

Abstract

The AVHRRs instruments onboard the series of NOAA satellites offer the longest available meteorological data records from space. These satellites have drifted in orbit resulting in shifts in the local time sampling during the life span of sensors onboard.

5 Depending on the amplitude of a diurnal cycle of the geophysical parameters derived, orbital drift may cause spurious trends in their time series. We investigate tropical deep convective clouds, which show pronounced diurnal cycle amplitude, to bracket an upper bound of the impact of orbital drift on their time series. We carry out a rotated empirical orthogonal function analysis and show that the REOFs are useful in delineating orbital drift signal and, more importantly, in correcting this signal in the time series of convective cloud amount. These results will help facilitate the derivation of homogenized data series of cloud amount from NOAA satellite sensors and ultimately analyzing trends from them. However, we suggest detailed comparison of various methods and their rigorous testing before applying final orbital drift corrections.

15 1 Introduction

Nearly 30 yr of data from the Advanced Very High Resolution Radiometers (AVHRRs) onboard the National Oceanic and Atmospheric Administration (NOAA) satellite series constitute the longest continuous meteorological space based measurements. These long-term measurements at high spatio-temporal resolutions and at carefully chosen spectral wavelengths make them extremely valuable for climate monitoring purposes and process based studies (Rossow and Schiffer, 1999; Karlsson, 2003; Heidinger and Pavolonis, 2009; Schulz et al., 2009). The AVHRR data in principle could be used for investigating variability and trends in essential climate variables at the decadal time scales. Deriving global and regional cloud climatologies is just one example of scientific usefulness of AVHRR data in improving our understanding of the Earth System (Rossow and Schiffer, 1999; Karlsson, 2003; Heidinger and Pavolonis,

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2009; Devasthale and Grassl, 2009a; Devasthale and Fueglistaler, 2010). However, the NOAA satellites on which AVHRR sensors are mounted have drifted in their orbit during the lifespan (Ignatov et al., 2004). The drifting leads to the delay in their time of observation, which subsequently results in inconsistent time sampling of clouds. This observational delay could further lead to artifacts in the time series of clouds (Devasthale and Grassl, 2007). Therefore, it is necessary to address this issue before the long-term AVHRR data can be used for climatological trend analysis.

There have been few efforts in the past to correct for the drift signal in the time series of other geophysical climate variables. For example, Waliser and Zhou (1997) and Lucas et al. (2001) applied rotated empirical functions (REOF) analysis to remove drift and satellite platform change related biases from the outgoing longwave radiation dataset. Jin and Treadon (2003) corrected the bias in land surface skin temperatures. However, the correction of the time series of cloud amount has not been attempted so far. Since cloud properties are listed as essential climate variables and play a significant role in the Earth's Radiation Budget, it is imperative to explore the methodologies to correct for the drift signal in the time series of cloud amount so that the data can be eventually used for trend analysis. In the subsequent sections, we demonstrate the usefulness of REOFs in correcting the drift signal. In the present study, we focus on the Indian summer monsoon area (0° N– 40° N, 60° E– 100° E), a region which shows pronounced diurnal cycles in cloud fraction related to tropical deep convection. The June-July-August-September (JJAS) season is selected from the years 1982 to 2006.

2 Data and methodology

We used level 1b AVHRR Global Area Coverage (GAC) data with a nominal spatial resolution of 5 km by 3 km for the analysis. The solar and thermal channels of the AVHRRs are intercalibrated as explained in the work of Devasthale and Grassl (2009a, b). The brightness temperatures derived from the thermal channels are used in cloud detection and cloud typing and, therefore, they are validated in order to ensure homogenization

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of the data across different NOAA platforms (Devasthale and Grassl, 2009b). The data from AVHRR sensors onboard NOAA-7, -9, -11, -14 and -16 are analysed. We select clouds with channel 4 (11.0 micrometers) brightness temperatures less than 220 K, which over the Indian summer monsoon area are most likely deep convective clouds and associated optically thick anvil cirrus clouds. They have strong diurnal cycle amplitude, and therefore the time series of these clouds most likely shows the spurious trends arising due to inconsistent time sampling caused by orbital drift (Devasthale and Grassl, 2007).

The methodology to correct for orbital drift signal is conceptually based on the original work of Waliser and Zhou (1997). In order to avoid repetition, readers are urged to refer the works by Waliser and Zhou (1997) and Lucas et al. (2001) for the mathematical basis and theoretical framework of our approach. First, the time series (at each one degree by one degree grid point) of monthly mean convective cloud anomalies is prepared by subtracting the time series mean. An EOF analysis is performed and first twenty modes are retained. The EOF loadings, defined as the time series of the first seven principal components (or EOF modes), are rotated using the varimax rotation. The modes that contain an orbital drift signal are identified visually. Synthetic loadings were then computed for these contaminated modes by fitting linear regression between EOF loadings and the local time of observation (see Lucas et al., 2001 for further details). These synthetic loadings were removed from the anomaly dataset. This yields a new dataset with the orbital drift signal removed.

3 Results of the REOF analysis

The EOF analysis is done on the regional time-series of the AVHRR area coverage of clouds with channel 4 brightness temperatures below 220 K. The REOFs disentangle orbital drift signals better than unrotated EOFs. This is demonstrated in Fig. 1, which shows the correlation of the first seven EOF loadings with the local time of observation using the unrotated and rotated EOFs. In the unrotated case (Fig. 1, left panel), five

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of the seven modes are contaminated by the orbital drift signal, while in the latter case (Fig. 1, right panel) a strong signal is seen in only two modes (modes 1 and 3). The spatial pattern of REOFs for the first seven modes is shown in Fig. 2. The variance explained by the first seven modes is 19.0 %, 13.5 %, 6.98 %, 5.16 %, 4.08 %, 3.67 % and 3.05 % respectively. The mode 2 shows the pattern of variability that we are actually looking for in the data. The loadings of modes 1 and 3 are regressed against the time of observation. The linear relationship between the loadings and the local time of observation is used to compute new synthetic loadings. They are shown in Fig. 3 in red color. These synthetic loadings are constructed to represent the contribution from the orbital drift signal to the temporal evolution of convective and thick anvil cloud fraction in the AVHRR time series. The corrected dataset is computed by removing these synthetic loadings from the original dataset. Figure 4 shows the spatial distribution of the correlation of time series of convective cloud fraction at each grid point with the time of observation with and without the orbital drift correction. Very high correlation values (in the range of ± 0.6) indicate significant contamination of the temporal evolution of convective cloud amount in the uncorrected AVHRR time series by orbital drift especially over land, where the amplitude of the diurnal cycle of these clouds is very large. After correction, correlations are reduced considerably confirming that the method based on REOFs quite efficiently removes the artificial orbital drift signal from the time series of cloud amount.

Having demonstrated that the main purpose of identifying and removing the orbital drift signal is achieved, it is important to verify whether the information to be analysed is not removed at the same time. Thus, the remaining question is whether the natural variability in the corrected dataset is preserved. Data from MODERate resolution Imaging Spectroradiometer (MODIS) onboard NASA's Aqua satellite is used to answer this question. In contrast to the NOAA satellites, the Aqua satellite orbit is stable in its time of observation. A comparison is possible since Aqua satellite on which the MODIS instrument is mounted also observes the study region in the afternoon orbit similar to that of NOAA-16 satellite (which has drifted in orbit). Therefore, the REOF analysis

was performed on AVHRR/NOAA-16 data (JJAS months) for 2001 to 2006 period. The AVHRR and MODIS data (Level 2 Cloud Products, Version 5) from 2006 were used for comparison, as the drift is largest towards later years than the year 2001. A comparison of the cloud cover statistics is given in Table 1. For all statistical quantities, the corrected AVHRR data is closer to the MODIS than the uncorrected AVHRR data. The histogram of cloud fraction (Fig. 5) confirms that indeed the frequency distribution of corrected AVHRR data compares better with the MODIS reference data than for original data. Waliser and Zhou (1997) and Lucas et al. (2001) have previously argued that the use of synthetic loadings removes only orbital drift signal from the dataset. Our comparison results support their argument.

4 Conclusions and discussions

We demonstrate that the REOFs efficiently delineate the orbital drift signal in the time series of convective cloud fraction, and more importantly, show the usefulness in correcting the time series of cloud amount for drift signal. These results have special significance in the context of climate monitoring from space, since NOAA satellite sensors (AVHRR, HIRS, TOVS) offer the longest continuous data records from space which can be used for climate studies with emphasis on essential climate variables like clouds. An accurate intercalibration of AVHRR sensors and the removal of orbital drift signal are the two key issues that need to be addressed before these data can be used for long-term trend analysis of cloud properties. While the scientific community is currently arriving at a consensus on the accurate intercalibration methodologies, the present study tries to tackle the other important issue. It has to be noted here that we present a case study where the orbital drift signal is extreme, since the diurnal cycle of deep convective clouds has very large amplitude. This provides an upper bound of the possible orbital drift impact. However, the drift signal in the total cloud fraction could be weak (due to weak diurnal cycle amplitude of total cloud fraction resulting from the compensating effects of phase lags of maximum in the diurnal cycles of different cloud types)

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or even absent (depending on cloud type, latitude and season). This explains the fact that in our case study the first and the third modes of EOFs were contaminated by a drift signal (dominating the variability in the dataset), while in the study by Waliser and Zhou (1997) and Lucas et al. (2001) where they investigated the outgoing longwave radiation time series, the affected modes were 4th and 3rd (relatively weak contamination) respectively. In a cautionary note, we would like to mention that, in practice, there are other aspects that need investigation. For example, it is important to investigate how many modes have to be rotated (e.g. according to a Preisendorfer N rule significance test as used by Lucas et al. (2001)) and which rotation method is most suitable. A detailed comparison with other statistical tools (e.g. Hilbert Huang Transform) and methods (e.g. using diurnal cycle) is also needed to examine the relative benefits of other methods. It is also necessary to rigorously test that the large scale statistical features are preserved in the corrected data set. All of these issues need consideration, and will be investigated in future, before we apply final corrections to the climatological time series. Nonetheless, the REOFs analysis certainly is a promising approach.

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Table 1. Statistical comparison of uncorrected and corrected AVHRR data with the MODIS cloud product for JJAS 2006 over the study area.

	Observed AVHRR/N16	Corrected AVHRR/N16	Modis/AQUA
min	0	0	0
max	0.3622	0.3469	0.3342
mean	0.05441	0.04566	0.04357
median	0.04629	0.03109	0.03299
std. dev.	0.04834	0.04654	0.04448

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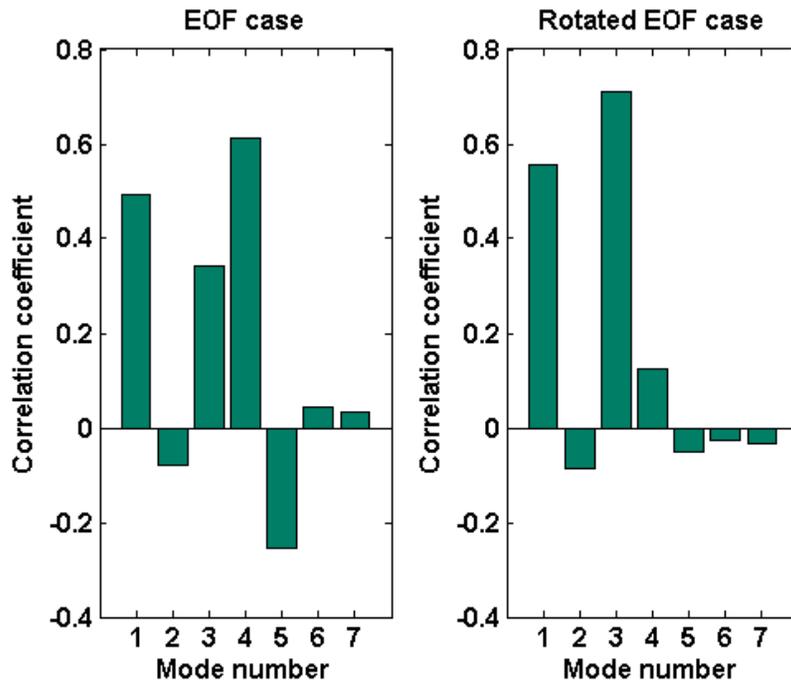


Fig. 1. The correlation of first seven EOF loadings with the time of observation for the unrotated (left panel) and rotated (right panel) EOF cases.

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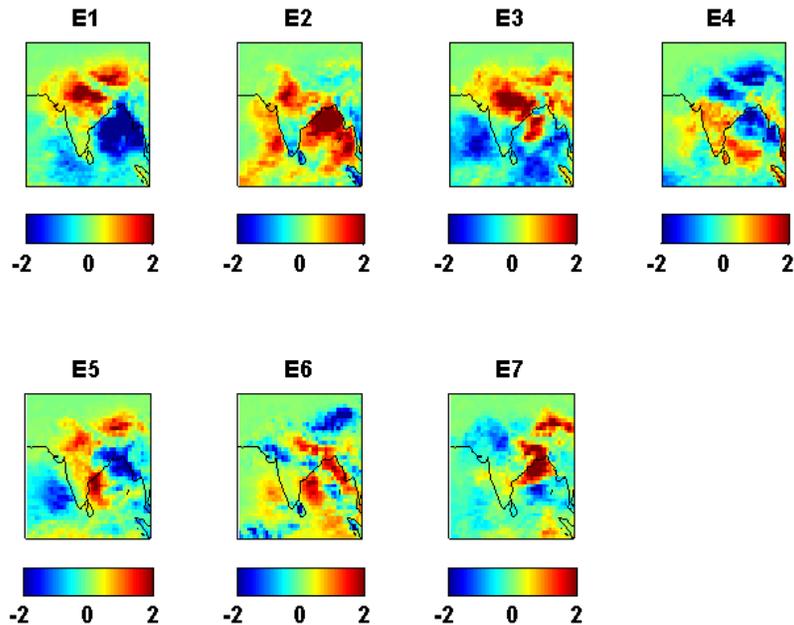


Fig. 2. The spatial pattern of EOF vectors in the rotated case. The variance explained by the first seven modes are 19.0%, 13.5%, 6.98%, 5.16%, 4.08%, 3.67% and 3.05%, respectively.

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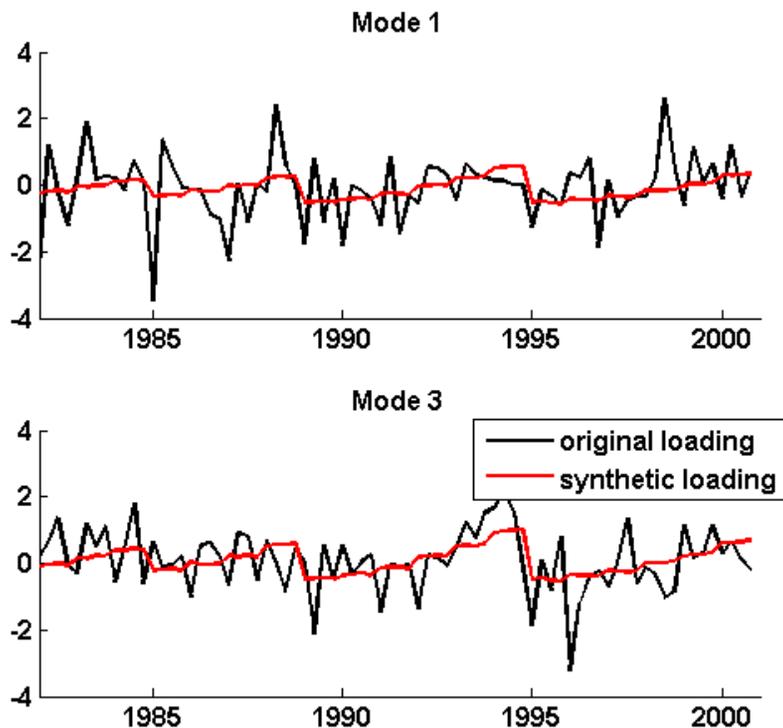


Fig. 3. The EOF loadings for modes 1 and 3 in rotated case (black line) and corresponding synthetic loadings (in red line) computed by linearly regressing the loadings with the time of observation.

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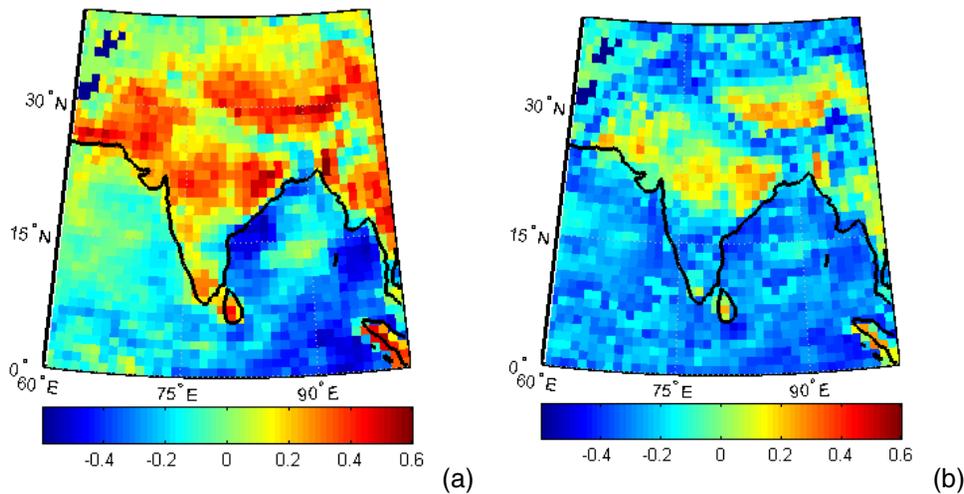


Fig. 4. The spatial pattern of correlation of time series of deep convective cloud amount at each grid point with the time of observation for the original AVHRR dataset (left panel) and after drift signal removal (right panel). The correlations are reduced considerably in the latter case.

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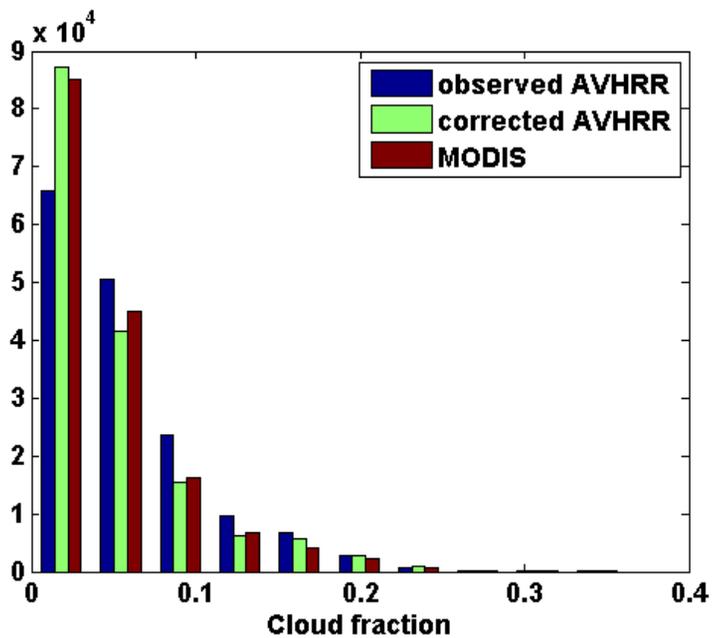


Fig. 5. Frequency distribution of optically thick convective cloud fraction (BT < 220 K) for JJAS 2006 for original and corrected AVHRR data compared with MODIS over the study area.

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