# APPLICATION AND VALIDATION OF AN ARTIFICIAL NEURAL NETWORK APPROACH FOR THE FAST ESTIMATION OF THE TOTAL PRECIPITABLE WATER (TPW) FROM AHI DATA

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- Introduction [Total Precipitable Water (TPW)]
- Algorithm [Artificial Neural Network (ANN)]
  - Data
  - Method
  - Results
- Validation
- Further study



## INTRODUCTION

- The amount of water vapor in the atmosphere is responsible for determining the amount of precipitation a region can receive
- Total Precipitable water (TPW) is the depth of water in a column of the atmosphere, if all the water in that column were precipitated as rain. As a depth, the precipitable water is measured in millimeters (mm)

• TPW = 
$$\frac{1}{\rho_w g} \int_{P_s}^0 q(p) \cdot dp$$

$$\begin{split} \rho_w &: \text{water density (1000 [kg/m^3])} \\ \text{g} : \text{gravitational constant (9.8 [m/s^2])} \\ \text{q(p)} : \text{mixing ratio (g/kg) of water vapor in hPa at} \\ & \text{pressure level p} \\ \text{p}_\text{s} : \text{surface air pressure [hPa]} \end{split}$$

 The TPW shows the distribution of moisture. It can help the severe weather to improve forecast (eg., Convective storms, heavy rain, flood etc.)

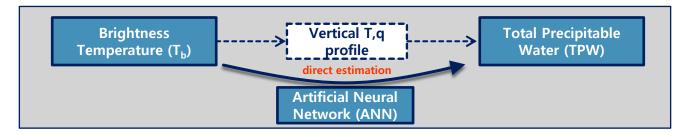
(eumetrain.org)

# INTRODUCTION

#### The retrieval methods of TPW using the satellite data

	Integration	Split-Window	ANN		
Method	• The integration from the retrieved vertical profiles of temperature and humidity using the equation	• The calculation using the ratio of the brightness temperatures for the split-window channels	• The statistical method to directly estimate the TPW from the brightness temperature		
Characteristic	<ul> <li>High accuracy due to the vertical profiles</li> <li>Requirements of too high computer load</li> <li>Low temporal-spatial resolution</li> </ul>	• Requirement of the supplementary data (NWP models data)	<ul> <li>High temporal and spatial resolution</li> <li>Independence from the NWP models</li> <li>Sensitive to the training dataset</li> </ul>		

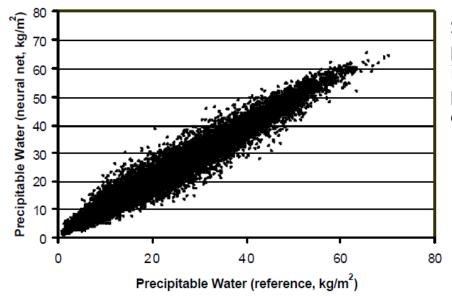
Schematic diagram of estimation the TPW using ANN algorithm



### INTRODUCTION

#### Previous study

König et al. (2002) have described a reliable correlation between the derived TPW using the ANN and the observation data



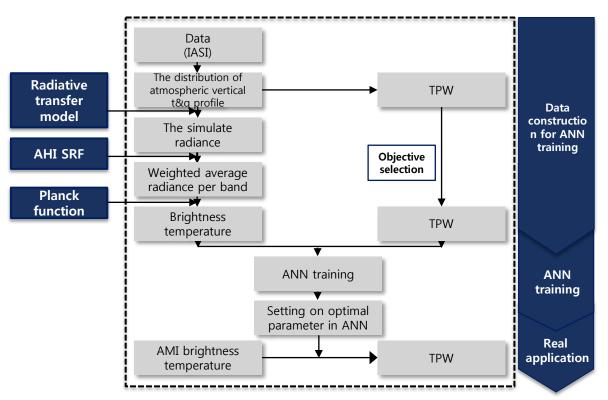
Scatter plot of neural network derived precipitable water compared to independent reference data from the physical method (correlation coefficient 0.97)

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(König et al., 2002)
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# ALGORITHM

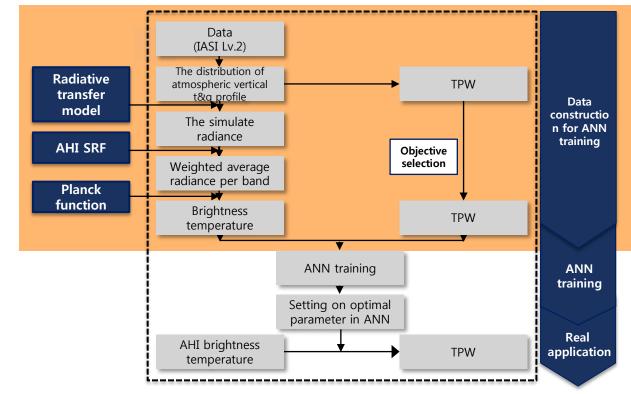
#### The retrieval algorithm using ANN(Artificial Neural Network)

The application of an artificial neural network approach for the fast estimation of the TPW

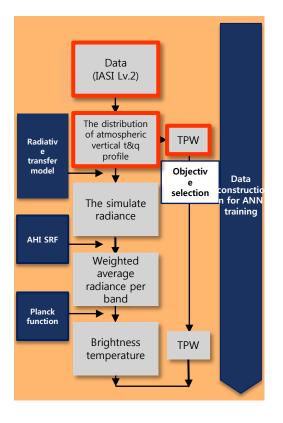


### ALGORITHM – STEP1 (DATA CONSTRUCTION FOR ANN TRAINING)

 The retrieval algorithm using ANN



# DATA



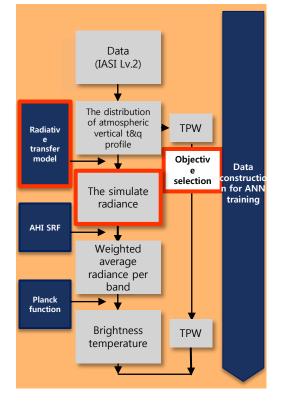
#### The atmospheric profiles of IASI Level2 data

- IASI (Infrared Atmospheric Sounding Interferometer) : a key payload element of the Metop series of European meteorological polarorbit satellites (9:30 AM equator crossing orbit).
- IASI Level 2 data was collected in clear-sky conditions in <u>Extended Northern Hemisphere</u> (ENH) region (10.2°N-46.7°N, 92.1°E-161.8°E) of <u>COMS from January to December in 2011 to</u> 2014.

Product	Accuracy	Sampling	Timeliness	
Temperature	1 K (2K stratosphere)	IFOV	3 hours	
Relative humidity	10 %	IFOV	3 hours	
Cloud cover	10 %	IFOV	3 hours	
Cloud top temperature	2 K	IFOV	3 hours	
Cloud top height	300 m	IFOV	3 hours	

8

# **METHOD**



#### Objective selection for the ANN training

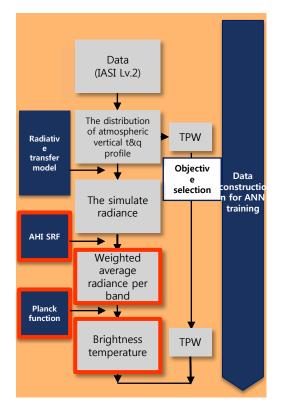
TPW Range (mm)	Number	TPW Range (mm)	Number	TPW Range (mm)	Number
0-5	10,178	5-10	10,178	10-15	10,178
15-20	10,178	20-25	10,178	25-30	10,178
30-35	10,178	35-40	10,178	40-45	10,178
45-50	10,178	50-55	10,178	55-60	10,178
60-	10,178	Total		10,178 × 13 = 132,314	

#### Radiative transfer model : MODTRAN (MODerate resolution atmospheric TRANsmission)

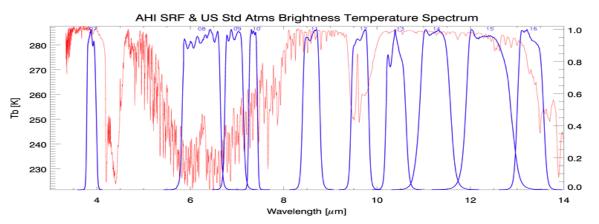
MODTRAN version 5.2.2; MODTRAN is a "narrow band model" atmospheric radiative transfer code. The spectral range extends from the UV into the far-infrared (0 – 50,000 cm-1), providing resolution as fine as 0.2 cm-1)

http://modtran5.com/about/index.html

### **METHOD**

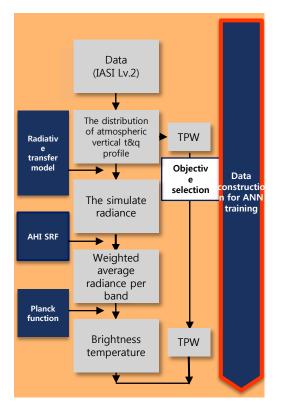


#### Weighted average radiance per band



#### AHI SRF & US standards Atmospheric brightness temperature spectrum

### **METHOD**



### The construction of a database for the training of ANN

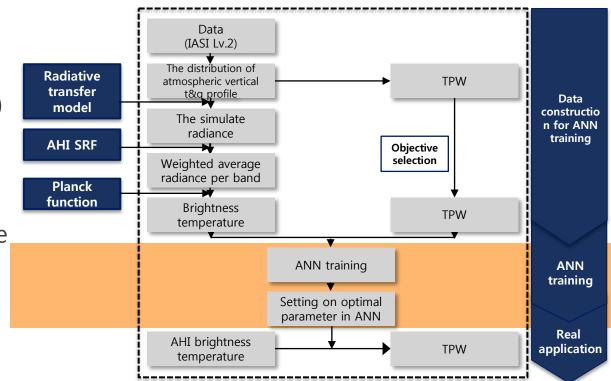
	•						
Total 132,314 개	$\begin{array}{c} 0.176, 0.636, 30.263, 93.415, \\ 0.886, 0.707, 35,865, 95,1153, \\ 0.984, 0.640, 35,400, 35,1476, \\ 0.985, 0.707, 35,176, \\ 0.985, 0.707, 35,176, \\ 0.985, 0.707, 35,176, \\ 0.985, 0.902, 33,178, 37,147, \\ 0.985, 0.903, 33,178, 37,247, \\ 0.985, 0.903, 33,178, 37,257, \\ 0.947, 0.973, 33,176, 37,147, \\ 0.955, 0.993, 33,178, 37,257, \\ 0.947, 0.973, 33,178, 37,257, \\ 0.947, 0.973, 33,174, 37,257, \\ 0.931, 0.725, 31,144, 32,246, \\ 0.931, 0.725, 31,144, 32,246, \\ 0.935, 0.963, 33,174, 35, \\ 0.964, 0.775, 34, 33,161, \\ 0.966, 0.996, 33, 144, 32, 246, \\ 0.966, 0.966, 0.973, 34, 345, \\ 0.966, 0.973, 0.933, 344, \\ 0.943, 0.963, 34,125, \\ 0.964, 0.773, 34, 345, \\ 0.964, 0.973, 34, 345, \\ 0.964, 0.973, 34, 345, \\ 0.964, 0.973, 34, 345, \\ 0.944, 0.963, 31, 361, 35, 35, 269, \\ 0.964, 0.973, 0.973, 34, 345, \\ 0.964, 0.963, 31, 351, 352, 299, \\ 0.964, 0.963, 31, 351, 352, 299, \\ 0.964, 0.963, 31, 351, 352, 299, \\ 0.964, 0.963, 31, 351, 352, 299, \\ 0.964, 0.963, 31, 351, 352, 352, \\ 0.964, 0.977, 34, 34, 966, 34, 355, 352, \\ 0.964, 0.977, 34, 34, 966, 34, 355, 352, \\ 0.964, 0.977, 352, 306, 31, 353, 352, \\ 0.964, 0.977, 33, 246, 33, 358, 352, \\ 0.964, 0.977, 32, 228, 94, 634, 355, \\ 0.964, 0.977, 32, 228, 94, 368, \\ 0.964, 0.977, 32, 228, 94, 368, \\ 0.964, 0.977, 32, 228, 94, 368, \\ 0.964, 0.977, 32, 228, 94, 353, \\ 0.952, 0.957, 753, 253, 263, 33, 355, \\ 0.953, 0.957, 753, 253, 263, 33, 355, \\ 0.954, 0.777, 32, 228, 94, 368, \\ 0.977, 32, 228, 94, 368, \\ 0.977, 32, 228, 94, 358, \\ 0.952, 0.957, 753, 252, 352, 353, 355, \\ 0.955, 0.958, 0.957, 753, 252, 352, 353, 355, \\ 0.955, 0.958, 0.957, 753, 252, 353, 355, \\ 0.955, 0.957, 352, 306, 353, 355, \\ 0.957, 0.957, 352, 306, 353, 356, 353, 355, \\ 0.958, 0.957, 352, 306, 353, 356, 353, 355, \\ 0.958, 0.958, 0.957, 753, 352, 355, 353, 355, \\ 0.958, 0.958, 0.957, 753, 352, 355, 355, 355, \\ 0.958, 0.958, 0.957, 753, 352, 355, 355, 355, 355, \\ 0.958, 0.958, 0.957, 753, 352, 355, 355, 355, 355, 355, 355, 3$	$\begin{array}{c} 52,95, 244,02, 252,03\\ 53,35, 244,59, 251, 245, 252, 263\\ 53,35, 244,59, 251, 245, 274, 257, 245, 274, 257, 245, 257, 257, 257, 257, 257, 257, 257, 25$	$\begin{array}{c} 254, (2) & 259, (38), (244, (38), (254, (36), (254, (254, (36), (254, ($	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{c} 6, 85, 0, 0, \\ 6, 632, 0, 0, \\ 6, 123, 78, 0, 0, \\ 3, 160, 0, 0, 0, 0, \\ 3, 160, 0, 0, 0, 0, \\ 10, 503, 0, 0, 0, \\ 10, 503, 0, 0, 0, \\ 10, 503, 0, 0, 0, \\ 10, 503, 0, 0, 0, \\ 10, 503, 0, 0, 0, \\ 10, 10, 0, 0, 0, 0, \\ 10, 10, 0, 0, 0, 0, \\ 10, 10, 0, 0, 0, \\ 10, 10, 0, 0, 0, \\ 10, 10, 0, 0, 0, \\ 10, 10, 0, 0, 0, \\ 10, 10, 0, 0, 0, \\ 10, 10, 0, 0, 0, \\ 10, 10, 0, 0, 0, \\ 10, 10, 0, 0, 0, \\ 10, 10, 0, 0, 0, \\ 10, 10, 0, 0, 0, 0, \\ 10, 10, 0, 0, 0, 0, \\ 10, 10, 0, 0, 0, \\ 10, 10, 0, 0, 0, 0, \\ 10, 10, 0, 0, 0, 0, \\ 10, 10, 0, 0, 0, \\ 10, 10, 0, 0, 0, \\ 10, 10, 0, 0, 0, \\ 10$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$

- Input : cyclic\_day, cyclic\_time, latitude, longitude, satellite zenith angle, the 9 simulated Tb (6.19, 6.95, 7.34, 8.5, 9.61, 10.35, 11.2, 12.3, 13.3 μm), the 4 simulated DCD ((11.2-6.19), (11.2-6.95), (11.2-7.34), (11.2-12.3)), TPW
- Output : Target\_TPW

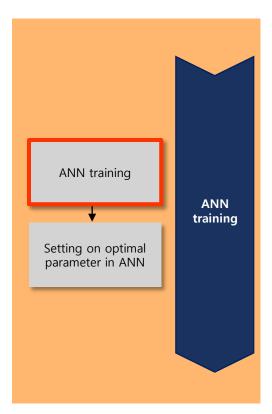
# ALGORITHM – STEP2 (ANN TRAINING)

#### The retrieval algorithm using ANN(Artificial Neural Network)

 The application of an artificial neural network approach for the fast estimation of the TPW

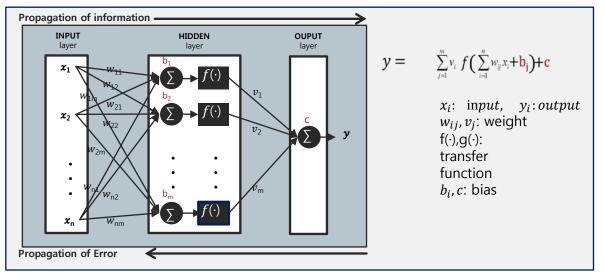


# MODEL



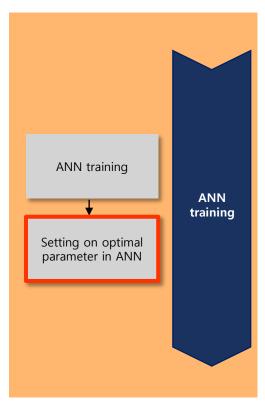
#### ANN(Artificial Neural Network) training

Feedforward Multilayer Perceptron Neural Net.



<sup>(</sup>Blackwell & Chen, 2009)

### RESULTS



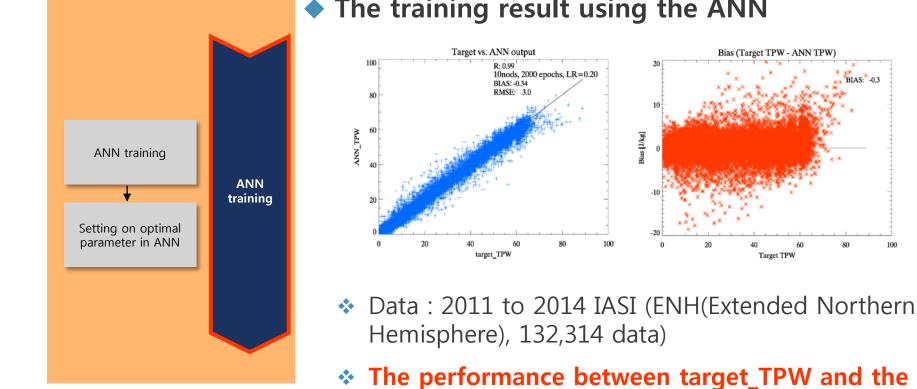
#### The results of the sensitivity test depending on the model architecture

The number of hidden neuron, learning rate and epochs



- Data : 2011 to 2014 IASI (ENH (Extended Northern Hemisphere), 132,314 data) - training dataset (80%), test dataset (10%), validation dataset (10%)
- The error statistics depending on the model architecture are monitored for the optimal tuning
  - Hidden Neuron: 10, Learning Rate: 0.2, Epoch: 2000

### RESULTS



#### The training result using the ANN

ANN\_TPW has a high correlation with low bias

15

BIAS:\* -0.3

80

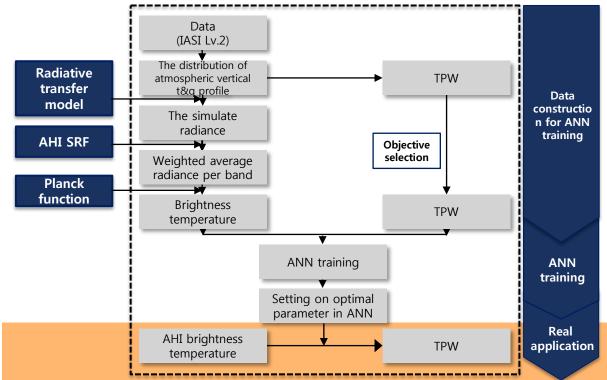
60

100

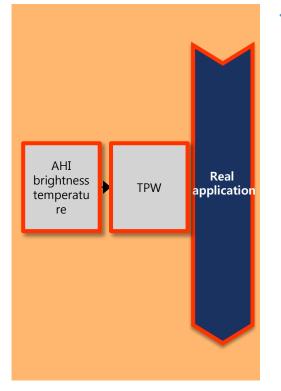
# ALGORITHM – STEP3 (REAL APPLICATION)

#### The retrieval algorithm using ANN(Artificial Neural Network)

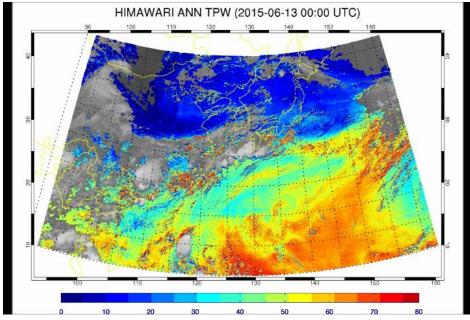
The application of an artificial neural network approach for the fast estimation of the TPW



### RESULT



#### The retrieval images applied to the AHI data (2015-06-13 ~ 14)



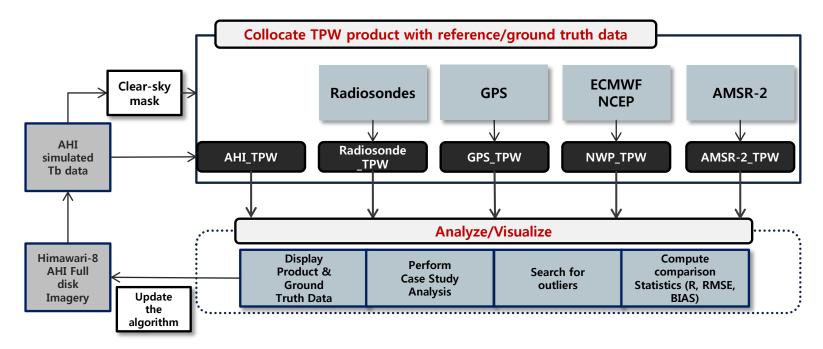
### VALIDATION

- The validation of the TPW retrieval algorithm
  - Using the NWP (Numerical Weather Prediction) model data: ECMWF, NCEP
  - Using the Radiosonde data
  - Using the microwave satellite data (AMSR-2)
  - Using the GPS (global positioning system)
  - It will be expected that the direction of the operational algorithm can be suggested by the comparison of the performance using a variety of measurements

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# VALIDATION

### Validation strategies

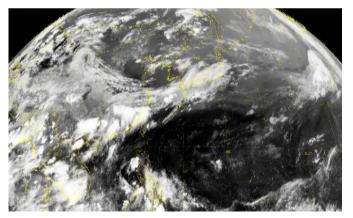


\* GOES-R AWG Product Validation Tool Development

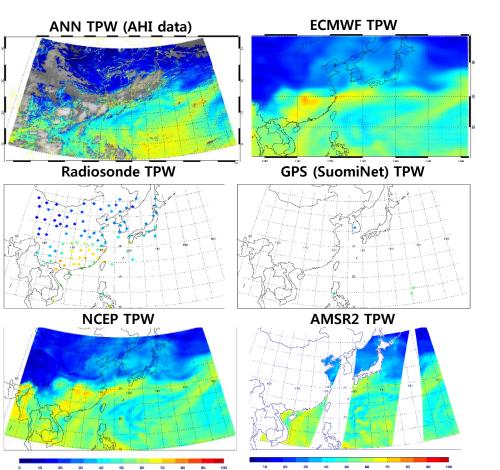
# VALIDATION

Qualitative analysis
 Display the product
 Case) 20150613 12 UTC

MI Cloud Image 20150613 12 UTC



http://nmsc.kma.go.kr



# FURTHER STUDY

#### Improvement of training dataset

- Modifying the simulation process of the bright temperatures for the training
- Quality control
- Bias correction

#### Validation - Quantitative analysis

compute the comparison statistics (R, RMSE, BIAS)

### REFERENCE

- Blackwell W. J. and F. W. Chen, 2009: Neural Networks in Atmospheric Remote Sensing, Massachusetts Institute of Technology, MA, USA, pp98
- König, M., Tjemkes, S., & Kerkmann, J., 2002: Atmospheric instability parameters derived from MSG SEVIRI observations. In *Proc. The 2003 EUMETSAT Meteorological Satellite Conference*
- Jaime D. et al., GOES-R AWG Product Validation Tool Development (Derived Motion Winds)
- <u>http://www.eumetrain.org/</u> (Total precipitable water)

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