Polar Amplification Helps Forecast Northern Temperature Anomalies

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Research Agenda

- Climate models, scenarios, and forecasts ...
  - ... typically rely on **linear approximations** of the relationship between climate & forcings (Matthews et al., 2009 *inter alia*)
  - ... assume exogeneity of anthropogenic and natural climate forcings, valid in the absence of **unmodeled nonlinearities**, especially "tipping points" (Pretis, 2021)
- Potential tipping points are predominantly located in the *northern* Northern Hemisphere (NH)
- The northern NH is warming particularly fast due to polar – specifically Arctic – amplification (PA or AA)
- **Contribution #1 (2nd R&R)**: PA can be structurally modeled and tested using observational data
- **Contribution #2 (in progress)**: Such a model of PA can improve medium-run forecasts of northern NH temperatures
- **Future work:** Can better medium-run forecasts **improve detection of tipping points**?

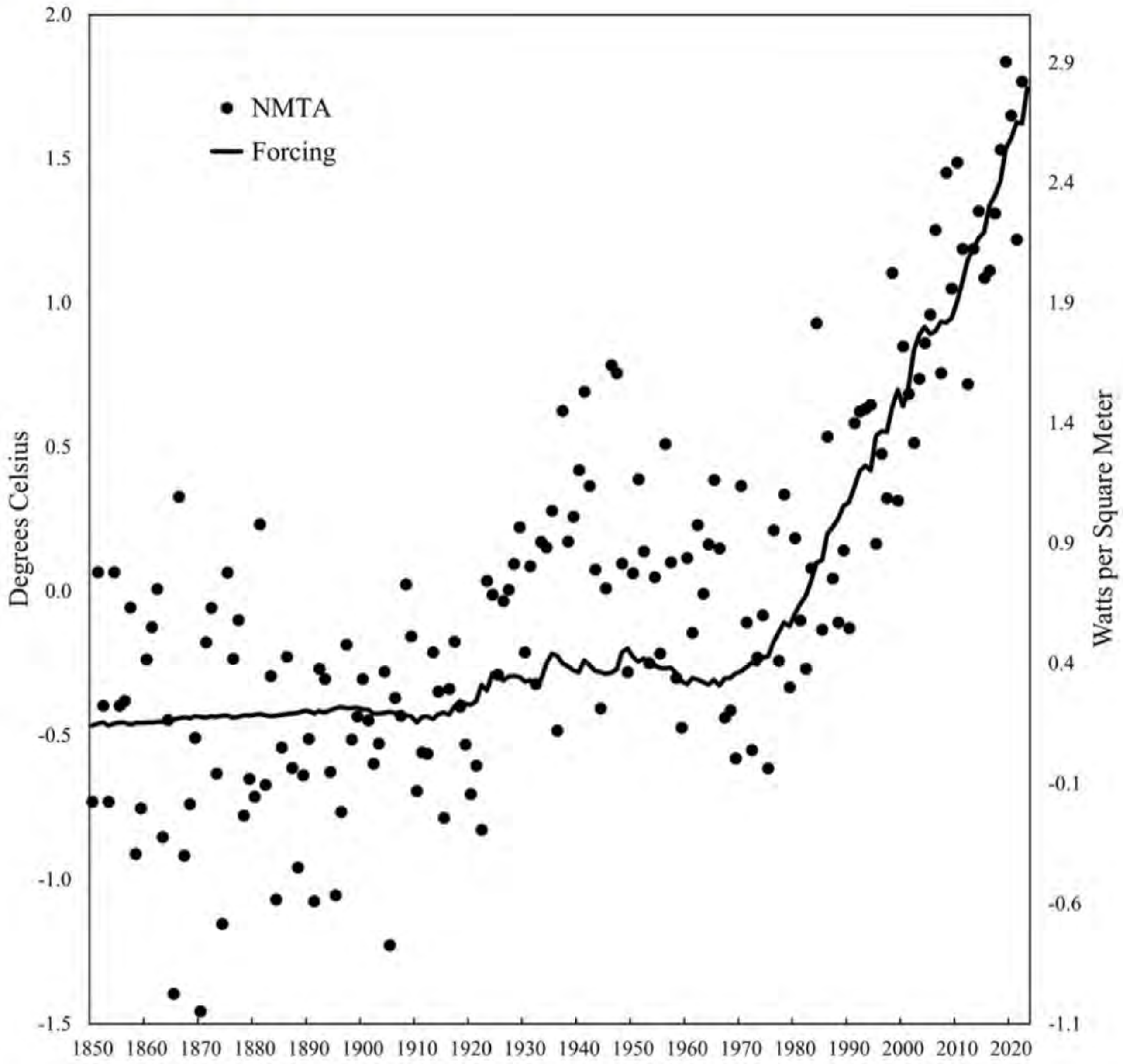
Data

Temperature: HadCRUT5 ensemble mean anomalies are available since 1850 for most 5 ° × 5 ° degree grid boxes in the NH.

- Data north of 75 °N: completely missing in some years
- 0-75 °N: $>$ 96% of the NH
- 50-75 °N: $\approx$ 10% of the globe
  - 4 of 9 potential tipping points (Lenton et al., 2008): Arctic summer sea ice, Greenland ice sheet, Atlantic thermohaline circulation, Boreal forest dieback
- T_t^- (demeaned: $\tilde{T}_t^-$): southern mean temperature anomaly (SMTA), area-weighted over 0-50 °N
- T_t^+ (demeaned: $\tilde{T}_t^+$): northern mean temperature anomaly (NMTA), area-weighted over 50-75 °N
- Southern Hemisphere temperature anomalies are not used.

Forcing: E_t (demeaned: $\tilde{E}_t$): Sum of anthropogenic forcings through 2023 (AR6, updated by Forster et al., 2024)

NMTA and Forcing



Benchmark Forecasting Models

#1 (UNI): Univariate/autoregressive

NMTA forecast ...

- ... is driven by the deterministic component of NMTA
- ... is grounded in end-of-sample NMTA observations

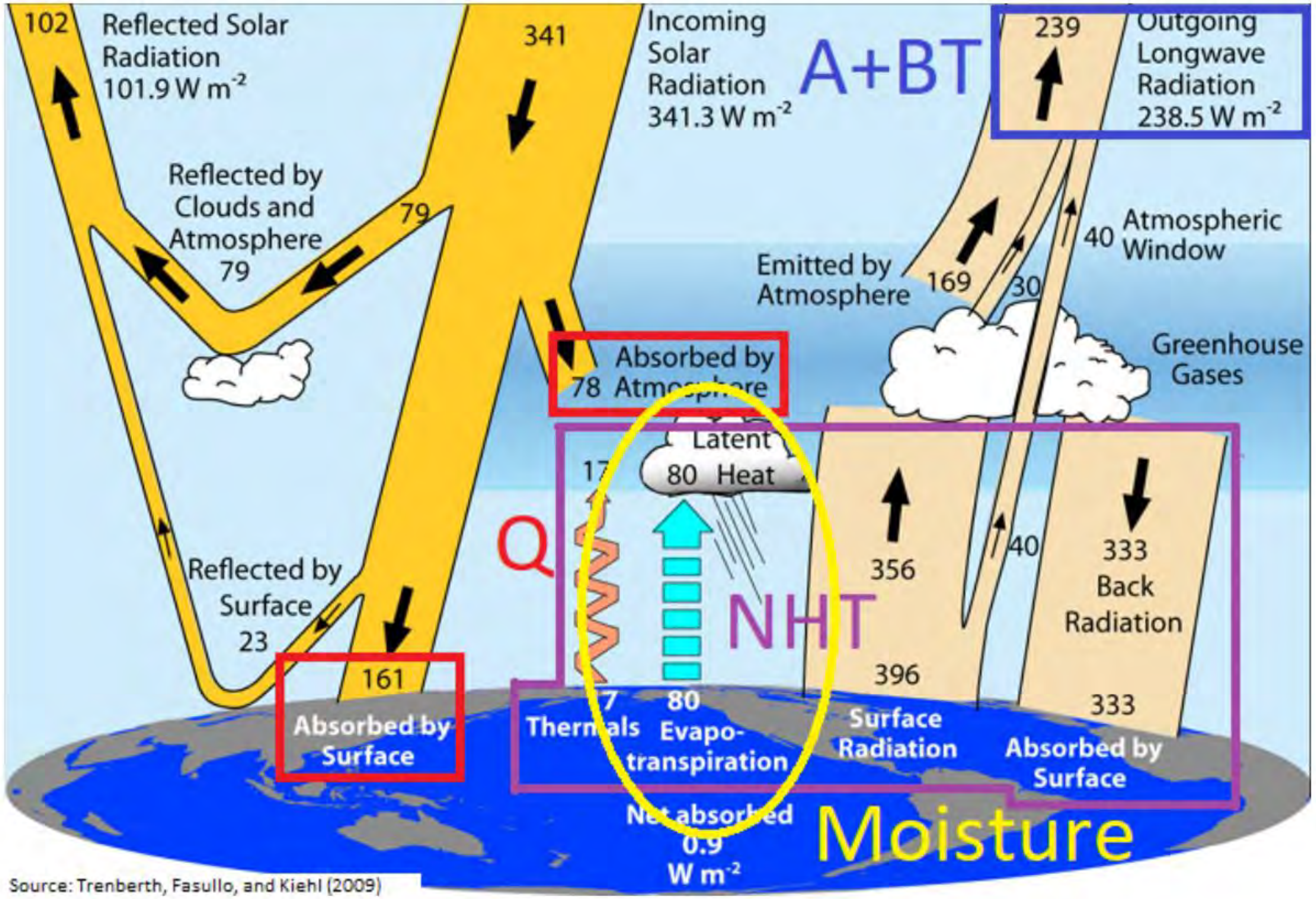
#2 (TSR): Time series regression

NMTA forecast ...

- ... exploits (long-run) physical relationship with forcing implied by energy balance
- ... is driven by the deterministic component of **forcing**, which is easier to estimate!

#3 (ARX/ARDL): Allows for short-run serial correlation

Energy Balance: Moisture Matters Locally



Source: Trenberth, Fasullo, and Kiehl (2009)

#4 (MEBM): Time series representation of a moist energy balance model based on theoretical physics models from the climate literature.

Some Details on Estimation & Forecasting

- Forecast up to $h = 1, \ldots, 10$ years using expanding training sets
  - 1850-1969 training set ($T = 120$), forecast 1970-79
  - 1850-1970 training set ($T = 121$), forecast 1971-80

    $\vdots$

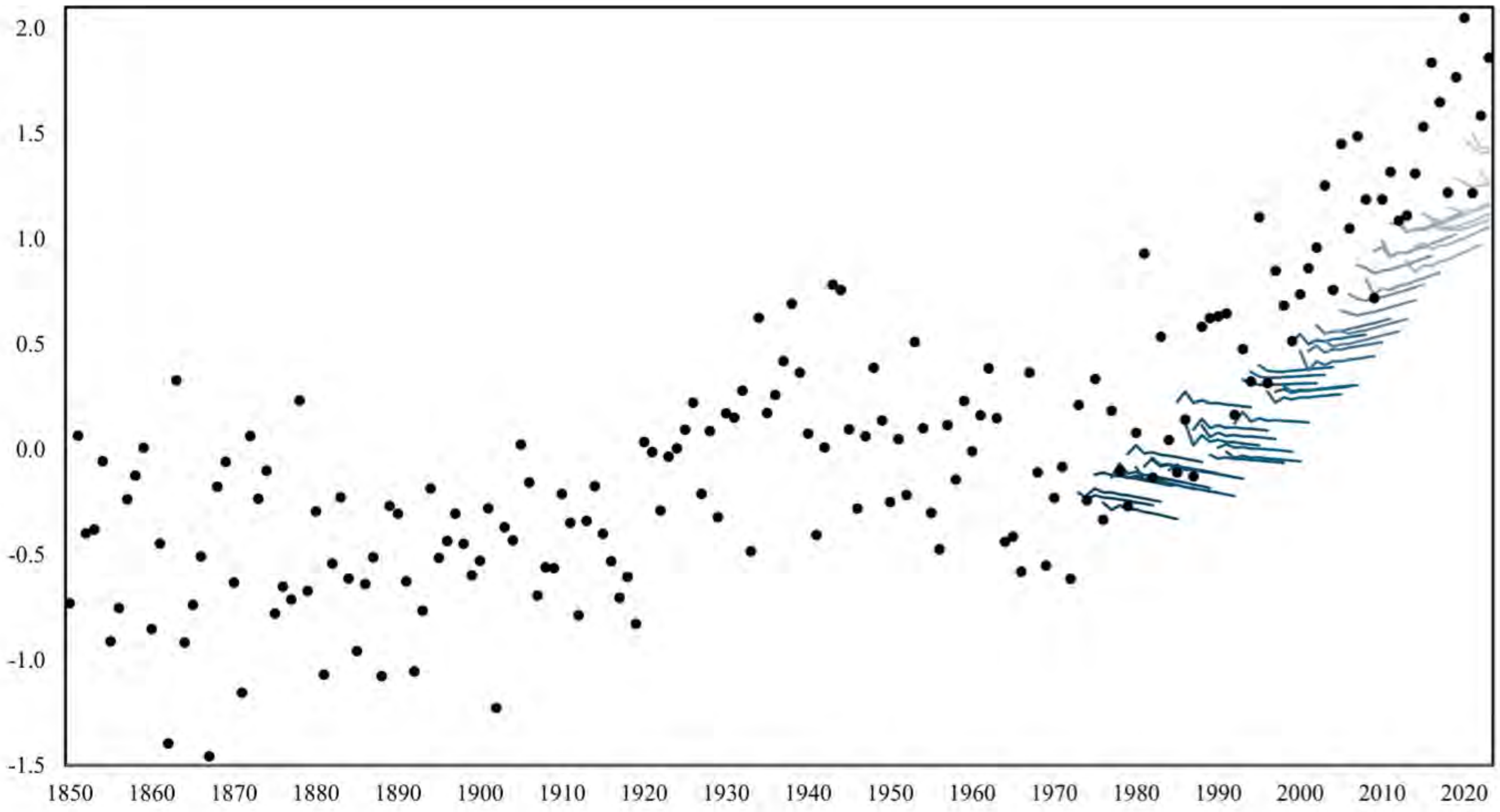
  - 1850-2021 training set ($T = 172$), forecast 2022-23
  - 1850-2022 training set ($T = 173$), forecast 2023
- Lag orders chosen from the 1850-1969 training set by failing to reject serial correlation across all trend specifications
  - UNI, TSR, ARX: One root estimated ($p = 1$) or a unit root and one root estimated ($p = 2$)
  - MEBM: One lagged difference of NMTA ($p = 2$)

Forecasting Specifications

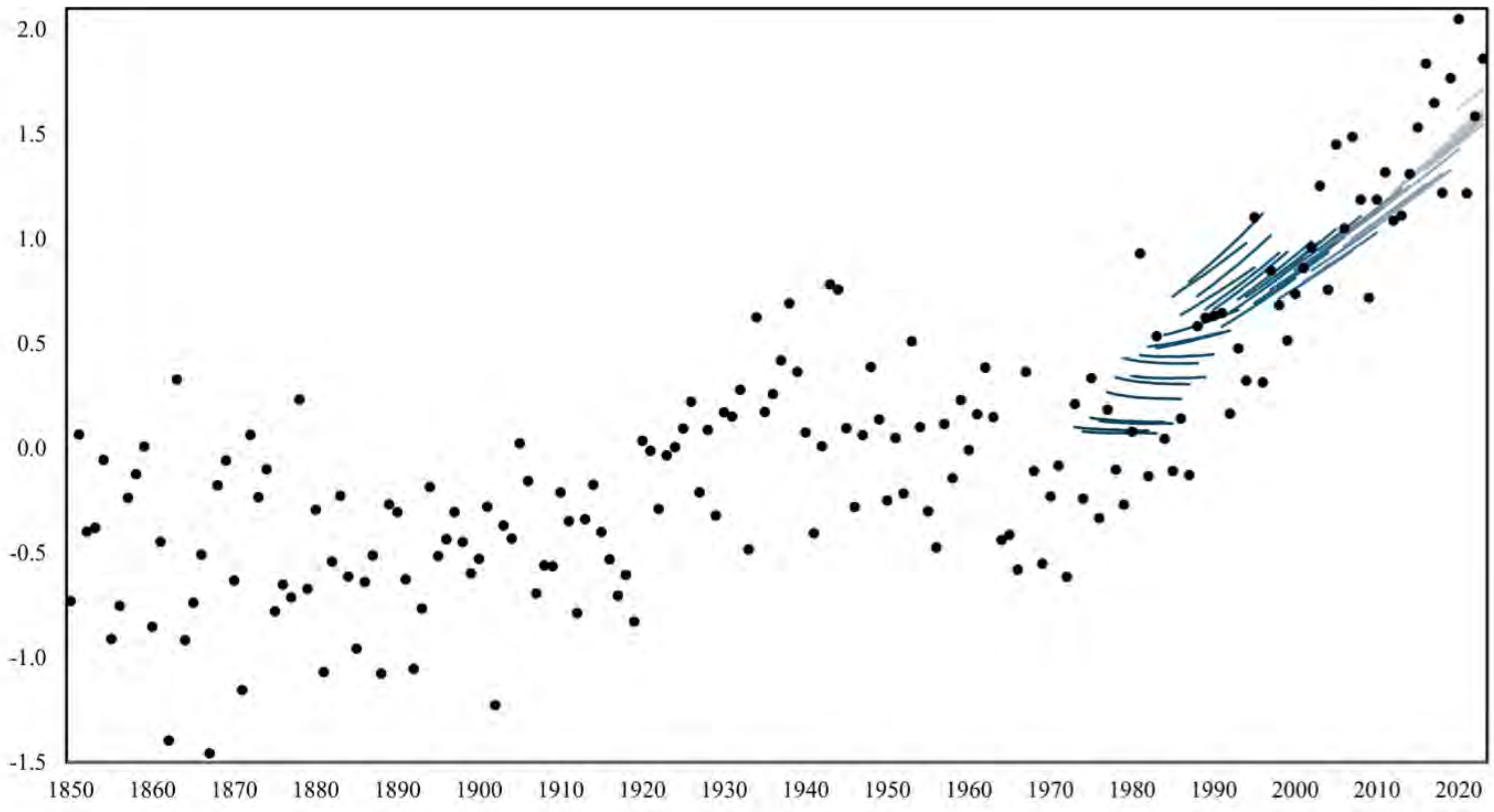
For each forecasting model, we consider eleven specifications:

1. $c_t = 1$, estimated root(s)
2. $c_t = 1$, unit root
3. $c_t = (1, t)'$, estimated root(s)
4. $c_t = (1, t)'$, unit root
5. $c_t = (1, t, t^2)'$, estimated root(s)
6. $c_t = (1, t, t^2)'$, unit root
7. $c_t = (1, t, t^2, t^3)'$, estimated root(s)
8. $c_t = (1, t, t^2, t^3)'$, unit root
9. $c_t = (1, t, \delta_1, \delta_1 t)'$, estimated root(s)
10. $c_t = (1, t, \delta_1, \delta_1 t, \delta_2, \delta_2 t)'$, estimated root(s)
11. Ensemble forecast: mean of those from specifications 1-10

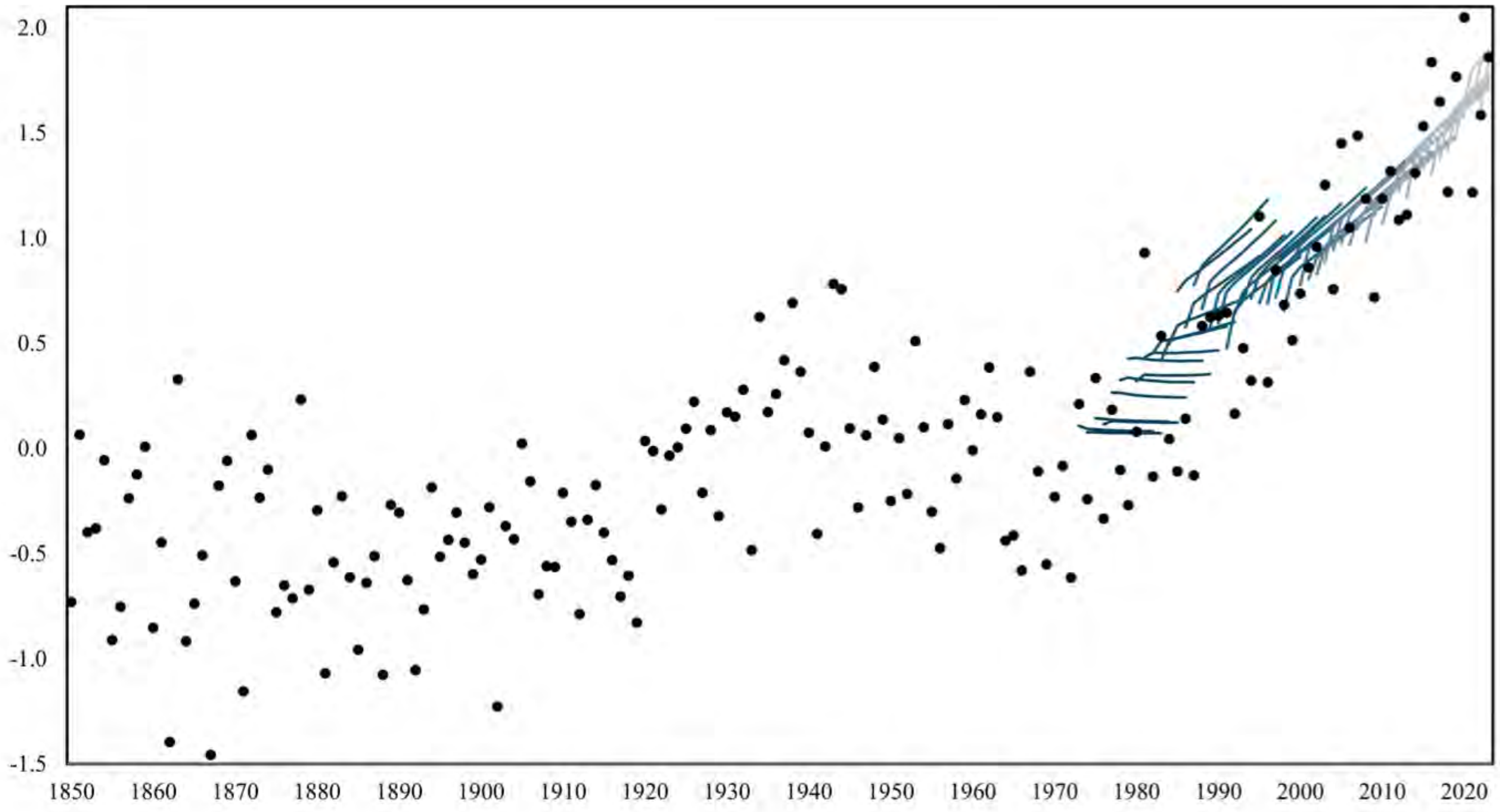
UNI Ensemble Forecasts



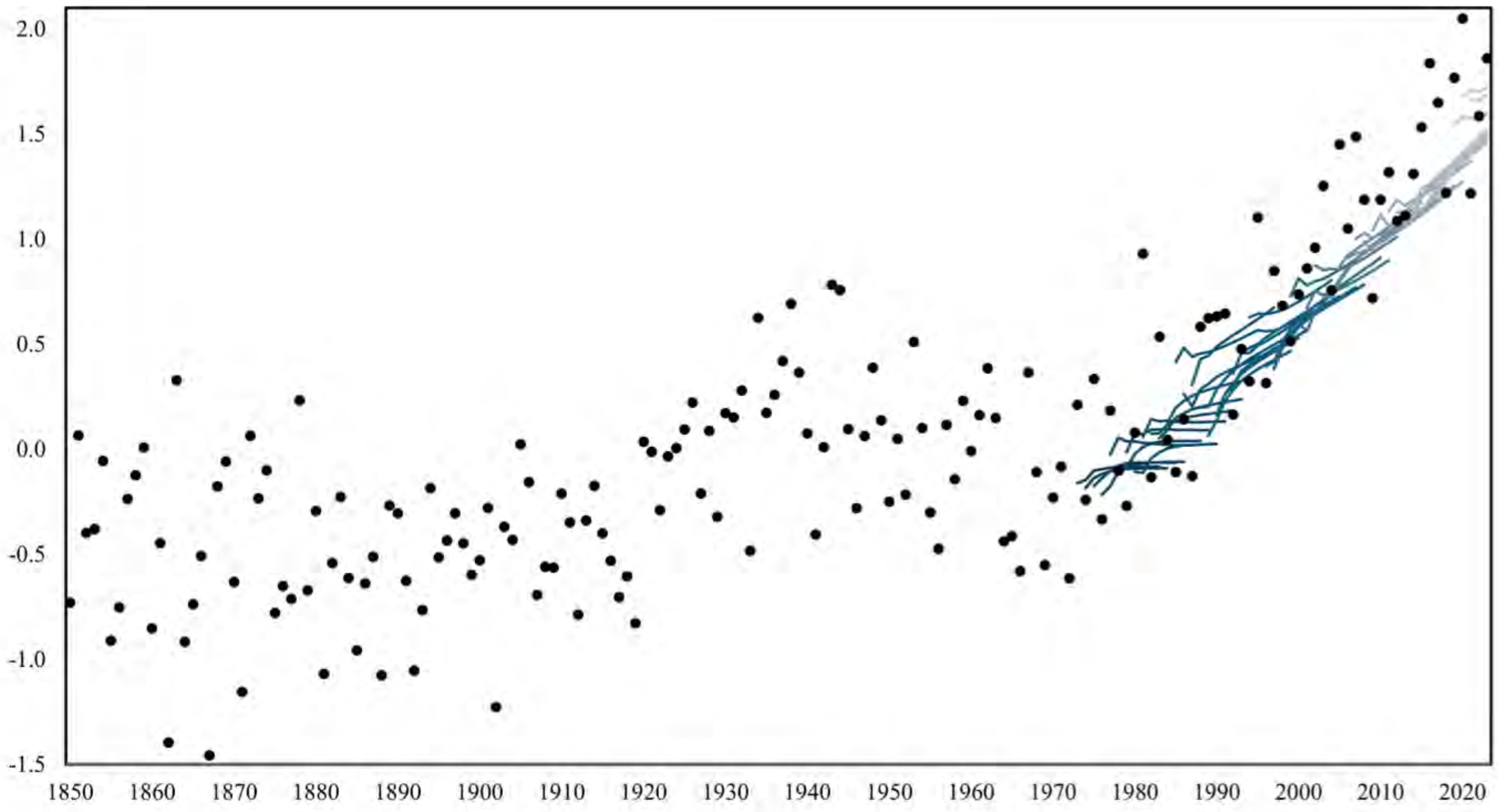
TSR Ensemble Forecasts



ARX Ensemble Forecasts



MEBM Ensemble Forecasts



Root Mean Square Errors (RMSEs)

UNI: Univariate Forecasts

		h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10
RW		0.456	0.408	0.439	0.454	0.461	0.472	0.484	0.476	0.546	0.545
Estimated root(s)	Constant	**0.567**	**0.764**	**0.893**	**0.989**	**1.052**	**1.095**	**1.125**	**1.152**	**1.173**	**1.194**
	Linear	**0.482**	**0.555**	**0.587**	**0.600**	**0.617**	**0.631**	**0.648**	**0.661**	**0.678**	**0.693**
	Quadratic	0.399	**0.424**	**0.444**	0.447	**0.464**	**0.477**	**0.497**	**0.510**	0.534	**0.550**
	Cubic	0.441	**0.480**	**0.520**	**0.557**	**0.594**	**0.640**	**0.683**	**0.738**	**0.795**	**0.853**
Unit roots	Constant	0.367	0.364	0.389	0.404	0.412	0.427	0.429	0.450	0.499	0.529
	Linear	0.365	0.361	0.383	0.393	0.395	0.404	0.399	0.411	0.456	0.479
	Quadratic	0.365	0.359	0.380	0.387	0.386	0.392	0.383	0.389	0.432	0.453
	Cubic	0.370	0.371	0.403	0.425	0.440	0.470	**0.484**	**0.522**	**0.588**	**0.642**
Breaks	One	0.365	0.371	0.389	0.399	0.420	0.448	0.464	**0.498**	0.527	**0.565**
	Two	0.342	0.351	0.374	0.382	0.393	0.409	0.435	0.455	0.485	0.514
Ensemble		0.368	0.385	0.419	0.440	0.460	**0.482**	**0.500**	**0.527**	**0.564**	**0.595**

[**Boldface** does not beat RW. Shaded is best of four.]

- Univariate forecasts with estimated roots do poorly
- Imposing a unit root or break(s) helps

Root Mean Square Errors (RMSEs)

TSR: Time Series Regression Forecasts

		h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10
RW		0.456	0.408	0.439	0.454	0.461	0.472	0.484	0.476	0.546	0.545
Estimated root(s)	Constant	0.406	0.397	0.406	0.405	0.402	0.394	0.401	0.420	0.448	0.467
	Linear	0.400	0.386	0.390	0.384	0.371	0.360	0.360	0.372	0.393	0.402
	Quadratic	0.397	0.379	0.378	0.365	0.351	0.334	0.330	0.332	0.344	0.345
	Cubic	0.395	0.376	0.374	0.362	0.347	0.332	0.324	0.326	0.335	0.339
Unit roots	Constant	0.400	0.377	0.372	0.361	0.354	0.337	0.339	0.351	0.373	0.385
	Linear	0.400	0.380	0.376	0.364	0.357	0.339	0.339	0.346	0.364	0.371
	Quadratic	0.400	0.382	0.381	0.366	0.356	0.335	0.332	0.329	0.341	0.339
	Cubic	0.401	0.385	0.386	0.373	0.363	0.344	0.338	0.336	0.345	0.345
Breaks	One	0.400	0.387	0.394	0.395	0.388	0.392	0.389	0.393	0.405	0.408
	Two	0.395	0.384	0.393	0.390	0.385	0.389	0.383	0.390	0.407	0.416
Ensemble		0.399	0.382	0.383	0.372	0.360	0.345	0.338	0.340	0.350	0.350

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- TSR does particularly well at long horizons: $h = 10$, e.g.

Root Mean Square Errors (RMSEs)

ARX: Autoregressive with Forcing Forecasts

		h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10
RW		0.456	0.408	0.439	0.454	0.461	0.472	0.484	0.476	0.546	0.545
Estimated root(s)	Constant	0.398	0.395	0.406	0.405	0.402	0.394	0.401	0.420	0.448	0.467
	Linear	0.393	0.403	0.409	0.402	0.390	0.377	0.375	0.385	0.404	0.414
	Quadratic	0.390	**0.412**	0.415	0.400	0.383	0.363	0.353	0.348	0.355	0.350
	Cubic	0.387	**0.433**	**0.446**	0.439	0.430	0.420	0.414	**0.415**	0.423	0.428
Unit roots	Constant	0.393	0.376	0.372	0.361	0.354	0.337	0.339	0.351	0.373	0.385
	Linear	0.393	0.394	0.390	0.373	0.361	0.338	0.333	0.333	0.346	0.349
	Quadratic	0.393	**0.415**	0.418	0.401	0.388	0.364	0.354	0.343	0.348	0.341
	Cubic	0.394	**0.442**	**0.458**	0.451	0.446	0.433	0.429	0.428	0.437	0.439
Breaks	One	0.392	**0.451**	**0.472**	**0.479**	**0.477**	**0.485**	**0.485**	**0.491**	0.506	0.514
	Two	0.388	**0.446**	**0.470**	**0.473**	**0.473**	**0.481**	0.480	**0.489**	0.508	0.521
Ensemble		0.392	**0.412**	0.417	0.407	0.395	0.380	0.371	0.369	0.377	0.376

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- RW does well for $h = 2$, so ARX does not always beat it
- ARX seems to do poorly with breaks
- ARX does particularly well at long horizons, $h = 10$, e.g.

Root Mean Square Errors (RMSEs)

MEBM: Moist Energy Balance Model Forecasts

		h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10
RW		0.456	0.408	0.439	0.454	0.461	0.472	0.484	0.476	0.546	0.545
Estimated root(s)	Constant	0.311	0.305	0.310	0.308	0.303	0.294	0.279	0.289	0.311	0.318
	Linear	0.311	0.306	0.311	0.311	0.307	0.302	0.293	0.306	0.331	0.342
	Quadratic	0.311	0.306	0.311	0.310	0.308	0.306	0.299	0.313	0.337	0.350
	Cubic	0.311	0.305	0.309	0.307	0.302	0.299	0.287	0.296	0.316	0.328
Unit roots	Constant	0.311	0.307	0.312	0.315	0.320	0.322	0.324	0.351	0.385	0.410
	Linear	0.311	0.306	0.312	0.313	0.317	0.317	0.317	0.338	0.369	0.391
	Quadratic	0.311	0.306	0.311	0.310	0.310	0.306	0.300	0.312	0.336	0.350
	Cubic	0.311	0.305	0.309	0.306	0.302	0.295	0.283	0.288	0.307	0.315
Breaks	One	0.311	0.306	0.310	0.310	0.305	0.306	0.292	0.296	0.313	0.317
	Two	0.311	0.306	0.311	0.309	0.304	0.305	0.287	0.290	0.307	0.312
Ensemble		0.311	0.306	0.310	0.309	0.306	0.302	0.291	0.301	0.322	0.332

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- MEBM always beats the RW
- MEBM does best across all trend specification up to $h = 7$
- MEBM does best across most trend specifications after $h = 7$

Main Contributions of This Line of Research

Understanding and forecasting temperature dynamics in the northern part of the NH is ...

- ... a priority for detecting many tipping points
- ... improved by using temps **outside of the northern part** in a **physically disciplined model designed for PA**

1. Create, identify, estimate, and test a simple yet structural time series model of polar amplification based on physical theory
   - **PA is statistically and physically significant**
2. Forecast northern temperatures using the proposed time series model of PA
   - **PA improves pseudo-out-of-sample forecasts**
   - Forecasts to 2035 under linearity (no tips) *to be done*

Future work: Can better medium-run forecasts of northern temperatures improve detection of global tipping points and hence global temperatures?