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Advancing the WRF-Solar Model to Improve Solar Irradiance Forecast in Cloudy Environments

Yangang Liu

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SETO Workshop on Solar Forecasting

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UNIVERSITY AT ALBANY State University of New York

Outline

- Recap of Key Project Elements
- Highlights since last Workshop
- Ongoing Work, Future Plan, & Challenges

Project Goal, Objectives and Tasks

❖ One Goal

- Improve WRF-Solar model for forecasting solar irradiances in cloudy environments

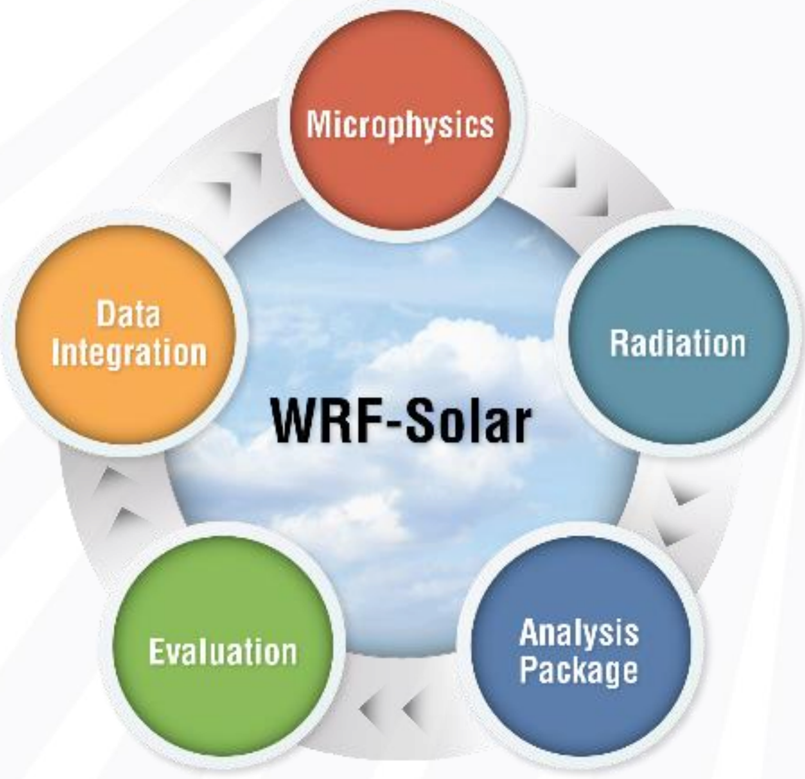
❖ Four Objectives

- Improve cloud microphysics
- Improve radiative transfer
- Develop analysis package
- Perform model evaluation

❖ Five Tasks

- Four objectives + Data integration

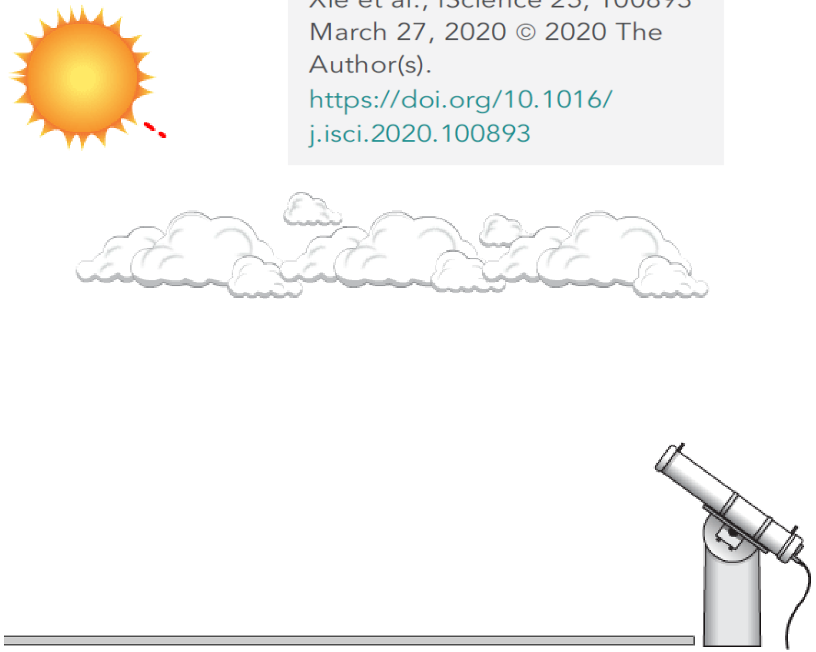
❖ BNL-NREL-SUNY Collaboration



Executive Summary

- Project well progressing into final stage, adjusted according to no cost extension
- Implemented/tested BNL cloud microphysics (BNL_MP) & quantified improvements
- Upgraded default WRF-Solar based on WRF (V3.6) to a new WRF-Solar based on WRF V4.1.2 & quantified the changes
- Upgraded FARMS to FARMS DNI and quantified improvements
- Developed novel analysis framework & demonstrated potentials in data analysis, model evaluation, and simultaneous forecasts of GHI, DNI and DHI
- Developed/implemented parameterization for turbulent entrainment-mixing
- Developed a proto-type framework for model calibration (auto-tuning)
- Two publications (iScience, 2020; Solar Energy, 2021) and more are in preparation; 10^+ conference (AMS and AGU) presentations

Highlight 1: from FARMS to FARMS-DNI



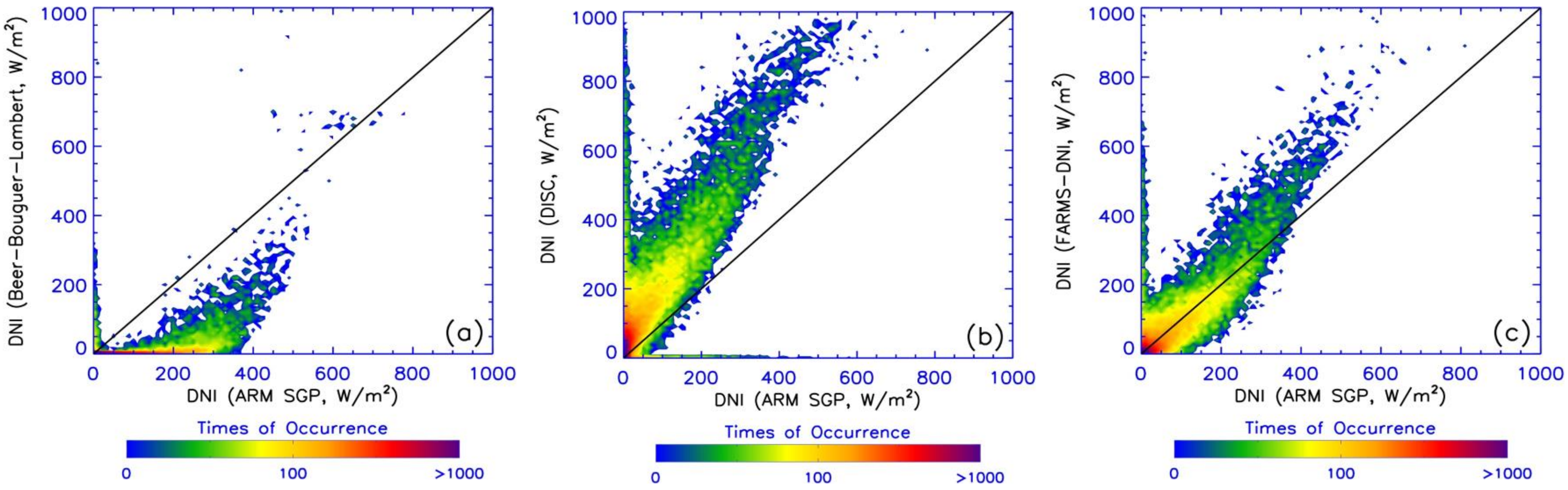
Xie et al., iScience 23, 100893
March 27, 2020
https://doi.org/10.1016/j.isci.2020.100893

A Physics-Based DNI Model
Assessing All-Sky Circumsolar Radiation

Yu Xie,[1,6,*] Manajit Sengupta,[1] Yangang Liu,[2,*] Hai Long,[3] Qilong Min,[4] Weijia Liu,[2,5] and Aron Habte[1]

- **FARMS has been upgraded to consider circumsolar region (FARMS-DNI).**
- **Details reported in iScience paper.**
- **Offline and online evaluations indicate potentially significant improvement in forecasting DNI (next).**

Observational Evaluation of FARMS-DNI



- Beer law underestimates DNI
- Empirical DISC overestimates DNI
- FARMS DNI improves DNI substantially

New parameterization for FARMS-DNI has been developed, implemented into NREL WRF-Solar, and evaluated (next slide).

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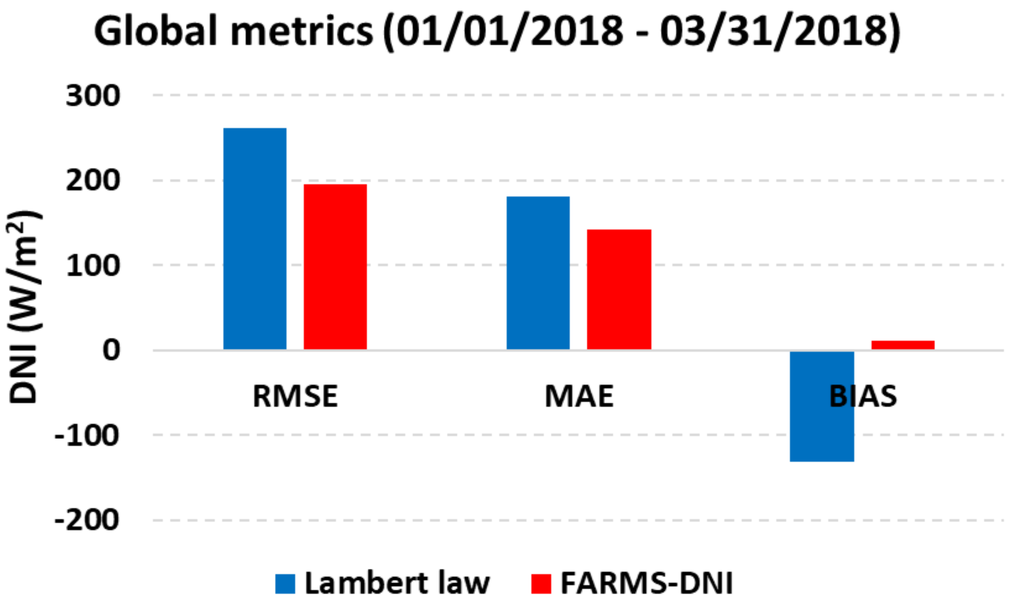
FARMS-DIN Improves WRF-Solar DNI significantly.

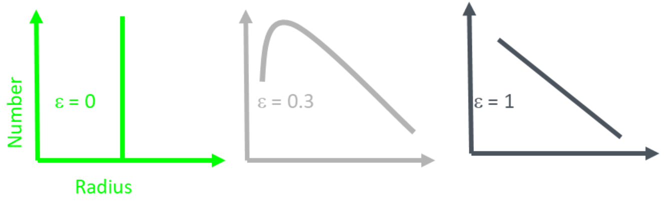


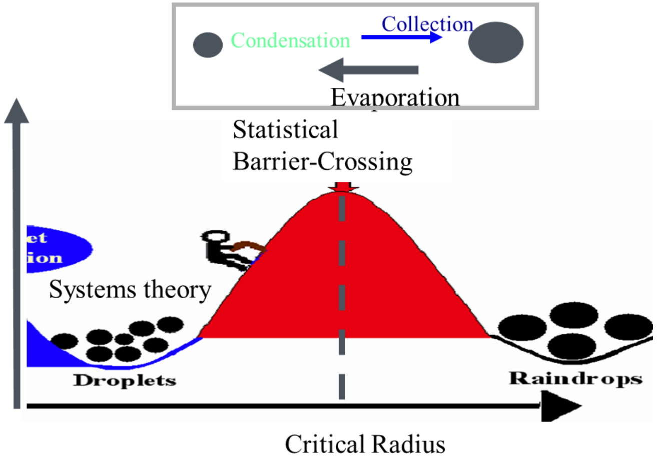
- We analyzed statistical metrics computed with all available data for the period of 01/01/2018 – 03/31/2018.
- Averaged data over 18 ARM-SGP sites were considered to evaluate model performances.
- There is an improvement from the FARMS-DNI with 25% decrease of RMSE and 21% decrease of MAE compared to the Lambert law (used in FARMS).

- **Refine and test it in BNL WRF-Solar, together with the other upgrades.**
- **Great potentials to improve solar energy forecast & beyond.**

Highlight 2: from Thom to BNL Microphysics

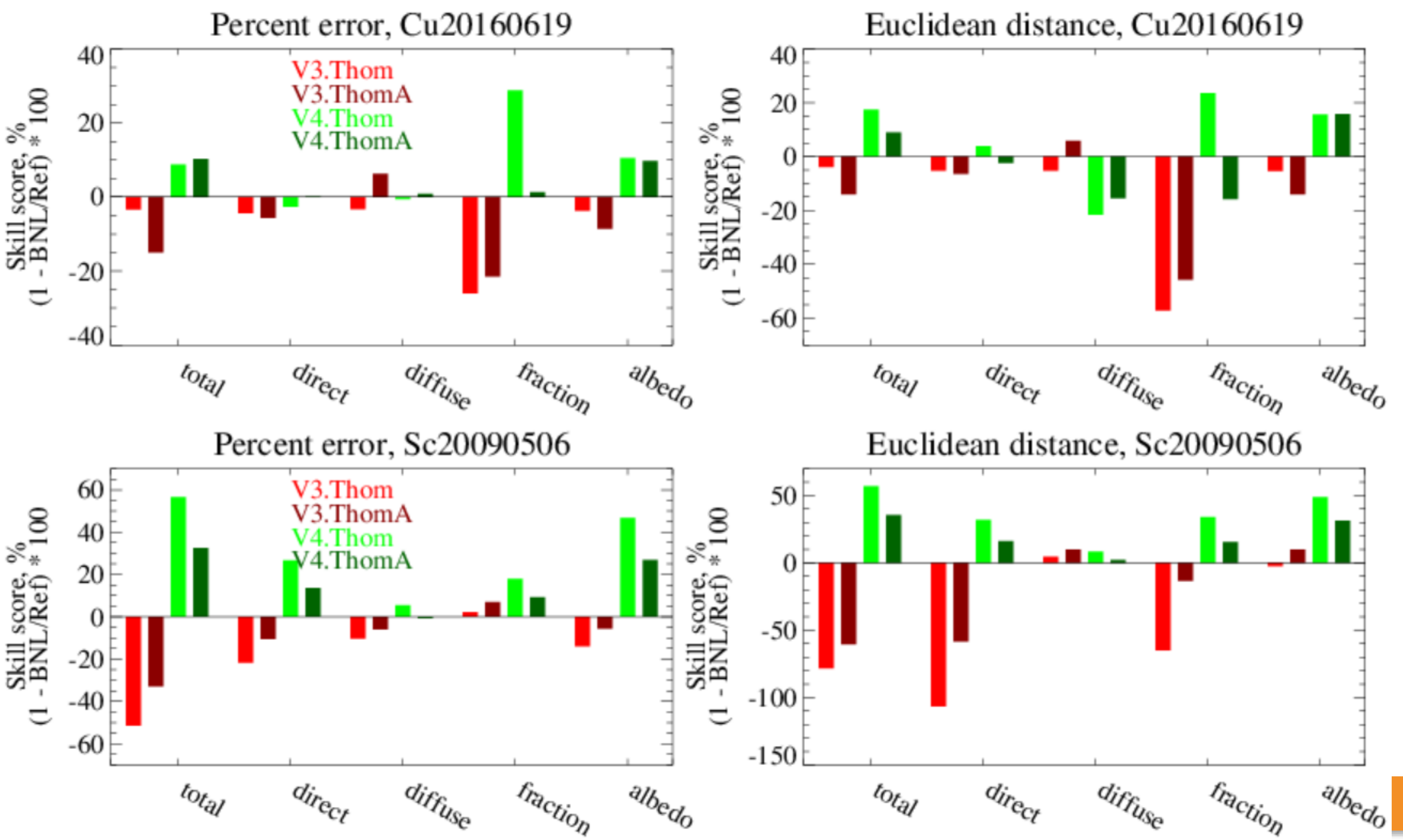
- Focus on those either poorly represented or not represented at all
- Consideration of relative dispersion in effective radius and autoconversion
- Consideration of turbulence effect via condensation rate β_{con}
- Aerosol-cloud interactions with dispersion effect
- Largely analytical with clear physics
- Turbulent entrainment-mixing processes (ongoing)



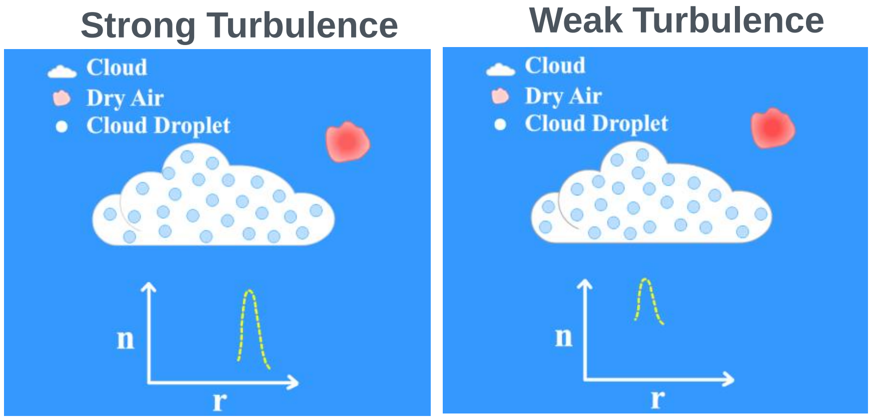


Performance of BNL Vs. Thom Cloud Microphysics

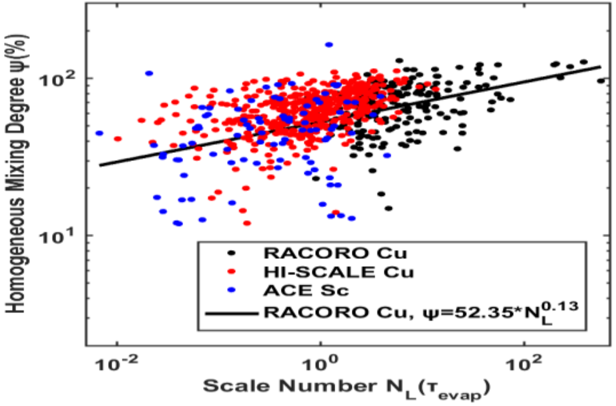
- Positive y means improvement
- BNL_MP improves new WRF-Solar up to 60%.
- Smaller improvement for Cu case due to smaller cloud fraction and water content
- Microphysics effect is coupled with other model components including different versions
- Cloud-dependent
- Additional effect from entrainment-mixing



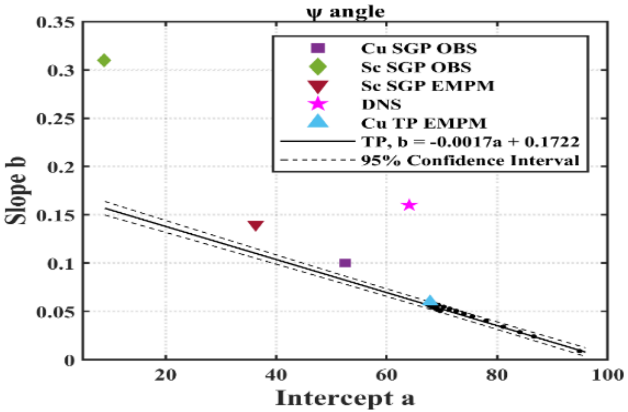
Representation of Turbulent Entrainment-Mixing Effect



Homogeneous Inhomogeneous

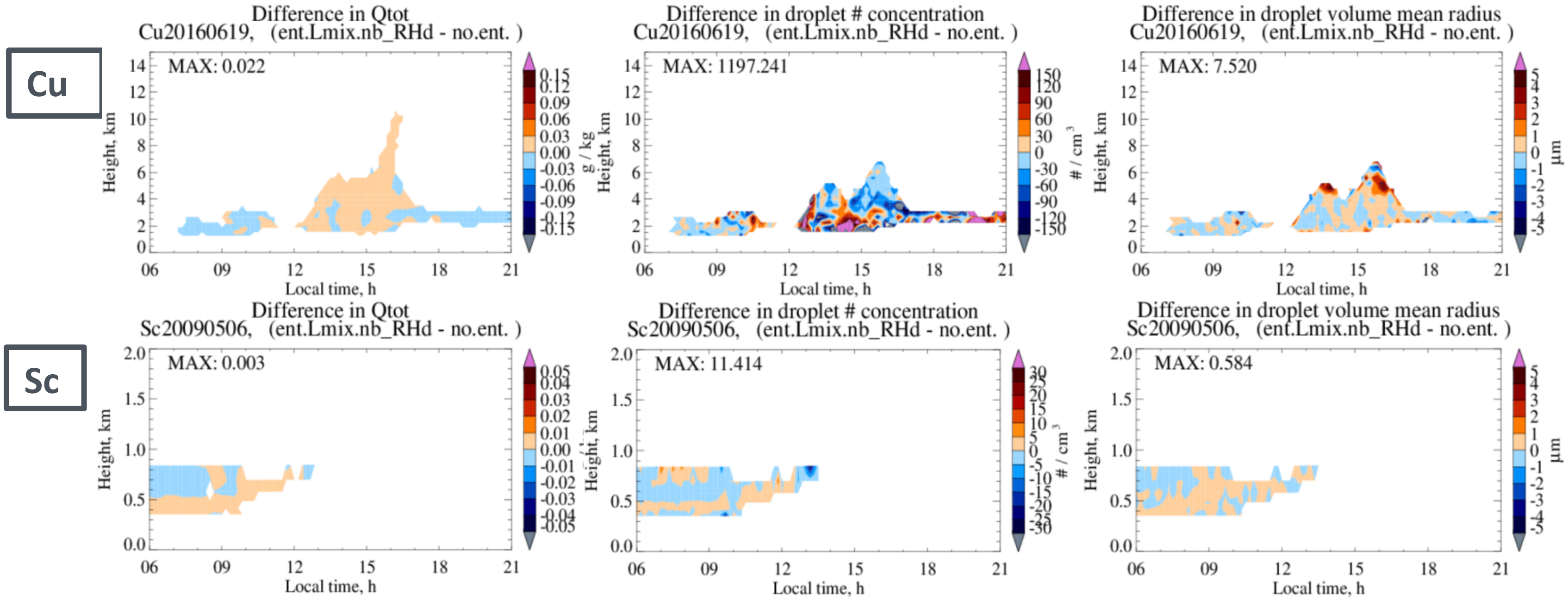


Different mechanisms affect droplet size distribution differently, including possible spectral shape in between the two idealized extremes.



$$\psi = aN_L{}^b, \quad b = -0.0017a + 0.1722$$

Effects of Turbulent Entrainment-Mixing Processes



- Contrasting influences in evaporating vs non-evaporating grids > Compensation between cloud edges & core? Dependence on cloud types?
- Effects of energy dissipation rate, entrained dry air relative humidity, & shallow cu parameterizations.

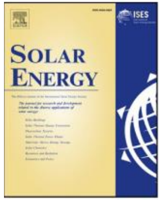
Highlight 3: Novel Analysis Framework

- Based on relationships between dimensionless parameters from total and direct irradiances.
- Separation of cloud fraction and albedo effects on solar irradiances.
- A hierarchy of physics-informed persistence models to forecast GHI, DNI and DHI.
- Potentials in integrating data-driven models with physical (WRF-Solar) forecast (ongoing)

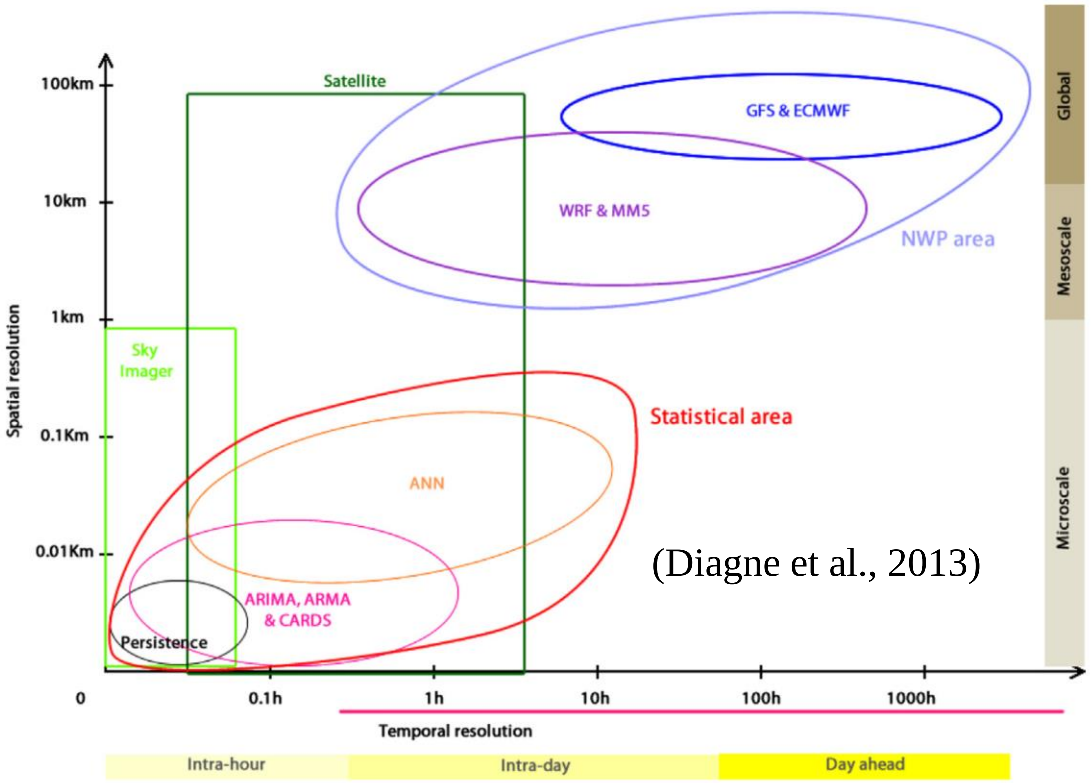
Solar Energy, Volume 215, Pages 252-265. https://doi.org/10.1016/j.solener.2020.12.045

Use of physics to improve solar forecast: Physics-informed persistence models for simultaneously forecasting GHI, DNI, and DHI

Weijia Liu [a,b,*], Yangang Liu [a,*], Xin Zhou [a], Yu Xie [c], Yongxiang Han [b], Shinjae Yoo [a], Manajit Sengupta [c]



Analysis Framework for Improving Forecast



(Diagne et al., 2013)

"Improve data-driven forecast"

Analysis Framework

"Improve WRF-Solar"

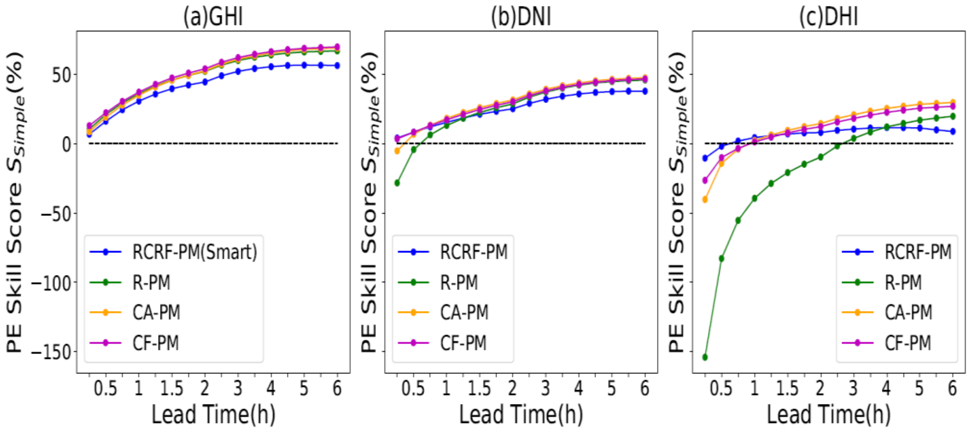
Physics-Informed Forecasting Hierarchy

- 4 levels of persistence forecast model forecasting GHI, DNI and DHI;
- The Higher the model level the clearer the representation of cloud radiative effects;
- Evaluated with decade-long obs. at ARM SGP (1998-2014);
- Higher level models perform better than lower-level models;
- Paper published in Solar Energy, 2021

$$\text{PE Score } (\mathrm{S_{ref}}) = (1 - \frac{PE_{model}}{PE_{ref}}) \times 100\%$$

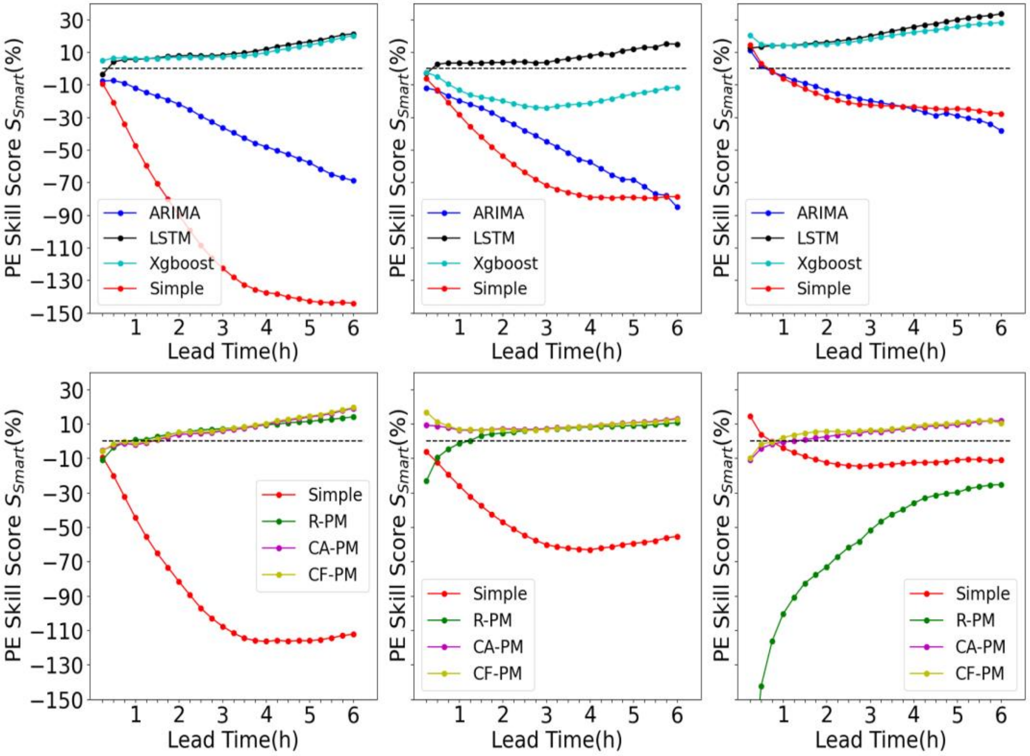
Table.1 A summary of cloud-radiation relationships at different levels of approximation

Hierarchy Level	Persistent Predictor	Cloud Physics Incorporated
1st level	$F^{dn}_{all,GHI}, F^{dn}_{all,DNI}, F^{dn}_{all,DHI}$	*No direct cloud physics*
2nd level	*K or RCRFs*	*Overall cloud effects*
3rd level	*R*	*Approximate separation of radiative effects from cloud albedo and cloud fraction*
4th level	α_r, f	*Clear separation of radiative effects from cloud albedo and cloud fraction*



Physics-Informed Vs. Machine Learning Models

- Percent skill score relative to smart persistence model.
- Improvement from physics-informed models is comparable to that of directly applying machine learning models, but much more computationally efficient.
- Value using both GHI and DNI in forecasting because they, together, contains cloud fraction and albedo effects.



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Highlight 4: Framework for “Auto-tuning” Parameters

WRF-Solar: y = F(**x**, parameters); Seek set of optimal parameters by minimizing the cost function(s).

- Needed for objectively “tuning” parameters following cloud conditions.
- Challenges

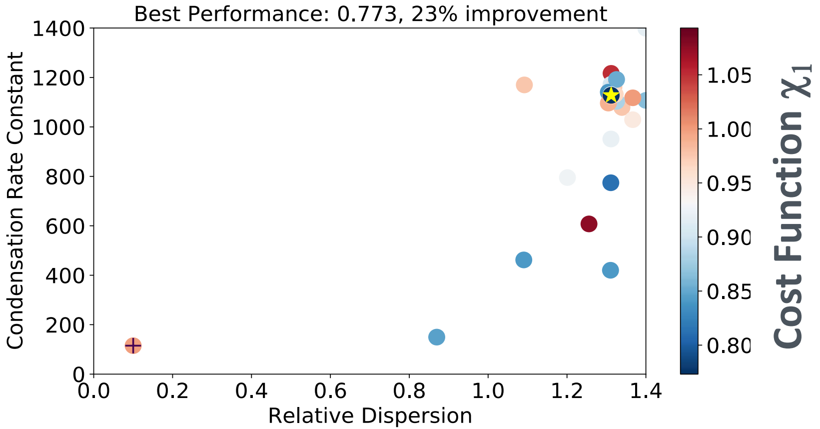
-- Computational cost (ML emulators & streaming & efficient parameter sampling)

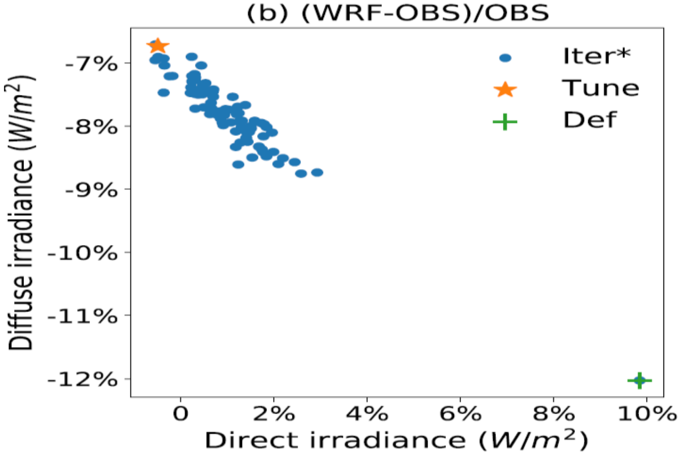
-- Multiple parameters & cost functions: Pareto optimality, e.g., optimizing multiple parameters to impove GHI and DNI forecasts.

-- Compensating errors in WRF-Solar & role of cost function

-- Smart cost functions (analysis framework)

-- Integration with WRF-Solar suite

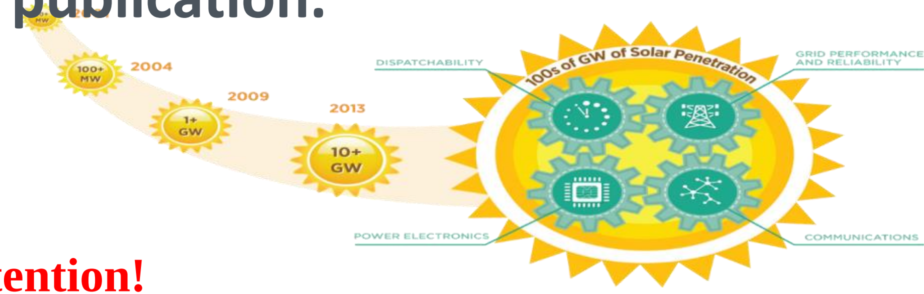




Still room for improvement by optimizing parameters that depends likely on cloud conditions.

Ongoing Work and Future Plan

- Freeze WRF-Solar upgrades for ARBITER forecast.
- Test/refine WRF-Solar with all parameterization upgrades.
- Continue developing/testing entrainment-mixing parameterization
- Continue developing/testing auto-tuning framework.
- Summarize/analyze results for publication.
- Finalize the deliverables.



Thanks for your attention!
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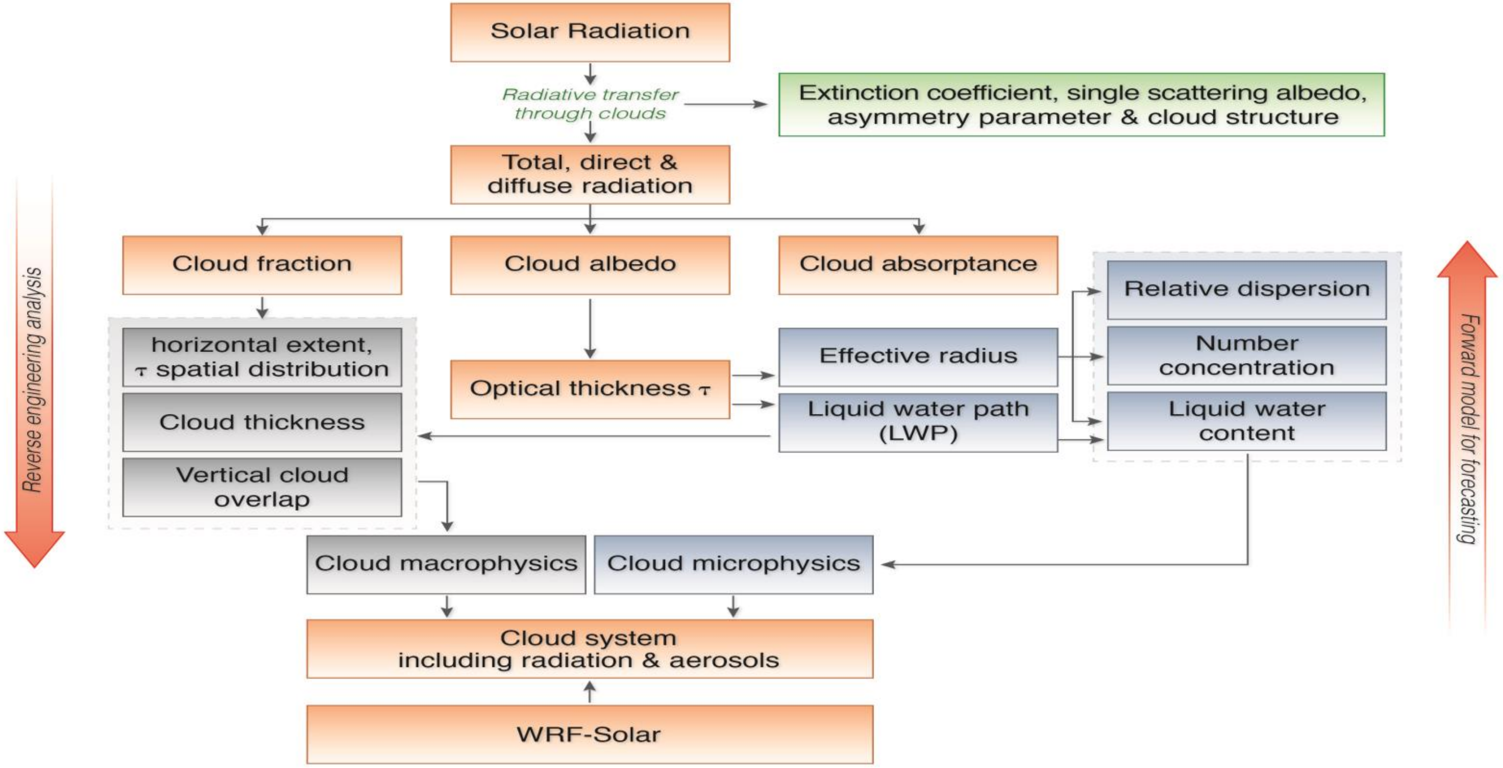
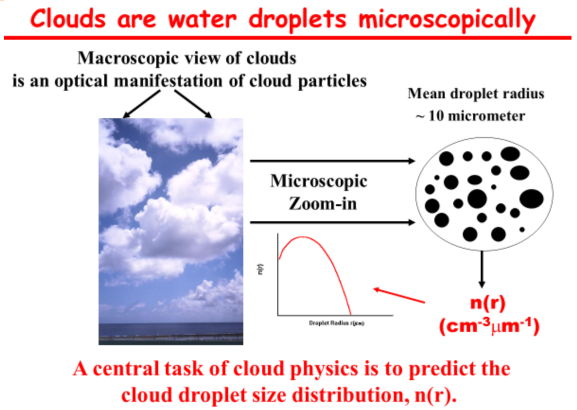
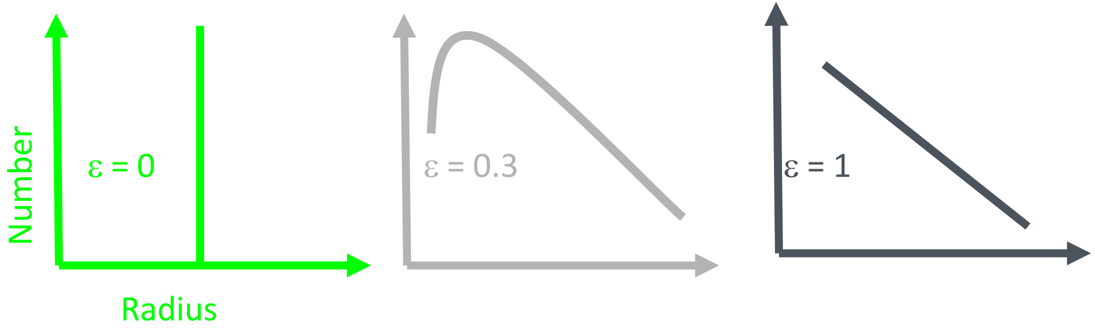
Backup slides

Radiation Tree for Studying Cloud Effects on Radiation



Relative Dispersion of Cloud Droplet Size Distribution

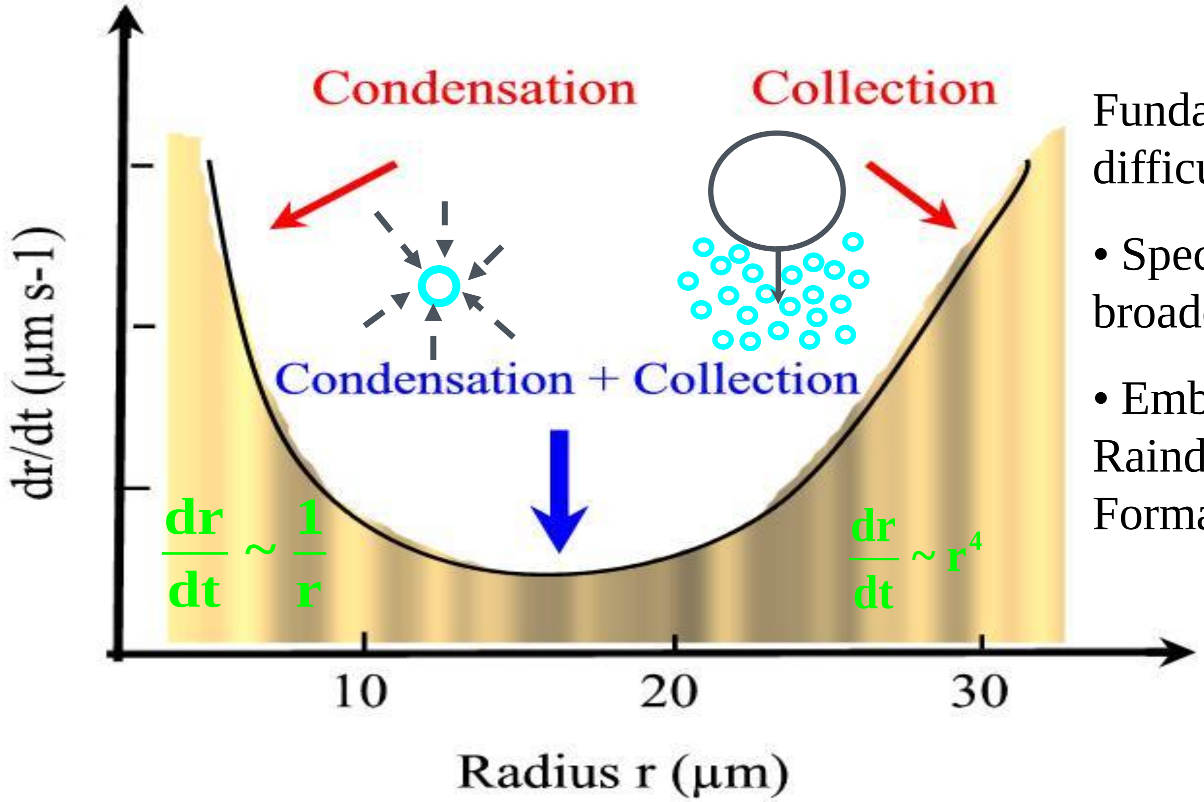




- Relative dispersion ε is the ratio of standard deviation to the mean radius
- Relative dispersion increases from left to right in above figures.
- Note the striking difference between the three diagrams, which all have the same water content and droplet concentration
- Most microphysics schemes assume constant relative dispersion
- A key feature of BNL microphysics is to explicitly relative dispersion

Critical radius next

Valley of Death and Drizzle Initiation

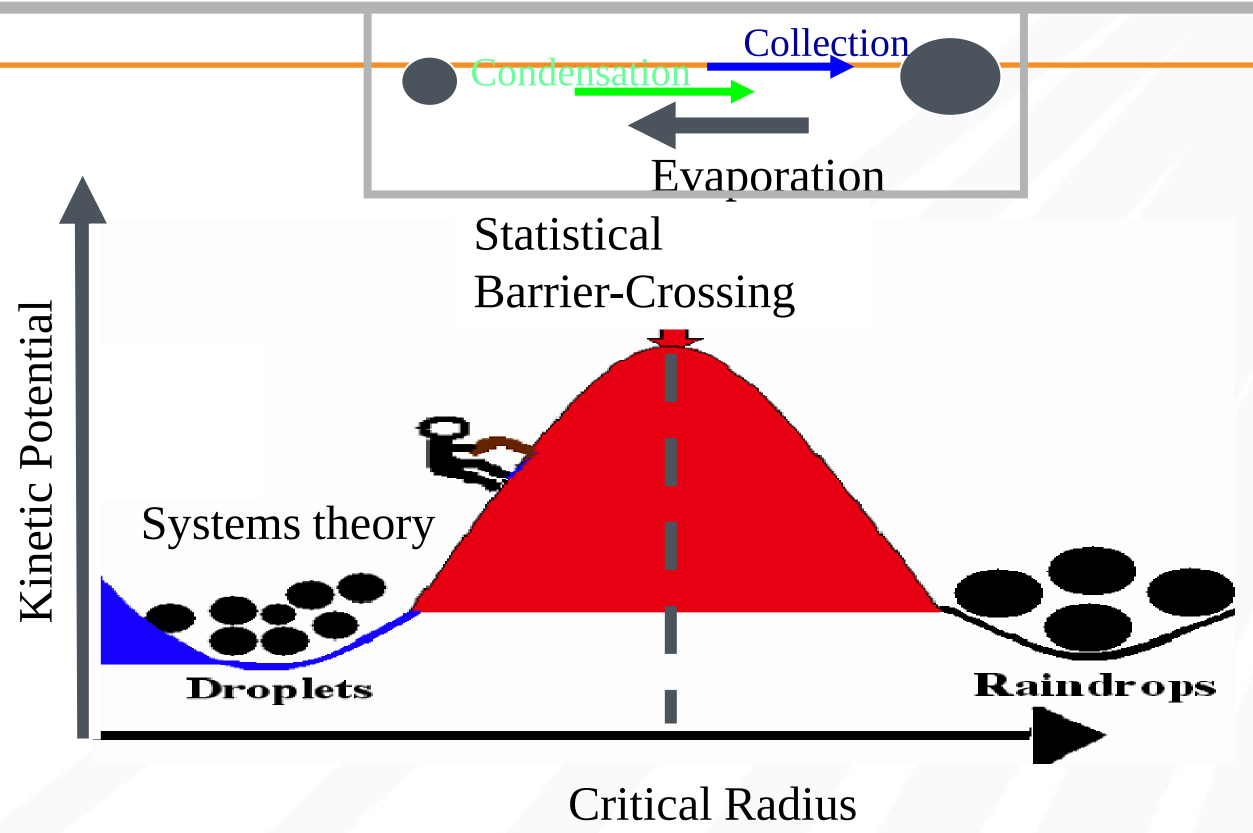


Fundamental difficulties:

- Spectral broadening
- Embryonic Raindrop Formation

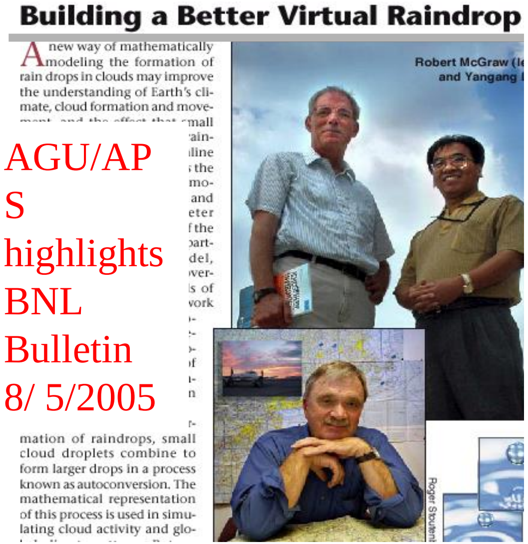
Rain initiation has been a persistent puzzle in cloud physics since 1940s. Again missing factors are turbulence & evaporation.

Mountain of Life: New Rain Initiation Theory

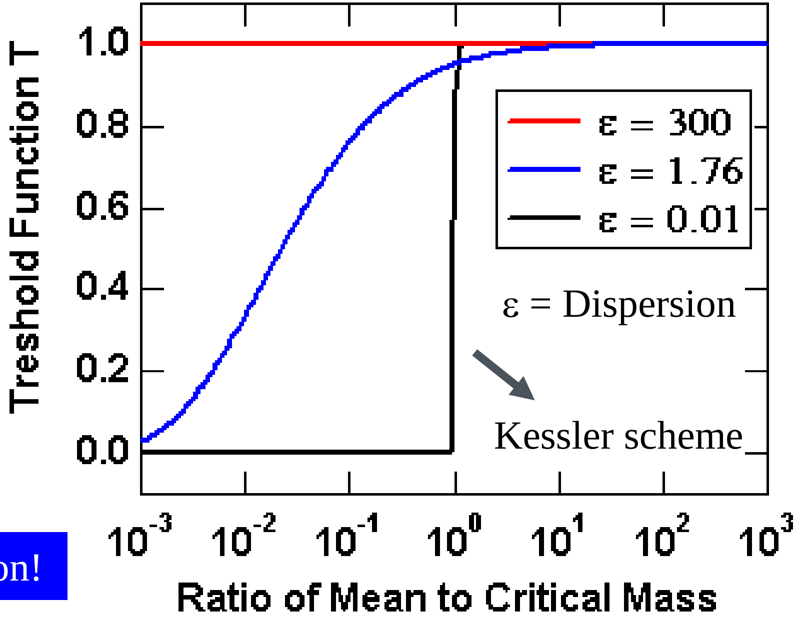


The new rain initiation theory (kinetic potential theory, KPT) combines statistical barrier crossing with the systems theory for droplet size distributions (McGraw & Liu, Phys. Rev. Lett., 2003; Phys. Rev., 2004), and provides physics for threshold.

Theoretical Autoconversion Schemes



AGU/APS highlights BNL Bulletin 8/ 5/2005

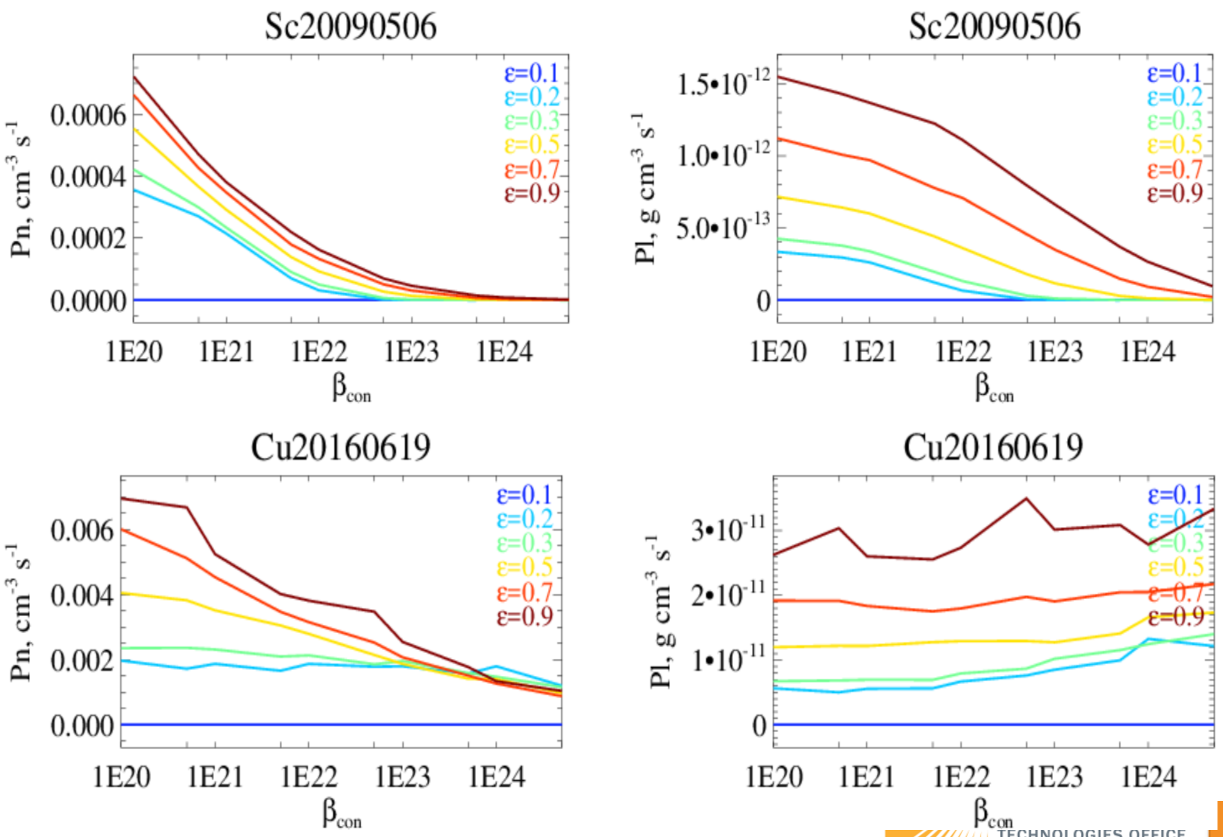


Note the importance of dispersion!

Combining the new rain initiation theory with theory for collision and coalescence of cloud drops leads to the BNL autoconverison parameterizations (Liu & Daum, JAS, 2004; Liu et al., GRL, 2004, 2005, 2006, 2007, 2009): **dispersion and critical radius**

Technical Accomplishments (T6.1): Autoconversion Rate

- Autoconversion rates increase with increasing relative dispersion, thus the radiative and cloud properties are more sensitive to β_{con} when ε is large.
- The perturbations of simulated properties in the Cu case is due to the perturbations in the autoconversion rates.
- The sensitivity of solar irradiance is not only determined by autoconversion, but also by cloud fraction, cloud droplet activation, evaporation etc.



Highlight 2: from Thom to BNL Microphysics

- Effective radius considering relative dispersion ε

$$r_e = \beta r_v, \qquad \beta = \frac{(1+2\varepsilon^2)^{2/3}}{(1+\varepsilon^2)^{1/3}}$$

- Autoconversion considering relative dispersion ε

$$P_{\mathrm{L}} = 1.1 \times 10^{10} \times \frac{\Gamma(\varepsilon^{-2})\,\Gamma\left(\varepsilon^{-2}+3, x_{cq}\right)\Gamma\left(\varepsilon^{-2}+6, x_{cq}\right)}{\Gamma^3(\varepsilon^{-2}+3)} N_c^{-1} L_c^3$$

$$P_{\mathrm{N}} = 1.1 \times 10^{10} \times \frac{\Gamma\left(\varepsilon^{-2}, x_{cq}\right)\Gamma\left(\varepsilon^{-2}+6, x_{cq}\right)}{\Gamma^2(\varepsilon^{-2}+3)} L_c^2$$

$$x_{cq} = \left[\frac{(1+2\varepsilon^2)(1+2\varepsilon^2)}{\varepsilon^6}\right]^{1/3} {x_c}^{1/3} \qquad x_c = \frac{\rho_w \nu}{\kappa^{1/2}} {\beta_{con}}^{1/2} N_c^{2/3} L_c^{-2}$$

- Aerosol-cloud interactions with dispersion effect

$$\boldsymbol{\varepsilon} = 1 - 0.7\exp(-\boldsymbol{\alpha} N_c),\ \boldsymbol{\alpha} = 0.003$$

- Explicit consideration of ε and condensation rate β_{con} (turbulence)
- Turbulent entrainment-mixing processes (ongoing)

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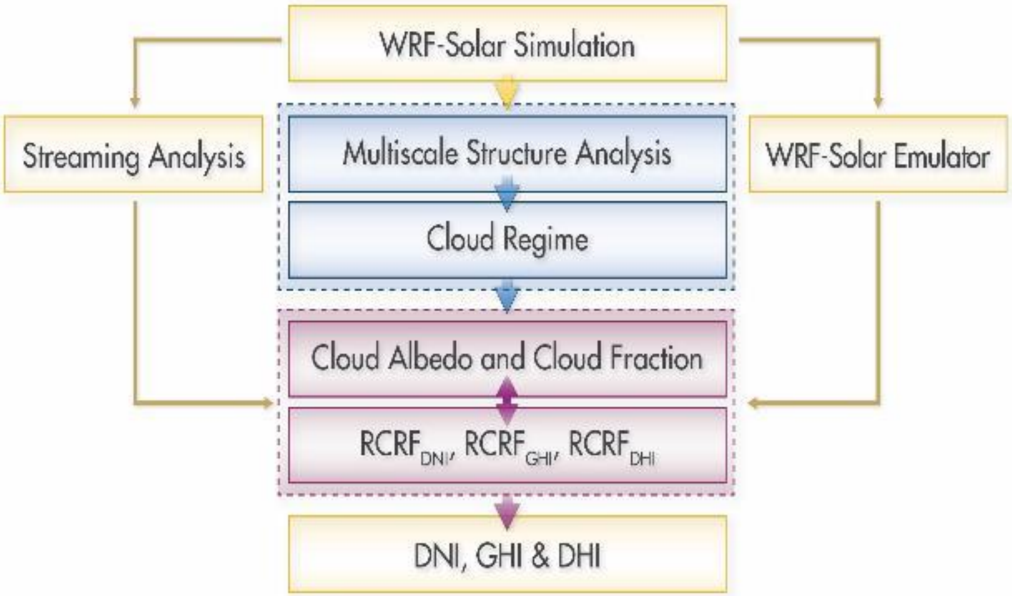
Task 3: Innovative Analysis Package

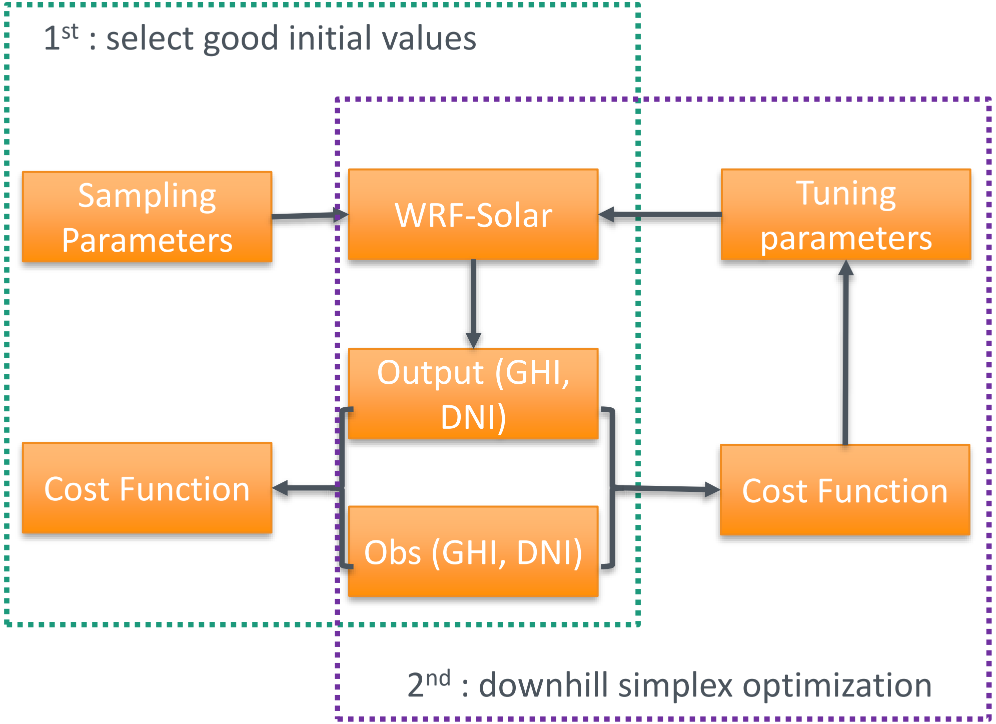
- Radiation-cloud relationships
- Cloud regimes
- Model/process emulator
- Streaming analysis



We will perform similar analysis for corresponding observational data to facilitate model evaluation and shorter-range forecasting as well.

Prototype Auto-Tuning Framework: Two-Step Downhill

- The convergence of downhill simplex (DS) method strongly depends on the quality of the initial values due to its local optimization ability.
- 1st step: select the three good initial values with lower tuning metrics by Latin Hypercube Sampling.
- 2nd step: DS searches the optimal solution by changing the shape of a simplex, which represents the optimal direction and step length.



y = F(**x**, parameters)

Seek model parameters to minimize the cost function based on model prediction Y and measurements.

Test case: Tuning relative dispersion and condensation rate constant

parameter	describtion	Default	Range
vdis	Relative dispersion of cloud droplet spectrum	0.1	0.01 - 1.4
beta_con	Condensation rate constant	1.15e23	1.02e20 – 1.67e24

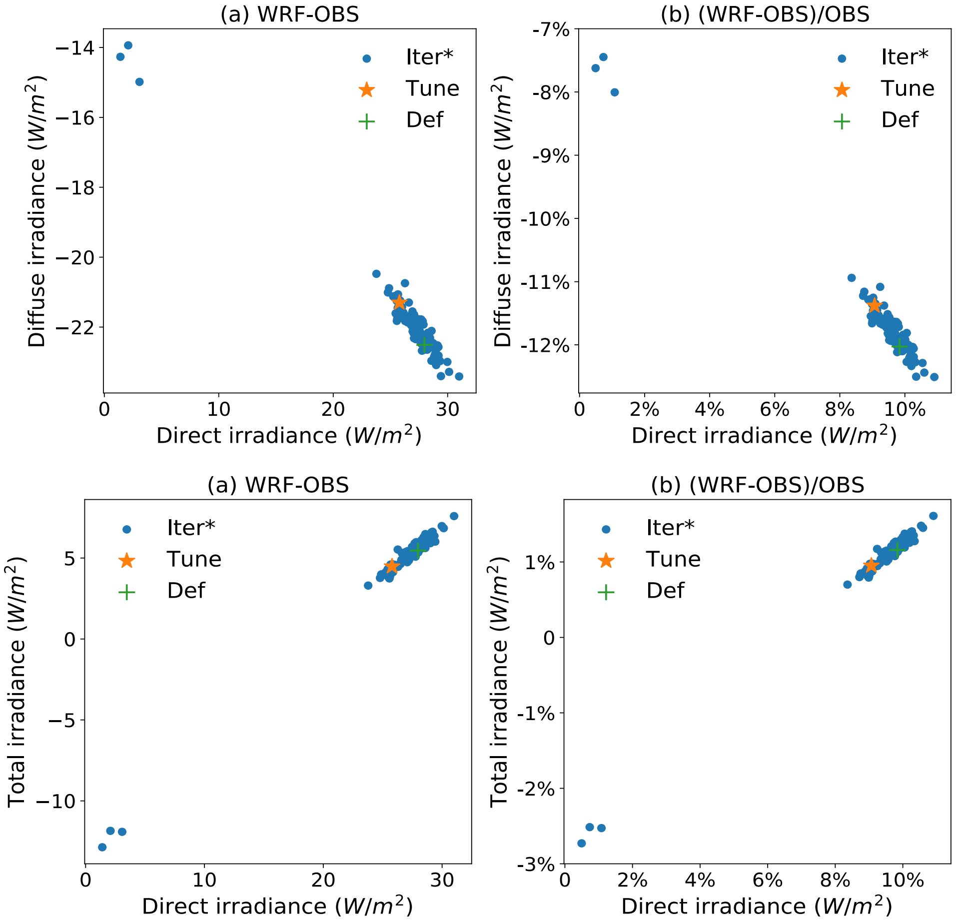
Cost Function:

$$\chi_1 = \frac{1}{2}\left[\frac{mse(x_m^{DIR}, x_o^{DIR})}{mse(x_r^{DIR}, x_o^{DIR})} + \frac{mse(x_m^{DIF}, x_o^{DIF})}{mse(x_r^{DIF}, x_o^{DIF})}\right]$$

$$\chi_2 = \frac{1}{2}\left[\frac{mse(x_m^{DIR}, x_o^{DIR})}{mse(x_r^{DIR}, x_o^{DIR})} + \frac{mse(x_m^{TOT}, x_o^{TOT})}{mse(x_r^{TOT}, x_o^{TOT})}\right]$$

where mse denotes the mean square error; x_m is the model outputs; x_o is the corresponding observation; x_r is model outputs from the control simulation with the default parameter values; subscripts DIR, DIF, and TOT denote the direct, diffuse and total irradiance, respectively.

Influence of Different Cost Functions



$$\chi_2 = \frac{1}{2}\left[\frac{mse(x_m^{DIR}, x_o^{DIR})}{mse(x_r^{DIR}, x_o^{DIR})} + \frac{mse(x_m^{TOT}, x_o^{TOT})}{mse(x_r^{TOT}, x_o^{TOT})}\right]$$

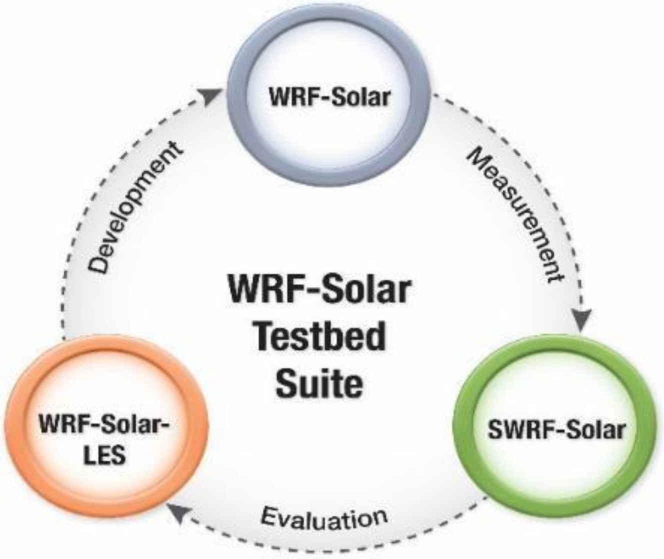
- Optimal pair of relative dispersion and condensate rate (star) improves direct, total, and diffuse irradiances compared to the default pair (cross)
- Compensating errors between direct and diffuse irradiances & trade-off of Pareto optimization.
- Sensitivity to cost function; on-going work with the dimensionless variables (B1, B2)
- Reduce computational cost with streaming ML emulators.

Task 4: Model Evaluation Framework

❖ **WRF-Solar Testbed Suite**

Adapt BNL Fast Physics Testbed:

- WRF-Solar
- WRF-Solar LES
- Single Column WRF-Solar (SWRF-Solar)



❖ **Evaluation Metrics Suite**

- Conventional metrics (e.g., RMSE)
- Relative Euclidean distance
- Taylor diagram
- New analysis package

In addition to quantifying the model-observation differences, our evaluation framework is designed to detect physical causes underlying the model-observation differences and to test new parameterizations.

WRF-Solar Suite Configurations

Table 1.1. WRF-solar configurations for the baseline simulation (Nested), large eddy simulation (LES), and single column model (SCM)

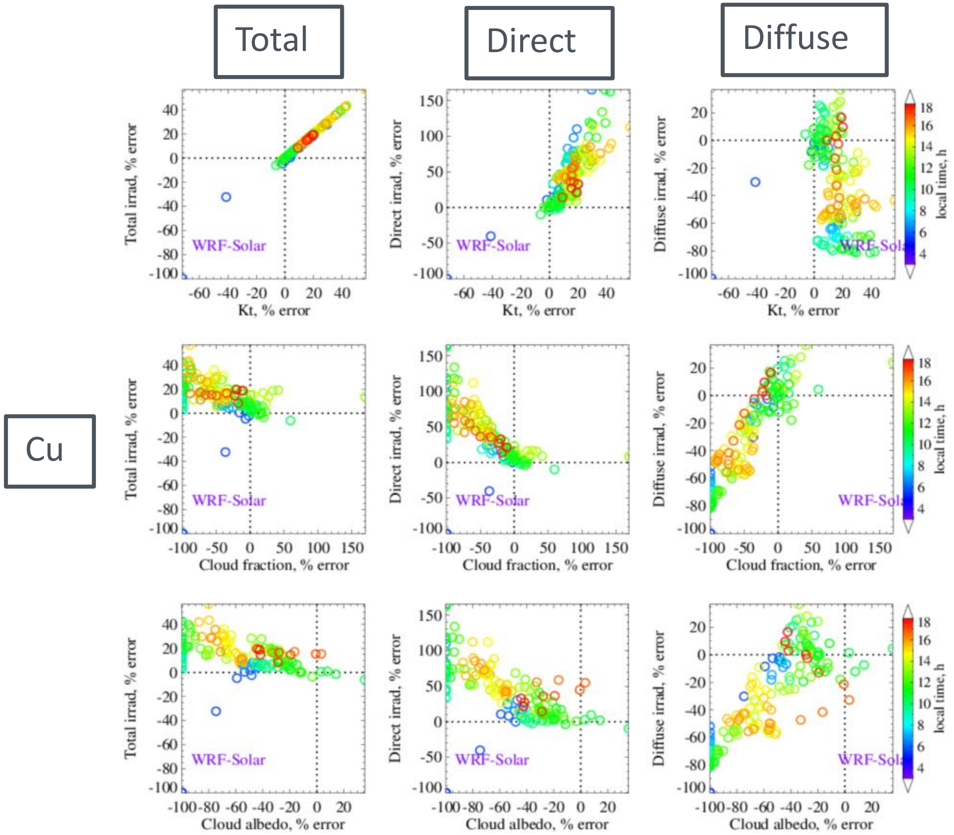
	Nested	LES	SCM
Boundary condition	NARR	VARANAL	VARANAL
# of domains	2	1	1
Size of (inner) domain	90km	14.4km	-
Horiz grid size (inner domain)	3km	100m	3km
# of vertical levels	50	227	50
Model top	100mb (~16000m)	14800m	14800m
Microphysics	Thompson scheme	Thompson scheme	Thompson scheme
Radiation (SW / LW)	RRTMG / RRTMG	RRTMG / RRTMG	RRTMG / RRTMG
Boundary layer	MYNN	-	MYNN
Land surface model	RUC	VARANAL*	VARANAL*
Cumulus parameterization	GF shallow cumulus	-	GF shallow cumulus

Summary of 8 Cases (5 Cu and 3 Sc)

	Cumulus Cases	Stratocumulus Cases
All Cases	• Larger errors cancel out in direct and diffuse irradiances leading to smaller error in total irradiance. • Larger errors in simulated cloud properties than in irradiances • Large errors in irradiances during the transition of the clouds • Possible error compensation from incorrect cloud structures	
Regime dependent	• Small cloud fraction, Smaller sensitivity to microphysics than Sc • Better simulated cloud structures (2D cloud fraction) in LES • Overestimated direct irradiance and underestimated diffuse irradiance • Better simulated direct irradiance than diffuse irradiance	• Large cloud fraction, Larger sensitivity to microphysics than Cu • Better simulated cloud structures (2D cloud fraction) in nested WRF-Solar • All simulations tend to underestimate the 2D cloud fraction (therefore the deeper clouds in LES results in better irradiances) • Better simulated diffuse irradiance than direct irradiance
Case dependent	• All short cases shows small sensitivity to microphysics, while the microphysics sensitivity start from the 2nd day of simulation of the 60 h case.	• Performance of LES, Nested WRF-Solar and SCM varies from case to case

Separation of Cloud Radiative Effects

- Simulated Irradiance vs simulated cloud properties
- New measures allow separation of clearness index error into cloud fraction and albedo errors & are more informative.
- Underestimated cloud fraction/albedo leads to overestimated total and direct irradiances but underestimated diffuse irradiance.
- Diffuse and direct irradiances are more problematic & error compensation.
- Similar results for other clouds

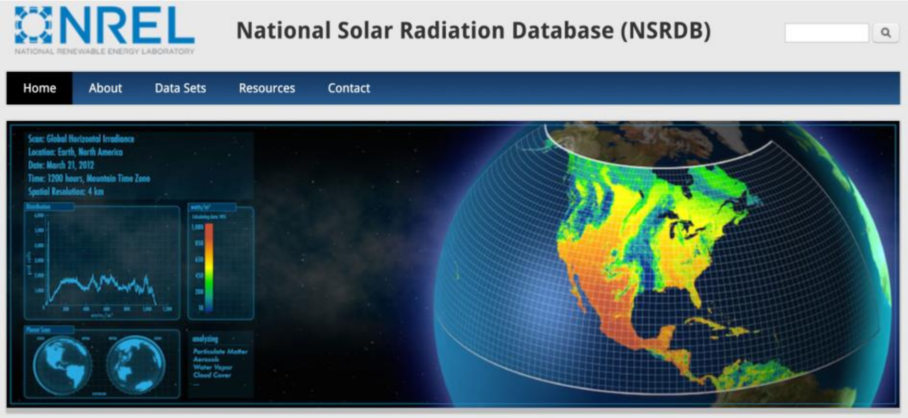


FARMS and FARMS-DNI

FARMS, the **F**ast **A**ll-sky **R**adiation **M**odel for **S**olar applications, is a physics-based radiative transfer model that efficiently (>500 times faster than the state-of-the-art models) computes all-sky solar radiation.

FARMS and the extension models have been used to support multiple DOE-sponsored projects on solar resource assessment and forecasting (e.g., WRF-Solar, NSRDB).

FARMS-DNI model provides a computationally efficient physics-based solution of DNI that considers the circumsolar region and improves DNI forecast in cloudy environment.



Lookup Table of Cloud Transmittance

- **97** wavelength
- **2** Cloud phase
- **39** Cloud Optical Thickness
- **28** Cloud Particle Size
- **43** Solar Zenith Angle
- **100-200** Viewing Direction

- 32-stream DISORT is used to compute the lookup table.
- 9.1×10^8 calculations, each takes ~1-2 seconds.
- **30-120** years by a single CPU.

ML Models vs. Physics-informed Persistence Models

- Using GHI and DNI further improves ML models compare to using GHI or DNI (top panel).
- Multi-variate ML models are better than physics-informed persistence models (bottom panel)
- Writing 2nd paper for SE
- Better integration of ML with physics.