Interactive Visual Analysis of Climate Data

Johannes Kehrer, Helwig Hauser, et al.

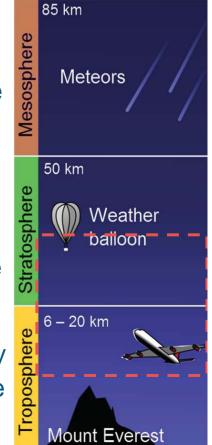
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Climatological Background

- Investigation and detection of climate change
- Upper troposphere-lower stratosphere
 - known to be sensitive
 - investigate key climate parameters
- Hypothesis generation
 - identify potential sensitive & robust indicator regions for climate change (e.g., certain height layers, latitudes)
 - characteristic climate signals, which deviate from natural climate variability
 - useful to monitor atmospheric change



Usual Workflow

- Set research focus
- Acquire data
- Iterate
 - explore / investigate data
 - formulate particular hypothesis
 - evaluate with statistics

Challenging to come up with new hypotheses

Goal: accelerate process (fast interactive visualization, more informed partner → more directed search)

Climate Data and Challenges

- Data sources
 → improved measurements & extensive simulations
- Challenges
 - large, multi-variate data
 - time-dependent
 - deficiencies within data
- Difficult to analyze / understand
 - usually statistical methods used
 - require prior knowledge
 - difficult to find "right" parameter settings







Data used in our Study



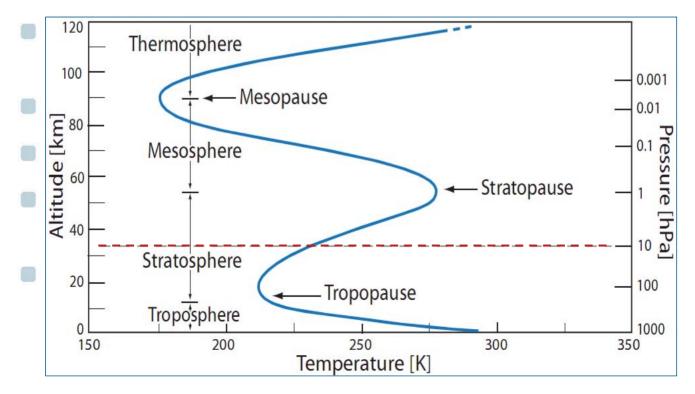
Climate Simulation Data

- ECHAM5 climate model, A2 scenario [MPI-M Hamburg] (IPCC 4th assessment report)
- temperature, years 1961–2061
- IPCC 20th century run before 2001
- 180.000 simulation cells
 → 2.5° x 2.5°, 18 pressure levels
- 108 time steps

Data used in our Study

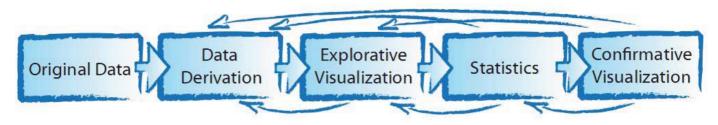
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Climate Simulation Data



Our Visual Exploration Process

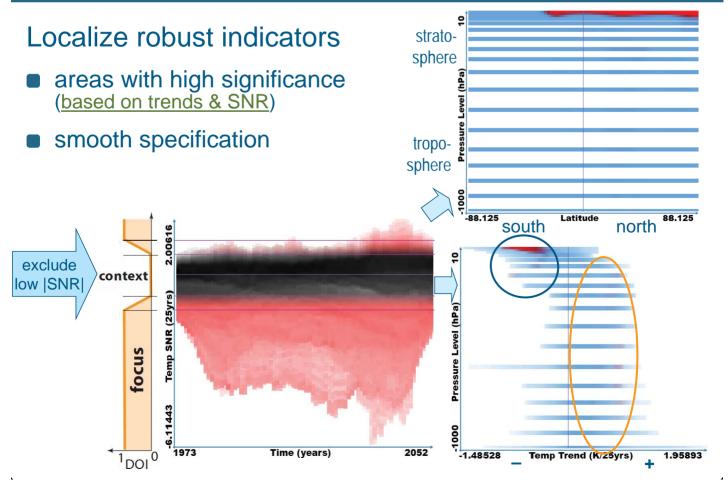




- Integrated data derivation → linear trends & signal to noise ratios (SNR)
- Interactive visual exploration for quick and flexible data investigation ("preview on statistics")
- Generated hypotheses evaluated using statistics

 trend testing [Lackner et al. 08]
- Narrow down parameters





Data Derivation: Linear Trends & SNR



[Ladstädter et al. 08]

- Smooth data ỹ: moving average over N years
- Linear trend:

$$trend_i = \frac{1}{N} (\tilde{y}_{i+N/2} - \tilde{y}_{i-N/2})$$

Linear trend fit curve:

$$fit_{i,j} = \widetilde{y}_{i-N/2} + [j - (i - N/2)] \cdot trend_i$$

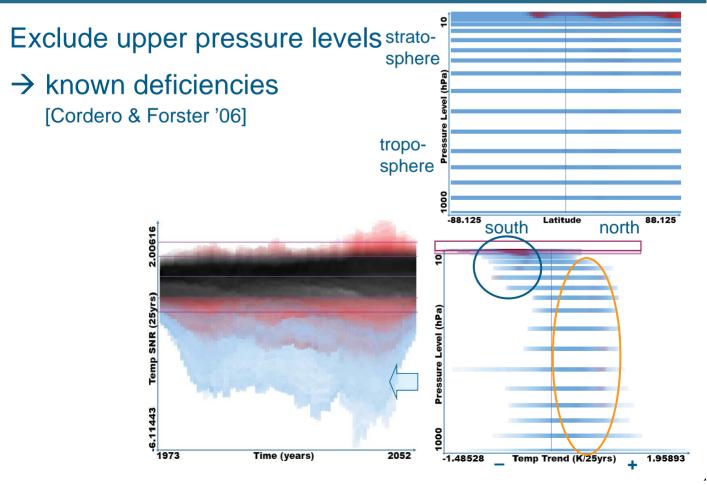
Detrended standard deviation:

$$s_{i} = \left[\frac{1}{N-1} \sum_{j=i-N/2}^{i+N/2} (y_{i} - fit_{ij})^{2}\right]^{1/2}$$

Signal-to-noise ratio:

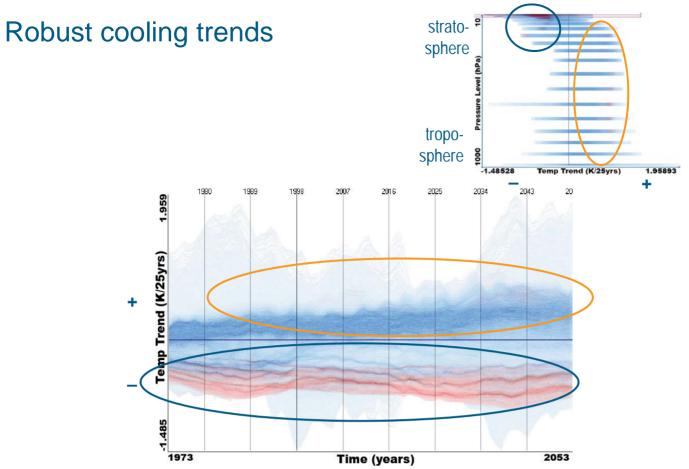
$$SNR_i = trend_i / s_i$$

Further Refinement



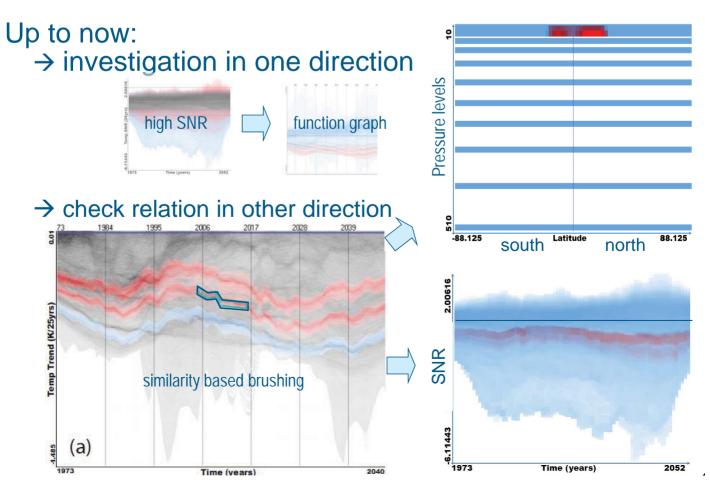
Explore Trend Variation over Time



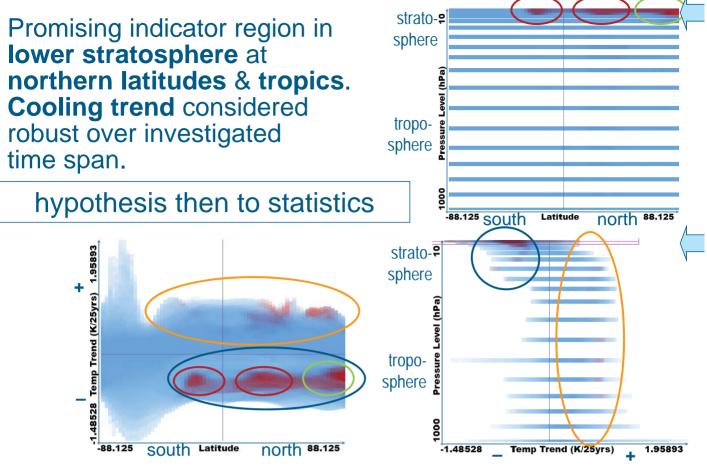


Analyze Relations between Dimensions





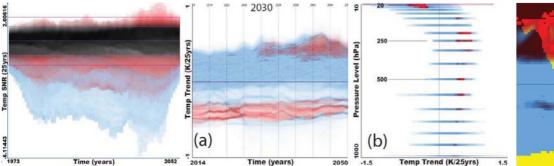


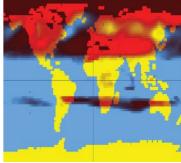


Hypothesis Generation with Visual Exploration



- Kehrer et al. Hypothesis generation in climate research with interactive visual data exploration. IEEE TVCG, 14(6):1579– 1586, 2008.
- Ladstädter et al. SimVis: an interactive visual field exploration tool applied to climate research. In New Horizons in Occultation Research, pages 235–245. Springer, 2009.
- Ladstädter et al. Exploration of climate data using interactive visualization. Journal of Atmospheric and Oceanic Technology, 27(4):667–679, 2010.

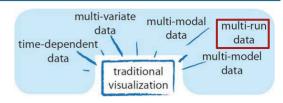


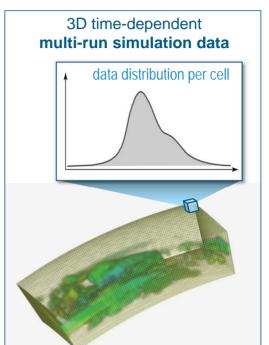


Higher-dimensional Scientific Data



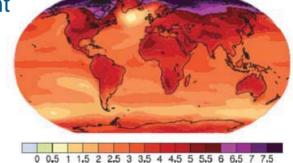
- some data values f(p) (e.g., temperature, pressure values)
- measured/simulated wrt. a domain p (e.g., 2D/3D space, time, simulation input parameters)
- If dimensionality of p > 3, then traditional visual analysis is hard
- Reducing the data dimensionality can help (e.g., computing stat. aggregates)





Reducing the Data Dimensionality

- Statistics: assess distributional characteristics along an independent dimension (e.g., time, spatial axes)
- Integrate into IVA through attribute derivation



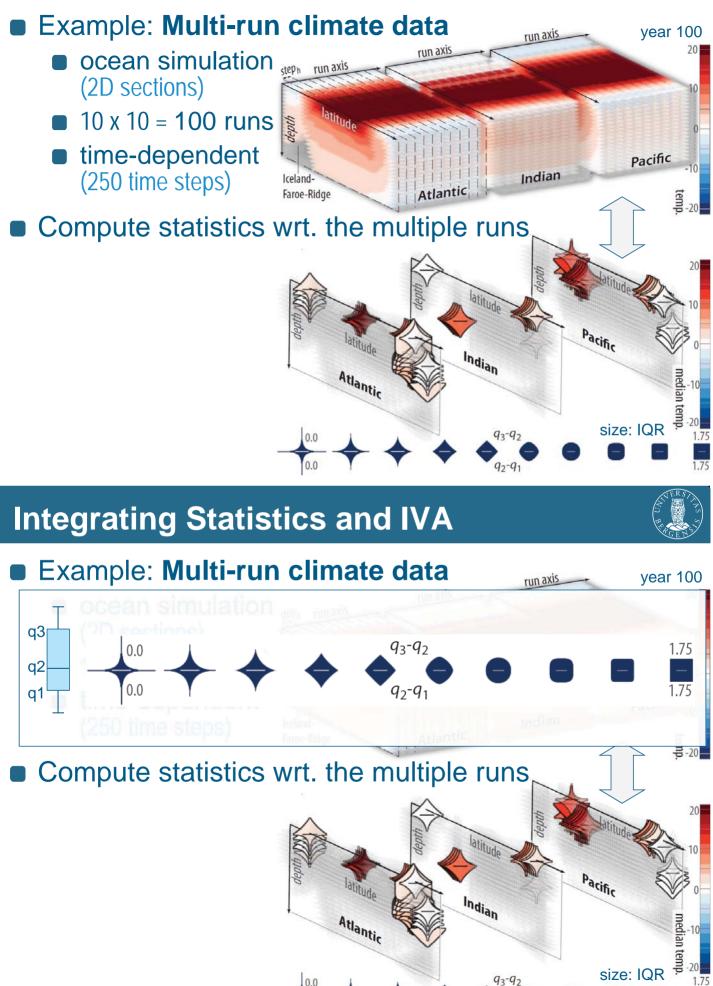
(°C) average temp. in ten years

1.5



Integrating Statistics and IVA

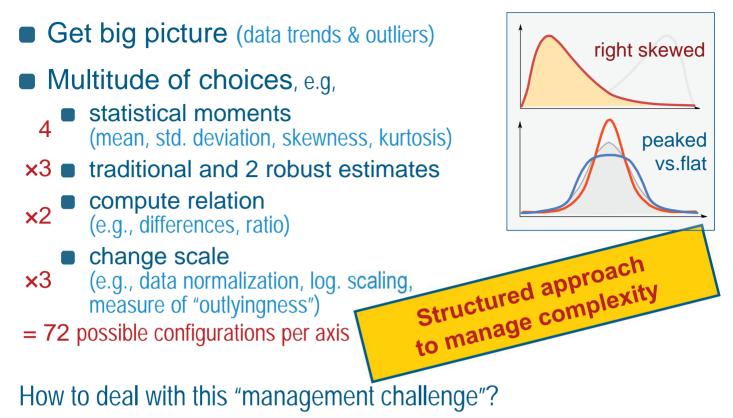




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Moment-based Visual Analysis



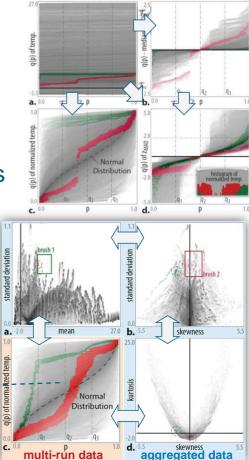


Moment-based Visual Analysis



- alter axis/attribute configuration (construct a multitude of informative views)
- maintain mental model of views
- classification of moment-based views





multi-run data

quantile plot (focus+context)

Iterative View Transformations



Change axis/attribute configuration of view

- change order of moment
- robustify moment

	med/MAD-based		traditional	octile-based	
1 st moment	$\operatorname{median}_{\Pi} \mathcal{T}_r$		mean <i>T_{ord}</i> 负 仓	$\overleftarrow{\tau}_{rol}$, median
2 nd moment	MAD	令①	stddev.	行贝	IQR
3 rd moment	skew _{MAD}	①①	skewness	介贝	skew _{oct}
4 th moment	kurt _{MAD}	①①	kurtosis	①①	kurt _{oct}

- compute relation (e.g., difference or ratio)
- change scale (e.g., normalize, z-standardization)

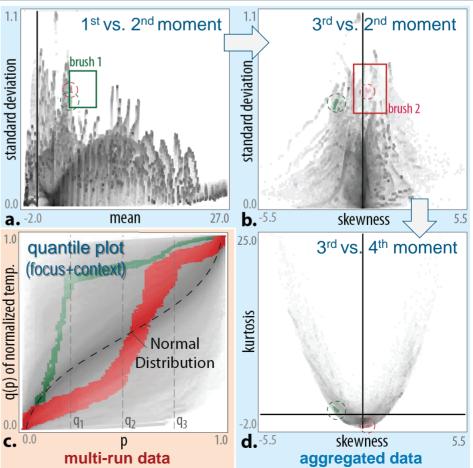
Closer related to data tranformations

Basic View Setup: Opposing Different Moments

change order of moment brush 1 standard deviation \mathcal{T}_{rob} med mean n_{Trob} Û Tord I 1) std.-dev. IQ ЛÛ J skey skewness IAD ₽ kurt Ŷ kurtosis D 0.0 mean -2.0 a. 1.0 quantile plot \rightarrow study relations

→ investigate basic characteristics of distributions

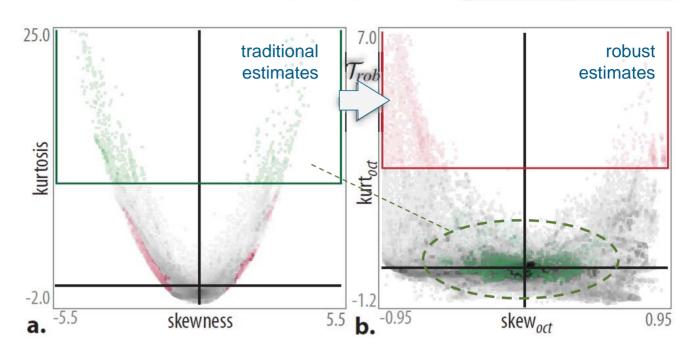
betw. moments



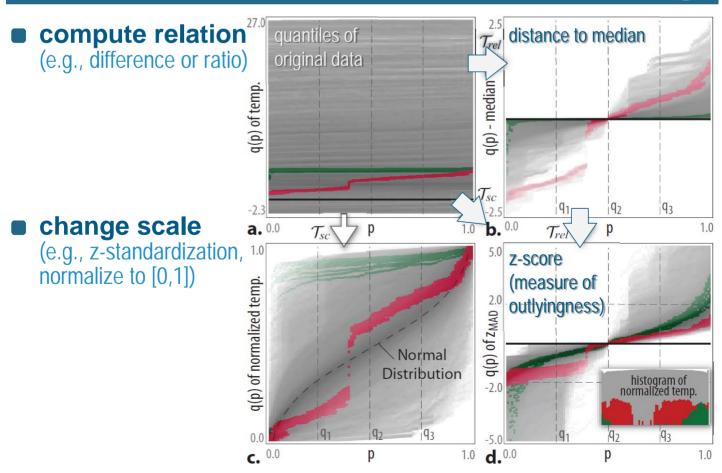
Views: Opposing Different Moments







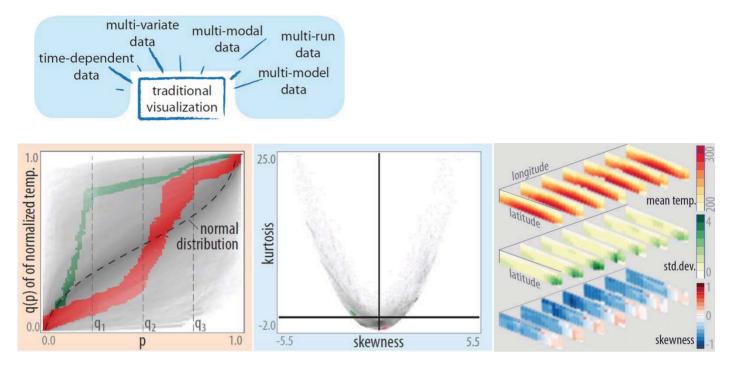
Other View Transformations



Moment-based Visual Analysis



J. Kehrer, P. Filzmoser, and H. Hauser. **Brushing moments in interactive visual analysis.** *CGF*, *29*(*3*):*813–822*, *2010*.



Conclusions

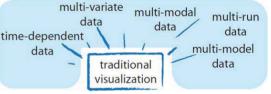
Study of multi-faceted data

- IVA across 2 data parts
 - relating multi-run data ⇔ aggregated statistics
 - analyst can work with both parts (e.g., check validity)

Integration of statistical moments

- traditional vs. robust statistics, outliers
- iterative view transformations
- interactive statistical plots (linking & brushing)

Workflow for hypothesis generation



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