

## P8.10 SEASONAL SURFACE SPECTRAL EMISSIVITY DERIVED FROM TERRA MODIS DATA

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### 1. INTRODUCTION

Surface emissivity is essential for many remote-sensing applications including the derivation of surface skin temperature from satellite-based infrared measurements, the determination of cloud detection thresholds, and the estimation of the surface longwave radiation emission, an important component of the energy budget of the surface-atmosphere interface. Brightness temperature differences, BTD, between 3.7 and 11.0- $\mu\text{m}$  observations are often indicative of the presence or absence of clouds. For clear scenes, the BTD is due to differences in atmospheric absorption and in surface emissivity  $\varepsilon$  between the two channels. Cloud phase, optical depth, and particle size further affect the BTD in cloudy scenes. Retrieval of cloud phase and effective particle size often relies on the value of BTD, which for optically thin clouds is affected by the surface emission and, at 3.7 $\mu\text{m}$ , the surface reflectance. Thus, the accuracy of cloud detection and particle size retrievals depends on the accuracy of the surface emissivity. The CERES (Clouds and the Earth's Radiant Energy System; see Wielicki et al., 1998) Project is measuring broadband shortwave and longwave radiances and deriving cloud properties from various images to produce a combined global radiation and cloud property data set. In this paper, simultaneous data from *Terra* MODIS (Moderate Resolution Imaging Spectroradiometer) taken at 3.7, 8.5, 11.0, and 12.0  $\mu\text{m}$  are used to derive the skin temperature and the surface emissivities at the same wavelengths. The methodology uses separate measurements of clear sky temperature in each channel determined by scene classification during the daytime and at night. The relationships between the various channels at night are used during the day when solar reflectance affects the 3.7- $\mu\text{m}$  radiances. A set of simultaneous equations is then solved to derive the emissivities. Global monthly emissivity maps are derived from *Terra* MODIS data while numerical weather analyses provide soundings for correcting the observed radiances for atmospheric absorption. These maps are used by CERES and other cloud retrieval algorithms.

### 2. DATA

*Terra* MODIS data taken during July and October 2002 and January and April 2003 were analyzed with the CERES cloud processing algorithms (e.g., Minnis et al. 2003). Each MODIS pixel is classified as either clear or cloudy using the latest update of the CERES method to obtain the clear-sky top-of-the-atmosphere (TOA) brightness temperatures  $T_i$  at 3.7, 10.8, 12.0, and 8.5  $\mu\text{m}$ , denoted channels  $i = 3, 4, 5,$  and 6, respectively. MODIS data have a nominal resolution of 1 km but are sampled at every 2 km for CERES. It is assumed that the scene classification by the method mentioned above is correct for all pixels and, therefore, the temperatures are uncontaminated by clouds. However, that is not always the case and some filtering is required. European Center Medium Range Weather Forecast (ECMWF) analyses provided every 6 hours at a resolution of 1° latitude and longitude were used to specify vertical profiles of atmospheric temperature, humidity, and ozone as well as initial values of surface skin temperature. Linear interpolation was used to match the soundings to the satellite observation times. Standard atmospheric values were used for profiles of other absorbing gases such as  $\text{NO}_2$  and  $\text{CH}_4$ .

### 3. METHODOLOGY

The basic approach solves a set of simultaneous equations to obtain surface emissivity. The method uses observations from both daytime and nighttime over the same area.

The relationship between the TOA and surface radiances can be approximated as

$$B(T_i) = \varepsilon_{ai}B(T_a) + (1-\varepsilon_{ai})B(T_{si}) \quad (1)$$

where  $B$  is the Planck function,  $\varepsilon_a$  and  $T_a$  are the effective atmospheric emissivity and effective atmospheric temperature, respectively. The radiance for  $T_{si}$ , the apparent skin radiating temperature, is determined using the correlated  $k$ -distribution method (Kratz 1995) with the atmospheric profiles to remove the molecular absorption. The  $k$ -distribution technique is used to compute the upwelling radiation at each ECMWF layer over the entire band pass of the channel using the appropriate filter function for the particular satellite imager channel. In the absence of solar radiation, the radiation balance at

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surface is

$$B_{\lambda}(T_{sl}) = \varepsilon_i B_{\lambda}(T_{skin}) \quad (2)$$

where  $T_{skin}$  is the skin temperature and  $T_{sl}$  is the effective radiating temperature of the surface. For simplicity, it assumed that  $\varepsilon_i$  does not depend on the viewing zenith angle, VZA. At night, the skin temperature can be expressed as

$$T_{skin} = B_i^{-1}[B_{\lambda}(T_{sl}) / \varepsilon_i] \quad (3)$$

where  $B_i^{-1}$  is the inverse Planck function. If the skin temperature is known, the emissivity can be solved for the remaining channels, e.g.,

$$\varepsilon_3 = [B_3(T_{s3})] / [B_3(T_{skin})] \quad (4)$$

Both  $T_{s3}$  and  $T_{s4}$  can be derived at night using (2) and the emissivity ratio,

$$\varepsilon_3' = \varepsilon_3 / \varepsilon_4 = [B_3(T_{s3})] / [B_3(T_{s4})] \quad (5)$$

can then be computed. If it is assumed that this ratio is a constant for a given surface, then the value of  $\varepsilon_3$  can be determined from data taken during the daytime. During the daytime, the apparent channel-3 surface temperature is

$$B_3(T_{s3}) = \varepsilon_3 [B_3(T_{skin})] + \alpha_3 \chi S_3' \quad (6)$$

where  $\chi$  is the anisotropic correction factor,  $\alpha_3$  is the surface albedo, and  $S_3'$  the solar radiation at the surface, is computed from the Earth-sun distance and solar-zenith-angle corrected solar constant attenuated by atmospheric absorption using the  $k$ -distribution method. Using Kirchoff's law,

$$\alpha_3 = (1 - \varepsilon_3). \quad (7)$$

Using (4), (5), and (7) to substitute for the emitted component and for the albedo on the right hand side of (6) and rearranging gives

$$\varepsilon_3 = 1 - \{B_3(T_{s3}) - \varepsilon_3' [B_3(T_{s4})]\} / \chi S_3' \quad (8)$$

Thus, (8) can be used to estimate  $\varepsilon_3$ . The absorption coefficients used for the thermal component are applied to the observed 3.7- $\mu\text{m}$  radiance to obtain  $B_3(T_{s3})$ . Although the atmospheric attenuation of the upwelling solar and emitted 3.7- $\mu\text{m}$  radiances is slightly different for each component, the differences should have a negligible impact on the result. Knowing  $\varepsilon_3$ ,  $T_{skin}$  can easily be solved from (6). Then,  $\varepsilon_4$ ,  $\varepsilon_5$  and  $\varepsilon_6$  are computed from (3).

This technique was tested theoretically using 3 different surface types with  $\varepsilon_3$  ranging from 0.73 to 0.97 and  $\varepsilon_4$  ranging from 0.93 to 0.99 using 91 soundings to represent a large range of atmospheric conditions. Previously, International Satellite Cloud Climatology

Project (Rossow and Schiffer, 1999) Advanced Very High Resolution Radiometer (AVHRR) data taken during 1986 and *Terra* MODIS data from April 2001 were processed using the same method described above to obtain channel 3, 4, and 5 emissivity maps (Chen et al. 2001, 2002). The resulting values of  $\varepsilon_3$  from the data were within 1% of the original value for all of the cases with the largest errors occurring for some desert (0.73) areas. RMS errors as large as 3% were found for  $\varepsilon_4$  with the greatest errors occurring over deserts. The values of  $T_3$  from daytime AVHRR data were often saturated over desert areas due to high afternoon skin temperatures and highly reflective surfaces, the source of the large errors over deserts. The mean errors were all negligible. The theoretical calculations assumed an isotropic surface reflectance and no VZA dependence of  $\varepsilon$ .

The *Terra* MODIS data were analyzed by computing  $\varepsilon_3'$  for each clear nighttime pixel and averaging the results within every 10' latitude-longitude box for a given orbit. A mean value of  $\varepsilon_3'$  was computed for each region and used to derive  $\varepsilon_3$ ,  $\varepsilon_4$ ,  $\varepsilon_5$ , and  $\varepsilon_6$ , from the daytime data to obtain mean values and standard deviations for each region. The values of  $\chi$  used in (8) were taken from the same models used by Trepte et al. (1999). Those models are generally applicable to visible or broadband solar channels. Averages were also computed for each IGBP surface type (Table 1) and used to fill in the results for regions with no data. These averages were only computed after filtering the regional results for unrealistic points that can arise due to poor representation of the actual temperature and humidity profiles by the ECMWF reanalysis, the presence of aerosols, or cloud contamination. The filters were developed from histograms of  $\varepsilon$  for each wavelength and IGBP type. Upper (1.0) and lower thresholds were set for each IGBP type and wavelength. *Terra* MODIS data from the 4 months in 2002 and 2003 were processed in this manner.

#### 4. RESULTS

Figures 1-4 show the distributions of  $\varepsilon_3$  derived from July and October 2002 and January and April 2003, respectively. The lowest values, between 0.68 and 0.75, occur over deserts, particularly in the western Sahara, the Empty Quarter of the Arabian Peninsula, and the Takliman

Table 1. IGBP surface type.

|                                  |                        |
|----------------------------------|------------------------|
| 1. evergreen needleleaf          | 2. evergreen broadleaf |
| 3. deciduous needleleaf          | 4. deciduous broadleaf |
| 5. mixed forests                 | 6. closed shrublands   |
| 7. open shrubland                | 8. woody savannas      |
| 9. savannah                      | 10. grasslands         |
| 11. permanent wetlands           | 12. croplands          |
| 13. urban                        | 14. mosaic             |
| 15. snow/ice                     | 16. desert             |
| 17. water                        | 18. tundra             |
| 19. coastline = 10% to 90% water |                        |

Table 2. Mean  $\epsilon_3$  for Northern Hemisphere.

| IGBP | Jan 2003 | Apr 2003 | Jul 2002 | Oct 2002 |
|------|----------|----------|----------|----------|
| 1    | 0.97     | 0.97     | 0.94     | 0.96     |
| 2    | 0.93     | 0.91     | 0.91     | 0.91     |
| 3    | 0.98     | 0.97     | 0.95     | 0.96     |
| 4    | 0.96     | 0.95     | 0.93     | 0.95     |
| 5    | 0.97     | 0.97     | 0.94     | 0.96     |
| 6    | 0.92     | 0.93     | 0.90     | 0.92     |
| 7    | 0.89     | 0.90     | 0.86     | 0.89     |
| 8    | 0.94     | 0.94     | 0.92     | 0.94     |
| 9    | 0.86     | 0.80     | 0.84     | 0.88     |
| 10   | 0.92     | 0.89     | 0.87     | 0.89     |
| 11   | 0.97     | 0.98     | 0.94     | 0.96     |
| 12   | 0.94     | 0.91     | 0.89     | 0.91     |
| 13   | 0.93     | 0.90     | 0.88     | 0.91     |
| 14   | 0.94     | 0.92     | 0.90     | 0.92     |
| 15   | 0.98     | 0.98     | 0.97     | 0.98     |
| 16   | 0.79     | 0.78     | 0.76     | 0.77     |
| 17   | 0.96     | 0.96     | 0.96     | 0.95     |
| 18   | 0.95     | 0.98     | 0.92     | 0.96     |
| 19   | 0.95     | 0.96     | 0.94     | 0.95     |

Desert in northwestern China. In heavily vegetated areas,  $\epsilon_3$  is generally greater than 0.90 with smaller values during Desert in northwestern China. In heavily vegetated areas, the peak growing seasons. The emissivity decreases to values between 0.85 and 0.90 in semiarid regions and to less than 0.85 in drier regions. It is generally greater than 0.95 in wet, coniferous areas and areas with dormant deciduous trees and snow cover.

The mean values of  $\epsilon_3$  for each of the IGBP types in the Northern Hemisphere are summarized in Table 2. The greatest seasonal variations occur in the lightly vegetated savannahs, grasslands, shrublands, and deserts. The most barren deserts like the Sahara do not show much seasonal variation. Some of the IGBP types, like tundra and deciduous needleleaf forests, are not well sampled and are not reliable especially during winter months. The ocean and snow categories are probably cloud contaminated and are not used for CERES. Instead, theoretical models are used for water, snow, and ice surfaces. The water surface model is based on the emissivities developed by Masuda et al. (1988). The snow-ice theoretical emissivity model is based on adding-doubling radiative transfer calculations that assume the snow can be represented as an ice cloud with an optical depth of 100 consisting of a hexagonal ice column with an aspect ratio of  $750 \mu\text{m} / 300 \mu\text{m}$ .

The mean October 2002 emissivities for each channel and IGBP type data in northern hemisphere are summarized in Table 3. The values for  $\epsilon_4$  and  $\epsilon_5$  are generally greater than their  $\epsilon_3$  counterparts, while the  $\epsilon_6$  values are between those for  $\epsilon_3$  and  $\epsilon_4$ .

To assess the results, the TOA channel-3 brightness temperatures were calculated from *Terra* MODIS October 2002 data using the emissivity maps generated from the above method (method1) and the MODIS Land Surface

Table 3. Mean  $\epsilon_3$ ,  $\epsilon_4$ ,  $\epsilon_5$ , and  $\epsilon_6$  for Northern Hemisphere

| IGBP | 3.7 $\mu\text{m}$ | 11.0 $\mu\text{m}$ | 12.0 $\mu\text{m}$ | 8.5 $\mu\text{m}$ |
|------|-------------------|--------------------|--------------------|-------------------|
| 1    | 0.96              | 0.99               | 0.99               | 0.92              |
| 2    | 0.91              | 0.98               | 0.96               | 0.95              |
| 3    | 0.96              | 0.99               | 0.99               | 0.92              |
| 4    | 0.95              | 0.99               | 0.99               | 0.94              |
| 5    | 0.96              | 0.99               | 0.99               | 0.94              |
| 6    | 0.92              | 0.98               | 0.98               | 0.91              |
| 7    | 0.89              | 0.97               | 0.98               | 0.90              |
| 8    | 0.94              | 0.99               | 0.98               | 0.93              |
| 9    | 0.88              | 0.97               | 0.96               | 0.94              |
| 10   | 0.89              | 0.97               | 0.97               | 0.92              |
| 11   | 0.96              | 0.99               | 0.99               | 0.90              |
| 12   | 0.91              | 0.97               | 0.98               | 0.94              |
| 13   | 0.91              | 0.97               | 0.97               | 0.93              |
| 14   | 0.92              | 0.98               | 0.98               | 0.94              |
| 15   | 0.98              | 0.99               | 0.99               | 0.91              |
| 16   | 0.77              | 0.93               | 0.95               | 0.82              |
| 17   | 0.95              | 0.99               | 0.98               | 0.94              |
| 18   | 0.96              | 0.99               | 0.99               | 0.90              |
| 19   | 0.95              | 0.99               | 0.98               | 0.92              |

Temperature Group (method2; see Ma et al., 2002), the observed values of  $T_4$ , and the ECMWF profiles. First, the skin temperature is derived from the observed  $T_4$ , the ECMWF profiles, and  $\epsilon_4$ . Then,  $T_3$  is computed using the skin temperature,  $\epsilon_3$ , the ECMWF profiles, and the bidirectional reflectance models. Differences between the predicted and observed values of  $T_3$  are summarized in Tables 4 and 5. Except for snow and urban surfaces, the mean daytime errors range from  $-0.5$  to  $-1.8$  K for method1 and from  $-4$  to  $0.5$  K for method2. The standard deviations vary between 3.1 and 4.6 K for method1 and between 3.5 and 5.5 K for method2. At night, the standard deviations range between 2 and 4 K from both methods. Excluding IGBP types 2 and 13, method2 yields smaller biases than method1 at night with a range of  $-0.8$  to  $1.6$  K compared with  $-2.2$  to  $0.3$  K. The sparse sampling of type 13 and the great potential for cloud contamination for broadleaf evergreen forests may contribute to the larger biases for type 2 surfaces. The day-night bias differences may also be due to changes in the surface moisture (e.g., dew or ground fog; Minnis et al., 1998) between the two measurement times. Considering both the day and night differences, both methods produce comparable results.

Other factors, besides cloud contamination and soil moisture changes, that can produce errors in the emissivity retrievals include the use of the broadband bidirectional reflectance models for the  $3.7\text{-}\mu\text{m}$  reflectance anisotropy, the possibility of a viewing zenith angle dependence of surface emissivity, errors in the temperature and humidity profiles, and inhomogeneities in the boxes used to average the values. Currently, no empirical or theoretical  $3.7\text{-}\mu\text{m}$  anisotropic reflectance models are available for vegetated surfaces. Without such models, it will not be possible to minimize the impact of anisotropy on the retrieval. Simultaneous dual-angle views from different satellites could be used to estimate

Table 4.  $T_3$  errors using  $\varepsilon_3$  for October 2002, daytime

| IGBP | $\Delta T$ (K) |      |              |      |
|------|----------------|------|--------------|------|
|      | from method1   |      | from method2 |      |
|      | mean           | std  | mean         | std  |
| 1    | -0.83          | 4.04 | 0.12         | 4.30 |
| 2    | -1.76          | 4.22 | -3.99        | 5.23 |
| 3    | -1.40          | 3.11 | 0.12         | 3.43 |
| 4    | -1.23          | 4.24 | -0.78        | 5.00 |
| 5    | -0.99          | 3.87 | 0.46         | 4.36 |
| 6    | -1.79          | 4.16 | -2.98        | 5.50 |
| 7    | -0.75          | 3.79 | -2.67        | 4.42 |
| 8    | -1.30          | 4.27 | -2.33        | 5.40 |
| 9    | -1.67          | 3.95 | -4.59        | 4.96 |
| 10   | -1.03          | 4.62 | -2.45        | 5.29 |
| 11   | -0.53          | 3.18 | 0.35         | 3.53 |
| 12   | -1.20          | 3.89 | -2.69        | 4.69 |
| 13   | -2.06          | 3.80 | -2.94        | 4.41 |
| 14   | -1.37          | 4.22 | -2.41        | 5.14 |
| 15   | -3.29          | 6.26 | -3.18        | 6.26 |
| 16   | -0.75          | 3.09 | -4.09        | 3.68 |
| 17   | 0.02           | 3.24 | 0.03         | 3.25 |
| 18   | 0.09           | 3.57 | 0.92         | 3.91 |
| 19   | -0.01          | 5.13 | 0.26         | 5.39 |

Table 5.  $T_3$  errors using  $\varepsilon_3$  for October 2002, nighttime

| IGBP | $\Delta T$ (K) |      |              |      |
|------|----------------|------|--------------|------|
|      | from method1   |      | from method2 |      |
|      | mean           | std  | mean         | std  |
| 1    | -0.88          | 3.12 | 0.08         | 3.24 |
| 2    | -3.52          | 4.33 | -2.61        | 4.76 |
| 3    | 0.27           | 2.33 | 1.63         | 2.40 |
| 4    | -1.49          | 3.54 | -0.54        | 3.73 |
| 5    | -1.16          | 3.31 | -0.24        | 3.45 |
| 6    | -1.74          | 3.74 | -0.28        | 3.84 |
| 7    | -0.61          | 3.13 | 0.27         | 3.17 |
| 8    | -1.35          | 3.79 | -0.27        | 4.06 |
| 9    | -2.18          | 3.61 | -0.80        | 3.91 |
| 10   | -1.26          | 3.47 | -0.26        | 3.54 |
| 11   | 0.24           | 2.97 | 1.44         | 3.08 |
| 12   | -1.55          | 3.18 | -0.56        | 3.36 |
| 13   | -2.34          | 2.97 | -1.27        | 3.02 |
| 14   | -1.82          | 3.49 | -0.87        | 3.70 |
| 15   | -0.66          | 3.52 | -0.43        | 3.54 |
| 16   | -0.86          | 2.84 | -0.08        | 2.83 |
| 17   | -0.25          | 2.35 | -0.24        | 2.35 |
| 18   | 0.71           | 3.06 | 1.87         | 3.07 |
| 19   | -0.84          | 3.80 | -0.28        | 3.89 |

the viewing zenith angle impact on the surface emissivity while higher spatial resolution data, like that used by Ma et al. (2002) can minimize the impact of spatial inhomogeneities. Given that the bias and standard deviations of the predicted  $T_3$  are relatively small over deserts, it is likely that the atmospheric correction and surface moisture could have greatest impact on surface emissivity retrievals. Thus, properly accounting for those impacts is more challenging, especially in moist regions.

## 5. CONCLUDING REMARKS

Compared to more sophisticated multi-spectral approaches, the results of the simple method applied here yields reasonable daytime and nighttime predictions of  $T_3$  for the MODIS data that were used in the determination of the emissivities. The current method explored is relatively simple and can be applied to most current operational satellite imager data. Although the results from this technique are currently being used to successfully predict clear-sky radiances for CERES cloud retrievals, there is still much room for improvement. Thus, the factors affecting the retrievals will be explored in the future to enhance the accuracy of the surface emissivity retrievals.

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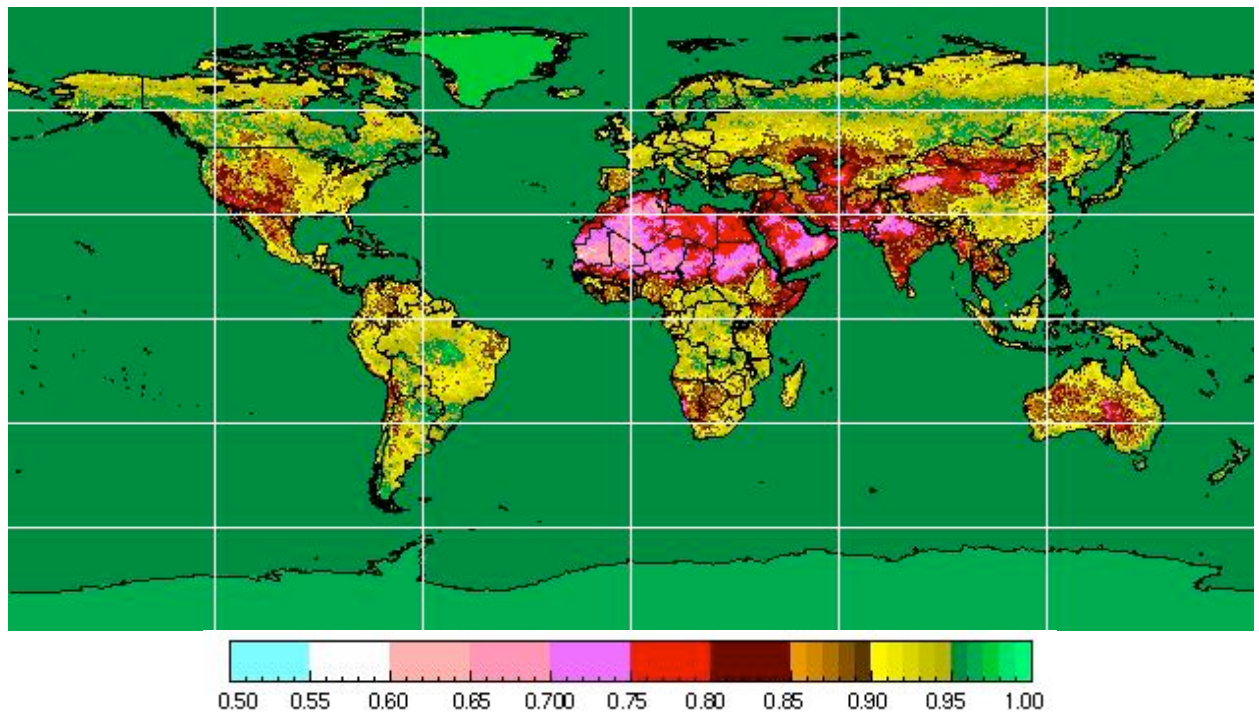


Fig. 1. Mean 3.7- $\mu$ m surface emissivities derived from Terra MODIS data, July 2002.

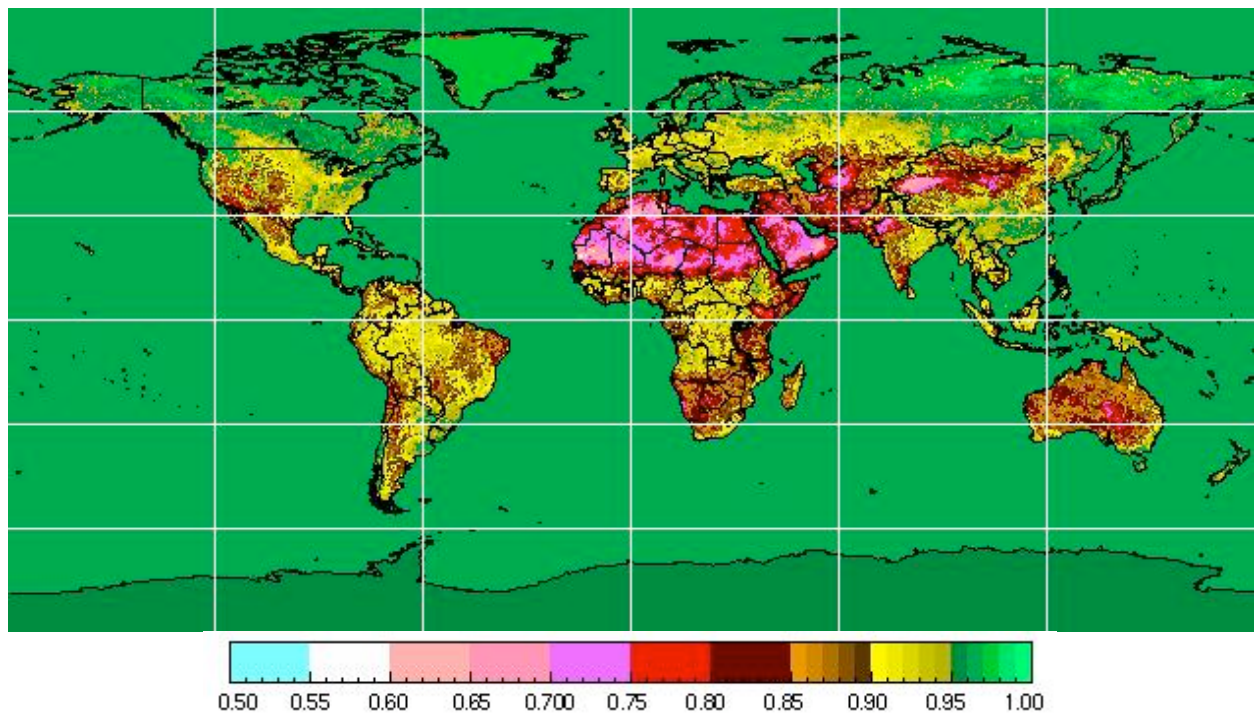


Fig. 2. Mean 3.7- $\mu$ m surface emissivities derived from Terra MODIS data, October 2002.

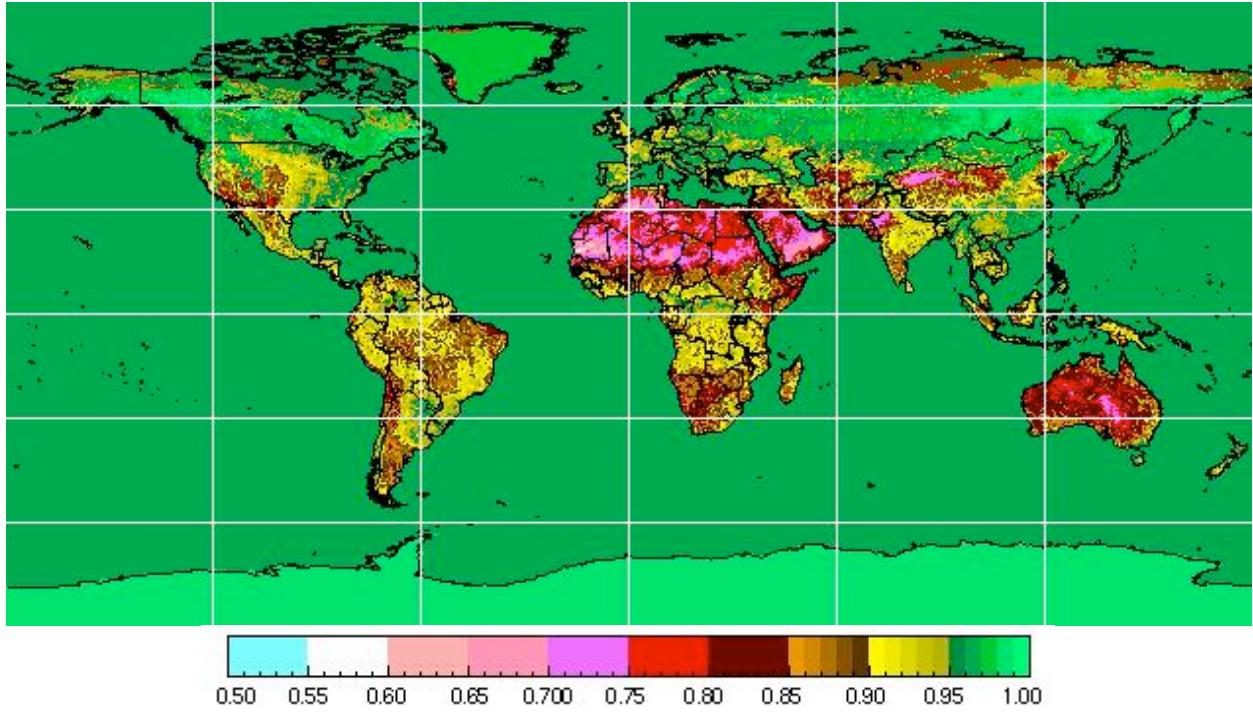


Fig. 3. Mean 3.7- $\mu\text{m}$  surface emissivities derived from Terra MODIS data, January 2003.

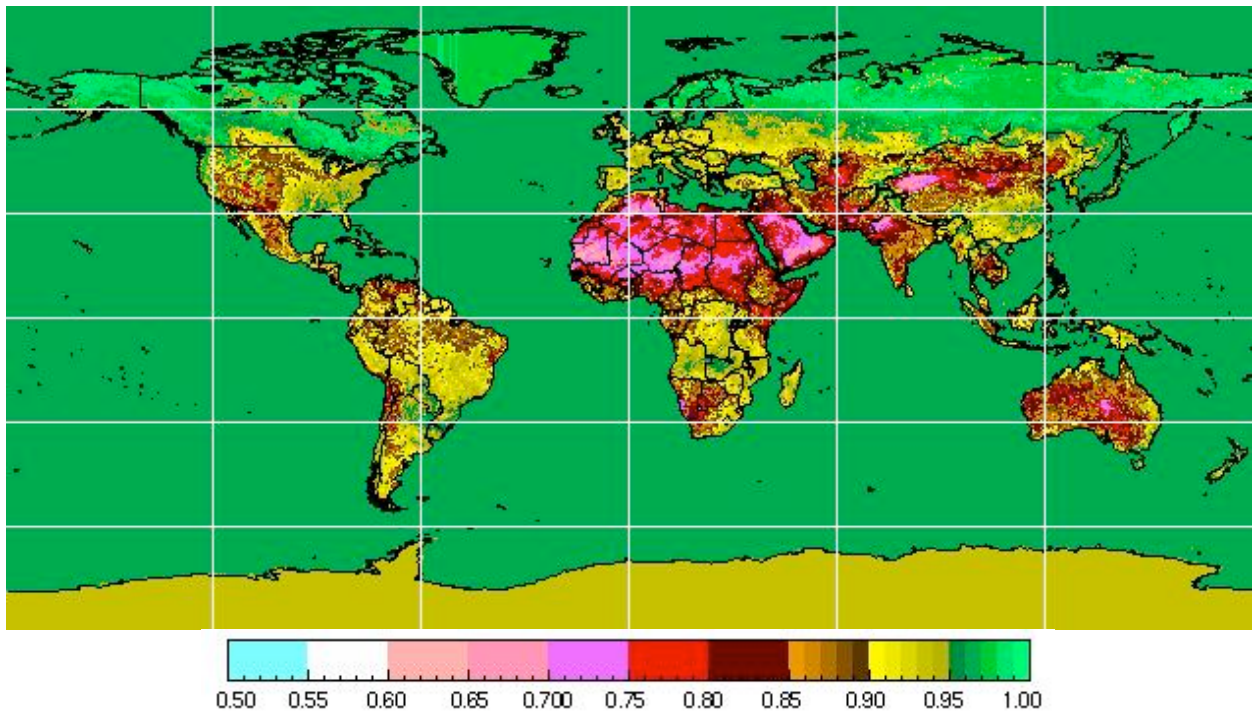


Fig. 4. Mean 3.7- $\mu\text{m}$  surface emissivities derived from Terra MODIS data, April 2003.