Extreme Air Quality Events Using a Hierarchy of Models: Present and Future

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--Questions--

Overall:

How are is the probability, frequency, duration, and severity of high pollution episodes likely to change under future emission and climate scenarios?

Related:

i) Under current conditions what is the probability of an extreme pollution event in the US?

ii) What are the geographic, meteorological, climatological, and chemical conditions that could contribute to extreme pollution episodes in the US?

iii) What parts of the country are particularly sensitive to extreme pollution events now and in the future?

iv) How do extreme pollution events relate to heat waves and temperature? What are the feedbacks between heat waves and severe pollution events? How important is the presence of biomass burning to extreme pollution events?

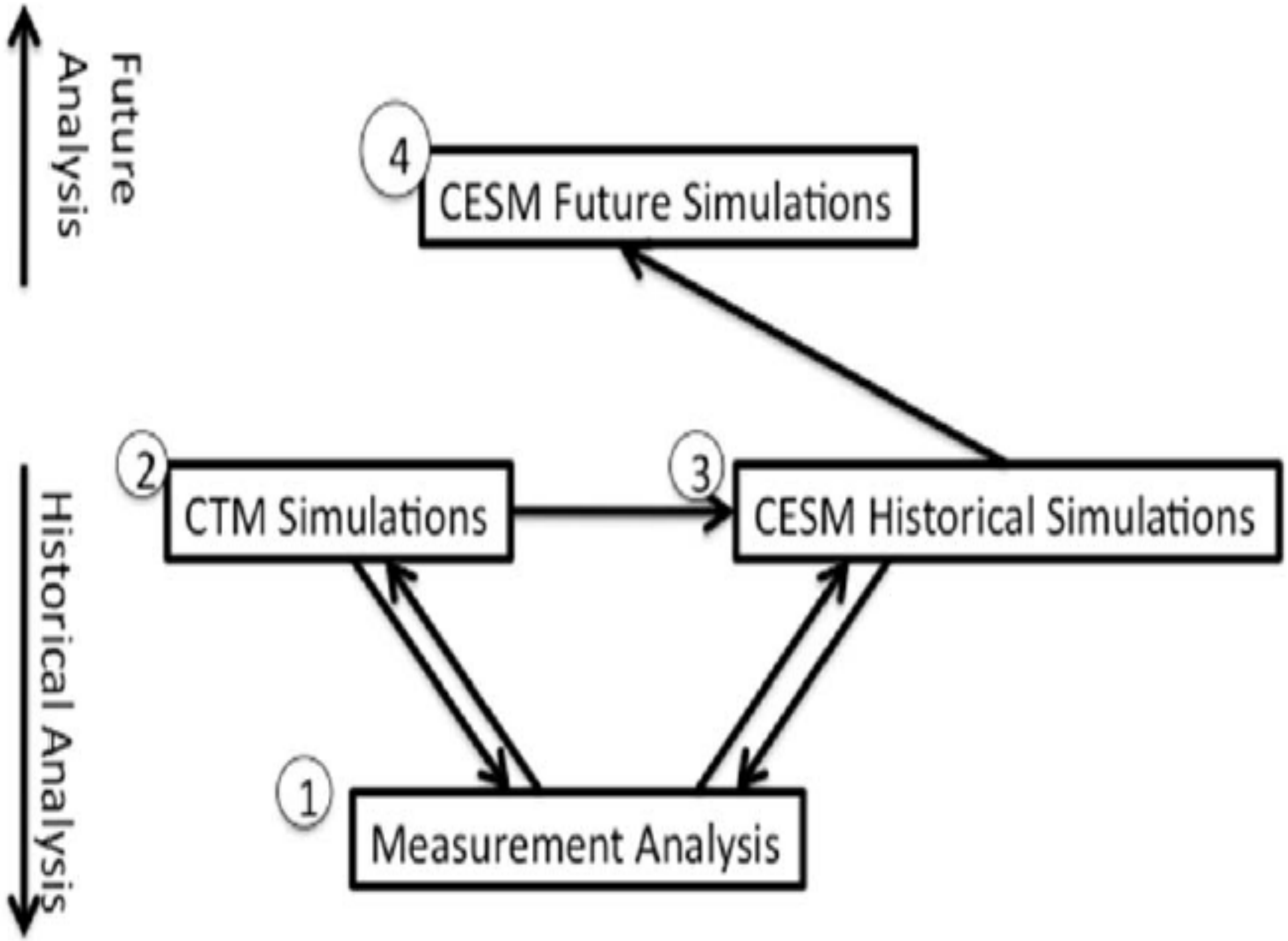
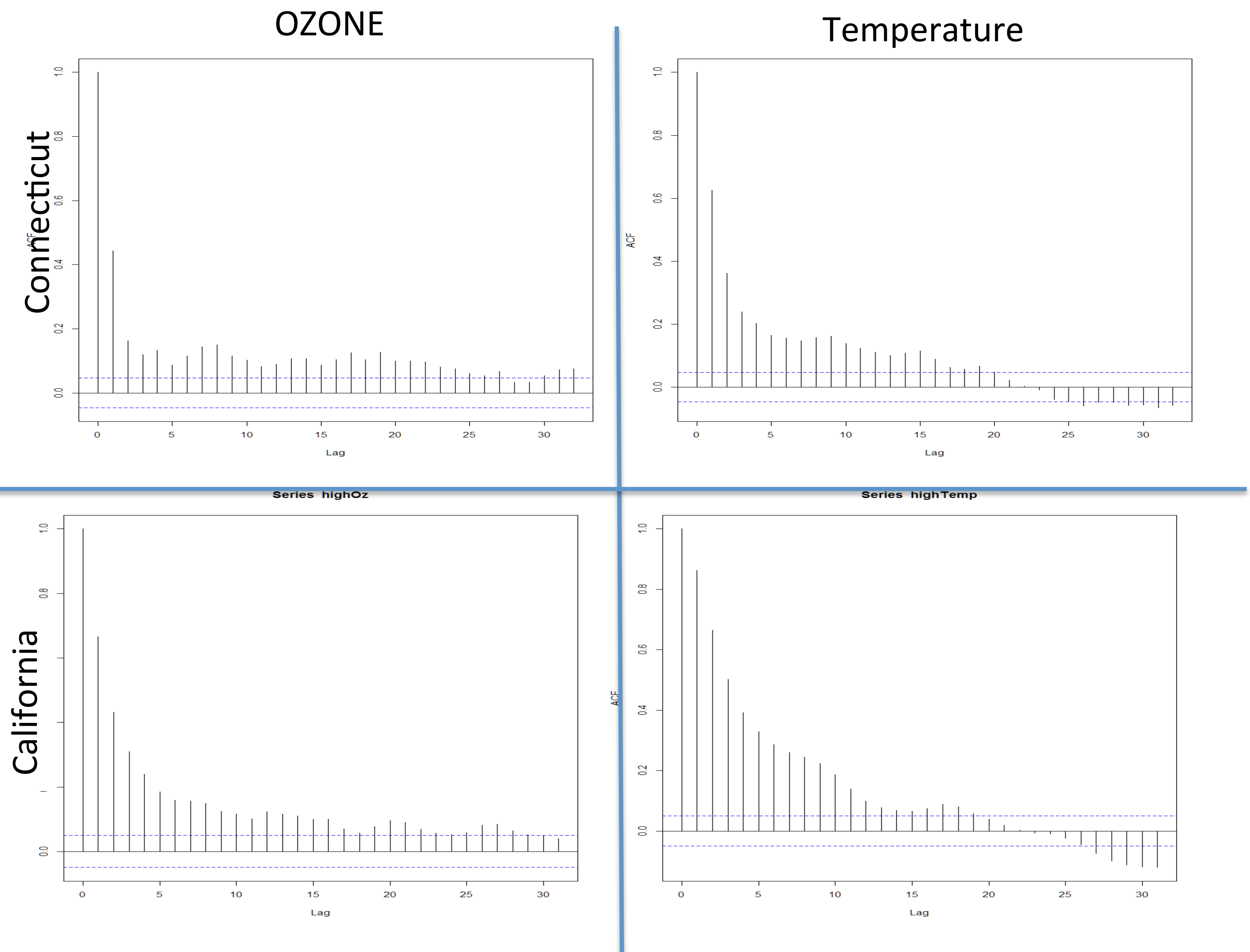


Figure 1: Overview of Analysis Plan

Task 1: Measurement Analysis

- Apply extreme value theory to measurements.
- Regional description of extreme events
- Extremal dependence between pollution and heat spells/ temperature
- Relationship between the severity and duration of the pollution events/blocking

Autocorrelation at Two Castnet Sites



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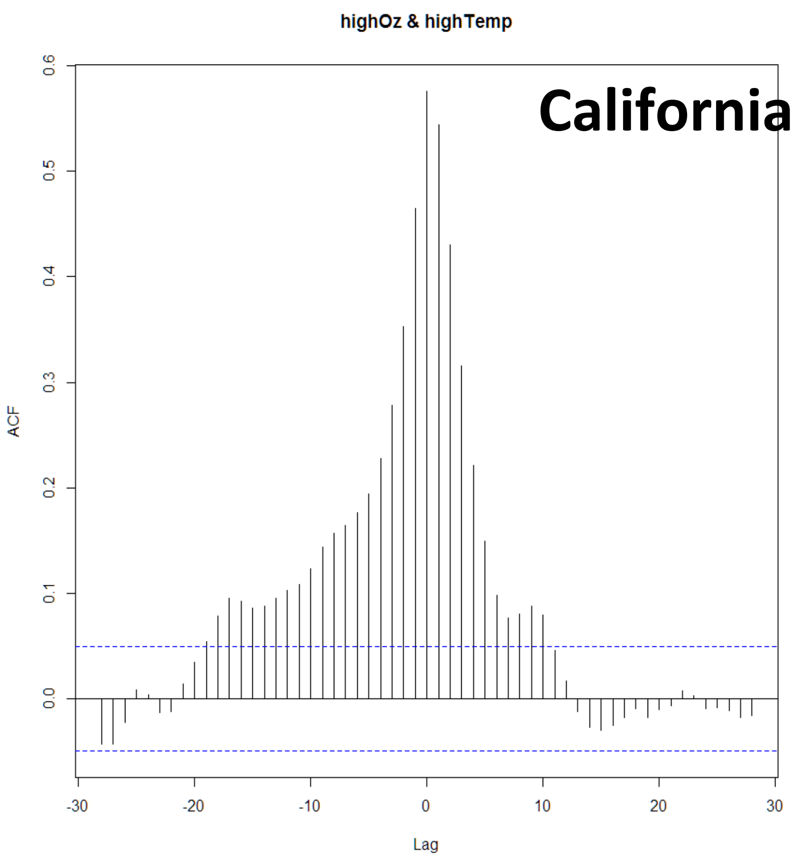
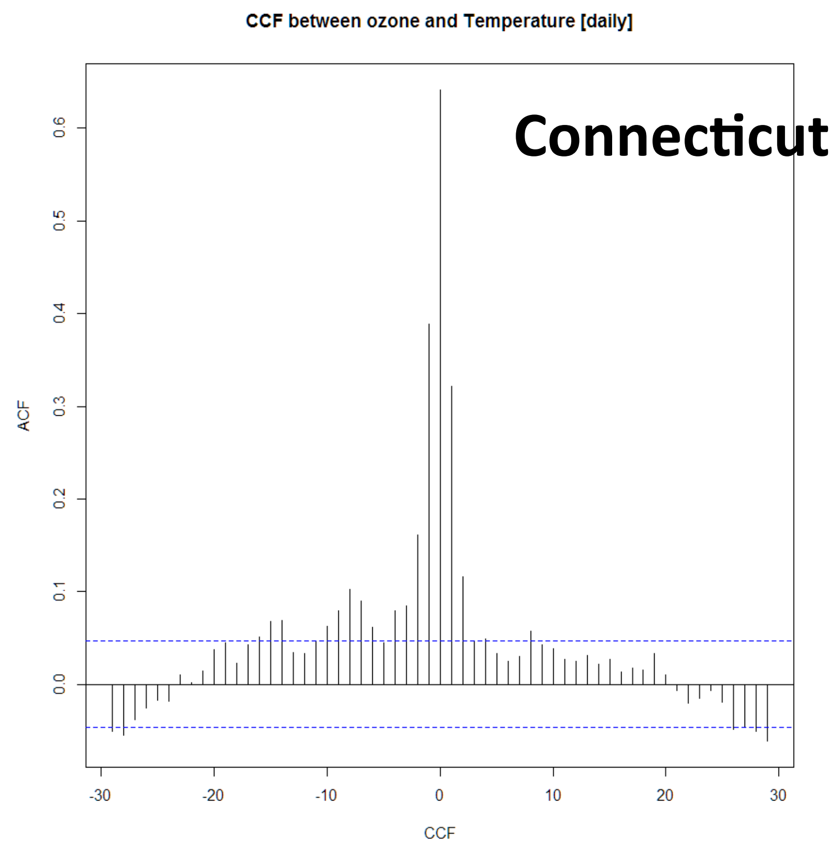
Ozone-Temperature Cross Correlations (Regional Differences)





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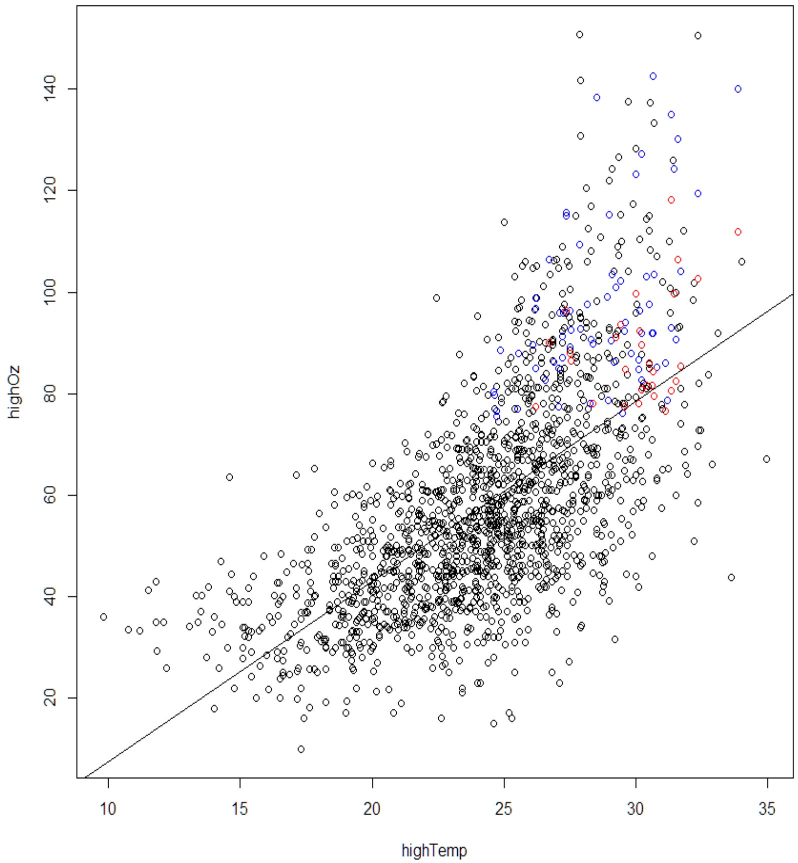
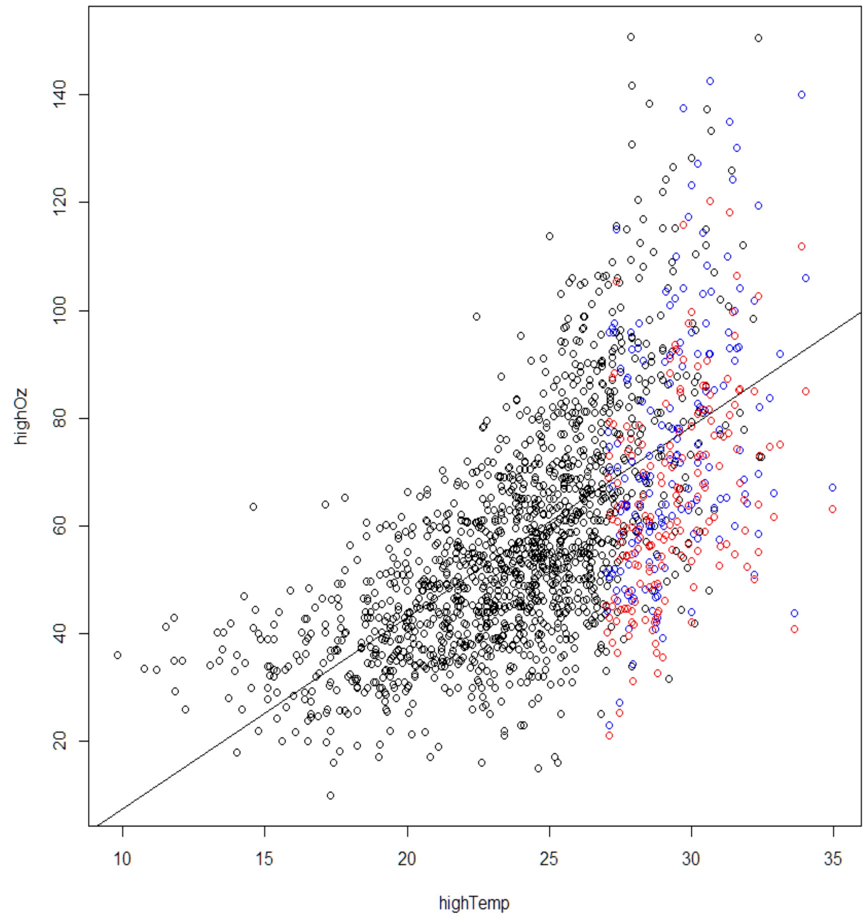
Ozone-Temperature Relationship Connecticut

Red (8 hour), Blue (Daily Max)
O3 > 75 ppb for 4 days



Red (8 Avg), Blue (Daily Max)
T > 27 C for 4 days



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Task 2: Extreme events in the Community Earth System Model (CESM)

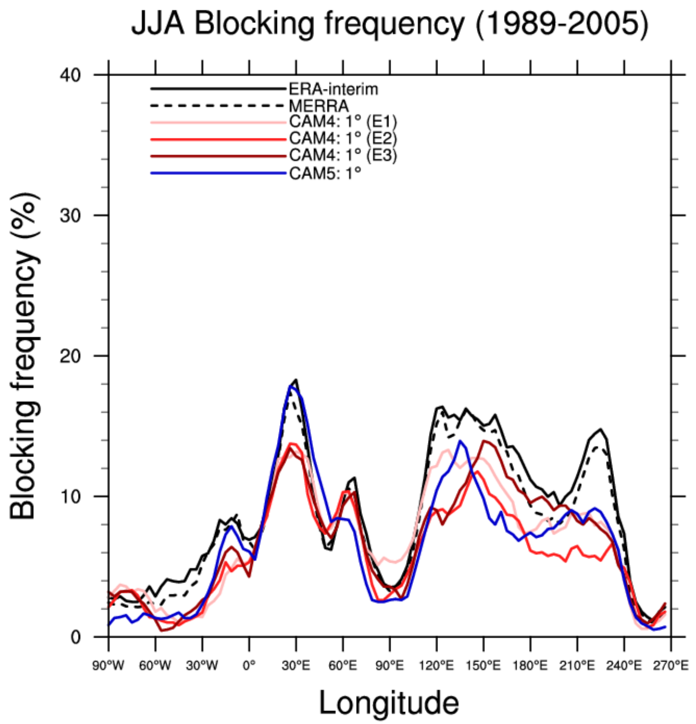
- Evaluate the ability of the CESM to simulate extreme events
- Improve simulation of extreme events in CESM
  - Meteorological Parameterizations
- Improve simulation of extreme events in CESM
  - Chemical Parameterizations

Errors in Climate Models

- Many climate models exhibit longstanding systematic model-errors, e.g. biases
- Individual models have problems in capturing meteorological extremes (Kharin et al., 2005)
- Meteorological variability in coarse resolution models is underestimated (Bell et al., 2010)
- One common source of model-error are unresolved subgrid processes

Summertime blocking in CAM

- JJA blocking frequency in different CAM ensemble members (E1-E3), Reanalyses and different CAM versions
- CAM4 underestimates summer-time blocking over European and Pacific sector
- CAM5 has greatly improved index over the European sector



Courtesy Rich Neale

Methodologies for Improving Variability in Climate Models

I. Deterministic Methodologies

– Increasing horizontal resolution
– Improving the deterministic parameterizations

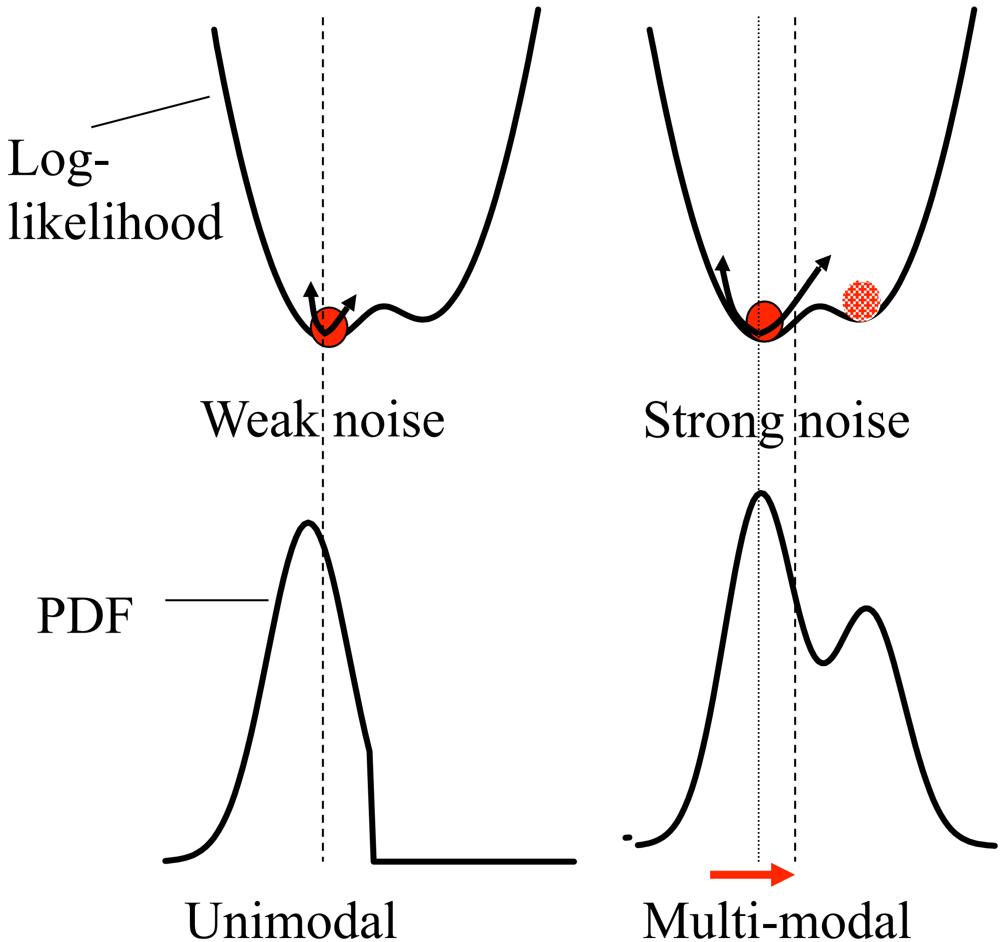
II. Stochastic Methodologies

1. Stochastic kinetic-energy backscatter scheme (SKEBBS)
– Rationale: A fraction of the dissipated kinetic-energy is scattered upscale and available as forcing for the resolved flow (Shutts, 2005)

2. Stochastically perturbed parameterization scheme (SPPT)
– Rationale: Especially as resolution increases, the equilibrium assumption is no longer valid and fluctuations of the subgrid-scale state should be sampled (Buizza et al. 1999)

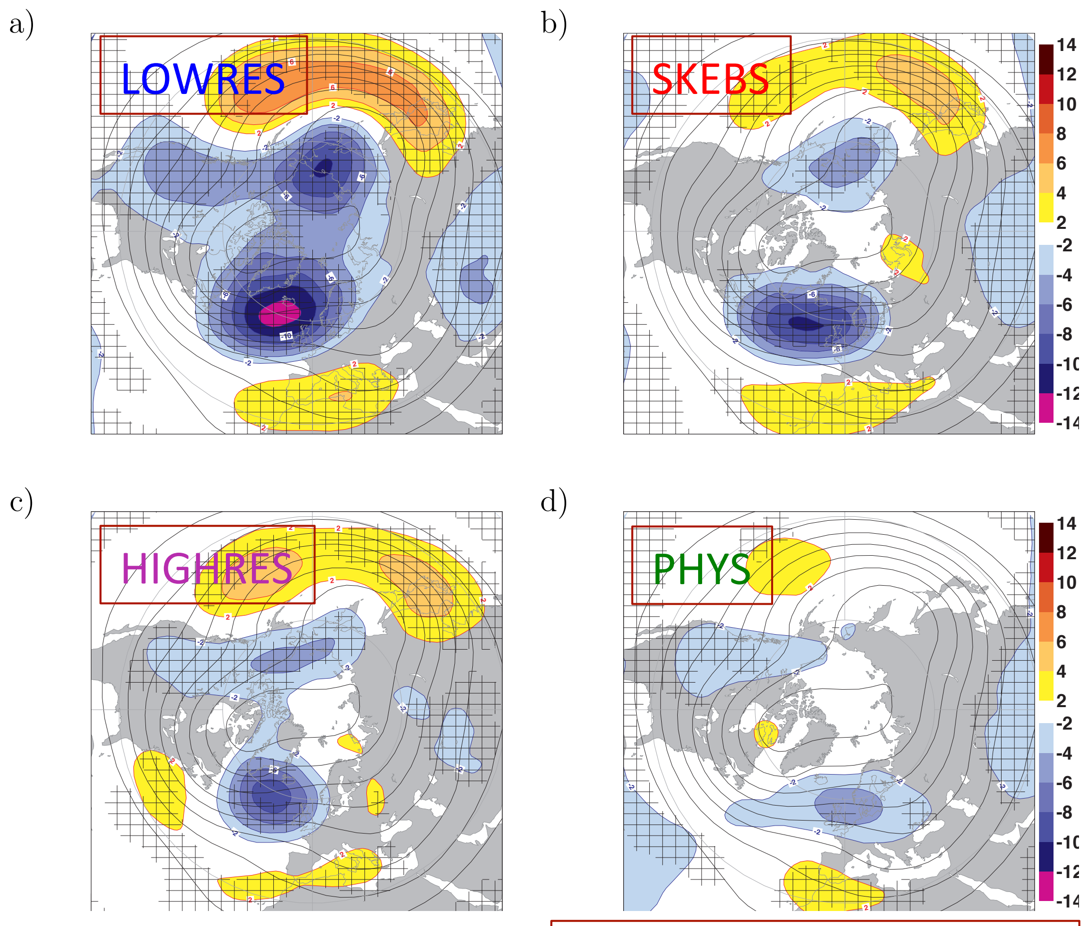
Potential to reduce model error

- Stochastic parameterizations can change the mean and variance of a PDF
- Impacts variability of model (e.g. internal variability of the atmosphere)
- Impacts systematic error (e.g. blocking precipitation error)



Mean systematic error of 500 hPa geopotential height fields

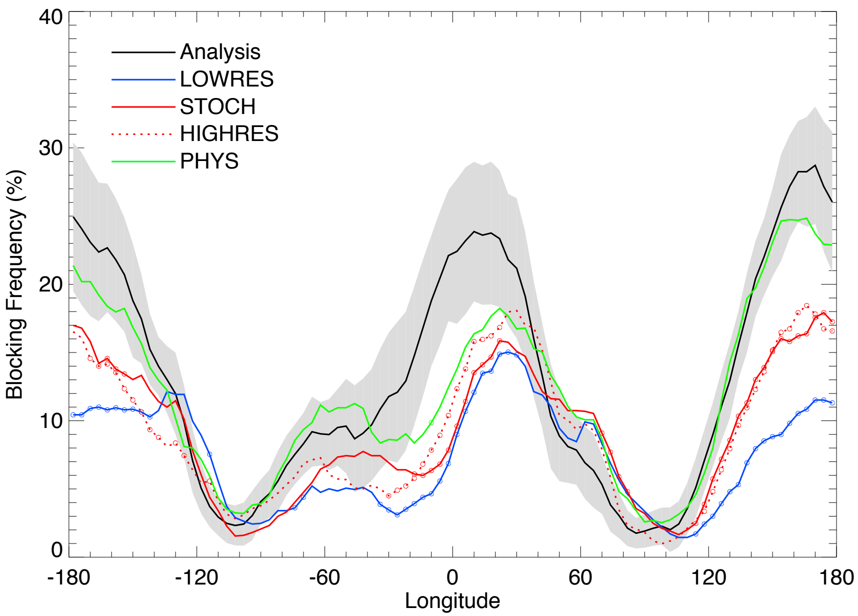
- Implemented in ECMWF IFS
- Reduction of z500 bias in all simulations with a model-error representation



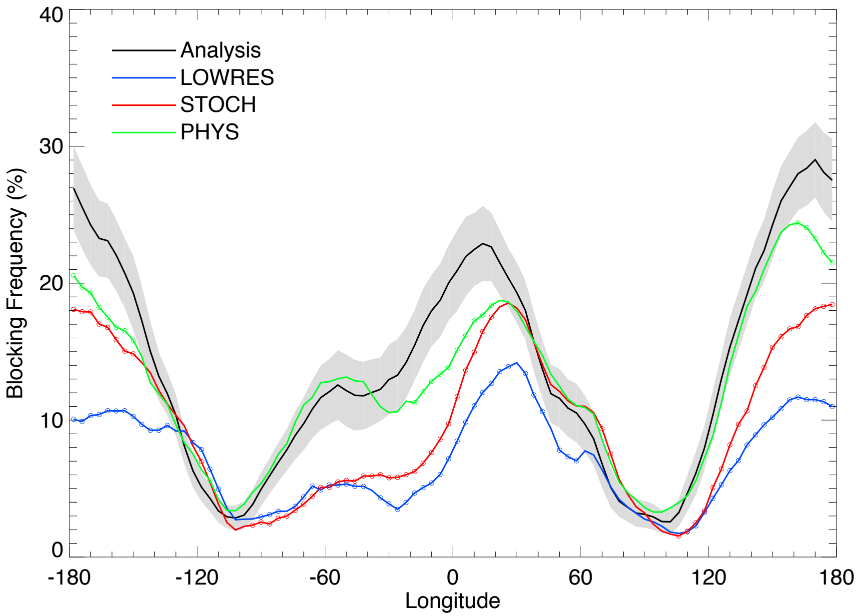
Berner et al. 2012, J.Clim

Frequency of wintertime Northern Hemisphere blocking events in ECMWF IFS

1990-2005



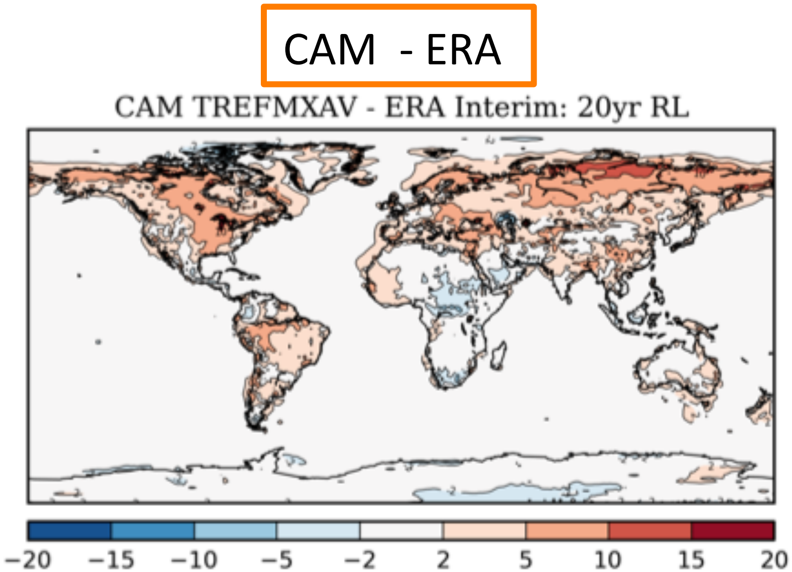
1962-2005

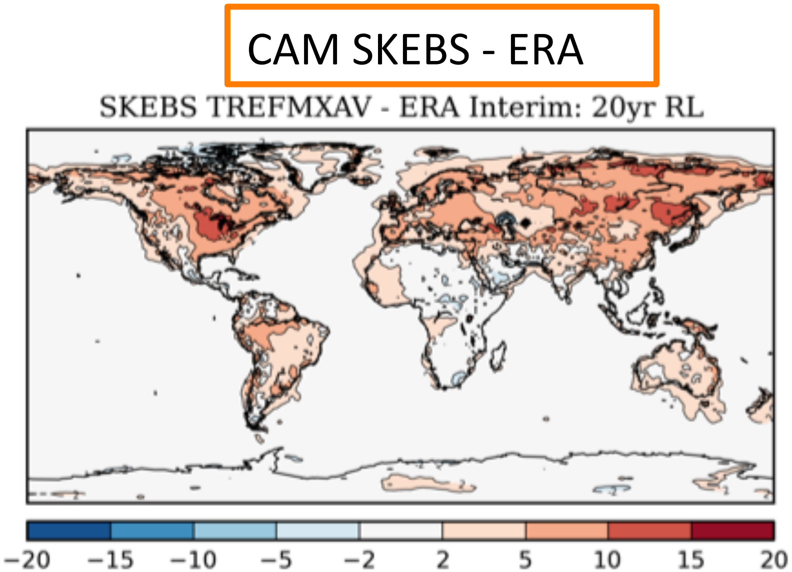


- Implementation of dissipation rates for SKEBS in CAM4 only at the very beginning

Berner et al. 2012

20-yr return levels for maximum Temperatures at 2m





- Differences of 20-yr return levels for maximum temperatures at 2m from ERA-Interim
- In certain regions (e.g. Mid-west) SKEBS has higher 20-yr return levels than CAM4
- Over many land regions, CAM4 has higher 20-yr return levels than ERA reanalysis
- Hence the impact of SKEBS is negative in some regions (e.g. the Mid-west), but positive in others Central Africa

Courtesy Tagle at al.

Variability in Climate Models

- NCAR task: Implement a stochastically perturbed physics scheme (SPPT) into CAM4 (Implementation completed, testing under way)
  - SPPT does not significantly impact the bias
  - Impact on variability is under investigation
- Assess the impact of SPPT and stochastic kinetic-energy backscatter scheme (SKEBS, partially implemented) on air quality (not yet evaluated)
  - previous results: SKEBS increases the 20yr return levels of T in 2m, but base model seems to overestimate extreme heat in the first place (completed)
  - Impact of SPPT and SKEBS on summertime blocking, after SKEBS is modulated with dissipation rates (started)
  - Impact of SPPT and SKEBS on variability across temporal and spatial scales (started)

Inclusion of Stochastic Processes in Fire Emissions

Wet

Dry

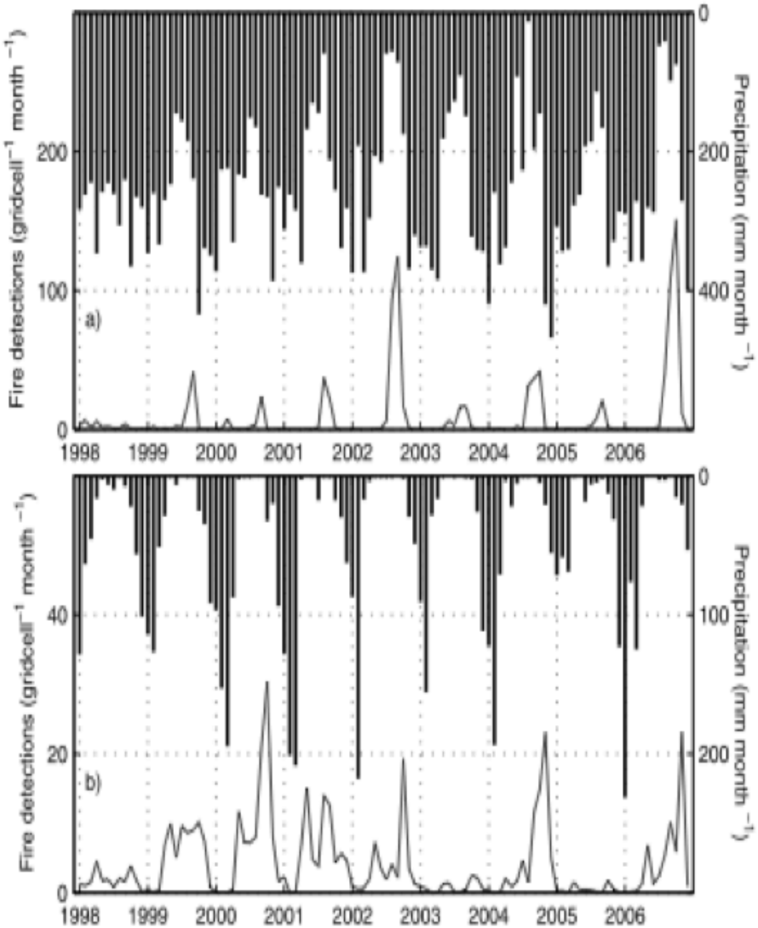
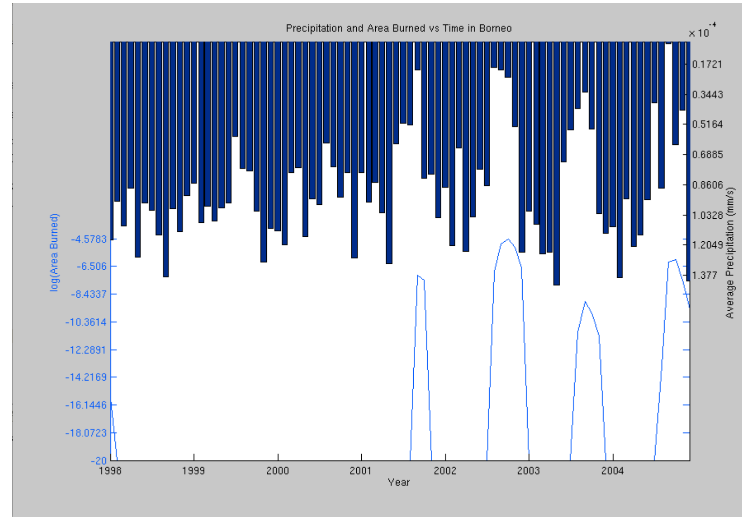


Figure 4. Time series of monthly precipitation and active fire detections for (a) a wet ecosystem (southern Borneo, latitude 2°S–4°S, longitude 110°E–116°E) where fire activity was higher during drought periods, (b) an arid ecosystem (northwest Australia, latitude 17°S–20°S, longitude 114°E–131°E) where fire activity was higher after a wet season with abundant rainfall, and (c) the same region as Figure 4b with average monthly fAPAR (not available for 2006) plotted instead of monthly precipitation.

Van der Werf etal: based on satellite data

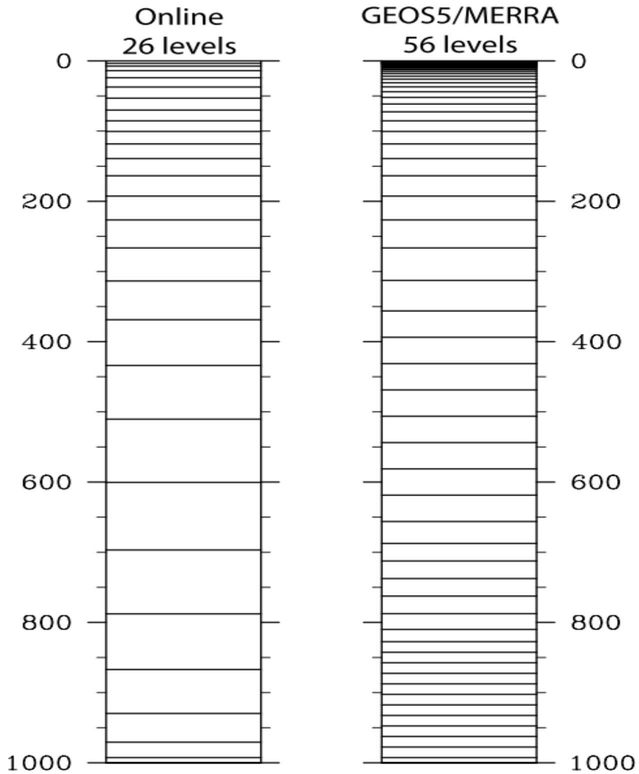


- While the CLM-CN prognostic fire model (Kloster et al., 2010) was tuned to match GFED in annual means, the frequency is very different (and wrong!).
- Inclusion of Stochastic processes should improve this simulation.

(slide courtesy of Spencer Clark and Natalie Mahowald)

Task 3: Evaluate extreme values in Chemical Models (CTMs and GCMs)

- Evaluation of ability to capture extreme events
- Impact of non-stationarity in extreme events
- Sensitivity to model formulation of chemistry

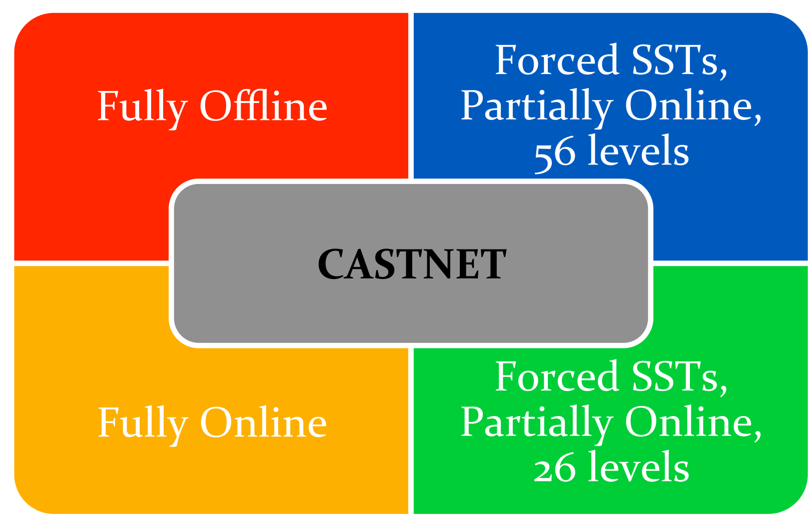


Overview of the Four Simulations

1 Fully Offline, 2 online (forced SSTs), 1 Fully Online

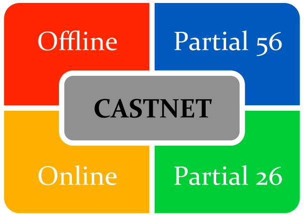
Emissions, Chemistry, Parameterizations, and time (1994 – 2005) identical for each simulation

Simulation	Meteorology	SSTs	# of Levels
Fully Offline	MERRA	Forced	56
Partially Online, Forced SSTs, 56 levels	calculated online	Forced	56
Partially Online, Forced SSTs, 26 levels	calculated online	Forced	26
Fully Online	calculated online	Simulated online, POP2	26

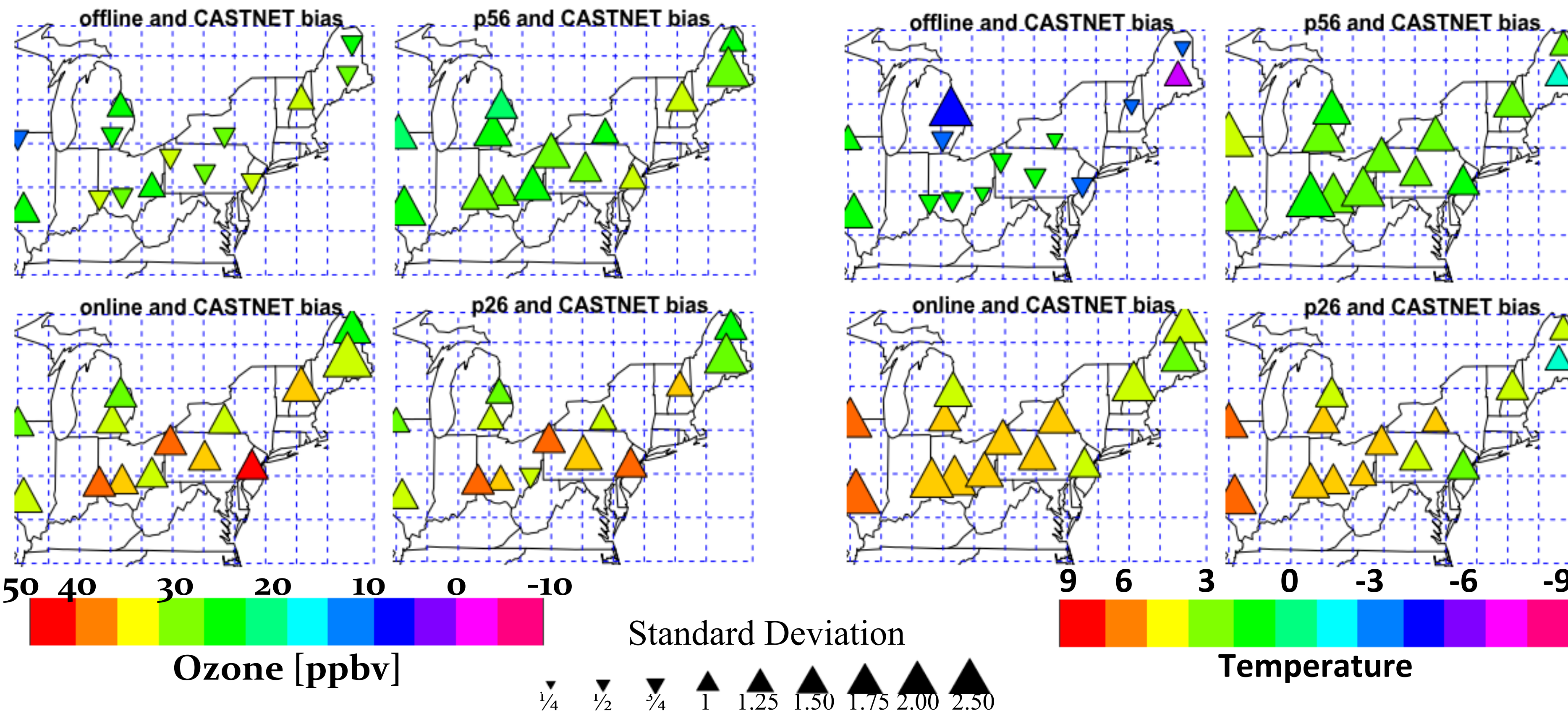


Brown-Steiner and Hess

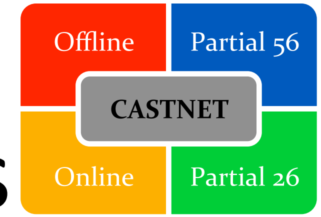
DM8H O_3 (left) & DMT(right) Biases



- Higher DM8H O_3 bias in Ohio/Pennsylvania region
- All of the online simulations show a higher SD in both DM8H O_3 and DMT than the offline simulation

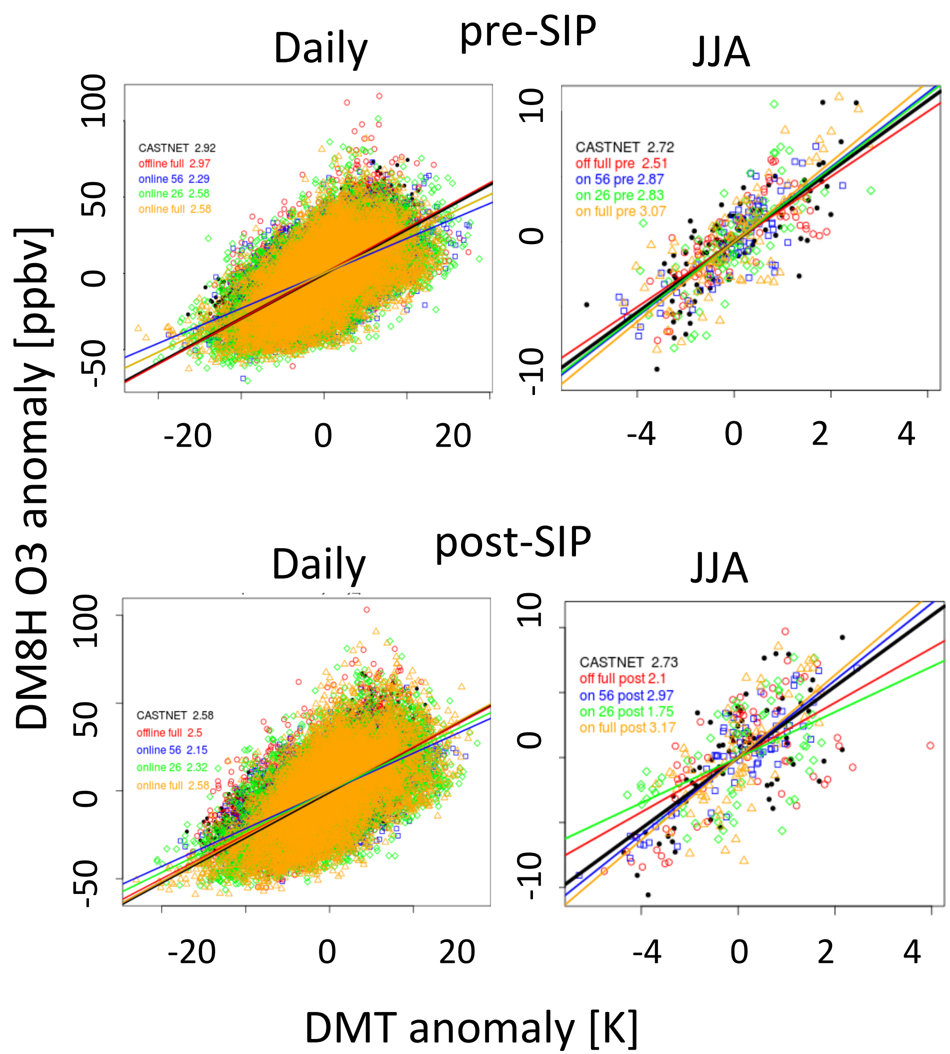


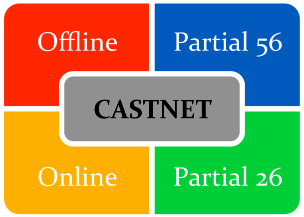
Climate Penalty Factor, comparis



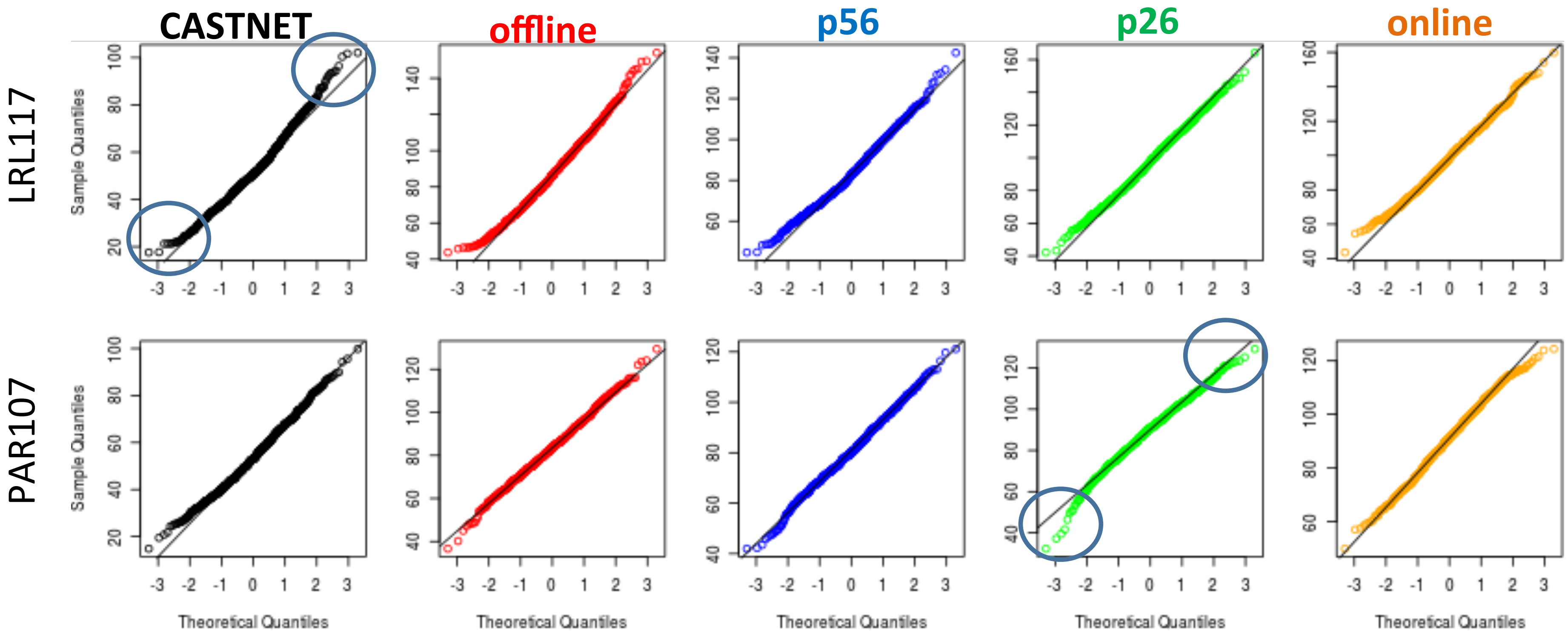
- Climate Penalty Factor (CPF) is the slope of the DM8H O3 and DMT relationships
- Pre- and Post-SIP results are significantly different for daily statistics

CPF [ppbv /K]	daily pre-SIP	daily post-SIP	JJA pre-SIP	JJA post-SIP
CAST NET	**2.92 ± 0.044**	**2.57 ± 0.044**	2.72 ± 0.23	2.73 ± 0.36
off	**2.97 ± 0.043**	**2.50 ± 0.039**	2.51 ± 0.23	2.11 ± 0.32
p56	**2.29 ± 0.041**	**2.15 ± 0.042**	2.87 ± 0.21	2.97 ± 0.20
p26	**2.58 ± 0.039**	**2.32 ± 0.038**	**2.83 ± 0.32**	**1.75 ± 0.34**
on	**2.58 ± 0.042**	**2.58 ± 0.043**	3.07 ± 0.25	3.17 ± 0.41



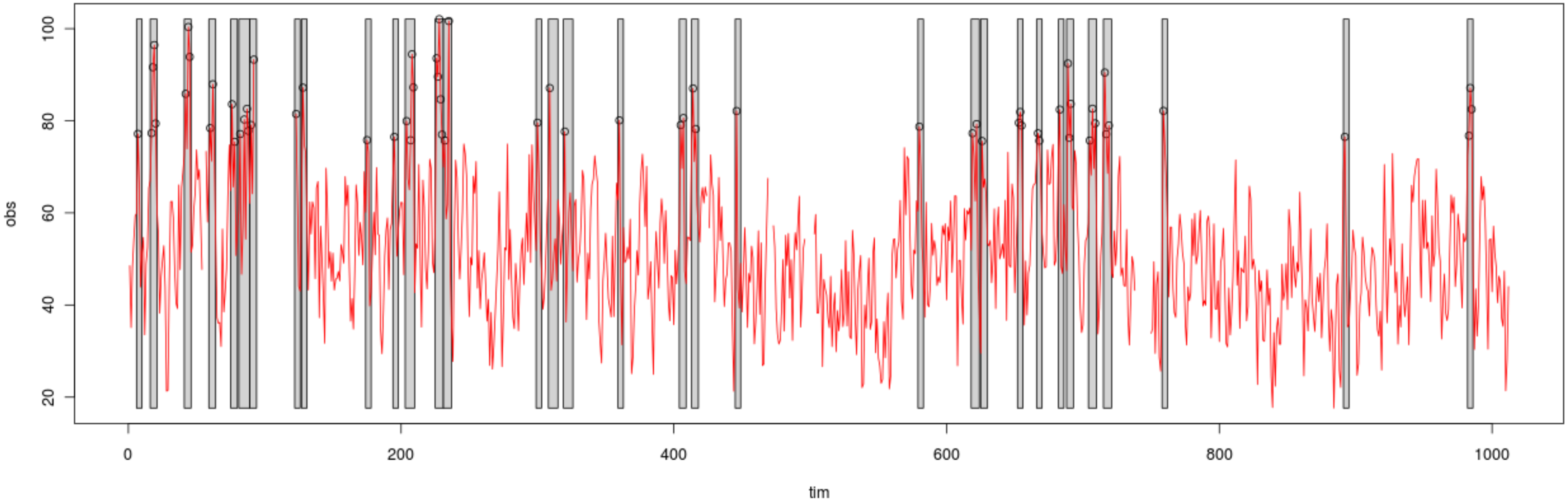


Gaussian Q-Q Plots



- Q-Q plots show that DM8H O3 distributions are not Gaussian, wider tails
- The two 26-level simulations do not behave the same way the 56-level simulations behave

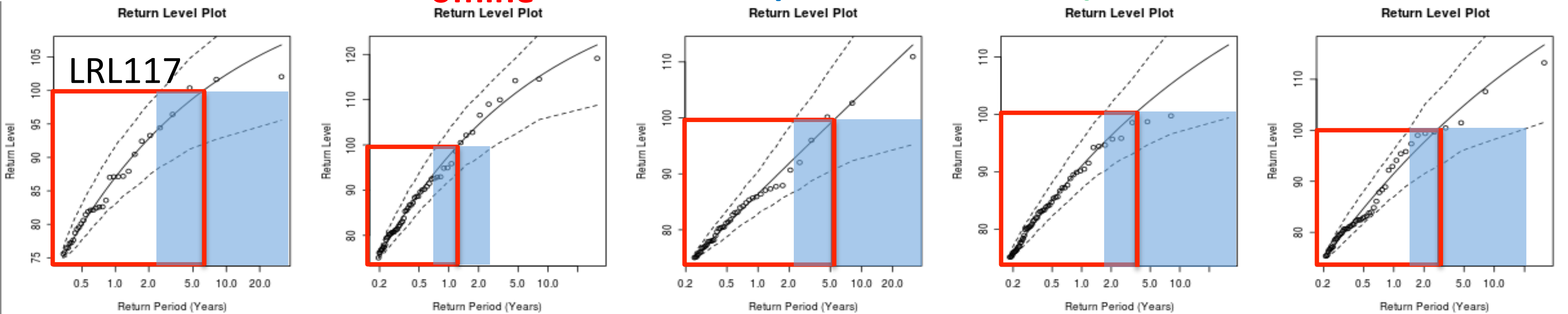
POT: Points over a Threshold



- For LRL117, a 75 ppbv threshold yields 33 events during the 11 years of summers

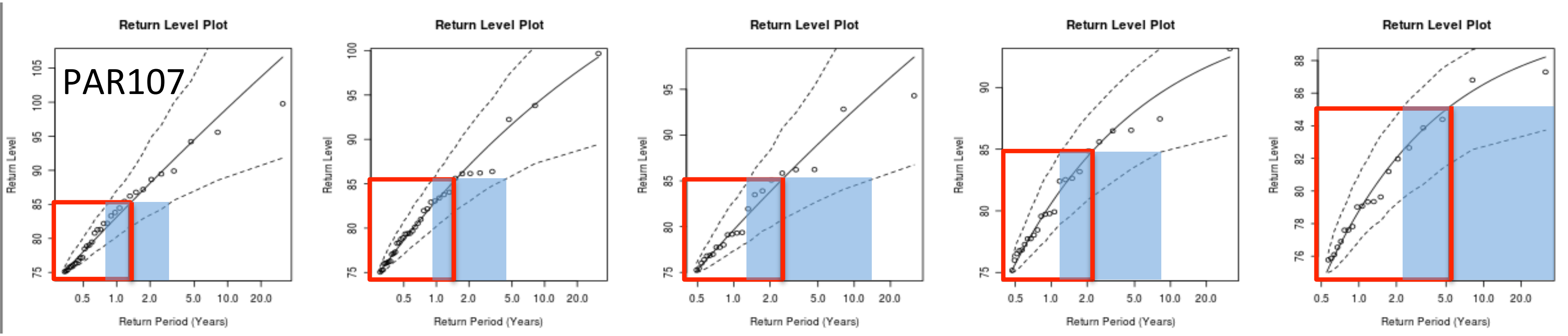
LRL117 and PAR107 Return Levels with Simulation Biases Removed

CASTNET **offline** **p56** **p26** **online**



On average, a 100 ppbv event happens every:

7 years 3 years 5 years 4 years 3 years



On average, an 85 ppbv event happens every:

1.5 years 1.5 years 2.5 years 2 years 2 years

Conclusions and Next Steps

Research is just beginning…

-Understand/quantify T-O3 relationships in model and observations

-Understand/quantify variability in GCMs and relate to heat-waves and blocking and long climate runs

-Methodologies for modifying variability in GCMs

-Understand/quantify model O3 biases/variability

-Stochastic biomass burning algorithims

-Future Simulations