Daytime Cloudless Sky Radiance Quantification with Ground-Based Aerosol and Meteorological Observations in the Shortwave Infrared

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ABSTRACT

Daytime spectral sky radiance, or sky brightness, is deceptively complex to predict accurately. The Laser Environmental Effects Definition and Reference (LEEDR) first-principles atmospheric model propagates the spectral radiance of the sun to a sensor by modeling the scattering, absorption, and transmission of the radiated light through representative atmospheric layers. For this application, LEEDR was used to ingest numerical weather prediction (NWP) models, and scale the boundary layer and incorporate aerosol loading with ground-based measurements. This study compares LEEDR-derived spectral sky radiance simulations that include measured climatological, measured meteorological, and aerosol loading data to direct sky radiance measurements. Direct measurements of the daytime sky are accomplished with a 1-m-aperture telescope and simultaneous I-band and J-band camera observations (~ 0.8 and $\sim 1.2 \mu\text{m}$, respectively). LEEDR models of the daytime sky are compared to I-band and J-band radiances at multiple azimuths, elevations, and observation times. Residual error analysis is used to determine the accuracy of models including numerical weather prediction data, historical climatology, scaled aerosol loading via in situ particle count measurements, and meteorological updates. Key findings motivate the inclusion of real-time particle count measurements into future daytime sky radiance models for increased scattering accuracy via realistic atmospheric aerosol loading.

1. Introduction

Accurate daytime sky radiance modeling in the near-infrared (NIR) and shortwave-infrared (SWIR) spectral bands is critical for emerging technologies such as daytime satellite custody and tracking, and quantum-key distribution where noisy backgrounds affect detectable signals and limit anticipated utility. The spectral radiance of the daytime sky is dependent on the time of day, season, atmospheric constituents, and local conditions. These conditions are in a state of constant fluctuation and may cause the spectral radiance of the sky to vary greatly from day to day. The direct solar radiation coming to Earth from the sun is attenuated by the atmospheric absorption and scattering. Sunlight interacts with atmospheric particles and molecules through single and multiple scattering processes resulting in some amount of spectral radiance coming out of all parts of

the sky whether cloudy or clear (Zibordi and Voss 1989). This detectable sky brightness can be separated into diffuse and direct components, which are primarily a function of two mechanisms: scattered radiation from the sun and emission by atmospheric constituents (Bell et al. 1960). However, for visible through SWIR wavelengths, scattering is critical and will be the primary loss mechanism considered in our analysis. Molecular scattering effects are directly proportional to λ^{-4} with the net result that blue light is scattered more than red light, and the sky is increasingly darker in the infrared. Quantifying the anticipated spectral radiance in the I and J bands (~ 0.8 and $\sim 1.2 \mu\text{m}$, respectively) is the focus of this study. While not exhaustive, quantification of a small subset of data will indicate model trends and reinforce the importance of aerosol content scaling to more accurately characterize the aerosol profile effects on sky radiance predictions. This research relies on the Laser Environmental Effects Definition and Reference (LEEDR) (Fiorino et al. 2014) model to propagate scattered light from the sun through the atmosphere and to the sensor.

LEEDR is an atmospheric characterization and radiative transfer code that calculates line-by-line (pointwise

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solutions for specific wavelengths) and spectral band solutions by creating “correlated, physically realizable profiles of meteorological and environmental effects (e.g. gaseous and particle extinction, optical turbulence, and cloud-free line of sight) data” (Courtney 2015). LEEDR was used to ingest volumetric numerical weather prediction models and scale the boundary layer and aerosol loading with ground-based measurements. LEEDR also has the ability to generate realistic atmospheric profiles from probabilistic climatology or observations and forecasts from numerical weather prediction models and atmospheric attenuation models. LEEDR makes radiative transfer calculations based on inputs that closely mirror the atmospheric conditions on a given date, time, and location thus provide more realistic approximation of the spectral sky radiance and atmospheric transmission than what could be obtained with inputs based solely on atmospheres (Wurst et al. 2017). Accurate results are possible by capturing the dominant radiometric transfer physics and atmospheric attenuation of each layer. As part of LEEDR’s verification and validation Burley et al. (2017) made comparisons of LEEDR’s calculated sky radiances against measurements in Germany in 2012 (Tohsing et al. 2014).

When sunlight propagates through a scattering medium (such as the atmosphere) it can be absorbed as well as scattered away from the direction of propagation (Eismann 2012). Both absorption and scattering are loss mechanisms. Using Beer’s law we can describe the irradiance transmission spectrum τ for a given material thickness z in Eq. (1):

$$\tau_\lambda = \exp(-\beta_e z). \quad (1)$$

For a homogeneous layer of the atmosphere, the combined effect of the scattering and absorption is characterized by the extinction coefficient β_e in Eq. (2) where, β_a is the absorption coefficient and β_s is the scattering coefficient, all with dimensions of inverse length:

$$\beta_e = \beta_a + \beta_s. \quad (2)$$

The absorption coefficient β_a is defined by the complex index of refraction κ for the medium at each wavelength λ ; thus,

$$\beta_a = \frac{4\pi\kappa}{\lambda}. \quad (3)$$

Mie scattering expressions can be greatly simplified under the assumption that the size of the spherical scatterer is significantly smaller than the wavelength of incoming radiation as is the case for visible wavelengths and longer (Eismann 2012). This is known as the Rayleigh

scattering regime and is governed by the following expression for the scattering coefficient β_s :

$$\beta_s = \frac{64M\pi^5 a^6}{3\lambda^4} \left| \frac{n^2 - 1}{n^2 + 2} \right|^2, \quad (4)$$

where a is the radius of the spherical scatterer, n is the index of refraction in the medium, and M are the number of scatterers per volume.

However, Rayleigh scattering can reasonably be assumed only for molecular scattering effects in the I and J bands. Aerosol distributions include sizes that require a full Mie calculation for each aerosol type and size distribution. In this study, LEEDR is used to determine the aerosol types, aerosol optical properties, and scaling of the aerosol distributions based on particle count measurements (Fiorino et al. 2014). Thus, modeling sky radiance for a particular ground site requires a comprehensive understanding of both the radiative transfer and the dynamic atmospheric conditions at a given observation time, date, and location.

2. Method

With the goal of determining error bounds of a baseline atmospheric model in predicting daytime sky radiance the methodology is as follows. Direct measurements of I- and J-band sky radiance are compared to atmospheric models using numerically predicted or locally averaged climatological profiles. In addition, aerosol profiles with altitude are scaled via in situ, real-time surface particle count measurements and ground-based meteorological measurements of temperature, pressure, dewpoint, and relative humidity are then used to scale the boundary layer. All experimental observations were taken in Albuquerque, New Mexico, on 20 March 2019.

a. LEEDR model generation

Previous research demonstrated that the most accurate sky radiance simulations are generated with various combinations of numerical weather prediction (NWP) models, and Extreme and Percentile Environmental Reference Tables (ExPERT) data, measured particle and meteorological observational inputs (Wolfmeyer et al. 2019). Thus, a subset of LEEDR radiance models were simulated as shown in Table 1.

1) NUMERICAL WEATHER PREDICTION

NWP models rely on mathematical representations of Earth’s atmosphere and oceans to forecast future weather based on current conditions. One such model

TABLE 1. Atmospheric models and input profiles.

Model designator	Atmospheric profile	Aerosol profile	Ground meteorological
A ^a	NWP ^b	GADS default	NWP ^b
B	NWP ^b	Scaled	NWP ^b
C	NWP ^b	GADS default	Measured
D	NWP ^b	Scaled	Measured
E ^a	ExPERT	GADS default	ExPERT
F	ExPERT	Scaled	Measured

^a Baseline model.^b GFS data.

is the Global Forecast System (GFS) produced by the National Centers for Environmental Prediction (NCEP). Satellite and ground-based observations from global sources are aggregated and compiled to generate initial conditions for the global forecasts. The global data assimilation and forecasts are made four times daily at 0000, 0600, 1200 and 1800 UTC. As more computing resources have become available, the GFS has also evolved to an operational horizontal resolution of 13 km at the equator. The atmosphere is divided into 64 vertical pressure layers with the top layer centered at 0.27 hPa (approximately 55 km) (National Weather Service 2016). The GFS NWP dataset is published for university, federal agencies and organizations via the NOAA Operational Model Archive and Distribution System (NOMADS) web interface (NCEP Central Operations 2019). LEEDR models utilizing NWP inputs will incorporate data from the most recent forecast to compare to the measured data for a given time for simplicity. Future models may interpolate between NWP forecasts bounding the measurement time for even higher fidelity.

2) EXPERT DATABASE

ExPERT is a 30-yr climatological database that provides specific regional surface and upper-air data to characterize correlated molecular absorption, aerosol absorption, and scattering by percentile for 573 sites throughout the world (Fiorino et al. 2014). The ExPERT database is preloaded into LEEDR and serves as the nominal baseline atmospheric conditions with allowable variances for season (either summer or winter) and time of day in 3-h time increments from 0000 to 2359 LT. All ExPERT sites have Global Aerosol Dataset (GADS) (Koepke et al. 1997) data associated with the site. If ExPERT data are not available for a specific location, GADS may be queried for a particular longitude and latitude. GADS provides aerosol constituent number densities and optical properties at 61 wavelengths from 250 nm to 40 μm on a $5^\circ \times 5^\circ$ grid worldwide (Fiorino et al. 2008).

FIG. 1. Summer and winter typical (ExPERT + GADS) J-band scattering, absorption, and extinction profiles by altitude for Albuquerque at 1.2 μm from 1500 to 1800 LT.

3) AEROSOL SCALING

LEEDR calculates an aerosol size distribution for each user-specified scenario, location, altitude, season, and relative humidity. Mie scattering is assumed for aerosol scattering and absorption calculations. Extinction, scattering, and absorption coefficients are calculated by assuming a dry environment and then varied with increasing humidity (Fiorino et al. 2014). Figure 1 shows the typical (ExPERT + GADS) J-band scattering, absorption, and extinction profiles by altitude and season for Albuquerque at 1.2 μm from 1500 to 1800 LT.

Within LEEDR, wavelength specific complex indices of refraction for GADS aerosol species are interpolated from preloaded datasets (Fiorino et al. 2014). However, the GADS aerosol loading may be adjusted to more closely match current conditions by scaling the entire profile based on surface-level particle count measurements (Wolfmeyer et al. 2019). The particle count data taken with the moderated aerosol growth with the water-based condensation particle counter (MAGIC-CPC) from aerosol dynamics during the observation window are shown in Fig. 2. These data were used to scale the default aerosol GADS number concentration to simulate more realistic absorption and scattering effects for that date and time. For Albuquerque, winter surface-level GADS aerosol default concentrations are 6519 parts per cubic centimeter (part cm^{-3}) and 7460 part cm^{-3} for summer. The measured particle counts below 1000 part cm^{-3} in Fig. 2 are likely due to the isolated showers and virga (precipitation not reaching the ground) that crossed through the area late on 19 March and early on 20 March 2019. Precipitation is very effective at scavenging out aerosol particles,

FIG. 2. CPC data (sizes: 5 nm to 2.5 μm) for Albuquerque on 20 Mar 2019 during the observation window. Winter surface-level GADS default aerosol concentrations are 6519 and 7460 part cm^{-3} for summer. Lower-than-average counts are likely due to precipitation, which is very effective at scavenging out aerosol particles.

which would account for lower than average measured particle counts at the ground level during the measurement.

4) METEOROLOGICAL OBSERVATIONS

Surface observations of temperature, pressure, dew point, and relative humidity may also be included in a given model to create a more realistic atmospheric profile in the boundary layer (Fiorino et al. 2014). The surface weather data during the observation window in this study are shown in Fig. 3.

b. Photometric band overview and filter selection

Electrooptical (EO) sensors can be divided into categories relating to the detection wavelengths of the sensor. Visible (Vis), NIR, and SWIR sensors detect reflected radiation from the sun. Vis–SWIR sensors systems are passive, low-cost, and relatively high-resolution systems. Systems of low-cost Vis sensors are currently contributing to useful nighttime satellite detection and astronomy (Murison and Monet 2015). However, as the daytime sky is particularly bright in the visible band, these sensors are only thought to be useful during the hours of local darkness for the ground site. This research seeks to validate the predictions of NIR and SWIR models of diminished daytime sky radiance to inform future studies into the utility of low-cost SWIR sensors as a partial solution for daylight imaging.

Since catalog stars were used as calibration objects with filter-specific-based fluxes (Wenger et al. 2000), it was necessary to filter the incoming NIR and SWIR radiance for direct comparison. Additionally, since real-time simultaneous measurements of both the daytime

FIG. 3. Meteorological data for Albuquerque on 20 Mar 2019 during the observational window.

sky and calibration objects were desired, NIR and SWIR bandpass filters were required to remain fixed within the optical path. To accommodate these constraints, I-band (centered at 0.79 μm) and J-band (centered at 1.2 μm) filters were selected as representative NIR and SWIR band filters, respectively. Details regarding the I- and J-band filters are shown in Table 2.

c. Measurement collection

Daytime sky images were obtained via a 1-m aperture diameter, Ritchey–Chretien telescope and simultaneous imaging via a 1- μm longwave pass dichroic filter placed in the optical path. With this filter in the optical path, simultaneous measurements of both I- and J-band (~ 0.8 and ~ 1.2 μm , respectively) sky radiances were possible. Specifically, two cameras were used: 1) Q-Imaging Rolera E-MC² visible-band camera with a Johnson–Cousins I-band filter centered at 0.79 and 0.18 μm bandwidth; 2) Xenics Xeva-1.7–320 infrared camera with indium–gallium–arsenide (InGaAs) detector filtered to J band at 1.2- and 0.12- μm bandwidth. A large telescope dome with oculus functioned as a light baffle to limit the interference of extraneous light for direct measurements of the daytime sky.

d. Measurement calibration

Camera calibration observations were performed at night by comparing the received instrument magnitude

TABLE 2. Filter selection specifications.

Filter	Band	Wavelength center (μm)	Bandwidth (μm)
I	NIR	0.79	0.18
J	SWIR	1.2	0.12

TABLE 3. Stellar calibration targets (Wenger et al. 2000).

Star name	Spectral type	Temp (K)	I flux (magnitude)	J flux (magnitude)	Observation azimuth (°)	Observation elevation (°)	Air mass
HIP 104214	K5V	4526	3.54	3.12	56.61	21.12	2.775
HIP 69483	A7IV	6699	~4.3	4.21	346.45	72.63	1.048
HIP 74666	G8IIIFe-1 B	4847	2.25	1.8	93.24	77.08	1.026
HIP 77052	G2.5V B	5683	5.1	4.59	153.69	54.68	1.226
HIP 77052	G2.5V B	5683	5.1	4.59	155.05	54.98	1.221
HIP 96895	G1.5Vb B	5830	5.17	5.091	49.69	38.84	1.595
HIP 104217	K7V B	4077	3.55	3.55	56.61	21.12	2.775
HIP 69481	F2V C	6699	~6.25	5.86	346.45	72.63	1.048

in each band to the catalogue magnitude shown in Table 3. The calibration measurements were performed at night to 1) ensure that clear images were obtained of dim astronomical targets and 2) minimize the ambient background photon noise (shot noise) arriving to the detector. With significantly less background noise, the dark sky background enabled a more direct comparison between the anticipated catalog flux of the star and the measured photometric intensity arriving to the detector. Given two color bands it is possible to fit standard stars using linear least squares expressed as Eqs. (5) and (6) for the I and J bands, respectively (J. Drummond 2019, 2–13, unpublished manuscript). The linear, multivariate form of Eqs. (5) and (6) are used to establish a relationship between the two independent variables of air mass X and color coefficient c on the single dependent variable of magnitude index, $I - i$ or $J - j$, where I and J are catalogue magnitudes and i and j are the instrument magnitudes for the respective bands (Drummond 2004, 1–4):

$$A_I + k_I X + c_I(I - J) = I - i, \quad (5)$$

$$A_J + k_J X + c_J(I - J) = J - j, \quad (6)$$

where A is the instrumental zero point, k is the extinction coefficient, and c is the color coefficient. Since both the I- and J-band cameras were mounted to the same optic, $X_i = X_j$ as both bands are sensing through equivalent air mass. The color coefficient c corrects for flux variations among the catalogued stars at the color bands of interest. Different temperature stars have different fluxes within a single band. To compare them directly, the flux is corrected by the c term to normalize the flux between various temperature stars within the

band. If we define i_0 and j_0 in Eqs. (7) and (8), and then subtract Eq. (5) from Eq. (6), the resulting relationship may be shown as Eq. (9):

$$i_0 = i + A_i + k_i X, \quad (7)$$

$$j_0 = j + A_j + k_j X, \quad (8)$$

$$I - J = \frac{i_0 - j_0}{1 - (c_i - c_j)}. \quad (9)$$

The instrumental magnitude for the I-band camera i is calculated using Eq. (10). J-band instrumental magnitude j is calculated similarly:

$$i = -2.5 \log_{10}(\text{count s}^{-1}). \quad (10)$$

Equations (5), (6), (9), and (10) are used with calibration targets from Table 3 to generate the values for A , k , and c shown in Table 4. The coefficients generated from catalogued targets in Table 3 are used to calibrate the photometric intensity of unknown targets in Eq. (12).

e. Measurement to photons

Once the coefficients A , k , and c are known for each color band from Table 4, it is possible to determine the anticipated catalogue index (I or J) of an unknown image given the instrument magnitude (i or j) and elevation (or equivalent air mass). Using a Planck function for a 0 visual magnitude, A0 class star (10 800 K), the flux density P is calculated for each λ within each band. The total photons per second for a given spectral bandwidth n_{total} is the sum of all photons within the band

TABLE 4. Linear least squares fit coefficients.

	A_I (magnitude)	k_I (unitless)	c_I (magnitude)	A_J (magnitude)	k_J (unitless)	c_J (magnitude)
Coefficient	23.1143	-0.6707	-0.3582	23.7036	-0.2014	1.0954
Std dev	1.3686	0.8708	1.6689	0.6235	0.3933	1.0466

FIG. 4. All-sky image taken near Albuquerque Sunport, KABQ, at approximately (left) 1345 (sunrise), (center) 1530, and (right) 1700 UTC 20 Mar 2019. Passing clouds are present especially in 1700 UTC image. Cloud presence near 1700 UTC, particularly in southwest sky near telescope measurement FOV, increases the overall radiance received at telescope aperture.

accounting for transmission losses τ_λ and sensor spectral responsivity losses QE_λ , given the respective bandwidth $d\lambda$ and the area of the telescope aperture πr^2 . This relationship is given in Eq. (11). Since the bandwidths of interest are relatively narrow compared to the total overall detector sensitivity, the spectral response was assumed to be constant across each respective band. Sensor spectral responsivities of 0.4 and 0.81 were used for the Rolera and Xenics cameras, respectively (Herrmann and Bucksch 2015; Xenics Infrared Solutions 2019):

$$n_{\text{total}} = \sum_{\text{bandwidth}} (P_\lambda \tau_\lambda QE_\lambda) d\lambda \pi r^2. \quad (11)$$

Based on the sensor calibration coefficients in Table 4, the estimated count per second n_{cps} of a zero-visual-magnitude, A0 class star (10 800 K) is shown in Eq. (12); A is the band representation of either A_i or A_j as required:

$$n_{\text{cps}} = 10^{0.4A}. \quad (12)$$

Thus, the photons per count n_{ppc} is the ratio of photons per second n_{total} to the count per second n_{cps} as shown by:

$$n_{\text{ppc}} = \frac{n_{\text{total}}}{n_{\text{cps}}} = \frac{\sum (P_\lambda \tau_\lambda QE_\lambda) d\lambda \pi r^2}{10^{0.4A}} = \frac{\text{photons s}^{-1}}{\text{count s}^{-1}} = \frac{\text{photons}}{\text{count}}. \quad (13)$$

The total counts from each direct sky-radiance measurement image n_{cpIm} may then be converted to an estimated photon flux Φ_{image} using

$$\Phi_{\text{image}} = n_{\text{cpIm}} n_{\text{ppc}}. \quad (14)$$

f. LEEDR model to photons

LEEDR radiances may be converted to photons for direct comparison to measured flux through a series of conversions. First, the energy per photon is calculated in each band via Eq. (15):

$$E_p = \frac{hc}{\lambda}. \quad (15)$$

LEEDR simulates the atmospheric conditions (including molecular and aerosol scattering and absorption), sun position, and look angles. Band-integrated radiances, shown as L_{LEEDR} ($\text{W cm}^{-2} \text{ sr}$), may then be multiplied by the area of the telescope aperture A_{aperture} , the steradian field of view of the sensor $\text{FOV}_{\text{sensor}}$, and the sensor-specific spectral response QE_{sensor} . The equivalent photon flux from each LEEDR calculated radiance Φ_{LEEDR} may be calculated using

$$\Phi_{\text{LEEDR}} = L_{\text{LEEDR}} (1/E_p) A_{\text{aperture}} \text{FOV}_{\text{sensor}} QE_{\text{sensor}}. \quad (16)$$

Cloud contributions to sky radiances were considered to be negligible during each observation/modeling window. However, weather observations from near the Albuquerque Sunport, KABQ, indicate the sky was not completely clear during the observation/modeling time period near 1700 UTC with a few passing clouds occurring as shown in Fig. 4. Clouds near the FOV could affect the overall radiance received in the telescope aperture. Future work may consider the effects of clouds on the radiative transfer as other research has successfully demonstrated the efficacy of a systems capable of examining the complex interactions of clouds and atmospheric conditions and their effects on remote sensing systems (Burley et al. 2019).

FIG. 5. LEEDR sky radiance validation illustration. Time steps 1–3 correlate to illumination angles to observation windows at 1345 (sunrise), 1530, and 1700 UTC. Points A–G correlate to example observation location with elevations between 30° and 90° and azimuths of 45° and 225°.

3. Results

Direct sky radiance measurements on 20 March 2019 were taken in Albuquerque at various elevations during observation time windows of 1345 (sunrise), 1530, and 1700 UTC along azimuth lines of 45° and 225°. A visual representation of the measurement campaign is shown in Fig. 5. The observation time windows were 15 min long, wherein the daytime sky radiance was assumed to be constant. This assumption allowed for large slewing maneuvers of the telescope and observations at multiple azimuths and elevations locations with a single optic.

Figure 6 shows LEEDR model sample points at spatially diverse azimuths and elevations that are used to generate the left panels of Figs. 7–9. Bandwise averages

of I- and J-band sky radiance were calculated from sky radiance spectra for 433 sample points using model E inputs from Table 1. Model E used an ExPERT derived atmospheric profile, GADS default aerosol profile, and ExPERT meteorological inputs to model the spectral sky radiance. LEEDR models A–E using ExPERT climatology, NWP, scaled/unscaled aerosols, and observed meteorology as detailed in Table 1 were also generated for 20 March 2019 along incremental elevations for the azimuths of 45° and 225°. Bandwise average radiances for each of the LEEDR models A–E are shown in the right panels of Figs. 7–9.

Sky radiance is notoriously difficult to model near sunrise and sunset due to refractive effects of the atmosphere as the sun sits just below the horizon. At sunrise and sunset, large variations in radiant intensity occur on the order of minutes, which approaches the scale of the observation time window. Consequently, error residuals in sky radiance are expected to be higher. The results of LEEDR models are shown in Fig. 7 for 1345 UTC 20 March 2019 in Albuquerque using input parameters from Table 1 and include multiple elevations along the azimuth lines of interest. Figure 7 also shows that LEEDR radiance models that include scaled GADS default aerosols predict photon fluxes closer to the measured flux. A detailed plot of the residuals for each model is shown in Fig. 10.

Figure 8 details the predicted and measured radiances at 1530 UTC or 1.75 h postsunrise. LEEDR is able to predict radiances quite closely along azimuth 225°.

FIG. 6. LEEDR model sample points at spatially diverse azimuths and elevations used to generate plots A and C of Figs. 7–9. Bandwise averages of I- and J-band sky radiance were calculated from sky radiance spectra for 433 sample points using model E inputs from Table 1. Model E used an ExPERT derived atmospheric profile, GADS default aerosol profile, and ExPERT meteorological inputs to model the spectral sky radiance.

FIG. 7. Sky radiance at 1345 UTC 20 Mar 2019 (sunrise) Albuquerque. (a) I-band ($0.8 \mu\text{m}$) LEEDR baseline ExPERT climatology with observational sample points (red). (b) I-band direct measurement data and LEEDR models with input parameters detailed in Table 1 for azimuths 45° – 225° . (c) J-band ($1.2 \mu\text{m}$) LEEDR baseline ExPERT climatology with observational sample points (red). (d) J-band direct measurements and LEEDR models for azimuths 45° – 225° . Cloudless skies were assumed for all simulations. Near-cloudless conditions were observed during radiance measurement as shown in Fig. 4 (left) at 1345 UTC.

Scaling aerosols for both NWP and ExPERT models reduces the intensity of photon flux, and trends toward measured values. A detailed plot of the residuals for each model is shown in Fig. 10.

Figure 9 measurements of photon flux at 1700 UTC or 2.25 h postsunrise. Measured flux values are bounded by the predictions along the 45° azimuth line. However, significant cloud presence as shown in Fig. 4 increased the measured sky radiance along the 225° azimuth line. Since current models do not include clouds, all models tended to underestimate the photon flux along the 225° azimuth line. As clouds likely contributed to higher measured fluxes in this region, direct measurements along the 225° azimuth line at 1700 UTC will be excluded from the residual analysis in Fig. 10 and Table 5. Scaling the GADS default aerosols with in situ measurements once again reduces the sky brightness for elevations along the 45° azimuth line. A detailed plot of

the residuals for each model is shown in Fig. 10. During daytime detection, background limited detection was observed as the dominant noise phenomenology for I- and J-band images with standard deviation of $\Phi_{\text{meanImage}}$ approximately equivalent to the $\sqrt{\Phi_{\text{meanImage}}}$ flux intensity.

Model residuals are calculated at each measurement point by simply subtracting the measured photons from the anticipated photons and are shown in Fig. 10.

The mean residual photon flux error Φ_{meanRE} is given in terms of photons per second and is calculated using Eq. (17), thus positive values for Φ_{meanRE} result from mean predicted LEEDR radiances greater than those that were measured. The mean residual error at each elevation is shown in Fig. 10. Residuals at observation times of 1345, 1530, and 1700 UTC are shown together in Fig. 10 for comprehensive error analysis and

FIG. 8. Sky radiance at 1530 UTC 20 Mar 2019 Albuquerque. (a) I-band ($0.8 \mu\text{m}$) LEEDR baseline ExPERT climatology with observational sample points (red). (b) I-band direct measurement data and LEEDR models with input parameters detailed in Table 1 for azimuths 45° – 225° . (c) J-band ($1.2 \mu\text{m}$) LEEDR baseline ExPERT climatology with observational sample points (red). (d) J-band direct measurements and LEEDR models for azimuths 45° – 225° . Cloudless skies were assumed for all simulations. Near-cloudless conditions were observed during radiance measurement as shown in Fig. 4 (center) at 1530 UTC.

visualization. However, I- and J-band data points from Fig. 9 along azimuth 225° are excluded from residual analysis due to passing clouds from Fig. 4. LEEDR model sensitivity to particle count and meteorological measurement uncertainty was significantly lower than the model residual error. Drier climates are less affected by meteorological measurement errors as significant scattering effects begin to occur near $\sim 70\%$ relative humidity when the size of the aerosol scatterers significantly increases (Zieger et al. 2013). The surface-level relative humidity for Albuquerque during observation is shown in Fig. 3:

$$\Phi_{\text{meanRE}} = \Phi_{\text{LEEDR}} - \Phi_{\text{meanImage}}. \quad (17)$$

To compare the accuracy of the LEEDR models, the total mean photon flux across all observation time windows and combination of azimuth and elevation position

by model are shown in Table 5 as $\Phi_{\text{meanTotal}}$ using Eq. (18) given n_{obs} observations:

$$\Phi_{\text{meanTotal}} = \frac{\sum_{\text{obs.time}} \sum_{\text{position}} \Phi_{\text{LEEDR}}}{n_{\text{obs}}}. \quad (18)$$

Thus, the temporally and spatially averaged mean residual error percentage is calculated in Eq. (19) and listed in Table 5 for each LEEDR model. The NWP and ExPERT baseline LEEDR models are models A and E, respectively, as shown in Table 1:

$$\text{Error}_{\text{mean}} = \frac{\Phi_{\text{meanTotal}}}{\Phi_{\text{meanImage}}} - 1. \quad (19)$$

Several trends may be identified from the residuals in Fig. 10:

FIG. 9. Sky radiance at 1700 UTC 20 Mar 2019 Albuquerque. (a) I-band ($0.8\ \mu\text{m}$) LEEDR baseline ExPERT climatology with observational sample points (red). (b) I-band direct measurement data and LEEDR models with input parameters detailed in Table 1 for azimuths 45° – 225° . (c) J-band ($1.2\ \mu\text{m}$) LEEDR baseline ExPERT climatology with observational sample points (red). (d) J-band direct measurements and LEEDR models for azimuths 45° – 225° . Cloudless skies were assumed for all simulations. Clouds were detected in the southwest sky during radiance measurement near the 225° azimuth line as shown in Fig. 4 (right) at 1700 UTC. Clouds increase scattering effects and may lead to higher sky radiances than may otherwise be predicted.

- 1) Residual error is greatest at lower elevations in both bands.
- 2) LEEDR tends to underestimate sky radiance in the I band (blue symbols of Fig. 10) at low elevations.
- 3) LEEDR tends to overestimate sky radiance in the J band (red symbols of Fig. 10) at low elevations.
- 4) The mean residual error is lower in the I band than in the J band.
- 5) Baseline LEEDR models (circles) are more likely to overestimate sky radiance in both bands.
- 6) The F I-band model has the lowest $\text{Error}_{\text{mean}, I}$.
- 7) The B J-band model has the lowest $\text{Error}_{\text{mean}, J}$.
- 8) Models A and E are considered baseline models and have residual errors within one order of magnitude of $\Phi_{\text{mean image}}$.
- 9) NWP_{baseline} models (A) outperform ExPERT_{baseline} models (E) in both bands by comparing $\text{Error}_{\text{mean}}$.
- 10) Including scaled aerosols (models B, D, and F) improve baseline models (models A and E, respectively).
- 11) Including meteorological data alone (model C) reduces performance from model A in I band, improved performance in J band.

Other trends are identifiable from the residual data in Table 5:

- 1) Baseline LEEDR models A and E conservatively overestimate the sky radiance (with no clouds present) with positive $\text{Error}_{\text{mean}}$ values for each model in both bands.

Direct sky measurements in both I and J bands were compared to sky radiance simulations derived using NWP and ExPERT atmospheric profiles in LEEDR. Cloudless skies were assumed for all simulations. This assumption

FIG. 10. Magnitude of mean residual error Φ_{meanRE} by elevation. Residuals at observation times of 1345, 1530, and 1700 UTC are shown together with the exception of I- and J-band data points at 1700 UTC from Figs. 9b and 9d along azimuth 225°. These 12 data points from Figs. 9b and 9d were excluded from this mean residual analysis due to the increased radiance contribution from passing clouds as shown in Fig. 4. Mean photon flux values are compared using a 1-s integration time. Photon flux residuals are calculated via Eq. (17). During daytime detection, background limited detection was observed as the dominant noise phenomenology for I- and J-band images with standard deviation of $\Phi_{\text{meanImage}}$ approximately equivalent to the $\sqrt{\Phi_{\text{meanImage}}}$ intensity. LEEDR model sensitivity to particle count and meteorological measurement uncertainty was significantly lower than the model residual error.

appears to be valid at 1345 and 1530 UTC; however, passing clouds were observed in the southwestern sky near 1700 UTC as shown in Fig. 4. Baseline models A and E from Table 1 using GADS default aerosol profiles were demonstrated to have mean photon fluxes $\Phi_{\text{meanTotal}}$ within one order of magnitude of the measured photon flux $\Phi_{\text{meanImage}}$, as shown in Table 5, where mean fluxes are averaged temporally and spatially for each model. Positive residual errors for models A–F imply that LEEDR tends to slightly overestimate the spectral sky radiance on average. This finding implies that LEEDR models may be used as conservative estimate of spectral sky radiance if no clouds are present.

For all models A–F, I-band sky radiance models had reduced error over that of the J band. Baseline NWP models exceeded the performance of baseline ExPERT models in both I and J bands as shown in Table 5. Ground-based measurements of temperature, pressure, dewpoint, and relative humidity were included in models C, D, and F as meteorological data. In the I band, inclusion of meteorological data saw slightly decreased model accuracy from model A $\text{Error}_{\text{meanI}}$ to model C $\text{Error}_{\text{meanI}}$. The J-band model (C) $\text{Error}_{\text{meanJ}}$ had increased accuracy from model A $\text{Error}_{\text{meanJ}}$. Aerosol profiles were also scaled from GADS default values described in section 2 according to ground-based in situ measurements at the observing site. Inclusion of scaled aerosols in the models B, D, and F significantly increased I- and J-band accuracy over baseline models A and E as shown in Table 5. The highest performing model in this analysis was model F, which included ExPERT data, scaled aerosols, and meteorological measurements in the I band, and model B in the J band, which included NWP data and scaled aerosols. Future research may include measurements at an increased diversity of ground sites, times, dates and azimuths/elevations. Future models may incorporate clouds to simulate increased spectral radiance when near the telescope FOV.

Spectral sky radiance of the daytime sky is dependent on the time of day, season, atmospheric constituents, and fluctuating conditions. Baseline NWP and ExPERT models were both shown to have one order of magnitude errors. In all cases, model accuracy was greatly increased with the inclusion of in situ particle count data to scale the GADS default aerosol loading profile. Boundary layer sizing via surface-based meteorological data had less of an impact than aerosol scaling in the overall prediction of spectral sky radiance. Near-real-time measurements may be used in conjunction with daytime sky radiance models to adjust tasking lists for daytime satellite custody applications or refine performance availability for quantum-key distribution applications. However, if real-time measurements are not possible, LEEDR model predictions of sky radiance are shown to

TABLE 5. Mean residual error for LEEDR models A–F. Mean photon fluxes Φ are given in photons per second. Letters in parentheses indicate data or profiles used in the model as follows: N = NWP; S = scaled aerosols; M = observed meteorology; E = ExPERT climatology.

		A (N)	B (N + S)	C (N + M)	D (N + S + M)	E (E)	F (E + S + M)
$\Phi_{\text{meanImage}}$	3.98×10^9	5.76×10^9	2.71×10^9	6.01×10^9	3.09×10^8	6.22×10^9	3.38×10^8
$\text{Error}_{\text{meanI}}$	—	+44%	−32%	+51%	−22%	+56%	−15%
$\Phi_{\text{meanTotalI}}$	1.97×10^9	8.85×10^9	1.96×10^9	8.14×10^9	1.90×10^9	1.02×10^{10}	2.08×10^9
$\text{Error}_{\text{meanJ}}$	—	+349%	−1%	+313%	−3%	+419%	+5%

conservatively estimate realistic daytime sky flux intensities for cloudless skies.

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