An Evaluation of Satellite Remote Sensing Data Products for Land Surface Hydrology: Atmospheric Infrared Sounder*

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ABSTRACT

The skill of instantaneous Atmospheric Infrared Sounder (AIRS) retrieved near-surface meteorology, including surface skin temperature (T_s), air temperature (T_a), specific humidity (q), and relative humidity (RH), as well as model-derived surface pressure (P_{surf}) and 10-m wind speed (w), is evaluated using collocated National Climatic Data Center (NCDC) in situ observations, offline data from the North American Land Data Assimilation System (NLDAS), and geostationary remote sensing (RS) data from the Spinning Enhanced Visible and Infrared Imager (SEVIRI). Such data are needed for RS-based water cycle monitoring in areas without readily available in situ data. The study is conducted over the continental United States and Africa for a period of more than 6 years (2002–08). For both regions, it provides for the first time the geographic distribution of AIRS retrieval performance. Through conditional sampling, attribution of retrieval errors to scene atmospheric and surface conditions is performed. The findings support previous assertions that performance degrades with cloud fraction and that (positive) bias enhances with altitude. In general AIRS is biased warm and dry. In certain regions, strong AIRS–NCDC correlation suggests that bias-driven errors, which can be substantial, are correctable. The utility of the error characteristics for prescribing the input-induced uncertainty of RS retrieval models is demonstrated through two applications: a microwave soil moisture retrieval algorithm and the Penman–Monteith evapotranspiration model. An important side benefit of this study is the verification of NLDAS forcing.

1. Introduction

Improving our ability to observe, understand, and model regional and global atmospheric and terrestrial water and energy cycles is an unresolved objective of the World Climate Research Programme (WCRP) Global Energy and Water Cycle Experiment (GEWEX). Once limited by a scarcity of land surface observations, water and energy budget studies now have access to a multitude of satellite remote sensing (RS)-derived datasets, including surface skin temperature (T_s ; Holmes et al. 2009), soil moisture (SM; Gao et al. 2006; Lu et al. 2009; Njoku et al. 2003), precipitation (P ; Hsu et al. 1997; Hsu et al. 1999; Huffman et al. 2003; Sorooshian et al. 2000), runoff

(Q ; Alsdorf et al. 2008; Birkett, 1998; Frappart et al. 2006), radiative fluxes (Stackhouse et al. 2000; Zhang et al. 2004), vegetative properties (Ganguly et al. 2008; F. Gao et al. 2008; Tucker et al. 2005), snow cover area (SCA; Hall et al. 2002), snowpack water equivalent (SWE; Kelly et al. 2003), terrestrial water storage (TWS; Tapley et al. 2004), and atmospheric temperature and humidity profiles (Susskind et al. 2003, 1997), available globally with temporal frequency of a few days to twice daily at spatial resolutions of 1–250 km. The RS datasets offer an unprecedented potential of tightening constraints on terrestrial water and energy budgets [Eqs. (1)–(2)] through direct observations of ΔS , P , Q , and R_n and indirect (retrieved) estimates of H , λE , and G , where ΔS is the change in TWS, R_n is the net radiation flux, H is the sensible heat flux, λ is the latent heat of vaporization ($\lambda \approx 2.45 \text{ MJ kg}^{-1}$ at 20°C), E is the evapotranspiration, and G is the soil heat flux at the earth's surface:

$$\Delta S = P - E - Q, \quad (1)$$

$$R_n = H + \lambda E + G. \quad (2)$$

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For example, Ferguson et al. (2010) utilized the suite of sensors onboard the National Aeronautics and Space Administration (NASA) Earth Observing System (EOS) *Aqua*, including the Atmospheric Infrared Sounder/Advanced Microwave Sounding Unit/Humidity Sounder Brazil (AIRS/AMSU/HSB, hereafter AIRS), the Clouds and Earth's Radiant Energy System (CERES), and the Moderate Resolution Imaging Spectroradiometer (MODIS) to estimate daily RS- E over the continental United States (CONUS) at 5-km resolution. These RS- E estimates were subsequently used by Sheffield et al. (2009), together with Gravity Recovery and Climate Experiment (GRACE; Tapley et al. 2004) ΔS and the Tropical Rainfall Measuring Mission (TRMM) Multisatellite Precipitation Analysis (TMPA; Huffman et al. 2007) or the Climate Prediction Center (CPC) morphing technique (CMORPH; Joyce et al. 2004) P , to demonstrate over the Mississippi River basin the feasibility of monitoring the terrestrial water budget exclusively with RS data. Feasibility was confirmed, but the water balance closure error was shown to be on the order of the basin's Q , underscoring basic inconsistency among current state-of-the-art RS products. Other studies have demonstrated significant improvements in the accuracy of numerical weather prediction (NWP) forecasts and land surface hydrology model outputs through data assimilation (DA) of one or several of the aforementioned RS datasets (Andersson et al. 2007; Andreadis and Lettenmaier 2006; Crow and Wood 2003; Margulis and Entekhabi 2003; Pan and Wood 2009; Reichle et al. 2008; Walker and Houser 2001). In the absence of a sufficient in situ network (e.g., Africa), NWPs and RS observations provide the only tools for hydrology.

Migrating from single process, single variable oriented approaches to synergistic frameworks, like DA, or the hydrological consistency approach of McCabe et al. (2008) that integrate several diverse variables is to exploit fully the information content of available RS observations. Such efforts culminate in value-added level 4 "knowledge" (Asrar and Dokken 1993) data products, of which E is a primary example.

Over land, climate may be viewed as a complex balance of many highly coupled processes that collectively drive the exchanges of moisture and energy between soil, vegetation, and the overlying atmospheric planetary boundary layer (PBL; e.g., Betts et al. 1996; Dirmeyer 2006; Ek and Holtslag 2004; Shuttleworth 1988). Measurement of any number of these states, fluxes, or related variables, either concurrently or independently, at varying time steps and resolution as is often the reality with RS, provides an opportunity to establish confidence in the derived quantities through hydrological consistency. For example, for drought monitoring observations of low soil

moisture alone may be insufficient because of the sensing depth (1–3 cm) and sampling (i.e., mixed pixels) limitations. Closely timed observations of zero P , low humidity, high T_s , and low Q , would improve the reliability of such monitoring (Luo and Wood 2007). Likewise, SM combined with P (warm season) or SM combined with P , T_s , SCA, and SWE (cold season) should reduce flood forecasting errors (Bindlish et al. 2009; Crow et al. 2005; Hong et al. 2007; Kumar et al. 2008). Linked, derived products enable independent uncertainty estimates, as demonstrated for P using SM (Crow and Bolten 2007), but the performance can benefit mutually (Crow et al. 2009).

That the land surface and atmospheric processes feedback on one another (i.e., coupling) has important implications for hydrologic intensification (see Huntington 2006) that may occur under a changing climate. Remote sensing offers the only viable method for quantifying through observation at regional to global scales, hydrologic sensitivity to climate change, including the strength of land–atmospheric coupling. The absence of an objective, multiseason, observation-based quantification of large-scale coupling strength has been recognized as a "major obstacle to the evaluation of model performance and development" (Guo et al. 2006). The GEWEX Global Land–Atmosphere Coupling Experiment (GLACE; Guo et al. 2006; Koster et al. 2006) called attention to distinct multimodel coupling "hot spots" located in the Sahel, the central Great Plains, India, and eastern Asia. To what extent are these spatial patterns of simulated coupling strength reflective of reality, and not just an artifact of the models (Koster et al. 2003)?

To truly address any of these issues requires that we first answer the following question: How well do we observe the underlying variables? Our current environment is characterized by an abundance of (RS) data that is of poorly quantified skill, a consequence of which is our present inability to prescribe meaningfully confidence limits to model outputs.

With these issues in mind, the aim of this paper is to validate "indirect" variables, including T_s , 2-m air temperature (T_a), and humidity—both relative (RH) and specific (q), such that confidence in derived coupling diagnostics, E and SM , for example, may be achieved. Historically, these variables have been undervalued. We focus on the evaluation of AIRS, the most advanced atmospheric sounding system ever deployed in space (Chahine et al. 2006). Our analyses span a greater than 6-yr period (2002–08) over two highly diverse (both in climate and potential applicability) domains: CONUS and Africa. We evaluate the data against observations from more than 2000 ground stations from the National Climatic Data Center's (NCDC) Integrated Surface Database (ISD; Lott et al. 2001), offline data from the North

American Land Data Assimilation System (NLDAS; Mitchell et al. 2004), and estimates of T_s over Africa from the Meteorological Satellites (Meteosat) Second Generation's (MSG) Spinning Enhanced Visible and Infrared Imager (SEVIRI; Schmetz et al. 2002). We quantify retrieval accuracies over a broad range of surface and atmospheric conditions. Specifically along gradients in T_a or T_s , cloud albedo (α_{cloud}), total column precipitable water vapor/ice (pwv), elevation, topographic (vertical) complexity (vc), land cover (lc) class, leaf area index (LAI), snow cover, and season. Using statistics of bias, random error, and nonparametric correlation, we map the distribution of mean retrieval accuracies and provide a summary of conditions for which we expect retrievals to be most and least skillful.

2. Study domains and period

We focus our analyses on two regions: the CONUS domain (25°–53°N, 125°–67°W) and Africa (40°S–40°N, 20°W–55°E), which we hold to be global end members with respect to ground station network densities, and coincidentally the potential impact of RS data assimilation to weather forecast skill. CONUS boasts the highest-density openly available ground measurement network in the world, making it one of the most suitable domains for validating satellite-based near-surface variables. On the other hand, parts of Africa are the most data sparse in the world. Together, the two domains offer a large variety of retrieval conditions (in terms of both landscapes and climate) for which to evaluate retrieval accuracies. The total study period spans from September 2002 through December 2008, with two exceptions: 1) analyses using CERES-derived α_{cloud} are limited to September 2002–August 2007, and 2) analyses using SEVIRI T_s are limited to July 2005–2009 (see section 3). Only the ascending, or afternoon (~1:30 p.m. local time) overpass, is considered. Daytime retrievals are both more challenging and valuable than similar nighttime measurements because they capture the effects of differential heating and evaporation, or surface water and energy fluxes, which we aim to help quantify and that may feedback on the atmosphere.

3. Data and methods

Table 1 provides an overview of the 13 data products used in this study. Because of space constraints, we refer the reader to Ferguson et al. (2010) for a description of the following datasets: 1) the National Centers for Environmental Prediction Global Forecast System (NCEP GFS) surface pressure [packaged with AIRS Level 2 Support Product Dataset (AIRX2SUP)], 2) the Global Modeling and Assimilation Office (GMAO/GEOS-3)

and the European Centre for Medium-Range Weather Forecasts (ECMWF) near-surface wind fields [packaged with the CERES Single Scanner Footprint (SSF)], 3) the NLDAS NCEP Eta Data Assimilation System (EDAS) forcing (see also Cosgrove et al. 2003), 4) the Variable Infiltration Capacity (VIC) model (Troy et al. 2008) surface temperature, and 5) the MODIS for North American Carbon Program (NACP; Wofsy and Harriss 2002) temporally smoothed and spatially complete leaf area index (F. Gao et al. 2008). All other datasets are briefly summarized herein. Note that NLDAS–VIC T_s will be implied when general reference to “NLDAS T_s ” is made.

a. Remote sensing products

1) AIRS

The AIRS on NASA *Aqua* provides twice-daily global coverage of the atmospheric infrared spectrum (3.7–15.4 μm) in 2378 channels across three windows: 3.74–4.61, 6.20–8.22, and 8.8–15.4 μm . It is accompanied on *Aqua* by the AMSU, which measures microwave radiances at 15 channels between 23 and 89 GHz. Combined measurements from AIRS and AMSU serve as inputs to the AIRS cloud-clearing algorithm (Chahine 1974, 1977; Chahine et al. 2001, 2006) that enables successful soundings 47.5% and 72.3% of the time over land and ocean, respectively (Susskind et al. 2003).

AIRS was designed to provide sounding data with vertical resolution and accuracies on par with point-based radiosonde observations (RAOBs; 1-K RMS error in 1-km tropospheric layers and 20% RMS error in 2-km tropospheric layers for water vapor), but available globally, for the purpose of improved weather prediction through data assimilation (Susskind et al. 2006). Primary retrievals include atmospheric temperature and humidity profiles, ozone profiles, sea/land surface skin temperature, and cloud properties, including outgoing longwave radiation (Aumann et al. 2003). The observed RMS error can be described as the sum of four terms: 1) instrument noise and forward retrieval model error under perfectly cloud-free and uniform scene conditions, 2) errors introduced by the cloud-clearing algorithm, 3) errors in surface emissivity, and 4) temporal and spatial collocation errors (Chahine et al. 2006).

Since the launch of AIRS in May 2002, significant improvements (version updates) have been made to the original AIRS retrieval algorithm (Susskind et al. 1998)—these are well documented in Susskind et al. (2003) and Susskind et al. (2006). The current state of the AIRS retrieval algorithm, version 5, implements a radiative transfer algorithm (RTA) that accounts for nonlocal thermodynamic equilibrium (NLTE) effects on the shortwave channels, incorporates a new, accurate

TABLE 1. Data products used in this study: their source, spatial and temporal resolution, and coverage.

Variable field(s)	Source (product)	Resolution	Coverage
Satellite remote sensing			
Skin temperature, 2-m air temperature, specific and relative humidity	AIRS V5, V5.2 (AIRX2SUP)	45 km/instantaneous	Global
Skin temperature	MSG–SEVERI (SAF-LST)	5 km/15 min	MSG disc
Downward shortwave radiation	CERES Ed. 2B, 2C (SSF-46,47)	20 km/instantaneous	Global
UMD land cover classification	MODIS V4 (MOD12Q1)	1 km/yearly	Global
MODIS for NACP leaf area index	MODIS V5 (MOD15A2GFS)	500 m/8-daily	North America
Snow coverage	MODIS V5 (MOD10C1, MYD10C1)	0.05°/daily	Global
Topography	SRTM V4	90 m/static	60°N–60°S
Ground meteorological observations			
2-m air temperature, 2-m dewpoint temperature, 2-m relative humidity, 10-m wind speed, surface pressure	NCDC ISD (Africa), QCLCD (CONUS)	point/hourly	CONUS (~1500 stations) and Africa (~550 stations)
Model forcing/output			
2-m temperature, 2-m specific humidity, 10-m U wind component, 10-m V wind component, surface pressure	NLDAS (EDAS/Eta-based real-time forcing dataset)	0.125°/hourly	NLDAS domain
Surface temperature	VIC–NLDAS	0.125°/hourly	CONUS
10-m U wind component, 10-m V wind component	DAO (GEOS-3) or ECMWF	20 km/3- or 6-hourly	Global
Surface pressure	NCEP–GFS	T254/6-hourly	Global
Topography	GTOPO30	30''/static	Global

cloud clearing algorithm using AIRS spectra only, and provides for the first time, case-by-case product error estimates (Susskind et al. 2010).

(i) Preprocessing

Here, we use AIRS T_s (TSurfStd), T_a (TSurfAir), total column precipitable water vapor (pwv; totH2OStd), and near-surface atmospheric temperature (TAirSup) and moisture (H2OCDSup) profiles obtained from the 100-layer AIRX2SUP version 5 (from 1 September 2002 to 30 September 2006) and version 5.2 (from 1 October 2007 to 31 December 2008). We calculate RH (%) and q (kg kg^{-1}) by first solving for the thickness, Δz (m), of the near-surface atmospheric layer using the hydrostatic approximation and ideal gas law:

$$\Delta z = \frac{R\bar{T}_{a-1}}{g} \log\left(\frac{P_{\text{surf}}}{P_1}\right), \quad (3)$$

where R is the specific gas constant for dry air ($287.05 \text{ J kg}^{-1} \text{ K}^{-1}$), $\bar{T}_{a-1}$ is the mean layer temperature (K) interpolated from the surface (T_a) and bounding top (T_1) AIRS level temperatures as a linear function of the logarithm of AIRS (NCEP–GFS) pressure (pressSupp), g is the gravitational acceleration (9.807 m s^{-2}), and P_{surf} (hPa) and P_1 (hPa) are the surface and bounding top AIRS pressure levels, respectively. Next, the water vapor in the layer, $\text{pwv}_{\text{surf}-1}$ (kg m^{-2} or mm) is calculated by

$$\text{pwv}_{\text{surf}-1} = 10(\text{H2OCDSup}_{\text{surf}-1}) \frac{M}{N_A}, \quad (4)$$

where M is the molecular mass of water ($18.016 \text{ g mol}^{-1}$), N_A is the Avogadro constant ($6.022 \times 10^{23} \text{ molecules mol}^{-1}$), and $\text{H2OCDSup}_{\text{surf}-1}$ is the layer amount of water vapor in molecules per centimeters squared, which is interpolated from the bounding bottom (H2OCDSup_0) and top (H2OCDSup_1) AIRS layer water vapor amounts, using linear interpolation with logarithmic pressure (Olsen 2007). Then, the vapor pressure, e (Pa), and saturation vapor pressure, e_s (Pa) are computed by Eqs. (5) and (6), respectively:

$$e = R_v \bar{T}_{a-1} \left(\frac{\text{pwv}_{\text{surf}-1}}{\Delta z} \right), \quad (5)$$

$$e_s = 611 \exp\left(17.27 \frac{\bar{T}_{a-1} - 273.15}{\bar{T}_{a-1} - 35.85}\right), \quad (6)$$

where R_v is the gas constant for water vapor ($461.0 \text{ J kg}^{-1} \text{ K}^{-1}$). Finally, q and RH are solved via Eqs. (7) and (8), respectively:

$$q = 0.622 \frac{e}{100P_{\text{surf}}}, \quad (7)$$

$$\text{RH} = 100 \frac{e}{e_s}. \quad (8)$$

AIRS footprint values of 13.5 km (at nadir) resolution are quality screened and then spatially interpolated to a 0.125° geographic coordinate system using an inverse-distance-squared interpolation scheme with a great-circle search radius of 75 km. In the case of T_a and T_s , quality-screened footprint values are first elevation corrected from the AIRS topography (topog) to sea level, then interpolated to grids, and finally, elevation corrected to match the NLDAS 0.125° elevation using a mean environmental lapse rate (ELR) of $-6.5^\circ\text{C km}^{-1}$, consistent with that applied by NLDAS (Cosgrove et al. 2003) and the Project for Intercomparison of Land surface Parameterizations (PILPS; Bowling et al. 2003). Errors do depend on pressure (elevation) differences (see Fig. A1) and it is feasible to compute an ELR on-the-fly with AIRS (see supplemental Table S1 in the online supplement: <http://dx.doi.org/10.1175/2010JHM1217.s1>), however at CONUS scale, errors were not found to be sensitive to the precise ELR applied (see supplemental Fig. S1). Whereas T_s and T_a are level quantities, q and RH are layer averages, valid for the lowest atmospheric layer (bounded on the bottom by the surface), and therefore were not corrected for elevation. Since the manner in which AIRS quality flags are applied at the footprint scale does substantially affect the sampling and thus the retrieval accuracy characteristics of the gridded product, we provide a summary of our protocol in the appendix.

(ii) Near-surface air temperature and humidity

Previously, AIRS T_a and q have been evaluated as part of the total vertical profile. Divakarla et al. (2006) compared AIRS temperature and water vapor profiles against collocated RAOBs at 538 stations globally for a 2-yr period (September 2002–December 2004) amounting to more than 82 000 intercomparisons. Over mid-latitude land (50° – 23°N , 50° – 23°S), RMS differences of T_a and q ranged from 1.75 ($P = 1000$ hPa) to 1.25°C ($P = 800$ hPa) and 22 ($P = 1000$ hPa) to 27% ($P = 800$ hPa), respectively (Divakarla et al. 2006). Tobin et al. (2006), through a collaborative effort between the NASA–EOS project and the Department of Energy Atmospheric Radiation Measurement (ARM) program, performed a more targeted intercomparison over multiyear periods at three ARM sites using *Aqua* overpass-dedicated RAOBs. At the ARM Southern Great Plains (SGP) facility, they reported mean RMS differences of approximately 2°C and 25% for T_a and q , respectively (Tobin et al. 2006). Other studies have intercompared AIRS profiles with forecast models, such as the NCEP–GFS and ECMWF (Divakarla et al. 2006; Susskind et al. 2006).

The most thorough regional assessment of AIRS T_a to date, to our knowledge, was completed by W. H. Gao et al. (2008) using collocated observations from 540 meteorological stations in China (15° – 55°N , 75° – 130°E) for 2 months (July 2004 and January 2005). Using data of nominal quality (Qual_Temp_Profile_Bot < 2), mean RMS differences for daytime retrievals in July and January were found to be 3.4° and 2.8°C, respectively.

Beyond these studies, the best approximation of AIRS accuracies may well be error estimates for the Television and Infrared Observation Satellite (TIROS) Operational Vertical Sounder (TOVS), a first generation AIRS if you will. For example, Lakshmi et al. (2001) showed TOVS afternoon T_a retrievals were biased by +2.1°C with RMS differences of 3.8°C relative to 26 stations distributed over the Arkansas–Red River basin.

(iii) Surface temperature

Owing to subfootprint-scale spatial heterogeneity in surface emissivity, T_s products remain the most challenging (along with SM) to validate. Thermal infrared (TIR)-based RS sources including: MODIS, the Advanced Very High Resolution Radiometer (AVHRR), Geostationary Operational Environmental Satellites (GOES), geostationary Meteosat satellites, and the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), offer at a minimum, the opportunity for independent quality checks of T_s . Knuteson et al. (2008) performed a global intercomparison between average monthly AIRS level 3 version 5 T_s and upscaled MODIS level 3 (MYD11C3) collection 4 T_s for July 2003. Across all land cover classes, excluding cases of snow/ice cover, AIRS and MODIS T_s agreed within 0.5° and 1.5°C for the night and daytime overpasses, respectively. The AIRS Science Team's current estimate of AIRS T_s accuracy is 2°–3°C, globally.

(iv) Total column precipitable water vapor

We use AIRS pwv to evaluate the impact of water vapor on retrieval performance. Raja et al. (2008) showed strong agreement ($0.91 \leq R \leq 0.98$) between AIRS and Global Positioning System (GPS) pwv, using more than 375 National Oceanic and Atmospheric Administration (NOAA) Earth System Research Laboratory (ESRL; see online at <http://gpsmet.noaa.gov>) stations over CONUS, for the period of April–October 2004. The monthly mean bias (AIRS minus GPS) and RMS differences exhibited a systematic seasonal trend, ranging from –1.2 mm (July) to +0.75 mm (April), and 4.5 mm (July) to 3.0 mm (April), respectively (Raja et al. 2008).

A special issue of the *Journal of Geophysical Research* (2006, Vol. 111) details many of the AIRS Science Team's validation activities (see Fetzer 2006).

2) SEVIRI/METEOSAT

The European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) Land Surface Analysis-Satellite Applications Facility (LSA-SAF) generates, on an operational basis, T_s from the SEVIRI/Meteosat. SEVIRI T_s is available for a period of more than 4 yr (July 2005 to the present) at the full SEVIRI temporal (~ 15 min) and spatial (~ 3 km) resolution and quality screened for satellite zenith view angle (SZA) $> 60^\circ$ and cloud cover. The retrieval algorithm is based on the generalized split-window (GSW) algorithm of Wan and Dozier (1996), initially developed for AVHRR and MODIS, but adapted for SEVIRI's 10.8 and 12.0 μm channels (Madeira 2002). The algorithm's parameters are functions of the SZA and pwv (obtained from ECMWF forecasts). The channel surface emissivity is computed as the area-weighted mean of bare soil and vegetation emissivities, where the fractional vegetation cover is a SAF-retrieved product (Garcia-Haro et al. 2005) and emissivities are preassigned by class in a land cover map (Peres and DaCamara 2005; Trigo et al. 2008a). The complete methodology is provided in the SAF Land Surface Temperature (LST) Product User Manual (available online at <http://landsaf.meteo.pt/>).

Errors in SEVIRI T_s are known to derive from uncertainties in surface emissivity, topographic complexity (vc), pwv, and SZA (Freitas et al. 2010; Trigo et al. 2008b). Theoretically, given an uncertainty of 1% in SAF emissivity, SEVIRI T_s accuracies should fall within a range of $\pm 2^\circ\text{C}$ (Kabsch et al. 2008; Trigo et al. 2008a). The most pronounced errors occur due to the presence of undetected clouds (NWC-SAF 2010). Using matchups at two independent ground radiometers located at the SAF validation station in Mitra, Portugal (38.54°N , 8.00°W) for 61 and 35 days in 2006, Kabsch et al. (2008) found SEVIRI T_s to be systematically biased high ($+2.5^\circ\text{C}$) at the approximate time of *Aqua*'s daytime overpass.

From its native resolution, SEVIRI T_s was first elevation corrected to sea level and then resampled to 0.125° geographic coordinates using box averaging. Next, the 0.125° values were elevation corrected to GTOPO30 (see below) mean elevation. Finally, the 0.125° SEVIRI T_s record was queried using a temporal window of ± 59 min, or in other words ± 3 SEVIRI time steps, to determine the nearest temporal match to the coincident AIRS retrieval. The current LSA-SAF T_s retrieval algorithm (version 7.2) has benefited from a series of modifications over the period of record (Trigo et al. 2008b). Unfortunately, a complete reprocessing of the time series has not occurred. Therefore, we use the discontinuous SEVIRI T_s record as is. Beginning on 8 July 2008, the LSA-SAF T_s product provides greater spatial

coverage and case-by-case error estimates. We sample this later period using the legacy LSA-SAF “nominal” and “below nominal” accuracy levels, or $\text{RMS} < 2^\circ\text{C}$, and $\text{RMS} > 2^\circ\text{C}$, to match the spatial coverage of the earlier record.

3) CERES

The hourly CERES *Aqua* SSF top-of-atmosphere (TOA)/Surface Fluxes and Clouds product contains high-accuracy instantaneous surface and TOA radiation budget datasets from measurements taken by CERES broadband radiometers and a 19-channel subset of the 36-channel MODIS (also onboard *Aqua*). We use the downward shortwave ($\text{SW}\downarrow$) model B estimates, calculated by the Langley Parameterized SW Algorithm (LPSA; Darnell et al. 1992; Gupta et al. 2001) to produce 0.20° daily global maps of α_{cloud} . We first apply an inverse-distance-weighting scheme with a search radius of 0.80° to interpolate SSF footprint values (20 km at nadir) to 0.20° geographic coordinates. Then, we calculate α_{cloud} by the following relation:

$$\alpha_{\text{cloud}} = 1 - \frac{\text{SW}_i}{\text{SW}_{\text{clear}}}, \quad (9)$$

where SW_i is the time-of-overpass $\text{SW}\downarrow$, and SW_{clear} is the maximum $\text{SW}\downarrow$ over an 8-day, $1^\circ \times 1^\circ$ spatial window centered on the pixel of interest. By calculating α_{cloud} in this way, we inherently correct for local atmospheric effects, including dust and smoke. The most current edition, edition 2C, was available only for January and May 2006, and December 2006–August 2007. For all other months, edition 2B was used. Edition 2B and 2C differ only by the collection version of MODIS input, with the later using collection 5 and the prior using collection 4.

AIRX2SUP (see above) does include a TIR cloud fraction (TotCld_4_CCfinal) estimate valid for the AIRS field of regard (45 km) that generally agrees well with α_{cloud} (CONUS: $\tau = 0.41$). However, we found that α_{cloud} was a stronger explanatory variable of accuracy (see supplemental Figs. S4–S5) over arid regions.

4) MODIS LAND COVER CLASSIFICATION

The MODIS *Terra* collection 4, 1-km yearly 1c classification product (MOD12Q1; Friedl 1996) 14-class University of Maryland (UMD) scheme (Hansen et al. 2000) was used. Data tiles were first mosaiced and then reprojected from their native sinusoidal projection to 0.01° geographic coordinates using the MODIS Reprojection Tool (MRT) version 4.0. Since, at the time of writing, MOD12Q1 was only available for years 2001–04, year 2004 was used.

TABLE 2. The number of NCDC ground meteorological stations included in the analyses, listed by variable and domain. The percent of culled stations is denoted in parentheses.

Subdomain	Surface pressure	Relative humidity	Specific humidity	Air temperature	10m wind
CONUS (NLDAS vs NCDC)	1480 (0.6%)	1491 (0.1%)	1489 (0%)	1490 (0%)	1488 (0.3%)
CONUS (AIRS vs NCDC)	1467 (1.5%)	1489 (0.3%)	1490 (0%)	1491 (0%)	1379 (4.0%)
Africa (AIRS vs NCDC)	420 (2.8%)	554 (2.1%)	424 (1.4%)	561 (0.4%)	443 (17.4%)

5) GTOPO30

The GTOPO30 global 30 arc second (~ 1 km) digital elevation model (DEM) was first resampled to 0.125° geographic coordinates using box averaging and then applied to elevation correct the AIRS and SEVIRI temperature products (see above). This ensures topographic consistency, since NLDAS (and NLDAS-VIC) data are also GTOPO30 based.

6) SRTM-90M

The void-filled Shuttle Radar Topography Mission (SRTM) version 4, 90-m DEM (Reuter et al. 2007) was used to generate 0.125° fields of vc , defined as the standard deviation of SRTM 90-m elevation.

7) MODIS SNOW COVER

We use the MODIS *Terra* (MOD10C1) and MODIS *Aqua* (MYD10C1; Hall et al. 2002) collection 5 0.05° daily global *SCA* products. These products were created using the daily MODIS *Terra* and MODIS *Aqua* 500-m tile products, MOD10A1 and MYD10A1, respectively. MYD10C1 is currently considered “provisional,” while MOD10C1 has been well validated (Hall and Riggs 2007).

b. In situ data

For the total record, hourly observations of 10-m wind (w), T_a , 2-m dewpoint temperature (T_d), and surface pressure (P_{surf}) or alternatively, altimeter setting (alt), were obtained from the NCDC ISD. The ISD comprises worldwide surface weather observations from approximately 20 000 stations historically (~ 12 000 available for 1995–2007), collected and stored from sources such as: the Automated Weather Network (AWN), the Global Telecommunications System (GTS), the Automated Surface Observing System (ASOS), as well as data keyed from paper forms (Lott et al. 2001). ISD data have undergone extensive automated quality control (Lott, 2004). Over CONUS, NCDC maintains an additional, more extensively screened database called the Quality Controlled Local Climatological Database (QCLCD).

For this study, data for Africa were obtained from ISD (available 27 January 2009; available online at ftp://

ftp.ncdc.noaa.gov/pub/data/noaa/); data for CONUS were obtained from QCLCD v1.4 (available 28 January 2009; available online at http://cdo.ncdc.noaa.gov/qclcd_ascii/). Only observations satisfying the strictest quality flags were accepted. Furthermore, only stations with more than 50 matched (within ± 90 min of the overpass) observations were considered. The median sample size per station over CONUS and Africa was 1695 ± 642 and 642 ± 462 , respectively. Stations that satisfied the initial sample size criterion were then screened once more on a per variable basis using the Kendall's τ correlation metric (hereafter τ). Any station/variable for which AIRS (NLDAS)–NCDC time series failed to correlate at the $p = 0.01$ significance level were culled from the analyses (see Table 2). Over CONUS and Africa, approximately 1500 and 500 stations were included, respectively (see Table 2).

For many stations in Africa, pressure is reported in the form of an altimeter setting. In these cases, P_{surf} is calculated following Eqs. (10)–(12):

$$P_{\text{surf}} = (\text{alt}^n - Bh \times 10^{-8})^{1/n} + 0.3, \quad (10)$$

$$B = \frac{RT_a}{g}, \quad (11)$$

$$n = \frac{R \times \text{ELR}}{g}, \quad (12)$$

where P_{surf} is in units of hPa, h is the station elevation in meters (m), alt is in hPa, and T_a is in K. When RH is not provided, it is computed from the dewpoint temperature, T_d , and T_a through an approximation of the Clausius–Clapeyron equation:

$$\text{RH} = 100 \exp \left\{ 17.27 \left[\left(\frac{T_d}{237.3 + T_d} \right) - \left(\frac{T_a}{237.3 + T_a} \right) \right] \right\}, \quad (13)$$

where RH is in percent, T_d is in $^\circ\text{C}$, and T_a is also in $^\circ\text{C}$. Specific humidity, q (kg kg^{-1}), is not available directly from observations and is calculated from Eq. (7), where e is the partial pressure of water vapor in Pa as given by Eq. (14):

TABLE 3. Overview of the break points utilized in the conditional sampling analyses over CONUS (section 4a) and Africa (section 4b). (from top to bottom) Roughly correspond with the box plots (from left to right) in Figs. 7 and 11. The break points for cloud albedo were identical for both domains.

Clouds (α_{cloud})	CONUS					Africa			
	AIRS surface (T_s) or air (T_a) temperature ($^{\circ}\text{C}$)	Total column precipitable water vapor/ice (pwv) (mm)	Elevation (m)	Vertical complexity (vc) (m)	Leaf area index (LAI)	Total column precipitable water vapor/ice (pwv) (mm)	Elevation (m)	Vertical complexity (vc) (m)	Leaf area index (LAI)
0	<0	0	0	0	0	0	0	0	0
0.05	0	3.18	236	9.6	0.43	6.34	284	7.2	0.33
0.2	20	6.00	418	17.9	0.79	11.37	436	14.4	0.60
0.4	30	9.92	740	36.4	1.22	17.49	640	25.6	0.95
0.6		14.37	1622	108.1	2.01	25.20	1063	58.6	1.74
		21.04				35.41			
		34.29				46.35			

$$e = 611 \exp \left[17.27 \left(\frac{T_d}{237.3 + T_d} \right) \right]. \quad (14)$$

c. Methods

For all comparisons, we compute three sample statistics: bias, unbiased RMS (ubRMS, a.k.a. the random error), and Kendall's τ nonparametric correlation. Bias is calculated by

$$\text{bias} = \frac{1}{n} \sum_{i=1}^n (\text{AIRS}_i - \text{meas}_i), \quad (15)$$

where meas_i is the in situ, or otherwise “true” measurement. The ubRMS is calculated by

$$\text{ubRMS} = \sqrt{\text{RMS}^2 - \text{bias}^2}, \quad (16)$$

where

$$\text{RMS} = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (\text{AIRS}_i - \text{meas}_i)^2}, \quad (17)$$

and n represents the sample size. In the case of q and RH, relative bias and relative ubRMS (ubRMSP) are used instead:

$$\begin{aligned} \text{relative bias} &= \frac{\text{bias}}{\overline{\text{meas}}} \times 100, \\ \text{ubRMSP} &= \frac{\text{ubRMS}}{\overline{\text{meas}}} \times 100, \end{aligned} \quad (18)$$

where $\overline{\text{meas}}$ is the time series mean of the measured quantity (i.e., NLDAS q or NLDAS RH). This approach provides easily interpreted/applied values that are minimally influenced by errors during dry extremes, but still normalized by the annual mean climatology. Differentiation between bias and random error becomes less meaningful as the correlation, or confidence in the bias correction, diminishes. Reference to the “agreement” of

two datasets shall imply the Kendall's τ correlation. Likewise, reference to “uncertainty” or “accuracy” shall imply the ubRMS (or ubRMSP).

4. Results

Over CONUS we first evaluate the AIRS and NLDAS data against NCDC in situ observations [section 4a(1)] and then evaluate AIRS relative to NLDAS offline data [section 4a(2)]. Spatially and temporally continuous (hourly) fields of elevation-corrected and validated (Luo et al. 2003; Mitchell et al. 2004) NLDAS meteorology afford the maximum number of matchups with AIRS. We exploit these data characteristics to evaluate the skill of AIRS retrievals over a broad range of surface and atmospheric conditions [section 4a(2)]. Specifically, we take sample subsets along gradients (generally quintiles) of AIRS T_s or T_a , α_{cloud} , pwv, elevation, vc, UMD 1c class, LAI, and season, including SCA. The precise break points that we employed are provided in Table 3, listed by domain. Quintiles were used for the pwv (calculated from the January through December 2004 distribution), elevation, vc, and LAI. In the case of pwv, two supplemental levels—the 5th and 95th percentile—were also included. The break points for α_{cloud} and T_s or T_a were selected arbitrarily. The warm and cold seasons correspond to the months of May–September and October–April, respectively. Similar analyses were carried out over Africa between AIRS and NCDC [section 4b(1)] and AIRS and SEVIRI [section 4b(2)]. Quoted statistics are for the total record, unless otherwise noted.

a. Continental United States

1) COMPARISON WITH NCDC

Figures 1 and 2 illustrate the spatial distribution of AIRS–NCDC (Fig. 1) and NLDAS–NCDC (Fig. 2)

FIG. 1. Mean AIRS–NCDC bias (T_a) and relative bias (q and RH) computed for the total record.

mean bias (T_a) and relative bias (q and RH). Figure 3 shows the spatial distribution of correlation between GFS and NCDC P_{surf} and GEOS-3 and NCDC w . Figure 4 provides side-by-side comparisons of the frequency distributions of error statistics from AIRS/GFS/GEOS-3–NCDC and NLDAS–NCDC matchups for all variables—the mean statistics of which have been summarized in Table 4.

Figure 1 shows a strong east (cold or neutral) to west (warm) transition in AIRS T_a bias occurs near

97.5°W—right along the hot spot region and typical strong vegetation/soil moisture gradient, not mirrored by NLDAS. The T_a bias is well correlated with elevation ($\tau = 0.49$, Pearson's $R = 0.62$), particularly for mean elevations greater than 500 m, with slope of $+2.1^\circ\text{C km}^{-1}$. For a majority of the Midwest, T_a is shown to have an absolute bias of less than 1°C . Over central Iowa ($41^\circ\text{--}43^\circ\text{N}$, $94^\circ\text{--}92^\circ\text{W}$, $n = 53$), T_a is in fact unbiased (0°C , $n = 16$). Elsewhere, along the Texas–Oklahoma border ($34^\circ\text{--}37^\circ\text{N}$, $103^\circ\text{--}98^\circ\text{W}$) the mean bias is $+3.0^\circ\text{C}$ ($n = 24$)

FIG. 2. As in Fig. 1, but for the NLDAS-NCDC intercomparisons.

and along the Gulf Coast (29°–31.5°N, 95°–85°W) the mean bias is -2.1°C ($n = 53$).

Figures 1 and 4 show that q is predominantly biased dry (negative). If we consider the same regions (as above), we find q to have a relative bias of +0.7% (Texas–Oklahoma), -17.7% (Gulf Coast), and -19.9% (central Iowa). On the other hand, RH has a slight positive (wet) bias over CONUS. Although, over the same regions, RH has a relative bias of -2.5% (Texas–Oklahoma), $+0.2\%$ (Gulf Coast), and -14.2% (central Iowa). Most of the dry bias in RH occurs within

a distinct band known as the Midwest “corn belt” (see Fig. 1).

As shown in Fig. 4, there is a bimodal distribution of GFS-NCDC (and NLDAS-NCDC) P_{surf} correlation and random error. We determined that the area east of 97.5°W was the source of this pattern. For example, 35 of 69 stations in Illinois have a τ less than 0.20 and ubRMS greater than 7.5 hPa. Of the remaining stations, 32 have a τ greater than 0.84 and ubRMS less than 2.0 hPa. Overall, both GFS and NLDAS P_{surf} and GEOS-3 and NLDAS w datasets are most uncertain west of 104°W

FIG. 3. (top) GFS-NCDC P_{surf} (hPa) and (bottom) GEOS-3-NCDC w (m s^{-1}) Kendall's τ correlation computed for the total record.

(west). The median RMS error for GFS (NLDAS) P_{surf} is 21.1 hPa (10.1 hPa) in the west ($n \sim 300$) and 6.2 hPa (4.6 hPa) in the east ($n \sim 1160$). The median RMS error for GEOS-3 (NLDAS) w is 2.2 m s^{-1} (2.1 m s^{-1}) in the west and 1.7 m s^{-1} (1.8 m s^{-1}) in the east. GFS P_{surf} is distinctly biased low in the West (median = -17.9 hPa), but nearly unbiased in the East (median = $+0.4 \text{ hPa}$). Area-mean GFS P_{surf} is biased relatively low in northern New York, New Hampshire, and Vermont (-10.9 hPa , $n = 39$) and high in the Midwest (Minnesota, Wisconsin, Iowa, and Illinois: $+5.0 \pm 6.8 \text{ hPa}$, $n = 263$) and Virginia and North Carolina ($+6.1 \text{ hPa}$, $n = 96$). GEOS-3 w is biased low in Texas, Oklahoma, Kansas, eastern New Mexico, and southern California ($-0.73 \pm 0.63 \text{ m s}^{-1}$, $n = 257$) and slightly high along the eastern coast (Delaware, Maryland, Virginia, North Carolina, South Carolina, and Georgia: $+0.5 \pm 0.5 \text{ m s}^{-1}$, $n = 170$). Over CONUS, GFS P_{surf} and GEOS-3 w have mean biases of -2.5 hPa and -0.1 m s^{-1} , respectively (Table 4). Agreement between GFS and NCDC P_{surf} ($\tau = -0.54$), and to a lesser extent GEOS-3 and NLDAS w ($\tau = -0.29$), was found to be anticorrelated with vc.

Relative to the NCDC stations (truth), NLDAS, and AIRS/GFS/GEOS-3 exhibit different error characteristics

(Fig. 4). For all variables, NLDAS forcing is consistently better correlated with less uncertainty relative to AIRS/GFS/GEOS-3. Differences between GFS and NLDAS P_{surf} and GEOS-3 and NLDAS w , which are both model outputs, may be attributed to issues of scale (GFS $P_{\text{surf}} \sim 45 \text{ km}$, GEOS-3 $w \sim 20 \text{ km}$, and NLDAS $\sim 12.5 \text{ km}$).

Relative to NCDC, AIRS, and NLDAS: 1) T_a are similarly biased ($\pm 0.5^\circ\text{C}$) over Iowa, Missouri, southern Wisconsin, and eastern Oklahoma; 2) q are similarly biased ($\pm 5\%$) over northern and western Texas and western Oklahoma; and 3) RH are similarly biased ($\pm 5\%$) over the larger part of CONUS, but disagree in sign over the Midwest (e.g., Minnesota, Wisconsin, Iowa, northern Illinois, northern Indiana, Ohio), and the Southeast (e.g., Alabama, Georgia, South Carolina, North Carolina, and Virginia). However, the domain-averaged bias of AIRS (-10.3%) and NLDAS ($+8.8\%$) q are of opposite sign (Table 4). Over California's Sacramento River valley ($n = 25$), both AIRS and NLDAS are shown to be biased warm (AIRS: $+1.6^\circ\text{C}$; NLDAS: $+2.3^\circ\text{C}$) and dry (AIRS q : -14.5% ; NLDAS q : -6.8%).

When NLDAS is used as the surrogate truth (next section) for calculating AIRS bias, the true AIRS bias (i.e., AIRS minus NCDC) may be under (subtractive) or

FIG. 4. Frequency distributions of NLDAS-NCDC (black) and AIRS (T_a , q , and RH)/GFS (P_{surf})/GEOS-3 (w)-NCDC (gray) error statistics over CONUS computed for the total record. The bias and ubRMS differences for q and RH are provided in relative terms (ubRMS), as discussed in section 3. (left and middle) The plotting limits for the bias and random error are the minimum 5th and maximum 95th percentiles of the two samples. The number of contributing stations differs by variable (see Table 2).

over (additive) represented—a function of the inherent NLDAS-NCDC error characteristics. Accordingly, it is feasible that the sign of the true AIRS-NCDC bias differs from the calculated AIRS-NLDAS bias. Such

cases are fairly limited, but do occur at 7.1% (q), 9.8% (T_a), and 12.0% (RH) of the NCDC stations.

The representativeness of the NCDC ground station network at the scale of AIRS, especially in the West,

TABLE 4. Summary of the mean error statistics for the AIRS (T_a , q , and RH)/GFS (P_{surf})/GEOS-3 (w)–NLDAS (CONUS and Africa), and NLDAS–NCDC (CONUS) meteorology. Values are calculated using all available stations (see Table 2) for the total record.

Comparison pair	Bias (relative bias)	ubRMS (ubRMSP)	Kendall's τ
Air temperature (T_a)			
AIRS–NCDC	+0.2°C	3.4°C	0.80
NLDAS–NCDC	+0.5°C	2.0°C	0.88
AIRS–NCDC (Africa)	+1.0°C	3.4°C	0.61
Specific humidity (q)			
AIRS–NCDC	−0.9 g kg ^{−1} (−10.3%)	2.3 g kg ^{−1} (28.4%)	0.67
NLDAS–NCDC	+0.5 g kg ^{−1} (+8.8%)	1.3 g kg ^{−1} (17.7%)	0.82
AIRS–NCDC (Africa)	−1.4 g kg ^{−1} (−12.4%)	3.2 g kg ^{−1} (27.9%)	0.45
Relative humidity (RH)			
AIRS–NCDC	−1.8% (−1.4%)	13.3% (27.9%)	0.51
NLDAS–NCDC	+1.6% (+3.4%)	11.3% (22.6%)	0.64
AIRS–NCDC (Africa)	−5.1% (−10.5%)	12.2% (29.7%)	0.48
Surface pressure (P_{surf})			
NCEP–GFS–NCDC	−2.5 mb	5.7 mb	0.56
NLDAS–NCDC	+4.1 mb	4.7 mb	0.63
NCEP–GFS–NCDC (Africa)	−0.9 mb	4.4 mb	0.51
10-m wind (w)			
DAO (GEOS-3) or ECMWF–NCDC	−0.1 m s ^{−1}	1.8 m s ^{−1}	0.40
NLDAS–NCDC	+0.6 m s ^{−1}	1.7 m s ^{−1}	0.53
DAO (GEO-3) or ECMWF–NCDC (Africa)	+0.1 m s ^{−1}	2.2 m s ^{−1}	0.27

where station density falls off and vc increases, is disputable. Station data is also not without error. Biases are introduced through the affect of localized influences due to imperfect siting (i.e., proximity to trees, buildings, and parking lots; Davey and Pielke 2005). We therefore argue that NLDAS forcing, the accuracy of which we have demonstrated, rather than NCDC stations, is more appropriate for comparisons conducted on the scale order of AIRS. Accordingly, in the conditional sampling analyses to follow, we use NLDAS forcing as surrogate truth.

2) COMPARISON WITH NLDAS

Figure 5 shows the geographic distribution of AIRS warm season retrieval accuracies relative to NLDAS. Overall, patterns in AIRS–NCDC (Fig. 1) and AIRS–NLDAS (Fig. 5) bias are spatially coherent. The median AIRS–NLDAS biases were found to be +2.1°C (T_s), −0.5°C (T_a), −17.5% (q), and −7.0% (RH). The median random errors are 4.4°C (T_s), 3.2°C (T_a), 20.8% (q), and 22.3% (RH). Agreement between AIRS and NLDAS is generally strong with median τ s of 0.62 (T_s), 0.66 (T_a), 0.55 (q), and 0.48 (RH). For T_s , the ubRMS local maxima are centered over the Midwest corn belt and the West Texas high plains. For T_a , q , and RH, the largest uncertainty is observed in the West, but particularly in California and Nevada for q and RH. Local minima in correlation occur over the Southeast (T_s and T_a) and along the Gulf Coast and Pacific Northwest (q).

The patterns of RH error and correlation represent the combined effect of T_a and q accuracy characteristics. Across CONUS, q is biased dry (negative) with the exception of the Cascade, Sierra Nevada, and Peninsular mountain ranges of California, which coincidentally, are also local maxima of uncertainty (ubRMSP > 30%). Anomaly correlations computed using a climatological (2002–08) ± 5 -day moving average of each respective product/variable (AIRS and NLDAS), show that seasonality does impact the error characteristics—much more so for humidity than temperature. [Supplemental Fig. S2 details the seasonal dependence for each of the 13 major river basins in CONUS, as calculated from AIRS footprint (not gridded) retrievals.]

Figure 6 provides maps of AIRS surface air temperature gradient ($T_s - T_a$) error characteristics, also for the warm season. The bias is positive for all pixels, with a median of +2.1°C and 95th percentile equal to +6.1°C. The median τ and ubRMS differences were 0.2° and 3.4°C, respectively. Over the domain, we observed an anticorrelation between bias and LAI ($\tau = -0.46$) and a positive correlation between elevation and bias ($\tau = 0.28$). Here, LAI is calculated as the 4-yr (2003–06) warm season mean MODIS for NACP product (F. Gao et al. 2008; Jonsson and Eklundh, 2004). The strongest correlation occurs over the Great Plains.

The fact that the AIRS $T_s - T_a$ gradient has a strong (positive) bias relative to NLDAS, particularly over the West, suggests that NLDAS–VIC sensible heat flux (H)

FIG. 5. Statistical summary of the AIRS–NLDAS T_s , T_a , q , and RH intercomparisons computed for the warm season only. (from top to bottom) Bias (RS minus modeled), ubRMS(P), Kendall's τ correlation, and Kendall's τ anomaly correlation are illustrated, respectively. Out of 1165 days, the average 0.125° pixel has 704 ± 80 AIRS–NLDAS matchups, respectively.

may be too high (and evapotranspiration too low). This corroborates the finding of Ferguson et al. (2010), which showed NLDAS upward longwave radiation ($LW\uparrow$) was biased low relative to International Satellite Cloud Climatology Project (ISCCP; Schiffer and Rossow 1983) $LW\uparrow$. Specifically, they found mean daily differences of 19.7 and 22.7 W m^{-2} over the Colorado and Great basins, respectively. At mean temperatures of 15°C , this translates into $\sim 4^\circ\text{C}$ difference in T_s .

The remainder of this section is devoted to summarizing the comparative shifts in AIRS accuracies (relative to NLDAS) with scene (both atmospheric and surface) conditions (Fig. 7). The underlying statistics (i.e., the 5-number summary) plus the means are provided for all boxplots in supplemental Tables S3–S6. Unless otherwise noted, 1) the difference in means between all histograms for a given condition (i.e., α_{cloud}) are significant at the

$p = 0.05$ level and 2) all cited statistics are medians of their respective distributions across CONUS.

It is important to note that neither the geographic coverage (i.e., the number of pixels) nor the quantity of sample pairs per pixel is constant for each histogram, but in fact varies widely, even between variables. For example, there are very few pixels south of 35°N included in the $T_a < 0^\circ\text{C}$ sample or west of 97.5°W (except western Washington and Oregon) included in the $\alpha_{\text{cloud}} > 0.6$ sample. Samples conditioned on lc class are particularly diverse in their coverage, and thus, have been addressed explicitly in Table 5. With the exception of a few land cover classes (i.e., lc03 over CONUS and lc01, lc03, and lc05 over Africa) that were eliminated from our analyses on the basis of insufficient data, there is ample coverage for each of the remaining samples. For the total record, our analyses considered 75 050 (179 380) 0.125° pixels

FIG. 6. Error summary of intercomparisons between the AIRS-derived ($T_s - T_a$) and model-generated (VIC T_s - NLDAS T_a) surface air temperature gradient computed for the warm season only. The minimum and maximum Kendall's τ correlation is approximately -0.2 and $+0.5$, respectively. (top) Pixels for which the correlation is not statistically significant at the $p = 0.01$ level are indicated by the absence of color (i.e., white).

over CONUS (Africa) each with 1700 ± 205 (470 ± 185) data pairs.

(i) Season

The T_a retrievals exhibit a negative bias (-0.5°C) during the warm season and slightly positive bias ($+0.1^\circ\text{C}$) during the cold season. Relative to the cold season, T_a ubRMS differences are reduced from 3.8° to 2.5°C and τ is increased from 0.73 to 0.78 , when snow covered-only scenes are considered. This finding is reasonable, considering the presence of snow inhibits the influence of differential surface heating on the lower atmosphere, and hence, the development of thermal gradients. Conversely, snow cover diminishes the correlation between AIRS and NLDAS T_s (0.69 to 0.46) and RH (0.42 to 0.13). The distribution of T_s ubRMS is particularly heavy tailed

(5th percentile = 3.0°C , 95th percentile = 6.8°C) for snow covered-only retrievals, which may be the result of snow/no-snow discrepancies between NLDAS and MODIS. The mean values of total and warm season bias in q and of warm and cold season τ do not differ significantly.

(ii) Surface/air temperature

Of all sample subsets, agreement between AIRS and NLDAS T_s reaches its minimum ($\tau = 0.43$) for subzero surface temperatures Centigrade. Under the same conditions, random errors in T_a (4.2°C) and q (32.6%) are at or near study maximums, which may explain the minimum in τ for RH (0.08). Correlation between AIRS and NLDAS T_a is low at both temperature extremes ($T_a < 0^\circ\text{C}$, $\tau = 0.43$; $T_a > 30^\circ\text{C}$, $\tau = 0.44$), while correlation between AIRS and NLDAS q is relatively

FIG. 7. Box plots of the AIRS–NLDAS T_s , T_a , q , and RH error statistics for a broad range of scene compositions. Each box plot corresponds with a distinct set of match-ups sampled conditionally along the gradient (generally, at quintiles) of the respective surface variable or atmospheric condition. (left to right) The record is analyzed by season: all, warm, and cold season, and snow-covered; AIRS T_s or T_a ; clouds (α_{clouds}); AIRS pwv; GTOPO30 mean surface elevation; SRTM vc; UMD lc: lc01, lc02, lc04, lc05, lc06, lc07, lc08, lc09, lc10, lc12, lc13, lc16; and MODIS for NACP LAI. The specific break points are detailed in Table 3. The whiskers extend to the 5th and 95th percentiles. The bull's-eye denotes the median. The figure is provided in tabular form in supplemental Tables S3–S6.

TABLE 5. The land cover composition at 0.125° for CONUS and Africa, according to the MOD12Q1 UMD classification product, listed by population density and percent coverage.

UMD land cover class	Class No.	CONUS	Africa
Evergreen needleleaf forest	1	11 102 (14.9%)	20 (0%)
Evergreen broadleaf forest	2	559 (0.8%)	15 102 (8.4%)
Deciduous broadleaf forest	4	3584 (4.8%)	313 (0.2%)
Mixed forests	5	8891 (11.9%)	27 (0%)
Closed shrubland	6	466 (0.6%)	598 (0.3%)
Open shrubland	7	13 311 (17.9%)	23 559 (13.1%)
Woody savannas	8	1950 (2.6%)	22 099 (12.3%)
Savannas	9	114 (0.2%)	33 619 (18.7%)
Grasslands	10	12 588 (16.9%)	9902 (5.5%)
Croplands	12	20 664 (27.8%)	4404 (2.5%)
Urban/built-up	13	663 (0.9%)	256 (0.1%)
Barren or sparsely vegetated	16	536 (0.7%)	69 290 (38.6%)

constant with temperature. Although for warmer scenes ($T_a > 20^\circ\text{C}$), ubRMSP in q is reduced.

(iii) Cloud albedo

The accuracies of T_a , T_s , q , and to a lesser extent RH, are all strongly linked to cloud coverage. Under clear skies ($\alpha_{\text{cloud}} < 0.05$), the AIRS–NLDAS correlation is strongest for all variables: $0.80(T_s)$, $0.86(T_a)$, $0.75(q)$, and $0.49(\text{RH})$. With increasing clouds, correlation diminishes sharply and random errors also trend upward. Bias in T_s (T_a) changes in sign with cloud cover, from $+3.6^\circ\text{C}$ ($+1.6^\circ\text{C}$) for clear skies to -5.5°C (-4.1°C) for overcast conditions ($\alpha_{\text{cloud}} > 0.6$). Bias in q grows in (negative) magnitude with increasing cloud coverage, from -9.7% (clear) to -29.0% (overcast). Traversing the gradient in α_{cloud} , the dry (negative) bias in q and coincident cold (negative) bias in T_a counteract to constrain bias in RH within the range of -7.2% ($0.05 \leq \alpha_{\text{cloud}} < 0.2$) to -7.5% ($0.4 \leq \alpha_{\text{cloud}} < 0.6$) for typical cloud conditions. In a separate comparison (not shown), we found that the bias in T_a for mostly cloudy ($0.4 \leq \alpha_{\text{cloud}} < 0.6$) and overcast scenes differed insignificantly from biases calculated using cold season-only retrievals for corresponding cloud types. We therefore suggest that clouds and not ambient temperature drive the seasonal error characteristics (above). Geographically, the largest differences between clear-sky and mostly cloudy T_s (T_a) bias occur over parts of Nevada, California, and Oregon (approximately $40^\circ\text{--}44^\circ\text{N}$, $121^\circ\text{--}116^\circ\text{W}$), with ranges of 7.6°C (5.3°C). For T_s , an additional local maxima in clear-minus-cloudy sky bias exists over western Texas ($30^\circ\text{--}34^\circ\text{N}$, $104^\circ\text{--}101^\circ\text{W}$, $+8.2^\circ\text{C}$).

(iv) Precipitable water vapor

For all variables, the distribution of AIRS–NLDAS τ has the widest spread for dry atmospheres ($\text{pwv} < 3.18 \text{ mm}$). AIRS–NLDAS agreement is strongest for average pwv conditions. Accuracies for average conditions of pwv (20th–60th percentile) do not differ strongly. The impact of scene pwv on RH bias generally coincides with that of q and not T_a —trending toward positive with increasing pwv. However, the trend in uncertainty of RH corresponds with the general trend in uncertainty of T_a .

Along a gradient of increasing pwv, uncertainty in q is shown to diminish sharply: from 38.4% ($\text{pwv} < 3.18 \text{ mm}$) to 15.1% ($\text{pwv} > 34.29 \text{ mm}$). This inverse relationship between random error and pwv seemingly contradicts the trend between random error and clouds (above). Here, we emphasize that α_{cloud} and pwv are not one in the same. While clouds exist at varying (and often multiple) levels of the atmosphere, pwv is driven by the lowest (and most humid) layers in the atmosphere. Therefore, pwv is strongly linked with RH, not necessarily α_{cloud} . High pwv samples should correspond with warm and humid events/regions. Accordingly, the error characteristics should be similar to those from high T_a samples ($T_a > 20^\circ\text{C}$), which Fig. 7 confirms.

(v) Elevation

We previously noted a direct relationship between T_s , T_a , and $T_s - T_a$ bias and mean elevation. In terms of their bias, q and RH only exhibit sensitivity in the uppermost quintiles of elevation. The uncertainty in RH is shown to increase with elevation, coincident with diminished correlation of q and increased (positive) bias in T_a .

In another experiment (not shown), we considered the same intervals in elevation for clear-sky-only retrievals in order to isolate strictly elevation-dependent effects. We found that the trends for all-sky cases (see Fig. 7) remain consistent. However, the magnitude of T_s and T_a (warm) bias increased significantly for all quintiles under clear skies. In terms of T_a , for example, biases for each quintile shifted from: -1.6° to $+0.4^\circ\text{C}$, -1.1° to $+0.5^\circ\text{C}$, -0.6° to $+1.2^\circ\text{C}$, 2.1° to 3.7°C , and 2.9° to 5.1°C . Likewise, for T_s , biases shifted from -0.2° to $+2.5^\circ\text{C}$, 0° to 2.5°C , 0.4° to 2.9°C , 3.8° to 6.2°C , and 5.2° to 8.2°C .

(vi) Vertical complexity

Trends in error with increasing vc, were consistent with those observed for elevation (above). Given the strong correspondence between elevation and vc, this is not surprising. However, the trend is less distinct, with fatter-tailed distributions of bias for each interval of vc relative to elevation quintile counterparts. Therefore,

we hold that elevation, and not vc , is the driving variable.

(vii) UMD land cover class

Land cover classes effectively aggregate the influences of regional climatology (atmospheric and radiative forcing), terrain, vegetation thickness (LAI), and heterogeneity (emissivity) influences on AIRS retrievals. Large bias-driven uncertainty in T_s ($+3.6^\circ$ to $+7.6^\circ\text{C}$) and T_a ($+1.9^\circ$ to $+3.3^\circ\text{C}$) is shown for retrievals over shrublands (lc06, lc07), grasslands (lc10), and barren ground (lc16). Over evergreen broadleaf (lc02), deciduous broadleaf (lc04), and mixed forests (lc05), the range of T_s (-0.4° to 0°C) and T_a (-2.2° to -1.3°C) bias is comparatively lower. However, the fact that the range (5th–95th percentile) over evergreen needleleaf forest (lc01) is nearly 4 times broader suggests that factors other than vegetation are dominating retrieval accuracy. For all variables, there are multiple pairs of landcover classes that yield insignificantly different error statistics relative to one another. The RH has the greatest uncertainty over shrubland (lc06, ubRMSP = 39.2%; lc07, ubRMSP = 36.7%) and barren ground (ubRMSP = 40.6%). Over savannas (lc09), the AIRS and NLDAS RH exhibit the best agreement ($\tau = 0.56$), but AIRS and NLDAS q are least correlated ($\tau = 0.39$). Over open shrubland (lc07), q is nearly unbiased ($+1.0\%$).

(viii) LAI

Trends in bias, ubRMS, and τ are shown to be inversely related to LAI. Between the lowest and uppermost quintile of LAI, ubRMS(P) is reduced from 5.6° to 4.2°C , 3.8° to 3.0°C , 30.7% to 18.0% , and 28.7% to 18.6% in the case of T_s , T_a , q , and, RH, respectively. Biases in T_s (T_a) shift from $+2.1^\circ$ to -0.5°C ($+1.7^\circ$ to -1.8°C) along the gradient of LAI. With increasing LAI, it is possible that the respective surfaces for which NLDAS and AIRS T_s and T_a are representative are diverging.

b. Africa

1) COMPARISONS WITH NCDC

Figures 8 and 9 are maps of the AIRS/GFS/GEOS-3–NCDC error statistics over Africa. Africa has been divided into four subdomains: Sahara (SAH: 18° – 30°N , 20°W – 65°E), western Africa (WAF: 12°S – 18°N , 20°W – 22°E), eastern Africa (EAF: 12°S – 18°N , 22° – 52°E), and southern Africa (SAF: 35° – 12°S , 10°W – 52°E) for which the regional mean error statistics are provided. Domain-averaged values are provided in Table 4. Analyses are limited by station coverage and density, which is especially sparse (or nonexistent) over the Sahara Desert (15° – 30°N), central Africa (i.e., Angola, Congo, Democratic

Republic of the Congo, Equatorial Guinea, Uganda, and Zambia), and Somalia. The foremost limiting factor in our analyses was the availability of P_{surf} , which is only reported at 75% of the stations (see Table 2).

AIRS temperature and humidity retrievals exhibit relatively higher uncertainties over the SAH and EAF, and SAH and SAF, respectively (see Fig. 8). Over SAH, q (-30.3%) and RH (-25.6%) exhibit substantial negative biases, while T_a is biased negatively over SAH (-1.4°C) and WAF (-1.6°C) and positively over EAF ($+4.6^\circ\text{C}$) and SAF ($+3.5^\circ\text{C}$). Consistent with findings over CONUS, increases in T_a bias were found to correlate ($\tau = 0.41$) with increases in elevation (not shown). Notably, the mean slope of the relationship is of much larger magnitude ($+10.7^\circ\text{C km}^{-1}$ above 500 m). GFS P_{surf} is correlated ($\tau = 0.39$) with large random errors (4.9 hPa) over the EAF, likely due to the regions' terrain. The range in P_{surf} bias and ubRMS across the four subdomains is -4.8 to $+2.7$ and 3.1 to 4.9 hPa, respectively. Agreement between GEOS-3 and NCDC w is poor for all regions, but at a minimum over EAF ($\tau = 0.20$). The range in w bias and ubRMS across the four subdomains is -0.3 to $+0.5$ and 2.0 to 2.5 m s^{-1} , respectively.

2) COMPARISONS WITH SAF-LST

Figure 10 illustrates results from AIRS-SEVIRI T_s intercomparisons over Africa for the total record. For 98% of the pixels, AIRS is biased warm relative to SEVIRI. The median bias, ubRMS, and τ are $+0.5^\circ\text{C}$, 3.9°C , and 0.68, respectively. The 95th percentile of bias is $+6.4^\circ\text{C}$. For a subdomain of the African Monsoon Multidisciplinary Analysis (AMMA) study region (12.5° – 17.5°N , 2.5°W – 2.5°E), T_s is biased by $+1.9^\circ\text{C}$ with a ubRMS of 4.6°C , and τ of 0.58. The correlation between T_s bias and elevation is not particularly strong ($\tau = -0.14$). Nevertheless, the largest biases are found above 1000 m in elevation, with the exception of the Sahara.

Figure 11 (which is presented quantitatively in supplemental Fig. S7) shows results from conditional sampling analyses. As with CONUS, the range in geographic coverage of samples conditioned on landcover class warranted disclosure (see Table 5). Seasonality is less straightforward when considering Africa as a whole and therefore replaced with SEVIRI quality levels: “nominal” and “below nominal.” Use of nominal quality-only (RMS $< 2^\circ\text{C}$) SEVIRI T_s data has the primary effect of reducing coverage to 122 100 (0.125°) pixels located south of the 16°N parallel (and the Sahara). Relative to all available matchups ($+0.5^\circ\text{C}$), nominal quality-only sampling yields a marginally lower bias (-0.1°C). However, the mean ubRMS differs by only 0.08°C between sampling approaches; the agreement is actually lower for the nominal quality-only sample (nominal, $\tau = 0.64$;

FIG. 8. Statistical summary of AIRS–NCDC T_a (°C), q (%), and RH (%) for the total record. (top to bottom) Bias (RS minus modeled), ubRMS(P), and Kendall's τ correlation are illustrated, respectively. (left to right) The bracketed values at the bottom are regional means for the Sahara ($n \sim 50$), western Africa ($n \sim 150$), eastern Africa ($n \sim 80$), and southern Africa ($n \sim 150$) domains.

all, $\tau = 0.68$). LSA–SAF applies a cloud mask, which is why there is no data available for intercomparison in overcast conditions ($\alpha_{\text{cloud}} > 0.6$).

The error characteristics derived from RS product–product (this section) and RS product–model [section 4a(2)] intercomparisons were determined to be fairly robust despite the geographic diversity of the domains

over which they were computed. For example (positive) bias in T_s is reduced, random error is enhanced, and correlation weakened with increasing α_{cloud} . With increasing LAI, bias, random error, and correlation were also reduced. Conversely, we did not observe similar trends in bias and random error as a function of pwv, elevation, or vc. Bias and ubRMS both increase with

FIG. 9. As in Fig. 8, but for GFS–NCDC P_{surf} (hPa) and GEOS-3–NCDC w (m s^{-1}). Boxed gray question marks on the bias for w indicate stations that were culled (see section 3).

pwv over Africa (unlike AIRS–NLDAS) but, correlation diminishes (like AIRS–NLDAS). In fact, the greatest overall consistency is observed in scenes of the lowest pwv (< 6.34 mm), for which bias, ubRMS, and τ are -0.9°C , 2.1°C , and 0.80, respectively. For clear-skies, the bias is reduced (-0.12°C), but we observe less overall agreement (ubRMS = 3.7°C , $\tau = 0.66$). With regard to elevation and vc, bias and ubRMS are either reduced or

remain constant. The fact that the relative range in τ for each quintile of elevation, vc, and lc type is substantially broader relative to that observed over CONUS is also noteworthy. We hypothesize that both RS retrievals are similarly (and consistently, with respect to one another) affected by factors that vary with altitude (i.e., elevation, vc, and lc), but that SEVIRI is relatively more sensitive to pwv. The strongest and weakest AIRS–SEVIRI

FIG. 10. Error characteristic summary from the AIRS-SEVIRI T_s intercomparisons over Africa. The bias is defined as AIRS T_s - SEVIRI T_s . All data pairs for which the AIRS nominal quality flag was satisfied (i.e., flag < 2) were included. There were no cases of negative correlation and all correlations were significant at the $p = 0.01$ level. Less than 2% of the pixels showed a negative bias of which most are located along the coastal perimeter.

correlation occurs over barren ground (0.73) and evergreen broadleaf forest (0.39), respectively.

5. Significance of error characteristics

a. Soil moisture and cloud base height

The error characteristics identified in this study have nontrivial implications to a multitude of applications in

land hydrology. In Fig. 12a, we illustrate the sensitivity of Princeton's remotely sensed X-band soil moisture (SM) retrievals (Gao et al. 2006) to errors in T_s across the vegetation gradient. The envelope of SM sensitivity ($0.6\% - 3.5\% ^\circ\text{C}^{-1}$) is bounded by the relative vegetation extremes of Jornada basin, New Mexico (barren) and Little River, Georgia (croplands). Figures 12b and 12c show the sensitivity of cloud base height (LCL; refer to

FIG. 11. As in Fig. 7, but for AIRS-SEVIRI T_s over Africa. Note that season has been replaced by quality control (QC): AIRS-only (left, flag < 2); nominal SAF (right, RMS < 2°C), there is no box plot for $\alpha_{\text{cloud}} > 0.6$; and only lc classes lc02, lc04, lc06, lc07, lc08, lc09, lc10, lc12, lc13, and lc16 (from left to right) are included. The specific break points are detailed in Table 3. The figure is provided in tabular form in supplemental Table S7.

FIG. 12. (a) Sensitivity of Princeton's 10.7-GHz (Gao et al. 2006) remote sensing soil moisture (SM) retrievals to T_s during 21–24 Jul 2003 for three sites of different vegetation water content (vwc): Jornada Basin, New Mexico (32.5°N, 106.8°W; vwc = 0.1 kg m², $\Delta\text{SM}/\Delta T_s \sim 3.5\%^\circ\text{C}^{-1}$), Walnut River, Kansas (37.5°N, 96.9°W, vwc = 0.8 kg m², $\Delta\text{SM}/\Delta T_s \sim 1.0\%^\circ\text{C}^{-1}$), and Little River, Georgia (31.6°N, 83.7°W, vwc = 6.2 kg m², $\Delta\text{SM}/\Delta T_s \sim 0.6\%^\circ\text{C}^{-1}$). (b) Impact of errors in T_a on the calculation of cloud base height over a range of humidity. (c) As in (b), but in terms of q .

Bolton 1980) to errors in T_a (~ 10 hPa $^\circ\text{C}^{-1}$) and q [~ 20 hPa (g kg⁻¹)⁻¹]. In the lower atmosphere, LCL dependence on P_{surf} is negligible (not shown). By construct, RH and LCL are closely linked.

b. Evapotranspiration

Using the AIRS–NLDAS biases calculated for warm season (see Fig. 5), we assessed the impact of applying bias correction on AIRS T_a , T_s , and RH inputs to estimates of 4-yr (2003–06) mean warm season daytime RS– E for 12, $1^\circ \times 1^\circ$ regions of varying land cover and climate, and 7 major hydrological basins in CONUS (Table 6). RS– E was calculated using the modified Penman–Monteith (P–M) formulation (Mu et al. 2007), replacing GMAO meteorological inputs with inputs from AIRS and CERES, as formally described in Ferguson et al. (2010). Included in the set of study sites are five U.S. Department of Agriculture Agricultural Research Service (USDA–ARS) experimental watersheds and four BigFoot (Cohen et al. 2006; Turner et al. 2006) sites. We note here that Lamont and Little Washita, Oklahoma are contained within the North American hot spot for land–atmosphere coupling (Koster et al. 2004). Daytime VIC– E minus the free-water (canopy) evaporation component, which is not accounted for in the P–M framework, is included in Table 6 and serves as our best estimate of truth. With bias correction applied, RS– E is reduced over the semiarid Colorado (–23%) and arid great (–18%) basins and enhanced by 8%–30% over the remaining temperate basins. Since the VIC model uses inputs from NLDAS, it is not surprising that bias-corrected RS– E estimates at basin-scale shift in the direction of correspondent VIC– E estimates. Additionally, we show (Table 6) that biases of ± 0.5 and ± 1.0 m s⁻¹ in w can contribute an additional –5.8% to +3.9% and –13.0% to +6.4% uncertainty to basin-scale RS– E , respectively. Bias correction did impact the RS– E sampling characteristics because for pixels where net radiation became negative due to the correction of T_s , RS– E was set to missing.

VIC– E is not without uncertainty. Considering the degree of irrigation in Fresno and the greater Sacramento River valley, a warm season E of 15.6 mm month⁻¹ seems unrealistic and is probably due to ignoring the effects of irrigation in this version of VIC. Nevertheless, the scope of this study precludes further investigation.

For Africa, assuming typical atmospheric and radiative conditions [$P_{\text{surf}} = 977$ hPa, $T_s = 30.4^\circ\text{C}$, $w = 1.9$ m s⁻¹, $R_n = 9.56$ MJ m⁻² day⁻¹, momentum roughness length (Z_{om}) = 0.015 m, water vapor roughness length = $Z_{om}(10 \text{ m})^{-1}$], potential evaporation (PE) from bare soil was estimated to be 419 cm yr⁻¹ using the P–M equation (Monteith 1964) with surface resistance set to 0. If we

TABLE 6. The impact of bias correction of AIRS meteorology (T_a , T_s , RH, and w) on the 4-yr (2003–06) mean warm-season RS– E (mm month^{-1}) for 12 sites ($1^\circ \times 1^\circ$ centered domains) and 7 major hydrologic basins across CONUS. RS– E corresponds with Ensemble 1 in Ferguson et al. (2010).

Location	Lat	Lon	UMD* land cover	Daytime VIC– E (mm month ^{−1})	Warm-season daytime RS– E (mm month ^{−1})			
					Uncorrected	Bias corrected for T_s , T_a , and q	ΔE (%) with $w \pm 0.5$ (m s ^{−1})	ΔE (%) with $w \pm 1.0$ (m s ^{−1})
USDA–ARS long-term experimental watersheds								
Little River, GA	31.61°N	83.66°W	Crop	114.5	80.2	124.4	[−4.9, 3.4]	[−11.0, 5.9]
Walnut Creek, IA	41.02°N	93.70°W	Crop	111.1	66.6	77.0	[−1.9, 1.5]	[−4.1, 2.8]
Little Washita, OK	34.95°N	97.98°W	Grass	72.8	61.8	65.4	[−4.9, 3.5]	[−11.4, 6.0]
Walnut Gulch, AZ	31.72°N	110.68°W	Oshrub	30.6	37.8	24.8	[−6.1, 4.0]	[−14.0, 6.8]
Reynold’s Creek, ID	43.15°N	116.75°W	Grass	48.7	31.0	19.7	[−10.2, 6.7]	[−23.0, 11.3]
BigFoot sites								
Harvard Forest, MA (HARV)	42.54°N	72.17°W	DBF	72.5	87.6	96.6	[−0.9, 0.8]	[−1.9, 1.4]
Bondville, IL (AGRO)	40.00°N	88.29°W	Crop	123.9	69.3	80.1	[−1.6, 1.3]	[−3.4, 2.4]
Park Falls, WI (CHEQ)	45.95°N	90.27°W	DBF	57.3	85.6	92.4	[−0.8, 0.7]	[−1.8, 1.3]
Sevilleta, NM (SEVI)	34.36°N	106.70°W	Oshrub	28.1	32.8	20.2	[−7.5, 5.1]	[−17.1, 8.6]
Additional sites of interest								
Lamont, OK ⁺	36.62°N	97.50°W	Crop	73.6	48.7	49.5	[−5.3, 3.7]	[−12.0, 6.5]
Fort Peck, MN	48.31°N	105.10°W	Grass	52.5	37.6	34.7	[−5.9, 4.3]	[−13.2, 7.7]
Fresno, CA	36.77°N	119.72°W	Crop	15.6	56.3	88.2	[−4.5, 3.0]	[−9.9, 5.2]
Major hydrologic basins								
Arkansas–Red	—	—	Grass	68.6	61.9	75.6	[−3.6, 2.7]	[−8.1, 4.7]
Colorado	—	—	Oshrub	33.0	37.0	28.5	[−5.0, 3.4]	[−11.3, 5.8]
Great	—	—	Oshrub	35.5	36.5	30.1	[−5.8, 3.9]	[−13.0, 6.4]
Lower Mississippi	—	—	Crop	108.1	91.3	119.5	[−3.6, 2.8]	[−8.0, 4.9]
Upper Mississippi	—	—	Crop	91.1	70.3	85.0	[−1.7, 1.4]	[−3.8, 2.6]
Missouri	—	—	Grass	68.8	46.1	49.7	[−4.8, 3.5]	[−10.6, 6.2]
Ohio	—	—	Crop	94.3	88.8	106.6	[−2.3, 1.8]	[−5.0, 3.1]

* Crop: cropland; Grass: grassland; Oshrub: open shrubland; DBF: deciduous broadleaf forest.

⁺ ARM Central Facility.

apply constant daytime biases in T_s of $+1^\circ$, $+3^\circ$, $+6^\circ$, $+9^\circ\text{C}$, correspondent estimates of PE increase by 1%, 2.9%, 5.5%, and 7.9%, respectively.

6. Summary and conclusions

This study represents a careful assessment of AIRS-derived near-surface meteorology (T_s , T_a , q , RH, and $T_s - T_a$), GFS P_{surf} , and GEOS-3 w through intercomparison with ground measurements (NCDC), offline model output (NLDAS), and geostationary RS retrievals (SEVIRI). Our objective was threefold: 1) to quantify the mean accuracies of AIRS retrievals over an extensive domain; 2) to identify the scene conditions (atmospheric and surface) for which retrievals are particularly skillful, or conversely, prone to error; and 3) to quantify the impacts of these uncertainties on land surface hydrology variables E and SM. The nature of the task is that error estimates—and these conclusions—are invariably a product of several

factors, beginning foremost with the quality screening protocol that is applied at the footprint level, the spatial interpolation technique, and ultimately, the domain and season that the analysis is conducted.

We focused this study on evaluating the 0.125° gridded AIRS product [section 3a(1)] over CONUS and Africa, but for the benefit of our discussion, also provided summary error statistics at the AIRS footprint (13.5 km) scale (Fig. A1, supplemental Figs. S1–S5) over CONUS. Through conditional sampling, we explicitly investigated retrieval errors across gradients in ambient surface and air temperature, cloud albedo, total column precipitable water vapor/ice, elevation, topographic complexity, land cover class, leaf area index, snow cover, and season (Figs. 7 and 11). Under the best retrieval conditions—clear skies—the interquartile range of AIRS–NLDAS RMS errors were found to be 3.7° – 7.7°C (T_s), 2.3° – 4.6°C (T_a), 26.9% – 27.2% (q), and 26.2% – 32.2% (RH). Over Africa, AIRS–SEVIRI T_s

intercomparisons yielded an interquartile RMS range of 3.6°–4.8°C for clear skies and significantly lower (2.4°–2.6°C) for atmospherically dry ($\text{p}_{\text{wv}} < 6.34 \text{ mm}$) conditions. Using data matchups at ~ 1500 NCDC ground stations, we found mean AIRS/GFS/GEOS-3–NCDC (NLDAS–NCDC) RMS errors of 3.8°C (2.3°C), 32.0% (21.3%), 30.7% (24.4%), 12.1 hPa (9.3 hPa), and 1.9 m s^{-1} (2.0 m s^{-1}) for T_a , q , RH, P_{surf} , and w , respectively. Notably, the accuracy of NLDAS forcing has only previously been verified for a 3-yr period (1996–99) over the SGP (Luo et al. 2003; Mitchell et al. 2004). Using ~ 500 NCDC stations in Africa, mean AIRS/GFS/GEOS-3–NCDC RMS errors were found to be 4.6°C (T_a), 33.8% (q), 34.3% (RH), 11.0 hPa (P_{surf}), and 2.4 m s^{-1} (w).

In general, AIRS q and T_a were shown to be biased dry (CONUS: -10.3% ; Africa: -12.4%) and (slightly) warm (CONUS: $+0.2^\circ\text{C}$; Africa: $+1.0^\circ\text{C}$). Previously, dry biases were also noted in AIRS–GPS p_{wv} comparisons over CONUS (Raja et al. 2008). The interquartile ranges in AIRS–NLDAS T_a and q RMS (above) encompass prior estimates of 2.8°C (January) and 3.4°C (July) for China (W.H. Gao et al. 2008) and 27% ($P = 800 \text{ hPa}$) globally (Divakarla et al. 2006). Biases in T_a were shown to correlate well with elevation (above 500 m), as best illustrated by the east (negative) to west (positive) gradient in bias over CONUS (Fig. 1). This supports similar findings of Jones et al. (2010) and Gao et al. (2008b) with AIRS and Lakshmi et al. (2001) with TOVS. We suggest that this correlation is induced by changes in several variables with altitude, including lc class, LAI, and humidity. Because of the combined effects of errors in T_a and q , RH had a much lower bias (CONUS: -1.4% ; Africa: -10.5%). There is a distinctly negative-biased band of RH correspondent with the Midwest “corn belt” (Fig. 1).

Collectively, our findings indicate that the gridded near-surface AIRS variables are not meeting the 2° – 3°C (T_s), 1.0°C (T_a) and 20% (q and RH) RMS accuracy criterion set forth by the AIRS Science Team. Of course, within the CONUS and Africa subdomains, there exists substantial spatial diversity in error characteristics. For example, mean errors are clearly affected by the west CONUS and Sahara Africa. Moreover, the NLDAS and NCDC datasets do have inherent uncertainty. Mitchell et al. (2004) determined that NLDAS–VIC T_s had an RMS of 4.5°C relative to the Geostationary Operational Environmental Satellite (GOES) over the north-central CONUS during July 1999. And this study’s findings [section 4a(2)], taken jointly with those of Ferguson et al. (2010), suggest that NLDAS–VIC T_s is biased cold over the west CONUS.

AIRS provides a unique set of variables for land surface hydrological studies that are ideally available

coincidentally (in time and space) with radiation and microwave measurements from the CERES and the Advanced Microwave Scanning Radiometer–Earth Observing System (AMSRE–E) sensors, also on board NASA’s *Aqua*. In section 5, we quantified the impact of errors in T_s on microwave soil moisture retrievals and estimates of PE , errors in T_a and q on estimates of LCL, and errors in T_s , T_a , RH, and w on estimates of warm-season daytime $RS-E$. These limited examples derive from a much larger set of applications for which there is a clear need for confidence/error estimates to quantify input-driven uncertainty. Despite challenges to skillful retrievals, the strength of RS remains to be that it provides accurate patterns of real-life land surface variability, which is currently missing from land hydrology and atmospheric analyses (McCabe et al. 2008).

Throughout this study, an underlying question was whether beyond CONUS, in data-scarce regions such as Africa, could AIRS uncertainty be quantified a priori as a function of scene atmospheric and surface conditions? Our conclusion is that although this may be feasible, multiple explanatory variables are necessary and it will likely require regional and temporally varying regression relationships that may only be obtainable through initial AIRS versus truth intercomparisons.

Only the ascending (~ 1330 local time) retrievals have been evaluated. In the future, our framework may be transferred to nighttime retrievals, as well as expanded globally. Given insights gained from this study, we would divide the analysis by river basin, as we have done here for the footprint-scale intercomparisons (supplemental Figs. S2–S5), and vary the search radius of the interpolation scheme as a function of mean pressure difference with distance (see supplemental Table S2).

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FIG. A1. AIRS footprint error characteristics over CONUS as a function of footprint to station (GFS – NCDC) pressure differences calculated using the total record (2002–08, or $n \sim 9\,000\,000$). (a)–(c) The bias (AIRS – NCDC) of T_a , relative bias of q , and relative bias of RH is illustrated, respectively. (d)–(f) The RMS of T_a , q , and RH is illustrated, respectively. The CONUS mean response is indicated by the bars; symbols indicate basin-scale responses. Basin errors are only plotted for a particular bin if greater than 500 data pairs are available. Notably, station distribution is not uniform (see Fig. 1). The mean pressure difference varies with distance across basins (see supplemental Table S2). The following abbreviations were applied: A-R: Arkansas-Red; CAL: California; COL: Colorado; PNW: Pacific Northwest; M-A: Mid-Atlantic; GLK: Great Lakes; GR: Great; T-G: Texas-Gulf; LMISS: Lower Mississippi; UMISS: Upper Mississippi; MISSO: Missouri; OH: Ohio; RIO: Rio Grande.

The GTOPO30 DEM was obtained from the U.S. Geological Survey's Center for Earth Resources Observation and Science (EROS) Data Center (see online at <http://edc.usgs.gov/>). The MOD12Q1 land cover dataset was obtained from the NASA-developed Earth Observing System (EOS) Clearinghouse (ECHO) through the NASA Warehouse Inventory Search Tool (WIST; see online at <https://wist.echo.nasa.gov/>). MODIS snow products were obtained through the National Snow and Ice Data Center (NSIDC; see online at <http://nsidc.org>) Distributed Active Archive Center. The MRT is maintained and distributed by the NASA Land Processes Distributed Active Archive Center (LPDAAC; see online at <https://lpdaac.usgs.gov/>).

APPENDIX

The use of AIRS level 2 version 5 quality flags for T_s , T_a , q , and RH is summarized herein: T_s : Only AIRS footprint T_s (TSurfStd) that satisfied Qual_Surf <2.0 were accepted. In fact, the highest-quality designation assigned to AIRS T_s over land is 1.0 or “good” quality.

T_a : If $\text{PGood} \geq P_{\text{surf}}$, the AIRS footprint T_a (TSurfAir) was accepted. AIRS temperature retrievals at or above PGood are included in the generation of AIRS level 3, $1^\circ \times 1^\circ$ gridded products. If $\text{PGood} \geq P_{\text{surf}}$, the version 4 legacy quality flag, Qual_Temp_Profile_Bot, was also found to be <2.0 and

vice versus. Only 18% of all retrievals where $P_{\text{Good}} \geq P_{\text{surf}}$ satisfied the condition $P_{\text{Best}} \geq P_{\text{surf}}$.

q and RH: If $\text{Qual_H2O} < 2.0$ and $P_{\text{Good}} \geq P_{\text{surf}}$, the AIRS near-surface level temperatures (TAirSup) and humidity (H2OCDSup) were accepted. For all cases, if $\text{Qual_H2O} < 2.0$, then $P_{\text{Good}} \geq P_{\text{surf}}$. Conversely, $\text{Qual_H2O} < 2.0$ is not satisfied in 4.7% of the cases where $P_{\text{Good}} \geq P_{\text{surf}}$.

We note that for each of the variables, the AIR-SX2SUP product does include error estimates; namely, TSurfStdErr (T_s), TAirStdErr (T_a), and H2OCDSupErr (q and RH). We were reluctant to constrain the sample set (and risk imparting a significant sampling bias) by applying arbitrary error thresholds on error estimates of unprescribed confidence and ultimately elected not to use these. For example, over the ~1500 NCDC stations in CONUS, we determined that 26% (15%) of all retrievals where P_{Good} (P_{Best}) is $\geq P_{\text{surf}}$ would not satisfy TSurfStdErr $< 5.0^\circ\text{C}$. Retrieval error characteristics can be investigated at the gridded product level (as in this study), or alternatively at footprint scale. We have investigated the bias and RMS error characteristics of footprint (prior to interpolation) values as a function of pressure difference (Fig. A1), season, pwv (totH2OStd), AIRS IR cloud fraction (TotCld_4_CCfinal), and CERES α_{cloud} —these later analyses are illustrated in supplemental Figs. S2–S5.

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