

Spatial-temporal Modeling of Ambient Ozone

Lucy Lu, Sam Yin

DSS, Duke University

May 2, 2017

Outline

- 1 Data
- 2 Modeling Ideas
- 3 Results
- 4 Discussion

Introduction

- Ground level ozone (ppb)
- Collected at 1249 sites in the U.S. from 06/01/2015 00:00:00 to 06/30/2015 23:00:00 at hourly frequency.

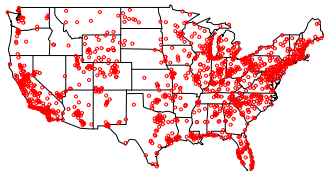


Figure 1: Map of ozone sites across the U.S.

Data Preprocessing

- Keep sites where data completeness is at least 95%
- Divide the U.S. into 25 subregions and model by region
- Impute missing values by averaging the two closest available observations along the temporal dimension

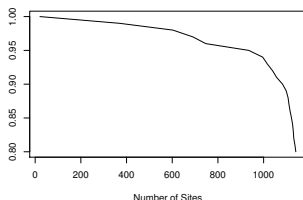


Figure 2: Cut-off percentage of completeness by number of sites

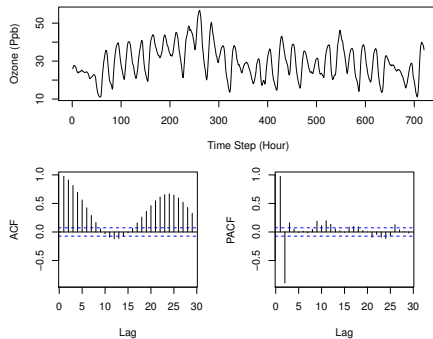


Figure 3: Time series display of average ozone (of all sites) in region 1

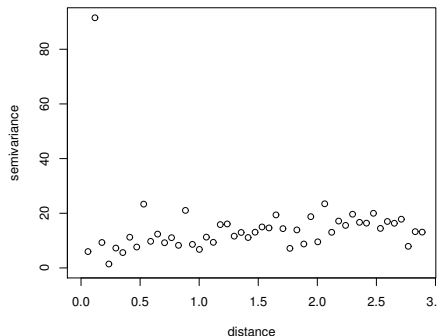


Figure 4: Variogram of average ozone (of all time steps) in region 1

Assuming no dependence between spatial and temporal dimensions, we build models with the additive structure (2). In other words, $\alpha(t)$ is constant to all sites at a given time point, and $\omega(s)$ is constant at all time points given a specific site.

$$y(s, t) = w(s, t) + e(s, t) \tag{1}$$

$$= \alpha(t) + \omega(s) + \epsilon(s, t) \tag{2}$$

Modeling Ideas (cont.)

Temporal specification:

① AR(1): $\alpha(t) = \delta + \phi\alpha(t-1)$

② MA(1): $\alpha(t) = \delta + w_t + \theta w_{t-1}$, $w_{1:T} \stackrel{\text{i.i.d.}}{\sim} N(0, \sigma_w^2)$

Spatial specification:

$$\omega(\tilde{s}) \sim \text{MVN}(\mathbf{0}, \Sigma_\omega) \quad (3)$$

where $\{\Sigma_\omega\}_{ij} = \sigma_\omega^2 \exp(-\phi_\omega \|s_i - s_j\|_2)$ for $i \neq j$

Error specification:

$$\epsilon(s, t) \sim N(0, \sigma_\epsilon^2) \quad (4)$$

- Use a 120-hour learning window for every next-hour ozone forecast
- Use 47 sites for model training and 24 sites for kriging
- JAGS, 4000 iterations, 3000 burn-ins, 3 chains
- First make next-hour forecasts at observed sites, then kriging to unobserved sites by sampling from conditional multivariate normal distribution with covariance specified by GP

Evaluation Criteria

$$\text{PMSE} = \frac{\sum_{t=1}^m \sum_{s=1}^n (\hat{y}(s, t) - y_{\text{obs}}(s, t))^2}{mn}$$

$$\text{Average Interval Length} = \frac{\sum_{t=1}^m \sum_{s=1}^n \text{Length of 95\% CI at Time } t \text{ Site } s}{mn}$$

$$\text{Coverage} = \frac{\sum_{t=1}^m \sum_{s=1}^n \mathbf{1}(y_{\text{obs}}(s, t) \in 95\% \text{ CI})}{mn}$$

$$\text{CRPS} = E_F |y(s, t) - y_{\text{obs}}(s, t)| - \frac{1}{2} E_F |y(s, t) - y'(s, t)|$$

Model	PMSE	Interval	Coverage	CRPS
AR(1)	17.7	12.98	0.85	2.36
MA(1)	126.24	36.56	0.91	6.56

Table 1: Summary of predictive performance at fitting sites (47)

Model	PMSE	Interval	Coverage	CRPS
AR(1)	60.08	12.84	0.79	4.29
MA(1)	38.00	27.49	0.92	3.45

Table 2: Summary of predictive performance at kriging sites (24)

Results (cont.)

AR(1)	Mean	95% CI	MA(1)	Mean	95% CI
σ_ω^2	4.32	(3.59, 5.20)	σ_ω^2	49.97	(44.95, 55.55)
ϕ_ω	0.15	(0.10, 0.20)	ϕ_ω	0.57	(0.48, 0.67)
ϕ	0.88	(0.87, 0.89)	θ	1.06	(0.76, 1.44)
δ	3.83	(2.80, 5.14)	σ_w^2	13.26	(7.76, 20.21)
σ_ϵ^2	6.40	(6.07, 6.75)	δ	25.51	(24.11, 26.94)
			σ_ϵ^2	14.68	(13.00, 16.41)

Table 3: Summary of parameter posterior distributions

Results (cont.)

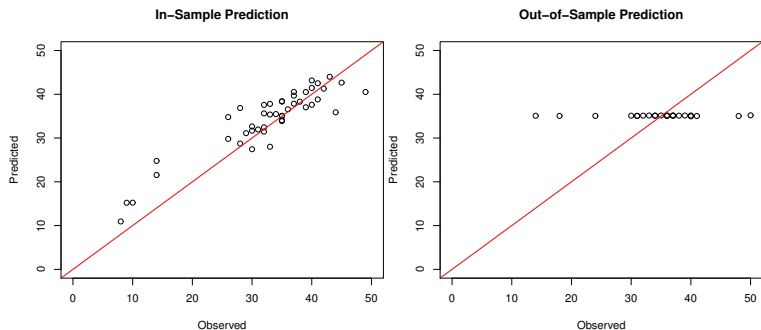


Figure 5: Predicted vs observed ozones, AR(1)

Results (cont.)

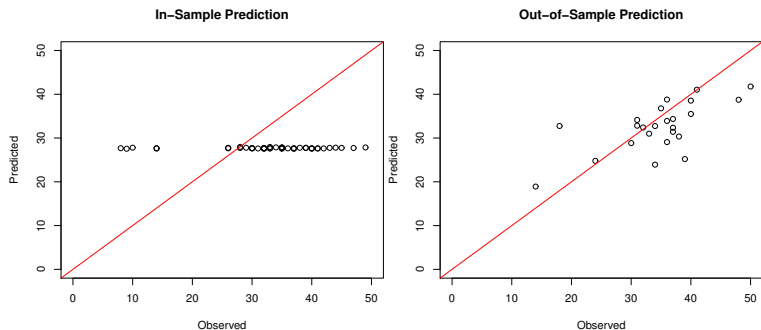


Figure 6: Predicted vs observed ozones, MA(1)

- In-sample vs. Out-of-sample (kriging) prediction
- Time series
- Additive assumption & Computational efficiency