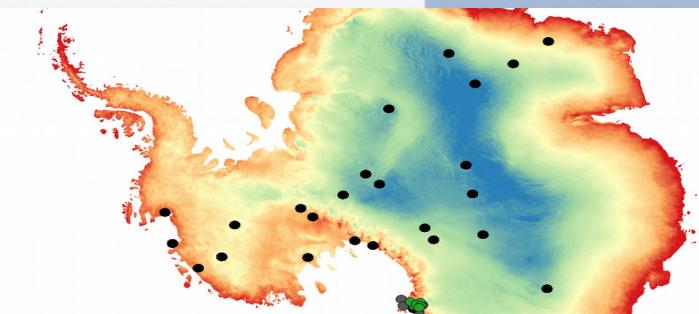




Machine-learning based modelling of spatial and spatio-temporal environmental data

Part 1: Introduction to:

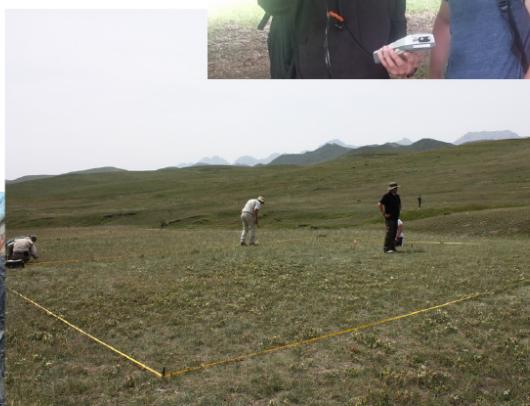
- *Spatio-temporal model training and prediction*
- *Cross validation*
- *Variable selection for spatio-temporal models*



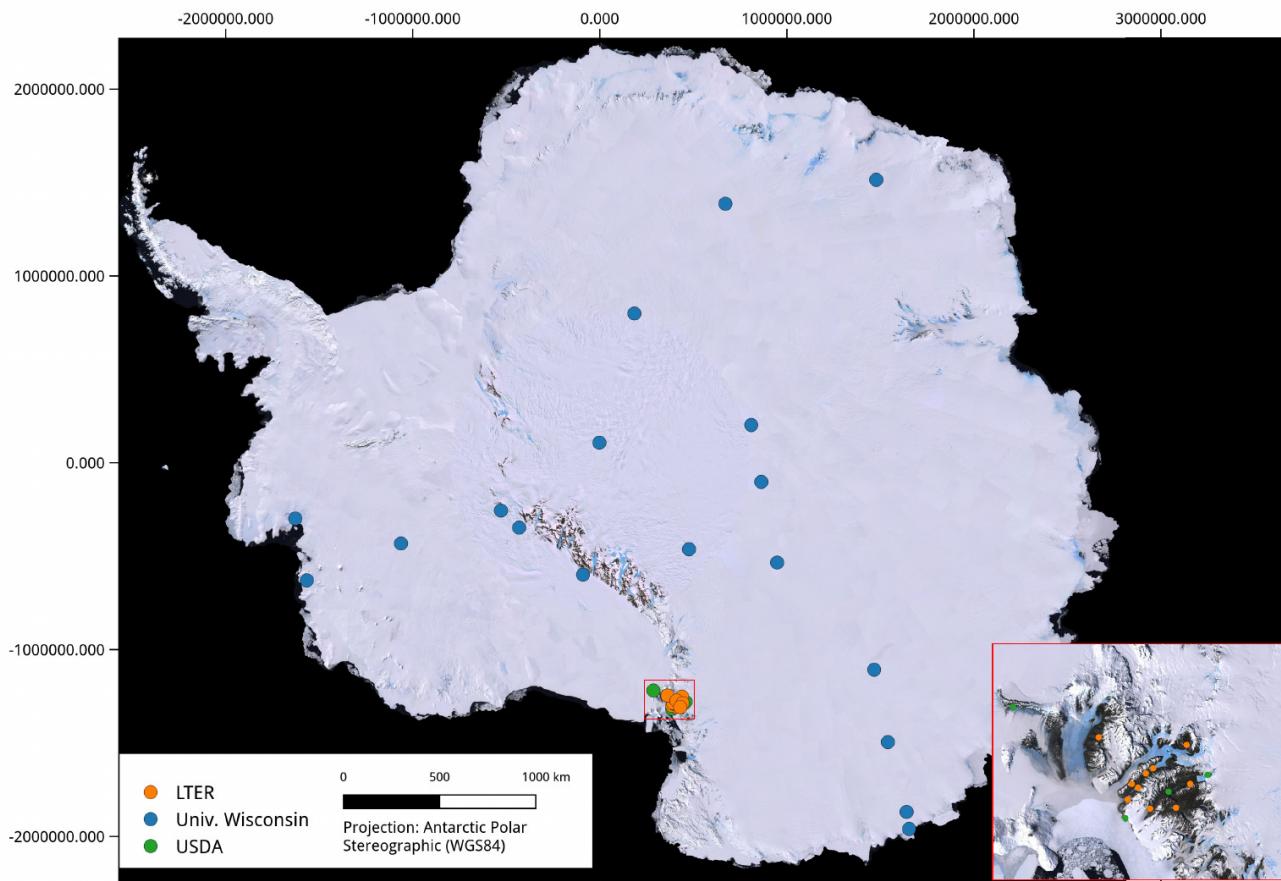
Hanna Meyer

Common problem in environmental science

Local sampling vs need for spatially continuous information



Example: Monitoring Air Temperature in Antarctica

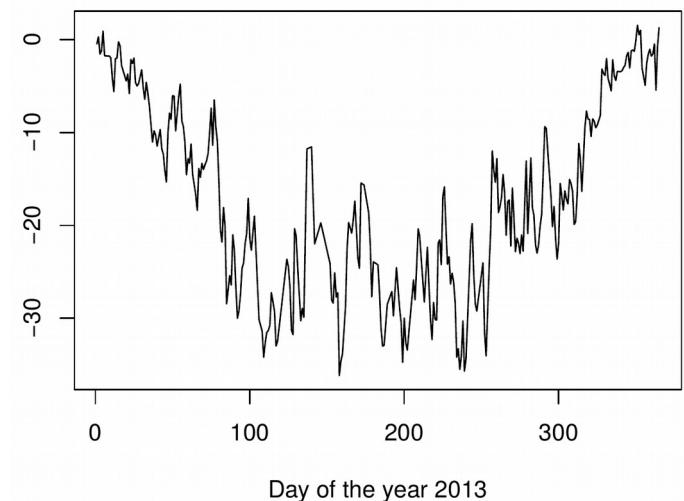


Meyer et al. (2016)

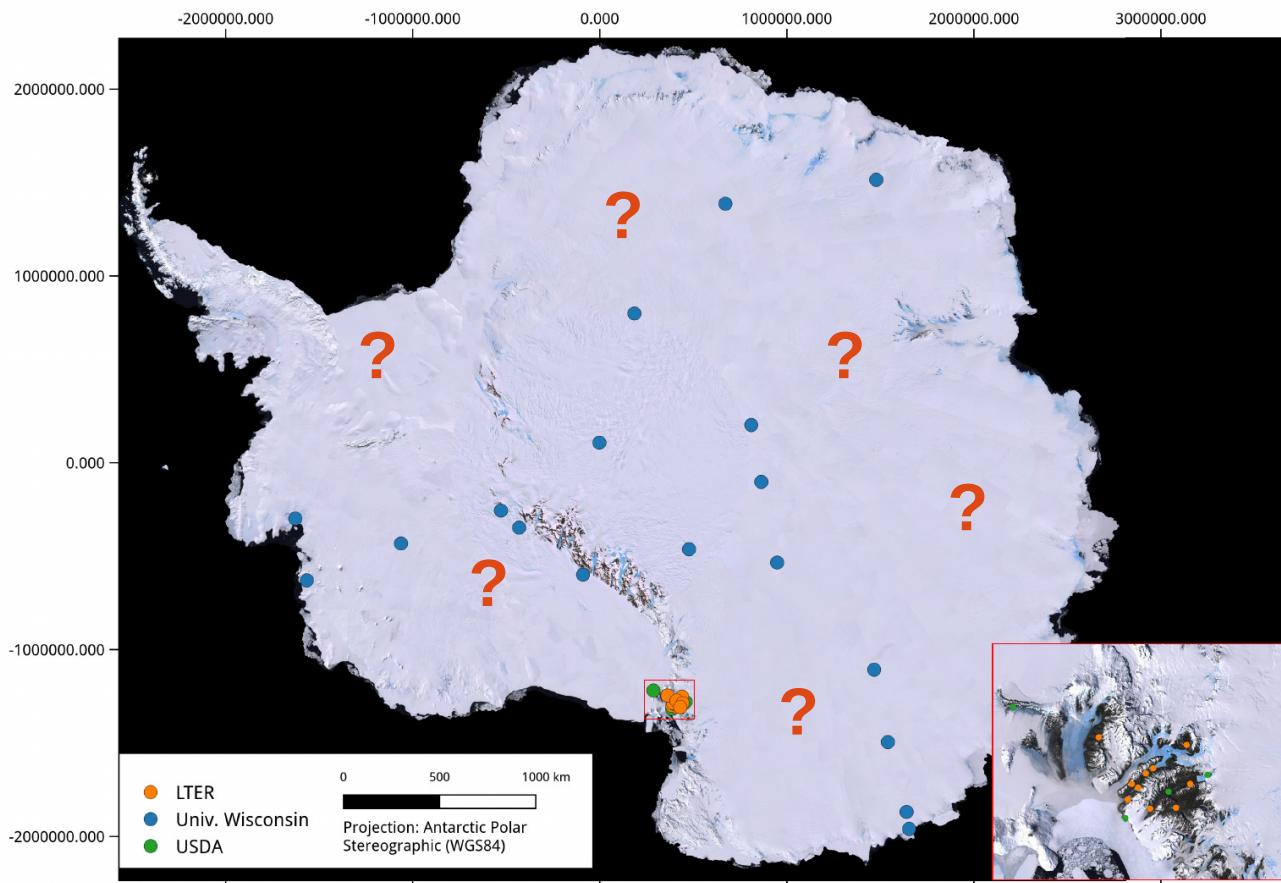


<http://amrc.ssec.wisc.edu/>

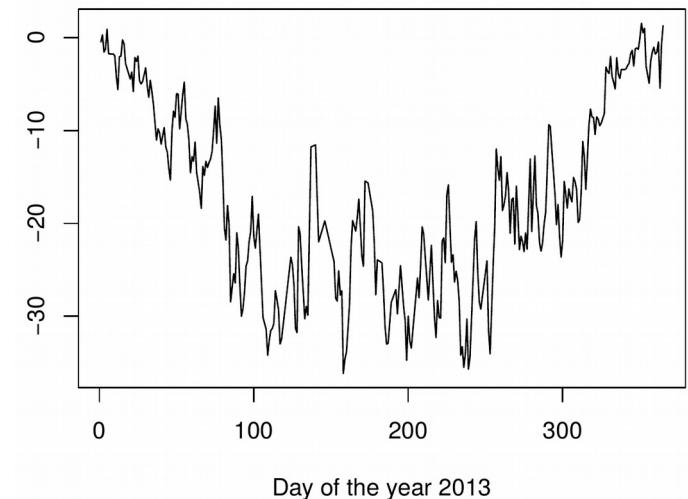
Time Series of 'Marble Point'



Example: Monitoring Air Temperature in Antarctica

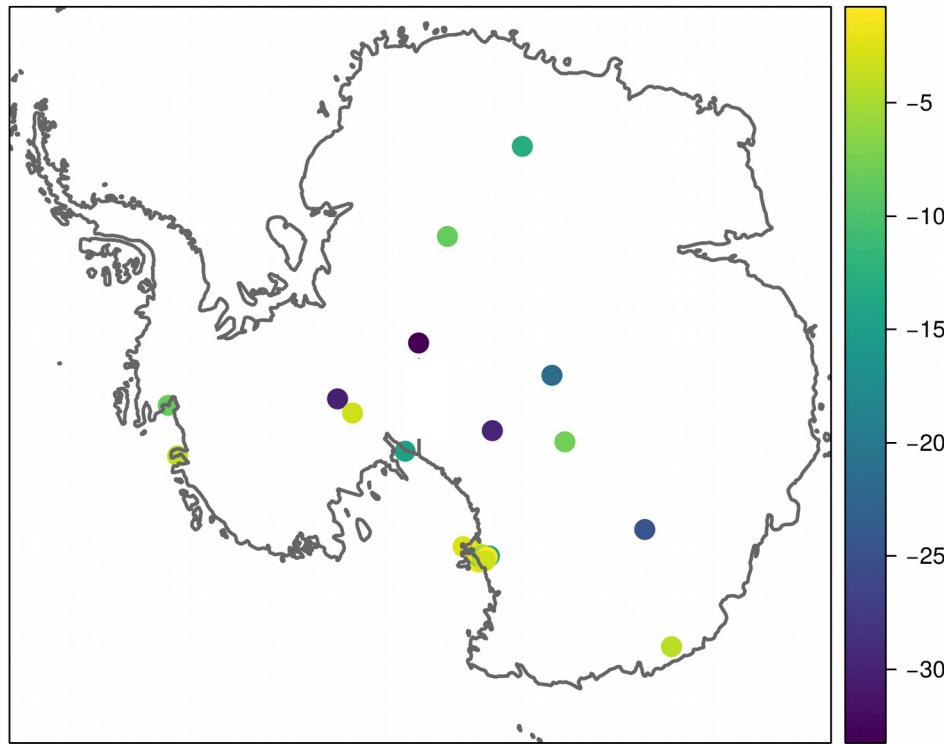


Time Series of 'Marble Point'

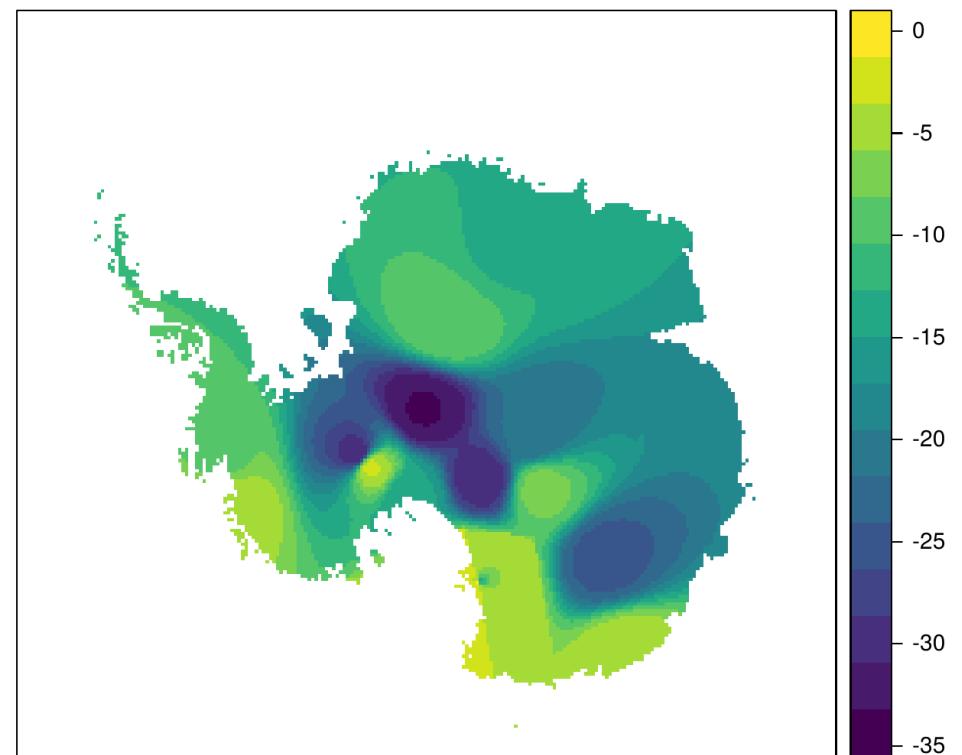


First approach: Simple spatial interpolation

Measured mean air temperature on 10.01.2013

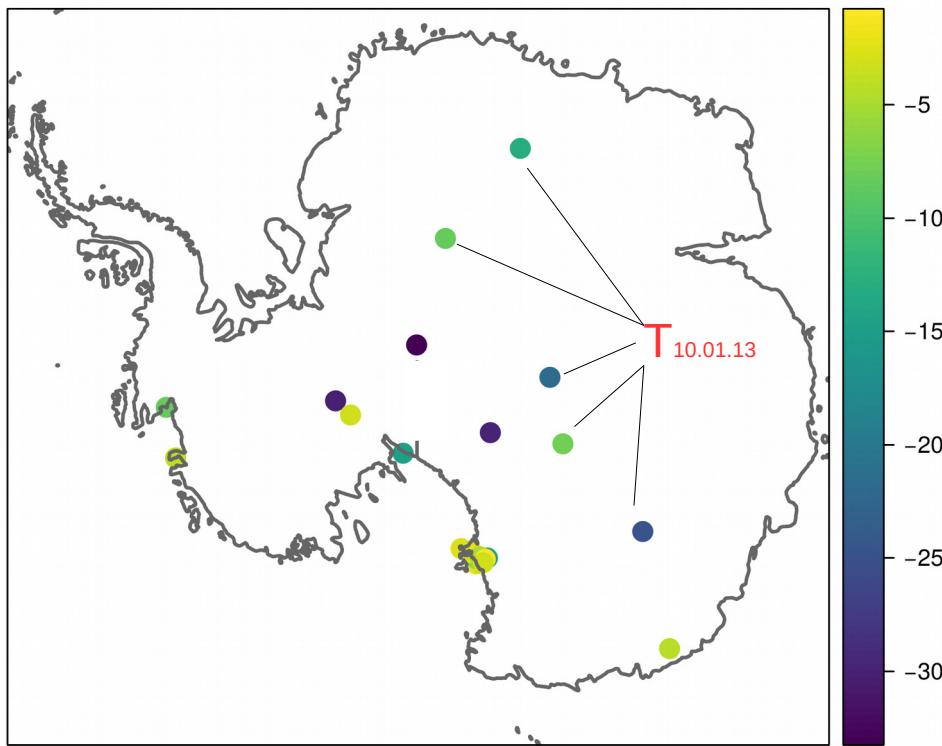


Interpolated mean air temperature on 10.01.2013

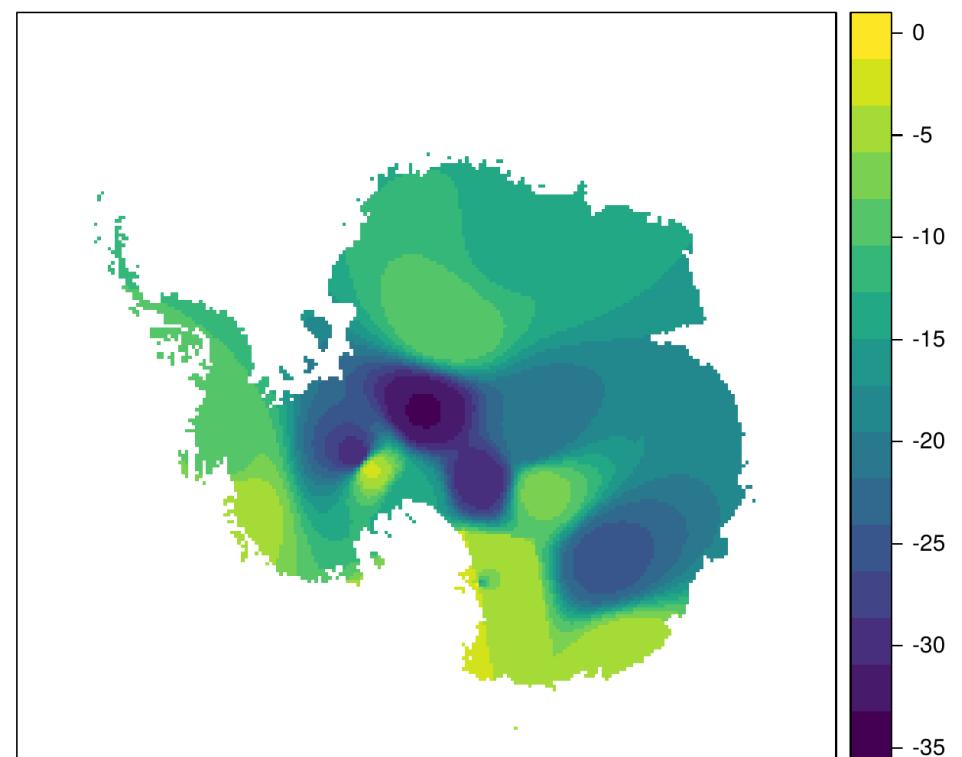


First approach: Simple spatial interpolation

Measured mean air temperature on 10.01.2013

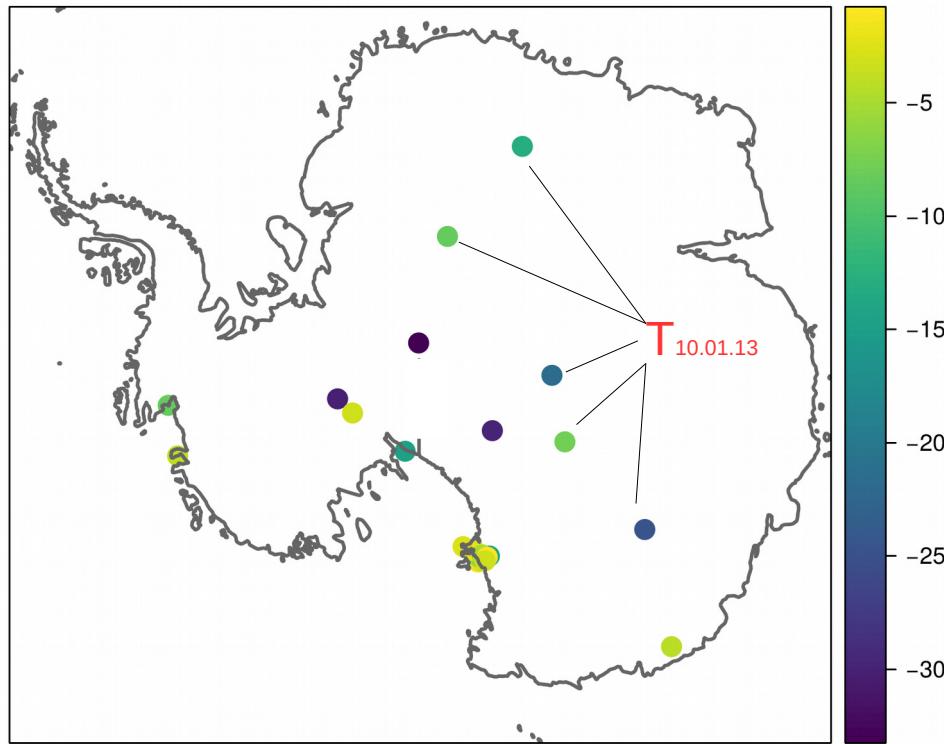


Interpolated mean air temperature on 10.01.2013

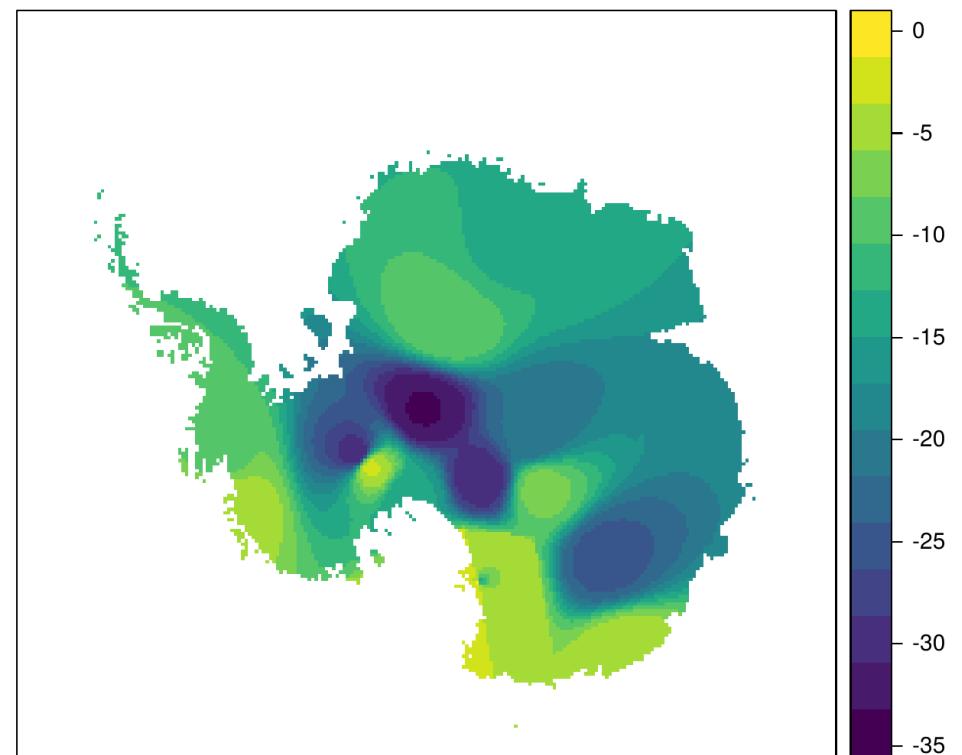


First approach: Simple spatial interpolation

Measured mean air temperature on 10.01.2013



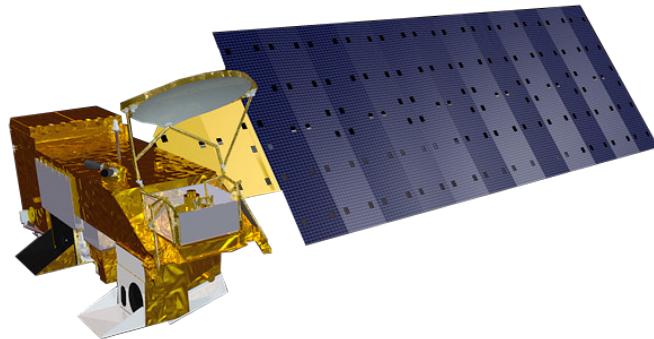
Interpolated mean air temperature on 10.01.2013



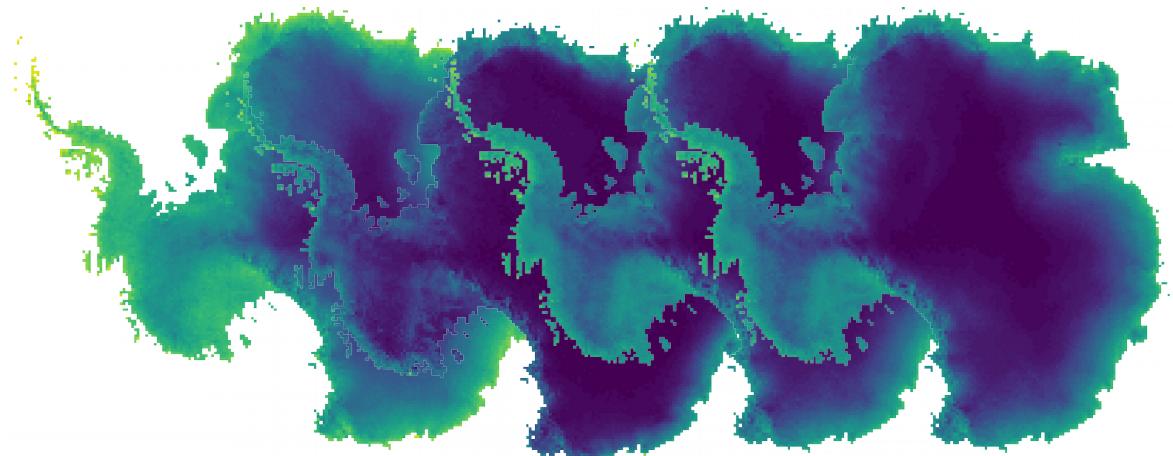
Problem: Distance not always a meaningful predictor,
Dependency on field data

Spatio-temporal predictors are needed

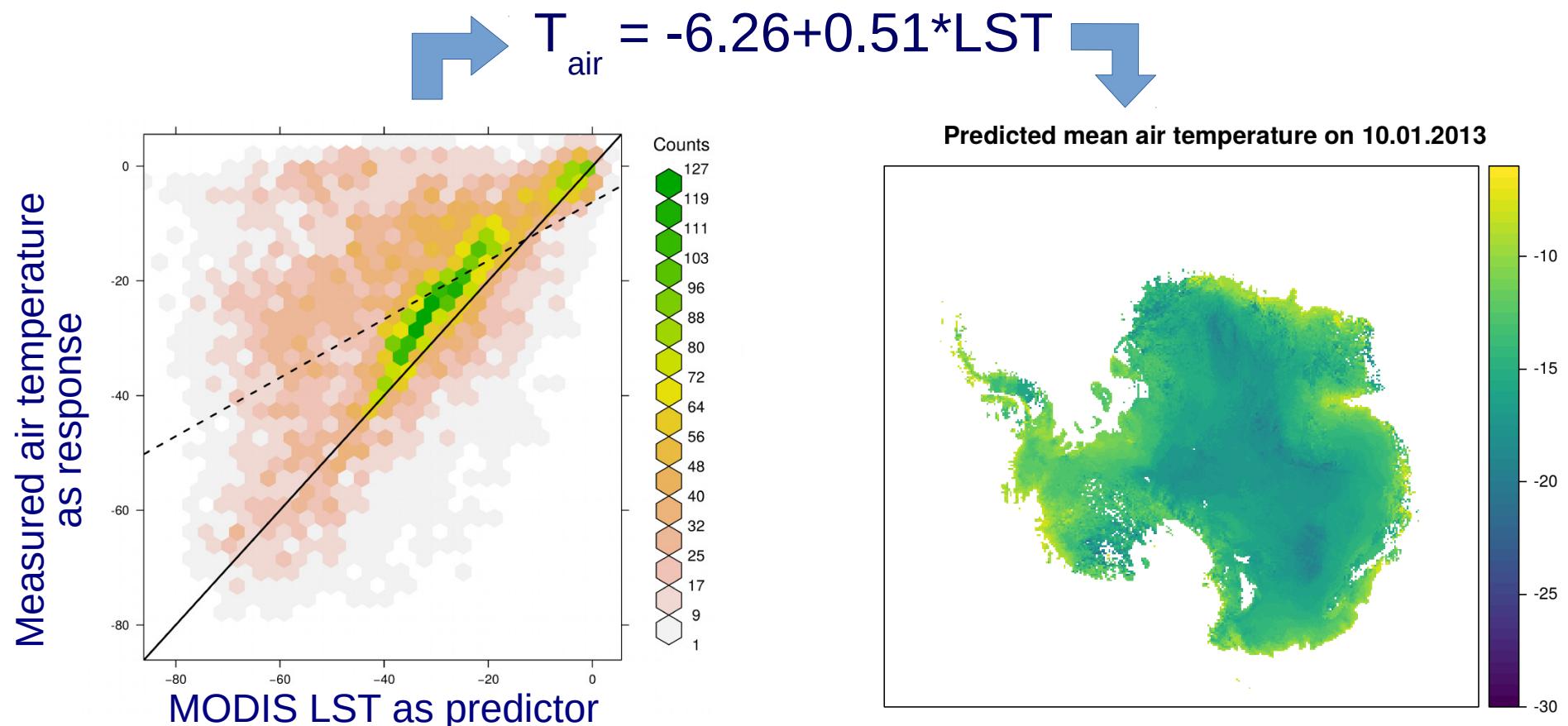
- No way around remote sensing (e.g. from drones, air planes, satellites)!!
- Assumption: Spectral properties are related to the target
- For this example: e.g. MODIS LST (4 times per day, 1km spatial resolution)



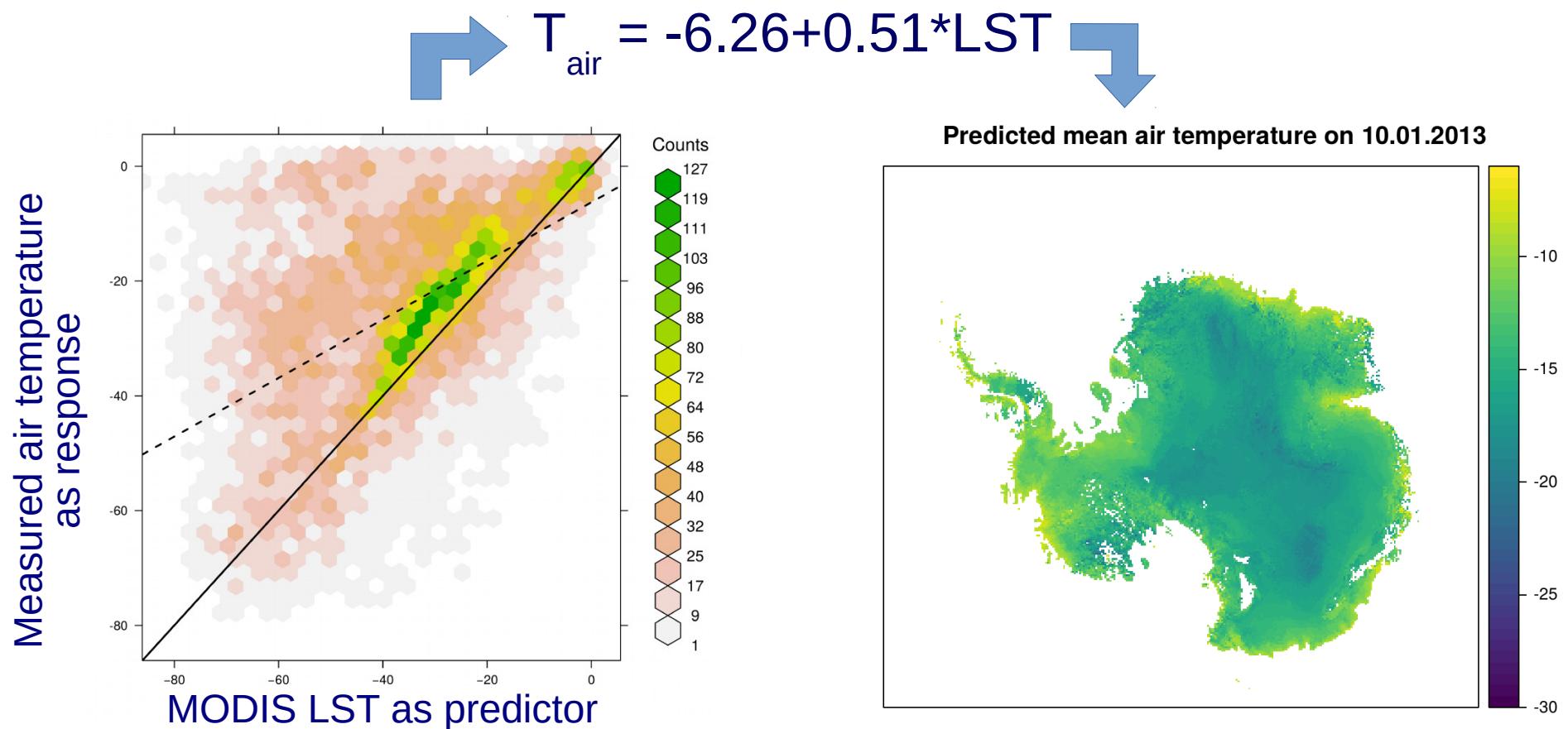
By National Aeronautics and Space Administration (NASA)
[Public domain], via Wikimedia Commons



Parametric modelling approaches

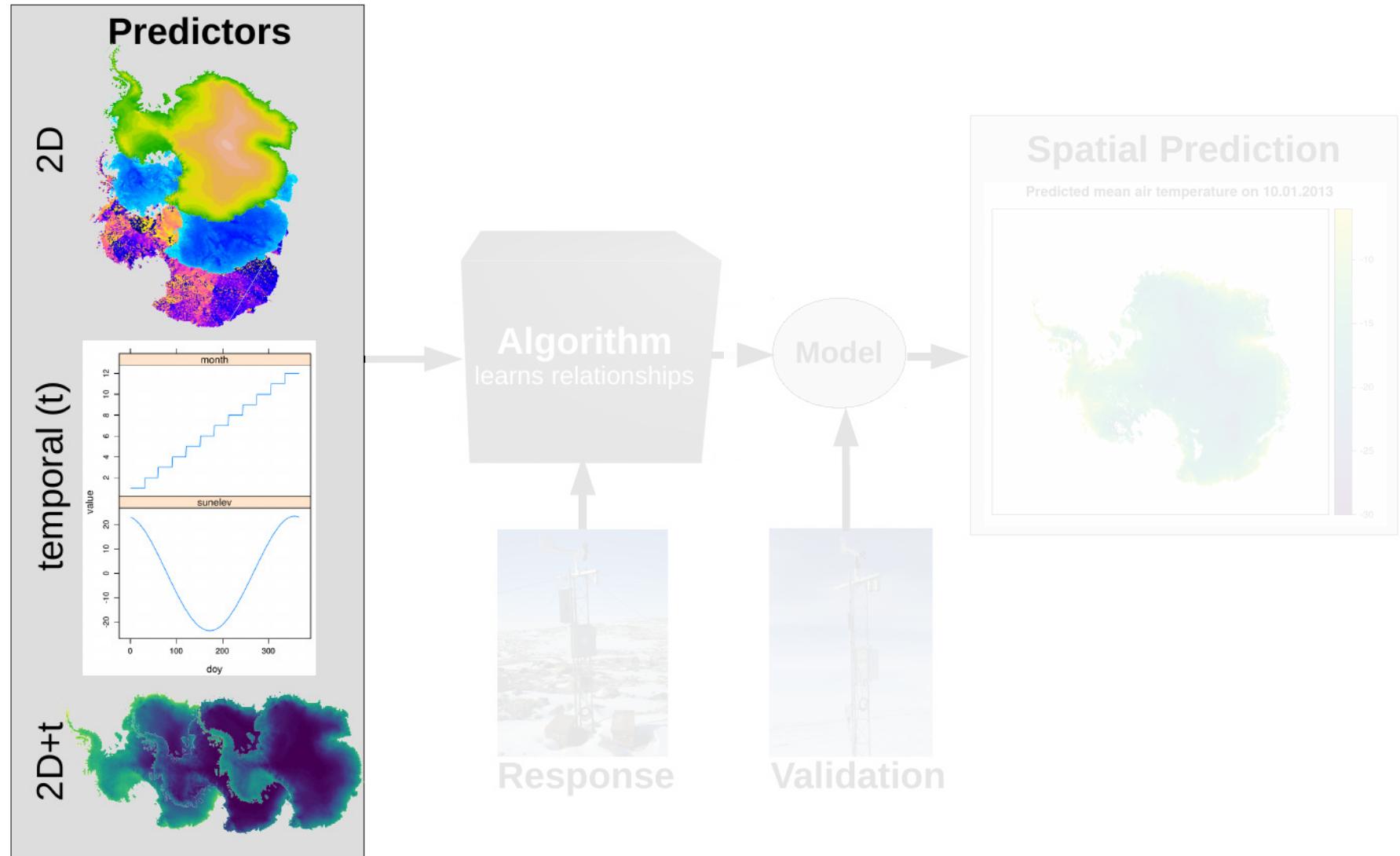


Parametric modelling approaches

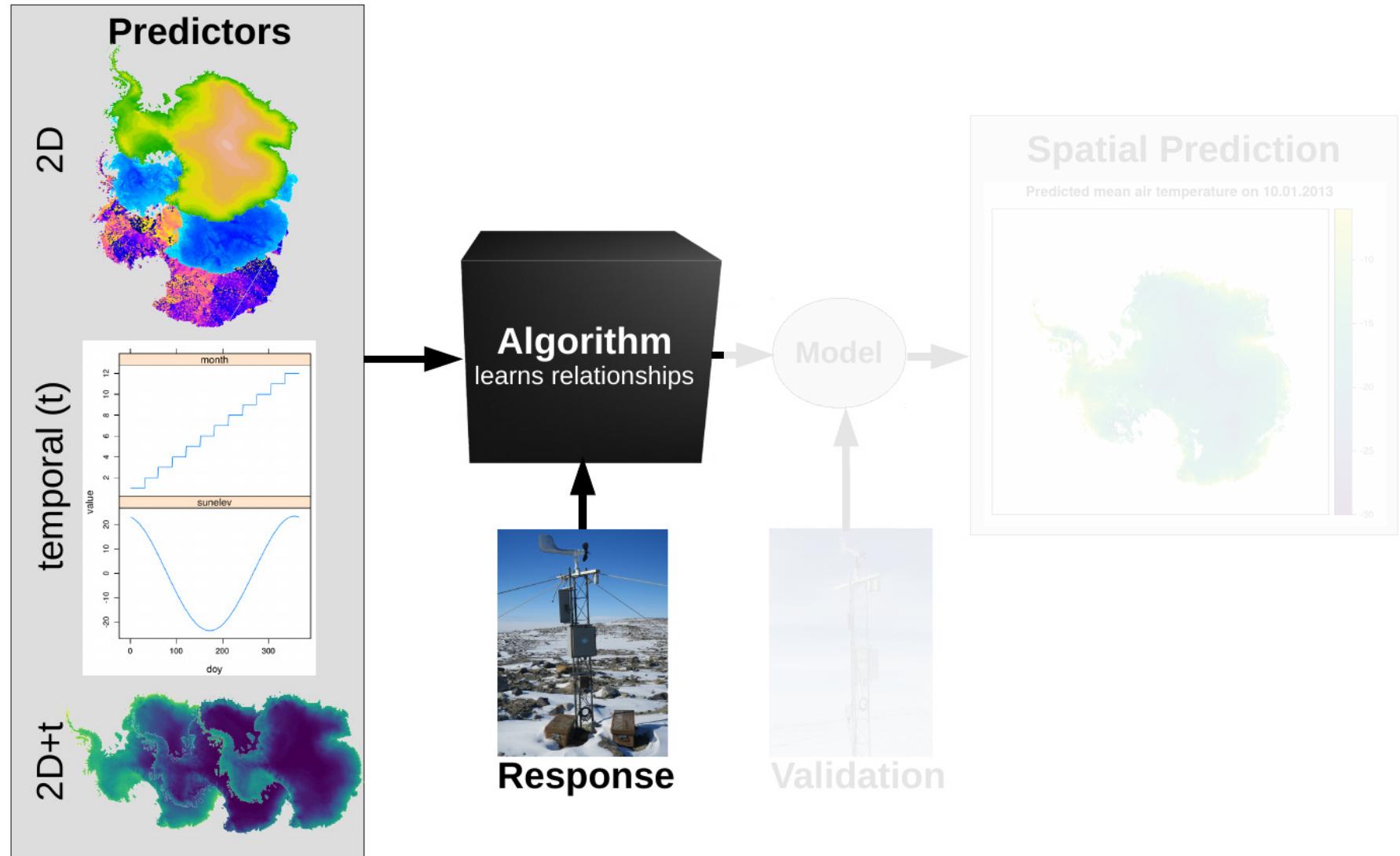


Problem: fixed relationships, limited number of predictors,
But need for flexible models

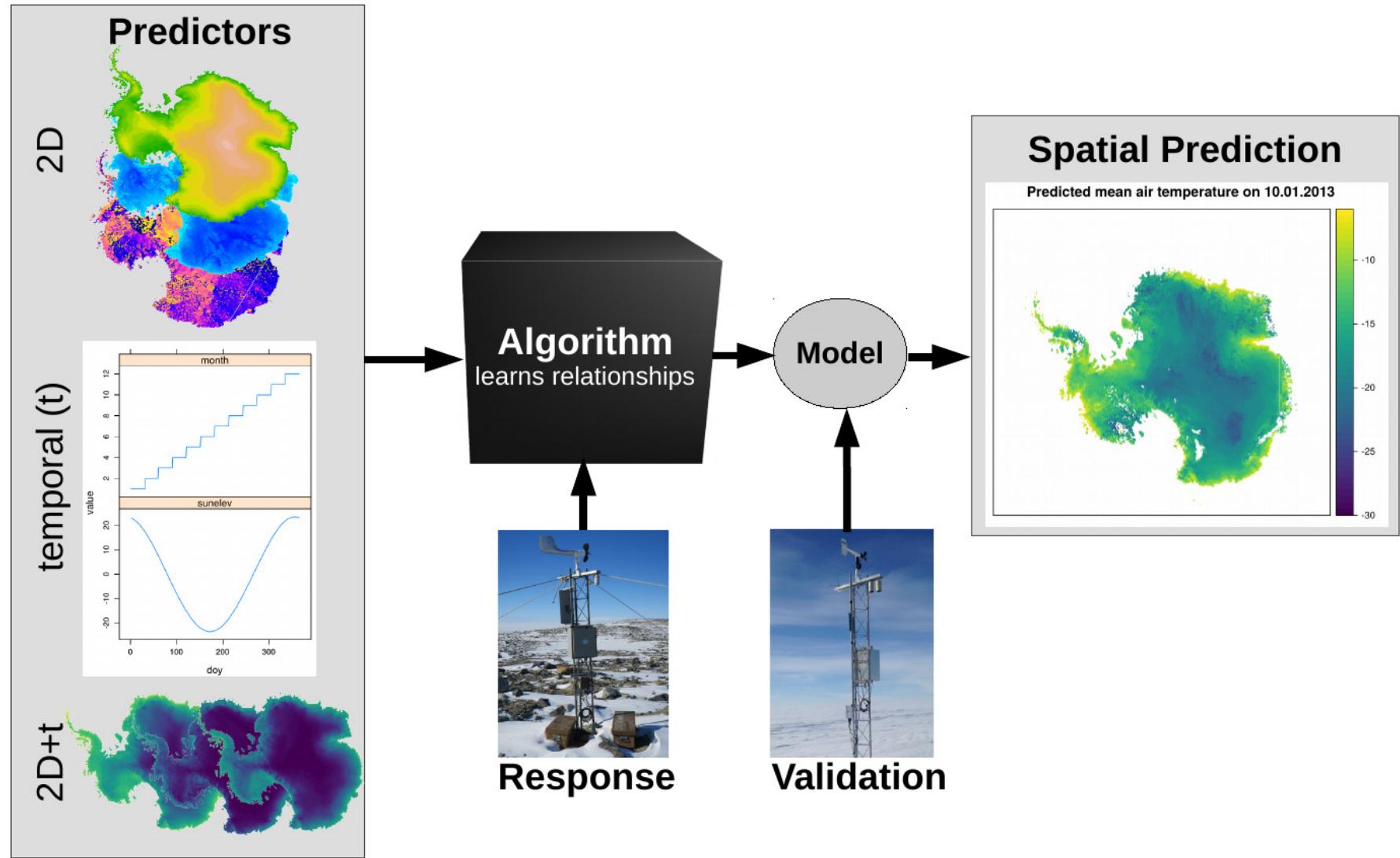
The Machine learning way



The Machine learning way

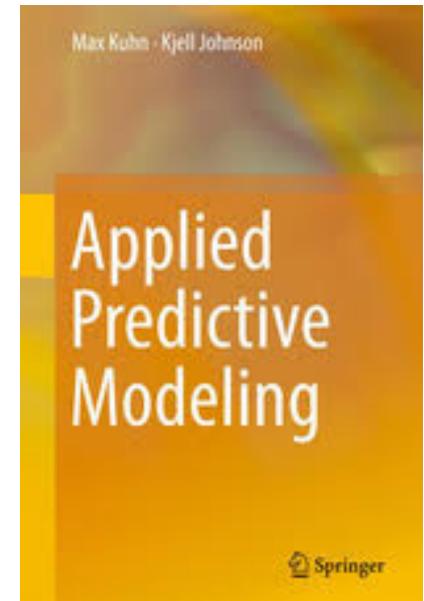


The Machine learning way



Machine learning in R

- Many packages for different ML algorithms (e.g. randomForest)
- For classification and regression problems
- Caret (Classification And REgression Training) is a wrapper package allowing access to many algorithms via a unified syntax
 - Overview of algorithms:
<http://topepo.github.io/caret/train-models-by-tag.html>
 - Supporting functionality for cross-validation etc.
 - Further reading: Applied predictive modelling
(with R code examples)



Machine learning in R using caret is easy....

Step one: Model training

Training data:

	Predictors				Response	
--	------------	--	--	--	----------	--

Station	Date	LST	Elevation	Aspect	...	Measured Tair
A	2017/01/01	-5	1000	S		-2
B	2017/01/01	0	200	S		-2
C	2017/01/01	-10	3000	E		-5
A	2017/07/01	-40	1000	S		-45
B	2017/07/01	-30	200	S		-30
C	2017/07/01	-60	3000	E		-70
A	2017/10/01	-20	1000	S		-22
B	2017/10/01	-10	200	S		-9
C	2017/10/01	-25	3000	E		-30

Machine learning in R using caret is easy....

Step one: Model training

Training data:

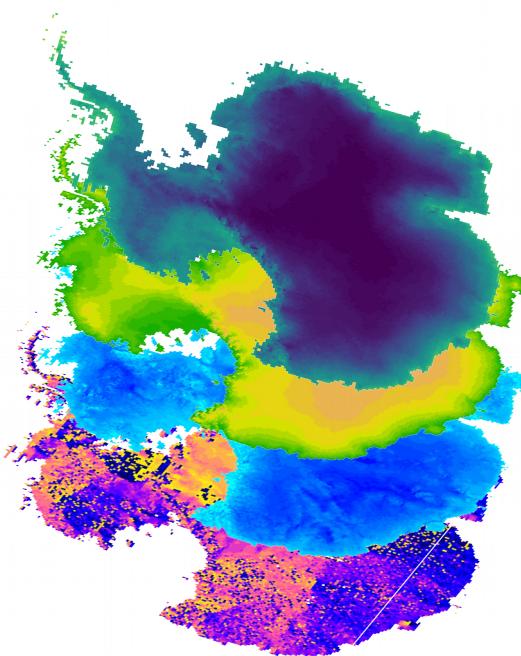
Station	Date	Predictors				Response	
		LST	Elevation	Aspect	...	Measured Tair	
A	2017/01/01	-5	1000	S		-2	
B	2017/01/01	0	200	S		-2	
C	2017/01/01	-10	3000	E		-5	
A	2017/07/01	-40	1000	S		-45	
B	2017/07/01	-30	200	S		-30	
C	2017/07/01	-60	3000	E		-70	
A	2017/10/01	-20	1000	S		-22	
B	2017/10/01	-10	200	S		-9	
C	2017/10/01	-25	3000	E		-30	

How to do it in R

```
library(caret)
model <- train(predictors,
                 response,
                 method="rf")
```

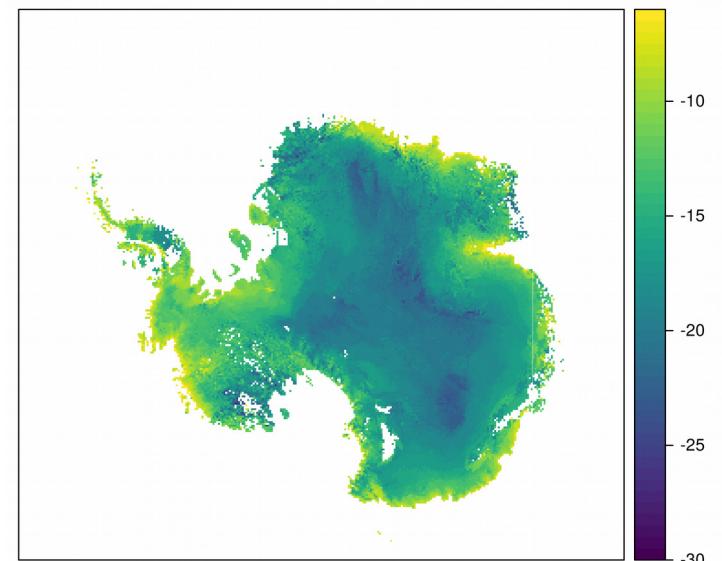
Machine learning in R using caret is easy....

Step two: Spatial prediction



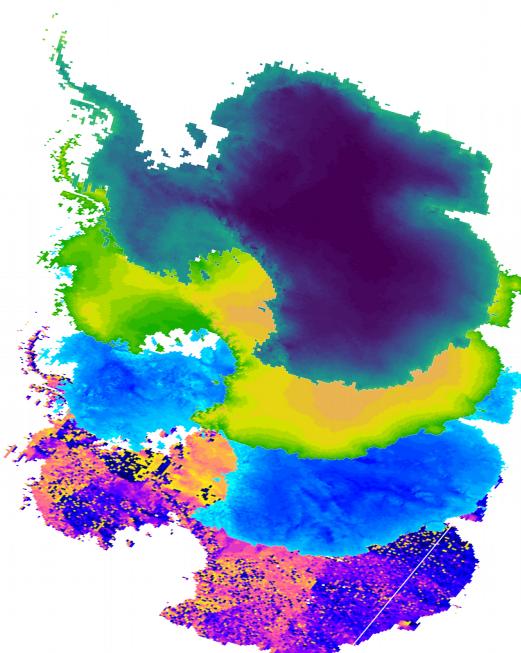
+ trained model =

Predicted mean air temperature on 10.01.2013



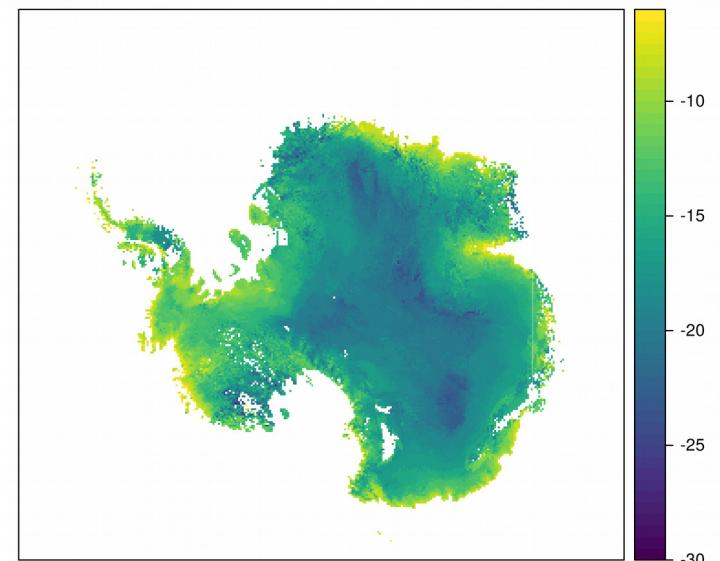
Machine learning in R using caret is easy....

Step two: Spatial prediction



+ trained model =

Predicted mean air temperature on 10.01.2013



How to do it in R

```
library(raster)
pred_sp <- stack(predictors)
prediction <- predict(pred_sp,model)
```

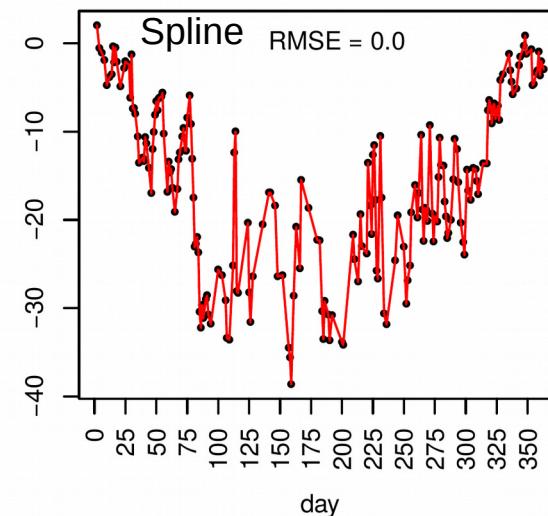
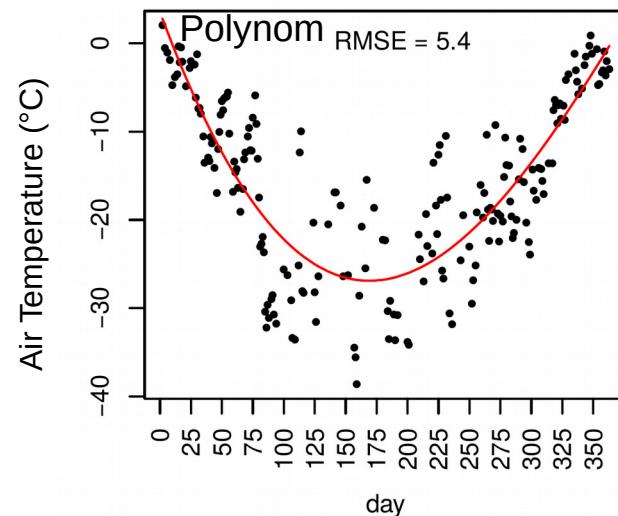
...But how good is the model?



<https://xkcd.com/1838/>

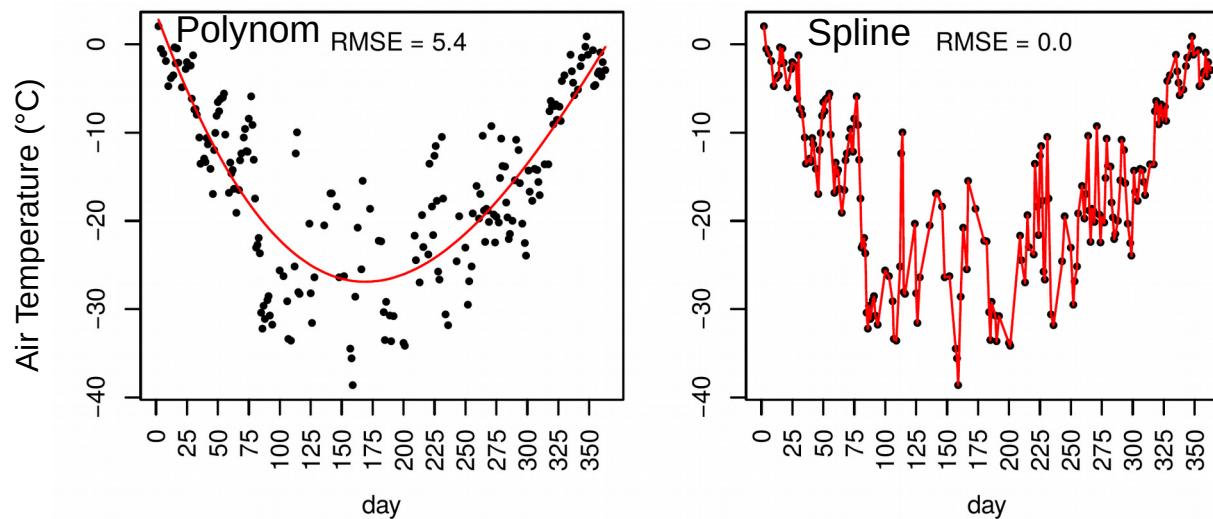
...But how good is the model?

Model training

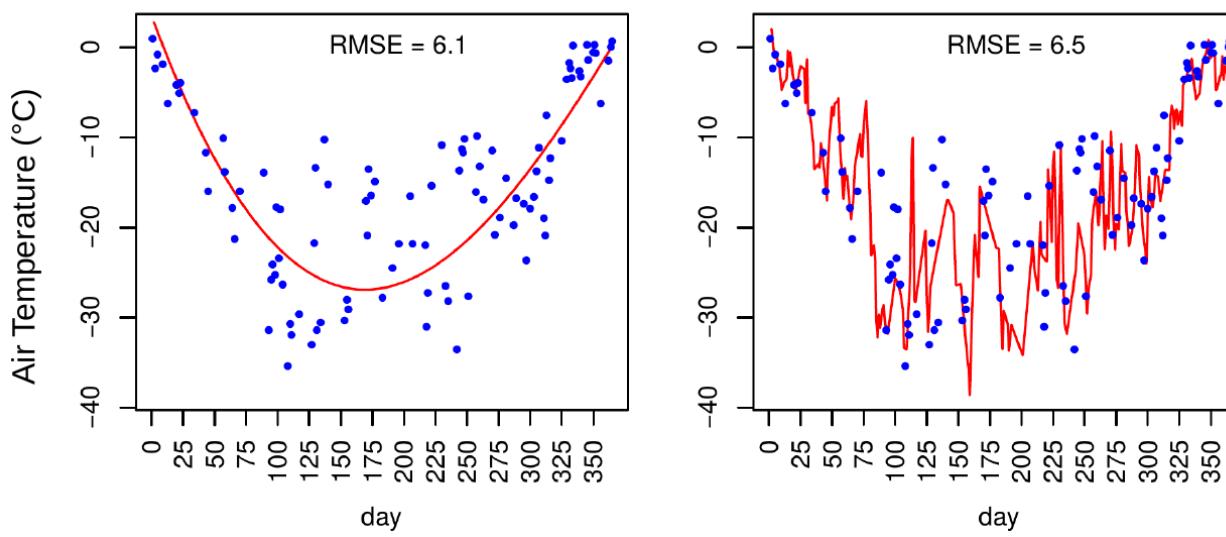


...But how good is the model?

Model training (2/3 of the data)

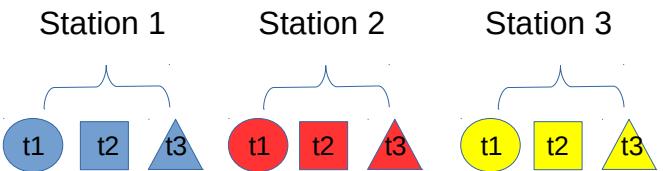


Model validation (1/3 of the data)



Random Cross-validation

Total data set



Training data

Test data

Random k-fold CV	Training data						Test data		
	Fold 1			Fold 2			Fold 3		

Random Cross-validation

How to do it in R

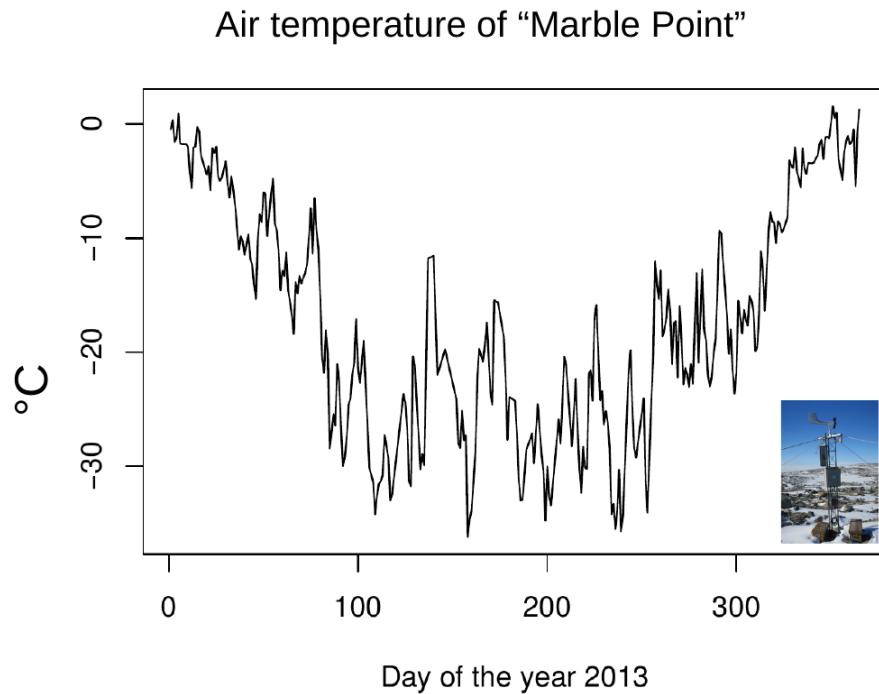
```
model <- train(predictors,  
                 response,  
                 method="rf",  
                 trControl=trainControl(method="cv"))
```

```
> model  
Random Forest  
  
30666 samples  
 10 predictor  
  
No pre-processing  
Resampling: Cross-Validated (10 fold)  
Summary of sample sizes: 27598, 27602, 27599, 27599, 27600, 27601, ...  
Resampling results:  
  
RMSE      Rsquared  
5.554594  0.8986016
```

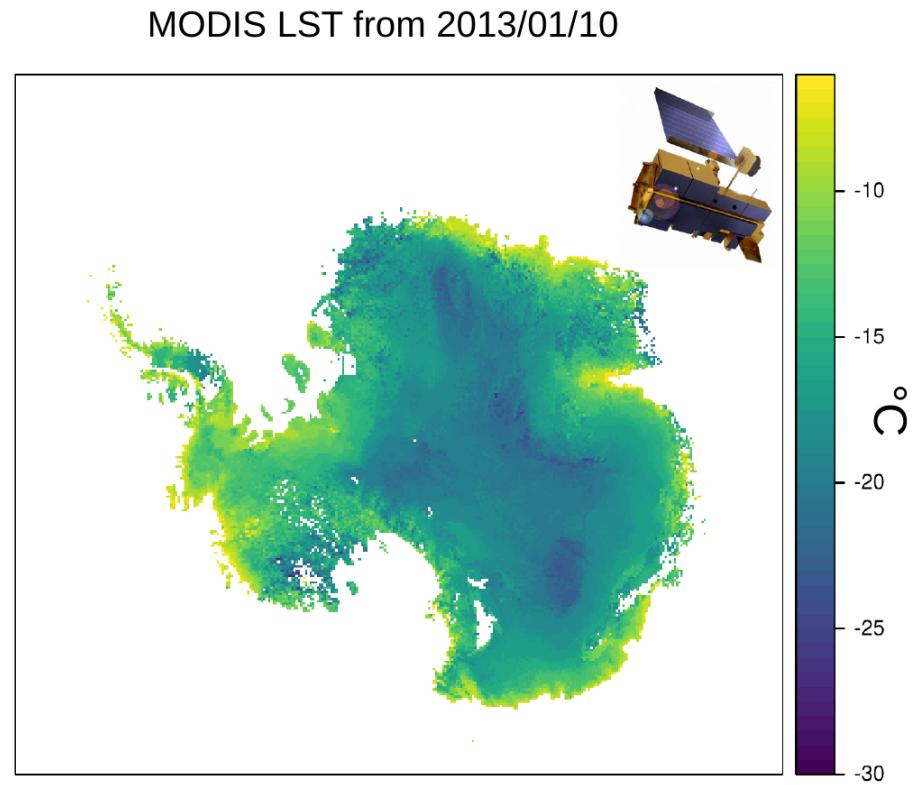
Tuning parameter 'mtry' was held constant at a value of 2

Problem with spatial (and temporal) data

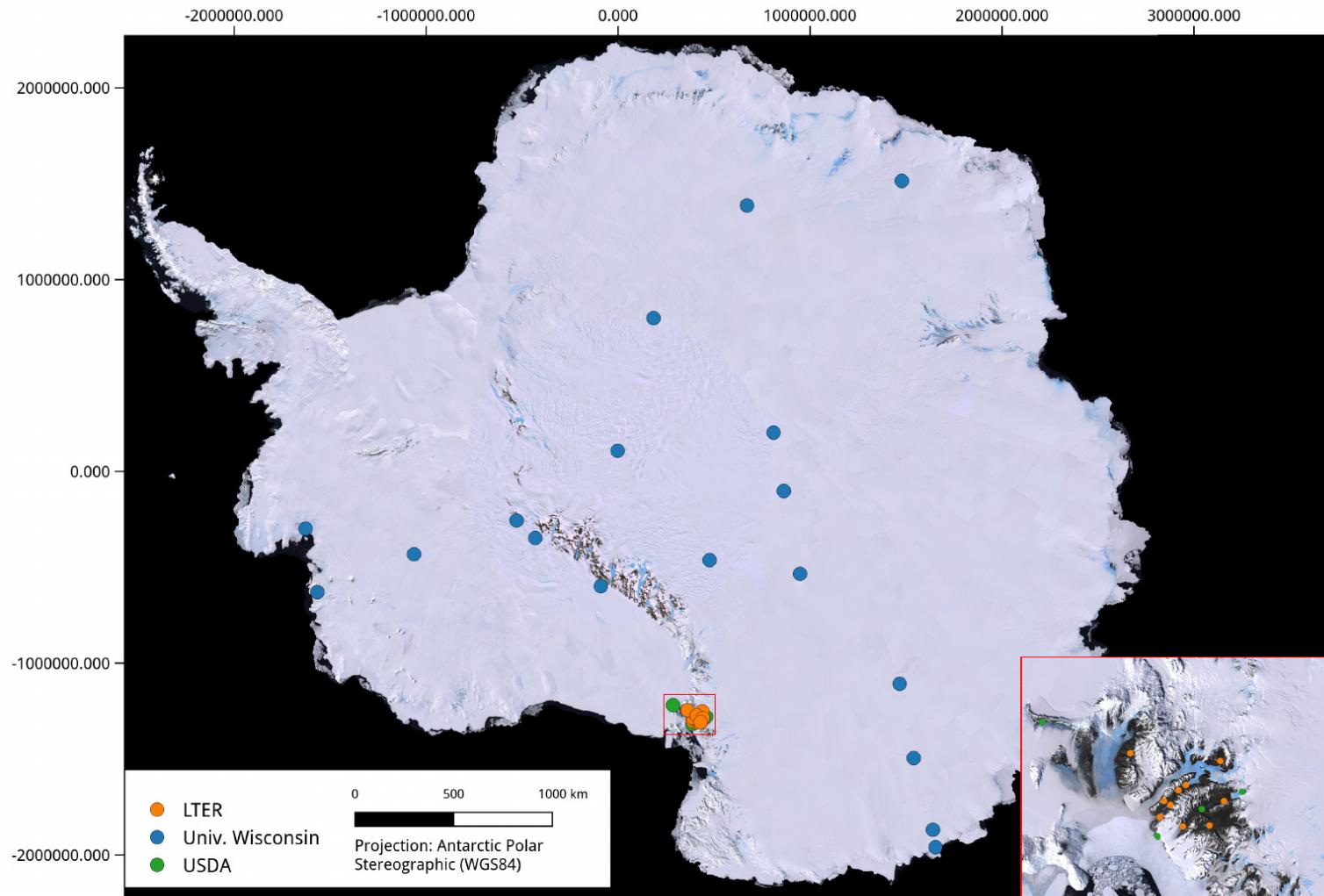
Temporal autocorrelation



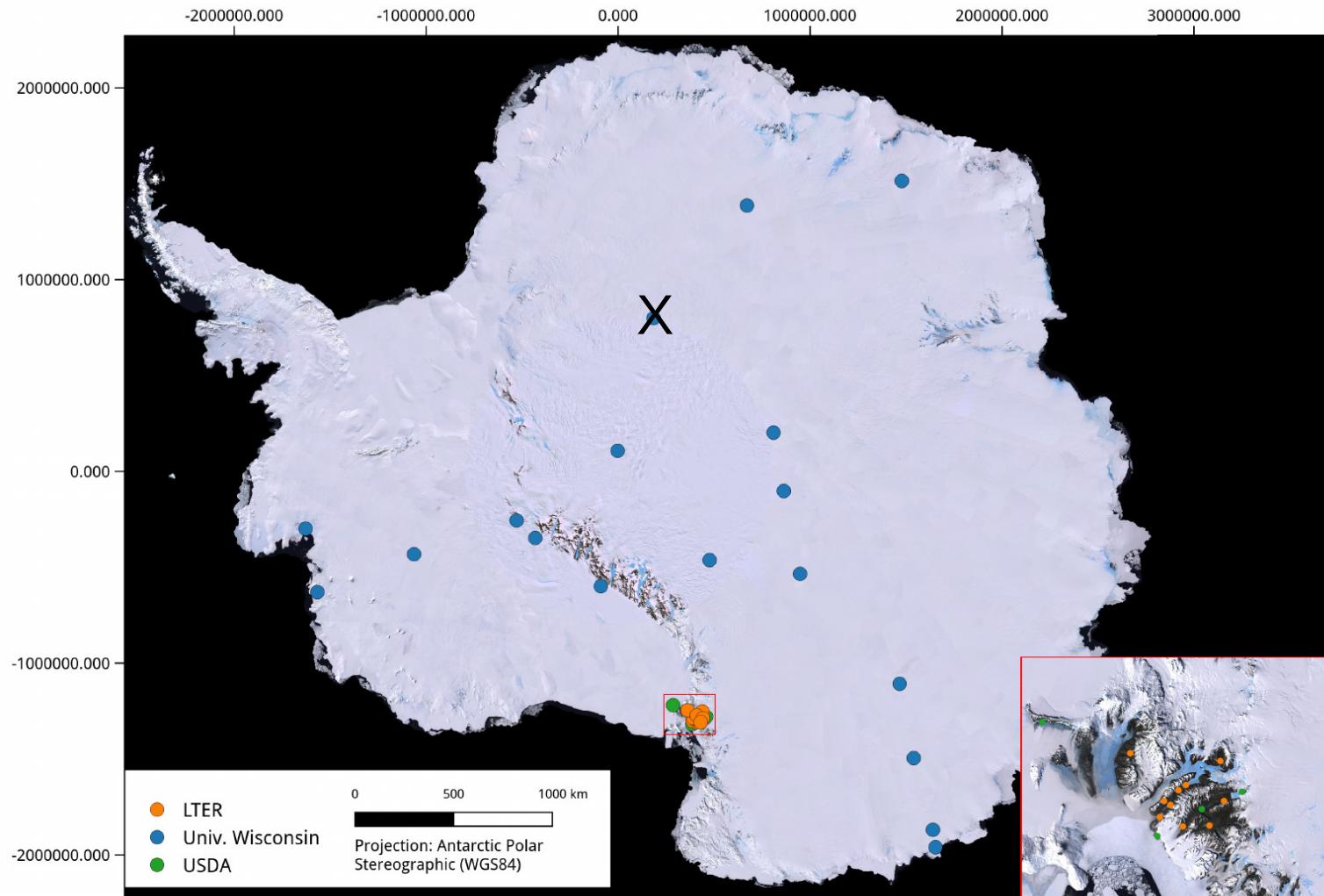
Spatial autocorrelation



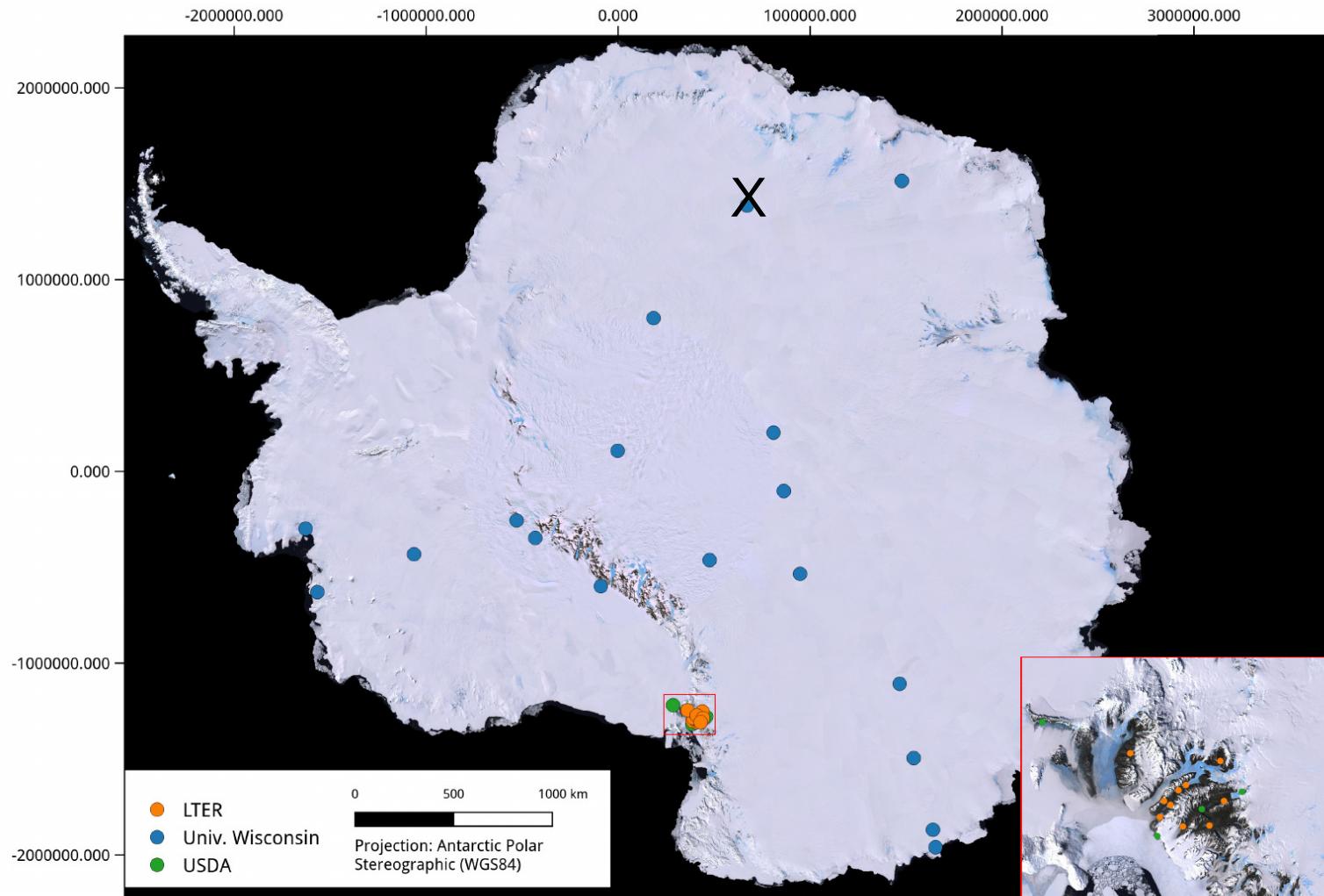
Target-oriented Cross-validation



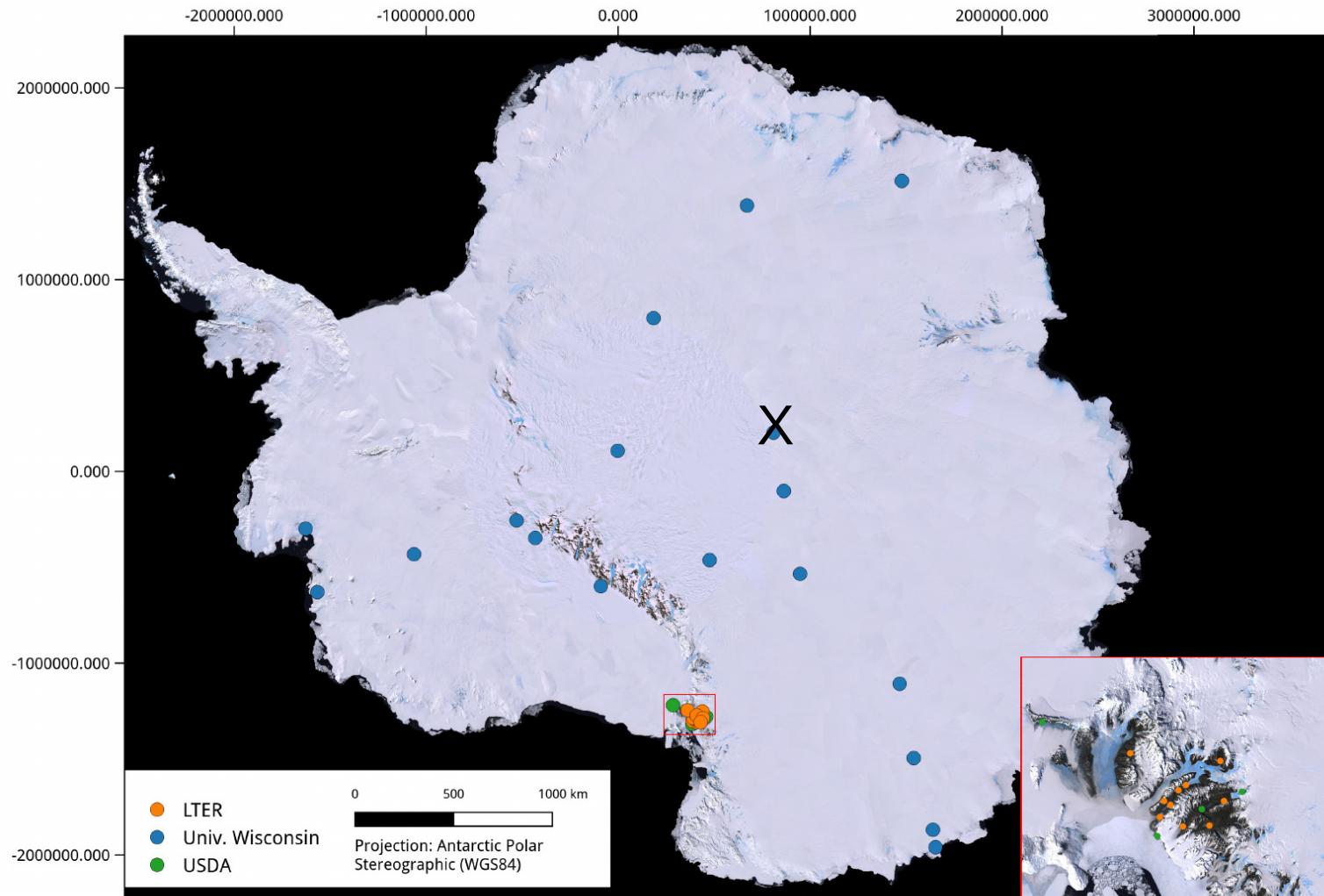
Target-oriented Cross-validation



Target-oriented Cross-validation

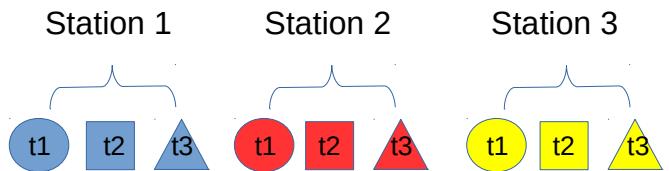


Target-oriented Cross-validation



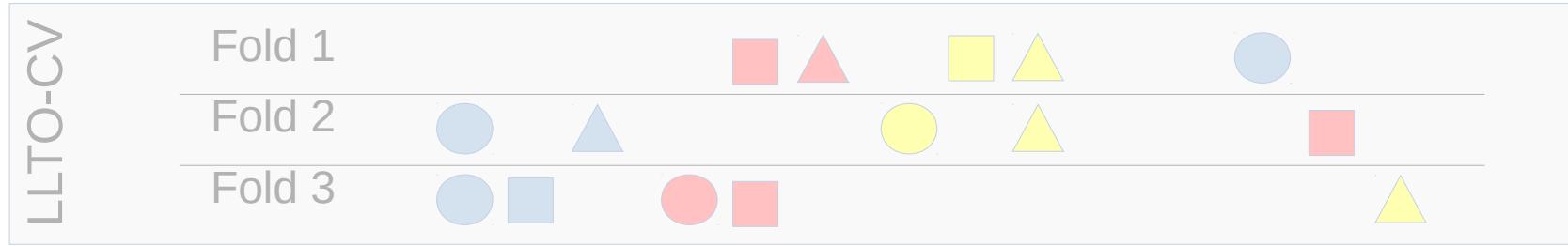
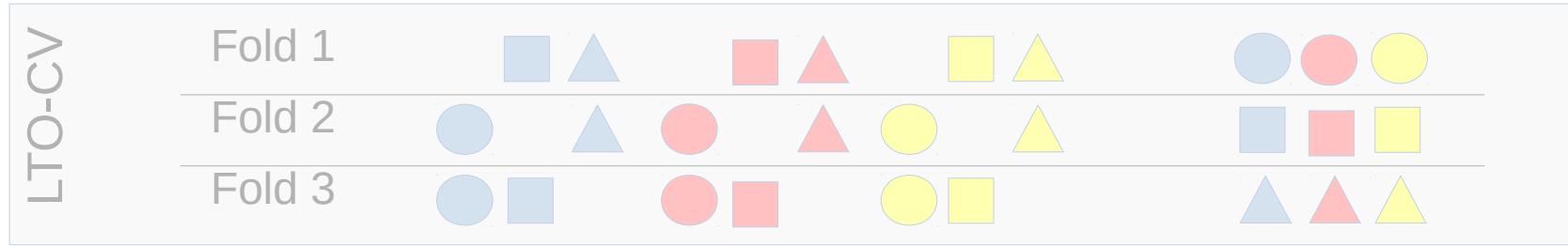
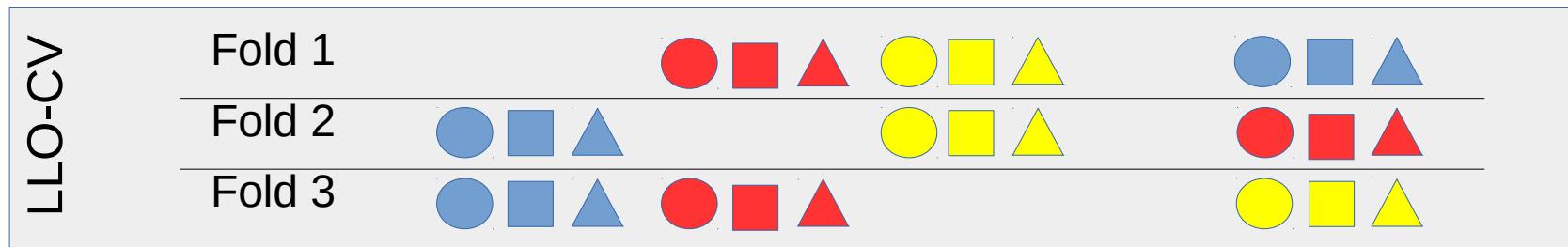
Target-oriented Cross-validation

Total data set



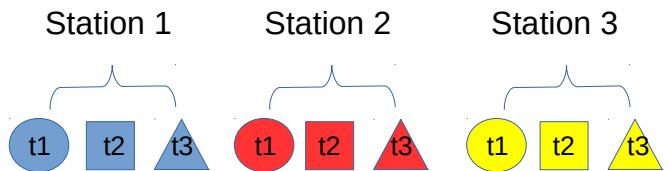
Training data

Test data



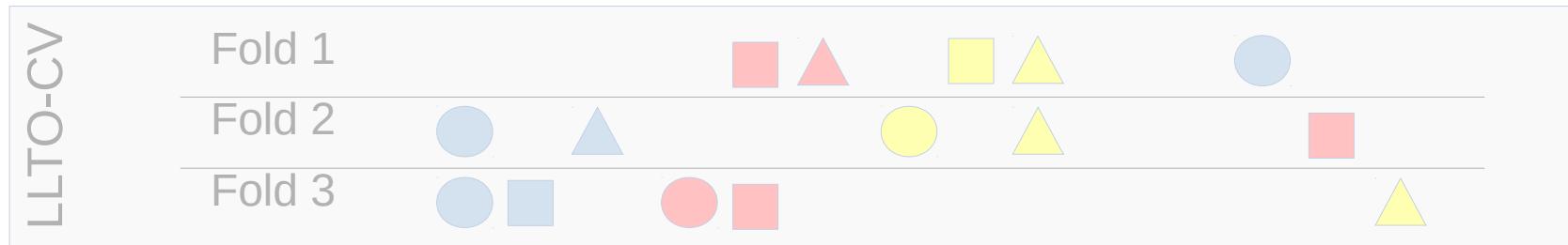
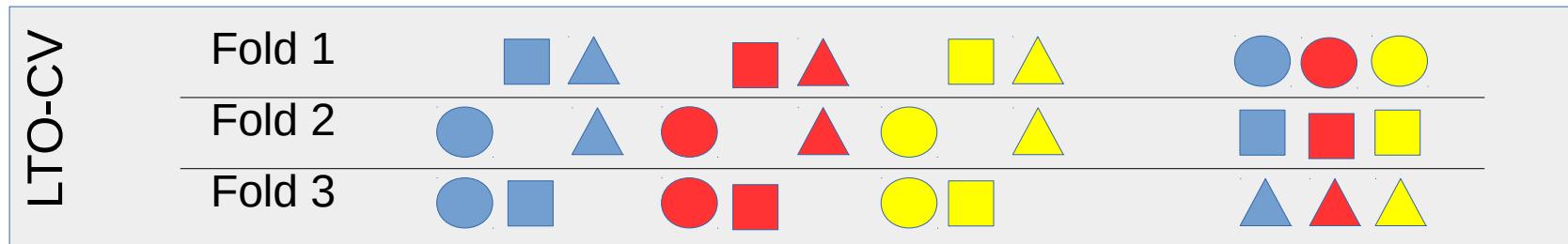
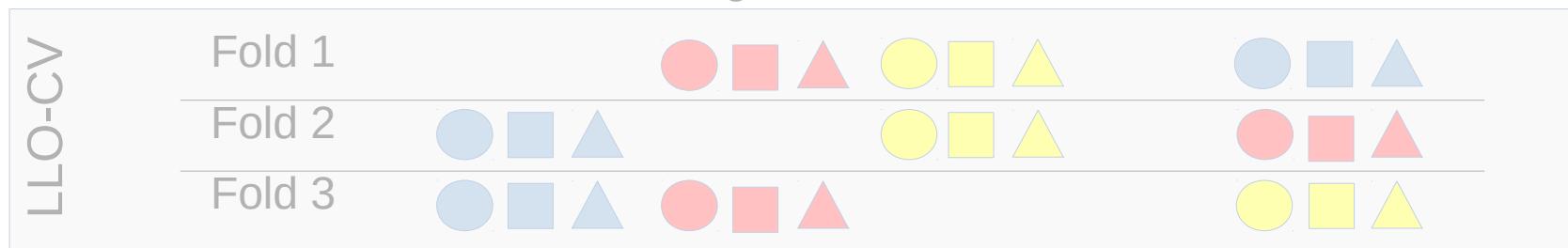
Target-oriented Cross-validation

Total data set



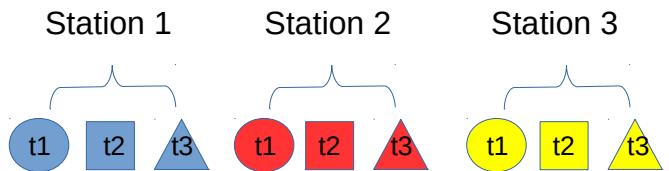
Training data

Test data



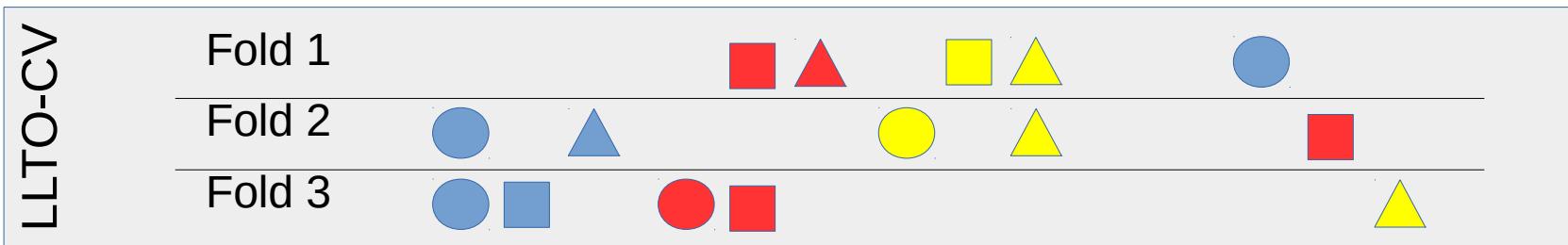
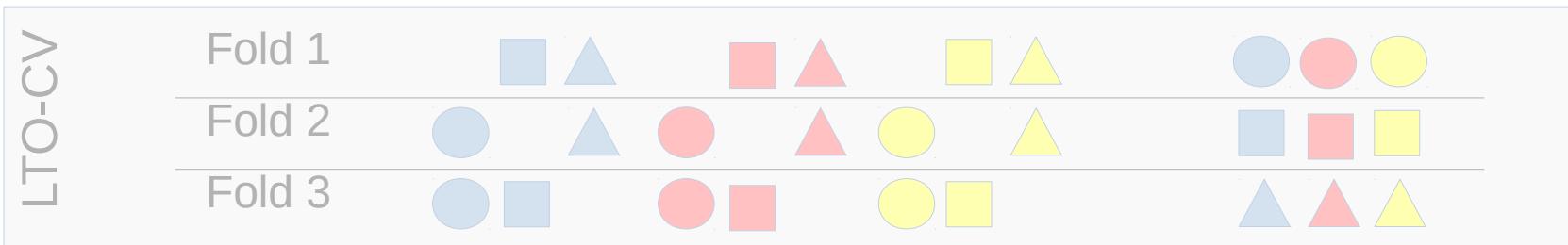
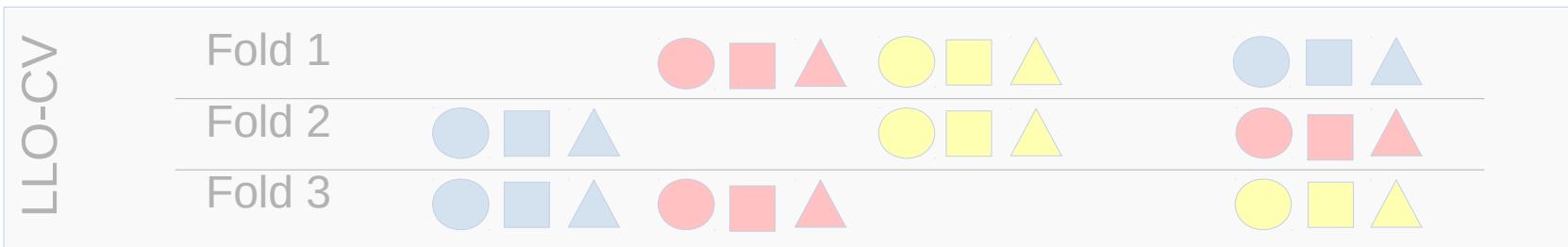
Target-oriented Cross-validation

Total data set



Training data

Test data



Target-oriented Cross-validation

How to do it in R

```
library(CAST)
indices <- CreateSpacetimeFolds(trainingData,
                                  spacevar="Station")
model <- train(predictors,
                response,
                method="rf",
                trControl=trainControl(method="cv",
                                       index = indices$index))
```

Target-oriented Cross-validation

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                                  spacevar="Station")
model <- train(predictors,
                response,
                method="rf",
                trControl=trainControl(method="cv",
                                       index = indices$index))
```

```
> model
Random Forest

30666 samples
  10 predictor

No pre-processing
Resampling: Cross-Validated (10 fold)
Summary of sample sizes: 27610, 28040, 26884, 27501, 28038,
Resampling results:
```

RMSE	Rsquared
14.52991	0.513388

Tuning parameter 'mtry' was held constant at a value of 2

Target-oriented Cross-validation

How to do it in R

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library(CAST)
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Resampling results:

  RMSE      Rsquared
  14.52991  0.513388

Tuning parameter 'mtry' was held constant at a value of 2

> summary(lm(model$pred$pred~model$pred$obs))

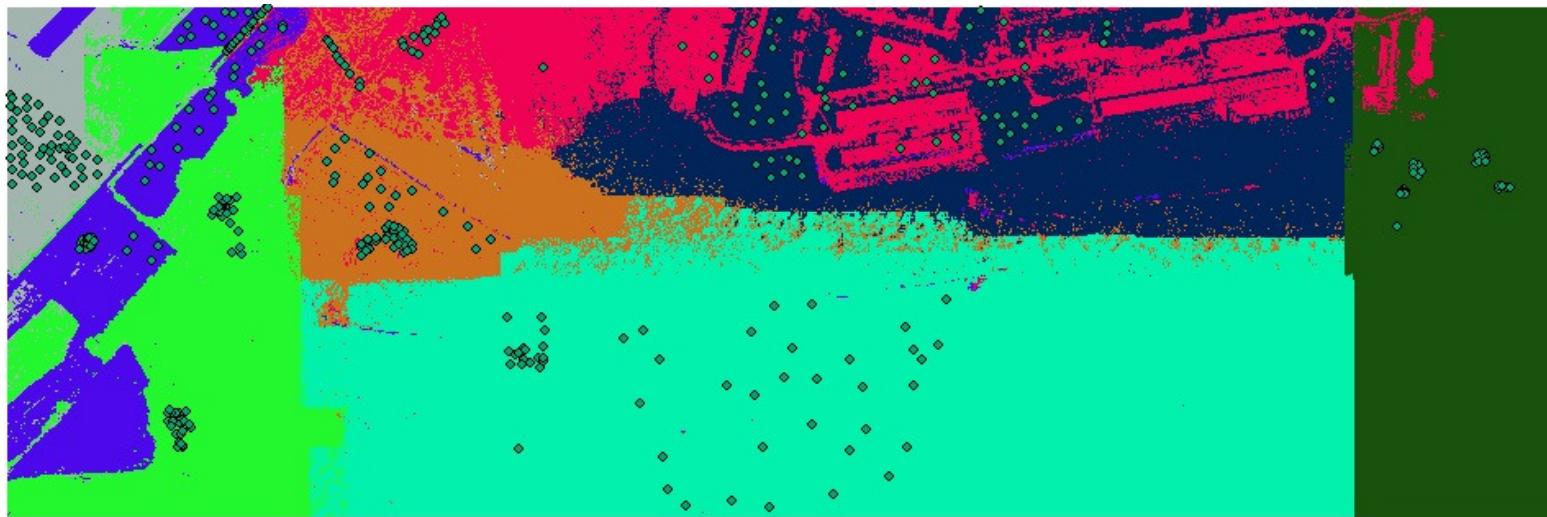
Call:
lm(formula = model$pred$pred ~ model$pred$obs)

Residuals:
    Min      1Q   Median      3Q     Max 
-38.945 -6.416   1.898   8.771  29.176 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) -16.927454   0.127665 -132.59   <2e-16 ***
model$pred$obs  0.389932   0.003918   99.52   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 11.84 on 30664 degrees of freedom
Multiple R-squared:  0.2441,    Adjusted R-squared:  0.2441 
F-statistic: 9905 on 1 and 30664 DF,  p-value: < 2.2e-16
```

Overfitting due to misinterpretations of variables

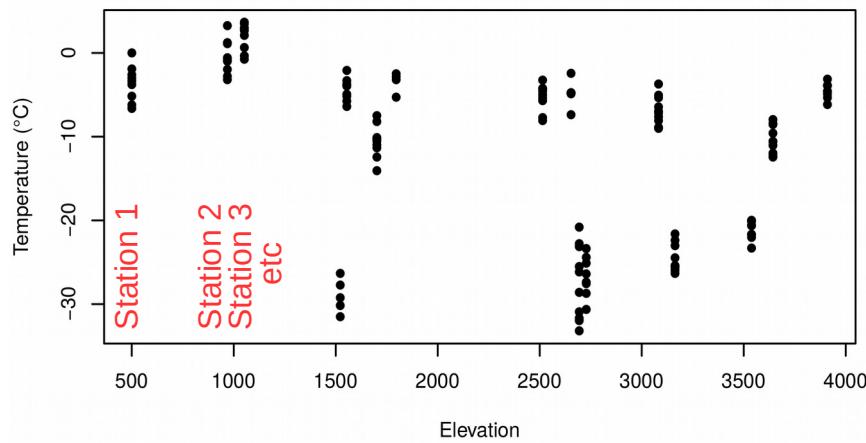


<https://gis.stackexchange.com/questions/111932/classified-images-of-randomforest-classification-look-clustered>

Overfitting due to misinterpretations of variables

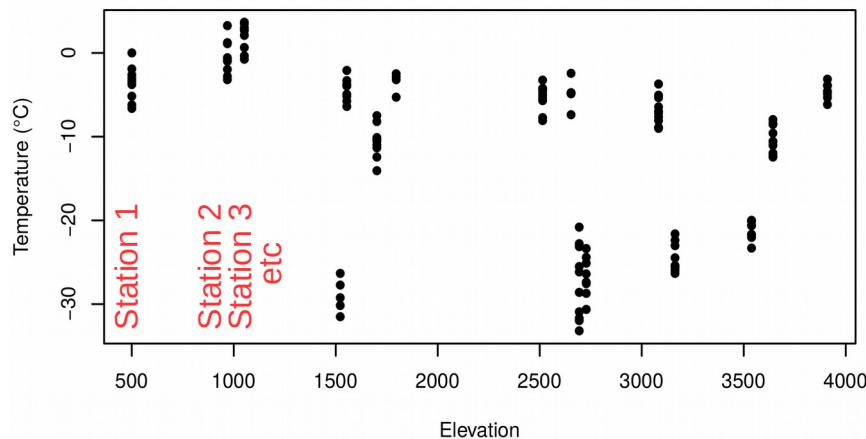
Station	Date	LST	Elevation	Aspect	...	Measured Tair
A	2017/01/01	-5	1000	S		-2
B	2017/01/01	0	200	S		-2
C	2017/01/01	-10	3000	E		-5
A	2017/07/01	-40	1000	S		-45
B	2017/07/01	-30	200	S		-30
C	2017/07/01	-60	3000	E		-70
A	2017/10/01	-20	1000	S		-22
B	2017/10/01	-10	200	S		-9
C	2017/10/01	-25	3000	E		-30

Overfitting due to misinterpretations of variables

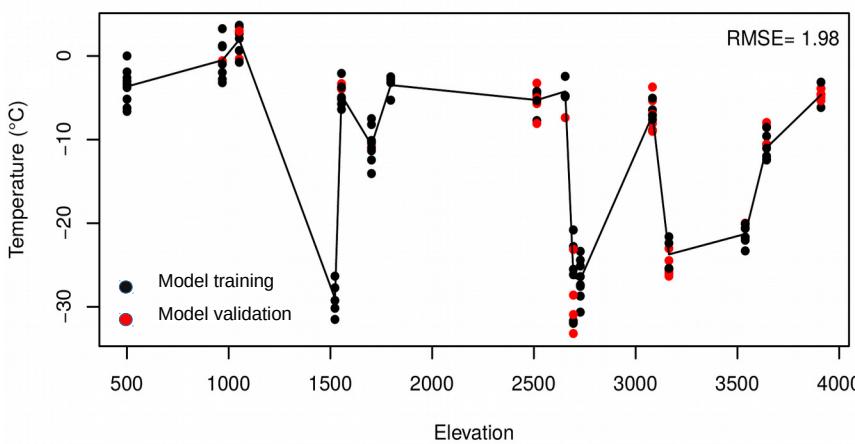


Unique spatial variable for each location
(e.g. elevation)

Overfitting due to misinterpretations of variables

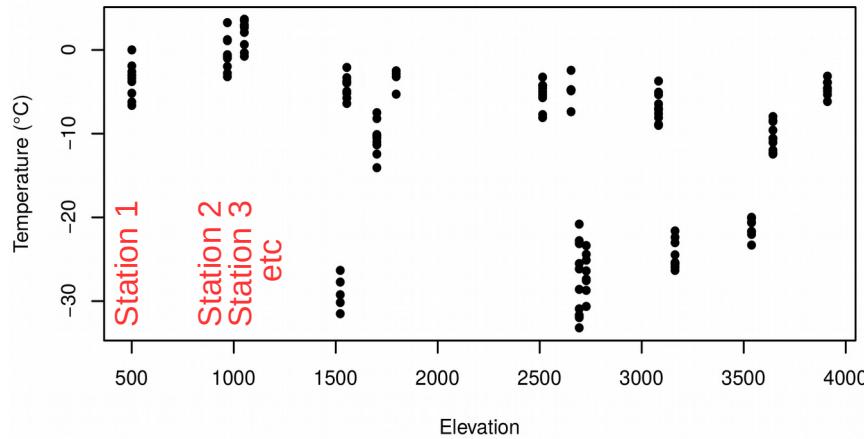


Unique spatial variable for each location
(e.g. elevation)

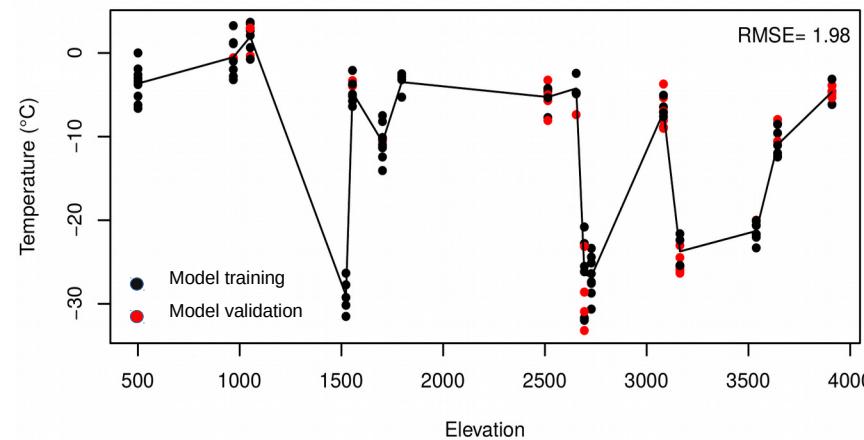


Internal result: elevation is important for the model

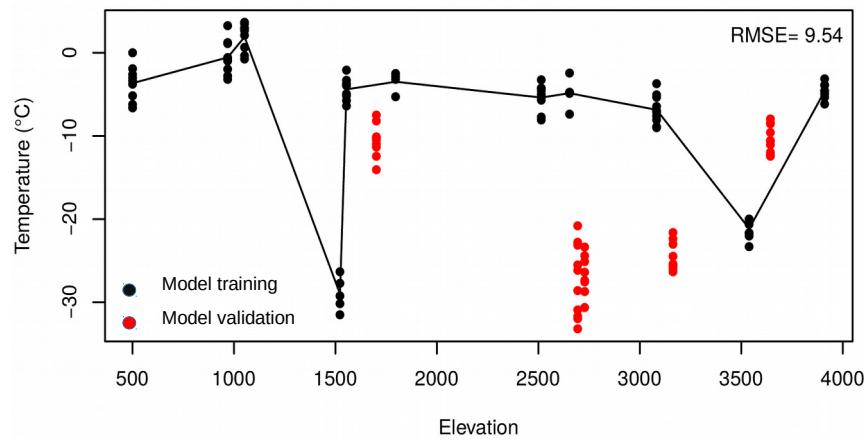
Overfitting due to misinterpretations of variables



Unique spatial variable for each location
(e.g. elevation)



Internal result: elevation is important for the model



...but importance originates from ability of the algorithm to access the individual time series and not from spatial meaning

“Target-oriented” variable selection

```
for each resampling iteration do
    Partition the data into training and test data
    Tune and train models using all possible 2-variable combinations
    Predict on test data and calculate model performance
end
```

LLO cross-validation!

Which 2 variables lead to the best model?

Keep the best performing 2-variable model ($model_{best}$)

```
for each additional number of variables  $i$ ,  $i=3\dots N$  do
```

```
    for each remaining variable  $V_R$  do
```

```
        for each resampling iteration do
```

Partition the data into training and test data

Tune and train models using the variables of $model_{best}$ and V_R

Predict on test data and calculate model performance

```
        end
```

LLO cross-validation!

Which further variables improve the model?

```
    end
```

```
    if  $mean(error \ of \ model_i) > mean(error \ of \ model_{best})$  then
```

| break

```
end
```

Keep the best performing i-variable model ($model_{best}$)

```
end
```

“Target-oriented” variable selection in R

How to do it in R

```
library(CAST)
indices <- CreateSpacetimeFolds(trainingData,
                                  spacevar="Station")
model <- ffs(predictors,
              response,
              method="rf",
              trControl=trainControl(method="cv",
                                      index = indices$index))
```

“Target-oriented” variable selection in R

How to do it in R

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```

```
> model
Random Forest

30666 samples
  5 predictor

No pre-processing
Resampling: Cross-Validated (10 fold)
Summary of sample sizes: 27610, 28040, 26884, 27501, 28038,
Resampling results:

RMSE      Rsquared
11.60326  0.596083

Tuning parameter 'mtry' was held constant at a value of 2
```

“Target-oriented” variable selection in R

How to do it in R

```
library(CAST)
indices <- CreateSpacetimeFolds(trainingData,
                                  spacevar="Station")
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              method="rf",
              trControl=trainControl(method="cv",
                                      index = indices$index))
```

```
> model
Random Forest
30666 samples
  5 predictor
No pre-processing
Resampling: Cross-Validated (10 fold)
Summary of sample sizes: 27610, 28040, 26884, 27501, 28038,
Resampling results:
RMSE      Rsquared
11.60326  0.596083

Tuning parameter 'mtry' was held constant at a value of 2
```

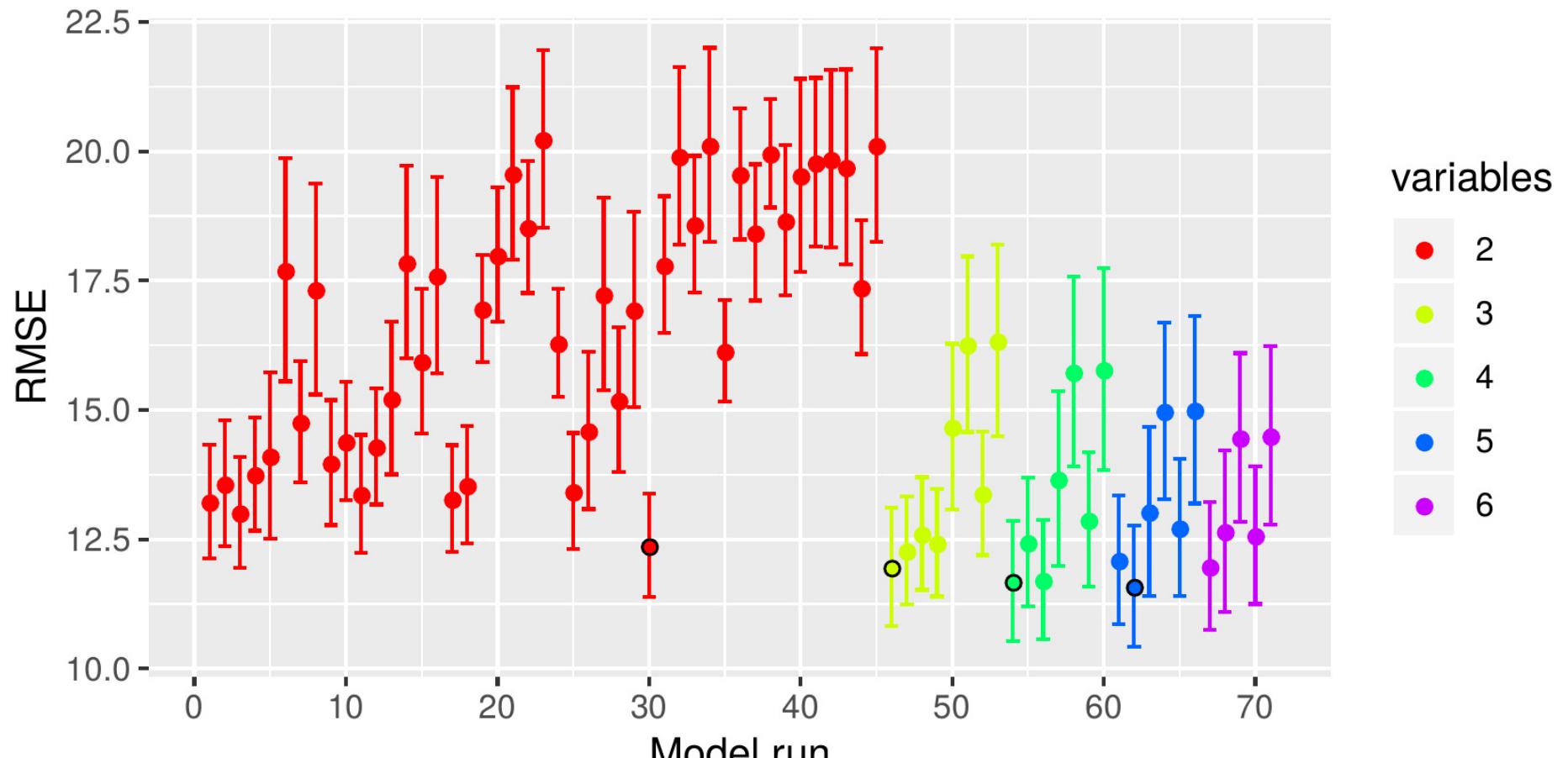
```
> summary(lm(model$pred$pred ~ model$pred$obs))
Call:
lm(formula = model$pred$pred ~ model$pred$obs)

Residuals:
    Min      1Q  Median      3Q     Max 
-31.0891 -5.1795  0.6637  6.7039 30.3651 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) -13.433596   0.101226 -132.7   <2e-16 ***
model$pred$obs  0.516511   0.003107  166.3   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.391 on 30664 degrees of freedom
Multiple R-squared:  0.4741,    Adjusted R-squared:  0.4741 
F-statistic: 2.764e+04 on 1 and 30664 DF,  p-value: < 2.2e-16
```

“Target-oriented” variable selection in R



Selected variables: “LST”, “month”, “ice”, “season”, “sensor”

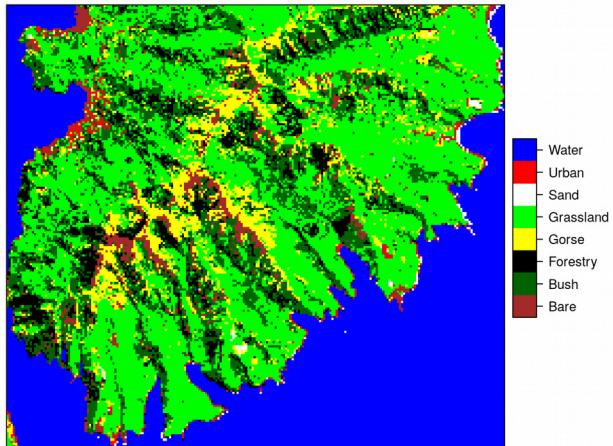
Take home messages

- ML has great potential for spatial and spatio-temporal predictions
- Caret allows for easy model training
- But spatial data need adapted ML frameworks
- Target-oriented error assessment is important: LLO as shown here or block CV (Roberts 2015), spatial CV (Brenning 2012)
- Risk of overfitting by misinterpretation of predictor variables
- Avoid overfitting by careful variable selection (e.g. automatically via CAST)

Outlook computer practice

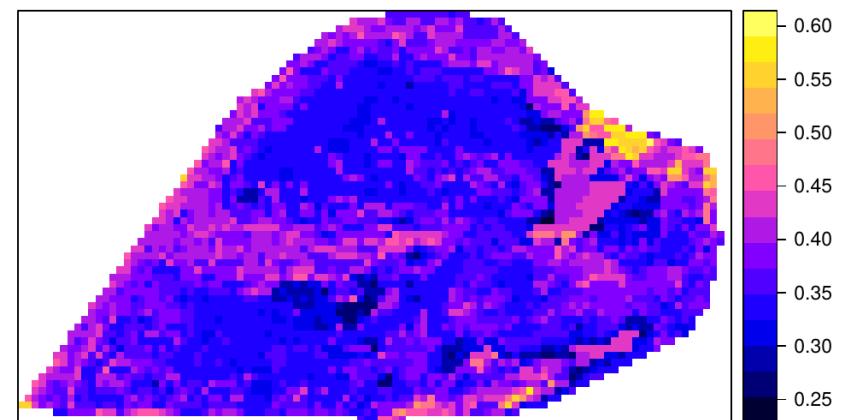
Case Study I: Land cover classification

- Task: Identify the invasive gorse on the Banks Peninsula in New Zealand based on Sentinel satellite data
- Technical Challenge: “Simple” ML model training for spatial predictions



Case Study II: Spatio-temporal predictions

- Task: Model soil moisture in space and time for the cookfarm
- Technical Focus: Sensitivity of ML to different CV strategies and variable selection



References

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