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SATELLITE RETRIEVAL OF LAND SURFACE TEMPERATURE: CHALLENGES AND OPPORTUNITIES

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ABSTRACT

Land surface temperature (LST) is a key climatological variable that provides an estimate of energy available at the earth's surface. The National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) has measured the earth's brightness temperature, a function of LST, at moderate resolution (1.1- to 4.4. km) on a daily basis for nearly three decades. These data may potentially reveal LST trends related to climate change, however significant challenges must be overcome in developing the needed data set. For example, NOAA-AVHRR orbit and sensor characteristics impart temporal and spatial artifacts that impair product accuracy, especially in a long-term time series or Climate Data Record (CDR). In this article, we describe the main challenges in developing an accurate, temporally-normalized LST CDR from AVHRR. We especially consider the issues of global emissivity variability and its uncertainty, and introduce an emissivity data set in development that addresses these issues.

1. INTRODUCTION

Detecting climate change, understanding and attributing change to specific climate processes, and projecting climate impacts on the Earth system requires, among other capabilities, a long-term (many decades), consistent and comprehensive data series. Indeed, many climate trends are small and can only be distinguished from short-term variability through careful analysis of such Climate Data Records (CDRs). The National Research Council offered a more formal definition of a CDR, i.e., a "time series of measurements of sufficient length, consistency, and continuity to determine climate variability and change" (NRC, 2004).

Land surface temperature (LST) provides insight into the biophysical processes which govern the balances of water and energy at the land surface, as well as variability and trends in the Earth System. The Global Climate Observing System (GCOS; 2003) identified LST as an essential supporting variable for land surface analysis, and the US Climate Change Science Program (CCSP; 2006) lists longwave surface energy budget (derived from LST) as one of its key external or feedback observations.

In this article, we identify research issues for developing a multi-decadal LST CDR suitable for climate change analyses.

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2. AVHRR

Development of a moderate resolution LST CDR can perhaps best be accomplished from the succession of NOAA polar orbiting satellites carrying the AVHRR (1981- to present). In addition to providing continuous observations with highly similar sensors, this afternoon-orbit series overlaps the more advanced NASA Aqua MODIS (2002- to present) sensor and will partially overlap the future VIIRS (expected service from 2010- to ~2026). Such overlap allows extensive opportunities for both cross-sensor validation and near-seamless time-series continuity beyond the AVHRR lifetime. Indeed, the VIIRS has very similar thermal infrared bandpasses to AVHRR.

2.1 *Sensor Characteristics Affecting CDR Quality*

AVHRR is a cross-track scanning system onboard the NOAA sun synchronous satellites. The overpass time (nominally 1330 h equator crossing) corresponds to a period where surface temperatures are both close to their daily peaks and are more temporally stable – desirable characteristics for climate science research, measurement signal-to-noise behavior, and observation stability.

One of the greatest challenges in LST estimation is atmospheric correction. Given the water vapor continuum in thermal portion of the spectrum, the relatively wide bandpass AVHRR measurements (compared to the more contemporary MODIS) are more vulnerable to atmospheric contamination. Further, each AVHRR in the series has slightly different spectral response functions. The differences require that algorithm and ancillary database (e.g., emissivity) development be unique but consistent for the respective sensors.

3. DEVELOPING AN AVHRR CDR ALGORITHM

A CDR algorithm must work well with all instruments in the multisensor time series, must be accurate and robust over all global environmental conditions, and must be computationally efficient. Although several LST algorithm types exist (Hook et al., 2006), the split window approach is most commonly used with AVHRR given the sensor's limited thermal bandset. With split window algorithms, the radiative transfer effects in the infrared are linearized as a function of measurements in two or more infrared bands, observation sampling geometries and (generally) surface emissivity. Split window approaches require prior information about surface emissivity. Yu et al. (2008) recently intercompared many commonly-used algorithms for potential use in CDR generation.

3.1 *Key Challenges*

Several factors must be addressed in developing an AVHRR CDR algorithm, including water vapor correction, emissivity correction, consistent upstream processing (calibration, geolocation and cloud clearing), temporal variability, and sun-view variability. Below, we focus on three that are among the most challenging: 1) temporal normalization of measurements, 2) angular normalization of measurements, and 3) 1) global emissivity data and their development.

3.2 *Temporal normalization*

A particular challenge with AVHRR data is caused by the drift of the satellite platforms to later equatorial crossing times (from 1330 to >1630 h). The drift causes systematic biases in both shortwave and thermal IR measurements (Privette et al., 1994). This drift is particularly troublesome for LST, since its impacts may incorrectly suggest large-scale surface cooling during the lifetime of a given sensor. AVHRR thermal data suffer from a second time-related bias since each swath spans about 2 hours in local observation time for scans near the equator (this time difference increases with latitude). Assuming a typical earth diurnal temperature cycle, locations across a scene are therefore sampled at different points on the diurnal cycle.

Multiple correction approaches (Gutman, 1999; Jin and Treadon, 2003) have been proposed to address the orbital drift effect. For example, Susskind et al. (1997) recently described a Fourier Series correction developed by fitting sounder-derived LST vs. time-of-day for all NOAA polar orbiting satellites. The resulting functions can then used to adjust AVHRR LST retrievals from drifted satellites to a fixed time of day (e.g., 1330; see Pinheiro et al., 2006b, for details). Each of these methods requires assumptions which tend to be violated on a per-pixel basis. To date, the different methods for temporal correction have not been compared, however this step is critical if surface temperature climatic trends are to be detected. Temporal correction is also required for proper co-calibration with MODIS and VIIRS, and the overlapping periods of AVHRR with these sensors provides an excellent opportunity for testing time-normalization schemes since the resulting LST estimates can be compared with the non-drifted MODIS or VIIRS observations

3.3 *Angular-normalization*

Recently, Pinheiro et al. (2004) revealed significant directional effects (angular anisotropy) in AVHRR-derived LST products. Contrary to emissivity microscopic anisotropy, the LST structural anisotropy stems from the different proportions of surface components (each with a distinct temperature) observed by a sensor at different sun-view geometries. Indeed, that study found 'hot spot' values (where the sun and view directions coincide to eliminate observable shadows) up to 9 K greater than nearby non-hot spot directions in AVHRR LST values over African savannas. Recent results from the GOES program (Yu, personal communication, 2007) corroborate these results with geostationary data.

Potentially, directional effects can be modelled such that the LST product could be normalized to the nadir direction. For example, the Modified Geometric Projection (MGP) model (Pinheiro et al, 2006a) estimates directionally-dependent scene LST. Its input fields include surface structural information (e.g., tree cover fraction, tree crown width, etc.), observation information (e.g., sun-view geometry) and endmember temperatures (e.g., tree crown temperature) as input. The vegetation structural information required for this model is increasingly available globally (e.g., MODIS continuous fields product or space-based LIDAR products). However, we know of no globally applicable approach for independently determining endmember temperatures. Improving this or other approaches to correct LST angularly anisotropy will likely require a concerted effort.

3.4 *Surface Emissivity*

We recently estimated the sensitivity of nine published algorithms to emissivity errors by determining the partial derivatives of LST to emissivity (Yu et al., 2008). The results suggest that, under typical conditions, modest emissivity errors (e.g., 0.01) can lead to significant LST errors (2 K).

Several remote sensing methods have been proposed to estimate emissivity (e.g., Becker & Li, 1990; Van de Griend & Owe, 1993; Becker & Li, 1995), however these tend to require many spectral bands (unavailable with AVHRR) or atmospheric data, are computationally expensive, and have mixed results.

Therefore, most current split window algorithms use values obtained by associating laboratory emissivity data with land cover maps. For example, the MODIS split window algorithm uses modified laboratory data from Snyder et al. (1998) together with the MODIS land cover product (MOD12Q1). These approaches do not accommodate within-class variability. Pinheiro et al (2006c) recently addressed the latter shortfall by estimating a pixel's effective emissivity across the African continent as the spatially-weighted ensemble of its endmember emissivities, where an “endmember” is defined as a class of scene components assumed to have the same emissivity (e.g., woody vegetation or tree crowns, herbaceous background, and bare soil background). The endmember cover fractions are determined from the MODIS-derived Vegetation Continuous Fields product of Hansen et al. (2003). The resulting emissivity maps include both inter- and intra-class variability. This method was recently applied globally.

Nevertheless, these maps represent spatial variability only. Methods to incorporate temporal variability (e.g., from meteorology, seasonality and vegetation phenological changes) are less mature. We are aware of only one operational approach: the official MODIS LST split window algorithm (Wan and Dozier, 1996) includes separate green and senescent emissivity maps.

To address both spatial and temporal variability, we recently developed two global emissivity maps corresponding to the locally limiting conditions of maximally green and senescent vegetation (see Figure 1, Figure 2) following the method described in Pinheiro et al. (2006c). We then generated monthly emissivity maps using a temporal weighting approach based on local normalized leaf area index (LAI). A 6-year MODIS LAI climatology was used for this purpose (R. Myneni, personal communication, 2007). Other vegetation related products such as the normalized difference vegetation index (NDVI) are also being evaluated for this purpose.

Finally, many studies (e.g., Lagourde and Kerr, 1993; Sobrino et al., 2005; Wong et al., 1996) have shown that emissivity varies with view angle, both at the microscopic and macroscopic level. The latter effect is in part due to the different proportions of surface endmembers observed at different viewing geometries, similar to the LST effect previously described. In a modeling study, Yu et al. (2006) found that use of a constant nadir emissivity with wide field-of-view sensors can cause LST retrieval errors up to 1.0 K at large (>45 deg.) view angles..

Little work has been done so far in the community to correct for the angular effect. The official MODIS split window algorithm accounts for directional emissivity by modulating laboratory emissivity values at high view zenith angles (only). We recently developed a different approach based on the MGP model (Pinheiro et al., 2006a). The model predicts the proportions of tree crown, background and soil observable by the satellite. If the emissivity of these endmembers is known (e.g., from a laboratory emissivity library), the aggregate pixel emissivity can be computed for any observation direction. Undoubtedly, other approaches exist and an intercomparison study would be valuable.

4. CONCLUSIONS

A continuous nearly 30 year record of afternoon global brightness temperature data exists from the NOAA AVHRR family of polar orbiting sensors. These potentially can be developed into a Land Surface Temperature (LST) Climate Data Record that addresses GCOS and CCSP needs, however, complex challenges remain in its development. We described three issues requiring particular attention, including, 1) correction of LST temporal variability arising from orbital drift and the varying local observation times of pixels across wide swaths, 2) development of corrections for LST angular anisotropy and 3) development of improved emissivity maps which vary continuously with time and space. Requisite emissivity maps are currently in development at NOAA’s National Climatic Data Center. Satisfactory resolution of these issues will likely provide a data set capable of revealing the small but persistent trends generally associated with climate change signals.

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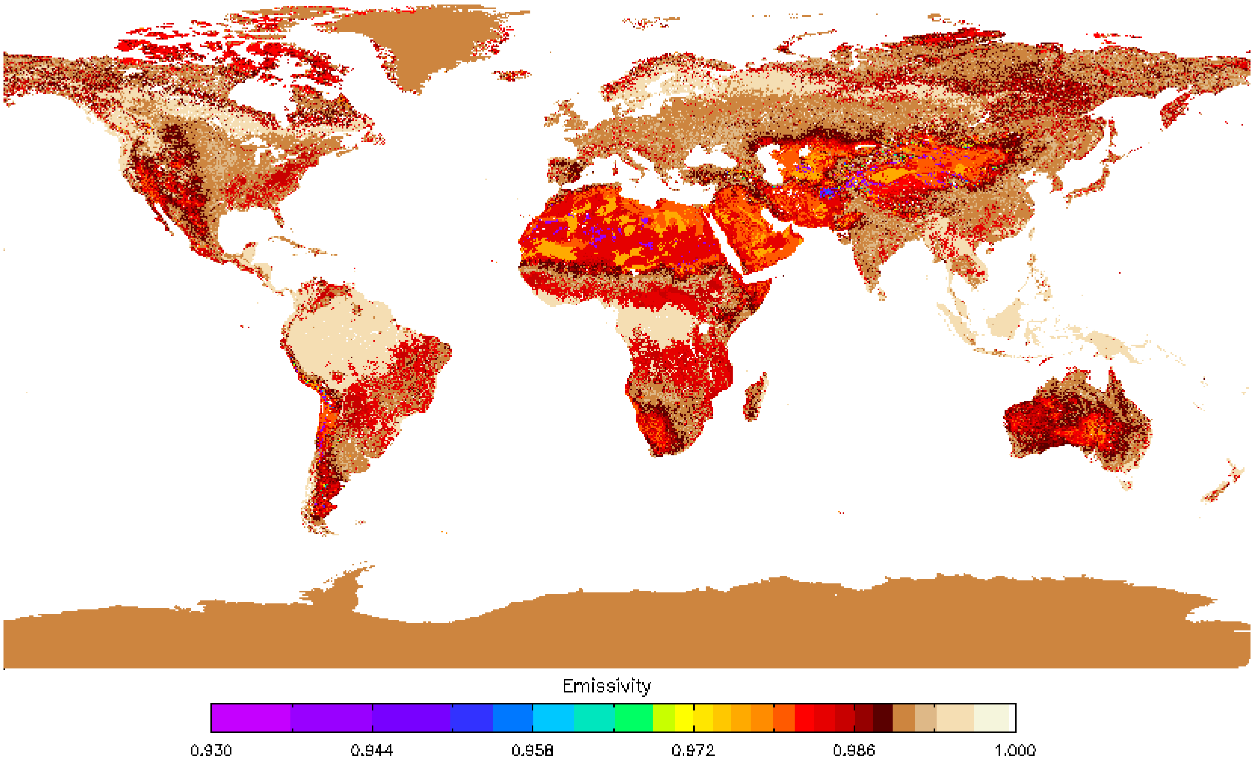

Figure 1: Emissivity (near 10.5 microns) for maximally green phenological conditions globally.

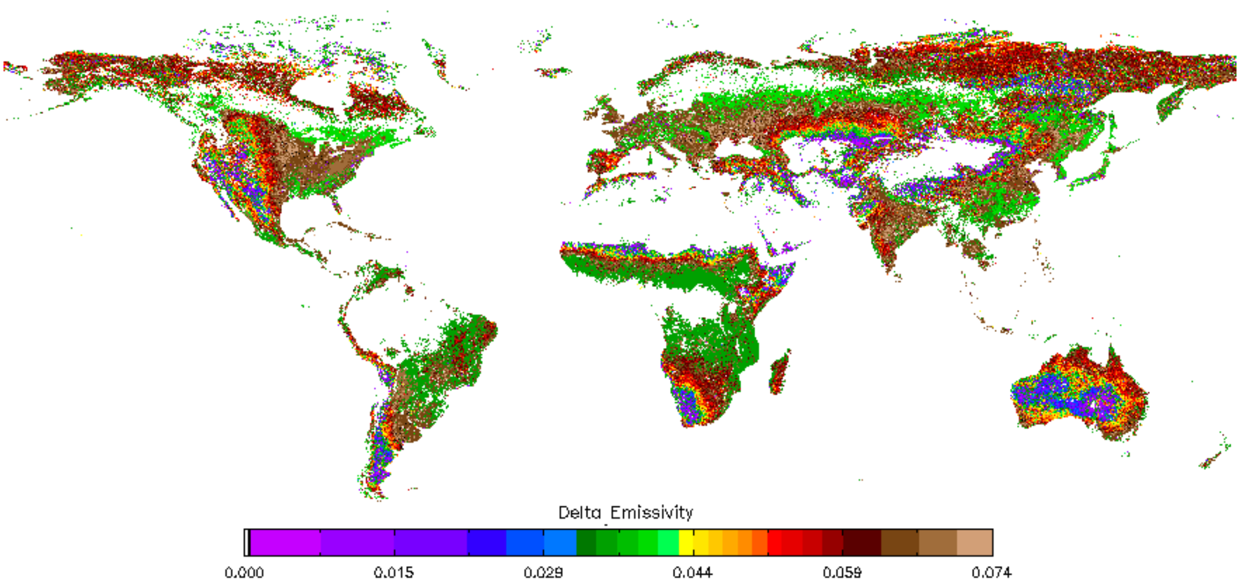

Figure 2: Difference of emissivities (near 10.5 microns) between maximally green and senescent conditions.