Does Europe's wind show signs of the solar cycle?

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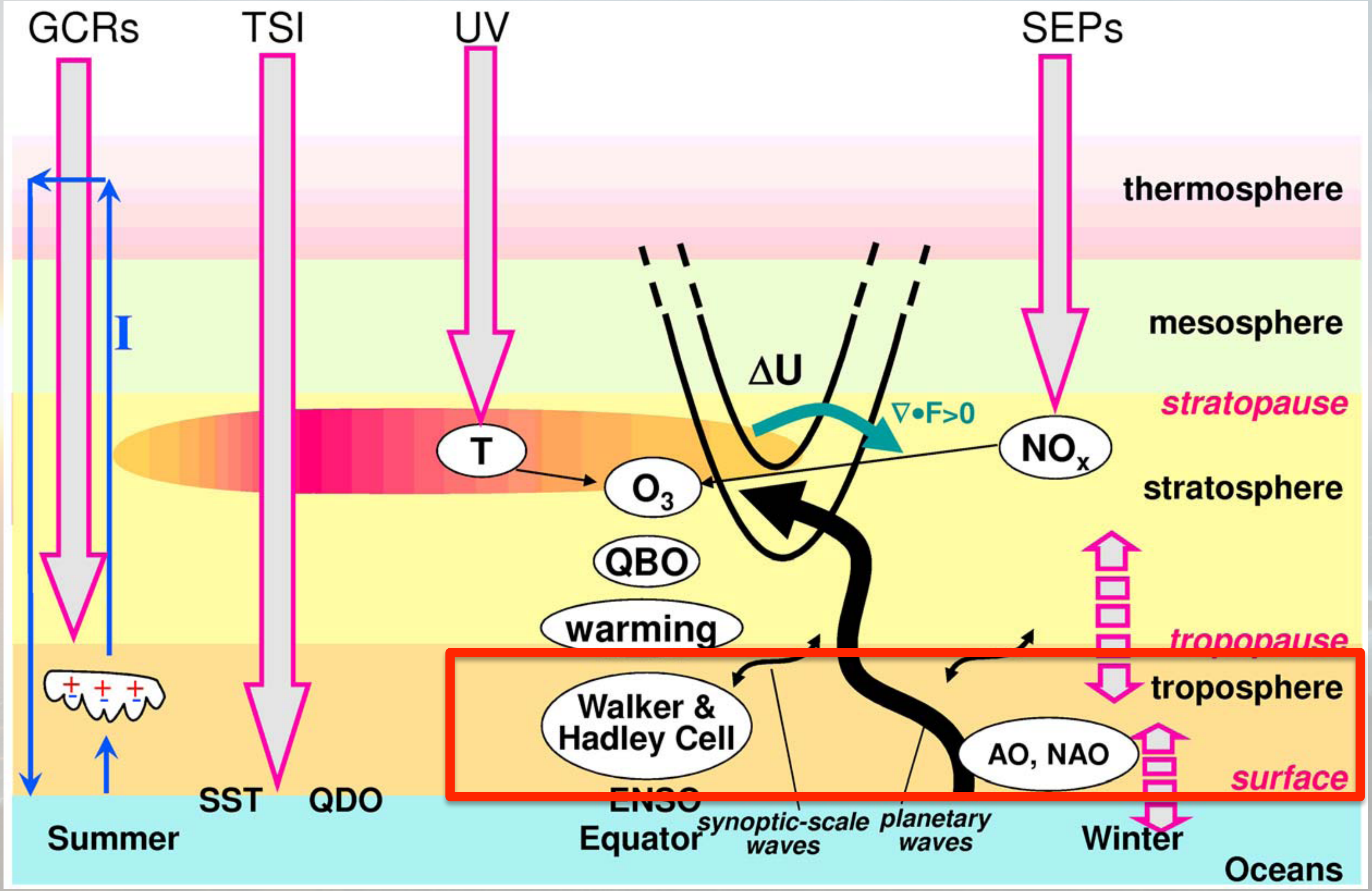
Theoretical solar influence on climate

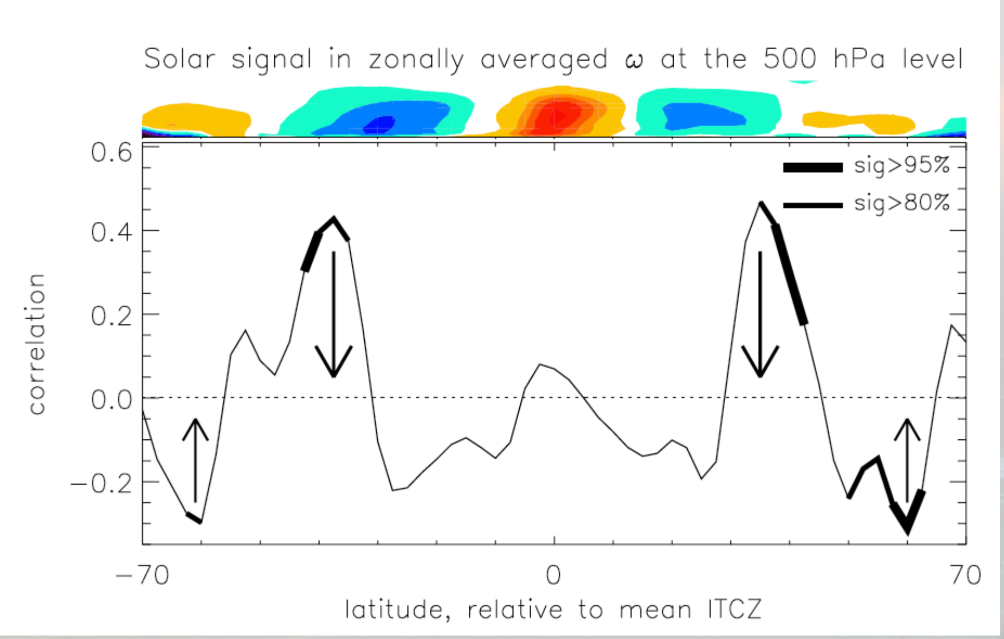


Kodera & Kuroda , 2002

Some evidence of a tropospheric response to the 11-year solar cycle

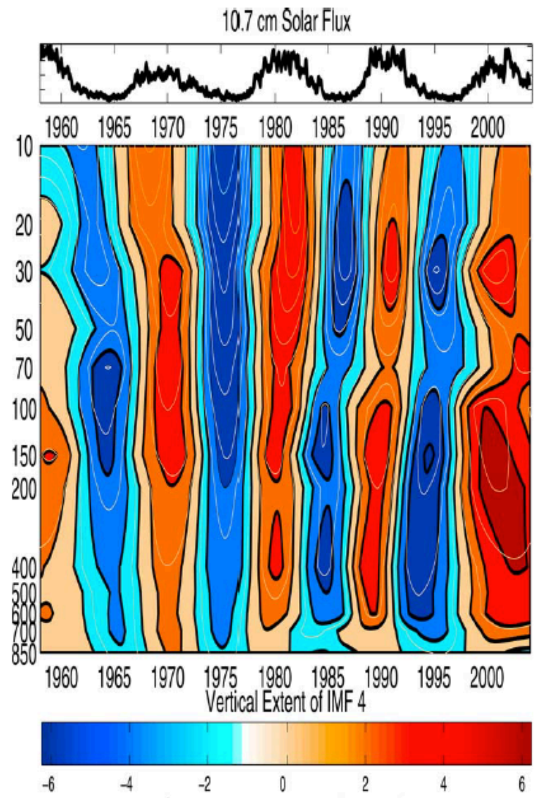
Solar signal in tropospheric temperature, humidity, sea level pressure, geopotential height, and tropospheric circulation patterns (eg. Gleisner and Thejll, 2003; Kuroda and Kodera, 2005; Coughlin and Tung, 2004; Dima et al., 2005; Huth et al., 2008)

Gleisner and Thejll, 2003



Fourth mode of geopotential height

Based on NCEP/NCAR reanalysis data



Coughlin and Tung, 2004

- Strong solar signal in mid-latitude cyclonic activity
- Solar signals can be lost due to spatial & temporal averaging

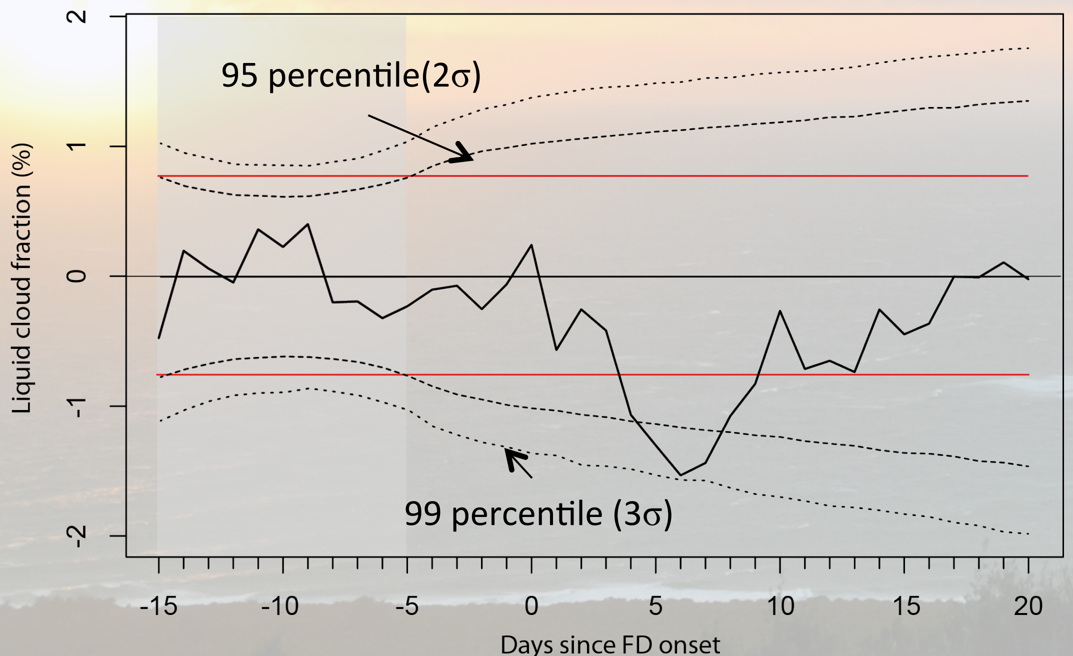
Identification of solar—terrestrial links has many issues

- Despite much research large uncertainty still remains
- Exact (amplifying) mechanisms linking solar activity to climate are still poorly understood ➔ not always possible to even evaluate them
- Most studies are purely statistical ➔ tests of significance may be accompanied by ambiguities (data selection, treatment, methods and assumptions). Vulnerable to autocorrelations, smoothing, human bias and post-hoc hypotheses.
- Such difficulties in relation to solar—terrestrial field described by **Pittock** 1979, 1978

Big variability (noise) can be mixed with an expected signal

- Weather/climate is highly variable (i.e. noise) ➔ only small fraction can reasonably be linked to solar activity (i.e. signal)
- Climate data have strong spatio-temporal auto-correlation ➔ complicates statistical tests

Example with clouds:



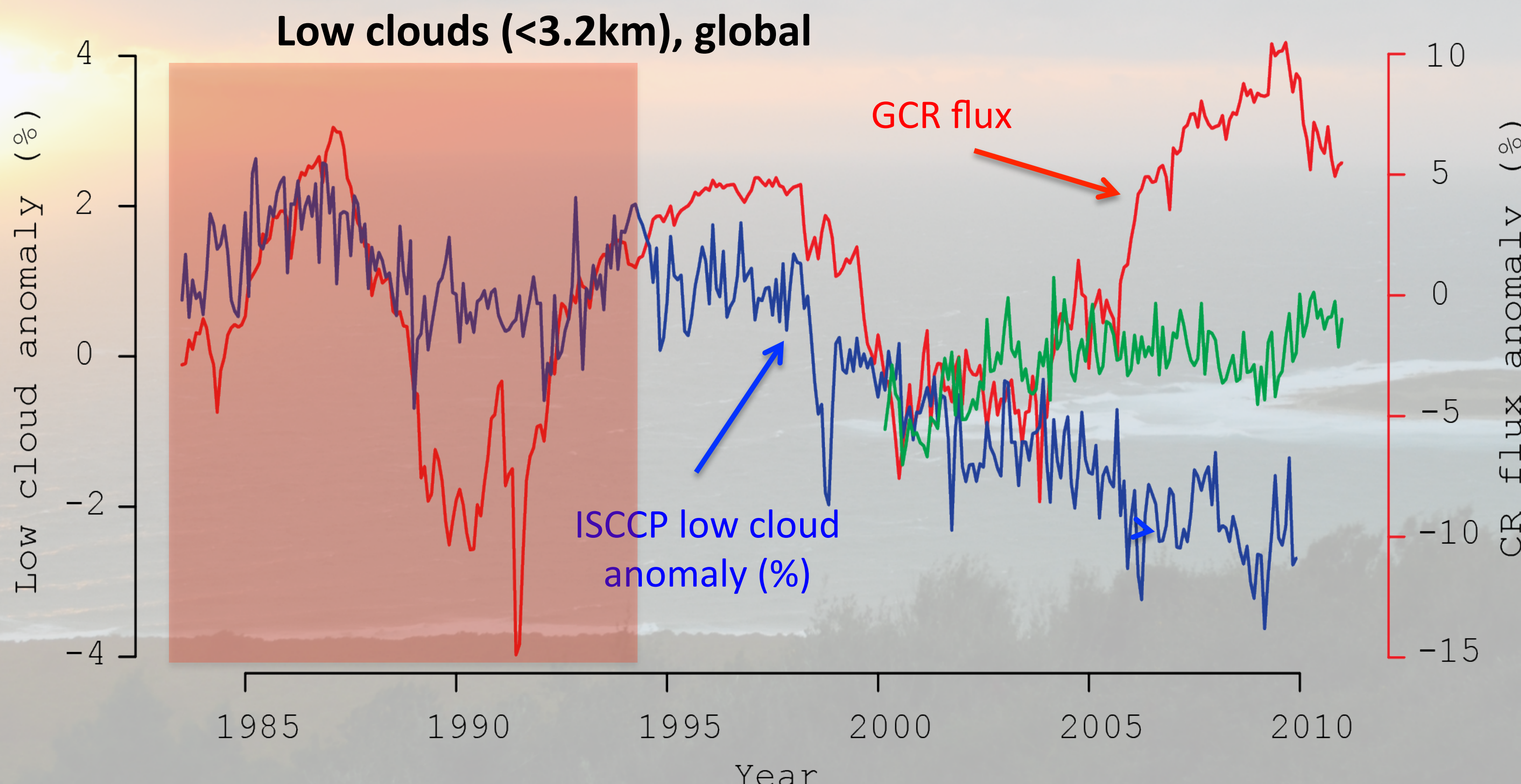
Laken and Čalogović (2013), SWSC

CDF's from MC's show overly simplistic tests commonly applied (e.g. T-test) do not reliably asses significance

Dashed/dotted lines show **correctly** adjusted 2 and 3σ confidence intervals (CI) – calculated from 10,000 MC simulations, red line shows CI (2σ) calculated based on normalization period assuming that data aren't temporally auto-correlated.

Longer duration datasets should be used

- Climatic data are spatially auto-correlated ➔ increased observation density (spatial) doesn't reduce much uncertainty
- Modern (satellite) datasets cover few solar cycles ➔ thus few independent data points exist
- Correlations appear significant only over short-timescales



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)

Open-access coding solution

- 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.
- 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

IP[y]: Notebook Wind_work Last Checkpoint: Nov 16 02:15 (autosaved)

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Code Cell Toolbar: None

Is a solar signal embedded in a century of synoptic wind data?

This iPython notebook reads in daily HB synoptic data, converts it into monthly counts by wind direction, and then composite by solar cycle occurence with MC-significance testing.

Benjamin A. Laken & Jasa Calogovic, November 2014

In [1]:
```
# Import required modules
import numpy as np
import pandas as pd
import scipy as sci
from scipy import stats
import matplotlib.pyplot as plt
import datetime as dt
import random
import custom_funcs as custom          # legacy code (shouldn't be used)
```

Read all data for analysis and create time axes

In [2]:
```
# Read the HB and SSN data from csv files held on a public server, then index the dates
HB_data = pd.read_csv('HB_daily.csv')
HB_data.index = pd.date_range('18810101', '20001231', freq='D')

SN_data = pd.read_csv('NOAA_SSN_monthly.csv')
SN_data.index = pd.date_range('17490101', '20140930', freq='M')
```

In [23]:
```
# Nasty error - 'NA' wind type has been auto-assigned to np.nan value. Need to forcibly convert
# it back to a string.
na_mask = []
```

iPhyton environment

IP[y]: Notebook Wind_work Last Checkpoint: Nov 16 02:15 (autosaved)

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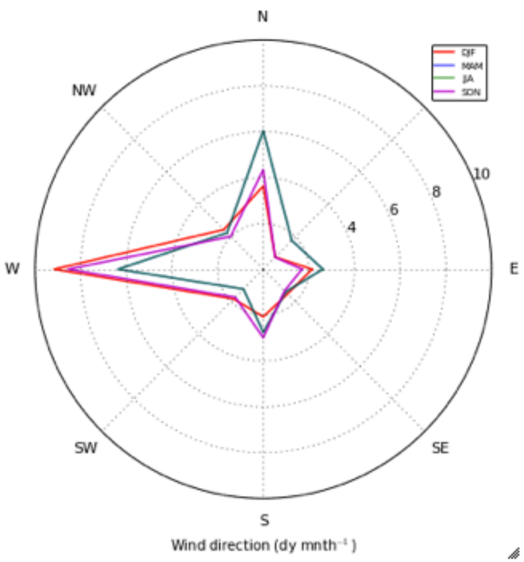
```
leg1=ax1.legend(["DJF","MAM","JJA","SON"], loc=0,prop={'size':7},numpoints=1,markerscale=5.,frameon=True,fancybox=True)
leg1.get_frame().set_alpha(1.0)  # make the ledgend semi-transparent

ax1.set_xticklabels(wind_dir, fontsize=11)
ax1.set_yticklabels(ylabs, fontsize=11)
ax1.set_xlabel(r"Wind direction (dy mnth$^{-1}$)", fontsize=10)
ax1.grid(True)

#plt.savefig('HB_seasonal.pdf', dpi=900)
plt.show(fig_pl)
```

```
<matplotlib.figure.Figure at 0x110842fd0>
```



Hess and Brezowsky (HB) data

- Catalogue of synoptic conditions: 29 types, defined by the position of major pressure, direction of airflow, and (anti)cyclonicity
- Data regularly updated and several times revised
- Concentrating on Central Germany: strong spatial autocorrelation = HB indicative of conditions over Central Europe
- Data extend back to **1881** ➔ covers more than **11 solar cycles**!

Composite analysis of major wind directions over Central Europe

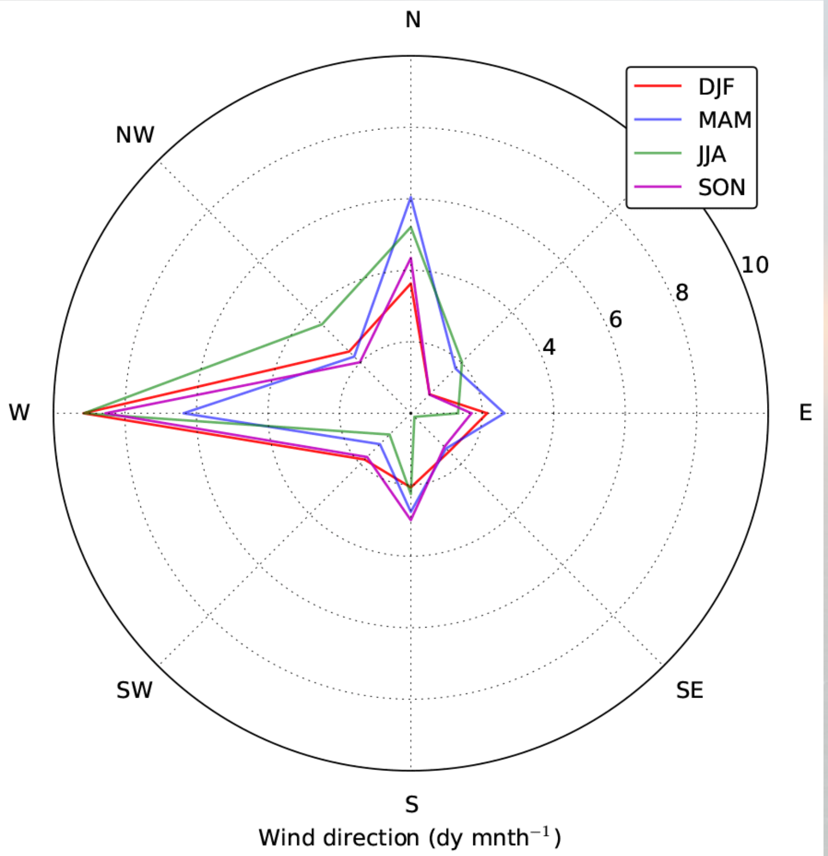
- HB types can be converted to 8 major wind directions
- Daily data binned to monthly timescale
- 12-month composites centered on key months of solar max. & min. (based on sunspot data)
- CDF from MC techniques obtain the significance of results

Conversion table

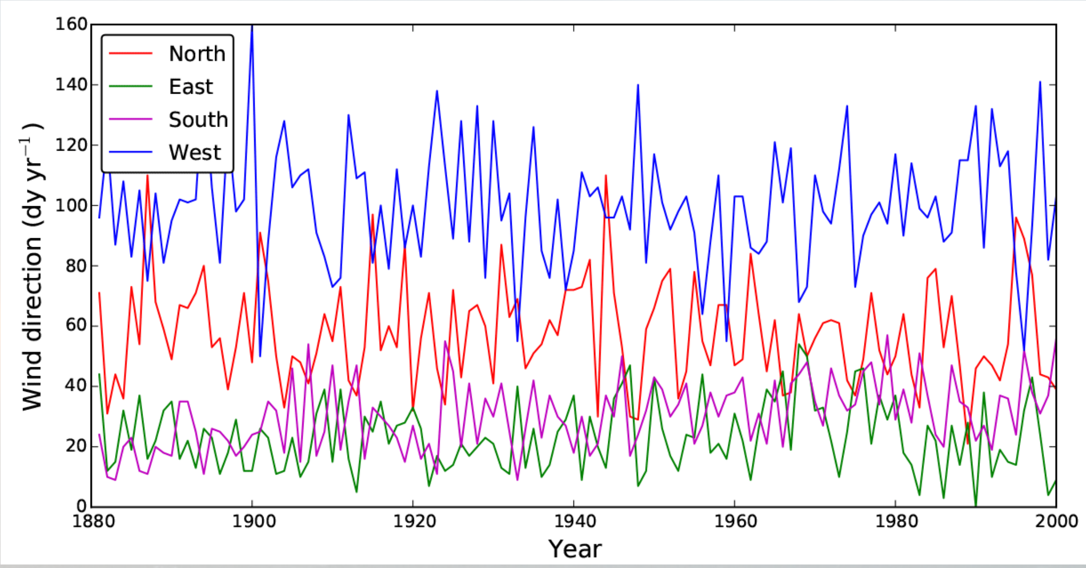
Direction	H-B types
N	'NA','NZ','HNA','HNZ','HB','TRM'
NE	'NEA','NEZ'
E	'HFA','HFZ','HNFA','HNFZ'
SE	'SEA','SEZ'
S	'SA','SZ','TB','TRW'
SW	'SWA','SWZ'
W	'WZ','WS','WA','WW'
NW	'NWA','NWZ'

Seasonal and annual HB statistics

Seasonal wind flow climatology

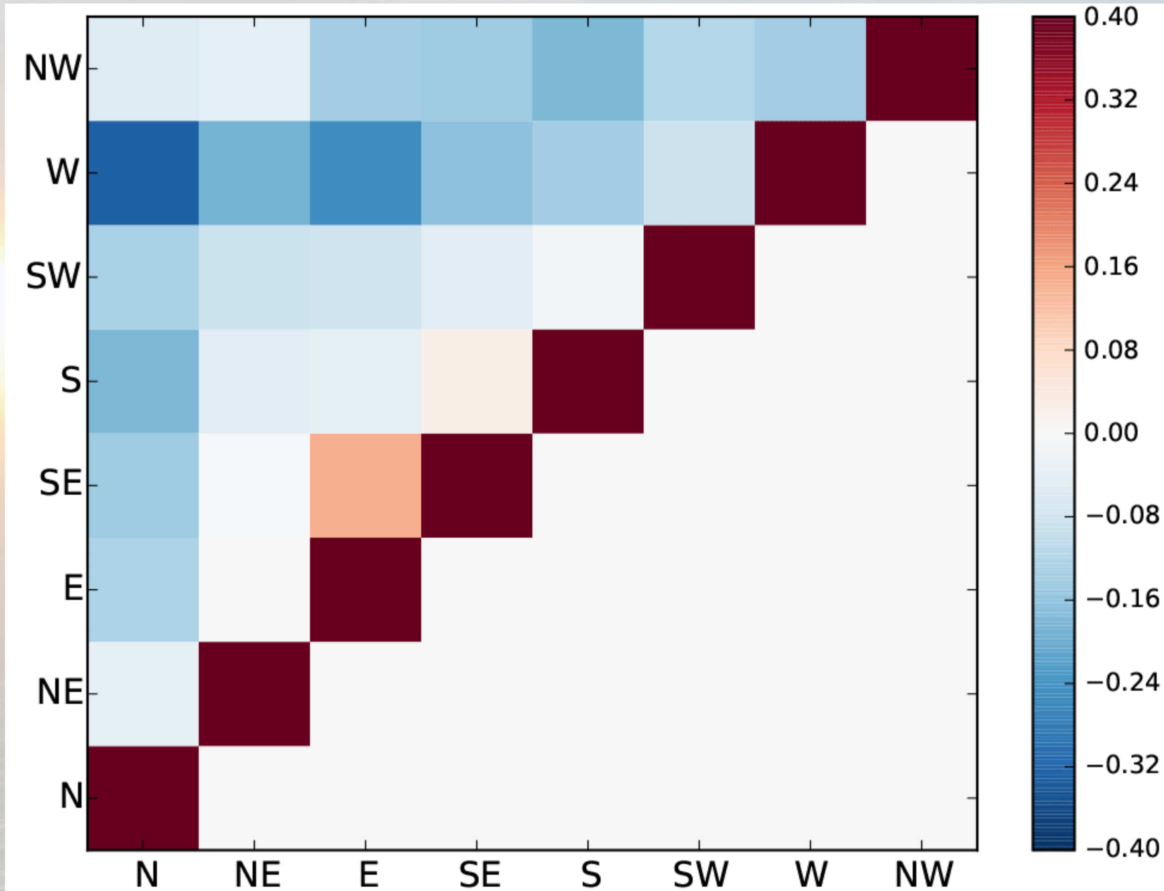


Annual wind flow climatology



- Westerlies are reduced in spring when northerlies are more pronounced
- Northerlies are more pronounced in summer than in winter
- Dominant flow = westerlies
- All wind directions show nearly constant long term trend (annual data)

Correlation matrix for all directions



- Tests if wind directions are coupled (anti-correlated) over seasonal and annual timescales
- Stronger anti-correlation between northerlies and westerlies

Results

slides removed by author, available on request as private communication

Further work and improvements

- Implementation of various lags
- Test the response to other climate forcings (eg. volcanic forcing)
- Extension of analysis to other climatological long record datasets (eg. Europe, North America, ship records)
- Preparation of iPython notebook scripts to be more easily readable and usable

Conclusions

- Identification of solar—terrestrial links connected to many issues ➔ much uncertainty still pervades
- Open access coding approach (iPython) allows us to better share experience/knowledge and solve some of the difficulties of past studies
- Preliminary composite analysis of HB data shows significant shifts in main wind flows (westerlies and northerlies) during solar minimum and maximum

Thank you!

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