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Application of Artificial Neural Network for the direct estimation of atmospheric instability from a geostationary satellite imager

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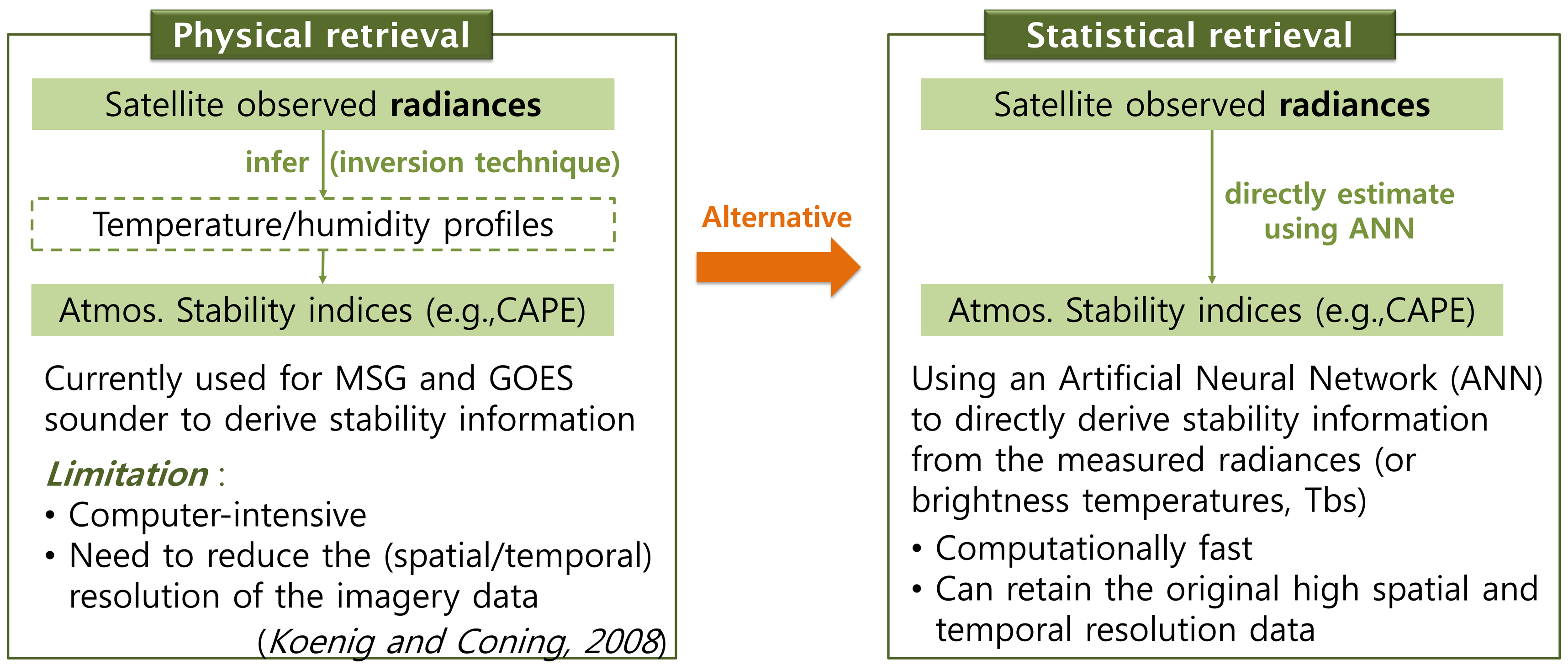
Introduction

Advanced Meteorological Imager (AMI)

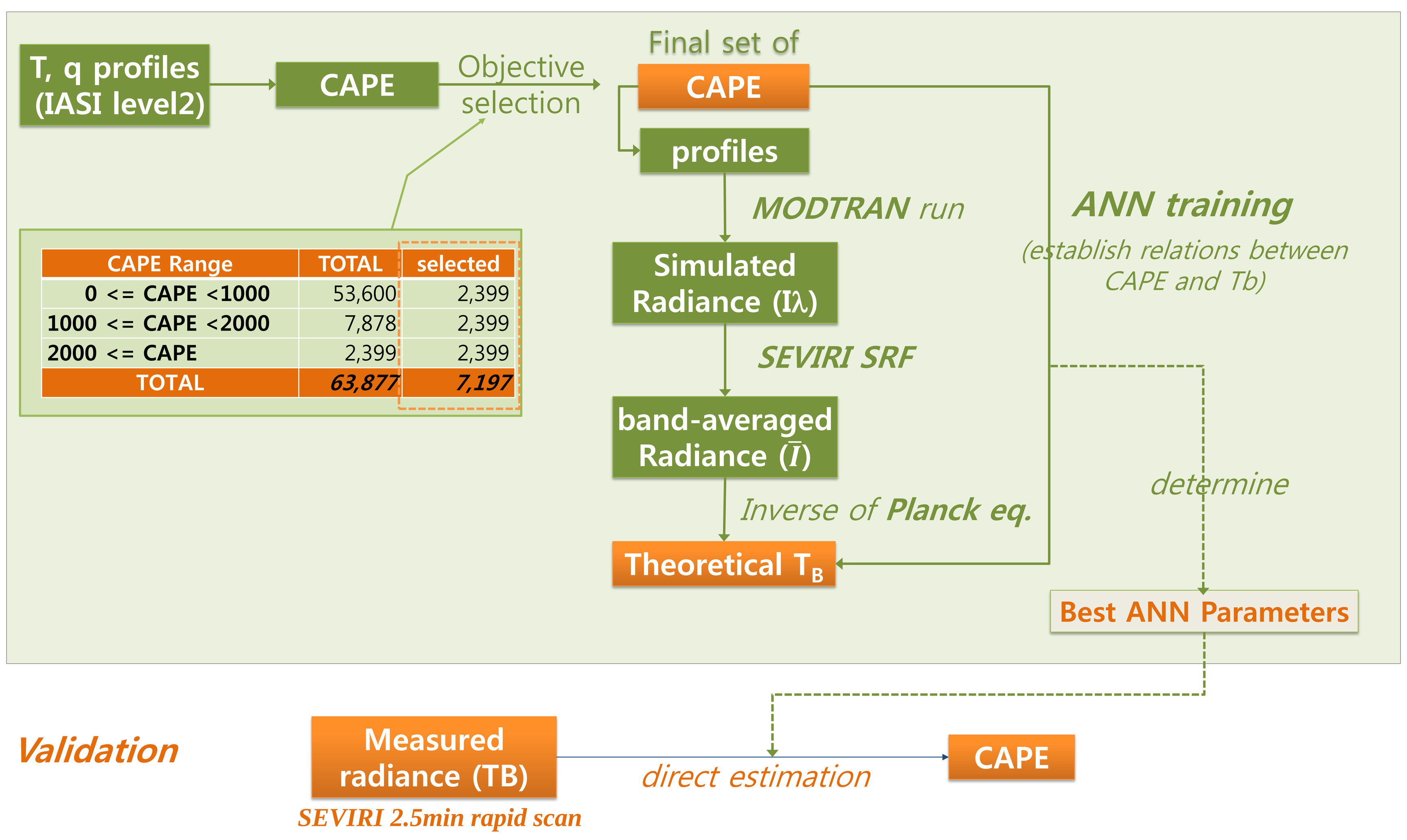
- AMI will be onboard next generation Geostationary Korea Multi-Purpose Satellite (GEO-KOMPSAT-2A) in 2018
- Designed to have improved spectral, temporal, and spatial resolution compared to the first generation imager, so many new and improved value-added products are expected to be produced
- Among the new products, **atmospheric instability information** is one of the important new possibilities with the pseudo-sounding capability of the imager, and this information could provide a significant addition for the nowcasting activities: Convective Available Potential Energy (CAPE) is selected for the study

Approaches to retrieve instability information from Imagers



Data and Methodology

Work Flow



CAPE Range	TOTAL	selected
0 <= CAPE <1000	53,600	2,399
1000 <= CAPE <2000	7,878	2,399
2000 <= CAPE	2,399	2,399
TOTAL	63,877	7,197

DATA

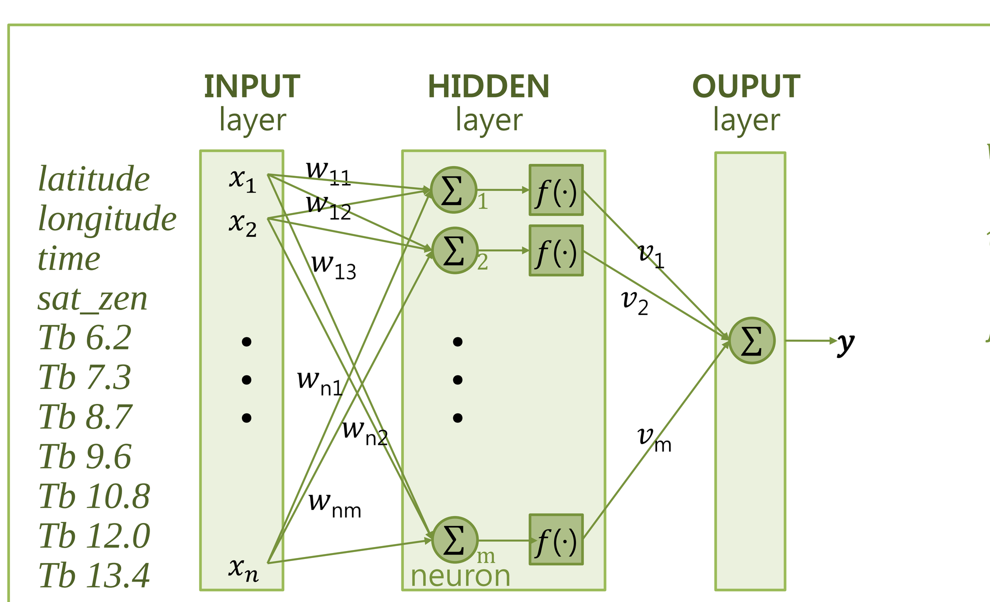
- **IASI (Infrared Atmospheric Sounding Interferometer) Level 2 Measurements**
  - used for the simulation of SEVIRI Tb
  - Temperature and humidity profiles from Jan. to Dec. in 2012 between 35N-75N latitude and 75W-75E longitude
- **SEVIRI (Spinning Enhanced Visible and InfraRed Imager) 2.5min rapid scan data**
  - used for the characterization and validation of the ANN model
  - Tbs of the seven IR channels, satellite zenith angle, lat/lon in June 20, 2013

Radiative Transfer Model

- **MODTRAN** (MODerate resolution TRANsmission) v. 5.2.2
  - used for the simulation of the upwelling radiances at TOA
  - Simulated radiances are band-averaged over SEVIRI spectral response function (SRF)

Artificial Neural Network (ANN)

- **Multi-Layer Perceptron feedforward backpropagation Algorithm**
  - used to find the relation between the simulated Tb and CAPE and to retrieve CAPE directly from the measured Tb



x_i : input , y: output
w_{ij} : connection strength(weight) between input neuron i hidden neuron j
v_j : connection strength between hidden neuron j and the output neuron
$f(\cdot)$: activation(transfer) function (hyperbolic tangent)

$$y = \sum_{j=1}^{m} v_i \, f\left(\sum_{i=1}^{n} w_{ij} x_i\right)$$

(Blackwell & Chen, 2009)

- network weights are updated in the direction in which the error (difference between the desired output and the actual output) decreases most rapidly
- For every iteration (epoch), the network fitness is evaluated by root mean square error (RMSE)

$$RMSE = \sqrt{\frac{\sum_p (y_{target}{}^{(p)} - y^{(p)})^2}{\#\ of\ pattern}} \qquad p: pattern(sample\ size)$$

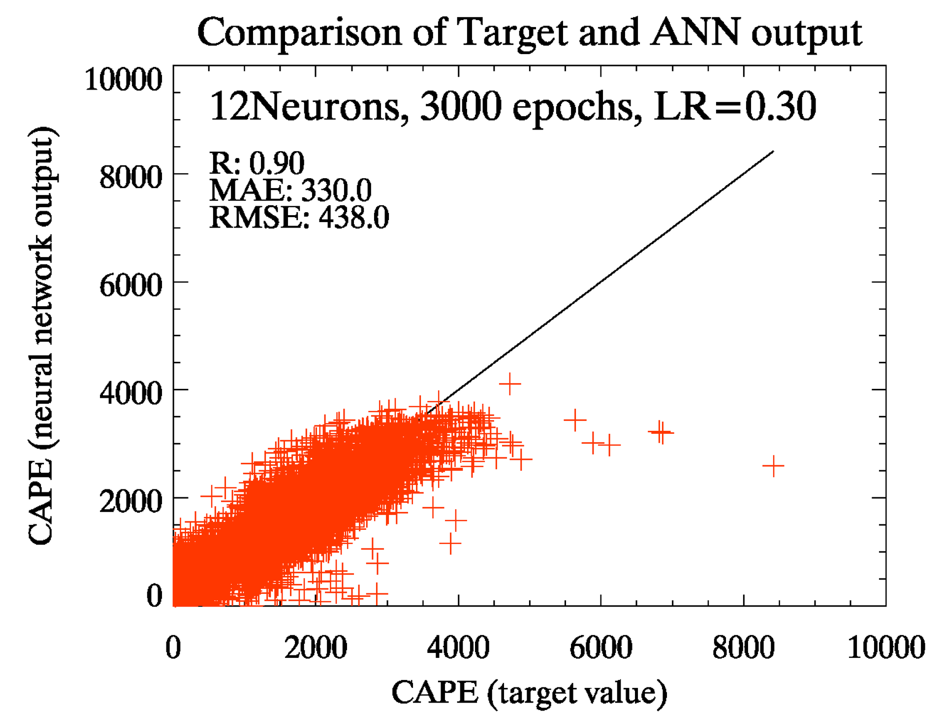
Results and Discussion

Network training with IASI data

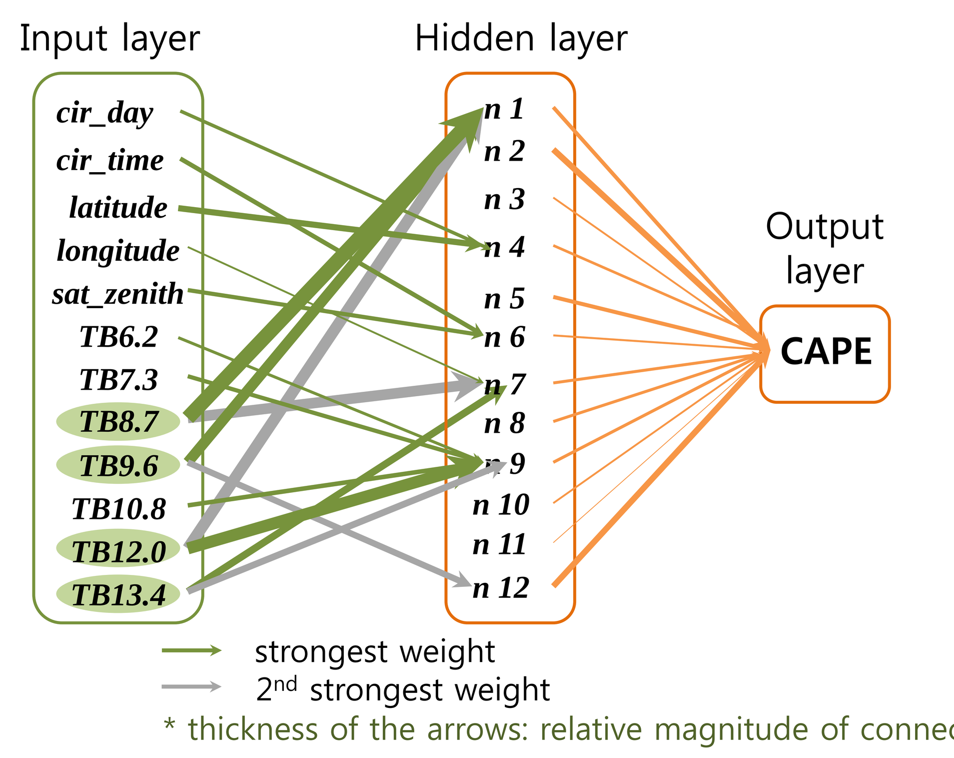
Necessary vertical T and q profiles for training are from the retrieved values from IASI, obtained from EUMETSAT

To construct a uniform set of training data, the same amount of data (2,399) from three different CAPE ranges, total 7,197, was selected out of 63,877 profiles.

The combination of ANN parameters that produces best algorithm performance is:
- *the number of hidden neuron:* 12
- *the number of epochs:* 3000
- *Learning rate:* 0.3



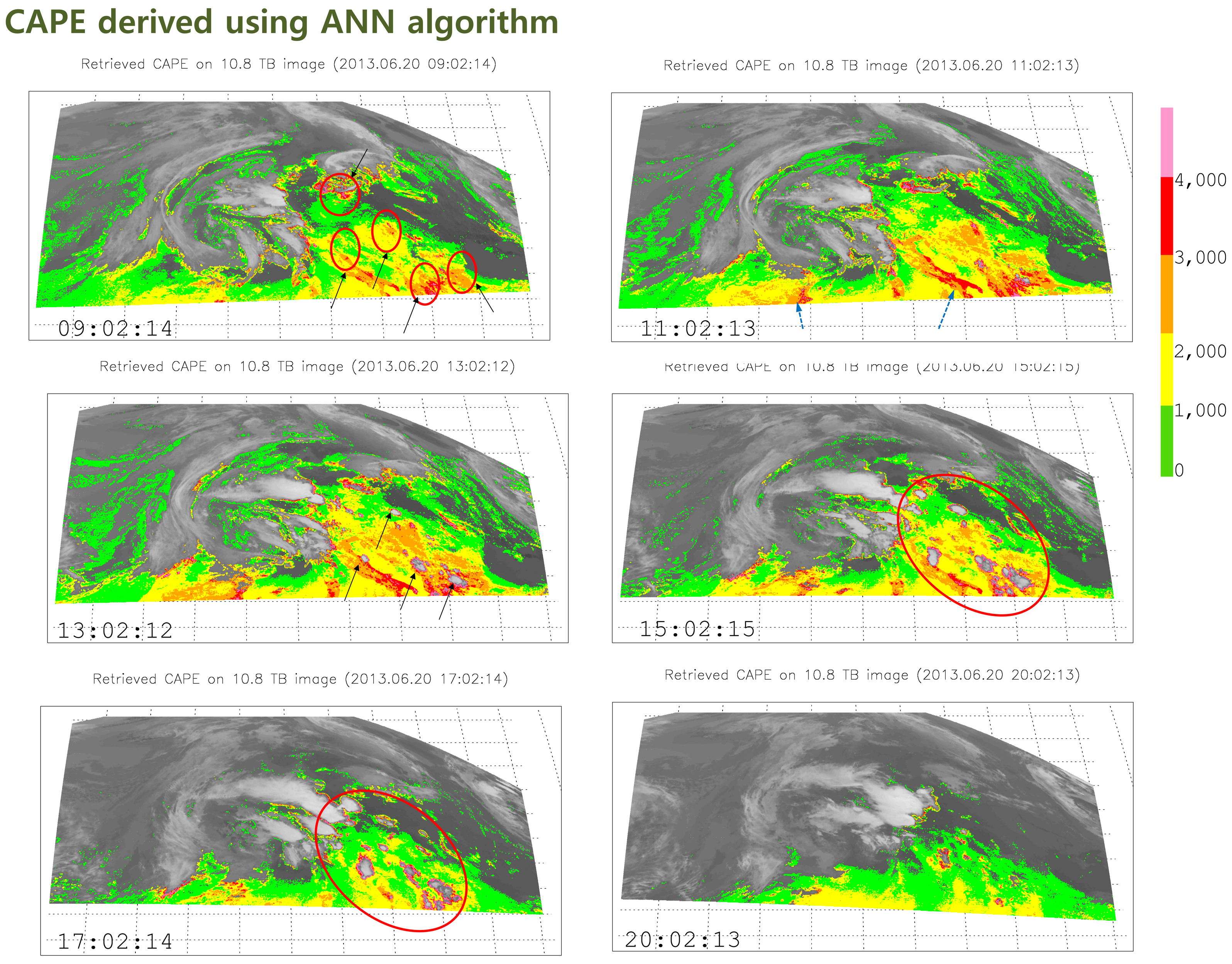
Combination of weights that results in the best network performance



INPUT	Total weights ($\Sigma W_{IH} x W_{HO}$)
circular day	0.09
circular time	0.22
Latitude	0.02
Longitude	0.32
Sat. zenith	-0.18
Tb6.2	-0.71
Tb7.3	1.56
Tb8.7	6.79
Tb9.6	4.63
Tb10.8	-0.38
Tb12.0	-7.04
Tb13.4	-4.17

- The analysis of final combination of weights reveals that among 12 input variables, brightness temperatures, particularly Tb8.7 and Tb12.0, are identified as discriminating input measurements, having strong connections with the neurons in the hidden layer
- Detailed connections for each variable need further investigation

CAPE derived using ANN algorithm



- **Significant features**
  - During the afternoon hours (at around 13:02 UTC) several convective clouds begin to pop up over the regions where the CAPE values are relatively high (marked with arrows and circles at 09:02 UTC image) and developed to the severe convective clouds (at 15:02 UTC)
  - High CAPE values around the leading edges of clouds induce a further development, while weaker CAPE values around the trailing edges result in weakened convective activities. Significance will be assessed with more case studies and quantitative validation.
  - No significant convection occurs over high CAPE areas in the morning images (at around 11:02 UTC marked with dashed blue arrows) which requires further investigation
- **Further study**
  - Apply the model to more special observation data and compare with CAPE values from the radiosonde for the quantitative validation

References

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