Entering the Era of +30-Year Satellite Cloud Climatologies: A North American Case Study

MICHAEL J. FOSTER
Cooperative Institute for Meteorological Satellite Studies, University of Wisconsin–Madison, Madison, Wisconsin

ANDREW HEIDINGER
NOAA/NESDIS/Center for Satellite Applications and Research, Madison, Wisconsin

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ABSTRACT

The emergence of satellite-based cloud records of climate length and quality hold tremendous potential for climate model development, climate monitoring, and studies on global water cycling and its subsequent energetics. This article examines the more than 30-yr Pathfinder Atmospheres–Extended (PATMOS-x) Advanced Very High Resolution Radiometer (AVHRR) cloudiness record over North America and assesses its suitability as a climate-quality data record. A loss of ~4.2% total cloudiness is observed between 1982 and 2012 over a North American domain centered over the contiguous United States. While ENSO can explain some of the observed change, a weather state clustering analysis identifies shifts in weather patterns that result in loss of water cloud over the Great Lakes and cirrus over southern portions of the United States. The radiative properties of the shifting weather states are characterized, and the results suggest that extended cloud satellite records may prove useful tools for increasing knowledge of cloud feedbacks, a long-standing issue in the climate change community.

1. Introduction

The first Intergovernmental Panel on Climate Change (IPCC) report (Houghton et al. 1990) states: “The ranges in the climate predictions . . . reflect the uncertainties due to model imperfections, the largest of these is cloud feedback (those factors affecting the cloud amount and distribution and the interaction of clouds with solar and terrestrial radiation), which leads to a factor of two uncertainty in the size of the warming” (p. XXVII). Over two decades later, the divergence in climate sensitivities among climate models still relates strongly to cloud feedbacks (Arakawa 2004; Bony and Dufresne 2005; Cess et al. 1989, 1996; Randall et al. 2003; Zelinka and Hartmann 2012). Initiatives such as the Cloud Feedback Model Intercomparison Project (CFMIP) have resulted in climate model intercomparisons designed to identify and isolate physical processes that cause these differences (Bretherton et al. 2004; Covey et al. 2003; Meehl et al. 2005). Satellite simulators facilitate validation of model output against observations (Chepfer et al. 2008; Haynes et al. 2007; Klein and Jakob 1999; Webb et al. 2001). The Global Energy and Water Cycle Experiment (GEWEX) Cloud Climatology Assessment evaluated the sensitivities of multiple global satellite cloud records allowing for more meaningful intercomparisons and use with models (Stubenrauch et al. 2013). Recently studies have emerged that use sensors on the National Aeronautics and Space Administration (NASA) Aqua and Terra satellites, with record lengths on the order of a decade, to estimate short-term cloud feedbacks (Dessler 2010; Dessler and Loeb 2013; Zhou et al. 2013). Despite the progress made by these and other enterprises, this cloud feedback uncertainty persists.

This article is concerned with a new chapter in this story: global satellite-based cloud records that have reached sufficient length to observe some changes in cloud amounts and processes on climate time scales. One such record is Pathfinder Atmospheres–Extended (PATMOS-x) derived from the Advanced Very High Resolution Radiometer (AVHRR); an imager flown on
the National Oceanic and Atmospheric Administration (NOAA) polar-orbiting environmental satellite series since 1978 (Heidinger et al. 2014). It is likely that some processes affecting long-term cloud feedbacks will take several decades and even centuries to resolve (Shell 2012). However, short-term cloud feedback studies based on satellite records (Dessler 2010; Dessler and Loeb 2013; Zhou et al. 2013) rely on climate variations on shorter time scales, like El Niño–Southern Oscillation (ENSO), for the surface temperature differences necessary to calculate feedback sensitivity. Consequently, Zhou et al. (2013) found that some of the largest observed feedbacks were caused by dramatic shifts in high- or low-cloud amounts at one latitude and were generally offset at another. This is because instead of long-term changes in cloud properties they were observing spatial rearrangement of atmospheric conditions characteristic of ENSO. The point being that extended satellite records, such as PATMOS-x, may observe similar spatial and temporal redistribution of atmospheric conditions that provide dramatic shifts in high- or low-cloud amounts and may become more robust over time.

A caveat to using historic satellite records is that they suffer from heritage issues. In the case of AVHRR this means a lack of onboard calibration systems and sensor-to-sensor consistency issues incumbent in merging records from 15 separate satellites: each subject to orbital drift and designed for meteorological as opposed to climatological applications. Here, we explore whether the methods used to address these issues are sufficient to make the AVHRR record of sufficient quality and consistency for some climate applications. The test case is a region over North America centered over the contiguous United States. Section 2 describes the datasets used in this work; in section 3 we observe the AVHRR record of cloudiness over the region and attempt to validate that record against the Interim European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis (ERA-Interim). Section 4 tracks changes in the physical and optical properties of clouds over the AVHRR record, focusing on radiative impacts and by proxy energy budget. Section 5 looks at potential sources of the changes observed in cloudiness, and in section 6 we discuss the results from this work and report our conclusions.

2. Data description

The vehicle for processing AVHRR is PATMOS-x, developed at NOAA/National Environmental Satellite, Data, and Information Service (NESDIS) and the University of Wisconsin–Madison (Heidinger et al. 2014). The four-channel AVHRR record, with central wavelengths at 0.63, 0.86, 3.75, and 10.8 μm, begins in 1978 with the launch of the successor to Television Infrared Observation Satellite (TIROS-N); however, this study focuses on the five-channel record (includes central wavelength at 12.0 μm), which began in August 1981 with the launch of NOAA-7. Processing is done using global area coverage (GAC) data, for which each pixel is the mean of four 1.1-km AVHRR pixels, representing an area of approximately 3 km × 5 km. PATMOS-x files use a sampled pixel-level format fit to a 0.1° equal-angle global grid called level 2b. Ancillary data include snow cover and vertical profiles of water vapor and temperature taken from 6-hourly National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR) (Saha et al. 2010).

PATMOS-x employs a naïve Bayesian cloud detection scheme that uses multiple classifiers and surface types (Heidinger et al. 2012). The scheme is calibrated against Cloud–Aerosol Lidar and Infrared Pathfinder Satellite Observations (CALIPSO) simultaneous nadir overpasses (SNOs) with NOAA-18. The detection skill of the scheme is dependent on a number of factors such as surface type and viewing geometry. For example, detection over polar regions remains a challenge because of highly reflective surfaces and cold temperatures: the probability of correct daytime cloud detection over snow or sea ice in the Arctic is 0.88 (relative to the CALIPSO training data), while over the deep ocean it is 0.97. Small day/night discrepancies exist because of differences in classifier availability. Similarly enhanced visible scattering near the terminator can cause anomalous detection.

A key attribute of any climate record is consistency, so any factor that could change a measurement/product over time must be well understood. Two areas of particular concern for the AVHRR record are instrument calibration and shifting satellite local crossing time. Vicarious calibration of the AVHRR visible channels uses traditional AVHRR–AVHRR SNOs and stable Earth targets but also leverages the capabilities of the more modern Moderate Resolution Imaging Spectroradiometer (MODIS) sensors (Heidinger et al. 2010). For satellite drift, a method of fitting a two-harmonic sinusoidal function to a climatologically derived diurnal cycle and subsequently correcting for drift has been developed (Foster and Heidinger 2013). This method is applied to each 1° × 1° box for each month of the year in this dataset to account for seasonal and geographic variability.

3. Observed North American cloudiness

a. Diurnally corrected record

The spatial domain being examined encompasses part of the North American continent, centered on the
contiguous United States. The domain spans from 25° to 55°N and from 125° to 65°W. Figure 1 shows time series of total cloudiness as recorded by each AVHRR sensor in the PATMOS-x record for the domain. Figure 1 (top) represents the record with no diurnal correction applied. Differences between satellites may in part be due to synoptic variability as in most cases satellites flying concurrently have overpass times that differ by several hours. Exceptions include NOAA-18 and NOAA-19 flying concurrently in a 0130/1330 local time (LT) orbit and NOAA-17 and MetOp-A flying concurrently in a 0930/2130 LT orbit. However, in Fig. 1 it is clear that satellite drift is affecting the record. The transitions from NOAA-7 to NOAA-9 in 1985 and from NOAA-9 to NOAA-11 in 1989 show clear disconnects, yet all three satellites were launched in similar orbits. Figure 1 (bottom) shows the diurnally corrected time series. The efficacy of the diurnal correction may be assessed using the monthly differences between satellites with concurrent orbits. The measurement from the satellite with the later launch date is subtracted from that of the earlier, and for months with more than two satellites in orbit all pairing combinations are calculated. Doing this, we find the uncorrected record has a median difference in cloudiness of 2.2%, a standard deviation of 2.6%, correlation of 0.92, and a slope to the linear fit of the data of −0.68% decade⁻¹. For the diurnally corrected record, the median difference reduces to 0.9%, the standard deviation reduces to 1.3%, and the linear slope reduces to −0.48% decade⁻¹, while the correlation increases to 0.98.

b. Comparison against ERA-Interim

Figure 2 shows a comparison of the PATMOS-x record against ERA-Interim (Dee et al. 2011), which uses the ECMWF numerical model along with observations assimilated from balloon, aircraft, satellite, and surface instrumentation to provide global surface and atmospheric conditions. One reason ERA-Interim was chosen for this comparison is that it spans the length of the PATMOS-x record (1979–present). Another is that cloud amount is diagnosed and independent of AVHRR measurements. A consideration when using reanalysis products is that fluctuating sources of ingested observations make trend detection a challenge. In this case, our primary objective is to determine whether major
artifacts not addressed by intercalibration or diurnal correction exist in the PATMOS-x record, for which we believe reanalysis to be an appropriate choice. For example, the period following the eruption of El Chichón recorded some of the highest cloud amounts in PATMOS-x, begging the question of whether this was real or a spurious effect caused by stratospheric aerosol. For the comparison, we used monthly values calculated from daily means. Anomalies were generated by subtracting monthly means to remove the seasonal cycle as well as offsets between the records. Offsets among different cloud records are not unusual, as the definition of what constitutes cloud varies with an instrument’s spectral range and spatial resolution or, in the case of numerical models, the parameterization being used. In this case an offset did exist, with PATMOS-x having cloudiness $\sim$15% higher than ERA-Interim.

Figure 2 (top) shows monthly cloudiness anomalies for both records with no major artifacts present. The correlation value between the two records is 0.82, with some seasonal variation therein [December–February (DJF) = 0.82, March–May (MAM) = 0.84, June–August (JJA) = 0.66, and September–November (SON) = 0.88]. Figure 2 (bottom) shows the numerical differentiation of the records, performed using three-point Lagrangian interpolation in a scatterplot. We find that after the seasonal signal is removed the sign of the month-to-month changes in cloudiness agree 77% of the time, and for those months when the signs differ the values tend to be small.

Figure 3 depicts the seasonal spatial distribution of PATMOS-x AVHRR cloud change with a statistical test applied. The statistical approach used for this analysis comes from previous studies (Weatherhead et al. 2002, 1998). The uncertainty estimate used when calculating the linear slope of the record is the standard deviation of daily values for each month, to which both natural variability and measurement uncertainty contribute. For the slope of the linear fit $\omega$, we assume that a trend at the 95% confidence level is established when $|\omega/\sigma_\omega| > 2$, where $\sigma_\omega$ is the standard deviation of $\omega$. Subsequently the number of years $n^*$ that it would take for $\omega$ to be considered a significant trend with a probability of 0.90 is

$$n^* = \left[\frac{3.3\sigma_N}{\omega(1-\phi)}\right]^{2/3} = \left[\frac{3.3\sigma_N}{\omega} \left(\frac{1 + \phi}{1 - \phi}\right)\right]^{2/3},$$

where $N$ is the noise of the time series, $\phi$ is the autocorrelation of $N$, and $\varepsilon$ is the white noise. This analysis is completed for each $1^\circ \times 1^\circ$ box in the North American domain, resulting in estimates of $\omega$ and $n^*$. Those boxes for which the length of the record exceeds the $n^*$ estimate are overlaid by white stippling in Fig. 3. Boreal fall has the largest spatial extent of negative trends that meet these criteria: extending throughout most of the continental United States, excluding only some portions of the Pacific Northwest. Decreases in cloudiness in the Pacific Northwest are seen during the winter and summer months, while in the spring the largest losses are seen in the southwestern United States and Gulf of Mexico. For all four seasons decreasing cloud amount
(also see Fig. 4a) is seen in large areas of the southern coast and southwestern regions of the United States, the Gulf of Mexico, and the Great Lakes region. A statistically significant positive cloudiness trend is seen during the winter months in southeastern Canada. While the statistical test accounts for noise and natural variability, it does not account for systematic bias. In this case, the time of year and location suggest snow cover may be a contributing factor since, as previously mentioned, lack of radiometric contrast over highly reflective and cold surfaces can inhibit cloud detection for satellite imagers (Eastman and Warren 2010). For this reason, we feel additional work is required to determine the veracity of this trend.

Figure 4 maps show annual changes in various PATMOS-x cloud parameters with the same statistical test applied. There are several interesting points: the outgoing longwave radiation (OLR) maps (Figs. 4d,e) both show statistically significant increases in OLR spatially correlated with the decrease in total cloudiness (Fig. 4a). Cloudy-sky OLR (Fig. 4e) is very closely correlated with cloud-top pressure (CTP) (Fig. 4i). The observed increase in CTP (decrease in cloud height) over much of the southern United States would result in warmer clouds that emit more longwave radiation. The all-sky OLR (Fig. 4d) shows additional OLR relative to cloudy-sky OLR, which can be explained by the corresponding decrease in total cloudiness, which would result in greater OLR contributions from the relatively warmer surface. This consistency with the OLR measurements is meaningful as OLR has no dependencies on ancillary data and is derived solely from the 11- and 12-µm channels, meaning the terrestrial radiative budget suggests the observed decrease in cloudiness is not an artifact of the ancillary data being used. The observed changes in the southern portion of the United States may also in part be explained by differences between water versus ice clouds. Figure 4b (liquid water cloud) and Fig. 4c (ice cloud) show that most of the decrease in total cloudiness seen in the southern United States, Atlantic Ocean, Pacific Ocean, and Gulf of Mexico are due mostly to decreases in ice cloudiness. In fact, in those regions there is either no change or modest increases in liquid water cloudiness. It is possible and even likely that some of the apparent increase in liquid water cloudiness is due to the AVHRR’s ability to observe clouds previously masked by the presence of cirrus. Regardless, it explains the increase in CTP (decrease in cloud height) seen in these areas. Conversely, over much of the northwest portions of the domain and particularly over the Great Lakes, the decrease in total cloudiness is due mainly to a loss of liquid water cloud. There is
a corresponding decrease in visible albedo and cloud optical thickness $\tau$ in those regions, which is likely due to enhanced scattering of visible light by liquid cloud particles relative to that of ice particles.

4. Weather state analysis

To better understand the mechanisms by which such loss of cloudiness may occur we apply a $k$-means clustering algorithm (Anderberg 1973) to joint histograms of CTP and $\tau$. Similar histograms are generated by the International Satellite Cloud Climatology Project (ISCCP) cloud product and have been used in various weather state (WS; also referred to as cloud regime) identification studies (Gordon et al. 2005; Jakob and Tselioudis 2003). Two of the most recent studies look at mechanisms for deep convection and precipitation extremes in the tropics (Rossow et al. 2013; Tan and Jakob 2013). The $k$-means clustering algorithm randomly selects $k$ histograms and assigns them to be centroids: each representative of a discrete weather state. For all other histograms, the Euclidean distance from each centroid is calculated and the shortest distance determines to which weather state the histogram belongs. Each centroid is then recalculated to be the mean of its constituent histograms. This process reiterates until histogram membership for each of the weather states becomes static or a predetermined number of iterations is reached. The CTP–$\tau$ joint histograms are derived daily from PATMOS-x for each $1^\circ \times 1^\circ$ box in the North American domain. Since the level-2b PATMOS-x format contains a subsampled measurement every $0.1^\circ$, each CTP–$\tau$ joint histogram is generated with at least 100 measurements (we use a minimum threshold of 50 measurements). The $\tau$ retrieval algorithm is dependent on the AVHRR visible channels, and as such no $\tau$ values are available at night. Instead, we chose to use afternoon ascending satellite overpasses diurnally corrected to 1430 LT using the same method as that for cloudiness (Foster and Heidinger 2013). The motivations behind this decision are 1) afternoon ascending overpasses are available throughout almost the entire record and 2) these overpasses are generally at or near 1430 LT, minimizing the need to make large corrections. This generated over 12 million histograms to be used in the clustering analysis. The selection of the number of centroids $k$ is a somewhat subjective part of the process, yet there are objective criteria that may be used to help selection, such as assuring that the distance between centroids is greater than that between centroids and their member histograms and centroid patterns remain consistent with varying initial conditions (Rossow and Schiffer 1999). For this second criterion, the clustering algorithm is run multiple times using randomly selected histograms as initial centroids, and the subsequent final centroid patterns should be similar regardless of initial selection. Minimizing the variance among cluster centroids and their member histograms is then used to select final centroid patterns. The goal is to identify the maximum number of weather states allowable without producing so much overlap as to make them indistinguishable. For this analysis, the number of distinct weather states identified is six. Figure 5 shows the mean centroids representative of each weather state. Some of the weather states are composed primarily of high cirrus cloud: WS1, WS2, and WS6 fall under this category. These weather states often include convectively active weather patterns. WS3 and WS5 contain some midlevel cloud along with some weather patterns composed of multiple coincident cloud types. Finally, WS4 is a suppressed regime composed primarily of boundary layer clouds. The mean total cloudiness for each weather state is also shown in Fig. 5, ranging from 78% (WS4) to 100% (WS1).

The weather states frequency of occurrence experience a relatively stable seasonal cycle, though there is some interannual variability. However, of the six identified weather states five of them have experienced a relative decrease between 1982 and 2012. The exception is WS4, whose relative frequency has increased by approximately 3% over this period. When comparing all weather states, WS4 has the second lowest median value of total-sky albedo (0.442 in a range of 0.441–0.508) and the highest value of OLR (216 W m$^{-2}$ in a range of 207–216 W m$^{-2}$). The values of albedo and OLR are representative of the entire scene where a weather state is present. This means that OLR is composed of contributions from both the cloudy and clear portions of the sky, and the cloud albedo is normalized by the cloud fraction for each scene. This explains why WS4, which is composed of mostly low-level water clouds but has the lowest mean cloud amount, has a lower mean cloud albedo than weather states composed of thin cirrus.

Figure 6 shows the seasonal relative frequency of occurrence (RFO) of WS4 for the 1982–2012 PATMOS-x record. The patterns correspond to where we would expect boundary layer clouds to be present, giving confidence that the weather states identified by the cluster analysis have physical weather pattern analogs. WS4 is by far the most common weather state off the western coast of California and peaks in the summer, consistent with the expected pattern for stratuscumulus decks composed of boundary layer clouds. Similarly, WS4 has an increased frequency of occurrence over the Great Lakes during the winter months, where we might expect the creation of lake effect clouds. Figure 7 shows...
how the relative frequency of occurrence of WS4 has changed over the 1982–2012 period. The largest changes have occurred over the southern United States, Atlantic Ocean, Pacific Ocean, and Gulf of Mexico. In fact comparison of Fig. 7 with Fig. 3 shows that many of the areas where the relative frequency of occurrence of WS4 has seen the largest increase correspond to the areas where the greatest loss of cloudiness have been observed. Figure 8 shows the change of WS1, an overcast cirrus regime. Areas where WS1 experiences decadal rates of decrease often overlap those areas where the converse is true for WS4 (e.g., the southern Unites States and Gulf of Mexico). This finding is consistent with our prior analysis, since the mean cloudiness of WS4 is 78% (the lowest of all weather states) while for WS1 it is 100%. Thus, an increase in the occurrence of WS4 at the expense of WS1 would imply a decrease in total cloudiness.

5. Attribution

The pattern of cloudiness change seen in Fig. 3 is reminiscent of that seen during phases of ENSO. Positive anomalies over the Gulf Coast coupled with negative anomalies over southeastern portions of Canada during the winter are consistent with a strengthening influence of the subtropical jet stream because of the presence of El Niño. Over the course of the record several positive and negative phases of ENSO were experienced: we make use of this by generating a fit

**FIG. 5.** Two-dimensional centroids resulting from the k-means clustering of cloud-top pressure–cloud optical depth joint histograms. Each centroid is representative of a discrete WS found over the specified North American domain (25°–55°N, 125°–65°W). The mean total cloudiness (%) is located at the top of (a)–(f).
function between a multivariate ENSO index (Wolter and Timlin 1998) (located online at http://www.esrl.noaa.gov/psd/enso/mei/table.html) and total cloudiness. We do this separately for each month of the year and $1^\circ \times 1^\circ$ box to capture seasonal and geographic variability. We then normalized the record to ENSO-neutral conditions (setting the multivariate ENSO index equal to 0). The mean value of the multivariate ENSO index over the period of the PATMOS-x AVHRR record is 0.26, meaning the distribution of ENSO phases favors the positive (El Niño). Figure 9 shows seasonal rates of change in total cloudiness after this normalization process. It is clear that this process reduces the magnitude of the change; for example, decreases in cloudiness seen during the fall and increases over the Midwest seen during the winter in Fig. 3 are much less pronounced in Fig. 9. In addition, the linear trend in cloudiness from Fig. 2 is
reduced from $-1.4\%$ to $-0.9\%$ decade$^{-1}$ for the ENSO-normalized record. This suggests that ENSO can explain some but not all of the observed change.

6. Conclusions

With the advent of +30-yr satellite records comes the study of clouds and their optical properties on longer time scales. Potential applications include regional trend detection, model development, and hydrological and energetics budget studies. Here we look at one such record, PATMOS-x AVHRR, over a North American region centered over the contiguous United States. Diurnal correction of the data reduces the median month-to-month cloudiness difference as observed by concurrent satellites to less than 1% and increases the correlation to 0.98. The PATMOS-x AVHRR record is compared to ERA-Interim to determine whether synoptic, seasonal, and long-term variability is being sufficiently captured, and it is found the two records are

![Figure 8](image1.png)

Fig. 8. As in Fig. 7, but for WS1.

![Figure 9](image2.png)

Fig. 9. Seasonal maps of cloudiness rate of change normalized to ENSO-neutral conditions. As in Fig. 3, but normalized using a multivariate ENSO index (Wolter and Timlin 1998).
in good agreement. The existing uncertainty, consisting of contributions from natural variability, algorithm uncertainty, and sensor-to-sensor variability, is then used to determine whether statistically significant trends in cloudiness can be found. It is found that, according to one statistical test (Weatherhead et al. 1998), significant decreases in total cloudiness exist in southern and southwestern portions of the United States as well as the Great Lakes region. OLR measurements derived without ancillary data dependencies support this analysis, suggesting the trend is not the result of errors/biases in ancillary data.

A clustering algorithm is employed to shed light on weather pattern changes that may factor into decreasing cloudiness. Six distinct weather states are identified over the specified North American domain. It is found that WS4, a weather state consisting of low-level boundary layer clouds, has been increasing relative to the other weather states and that this increase is most pronounced in the areas where decreasing cloudiness is observed. This suggests a loss of cirrus cloud in the southern United States and those portions of the Atlantic Ocean, Pacific Ocean, and Gulf of Mexico. The relative increase in low-level water clouds scene may in part be due to fewer clouds being masked from view by cirrus, but the result is the same: lower and fewer clouds leading to greater measured OLR and lower total-sky cloud albedo, which in turn lead to a net warming effect for the surface radiative budget. Attribution to phases of ENSO is explored, and it is found that asymmetrical distribution favoring a positive phase in ENSO may explain some but not all of the observed change.

The analysis presented here suggests that for this region the PATMOS-x AVHRR cloud record is able to detect changes in cloud properties at statistically significant levels. Using redistribution of weather states to identify dramatic shifts in cloudiness and cloud properties, and the subsequent characterization of the radiative properties of these weather states, may help increase our understanding of cloud feedbacks. In this study we use OLR and albedo as metrics for describing the radiative properties of the weather states, but a solar insolation product has recently been added to the suite of PATMOS-x products, so future studies could include top of the atmosphere radiative fluxes. Other advantages of using PATMOS-x include the variety of cloud products (e.g., cloud-top pressure, optical depth, cloud type) that would allow for differentiation among cloud feedbacks. PATMOS-x also retrieves surface temperature, though only for cloud-free areas. A related challenge of using an imager-based record is identifying multilayer clouds and their subsequent effect on optical property retrievals. In addition, other potential causes of these changes should be explored: there is overlap between the areas where the greatest loss of cloud is observed and relative concentrations of atmospheric aerosol, at least in the southern United States (Ford and Heald 2013). PATMOS-x produces an aerosol product, but only over water. It is possible changes in aerosol loading could be contributing to these results.

This case study is limited to a single region over North America, and results from other regions of the world would require similar validation. For example, satellite imagers often have difficulty differentiating between clouds and snow or sea ice; this is especially true in colder regions where the temperature of the clouds often does not vary greatly from that of the surface. The positive trend in cloudiness seen over southeastern Canada during winter may be caused in part by this issue and warrants further study. Regardless, these results are a promising step toward the goal of providing climate-quality global satellite cloud records.

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REFERENCES
Dec, D. P., and Coauthors, 2011: The ERA-Interim reanalysis: Configuration and performance of the data assimilation