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# Cloud Detection and Classification Algorithms for Himawari-8 Imager Measurements Based on Deep Learning

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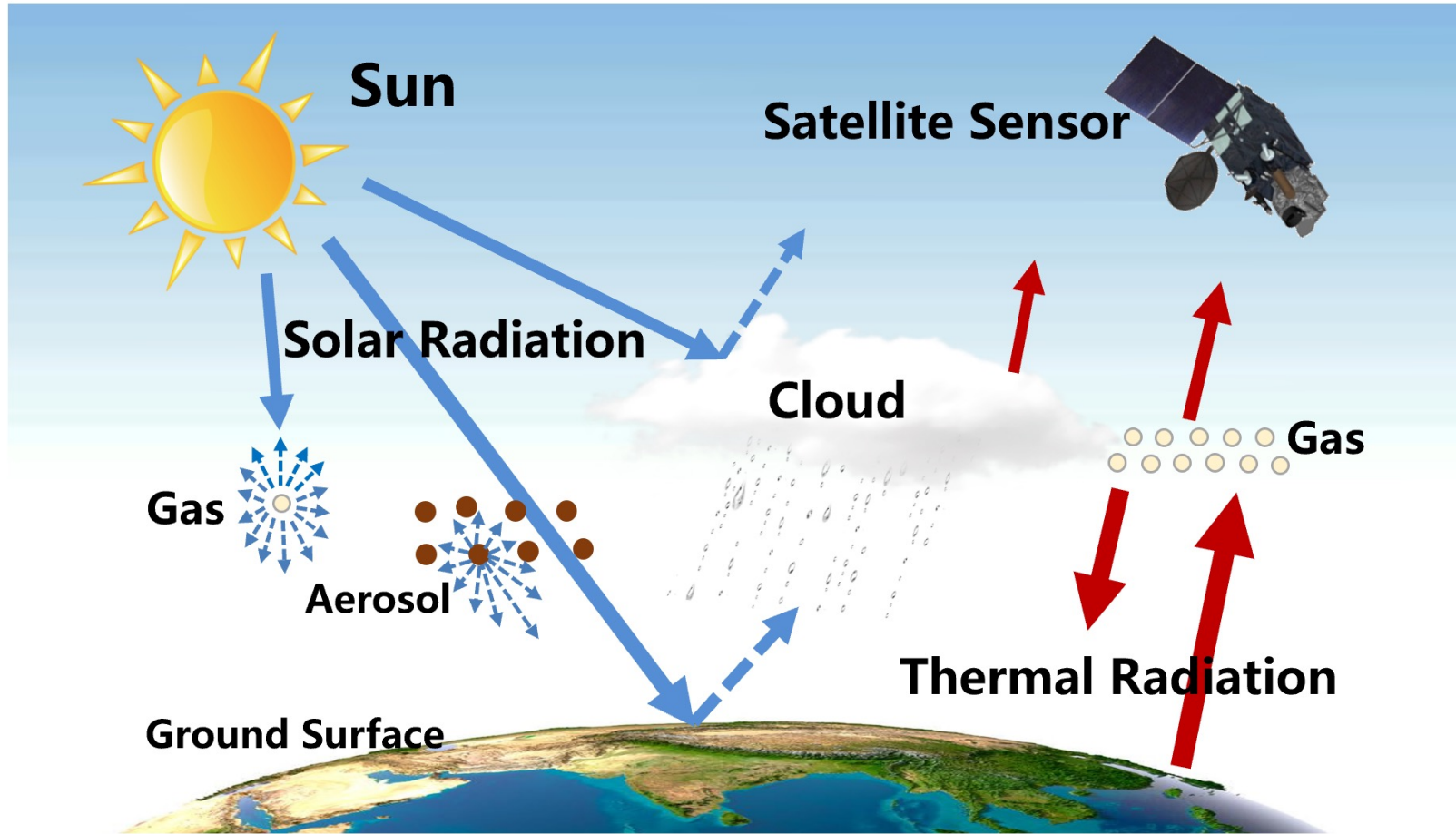
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# Introduction



**Schematic diagram of atmospheric radiative transfer process**

Clouds affect short-range weather process, climate change and atmospheric circulation by regulating the global radiation budget. Satellite observation provides an effective way to monitor the earth-atmospheric system over regional and global scales in high spatiotemporal resolution.



# Introduction

- ✓ **Cloud mask algorithms** are typically designed using sequential tests or decision trees involving multiple thresholds.
- ✓ Traditional **cloud phase determination algorithms** are established based on **reflectance differences** (RDs, e.g., 2.1 and 1.6  $\mu\text{m}$ ), or **brightness temperature differences** (BTDs, e.g., 8.5 and 11  $\mu\text{m}$ ).
- ✓ **Multilayer clouds detection** are typically inferred from the discrepancy between the retrieved **SWIR and TIR** cloud phases.

**Machine-learning-based algorithms** are more suitable to deal with **cloud-related problems involving complex nonlinear problems and controlled by many dominant factors.**



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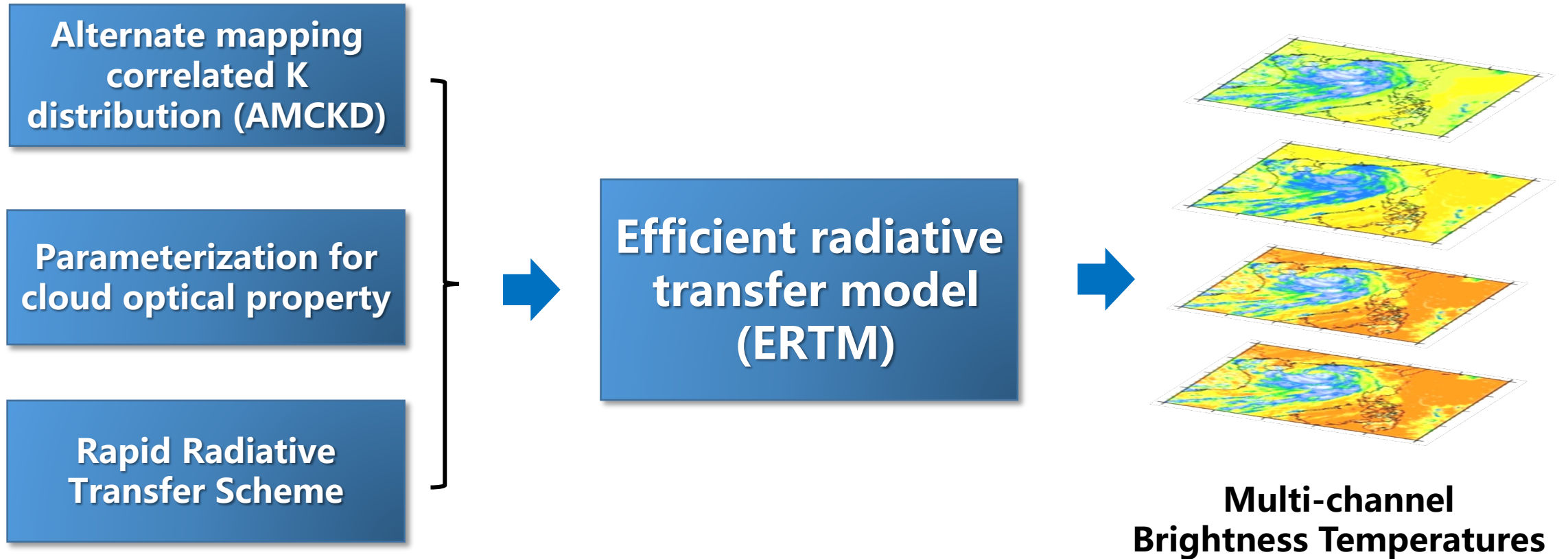
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# Data and Method

## Sensitive Study

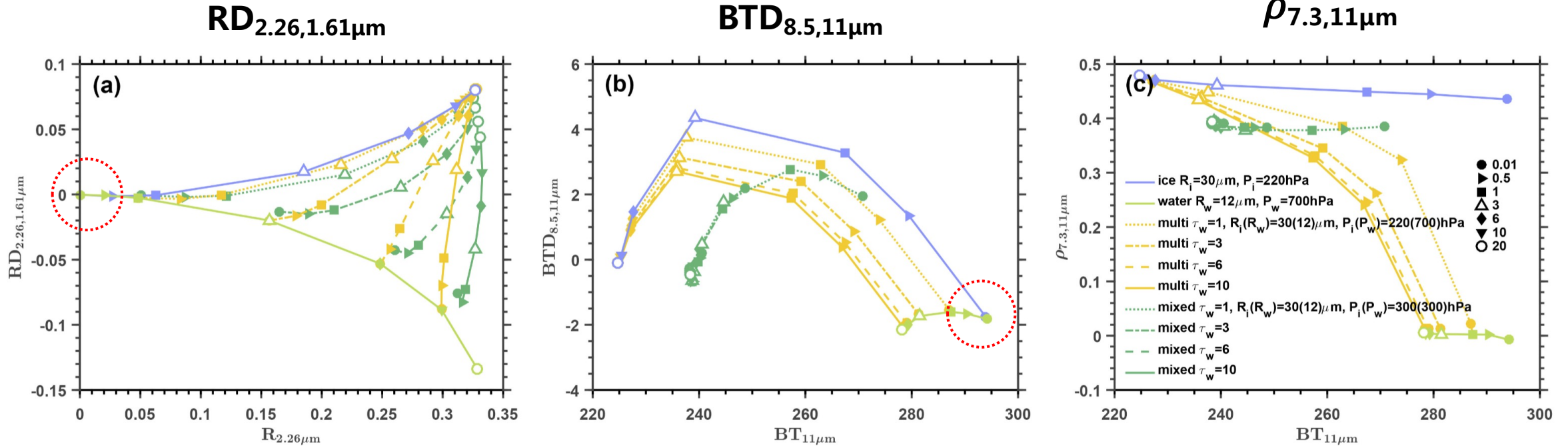


**Efficient radiative transfer model (ERTM) is capable of simulating brightness temperatures observed by the Advanced Himawari Imager (AHI) under clear and cloudy atmosphere.**



# Data and Method

## Sensitive Study



$$\rho_{\lambda_1, \lambda_2} = \frac{BT_{obs, \lambda_1} - BT_{clr, \lambda_1}}{BT_{obs, \lambda_2} - BT_{clr, \lambda_2}}$$

$BT_{obs, \lambda}$ : observed brightness temperature

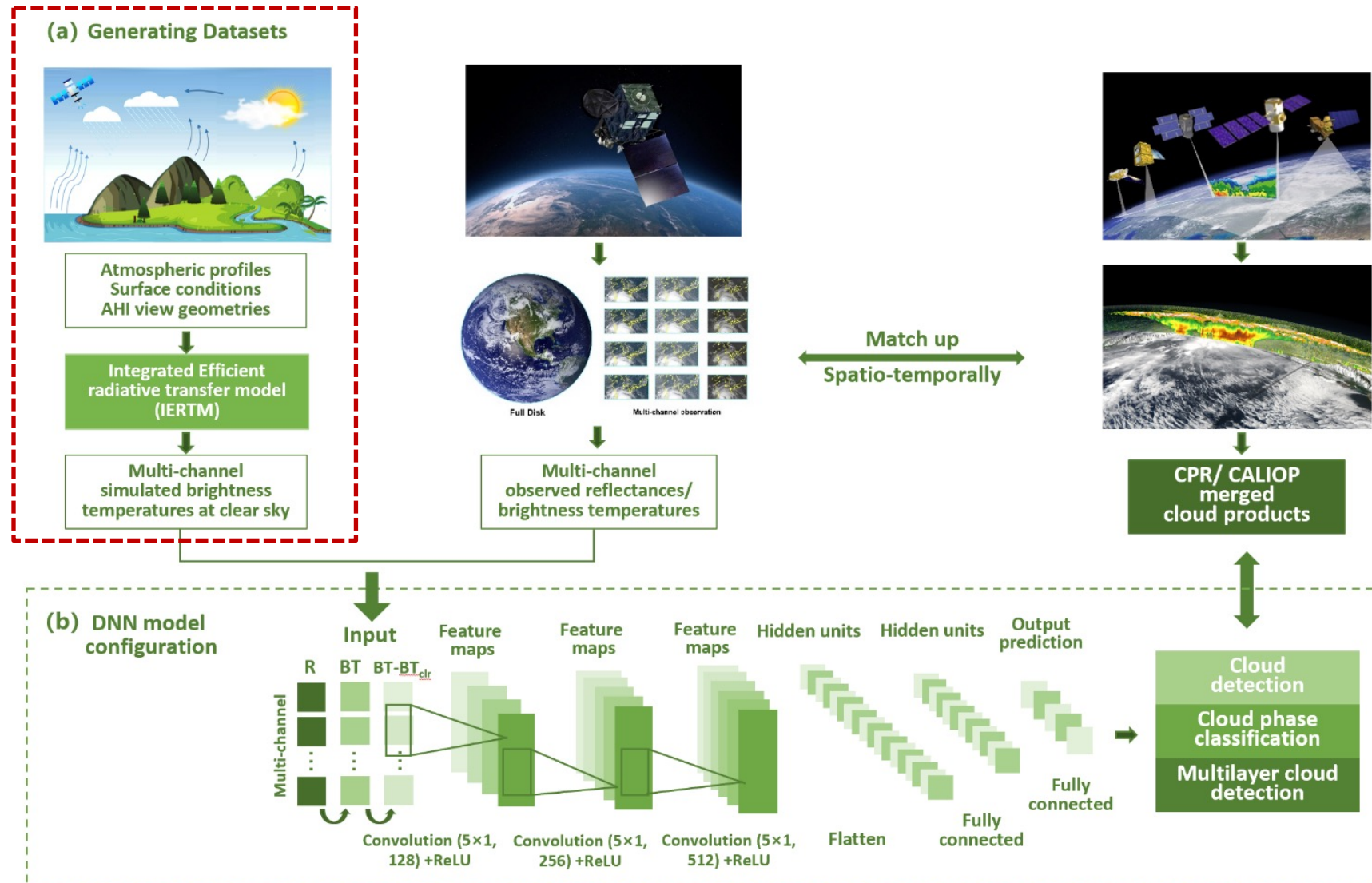
$BT_{clr, \lambda}$ : simulated clear-sky brightness temperature

- single-layer ice clouds
- single-layer water clouds
- single-layer mixed-phase clouds
- multilayer clouds





# Data and Method



(a) Flowchart of the generating datasets. (b) Deep neural network (DNN) model configuration.



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# Results and Discussion

## 3.1 Overall Evaluation of DNN Models

Overall evaluation scores of the DNN all-day and daytime models with different predictors and a fixed model configuration.

Model	Model input	Precision	Recall	F1-measure measure
All-day model without considering clear-sky radiance	BT[6.9-13.3 $\mu$ m], $\mu_{SAZ}$	0.76	0.76	0.75
All-day model considering clear-sky radiance	BT[6.9-13.3 $\mu$ m], BT-BT <sub>clear</sub> [6.9 – 13.3 $\mu$ m]	0.81	0.81	0.81
Daytime model without considering clear-sky radiance	BT[6.9-13.3 $\mu$ m], R[0.47-2.3 $\mu$ m], $\mu_{SOZ}$ , $\mu_{SAZ}$ , $\mu_{SAA-SOA}$	0.83	0.82	0.82
Daytime model considering clear-sky radiance	BT[6.9-13.3 $\mu$ m], BT-BT <sub>clear</sub> [6.9 – 13.3 $\mu$ m], R[0.47-2.3 $\mu$ m], $\mu_{SOZ}$ , $\mu_{SAZ}$ , $\mu_{SAA-SOA}$	0.85	0.84	0.84



Note that  $\mu_{SAZ}$  is the cosine of satellite zenith angle; SOZ is solar zenith angle; SAA is satellite azimuth angle; SAA is solar azimuth angle.



# Results and Discussion

## 3.2 Evaluation of Cloud Mask

$$POD_{clr} = \frac{T_{clr}}{T_{clr} + F_{clr}},$$

Probability of detection (POD)

$$POD_{cld} = \frac{T_{cld}}{T_{cld} + F_{cld}},$$

$$FAR_{clr} = \frac{F_{cld}}{F_{cld} + T_{clr}},$$

False alarm ratio (FAR)

$$FAR_{cld} = \frac{F_{clr}}{F_{clr} + T_{cld}},$$

$$HR = \frac{T_{clr} + T_{cld}}{T_{clr} + T_{cld} + F_{clr} + F_{cld}},$$

Hit rate (HR)

$$KSS = \frac{T_{clr}T_{cld} - F_{clr}F_{cld}}{(T_{cld} + F_{cld})(T_{clr} + F_{clr})},$$

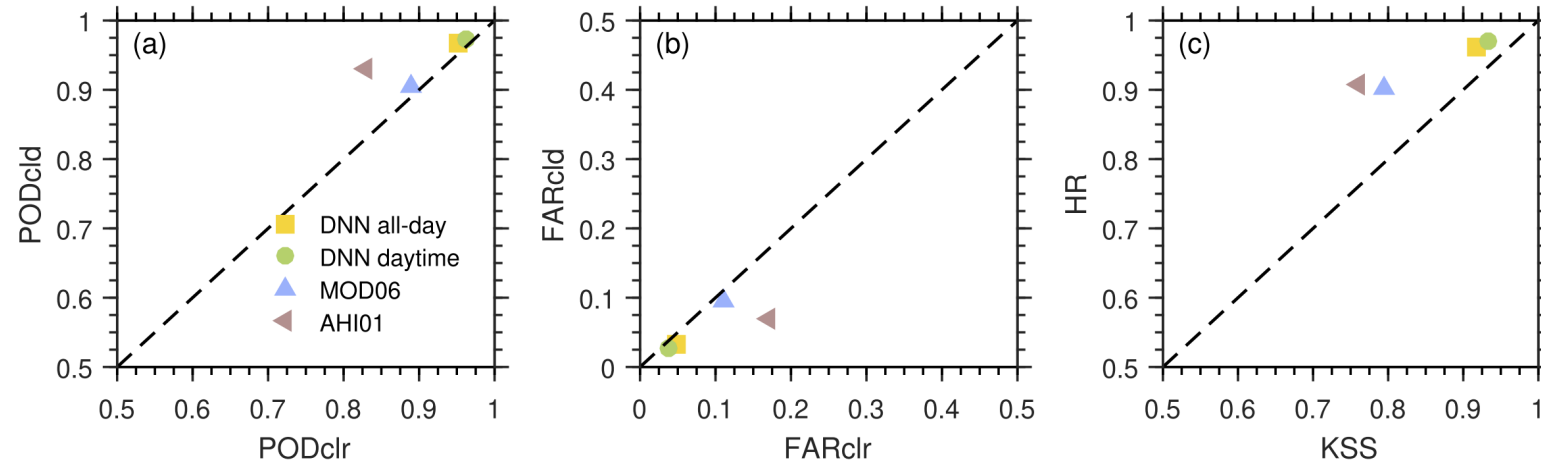
Hanssen–Kuiper skill score (KSS)



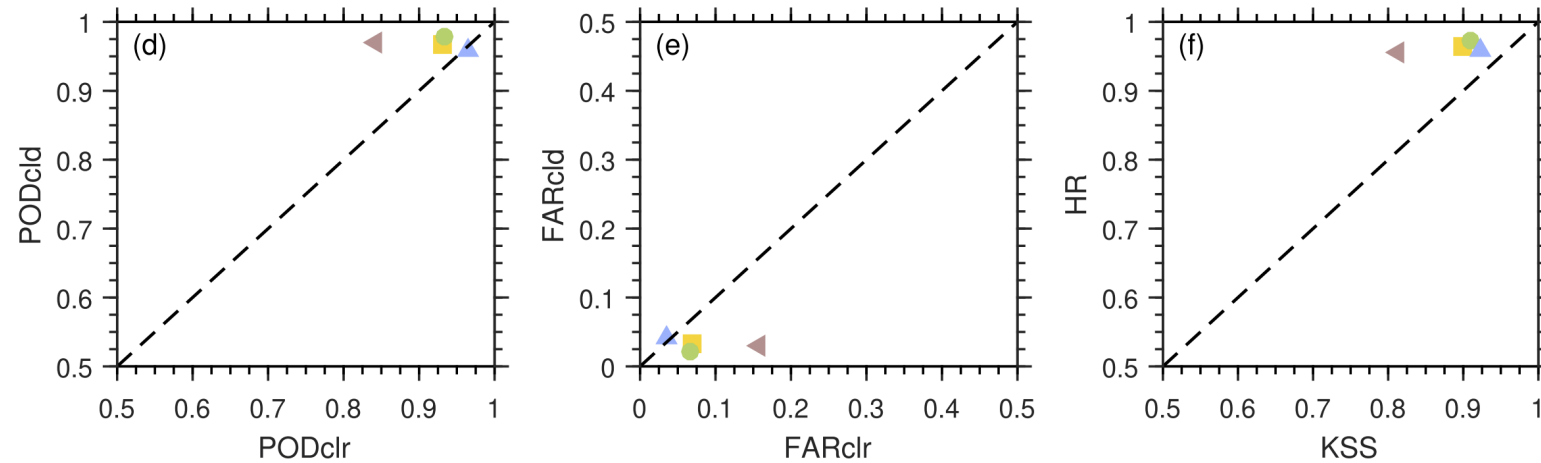
# Results and Discussion

## 3.2 Evaluation of Cloud Mask

Land



Sea

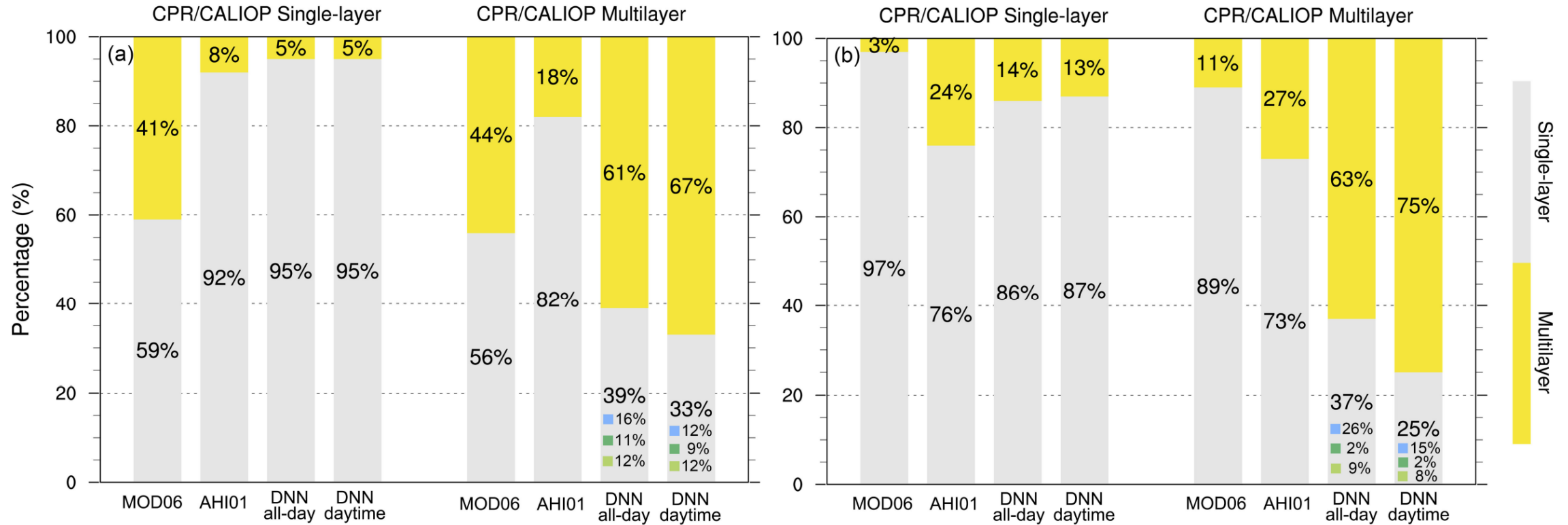


Evaluation metrics including POD, FAR, HR, and Hanssen–Kuiper skill score (KSS) for cloud mask from two DNN models and MODIS and AHI products.



# Results and Discussion

## 3.3 Evaluation of Multilayer Cloud Detection

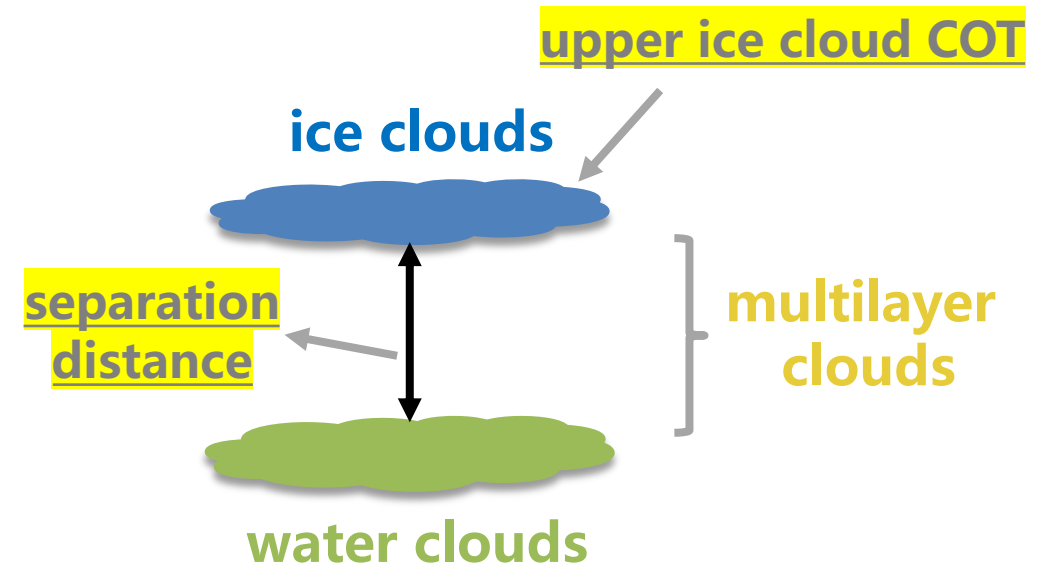
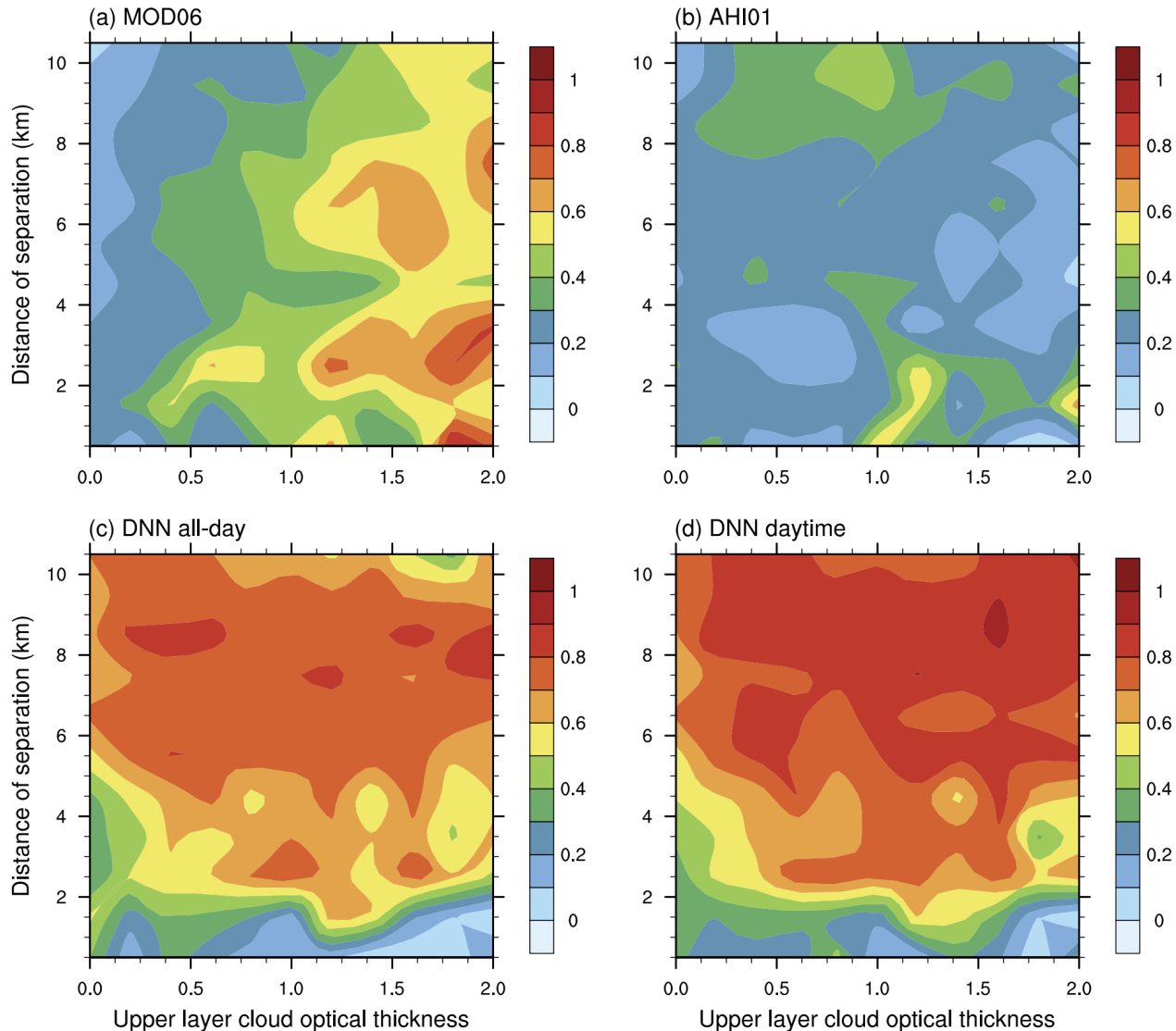


Percentages of single-layer and multilayer clouds from two DNN models and MODIS and AHI products. The left (a) and right panels (b) are for the collocated cloudy pixels with total COT larger and smaller than 1, respectively.



# Results and Discussion

## 3.3 Evaluation of Multilayer Cloud Detection



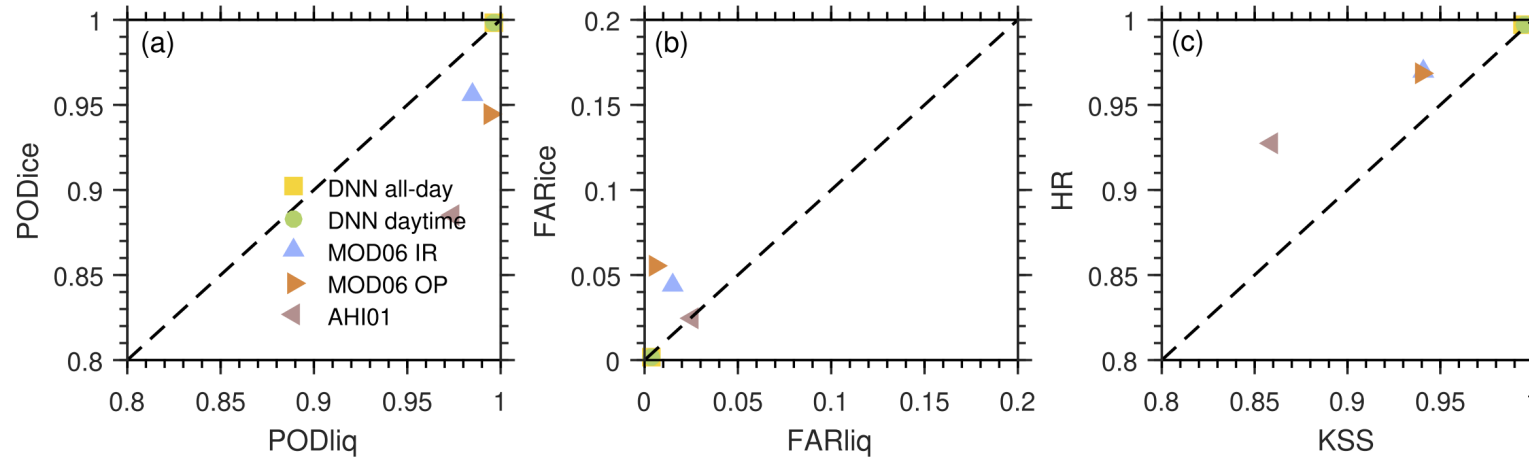
Probabilities that MODIS and AHI products (a and b) and DNN models (c and d) correctly identify a multilayer cloud, given the **separation distance** and the **upper ice cloud COT**, respectively.



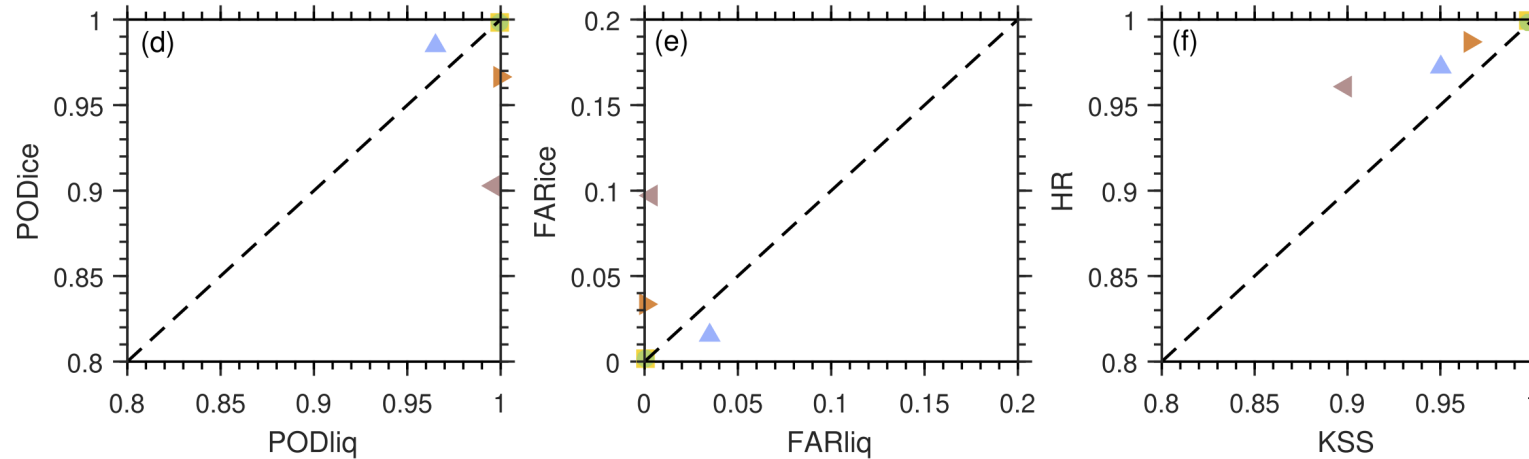
# Results and Discussion

## 3.4 Evaluation of Single-Layer Cloud Phase

Land



Sea



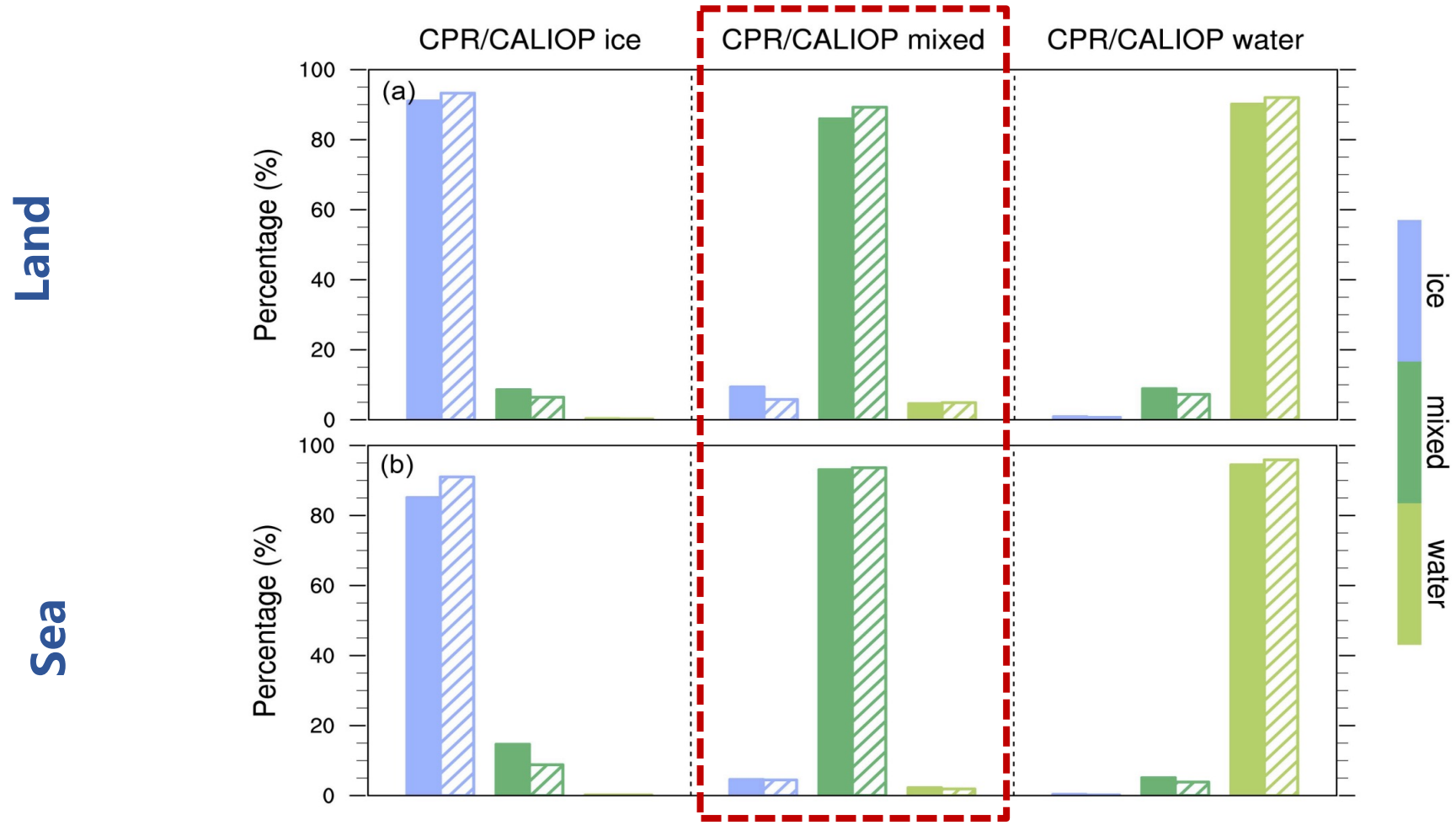
Evaluation metrics including POD, FAR, HR, and Hanssen–Kuiper skill score (KSS) for the discrimination of ice and water cloud phase from two DNN models and MODIS and AHI products.





# Results and Discussion

## 3.4 Evaluation of Single-Layer Cloud Phase



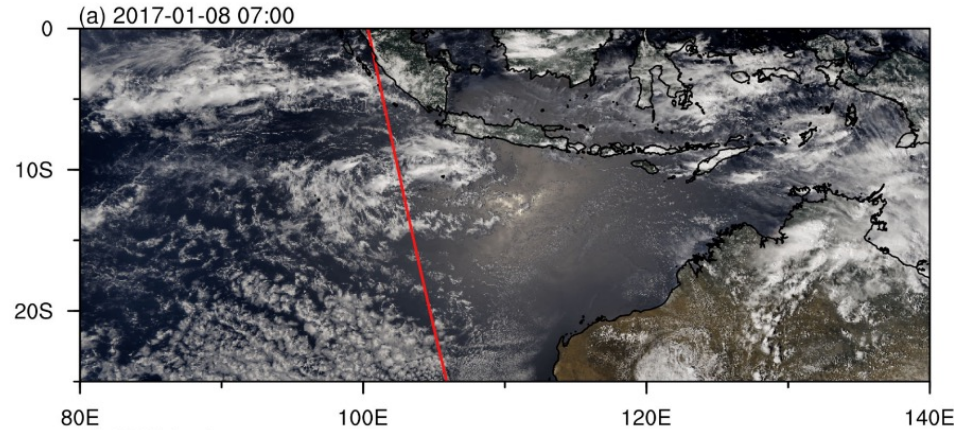
Percentages of single-layer ice, mixed phase, and water cloud identification from DNN all-day (solid bars) and daytime (hatched bars)



# Results and Discussion

## 3.5 Case Demonstration

(a) Natural color image ( 0.65, 0.86, and 0.46 $\mu\text{m}$  )



( b ) DNN daytime

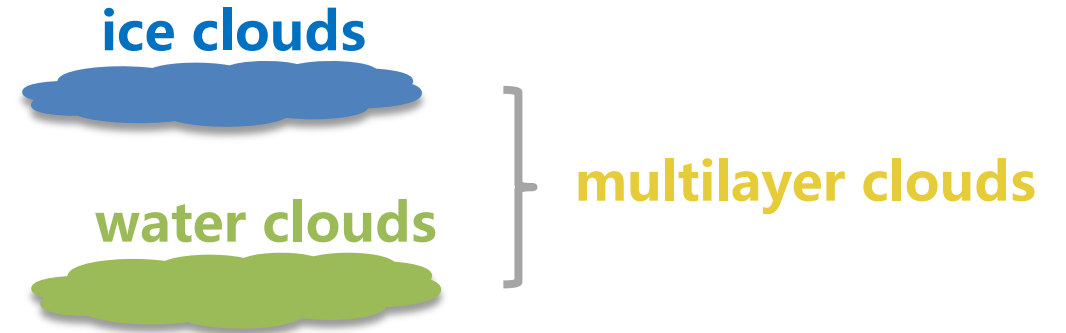
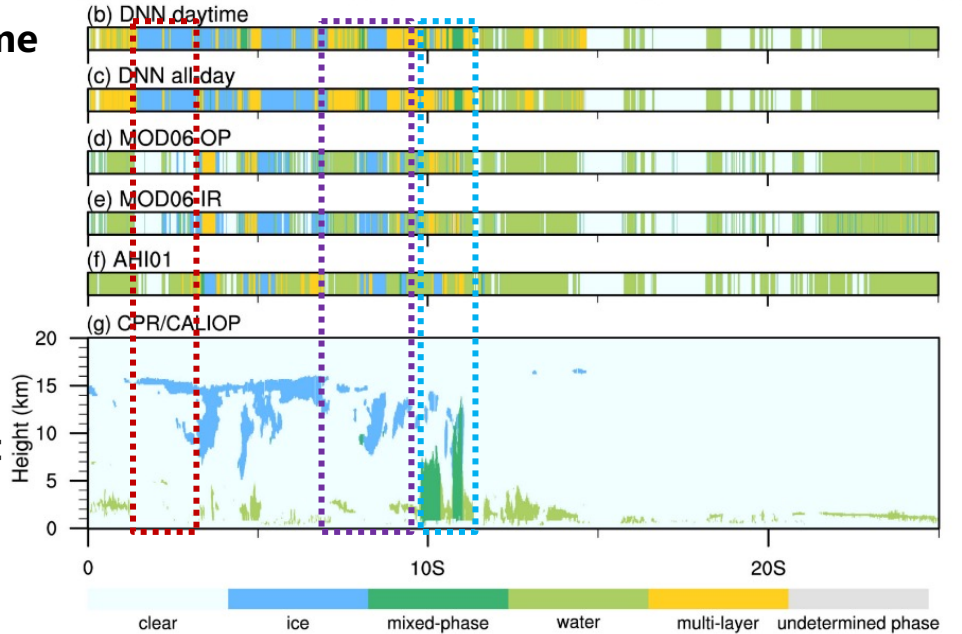
( c ) DNN all day

( d ) MOD06 OP

( e ) MOD06 IR

( f ) AHI01

( g ) CPR/CALIOP merged product



- ✓ 1 ) DNN models have superior capability in detecting the **optically thin cirrus**.
- ✓ 2 ) **Multilayer cloud** detection by DNN models is more consistent with CPR/CALIOP than two official products.
- ✓ 3 ) DNN models can provide effective **mixed-phase cloud** identification.



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# Conclusion

- ✓ A deep-learning-based cloud detection and classification algorithm for AHI measurements from Himawari-8 has been developed.
- ✓ It is shown that the DNN models outperform the official MODIS and AHI products in cloud detection and phase discrimination, and the enhancement is more significant over land than over water surface.
- ✓ DNN models have superior capability in detecting the optically thin cirrus. DNN models can also provide effective mixed-phase cloud identification.
- ✓ Multilayer cloud detection by DNN models is more consistent with CPR/CALIOP than two official products.





**Thanks!**

