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The vulnerability of winter wheat in Germany to air temperature, precipitation or compound extremes is shaped by soil-climate zones

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ABSTRACT

Whether hydroclimatic extremes cause yield losses or failures not only depends on their intensity but also on local environmental conditions. These conditions shape the capacity to buffer climatic shocks and thus necessitate a regionally specific impact assessment and adaptation planning. However, the degree to which different environmental conditions affect climate impacts on yields and its spatiotemporal variability across Germany is relatively unknown. In this study, we use a regression-based crop-climate modelling approach for 71 regions, classified according to soil and climate characteristics and investigate region-specific vulnerabilities of winter wheat yields to hydroclimatic extremes for the period 1991–2019. We account for the co-occurrence of temperature and moisture impacts (i.e. compound effects) as well as for local soil-climate conditions. On average, our models can explain approx. 67 % of past winter wheat yield variations. Despite the rather homogeneous climate in Germany, the results reveal clear geographic differences across different soil-climate regions. While the north-eastern regions show a clear dominance of drought impacts, southern regions show stress due to moisture excess. Heat impacts can clearly be linked to the warm regions along the western part of the country. Overall, compound dry-hot extremes pose the strongest and most widespread risk for winter wheat yields in Germany, being responsible for approx. 38 % and in some regions for up to 50 % of past yield variations. Based on the identified regional differences in hydroclimate susceptibility, we can define four geographic risk clusters, which exhibit vulnerability to climatic extremes such as summer droughts, winter droughts, summer heat waves, and winter moisture excess. The identified risk clusters of heat and moisture stresses could inform regional-specific adaptation planning.

1. Introduction

The summers of 2003 and 2018 are egregious examples during which very high temperatures and simultaneously low precipitation rates led to significant yield losses in Germany and Europe (Beillouin et al., 2020; Ciais et al., 2005; Webber et al., 2020). With increasing climate variability and an intensifying hydrological cycle, temperature and precipitation extremes already occur more frequently than in the past and are predicted to become even more frequent and intense in the future. Climate extremes may also occur more frequently as spatially and temporally compound events (Lesk et al., 2022). This rise in extremes will challenge future wheat production, necessitating the need for appropriate adaptation strategies to enhance the stability of winter wheat yields, one of Germany's major staple crops. Yet, adaptation measures have to be tailored not only to risks but also to regions, as local environmental characteristics like soil conditions, topography and local climate variability might influence the capacity of a region to buffer and react to climate extremes. While in years with pronounced temperature peaks, like 2003, during which most regions experienced substantial yield losses, some regions were still able to produce above-average wheat yields (Fig. 1, grey bars). Hence, regions are affected differently by weather events owing to their varying response to climatic stresses, due to locally specific environmental conditions or particular management strategies. As Bönecke et al. (2020) and Riedesel et al. (2024) point

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out, a particular focus should be laid on regional soil characteristics, as they influence the capacity to buffer adverse climatic effects.

While risks for winter wheat cultivation in Germany and beyond, along with adaptation options to climate change, have been discussed before (Schmitt et al., 2022; Webber et al., 2020), the influence of soil, regional climate conditions and crop phenology have rarely been disentangled. We therefore explicitly separate the impacts of individual from compound extremes and consider regional-specific environmental conditions in our study. We chose a regression-based statistical modelling approach and implicitly account for temperature and precipitation extremes, as well as compounding effects. In addition, we account for spatial variation of impacts. We base our analysis on soil-climate regions (hereafter referred to as *SCR*) of Germany as defined by Roßberg et al. (2007), accounting for heterogeneities in both climate and soil attributes. This is an important difference to most other statistical crop-climate impact assessments, which often base their analysis on administrative regions, such as districts or counties, which are defined largely independent of physical characteristics (Conradt et al., 2016; Gornott and Wechsung, 2016; Lüttger and Feike, 2018; Mirschel et al., 2014).

Therefore, the central objectives of this study are to (i) identify the main climatic drivers of winter wheat yield variations in Germany, dissected into soil-climate zones and seasonal components, (ii) study differences in their regional impacts, and (iii) quantify the relative contributions of single and compound effects to yield losses. Lastly, we discuss the methodology presented in this paper and evaluate its strengths and weaknesses.

2. Data and methods

2.1. Input data

Our regression-based crop-climate models are constructed based on district-level yield data (NUTS3 level), averaged over each soil-climate region (dependent variable) and agroclimatic indices, which present variables representing heat, drought and compound stresses for winter wheat cultivars (independent variables; Table 1). Yield data was obtained from German federal and regional offices for statistics. Further information and links to the data sets can be found in SI, Table S.1. The indices are derived from temperature, precipitation and solar radiation data sets (EOBS; Copernicus Climate Change Service, 2020) as well as from data on soil moisture deficit, plant transpiration (GLEAM-Hybrid; Koppa et al., 2022) and soil moisture contents (SALTO; Merz et al., 2020). We define our climatic indices based on soil-climate regions (SCR; Roßberg et al., 2007), extracting the mean daily climate, soil-water and plant-water data within each SCR. We then use the aggregated data to calculate regional agroclimatic indices. Yield data as well as climate and hydrological data are remapped to these regions. Remapping is done by calculating the mean of all districts/pixels, which fall within one SCR polygon. A district/pixel falls into a polygon, when it's centre lays within a specific soil-climate region boundary. We do not assign weights based on the proportion of the pixel, which falls into a polygon. All data sets cover the time period 1991–2019.

Table 1
Data sets used in this study.

Variable	Data set	Source	Description, temporal and spatial resolution
Yield	District-level yield	Federal and regional offices for statistics	Annual district-level winter wheat yield data (NUTS3 level)
Temperature, precipitation, solar radiation	EOBS	Copernicus Climate Change Service 2020	The data provides observation-based, gridded, historical climate data over Europe. In this study we use EOBS data at a spatial resolution of 0.25° x 0.25°, at daily temporal resolution.
Soil moisture deficit (SMD) and ET	GLEAM-Hybrid	Koppa et al. 2022; Martens et al., 2017	The data set provides ET and SMD data at a spatial resolution of 0.25° x 0.25° and at daily temporal resolution. GLEAM is a process-based land-atmosphere model, which dynamically simulates environmental state variables such as SMD and ET for historical periods.
Soil moisture	SALTO	Merz et al. 2020	The data set provides soil moisture data at a spatial resolution of 8 km x 8 km and at daily temporal resolution. Soil moisture is given as a relative unit [%], indicating the current soil moisture status compared to a maximum possible soil moisture content at field capacity. Soil moisture is dynamically simulated using the process-based hydrological SALTO model.
Soil-climate regions	SCR	Roßberg et al. 2007	Soil-climate regions are delineated based on soil quality characteristics (dt. 'Bodengüte") and dominating temperature and precipitation patterns.

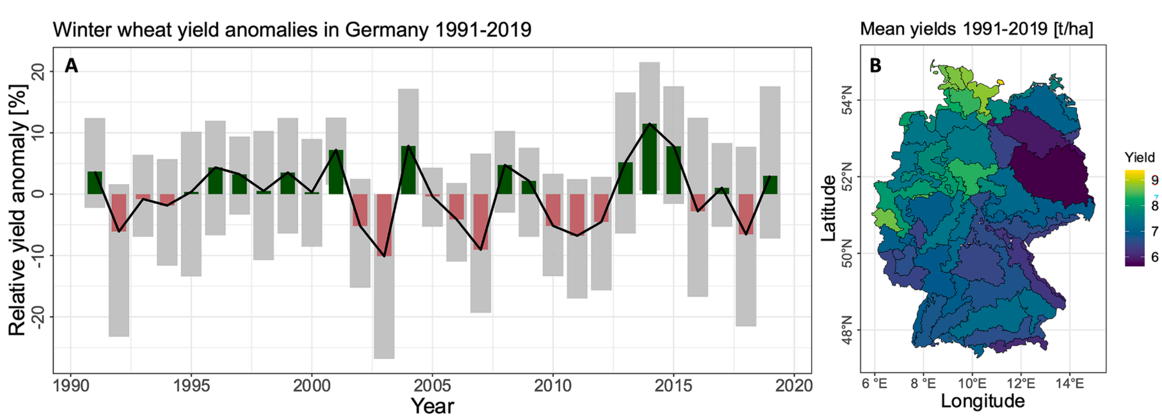

Fig. 1. Winter wheat yield anomalies in Germany between 1991 and 2019 (A) and regional differences in average yields (B). Grey bars in A encompass the 5th and 95th percentiles of winter wheat yield across all soil-climate regions. Relative anomalies are calculated based on detrended region-specific yield time series, subtracting a quadratic trend, and dividing the detrended time series by the trend-defined expected value for each year and each soil-climate region.

2.2. Definition of agroclimatic indices for heat, drought and compound stresses

To identify the main climatic drivers of winter wheat yield fluctuations in Germany, we define a set of agroclimatic indices which represent heat, moisture and compound heat-moisture stresses as well as growth factors for winter wheat. The selection is made based on commonly chosen indices in statistical crop-climate modelling studies (Bönecke et al., 2020; Laudien et al., 2020; Lobell et al., 2011; Romanovska et al., 2023) and on a commentary on the importance of compound effects by (Lesk et al., 2022). The indices chosen for this study are listed in Table 2 and their respective relevance for winter wheat growth are outlined in the SI, Section 4. Here we also outline, why we chose to use soil moisture deficit (SMD) as well as soil moisture, even though they are linked and might exhibit a similar stress for crop growth.

All indices are calculated based on daily data using the data sets listed in Table 1, which we remap to match the spatial extend of the soil-climate regions (SCR). Subsequently, we calculate each indicator at the spatial resolution of SCRs. Each of the indicators is calculated twice: once for the vegetative season (with a suffix of "_v" to the name) and once for the reproductive season (suffix "_r"). Details of single indices and their units can be found in the SI, Section 4.

2.3. Data pre-processing and variable selection procedure

All agroclimatic indices are calculated separately for the vegetative and the reproductive phases of the growing cycle and separately for each soil-climate region. For winter wheat in Germany, we define the vegetative phase as the period from sowing (October) to heading (March) and the reproductive phase from end of heading (April) to maturity/harvest (July), which aligns with the mean observed phenological periods in Germany (DWD Climate Data Center, 2021). The vegetative phase covers the sub-phases of germination (BBCH 0–9), emergence and leaf development (BBCH 10–19), tillering (BBCH 20–29), stem elongation (BBCH 30–39) and booting (BBCH 40–49). The reproductive phase covers the sub-phases of heading (BBCH 50–59), flowering (BBCH 60–69), milk ripening (BBCH 71–89), and senescence (BBCH 90–99) until harvest (see also Bönecke et al., 2020).

All indices are standardized subtracting their mean and dividing by their standard deviation, to allow for comparing and jointly interpreting individual agroclimatic impacts on winter wheat yields using variable coefficients. Soil-climate region specific yield time series are detrended to remove management-dependent long-term trends (SI Fig. S.2 and section 5). In addition, they are log-transformed to ensure a Gaussian normal distribution of our dependent variable. Subsequently, we apply a two-step variable selection, starting with pre-selecting the most influential compound variables to reach an equal number of compound and single variables for the second step, as otherwise the much larger number of compounds would skew the selection procedure. We limit the selection to the group size of heat and moisture variable groups, comprising 18 variables. Next, the pre-selected multiplicative interaction terms are merged with the explicitly calculated compound variables VPD and ETact, as well as with the single heat and moisture variables to total of maximum 58 variables and the selection is re-run. For both selection steps we use LASSO regression, separately for each soil-climate region, defining the most influential variables as those with the highest R^2 contribution. Variables are pruned before the regression by (i) removing variables with zero variances and (ii) removing collinear variables (correlation coefficient $r > 0.7$). We allow at most seven variables per model, showing the highest correlation with yield variations, to avoid model-overfitting. Our approach thus closely follows Laudien et al. (2020), but adds the separate filter step for compounds.

2.4. Model setup

To quantify the impacts of heat and drought stresses on winter wheat yields in Germany in a spatially discrete manner, we use a separately estimated time series model for each region (STSM: Gornott and Wechsung, 2016), which can account for site-specific climatic impacts. Compound stress variables (c) are included as explicitly calculated aggregate variables (ET_{act} and VPD) or as multiplicative interaction terms between moisture and temperature variables (Table 1).

The multiple regression model is given by the function:

$$\log(yield_{it}) = \log\beta_{i0}\sum_{j=1}^{J}\beta_{ij}\log w_{ijt} + \sum_{k=1}^{K}\beta_{ik}\log h_{ikt} + \sum_{l=1}^{L}\beta_{il}\log c_{ilt} + \log u_{it} \quad (1)$$

$yield$ = yield time series as trend anomaly;
i = spatial subunit (here: soil – climate regions);
t = time step in years;
β_0 = intercept;
β = coefficient of independent variables w, h, and c;
j = number of all selected moisture stress related climate variables for model i;
k = number of all selected heat stress related climate variables for model i;
l = number of all selected combined moisture and heat stress climate variables for model i;
w = water stress variable (climatic indicator);
h = heat stress variable (climatic indicator);
c = compound stress variable (climatic indicator);
u = error term

2.5. Model validation

Based on the approach of Laudien et al. (2020) and Romanovska et al. (2023), we conduct a commonly used leave-one-out cross validation (LOOCV – level 1) and a more stringent LOOCV– level 2 validation (SI, section 6). The evaluation of the model performances is based on the coefficient of determination (R^2) between simulated and observed absolute yields, for single SCRs as well as for entire Germany. To assess the explanatory power of each predictor variable, we calculate separate explained variances for each selected predictor, dividing the individual sum of squared residuals of a single independent variable by the total sum of squared residuals of all independent variables.

To obtain the annual share of explained yield variation by temperature, moisture and compounding stresses, we weigh the normalized indicators by their respective share of explained variation and get an annual index of temperature, moisture and compound impacts as follows:

Table 2
Agroclimatic indices.

Agroclimatic Index	Long name and definition
Temperature	
Tmax	Median of maximum daily temperatures
Tmin	Median of minimum daily temperatures
GDD	Growing Degree Days – sum of days with optimal growing conditions
EDD_I27	Intensity of hot days – sum of Extreme Degree Days with Tmax > 27 °C
EDD_F27	Frequency of hot days – number of Extreme Degree Days with Tmax > 27 °C
EDD_D27	Duration of hot days – maximum consecutive Extreme Degree Days with Tmax > 27 °C
EDD_I31	Intensity of very hot days – sum of Extreme Degree Days with Tmax > 31 °C
EDD_F31	Frequency of very hot days – number of days with Tmax > 31 °C
EDD_D31	Duration of very hot days – maximum consecutive Extreme Degree with Tmax > 31 °C
Moisture	
PrecipI_sum	Intensity of precipitation – sum of precipitation
PrecipF_b01	Frequency of dry periods – number of days with precipitation < 0.1 mm
PrecipD_b01	Duration of dry periods – maximum consecutive days with precipitation < 0.1 mm
SmdI_sum	Intensity of soil moisture deficit (SMD) – sum of daily SMD [min. stress = 1, max. stress = 0]
SmdF_b1	Frequency of soil moisture deficit – number of days with SMD < 1
SmdD_b1	Duration of soil moisture deficit – maximum consecutive days with SMD < 1
SmI_sum	Intensity of soil moisture availability – sum of soil moisture
SmF_b06	Frequency of low soil moisture contents – number of days with soil moisture < 60 % at field capacity
SmD_b06	Duration of low soil moisture contents – maximum consecutive days with soil moisture < 60 %
Compound	
ETact	Actual plant evapotranspiration – sum of ETact (crop-physiological interaction)
VPD	Vapor pressure deficit – mean of VPD (heat-moisture interaction)
[Moisture]*[Temperature]	Moisture variable*temperature variable (crop-atmosphere interaction); this comprises 324 variables in total (18 temperature * 18 moisture variables)

$$Index_{x_t} = \sum_{i=1}^{I} \sum_{x=1}^{X} V\_norm_{xti} * \frac{Explained\ variance_{xi}}{Total\ explained\ variance_i} \tag{2}$$

$$\begin{aligned} &with: \\ &x = moisture,\ temperature\ or\ compound\ variable; \\ &t = time\ (year); \\ &i = soil - climate\ region; \\ &V_{norm} = normalized\ variable \end{aligned}$$

2.6. Definition of climate risk clusters

A climate risk cluster is defined as a region which reacts particularly sensitive to a specific category of climatic stresses (i.e. temperature, moisture or compound category). For example, in the case of particularly dry conditions in summer, indicated by high importance of moisture related agroclimatic indices during the reproductive phase, a region would be classified as “too dry in summer”. To identify a risk cluster, we select the most important variables for each SCR (explained variance multiplied by the selection frequency of the respective variable; SI section 7) and examine whether they show a clear dominance of a particular variable group (i.e. moisture, heat, or compound group), hinting towards the prevalence of a specific risk factor for yields (e.g. risk of summer droughts). A region is defined as part of a risk cluster if the total explained variance of all variables which contribute to the risk factor is greater than 10 % (for 5 %- and 20 %-thresholds see SI, Fig. S.4).

Table 3
Average model performances of all 71 soil-climate region models.

Performance criteria	Training (in-sample)	Validation LOOCV-1 (out-of-sample)	Validation LOOCV-2 (out-of-sample)
Mean R^2 (single soil-climate regions)	0.67	0.44	0.29
Mean R^2 (entire Germany)	0.81	0.70	0.55

3. Results and discussions

3.1. Model performances

Average total simulated wheat yields for Germany of the full (in-sample) model show a good fit with observed yield fluctuations (R^2 = 0.81; Fig. S.3). Similarly, the two cross-validation levels (LOOCV-1 and LOOCV-2) present clear correlations with R^2-values of 0.70 and 0.55 respectively (Table 3). The fact that model performances between all three simulations do not strongly vary hints towards a robust variable selection, which is independent of the different selection methods applied for LOOCV-1 and LOOCV-2. Model overfitting can therefore be ruled out, underlining that substantial parts of yield variance can be explained by climate fluctuations.

3.2. Impact of heat, moisture and compound impacts on winter wheat yields

Our results show that temperature, moisture and compound effects significantly impact winter wheat yields in Germany. On average, approx. 67 % of yield variability can be explained by climatic impacts in each SCR (Table 3). At the same time, our results show that region-specific soil-climate conditions matter strongly in defining the strength and the cause of yield losses. Disentangling the impacts of moisture, heat, and compound heat-moisture impacts reveals that the individual regions are differently responsive (Fig. 2).

3.2.1. Yield losses explained by moisture impacts

Moisture impacts were found to affect yield variations particularly in the warm and dry north-east and central-north of the country, but also in the wetter southern regions, such as in the Black Forest and in the regions of the Danube and Inn river valleys (Fig. 2A; a map with the geographic regions highlighted in this publication can be found in Fig. S1, in the supplementary material). On average, approx. 16 % of yield fluctuations can be ascribed to moisture impacts alone, which highlights the importance of optimal moisture condition for stable winter wheat yields. Similarly, the interannual variations of moisture anomalies (Fig. 2D) reveal the importance of moisture impacts on yields in Germany and show that years with high yield losses (1992, 2003, and 2018) show a particularly high contribution of moisture stress. Year 2007, which likewise shows high yield losses, experienced on average low moisture stress (very dry April but wet remaining reproductive season), indicating that yield losses in this year have to be attributed to climatic stresses which cannot be captured by the selected indicators or to non-climatic impacts, e.g. plant viruses such as the yellow dwarf virus which severely affected the 2007-yields (Bayrische Landesanstalt für Landwirtschaft, n.d.). The most important moisture stress variables are soil moisture deficit during the spring and summer seasons (*SmdI_sum_r*), long dry spells during winter (*PrecipD_b01_v*) and long dry spells during spring and summer (*PrecipD_b01_r;* Fig. 3).

Our regional assessment shows, that soil moisture deficits during the reproductive season (*SmdI_sum_r*), was found to be the strongest cause for yield failures in central-north and north-east Germany, explaining on average 16 % of past yield variations (Fig. S.4A). In single soil-climate regions, such as the inland areas of the north-eastern lowlands, this

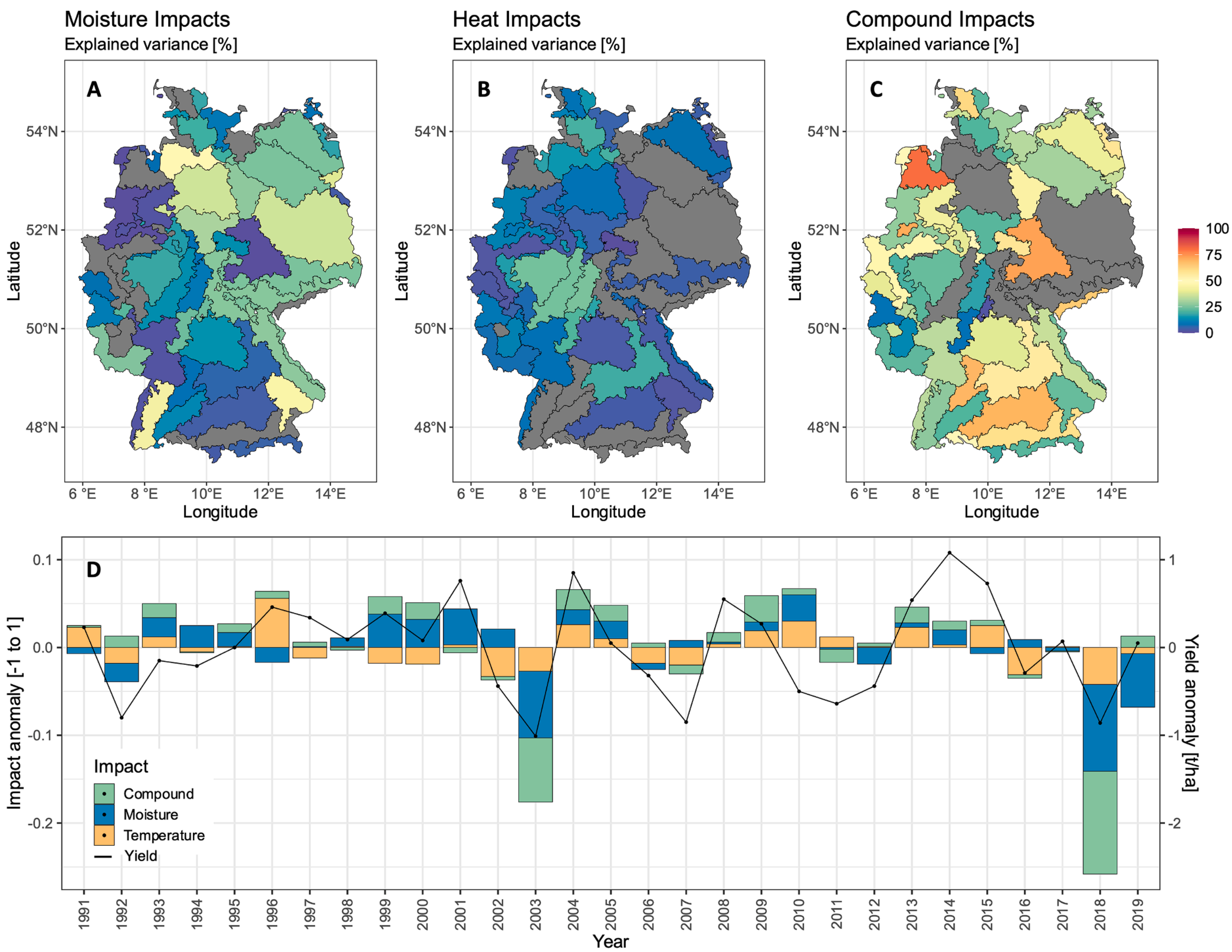

Fig. 2. Regional specific impacts of moisture (A), heat (B) and compound effects (C) and the average annual share of each impact group (i.e. moisture, heat or compound effects; left y axis) on winter wheat yields (right y axis) between 1991 and 2019 (D). Positive impact anomalies describe below average stresses, and negative anomalies describe above average stress. Grey regions in A, B and C represent regions where no moisture (A), heat (B), or compound impact (C) are found.

variable explains up to 47 % of yield variations. The north-eastern regions present drought-prone areas of sandy and diluvial soils with low water holding capacities (Kahlenborn et al., 2021; Roßberg et al., 2007) and cover areas of lowest winter wheat yield potential (Fig. 1). Our results underline their high vulnerability towards climatic impacts and their low potential to buffer adverse effects of dry periods during spring and summer months.

The north-west of the country is comparably less affected by soil moisture deficits, but also shows a clear negative impact of summer droughts on yield. Here, prolonged durations of dry spring and summer periods (*PrecipD_b01_r*) can explain on average 7 % of yield variations (Fig. S.4F). Similar to the regional distribution of plant water deficit impacts, the highest impacts can be found in regions with sandy soils (e. g. sandy north-western lowlands).

Our results align with findings of Schmitt et al. (2022), who found that summer droughts are the main driver of wheat yield failures in Germany. This is due to winter wheat production in Germany being nearly entirely rain-fed and hence highly dependent on precipitation as its only moisture source (Webber et al., 2018). The importance of moisture availability during the reproductive (spring/summer) season can be explained by the need for optimal moisture conditions particularly during the months around anthesis. A lack of moisture availability during this critical phenological phase can drastically reduce the plant's photosynthetic activity and negatively influence yields (Reynolds et al., 2022).

In the central part of the country, yields are found to react more sensitive to long durations of dry periods during the winter season (*PrecipD_b01_v*; Fig. S.4C). In some regions up to 29 % of yield variation can be explained by this predictor alone. These are primarily regions, characterized by fertile loess soils with high water holding capacities and favourable conditions for farming (Roßberg et al., 2007). Sufficiently wet winter periods seem crucial for filling soil moisture storages in these regions, from which the winter crop can benefit during dry spring and summer months.

A low frequency of dry spells between October to March (*PrecipF_b01_v*) is found to be the main cause for wheat yield failures in the south of Germany (Fig. 4C), explaining on average 10 % and in some regions up to 29 % of yield variability (Fig. S.5I). Recurring wet spells during the vegetative period in these regions, particularly during the sowing phase, have delayed sowing in the past (Webber et al., 2020), which increases the risk of frost damages during the early growth stage and therefore the risk for yield failures. Based on these results, we can distinguish three moisture risk clusters, which show the need to adapt winter wheat cultivation to i. spring and summer droughts (Fig. 4A); ii. winter drought (Fig. 4B), and iii. periods of moisture excess during winter (Fig. 4C).

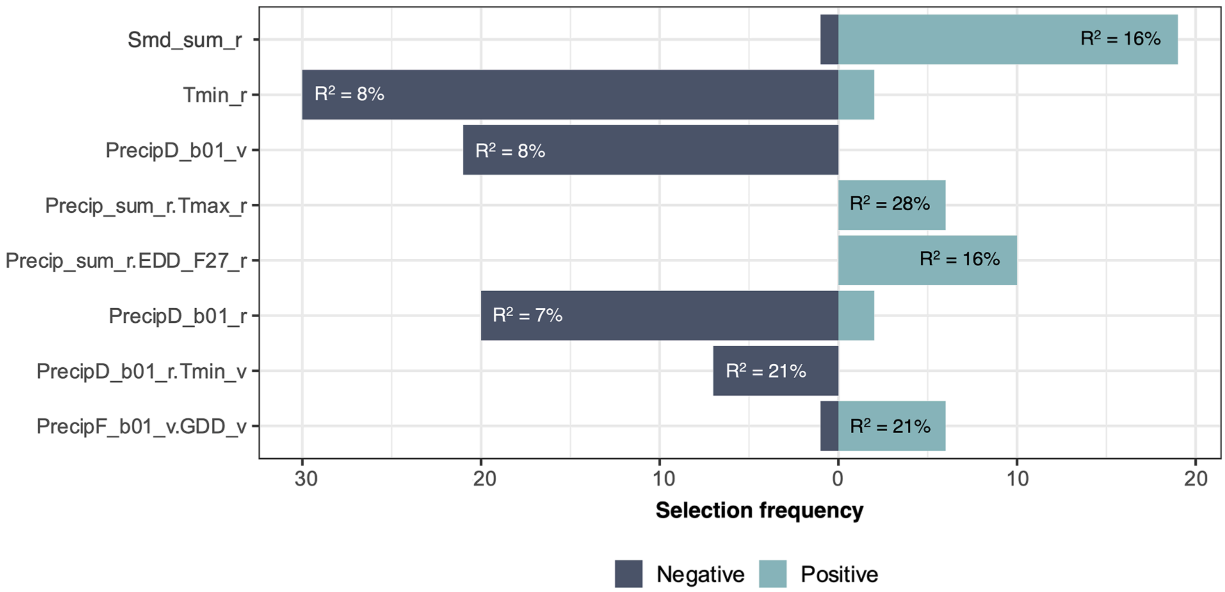

Fig. 3. Selection frequency, importance (R^2) and impact on yield (negative/positive) of the eight most important predictor variables. The weighted importance (= selection frequency*R^2) is ranked from top to bottom. There are three levels of information: first, the direction indicates if the respective variable shows a negative (dark blue) or positive (light blue) correlation with yield. Second, the extent on the X-axis represents the frequency by which the variables were selected (possible maximum = 71; total number of models). Third, the R^2 values in each box indicate the average explained variance of each variable. See Fig. S.5 for full list.

3.2.2. *Yield losses explained by heat impacts*

Heat related effects show stronger explanatory power in models in the west of Germany, particularly along the heat-prone Rhine River valley, in the low mountain ranges in the central-west and in the lowland areas in the north-west of Germany (Fig. 2B). On average, heat impacts explain 9 % of yield variations. In the north-east of the country, they show limited impacts on yield level fluctuations. Notably, the main temperature-related impact affecting wheat yields independently of co-occurring moisture deficits is the minimum temperature during the reproductive season (*Tmin_r*); this is the second most selected predictor variable (Fig. 3). High minimum temperatures can explain on average 8 %, and in single regions up to 25 % of yield variations. The negative impact of high minimum temperatures (i.e. night-time temperatures) has been identified by a series of studies as an important factor for causing yield failures (García et al., 2015, 2016; Hein et al., 2019; Sadok and Jagadish, 2020). High night-time temperatures, particularly during the seed-filling period, as captured by our *Tmin_r* variable, could clearly be linked to declines in winter wheat crops (Hein et al., 2019). The main physiological cause behind these yield losses is an insufficient carbon supply for plant and seed growth due to enhanced night-time respiration and possibly a faster leave senescence (Sadok and Jagadish, 2020). Considering that global night-time temperatures are rising faster than day-time temperatures (Sillmann et al., 2013) this phenomenon, which already shows a measurable impact, might pose an increasing risk for winter wheat yields in Germany. However, heat impacts vary significantly from region to region, as well as from year to year (Fig. 2D), which underlines the importance of region-specific adaptation strategies. Based on our results we define one heat risk cluster, which covers primarily the regions in the centre and west of the country, encompassing favourable arable lands of the central agricultural regions and central low mountain ranges (Fig. 4D).

3.2.3. *Yield losses explained by compound impacts*

Our results reveal that compounding effects pose the strongest risk for winter wheat yields, explaining on average approx. 38 % and in some regions up to 50 % of past yield variations. The results are consistent with recent findings of compound effects posing a particular risk for crop yields (Heino et al., 2023; Lesk et al., 2022). Even though overall large knowledge gaps still exist regarding the interplay of heat and water stress and its effect on plant growth (Siebert, Webber, and Rezaei, 2017, 2017; Zampieri et al., 2018), recent studies suggest that co-occurring heat and drought events results in synergistic effects and have a stronger negative impact than single stressors alone (Rezaei et al., 2023). For Germany, this is particularly evident with regard to heat stress. As outlined above, high day-time temperatures alone rarely cause significant yield losses. But the co-occurrence of high day-time temperatures and low precipitation rates during the reproductive phase (*Precip_sum_r*Tmax_r* and *Precip_sum_r*EDD_I27_r*) are amongst the most decisive factors controlling wheat yields (Fig. 3). The impacts of compound effects on the plant physiology are complex. A common effect is stomata closure as a response to a lack in moisture availability, entailing less transpiration and thus a reduced cooling of plant tissue. This eventually increases leaf temperatures, particularly when ambient heat prevails, which can cause significant damage to the crop (Abdelhakim et al., 2021).

The interannual variation of compound effects between 1991 and 2019 (Fig. 2D) shows that co-occurring heat and moisture stresses vary significantly between years. Our results furthermore reveal that in those regions which show pronounced vulnerability towards compound effects, single heat and moisture stress effects are negligible or non-existent (Figs. 2A–C and S.3). Unlike the separate moisture and temperature impacts, single compound impacts cannot clearly be attributed to specific soil-climate regions. This might be due to their complex combinations, which lead to the selection of highly specific predictor variables for each region. Areas which are strongly affected by co-occurring heat and moisture stresses are the Alpine foothills and adjacent northern areas, as well as productive agricultural lands in loess regions in the south-west and centre-east of Germany (Fig 2C). Based on our results, we cannot detect a clear risk cluster for compounding impacts, but Fig. 4E highlights that their impacts have to be considered in vast parts of the country.

3.3. *Strengths and weaknesses of the proposed methodology to assess climate impacts on winter wheat yields*

Our approach of using a spatially distributed linear regression model shows promising results in identifying main climatic drivers of winter wheat yield variations and in ascribing these drivers to soil-climate

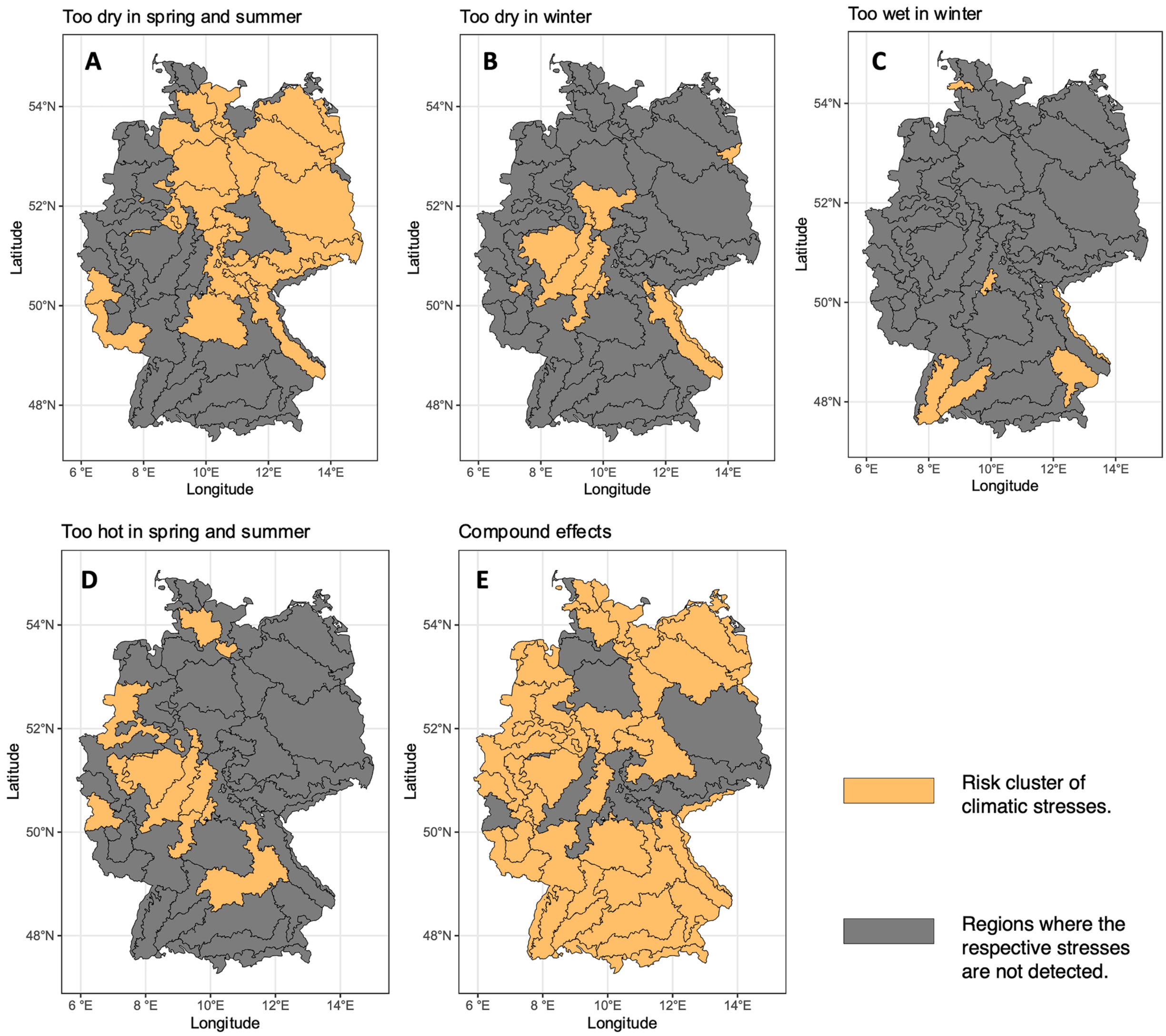

Fig. 4. Risk cluster of a particular climatic stress showing regions of drought risks in summer (A), regions of drought risks in winter (B), regions of water excess in winter (C), regions of heat risks in summer (D), and regions where compound effects impact wheat yields (E).

regions as well as to seasonal components. We explicitly account for compounding effects, which are often missing in statistical crop-climate models and only recently have been integrated (Bönecke et al., 2020). Our results show that compound impacts are the dominating stress factors which control yield levels and should consequently be integrated in climate impact studies. We present a first step towards an interpretable modelling framework which allows for the inclusion of spatially and seasonally differentiated compounding effects.

The approach furthermore allows for a separation of heat, moisture and compound stresses on winter wheat at SCR level. This could be of interest for the selection of stress- and region-dependent adaptation strategies. Grouping multiple impacts of one stress-category into larger risk clusters (Fig. 4) can give further information on region- and season-specific adaptation requirements. Each risk cluster demands a different set of adaptation measures to optimally cope with the region-specific adverse climatic impacts on yields. In addition, the approach enables us to quantify the relative contributions of single and compound effects to yield losses and assess their interannual differences (Fig. 2). This can be of importance when planning and prioritizing adaptation strategies for the most frequent and most important drivers of yield losses.

However, despite these strengths, our simple mathematical formulation (e.g. multiplicative compounds and linear unidirectional relationships between seasonal yield and seasonal climatic impacts) has limitations. Due to its mathematical form as well as the coarse split of the growing season into only two phenological phases, our approach may fall short of the physiological realities of weather impacts, which may be non-linear, bidirectional, seasonally divergent and temporally staggered. An alternative approach to address these limitations could be, for example, the application of machine learning based approaches with a temporal resolution based on most important phenological phases. Another point to consider is that the nature of our regression-based approach may gloss over minor climatic impacts when there is a clearly dominating impact on yield dynamics. For example, the sandy regions in the north-east of the country stand out as regions where summer dryness affects wheat yield the strongest (Fig. 4A). This does not mean that other stresses (e.g. winter dryness) are absent in this region. Compared to the dominating effect they are however statistically less important and are therefore 'neglected'. Comparing the results with those from process-based crop models (e.g. Nendel et al., 2023; Webber et al., 2020) with a finer temporal stress-disaggregation, could further assist in increasing the robustness of the results. A finer separation of phenological phases, as done by Bönecke et al. (2020) and Riedesel et al. (2024), would help to better identify critical phenological phases, which are particularly sensitive to adverse climate impacts. Considering only the vegetative and the reproductive season, as done in this study, does not resolve impacts at important phenological steps, e.g. temperature stress around anthesis. However, spatially distributed data availability of temporal and spatial highly variable starting and ending dates of single phases is limited. Model stability is another trade-off factor, as more seasonal indices along with their interactions increase the number of explanatory variables.

4. Conclusion

In this study, we were able to detect the main climatic drivers of winter wheat yield anomalies in Germany based on a spatially distributed multiple regression model approach which accounts for regionally distinct soil-climate characteristics. The integration of compound impacts, as multiplicative interaction terms, allowed us to consider co-occurring effects of heat and moisture extremes. Our results highlight that these compounding effects are the dominating factor for causing yield losses and are hence crucial to consider in modelling frameworks which analyse climate impacts on yields. We could show that our approach offers a consistent framework to assess multiple stressors and their numerous interactions, which does not rely on extensive field and laboratory data collection. The assessment presented here can be done using publicly available data sets only. This could be of particular interest in regions where farm-level data is unavailable and a nationalwide analysis is desired which accounts for difference in regional soil-climate conditions.

Finally, using our modelling framework, we were able to identify stress-specific risk clusters of adverse climate impacts for winter wheat in Germany. Bearing in mind that adaptation measures depend primarily on a farm-specific cost-benefit analyses, skills, technology and local environmental and economic conditions, such region-specific results can be an inception for basing adaptation incentives on region- and season specific risks.

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CRediT authorship contribution statement

Rike Becker: Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Bernhard Schauberger:** Writing – review & editing, Supervision, Methodology. **Ralf Merz:** Writing – review & editing, Methodology. **Stephan Schulz:** Writing – review & editing, Methodology. **Christoph Gornott:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no conflict of interest.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.agrformet.2024.110322.

Data availability

I have shared the link to my data and further data can be made available on request.

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