

1        **ANALYZING THE ANISOTROPY OF THERMAL INFRARED EMISSIVITY OVER ARID REGIONS**  
2        **USING A NEW MODIS LAND SURFACE TEMPERATURE AND EMISSIVITY PRODUCT (MOD21)**

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7        **ABSTRACT**

8        The MOD21 Land Surface Temperature and Emissivity (LST&E) product will be included in  
9        forthcoming Moderate Resolution Imaging Spectroradiometer (MODIS) Collection 6. Surface  
10       temperature and emissivities for thermal bands 29 (8.55  $\mu\text{m}$ ), 31 (11  $\mu\text{m}$ ) and 32 (12  $\mu\text{m}$ ) will  
11       be retrieved using the Advanced Spaceborne Thermal Emission and Reflection Radiometer  
12       (ASTER) Temperature and Emissivity Separation (TES) method adapted to MODIS at-sensor  
13       spectral radiances, previously corrected with the Water Vapor Scaling method (MOD21  
14       algorithm). We simulated MOD21 product estimates over two different sandy deserts (i.e.  
15       White Sands and Great Sands) using a series of MODIS scenes from 2010 to 2013. The  
16       objective of this study was to evaluate the anisotropy of the thermal infrared emissivity over  
17       semiarid regions, since angular variations of thermal infrared emissivity imply important  
18       uncertainties in satellite LST retrievals. The obtained LSEs and their dependence on zenith  
19       viewing angles were analyzed. Results from the MOD21 simulated algorithm showed that band  
20       29 LSE decreased up to 0.038 from nadir to zenith angle of 60°, while LSEs for bands 31 and 32  
21       did not show significant variation. MOD21 LSE for band 29 also showed mean differences  
22       between night and daytime retrievals of +0.027 for WS and +0.009 for GS. These differences  
23       can be attributed to the water vapor adsorption of the soil from the atmosphere. MOD21  
24       nadir and off-nadir LSEs showed a good agreement with laboratory emissivity measurements,

25 and were used to validate with satellite data a zenithal-dependent emissivity model proposed  
26 in a previous study.

27 **KEYWORDS:** Emissivity, MODIS, anisotropy, MOD21, TES, angular effects.

## 28 **1. INTRODUCTION**

29 Land Surface Temperature and Emissivity (LST&E) is one of the most important Earth System  
30 Data Records (ESDR's) identified by NASA (King, 1999). LSE, defined as the ratio of the surface  
31 emitted radiance to the radiance emitted from a black body at the same thermodynamic  
32 temperature (Norman & Becker, 1995), is an intrinsic property of the Earth surface that  
33 governs the absorption and emission of energy in the TIR region. Precise and accurate  
34 estimates of TIR LSEs are of prime interest to retrieve LST with small uncertainty and bias (Li et  
35 al., 2007). LST is an important variable controlling most physical, chemical and biological land  
36 processes, useful in several disciplines like agro-meteorology, climatology or hydrology. LST is  
37 used, for instance, to study desertification processes, evapotranspiration (Sánchez et al., 2008)  
38 or surface-atmosphere interactions (Jacob et al., 2002; Qin et al., 2008).

39 Many applications can be carried out with the LSE itself, for instance, analyses of land use  
40 change (French et al., 2008, Hulley et al., 2014) or land cover characterization (French &  
41 Inamdar, 2010). LSE changes with soil moisture content (Mira et al., 2010; García-Santos et al.,  
42 2014), type of surface cover (French et al., 2008), surface roughness (Mushkin and Gillespie,  
43 2005), and sensor viewing geometry (García-Santos et al., 2012).

44 Current remote sensing techniques pursue a maximum uncertainty of  $\pm 1$  K or less in LST  
45 retrievals (Li et al., 2013). Some studies showed errors of  $\pm 1$  to  $\pm 2$  K in LST using the single-  
46 channel method (Dash et al., 2002). LST errors from the Moderate Resolution Imaging  
47 Spectroradiometer (MODIS) generalized split-window (GSW, Wand & Dozier, 1996) are  
48 generally within  $\pm 1$  K for sites with stable atmospheric conditions, except semi-arid and arid

49 regions (Wan and Li 2008, Wan 2014). Uncertainties of  $\pm 1$  to  $\pm 2$  K were found for the LST  
50 product of the Spinning Enhanced Visible and Infrared Imager (SEVIRI) instrument (Freitas et  
51 al., 2010). An average precision of  $\pm 1.6$  K was found for the LST product of the Geostationary  
52 Operational Environmental Satellite R-Series (GOES-R) Program over six different validation  
53 sites (Yu et al., 2012). Comparisons between *in situ* LST and the Visible Infrared Imaging  
54 Radiometer Suite (VIIRS) derived LSTs showed errors up to  $\pm 4$  K over arid and semi-arid areas  
55 (Guillevic et al., 2014). The Temperature and Emissivity Separation (TES) algorithm (Gillespie et  
56 al., 1998) retrieved LST and LSE from the Advanced Spaceborne Thermal Emission and  
57 Reflection Radiometer (ASTER) sensor with errors within  $\pm 1.5$  K and of  $\pm 0.005$  to  $\pm 0.03$ ,  
58 respectively (Hulley et al., 2008).

59 The effect of Thermal Infrared (TIR) emissivity on LST uncertainty is very important. Galve et al.  
60 (2008) showed that using the SW algorithm, an emissivity uncertainty of  $\pm 0.005$  results in a LST  
61 uncertainty of  $\pm 0.7$  K. Hulley & Hook (2009a) showed mean differences for the TIR emissivities  
62 from MODIS bands 29 ( $8.55 \mu\text{m}$ ), 31 ( $11 \mu\text{m}$ ) and 32 ( $12 \mu\text{m}$ ) of sand samples collected at the  
63 Namib desert (Namibia), of 1.06%, 0.65% and 1.93%, for MOD11B1 versions V4, V4.1 and V5  
64 (Wan, 1999), respectively. The angular dependence on emissivity of land surfaces must be  
65 taken into account, since according to Lagouarde et al. (1995), LST measurements for a smooth  
66 bare soil at nadir and at  $60^\circ$  showed differences up to 2 K.

67 In particular, variation of LSE with viewing angle has been shown to be significant in several  
68 studies, carried out primarily in field or laboratory conditions. Labed and Stoll (1991) showed  
69 that the TIR emissivity of a sand sample does not present angular dependence on the zenith  
70 angle up to values greater than  $50^\circ$  and this decrease does not exceed 4.5% for larger zenithal  
71 viewing angles. According to Lagouarde et al. (1995), for samples whose texture implies  
72 particles size less than 4–5 cm, the effects associated with angular measurements of  
73 brightness surface temperature are caused by the anisotropy of the surface emissivity. In

74 Cuenca and Sobrino (2004), emissivity of a sand sample showed a decrease with zenith angle  
75 ( $\theta$ ) of around 2% at spectral ranges 8–14  $\mu\text{m}$ , 11.5–12.5  $\mu\text{m}$  and 10.3–11.3  $\mu\text{m}$ , but presented  
76 a pronounced decrease of 5% at 8.2–9.2  $\mu\text{m}$ . Recently García-Santos et al. (2012) and (2014)  
77 showed the LSE decrease at large zenith angles ( $\theta \geq 40^\circ$ ) for a set of bare soils under controlled  
78 surfaces roughness, especially for dry sandy soils with high quartz content, with emissivity  
79 differences of 14% relative to nadir values. However, there are few studies dealing with the  
80 anisotropy of LSE observed from sensors onboard orbiting satellites. For instance, Petitcolin et  
81 al. (2002) showed a decrease of up to 3% in bare soil emissivity in Advanced Very High  
82 Resolution Radiometer (AVHRR) channels 4 (10.3 - 11.3  $\mu\text{m}$ ) and 5 (11.5 - 12.5  $\mu\text{m}$ ) using the  
83 Temperature Independent Spectral Indices (TISIE) concept (Becker and Li, 1990), and Ren et al.  
84 (2011) found a minimal variation of LSE for MODIS band 29 with the zenith angle ( $< 0.005$ ) for  
85 barren surfaces when analyzing the MOD11B1 product (Wan, 2007) at 5x5  $\text{km}^2$  resolution.

86 The objective of the present study is to analyze the anisotropy effects on LSE of bare soils as  
87 retrieved from the new MOD21 algorithm which provides 1 km resolution LSTs and LSEs in  
88 MODIS bands 29 (8.55  $\mu\text{m}$ ), 31 (11  $\mu\text{m}$ ) and 32 (12  $\mu\text{m}$ ) (Hulley et al., 2012a). The recently  
89 proposed MOD21 product is an adaptation of the ASTER TES algorithm (Gillespie et al., 1998)  
90 to the MODIS sensor. MODIS TIR at-sensor radiances are atmospherically corrected applying  
91 the Water Vapor Scaling (WVS) method (Tonooka 2005) to coincident MOD07 profiles in order  
92 to minimize atmospheric correction errors. Since the MOD21 product was not available for this  
93 study, we implemented the MOD21 algorithm following the Algorithm Theoretical Basis  
94 Document (Hulley et al. 2012a) to simulate the MOD21 product.

95 The study was carried out over two very homogeneous desert areas: the White Sands (WS)  
96 National Monument and the Great Sands (GS) National Park. Arid regions were selected  
97 because they are pseudo-invariant dune sites and present the most pronounced decrease of  
98 LSE with viewing angle in the TIR region (García-Santos et al., 2012), especially in the

99 Reststrahlen band from 8 to 9  $\mu\text{m}$  (MODIS band 29). WS is composed by gypsum, which shows  
100 a notable Reststrahlen feature as observed from laboratory measurements (Baldrige et al.,  
101 2009). GS is composed mainly of quartz (Madole et al., 2008), which is the most important  
102 component in many sandy deserts and also shows the Reststrahlen effect. Desert surfaces  
103 have also been recognized as optimal targets for long-term validation and calibration of  
104 thermal infrared data (de Vries et al., 2007).

105 The two sites chosen in this study were also selected by Hulley et al. (2009) to validate ASTER  
106 LSE retrievals. According to Hulley et al. (2009), sand dunes of WS are displaced around 10 m  
107 per year in the North-East direction (McKee, 1966), changing consequently the landscape of  
108 the region over a long time period, which implied a temporal variation of ASTER band 11 (8.6  
109  $\mu\text{m}$ ) emissivity of 3.1 %, based on 11 ASTER scenes over WS from 2000 to 2008. However,  
110 French et al. (2008) found a temporal emissivity variation lower than 0.3% per year at WS  
111 analyzing 9 ASTER scenes from 2001 to 2003. The spatial emissivity variation of a 1 x 1  $\text{km}^2$   
112 target site (averaged value of 10x10 ASTER pixels) was 1.2 % for the total 11 observations  
113 (Hulley et al., 2009). Regarding GS, a temporal variation of 1.7 % in emissivity for ASTER band  
114 11 was found analyzing 6 ASTER scenes from 2000 to 2008. A spatial emissivity variation of 0.9  
115 % was observed for the whole observations (Hulley et al., 2009).

116 It is worth to note that LST&E retrievals from a preliminary MOD21 product were validated in  
117 16 different type cover sites, including water, forest, shrublands and barren places (Hulley et  
118 al., 2012a). LST results in pseudo-invariant dune sites showed an average bias of +0.2 K and  
119 root-mean-square-error (RMSE) of  $\pm 1.6$  K when using the R-based method (Coll et al., 2009;  
120 Wan and Li, 2008). LSE results showed an average bias of +0.0005, and RMSE of  $\pm 0.006$   
121 between laboratory measurements and MOD21 LSE in band 31 (11  $\mu\text{m}$ ) for the same pseudo-  
122 invariant dune sites (see Table 10 in Hulley et al. 2012a).

123 The paper proceeds as follows. Section 2 describes the two test sites selected to carry out the  
124 study. Section 3 explains briefly the main notions of the MOD21 algorithm. The data used and  
125 the application of the MOD21 algorithm is explained in Section 4. The main results regarding  
126 LSE anisotropy over the two sites are shown and discussed in section 5, including a comparison  
127 with field data. Finally, conclusions are outlined in section 6.

## 128 **2. STUDY AREAS**

129 The White Sands (WS) National Monument (Fig. 1a), located in Tularosa Valley (South-central  
130 New Mexico, USA) is a dune system desert at 1216 m above sea level, with an area of 704 km<sup>2</sup>  
131 and a maximum dune height of 10 m. The grain size is considered fine sand and the major  
132 mineralogy component is gypsum according to X-ray diffraction measurements (Hulley et al.,  
133 2009).

134 The second site selected was the Great Sands (GS) National Park (Fig. 1b), located in the San  
135 Luis Valley (Colorado, USA). GS covers an area of 104 km<sup>2</sup> at 2560 m above sea level and the  
136 maximum dune height (230 m) is quite larger than WS dunes. GS is also a sand dune system  
137 desert, created from quartz and volcanic fragments derived from Santa Fe and Alamosa  
138 formations. The major mineral is quartz, with minor traces of potassium and feldspar. The  
139 grain size of the sand is medium to coarse according to the X-ray diffraction measurements  
140 (Hulley et al., 2009).

141 For the present study, coordinates of the WS sampling are 32.8038° N, 106.2742° W (blue  
142 point in Fig. 1a) and for GS are 37.7589° N, 105.5514° W (blue point in Fig. 1b). These areas are  
143 coincident with the regions selected by Hulley et al. (2009) to collect soil samples for  
144 laboratory emissivity and soil composition measurements.

145 **INSERT FIGURE 1**

146 According to Mira et al. (2010) and García-Santos et al. (2014), WS is 100% sand, which is  
147 composed of gypsum in 99% and quartz in 1%. On the other hand, according to the *Soil Survey*  
148 *webpage tool* (<http://websoilsurvey.sc.egov.usda.gov/App/HomePage.htm>, last access  
149 September 2014), GS is composed of sand in 98%, silt in 1.5 % and clay in 0.5 %. GS is  
150 composed of quartz in 28% and volcanic rock in 52% (Madole et al., 2008).

### 151 **3. MODIS AND ANCILLARY DATA USED TO SIMULATE MOD21 PRODUCT**

152 The MOD21 product was not available at the time of the present study. For that reason, it was  
153 simulated following the algorithm theoretical basis document (Hulley et al., 2012a) as  
154 described in section 4. In this way, we were able to retrieve LST&E at 1 km<sup>2</sup> spatial resolution  
155 twice a day, using the MODIS-Terra products MOD021KM and MOD07.

156 The MOD21 algorithm is applied to the TOA MODIS radiances from bands 29, 31 and 32,  
157 included in the MOD021KM product (MODIS Characterization Support Team, 2012). The Level  
158 1B collection contains calibrated and geolocated radiances in  $W m^{-2} \mu m^{-1} sr^{-1}$  for all 36 MODIS  
159 spectral bands at 1 km resolution. Radiances were extracted from the *EV\_1KM\_Emissive*  
160 *Science Data Sets (SDS)* for TIR emissive spectral regions, included in the HDF format MODIS  
161 product.

162 Atmospheric profiles are provided by the MOD07 product (Seemann et al., 2006). These  
163 profiles are used for the atmospheric correction of the geo-located TOA radiances. The Level 2  
164 MOD07 product consists of several atmospheric parameters produced day and night at 5 km ×  
165 5 km resolution. Air temperature and moisture profiles are provided at 20 vertical levels.  
166 Uncertainties attributed to the atmospheric parameters provided by MOD07 product are: ±1.9  
167 K for air temperature, ±4 K for the dew point, and ±10 % for relative humidity (Seemann et al.,  
168 2006).

169 In the MOD21 simulated product, it is necessary to discriminate between bare soils and  
170 graybody surfaces (water and vegetation). This was done from normalized difference  
171 vegetation index (NDVI) data from the monthly MOD13A3 product at 1 km<sup>2</sup> spatial resolution  
172 (Solano et al., 2010). According to Hulley et al. (2012a), we considered pixels with 0<NDVI≤0.3  
173 as bare soil, and pixels with NDVI<0 (water) and NDVI>0.3 (vegetation) as graybodies.

174 A set of MODIS images acquired during 4 years (2010 to 2013) over both selected deserts was  
175 considered for the application of the MOD21 algorithm. The total number of MODIS scenes for  
176 each study area was 6034 MOD021KM and MOD07 product images (3017 each) and 48 scenes  
177 of the MOD13A3 product.

#### 178 **4. MOD21 ALGORITHM THEORETICAL BASIS**

179 In this section, the main theoretical basis of the forthcoming MOD21 product is explained  
180 describing the atmospheric correction performed by the Water Vapor Scaling (WVS) method  
181 (Tonooka, 2005) and the modified TES method adapted to the three MODIS thermal bands 29  
182 (8.55 μm), 31 (11 μm) and 32 (12 μm). Originally, the WVS and TES methods were developed  
183 for the five TIR bands of the ASTER instrument.

##### 184 4.1 Water Vapor Scaling (WVS) Method

185 The top-of-atmosphere (TOA) radiances ( $L_{sen,i}$ ) measured by the MODIS sensor must be  
186 previously corrected for atmospheric effects using the radiative transfer equation, in order to  
187 obtain the at-surface radiance ( $L_{sur,i}$ ) in band  $i$  ( $i=29, 31$  and  $32$ ) as:

$$188 \quad L_{sur,i} = \frac{L_{sen,i} - L_i^\uparrow}{\tau_i} \quad (1)$$

189 where  $L_i^\uparrow$  and  $\tau_i$  are the atmospheric path radiance and transmittance, respectively. View  
190 angle is not included in Eq. (1) for simplicity.



191 The atmospheric terms in Eq. (1) are calculated using the 5x5 km<sup>2</sup> atmospheric profiles  
 192 provided by the MOD07 product (Seemann et al., 2006), which are introduced in the  
 193 MODTRAN radiative transfer code (version 5.2.1, Berk et al., 2006). These terms are retrieved  
 194 from outputs of a MATLAB code provided by Griffith (2012), which runs the atmospheric  
 195 profiles into the MODTRAN iteratively. However, since TES is a very sensitive method to  
 196 atmospheric correction uncertainties, especially over graybodies such as vegetation, snow or  
 197 water (Coll et al., 2007; Hulley & Hook 2009b), the atmospheric variables need to be previously  
 198 refined by applying the WVS method (Tonooka, 2005) in order to minimize error on LST&E.

199 The first step of the WVS method is to calculate the at-surface brightness temperature from  
 200 the at-sensor brightness temperature measured at the three selected MODIS bands, based on  
 201 a multichannel algorithm dependent on the total column water (*TCW*, in cm):

$$202 \quad T_{g,i} = \alpha_{i,0} + \sum_{k=1}^n \alpha_{i,k} T_k \quad (2)$$

$$203 \quad \alpha_{i,k} = p_{i,k} + q_{i,k} TCW + r_{i,k} TCW^2 \quad (3)$$

204 where *i* is band number, *n* number of bands,  $\alpha_{i,k}$  are band-dependent coefficients calculated  
 205 from *p*, *q* and *r* which are regression coefficients for each band, *T<sub>k</sub>* is the brightness surface  
 206 temperature for band *k* (in K) and *T<sub>g,i</sub>* is the brightness surface temperature for band *i*.

207 The WVS method enhances the accuracy of water vapor atmospheric profiles on a pixel-by-  
 208 pixel and band-by-band basis by computing a water vapor scaling factor  $\gamma$ , which is used to  
 209 recalculate the atmospheric transmittance ( $\tau_i$ ) and atmospheric path radiance ( $L_i^\uparrow$ ), and it is  
 210 defined by:

$$211 \quad \gamma^{\alpha_i} = \frac{\ln \left( \frac{\tau_i(\theta, \gamma_2)^{\gamma_1 \alpha_i}}{\tau_i(\theta, \gamma_1)^{\gamma_2 \alpha_i}} \left( \frac{B_i(T_{g,i}) - \frac{L_i^\uparrow(\theta, \gamma_1)}{1 - \tau_i(\theta, \gamma_1)}}{L_i - \frac{L_i^\uparrow(\theta, \gamma_1)}{1 - \tau_i(\theta, \gamma_1)}} \right)^{\gamma_1 \alpha_i - \gamma_2 \alpha_i} \right)}{\ln \left( \frac{\tau_i(\theta, \gamma_2)}{\tau_i(\theta, \gamma_1)} \right)} \quad (4)$$

212 where  $\alpha_i$  is a band model parameter,  $\gamma_1=1$  and  $\gamma_2=0.7$  are typical values (Tonooka, 2005),  
 213  $\tau_i(\theta, \gamma_{1,2})$  are transmittances and  $L_i^\uparrow(\theta, \gamma_{1,2})$  are path radiances calculated with water vapor  
 214 profile scaled by  $\gamma_{1,2}$ .

215 The scaling factor ( $\gamma$ ) is firstly calculated for graybody pixels. For non-graybody pixels,  $\gamma$  is  
 216 calculated after horizontally interpolating and smoothing the scaling factor from all the  
 217 graybody surfaces adjacent to the remaining pixels in an *effective radius* of 50 km (Hulley et al.,  
 218 2012a). Once  $\gamma$  has been calculated, or interpolated and smoothed, the atmospheric  
 219 parameters  $\tau_i$  and  $L_i^\uparrow$  are obtained as

$$220 \quad \tau_i(\theta, \gamma) = \tau_i(\theta, \gamma_1)^{\frac{\gamma^{\alpha_i - \gamma_2^{\alpha_i}}}{\alpha_i - \gamma_2^{\alpha_i}}} \cdot \tau_i(\theta, \gamma_2)^{\frac{\gamma_1^{\alpha_i - \gamma^{\alpha_i}}}{\alpha_i - \gamma^{\alpha_i}}} \quad (5)$$

$$221 \quad L_i^\uparrow(\theta, \gamma) = L_i^\uparrow(\theta, \gamma_1) \cdot \frac{1 - \tau_i(\theta, \gamma)}{1 - \tau_i(\theta, \gamma_1)} \quad (6)$$

222 The hemispherical downwelling sky radiance ( $L_{hem,i}^\downarrow$ ), which is required for the application of  
 223 the TES method, can be obtained from a non-linear equation, as a function of the path  
 224 radiance at nadir view as follows:

$$225 \quad L_{hem,i}^\downarrow(\gamma) = a_i + b_i \cdot L_i^\uparrow(0^\circ, \gamma) + c_i \cdot L_i^\uparrow(0^\circ, \gamma)^2 \quad (7)$$

$$226 \quad L_i^\uparrow(0^\circ, \gamma) = L_i^\uparrow(\theta, \gamma) \cdot \frac{1 - \tau_i(\theta, \gamma)^{\cos \theta}}{1 - \tau_i(\theta, \gamma)} \quad (8)$$

227 Values of coefficients in equations (2)-(6) as well as further details about the WVS method can  
 228 be found in chapter 5 of Hulley et al. (2012a).

#### 229 4.2 Temperature and Emissivity Separation (TES) Method

230 Eq. (1) is composed by the radiance emitted by the surface and the reflected hemispherical  
 231 downwelling radiance ( $L_{hem}^\downarrow$ , obtained from the WVS as described above):

$$232 \quad L_{sur,i} = \varepsilon_i B_i(T) - [1 - \varepsilon_i] L_{hem,i}^\downarrow \quad (9)$$

233 where  $\varepsilon_i$  is the surface emissivity, and  $B_i(T)$  is the Planck function for blackbody spectral  
234 radiance at temperature  $T$ .

235 The TES method starts with the Normalized Emissivity Method (NEM) module, which requires  
236  $L_{sur,i}$  and  $L_{hem,i}^\downarrow$ , together with an initial  $\varepsilon_i$  value ( $\varepsilon_i=0.98$  in this study) to calculate  $B_i(T)$  from  
237 eq. (9). The next step is inverting the Planck function and retrieving a temperature in the three  
238 MODIS bands 29, 31 and 32. The maximum of these three temperatures is selected ( $T_{NEM}$ ).  
239 Now this  $T_{NEM}$  is used to calculate  $B_i(T_{NEM})$ , and three emissivities (one per spectral band) are  
240 retrieved from eq. (9). With these emissivities,  $L_{sur,i}$  is recalculated using Eq. (9). This process  
241 is repeated until convergence; that is when the change in  $L_{sur,i}$  between iterations is less than  
242 a threshold; equivalent to the sensor noise-equivalent differential temperature ( $\pm 0.05$  K for  
243 MODIS).

244 The RATIO module uses the NEM emissivities to calculate the beta ( $\beta_i$ ) spectrum as the ratio of  
245 each band emissivity to the average emissivity value ( $\bar{\varepsilon}$ ), as follows:

$$246 \quad \beta_i = \frac{\varepsilon_i}{\bar{\varepsilon}} \quad (10)$$

247 The Maximum-Minimum Difference (MMD) is obtained from the  $\beta_i$  spectrum as  
248  $MMD = \max(\beta_i) - \min(\beta_i)$ . Finally the MMD value is introduced in an empirical relationship to  
249 calculate the minimum emissivity as:

$$250 \quad \varepsilon_{min} = \alpha_1 - \alpha_2 MMD^{\alpha_3} \quad (11)$$

251 where  $\alpha_1=0.985$ ,  $\alpha_2=0.7503$  and  $\alpha_3=0.8321$  are coefficients given in Hulley et al. (2012a).

252 From the minimum emissivity of Eq. (11) and the  $\beta_i$  spectrum, the absolute emissivity is  
253 obtained through

$$254 \quad \varepsilon_i = \frac{\varepsilon_{min} \beta_i}{\min(\beta_i)} \quad (12)$$

255 Finally the LST is calculated using the maximum value of the TES emissivities in Eq. (9) for the  
256 band where the maximum emissivity occurs.

257 Hulley et al. (2012b) derived a quadratic polynomial that predicts the uncertainty in MOD21  
258 LST&E retrievals depending on the total column water and zenith angle ( $\theta$ ). Coefficients for the  
259 LST and emissivity uncertainty polynomials are dependent on surface type (gray bodies,  
260 transition zones or bare surfaces) (Hulley, personal communication). Further details about the  
261 MOD21 product can be found in the MOD21 ATBD (Hulley et al., 2012a).

262 Two limitations were imposed to the MODIS data in order to reduce the uncertainty in the  
263 MOD21 results. First, only scenes with a TCW lower or equal than 1.5 cm were used. The TCW  
264 limitation was imposed because, for viewing zenith angle of  $53.7^\circ$  and TCW values larger than  
265 1.5 cm, MOD21 results show LST predicted errors larger than  $\pm 1$  K, and band 29 LSE errors of  
266  $\pm 0.03$  for rocks, soils and sand surfaces (Hulley et al., 2012a). Therefore, limiting the study to  
267 drier atmospheres reduced the uncertainty on LSE retrievals for our selected soils.

268 The second limitation was that only MODIS scenes were considered with at least 70% of cloud-  
269 free pixels inside the 50 km radius circle centered in the selected coordinates. The reason is to  
270 get enough cloud-free, graybody pixels in the 50 km radius circle and therefore to improve the  
271 interpolation and smoothing of the WVS  $\gamma$  factors for the non-graybody pixels. Figure 2 shows  
272 an example of the graybody pixels included in the 50 km radius for the two sites. Both scenes  
273 were obtained from monthly NDVI data of the MOD13A3 product for April, 2010. All pixels  
274 with  $NDVI < 0$  (water) or  $NDVI > 0.3$  (vegetation) were considered as graybody, whereas the  
275 remaining pixels were considered as bare soil. The mean number of pixels included inside the  
276 circle is around 7400, for which around 900 pixels were considered as graybody (12%) for WS  
277 and 4200 pixels (57%) for GS. As observed in Fig. 2, because of the lower number of graybody  
278 pixels, the interpolation and smoothing of the  $\gamma$  factors is more difficult for WS than for GS.  
279 However, we consider that they are enough for the application of the WVS method.

280

INSERT FIGURE 2

281 After applying the TCW and cloud limitations, 686 scenes (335 daytime and 351 nighttime)  
282 were selected for WS, and 689 scenes (366 daytime and 323 nighttime) were selected for GS.  
283 LSEs were obtained using the MOD21 simulated product for MODIS bands 29, 31 and 32 at  
284 different viewing angles. While the selected data covered adequately the zenith viewing angle  
285 range of MODIS (0°-65°) over the two sites, the azimuthal viewing angles were limited to a  
286 relatively narrow range. For nighttime overpasses, the azimuthal angles (from North) were  
287 between -94° and -105° for WS, and between -92° and -103° for GS (MODIS crossing the West  
288 side of the sites); and between 74°- 83° for WS, and 73°- 92° for GS (MODIS crossing the East  
289 side of the sites). For daytime overpasses, the azimuthal angles are between -75° and -117° for  
290 WS, and -72° and -84° for GS (West side overpass); and between 80° - 102° for WS, and 94° -  
291 108° for GS (East side overpass). In summary, we divided azimuthal observations in two  
292 different orientations, West or East, considering zenithal observation angles negative for West  
293 azimuths and positive for East azimuths.

294 The procedure to obtain a LSE value for a specific zenith angle ( $\theta$ ) was as follows. For each  
295 MODIS scene and site only pixels no more than 1 km away from the site coordinates were  
296 considered. For such pixels (usually 4), a spatially-averaged LSE value was calculated. The  
297 spatially-averaged LSE values were grouped by zenith viewing angle into 1° wide intervals from  
298 -65° to 65°. According to Schneider et al. (2012), robust statistics are recommended because  
299 they minimize the influence of possible outliers and can be considered more consistent than  
300 standard statistics. For that reason, we calculated the median (Me) and the robust standard  
301 deviation (RSD) to all the zenithal-grouped LSE values to obtain the emissivity value and the  
302 corresponding uncertainty, respectively, for a specific zenith angle interval. The RSD is defined  
303 as:

304

$$\text{RSD} = \text{Me}(|\varepsilon_i - \text{Me}(\varepsilon_i)|) \cdot 1.4826 \quad (13)$$

305 **5. RESULTS AND DISCUSSION**

306 Figure 3 shows maps of LST&E MOD21 simulated product at MODIS scale (1 km<sup>2</sup>) for the two  
307 studied regions. The desert area is outlined and the sampling site is marked in both cases.  
308 From these data, the average values  $\pm$  standard deviation of the emissivity and LST of the four  
309 pixels within the blue square were 0.783  $\pm$ 0.010 (band 29), 0.971  $\pm$ 0.001 (band 31), 0.965  
310  $\pm$ 0.001 (band 32) and 17.2  $\pm$ 0.3 K (LST) for WS. For GS, the LST&E values were 0.896  $\pm$ 0.004  
311 (band 29), 0.949  $\pm$ 0.002 (band 31), 0.969  $\pm$ 0.001 (band 32) and 36.4  $\pm$ 0.4 K. These examples  
312 show the spatial homogeneity in LST&E of the selected sites.

313 The LSE maps for band 29 show the lowest values in areas within the desert sites, as a  
314 consequence of the quartz and gypsum Reststrahlen feature at 8-9  $\mu$ m. LSE for bands 31 and  
315 32 shows close and uniform values along the WS desert extension. In GS, LSE for band 31 is  
316 significantly lower than for band 32, both values being also uniform over the desert area.

317 INSERT FIGURE 3

318 5.1 Analysis of uncertainties

319 Maximum, minimum and average RSD values for both WS and GS sites are shown in Table 1 for  
320 the three MODIS thermal bands 29 (8.4 - 8.7  $\mu$ m), 31 (10.78 - 11.28  $\mu$ m) and 32 (11.77 - 12.27  
321  $\mu$ m). Uncertainties in table 1 are both for nighttime and daytime. Uncertainties predicted from  
322 Hulley et al. (2012b) over WS and GS ranged from  $\pm$ 0.016 to  $\pm$ 0.023 for band 29, and between  
323  $\pm$ 0.012 and  $\pm$ 0.014 for bands 31 and 32 (for the two selected sites and both nighttime and  
324 daytime). Therefore, our uncertainties were within the uncertainties predicted by Hulley et al.  
325 (2012b) for all viewing angles for bands 31 and 32, but were slightly higher for band 29.

326 INSERT TABLE 1

327 5.2 Analysis of nadir emissivities

328 a) Comparison with laboratory data

329 Figure 4 shows MOD21 simulated LSE retrievals at near-nadir ( $2^{\circ}$ - $16^{\circ}$ ) at both sites for day  
330 (17H-19H UTC, 10H-13H Local Time) and nighttime (4H-6H UTC, 21H-24H Local Time) MODIS  
331 overpasses. For both sites, MOD21 LSE is compared with emissivity values obtained from  
332 laboratory spectral measurements for samples collected from the study areas (Glynn Hulley,  
333 personal communication), which were weighted for MODIS-Terra bands 29, 31 and 32 using  
334 the appropriate filter functions.

335 INSERT FIGURE 4

336 Table 2 shows the difference between the above mentioned measured emissivity and that  
337 calculated from MOD21 algorithm, both day ( $\Delta\epsilon_d$ ) and night ( $\Delta\epsilon_n$ ) in the two studied areas. In  
338 both sites results showed that MOD21 LSEs overestimated band-averaged laboratory values,  
339 independently of the time overpass and sensor spectral band. LSE values for bands 31 and 32  
340 (for both sites and sensor overpass) can be considered in good agreement with laboratory  
341 data, because they were within the predicted uncertainty ( $\pm 0.001$  to  $\pm 0.012$ ).

342 However, MOD21 LSE for band 29 showed the highest discrepancies between day and  
343 nighttime overpasses. So for WS site daytime LSE overestimated laboratory emissivity data,  
344 but this overestimation is explained in terms of uncertainty ( $\pm 0.014$  to  $\pm 0.022$ ). This was not  
345 the case of nighttime LSE overestimation for band 29. Similarly to WS, overestimation of  
346 MOD21 LSE for band 29 in GS was justified in terms of the associated uncertainty ( $\pm 0.019$  to  
347  $\pm 0.030$ ) for the daytime sensor overpass, but not for the nighttime overpass.

348 It is worth to note that despite the poor interpolation and smoothing for the application of the  
349 WVS method in the WS case, the uncertainty associated the LSE retrieval was lower than or of  
350 the same order as for the GS site (Figure 4), where the interpolation and smoothing process  
351 was theoretically better, since there were more graybody pixels surrounding the desert.

352

INSERT TABLE 2

353 b) Soil moisture effect observed between day and nighttime

354 Figure 4 shows a bias in band 29 LSE depending on the sensor time overpass, so for nighttime,  
355 band 29 LSE presented a value +0.027 larger than for the daytime overpass at the WS site. For  
356 the same site, the bias between night and daytime LSE for bands 31 and 32 was 0.004 and  
357 0.001, respectively. For GS (Figure 4b) nighttime LSEs showed an average value 0.010, 0.002  
358 and 0.003 larger than the corresponding daytime value for bands 29, 31 and 32, respectively.  
359 According to Hulley et al. (2012a), daily variation in surface soil moisture is the main factor  
360 potentially affecting the temporal stability of dune sites, since emissivity increases with soil  
361 moisture (Mira et al., 2010; Hulley et al., 2010; Sánchez et al., 2011; García-Santos et al., 2014).  
362 The positive bias between nighttime and daytime emissivities obtained using satellite  
363 estimates over desert areas has been observed in previous studies. Li et al. (2012) used LSE  
364 retrievals from the geostationary SEVIRI sensor over the whole Sahara desert to show night-  
365 day differences up to 0.03 for the 8.7  $\mu\text{m}$  channel. LSEs for channels 10.8  $\mu\text{m}$  and 12  $\mu\text{m}$   
366 showed no significant diurnal variation. Similar results were obtained by Masiello et al. (2014)  
367 with Infrared Atmospheric Sounding Interferometer (IASI) data over the Sahara desert and by  
368 Rozenstein et al. (2015) using SEVIRI data and field spectral measurements over the Sinai and  
369 Negev deserts. The night-day LSE variations observed in our two selected sites (Figure 4) were  
370 in good agreement with those results.

371 Since rainfall events are rare in desert areas and cannot explain the systematic night-day  
372 emissivity bias observed, we checked the possibility of dew formation over the WS site using  
373 hourly meteorological data from the Holloman weather station  
374 ([http://www.wunderground.com/weather-forecast/US/NM/Holloman Air Force Base.html](http://www.wunderground.com/weather-forecast/US/NM/Holloman_Air_Force_Base.html)),  
375 located 10 km away from the WS site. Dew is only formed when the air temperature is equal  
376 or lower than the dew point temperature, which only occurred in 20 cases out of the 1461



377 days analyzed in 2010-2013. Using data for the same weather station, we found that rainfall  
378 occurred only for 84 out of 1460 days. Therefore, nighttime dew formation and rainfall cannot  
379 be the cause of the night-day LSE differences for the majority of the scenes. A similar  
380 conclusion was drawn by Li et al. (2012), Masiello et al. (2014), and Rozenstein et al. (2015),  
381 who found very unlikely the formation of dew in arid, desert areas. They attributed the  
382 nighttime increase of the soil moisture to direct water vapor adsorption by the soil, which  
383 happens when the relative humidity of the soil pores is lower than the relative humidity of the  
384 air, and the air temperature is higher than the dew point temperature (Agam & Berliner,  
385 2006). Water vapor adsorption has a diurnal cycle, decreasing during the day (beginning 1-2  
386 hours before the sunrise) and increasing at night (beginning 2-4 h before the sunset).  
387 Experimental measurements in a dry desert area showed that water vapor adsorption can  
388 increase the soil moisture in the uppermost 1-cm soil layer by 2% (Agam & Berliner, 2006).  
389 Therefore, we consider that the night-day LST differences were likely due to variations in soil  
390 moisture caused by water vapor adsorption. The different magnitude of the effect in WS and  
391 GS may be due to the different nature of the soils, and the higher altitude of the GS site where  
392 less atmospheric water vapor is available. However, further studies would be required  
393 including the analysis of LSE retrieval for other desert sites in combination with meteorological  
394 data, or dedicated field campaigns with meteorological, soil moisture and LSE measurements,  
395 which are out of the scope of the present paper.

### 396 5.3 Angular variation of emissivities

397

INSERT FIGURE 5

398 Figure 5 shows the MOD21 LSE variation with zenith angle for the three bands and the two  
399 sites selected. It shows that LSE for the three MODIS thermal bands was almost completely  
400 independent of the azimuthal orientation (West and East overpasses, see section 4). Table 3  
401 shows the absolute value of the average differences between West and East LSEs for the same

402 zenithal angle at both studied sites and for the two different MODIS time overpasses. Results  
403 showed that LSE could be considered independent of the azimuthal observation since the  
404 possible variation is lower than the corresponding uncertainty associated to all spectral bands  
405 and sensor overpass times (see Table 1).

406 INSERT TABLE 3

407 Regarding the zenithal dependence, LSE in MODIS bands 31 and 32 were nearly constant and  
408 independent of viewing angle and sensor overpass time. Table 4 shows the average LSE value  
409 and RSD for all zenithal angles of Figure 5 for MODIS bands 31 and 32 and both sites.  
410 Maximum difference between nadir and off-nadir LSE ( $\Delta\epsilon_{\theta}$ ) were also included. As observed in  
411 Table 2, possible angular variations of LSE in MODIS bands 31 and 32 over arid regions were  
412 smaller than the uncertainty associated to retrieved LSE values.

413 INSERT TABLE 4

414 However, results were different for MODIS band 29, in which the LSE dependence on viewing  
415 angle was significant both at night and day. Band 29 LSE retrieved from MOD21 decreased  
416 with  $\theta$  independently of the azimuthal orientation and the passing time of the sensor. LSE  
417 reached a maximum decrease, between values at  $\theta \leq 15^\circ$  and values at  $\theta \geq 50^\circ$ , of 0.030  
418 (nighttime) and 0.038 (day time) for WS, and 0.033 (nighttime) and 0.021 (daytime) for GS.  
419 Such decreases cannot be explained in terms of uncertainties and only the anisotropy  
420 associated to sandy soil emissivity (Labeled & Stoll, 1991; Cuenca & Sobrino, 2004; García-Santos  
421 et al., 2012) can be the reason.

#### 422 5.4 Validation of an emissivity anisotropy model

423 García-Santos et al. (2014) analyzed the variation of LSE with viewing angle ( $\theta$ ) and soil  
424 moisture (SM) using laboratory measurements taken with a multispectral thermal radiometer  
425 CIMEL Electronique CE-312 (Brogniez et al. 2003) at five different spectral bands within 8-14

426  $\mu\text{m}$ . García-Santos et al. (2014) also derived a polynomial expression of the relative-to-nadir  
427 LSE as a function of  $\theta$  and SM according to:

$$428 \quad \varepsilon_{ri}(SM, \theta) = a_i + b_i SM + c_i \theta + d_i SM^2 + e_i SM \theta + f_i \theta^2 \quad (14)$$

429 where  $\varepsilon_r$  is the relative-to-nadir emissivity,  $i$  is the spectral band, and coefficients  $a$ ,  $b$ ,  $c$ ,  $d$ ,  $e$   
430 and  $f$  are polynomials dependent on percentages of quartz (Q) and clay (C) content of the  
431 considered soil sample, following the expression:

$$432 \quad a_i(C, Q) = p_0 + p_1 C + p_2 Q + p_3 C^2 + p_4 C Q + p_5 Q^2 \quad (15)$$

433 Equation (15) also holds for coefficients  $b$  to  $f$ . Values and uncertainties of the regression  
434 coefficients  $a$ - $f$  and  $p_0$ - $p_5$  are tabulated in Garcia-Santos et al. (2014). SM data can be obtained  
435 twice a day and at spatial resolution of 40 km<sup>2</sup> using the measurements of the SMOS  
436 instrument (Soil Moisture and Ocean Salinity, Mecklenburg et al.,2012) with an uncertainty of  
437  $\pm 0.3 \text{ m}^3/\text{m}^3$  (units of volumetric SM). The zenithal angle is well established by the MODIS  
438 sensor. Finally, percentages of C and Q can be obtained from different techniques described in  
439 Singh and Kathpalia (2007) and Ninomiya and Fu (2001), respectively, with an uncertainty  
440 between 0.7 % and 0.18 %. We made a simple sensitivity analysis of the emissivity model to  
441 the uncertainties associated to the input data SM, C and Q. We calculated the difference  
442 between the LSE obtained through eqs. (14) and (15) considering the prescribed values of  
443 SM=0, C and Q (given in section 2 for both sites) and that obtained after increasing/decreasing  
444 these values by their corresponding uncertainties given above. Results showed an average LSE  
445 uncertainty of  $\pm 0.009$  for both sites.

446 The LSE anisotropy for MODIS band 29 observed in this study for the WS and GS deserts was  
447 compared to that predicted by Eqs. (14) and (15). Only results for daytime MODIS overpasses  
448 were used to assure dry soil conditions considering SM zero in Eq. (14), since analyzing hourly  
449 data from a weather station near to WS site no rainfall events were found coincident or close

450 to MODIS daytime overpasses. Moreover, no measured values of SM were available and SM  
451 data from SMOS was not considered since spatial resolution of SMOS ( $40 \text{ km}^2$ ) is much large  
452 than MODIS ( $1 \text{ km}^2$ ) and more important, there is about 3:30 h hour delay between MODIS  
453 and SMOS overpasses (SMOS daytime pass at 12:30-13:30 UTC and nighttime pass at 1:30-2:30  
454 UTC) in both areas. According to Hulley et al (2012a) the lifetime of soil moisture at the dune  
455 sites is most likely small due to large sensible heat fluxes, high evaporation rates, in addition to  
456 rapid infiltration. It is worth to note that WS was one of the 12 bare soil samples analyzed in  
457 García-Santos et al. (2014), so values of LSE at specific zenith angles were measured in  
458 laboratory conditions, and they can be used to validate MOD21 LSE values in WS.

459 Figure 6 shows MODIS band 29 LSEs for WS and GS, comparing MOD21 retrievals averaged for  
460 all the East and West orientations (since there was not azimuthal dependence on azimuthal  
461 observation according to Table 3) with the model-predicted LSE values, calculated by  
462 multiplying the most close-to-nadir MOD21 emissivity value (0.809 for WS and 0.909 for GS) by  
463 the values given by Eq. (14). WS emissivity values measured in García-Santos et al. (2014) for  
464 channel 5 ( $8.4\text{-}8.9 \mu\text{m}$ ) of the CE-312 instrument in the zenith angle range  $10^\circ\text{-}60^\circ$  (with a  $10^\circ$   
465 interval), were also included in Figure 6.

466 INSERT FIGURE 6.

467 Results from Figure 6 showed that LSE anisotropy predicted by Eqs. (14) and (15) (García-  
468 Santos et al.,2014) agreed with MOD21 retrievals, with an average bias between predicted and  
469 retrieved LSE of  $-0.003$  for WS and  $+0.005$  for GS and RMSE of  $\pm 0.009$  and  $\pm 0.010$  for WS and  
470 GS, respectively. Therefore Eqs. (14) and (15) are applicable to satellite data at the MODIS  
471 spatial resolution, at least for the WS and GS bare soils.

## 472 **6. CONCLUSIONS**

473 LST&E MOD21 will be part of the future MODIS collection 6 products. The TES algorithm was  
474 implemented together with the WVS method for use with the three MODIS thermal bands 29,  
475 31 and 32. MOD21 data were simulated over the WS and GS deserts to analyze the anisotropy  
476 of LSE. Results showed that LSE did not depend on the zenithal viewing angle for bands 31 and  
477 32 (11 and 12  $\mu\text{m}$ ). However, LSE decreased significantly with zenith angle for band 29 (8.55  
478  $\mu\text{m}$ ), reaching differences up to 0.038 from nadir values. LSE for band 29 showed a bias  
479 depending on the sensor time overpass, so for nighttime passes, band 29 LSE presented a  
480 value +0.027 (WS) and +0.008 (GS) greater than LSE for the respective daytime overpass,  
481 independently of the viewing angle. An explanation could be the increase of the soil moisture  
482 due to water vapor adsorption, and therefore the corresponding increase of LSE.

483 Nadir LSE values and observed zenithal variations retrieved from MOD21 measurements were  
484 compared with predicted values from an empirical model based on angular LSE measurements  
485 taken under field conditions. Results showed the validity of the proposed parameterization  
486 and its applicability to satellite data for a MODIS pixel resolution (1  $\text{km}^2$ ), since MOD21 LSE  
487 retrievals agreed with laboratory measurements.

488 The good agreement between laboratory LSE measurements and MOD21 LSE retrievals at  
489 different zenithal angles contributes to the validation of the forthcoming MOD21 LST&E  
490 product.

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## TABLES

Table 1. Maximum, minimum and average RSD values for both studied sites and MODIS overpass time at the three spectral bands 29 (8.4 - 8.7  $\mu\text{m}$ ), 31 (10.78 - 11.28  $\mu\text{m}$ ) and 32 (11.77 - 12.27  $\mu\text{m}$ ).

	White Sands			Great Sands		
	B29	B31	B32	B29	B31	B32
Maximum	$\pm 0.03$	$\pm 0.008$	$\pm 0.008$	$\pm 0.03$	$\pm 0.014$	$\pm 0.014$
Minimum	$\pm 0.006$	$\pm 0.0002$	$\pm 0.0002$	$\pm 0.009$	$\pm 0.0005$	$\pm 0.0005$
Average	$\pm 0.015$	$\pm 0.001$	$\pm 0.001$	$\pm 0.017$	$\pm 0.004$	$\pm 0.004$

Table 2. Difference between band-averaged emissivity from laboratory spectra and emissivity from the MOD21 algorithm for bands 29, 30 and 31 in both studied sites. Results are obtained for both day ( $\Delta\epsilon_d$ ) and night ( $\Delta\epsilon_n$ ) sensor overpass.

	White Sands		Great Sands	
	$\Delta\epsilon_d$	$\Delta\epsilon_n$	$\Delta\epsilon_d$	$\Delta\epsilon_n$
B29	-0.017	-0.044	-0.036	-0.044
B31	0.008	0.012	-0.011	-0.013
B32	0.007	0.008	-0.002	-0.005

Table 3. Absolute value of the average difference between West and East LSEs for the same zenithal angle. Results are shown for the three MODIS thermal bands in both sites and for the two different sensor time overpasses.

	White Sands		Great Sands	
	Daytime	Nighttime	Daytime	Nighttime
B29	0.007	0.008	0.005	0.007
B31	0.0007	0.0007	0.002	0.002
B32	0.001	0.0002	0.0003	0.0004

Table 4. Average emissivity value and RSD for all the zenithal angles and maximum difference between nadir and off-nadir ( $\Delta\epsilon_\theta$ ) of the LSE for the MODIS bands 31 and 32 in both selected sites.

	White Sands		Great Sands	
	B31	B32	B31	B32
Average	0.958	0.968	0.948	0.969
RSD	$\pm 0.001$	$\pm 0.0004$	$\pm 0.002$	$\pm 0.005$
$\Delta\epsilon_\theta$	0.003	0.001	0.001	0.002

### **List of Figure Captions**

**Figure 1.** Geo-located Google Earth images showing of the two selected sites a) White Sands and b) Great Sands. Pictures of the two sites at ground level are shown.

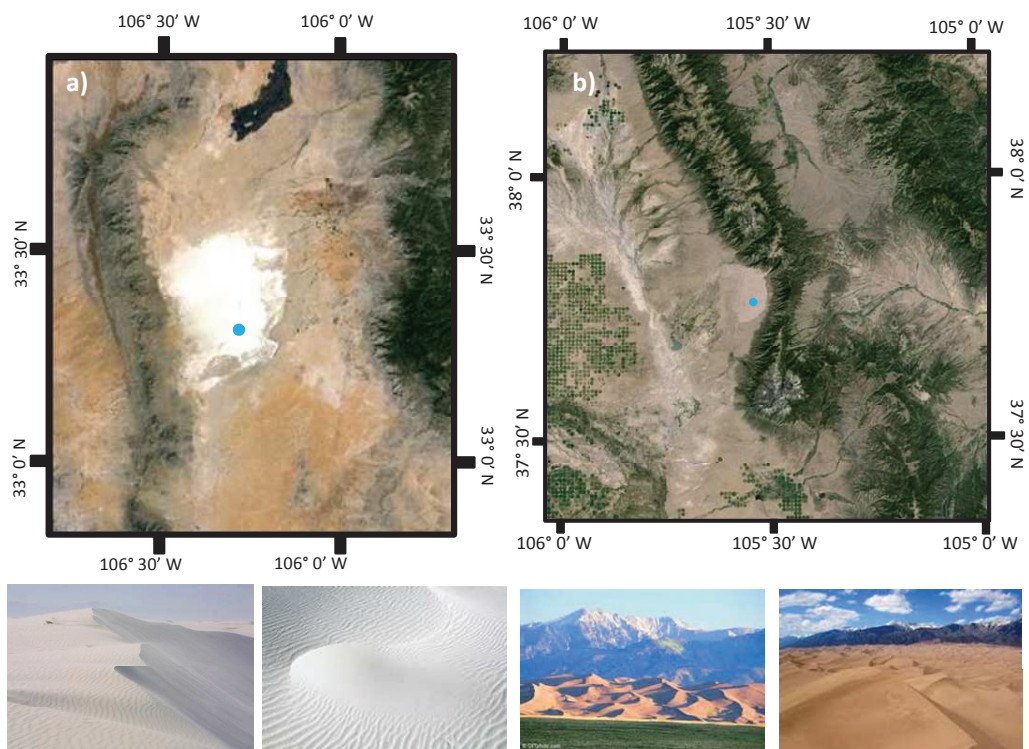
**Figure 2.** Maps of graybody pixels (in black), corresponding to water or vegetation, and bare soil pixels (in white) for a) White Sands and b) Great Sands sites. The border of the two deserts is outlined in green. The 50-km circumference centered on the selected coordinates (blue point) is shown in red.

**Figure 3.** Maps of LST&E from the MOD21 simulated algorithm for White Sands, DOY 68, 2010 (left) and Great Sands, DOY 259, 2012 (right). The desert area is outlined and the 4 pixels used to obtain the LST&E are delimited by a blue square in both sites.

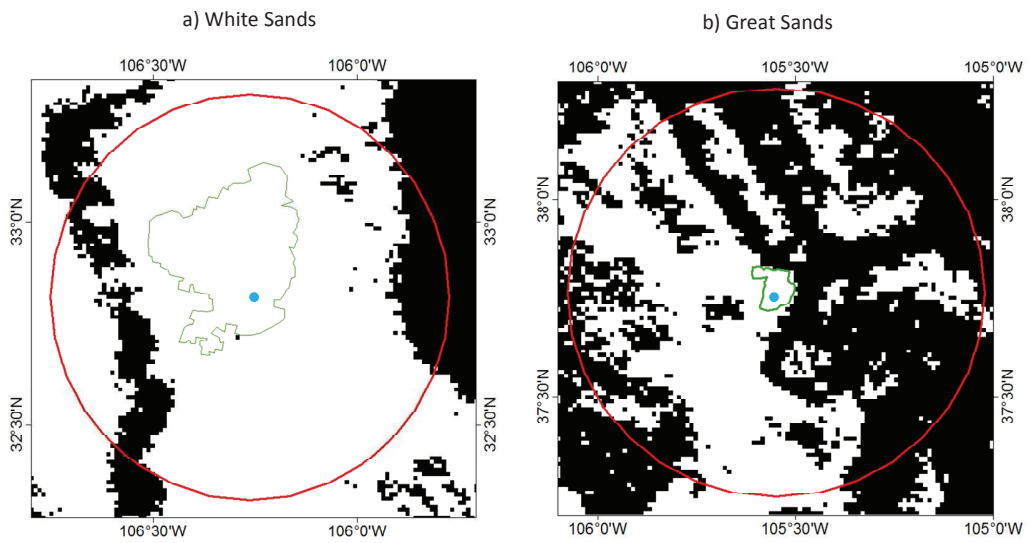
**Figure 4.** Comparison of MOD21 simulated LSE retrievals at near-nadir ( $2^{\circ}$ - $16^{\circ}$ ) for White Sands and Great Sands for day time (WS\_MOD21\_day and GS\_MOD21\_day) and nighttime (WS\_MOD21\_night and GS\_MOD21\_night) overpasses, with laboratory emissivity values for both sites (Hulley, personal communication) averaged to MODIS bands 29, 31 and 32. Uncertainties associated to MOD 21 LSEs were the average RSDs and uncertainties for the laboratory emissivity were provided by Dr. Hulley.

**Figure 5.** Zenithal variation of emissivity estimates from MODIS thermal bands over a) White Sands and b) Great Sand. Positive (negative) zenith angles correspond to East (West) azimuth angles. RSDs (see section 4) for each zenithal LSE value are shown as uncertainty bars.

**Figure 6.** Comparison of MOD21 LSE in band 29 for White Sands and Great Sands with predicted values calculated from Eqs. (14) and (15). Field emissivity measurements for a White Sands sample are also included.

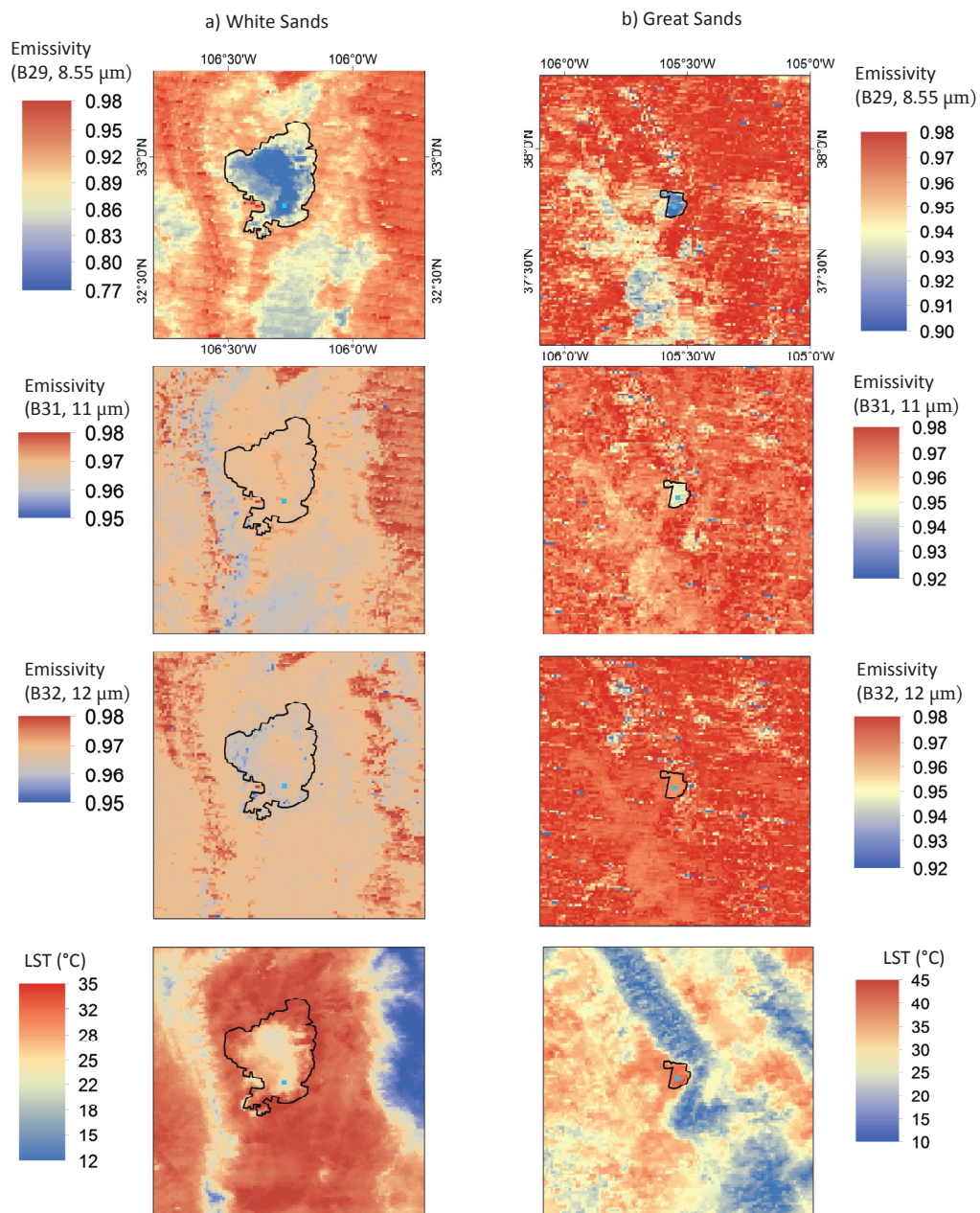


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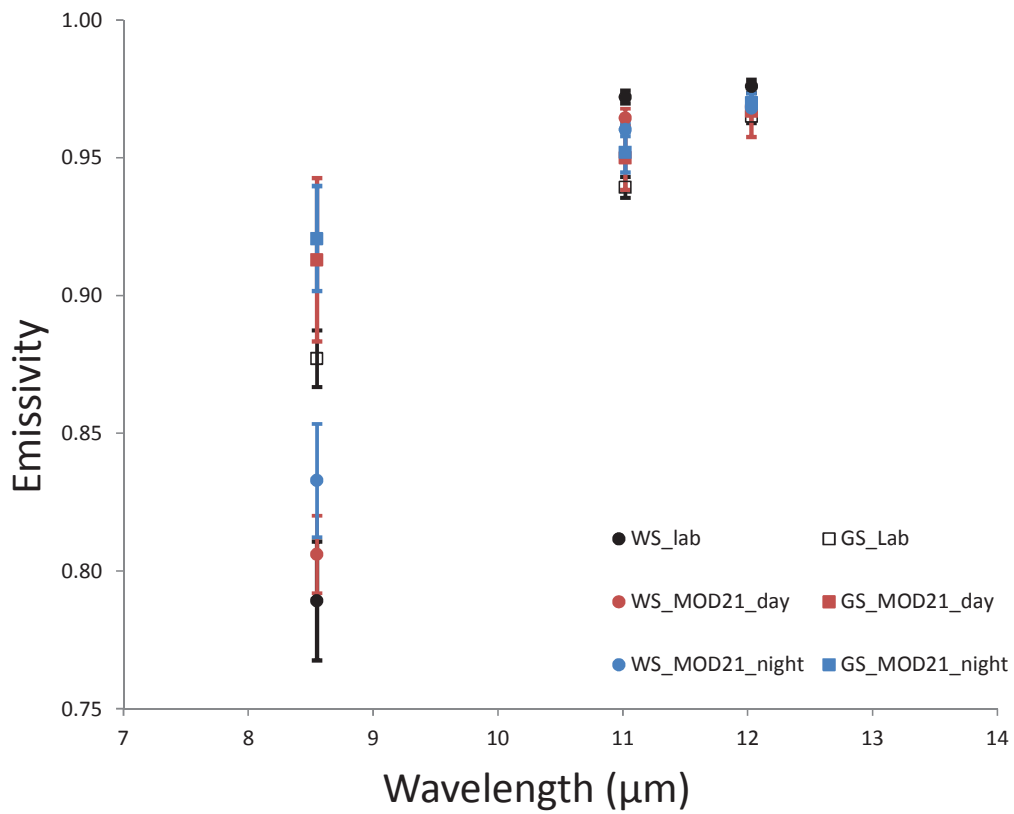


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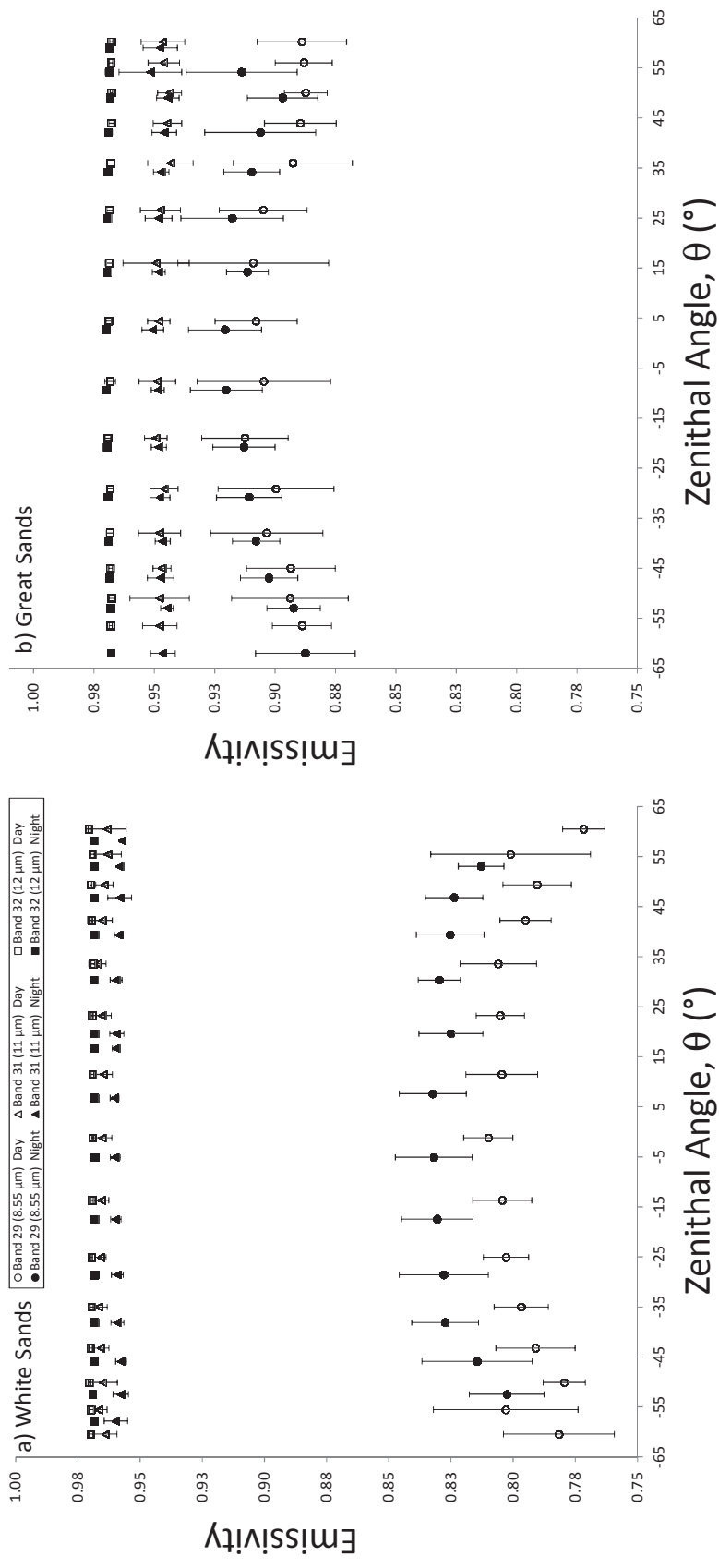


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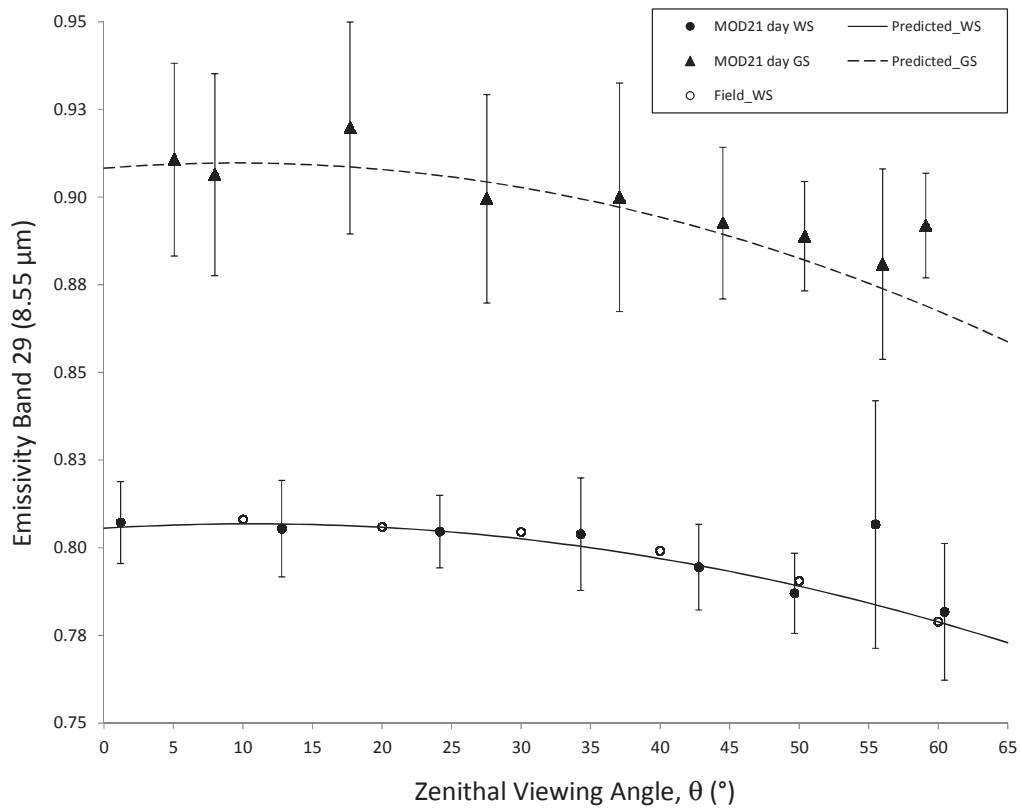


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