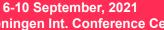
OPEN DATA SCIENCE EUROPE WORKSHOP

Introduction to spatial and spatiotemporal data in R

Sept 6, 2021: 9:00 - 10:30





Programme



Day 1 Sept 6, 2021



9:00 - 10:30

Introduction to spatial and spatiotemporal data in R

By **Tomislav Hengl** Spatiotemporal Ensemble ML in R / computing with Cloud-Optimized GeoTIFFs



11:00 - 12:30

Modeling with spatial and spatiatemporal data in R

By **Tomislav Hengl** Spatiotemporal Ensemble ML in R / computing with Cloud-Optimized GeoTIFFs



13:30 - 15:00

Spatiotemporal Ensemble ML in R

By **Tomislav Hengl** Spatiotemporal Ensemble ML in R / computing with Cloud-Optimized GeoTIFFs



15:30 - 17:00

Computing with Cloud-Optimized GeoTIFFs

By **Tomislav Hengl** Spatiotemporal Ensemble ML in R / computing with Cloud-Optimized GeoTIFFs



Day 2 Sept 7, 2021



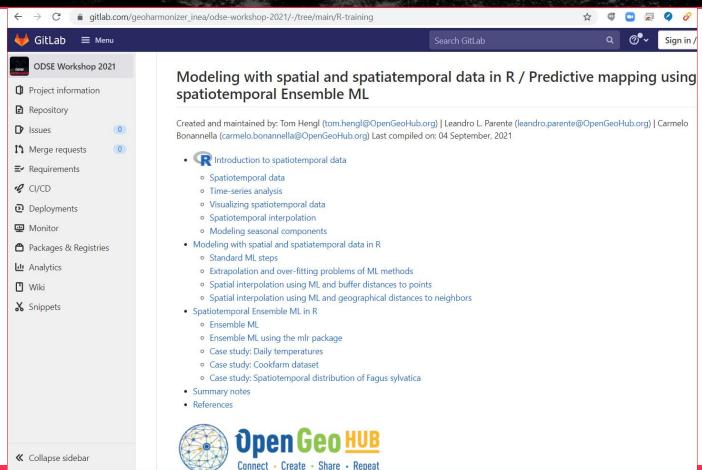
9:00 - 10:30

Data visualization: from R to Google Earth and QGIS

By **Tomislav Hengl** Spatiotemporal Ensemble ML in R / computing with Cloud-Optimized GeoTIFFs

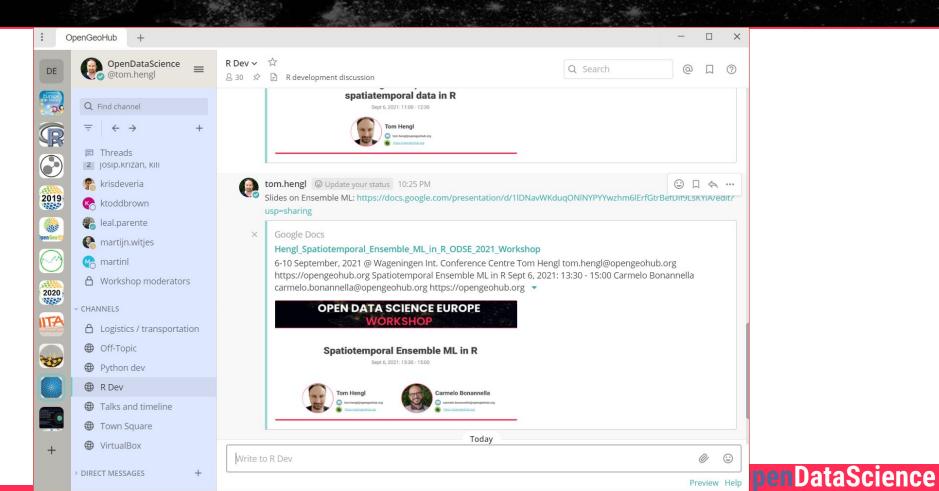


Rmarkdown notebook



A lot of code, a lot of real-life datasets and examples

https://mattermost.opengeohub.org/opendatascience/channels/r-dev

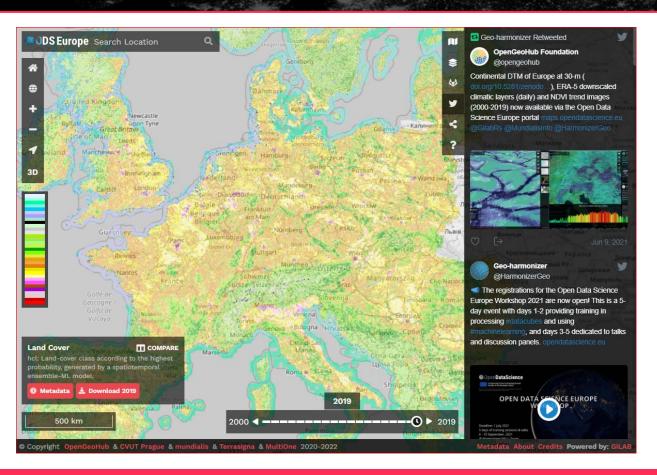


With the right motivation, you can learn R in 1 day!



<u> DataScience</u>

An Open Environmental Data Cube for Europe



https://maps.opendatascience.eu

Currently almost 10TB data available as Cloud-Optimized GeoTIFFs

Outline

- Spatial vs spatiotemporal data;
 - Key difference between the two,
 - Time dimension -> easy to plot, difficult to model (especially to predict the future!),
- Time-series analysis;
- Visualizing spatiotemporal data (some examples);



- geographic location (longitude and latitude or projected X, Y coordinates);
- spatial location accuracy or size of the block / volume in the case of bulking of samples;
- height above the ground surface (elevation);
- start and end time of measurement (year, month, day, hour, minute etc.);



Analysis of spatiotemporal data is somewhat different from pure spatial analysis.

Time is not just another spatial dimension i.e. it has specific properties and different statistical assumptions and methods have been developed for spatio- temporal data than for spatial data.

For an introduction to spatiotemporal data in R please refer to the **spacetime package** tutorial (Pebesma & others, 2012).



spacetime: Spatio-Temporal Data in R





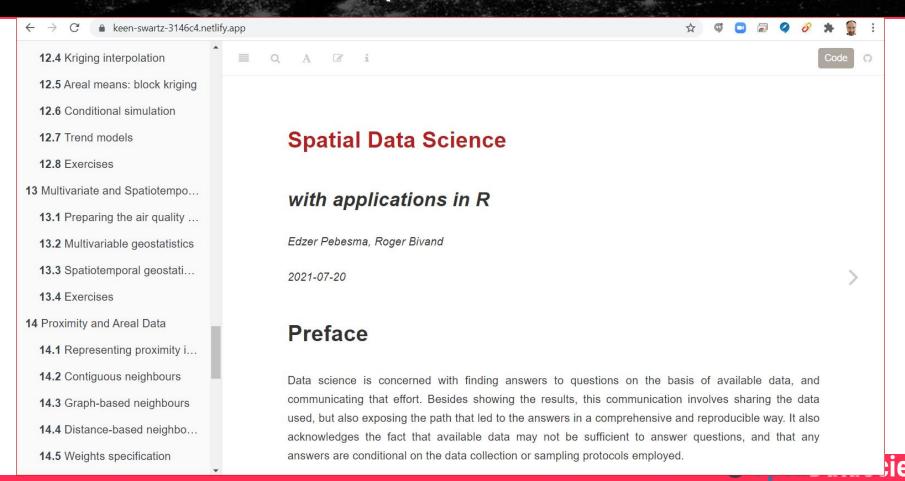
Edzer Pebesma

Abstract

This document describes classes and methods designed to deal with different types of spatio-temporal data in R implemented in the R package **spacetime**, and provides examples for analyzing them. It builds upon the classes and methods for spatial data from package **sp**, and for time series data from package **xts**. The goal is to cover a number of useful representations for spatio-temporal sensor data, and results from predicting (spatial and/or temporal interpolation or smoothing), aggregating, or subsetting them, and to represent trajectories. The goals of this paper are to explore how spatio-temporal data can be sensibly represented in classes, and to find out which analysis and visualisation methods are useful and feasible. We discuss the time series convention of representing time intervals by their starting time only. This vignette is the main reference for the R package **spacetime**; it been published as Pebesma (2012), but is kept up-to-date with the software.



Pebesma & Bivand: Spatial Data Science



Spacetime reference example in KML

```
<Placemark>
  <name>Bilogora</name>
  <TimeStamp>
    <begin>2008-02-17T00:00:00Z</begin>
    <end>2008-02-18T00:00:00Z</end>
  </TimeStamp>
  <Point>
   <coordinates>17.2057,45.8851,0/coordinates>
  </Point>
</Placemark>
```

Spatio-Temporal Data Types:

An Approach to Modeling and Querying

Moving Objects in Databases*

Martin Erwig ¹
Ralf Hartmut Güting ¹
Markus Schneider ¹
Michalis Vazirgiannis ¹⁺²

Praktische Informatik IV
 Fernuniversität Hagen
 D-58084 Hagen
 GERMANY

2) Computer Science Division
Dept. of Electr. and Comp. Engineering
National Tech. University of Athens
Zographou, Athens, 15773
GREECE

Abstract: Spatio-temporal databases deal with geometries changing over time. In general, geometries cannot only change in discrete steps, but continuously, and we are talking about moving objects. If only the position in space of an object is relevant, then *moving point* is a basic abstraction; if also the extent is of interest, then the *moving region* abstraction captures moving as well as growing or shrinking regions. We propose a new line of research where moving points and moving regions are viewed as three-dimensional (2D space + time) or higher-dimensional entities whose structure and behaviour is captured by modeling them as abstract data types. Such types can be integrated as base (attribute) data types into relational, object-oriented, or other DBMS data models; they can be implemented as data blades, cartridges, etc. for extensible DBMSs. We expect these spatio-temporal data types to play a similarly fundamental role for spatio-temporal databases as spatial data types have played for spatial databases. The paper explains the approach and discusses several fundamental issues and questions related to it that need to be clarified before delving into specific designs of spatio-temporal algebras.

Erwig, M., Gu, R. H., Schneider, M., Vazirgiannis, M., & others. (1999). Spatio-temporal data types: An approach to modeling and querying moving objects in databases. *GeoInformatica*, *3*(3), 269–296. http://dx.doi.org/10.1023/A:1009805532638



For <u>ERWIG et al.</u> (1999) spatio-temporal data sets and corresponding databases can be matched with the two major groups of features: (1) moving or dynamic objects (discrete or vector geometries), and (2) regions (fields or continuous features).



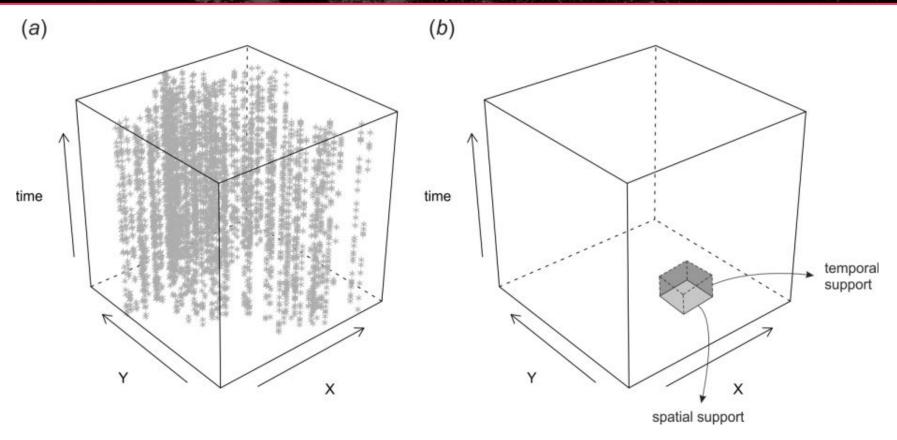
Fields / regions:

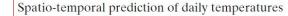
Usually one of the three:

- 1. quantity or density of some material or chemical element,
- 2. energy flux or any similar physical measurements,
- 3. probability of occurrence of some feature or object,



Spacetime cube (2D+T)







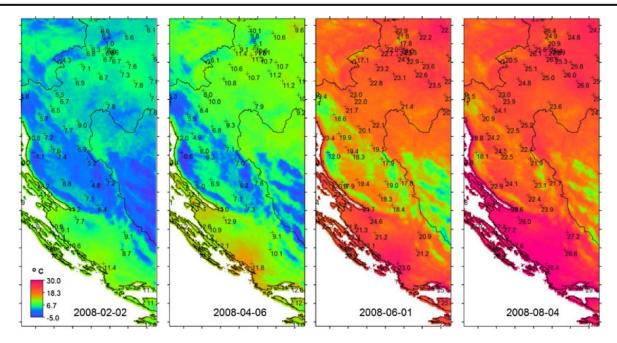


Fig. 8 Mean daily temperatures for four arbitrary dates predicted using spatio-temporal regression-kriging and actual observed values. Because the prediction model is significant (84%)

of variability explained by the model), it may be used to map space-time patterns in the neighboring countries

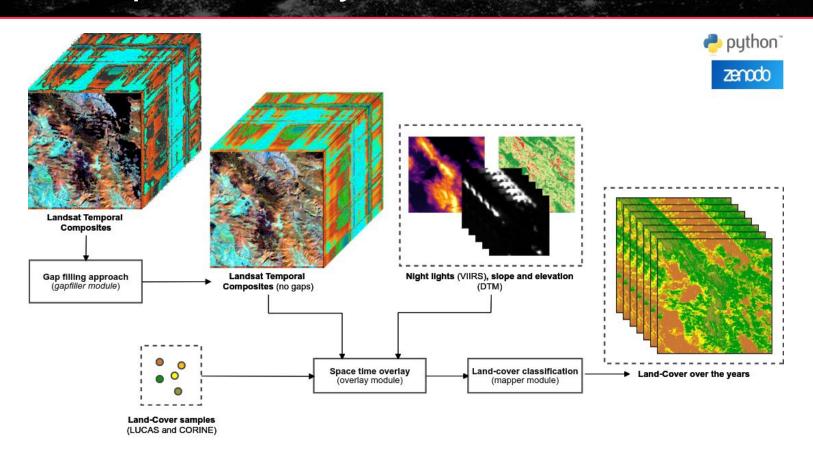
in the gstat
package allows
for producing
spacetime
predictions from
point
observations

krigeST function

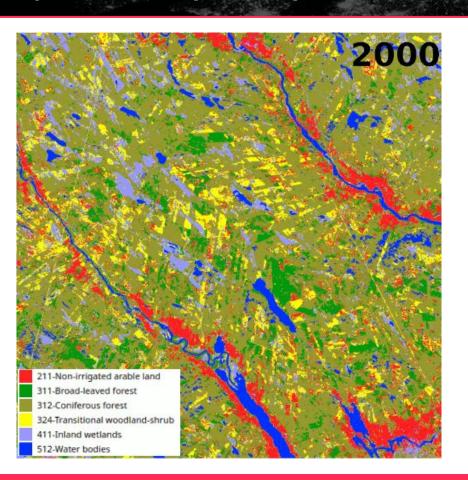
Source: <u>10.1007/s00704-011-0464-2</u>



Spatiotemporal overlay



Spatiotemporal predictions



This animation shows the land-cover classes for an area located in Sweden (tile 22497) according to the space time predictions. This example is a small use case that used 680 point samples, obtained in different years, to train a single model and to predict the land-cover in the region over the time.

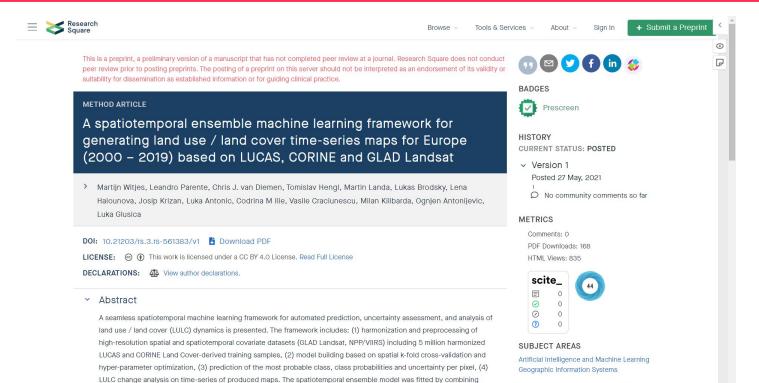
https://maps.opendatascience.eu



Spatiotemporal predictions

random forest, gradient boosted trees, and artificial neural network, with logistic regressor as meta-learner. The results

show that the most important covariates for mapping LULC in Europe are: seasonal aggregates of Landsat green and nearinfrared bands, multiple Landsat-derived spectral indices, and elevation. Spatial cross-validation of the model indicates



MORE FROM RESEARCH SQUARE

Multi Evargeeian Drogramming

Jenny 5 - the robot

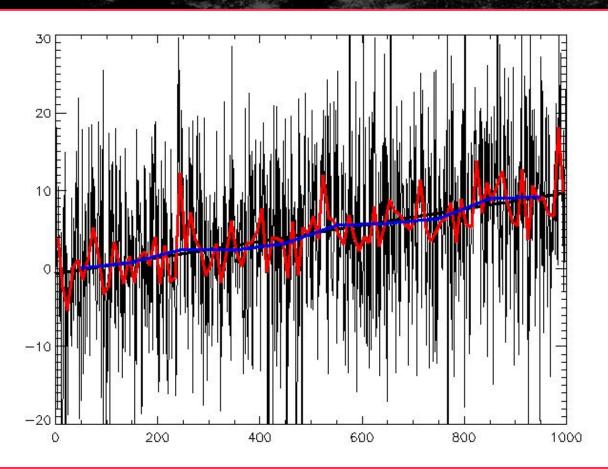


	2D	3D	2D+T	3D+T	
longitude	\checkmark	\checkmark	\checkmark	\checkmark	
latitude	\checkmark	\checkmark	\checkmark	\checkmark	
altitude		\checkmark		\checkmark	
time			✓	✓	
minimum # of variogram parameters	3	4	4*	5*	
# of prediction locations	N_s	$N_s \times N_d$	$N_s \times N_t$	$N_s \times N_d \times N_t$	

^{*}Temporal anisotropy parameter

JpenDataScience

Time-series data



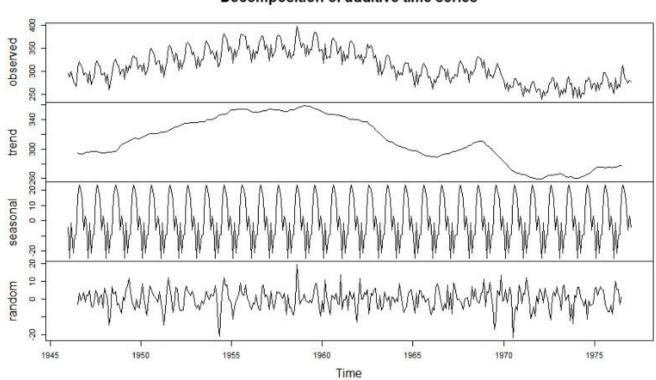
A time series is a series of data points indexed (or listed or graphed) in time order. Most commonly, a time series is a sequence taken at successive equally spaced points in time. Source:

https://en.wikipedia.org/wiki/Time_series

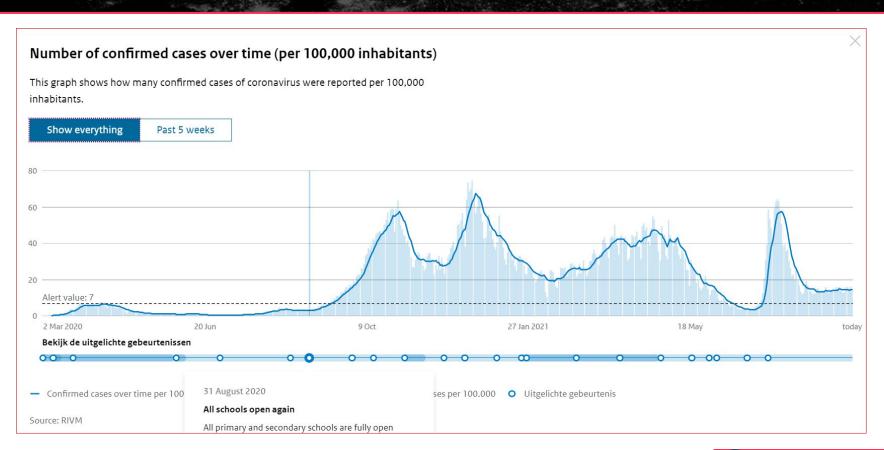


Time-series components

Decomposition of additive time series



Time-series (something very actual)





Time-series components

Time-series (signal) can be decomposed into four groups of components:

- 1. Long-term component (**trend**) determined by long-term geological and extraterrestrial processes,
- 2. Seasonal monthly and/or daily component (seasonality) determined by Earth rotation and incoming sun radiation,
- 3. Variation component which can be due to semi-chaotic behavior and/or local factors (hence autocorrelated), and
- 4. Pure noise i.e. measurement errors and similar,



Long-term component: example global temperature

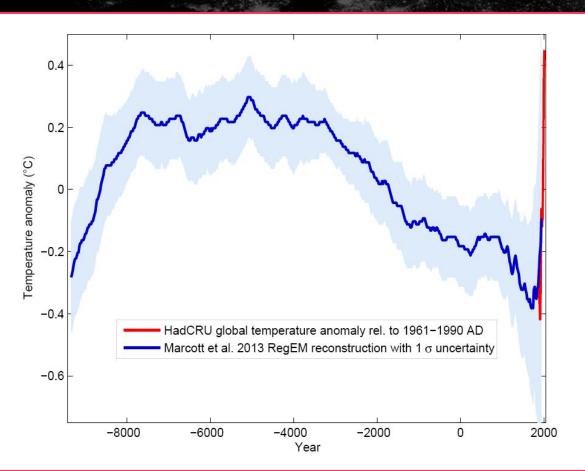
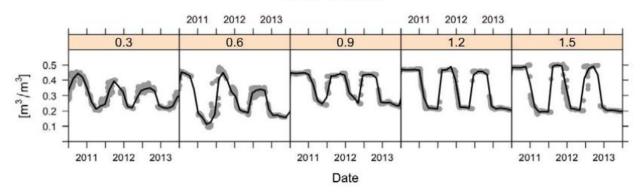


Figure: Global temperature reconstruction from proxy data of Marcott, Shakun, Clark, & Mix (2013). This shows how global temperature varies on long-term term. Graph by: Klaus Bitterman.

Example of seasonality pattern





Temperature

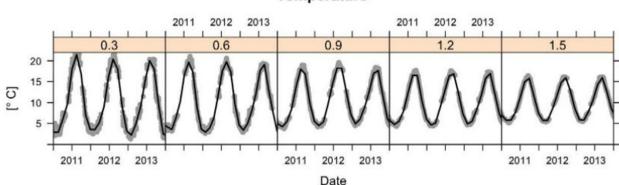


Figure: Sensor values from five depths (0.3, 0.6, 0.9, 1.2, and 1.5 m) at one station at Cook Agronomy Farm from January 2011—January 2014. The black line indicates locally fitted splines (Gasch et al., 2015).



Visualizing spatiotemporal data

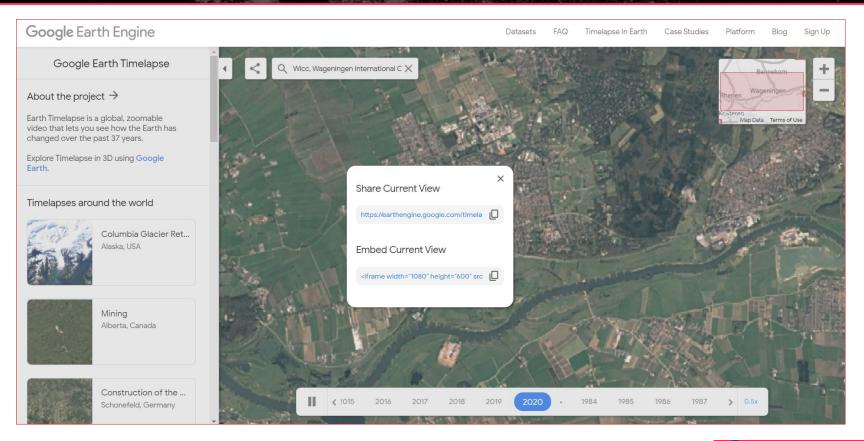
There are three possible groups of ways to visualize spatiotemporal data:

- 1. Using static images showing trend parameters together with time-series plots at selected representative point locations.
- 2. Using **time-slices** or series of visualizations of the same spatial domain but changing in time.
- 3. Using animations or interactive plots with time-sliders allowing users to choose speed and direction of animation.

Example: foot and mouth disease data

```
library(plotKML)
data(fmd)
fmd0 <- data.frame(fmd)</pre>
coordinates(fmd0) <- c("X", "Y")</pre>
proj4string(fmd0) <- CRS("+init=epsg:27700")</pre>
fmd_sp <- as(fmd0, "SpatialPoints")</pre>
dates <- as.Date("2001-02-18") + fmd0$ReportedDay</pre>
library(spacetime)
fmd_ST <- STIDF(fmd_sp, dates, data.frame(ReportedDay=fmd0$ReportedDay))</pre>
data(SAGA_pal)
## Not run:
plotKML(fmd_ST, colour_scale=SAGA_pal[[1]], open.kml = FALSE)
```

Example: Google time-lapse





Visualizing spacetime data in R

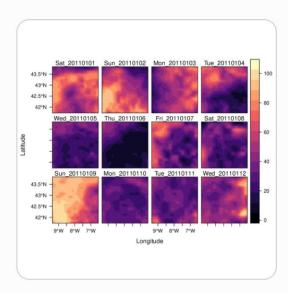
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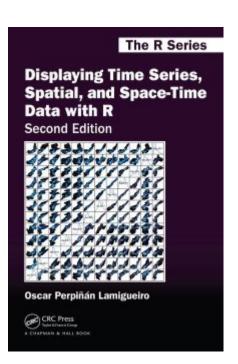
Raster data
Spatial point data
Code

Spatio-temporal data - Displaying time series, spatial and space-time data with R

Raster data

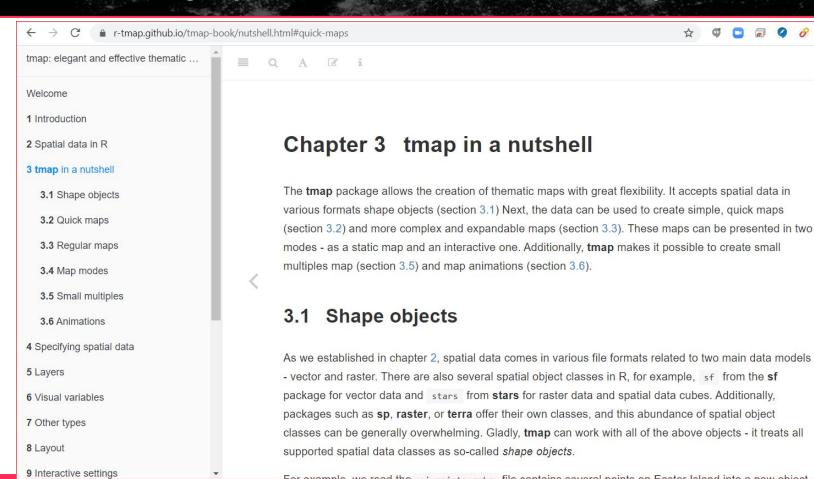
Level plots





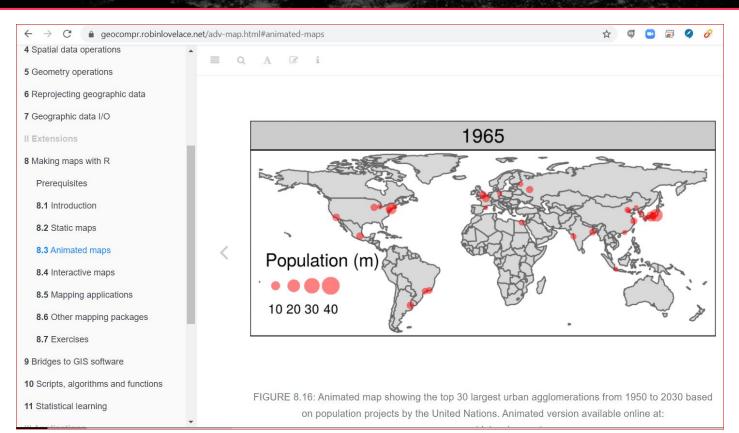


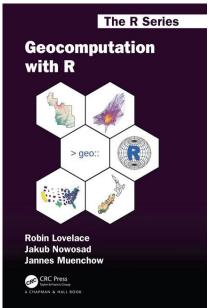
Visualizing spacetime data in R: tmap



ataScience

Animated maps (Geocomputation with R)





Summary

- Spatiotemporal data (2D+T, 3D+T) is at the order of magnitude more complex than spatial data (larger data volumes, more complex interactions, ideally we would like to understand processes);
- For data to be usable for spatiotemporal modeling it needs to have known (at least): lon, lat, location error, begin, end-time of measurement;
- There are in principle four main groups of methods for modeling spacetime data: (1) geostatistics, (2) ML, (3) process-based modeling, (4) hybrid methods;

