# Machine Learning (ranger package) as a framework for spatial and spatiotemporal prediction

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# Random Forest as a generic framework for predictive modeling of spatial and spatio-temporal variables

Research article | Biogeography | Soil Science | Computational Science | Data Mining and Machine Learning | Spatial and Geographic Information Science

Tomislav Hengl[1], Madlene Nussbaum[2], Marvin N Wright[3], Gerard B.M. Heuvelink[4]

March 14, 2018

## Author and article information

## Abstract

Random forest and similar Machine Learning techniques are already used to generate spatial predictions, but spatial location of points (geography) is often ignored in the modeling process. Spatial auto-correlation, especially if still existent in the cross-validation residuals, indicates that the predictions are maybe biased, and this is suboptimal. This paper presents a random forest for spatial predictions framework (RFsp) where buffer distances from observation points are used as explanatory variables, thus incorporating geographical proximity effects into the prediction process. The RFsp framework is illustrated with examples that use textbook datasets and apply

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# RFsp — Random Forest for spatial data (R tutorial)

Hengl, T., Nussbaum, M., and Wright, M.N.





https://github.com/thengl/GeoMLA

**Abstract**: This tutorial explains how to use Random Forest to generate spatial and spatiotemporal predictions (i.e. to make maps from point observations using Random Forest). Spatial auto-correlation, especially if still existent in the cross-validation residuals, indicates that the predictions are maybe biased, and this is suboptimal. To account for this, we use Random Forest (as implemented in the ranger package) in combination with geographical distances to sampling locations to fit models and predict values. We describe eight typical situations of interest to spatial prediction applications: (1) prediction of 2D

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RESEARCH ARTICLE

## SoilGrids250m: Global gridded soil information based on machine learning

Tomislav Hengl, Jorge Mendes de Jesus, Gerard B. M. Heuvelink, Maria Ruiperez Gonzalez, Milan Kilibarda, Aleksandar Blagotić, Wei Shangguan, Marvin N. Wright, Xiaoyuan Geng, Bernhard Bauer-Marschallinger, Mario Antonio Guevara, Rodrigo Vargas, Robert A. MacMillan, [ ... ], Bas Kempen [ view all ]

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### Abstract

This paper describes the technical development and accuracy assessment of the most recent and improved version of the SoilGrids system at 250m resolution (June 2016 update). SoilGrids provides global predictions for standard numeric soil properties (organic carbon, bulk density, Cation Exchange Capacity (CEC), pH, soil texture fractions and coarse fragments) at seven standard depths (0, 5, 15, 30, 60, 100 and 200 cm), in addition to predictions of depth to bedrock and distribution of soil classes based on the World Reference Base (WRB) and USDA classification systems (ca. 280 raster layers in total). Predictions were based on ca. 150,000 soil profiles used for training and a stack of 158 remote sensing-based soil covariates (primarily derived from MODIS land products, SRTM DEM derivatives, climatic images and global

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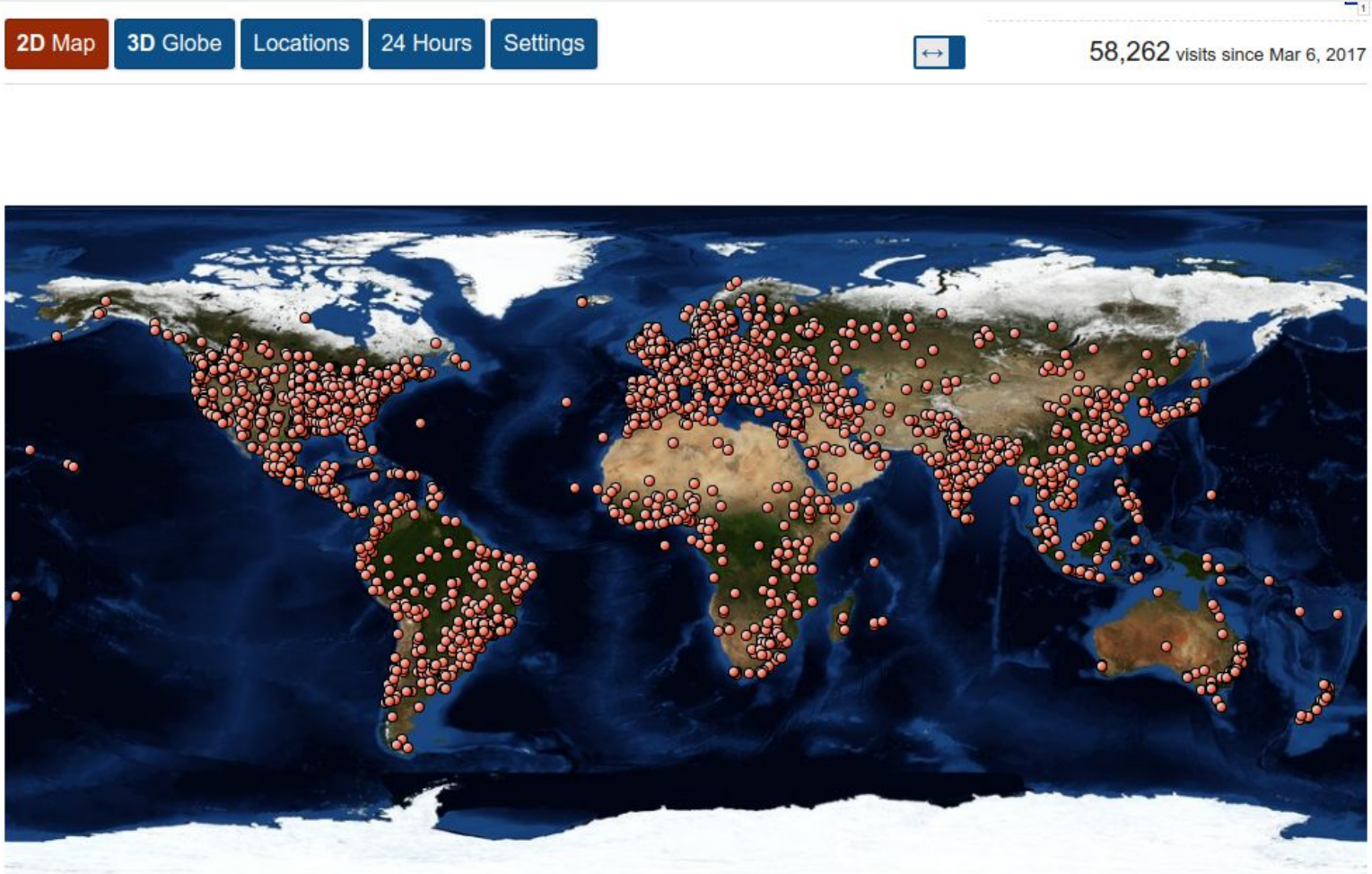
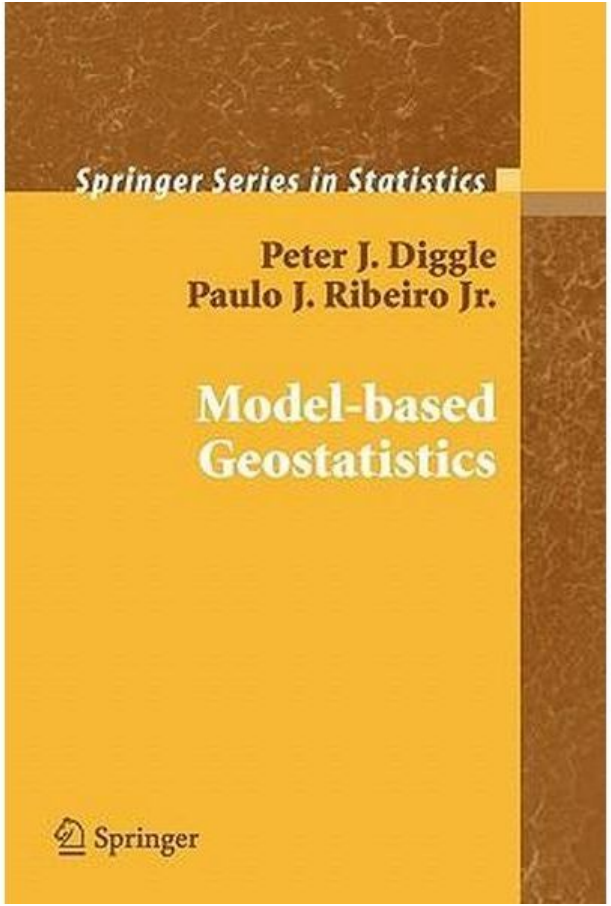
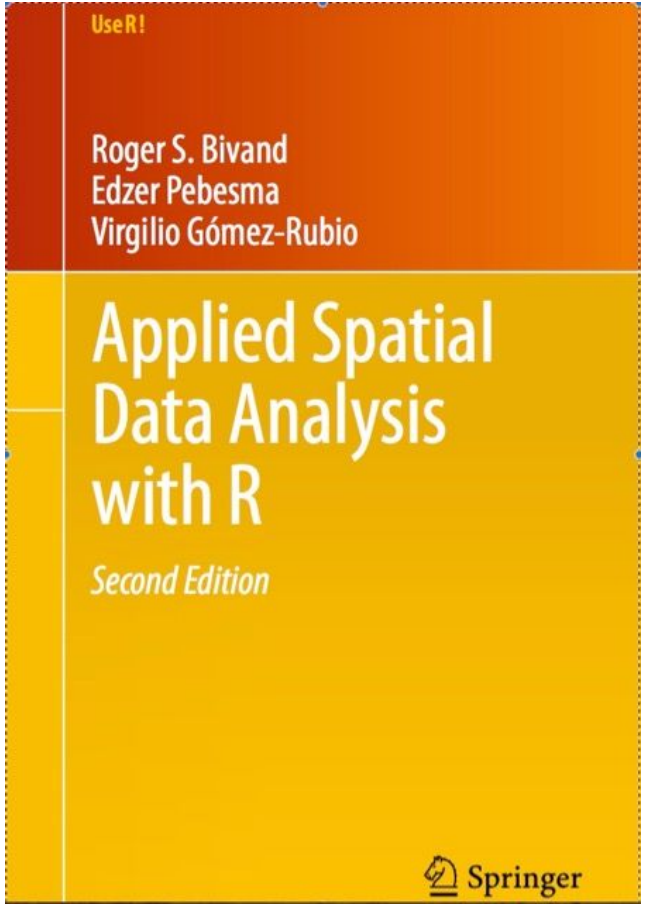
# Open global data on soils



# Kriging has been a synonym for geostatistics since 1960s



# Standard steps

1. Determine distribution of the target variable and appropriate transformation (normal, log-normal, zero-inflated, Gamma, Poissonic ...)
2. Fit variogram (WLS, REML, ...), deal with multicolinearity (PCA?), non-stationary properties, support size, mixed effects…
3. Predict (mean values and uncertainty)
4. Validate predictions (mapping accuracy)

# Variogram modeling and predictions (kriging)

```
R> zinc.vgm <- likfit(zinc.geo, lambda = 0,
ini=c(var(log1p(zinc.geo$data)), 500), cov.model
= "exponential")

R> zinc.ok <- krige.conv(zinc.geo, locations =
locs, krige = krige.control(obj.m = zinc.vgm))
```

krige.conv: model with constant mean
krige.conv: performing the Box-Cox data transformation
krige.conv: back-transforming the predicted mean and variance
krige.conv: Kriging performed using global neighbourhood

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A generic framework for spatial prediction of soil variables based on **regression-kriging** [PDF] researchgate.net
T Hengl, GBM Heuvelink, A Stein - Geoderma, 2004 - Elsevier
A methodological framework for spatial prediction based on **regression-kriging** is described and compared with ordinary kriging and plain regression. The data are first transformed using logit transformation for target variables and factor analysis for continuous predictors
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IOA Odeh, AB McBratney, DJ Chittleborough - Geoderma, 1995 - Elsevier
Several methods involving spatial prediction of soil properties from landform attributes are compared using carefully designed validation procedures. The methods, tested against ordinary kriging and universal kriging of the target variables, include multi-linear regression,
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T Hengl, GBM Heuvelink, DG Rossiter - Computers & geosciences, 2007 - Elsevier
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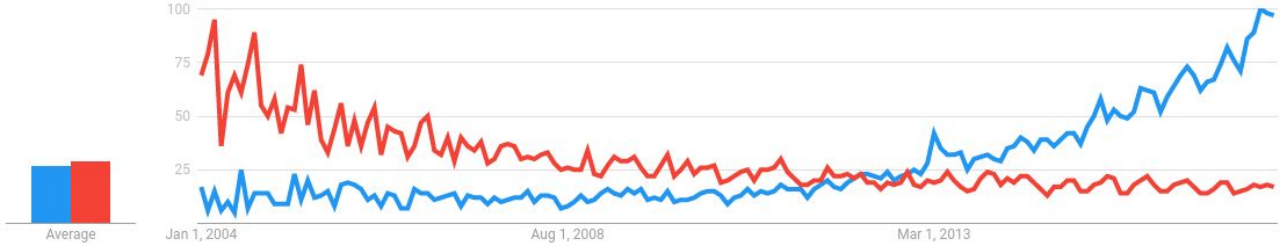
Interest over time




Interest by region

# MLA is interesting for generating sp, however...

Spatial auto-correlation, especially if still existent in the cross-validation residuals, indicates that the predictions are maybe biased, and this is suboptimal.

To account for this, we use Random Forest (as implemented in the ranger package) in combination with geographical distances to sampling locations to fit models and predict values.

# Solution: RFsp

$$Y(\mathbf{s}) = f(\mathbf{X}_G, \mathbf{X}_R, \mathbf{X}_P) \tag{18}$$

where $\mathbf{X}_G$ are covariates accounting for geographical proximity and spatial relations between observations

$$\mathbf{X}_G = (d_{p1}, d_{p2}, \ldots, d_{pN}) \tag{19}$$

where $d_{pi}$ is the buffer distance (or any other complex proximity upslope/downslope distance, as explained in the next section) to the observed location $pi$ from $\mathbf{s}$ and $N$ is the total number of training points. $\mathbf{X}_R$ are surface reflectance covariates, i.e. usually spectral bands of remote sensing images, and $\mathbf{X}_P$ are process-based covariates.

# Geographical distances (proximity)

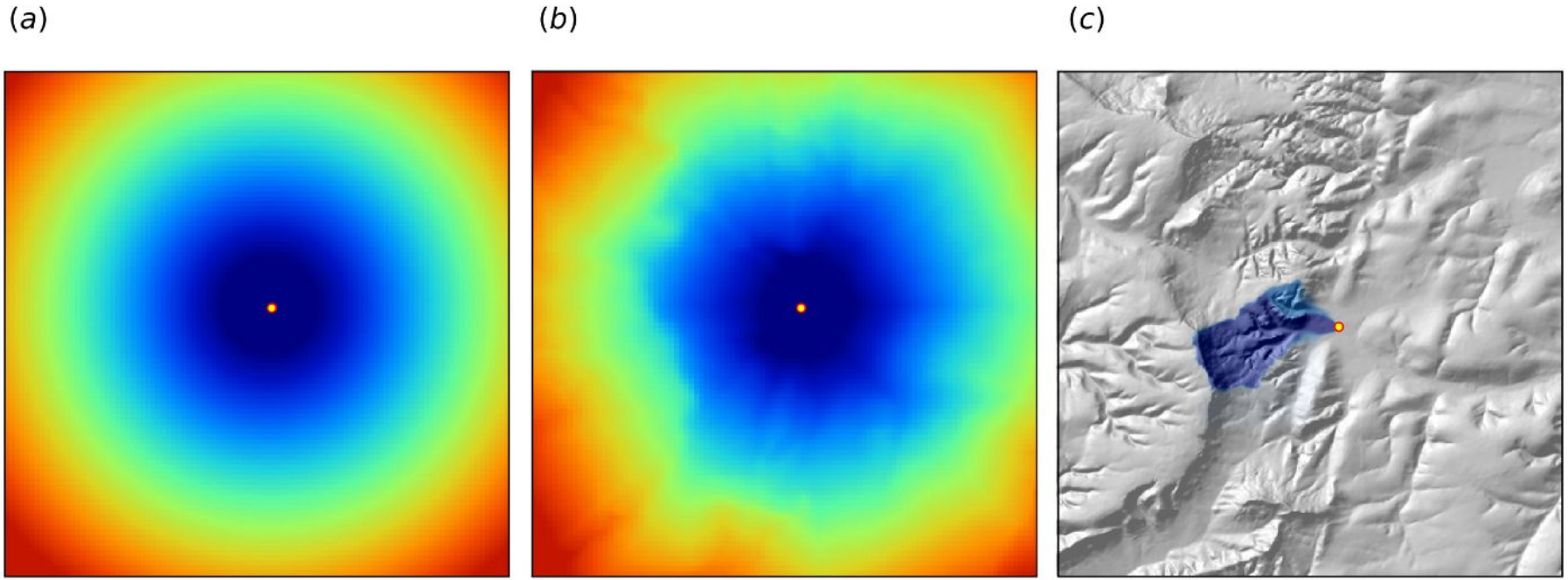
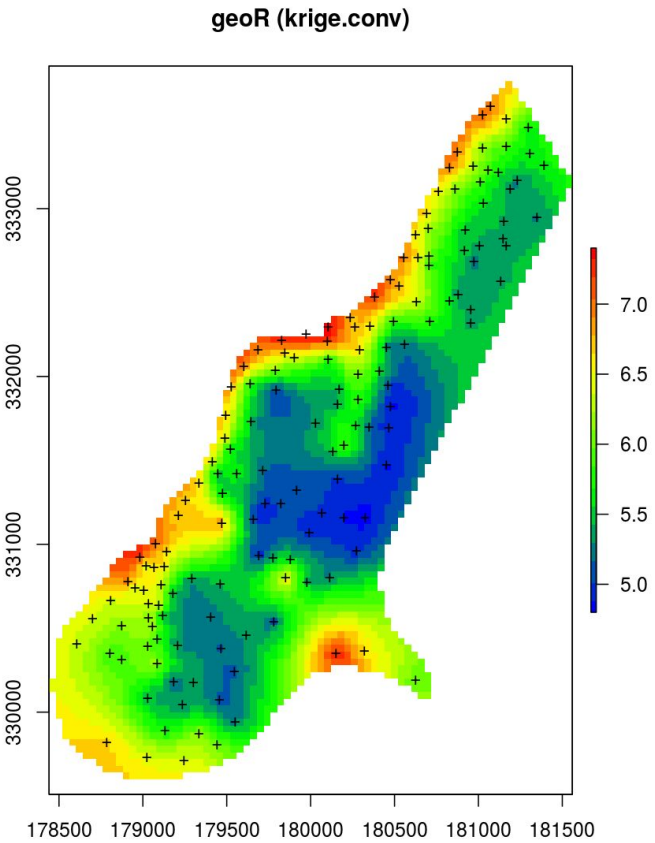


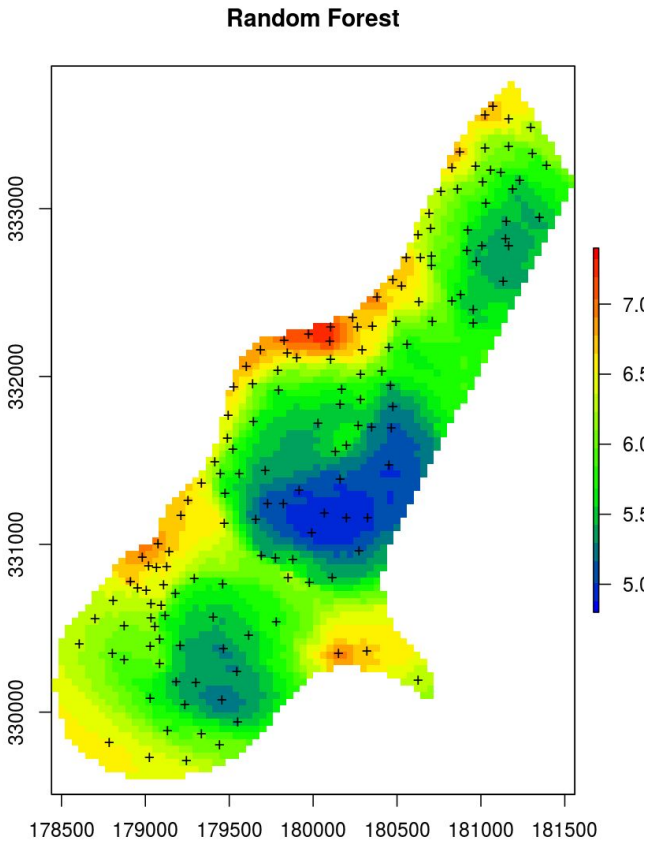

**Figure 2.** Examples of distance maps to some location in space (yellow dot) based on different derivation algorithms: (a) simple Euclidean distances, (b) complex speed-based distances based on the gdistance package and Digital Elevation Model (DEM) (van Etten, 2017), and (c) upslope area derived based on the DEM in SAGA GIS (Conrad et al., 2015). Case study: Ebergötzen (Böhner et al., 2006).

# Variogram modeling and predictions (kriging)

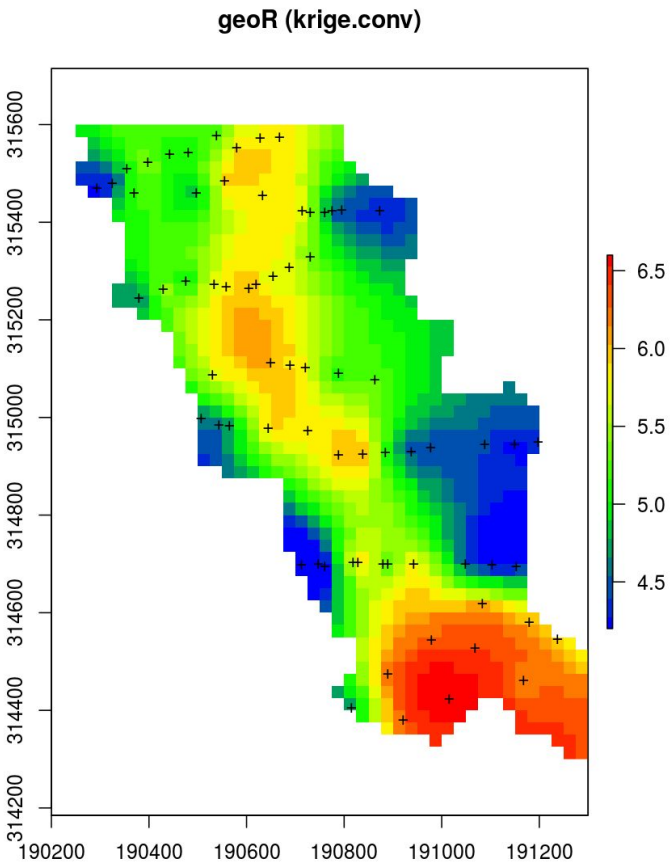
```
R> grid.dist0 <- buffer.dist(meuse["zinc"],
meuse.grid[1], as.factor(1:nrow(meuse)))

R> ov.zinc <- over(meuse["zinc"], grid.dist0)

R> m.zinc <- ranger(as.formula(paste("zinc ~",
paste(names(grid.dist0), collapse="+")),
cbind(meuse@data["zinc"], ov.zinc))

R> zinc.rfd <- predict(m.zinc, grid.dist0@data)
```

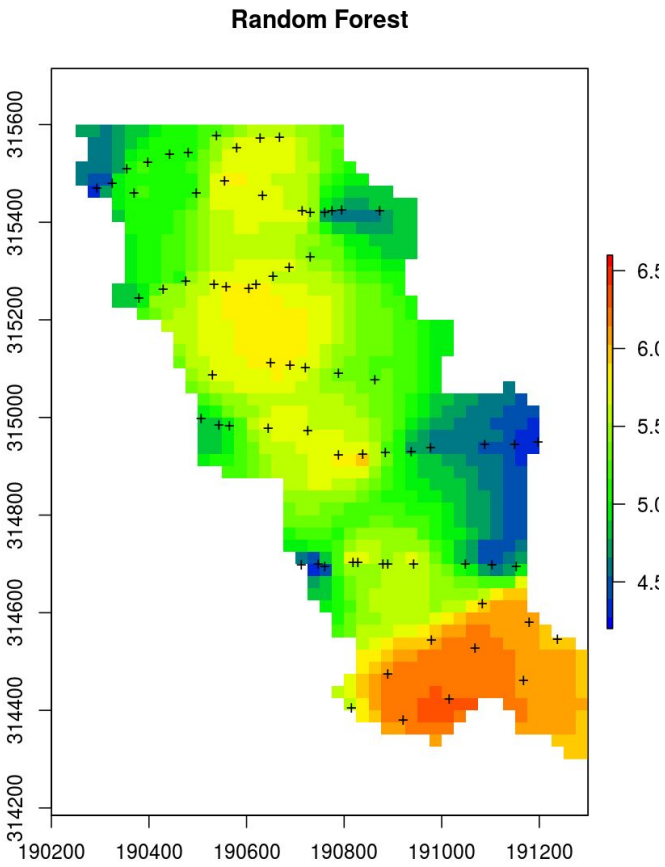
# Meuse data set



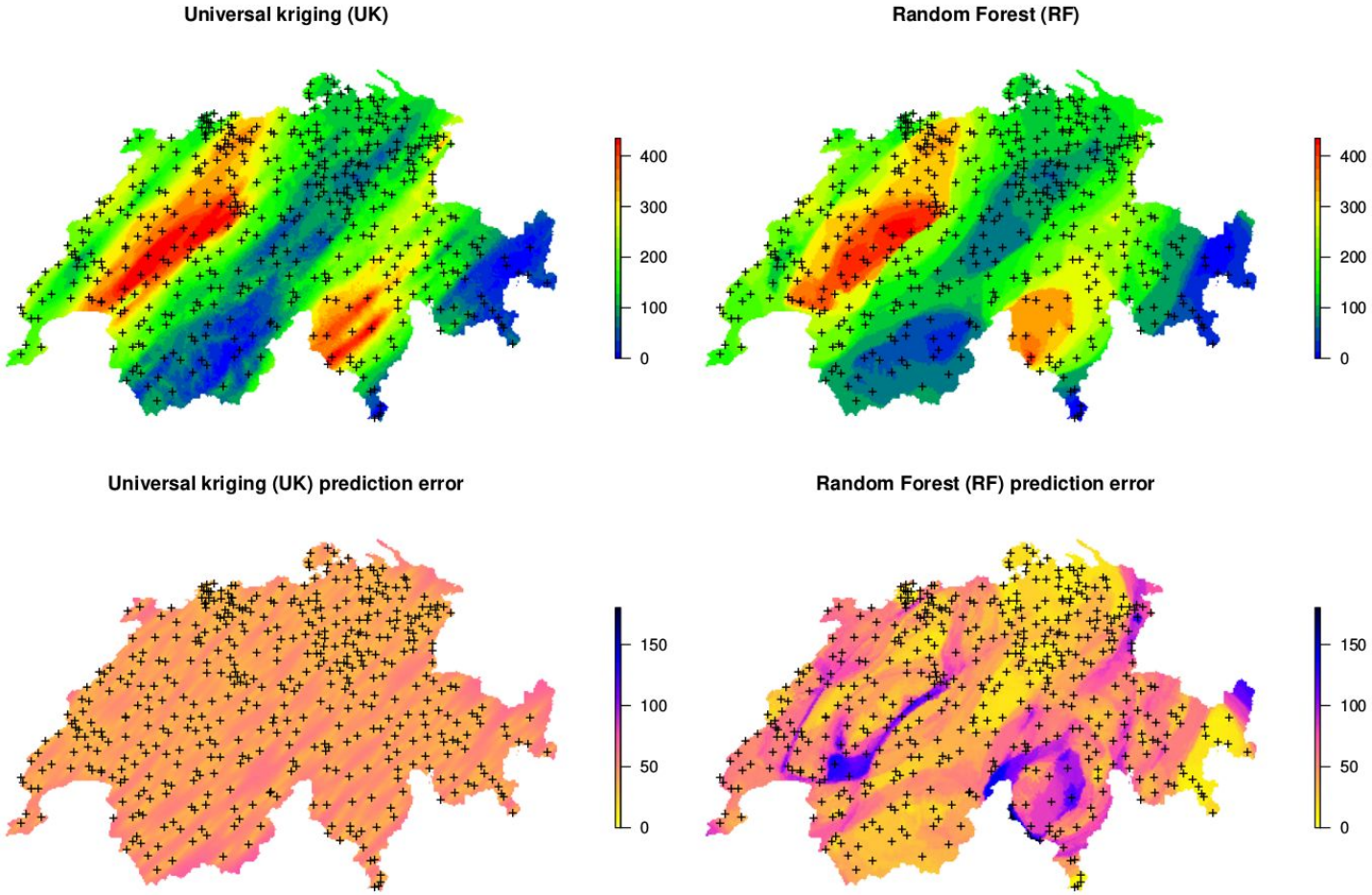



# Geul data set

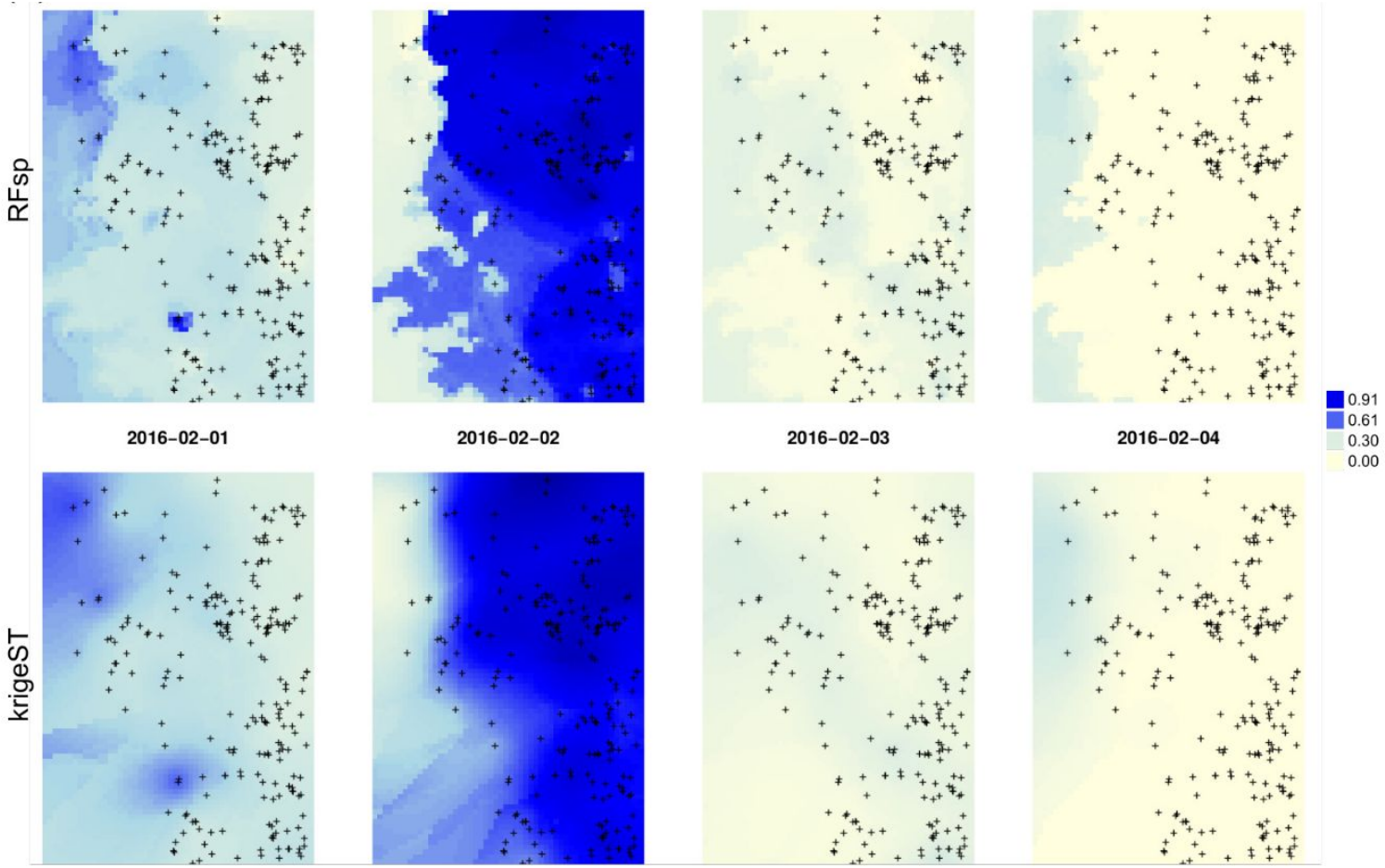


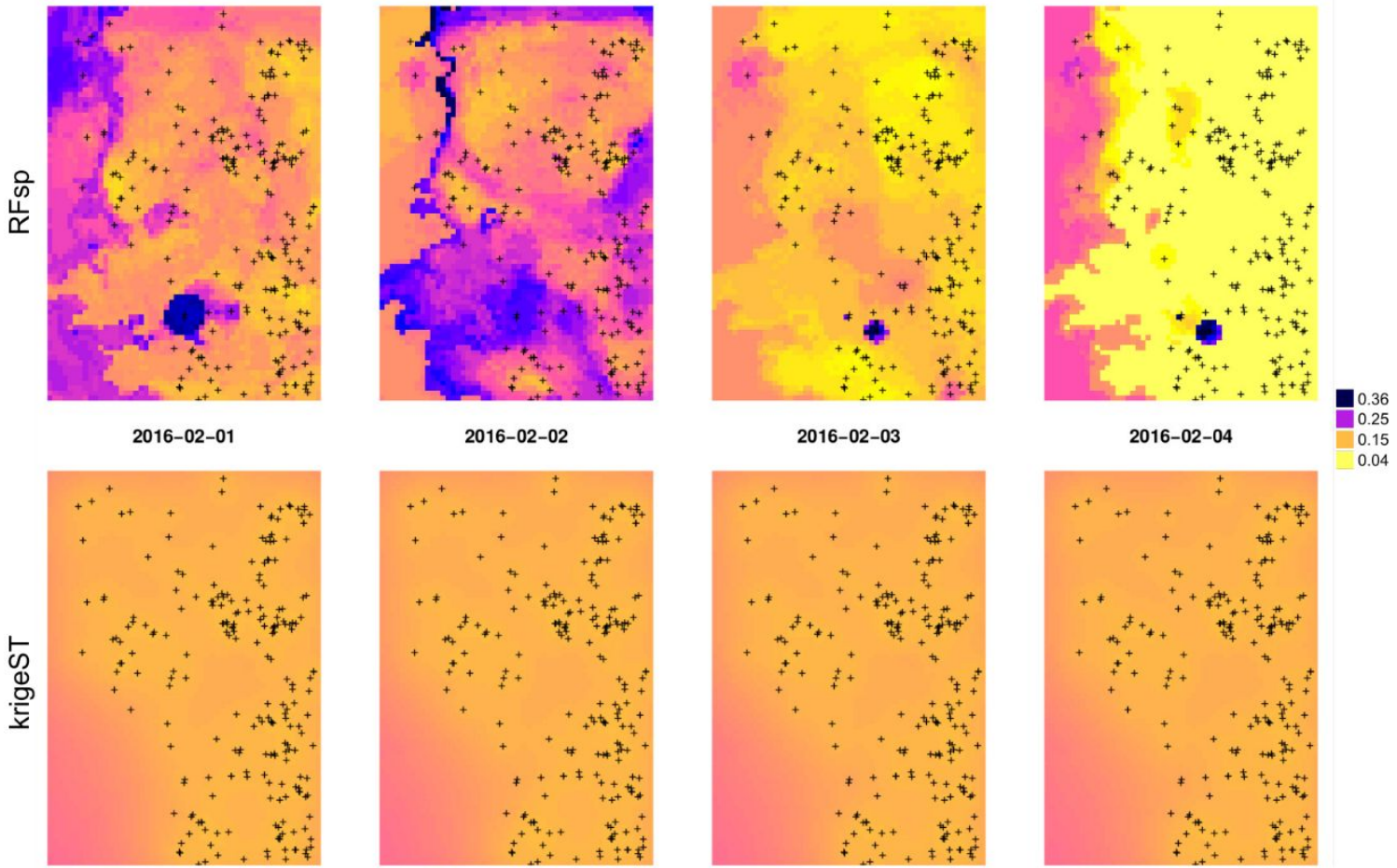
# SIC97 data set



# Daily precipitation (spatiotemporal)



# Daily precipitation (spatiotemporal) prediction error maps



# Summary results

Our results indicate that RFsp can produce comparable results to model-based geostatistics. The advantage of RFsp over model-based geostatistics is that RFsp requires much less statistical assumptions and is easier to automate (and scale up through parallelization). For smaller data sets with linear relationships model-based geostatistics could still a better choice.

RFsp is still an experimental method and application with large data sets (>>1000 points) is not recommended.

# Advantages of RFsp vs kriging

- ★ No stationarity requirements.
- ★ No Normal distribution requirements.
- ★ No problems with choosing the right variogram (in fact, there is no need for a vgm at all!!).
- ★ No (serious) problems with hot-spots.
- ★ More complex distances can be added.

# Problems to solve

1. Extrapolation problems (quality of spatial sampling)
2. Computation intensity very high
3. Validation with spatial declustering (over-fitting problems)
4. Match geostatistical simulations, co-kriging etc.

# RF is not a good idea for extrapolation

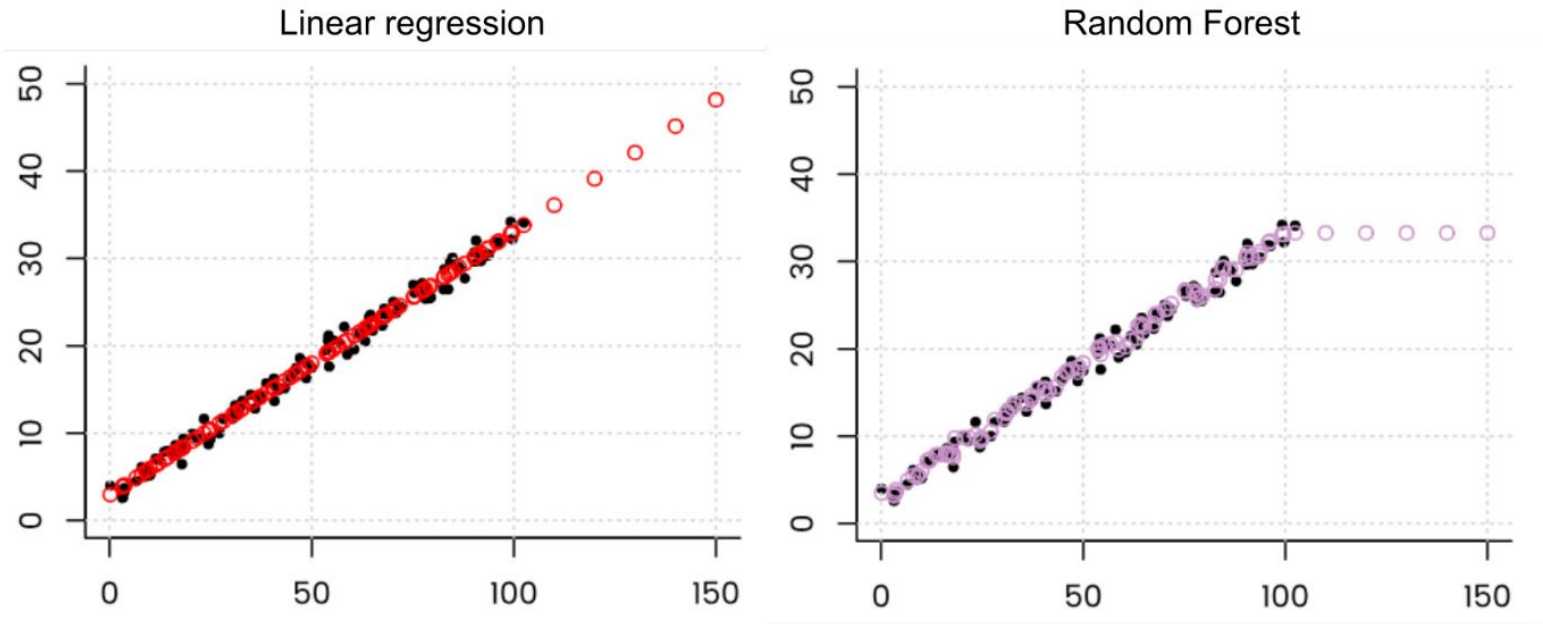



**Figure 14.** Illustration of the extrapolation problem of Random Forest based on the code examples from Peter Ellis (http://freerangestats.info). Even though Random Forest is more generic than linear regression and can be used also to fit complex non-linear problems, it can lead to completely nonsensical predictions if applied to extrapolation domains.

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# Questions?