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Automatic atmospheric correction for shortwave hyperspectral remote sensing data using a time-dependent deep neural network

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Abstract

Atmospheric correction is an essential step in hyperspectral imaging and target detection from spectrometer remote sensing data. State-of-the-art atmospheric correction algorithms either require field-measurements or prior knowledge of atmospheric characteristics to improve the predicted accuracy, which are computationally expensive and unsuitable for real time application. In this paper, we propose a time-dependent neural network for automatic atmospheric correction and target detection using multi-scan hyperspectral data under different elevation angles. Results show that the proposed network has the capacity to accurately provide atmospheric characteristics and estimate precise reflectivity spectra for different materials, including vegetation, sea ice, and ocean. In addition, experiments are designed to investigate the time dependency of the proposed network. The error analysis confirms that our proposed network is capable of estimating atmospheric characteristics under both hourly and diurnally varying environments. Both the predicted results and error analysis are promising and demonstrate that our network has the ability of providing accurate atmospheric correction and target detection in real time.

Keywords: hyperspectral, deep learning, atmospheric correction, neural network, reflectivity

1. Introduction

The electromagnetic radiation characteristics of a material's absorption and emission are determined by its unique molecular composition and texture. This provides an opportunity to obtain information necessary for identifying objects using remote sensing techniques, instead of field measurements. One of such technique is hyperspectral imaging (HSI), which has been proven to be a powerful tool to identify any given object of interest on the surface of the Earth, without any direct physical contact, by retrieving their unique spectral signatures (Adão et al., 2017;

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7 Ghamisi et al., 2017; Manolakis et al., 2019). With recent developments in imaging spectroscopy, vast quantities of
8 spectrometer data with rich spectral, spatial, and temporal information have been collected by sensors from airborne
9 and spaceborne platforms (Teke et al., 2013). The collection of hyperspectral remote sensing data is deeply affected
10 by the absorption and scattering of the atmosphere. For instance, atmospheric water vapor is efficient at absorbing
11 incoming solar radiation in bands centered at approximately 0.94, 1.14, 1.38, 1.88, and 2.7 μm . Only approximately
12 half of the 0.4-2.5 μm spectrum can be transmitted without absorption from atmospheric gases (Gao et al., 2006).
13 In addition, the shorter wavelength spectral region below 1 μm is also affected by molecular and aerosol scattering.
14 Thus, to study the spectral properties of the Earth and retrieve its reflectivity, atmospheric effects must be removed
15 from the spectrometer data.

16 Atmospheric correction algorithms for hyperspectral imaging data are generally divided into two major classes
17 based on whether any physical mechanisms of solar transportation are involved, in which delineates the interaction
18 between environment and surface. The first class consists of scene-based empirical methods, such as internal average
19 reflectance (Kruse, 1988, or IAR), flat-field correction (Roberts et al., 1986), and empirical line approach (Conel
20 et al., 1987, or ELA), which are computationally efficient and can be accurate with sufficient information from field
21 measurements. However, these approaches either may cause unrealistic absorption features in the corrected reflectance
22 spectra because of their robust assumptions (Clark and King, 1987; DiStasio Jr and Resmini, 2010), or require a prior
23 knowledge of in-scene elements, i.e., field-measured reflectance spectra, for at least one bright target and one dark
24 target which does not adapt for some scenarios (Conel et al., 1987; Aspinall et al., 2002).

25 The other class of atmospheric correction algorithms are radiative transfer approaches (Gao et al., 1993; Gao
26 and Davis, 1997; Adler-Golden et al., 1999; Siewert, 2000; Mayer, 2009; Duan et al., 2010) that take advantage
27 of the known physical mechanisms of interactions between environments and surface targets. For instance, with
28 an assumption of a simple homogeneous layer of atmosphere, the *Pstar* computational model was built to provide a
29 discrete ordinate solution that only works under an optically-thin atmospheric condition (Siewert, 2000). The *MYSTIC*
30 code is optimized using a Monte-Carlo algorithm that allows a more complex heterogeneous atmospheric profile
31 and provides the solution with a high accuracy, however, its implementation is much more computationally expensive
32 and may generate statistical noise (Emde et al., 2010; Mayer, 2009). The *SOSVRT* radiative transfer model uses
33 successive-order-scattering (SOS) method that leads to improvement in modeling atmospheric scattering, however
34 challenges remain in its ability to converge when the atmosphere is the optically-thick and the observing angles are
35 oblique (Duan et al., 2010). These first-principle approaches are capable of retrieving high accuracy reflectance spectra
36 with prior knowledge of atmospheric characteristics by modeling the absorption and scattering effects of atmosphere.
37 However, the explicit atmospheric spectra simulations are not only computationally expensive, but require accurate

38 characterization of the atmosphere and precise characteristics of sensors (Siewert, 2000; Qu et al., 2003; Gao et al.,
39 2009).

40 The combination of empirical methods and radiative transfer approach have also been proposed to accelerate the
41 process of atmospheric correction for multi-channel hyperspectral remote sensing data (Qu et al., 2003; Gao et al.,
42 2009; Markelin et al., 2017; Katkovsky et al., 2018), however, its performance is a trade-off between computational
43 efficiency and accuracy. Thus, an accurate, fast, and automated atmospheric correction approach is desired to retrieve
44 the emitted and reflected radiance of the target at the Earth's surface from the hyperspectral remote sensing data.

45 Recent advances in agile collection platforms overcome the fixed nadir looking geometry settings of past instru-
46 ments, which allow users to measure additional solar and atmospheric radiative components of the radiative transfer
47 equation (RTE). Additionally, the new generation of agile sensors have the ability to revisit a scene in seconds under
48 variant looking angles. The rapid multi-scan collecting capacity and the geometric diversity of modern hyperspectral
49 collecting systems provide a new opportunity to develop a more complete solution to the fundamental RTE because of
50 their retrieval of full spatial dimensionality and multiple temporal components. Furthermore, the abundant spectral-
51 spatial information in multi-scan hyperspectral remote sensing data enables the adoption of the fully data-driven
52 methods, such as deep learning technique, in hyperspectral image analysis.

53 Deep learning technique, as a branch of machine learning and artificial intelligence methods, has shown research
54 and operational success across various fields. A representative framework of deep learning is the deep neural network
55 (DNN). For image processing applications, the convolution neural network (CNN) has demonstrated its superiority
56 since it can be formulated with a relatively small number of trainable parameters. Various architectures of CNN have
57 been designed for different imaging tasks such as AlexNet (Krizhevsky et al., 2012), VGG-16 (Simonyan and Zis-
58 serman, 2014), U-Net (Ronneberger et al., 2015), Inception (Szegedy et al., 2015, 2016), ResNet (He et al., 2016),
59 and DenseNet (Huang et al., 2017). Beyond that, progresses of applying CNN in discipline of hyperspectral image
60 analysis have also been made. For instance, Yu et al. (2017) demonstrated the hyperspectral image classification
61 using a CNN outperforms other state-of-the-art methods. Xu et al. (2020) proposed an encoder-decoder neural net-
62 work to remove atmospheric effects from long wavelength multi-scan hyperspectral data. These studies have shown
63 the potential use on DNNs in its application to hyperspectral image analysis. However, seasonal and diurnal cycle
64 variations of atmosphere were not taken into account in data collection, which limits the performance and feasibility
65 of deep learning in some realistic scenarios. In addition, deep learning application using the shortwave spectrum of
66 hyperspectral data remain in an unexplored area because of the complexity of the spectral-spatial nature.

67 In this paper, we design a time-dependent neural network to solve every radiative component of RTE from the at-
68 sensor total radiance using shortwave spectra. The proposed network is partially convolution-based, but involves two

69 temporal factors, i.e., collection *day* of the year and *time* of the day, using the fully connected layers. We expect the
70 time-dependency of such a neural network to capture the diurnally-and-hourly varying characteristics of atmospheric
71 environment, which can improve the accuracy of estimating the target’s reflectivity spectra. This paper is organized as
72 follows: first, we introduce the theoretical deep learning solution of the RTE and discuss the architectural design of the
73 time-dependent neural network; second, we describe the hyperspectral data simulation, the required pre-processing
74 of input and labelled data, and the network training process. The performance of our designed neural network is
75 then evaluated by analyzing the discrepancy between the ground-truth solar and atmospheric radiative components of
76 RTE and the predicted results. The target’s reflectivity is retrieved as an additional indicator to evaluate the network’s
77 ability. Finally, the contribution of the two temporal factors and the composition of the training dataset to the network’s
78 prediction skill are also discussed.

79 2. Methodology

80 In this section, we first briefly review the concepts of radiative transfer modeling, and different components of the
81 RTE. Then, the fully-data driven deep learning solution of the RTE will be introduced following by the discussion of
82 the neural network architecture to adapt for the diurnal and hourly variations of atmospheric conditions.

83 2.1. Radiative transfer modeling

84 In addition to the chemical and physical compositions of the target, the hyperspectral remote sensing data is also
85 highly affected by the solar-sensor’s geometry settings and the absorption and scattering by atmosphere, including
86 gases, aerosols, water vapor, and clouds. The physical transportation of radiative energy can be described by the RTE,
87 and its mathematical expression (Schott, 2007) is written as

$$\begin{aligned}
 L_{\lambda} = & \frac{\cos\sigma}{\pi} E_{s\lambda} r(\lambda) \tau_1(\lambda) \tau_2(\lambda) + L_{T\lambda} \epsilon(\lambda) \tau_2(\lambda) + L_{us\lambda} + L_{u\epsilon\lambda} \\
 & + [F(L_{ds\lambda} + L_{d\epsilon\lambda}) + (1 - F)(L_{bs\lambda} + L_{b\epsilon\lambda})] r(\lambda) \tau_2(\lambda)
 \end{aligned} \tag{1}$$

88 where T is the target’s temperature in Kelvin, s represents that the component is solar-related, ϵ denotes the self-
89 emitted thermal component, d (u) is the downwelling (upwelling) component, and b is a reminder that the component
90 pertains to the background. F is the fraction of hemisphere is obscured by background objects, and is also known as
91 the shape factor. λ denotes the wavelength of the solar radiance. The physical meaning of each RTE component is
92 listed in Table 1.

Table 1: Physical meaning of each component in RTE

Components	Units	Physical meaning
$E_{s\lambda}$	W/m^2	Extraterrestrial solar irradiance
σ	—	Incident angle of solar irradiance
$r(\lambda)$	—	Spectral reflectivity of the target
$\varepsilon(\lambda)$	—	Spectral emittance of the target
$\tau_1(\lambda)$	—	Atmospheric transmission on the sun-target path
$\tau_2(\lambda)$	—	Atmospheric transmission on the target-sensor path
$L_{T\lambda}$	$Wcm^{-2}sr^{-1}\mu m^{-1}$	Spectral radiance of a blackbody at temperature T
$L_{ds\lambda} + L_{de\lambda}$	$Wcm^{-2}sr^{-1}\mu m^{-1}$	Sum of solar and atmospheric downwelling spectral radiance
$L_{bs\lambda} + L_{be\lambda}$	$Wcm^{-2}sr^{-1}\mu m^{-1}$	Sum of background reflected and self-emitted spectral radiance
$L_{us\lambda} + L_{ue\lambda}$	$Wcm^{-2}sr^{-1}\mu m^{-1}$	Sum of solar and atmospheric upwelling spectral radiance

In Table 1, $L_{T\lambda}$ is the emitted radiance of a blackbody, also referred to as the Planck's Law:

$$L_{T\lambda} = 2hc^2\lambda^{-5}(e^{\frac{hc}{\lambda kT}} - 1)^{-1} \quad (2)$$

where, h is Planck's constant, c is the speed of light, and k is the Boltzmann gas constant. To achieve energy balance all incident flux must be either transmitted, reflected, or absorbed, i.e., $\tau(\lambda) + r(\lambda) + \alpha(\lambda) = 1$. Thus, the spectral emittance of an opaque surface can be calculated by its reflected radiance: $\varepsilon(\lambda) = 1 - r(\lambda)$ because of its zero transmissivity (i.e., $\tau(\lambda) = 0$) and the equivalence of the absorptivity and the emissivity (i.e., $\alpha(\lambda) \equiv \varepsilon(\lambda)$). Assuming the object of interest is located in an open area, i.e., $F = 1$, Equation (1) can be reformulated as

$$\begin{aligned} L_\lambda &= \tau_2(\lambda)r(\lambda) \left[\frac{cos\sigma}{\pi} E_{s\lambda}\tau_1(\lambda) + L_{ds\lambda} + L_{de\lambda} \right] + \varepsilon(\lambda)\tau_2(\lambda)L_{T\lambda} + L_{us\lambda} + L_{ue\lambda} \\ &= \tau_2(\lambda)r(\lambda)L_{down}^M + [1 - r(\lambda)]\tau_2(\lambda)L_{T\lambda} + L_{solar_scat1}^M + L_{solar_scat2}^M + L_{path_emit}^M + L_{path_scat}^M \end{aligned} \quad (3)$$

where, $L_{down}^M = \left[\frac{cos\sigma}{\pi} E_{s\lambda}\tau_1(\lambda) + L_{ds\lambda} + L_{de\lambda} \right]$ describes the downwelling radiance in which the ground reflected radiance received at the sensor can be delineated as $\tau_2(\lambda)r(\lambda)L_{down}^M$; The solar scattering components are $L_{us\lambda} = L_{solar_scat1}^M + L_{solar_scat2}^M$ where the right hand of equation $L_{solar_scat1}^M$ and $L_{solar_scat2}^M$ represent the single- and multiple-scattering solar radiances, respectively; and $L_{ue\lambda} = L_{path_emit}^M + L_{path_scat}^M$ demonstrates atmospheric thermal radiance in and scattered to the light-of-sight (LOS) path.

2.2. Deep learning solution of the RTE

Instead of using a single viewpoint in traditional radiative transfer approaches, the multi-scan hyperspectral geometry settings allow users to re-evaluate the RTE using a fully data-driven deep learning technique. The desired input of such a neural network will be multi-scan multispectral remote sensing data collected in a rapid sequence. The high temporal scanning frequency allows us to consider atmospheric conditions to be constant for the multi-scan data

109 collected at specific time and the multiple downlooking angles circumvents the underdetermined problem. The aim of
 110 the neural network is to study all atmospheric characteristics that affect the total radiance observed by the sensors. In
 111 other words, an applicable network should be capable of retrieving all solar and atmospheric coherent radiative com-
 112 ponents of the RTE, including $\tau_2(\lambda)$, L_{down}^M , $L_{solar_scat1}^M$, $L_{solar_scat2}^M$, $L_{path_emit}^M$, and $L_{path_scat}^M$, which will subsequently be
 113 referred to as the six solar and atmospheric RTE components. However, due to the rapidly changing environment and
 114 the varying incident angles between the Sun and target, it is still unrealistic to directly decompose the total radiance
 115 $L_{T\lambda}$ into all atmospheric components using a single equation without any prior knowledge, even with the assistance
 116 of the multi-scan hyperspectral data. To take into account the diurnal and hourly variability of atmosphere and their
 117 impacts on the incoming solar radiation and climatological atmospheric conditions, two temporal factors, *day* of the
 118 year and *time* of the day, need to be considered in the network design. With all these information having been correctly
 119 placed, the fundamental formulation of the desired neural network for atmospheric correction on hyperspectral data is
 120 written as

$$\tau_2(\lambda), L_{down}^M, L_{path_emit}^M, L_{path_scat}^M, L_{solar_scat1}^M, L_{solar_scat2}^M = \Omega(L_{\lambda\theta}, day, time) \quad (4)$$

121 where the label θ represents the elevation angle in the observation geometry, $L_{\lambda\theta}$ is the total radiance under multiple
 122 elevation angles received at a certain *time* and *day* by the sensor. Ω represents a sequence of input preprocessing, net-
 123 work implementation, and output postprocessing. After obtaining the final estimations using Ω , the target's reflectivity
 124 can be calculated as

$$r(\lambda) = \frac{(L_{\lambda\theta} - L_{us\lambda} - L_{ue\lambda})/\tau_2(\lambda) - L_{T\lambda}}{L_{down}^M - L_{T\lambda}} \quad (5)$$

125 2.3. Network architecture

126 Various neural network architectures have been developed for different types of tasks. Here, similarly to general
 127 image processing, we adopt the encoder-decoder CNN as the major framework for the atmospheric correction prob-
 128 lem. However, as previously discussed, the encoder-decoder architecture needs an adjustment to incorporate the two
 129 temporal factors (i.e., two scalar values) to adapt to both the diurnal and variability in atmospheric conditions and the
 130 varying incident angles.

131 In Figure 1, we plot the architecture for our time-dependent neural network for atmospheric correction on multi-
 132 scan hyperspectral data. There are three primary blocks including an encoder, the fully-connected layers in latent
 133 space, and a decoder. All detailed parameterizations in each layer are listed in Table 2. Our neural network accepts a
 134 total radiance relieved at the sensor with 150 wavelength bands (height) from 0.4 μm to 3.0 μm under 13 elevation

135 angles (width) from 30° to 90°.

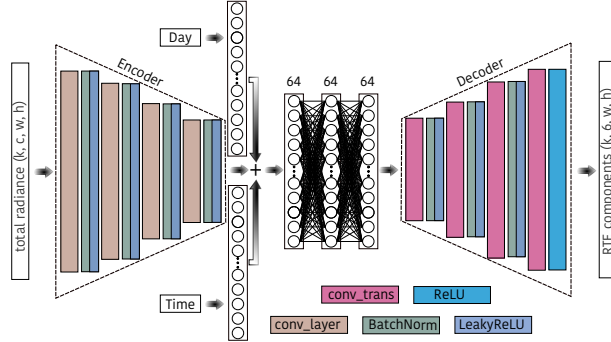


Figure 1: The architecture of the proposed time-dependent neural network.

Table 2: Detailed parameters of the proposed time-dependent CNN shown in Figure 1.

Operation Layer		Number of Filers	Size of Each Filter	Stride	Padding	Output Size (c x h x w)
Input	total radiance	-	-	-	-	1x150x13
Encoder	Conv_layer_1	64	4x3x1	2x2	1x1	64x75x7
	Conv_layer_2	128	5x3x64	2x2	1x1	128x37x4
	Conv_layer_3	256	5x3x128	2x2	1x0	256x18x1
	Conv_layer_4	64	18x1x256	1x1	0x0	64x1x1
Fully Connected Layers	FC_day	-	-	-	-	64
	FC_time	-	-	-	-	64
	FC_1	-	-	-	-	64
	FC_2	-	-	-	-	64
	FC_3	-	-	-	-	64
Decoder	Conv_trans_1	256	18x1x64	1x1	0x0	256x18x1
	Conv_trans_2	128	5x4x256	2x2	1x0	128x37x4
	Conv_trans_3	64	5x3x128	2x2	1x1	64x75x7
	Conv_trans_4	6	4x3x64	2x2	1x1	6x150x13

136 The encoder in our architecture is designed to remove repetitive information from the multi-scan hyperspectral
 137 data by analyzing the invariance of the target’s reflectivity with different elevation angles. To preserve the detailed
 138 information while reducing spatial dimensionality of the inputs, instead of using the max pooling layer, we adopt stride
 139 convolution in the encoder to compress the input into a latent space vector. The global convolutional filters with size
 140 of $18 \times 1 \times 256$ are applied in the last convolution layer of the encoder (see in Table 2) to avoid vast parameterizations
 141 in the latent space. Each convolution layer in the encoder is followed with a batch-normalization layer and a leaky
 142 rectifier unit (LeakyReLU) activation layer.

143 In the latent space, we use two independent fully connected layers to handle the two temporal factors: *day* of the
 144 year and *time* of the day, in which the outputs of these two layers are added into the encoder generated latent space
 145 vector. Then, three fully connected layers with 64 neurons in each are employed to decompose the summarized latent

146 space vector into a RTE involved vector which will be expanded by the decoder into the same readable dimension as
147 the input. A LeakyReLU transformation is carried out after every fully connected layer. Transposed convolutions are
148 also applied as the upsampling strategy in the decoder, and a combination of a batch-normalization and a LeakyReLU
149 are implemented after each transposed convolution layer, except for the last one which is followed by a ReLU acti-
150 vation. The outputs of the final ReLU layer are the solved six RTE components stored in different channels with the
151 same order of as illustrated in the left hand of Equation (4).

152 3. Numerical examples

153 In this section, synthetic multi-scan hyperspectral data are simulated using *MODTRAN* (Adler-Golden et al., 1999;
154 Berk et al., 2014) to train and validate the ability of the time-dependent neural network. After obtaining six predicted
155 solar and atmospheric radiative components of the RTE using the trained network, the target’s reflectivity can also be
156 calculated using Equation (5) to further examine the performance of the proposed network.

157 3.1. Data simulation

158 *MODTRAN* software is chosen for synthetic hyperspectral data simulation. We assume that the target is located
159 at (40.7934 N, 77.86 W) in an open area, i.e., the shape factor $F = 1$, which lies at the Pennsylvania State University,
160 University Park, PA, USA. These synthetic data were used to plan a data collection campaign, Nittany Radiance 2019,
161 that occurred on the premises of the Pennsylvania State University, University Park campus on April 2019 to collect
162 aerial hyperspectral remote sensing scenes as well as ground truth measurements. The at-sensor total radiance is
163 collected by an airborne sensor with a constant range 5000 m and a fixed azimuth. The temperature of the target is
164 set to 350K. In every data recording process, the total radiance is measured under 13 elevation angles starting from
165 30° to 90° at 5° intervals. Additionally, for each target, the data is collected eight times a day from 6:00am to 8:00pm
166 (represents local time subsequently) at 2 hours intervals all year.

167 The airborne sensor has a spectral resolution of 17.5 nm to record radiative signals at 150 wavelength bands
168 between 0.4 μm and 3.0 μm . With such a parameterization setting, for every material, we have 365×8 radiance maps
169 of size 150×13 . The simulations are performed on 48 target materials, including 42 *MODTRAN* builtin materials,
170 and six opaque Lambertian gray bodies with different constant reflectivities across the spectrum, which are 0.05, 0.1,
171 0.3, 0.5, 0.8, 1.0.

172 In Figure 2, the total radiances with 13 elevation angles for two different materials received at 2:00pm on January
173 10th and their corresponding targets’ reflectivity spectra are plotted. Figure 2a shows the total radiance for a Lam-
174 bertian gray with a 0.3 constant reflectivity shown in Figure 2b. For the target with a constant reflectivity, prominent

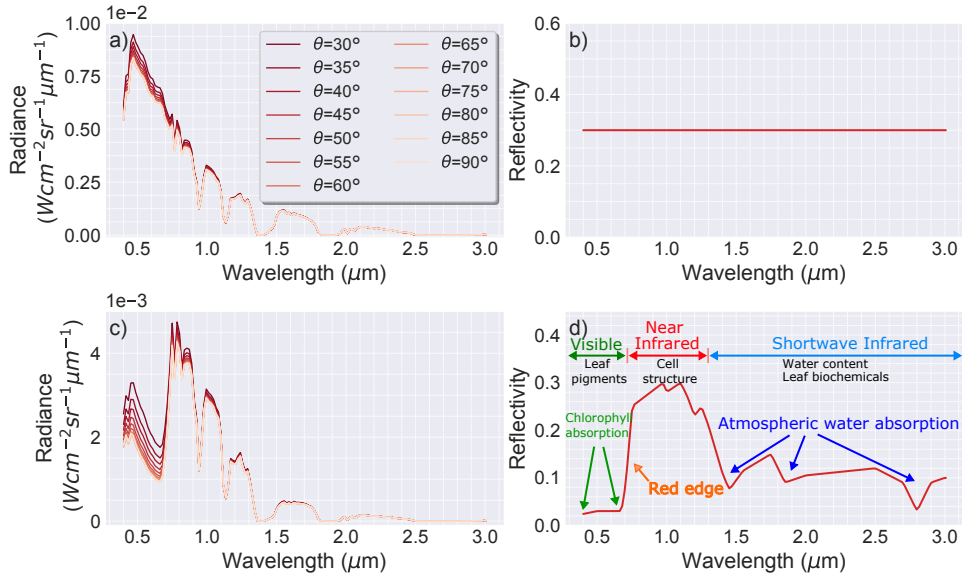


Figure 2: The at-sensor spectra for a Lambertian gray body with a 0.3 constant reflectivity and an evergreen needle forest received at 2:00pm on January 10th. a) the total radiance for the gray body, b) the gray body's reflectivity spectra, c) the total radiance for an evergreen needle forest, d) the reflectivity of the evergreen needle forest.

175 contributions of the elevation angle in sensor-received total radiance are only observed in the visible and near-infrared
 176 bands. The elevation angle's influence vanishes as the wavelength increases.

177 To study the elevation angle's influence on the total radiance for different materials, the simulated total radiances
 178 under 13 elevation angles for an evergreen needle forest collected at the same time and date (2:00pm on January 10th)
 179 are shown in Figure 2c, with the coherent target's reflectivity shown in Figure 2d. Compared to the total radiance
 180 spectrum for the gray body, the elevation angle caused distinction of the total radiance for the vegetation target
 181 manifests strongly in the visible spectrum, which is likely caused by the unique strong chlorophyll absorption. In
 182 addition, we find that, as the elevation angle increasing (i.e., shorter transmitting path in atmosphere), there is a
 183 decrease in the total radiance received at the sensor. This is due to the decrease in solar scattering with increasing
 184 elevation angle, as will be confirmed later in Figure 3.

185 During the *MODTRAN* simulation, the six solar and atmospheric spectra are also preserved, which after prepro-
 186 cessing are considered as the ground-truth labeled data for the neural network. These six RTE radiative components
 187 for the evergreen needle forest are plotted in Figure 3, and the corresponding total radiance is shown in Figure 2c.
 188 Figure 3a shows that atmospheric transmission is directly proportional to the elevation angle. There are three atmo-
 189 spheric complete absorption bands centered at 1.38 μm , 1.88 μm , and 2.7 μm , respectively. As expected, Figure 3b
 190 shows that the elevation angle has no impact on the downwelling radiance. Figure 3c and 3d show that atmosphere
 191 self-emitted thermal and scattering radiances are negligible in the visible and near-infrared regions. On the contrary,

192 the solar scattering radiances are only observed in the visible and near-infrared regions shown in Figure 3e and 3f.
 193 Furthermore, the atmospheric emitted and scattering as well as the solar single and multiple scattering all decrease
 194 with increasing elevation angle (Figure 3c,d,e,f), consistent with the total radiance shown in Figure 2c.

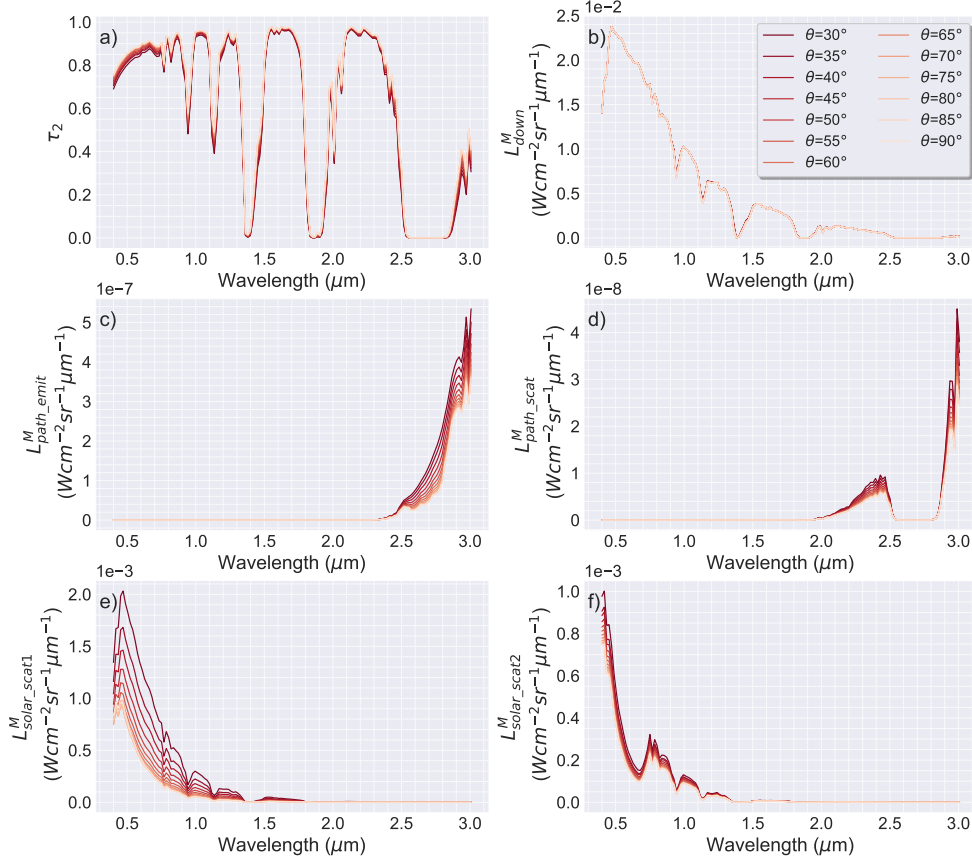


Figure 3: Six solar and atmospheric radiances for an evergreen needle forest simulated at 2:00pm on January 10th. a) atmospheric transmission $\tau_2(\lambda)$, b) downwelling radiance L_{down}^M , c) atmospheric self-emitted thermal radiance $L_{path_emit}^M$, d) atmospheric scattering radiance $L_{path_scat}^M$, e) solar single scattering radiance $L_{solar_scat1}^M$, f) solar multiple scattering radiance $L_{solar_scat2}^M$.

195 3.2. Input and labeled data preparation

196 Before feeding the simulated total radiance maps into the designed network with architecture shown in Figure 1,
 197 we observe that the radiance dramatically decreases as the spectral band moves from the visible to the shortwave
 198 infrared region. For such a skewed input a large number of convolutional layers would be required to balance the
 199 contribution of different spectral bands and to reduce the risk of losing significant features in the shortwave infrared
 200 band due to the weight sharing in the CNN. Increasing the number of convolutional layers, however, not only incurs a
 201 heavy computational burden, but significantly increases the degrees of the freedom between the input and the output
 202 of the network making it harder to train.

203 An alternative approach is preprocessing the data to reduce the degrees of freedom of the network’s input and
 204 output, while keeping the simplicity of the network. To do so, we calculated the Sun’s blackbody spectrum at 5778K
 205 using Planck’s Law (Equation (2)) as shown in Figure 4. To preprocessing the total radiance, we divide the total
 206 radiance by the blackbody spectrum for every spectral band then multiply by a constant value of 10^5 to re-scale the
 207 value into the range of $[0, 1]$. This preprocessed data will subsequently be referred to as the normalized total radiance
 208 map or the input of the network. The total radiance maps and their normalization for a gray body with a constant
 209 reflectivity of 0.3 and an evergreen needle forest are shown in Figure 5.

210 The maximum spectral values along every wavelength band and observation time are computed for each solar and
 211 atmospheric radiance to prepare the labeled data for the network’s training stage. Each component is then divided
 212 by its corresponding maximum spectrum along each wavelength band and observation time. The final outputs of the
 213 network are six normalized solar and atmospheric radiance maps, which can be converted into the correct magnitude
 214 by multiplying by their corresponding maximum spectra at each wavelength and observation time. The matrix view
 215 of these six RTE components and their normalizations are shown in Figure 6.

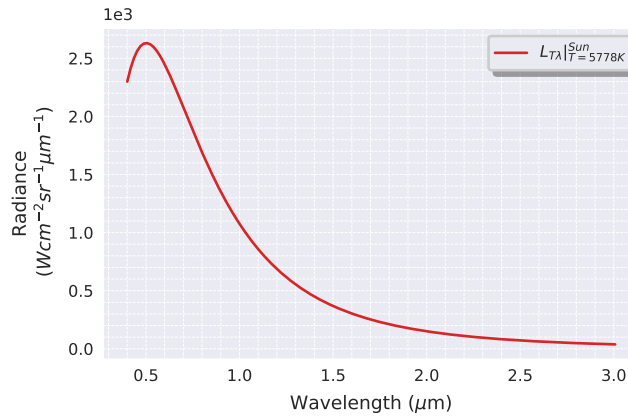


Figure 4: The spectrum of a blackbody at Sun’s temperature 5778K.

216 3.3. Training and validation

217 The total radiance for 48 materials are simulated, which includes 42 *MODTRAN* builtin materials and six Lamber-
 218 tian gray bodies with different constant reflectivities. We chose hyperspectral simulations for 15 builtin vegetations
 219 and six gray bodies with varying constant reflectivities and randomly selected at different collecting time for each
 220 material as training (80%) and validation (20%) examples. The data simulated using the remaining 27 materials are
 221 treated as the test dataset. Thus, we have 49056 training examples in total, 12264 validation examples, and 78,840
 222 examples in the test dataset. During the training stage, an ℓ_2 -norm objective function is applied to measure the dis-

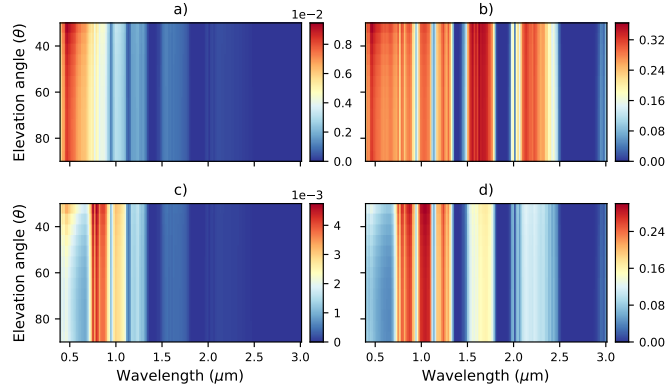


Figure 5: Matrix view of the total radiance and its normalization received at 2:00pm on January 10th. a) the total radiance for a Lambertian gray body with a 0.3 constant reflectivity. b) the normalized total radiance for the Lambertian gray body, c) the total radiance for an evergreen needle forest, d) the normalized total radiance for the evergreen needle forest.

223 discrepancy between the output of the network and its corresponding normalized ground-truth. In addition, the adaptive
 224 momentum estimation, or Adam, algorithm (Kingma and Ba, 2014) with an initial learning rate 5×10^{-4} is adopted
 225 to optimize all trainable parameters in the network by minimizing the objective function. The training process is
 226 implemented with 10 Nvidia Tesla P100-PCIe GPUs.

227 After training for 300 epochs, the network is evaluated using the simulated data for the 27 withheld materials
 228 from the test dataset. We applied the trained network to the evergreen needle forest extracted from the test dataset.
 229 The predicted results of six ground-truth solar and atmospheric radiances simulated at 2:00pm on January 10th are
 230 plotted in Figure 7. From left to right in columns, they are six ground-truth atmospheric and solar radiances, predicted
 231 results using the proposed network, and the residuals of the first two columns, respectively. The results show that
 232 the residuals are at least one order of magnitude smaller than their corresponded ground-truth components. It is fair
 233 to say that the proposed network has the capacity of accurately estimating atmospheric characteristics from the at-
 234 sensor total radiance with the two temporal factors. The instantaneous evaluation of the neural network provides an
 235 opportunity for real time atmospheric correction and target detection.

236 With the predicted six components shown in Figure 7, the reflectivity of the evergreen needle forest is retrieved
 237 using Equation (5), which is conceived as an additional indicator to evaluate the performance of the proposed network.
 238 Figure 8 shows the comparison of the actual reflectivity spectra of the evergreen needle forest and our predicted
 239 results. The three atmospheric complete absorption bands approximately centered at 1.38 μm , 1.88 μm , and 2.7 μm ,
 240 respectively, are colored in white in Figure 8. In these three atmospheric absorption bands, the target's reflectivity is
 241 not retrieved as expected. Other than that, the orange dots represents the mean of the 13 predicted reflectivity spectra
 242 using various elevation angles, while the green error bar delineates the standard deviation of the 13 predictions. It

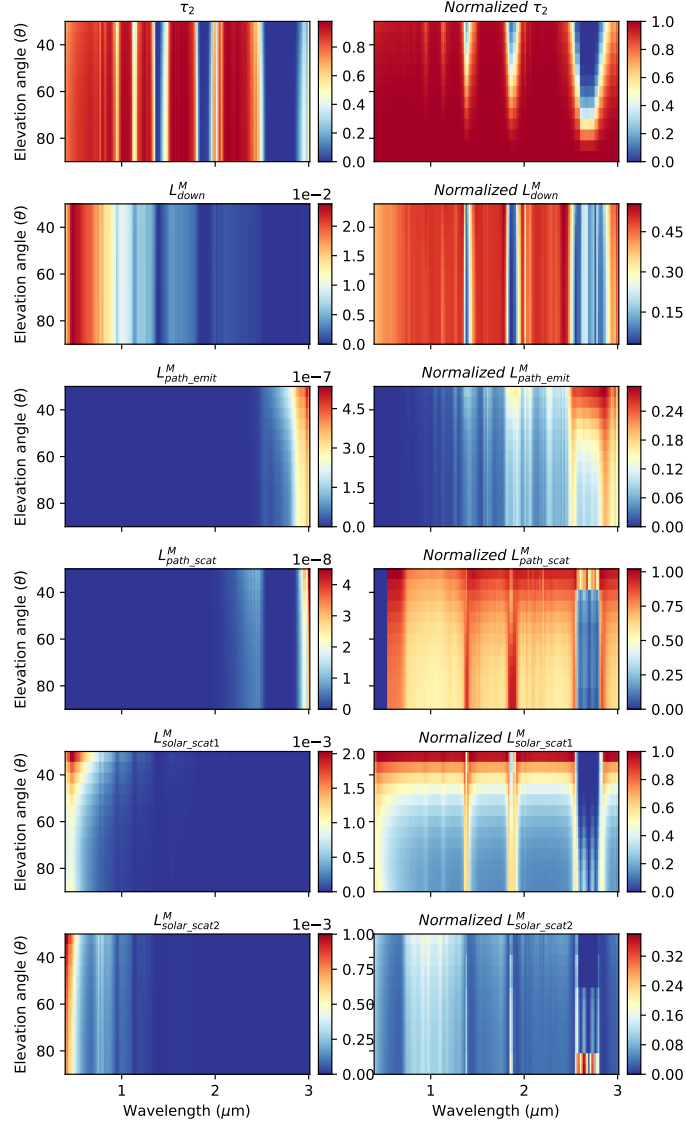


Figure 6: Matrix view of six solar and atmospheric radiative components for the evergreen needle forest and their normalizations. In the first column, from top to bottom, they are $\tau_2(\lambda)$, L_{down}^M , $L_{path_emit}^M$, $L_{path_scat}^M$, $L_{solar_scat1}^M$, $L_{solar_scat2}^M$, respectively, and their normalizations are aligned in the second column.

243 shows that the predicted reflectivity is well matched with the ground-truth (indicated in black dashed line). In addition,
 244 the small standard deviation demonstrates the high stability of the proposed network under multi-scan geometry
 245 setting.

246 4. Discussion

247 Our analysis shows that the proposed time-dependent network is capable of accurately providing atmospheric
 248 characteristics and target's spectral signature from multi-scan hyperspectral data with two temporal factors; its results

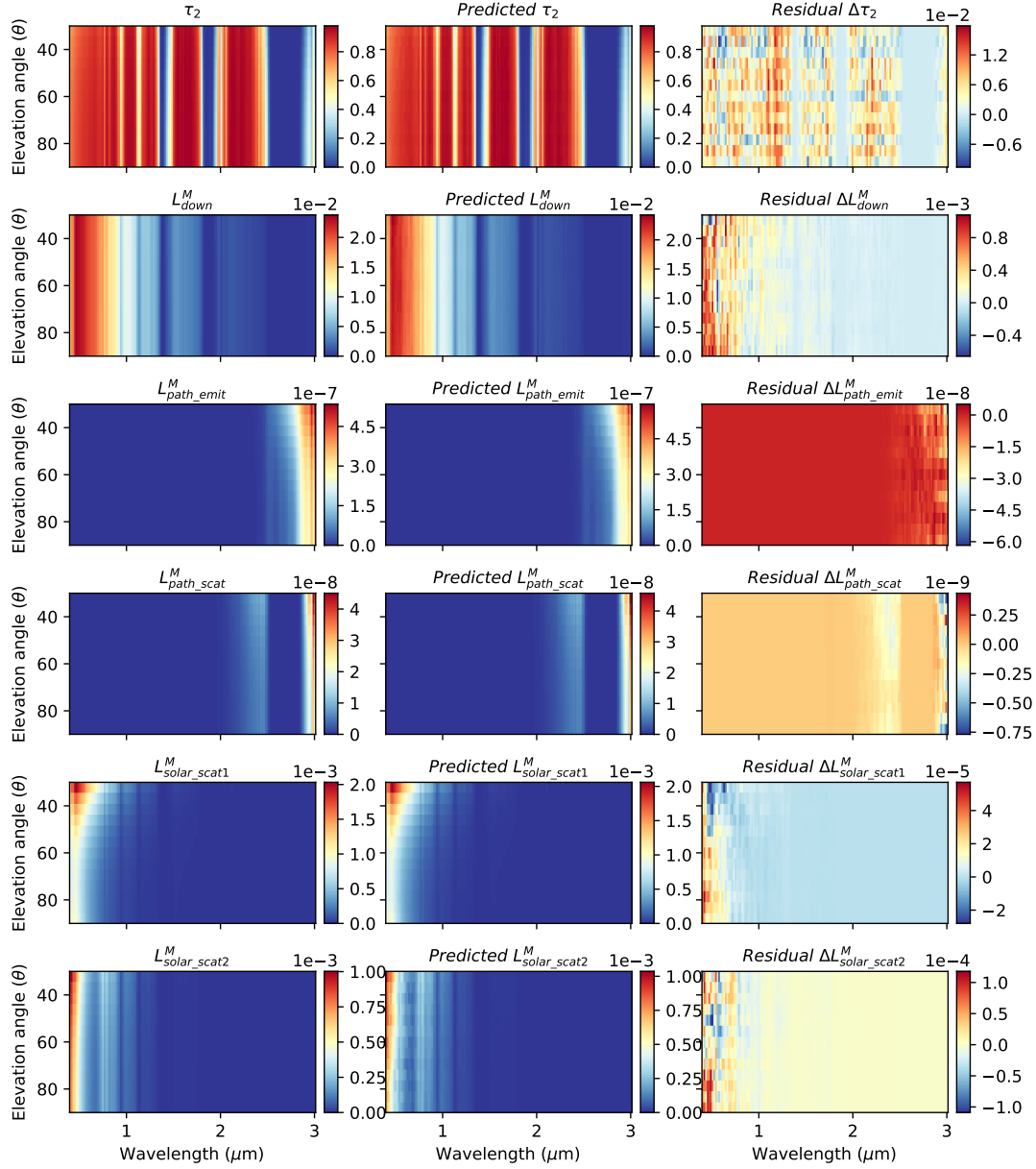


Figure 7: The comparison of six solar and atmospheric radiances of an evergreen needle forest collected at 2:00pm on January 10th and our predicted results. From left to right in columns, they are the ground truth of six RTE components, our predicted results, and the residuals, respectively.

249 can be used to obtain a precise prediction of the target's reflectivity, which can be applied to real time atmospheric
 250 correction and target detection by comparing the predicted reflectivity with spectral signatures in database library.
 251 However, more studies need to be made to understand the time dependency of the network. To study the contributions
 252 of two temporal factors in the final prediction, two experiments are carried out: 1) feeding the well trained network
 253 with a wrong *day* and a correct *time* factors for a specific target; 2) feeding the well trained network with a correct

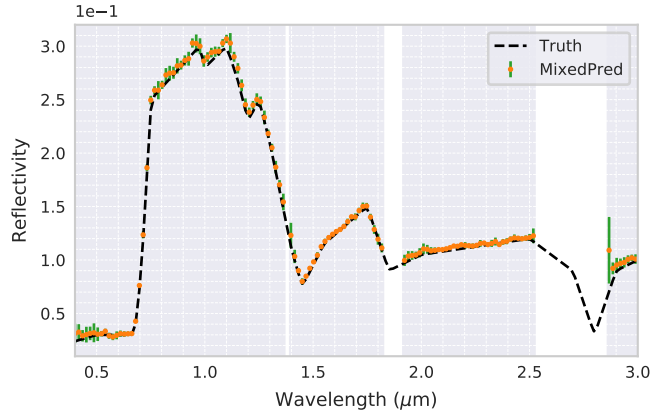


Figure 8: The comparison between the actual reflectivity (black dashed line) of the evergreen needle forest and our predicted results using the total radiance collected at 2:00pm on January 10th. The orange dots represent the mean of 13 predicted reflectivities using different elevation angles, and the green error bar is the standard deviation of 13 predictions.

254 *day* and a wrong *time* factors for a specific target.

255 In the first experiment, we test the impact of the *day* factor on the network prediction. The hyperspectral at-sensor
 256 radiance map collected at 2:00pm on the 178th day of the year (June 27th) is chosen as an example. The collected
 257 total radiance map and a correct *time* factor (2:00pm) are repeatedly fed into the well trained network but with a
 258 *day* factor selected starting from 1 to 365. After every evaluation, the mean absolute residuals between the predicted
 259 results and six normalized ground-truth components are calculated, and the result is plotted in Figure 9, where the
 260 orange line represents the mean absolute error (MAE) of residuals using 13 elevation angles with light blue colored
 261 area denoting the standard deviation of residuals with different elevation angles. In Figure 9, we observe that the mean
 262 error of the prediction reaches a minimum when the correct *day* factor, i.e., the 178th day of the year, is fed into the
 263 network. However, as the input *day* factor moves away from the correct date, the predicted error increases, as well as
 264 its standard deviation. Furthermore, an approximately symmetric about the 178th day is shown in Figure 9, which can
 265 be explained by the approximate symmetrical atmospheric characteristics about summer. Therefore, it is reasonable
 266 to conclude that the proposed network has the ability of adapting to a diurnal changing atmospheric environment.

267 In the second experiment, we select eight total radiance maps for the evergreen needle forest collected at different
 268 times on the 178th day of the year as input of the network, respectively. The correct *day* factor is imported with a
 269 randomly selected *time* value, from 6:00am to 8:00pm with a two hour interval. Similarly to the first experiment,
 270 after each evaluation, the mean absolute errors of the predicted results and six normalized ground-truth components
 271 are calculated along wavelength and elevation angle axes. The confusion matrix of MAE is displayed in Figure 10.
 272 As expected, the smallest predicted errors at each time are located on the main diagonal, and the largest errors are
 273 appeared at the farthest way of the correct time. The prediction error also increases as the coordinate moves away

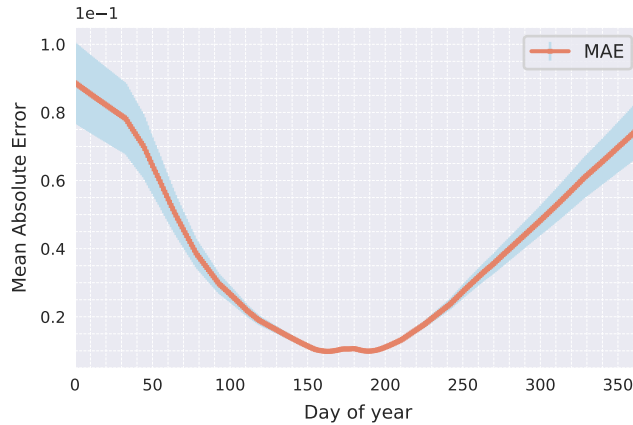


Figure 9: The error analysis of the *day* temporal factor by feeding a random *day* value into the network with the data collected at 2:00pm on the 178th day of the year.

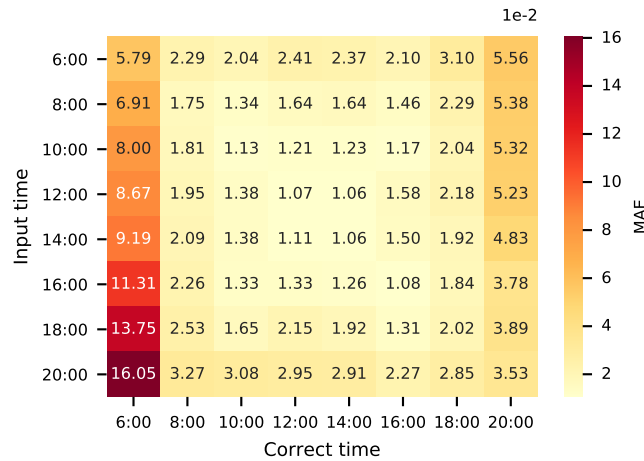


Figure 10: The error analysis of the *time* temporal factor by feeding a random *time* value into the network with data collected from 6:00 to 20:00 with two hour intervals on the 178th day of the year.

274 from the main diagonal. These results suggest that our network is capable of accurately predicting atmospheric
 275 characteristics with an diurnally-and-hourly varying atmospheric environments. In addition, we observe that the
 276 MAE increases as the collection time moves away from noon along the main diagonal. This is possibly caused by
 277 the weak radiation at sunrise times which leads to the relative higher percentage errors comparing to data collected
 278 at noon. Though our experiment is conducted at the Pennsylvania State University, University Park, PA, USA, it is
 279 straightforward to be generalized to diurnally collected hyperspectral data at other locations.

280 To understand the importance of the ‘mixed’ training dataset, the proposed network is also trained separately with
 281 15 vegetations and six gray bodies with varying constant reflectivities. These three networks are then applied to the
 282 test dataset including 27 materials separately. We extracted the predicted results for 24 materials at 2:00pm on January

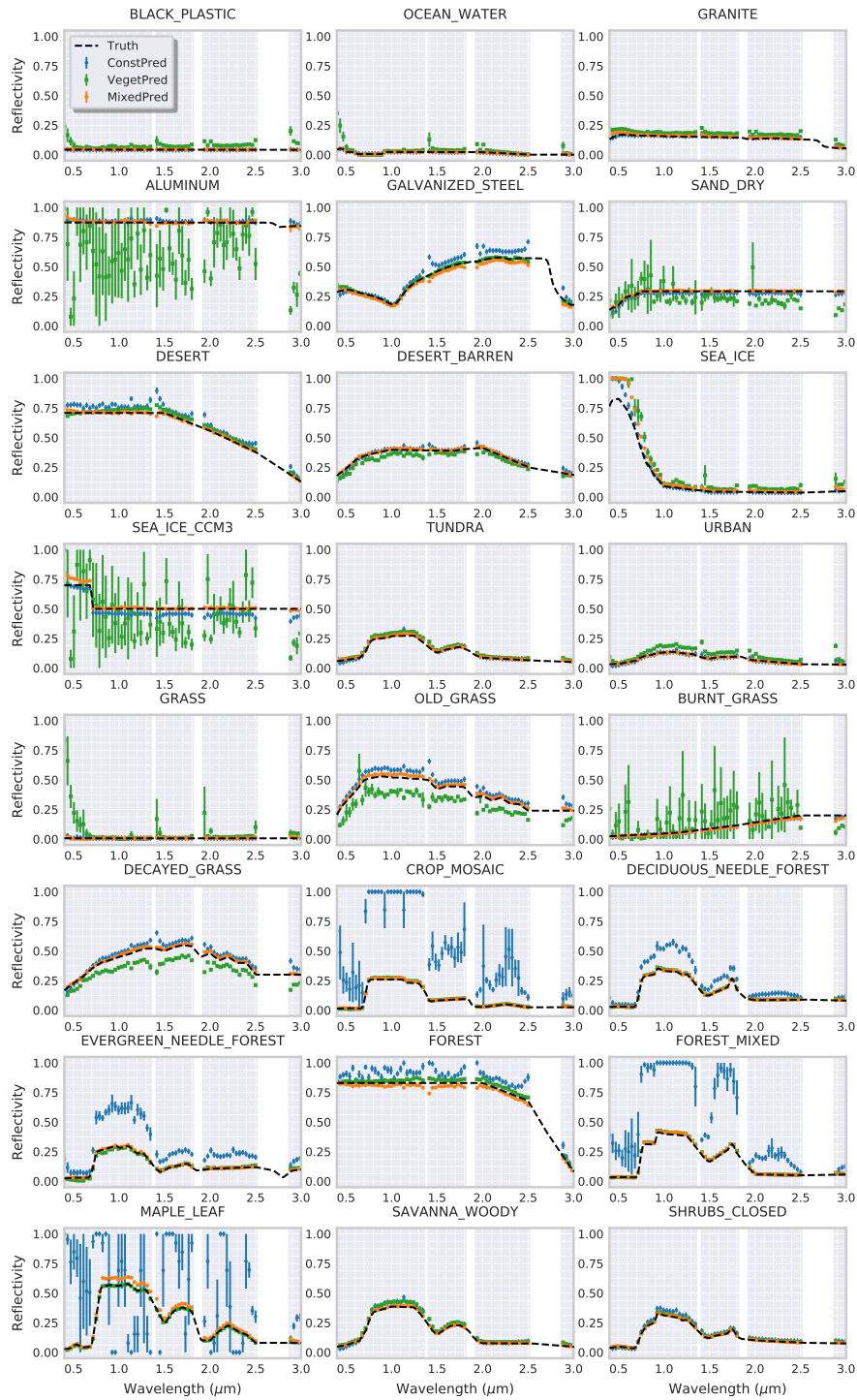


Figure 11: The comparison of the ground-truth reflectivities and predicted results using networks trained by three different datasets, with dashed-black line showing the ground-truth reflectivity spectra of the targets, blue showing predictions using network trained with six gray bodies, green showing predictions using network trained with 15 vegetations, orange showing predictions using network trained with a mixture of both. The dot (vertical line) represents the mean (standard deviation) of 13 predictions using different elevation angles.

283 10^{th} from the test dataset, and calculated the estimated reflectivities. The comparisons of the retrieved reflectivities
284 and their ground-truths are shown in Figure 11. The dot represents the mean of 13 predicted reflectivity spectra with
285 variant elevation angles and the vertical line is corresponding to the standard deviation of 13 predicted results. The
286 dot/line color represents the estimated results from the network used, with blue showing the network trained with
287 six gray bodies only; green showing the network trained with 15 vegetations only, and orange showing the network
288 trained with a mixture of vegetation and six gray bodies.

289 The comparison shows that the network trained with six gray bodies is capable of retrieving the spectral signatures
290 of the target that does not dramatically changes. However, it fails to predict most of vegetations' reflectivity spectra
291 because of their complex spectral signatures. On the contrary, the network trained with 15 vegetations is able to
292 precisely predict the spectral signatures of vegetations and most of other materials. However, its prediction for the
293 materials with smoothly varying spectra, for instance, aluminum, sea ice, and burnt grass, has a very high standard
294 deviation which implies a lower stability of the network's performance for these materials. In other words, for those
295 with smooth spectral signatures, the prediction accuracy using the network trained with 15 vegetations is highly
296 dependent to the elevation angle. The network trained with the 'mixed' training dataset outperforms both of these
297 two separately trained networks on both vegetation and other materials with a negligible standard deviation. Thus, a
298 mixture of vegetations and six gray bodies with different constant reflectivities is essential to improve and stabilize
299 the performance of the network on a wide variety of targets.

300 Though the accuracy and capacity of our designed network is promising, one important practical consideration
301 is that it only accepts a multi-scan hyperspectral data with no missing elevation angle (30° -to- 90°) or wavelength
302 band ($0.4\mu\text{m}$ -to- $3.0\mu\text{m}$). The standard deviation of the predicted error using different elevation angles is marginal,
303 which is a positive indicator that the network may be stable for applications using data with missing elevation angles.
304 The detailed investigation and compensation of applying the network with incomplete data is an ongoing research.
305 Furthermore, settled geometry settings are assumed through our entire experiments and analysis, such as the unitary
306 spatial resolution of the airborne sensor and the fixed observation range and azimuth. However, the application on the
307 hyperspectral remote sensing data collected with different geometry settings can be implemented by finetuning our
308 trained network based on a strategy of transfer learning.

309 **5. Conclusions**

310 The multi-scan hyperspectral remote sensing data collected by the new generations of agile sensors contains
311 multiple spectral and temporal information within the full spatial dimensionality. This provides an opportunity for
312 real time atmospheric correction and target detection by taking advantages of deep learning methods. In this paper,

313 we designed a time-dependent neural network to estimate atmospheric characteristics and solar scattering radiances
314 at a given time and day from the at-sensor total radiance. The results of our analysis show that the proposed network
315 is able to accurately provide atmospheric characteristics at given times and precisely retrieve the reflectivity spectra
316 of various materials, including vegetation and ocean. In addition, the retrieved reflectivity spectra using multi-scan
317 hyperspectral data provide an approximation of the estimated error from perspectives of varying elevation angles.
318 This approach is fully data-driven and well-suited for real time applications.

319 To investigate the time dependency of the proposed network, we introduce two experiments by feeding the net-
320 work with incorrect temporal factors separately. The first experiment shows that the predicted error increases as the
321 day factor moves away from the correct date. The prediction error has an approximate symmetric behavior which is
322 consistent with the approximate symmetry of atmospheric characteristics about summer. With the first experiment, we
323 may conclude that our network is able to precisely providing atmospheric characteristics and target detection under
324 a daily changing environment. In the second experiment, our analysis shows that the predicted error significantly in-
325 creases and its minimum located at the main diagonal corresponding to the correct time input. The second experiment
326 confirms that the proposed network has the ability of accommodating a hourly varying atmospheric condition and
327 providing precise predictions. In addition, the sensitivity tests have shown that in order to make accurate predictions
328 for a wide variety of targets, it is critical to train the network with a mixture of targets including both vegetations
329 and gray bodies with varying constant reflectivities. Though assumptions have been made on the geometry settings,
330 real-time applications of such a time-dependent network on hyperspectral data from different collecting systems are
331 possibly implemented by finetuning the network with a transfer learning strategy. In our future work, applying the
332 network with incomplete data and real data will be discussed and analyzed.

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