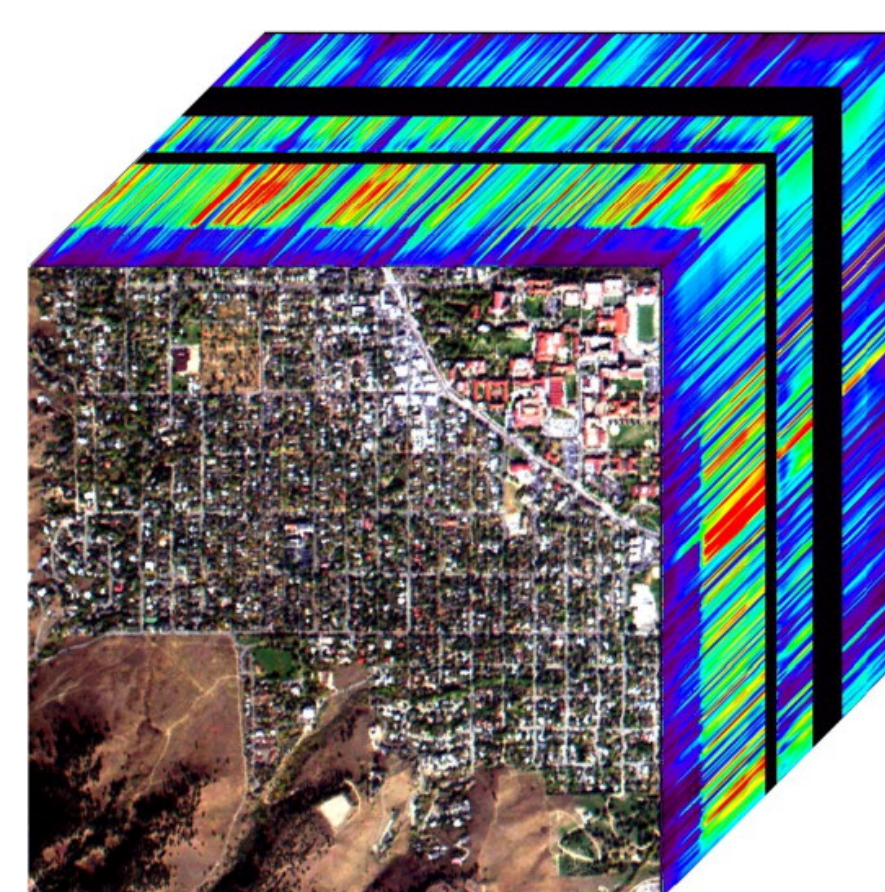


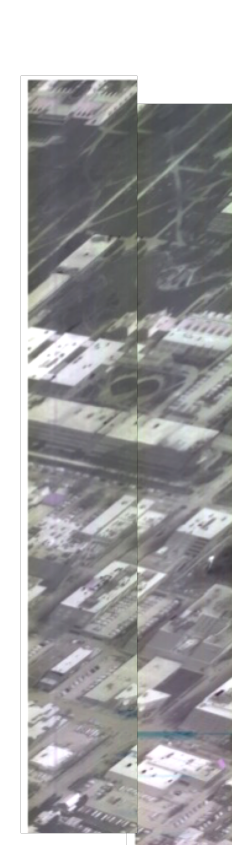
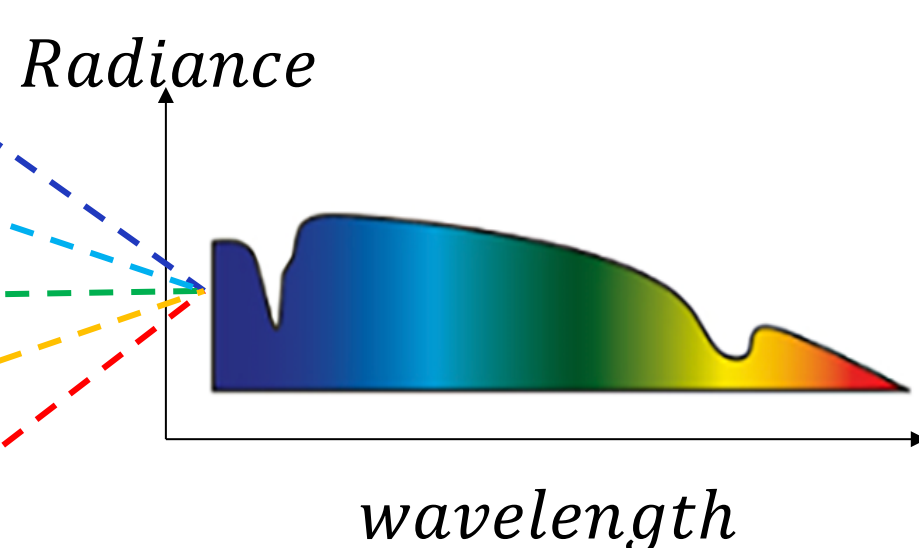


Introduction

The current state-of-the-art science approach to analyze hyperspectral images derives from existing radiance algorithms and tools developed since early 1990s. Many simplifying assumptions have been made in atmospheric correction, target radiative properties or sensors, where a single geometric solution is applied to every pixel of a spectral image. We know this solution to be expedient but also, error inducing. To fill this gap, our research will expand the existing radiance algorithms for full geometric diversity by using multiple hyperspectral images acquired by *Blue Heron* Longwave Hyperspectral sensor. A machine learning solution based on convolutional neural network is used to learn the relationships between the total radiance observed at the sensor and different atmospheric components under different atmospheric conditions. The goal is to perform an atmospheric correction on the total radiance received at sensors and retrieve the target spectral properties.

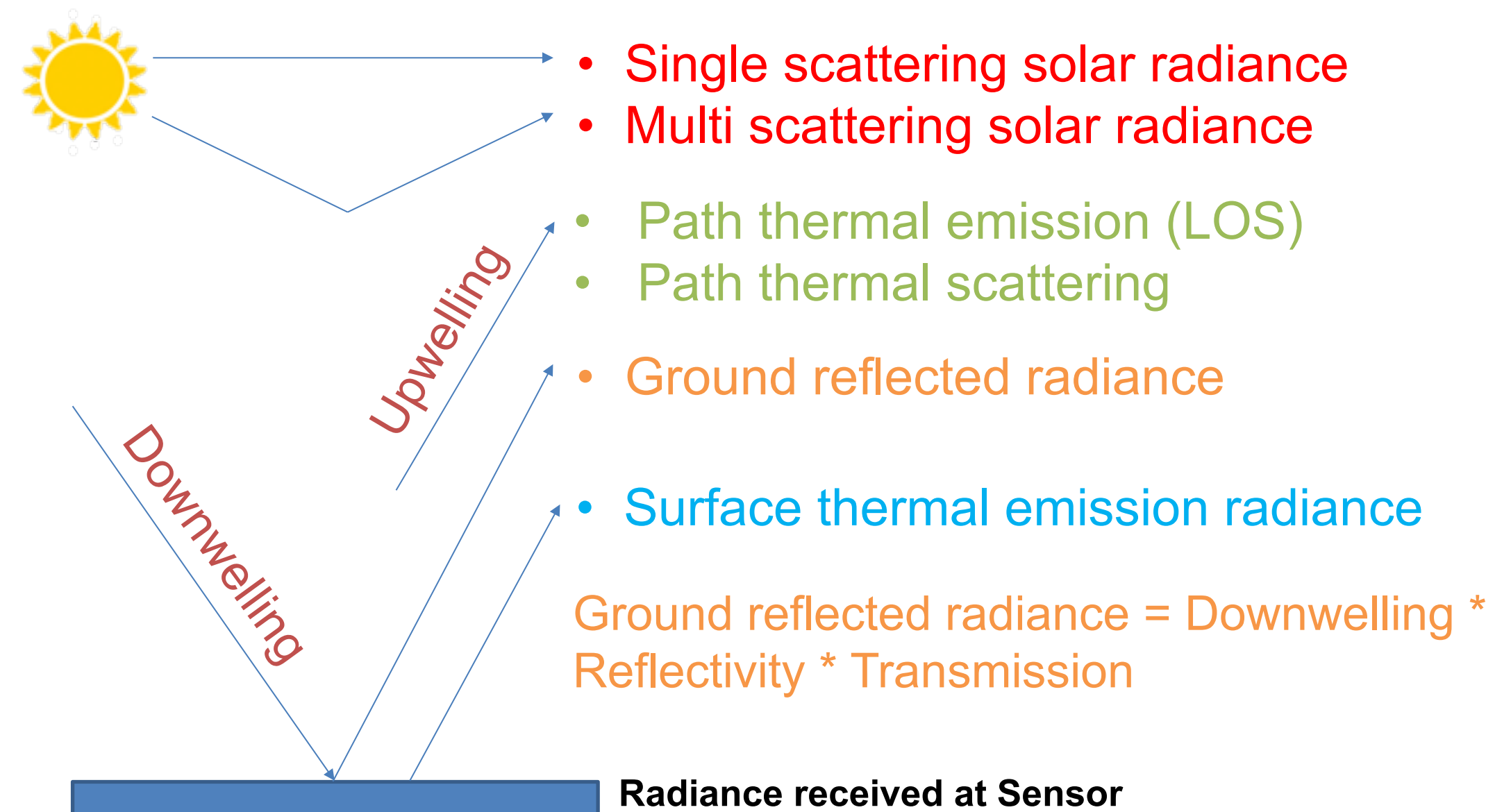
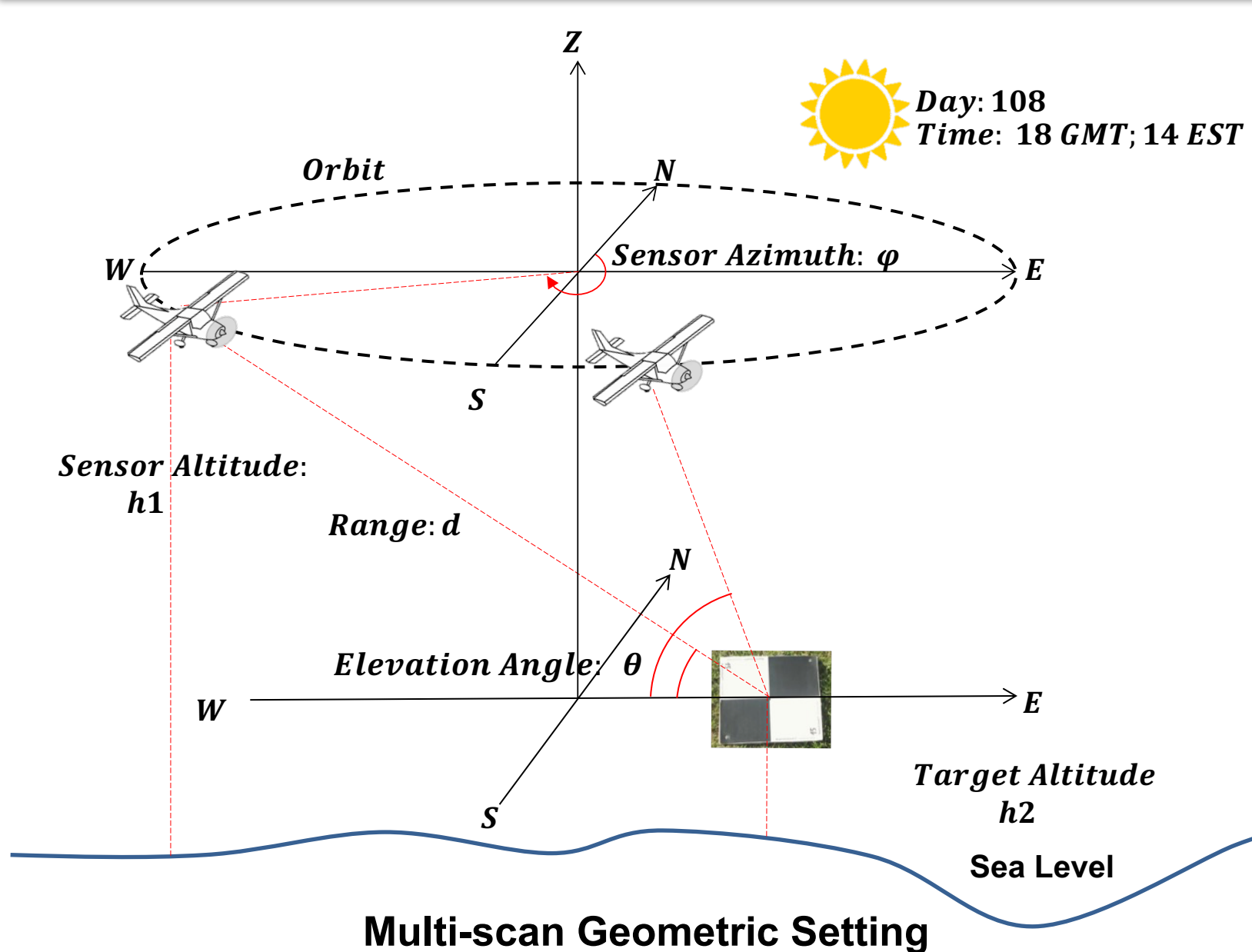


Hyperspectral Images



Nittany Radiance2019 Data Collection

Data



Methods

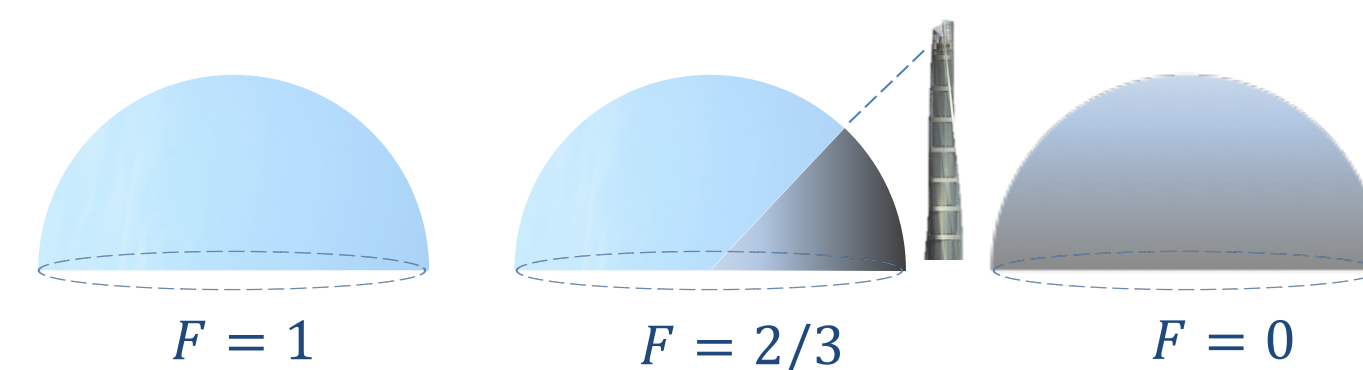
Radiance Equation & MODTRAN Simulation

$$L_{\lambda} = \left[E_{s\lambda} \cos(\sigma) \tau_1(\lambda) \frac{r(\lambda)}{\pi} + \varepsilon(\lambda) L_{T\lambda} + F(L_{ds\lambda} + L_{de\lambda}) r(\lambda) + (1-F)(L_{bs\lambda} + L_{be\lambda}) r(\lambda) \right] \tau_2(\lambda) + L_{us\lambda} + L_{ue\lambda}$$

Solar Direct Emission Surface Emission Downwelling Background Transmission Upwelling

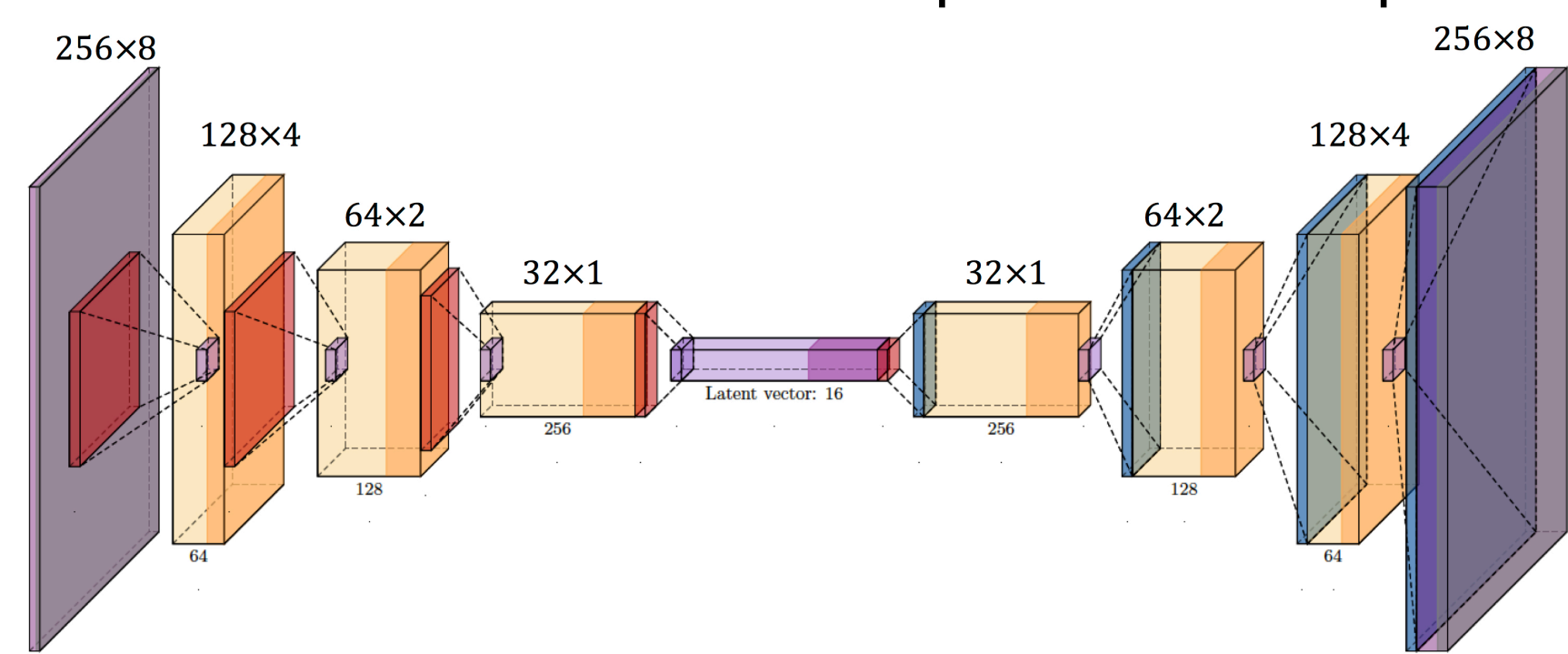
Assumptions:

- $r(\lambda) = 1 - \varepsilon(\lambda)$, $r(\lambda)$: reflectivity; $\varepsilon(\lambda)$: emissivity
- $F = 1$, F : shape factor of the opening atmosphere
- $r(\lambda) = \frac{(L_{\lambda} - L_{us\lambda} - L_{ue\lambda}) / \tau_2(\lambda) - L_{T\lambda}}{L_{down} - L_{T\lambda}}$



Machine Learning

- Convolutional Neural Network:** a set of learnable kernels as the convolution layers parameters
- Autoencoders:** a CNN where the input is the same as the output
- Encoder:** compress the input into a lower-dimensional representation
- Decoder:** reconstruct the output from the representation in latent space



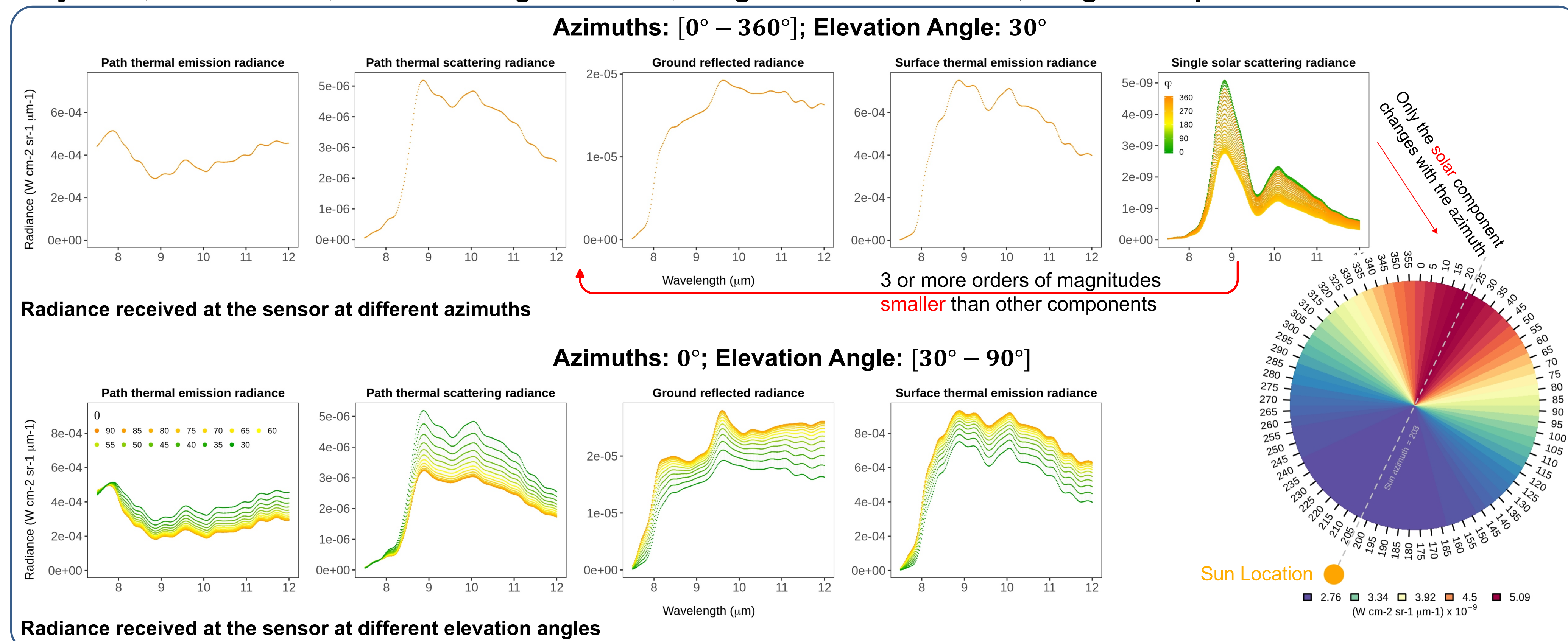
Convolutional Neural Network Structure

299040 256x8 matrices over wavelengths and angles as training data

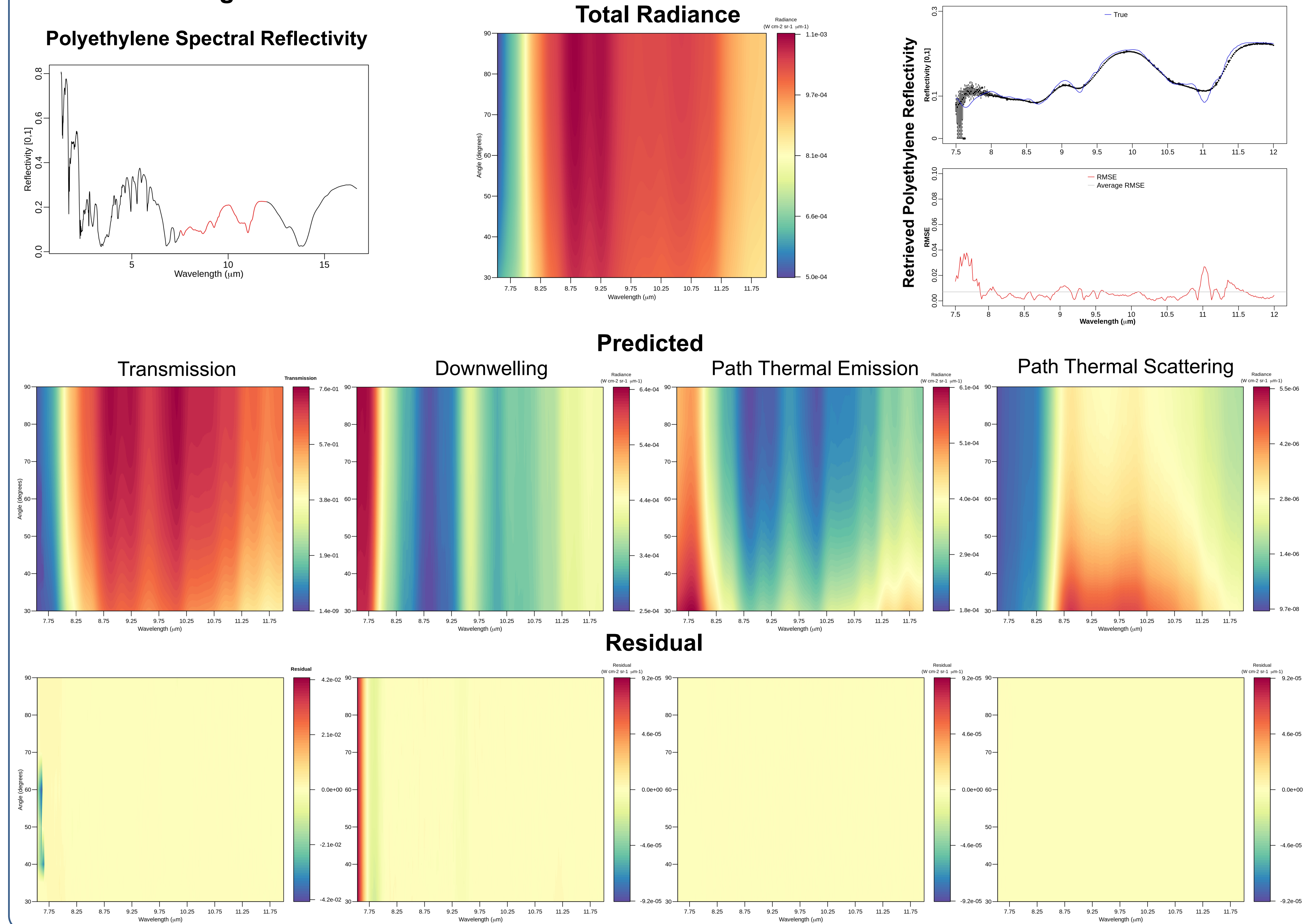
Wavelength	[7.5, 12] by every 0.0175 (μm)
Days	[1, 365]
Time	[2, 6, 10, 14, 18, 22] (: 00)
Reflectances	[5, 10, 15, 30, 50, 80, 100] (%)
Angles	[30, 35, 40, 50, 60, 70, 80, 90] ($^{\circ}$)
Millions of MODTRAN simulations	

Results

Day: 108; Time: 14:00; Sensor Range: 5000 m; Target Reflectance: 0.1; Target Temperature: 320 K



Machine Learning Solution



Conclusions

This research presents an Artificial Intelligence/Machine Learning (AI/ML) based solution to characterize the impact of varying atmosphere influence at different vantage points with increased spatial and temporal dimensionality. We have demonstrated that our proposed solution is able to model and predict the atmospheric transmission, upwelling and downwelling radiance as a function of angles, given as input the total radiance at the sensor, within one order of magnitude or less errors when compared to the traditional radiative transfer (RT) models for the same components, as well as retrieve the target spectral properties. This research can improve the atmospheric correction and target detection in non-ideal conditions, where current state-of-the-art science approach based on a single hyperspectral image normally fail.

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