Using the Climate to Model Atmospheric Carbon Monoxide

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GRADS Symposium

Golden, CO (or on the world wide web!)

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

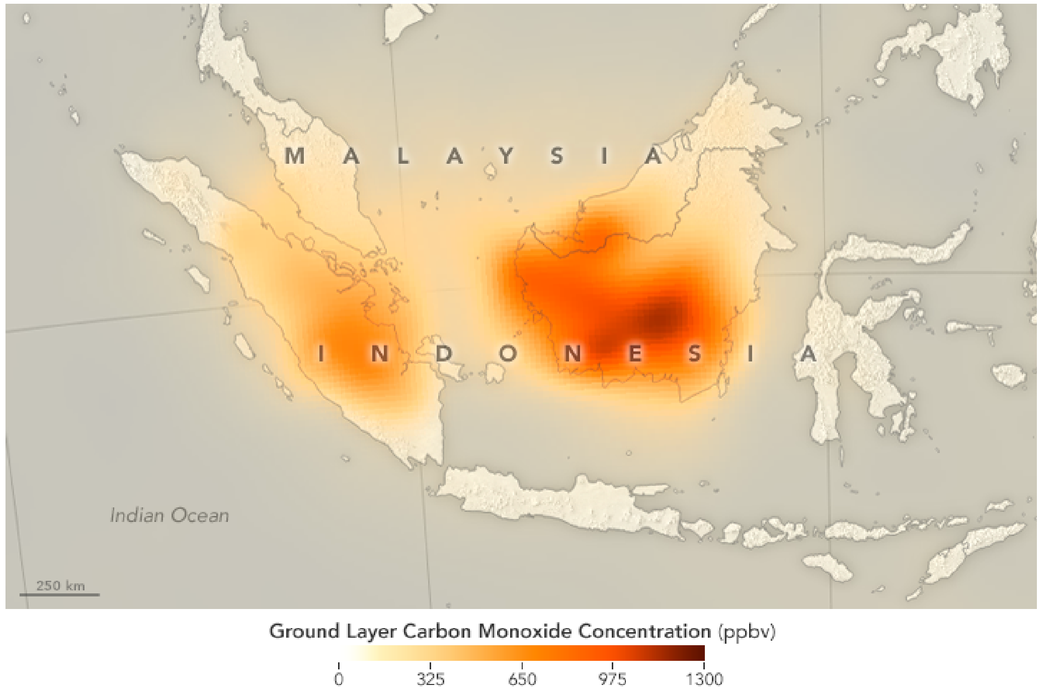
Why model CO?

1) Fires are the primary source of CO 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

2015 Indonesia Fires



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.

Will Daniels, wdaniels@mines.edu

2019 - 2020 Australia Fires

Canberra, Australia
January 2020

Brisbane pharmacies run out of face masks amid bushfires

By Holly Richardson and staff

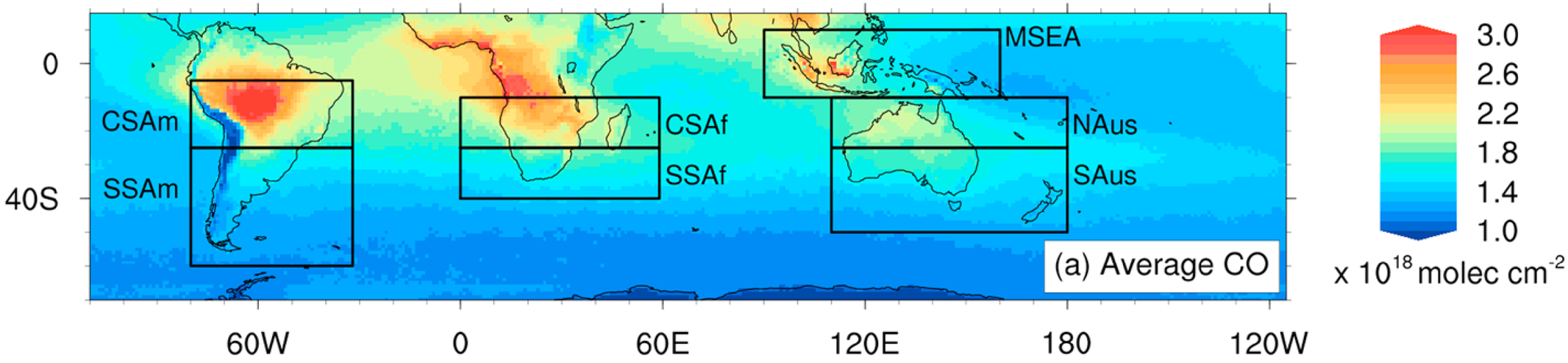
Updated 23 Jan 2020, 7:09pm

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.

Response Variable

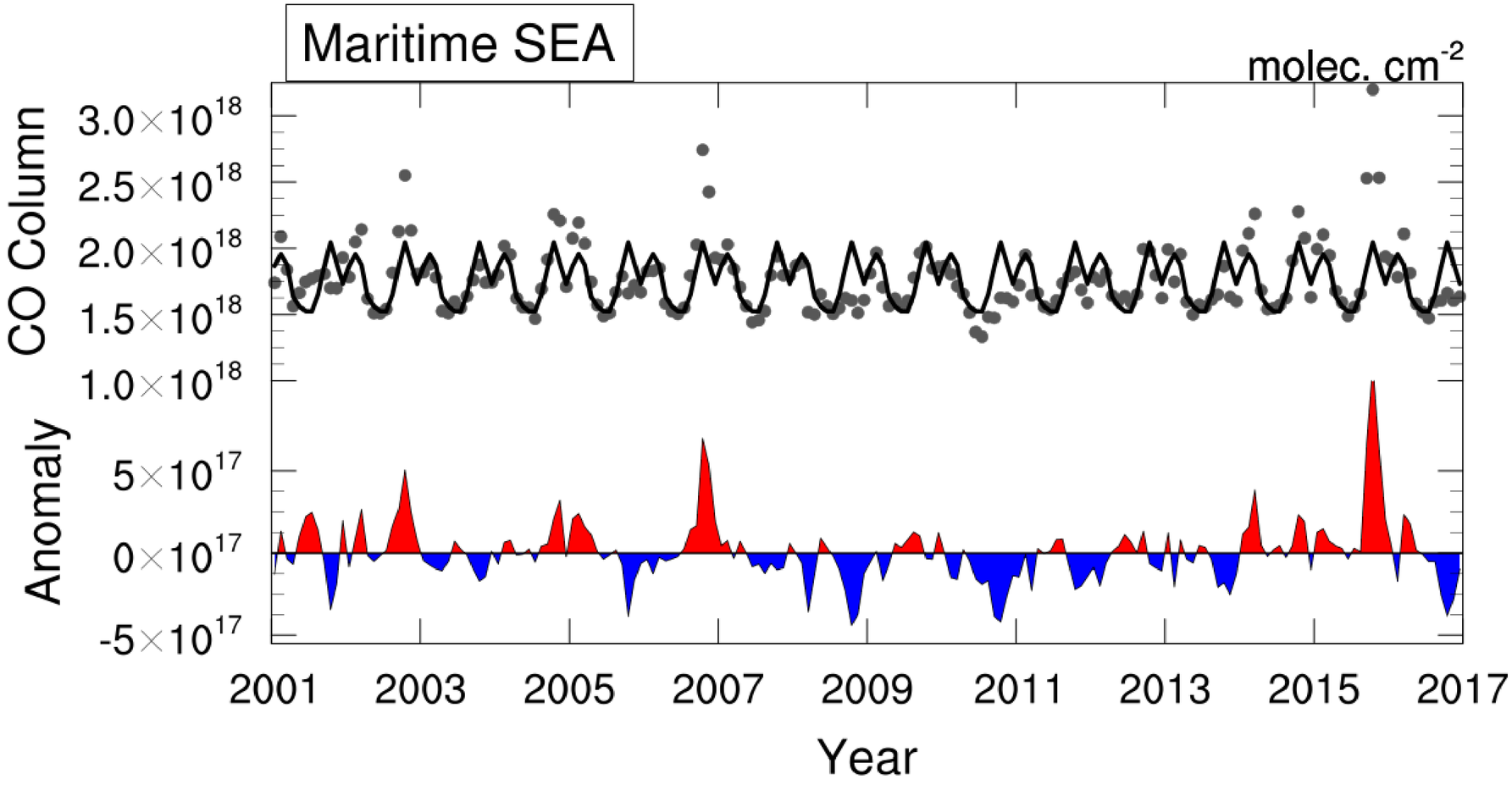
- CO measurements from MOPITT instrument on board the Terra satellite
- CO is aggregated into seven biomass burning regions
- A separate model is created for each region



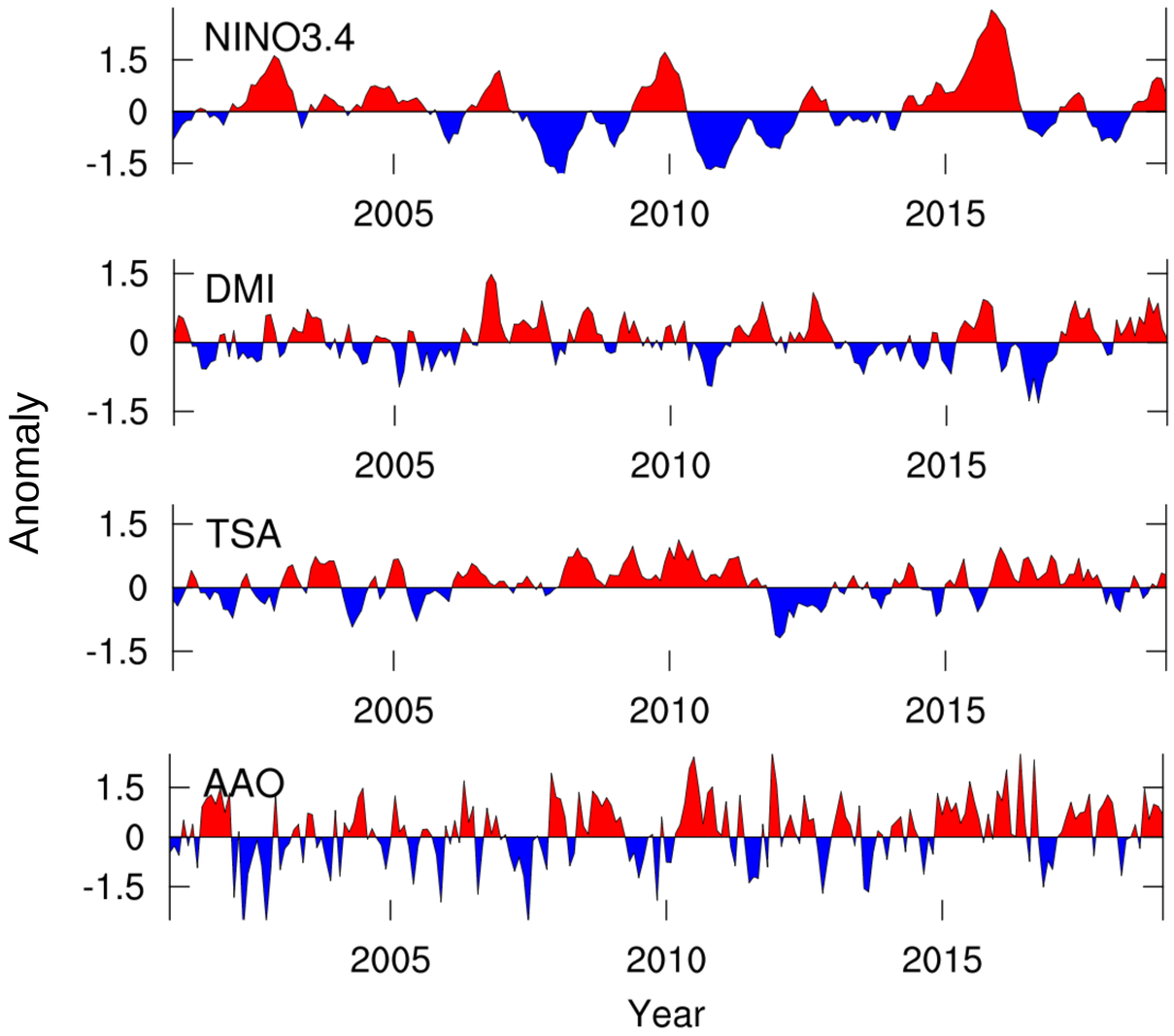
R. R. Buchholz et al., “Links Between Carbon Monoxide and Climate Indices for the Southern Hemisphere and Tropical Fire Regions,” J. Geophys. Res. Atmos., vol. 123, no. 17, pp. 9786–9800, Sep. 2018.

Response Variable

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



Predictor Variables



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

Predictor Variables: Climate indices, lagged at time t - τ

R. R. Buchholz et al., "Links Between Carbon Monoxide and Climate Indices for the Southern Hemisphere and Tropical Fire Regions," J. Geophys. Res. Atmos., vol. 123, no. 17, pp. 9786–9800, Sep. 2018.

Statistical Model

We use a lagged multiple linear regression model with first order interaction terms to explain the relationship between atmospheric CO and month-averaged climate indices.

$$CO(t) = \mu + \sum_{k} a_k \cdot \chi_k(t - \tau_k) + \sum_{i,j} b_{ij} \cdot \chi_i(t - \tau_i) \cdot \chi_j(t - \tau_j)$$

Main Effects

Interaction Terms

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

μ - constant mean displacement

χ - climate indices

τ · lag value for each index in months

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How do we perform variable selection?

How do we pick lag values?

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Main Effects

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How do we perform variable selection?

We created the R package *regClimateChem*

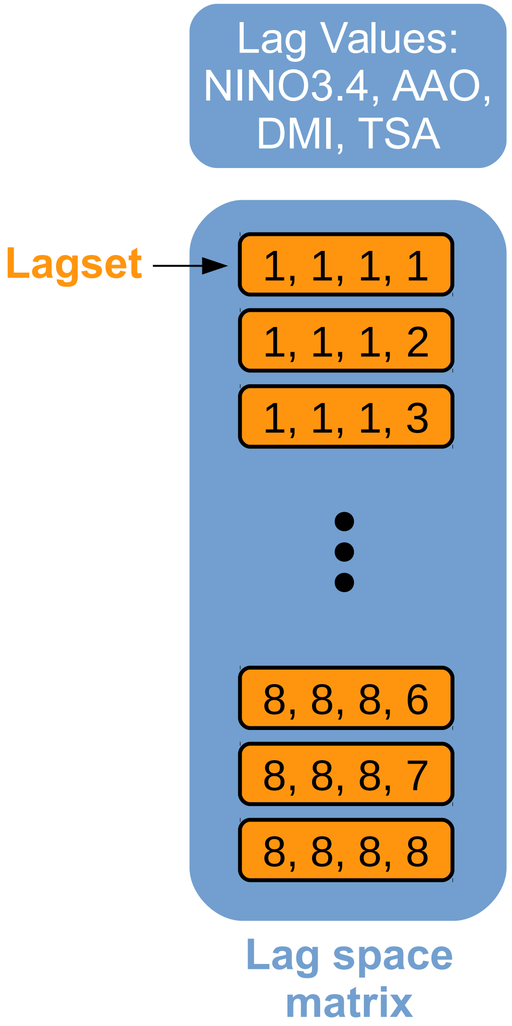
- Best Subset Selection — Exhaustive Option
- Genetic Search Algorithm — Non-Exhaustive Options
- Stepwise Selection — Non-Exhaustive Options

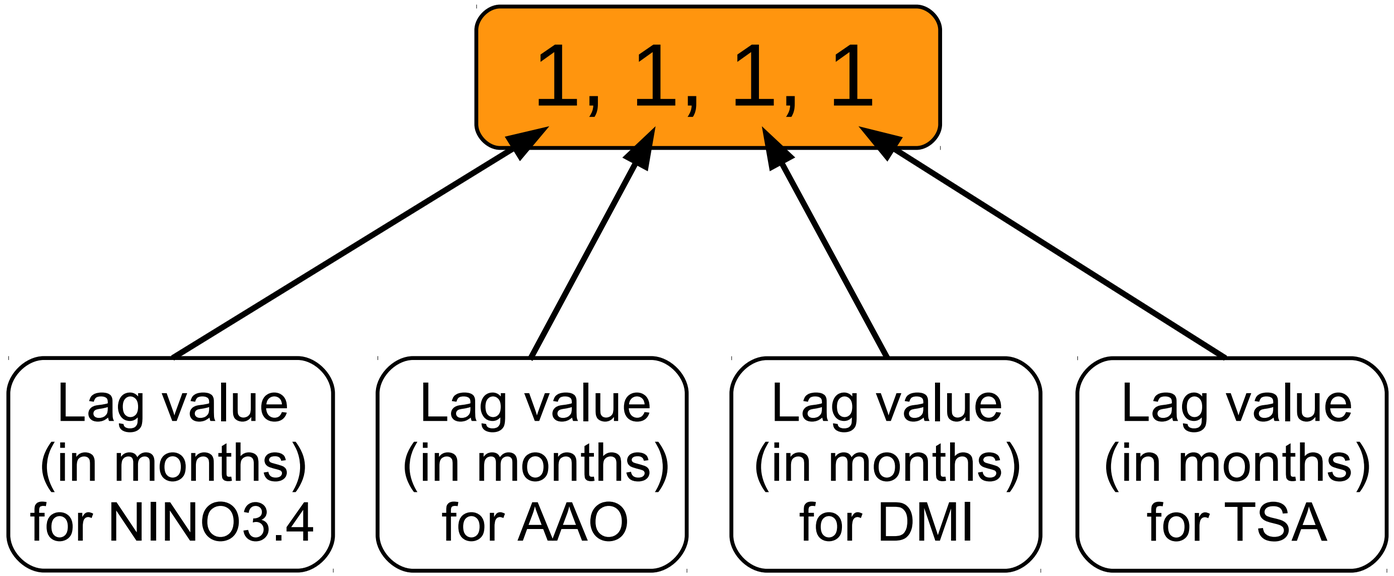
Better model accuracy

Longer runtime

How do we pick lag values?

Instead of performing variable selection on the entire parameter space, we break it up by **lagset**.





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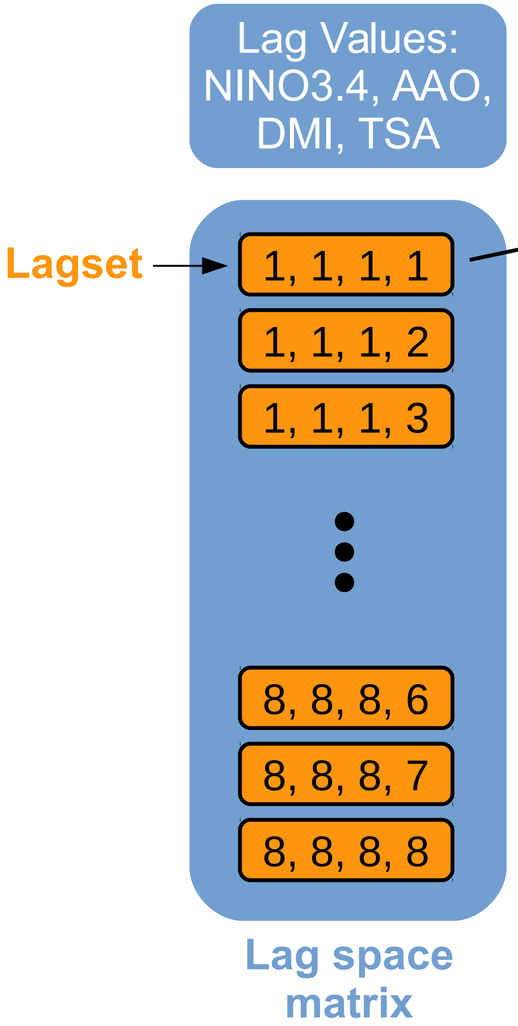

Lagset #1, Available Regressors

Index	NINO3.4	AAO	DMI	TSA
Lag Value	1	1	1	1

Model #1

Information Criteria: R^2_{Ajd}, C_p, AIC, **BIC**

BIC balances **model complexity** and **model fit**

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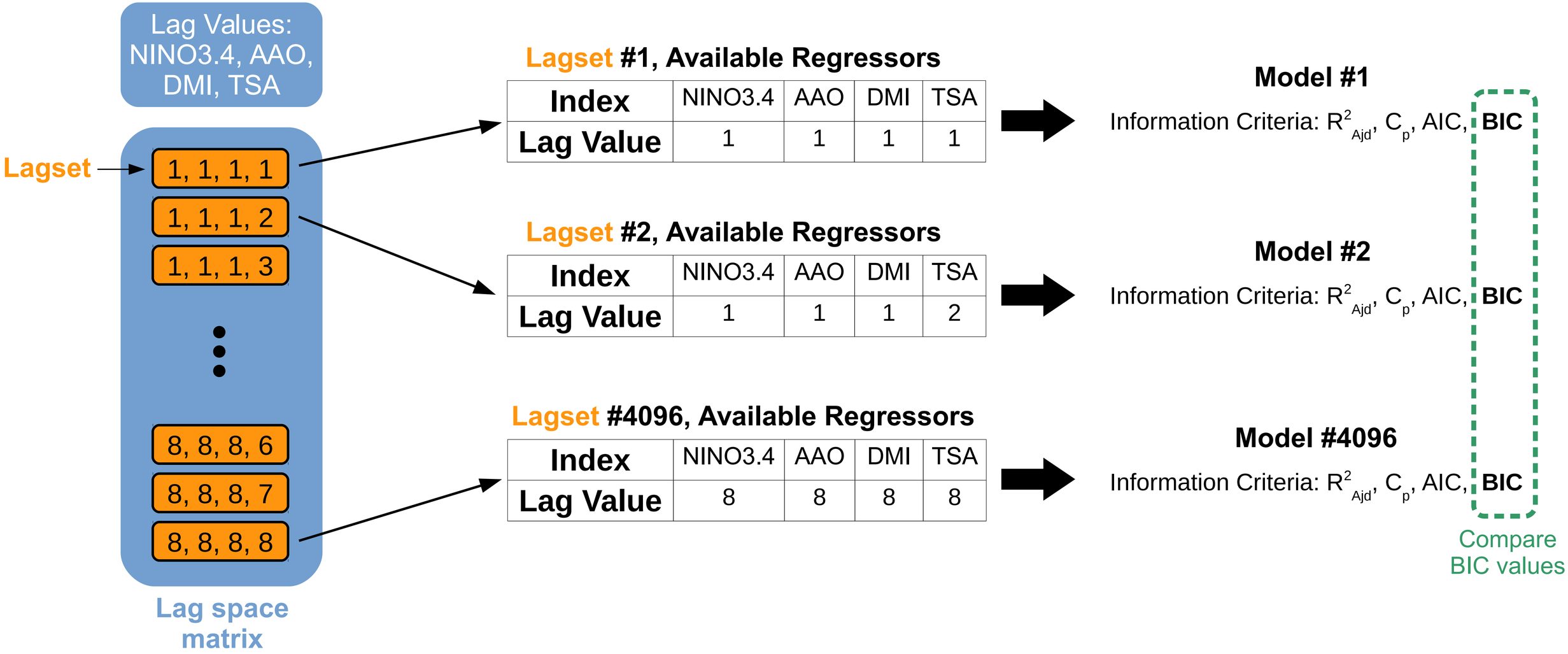
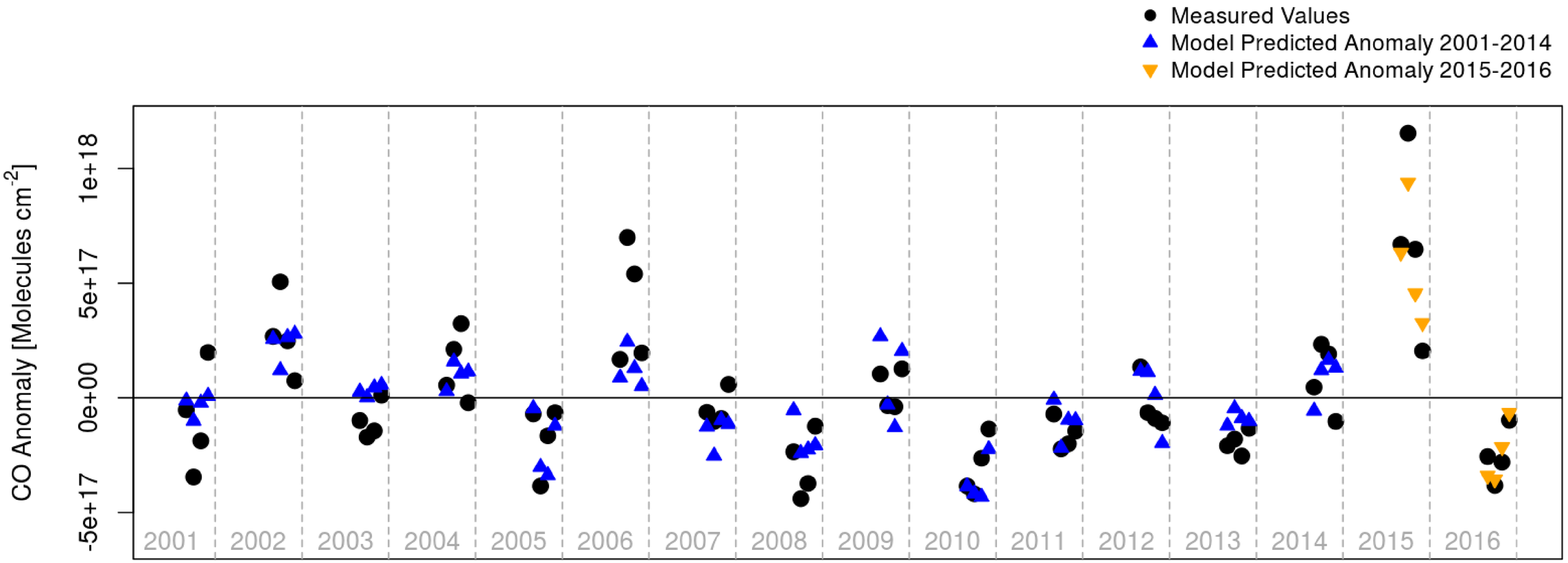


Model Validation: Maritime SEA

We train the model on 2001-2014 data and test it on 2015-2016 data



Conclusion & Take Aways

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We are using variability in the climate to model atmospheric CO

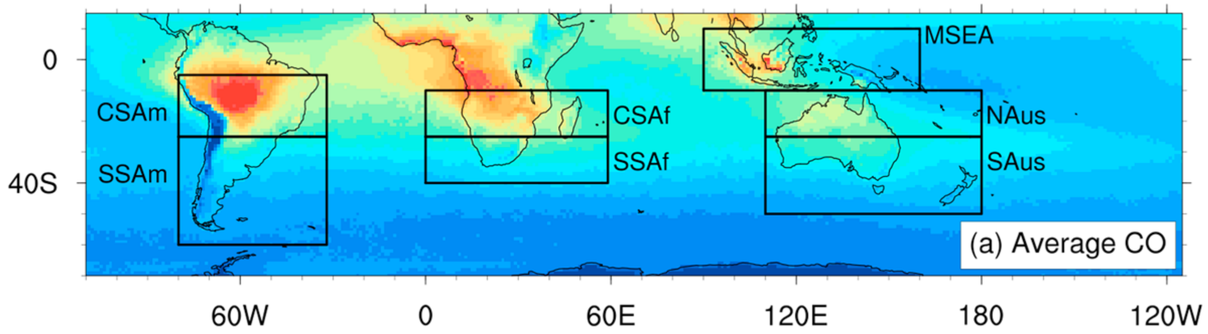
Current models perform reasonably well

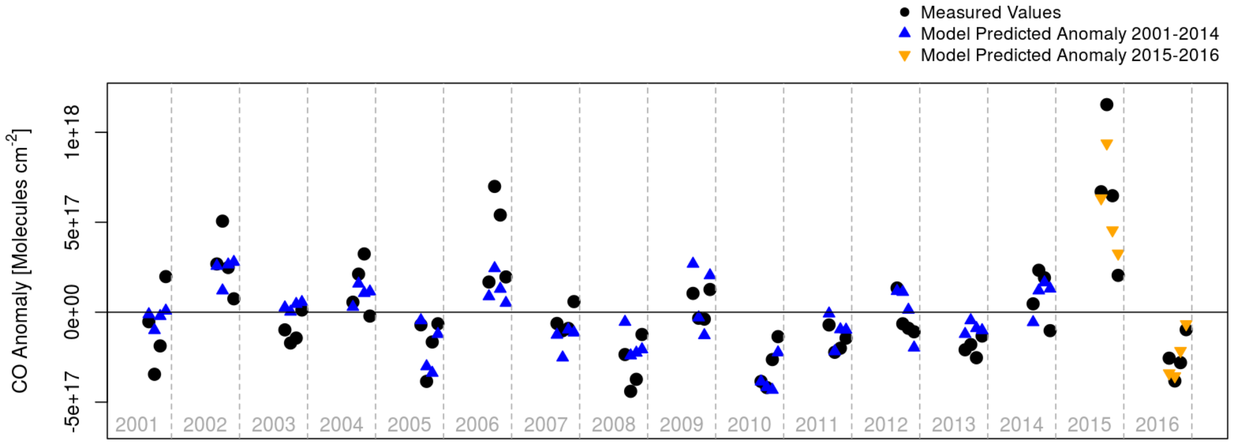
Response Region	R^2_{Adj}
Maritime SEA	0.72
North Australasia	0.69
South Australasia	0.56
Central South Africa	0.46
South South Africa	0.57
Central South America	0.60
South South America	0.58

Future Work

- Apply models to recent Australia fires
- Set up advanced warning system
- Investigate scalability of variable selection algorithms
- Optimize genetic algorithm parameters
  - See MURF talk by Meera Duggal!

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





Thank you! Questions?

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