Predicting the impact of climate change on severe wintertime particulate pollution events in Beijing using extreme value theory

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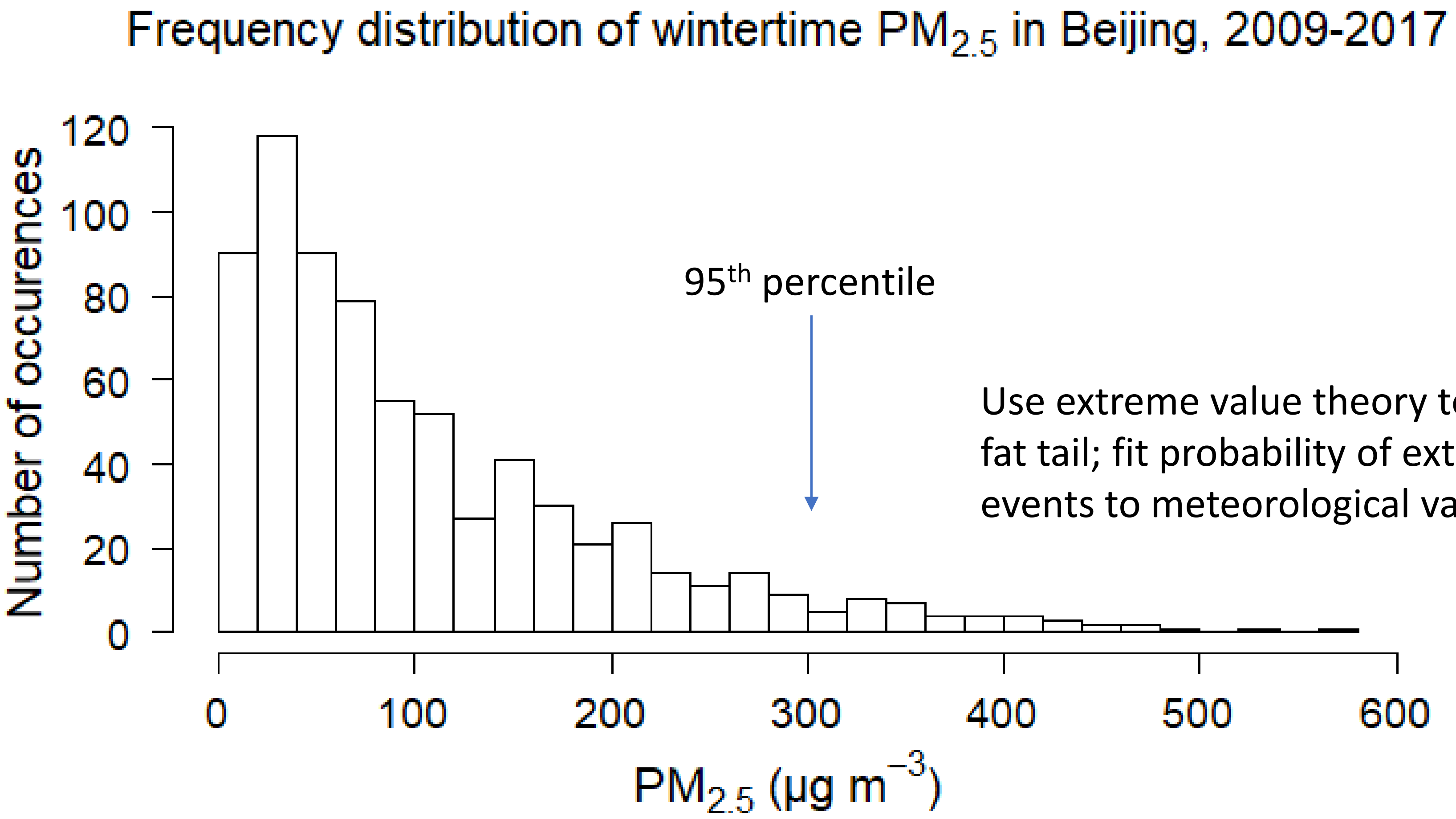
Observed winter $PM_{2.5}$ in Beijing: a heavy tail



Use extreme value theory to model fat tail; fit probability of extreme events to meteorological variables

How does extreme value theory work?

- Our model consists of three parameters:
  - location (μ, analogous to mean)
  - scale (σ, analogous to standard deviation)
  - shape (ξ, describes curvature of distribution)
- When fitting a distribution to data, you are really finding the parameter values that **best explain your observations**. This is done by finding the parameters that maximize the *likelihood estimator* L:

$$L(\mu, \phi, \xi) = \underbrace{\exp\left(-\frac{1}{n_a}\sum_{t=1}^{n}\left(1+\frac{\xi(u-\mu)}{\phi}\right)^{-\frac{1}{\xi}}\right)}_{(a)} \underbrace{\prod_{1}^{n}\left(\frac{1}{\phi}\left(1+\frac{\xi(y_t-\mu)}{\phi}\right)^{-\frac{1}{\xi}-1}\right)^{I(y_t>u)}}_{(b)}$$

How does extreme value theory work?

- y_t represents daily mean $PM_{2.5}$ for winter days $t \in [1, n]$ in 2009-17
- u represents a threshold of interest (300 µg/m^3) and n_a the number of winter observations per year (90).
- $I(y_t > u)$ is an indicator function (evaluates to 1 if true, 0 if false).
- Our goal: optimize L numerically for all observations

$$L(\mu, \phi, \xi) = \underbrace{\exp\left(-\frac{1}{n_a}\sum_{t=1}^{n}\left(1 + \frac{\xi(u-\mu)}{\phi}\right)^{-\frac{1}{\xi}}\right)}_{(a)} \underbrace{\prod_{1}^{n}\left(\frac{1}{\phi}\left(1 + \frac{\xi(y_t-\mu)}{\phi}\right)^{-\frac{1}{\xi}-1}\right)^{I(y_t>u)}}_{(b)}$$

How does extreme value theory work?

- Factor (b) represents days where observed $PM_{2.5}$ exceeds a threshold explicitly as a product of independent generalized Pareto densities
- Factor (a) represents data from all days, even if they are not extreme
- By classing data into two categories (extreme and not extreme), we have a **unique strength in modeling tail behavior**
  - High bias, traditionally unavoidable in predicting extremes, tends to vanish

$$L(\mu,\phi,\xi) = \underbrace{\exp\left(-\frac{1}{n_a}\sum_{t=1}^{n}\left(1+\frac{\xi(u-\mu)}{\phi}\right)^{-\frac{1}{\xi}}\right)}_{(a)}\underbrace{\prod_{1}^{n}\left(\frac{1}{\phi}\left(1+\frac{\xi(y_t-\mu)}{\phi}\right)^{-\frac{1}{\xi}-1}\right)^{I(y_t>u)}}_{(b)}$$

Accounting for meteorology

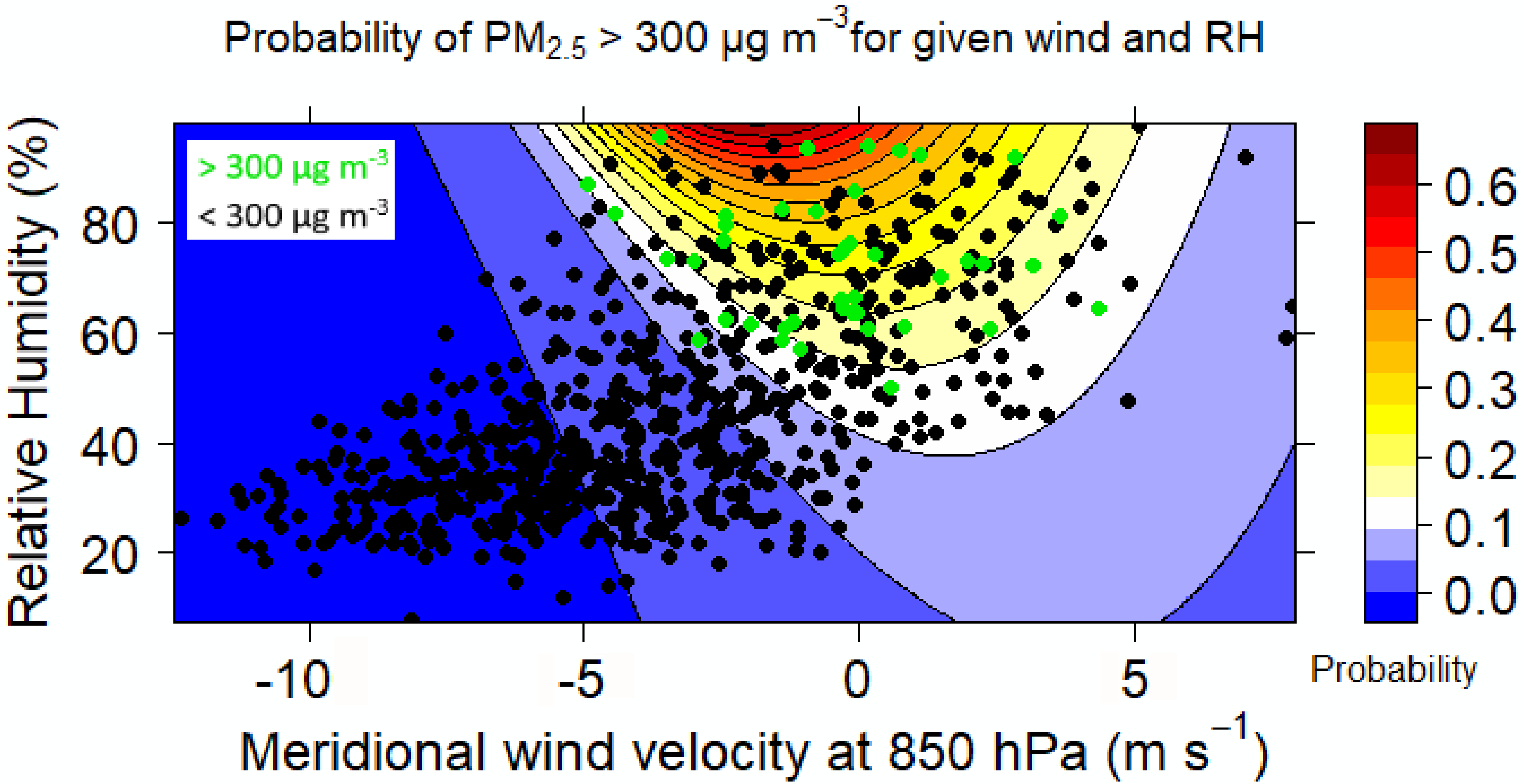
- Particulates correlate with meteorological variables like RH, V850, vertical temperature gradient ($\delta T_{850\text{-}250}$), and meridional gradient of 500hPa zonal wind (δU_{500})
- We can write location parameter and scale parameter as functions of these meteorological variables, then use information theory to determine best model (V850, RH).
- The probability that daily mean $PM_{2.5}$ (*y)* will exceed a threshold *u* given (*v, r*) is modeled with the marginal distribution

$$P(y > u \mid v, r) = \frac{1}{n_a}\left(1 + \xi\left(\frac{u - \mu_{v,r}}{\phi_v}\right)\right)^{-1/\xi}$$

with

$$\mu_{v,r} = av + br + c$$
$$\phi_v = e^{dv+f}$$

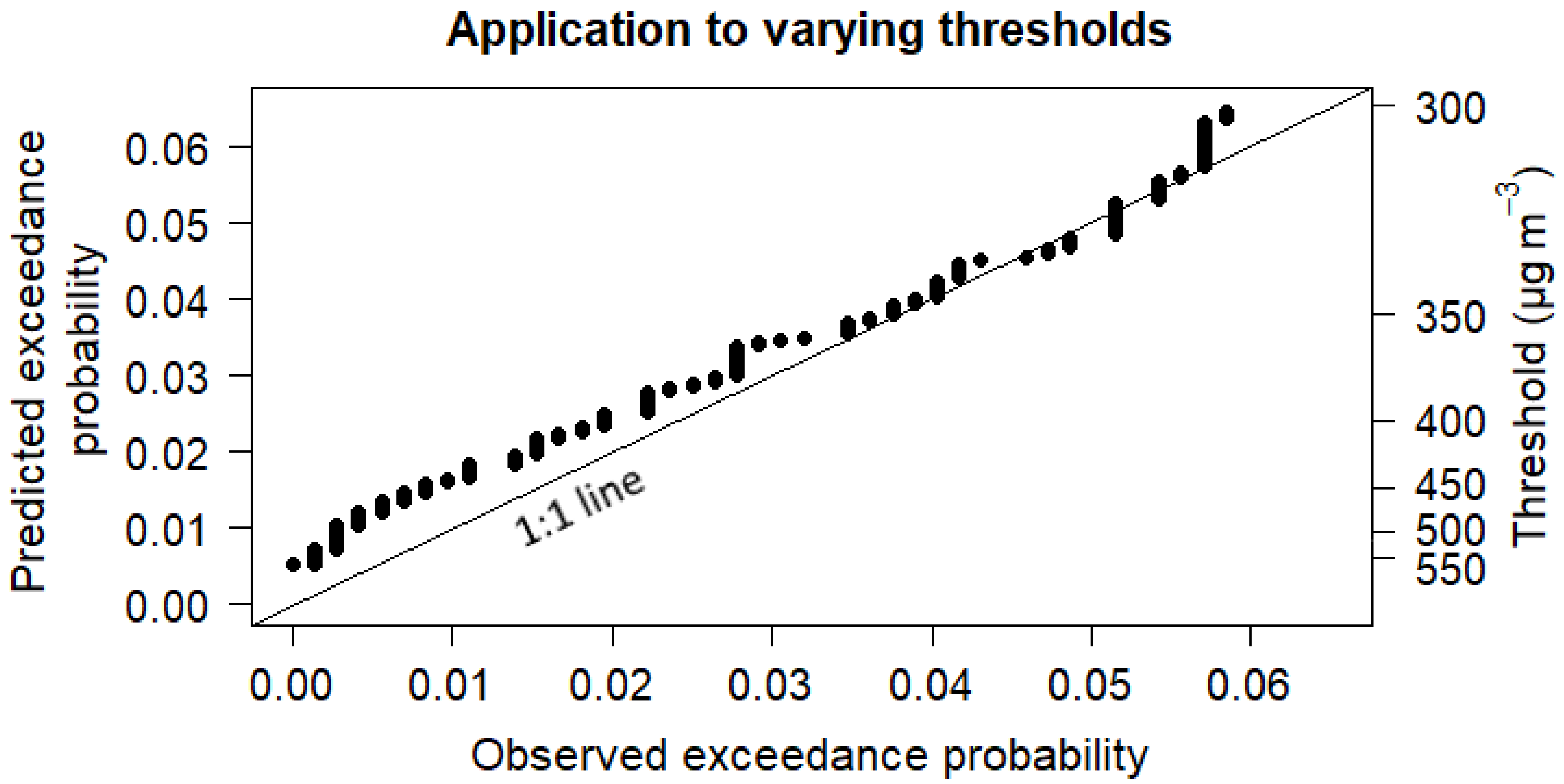
Evaluating model performance



Contours: model
Dots: observations

Covariates carry more information together than apart!

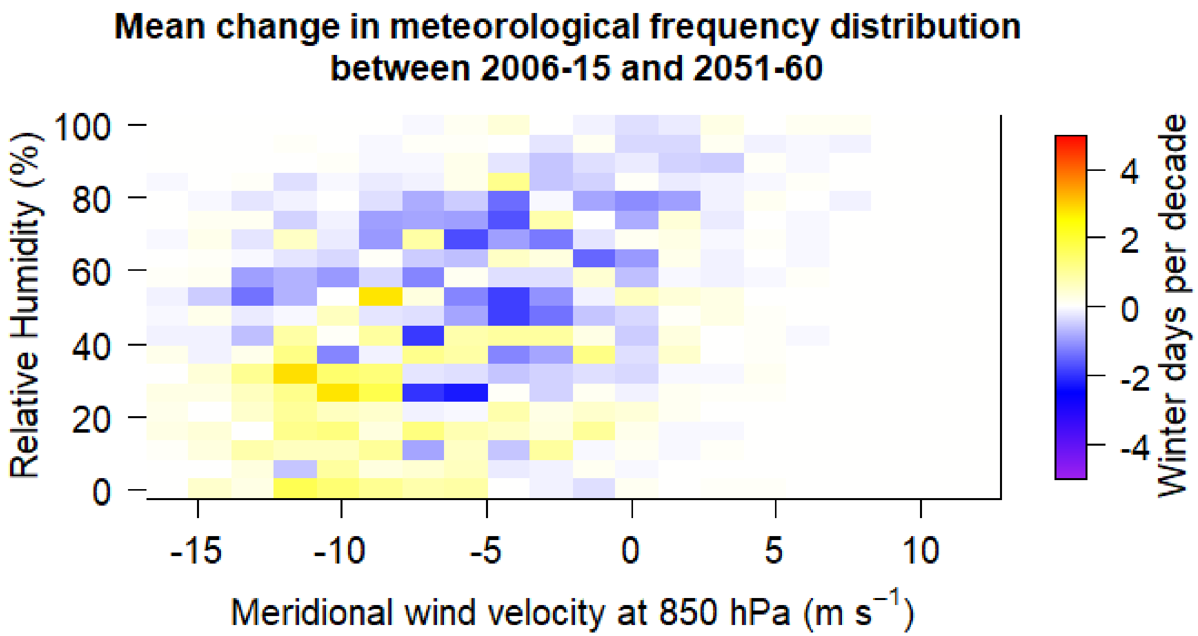
Evaluating model performance



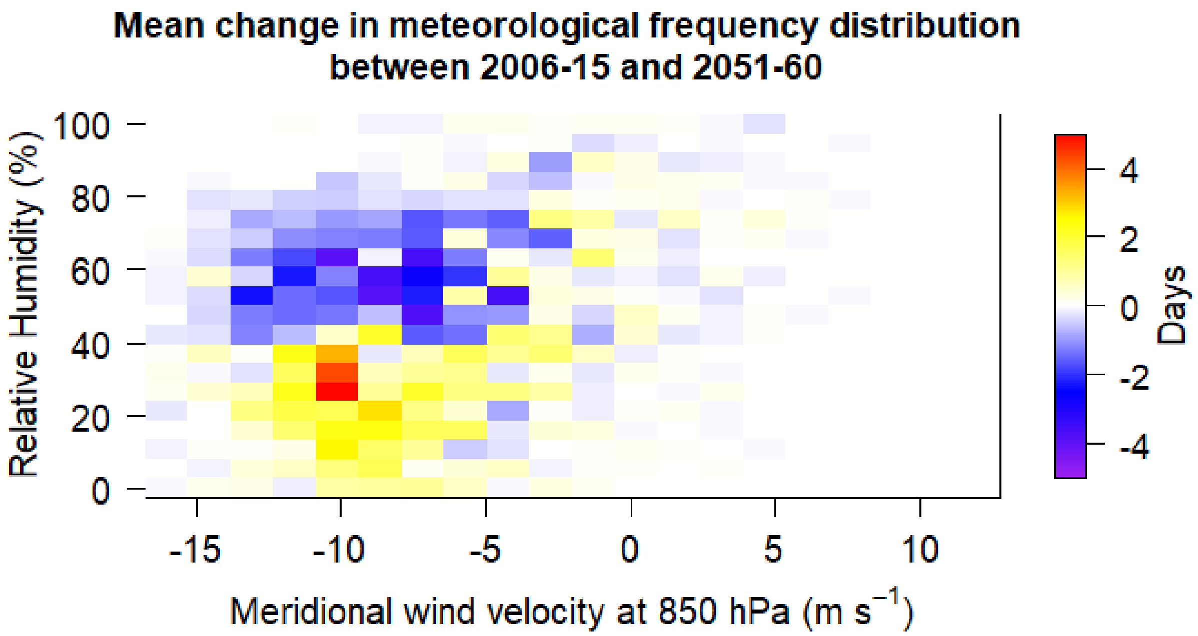
Can verify threshold invariance assumption

What happens with climate change?

RCP4.5 CMIP5 multimodel ensemble

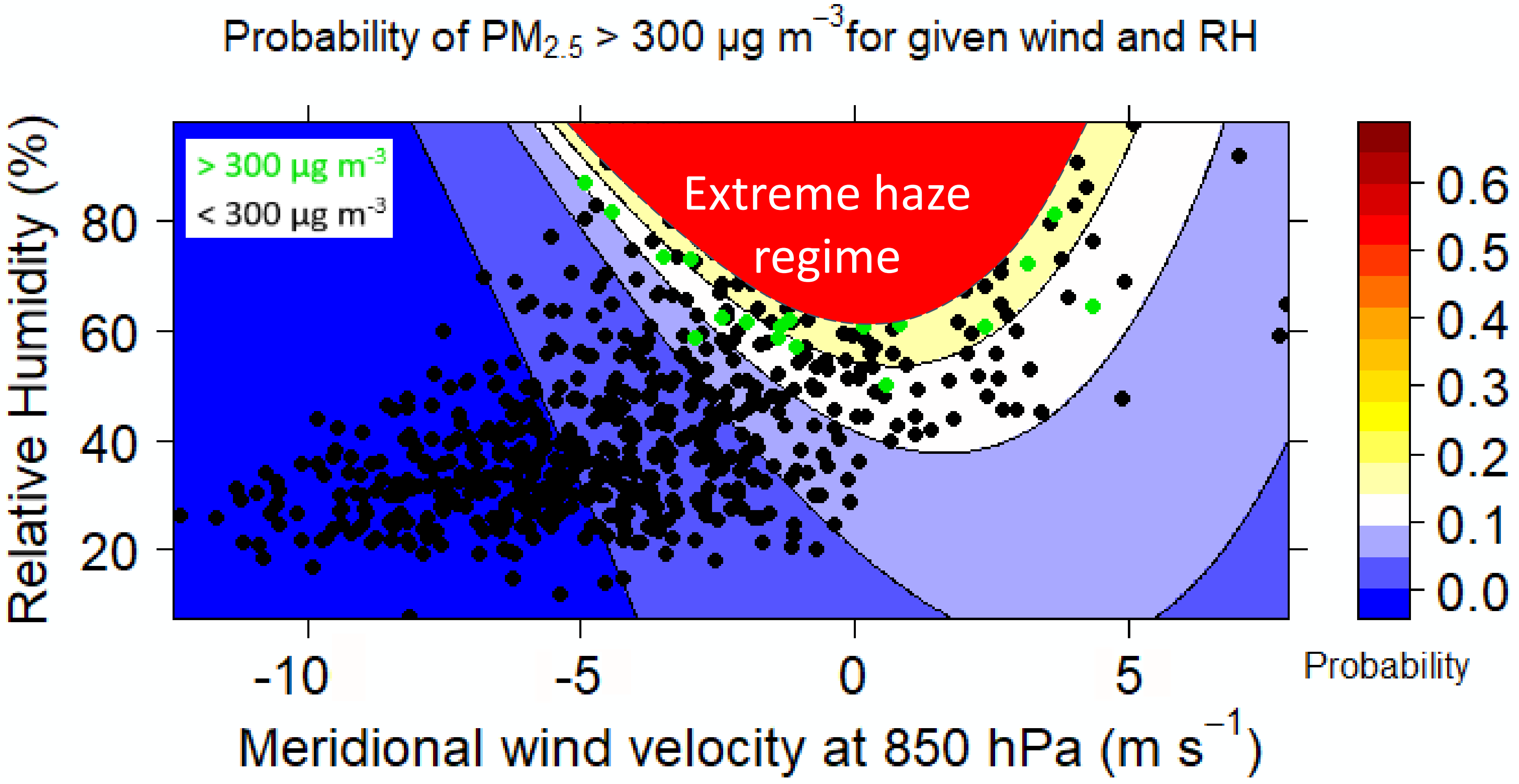


RCP8.5 CMIP5 ensemble

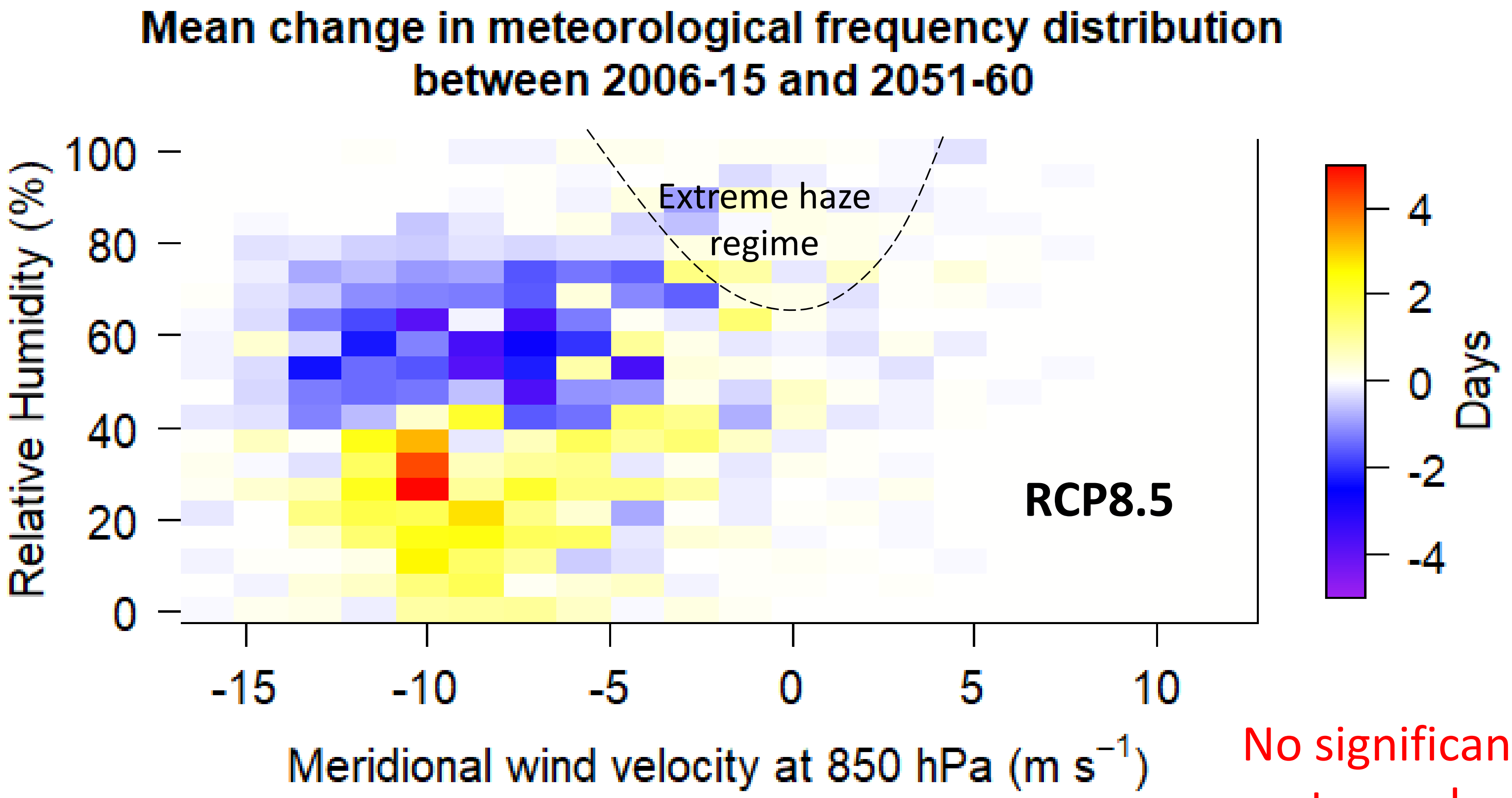


Remember: Covariates carry more information together than apart!

Where are we sensitive in RH-V850 space?

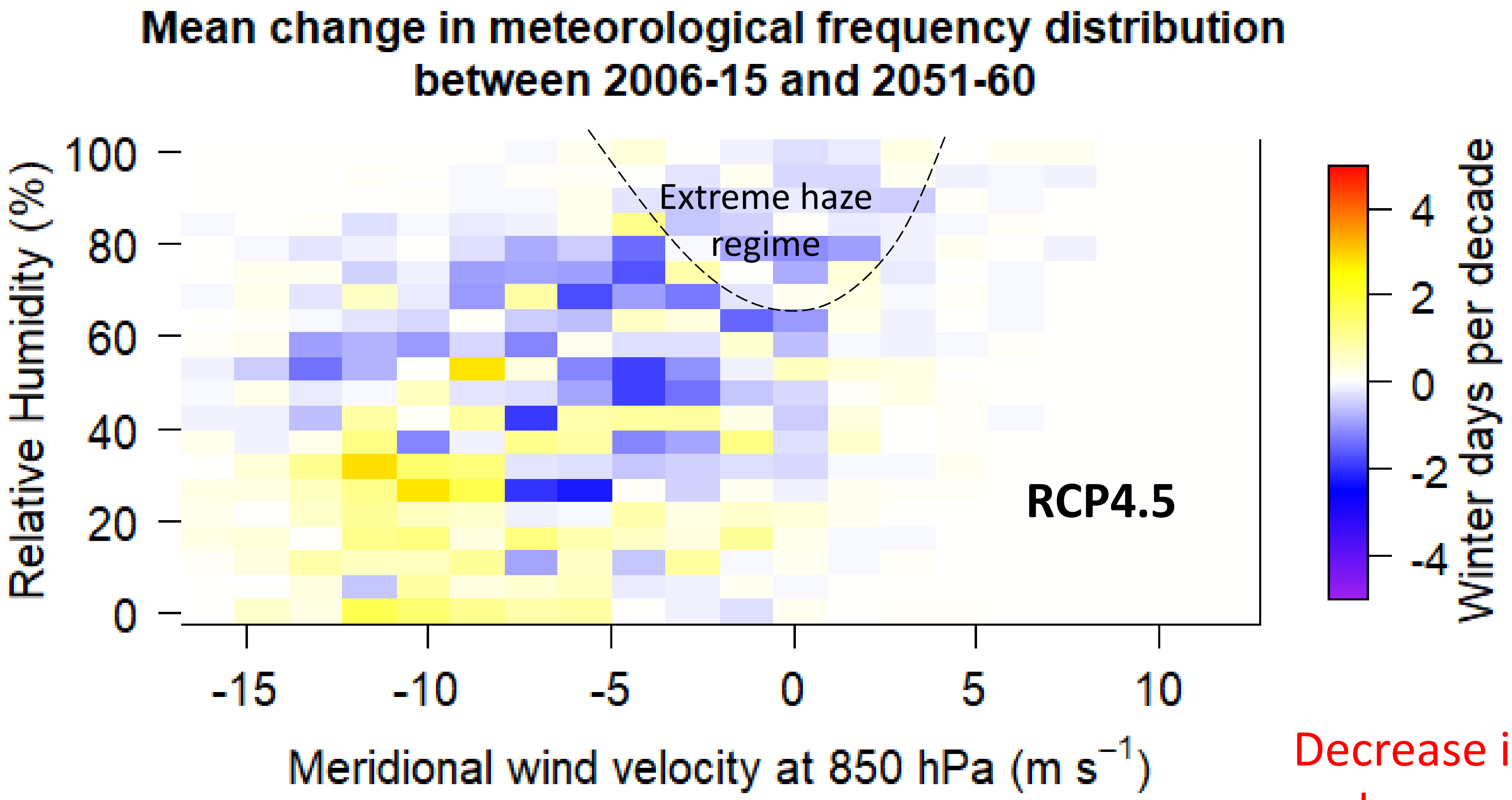


What does this climate sensitivity imply?



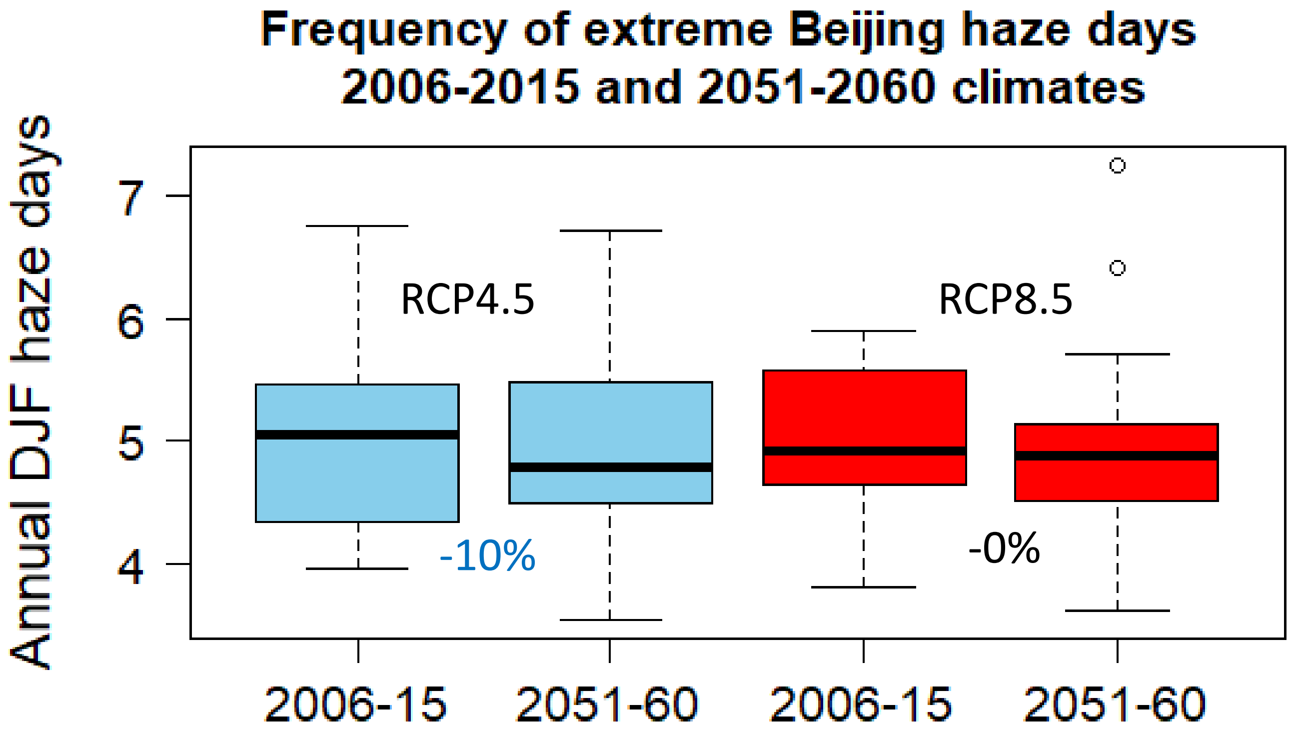
No significant change in extreme haze regime!

What does this climate sensitivity imply?



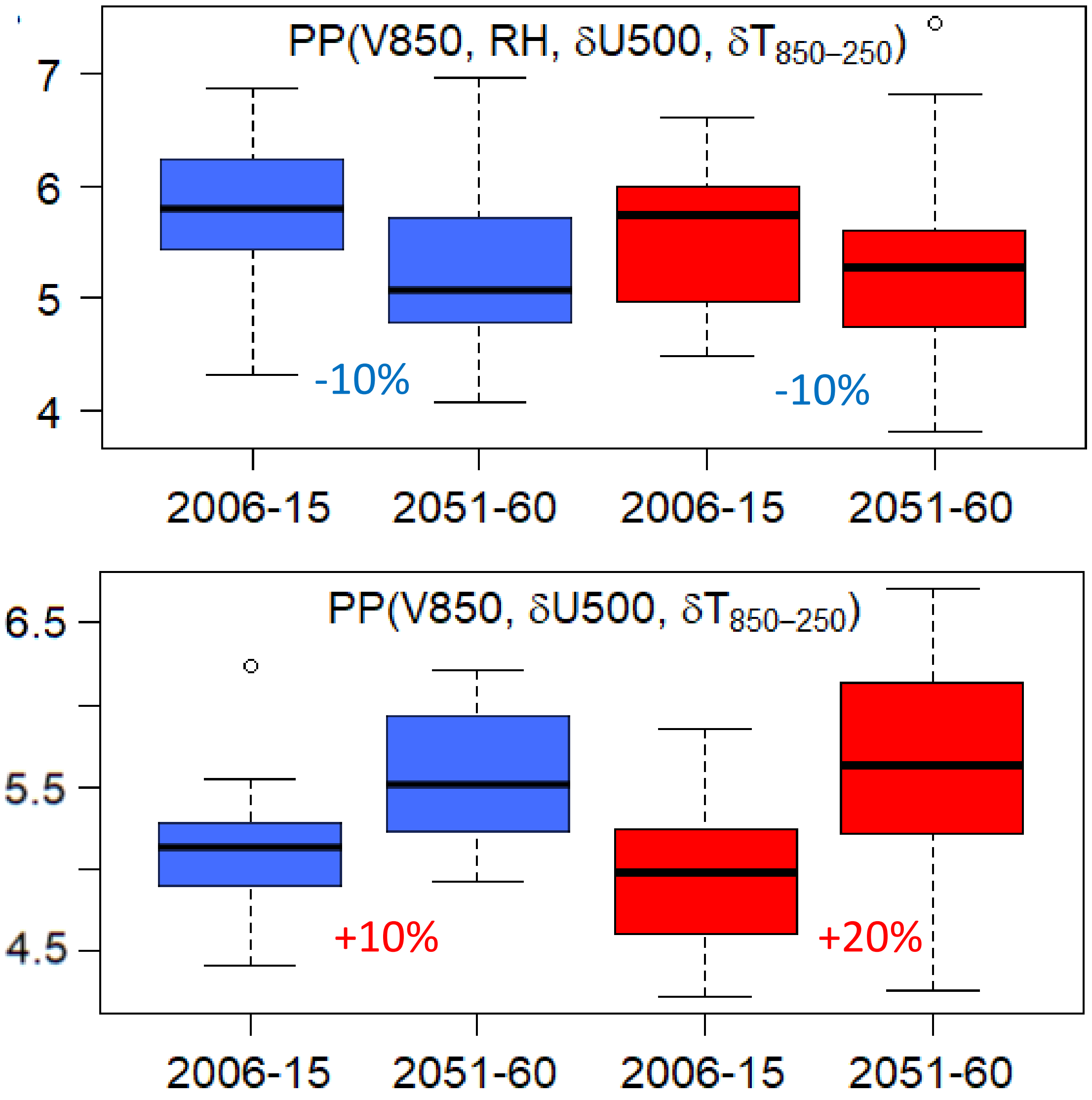
Decrease in days in haze regime!

A more quantitative calculation



- Compute for each CMIP5 model by integrating probability over 2D met space.
- Decrease under RCP4.5 is significant at the 5% level with 0.58 ± 0.39 fewer haze days per year by 2060.
- Of the models considered, 69% show a decrease.

Other models with different meteorology



- In top model, add in two additional variables. This lowers AIC (inferior model) but reflects similar physics to PP(V850, RH) model.
- In bottom model, omit RH but keep two additional variables. Removing RH leads us to predict a dramatic increase in extreme particulate events.

Conclusions

- If you are interested in extremes, model the tails. The Poisson Point Process (PP) model allows for maximum information to be incorporated in fit.
  - Covariates dramatically improve model predictive power to a point (overfit).
- Relative humidity and low-troposphere meridional winds (V850) give us strong predictive power for particulate events in Beijing.
- Climate change should not increase the frequency of extreme winter particulate events in Beijing; more likely to decrease them.
- Exclusion of RH from PP model will lead to opposite prediction.

Thank you!

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