Probability Assessments of an Ice-Free Arctic: Comparing Statistical and Climate Model Projections

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Climate Econometrics

Good arbitrage:
Econometrics can contribute to climate science.

– Traditionally: Trend, seasonality, cycles, long memory, regime switching, structural change, volatility, nonlinearity, optimal prediction, ...

– Recently: High dimensionality, shrinkage, selection, nonparametric nonlinearity, network topology and connectedness, real-time, ...

– Always: Dynamic predictive stochastic modeling.

Good scientific cause:
Climate is hugely important moving forward.

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Virtual Seminar on Climate Economics

Federal Reserve Bank of San Francisco

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2020 EMCC-V: Econometric Models of Climate Change Conference

The fifth conference on econometric models of climate change will take place at the **University of Victoria (Victoria, BC, Canada) on 27-28 August 2020.**

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Climate Change

A shift in the (huge) joint conditional distribution describing the state of the atmosphere, oceans, and fresh water.

– Many aspects of climate change.

– Extremely high-dimensional state vector.

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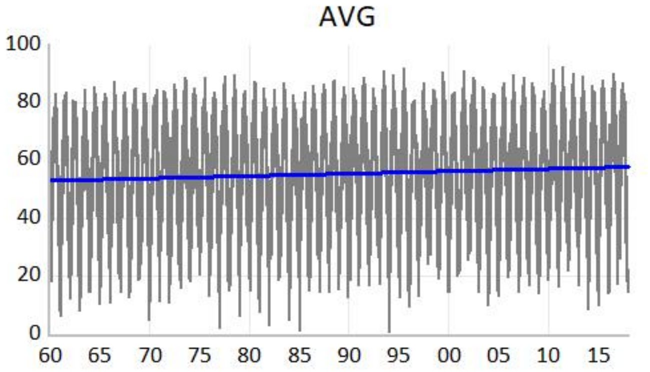
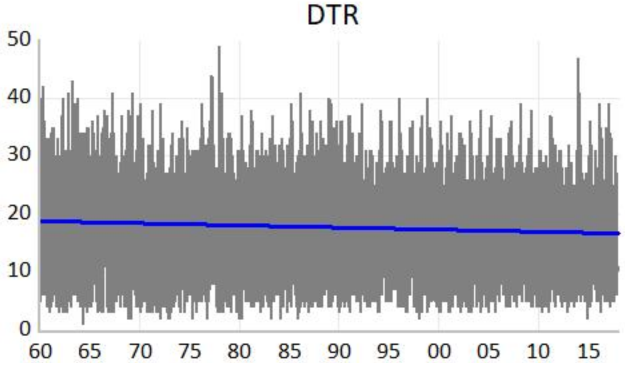
Average Daily Temperature, $AVG = (MAX+MIN)/2$

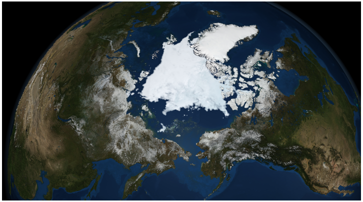


Diurnal Temperature Range, DTR = (MAX-MIN)



And more:
Cold spell intensities and durations; frost days; growing season length; ice days; summer days; tropical nights; heatwave intensities and durations, ...

Arctic Sea Ice



Viewing the future:
The Arctic is warming twice as quickly as the planet.

Global Climate $\longrightarrow$ Arctic Climate $\longrightarrow$ Arctic Sea Ice

Worrisome feedbacks: Albedo falls as ice and snow melt; methane released as permafrost melts; etc.

Global Climate $\longleftarrow$ Arctic Climate $\longleftarrow$ Arctic Sea Ice

Global economic aspects, local economic aspects, geopolitical aspects, ...

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(Univariate) Statistical Questions

How quickly is Arctic sea ice decreasing?

With what pattern is Arctic sea ice decreasing?

How do the speed and pattern vary across months?

When will we have the first ice-free Arctic September?

When will we have the first ice-free Arctic summer?

Point forecasts? Interval forecasts? Density forecasts?

Do the statistical patterns
match those of structural climate "dynamic models"?

If not, what is the nature of the deviation?

Can answers to these statistical questions
complement and promote structural climate science?

Arctic Sea Ice:
Data, Statistical Models, and Climate Models

Data

Monthly sea ice extent (SIE), 11/1978 - 10/2019

Statistical model projections

$$SIE = trend + seasonal + inertial\ dynamics + shock$$

Climate model projections

Mean SIE projections from CMIP5 climate models

Data: Sea Ice Area and Extent

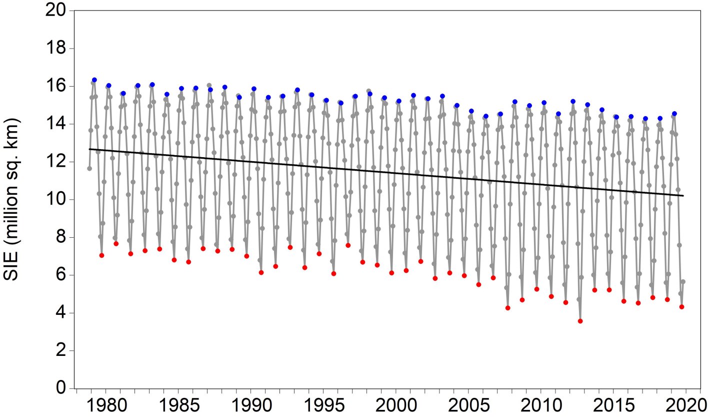
Consider a grid cell of size 1.
Satellite measures grid-cell brightness on day t.
Brightness is algorithmically converted into concentration, c_t.

$$SIA_t = \begin{cases} 0, & \text{if } c_t \leq .15 \\ c_t, & \text{otherwise} \end{cases}$$

$$SIE_t = \begin{cases} 0, & \text{if } c_t \leq .15 \\ 1, & \text{otherwise} \end{cases}$$

We use monthly average NSIDC SIE, 11/1978 - 10/2019

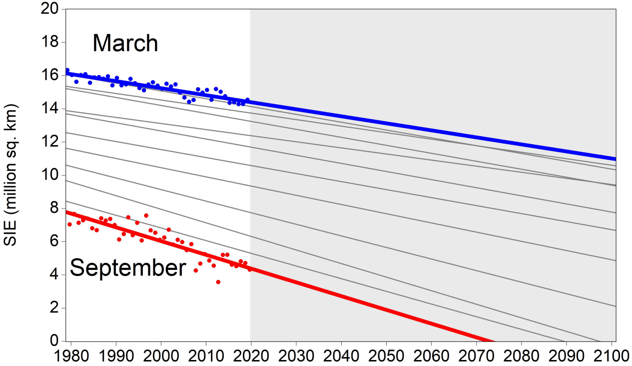
Arctic Sea Ice Extent



Statistical Model Projections

$$SIE_t = \sum_{i=1}^{12} a_i \, D_{it} + \sum_{j=1}^{12} b_j \, D_{jt} \cdot TIME_t + \varepsilon_t$$

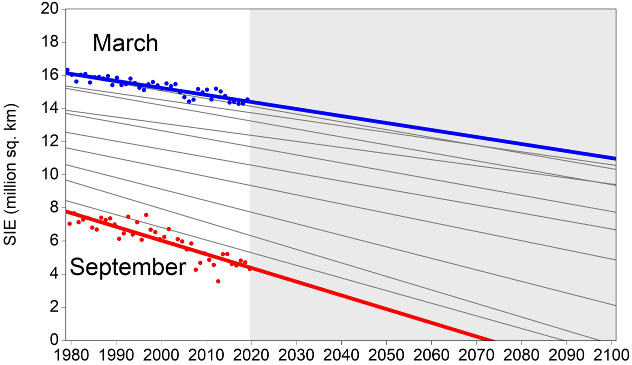
$$\varepsilon_t = \rho \varepsilon_{t-1} + v_t$$
$$v_t \sim (0, \sigma_v^2)$$



A "Shadow Ice" Interpretation

$$SIE_t^* = \sum_{i=1}^{12} a_i \, D_{it} + \sum_{j=1}^{12} b_j \, D_{jt} \cdot TIME_t + \varepsilon_t$$

$$\varepsilon_t = \rho \varepsilon_{t-1} + v_t$$
$$v_t \sim (0, \sigma_v^2)$$
$$SIE_t = max(SIE_t^*, \ 0)$$



Quadratic Trend

$$SIE_t^* = \sum_{i=1}^{12} a_i D_{it} + \sum_{j=1}^{12} b_j D_{jt}\, TIME_t + \sum_{k=1}^{12} c_k D_{kt}\, TIME_t^2 + \varepsilon_t$$

$$\varepsilon_t = \rho\varepsilon_{t-1} + v_t$$
$$v_t \sim (0, \sigma_v^2)$$
$$SIE_t = max(SIE_t^*,\ 0)$$

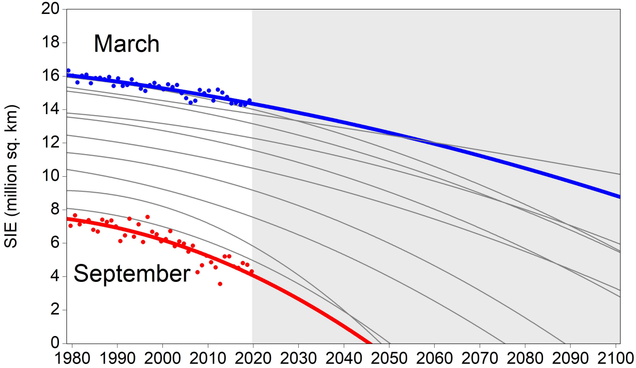


Table: Akaike and Bayes Information Criteria for Quadratic Coefficient Constraints

	(1) NONE	(2) Seq	(3) NSeq	(4) Seq+NSeq	(5) ALLeq	(6) ALL0
AIC	-0.0673 [3]	-0.0651 [4]	**-0.0913 [1]**	**-0.0877 [2]**	-0.0639 [5]	-0.0569 [6]
BIC	0.2569 [6]	0.2421 [5]	**0.1647 [2]**	**0.1513 [1]**	0.1665 [4]	0.1649 [3]

Restricted (Simplified) Quadratic Trend

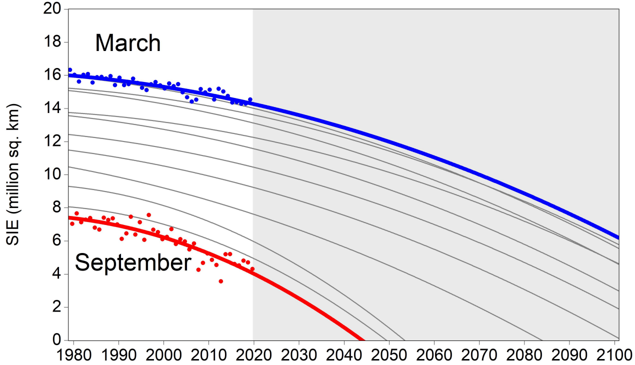
$$SIE_t^* = \sum_{i=1}^{12} a_i D_{it} + \sum_{j=1}^{12} b_j D_{jt} \, TIME_t + \sum_{k=1}^{12} c_k D_{kt} \, TIME_t^2 + \varepsilon_t$$

$$c_8 = c_9 = c_{10}, \; c_{11} = c_{12} = c_1 = \ldots = c_7$$

$$\varepsilon_t = \rho \varepsilon_{t-1} + v_t$$

$$v_t \sim (0, \sigma_v^2)$$

$$SIE_t = max(SIE_t^*, \; 0)$$



Simplified Quadratic With Standard Error Bands

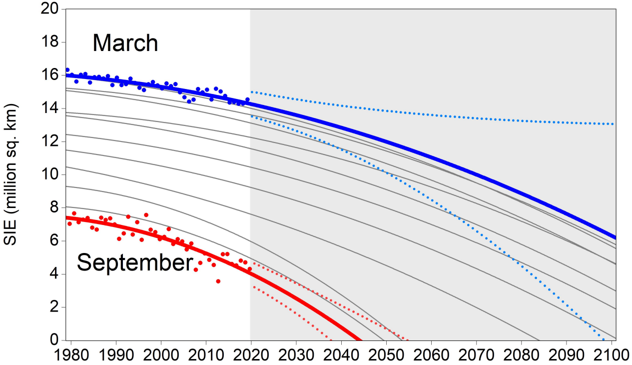
$$SIE_t^* = \sum_{i=1}^{12} a_i D_{it} + \sum_{j=1}^{12} b_j D_{jt} \, TIME_t + \sum_{k=1}^{12} c_k D_{kt} \, TIME_t^2 + \varepsilon_t$$

$$c_8 = c_9 = c_{10}, \; c_{11} = c_{12} = c_1 = \ldots = c_7$$

$$\varepsilon_t = \rho \varepsilon_{t-1} + v_t$$

$$v_t \sim (0, \sigma_v^2)$$

$$SIE_t = max(SIE_t^*, \; 0)$$



$$\left(\pm 2s \sqrt{1 + x_t'(X'X)^{-1} x_t} \right)$$

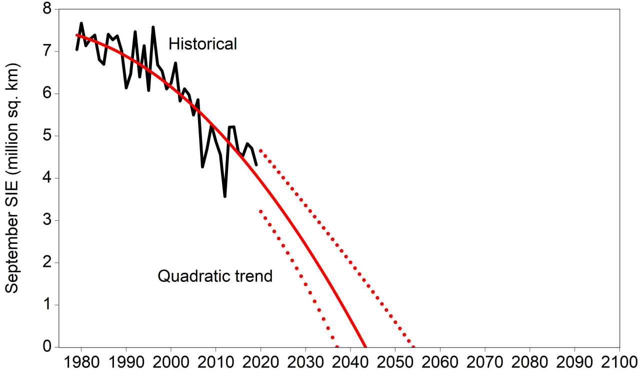
Climate Model Projections

Coupled Model Intercomparison Project (CMIP5)

Mean CMIP5 projections starting in 2006

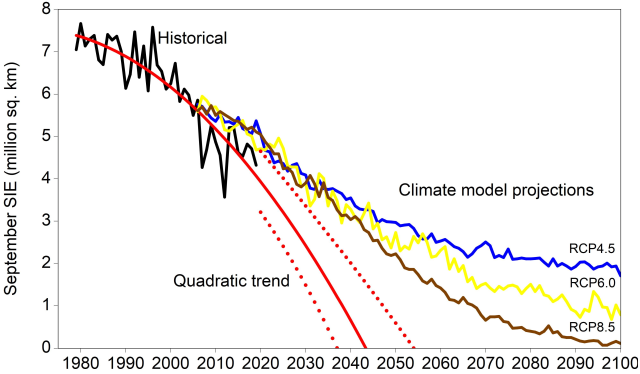
Three emissions scenarios:
RCP8.5 (high), RCP6.0 (medium high), RCP4.5 (medium)

September

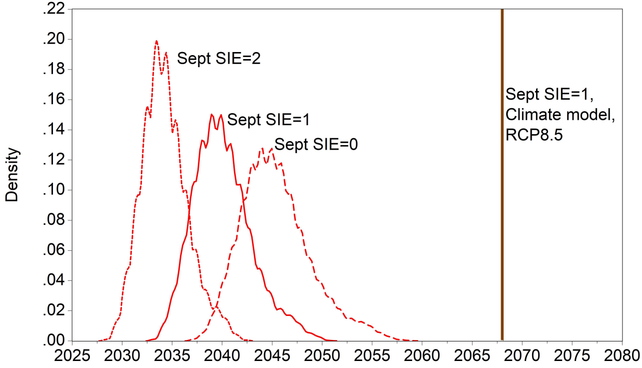


September SIE (million sq. km)
8
7
6
5
4
3
2
1
0
1980 1990 2000 2010 2020 2030 2040 2050 2060 2070 2080 2090 2100
Historical
Quadratic trend

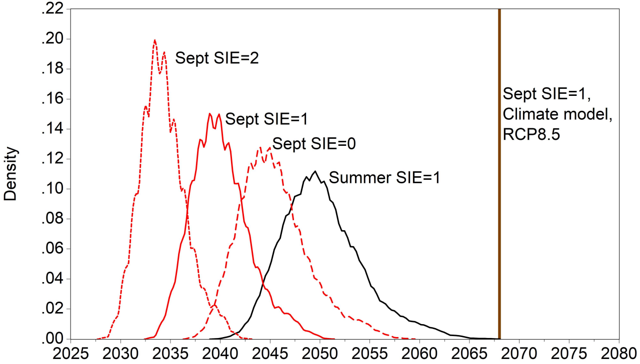
Climate Model Projections



Statistical Model Projections (Density Forecasts) for First Ice-Free September...



Or First Ice-Free Summer...



Conclusions

Increasingly rapid decline in Arctic sea ice.

Sixty percent probability of ice-free September in 2030s!

Much earlier than climate model simulations.

Moving Forward: What Role for Statistical Models of Arctic Sea Ice?

As we have emphasized:
They provide informative and useful probabilistic forecasts.

But there is more:
They complement structural climate science.

– A buttress for climate model theoretical weak-points

– A benchmark for climate model evaluation and estimation (Indirect Inference)

– A filter for climate model selection