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Climate change impacts on long-term field experiments in Germany

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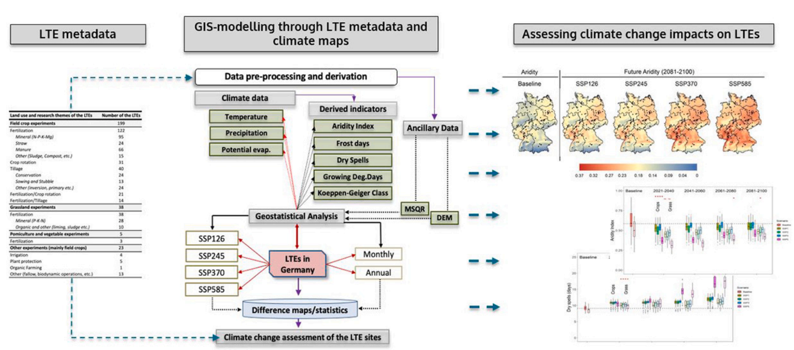
HIGHLIGHTS

- The effects of climate change on Long-Term Field Experiments (LTE) sites were assessed using Germany as a case study.
- 150 LTEs were estimated to shift from humid and dry sub-humid to semi-arid conditions.
- Frost days in LTE areas are expected to decline by 81%, and the growing season to lengthen by up to 92%.
- No considerable correlation between soil quality and agroclimatic indicators were found on the LTE sites.

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: Long-Term Field Experiments (LTEs) were implemented to study the long-term effects of different management practices, including tillage, fertilization and crop rotation under otherwise constant conditions. Climate change is expected to change these conditions, challenging interpretation of LTE data with regard to the distinction between climate change and management effects.
OBJECTIVE: The objective of the study was to quantify the expected, spatially differentiated changes of agro-climatic conditions for the German LTE sites as a precondition for modelling and LTE data interpretation.
METHODS: We developed a framework combining spatially distributed climate data and LTE metadata to identify the possible climatic changes at 247 LTE sites with experiments running for 20 years or more. The LTEs were classified using the following categories: fertilization, tillage, crop rotation, field crops or grassland, conventional or organic. We utilized climate variables (temperature, precipitation) and agroclimatic indicators (aridity, growing degree days, etc.) to compare a baseline (1971–2000) with future periods (2021−2100) under the IPCC's Shared Socio-economic Pathways (SSP). A comprehensive LTE risk assessment was conducted, based on changes in climate variables and agroclimatic indicators between baseline and future scenarios.
RESULTS AND CONCLUSIONS: Under the most extreme scenario (SSP585), 150 LTEs are expected to shift from humid and dry sub-humid to semi-arid conditions. Frost days in LTE areas are expected to decline by 81%, and

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the growing season to lengthen by up to 92%. The spatial differentiation of expected climate change also facilitates the identification of suitable sites for future agricultural practices and may inform the design of new LTEs.

SIGNIFICANCE: Our results may guide the interpretation of LTE data regarding the effect of climate change, facilitating future soil crop modelling studies with LTE data and providing information for planning new LTE sites to support future agricultural research and/or adapting management on existing LTE sites. The framework we developed can easily be transferred to LTE sites in agricultural regions worldwide to support LTE research on climate change impacts and adaptation.

1. Introduction

Long-Term Field Experiments (LTEs) are agricultural research experiments for monitoring yields, soil and crop properties under different management practices and otherwise constant conditions (ceteris paribus conditions). They are defined as having a minimum duration of 20 years (Grosse and Hierold, 2019). LTEs have been set up on various soil types and climatic conditions, and some of them have existed for 100 years or longer.

Since agricultural productivity depends on climatic variables, projected climate change will change the ceteris-paribus conditions LTEs are based on. Rising temperature changes in precipitation frequency and intensity, and rising atmospheric CO_2 concentrations significantly affect crop growth in the European region. In addition to temperature increases, prolonged droughts could exacerbate water shortages and crop yield failures, depending on the respective crops' growth thresholds. Moreover, increasing extremes, including dry and wet spells or heat stress, may decrease crop production (Mechler et al., 2009). This is also true for Germany, where climate change is expected to have long-term impacts on agriculture with intense heat and cold waves, flooding, and limited water availability (Brasseur et al., 2017). Soil organic carbon (SOC) content is expected to decrease because of rising temperature, lower soil moisture content in wet sites which accelerates SOC decomposition in wet sites, and increasing vegetation period lengths. This challenges climate change mitigation efforts, adds green house gas emissions and decreases soil health (Wiesmeier et al., 2016; Riggers et al., 2021). These potential effects on agriculture and the carbon balance are highly relevant, considering that about half of the German land area is used for farming (EEA, 2019). For the agricultural sector, adapting management practices to climate change is an essential task to maintain crop productivity.

For conveiving and modelling spatially differentiated yields and soil-crop interactions under different natural and management conditions, LTEs provide an essential infrastructure that enables the assessment of long-term climate change effects on agricultural variables, including crop productivity, carbon fluxes, or soil-water balances. Understanding the amount of change in ceteris-paribus conditions in these experiments is critical for distinguishing between management practices and climate change effects. Many studies have analyzed the vulnerability of agricultural production to climate change (Collins et al., 2013; Khan et al., 2016), focussing on the impacts on crops or crop rotations (Pirttioja et al., 2015; Dixit et al., 2018; Saddique et al., 2020). For instance, these studies have highlighted how increasing temperatures and changes in moisture may cause yield losses of up to 40% in many crops (i.e., maize, wheat, soybean). Results by Addy et al. (2022) confirm that incresing temperatures and overall drier years during the twenty-first century will reduce fodder grass yields in autumn, winter and spring. These studies have also highlighted the importance of field observations in projecting the future climate. Notably, long time series of data are needed to assess the effect of climate change on agricultural production, to calibrate model predictions and to verify their results, ideally with constant agricultural management. Addressing the importance of the field experiments for studying climate and agricultural interactions, Körschens (1997; 1994) implemented a detailed compilation of LTEs with over 20 years of duration, including various research themes, meteorological and soil data. Grosse et al. (2020a) conducted a descriptive analysis of the geospatial distribution of the LTEs in Germany concerning climatic water balance and soil fertility factors. The impact of climate change on agriculture can be conceptualised by combining field observations and the agro-climatic components (i.e. drought, frost days, growing season) (Mechler et al., 2009). Accordingly, awareness of the potential of LTEs for climate change research is increasing. To our knowledge, no studies have yet addressed the effects of climate change at LTE locations considering geospatial variability.

For future based estimations, Representative Concentration Pathways (RCPs) based on the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) have commonly been integrated for agricultural and environmental modelling and spatial analysis (Donmez et al., 2016; Vos et al., 2016). Although the RCPs have provided common reference points for climate science research in the last decade, there was a demand for also including the societal challenges by catalysing the mitigation and adaptation processes. Over the RCP scenarios, new pathways known as the Shared Socioeconomic Pathways (SSPs) have been built as essential inputs for climate change research, feeding into the IPCC sixth assessment report published in 2021. The new SSPs offer four main pathways, SSP126, SSP245, SSP370, and SSP585, based on the effects of assumed societal actions on greenhouse gasses emissions. Since the SSP scenarios have been developed only recently, their translation into agricultural scenarios, such as the work by Mitter et al. (2020), and their integration into agricultural-based studies is still ongoing.

Using Germany as a test case, we aim to fill the current research gap by providing information on the possible future implications of climate change on LTEs. The objective of the study was to quantify the expected, spatially differentiated changes of agroclimatic conditions for the German LTE sites as a precondition for modelling and LTE data interpretation. We compared a baseline (1971–2000) with future SSP scenarios up to 2100 by spatially analysing agroclimatic indicators (aridity index, frost days, growing degree days in growing season length etc.) for all LTE sites. Our study not only projects climatic changes at the regional level but also geospatially represents the potential climate change impacts on the LTEs by combining agroclimatic factors and SSP scenarios with soil variations in a comprehensive GIS framework. We focus on how the projected changes will affect LTEs across various locations, soil quality classes and research themes and their experimental settings at the national level. This facilitates the interpretation of LTE data for future projections of soil properties and crop growth. It also helps to adapt LTE experiments to changed climatic settings and/or for planning new LTEs which in turn, facilitates the contribution of LTEs to a more adaptive, resilient and productive agriculture.

2. Study area and data

2.1. Study area

The study was conducted at the LTEs located in Germany (Fig. 1). The agricultural sector in Germany is one of the largest producers in the European Union, and half of the land area in Germany is used for agriculture (approx. 165,950 km^2) (Asseng et al., 2019; BMEL, 2021). Agricultural production is at a high technology level, and the average yield gap is low (van Grinsven et al., 2015). Farmlands are mainly used as arable lands (70%) for food and bioenergy production, grasslands (28%) for livestock feeding purposes and perennial crops (2%) such as orchards (DESTATIS, 2021).

In accordance with the importance of the German agricultural sector, there are 247 LTE for long-time studies of fertilization, tillage, crop choices and crop rotations. The records of these experiments are collected and managed by multiple research initiatives, and a metadata overview has recently been compiled as part of the BonaRes research project. It is a funding initiative of the German Federal Ministry of Education and Research (BMBF) with the ultimate goal of improving the productivity function of soils while maintaining or even improving the other soil functions (www.bonares.de).

2.2. LTE overview in Germany

We used the collection of 247 LTEs across Germany with a minimum of 20 years of duration derived by Grosse et al. (2020b) and Donmez et al. (2022). The LTEs can be classified according to their land use and experimental setting. The land use classes were field crops, grassland and pomiculture, and the main experimental settings addressed fertilization, tillage, and crop rotations, as well as combinations thereof. The number of the LTEs categorized by the land use and experimental settings is provided in Table 1.

The majority of the LTEs are field crop experiments. 38 experiments

Table 1
Land use and research themes of the LTEs (multiple assignments exist).

Land use and research themes of the LTEs	Number of the LTEs
Field crop experiments	199
Fertilization	122
Mineral (N-P-K-Mg)	95
Straw	24
Manure	66
Other (Sludge, Compost, etc.)	15
Crop rotation	31
Tillage	40
Conservation	24
Sowing and Stubble	13
Other (inversion, primary etc.)	24
Fertilization/Crop rotation	21
Fertilization/Tillage	14
Grassland experiments	38
Fertilization	38
Mineral (P-K-N)	28
Organic and other (liming, sludge etc.)	10
Pomiculture and vegetable experiments	5
Fertilization	3
Other experiments (mainly field crops)	23
Irrigation	4
Plant protection	5
Organic Farming	1
Other (fallow, biodynamic operations, etc.)	13

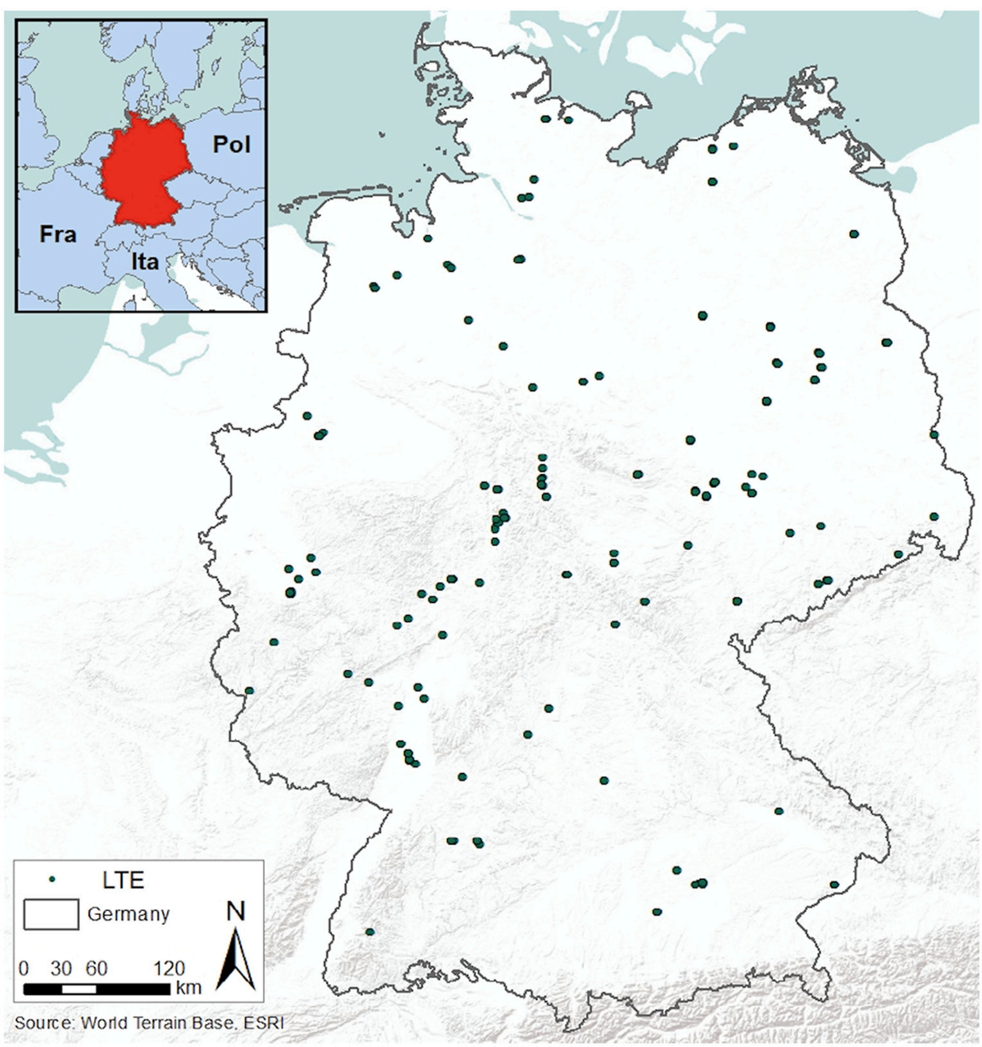

Fig. 1. Distribution of the studied LTEs in Germany (Source: (BonaRes Repository, 2021), LTE overview map: https://lte.bonares.de.

are on grassland, and five investigate pomiculture and vegetables. The status of the LTEs (ongoing or terminated) was not considered in our analysis, and the locations of all LTEs were taken into account. This is because the existence of an LTE indicates the presence of critical research infrastructure close to the respective site that may allow its reactivation to initiate new LTE experiments. Some LTEs were assigned to multiple experimental settings, mainly combinations of fertilization experiments with tillage or crop rotation experiments. Our assignments are consistent with Grosse et al. (2020a) and Berti et al. (2016). Effects of mineral fertilization (N, P, K) are addressed in 95 field crop experiments and 28 grasslands experiments where liming and sludge were classified into the other classes. 15 of the field crop LTEs assessing effects of fertilization were grouped in the mixed category, including, e.g., sludge and compost treatments. The LTE sizes ranged between 0.03 and 672 ha (on average 25.91 ha).

The majority of the LTEs included in the study were run by state authorities, universities and research institutions. Most of these LTEs have also been mentioned in numerous studies (Körschens, 1994; Körschens, 1997; Körschens, 2000; Debreczeni and Körschens, 2010). Further detailed information on the LTEs in Germany (research parameters, status, duration, etc.) is available in Grosse and Hierold (2019), Donmez et al. (2022) and through a web-based LTE overview map (lte.bonares.de) running on the BonaRes repository. It is the ambition of the BonaRes repository to make LTE data available for reuse. Currently, the research data for 3 LTE sites are freely available for reuse, while numerous datasets are in the process of open access publication.

2.3. Baseline and projected climate data and spatial information

Two sets of climate data, namely baseline and future conditions, were used in the study. Climate data for the baseline period comprised temperature and precipitation, derived from Germany's National Meteorological Service (DWD). We obtained future climate data from the WorldClim database (Worldclim, 2021) for Europe with 2.5 min (5 km) spatial resolution. The dataset was produced through the Coupled Model Intercomparison Project Phase 6 (CMIP6) described in Eyring et al. (2016). It includes monthly minimum temperature, maximum temperature, and precipitation available for nine global climate models (GCMs) up to 2100. We used the mean data of these GCMs, including the averages over 20-year periods (2021–2040, 2041–2060, 2061–2080, 2081–2100). Four emission scenarios of the SSP126, SSP245, SSP370 and SSP585 were used for future climate projections in Germany. Among the existing SSP scenarios, we did not use SSP4 in our study due to its similar climate forcing potential with the SSP370. It aimed high challenges to adaptation and therefore excluded from our analyses since our research aimed to represent mainly mitigation. Excluding one scenario from the workflow provided a considerable advantage of computational power in our spatial analyses. Each SSP used in the study corresponds to Representative Concentration Pathways (RCP) climate scenarios. For instance, SSP5–8.5 corresponds to RCP8.5 where SSP3–7.0 ranges between RCP6.0 and RCP8.5 and SSP1–2.6 is similar to RCP2.6. The codes of the SSPs were expressed without dots and hyphens (i.e. SSP585) to avoid confusion in data processing and analysis.

We spatially obtained and overlayed the baseline climate data and future climate predictions to derive agriculture-related factors, including drought and growing season-specific indicators used in a comprehensive climate assessment. The indicators produced in the study using the Worldclim climate variables are listed in Table 2.

The Müncheberg Soil Quality Rating (MSQR) map (BGR, 2014), showing soil quality classes for arable land over the whole of Germany at 250 m resolution, was used to assess the climatic effects on different soil quality classes in LTEs. A Digital Elevation Model at 90 m spatial resolution was obtained from the Shuttle Radar Topography Mission (SRTM) from the U.S. Geological Survey (USGS) data hub for resampling the climate maps for downscaling. A list of the datasets used in this study is given in Table 3.

Table 2
Agroclimatic indicators used in the study and the climate variables they are based on.

ID/ Acronym	Name	Unit	Variable	Temporal span	Sources
Drought Indicators					
AI	Aridity Index	–	T_g	1971–2000 2021–2100	(Li et al., 2017)
Ds	Dry spells	days	P		(Barron, 2004)
Soil and growing season-specific indicators					
Fd	Frost days	days	T_g		(CCCS, 2020)
GDD	Growing degree days	^{0}C days yr^{-1}	T_g	1971–2000 2021–2100	(CCCS, 2020)
KGc	Koeppen-Geiger Classification	–			(Beck et al., 2018)

T_g: Daily temperature, P: Precipitation.

The MSQR data used in this study has been produced exclusively for arable land, combining basic soil parameters with a visual procedure for assessing soil structure and degradation to derive soil quality classes (Mueller et al., 2009). The approach integrates eight fundamental soil indicators with 13 hazard indicators. The procedure is an up-to-date, internationally acknowledged and applied method to assess soil quality (Bünemann et al., 2018). Because of its focus on soil structure and soil degradation characteristics, most (albeit not all) of the indicators are sensitive to interactions between climatic changes and agricultural soil management, which makes it particularly useful for the scope of this study.

We selected the agroclimatic indicators based on their characteristics representing the climate change, growing season, soil health and water conditions. Applicability and prevalence were additional input and indicator selection factors, chosen to produce valid outputs relevant to agriculture and LTE research.

The LTE metadata set used in our study was derived from the BonaRes data repository conducted at ZALF, Germany. Metadata of the LTEs used in the study comprised the location, land use and management operation categories, experimental settings, duration and soil and crop-related research parameters (Grosse and Hierold, 2019).

3. Methods

The methodology of our study comprised five steps, namely, i) data pre-processing, ii) deriving and projecting indicators, iii) acquisition and classification of the LTE metadata, iv) geostatistical analysis of the agroclimatic indicators across the LTEs, v) geospatial analysis of MSQR and indicators and difference map derivation. The workflow of the methods used in this study is shown in Fig. 2.

3.1. Data pre-processing

The format and attributes (georeferencing, map projection, resolution, etc.) are usually different among spatial datasets, leading to consistency problems during overlaying and merging operations. Data preprocessing is a significant step contributing to standardising and thus using different datasets in an analysis framework. Geometric correction is the first and most crucial part of data pre-processing, representing a process of image transformation regarding its map projection to remove geometric distortions. In this process, we recorded the present and future climate data geometrically according to ETRS89 Lambert Azimuthal Equal Area at 1 km spatial resolution. The grid origin is 4.22 m west of the projection center point (52 N, 10E) and 3333 south of the projection center point (52 N, 10E) with D_ETRS_1989 datum. The grid

Table 3
Datasets used in the study.

ID/Acronym	Name	Unit	Variable	Temporal span	Sources
Climatic Variables					
CLIM1	Minimum temperature*, **, ****	°C	T_n		
CLIM2	Maximum temperature*, **, ****	°C	*Tm*	*1971–2000	*W, **C, ***CP, ****DWD
CLIM3	Precipitation*, **, ****	mm	*P*	**2021–2100	
	Potential evaporation***	m s-1	P_e		
Spatial Data					
DEM	Digital Elevation Model	m			USGS data hub
MSQR	Müncheberg Soil Quality Rating	Quality classes			(BGR, 2014)
Long-Term Field Experiments					
	Land use	–	*Fieldcrops, grasslands*		
LTE metadata	Management operations	–	*Fertilization, crop rotation, tillage*		BonaRes Repository (bonares.de)
	Locations	–	*Coordinates*		

*W: WorldClim Historical Climate Data V2, **C: CMIP6, ***CP: Copernicus Climate Change Service, ****DWD: Deutscher Wetterdienst (DWD). (Tn: Min. temperature, Pe: Potential evaporation, Tm: Max. temperature).

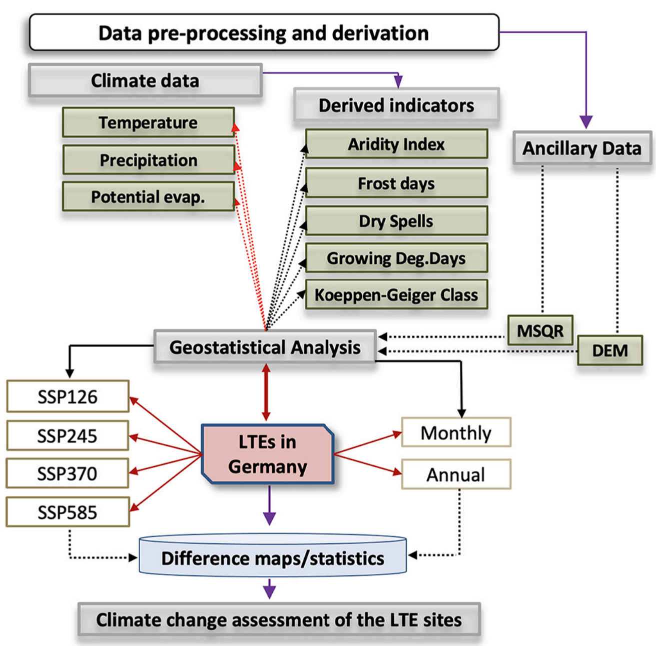

Fig. 2. Flowchart of the applied methodology in the study.

extent covers Germany with 701 columns and 883 rows. The projection of the DEM used in the study was recorded to be compatible with the climate maps.

Since the GCMs may not accurately predict climate in all locations, calibration is essential to reducing the dataset's uncertainty. The spatial data obtained from the CMIP database were readily calibrated and bias-corrected through WorldClim v2.1 as baseline climate (Worldclim, 2021). The climate maps derived from the Worldclim database were resampled from the native coarse resolution (5 km) to higher resolution (1 km grid spacing) using the nearest neighbour method as described in Mitchell (2005). Data pre-processing was completed in a GIS environment.

3.2. Deriving and projecting the indicators

Five agroclimatic indicators, including aridity index, dry spells, frost days, growing degree days and Koeppen-Geiger classes, were derived from the pre-processed maps and utilized to assess the effects of the climatic changes on the LTE sites. These indicators are particularly selected due to their close linkage to factors affecting agricultural productivity, including drought and growing season length. For instance, these factors may directly affect growing conditions, measures (such as irrigation), crop growth, access to fields, planting and harvesting that are directly related to LTE planning and continuous management. In principle, we reproduced and bias-corrected the soil, drought and growing season-specific indicators using the climate variables from the CMIP6 dataset for each SSP scenario in baseline and future periods at 1 km resolution as described in CCCS (2020) and Navarro-Racines et al. (2020).

SSPs offer a range of global warming scenarios, resulting in an increase of 1.3 °C to 5.1 °C above pre-industrial levels in 2100. The SSPs are based on five narratives describing broad socioeconomic trends shaping future society. SSP126 is the most positive of the five pathways, designed to limit warming by 2 °C by 2100. SSP245 represent scenarios with stronger climate change mitigation and thus lower emissions that the world is assumed to follow a path of continuing social, economic, and technological trends, resulting in a warming of 2.1 to 3.5 °C. SSP370 assumes increases in emissions to 76–86 Gt CO_2 eq. by 2100 and an associated temperature increase by 2.8–4.6 °C. SSP4 and SSP585 are characterised by rapid technological progress in low-carbon energy sources. The SSP4 assumes a temperature increase of 3.5–3.8 °C, while SSP585 assumes increases of 3.3–5.7 °C (IPCC, 2021).

3.2.1. Aridity index (AI)

AI is an important indicator for the occurrence of droughts, which in the context of agricultural production refers to situations where soil moisture levels during the vegetation period are insufficient to meet crop requirements. Due to the variable nature of aridity, the calculation of the aridity index is not straightforward. It is usually calculated as a function of the interaction between rainfall, temperature and evaporation, reflecting the temporal variability of water availability and precipitation distribution during the growing season. As a quantitative indicator for the water deficiency level at a specific location, we calculated the AI by dividing the monthly precipitation, and potential evaporation monthly and then averaged for each year in the baseline and future scenario periods (FAO, 1989; Li et al., 2017). Potential evaporation (Eq. (1)), used as an input for the AI calculation, was calculated based on the Penman-Monteith approach (Allen et al., 1998).

$$AI = \frac{ET_0}{Pre} \tag{1}$$

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T_a + 273} U_2(es - ea)}{\Delta + \gamma(1 + 0.34U_2)} \tag{2}$$

R_n is the net radiation at the crop canopy surface (MJ m^{-2} d^{-1}). It can be estimated by the difference between the net shortwave radiation (R_{ns}) and the net long-wave radiation (R_{nl}) (Li et al., 2017), G is the soil heat flux density (MJ m^{-2} d^{-1}) calculated by the difference of the mean daily air temperature between two continuous days, T_a is the mean daily air temperature at 2 m height. U_2 is the wind speed at 2 m height (ms^{-1}), and *es* and *ea* are the saturation and actual vapour pressure (kPa), respectively. Δ is the slope of saturated vapour pressure per air temperature (kPa· °C $^{-1}$), and γ is the psychrometric constant (kPa °C $^{-1}$). The AI is classified into five main groups, namely humid (AI >0.65), dry sub-humid (0.50 < AI ≤0.65), semi-arid (0.20 < AI ≤0.50), arid (0.05 < AI ≤0.20), hyper-arid (AI <0.05) (Abatzoglou et al., 2018).

3.2.2. Dry spells (Ds)

Ds is defined as periods of consecutive days without rainfall. Analysing the distribution probability of dry spells, including their occurrence and duration, can provide relevant information for agricultural management (Deni et al., 2010). As a function of daily precipitation, the maximum number of consecutive days without rainfall was derived from the CMIP. We derived *Ds* as described in Adane et al. (2020). The maximum length of dry spells in a year was calculated first. Then, we computed the number of Ds by setting a minimum threshold of five dry days in the vegetation period.

3.2.3. Frost days (Fs)

Freezing temperatures can damage some crops while others need frost to germinate. The length of the frost period affects the length of the vegetation period. Frost events can be divided into light frost (−2 to 0 °C) and complex frost (below −2 °C). We calculated *Fs* based on the monthly and the annual number of days with minimum temperature below 0 °C occurring in vegetation development stages.

3.2.4. Growing degree days (GDD) in the growing season

GDD is a bioclimatic indicator based on the heat accumulation during the growing season to estimate the growth and development of crops. In its basic concept, crop growth occurs if the temperature exceeds a temperature development threshold called base temperature. The base temperature is different for each crop (e.g., for wheat approx. 5 °C). We included *GDD* as an indicator relevant for potential future crop rotation strategies of the LTEs. We calculated it by summing days with a mean temperature above 5 °C. GDD was also used to calculate the start and end of the growing season. The beginning of the growing season was defined by the first five consecutive GDD days in a year, the end by the last five consecutive GDD. We calculated monthly and annual growing degree days to monitor the long-term fluctuations of the cultivation potential for different crops in German LTEs.

3.2.5. Koeppen-Geiger classification (KGc)

The KGc system is a representative climate classification that partitions climatic zones into subclasses based on seasonal surface air temperature and precipitation (Köppen, 1936). Our study found *KGc* useful for multiple issues related to climate change, such as for the growth behaviour of different crop species. This information is helpful for the planning of future crop rotation schemes of LTEs. We generated KGc maps for the SSP scenarios, using the ensemble of climate maps of precipitation and temperature in a multi-step GIS methodology described in Cui et al. (2021). Thus, we derived the future KGc map using the projection data from the CMIP6 GCM dataset.

3.3. Acquisition and classification of the LTE metadata

The metadata of the LTEs was extracted from the BonaRes repository (BonaRes, 2020). It has been initially compiled through literature review and personal communications with LTE holders (Grosse et al., 2020a). The repository, including all metadata, is freely available and organised according to international data standards, including FAIR, Inspire and DataCite (BonaRes, 2020; Hoffmann et al., 2019). Based on the metadata, we categorized LTEs according to their land use and research theme into five main classes, namely Field crops-Crop rotation (F-CR, Field crops-Fertilization (F-F), Field crops-Tillage (F-T), Grassland-Fertilization (G-F), Pomiculture-Fertilization (PM-F). Land use and management operations were subgrouped as factorial experiments by Field crops-Fertilization/Crop Rotation (F-F/CR), Field crops-Fertilization/Tillage (F-F/T) and Grassland-Fertilization (G-F).

3.4. Geostatistical analysis of the indicators across the LTEs

We implemented a comprehensive spatial and temporal data analysis. First, we selected the LTEs with research themes that included fertilization, tillage, or crop rotation and extracted the indicator values at their locations. For each scenario and time interval, the extracted data from the maps were grouped by month, and the values were averaged across LTEs using R version 4.0.4 (R Core Team, 2021) and the R package "tidyverse" (Wickham et al., 2019). Each indicator was averaged across cropland and grassland LTEs for each scenario and time step.

Statistical analysis for deviations between baseline and SSP scenarios was conducted across 20-year time spans based on future climate data availability in the Worldclim database. Normal distribution and homogeneity of variances of model residuals were checked using a Shapiro and Levene test (Fox and Weisberg, 2019). Since the normal distribution of residuals was not present in most models, we used a Kruskal-Wallis test with multiple comparison extensions (Giraudoux et al., 2021).

3.5. Geospatial analysis of MSQR and indicators and difference map derivation

We combined the MSQR map and the indicator maps to reveal changes across the different SSP scenarios. The MSQR values were divided into six classes based on yield potential: extremely low, very low, low, medium, high, and very high (Daedlow et al., 2018; Grosse et al., 2020b). For each class, average indicator values were calculated. Results were then combined to assess the changes in the indicators for each soil quality class over the LTE regions. The correlation between the agroclimatic indicators and soil quality classes over the LTE regions was analyzed using the Pearson correlation which measures the linear correlation between two data sets (Taraldsen, 2020). It was represented by the determination coefficient (r) which ranges between −1 and 1, where 1 indicates a perfect correlation between data sets.

Moreover, we produced difference maps of the climatic variables and the indicator maps to use as a basis for the LTE-oriented climate change assessment. First, the pixel sizes and projections of the rasters were standardized to ensure the geographically overlapping of the input maps. Then, grid value differences between baseline and future rasters were calculated using the subtraction algebra commands on a cell-by-cell GIS environment. We subtracted the climate variables and indicators for each cell in the 2071–2100 maps of each SSP scenario from the respective values in the baseline periods. All input maps comprised floating numbers to account for slight differences between the rasters. Following this, we mapped the risk for continuing LTEs without adapting the management. For this, we applied an optimized hot spot analysis (OHS) as described in Zerbe et al. (2022) to analyse changes in climate variables and agroclimatic indicators between the baseline and the SSP scenarios. LTEs were classified into those where these changes posed no significant risk, those with a lower risk and those with a higher risk. For the low and high risk categories, we distingished between 90%, 95% and 99% confidence intervals. Higher risk stated an increase in heat stress and drought, while lower risk groups showed a decrease in climatic stresses in LTE sites.

4. Results and discussion

The results comprise outputs that combine spatial agroclimatic indicators, soil quality classes and LTE research themes in Germany.

Outcomes were assessed under three perspectives, namely i) future temperature and precipitation changes in German LTE sites, ii) effects of the soil, drought and growing season indicators on LTE research themes, and iii) effects on LTE sites representing the soil qualities.

4.1. Future temperature and precipitation changes in German LTE sites

The first step in our analysis comprised assessing temperature and precipitation changes in Germany, aggregating the large volume of spatial data incorporated with the LTE locations. The overall projected change for these variables is illustrated in Fig. 3, based on the ensemble of mean monthly values, for 20 years intervals as obtained from the Worldclim.

197 LTEs were on arable land, and 39 LTE were on grassland. The mean temperature for the arable LTE was 8.94 °C for the baseline period. It increased up to+2 °C for SSP126 to approx. +4 °C for SSP585 in 2081–2100, respectively. The temperature changes ranged between 2 and 5 °C for each agricultural management group of LTE in the given scenarios by the end of the century. This is a critical output for defining climate conditions for crop growth under different management strategies.

Precipitation is one of the most critical factors for crop growth during germination and fruit development stages by affecting soil moisture and water stress. It affects the growing speed of the plants and the length between seeding and harvest. Our analysis estimated an increase in rainfall during spring months for SSP126 and SSP245 scenarios for all 20 years intervals, including 2021–2040, 2041–2060, 2061–2080 2081–2100. The precipitation change from baseline to SSP585 showed a substantial increase between March and June in line with the future projections of the DWD (DWD, 2021). For the SSP585 scenario, a

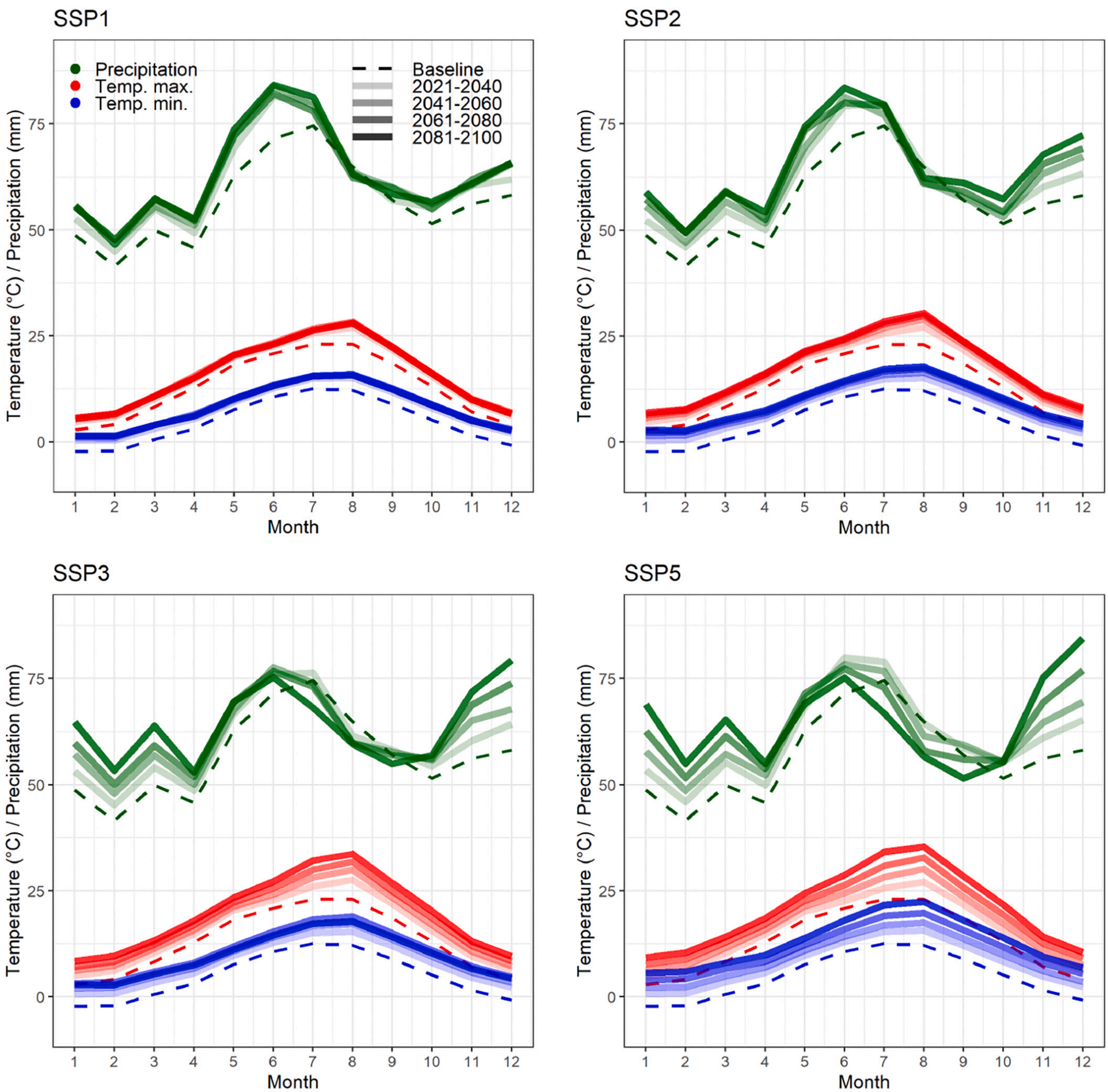

Fig. 3. Monthly temperature and precipitation changes in future scenarios averaged over the LTE regions.

remarkable decrease may occur in the autumn months, especially in September, when the early winter crops (e.g., winter barley, winter rye, rape) are cultivated and the late summer crops (e.g., maize, sugar beets) still grow. Inconsistent variations in precipitation are expected in northern Europe, but precipitation is projected to increase in the LTE sites. A considerable increase of up to 100 mm is expected to occur in the sites of the arable LTE. An increase in precipitation from 670 to 764 mm was calculated for arable LTE sites with fertilization treatment. As in many areas in Germany water availability is the limiting factor for plant growth, and an increase in precipitation may benefit yield. It may, however, also lead to runoff and water erosion when infiltration is limited and fields are inclined. Conservation tillage and mulch sowing can improve infiltration capacity through surface coverage and well-established soil pore systems.

Besides precipitation, the temperature is a critical variable. Higher temperatures may cause yield reductions and encourage the proliferation of pests that may threaten food provision (Asseng et al., 2019; Ottman et al., 2012; Webber et al., 2018). The temperature was computed, and minimum, maximum, and mean values were assessed for the effects of temperature on crop growth processes. For min. Temperature, a continuous increase was found every 20 years timestep during the 2021–2100 period. The highest increase was predicted in SSP585 during July and August. For max. Temperature, SSSP585 also showed an increase of up to +5 °C compared to the baseline in August, affecting crops harvested in autumn such as maize or sugar beets. The difference maps of mean annual precipitation, as well as the (absolute) mean annual temperatures are shown in Fig. 4.

We found strong differences in precipitation and temperature in terms of their spatial distribution in Germany and at the LTE locations. An increase in surface temperatures is likely to be strongest in south and east Germany where mostly wheat and barley are grown. 20 LTEs located in south Germany were estimated to face annual mean temperature increases between 4 and 6 °C, which can lead to heat stress for all types of crops significantly affecting their development negatively. Northern regions in Germany are expected to be warmer than the other locations, directly affecting the heat stress over the crops. An increase in precipitation was observed on average in Germany and it is expected to increase in the south between 16 and 99 mm, leading to improved water availability for agriculture. The inconsistent spatial variation of temperature and precipitation over different parts of Germany can bring an

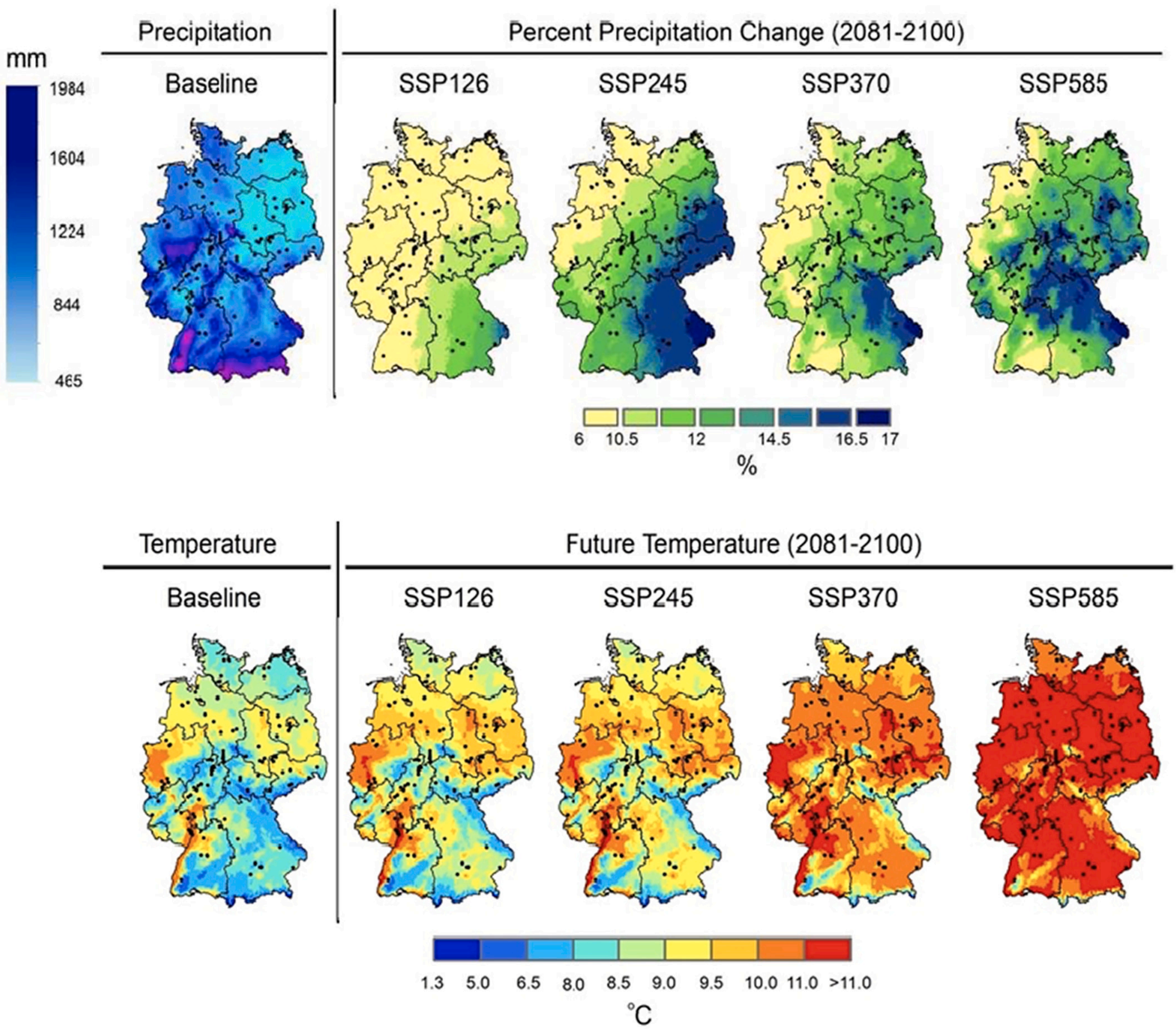

Fig. 4. Precipitation change (%) and mean annual temperature (°C) maps from baseline to future (2081–2100). Black dots represent the German LTE sites.

unanticipated response of crop-related parameters such as insects, weeds, soil organic matter and cause adaptation difficulties to cropping patterns.

4.2. Effects of the soil, drought and growing season indicators on LTE research themes

Each crop type comes with specific optimum temperature, and precipitation ranges. Crops will therefore respond differently to climate change. They can survive and develop in suitable areas where temperatures are within their growth thresholds. Furthermore, crop production is highly dependent on water availability. In our study, we derived indicators related to water availability and temperature for the cropland and grassland LTE sites. Drought (AI and Ds) and growing season indicators (Fd, GDD, KGc) for fieldcrop and grassland LTE sites were used to reveal the land-use based changes of soil and water components in future. Present to future trends under the SSP scenarios in 20-year intervals are shown in Fig. 5. The changes in these indicators, computed scenario-wise, are provided in Table 4. Scenario-wise variations of the agroclimatic indicators for 2081–2100 in LTE land use and management operations are summarized in Appendix 1.

Comparing the LTEs under SSP scenarios, for each indicator grassland LTEs showed a more significant variation than the arable LTEs. This may be partly due to the smaller number of grassland LTE sites. For all indicators, changes with regard to the baseline are evident in SSP585 in the 2081–2100 period. The deviation is considerable for dry spells and frost days. A sharp decrease in frost days for arable LTEs is projected for all SSPs, while an increase in GDD in the growing season is expected for both arable and grassland LTE categories. The change is expected to be stronger for aridity in the arable LTEs. This reflects the situation that most of the grassland LTEs in Germany are located in marginal areas that are either particularly dry or particularly wet (Grosse et al., 2020a).

A significant increase in GDD in the growing season is expected due to temperature and precipitation changes in SSP585 for 2081–2100. We also found a considerable increase in GDD for grassland LTE sites for SSP370 in the 2061–2080 and 2081–2100 intervals. Based on an assumed 5 °C threshold, GDD will likely increase up to approx. 141 days for the SSP126 scenario by the end of the century. Plant growth rates can benefit from higher temperatures, and thus GDD increases; however, this may not necessarily lead to increased production (Iizumi et al., 2017). Unless stressed by other environmental factors such as water deficits, the development rate for many plants depends on daily air temperature during the period from emergence to maturity. Because many developmental stages of plants and insects depend on the accumulation of specific quantities of heat, it is possible to predict when these stages occur during a growing season, regardless of differences in year to year temperatures (Iizumi and Ramankutty, 2016; Wiebe et al., 2015). Results of GDD projections provide indications for future adaptation options of arable and grassland management at LTE sites.

Based on the Koeppen-Geiger classification, the LTE sites are classified as warm temperate and humid, with typical hot summer conditions. Future projections foresee a change from a warm temperate climate, fully humid, warm summer (Cfb) to a warm temperate climate, fully humid, hot summer (Cfa) class in the LTE sites. This indicates a longer duration of warmer temperatures in the summer season that directly affect vegetation growth. Consequently, changes in the AI are expected to affect regional water resources, and therefore, agricultural management. The primary importance of AI fluctuations is testing the boundaries of the AI classes between the regions and their potential effects on water resources and agricultural productivity (Huang et al., 2015). The variations of LTE land use in AI classes can be seen in Table 5.

The mean annual AI value of Germany was 0.65 under baseline conditions. The AI ranges changed strongly under the SSP scenarios. We calculated a shift of up to 0.38 in the 2081–2100 period under the SSP585 scenario. An increase in aridity is projected while mean annual precipitation is also increasing, and the significant impacts on ecosystems can be expected to come with this increase in line with Milly and Dunne (2020). It indicates that the temperature increases (up to 5 °C),

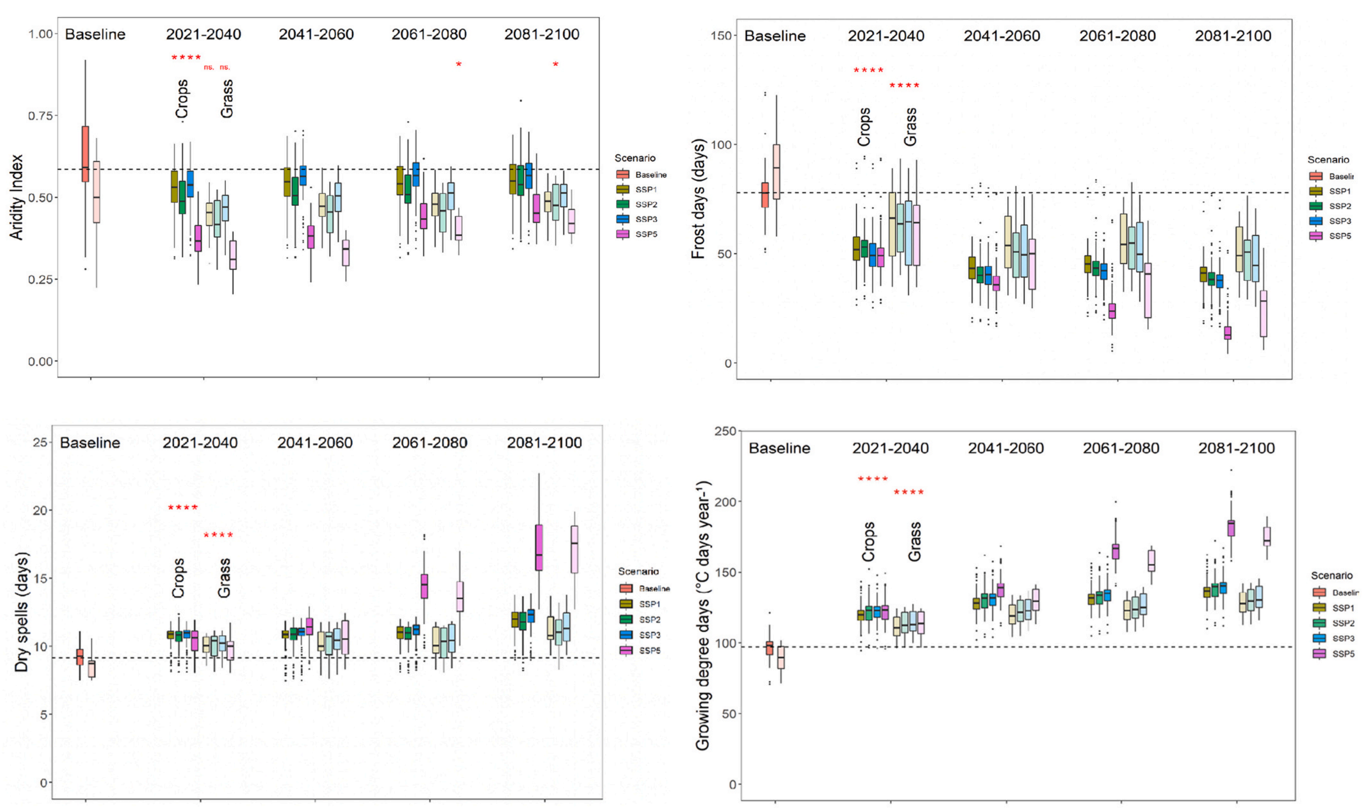

Fig. 5. Present to future trends of the LTE land-use types for each indicator in 20-year intervals under the SSP scenarios.

Table 4
Scenario-wise changes in agroclimatic indicators in 2081–2100 (averaged for the LTE locations).

ID	Indicator	Unit	Present	SSP126	SSP245	SSP370	SSP585
AI	Aridity Index	–	0.65	0.55	0.50	0.50	0.40
Ds	Dry spells	days	9.1	11.7	11.6	11.9	16.9
Fd	Frost days	days	78.4	41.7	39.7	38.8	15.2
GDD	Growing degree days	^{0}C days year^{-1}	99	141	143	145	190
KGc	Koeppen-Geiger Classification	–	Cfb*	Cfa*	Cfa*	Cfa*	Cfa*

*Cfb = Warm temperate climate, fully humid, warm summer, *Cfa = Warm temperate climate, fully humid, hot summer.

Table 5
Representation of the variations of LTE land use in AI classes (some LTE were assigned to multiple research themes).

Aridity classes	Scenarios	Fieldcrops				Grassland	Pomiculture
		F-CR	F-F	F-F/CR	F-F/T	G-F	PM-F
Humid	*Baseline*	2	41	6	5	15	
	SSP126		8	1	2		
	SSP245		7		2		
	SSP370		6		2		
	SSP585						
Dry sub-humid	*Baseline*	5	66	9	5	17	1
	SSP126	4	87	9	8	17	1
	SSP245	4	78	9	4	15	1
	SSP370	4	82	9	7	12	1
	SSP585		22	1	3		
Semi-arid	*Baseline*						
	SSP126	3	12	5		15	
	SSP245	3	22	6	4	17	
	SSP370	3	19	6	1	20	
	SSP585	7	85	14	7	31	1
Arid	*Baseline*						
	SSP126						
	SSP245						
	SSP370						
	SSP585					1	

Humid Dry sub-humid Semi-arid Arid

(F-CR, Field crops-Fertilization (F-F), Field crops-Tillage (F-T), Grassland-Fertilization (G-F), Pomiculture-Fertilization (PM-F). Land use and management operations were subgrouped as factorial experiments by Field crops-Fertilization/Crop Rotation (F-F/CR), Field crops-Fertilization/Tillage (F-F/T) and Grassland-Fertilization (G-F).

lead to increased rainfall rather than snow and snowpack; therefore, a reduction in surface albedo further increases evaporation, evapotranspiration (Overpeck and Udall, 2020). The outcome of these events can indicate increasing drought impacts, even if the mean annual conditions become wetter in response to climate change. Therefore, aridity is expected to affect the LTE locations, their water balance, and research themes in the future. 82 arable LTEs and 15 grassland were classified in the humid zone. Under baseline conditions, most LTEs are grouped in the dry sub-humid zone. In the SSP scenarios, the number of LTEs with field crops - fertilization themes are expected to show a remarkable shift towards the semi-arid zone. This shift is also considerable for field crop-crop rotation themes, with 7 LTEs shifting to this category in the SSP585 scenario. While the majority of the grassland LTEs will change from the dry-subhumid zone to semi-arid conditions, one grassland LTE will even shift to the arid zone by the end of the century. The cumulative distribution of the LTEs in different zones shows that there were 102 LTEs grouped in the dry sub-humid zone for the baseline period. There were 26 LTEs expected to remain in these conditions under SSP585, while the rest is likely to shift to the semi-arid zone. Our results indicated a shift of 150 LTEs from humid and dry sub-humid conditions to the semi-arid zone. Most of these LTEs are located in central Germany, where the drought conditions are relatively robust. To reveal the scale of the potential climatic impacts on LTEs in the future, we have conducted an LTE risk assessment based on changes between the baseline and future scenarios (SSP126 and SSP5). In particular, we assessed changes in the climate variables and the agroclimatic indicators (Fig. 6).

The LTE risk assessment helped to identify the potential effects of projected climatic changes on LTE sites. We classified LTEs from low to high-risk groups in different confidence levels. Higher risk groups identified the LTEs that, by the end of the century, may not be maintained in their current form without adaptive management or transformation. The OHS results showed that LTEs marked in red indicated a high-risk group due to temperature increases and prolonged drought in southwestern Germany, particularly in the federal states of Rheinland-Pfalz and Baden-Württemberg regions. Comparing SS126 to SSP585, in SSP585 LTEs in the western areas were projected to shift from lower to higher risk groups. The compilation of the risk assessment through the OHS showed that in the SSP126 scenario, 10 out of 247 LTE sites (4%) were predicted to be in the high-risk group. In the SSP585 scenario, this number increased to 15 LTEs, with confidence levels of 95% or higher.

The GDD in the growing season results of our study can be used to assess the suitability of an LTE site for the production of a particular field crop and to predict the maturity and cutting dates of forage crops. The growth stages of crops can even be estimated by engaging with harvest days, fertilizer applications, and their timing under heat stress. For instance, the main field crops planted in the LTEs are maize, winter wheat and barley. These crops usually have a 5 °C base temperature for GDD estimations (Grigorieva et al., 2010). Addressing the temperature increases in the future under SSP scenarios, GDD are expected to be longer. Difference maps of the agroclimatic indicators were derived for spatially distributed assessments of future changes (Appendix 2).

LTEs have been affected by climatic changes in the last decadesi therefore, the implications of these changes on LTEs this is not only a future problem. Their contribution and role in agricultural sustainability and environmental change were closely linked (Ingram and Gregory, 1996; Schädler et al., 2019). The progressive shifts in precipitation and temperature of many European LTEs over the past 50 years showed a tight linkage between crop productivity and soil C change as a unifying theme in subhumid and semiarid environments (Rasmussen et al., 1998). In Germany, the timing of seasonal water availability in recent decades affected above- and below-ground productivity in grasslands experiments (Denton et al., 2017). Moreover, the number of frost days and varying growing degree days in many experiments in the last decades have directly affected the potential for plant growth (Rasmussen et al., 1998; Beier et al., 2004; Schädler et al., 2019).

Compared to our 1971–2000 baseline, the projected changes in temperature and precipitation are expected to affect critical climatic indicators in 2081–2100. Changes in indicators significant to agriculture and LTE management show more frost-free and prolonged growing seasons. Changes in GDD were stronger than changes in the number of frost days. Frost days are expected to be fewer, between −12 to −66 days a year. At this point, if phenology changes faster than frost occurrence,

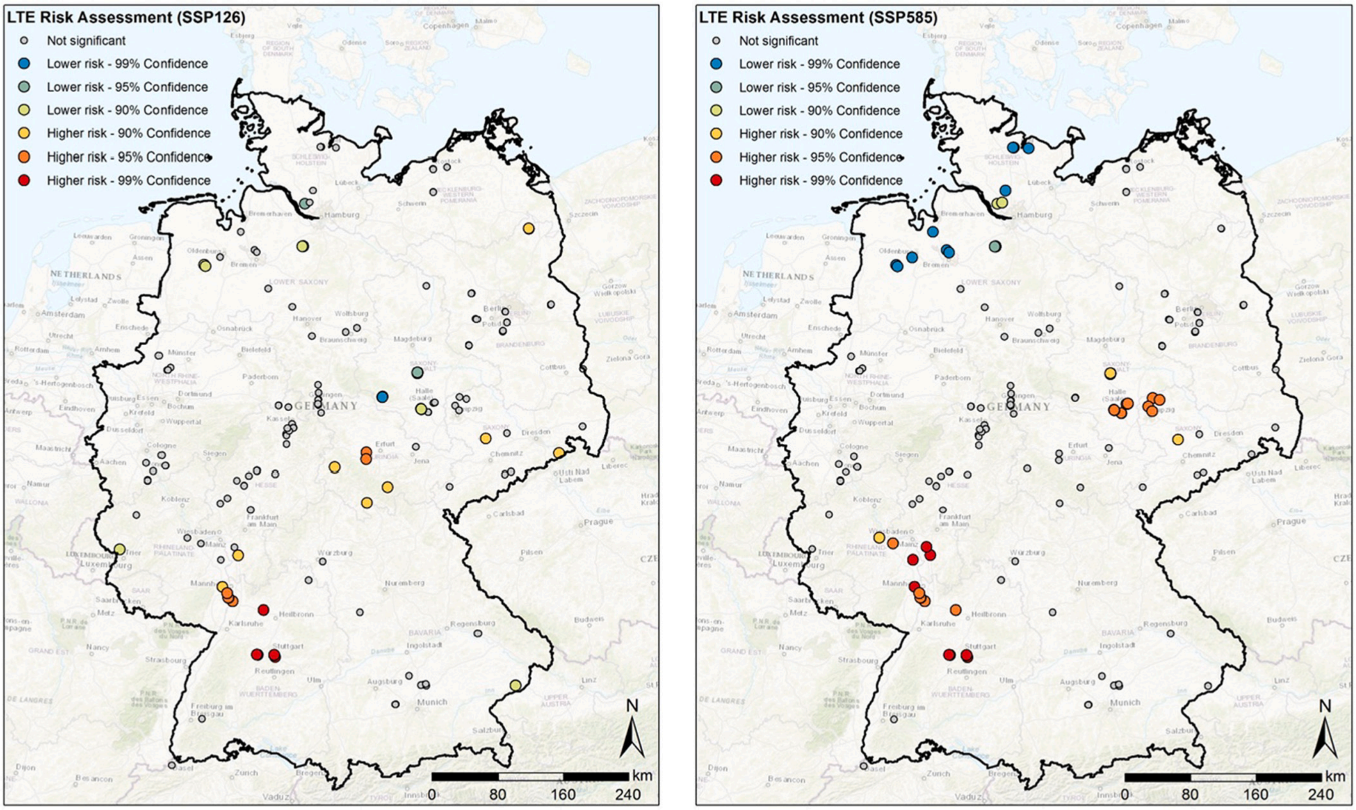

Fig. 6. LTE risk assessment from baseline to future in SSP126 (left) and SSP5 (right) based on the changes in the agroclimatic indicators.

then the risk of frost damage increases which may directly affect the experiments and their management. Since heat stress is likely to occur in the southern regions of Germany, a shift in the climatic zone from the Mediterranean to the northern areas should be considered. Therefore, new crops that are more suitable for warmer conditions, such as soy, can become mainstream crops in the future, though in some cases irrigation may be needed. On the aridity index map, similar effects of temperature changes were projected in southern Germany with increasing drought trends for 2081–2100. However, until the end of the century, AI is not expected to reach a critical level for the three scenarios SSP126, SSP245 and SSP370.

4.3. *Effects on LTE sites representing the soil qualities*

A comprehensive assessment of drought and growing season indicators based on the MSQR rating of LTE sites was performed using the MSQR map (Fig. 7). Scenario-wise comparisons of the LTEs for each indicator versus the soil quality classes were performed (Fig. 8).

Based on our spatial and temporal AI analysis of the LTE sites, we found that the aridity conditions in most of the LTE sites will be rising in all SSP scenarios. The shift in the aridity classes is also expected to be strongest in SSP585 for each soil quality class. However, the LTEs on low-quality soils are expected to be affected less. SSP126 and SSP245 show medium increases in the 2081–2100 period. 14 LTE sites in southern Germany with fertilization and tillage treatments are likely to be affected more than the grassland and pomiculture sites. For all SSP scenarios, 18 LTE sites in northern Germany were not showing any drought risk due to increasing temperatures.

We applied the Pearson test to evaluate the correlation between the soil quality classes and the agroclimatic indicators. The test was applied with a 95% confidence interval. A matrix plot of the soil quality derived from the MSQR and the indicators is given in Fig. 9.

The Pearson test showed no considerable correlation between soil quality and agroclimatic indicators. r ranged from −0.21 to 0.21, indicating a negative relationship between soil quality and climatic changes. The highest correlation of the soil quality classes was computed by the GDD ($r = 0.21$) while negatively correlated with the frost days ($r = -0.21$). Although the SQR showed a weak correlation, some of the agroclimatic indicators indicated a remarkable spatial autocorrelation with each other. For instance, the r between AI and dry spells was 0.84, which can be considered highly significant. However, dry spells and frost days indicated a negative correlation which showed no particular relationship in their spatial patterns. Besides, it could also be omitted that the aridity correlates with rain and frost days with temperature.

The seasonal crop growth may vary significantly due to differences in soil–water potential (Spinoni et al., 2015) and aridity (Goparaju and Ahmad, 2019). Besides soil properties, cultivated agriculture crops in the LTEs vary across regions due to variability, mostly in precipitation, temperature and potential evapotranspiration. We evaluated the German LTEs' drought potential based on treated crops and AI, including their spatial pattern, to facilitate conceptualizing climate-related adaptation schemes. Higher values of AI indicate humid conditions (Zomer et al., 2008).

Longer dry spells indicate a soil-water deficit that may cause crop water stress (Barron, 2004). Our dry spell analyses showed a range of 8 to 9 days a year for the present conditions over LTE sites. Dry spell length was computed to extend to 10 to 12 days under SSP126, which can be interpreted as a potential yield-limiting factor for crop growth. The number of dry spells tends to increase for the LTEs with extremely low and low soil quality classes. This increase is remarkably higher in SSP585 than in the other scenarios. For GDD in the growing season, an increase will occur for sites in low quality and medium quality soils. For the frost days, the LTEs on medium quality soils showed a reduction of up to −60 days by the end of the century from SSP126 to SSP585. The LTE operators need to consider the potential damages of dry spells. Dry spell analyses showed that potentially yield-limiting dry spells are

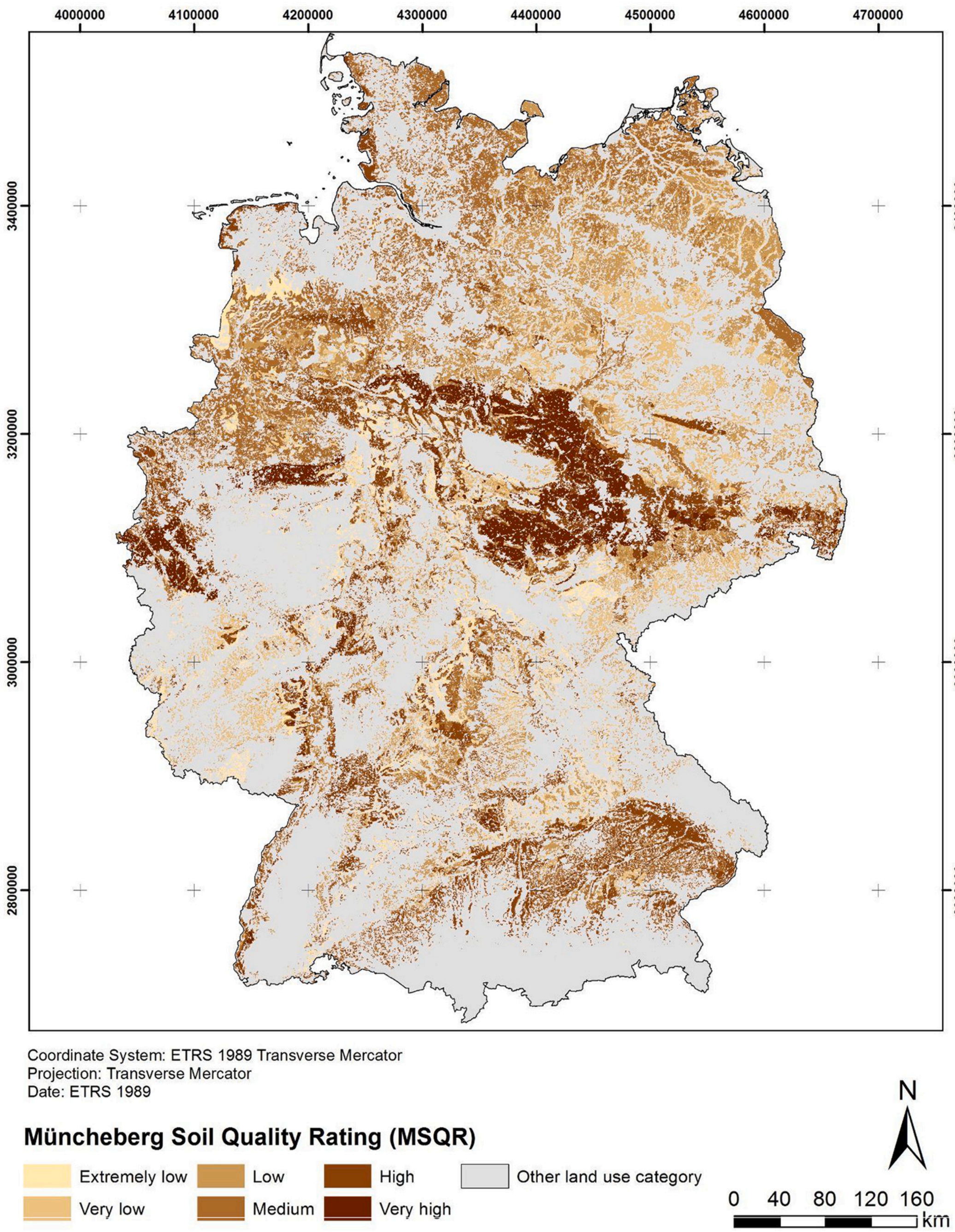

Fig. 7. Müncheberg Soil Quality Rating map (BGR, 2014).

mainly expected for LTEs located in central Germany.

5. Conclusions

Climatic changes are projected to affect agricultural yield, management and bioeconomics. These changes will make the continuation of many LTEs more challenging in the following decades. The main aim of our study was to assess the effect of climatic changes on the LTE locations by evaluating climate variables, drought and growing season indicators for agricultural management over a baseline and future periods. Our results provide an essential overview that supports the interpretation of LTE data, where separating the effects of experimental treatments from the impacts of climate change is a novel challenge. As climatic changes may make it difficult to maintain some LTEs without adapting the management, our results can be used for coordinated approaches by LTE-holders to select essential LTEs which should be continued unchanged to ensure a limited number of critical experiments. These LTEs that are continued unchanged will create invaluable insights into the effects of climate change on agricultural production and provide as a basis for model calibration and testing.

On the other hand, the spatial differentiation of expected climate change effects also facilitates the identification of suitable sites for future agricultural practices and may inform the design of additional LTEs. These sites could provide insights into the long-time efficiency of climate change adaptation measures, especially when comparing pairs of LTEs with similar agro-climatic conditions representing conventional and adapted management. Furthermore, our results allow pairing and comparing of sites representing similar or exchanging agronomic conditions, today, such as amount of rainfall, maximum temperatures or duration of drought spells, that are expected for the future at the second

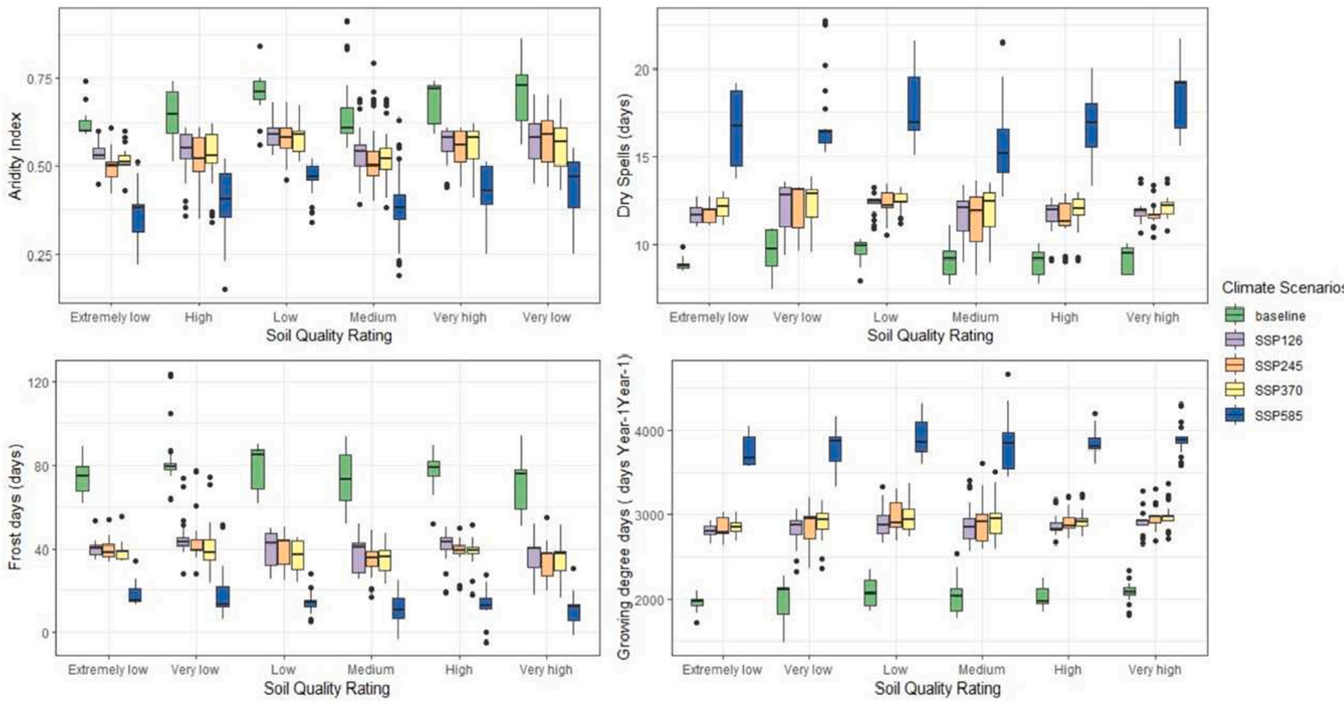

Fig. 8. Scenario-wise comparison of the LTEs for each indicator versus the soil quality classes defined in the Müncheberg Soil Quality Rating map.

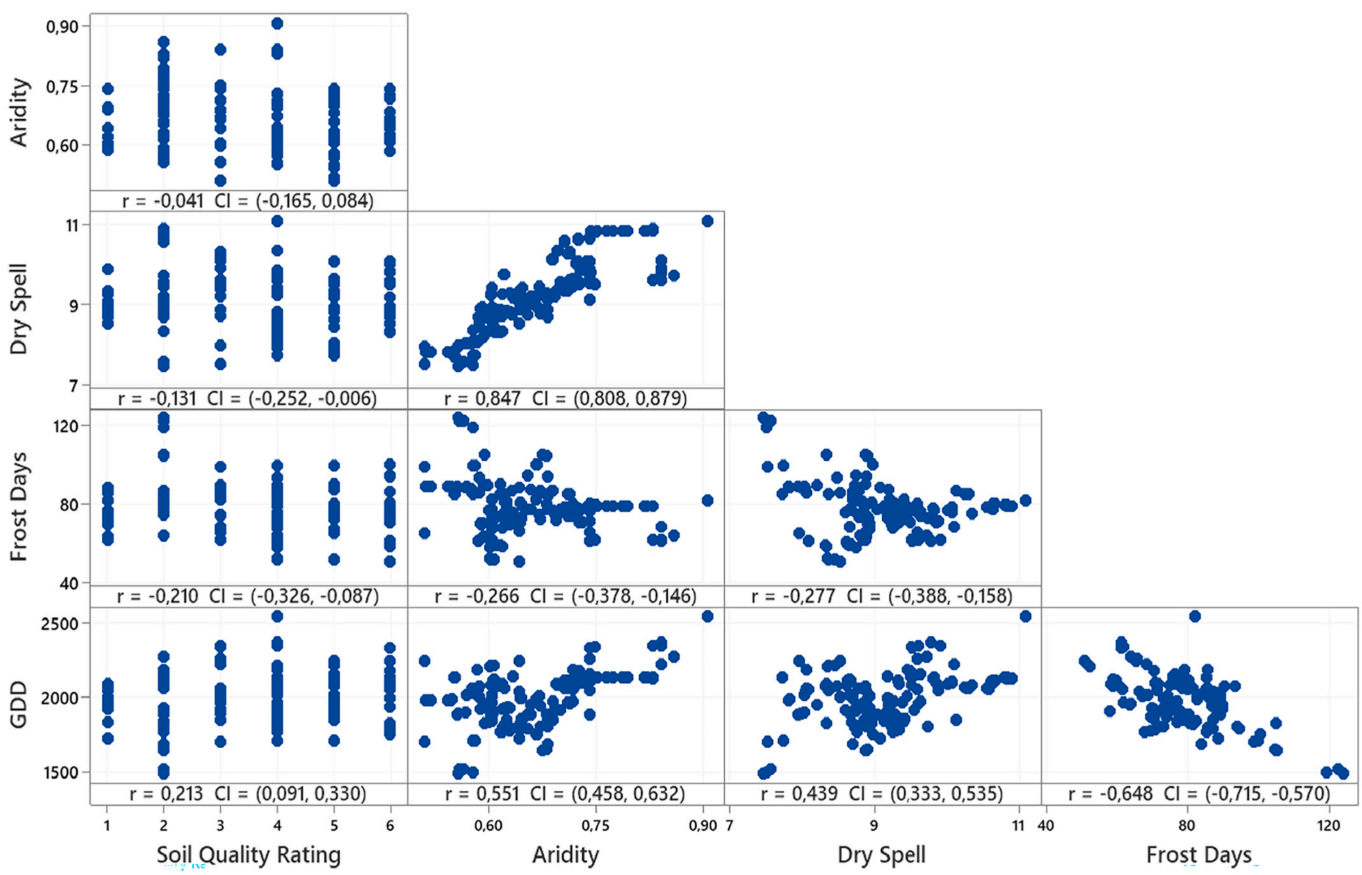

Fig. 9. Matrix plot of the soil quality rating and the agroclimatic indicators (Soil Quality Rating 1: extremely low, 2: very low, 3: low, 4: medium, 5: high, 6: very high.

site. In this way, the design and running of LTEs at the second site could directly profit from experience gained at the first one. Due to the speed at which climate change is occuring and impacting agriculture, there is a high degree of urgency to newly install or modify LTEs so that they allow researchers to assess the long-time effects of mitigation measures and provide policy makers with critical recommendations. Furthermore, as coordinated approaches between multiple LTE holders are likely to require long deliberations and negotiations, networking ought to start as soon as possible. Managers of both existing and new LTEs should also consider expanding the suite of measured parameters in order to better capture climate change effects. Beyond yield, critical parameters could include soil organic carbon content, soil moisture dynamics, drought stress or microbial activity. Addressing the long-term climatic changes associated with the LTE research themes, various potential adaptation strategies can be tested in the ongoing experiments, including the selection of crops, timing for management operations and pesticide use. Increasing the resilience of agricultural systems through experiments on how to mitigate the impacts of climate change on agricultural productivity is a promising approach. For this, a monitoring plan can be implemented to assess effective and profitable options comprising varied experimental methods, fertilization, tillage and crop rotations with suitable crop species for climate change adaptation. Evaluation of the trends of climatic changes from past to future in LTEs were useful in the study to reflect measures of effectiveness for potential preventative actions and implications for future use.

Implementing an experiment-based study has many difficulties, including a lack of digital records and data access issues. LTE data and resources such as the BonaRes repository that allow open access to them and follow the EU's FAIR principles constitute invaluable resources that support coordinated research efforts at the local, national and international level. In this regard, the LTE overview map in the BonaRes repository (BonaRes Repository, 2021) provides a remarkable advantage and opportunity for the LTE data acquisition, management and provision for research purposes. This assists in increasing the visibility of the LTE metadata and research data. Data holders and related institutions can be helpful in future research collaborations in agricultural and soil research. There are numerous LTE records from Germany and other European countries (e.g. Austria, England, Spain, Sweden, Turkey) in the BonaRes repository, where international collaborations continuously expand.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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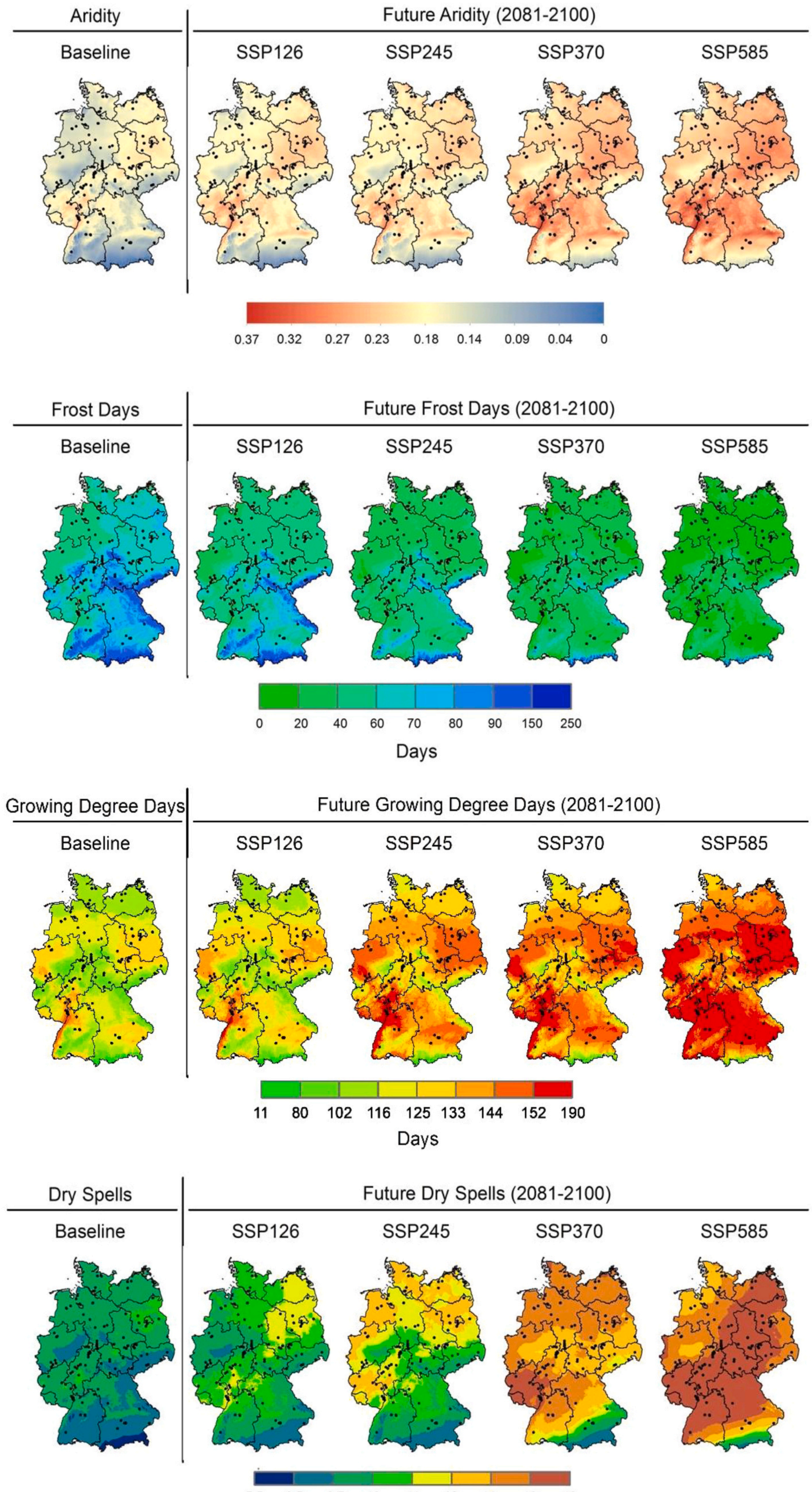
Appendix 1. Scenario-wise variations of the agroclimatic indicators for 2081–2100 in LTE land use and management operations.

Indicators	Scenario	LTE land use and management operations						
		Fieldcrops					Grassland	Pomiculture
		F-CR	*F-F*	*F-T*	*F-F/CR*	*F-F/T*	*G-F*	*PM-F*
Number of LTEs		31	122	40	21	14	38	4
	Baseline	8.84	8.99	9.08	8.98	9.22	8.25	9.20
	SSP126	10.93	11.06	11.14	11.07	11.33	10.34	11.20
Mean temperature (°C)	SSP245	12.46	12.54	12.63	12.58	12.80	11.83	12.62
	SSP370	12.67	12.70	12.82	13.77	13.94	11.99	12.64
	SSP585	13.89	13.90	14.02	13.99	14.13	13.19	13.78
	Baseline	734.0	670.7	672.9	686.9	610.9	753.3	731.0
	SSP126	821.7	742.8	745.6	764.5	674.5	841.0	797.0
Precipitation (mm)	SSP245	843.3	764.1	767.6	787.3	695.9	867.1	814.9
	SSP370	828.7	755.1	757.3	773.8	688.4	859.6	814.2
	SSP585	835.1	764.2	765.9	779.5	694.7	868.2	822.7
	Baseline	0.65	0.68	0.70	0.65	0.70	0.63	0.58
	SSP126	0.50	0.55	0.58	0.53	0.58	0.50	0.53
Aridity index	SSP245	0.50	0.55	0.55	0.53	0.58	0.48	0.48
	SSP370	0.50	0.55	0.55	0.53	0.58	0.48	0.50
	SSP585	0.35	0.43	0.43	0.38	0.45	0.35	0.38
	Baseline	8.70	9.20	9.21	8.94	9.80	8.65	8.87
	SSP126	10.85	11.74	12.01	11.40	12.34	11.24	12.02
Dry spell (days)	SSP245	10.76	11.69	11.87	11.20	12.46	11.08	11.99
	SSP370	11.05	12.03	12.20	11.55	12.35	11.42	12.47
	SSP585	16.02	16.69	18.45	16.98	17.52	16.94	15.28
	Baseline	78.57	76.02	77.54	79.23	75.07	88.89	66.78
	SSP126	40.59	39.79	40.76	41.23	38.78	50.87	35.45
Frost days	SSP245	37.68	38.04	39.68	39.08	33.89	49.15	34.89
	SSP370	37.76	37.40	37.57	37.88	34.60	47.91	33.28
	SSP585	11.45	13.83	16.41	13.86	8.80	24.25	11.04
	Baseline	101	101	102	104	105	101	92
	SSP126	143	143	144	146	145	144	134
GDD	SSP245	144	144	146	148	148	146	136
	SSP370	146	146	148	149	149	147	138
	SSP585	191	190	193	195	196	194	182

(F-CR: Fieldcrops-Crop rotation, F-F: Fieldcrops-Fertilization, Fieldcrops-Tillage, G-F: Grassland-Fertilization, PM-F: Pomiculture-Fertilization).



Appendix 2. Spatial distribution of the differences of agroclimatic indicators from present to 2081–2100.

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