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Estimating Morning Change in Land Surface Temperature from MODIS Day/Night Observations: Applications for Surface Energy Balance Modeling

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Abstract

Observations of land surface temperature (LST) are crucial for the monitoring of surface energy fluxes from satellite. Methods that require high temporal resolution LST observations (e.g., from geostationary orbit) can be difficult to apply globally because several geostationary sensors are required to attain near-global coverage (60°N to 60°S). While these LST observations are available from polar-orbiting sensors, providing global coverage at higher spatial resolutions, the temporal sampling (twice daily observations) can pose significant limitations. For example, the Atmosphere Land Exchange Inverse (ALEXI) surface energy balance model, used for monitoring evapotranspiration and drought, requires an observation of the morning change in LST - a quantity not directly observable from polar-orbiting sensors. Therefore, we have developed and evaluated a data-mining approach to estimate the mid-morning rise in LST from a single sensor (2 observations per day) of LST from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor on the Aqua platform. In general, the data-mining approach produced estimates with low relative error (5 to 10%) and statistically significant correlations when compared against geostationary observations. This approach will facilitate global, near real-time applications of ALEXI at higher spatial and temporal coverage from a single sensor than currently achievable with current geostationary datasets.

Index Terms and Keywords

1812 Drought; 1818 Evapotranspiration; 1847 Modeling; 1855 Remote Sensing

1.0 Introduction

Thermal infrared retrievals of land surface temperature (LST) have been shown to be a valuable remote sensing-based input for land surface applications related to estimation of surface energy balance, retrieval of soil moisture information, drought monitoring, data assimilation and monitoring of consumptive water use (Carlson et al. 1981, 1986, 1994; Price 1983; McNider et al. 1994; van den Hurk et al. 1997; Jones et al. 1998; Anderson et al.

2007a,b;2011a,b; Hain et al. 2009; 2011; 2012). While most of these applications have been developed from methodologies that use instantaneous LST, other approaches exploit the temporal nature of LST, (Anderson et al. 1997; 2011a; McNider et al. 1994, Kustas et al. 2001). The temporal evolution of LST in the morning has been shown to be indicative of soil moisture conditions and plays a pivotal role in estimating the partitioning of available energy between sensible and latent heat fluxes (Price 1980; Wetzel and Chang, 1987; Mahfouf 1991; Anderson et al. 1997). In general, drier land surfaces heat more rapidly than wet surfaces under the increasing morning solar radiation load. Also, time-differential measurements of LST typically have higher accuracy than instantaneous measurements. The time differencing generally reduces impacts of errors in sensor calibration, atmospheric corrections and emissivity specifications on LST retrievals by removing the time-invariant component of these errors.

The Atmosphere-Land Exchange Inverse (ALEXI) model (Anderson et al. 1997; 2007; 2011a) is an example of diagnostic land-surface modeling system that exploits the morning LST rise signal for retrieving components of the surface energy balance. ALEXI uses a time-differential estimate of LST change in the mid-morning (1.5 after sunrise to 1.5 hours before local noon; LST_{ALEXI}). The ALEXI framework has been used in a wide range of applications including the estimation of daily evapotranspiration (Anderson et al. 2011a; 2012; Cammalleri et al. 2013, 2014), retrieval of soil moisture (Hain et al. 2009; 2011; 2012) and as a drought monitoring tool (Anderson et al. 2007a, b; 2011b; 2013). An ALEXI-based system, the GOES Evapotranspiration and Drought (GET-D) product system, has recently been transitioned into operations at NOAA's Office of Satellite and Product Operations and provides ALEXI data products at 8-km spatial resolution over North America.

To this point, applications of ALEXI have depended on regional geostationary satellites (e.g., Geostationary Operational Environmental Satellite (GOES)) for estimating

LST_{ALEXI} , as geostationary sensors are typically the only source of high temporal resolution (less than 1 hour) LST. While much of the global land surface (60°N to 60°S) is covered by geostationary sensors, a global application of ALEXI would require 4+ geostationary data streams to produce a full mosaic of LST and would be difficult to operationally support. Another consideration is that each geostationary sensor in the global constellation can have significantly different thermal retrieval algorithms along with spatial, temporal and/or spectral differences, and these characteristics may have changed significantly over the satellite period of record. Finally, high-latitude sampling from geostationary sensors is not possible as oblique satellite view angles limit the ability of the sensors to accurately estimate LST beyond 60° in latitude.

One possible solution to the aforementioned limitations with geostationary sensors is to use observations from polar orbiting platforms, such as from the Advanced Very High Resolution Radiometer (AVHRR), the Moderate Resolution Imaging Spectroradiometer (MODIS) and the Visible Infrared Imaging Radiometer Suite (VIIRS). Polar orbiting sensors typically provide estimates of LST twice daily at consistent local times: one nighttime observation and one daytime observation. While this does not provide a direct observation of the LST_{ALEXI} quantity needed by ALEXI, the day-night LST difference does contain the mid-morning rise within its larger temporal sample (Figure 1).

Previous studies have successfully developed methods to use temporally sparse observations of LST, from sensors such as MODIS or AVHRR, to estimate the diurnal cycle of LST (Jin et al. 1999; Gottsche and Olesen 2000; Aires et al., 2004; Sun et al. 2005; Inamdar et al. 2008; Holmes et al. 2013; Duan et al. 2014). Each of these methods relied on more than two observations per day, which allows for a more physically constrained diurnal fit for LST. The most commonly used method is based on the (diurnal temperature cycle) DTC approach as described by Gottsche and Olesen (2000), which requires estimates of amplitude and minimum LST over the diurnal cycle. This necessitates that a sufficient number of observations be available to constrain the LST time series and limit the impact of data outliers during the diurnal fitting process. For example, Holmes et al. (2013) required at a minimum of four observations to attempt a fit to the sparse LST observations, and Inamdar et al. 2008 used four observations per day from MODIS on both the Terra and Aqua platforms.

When sufficient consistent diurnal thermal sampling is available from multiple platforms, a method like DTC would ideally be exploited to provide the LST_{ALEXI} inputs required by ALEXI. However, there is also value in developing single sensor approaches. A single-sensor strategy has two logistical advantages over a multi-sensor strategy such as DTC. First, based on cloud climatology analyses there is an on average 25% higher probability of obtaining a clear day-night acquisition pair with a single sensor (e.g., Aqua MODIS) than there is of obtaining four clear LST retrievals in a given day with two sensors (Terra+Aqua MODIS). This significantly improves the global coverage in LST_{ALEXI} on a given day. Second, an operational global ALEXI system based on twice-daily observations from a single sensor has less inherent operational “risk” related to potential sensor failure and less data processing requirements than a system where multiple sensors are needed.

While a physically based approach like DTC may not be able to reliably fit a diurnal curve to just two daily LST samples, more empirical machine learning approaches may be able to extract the required fixed window LST_{ALEXI} information required for operational ALEXI execution with a single sensor. To this end, this paper evaluates a rule-based regression tree data-mining approach developed to relate twice-daily observations of day/night LST and other predictor variables from a single sensor to estimate LST_{ALEXI} . The method is tested using LST data from Aqua MODIS, comparing MODIS-predicted LST_{ALEXI} values with GOES-observed LST_{ALEXI} over the period 2007–2014. Additionally, the GOES-observed LST_{ALEXI} and MODIS-predicted LST_{ALEXI} are used within the ALEXI modeling framework to generate multi-year Evaporative Stress Index (ESI) datasets. The resulting ESI datasets are compared against an independent reference dataset, in this case 0–100 cm soil moisture anomalies from the North American Land Data Assimilation System (NLDAS), to assess the utility of the new approach.

2.0 ALEXI and the Evaporative Stress Index (ESI)

ALEXI is based on an implementation of the two-source energy balance (TSEB) model of Norman et al. (1995), which addressed many of the documented challenges with single-source models in monitoring surface energy fluxes using remote sensed LST (Kustas and Anderson, 2009). This two-source approximation treats the LST of the land surface as a

composite of nominal soil and canopy temperature components partitioned by the fraction of green vegetation cover. The TSEB separately balances components of the energy budgets for the soil and canopy components. In the ALEXI framework, regional application is achieved by coupling the TSEB with an atmospheric boundary layer (ABL) model to internally simulate land–atmosphere feedbacks on near-surface air temperature (Anderson et al. 1997; 2007, Mecikalski et al. 1999). The ABL component of ALEXI relates the morning rise in potential temperature within the mixed layer to the time-integrated influx of H from the surface. (McNaughton and Spriggs 1986; Anderson et al. 1997). A derivative product of ALEXI, the ESI, has become a leading indicator of developing and persistent water and/or vegetation stress during times of drought (Anderson et al. 2011; 2013; Otkin et al. 2013; 2014). The ESI represents standardized anomalies in a normalized clear-sky ratio of actual to reference evapotranspiration (ET) ($f_{RET} = ET/ET_{ref}$), where ET is actual ET and ET_{ref} is the FAO-96 Penman-Monteith reference ET for grass (Allen et al. 1998). The use of reference ET as a scaling flux minimizes impacts of non-moisture related drivers on ET such as seasonal variations in radiation load (Anderson et al. 2015).

3.0 Data

3.1 GOES Land Surface Temperature

GOES LST was retrieved at a temporal resolution of 30 minutes using the standard operational NOAA calibration and a single channel inversion of 11 μm GOES East (75°W) and GOES West (105°W) Imager brightness temperature (T_b) observations based on the algorithm of Price (1983). Atmospheric profiles of temperature and water vapor needed for atmospheric correction and the single channel inversion were obtained from the NOAA Climate Forecast System Reanalysis (CFS-R; Saha et al. 2010). Cloud-contaminated retrievals of LST were flagged and rejected using a combination of GOES visible reflectance data and a bi-spectral composite threshold methodology based on GOES 3.7 μm and 11 μm T_b (Jedlovec et al. 2008). The resolution of GOES is 4-km at nadir but is closer to 8-km at higher latitudes. Therefore, the GOES data were aggregated to 8-km to be able to include higher latitude information over Canada in the validation. GOES LST time-series were then temporally interpolated at each 8-km pixel to estimate LST_{ALEXI} over the prescribed ALEXI time window.

3.2 MODIS Land Surface Temperature

Twice-daily observations (1:30 am/pm local solar time) of LST were obtained from standard products from the MODIS Aqua sensor, retrieved using a generalized split-window atmospheric compensation technique (Wan et al. 2002; 2004; 2007). While the MODIS correction technique is different from the single channel approach used for GOES, this is not expected to cause issues because the focus here is on LST_{ALEXI} rather than absolute LST retrievals. LST data were extracted from the daily L3 global 0.05 Climate Modeling Grid LST product (MYD11C1) and re-sampled to the study domain at 8-km resolution, applying product QC flag low quality LST retrievals and masking pixels with satellite view angles greater than 60°.

3.3 Predictor datasets

The predictor variables used in this study include: MODIS day-night LST difference, MODIS daytime LST, MODIS nighttime LST, leaf area index (LAI), land cover classification, emissivity, surface albedo, topographic variability, the time length of the ALEXI window and the average annual precipitation. The LAI data were obtained from the 8-day MODIS LAI composite product (MOD15A; Myneni et al. 2002), albedo data were obtained from the 16-day MODIS albedo composites (MOD43C; Moody et al. 2005), surface emissivity data were obtained from the ASTER Global Emissivity Dataset (Hulley et al. 2015), land cover classification from the University of Maryland (UMD) global land cover dataset (Hansen et al. 2000), and topographic variability for the 0.05° study domain was sampled using the 1-km GTOPO DEM (LP DAAC, 2004) dataset.

3.4 Comparison data sets

Several datasets are used in the evaluation of the GOES-observed and MODIS-predicted LST_{ALEXI} , including modeled soil moisture fields from the Noah LSM in the North American Land Data Assimilation System (NLDAS; Xia et al. 2012a,b). The GOES-observed and MODIS-predicted LST_{ALEXI} were each used as inputs into ALEXI and processed over the period of 2003–2015 at a spatial resolution of 8-km over the CONUS. From each model run, time series of the ESI were computed following Anderson et al. (2011). Modeled soil moisture was obtained from the NLDAS Noah LSM simulation over the 2003–2015 period at a spatial resolution of 0.125°. The first soil moisture layers in Noah (0–10 cm; 10–40 cm; and 40–100 cm) were extracted and layer-depth weighted to compute a 0–100 cm soil moisture estimate. The first two statistical moments of the time series were computed and normalized anomalies ($\frac{obs - \mu}{\sigma}$), where μ is the mean value and σ is the standard deviation, were computed from the 0–100 cm soil moisture estimates to maintain consistency with the anomaly computation used in ESI.

4.0 Methodology

The proposed regression rules for retrieving LST_{ALEXI} from MODIS day-night LST differences were developed over a validation period of 2007 to 2014. All necessary training/predictor datasets were processed and remapped to a domain covering North America at a spatial resolution of 8-km, as described above. To ensure the highest quality training and predictor datasets, additional quality control of all the training and predictor data was performed beyond the application of product-level QA/QC. This included filtering of extreme data outliers and other methods where observations were deemed of poor quality and removed (e.g., LST_{ALEXI} or MODIS day-night LST difference less than zero – a symptom of undetected clouds). The analysis was limited to snow-free pixels using a dynamic snow mask derived from the 16-km NOAA Interactive Multi-sensor Snow and Ice Mapping System snow cover product (Ramsey, 1998).

4.1 Data Mining Approach to Predicting LST_{ALEXI}

In this study, we assess the use of a data mining approach to estimating LST_{ALEXI} based on the suite of identified predictor datasets. This approach utilizes a rule-based tree

regression algorithm (RuleQuest, Cubist), which was used to compute a set of rules linking the predictor variables outlined in Section 2.3 with the GOES-observed LST_{ALEXI} training data. Of the predictor variables tested, the following were shown to exhibit the strongest relationships with the training data: (1) MODIS day-night LST difference; (2) MODIS day LST; (3) MODIS night LST; (4) leaf area index; and (5) topographic variability. These variables were therefore used in the final regression models. Testing also revealed that performance was improved when models were developed for subsets of pixels segregated by thresholds in maximum vegetation cover fraction (fc_{max}) and annual precipitation (P), rather than using a single model developed for all global pixels in bulk. Maps of fc were computed by inverting LAI using a canopy gap fraction method (Norman et al. 1995), and then the maximum fc value sampled over the study period (2003–2015) was extracted at each pixel. Improved prediction under segregation by pixel-based fc_{max} and P is a reasonable finding. A certain degree of inherent climate information is contained within fc_{max} and P regimes, providing a mechanism for the data mining algorithm to develop better relationships between subsets of observation and predictor data. Therefore, separate tree-based regression models were developed using the predictor variables designated above for the following range in fc_{max} : (0–25%; 25–50%; 50–75%; 75–100) and in P : (0–500 mm/yr; 500–1000 mm/yr; 1000–5000 mm/yr). To minimize the effect of over-fitting, Cubist was limited to developing 20 “rules” for each model. The MODIS-predicted values of LST_{ALEXI} generated for the evaluation in Section 5.0 were generated on a daily time step for the period of 2007 to 2014.

5.0 Evaluation of MODIS-predicted LST_{ALEXI}

MODIS-predicted LST_{ALEXI} products were evaluated against GOES-observed LST_{ALEXI} over North America over the validation period from 2007 to 2014. The validation of the daily MODIS-predicted LST_{ALEXI} were assessed by using a f-fold (10 folds used) cross validation technique over the validation period (2007–2014). Figure 2 shows the comparison of MODIS and GOES-predicted samples ($n = 226,419,494$ observations) developed from this f-fold process over this validation period. In general, the MODIS-predicted LST_{ALEXI} agrees very well with the GOES LST_{ALEXI} observations, with an R^2 value of 0.96. Consistency in the computed R^2 values is observed over seasonal subsets of the two datasets, with values of 0.91 for January – March, 0.94 for April – June; 0.94 for July – September; and 0.92 for October – December. Averaged over the domain and study period, the bias between the two datasets is near zero (-0.01 °K) and the normalized RMSE is found to be about 9% (RMSE=1.84 °K). A breakdown of annual (2007–2014) validation statistics can be found in Supplemental Information, Table S1. Likewise, when sampled over the same seasonal subsets, consistency in normalized RMSE remain in the 8 to 15% range, although absolute values of RMSE are smaller (larger) in the cold (warm) season when lower (high) mean LST_{ALEXI} is observed.

Figure 3 shows the spatial distribution of the seasonal bias and normalized RMSE over the 2007–2014 validation period for the January-March (JFM), April-June (AMJ), July-September (JAS), and October-December (OND) seasonal intervals. Due to the constraint of only considering snow-free LST observations, the spatial sampling over North America varies from the cold season, when large sections of the northern CONUS and Canada are

flagged, to the warm season when maximum coverage is obtained. The seasonal subsets of the dataset show the expected evolution of LST_{ALEXI} over North America. Generally, LST_{ALEXI} values range from 3 to 9 K over wet and/or highly vegetated regions and from 15 to 27 K over the semi-arid to arid regions of the western US and Mexico.

While the domain-averaged bias is found to be near zero and most regions exhibit seasonal bias values between -0.5° and 0.5° K, areas of higher bias are noted. The largest values of bias are noted in the western US, with some areas exhibiting positive and negative biases with magnitudes on the order of $1-2^{\circ}$ K. The largest positive and negative biases are in regions where LST_{ALEXI} is high, so the relative bias in these regions is not much larger than in other parts of the west. Some of these biases occur in regions of complex terrain and may be related to surface emissivity and differences in the geometry of satellite view angles between GOES and MODIS.

Over the same seasonal periods, spatial values of normalized RMSE were also computed as shown in Figure 3. In general, most of the study domain has normalized RMSE values on the order of 5 to 20%, with larger values found in the western US (where some of the larger values of absolute bias are found) and over Canada and South America. The regions with the best performance includes the west coast of the US and the central and eastern US. Regions where larger values of normalized RMSE are observed are likely attributed to inadequate screening of snow cover extent in Canada during the cold season and inadequate screening of cloud cover in Canada and South America. Cloud detection algorithms for both GOES and MODIS are prone to larger errors during the cold season as the discrimination between a cold land surface and low cloud cover is more difficult, especially for the nighttime MODIS observations. In South America, poor detection of low clouds and fog in the morning can lead to large errors in GOES LST_{ALEXI} and also lead to poor retrievals of MODIS LST during the nighttime hours, as the observed temperature of low clouds can easily be mistaken by a cloud detection algorithm as an estimate of clear-sky LST.

5.1 Comparison of ESI from GOES and MODIS LST_{ALEXI} over CONUS

To further assess the utility of MODIS-predicted LST_{ALEXI} , ALEXI simulations were processed and ESI was generated over a longer 2003–2015 period using: (a) GOES-observed LST_{ALEXI} and (b) MODIS-predicted LST_{ALEXI} . In addition, soil moisture (SM) anomalies from NLDAS-2 Noah simulations (Xia et al. 2012a, 2012b) were computed and used as a basis of comparison. Prior work has demonstrated that ALEXI ESI and Noah LSM SM show strong spatial correlation over the CONUS (Anderson et al. 2011; Hain et al. 2011); thus, Noah is used here as the “reference” anomaly dataset to assess the impact of the different LST_{ALEXI} inputs. Here, the Noah SM estimates represent a layer-weighted average of the first three Noah soil layers (0–10 cm; 10–40 cm; 40–100 cm). The Noah LSM SM anomaly was computed over the same period of record as ALEXI (2003–2015) and all three datasets were spatially re-sampled to a 8-km CONUS grid. Figure 4 shows the comparison between NLDAS SM, GOES ESI and MODIS ESI for 2003–2015, showing anomalies for the June–Aug timeframe in each year. Agreement between the various drought depictions was quantified by computing spatial anomaly correlation (r) for each month

during the warm season (May to September) for each year in the period of record (2003–2015).

The average yearly warm season spatial anomaly correlations show no statistically significant difference between ESI computed using GOES-observed LST_{ALEXI} and MODIS-predicted LST_{ALEXI} when compared to Noah SM anomalies. The anomaly correlation for GOES observed LST_{ALEXI} and Noah SM averaged over 2003–2015 is 0.63, while the MODIS-predicted LST_{ALEXI} and Noah SM average spatial anomaly correlation is 0.61. Generally, ESI generated from MODIS-predicted LST_{ALEXI} shows slight annual decreases in correlations when compared to ESI generated from GOES-observed

LST_{ALEXI} (2004–2008, 2010, 2011, 2013–2014); however, small increases in correlation which are not statistically significant are observed in 2003, 2009, 2012, 2015. In general, there is no statistically significant difference in correlations between the two ESI datasets.

6.0 Conclusions

This study evaluated the potential use of day-night land surface temperature (LST) observations from polar orbiting sensors such as MODIS, AVHRR and VIIRS towards estimating LST_{ALEXI} , the key input for the Atmosphere Land Exchange Inverse (ALEXI) surface energy balance model. ALEXI is currently used for operational monitoring of evapotranspiration, drought and soil moisture status over North America using high temporal resolution LST retrievals from the GOES geostationary satellites. The ability to retrieve

LST_{ALEXI} from a single polar sensor, such as MODIS, provides a unique opportunity for operational global applications of ALEXI with better temporal sampling than methods that need multiple sensors to constrain the diurnal cycle of LST and significantly less data volume and processing requirements.

A tree regression data mining technique was employed to predict LST_{ALEXI} from twice-daily MODIS LST retrievals, based on a number of predictor datasets which were found to have strong correlations with GOES-observed LST_{ALEXI} . An evaluation of LST_{ALEXI} retrievals from the validation period (2007–2015) showed that the MODIS-predicted

LST_{ALEXI} agreed well with the GOES-observed LST_{ALEXI} . Values of normalized RMSE in MODIS LST_{ALEXI} were on the order of 8 to 20% (~9 to 10% domain average) over the seasonal subsets that were tested. As an additional test of utility for drought monitoring, both datasets were used in ALEXI to generate the ESI datasets over the CONUS. The two ESI datasets were compared against a “reference dataset”, in this case, NLDAS Noah soil moisture anomalies over the 2003 to 2015 period. It was found that there were no statistically significant differences in correlation between the GOES-observed LST_{ALEXI} and Noah and the MODIS-predicted LST_{ALEXI} and Noah. Based on these analyses, we conclude that the proposed methodology to estimate LST_{ALEXI} from twice-daily observations of LST from a single sensor can effectively generate LST_{ALEXI} with an accuracy comparable to that of current geostationary sensors and can be considered a complement to other methods that can estimate diurnal LST from sparse temporal observations, yet require more than two observations per day. A hybrid methodology could be implemented, fully exploiting multiple daily observations when available, but augmenting spatiotemporal coverage with the data mining approach in regions where only two retrievals

are possible on a given day. Additionally, the methodology tested here will allow for the use of higher resolution MODIS and VIIRS data (375-m to 1-km) for use in ALEXI, an application of the method using 1-km MODIS LST is shown in the Supplemental Information, Figure S2).

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Key Points

- Twice daily (day/night) observations of land surface temperature (LST) from polar orbiting satellites can provide accurate estimates of the mid-morning rise in LST
- This approach was used to generate an Evaporative Stress Index dataset over the CONUS which compared favorably to an independent soil moisture anomaly dataset
- The new approach provides an operational path forward to globally applying surface energy balance models such as ALEXI, based on twice-daily observations from a single sensor.

Figure 1.

Example of the estimation of LST_{ALEXI} using idealized data during the ALEXI sampling window (red circles) and the normal twice-daily day/night observations from MODIS Aua (green circles). For comparison, the black circles show a LST time series that is typically available from geostationary sensors.

Figure 2.

Scatterplot and domain averaged error statistics (R^2 : coefficient of determination; Bias, MAE: mean absolute error; RMSE: root mean squared error) of all available observations during the validation period (2007–2015) between GOES-observed LST_{ALEXI} and MODIS-predicted LST_{ALEXI} .

Figure 3. Seasonally averaged bias (MODIS-GOES; left column) and normalized RMSE (right column) for a) January–March, b) April–June, c) July–September, and d) October–November.

Figure 4.

Anomaly comparison for Noah 1-m soil moisture (left column), 12-week ESI composites ending 31 August for GOES-observed LST_{ALEXI} (middle column) and MODIS-predicted LST_{ALEXI} (right column) for 2003–2015. Anomaly comparison for Noah 1-m soil moisture (left column), 12-week ESI composites ending 31 August for GOES-observed LST_{ALEXI} (middle column) and MODIS-predicted LST_{ALEXI} (right column) for 2003–2015.