Silage Maize Yield estimates using Soil Moisture Climate Projections

Michael Peichl[1], Stephan Thober[1], Luis Samaniego[1], Bernd Hansjuergens[1], Andreas Marx[1,2]

[1] Department Computational Hydrosystems, Helmholtz Centre for Environmental Research - UFZ, Permoserstrasse 15, D-04318 Leipzig, Germany

[2] Climate Office for Central Germany, Helmholtz Centre for Environmental Research - UFZ, Permoserstrasse 15, D-04318 Leipzig, Germany

E-mail: `michael.peichl@ufz.de`

Abstract. Silage maize is one of the most widespread cultivated plants in Germany because it is a main supplier of biomass in the course of the energy transition. Silage maize yield is susceptible to unfavorable environmental conditions such as dry and wet spells. Knowledge of these factors can help to mitigate welfare losses and can be used to estimate the impact of climate change on crop yields. Statistical crop models routinely use meteorological variations to estimate crop yield although soil moisture constitutes the primary source of water for plant growth. In an earlier study, the intra-seasonal predictive capacity of soil moisture for the estimation of silage maize yields in Germany was investigated (Peichl et al. 2018). The main result is that soil moisture anomalies have exploratory skills which vary in magnitude and direction depending on the month. The most important seasonal effects are then combined here in a reduced panel model to enable a more holistic climate impact assessment. These effects are soil moisture of June and August, which show opposite detrimental effects, and July temperature and precipitation. It is worth noting that the models used in this study neglect effects such as increased CO_2 fertilization and agricultural adaptation measures. To estimate soil moisture anomalies, climate projections derived from five regional climate models (RCMs) of the ENSEMBLES project under A1B scenario are used to force the mesoscale Hydrological Model (www.ufz.de/mHM). The meteorological data are demeaned to correct for systematic biases of the RCMs. The approach is based solely on anomalies. Silage maize yield variations are predicted for the reference period 1971 2000 and projected for the climate periods 2021 - 2050 and 2070 - 2099. For all RCMs, on average crop yield is projected to decrease for both climate periods ranging from -1.2 to -10.5 decitonnes/hectar (dt/ha) for the period 2021 2050 and -3.7 to -39.1 dt/ha until the end of the century. The maximum projected yield loss is less than 10 % of the average yield in Germany for the period 1999 2015 (447 dt/ha). Among the different explanatory variables no single driver of crop yield anomalies could be identified. This highlights that multiple seasonal determinants are required for accurate estimation of crop yield variation.

Keywords: silage maize, climate change, Germany (3 - 7 words)

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1. Introduction

Based on the current research on silage maize sensitivity to monthly weather and soil moisture impacts a predictive model shall be established. So far, the goal was to evaluate the causal effects of soil moisture anomalies on a monthly basis. So far, time dependent effects of soil moisture have been evaluated. For instance extreme wetness in the early period and extreme dryness in August are responsible for diminished silage maize yield. Further, the focus was on in-sample variation. This has methodological implications, as for instance the use of parametric standard errors and the control for confounding factors. Also, it allows to use plm package, which is not so good suited for predictions. Now, we derive heuristacially a model which relies on the seasonal effects observed in the paper before.

2. Data and Methods

2.1. Training Data

2.2. Method

2.2.1. Model without fixed effects but demeaned data. Combined model from paper 1, excluding the fixed effects. Here, test for fixed effects can be included. In that context we also can mention some interpretation particularities (together with using anomalies in the predictor variables.)

2.2.2. Test Results

2.3. Climate Data

3. Results and Discussion

3.1. Goodness of Fit and Model Coefficients

In and out of sample goodness of fit.

3.2. Scatter-plot

3.3. Projections

3.3.1. Violin Plots

3.3.2. Yield Maps with Wilcoxon Rank Tests

3.3.3. Maps of Structural Patterns of Yield and Explanatory Variables.

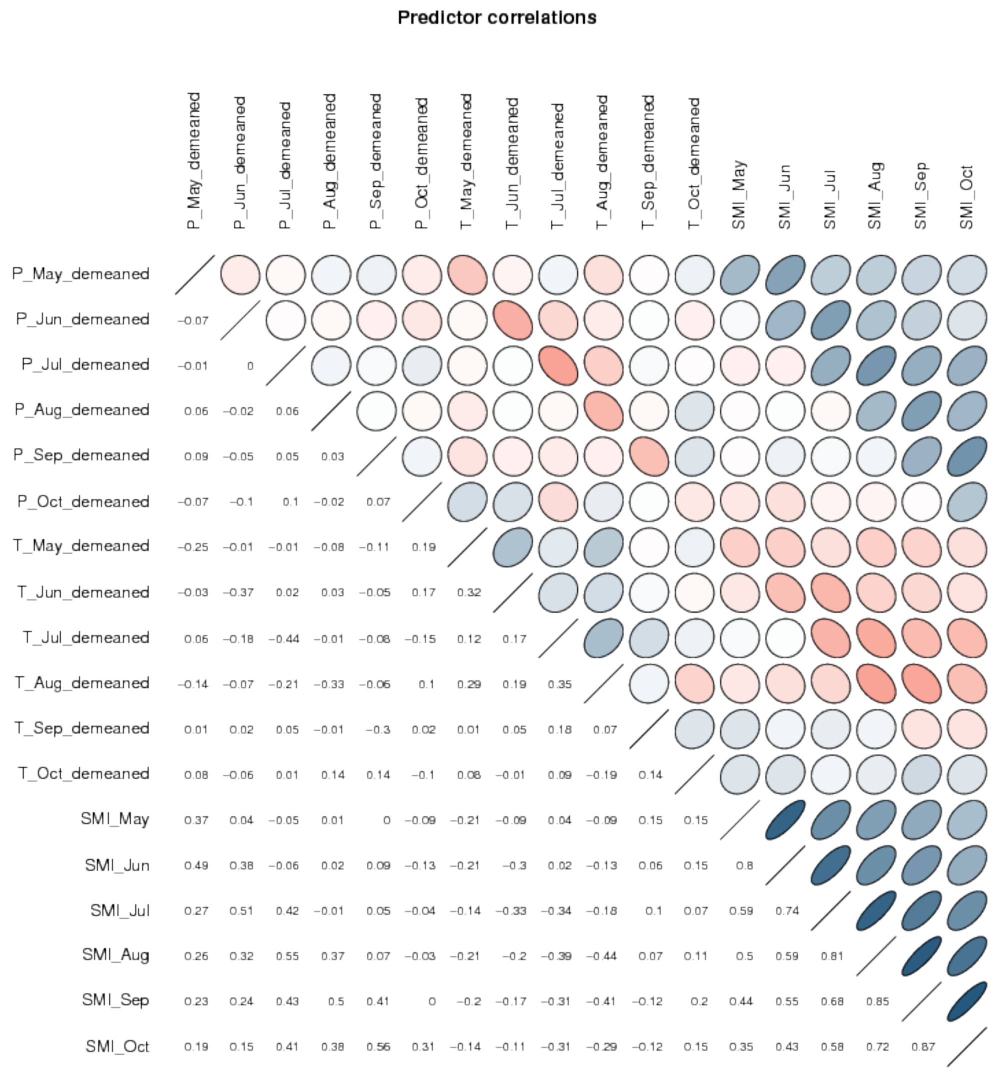

Figure 1. Pearson Correlation of the possible predictors used in the model.

4. Discussion

References

Table 1.

	Base Model	
	silomaize	
	Standard	Driscol - Kraay
poly(P_Jul)^1	0.264***	0.264***
	(0.028)	(0.033)
poly(P_Jul)^2	0.001**	0.001
	(0.0003)	(0.001)
poly(P_Jul)^3	−0.00001***	−0.00001**
	(0.00000)	(0.00000)
poly(T_Jul)^1	−6.443***	−6.443***
	(0.634)	(1.001)
poly(T_Jul)^2	−4.050***	−4.050***
	(0.305)	(0.291)
poly(T_Jul)^3	0.703***	0.703***
	(0.078)	(0.104)
SMI_Jun6drght_svr	10.622***	10.622***
	(2.196)	(2.880)
SMI_Jun6drght_mdrt	8.723***	8.723***
	(1.988)	(2.303)
SMI_Jun6dry	3.198*	3.198*
	(1.722)	(1.763)
SMI_Jun6wt	−6.155***	−6.155**
	(2.203)	(2.462)
SMI_Jun6wt_abndnt	−12.173***	−12.173***
	(2.660)	(3.813)
SMI_Jun6wt_svr	−52.091***	−52.091***
	(3.618)	(5.850)
SMI_Aug6drght_svr	−47.447***	−47.447***
	(2.609)	(3.820)
SMI_Aug6drght_mdrt	−21.952***	−21.952***
	(2.066)	(2.837)
SMI_Aug6dry	−8.200***	−8.200***
	(1.771)	(2.495)
SMI_Aug6wt	0.656	0.656
	(2.084)	(1.800)
SMI_Aug6wt_abndnt	−3.447	−3.447
	(2.428)	(2.431)
SMI_Aug6wt_svr	−10.703***	−10.703***
	(3.548)	(3.755)
Constant	18.905***	18.905***
	(1.155)	(1.527)
Observations	4,625	4,625
R^2	0.389	0.389
Adjusted R^2	0.387	0.387
F Statistic (df = 18; 4606)	162.900***	162.900***
Note:	*p<0.1; **p<0.05; ***p<0.01	

Mean of all comIds	SMI_Jun_mean	SMI_Jul_mean	SMI_Aug_mean	SMI_Jun_median	SMI_Jul_median	SMI_Aug_median
SMHI 2000	0.5	0.5	0.5	0.510	0.507	0.505
SMHI 2050	0.526	0.511	0.483	0.537	0.538	0.504
SMHI 2100	0.517	0.363	0.373	0.559	0.308	0.333
MPI 2000	0.5	0.5	0.5	0.507	0.511	0.506
MPI 2050	0.428	0.447	0.411	0.395	0.431	0.393
MPI 2100	0.404	0.310	0.285	0.374	0.250	0.204
KNMI 2000	0.5	0.5	0.5	0.489	0.500	0.505
KNMI 2050	0.445	0.485	0.474	0.439	0.488	0.481
KNMI 2100	0.477	0.405	0.391	0.505	0.383	0.358
ICTP 2000	0.5	0.5	0.5	0.504	0.499	0.506
ICTP 2050	0.457	0.465	0.481	0.432	0.459	0.490
ICTP 2100	0.407	0.333	0.354	0.380	0.285	0.300
DMI 2000	0.5	0.5	0.5	0.498	0.501	0.508
DMI 2050	0.565	0.539	0.500	0.585	0.562	0.502
DMI 2100	0.616	0.584	0.584	0.675	0.612	0.628

Figure 2. Comparision of the SMI develpment of each RCM.

Figure 3. Scatterplot of the observed silage Maize Anomaly Data against the predicted data with the standard model considering SMI of June and August and Meteorology of July using observed data. The time period is 1999 to 2015.

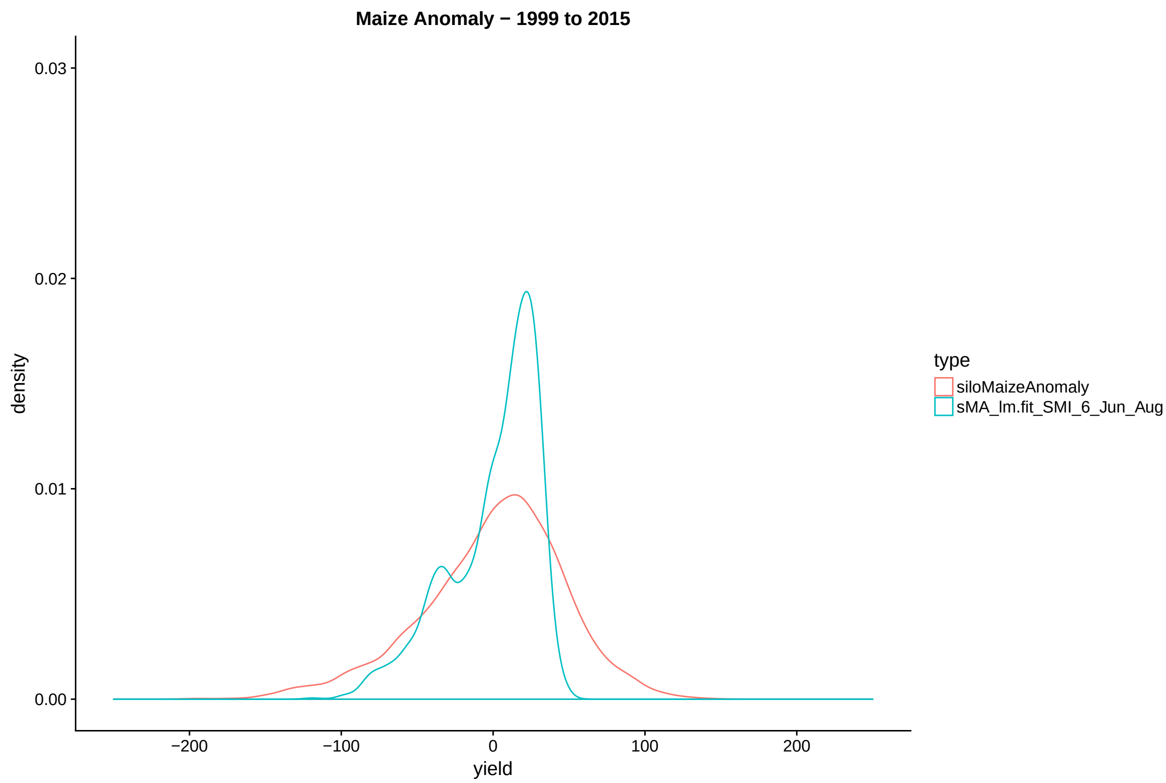

Figure 4. Density Plot of the observed silage Maize Anomaly Data against the predicted data with the standard model considering SMI of June and August and Meteorology of July using observed data. The time period is 1999 to 2015.

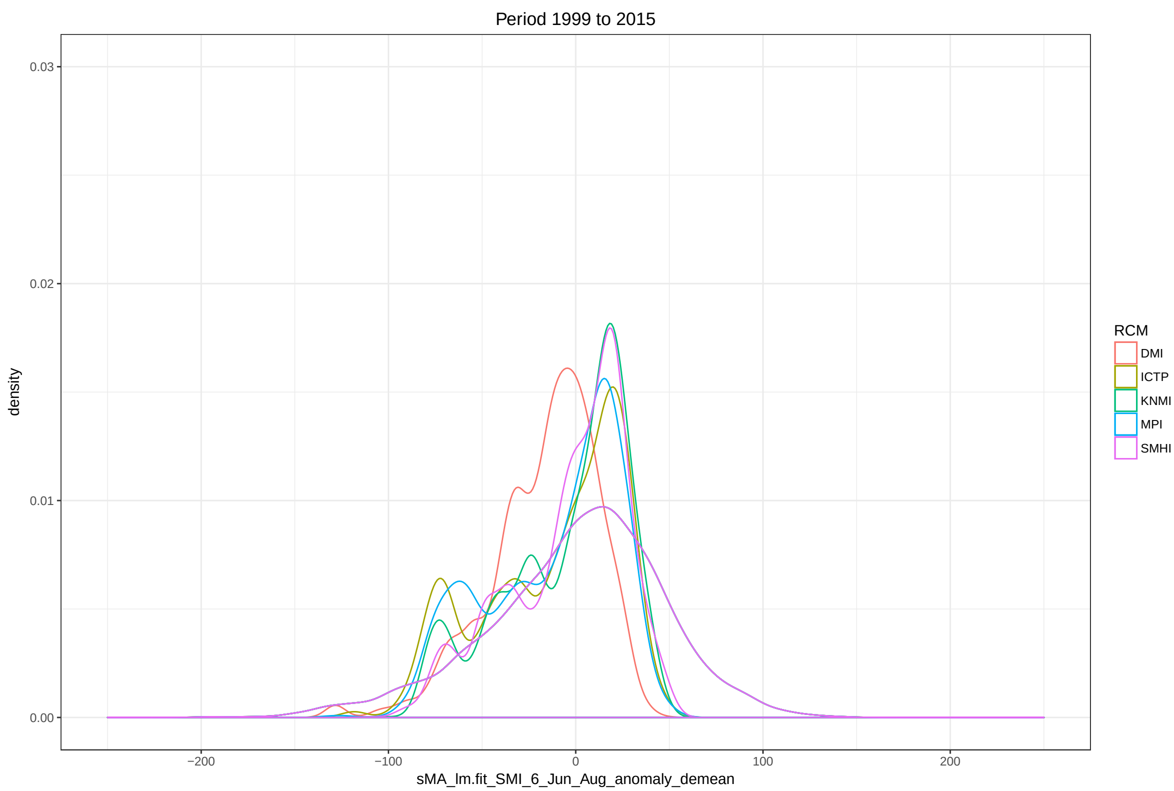

Figure 5. Density Plot of the observed silage Maize Anomaly Data against the predicted data with the standard model considering SMI of June and August and Meteorology of July using data derived from the RCMs. The time period is 1999 to 2015.

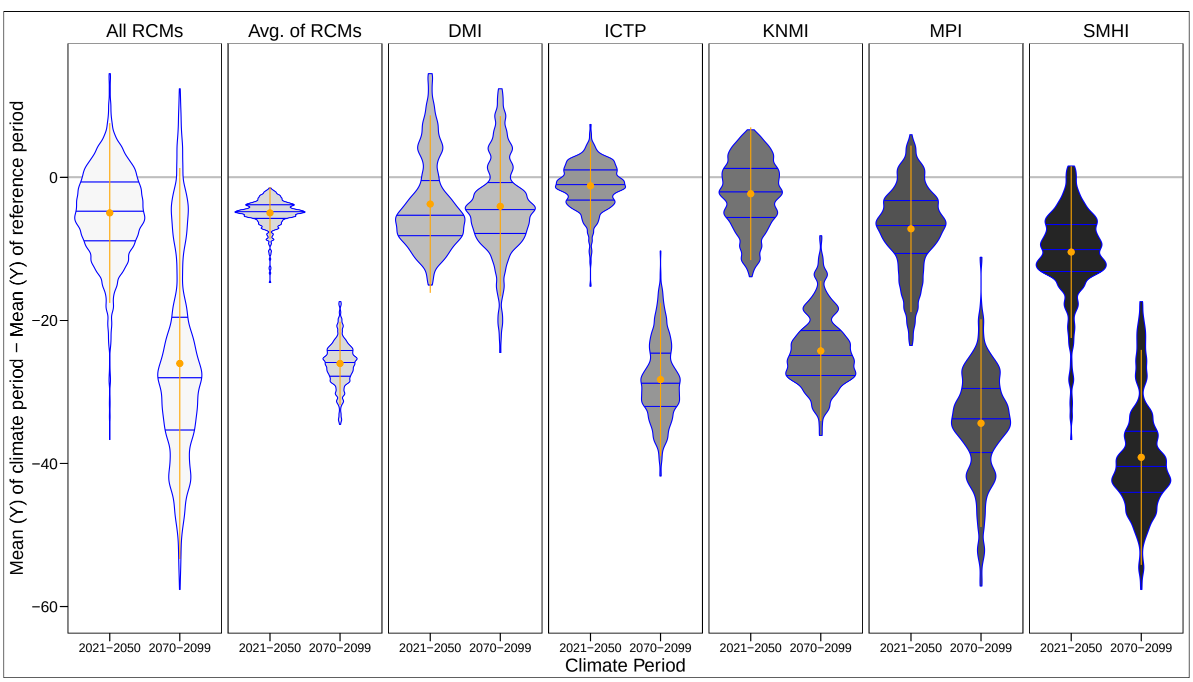

Figure 6. Violin Plot of the predicted yield for the periods 2021 - 2050 and 2070 - 2099 compared against the reference period 1971 - 2000. The first panel shows the cumulated results for all RCMs, the other five for each RCM separately.

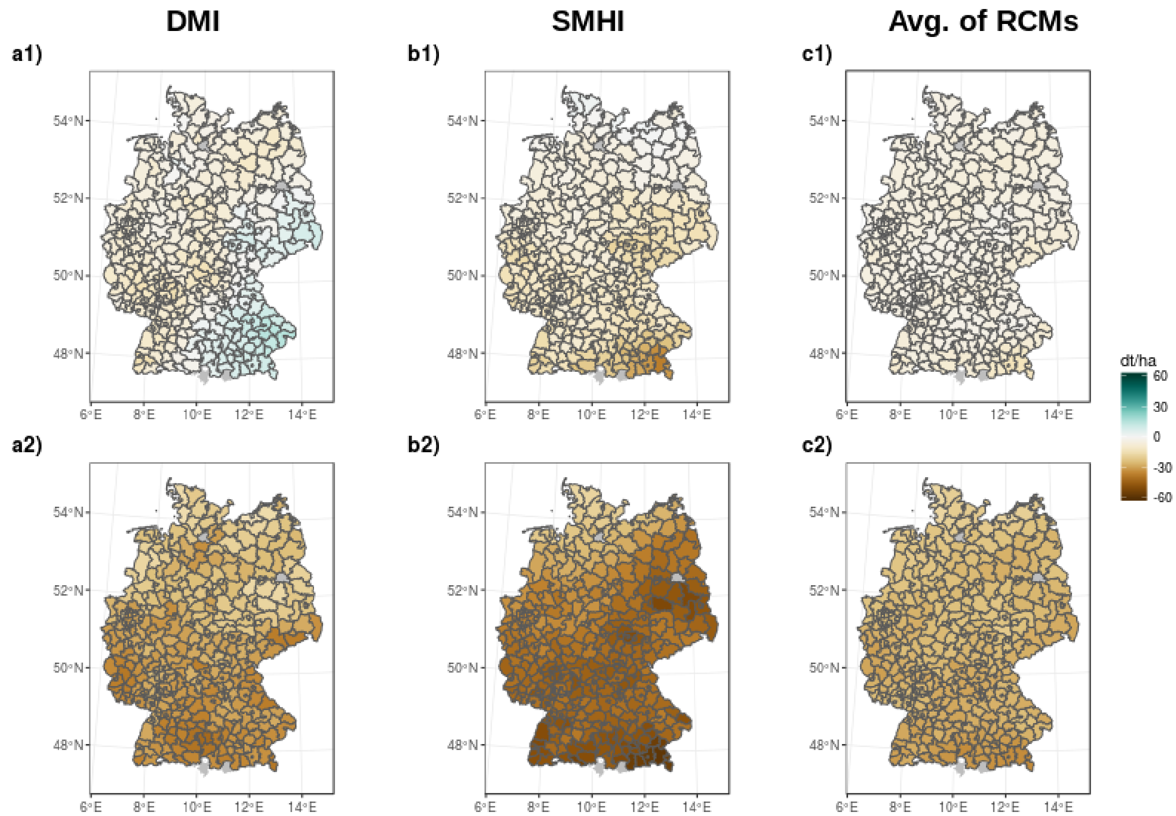

Figure 7.

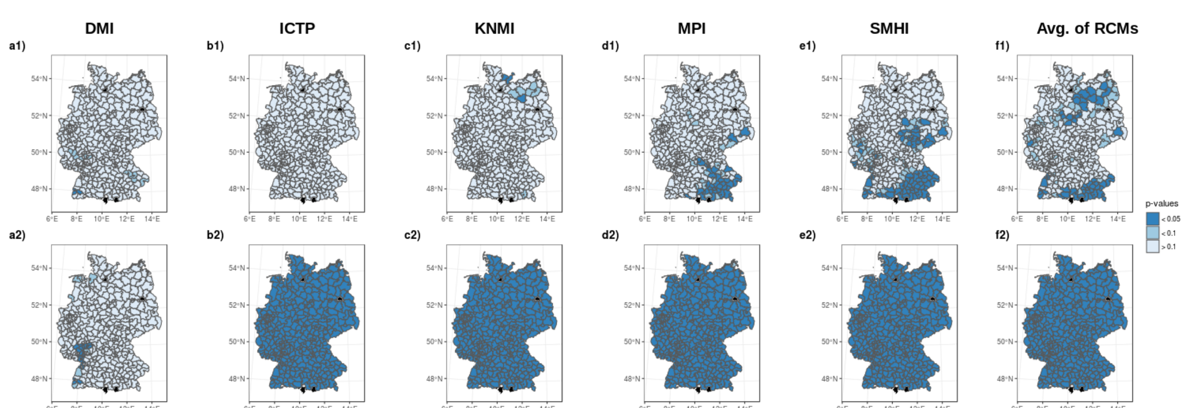

Figure 8.

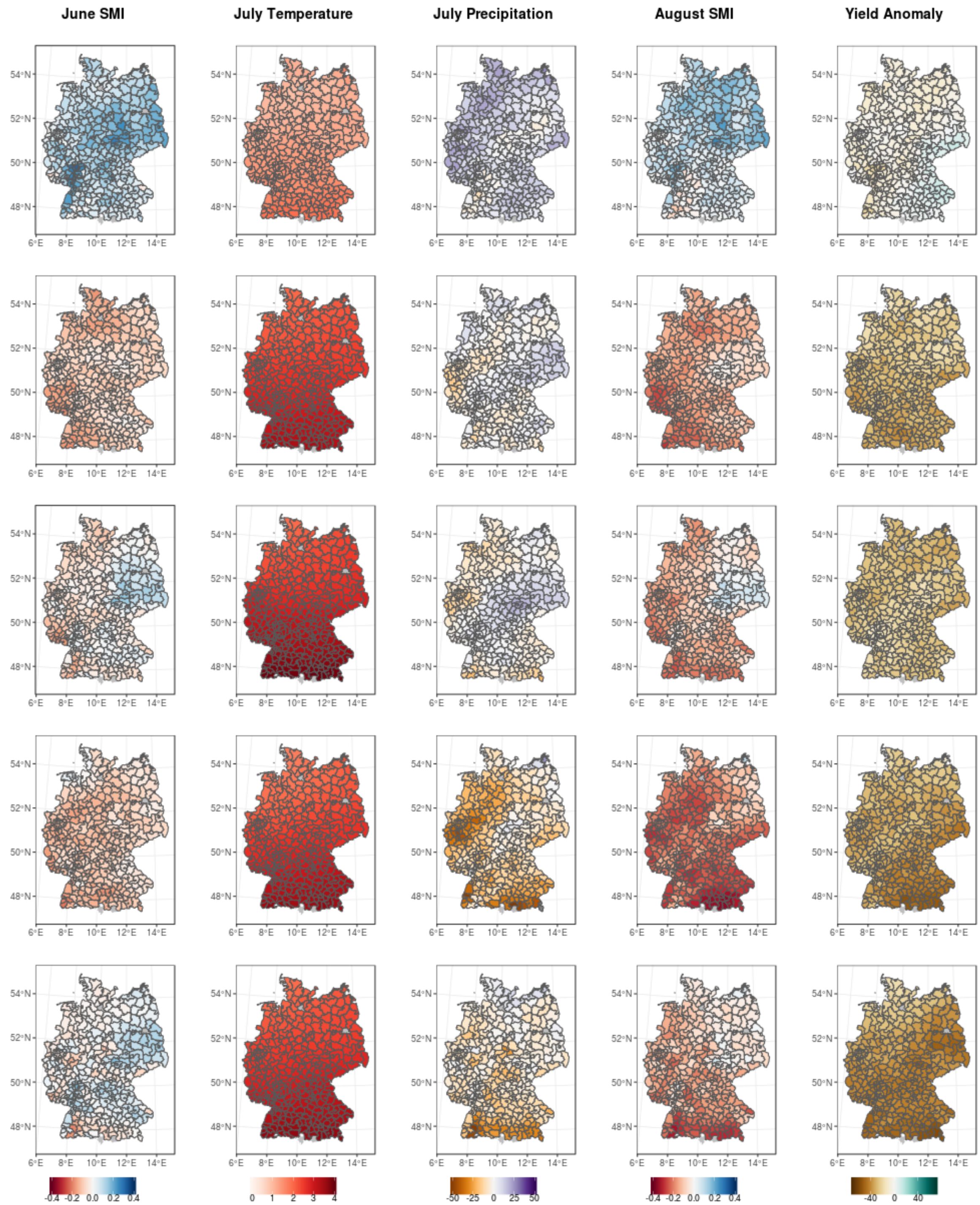
June SMI
July Temperature
July Precipitation
August SMI
Yield Anomaly
54°N
52°N
50°N
48°N
6°E
8°E
10°E
12°E
14°E
-0.4 -0.2 0.0 0.2 0.4
0 1 2 3 4
-50 -25 0 25 50
-0.4 -0.2 0.0 0.2 0.4
-40 0 40

Figure 9.