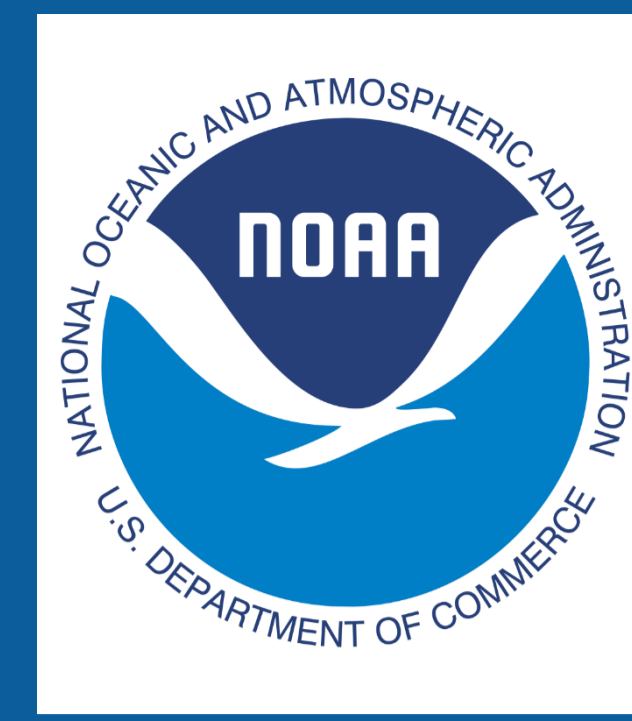


# Understanding and predicting the distribution of surface solar irradiance beneath shallow cumulus clouds

Jake J. Gristey (Jake.J.Gristey@noaa.gov)<sup>1,2</sup> | Graham Feingold<sup>2</sup> | Ian B. Glenn<sup>3</sup> | K. Sebastian Schmidt<sup>4</sup> | Hong Chen<sup>4</sup>

<sup>1</sup>Cooperative Institute for Research in Environmental Sciences, CU Boulder | <sup>2</sup>Chemical Sciences Laboratory, NOAA | <sup>3</sup>Joint Institute for Regional Earth System Science and Engineering, UCLA | <sup>4</sup>Laboratory for Atmospheric and Space Physics, CU Boulder



Check out my CIRES profile:



## Motivation & Aim

- Ubiquitous shallow cumuli exhibit marked 3D structure leading to complex variability in surface solar irradiance (SSI).
- We aim to understand and predict the SSI variability by examining relationships with the cloud-aerosol environment.
- Such relationships are of scientific interest to gain insight into the drivers of SSI variability, as well as of practical importance for efficient and accurate SSI simulation.

## Cloud-Aerosol-Radiation Simulations

- More than 40 days spanning the summers of 2015-2018 that each develop shallow cumulus clouds at the Southern Great Plains (SGP) site in Oklahoma are identified for analysis.
- Large eddy simulation (LES) – with horizontal grid spacing of 100x100 m and domain size of 24 km – is run using observed conditions at the SGP site on each day, including observationally-constrained aerosol variability.
- The LES cloud and humidified aerosol are ingested into Monte-Carlo 3D radiative transfer for realistic SSI computation.

## Significance of 3D Cloud Radiative Effect

- The observed shape of the SSI probability density function (PDF) is only reproduced with 3D radiative transfer (Fig. 1).

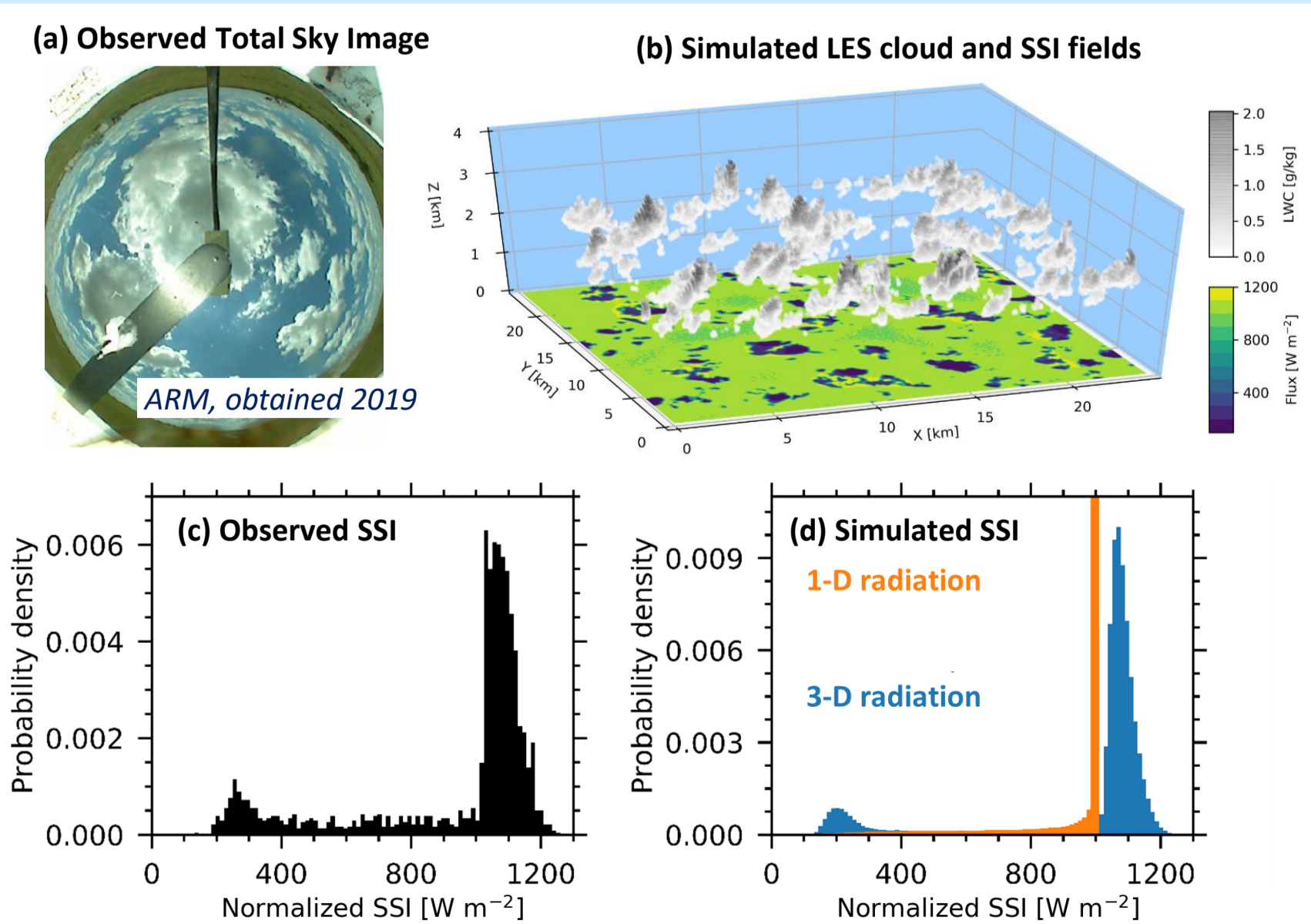


Fig. 1. Observations and simulations of shallow cumulus clouds and associated SSI PDFs on the afternoon of 27 June 2015 at the SGP site in Oklahoma.

## Machine Learning Setup to Represent 3D Cloud Radiative Effect

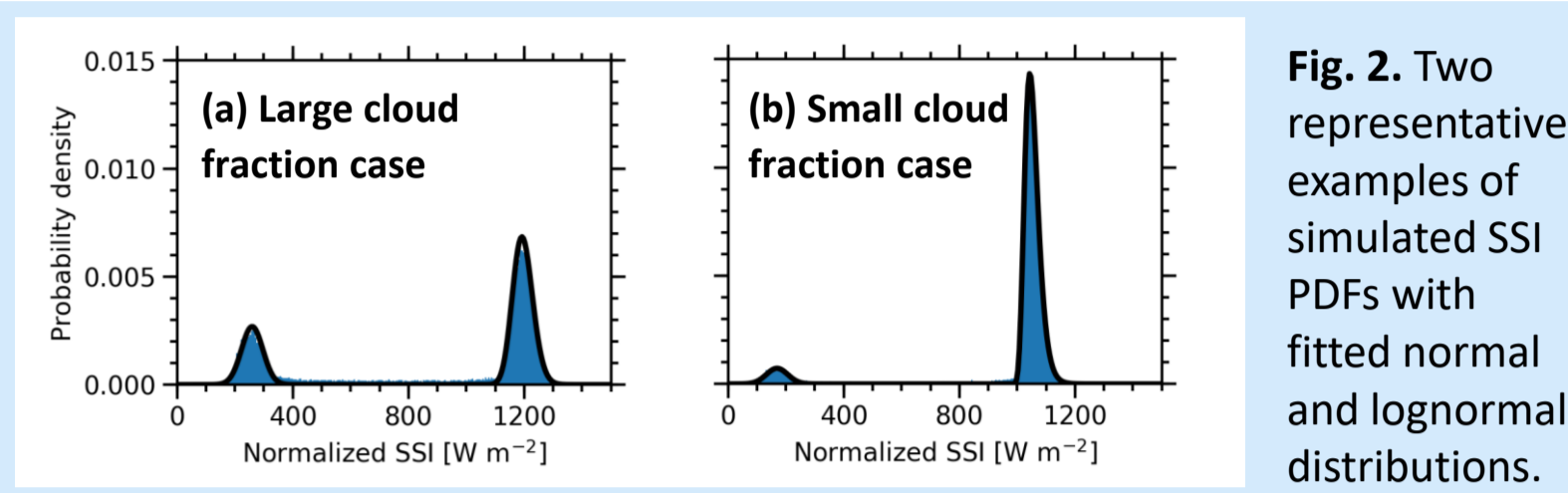


Fig. 2. Two representative examples of simulated SSI PDFs with fitted normal and lognormal distributions.

- Fit normal and lognormal functions to small and large irradiance modes (Fig. 2) and seek relationships between 6 cloud field properties and 7 SSI PDF fit parameters (Table 1).

Table 1. Machine learning inputs and outputs.

Cloud field properties (inputs)	SSI PDF fit parameters (outputs)
Mean cloud fraction: $\bar{f}_C$	Lognormal location parameter: $\theta$
Dispersion in liquid water path: $D(LWP)$	Lognormal shape parameter: $s$
Mean drop number concentration: $\bar{N}_C$	Lognormal scale parameter: $m$
Mean projected cloud area: $\bar{A}_C$	Normal location parameter: $\mu$
Mean distance to nearest cloud: $\bar{D}_{C-NN}$	Normal shape parameter: $\sigma$
Cosine of solar zenith angle: $\cos(SZA)$	Weight of small irradiance mode: $w_1$
	Weight of large irradiance mode: $w_2$

- Two machine learning algorithms with fundamentally different architectures are used to build the relationships (Fig. 3):
  - A random forest (RF): A set of decision trees each making binary predictions at nodes within the trees.
  - An artificial neural network (ANN): A deep series of layers, each containing nodes that apply a non-linear function to a weighted combination of input from the previous layer.

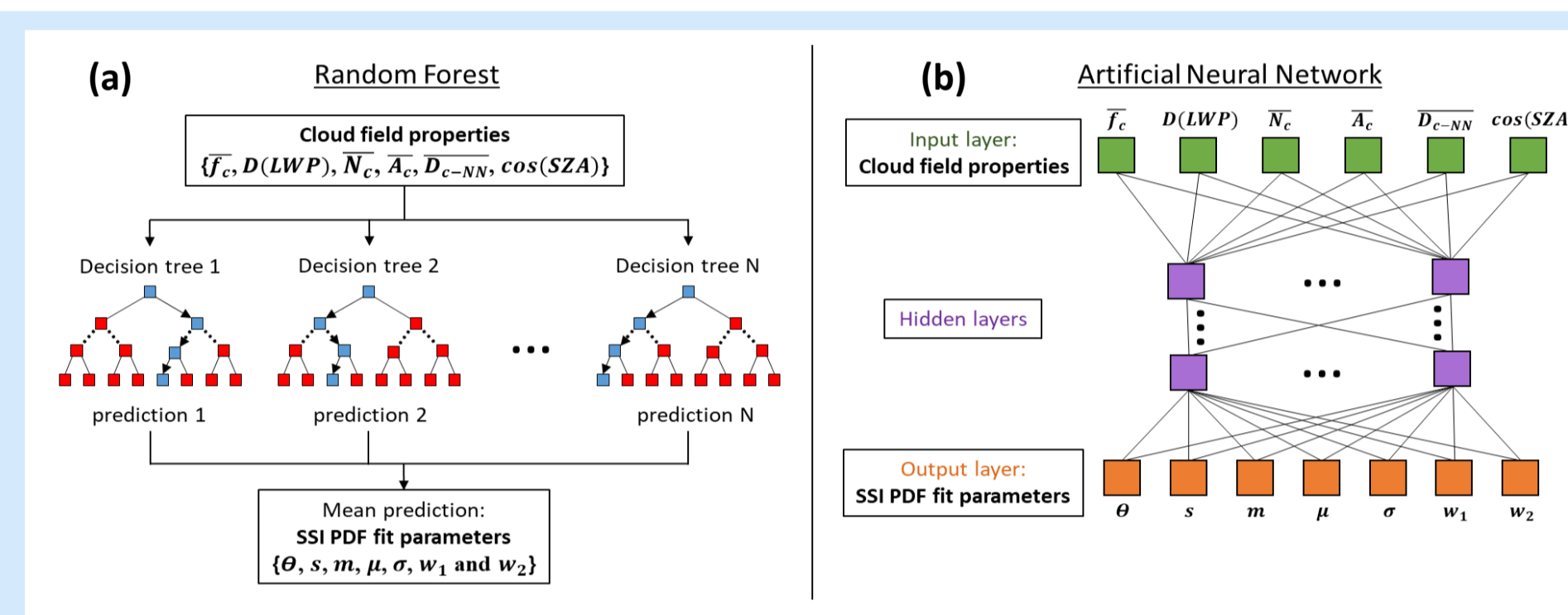


Fig. 3. Machine learning architectures employed.

## Key Findings

- Surface solar irradiance variability beneath continental shallow cumulus clouds is complex but can be predicted accurately with just a handful of key cloud field properties using machine learning algorithms.
- Aerosol can additionally perturb the distribution of surface solar irradiance and is under investigation.
- Results have immediate use for surface energy assessments, with several other promising applications.

## Prediction of Surface Solar Irradiance

- Predicted PDF fit parameters by the trained RF and ANN algorithms are used to reconstruct the SSI PDFs (Fig. 4).

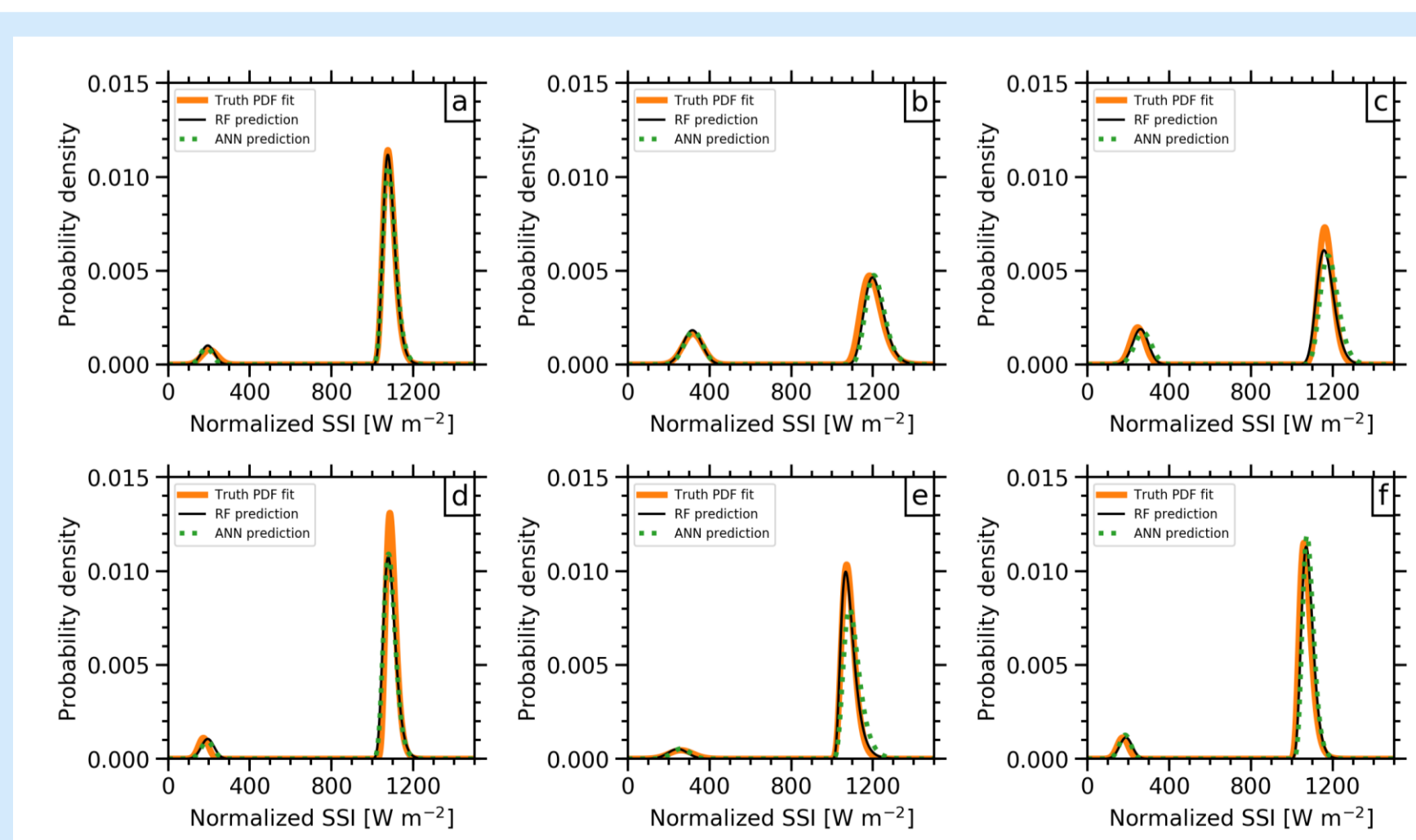


Fig. 4. Six random predictions of SSI PDFs on held-out test data.

- Predictions capture variations in the shape and size of both modes. Note that 1D radiative transfer (Fig. 1d) does not capture even the bimodal shape, let alone the detailed variations.
- The relative importance of each cloud field property is quantified by importance metrics (Table 2).

Table 2. Relative importance of the input cloud field properties

Input	RF impurity importance (%)	RF permutation importance (%)	ANN permutation-importance (%)
$\bar{f}_C$	63.0	74.2 ± 4.1	68.0 ± 4.0
$D(LWP)$	11.3	11.8 ± 0.7	9.6 ± 0.7
$\bar{N}_C$	7.5	4.5 ± 0.4	4.7 ± 0.4
$\bar{A}_C$	4.4	2.2 ± 0.2	9.1 ± 0.6
$\bar{D}_{C-NN}$	6.6	3.1 ± 0.3	3.2 ± 0.3
$\cos(SZA)$	7.3	4.3 ± 0.3	5.3 ± 0.5

- $\bar{f}_C$  and  $D(LWP)$  are most valuable, but even the less important inputs provide predictive value; detailed cloud properties matter.

## Aerosol Influence on Surface Solar Irradiance

- Aerosol between cloud can further perturb the SSI PDF (Fig. 5).

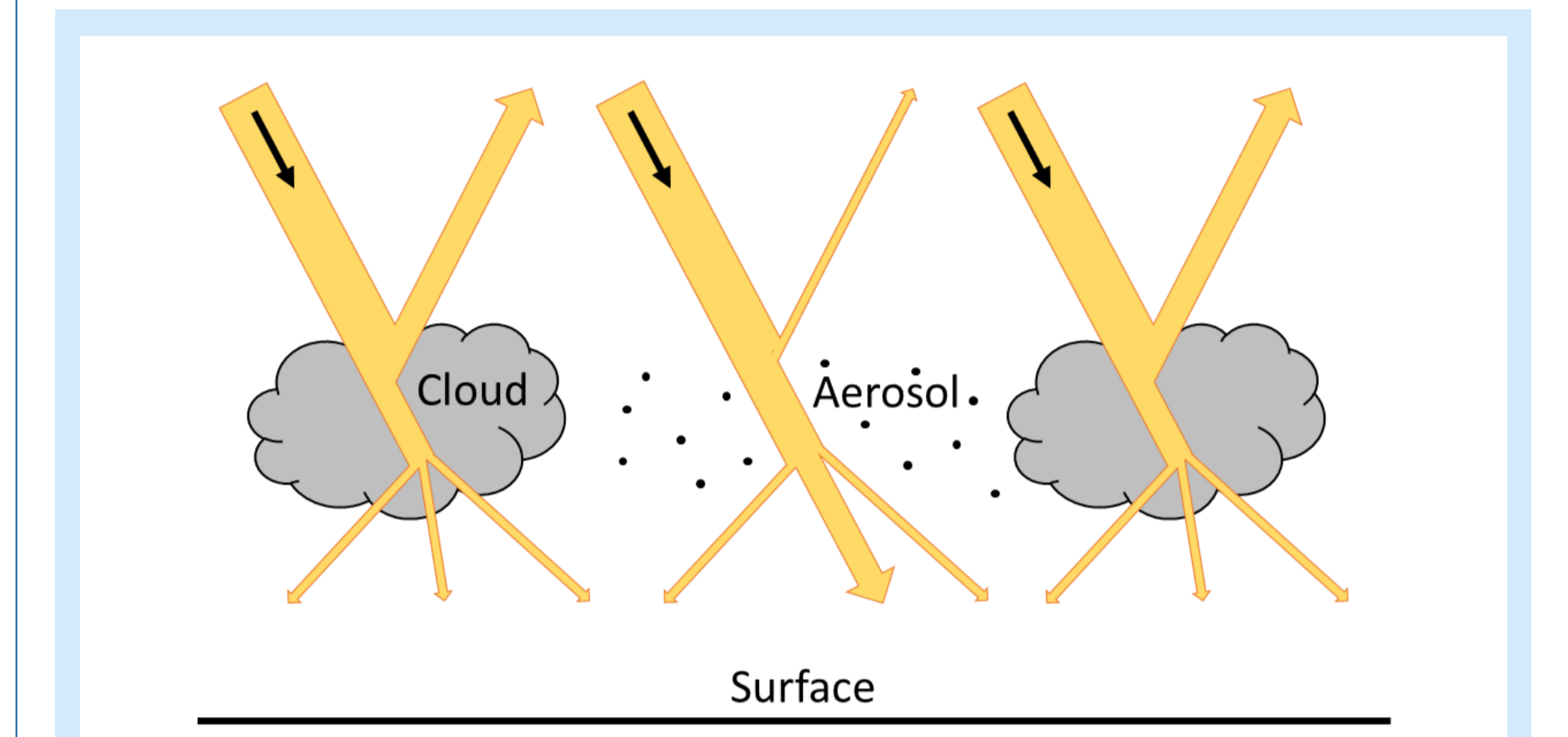


Fig. 5. Schematic showing aerosol influence on SSI in the presence of cumulus clouds.

- Preliminary simulations assume aerosol are ammonium sulfate and their humidified optical properties are calculated by allowing them to swell to their equilibrium size according to the ambient relative humidity.

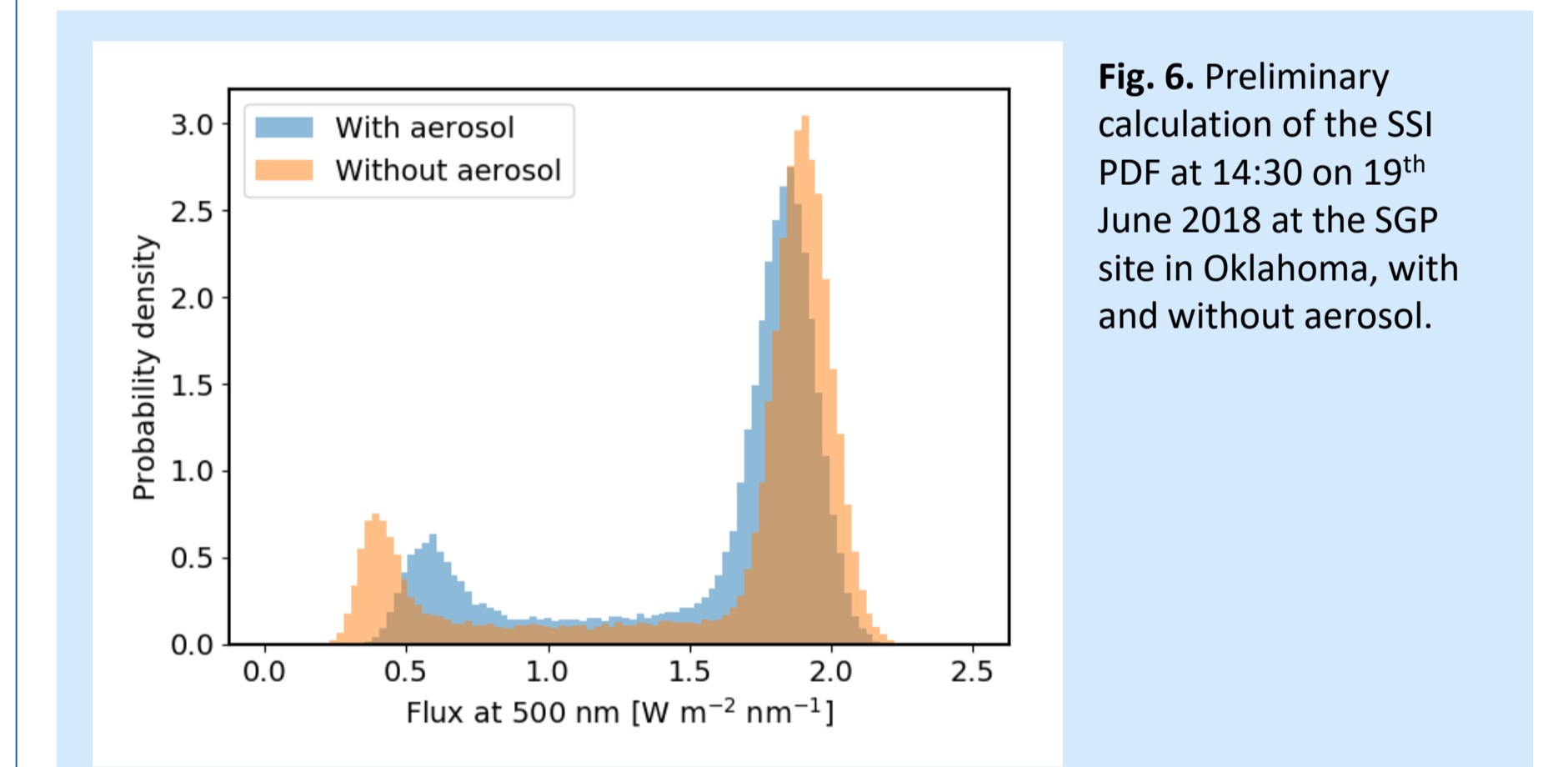


Fig. 6. Preliminary calculation of the SSI PDF at 14:30 on 19<sup>th</sup> June 2018 at the SGP site in Oklahoma, with and without aerosol.

- Aerosol brightens cloud shadows and darkens gaps between them, bringing both SSI PDF modes closer together (Fig. 6).

## Applications and future work

- A machine learning approach can provide accurate simulated magnitudes of SSI and, when combined with photovoltaic cell characteristics, reliable estimates of solar renewable energy.
- Future work will further investigate how aerosol variability can perturb the SSI PDF, potentially incorporating aerosol properties into the machine learning prediction of SSI.

## References

- Gristey et al., *in prep.*, 2021: Influence of aerosol embedded in shallow cumulus cloud fields on the surface solar irradiance.
- Gristey et al., *GRL*, 2020: On the relationship between shallow cumulus cloud field properties and surface solar irradiance.
- Gristey et al., *JAS*, 2020: Surface solar irradiance in continental shallow cumulus fields: observations and large eddy simulation.