

# A critical look at cosmic ray - cloud link: Forbush decreases and cloud cover



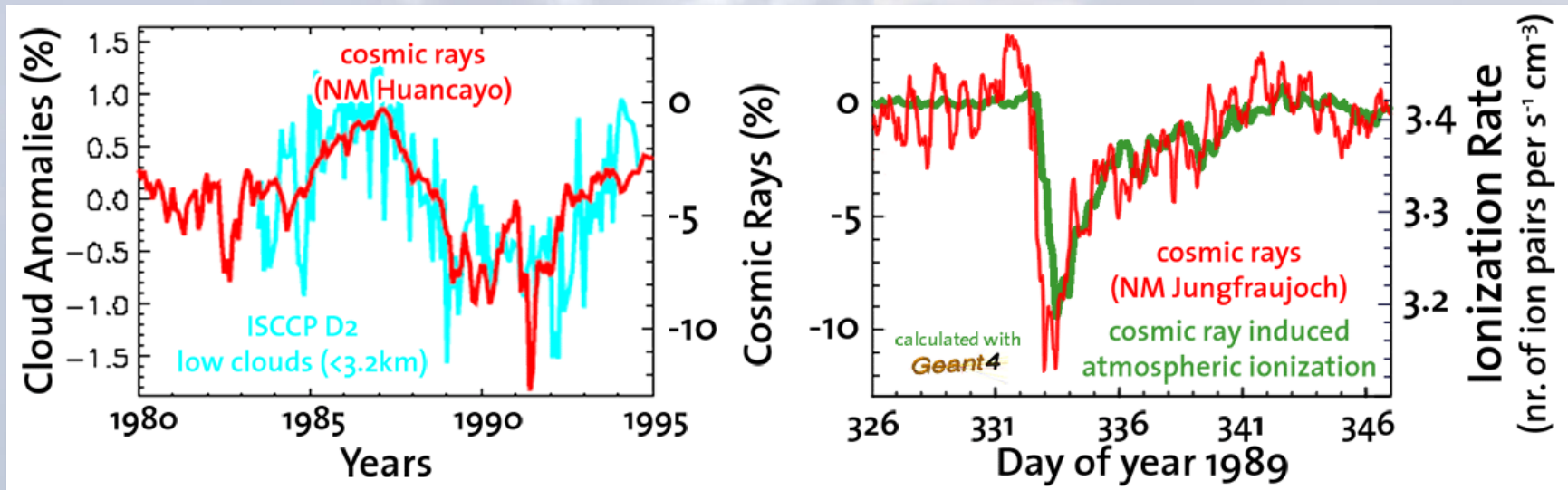
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Hvar Observatory  
Faculty of Geodesy  
Zagreb, Croatia



# Short-term studies - opportunity to test GCR-cloud hypothesis

- Short-term changes in cosmic rays (Forbush decreases) are comparable to variations during the solar cycle.

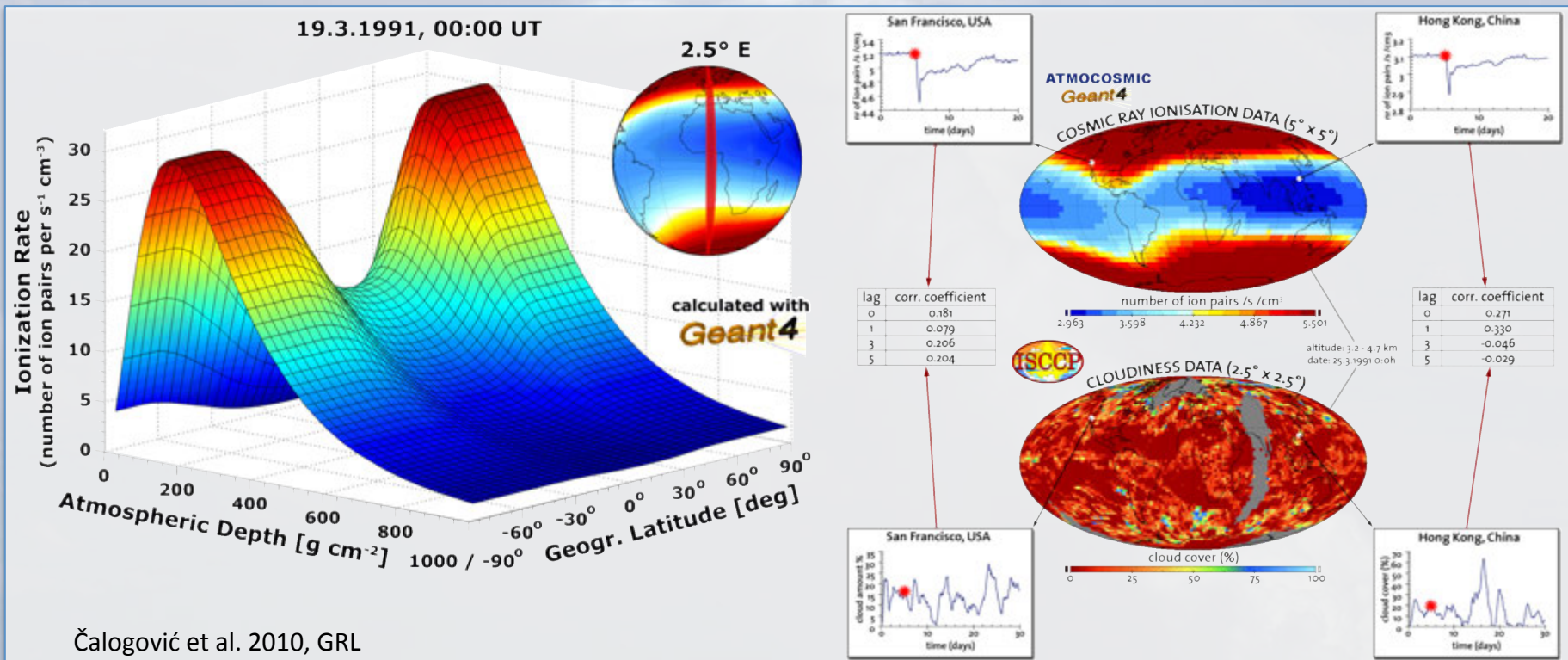


Čalogović et al., 2010

- **Advantages:** some important unwanted factors that influence long-term studies are removed (ENSO, volcanic eruptions, satellite calibration errors)
- **Disadvantages:** Meteorological variability (noise) in clouds has to be **reduced** to be able to detect the solar-related changes (signal), **limited** number of high-magnitude Forbush decreases (several pro cycle)

# Analysis of ISCCP cloud cover during 6 biggest Forbush decreases (1989-1998)

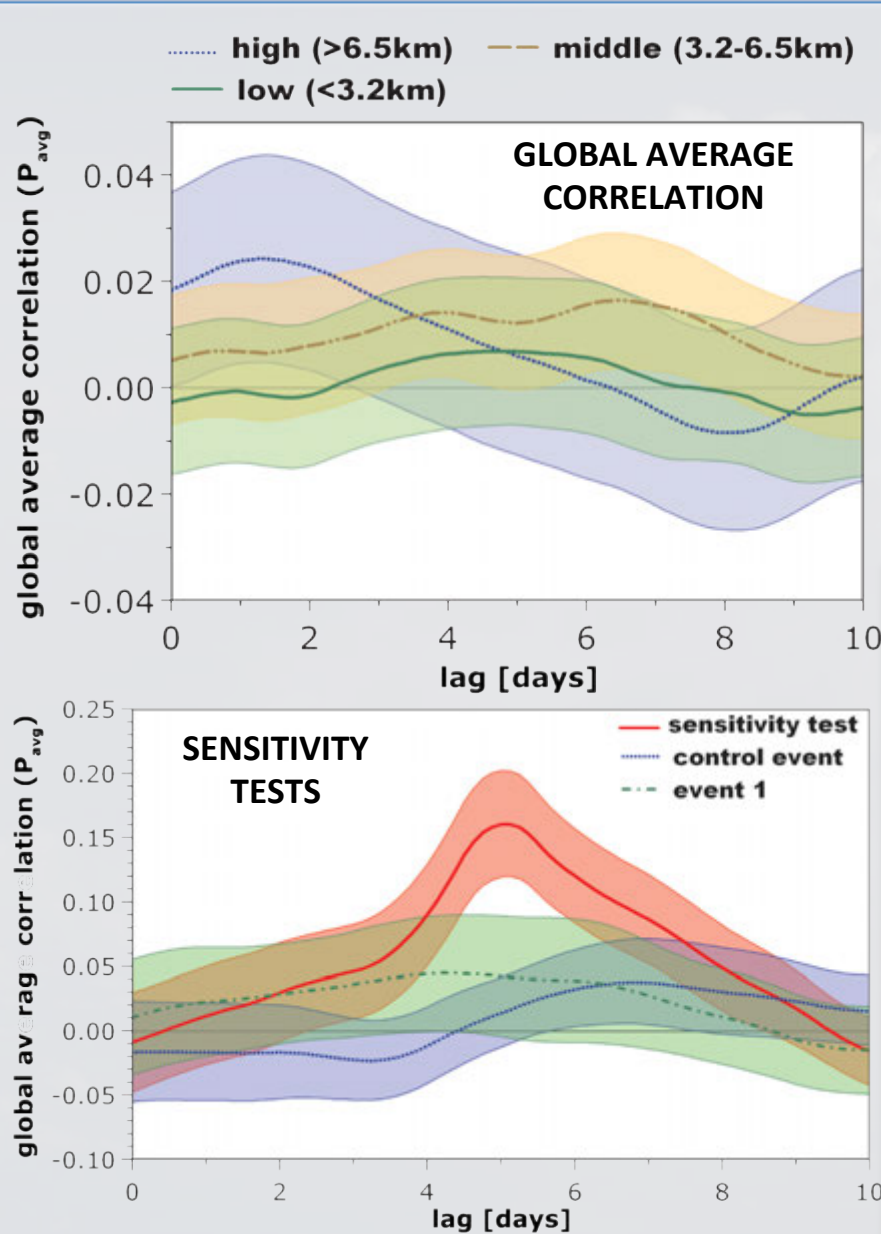
- Forbush events with decreases in CR flux > 9 %
- calculated cosmic ray induced ionization rate (GEANT4, 2.5°x2.5°)
- independent correlation analysis of all grid cells for each lag (10 days)
- in total 8.6 milion correlations calculated





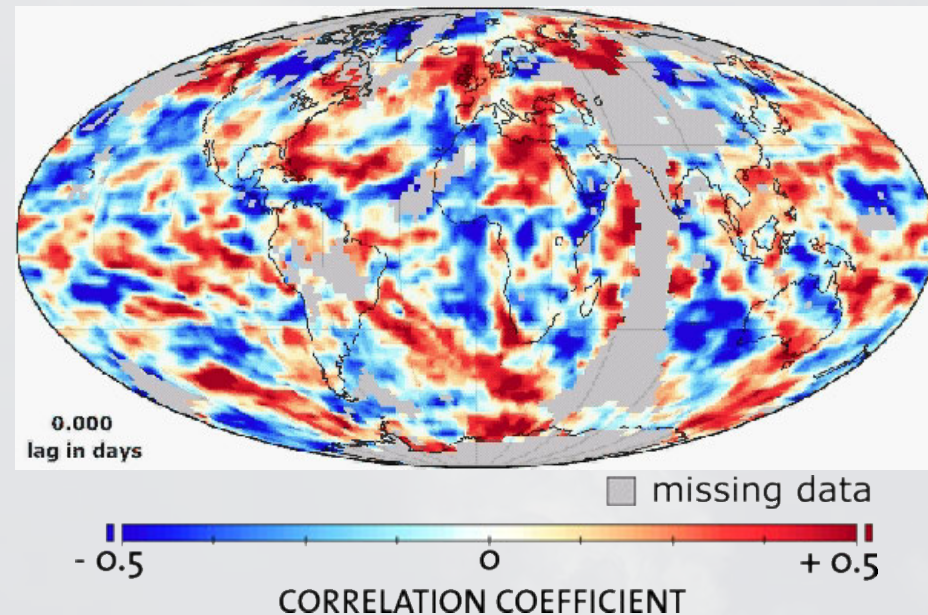
# Results

Čalogović et al., 2010, GRL



- No significant correlations found in all 6 Forbush events together, in analysis of individual events or cloud layers (low, middle, high cloud cover)
- No significant differences for obtained correlations in different areas (low and high latitudes, land, oceans)
- Method is enough sensitive to detect global cloud changes

Low clouds (0-3.2 km), Fd 1



# Short-term studies using Forbush decreases show conflicting results

- **positive correlations:**

Tinsley & Deen, 1991; Pudovkin & Vertenenko, 1995; Todd & Kniveton, 2001; 2004; Kniveton, 2004; Harrison & Stephenson, 2006; Svensmark *et al.*, 2009; Solovyev & Kozlov, 2009; Harrison & Ambaum, 2010; Harrison *et al.* 2011; Okike & Collier, 2011; Dragić *et al.* 2011; 2013; Svensmark *et al.*, 2012; Zhou *et al.* 2013; Aslam & Badruddin, 2015

- **negative correlations:**

Wang *et al.*, 2006; Troshichev *et al.*, 2008

- **no correlations or inconclusive results:**

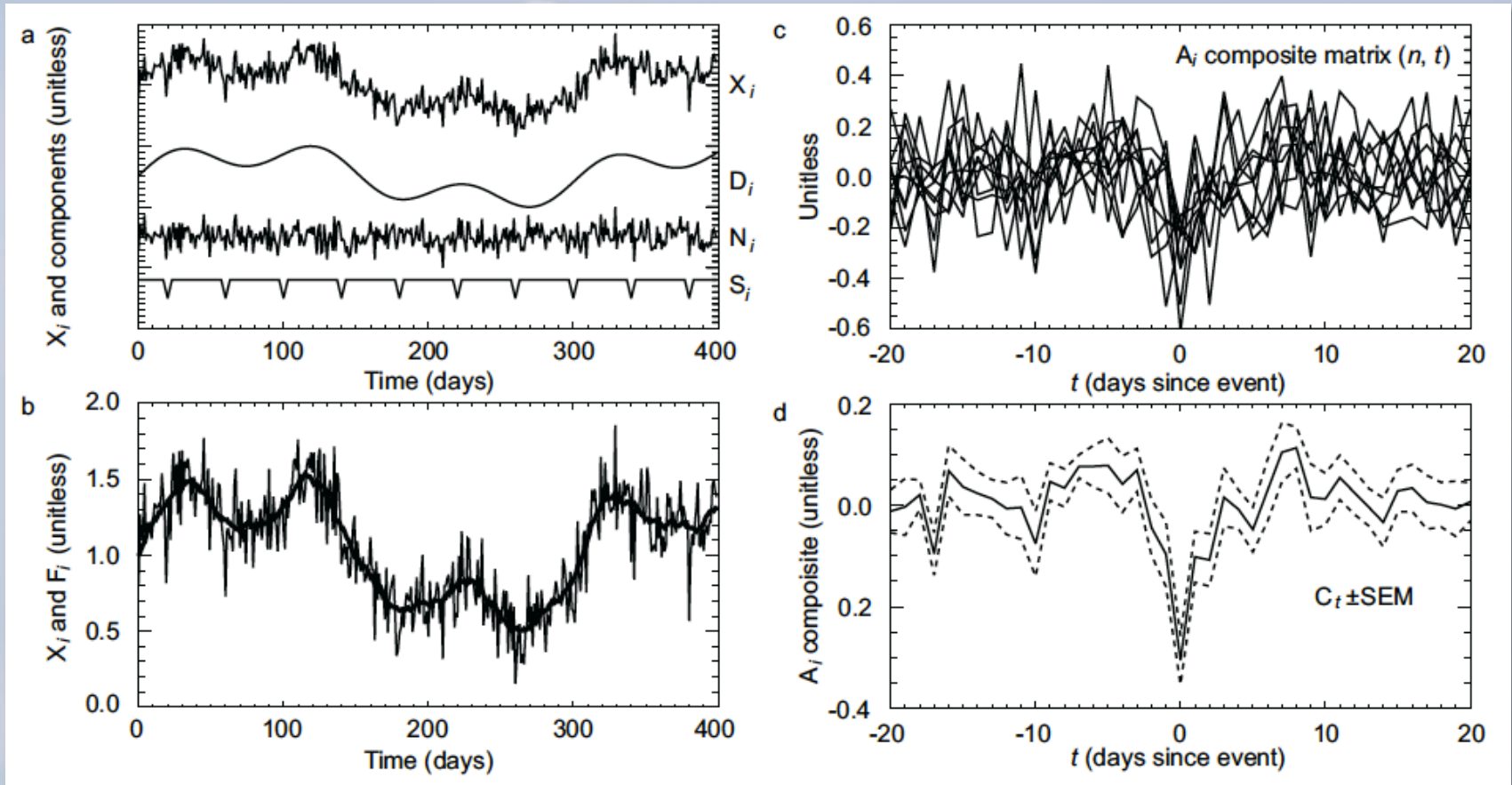
Pallé & Butler, 2001; Lam & Rodger, 2002 ; Kristjánsson *et al.*, 2008 ; Sloan & Wolfendale, 2008; Laken *et al.*, 2009; Čalogović *et al.*, 2010; Laken & Kniveton 2011; Laken *et al.*, 2012; Erlykin and Wolfendale, 2013

# Possible reasons

- there is no relationship between cosmic rays and clouds
- a relationship is too weak to detect (signal to noise ratio)
- other solar parameters may interfere with the results (e.g. TSI, UV) – problem with **signal attribution**
- relationship exists but it is constrained by the atmospheric conditions at the time

# How to isolate the signal using composite?

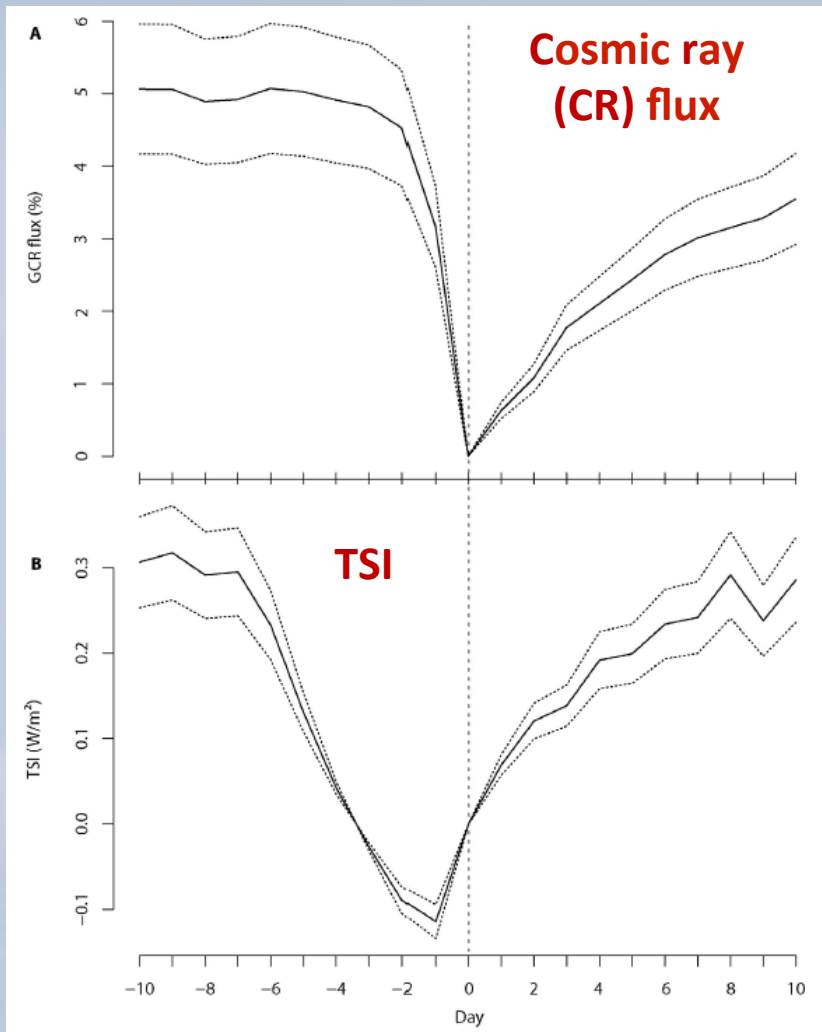
Superposed epoch analysis or conditional sampling



- Successive averaging of events (in time or space)
- Used to increase signal-to-noise ratio (SNR)
- Enable detection of small amplitude signal against large variability

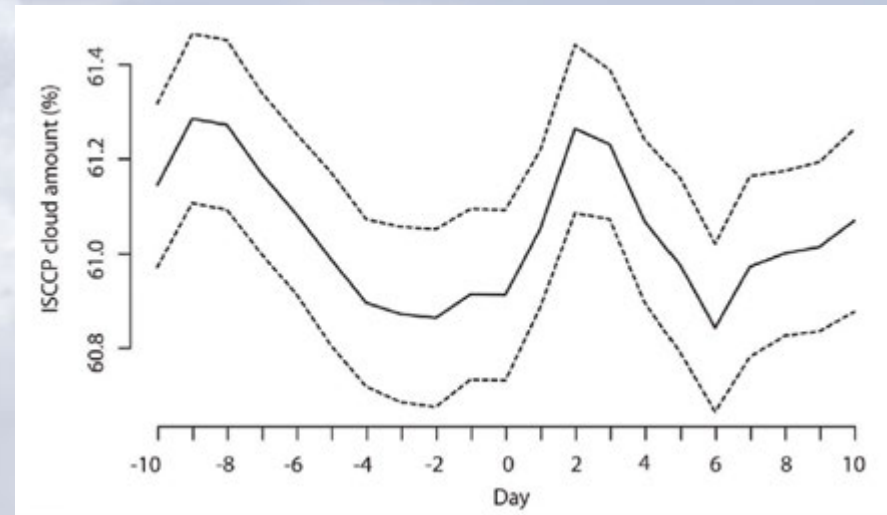


# TSI influences the cloud cover?



Laken et. al., 2011 (JGR)

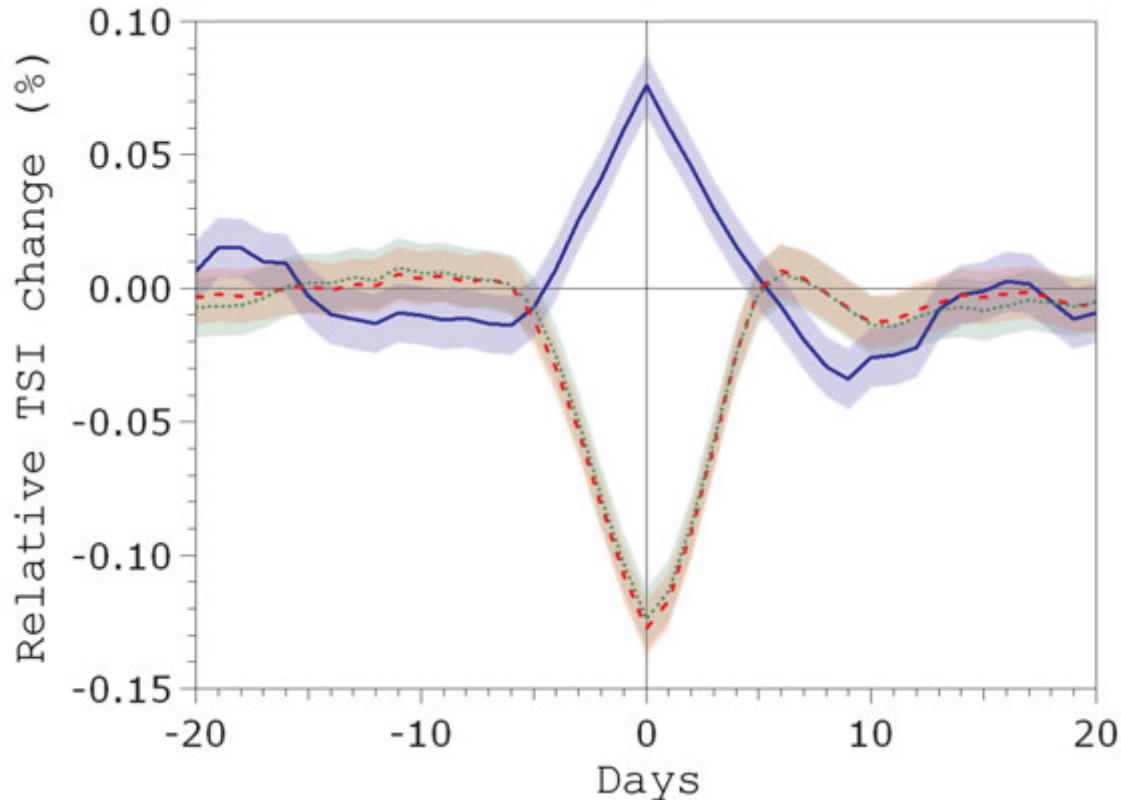
## ISCCP cloud cover



- Composite (superposed epoch) analysis of 123 Forbush decrease events
- cloud cover decreases about 2 days **before** the onset of Forbush decrease (CR flux)



# TSI data and composite samples



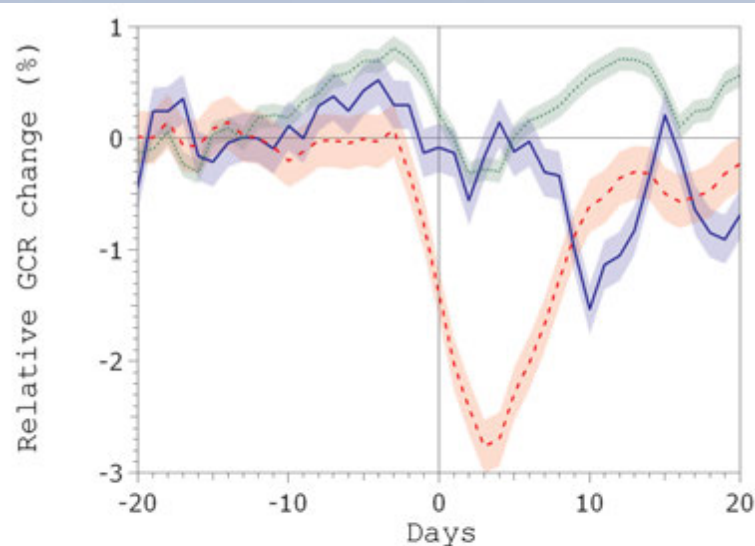
- TSI increase (19 events)
- - - TSI decrease (48 events)
- ... TSI decrease (37 events) without decrease in CR
- SEM - TSI increase
- SEM - TSI decrease
- SEM - TSI decrease without decrease in CR

- Active Cavity Radiometer Irradiance Monitor (ACRIM) reconstruction, 1978-present, daily values
- 3 composite samples:
  - largest increases in TSI (19 events)
  - largest decreases in TSI (48 events)
  - largest decreases in TSI without significant CR variations (37 events)

Laken & Čalogović, 2011 (GRL)

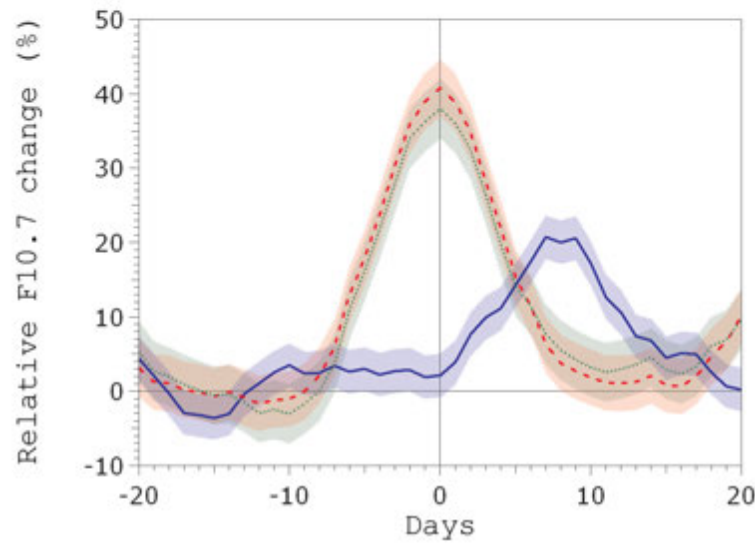
# GCR and F10.7 (EUV) composites

GCR



- CR flux data – Climax neutron monitor ( $R_c=2.99\text{GeV}$ )
- F10.7 (2800Mhz) data – proxy of extreme ultraviolet solar activity (EUV)

UV

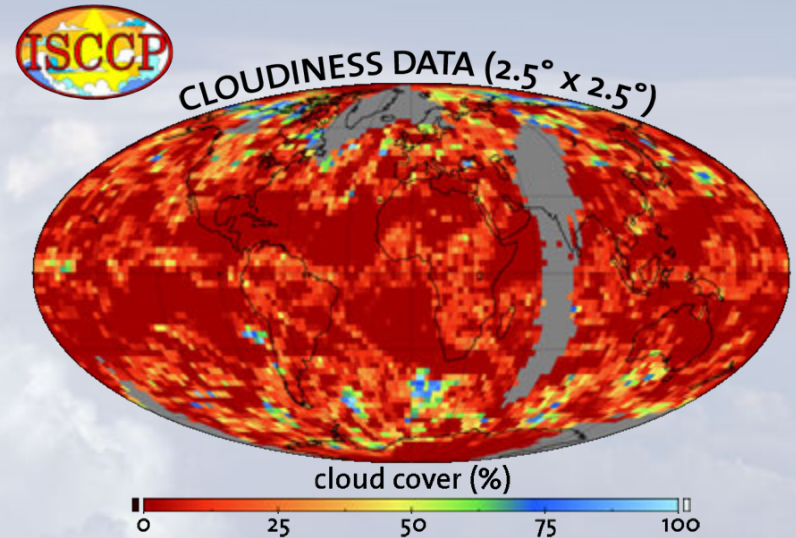


- all composites (TSI, CR, F10.7) correlated with corresponding cloud data using a lag of 20 days

— TSI increase (19 events)  
-- TSI decrease (48 events)  
... TSI decrease (37 events) without decrease in CR  
□ Standard Error of the Mean (SEM) - TSI increase  
□ SEM - TSI decrease  
□ SEM - TSI decrease without decrease in CR

# Cloud data

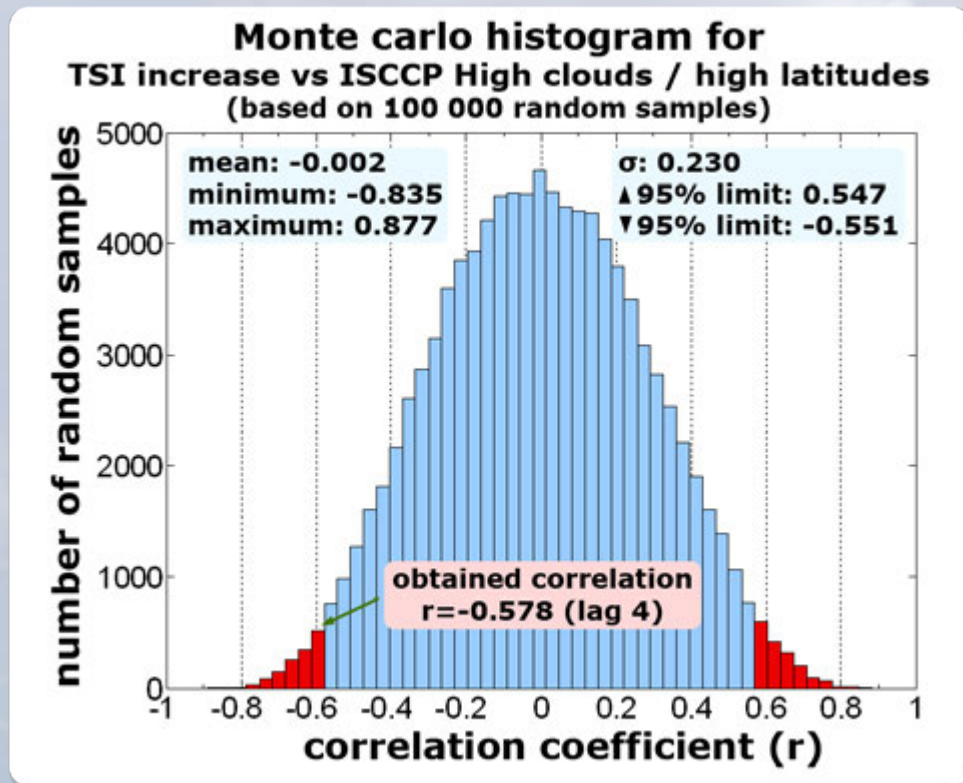
- International Satellite Cloud Climatology Project (ISCCP) D1 dataset, IR data, 1983-2008, temporal resolution 3h, equal-area grid ( $280 \times 280 \text{ km}^2$ )
- 3 different altitude levels: high ( $>6.5 \text{ km}$ ), middle ( $3.2 - 6.5 \text{ km}$ ) and low ( $0 - 3.2 \text{ km}$ ) clouds
- daily averaged
- area-averaging was applied for different regions:
  - global
  - low latitudes ( $<45^\circ$ )
  - high latitudes ( $>45^\circ$ )
  - regions over land
  - regions over ocean





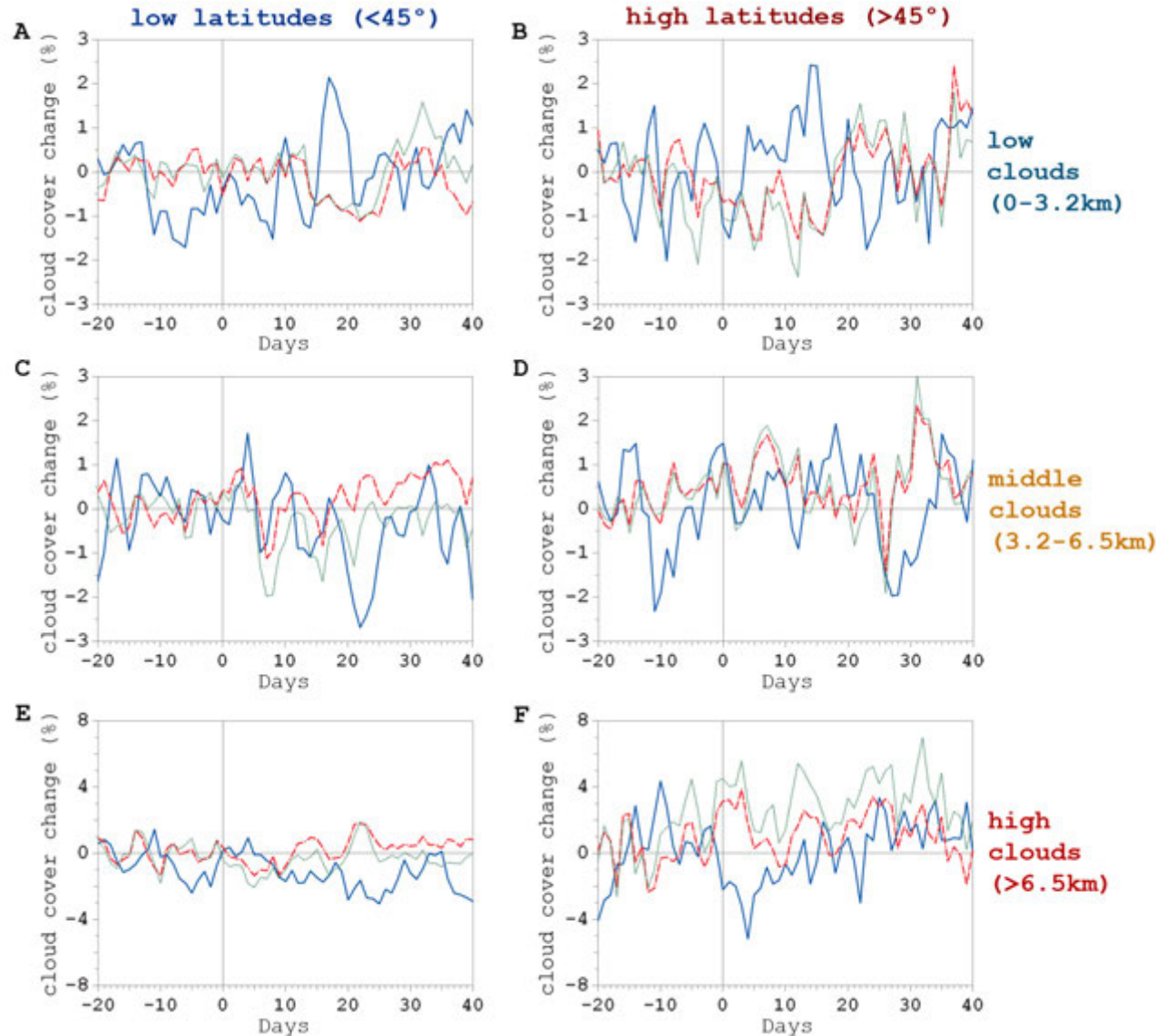
# Monte Carlo tests

- employed to establish the threshold significance values for the correlation coefficients ( $r$ )
- for each parameter 100 000 randomly generated  $r$



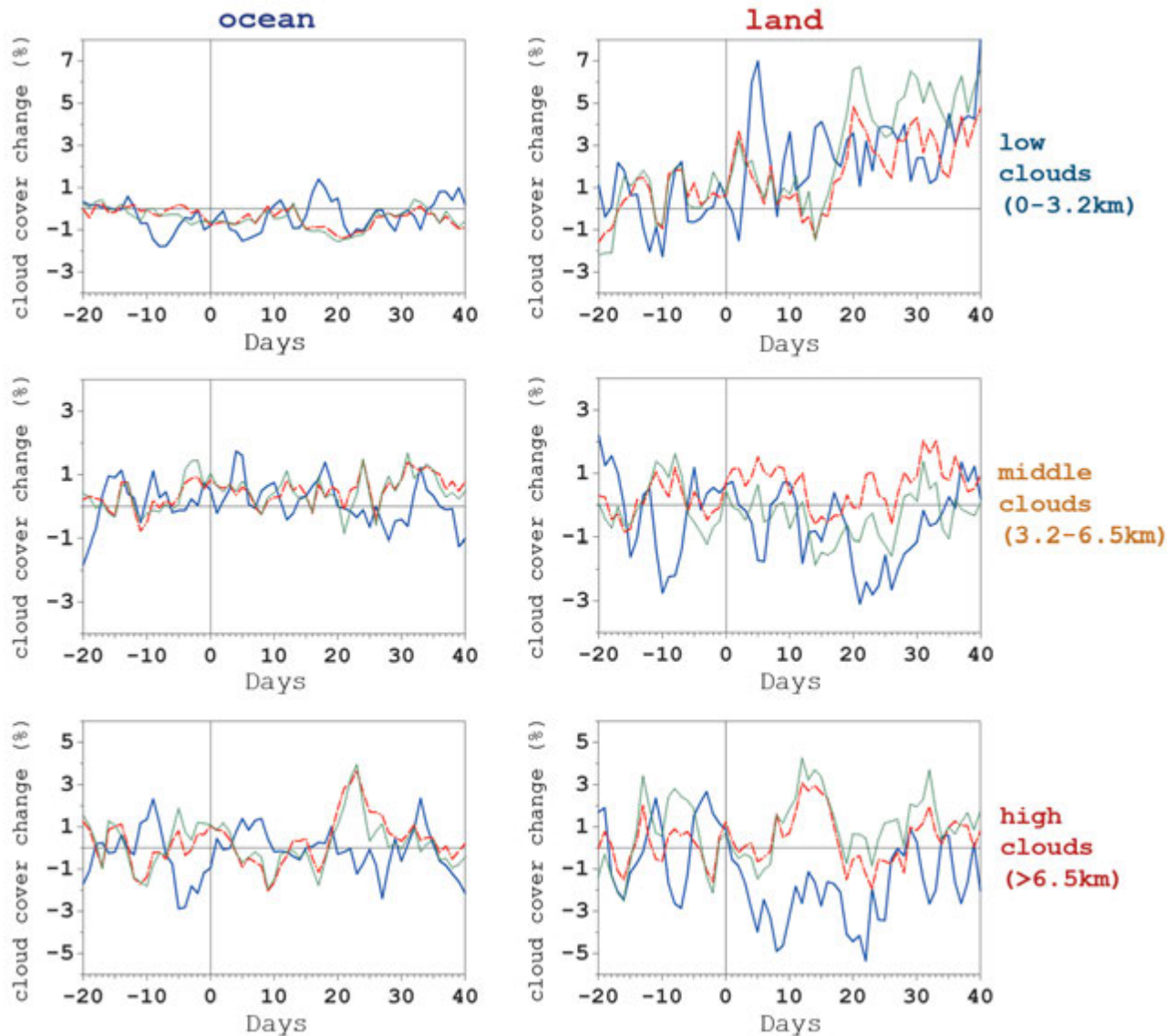
- Shapiro-Wilk test of normalcy: all  $r$  are normally distributed ( $W = 0.996$ ,  $p = 4.8 \times 10^{-10}$ )
- statistical significance set by two-tailed 0.95 percentile MC generated  $r$  values

# Cloud composites – low and high latitudes



- no significant correlations with TSI, CR and UV composites

# Cloud composites – ocean and land

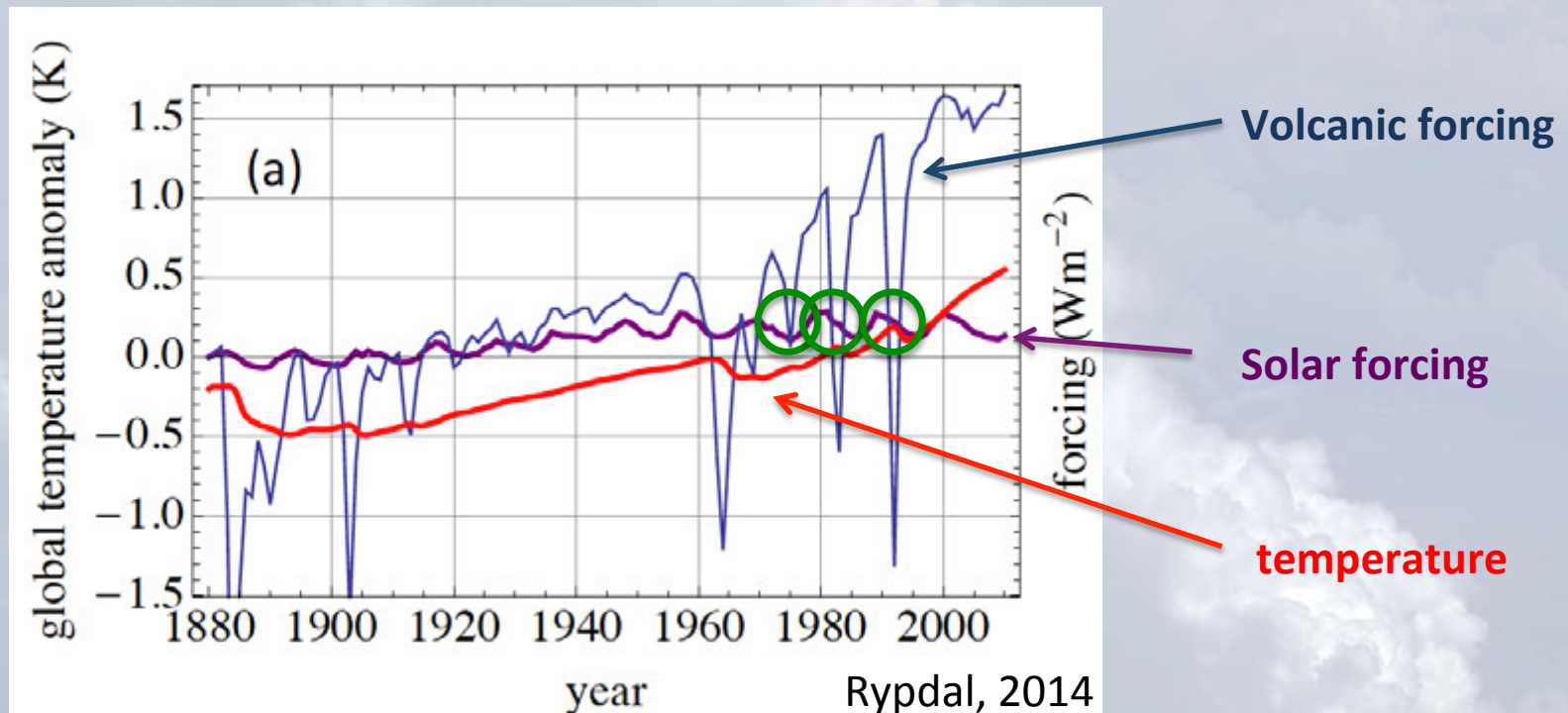


- no significant correlations with TSI, CR and UV composites



# If some climate signal is found - it should be properly attributed to solar forcing

- Other external and internal factors influencing the climate parameters should be identified → eg. attribution by multiple regression or models (if possible)
- Last few solar cycles coincidentally match with strong volcanic eruptions (volcanic forcing)

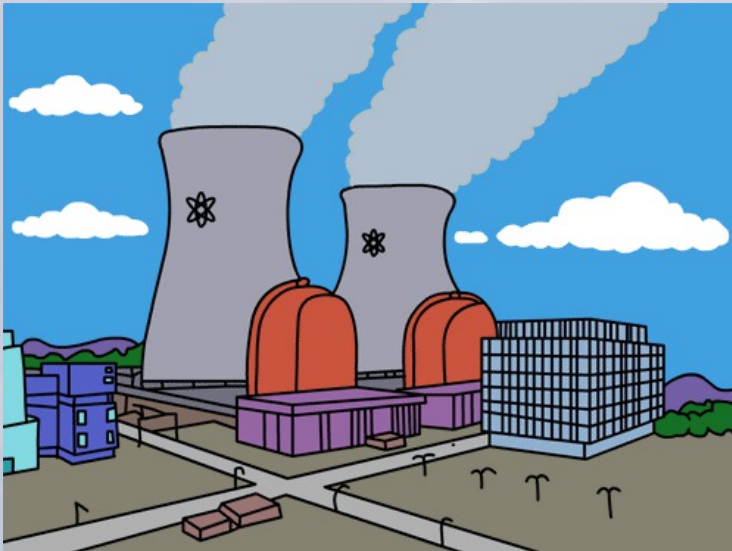


# Student question and discussion

**Aleksandra Skakun**

Shortly present the results from Svensmark and Friis-Christensen, 1997 or Friis-Christensen and Lassen, 1991. What are some weaknesses of their studies? Using an example (e.g. such as a GCR–cloud or GCR-temperature correlation) explain the limitations of a correlation analysis in relation to supporting specific solar–terrestrial mechanisms.

How improper statistical tools or data handling can lead to misleading or erroneous results that can have important (bad) implications?



Aleksandra Skakun



## Length of the Solar Cycle: An Indicator of Solar Activity Closely Associated with Climate

E. Friis-Christensen; K. Lassen

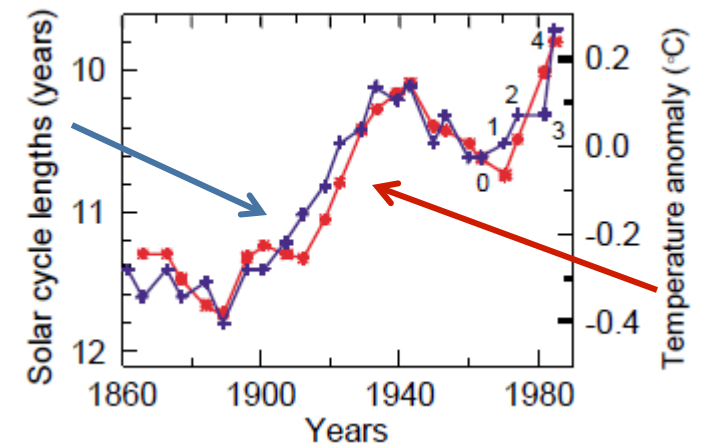
*Science*, New Series, Vol. 254, No. 5032. (Nov. 1, 1991), pp. 698-7

Solar cycle length



Northern Hemisphere land air temperature

1991



## Influence of Cosmic Rays on Earth's Climate

Henrik Svensmark\*

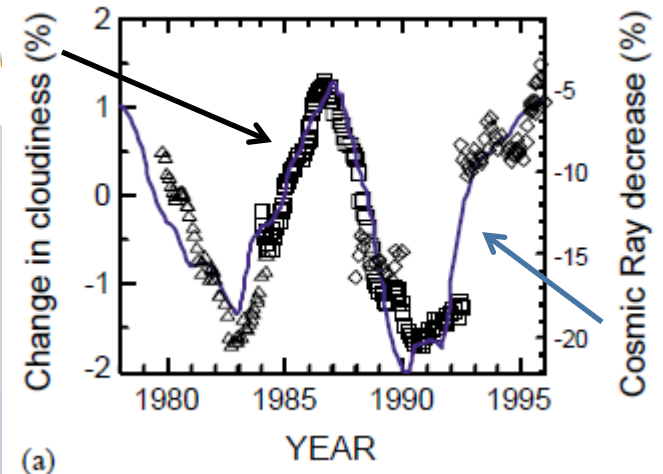
*Solar-Terrrestrial Physics Division, Danish Meteorological Institute, Lyngbyvej 30, DK-210*  
(Received 16 September 1997; revised manuscript received 17 July

Intensity of galactic cosmic rays



Total cloud cover

1998



## Length of the Solar Cycle: An Indicator of Solar Activity Closely Associated with Climate

E. Friis-Christensen; K. Lassen

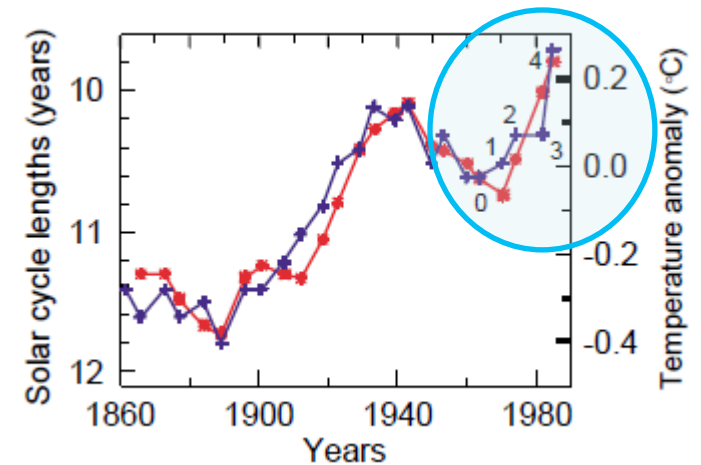
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## Influence of Cosmic Rays on Earth's Climate

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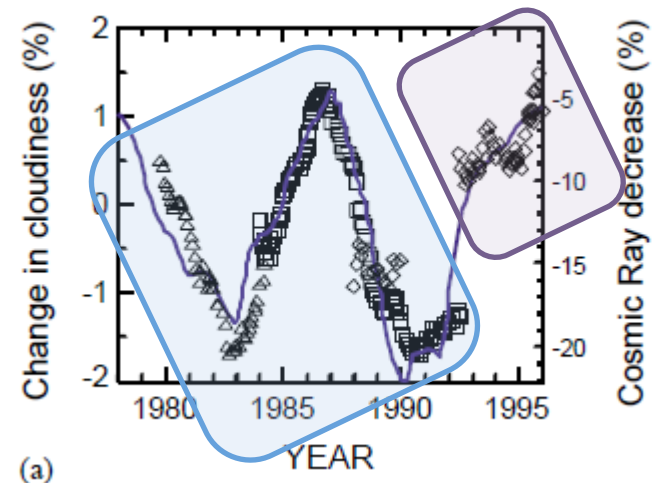
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Intensity of galactic cosmic rays

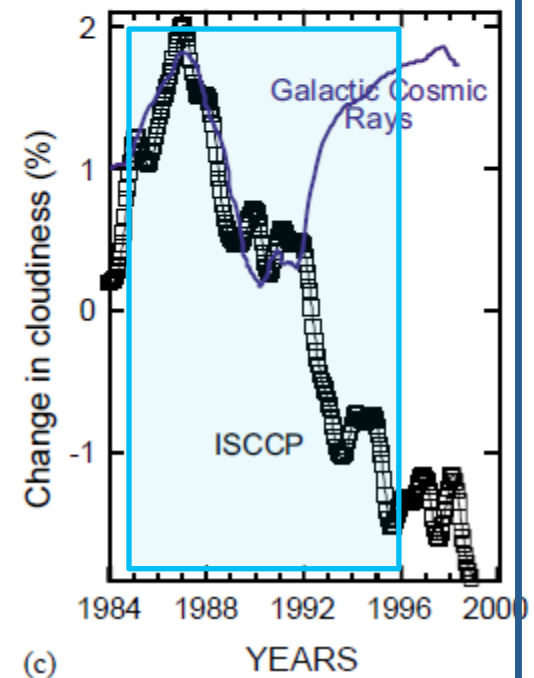
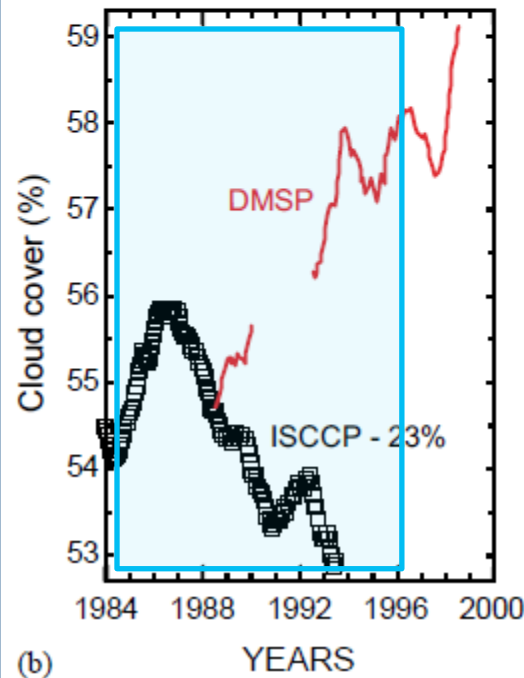
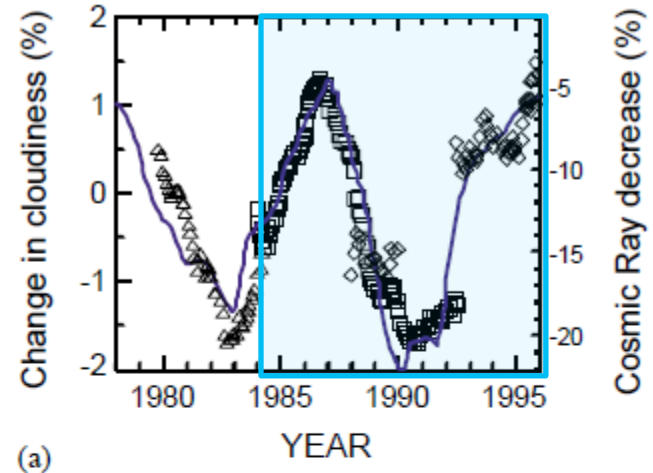
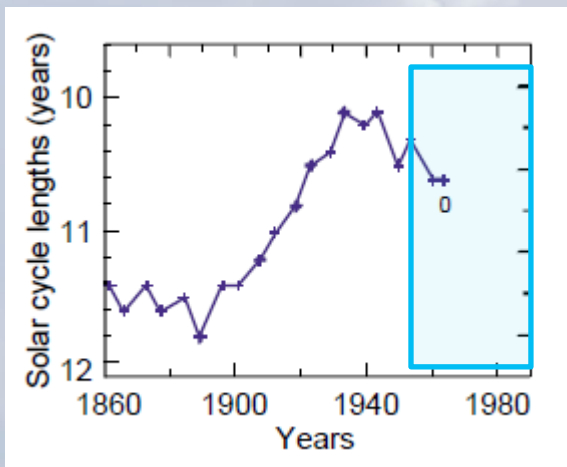
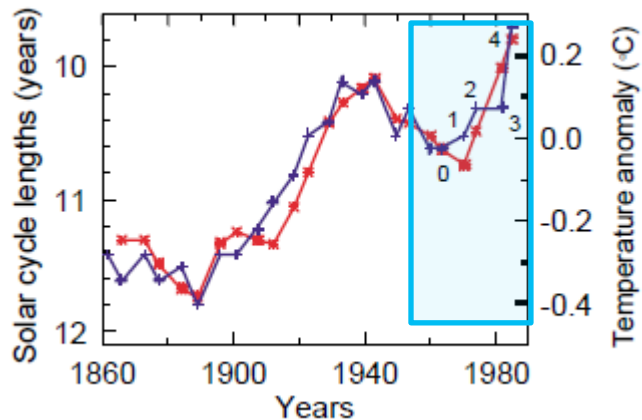


Total cloud cover

1998



# It should be...





# What to do?

- @ Understand the properties of the data
- @ Choose statistical methods appropriate both to the properties of the data and the purpose of the analysis
- @ Critically examine the statistical significance of the result
- @ Endeavor to derive a physical hypothesis
- @ Test the result on one or more independent data-sets



# Do not over-state the statistical or practical significance of the result!!

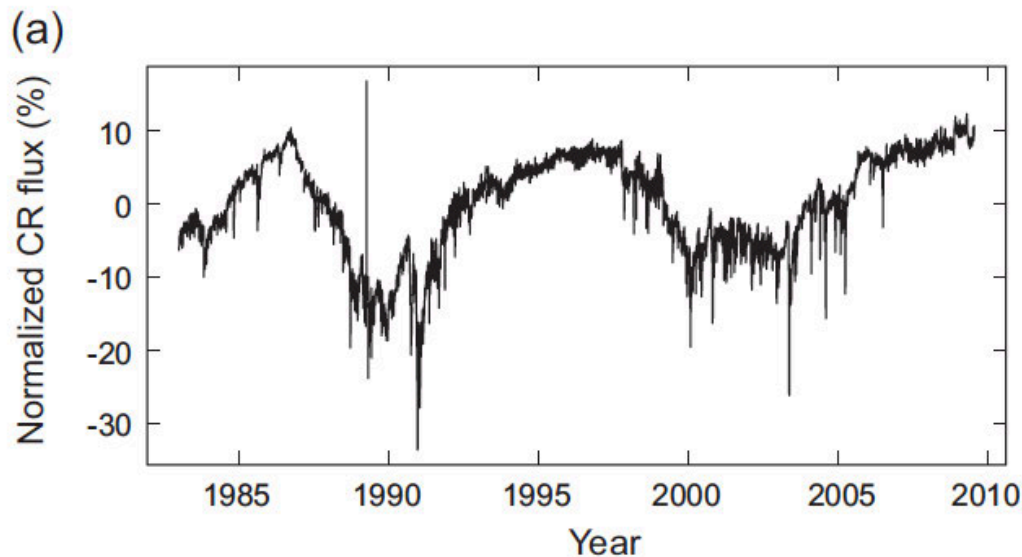


# Possible methodological reasons for conflicting results

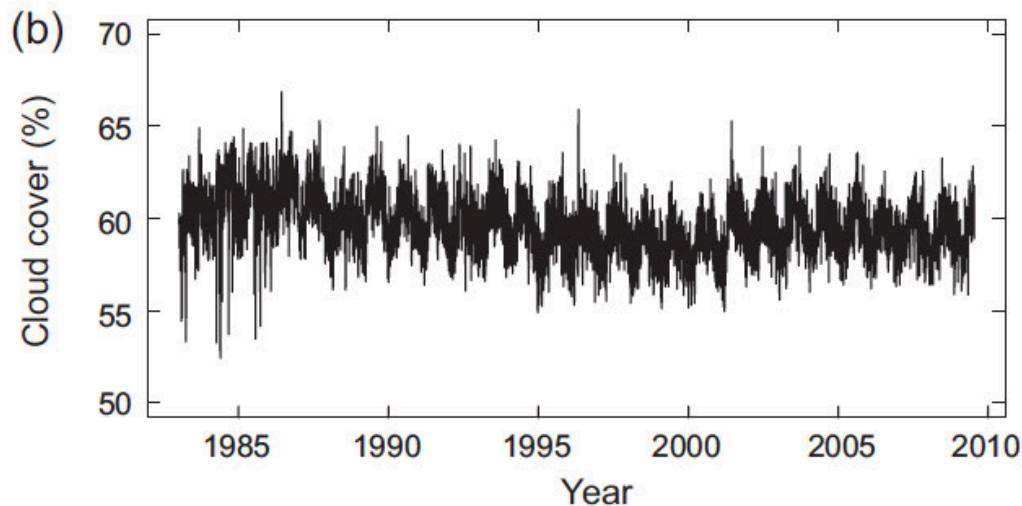
- inappropriate or no data filtering
- wrong statistical assumptions and/or improper use of statistical tools
- “quality” and properties of cloud datasets (**autocorrelated data**)

**So how to test the CR-cloud link reliably ?**

# Cosmic ray flux and cloud data



Daily averaged  
normalized cosmic ray  
flux (%)  
calculated from Climax  
Colorado and Moscow  
neutron monitors



Global and daily  
averaged ISCCP D1 (IR-  
detected) cloud cover  
(%)

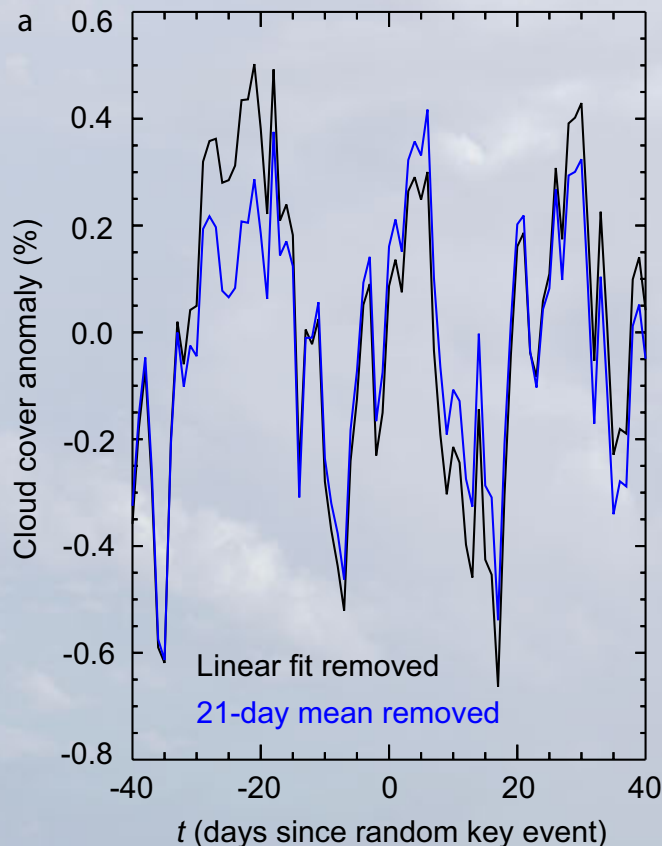


# Composites should be made with anomalies rather than raw data...

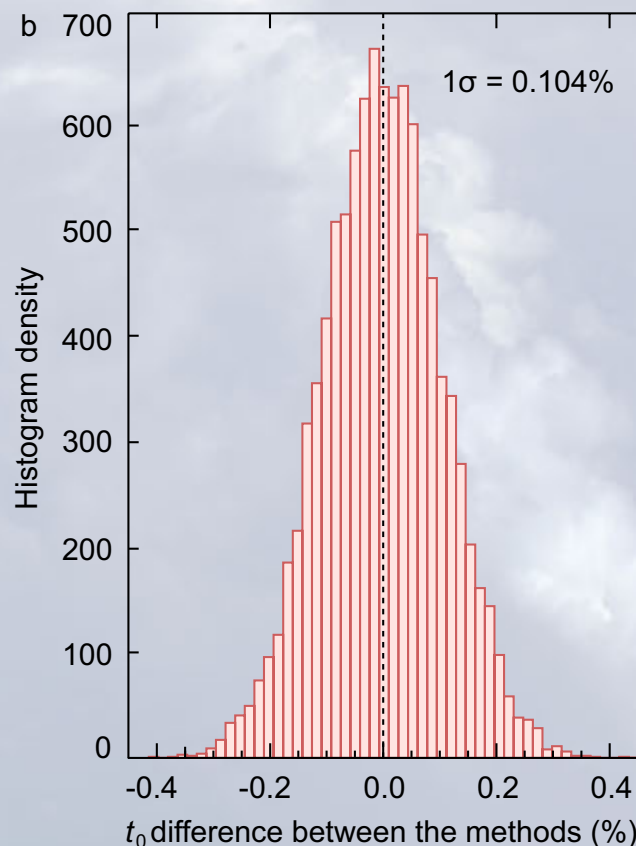
... to minimize variations in data unconnected with hypothesis testing (high-pass filtering)

Comparison of two methods to remove long-term variations ( $n=20$ ): linear trends removed (black), and a only 21-day running mean removed

a) one random composite over  $t_{\pm 40}$



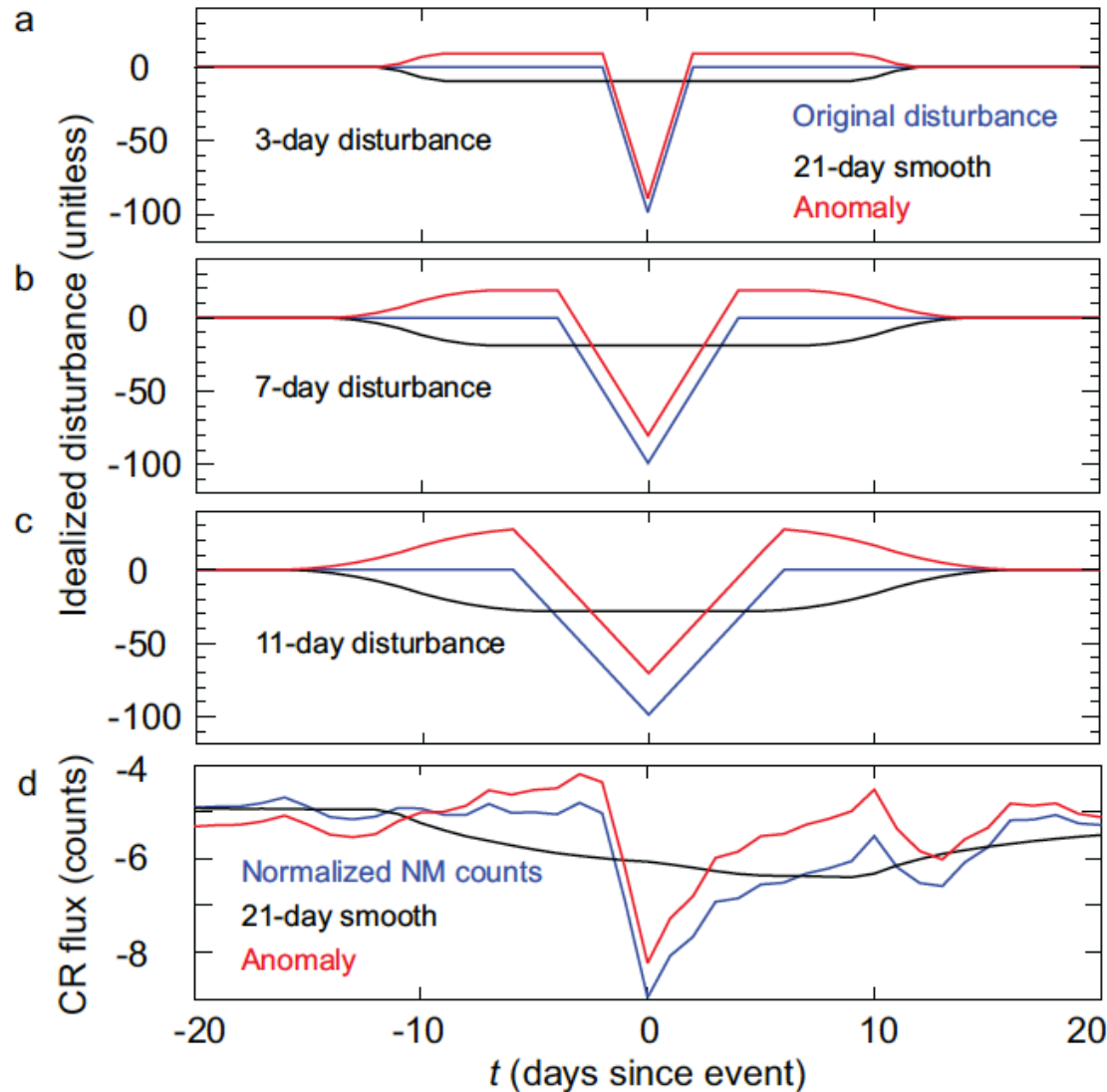
b) 100,000 composites at  $t_0$



Differences (b), indicates remaining non-linear variations in composite from synoptic scale variability. If not removed, this will bias results of composites.

Proper selection of smooth filter width is needed to prevent signal attenuation (duration of searched signal is 1/3rd width of smooth filter)

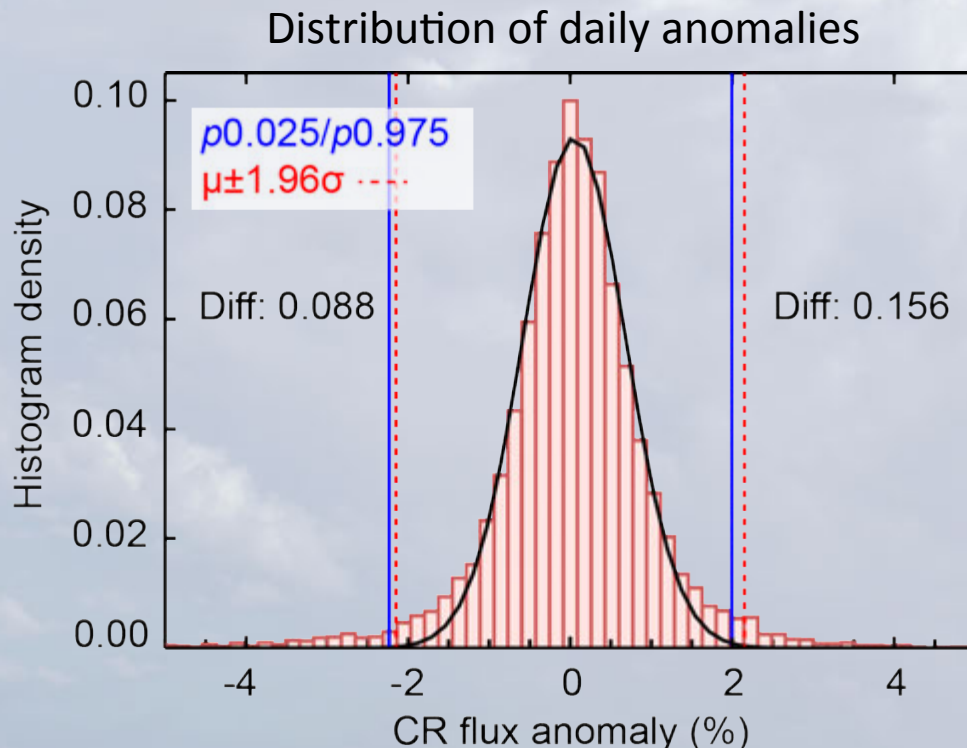
# Overshoot / undershoot effects by filtering the data with different filters (running mean)



For deviations at timescales of approx. 1/3rd the width of the smooth filter, disturbance attenuation is very small or negligible.

# Calculate thresholds for statistical significance with Monte Carlo approach

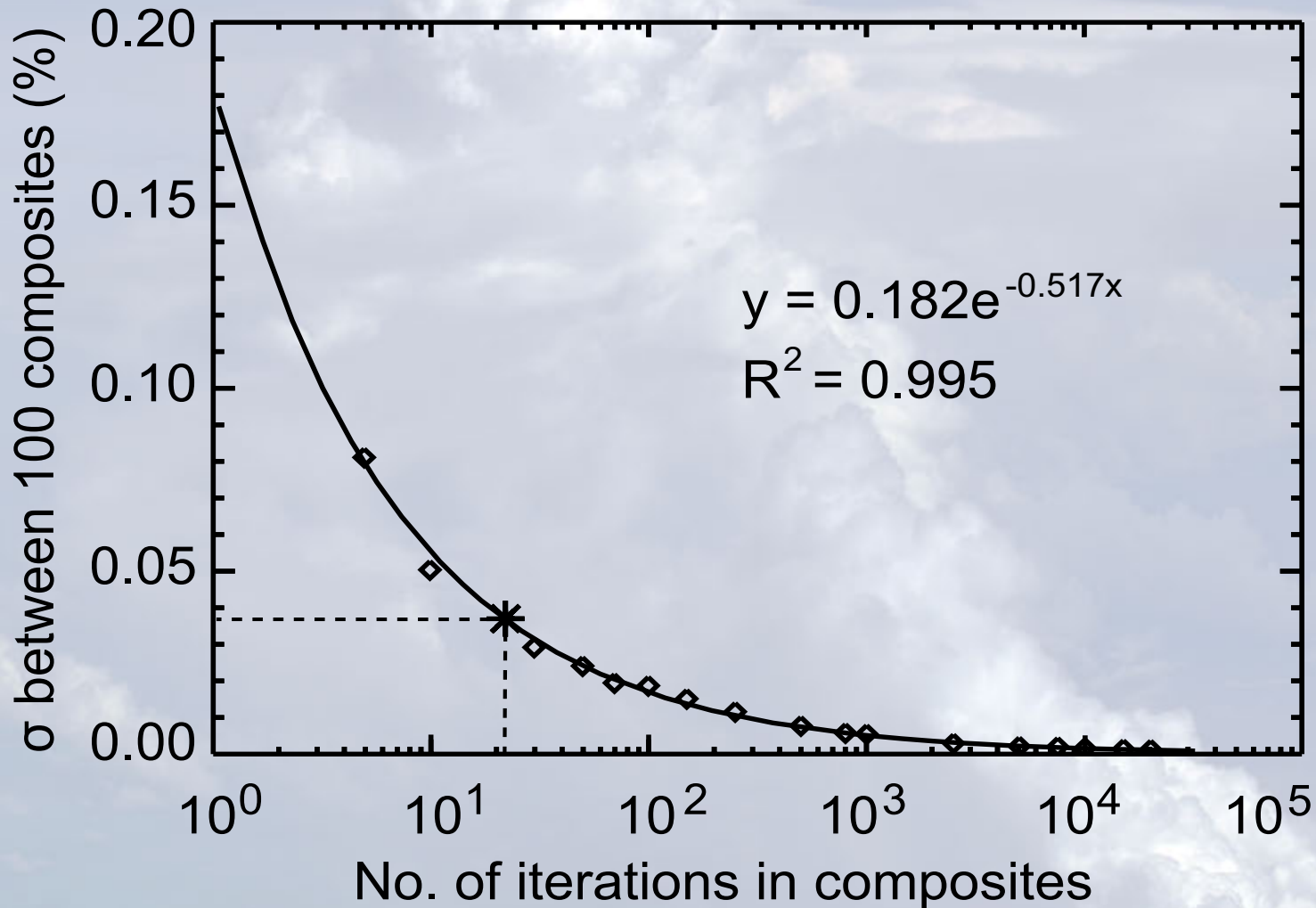
By generating **large populations of random events** identical in design to a composite with real events, the **probability ( $p$ )** of obtaining a given value by chance in a composite with real events **can be accurately known**.



This has **advantages over traditional tests** (e.g. T/U tests), as it requires **no minimum sample size** or specific distribution, and it doesn't need **adjustment for autocorrelation**.

Laken & Čalogović, SWSC, 2013

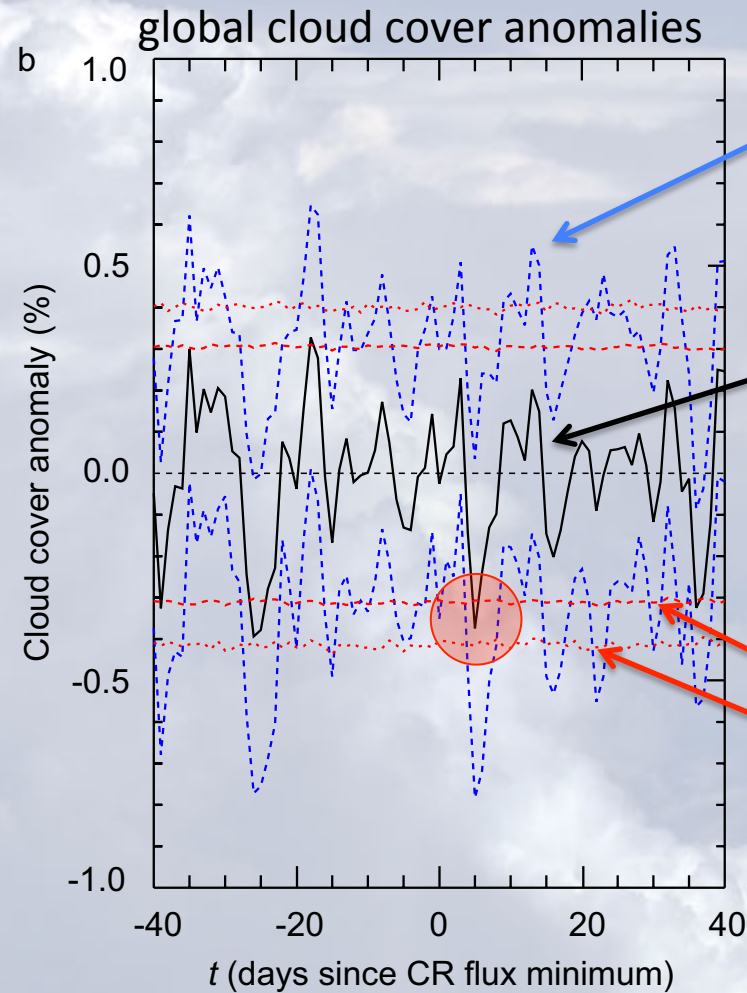
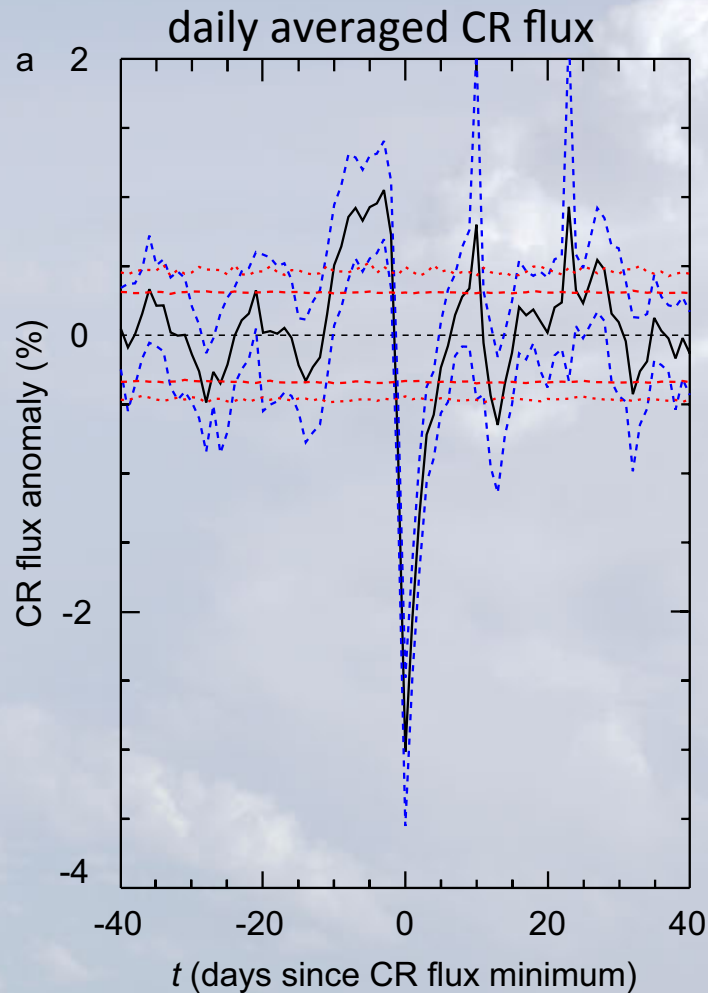
# How many Monte Carlo iterations are enough to get reliable significance intervals?



Laken & Čalogović, SWSC, 2013



# Composites and significance intervals



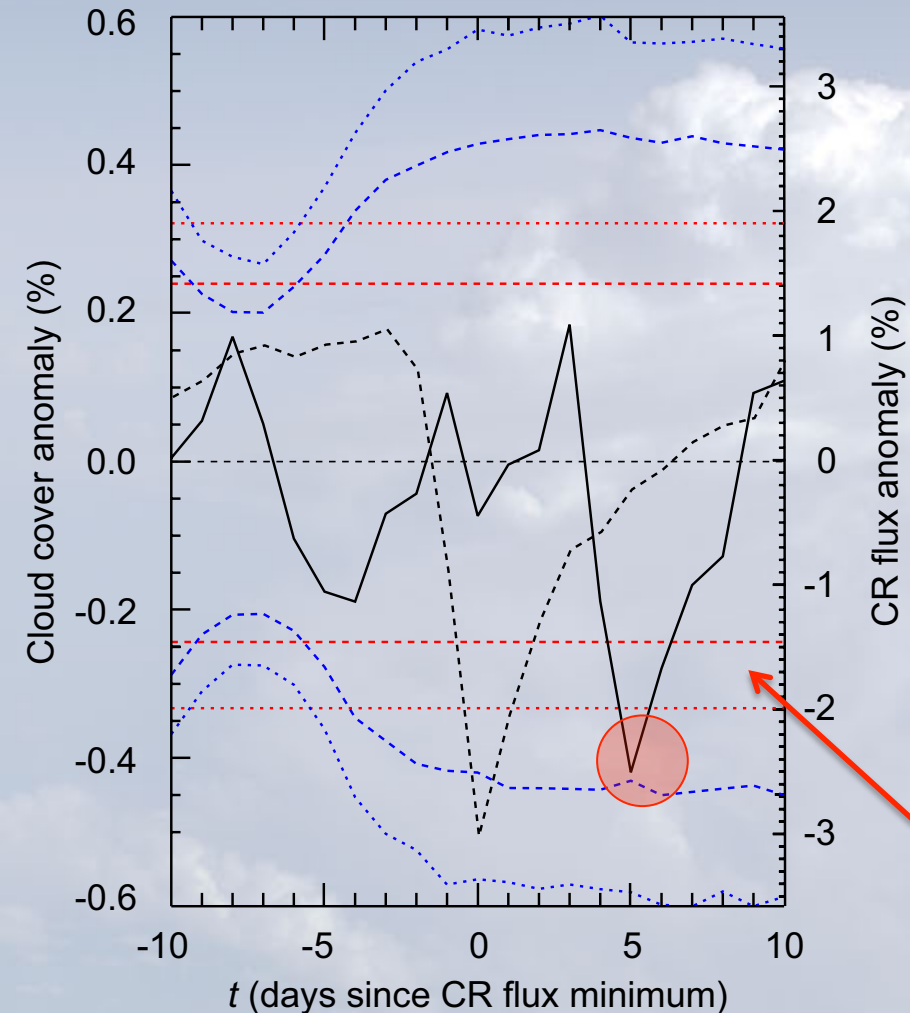
$\pm 1.96$   
Standard  
error of mean  
(SEM)

Anomalies  
(daily mean –  
21-day  
running  
mean)

Confidence  
intervals at  
**p0.05** and  
**p0.01**  
levels  
(obtained from  
PDF of 10,000  
Monte Carlo  
simulations)

Composites consists of 44 events

# How to obtain a false positive

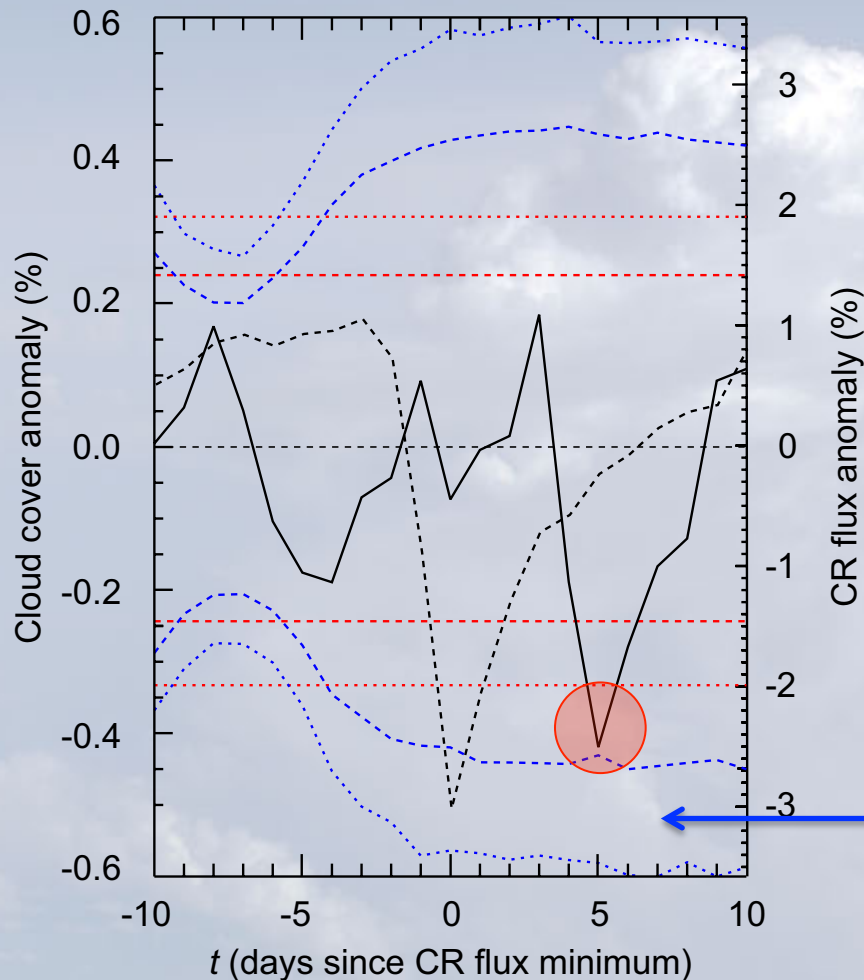


## Cookbook...

- Identify a base or 'undisturbed' period before the key events, that represent 'normal conditions' (e.g. shown example uses  $t_{-10} - t_{-5}$ )
- Calculate deviations against this 'undisturbed' period (i.e. subtract every  $t$  point from mean of 'normal conditions')
- Statistically compare the data to the 'undisturbed' period (e.g. T-test, or even MC from the base period [**red lines p0.05 p0.01**])

**Normalization to base period reduces population variability towards base period, narrowing confidence intervals.**

# How to avoid a false positive



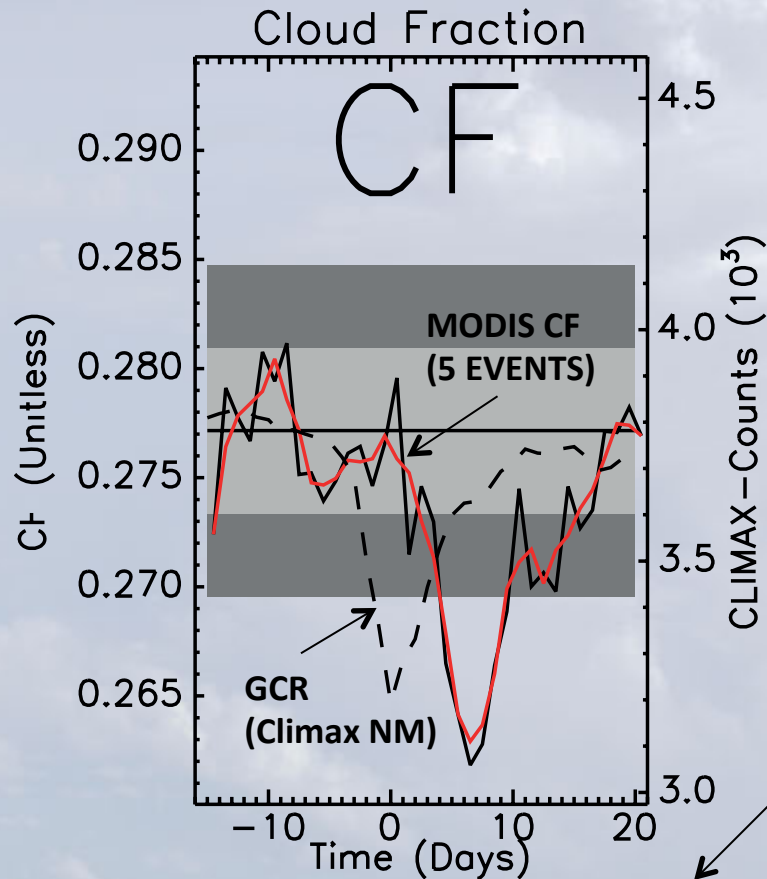
## Overcoming bias with Monte Carlo (MC):

- Use confidence intervals from PDFs obtained with MCs, calculated **independently** for each  $t$  point
- Autocorrelation effects are automatically taken in to account (random samples in the MC all treated with an identical approach to the analyzed composite [blue lines p0.05 p0.01])

**Two different results for  $t_{+5}$  (the above with a mean  $p < 0,05$  and the earlier, with a mean  $0.01 > p > 0.05$  so which is correct?)**

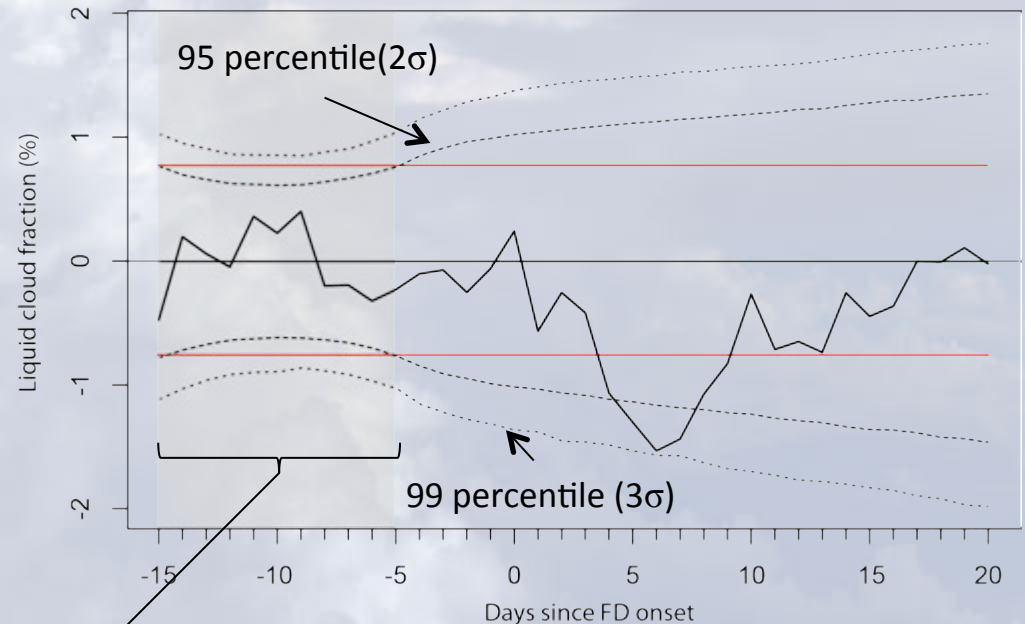
# Big variability in the clouds can be often mixed with the expected signal!

Svensmark et al. 2012, ACPD



Data NORMALIZED between period of day -15 and day -5

Laken, Čalogović, Beer and Pallé (2012), ACPD



Dashed/dotted lines show **correctly** adjusted 2 and 3 $\sigma$  level – calculated from 10,000 MC simulations

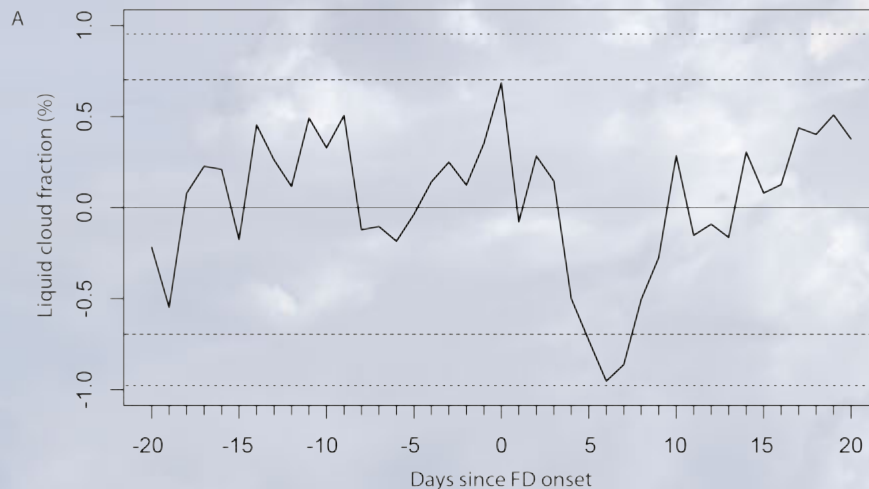
**Proper statistical tests (MC simulations) are needed to assess the correct statistical significance!**



# Extension to longer analysis periods reveals no unusual variability in clouds during Fd events

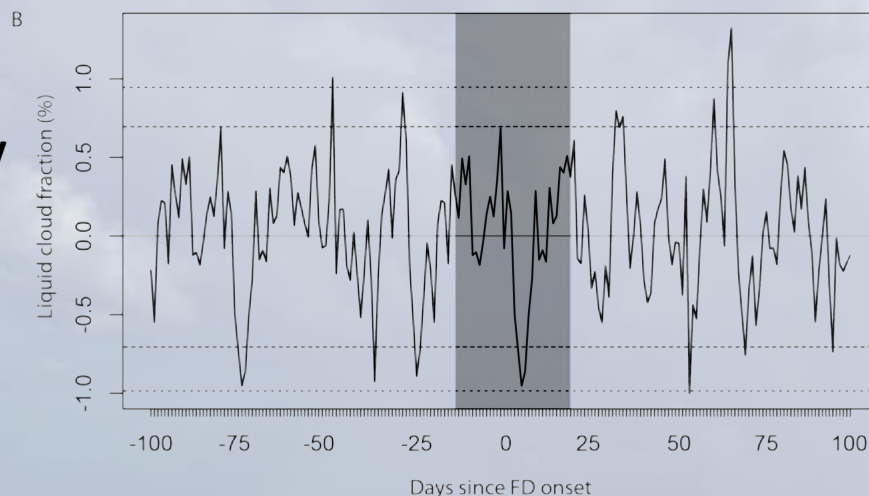
MODIS Liquid cloud fraction changes using 5 biggest Fd events from Svensmark et al. (2012)

**±20 day  
analysis  
period**



Values are anomalies from 21-day moving averages (i.e. mean of each day subtracted from 21-day moving average).

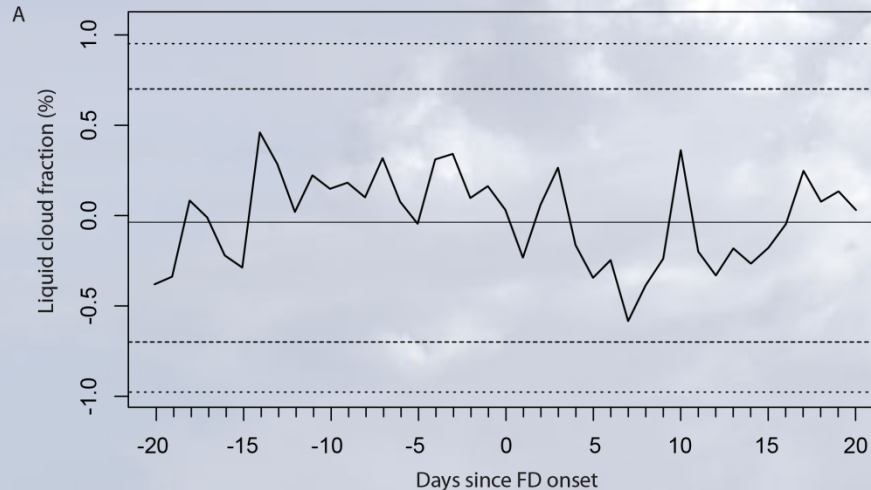
**±100 day  
analysis  
period**



Dashed and dotted lines indicate the 95th and 99th (two-tailed) percentile confidence intervals respectively calculated from 100,000 Monte Carlo simulations.

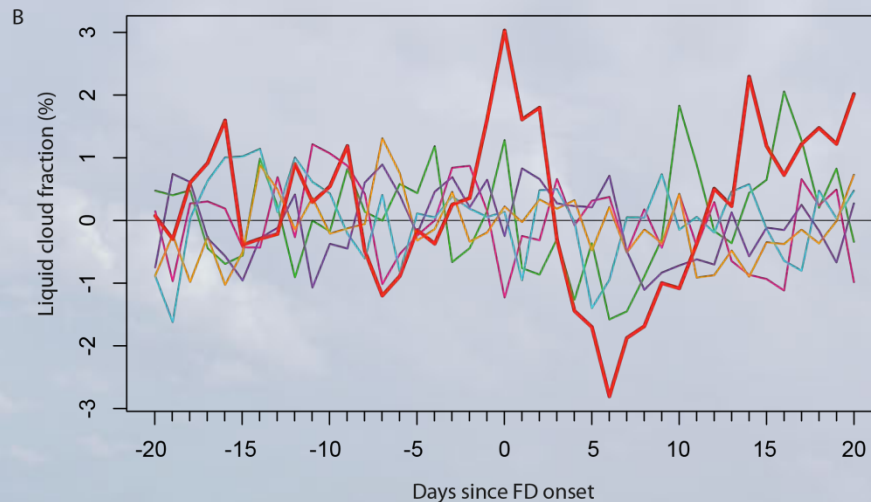
Laken, Čalogović, Beer and Pallé (2012), *ACPD*

# Just one event (and eventually outlier) can influence the whole composite



MODIS cloud fraction composite for Fd events 1, 3, 4, 5, 6 ranked by Svensmark et al. 2012

By replacing the event 2 with event 6 there are no significant changes in the composite!



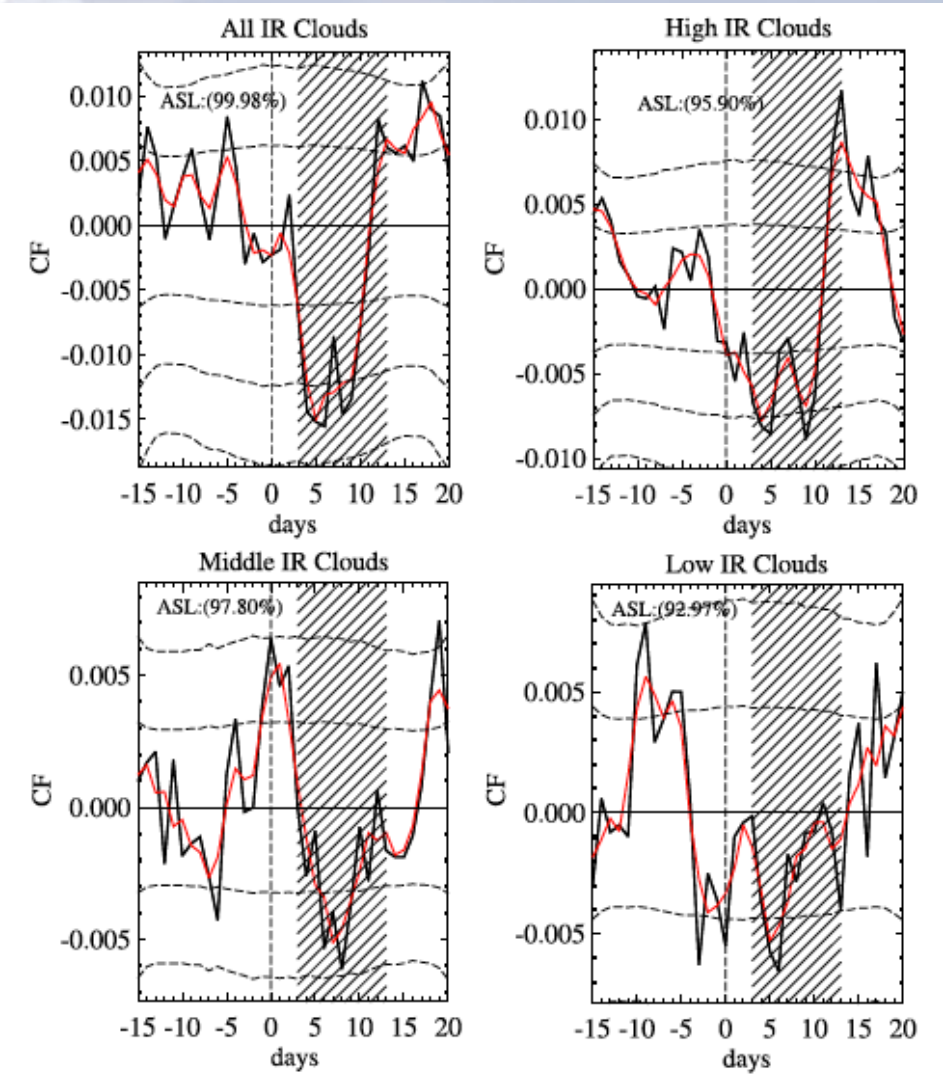
Individual 5 Fd events plotted against event 2 (19.1.2005) where is clear that all significance in Svensmark composite comes from event 2.

Laken, Čalogović, Beer and Pallé (2012), *ACPD*

# New results from Svensmark et al., 2016 again claim strong CR induced changes in clouds

ISCCP, cloud fraction (CF) for different cloud altitudes

- Analyze various cloud and aerosol data: AERONET (CCN data), SSM/I (liquid water content), ISCCP (low, middle, high clouds over the oceans), MODIS (cloud effective emissivity, optical thickness, liquid water, cloud fraction, LWP, effective radius)
- In almost all parameters response on 95% level is found
- Authors sort 26 Forbush decrease events to their size and use only strongest 5 events



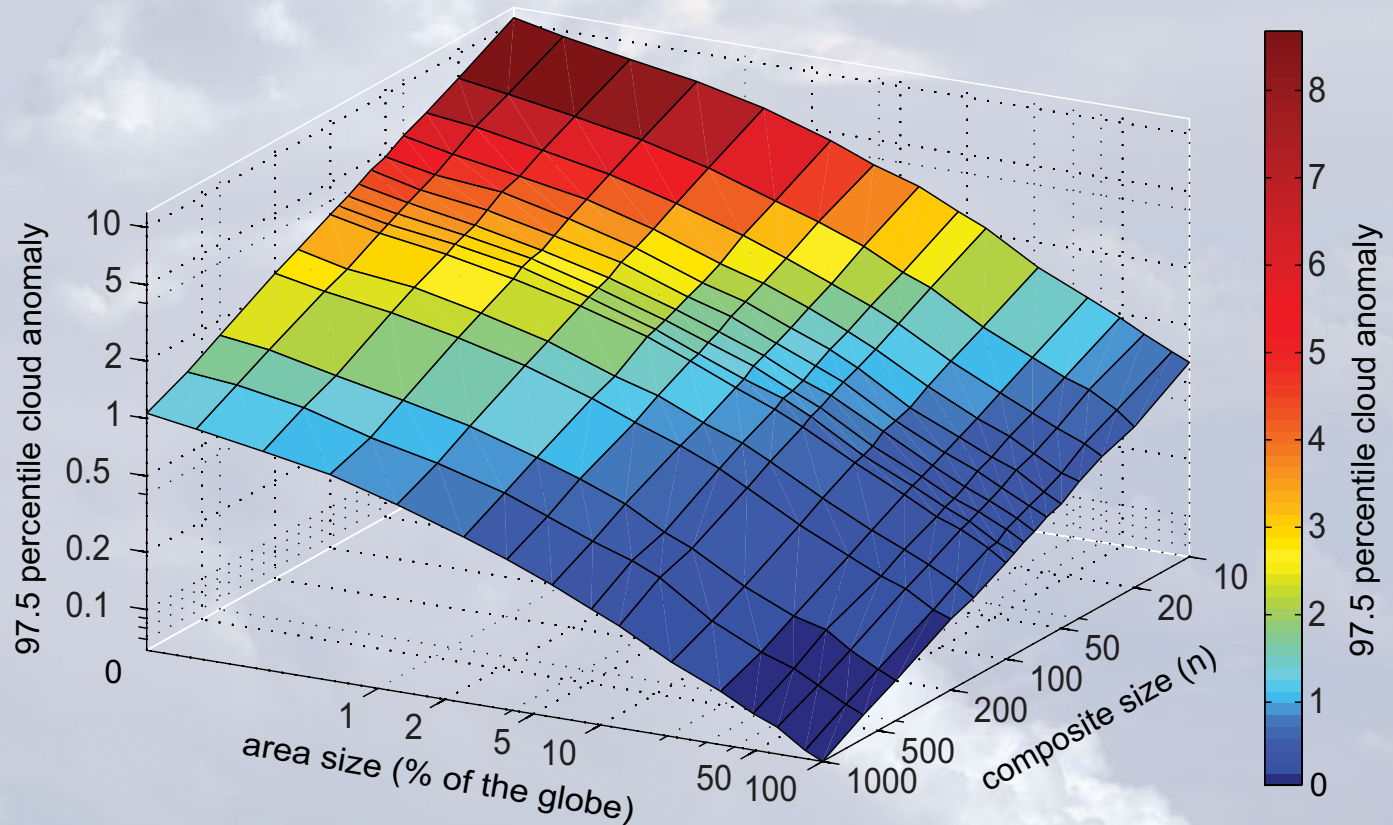
Svensmark et al., 2016, JGR

# Size of sample area and number of events impact the noise

Noise levels of data govern detectability of a signal. The noise varies with both the spatial area ( $a$ ) that is averaged, and the number of composite events ( $n$ ).

'Noise' indicated by 97.5<sup>th</sup> percentile values from 10,000 random composites of varying  $a$  and  $n$  size.

Each point of grid represents another independent set of 10,000 MC simulations

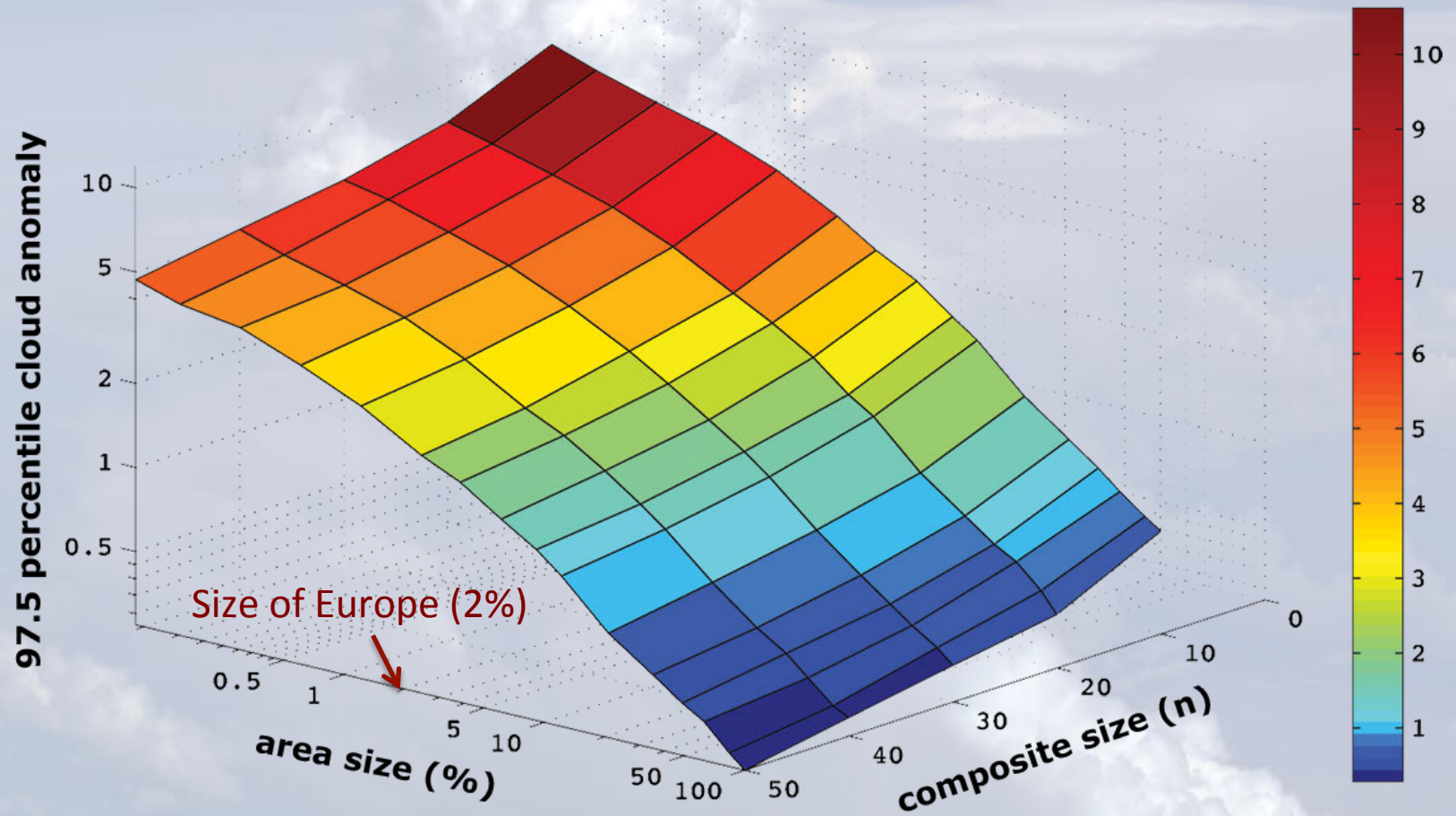


Laken & Čalogović, SWSC, 2013

possible to see how large  $a$  and  $n$  would need to be at minimum to see a hypothesized effect.



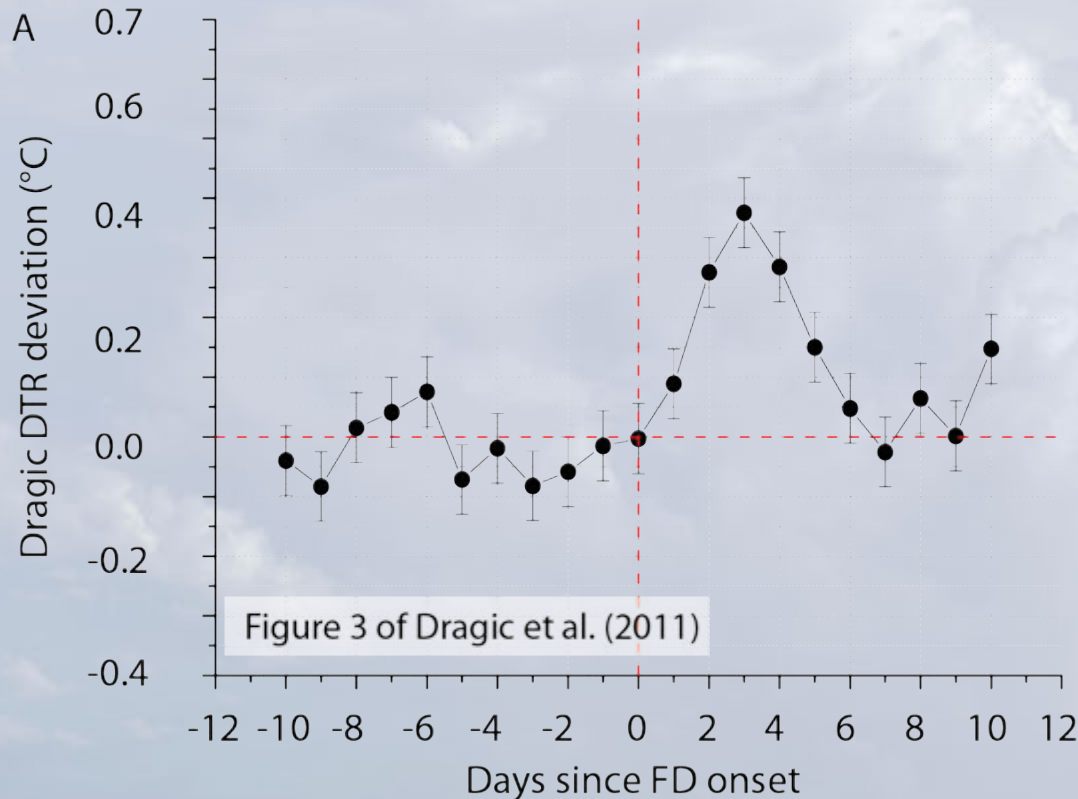
# Majority of Fd studies use less than 50 events ( $n < 50$ )



Studies using only strong Fd events have usually **less than 10 events**

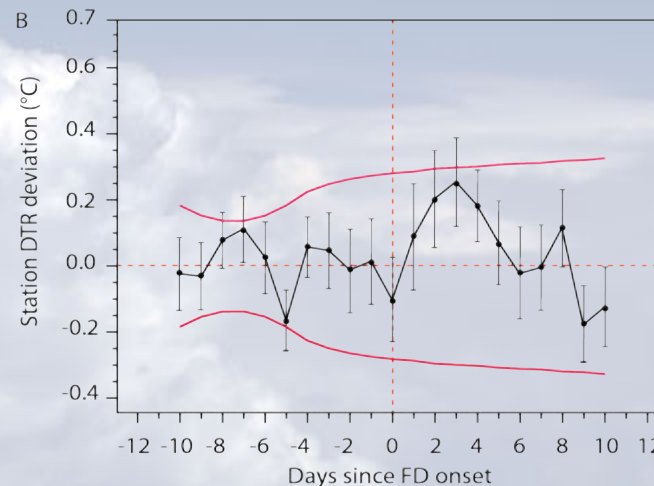
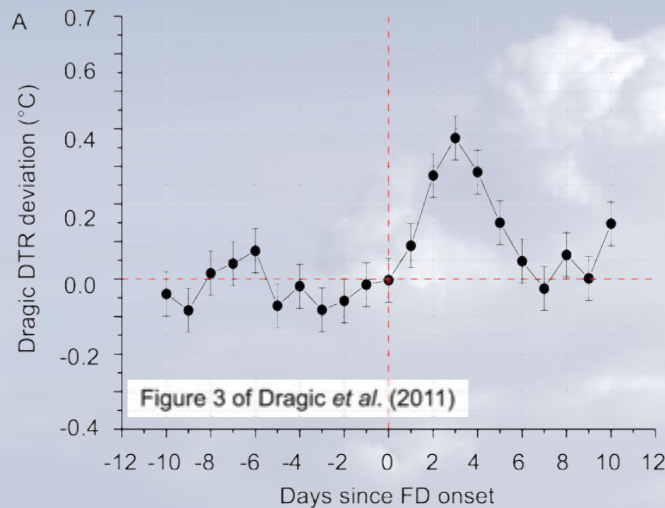
# DTR shows response to Fd events?

- Surface level Diurnal Temperature Range (DTR) → effective proxy for cloud cover (indirect cloud data)
- DTR has longer time span than satellite cloud observations → allows to have the larger number of Forbush events

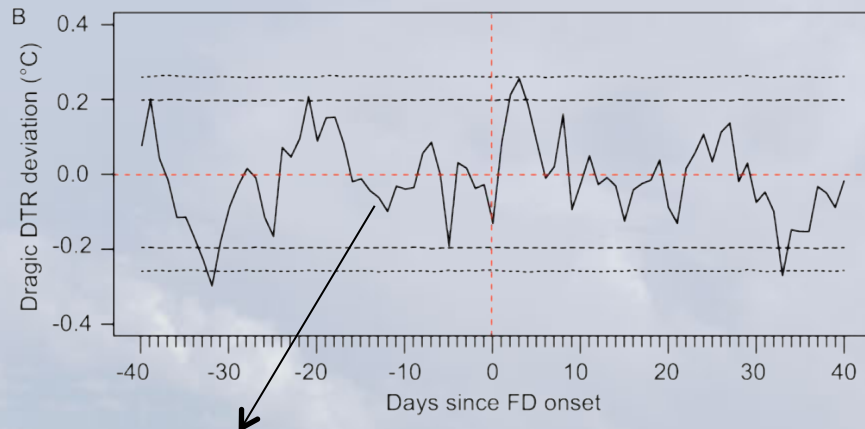


- Dragić et al. (2011) used composite of 37 Fd events (>7%) that show significant increase in DTR → support for GCR-cloud hypothesis

# Analysis of Dragić et al. (2011) results



Dragić et al.  
Normalization  
of data in period  
from  $t_{-10}$  to  $t_{-5}$   
and 99%  
significance  
intervals

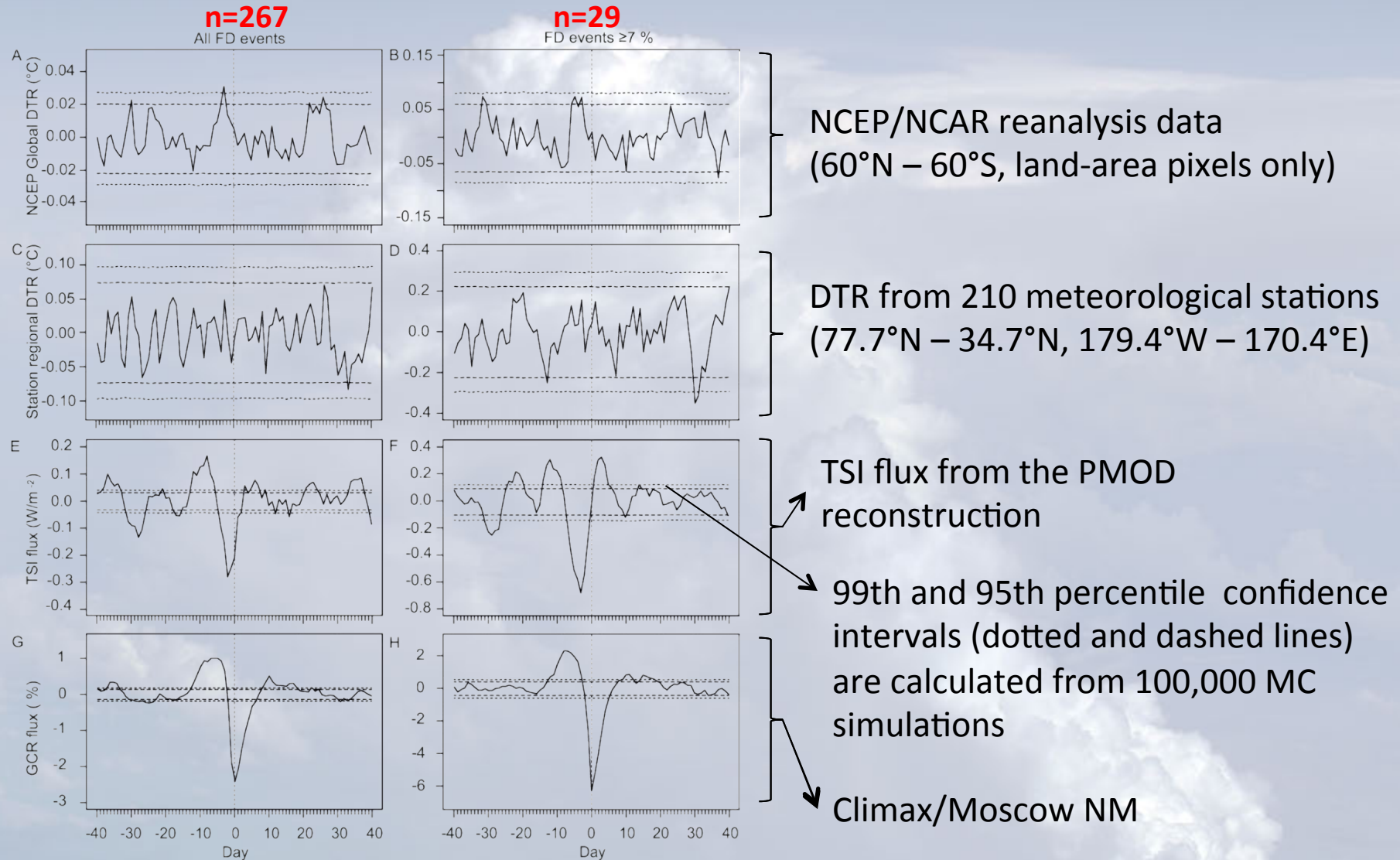


Significance intervals calculated from  
100 000 Monte Carlo simulations (using  
21-day running average)

Analysis of the same data as in  
Dragić et al. (DTR data and 37  
Forbush events) shows that  
authors didn't estimate correctly  
statistical significance using t-test  
and certain statistical  
assumptions.

Laken, Čalogović, Shahbaz and Pallé (2012), JGR

# Detailed analysis shows that there is no DTR response during Forbush events

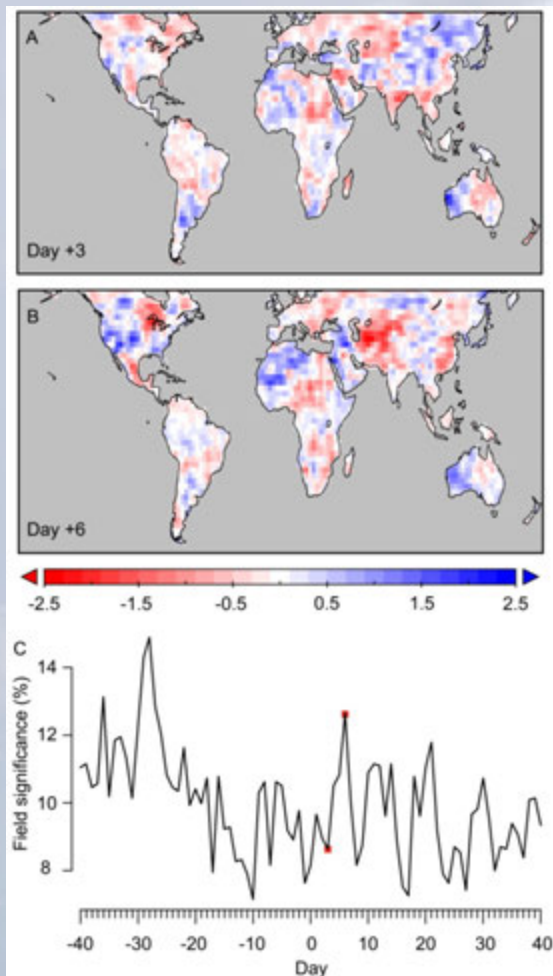


Laken, Čalogović, Shahbaz and Pallé (2012), JGR



# DTR shows no response to GCR or solar activity

Spatial distribution of DTR anomalies between day +3 and +6



Long term analysis (60 years of data) shows also that there is no significant periodicities in DTR data connected to the solar periodicities (e.g. 11-year, 1.68-year ).

**In conclusion, there is no evidence to support claims of a link between DTR and solar activity.**

Laken, Čalogović, Shahbaz and Pallé (2012), JGR

# Various issues that contributed to conflicting results of studies

- **Data filtering** - interference from variability in data at time scales greater than those concerning hypothesis testing, which may not necessarily be removed by accounting for linear trends over the composite periods
- **Normalization procedures** which affect both the magnitude of anomalies in composites, and estimations of their significance
- The application of statistical tests unable to account for **autocorrelated data** (e.g. student t-test)
- **Issues of signal-to-noise ratios** connected to spatio-temporal restrictions (e.g. by decreasing analyzed region size the searched signal may be buried in noise)

# Identification of solar—terrestrial links has many difficulties

- Weather and climate are **highly variable** over all time-scales - only a small fraction of this variance (signal) could reasonably be ascribed to solar activity (rest is considered as noise).
- Statistical properties of climatic datasets are unstable (**non-stationary**) – significant correlations over short timescales may disappear.
- Climatic data are spatially **autocorrelated** -> number of observations globally doesn't reduce uncertainty -> no good substitute for long duration datasets. **Problem:** modern satellite-era datasets only cover around three solar cycles.

Pittock, 1978; 1979, 1982

# Identification of solar—terrestrial links has many difficulties

- ***a posteriori* selection of data** (“cherry picking”) – one sample may have a statistically significant correlation, but drawn from a larger quantity of data which doesn't show the same relationship.
- Exact (amplifying) mechanisms linking solar activity to climate are still poorly understood -> not always possible to evaluate them with models (not testable = unscientific)
- Most **studies are purely statistical** -> tests of significance may be accompanied by ambiguities in data selection and treatment, applied methods, or assumptions— including human bias, autocorrelations, smoothing, and post-hoc hypotheses.
- Many of these issues already described by **Pittock 1979, 1978**



# Pittock, 1979 recommendations

- Understand properties of the data (errors, biases, scatter, autocorrelation, spatial coherence, frequency distribution, stationarity)
- Choose statistical methods appropriate both to the properties of the data and the purpose of the analysis
- Critically examine the statistical significance of the result, making proper allowance for spatial coherence, autocorrelations, smoothing and data selection
- Test the result on one or more independent data sets, or sub-sets of the original data
- Endeavor to derive a physical hypothesis which can be tested on independent data sets, preferably at some other stage in the hypothesized chain of cause and effect
- Estimate the practical significance of the result (fraction of the relevant total variance which can be predicted or explained)
- Set out the properties and limitations of the data, the statistical methods used (including data selection and smoothing), and any assumptions, reservations or doubts
- Do not over-state the statistical or practical significance of the result

# Open-access coding solutions

- Importance of reliable methods and statistical tests to overcome some of mentioned difficulties: **communal analysis approach**
- Implementation of robust significance testing (e.g. MC method)
- Python (completely free, all computer platforms)
- **iPython**: code in small editable units, descriptions and figures between code. Rapidly shared and replicated, runs in any internet browser
- Simple to run code on remote computers (cloud)
- Public **Git** repositories for instant download of analysis or upload tracked changes
- Allows even low skill programmers to follow the analysis. Viewed online, any system (only internet browser needed)
- Using **FigShare** (DOI number) code can be added as supplement to publications

# iPhyton environment

**jupyter** Composite\_method\_examples (autosaved) Python 2

File Edit View Insert Cell Kernel Help

Cell Toolbar: None

## Composite analysis with Monte Carlo methods: an example with cosmic rays and clouds

**Benjamin A. Laken & Jasa Čalogović**

This is an iPython notebook version of [Laken & Čalogović, 2013, doi:10.1051/swsc/2013051](#), published in the *Journal of Space Weather and Space Climate*. Originally, this work was supported by [IDL code](#), succeeded by this notebook.

Code in Python 3, by [B. Laken](#)

**Cite this article as:** Laken B.A. & Čalogović J.: Composite analysis with Monte Carlo methods: an example with cosmic rays and clouds. *J. Space Weather Space Clim.*, 2013, 3, A29, doi:<http://dx.doi.org/10.1051/swsc/2013051>.

### Abstract

The composite (superposed epoch) analysis technique has been frequently employed to examine a hypothesized link between solar activity and the Earth's atmosphere, often through an investigation of Forbush decrease (Fd) events (sudden high-magnitude decreases in the flux cosmic rays impinging on the upper-atmosphere lasting up to several days). This technique is useful for isolating low-amplitude signals within data where background variability would otherwise obscure detection. The application of composite analyses to investigate the possible impacts of Fd events involves a statistical examination of time-dependent atmospheric responses to Fds often from aerosol and/or cloud datasets. Despite the publication of numerous results within this field, clear conclusions have yet to be drawn and much ambiguity and disagreement still remain. In this paper, we argue that the conflicting findings of composite studies within this field relate to methodological differences in the manner in which the composites have been constructed and analyzed. Working from an example, we show how a composite may be objectively constructed to maximize signal detection, robustly identify statistical significance, and quantify the lower-limit uncertainty related to hypothesis testing. Additionally, we also demonstrate how a seemingly significant false positive may be obtained from non-significant data by minor alterations to methodological approaches.

```
p4b = figure(figsize=(100, plot_height=400), title=None, toolbar=TOOLBAR)
p4b.subplots(2, 1, bottom=0, left=edges[0], right=edges[1],
            fill_color="#f99900", line_color="#f99900", legend="NO population")
avale_pdf = sp.linspace(-0.1, 0.1, num=100, endpoint=True)
p4b.plot(avale_pdf, qm_pdf(x_val=avale_pdf, surp=average(fit_diffs), sigma=sigma(fit_diffs)),
        legend="PDF", color="black", line_width=1.5)
p4b.legend.location = "top_left"
p4b.xaxis.axis_label = "Diff. b/w two methods to calc. anomalies (at t)"
p4b.xaxis.axis_label_text_font_size = '10'
p4b.yaxis.axis_label = "Probability density"
p4b.yaxis.axis_label_text_font_size = '10'

fig4 = gridplot([p4a, p4b])
show(fig4)
del fit_diffs # free the memory
```

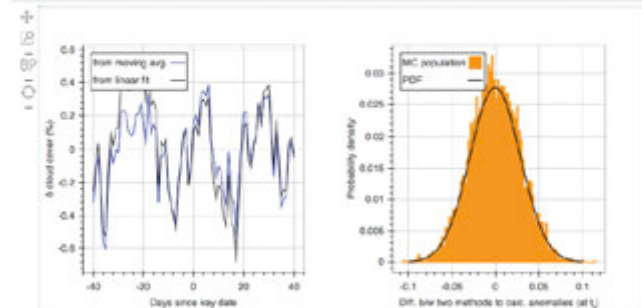


Figure 4 (a) Left panel: one random instance of  $g = 20$  events, for both linearly detrended data (black line) and an anomaly from a 21-day moving average (blue line). Differences between these two curves show the possible influences of intermediate timescales on the data. (b) Right panel: the differences between these curves at  $t_0$  for 10,000 random instances (of  $g = 20$ ). The histogram shows a  $1\sigma$  value of 0.1%, a non-trivial difference which may influence the outcome of a composite analysis.

• nb. The text above reflects the original paper, but from the re-code it seems  $1\sigma = 0.01\%$ . Not sure yet where the larger deviation came from in the original, but may potentially be a bug.

Notebook viewer on-line:

<http://tinyurl.com/composite-methods>

GitHub repository (download and run it locally):

[https://github.com/benlaken/Composite\\_methods\\_LC13](https://github.com/benlaken/Composite_methods_LC13)

# Conclusions

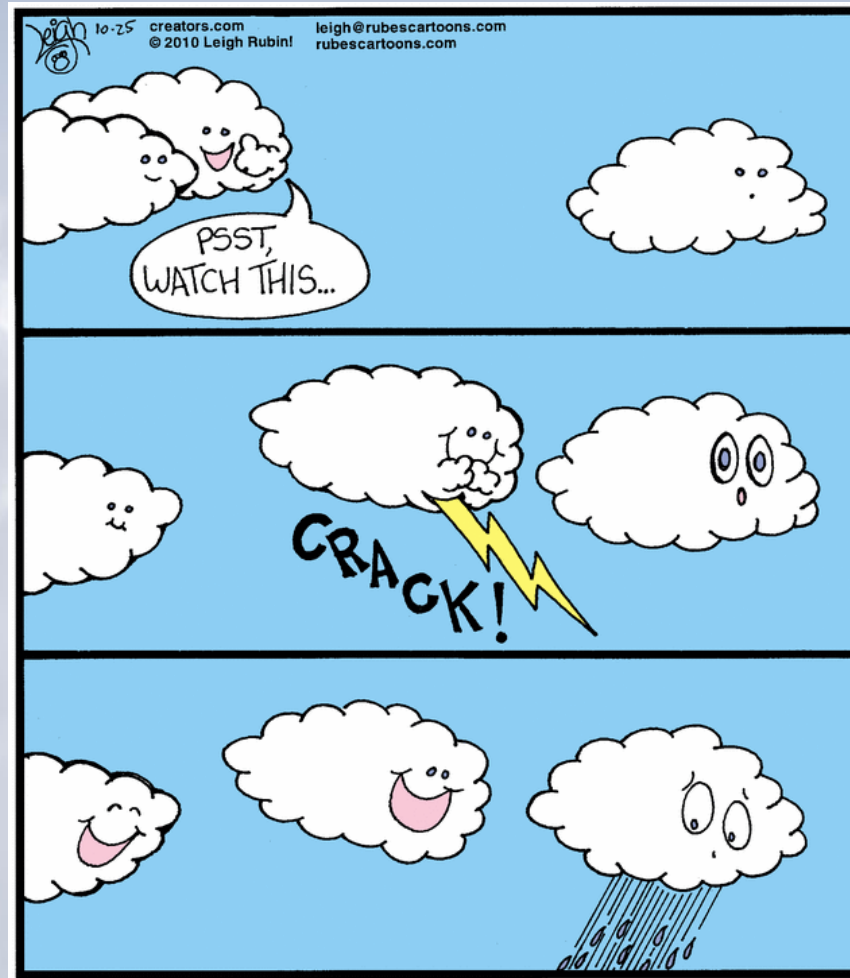
- Satellite cloud estimates are fraught with limitations and calibration errors, meaning **long-term analysis is problematic at best**, and, as in the case of commonly used ISCCP data, is fundamentally flawed.
- Co-variance of solar-related parameters (UV, TSI, CR flux, solar wind) make **signal attribution difficult**.
- **Climate variability and volcanic activity**, operating over time-scales similar to the solar cycle, make disambiguating causes of cloud cover change difficult.
- Composite analysis of FD and GLE events is often compromised by the difficulties of statistical analysis of **autocorrelated data**. This is compounded by the application of inappropriate and black-box statistical tests.
- Changing **signal-to-noise ratios** connected to **spatio-temporal restrictions** in composites have generally not been sufficiently taken into account in composite studies, leading to widespread false-positive statistical errors.



# Conclusions

- Methodological differences and inappropriate statistics in composite analysis can produce conflicting results. These are the likely source of discrepancies between cosmic ray – cloud composite studies.
- Present cloud datasets are limited to detect a small changes in cloud cover as well to detect the regional cloud changes (<several thousand km) due to the big natural cloud variability (noise). Thus, localized and/or small effect on cloud cover can't be completely excluded.
- **No compelling evidence** to support a global cosmic ray-link using the satellite cloud data (ISCCP, MODIS) with long- or short-term (Fd) studies.
- If cosmic ray-cloud relationship is second order (small and dynamic changes to cloud cover over certain regions) then it may be very difficult to detect it with currently available techniques and datasets.

# Thank you for your attention!



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