Journal of Atmospheric and Solar-Terrestrial Physics 68 (2006) 2164–2172

Journal of ATMOSPHERIC AND SOLAR-TERRESTRIAL PHYSICS

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Correlation between clouds at different altitudes and solar activity: Fact or Artifact?

I.G. Usoskin[a,*], M. Voiculescu[b], G.A. Kovaltsov[c], K. Mursula[d]

[a] *Sodankylä Geophysical Observatory (Oulu Unit), University of Oulu, Finland*
[b] *"Dunarea de Jos" University of Galati, Romania*
[c] *Ioffe Physical–Technical Institute, 194021 St. Petersburg, Russia*
[d] *Department of Physical Sciences, University of Oulu, Finland*

Received 14 February 2006; received in revised form 26 July 2006; accepted 10 August 2006
Available online 20 September 2006

Abstract

Studies of the relation between cosmic rays (CR) (solar activity) and atmospheric cloudiness are mostly based on the satellite ISCCP cloud data. However, doubts have been cast that these relations can be an artifact of instrumental effects, i.e., of the masking/obscuring low clouds by higher clouds in the satellite view. If this is the case, most of the earlier results based on ISCCP data would be devaluated. Here, we reanalyze the ISCCP cloud coverage data and its relation with the cosmic ray-induced ionization, and show that the correlation between low clouds and CR is affected by higher clouds in some geographical regions, but not everywhere. In turn, our results show that low clouds also may affect the relation of higher clouds with CR in some regions. Accordingly, correlation analysis can be performed only when the strong relation between clouds of different types is taken into account. In particular, studies based on global or latitudinal (zonally averaged) cloud data should be revised.

Keywords: Cosmic ray-induced ionization; Cosmic rays; Atmosphere; Climate; Solar-terrestrial relations; Cloud cover

1. Introduction

The investigation of the relation between solar activity and the cloud coverage is an important issue for understanding the global climate change. Presently, such a relationship can be physically interpreted as one (or a combination) of the following mechanisms: the direct effect of the cosmic ray-induced ionization (CRII) on the formation of cloud condensation nuclei (Marsh and Svensmark, 2000, 2003a; Yu, 2002), the electro-freezing effect on clouds due to the vertical current system induced by solar wind interaction with the magnetosphere (Tinsley, 1996), and the indirect cloud modulation by UV-heating of the stratosphere and consequent changes in the circulation pattern (Haigh, 1996, 2002) or by the total solar irradiance (Kristjansson et al., 2002). These mechanisms may dominate at different altitudes, leading to different correlations between different cloud types and solar proxies. Note that correlation studies can hardly distinguish between the above-mentioned mechanisms because of the strong mutual relation between the different

*Corresponding author. Fax: +358 8 5531303.
E-mail address: Ilya.Usoskin@oulu.fi (I.G. Usoskin).

1364-6826/$ - see front matter
doi:10.1016/j.jastp.2006.08.005

solar indices (e.g., the CR flux, geomagnetic activity, or UV variations). The idea of a relation between the CRII of the atmosphere and cloud formation was presented several decades ago (e.g., Dickinson, 1975; Tinsley et al., 1989). Recent results have suggested that the low-cloud amount (LCA) has a high degree of correlation with the flux of galactic CR impinging on the Earth. Svensmark and Friis-Christensen (1997), Marsh and Svensmark (2000, 2003a, b), and Pallé Bago and Butler (2000) studied the globally averaged LCA in 1984–1994 and CR recorded by a neutron monitor and found that the two quantities are highly correlated. Pallé et al. (2004) and Usoskin et al. (2004a) showed that the correlation between the LCA and the modelled CRII has a geographical pattern. Low clouds that have a particularly strong cooling effect on climate are of particular interest for studies of the variable solar activity affecting terrestrial climate (Marsh and Svensmark, 2000).

Because of the scarcity of ground-based cloud observations, satellite-based cloud data collected in the ISCCP database are commonly used in such studies. Lately, doubts have been cast on the purity of LCA data in ISCCP, suggesting that they may be obscured by middle and high clouds in the satellite view (see, e.g., Wang and Rossow, 1995; Marsh and Svensmark, 2003b; Norris, 2005; Pallé, 2005). On the other hand, thick low clouds may in turn affect the determination of higher clouds over different backgrounds (Hahn et al., 2001). Therefore, the question of whether the earlier found LCA–CRII relation is real or induced by the problems of low-cloud observations from space is still open (Pallé, 2005). Here, we aim to clarify this question by a thorough reanalysis of the ISCCP cloud data in 1984–2004.

2. Data, methods, and nomenclature

2.1. Data

Here, we analyze the monthly and annual cloud amount (percentages of the area covered by clouds of a given type) in 1984–2004 as given by the ISCCP-D2 dataset (http://isccp.giss.nasa.gov) in the IR range, in the geographical grid of $5^\circ \times 5^\circ$. The ISCCP database distinguishes between three types of clouds depending on the cloud top pressure P: low ($P > 680$ mb), middle ($440 < P < 680$ mb), and high ($P < 440$ mb) clouds. We will call them here L-, M-, and H-clouds, respectively. Note that multi-layer clouds are identified in ISCCP by their top. Thus, e.g., coexisting L-, M-, and H-clouds would be only identified as H-clouds (see Rossow et al., 2005 for details). Since M- and H-clouds may complement each other in obscuring L-clouds in satellite observations, we join them together as S-cloud amount (SCA), which is the sum of H- and M-cloud amounts in a given grid cell. As the tropospheric CRII, we use the results of a recent model calculation (Usoskin et al., 2004b; Usoskin and Kovaltsov, 2006) at two layers with barometric pressures of about 700 and 450 mb, corresponding to L- and S-clouds, respectively. Henceforth, we will also call SCA, LCA, and CRII as S (sum), L (low), and I (ionization) variables, respectively.

2.2. Bivariate and partial correlations

Fig. 1a illustrates a possible cause-and-effect scheme, where the CRII affects S-clouds which mask the L-clouds and thereby introduce a spurious correlation between CRII and LCA. Fig. 1b illustrates another possible scheme of a CRII–LCA link, inducing a spurious SCA–CRII correlation. We try to clarify this problem and study the mutual relations between the three variables using bivariate (full) and partial correlations. Henceforth, we will call R_{XY} the bivariate correlation coefficient between X and Y variables. While the bivariate correlation, e.g., R_{IL}, cannot differentiate between all possible links between the I and L variables, including indirect relations via other factors, e.g., S (see Fig. 1a), the partial correlation $P_{I(S)L}$ removes the effect of the third variable, S and corresponds to the direct $I \rightarrow L$ link. The partial correlation

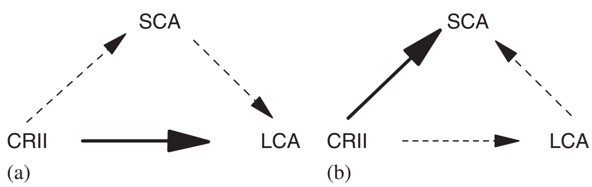

Fig. 1. Scheme of the partial correlation. Panel (a) corresponds to spurious correlation between the cosmic ray-induced ionization and the low-cloud amount (CRII → LCA solid arrow) with the intervening mid + high-cloud amount (SCA, dotted arrows), while panel (b) corresponds to spurious correlation between the ionization and the mid + high-cloud amount (CRII → SCA solid arrow) with the intervening low-cloud amount.

coefficient $P_{X(Z)Y}$ is computed as follows:

$$P_{X(Z)Y} = \frac{R_{XY} - R_{XZ}R_{ZY}}{\sqrt{(1-R_{XZ}^2)(1-R_{ZY}^2)}}, \quad (1)$$

and corresponds to the partial correlation between X and Y variables, with Z variable being fixed. Besides the partial and bivariate correlations, we are also interested in their differences, like $D_{X(Z)Y} = P_{X(Z)Y} - R_{XY}$. The partial correlation coefficient equals the bivariate correlation coefficient if the third variable (Z) does not correlate with the two other variables or is constant. For cases when the LCA is correlated with the CRII, $R_{IL} > 0$, one can draw the following conclusions depending on the sign of $D_{I(S)L}$: (1) $D = 0$ implies that the bivariate CRII–LCA correlation is real (no intervening/suppressing effect of the S variable); (2) $D < 0$ implies that the S variable is partly responsible (intervening) for the CRII–LCA relation (if $P_{I(S)L} = 0$, the whole correlation is spurious); (3) $D > 0$ implies that the CRII–LCA correlation is suppressed by the S variable. For $R_{IL} < 0$ the signs of $D_{I(S)L}$ in the above interpretation must be inverted. Thus, comparing partial and bivariate correlations one can determine the nature and level of true and spurious correlations between two variables, taking into account a possible effect of a third related variable.

2.3. Significance estimate

It is important to know not only the absolute value of the correlation coefficient, but also its significance, i.e., the probability that the correlation is real and not due to a random coincidence. Standard formulas that are used to estimate the significance are based on the assumption that data points are mutually independent and obey Gaussian distribution. However, this is often an invalid assumption for real data. In such a situation, a Monte-Carlo test can be applied to estimate the significance, as described below.

Let us consider the correlation between X and Y time series, whose bivariate correlation coefficient is R_{XY}. A series X is then randomized (see below) to produce a new X' series, and the value of $R_{X'Y}$ is computed and compared with R_{XY}. Next, the Y series is randomized in a similar way to compute $R_{XY'}$. This procedure is repeated N times, and the number N^* is computed, which is the number of cases (within the total of N simulations) when either $R_{X'Y}$ or $R_{XY'}$ exceeds R_{XY} in absolute values. Finally, the significance is defined as

$$s = N^*/N \cdot 100\%. \quad (2)$$

There are two common ways to randomize the initial series, i.e., to produce X' from X. One method is to obtain the X' series by randomly shuffling the X series. Although keeping the distribution of the data points, this method destroys all relations between neighboring points, and therefore can be applied only if the data series are not serially correlated. Otherwise this method overestimates the significance. Another method takes into account the serial correlation between the data points and consists of three steps (Ebisuzaki, 1997): first, the FFT transform of the original X series is computed; secondly, the phase of the FFT series is randomized while keeping the amplitude; thirdly, the X' series is obtained by an inverse FFT transform of the phase-randomized series. This method, called the non-parametric random phase test, preserves the autocorrelation function of the original series. However, this method seems to underestimate the significance of correlation if the power spectrum of the original series is dominated by a single strong peak (the dominant periodicity in the data series).

We have calculated the significance of correlations using both randomization methods. The significance test has been applied to R_{IL} calculated using annual values of CRII and LCA in each geographical cell, and Fig. 2a shows the computed significance as a function of the correlation coefficient. Gray and black curves correspond to the random shuffling and random phase methods of randomization, respectively. Each curve depicts a 9-point running mean over about 2500 individual points. The significance estimate for the partial correlation $P_{I(S)L}$ is shown in Fig. 2b. In this case, all the three variables (I, S, and L) have been randomized as described above. One can see that the two methods yield slightly different significance values, but we can safely regard values of both bivariate and partial correlation coefficients above 0.4 as significant (confidence level above 90%). We will regard the values above 0.3 as marginally significant (confidence level 80%).

3. Results

3.1. Temporal correlations

Here, we study annual data (in order to avoid the seasonal cycle) for the 1984–2004 interval. First we consider the bivariate correlations between LCA,

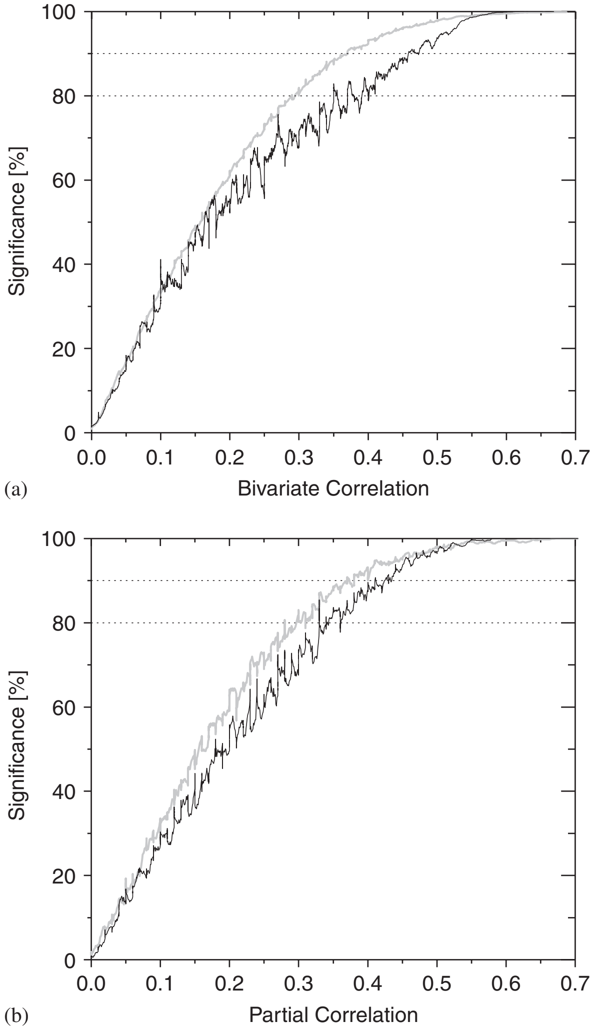

Fig. 2. Significance estimates of the correlation coefficients for bivariate (panel a) and partial (panel b) correlations. The significance has been computed by the Monte-Carlo method (see text), using random data shuffling (gray curves) and the non-parametric random phase test (solid curves). Two dotted lines represent the significant (90%) and marginally significant (80%) levels.

SCA, and CRII as shown in the upper panels of Fig. 3 (cf., Figs. 3a, b and g, respectively, in Pallé, 2005). As discussed in Section 2.3, dark blue (<-0.4) and red/brown (>0.4) areas correspond to significant correlation, while white depicts areas with no significant correlation. The bivariate correlation between CRII and LCA, R_{IL} (IL panel), is mostly positive and the regions of positive correlation depict clear geographical patterns: they are strongest at middle latitudes and in the western part of Indian ocean. On the other hand, R_{IS} is mostly negative. Regions of high negative correlation are found at Atlantic middle–high latitudes, over most of the American continent and over the tropics of the Pacific ocean. The SCA–LCA anti-correlation is very strong and nearly uniform over the globe with some spots of positive correlation in the tropics, in regions of very small SCA. This led Pallé (2005) to suggest that the earlier found correlation between CRII and LCA (Pallé et al., 2004; Usoskin et al., 2004a) may be an artifact of the CRII $\rightarrow$ SCA and SCA $\rightarrow$ LCA relations (see Fig. 1a). In the following we will study this idea quantitatively using partial correlations.

The partial correlations are shown in the middle row of Fig. 3. Panel I(S)L shows the $P_{I(S)L}$, viz. the partial correlation between CRII and LCA with fixed SCA, and tests the hypothesis shown in Fig. 1a. If the CRII–LCA relation was induced by obscuring S-clouds, $P_{I(S)L}$ should be small, also in those regions where the bivariate CRII–LCA correlation was found to be large. However, areas of strongly positive $P_{I(S)L}$ are seen in the I(S)L panel, forming a closely similar geographical pattern as in the bivariate CRII–LCA correlation. This shows that the CRII–LCA relation is not largely affected by SCA. However, there are some areas (e.g., in South Pacific) of positive R_{IL} that are not observed in $P_{I(S)L}$, implying that the CRII–LCA relation in these areas is indeed affected by S-clouds (cf. Marsh and Svensmark, 2003b).

Panel D_I(S)L (bottom left) of Fig. 3 shows the difference $D_{I(S)L}$ between the mid- and top panels above it and gives additional information on the geographical pattern of the CRII–LCA relationship. Blue-colored regions include areas where the CRII–LCA correlation may, at least partly, be caused by the intervening effect of S-clouds. Note that not all these blue regions correspond to positive CRII–LCA correlation, but, e.g., in North America and the Arctic, they may be due to the suppression of a negative CRII–LCA correlation. However, we note that some of these regions, e.g., the American continent, are almost free of low clouds. Interpretation of $D_{I(S)L} \approx 0$ (white areas) is not straightforward. On one hand, it may correspond to equal significant bivariate and partial correlations, i.e., where the apparent CRII–LCA relation is real and not affected by SCA. On the other hand, it can simply reflect the absence of bivariate correlation ($R_{IL} \approx 0$). In order to distinguish between them, we have hatched in red areas of significant positive R_{IL} (red areas in panel IL). The positive CRII–LCA

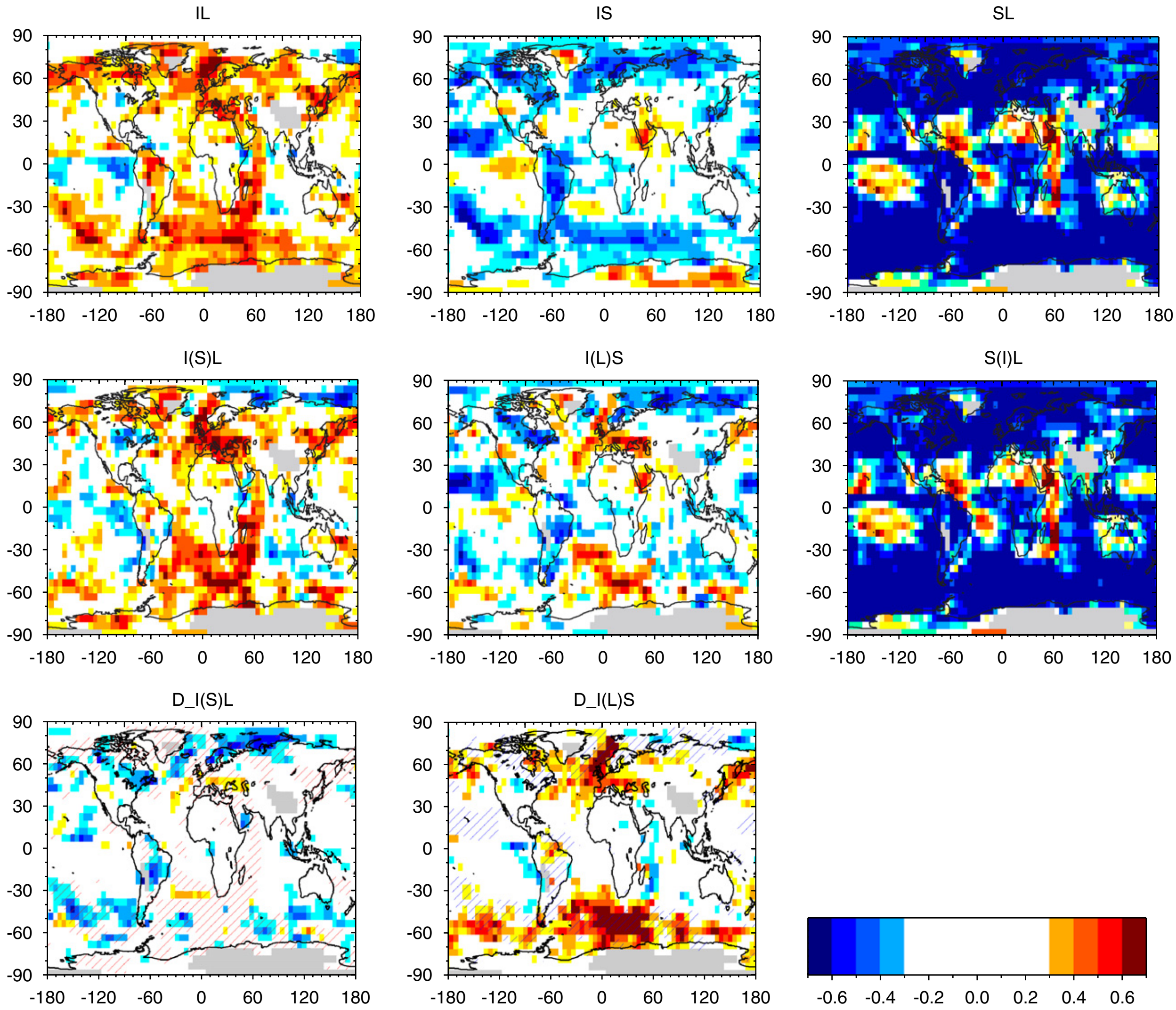

Fig. 3. Geographical distribution of the bivariate (upper row) and partial (middle row) correlation coefficients between the low-cloud amount (LCA), the mid + high-cloud amount (SCA) and the cosmic ray-induced ionization (CRII) variable as well as of the difference (bottom row) between the two upper panels (see Section 2 for definition). Red hatched areas in the panel D_I(S)L correspond to significant positive bivariate CRII–LCA correlation (red areas in the panel IL), while blue hatched areas in the panel D_I(L)S correspond to significant negative bivariate CRII–SCA correlation (blue areas in the panel IS). The bottom right panel shows the color scale for all panels.

global correlation found earlier is not uniform: it is real in most regions but spuriously induced by SCA–LCA relation in other areas, the largest being the South Pacific. It is interesting to note that, while there are large areas of strong real CRII–LCA correlation, no latitudinal zone is free from the intervening effect of S-clouds in some longitude sectors. Therefore, not only results based on global averages but also those based on zonal averages are likely to be distorted.

Next we check the opposite hypothesis, i.e., that LCA affects the CRII–SCA relation (see Fig. 1b). The LCA $\rightarrow$ SCA link corresponds to a possible distortion of H- and M-clouds defined by satellites over backgrounds of thick L-clouds (Hahn et al., 2001). Such a link would yield different masking effects over different backgrounds (oceans and mainlands). The I(L)S panel in Fig. 3 depicts the partial $P_{I(L)S}$ correlation, i.e., the correlation between CRII and SCA with LCA being fixed. Surprisingly, it shows two large regions of positive CRII–SCA correlation (South Atlantic and Europe) that are absent in the bivariate correlation plot (panel IS). In the distribution of $D_{I(L)S}$, most of the globe is white-colored, i.e., L-clouds do not affect the CRII–SCA relations. However, two latitudinal zones around 50–60°, including the two above-mentioned regions of positive $P_{I(L)S}$, are red-colored, implying that the CRII–SCA correlation is strongly obscured by L-clouds. This intervening is particularly strong in South Atlantic and Gulf-stream areas, where the LCA is also large and could affect the observation of middle clouds. These results suggest that in these regions SCA is positively correlated with the CRII and the bivariate anti-correlation is in fact due to the obscuring effect of the intervening LCA → SCA relation.

It is important to note that the geographical areas of strong SCA intervening the CRII–LCA relation and LCA intervening the CRII–SCA relation (see the two lowest panels in Fig. 3) are spatially different and do not largely overlap. Accordingly, regions where L-clouds affect the CRII–SCA relation can be separated from those where S-clouds affect the CRII–LCA relation.

We have also computed the partial correlation coefficient between L- and S-clouds keeping the I- variable fixed. The bivariate and partial correlations almost coincide (see panels SL and S(I)L in Fig. 3), and the value of $D_{S(I)L}$ (not shown) is about zero around the globe. This means that the anti-correlation between the L- and S-clouds in the ISCCP database is not affected by CRII. Such a correlation analysis cannot show whether this anti-correlation is an artifact caused by instrumental effects (e.g., obscuring of L-clouds by S-clouds) or a fact due to a real physical mechanism preventing coexistence of high clouds with low clouds. However, different types of clouds are not independent (see, e.g., Warren et al., 1985; Hahn et al., 2001) and their coexistence is limited by physical mechanisms/meteorological conditions, which are different in different regions. Accordingly, the observed SCA–LCA relation shown in Fig. 3 is not homogeneous, and the two variables even correlate in some tropical areas, a pattern which is not expected in case of masking.

3.2. Spatial correlations

As discussed above, the relation between LCA and SCA does not depend on the solar activity,

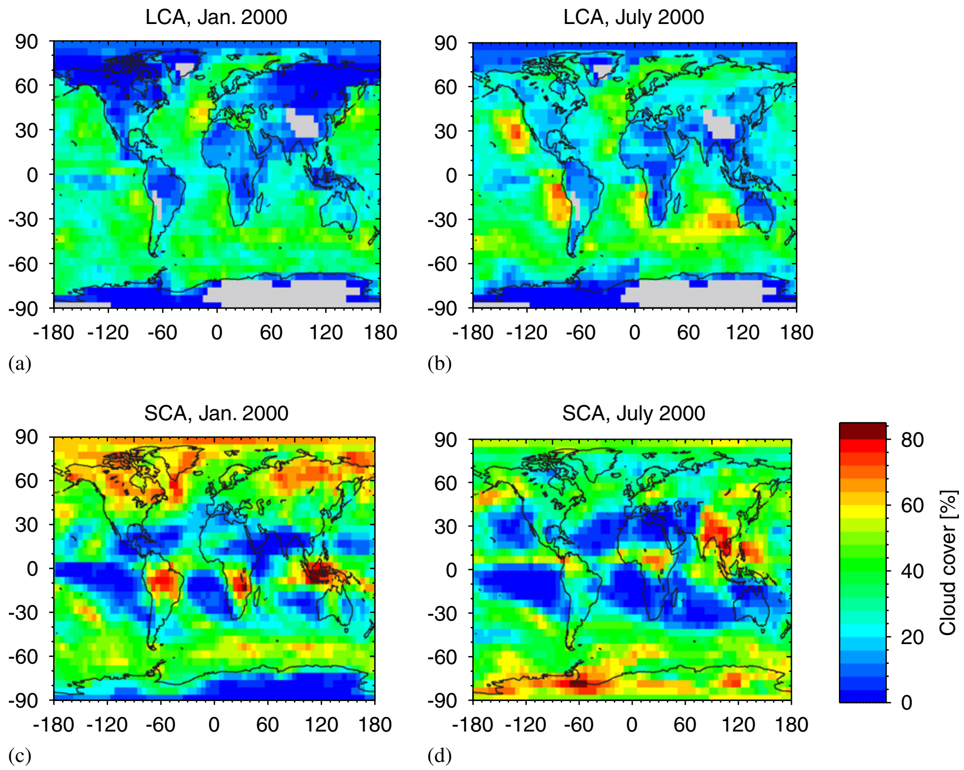

Fig. 4. Observed cloud cover during January 2000 (left panels) and July 2000 (right panels). Top and bottom rows correspond to low clouds (LCA) and mid + high clouds (SCA). The rightmost panel shows the color scale for all panels.

implying that this relation is direct (either physical or instrumental), not related to a possible modulation of cloud amount by CRII. Although a correlation analysis does not show the cause for the strong anti-correlation between low clouds and high + middle clouds, indirect indications suggest that there are physical links, e.g., meteorological conditions, that prevent the coexistence of different types of clouds (Hahn et al., 2001). In other words, a high SCA would imply a real absence of LCA. Let us consider the geographical distribution of cloudiness. Fig. 4 shows monthly cloud covers for one winter (January) and one summer (July) month of a randomly chosen year 2000. Since the instrumental masking is an immediate effect, one would expect to see similar patterns when comparing Fig. 4a and c (or b and d) with each other. However, the patterns are quite different: LCA depicts an apparent geographical pattern with significantly less clouds over continents than over oceans, while SCA is dominated by a zonal pattern. Masking would result in an instantaneous global anti-correlation between LCA and SCA. Fig. 5 shows the spatial correlation between the geographical distributions of LCA and SCA shown in Fig. 4. For each grid cell, we have computed the correlation coefficient between LCA and SCA values within a $\pm 15^\circ$ latitude by $\pm 25^\circ$ longitude rectangle ($7 * 11 = 77$ grid cells) around the cell. One can see that there are some large areas of strong negative correlation (blue), which roughly correspond to regions of high SCA (see red areas in Fig. 4c and d)—tropical regions and high latitudes in the winter hemisphere. However, a large part of the globe is free of the negative relation between LCA and SCA, indicating that masking does not dominate. This suggests that the globalwide strong LCA–SCA anti-correlation (see panel SL of Fig. 3) is largely due to a physical mechanism, which may operate on a longer time scale, rather than due to the (instantaneous) masking. We note that Mediterranean-Gulfstream, Japanese, and South Atlantic regions are mostly free of the LCA–SCA relations, strengthening thus the above drawn conclusions. While only year 2000 is discussed here, we have checked that the pattern remains roughly the same for other years also.

4. Discussion and conclusions

As shown in the previous section, the positive CRII–LCA correlation could be partly induced by the SCA → LCA relation in some geographical areas (e.g., South Pacific, North Eurasia). On the other hand, there are large geographical regions where the positive correlation between CRII and LCA is not intervened by middle and high clouds. Therefore, the relation between LCA and CRII (or other solar activity indices) can be safely studied using the ISCCP database in these regions, in particular in Europe, South Atlantic, West Indian, and Northwest Pacific regions. It is important to note that Europe, which is the source of many paleoclimatic reconstructions used in earlier studies, is included among these "safe" regions. Hence, the CRII–LCA correlation in these regions is real and not caused by intervening SCA, i.e., $R_{IL} \approx P_{I(S)L}$.

We have also found two large regions, South Atlantic and North Atlantic/Europe, where L-clouds obscure the CRII–SCA correlation, and where detection of S-clouds in ISCCP may be affected by thick low clouds over oceans. After removing the intervening effect of the L-clouds, these areas have positive CRII–SCA correlation, indicating that earlier results on the CRII–SCA

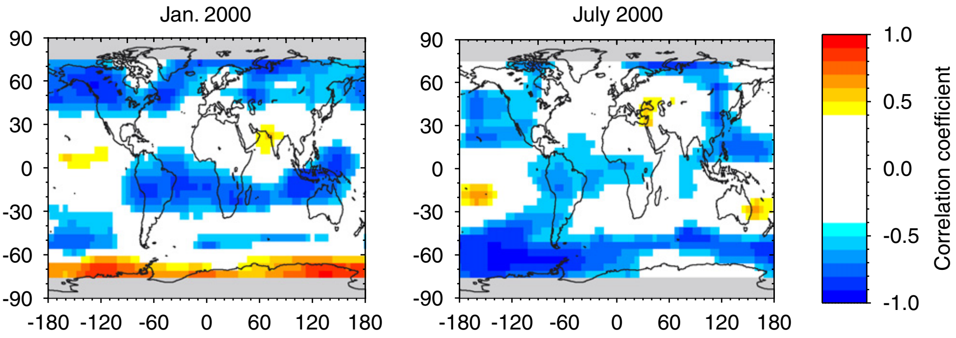

Fig. 5. Spatial cross-correlation (see text) between LCA and SCA shown in Fig. 4 for January 2000 and July 2000. The rightmost panel shows the color scale for all panels.

anti-correlation based on bivariate studies are not entirely correct and should be revised. Note that these areas have a relatively high amount of high and/or middle clouds.

The comparisons between the global distribution of the L-clouds and S-clouds and their correlation for different seasons show that they have patterns, unexpected in case of masking. We suggest that the strong negative LCA–SCA relation is due not only to the immediate instrumental effect but is most likely caused by a physical mechanism. Our analysis shows that earlier results based on (bivariate) correlation between any solar proxy and a particular cloud type in the ISCCP database may be distorted when using global or even latitudinal (zonally averaged) data. Therefore, future studies should be limited to specific geographical areas, viz., Europe, South Atlantic, West Indian, and Northwest Pacific regions, where the correlation is not greatly distorted.

Concluding, the answer to the title question is not unambiguous: the CRII–LCA relation is an artifact of the used data set in some geographical regions, but a real fact in other areas. Accordingly, the earlier results studying the correlation between LCA and CRII should be revised. The CRII–SCA relation is, in turn, also partly obscured by LCA variations. In order to avoid erroneous results in correlation studies, cloud data should be purified from the strong mutual SCA–LCA anti/correlation before analysis. As a final remark, we would like to note that although only results related to CRII were shown here, similar results are obtained for UV or other solar proxies whose variations are concurrent to those of CR.

Acknowledgments

The ISCCP project is acknowledged for the cloud data. Support from the Academy of Finland, the Finnish Academy of Science and Letters Vilho, Yrjö and Kalle Väisälä Foundation, and the Russian Academy of Sciences (Programme of Fundamental Research No. 30) are gratefully acknowledged.

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