Multi-Index Attribution of Beijing's 2013 "Airpocalypse"

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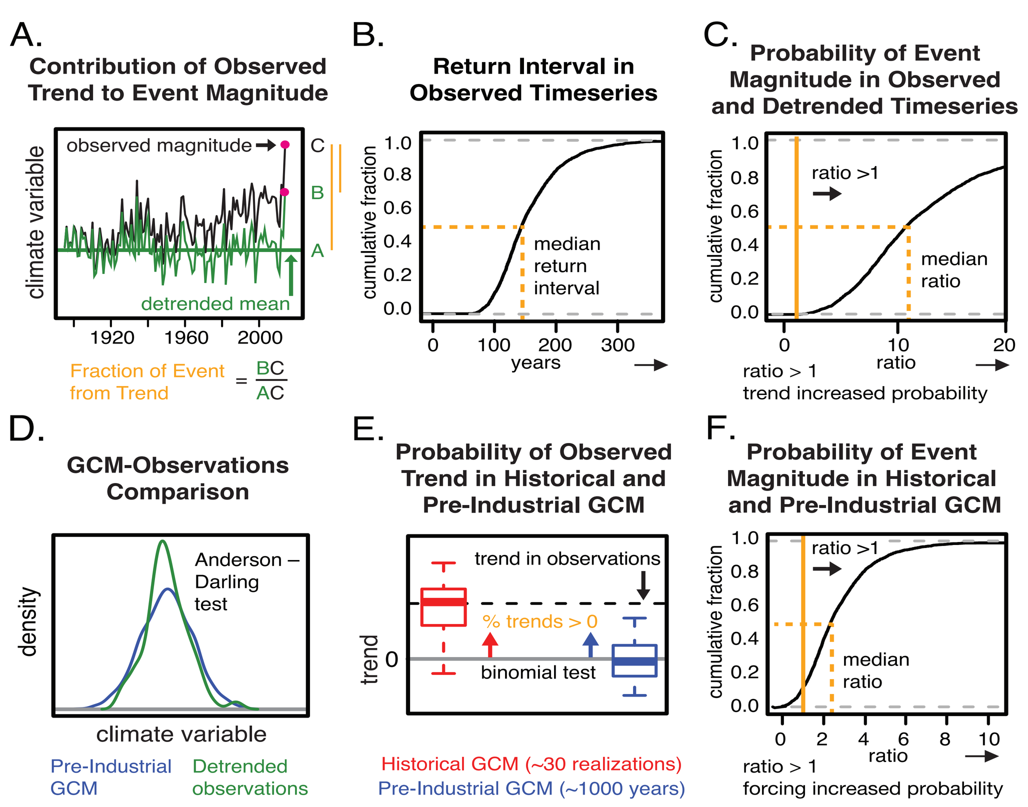
Abstract

Poor air quality events are the result of the emission of pollutants and the meteorological conditions favorable to their accumulation in the near-surface environment. The most important of these meteorological conditions include lack of precipitation, low wind speeds, and vertical temperature inversions. Here we assess whether anthropogenic climate change has altered these meteorological conditions in the observational record. We use three indices that quantify poor air quality: The Pollution Potential Index (PPI; Zou et al., 2017), which measures temperature inversions and surface winds, the Haze Weather Index (HWI; Cai et al., 2017), which measures temperature inversions and mid-level winds, and the Air Stagnation Index (HWI; Horton et al., 2014), which measures precipitation, surface winds, and mid-level winds. Drawing on the attribution methods of Diffenbaugh et al. (2017), we assess the contribution of observed meteorological trends to the magnitude of air quality events, the return interval of events in the observational record, historical simulated climate, and pre-industrial simulated climate, and the probability of the observed trend in historical and pre-industrial simulated climates. Particular attention is paid to Beijing's January 2013 air quality, as an example of an air quality event to which a set of single-event attribution metrics can be applied.

Methods

We use an attribution framework developed by Diffenbaugh et al. (2017) to assess the contribution of climate change to the magnitude of air quality events, the probability of those events, and the probability of the trend in the observational record. We evaluate the change in event magnitude from the observed timeseries to the detrended timeseries (A), the change in return interval (B) from the observed to the detrended timeseries (C) and from the pre-industrial to the historical simulations (D, F), and the likelihood of the observed trend in the historical and pre-industrial simulations (E).



We use the CESM Large Ensemble (CESM-LE), a set of 30 historical realizations with different initial conditions, to generate a sample of the historical climate from 1979 to 2005 (Kay et al., 2015). The simulation is extended to 2016 by adding the first ten years of the CESM-LE RCP8.5 runs to each realization. This accounts for internal variability that may bias a single realization and more fully covers the probability space of the historical and pre-industrial climates. We use the CESM-LE pre-industrial control realization, from 402-2200, to assess the change from the pre-industrial to the historical climate.

Observations are drawn from the NCEP R1 reanalysis project. Each air quality meteorology index is calculated over the period from 1979-2016 for comparison to the historical and pre-industrial climates. We use January monthly-mean data for the PPI, DJF daily data for the HWI, and annual daily data for the ASI, following the methods used when each index was originated.

We also extract the Air Temperature Gradient Index, a component of the PPI, to measure the spatial patterns of January temperature inversions in the Beijing area. Inversions are defined using self-organizing map cluster analysis, which provides a set of the typical temperature gradient patterns in the observed, historical, and pre-industrial climates (Horton et al., 2015). We use a simple three-node configuration to represent the temperature gradient: a highly unstable atmosphere, a very shallow gradient, and a highly stable atmosphere. The algorithm is trained on the observations, and the resulting patterns are applied to the simulated runs. We then apply the attribution metrics to the timeseries of maximum duration of node 3, as a proxy for the intensity of significant inversions over the Beijing area.

Air Quality Indices

Haze Weather Index (Cai et al., 2017): Temperature gradient between 200mb and 850mb plus strength of 850 mb southerly winds plus an index of the weakening of northwesterly wind through Beijing. Daily resolution. The January 2013 event is defined as the maximum five-day running mean in January 2013.

Air Stagnation Index (Horton et al., 2014): An index that determines whether a day is considered stagnant (if precipitation < 1mm, surface winds < 3.2 m/s, and 500-mb winds < 13 m/s). Daily resolution.

Pollution Potential Index (Zou et al., 2017): (Air Temperature Gradient Index * 0.7) - (Wind Speed Index * -0.73) / (|0.7| + |-0.73|). Monthly-mean resolution.

Air Temperature Gradient Index (Zou et al., 2017): Potential temperature at 925mb minus potential temperature at 1000mb, minus the long-term mean of that gradient divided by its standard deviation.

Wind Speed Index (Zou et al., 2017): Surface wind speed minus long-term mean surface wind speed, divided by the standard deviation of the surface wind speed.

Based on trends in both January ASI and annual ASI, the annual ASI appeared more meaningfui, so it is used as the basis for these calculations. Cai et al. (2017) have shown that the ASI does not effectively describe winter air quality China, which motivated our use of these other indices.

Summary

- Some effect of climate change on some indices
- Depends on definition of both index and event
- Important to attribute both trend and event

Future Directions

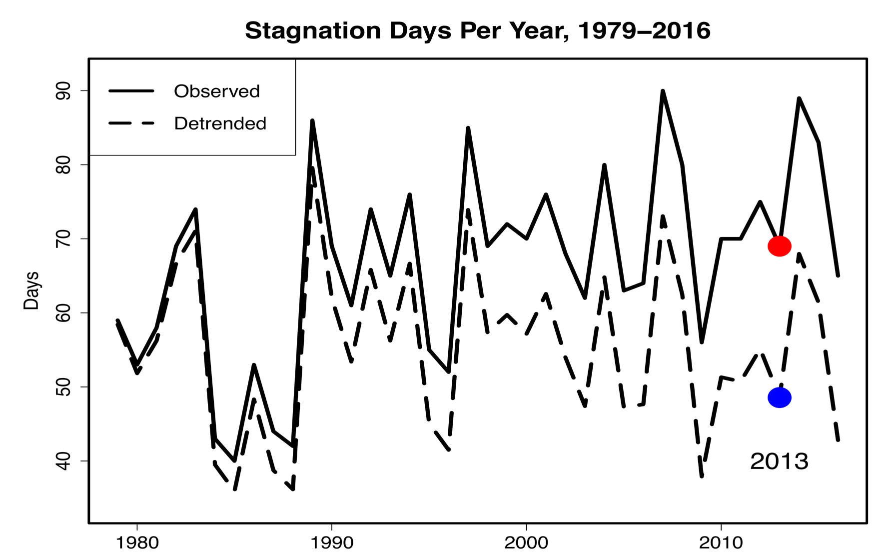
- Optimal cluster configuration for ATGI SOMs
- Influence of sea ice and snow cover on CESM PPI output
- Synoptic circulation (e.g. GPH) and indices

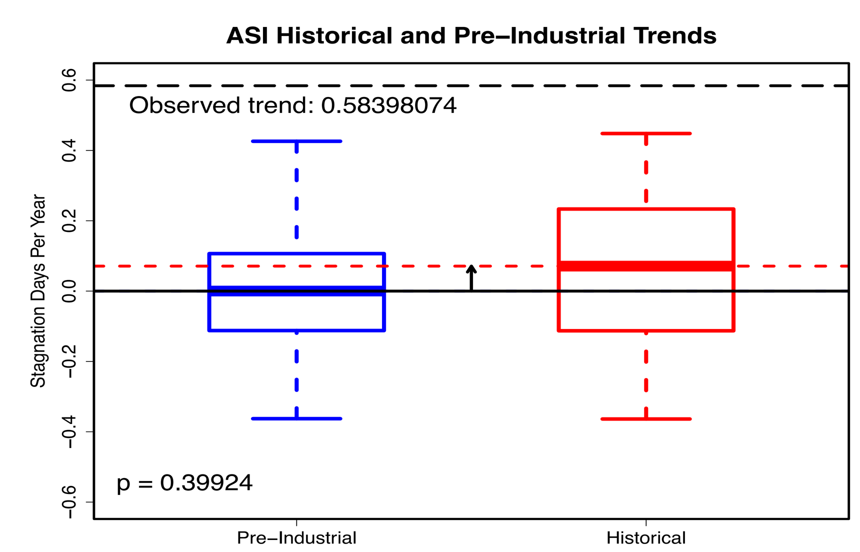
Air Stagnation Index

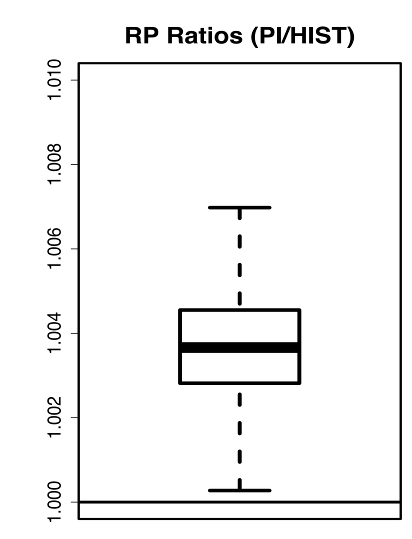
Trend (per year): 0.58 ($p < 0.002$)
Change in magnitude from trend: 1.48

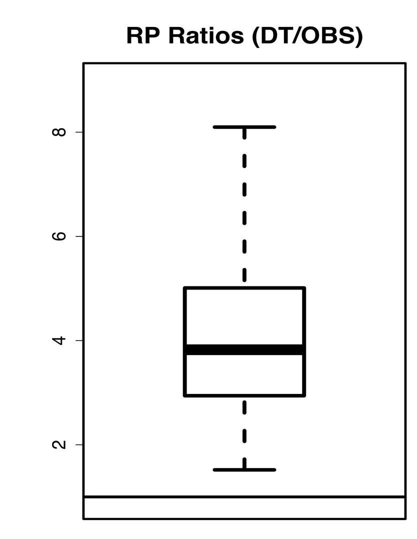
GCM A-D test $p = 0.92$
HIST fraction agree with trend: 55.2% ($p = 0.399$)

Median Δreturn period from trend: 3.79 (100% > 1)
Median Δreturn period PI/HIST: 1.004 (99.8% > 1)





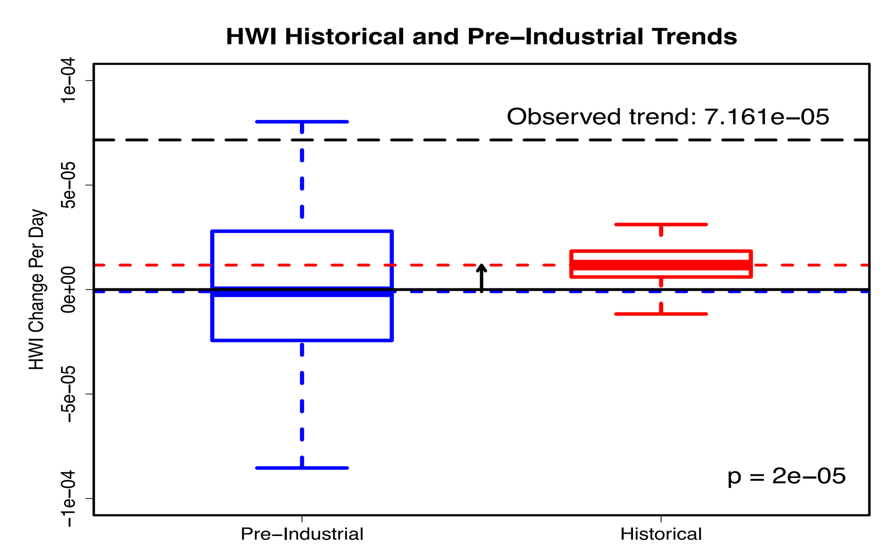


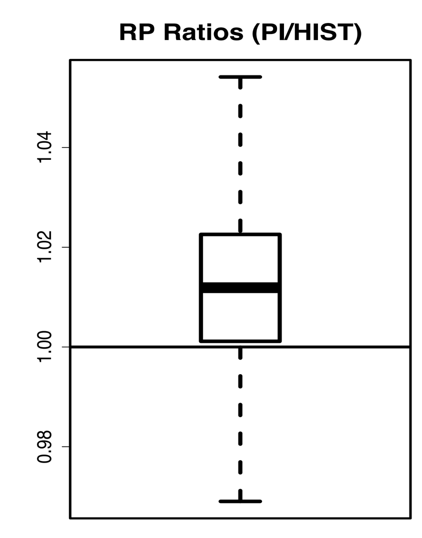


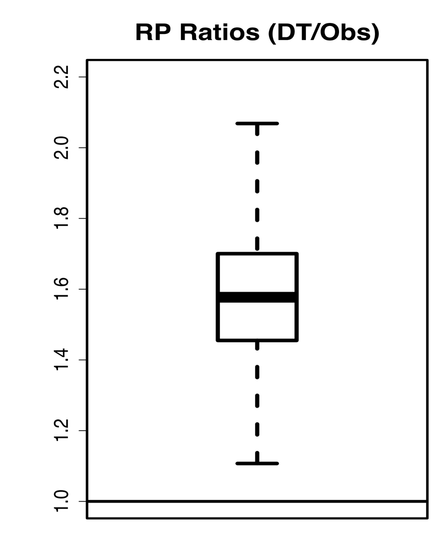
Haze Weather Index

Trend (per year): 7.16e-5 ($p < 3e-8$)
Change in magnitude from trend: 0.156
Median Δreturn period from trend: 1.57 (100% > 1)
GCM A-D $p = 0.373$
HIST fraction agree with trend: 86.7% ($p < 3e-5$)
Median Δreturn period PI/HIST: 1.01 (76.6% > 1)

The Haze Weather Index uses five-day running mean data instead of monthly or annual data, so a timeseries plot was excluded due to legibility.



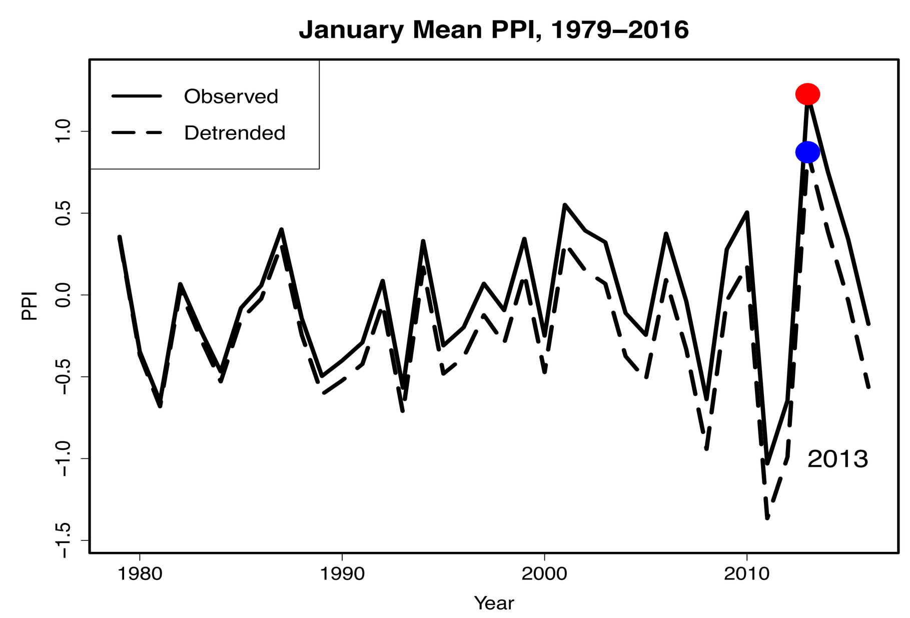


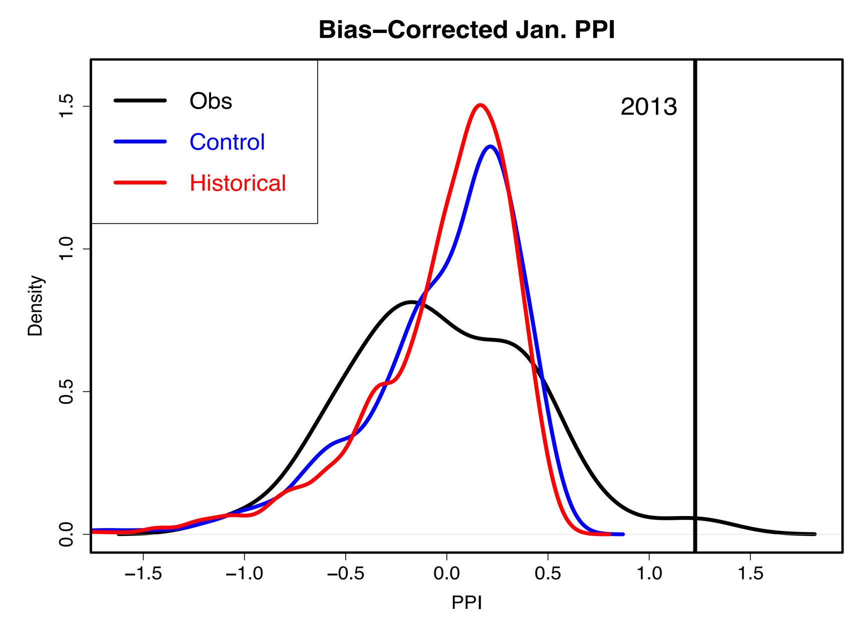


Pollution Potential Index

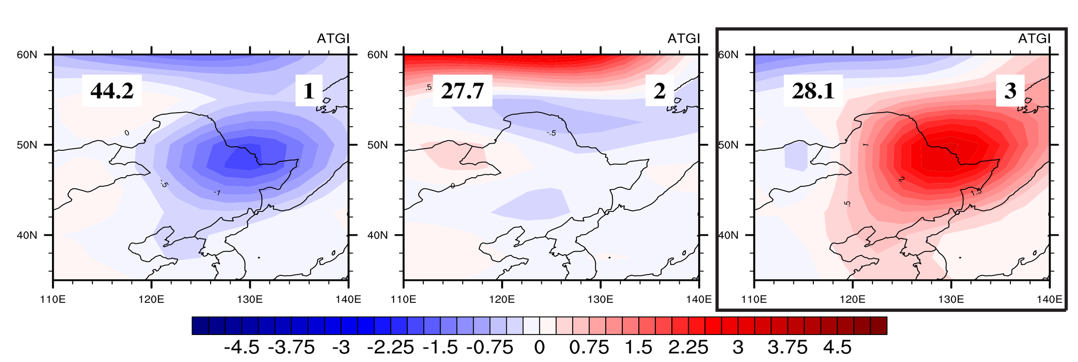
Trend (per year): 0.01 ($p = 0.132$)
Change in magnitude from trend: 0.25
Median Δreturn period from trend: UNDEFINED
GCM A-D $p = 0.201$
HIST fraction agree with trend: 17.1% ($p = 0.999$)
Median Δreturn period PI/HIST: UNDEFINED

The simulated runs do not capture the upper tail of the observations, so attempts to measure the return period of the 2013 event in the simulations return infinite or undefined return periods. The same result occurs when measuring the event's return period in the detrended observations, due to its unprecedented nature.





Air Temperature Gradient Index (Inversions)



Trend (per year): 0.089 ($p = 0.056$)
Change in magnitude from trend: 0.43
GCM A-D $p = 0.056$

Median Δreturn period from trend: 3.31 (84.7% > 1)
HIST fraction agree with trend: 56.7% ($p = 0.033$)
Median Δreturn period PI/HIST: 1.49 (79.6% > 1)