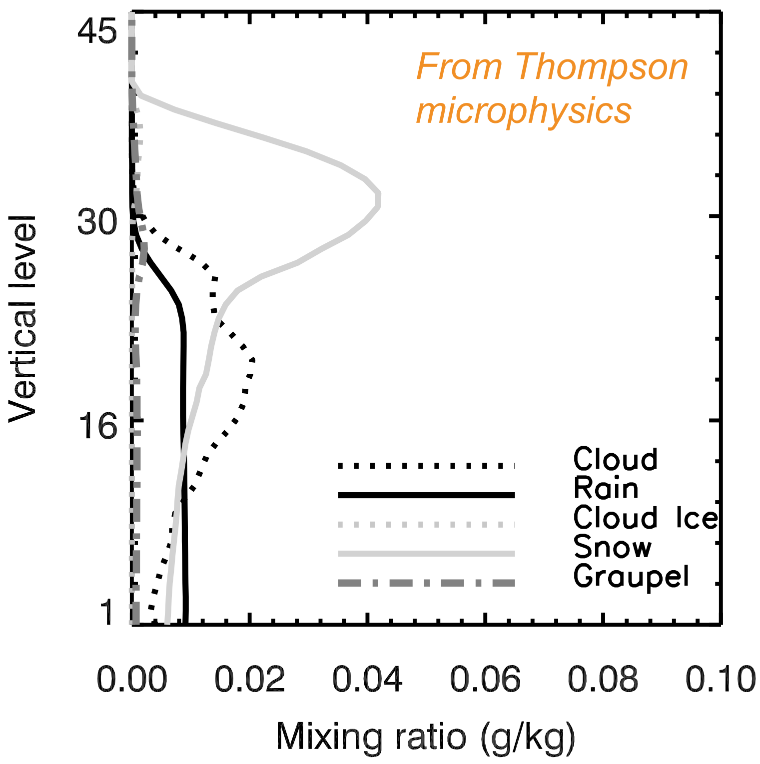
$$\Delta y = \Delta x \times \frac{dy}{dx}$$

Method 1: $\Delta x = error\ based\ on\ experience$

Method 2: $\Delta x = value\ of\ x\ itself$

Method 3: $\Delta x = standard\ deviation\ of\ x$ $(from\ 1\ day\ simulation)$ $at\ each\ vertical\ layer$

Averaged vertical distributions of hydrometeors for 6480 cases



Sensitivity Analysis of FARMS

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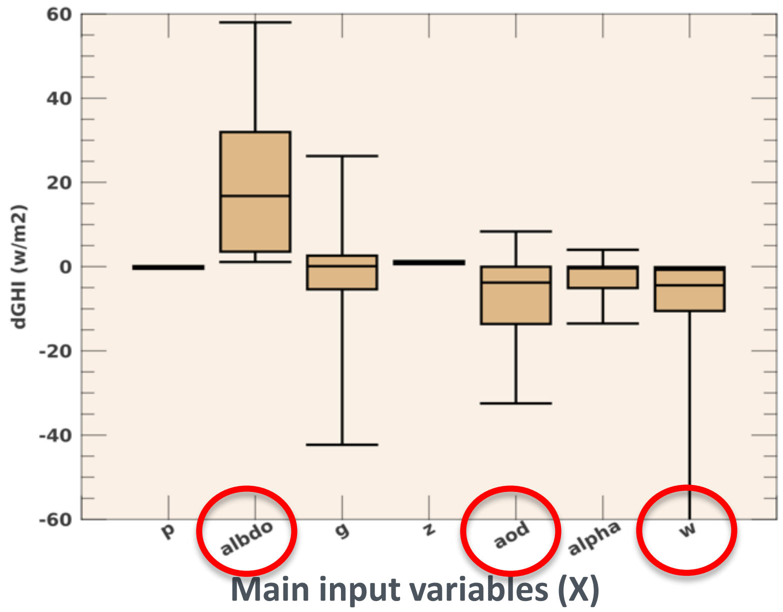
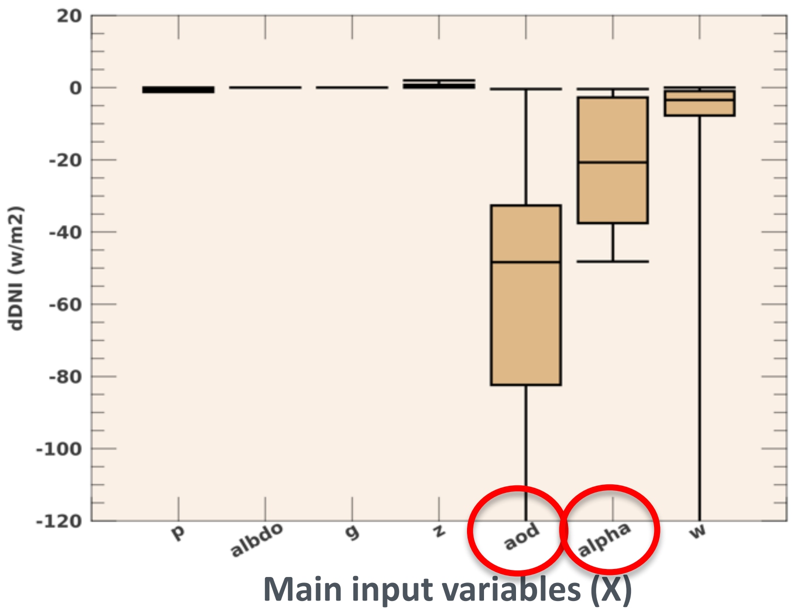
Sensitivity of GHI in clear-sky



Sensitivity of DNI in clear-sky



- The results show that GHI is sensitive to albedo, asymmetry parameter (g), aerosol optical depth (AOD), Angstrom exponent (alpha), and water vapor (w) and less sensitive to pressure (p) and solar zenith angle (z).
- The results show that DNI is sensitive to aerosol optical depth (AOD), Angstrom exponent (alpha), and water vapor (w).

Sensitivity Analysis of FARMS

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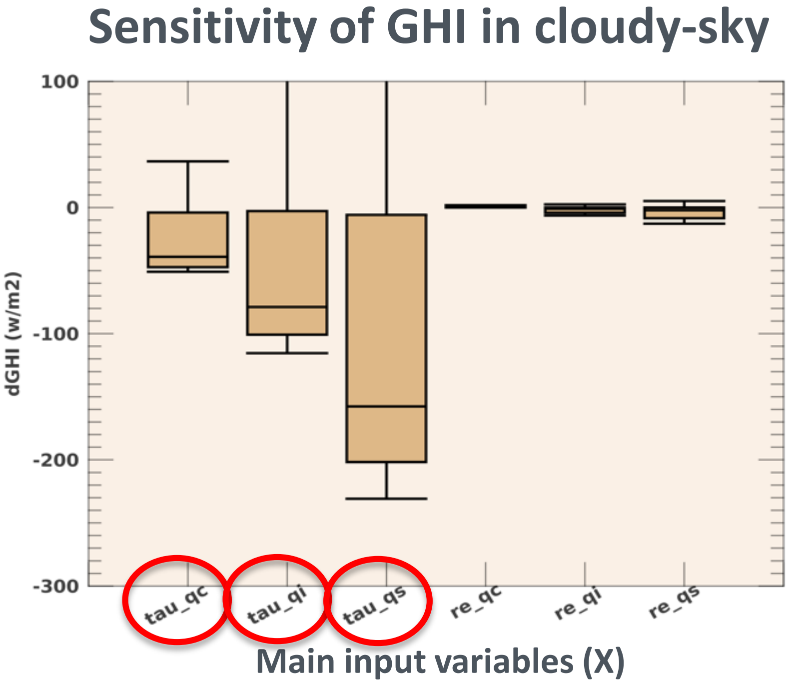

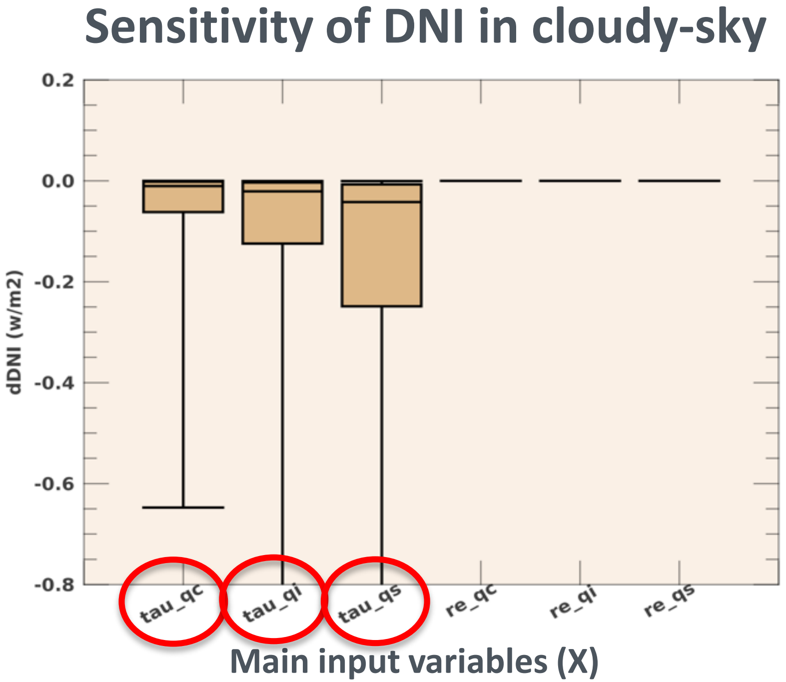

- **In cloud-sky conditions, both GHI and DNI are more sensitive to cloud optical depth (tau) than effective radius (re).**

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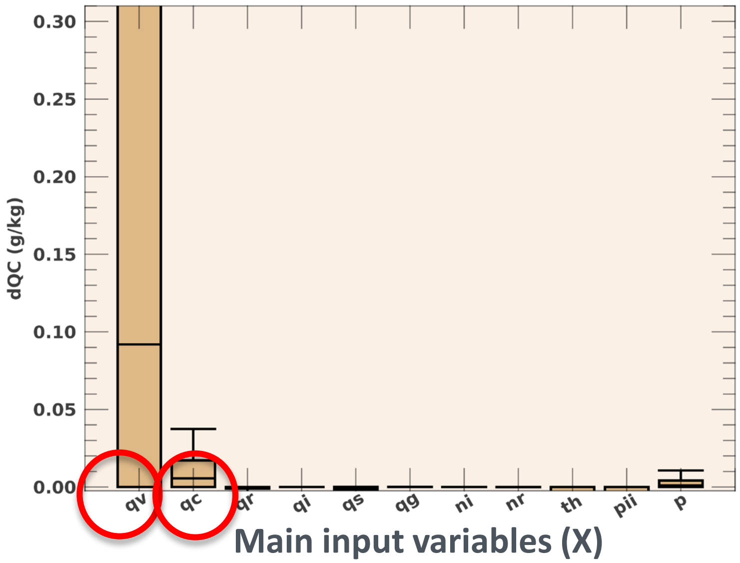
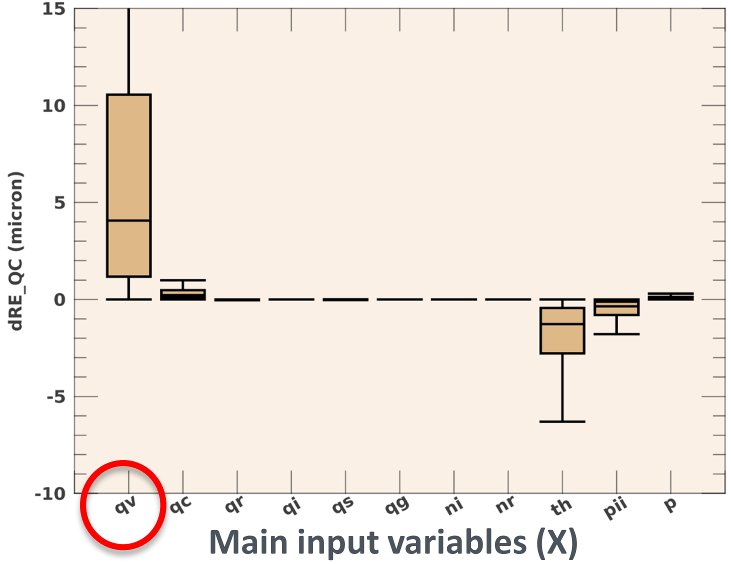
Sensitivity Analysis of Thompson Microphysics

Cloud water mixing ratio



Effective radius of cloud water



- Main input variables of Thompson scheme are the vertical profiles of cloud mixing ratios, number concentrations of cloud particles, water vapor, temperature, and pressure.
- The relevant output variables are mixing ratios and effective sizes of cloud liquid water, cloud ice, and snow particles.
- The cloud water variables are sensitive to water vapor and cloud mixing ratios.

Sensitivity Analysis of Thompson Microphysics

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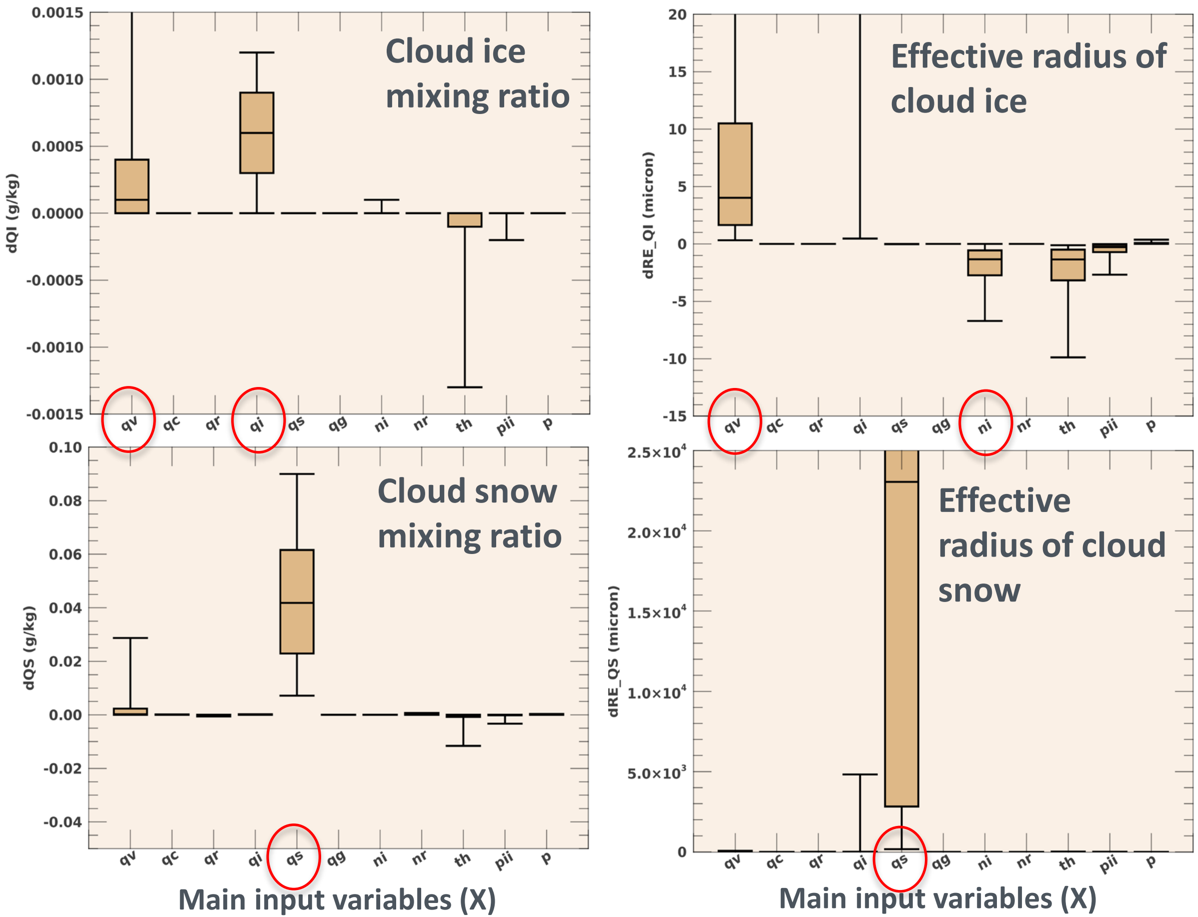

- Similar to the cloud water, the cloud ice mixing ratio, and effective radius are sensitive to water vapor and cloud ice mixing ratios.

- The sensitivity of effective radius of snow with respect to snow mixing ratio is very high.

- Most of hydrometeor mixing ratios tend to be sensitive to themselves, because these variables are intent INOUT variables in Thompson module.

Sensitivity Analysis of Noah LSM

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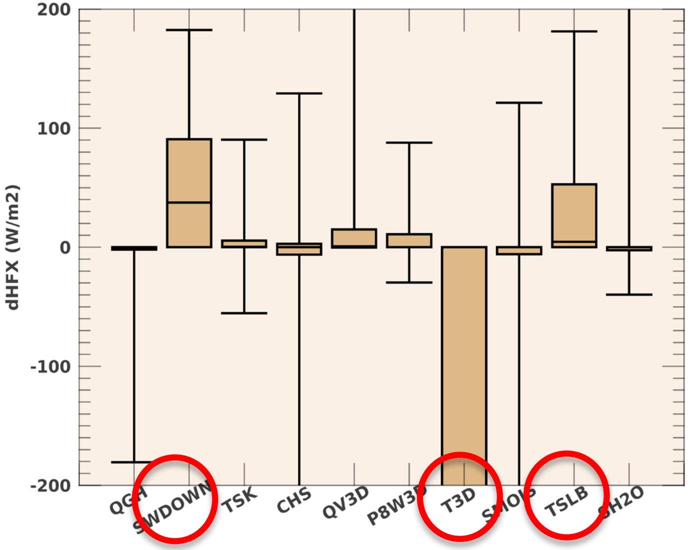
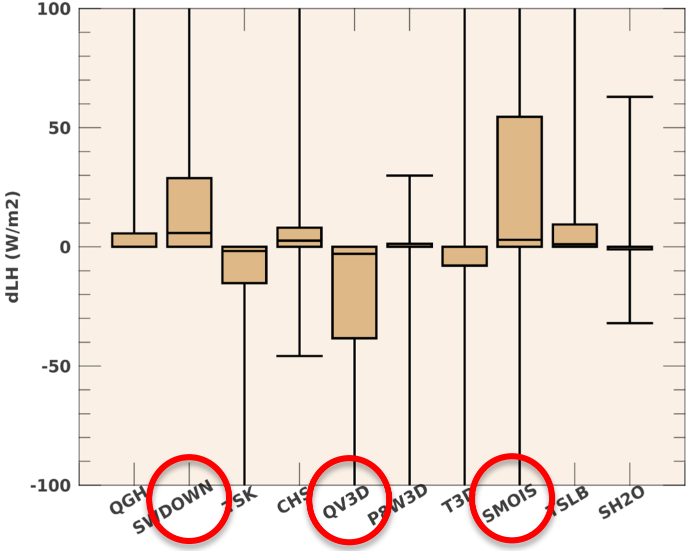
Sensible heat flux



Main input variables (X)

Latent heat flux



Main input variables (X)

Main input variables

T3D: temperature
TSLB: soil temp
SWDOWN: downward shortwave flux
SMOIS: total soil moisture content
QV3D: water vapor mixing ratio
CHS: surface exchange coefficient for heat and moisture
ALBEDO: surface albedo

- **Sensible heat flux is sensitive to temperature, soil temperature, and downward shortwave flux.**
- **Latent heat flux is sensitive to soil moisture content, water vapor mixing ratio, and downward shortwave flux.**

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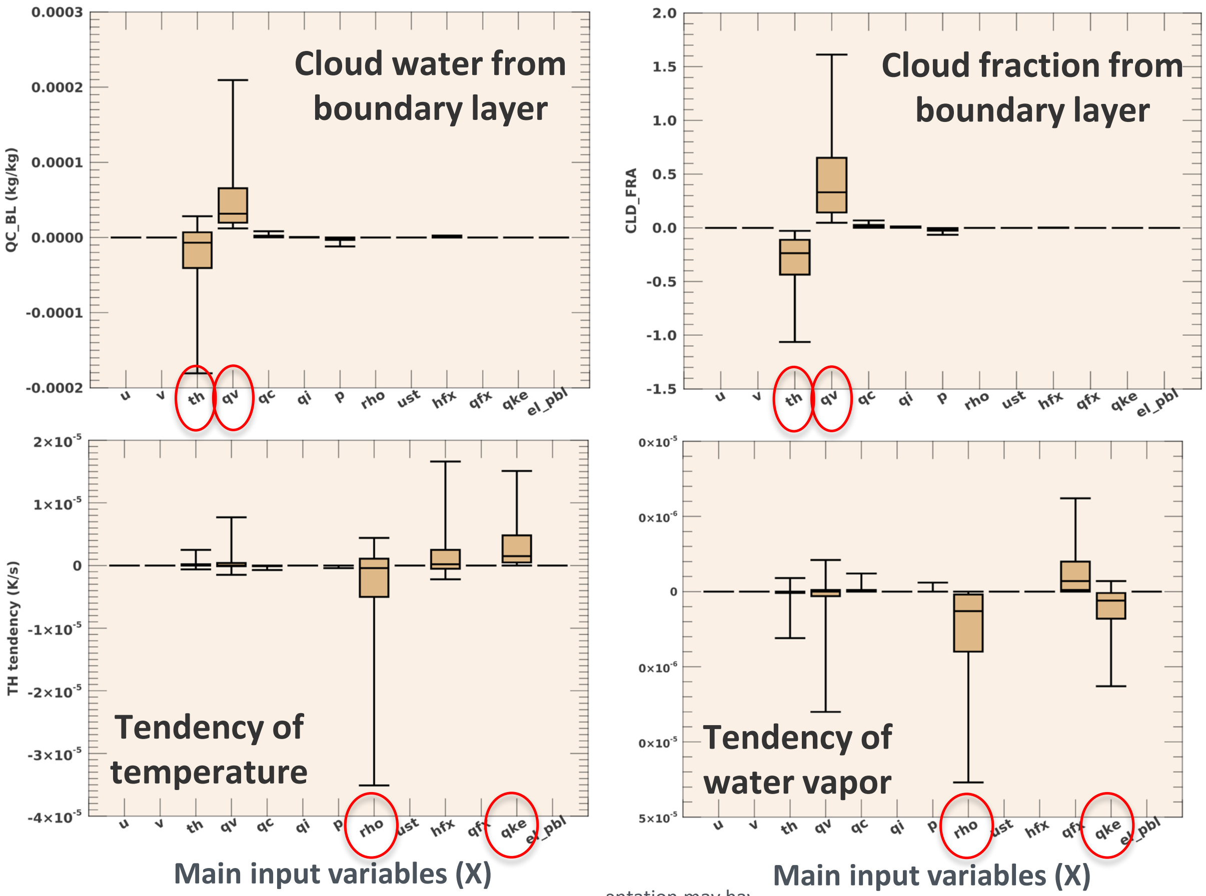
Sensitivity Analysis of MYNN PBL



- Cloud water and cloud fraction from boundary layer are sensitive to Air temperature (th) and water vapor mixing ratio (qv).
- Tendency variables for temperature and water vapor are commonly sensitive to Density (rho) and turbulent kinetic energy (qke).

Sensitivity Analysis of Deng Shallow Cumulus

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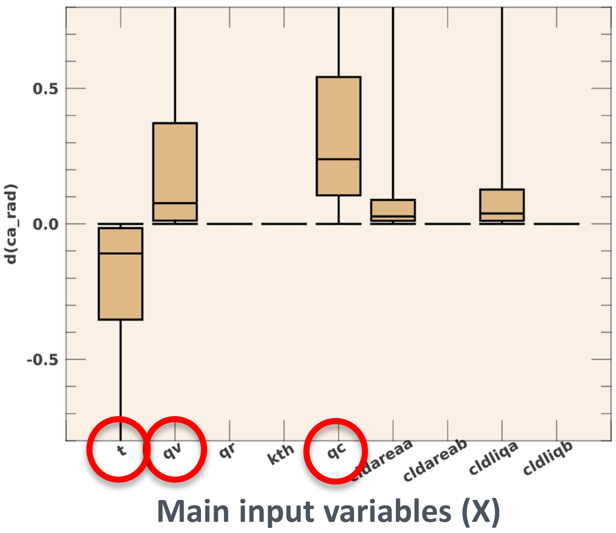
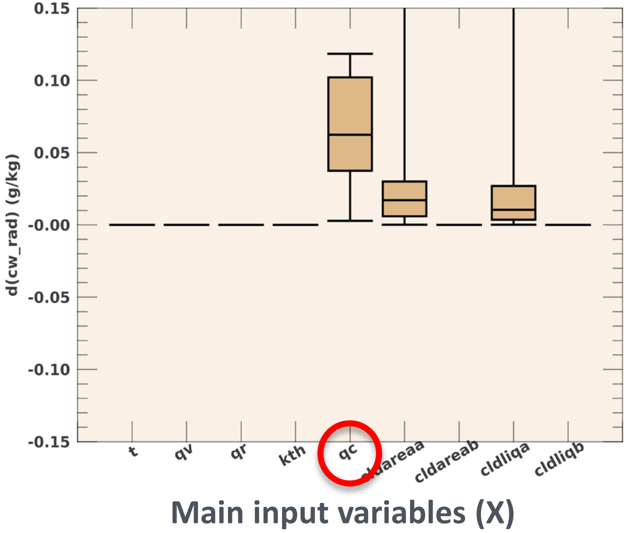
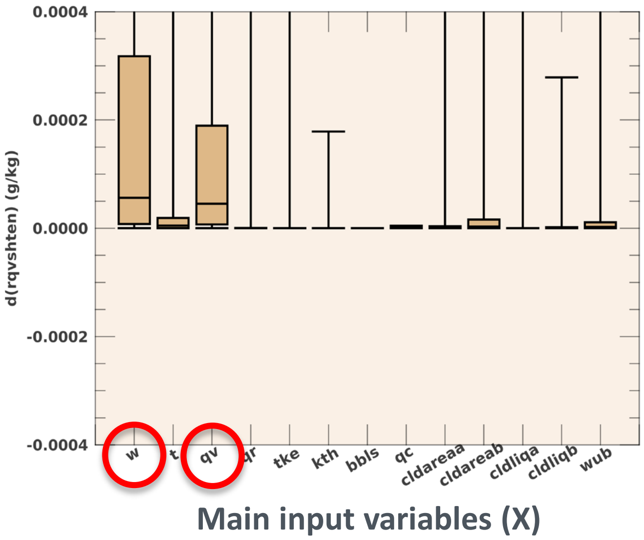
Effective cloud fraction for radiation



Effective cloud water for radiation



Tendency of water vapor



- **Effective cloud fraction for radiation is sensitive to temperature (t), water vapor (qv), and cloud water mixing ratio(qc).**
- **Vertical velocity (w) is also confirmed as an important variable for tendency of water vapor.**

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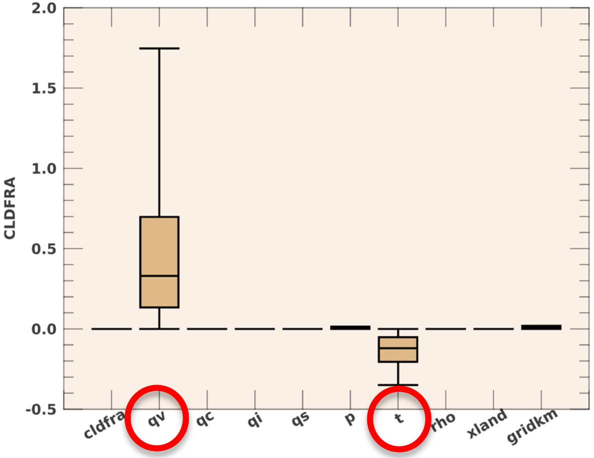
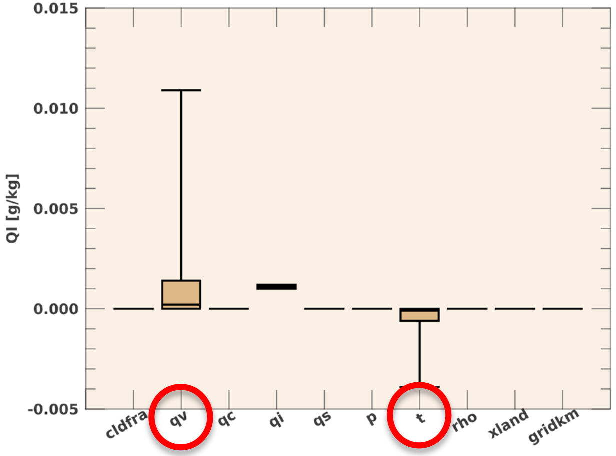
Sensitivity Analysis of Unresolved Cloud Fraction

Cloud fraction



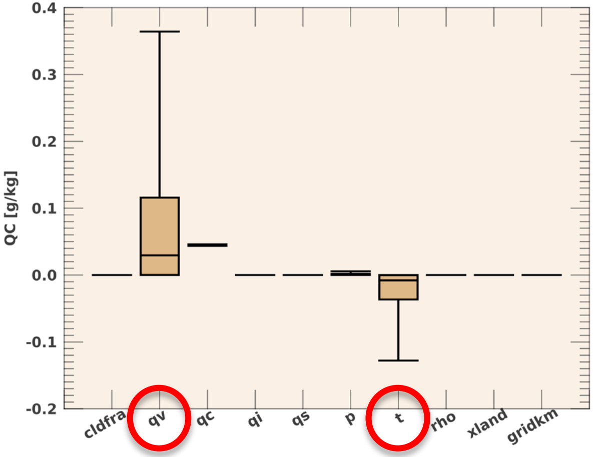
Main input variables (X)

Cloud ice mixing ratio



Main input variables (X)

Cloud water mixing ratio



Main input variables (X)

- **Similar to the Deng shallow cumulus scheme, cloud fraction and mixing ratio variables are sensitive to water vapor (qv) and temperature (t).**

Down-selection of Variables to Perturb

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n	Variable	Name in code	Location	Pert. Type
1	Albedo	ALBEDO	Inside FARMS	%
2	Aerosol optical depth	AOD5502D	Inside FARMS	%
3	Angstrom wavelength exponent	Angexp2d	Inside FARMS	%
4	Asymmetry factor	Aerasy2d	Inside FARMS	%
5	Water vapor mixing ratio	QVAPOR	Inside FARMS, MYNN, Thompson, Noah, Deng, and Icloud3	%
6	Cloud water mixing ratio	QCLOUD	Inside FARMS, MYNN, Thompson, and Deng	%
7	Ice mixing ratio	QICE	Inside Thompson	%
8	Snow mixing ratio	QSNOW	Inside FARMS and Thompson	%
9	Ice number concentration	NI	Inside Thompson	%
10	Temperature	Theta	Inside MYNN, Noah, Deng, and Icloud3	%
11	Turbulent kinetic energy	QKE	Inside MYNN	%
12	Soil moisture content	SMOIS	Inside Noah	%
13	Soil temperature	TSLB	Inside Noah	%
14	Vertical velocity	W	Inside Deng	%

- **Variables selected to perturb based on our sensitivity analysis for 6 parameterizations.**
- **We perturb the variables inside the parameterizations (i.e. inside the WRF-Solar modules).**

Strategy for Adding Stochastic Perturbations

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n	Variable	Std	Lambda	Tau	Cut_off	Seed	Vert_s
1	ALBEDO	0.10	100000.0	86400.0	3.0	17	0
2	AOD5502D	0.25	100000.0	3600.0	3.0	18	0
3	Angexp2d	0.10	100000.0	3600.0	3.0	19	0
4	Aerasy2d	0.05	100000.0	3600.0	3.0	20	0
5	QVAPOR	0.05	100000.0	3600.0	3.0	21	1
6	QCLOUD	0.10	100000.0	3600.0	3.0	22	1
7	QICE	0.10	100000.0	3600.0	3.0	23	1
8	QSNOW	0.10	100000.0	3600.0	3.0	24	1
9	NI	0.05	100000.0	3600.0	3.0	25	1
10	Theta	0.001	100000.0	3600.0	3.0	26	1
11	QKE	0.05	80000.0	600.0	3.0	27	1
12	SMOIS	0.10	80000.0	21600.0	3.0	28	1
13	TSLB	0.001	80000.0	21600.0	3.0	29	1
14	W	0.10	80000.0	21600.0	3.0	30	1

Characteristics of the perturbation

- Std - Standard deviation
- Lambda - Length scale
- Tau - Time scale
- Cut_off - Cut off tail
- Seed - Random seed
- Vert_s - 0) 2D or 1) 3D variable

- **The characteristics of the stochastic perturbations for each variable will be specified.**
- **We have developed WRF-Solar to generate multiple stochastic perturbations.**
- **The stochastic perturbations for selected variables will be stored in the array (e.g. pert3d(i,k,j,n)).**
- **We have linked the perturbations in pert3d to the physics and are testing it.**

WRF-Solar Validation using Measurement and NSRDB

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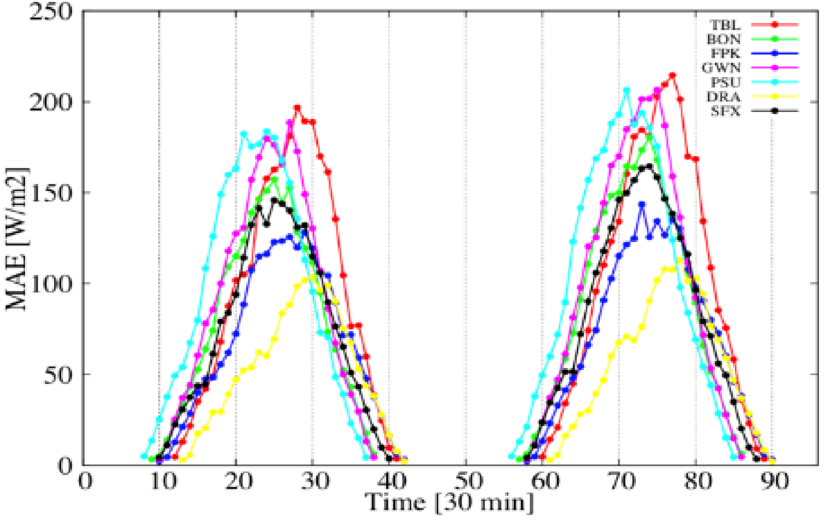
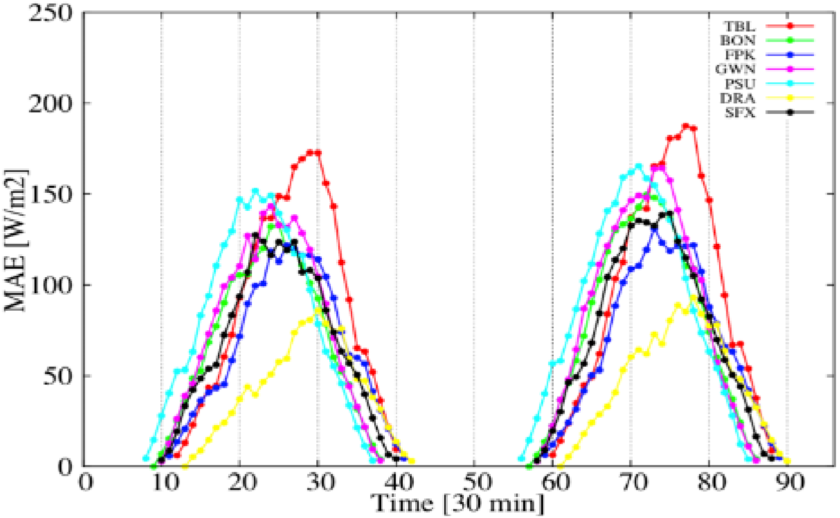
WRF-Solar baseline case evaluation (1-yr, 9km resolution, RAP analysis for initial and boundary conditions)

MAE of GHI compared with SURFRAD



MAE of GHI compared with NSRDB



- Automatic process of WRF-Solar runs has been developed on NREL HPC (Eagle system).
- WRF-Solar simulations for day-ahead forecasts were run for 2017 covering CONUS.
- The 1-yr simulations of WRF-Solar were evaluated using SURFRAD and NSRDB data.

NSRDB and SURFRAD errors characteristics are similar with NSRDB comparison demonstrating smaller errors indicating that the NSRDB can be used for model evaluation.

Preliminary Result from WRF-Solar Ensemble Simulations

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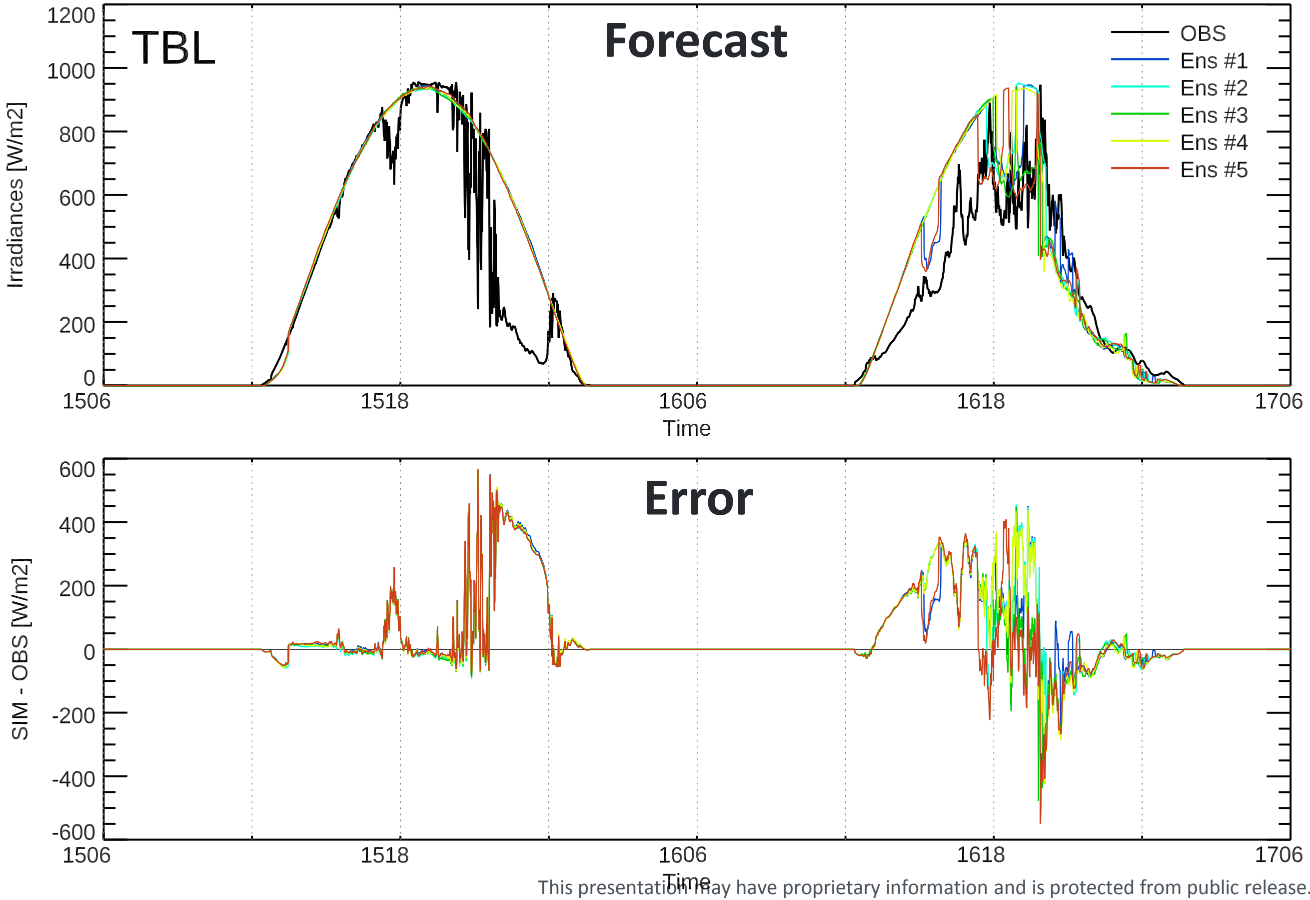

- **The stochastic perturbations for 7 variables were implemented to the FARMS and five WRF-Solar ensemble simulations were tested.**
- **The impact of perturbations on five ensemble members was more pronounced in cloudy conditions.**

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Concluding Remarks

- Tangent linear models were developed for six physics schemes of WRF-Solar using TAF.
- The validation of the TL codes were strictly verified with linearity tests and the test results indicate that TL codes were developed correctly.
- Highest sensitivity variables were identified with the TL method for the WRF-Solar modules individually.
- A methodology to stochastically perturb relevant variables for producing probabilistic solar forecasts was developed.
- Optimized ensemble members will be designed through the sets of perturbed variables and ensemble calibration.

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Accomplishments/Products

We have delivered four conference presentations and submitted two abstracts to the 99th AMS Annual Meeting, the 2019 Joint WRF/MPAS Users' Workshop, the EU PVSEC 2019, and the 100th AMS Annual Meeting.

Jimenez, P. A., M. Sengupta, Y. Xie, J. H. Kim, J. Dudhia, and B. Kosovic, "Enhancing WRF-Solar to Provide Probabilistic Cloud Optimized Day-Ahead Forecasts", American Meteorological Society Annual Meeting, Phoenix, USA, Jan 2019.

Kim, J. H., P. A. Jimenez, M. Sengupta, J. Yang, J. Dudhia, Y. Xie, B. Kosovic, "Enhancing WRF-Solar to Provide Solar Irradiance Probabilistic Forecasts", the 2019 Joint WRF/MPAS Users' Workshop, Boulder, USA, Jun 2019.

Yang, J., M. Sengupta, Y. Xie, P. A. Jimenez, J. H. Kim, "Adjoint Sensitivity Analysis of FARMS for Forecasting Variables of WRF-Solar", the 2019 Joint WRF/MPAS Users' Workshop, Boulder, USA, Jun 2019.

Yang, J., M. Sengupta, Y. Xie, P. A. Jimenez, J. H. Kim, "Adjoint Sensitivity of FARMS to the Forecasting Variables of WRF-Solar", the 36th European Photovoltaic Solar Energy Conference and Exhibition, Marseille, France, Sep 2019.

Yang, J., M. Sengupta, Y. Xie, P. A. Jimenez, J. H. Kim, "Sensitivity Study for Forecasting Variables of WRF-Solar Using a Tangent Linear Approach", American Meteorological Society Annual Meeting, Boston, USA, Jan 2020. (submitted)

Kim, J. H., P. A. Jimenez, M. Sengupta, J. Yang, J. Dudhia, Y. Xie, "Enhancing WRF-Solar to Provide Solar Irradiance Probabilistic Forecasts under All-sky Conditions", American Meteorological Society Annual Meeting, Boston, USA, Jan 2020. (submitted)

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Thank you

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Overview of Tasks (BP1 and BP2)

BP1	BP2
Task 1: Sensitivity Study of WRF variables (completed) Subtask 1.1: Install and test adjoint compiler Subtask 1.2: Develop adjoint models for WRF-Solar modules Subtask 1.3: Study sensitivity of WRF-Solar modules using adjoint models **Task 2: Data Acquisition for Model Calibration and Validation (completed)** Subtask 2.1: Develop satellite-based validation datasets Subtask 2.2: Acquire surface-based solar radiation datasets Subtask 2.3: Acquire meteorological datasets for validation **Task 3: WRF Model Calibration (completed)** Subtask 3.1: Develop WRF-Solar capabilities to enable perturbation of variable	**Task 4: Data Acquisition for Model Calibration and Validation (on-going)** Subtask 4.1: Develop satellite-based validation data sets Subtask 4.2: Acquire surface-based solar radiation datasets Subtask 4.3: Acquire meteorological datasets for validation **Task 5: WRF Model Calibration (on-going)** Subtask 5.1: Develop WRF-Solar capabilities to enable perturbation of variables Subtask 5.2: Down-select variables for optimizing ensembles in WRF-Solar Subtask 5.3: Calibrate ensembles **Task 6: WRF Model Calibration** Subtask 6.1: Benchmark improvements in WRF-Solar probabilistic forecasts