Using shape constrained additive models (SCAM) to quantify climate and site effects on forest productivity

Dr. Matthias Albert and Dr. Matthias Schmidt,
Abt. Waldwachstum, NW-FVA

NW-FVA

Workshop on Applied Statistics in Ecological and Environmental Science
Freiburg, November 7-9, 2012

Outline

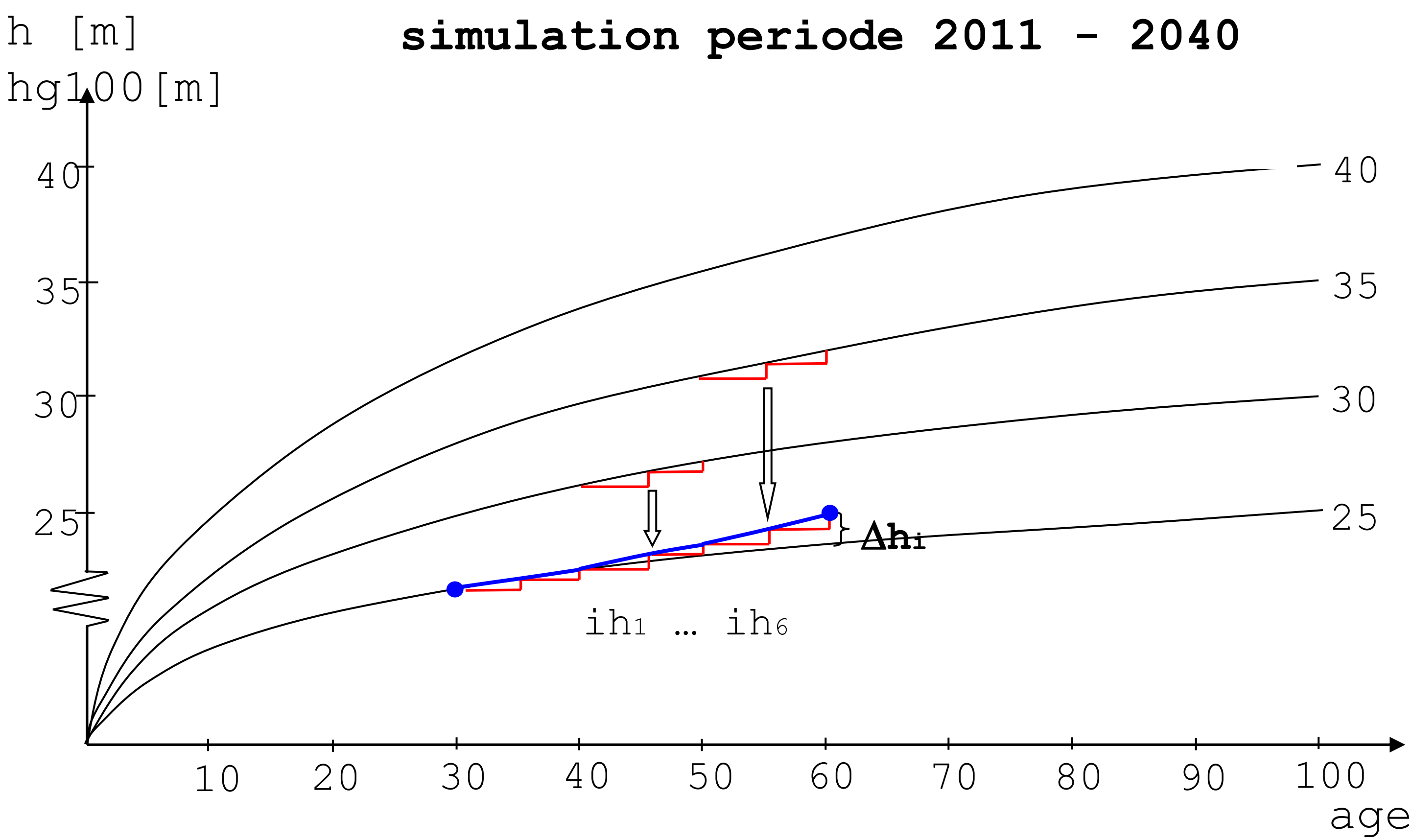
1. Motivation
2. Comparison first model approach and new method
3. Data base
4. Model formulation
5. Sensitivity analysis and first results
6. Conclusions, challenges and open questions

1. Motivation

Forest Growth – Climate Change

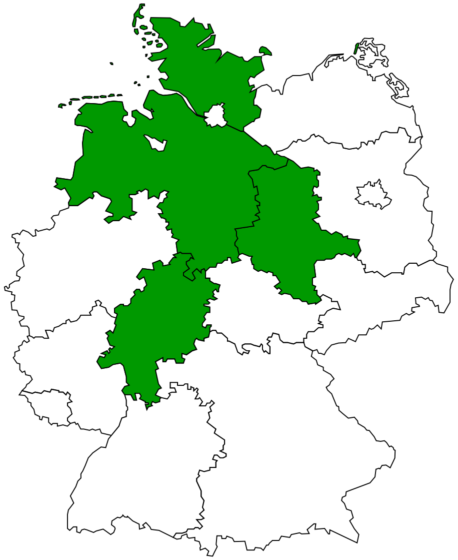
change = dynamics = static models have to be replaced

Principle of constant site conditions is not valid anymore even for medium term periods



1. Motivation

Developing mitigation and adaptation strategies

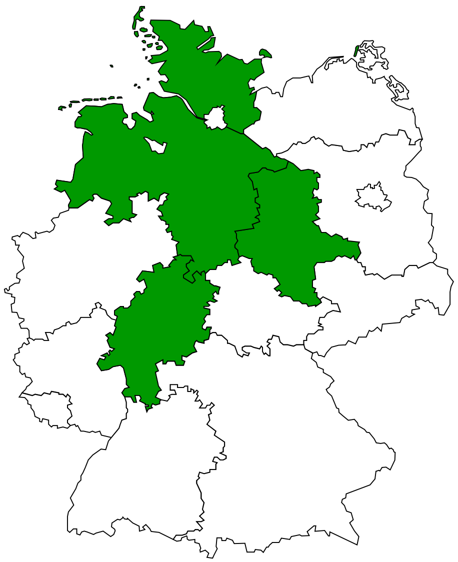


site-productivity relationship = f [**climate change**]

?

1. Motivation

Developing mitigation and adaptation strategies



site-productivity relationship = f [**climate change**]

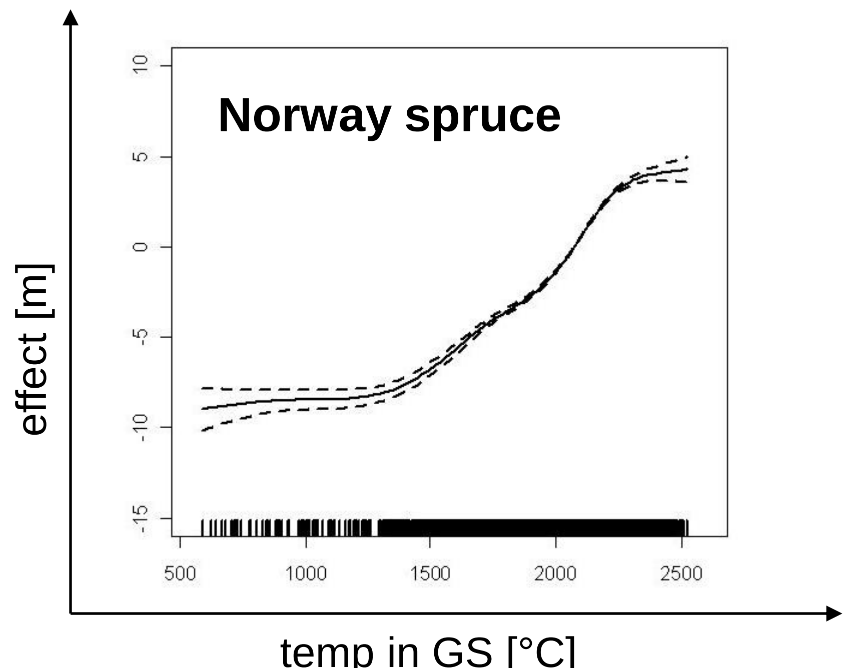
2. First Model Approach

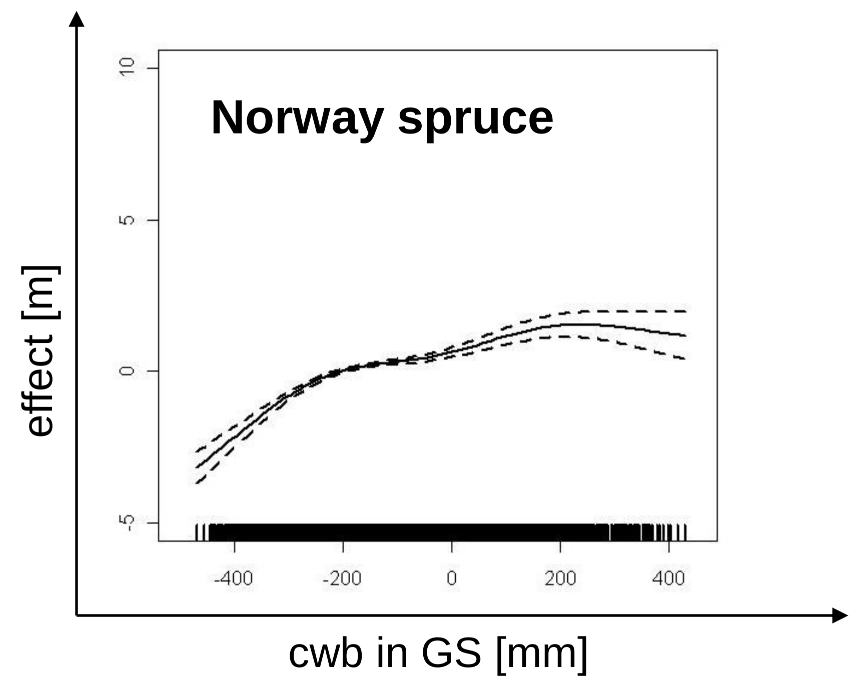
-GAM, parameterized with nationwide data set
-Climate variables modeled with WETTREG
-Mean values for climate normal period 1961 to 1990

R version 2.10.0
library mgcv 1.6-0

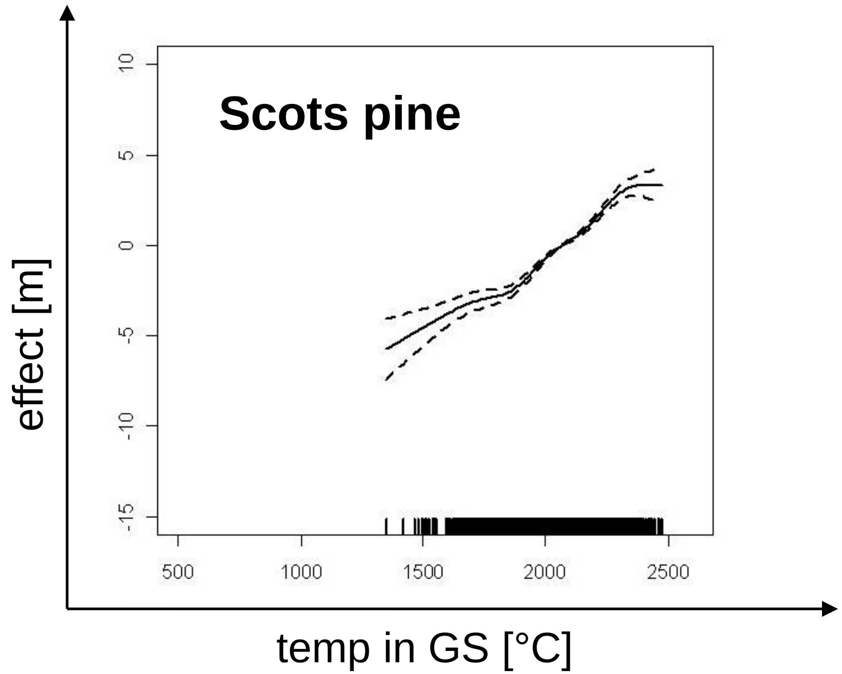
$$hg100_i = \alpha_i + nut_i^T \beta + f_1(temp_i) + f_2(cwb_i) + f_3(asm_i) + f_4(Ndep_i) + f_5(lon_i, lat_i) + \varepsilon_i$$
$$\varepsilon_i = N(0, \sigma^2)$$

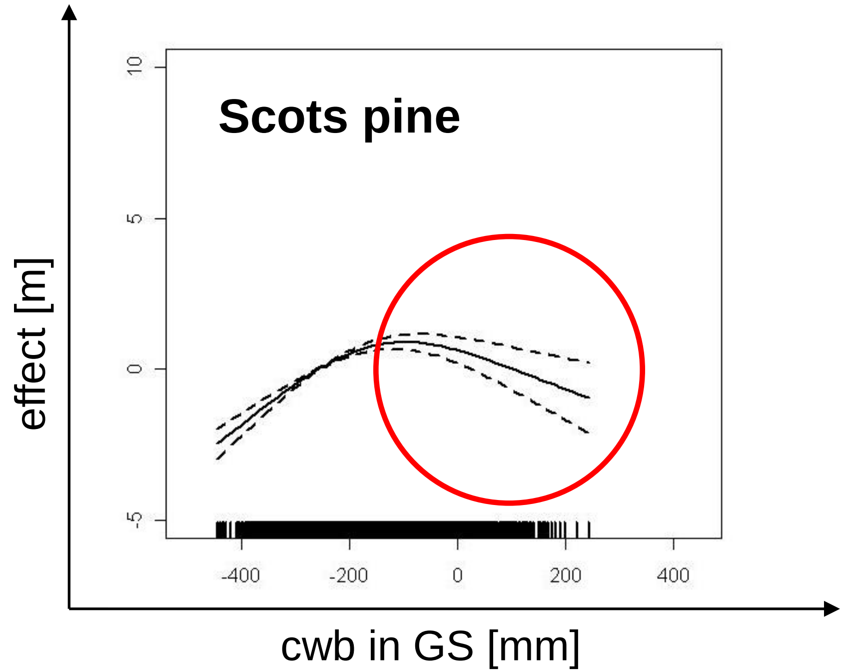
spruce: $R^2 = 0.44$ se = 3.1 m





2. First Model Approach





NW-FVA
Nordwestdeutsche Forstliche Versuchsanstalt

HESSEN

2. New Method

Hope for improvement

-measured climate values (DWD data)

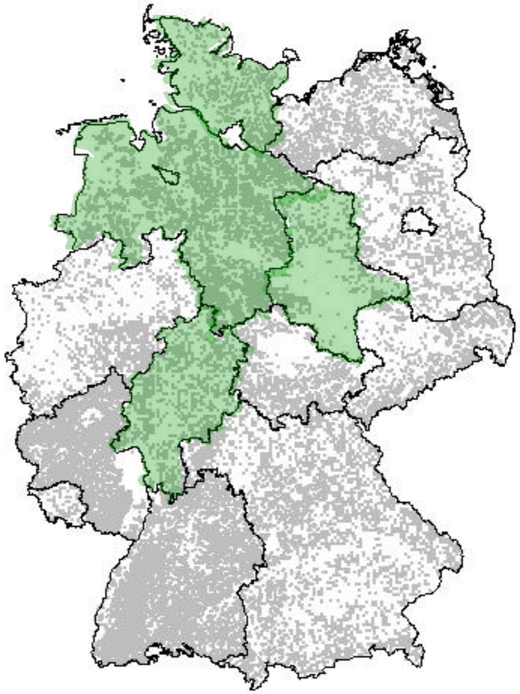
-dynamic reference period for each stand: time of establishment to inventory date

-SCAM technology to prevent unplausible effect curves

-logarithmic transformation, i.e. exponential multiplicative combination of explanatory variables

R version 2.14.1
library mgcv 1.7-12
library scam 1.1-1

3. Data base



Yield data:
- ***inventory data*** of National Forest Inventory and Lower Saxony Forest Enterprise Inventory
- ***site index*** (modeled) (*Schmidt, 2008*)

for spruce: N=57,096

4. Model Formulation

Model stage 1

$$\log(E[hg100_i]) = \alpha_1 + f_1(Temp_i) + f_2(Ari_i) + \varepsilon_i; \quad E[hg100_i] \sim \mathit{Gamma}$$

Model stage 2

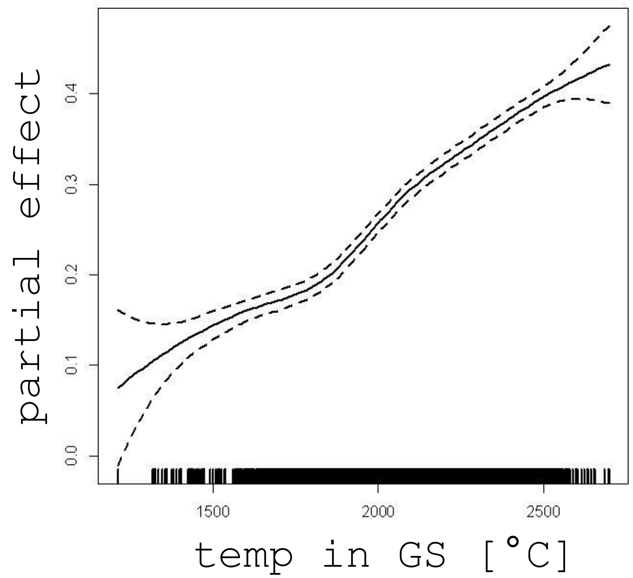
$$\log(E[hg100_i]) = \alpha_1 + nut_i^T\beta + \hat{f}_1(Temp_i) + \hat{f}_2(Ari_i) + f_3(asm) + f_4(Ndep_i)$$
$$+ f_5(lon_i, lat_i) + \varepsilon_i; \quad E[hg100_i] \sim \mathit{Gamma}$$

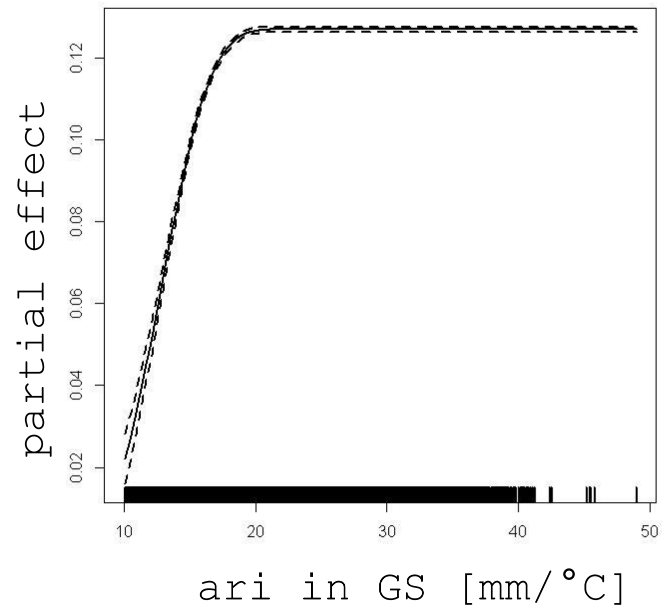
monotone increasing P-splines bs="mpi"

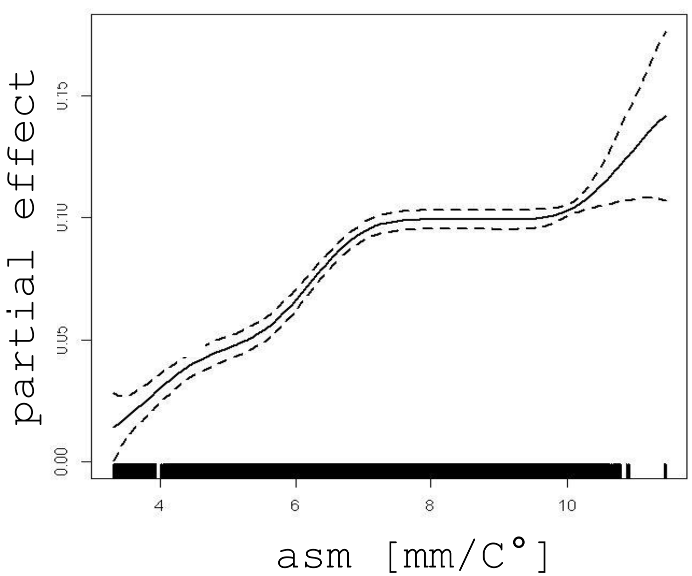
Norway spruce **R^2=0.42; se=3.2 m**

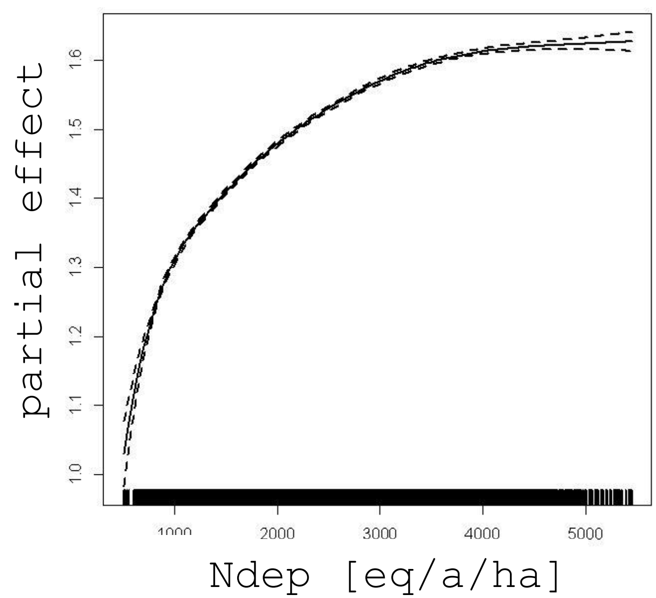
```
Stage 1
Parametric coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)   3.0430     0.1312    23.2   <2e-16 ***

Approximate significance of smooth terms:
              edf Ref.df      F  p-value
s(tempsum) 4.903  4.903 974.82  < 2e-16 ***
s(ari)     1.017  1.017  66.16 2.53e-16 ***

Stage 2
Parametric coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.460414   0.182703   7.993 1.34e-15 ***
nut314       0.027679   0.002772   9.985  < 2e-16 ***
nut321      -0.101653   0.003688 -27.560  < 2e-16 ***
nut322      -0.005868   0.002643  -2.220   0.0264 *
nut323       0.037575   0.002409  15.595  < 2e-16 ***

Approximate significance of smooth terms:
                edf  Ref.df      F p-value
s(ndep)       5.966   5.966 2377.9  <2e-16 ***
s(mod_nFK)    3.938   3.938  154.2  <2e-16 ***
s(lon,lat) 171.837 171.837  141.0  <2e-16 ***
```

4. Model Formulation

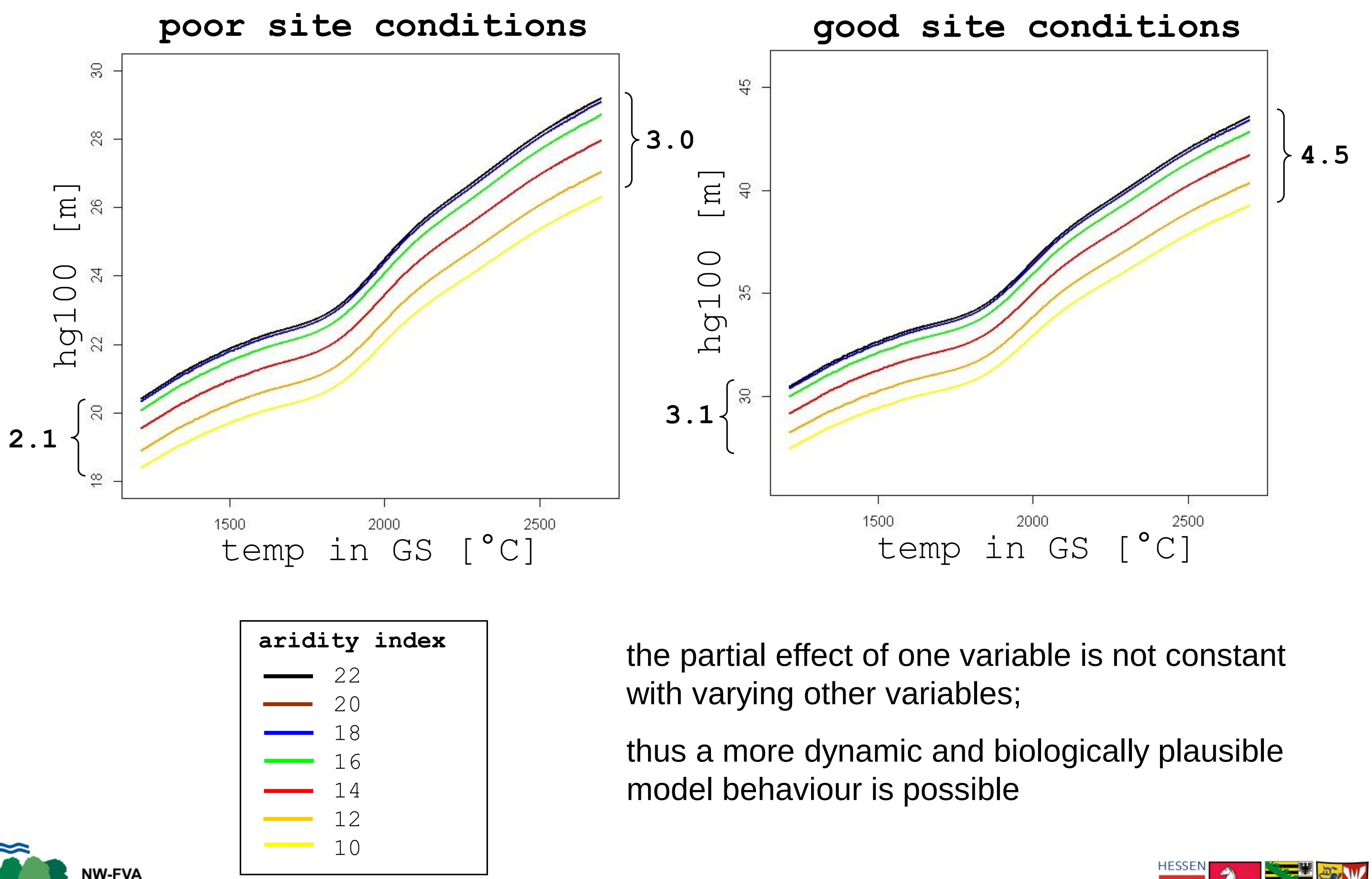








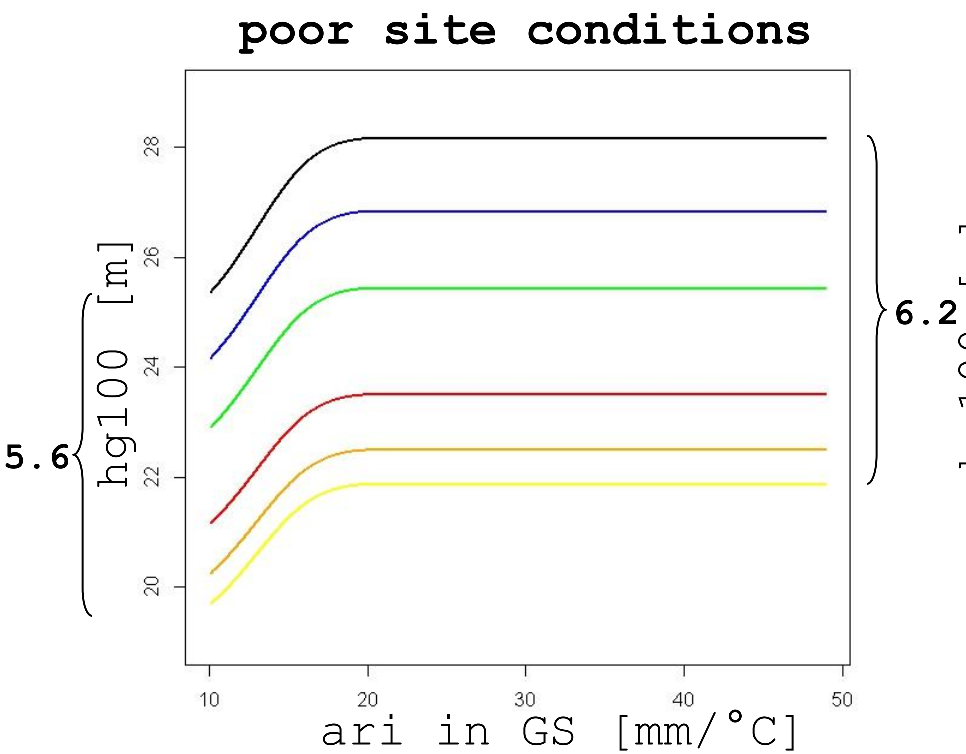
5. Sensitivity and Results

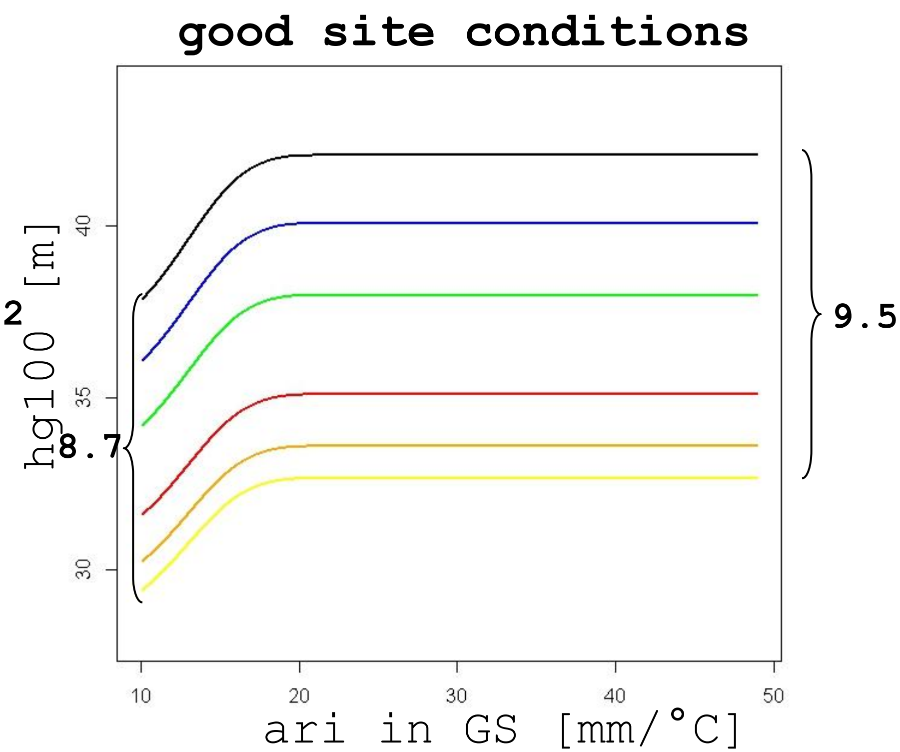


the partial effect of one variable is not constant with varying other variables;

thus a more dynamic and biologically plausible model behaviour is possible

5. Sensitivity and Results



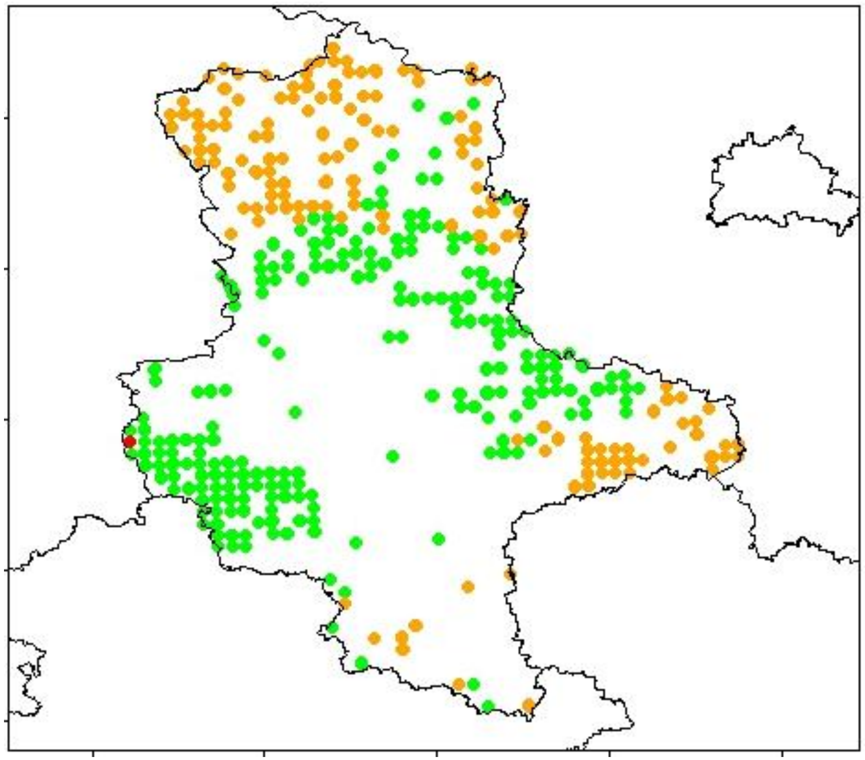


temp	
black	2500
blue	2300
green	2100
red	1900
orange	1700
yellow	1500

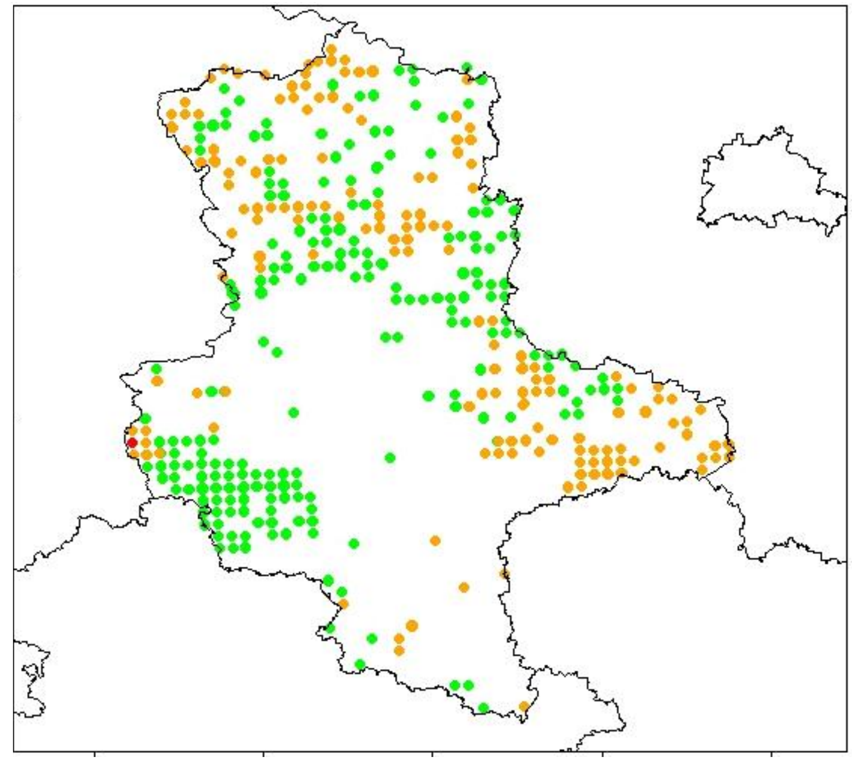
5. Sensitivity and Results

Status quo

GAM



SCAM

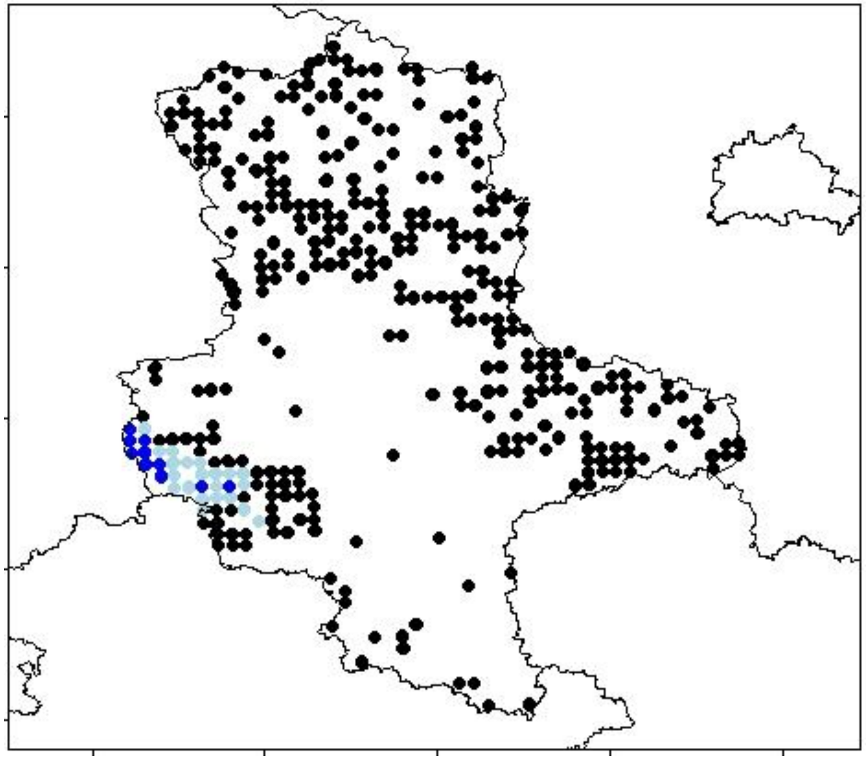


- I.5 yield class (and better)
- I.5 to II.5 yield class
- II.5 yield class (and worse)

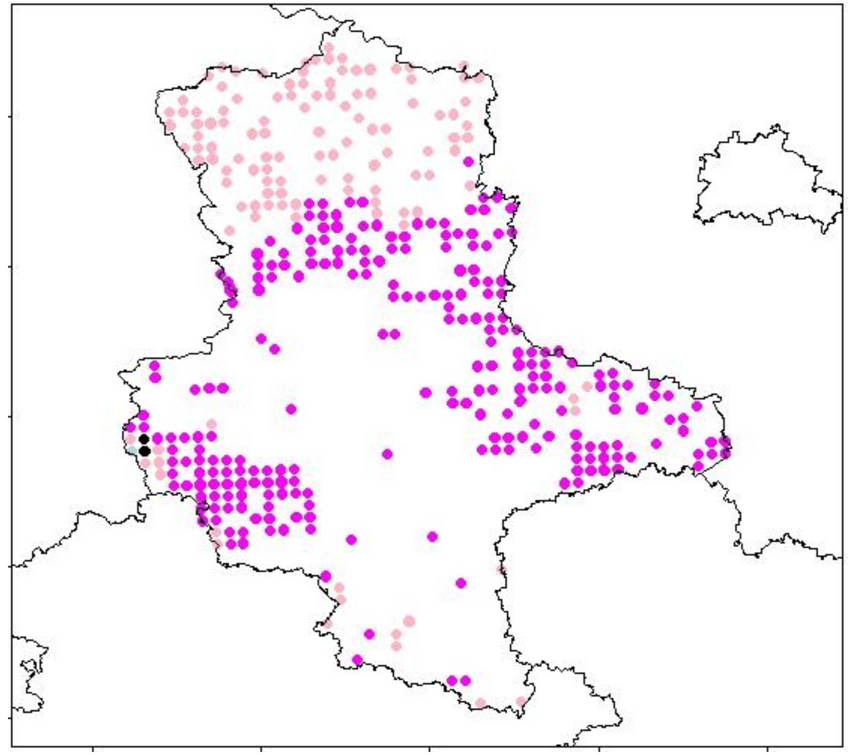
5. Sensitivity and Results

2011 – 2040

GAM



SCAM



projection WETTREG2010, scenario A1B, var05

- > 7,5 %
- 2,5 % to 7,5 %
- -2,5 % to 2,5 %
- -2,5 % to -7,5 %
- < -7,5 %

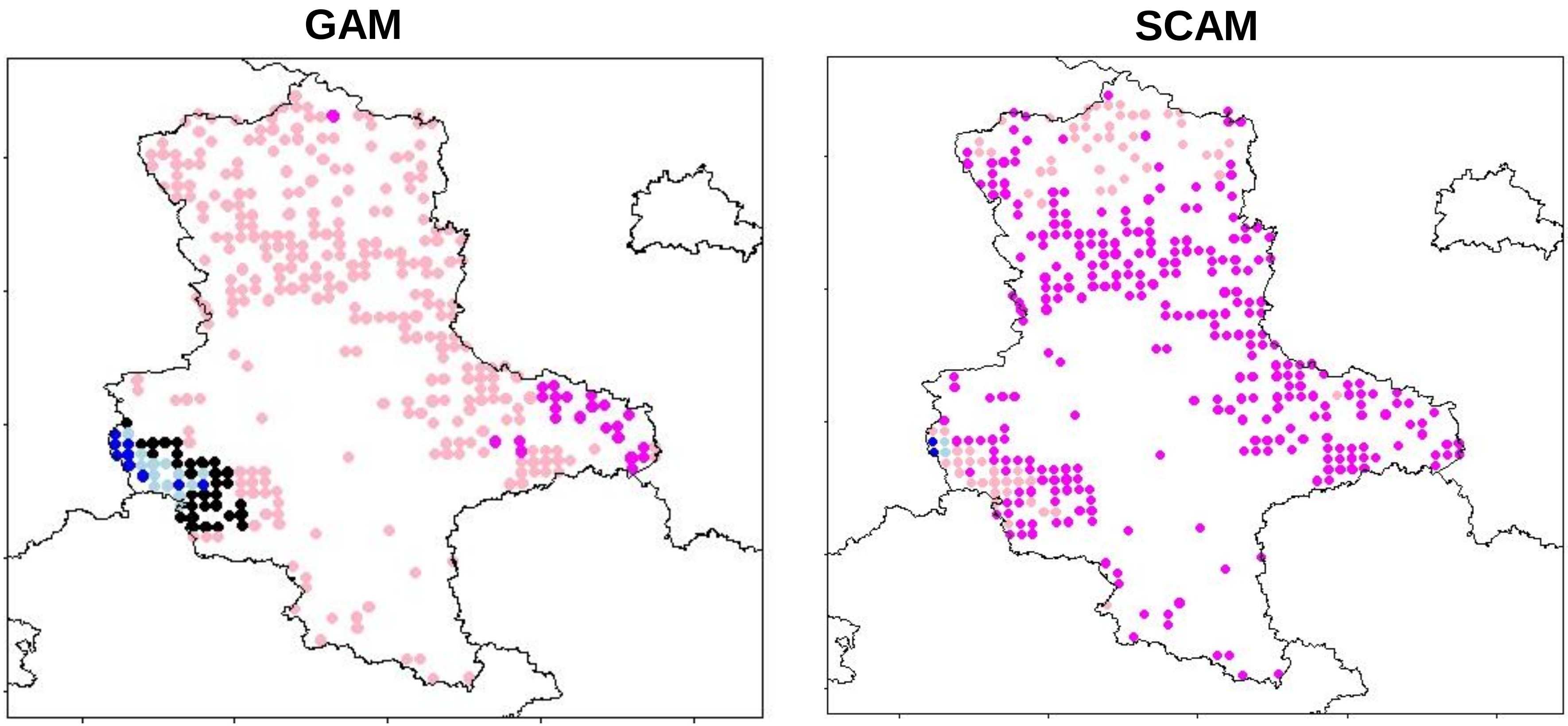
NW-FVA

Nordwestdeutsche Forstliche Versuchsanstalt

HESSEN

5. Sensitivity and Results

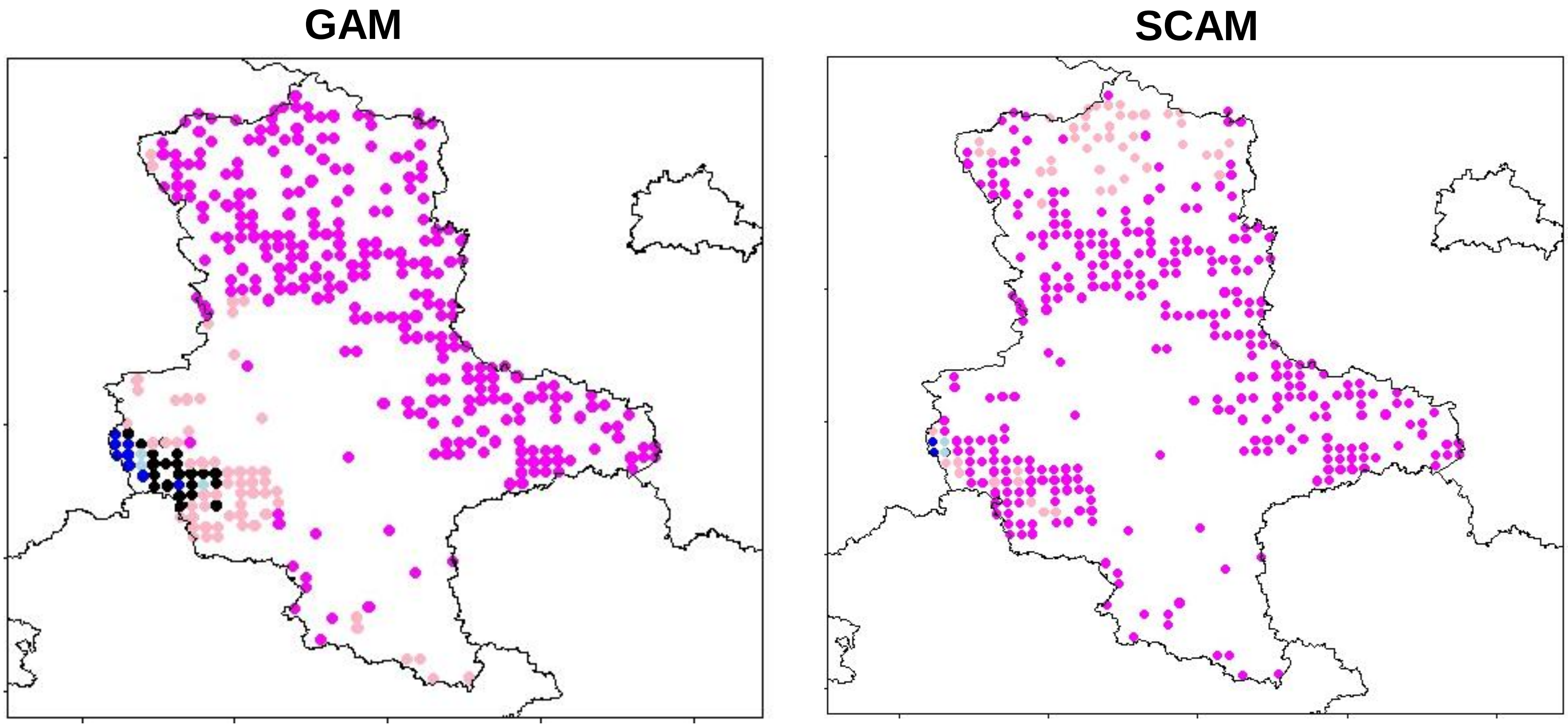
2041 - 2070



> 7,5 %
2,5 % to 7,5 %
-2,5 % to 2,5 %
-2,5 % to -7,5 %
< -7,5 %

5. Sensitivity and Results

2071 - 2100

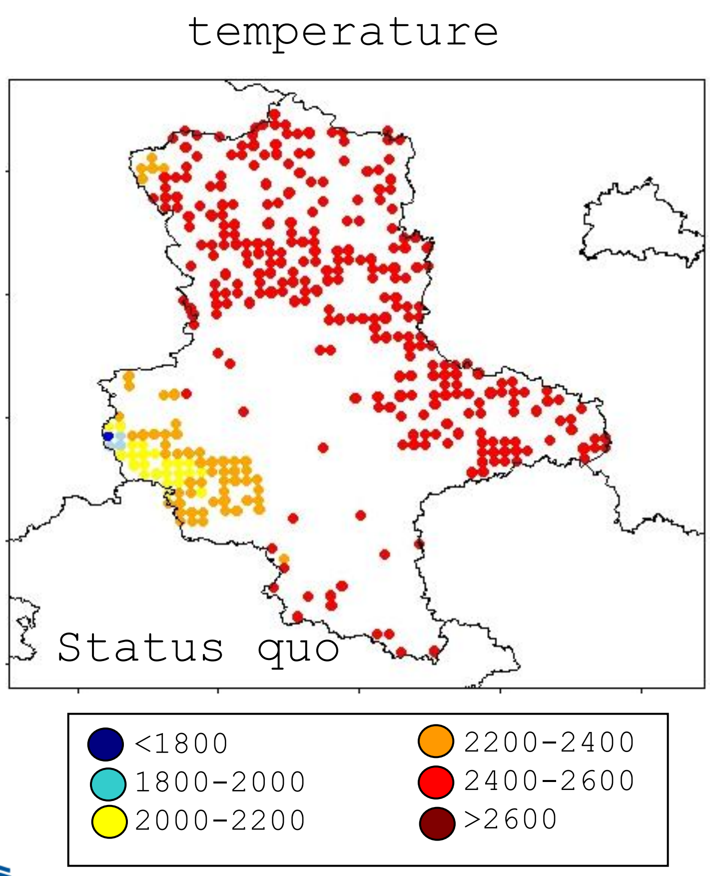


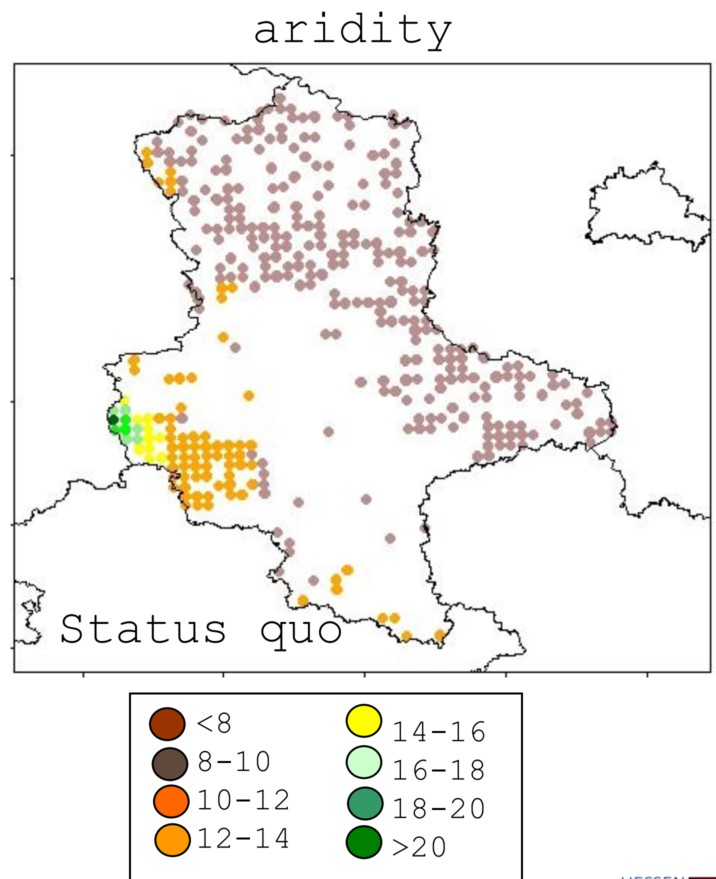
- > 7,5 %
- 2,5 % to 7,5 %
- -2,5 % to 2,5 %
- -2,5 % to -7,5 %
- < -7,5 %

6. Conclusions, challenges, questions

GAM formulation shows more dynamics over time, SCAM indicates servere change in first period, rather few changes in following predictions

Which behaviour is more realistic, i.e. best represents projected climate change?

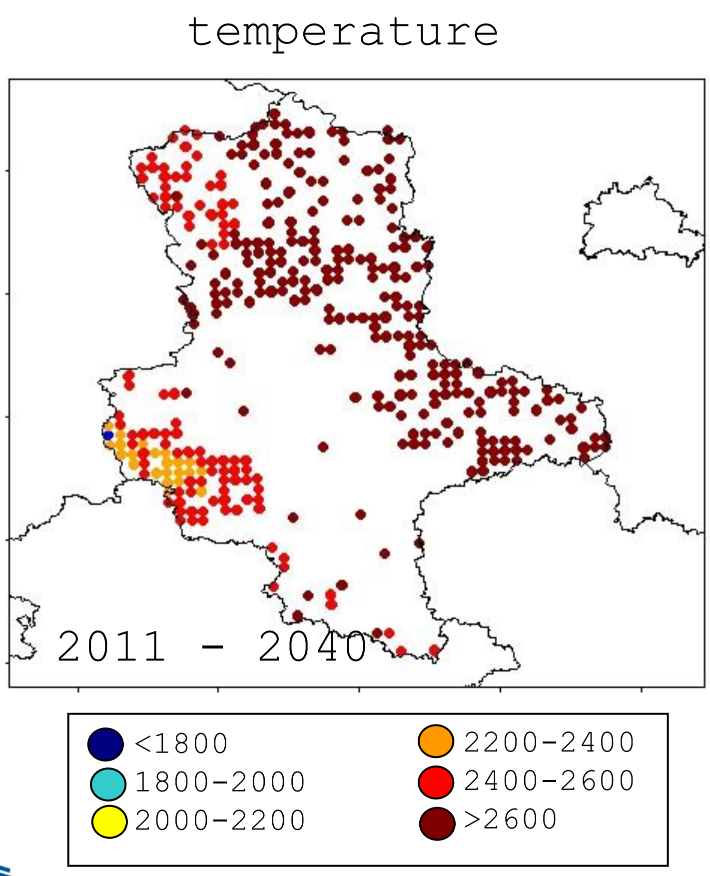


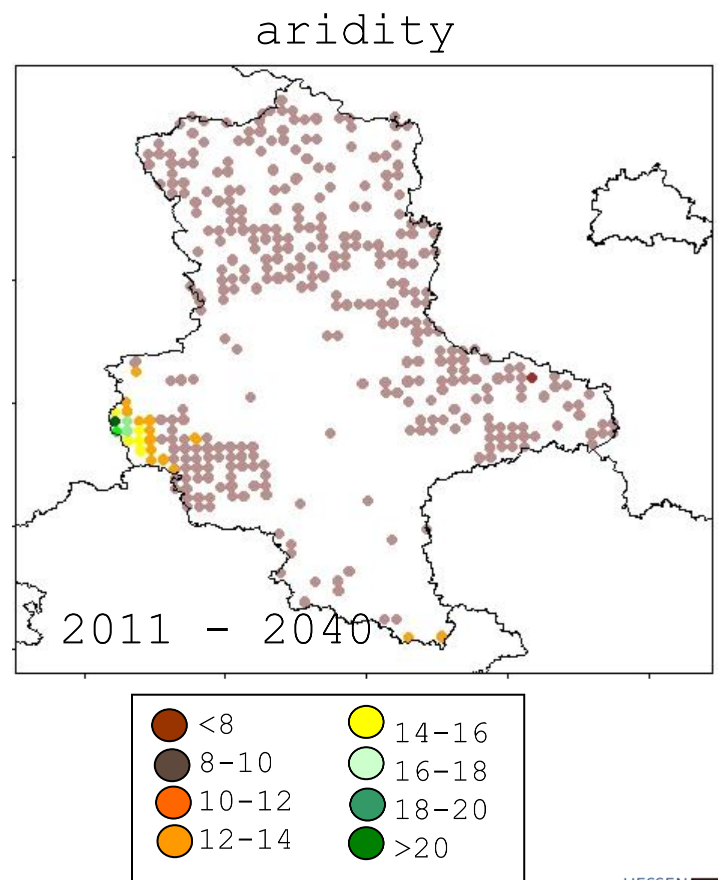


6. Conclusions, challenges, questions

GAM formulation shows more dynamics over time, SCAM indicates servere change in first period, rather few changes in following predictions

Which behaviour is more realistic, i.e. best represents projected climate change?





NW-FVA
Nordwestdeutsche Forstliche Versuchsanstalt

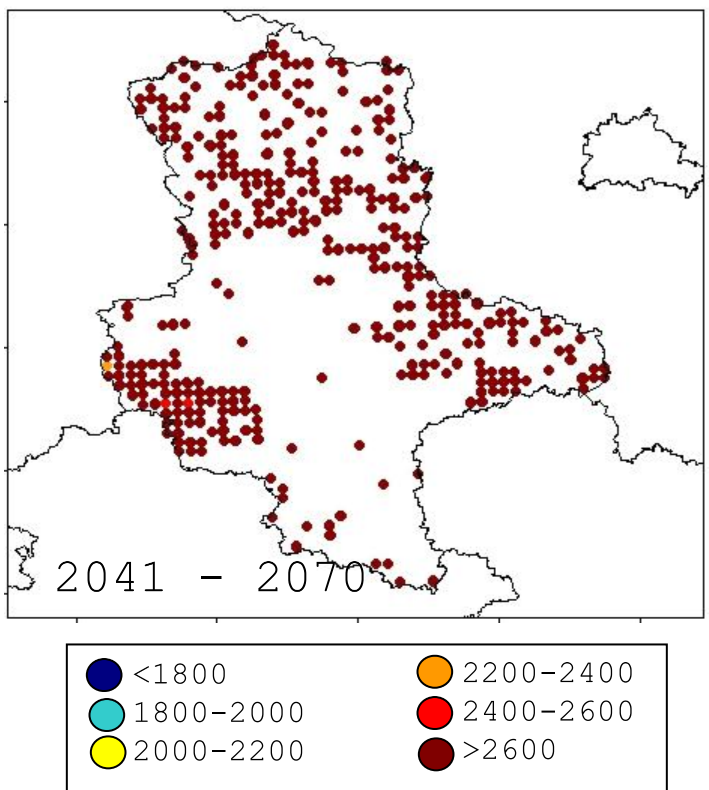
HESSEN

6. Conclusions, challenges, questions

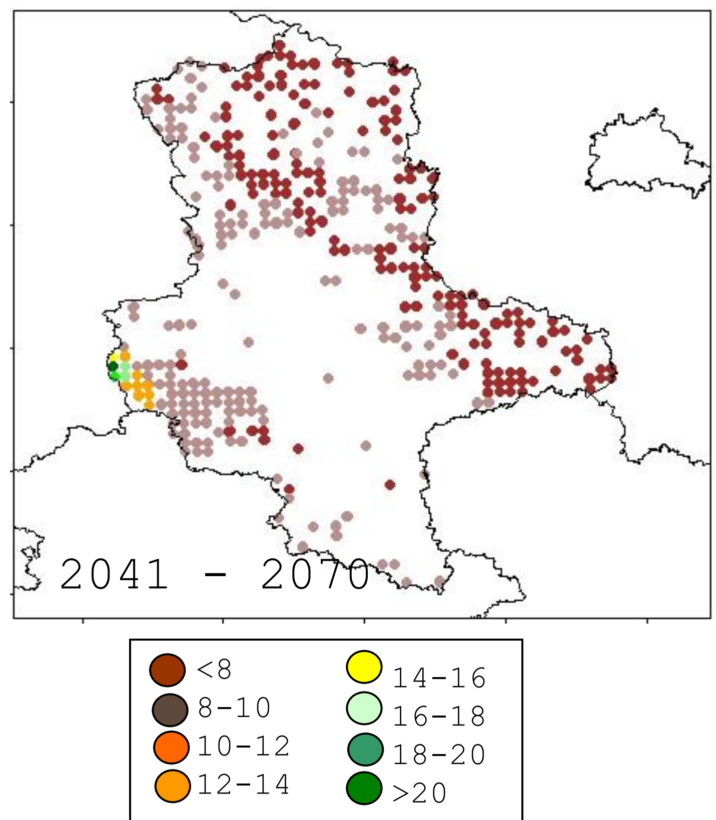
GAM formulation shows more dynamics over time, SCAM indicates servere change in first period, rather few changes in following predictions

Which behaviour is more realistic, i.e. best represents projected climate change?

temperature



aridity

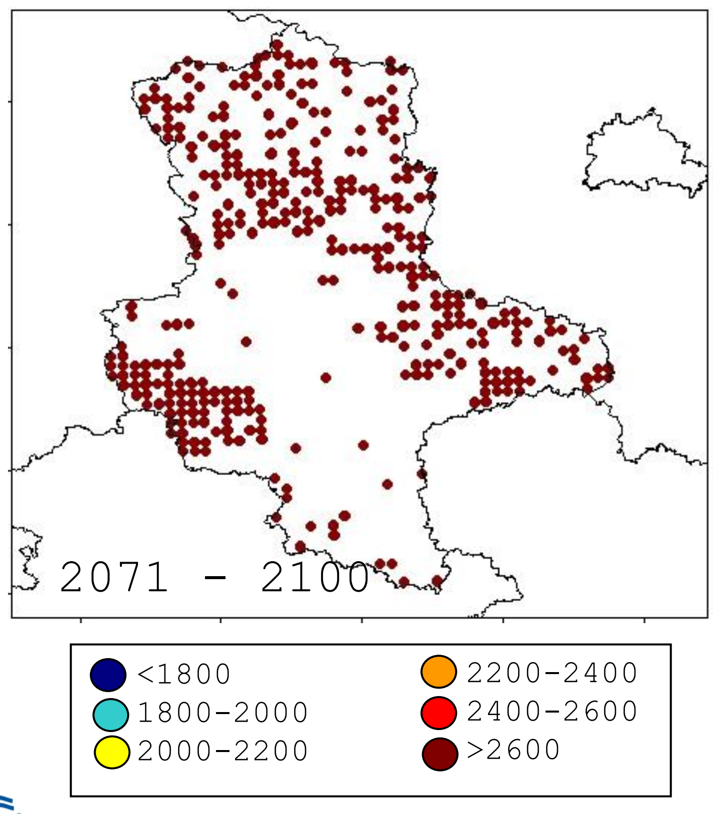


6. Conclusions, challenges, questions

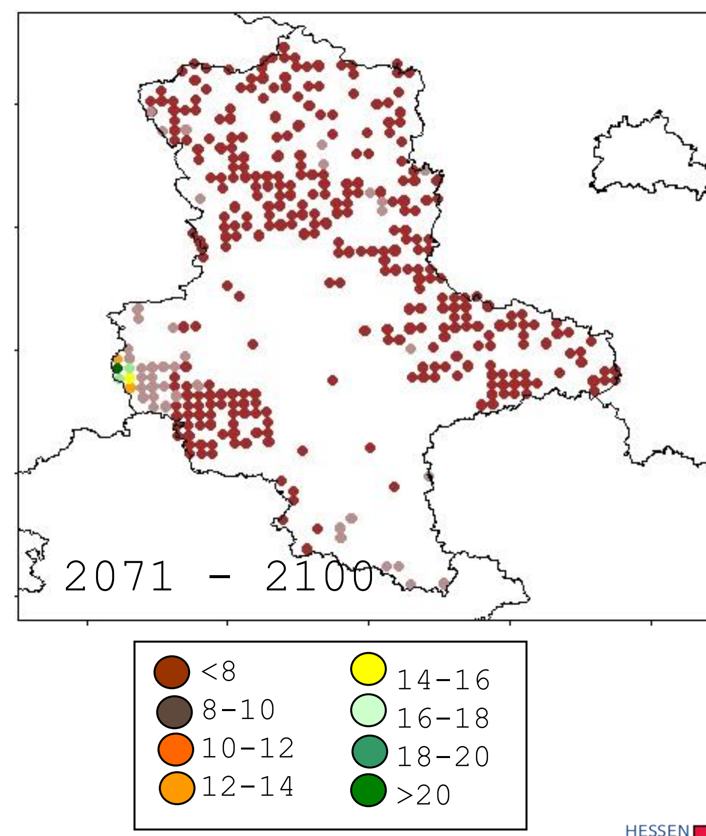
GAM formulation shows more dynamics over time, SCAM indicates servere change in first period, rather few changes in following predictions

Which behaviour is more realistic, i.e. best represents projected climate change?

temperature



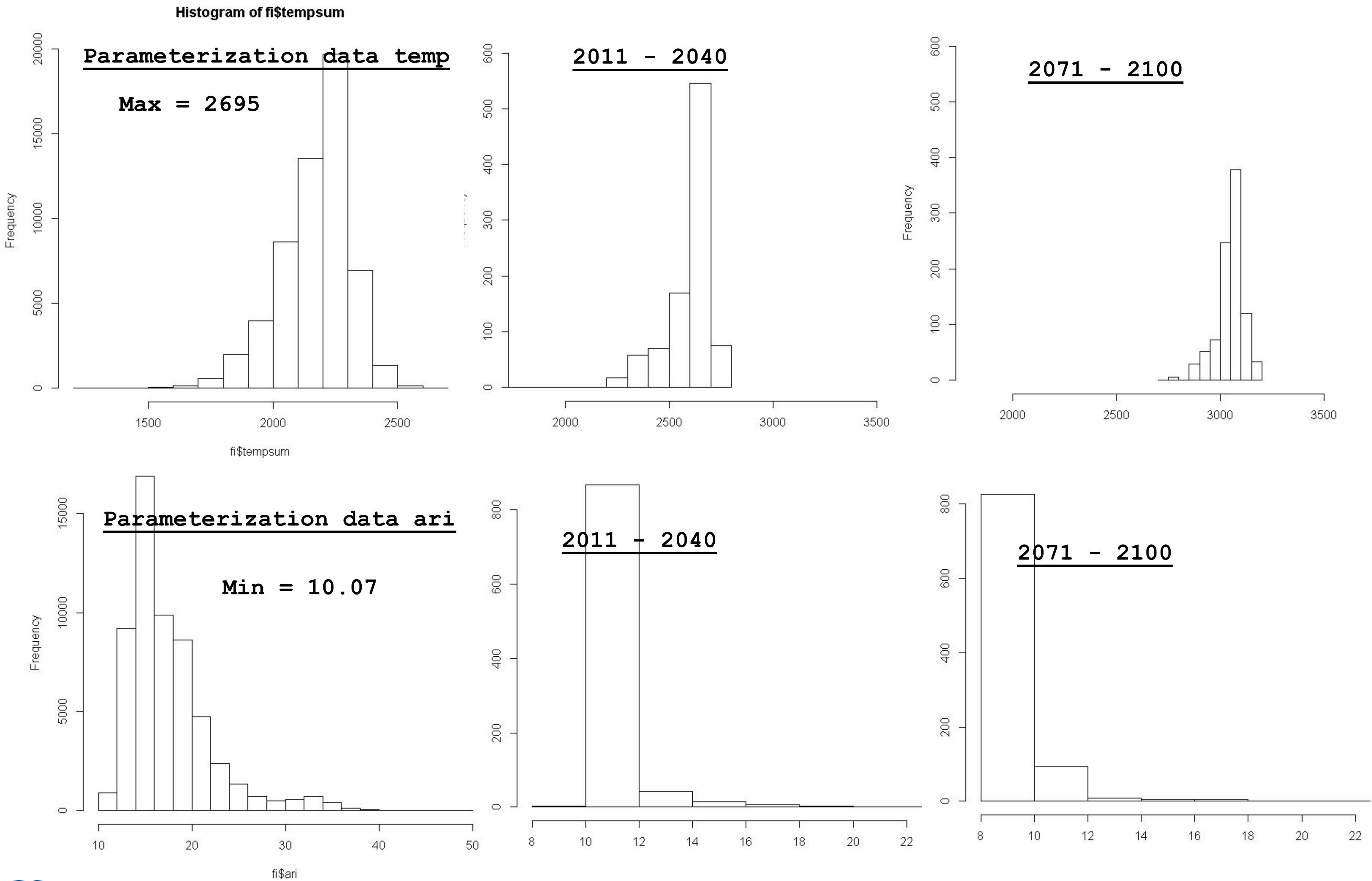
aridity



NW-FVA
Nordwestdeutsche Forstliche Versuchsanstalt

HESSEN

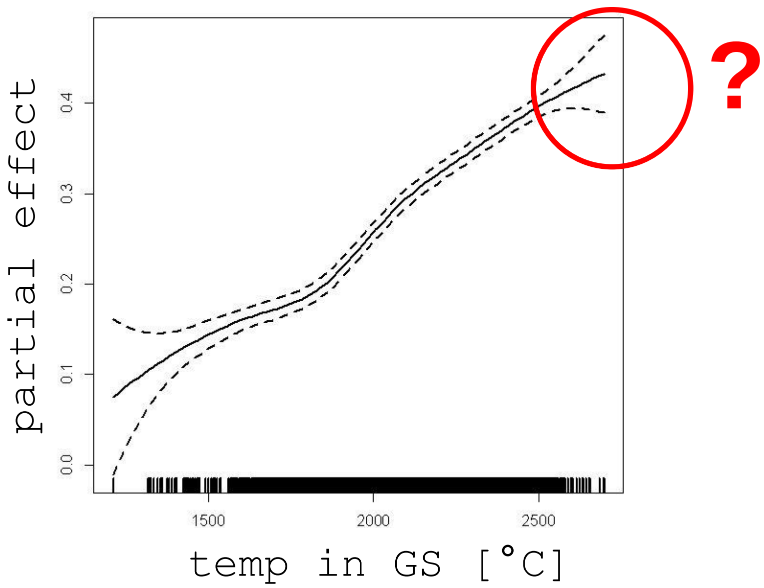
6. Conclusions, challenges, questions



6. Conclusions, challenges, questions

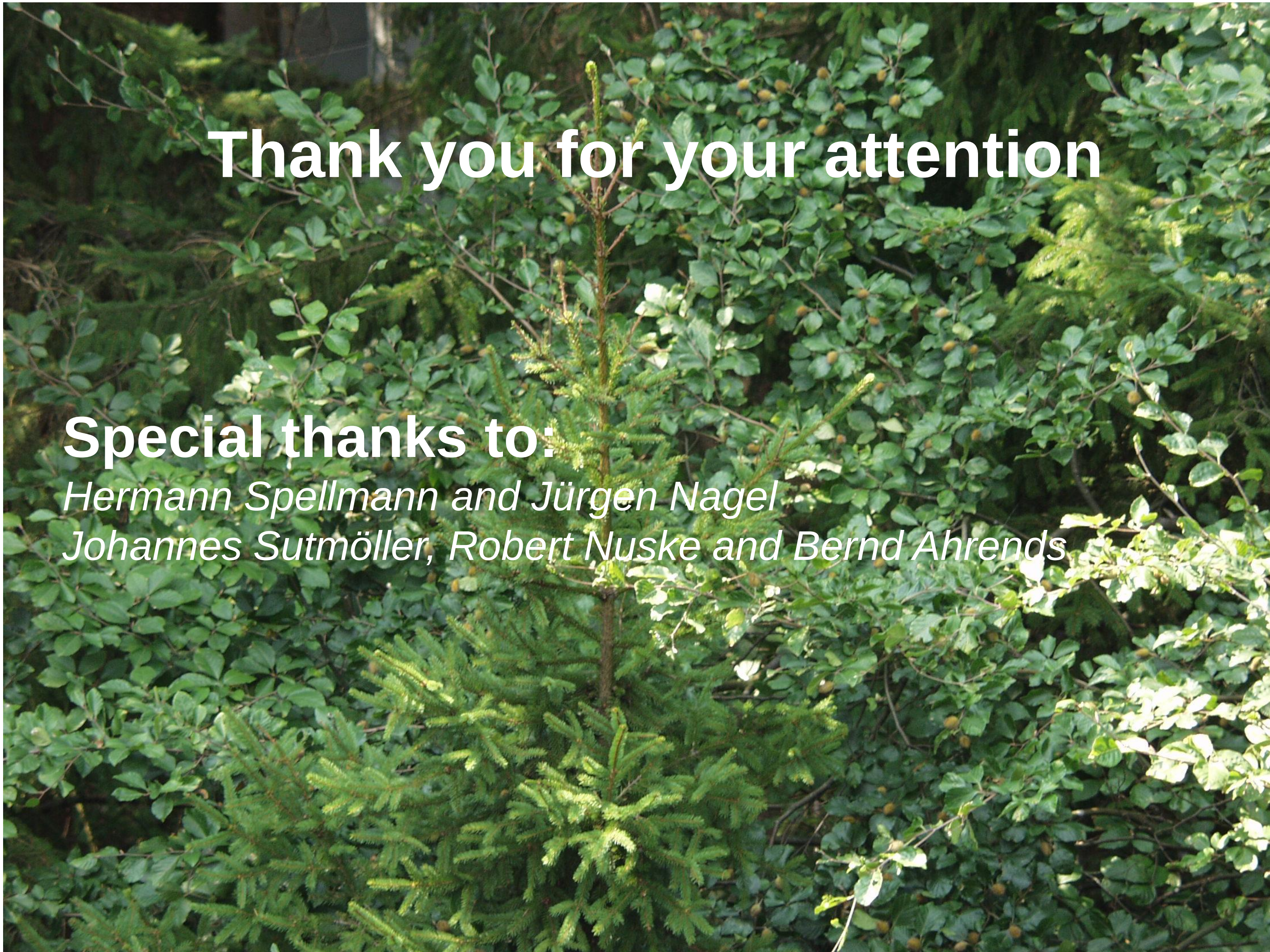
One conclusion, one challenge …

SCAM formulation has a severe extrapolation problem; fit an approximation function



One question …

Is there any chance to better discriminate between effects of correlated predictors?



Thank you for your attention

Special thanks to:

Hermann Spellmann and Jürgen Nagel
Johannes Sutmöller, Robert Nuske and Bernd Ahrends