The Observed State of the Energy Budget in the Early 21st Century

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ABSTRACT

This study documents new observational benchmarks of global and continental energy budgets and their seasonal variability from the recent golden era of Earth-observing satellites. Combining available datasets spanning the first decade of the twenty-first century reveals that the net radiative flux into the Earth’s surface exceeds turbulent heat flux estimates by 13-24 W m\(^{-2}\). The largest imbalances occur over oceanic regions where the component algorithms operate independent of closure constraints. Rigorous assessment of the uncertainties in each dataset suggests that these surface energy imbalances fall within anticipated error bounds but the systematic nature of the required adjustments across different regions and the fact that their magnitudes often approach acceptable limits suggests that biases may be present in one or more datasets.

To reintroduce energy and water cycle closure into independently-derived flux datasets, a novel variational method for objectively imposing balance constraints is introduced that explicitly accounts for uncertainties in all component fluxes. Applying the analysis to a ten-year record of satellite observations suggests that globally, 180 W m\(^{-2}\) of atmospheric longwave cooling is balanced by 74 W m\(^{-2}\) of shortwave absorption and 106 W m\(^{-2}\) of latent and sensible heating. At the surface, 527 W m\(^{-2}\) of downwelling radiation is balanced by 399 W m\(^{-2}\) of thermal emission, 22 W m\(^{-2}\) of shortwave reflection, and 106 W m\(^{-2}\) of turbulent heat transfer. The resulting implied residual heat flux into the oceans (0.45 W m\(^{-2}\)) is consistent with recent observations of changes in ocean heat content. Budgets are also presented for each of 7 continents and 9 ocean basins on annual and monthly scales.
1. Introduction

Spatial and temporal variations in the flows of energy between the surface, atmosphere, and space play a central role in establishing the large-scale atmosphere and ocean circulation patterns that ultimately drive both weather and climate (e.g. Hartmann et al. 1984; Lau and Peng 1987; Slingo and Slingo 1988, 1991; Lee et al. 2001; Schumacher et al. 2004). The sensitivity of the climate system to external forcings is, therefore, governed by the energy imbalances they induce and the partitioning of these imbalances between the atmosphere, ocean, and cryosphere (Trenberth 2009; Trenberth et al. 2014). As a result, several recently documented biases in climate models such as insufficient low cloud cover in subtropical subsidence regions (Kay et al. 2012), warm sea surface temperature (SST) biases in the Southeast Pacific (Yu and Mechoso 1999; Dai 2003), the presence of a ubiquitous tropical rain band south of the equator (Li et al. 2004; Masunaga and L’Ecuyer 2009), premature onset of deep convection, particularly over land (Davis et al. 2003; Dai and Trenberth 2004; Grabowski et al. 2006), and underestimates of the Walker circulation response to El Niño (L’Ecuyer and Stephens 2007; Su and Jiang 2013) are likely connected to errors in the representation of energy flows in these models. The need to resolve these biases to improve future climate predictions motivates the development of accurate observationally-based benchmarks of energy flows to evaluate and refine model physics (Bony and coauthors 2006).

Characterizing energy exchanges between the surface, atmosphere, and space from observations has been the subject of vigorous research for more than a century (Abbot and Fowle 1908; Dines 1917). It wasn’t until the late twentieth century, however, that satellite observations revolutionized our understanding of Earth’s radiative balance by providing a unique global perspective on the spatial distribution of incoming and outgoing radiation at the top of the atmosphere. Early satellite studies demonstrated that the Earth was darker and warmer than previously believed and that there was a stronger gradient of absorbed solar energy between the tropics and the mid-latitudes (Vonder Haar and Suomi 1969; Vonder Haar et al. 1972). Following these initial discoveries, satellite observations with improved
calibration and increased spatial and temporal resolution have played central role in refining estimates of all key factors governing energy balance at both the top of the atmosphere and at the surface (e.g. Kiehl and Trenberth 1997; Rossow et al. 1995; Zhang et al. 2004; Lin et al. 2008; Trenberth et al. 2009; Stephens et al. 2012b).

The last decade can be considered a golden era in satellite Earth observation, especially for observations of direct relevance to the Earth’s energy budget. Clouds and Earth Radiant Energy System (CERES) instruments aboard the Tropical Rainfall Measuring Mission (TRMM), Terra, and Aqua satellites, for example, have provided improved observations of the exchange of longwave and shortwave radiation at the top of the atmosphere (TOA) (Wielicki et al. 1996; Loeb et al. 2001). When coupled with water vapor estimates from the Atmospheric Infrared Sounder (AIRS) and cloud and aerosol information from the Moderate Resolution Imaging Spectroradiometer (MODIS), CloudSat, and the Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation (CALIPSO), these observations have also lead to significant refinement to estimates of surface radiative fluxes (Stackhouse, Jr. et al. 2001; L’Ecuyer et al. 2008; Kato et al. 2011). The TRMM Microwave Imager (TMI) and Precipitation Radar (PR) as well as the Advanced Microwave Sounding Radiometer-EOS (AMSR-E) aboard Aqua have provided new insights into the global distribution of latent heat release in precipitation and surface turbulent heat fluxes. Since its inception, the mission of NASA’s Energy and Water cycle Study (NEWS) has been to bring together complementary expertise and datasets from these distinct missions to provide a comprehensive view of the water and energy cycle consequences of climate change (NSIT 2007). Toward this goal, this study and its water cycle companion (Rodell et al. 2014) combine the new insights gleaned from this golden age of satellite Earth observation to quantify the current state of the water and energy cycles.

Several studies have recently sought to provide updated observational estimates of energy balance on global (Trenberth et al. 2009; Kato et al. 2011; Stephens et al. 2012b; Kato et al. 2013) and regional scales (Fasullo and Trenberth 2008a,b; Trenberth and Fasullo 2013a,b).
A number of these studies point out that significant imbalances exist in both the atmospheric and surface energy budgets when unadjusted independent observational estimates of the component fluxes are combined. While adjustments to specific component fluxes have often been introduced, this has led to discrepancies in the resulting energy budget estimates. A comparison of the energy balance diagrams reported in Figure 1 of Trenberth et al. (2009) and Figure B1 of Stephens et al. (2012b), for example, reveals significant differences in downwelling longwave and shortwave fluxes and latent heating that arise from the specific choices made when adjusting fluxes to satisfy balance. This study seeks an objective approach to imposing closure constraints that embraces the NEWS paradigm of integrating detailed knowledge of the characteristics of each component dataset to generate observational benchmarks of global and continental-scale energy budgets and their seasonal variability using state-of-the-art satellite observations.

Drawing inspiration from the early efforts of Dines (1917), this study derives closed global and continental-scale energy budgets from the latest independent satellite datasets. Dines combined the best estimates of several key radiative and non-radiative fluxes available at the time with carefully thought out closure arguments to construct a comprehensive depiction of global energy balance. Here, a similar approach of imposing closure constraints is adapted to state-of-the-art large-scale energy flux datasets derived from NASA’s latest Earth Observing System (EOS) satellites. Using well-documented variational methods (Rodgers 2000; Kalnay 2003), atmospheric and surface energy and water cycle closure equations are incorporated as soft constraints, yielding balanced energy budgets on continental scales with modest adjustments to each of the component fluxes based on rigorous estimates of their uncertainties. The approach has a number of advantages over previous efforts to produce an observation-based balanced energy budget: (1) it provides a uniform framework for integrating novel satellite observations of energy and water fluxes from disparate sources, (2) it explicitly accounts for the relative uncertainties in all component fluxes, (3) it allows energy and water cycle balance constraints to be applied simultaneously, linked through latent
heating, and (4) it provides quantitative metrics for evaluating how well balance could be achieved.

The method is used to generate observational benchmarks of the key components of the Earth’s energy balance on both global and continental scales and document their seasonal cycles using several recently-developed satellite datasets. These datasets are then used to assess the degree to which global and continental energy budgets balance on annual scales in Section 3. A novel optimization approach is introduced in Section 4 and used to generate closed global and regional energy budgets over the past decade that satisfy all relevant energy and water cycle constraints. Beyond accounting for the relative accuracy of each dataset, the approach simultaneously imposes energy and water cycle constraints on the system providing a powerful tool for adding physical constraints that cannot be applied to individual datasets. It is argued that the resulting set of physically consistent energy budget and water cycle estimates (the latter reported in Rodell et al, 2014) and associated error bars represent our current state of knowledge based on modern satellite datasets.

2. Datasets

The goal of this study is to document observational benchmarks of all fluxes of energy within the atmosphere and at the surface on time and space scales that begin to capture regional variability without exhibiting prohibitive sensitivity to measurement noise. The analysis focuses on the decade from approximately 2000-2009 to benefit from the availability of several new datasets developed during this golden age of Earth observing satellites. A ten year period is adopted to smooth out interannual variations that may exert a strong influence over shorter time periods with the caveat that this choice also averages climate trends that may have occurred during this time. Due to data availability at the time of analysis, some datasets span slightly different periods (e.g. 1998-2007) but the impact of these differences on the results is expected to be smaller than the uncertainties in each dataset given the long
The need to satisfy these demands considerably narrows the number of observational or observation-integrating datasets suitable for the current study. The datasets listed in Table 1 were chosen specifically because they span the period of interest and are sufficiently mature to allow robust estimates of uncertainties to be established. It is acknowledged that some choices were required in compiling the final energy budgets presented here. In some cases when multiple estimates of a particular flux were available they were averaged to generate the final flux estimate. For other fluxes, only one dataset was available or a particular dataset was chosen based on acceptance in the community as the standard. As this work was conducted under the auspices of NEWS, datasets provided by members of the NEWS team appear prominently in the analysis. NEWS datasets are widely available, undergo regular ongoing refinement, facilitate consistency through common time and space grids, and enable direct access to the expertise required to assign robust uncertainty assessments to all flux estimates. While alternative datasets of similar quality certainly exist we argue that it is not currently possible to definitively demonstrate that any should be preferred over those chosen here. This does not mean that the chosen datasets have been anointed as the best nor should it be construed as a dismissal of others. To the contrary, considerable effort has been made to ensure that the associated error estimates accurately reflect both the quality of each individual dataset and the range of estimates that may be obtained from all viable alternatives. Brief descriptions of each dataset used in this analysis are provided below but the reader is directed to the cited literature for details.

a. Radiative Fluxes

The global average TOA solar insolation is taken to be $340 \pm 0.1$ based on the recent total solar irradiance measurements from the Solar Radiation and Climate Experiment (SORCE) (Kopp and Lean 2011). Satellite measurements of other TOA and surface radiative fluxes derive from three NASA global radiation products: the CERES outgoing broadband flux...
product Wielicki et al. (1996), the International Satellite Cloud Climatology Project Flux Data (ISCCP-FD) (Zhang et al. 2004), and the Global Energy and Water Cycle Experiment (GEWEX) Surface Radiation Budget (SRB) dataset (Gupta et al. 1999; Stackhouse, Jr. et al. 2001). The ISCCP and SRB products calculate TOA and surface radiative fluxes based on satellite observations of the spatial distribution of clouds, aerosols, surface albedo, skin temperature, and emissivity constrained with atmospheric temperature and humidity profiles from reanalyses. Each are compared against more direct measurements of broadband radiative fluxes at the TOA from CERES. A key aspect to each of these datasets is that all of the most relevant variables defining the propagation of radiation fluxes through the atmosphere, including cloud and aerosol optical properties, are obtained from satellite multi-channel narrow band measurements, not from models. For the analyses that follow we adopt mean values of all TOA and surface radiative fluxes obtained by averaging ISCCP-FD and SRB datasets as the benchmark radiative fluxes.

(i) Multi-sensor A-Train Products

Although they launched in 2006, late in the decade of interest for this study, CloudSat (Stephens et al. 2008) and the Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation (CALIPSO) (Winker et al. 2010) in combination with the other sensors in the A-Train constellation provide perhaps the tightest observational constraints on surface radiative fluxes available (L’Ecuyer and Jiang 2010). These new active sensors provide valuable insights into the vertical structure of clouds and aerosols that can have a significant impact on downwelling fluxes at the surface. While the new CloudSat and CALIPSO atmospheric radiative flux datasets lack the sampling and duration required to generate the decadal climatologies developed here, comparisons with two such datasets over the 2007 calendar year are used to account for the effects of uncertainties in cloud boundaries, incorrect classification of multi-layered cloud systems, and neglecting precipitating hydrometeors in the error budgets.
(ii) CloudSat 2B-FLXHR-lidar

The 2B-FLXHR-LIDAR algorithm, described by Henderson et al. (2013), is the basis for CloudSat’s standard merged radiative fluxes and heating rates product. 2B-FLXHR-LIDAR blends information from CloudSat, CALIPSO, Moderate resolution Imaging Spectroradiometer (MODIS), and Advanced Microwave Scanning Radiometer for EOS (AMSR-E) to generate vertical profiles of radiative heating consistent with the most comprehensive description of surface, cloud, precipitation, and aerosol properties available from current satellite platforms. The algorithm supplements vertical distributions of cloud and precipitation water content and effective radii from CloudSat’s 94 GHz Cloud Profiling Radar (CPR) with characteristics of undetected thin cirrus and stratus clouds derived from CALIPSO and MODIS observations. Vertical profiles of aerosol type and optical depth are constrained using CALIPSO and surface albedo and emissivity estimates are assigned by coupling the IGBP global land surface classification to estimates of snow and sea ice extent from the passive microwave-derived Near-real time EASE-Grid daily global Ice concentration and Snow Extent (NISE) dataset (http://nsidc.org/data/docs/daac/nise1_nise.gd/html). At present these cloud, aerosol, and surface properties are combined with ancillary temperature and humidity profiles from the European Centre for Medium-range Weather Forecasts (ECMWF) analyses and used to initialize a two-stream doubling-adding radiative transfer model to derive radiative flux profiles for each 1.4×1.8 km CloudSat footprint at the 240 m vertical resolution of the CPR. Additional details concerning the approach and assessments of relevant uncertainties can be found in L’Ecuyer et al. (2008) and Henderson et al. (2013).

(iii) CALIPSO, CloudSat, CERES, and MODIS (CCCM) Merged Data Set

The CCCM data product is an independent level 2 daily product containing CALIPSO-CloudSat merged cloud vertical profiles (cloud top and base height) and cloud properties such as liquid and ice water contents, extinction coefficient profile, as well as aerosol prop-
erties derived from CALIPSO. Cloud and aerosol properties are extracted from CALIPSO (Ed3 VFM, 5 km cloud profile, and 5 km aerosol layer) and CloudSat (Release 4 CLDCLASS and CWC-RO) products and averaged over the 20 km CERES footprint. The dataset itself, however, maintains the spatial resolution of original CALIPSO and CloudSat products. The process of merging CALIPSO and CloudSat derived cloud vertical profiles is explained in Kato et al. (2010) while the computation of irradiance profiles is described in Kato et al. (2011). CERES TOA irradiances and irradiance profiles computed using CALIPSO, CloudSat, and MODIS-derived cloud and aerosol properties are also included.

b. Oceanic Turbulent Heat Fluxes

Turbulent heat fluxes over the ocean derive primarily from SeaFlux version 1.0. SeaFlux (Curry and Coauthors 2004) estimates turbulent heat fluxes from the ocean surface by applying bulk formulas to atmospheric temperature and humidity parameters provided by Special Sensor Microwave/Imager (SSM/I) retrievals using a newly-developed neural net algorithm (Roberts et al. 2010). A modified sea surface temperature dataset that specifically accounts for diurnal warming (Bogdanoff and Clayson 2014) is included to reduce both mean biases in comparisons with in situ data and systematic errors at extremely low and high humidities. Air temperature retrievals using this method have shown the greatest increase in accuracy compared to other products, with biases now under 0.25°C across the spectrum of air-sea temperature differences. Winds are derived from the Cross-Calibrated Multi-Platform (CCMP) level 2.5 gridded swath product using a novel interpolation method based on temporal evolution in reanalyses (in this case the Modern Era Retrospective-Analysis for Research and Applications, MERRA). This model-based interpolation uses the time tendencies from a high-resolution model analysis but is driven through the satellite observations in a smooth manner. The resulting SeaFlux dataset is produced at a higher 0.25° spatial and 3-hourly temporal resolution than other satellite-based turbulent heat flux products. The version of the SeaFlux product used here covers the 1998-2007 time period and integrates the Colorado
State University SSM/I calibrated brightness temperature dataset (C. Kummerow, personal communication, 2011).

c. Terrestrial Turbulent Heat Fluxes

The terrestrial counterparts to the ocean turbulent heat fluxes (or evapotranspiration, ET, for consistency with the companion water cycle study) are much more difficult to estimate because ET is highly variable in space and time and ground-based observations (weighing lysimeters and eddy covariance measurements) are sparse and may not be representative of the continental scales targeted in this study. Satellite retrieval algorithms, on the other hand, offer more desirable spatial sampling but their accuracy is severely limited by the assumptions required and the sparseness of in situ observations available for calibration and validation. Physical and empirical models of land surface processes offer a third alternative but their accuracy is again limited by the quality of the input data and simplifications inherent to numerical models Rodell et al. (2004a). Based on these considerations and the lack of a clear consensus regarding superiority of any particular approach, estimates of terrestrial turbulent heat fluxes and their uncertainties for the current study were obtained from the average and standard deviation of three independent sources.

(i) Princeton Satellite-based Evaporation

The Princeton terrestrial ET algorithm uses the Penman-Monteith approach (Monteith 1965) with all model inputs and forcings, with the exception of wind and surface pressure, derived from satellite remote sensing. Surface resistance (the resistance of vapor flow through the transpiring crop and evaporating soil surface) is adjusted and ecophysiological constraints are applied to account for changing environmental factors. Evaporation and sublimation over snow-covered regions is calculated using a modified Penman equation. Instantaneous latent and sensible heat fluxes computed at the time of satellite overpass are linearly scaled to
the equivalent daily evapotranspiration using the computed evaporative fraction and the
day-time net radiation. Nighttime evaporation is modeled as a constant fraction (10%) of
daytime evaporation. Interception losses (evaporation from the vegetation canopy) are
computed using a simple water budget model. More detail can be found in (Vinukollu et al.
2011). Both input meteorology and latent and sensible heat outputs have been extensively
evaluated against eddy-covariance towers data across the U.S. at the site scale on a monthly-
mean basis. Multi-year means are then compared against climatological evapotranspiration
estimates over 26 major river basins and zonal means are evaluated on an annual basis. Good
correlations are found with in situ data and the dataset is found to capture both seasonal
cycles and major drought events.

(ii) MERRA

The NASA/GMAO MERRA reanalyses assimilates conventional in situ observations,
satellite radiances, and several remotely sensed retrieved data sets over the duration of the
water and energy budget data are reported hourly on a nominal 0.5°x0.67° grid taking
special care to report all relevant budget terms so that closure can be achieved. Like all
reanalyses, analyzed perturbations of the model state variables exert significant influence on
the physics budgets (Roads et al. 2002) which leads to imbalances in the physical terms of
the budget. In MERRA, this influence is computed from the data assimilation and provided
as a tendency term (called the analysis increment) in the budget equation that is used here
to correct turbulent heat fluxes using regression equations based on (Bosilovich and Schubert
2001). The quality of the MERRA global water and energy budgets is discussed in detail
in Bosilovich et al. (2011) and Trenberth et al. (2011) who point out that there are regions
over land where evapotranspiration can exceed precipitation.
(iii) **GLDAS**

The Global Land Data Assimilation System (GLDAS) Rodell et al. (2004b) is a quasi-operational implementation of the Land Information System software (Kumar et al. 2006) that generates optimal estimates of soil moisture, temperature, evapotranspiration, and runoff (among other parameters) by integrating satellite- and ground-based observational data products within a suite of land surface models (LSMs). Here, GLDAS ET estimates derive from the mean and standard deviation of 1.0° resolution output from a four-member ensemble that included the Noah (Chen et al. 1996; Ek et al. 2003; Koren et al. 1999), Community Land Model (CLM) version 2 (Bonan 1998), Variable Infiltration Capacity (VIC) (Liang et al. 1994), and Mosaic (Koster and Suarez 1996) LSMs. Each model was forced with a combination of meteorological fields (air temperature, humidity, wind speed, and surface pressure) from the National Centers for Environmental Prediction (NCEP) Global Data Assimilation System product, 3-hourly precipitation fields from a downscaled version of the GPCP One-Degree Daily (1DD) product version 1.1 (Huffman et al. 2001), and downward shortwave and longwave radiation fields from the Air Force Weather Agency (AFWA) cloud analyses using the schemes of Shapiro (1987), Idso (1981), and Wachtmann (1975). Land cover data from the University of Maryland (Hansen et al. 2000), soils data from Reynolds et al. (2000), and the GTOPO30 digital elevation model were used to parameterize the land surface in all models. The GLDAS simulations were spun up from 1979 and multi-year means were computed for each month by averaging the four models over the period 1998-2008. Inland water bodies (e.g., the Great lakes) and ice sheets (Greenland and Antarctica) not modeled by GLDAS were filled with MERRA data in order to conform to the continental delineation defined for this study.
d. Atmospheric Latent Heat Release

Global precipitation observations offer an independent constraint on non-radiative heat transfer from the surface to the atmosphere and provide an additional pathway for coupling the energy and water cycles in the optimization procedure described below. While detailed accounting of specific microphysical processes is required for deriving vertical profiles of latent heating, the total condensate removed from the atmosphere in the form of precipitation provides a tight constraint on the column-integrated latent heat release on the large time and space scales considered here (Tao et al. 1993). The Global Precipitation Climatology Project (GPCP) monthly Satellite-Gauge precipitation analysis (Adler et al. 2003; Huffman et al. 2009), version 2.2, is adopted as the exclusive dataset to derive atmospheric latent heating in this study.

The multi-satellite merged GPCP dataset provides global, monthly estimates of surface precipitation at 2.5° resolution from 1979 to present though this study made use of the period January 2001 to December 2010, the most recent 10-year period available at the time the analysis began. The product employs precipitation estimates from the 6:00 am and 6:00 pm (local time) low-orbit satellite Special Sensor Microwave Imager (SSM/I) and Special Sensor Microwave Imager and Sounder (SSMIS) microwave data to perform a monthly, regional calibration of geosynchronous-orbit satellite infrared (IR) data in the latitude band 40°N-S. At higher latitudes the SSM/I and SSMIS microwave estimates are combined with estimates based on Television Infrared Observation Satellite (TIROS) Operational Vertical Sounder (TOVS) or Atmospheric Infrared Sounder (AIRS), calibrated by gauges over land and microwave estimates over ocean at lower latitudes, to provide globally complete satellite-based precipitation estimates.
e. Uncertainties

For the observational benchmarks generated here to serve as a basis for future comparisons, it is critical to establish realistic error bounds representative of current capabilities to constrain each flux. Uncertainty estimates not only establish the current state of knowledge and indicate areas to target for improvement but they supply critical input to the objective approach for introducing balance constraints discussed below. Assessing uncertainty poses a significant challenge for global satellite datasets that are typically only validated at a limited number of locations and often with in situ instrumentation with different fields of view, sample volumes, and sensitivities as their satellite-based counterparts. To address this issue, rigorous error estimates in all energy cycle fluxes presented here are derived by combining the results from years of effort by individual algorithm developers based on comparisons of independent datasets, statistical validation against long-term in situ observations, and rigorous sensitivity studies.

Uncertainties in radiative fluxes are established from the standard deviation of four independent datasets (SRB, ISCCP-FD, 2B-FLXHR-lidar, and C3M) supplemented with comparisons against direct radiation measurements and sensitivity studies. Random errors in continent-scale monthly mean TOA radiative fluxes from each of these products are generally thought to be less than 5 Wm\(^{-2}\). Loeb et al. (2009) note that uncertainties in CERES global annual mean net outgoing radiation may be as large as 4.4 Wm\(^{-2}\) (2\(\sigma\)) but these data have also been shown to provide a very stable long-term reference (Loeb et al. 2007; Lin et al. 2008; Loeb et al. 2009). For example, the errors in the long-term anomalies are \(\sim 1\) Wm\(^{-2}\) or less due to the stable relative calibration of the observations and verified using comparisons against absolute ocean heat storage measurements Loeb et al. (2009, 2012).

At the surface, comparisons against Baseline Surface Radiation Network (BSRN) suggest that regional monthly mean bias errors in the current ISCCP-FD and SRB products can much larger, approaching 10 Wm\(^{-2}\) on the continental and ocean basin scales examined here (Zhang et al. 2004).
To avoid underestimating uncertainties due to chance similarities in algorithm implementation, these error estimates are compared against an alternate set of error bounds derived from comparisons against ground-based instrumentation (Kato et al. 2013) and comprehensive sensitivity studies using both the ISSCP-FD and CloudSat 2B-FLXHR-lidar algorithms (Zhang et al. 1995; Henderson et al. 2013). Sensitivities are established by perturbing all key algorithm inputs and assumptions by amounts consistent with their intrinsic uncertainties and reprocessing an entire year of flux calculations (representing billions of individual pixels) to quantify the impact on the computed radiative fluxes. It is found that uncertainties derived from the standard deviations of the four datasets generally capture algorithm sensitivities to errors in input parameters with two important exceptions. The standard deviations of regional downwelling LW radiation (DLR) between the four datasets are sometimes slightly smaller than errors that could result from uncertainties in lower tropospheric humidity and, to a lesser extent, cloud liquid water path. Likewise, standard deviations of downwelling SW radiation (DSR) were smaller than those estimated based on sensitivities to errors in assumed cloud water content and microphysical properties. Uncertainties in DLR and DSR were, therefore, increased slightly to arrive at the error estimates summarized below. On regional scales (see Table 2), fractional uncertainties are consistent with the RMS differences between satellite-based estimates and ground-based observations reported by (Kato et al. 2013). The uncertainties adopted here for global scale fluxes (Table 3) are larger than the biases quoted in that study and may, therefore, represent somewhat conservative estimates.

Uncertainties in SeaFlux latent and sensible heat fluxes are adapted from previous assessments based on a combination of sensitivity studies, comparisons against in situ observations, and comparisons against other satellite-derived products (Roberts et al. 2010; Clayson et al. 2014). As noted above, uncertainties in turbulent heat fluxes over land are computed as the standard deviation of the three independent datasets.

The core monthly GPCP merged product uses high quality microwave observations to
calibrate or adjust IR estimates, which have superior sampling, but poorer quality. Bias
adjustment of satellite estimates using gauges over land provides an improved land product.
Absolute magnitudes are considered reliable and inter-annual changes are robust. Because
of the inhomogeneous nature of the satellite information included in the data set, trends
and other small signals should be interpreted cautiously. The monthly dataset includes
fields of random error estimates, which were used to develop 10-year climatological errors
for this analysis. Precipitation from heavy events and that in mountainous areas may be
underestimated, although GPCP version 2.2 is improved in this regard over previous versions
(Adler et al. 2012).

3. The Observed Global Energy Budget at the Start of
the 21st Century

The annual mean global energy budget for the first decade of the 21st century obtained
using the datasets described above is presented in Figure 1. TOA radiative fluxes are consis-
tent with those reported in other recent efforts to document the global energy budget. Solar
insolation of 340 Wm\(^{-2}\) is balanced by 102 Wm\(^{-2}\) of outgoing shortwave radiation (OSR)
and 238 Wm\(^{-2}\) of outgoing longwave radiation (OLR) yielding a planetary albedo of 0.3 ±
0.012 and a global emitting temperature of 254.5 ± 0.5 K. For historical perspective, these
values agree very well with the early estimates from Nimbus 3 observations reported more
than four decades ago by Vonder Haar et al. (1972) (0.29 and 254 K) though the present
estimates are likely considerably more precise.

Energy fluxes between the atmosphere and surface, on the other hand, differ consider-
ably from those reported by Trenberth et al. (2009) and Stephens et al. (2012b) since no
surface or atmospheric energy balance constraints have been applied. Most notably, the
current estimates of DLR and DSR are 11 Wm\(^{-2}\) and 7 Wm\(^{-2}\) higher than those reported
by Trenberth et al. (2009) while latent heating is 11 Wm\(^{-2}\) lower than that reported by
Stephens et al. (2012b). As a result, the raw observations lead to imbalances in both the surface and atmospheric energy budgets. Figure 1 suggests that our current best-estimates of downwelling radiation at the surface and atmospheric radiative flux divergence exceed turbulent heat transfer from the surface to the atmosphere by 16 Wm$^{-2}$ and 12 Wm$^{-2}$, respectively, on the annual-average. Comparison of energy budgets derived using all possible combinations of the alternative datasets listed above (not shown) suggest that these imbalances are not unique to the specific choice of datasets adopted here. Global annual mean surface energy imbalances, for example, range from 13 to 24 Wm$^{-2}$ depending on the combination of datasets used.

a. *Continental and Basin Scales*

Given the importance of the partitioning of energy between the atmosphere and surface and the fact that the largest energy imbalances are found at the surface, it is important to seek the source of these imbalances. A summary of the contributions of individual continents and ocean basins to the global mean surface energy balance is presented in Figure 2. Surface radiative fluxes have been combined into a net surface radiative flux for brevity ($F_{NET} = DLR + DSR - ULW - USW$). Estimated uncertainties in each of these parameters, expressed as a 1σ deviation about the mean value, are presented in Figure 3 for comparison.

Surprisingly, while most fluxes are more accurately constrained by satellite observations over the oceans, these regions tend to exhibit the largest energy imbalances. Uncertainties in net radiation into the oceans, for example, are $\sim$10 Wm$^{-2}$ due, in part, to the high confidence in the low albedo of the dark ocean surface and the much smaller diurnal cycle of ocean temperatures. Uncertainties in latent heating estimates tend to be larger over oceans than over land due to larger evaporation but this is at least partially offset by much smaller uncertainties in ocean sensible heat transfer. When combined, this results in smaller flux uncertainties over ocean basins than over land yet the energy imbalances in Figure 2 are clearly larger over oceans than over land.
This apparent contradiction between Figures 2 and 3 may be partially explained by differences in the way turbulent heat fluxes are derived over land relative to over oceans. Satellite-based land flux algorithms like the Princeton ET approach directly incorporate closure constraints and ingest surface radiative fluxes while the SeaFlux turbulent heat fluxes are derived independent of surface radiation. As a result, imbalances between downwelling radiation and latent heating over ocean basins are the primary driver of global surface energy imbalances. The integrated surface energy budget over land produces an imbalance of just -3 Wm$^{-2}$ while integrating all oceans basins results in an imbalance of 26 Wm$^{-2}$.

By comparison, the current best estimate of changes in ocean heat content (OHC) since 2005 derived from the well-calibrated Argo array is just 0.6 ± 0.4 Wm$^{-2}$ (Willis et al. 2009; Lyman et al. 2010), nearly two orders of magnitude smaller than the imbalances implied by combining the component fluxes. With the exception of the Antarctic circumpolar current that is not responsible for significant heat transport, all of the major wind-driven gyres lie entirely within individual basins so it is unlikely that heat transport between basins by deep ocean circulations can account for such large imbalances. Furthermore, achieving balance through heat transport would require compensating positive and negative imbalances in adjacent basins yet Figure 2 suggests that the imbalances are of the same sign in all ocean basins.

A closer look at Figures 2d and 3d also suggests that the magnitude of the imbalances in a number of the ocean basins (e.g. the South Atlantic) exceed the combined uncertainty in the component fluxes. Recall, however, that the uncertainties reported represent one standard-deviation error bars on each component flux and that the combined uncertainties assume that the component errors are uncorrelated. Imbalances that exceed the reported uncertainties may, therefore, be explained by either an uncertainty of more than one standard deviation in one or more component fluxes or correlation between two or more uncertainties. A closer look at the uncertainties in all component fluxes compiled in Table 2 reveals that the net surface energy imbalance of 28 Wm$^{-2}$ in the South Atlantic could be nearly eliminated.
if DLR and DSR are reduced by their $1\sigma$ uncertainties while ULW, USW, $Q_s$, and E are increased by theirs. While it seems unlikely that estimates of downwelling and upwelling fluxes would be biased in precisely this manner, this example illustrates that balance can, in principle, be achieved within the stated uncertainties of the component fluxes. This concept is explored quantitatively in the next section where we introduce a general framework for adjusting component fluxes subject to relevant balance constraints.

4. Objectively Imposing Balance Constraints

The presence of large surface energy imbalances over the oceans highlights the challenge of integrating independent datasets into a more complete budget. While it is desirable to maintain independent algorithms for each of the component fluxes for practical reasons and to avoid unwanted correlations that may influence subsequent analyses, global and regional energy budget and water cycle closure relationships provide valuable information that is neglected when component fluxes are derived in isolation. Since closure arguments do not apply on the scales of instantaneous satellite fields of view from which the individual fluxes are derived (especially over oceans), it is not possible to invoke such constraints on individual retrievals but they may be applied a posteriori to averages over larger time and space scales. Motivated by a desire to generate a balanced energy budget subject to all available constraints including the latest in situ estimates of changes in ocean heat content, we propose a new objective approach for adjusting all component fluxes that explicitly accounts for the relative accuracy to which they are known. The method is sufficiently general that it can simultaneously include both energy and water balance constraints to take advantage of the coupling introduced through latent heating.

There are several different approaches for solving an optimization problem of this type. Adapting concepts from the variational data assimilation and optimal estimation retrieval communities, the method adopted here seeks to recast the problem into a form that minimizes
a cost function subject to a prescribed set of constraints. In general, any energy or water balance constraint can be written in the form:

$$R = \sum_{i=1}^{M} F_i - \sum_{o=1}^{N} F_o$$  \hspace{1cm} (1)$$

where the $F_i$ and $F_o$ represent all fluxes into and out of the system, respectively and the residual, $R$, represents the net storage in the system. The goal is to find the most likely vector of fluxes, $F = [F_i, F_o]$, given the vector of independent observational flux datasets $F_{obs} = [F_{i,obs}, F_{o,obs}]$, and the observed value of the residual, $R_{obs}$. At the Earth’s surface, for example, downwelling longwave and shortwave radiation ($F_i$) are balanced by reflected shortwave radiation, emitted longwave radiation, and fluxes of latent and sensible heat from the surface to the atmosphere ($F_o$) to within a very small residual. As previously stated, recent analysis of OHC from the Argo array suggest that the residual ocean heat storage, $R_{obs}$ is on the order of $0.6 \pm 0.4$ Wm$^{-2}$. Given the high (absolute) accuracy of the OHC constraint compared to the component fluxes, obtaining the optimal $F$ requires adjusting each of the component fluxes within their respective error bounds in such a way as to reduce the implied storage to lie within the error bars on $R_{obs}$.

This is achieved by invoking two common (and necessary) assumptions concerning the uncertainties in the component fluxes: that they are random and Gaussian. While it is difficult to justify either of these assumptions, they are the preferred choice in the absence of definitive bias or error distribution information. Under these assumptions, optimal flux values will maximize the joint probability:

$$P(F|F_{obs},R_{obs}) = e^{-(F-F_{obs})^T S^{-1}_{obs} (F-F_{obs})} \times e^{-\frac{(R-R_{obs})^2}{\sigma_R^2}}$$  \hspace{1cm} (2)$$

where the distinction between the incoming and outgoing fluxes has been dropped for simplicity. $S_{obs}$ is the error covariance of all fluxes derived from the uncertainty analyses described above and $\sigma_R^2$ is the error variance in the heat storage constraint. The maximum occurs when the cost function:

$$J = (F - F_{obs})^T S^{-1}_{obs} (F - F_{obs}) + \frac{(R - R_{obs})^2}{\sigma_R^2}$$  \hspace{1cm} (3)$$
is a minimum. Since the residual, $R$, is just a linear combination of the component fluxes, the cost function is quadratic and can be minimized exactly by setting the derivative with respect to $F$ equal to 0. Optimal values of the component fluxes are given by:

$$F = F_{\text{obs}} + S_FK^T S^{-1}_{\text{obs}} (R_{\text{obs}} - KF_{\text{obs}}) \tag{4}$$

where $K$ is the Jacobian of $R$ with respect to the component fluxes and $S_F = (K^T S_{y}^{-1} K + S_{obs}^{-1})^{-1}$ is the error covariance for the component fluxes after optimization. If Gaussian statistics are assumed, Eqn. (4) represents both the most probable posterior estimate and minimum variance estimate of the parameters of interest subject to the constraint imposed by the residual or storage, $R$ (L’Ecuyer and Stephens, 2002). As a metric for establishing the quality of the final ‘fit’, one can apply the $\chi^2$ test to the results. A value of the quantity:

$$\chi^2 = (F - F_{\text{obs}})^T S_{\text{obs}}^{-1} (F - F_{\text{obs}}) + \frac{(R - R_{\text{obs}})}{\sigma_R^2} \tag{5}$$

that is less than or equal to the number of degrees of freedom in the system (i.e. the number of fluxes being optimized) indicates that the resulting flux adjustments do not drastically violate the error assumptions. A larger value of $\chi^2$ is indicative of larger than anticipated biases in one or more of the component fluxes. Another simple metric of the success of the optimization is a simple comparison of the magnitudes of the adjustments made to each component flux against their estimated uncertainties. Energy budget residuals, computed as the sum of the adjustments to the component fluxes, that exceed associated error bounds are indicative of areas where balance could not be adequately achieved.

One of the principal advantages of this approach lies in the fact that it can be scaled to arbitrarily complex problems involving any number of fluxes and constraints. In particular, it can be used to establish an explicit link between energy budget and water cycle through the connection between latent heating, evaporation, and precipitation. In this way disparate observational datasets that are seldom considered together, such as radiative fluxes and surface runoff, can be coupled to their mutual benefit through their relationships to precipitation and evaporation in energy and water budget closure equations. This simultaneous
accounting of both energy and water cycles is a unique aspect of this study and the companion water cycle paper that allows twice as many closure constraints to be leveraged to provide an internally-consistent set of estimates of energy and water fluxes representative of the climate in the first decade of the 21st century.

a. Application to Energy and Water Budgets

This method for imposing closure constraints on independent observational flux datasets has been applied to annual and monthly mean energy and water fluxes on global and continental scales. Over land surfaces, energy and water cycle closure require (in energy units):

\[ L_v (dS_{co,i}) = P_{co,i} - E_{co,i} - Q_{co,i} \] (6)
\[ NET_{co,i} = DLR_{co,i} + DSR_{co,i} - ULW_{co,i} - USW_{co,i} - Q_{s,co,i} - L_v E_{co,i} \] (7)

where \( dS \) is the change in surface water storage and \( NET \) represents energy absorbed at the surface. All other fluxes are as defined in Table 3 and \( L_v = 2500 \text{ kJ kg}^{-1} \) is the latent heat of vaporization. Similarly, in the atmosphere we require:

\[ L_v (dW_{co,i}) = C_{co,i} - P_{co,i} - E_{co,i} \] (8)
\[ NETA_{co,i} = F_{co,i} - OLR_{co,i} - OSR_{co,i} - DLR_{co,i} - DSR_{co,i} + ULW_{co,i} + USW_{co,i} + Q_{s,co,i} + L_v P_{co,i} + CS_{co,i} \] (9)

where \( dW \) is the change in precipitable water in the atmospheric column, \( NETA \) represents atmospheric heat storage, and \( CS \) is the atmospheric convergence of dry static energy. These equations apply to all continents, \( i \), on annual or monthly scales and explicitly demonstrate how fluxes of energy and water are coupled through the latent heat release. Similar equations apply to each ocean basin with one important distinction: an additional term must be added to each of the surface budget equations (6) to account for water and heat transports between basins that occur on all time and space scales.
On global scales, mass continuity and water balance also require:

\[ L_v (dS_L + dS_O) = dW_L + dW_O \]  (11)

\[ L_v (C_L) = -C_O \]  (12)

\[ Q_L = Q_O \]  (13)

\[ OT_O = 0 \]  (14)

\[ CS_L = -CS_O \]  (15)

where the subscripts \( L \) and \( O \) correspond to the sum over all land regions and ocean regions, respectively. \( OT_O \) represents the net oceanic transports (of heat or water) integrated over all ocean basins.

To account for the additional complications of storage and transport on monthly scales, the optimization is executed in stages. First, the continental energy and water budgets are optimized simultaneously on annual scales taking advantage of the fact that \( dS_{co,i} \), \( dS_O \), \( dW_{co,i} \), and \( dW_O \) vanish on an annual mean if it is assumed that the climate is approximately stationary over the decade considered. Similarly, \( NET_{co,i} \), \( NETA_{co,i} \), and all of the \( NETA_O \) are extremely small over the time period considered since most of the excess energy into the Earth’s climate system is absorbed into the oceans (Trenberth et al. 2014). Only the small residual flux of energy into the oceans needs to be considered on these scales and this can be estimated from changes in OHC.

Application of closure relations in oceanic regions is further complicated by the heat exchanges between basins. Observations of ocean heat transport are more limited and do not map well onto the ocean basins defined here so a single set of balance constraints are initially applied to the sum of all oceanic regions in order to make use of the closure relations in Eqn. (11). The net oceanic flux adjustment is then partitioned among the individual basins using a Lagrange multiplier approach that inversely weights changes according to the error variances of the individual monthly estimates. Energy balance closure on monthly scales is also complicated by heat transport and storage. Lacking accurate global observations these
quantities, energy balance constraints are not applied directly on monthly scales. Instead, monthly best guess fluxes are defined such that they match the sum to the optimized annual mean fluxes through incremental adjustments that are inversely proportional to their best guess uncertainties. Again, a Lagrange multiplier approach is used to partition the residual between the adjusted annual mean and the sum of the unadjusted monthly mean fluxes among the individual months. Additional details can be found in the companion manuscript by Rodell et al. (2014).

b. Constrained Global Energy Budget

Application of Eqn. (4) assuming a surface energy residual consistent with current estimates of OHC changes $0.6 \pm 0.4 \text{ Wm}^{-2}$ and vanishing atmospheric convergence and runoff on global scales yields the estimates of the surface energy budget and water cycle reported in the right hand column of Table 3. As should be expected almost all fluxes are adjusted through the optimization process with the largest changes in parameters that are the least well constrained by observations such as evaporation and DLR.

Global mean precipitation provides a clear example of the benefits of applying energy and water cycle constraints together. Since observed precipitation exceeds evaporation, if water cycle closure were enforced in isolation, global mean precipitation would be reduced by 1 Wm$^{-2}$ with a corresponding increase in evaporation to achieve balance. The resulting latent heat release, however, would not be sufficient to balance atmospheric radiative cooling. The addition of the energy balance constraint causes both precipitation and evaporation to be increased, yielding fluxes that simultaneously close the global water cycle and match observations of ocean heat storage.

It is encouraging that the resulting flux estimates lie within the ranges implied by the uncertainties in the observed fluxes. The magnitudes of the adjustments are also generally consistent with published estimates of the uncertainties in each component flux. The precipitation adjustment, for example, falls within the uncertainty estimates provided by (Adler
et al. 2012) while adjustments to DLR are consistent with the findings of (Stephens et al. 2012a). Furthermore, $\chi^2 = 1.9$, suggesting that the resulting ensemble of fluxes is consistent with assumed errors given that this problem is characterized by nine degrees of freedom.

The error bounds on all fluxes are also reduced in the optimization process but it must be emphasized these no longer represent the accuracy of the observations and should not be viewed as uncertainties in the traditional sense. Instead, they represent improved confidence in the overall ensemble of fluxes owing to the addition of balance constraints that are known to a much higher degree of confidence than the original observations but were not previously included in the independent algorithms. The error estimates associated with the unadjusted fluxes should be adopted when quoting uncertainties in individual flux datasets. The reduced error bounds also reflect the assumption that the uncertainties in the component fluxes are random and Gaussian. In reality this is unlikely to be the case but is justified in the absence of conclusive evidence for biases in any particular observations.

The optimized estimates of global energy fluxes produced here (Figure 4) represent a compromise between recently published energy budgets. The present estimates of precipitation and evaporation, for example, are very similar to those reported by Trenberth et al. (2009) while sensible heating and DSR are in closer agreement with Stephens et al. (2012b). The estimates of DLR in the present study fall between the estimates from these two earlier studies highlighting an important implication of the assumption that the errors are random and Gaussian. While the optimization reduces DLR in an effort to reduce surface energy imbalances, improved cloud base and multi-layer cloud information provided by active sensors suggests that estimates of DLR from passive measurements (like those used here) are more likely biased low since they miss some emission from obscured low clouds (Stephens et al. 2012a). If the initial guess DLR were increased to account for such a bias the optimized value would likely be larger but it is difficult to justify such an adjustment since these recent observations do not span the period of interest. More generally, it can be argued that in the absence of definitive evidence of specific biases in any of the component fluxes,
the optimization presented here produces the most objective method for imposing balance constraints on the energy and water cycle. We further suggest that in the event biases are identified in component fluxes, they should be corrected at the algorithm level as opposed to the stage when they are combined into a global budget.

c. Continental and Basin Scales

The distribution of annual mean surface energy fluxes for all continents and ocean basins after imposing balance constraints is presented in Figure 5. A complete summary of all component fluxes and corresponding uncertainties after optimization is compiled in Table 4 for reference. In general the net radiation incident on the ocean surface has been diminished in all basins through reductions to both DLR and DSR while precipitation and evaporation have both increased. Over continents the picture is more varied with surface radiation increasing over Africa and to a lesser extent South America, Australia, and Eurasia but decreasing over North America and Antarctica. Latent and sensible heat adjustments mirror those in radiation increasing over continents where radiation is reduced and decreasing over continents where radiation is increased.

The effect of imposing balance constraints is clearly evident in the global distribution of annually-averaged energy into the surface after optimization (see Fig. 5d). The component fluxes are now balanced over all continents as anticipated. While the energy budgets of individual basins do not necessarily balance since the oceans can transport heat, imbalances are significantly smaller than those in Figure 2d and now exhibit both surpluses and deficits that would more readily support balance by transport. The Gulf of Mexico and Caribbean Sea, for example, exhibit strong heating that likely balances weak overall cooling in the much larger North Atlantic basin.

The refinements to all annually-averaged surface energy fluxes in each continent and ocean basin are isolated in Figure 6. As in the global case, adjustments generally fall within the ranges implied by the uncertainties in each component flux but several oceanic adjustments
approach the maximum allowed by their uncertainties. This, coupled with the fact that fluxes tend to be adjusted in the same sense (increased or decreased) in all basins, suggests that biases exist in some of the component fluxes. Latent heat fluxes (both precipitation and evaporation) are generally adjusted by smaller increments in the current optimization than is argued by Stephens et al. (2012b) likely owing to the additional water cycle constraints applied in the current analysis. The physical coupling of the energy and water cycles introduced here allows other hydrologic parameters such as runoff and atmospheric moisture convergence to influence the magnitudes of the adjustments in the current analysis. Thus while initial energy imbalances suggest that latent heating should be increased significantly, water cycle constraints limit the magnitude of the adjustments since precipitation already exceeds the sum of evaporation and runoff (see companion water cycle paper for additional details). Residual imbalances are, therefore, transferred to the radiative fluxes resulting in larger adjustments to DLR and DSR. Although there is no way to demonstrate that the adjustments presented here are more realistic than those proposed elsewhere, they have the advantage that the methodology guarantees that the resulting fluxes satisfy both energy and water cycle constraints.

d. Seasonal Cycles

In most locations the largest regional climate fluctuations are modulated by seasonal variations in solar insolation. Annual cycles of regional energy budgets, therefore, provide a first-order mode of climate variability that must be captured if we are to predict more subtle inter-annual changes. One of the advantages of the blending methodology introduced above is that it is fully scalable to problems with larger dimensionality, provided suitable energy and water cycle closure constraints can be defined. As a result, the methodology is an ideal tool for documenting the seasonal cycle of all component energy fluxes on continental and ocean basin scales subject to the regional, time-dependent constraints summarized in the Appendix. Estimates of the uncertainty in each monthly-mean flux are derived using the
The seasonal cycles of all fluxes contributing to TOA energy balance are summarized in Figures 7 and 8 for all continents and ocean basins, respectively. For brevity, only optimally blended results are shown and fluxes have been plotted in W m$^{-2}$ to facilitate displaying all regions in a single figure. The results should be multiplied by the appropriate areas in Table 2 to accurately reflect the partitioning of energy between regions. With the exception of Africa, net TOA radiation exhibits an annual period wave mode in all regions that tracks the periodicity of solar radiation. The peak emission of longwave radiation in each ocean basin generally lags the peak in incoming solar radiation by one month while over most continents this lag increases to two months (e.g. North America and Eurasia). The only exception is Africa, the only region with appreciable area in both hemispheres, where a unique bimodal structure in net radiative balance at TOA is observed with peaks in the spring and fall seasons.

Equivalent seasonal cycles in surface fluxes are presented in Figure 9 (continents) and Figure 10 (basins). Lags in longwave fluxes relative to shortwave fluxes are enhanced over the oceans and muted over the continents relative to TOA. For example, peaks in both longwave emission and DLR lag surface shortwave radiation by at least two months over all major ocean basins while the peaks in all radiative fluxes generally coincide over land. This may reflect a lag in ocean heating owing to the larger heat capacity of oceans relative to land but also suggests that changes in atmospheric properties strongly modulate the connection between peak surface emission and OLR over continents.

In all ocean basins, turbulent heat transfer is dominated by latent heating from evapotranspiration. In the large ocean basins, summer-time minima and winter-time peaks in evaporation tend to reinforce the annual cycle in solar insolation into the oceans causing large seasonal reversals in the net energy exchanged between the oceans and overlying atmosphere. As noted above, these exchanges do not necessarily integrate to zero over the course of the year for individual ocean basins due to ocean heat transport, but residuals are
generally less than 10 % of the amplitude of the seasonal cycle (Figure 5). Over the continents, latent and sensible heat both contribute to the net turbulent heat transfer between the surface and the atmosphere, significantly enhancing the seasonal cycle in fluxes of energy from the surface to the atmosphere. The observed summer maxima and winter minima in turbulent heat fluxes over land play an important role in balancing corresponding changes in DSR leading to seasonal cycles in net energy exchange between land surfaces and the overlying atmosphere with amplitudes generally less than 4 % of the component upwelling and downwelling fluxes.

There are substantial hemispheric asymmetries in the polar regions with Antarctica on average 20 K colder and 10 % brighter than the Arctic. The coldest monthly surface emission observed on the planet is 147 Wm$^{-2}$ in Antarctica in August, corresponding to a mean surface temperature of 225 K. By comparison, the minimum monthly emitted flux in the Arctic is 203 Wm$^{-2}$ in February, implying a minimum temperature of 245 K. The Arctic also exhibits far stronger variations in TOA net radiation over the course of the year, losing more than 180 Wm$^{-2}$ in November while gaining a small 20 Wm$^{-2}$ in July. By contrast, Antarctica does not receive a net surplus of TOA radiation in any month but also never loses more than 150 Wm$^{-2}$ during any month of the year. At the surface, both regions experience net energy gains in the summer months that are offset by corresponding energy losses in the winter.

In the Arctic, there is a clear seasonal asymmetry in the net energy exchange between the atmosphere and surface owing to the buffering effects of sea ice that shift the peak surface reflection and emission relative to incoming solar radiation.

As time and space scales are reduced, establishing balance becomes increasingly difficult due to the increased likelihood of biases in global observational datasets. For example, the annual-continental scale optimization involves 73 degrees of freedom and results in $\chi^2 = 21$ while the monthly-continental scale optimization results in $\chi^2 = 547$ with 660 degrees of freedom. Thus while $\chi^2$ indicates an acceptable overall fit in both cases, the average adjustment approaches the magnitude of the assumed uncertainties in the monthly-continental
scale optimization. To provide a more detailed metric for assessing our ability to achieve balance within individual continents and basins, surface budget adjustments are compared against initial error bounds in Figures 11 and 12. Energy budget residuals (indicated by the sum of the adjustments to individual flux components) are within error bounds over all continents and in the smaller Caribbean, Mediterranean, and Black Seas. Residuals in the North Pacific, South Pacific, and Indian Oceans, however, all exceed associated closure errors. The adjustments applied to DLR, DSR, and latent heat fluxes all exceed their corresponding uncertainty estimates suggesting that the observational estimates of some component energy fluxes may exhibit biases on regional scales that exceed anticipated sources of uncertainty in the antecedent algorithms.

5. Discussion

Recent attempts to document global energy balance using modern satellite datasets have yielded depictions of the global energy budget that differ in several key ways, most notably in their estimates of downwelling longwave radiation and latent heating. The present study revisits the issue of imbalances in observationally-derived energy flux datasets with the goal of establishing objective benchmarks of the current state of the global energy budget and its distribution on continental and ocean basin scales. The two sets of energy budget estimates reported address two important questions: “How well do current observations constrain the energy budget?” and “To what extent can balance be objectively imposed within rigorous estimates of the uncertainties in the component fluxes?”

In the absence of balance constraints, various combinations of available satellite datasets suggest that globally and annually-averaged surface radiative fluxes exceed corresponding turbulent energy fluxes by 13-24 Wm$^{-2}$. These imbalances occur primarily in oceanic regions where all component fluxes are derived independently. The systematic trend for downwelling radiative fluxes to exceed turbulent heat fluxes across all major ocean basins is more indica-
tive of biases than of random errors. This is, perhaps, not surprising since the complexities of deriving energy and water fluxes from remote measurements necessitates independent algorithms that use distinct observations and assumptions. However, since the flux datasets are developed in isolation, valuable energy budget and water cycle closure information that could help mitigate biases is omitted.

In an effort to reintroduce this closure information and address the need for a balanced monthly, continental-scale energy budget dataset for model evaluation, a method has been developed to objectively impose well-defined global and regional energy and water balance constraints on the system. While the resulting flux estimates can no longer be traced to unique observational origins, they constitute a balanced ensemble that maintains consistency with the original component datasets and their estimated uncertainties. A careful examination of several performance metrics reveals important insights into our ability to close regional energy budgets with current satellite-based energy flux datasets. The results suggest that energy balance residuals are generally less than expected closure errors but residuals in some regions lie near the extremes implied by the prescribed uncertainty ranges, especially on monthly timescales.

This study and the companion paper by Rodell et al. (2014) provide our best estimates of energy flows and water fluxes on monthly and continental scales based on current observational capabilities. The fluxes simultaneously satisfy all relevant energy and hydrologic cycle closure constraints while preserving the information contained in the original observationally-derived datasets through direct use of rigorous uncertainty estimates. The results provide important benchmarks of the climate at the beginning of the 21st century against which future observing system improvements can be measured. The results also provide important standards with which to evaluate the representation of the energy budget and its seasonal cycle in climate models through ongoing assessments like the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al. 2012). The complete observational energy and water budget analysis described here and in the companion paper by Rodell et al. (2014) is
available for download from the NASA NEWS website: (http://www.nasa-news.org/). This dataset includes all energy and water cycle fluxes on continental and monthly space and time scales both prior to and after the addition of relevant balance constraints.

Despite its strengths, there are some important caveats associated with the current analysis. First, a decision was made to focus on the golden age of satellite observations in the first decade of the new millennium as opposed to developing a true climatology that is commonly defined to correspond to a 30-year period. Given the recent advances in instrumentation over this period and the challenges associated with creating longer term climate records from multiple satellite platforms, this choice appears to be justified, but it should be noted that the results presented here may be influenced by decadal variability. On the other hand, trends that may be present in any of the component fluxes over the ten year period, such as melting of the Greenland ice sheet, were intentionally averaged to avoid the influence of interannual variability.

While considerable effort was made to include information from a range of high quality observational data sources, some datasets were chosen for inclusion in this study based on the expertise of the members of the NEWS team. In some cases, the methods used for combining datasets, establishing uncertainties, and using reanalyses to fill observational gaps were driven by convenience and may not be optimal under all conditions. Likewise, there is no rigorous justification for assuming that uncertainties in component fluxes are unbiased and Gaussian in the optimization. Biases in any of the component fluxes reduce the veracity of the resulting balanced flux estimates and associated uncertainty ranges. In the absence of quantitative information regarding such biases, however, it is not clear that alternative assumptions should be preferred over those adopted here.

It should be emphasized that this study would not have been possible without the recent advances in Earth observing capabilities provided by the TRMM, Gravity Recovery And Climate Experiment (GRACE), Aqua, Terra, Aura, CloudSat, and CALIPSO satellites and corresponding tools for integrating these measurements into assimilation systems like...
MERRA and GLDAS. The results presented here point to the need for continued observation and refinement of satellite flux algorithms yet all of these missions are now operating well beyond their design lifetimes, in some cases without concrete plans for a successor. Given the importance of observing climate variability, systematic planning for future missions with new technologies for improving the absolute accuracy of component fluxes and establishing the factors that modify them is critical. Particular attention should be given to quantifying biases in component fluxes on regional scales, and it is anticipated that analysis of data from the recently launched Global Precipitation Mission (GPM), Soil Moisture Active Passive (SMAP), and Suomi NPP, missions will facilitate progress toward this goal. The approach outlined here provides a framework for integrating these new observations and reintroducing relevant balance information to identify biases. As uncertainties in observational datasets are reduced through new technology and refined algorithms, it may no longer be possible to objectively achieve balance. Such a breakdown (indicated by either large $\chi^2$ or unrealistically large adjustments to one or more fluxes) would provide direct evidence of biases in individual datasets.

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This study is the result of a collaboration of multiple investigators each supported by the NASA Energy and Water Cycle Study (NEWS) program. The goal of NEWS is to foster large collaborative research activities that cross traditional disciplinary boundaries to improve understanding and prediction of the global energy and water cycles. All data generated in the course of this work can be accessed through the NEWS website: http://www.nasa-news.org/. This dataset summarizes the original observationally-based estimates of all component fluxes for each continent and ocean basin on monthly and annual scales as well means over all oceans, all continents, and the global mean. A companion dataset provides optimized versions of all component fluxes in the same format. GEWEX SRB data were obtained from the NASA Langley Research Center Atmospheric
Sciences Data Center NASA/GEWEX SRB Project. The C3M product (edition B1) was obtained from http://eosweb.larc.nasa.gov/PRODOCS/ceres-news/table_ceres-news.html. ISCCP D2 data were obtained from the International Satellite Cloud Climatology Project web site (http://isccp.giss.nasa.gov) maintained by the ISCCP research group at the NASA Goddard Institute for Space Studies, New York, NY. 2B-FLXHR-lidar data were obtained through the CloudSat Data Processing Center (http://www.cloudsat.cira.colostate.edu). The GPCP combined precipitation data were provided by the NASA/Goddard Space Flight Center’s Laboratory for Atmospheres (at http://precip.gsfc.nasa.gov), which develops and computes the dataset as a contribution to the GEWEX Global Precipitation Climatology Project. MERRA data used in this study have been provided by the Global Modeling and Assimilation Office (GMAO) at NASA Goddard Space Flight Center through the NASA GES DISC online archive.
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<td>AVHRR</td>
<td>CloudSat, CALIPSO, MODIS</td>
<td>Henderson et al. (2013)</td>
</tr>
<tr>
<td></td>
<td>MODIS, AMSR-E</td>
<td>CALIPSO, MODIS</td>
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<tr>
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<td>C3M</td>
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<tr>
<td>Land Turbulent Heat Fluxes</td>
<td>AIRS, CERES, MODIS, AVHRR</td>
<td>Numerous SSM/I, SSMIS, GOES-IR, TOVS, AIRS</td>
<td>Vinnikov and Coauthors (2011) and Bosilovich et al. (2011)</td>
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<td></td>
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<td>Rienecker and Coauthors (2011)</td>
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<td>Rodell et al. (2011)</td>
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<td>Atmospheric Latent Heating</td>
<td>GPCP v.2.2</td>
<td>SSM/I, SSMIS, GOES-IR, TOVS, AIRS</td>
<td>Adler et al. (2003)</td>
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<tr>
<td></td>
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<td>Huffman et al. (2009)</td>
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Table 2: Contributions of individual continents and ocean basins to the annual-mean energy flux into the Earth’s surface. Fluxes are reported in PetaWatts ($10^{15}$ Watts) so that the values reported for individual regions reflect the partitioning of the global total (last row) between them (Fasullo and Trenberth 2008a). For conversion purposes, 1 Wm$^{-2}$ globally equates to 0.511 PW while for global land 1 Wm$^{-2}$ = 0.147 PW and global oceans 1 Wm$^{-2}$ = 0.364 PW. The areas (in $10^{12}$ m$^2$) of all continents and basins as defined in Figure 2 are provided for converting fluxes in individual regions. The full names of each term are provided in Table 3.

<table>
<thead>
<tr>
<th>Map</th>
<th>Continent/Basin</th>
<th>Area</th>
<th>P</th>
<th>E</th>
<th>DLR</th>
<th>DSR</th>
<th>ULW</th>
<th>USW</th>
<th>SH</th>
</tr>
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<tr>
<td>01</td>
<td>North America</td>
<td>24.03</td>
<td>1.35 ± 0.07</td>
<td>0.82 ± 0.07</td>
<td>6.95 ± 0.13</td>
<td>3.76 ± 0.17</td>
<td>8.27 ± 0.13</td>
<td>0.63 ± 0.09</td>
<td>0.66 ± 0.17</td>
</tr>
<tr>
<td>02</td>
<td>South America</td>
<td>17.73</td>
<td>2.31 ± 0.11</td>
<td>1.40 ± 0.08</td>
<td>6.66 ± 0.10</td>
<td>3.68 ± 0.15</td>
<td>7.71 ± 0.07</td>
<td>0.46 ± 0.06</td>
<td>0.96 ± 0.13</td>
</tr>
<tr>
<td>03</td>
<td>Eurasia</td>
<td>53.23</td>
<td>3.06 ± 0.18</td>
<td>1.77 ± 0.28</td>
<td>15.9 ± 0.44</td>
<td>8.70 ± 0.50</td>
<td>19.5 ± 0.73</td>
<td>1.79 ± 0.12</td>
<td>1.86 ± 0.38</td>
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<tr>
<td>04</td>
<td>Africa</td>
<td>29.90</td>
<td>1.66 ± 0.08</td>
<td>1.32 ± 0.11</td>
<td>10.9 ± 0.22</td>
<td>7.10 ± 0.31</td>
<td>13.8 ± 0.19</td>
<td>1.68 ± 0.06</td>
<td>1.87 ± 0.21</td>
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<td>2.70 ± 0.07</td>
<td>1.77 ± 0.09</td>
<td>3.50 ± 0.11</td>
<td>0.34 ± 0.05</td>
<td>0.60 ± 0.06</td>
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<tr>
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<td>0.53 ± 0.02</td>
<td>0.25 ± 0.02</td>
<td>0.60 ± 0.03</td>
<td>0.02 ± 0.01</td>
<td>0.05 ± 0.02</td>
</tr>
<tr>
<td>07</td>
<td>Antarctica</td>
<td>12.70</td>
<td>0.18 ± 0.05</td>
<td>0.01 ± 0.01</td>
<td>1.76 ± 0.22</td>
<td>1.62 ± 0.13</td>
<td>2.18 ± 0.09</td>
<td>1.23 ± 0.13</td>
<td>-0.2 ± 0.09</td>
</tr>
<tr>
<td>08</td>
<td>Arctic Ocean</td>
<td>10.15</td>
<td>0.21 ± 0.11</td>
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<td>2.32 ± 0.07</td>
<td>0.99 ± 0.04</td>
<td>2.61 ± 0.03</td>
<td>0.48 ± 0.09</td>
<td>0.07 ± 0.03</td>
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<td>Caribbean Sea</td>
<td>4.345</td>
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<td>0.55 ± 0.05</td>
<td>1.76 ± 0.03</td>
<td>1.06 ± 0.03</td>
<td>1.99 ± 0.01</td>
<td>0.05 ± 0.01</td>
<td>0.05 ± 0.02</td>
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<td>0.56 ± 0.03</td>
<td>1.09 ± 0.01</td>
<td>0.03 ± 0.01</td>
<td>0.06 ± 0.02</td>
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<td>0.03 ± 0.01</td>
<td>0.15 ± 0.01</td>
<td>0.08 ± 0.01</td>
<td>0.18 ± 0.01</td>
<td>0.00 ± 0.01</td>
<td>0.01 ± 0.01</td>
</tr>
<tr>
<td>12</td>
<td>North Pacific</td>
<td>81.77</td>
<td>9.02 ± 0.74</td>
<td>7.76 ± 0.69</td>
<td>31.3 ± 0.51</td>
<td>16.7 ± 0.47</td>
<td>35.1 ± 0.31</td>
<td>0.97 ± 0.09</td>
<td>1.22 ± 0.29</td>
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<td>13</td>
<td>North Atlantic</td>
<td>43.38</td>
<td>3.54 ± 0.38</td>
<td>4.06 ± 0.33</td>
<td>15.6 ± 0.23</td>
<td>8.12 ± 0.27</td>
<td>17.7 ± 0.17</td>
<td>0.51 ± 0.04</td>
<td>0.80 ± 0.18</td>
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<tr>
<td>14</td>
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<td>27.1 ± 0.38</td>
<td>14.5 ± 0.40</td>
<td>30.6 ± 0.23</td>
<td>0.94 ± 0.07</td>
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<tr>
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<td>19.3 ± 0.36</td>
<td>40.4 ± 0.33</td>
<td>1.35 ± 0.09</td>
<td>1.64 ± 0.37</td>
</tr>
<tr>
<td>16</td>
<td>South Atlantic</td>
<td>46.51</td>
<td>2.83 ± 0.37</td>
<td>3.58 ± 0.28</td>
<td>15.7 ± 0.18</td>
<td>8.35 ± 0.28</td>
<td>17.8 ± 0.14</td>
<td>0.69 ± 0.08</td>
<td>0.81 ± 0.18</td>
</tr>
<tr>
<td>NA</td>
<td>Continents</td>
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<tr>
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<td>69.8 ± 1.85</td>
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<td>5.96 ± 1.36</td>
</tr>
<tr>
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<td>Global</td>
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<td>39.7 ± 3.59</td>
<td>38.1 ± 3.42</td>
<td>176. ± 3.09</td>
<td>96.6 ± 3.18</td>
<td>203. ± 2.50</td>
<td>11.1 ± 0.93</td>
<td>11.6 ± 2.39</td>
</tr>
</tbody>
</table>
Table 3. Observed components of the global and annually averaged energy budget and their uncertainties before and after optimization. All values are reported in energy flux units (Wm$^{-2}$). The reader is referred to the companion water cycle paper (Rodell et al. 2014) for additional details regarding runoff, atmospheric convergence, and water storage datasets used in the water budget closure equations.

<table>
<thead>
<tr>
<th>Full Name</th>
<th>Abbreviation</th>
<th>Original</th>
<th>Constrained</th>
</tr>
</thead>
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<tr>
<td>Incoming Solar</td>
<td>F</td>
<td>340 ± 0.5</td>
<td>340 ± 0.5</td>
</tr>
<tr>
<td>Outgoing Shortwave</td>
<td>OSR</td>
<td>102 ± 4</td>
<td>102 ± 2</td>
</tr>
<tr>
<td>Outgoing Longwave</td>
<td>OLR</td>
<td>238 ± 3</td>
<td>238 ± 2</td>
</tr>
<tr>
<td>Downwelling LW at SFC</td>
<td>DLR</td>
<td>344 ± 6</td>
<td>341 ± 5</td>
</tr>
<tr>
<td>Downwelling SW at SFC</td>
<td>DSR</td>
<td>189 ± 6</td>
<td>186 ± 5</td>
</tr>
<tr>
<td>Surface Emitted</td>
<td>ULW</td>
<td>398 ± 5</td>
<td>399 ± 4</td>
</tr>
<tr>
<td>Surface Reflected</td>
<td>USW</td>
<td>22 ± 2</td>
<td>22 ± 2</td>
</tr>
<tr>
<td>Sensible Heat</td>
<td>SH</td>
<td>23 ± 5</td>
<td>25 ± 4</td>
</tr>
<tr>
<td>Atmospheric Latent Heat (Precipitation)</td>
<td>P</td>
<td>78 ± 7</td>
<td>81 ± 4</td>
</tr>
<tr>
<td>Surface Latent Heat (Evaporation)</td>
<td>E</td>
<td>75 ± 7</td>
<td>81 ± 4</td>
</tr>
<tr>
<td>Atmospheric Convergence</td>
<td>C</td>
<td>-0.6 ± 4</td>
<td>0 ± 1</td>
</tr>
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<td>0</td>
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<td>-4</td>
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<td>dS</td>
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<td>Atmospheric NET (derived)</td>
<td>NETA</td>
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Table 4: As in Table 2 but after imposing relevant energy and water balance constraints.

<table>
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<th>Continent/Basin</th>
<th>P</th>
<th>E</th>
<th>DLR</th>
<th>DSR</th>
<th>ULW</th>
<th>USW</th>
<th>SH</th>
</tr>
</thead>
<tbody>
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<td>01</td>
<td>North America</td>
<td>1.41 ± 0.06</td>
<td>0.79 ± 0.06</td>
<td>6.90 ± 0.12</td>
<td>3.65 ± 0.15</td>
<td>8.33 ± 0.12</td>
<td>0.12 ± 0.08</td>
<td>0.77 ± 0.15</td>
</tr>
<tr>
<td>02</td>
<td>South America</td>
<td>2.34 ± 0.09</td>
<td>1.37 ± 0.07</td>
<td>6.69 ± 0.09</td>
<td>3.75 ± 0.12</td>
<td>7.70 ± 0.07</td>
<td>0.45 ± 0.06</td>
<td>0.92 ± 0.11</td>
</tr>
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<td>19.3 ± 0.54</td>
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<td>1.67 ± 0.06</td>
<td>1.73 ± 0.19</td>
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<td>Africa</td>
<td>1.63 ± 0.07</td>
<td>1.33 ± 0.07</td>
<td>11.0 ± 0.19</td>
<td>7.41 ± 0.04</td>
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<td>1.82 ± 0.06</td>
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<td>0.31 ± 0.002</td>
<td>0.10 ± 0.002</td>
<td>0.53 ± 0.002</td>
<td>0.25 ± 0.002</td>
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<td>0.20 ± 0.002</td>
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<td>1.80 ± 0.008</td>
<td>3.43 ± 0.009</td>
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<td>0.61 ± 0.001</td>
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<td>1.58 ± 0.012</td>
<td>2.20 ± 0.008</td>
<td>1.27 ± 0.012</td>
<td>0.62 ± 0.009</td>
</tr>
<tr>
<td>09</td>
<td>Caribbean Sea</td>
<td>0.37 ± 0.004</td>
<td>0.53 ± 0.005</td>
<td>1.75 ± 0.017</td>
<td>1.06 ± 0.031</td>
<td>1.99 ± 0.033</td>
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<td>1.44 ± 0.008</td>
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<td>Mediterranean Sea</td>
<td>0.12 ± 0.002</td>
<td>0.29 ± 0.004</td>
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<td>0.56 ± 0.002</td>
<td>0.58 ± 0.001</td>
<td>0.38 ± 0.001</td>
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<tr>
<td>11</td>
<td>North Pacific</td>
<td>0.36 ± 0.005</td>
<td>0.82 ± 0.010</td>
<td>2.86 ± 0.019</td>
<td>1.54 ± 0.023</td>
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<td>0.99 ± 0.009</td>
<td>1.44 ± 0.008</td>
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<tr>
<td>13</td>
<td>North Atlantic</td>
<td>3.640 ± 0.38</td>
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<td>27.2 ± 1.13</td>
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<td>6.19 ± 0.48</td>
<td>5.0 ± 0.03</td>
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<tr>
<td>16</td>
<td>Indian Ocean</td>
<td>3.17 ± 0.16</td>
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<td>128. ± 3.87</td>
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<td>168. ± 3.92</td>
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<td>95.1 ± 2.73</td>
<td>203. ± 2.19</td>
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<td>41.2 ± 2.16</td>
<td>174. ± 0.67</td>
<td>95.1 ± 2.73</td>
<td>203. ± 2.19</td>
<td>11.3 ± 0.90</td>
<td>12.3 ± 2.21</td>
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<td>41.2 ± 2.16</td>
<td>174. ± 0.67</td>
<td>95.1 ± 2.73</td>
<td>203. ± 2.19</td>
<td>11.3 ± 0.90</td>
<td>12.3 ± 2.21</td>
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### List of Figures

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>The observed annual-mean global energy budget of the Earth over the period 2000-2009. All fluxes are expressed in Watts per square meter (Wm(^{-2})).</td>
<td>52</td>
</tr>
<tr>
<td>2</td>
<td>Annual-mean surface energy fluxes for each of the six continents and nine ocean basins adopted in this study. Net downwelling surface radiation (downwelling minus upwelling LW + SW radiation) is shown in panel (a), latent and sensible turbulent heat fluxes are presented in panels (b) and (c). Panel (d) illustrates the resulting net surface energy imbalances defined as the difference between radiation and the two turbulent heat fluxes. Corresponding global (GLB), continental (LND), and ocean basin (SEA) means are summarized on the right side of the figure (in Wm(^2)).</td>
<td>53</td>
</tr>
<tr>
<td>3</td>
<td>Estimated uncertainties in observed annual-mean surface (a) radiative fluxes, (b) sensible heat fluxes, and (c) latent heat fluxes for all major continents and ocean basins. The uncertainty in net surface-atmosphere energy exchange in panel (d) is computed assuming that the errors in the component fluxes are independent (i.e. (\delta(x_1 + x_2 + \ldots + x_N) = \sqrt{\sum_{i=1}^{N} \delta x_i^2})).</td>
<td>54</td>
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<td>4</td>
<td>As in Figure 1 but after application of relevant energy and water cycle balance constraints.</td>
<td>55</td>
</tr>
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<td>5</td>
<td>Net energy exchange from the atmosphere to the surface after objectively introducing all relevant continental-scale energy and water cycle constraints.</td>
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<tr>
<td>6</td>
<td>Adjustments to radiation, sensible heat, and latent heat fluxes during the optimization process.</td>
<td>57</td>
</tr>
<tr>
<td>7</td>
<td>Annual cycle of top of atmosphere radiative fluxes for each continent defined in Figure 2. The heavy black line represents the net radiation into the region.</td>
<td>58</td>
</tr>
<tr>
<td>8</td>
<td>As in Figure 7 but for each ocean basin.</td>
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</tr>
<tr>
<td>9</td>
<td>Annual cycle of surface energy fluxes for each continent defined in Figure 2. Net energy into the surface is presented as the heavy black line.</td>
<td>60</td>
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</table>
10 As in Figure 9 but for each ocean basin.

11 Assumed uncertainties in all surface energy fluxes (right bars) and adjustments incurred as a result of applying balance constraints (left bars) for each continent defined in Figure 2.

12 As in Figure 11 but for each ocean basin.
**Fig. 1.** The observed annual-mean global energy budget of the Earth over the period 2000-2009. All fluxes are expressed in Watts per square meter (Wm$^{-2}$).
Fig. 2. Annual-mean surface energy fluxes for each of the six continents and nine ocean basins adopted in this study. Net downwelling surface radiation (downwelling minus upwelling LW + SW radiation) is shown in panel (a), latent and sensible turbulent heat fluxes are presented in panels (b) and (c). Panel (d) illustrates the resulting net surface energy imbalances defined as the difference between radiation and the two turbulent heat fluxes. Corresponding global (GLB), continental (LND), and ocean basin (SEA) means are summarized on the right side of the figure (in Wm$^2$).
Fig. 3. Estimated uncertainties in observed annual-mean surface (a) radiative fluxes, (b) sensible heat fluxes, and (c) latent heat fluxes for all major continents and ocean basins. The uncertainty in net surface-atmosphere energy exchange in panel (d) is computed assuming that the errors in the component fluxes are independent (i.e. \( \delta(x_1 + x_2 + \ldots + x_N) = \sqrt{\sum_{i=1}^{N} \delta x_i^2} \)).
Fig. 4. As in Figure 1 but after application of relevant energy and water cycle balance constraints.
Fig. 5. Net energy exchange from the atmosphere to the surface after objectively introducing all relevant continental-scale energy and water cycle constraints.
Fig. 6. Adjustments to radiation, sensible heat, and latent heat fluxes during the optimization process.
Fig. 7. Annual cycle of top of atmosphere radiative fluxes for each continent defined in Figure 2. The heavy black line represents the net radiation into the region.
Fig. 8. As in Figure 7 but for each ocean basin.
Fig. 9. Annual cycle of surface energy fluxes for each continent defined in Figure 2. Net energy into the surface is presented as the heavy black line.
Fig. 10. As in Figure 9 but for each ocean basin.
Fig. 11. Assumed uncertainties in all surface energy fluxes (right bars) and adjustments incurred as a result of applying balance constraints (left bars) for each continent defined in Figure 2.
Fig. 12. As in Figure 11 but for each ocean basin.