# Expanded Dimensionality for Image Spectroscopy via Machine Learning

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### Abstract

The generalized solution for the radiance equation is expanded by exploiting multiple hyperspectral image scans acquired by aerial platforms at different viewing angles. A machine learning solution based on convolutional neural networks is used to learn the relationships between the total radiance observed at the sensor, and different atmospheric components of the radiance equation. The goal is to precisely characterize the atmosphere, in order to properly solve the radiance equation, in which atmospheric components constitute important input. Traditionally, these atmospheric components are only estimated from averages of pixels, or assigned using heuristics tables. Compared to traditional image spectroscopy, this expanded radiance equation and machine learning solution integrates quantitative mathematical modeling, multiple scanned hyperspectral images and artificial intelligence. The solution is able to model and predict the transmittance, downwelling and upwelling components of the radiance equation with increased spatial and temporal dimensionality. It's promising to use different combinations of the multiple scans to parameterize the radiance equation and improve the target detection in varying atmospheric conditions, where current solutions based on a single hyperspectral image normally fail. This works presents initial results of an expanded mathematical solution, along with the results from the convolution networks. Synthetic data were generated using the MODTRAN atmospheric software to simulate different vintage points, atmospheric models, time of the day and year, for an array of specific targets with varying reflectances. More specifically, MODTRAN was used to simulate Longwave Infrared Red between 7.5 and 12 microns with a 17.5 nanometers spectral sensitivity, which correspond to the range and resolution of the Blue Heron Longwave Hyperspectral sensor. Results from the convolutional neural network indicate our machine learning solution is computationally faster than the traditional radiative transfer (RT) model and is able to characterize the impact of varying atmospheric conditions on the at-sensor radiance components.

# Expanded Dimensionality for Image Spectroscopy via Machine Learning

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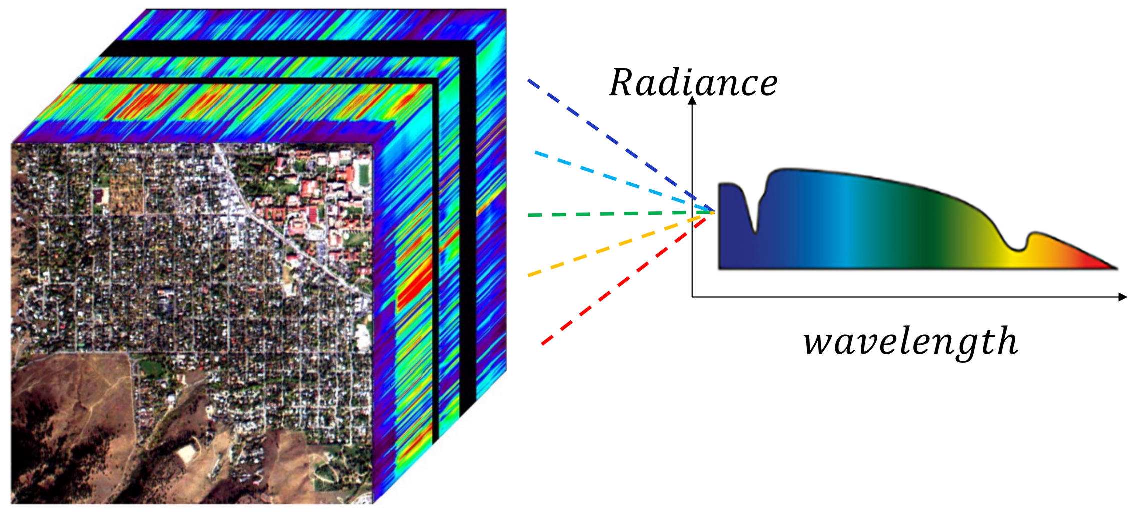
## Introduction

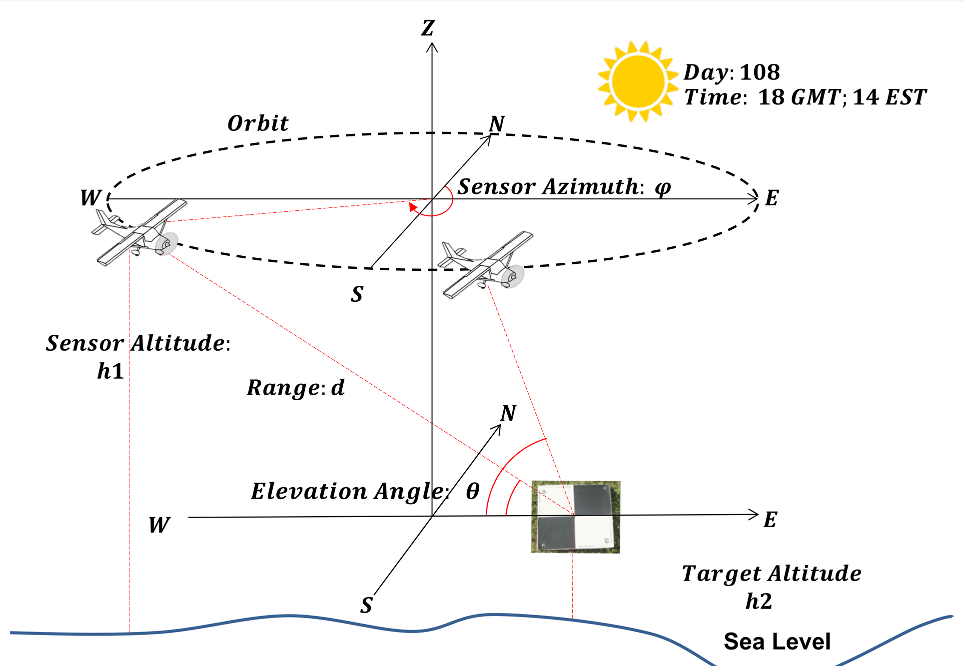
The current state-of-the-art science approach to analyze hyperspectral images derives from existing radiance algorithms and tools developed since early 1990s. Many simplifying assumptions have been made in atmospheric correction, target radiative properties or sensors, where a single geometric solution 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.



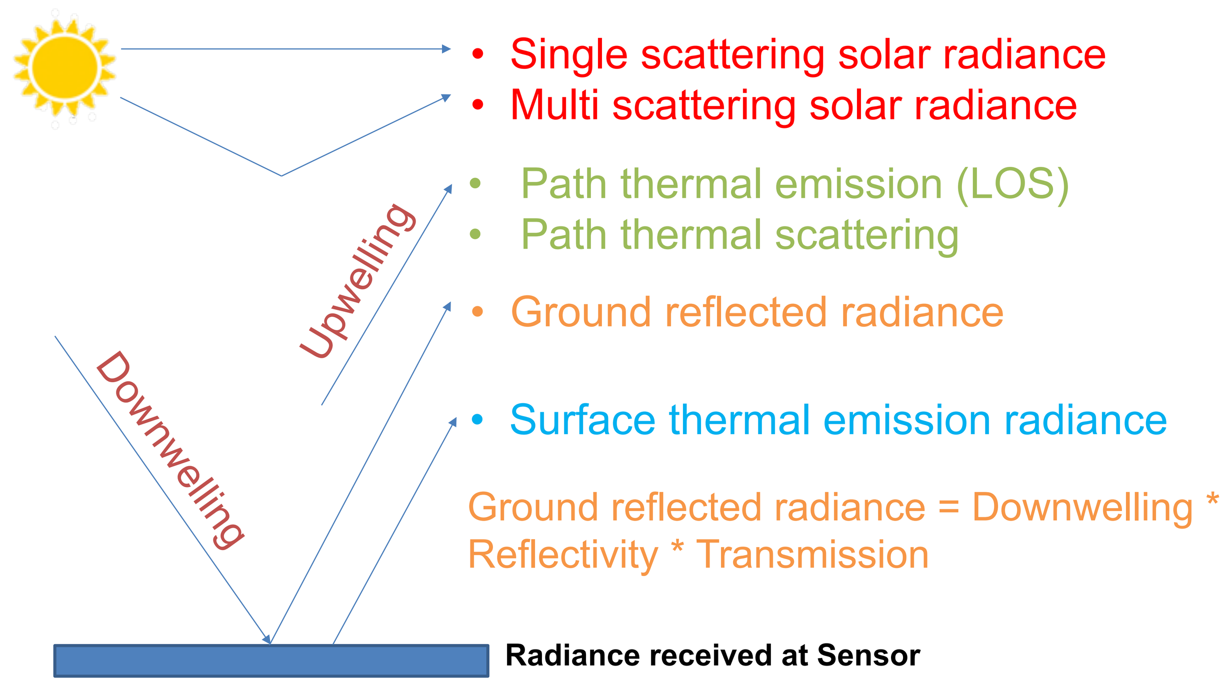

Hyperspectral Images

Nittany Radiance2019 Data Collection

## Data




Multi-scan Geometric Setting




Radiance received at Sensor

## Methods

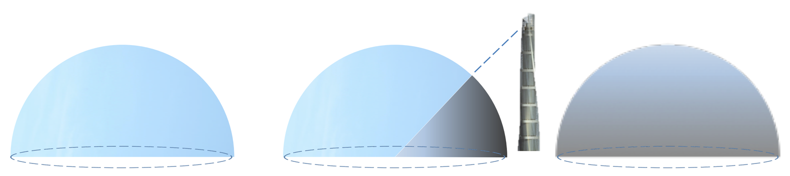
### Radiance Equation & MODTRAN Simulation

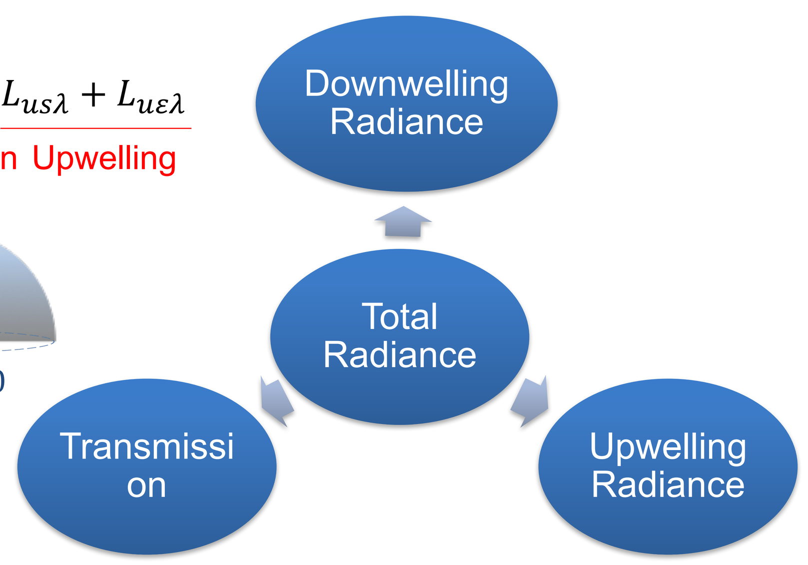
$$L_\lambda = \left[ E_{s\lambda} \cos(\sigma)\, \tau_1(\lambda) \frac{r(\lambda)}{\pi} + \varepsilon(\lambda) L_{T\lambda} + F(L_{ds\lambda} + L_{d\varepsilon\lambda}) r(\lambda) + (1-F)(L_{bs\lambda} + L_{b\varepsilon\lambda}) r(\lambda) \right] \tau_2(\lambda) + L_{us\lambda} + L_{u\varepsilon\lambda}$$

Solar Direct Emission Surface Emission Downwelling ~~Background~~ Transmisssion Upwelling

**Assumptions:**

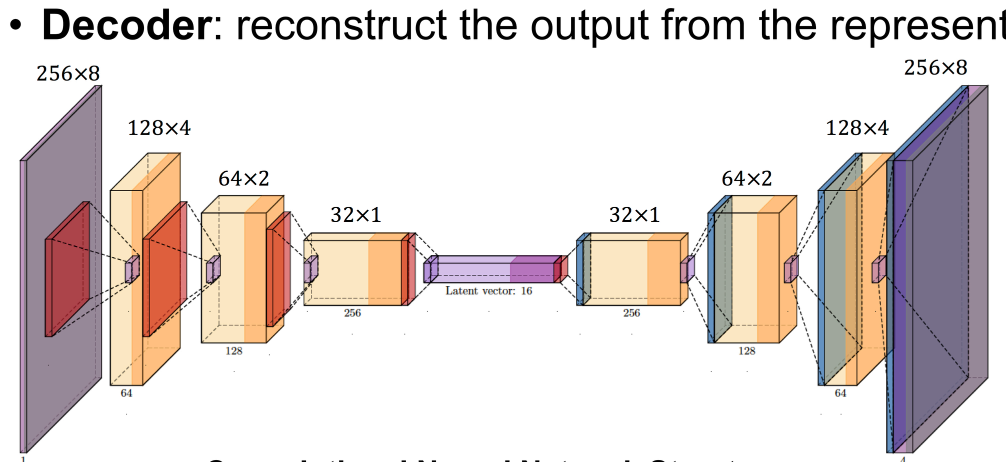
1. $r(\lambda) = 1 - \varepsilon(\lambda)$, $r(\lambda)$: reflectivity; $\varepsilon(\lambda)$: emissivity
2. $F = 1$, $F$: shape factor of the opening atmosphere
3. $r(\lambda) = \frac{(L_\lambda - L_{us\lambda} - L_{u\varepsilon\lambda})/\tau_2(\lambda) - L_{T\lambda}}{L_{down} - L_{T\lambda}}$




### 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

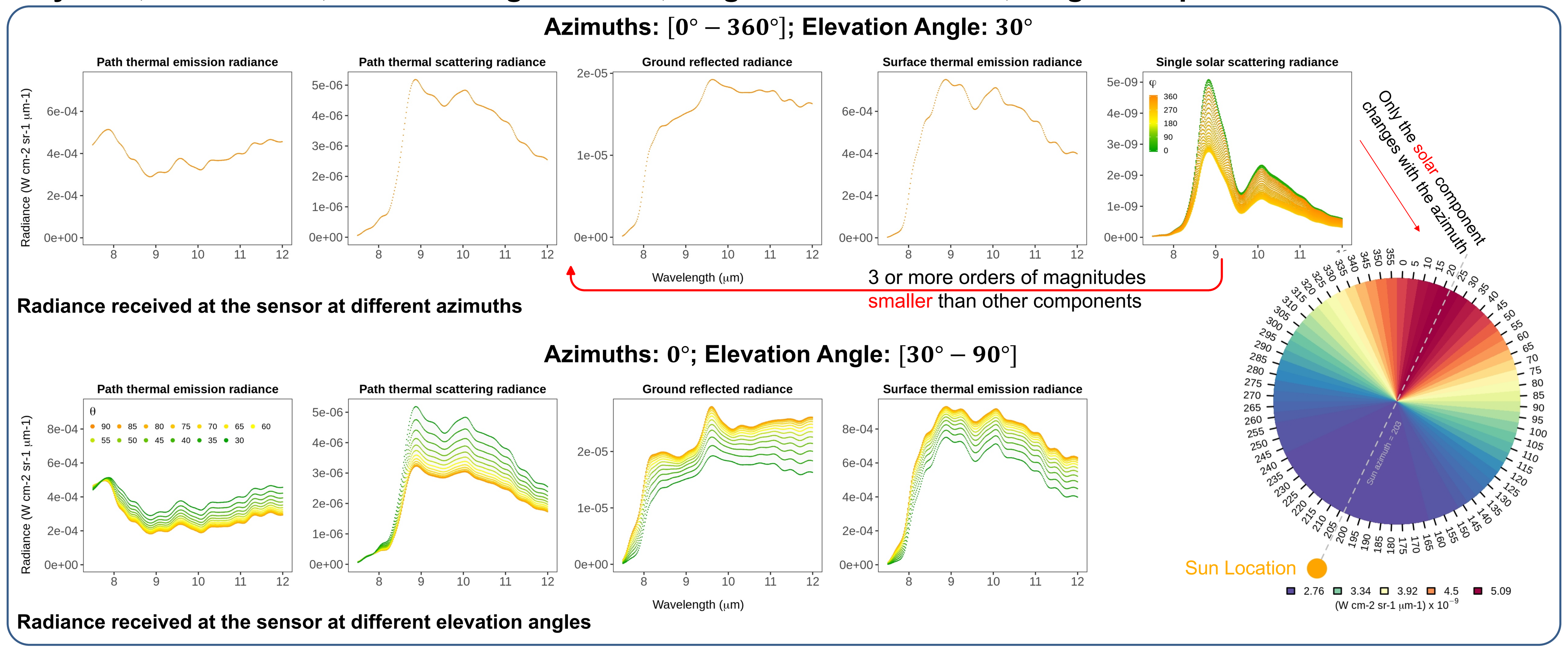
299040 256×8 matrices over wavelengths and angles as training data

| | |
|---|---|
| *Wavelength* | $[7.5, 12]$ *by every* $0.0175$ ($\mu m$) |
| *Days* | $[1, 365]$ |
| *Time* | $[2, 6, 10, 14, 18, 22]$ (:00) |
| *Reflectances* | $[5, 10, 15, 30, 50, 80, 100]$ (%) |
| *Angles* | $[30, 35, 40, 50, 60, 70, 80, 90]$ (°) |

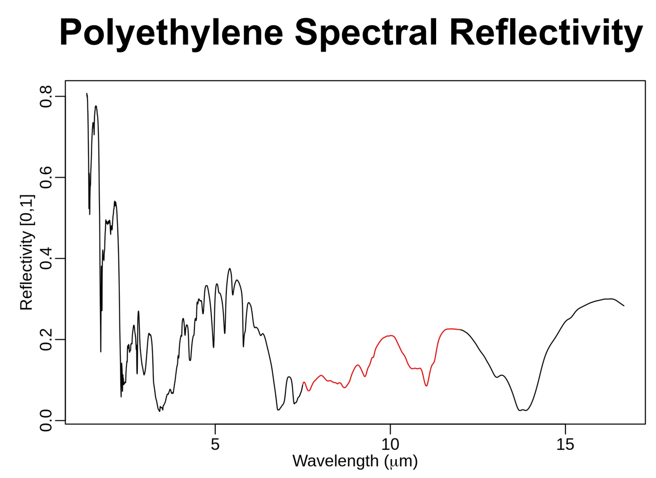
*Millions* **of MODTRAN simulations**

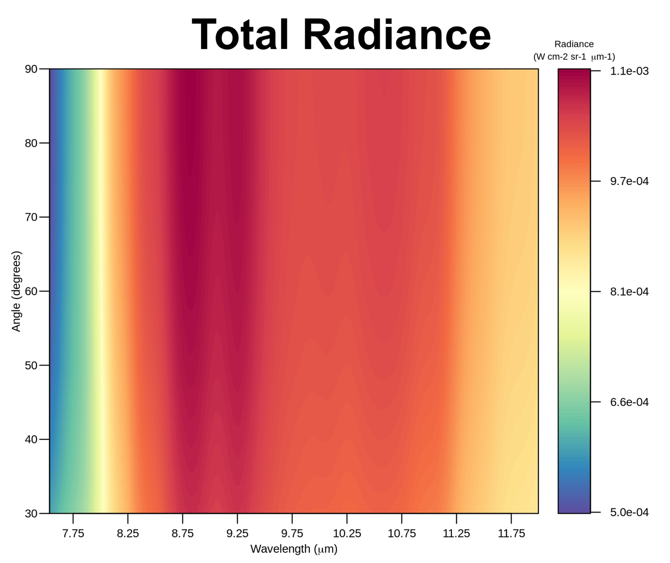
## Results

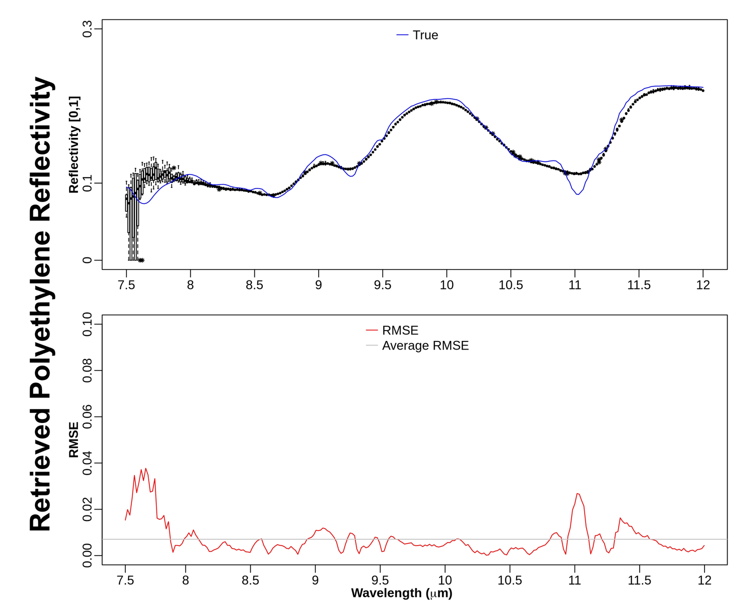
**Day: 108; Time: 14:00; Sensor Range: 5000 m; Target Reflectance: 0.1; Target Temperature: 320 K**

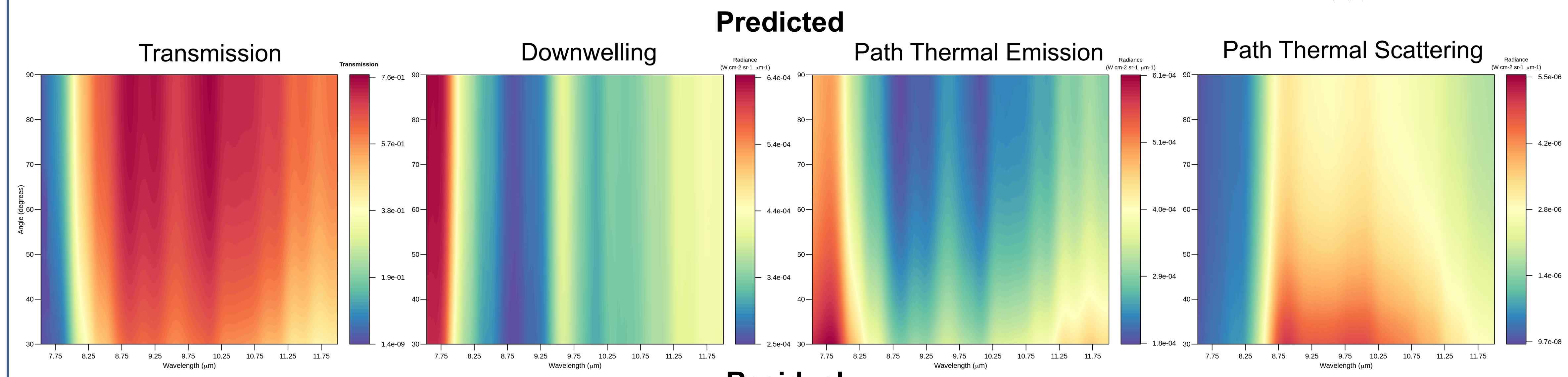


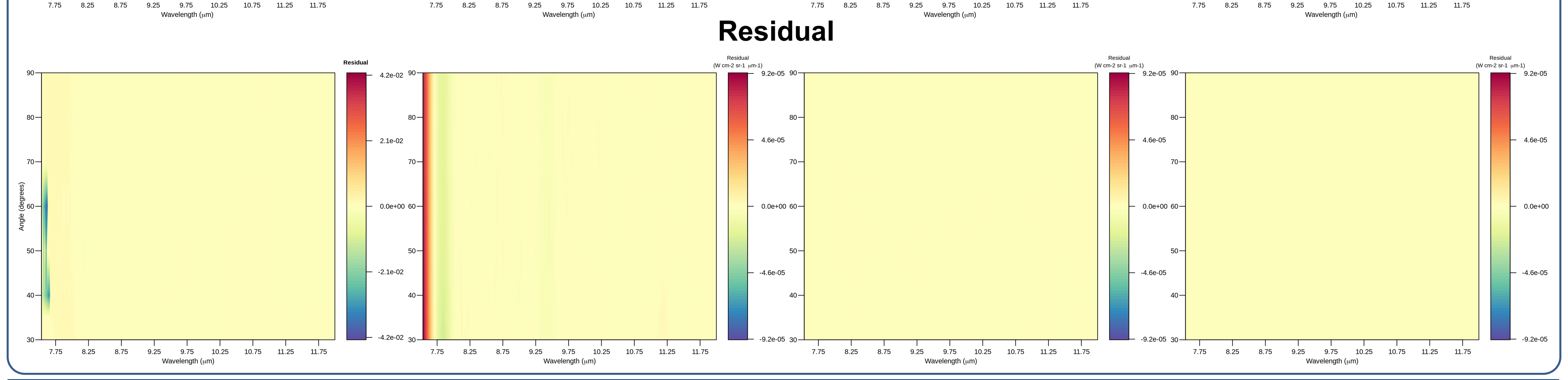

### Machine Learning Solution




## 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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