Using Atmospheric Carbon Monoxide Models to Predict Fire Season Intensity

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Spatial & Temporal Statistics Symposium

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Big Picture: We are using natural variability in the climate to model atmospheric carbon monoxide (CO) concentrations.

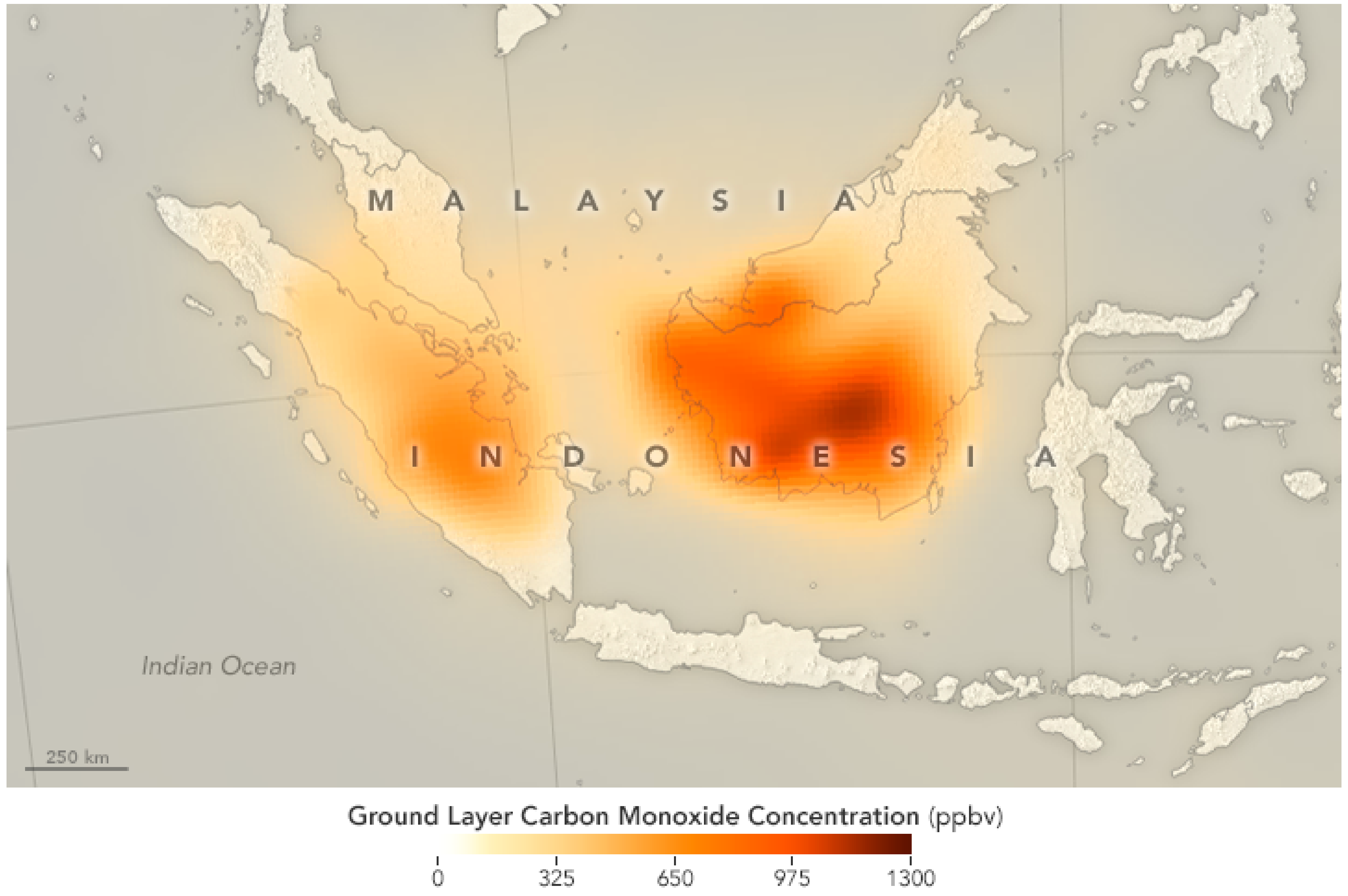
Why model CO?

1) Fires are the primary source of CO variability in the Southern Hemisphere

2) CO can be used as a proxy for fires

3) Predictive CO models can:
   - Help countries prepare for large burn events
   - Help explain the relationship between climate and atmospheric chemistry

2015 Indonesia Fires | CO Data from MOPITT



Fires Put a Carbon Monoxide Cloud over Indonesia. NASA, 1 Sept. 2015, earthobservatory.nasa.gov/images/87119/fires-put-a-carbon-monoxide-cloud-over-indonesia.

Fire Preparation

2019 - 2020 Australia Fires

Canberra, Australia
January 2020

Brisbane pharmacies run out of face masks amid bushfires and coronavirus fears

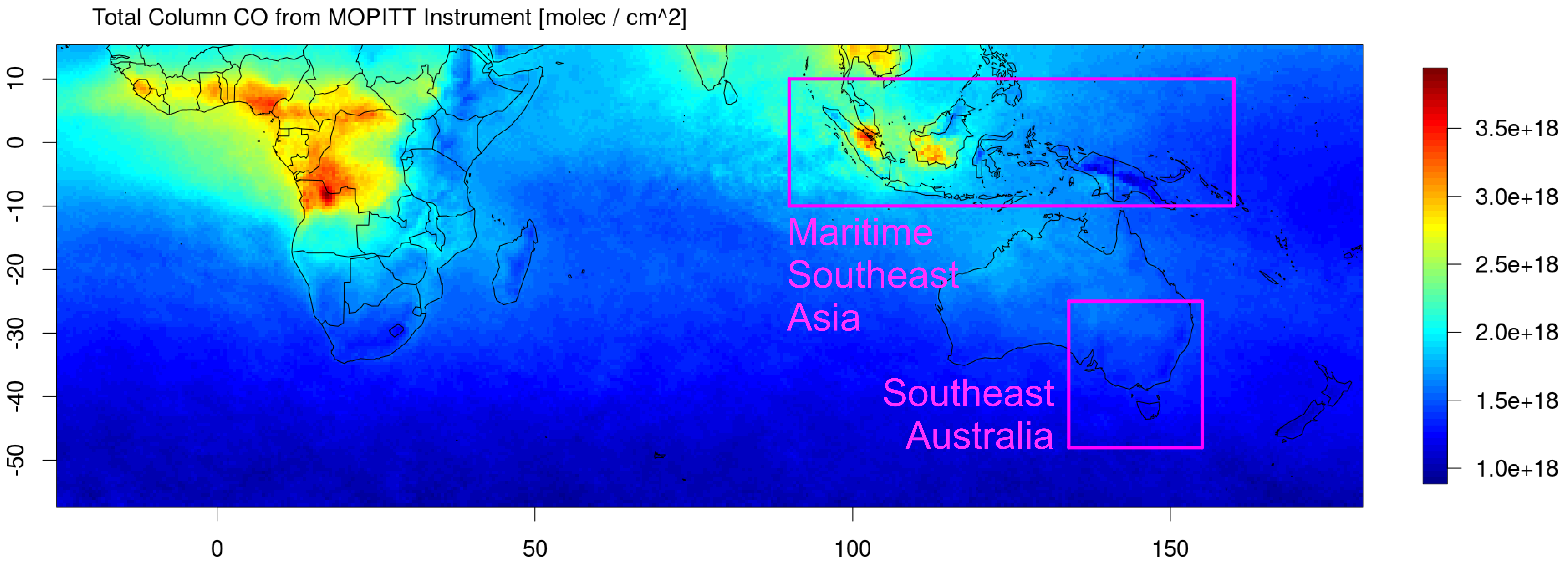
By Holly Richardson and staff

Updated 23 Jan 2020, 7:09pm

ABC News (Australian Broadcasting Company)

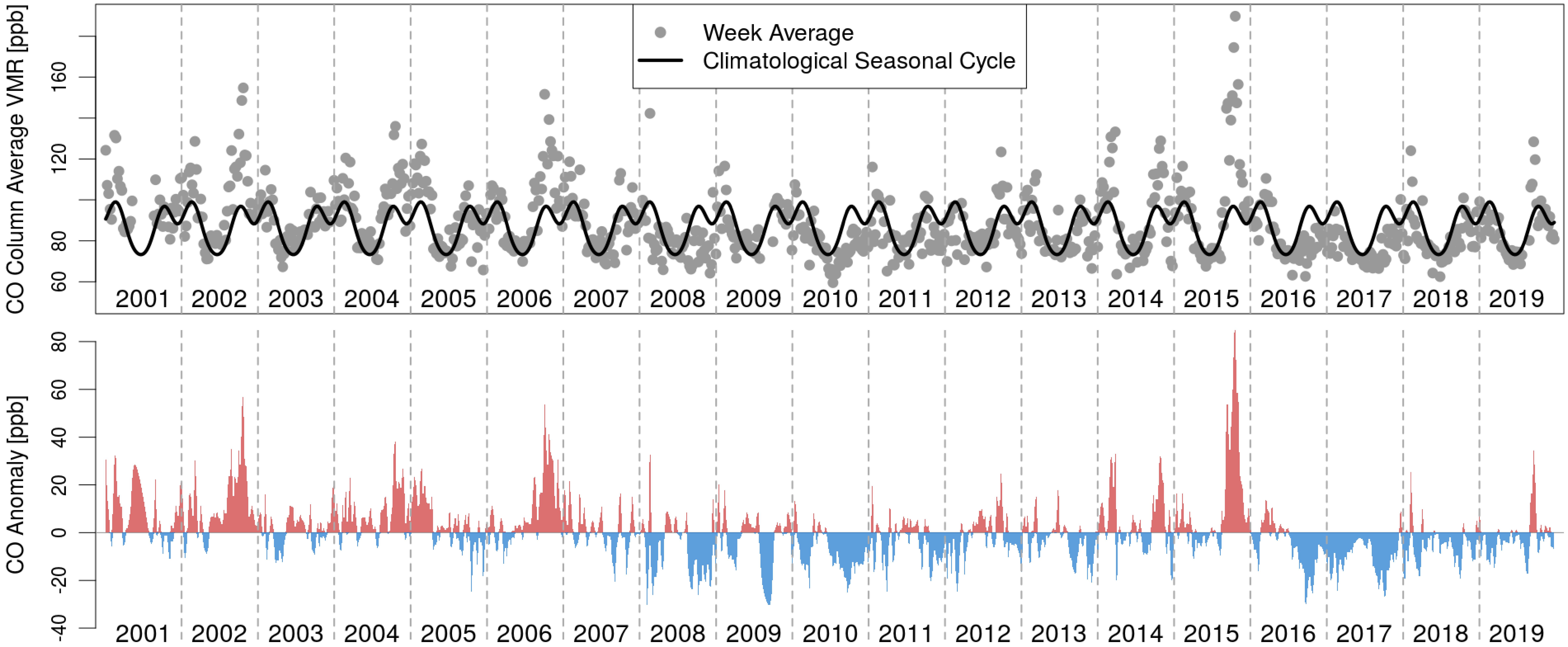
Richardson, Holly. "Pharmacies Run out of Face Masks amid Bushfires and Coronavirus Fears." ABC News, 24 Jan. 2020, www.abc.net.au/news/2020-01-24/face-mask-shortage-brisbane-bushfire-smoke-coronavirus-fears/11895300.

- CO measurements from MOPITT instrument on board the Terra satellite
- CO is aggregated into two biomass burning regions
- A separate model is created for each region, we will focus on Maritime SE Asia



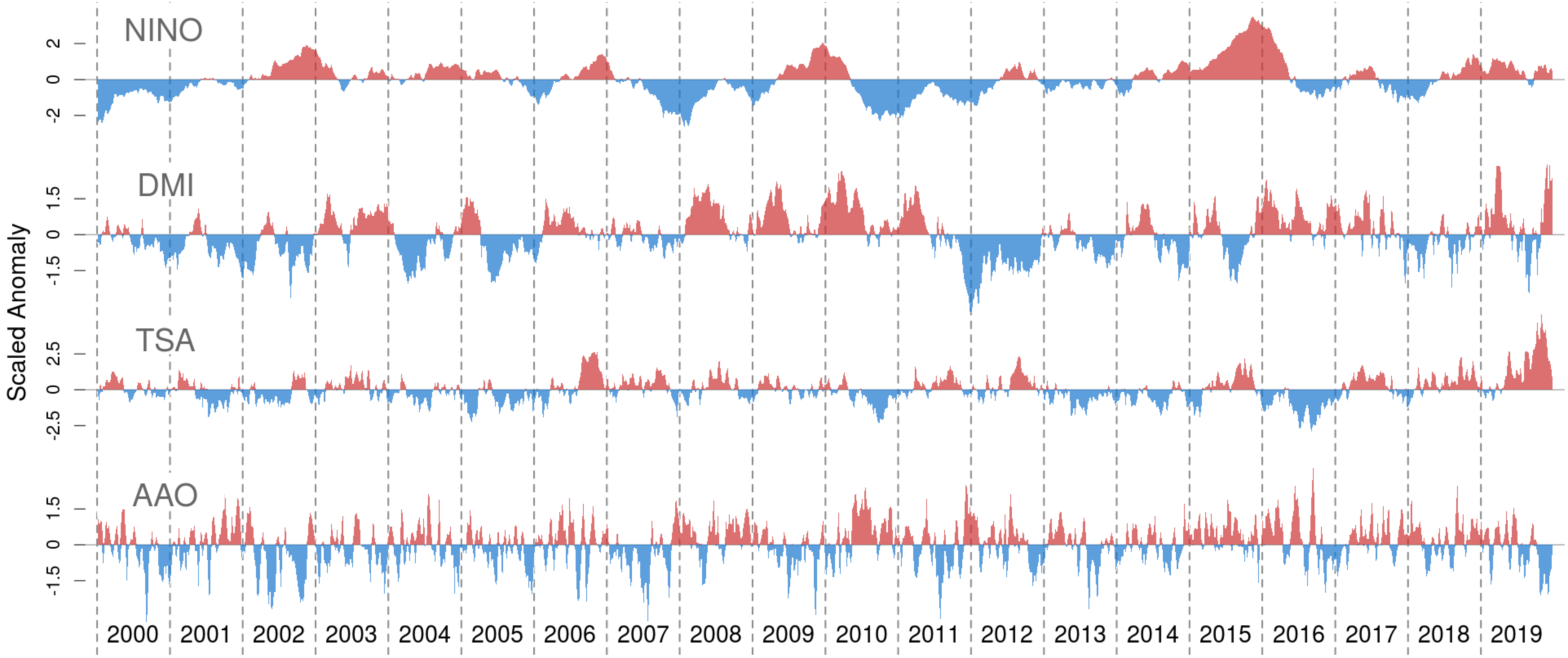
Response Variable

Response Variable: De-seasonalized CO anomaly at a given time, t



Predictor Variables

- **Climate indices** are metrics that summarize aperiodic changes in climate
- Burn events are related to climate through availability and dryness of fuel



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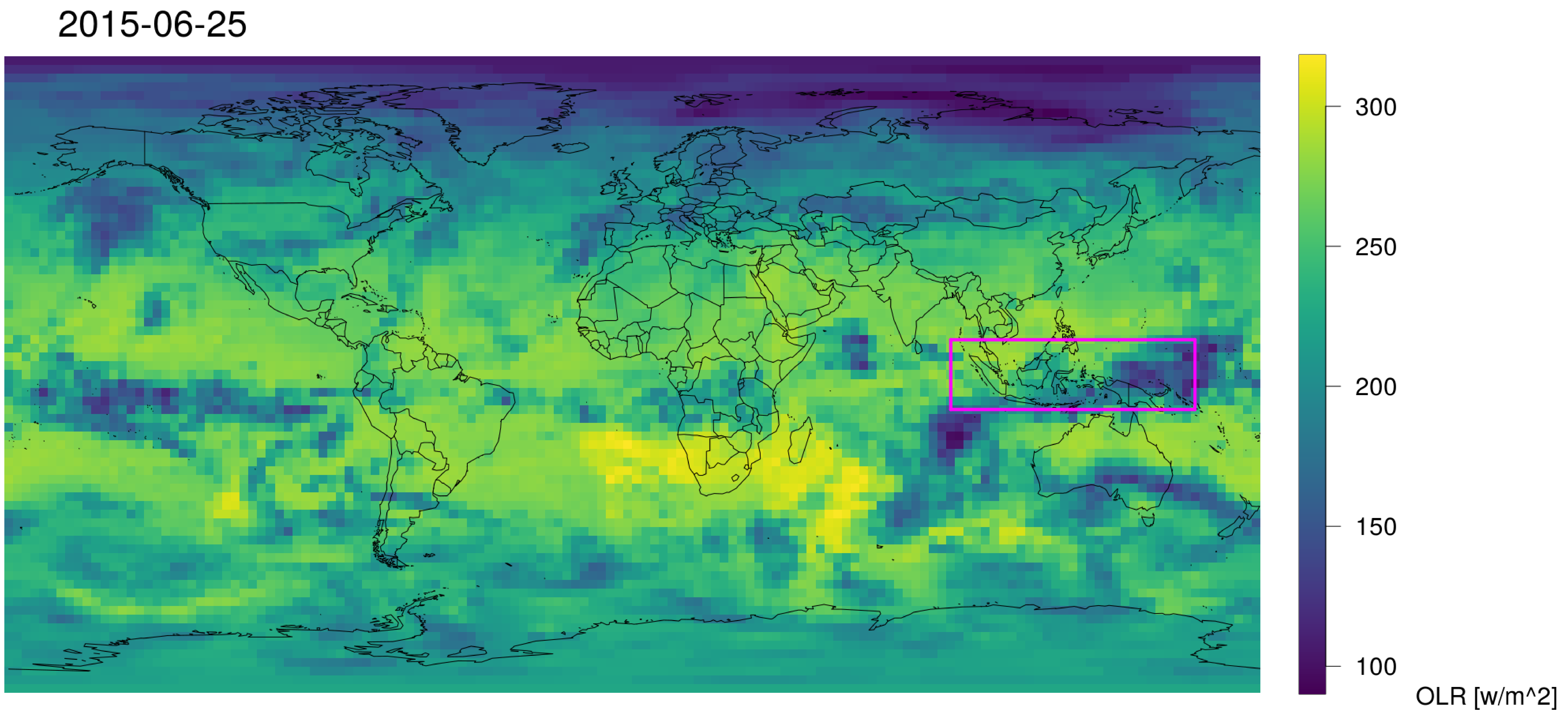
Predictor Variables

- **Outgoing longwave radiation (OLR)** is energy emitted to space through infrared radiation
- Low OLR values indicate presence of cloud cover



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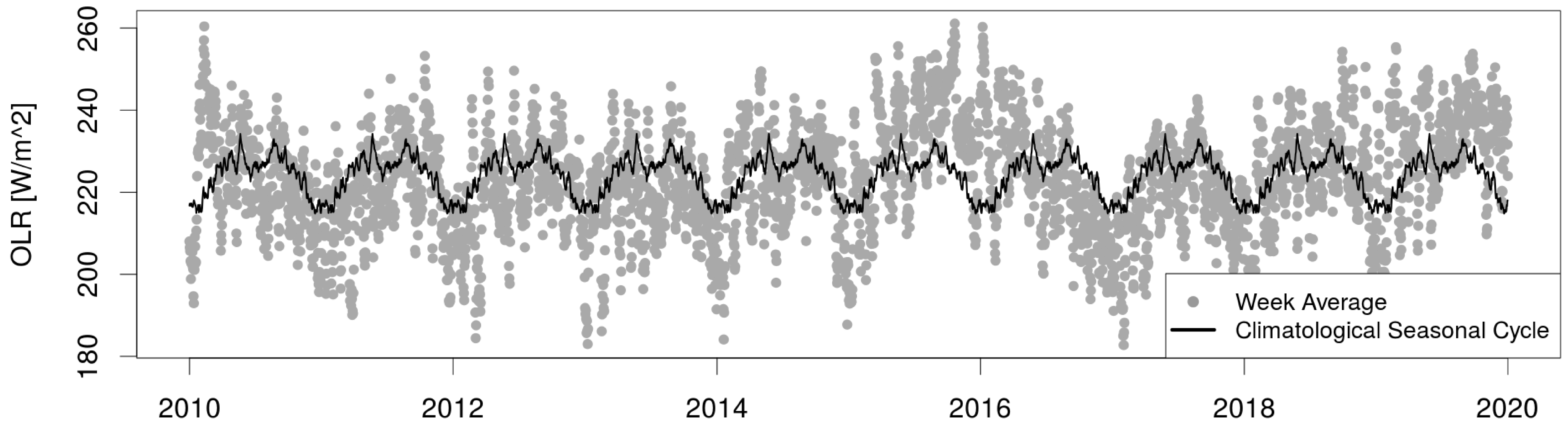
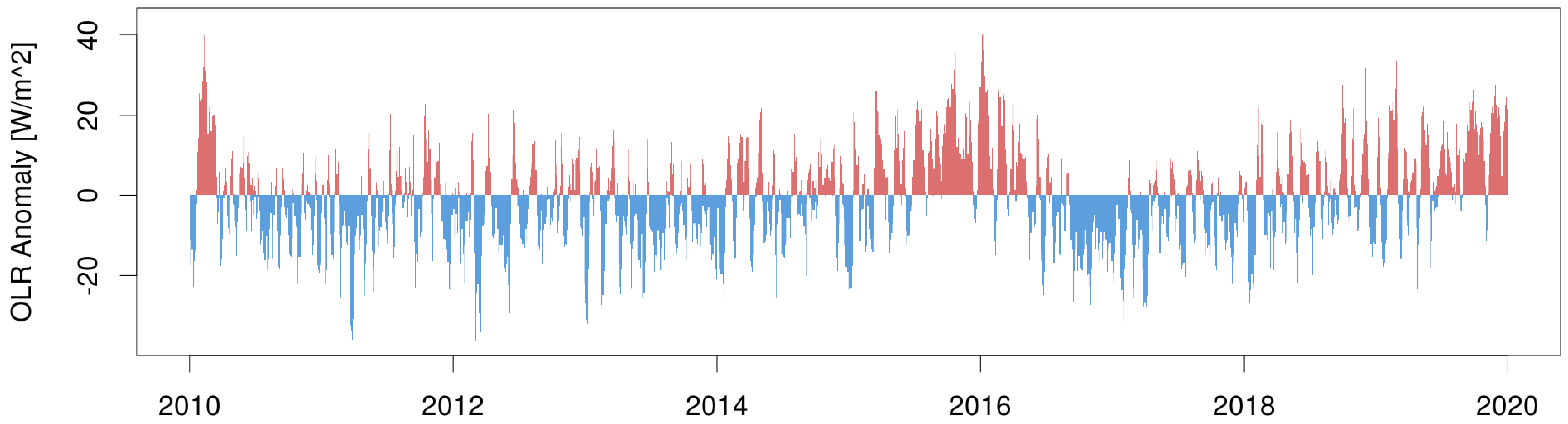
Predictor Variables: Climate indices and OLR anomalies, lagged at time t – τ.





We use a lagged multiple linear regression model with first order interactions

$$CO(t) = \mu + \underbrace{\sum_k a_k \cdot \chi_k(t - \tau_k)}_{\text{Main Effects}} + \underbrace{\sum_{i,j} b_{ij} \cdot \chi_i(t - \tau_i) \cdot \chi_j(t - \tau_j)}_{\text{Interaction Terms}}$$

CO(t) - CO anomaly in a given response region, at time *t*

μ - constant mean displacement

χ - climate indices & OLR anomalies

τ - lag value for each index in months

Statistical Model

We use a lagged multiple linear regression model with first order interactions

$$CO(t) = \mu + \underbrace{\sum_{k} a_k \cdot \chi_k(t - \tau_k)}_{\text{Main Effects}} + \underbrace{\sum_{i,j} b_{ij} \cdot \chi_i(t - \tau_i) \cdot \chi_j(t - \tau_j)}_{\text{Interaction Terms}}$$

How do we perform variable selection?

How do we pick lag values?

We use regularization for both variable and lag selection. The program:

1) Create design matrix
   - Include all covariates at lags 1-52

nino_1,	nino_2,	… ,	nino_52
dmi_1,	dmi_2,	… ,	dmi_52
tsa_1,	tsa_2,	… ,	tsa_52
aao_1,	aao_2,	… ,	aao_52
olr_1,	olr_2,	… ,	olr_52

We use regularization for both variable and lag selection. The program:

1) Create design matrix
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2) Set up the regularization
   - Start with the LASSO

LASSO Objective Function

$$\hat{\beta} = \arg\min_{\beta} \sum_{i=1}^{n} (Y_i - X_i\beta)^2 + \lambda \sum_{j=1}^{p} |\beta_j|$$

Controls model fit

Controls model complexity or size

Variable and Lag Selection via Regularization

We use regularization for both variable and lag selection. The program:

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2) Set up the regularization
   - Start with the LASSO
   - Introduce a more flexible penalty, the minimax concave penalty (MCP)

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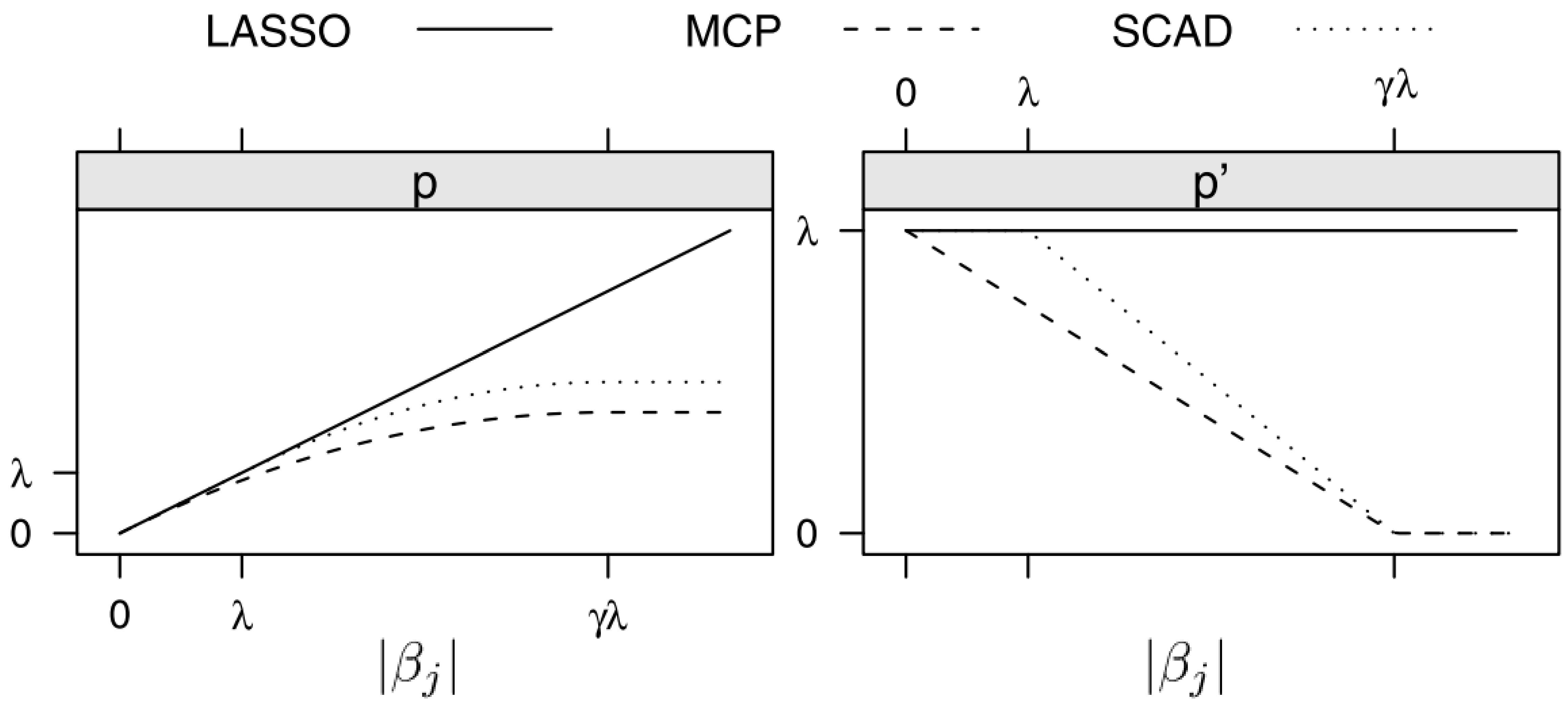

Patrick Breheny. Jian Huang. "Coordinate descent algorithms for nonconvex penalized regression, with applications to biological feature selection." The Annals of Applied Statistics, 5(1) 232-253 March 2011.

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   - Introduce a more flexible tuning parameter, the extended Bayesian information criterion (EBIC)

LASSO Objective Function

$$\hat{\beta} = \arg\min_{\beta} \sum_{i=1}^{n} (Y_i - X_i\beta)^2 + \lambda \sum_{j=1}^{p} |\beta_j|$$

$\gamma_{EBIC} \in [0, 1]$ is used to select λ

EBIC = BIC, Larger Models

Smaller Models

Patrick Breheny. Jian Huang. "Coordinate descent algorithms for nonconvex penalized regression, with applications to biological feature selection." The Annals of Applied Statistics, 5(1) 232-253 March 2011.

Variable and Lag Selection via Regularization

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1) Create design matrix
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2) Set up the regularization
   - Start with the LASSO
   - Introduce a more flexible penalty, the minimax concave penalty (MCP)
   - Introduce a more flexible tuning parameter, the extended Bayesian information criterion (EBIC)

3) Vary over free parameters
   - Perform grid search over γ_{MCP} and γ_{EBIC}
   - At each parameter combination, use RAMP algorithm to compute solution path
   - Results in a "best model" for each γ_{EBIC}

LASSO Objective Function

$$\hat{\beta} = \arg\min_{\beta} \sum_{i=1}^{n} (Y_i - X_i\beta)^2 + \lambda \sum_{j=1}^{p} |\beta_j|$$

LASSO → λ
MCP → γ_{MCP}
EBIC → γ_{EBIC}

Patrick Breheny. Jian Huang. "Coordinate descent algorithms for nonconvex penalized regression, with applications to biological feature selection." The Annals of Applied Statistics, 5(1) 232-253 March 2011.
Ning Hao, Yang Feng & Hao Helen Zhang (2018) Model Selection for High-Dimensional Quadratic Regression via Regularization, Journal of the American Statistical Association, 113:522, 615-625

Best Models for Maritime SE Asia

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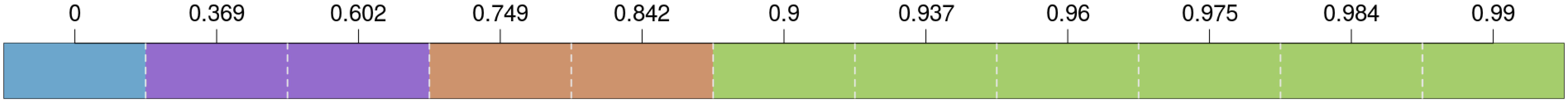
Best models optimized over γ_{MCP} and λ for a logarithmic sequence of γ_{EBIC}



	Est (Std. Error)
(Intercept)	0.3 (0.70)
nino_4	7.6 (0.83)
dmi_1	5.7 (0.79)
dmi_12	-6.1 (0.75)
dmi_43	1.8 (0.65)
tsa_3	-2.2 (0.64)
aao_2	-3.6 (0.61)
aao_38	-2.2 (0.64)
aao_51	-1.6 (0.63)
olr_1	2.3 (0.74)
olr_13	3.4 (0.71)
nino_4:olr_1	3.2 (0.66)
nino_4:dmi_1	3.2 (0.81)
dmi_1:dmi_12	-4.5 (0.56)
nino_4:aao_51	-4.2 (0.77)
tsa_3:olr_1	-2.3 (0.63)
aao_2:olr_13	-2.1 (0.68)
nino_4:aao_2	-1.8 (0.70)

Standard error: 10.22
Multiple R-squared: 0.70
Adjusted R-squared: 0.68
DF: 17

	Est (Std. Error)
(Intercept)	0.1 (0.72)
nino_4	7.3 (0.85)
dmi_1	6.1 (0.86)
dmi_12	-7.5 (0.78)
dmi_37	2.3 (0.69)
aao_2	-2.7 (0.62)
aao_51	-2.3 (0.65)
olr_1	2.7 (0.74)
olr_12	2.3 (0.75)
olr_20	1.6 (0.70)
nino_4:olr_1	2.8 (0.70)
nino_4:dmi_12	-2.7 (0.78)
aao_51:olr_1	-2.8 (0.64)
nino_4:dmi_37	-4.8 (0.66)
dmi_12:dmi_37	2.1 (0.73)
dmi_1:dmi_12	-2.2 (0.65)

Standard error: 10.38
Multiple R-squared: 0.68
Adjusted R-squared: 0.67
DF: 15

	Est (Std. Error)
(Intercept)	-0.38 (0.68)
nino_4	7.85 (0.85)
dmi_1	4.11 (0.78)
dmi_12	-6.50 (0.77)
dmi_37	2.09 (0.66)
tsa_13	-1.01 (0.68)
aao_2	-2.32 (0.64)
aao_51	-2.01 (0.65)
olr_1	2.80 (0.76)
olr_12	2.58 (0.74)
nino_4:olr_1	3.21 (0.71)
nino_4:dmi_12	-4.19 (0.69)
aao_51:olr_1	-2.74 (0.67)
nino_4:dmi_37	-4.28 (0.66)

Standard error: 10.67
Multiple R-squared: 0.66
Adjusted R-squared: 0.65
DF: 13

	Est (Std. Error)
(Intercept)	-1.6 (0.78)
nino_4	7.2 (0.78)
dmi_4	7.2 (0.93)
dmi_12	-8.0 (0.87)
aao_51	-3.1 (0.67)
olr_1	3.5 (0.79)
I(nino_4^2)	2.5 (0.54)
nino_4:olr_1	3.5 (0.76)
nino_4:dmi_12	-6.5 (0.77)
aao_51:olr_1	-2.3 (0.67)

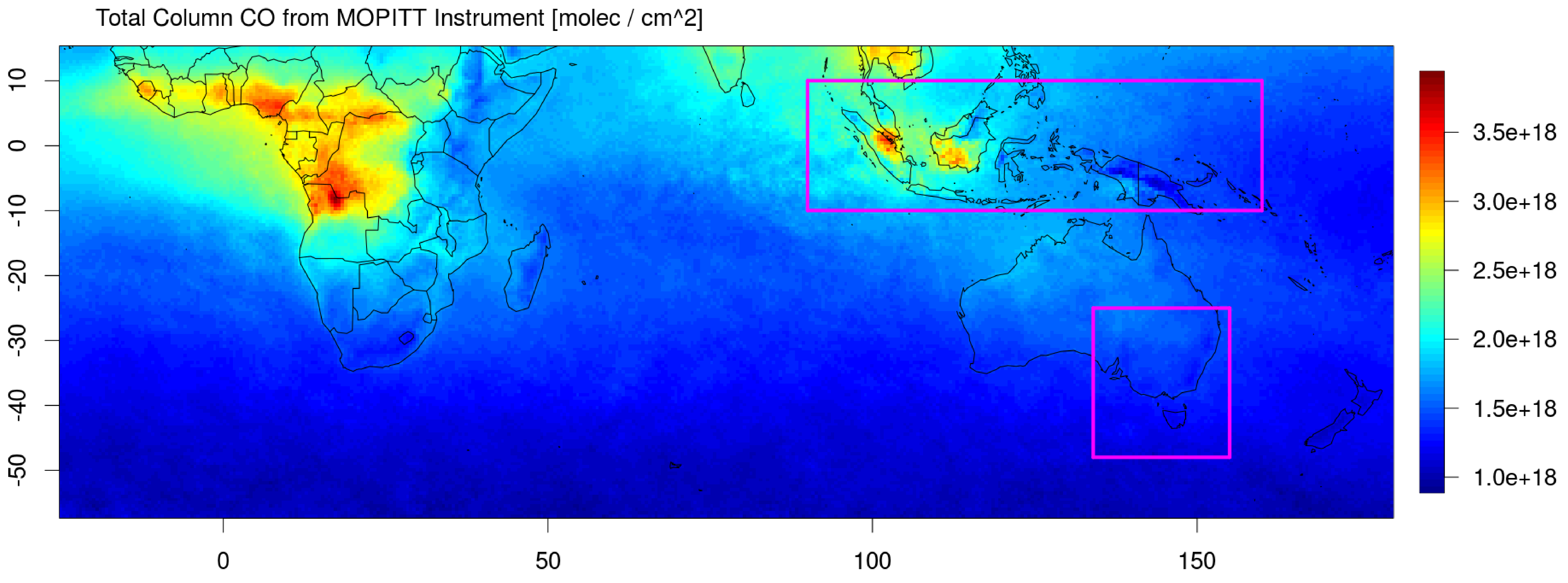
Standard error: 11.42
Multiple R-squared: 0.61
Adjusted R-squared: 0.60
DF: 9

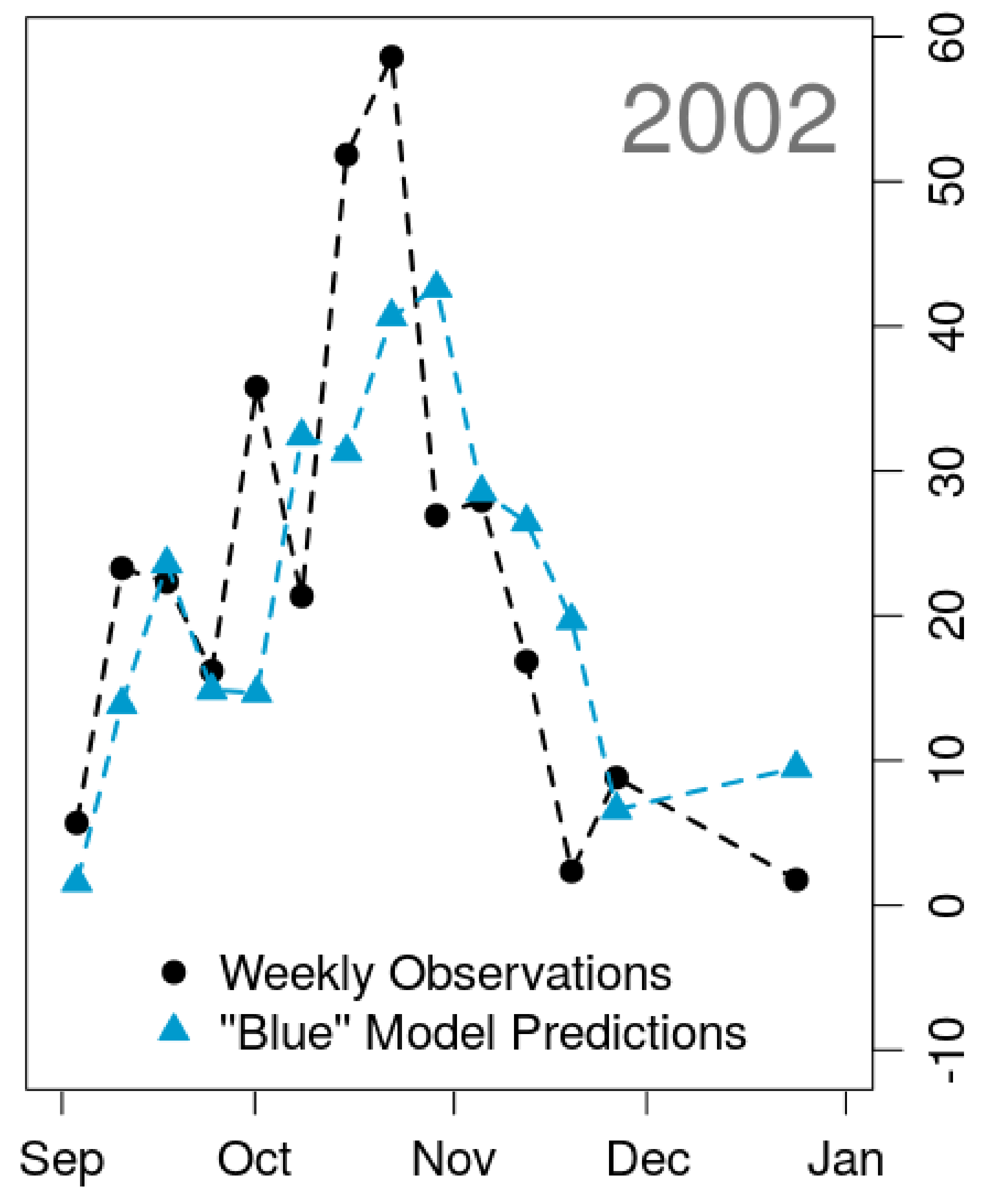
Maritime SE Asia Model Predictions

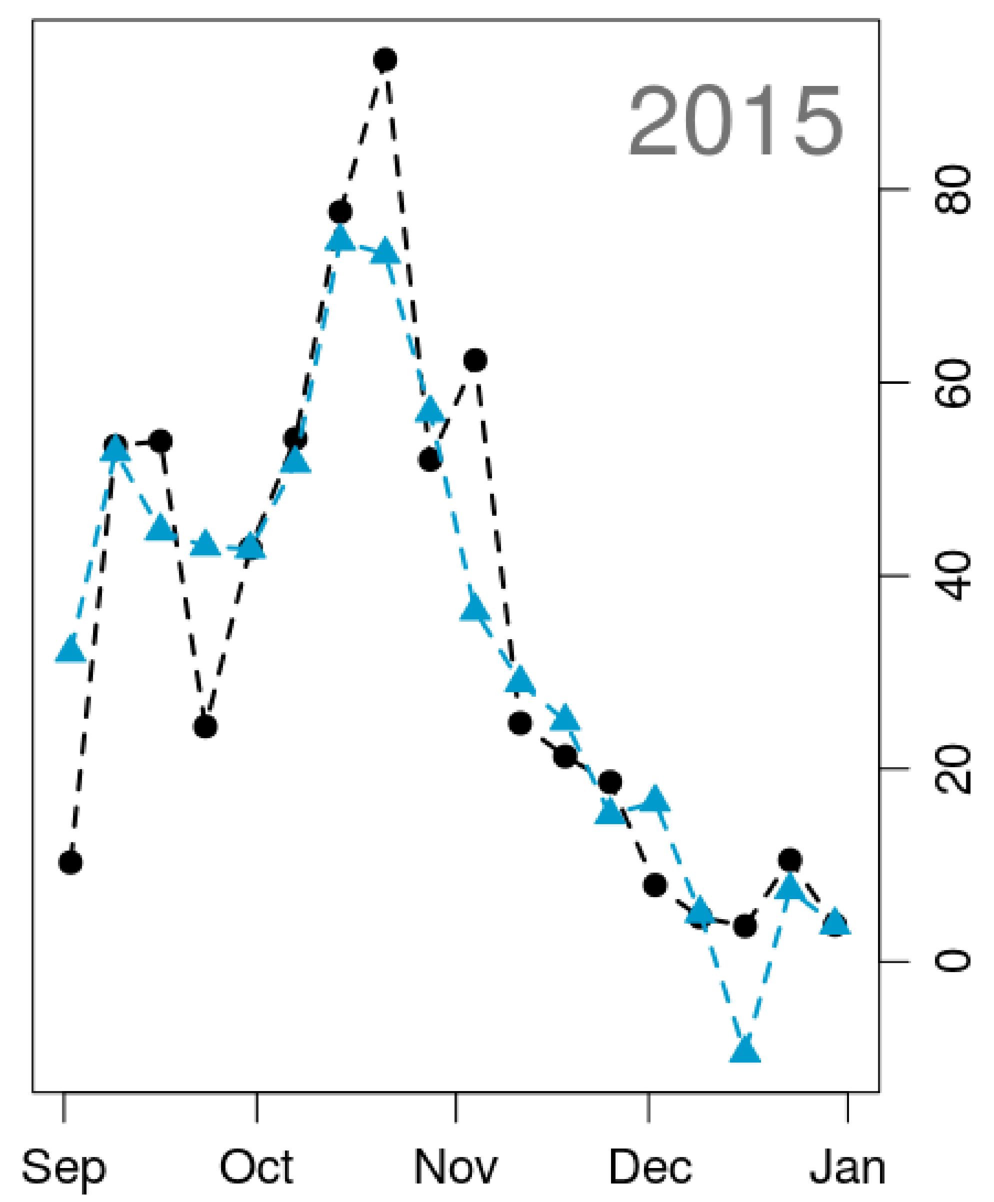
Take-Aways:

We are using variability in the climate to predict atmospheric CO, a proxy for fire season intensity

- Identifying the optimally performing models at various complexities allows us to identify the most significant predictors and lags.
- Model performs well and is able to capture peaks in Maritime SE Asia.







Conclusion & Future Work

Take-Aways:

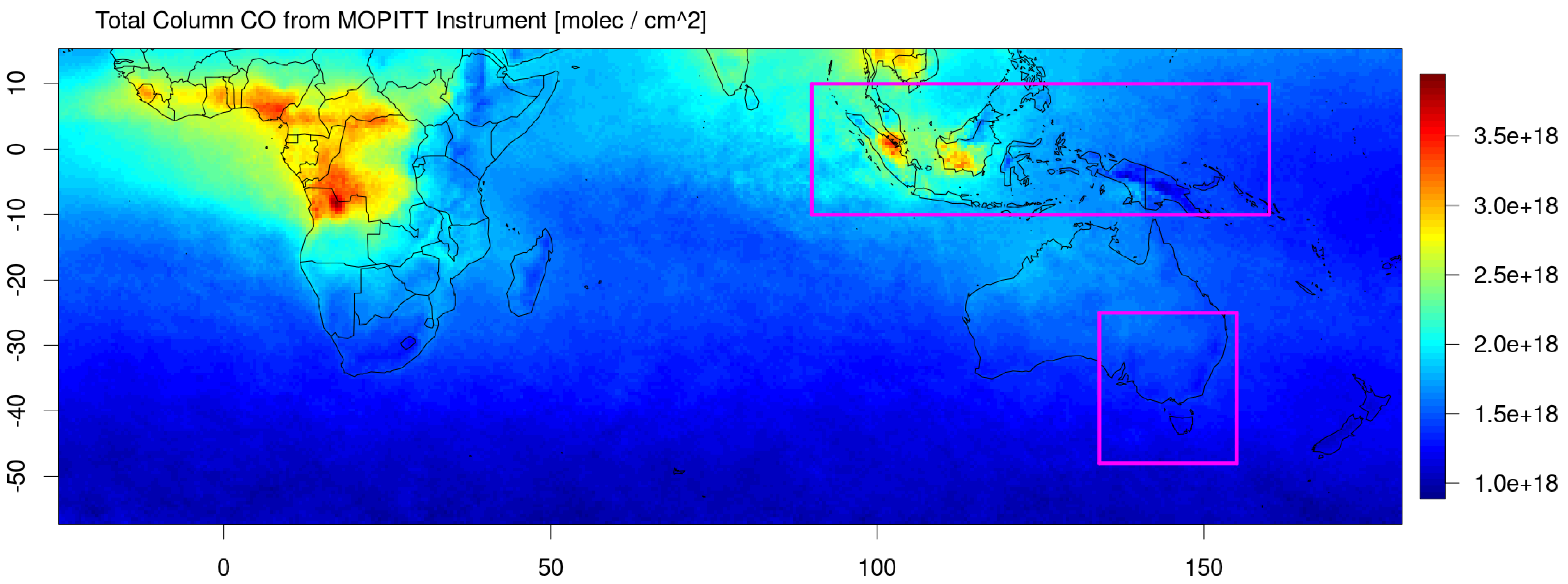
We are using variability in the climate to predict atmospheric CO, a proxy for fire season intensity

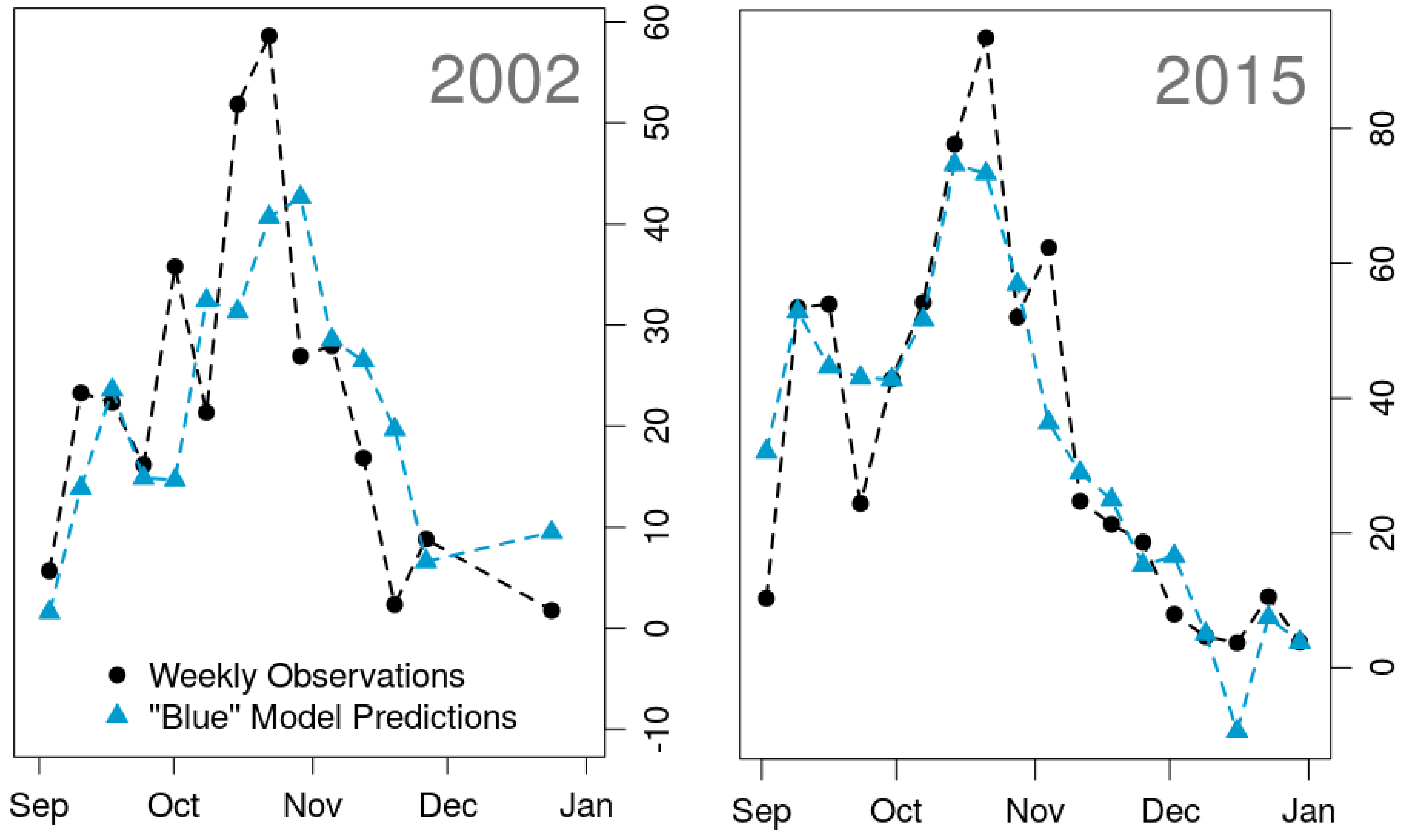
- Identifying the optimally performing models at various complexities allows us to identify the most significant predictors and lags.
- Model performs well and is able to capture peaks in Maritime SE Asia.

Future Work:

- Increase minimum lag limit to see how far in advance we can make good predictions

“Cheyenne.” Cheyenne | Computational Information Systems Laboratory, www2.cisl.ucar.edu/resources/computational-systems/cheyenne





Thank you! Questions?

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