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Statistical Modeling of Extreme PM2.5 Concentration in Saudi Arabia Using Deep Learning

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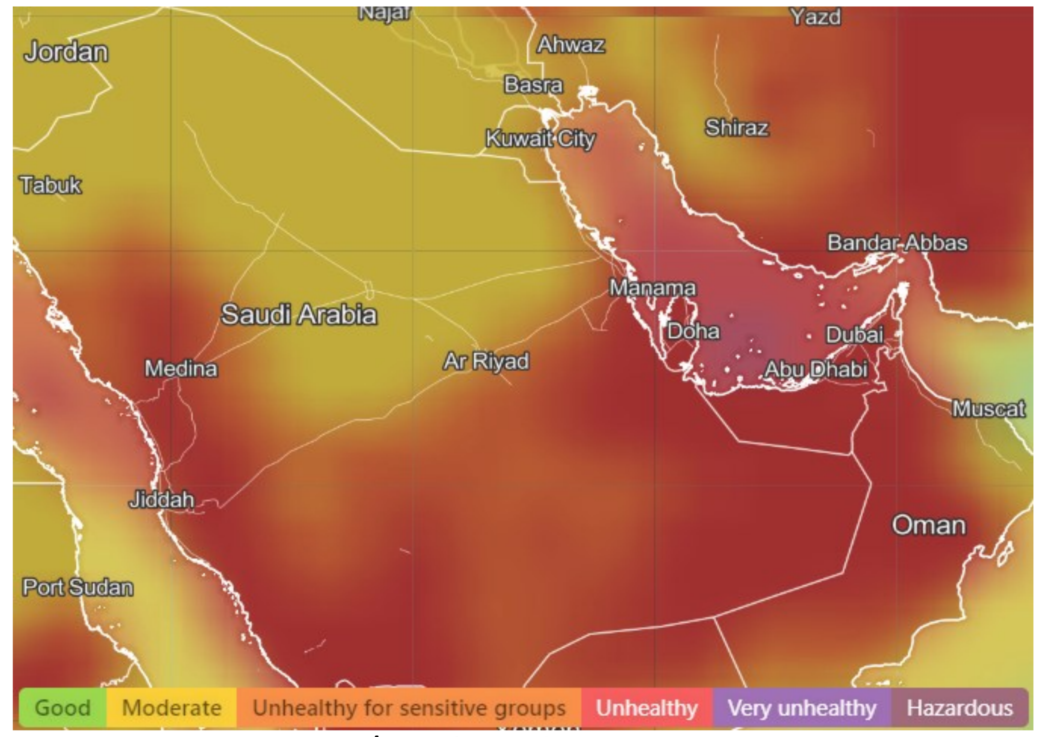
Motivation

- Saudi Arabia is ranked 21st in the world in terms of poor air quality.
- PM2.5 is one major air pollutant and extreme PM2.5 concentration in the air is highly unhealthy.
- Identifying regions with extreme PM2.5 concentration is necessary for warning and mitigation.



From www.iqair.com/saudi-arabia

Objectives

- Produce spatial exceedance probability maps and consider temporal variation.
- Model high threshold exceedances of PM2.5 concentration incorporating relevant covariate information.
- Build a deep learning-based spatiotemporal generalized Pareto distribution (GPD) model, that combines the strength of extreme-value theory models with the representation power of artificial neural networks.

PM2.5 data

Monthly ground-level PM2.5 concentration ($\mu g/m^3$) that combines data from a number of sources.
Our study includes 36 predictors. Some of them are:

- Meteorological variables from the ERA5 reanalysis on land surface
- Land cover proportions that are provided by Copernicus, the EU's Earth observation program
- Orographical variables that are derived from Amazon Web Services terrain tiles

Methodology

- A statistically justified model by **extreme-value theory** for the tail of a random variable is the GPD with the following distribution function (CDF)

$$H(y) = 1 - \left(1 + \frac{\xi y}{\sigma}\right)^{-\frac{1}{\xi}},$$

where $\sigma > 0$ and $\xi \in \mathbb{R}$ are the scale and shape parameters, respectively. In other words, for large u, we have

$$\Pr(Y > u + y \,|Y > u) \approx H(y), \qquad y > 0.$$

- The GPD is fitted to the exceedances $(y_i - u)|y_i > u$, for some large threshold u.
- We assume ξ to be unknown but fixed over space and time.
- σ is assumed to be varying across space and time (denoted by $\sigma(s,t)$), and

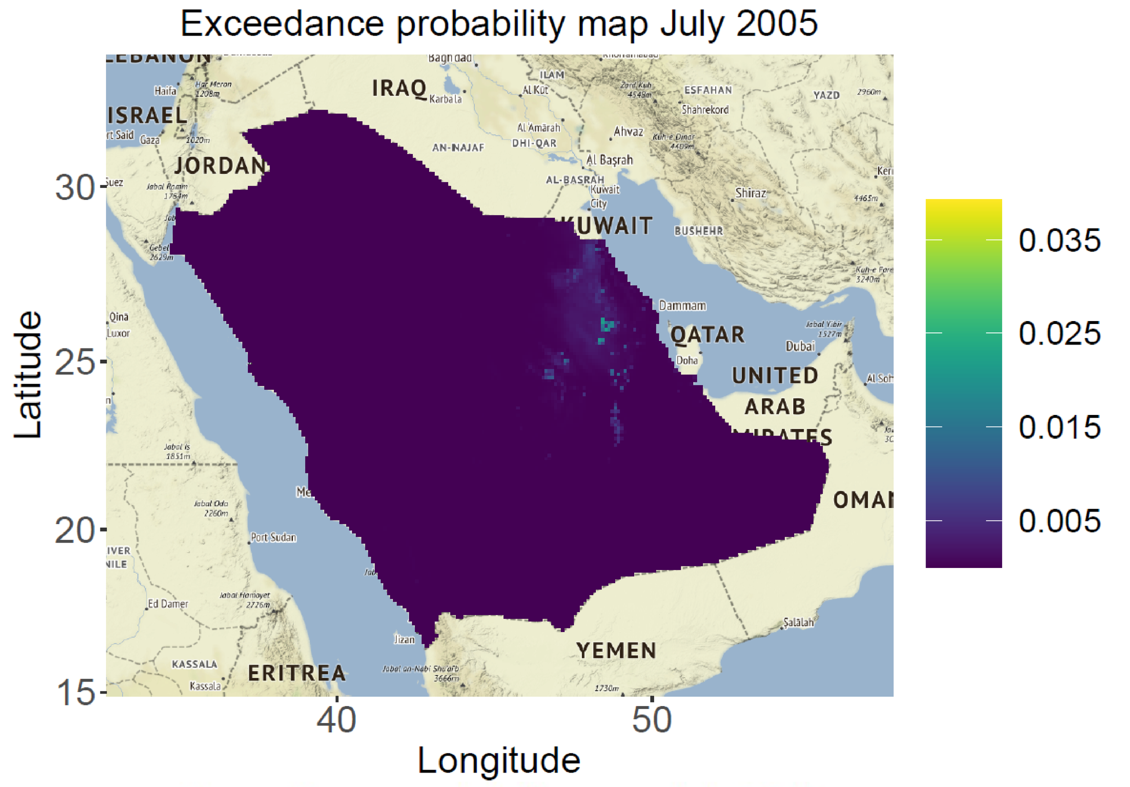
$$\log(\sigma(s,t)) = f(X_1(s,t), \dots, X_{36}(s,t)),$$

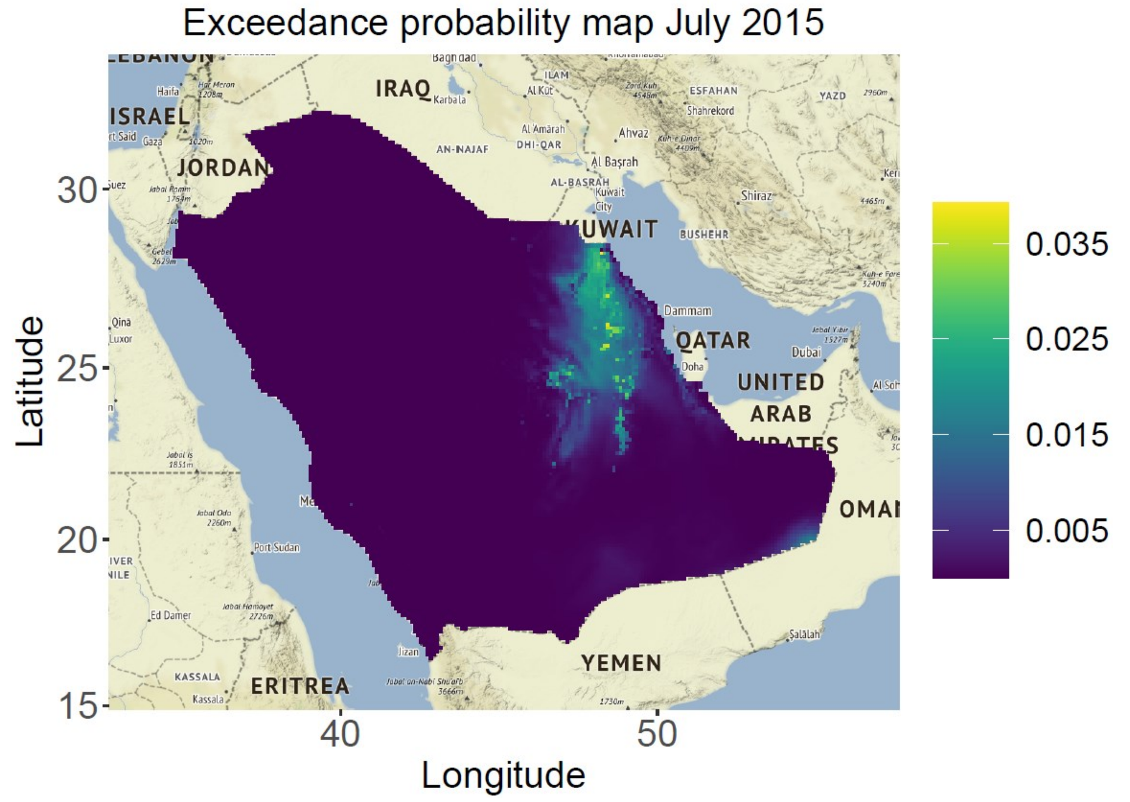
where f is an unknown nonlinear function.
- The parameters $\sigma(s,t)$ and ξ are estimated using **neural networks** with a single negative log-likelihood loss function.
- The dense neural network we used for σ has 4 layers with 87 neurons and 1291 learnable parameters while ξ network has only one layer with only one learnable parameter.
- The threshold level for the GPD is a quantile, estimated by another neural network minimizing the tilted loss, given by

$$e(y,\hat{y}) = \frac{1}{N}\sum_{i=1}^{N} \max\{\tau(y_i - \hat{y}_i), (\tau - 1)(y_i - \hat{y}_i)\}$$

where $\tau \in (0,1)$ is a pre-specified probability.

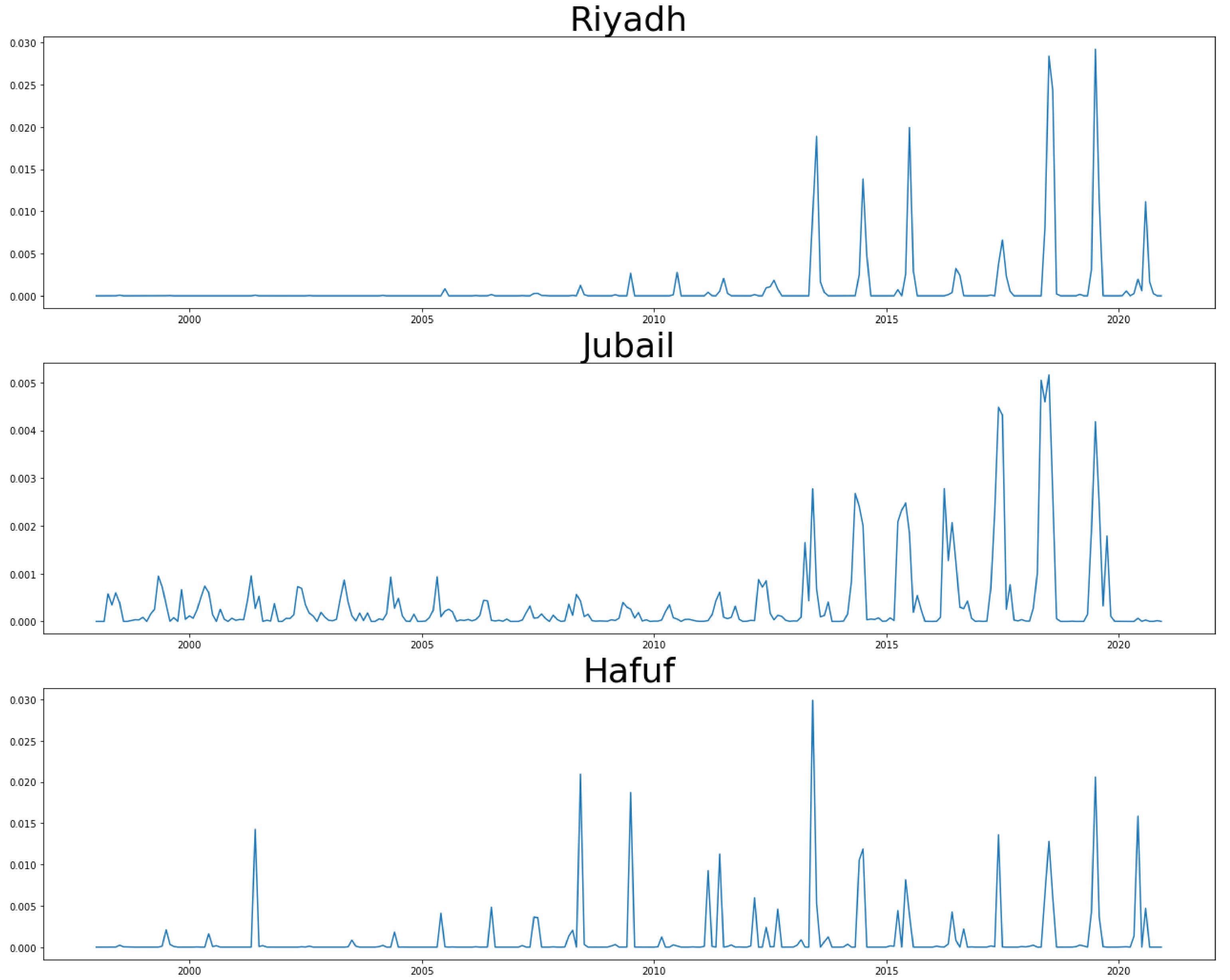
Results





The maps show the monthly probability estimates of exceeding the threshold of **150.4 $\mu g/m^3$**, which is considered unhealthy level by the U.S. Environmental Protection Agency (EPA).

The exceedance probability in major cities



Conclusion

- Our deep learning model can predict the probability of exceeding the unhealthy threshold and learn the complicated relationships between the output and the covariates.
- The results show that the exceedance probability is highly dependent on spatial and temporal location.
- Exceedance probability from different cities reveal an **alarming increase in pollution** over the years.
- In future research, it would be interesting to use convolutional and/or recurrent neural networks to more effectively capture spatio-temporal characteristics.