Space-Time Reading Group

Autumn 2019

Welcome

Welcome to the Space-Time Reading Group!

This quarter we'll be reading *Spatio-Temporal Statistics with R* by Cressie, Zammit-Mangion, and Wikle.

We hope that everyone will be able to learn and participate regardless of background/familiarity with spatial statistics.

Please reach out with questions/comments/suggestions!

Recent Quarters

- Spring 2019: Recent papers (using dynamical models to design statistical models)
- Winter 2019: Recent papers (members' research)
- Autumn 2018: *Advanced Spatial Modeling with Stochastic Partial Differential Equations Using R and INLA*

Chapter One: *Introduction to Spatio-Temporal Statistics*

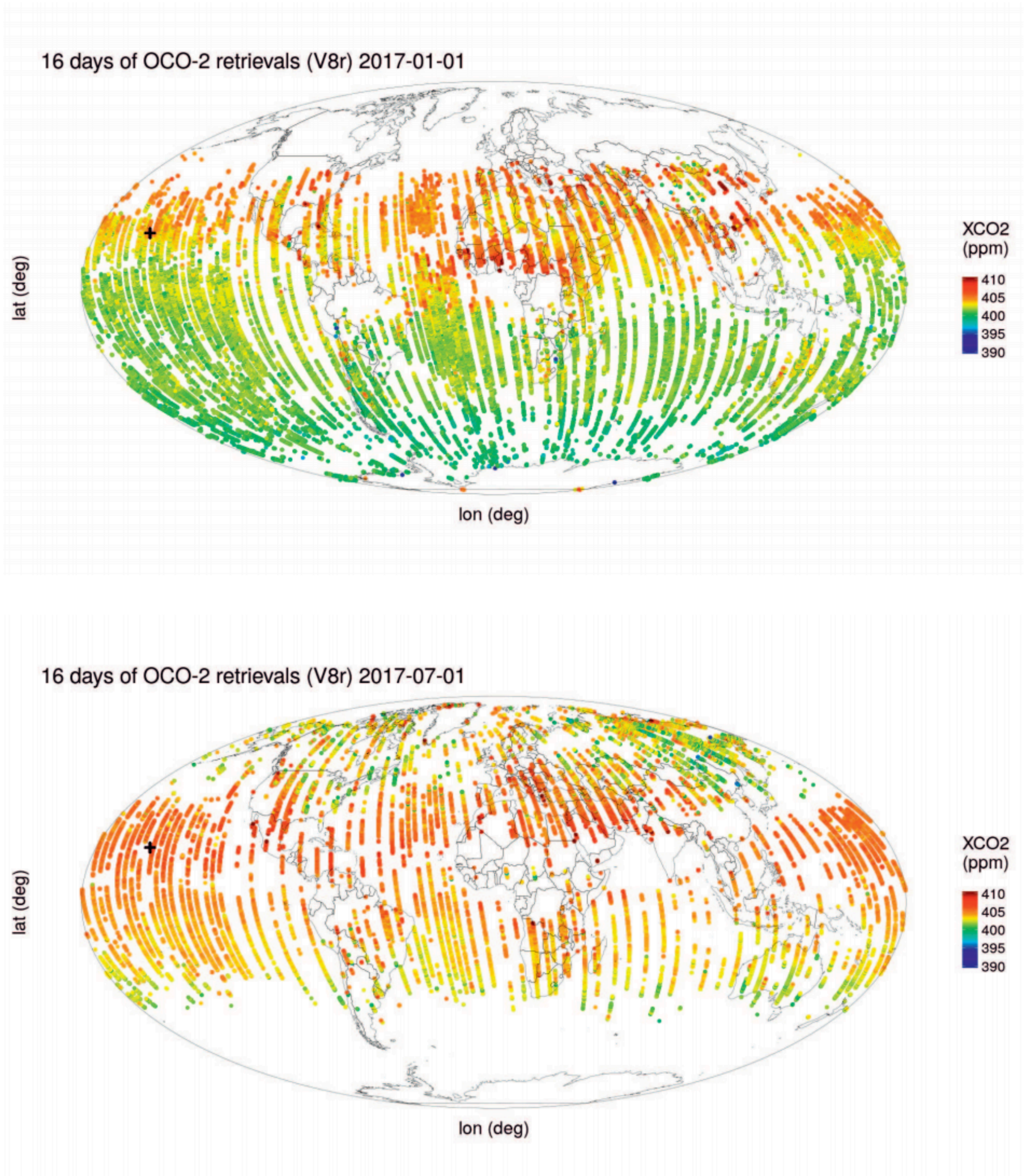

Figure 1.2: Sixteen days of CO_2 data from the OCO-2 satellite. Top: Data from 25 December 2016 to 09 January 2017 (boreal winter). Bottom: Data from 24 June 2017 to 09 July 2017 (boreal summer). The panel titles identify the eighth day of the 16-day window.

Spatio-Temporal Data

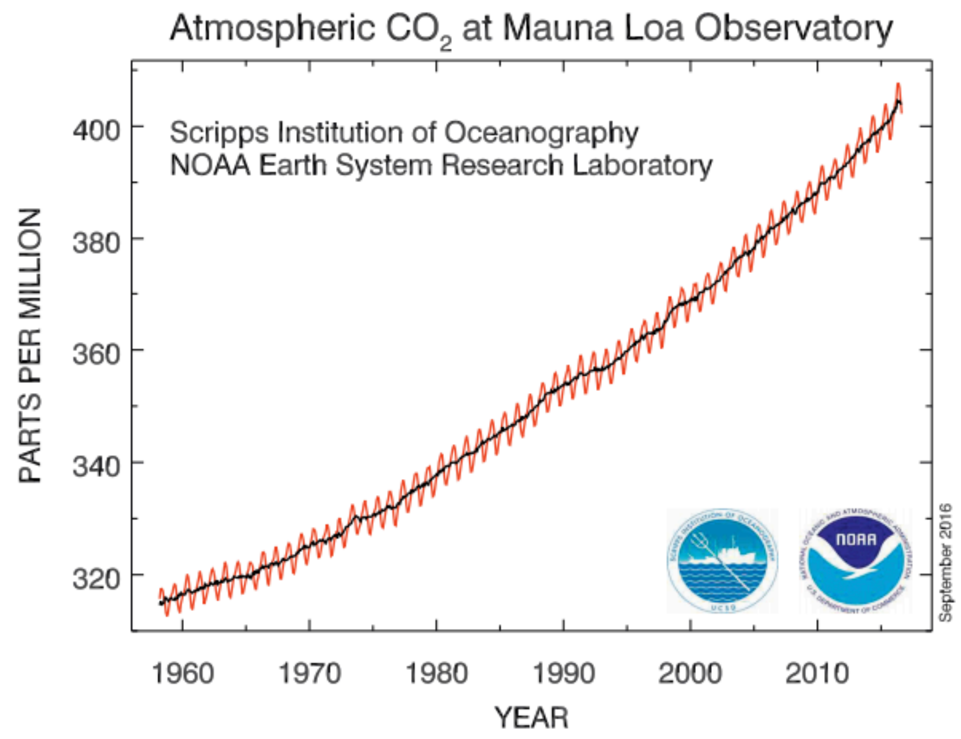

Figure 1.3: Monthly mean atmospheric CO_2 (ppm) at the NOAA Mauna Loa Observatory, Hawaii. The smooth line represents seasonally corrected data (Credit: Scripps Institution of Oceanography and NOAA Earth System Research Laboratory).

Spatio-Temporal Data

- Easy enough to conceptualize time series or spatial “snapshots”

- What about the “space-time cube”?

    - Need to account for correlation across both time and space, as well as possible interactions

    - Tobler’s first law of geography: "*Everything is related to everything else, but near things are more related than distant things.*"

Why *statistics*?

- Suppose that a spatiotemporal process (e.g. temperature) follows physical, dynamical rules…
  - Statistics can help us to model physical phenomena that are poorly understood or computationally intractable to resolve
  - *Mechanistically motivated models* incorporate information about physical dynamics into statistical models

Goals of Spatio-Temporal Statistics

- Prediction in space and time (filtering and smoothing)
- Inference on model parameters
- Forecasting in time

Descriptive or Dynamic?

There have been two approaches to spatio-temporal statistical modeling that address the goals listed above. These are the "two Ds" referred to in the title of this subsection, namely the *descriptive* approach and the *dynamic* approach. Both are trying to capture statistical dependencies in spatio-temporal phenomena, but they go about it in quite different ways.

Probably the simplest example of this is in time-series modeling. Suppose that the dependence between any two data at different time points is modeled with a stationary first-order autoregressive process (AR(1)). *Dynamically*, the model says that the value at the current time is equal to a "propagation factor" (or "transition factor") times the value at the previous time, plus an independent "innovation error." This is a mechanistic way of presenting the model that is easy to simulate and easy to interpret.

Descriptive or Dynamic?

- **Descriptive**: study a process in terms of its mean and covariance.
  - kriging (Gaussian process regression), variograms, parametric families of covariance functions, separable covariance functions
  - “marginal”
- **Dynamic**: study a spatial process changes through time mechanistically (or probabilistically)
  - Time series approaches, nonseparable covariance functions, transition matrices
  - “conditional”

Berliner's Hierarchical Statistical Model

- **Data:** Observed data *conditionally independent* given the process
- **Process:** Underlying process governing spatiotemporal correlations
- **Parameter**: Unknown parameters governing data/ process (prior distributions)

Berliner's Hierarchical Statistical Model

1. Data model: [data | process, parameters]
2. Process model: [process | parameters]
3. Parameter model: [parameters]

Importantly, each of these levels could have sub-levels, for which conditional-probability models could be given.

Ultimately, we are interested in the posterior distribution, [process, parameters | data] which, conveniently, is proportional to the product of the levels of the BHM given above:

$$\begin{aligned}[\text{process, parameters} \mid \text{data}] \propto\ & [\text{data} \mid \text{process, parameters}] \\ & \times [\text{process} \mid \text{parameters}] \\ & \times [\text{parameters}],\end{aligned}$$

Chapter 2

Exploring Spatio-Temporal Data

- Visualization of spatiotemporal data
- Representing spatio-temporal data in R
- Exploratory analysis of spatio-temporal data
  - Diagnostic plots
  - Empirical orthogonal functions

Chapter 3

Spatio-Temporal Statistical Models

- Prediction/Forecasting
- Estimation/Parameter inference
- Hierarchical models

Chapter 4

Descriptive Spatio-Temporal Statistical Models

- Modeling/estimating covariance structure
- Random effects/basis function models
- (Latent) Gaussian process models

Chapter 5

Dynamic Spatio-Temporal Statistical Models

- Specifying and parametrizing model dynamics for latent linear Gaussian DSTMs
- Model fitting, parameter dimension reduction
- Nonlinear DSTMs

Chapter 6

Evaluating Spatio-Temporal Statistical Models

- Model validation/checking
- Model selection

Case Studies

Case Study: Physical-Statistical Bayesian Hierarchical Model for Predicting Mediterranean Surface Winds

Case Study: Quadratic Echo State Networks for Sea Surface Temperature Long-Lead Prediction

Helpful Resources

Spatio-Temporal Statistics with R **(*Book Website*)**

Reading Group Website

Reading Group Listhost