Daily land surface air temperature retrieval from AMSR-E: Comparison with AIRS/AMSU

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Draft 3
Revised: Feb. 23, 2009

Intended for Submission to IEEE JSTARS special issue on Microwave Land Hydrology and Remote Sensing
Abstract

We developed a satellite microwave remote sensing approach to retrieve daily maximum and minimum land surface air temperatures from the Advanced Microwave Scanning Radiometer for EOS (AMSR-E). The approach accounts for vertically integrated atmospheric water vapor absorption, and variable surface emissivity due to open water and vegetation biomass. AMSR-E derived temperatures were evaluated over the terrestrial Northern Hemisphere using \textit{in situ} surface weather station data and similar remote sensing products jointly derived from the Atmosphere Infrared Sounder (AIRS) and Advanced Microwave Sounding Unit (AMSU; henceforth referred together as AIRS). AMSR-E derived air temperatures reflect regional climate, land cover and topographic gradients, and are within approximately 3.5 K (RMSE) of \textit{in situ} weather station measurements considering overall spatial biases with improved accuracy for dense vegetation (1.5 – 3.0 K). Temperature retrieval error increases with decreasing vegetation optical depth, ranging up to ≈ 4 K for barren land. The AIRS and AMSR-E temperature retrievals show generally better agreement with each other than with \textit{in situ} station observations, and are within 1.0 – 2.8 K over vegetated land, while substantial disagreement (> 6 K) occurs over some deserts and mountainous regions. Potentially synergistic information produced by the AMSR-E temperature algorithms include open water fraction, vegetation optical depth and atmospheric water vapor, which corresponds closely ($R^2 = 0.58; p < 0.01$) with the AIRS atmospheric mixing ratio. The results of this study provide a new approach for global assessment and monitoring of land surface air temperatures with well-quantified accuracy.
Our ability to estimate regional impacts of near term (< 100 yrs.) climate change is limited by uncertainty in land-atmosphere feedbacks; including water, energy, and biophysical trace gas exchange [Denman 2007]. Simulations of regional land-atmosphere interactions are hampered by uncertainty in driving metrological state variables that are not easily observable at regional scales. One such variable, surface (∼ 2 m height) air temperature, integrates key information on the state of the land-atmosphere interface and is a fundamental driver of hydrological and ecological process models.

Daily maximum and minimum surface air temperatures \((T_{mx} \text{ and } T_{mn})\) are related to the partitioning of net incident solar radiation into sensible and latent heat and the turbulent exchange of energy between the land surface and atmosphere. Surface air temperature diurnal variability is therefore responsive to incoming solar radiation [Bristow and Campbell 1984], surface moisture status [Renzullo 2008; Crow 2008] and atmospheric humidity [Kimball 1997]. This relationship is strongly controlled by land cover, including the type, moisture status and amount of vegetation, which mediates surface-to-air heat exchange [Nemani 1993; Pridhodko 1997].

Uncertainties in driving meteorology, including air temperatures, can represent a significant amount of the overall error in regional land surface simulations [Mu 2007, Heinsch 2006; Zhao 2006]. Temperature information for regional land surface modeling is currently available from \textit{in situ} weather stations, model reanalysis, and satellite remote sensing observations including thermal infrared land surface temperature (LST), atmospheric soundings, and satellite microwave radiometer retrievals [Holmes et al. 2009]. Regional temperature maps
derived from \textit{in situ} weather stations are strongly constrained by measurement uncertainty and sparse station networks, leading to inconsistent sampling over much of the globe. Model reanalysis temperature products utilize various \textit{in situ} measurement and satellite observations to constrain global atmospheric model simulations, but are currently limited to relatively coarse (1° or greater) spatial resolutions globally, and may also have significant biases where observations are sparse and surface processes are spatially heterogeneous [Zhao 2006; Zhang 2007]. Satellite infrared (IR) remote sensing based LST can provide accurate land surface skin temperature information, but is limited to clear-sky conditions due to signal degradation by cloud cover, smoke and other atmospheric aerosols.

Microwave radiometry from polar-orbiting spacecraft provides opportunities for accurate global surface air temperature retrievals, including observations day-or-night under cloudy, non-precipitating conditions, with approximate 3 day or better temporal repeat. Passive microwave sensors respond to the physical temperature and emissivity of the atmosphere-land surface continuum. Sensor frequency and microwave emission properties of the sensor footprint determine the effective temperature sensing depth, which is the degree to which the temperature retrieval reflects soil, vegetation or atmosphere conditions. The sensor footprint emissivity is determined by the constituent dielectric and scattering properties of the scene. Primary factors influencing land surface dielectric properties include the amount of liquid water present in the form of open water bodies, soil moisture, dewfall and canopy water content, and water contained within living plant material. Microwave scattering of the land surface is determined by surface dielectric properties and the orientation, geometry and size of individual landscape elements, including water droplets, sand grains, and plant leaves relative to the observing wavelength [Matzler 2006].
Methods for satellite microwave remote sensing of surface temperature over land are less
developed in comparison to sea surface temperature (SST) or LST retrieval from optical-IR
remote sensing. Land surface radiometric properties are heterogeneous and difficult to model,
whereas the radiometric footprint and spatial resolution is characteristically coarser and the
emissivity more variable in the microwave spectral region than for optical-IR wavelengths.

Nevertheless, previous studies have shown strong relations between microwave brightness
temperatures ($T_b$) and physical temperature for specific regions and land cover types [McFarland
1990; Pulliainen 1997; Fily 2003; Jones 2007; Gao 2008].

Spatial and temporal variability in surface emissivity and atmospheric conditions is
problematic for land surface temperature retrievals from satellite microwave remote sensing
[Njoku 1995; Jones 2007]. Variable emissivity caused by snow, open water, and wet soil has
been reported to adversely affect surface temperature retrievals [McFarland 1990; Pulliainen
1997]. Methods have been developed to account for the effects of variable open water fraction
on land surface temperature retrievals using horizontal and vertically polarized brightness
temperatures [Fily 2003; Gao 2008]; these methods are generally limited to heavily-vegetated
(e.g. forest) regions where the land fraction of the H-polarized emissivity is relatively constant
and insensitive to dynamic changes in soil moisture or vegetation biomass [Jones 2007]. High
frequency ($\geq 18$ GHz) channel differences have also been used to correct for open water effects,
though significant error is reported where the open water fraction of the sensor footprint exceeds
0.2, potentially indicating increased sensitivity to atmospheric factors with increasing water
fraction [Bassist 1998]. Masking areas with significant open water fraction, another approach
for mitigating satellite microwave based temperature retrieval errors, can result in significant
information loss for some regions including the Arctic, although a relatively small area is
affected on a global basis [Holmes 2009]. Satellite optical-IR remote sensing derived LST and
International Satellite Cloud Climatology Project (ISCCP) satellite-model reanalysis data
[Prigent 1997] have been used to estimate microwave land surface emissivities. Such
approaches provide valuable insight regarding global emissivity variability, but are limited by
optical-IR remote sensing and model reanalysis data sources.

In the present study we develop a method to retrieve daily maximum and minimum air
temperature of the land surface using multi-frequency, dual polarized brightness temperature ($T_b$)
observations from the Advanced Microwave Scanning Radiometer for EOS (AMSR-E) deployed
on the Aqua satellite. The objectives of this study are to $i)$ develop a robust algorithm for daily
air temperature retrieval under varying surface and atmospheric conditions, $ii)$ evaluate
geographic patterns of the retrieved temperatures and $iii)$ assess the effects of variable land
cover, terrain and atmospheric conditions on AMSR-E temperature retrieval accuracy. We
derive temperature from AMSR-E by inversion of a simplified semi-physical $T_b$ model while
accounting for variable surface and atmospheric conditions. We assess spatial patterns in
retrieved parameters, assess correspondence between AMSR-E and AIRS retrievals, and
establish uncertainty of satellite air temperature retrievals relative to $in situ$ daily air temperature
measurements from the Northern Hemisphere World Meteorological Organization (WMO)
surface station network.

II. DATA PROCESSING AND ANALYSIS

A. Satellite Data Processing
The AMSR-E and AIRS/AMSU instruments are deployed together on the Aqua satellite. Aqua is polar orbiting with 1:30 A.M (descending pass)/P.M. (ascending pass) Coordinated Universal Time (UTC) equatorial crossings. AMSR-E measures V and H polarized $T_b$ at six frequencies (6.9, 10.7, 18.7, 23.8, 36.5, 89.0 GHz), scanning conically in the forward direction at a constant incidence angle of 55° from nadir [Kawanishi 2003]. The native resolution varies from $\approx 5$-km for 89 GHz to $\approx 50$-km for 6.9 GHz and is $\approx 22$-km for the 18.7 and 23.8 GHz channels. The Level 2A swath data product, in which all channels are spatially re-sampled to a common resolution [Ashcroft and Wentz 1999], was binned into a 25-km resolution polar Equal Area Scalable Earth (EASE) Grid [Armstrong and Brodzik 1995]. Each swath contains 243 footprints and the outer 10 footprints were dropped to reduce contamination by the sensor cold sky mirror partially blocking the low-frequency (6.9 and 10.7 GHz) AMSR-E antennae beam [Wentz 2007] effectively narrowing the swath width by $\approx 140$ km (8 %). The resulting dataset is equivalent to that used to derive the NASA Level 3 soil moisture product [Njoku 2008]. A 6.9 and 10.7 GHz radio frequency interference (RFI) mask was applied using the method of [Njoku and Chan 2005] with the additional condition $T_{bh}/T_{bv} < 1$ to eliminate additional regions with H-polarized RFI. Snow cover and precipitation events were masked using a scattering index threshold adopted from the Special Sensor Microwave Imager (SSM/I) [Ferraro 1995]. Grid cells with > 50 % open water and permanent ice were excluded using the GLDAS land cover classification (Section II B.). For this investigation we derived AMSR-E temperatures for the time period between May 30 and September 7, 2003 to reduce freeze-thaw and snow cover impacts on algorithm results.

The AIRS and Advanced Microwave Sounding Unit (AMSU) on Aqua produce synergistic atmospheric temperature and humidity soundings. Both AIRS and AMSU are cross-
track scanning sounders. AIRS has 2378 IR spectral channels ranging from 3.74 to 15.4 μm [Aumann 2003]. AMSU is a microwave radiometer consisting of two units (A1 and A2) which measure microwave radiance for 15 channels ranging from 31.4 to 183 GHz and 5 channels ranging from 9-23.8 GHz, respectively [Rosenkranz 2001]. Each AIRS 15-km footprint (nadir) is centered within 40-km (nadir) AMSU footprints and the spatial resolution increases toward swath edges. The accuracy of the soundings is approximately ±1 K for clear skies, decreasing to ±2 K for the lowest sounding level for up to 80 % cloud cover based on comparisons with ECMWF forecast model simulations [Susskind 2006]. AIRS produces surface air and skin temperature retrievals in conjunction with the soundings. Surface air temperature is estimated by linearly extrapolating the temperature of the lowest sounding level (0 to 1 km height or the 880 mb) to the surface pressure level [Susskind 2006]. We re-sampled high quality data (QC < 2) to a 0.25 ° (≈ 27 km) resolution grid from the AIRS/AMSU version 5 L2 swath product in a geographic projection using inverse distance squared weighting and re-projected the 0.25 ° geographic grid to the polar EASE-grid.

B. Ancillary Land Cover Data

Land cover classification information was obtained from the Global Land Data Assimilation System (GLDAS) to aid in the interpretation of algorithm results [Roddell 2004]. The GLDAS 0.25° grid product represents fractional coverage and dominant coverage of 14 University of Maryland (UMD) land cover classes derived at 1-km resolution from Moderate Resolution Imaging Spectroradiometer (MODIS) [Justice 2002]. We re-projected the GLDAS
land cover datasets from a 0.25° resolution geographic projection to the AMSR-E polar EASE-grid projection.

C. Surface Station Network

Daily maximum and minimum surface (≈ 2 m height) air temperatures were obtained from the National Climate Data Center (NCDC) Global Summary of the Day for ≈ 5000 World Meteorological Organization (WMO) weather stations within the Northern Hemisphere domain. The dominant land cover class for each weather station location was determined from the MODIS land cover class of the overlying EASE grid cell (see Section II. B.). Stations within areas defined as water or permanent ice were excluded. We also excluded pixels with < 100 days of acceptable $T_b$ data (Section II A.), but avoided excluding areas with significant data rejection due to 6.9 GHz RFI, particularly over the continental USA, because the higher frequency channels (≥10.7 GHz) are generally unaffected by RFI.

D. Analysis Methods

We determine AMSR-E frequencies most sensitive to daily $T_{mn}$ and $T_{mx}$ using a correlation analysis. Our algorithm development criteria required retrieval of daily air temperatures, while accounting for atmospheric water vapor ($V$, mm), open water fraction ($f_w$), and vegetation transmissivity ($t_v$) effects. Spatial patterns of annual means of the AMSR-E temperature retrievals and co-retrieved geophysical parameters were evaluated by examining spatial and temporal patterns of the retrievals in relation to latitude, land cover and elevation.
gradients. We assess physical consistency of parameter retrievals over the entire time period and study domain with parameter probability density distributions (PDFs). We assess the relative agreement between AMSR-E and AIRS temperature retrieval spatial and temporal patterns using pixel-wise and regional summary statistics, while we determine the relative accuracy of retrievals using in situ temperature measurements from WMO surface weather stations. We stratify surface weather stations by general land cover class into algorithm development and test groups for each of three latitudinal bands (Table 1; Figure 1): “Boreal” (≥ 55° N), “Temperate” (≥35° N to < 55° N), and “Tropical” (< 35° N). A representative collection of stations was randomly selected from each latitude band and land cover class into 270 development and 273 test stations for a total of 543 stations. Patterns of agreement were assessed relative to ancillary factors, including station elevation and AMSR-E derived $V_f$, $f_w$, and $t_c$, and the average daily difference between AIRS derived air and skin temperatures ($\Delta T_{skin}$).

We employ the following statistics to quantify AMSR-E temperature retrieval accuracy in relation to WMO weather station measurements and alternative temperature retrievals from AIRS: the root mean square error (RMSE) is especially sensitive to outliers and bias and was used as a conservative measure of retrieval uncertainty; the mean absolute error (MAE) was used as an alternative uncertainty metric that is less sensitive to outliers than the RMSE; the mean residual (MR) indicates retrieval bias and was calculated as the mean of Observed (WMO or AIRS) less Retrieved (AMSR-E) conditions; the coefficient of determination ($R^2$) was used as an indicator of bias-independent correspondence between the temperature retrievals; and the correlation coefficient (R) was used to assess the relative strength and sign (±) of correlations between temperature retrievals and ancillary factors. Statistical summaries were calculated for the regional domain by pooling data from all test stations to represent the uncertainty for any
random observation within the study spatial and temporal domains. Cumulative site-to-site biases increase pooled uncertainty making it a particularly conservative measure. The RMSE, which measures variance, will have a $\chi^2$ probability distribution (skewed toward larger values) and for such distributions the median is a more appropriate measure of central tendency than is the mean. Therefore, median summary statistics for sites within each group quantify uncertainty for a “typical” location within individual land cover classes and latitudinal bands.

III. MICROWAVE PHYSICAL INTERACTIONS

A. Atmospheric Model

Microwave radiance observed by a space borne sensor at polarization $p$ and frequency $f$ is proportional to the effective physical temperature of the surface-atmosphere continuum by the Rayleigh-Jeans approximation and expressed as brightness temperature, $T_b$ in Kelvin [Matzler 2005]:

$$T_{b(p,f)} = T_u + t_{a(f)}[T_{b(p,f)} + (1 - \epsilon_{(p,f)})T_d]$$

(1)

Where, $T_{b(p,f)}$ is the upwelling surface brightness temperature (K), $\epsilon_{(p,f)}$ is the surface emissivity (dimensionless), $T_u$ and $T_d$ are the respective up and down welling atmospheric brightness temperatures (K), and $t_{a(f)}$ is the atmospheric transmissivity (dimensionless). Atmospheric absorption primarily occurs in the lower troposphere for “window” channels such as those on the imaging sensors AMSR-E and SSM/I, and $T_u = T_d = (1 - t_{a(f)})T_a$, becomes a reasonable
approximation [Weng and Grody 1998], where $T_a$ is the integrated lower troposphere air
temperature. However, $T_a$ is generally slightly cooler than $T_d$ as a result of cosmic background
radiation [Wentz 1997]. Low emissivity surfaces, such as open water, provide a relatively dark
background, increasing the sensitivity of $T_b$ to atmospheric absorption in (1).

Atmospheric transmissivity and optical depth ($\tau_{a(f)}$, dimensionless) are defined as

$$t_{a(f)} = \exp(-\tau_{a(f)})$$
$$\tau_{a(f)} = \int_0^{z_{toa}} k(z)dz$$

(2)

Where $z$ (m) is the height above the terrestrial surface to the top of the atmosphere ($z_{toa}$) and
$k(z)$ (m$^{-1}$) is the atmospheric extinction with height. The term $\tau_{a(\theta)}$ is primarily sensitive to
oxygen, water vapor, and cloud liquid water absorption in the lower troposphere with respect to
the angle between the view path and nadir ($\theta$) [Wentz 1997]:

$$\tau_{a(f)} = \sec(\theta)[A_o + A_v + A_L]$$

(3)

Oxygen absorption ($A_o$) is relatively constant because oxygen is well mixed throughout the
global atmosphere. Water vapor absorption ($A_v$) has little effect on $\tau_a$ at lower frequencies ($\leq$10
GHz), but increases at higher frequencies (>10 GHz) with the exception of a weak rotational
absorption line at 22.2 GHz, broadened by decreases in total atmospheric pressure, increasing
absorption at adjacent frequencies such as 18 GHz. Precipitation and cloud liquid water
extinction ($A_L$) increase strongly for higher frequencies (36 and 89 GHz).

B. Land Surface Emissions Model
Microwave radiation properties of the terrestrial land surface are much more heterogeneous than atmospheric clear sky or open ocean conditions and $T_{\text{surf}(p,f)}$ emitted from the terrestrial surface is a function of the physical temperature, dielectric properties, size, orientation, specific density, and land cover composition within sensor field-of-view (FOV). For a scene composed of a mixture of open water and land:

$$T_{bs(p,f)} = f_w T_{bw(p,f)} + (1 - f_w) T_{bl(p,f)}$$  \hspace{1cm} (4)

Where $T_{bw(p,f)}$ and $T_{bl(p,f)}$ are respective brightness temperatures (K) for water and land, and $f_w$ is the open water fractional coverage (dimensionless) within the FOV. Even a small fraction of open water (>0.05) has a strong impact on surface emissions due to the relatively high dielectric constant of water [Gao 2006]. Terrestrial landscapes, particularly at high latitudes, contain numerous water bodies and inundated areas, the area of which may vary seasonally.

The land fraction brightness temperature ($T_{bl(p,f)}$) in (4) for the majority of the land surface can be simplified by a layer of semi-transparent vegetation over smooth, bare soil with emissivity ($\varepsilon_{os(p,f)}$) expressed using the familiar $\tau-\omega$ model [Mo et al. 1982]:

$$T_{bl(p,f)} = T_{soil} \varepsilon_{os(p,f)} t_c + T_{can} (1 - \omega) (1 - t_c) [1 - (1 - \varepsilon_{os(p,f)}) r_c]$$  \hspace{1cm} (5)

where $T_{soil}$ and $T_{can}$ are the respective soil and canopy temperatures (K) and $\omega$ is the dimensionless forward single-scattering albedo of the vegetation canopy. Eqn (5) does not account for multiple scattering within the vegetation canopy and is considered valid only for
lower frequencies ($\leq 18$ GHz) [Njoku 2006; Matzler 2006]. The canopy transmissivity ($t_c$) is

defined in terms of the equivalent vegetation water content ($g$, kg m$^{-2}$) and is analogous to
atmospheric transmissivity in (2) [Njoku 2006]:

\[
  t_{c(f)} = \exp(-\tau_{c(f)}) \quad \tau_{c(f)} = \alpha_{c(f)} g = b_{c(f)} h_{c(f)} g \sec(\theta)
\]

Where $\alpha_{c(f)}$ (m$^2$ kg$^{-1}$) combines angular, and frequency dependent canopy loss ($b_{c(f)}$; m$^2$ kg$^{-1}$) and
roughness factors ($h_{c(f)}$; dimensionless), allowing $t_c$ to account for both canopy extinction and
surface roughness. Reported values for $b_{c(f)}$ and $h_{c(f)}$ (i.e. $\alpha$) vary widely in the literature, but appear
to follow a power law relationship, saturating at higher frequencies [Njoku 2006]. The soil
emissivity ($\varepsilon_{soil(p,f)}$) is related to the dielectric properties of the soil and calculated for specular
surfaces using the Fresnel equations [Ulaby 1989]. For low frequencies ($\leq 18$ GHz), soil
dielectric properties vary strongly with water content and mineral type [Grody and Weng 2008].
Volume scattering of high frequency microwaves by sand and snow have the greatest impact for
higher frequencies (36 GHz and 89 GHz frequencies).

IV. TEMPERATURE ALGORITHM FORMULATION

A. Correlation of $T_b$ to Station $T_{mn}$ and $T_{mx}$

The most favorable AMSR-E channels for surface temperature retrieval are less sensitive
to cloud and surface emissivity variations. The AMSR-E ocean SST retrieval algorithms employ
lower frequency ($\leq 10.7$ GHz) channels to minimize atmospheric effects. However, land
emissivity is more variable for these channels relative to higher frequencies, due to strong heterogeneity in land cover and soil moisture. Previous investigations have therefore used intermediate (e.g. 18-36 GHz) frequencies which balance sensitivity to atmosphere (higher frequencies) and surface (lower frequencies) emissivities [Weng and Grody 1998; Fily 2003; Holmes 2009].

We conducted a correlation analysis between $T_b$ values from individual AMSR-E channels and corresponding daily air temperatures from in situ weather stations to determine AMSR-E frequencies with the highest a priori correlations to $T_{mn}$ and $T_{mx}$. These results were corroborated using model based $T_b$ simulations. Only V-polarized $T_b$ values for land ($f_w < 0.05$) were considered as V polarization is less impacted by surface emissivity and atmospheric variations [Pulliainen 1997; Bassist 1998]. The $T_b$ simulations were conducted using the model function described in Section III for randomly varying inputs, which were given realistic covariance structure with surface temperature, $T_s$. Soil moisture was assigned a moderately weak negative correlation with $T_s$, atmospheric water vapor a moderately strong Clausius-Clapeyron (exponential) type relation with $T_s$, and $T_a$ a strong positive correlation with $T_s$.

Correspondence of $T_b$ with $T_{mx}$ and $T_{mn}$ increases at higher frequencies and follows a similar pattern for most land cover types (Figure 2). This pattern is due to greater sensitivity of lower frequency channels to surface emissivity (decreased correlation) and the increased sensitivity of higher frequency channels to atmospheric temperature (increased correlation). The 23 GHz frequency generally shows the strongest correlations with air temperatures across all land cover classes relative to other AMSR-E frequencies. Strong temperature correspondence at this frequency is induced by the correlation between water vapor and surface air temperature.
through the Clausius-Clapeyron relation and reduced sensitivity of the 23 GHz frequency to surface emissivity, confirmed by model simulations.

B. Simplified Emission Model Inversion for Daily Surface Air Temperatures

Our approach employs $T_b$ ratios from the 18.7 and 23.8 GHz channels to iteratively determine vertically integrated atmospheric water vapor ($V$, mm), open water fraction ($f_w$ dimensionless), and vegetation transmissivity ($t_c$, dimensionless) and then uses this information to solve for effective surface temperature ($T_s$). Closely spaced channels provide contrast between atmospheric and surface emissivity variations. $T_b$ is expressed as a linear function (rather than a quadratic) of $t_{a(f)}$ and $t_c$ by considering directly upwelling radiation only:

$$T_b(p,f) = T_s[t_{a(f)}\varepsilon_{l(p,f)} + (1 - t_{a(f)})\delta] \quad \delta \approx \frac{T_s}{T_s}$$ (7)

$$\varepsilon_{l(p,f)} = f_w\varepsilon_{w(p,f)} + (1 - f_w)\varepsilon_{l(p,f)}$$ (8)

$$\varepsilon_{l(p,f)} = \varepsilon_{os(p,f)}t_c + (1 - \omega)(1 - t_c)$$ (9)

Where $T_s$ is the weighted effective temperature of the scene ($T_s \approx T_a \approx T_{soil} \approx T_{can}$), and the values $\varepsilon_{l(p,f)}$ and $\varepsilon_{w(f,p)}$ are the respective land fraction and open water emissivities. The vegetation transmissivity ($t_{c,1823}$) is assumed polarization independent and equivalent at 18 and 23 GHz frequencies. The dimensionless ratio of air to surface temperature ($\delta$) relaxes the assumption $T_s \approx T_a$, open water emissivity ($\varepsilon_{w(p,f)}$), baresoil emissivity ($\varepsilon_{os(f,p)}$) and vegetation single-scattering
albedo ($\omega$) are assigned as constant parameters (Table 2). The polarization independence of $t_c$ and $\omega$ is physically tractable for randomly oriented vegetation elements, a reasonable assumption for coarse-resolution satellite observations [Ulaby 1989; Matzler 2006], although $t_c$ may be slightly lower at 23.8 GHz than 18.7 GHz. The linear assumption in (7) is not as limiting as it may seem because surface reflection is low for high-emissivity land surfaces and antennae gain averages sub-grid scale emissions of heterogeneous scenes. A simplified linear model may have less bias relative to effective pixel-average quantities than a non-linear model [Chang and Milan 1982; Rastetter 2002].

We iteratively retrieve vegetation opacity ($t_c$), open water ($f_w$), and atmospheric water vapor using three temperature-insensitive $T_b$ ratios:

\[
MAWVI = \frac{T_{b_{23}} - T_{b_{18}}}{T_{b_{v18}} - T_{b_{h18}}} = \beta \left( \frac{t_{a23}}{t_{a18}} \right) = \beta \left( \frac{\varepsilon_{v23} - \varepsilon_{h23}}{\varepsilon_{v18} - \varepsilon_{h23}} \right)
\]

(10)

\[
F_h = \frac{T_{b_{h18}}}{T_{b_{h23}}} \quad P = \frac{T_{b_{h18}}}{T_{b_{v18}}}
\]

(11, 12)

The expression for MAWVI (Microwave Atmospheric Water Vapor Index) is derived from (7). The subscripts 18, 23 and v, h denote respective frequencies and polarizations. MAWVI is relatively insensitive to the $\beta$ term because the surface emissivity polarization differences are relatively small for the two closely spaced channels (i.e. $\beta$ is near unity). We use $F_h$ in (11), rather the corresponding V-polarization expression, because the H-polarization is more responsive to vegetation canopy absorption.
We determine vertically integrated water vapor content ($V$, mm) from the MAWVI:

$$V = \log\left(\frac{\text{MAWVI}}{\beta}\right) \cos(\theta) + a_{O23} - a_{O18} \sqrt{(a_{v18} - a_{v23})}$$  \hspace{1cm} (13)

Where $a_{O23}$, $a_{O18}$, and $a_{v18}$, $a_{v23}$ are the oxygen and water vapor absorption coefficients at nadir adapted from the AMSR-E ocean atmospheric model [Wentz 2002]. We linearized and doubled the values of $a_{v18}$ and $a_{v23}$ from Wentz [2002] to obtain reasonably-scaled values of $V$ (0 to 70 mm) over land. The atmospheric transmissivity for the 18 and 23 GHz channels is calculated from (2, 3). Cloud liquid water extinction is considered insignificant.

Open water fraction ($f_w$) and vegetation transmissivity ($t_v$) unknowns are determined from expressions for $F_h$ and $P$ using (7-9):

$$t_v = \frac{Wp(Tf + Cf) - Tp(Wf + Cf) + Cp(Tf - Wf)}{Bp(Wf - Tf) + Bf(Tp - Wp)}$$  \hspace{1cm} (14)

$$f_w = \frac{Tp + t_{a18}(\varepsilon_{h18} - P\varepsilon_{v18})}{t_{a18}[P(\varepsilon_{wv18} - \varepsilon_{h18}) + (\varepsilon_{h18} - \varepsilon_{wh18})]}$$  \hspace{1cm} (15)

where

$$Bp = t_{a18}(\varepsilon_{osh18} - 1 + \omega) \quad Bf = t_{a23}(\varepsilon_{osh23} - 1 + \omega) - t_{a18}F_h(\varepsilon_{osh18} - 1 + \omega)$$

$$Cp = t_{a18}(1 - \omega)(1 - P) \quad Cf = (1 - \omega)(t_{a23} - t_{a18}F_h)$$

$$Tp = (1 - t_{a18})(1 - P)\delta \quad Tf = [(1 - t_{a23}) - F_h(1 - t_{a18})]\delta$$

$$Wp = t_{a18}(P\varepsilon_{wv18} - \varepsilon_{wh18}) \quad Wf = t_{a18}F_h\varepsilon_{wh18} - t_{a23}\varepsilon_{wh23}$$
The \( w \) and \( l \) subscripts denote water and land, respectively. The equation series (11-15) is applied iteratively for sequential updating of \( V, f_w \) and \( t_c \). We find that five iterations stabilize the retrieved regional \( V \) probability distribution function (PDF) without excessive computational burden. The surface temperature is then calculated by inverting (7), the terms of which are now specified.

The model reproduces the observed variation in the three \( T_b \) ratios for the domain and study period as shown by bivariate histograms overlain by model results (Fig. 3). Over forests the polarization difference is very small, and the MAWVI index is poorly conditioned. Slight offsets from the origin (e.g. adding small constants (\( \approx 1 \) K) to the numerator and denominator in (11)) improve conditioning, although correct estimates of \( V \) over such surfaces are not crucial for determining \( T_s \). The \( F_h \) and \( P \) plots form a roughly triangular shaped region for each \( V \) value, the vertices of which represent \( f_w = 0, t_c = 1 \), and \( t_c = 0 \), graphically demonstrating the basis for the algorithm. The algorithm is run on AMSR-E descending (A.M.) and ascending (P.M.) \( T_b \) inputs to determine daily \( T_{mn} \) and \( T_{mx} \), respectively. The \( f_w \) and \( t_c \) parameters are conserved between A.M. and P.M. overpasses; however, we derive these parameters for each overpass because descending and ascending swaths may not overlap on a daily basis, especially for locations < 50° N. An empirical correction was applied to account for temperature differences between the local time of satellite retrievals and the timing of \( T_{mx} \) and \( T_{mn} \); multiple linear regression corrections (Table 3) were developed to transform AMSR-E and AIRS overpass effective temperatures (\( T_s \) and \( T_a \)) to daily \( T_{mn} \) and \( T_{mx} \) using AMSR-E retrieved \( t_c \) and latitude as explanatory variables.

V. RESULTS AND DISCUSSION
A. AMSR-E Northern Hemisphere Temperature Retrieval Patterns

The mean annual temperature patterns from AMSR-E generally follow expected geographic trends (Figure 4). The temperature retrievals generally decrease with increasing latitude and elevation. The cold Tibetan plateau and adjacent warm temperatures of the Gobi desert are evident, as are similar topographically driven temperature gradients between adjacent low lying areas and prominent mountain ranges which include the Himalaya and Karakorum, Alps, Eritrean Highlands (Northeast Africa) and central Rocky Mountain regions. Temperature contrasts between moderate coastal regions and more extreme inland climates are also evident, including the moderate temperatures of coastal Mexico relative to the interior. The extreme heat of the Sahara desert also contrasts with milder temperatures of the more vegetated Sahel region of Africa. However, the observed diurnal temperature difference is too small for portions of the Sahara and Arabian Peninsula, which is primarily driven by spatial patterns in $T_{\text{min}}$.

Co-retrieved land surface parameters, including open water fraction ($f_w$) and vegetation transmissivity ($t_v$) and atmospheric water vapor content ($V$), also show reasonable patterns in accordance with global climate and land cover variability (Fig. 4). Vegetation transmissivity ($t_v$) corresponds with regional gradients in land cover and vegetation biomass, including the large $t_v$ gradient between desert regions and temperate and tropical forests. Previous studies have shown a regional increase in $t_v$ for central Canada [Njoku 2006]. The approach from this investigation corrects for the open water effects and shows relatively low transmissivity for boreal forest and arctic tundra. The northern extent of tree line between boreal and arctic regions is represented by a subtle increase in $t_v$. The AMSR-E open water fraction ($f_w$) retrieval displays the relative
abundance of open water bodies in boreal and tundra regions, particularly for north central Canada. The \( f_w \) retrievals also show a substantial amount of open water in some arid regions of the northern Sahara and middle-East, which reflect seasonal flooding or irrigation, particularly in the Tigris and Euphrates river valleys, although other portions of this region require further investigation.

Moist tropical regions including India, Indonesia and Southeast Asia show characteristically high \( V \), while relatively humid areas of the Southeast and Midwestern USA also show high water vapor content. In contrast, colder, drier regions including the Tibetan plateau, central Asia, and the Arctic show relatively low water vapor contents. Close correspondence was found between AMSR-E water vapor retrievals and AIRS surface layer mixing ratio (g kg\(^{-1}\)) product \((R^2 = 0.58; p < 0.01)\). Regions where the AMSR-E \( V \) retrievals are considered unreliable due to a poorly conditioned MAWI index were confined to boreal and equatorial forests with \( Tb_{v18} - Tb_{h18} \leq 1 \). Our results indicate that most continental land areas have H-polarization emissivity low enough to allow atmospheric water vapor retrieval over land from AMSR-E.

Histograms of retrieved \( V, f_w, \) and \( t_c \) PDFs for the study period were constructed to calibrate the AMSR-E algorithm and provide further verification of co-retrievals (Fig. 4). Temporal offsets in the \( V \) PDFs are expected because warm afternoon air \((T_{mx})\) can hold more water vapor than cool morning air \((T_{mn})\). The AMSR-E open water fraction retrievals contain a substantial number of negative values (the mode is -0.03). Most negative \( f_w \) values occur in deserts and barren and sparsely vegetated regions. Too much or too little (negative) open water in the Sahara and Middle East regions indicate that the true emissivity may be related to factors other than open water such as mineral composition, volume scattering in sand fields, or surface
roughness. The $f_w$ PDFs also show slight differences between descending ($T_{mn}$) and ascending ($T_{mx}$) retrievals, which is also a likely algorithm artifact caused by greater surface to air temperature gradients in the afternoon.

B. Comparisons between AMSR-E and AIRS temperature retrievals

Vegetated temperate and boreal regions show generally close agreement between AMSR-E and AIRS temperature products ($R^2 > 0.8$ and RMSE $\leq 2.5$ K; Fig 5). The high correspondence lends confidence to the accuracy of the two temperature products for vegetated regions and indicates that the AMSR-E emissivity model generally captures surface emissivity variations of the dominant global vegetation classes. Relative agreement between AMSR-E and AIRS temperature retrievals declines substantially in desert regions. We attribute lower correspondence over many arid regions including northern Africa, central Asia, and the Southwestern United States to the limitations of the relatively simple AMSR-E algorithm to capture complex emissivity variations over sparsely vegetated desert landscapes. The crescent shape of $T_{mn}$ bias over Saudi Arabia corresponds to an area associated with limestone deposits [Grody and Weng 2008], which have a higher soil dielectric constant and lower surface emissivity than surrounding areas composed of more common silica sands. In addition to mineral dielectric effects, dielectric effects from desert salt pans, scattering sands, fine scale surface roughness and terrain variability are some of the many factors that contribute to desert surface emissivity variations [Prigent 1999] and also impact AMSU channels [Grody 2008]. Highly variable near-surface lapse rates in arid and mountainous regions may also cause biases that shift between $T_{mn}$ and $T_{mx}$ for AIRS and AMSR-E temperature estimates in these regions.
The correlation between AMSR-E and AIRS temperatures declines substantially for tropical latitudes (<30° N). Low correlation is observed despite reasonable RMS errors (∼3 K). Enhanced cloud coverage in tropical forest regions likely decreases temperature correspondence (Section V). This factor also appears to impact sites along the Northwest coast of North America. The correlation decline may be partially attributed to sparser temporal sampling of the polar orbiting Aqua satellite at lower latitudes and reduced seasonal temperature variation relative to higher latitudes.

The percentage of days with observations from both sensors declines with latitude from 100 % near the poles to 45 % at the equator as a result of Aqua’s polar orbit. AMSR-E has fewer observations than AIRS, 69.3 % and 69.4 % versus 80.3 % and 79.2 % respectively for descending and ascending orbits. AMSR-E’s fewer observations is foremost the result of narrower swath width than AIRS for low latitude locations (See Section II A) and to a lesser extent, snow cover at high latitudes. AMSR-E data loss from precipitation causes minor differences in observation counts relative to AIRS as AIRS data loss also occurs for such events. AIRS has greater ascending pass data loss in the Western Sahara, Arabian Peninsula, and Gobi deserts relative to AMSR-E.

Hemispheric agreement between AMSR-E and AIRS daily air temperatures follow a seasonal cycle (Fig. 6). The RMSE differences between AIRS and AMSR-E derived $T_{mn}$ varies from a mean maximum of 2.9 K in early June to a low of 2.2 K in mid July (Fig. 5). Similarly, RMSE differences for $T_{mx}$ vary from 3.3 K in June to 2.7 K in July. The seasonal RMSE pattern is reflected in the bias, where AMSR-E overestimates $T_{mx}$ and $T_{mn}$ in June relative to AIRS by 0.6 K, although the bias diminishes by mid-July. Seasonal patterns of AIRS and AMSR-E
temperature differences are likely driven by broad-scale climate patterns affecting temperature retrieval accuracy, including the seasonal onset of monsoon moisture and associated cloudiness.

C. AMSR-E and AIRS Daily Temperatures Relative to WMO Station Observations

The overall uncertainty of AMSR-E temperature retrievals relative to WMO validation sites is 3.5 K (RMSE) for $T_{mn}$ and $T_{mx}$ (Table 4). Corresponding uncertainties for the AIRS temperature retrievals are 3.8 K and 3.4 K, respectively. In contrast, the agreement is better between AMSR-E and AIRS daily air temperatures (RMSE = 3.2 K for $T_{mn}$ and 2.7 K for $T_{mx}$) than comparisons between either satellite based retrieval and WMO site measurements. The MAE for all temperature comparisons is less than 3 K, indicating the impact of biases on the RMSE. Lower RMSE between AMRS-E and AIRS relative to AMSR-E and WMO was related to the proportion of dominant land cover ($R = -0.15; p < 0.05$) and elevation ($R=0.20; p < 0.01$) for $T_{mn}$ and correlations with $T_{mx}$ were of similar sign but not significant, indicating that AMSR-E and AIRS retrievals reflect similar spatial scales relative to in situ station measurements which may not adequately represent sub-grid scale temperature variability within the 25 km grid cell, especially over heterogeneous terrain.

Median differences between satellite retrievals and in situ air temperatures were approximately 2 to 3 K, and ranged from 1.4 K to more than 4 K (Fig. 7). The AMSR-E retrievals showed improved agreement over AIRS for the majority of WMO station land cover groups, while land cover classes showing poorer AMSR-E agreement were associated with greater bias, rather than reduced correlation. Additionally, the AIRS and AMSR-E retrievals showed generally closer agreement with each other than with the in situ station observations for
most WMO station land cover groupings, although the pattern was consistently reversed for barren areas.

Relations between AMSR-E and AIRS retrievals and WMO station temperatures varied by station elevation and the open water fraction of the grid cell (Table 5). Temperature correspondence between surface station observations and sensor retrievals was reduced at higher elevations for both AMSR-E and AIRS as shown by respective 0.7-0.8 K and 0.35-0.38 K RMSE increases for every 1000 m rise in station elevation, part of which is attributable to 0.8 K of associated warm bias for AIRS. An increasing warm bias in the AIRS temperature product in relation to surface weather station elevation was also noted by Gao [2008] over China. The apparent influence of elevation on sensor-station temperature differences may be due to increasing mismatches between sensor FOV averaged temperatures and sub-grid scale thermal gradients over complex terrain. The AMSR-E temperature retrievals showed a cold bias of 2-3.5 K for up to 50 % open water coverage, with a stronger effect for \( T_{mx} \) than for \( T_{mn} \), which was attributed to temperature contrasts between relatively cool water bodies and in situ station measurements of adjacent land areas, where land-water temperature contrasts are minimized in the early morning prior to the onset of daily solar radiation loading.

We find a trend of increasing error with decreases in vegetation biomass for AMSR-E and AIRS temperature results, ranging from 1.5-2.5 K for forested locations to sparsely vegetated locations with maximum errors of approximately 4 K relative to WMO station measurements (Table 5). This trend was most prominent for the boreal latitudes and greater for \( T_{mx} \) (2-3 K) relative to \( T_{mn} \) (2 K). Disagreement among the datasets was greatest for barren locations in all latitudinal bands, corroborating regional results (Section IV B). High latitude barren areas are primarily located near arctic coastal areas of Svalbard and the Canadian
archipelago where relatively coarse resolution satellite retrievals may reflect sub-grid scale snow
fields, and sea ice floes. Lower temperature accuracy for AIRS over desert mid-latitude
locations has also been reported by Gao [2008], although for such locations AIRS and AMSR-E
show roughly equivalent accuracy relative to WMO station temperatures. The difference
between AIRS skin and air temperatures is closely related to the biomass gradient \( R = 0.75; p <
0.01 \), where a 4.8 K decrease occurs from the desert to forest transition \( t_c = 0.7 \) to \( t_c = 1 \). Air
and surface temperatures are similar in densely vegetated areas due to enhanced latent energy
exchange and greater vegetation surface area contact with the adjacent air, whereas sensible heat
transfer dominates in sparsely vegetated desert areas.

Forests in the tropical latitudes deviated from the general pattern observed for other
latitudinal bands with larger (2.8 – 4 K RMSE) differences between AMSR-E and AIRS
retrievals relative to WMO station temperatures. Increasing cloud liquid water and deep
convective storm systems for this region is one possible explanation for these differences as
AIRS accuracy is expected to decline with increasing cloud coverage [Susskind 2006]. The
AIRS retrievals show frequent, intermittent negative daily temperature anomalies relative to
station observations that are reflected in the mean residual bias (MR) statistics in support of this
explanation. The AMSR-E retrievals show better accuracy than AIRS with respect to tropical
forest station temperatures, which we attribute to reduced sensitivity of lower frequency
microwaves to clouds.

VI. CONCLUSION
We find that the AMSR-E 18.7 and 23.8 GHz frequencies can be used to derive minimum and maximum daily air temperature along with other valuable surface and atmospheric parameters over the terrestrial Northern Hemisphere. Uncertainty in derived temperatures is generally 2-3 K for vegetated regions > 30 °N, with larger bias-driven uncertainty (4-6 K), for desert and mountainous regions relative to WMO surface stations, which we attribute to microwave surface emissivity variations and variable near surface temperature gradients. Uncertainty regarding microwave emissivity in desert regions underscores the need for future development of desert bare soil emission models for microwave geophysical parameter retrieval in these regions. Cloud cover in tropical forest regions also appears to influence AIRS temperature retrieval accuracy more than AMRS-E though both were impacted. For most vegetated regions we find somewhat better temperature accuracy from AMSR-E relative to AIRS, but AMSR-E may contain more bias in several locations, although AMSR-E has 10-11 % less data coverage than AIRS due primarily to narrower swath width. The AIRS and AMSR-E derived temperatures generally corresponded better with each other than with in situ station observations. AMSR-E derived temperatures and co-retrieved open water fraction, vegetation optical depth, and atmospheric water vapor parameters reproduce expected regional patterns, although some discrepancies exist for desert regions. The AMSR-E derived atmospheric water vapor corresponds closely with the AIRS mixing ratio product. Future evaluation of AMSR-E co-retrievals should be verified with independent datasets including MODIS vegetation products, re-analyses, and radiosondes.

Spatial representation mismatches between in situ station measurements and the resolution of individual satellite sensors limit our ability to quantify uncertainty. The satellite retrievals reflect horizontally and vertically effective temperatures, which may differ
significantly from sparse station observations within a 25-km grid cell. It is difficult to assess whether AIRS or AMSR-E retrievals are reliable where the station network is sparse, especially over desert and mountainous regions. Data assimilation-type approaches to validation will ultimately be required to help overcome the limitations of sparse station networks and exploit synergies between different sensor products [Crow 2007; McCabe 2008; Renzullo 2008].

We present an algorithm in this study that provides daily surface air temperature information from satellite multi-frequency microwave remote sensing with well-quantified regional uncertainty relative to surface observations. The approach can readily be extended to the global domain and additional years as the key factors influencing accuracy and spatial variability are present in the Northern Hemisphere. The results are sufficiently accurate for regional analysis of temperature patterns and environmental gradients, and are appropriate inputs for global atmospheric and land surface models.

ACKNOWLEDGEMENTS

Portions of this work were conducted at the Jet Propulsion Laboratory of the California Institute of Technology and the University of Montana under contract to the National Aeronautics and Space Administration (NASA). We gratefully acknowledge financial support from the NASA Terrestrial Hydrology and Ecology programs. The daily surface weather station data for this study were provided by the National Climatic Data Center.
REFERENCES


### Table 1: Sample sizes of WMO stations used for algorithm development (Development Set) and validation (Test Set). WMO stations are stratified by latitudinal band (columns) and MODIS UMD land cover class (rows). See Section II D. for latitudinal band explanation and Figure 1 for land cover abbreviations.

<table>
<thead>
<tr>
<th></th>
<th>Development Set</th>
<th>Test Set</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Boreal</td>
<td>Temperate</td>
</tr>
<tr>
<td>ENF</td>
<td>10</td>
<td>9</td>
</tr>
<tr>
<td>EBF</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>DNF</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>DBF</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>MNC</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>WOD</td>
<td>17</td>
<td>9</td>
</tr>
<tr>
<td>WGR</td>
<td>16</td>
<td>9</td>
</tr>
<tr>
<td>CSH</td>
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<td>2</td>
</tr>
<tr>
<td>OSH</td>
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<td>15</td>
</tr>
<tr>
<td>GRS</td>
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<td>19</td>
</tr>
<tr>
<td>CRP</td>
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<td>22</td>
</tr>
<tr>
<td>BAR</td>
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<td>7</td>
</tr>
<tr>
<td>URB</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Totals</td>
<td>83</td>
<td>101</td>
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### Table 2: Radiative transfer model parameters used to derive surface air temperature from AMSR-E 18.7 and 23.8 GHz $T_b$ inputs.

<table>
<thead>
<tr>
<th>Physical Model Parameters</th>
<th>Symbol</th>
<th>18.7 GHz</th>
<th>23.8 GHz</th>
</tr>
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<tbody>
<tr>
<td>Veg./Roughness single scattering albedo</td>
<td>$\omega$</td>
<td>0.05</td>
<td>0.05</td>
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<td>Dry bare soil surface emissivity (V-pol.)</td>
<td>$\varepsilon_{sv}$</td>
<td>0.994</td>
<td>0.975</td>
</tr>
<tr>
<td>Dry bare soil surface emissivity (H-pol.)</td>
<td>$\varepsilon_{sh}$</td>
<td>0.771</td>
<td>0.781</td>
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<td>Open water emissivity (V-pol.)</td>
<td>$\varepsilon_{sv}$</td>
<td>0.630</td>
<td>0.685</td>
</tr>
<tr>
<td>Open water emissivity (H-pol.)</td>
<td>$\varepsilon_{sh}$</td>
<td>0.336</td>
<td>0.421</td>
</tr>
<tr>
<td>Water Vapor mass absorption coefficient</td>
<td>$a_v$</td>
<td>0.0034</td>
<td>0.0104</td>
</tr>
<tr>
<td>Oxygen mass absorption coefficient</td>
<td>$a_o$</td>
<td>0.0103</td>
<td>0.0131</td>
</tr>
<tr>
<td>Initial emissivity difference ratio multiplier</td>
<td>$\beta_0$</td>
<td>0.88</td>
<td>0.88</td>
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</table>
Table 3: Multiple regression model parameters used to correct for air temperature differences between satellite (AMSR-E and AIRS) local overpass time and timing of $T_{mx}$ and $T_{mn}$. See text Section IV for parameter descriptions.

<table>
<thead>
<tr>
<th>Empirical Parameters</th>
<th>AMSR-E</th>
<th>AIRS</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Parameter for surface to air temperature ratio $\delta$</td>
<td>0.98</td>
<td>0.96</td>
</tr>
<tr>
<td>2 Surface to air temperature correction $c_0$</td>
<td>-0.8</td>
<td>2.0</td>
</tr>
<tr>
<td>2 Surface to air temperature correction $c_1$</td>
<td>12.0</td>
<td>-9.2</td>
</tr>
<tr>
<td>2 Surface to air temperature correction $c_2$</td>
<td>-19.0</td>
<td>0.0</td>
</tr>
<tr>
<td>3 Overpass time regression coeff. (constant) $m_0$</td>
<td>22.53</td>
<td>55.50</td>
</tr>
<tr>
<td>3 Overpass time regression coeff. (temperature) $m_1$</td>
<td>0.93</td>
<td>0.83</td>
</tr>
<tr>
<td>3 Overpass time regression coeff. (latitude) $m_2$</td>
<td>-0.07</td>
<td>-0.09</td>
</tr>
</tbody>
</table>

1 Used in radiative transfer model eqn. (7); $T_a = T_s + c_0 + c_1(t_c) + c_2(t_c^2)$; $T_{a, adjusted} = m_0 + m_1(T_{a, retrieved}) + m_2(Lat.)$.

Table 4: Summary statistics of relative agreement between AMSR-E and AIRS derived Northern Hemisphere temperature results, and in situ daily air temperature measurements pooled for 273 WMO test sites.

<table>
<thead>
<tr>
<th>$T_{mn}$ (K)</th>
<th>$R^2$</th>
<th>RMSE</th>
<th>MAE</th>
<th>MR</th>
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</thead>
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<tr>
<td>AMSR-E vs. WMO</td>
<td>0.85</td>
<td>3.5</td>
<td>2.7</td>
<td>0.02</td>
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<tr>
<td>AIRS vs. WMO</td>
<td>0.81</td>
<td>3.8</td>
<td>2.9</td>
<td>0.30</td>
</tr>
<tr>
<td>AMSR-E vs. AIRS</td>
<td>0.85</td>
<td>3.2</td>
<td>2.4</td>
<td>-0.05</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$T_{mx}$ (K)</th>
<th>$R^2$</th>
<th>RMSE</th>
<th>MAE</th>
<th>MR</th>
</tr>
</thead>
<tbody>
<tr>
<td>AMSR-E vs. WMO</td>
<td>0.79</td>
<td>3.5</td>
<td>2.7</td>
<td>0.12</td>
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<tr>
<td>AIRS vs. WMO</td>
<td>0.83</td>
<td>3.4</td>
<td>2.5</td>
<td>0.14</td>
</tr>
<tr>
<td>AMSR-E vs. AIRS</td>
<td>0.86</td>
<td>2.7</td>
<td>2.0</td>
<td>0.07</td>
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Table 5: Correlations and trends of uncertainty (RMSE) and bias (MR) at WMO sites are shown relative to surface and atmospheric factors for AMSR-E (AIRS in parenthesis). Numbers shown in bold are significant at the \( p < 0.01 \) level, all other numbers are significant at \( p < 0.05 \). Non-significant relations are denoted as \( \text{NS} \).

<table>
<thead>
<tr>
<th>Factor</th>
<th>Units</th>
<th>( T_{mn} ) (K)</th>
<th>( T_{mx} ) (K)</th>
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<tbody>
<tr>
<td></td>
<td></td>
<td>( R )</td>
<td>Slope</td>
</tr>
<tr>
<td>Latitude</td>
<td>( ^\circ ) N</td>
<td>\text{NS} (\text{NS})</td>
<td>\text{NS} (\text{NS})</td>
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<tr>
<td>Elevation</td>
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<td>Dom. Cover</td>
<td>%</td>
<td>\text{NS} (\text{NS})</td>
<td>\text{NS} (\text{NS})</td>
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<tr>
<td>AMSR-E ( V )</td>
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<td>-0.04 (\text{NS})</td>
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<tr>
<td>AMSR-E ( f_w )</td>
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<td>\text{NS} (\text{NS})</td>
<td>\text{NS} (\text{NS})</td>
</tr>
<tr>
<td>AMSRE ( t_c )</td>
<td>dim</td>
<td>0.23 (-0.13)</td>
<td>2.08 (-0.76)</td>
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<tr>
<td>AIRS ( \Delta T_{skin} )</td>
<td>K</td>
<td>0.19 (-0.17)</td>
<td>0.04 (-0.03)</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Factor</th>
<th>Units</th>
<th>MR</th>
<th>( R )</th>
<th>Slope</th>
<th>( R )</th>
<th>Slope</th>
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</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>( R )</td>
<td>Slope</td>
<td>( R )</td>
<td>Slope</td>
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<tr>
<td>Latitude</td>
<td>( ^\circ ) N</td>
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<tr>
<td>Dom. Cover</td>
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<td>\text{NS} (\text{NS})</td>
<td>-0.15 (-0.14)</td>
<td>-0.02 (-0.02)</td>
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<tr>
<td>AMSR-E ( V )</td>
<td>mm</td>
<td>\text{NS} (\text{NS})</td>
<td>\text{NS} (\text{NS})</td>
<td>\text{NS} (0.24)</td>
<td>\text{NS} (0.05)</td>
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</tr>
<tr>
<td>AMSR-E ( f_w )</td>
<td>dim</td>
<td>0.29 (0.29)</td>
<td>5.83 (4.27)</td>
<td>0.37 (\text{NS})</td>
<td>7.17 (\text{NS})</td>
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<tr>
<td>AMSRE ( t_c )</td>
<td>dim</td>
<td>-0.13 (\text{NS})</td>
<td>-2.08 (\text{NS})</td>
<td>\text{NS} (\text{NS})</td>
<td>\text{NS} (\text{NS})</td>
<td></td>
</tr>
<tr>
<td>AIRS ( \Delta T_{skin} )</td>
<td>K</td>
<td>-0.14 (-0.19)</td>
<td>-0.06 (-0.06)</td>
<td>\text{NS} (\text{NS})</td>
<td>\text{NS} (\text{NS})</td>
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Figure 1: Distribution of Northern Hemisphere MODIS UMD land cover classes and WMO stations used for algorithm development and testing (right). The land cover classes and WMO stations are summarized (at left) within three Northern Hemisphere latitudinal bands (Boreal, Temperate and Tropical); the relative proportions of each land cover class (and WMO stations within each land cover class) are expressed as a proportion (%) of the total land area (or total stations) within each latitudinal band. The categories are sorted in order of decreasing percent cover based on areal representation.
Figure 2: Time-series linear cross correlations (R) between AMSR-E daily descending/ascending $T_{bv}$ values and corresponding $T_{mn}/T_{mx}$ observations from in situ WMO station observations. The correlations are plotted by frequency (abscissa), where individual lines represent distinct MODIS land cover classes. The filled stars represent radiative transfer model results derived from randomly generated temperature, atmospheric and vegetation inputs.

Figure 3: Bivariate histogram scatterplots of a) numerator and denominator of the MAWVI ratio (10) and b) Northern Hemisphere AM overpass $F_h$ (11) and $P$ (12) ratios forming the basis of the surface emissivity model. Red regions primarily represent land areas (most observations), whereas blue areas generally reflect open water (fewer observations). Model results for two levels of atmospheric water vapor ($V$) are shown for reference and indicate triangular shaped regions enclosing all possible surface $f_w$, $t_c$ conditions for a given water vapor content. Markers
point in direction of increasing $t_c$ (filled markers) or $f_w$ (open markers). Data represent Northern Hemisphere A.M. land conditions for the 2003 study period.

**Figure 4:** Mean daily maps of AMSR-E retrieved parameters for the 2003 study period. Open water fraction ($f_w$) and vegetation optical depth ($\tau_c$, angle corrected and used in favor of $t_c$ to improve scaling) are presented for the descending overpass, while $T_{mn}$, $T_{mx}$, and atmospheric water vapor ($V$) are presented for both overpasses. PDFs are also presented (lower right) for Northern Hemisphere daily retrieved surface and atmospheric states including daily retrievals for both ascending (Asc.) and descending (Desc.) satellite overpasses.
Figure 5: Maps of Northern Hemisphere regional correspondence between AMSR-E and AIRS $T_{mn}$ and $T_{mx}$ retrievals over the study period.
Figure 6: Northern Hemisphere mean daily temporal variation in AMSR-E and AIRS derived $T_{mn}$ and $T_{mx}$ RMSE and mean bias (MR) for the study period.

Figure 7: Summary statistics between AMSR-E and AIRS temperature retrievals relative to WMO station observations, and between AMSR-E and AIRS relative to each other. The statistics are summarized by land cover class for the three latitudinal bands, where the bars represent group medians for each statistic. The number of WMO stations in each land cover class is shown in Table 1. See Section II D. for statistical abbreviations.