# PIK Report

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# CORRELATION ANALYSIS OF CLIMATE VARIABLES AND WHEAT YIELD DATA ON VARIOUS AGGREGATION LEVELS IN GERMANY AND THE EU-15 USING GIS AND STATISTICAL METHODS, WITH A FOCUS ON HEAT WAVE YEARS

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## *Abstract and Factsheet*

Crop yields are sensitive to climate variability. They also respond to inter-annual weather variability in essentially every phase of the vegetation period. Inter-annual dependencies are evident in oscillating wheat yield figures, yet have not been given the attention expected. How inter-annual wheat yield variability is affected by weather needs clarification, especially in the light of human induced climate change and increasingly intense and likely heat waves in Europe.

This study applies geostatistical methods and GIS (geographic information systems) to analyze spatial and temporal variability of wheat on three aggregation levels in Europe (EU-15, German states level, and county level in one German state). Daily homogenized weather data and annual statistical data on wheat yields were analyzed for these purposes.

Residuals are separated from long term yield trends with an extensively validated method and represent the base values for weather induced, short term inter-annual variations. They are correlated with selected climate variables in multiple regression models for qualitative and quantitative analyses of yields' weather sensitivity.

The main focuses are

- to what extent inter-annual wheat yield variability can be explained by weather influences, and further, by selected meteorological parameters, and how sensitive they are to them. Heat wave years are given particular attention.
- an extensive analysis of effects of the 2003 heat wave in Europe on wheat and winter wheat yields.
- modeling wheat yields with multiple linear regression using yield anomalies as estimates for weather induced yield variations.
- the analysis of results with GIS and statistical methods, applied also to analyze spatial-temporal variability and to address transitional scaling effects between the aggregation levels in question.

The study produced the following results.

- Estimates of inter-annual yield variability through multiple linear regression of monthly climate variables are achieved with moderate to good explanations of variance, varying by the scale applied. $R^2$ are comparable to similar studies performed in the past.
- Regions with linear trends in increasing yield figures are distinguished from ones with break points in the trend. Possible explanations are discussed.
- Absolute anomalies show an increasing trend, relative anomalies show a decreasing trend.
- Quantitative and qualitative analysis of wheat yield anomalies provide evidence for record yield collapses and identify “winners” and “losers” of the 2003 heat wave. Results can contribute to outlining future yield patterns in the light of a predicted increase of such heat wave events.
- Geostatistical and spatial analyses showed that marked homogeneous negative anomalies corresponded with the core extent of the stationary high pressure zone over Germany, France, and Austria. Countries north of the high pressure core recorded small negative to record high anomalies.
- In 8 selected heat wave years impact assessment of weather on crop yields showed that such events do not essentially lead to yield loss. This necessitates further studies of weather impact with high resolution data.
- Explorative results from simulating yield anomaly trends with climate scenario data indicate steady to markedly declining anomalies into the mid 21st century.
- Comparative studies of methods evaluating agronomic years illustrate how sensitive results are to the reference units selected.

Subsequent studies are recommended to incorporate

- high resolution climate data and phenological information of plant development phases into modeling wheat yield variability with inter-annual variations as well as applying wheat growth models
- more complex climate variables such as drought indices in using yield anomalies as estimates for weather induced variations to improve estimates and shed light on the effects of increasingly intense and likely heat waves.

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# 1 Introduction[1]

How crop yield variability is related to climate and weather has been a question of vital interest to humans for millennia. Its discussion in scientific terms has been promoted by meteorologists, climatologists, geographers, and agroeconomists for centuries. Statistical methods are often applied for studying such relationships.

The weather during a crop's life span influences crop growth and yields, which show varying sensitivity to both climatological means and inter-annual weather variability (BAUMANN AND WEBER, 1966; BEINHAUER, 1977; CHMIELEWSKI AND POTTS, 1995; MEARNS et al., 2002; ASSENG et al., 2004). It directly affects phenology, photosynthesis, and other physiological processes. Indirect impacts include nutrient availability, weeds, pests and diseases, and machinability (HOOKER, 1922; SWANSON 1979; SOUTHWORTH, 2002). BAUMANN AND WEBER (1996) concluded from their investigations in weather differences between favorable and unfavorable years for crop yields that every episode of the vegetation period can more or less influence crop yields.

To what extent crop yields represent a measure of sensitivity to inter-annual meteorological variations has not yet been fully discerned. The main objective in this study is to shed light on this issue. The hypothesis states that the long-term trend in yield series is driven by technical and seed quality advancement, and can be approximated by single or bilinear regression fits. In temporal and statistical contrast thereof, the short-term inter-annual yield variations can be explained to an extent by meteorologically induced factors, or weather variation, to which crops are sensitive. If the influence of these factors is quantified and subtracted from the yield series, the residuals represent the remaining influence of other factors.

Qualitative and quantitative model analyses are conducted to determine crop yield sensitivity to inter-annual meteorological variations. Statistical, predominantly multiple regression analyses, and GIS (Geographic Information System) methods are applied. The study hereby focuses on influence of weather on yields through qualitative and quantitative model analysis. Explaining the biological implications of crop development directly and indirectly influenced by weather, however, is not a goal here.

[1] To a large extent this PIK Report is based on a diploma thesis written at PIK and submitted to the Humboldt-University Berlin in November 2004.

Results are of interest to vulnerability assessments in climate impact research, especially in the light of findings that indicate increased and increasing likelihood of extreme weather events like the heat wave summer in 2003 in the course of climate change (SENERIVATNE et al., 2002; BENISTON, 2003; SCHÄR, 2004), as well as current studies predicting shifts in weather patterns, including increases in mean temperature and variability in central Europe throughout the 21st century (IPCC A AND B, 2001; SCHÄR, 2004). The response of crop yield anomalies to this particular heat wave event in 2003 is analyzed on all selected areas of interest, which include all former 15 European Union countries (hereafter EU-15), selected German federal states, and all counties in the German federal state of Baden-Württemberg. Furthermore, the study of winter wheat yields' sensitivity to selected climate variables in past heat wave events in Germany will help to evaluate better how strongly anomalies are driven by such events.

Simulations determining wheat sensitivity to increasing climate variability (MEARNS, 1992; SOUTHWORTH, 2002; ASSENG, 2004) suggest closing with conclusively simulating winter wheat anomaly variability on the grounds of selected data series and climate scenario data. This research can contribute to showing how crop yield anomalies respond to climate scenario data.

In an early study done by HOOKER (1922), weekly meteorological parameters returned significant correlation coefficients for crops in British counties even into the year before harvest. The 8 week time periods for independent variables took into account the varying times of sowing, flowering, and harvesting. More complex statistical analyses have been conducted since, taking more independent variables into the equation and delivering better explanatory qualities for yield figures. Statistical modeling of weather impact on inter-annual oat yield variability for a test station by means of multiple linear regression analysis showed largely varying degrees of correlation, depending on the variables themselves and their temporal resolution (BAUMANN & WEBER, 1996). The authors opted for time increments that varied depending on the predictor and season for adjusting the variables to shifting plant growth and phenological phases. CHMIELEWSKI and POTTS (1995) also selected a test station for similar analyses, but focused on the impact of long-term climate change on crop yields. The latter 2 studies assert inter-annual and climatic influences on yields through multiple regression analysis, a method also used by ALEXANDROV & HOOGENBOOM (2001). A combination of quarterlies and months was chosen by SUPIT

(1997) for focusing on the climatic seasonal variations and trends. On yet another spatial and temporal scale, positive significant correlations were determined between the sea surface temperature anomalies induced by climate phenomena El Niño and La Niña and wheat yields in the U.S. corn belt (PHILLIPS et al., 1999). Thus, research on both long-term climate change and inter-annual weather variability affecting crop yields has been conducted on various scales of interest. The core message of these findings are variations in studies published so far concerning (1) influencing factors on selected crop yields, (2) their temporal resolution for determining to what extent yield variability can be explained by other sources, (3) crops, and (4) the geographical scale of interest. How these topics are dealt with is established in the subsequent paragraphs.

Analysis of long-term yield changes for wheat, maize and rice in 188 countries over the past 40 years have revealed four main trends, with a one showing a prevalence of linear growth in Europe (HAFNER, 2003). However, limits to globally observed patterns of increasing yields are becoming evident in long-term wheat data series (CALDERINI AND SLAFER, 1998).

The primary factor for linear yield increase is associated with a long-term technical advancement trend, which comprises three components: (1) biological and chemical; (2) mechanical; and (3) management advancement (SWANSON et al, 1979). Table 1 illustrates what each component is broken down into. Long-term trend drivers are subtracted from actual yields, isolating annual absolute anomalies in order to determine their sensitivity to inter-annual weather variability. The trend is factored out by subtracting the best linear regression fit line (PHILLIPS et al., 1999; SWANSON et al., 1979). Annual yield anomalies indicating positive or negative deviations of detrended yields from the mean are obtained by subtracting the intercept value. It is important to note that the weather influences remain implicitly embedded in detrended crop yield values. Monotone trends induced by climate change are factored out. A conceivable residual induced by climate change can remain embedded in the form of potential yield adjustments through changing El Nino Southern Oscillation (ENSO) and the North Atlantic Oscillation (NAO) amplitudes.

Table 1. Quantifiable and unquantifiable influences on crop yields. Derived from SWANSON et al. (1979)

| Influence | Subtracted from crop yields through linear detrending | Remains in crop yields |
|---|---|---|
| *Biological and chemical* | New cultivar sorts<br>Herbicides<br>Insecticides<br>Fertilizer | Plagues<br>Diseases<br>Varying nutrient supply<br>Different crop type cultivation |
| *Mechanical* | Mechanical advancement<br>Equipment | |
| *Management* | Field alternation<br>Field treatment | |
| *Atmospheric* | Climate change | Weather variation<br>Extreme weather events |

Parasitic infestation, diseases, varying nutrient supply, different cultivar types all have direct or indirect influence on crop yields. If these factors were quantifiable as well, they could also be systematically ruled out of crop yields.

Yield sensitivity to basic meteorological variables (temperature means, temperature sums, and precipitation sums) has been studied extensively through regression analyses (HOOKER, 1922; BAUMANN 1966; SWANSON, 1979; CHMIELEWKSI, 1995; ALEXANDROV, 2001; SOYA, 2003). But solely focusing on these simple parameters and calculations may discount dependencies on other meteorological parameters or indices derived from them. For instance, the effect of monthly precipitation sums on crops strongly depends on temperature, potential evapotranspiration, and sunshine duration.

In this study, the weather influence on crop yields is modeled with monthly meteorological parameters and further indices. These independent variables are summarized as monthly climate variables, or predictors, when appropriate. Yield anomalies inter alia containing the fraction of yield apportioned to inter-annual weather variation represent the dependent variable. Crop yield sensitivity to inter-annual weather variation is determined in multiple regression analyses. Sensitivity analysis is measured with 6 relatively simple monthly climate variables with evident connections to crop development. One of this study's objectives is to test them and draw conclusions about applying the methodology to more complex parameters, different temporal resolutions of climate variables and control variables. Here, tons per hectare [t $ha^{-1}$] is the standard unit for crop yields and yield anomalies because it

is weighted to a unified area and enables comparability among regions of different size, as opposed to total production or seed bulk measurements.
It is useful to briefly summarize pivotal facts on wheat and winter wheat, the crops selected for sensitivity and variability analysis. Winter wheat *Triticum aestivum* L. is a cereal crop that is planted in autumn and is cultivated throughout the study areas. The highly adaptable crop responds to warmer temperatures with reduced crop and grain growth duration (SOUTHWORTH et al., 2002). Lower yields are then expected in regions where conditions are otherwise optimal. Tolerated temperatures under which wheat is grown range between -40 and +40°C (WITTWER, 1995). Planting season is in the fall, germination begins before winter. Snow covers are endured. Quick growth sets in prior to summer heat (WITTWER, 1995). In Germany, winter wheat is sowed between mid September and the beginning of November, and harvested in August (AGRARIAN PUBLISHING UNION, 1982). Crop yields are referred to as yields hereafter, unless it is useful to append the reference to crops in general or to a specific crop.
Studies are performed on different spatial scales for analyzing yield data with statistical and GIS methods. The 3 scales are each represented by units on the same aggregation level: yield data appended to EU-15 countries (wheat, 1961-2003), the federal states of Germany (winter and summer wheat, cereals combined, 1951-2003), and counties of the federal state Baden-Württemberg (winter wheat, 1970-2003) was obtained, compiled, and analyzed. A single administrative unit within any level is referred to as a unit. Results and the spatial distribution thereof are compared within and among the 3 study areas. In the process of aggregation, the amount of territorial units and attribute data is continuously reduced by deriving larger objects according to higher administrative levels (BARTHELME, 2000; BILL & ZEHNER, 2001). Disaggregation is the opposite procedure.
Table 2 indicates that unit numbers increase with each administrative step downward, whereas land area, average area per unit, and information generalization decreases (BARTHELME, 2000; BILL, 2001). Geodata and crop data was incorporated into the Geographic Information System Software ArcGIS 8.0 for data administration and analysis.

Table 2. Aggregation and area statistics of the study areas. The sum of units and average area for Germany refer to the 8 of total 16 federal states studied.

| Study area | Area [km$^2$] | Territorial units of interest | Sum of units | Average area (Area / Sum of units) [km$^2$] |
|---|---|---|---|---|
| *EU-15* | 3.242.614 | Countries | 15 | 216.174 |
| *Germany* | 246.978 | Federal states | 8 | 30.872 |
| *Baden-Württemberg* | 35.752 | Counties | 44 | 813 |

The purpose of using different aggregation levels is to respectively study the correlation of modeled yield anomalies and their sensitivity to inter-annual climate data on various scales and to draw conclusions for trend and scaling issues through comparing results within and among aggregation levels. Actual yield trends and the position of yield indices in the heat wave year of 2003 within them are extensively considered. Different impacts of this heat wave and contrasting model quality with different data resolution in the same spatial area are assumed. Hence the question arises: which aggregation level contains information as accurate as necessary and generalized as possible to adequately meet the stated problems? Results could shed light on favorable aggregation levels for anomaly modeling, as well as on up- and downscaling them to different aggregation levels. Since the study's spatial scales coincide with one separate aggregation level each, they are addressed by the terms country, federal state, and county level.

# 2 Area of interest, methodology and data

## 2.1 Study area

Three areas segmented on different hierarchical aggregation levels are selected as study areas. The highest aggregation level is represented by EU-15 countries, Germany is investigated on the disaggregated level of 8 western German federal states (hereafter the federal states refers to the following: Bavaria, Baden-Württemberg, Hesse, North Rhine-Westphalia, Lower Saxony, Rhineland-Palatinate, Saarland, and Schleswig-Holstein, unless noted otherwise). The city-states Berlin, Bremen and Hamburg inconsistently produce negligible crop amounts and thus have been excluded. The 44 counties composing the federal state of Baden-Württemberg in southwestern Germany comprise the lowest aggregation level. Conclusively, the different aggregation levels and their chosen spatial extents represent different spatial scales. Administrative territorial units serve as mergers of agricultural and statistical data.

## 2.2 Data – spatial allocation, acquisition and condition

### 2.2.1 Yield data

#### *2.2.1.1 EU-15, countries*

Country specific wheat yield data from 1961-2003 (annual values) was extracted from the Food and Agricultural Organization of the United Nations (FAO) Database FAOSTAT. These yields represent the harvested production per unit of harvested area, and in most cases this yield data was obtained by dividing the crop production by the area harvested, not sown (FAOSTAT statistical unit).

The figures were converted into tons per hectare [t ha$^{-1}$]. The pertinent geodata representing the spatial equivalent to the level 0 of the Nomenclature of Units for Territorial Statistics (NUTS) was available at PIK. NUTS was developed to unify the various administrative unit levels throughout the EU-15 to 3 aggregation levels (EUROPEAN COMMISSION, 2003).

#### *2.2.1.2 Germany, federal states*

Annual yield data from 1951-2003 for spring wheat, winter wheat, wheat combined (also including spelt, durum wheat) and cereals combined were acquired for German federal states and for total Germany from the German Federal Statistical Office

DESTATIS. The larger portion was only available in print and had to be scanned and text recognized. New digitized figures were verified extensively. Only data from the former West German States was available for this time frame. The decision to omit the 5 eastern German states (comprising the area of former East Germany) from trend and multiple regression analysis was forced by their short data series, starting in 1990. Although the data was available on county levels in print, it was reluctantly turned down due to time restrictions because: (1) the time consuming process of digitizing the large number of series; and (2) the counties within this area were constitutively regrouped to different boundaries after the reunification in 1990, meaning that a database for calculating yields would have been necessary.

#### *2.2.1.3 Baden-Württemberg, counties*

A dataset provided by the Institute for Agropolitical Market Research IAP (1996) in Bonn, Germany contained yield values for winter wheat on a county basis from 1970 or 1973 to 1999 for 39 out of 44 counties. I chose not to reduce the longer series to a start in 1973. This was dismissed as unnecessary because the models of each county are not applied to another. Inconsistent yield data for other crops confined the crops analyzed on a county level to winter wheat. The study covered all of Baden-Württemberg, excluding five city counties with inconsistent yield data.

Each county series was supplemented with yield data up to 2003 through the online source of the State Bureau of Statistics, Baden-Württemberg (Aug. 2004), which enabled a comprehensive analysis of the heat wave in 2003. Extending the data series had no effect on regression modeling since appropriate homogenized climatic data was available only up to December 2000. The IAP dataset takes various county border reforms in the past decades into consideration.

### 2.2.2 Climate data

#### *2.2.2.1 Temporal resolution of climate data and climate variables*

A database of climate stations that contain homogenized daily values for computing the 6 climate variables in question was at my disposal at PIK. The temporal resolution of the variables had to be generalized to a scale on which they could be used as predictors of yields. A monthly temporal resolution as chosen by CHMIELEWSKI (1995) is selected for indices because it sufficiently reflects the general course of weather in Germany. Monthly values avoided an excessive number of variables and posed a resolution adequate for generalizing climate data without factoring out heat wave events. Multiple regression results pertain to fixed time periods instead of phenological phases. Daily and weekly variability was generalized to monthly data. This does not filter out weather information and phases critical to crop development (FRANKE, 1992). All selected climate stations providing climate data for sensitivity and heat wave analyses are listed in the annex (7.1).

#### *2.2.2.2 Homogenized climate data*

Daily values of data series homogenized at PIK were condensed to monthly values for the selected climate stations in the federal states and the counties of interest in Baden-Württemberg. In the latter case, precipitation stations were added if no climate station within a unit met the criteria. Daily values of meteorological parameters besides precipitation had been interpolated beforehand. Homogenizing included eliminating apparent measurement errors, and complementing missing values. The methodology of homogenizing and updating these climate datasets is explained by Österle (2003). Altogether, I exclusively used homogenized series, from 1951-1998 on the aggregation level of federal states, and from 1970-2000 for counties in Baden-Württemberg.

#### *2.2.2.3 Climate scenario data*

Daily scenario weather data from January 1$^{st}$, 2001– December 31$^{st}$, 2055 computed at PIK is used to model yield anomalies for selected counties in Baden-Württemberg. A moderate temperature increase of 1.2-1.4 K had been impressed on to the local measurements, and other meteorological parameters were consistently adjusted by a specialized statistical downscaling method (WERNER & GERSTENGARBE, 1997; MENZEL et al., 2003).

### 2.2.3 Selected crops

Crops investigated for long-term trends and heat wave 2003 analysis included spring wheat, winter wheat, wheat combined (also including spelt, durum wheat) and cereals combined. I chose winter wheat anomalies as the dependent variable for multiple regression and sensitivity analysis on the two aggregation levels of Germany and Baden-Württemberg for various reasons: (1) winter wheat ranks as the wheat crop with the largest harvested area, highest total production and amount of yields at the levels the analyses were conducted on; (2) its data consistency was the highest among available cereals; (3) it is cultivated throughout all comprised territorial units; and (4) the life cycle reaches into the year before harvest, enabling the study of weather impact on yields over a year prior to harvest. This is advantageous for determining if statistical connections exist between weather before sowing begins and actual yield figures. This notion stresses that the focus here is on statistical correlations rather than physiological causes.

## *2.3 Yields – the measure of choice*

Studies are performed on annual values of actual, expected yields and yield anomalies in t $ha^{-1}$. Relative yield anomalies are expressed in percent [%]. The advantage of the yield unit lies in its measurement of production per fixed area size, enabling comparisons among all aggregation levels and units. Long-term technically induced trends or short-term inter-annual weather variability influence would be distorted in other measurement methods. The overall production in tons per administrative unit, another commonly used measure, is dependent inter alia on the extent of the units' area and is not a measure for comparing among areas. This also applies to the measure of area harvested. In theory, either the area planted or area harvested could be implemented as the measure.
The difference between results and the danger of evident misinterpretation can be made clear through crops affected by severe drought periods or areas affected by major storms. In such cases, differentiating between sowed areas and the much smaller area actually harvested due to crop damage is crucial to comparing the yield values. Results would be substantially higher in the latter calculation.

## *2.4 Heat wave analysis*

Winter wheat anomalies in 2003 were studied on the federal state level and county level, wheat was studied on the EU-15 country aggregation level.
Calculating absolute and relative anomalies, standard deviations, and a measure for determining how intense the deviations were allowed extensive analysis of how to interpret yields in 2003 in the light of the complete time series. The latter is achieved by dividing the absolute anomaly by the standard deviation. Rankings of both absolute and relative anomalies in each pertinent administrative unit provide further means for evaluating the significance of the extreme weather event. In order to address the spatial differences on all aggregation levels, all results are generated into maps with GIS. Results emphasize the necessity of taking the issues of yield

data generalization and scaling into consideration, as indicated by SCHULZE (2000). Replacing single linear with bilinear fits to long-term crop series on the EU-15 level show the importance of adjusting trend fits lines to each country, as results of the two fits lead to markedly diverging conclusions. Tables including the calculated statistical parameters identify the administrative units on each aggregation scale that were affected or benefited most. This helps classifying the units and determine the impact on each unit and level.

Further heat wave years in Germany were derived using a temperature driven criteria catalogue of statistical parameters for 5 climate stations. They were selected to outline an area encompassing most of Germany and can be viewed in the annex (7.1). The climate stations were originally selected and maintained on the grounds of their long-term data series spanning the 20$^{th}$ century for verifying studies performed by BENISTON (2003) in this time series. The author had analyzed positive temperature records in the past century for comparative figures to the heat wave summer of 2003.

A year was considered a heat wave year if an average 15 or more summer days exceeded the 90$^{th}$ percentile of the climate stations' mean summer maximum temperatures in June, July and August. Results were compared to the years with the highest average number of days of persistent threshold exceedance, meaning consecutive days with temperature maxima over the 90$^{th}$ percentile. The use of percentiles in the upper extreme of the probability density function as temperature thresholds is relevant for identifying heat waves and assures independence among station means. The 90$^{th}$ percentile was defined as the upper extreme of temperature by IPCC (2001, A).

## *2.5 Technical advancement: Long-term linear trend analysis*

Long-term trend drivers were subtracted from actual yields for determining annual absolute anomaly sensitivity to inter-annual weather variability.

### 2.5.1 Model for linear fit

According to SWANSON (1979), a single linear fit is sufficient for its accurate description, even if no modifications to macroeconomical regulations are taken into account. As Badeck (2004) and HAFNER (2003) have found, these can be indicated by modeling multilinear fits that further reduce the sum of squared residuals. In both cases, technological advancement is assumed to be a constant. My test runs and more accurate fits to eastern European countries showed that linear fit lines also suggest distinct response to politically driven reorientation of the agroeconomical sector after 1990. The detrending model was applied to all yield series on each aggregation level.

The best linear fit line is calculated through linear regression and represents expected annual yields. The technologically induced trend was then removed by a method extensively applied and validated (SWANSON & NYANKORI, 1979; PHILLIPS et al., 1999; ALEXANDROV & HOOGENBOOM, 2001), according to the following equation:

$$Y_d = Y_a - (b * n) \tag{1}$$

where $Y_d$ = detrended yield; $Y_a$ = actual yield; $b$ = slope in tons pre hectare and year [t $ha^{-1}$ $y^{-1}$] of linear trend; and $n$ = number of year (first year in data range = 1). Statistical analyses have indicated that tested nonlinear approximations of yield increase do not improve linear trend equations. This remains the case when the effect of weather is integrated (SWANSON, 1979). Generally, detrended values were obtained by subtracting the product of slope and number of year in the series. Subtracting the intercept value from these figures resulted in the series' anomalies. If not noted otherwise, (detrended) absolute anomalies are referred to as anomalies. Expected yields are yields indicated by the linear fit lines. Relative anomalies are obtained by calculating the percent of deviation from actual to expected yields.

### 2.5.2 Bilinear Trends

In a study on changes in yields and yield residuals in wheat during the 21$^{st}$ century, CALDERINI AND SLAFER (1998) observed breaking points in steady and sloped yield gains in some European countries within the past 10-20 years. Yields stagnated or even decreased after these points. The question arises if these findings can be verified in this study or even expanded to other countries.

### 2.5.3 Model for bilinear fit

A model was developed for minimizing the yield residuals (differences of annual and expected yields) by applying a bilinear regression model to each dataset to determine if the bilinear trend reduced single linear fit residuals. The fit which produced the lowest residuals was selected. Coefficients of determination and residual analyses of squared deviation sums served as criterions for considering an improved model. The model determined the best fit for the year of a breaking point and a successive second linear fit to the yield series. The slope and intercept of the original single linear fit were adjusted accordingly. If (1) the coefficient of determination undercut that of the monolinear fit, thus decreasing the squared sum of residuals and (2) the supplementary trend contained a statistically maintainable series of years, the bilinear model was accepted. Two slope values, the intercept and the year in which the two linear fits converge were established iteratively by the model. The linear regression equation with one slope was applied to years preceding the modeled breaking point year. Otherwise, the sum of both equations was calculated (or difference, depending on the second slope).

## *2.6 Anomalies*

Deviations from expected yields are calculated through 2 methods. In both cases, the linear fit, i.e. expected yield values, represent the null value. However, while the absolute values deviate from 0 t $ha^{-1}$ of detrended yields, the relative anomalies are calculated in relation to expected yields. A standardized anomaly index became necessary to estimate the deviation of yields in heat wave years from the unit specific standard deviation in the time series. Hereafter, the term yield indices is applied when useful to refer to all 3 anomaly modes. Figures that pertain to modulated anomalies are explicitly indicated as such and must not be confused with absolute anomalies, which are discussed in the following.

### 2.6.1 Absolute anomalies

In order to determine the tendency and intensity of annual yield anomalies, the intercept of the regression equation is subtracted from each detrended yield series, thus rendering the deviating value from the expected yields without the long-term technical trend influence. Thus, the x-axis then represents the linear trend line. Resulting annual residuals of actual yields signify the dependent variables in multiple regression analysis for determining the influence of inter-annual weather variation. If not indicated otherwise, anomalies refer to (detrended) absolute anomalies [t $ha^{-1}$]. The focus is on absolute anomalies as yield indices, so in addition, detrended figures refer to them if not indicated otherwise. They are calculated from detrended values:

$$A_a = Y_d - c \tag{2}$$

where $A_a$ = (absolute) anomaly; $Y_d$ = detrended value; and $c$ = intercept of linear regression fit.

### 2.6.2 Relative anomalies

Comparing yield anomalies among different plants and areas with diverging climatic conditions made a relative measure necessary. Relative anomaly values are supplemented by calculating the percentage the actual yields deviate from the expected values. The expected values represent points on the linear trend line. Therefore, subtracting them from actual yields also leads to detrended values. Relative anomalies [%] are calculated according to the following equation:

$$A_r = \frac{(Y_a - Y_e)}{Y_e} * 100 \tag{3}$$

where $A_r$ = relative anomaly; $Y_a$ = actual yield; and $Y_e$ = expected yield on the linear fit line. Subtracting expected yields from actual yields leads to relative anomalies.

### 2.6.3 Standardized anomaly index

Standardized anomalies are predominantly applied for comparative reasons among large units. A unit's absolute anomaly (A) in 2003 is divided by the standard deviation (S) of the anomaly series. This takes spatial differences among units into consideration that result in widely contrasting direct and indirect impacts on cultivating conditions. This is particularly important for analyses on the EU-15 level. Values standardized in this manner (hereafter simplified as AS [A $S^{-1}$]) measure if and in how far annual figures are affected by an extreme weather event relative to the standard deviation of the time series. Those from +1.00 to -1.00 range within the standard deviation, those beyond are increasingly unlikely.

### 2.6.4 Trend detection for anomaly modes

It was assumed that the increasing yields evident in all units cause absolute anomalies to inflate over time, distorting the interpretation of seemingly more intense anomalies. Increasing relative anomalies can indicate changes in climate variability and mean values. To verify this, federal states datasets for 5 crops were analyzed. Different crops were used as opposed to one crop in various federal states to detect crop specific changes and to compare results. In order to detect trends in series, linear trends were applied and plotted together with yield indices. The modulated values of both absolute and relative anomalies were calculated in order to determine if the assumed linear trends in time series exist.

## *2.7 Inter-annual weather variability and yield sensitivity analysis*

Multiple linear regression models for yield anomalies and monthly climate variables were calculated from daily values for each unit composing the lower two aggregation levels Germany and Baden-Württemberg. The time series for the former ranged from 1951-1998, and 1951-2000 for the latter. Programming was implemented in FORTRAN. 1 climate station per unit supplied the representative climate data. 1 climate station was selected for each administrative unit to provide a representative dataset. Therefore, the climatological generalization on both levels varies and this was expected to be portrayed in the statistical results.

### 2.7.1 Climate variables selected as predictors

The objective was to apply spatially applicable, relatively simple monthly climate variables with consistent spatial and temporal data availability for studying yield sensitivity. The variables, a brief description, and the purpose for incorporating them are introduced in the following. Table 3 gives an overview of all variables considered. It is important to distinguish between the number of independent variables that are tested through criteria, selection methods, and thresholds (a total of 102 per model) and the number of independent variables a model is actually fit with (i.e. the number of variables actually accepted to a model, a maximum of 13 in this study).

Table 3. Data series, temporal resolution and climate variables used as predictors for multiple regression analyses

<table>
<tr><th>Aggregation Level</th><th>Predictor</th><th>Time series</th><th>Months</th><th>Sum of monthly Variables</th></tr>
<tr><td>Germany, federal states</td><td rowspan="2">Temperature average<br>Precipitation sum<br>deMartonne aridity index<br>Potential evapotranspiration<br>Climatic water balance<br>Temperature sum >= 5°C</td><td>1951-1998</td><td rowspan="2">Jan.-Oct., harvest year<br>June-Dec., sowing year</td><td rowspan="2">102</td></tr>
<tr><td>Baden-Württemberg, counties</td><td>1951-2000</td></tr>
</table>

#### *2.7.1.1 Average temperature and monthly precipitation sum*

The purpose of studying yield sensitivity to temperature means or temperature sums (hereafter TS) and precipitation sums (hereafter PS) as independent variables has been discussed in the introduction.

#### *2.7.1.2 5°C temperature sum*

Temperature sums above thresholds (hereafter WS) often give a better account of temperature conditions necessary for plant growth than averages do. The 5°C threshold was chosen because of the suppressed plant growth below this value (LESER, 1997). All daily temperatures >=5°C are added up to monthly sums.

#### *2.7.1.3 Potential evapotranspiration*

Evapotranspiration is the process of energy dissipation from radiation or heat. Potential evapotranspiration (hereafter PET) refers to the maximum amount possible under the given conditions and is always higher than or equals the actual evapotranspiration (DVWK, 1996; HÄCKEL, 1999). Calculating the actual evapotranspiration parameter poses major difficulties due to frequent lack of required data on soil, coverage, water content and high spatial and temporal variations in transpiration conditions (MÜLLER-WESTERMEIER, 2000; WEISCHET, 1997). PET was selected because: (1) as a hydrometeorological parameter comprising evaporation and transpiration, PET is of large importance in quantifying interactions between weather and cultivars; (2) it plays an important role in both water and energy balance models (DVWK, 1996; WEISCHET, 1997); and (3) it helps express wetness conditions and water stress to which cultivars are sensitive. Both directly affect yields as agro-climatic constraints (GAEZ, 2004).

I chose to implement the formula following *Turc/Ivanov* for calculating monthly PET values from numerous empirically developed methods. It takes global radiation, temperature, and relative humidity for dry areas into account, integrating meteorological parameters beyond temperature and precipitation.

All necessary measurements for calculating monthly climate variables were available for the selected climate stations on a daily basis. This criterion was not met by the more comprehensive and accurate formula after *Penman*, which also includes wind parameters (HÖLTING, 1996; DVWK, 1996). *Turc/Ivanovs*' approximation to its accuracy make the PET calculation selected a sufficient choice, although it produces results slightly lower than optimal in Germany.

### 2.7.1.4 Climatic water balance

The climatic water balance (hereafter CWB) indicates the difference of precipitation and potential evapotranspiration in mm. A positive result is interpreted as the water amount that precipitation exceeds PET by and consequently can run off into adjacent areas or fill up soilwater storage. A negative result indicates the amount PET surpasses precipitation by and must be contributed to this location in order to equalize the water balance (MÜLLER-WESTERMEIER, 2000; HÄCKEL, 1999). Both $C_3$ and $C_4$ crops react to water stress on plants, which is indicated by CWB. The annual cycle of CWB is conditioned by PET to a varying degree.

### 2.7.1.5 De Martonne aridity index

Precipitation must be coupled with other parameters to accurately address its effect on crops. This can be done with the empirically developed aridity index following *de Martonne* (hereafter DMI) in 1927. It provides a quantitative measure for the degree of aridity (MÜLLER-WESTERMEIER, 2000), and is defined as

$$DMI = \frac{PS}{T + 10} \tag{4}$$

where $DMI$ = de Martonne Index ; $PS$ = precipitation sum [mm]; and $T$ = mean temperature of time of interest. Results not only depend on the given parameters but also on the time range applied for precipitation sums and temperature means. The aridity threshold is defined as i=20.

The simple equation has its flaws: (1) the DMI assumes that the temperature alone sums up all the factors which evapotranspiration can be dependent on; (2) equating monthly with annual values does not lead to comparable results (WEISCHET, 1997). However, this simple aridity index shows scientifically applicable results when used in Germany and Baden-Württemberg (MÜLLER-WESTERMAYER, 2000). More importantly, it fits the approach of testing relations between a simple aridity index and yields, a purpose particularly evident in the light of the 2003 heat wave analysis.

Annual courses of CWB and DMI as described by Müller-Westermeyer (2000) correspond to a large extent in Germany. High DMI values from November through March are matched by exclusively positive CWB values. Lower DMI values dominate during the rest of the year besides in the German Alps, where low to negative values are measured for CWB, respectively.

### 2.7.2 Sum and time range of predictors

Climate variables were calculated for months from June of the sowing year to October in the year of harvest. This range corresponds with the average winter wheat life span, the crop of interest for multiple regression analysis in Germany (AGRIAN PUBLISHING UNION, 1982). Various factors influence crop physiology and growth at each development stage. November and December of the harvest year were excluded. Altogether, 102 monthly variables were tested for inclusion to each multiple regression model (6 climate variables* [ 7 months of previous year + 10 months of current year ] ).

### 2.7.3 Climate station selection

Representative climate stations from the German National Meteorological Service (Ger. Deutscher Wetterdienst, hereafter DWD) were selected for the administrative unit the yield series referred to. GIS methods, statistical methods and a criteria catalog were combined in an approach to distill one climate station for each German federal state and each county in Baden-Württemberg from over 600 available climate stations.

Criteria for extracting a preselection from the PIK database DWD climate stations were chosen to guarantee only consistent, homogenized daily data series. First, climate stations were extracted from the database that contained (1) homogenized daily datasets of all climatic parameters required for calculating the monthly climate variables; and (2) consistent series starting before the available yield data series began. Precise maps of wheat production areas were not available, so alternatively only climate stations either within CORINE Landcover 1990 (CRC) class of non-irrigated farmland or within 1 km buffers with a class coverage of at least 50% and below 800 m sustained exclusion.

The final selection step was to separately correlate winter wheat yield series of counties containing the remaining climate stations with the yield series of the federal state they are located in. The climate station in the highest correlating county series was selected. This method was favored over an analysis of annual average yield deviations or long-term means for the following reasons: (1) correlating annual county and federal state yields does not consider the actual value proximity of the yields, but instead weight the tendency and annual differences of the respective crop; (2) the objective was to determine similarity to the inter-annual variations of the federal state series, regardless of the absolute levels of values, and not to absolute crop values.

Average deviations from annual value averages would not take this point into consideration, which is crucial for an expressive degree of representability. A ranking method was preferred to a correlation threshold in order to guarantee that all states were represented by 1 climate station. The implicit fragment of autocorrelation between a county and a federal state yield series was considered negligible and not excluded.

Only precipitation stations with interpolated further climate data for calculating the selected variables passed the selection criteria for Saarland. The length of time series applied for correlation analyses differed between federal states, but was consistent between the federal state and counties. Correlation coefficients ranged from 0.96-0.99.

This statistical selection procedure did not apply to climate station selection in counties in Baden-Württemberg (for county specific models), because the yield data on the further disaggregated level (Gemeinden, Ger. townships) was not available. Instead, the climate stations in the few counties containing more than one that matched the preceding criteria were compared. The climate station with the lowest altitude and the largest surrounding farm land coverage was accepted. Climate stations representing federal states and counties are listed in the annex (7.1).

### 2.7.4 Programming

The computation of monthly climate variables from daily values was programmed with FORTRAN 90, which enabled easy future use at PIK. Test runs and verification of script outputs were performed.

### 2.7.5 Data preparation for sensitivity analysis

The last step before modeling consisted in combining the dependent and independent variables into a format that enabled the highest compatibility and flexibility with the software chosen for statistical modeling (SPSS). Tables containing the associated statistical units' yield anomalies (absolute and relative) and the meteorological predictors were produced for each unit in question.

### 2.7.6 Multiple linear regression analysis

How do winter wheat yield anomalies detracted from technical advancement trends cohere with monthly climate variables? I chose multiple linear regression modeling with SPSS as the constitutive method for studying this and yield sensitivity to inter-annual meteorological variability because: (1) multiple regression analysis has prevailed in studies of similar nature in statistically showing relationships between crop yields and weather (HOOKER, 1922; BAUMANN, 1966; CHMIELEWSKI, 1995; ALEXANDROV, 2001); (2) such models often form the basis estimating agricultural production under specific climatic circumstances (ALEXANDROV & HOOGENBOOM, 2001); and (3) determining intensity of statistical connections between yield anomaly variability and weather parameters was prioritized over the causal explanation of annual yield anomalies.

Models were conducted for federal states and for counties of Baden-Württemberg. The applicability of the chosen methodology was tested on two aggregation levels. Winter wheat represented the dependent variable. EU-15 countries were excluded from analysis on grounds of time constraints.

Both the coefficient of determination $R^2$ and the adjusted $R^2$ were calculated for each model. I chose $R^2$ values for further analysis for the following reasons: (1) the size of samples for each yield series was identical on a federal state level (55), and amounted to 34 or 31 on the county level, which was considered a negligible difference (6%); (2) the numbers of observations were high enough to dismiss the argument of suspect results; (3) model results were used exclusively for the aggregation unit they were devised for, with the exception of the Baden-Württemberg federal state model.

#### *2.7.6.1 Method for selecting predictors*

I chose forward selection, a stepwise variable selection procedure in SPSS, to sequentially enter the monthly climate variables into the model. This means that the model equation was blank to start with. All parameters entered had to meet the entry criterion of F=0.05 probability level (5% error level), and could not force an already entered parameter above the criterion. The parameter with the highest positive or negative coefficient was entered first, followed stepwise by the parameter with the highest partial correlation, until none more could pass the entry criterion (SPSS, 2003). This iterative approach barred variables only negligibly contributing to the prediction of winter wheat anomalies, and was efficient when dealing with such a large number of predictors. It substantially narrowed down the number of accepted variables to a maximum of 9 on the federal state level (number of yield observations: 54, 1950-2003) and 13 on the county level (number of yield observations: 34 or 31, 1970-2003 and 1973-2003).

#### 2.7.6.2 Model validation and sensitivity analysis through statistical parameters

Resulting multiple regression model statistics served as bases for qualitative and quantitative model evaluation and sensitivity analysis of yield anomalies to the model predictors. Models were tested for each federal state using unhomogenized climate data in 1999 and 2000. Residual analysis validated yield results, indicating the model applicability for yield anomaly prediction. However, sensitivity analysis was the main purpose of modeling, not future anomaly prediction. $R^2$ values stated how much of the total variance was explained, changes in $R^2$ referred to each accepted variable's contribution to explaining inter-annual yield anomaly variance. Pre-adjusted probability of F (error level in %) accounted to the confidence and probability of error.

Regression coefficients assumed an important role in analyzing the sensitivity of winter wheat anomalies. Parameter constellations revealed if and in what manner anomalies change with each accepted monthly climate variable. Non standardized B coefficients (regression coefficients) and their standard errors gave qualitative insight into the goodness of coefficient estimation. Furthermore, they were used to in regression equations for calculating the modeled yield anomalies for each administrative unit. Standardized ß coefficients (standardized regression coefficients, hereafter ß values) represented the measure of actual sensitivity by indicating how the dependent variable (yield anomaly) changes if the standardized monthly climate variable in question changes by 1. ß values represented the pivotal coefficient for sensitivity analysis. The absolute values indicate the variables' relative importance for predicting the anomaly. This provided further insight into how yield anomalies correspond to monthly values of the predictors. Combining equations of the technical advancement regression and the multiple regression model enabled me to account for the total explained variance of the actual data series. Residuals were calculated in order to quantify the fraction of the yield anomalies associated with yield influencing factors beyond technical advancement and inter-annual weather variability.

### 2.7.7 Simulating anomalies with climate scenario data

Simulating winter wheat anomaly variability with selected county data series and climate scenario data allowed me to detect changes in (1) overall inter-annual variability and (2) frequency of extreme anomaly peaks or dips. Trends were determined for these reasons. Only models with a high goodness of fit were taken into consideration. Anomalies were simulated from 2001-2055 for five county models in Baden-Württemberg with $R^2$ values among the highest (over 0.75).

Table 4 comprises the studies performed on each aggregation level and can serve as a look-up reference when necessary.

Table 4. Overview of studies performed on each aggregation level. Shaded boxes indicate studies missing on this level.

| **Area of interest** / **Studies** | | **EU-15, countries** | **Germany, federal states** | **Baden-Württemberg, counties** |
|---|---|---|---|---|
| *Heat wave 2003 analysis* | *Time series*<br>*Crops* | 2003<br>wheat, maize | 2003<br>winter wheat, spring wheat, all cereals, all wheat | 2003<br>winter wheat |
| *Long-term trend analysis with detrended anomalies* | *Time series*<br>*Crops* | 1961-2003<br>wheat, maize | 1950-2003<br>winter wheat | 1970-2003, only on selected county<br>winter wheat |
| *Inter-annual variation and Sensitivity analysis with yield anomaly models* | *Time series*<br>*Crops* | | 1951-2003<br>winter wheat | 1970-2003<br>winter wheat |
| *Simulated yield anomalies with climate scenario data* | *Time series*<br>*Crops* | | | 2001-2055<br>winter wheat |

### 2.7.8 Mapping qualitative and quantitative results of models

Dominating parameter constellations in models were visualized on both aggregation levels with GIS, and their spatial distribution was evinced. This helped detect regional accumulations of the highest correlating variables and differences between aggregation levels and administrative units therein. Quantitative analysis results were mapped for the same purpose.

Models derived from applying the federal state model of Baden-Württemberg to each county, and county specific models were extensively compared. Conclusions were drawn for issues addressing scaling and generalization problems.

## *2.8 GIS implementation and scaling*

Focusing on a single scale can obscure important processes that only become obvious at either a finer or broader scale (SCHULZE, 2000). GIS is applied here to represent the static spatial state, and partly changes of study results. Results of heat wave analyses, model results, and sensitivity analyses were visualized. Generally, all results applicable to the administrative units were integrated into a GIS to ascertain their spatial patterns and distributions. It must be emphasized here that data from representative single points (climate stations) was extrapolated to sometimes large administrative units (federal states), contrasting systematically aggregated yield data.

# 3 Results

## 3.1 Linear trend fit lines of yield series

Single and bilinear fit lines were determined for wheat yields in each unit on both the EU-15 and German federal states level in order to provide a basis for detrending.

Table 5 allows direct comparison of linear fit lines among the same crop type between the aggregation levels of EU-15 countries and German federal states. It is important to take the following into account: (1) total EU-15 yields were directly extracted from the FAO database and then processed, and do not represent an average for EU-15 countries, unless indicated otherwise; (2) figures for Belgium and Luxemburg are combined throughout the study; (3) the length of time series differ between aggregation levels; (4) figures highlighted green or red in tables indicate the highest or lowest value in the category. This visual aid for tables is maintained throughout the study.

Table 5. Single and bilinear equations and $R^2$ values of linear fit lines to long-term wheat yield series in German federal states (1950-2003) and EU-15 countries, and the total EU-15 (1961-2003). x is the *number* of the year in question (first year in series = 0, last year in series from 1950-2003 is 54, last year in 1961-2003 series is 43). If the difference between the *actual* year in question (y) and the breaking point year is >=0, the difference is multiplied with the second slope for EU-15 countries with bilinear fit lines. Furthermore, the increase of $R^2$ with bilinear fits is indicated. The averages refers to all units on that particular aggregation level.

| Aggregation Level | Aggregation unit | Linear equation | $R^2$ | Bilinear $R^2$ Increase |
|---|---|---|---|---|
| German federal states | *Baden-Württemberg* | 0.089x+2.1114 | 0.92 | |
| | *Bavaria* | 0.0942x+2.081 | 0.91 | |
| | *Hesse* | 0.0982x+2.2651 | **0.93** | |
| | *Lower Saxony* | 0.1118x+2.2745 | 0.92 | |
| | *North Rhine-Westphalia* | 0.121x+1.9814 | 0.92 | |
| | *Rhineland-Palatinate* | 0.0837x+2.2922 | 0.91 | |
| | *Saarland* | 0.0893x+1.6123 | **0.93** | |
| | *Schleswig-Holstein* | 0.1289x+2.2909 | **0.93** | |
| | ***Average*** | | **0.92** | |
| EU-15 countries,and total EU-15 | *Austria* | 2.46+0.09(y-1961)-0.11(max [ 0;y-1990 ] ) | 0.87 | 0.07 |
| | *Belgium and Luxemburg* | 0.1189x+3.1098 | 0.87 | |
| | *Denmark* | 0.0924x+3.7764 | 0.87 | |
| | *Finland* | 1.74+0.05(y-1961)-0.12(max [ 0;y-1995 ] ) | 0.61 | 0.05 |
| | *France* | 0.1144x+2.662 | 0.92 | |
| | *Germany* | 0.1093x+2.8955 | **0.93** | |
| | *Greece* | 1.29+0.07(y-1961)-0.09(max [ 0;y-1980 ] ) | 0.68 | **0.32** |
| | *Ireland* | 0.1551x+2.6304 | 0.92 | |
| | *Italy* | 1.95+0.04(y-1961)-0.08(max [ 0;y-1994 ] ) | 0.80 | 0.08 |
| | *Netherlands* | 0.1218x+3.8022 | 0.89 | |
| | *Portugal* | 0.74+0.03(y-1961)-0.05(max [ 0;y-1991 ] ) | **0.46** | 0.12 |
| | *Spain* | 0.86+0.05(y-1961)-0.03(max [ 0;y-1988 ] ) | 0.75 | 0.02 |
| | *Sweden* | 0.0759x+3.2567 | 0.81 | |
| | *United Kingdom* | 3.30+0.12(y-1961)-0.11(y-1996) | 0.90 | **0.009** |
| | ***Average*** | | **0.72** | **0.10** |
| | ***EU-15*** | **1.89+0.11(y-1961)-0.18(max[0;y-1998])** | **0.96** | **0.01** |

For wheat, all 8 German federal states were modeled best with a single linear fit line. A better fit line was not achieved by applying the bilinear model. The average $R^2$ for the 8 studied federal states (0.92) is slightly lower than that of total Germany as a single unit (0.95). Fit lines all lie in the compressed $R^2$ range of 0.91-0.93. Intercepts of the equations compose a similarly condensed range (1.61-2.29 t $ha^{-1}$). Only Saarland deviates markedly at 1.61 t $ha^{-1}$. The exclusively positive slopes range between 0.08 t $ha^{-1}$ $y^{-1}$ (Rhineland-Palatinate) and 0.12 t $ha^{-1}$ $y^{-1}$ (North Rhine-Westphalia). Average linear fit lines for the 8 federal states have an $R^2$ of 0.87 (cereals) or higher for winter wheat (0.92), spring wheat (0.87) and corn maize (0.89). Analogous values for the total of Germany are higher. The linear fit line of corn maize explains 96% of the overall variance, the highest overall percentage in Germany or a federal state. This is counterbalanced by the lowest $R^2$ value of 0.70 for the same product in Saarland. Similarities among states pertaining to $R^2$, exclusively positive slopes and intercept values, shift negligibly and characterize a steady rising trend as a pattern resembled in all crops and states. These findings correspond well with the hypothesized long-term driving factor of yield increase.

Values are generally lower on the EU-15 level and display a higher variance and variability. Conditions for cultivating wheat are much more heterogeneous, inter alia due to vast climatic differences among regions. The average $R^2$ for linear trends explains 20% less of the total variance than for German federal states. A minimum of 46% explained variance (Portugal) is a marked counterweight to the respective value in Germany. Crop yields and $R^2$ figures are higher in western and central Europe. Linear fit line intercepts among the 15 countries span approximately 3 t $ha^{-1}$. The highest intercept in the Netherlands (3.8 t $ha^{-1}$) exceeds that of Portugal (0.74 t $ha^{-1}$) by a factor four. Slopes accord to this high variance in EU-15 countries. Up until the breaking point year in Portugal, Ireland (0.16 t $ha^{-1}$ $y^{-1}$) displays an expected annual yield increase over five times as steep as Portugal's (0.03 t $ha^{-1}$ $y^{-1}$).

Bilinear trends reduce the squared sum of residual of single linear fits in 7 time series. In geographic terms, the United Kingdom is the only country outside of southern Europe with such a time series, and also is the exception to the rule that bilinear fit lines correspond to countries with low yields (Spain not included). The overall unexplained variance of yields subsequently fit with a second linear trend was reduced by an average 10%. Substantial improvements in models were achieved for Greece (+0.32) and Portugal (+0.12). All countries with the exception of Greece (1980) have breaking points in the nineties. Varying modifications are made to exclusively rising slopes at breaking points. The EU-15 in total experiences the most pronounced readjustment at a loss of -0.18 t $ha^{-1}$ $y^{-1}$ and Spain the slightest (-0.03 t $ha^{-1}$ $y^{-1}$). However, it must remain clear that negative second slopes do not equate to decreasing yields. The difference between first and second slope shows how yields develop after breaking points: thus, expected yields in Spain (+0.02 t $ha^{-1}$ $y^{-1}$) and the UK (+0.01 t $ha^{-1}$ $y^{-1}$) are still increasing, but at a lower rate per year, while yields in Italy (-0.04 t $ha^{-1}$ $y^{-1}$), Finland (-0.07 t $ha^{-1}$ $y^{-1}$) and the EU-15 in total (-0.07 t $ha^{-1}$ $y^{-1}$) are decreasing at the quickest rate per year.

Up until the breaking points, all country units considered show increasing yield trends with varying steepness when fit with a regression line. Central and western EU-15 countries return the highest $R^2$ values (including Sweden), all above 0.75. Lowest $R^2$ values associate to the countries with the least increase in yields and the lowest expected yields in 2003. Single linear and bilinear fit lines to all observed crops on the two aggregation levels produce fair to near perfect approximations to the actual yields. $R^2$ values exceed 0.5 in all cases except for wheat yields in Portugal. $R^2$ average in German federal states is markedly higher than in EU-15 countries.

### 3.1.1 Improving $R^2$ values through bilinear fits

Second order polynomial trend lines were plotted to the residuals of linear fits. Non random residuals were evident in 7 of the EU-15 countries. As the trends of linear fit residuals for Germany and Greece show in Fig. 1, the trend line of the bilinear fitted series for Greece clearly reduces residuals and approximates a random non biased distribution around 0 mean. A considerable reduction of residuals for the pertinent wheat series in Greece is achieved through a bilinear fit, cutting down unexplained residual variance from 49% to 0.002%.The residuals of single linear fitted German wheat display the factually best single linear approximation. Only 0.004% of residual variance remain to be accounted for.

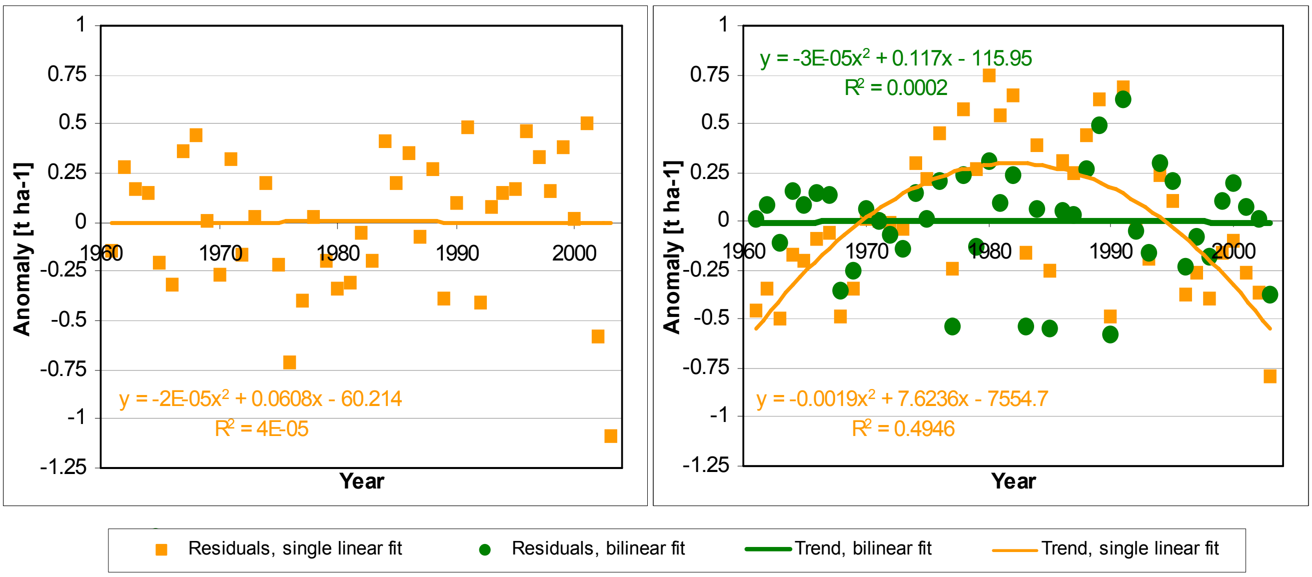
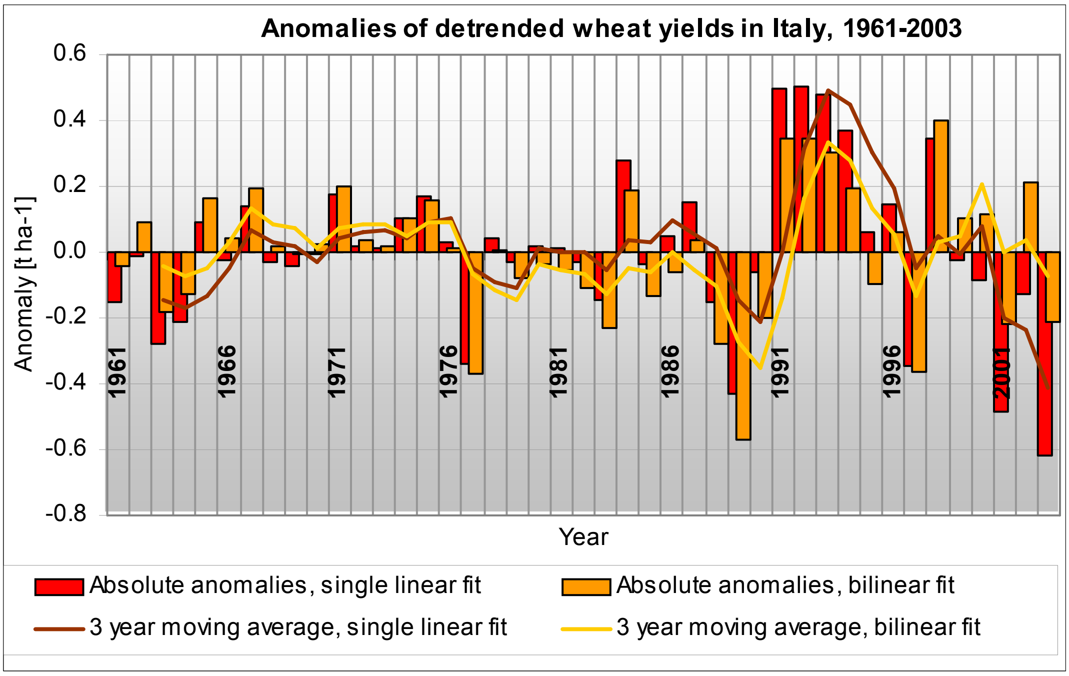
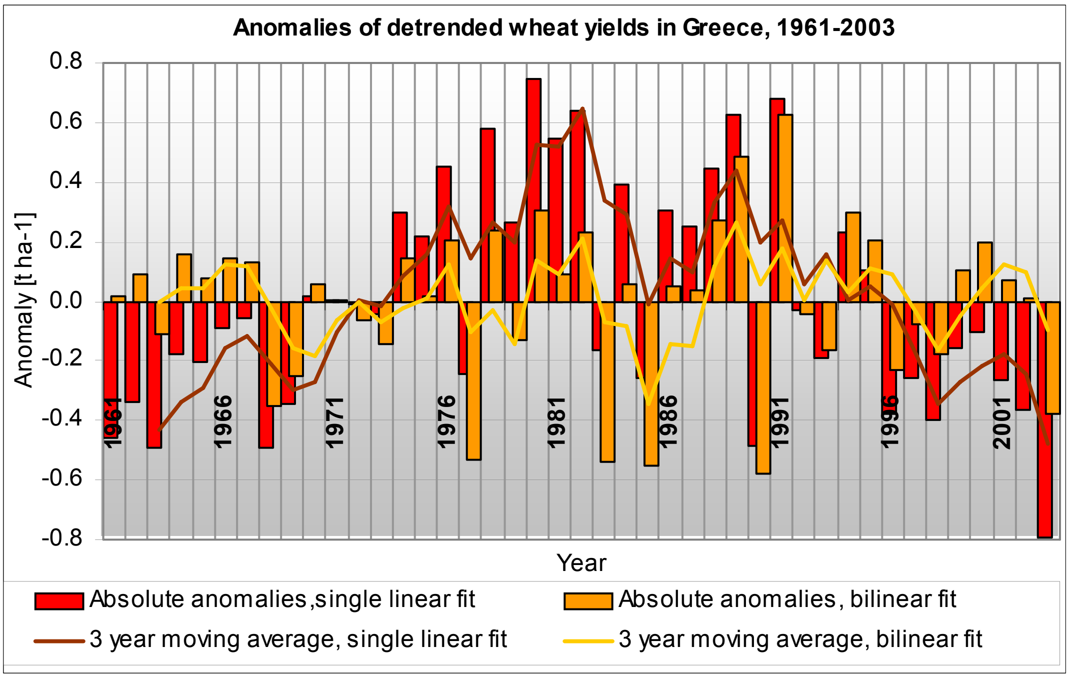



Fig. 1. Residuals of single linear and bilinear fits for wheat in Germany and Greece, 1961-2003. $R^2$ is significantly increased by the bilinear fit for wheat data in Greece.

Preceding bilinear fit tests not only provide a more realistic trend projection but also avoid misinterpretations of inadequately detrended data. In Fig. 2 single linear detrending in Italy projects a drastic plunge in absolute anomalies of wheat yields between 1990 and 2003, as displayed by the 3 year moving average. The bilinear fit reducing the square sum of residuals presents a similar descent, before stabilizing after 1997. So overall, the amplitude between 1990 and 2003 is more compressed, with a reduced variance of the single fit line anomalies of 69% (0.04 t $ha^{-1}$ compared to 0.13 t $ha^{-1}$). The average was cut back from 0.05 t $ha^{-1}$ to 0.00 t $ha^{-1}$ (Fig. 2).




| 1990-2003 | single | bilinear |
|---|---|---|
| *stdev* | 0,37 | 0,20 |
| *variance* | 0,13 | 0,04 |
| *avg* | 0,05 | 0,00 |
| *max* | 0,50 | 0,40 |
| *min* | -0,62 | -0,57 |




| 1980-2003 | single | bilinear |
|---|---|---|
| *stdev* | 0,42 | 0,26 |
| *variance* | 0,18 | 0,07 |
| *avg* | 0,05 | 0,00 |
| *max* | 0,74 | 0,62 |
| *min* | -0,79 | -0,58 |

Fig. 2. Comparison of yield anomalies detrended with single fit lines and bilinear fit lines for wheat in Italy and Greece, 1961-2003. Statistical parameters in the appended tables refer to the duration of the second linear fit line series

The statistical parameters are modified in a similar manner in the Greek anomaly series, but the tendencies of positive and negative anomalies are more pronounced. Variability is markedly reduced by applying a bilinear fit line starting in 1980, which readjusts the statistical parameters as displayed in the supplementary table. The steady rise to more positive anomalies from 1961 to 1980 and their decline thereafter is transformed into a lower variability series with more extreme negative anomalies and less markedly positive anomalies. The exception is the 2003 anomaly. However, the 2003 negative anomaly is less markedly modified to a less negative figure than through the bilinear fit line in Italy. It is important to note that anomaly averages of single linear fit figures in the supplementary tables diverge from 0 after the breaking point. This is because only the portion of the series starting at the breaking point is taken into account. Otherwise, averages would properly equal 0.

### 3.1.2 Comparing yield trends on aggregation levels in Germany

Next, linear models for Baden-Württemberg are taken into consideration and compared to the federal state and country figures in Fig. 3. $R^2$ values for actual yields of all crops are generally slightly higher for Germany than they are for the federal states. County values lie below them. This is a result of what is referred to as the modifiable areal unit problem (MAUP). It becomes evident in the actual winter wheat series, where results are dependent on the yield data and the different spatial units the statistical data pertains to. In turn, results are affected by the chosen units, since they are in a sense an arbitrary division of space, i.e. a modifiable areal unit (SHEPHARD et al., 2004). Higher explained variance of yields in higher aggregation levels are attributed to leveling effects through aggregating yields subject to varying influences. Regionally confined extreme events are relativized. An exception to this, which represents an outlier in all 3 aggregation levels, is the heat wave event in 2003 that lead to massive drops in yields. This finding is extensively discussed (see 4.4) and stresses the response of wheat and winter wheat to larger scale adverse weather conditions, as opposed to regionally confined conditions.

The higher the aggregation level, the more explained variance per aggregation is associated with less pronounced inter-annual variations, such as in 1983, 1986 (negative anomalies), and 1984 (positive anomalies, Fig. 3). Very similar $R^2$ values for wheat and maize were achieved for countries adjacent to Germany. This suggests that similar climatic conditions are a predominant driver of crop yields under comparable technological advancement. Diverging inter-annual yield variability is evident in degree and often in tendency among the 3 scales, while the slopes only depart slightly. Arguably, variability is the defining characteristic for comparing these series (Fig. 3).

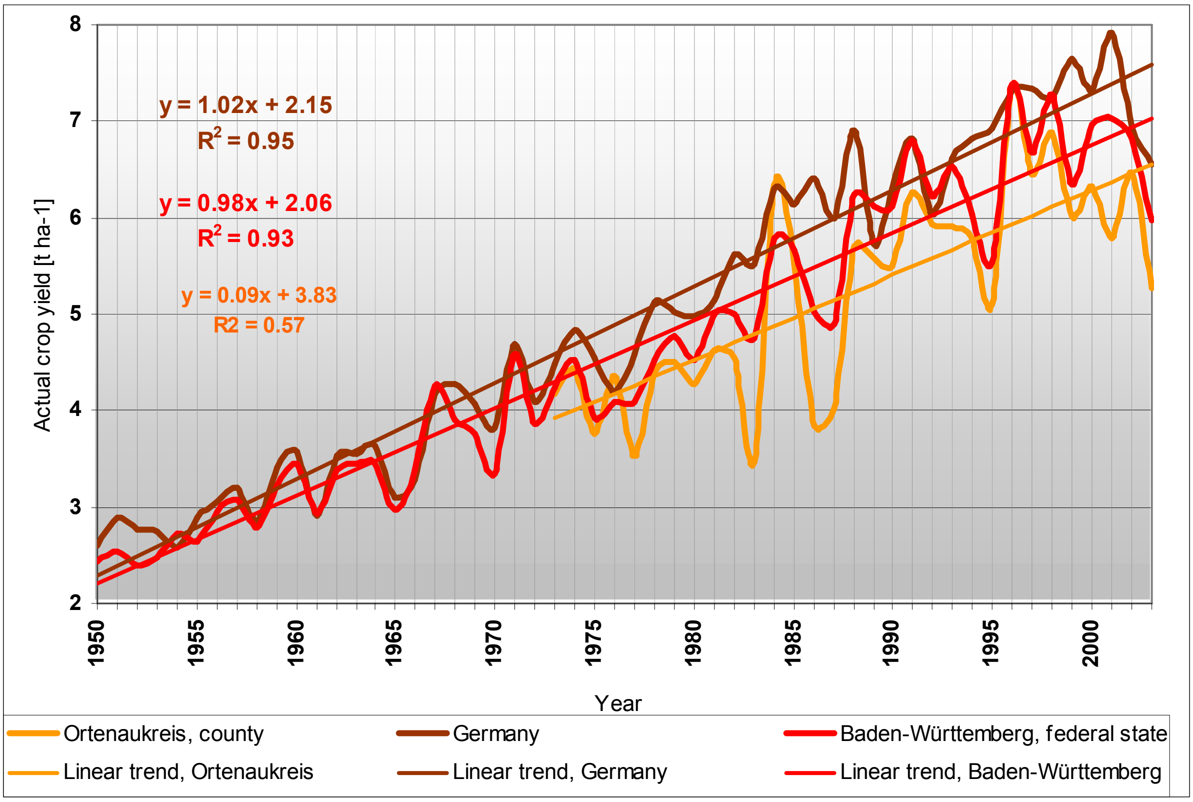



Fig. 3. Actual yields of winter wheat on 3 aggregation levels in Germany: County of Ortenaukreis in Baden-Württemberg (1973-2003), Baden-Württemberg, and Germany (1950-2003) including the accordant linear regression equations

### *3.2 Absolute and relative anomaly trends*

It was assumed that absolute anomalies in units with a steady rise of expected yields would increase over time in the series from 1950-2003. This assumption is based on the overall increase in yields possibly leading to larger deviations from expected figures. In order to detect any such trends, relative and absolute anomaly figures were turned into moduli for wheat, winter wheat, summer wheat, cereals, and maize, and compared. In this section (3.2) on anomaly trends both absolute and relative anomalies refer to modulated figures.

A positive linear trend was observed in each absolute anomaly series on the aggregation level of Germany. Figures of absolute anomalies increased for all observed crops between 1950-2003, with rises in slopes across the board. Maize experienced the highest increase (0.3 t ha$^{-1}$), doubling the lowest increase for combined cereals (0.1 t ha$^{-1}$).

Results for relative anomalies markedly differ for the same areas, cultivars, and time series. Linear trends show an opposite tendency of relative anomalies' modulated values. Summer wheat (+1.3%) shows the only positive trend. Both winter wheat anomaly indices and their antidromic trends are juxtaposed in Fig 4. Absolute values of relative winter wheat anomalies decrease in favor of smaller figures, the opposite of the absolute anomaly influx. Conclusively, both anomalies react antithetically over time in Germany.

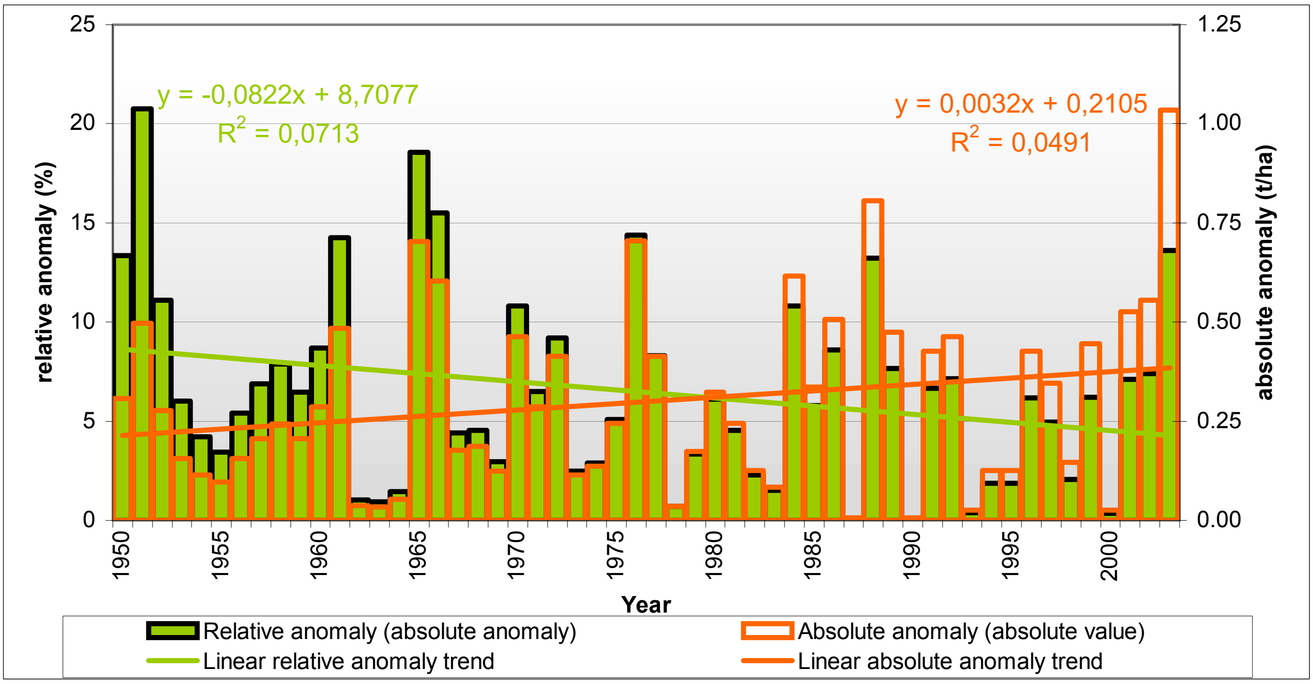



Fig. 4. Opposing trends in absolute figures of relative and absolute anomalies of winter wheat in Germany,1950-2003

The extreme anomalies closing the series in 2003 steepen the 5 positive absolute anomaly slopes, while they level relative anomaly slopes. The tendency remains the same in all cases if figures for 2003 are excluded from the series. Four out of five crops experience the highest overall absolute anomaly in 2003. The anomaly for spring wheat ranks 4$^{th}$ highest. Winter wheat ranks lowest in 2003 among absolute anomalies and 6$^{th}$ lowest among relative anomalies.

This underlines slightly differing calculations made by the 2 indices. The large anomalies in 2003 serve as an example for the influence of the selected anomaly on results and interpretation. More pronounced absolute anomalies suggest higher crop sensitivity in the second half of the series than relative anomalies.

Given the steady near linear increase of crops in Germany, this leads to the following interpretations for 4 out of 5 crops: An increase of the size of deviations from the trend line is observed for absolute anomalies. At the same time, this is counterbalanced by the increase of expected yields, leading to smaller deviations of relative anomalies. A synthesis of these interpretations leads to the notion that expected yields are increasing more than absolute anomalies are.

### 3.3 *Anomaly characteristics*

A key characteristic of anomaly series is the inter-annual variability, as shown in Fig. 5. Variations of and between positive and negative figures are the rule and the mean state. This applies to either type of anomaly, both relative and absolute. By subtracting the long-term trend from actual yields the residuals represent the inter-annual fluctuation of yields around expected values. Intensity varies among and within each aggregation level, and lower yields do not generally correspond with lower anomalies. As shown in Fig. 5, variance and standard deviation of the shorter Ortenaukreis absolute anomaly series (1973-2003) exceed the values for all of Germany approximately by a factor 3 and 2 (0.49 t ha$^{-1}$ compared to 0.14 t ha$^{-1}$; 0.69 t ha$^{-1}$ to 0.37 t ha$^{-1}$).

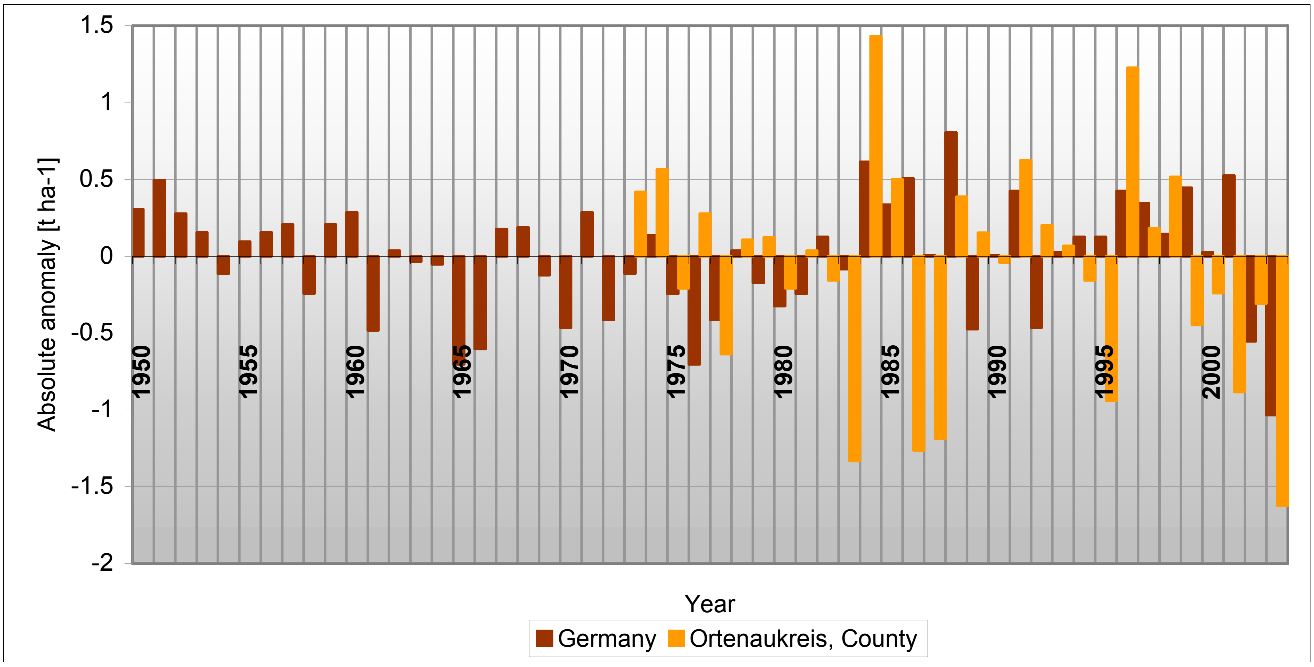



Fig. 5. Winter wheat absolute anomalies on different aggregation levels: Germany and the Ortenaukreis county in Baden-Württemberg

## 3.4 *Analyzing wheat and winter wheat anomalies in the heat wave year of 2003*

A comprehensive analysis of anomaly variability in 2003 was performed for the study of yield anomalies and their significance on all aggregation levels. Results exemplify anomaly sensitivity to such a meso-scale extreme weather event.

The following section investigates how yield anomalies in a particular year vary on different aggregation levels and scales. The year in question, 2003, was highlighted by a record summer heat wave in large parts of Europe and provided insights as to how an extreme weather event shifts yield figures stripped of the long-term trend. Furthermore, figures for 2003 are additionally put into the context of all anomalies in the data series using qualitative and quantitative statistical methods. Analyzing yield indices in a year of such a heat wave event sets the stage for the ensuing results of investigating yield sensitivity toward inter-annual weather variability. All three aggregation levels were taken into consideration to allow an extensively comparative approach. Wheat is analyzed on the EU-15 level, winter wheat in Germany and Baden-Württemberg.

### 3.4.1 The meteorological and agricultural situation in Europe

Before extensively analyzing the anomalies in 2003, a brief summary is given of the meteorological and agricultural situation from January to September of this year on all 3 aggregation levels. The order in which they are discussed reflects the downscaling from the smallest to largest scale. A preliminary statistical analysis of summer time series of mean temperatures (June, July, August) from 1761-2003 in Germany was conducted by SCHÖNWIESE et al. (2003). The summer of 2003 was the warmest on record. LUTERBACHER et al. (2004) conclude from multiproxy reconstructions of monthly and seasonal surface temperature fields for Europe that the summer of 2003 was very likely warmer than any other in Europe since 1500.

An unusually stable high pressure zone anchored over central Europe was flanked by low pressure areas, corresponding to a Rossby wave (SCHÖNWIESE et al., 2003). Dominance of regenerating high pressure exposure in June and from mid July through August formed a barrier for rain bearing depressions. It also caused record high mean temperature streaks in central and southern European countries as well as high sunshine duration, breaking long standing record figures (Beniston, 2003; DWD, 2003; Müller et al., 2003).

Winter crops had been regionally affected by a harsh winter in advance. The unusually high temperatures accelerated crop development by up to 20 days, and the rapidly ripening winter crops were already widely exposed to low soil moisture. Quality and quantity of crop harvest were markedly reduced in these areas by the extreme weather conditions and high moisture demand (JRC, 2003; UNEP, 2004).

### 3.4.2 The meteorological and agricultural situation in German federal states

In the summer months, daily mean temperature (19.6°C) exceeded the reference figure from 1961-1990 by 3.4 K, an event that can be expected every 455 years if the progressive warming trend of the past decades is taken into consideration (DWD, 2003; SCHÖNWIESE et al., 2003). June and August area averaged temperatures were the highest since commencing area averaging in Germany in 1901. July was the 7$^{th}$ warmest since 1901. Furthermore, the summer of 2003 was the 5$^{th}$ driest since 1901 and the sunniest since 1951. A temperature gradient in Germany from northeast to southwest was determined.

Winter wheat sowing proceeded under generally favorable conditions, but since spring had also been relatively dry and the heat led to increased evapotranspiration, wheat cultivars were severely damaged throughout Germany. Premature development of the cereals accelerated ripeness, and soil moisture was insufficient during seed ripening and fructification (JRC, 2003). The only wheat yields comparable to expected figures were reported from Schleswig-Holstein. Negative relative wheat anomalies in northwestern Germany (approximately -10%) were half as low as in Bavaria in the southeastern part. Collapses down to 20% of the expected wheat yields were suffered in Brandenburg and Saxony (DAINET, 2003; DBV, 2003; JRC, 2003).

### 3.4.3 The meteorological and agricultural situation in Baden-Württemberg counties

Winter wheat had been stressed by a cold winter in February, 3 K below the long-term average. The series of high pressure zones began thereafter with short interruptions, causing a drastic water deficit in high evaporation figures by May. They were accentuated in the brunt of the heat wave in June and August. Mannheim and Öhringen (northern Baden-Württemberg) reported precipitation sums of 12mm and 15mm in June, 15% and 18% of the German area average (82 mm). The result was a considerable loss of yields. The highly unusual drought was terminated by abundant

rainfall in October (LÖPMEIER, 2004). In Karlsruhe, the daily mean temperature from July 7th to August 29th equaled or exceeded 25°C, amounting to 54 consecutive summer days. A record breaking mean daily maximum temperature of 30.6°C was reported in August. New records were set for sunshine duration, daily temperature maximum (40.3°C) , and heat days (53). Freiburg i. Br. reported 83 climatic summer days (maximum temperature >25.0°C) in the summer months, 9 days short of total summer days. The August mean temperature of 25.5°C exceeded that of the long-term mean in Algiers, Algeria by 0.6°C (MÜLLER et al., 2003). The past 200 years do not show a comparable summer (MÜLLER et al, 2003; SCHÖNWIESE et al., 2003).
The heat wave had a negative, albeit heterogeneous impact on aggregation units at all levels. Additionally, record high anomalies were documented in areas beyond the core of the heat wave. While yields in Germany and Baden-Württemberg are unanimously below average as a result of sensitive response to the adverse meteorological conditions, more heterogeneous harvests are observed on the EU-15 country level.

### 3.4.4 Yield index results for wheat in EU-15 countries

Table 6 summarizes quantitative and qualitative indices for each country to determine how 2003 harvests in each of the EU-15 countries fit into the respective long-term yield series from 1961-2003 (43 years). The standard deviation [S] indicates the absolute detrended yield anomaly in t $ha^{-1}$. France (-3.22 A $S^{-1}$) and Germany (-3.14 A $S^{-1}$) show the lowest negative standardized anomaly index AS (see 3.6.3). Both countries had the lowest anomaly rankings in each time series in 2003. Anomalies exceeded the country specific standard deviation by more than factor three. Austria follows with -1.52 A $S^{-1}$, the 4th lowest anomaly since 1961. Northern Italy was also located in the core of the high pressure zone and Italian yield shows the 7th lowest anomaly in the series. Greece experienced the 5th lowest wheat anomaly since 1961. The absolute anomalies of all these countries excluding Italy are in the lowest 10% quantile of their series.

Table 6. Wheat anomaly indices in 2003 in EU-15 countries in the context of the data series from 1961-2003. Red values mark the least favourable results, green values mark the most favourable.

| Country | Standard deviation (S) [t $ha^{-1}$] | Absolute Anomaly (A) [t $ha^{-1}$] | AS [A $S^{-1}$] [t $ha^{-1}$] | Rank (A) | (A) in 9th Quantile | (A) in 1st Quantile | Relative anomaly |
|---|---|---|---|---|---|---|---|
| *Austria* | 0.33 | -0.50 | -1.52 | 4 | 1 | | -10.3 |
| *Belgium and Luxemburg* | 0.57 | 0.10 | 0.18 | 26 | | | 1.2 |
| *Denmark* | 0.45 | 0.08 | 0.18 | 28 | | | 1.0 |
| *Finland* | 0.43 | 0.11 | 0.26 | 19 | | | 3.7 |
| *France* | 0.41 | **-1.33** | **-3.22** | 1 | 1 | | **-17.5** |
| *Germany* | 0.35 | -1.09 | -3.14 | 1 | 1 | | -14.4 |
| *Greece* | 0.26 | -0.37 | -1.43 | 5 | 1 | | -16.4 |
| *Ireland* | 0.59 | -0.39 | -0.66 | 13 | | | -4.2 |
| *Italy* | 0.20 | -0.21 | -1.04 | 7 | | | -7.0 |
| *Netherlands* | 0.54 | 0.08 | 0.14 | 25 | | | 0.9 |
| *Portugal* | 0.27 | -0.03 | -0.13 | 20 | | | -2.7 |
| *Spain* | 0.32 | 0.16 | 0.49 | 33 | | | 8.0 |
| *Sweden* | 0.46 | **1.07** | **2.35** | **43** | | 1 | **16.5** |
| *United Kingdom* | 0.47 | -0.12 | -0.26 | 21 | | | 0.0 |
| ***EU-15*** | **0.21** | **-0.13** | **-0.64** | **13** | | | **-2.4** |

Negative anomalies (9 cases) prevail positive anomalies (6 cases). Sweden shows a markedly positive AS (+2.35 A $S^{-1}$), benefiting largely from the highest ranked anomaly since 1961 and representing the only single absolute anomaly figure in the 90% quantile. Other positive figures are below +0.50. The tendency of unfavorable to severe anomalies in 2003 is shown in the 13$^{th}$ lowest ranking EU-15 wide absolute anomaly (-0.61 t $ha^{-1}$) in the series. However, a far more drastic figure of -1.61 t $ha^{-1}$ was produced in country data exclusively fit with single linear trends, for which the rank slips to lowest in the series.

Results attributing to absolute, country weighted, and relative anomalies help clarify the patterns and differences among them (Table 6). Absolute anomalies, AS, and relative anomalies show identical tendencies for each country, while the degree of deviations shift slightly. Shifts in these values and ranks stemming from the linear (single and bilinear) fit lines to yield series of EU-15 countries are extensively considered in the discussion section.

A broadly corresponding pattern of countries in which yields were substantially affected is determined in the 3 yield indices plotted in Fig. 6: France, Germany, Italy, Austria, and Greece show results among the lowest in each plot with anomalies and AS below each respective standard deviation, the Italian absolute anomaly excluded.

Two conspicuous patterns were determined at this aggregation level. First, the countries affected most by wheat yield loss coarsely outline the main region influenced by the regenerating high pressure zones over central Europe. French and German agricultural productions were severely dented, and Austria suffered a similar albeit less extreme loss. In Greece, the agricultural situation of wheat yields was comparably severe. The actual wheat yield was 16.4% below the expected value, 1% higher than the figure of France. Whether this was caused by similar influences remains to be explained.

The second pattern counters the first in terms of anomaly tendency but not in intensity: a gradient of countries along the North and Baltic Sea show persistently positive figures within all 3 mapped values with absolute anomalies ranking between 25$^{th}$ highest (in Finland) and highest (in Sweden) in each data series (Fig. 6). Positive indices in Belgium and Luxemburg, the Netherlands, Denmark, and Sweden contrast the adjacent countries with negative yield outcomes. While the Benelux countries and Denmark show marginally positive absolute anomalies and AS (between 0.08 and 0.10t t $ha^{-1}$; 0.14 and 0.18 A $S^{-1}$, respectively) as well as surpluses of relative anomalies up to 5%, Sweden exhibits the highest values in each category and surpasses the expected yield by 16.5%. The favorable crop yield results in Finland much resembles those of the Benelux Countries. To which degree a connection can be made between these figures and this strip's location within front interaction between the high pressure zones and flanking depressions remains to be discussed.

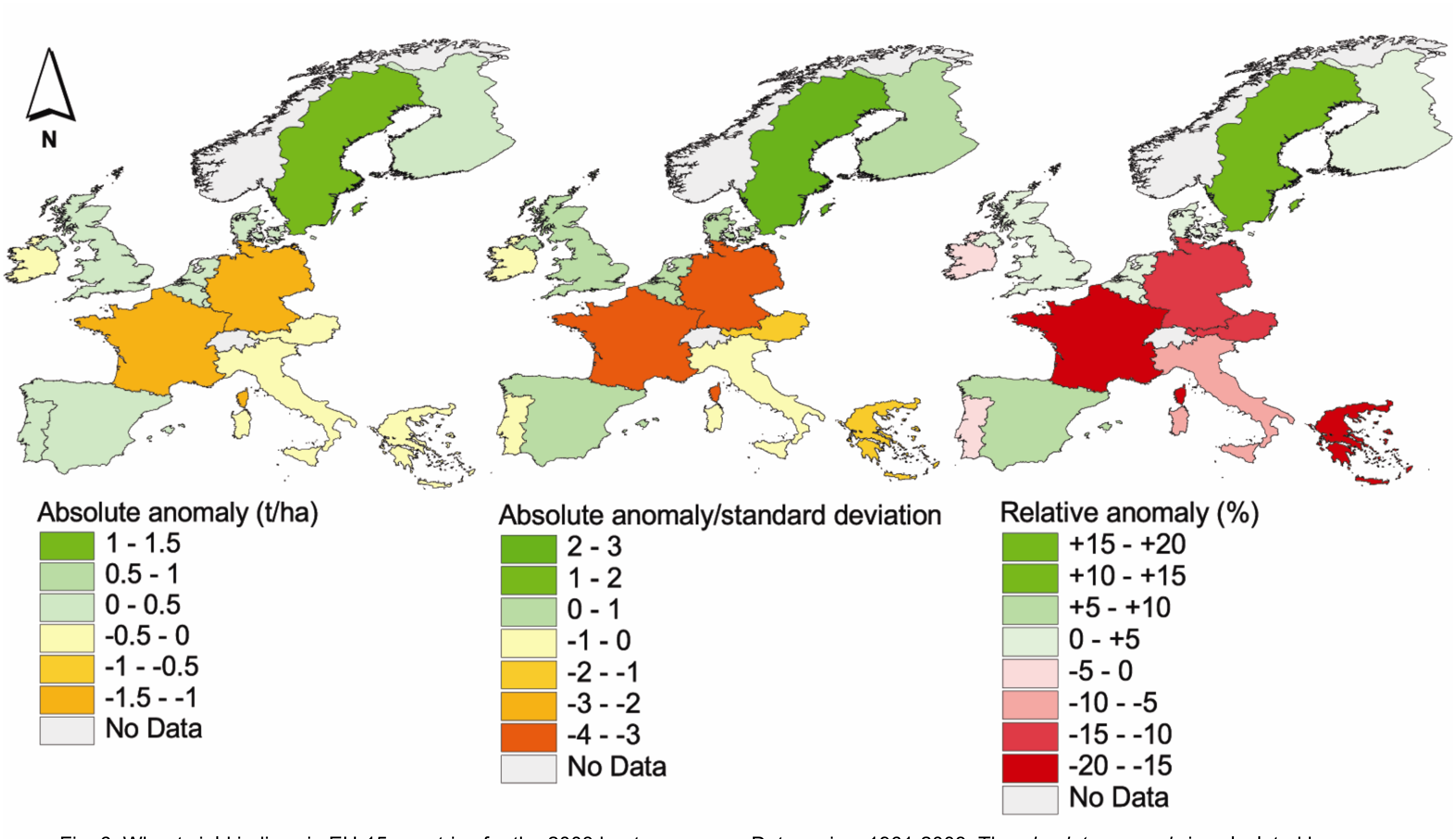



Fig. 6. Wheat yield indices in EU-15 countries for the 2003 heat wave year. Data series: 1961-2003. The *absolute anomaly* is calculated by subtracting the long-term technical trend influence from the yield series, indicating the deviation from the expected yield in the year of interest. It is divided by the yield series' standard deviation for indicating the likelihood of its yield figure and for comparative purposes among countries (*Absolute anomaly / standard deviation*). The *relative anomaly* expresses the absolute anomaly in percent for comparative purposes among countries.

### 3.4.5 Yield index results for winter wheat in German federal states

Winter wheat was analyzed on a federal state level to guarantee compatibility with county data for Baden-Württemberg, for which only winter wheat figures were available. In 2003, negative results for winter wheat indices prevail throughout the 8 federal states studied within the time series from 1950-2003. Fig. 7 accords to anomaly index studies on the EU-15 country level. All federal states besides North Rhine-Westphalia show negative yield anomalies higher than 1 standard deviation. Bavaria undercut it by more than a factor 3 (-3.12 A $S^{-1}$), Saarland and Baden-Württemberg by -2.80 and -2.54 A $S^{-1}$ (Table 7). The 4 southern federal states (Bavaria, Baden-Württemberg, Rhineland-Palatinate and Saarland) display the four lowest figures for each index and were generally hit more severely. Actual yields were 10-19% lower than expected (-19% in Bavaria), and absolute anomalies were continuously among the 3 lowest on record (lowest for Bavaria and Baden-Württemberg). Overall, winter wheat yields in Bavaria were cut back most severely.

Although all negative, Hesse, North Rhine-Westphalia and Schleswig-Holstein show the least affected winter wheat yields and the highest figures of all indices.

Table 7. Wheat anomaly indices in 2003 in German federal states in the context of the data series from 1950-2003. The *absolute anomaly* is calculated by subtracting the long-term technical trend influence from the yield series, indicating the deviation from the expected yield in the year of interest. It is divided by the yield series' standard deviation for indicating the likelihood of its yield figure and for comparative purposes among countries (*Absolute anomaly / standard deviation*). The *relative anomaly* expresses the absolute anomaly in percent for comparative purposes among countries.

| Federal State | Standard deviation (S) | Absolute anomaly (A) | AS [A $S^{-1}$] | Relative anomaly | Actual yields [t $ha^{-1}$] | Expected yield | Rank of A |
|---|---|---|---|---|---|---|---|
| *Schleswig-Holstein* | **0.57** | -0.65 | -1.13 | -6.96 | **8.64** | **9.29** | **10** |
| *Saarland* | **0.39** | -1.10 | -2.80 | -16.78 | **5.45** | **6.55** | **1** |
| *Rhineland-Palatinate* | 0.41 | -0.82 | -2.02 | -11.93 | 6.05 | 6.87 | 2 |
| *North Rhine-Westph.* | 0.54 | **-0.51** | **-0.94** | **-5.95** | 8.06 | 8.57 | **10** |
| *Lower Saxony* | 0.52 | -0.99 | -1.90 | -11.79 | 7.40 | 8.39 | 3 |
| *Hesse* | 0.42 | -0.58 | -1.39 | -7.68 | 7.03 | 7.61 | 7 |
| *Baden-Württemberg* | 0.41 | -1.05 | -2.54 | -14.94 | 5.97 | 7.02 | **1** |
| *Bavaria* | 0.45 | **-1.40** | **-3.12** | **-19.32** | 5.84 | 7.24 | **1** |
| *MEAN* | 0.46 | -0.89 | -1.98 | -11.92 | 6.81 | 7.69 | 4 |
| *MAX* | 0.57 | -0.51 | -0.94 | -5.95 | 8.64 | 9.29 | 10 |
| *MIN* | 0.39 | -1.40 | -3.12 | -19.32 | 5.45 | 6.55 | 1 |

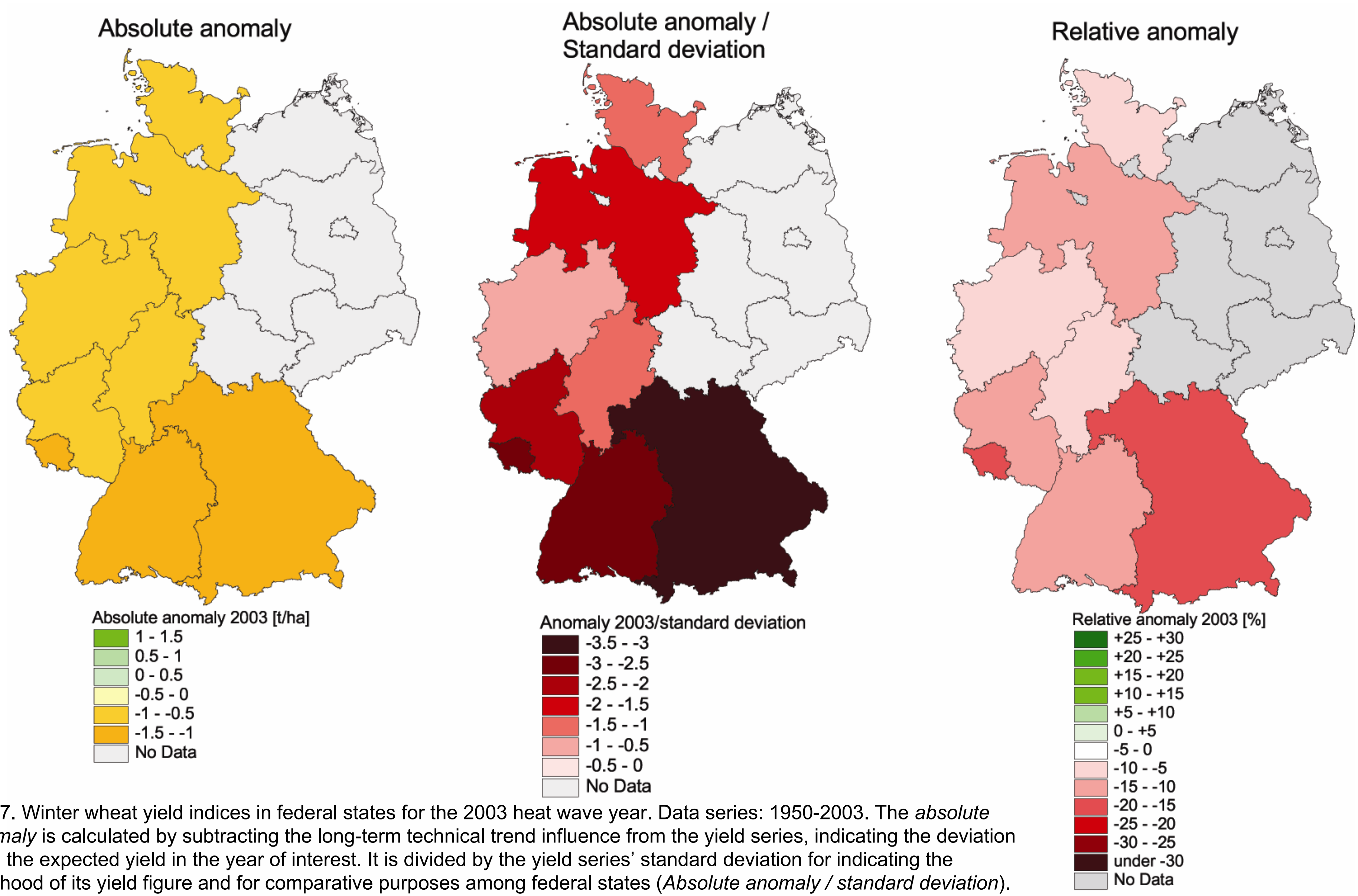



Fig. 7. Winter wheat yield indices in federal states for the 2003 heat wave year. Data series: 1950-2003. The *absolute anomaly* is calculated by subtracting the long-term technical trend influence from the yield series, indicating the deviation from the expected yield in the year of interest. It is divided by the yield series' standard deviation for indicating the likelihood of its yield figure and for comparative purposes among federal states (*Absolute anomaly / standard deviation*). The *relative anomaly* expresses the absolute anomaly in percent for comparative purposes among federal states.

### 3.4.6 Yield index results for winter wheat in Baden-Württemberg

In the following section, results of yield indices on smallest scale the highest resolution data are presented. Consistent winter wheat data was available from 1970-2003, or 1973-2003 for 37 out of 45 counties (82%) in Baden-Württemberg. The 7 counties unaccounted for, exclusively city counties, had inconsistent data series with low winter wheat production.

Yield indices in 2003 are mapped and labeled for all considered counties in Fig. 8. An average 1.12 t $ha^{-1}$ less than the pertinent counties' expected winter wheat yields (6.89 t $ha^{-1}$) was harvested in all counties, the lowest ratio of any year. Even the highest actual yield (6.80 t $ha^{-1}$ in the Alb-Donau county) turned out lower than the average expected yields, which demonstrates the all encompassing spatial extent of low yields in 2003 in this area. Standardized absolute anomalies also exemplify the holistic spatial impact of the weather in 2003: On average, absolute anomalies were 2.21 times lower than the counties' long-term standard deviation, with a maximum of -1.50 A $S^{-1}$ and minimum of -3.09 A $S^{-1}$.

Absolute and relative anomalies of all studied counties fall drastically short of expected long-term figures. The average absolute anomaly (-1.18 t $ha^{-1}$) is below the 1st percentile (-0.95 t $ha^{-1}$) for absolute figures in Baden-Württemberg from 1970-2003. Only 1 county suffered a relative loss of less than 10% (Reutlingen, -8.2 %). 22% (8 counties) dealt with relative anomalies dropping under 20% of the expected yield, falling below of the average loss of 17%. No distinct pattern can be derived from plotted anomalies in Fig. 8. However, relative classification of counties corresponds well between both indices. Counties composing the Upper Rhine Trench are affected less, excluding the county clearly hit most severely: Breisgau-Hochschwarzwald that shows the lowest AS, absolute, and relative anomaly in Baden-Württemberg, all ranking lowest in the county record (1973-2003). The other region that was less affected comprise the counties Esslingen, Göppingen, and Reutlingen, all with figures in the upper 95% percentile of each index.

Mapped rankings of both anomalies (Fig. 9) show the placement of 2003 figures relative to all 34, or 31 considered annual values. For 73% of the studied counties, the harvest in 2003 marked the lowest absolute anomaly in the data series. It was the lowest, second, or third lowest for each county. 51% experienced the highest negative deviation from the expected yields, and all figures were among the lowest 5 relative anomalies. Likewise, the spatial distribution of counties with lowest ranking

absolute and relative anomalies in 2003 show high resemblance: 84% of the counties with the lowest relative anomaly placement rank lowest in both anomalies, and 78% of the counties with the lowest absolute anomaly.
Winter wheat showed a highly sensitive reaction to the record heat wave summer in 2003. The lowest absolute anomaly between 1950-2003 ($-1.04$ t $ha^{-1}$) on the aggregation level of Baden-Württemberg is composed by consistently unfavorable to severely decimated yields in 2003 at the county level. In homogeneity, intensity, and spatial location, the unusually negative outcome therein corresponds well with the largely stable weather conditions in Baden-Württemberg close to the core of the high pressure zones over central Europe in the summer of 2003.

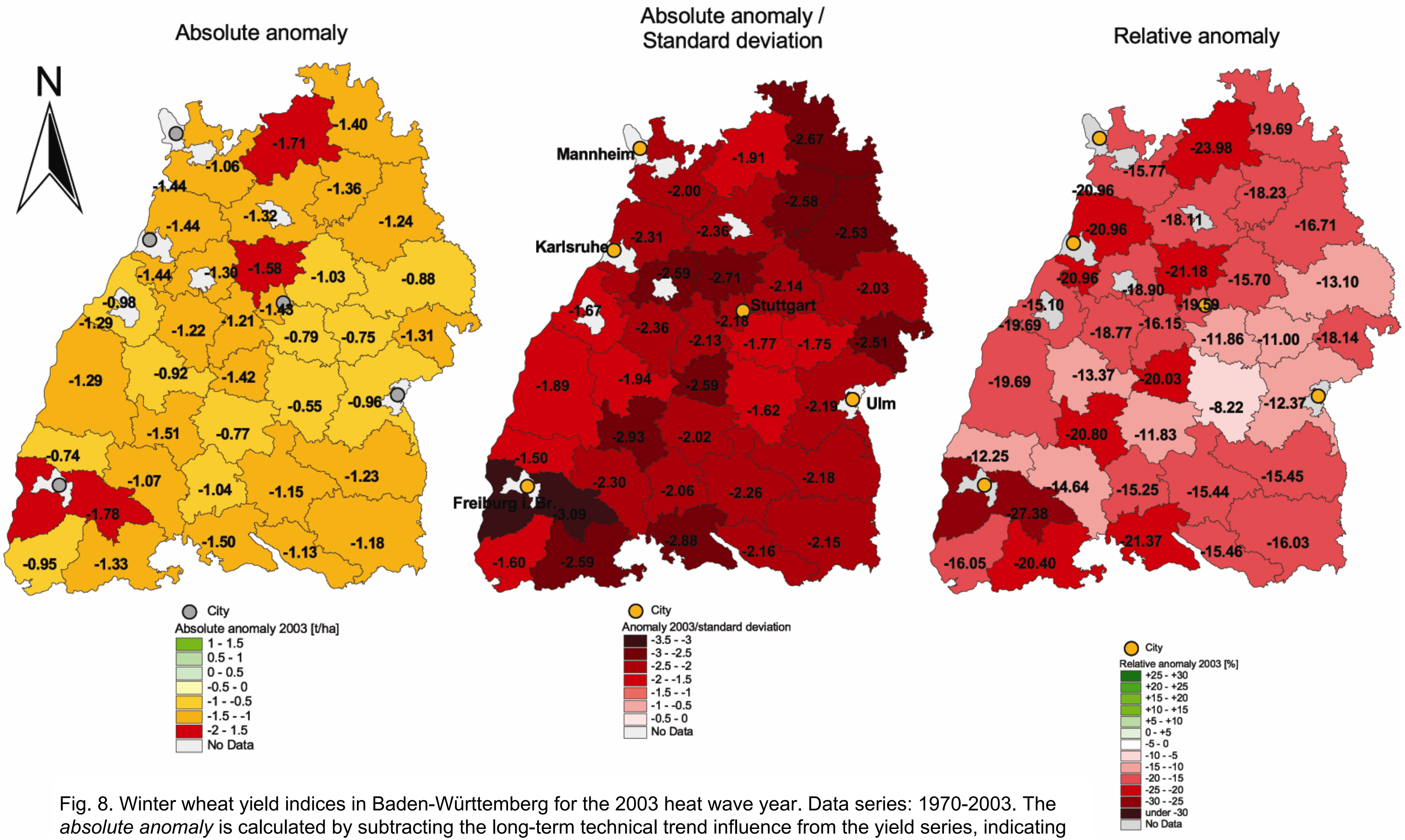



Fig. 8. Winter wheat yield indices in Baden-Württemberg for the 2003 heat wave year. Data series: 1970-2003. The *absolute anomaly* is calculated by subtracting the long-term technical trend influence from the yield series, indicating the deviation from the expected yield in the year of interest. It is divided by the yield series' standard deviation for indicating the likelihood of its yield figure and for comparative purposes among counties (*Absolute anomaly / standard deviation*). The *relative anomaly* expresses the absolute anomaly in percent for comparative purposes among counties.

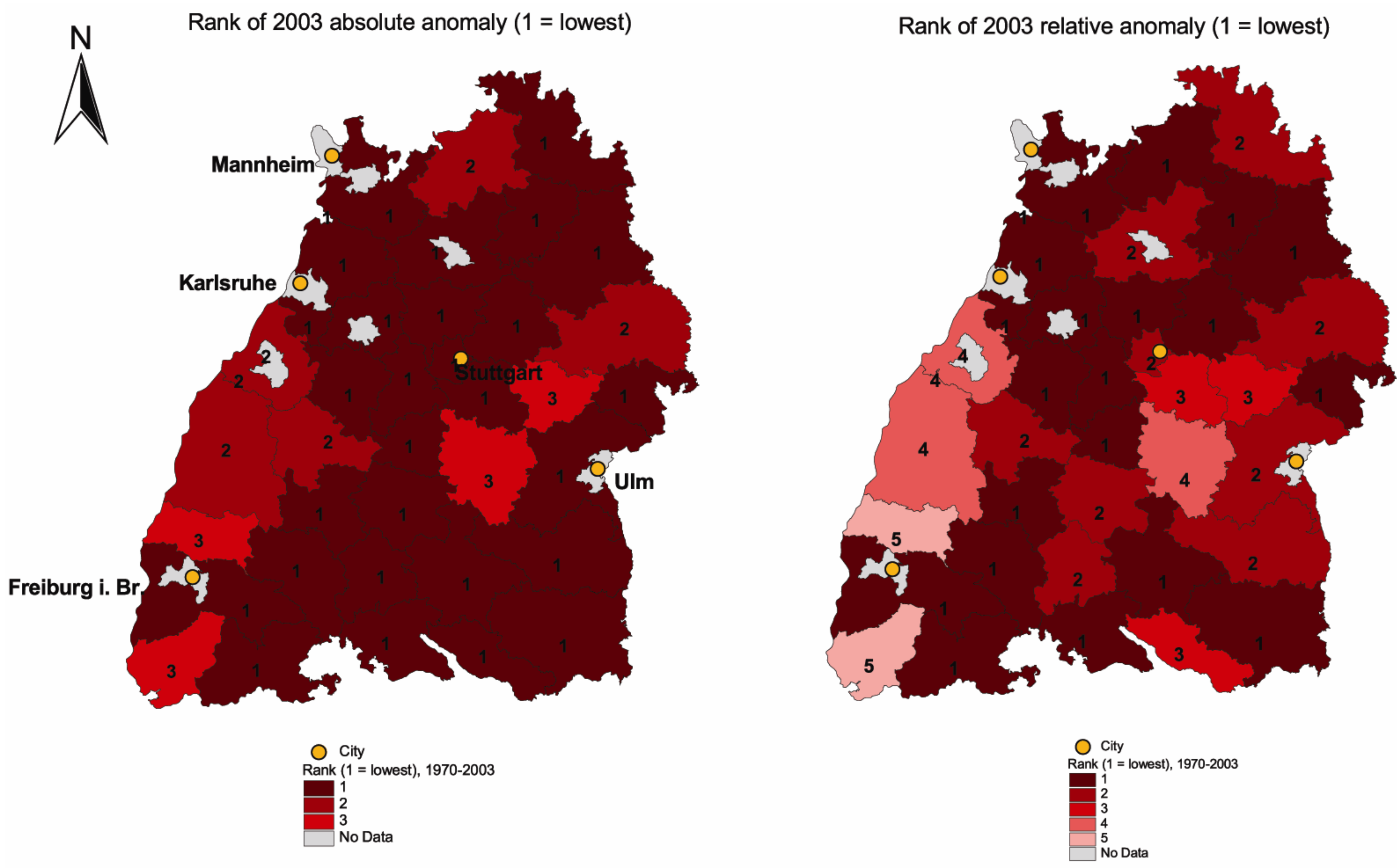



Fig. 9. Winter wheat yield ranks in Baden-Württemberg for the 2003 heat wave year. Data series: 1970-2003. The *absolute anomaly* is calculated by subtracting the long-term technical trend influence from the yield series, indicating the deviation from the expected yield in the year of interest. It is divided by the yield series' standard deviation for indicating the likelihood of its yield figure and for comparative purposes among counties (*Absolute anomaly / standard deviation*). The *relative anomaly* expresses the absolute anomaly in percent for comparative purposes among counties.

### 3.4.7 Comparisons among scales

Neither for wheat nor for winter wheat data were continuous time series including the year 2003 available across the 3 scales under consideration: EU-15 countries, German federal states, and counties in Baden-Württemberg. However, comparing wheat yields on the EU-15 level with winter wheat yields in the 2 lower aggregation levels is justifiable with winter wheat making up the vast majority of all wheat grown in EU-15countries, and in particular in Germany and Baden-Württemberg. The highlighted regional differences point out a northwest-southeast gradient of wheat yield losses from the North Sea inland. Relative anomalies and quotients decrease sharply between the Netherlands to Bavaria before increasing in Austria. Similar minima are observed in Baden-Württemberg. However, a supporting gradient is not detectable on the county scale. This provides evidence that yields there pose a measure for sensitivity to weather variation, as the gradient coincides well with part of the core area the heat wave covered.

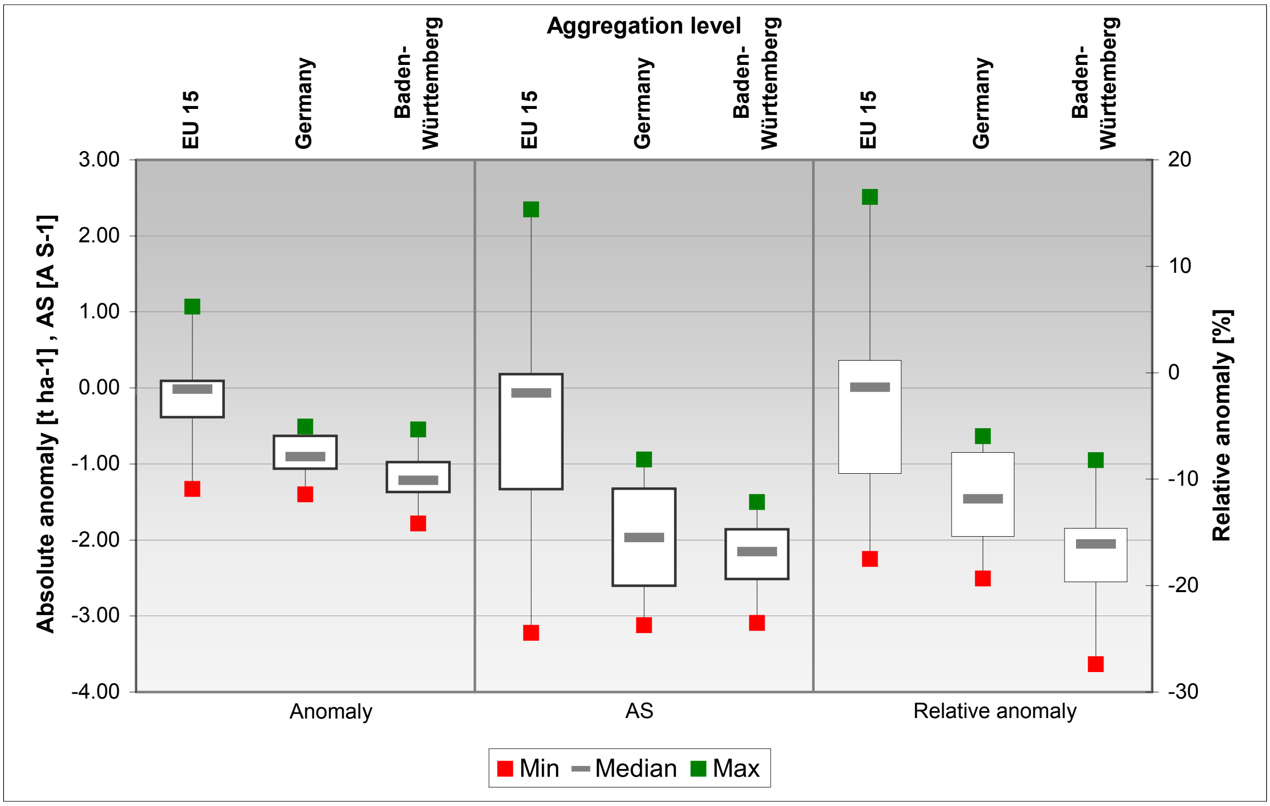



Fig. 10. Distribution of winter wheat yield anomalies in 2003 for the units comprising each aggregation level (EU 15 = 15 countries, Germany = 8 federal states, Baden-Württemberg = 44 counties) . Each white box comprises 50% of the aggregation level units' values, the black vertical lines above and below indicate the upper and lower 25%.

Fig. 10 gives an overview of boxplotted quartiles, medians, and averaged extremes of winter wheat indices. Findings shown here do not address scaling effects due to diverging areas of interest. However, comparisons among yield indices give an overview of the outcome of harvests in the heat wave year of 2003 on different levels. The sum of units per level ranges from 8 (Germany) to 37 (Baden-Württemberg). The range of value shrinks with each hierarchy level downward in the case of AS, corresponding to a reduction of area. The large area encompasses different influential factors and response to the regional climate. The middle 50% of figures ($2^{nd}$ and $3^{rd}$ quartile) decreases in range with each successive disaggregation for each index.

The EU-15 countries span index ranges far greater than the units in lower aggregation levels do. This can be largely explained by the prominent figures for Sweden, and by the finding that only part of the EU-15 harvests suffered adverse effects from the heat wave. Both anomalies define a wide range in Baden-Württemberg than in Germany, in which the figures up to the $3^{rd}$ quantile are markedly low. This is a result of the 2003 minima in Baden-Württemberg. Relative anomalies are distributed more broadly in Baden-Württemberg than in Germany due to greater yield damage suffered.

In 2003, winter wheat harvests were damaged severely on each aggregation level, although the totality of the affected area varies on each scale. The intensity of negative results increases down to Baden-Württemberg as a result of it's approximation to the core of the heat wave and it's spatial restriction. At the same time, median values decrease in each case mainly due to the extent to which each level was stricken by the heat wave. Central European countries were affected by very low to record low index figures. The exemption of the Benelux Countries and Denmark, conveying positive results, suggests a gradient of increasing damage from regions influenced by the Atlantic southeastward. Results in observed federal states and counties support this finding. Homogeneity of negative results is highest on the county level, with no identifiable spatial gradient.

## *3.5 Multiple regression analysis models for German federal states*

Multiple regression analyses were performed with forward selection at a 5% error level for federal states and all counties. The objectives were to determine to which monthly climate variables anomaly series are most sensitive, and to what extent a prediction of anomalies is possible through inter-annual weather variation specified in the selected variables. Spatial and qualitative differences in model composition are analyzed extensively.

### 3.5.1 Model comparison and analysis

2 model runs were conducted, setting the tolerance criterion to 5% and 10% error level. Multiple regression analyses fit equations to the absolute anomalies. Table 8 shows the winter wheat variance figures explained by single linear (for long-term yield trend) and multiple regression models (for short-term yield anomaly variation) for each federal state. Anomaly models with a 5% error level explain an average 4.0% of total yield variance and 56.6% of inter-annual anomaly variability. The models with a 10% error level include an average 5.6 monthly climate variables more to each multiple regression to explain a total of 0.9% more inter-annual variance. The number of variables included at the 10% error level is twice as large as at the 5% error level (2-18 as opposed to 1-9). In terms of $R^2$ values, the range spans 62.5% at a 5% error level and 71.0% at a 10% error level. Only Saarland and Rhineland-Palatinate (9.4%, 16.7%) models explain less than half of the inter-annual anomaly variability in both cases, particularly contrasting to models of adjacent states. Hesse and Saarland $R^2$ values diverge substantially among models: 4 additionally accepted variables contribute to an $R^2$ 0.22 higher than that of the 5% error level model (0.20) in Saarland, and 0.49 higher with 14 more values accepted at a 10% error level for Hesse. In the other cases, values differ by an average of 7.1% explained by an average 1 variable more included in the models with a 10% error level, with $R^2$ values for 5% error level models varying between 52.1% and 71.9%. Models are identical in the cases of Baden-Württemberg and North Rhine-Westphalia.

Table 8. Multiple regression model results for 2 error levels in German federal states. Variances explained by long-term trends and multiple regression models and their sums are included. The Variance (L) pertains to the percentage of overall actual yield variance explained by the linear regression models, while (I) pertains to the percentage of detrended, inter-annual anomaly variance explained by the,multiple linear regression models.Weather and anomaly data series: 1951-1998

| Federal state | Error level [%] | Indep. variables | Variance explained by models [%] | | | | |
|---|---|---|---|---|---|---|---|
| | | | Sum (L + I) | Long term trend (L) | Inter-annual variability (I) | $R^2$ 10%-5% error level model | I to total variance |
| *Bavaria* | 5 | 7 | 97.2 | 91.6 | 66.5 | | 5.6 |
| | 10 | 8 | 97.4 | 91.6 | 69.2 | 2.7 | 5.8 |
| *Baden-Württemberg* | 5 | 7 | 97.4 | 92.2 | 67.1 | | 5.3 |
| | 10 | 7 | 97.4 | 92.2 | 67.1 | **0.0** | 5.3 |
| *Hessen* | 5 | 4 | 95.7 | 93.1 | 38.3 | | 2.7 |
| | 10 | **18** | **99.1** | **93.1** | **87.7** | **49.4** | 6.1 |
| *North Rhine-Westphalia* | 5 | 7 | 97.1 | 92.4 | 61.8 | | 4.7 |
| | 10 | 7 | 97.1 | 92.4 | 61.8 | 0.0 | 4.7 |
| *Lower Saxony* | 5 | 9 | 97.8 | 92.0 | 71.9 | | 5.8 |
| | 10 | 12 | 98.4 | 92.0 | 79.7 | 7.8 | **6.4** |
| *Rhineland Palatinate* | 5 | **1** | **92.1** | **91.3** | **9.4** | | **0.8** |
| | 10 | 2 | 92.7 | 91.3 | 16.7 | 7.3 | 1.5 |
| *Saarland* | 5 | 2 | 94.4 | 92.9 | 20.3 | | 1.4 |
| | 10 | 6 | 96.0 | 92.9 | 43.0 | 22.6 | 3.0 |
| *Schleswig-Holstein* | 5 | 4 | 96.3 | 92.3 | 52.1 | | 4.0 |
| | 10 | 5 | 96.7 | 92.3 | 56.3 | 4.2 | 4.3 |
| *Mean* | 5 | 5.6 | 96.2 | 92.1 | 52.4 | | 4.1 |
| | 10 | 8.4 | 97.0 | 92.1 | 62.6 | 10.2 | 4.9 |

The lower probability of error in 5% error level models and overall model similarities excluded the models with a 10% error level from further implementation. 6 out of 8 models explain 52.1-71.9% absolute anomaly variability with 9 variables at most. The 2 models coupled for L and I, one single linear regression equation and the multiple regression, explained an average 96.2% of overall actual winter wheat yields in the federal states. $R^2$ values explaining variability variance are lower than those fit to the long-term technical advancement trend. Short-term inter-annual sensitivity of winter wheat to weather conditions is more complex than the response to the long-term trends. This is supported by multiple regression models performed on actual yields for all counties, which produced an average $R^2$ value of over 0.70.

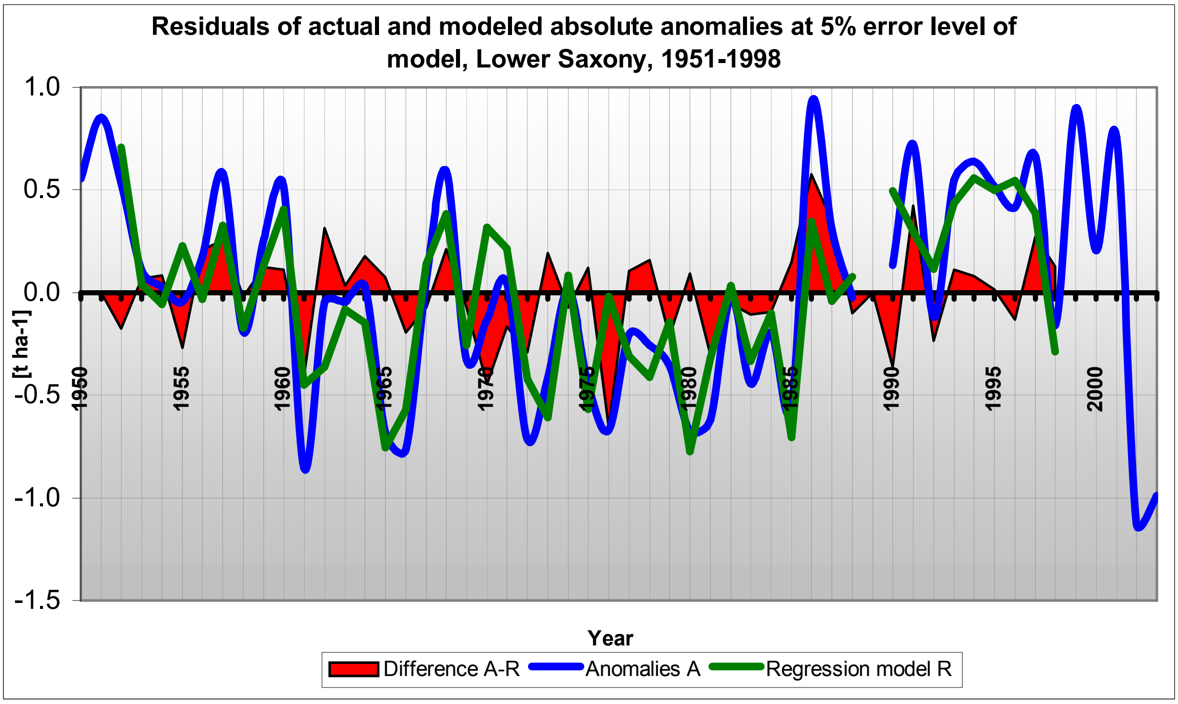



Fig. 11. Actual (A) and modeled yield anomalies (R) of winter wheat at a 5% error level and residuals [A-R] for the German federal state Lower Saxony ($R^2$=0.71). The difference A-R is illustrated in the area shaded red. Data series: 1951-1998

The actual and modeled anomalies are shown in Fig. 11 for the model with the highest $R^2$. Generally, actual inter-annual variability of winter wheat is greater both in amplitude and intensity. The average standard deviation is 3 times higher (0.38 t $ha^{-1}$ compared to 0.12 t $ha^{-1}$). The average anomaly range of 2.1 t $ha^{-1}$ exceeds the modeled range (1.5 t $ha^{-1}$) by 0.6 t $ha^{-1}$. Very high yields are underestimated more than very low yields are overestimated, and positive extremes are accounted for less than negative extremes. Fig. 11 shows how the anomaly tendency is modeled to a satisfactory degree, while the 10 highest positive anomalies (>=0.5 t $ha^{-1}$) are underestimated in 9 cases. These findings are applicable to the other federal state models. Negative modeled anomalies <= -0.5 correspond better with actual anomalies. Here, inter-annual variability of modeled winter wheat absolute anomalies corresponds best with to actual figures. Modeled standard deviation (0.38 t $ha^{-1}$) falls 0.08 t $ha^{-1}$ short of the actual anomaly series' 0.46 t $ha^{-1}$.

The series modeled best shows a good general approximation to the actual anomaly tendency and course (Fig. 11), which is also present in other federal state models >=0.5, but to a lesser degree.

### 3.5.2 Multicollinearity

The question of multicollinearity as a potentially burdening factor for models' goodness of fit is considered further in the discussion section (5.6.2). One or more predictors display an almost perfect degree of correlation if one independent variable is the linear function of others. In this undesirable situation of multicollinearity redundant effects among them become inseparable (SPSS, 2003). Such events could be assumed for some of the selected climate variables, but results of multicollinearity tests show that these assumptions were not justified.

### 3.5.3 Model testing

On short notice the opportunity arose to conduct first non extensive tests for evaluating federal state models on newly obtained homogenized climate data for the two years following the fit period from 1951-1998. As the actual analysis of model results is prioritized over the fits' prediction capabilities, this evaluation method posed a basis sufficient enough for the purpose. The first step of model evaluation could have been succeeded by cross-validation, but this was turned down in the further course of the study due to time restrictions. Therefore, other testing methods in similar studies, such as the prediction of a year in the fit period through all remaining years applied by BAUMANN & WEBER (1966), are factored out.

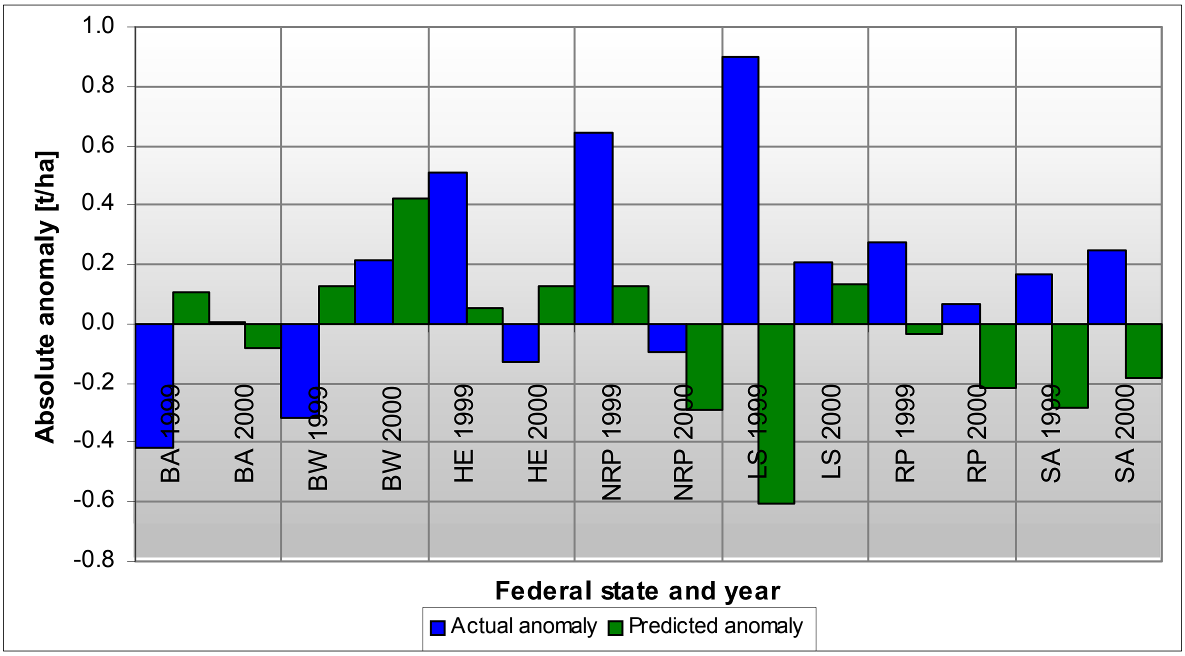



Fig. 12. Testing the linear fit winter wheat yield models for the fit period from 1951-1998: Actual and predicted yield anomalies of winter wheat for test years in 1999 and 2000 in German federal states

The yield anomalies of 1999 and 2000 predicted by multiple regression are plotted with the actual anomalies in each federal state in Fig. 12. Figures of the modeled anomalies undercut the degree of actual anomalies in all cases. As noted above, the higher anomalies are not adequately modeled with the regression fit, which remains to be further analyzed and improved. $R^2$ amounts to 0.11. Standard deviation and variance of the modeled yields in test years all fall below those of the fit line for the federal model.

Generally, the anomalies in 2000 were modeled better than in 1999. Erring predictions in Lower Saxony particularly stand out in 1999. The large positive anomaly strongly contributes to an average residual variance of 0.24. Average residual variance exceeds the anomaly variance (0.12) and the low predicted anomaly variance (0.07).

It remains to be investigated if these observations are caused by unusual weather development in test years, especially in 1999, or if they adhere to imprecisions in the models. Overall, the models do not produce applicable forecasts in the 2 years predicted. Model verification was not performed for Baden-Württemberg county model results due to the time available.

## *3.6 General yield sensitivity analysis - distribution functions of actual winter wheat anomalies*

Sensitivity analysis of federal state models is broken down into two separate studies. First, the general sensitivity of actual anomalies is determined through comprehensive analysis of their distribution patterns. Then the modeled anomalies are comparatively analyzed using the same statistical methods in order to determine sensitivity differences and first conclusions are drawn on sensitivity to inter-annual weather variation. In the following, the results of quantitative and qualitative analysis are discerned in order to determine to which degree model variation can be apportioned to independent variation sources.

A key question in this model analysis is how sensitive anomalies are to which climate variables. Model coefficients give insight to these questions. $R^2$ values do not allow direct statements on anomaly sensitivity. However, the standardized regression coefficient *ß* is the estimate for how the dependent anomaly responds when the independent variable is changed by one unit. The absolute value expresses its relative importance for prediction: the higher the coefficient (ß value), the more it contributes to the prediction. It furthermore represents the standardized sensitivity of anomalies to a climate variable as the first derivative of *dy* after *dx*, independent of the observation unit. Partial correlation coefficients indicate the relation of *y* to one independent variable *x* revised of correlation to other independent variables. The standard error of the non-standardized regression coefficient B specifies the goodness of the coefficient estimation.

Table 9 lists parameters that extensively characterize each federal state anomaly distribution. Skewness and kurtosis help summarize the shape of anomaly function. The parameters describe the degree of symmetry and the relative peakedness or flatness in the variable distribution. Negative skewness means more than 50% of the returns are to the right of the mean or that the returns on the left of the asset's mean are further left than right. Positive kurtosis refers to a relatively thin, spiked distribution, a negative kurtosis to relatively flat, leveled one. Extremely positive or negative yield anomalies increase the kurtosis.

Table 9. Statistical distribution parameters of winter wheat absolute anomalies in German federal states from 1950-2003

| Statistical parameter | Bavaria | Baden-Württemb. | Hesse | North Rhine-Westphalia | Lower Saxony | Rhineland-Palatinate | Saarland | Schleswig-Holstein |
|---|---|---|---|---|---|---|---|---|
| *Skewness* | **0.18** | -0.09 | -0.52 | -0.13 | -0.11 | -0.67 | **-0.77** | -0.36 |
| *Kurtosis* | **2.27** | 0.05 | -0.44 | -0.51 | -0.74 | 1.20 | 0.16 | **-0.77** |
| *Standard deviation* | 0.45 | 0.41 | 0.42 | 0.54 | 0.52 | 0.41 | **0.39** | **0.57** |
| *Minimum* | **-1.40** | -1.05 | **-1.00** | -1.27 | -1.13 | -1.37 | -1.10 | -1.34 |
| *1st quartile* | -0.30 | -0.27 | -0.28 | -0.35 | -0.36 | -0.22 | **-0.20** | **-0.40** |
| *Median* | 0.02 | 0.01 | 0.13 | **-0.02** | **-0.02** | 0.04 | **0.09** | 0.02 |
| *3rd quartile* | **0.18** | 0.24 | 0.32 | 0.38 | **0.52** | 0.26 | 0.26 | 0.49 |
| *Maximum* | **1.45** | 1.00 | 0.80 | 0.95 | 0.92 | 0.81 | **0.73** | 0.88 |
| *Range 1st-3rd quart.* | **0.48** | 0.51 | 0.59 | 0.73 | 0.87 | **0.48** | 0.46 | **0.88** |
| *Range min-max* | **2.85** | 2.05 | **1.80** | 2.22 | 2.05 | 2.18 | 1.83 | 2.22 |

Anomaly figures in the $2^{nd}$ and $3^{rd}$ quartile, composing 50% of each data series, generally range between +0.5 ($3^{rd}$ quantile) and -0.5 t $ha^{-1}$ ($1^{st}$ quantile) in each federal state, excluding Lower Saxony (+0.52 t $ha^{-1}$ for $3^{rd}$ quantile, Table 9). 7 distributions (data series 1950-2003) show a slight negative skewness, ranging from -0.09 in Baden-Württemberg to -0.77 in Saarland, and all maximum anomalies are lower than the absolute minimum figures. In Bavaria, the diverging case , skewness is +0.18, and the maximum is higher. In 7 out of 8 cases this supports the assumption that negative anomalies reach further to the left (smoother slope) than positive do to the right (steeper slope), possibly caused by physiological constraints of crop growth dominating near optimal conditions in these areas. Kurtosis values are also close to 0 (kurtosis of a Gaussian distribution), excluding those of Bavaria and Rhineland-Palatinate (+2.27 and +1.20). These federal states show more spiked centers and thinner tails due to low negative outliers and accumulation of anomalies close the 0.

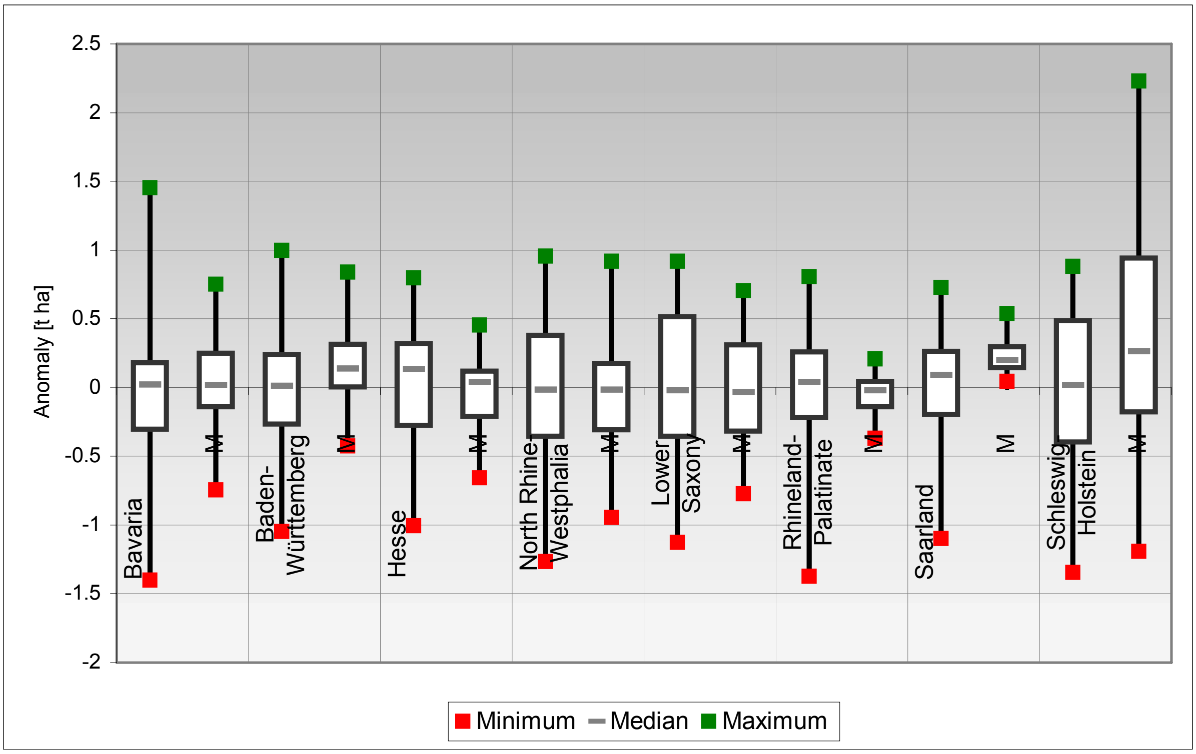
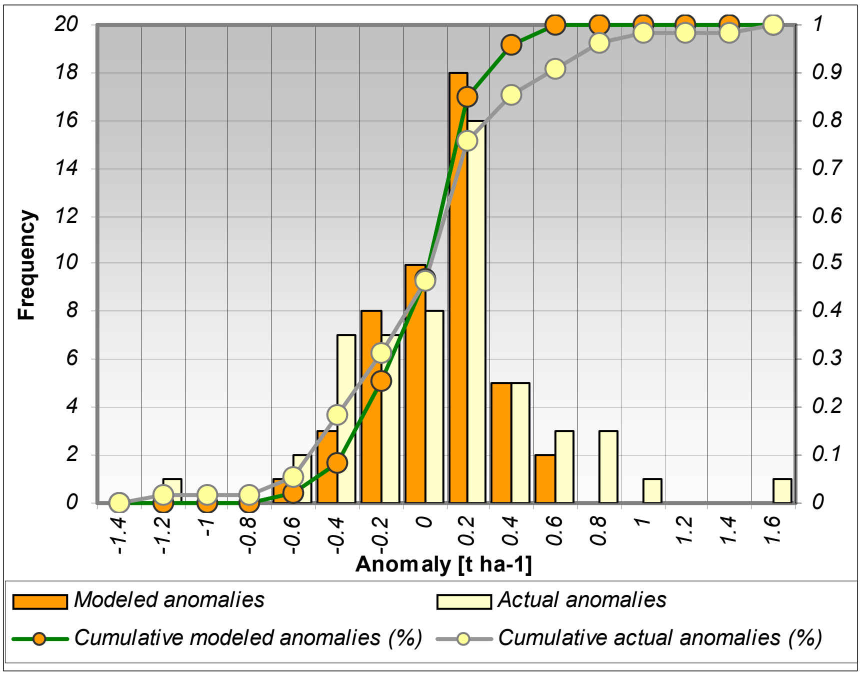



Fig. 13. Distribution of actual and modeled winter wheat anomalies in German federal states from 1951-2003. Modeled series are labeled with an M. Each white box comprises 50% of the yield anomaly values, the black vertical lines above and below indicate the upper and lower 25%

There is a marked south-north gradient from values spiked and condensed around the mean to a flatter distribution with heavier tails, as shown in the cumulative frequency distributions of its beginning (Bavaria) and endpoint (Schleswig-Holstein) in Fig. 13. This corresponds with stretched or condensed 2$^{nd}$ and 3$^{rd}$ quantiles of actual winter wheat anomalies. Ranges from the 1$^{st}$ to 3$^{rd}$ quartile are smallest in Bavaria (0.48 t ha$^{-1}$) and highest in Schleswig-Holstein (0.88). This divergence in distributions is best exemplified by the according high and low class frequency of actual anomalies shown in Fig. 14 (the modeled cumulative frequencies in the figure are discussed in Section 4.7.3). A transition between the diverging distributions occurs in the federal states between them.

These findings lead to the following conclusions: (1) influencing factors on winter wheat in northern federal states with more evenly distributed anomalies (Schleswig-Holstein, Lower Saxony, and North Rhine-Westphalia) differ from those in southern federal states in combination and/or in intensity; (2); the transition between the two states is gradual; and (3) the frequency of greater yield variations is higher in northern federal states at the expense of the frequency of low deviations, which suggests a higher sensitivity to weather there than in the series with the highest kurtosis (Bavaria, 2.85 t $ha^{-1}$, highest minimum and maximum), suggesting a lower sensitivity.



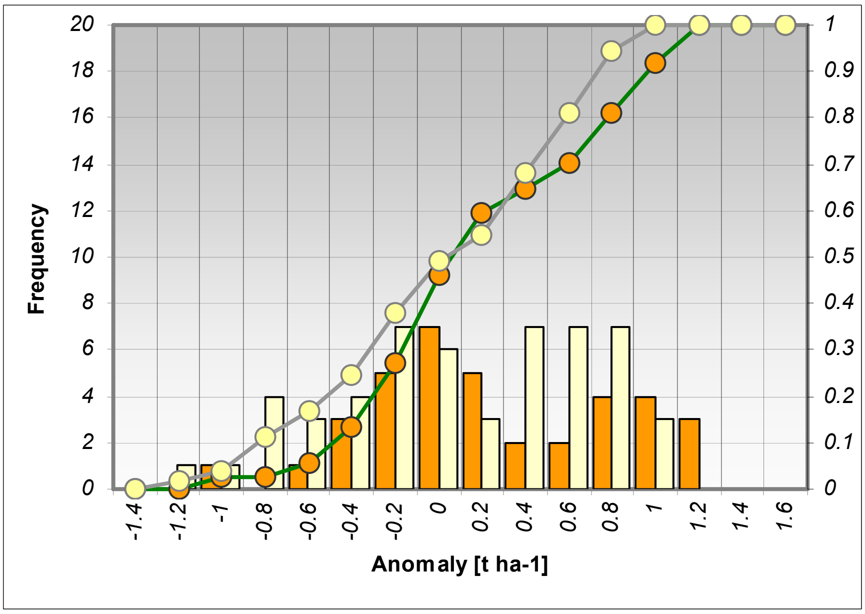




Fig.14. Cumulative frequency distributions for actual (1950-2003) and modeled winter wheat anomalies in the German federal states Bavaria (1952-1998) and Schleswig-Holstein (1952-1988)

These conclusions are supplemented with the notion that the skewness distinctly correlates with the federal state size (the correlation coefficient is +0.91). Average anomaly distributions are displayed more precisely in smaller federal states. The mean of each anomaly data series is 0, so if the relative size of cultivation areas are similar, this relation suggests that the positive anomalies aggregated over smaller areas tend to be more frequent. They display a better image of local anomalies. On the other hand, this means the larger the area the series represents, the more the distribution approximates a standard distribution. This is a result of anomalies compensating and complementing each other. In this case, Saarland would be the most accurate image of local crop conditions: a steep decrease of frequency to the right of the center is caused by insoluble constraints despite conditions being optimally exploited. Adversely, a longer tail to the left is caused by fair to unfavorable conditions for anomalies.

The extreme figures of the non-standardized data series are not excessively high and provide evidence against the assumption that the anomalies might be illegitimate due to violations of normality.

## *3.7 Yield sensitivity to climate variables*

After discerning sensitivity for possible influential factors, how and to what extent do winter wheat anomalies respond to the weather influence modeled by specific climate variables? The following section summarizes the distributions of modeled anomalies. Furthermore, it remains to be determined to which degree they are adversely or beneficially affected by monthly climate variables accepted to the multiple regression models as a response to monthly weather variation between June of the pre-harvest or sowing year and October of the harvest year. Thus, variation of anomalies on a year to year basis can be apportioned both qualitatively and quantitatively to different sources of variation represented by monthly climate variables.

Monthly climate variables used for the analysis include values from 1951-1998. However, anomalies in 1951 were excluded because homogenized climate data was not available for 1950 sowing year calculations. The source of influence apportioned to monthly climate variables qualitatively and quantitatively contributes to total influences on winter wheat anomalies.

### 3.7.1 Multiple regression equations as models for federal states

Multiple regression analysis resulted in the following relationships between detrended winter wheat anomalies and selected monthly climate variables:

Bavaria (5)

$$Y_{BA} = 1.393 + 0.004 * WS_{\_Oct} + 0.003 * TS_{Aug} - 0.047 * PET_{\_Nov} - 0.050 * DMI_{Apr} - 0.003 * PS_{Jul} - 0.004 * WS_{Jun} - 0.011 * PET_{Jun}$$

Baden-Württemberg (6)

$$Y_{BW} = 0.624 - 0.003 * CWB_{Apr} - 0.003 * TS_{\_Nov} + 0.009 * PET_{Aug} - 0.044 * PET_{\_Dez} + 0.003 * WS_{\_Oct} - 0.003 * PS_{\_Aug} - 0.008 * PET_{Jun}$$

Hesse (7)

$$Y_{HE} = 0.164 - 0.003 * CWB_{Apr} + 0.068 * PET_{Jan} - 0.002 * CWB_{\_Nov} - 0.041 * DMI_{\_Jul}$$

North Rhine-Westphalia (8)

$$Y_{NRW} = -2.068 - 0.007 * CWB_{Apr} + 0.006 * PS_{\_Aug} + 0.094 * DMI_{Oct} + 0.002 * WS_{Jul} - 0.057 * PET_{Feb} + 0.005 * TS_{Aug} - 0.003 * WS_{Jun}$$

Lower Saxony (9)

$$Y_{LS} = -1.063 - 0.005 * CWB_{Apr} - 0.002 * PS_{Jun} + 0.009 * PS_{Oct} + 0.008 * PS_{\_Aug} - 0.005 * WS_{Sep} + 0.012 * PET_{Jul} - 0.004 * PS_{\_Jun} + 0.002 * WS_{Oct} + 0.004 * PS_{Mar}$$

Rhineland-Palatinate (10)

$$Y_{RP} = 0.884 - 0.03 * WS_{Jun}$$

Saarland (11)

$$Y_{SA} = -0.091 - 0.063 * DMI_{\_Oct} + 0.027 * PET_{Feb}$$

Schleswig-Holstein (12)

$$Y_{SH} = 0.027 * + 0.012 * TS_{Apr} + 0.040 * WS_{Feb} - 0.022 * PET_{\_Jun} - 0.007 * CWB_{\_Jul}$$

Calculations and abbreviations for climate variables are explained in Table 10, and $Y_{II}$ = absolute anomalies of detrended winter wheat in Bavaria, Baden-Württemberg, Hesse, North Rhine-Westphalia, Lower Saxony, Rhineland-Palatinate, Saarland and Schleswig-Holstein, the 2 suffixed capital letters indicating the federal state; and for example $CWB_{Jan}$ = the climate variable with the pertaining month as a subscript, whereas a prefixed "_" indicates months in the year previous to harvest (sowing year).

Table 10. Abbreviations and methods for calculating the monthly climate variables that compose the federal state yield models for Germany

| Climate variable | Abbreviation | Calculation |
|---|---|---|
| Average temperature sum | TS | $\sum_{i=1}^{d\max} T_{avg}$ |
| Monthly precipitation sum | PS | $\sum_{i=1}^{d\max} P_{sum}$ |
| $\geq$5°C temperature sum | WS | $\sum_{i=1}^{d\max} T_{\max} \geq 5°C$ |
| Potential evapotranspiration | PET | for $T_{\max} \geq 5°C$:<br>$\sum_{i=1}^{d\max} 0.0031 * Cf * (G_{irr} + 209) * \frac{T}{T+15}$<br>where $Cf = 1$ if $H_{rel} \geq 50\%$<br>and $Cf = 1 + \frac{(50 - H_{rel})}{70}$ if $H_{rel} \geq 50\%$<br>for $T_{\max} < 5°C$:<br>$\sum_{i=1}^{d\max} 0.000036 * (100 - H_{rel}) * (T + 25)^2$ |
| Climatic water balance | CWB | $\sum_{i=1}^{d\max} \frac{PET}{P_{sum}}$ |
| De Martonne aridity index | DMI | $\sum_{i=1}^{d\max} \frac{P_{sum}}{T+10}$ |

$R^2$ values for each model can be looked up in Table 8. Months pertain to harvest year months if not indicated otherwise.

In Bavaria, sowing year October WS (ß=+0.336) correlates highest with anomalies. Sowing year November PET (ß= -0.312) shows the second highest ß value. This means yield anomalies benefit from warmer Octobers >=5°C and lower PET in the following month. Both suggest that winter wheat yields are sensitive to weather during or after late sowing periods. They are the most reliable predictors for yield anomalies of the successive harvest. Dryer Aprils have a positive impact on anomalies in Bavaria, as well: the acceptance of April DMI of (ß=–0.215) to the model increases the explained $R^2$ by 8.3%.

In Baden-Württemberg, sowing year October WS (ß=+0.283) is of relative importance for favorable anomalies, yet less than in Bavaria. 4 out of 8 accepted climate variables originate from the time of average sowing between August and November. Varying PET in 3 months sums up to 0.23 of the total $R^2$ of 0.67.

Variations in CWB figures contribute 23.6% to the overall 38.3% of anomaly variance explained in Hesse. Negative ß-coefficients in April (-0.382) and in sowing year November (-0.319) indicate that winter wheat is beneficially influenced by low CWB rates in Hesse.

Anomalies in North Rhine-Westphalia show a slight sensitivity to April CWB (-0.399, highest in North Rhine-Westphalia) and the lowest sensitivity to weather variation during the sowing season. Out of all states they are also most sensitive to temperature sums during summer and harvesting (August): a warmer August (ß=+0.364) and sum of T>=5°C in July (ß=+0.183) contribute to more favorable anomalies as a cooler June (ß=-0.233) does respectively.

The equation for Lower Saxony contains the highest amount of climate variables (9). An input of 25.8% of the 71.9% explained overall variance stems from April CWB. Yields are highly sensitive to PS variability, and modeled figures explain 29.1% of their variance from 5 monthly PS figures. They respond to anomalies increasing to higher PS in 3 months (October, sowing year August, and March), and a negative in 2 (June and sowing year June). October PS shows the highest absolute ß (+0.585) in any model. WS has a marked correlation with anomalies in this month and in the month before (ß=+0.212;-0.410).

The only variable accepted to the model in Rhineland-Palatinate indicates that warmer Junes are adverse to yields at a 5% error level (WS, ß=-0.306).

Monthly anomalies in Saarland respond sensitively to periods before distinct accumulation of biomass in spring. Anomalies markedly increase with lower sowing year October DMI (ß=-0.378) and less so with higher PET in February (ß=+0.310).

April TS correlates highest with anomalies in Schleswig-Holstein (ß=+0.379) which contrasts to the dominating precipitation influence in April CWB figures in adjacent states. Winter wheat in the northernmost federal state responds stronger to temperature than precipitation in April. It benefits from warmer weather in February as well (ß=+0.345). CWB figures in July have a similar effect on anomalies here as in other states in April (ß=-0,262).

### 3.7.2 April climatic water balance

The prominent role of April CWB as the best predictor for anomalies requires a closer look at its coefficients in the 4 federal models in which it correlates highest with anomalies. April CWB is the first variable included in 4 out of 8 federal states (Baden-Württemberg, North Rhine-Westphalia, Hesse, Lower Saxony, all $R^2$ above 50%) at a 5% error level and correlated highest with the anomalies each time. The consistently negative ß values between -0.365 (Baden-Württemberg) and -0.399 (North Rhine-Westphalia) show that low or negative CWB values result in higher yields and vice versa, considerably effecting winter wheat anomalies.

The driving climate variable behind the negative correlation between April CWB and yields in the 4 federal states can be attributed to temperature and/or precipitation. Detracting April CWB from the forward selection regression analysis results in a replacement by April PS as the variable with the highest correlation in three cases. All ß coefficients are negative, ranging between -0.37 and -0.41. In North Rhine-Westphalia, April PET correlates highest with the yield anomalies. April PS are the driving force behind the prominent position of April CWB as the single variable explaining the most overall variance. Lower precipitation sums benefit from higher yields, and in the case of North Rhine-Westphalia higher April PET has a similar effect. April TS do not play a comparable role in these federal states. Positive or even high CWB values exasperate sufficient biomass growth for high yields. Dryer Aprils promote positive, while moister Aprils induce negative anomalies.

The most variables accepted to the 8 models pertained to April and June, both months having 6 entries. 41 variables were entered altogether. It was found that in June anomalies decrease with higher WS, PET, and PS for all 6 entries. So generally, June TS and PS conditions are not optimal. June WS has the second most distinct impact on anomalies after April CWB. Variables for February, July, August, and October of the harvest year, as well as August, October, and November of the sowing year are counted 3 times each. Altogether, 41.5% of the monthly climate variables retained by forward selection attribute to summer months in the sowing and harvest year, which suggests that winter wheat yields are most sensitive to weather in these seasons. 29.3% thereof (12 variables) correspond to the harvest year summer season. 2 months out of 17 play no role in predicting anomalies (sowing year September and May of the harvest year). The monthly distribution of variables correlates at +0.28 with the succession of months. The trend line of both plotted against each other shows a slight increase of monthly counts during the 17 selected months.

### 3.7.3 Distribution function of modeled yields

The next step is to compare the statistical parameters and distributions of modeled winter wheat anomaly series with those of actual anomaly series distributions as a summary of sensitivity to inter-annual weather variation.

ß values range in the interval between +0.424 and -0.585 (for July PET and October PS, both in Lower Saxony). No month or climate variable stands out with an overt dominance, and ß values rarely exceed +/-0.5. These findings show how winter wheat yields in Germany are sensitive to an array of monthly conditions that compensate and add up to the adverse, indifferent, or beneficial effects the yields are sensitive to. Anomaly figures as direct responses to the character of monthly climate variables are unequally determined by the predictors, which account for between 9.4% (Rhineland-Palatinate) and 71.9% (Lower Saxony) of the anomaly variance in federal state models. This is evident in the contrasting boxplots (Fig. 13) and cumulative frequency distributions of the best and lowest fit models. Cumulative class frequency for models explaining more than 50% of actual anomaly variance correspond well with actual frequency, while actual and modeled class frequency among Rhineland-Palatinate and Saarland deviate drastically: 2 classes account for over 90% of the values (-0.2 - 0, 0 - +0.2 for the former, and 0 - +0.2, +0.2 - +0.4 for the latter). Skewness is retained in modeled distributions in all cases except Rhineland-Palatinate, Saarland, and Schleswig-Holstein. However, relative peakedness or flatness only resemble the actual distribution in Lower Saxony and Hesse (Table 9 and 11). Minimum and maximum figures are lower in all modeled series in accordance with the identified systematic underestimation of actual anomalies. The lower the $R^2$ value, the more the center classes in the distribution are overestimated in frequency. Generally, the models of weather induced anomalies tend to reproduce the small anomaly distribution well, at the expense of larger anomalies. For example, modeled 2$^{nd}$ and 3$^{rd}$ quartiles show a satisfactory resemblance in Bavaria, Baden, North Rhine-Westphalia, and Lower Saxony in the boxplots (Fig. 13), while the upper and lower quartile lack it. The aforementioned models allow an overall estimation of yields toward monthly climate variables, while models with markedly lower goodness of fit do not.

Boxplotted Schleswig-Holstein model values stand out as the only series with a larger span of figures than the actual anomaly series. The excessively large distribution figures in Table 11 are caused by high modeled positive anomalies in the 1990s. 6 out of 8 are larger than +1 t $ha^{-1}$ while actual anomalies all range between +0.5 and -0.5. In Fig. 14, the cumulative frequency distribution of modeled anomalies was plotted without Schleswig-Holstein figures from 1990 to 1998, and yield data was not available for 1989. In this figure, distributions for Bavaria and Schleswig-Holstein show an overall appropriate fit to the diverging actual distributions discussed there. This means that the north-south gradient of flatter to more spiked distribution shapes is also evident in modeled anomalies, which in turn suggests that anomaly distributions are driven by weather differences. However, comparing Table 11 with Table 9, displaying the distribution parameters for actual anomalies, reveals that skewness and kurtosis are seldomly accurately maintained in modeled series. The following conclusion is drawn for the series which do explain a distinct amount of overall anomaly variance: yield sensitivity to weather conditions alone can not explain the shape of actual anomaly functions at the resolution of data used and the climate stations selected.

Table 11. Statistical distribution parameters of modeled winter wheat anomalies German federal states from 1950-2003

| Statistical parameter | Bavaria | Baden-Württemb. | Hesse | North Rhine-Westphalia | Lower Saxony | Rhineland-Palatinate | Saarland | Schleswig-Holstein |
|---|---|---|---|---|---|---|---|---|
| *Skewness* | 0.10 | 0.25 | **-0.35** | -0.08 | -0.16 | -0.18 | **0.60** | 0.46 |
| *Kurtosis* | -0.20 | **0.31** | -0.03 | 0.24 | **-0.83** | 0.04 | -0.17 | -0.07 |
| *Standard deviation* | 0.34 | 0.28 | 0.25 | 0.40 | 0.38 | **0.12** | **0.12** | **0.74** |
| *Minimum* | -0.74 | -0.42 | -0.66 | -0.94 | -0.77 | -0.37 | **0.05** | **-1.19** |
| *1st quartile* | -0.14 | 0.00 | -0.21 | -0.31 | **-0.32** | -0.14 | **0.14** | -0.18 |
| *Median* | 0.02 | 0.14 | 0.04 | -0.01 | **-0.03** | -0.02 | 0.20 | **0.27** |
| *3rd quartile* | 0.25 | 0.31 | 0.12 | 0.18 | 0.31 | **0.04** | 0.30 | **0.94** |
| *Maximum* | 0.75 | 0.84 | 0.45 | 0.92 | 0.71 | **0.21** | 0.54 | **2.23** |
| *Range 1st-3rd quart.* | 0.39 | 0.31 | 0.33 | 0.48 | 0.63 | 0.18 | **0.15** | **1.12** |
| *Range min-max* | 1.49 | 1.26 | 1.11 | 1.86 | 1.48 | 0.57 | **0.49** | **3.42** |

## *3.8 Sensitivity analysis in counties in Baden-Württemberg*

Analysis of distribution functions on the county level in Baden-Württemberg was ruled out due to the time available. ß values and partial correlation coefficients of the monthly climate variables most often included to county models were compared with findings on the higher aggregation level. Models derived from differently scaled data were also compared. Consequently, diverging results stemming from scaling and models are juxtaposed with quantitative and qualitative methods. The availability of homogenized climate data from 1971 to 2000 temporally restricted the winter wheat data time series.

### 3.8.1 Quantitative model analysis

Producing models on two different aggregation levels, federal state and county, contributed not only to determining the applicability of models on scales with higher resolution data, but also to establishing the appropriate scale for modeling inter-annual sensitivity to yield anomalies. 2 models were derived for 39 of 44 counties using county specific winter wheat series and climate data. First, the Baden-Württemberg federal state model (hereafter federal model) was applied to all counties by entering all the formerly accepted climate variables. Second, the forward selection method used on the federal state scale was applied to each county dataset to produce scale specific models (hereafter county specific model). Both model approaches had threshold values of 5% error level. The climate stations selected for each county can be viewed in the annex (7.1).

The $R^2$ average of the county specific models (0.59) explains an average 23% more inter-annual anomaly variability than that of the federal models. Its fits to existing anomalies are substantially better for predicting inter-annual figures (Table 12).

Table 12. Average $R^2$ values and statistical parameters of county specific compared to federal state models applied to 39 out of 44 counties in the German federal state Baden-Württemberg

| Statistical parameter | County specific Model | Federal state model |
|---|---|---|
| *Mean* | 0.59 | 0.34 |
| *Minimum* | 0.15 | 0.13 |
| *Maximum* | 0.98 | 0.51 |
| *Variance* | 0.05 | 0.01 |
| *Standard dev.* | 0.21 | 0.09 |
| *Range* | 0.83 | 0.38 |

The table gives an overview of each model's average statistical parameters. $R^2$ values range from 0.15 to 0.98 among county specific models and from 0.13 to 0.51 among federal models. Climate data and winter wheat yield data from the county the anomaly prediction is modeled with explains up to almost 4 times more overall variance than variables of the federal state do (Freudenstadt county, 0.62 compared to 0.13). in 33 out of 39 cases (84.6%), anomalies are modeled with a better goodness of fit if monthly climate variables are not preselected on a different aggregation level.

Fig. 15 juxtaposes the widely contrasting $R^2$ values of both models for counties. It shows a zonal distribution of $R^2$ classes above and below a strong fit of 0.60 in the southern half of Baden-Württemberg. Most counties bordering Switzerland all have $R^2$ fits considerably below 0.60, while those in the broad strip to the north are considerably above and among the best fits, with one exception. In the case of county specific models, winter wheat anomalies in the northern half of Baden-Württemberg generally show a more heterogeneous pattern of $R^2$ compared to the southern half. This partition is not evident in the federal models: the sensitivity appears more balanced, which in turn suggests that the selected climate station is representative for Baden-Württemberg. However, spatial variations of monthly climate parameters in county specific models are large enough to assume either altering weather influences within Baden-Württemberg, or climate stations approximating the course of monthly weather in counties to a varying degree.

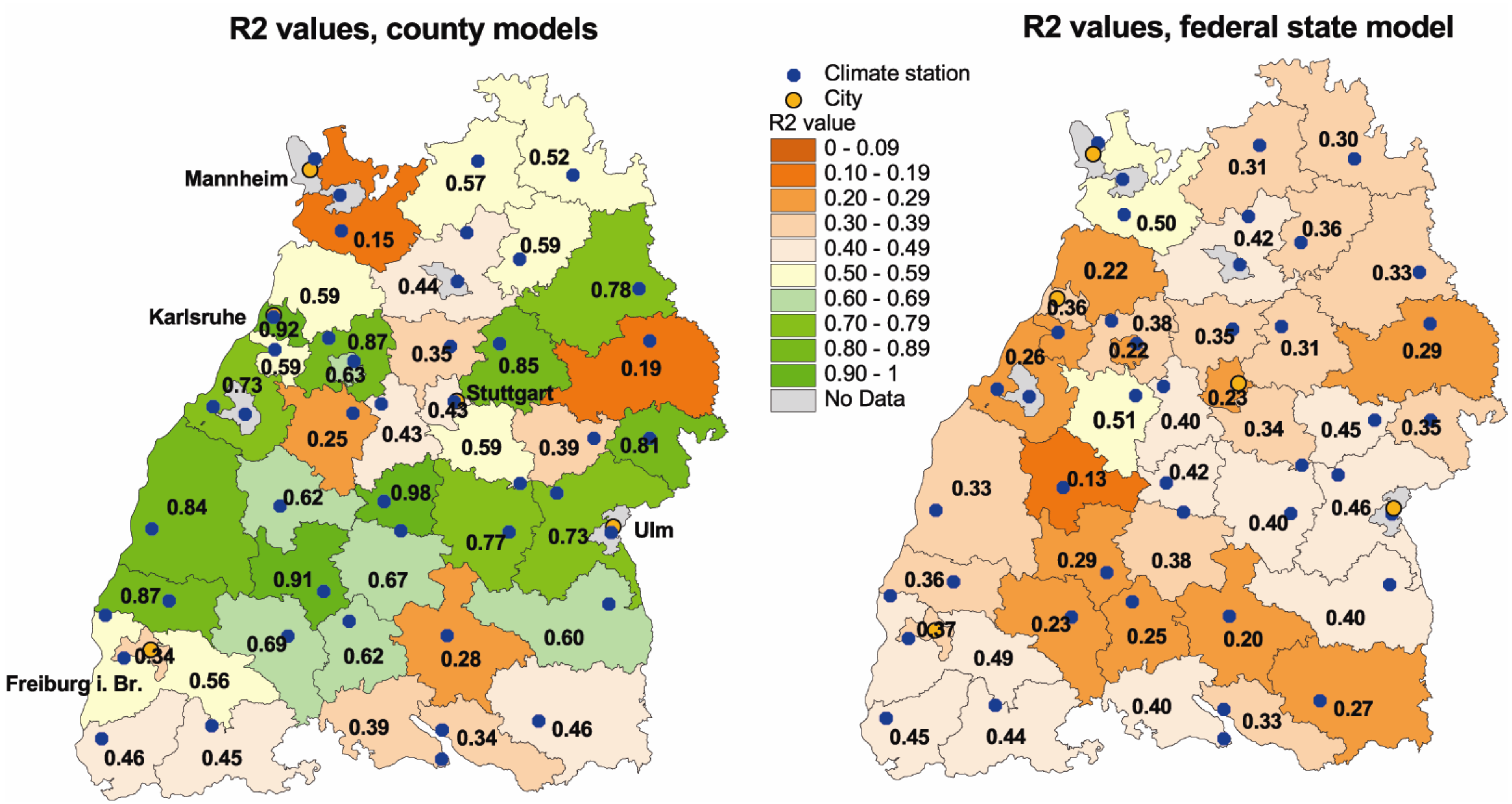



Fig. 15. $R^2$ values of county specific and federal state models for counties in Baden-Württemberg. Data series: 1970-1998. The forward selection method used on the federal state scale was applied to each county dataset to produce "county specific models", independent of the federal state model. The Baden-Württemberg federal state model (see equation (6)) was applied to all counties by feeding it data from each county to produce the "federal state models".

$R^2$ standard deviation among county specific models averages at 0.21, 0.12 higher than among federal models (0.09). $R^2$ values are higher in 32 county specific models, lower in 6 cases, and identical in one case.

Similarities are abound when absolute anomalies are replaced by relative anomalies in county specific calculations. However, they return slightly lower $R^2$ values, averaging 0.04 less. They exceed absolute anomalies half as often (10 times) and show a higher overall standard deviation (0.26). Both anomalies produce the same range of $R^2$ values (0.15-0.98). These findings further support the notion that weather information in relative anomalies is overlapped by inherent technical advancement trends, distorting analyses of sensitivity to inter-annual weather variation. Actual winter wheat yields are not viable for this purpose because the long-term trend superimposes the smaller inter-annual variation.

### 3.8.2 Qualitative sensitivity analysis

In order to determine the spatial distribution of climate variables in county specific models, the 3 highest partial correlation values for each model were determined and counted. This established in how far the first 3 climate variables accepted to the federal state model of Baden-Württemberg are also spatially inherent in county specific models. Fig. 16 and Table 13 show the overall spatial and sensitivity induced dominance of the 2 most commonly selected monthly climate variables. The ß values (standardized ß coefficients, standardized regression coefficients) represent the measure of actual sensitivity by indicating how the dependent variable (yield anomaly) changes if the standardized monthly climate variable in question changes by 1. The absolute values indicate the variables' relative importance for predicting the anomaly.

June PET in the sowing year is among the 3 highest correlating variables in 17 out of 39 county models (44%). Consistently negative ß values range between -0.33 and -0.71 and show partial correlation coefficients up to -0.97 (Table 13). Winter wheat anomalies respond to lower PET values with more favorable anomalies. This extent of sensitivity was not identified to any climate variable in federal state models. Sensitivity to the according variable on a federal scale in Baden-Württemberg was lower (ß= -0.35).

Table 13. Sensitivity of winter wheat anomalies to the 2 monthly climate variables most commonly accepted into county specific models in Baden-Württemberg. ß values represent the measure of actual sensitivity by indicating the yield anomaly if the standardized monthly climate variable in question changes by 1.

| | June PET (Sowing year) | | April PS (Harvest year) | |
|---|---|---|---|---|
| | *ß value* | *Partial correlation* | *ß value* | *Partial correlation* |
| **Minimum** | -0.71 | -0.97 | -0.72 | -0.76 |
| **Maximum** | -0.33 | -0.40 | -0.46 | -0.57 |
| **Average** | -0.54 | -0.70 | -0.55 | -0.65 |

April PS, the other variable entered to more than 5 models, correlates highest with the anomalies in all 6 entries. With an average negative ß value of -0.55, winter wheat anomalies in the pertaining counties are more sensitive to April PS than June PET variability in the sowing year: the less precipitation in April, the higher the positive anomalies. This prominent position of April PS influence on anomalies corresponds with the findings on the federal state level, but, as shown in higher ß values, anomalies are more sensitive to varying precipitation on a county level than on the federal state level. However, no equivalent to June sowing year PET in frequency or magnitude is apparent on the federal state level.

Fig. 16 maps the spatial distribution of the 2 monthly climate variables most commonly accepted into county specific models. It shows a particular dominance of June PET frequency in eastern and northeastern Baden-Württemberg. April PS do not show an evident pattern. No county specific model contains both variables.

Mapped counties with $R^2$ values >= 0.30 (federal state model, Fig. 15) and the 2 climate variables anomalies react most sensitively to (Fig. 16) show a marked spatial correlation. Counties with average and above average $R^2$ values in the federal state models widely correspond with them, indicating high $R^2$ changes with the acceptance of these variables to models.

Although the multiple regression equation of the federal state model for Baden-Württemberg (see 4.7.1) is reflected to a degree in county specific models, it is not generally evident. In addition to the 2 climate variables extensively discussed, sowing year October WS and sowing year November PET show 4 and 3 counts in the highest 3 partially correlating variables. Both respond to higher values with decreasing yield anomalies.

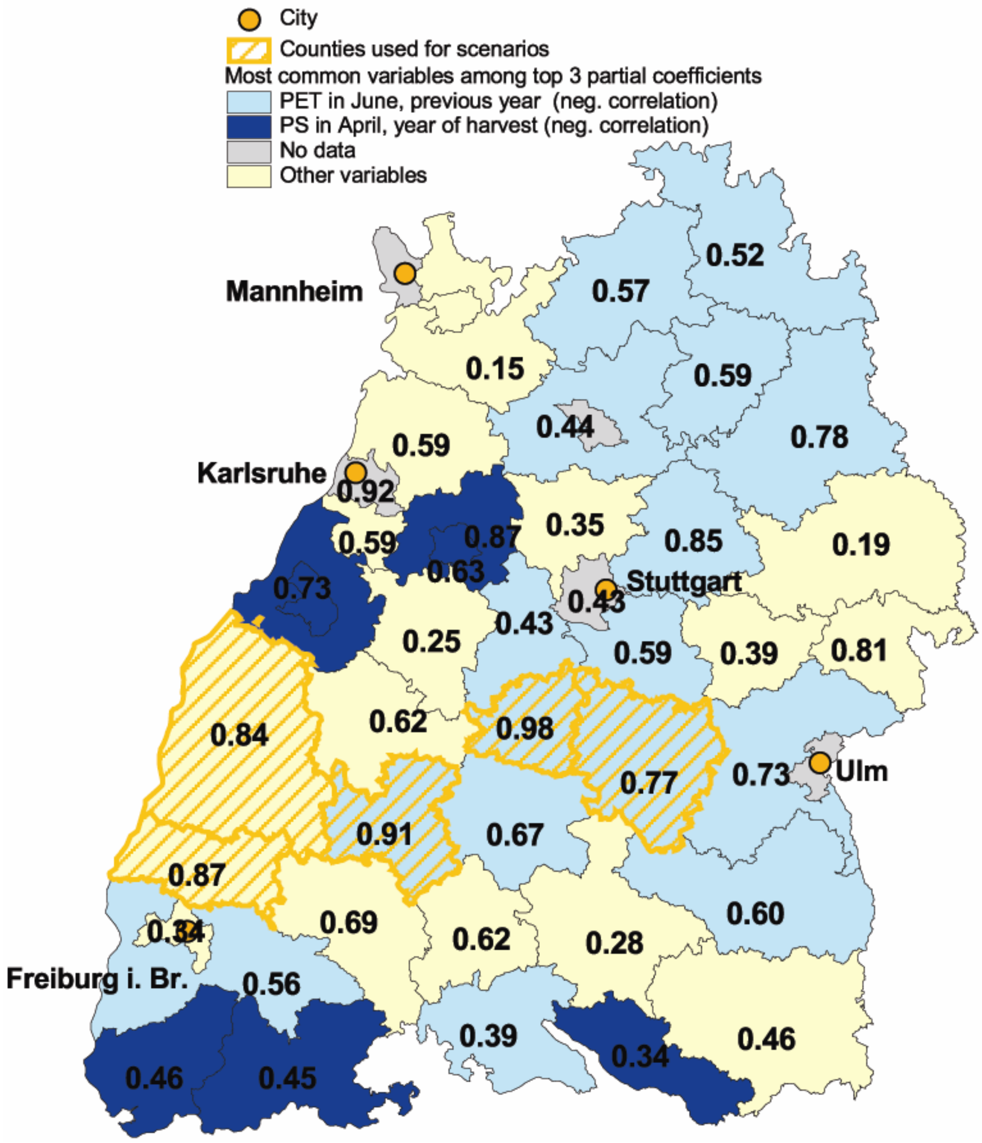



Fig. 16. Most common monthly climate variables among top 3 partial coefficients for each county specific yield model in Baden-Württemberg. Winter wheat yield anomalies were simulated for the 2001-2055 (see following section 4.9) in counties highlighted and striped orange.

### *3.9 Winter wheat anomaly development under climate scenario data*

In the preceding chapters, anomaly series for the past decades were comprehensively analyzed, and a recent extreme weather event was linked to further sensitivity analysis. As a final experiment, the development of anomalies as a response to climate scenario data was simulated. Winter wheat anomalies were simulated from 2001-2055 with climate scenario data for 5 climate stations in counties with county specific model $R^2$ values >=0.75. Thus, only models with a highly distinct goodness of fit were considered. The counties (Emmendingen, Ortenaukreis, Reutlingen, Rottweil, and Tübingen) used for scenarios are highlighted in Fig. 16. The scenario data is based on a moderate temperature increase of +1.2 -

+1.4 K to 2055 resulting from a simulation run from the global climate model ECHAM4-OPYC3 (MENZEL et al., 2003). The temperature is impressed on to local temperature series as a linear trend. The run is driven by the A1 $CO_2$ emission scenario. A continuation of the detected rising linear long-term trend for winter wheat yields was assumed for the study. The objective of this concluding study was to determine how anomalies and their variability develop under the assumption of a changing climate scenario, and what the simulated trends suggest for anomaly means and variability at an extended anomaly series ranging from 1971-2055.

Development of average anomalies ranges from steady to increasingly (a) pronounced inter-annual variability and (b) negative anomalies. Fig 17. gives an overview of the tendencies in 3 graphs. Reutlingen data shows a slightly decreasing trend of anomaly figures in the polynomial trend (3rd order). Tübingen yields show a high variance shift, accompanied by a steady increase of negative anomalies starting around 1990. Ortenaukreis data shows a more drastic decrease with effectively no variance shift.

Generally, anomalies decrease to more negative figures in all counties tested. Slopes of linear trend lines for anomalies' absolute figures vary from nearly planar for Reutlingen (0.0012 t $ha^{-1}$ $y^{-1}$) and for Rottweil (0.0015 t $ha^{-1}$ $y^{-1}$) to a steeper drop for Ortenaukreis (0.0112 t $ha^{-1}$ $y^{-1}$). Linear characters of slopes with 3rd order polynomial trend lines point out steady decreases throughout.

4 out of 5 counties show an increasing number of negative anomalies. The polynomial trend lines assure a near linear slope of varying degree in each case. Merely 5 positive anomalies were simulated for Ortenaukreis in the 21st century, where climate scenario data has the most increasingly detrimental effect on winter wheat anomalies (Fig. 17). Here, a decrease of 1.50 t $ha^{-1}$ is observed between the linear trend line intercept of +0.25 t $ha^{-1}$ in 1970 and a closing figure of -1.25 t $ha^{-1}$ in 2055. Rottweil displays steady anomaly variation and a slight increase in absolute values. So despite the spatial adjacencies among these counties all located in southern Baden-Württemberg the development of anomaly variance and intensity is diverse.

Shifts in anomaly variability were determined based on changes in variance between 1971-2000 and 2001-2055. Variance increased in 4 counties (Table 14). While variance for simulated anomalies is almost equivalent in the county most adversely affected (Ortenaukreis, +7%), it increases by +47% in Rottweil, and doubles in

Tübingen (+104%) and Emmendingen (+112%, Table 14). Variance in Reutlingen decreases by approximately a third (-38%). Overall, a tendency towards higher winter wheat anomaly variability is evident in most of the simulated data trends. This observation does not generally attest to a positive or negative anomaly trend and vice versa. But anomalies predominantly respond to the climate scenario data with increased variability and adverse anomalies in this study.

Anomaly variability increases markedly in 3 cases that correspond to accretive negative anomaly development under the assumption of a moderate rise in temperature. This is contrasted by a relative stability of variance and mean anomalies in 2 counties. Given the spatial proximity among studied counties, such diverse negative effects can hardly be explained by their climatic differences, but rather by differing climate variables among their models. They are attributed to the effects of different constellations of monthly climate variables among models. ß values remain constant for both past and future anomaly estimations. This sensitivity is addressed by increasing adverse anomalies under the climate scenario data, resulting in decreasing average anomalies.

Simulations on all county data series would provide a better starting basis for evaluating these results. Winter wheat anomalies were simulated for 5 counties only, so results must not be overestimated.

Table 14. Variance changes of actual and simulated winter wheat anomaly series between the periods 1970-2000 and 2001-2055 in selected counties in Baden-Württemberg

| **County** | **Variance 1970-2000** | **Variance 2001-2055** | **Difference [%]** | **R2, county specific model** |
|---|---|---|---|---|
| *Ortenaukreis* | 0.44 | 0.47 | +7 | 0.84 |
| *Reutlingen* | 0.11 | 0.08 | -38 | 0.77 |
| *Rottweil* | 0.19 | 0.28 | 47 | 0.91 |
| *Emmendingen* | 0.25 | 0.53 | +112 | 0.87 |
| *Tübingen* | 0.25 | 0.51 | +104 | 0.98 |

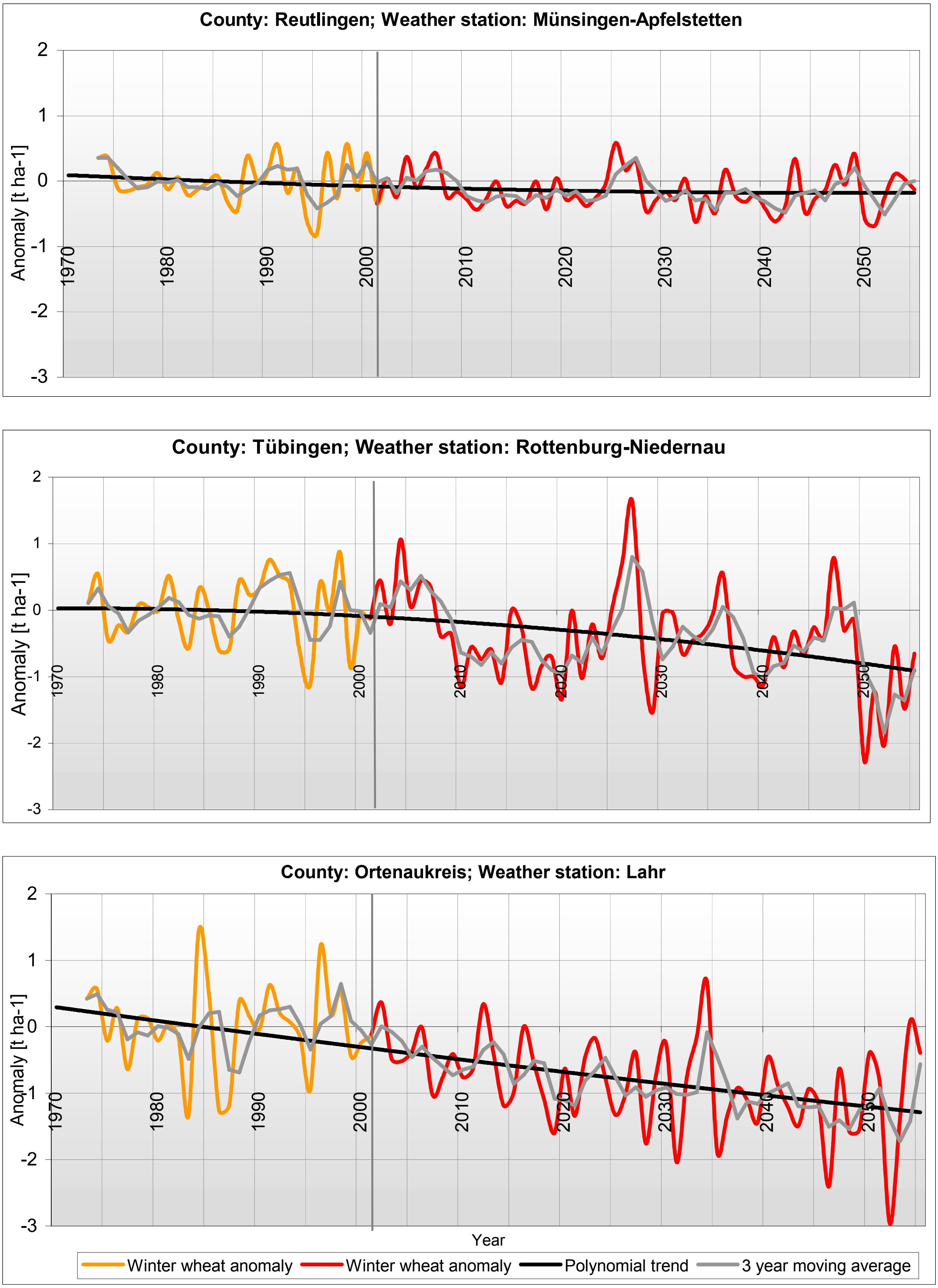



Fig. 17. Selected anomaly simulations for 3 Baden-Württemberg counties. The actual anomalies range from 1973-2000 (orange), and the simulated anomalies range from 2001-2055 (red). The scenario data impressed on to local temperature series as a linear trend is based on a temperature increase of +1.2 - +1.4 K to 2055 (simulation run from the global climate model ECHAM4-OPYC3). The run is driven by the A1 $CO_2$ emission scenario. A continuation of the detected rising linear long-term trend for winter wheat yields was assumed for the study.

### 3.10 Heat wave year analysis

A strictly temperature driven criteria catalogue was applied for determining years in which additional constraints on yields were expected due to unusually warm weather conditions. 5 climate stations selected to encompass most of Germany provided the climate data to determine heat wave years. They are listed in the annex (7). Years with 15 or more summer days exceeding the 90$^{th}$ percentile of climate station mean summer maximum temperatures in June, July, and August were considered heat wave years in German federal states. The years that meet this criterion match those with the highest average number of consecutive days with temperature maxima over the 90$^{th}$ percentile. Thus, regionally confined heat waves were excluded in favor of those covering most of Germany. Homogenized daily data was used from 1951-1998, amounting to 47 years. The heat wave summer of 2003 was not included due to lack of available homogenized climate data.

The years were crosschecked with area averaged summer temperature anomalies in Germany deviating from the 1961-1990 mean for June, July, and August, as performed by SCHÖNWIESE et al. (2003). These 3 studies are aligned in Table 15, and the 7 admitted years coincide almost completely. Years accepted due to threshold exceedance and its persistence are identical, while their ranks diverge. Of these years, 5 out of 7 are summers with positive temperature anomalies among the 7 highest between 1951 and 1998, as determined by SCHÖNWIESE et al. (2003). Years selected in all categories include 1994, 1992, 1983, 1976, 1995. 1952 and 1964 are missing in the category of area averaged summer temperature anomaly. 1994 ranks first in each category. 11.4 out of 24 average days were consecutively below the 90$^{th}$ temperature percentile.

Table 15. Years with number of days during which mean daily temperatures exceed the 90$^{th}$ quantile threshold >=15 days, compared to persistence of this threshold exceedance, and highest summer anomalies in K above the CLINO average from 1961-1990 in Germany. Each year is consistently marked with the same color. Years not selected for the threshold exceedance category are black.

| | **Threshold exceedance** | | **Persistence of threshold exceedance** | | **Summer temperature anomaly** | |
|---|---|---|---|---|---|---|
| **Rank** | **Year** | **Days** | **Year** | **Days** | **Year** | **K** |
| *1* | 1994 | 24 | 1994 | 11,4 | 1994 | 2,1 |
| *2* | 1992 | 18,8 | 1976 | 11,2 | 1992 | 2,1 |
| *3* | 1983 | 18,6 | 1983 | 10,8 | 1983 | 1,9 |
| *4* | 1995 | 17,8 | 1952 | 9,4 | 1976 | 1,4 |
| *5* | 1976 | 17,4 | 1964 | 8,4 | 1959 | 1,4 |
| *6* | 1964 | 16,6 | 1995 | 8,2 | 1995 | 1,4 |
| *7* | 1952 | 16,2 | 1992 | 7,8 | 1997 | 1,4 |

Average ranks of all 8 federal states' winter wheat anomalies correspond well to total anomaly ranks in the German dataset, differing a maximum of 4 ranks (Table 16). The exception is 1992, with cumulated federal state anomalies ranking 23 places higher. This explained by the inclusion of the 5 new federal states, which were affected far more severely. This event, tagged as the "North Summer", has been extensively studied (SCHELLNHUBER et al., 1994). The average ranks and anomalies of the 8 federal states were used instead of the German totals because they do not include city states and the new federal states as of 1990, which are not studied here.

Table 16. Average winter wheat anomalies and ranks in heat wave years (1=lowest), averaged each year with the figures of federal states in Germany. Data series: 1951-1998 (48 years, or ranks). Ranks refer to actual absolute anomalies.

| | **Rank** | | **Average anomaly [t ha$^{-1}$]** | | |
|---|---|---|---|---|---|
| **Heat wave year** | **8 federal states** | **Germany, total** | **Absolute** | **Modeled** | **Difference** |
| *1952* | 38 | 38 | 0.38 | -0.11 | 0.49 |
| *1964* | 22 | 19 | -0.04 | -0.43 | 0.39 |
| *1976* | 4 | 1 | -0.82 | -1.15 | 0.33 |
| *1983* | 14 | 18 | -0.33 | -0.82 | 0.49 |
| *1992* | 29 | 6 | 0.10 | -0.39 | 0.49 |
| *1994* | 26 | 28 | 0.03 | -0.48 | 0.52 |
| *1995* | 27 | 27 | 0.10 | -0.45 | 0.55 |

Winter wheat anomalies rank an average 20$^{th}$ lowest or 28$^{th}$ highest in heat wave years in Germany, close to the median rank (25). Anomalies in 1976 were the 4$^{th}$ lowest in the time period between 1951 and 1998 and ranked lowest when calculated for total German yields. 1976 produced the only distinctly high anomaly of all 7 selected years, with an average anomaly of -0.82. 3 out of 7 anomalies are in fact positive, while modeled anomalies are exclusively negative, as shown in Table 16. On one hand, this shows that average anomalies alone do not stipulate sensitive crop response to warm weather conditions. On the other hand, modeled anomalies predict more adverse anomalies in each year. These findings suggest an inclusion of further yield driving factors to explain average yield anomaly outcomes in heat wave years. Years with the lowest area averaged precipitation sums for Germany, also determined by SCHÖNWIESE et al. (2003), show that lower PS sums correspond well with lower anomaly ranks in each heat wave year. However, low precipitation sums and high threshold exceedance do not always resemble adverse anomalies. In 1952, the 5$^{th}$ lowest precipitation sum and high values of daily threshold exceedance were measured in a year with the 11$^{th}$ highest winter wheat anomaly.

Averaged modeled heat wave year anomalies (-0,55 t ha$^{-1}$) undercut actual anomalies (-0.08) by 0.47 t ha$^{-1}$. The estimations vary among states, as do the variables that account for them. The federal state specific variables in summer months of the harvest year and their contributions to the anomaly estimate are the focus of interest here.

Table 17. Average absolute anomalies (t ha$^{-1}$) in heat wave years and those modeled by multiple linear regression solely with harvest year summer climate variables of each federal state model in Germany. See Table 10 for the explanation of the climate variable abbreviations.

| Federal State | Average Anomaly | Summer variable contribution | Modeled Anomaly | Variables in summer months |
|---|---|---|---|---|
| *Bavaria* | -0.07 | 0.17 | -0.01 | August TS, July PS, June WS |
| *Baden-Württemberg* | -0.24 | 1.01 | 0.03 | August PET |
| *Hesse* | -0.13 | | 0.01 | |
| *Lower Saxony* | 0.03 | 2.19 | 0.05 | June PS, July PET |
| *North Rhine-Westphalia* | 0.07 | 1.39 | 0.20 | July WS, August TS, June WS |
| *Rhineland-Palatinate* | -0.15 | -1.03 | -0.15 | June WS |
| *Saarland* | -0.15 | | 0.23 | |
| *Schleswig-Holstein* | -0.04 | | 1.00 | |

Table 17 lists actual and modeled anomalies averaged for each federal state in heat wave years. Additionally, the modeled anomaly portion contributed by summer months is included. For this purpose, the pertinent regression coefficient (B) of each summer climate variable selected for the model is multiplied by the monthly climate variable figure.

Average modeled anomalies incorporating all climate variables deliver satisfactory results when compared with the actual figures. The exception, Schleswig-Holstein, deviates from this finding due to the excessive anomaly figures modeled in the 1990s, which have been discussed in a preceding section (3.7.3). In 5 out of 8 federal state models, climate variables in June, July, or August contribute to the modeled figures (Table 17). However, with the exception of Bavaria, the contributions deviate considerably from the actual anomalies. Monthly climate variables for non-summer months reduce modeled anomaly figures to better fits in all studied federal states besides Rhineland-Palatinate, for which the variables increase the modeled anomaly to the exact actual figure. Selected figures tend to overestimate anomalies. Modeled anomalies overestimate heat wave year anomalies by an average 0.25 t ha$^{-1}$, while the selected variables alone deviate with an average 0.81 t ha$^{-1}$. The models do not show a negative sensitivity to extreme summer heat necessary for a more accurate estimation of anomalies. In fact, 3 out of 5 summer climate variable sums indicate a markedly beneficial effect on yields and anomaly sensitivity to extreme weather events. However, the finding that average anomalies in heat wave years predominantly occupy midfield ranks emphasizes that extreme weather events do not always cause adverse anomalies. Finally, moderate ß values of summer monthly climate variables summarize averaged anomaly sensitivity to weather variability in the complete time series, and not to extreme weather events alone. Varying periods and intensity of unusually warm weather are either not covered in the models, or the monthly time scale is too coarse.

# 4 Discussion

## 4.1 Inter-annual weather variability and yield sensitivity analysis

### 4.1.1 Important findings

Before interpreting the results of multiple regression modeling and sensitivity analysis in the context of similar studies, the study's most important findings in these fields are summarized in the subsequent section. The following summary focuses on methodology, model analysis, and determining sensitivity to weather rather than explaining cited literature's different results and climatic differences among study areas.

The combined models that approximate long-term trends through single and bilinear regression fits and inter-annual yield variations through multiple linear regression explain an average 96.2% of all winter wheat yield variance in the 8 federal states included in the study. An average 52.4% of the anomaly variance is explained by monthly climate variables for modeling weather variation, to which yields respond with varying sensitivity. Yields are most sensitive to April CWB, the climate variable with the highest correlation in 4 out of 8 federal state models. Their ß values average at -0.38, indicating that yields are most sensitive to wetter Aprils and respond with decreases, as shown through further analysis of April TS and PS. This can be explained by high precipitation clogging soils and obstructing root development (HOOKER, 1922). The average April CWB partial correlation coefficient is -0.51. Federal state models are sensitive to a combination of meteorological factors rather than a single monthly climate variable. 41.5% of the selected monthly climate variables winter wheat anomalies are most sensitive to allude to summer months. Goodness of fit to anomaly series of federal state accounts for over 50% of winter wheat anomaly variance in 5 out of 8 states. $R^2$ values range between 0.71 (Lower Saxony) and 0.09 (Rhineland-Palatinate).

County specific models (average of 59%) explain 25% more variance than county models based on the higher aggregated federal state model (average of 34%). Higher partial correlation coefficients between winter wheat yields and monthly climate variables are also determined on the lowest aggregation level. A maximum of 13 variables are accepted to 1 model, explaining 98% of winter wheat anomaly variance through modeling the inter-annual weather influence on crops. A mere 2% of residuals attribute to unaccounted for weather impact or influences beyond weather. The partial correlation coefficient of sowing year June PET is among the 3 highest for monthly climate variables in 17 out of 39 county models (44%). It shows a negative coefficient of -0.40 up to -0.97, the latter being a near perfect negative correlation. Thus, winter wheat yield anomalies are especially sensitive June PET values before sowing has even taken place, and high rates correspond with notably decreased yields. This suggests that drier weather has a highly beneficial effect on the ripening seeds predestined for sowing in the following year. The climate variable accepted to models second-most is April PS, which shows that it also affects yields on a level lower than the federal state aggregation level. There, the adverse effect of higher April CWB on yields was accredited to high precipitation. ß values (-0.46 to -0.72), however, are higher on the county level. Partial correlation coefficients are also greater, ranging from -0.57 to -0.76.

### 4.1.2 Interpretations and comparisons

HOOKER (1922) found a less pronounced negative correlation between sowing year June PS and wheat yields in more basic correlation analyses of wheat and temperature and precipitation sums in England: Partial correlation between wheat yield and rainfall and temperature sums in overlapping periods of 8 weeks from sowing year spring until after harvest for a county in England were highest in October of the sowing year (-0.49) and February of the harvest year (-0 50).

The average $R^2$ of federal and county models are similar to Baumann & Weber's results (1966). Their study on relations between oat yields and weather at a field experiment in Schleswig-Holstein found by means of multiple regression analysis that 6 out of 15 indices with varying temporal resolution led to a minimization of residuals and explained 59.4% of yields for the single data series investigated. They preselected temperature averages, precipitation sums, and threshold temperature sums with a method detecting significant weather differences between years with high and low yields. Then they applied backward elimination to composing the regression model. This led to partial correlation coefficients which were slightly higher than correlations on the federal state level, but comparable to its county level coefficients. The authors' different methodology and higher resolution spatial scale reached similar results concerning $R^2$ values.

ALEXANDROV & HOOGENBOOM (2001) developed statistical crop-weather models with a stepwise multilinear regression for local level winter wheat in Georgia, U.S.A. Their study implemented detrended yield anomalies, and anomalies of precipitation, minimum, and maximum temperature. The monthly and multi-monthly predictors derived from 85 climate stations explained 60% of yield variance at a 5% error level. Thus, weather factors determined the variance of wheat anomalies with a similar goodness of fit calculated here on a county level. The authors' segmentation of the area in question into climatically homogeneous areas enabled them to measure a more exact correspondence between aggregated yields and climate, spatially matching them to each other. As my county specific models' adherence to administrative rather than homogeneous climatic units demonstrates, this does not improve results in terms of a better goodness of fit to winter wheat yields.

44% of the county models in this study explain more than 60% of overall yield anomaly variance. These models are possibly a result of climate stations approximating the climate better in the counties the yields were aggregated in. If this is the case, then the models that explain less variance could be improved by data from more representative climate stations. Not only would this improve overall $R^2$, it would also argument for studying weather influence on yield variability with less aggregated data in smaller units. If this is not the case, then differences of anomaly influencing factors among counties may account for large deviations in model $R^2$s.

CHMIELEWSKI & POTTS's (1995) study on the relationship between meteorological variables and non detrended yields derived its findings from a long-term winter wheat field experiment in Rothamstead, England. They found that monthly average minimum, maximum and average air temperatures explained 33% of long-term yield variance. Relationships were approximately linear. Correlation coefficients were highest with 9-month precipitation sums (-0.48). This and BAUMANN & WEBER's findings in 1966 show that yield variance (not detrended) explained through simple climate variables can vary markedly at the local level. Further studies determining whether this is caused by methodological or climatic differences are necessary in order to adjust a method best fit to the common objectives here.

## *4.2 Heat wave analysis*

### 4.2.1 Heat wave 2003

In 2003, winter wheat harvests were damaged severely on each aggregation level. The totality of the adversely affected area on each scale varies. Expectedly, homogeneity of negative results for all considered yield indices (anomaly, A $S^{-1}$, relative anomaly) increases with each disaggregation and associated spatial restriction. Median values of units' yield indices decrease with increasing spatial resolution, due to rising proximity of each higher resolution scale to the core of the heat wave. Given the location of the study areas, this means an increase of statistically unusual and adverse yields towards the center of the EU-15, meaning eastern France and southwest Germany. Central EU-15 countries experienced very low to record low index figures, as results in this study show.

The EU-15 countries lay out a heterogeneous pattern of responses to the historic heat wave. Homogeneity of negative results increases with each higher resolution within each aggregation level observed, and is highest on the county level, with no identifiable spatial gradient. The contrast between these figures and those recorded in the Benelux Countries and Denmark, all 4 of which measured positive results, suggests a gradient of increasing damage from Atlantic regions southeastward.

The core of the high pressure zones located over Europe in the first half of summer was located in central and northern Europe (MÜLLER ER AL., 2003). The most severely affected areas in terms of wheat yield indices correspond to the spatial delimitation of the heat wave by UNEP (2004): an area from northern Spain to the Czech Republic, and from northern Germany to southern Italy recorded average temperatures deviating more than +2°C from the average. The center of action in southern France, outlined by the highest temperature deviation, corresponds with the country series showing the highest negative anomaly, AS, and relative anomaly. Here, summer excesses of up to 5 standard deviations of average temperature deviation in this area (SCHÄR et al., 2004) are met with over 3 standard deviations of the yield anomaly (-3.22 A $S^{-1}$). The French AS average was nearly matched by a single county average in the less severely affected state of Baden-Württemberg (minimum AS was –3.09 A $S^{-1}$ here). Estimated damage to farms in France was between 1.1 and 4.4 billion US $ (HOUSEGO, 2003).

A transect of areas with less affected yields was identified, ranging from the Benelux Countries over Denmark to Finland. Countries in the determined transect of indifferent to distinctly positive yield anomalies flank the center of action and correspond with lower positive temperature deviations (+1-2°C). In the cases of Sweden, which recorded the highest yield and positive anomaly in the data series, and Finland, this suggests that such temperature deviations provide better conditions for wheat than currently present. Consequently, the two identified gradients and transects contrast strongest between yield indices in Sweden (highest yield anomaly in data series) and Germany (lowest). This is exemplified by the following permutation: In 2003, Germany harvested Sweden's expected average yield (6.5 t $ha^{-1}$, 16% *below* expected yields), and Sweden harvested Germany's expected yield (7.6 t $ha^{-1}$, 16% *above* the expected yield).

Altogether, the historic heat wave holds a unique position in Europe's long-term data series, both for its intensity and spatial extent. This position is not matched by negative wheat yield indices on the EU-15 level. At the same time, the two approximate in rank with each higher resolution scale of the areas of interest. In the EU-15, wheat yield anomalies were the 13$^{th}$ lowest in the summer of 2003 in the data series starting in 1961, which was very likely warmer than any other in Europe since 1500 (LUTERBACHER et al., 2004). The rank drops to lowest if a single linear trend fit line is used for the EU-15, which is discussed extensively in section 5.5.2. Germany and Baden-Württemberg experienced their lowest winter wheat anomalies since 1950 and 1970 in their warmest summer since 1761 (Schönwiese et al., 2003). 30 out of 39 counties in Baden-Württemberg had the lowest AS in the data series.

### 4.2.2 Heat wave selection and sensitivity analysis

Heat waves in Germany since 1950 were determined according to 2 averages: (1) the average number of summer days exceeding the 90$^{th}$ percentile of 5 climate stations' mean summer maximum temperatures in June, July and August; and (2) the average number of consecutive days with temperature maximums over the 90$^{th}$ percentile. The 7 years selected correspond well with years showing the highest area averaged summer temperature anomalies. Using the models previously derived, the following section summarizes findings of correlation studies between extreme weather and deviating yield figures in similar studies, and then evaluates the objective of judging how strongly anomalies are driven by extreme weather, in this case heat wave events. Thereby, it is important to take into account that other factors which influence crops are not considered here: for example, effects of $CO_2$ fertilization are higher at increased temperatures (WHEELER et al., 1996), while soil moisture depletion and lack of convective rainfall reduce yields, all processes that characterized the 2003 heat wave (BENISTON, 2004). Furthermore, other stress events coinciding with sensitive crop development phases significantly contribute to variations in grain yields (BATTS et al., 1997). So it must be stressed here that extreme temperatures alone do not cause the negative yields.

CHMIELEWSKI & POTTS (1995) determined the influence of unusual weather years on yields in Rothamsted, southern England, by isolating yields that occurred in years within the upper and lower quartiles of monthly climate variables on one hand, and isolating upper and lower quartile yields on the other. The authors found that low yields always corresponded with relatively cold and wet years, while dry weather was beneficial.

SOJA & SOJA (2003) investigated the monthly weather that caused the lowest winter wheat harvests by normalizing harvests of Austrian federal states and extracting those below the $5^{th}$ percentile of relative anomalies and quantile thresholds for absolute anomalies. Cold Februarys with negative deviations from average values recurred in these extreme harvest years.

Modeled yield sensitivity to weather variation often falls short of responding to extreme weather in distinctly deviating anomaly years. BAUMANN (1996) draws a connection between weather conditions and optimal yield rates. Accordingly, years with yields below the optimal rates must have weather patterns deviating from these conditions. However, findings in the experiments performed by HOOKER (1922, outlined in 2.1.2) stand in contrast to this finding: results in highest and lowest yields did not appear to have significantly higher partial correlation coefficients to temperature and precipitation sums. At the same time, the actual yields often exceeded the calculated values without offering an explanation through particular events. Moreover, they were recorded in years with persistently (un)favorable conditions as opposed to extreme weather events alone.

Winter wheat ranks among the 8 federal states were averaged for heat wave years. They are scattered throughout the range of 48 year ranks, averaging at $20^{th}$ lowest. This suggests that (1) yields are sensitive to more than summer temperatures that exceed the thresholds used for heat wave selection here, and (2) heat waves may even have beneficial effects on yield anomalies. Furthermore, the diverging ranks suggest that the criteria for selecting heat wave years in Germany are a unifying factor for years with otherwise diverging characteristics. The fact that only one year (1976, -0.82 t $ha^{-1}$) out of 3 negative anomalies showed a distinct drop confirms that streaks of excessive heat alone do not trigger large yield reductions.

Exclusively negative figures of averaged modeled anomalies indicate that they are more sensitive to the temperature rises than the actual anomalies are: the latter are underestimated in each run by an average 0.47 t $ha^{-1}$. However, the modeled figures approximate actual anomalies well when averaged for each federal state, besides Schleswig-Holstein, in heat wave years: the difference is halved to 0.25 t $ha^{-1}$. Sensitivity to weather variation in summer months is evident in 5 out of 8 models. The summer climate variables of each federal state model that contribute to anomaly figure are temperature driven or involve temperature as a parameter in 8 out of 10 cases. However, (1) processes beyond those in summer months superimpose their explanatory capabilities; (2) positive and negative sensitivity counterbalance each other. Thus, summer variables alone only approximate the modeled anomaly in Bavaria.

Modeled heat wave year anomalies averaged for each federal state strongly respond to the summer climate variables in heat wave years in 4 out of five case, and show deviations of over 1 t $ha^{-1}$. In Lower Saxony, modeled yields respond to June PS and July PET with an average yield deviation of over 2 t $ha^{-1}$ in heat wave years.

Conclusively, modeled yields tend to respond distinctly to summer climate variables in heat wave years, but these responses must be put into the context of overall weather influence on winter wheat anomalies within the total range of observed months. In addition, some federal state models, all 3 explain less than 50% of total anomaly variance, show no sensitivity to summer weather (Hesse, Saarland, Schleswig-Holstein).

Analyzing the response to the heat wave summer in 2003 would provide further insights into (1) how modeled anomalies are sensitive to unusually warm periods spanning months, as opposed to weeks; and (2) when heat wave effects superimpose the counterbalancing effect of weather variability on yields beyond summer months. Summarizing the sensitivity to the most common climate variables here shows that higher June WS has adverse effects, and higher August TS has positive effects on yield anomalies.

## *4.3 Climate variables*

### 4.3.1 PET following Turc-Ivanov

Calculating potential evapotranspiration with the formula after *Penman* may contribute to the multiple regression models accounting for a greater part of overall anomaly variance than with the formula following *Turc/Ivanov*. Tests have shown that *Turc/Ivanov* returns deviating values early in the year, and correction factors were recommended for implementing the formula into models (DVWK, 1996). If calculated

PET values are in fact proportionally lower than actual measurements, as the tests had found for the federal states, then this systematic error is not expected to have distorted results on multiple regression models.

### 4.3.2 Predictors beyond temperature and precipitation sums

Several reasons affirm incorporating climate variables PET, CWB and DMI, in addition to often used temperature sums (TS and WS) and precipitation sums (PS): (1) they comprise 20 out of 41 (49%) of the monthly climate variables included in federal state models, and 81 out of 155 (53%) in county specific models; (2) they also provide a monthly variable that correlates highest with yield anomalies in 5 out of 8 federal state models (63%) and 23 out of 39 county specific models (59%); and (3) they contribute monthly variables most often correlating highest with yield anomalies on both levels model were calculated on. PET plays a prominent role in explaining yield anomaly variability on both scales.

### 4.3.3 Inclusion of further indices

As stated in the introduction, an objective is to test relatively simple monthly climate variables within the chosen methodological framework and draw conclusions about the applicability of this approach to other problems on the one hand, and about using more complex variables with different temporal resolutions on the other. Selected models on the county level explain 75% and more of winter wheat yield anomaly variability through monthly climate variables alone at a 5% error level and a maximum of 13 accepted variables. The average $R^2$ for the 39 counties is 0.59. The remaining variance unaccounted for can be attributed to 2 aspects: (1) influences on anomalies aside from weather; and (2) weather influences beyond that comprised by the included monthly climate variables. The yield and weather data are considered to be exempt of systematic errors. Thus, the findings do not suggest that the total weather influence is covered by the 6 variables, because adjacent administrative units with similar climate conditions often show strongly diverging model results. These discrepancies can hardly come from comprehensive shifts in weather influence patterns and other crop driving influences substantially changing. It is assumed that the spatial heterogeneity of model results and anomaly sensitivity can be improved in favor of more homogeneous federal models with an overall higher goodness of fit. Differences in models can not be deducted from climatic differences alone, which provides empirical evidence for this. For example, strongly contrasting models for the adjacent federal states Rhineland-Palatinate and North Rhine-Westphalia suggest shifts in climatic regimes that do not correspond with long-term observations.

The monthly climate variables produce figures that do not consider the meteorological situation in preceding weeks or months, nor short or long-term build ups of abnormal dryness or wetness, nor spatial and temporal high resolution extreme weather events. These events can have strong impacts on crops, but are not automatically inherent in figures I calculated. For example, the impact of events such as hailstorms and late frosts on yields can play an important role in explaining anomaly outliers otherwise falsely attributed to different factors, and increasing variability on finer aggregation levels.

Control variables for determining water stress, drought or crop moisture could account for extreme weather events impact on crops which are either shorter or longer than the selected temporal resolution, or are averaged in the monthly calculations. For example, the Palmer Drought Severity Index (PDSI) and Crop Moisture Index (CMI) measure long-term (matter of months) and short-term drought (matter of weeks), respectively. They reflect rainfall and moisture deficit or excess and are useful for following the impacts of precipitation on agriculture (NOAA, A AND C). However, applicability of these semi official indices in the United States must be tested for the study area first. Furthermore, threshold variables could detect short extreme weather events, such as hailstorms or flash floods.

Variables calculated for shifting time windows of phenological phases could also be implemented in a consecutive study. Although they are not climate variables in the sense predictors abided by, yield sensitivity to them can be measured in an analogous approach.

### 4.3.4 Representative climate data

There is a compromise in model quality if the location point yield data is gathered at does not coincide with the location of the climate station selected for weather data. This can lead to the assumption that model quality declines with expanding area it represents. The model results on the federal state level do not support this assumption. In fact, $R^2$ values and federal state area in $km^2$ display a distinct correlation of 0.72, with the 4 largest federal states (Bavaria, Lower Saxony, North Rhine-Westphalia, Baden-Württemberg) showing the markedly highest $R^2$ values for models. This can be explained by the finding that variance decreases with increasing aggregation of yield data. In consequence, yields aggregated over a larger area and less prone to spatially confined weather events will be averaged more, considerably reducing outliers. This provides conclusions as to why models of the smaller federal states Saarland and Rhineland-Palatinate show less sensitivity to weather variation.

These results do not contradict the finding that county specific models in Baden-Württemberg explain more inter-annual yield anomaly variance than models on a federal state level. Counties are an average 3.6% of the size of Baden-Württemberg. Yield data for counties is (1) less aggregated and (2) more likely a closer fit to yield data located at the climate station than in federal states. So both the predictors and the dependent variable in the multiple regression models are better approximations of the aggregation unit they present on the one hand, and better approximations of each other spatially on the other.

County size ranges between 97.8 $km^2$ and 1854.8 $km^2$. $R^2$ values for county specific models and area in $km^2$ correlate at –0.09, displaying a near non existent correlation. This suggests that counties in this size range are equally adequate for the model methodology established. Results returned recommend (1) testing the adjustments and extensions to the methodology derived from the discussion so far; and (2) applying the methodology to differently sized counties in other federal states.

## *4.4 Further scaling issues*

In the subsequent section, conclusions will be drawn for to which aggregation level contains information as accurate as necessary and as generalized as possible, as well as for up- and downscaling issues. These objectives are met by comparing modeling yield anomalies and their sensitivity to inter-annual climate data on two scales, as stated in the introduction. The 2 scales coincide with the 2 aggregation levels in question, defined by administrative borders (federal states in Germany, and counties in Baden-Württemberg).

Different conclusions are made at different scales, and implementing GIS methods helped establish the appropriate scale for modeling effects of heat waves and climate variables on yields. For these reasons, I compared $R^2$ values produced by: (1) modeling county yield anomalies with county specific climate data; and (2) applying the federal state model to all counties. Results from asking the same questions on different scales contributed to revealing the scale best suited to pose the question on.

### 4.4.1 Up- and downscaling models

According to a brief introduction by STEIN et al. (2001), upscaling changes high resolution data towards a low resolution, and downscaling is the inverse process. Scaling, which entails process changes aside from spatial changes, resulting in constraints and feedbacks (SCHULZE, 2000), goes beyond simple (dis-)aggregation of values between levels. Scaling is thus complex, as processes can differ between scales and can require separate treatment for different components. In this study model downscaling signifies the simple and unmodified transference of a model derived from one aggregation unit to a finer scale therein, represented by finer aggregation units. This may have resulted in inaccuracies. More complex methods of downscaling in environmental studies have been applied by SCHULZE (2000) and STEIN et al. (2001).

### 4.4.2 Upscaling

Applying the federal state model to counties produced models with a distinctly lower average goodness of fit than county specific models. Further studies are necessary to discern how models based on data aggregated on a county level are suitable for explaining yield variability on a higher aggregation level. For example, the county model with the highest information content for estimating yield anomalies through weather could be determined with statistical criteria, and then applied to the pertinent federal state. This approach is the upscaling counterpart to the model downscaling applied here. The Akaike Information Criterion (AIC), a model fit measure, could provide the selection criteria for the model with the highest information content. It quantifies models' relative goodness of fit by balancing a model's complexity (i.e. number of explaining variables) with goodness of fit to its sample data.

### 4.4.3 Downscaling and further disaggregation

A further disaggregation from a county level to a borough (Ger. Gemeinde) level could determine whether yield sensitivity to weather rises further with even higher spatially resoluted data. This would be a preceding step for deriving models from more homogeneous units in terms of weather variability. Information content and detail, however, could increase at the expense of the appropriate spatial overview aimed at. Earlier studies cited in this context did not produce models approximating yield variability with climate variables notably better on a lower scale. By contrast, the findings in this study do not suggest that the methodology applied on federal state and county levels will lead to lower correlations on a local level than on levels modeled on. A climate stations' data could hereby be expected to explain yield anomaly outliers better on higher resolution scales. This is because the increase of information on spatially confined extreme weather events may lead to a better match of yield data and weather data variability.

### 4.4.4 Multiple regression analysis with actual yields

As a test, county specific model results were produced, but this time the dependent variable was represented by actual winter wheat yields instead of anomalies. This means that models did not explain variance of yield anomaly variability, the short-term characteristic of yield series, but rather long-term yield dependencies on monthly climate variables. The time series (1971-1998), area of interest (Baden-Württemberg counties), and methodology of multiple regression analysis were identical. Because of the focus on the weather information in detrended anomalies, results beyond $R^2$ values are not discussed here.

Average $R^2$ for the 39 counties reaches a soaring figure of 0.75, 0.16 higher than for anomaly models on the same scale. The standard deviation of the absolute anomaly models is halved to 0.06 t $ha^{-1}$. To what degree each component that was factored out through detrending contributes to this better fit remains an open question. If similar results for long-term yield model analysis are achieved on coarser scales and aggregation levels, arguments for the upscaling of yields model that rely exclusively on monthly climate variables could be further substantiated.

### 4.4.5 Influence by agroeconomic policies

Implemented EU policies may explain stagnant yields in bilinear fitted countries to an extent. In Italy for example, an area payment scheme determines an average productivity for a fixed area. The sum of money paid to farmers corresponds to this average, regardless of how much is harvested. The payments are higher for maize than for barley, which in itself would not diminish barley yield figures. It does have this effect though, because barley is ousted to areas with less favorable soil conditions (BADECK et al., 2004). If climate conditions enable further cultivation of maize, then it replaces barley, and overall barley yield per hectare decreases. A similar study could investigate if identified wheat yield changes in EU-15 countries fit with bilinear fit lines are related to comparably implemented policies.

This would provide an empirical explanation for the absence of bilinear trends in northern European Countries, where maize cultivation is either not an option due to climatic conditions, or only grows in confined areas and thus can not compete with wheat in the manner outlined for barley and maize.

## 4.5 Interpreting results of a statistical approach to yield anomaly analysis

### 4.5.1 Comparing results of a prognosis through Remote Sensing and a statistical data approach

Results of the heat wave 2003 analyses show how yields responded to this meso-scale extreme weather event. They were put into the context of long-term data series to qualitatively and quantitatively determine if in fact yields were as unusual as the weather event itself. This study has emphasized inter-annual variation as a distinct characteristic of yield figures. Therefore, comparing yield figures to those 1 year in advance, for instance, rather than to a trend, will lead to different conclusions. Additionally, the methodology of how yield data is gathered, assessed and evaluated also strongly influences results.

Fig. 18 shows how wheat yield changes diverge (1) by how the comparison is made and (2) how yield data is assessed. Map A is a reproduction of a yield change prognosis from 2002 to 2003 in % by monitoring agriculture with Remote Sensing as performed in the Joint Research Center (JRC) MARS project (2003), published in August 2003. Map B applies the same temporal comparison, but with FAO yield figures and with the methodology this study applied. So a Remote Sensing approach combined with yield models is juxtaposed to a statistical reproduction of the map. Map C shows the deviation of actual from expected yields of single and bilinear trends in %, as performed and explained in 3.4 and 3.5.3. The dataset used is identical to that in Fig. 6, but this time the legend used by JRC for defining percentage change classes is applied throughout. Map B shows larger yield change contrasts than A, with more countries showing yield changes over +3.5% (Ireland, Benelux countries), and countries with the lowest standardized anomaly deviations (Germany, France, Austria, Italy, see Table 6) dropping below JRC values. Map A implies a large scale negative change spatially, but milder in intensity. Map C shows a further accentuation of the contrasting figures in B and exhibits the beneficial (Sweden) and adverse (countries in core of high pressure zones) conditions well. 2003 yield changes are classified differently in 11 countries mapped in A and C.

The wheat yield figures in 2003 relative to long-term figures display changes in a different context, and with different results. This notion is best summarized by the diverging figures on the Iberian Peninsula. Portugal experienced a minor decrease of –2.7% relative to the long-term (bilinear) trend, while figures caved in over 20% relative to 2002 figures. Spain shows the same tendency, but with more moderate changes.

Changes detected in Map A do not allow qualitative conclusions about yields in 2003, because they do not take into consideration how favorable or unfavorable yields in 2002 were. While this approach can exemplify inter-annual yield variation, map C shows how yields deviated from long-term figures and indicates the intensity with which areas factually benefited or suffered losses. This is the favorable approach to qualitative and quantitative spatial analysis of a meso-scale heat wave events actual significance.

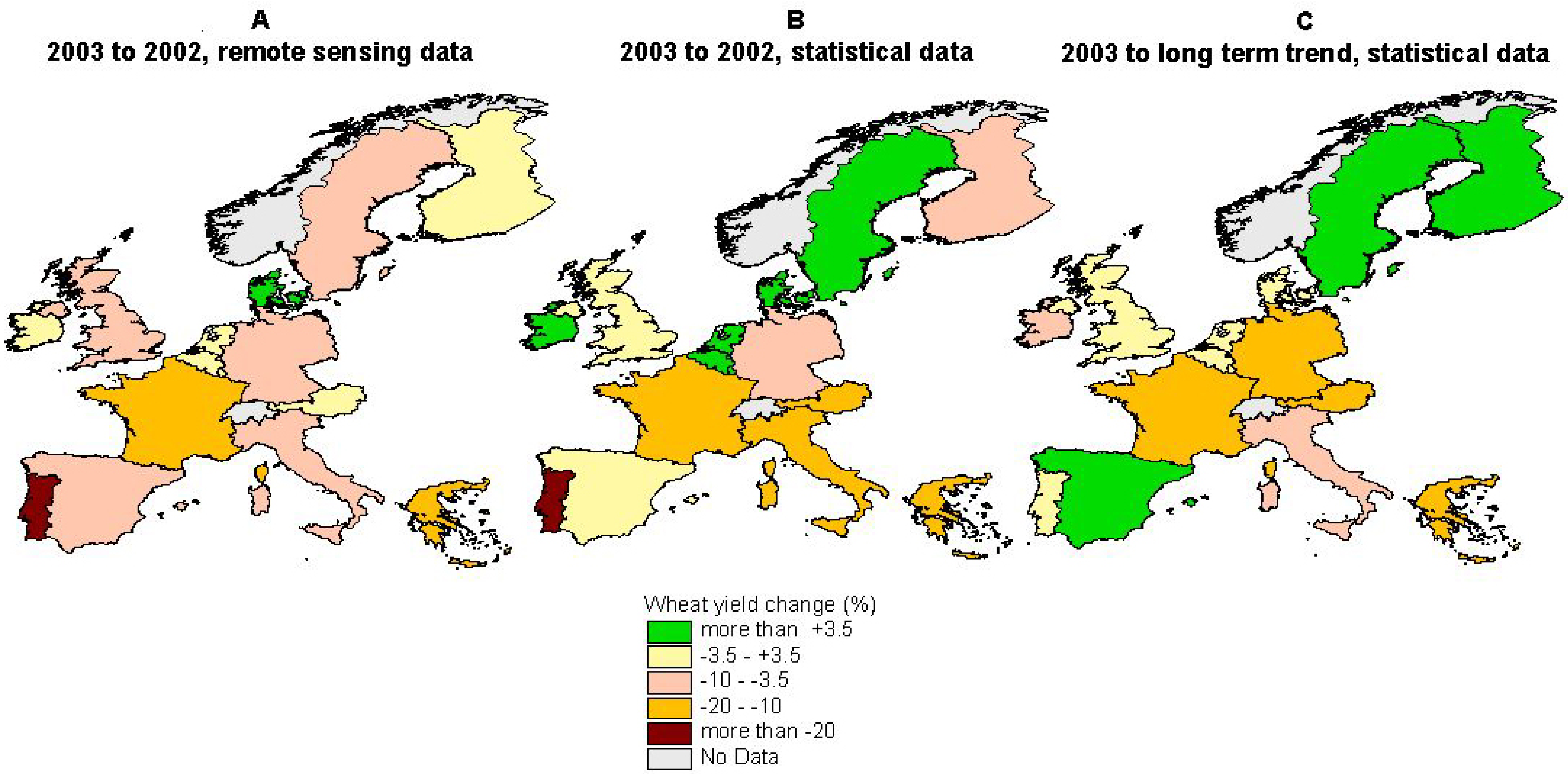



Fig. 18. Changes of wheat yields in 2003 in comparison to (1) 2002 figures and (2) expected figures of long-term trends in EU-15 countries. Map A is a reproduction of a yield change prognosis from 2002 to 2003 by monitoring agriculture with Remote Sensing as performed in the Joint Research Center (JRC) MARS project (2003). Map B applies the same comparison, but with FAO yield figures. Map C shows the deviation of actual from expected yields derived from single and bilinear trends. The dataset used is identical to that in Fig 6. The legend used by JRC was reproduced for this figure. Map A is a reproduction of a JRC map (JRC , 2003).

### 4.5.2 Qualitative changes through different methods for fitting yield trends

The preceding discussion shows how results of a Remote Sensing based prediction and an a posteriori analysis of statistical data approach can diverge, especially if compared to long-term trends. Table 18 displays implications of how this statistical data, and consequently yield sensitivity analysis, is highly dependent on how the long-term trend is derived.

Ranks of wheat anomalies in EU-15 countries from 2000-2003 and 1976 are listed for both single and bilinear trends (where found necessary), and for exclusively single linear trends. This qualitative assessment suggests 2 largely straying responses of wheat to influences beyond technological advancement on the EU-15 level since 2000. Lower numbers correspond to lower ranks and yield anomalies. Ranks since 2000 diverge by an average 16 ranks between fits. The overall EU-15 yield anomaly fit with the determined declining trend starting in 1998 (see Table 5 in section 4.1 for slope values) alternates between moderately low and high ranks in the anomaly ranking of single and bilinear fit lines to the left. It ranked 13$^{th}$ lowest in 2003, despite the heat wave, anomalies in two of the largest wheat producing countries (France and Germany) ranking lowest, and 3 more ranking in the lowest 10. The bulk of other countries have anomalies predominantly ranking in the 2$^{nd}$ and 3$^{rd}$ quantile. The lowest rank for single and bilinear fit lines was achieved in 1976 for the EU level. Total EU-15 yield data for calculating its rankings was downloaded from the FAOSTAT website as such, and was not calculated from the separate country figures used here.

Yields detrended by single linear fits alone suggest that influences on wheat yields were highly adverse in EU countries in 3 of the past 4 years, causing 3 of the 6 lowest anomalies since 1961. This negative anomaly streak culminates to the lowest anomaly rank in 2003. 8 country anomalies rank among the 10 lowest, 5 of them rank lowest. The 1976 figure ranks 3$^{rd}$ lowest here.

Table 18. Ranks of wheat anomalies of EU-15 countries in selected years. 1=lowest anomaly, 43=highest anomaly. Data series: 1961-2003

*Ranks of wheat anomalies, single and bilinear trends* | *Ranks of wheat anomalies, single linear trends*

| EU-15 country | 2000 | 2001 | 2002 | 2003 | 1976 | 2000 | 2001 | 2002 | 2003 | 1976 | EU-15 country |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *Austria* | 5 | 38 | 28 | **4** | 40 | 2 | 16 | 6 | **1** | 40 | *Austria* |
| *Belgium & Luxemburg* | 5 | 19 | 16 | **26** | 8 | 5 | 19 | 16 | **26** | 8 | *Belgium & Luxemburg* |
| *Denmark* | 24 | 17 | 5 | **28** | 3 | 24 | 17 | 5 | **28** | 3 | *Denmark* |
| *Finland* | 39 | 31 | 24 | **19** | 41 | 23 | 18 | 13 | **8** | 38 | *Finland* |
| *France* | 15 | 2 | 20 | **1** | 3 | 15 | 2 | 20 | **1** | 3 | *France* |
| *Germany* | 20 | 43 | 3 | **1** | 2 | 20 | 43 | 3 | **1** | 2 | *Germany* |
| *Greece* | 34 | 25 | 18 | **5** | 35 | 20 | 11 | 8 | **1** | 37 | *Greece* |
| *Ireland* | 37 | 24 | 5 | **13** | 1 | 37 | 24 | 5 | **13** | 1 | *Ireland* |
| *Italy* | 32 | 6 | 39 | **7** | 21 | 12 | 2 | 11 | **1** | 27 | *Italy* |
| *Netherlands* | 12 | 3 | 1 | **25** | 13 | 12 | 3 | 1 | **25** | 13 | *Netherlands* |
| *Portugal* | 35 | 2 | 39 | **20** | 27 | 20 | 1 | 26 | **4** | 32 | *Portugal* |
| *Spain* | 41 | 6 | 35 | **33** | 19 | 37 | 4 | 26 | **23** | 20 | *Spain* |
| *Sweden* | 15 | 7 | 16 | **43** | 24 | 15 | 7 | 16 | **43** | 24 | *Sweden* |
| *United Kingdom* | 34 | 3 | 33 | **21** | 1 | 23 | 2 | 20 | **5** | 1 | *United Kingdom* |
| ***EU-15*** | **35** | **11** | **39** | **13** | **1** | **24** | **2** | **6** | **1** | **3** | ***EU-15*** |

The evaluation differences in 2003 attest to modified bilinear anomalies for 7 EU-15 countries. Austria, Greece and Italy rank lowest with single fit lines, as opposed to 4th, 5th and 7th with bilinear fit lines. As Fig. 19 and Table 18 show, the assumed impact on yields relative to expected yields or long-term trends changes through adjusting fit lines to stagnating or declining wheat yields in the past decades.

Fig. 19 displays deviations of actual from expected wheat yields in 2003 in EU-15 countries. Single and bilinear fit lines for yield data are on the left, and exclusively single linear fit lines for yield data on the right. Positive changes of relative anomalies in all 7 modified yield series result in a less negative effect on Mediterranean Countries. The Greek relative anomaly improves by +13%. The Portuguese figure has the highest positive change (+19%). The area at the core of the heat wave remains far below expected yield figures, despite less negative deviations in Italy and Austria, and confirms how sensitively wheat yields responded to the weather situation there.

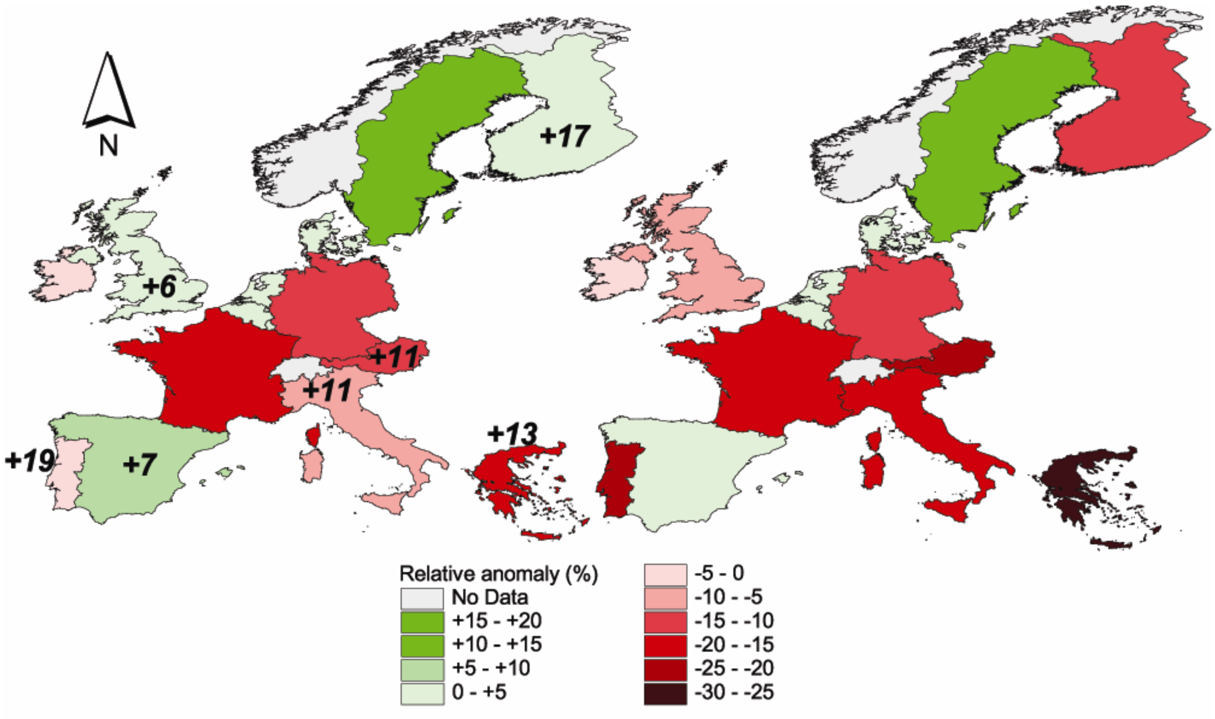



Fig. 19. Deviation of actual from expected wheat yields in EU-15 countries in 2003. Single and bilinear fitted yield trends are on the left, exclusively single linear fitted yield trends on the right. The numbers in the left maps represent the relative anomaly change in % for the countries with bilinear fit lines.

Anomalies are derived from long-term trends and respond to the varying impact of factors on an inter-annual basis. The trends are induced inter alia by technological advancement (SWANSON & NYANKORI, 1979; PHILLIPS et al., 1999) agropolitical regulations (BADECK et al., 2004) and climate change (CHMIELEWSKI & POTTS, 1995). Anomalies can not be used to directly determine what the driving factors of the long-term trends are. Therefore, interpreting causes of a stagnating wheat yield trend found for the EU-15 after 1998 is not an objective here. Yields in 2003 represent the last data cases in EU-15 country yield series. This must be considered here as a trend adjusting factor. Research on wheat yield trends in 188 nations by HAFNER (2003) showed that yield growth is not being limited by general physiological constraints on crop productivity, so the finding of such bilinear trends raises questions as to (1) whether the aforementioned trend can be attributed to modified driving factors; (2) what the driving force behind it is; and (3) in how far this trend will persist.

## 4.6 Statistical challenges in the applied models

### 4.6.1 Number of predictors

The number of predictors used to fit a model should be less than a fourth of the number of samples. A maximum of 13 monthly climate variables was accepted to a multiple regression model (to the county specific model of Tübingen, Baden-Württemberg, $R^2$=0.98). Only this model and the Karlsruhe ($R^2$=0.92) county model exceeds the quotient. The model for Rottweil, the county providing data for the 3rd best fit ($R^2$=0.91), has 8 accepted predictors. While the number of potential predictors is extremely high (102), the acceptance criteria reduce these to a statistically viable amount in all multiple regression models but 1.

### 4.6.2 Multicollinearity

The problems of collinearity and multicollinearity were not extensively addressed in the multiple regression analysis. Collinearity refers to a situation where one independent variable is a linear function of others and can result in a nearly total prediction of independent variables through other ones included (VOGEL, 2000; SPSS, 2003). This complicates separating redundant effects. For example, temperature sums >=5°C (WS) may be prone to collinearity with temperature sums >=0°C (TS) incorporated in the same models.

However, the tolerance of each variable accepted to federal state models do not confirm that multicollinearity needs more scrutiny here. Tolerance is defined as 1-$R^2$ for the regression of an accepted variable to all other variables accepted (without considering the dependent variable). Tolerance close to 0 indicates high multicollinearity and unstable ß values (SPSS, 2003). The lowest tolerance is 0.573, for July PET in the Lower Saxony model, and represents 1 of 2 values below 0.6. All other variables selected for multiple regression models have tolerance values between 0.981 and 0.678.

### 4.6.3 Adjusted $R^2$

Trade-off relationships between information content and the number of explaining variables were not considered in multiple regression analysis for discouraging potential overfitting. The AIC and adjusted $R^2$ take such effects into account. Reasons for considering $R^2$ over adjusted $R^2$ values were stated in the methodology section (3.7.6). However, if the study were to be repeated again, the adjusted $R^2$ would be used for studying multiple regression model results of the Baden-

Württemberg federal state model applied to each county. This would take into account that the sample sizes (yields in 31 or 34 years) are lower than the size the federal state level model is derived from (yields in 54 years). Adjusted $R^2$ would temper goodness of fit, because (1) it can drop with further variables accepted to the model, as opposed to the customary $R^2$; (2) less observations decrease adjusted $R^2$; and (3) higher amounts of independent variables decrease adjusted $R^2$. Conclusively, $R^2$ values for county models based on the Baden-Württemberg federal state model would be even lower, further broadening the gap of prediction quality between them and county specific models.

## *4.7 Variability: record high winter wheat yields and turnovers in Baden-Württemberg in 2004*

The following calculations are based on winter wheat yield data obtained from the Baden-Württemberg State Bureau of Statistics website (Sept. 2004) and close the discussion section. In 2003, the lowest winter wheat anomaly (-1.05 t $ha^{-1}$) in the Baden-Württemberg data series from 1950-2003 was calculated for the warmest summer in Germany since at least 1761 (SCHÖNWIESE et al., 2003). In 2004, it rebounded to the 3rd highest anomaly (+0.79 t $ha^{-1}$) in the highest yield anomaly change between 2 consecutive years (+1.85 t $ha^{-1}$). This equals a relative anomaly jump of 32%. Such inter-annual variability, referring to variations in the mean state of inter-annual yield indices, is the main characteristic of anomaly series in question and can be explained to an extent by meteorologically induced factors, or weather variation, to which crops are sensitive. This relationship between weather and crop yields prompts me to pose the following closing questions: (1) are inter-annual weather and, in turn, wheat yield variability increasing?; and (2) if so, how are wheat yields sensitive to such a weather variability increase? SOUTHWORTH et al. (2002) concluded from their climate and crop model analysis that climate variability is an influencing factor for wheat yields. MEARNS et al. (1992) in turn suggest that changes in climate variability, in addition to changes in mean conditions, could have serious effects on crops. So, finally, (3) does the yield sensitivity to such variability remain linear, or does it increase at a non-linear rate the more extreme the events are, as WAGNER (1999) has shown for simulated extreme high temperature run probabilities to increasing climate variability?

## 4.8 Limitations of spatial consistency through lacking data

Multiple regression analyses could not be conducted in all areas of interest, which cut back on the aim to perform all analyses on each aggregation level. First and foremost, although the overall compiled data situation can be positively reviewed, the availability and consistency of data series did pose a limiting factor: a comprehensive regression analysis of winter wheat yields in eastern German federal states was obtruded by lacking data. Series of crop yields in the former German Democratic Republic and the five federal states emerging from it after the Reunification in 1990 are incomplete and not included in the analyses. The Federal Statistical Office of Germany could not provide digital data for eastern German federal states before 1990. Specifically for this study the disadvantage lies in omitting spatially holistic results for Germany. Not only did the acquisition of gathered data take long, the availability of digitized data series was restricted. Compiling older data sources from annual statistical yearbook would have been possible, but refining them to the values appropriate for today's federal state boundaries was ruled out for reasons indicated in the methodology section (3.2.1.2). Altogether, restricted data access cut back analyses on the three aggregation levels to a degree, but did not threaten the applicability of the general methodology and approach. Time constraints already alluded to impeded a multiple regression analyses for EU-15 countries.

# 5 Conclusions

By modeling the weather influence on detrended winter wheat yield anomalies through multiple regression analysis, this study sought to determine to which degree yields can provide a measure of sensitivity to inter-annual weather variability. I relied on statistical methods to establish both the sensitivity to weather and which weather has beneficial or adverse effects on yields. Inter-annual weather variation was modeled through 6 monthly climate variables. In how far weather contributed to explaining yield anomaly variability was also addressed. These studies were performed on 2 scales segmented by 2 aggregation levels, namely on former West German federal states, and on Baden-Württemberg counties. Applying GIS methods helped determine spatial homogeneity or heterogeneity of modeled winter wheat yield anomalies as well as actual yield indices after the historic heat wave in 2003.

Changes in statistical coefficients, determining sensitivity and correlation, and yield variability occured between aggregation levels. These shifts hold for counties both in relation to the federal state Baden-Württemberg, and to other federal states. The average predictability of winter wheat yield anomalies, ß values of the highest correlating variables and partial correlation coefficients increase as the spatial resolution of the Baden-Württemberg model increases. These findings imply an amplification of yield sensitivity through disaggregation. The higher resolution data on county levels leads to better model results. Sensitivity is higher at the county level as a measure of winter wheat yield anomalies' response to weather. Thus, these findings confirm that focusing on one scale obscures important information that takes effect at a finer scale, a conclusion noted in SCHULZE's (2000) study on transcending scales in studies of climate change on agrohydrological responses. Conclusively, findings indicate advantages of a higher resolution approach for analyzing crop sensitivity to weather on different scales that are segmented into units of different aggregation.

More than half of the inter-annual variance of detrended yield anomalies can be explained by weather on both aggregation levels, to which anomalies can be highly sensitive. $R^2$ values exceed 90% in some counties models. Partial correlation coefficients and ß values of monthly climate variables most often selected by multiple regression models are substantially higher on the county level. Other studies cited here that employed similar methods do not show partial correlation coefficients of the scale found here between county-level yield anomalies or yields, and climate variables. The results of multiple regression model analysis discussed in the context of similar studies are consistent and sound enough on a low aggregation level, but do not suggest that the variation in yield anomalies apportioned to weather has yet been fully covered, both qualitatively and quantitatively. With the help of methodological improvements noted in the discussion section, up- and downscaling multiple regression models to different resolution data could be further tested.

Potential evapotranspiration plays a prominent role in explaining yield anomaly variability on both of the scales multiple regression analyses were conducted on. These findings meet 2 further objectives of this study, namely (1) testing the methodology on different scales to determine at which level the problems are best approached on; and (2) applying climate variables beyond those introduced in similar studies. In conclusion, arguments were provided to incorporate more complex variables in further studies, as the methodology used here arrived at solid results.

Multiple regression model analyses at a federal state level suggest that wetter Aprils are the primary cause of lower yield anomalies. Sowing year Junes with low potential evapotranspiration assume this role on a county level, but yields here are also sensitive to wetter Aprils. In the context of analyzing vulnerability as defined by the IPCC (2001, B), these findings of sensitivity can contribute to determining to which degree yields in the areas of interest are susceptible to, or unable to cope with changes in climates' mean state, variability and extremes.

I extensively analyzed detrended yield indices in the heat wave year 2003 on 3 different scales segmented by 3 aggregation levels. Wheat and winter wheat anomalies were put into the context of long-term data series to qualitatively and quantitatively determine if they were in fact as unusual as the weather event itself. Relative to the time series used, the negative anomalies approximate the historic rank of the heat wave with each higher resolution scale of the areas of interest. SOUTHWORTH et al. (2002) have shown that in areas where current growth of wheat is limited in some way, climate change may induce increased growth and higher yields. Studies predict the increasing occurrence of such summers as in 2003 in Europe in the 21st century (BENISTON, 2003) and results from regional climate models suggest that approximately every second summer will be as hot or hotter than 2003 by the end of the 21st century (LUTERBACHER et al, 2004). Thus, in the light of these findings, it can be assumed that the basic spatial patterns of yield anomalies found in this study for after the highly unusual heat wave in 2003 will become increasingly common in years to come.

# 6 References

## 6.1 Literature


AGRARIAN PUBLISHING UNION (1982): Bench mark figures for agriculture and horticulture. Frankfurt am Main.

ALEXANDROV, V. A., HOOGENBOOM, G. (2001): Climate variation and crop production in Georgia, USA, during the twentieth century. In: Climate Research, Vol. 17, p. 33-43.

ASSENG, S, JAMIESON, P. D., KIMBALL ,B., PINTER, P., SAYRE, K., BOWDEN, J. W., HOWDEN, S. M. (2004): Simulated wheat growth affected by rising temperature, increased water deficit and elevated atmospheric $CO_2$. In: Field Crops Research, Vol. 85, p. 85-102.

BADECK, F., Rizza, F., Stanca, A.M., Delogu, G. (2004). Produttività dell'orzo in Italia, prospettive per il futuro. In: Informatore Agrario : 61-63.

BARTHELME, N. (2000): Geomatics. Models, structures, functions. Berlin.

BATTS, G. R. ET AL. (1997): Effects of $CO_2$ and temperature on growth and yield of crops of winter wheat over four seasons. In: European Journal of Agronomy, Vol. 7, p. 43-52.

BAUMANN, H. , WEBER, E. (1966): Attempt of a statistical analysis of the relation between weather and yield by multiple regression. In: Notes from the German National Meteorological Service, Vol. 37.

BEINHAUER, R. (1977): The weather dependent yield formation of selected forage crop. In: Reports from the German National Meteorological Service.

BENISTON, M. (2003): The 2003 heat wave in Europe: A shape of things to come? An analysis based on Swiss climatological data and model simulations. In: Geophysical Research Letters, Vol. 31, p. 1-4.

BILL, R., ZEHNER, M. (2001): Encyclopedia of Geomatics. Heidelberg.

CALDERINI, D. F., SLAFER, G. A. (1998): Changes in yield and yield stability in wheat during the 20th century. In: Field Crops Research 57, p. 335-347.

CHMIELEWSKI, F.-M., POTTS, J. M. (1995): The relationship between crop yields from an experiment in southern England and long-term climate variations. In: Agricultural and Forest Meteorology, Vol. 73, p. 43-66.

EUROPEAN COMMISSION (2003): European regional statistics. Reference guide. Theme 1: General Statistics. Luxembourg.

FRANKE,W. (1992): Cultivar science. Cultivars of the mid latitudes, subtropics and tropics. Stuttgart.

GERMAN ASSOCIATION FOR WATER, WASTEWATER AND WASTE DVWK (1996): Determining transpiration on land and water surfaces. Bulletin of the German Association for Water, Wastewater and Waste DVWK, Vol. 238.

HÄCKEL, H. (1999): Meteorology. Stuttgart.

HAFNER, S. (2003): Trend in maize, rice, and wheat yields for 188 nations over the past 40 years: a prevalence of linear growth. In: Agriculture, Ecosystems and Environment, Vol. 97, p. 275-283.

HÖLTING, B. (1995): Hydrogeology. Stuttgart.

HOOKER, R. H. (1922): The weather and the crops in eastern England, 1885-1921. In: Quarterly Journal of the Royal Meteorological Society, Vol. 48, p. 115-138.

INSTITUTE FOR AGROPOLITICAL MARKET RESEARCH IAP (1996): RAUMIS Report 1996, Regionalized Agrarian and Environmental System for the Federal Republic of Germany. Bonn.

INTERGOVERNMENTAL PANEL ON CLIMATE CHANGE IPCC (2001, A): IPCC Third Assessment Report. Climate Change 2001: The Scientific Basis. Houghton, J. T., Ding, Y., Griggs, D.J., Noguer, van der Linden, M., Xiaosu, P. J. and D. (eds.). Cambridge.

INTERGOVERNMENTAL PANEL ON CLIMATE CHANGE IPCC (2001, B): IPCC Third Assessment Report. Climate Change 2001: Impacts, Adaptation and Vulnerability. McCarthy, J. J., Canziani, O.F., Leary, N. A., Dokken, D. J., White, K. S.(eds.). Cambridge.

JOINT RESEARCH CENTRE (JRC, 2003): Synthesis of the campaign 2002/2003 and start of the new 2003/2004 campaign. In: MARS Bulletin, Vol, 11, p. 1-21.

LESER, H. (ed., 1997): Dictionary of general geography. Braunschweig.

LÖPMEIER. F.-J. (2004): The agrometeorological situation. In: Climate status report 2003 of the German National Meteorological Service, p.84-93.

LUTERBACHER, J., DIETRICH, D., XOPLAKI, E., GROSJEAN, M., WANNER, H. (2004): European seasonal and annual temperature variability, trends, and extremes since 1500. In: Science, Vol. 303, p. 1499-1502.

MARS BULLETIN ON MONITORING AGRICULTURE WITH REMOTE SENSING (Nov. 18th, 2003): Synthesis of the new campaign 2003/2003 and start of the new 2003/2004 campaign. Vol. 11.

MEARNS, L. O., ROSENZWEIG, C., GOLDBERG, R. (1992): Effects of changes in interannual climatic variability on CERES-wheat yields: sensitivity and 2 $^{x}$ $CO_2$ general circulation model studies. In: Agricultural and forest meteorology, Vol. 31, p. 159-189.

MENZEL, L., GERSTENGARBE, F.-W., WERNER (2003): Regional differences of climate change and their influences on hydrological characteristics in Germany. In: Forum for Hydrology and Water Rationing, Vol. 1, p. 19-26.

MÜLLER-WESTERMEIER, G. (2000): The average climatological conditions in Germany (part III). In: Climate status report 1999 of the German National Meteorological Service, p. 50-60.

ÖSTERLE, H., GERSTENGARBE, F.-W., WERNER, P. C. (2003): Homogenizing and updating the climate dataset of the Climate Research Unit at the University of East Anglia, Norwich. In: Terra Nostra, Vol 6, 6. German Climate Conference, p. 326-329.

PHILLIPS, J., RAJAGOPALAN, B., CANE, M., ROSENZWEIG, C. (1999): The role of ENSO in determining climate and maize yield variability in the U. S. corn belt. In: International Journal of Climatology, Vol. 19, p. 877-888.

SCHELLNHUBER, H.-J., ENKE, W., FLECHSIG, M. (Hrsg., 1994): Extreme Northern Summer 1992. Meteorological characteristics, effects on near-natural and human influenced ecosystems, perception through society and situation-based policy-administrative and individual measures. Potsdam-Institute for Climate Impact Research, PIK Reports, Vol. 2, No. 2.

SCHULZE, R. (2000): Transcending scales of space and time in impact studies of climate and climate change on agrohydrological responses. In: Agriculture, Ecosystems, and Environment, Vol. 82, p. 185-212.

SCHÄR, C. VIDALE, P.L., LÜTHI, D., FREI, C., HÄBERLI, C., LINIGER, M. A., APPENZELLER, C. (2004): The role of increasing temperature variability in European summer heatwaves. In: Nature, Vol. 427, p. 332-336.

SCHÖNWIESE, C.-D., STAEGER, T., TROEMEL, S. (2004): Statistical-climatological analysis of the heat wave summer 2003 in Germany. In: Climate status report 2003 of the German National Meteorological Service, p.71-78.

SENERIVATNE, S. I., PAL, J. S., ELTAHIR, E. A. B., SCHÄR, C. (2002): Summer dryness in a warmer climate: a process study with a regional climate model. In: Climate Dynamics, Vol. 20, p. 69-85.

SOJA, A.-M., SOJA, G. (2003): Documenting impact of extreme weather events on agricultural production. In: Startproject climate protection: First analyses of extreme weather events and their impact in Austria. Chapter report StartClim3b.

SOUTHWORTH, J., PFEIFER, R. A., HABECK, M. RANDOLPH, J. C., DOERING, O. C., GANDAGHAR RAO, D. (2002): Sensitivity of winter whea yields in the Midwestern United States to future changes in climate, climate variability, and $CO_2$ fertilization. In: Climate Research, Vol. 22, p. 73-86.

SPSS 12.0. User’s Guide (2003). Chicago.

STEIN, A., RILEY, J., HALBERG, N. (2001): Issues of scale for environmental indicators. In: Agriculture, Ecosystems, and Environment, Vol. 87, p. 215-232.

SUPIT, I. (1997): Predicting national wheat yields using a crop simulation and trend models. In: Agricultural and Forest Meteorology, Vol. 88. p. 199-214.

SWANSON, E.R., NYANKORI, J. (1979) : Influence of weather and technology on corn and soy bean yield trends. In: Agricultural Meteorology, Vol. 20, p. 327-342.

VOGEL, F. (2000): Descriptive and concluding statistics. Munich.

WAGNER, D. (1999): Assessment of the probability of extreme weather events and their potential effects in large conurbations. In: Atmospheric environment, Vol. 33, p. 4151-4155.

WEISCHET, W (1997) : Introduction to general climatology. Stuttgart.

WITTWER, S.H. (1995): Food, climate, and carbon dioxide – the global environment and world food production. New York.

WHEELER, T. R., BATTS, G. R., ELLIS, R. H., HADLEZ, P., MORISON, J. (1996): Growth and yield of winter wheat (Triticum aestivum) crops in response to $CO_2$ and temperature. In: Journal of Agricultural Science, Vol. 127, p. 37-48.

## 6.2 Supporting online material

Food and Agricultural Organization, Global Agro-Ecological Zones GAEZ (no publication date): Global Agro-Ecological Zones. http://www.fao.org/ag/agl/agll/gaez/index.htm. Cited Jan 14th, 2004.

Food and Agricultural Organization, statistical unit FAOSTAT (no publication date). http://apps.fao.org/faostat/collections?version=ext&hasbulk=0&subset=agriculture. Cited Jan. 30th, 2003.

German Agrarian Information Net DAINET (Sept. 2003): Harvest 2003. http://www.dainet.de/index.cfm?nav=ernte. Cited Nov. 19th, 2003.

German Agrarian-Information Net DAINET (Sept. 2003): Harvest 2003. http://www.dainet.de/index.cfm?nav=ernte. Cited Nov. 19th, 2003.

German Farmers Association DBV (Aug. 8th, 2003): Third Harvest Report. http://www.bauernverband.de/konkret_864.htm. Cited Nov. 20th, 2003.

Housego, K. (August 23, 2003): Heat wave devastes French agriculture. http://www.clivar.org/recent/heat_impacts.htm. In: Toronto Star. Assessed Jan. 21st, 2004.

Joint Research Centre JRC (Aug. 14th, 2003): The Joint Research Centre (JRC) of the European Commission forecasts this years harvest deficits due to drought. http://www.jrc.it/dowload/press/releases/prcropyield200308.pdf. Cited Nov. 19th, 2003.

National Oceanic and Atmosperic Association NOAA (A, no publication date): The Palmer Drought Severity Index. http://www.drought.noaa.gov/palmer.html. Cited Nov. 24th, 2003.

National Oceanic and Atmosperic Association NOAA (C, no publication date): Climate of 2000 – June – August U:S: Drought, Heat Waves, and Wildfires. Http://lwf.ncdc.noaa.gov/oa/climate/research/2000/sum/us_drought.html. Cited Nov. 24th, 2003.

State Bureau of Statistics, Baden-Württemberg (August 2004): yield data on county level.http://www.statistik.baden-wuerttemberg.de/SRDB/home.asp?H=Landwirtschaft&U=02&T=05023014&E=KR. Cited Aug. 15th, 2004.

Shepard, E., Atkinson, D., Russo , A. (no publication date): Interpolation of Population Related Polygon Data. Information Technology Outreach Services, The University of Georgia, http://gis.esri.com/library/userconf/proc97/proc97/to300/pap298/p298.htm. Cited Nov. 22nd, 2004.

State Bureau of Statistics, Baden-Württemberg (September 2004): Combine harvesters harvest record yields at 33.6 million decitons. http://www.statistik.baden-wuerttemberg.de/ Pressemitt/2004298.asp. Cited Sept. 29th, 2004.

Technical University of Karlsruhe (2003): The record summer of 2003. Authors: MÜLLER, G., MÜHR, B., KOTTMEIER, C. http://www.imk.uni-karlsruhe.de/fi/fzk/seite_1145.php. Cited Jan. 21st, 2004.

United Nations Environment Program UNEP (2004): Impacts of summer 2003 heat wave in Europe. http://www.grid.unep.ch/product/publication/download/ew_heat_wave.pdf. Cited June 15th, 2004.

# 7 Annex - selected climate stations

Table 19. Climate stations selected with GIS methods for providing homogenized climate data for federal state models. The homogenized data was used for multiple regression analysis.

| Station Name/Location | Federal State | Longitude | Latitude | Station ID |
|---|---|---|---|---|
| *Hameln* | Lower Saxony | 9.33 | 52.12 | 1547 |
| *Gütersloh* | North Rhine-Westphalia | 8.35 | 51.88 | 1577 |
| *Simmern-Wahlbach* | Rhineland Palatinate | 7.60 | 50.00 | 2268 |
| *Grebenhain-Herchenhain* | Hesse | 9.27 | 50.48 | 2633 |
| *Laichingen* | Baden-Wuerttemberg | 9.70 | 48.50 | 2729 |
| *Westermarkelsdorf/Fehmarn* | Schleswig-Holstein | 11.07 | 54.53 | 3835 |
| *Augsburg-Mühlheim* | Bavaria | 10.93 | 48.43 | 4128 |
| *Berus* | Saarland | 6.68 | 49.27 | |

Table 20. Climate stations selected with GIS methods for providing homogenized climate data for county models in Baden-Württemberg. Climate scenario data of stations highlighted red was used for anomaly simulations. Climate data of precipitation stations with 5-digit numbers Ids was interpolated. They are located at the bottom of the table.

| Station Name/Location | County | Longitude | Latitude | Station ID |
|---|---|---|---|---|
| *Baden-Baden-Geroldsau* | Baden-Baden | 8.25 | 48.73 | 2701 |
| *Buchen* | Neckar-Odenwald-Kreis | 9.32 | 49.52 | 2685 |
| *Crailsheim-Ingersheim* | Schwäbisch Hall | 10.08 | 49.13 | 4099 |
| *Ellwangen/Jagst* | Ostalbkreis | 10.13 | 48.97 | 4100 |
| *Freudenstadt* | Freudenstadt | 8.42 | 48.45 | 2751 |
| *Hechingen* | Zollernalbkreis | 8.98 | 48.38 | 2754 |
| *Heidenheim/Brenz* | Heidenheim | 10.13 | 48.67 | 4102 |
| *Heilbronn* | Heilbronn; City | 9.23 | 49.15 | 2689 |
| *Karlsruhe* | Karlsruhe; City | 8.37 | 49.03 | 2698 |
| *Klippeneck* | Tuttlingen | 8.75 | 48.10 | 2758 |
| ***Lahr*** | **Ortenaukreis** | **7.83** | **48.37** | **2303** |
| *Laichingen* | Alb-Donau-Kreis | 9.70 | 48.50 | 2729 |
| *Lenningen-Schopfloch* | Esslingen | 9.53 | 48.53 | 2717 |
| *Mannheim* | Mannheim; City | 8.55 | 49.52 | 2695 |
| *Mergentheim, Bad-Neunkirchen* | Main-Tauber-Kreis | 9.77 | 49.48 | 2679 |
| ***Muensingen-Apfelstetten*** | **Reutlingen** | **9.48** | **48.38** | **2753** |
| *Neudenau* | Heilbronn | 9.27 | 49.30 | 2687 |
| *Oehringen* | Hohenlohekreis | 9.52 | 49.22 | 2684 |
| *Pforzheim-Eutingen* | Pforzheim; City | 8.75 | 48.90 | 2711 |
| *Sankt Blasien* | Waldshut | 8.13 | 47.77 | 2776 |

| | | | | |
|---|---|---|---|---|
| *Schallstadt-Mengen* | Freiburg im Breisgau; City | 7.72 | 47.97 | 2314 |
| *Stoetten* | Göppingen | 9.87 | 48.67 | 2728 |
| *Stuttgart-Neckartal* | Stuttgart; City | 9.22 | 48.78 | 2715 |
| *Überlingen/Bodensee* | Bodenseekreis | 9.18 | 47.77 | 2787 |
| *Ulm* | Ulm; City | 9.95 | 48.38 | 2730 |
| *Villingen-Schwenningen* | Schwarzwald-Baar-Kreis | 8.47 | 48.05 | 2739 |
| *Vogtsburg-Oberrotweil* | Breisgau-Hochschwarzwald | 7.63 | 48.10 | 2305 |
| *Weingarten* | Ravensburg | 9.62 | 47.80 | 2791 |
| *Althengstett* | Calw | 8.75 | 48.74 | 25131 |
| *Backnang* | Rems-Murr-Kreis | 9.43 | 48.96 | 25133 |
| *Ettlingen-Ettlingenweiler* | Karlsruhe | 8.38 | 48.93 | 25155 |
| ***Freiamt-Keppenbach*** | **Emmendingen** | **7.92** | **48.15** | **24106** |
| *Kandern-Sitzenkirch* | Lörrach | 7.63 | 47.72 | 28115 |
| *Koenigsbach-Stein* | Enzkreis | 8.63 | 48.97 | 25297 |
| *Konstanz* | Konstanz | 9.18 | 47.68 | 29107 |
| *Pleidelsheim* | Ludwigsburg | 9.20 | 48.95 | 25304 |
| ***Rottenburg-Niedernau*** | **Tübingen** | **8.90** | **48.47** | **25113** |
| ***Rottweil*** | **Rottweil** | **8.63** | **48.19** | **25018** |
| *Schwendi-Schoenebuerg* | Biberach | 9.94 | 48.16 | 25205 |
| *Sigmaringen* | Sigmaringen | 9.20 | 48.06 | 25035 |
| *Sinzheim-Leiberstung* | Rastatt | 8.10 | 48.75 | 25307 |
| *Weil Der Stadt* | Böblingen | 8.88 | 48.77 | 25300 |
| *Wiesloch* | Rhein-Neckar-Kreis | 8.68 | 49.30 | 25272 |

Table 21. Climate stations selected for determining heat wave years in Germany

| **Station Name/Location** | **Federal State** | **Longitude** | **Latitude** | **Station ID** |
|---|---|---|---|---|
| *Giessen* | Hesse | 8.67 | 50.58 | 2701 |
| *Hohenpeissenberg* | Bavaria | 11.02 | 47.80 | 2685 |
| *Karlsruhe* | Baden-Württemberg | 8.37 | 49.03 | 4099 |
| *Potsdam* | Brandenburg | 13.07 | 52.38 | 4100 |
| *Prague* | (Czech Republic) | 14.45 | 50.00 | 2751 |

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"The truth is, Pavlov's dog trained Pavlov to ring the bell just before the dog salivated"
George Carlin

PIK Report-Reference:

No. 1 3. Deutsche Klimatagung, Potsdam 11.-14. April 1994
Tagungsband der Vorträge und Poster (April 1994)

No. 2 Extremer Nordsommer '92
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H. Bugmann, A. Solomon (Mai 1995)

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H. Bugmann, Y. Xiaodong, M. T. Sykes, Ph. Martin, M. Lindner, P. V. Desanker, S. G. Cumming (Mai 1995)

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H. Bugmann, A. Fischlin (Mai 1995)

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D.-I. Müller-Wohlfeil, W. Lahmer, W. Cramer, V. Krysanova (Juli 1996)

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