New approaches based on ML for a range of climate prediction problems

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British Antarctic Survey
NATURAL ENVIRONMENT RESEARCH COUNCIL

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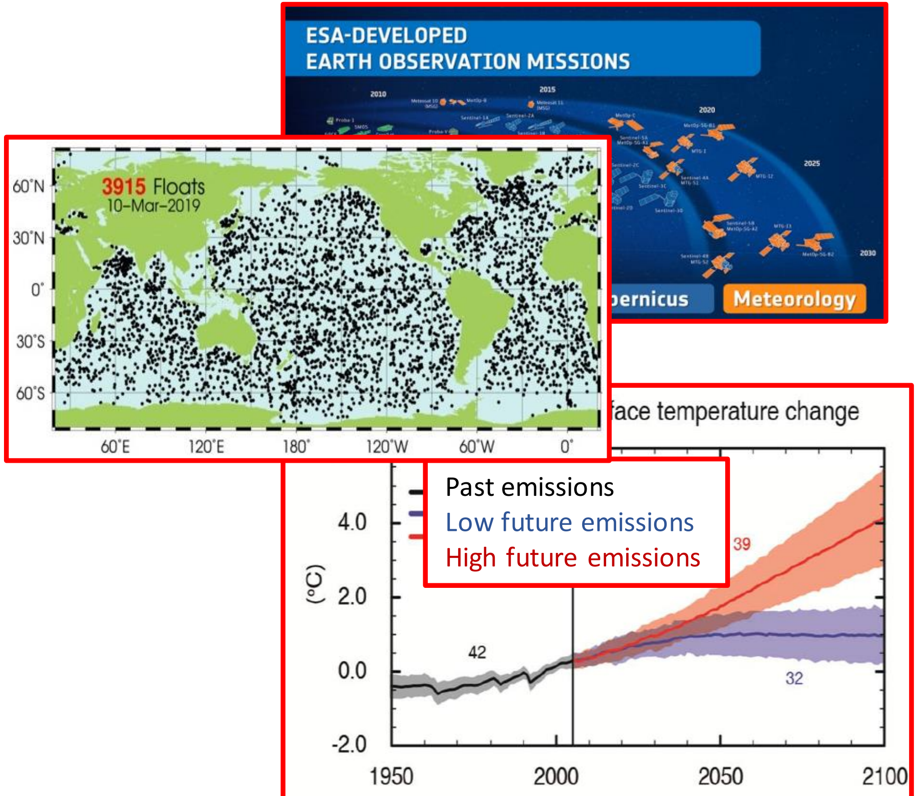
Need <u>actionable information</u> on climate risk…

…have <u>vast datasets</u> from satellites, networked sensors, computer simulations, etc.



Four examples

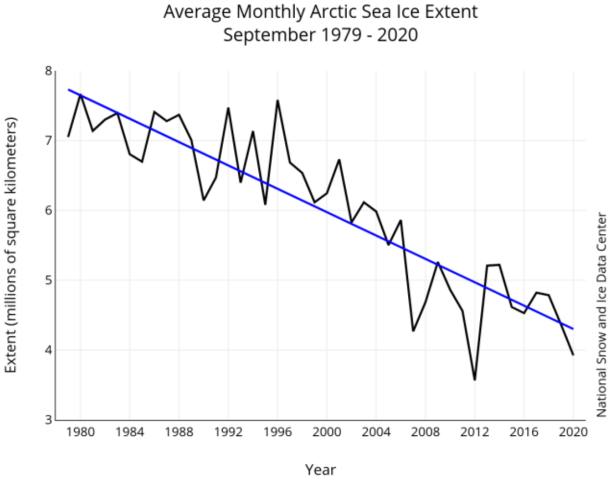
1. Sea ice forecast – CNNs out-performs dynamical forecast and linear trend at lead of 2 months & above.

2. Heatwave forecast – combine past observations & climate simulations to improve forecasts of extremes

3. Ocean forecast – explore physical basis for data-driven models

4. Hydrological forecast – improve flood forecasts

Example 1: seasonal sea ice forecast



Background: Arctic sea ice has a strong season cycle (summer melt reaching minimum extent in September). Also a strong downward trend over recent decades. Currently physics-based dynamical models and simple statistical forecasts.

Goal: Forecast sea ice for next six months using data-driven deep learning approach. Has implications for NH weather and may be useful for ecosystem management.

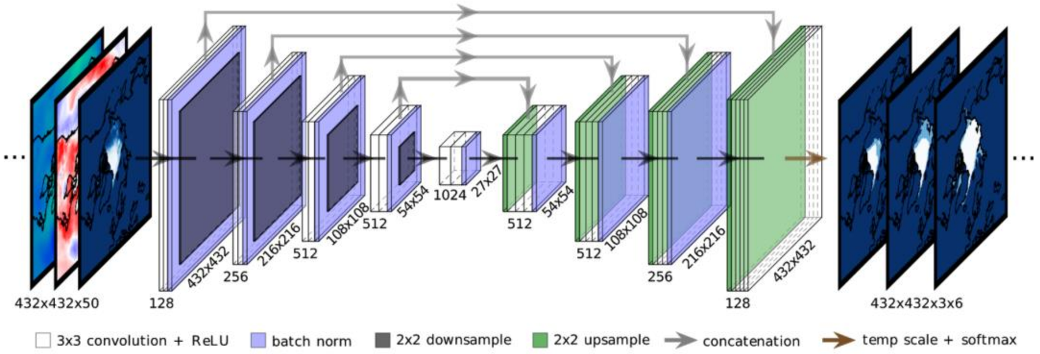
Approach: Slice of climate variable at specific time/altitude and sea ice satellite data both analogous to images input to CNNs.

Tom Andersson et al.

Example 1: seasonal sea ice forecast

Input: Sea ice concentration (SIC), 11 climate variables, statistical SIC forecast -> 50 channel input to ensemble of U-Net networks.

Task: Classification into open-water (SIC ≤ 15%); marginal ice (15% < SIC < 80%), and full ice (SIC ≥ 80%)



Approach: feature-extracting encoding path downsamples input data, decoding path upsamples the data. Pre-train with CMIP6, train with 1979-2011, validate with 2012-2017, test 2018-2020.

Output: 6mth forecast, 3 SIC classes

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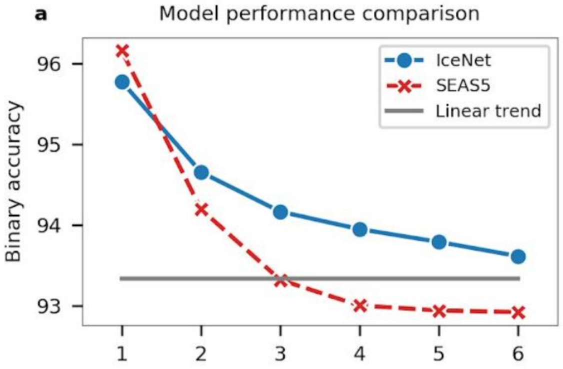
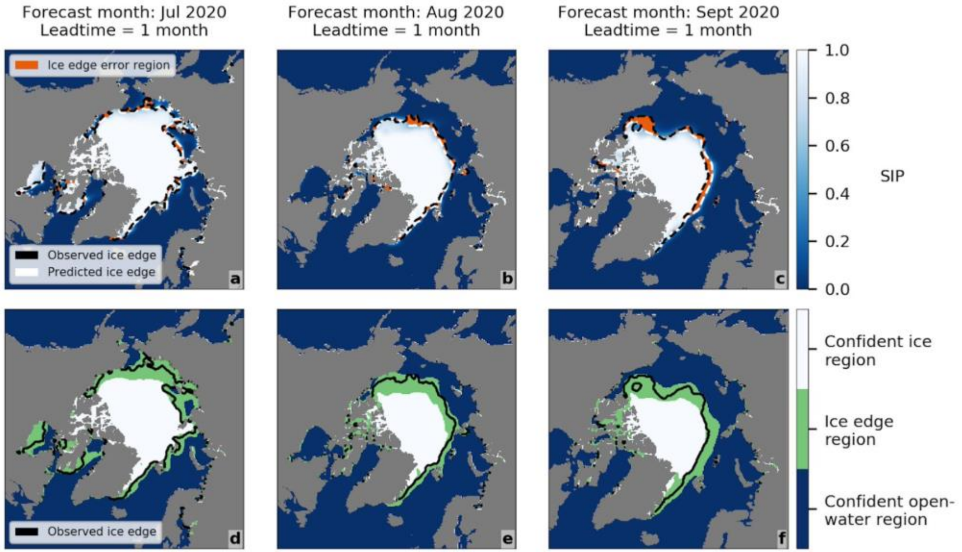
Example 1: seasonal sea ice forecast



Assessment: out-performs dynamical forecast and linear trend at lead of 2 months & above.



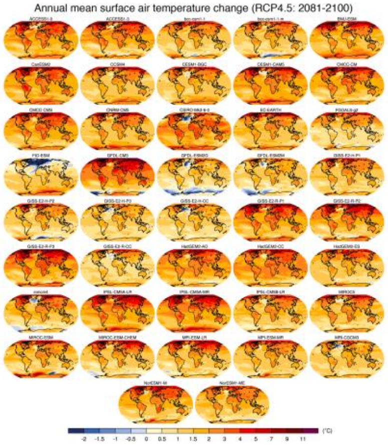
Results: for 2020, predicted ice edge is close to observed and within predicted edge region

Tom Andersson et al.

Example 2: heatwave forecast

Egypt heatwave death toll rises as temperatures reach 46C

More than 60 people have died this week, and another 580 are in hospital for heat exhaustion



Goal: Generate city-scale projections of extreme temperature by postprocessing climate model simulation at specific location that can then be used to access risk through supply chains, transport routes etc.

Labour productivity, infrastructure, transport and mortality all impacted by extreme heat.

Challenge: Raw output from climate models has systematic errors that need accounting for in a way that is sensitive to extremes, “bias correction”.

Input: Climate model data and observations (reanalysis).

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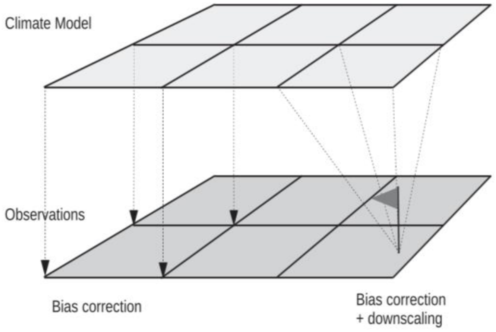
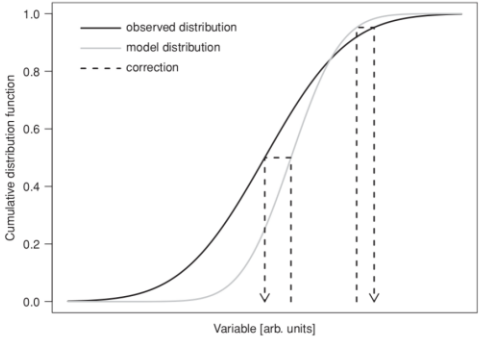
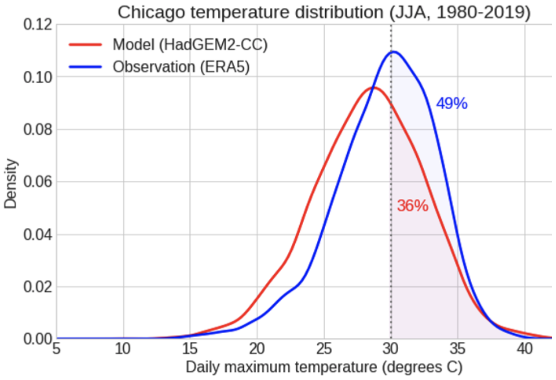
Example 2: heatwave forecast

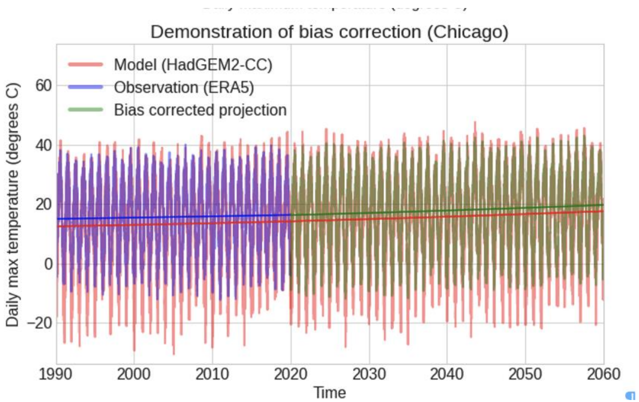
Approach: Learn statistical relationship from past (“historical”) data, then apply to future simulations.

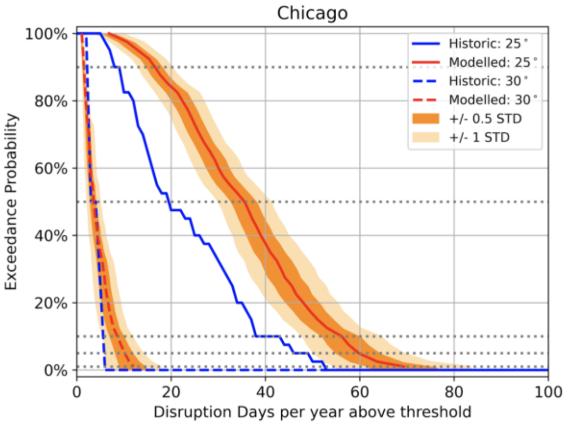
Biases often affect variance / tails, so correct for bias in different quantiles separately. Use 31-day window so seasonally evolving bias correction











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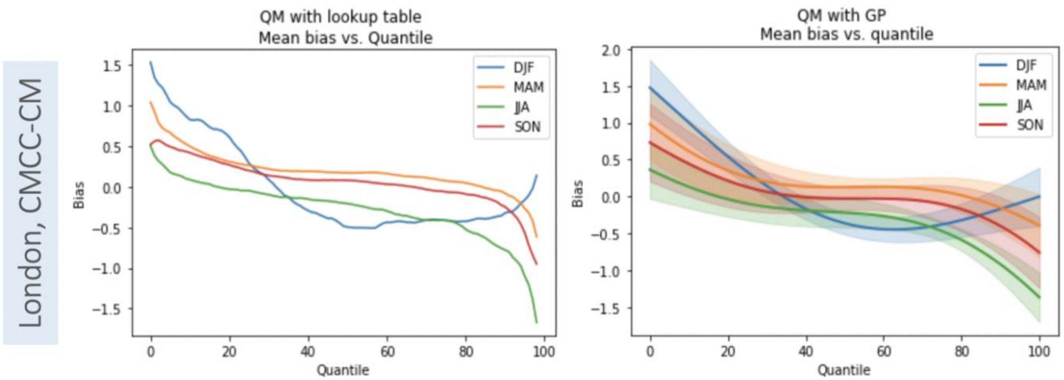
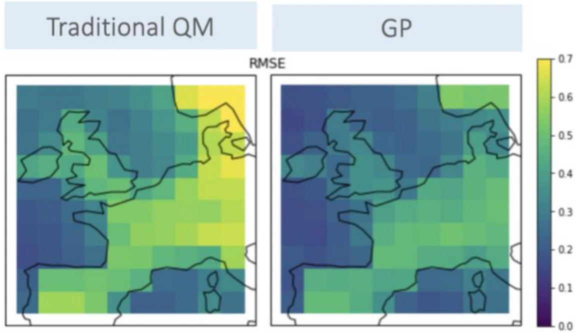
Example 2: heatwave forecast

Approach: Instead of explicitly calculating bias at each quantile for each month, find (learn) function mapping f: $T_{q(observed)} = f\,(T_{q(GCM)}, \text{quantile, day of year})$ + uncertainty range



extremes better represented with GPs & skill increased



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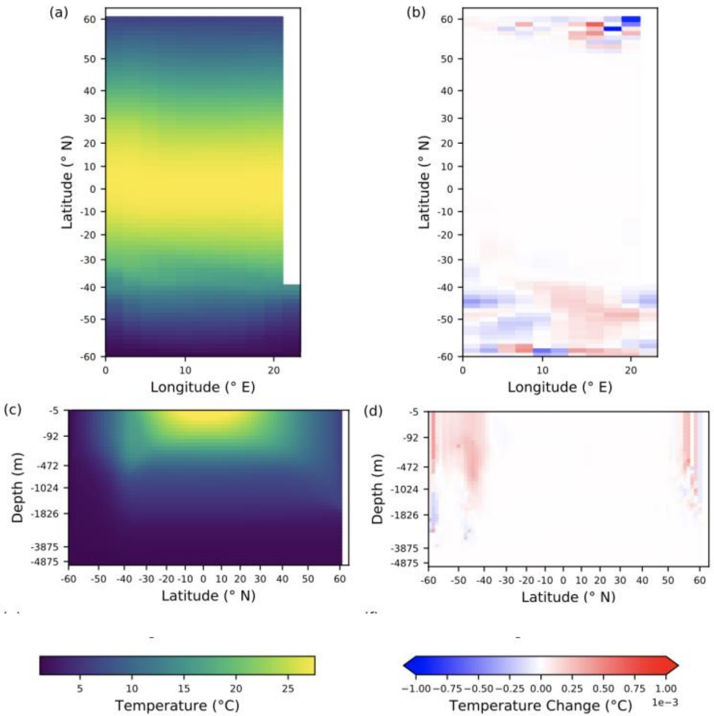
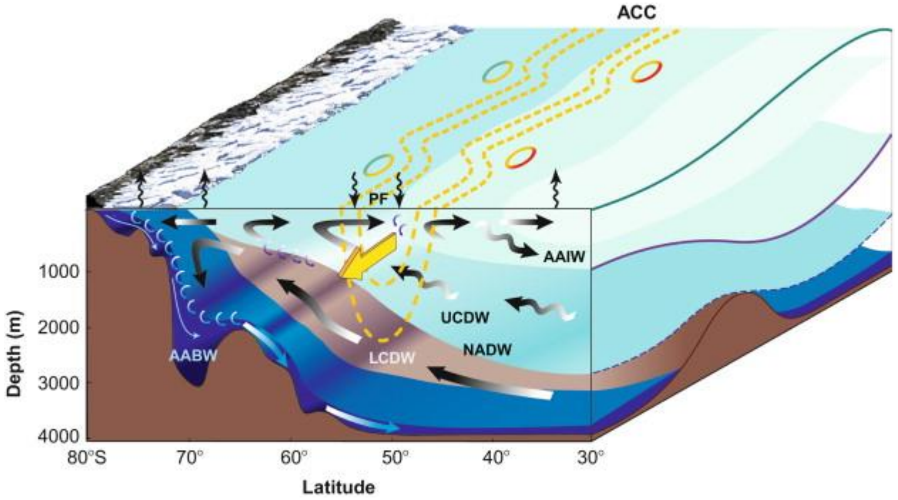
Example 3: ocean forecast



Simple model of Southern Ocean



Wind forcing & temperature/salinity restoration at surface. GM parameterization.

Overturning circulation.

Rachel Furner, et al.

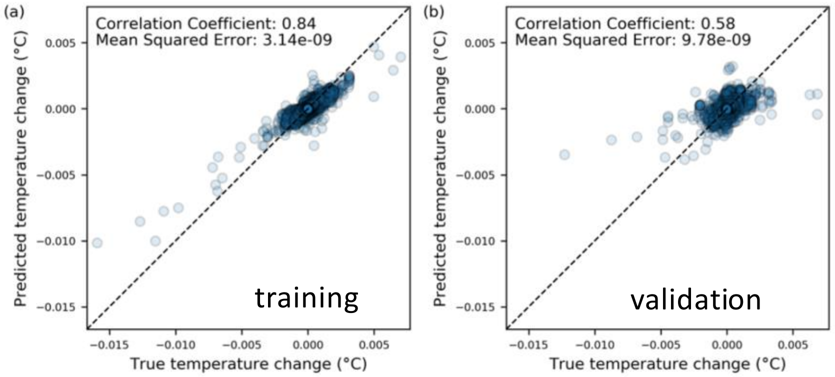
Example 3: ocean forecast

Goal: predict daily mean change in ocean temperature for any single grid cell, based on variables at surrounding locations at the current time step.

Assess physical basis, i.e. interpretability

Approach: linear regressor with *T, S, u, u*, SSH, lat, lon, depth & 2nd order polynomials.*

Model is trained by minimising least squares errors with ridge regularisation.



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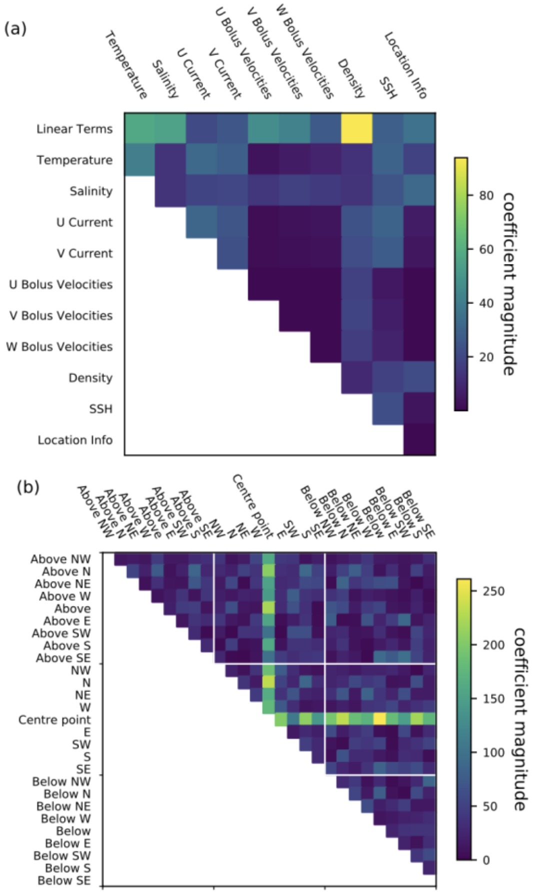
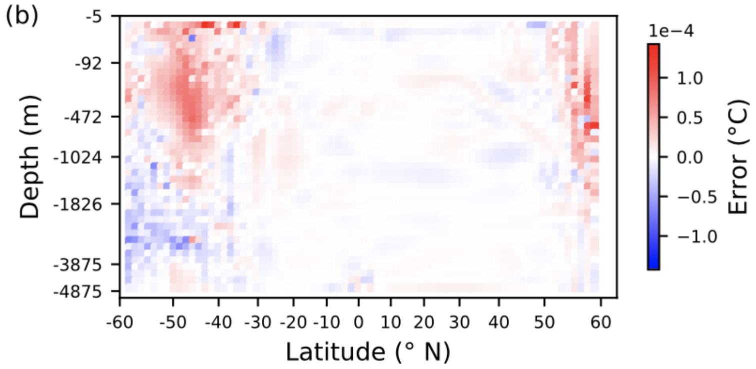
Example 3: ocean forecast



Results: coefficients show density & interaction between temperature at grid pt & surrounding grid pts most used (advection & diffusion related to temp grad).

Impact of withholding density is small. Withholding currents has greatest impact.

All physically meaningful.



Additional error when currents withheld

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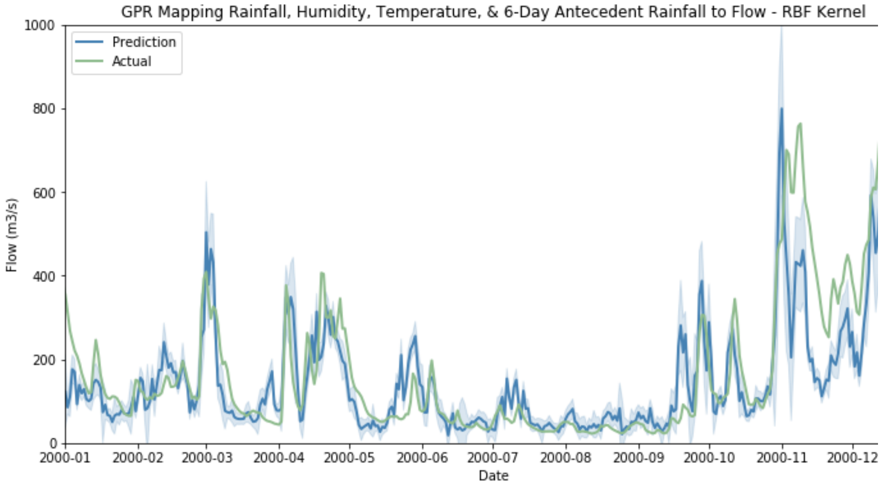
Example 4: hydrological forecast



Assume flow, Y, as a function catchment descriptors, θ_i, and of climatic variables, ψ_i

$$Y = f(\theta_1, \theta_2, \ldots, \theta_n, \psi_1, \psi_2, \ldots, \psi_n)$$

For a given catchment, the catchment descriptors are stationary. If these variables form the input space, $\mathbf{x}$, then let Y be described by a Gaussian Process, with mean function, μ, and covariance function, K.

$$Y = f(R_t, R_{t-1,\ldots,t-7}, T, H, V | \theta_1, \theta_2, \ldots, \theta_n, \psi_1, \psi_2, \ldots, \psi_{n-10})$$

The climatic variables assumed to be most relevant are rainfall, R_t, antecedent rainfall, $R\_(t{-}n)$, temperature, T, relative humidity, H, and windspeed, V.

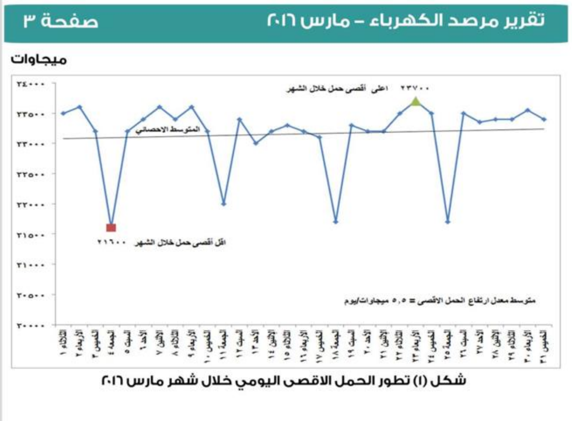
$$Y \sim \mathcal{GP}(\mu(\mathbf{x}), K(\mathbf{x}, \mathbf{x}'))$$

Robert Rouse

Extend further to account for correlated risks & map to data on impacts

Cairo (pop. 8m) on verge of energy crisis

- What will future demand be for air conditioning?
- How will this impact the energy network?



Design/regulations for:

- sustainable urban drainage
- thermal comfort in buildings

[uncertainties important]

How vulnerable is a country or system to climate disruption?

Conclusion:

Still early days, but data-driven approaches across a wide-range of climate problems show great promise in terms of predictive capability.

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