Temporal and Spatial Characteristics of Short-Term Cloud Feedback on Global and Local Interannual Climate Fluctuations from A-Train Observations

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ABSTRACT

Observations from multiple sensors on the NASA *Aqua* satellite are used to estimate the temporal and spatial variability of short-term cloud responses (CR) and cloud feedbacks λ for different cloud types, with respect to the interannual variability within the A-Train era (July 2002–June 2017). Short-term cloud feedbacks by cloud type are investigated both globally and locally by three different definitions in the literature: 1) the global-mean cloud feedback parameter λ_{GG} from regressing the global-mean cloud-induced TOA radiation anomaly ΔR_G with the global-mean surface temperature change ΔT_{GS} ; 2) the local feedback parameter λ_{LL} from regressing the local ΔR with the local surface temperature change ΔT_S ; and 3) the local feedback parameter λ_{GL} from regressing global ΔR_G with local ΔT_S . Observations show significant temporal variability in the magnitudes and spatial patterns in λ_{GG} and λ_{GL} , whereas λ_{LL} remains essentially time invariant for different cloud types. The global-mean net λ_{GG} exhibits a gradual transition from negative to positive in the A-Train era due to a less negative λ_{GG} from low clouds and an increased positive λ_{GG} from high clouds over the warm pool region associated with the 2015/16 strong El Niño event. Strong temporal variability in λ_{GL} is intrinsically linked to its dependence on global ΔR_G , and the scaling of λ_{GL} with surface temperature change patterns to obtain global feedback λ_{GG} does not hold. Despite the shortness of the A-Train record, statistically robust signals can be obtained for different cloud types and regions of interest.

1. Introduction

The accurate simulation of cloud properties is a longstanding challenge for modeling of regional climate and the global climate system (e.g., Randall et al. 2003; Boucher et al. 2013). Changes in cloud properties in response to surface temperature changes have profound impacts on Earth's radiation budget and hydrological cycle, contributing important feedbacks to climate change (Ramanathan et al. 1989; Slingo 1990; Stephens 2005; Norris et al. 2016; Su et al. 2017; Webb et al. 2017).

These responses and feedbacks occur across different time scales as a result of climate variability and external forcing (Andrews 2014; Zhou et al. 2015, 2016; Webb et al. 2017). Previous studies have demonstrated that the intermodel spread in climate sensitivity is largely due to differences in cloud feedback in response to long-term climate change (e.g., Stephens 2005; Bony et al. 2006; Vial et al. 2013; Webb et al. 2017). However, observational records, especially those of cloud properties, are deemed too short or too uncertain to monitor long-term cloud property trends, let alone provide direct constraints to long-term cloud feedback (Dessler 2010; Dessler and Loeb 2013; Zhou et al. 2015; Yue et al. 2017).

A few recent studies have established a strong correlation between the net global cloud feedback on short-term (interannual and decadal) and climate change time scales (Zhou et al. 2015; Colman and Hanson 2017,

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2018). Although the strong correlations appear to partially result from consistent responses of low clouds to the changes of large-scale dynamics (Zhou et al. 2015, 2017), the physical reasons for these strong correlations still require further investigation. Moreover, there is mounting evidence from model simulations showing the dependence of cloud feedback on different geographic patterns of surface temperature changes (Stevens et al. 2016). This so-called pattern effect (Stevens et al. 2016) points out the additional state dependence of cloud feedback, which is especially important for interpreting results from observations and understanding the relationships between cloud feedbacks defined locally and globally. As observational estimates and further study on the mechanisms of short-term cloud feedbacks remains necessary (Klein and Hall 2015), it is important to investigate the temporal and spatial characteristics of these short-term cloud feedbacks revealed by observations, which will potentially provide additional observational constraints to the climate model cloud feedback.

The global-mean cloud feedback is defined as the linear response of cloud-induced radiative flux changes at the top of the atmosphere (TOA) to mean surface temperature change. Numerical modeling experiments have indicated that the pattern and magnitude of the global-mean cloud feedback change with different patterns of surface temperature change over varying time scales and in response to different climate variability and forcing (Andrews 2014; Rose et al. 2014; Zhou et al. 2016; Colman and Hanson 2017). Therefore, short-term cloud feedback estimates from observations and comparisons with model simulations are sensitive to the time scale. Low-cloud feedback is often calculated at the local scale by correlating the changes of local cloud properties (such as cloud cover, and optical as well as geometrical thickness) or cloud-induced TOA radiation with change of local thermodynamic and dynamic properties (Gordon and Klein 2014; Qu et al. 2015; Ceppi et al. 2016; Terai et al. 2016; Myers and Norris, 2015, 2016; Seethala et al. 2015; McCoy et al. 2017; Klein et al. 2017) to understand various physical mechanisms for low-cloud feedbacks (Bretherton 2015). Armour et al. (2013) formulated the local climate feedbacks as a linearization about the local surface temperature (e.g., Boer and Yu 2003a,b). Assumed to be time invariant, their results show that temporally varying climate feedbacks in the instantaneous CO₂-doubling scenario primarily emerge from the scaling of time-invariant local feedbacks by different local temperature warming patterns, which are then summed globally to give the global climate feedback and hence climate sensitivity (Armour et al. 2013). Many studies have investigated the relationships between local and nonlocal feedbacks

and their impact on climate sensitivity (e.g., Feldt and Roe 2013a,b; Roe et al. 2015). By perturbing sea surface temperature (SST) within individual spatial patches in model experiments, Zhou et al. (2017) show that both local and nonlocal SST anomalies are capable of causing significant changes on the local cloud feedback, which they define as the global-mean cloud-induced TOA radiation change in response to local surface temperature change. Zhou et al. (2017) further suggest that the local cloud feedbacks are unlikely to be time invariant, and therefore the global cloud changes in response to an SST anomaly pattern cannot be reconstructed by the scaling relationship between local feedback and the pattern of local surface temperature change. The temporal variability of cloud feedbacks, as well as the relationships between the local and nonlocal contributions, warrants further investigation.

The short-term cloud feedback arising from El Niño–Southern Oscillation (ENSO) variations has been estimated from satellite observations. Dessler (2010) and Dessler and Loeb (2013) used monthly averages of satellite and reanalysis TOA all-sky fluxes, and reanalysis clear-sky fluxes and meteorological fields to quantify total cloud feedback. Zhou et al. (2013) and Ceppi et al. (2016) combined cloud radiative kernels (CRKs; Zelinka et al. 2012) that are derived using the Fu–Liou radiative transfer model (Fu and Liou 1992) with NASA’s *Terra* Moderate Resolution Imaging Spectroradiometer (MODIS; Barnes et al. 1998) Collection 5 (C5) cloud observations, enabling the quantification of satellite-based cloud feedback as a function of cloud type. However, Yue et al. (2017) show that the cloud responses derived from C5 are adversely impacted by calibration degradation and retrieval artifacts, which are largely corrected in the Collection (C6) *Aqua* MODIS cloud product. Yue et al. (2016) propose an observation-based CRK (obs-CRK) method that avoids inconsistencies between the kernels and the cloud response term, which are especially important in cloud feedback calculations. Therefore, it is necessary to reexamine these previous estimates of short-term cloud feedback using the *Aqua* MODIS C6 cloud record and the obs-CRKs that correspond with the satellite-observed clouds. Cloud feedback is a transient feature on shorter time scales. As a result, calculations of short-term cloud feedbacks are sensitive to the temporal range of the observations.

In this study we will quantify the short-term global and local cloud feedbacks over a time series in response to interannual climate variability during the A-Train era following the conventional cloud feedback framework that describes the linear part of the cloud radiative responses to the surface temperature change (e.g., Knutti

and Rugenstein 2015). The temporal and spatial signatures of the short-term cloud feedbacks will be examined in the near-simultaneous observations of atmospheric states, cloud properties, and TOA radiation from various sensors in the A-Train for a variety of cloud types. This study is the first step to improve our understanding on how the short-term cloud feedback derived from observations is relevant to climate models, what physical mechanisms affect short-term and long-term cloud feedbacks, and how satellite observations should be used to constrain cloud feedbacks in climate models. Partitioning cloud feedback by cloud type is an efficient approach to assessing the fidelity of cloud feedbacks estimated from both climate models and observations, as different cloud types have very distinct shortwave and longwave feedbacks (Hartmann et al. 1992; Williams and Webb 2009; Zelinka et al. 2012, 2016; Yue et al. 2016). Furthermore, different satellite sensors have observational strengths and limitations regarding the observation of certain cloud types (Pincus et al. 2012; Yue et al. 2011, 2013, 2017), which directly impacts the accuracy and uncertainty estimate of cloud feedback.

Section 2 describes the global and local cloud feedback definitions used in previous studies and their relationships. Section 3 describes the methodology and data used in this investigation including the obs-CRKs. Sections 4 and 5 provide results on the spatial and temporal variability of global and local short-term cloud feedbacks. Section 6 concludes with a discussion and summary of the main results.

2. Approaches to global and local cloud feedback calculations

The magnitude of the global cloud feedback λ_{GG} is conventionally defined as the change of the global-mean cloud-induced radiative anomaly at TOA (ΔR_G) in response to a 1-K change of global-mean surface temperature ΔT_{GS} :

$$\lambda_{GG}(c) = \frac{\Delta R_G(c)}{\Delta T_{GS}} = \frac{\overline{\Delta R(c, \phi)}}{\Delta T_{GS}}, \quad (1)$$

where c denotes cloud type, defined in this study by the joint histogram of cloud-top pressure (CTP) and cloud optical depth τ at each geographical location ϕ . The overbar is for the global-mean average. The subscript GG corresponds to ΔR_G (global) and ΔT_{GS} (global) in the numerator and denominator of the equation, respectively. Since $\Delta R_G(c) = \overline{\Delta R(c, \phi)}$ and ΔT_{GS} does not vary with location ϕ , as shown in Eq. (1), $\Delta R(c, \phi)/\Delta T_{GS}$ gives the spatial patterns of $\lambda_{GG}(c)$ with $\Delta R(c, \phi)$ as the local TOA cloud-induced radiative anomaly. Following

the CRK method (Zelinka et al. 2012; Zhou et al. 2013; Yue et al. 2016), the cloud radiative feedbacks can be written as a combination of the radiative kernels and the climate response term of cloud, both of which are functions of cloud type c and location ϕ . Thus, λ_{GG} in Eq. (1) can be rewritten as

$$\lambda_{GG}(c) = \overline{\text{CRK}(c, \phi) \Delta C(c, \phi)} / \Delta T_{GS}, \quad (2)$$

where $\text{CRK}(c, \phi)$ is the cloud radiative kernel, discussed in more detail in section 3a. This simple normalization against ΔT_{GS} has been used to determine how clouds contribute to the stability of global climate with respect to different forcings, and to quantify intermodel differences of cloud feedbacks. For total cloud, λ_{GG} has been shown to substantially vary with time in a variety of climate models and forcing scenarios (Gregory and Andrews 2016; Zhou et al. 2016; Colman and Hanson 2017).

The local feedback parameter (e.g., Armour et al. 2013; Rose et al. 2014; Roe et al. 2015) is defined as the local change in TOA radiation linearized against local surface temperature change $\Delta T_s(\phi)$. Extending this definition to cloud feedback, the local cloud feedback parameter for cloud type c at geographical location ϕ , $\lambda_{LL}(c, \phi)$, is calculated with the CRK method:

$$\lambda_{LL}(c, \phi) = \frac{\Delta R(c, \phi)}{\Delta T_s(\phi)} = \frac{\text{CRK}(c, \phi) \Delta C(c, \phi)}{\Delta T_s(\phi)}, \quad (3)$$

where the subscript LL corresponds with local cloud-induced ΔR and local ΔT_s . The relationship between λ_{GG} and λ_{LL} is given by following equation:

$$\begin{aligned} \lambda_{GG}(c) &= \Delta R_G(c) / \Delta T_{GS} = [\overline{\Delta R(c, \phi)}] / \Delta T_{GS} \\ &= \frac{\overline{\Delta R(c, \phi)}}{\Delta T_s(\phi)} \frac{\Delta T_s(\phi)}{\Delta T_{GS}} = \overline{\lambda_{LL}(c, \phi)} \frac{\Delta T_s(\phi)}{\Delta T_{GS}}. \end{aligned} \quad (4)$$

Colman and Hanson (2017, 2018) calculate cloud feedbacks at various time scales and “synthetic” feedbacks are calculated by scaling time-invariant local feedback parameters with different surface warming patterns. Their results showed that the short-term cloud feedbacks (interannual and decadal) exhibit strong correlations with the long-term cloud feedbacks in the abrupt $4 \times \text{CO}_2$ and RCP8.5 scenarios, and the synthetic cloud feedbacks reproduce reasonable values of global cloud feedback across different time scales. Other modeling studies have investigated the constant local feedback concept. Rose et al. (2014) used slab ocean aquaplanet GCM experiments to show that significantly different forcing and ocean heat uptake patterns can change the local feedback parameters.

As discussed previously, [Zhou et al. \(2017\)](#) use idealized model simulations to calculate the changes in global-mean cloud-induced TOA radiation anomalies ΔR_G in response to local SST changes. Following [Zhou et al. \(2017\)](#), by linearizing ΔR_G with respect to local ΔT_S , this “local” cloud feedback parameter λ_{GL} is defined as shown:

$$\lambda_{GL}(c, \phi) = \Delta R_G(c) / \Delta T_S(\phi) = \overline{\Delta R(c, \phi)} / \Delta T_S(\phi), \quad (5)$$

where the subscript GL corresponds to global ΔR_G and local ΔT_S . [Zhou et al. \(2017\)](#) related λ_{GL} to λ_{GG} [Eq. (1)] in a similar fashion as in Eq. (4) for λ_{GG} and λ_{LL} . However, the “local” feedback parameter λ_{GL} defined in Eq. (5) is different from λ_{LL} in Eq. (3). The relationship between λ_{GG} and λ_{GL} is

$$\begin{aligned} \lambda_{GG}(c) &= \Delta R_G(c) / \Delta T_{GS} = \Delta R_G(c) / \overline{\Delta T_S(c, \phi)} \\ &= 1 / [\overline{1 / \lambda_{GL}(c, \phi)}], \end{aligned} \quad (6)$$

where the overbars indicate the global average. Equation (6) shows that the global-mean feedback parameter λ_{GG} cannot be obtained by scaling λ_{GL} [Eq. (5)] with local surface temperature warming patterns, and that the nonlocal contributions are included in $\lambda_{GL}(c, \phi)$ by definition.

The different definitions discussed above reveal different and unique aspects of cloud feedback. We therefore expect that these cloud feedback parameters will produce very different magnitudes and spatial patterns. A better quantification of cloud feedbacks on different time scales and spatial scales remains a high priority to understand the climate system ([Knutti and Rugenstein 2015](#); [Webb et al. 2017](#)). This investigation aims at providing estimates on short-term cloud feedback from high-quality satellite observations and quantifying the different temporal and spatial variability of these local and global cloud feedback parameters within the A-Train era. Cloud cover responses (CR) are also calculated by replacing the TOA radiation anomaly with the cloud cover anomaly.

3. Data and methodology

The short-term cloud feedback calculations use a combination of nearly simultaneous observations from the Atmospheric Infrared Sounder (AIRS)/Advanced Microwave Sounding Unit (AMSU) ([Chahine et al. 2006](#)), MODIS, and the Clouds and the Earth’s Radiant Energy System (CERES; [Wielicki et al. 1996](#)) on NASA’s *Aqua* satellite ([Parkinson 2003](#)). Both the cloud responses and the obs-CRKs are directly derived from these observations in order to maintain consistency

between the kernels and the response terms. The obs-CRKs are calculated following the methodology in [Yue et al. \(2016\)](#). The cloud responses as a function of cloud type are obtained from monthly joint CTP- τ cloud histograms using the C6 *Aqua*-MODIS Level 3 (L3) product ([Yue et al. 2017](#)). Note that these results are based on daytime observations at the *Aqua* overpass time only. This sampling impact on the observation-based cloud feedback estimate has not been quantified yet, although little discernible impact is found for longwave cloud feedbacks in climate models when only the sunlit portion of the diurnal cycle of cloudiness is sampled ([Zelinka et al. 2012](#)). For shortwave cloud feedback, the nighttime values are simply set to be zero following earlier studies ([Zelinka et al. 2012](#); [Zhou et al. 2013](#)). No other diurnal adjustment is applied to either cloud or TOA flux measurements in order to avoid introducing additional artifacts to the observed CRK and cloud responses. As a result, the orbital sampling bias still exists due to inherent limitations of polar orbiting observations, causing uncertainty on short-term cloud feedbacks estimated from A-Train observations. The quantification of such uncertainty warrants further study using geostationary observations and/or numerical model simulations.

The global-mean surface temperature time series used in this study is from the combined land surface air and SST monthly anomalies from the NASA Goddard Institute for Space Studies (GISS) Surface Temperature Analysis (GISTEMP; [GISTEMP Team 2016](#); [Hansen et al. 2010](#)). The local surface temperature is from the European Centre Medium-Range Weather Forecasting interim reanalysis product (ERA-Interim) at $1^\circ \times 1^\circ$ resolution ([Dee et al. 2011](#)).

a. Observation-based cloud radiative kernels

The CRK is the TOA radiative sensitivity to changes of cloud in a given cloud regime and is calculated as the change of TOA cloud radiative forcing (CRF) due to a perturbation of one unit cloud fraction C for each cloud type ([Zelinka et al. 2012](#)). Following the obs-CRK method in [Yue et al. \(2016\)](#), CRKs are derived from collocated MODIS, AIRS, CERES, and reanalysis data within each $1^\circ \times 1^\circ$ grid box, for each cloud type and month. At each grid box, the CRF for cloud type c is separately calculated by grid box only if the grid box has both cloudy (for cloud type c) and clear observations available within the same month. We use the cloud properties from the C6 *Aqua* MODIS L2 data and the TOA radiative fluxes from the *Aqua* CERES L2 footprint data product, specifically the Single Satellite Footprint (SSF) TOA/surface fluxes and clouds edition 4A ([Loeb et al. 2016](#)). Clear sky is identified using a

FIG. 1. Temporal variability of the global- (solid lines) and tropical- (dashed lines) mean cloud cover responses (CR; % K^{-1} ; black lines) and cloud feedback parameter λ ($\text{W m}^{-2} \text{K}^{-1}$; colored lines) calculated using the three definitions given in section 2. Columns show (left) λ_{GG} , (center) λ_{LL} , and (right) λ_{GL} for (a)–(c) all cloud types, (d)–(f) high cloud, (g)–(i) middle cloud, and (j)–(l) low cloud. Net, shortwave, and longwave cloud feedbacks are indicated by green, blue, and red lines, respectively. For presentation purposes, λ_{LL} and CR_{LL} magnitudes are reduced by half, and λ_{GL} and CR_{GL} magnitudes are multiplied by 20. The starting point of the time series in the calculation is July 2006 (fixed-starting-point method). The x axes correspond with the end points in the time series such that the leftmost point is obtained with 10 years of data (July 2002–June 2012) and the rightmost point with 15 years of data (July 2002–June 2017). Gray lines are the zero lines.

threshold value of AIRS version 6L2 effective cloud fraction (ECF) < 0.02 (Kahn et al. 2014). One year (2009) of L2 swath data from different sensors, as well as the 3-hourly instantaneous Modern-Era Retrospective analysis for Research and Applications, version 2 (MERRA-2), atmospheric states and TOA clear-column radiation data (Gelaro et al. 2017), are collocated at the 45-km scale of the AIRS/AMSU field of regard (Lambertsen and Lee 2003). This approach ensures optimal correspondence among radiation, cloud, and atmospheric state variables, an essential ingredient for deriving obs-CRNs.

Forty-nine cloud types are specified by histograms partitioned with seven bins of CTP (edges at 50, 180, 310, 440, 560, 680, 800, and 1000 hPa) and seven bins of τ (edges at 0, 0.3, 1.3, 3.6, 9.4, 23, 60, and > 60). Following the International Satellite Cloud Climatology Project

(ISCCP) cloud histogram convention (Rossow and Schiffer 1999), high, middle, and low clouds are defined as clouds with $\text{CTP} \leq 440$ hPa, $440 < \text{CTP} \leq 680$ hPa, and $\text{CTP} > 680$ hPa, respectively. The optically thin, medium, and thick clouds are defined as clouds with $\tau \leq 3.6$, $3.6 < \tau \leq 23$, and $\tau > 23$, respectively.

The cloud-type specific climatology of cloud, atmosphere, and TOA radiation is then obtained by sorting the collocated instantaneous dataset into the CTP– τ pairs and spatial geolocation separately for each of the 12 months. The obs-CRNs are then calculated as

$$\text{CRN}(c, \phi) = \frac{\partial \text{CRF}(c, \phi)}{\partial C(c, \phi)}. \quad (7)$$

The differences in atmospheric temperature and moisture between clear and cloudy conditions contribute to a

FIG. 2. Correlation coefficients R of cloud feedback/response spatial patterns between different time periods with those obtained using data from July 2002 to June 2012. The x axis indicates the end points of data record used in the calculation. The definition of the line colors are as in Fig. 1.

longwave radiative flux difference at TOA that is not directly due to the cloud properties (Zhang et al. 1994). This is referred to as the longwave cloud masking effect. This effect is removed by differencing the clear-column ΔR in the clear and the cloudy sky, the latter of which is calculated by setting cloud fraction to zero in the radiative flux calculation obtained from MERRA-2 collocated with the satellite observations (Dessler and Loeb 2013). This approach produces a similar result as Yue et al. (2016), where the masking effect was calculated with the Fu-Liou scheme using the cloud-type-specific atmospheric states.

The obs-CRKs are derived empirically from readily available satellite observations and reanalysis data for cloud types determined by MODIS. Yue et al. (2016) showed that significant differences can exist between obs-CRKs and model-derived CRKs that arise mainly from cloud vertical structure. Yue et al. (2016) also show that the obs-CRKs are sensitive to the instrument characteristics and algorithm assumptions used in the

retrieval of cloud properties. Therefore, to obtain observation-based estimates of cloud feedback, it is necessary to derive instrument-specific CRKs to maintain consistency between clouds that produce the kernels and clouds that produce the response term.

b. Cloud cover responses and cloud feedbacks to interannual climate variability

An underlying ambiguity of cloud feedback results from compensating signals among different cloud types, spectral bands, and different spatial regions and altitudes wherein cloud changes occur. It is therefore imperative to separate these potentially confounding signals. Using the cloud observations from the *Aqua* MODIS instrument during July 2002 to June 2017, cloud cover responses (CR) and cloud feedback parameters λ by cloud type are calculated by linearly regressing the monthly anomalies of cloud cover ΔC and cloud-induced TOA radiative fluxes ΔR with the monthly anomaly of surface temperature, respectively (Zhou

FIG. 3. Uncertainty at the 90% statistical significance interval for global- (solid lines) and tropical- (dashed lines) mean cloud cover responses CR_{GG} ($\% K^{-1}$; black lines) and cloud feedback parameter λ_{GG} ($W m^{-2} K^{-1}$; colored lines). Results are shown for (top to bottom) all cloud types, high clouds, middle clouds, and low clouds. Net, shortwave, and longwave cloud feedbacks are indicated by green, blue, and red lines, respectively.

et al. 2013; Yue et al. 2017). All anomalies in this paper are calculated as the departure from the mean annual cycle computed over the time segment used in the calculation. The monthly joint CTP- τ histograms in the *Aqua*-MODIS L3 (MYD08) product report the occurrence frequency for different cloud types within each 1° latitude by 1° longitude bin. The monthly cloud fraction histogram anomaly $\Delta C(c, \phi)$ is then derived by normalizing the MYD08 histograms with MODIS monthly mean cloud areal coverage and the spatial area of the grid box. The contribution of cloud fraction anomaly $\Delta C(c, \phi)$ to the TOA radiation flux anomaly $\Delta R(c, \phi)$ is then obtained using the obs-CRKs derived for MODIS cloud observations (Yue et al. 2016):

$$\Delta R(c, \phi) = CRK(c, \phi) \Delta C(c, \phi). \quad (8)$$

To investigate the temporal variability of the short-term cloud response and cloud feedback, different intervals of the time series are used in the calculation by fixing the starting point at July 2002 and extending the end of the time series in each calculation by 1 month until reaching June 2017. The time series of CR and λ are obtained over different time intervals and the first points in these time series are derived from the first 10 years of *Aqua* (July 2002–June 2012). This method represents the typical way that an observational data record is used in studies on long-term temporal characteristics. Two additional sets of calculations are carried out: 1) anchoring the end point of the time series

FIG. 4. Global- (solid lines) and tropical- (dashed lines) mean cloud cover responses CR_{GG} ($\% K^{-1}$; black lines) and cloud feedback parameter λ_{GG} ($W m^{-2} K^{-1}$; colored lines) for each cloud type in the 3×3 CTP- τ histograms following the ISCCP convention: (a)–(c) high, (d)–(f) middle, and (g)–(i) low clouds are defined as clouds with $CTP \leq 440$ hPa, $440 < CTP \leq 680$ hPa, and $CTP > 680$ hPa, respectively. The optically (left) thin, (center) medium, and (right) thick clouds are defined as cloud with $\tau \leq 3.6$, $3.6 < \tau \leq 23$, $\tau > 23$, respectively. Line styles and colors are as in Fig. 1. Gray lines are the zero lines.

but extending the starting point backward by 1 month each time (the first calculation uses the latest 10 years of observations from July 2007 to June 2017) so that the strong 2015/16 El Niño event is always included in the time series, and 2) applying a moving time window over the entire data record that always covers 10 years of observations but moves forward by 1 month each time with the first calculation using July 2002–June 2012 data. These tests are carried out to verify whether the temporal variability of the A-Train era short-term cloud feedback is from different spatial patterns of surface temperature changes during different time periods, instead of from the impacts of different data record lengths in the regression calculation (Forster et al. 2016).

In section 2, we describe different approaches to quantify the global and local cloud responses and feedbacks. We will investigate both the temporal evolution and spatial structures using three different definitions for CR and λ by regressing the monthly anomaly time series of cloud cover and cloud-induced TOA radiation against the monthly surface temperature anomaly using a least squares fit:

- 1) The global cloud response CR_{GG} and cloud feedback parameter λ_{GG} calculated following Eq. (2). Two different calculations of the global mean are tested: (i) by performing a global mean of gridbox-based

- regression coefficients and (ii) by regressing the global-mean anomaly $\Delta R(c, \phi)$ or $\Delta C(c, \phi)$ against ΔT_{GS} . Very similar results are obtained with (i) and (ii); thus only (i) is reported unless stated otherwise.
- 2) The local cloud response CR_{LL} and cloud feedback λ_{LL} calculated using Eq. (3).
- 3) The local cloud response CR_{GL} and cloud feedback λ_{GL} calculated using Eq. (5).

The regional and global-mean magnitudes for definitions 2 and 3 are obtained by taking a regional and global mean of the regression coefficients at each grid box. The magnitudes of the global-mean values and their spatial patterns for definitions 1–3 outlined above are calculated using the observations described earlier in section 3. We then investigate the temporal dependence of cloud feedbacks and their spatial patterns for different cloud types with respect to interannual variability within the A-Train era. Uncertainties are reported at 90% confidence levels using the Student's t test.

4. Temporal variability of cloud response and cloud feedback parameter

The temporal variability of the global-mean magnitudes of different CR and λ is shown for high, middle,

FIG. 5. As in Fig. 4, but for cloud cover responses CR_{LL} ($\% K^{-1}$; black lines) and cloud feedback parameter λ_{LL} ($W m^{-2} K^{-1}$; colored lines) defined in Eq. (3).

and low clouds in Fig. 1 calculated using the fixed-starting-point method. The net, shortwave, and longwave short-term cloud feedbacks are shown by green, blue, and red, respectively, and CR with black lines. The x axes in Fig. 1 correspond with the end points in the time series such that the leftmost point is obtained with 10 years of data (July 2002–June 2012) and the rightmost point with 15 years of data (July 2002–June 2017). To more directly compare the temporal dependence of different variables, $0.5\lambda_{LL}(c, \phi)$ and $20\lambda_{GL}(c, \phi)$ are plotted and tropical-mean values are further reduced by half for presentation purposes. Much greater temporal variations exist for λ_{GG} and $\lambda_{GL}(c, \phi)$, while $\lambda_{LL}(c, \phi)$ is almost invariant within the A-Train era. The net global-mean short-term cloud feedback λ_{GG} (Fig. 1a) changes gradually from negative to positive. Similar temporal features are also shown in the results calculated using the moving-10-yr-time-window method (see Fig. S1 in the online supplemental material) although with a much higher statistical uncertainty due to the short time series used. This indicates that the temporal variability seen in Fig. 1 is not a result of using different data record lengths in the regression calculation. Using the fixed-end-point method, the temporal variability in the magnitude of global-mean total λ_{GG} and λ_{GL} (see Fig. S2) is smaller than the other two methods but still significant in λ_{GG} and λ_{GL} when considering individual cloud types. This is because the strong 2015/16 El Niño event is always

included in the time series in this test and dominates the spatial patterns of surface temperature changes for different time series in this calculation. Since consistent results on the short-term cloud feedback temporal variability are obtained with both the fixed-starting-point method and the moving-time-window method but with smaller statistical uncertainties, the remaining discussion is primarily based on the fixed-starting-point method.

Figure 2 shows the spatial correlation coefficients R for the patterns of cloud feedback/response for incremental changes in time period with those obtained using data from July 2002 to June 2012. Take CR_{GG} for example:

$$R(c, t) = \text{corr}[CR_{GG}(c, 02 - 12), CR_{GG}(c, 02 - t)], \quad (9)$$

where t is the end of the time series in the calculation. To first order, Fig. 2 illustrates a highly simplified version of the temporal variability of spatial patterns. The spatial patterns of λ_{LL} remain highly correlated with those derived using the first 10 years of satellite data ($R > 0.9$ for total cloud and for high and low clouds; see Figs. 1b, 1e, and 1k, respectively). The correlations, however, decrease significantly for λ_{GG} and λ_{GL} . While the correlation coefficients for middle-cloud λ_{LL} (Fig. 2h) show much higher temporal variability than for high (Fig. 2e) and low clouds (Fig. 2k), these changes are still smaller

FIG. 6. As in Fig. 4, but for cloud cover responses CR_{GL} ($\% K^{-1}$; black lines) and cloud feedback parameter λ_{GL} ($W m^{-2} K^{-1}$; colored lines) defined in Eq. (5). Note that the magnitudes of CR_{GL} and λ_{GL} are multiplied by 20 for presentation purposes.

than those for λ_{GG} (Fig. 2g) and λ_{GL} (Fig. 2i). The spatial patterns (to be shown in Figs. 8 and 11) furthermore indicate that very weak and noisy signals are obtained for middle cloud CR_{LL} and λ_{LL} .

From the relationships among the three cloud feedback parameters given in Eqs. (4) and (6), these results suggest that for short-term cloud feedback estimated from satellite observations: 1) the local cloud feedback defined following Armour et al. (2013) λ_{LL} is nearly time-invariant during the A-Train era; 2) the short-term cloud feedback λ_{GG} exhibits significant temporal changes that arise from different spatial patterns of surface temperature changes during different time periods (e.g., Colman and Hanson 2017); and 3) the local cloud feedback parameter λ_{GL} as defined in Zhou et al. (2017) also exhibits significant temporal change which is intrinsically linked to its definition. The nonlocal effect is included in the calculation of λ_{GL} through ΔR_G in the numerator of Eq. (5). Although middle clouds have a large temporal variation for λ_{GG} , this is mainly contributed from weak responses and feedbacks in high latitudes where satellite observations are more uncertain (see Figs. 7 and 10). Moreover, given the ambiguity in determining midlevel cloud with MODIS (Wang et al. 2016), caution is needed when interpreting the middle-cloud results.

Figure 3 depicts the uncertainty estimated at the 90% level of statistical significance for the magnitude of λ_{GG} .

Since the uncertainty in the global-mean cloud feedback estimate cannot be obtained by averaging local uncertainty values, results in Fig. 3 are calculated by regressing the global-mean cloud-induced TOA anomaly against ΔT_{GS} . The magnitude of the uncertainty decreases with time as more data increase statistical significance, and the magnitude of ΔT_{GS} increases during the 2015/16 El Niño event. While the uncertainty for total cloud feedback (low, middle, and high cloud types combined) is significantly larger than the magnitude of the feedback parameter itself, the uncertainty is greatly reduced for some cloud types when they are treated individually. Furthermore, the magnitude of uncertainty is much smaller in terms of CR, mainly due to noisy signals for the shortwave cloud feedback (blue lines in Fig. 3). As will be shown regarding the spatial patterns (Figs. S1–S6), statistical significance of observations is dependent on region and cloud type, which includes most of the tropics and the low clouds over subtropical ocean. Despite the temporal shortness of the record of satellite observations, statistically robust signals are obtained for certain cloud types and regions, resulting from instrument calibration and algorithm improvements (Yue et al. 2017). This shows that efforts to improve instrument calibration, cloud detection, and retrieval algorithms have direct benefit on the quantification of cloud feedback despite the short temporal record of the A-Train.

FIG. 7. The spatial patterns of cloud cover responses CR_{GG} ($\% K^{-1}$) for four different time periods: (left to right) July 2002–June 2012, July 2002–June 2015, July 2002–June 2016, and July 2002–June 2017. Results for (a)–(d) all cloud and (e)–(h) high, (i)–(l) middle, and (m)–(p) low clouds are shown. Results with only regions reaching a 90% statistically significant regression slope are shown in Fig. S3.

Figures 4–6 show the feedback parameters λ_{GG} , λ_{LL} , and λ_{GL} , respectively, for each bin in the 3×3 CTP- τ histograms. The cloud types exhibit a wide range of temporal variability of cloud cover responses and short-term feedbacks calculated with definitions like λ_{GG} (Fig. 4) and λ_{GL} (Fig. 6), with less temporal variability found for optically thin clouds in comparison to optically medium and thick cloud. The nearly time-invariant λ_{LL} type of responses and feedbacks (Fig. 5) holds for all cloud types, except slightly more variability is observed for medium optical thickness clouds (center column in Fig. 5). It is notable, however, that the magnitude of CR_{LL} and λ_{LL} is substantially different with respect to cloud type (Fig. 5).

The negative to positive transition of λ_{GG} for global total net cloud feedback (Fig. 1a) is primarily due to

reductions in magnitude of negative shortwave feedback of low cloud with medium τ (Fig. 4h) and increases in the magnitude of positive shortwave feedback of optically thick low clouds (Fig. 4i). The latter corresponds with a transition from near-zero to negative cloud cover response for optically thick low clouds (black line in Fig. 4i) and suggests that a transition to a less negative total low-cloud shortwave feedback shown in Fig. 1j is related to a decreasing optically thick low cloud cover anomaly with increasing global-mean surface temperature anomaly ΔT_{GS} . The increasing positive feedback from total high cloud (Fig. 1d) also contributes to the transition to a positive net total global feedback in Fig. 1a, in particular from increased positive shortwave feedback by optically thick high clouds (more negative

FIG. 8. As in Fig. 7, but for CR_{LL} . Results with only regions reaching a 90% statistically significant regression slope are shown in Fig. S4.

cloud response during 2015/16 El Niño event for this cloud type; see Fig. 4c). The high clouds with medium τ show an increased positive cloud response; however, their longwave and shortwave effects seem to compensate each other (Fig. 4b). The magnitude of λ_{GG} for optically thin clouds is much smaller than for other cloud types, which is related to the small TOA radiative sensitivity (kernel values) and the limited sensitivity of MODIS to cloud with $\tau < 0.4$ (Holz et al. 2008; Zhou et al. 2014). As shown in Fig. 5, the magnitudes of the shortwave and longwave components of λ_{LL} for the optically thin high and low clouds are much larger than those for λ_{GG} and λ_{GL} , which results from the large local cloud responses by these clouds (CR_{LL} ; black lines in Fig. 5). For local feedback λ_{GL} (Fig. 1, right column, and Fig. 6), the time variations before 2015 are fairly small

with more dramatic changes that are associated with the 2015/16 El Niño event.

The dashed lines in Figs. 1–6 are for tropical means (30°N–30°S) but with magnitudes reduced by half for presentation purposes. Although obtaining observational estimates of cloud feedbacks in the tropics neglects the effect of horizontal energy transport on the energy balance (Rose et al. 2014; Zhou et al. 2017), the results presented here show that similar conclusions regarding time dependence can be drawn for both tropical and global cloud feedbacks, while the magnitudes are generally 2–3 times larger in the tropics with a smaller statistical uncertainty for each cloud type (Fig. 3). This is likely because ENSO variability is the dominant mode of interannual climate variability with the strongest signals over the tropical ocean.

FIG. 9. As in Fig. 7, but for CR_{GL} . Results with only regions reaching a 90% statistically significant regression slope are shown in Fig. S5.

5. Spatial pattern of short-term CR and λ

The three definitions given in section 2 reveal different aspects of cloud feedback and thus different spatial patterns and magnitudes are expected. In this section, the characteristics of the spatial structures of CR (Fig. 7–9) and net cloud feedback parameters (Figs. 10–12) are shown for four different time periods: July 2002–June 2012 (first columns), July 2002–June 2015 (second columns), July 2002–June 2016 (third columns), and July 2002–June 2017 (fourth columns). These time periods are chosen because they correspond with a gradual change of λ_{GG} from negative, to zero, and then to positive values, and also with significant changes in high cloud during the 2015/16 El Niño event. (The regions that reach the 90% statistical significance level are shown in the supplemental material Figs. S3–S8.)

Both high clouds and low clouds produce changes in the spatial patterns of CR_{GG} (Fig. 7) and λ_{GG} (Fig. 10). High clouds (Figs. 10e–h) exhibit an increased magnitude of negative feedback in the central and eastern Pacific, and an increased positive feedback in the warm pool region due to the strong 2015/16 El Niño event. The warm pool response plays a dominant role such that it causes the global net cloud feedback λ_{GG} for high cloud to become increasingly positive around 2016 (Figs. 10g and 1d). For low clouds, the net cloud feedback in the southeastern Pacific flips from negative (Fig. 10m) to positive (Fig. 10p) with time, which, in turn, contributes to a less negative global-mean low-cloud feedback (Fig. 1j). Significant changes over the subtropical Pacific occur with respect to cloud type, including an increased magnitude of positive feedback for high clouds (Fig. 10g) and a decreased magnitude of negative low-cloud

FIG. 10. As in Fig. 7, but for net cloud feedback λ_{GG} ($\text{W m}^{-2} \text{K}^{-1}$). Definition in Eq. (2) is used before taking global mean. Results with only regions reaching a 90% statistically significant regression slope are shown in Fig. S6.

feedback in the central subtropical Pacific (Fig. 10o), and an increased magnitude of positive low-cloud feedback off the West Coast of United States (Fig. 10o). Middle-cloud (Figs. 7i–l and 10i–l) contributions are much smaller than high and low clouds, and are primarily located in the high latitudes where the uncertainties of satellite cloud observations are large and noise in the shortwave cloud feedback increases (not shown).

As previously pointed out, the spatial patterns remain nearly unchanged for CR_{LL} (Fig. 8) and λ_{LL} (Fig. 11) for each cloud type. Large and statistically significant signals are present over the tropical and subtropical ocean (see the supplemental figures) with signals reaching the 90% significance level regionally. This primarily results from a negative net feedback of high clouds (Figs. 11e–h) and a

positive low-cloud feedback (Figs. 11m–p) with respect to the local surface temperature change. The correlation coefficients between spatial patterns from different time periods are above 0.9 except for middle clouds (Fig. 3), for which the CR_{LL} and λ_{LL} are close to zero most everywhere.

Figures 9 and 12 show CR_{GL} and λ_{GL} , respectively. These local feedbacks are calculated by regressing the global cloud cover and cloud radiative forcing anomalies against the local surface temperature change. The spatial patterns for all cloud types combined (top rows in Figs. 9 and 12) shown in this study are similar to those in Zhou et al. (2017), which are derived from idealized model simulations by changing SSTs within different spatial patches using a Green function approach and CERES observations using the radiative kernel method

FIG. 11. As in Fig. 10, but for net cloud feedback λ_{LL} . Results with only regions reaching a 90% statistically significant regression slope are shown in Fig. S7.

(Shell et al. 2008). The temporally varying spatial patterns from satellite data shown here indicate that the local feedbacks defined in this fashion may be also driven by different local warming patterns, similar to CR_{GG} and λ_{GG} , supported by their relationship in Eq. (6). The magnitudes of CR_{GL} and λ_{GL} are much smaller than parameters with subscripts GG and LL, and smaller than those in Zhou et al. (2017). Figure 12 shows that high, middle, and low cloud types all significantly contribute to the net all-cloud feedback λ_{GL} .

6. Conclusions

Observations from multiple sensors on the NASA *Aqua* satellite are used to estimate the temporal and spatial variability of the short-term (interannual) cloud

responses (CR) and cloud feedback parameters λ for different cloud types using the interannual variability within the A-Train era (July 2002–June 2017). The calculations use a synergy of instantaneous observations from the Atmospheric Infrared Sounder (AIRS)/Advanced Microwave Sounding Unit (AMSU), Moderate Resolution Imaging Spectroradiometer (MODIS), and the Clouds and the Earth's Radiant Energy System (CERES), as well as the Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2). The observation-based cloud radiative kernel (obs-CRK) method (Yue et al. 2016) is applied to ensure consistency between the radiative kernels and climate response terms in the cloud feedback calculations. The Collection 6 (C6) *Aqua* MODIS cloud product is used to minimize impacts from calibration

FIG. 12. As in Fig. 10, but for net cloud feedback λ_{GL} . Definition in Eq. (5) is used. Results with only regions reaching a 90% statistically significant regression slope are shown in Fig. S8.

degradation and retrieval artifacts as demonstrated by Yue et al. (2017). The global and local cloud feedbacks are estimated from satellite observations using three different definitions in the literature: 1) the conventionally defined global-mean cloud feedback parameter λ_{GG} from regressing the global-mean cloud-induced radiation anomaly ΔR_G at the top of atmosphere (TOA) with the global-mean surface temperature change ΔT_{GS} ; 2) the local feedback λ_{LL} from regressing the local cloud induced TOA radiative flux change $\Delta R(c, \phi)$ with the local surface temperature change $\Delta T_S(c, \phi)$ (e.g., Armour et al. 2013); and 3) the local feedback λ_{GL} from regressing ΔR_G with $\Delta T_S(c, \phi)$ (Zhou et al. 2017).

With 15 years of observations, more significant temporal variability is found for λ_{GG} and λ_{GL} , while a nearly time-invariant λ_{LL} is found for all cloud types. The

magnitude of λ_{GG} gradually changes from a negative to positive global net cloud feedback between 2002 and 2017. This is primarily due to a less negative shortwave feedback for low clouds, and partially due to a rapid increase of positive high-cloud feedback in response to the strong 2015/16 El Niño event. With a (nearly) time-invariant local feedback λ_{LL} , the conventionally defined cloud feedback parameter λ_{GG} can be obtained by scaling λ_{LL} with different local surface warming patterns [cf. Eq. (4); Colman and Hanson 2017, 2018], which indicates the potential of using relatively short satellite observations to constrain the long-term cloud feedback in climate models. Such a scaling relationship does not hold between λ_{GL} and λ_{GG} , and the nonlocal effect is included in the λ_{GL} type of feedbacks by definition [cf. Eq. (6)]. The relationships between the local and global

cloud feedbacks are closely related to the atmospheric and oceanic energy transport of the climate system, and affect the uncertainty in regional climate predictability (Webb et al. 2006; Hwang and Frierson 2010; Feldl et al. 2014; Roe et al. 2015).

The spatial patterns remain nearly unchanged for CR_{LL} and λ_{LL} for each cloud type. However, significant temporal variations occurred for the patterns of CR_{GG} and λ_{GG} , as well as of CR_{GL} and λ_{GL} , within the A-Train era. High clouds generally show a negative net λ_{LL} and low clouds generally show a positive λ_{LL} in response to local temperature change when combining all optical depth ranges. (Note that optically thin high clouds show a positive net λ_{LL} as shown in Fig. 5a) These signals are large and statistically significant over the tropical and subtropical oceans. For the more conventionally defined short-term cloud feedback parameter λ_{GG} , the increasing of positive feedback from high clouds in the warm pool region dominates over the increased magnitude of negative feedback in the central and eastern Pacific in association with the strong 2015/16 El Niño event. This change, together with the negative to positive change in low-cloud net feedback in the southeastern Pacific Ocean, causes the global net cloud feedback λ_{GG} to gradually switch from negative to positive within the A-Train era. Although the feedback parameter λ_{GL} is calculated with respect to local temperature change, in its definition the nonlocal effect is included through the global-mean TOA radiation changes. The magnitude of λ_{GL} is much smaller than λ_{GG} and λ_{LL} , and also smaller than those derived using the radiative kernel method (Shell et al. 2008) by Zhou et al. (2017). Unlike λ_{GG} and λ_{LL} where the contributions from middle clouds are negligible, all cloud types (high, middle, and low) contribute significantly to the total cloud feedback for λ_{GL} .

Using the conventional linearized climate feedback framework, short-term cloud feedbacks by cloud type are estimated from A-Train observations with respect to local and global interannual climate variability. The statistical uncertainty of the satellite-based global-mean cloud feedback is large, more so for the shortwave component than the longwave component. However, this investigation shows that despite the short data record, statistically robust signals are derived from the A-Train to quantify the cloud response and feedback parameter for tropical high clouds and subtropical oceanic low clouds, which shows the capability of the synergy of A-Train observations in reducing the high- and low-cloud feedback uncertainties, a key objective identified by the 2017 decadal survey (National Academies of Sciences, Engineering, and Medicine 2018). Moreover, the temporal and spatial structures of short-term cloud feedback revealed by the satellite observations provide

additional observational constraints to the climate model cloud feedback. These new estimates of local and global cloud feedback parameters serve as a first step to understand the connections between cloud feedback, energy and moisture transport, and local energy budget. The capability of high-quality long-term observations shown in this study also highlights the importance of the continuous efforts to improve instrument calibration, cloud detection, and retrieval algorithms.

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