Weather you like it or not

Pre-season yield forecasting of malting barley with climate markers

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Agricultural programme – Soil and Plant Science
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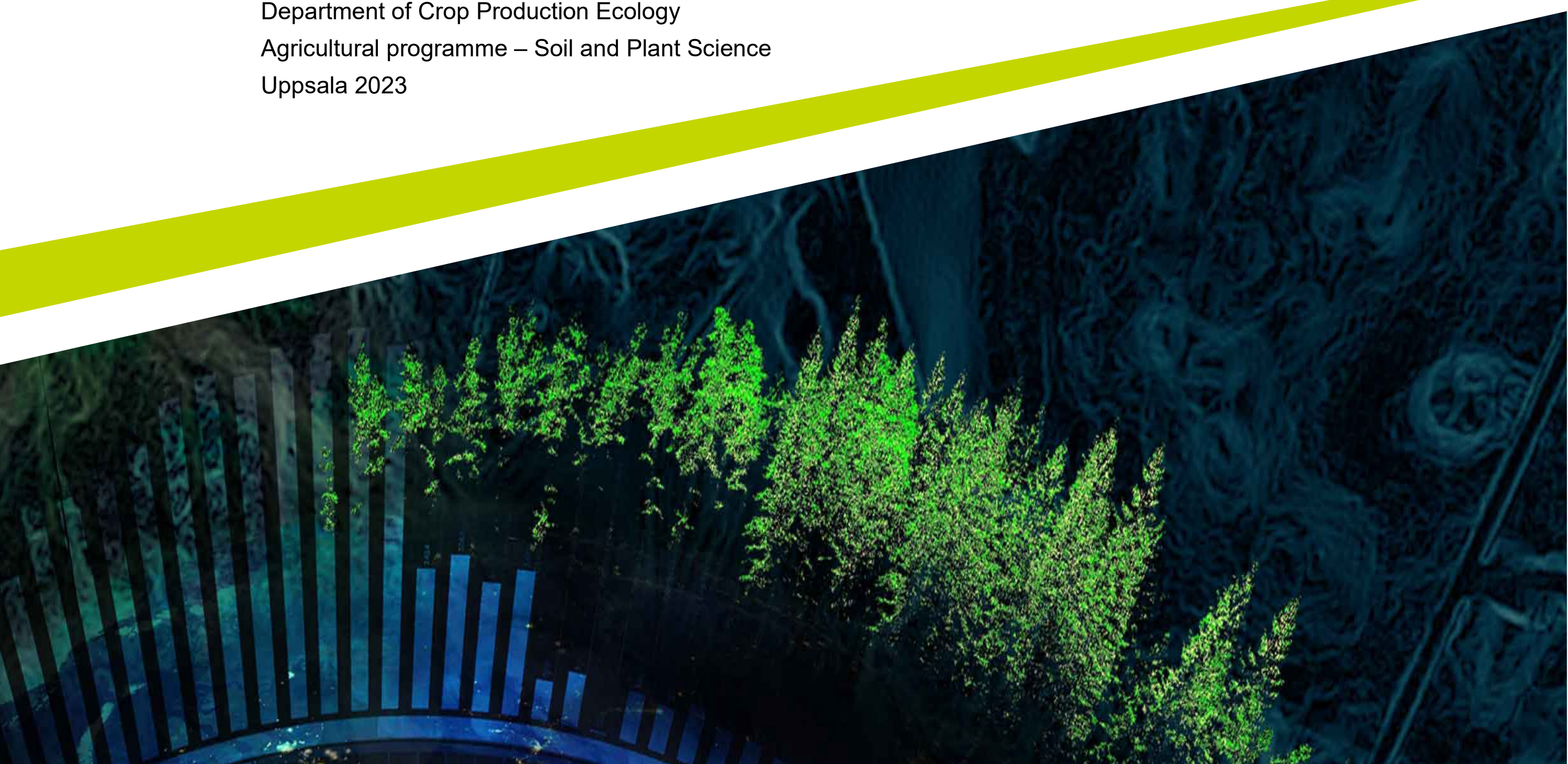

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Abstract

Different means of yield forecasting have been investigated in many publications, although very few with a focus on pre-season forecasting. Climate change and the increasing risk of extreme weather events is a threat to food production, and early yield predictions could therefore be beneficial for farmer's planning and management as a way towards more resilient food production. This thesis aims to explore if yield forecasting of malting barley in Southern Sweden can be done using climate markers of weather occurring during the 60 days before the beginning of the cropping season. Data from field trials, conducted between 1999 and 2018 and acquired from NTFS and SLU Fältforsk, were used as experimental data to calibrate and evaluate the CERES-Barley crop model. Three cultivars were used: Astoria, Irina and Propino. The model input additionally consisted of weather data from AgERA5 and soil profiles from ISRIC that were connected to the field trial sites. The climate markers and the simulated mean yields were tested with a linear mixed model analysis and a Pearson chi-square test in RStudio. The crop model was successfully calibrated, with Astoria being the best cultivar to mirror observed yields from different years and locations in Sweden. The results indicated, however, that none of the analysed climate markers during the 60 days prior to the beginning of the cropping season was able to explain malting barley yields, highlighting the difficulty in making early yield forecasts. One hypothesis for this lack of explanatory power from the climate markers on the yield of spring malting barley is that the effect of precipitation in the 60 days before the beginning of the cropping season is buffered by winter and early spring, when soils are usually at or close to field capacity.

Keywords: Yield forecasting, extreme weather, pre-season forecasting, climate markers, climate predictors, climate patterns, model calibration, DSSAT, crop model

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Abbreviations

LMM	Linear mixed model
MAE	Mean average error
N	Nitrogen
n.d.	No date
RRMSE	Relative root mean square error

1. Introduction

With climate change the demand of resilient food production is ever present. The uncertain future agriculture is facing as a consequence of climate change calls for new management tools to make food production more resilient (FAO 2015).

While yield is often directly related to, or explained by the weather during the cropping season, less is known about possible pre-season weather impacts on yield (Bellouini et al., 2020). As of today, there are various tools used to make forecasts of yield and quality forecasting such as remote sensing, statistics, crop models, satellites, seasonal patterns, and machine learning (Basso et al., 2013; Yaramasu et al., 2020; Qian et al., 2009; Ali et al., 2022; FAO 2015; Bannayan et al., 2003; Pettersson 2007). Many of these tools are, however, still not applicable, or very well adapted to make pre-season forecasts. The existing tools are also often heavily time consuming and as of now the geographical scope of forecasts is limited and not equally explored across the planet (Schauberger et al., 2020. For agriculture to better adapt to changing cropping conditions and the risks of extreme weather, pre-season forecasting could be a powerful tool. By knowing pre-season conditions, especially how extreme weather may interfere with yield, there is room for farmers to plan the cropping season (e.g. cultivar, fertilizer and sowing). This thesis will investigate how crop models and data of pre-season extreme weather events in Sweden might help to forecast yield levels of spring sown malting barley.

1.1. Objectives

The aim of this thesis is to investigate the possibility to forecast yield levels of malting barley and if yield is dependent on or affected by pre-crop season climate markers. This will be accomplished by using data from field trial experiments conducted in Southern Sweden of malting barley to calibrate the cropping model DSSAT CERES-Barley and run simulations using gridded weather data with characterization of extreme weather events. The two specific objectives for this thesis are:

- to calibrate the CERES-Barley model based upon data from field trial experiments.
- to analyse the correlation of yearly weather markers against simulated yields from the calibrated model to determine if pre-season climatic factors have the power to explain yield.

1.2. Background

1.2.1. Malting barley production in Sweden

Barley (*Hordeum vulgare*) is one of the oldest cultivated and remains to this day an important crop in Sweden. Today barley is grown for both animal feed and malting, making it economically important (Fogelfors 2016). In Sweden, malting barley is commonly grown as a spring crop. On a global scale, barley is the fourth most cultivated cereal, with Europe being the main producer of more than 60% of the total global production (FAOSTAT, 2023). In Sweden, two-row barley is the dominating variety for malting purposes and the production is mainly located in the southern parts of the country (Fogelfors, 2016).

For farmers, the key when producing malting barley is to obtain the right level of grain protein, between 9.5 and 11%. The protein level is very much dependent on abiotic factors such as temperature, day length, radiation, and nutrient availability at certain times of the plant's development (Pettersson, 2007). Location and development rate has also proved to be important contributors to the final beer quality (Johansson, 2011).

1.2.2. Climate change and extreme weather

Climate can be defined as the mean weather of the previous 30 years. Weather is described as variations of atmospheric conditions such as precipitation and temperature (Bolin Centre for Climate Research, 2019; SMHI, n.d.).

Farmers across Europe faced great yield losses during the 2018 cropping season due to extensive drought (Beillouin et al., 2020; Grusson et al., 2021). Extreme weather events such as drought and heavy rains have occurred in history but not to the same extent as the more recent ones. The term extreme weather events implies that a value of temperature, wind, or precipitation is either above or below a given threshold (IPCC 2021). The threshold that defines the dimension of extreme events are, however, not unified. Grusson and Barron (2021) found similar results when comparing different reanalysis products. In their results they could see that there was a large variability in how the different reanalysis products had quantified extreme weather events. According to a report from IPCC (2021), extreme weather events are expected to occur more often and appear more extreme. Looking into the conditions of Swedish agriculture, future predictions tell of increasing precipitation mainly during winter and spring and with increasing risk of droughts and intensive rainfalls during summer (SMHI, n.d.; Naturvårdsverket, n.d.) As Swedish agriculture is mainly rainfed, extreme weather trends may have a significant impact on crop production (Grusson et al., 2021). de Toro et al. (2015) investigated how the yield of the most common crops in different regions in Sweden from the year 1964 to 2014 have been affected by extreme weather. They found that precipitation events occur more often and that this may cause problems of logistics and timing during harvest. Similarly, to previously stated predictions, they could also observe a shift towards higher mean temperatures in Sweden.

What climate change ultimately means, in the perspective of plant biology, is a change in the environment and living conditions for crops and their interactions with other living beings (Bhadra et al., 2021). Changes in amounts, timing, and durations of parameters such as precipitation, solar radiation and temperature all impact the life cycle of plants. An example of this was presented in a recent paper by Kaseva et al. (2023). By comparing yield levels in Nordic barley cultivars against agrometeorological factors over a 40-year time period they found that the cultivars had become more vulnerable against irregular weather patterns. Direct impacts of extreme weather may cause physical damage to crops, delayed time for planting and harvest, temperature, and water stresses. Time and duration of extreme weather events are the basis that determine the scope of yield loss. Malmquist and Barron (2022) mapped definitions of extreme weather in the Nordic countries and found that, even though there is a lot of research in the field, there were so far no unified definitions of extreme weather events.

1.2.3. Extreme weather effects on barley phenology and yield

When discussing climate change, it is important to understand how phenology and growth are impacted by extreme weather. Under optimal conditions, both growth and development are decided by thermal time or heat sum. The heat sum of a given day is the mean temperature of that day, calculated using its minimum and maximum measured temperatures (Rawson & Macpherson Gómez 2000). In order for a plant to pass onto its next development stage, it needs to accumulate a certain thermal time, i.e., a running total of the mean temperature each day (Fig 1). The thermal time (Ritchie et al., 1998) can be defined as:

$$t_b = \sum_{i=1}^{n} (T_a - T_b) \qquad (1)$$

T_a = average daily air temperature
T_b = temperature where plant development stops
n = number of days

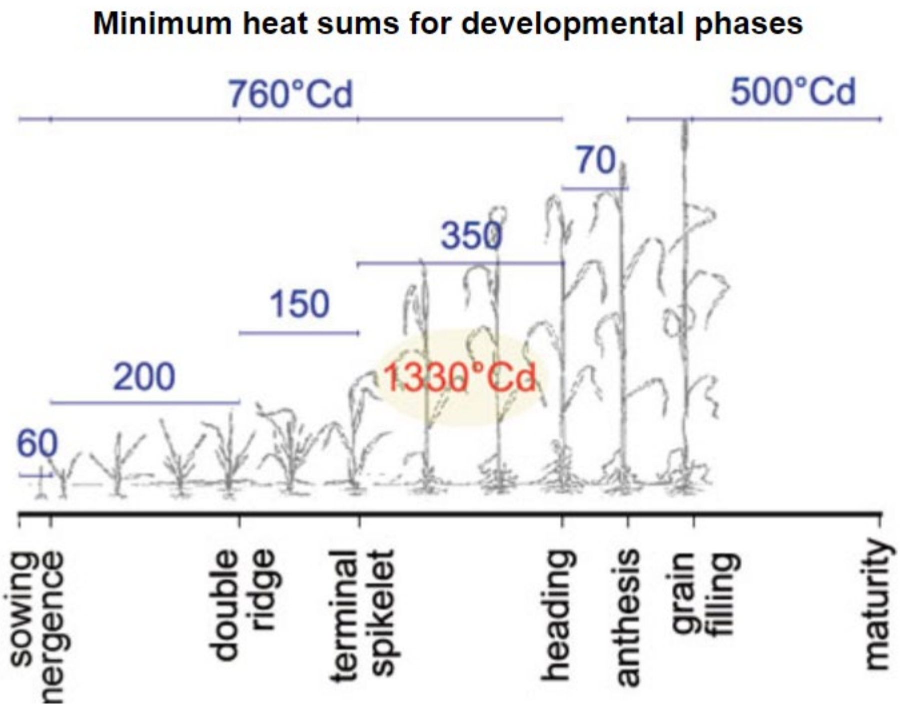

Figure 1. The temperature sum needed for a plant to go into its' next development stage, measured in degree days (°Cd). Figure made by HM Rawson (Rawson & Macpherson Gómez 2000).

Anthesis and kernel filling are critical stages regarding the quality formation of malting barley. Both extreme cold and high temperatures can negatively affect the number of flowers, which in turn determines the final kernel yield. During the initial growth phases of the plant, increasing temperatures induce a heightened rate of thermal accumulation within the crop, consequently leading to a shortened developmental duration (Petterson 2007). Subsequently, during later development stages, increased temperatures may induce physiological stress, leading to a reduced duration for grain filling. This, in turn, results in decreased starch content within the stem and an increase of grain protein levels, occasionally reaching unfavourable concentrations. (Schelling et al., 2002; Pettersson 2007; Al-Ajlouni 2016; Hakala et al., 2016; Saiyed et al., 2009). Frost damage can cause cell damage and may inhibit photosynthesis. In the earlier development stages the severity is not as large as when frost occurs in anthesis or heading (Frederiks et al., 2015; Martino et al., 2019). Another consequence relating to frost damage is that the grains might not be able to germinate which is crucial for the malting process.

Water stress occurs when the water potential falls below the threshold required for plant absorption (Havrlentova et al., 2021). Regarding germination, moisture is a catalyst for the germination of most of the cultivated species (Havrlentova et al., 2021; Kar 2011). Inadequate water availability after germination can lead to an uneven crop stand and reduced seedling survival. In response to water scarcity, the plant's short-term reaction mechanism is to close stomata to reduce evapotranspiration, leading to a decrease in the rate of photosynthesis (Havrlentova et al., 2021; Kar, 2011). Another effect following water deficiency is a reduced flower initiation and abortion, resulting in fewer grains per straw; when occurring during the grain filling phase, it can reduce the grain weight. During the grain filing stage, water deficiency may also lower the level of protein in the grains (Havrlentova et al., 2021). Conversely, stress may also be caused by an abundance of water (Zhou et al., 2020).

Soil saturation by waterlogging and flooding also impacts yield as the plant's root development is restricted due to insufficient oxygen, limiting respiration, resulting in anoxia and the production of reactive oxygen spices (Herzog et.al, 2016; Arslan Ashraf, 2012). These responses hinder overall plant growth, with the duration and timing of extreme weather events playing a crucial role in determining the ultimate impact on crop yield (Tian et al., 2021).

1.2.4 Yield forecasting with crop models

There are different approaches to make yield forecasts, such as remote sensing, machine learning and crop models. Crop models have the ability to concretize an already complex and dynamic system and have therefore been considered helpful tools in understanding, creating and making predictions in complex systems such as agriculture (Wallach et al., 2014). One main disadvantage of crop models is their inability to account for biotic stresses such as pests and weeds (Roberts et al., 2017; Lobell & Asseng, 2017). It is however important to note that a crop model is not able to fully predict the outcome of a cropping season, its power lies within its capability to make likelihood predictions based previous data of i.e., weather, agronomic management, and yield levels. To better list functions of cropping models, some differences, and similarities between process-based and statistical models are summarised in Table 1.

One example of a process-based crop model is the DSSAT (Decision support system for agrotechnology transfer) CERES-Barley crop model, which uses seven growth stages: germination, emergence, maximum primordia, end ear growth, beginning of grain fill, maturity, and harvest (Hoogenboom et al., 2022). To calculate plant growth CERES-Barely uses growing degree days (0ºC as base temperature) and photoperiod. A development stage is reached as a certain temperature has been accumulated. The CERES-Barley crop model makes daily calculations of plant growth and phenology based the model inputs. In similarity to other crop models the basic input data consist of:

- Local daily weather data of the cropping season
- Soil profiles
- Crop management information of the experiment (Hoogenbom et al., 2023)

Table 1. Comparison of general similarities and differences between process-based and statistical crop models. Adapted from Schibalski (2017) and Adams et al. (2013).

	Process-based	*Statistical*
Relationship type	Causal, dynamic	Correlative, static
Relative comprehensiveness	More comprehensive but not very general results	Less comprehensive but more general results
Incorporation of mechanism	Explicit	Implicit
Primary source of error	Unknown parameters and processes	Extrapolation due limited data availability
Parameters	Have ecological explanation	Have no ecological explanation
Model uncertainty	Higher	Lower
Data requirements	Higher and more specific	Lower, can be more general
Spatial scale for calibration	Low	Low to larger
Spatial scaling of prediction	Smaller to Larger	Best at scale of calibration

2. Methods

2.1. Study region

Southern Sweden extends over the 55-59th latitude and the 13-18th longitude and has a varied annual mean temperature circling 4°C and 7°C (Fig 2) (SMHI, 2023). Annual accumulated precipitation ranges between 400 to 1000 mm. The regional mean temperature during the summer period is around 18°C. In general, most precipitation is distributed during summer and autumn.

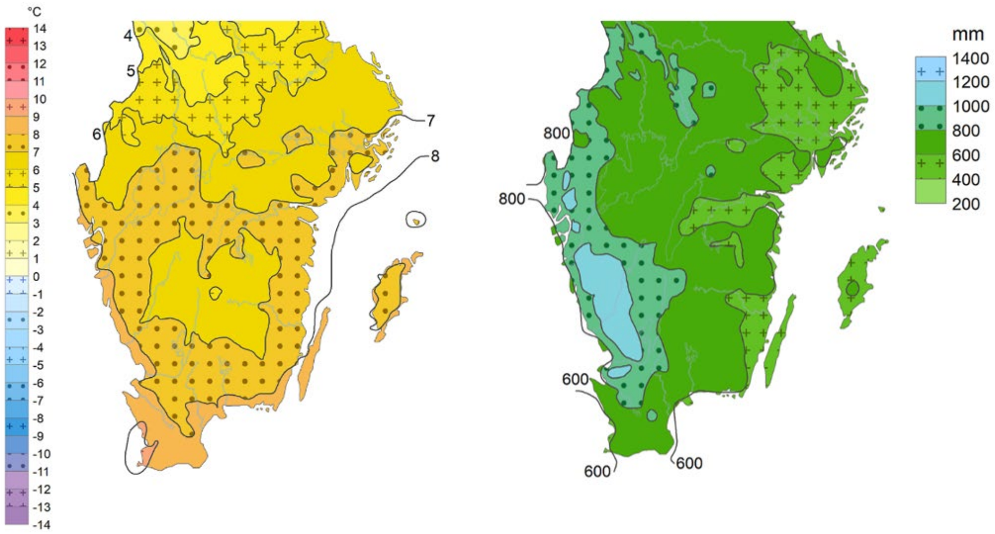

Figure 2. Maps adapted from SMHI presenting the mean annual amount of precipitation (left) and temperatures (right) of the years 1991 and 2020 in Sweden (2023).

2.2. Data

2.2.1. Field experiment data

In order to properly run a crop model, observations from field data are required for calibration, validation and further impact assessment studies. Data from field experiments on spring grown malting barley conducted between 1999 and 2018 in Götaland and Svealand, the southern part of Sweden, were used to calibrate and validate the model (locations of the field experiments are shown in Fig 3). The data consisted of 84 field experiments each containing

733 experiments and three malting barley cultivars: Astoria (253 experiments), Irina (279 experiments) and Propino (201 experiments). Experimental data for the years 2013 to 2018 were acquired from the Nordic Field Trial System (NFTS, 2022). Data on the earlier experiments were obtained from SLU Fältforsk (SLU Fältforsk, n.d.). The collected information included yield levels, management, fertilizer rates and harvest date.

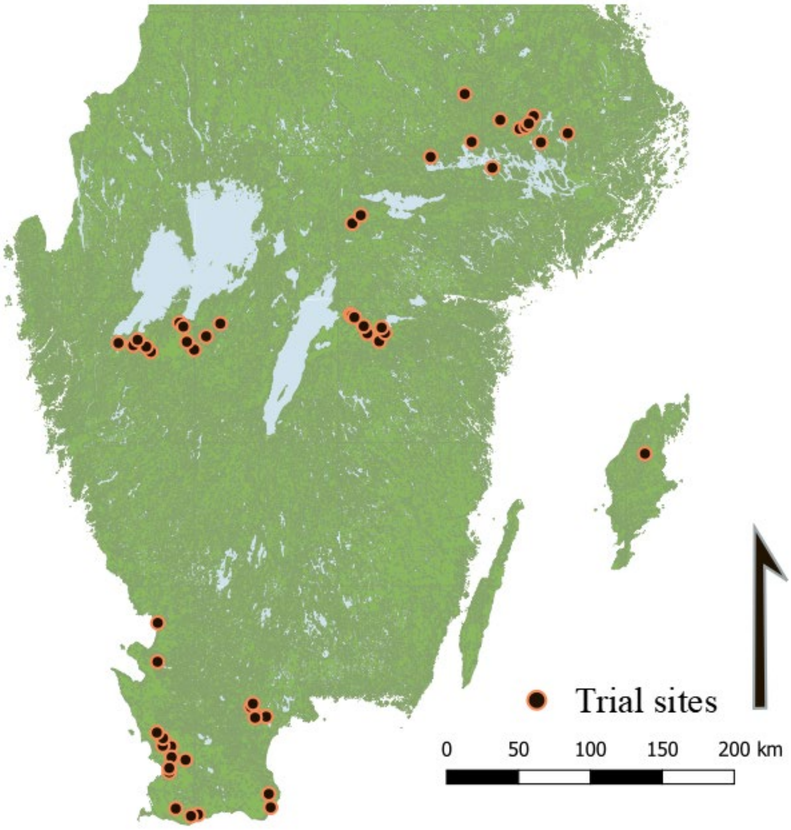

Figure 3. Overview map displaying the 84 trial site's locations in the regions of Götaland and Svealand used in the project as the main source of data. Map created in QGIS (2022), map layers obtained from Översiktskartan ©Lantmäteriet (2023).

To increase the number of experimental data (field observations) and improve the model performance, experiments with some missing information were also included. Since the missing information from the experiments were of dates and/or coordinates, these could still be incorporated without significantly affecting the outcome of the model calibration. The missing dates for sowing and fertilizer application were interpolated based on experiments from the same area.

Experimental sites lacking coordinates were randomly assigned coordinates within the corresponding municipal boundaries using data and maps from Lantmäteriet (2023). This allocation was executed using QGIS Geographic Information System (2022) version 3.24.0.

2.2.2. Soil and weather data

Soil profiles in a gridded format were obtained from ISRIC version 2.6 (IRI, 2015). The obtained soil profile data used in the DSSAT v 4.8 (Decision support system for agrotechnology transfer) CERES-Barley model contains information on horizon depths, soil grain properties, pH, organic carbon, saturation of aluminium and bulk density (Hoogenboom et al., 2003).

Weather data were procured from AgERA5, from Copernicus Climate data store (Copernicus Climate Change Service, 2019). The AgERA5 is a gridded long term reanalysis product featuring daily climate data of sun radiation, minimum and maximum temperatures between the years 1979 and 2018The AgERA5 was chosen based on the results from a review by Grusson and Barron (2022) where it was identified as the best performing (smallest deviation from a baseline of observed data) reanalysis product that is still producing data.

Since the simulation was to cover 40 years, the use of gridded data would ensure the absence of non-continuous data, which is a particularly common problem when covering broader geographical areas. The gridded weather and soil data were associated to each of the 54 experimental sites using QGIS to prepare a complete dataset needed to operate the crop model.

2.3. Crop modelling

To investigate the possibility to forecast yield with the help of climate markers, the CERES-Barley cropping model was used. The general method for calibrating and operating the CERES-Barley cropping model in this project is briefly explained by the schematic below (Figure 4). First the CERES-Barely model was calibrated using the observed data of three malting barley cultivars from the field trial experiments and the gridded weather data (using data described in Section 2.2). After the calibration was deemed successful, it was run to simulate yields between the years 1979 and 2018. Following the simulations, the obtained results were correlated in relation to various climate markers, with the objective of identifying those that could forecast yields.

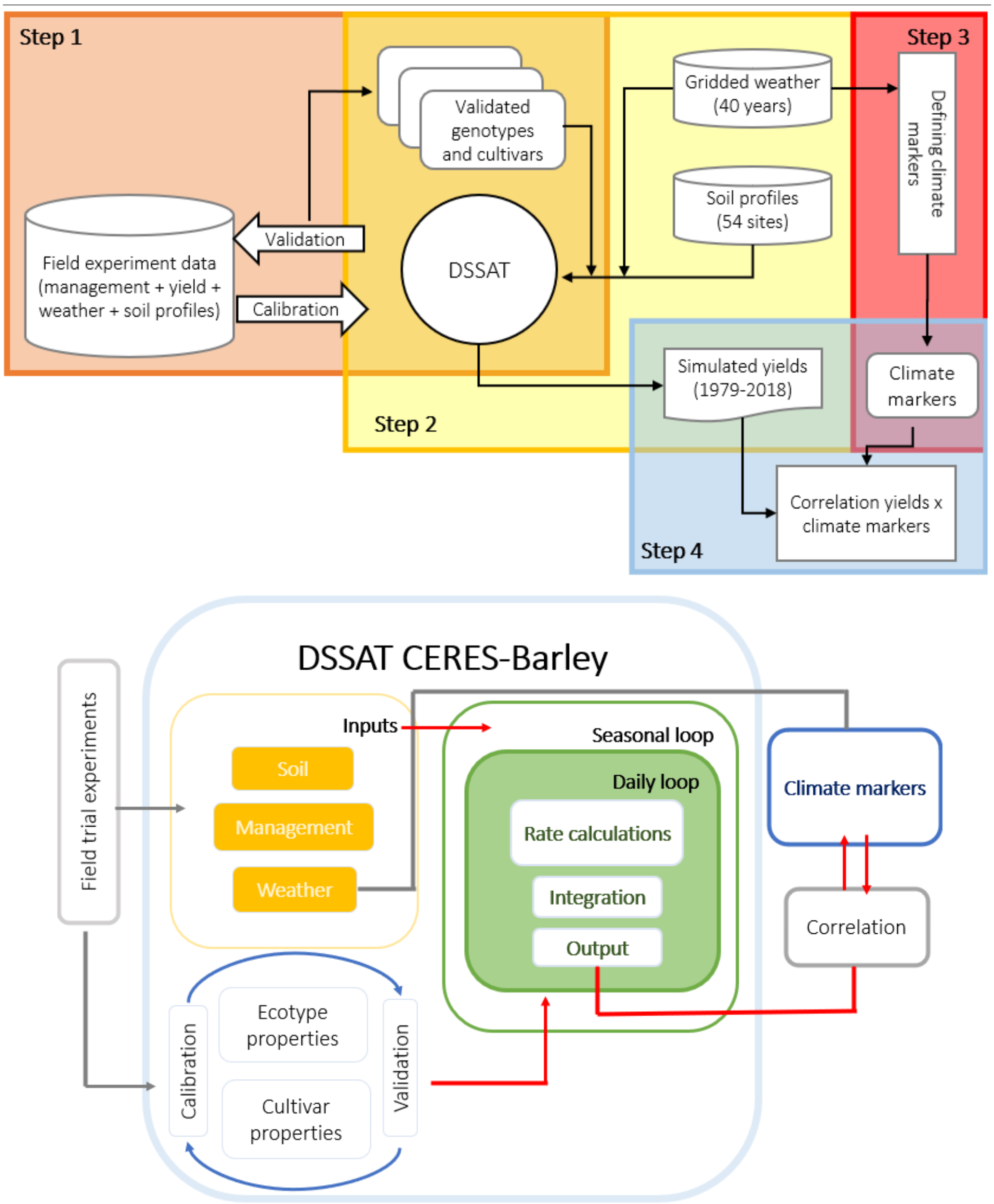

Figure 4. The summarised workflow of the modelling of CERES-Barley (above). Starting with calibrating and validating the model using field experiment data as input (Step 1), followed by conducting yield simulations (Step 2), the definition and calculation of climate markers (Step 3) and finally the correlation of yields with climate markers. (Step 4). The CERES-Barely crop model functions and workflow relating to the methodology of this project are explained in segments in the figure below. (Rozenbeek 2023).

2.3.1. Model input data

The model input data consisted of soil profiles, weather data and management data all described in section 2.2. The management input data mimicked the information from the 733 field experiments to fullest extent possible and contained the following:

- Sowing date
- Dates of fertilizer application
- Date of harvest
- Grain yield (kg/ha)

- Rates of nitrogen fertiliser
-

It was arbitrarily decided to make the following assumptions about agronomic management and base temperature consistent across all experiments:

- Row spacing: 12 cm
- Plant density 90 / m^2
- Broadcast incorporated fertilizer
- Ammonium nitrate fertilizer as N source
- Base temperature of 0°C

This unification was decided to make the calibration and the simulations easy to conduct and analyse, and made regardless of if there was specific information on e.g. type of fertilizer for certain field experiments.

2.3.2. Crop model calibration and evaluation

The aim of calibrating a model is to adjust coefficients the describe the model's behaviour according to real observations (Wallach et.al, 2021). In this project specifically genetic coefficients describing the variables determining *yield* and *maturity day* of the three cultivars Astoria, Irina and Propino were calibrated and validated against observed data from field experiments.

Each of the cultivar's parameter were then calibrated using 1500 iterations in the Generalized Likelihood Uncertainty Analysis, GLUESelect (Hogenboom et al., 2021). GLUE is a Bayesian approach that takes standard information and experimental data for the coefficient estimation. GLUE Select randomizes all possible values within a predetermined range for the cultivar coefficients. The range of values for each parameter is limited by observed data from different field trial experiments. Within the CERES-Barley model both cultivar coefficients and ecotype coefficients were used to calibrate the cultivars. The cultivar coefficients are calibrated based on specific traits of growth and development, while the ecotype coefficients consist of traits/parameters that are more constant for the specific crop and for it is grown (Hoogenboom et al., 2003). The ecotype for a cultivar was chosen based on how well it performed together with the cultivar coefficients during the calibration. The cultivar coefficients (Hoogenboom et.al 2023; Singh et al., 1998) that were calibrated are defined as follows:

- P1D Change of growth development rate due to photoperiod response (% reduction in rate/10 h drop in photoperiod)
- P5 Duration of grain filling phase, number of days >1°C that are needed [degree days]
- G1 Kernel number per unit canopy weight at anthesis [Kernel number/g]
- G2 Standard kernel size under optimum conditions [mg]
- G3 Standard, non-stressed mature dry tiller weight (including grain) [g]
- PHINT Number of days that are required for a leaf tip to appear [degree days]

Initially, only phenology-related cultivar coefficients (P1D, P5 and PHINT) were calibrated using 1500 runs. After satisfactory matching of the observed values for maturity, phenology-related coefficients where fixed and another round of 1500 simulations only for production-related parameters (G1, G2 and G3) was run. The split calibration approach, as suggested by Wallach et al. (2019), ensures that the growth parameters are adjusted according to the phenology parameters. The values of the coefficients in both the cultivar and ecotype files were further manually refined within certain ranges that were measured in the field experiments and additionally generated with GLUESelect. This ensured that there would be no occurrences of impossible combinations of parameter values. Additionally, adjustments were made to the field capacity parameters for select soil profiles. During the calibration of a cultivar, if there were any values exceeding the quantile ranges of the observed values for yield and maturity day were systematically removed to enhance the model performance.

The calibration was deemed complete when the model could mimic both *yield* and *maturity day* with an acceptable mean average error with the relative root mean square error, RRMSE. The RRMSE is a relative measurement and thus useful when working with different units, in this case both days and weight. For this work, it the RRMSE was interpreted as *optimal* if ≤10%, *good* if ≤20% while *fair* ≤30% and *poor* if >30% (Pachepsky & Rawls 2004). In this work, a calibration was considered valid only if the RRMSE of the validation for maturity date and yield levels was ≤30%.

2.3.3 Run of simulations

For each calibrated cultivar a simulation in CERES-Barley crop model was run with the gridded weather data for the years between 1979 and 2018 and the 54 sites. The simulation also included four fertilizer treatments, creating 8640 virtual experiments per cultivar. Each site and year had a sowing date corresponding to the start of the cropping season. The start of the cropping season was defined as the last day of the first period of five consecutive days with an average daily temperature above 5 °C that occurred after March 1st (FORMAS, 2020-2023). Four rates of nitrogen fertilizer: 0, 75, 100 and 125 kg nitrogen/ha were used as treatments for the cultivars on each sowing date, previously calculated in the FORMAS project (2020-2023). In total 54 sites, based on the trial locations from SLU Fältforsk and the same ones used in the model calibration, were used in the simulation. For the purpose of data management, the 54 sites were further divided into four distinct production regions, designated by the Swedish Board of Agriculture (Jordbruksverket, n.d.) (Fig 5). The region division facilitated the potential for making regional comparisons of historical observed yield data across various cropping seasons.

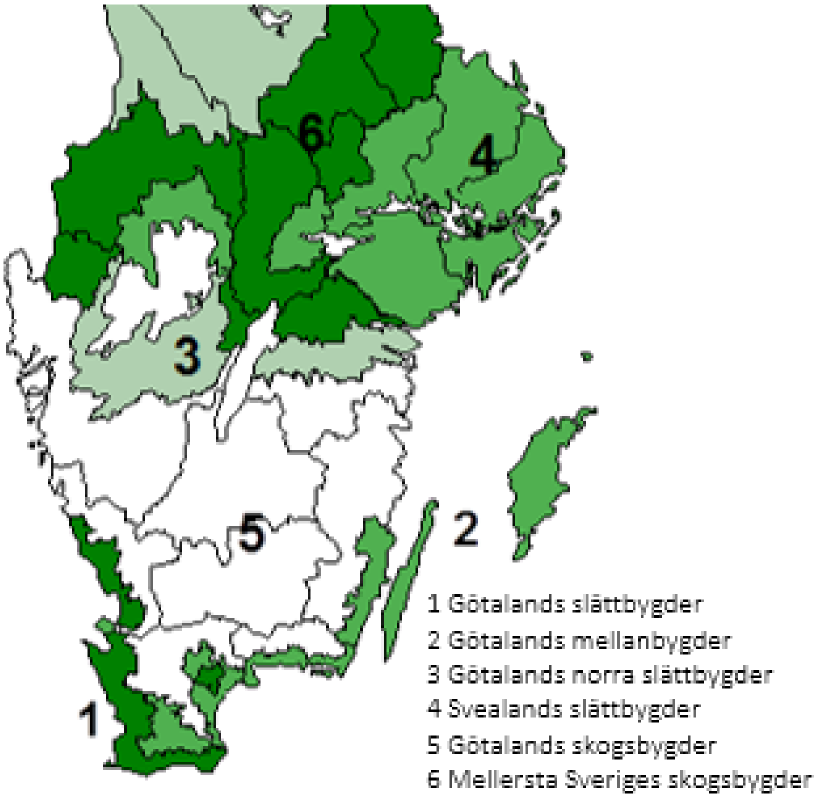

Figure 5. Production regions of southern Sweden. Region 1-4 covers the area in which the field trial experiments were conducted. Adapted from Jordbruksverket (n.d.)

2.4. Climate markers

The dataset of climate markers that was used in the analysis was provided by the project *Extreme weather and crop yield in Sweden* (FORMAS 2020-2023). The dataset consisted of defined values of different climate marker variables 60 days before the start of the cropping season. The variables were defined for the same 54 sites that were used in the crop simulation. For each site, the gridded weather dataset was established, comprising 17 distinct climate variables spanning every year from 1979 to 2018. Calculations made to define the climate markers are presented in Appendix 1. The variables were also classified in two ways and later used as separate datasets in the analysis: one with numerical variables and one with variable categorised as *extreme low, very low, low, regular, high, very high and extremely high*. Categorised values were defined within the interval presented below:

- *Extremely high* > 99^{th} percentile
- *Very high* >90^{th} ≤99^{th} percentile
- *High* >75^{th} ≤90^{th} percentile
- *Regular* > 25^{th} ≤75^{th} percentile
- *Low* ≤25^{th} >10^{th} percentile
- *Very low* ≤10^{th} >1^{st} percentile
- *Extreme low* ≤1^{st} percentile

The pre-season climate markers with their highest and lowest value are presented and described in Table 3.

Table 2. The climate marker variables (considered in the period of 60 days prior to the start of the cropping season) used for the statistical analysis and their definition including the highest and lowest value of each variable. The start of the cropping season changes depends on the year and location, and is defined as the last day of the first period of five consecutive days with an average daily air temperature above 5 °C that occurs after March 1st.

Climate marker variable	*Variable explanation*	*Variable nr.*	*Lowest value*	Highest value
Nb_ColdSpell	Number of Cold Spells, 6 days of temperatures below the 10th percentile of minimum daily temperatures (number).	Var1	0	5
Nb_DailyExtr_PcP	Number of daily extreme precipitation above the 99th percentile of the 40 years distributions of daily precipitation (number).	Var2	0	5
Nb_days_ColdSpell	Number of days included in Nb_ColdSpell (number).	Var3	0	29
Nb_days_ColdWet	Number of days included in Nb_WetDays and Nb_ColdSpell (number).	Var4	0	8
Nb_days_DrySpells_5d	Number of 5 days or more with precipitation <1mm (number).	Var5	0	56
Nb_days_WarmDry	Number of days included in dry spell, at least 5 days <1mm precipitation and Nb_WarmSpell (number).	Var6	0	16
Nb_days_WarmSpell	Number of days included in warm spells (number).	Var7	0	18
Nb_days_WetSpells_5d	Number of days with precipitation >=1mm included in wet spells of 5 days or more (number).	Var8	0	31
Nb_DrySpell_5d	Number of dry spells of 5 days or more with <1mm precipitation (number).	Var9	0	6
Nb_frost	Number of late frost days with minimum temperature below 0°C (number).	Var10	0	60
Nb_WarmSpell	Number of 6 days of temperatures above the 90th percentile of maximum daily temperatures (number).	Var11	0	4
Nb_WetDays	Number of wet days with a precipitation >=1mm (number).	Var12	4	41
Nb_WetSpell_5d	Number of wet spells of 5 days or more during the first 60 days of the cropping season (number).	Var13	0	4
Ratio_DailyExtr_PcP	Ratio of precipitation falling during extreme events, Daily precipitation above the 99th percentile of the 40 years distributions of daily precipitation (number).	Var14	0	0.67
Tmp_average	Average temperature during the first 60 days of the cropping season (Cº).	Var15	-3.38	5.59
Vol_Average_Wetday	Average precipitation volume per wet days (>1mm) (mm per day).	Var16	1.82	8.903
Vol_ToTal_PcP	Total Precipitation volume during the first 60 days of the cropping season (mm).	Var17	19.6	257

2.5. Correlation analysis

The statistical analysis aimed to assess the relationship between climate marker variables (as presented in Table 3) and the mean simulated yield (fertilized with 100 kg N/ha) using a chi-square test and a mixed linear model (LMM) analysis. All statistical analyses were conducted using RStudio version 4.2.2, and with expert guidance from a statistician affiliated with the

Statistics@SLU service at the Swedish University of Agricultural Sciences was sought. A visual summary of the statistical analysis is presented below in Figure 6.

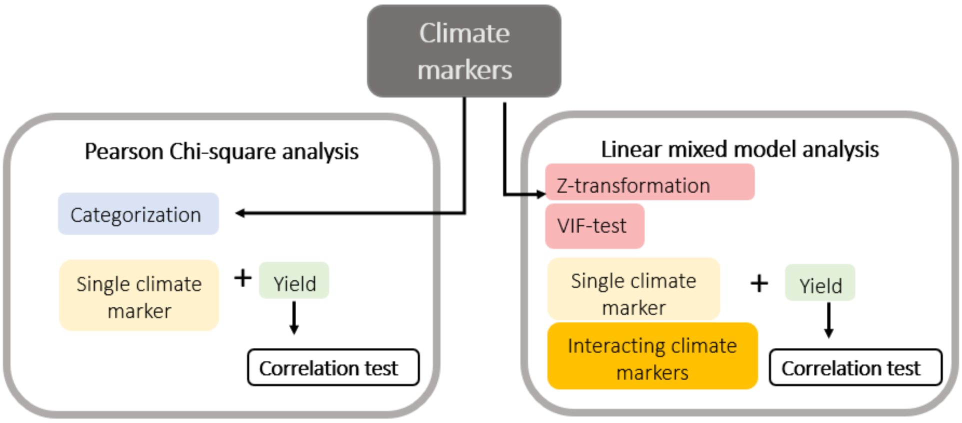

Figure 6. Flow chart of the statistical analysis procedures with climate markers against yield. The chart presents the procedures of the chi-square test (left) and the linear mixed model (right).

Initially, a pairwise correlation with a Pearson chi-square test was conducted on yield for every gridded weather data point and year for each climate marker categorical variable, as suggested by Khamis (2008). The simulated yield data for each site were also categorized into four levels, based on quartiles of site-specific yields: the 1st quartile represented low yields, the 2nd quartile represented low to high yields, the 3rd quartile represented high to low yields, and the 4th quartile represented high yields. An example of how the dataset for one site is presented in Appendix 2. The simulated yield of every site (Figure 3) was also categorised in four levels, according to the quartiles of the yield for each site. *Low* yields were represented the 1^{st} quartiles, a *lowhigh* yields represented the 2^{nd} quartile, *highlow* yields represented the 3^{rd} quartile and *high* yields represented the 4^{th} quartile.

The second analysis was the linear mixed model test. The analysis was run with a dataset of Z-transformed predictor variables and yield levels. Z-transforming data transform the values into dimensionless values that are comparable. The linear mixed model approach is suitable for normally distributed datasets where there might be an independence among variables (Brady et al., 2022). This approach was selected because it can account for both fixed and random effects, which is not feasible with the chi-square analysis. *Sites* (same as the experimental sites) served as random effects while the climate markers were clustered variables and functioned as fixed effects in the LMM. This was decided as the goal was to specifically investigate effects from the climate markers on yield, and the while the *site* was not the primal object. The choice of a LMM was made as it has been used in previous attempts to make yield forecasts (Verma et al., 2015; Mathieu and Aires 2018).

Before running the LMM the climate markers were filtered to ensure that predictor variables were independent and not correlated with each other. This was made with the variance inflation factor (VIF) using a step wise approach (Schierhorn et al., 2021). Variables with a VIF >10 were iteratively removed until all remaining variables had a VIF <10. For the analysis two models were fitted and correlated against yield; one model with the single climate marker variables and the second one was fitted with both single and pairwise interacting variables. This method aimed to determine whether there could be a distinct impact on yield from individual climate markers, as well as from combinations of these markers The script for the LMM in RStudio is showcased below in Figure 7.

```
### 1 ### Check for multicollinearity using VIF
# create a linear regression model
fit <- lm(Yield_kg_ha ~ ., data = crop_data)

#Define multiple linear regression model
model2 <- lm(Yield_kg_ha~
               Var1 +
               ...
               Var17,
             data = crop_data)

#Calculate the VIF to check for multicollinearity in each predictor variable in the model
vif(model2)

#Stepwise regression, remove with iteration fist variables with VIF-value higher >10
#Output VIF-model:> vif(model)

### 2 LMM model ###
# Create new columns to descirbe pairwise interaction between predictor variables
{
  crop_data$Var2_Var3 <- crop_data$Var2 * crop_data$Var3
  ...
  crop_data$Var16_Var17 <- crop_data$Var16 * crop_data$Var17
}
# Clustered model with each predictor alone and with an parirwise interaction
predictors <- crop_data[, c("Cent_yield","Year","Var2", ... "Var16_Var17")]
```

Figure 7. Script with description of the steps that was used in R.studio version 4.2.2. to conduct the Linear mixed model analysis, correlating Yield (Yield_kg_ha) with climate markers (Var1 etc.) (defined in Table 2).

3. Results

3.1. DSSAT Crop model calibration and validation

The parameters of the calibrated cultivars used for the simulation are presented below in Table 4.

Table 3. The coefficients of each cultivar (Astoria, Irina and Propino) that were calibrated in the GLUESelect tool and used in the cultivar file for the simulation in the DSSAT CERES-Barley cropping model.

Cultivar	P1D	P5	G1	G2	G3	PHINT	Ecotype
Astoria	40	500	18	50	5	60	US0001
Irina	0.2	646.1	35.25	59	5.548	60	SY0002
Propino	17.99	614.8	39.99	61.8	6.136	60	SY0003

* P1D = Photoperiod response (% reduction in rate/10 h drop in phenology phase)), P5 = Grain filling phase duration (degrees day), G1 = Kernel number per unit canopy weight at anthesis (#/g), G2 = Standard kernel weight under optimum conditions (mg), G3 = Standard, non-stressed mature tiller weight (including grain) (dry weight, grams), PHINT = Interval between successive leaf tip appearance in degrees day. Ecotype refers to a list of 19 traits/parameters that vary less often between similar cultivars, such as thermal time to emergence and first leaf stages.

The model calibration and validation showed closer alignment for *Maturity day* compared to *Yield* between simulated and observed values (Table 5). Specifically, for the 'Astoria' cultivar, no significant differences were observed post-validation, maintaining consistent R^2-value (0.86) and root mean square error RRMSE value (0.07). Overall, differences in the model's *Maturity day* variable calibration among cultivars were generally minimal. 'Astoria' exhibited the most linear variables, with R2 (0.86) and RRMSE (0.1). Notably, the calibration for Propino regarding yield reduced the mean average error, MAE, by 43%.

Table 4. Results from the model calibration and evaluation of DSSAT Ceres Barley of the cultivars Astoria, Irina and Propino which included the variables Yield (Yield kg/ha) and Day of maturity (Mat. day). The table presents the number of observed and simulated experiments (Nb.exp), the root mean square error (RRMSE), mean absolute error (MEA) and R-square values of the variables. The RRMSE is considered "optimal" if <10%, "good" if <20% "fair" if <30%, "poor" if >30% (Pachepsky & Rawls 2004).

		Calibration				Validation			
	Variables	Nb.exp	RRMSE (%)	MAE	R^2	Nb.exp	RRMSE (%)	MAE	R^2
Astoria	Mat. day	252	7	7.44	0.86	235	7	7.4	0.86
	Yield kg/ha	252	20	706	0.09	229	10	403	0.59
Irina	Mat. day	279	6	5.75	0.64	277	6	5.76	0.64
	Yield kg/ha	279	24	1065	0.59	273	22	1004	0.64
Propino	Mat. day	201	5	5.44	0.57	171	6	5.8	0.55
	Yield kg/ha	201	28	1215	0.19	171	15	698	0.51

3.2. Crop model simulation and assessment

The model's performance of simulating yield in each production region compared to the actual statistical data of observed yield from farmers is visualized in Figure 8a-d. Overall the simulated yield levels are below the observed yield levels. An important difference to mention is that the simulated yields have an adjusted moisture level of 0%, while the observed yields had an unspecified moisture level circling 14%. The reported yields differ from the simulated yields in such way that there is no knowledge of which cultivars, rates and types of fertilizer and management that has been used in the cultivation. These fields have also been exposed to biotic stresses such as pest and diseases that the crop model, in comparison, is unable to account for. It is important to take this into account as the model input is, in contrast, based on a few chosen locations and data from the field trial experiments where the management was very well documented In addition, the number of simulated fields are different in each region, for example, there was only one simulated field representing Region 2. The simulated yield levels in Region 2 are below 1000 kg/ha for the year 1979 and 2018 and do not mirror the reported yields. The diagrams in Figure 8a-d visualizes the model's capability to follow the main pattern of the reported yields, especially major yield drops and a tendency to underestimate yield. For the reasons above it is not possible it intended to make comparisons between simulated and reported yields, these graphs cannot therefore alone determine how well the model performed.

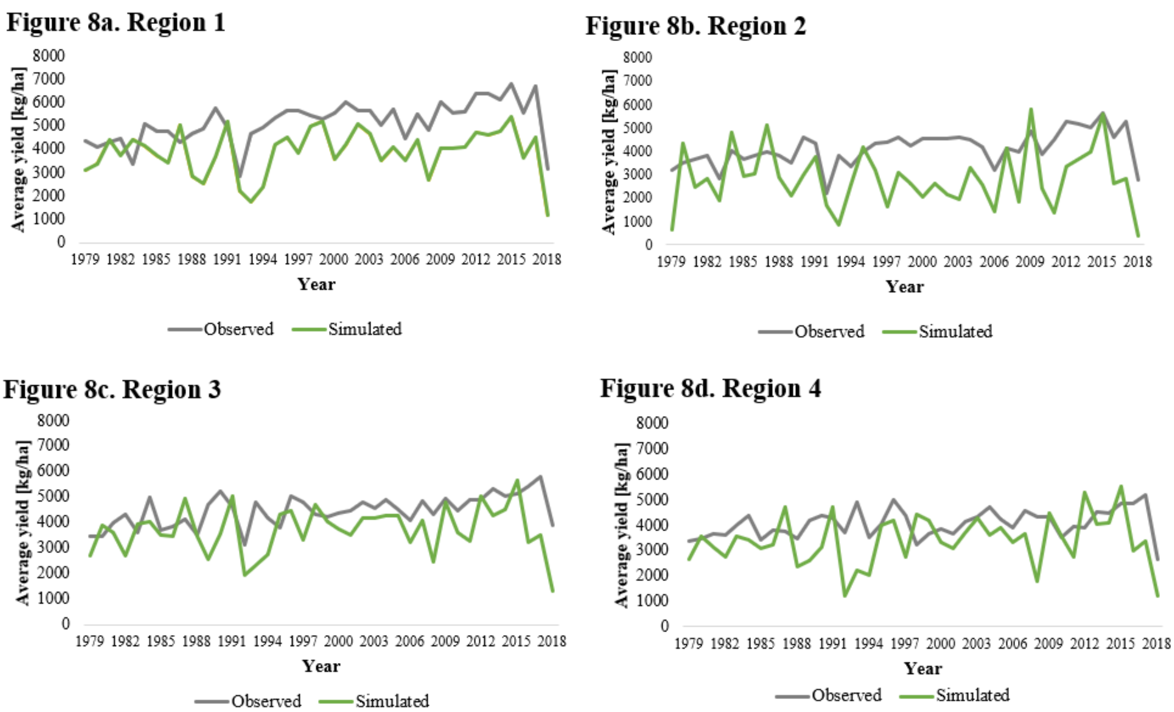

Figure 8 a-d. Regional average yield [kg/ha] simulated by the CERES-Barley crop model (green) and the average observed yield [kg/ha] from farmers (grey) to the Swedish Board of Agriculture (Jordbruksverkets statistikdatabas) in the production areas 1-4 in Sweden between 1979 and 2018 (Fig 4). The simulated yields include all three calibrated cultivars, fertilizer rate is 100 kg N/ha. Simulated yields had an adjusted level of 0% moisture; observed yields were adjusted according the moisture level reported in the source; if not indicated, the moisture level of 14% was assumed.

The simulated yield in each cultivar from the 54 sites, virtually fertilized with 100 kg N/ha, within each region is presented in a boxplot diagram (Figure 9). Region 2 exhibits an even yield distribution across the years and cultivars, and it is notable that the region only includes one experimental site. Among the regions, the different cultivars display a similar distribution. Propino had a higher yield median and a broader yield range in all the regions. The average yields of the cultivar were 3185 kg/ha for Astoria, 3396 kg/ha for Irina and 4577 kg/ha for Propino.

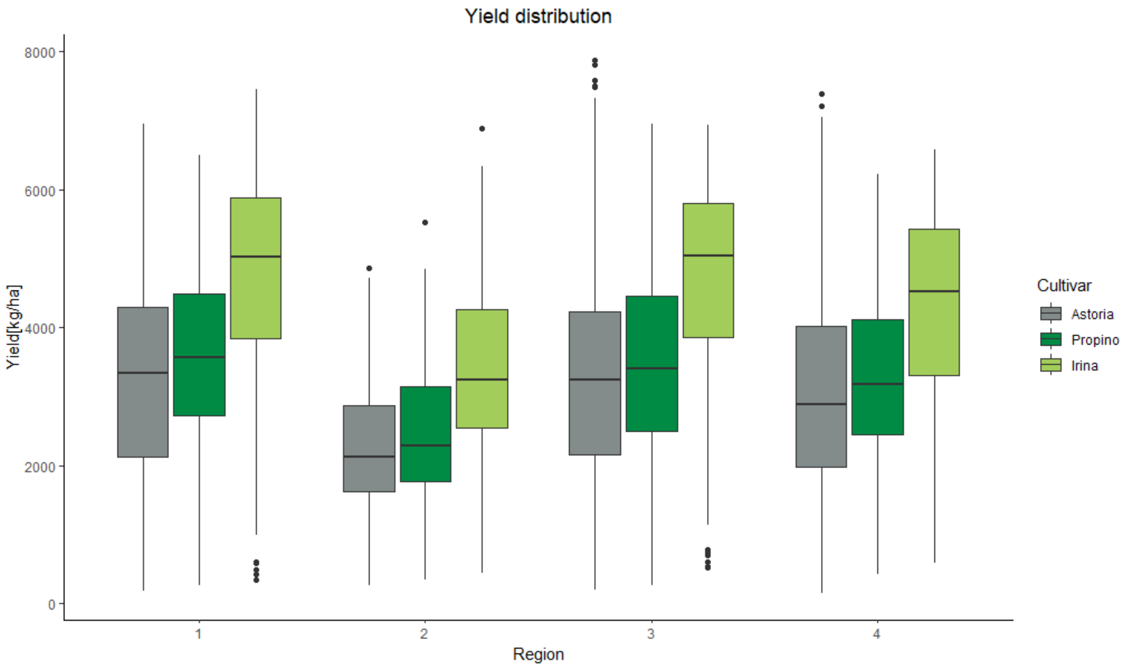

Figure 9. The simulated yields (kg/ha) of each cultivar; Astoria (grey), Irina (light green) and Propino (dark green) from the 54 fields in the production regions 1-4. Each field was fertilized with 100 kg N/ha. The box presents a distribution of yield values within the 2nd and 3rd quartile, separated by the median line. The whiskers and dots represent the distribution of yield values within the 1st and 4th quartiles. The dots indicate outlier values.

3.3. Climate marker correlation analysis

A few p-values within a significance level of 0,05% were found in the chi-square correlation analysis of climate markers and simulated yield levels (Table 6). The variable representing the climate markers Var6 (*Number of days included in dry spell and warm spell*) and Var11 (*Number of days included in a warm spell)* each had a significant interaction to six out of 54 sites. The other climate markers only explained yield levels to fewer sites. *Years* as a variable had a significant correlation to four of the sites. This result does not tell to what extent a variable impacts yield. It is also important to note that for only a few sites could a certain variable be used as an explanatory variable for yield. All results from the chi-square analysis are collected in Appendix 3.

Table 5. The significant p-values resulting from the chi-square analysis, testing the explanatory power of climate markers and yield on a specific site. Level of significance p<0.005. 18 sites (0023- , 1281-, 1641-, and 2012ERA5) presented a significant correlation to the following variables: Years, Var2, Var3, Var6, Var7, Var9, Var11, Var12, Var16 (Table 2).

Site	Years	Var 2	Var 3	Var 6	Var 7	Var 8	Var 9	Var 11	Var 12	Var 16
2039				0.022						
0007		0.025	0.004							
0053	1,74E-03				0.019					
1261					0.038					
0273	1.75E-02								3.26E-03	
1201	2.32E-02									8.32E-03
0006			0.008				0.032			
0068						0.019			3.17E-02	
1280					0.038			0.023		
1228								0.045		
1231					0.029					
1230				0.007	0.029			0.045		
1260			0.049	0.024	0.041			0.005		
0004	2.93E-02			0.049						
1930				0.009						
1148				0.002			0.024			
2021	3.97E.0.2				0.038					4.99E-02
1207								0.014		

The climate marker variables with VIF-values below 10 that were used in the linear mixed model analysis are showcased in Figure 10. There were no significant correlations between the VIF-sorted climate markers and the simulated yield levels when using a mixed linear model (Appendix 4). The highest correlation value (0.176) was found in an interaction of Var3 (*Number of days included in Cold Spells)* and Var5 (*Number of days included in dry spells of 5 days or more*). The interaction between Var5 and 14 (*Average temperature* and *Number of dry days*) exhibited the lowest association, with a coefficient of 0.001.

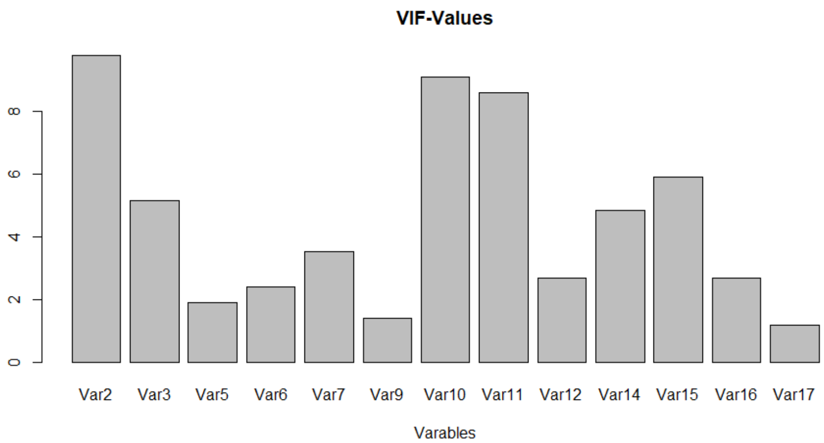

Figure 10. The analysed climate markers that were filtered with the VIF-function. Variables with VIF-value >10 were removed to avoid multicollinearity. Variables on the x-axis are: Number of daily extreme precipitation (Var2), Number of days included in Cold Spells (Var3), Number of days included in dry spells of 5 days or more (Var5), Number of days included in dry spell and warm spell (Var6), Number of days included in warm spells (Var7), Number of days included in wet spells of 5 days or more (Var8), Number of dry spells of 5 days or more (Var9), Number of late frost days OR Number of early frost days? (Var10), Number of warm Spells (Var11), Number of wet days (>1mm) (Var12), Ratio of precipitation falling during extreme event (Var14), Average temperature (Var15), Average precipitation volume per wet days (>1mm) (Var16), Total Precipitation volume (Var17).

4. Discussion

4.1. Model calibration and validation

The barley cultivars Astoria, Irina and Propino were estimated in the DSSAT CERES-Barely cropping model. After the model validation it was possible to observe that the model was able to mimic observed phenological maturity and yields. At regional level, the simulated values could also follow annual observation trends from statistical data (Figure 8a-d).

The variable *Day of maturity* was more similar to the observations than the yield variable (Table 4). This might be because there were fewer and more similar dates from the field trials, often linked to nearby weather stations and soil profiles. Focusing on the yield variable, the R^2 and MAE was different between the cultivars. It was unsurprising that the MAE was large due to the larger geographical scope containing different distinct growing condition that were included into the crop model. Other papers that calibrated and used the CERES-Barley crop model had in comparison better linearity between the observed and simulated values than this project (Al-Bakri et al., 2021; Rötter et al., 2021).

Even if the RRMSE was deemed *good* for both Astoria and Propino, the later cultivar had notably higher yields (Table 5, Figure 6 and 7). This may be explained by the cultivar coefficients: Propino has a large P5, G1, G2, and G3 in comparison to Astoria. This means that the cultivar had a longer grain filling period, both bigger and more kernels and a higher grain filling rate. Astoria, in comparison, had a much greater photoperiod response (40) in comparison to both Propino (17,99) and Astoria (0,2). This essentially means that Astoria was simulated with a lower rate of development during days with more than 10 hours of sunlight. During the summer period in Sweden the daylength is longer than the night-time, which means that the other cultivars were not as inhibited by the longer days as Astoria.

Compared to the reported yields from Swedish farmers, Astoria was the most similar cultivar (Figure 8). A reason as to why there were such a high difference in yield between the cultivars could be that some coefficients were exaggerated in the calibration, while others underestimated. Another point, which was highlighted by Beven and Freer (2001) is that the model performance could have showed similar, or the same output with another combination of parameter values. This could explain why some of the parameter values were different between cultivars,

It is not surprising that the MAE was large since variation is expected due to the geographical distribution with different growing conditions that were included into the crop model and based on the field trial locations.

In general, the simulated mean yields were lower than the ones reported to the Swedish board of Agriculture (Figure 8a-d). As mentioned, the adjusted water content may be one reason explaining the lower yields. The model's trend to underestimate yield levels aligns with a publication from Rötter et al. (2021) where the majority of the compared crop models all displayed an underestimation of yield. The comparison made in this project, however, only functions as a visualisation of how well the model may follow general trends of yield levels over the year. It cannot explain the CERES-Barley model's capacity and capability to calculate yield levels.

The question remains if the calibration could have increased the similarities between observed and simulated data if more information was used in the model input, with for example more detailed phenological observations and biomass data collected during the cropping season. One of the reasons to reduce the input was to make the modelling more user friendly with the consideration that a lot of data might increase possible errors within the data set and later in the simulation. Perhaps the calibration could have been better if only trials that included all data would have been used, in this case a few missing information were included. In that case the selection of data points would have been reduced. Although looking into the results from the statistical analysis it is not clear if a more thorough calibration would have given other results seeing as the correlations were so low for almost all extreme weather variables (Table 4), especially considering the large geographical distribution of the experiments, which might include aspects that could not be captured by the model.

4.2. Climate marker analysis

The chi-square analysis resulted in a few significant interactions between climate markers and yield levels in malting barley in 19 of 54 weather stations connected to experiment sites (Table 6). Due to the low number of interactions, it was challenging to find a pattern that could be used to explain a relationship between pre-season climate markers and yield levels of malting barley. It would also not be enough to support any kind of pre-cropping season decisions, such as planting density, amount of fertilizer to be applied, choice or cultivars, etc. It can however be noted that two of the climate markers did have significant correlations to the yield in six weather stations. These were related to warm spells and a combination of warm and dry spells. However, this does not explain what effect, positive or negative, these climate markers had on yield levels specifically. As a chi-square test will not be able to test combined effects of climate markers the linear mixed model approach was used. The results from linear mixed model analysis could not present any significant correlation between climate markers and yield levels.

While neither the linear mixed model nor the chi-square analysis showed any significant interactions or patterns between climate markers and yield, climate markers could still be useful for making pre-season predictions of yield. This was also discussed by Lalić et al. (2014), who conducted a similar experiment with climate marker predictors, although to make within season yield forecasts. They considered if an insignificant result could still hold importance which is hidden or difficult to explain.

A reason why there weren't any significant correlations when using the linear mixed model might be because of the physical conditions during spring. Soils in Sweden are very often already saturated before the sowing of a spring crop, either from melted snow coverage or the low temperatures keeping the soils moist during the winter season. This means that precipitation at this stage does not have an impact on the final yield, a point that Lalic et al. (2014) also made. It is therefore plausible that climate markers connected to precipitation might not be good explanatory variables for yield predictions in Sweden, at least for spring sown crops. In Table 7, possible explanations are briefly presented as to why the variables didn't exhibit any significant correlations.

Table 6. Brief explanation of how the variables are associated with the Swedish conditions for spring cultivation and how they may or may not have clear impact on yield.

Climate marker variable	*Explanation*
Nb_ColdSpell	Might delay sowing, cooler conditions during planting
Nb_DailyExtr_PcP	Soil already saturated might delay sowing
Nb_days_ColdSpell	No real connection to before sowing
Nb_days_ColdWet	No particular effect, might affect sowing
Nb_days_DrySpells_5d	Earlier sowing, limited water resources in early growth stages
Nb_days_WarmDry	Earlier sowing, limited water resources in early growth stages
Nb_days_WarmSpell	Earlier sowing, limited water resources in early growth stages
Nb_days_WetSpells_5d	No particular effect as the soil is probably already saturated
Nb_DrySpell_5d	Limited water resources in early growth stages
Nb_frost	Delayed sowing, shorter growth period,
Nb_WarmSpell	Possibility of earlier sowing
Nb_WetDays	No particular effect as the soil is probably already saturated
Nb_WetSpell_5d	No particular effect as the soil is probably already saturated
Ratio_DailyExtr_PcP	Does not really affect unless it is close to sowing
Tmp_average	Earlier sowing if high mean daily temperatures
Vol_Average_Wetday	No particular effect
Vol_ToTal_PcP	Affects sowing day with a possible delay if too much precipitation

It could be argued that the most evident effect on yield comes from weather patterns affecting physical soil conditions (notably high moisture or low temperatures) and therefore delaying the day of sowing. A similar result was also found in a study that investigated Finnish cultivar responses to weather fluctuations (Hakala et al., 2012). They could observe that cold spells taking place before planting resulted in later sowing which had an overall negative impact on the yield. Eckersten et al. (2010) tried to make pre-season and within season yield predictions of winter wheat for Sweden but found that it was difficult and argued that climate-related yield predictions are complex.

Other publications have generally focused the bigger picture of precipitation and temperature impacts instead of using more defined climatic markers. An example comes from a paper from Trnka et al. (2016) where they not only found that the growing conditions in Europe has changed since the beginning of the last century, but also that there has been change in which climate predictors have the most impact on yield. Similarly, to this project, they also used several climate markers in their weather/yield correlation. The same experiment also found that large amounts of precipitation before sowing had a negative effect on yield of almost all the 21 cultivars tested. One additional interesting finding was that yield predictors (climate markers) had changed during the tested period. The authors concluded that this indicated a change in crop growing conditions as they could also see that the impact of certain weather patterns had recently increased between 1991-2012. Another example of earlier attempts at yield forecasting of common crops, made with hindcasting, is made in a study by Iizumi et al. (2018). They found that pre-season forecasting of yield variability could be done successfully with a multi-model approach as a continuation of an earlier publication (Iizumi et al., 2013). Their previous publication from 2013 similarly shows how the yield predictions of wheat follows a similar pattern (Fig 11) to the simulation of the observed yields. This aligns with what this thesis' simulation also achieved (Figure 8 a-d). Although both Izumi's et al.'s (2013 & 2018) reports focus on global and national scale to make forecasts, it can be interpreted that for example temperature would have a great impact. This would perhaps not be generally true as temperature probably has a bigger impact in more arid parts of the world than in for example Sweden.

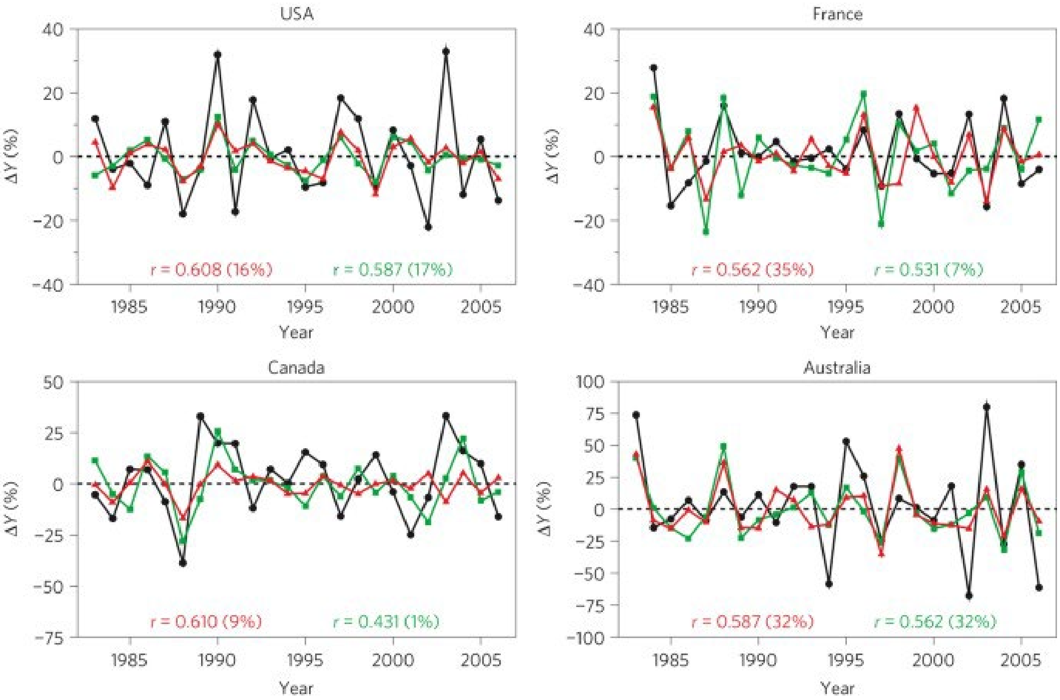

Figure 11. Pre-season forecasted (green), within season forecasted (orange) and observed (black) wheat yield variability from year 1985 to 2005 in USA, France and Canada. From Iizumi et al., 2013.

Even as there were no evident correlations between climate markers and yield for malting barley in Sweden, it is still important to note that it was possible to calibrate a crop model to mimic within season impacts and that the calibration could be considered successful. The model itself has the ability to account for pre-season impacts of the crop by running a water balance and also routines related to nitrogen dynamics, but its sensitivity to climate markers was not tested in detail. For this reason, data on climate markers might have the potential to help make pre-season or early predictions, which would be helpful to farmers planning and management. As other publications presented, it is a difficult and complex task to make pre-season forecasts of yield, although there is still a demand for making early forecasts.

Since this project included a large amount of data from field trial experiments, another approach could have been to use a statistical model instead of a process-based crop model. As this model focused on understanding yield and climate correlations, a simpler model such as a statistical model might have been sufficient for this purpose (Basso et al., 2013). When using the process-based crop model CERES-Barley, the main advantage was that it could make more complex calculations based on the ecology of a barley plant (Table 1). Initially this work aimed to also include barley grain protein levels, a variable that the model has a routine for and could potentially be accounted for. This was, however, not accomplished in this project because of early evidence that the model still was not able to properly simulate this parameter. The choice of a process-based model was also grounded in the quantity of data. One other benefit with process-based models is that they can be used to make extrapolations (Zhan et al., 2012). That would mean that the experiments simulated in a model could be applied to other regions than the ones tested, for example by only adding data on a few site-specific parameters such as weather and soil profiles. This is a limitation with the statistical model as the data is purely based on the data for a certain region.

For future research within this topic, it might be interesting to combine pre-season and within-season predictions. There might be other outcomes by changing the geographical scope. This approach would on one hand potentially include more data which could be useful, especially more phenological and biomass partitioning data. On one hand, increasing the geographical scope might make it less applicable or precise for field-level decision support. With an increasing dataset and scope there might be results that are hard to explain or understand when using a larger scale. Data on a smaller scale on the other hand is only useful in a limited area. A further development of this work could be to include other crops in the simulation and analysis, for example winter crops, or to analyse climate markers that occur in a closer time span seeing as the winter season in Sweden has a probable buffer function.

5. Conclusions

This thesis attempted to assess possibilities of using pre-season climate conditions together with a crop model in explaining yield levels of spring sown malting barley in southern Sweden.

The process-based crop model CERES-Barley was successfully calibrated for three malting barley cultivars. The explanatory power of climate markers was tested with a Pearson chi-square test and linear mixed model. A few significant interactions between climate markers and the simulated yield could be found in the chi-square analysis, but it lacked an overall pattern of significance to produce useful outcomes for decision support at field level. The linear mixed model was unable to find variable explaining yield levels. It may suggest that there are nonlinear effects or that other factors may have higher explanatory power than the tested climate markers.

One of the reasons behind the lack of sensitivity to climate markers could be due to soil buffering conditions in Swedish soils regarding water storage during winter and early spring. The findings of this work, however, cannot be taken as conclusive in stating that climatic conditions 60 days before the start of the cropping season do not have any forecasting explanatory power to yields in Swedish conditions. In order to increase the knowledge in the area, a more detailed pedological and climatic database needs to be available, as well as detailed information on crop phenology, yield, agronomic management and biotic stresses.

6. References

Adams, H.D., Williams, A.P., Xu, C., Rauscher, S.A., Jiang, X. & McDowell, N.G. (2013). Empirical and process-based approaches to climate-induced forest mortality models. *Frontiers in Plant Science*, 4, 438. https://doi.org/10.3389/fpls.2013.00438

Al-Ajlouni, Z.I., Al-Abdallat, A.M., Al-Ghzawi, A.L.A., Ayad, J.Y., Abu Elenein, J.M., Al-Quraan, N.A. & Baenziger, P.S. (2016). Impact of Pre-Anthesis Water Deficit on Yield and Yield Components in Barley (Hordeum vulgare L.) Plants Grown under Controlled Conditions. *Agronomy*, 6 (2), 33. https://doi.org/10.3390/agronomy6020033

Al-Bakri, J., Farhan, I., Al-Qinna, M., Al-Karablieh, E., Bergouli, K. & McDonnell, R. (2021). Assessment of Climate Changes and Their Impact on Barley Yield in Mediterranean Environment Using NEX-GDDP Downscaled GCMs and DSSAT. *Earth Systems and Environment*, 5 (3), 751–766. https://doi.org/10.1007/s41748-021-00238-1

Ali, A.M., Abouelghar, M., Belal, A.A., Saleh, N., Yones, M., Selim, A.I., Amin, M.E.S., Elwesemy, A., Kucher, D.E., Maginan, S. & Savin, I. (2022). Crop Yield Prediction Using Multi Sensors Remote Sensing (Review Article). The Egyptian Journal of Remote Sensing and Space Science, 25 (3), 711–716. https://doi.org/10.1016/j.ejrs.2022.04.006

Arslan Ashraf, Muhammad (2012). Waterlogging stress in plants: A review. *AFRICAN JOURNAL OF AGRICULTURAL RESEEARCH*, 7 (13). https://doi.org/10.5897/AJARX11.084

Bannayan, M., Crout, N.M.J. & Hoogenboom, G. (2003). Application of the CERES-Wheat Model for Within-Season Prediction of Winter Wheat Yield in the United Kingdom. *Agronomy Journal*, 95 (1), 114–125. https://doi.org/10.2134/agronj2003.1140a

Basso, B., Cammarano, D. & Carfagna, E. (2013). of Crop Yield Forecasting Methods and Early Warning Systems., 2013. https://www.semanticscholar.org/paper/of-Crop-Yield-Forecasting-Methods-and-Early-Warning-Basso-Cammarano/446c8d1d92a0ed8488bd1d9e2ad3efde5c5f2567 [2023-05-19]

Basfakta om klimat | SMHI (n.d.). https://www.smhi.se/klimat/framtidens-klimat/basfakta-om-klimat [2023-03-18]

Beillouin, D., Schauberger, B., Bastos, A., Ciais, P. & Makowski, D. (2020). Impact of extreme weather conditions on European crop production in 2018. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 375 (1810), 20190510. https://doi.org/10.1098/rstb.2019.0510

Beven, K. & Freer, J. (2001). Equifinality, data assimilation, and uncertainty estimation in mechanistic modelling of complex environmental systems using the GLUE methodology. *Journal of Hydrology*, 249 (1), 11–29. https://doi.org/10.1016/S0022-1694(01)00421-8

Bhadra, P., Maitra, S., Shankar, T., Hossain, A., Praharaj, S. & Aftab, T. (2022). Chapter 1 - Climate change impact on plants: Plant responses and adaptations. In: Aftab, T. & Roychoudhury, A. (eds) *Plant Perspectives to Global Climate Changes*. Academic Press. 1–24. https://doi.org/10.1016/B978-0-323-85665-2.00004-2

Bolin Centre for Climate Research, S.U. (2019). *Skillnaden mellan väder och klimat | Bolin Centre Database*. [text]. https://bolin.su.se/data/skillnanden-mellan-vader-och-klimat/ [2023-03-18]

Copernicus Climate Change Service (2019a). Agrometeorological indicators from 1979 up to 2019 derived from reanalysis. ECMWF. https://doi.org/10.24381/CDS.6C68C9BB

de toro, A., Nkurunziza, L., von Rosen, D & Eckersten, H. (2015). *Effects of extreme weather on yields of major cereal crops in Sweden: Analysis of long-term experiment data*.

Despotovic, M., Nedic, V., Despotovic, D. & Cvetanovic, S. (2016). Evaluation of empirical models for predicting monthly mean horizontal diffuse solar radiation. *Renewable and Sustainable Energy Reviews*, 56, 246–260. https://doi.org/10.1016/j.rser.2015.11.058

Eckersten, H., Kornher, A., Bergkvist, G., Forkman, J., Sindhøj, E., Torssell, B. & Nyman, P. (2010). Crop yield trends in relation to temperature indices and a growth model. *Climate Research*, 42 (2), 119–131. https://doi.org/10.3354/cr00867

Fågelfors, H. (red). (2014). Vår mat Odling av åker-och trädgårdsgrödor. Lund: Studentlitteratur AB.

FAO. 2020. Early Warning Early Action Report on Food Security and Agriculture (April-June 2020). Rome. https://doi.org/10.4060/ca8606en

FAOSTAT (2022) Crops and livestock products. (2022-12) https://www.fao.org/faostat/en/#data/QCL/visualize [2023-01-26]

Frederiks, T.M., Christopher, J.T., Sutherland, M.W. & Borrell, A.K. (2015). Post-head-emergence frost in wheat and barley: defining the problem, assessing the damage, and identifying resistance. *Journal of Experimental Botany*, 66 (12), 3487–3498. https://doi.org/10.1093/jxb/erv088

Global High-Resolution Soil Profile Database for Crop Modeling Applications - IFPRI HarvestChoice Dataverse (n.d.). https://dataverse.harvard.edu/dataset xhtml?persistentId=doi:10.7910/DVN/1PEEY0 [2023-03-19]

Grusson, Y. & Barron, J. (2022). Challenges in reanalysis products to assess extreme weather impacts on agriculture: Study case in southern Sweden. *PLOS Climate*, 1, e0000063. https://doi.org/10.1371/journal.pclm.0000063

Grusson, Y., Wesström, I. & Joel, A. (2021). Impact of climate change on Swedish agriculture: Growing season rain deficit and irrigation need. *Agricultural Water Management*, 251, 106858. https://doi.org/10.1016/j.agwat.2021.106858

Hakala, K., Jauhiainen, L., Himanen, S.J., Rötter, R., Salo, T. & Kahiluoto, H. (2012a). Sensitivity of barley varieties to weather in Finland. *The Journal of Agricultural Science*, 150 (2), 145–160. https://doi.org/10.1017/S0021859611000694

Havrlentova, M., Kraic, J., Gregusová, V. & Kovácsová, B. (2021). Drought Stress in Cereals – A Review. *Agriculture (Pol'nohospodárstvo)*, 67, 47–60. https://doi.org/10.2478/agri-2021-0005

Herzog, M., Striker, G.G., Colmer, T.D. & Pedersen, O. (2016). Mechanisms of waterlogging tolerance in wheat – a review of root and shoot physiology. *Plant, Cell & Environment*, 39 (5), 1068–1086. https://doi.org/10.1111/pce.12676

Hoogenboom G., Jones J.W., Porter C.H., Wilkens P.W., Boote K.J., Batchelor W.D., Hunt L.A., and Tsuji G.Y. (Editors). 2003. Decision Support System for Agrotechnology Transfer Version 4.0. Volume 1: Overview. University of Hawaii, Honolulu, HI

Hoogenboom, G., C.H. Porter, V. Shelia, K.J. Boote, U. Singh, J.W. White, W. Pavan, F.A.A. Oliveira, L.P. Moreno-Cadena, J.I. Lizaso, S. Asseng, D.N.L. Pequeno, B.A. Kimball, P.D. Alderman, K.R. Thorp, M.R. Jones, S.V. Cuadra, M.S. Vianna, F.J. Villalobos, T.B. Ferreira, W.D. Batchelor, J. Koo, L.A. Hunt, and J.W. Jones. 2021. Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.8 (DSSAT.net). DSSAT Foundation, Gainesville, Florida, USA. Wallach, D., Makowski, D., Jones, J.W. & Brun, F. (2019). Chapter 9 - Model Evaluation. In: Wallach, D., Makowski, D., Jones, J.W., & Brun, F. (eds) *Working with Dynamic Crop Models (Third Edition)*. Academic Press. 311–373. https://doi.org/10.1016/B978-0-12-811756-9.00009-5

Iizumi, T., Sakuma, H., Yokozawa, M., Luo, J.-J., Challinor, A.J., Brown, M.E., Sakurai, G. & Yamagata, T. (2013). Prediction of seasonal climate-induced variations in global food production. *Nature Climate Change*, 3 (10), 904–908. https://doi.org/10.1038/nclimate1945

Iizumi, T., Shin, Y., Kim, W., Kim, M. & Choi, J. (2018). Global crop yield forecasting using seasonal climate information from a multi-model ensemble. *Climate Services*, 11, 13–23. https://doi.org/10.1016/j.cliser.2018.06.003

International Research Institute for Climate and Society (IRI); Michigan State University (MSU); HarvestChoice, International Food Policy Research Institute (IFPRI), 2015, "Global High-Resolution Soil Profile Database for Crop Modeling Applications", https://doi.org/10.7910/DVN/1PEEY0, Harvard Dataverse, V2

IPCC, 2021: *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, In press, doi:10.1017/9781009157896.

Jordbruksverket (n.d.) Karta över Sveriges produktionsområden Tillgänglig: https://statistik.sjv.se/PXWeb/Resources/PX/Kartor/Produktionsomraden.html [2023-01-10]

Johansson, E. (2010). Proteiner i maltkorn påverkar ölkvaliteten. [Broschyr]. Fakta från Partnerskap Alnarp *Field Crops Research*, 293, 108856. https://doi.org/10.1016/j.fcr.2023.108856. [2023-03-10].

Jordbruksverkar. (n.d) Hektar- och totalskörd efter produktionsområde och gröda. År 1965-2021. https://statistik.sjv.se/PXWeb/pxweb/sv/Jordbruksverkets%20statistikdatabas/Jordbruksverkets%20statistikdatabas__Skordar/JO0601J02.px/table/tableViewLayout1/?rxid=5adf4929-f548-4f27-9bc9-78e127837625 [2023-01-10]

Kar, R.K. (2011). Plant responses to water stress. *Plant Signaling & Behavior*, 6 (11), 1741–1745. https://doi.org/10.4161/psb.6.11.17729

Kaseva, J., Hakala, K., Högnäsbacka, M., Jauhiainen, L., Himanen, S.J., Rötter, R.P., Balek, J., Trnka, M. & Kahiluoto, H. (2023). Assessing climate resilience of barley cultivars in northern conditions during 1980–2020. *Field Crops Research*, 293, 108856. https://doi.org/10.1016/j.fcr.2023.108856

Lalić, B., Eitzinger, J., Thaler, S., Vučetić, V., Nejedlik, P., Eckersten, H., Jaćimović, G. & Nikolić-Djorić, E. (2014). Can Agrometeorological Indices of Adverse Weather Conditions Help to Improve Yield Prediction by Crop Models? *Atmosphere*, 5 (4), 1020–1041. https://doi.org/10.3390/atmos5041020

Lobell, D.B. & Asseng, S. (2017). Comparing estimates of climate change impacts from process-based and statistical crop models. *Environmental Research Letters*, 12 (1), 015001. https://doi.org/10.1088/1748-9326/aa518a

Malmquist, L. & Barron, J. (2022). Identification and synthesis of agrometeorological extreme weather indicators for the temperate-boreal zone. https://res.slu.se/id/publ/116370 [2023-02-12]

Martino, D.L. & Abbate, P.E. (2019). Frost damage on grain number in wheat at different spike developmental stages and its modelling. *European Journal of Agronomy*, 103, 13–23. https://doi.org/10.1016/j.eja.2018.10.010

Mathieu, J.A. & Aires, F. (2018). Assessment of the agro-climatic indices to improve crop yield forecasting. *Agricultural and Forest Meteorology*, 253–254, 15–30. https://doi.org/10.1016/j.agrformet 2018.01.031

Naturvårdsverket (n.d.) *Effekter i Sverige* (n.d.). https://www.naturvardsverket se/amnesomraden/klimatforandringar/klimatet-i-framtiden/effekter-i-sverige/ [2023-03-12]

NFTS *(2022*). *Placering av enskilda försök*. https://nfts.dlbr.dk/Forms/forside.aspx [2022-09-31]

Ogutu, G.E.O., Franssen, W.H.P., Supit, I., Omondi, P. & Hutjes, R.W.A. (2018). Probabilistic maize yield prediction over East Africa using dynamic ensemble seasonal climate forecasts. *Agricultural and Forest Meteorology*, 250–251, 243–261. https://doi.org/10.1016/j.agrformet 2017.12.256

Pachepsky, Y. & Rawls, W.J. (2004). *Development of Pedotransfer Functions in Soil Hydrology*. Elsevier.

Pettersson, C.G. (2007). Predicting Malting Barley Protein Concentration. Doctoral thesis. Swedish University of Agricultural Sciences. Uppsala, 2007: https://res.slu.se/id/publ/14436

Powell, J.P. & Reinhard, S. (2016a). Measuring the effects of extreme weather events on yields. *Weather and Climate Extremes*, 12, 69–79. https://doi.org/10.1016/j.wace.2016.02.003

Qian, B., De Jong, R., Warren, R., Chipanshi, A. & Hill, H. (2009). Statistical spring wheat yield forecasting for the Canadian prairie provinces. *Agricultural and Forest Meteorology*, 149 (6), 1022–1031. https://doi.org/10.1016/j.agrformet 2008.12.006

Rawson, M.H & Macpherson Gómez, H. (2000). IRRIGATED WHEAT - Managing your crop. FAO. Rome, 2000.

Roberts, M.J., Braun, N.O., Sinclair, T.R., Lobell, D.B. & Schlenker, W. (2017). Comparing and combining process-based crop models and statistical models with some implications for climate change. *Environmental Research Letters*, 12 (9), 095010. https://doi.org/10.1088/1748-9326/aa7f33

Rötter, R.P., Höhn, J., Trnka, M., Fronzek, S., Carter, T.R. & Kahiluoto, H. (2013). Modelling shifts in agroclimate and crop cultivar response under climate change. *Ecology and Evolution*, 3 (12), 4197–4214. https://doi.org/10.1002/ece3.782

Rötter, R.P., Palosuo, T., Kersebaum, K.C., Angulo, C., Bindi, M., Ewert, F., Ferrise, R., Hlavinka, P., Moriondo, M., Nendel, C., Olesen, J.E., Patil, R.H., Ruget, F., Takáč, J. & Trnka, M. (2012). Simulation of spring barley yield in different climatic zones of Northern and Central Europe: A comparison of nine crop models. *Field Crops Research*, 133, 23–36. https://doi.org/10.1016/j.fcr.2012.03.016

Schauberger, B., Jägermeyr, J. & Gornott, C. (2020). A systematic review of local to regional yield forecasting approaches and frequently used data resources. *European Journal of Agronomy*, 120, 126153. https://doi.org/10.1016/j.eja.2020.126153

Schelling, K., Born, K., Weissteiner, C. & Kühbauch, W. (2003). Relationships between Yield and Quality Parameters of Malting Barley (Hordeum vulgare L.) and Phenological and Meteorological Data. *Journal of Agronomy and Crop Science*, 189 (2), 113–122. https://doi.org/10.1046/j.1439-037X.2003.00011.x

Schibalski, A. (n.d.). Statistical and process-based models for understanding species distributions in changing environments.

Singh U., Matthews R. B., Griffin T. S. , Ritchie J. T., Hunt L. A., Goenaga R. (1998). Title Gordon Y. Tsuji, Gerrit Hoogenboom, Philip K. Thornton (ed.) Understanding Options for Agricultural Production Vol.7. Kluwer Academic Publishers, p. 129-156

SLU Fältforsk (n.d.). *Enskilda försök.* https://www.slu.se/fakulteter/nj/om-fakulteten/centrumbildningar-och-storre-forskningsplattformar/faltforsk/resultat/enskilda/ [2023-01-31]

SMHI. Schimanke, S., Joelsson, M., Andersson, S., Carlund, T. & Wern, L. (n.d.). Observerad klimatförändring i Sverige 1860–2021.

Society (IRI), I.R.I. for C. and, University (MSU), M.S. & HarvestChoice, I.F.P.R.I. (IFPRI) (2018a). Global High-Resolution Soil Profile Database for Crop Modeling Applications. Harvard Dataverse. https://doi.org/10.7910/DVN/1PEEY0

Tian, L., Zhang, Y., Chen, P., Zhang, F., Li, J., Yan, F., Dong, Y. & Feng, B. (2021). How Does the Waterlogging Regime Affect Crop Yield? A Global Meta-Analysis. *Frontiers in Plant Science*, 12. https://www.frontiersin.org/articles/10.3389/fpls.2021.634898 [2023-03-18]

Trnka, M., Olesen, J., Kersebaum, K., Rötter, R., Brázdil, R., Eitzinger, J., Jansen, S., Skjelvåg, A., Peltonen-Sainio, P., Hlavinka, P., Balek, J., Eckersten, H., Gobin, A., Vucˇetić, V., Dalla Marta, A., Orlandini, S., Alexandrov, V., Semerádová, D., Šteˇpánek, P., Svobodová, E. & Rajdl, K. (2016). Changing regional weather-crop yield relationships across Europe between 1901 and 2012. *Climate Research*, 70 (2), 195–214. https://doi.org/10.3354/cr01426

Trnka, M., Rötter, R.P., Ruiz-Ramos, M., Kersebaum, K.C., Olesen, J.E., Žalud, Z. & Semenov, M.A. (2014). Adverse weather conditions for European wheat production will become more frequent with climate change. *Nature Climate Change*, 4 (7), 637–643. https://doi.org/10.1038/nclimate2242

Verma, U., Piepho, H.-P., Hartung, K., Ogutu, J. & Goyal, A. (2015). Linear Mixed Modeling for Mustard Yield Prediction in Haryana State (India). Journal of Mathematics and Statistical Science (ISSN 2411-2518, USA), 2015, 96–105

Wallach, D., Makowski, D., Jones, J.W. & Brun, F. (2019). Chapter 7 - Calibration of System Models. In: Wallach, D., Makowski, D., Jones, J.W., & Brun, F. (eds) *Working with Dynamic Crop Models (Third Edition)*. Academic Press. 251–274. https://doi.org/10.1016/B978-0-12-811756-9.00007-1

Wallach, D., Palosuo, T., Thorburn, P., Hochman, Z., Gourdain, E., Andrianasolo, F., Asseng, S., Basso, B., Buis, S., Crout, N., Dibari, C., Dumont, B., Ferrise, R., Gaiser, T., Garcia, C., Gayler, S., Ghahramani, A., Hiremath, S., Hoek, S., Horan, H., Hoogenboom, G., Huang, M., Jabloun, M., Jansson, P.-E., Jing, Q., Justes, E., Kersebaum, K.C., Klosterhalfen, A., Launay, M., Lewan, E., Luo, Q., Maestrini, B., Mielenz, H., Moriondo, M., Nariman Zadeh, H., Padovan, G., Olesen, J.E., Poyda, A., Priesack, E., Pullens, J.W.M., Qian, B., Schütze, N., Shelia, V., Souissi, A., Specka, X., Srivastava, A.K., Stella, T., Streck, T., Trombi, G., Wallor, E., Wang, J., Weber, T.K.D., Weihermüller, L., de Wit, A., Wöhling, T., Xiao, L., Zhao, C., Zhu, Y. & Seidel, S.J. (2021). The chaos in calibrating crop models: Lessons learned from a multi-model calibration exercise. *Environmental Modelling & Software*, 145, 105206. https://doi.org/10.1016/j.envsoft.2021.105206

Weissteiner, C.J. & Kühbauch, W. (2005). Regional Yield Forecasts of Malting Barley (Hordeum vulgare L.) by NOAA-AVHRR Remote Sensing Data and Ancillary Data. *Journal of Agronomy and Crop Science*, 191 (4), 308–320. https://doi.org/10.1111/j.1439-037X.2005.00154.x

West, B.T., Welch, K.B. & Galecki, A.T. (2022). *Linear Mixed Models: A Practical Guide Using Statistical Software*. Third edition. Abingdon Oxon. CRC Press. https://books.google.se/books?hl=sv&lr=&id=k3GwEAAAQBAJ&oi=fnd&pg=P

P1&dq=linear+mixed+model&ots=GZE6uw3obM&sig=qNyDg7ykKf8xiurEgOEwhWcbXig&redir_esc=y#v=onepage&q=linear%20mixed%20model&f=false
Zhan, Z., Fu, Y., Yang, R.-J., Xi, Z. & Shi, L. (2012). A Bayesian Inference based Model Interpolation and Extrapolation. *SAE International Journal of Materials and Manufacturing*, 5 (2), 357–364
Zhao, G., Hoffmann, H., Bussel, L.G.J. van, Enders, A., Specka, X., Sosa, C., Yeluripati, J., Tao, F., Constantin, J., Raynal, H., Teixeira, E., Grosz, B., Doro, L., Zhao, Z., Nendel, C., Kiese, R., Eckersten, H., Haas, E., Vanuytrecht, E., Wang, E., Kuhnert, M., Trombi, G., Moriondo, M., Bindi, M., Lewan, E., Bach, M., Kersebaum, K.-C., Rötter, R., Roggero, P.P., Wallach, D., Cammarano, D., Asseng, S., Krauss, G., Siebert, S., Gaiser, T. & Ewert, F. (2015). Effect of weather data aggregation on regional crop simulation for different crops, production conditions, and response variables. *Climate Research*, 65, 141–157. https://doi.org/10.3354/cr01301
Zhou, W., Chen, F., Meng, Y., Chandrasekaran, U., Luo, X., Yang, W. & Shu, K. (2020). Plant waterlogging/flooding stress responses: From seed germination to maturation. *Plant Physiology and Biochemistry*, 148, 228–236. https://doi.org/10.1016/j.plaphy.2020.01.020

Popular science summary

For as long as we have cultivated the soil, we have been reliant on weather conditions. During the last decades, we have experienced extreme weather events, more frequently than before. This has of course impacted the global production of food. Being aware of climatic conditions in one's area may lay the ground for choices in agricultural management such as which crops and cultivars to grow. However, we cannot yet use weather events prior the cropping season's start to truly know the yield levels of our crops. The possibility to make pre-season yield forecasts could prove to be useful in not only the planning but also the optimization of agricultural management.

The aim for this master project was to investigate correlations between pre-season climate indicators and yield levels of spring sown malting barley in southern Sweden. Climate indicators were used as a way to define certain extreme weather events that can occur during a cropping season and be damaging for the crop and its final yield. The parameters of the crop model CERES-Barley developed by DSSAT (Hoogenboom et al., 2023) were adjusted so that the simulated yield would match the data from field trial experiments over the region between the years 1999 and 2018. Data from field experiments, gridded weather data and soil profiles were used to calibrate a crop model that could simulate yield during 40 cropping seasons (from 1979 to 2018). The climate indicators were then used together with the simulated yields to see if they had connection or impact on the yield levels.

The results showed no significant correlations that could explain yield levels based on pre-season weather conditions. It might be the case that the statistical model that was used to make the analysis could not take other playing factors into account. One factor that could explain this is actually the weather itself. In Sweden the winter and autumn accumulates a lot of water in the soil through rainfall, and since the temperature is low during this season water does not evaporate, therefore water remains in the soil. This means that the soil, during the spring and before sowing, is already full of water, which generally provides good conditions for the crop establishment. Good soil conditions for sowing may explain a hidden effect from the other climate markers. There is more to discover within this field as both weather patterns and crop models are complex.

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Appendix 1

Examples from the script used in R.studio to calculate the start of the cropping season and to define climate markers (Formas 2020-2023).

```
for (f in 1:length(fileNames)){

        File=fileNames[f]
        load(paste0("./DataEachCell/" , File))

        ##rename Tav in TavTrue and
        ###create new array for Tav from Tmin and Tmax (for climate model data which not include Tav)
        names(CellData)[names(CellData) == "Tav"] <- "TavTrue"
        CellData$Tav=(CellData$Tmax+CellData$Tmin)/2

        ###prepare the list to received the data for each CS
        Prev60days_CSdata=list()
        CSDates=data.frame(Year=numeric(), DateStart=as.Date(character()),DateEnd=as.Date(character()),Comment=character())

        #loops to prepare the dataframe
         for (y in 1979:2019) {

           ##isolate year
           yeardata=CellData[!year(CellData$Dates) != y , ]

           ##find beginning of the cropping period = 5 continuous days with Tav>=5 degree Min date 1st March

           ##list of days with Tav>= 5 and removing the 3 first which can't be the 4th day with Tav>=5
             DateLimitStart=which(month(yeardata$Dates)==3 & day(yeardata$Dates)==1)
             DayUp5=which(yeardata$Tav>=5)
             DayUp5=DayUp5[!DayUp5<DateLimitStart]

               ##testing each of the DayUp5 to find the first one with 4 previous days also Tav>=5
               for (j in(DayUp5)){

                   if(yeardata$Tav[j-1]>=5 & yeardata$Tav[j-2]>=5 & yeardata$Tav[j-3]>=5 & yeardata$Tav[j-4]>=5){
                    DateStartCs=yeardata$Dates[j]
                    break }

               }
              rm(j, DayUp5, DateLimitStart)

          ##cut the dataset to keep only the 60days before the cropping season
          IndexStartCs=match(as.Date(DateStartCs), CellData$Dates)#find index of starting cropping season in the entire dataset
          IndexPrev60=IndexStartCs-60
          Prev60days_CSdatayearly=CellData[IndexPrev60:(IndexStartCs-1),]
          rm(IndexStartCs,IndexPrev60)

          ##adding the 60 prev days to the overall list:
          Prev60days_CSdata[[paste0("Cs",y)]]=Prev60days_CSdatayearly
             # creating a dataframe with overall PcP data from all cropping seasons to evaluate later the limit for the daily extremes
             Prev60days_CSdata_PcP_Array=numeric()
             for (y in 1979:2019) {
               Data=Prev60days_CSdata[[paste0("Cs",y)]]
               Prev60days_CSdata_PcP_Array=c(Prev60days_CSdata_PcP_Array,Data$PcP)
             }

             Prev60days_CSdata_Tmin_Array=numeric()
             for (y in 1979:2019) {
               Data=Prev60days_CSdata[[paste0("Cs",y)]]
               Prev60days_CSdata_Tmin_Array=c(Prev60days_CSdata_Tmin_Array,Data$Tmin)
             }

             Prev60days_CSdata_Tmax_Array=numeric()
             for (y in 1979:2019) {
               Data=Prev60days_CSdata[[paste0("Cs",y)]]
               Prev60days_CSdata_Tmax_Array=c(Prev60days_CSdata_Tmax_Array,Data$Tmax)
             }
```

```
############################### Calculating parameters Values

## create a data Frame to stock up the different parameters values
   Tbl60daysValue=data.frame(Years=(1979:2019),

                             # Total Precipitation (mm)
                             Vol_ToTal_PcP=replicate(41, NaN),

                             # Average temperature (?C)
                             Tmp_average=replicate(41, NaN),

                             # Number of frost days
                             Nb_frost=replicate(41, NaN),

## filling up the data frame with values
   #loops for each year

   Line_y=0

   for (y in 1979:2019) {

     Line_y=Line_y+1

     Data=Prev60days_CSdata[[paste0("Cs",y)]]

     # Total Precipitation (mm)
     Tbl60daysValue$Vol_ToTal_PcP[Line_y]=sum(Data$PcP)

     # Average temperature (?C)
     Tbl60daysValue$Tmp_average[Line_y]=mean(Data$Tav)

     # Number of frost days
     DayFrost=which(Data$Tmin<0)
     Tbl60daysValue$Nb_frost[Line_y]=length(DayFrost)
     rm(DayFrost)

 ##Spells
     #dataset with (pcp>=1mm) = 1 and dry days by 0
     Data1mm=Data$PcP
     Data1mm [Data1mm >=1] <- 1 #so 1=Wet Days
     Data1mm [Data1mm < 1] <- 0 #so 0=Dry Days

       #Dry Spells
       Sequence=rle(Data1mm)
       IndexToChange=which(Sequence$lengths<5)
       Sequence$values[IndexToChange] <- NA#Keeping only sequence >=5 days
       Sequence$values[Sequence$values == 1] <- NA #Keeping only dry sequence
       DrySpell=which(Sequence$values==0)

        #Number of dry spells  (5 days or more with precipitation <1mm)
        Tbl60daysValue$Nb_DrySpell_5d[Line_y]=length(DrySpell)

        #Total number of days included in dry spells
        Tbl60daysValue$Nb_days_DrySpells_5d[Line_y]= sum(Sequence$lengths[DrySpell])

      rm(Sequence,IndexToChange,DrySpell)
##Spells Temperature and precipitation together

     # Number of days included in WARM and DRY spell simultaneously
     #Dataset with (pcp>=1mm) = 0 and dry days by 1
     Data1mm=Data$PcP
     Data1mm [Data1mm >=1] <- 2 # temp values for Wet Days
     Data1mm [Data1mm < 1] <- 1 #so 1=Dry Days
     Data1mm [Data1mm == 2] <- 0 #so 0=Wet Days

 ## filling up the data frame with classifications
    #loops for each year

    index=0

    for (y in 1979:2019) {

      index=index+1

      # Total Precipitation (mm)
      Percentile=quantile(Tbl60daysValue$Vol_ToTal_PcP, probs = c(0,0.01, 0.1, 0.25, 0.5, 0.75, 0.90, 0.99, 1))

      yearvalue=Tbl60daysValue$Vol_ToTal_PcP[index]
      if (yearvalue>=Percentile[8]) {Tbl60daysClass$Vol_ToTal_PcP[index]="ExtremHigh"}
      if (yearvalue<=Percentile[2]){Tbl60daysClass$Vol_ToTal_PcP[index]="ExtremLow"}
      if (yearvalue>=Percentile[7] && yearvalue<Percentile[8]){Tbl60daysClass$Vol_ToTal_PcP[index]="VeryHigh"}
      if (yearvalue>Percentile[2] && yearvalue<=Percentile[3]){Tbl60daysClass$Vol_ToTal_PcP[index]="VeryLow"}
      if (yearvalue>=Percentile[6] && yearvalue<Percentile[7]){Tbl60daysClass$Vol_ToTal_PcP[index]="Hight"}
      if (yearvalue>Percentile[3] && yearvalue<=Percentile[4]){Tbl60daysClass$Vol_ToTal_PcP[index]="Low "}
      if (yearvalue>=Percentile[4] && yearvalue<=Percentile[6]){Tbl60daysClass$Vol_ToTal_PcP[index]="regular"}

      rm(yearvalue,Percentile)
```

Appendix 2

Table 7. Example of the table used for the chi-square analysis for the weather station 0004ERA5. The climate marker variables (1-17) values are each categorized in six levels: extreme low, very low, low, regular, high, very high *and* extremely high*. They were tested against year and yield. The yield levels were also categorized into four levels:* L, LM, LH *and* H*, based on the quantile range of the simulated yield levels of the site 0004.*

Years	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	Yield
1979	Hight	regular	regular	regular	Hight	VeryLow	regular	regular	regular	regular	regular	regular	regular	VeryHigh	regular	regular	regular	L
1980	VeryLow	Low	VeryHigh	VeryLow	Low	ExtremHigh	ExtremHigh	regular	regular	regular	regular	regular	regular	regular	regular	Hight	regular	LM
1981	VeryHigh	regular	regular	VeryHigh	Hight	regular	Low	regular	regular	ExtremHigh	VeryHigh	regular	regular	regular	regular	regular	regular	LH
1982	regular	regular	regular	regular	regular	VeryHigh	Hight	regular	regular	regular	regular	ExtremHigh	ExtremHigh	regular	regular	ExtremHigh	regular	LH
1983	regular	regular	regular	regular	regular	VeryLow	regular	regular	regular	regular	regular	regular	regular	VeryHigh	regular	regular	regular	H
1984	VeryLow	VeryLow	VeryHigh	VeryLow	regular	regular	VeryHigh	regular	regular	regular	regular	regular	regular	regular	regular	regular	regular	LM
1985	Hight	Hight	regular	VeryHigh	regular	VeryLow	VeryLow	regular	VeryHigh	regular	regular	VeryHigh	VeryHigh	regular	regular	regular	regular	LM
1986	regular	regular	regular	regular	regular	regular	regular	regular	regular	regular	regular	regular	regular	regular	regular	regular	regular	LM
1987	regular	regular	regular	regular	regular	regular	regular	regular	regular	regular	VeryHigh	ExtremHigh	VeryHigh	regular	VeryHigh	VeryHigh	regular	H
1988	Hight	regular	regular	ExtremHigh	regular	VeryLow	VeryLow	ExtremHigh	VeryHigh	regular	regular	regular	regular	regular	regular	regular	regular	L
1989	regular	VeryHigh	ExtremLow	regular	regular	regular	regular	regular	regular	regular	regular	regular	regular	regular	regular	regular	regular	L
1990	Hight	ExtremHigh	VeryLow	Hight	regular	regular	Low	regular	regular	regular	regular	ExtremHigh	VeryHigh	regular	regular	VeryHigh	regular	L
1991	Low	Low	regular	regular	Low	VeryHigh	regular	regular	regular	regular	regular	regular	regular	regular	Hight	regular	VeryHigh	H
1992	Low	regular	regular	Low	Hight	VeryHigh	Hight	regular	regular	regular	Hight	regular	regular	regular	regular	regular	regular	L
1993	Low	regular	regular	regular	Low	ExtremHigh	Hight	regular	Hight	regular	VeryHigh	regular	regular	VeryHigh	regular	regular	regular	L
1998	regular	regular	regular	Hight	regular	ExtremLow	ExtremLow	regular	VeryHigh	regular	regular	regular	regular	regular	regular	regular	regular	H
1999	regular	regular	regular	regular	regular	regular	regular	regular	regular	regular	Hight	regular	Hight	regular	regular	VeryHigh	regular	H
-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
2017	regular	Hight	regular	regular	Hight	regular	regular	regular	regular	regular	regular	VeryHigh	Hight	regular	regular	regular	regular	H
2018	regular	VeryLow	VeryHigh	regular	regular	regular	regular	regular	regular	regular	regular	regular	regular	regular	regular	regular	regular	L

Appendix 3

Table 8. The results from the Pearson chi-square analysis with the weather stations and climate markers. Bolded values are significant p-values within a significance level of >0.05.

WTH	Years	Vol_ToTal_PcP	Tmp_average	Nb_frost	Nb_WetDays	Vol_Average_Wetday	Nb_DrySpell_5d	Nb_days_DrySpells_5d	Nb_WetSpell_5d	Nb_days_WetSpells_5d	Nb_DailyExtr_PcP	Ratio_DailyExtr_PcP	Nb_WarmSpell	Nb_days_WarmSpell	Nb_ColdSpell	Nb_days_ColdSpell	Nb_days_WarmDry	Nb_days_ColdWet
0004ERA5	0.609	0.227	0.913	0.253	**0.029**	0.657	0.832	0.652	0.529	0.627	0.208	0.166	0.412	0.562	0.562	0.369	**0.049**	0.664
0006ERA5	0.538	0.397	0.061	0.801	0.970	0.132	**0.032**	0.145	0.148	0.465	0.181	0.083	0.788	0.921	0.366	**0.008**	0.837	0.314
0007ERA5	0.106	0.552	0.209	0.257	0.499	0.411	0.947	0.553	0.142	0.481	**0.025**	0.660	0.957	0.329	0.213	**0.004**	0.264	0.089
0023ERA5	0.235	0.704	0.060	0.420	0.475	0.363	0.123	0.705	0.152	0.635	0.886	0.837	0.299	0.800	0.874	0.178	0.653	0.888
0024ERA5	0.660	0.792	0.647	0.510	0.701	0.401	0.137	0.536	0.896	0.666	0.828	0.003	0.539	0.805	0.502	0.263	0.555	0.621
0039ERA5	0.708	0.232	0.359	0.440	0.108	0.620	0.784	0.208	0.539	0.133	0.388	0.778	0.200	0.733	0.167	0.214	0.406	0.428
0041ERA5	0.962	0.294	0.949	0.886	0.134	1.000	0.470	0.467	0.267	0.660	0.665	0.557	0.410	0.625	0.522	0.287	0.528	0.390
0052ERA5	0.505	0.502	0.219	0.085	0.262	0.842	0.851	0.312	0.723	0.302	0.815	0.969	0.870	0.625	0.294	0.428	0.753	0.075
0053ERA5	**1.74E-12**	0.317	0.178	0.368	0.523	0.080	0.130	0.835	0.204	0.905	0.410	0.465	NA	**0.019**	0.841	0.935	0.893	0.101
0067ERA5	0.758	0.671	0.431	0.425	0.103	0.733	0.095	0.686	0.648	**0.012**	0.167	0.273	0.205	0.839	0.896	0.175	0.075	0.529
0068ERA5	0.536	0.606	0.126	0.949	**0.032**	0.857	0.139	**0.019**	0.972	0.847	0.681	0.093	0.106	0.098	0.306	0.334	0.208	0.457
0093ERA5	0.483	0.397	0.450	0.949	0.403	0.837	0.182	0.979	0.861	0.296	0.465	0.488	0.588	0.625	0.366	0.175	0.757	0.555
0094ERA5	1.000	0.506	0.306	0.817	0.113	0.847	0.306	0.522	0.555	0.747	0.723	0.684	0.526	0.912	0.879	0.625	0.098	0.157
0114ERA5	0.352	0.322	0.060	0.312	0.898	0.597	0.182	0.629	0.861	0.241	0.954	0.175	0.857	0.295	0.366	0.438	0.671	0.555
0201ERA5	0.103	0.611	0.248	0.077	0.096	0.867	0.185	0.139	0.615	0.524	0.489	0.725	0.666	0.236	0.456	0.453	0.973	0.183
0273ERA5	**0.017**	0.695	0.107	0.050	**0.003**	0.053	0.596	0.369	0.751	0.854	0.478	0.731	0.806	0.274	0.456	0.188	1.000	0.183
0812ERA5	0.740	0.656	0.303	0.556	0.667	0.784	0.368	0.661	0.359	0.829	1.000	0.748	0.758	0.527	1.000	0.753	0.058	0.183
1146ERA5	0.130	0.638	0.449	0.316	0.936	0.133	**0.020**	0.879	0.065	0.514	0.145	0.297	0.324	0.645	0.738	0.360	0.077	0.053
1148ERA5	0.132	0.884	0.431	0.557	0.549	0.159	**0.024**	0.728	0.723	0.660	0.666	0.466	0.445	0.912	0.600	0.776	**0.022**	1.000
1150ERA5	0.387	0.636	0.370	0.070	0.732	0.197	0.798	0.462	0.432	0.592	0.983	0.971	0.399	0.589	0.564	0.195	0.818	0.497

WTH	Years	Vol_ToTal_PcP	Tmp_average	Nb_frost	Nb_WetDays	Vol_Average_Wetday	Nb_DrySpell_5d	Nb_days_DrySpells_5d	Nb_WetSpell_5d	Nb_days_WetSpells_5d	Nb_DailyExtr_PcP	Ratio_DailyExtr_PcP	Nb_WarmSpell	Nb_days_WarmSpell	Nb_ColdSpell	Nb_days_ColdSpell	Nb_days_WarmDry	Nb_days_ColdWet
1201ERA5	**0.023**	0.432	0.657	0.326	0.532	**0.008**	0.091	0.676	0.119	0.493	0.288	0.625	0.984	0.394	0.356	0.760	0.068	0.204
1207ERA5	0.915	0.312	0.254	0.751	0.717	0.251	0.274	0.909	0.608	0.796	0.752	0.737	**0.014**	0.261	0.347	0.287	0.548	1.000
1209ERA5	0.849	0.388	0.203	0.193	0.572	0.319	0.763	0.884	0.608	0.573	0.442	0.988	0.225	0.942	0.747	0.098	0.804	0.795
1228ERA5	0.371	0.150	0.607	0.566	0.149	0.420	0.319	0.399	0.188	**0.029**	0.776	0.442	**0.045**	0.534	0.981	0.426	0.350	0.519
1230ERA5	0.152	0.748	0.584	0.912	0.764	0.767	0.491	0.733	0.303	0.792	0.632	0.733	0.183	0.318	0.872	0.975	**0.007**	0.661
1231ERA5	0.433	0.384	0.922	0.587	0.811	0.536	0.138	0.662	0.918	0.183	0.815	0.870	0.488	**0.029**	1.000	0.331	0.487	0.598
1260ERA5	0.071	0.562	0.372	0.531	0.542	0.230	0.982	0.474	0.533	0.126	0.303	0.463	**0.005**	**0.041**	0.473	**0.049**	**0.024**	0.661
1261ERA5	0.093	0.483	0.887	0.777	0.819	0.475	0.918	0.553	0.071	0.590	0.808	0.438	0.059	**0.038**	0.759	0.731	0.139	0.183
1265ERA5	0.310	0.455	0.676	0.202	0.209	0.807	0.321	0.543	0.795	0.709	0.190	0.084	0.062	0.329	0.795	0.291	0.308	0.661
1280ERA5	0.117	0.723	0.113	0.602	0.902	0.408	0.263	0.502	0.063	0.351	0.815	0.514	**0.023**	**0.038**	0.529	0.950	0.896	0.489
1281ERA5	0.432	0.807	0.523	0.446	0.886	0.510	0.165	0.879	0.828	0.684	0.985	0.714	0.476	0.472	0.871	0.802	0.628	0.661
1282ERA5	0.696	0.814	0.983	0.943	0.943	0.688	0.317	0.966	0.681	0.884	0.835	0.203	0.183	0.974	0.446	0.557	0.209	0.207
1284ERA5	0.242	0.933	0.281	0.439	0.340	0.851	0.549	0.538	0.346	0.602	0.290	0.625	0.570	0.591	0.628	0.702	0.983	0.487
1641ERA5	0.117	0.909	0.130	0.104	0.742	0.857	0.844	0.985	0.142	0.093	0.954	0.731	0.317	0.514	0.055	0.955	1.000	0.183
1709ERA5	0.095	0.575	0.857	0.419	0.493	0.839	0.466	0.302	0.533	0.090	0.072	0.048	0.795	0.852	0.188	0.483	0.985	0.183
1866ERA5	0.111	0.479	0.974	0.928	0.804	0.279	0.078	0.558	0.434	0.145	0.666	0.644	0.283	0.375	0.476	0.438	0.091	0.183
1930ERA5	0.954	0.617	0.858	0.660	0.862	0.919	0.359	0.379	0.728	0.605	0.972	0.089	0.508	0.167	0.127	0.751	**0.009**	0.715
2012ERA5	0.144	0.216	0.635	0.644	0.487	0.993	1.000	0.834	0.163	0.673	0.575	0.454	0.141	0.828	0.673	0.142	0.130	0.539
2021ERA5	**0.040**	0.665	0.867	0.503	0.450	**0.050**	0.606	0.452	0.934	0.330	0.167	0.548	0.934	**0.038**	0.222	0.441	0.255	1.000
2024ERA5	0.654	0.725	0.382	0.445	0.660	0.386	0.885	0.514	0.660	0.441	0.539	0.739	0.957	0.847	0.312	0.648	0.821	NA
2091ERA5	0.928	0.300	0.324	0.817	0.710	0.410	0.905	0.308	**0.037**	0.887	0.443	0.667	0.714	0.789	0.943	0.138	0.175	1.000
2093ERA5	0.859	0.755	0.334	0.210	0.771	0.799	0.755	0.492	1.000	0.896	0.171	0.243	0.758	0.753	0.144	0.287	**0.022**	0.060
2094ERA5	0.568	0.532	0.417	0.399	0.503	0.253	0.755	0.648	0.204	0.089	0.836	0.270	0.186	0.959	0.783	0.871	0.991	0.060
2095ERA5	0.626	0.985	0.119	0.127	0.916	0.331	0.411	0.225	0.053	0.300	0.562	0.766	0.758	0.758	0.406	0.708	0.125	0.216
2170ERA5	0.608	0.319	0.259	0.225	0.998	0.172	0.210	0.998	0.051	0.087	0.504	0.467	0.714	0.463	0.879	0.139	0.152	0.212
2234ERA5	0.608	0.319	0.259	0.225	0.998	0.172	0.210	0.998	0.051	0.087	0.504	0.467	0.714	0.463	0.879	0.139	0.152	0.212

Appendix 4

Table 9. Results from the linear mixed model correlation analysis with Z-transformed data set. No variables were significant to the simulated yield. Significance is measured as -0,5>x>0,5. Variables explanation is found in Table 2. Level of significance p<0.005.

Variable	Correlation value	Variable	Correlation value
Yield_kg_ha	1.000	Var5_Var13	0.022
Var2	-0.025	Var5_Var13	0.022
Var3	0.051	Var5_Var14	0.052
Var4	-0.152	Var5_Var15	-0.011
Var6	0.115	Var5_Var16	0.025
Var7	0.130	Var5_Var17	-0.061
Var9	-0.056	Var7_Var9	-0.063
Var10	0.044	Var7_Var10	-0.090
Var11	0.049	Var7_Var11	-0.092
Var13	0.138	Var7_Var12	0.083
Var14	-0.021	Var7_Var13	0.096
Var15	0.024	Var7_Var14	-0.073
Var16	0.156	Var7_Var15	-0.006
Var17	0.001	Var7_Var16	0.108
Var2_Var3	0.103	Var7_Var17	-0.032
Var2_Var4	-0.024	Var6_Var9	-0.051
Var2_Var5	0.075	Var6_Var11	-0.110
Var2_Var6	0.062	Var6_Var12	0.033
Var2_Var7	0.062	Var6_Var10	-0.093
Var2_Var9	0.046	Var6_Var13	0.044
Var2_Var10	0.051	Var6_Var15	-0.041
Var2_Var11	0.043	Var6_Var16	0.106
Var2_Var12	-0.010	Var6_Var17	-0.015
Var2_Var13	-0.006	Var9_Var10	0.034
Var2_Var14	0.077	Var9_Var11	0.005
Var2_Var15	0.041	Var9_Var12	-0.036
Var2_Var16	0.021	Var9_Var13	-0.045
Var2_Var17	0.054	Var9_Var14	-0.063
Var3_Var4	0.018	Var9_Var15	-0.068
Var3_Var5	-0.086	Var9_Var16	-0.036
Var3_Var6	-0.071	Var9_Var17	-0.003
Var3_Var7	-0.060	Var10_Var13	0.018
Var3_Var9	-0.069	Var10_Var11	0.043
Var3_Var10	-0.063	Var10_Var12	-0.010

Variable	Correlation value	Variable	Correlation value
Var3_Var12	0.008	Var10_Var15	-0.021
Var3_Var13	0.020	Var10_Var16	-0.001
Var3_Var14	-0.096	Var10_Var17	-0.009
Var3_Var15	-0.096	Var11_Var13	0.043
Var3_Var16	0.004	Var11_Var12	-0.010
Var3_Var17	-0.084	Var11_Var14	-0.041
Var4_Var5	0.048	Var11_Var15	-0.021
Var4_Var6	-0.023	Var11_Var16	-0.001
Var4_Var7	-0.032	Var11_Var17	-0.009
Var4_Var9	0.018	Var12_Var13	-0.010
Var4_Var10	0.078	Var12_Var14	-0.041
Var4_Var11	0.075	Var12_Var15	-0.021
Var4_Var12	-0.097	Var12_Var16	-0.001
Var4_Var13	-0.105	Var12_Var17	-0.009
Var4_Var14	0.019	Var13_Var15	0.017
Var4_Var15	-0.035	Var13_Var14	-0.010
Var4_Var16	-0.093	Var13_Var16	0.079
Var4_Var17	0.011	Var13_Var17	-0.036
Var5_Var6	-0.046	Var14_Var15	-0.043
Var5_Var7	-0.046	Var14_Var16	-0.058
Var5_Var9	0.051	Var14_Var17	-0.036
Var5_Var10	0.067	Var15_Var16	0.007
Var5_Var11	0.093	Var15_Var17	-0.044
Var5_Var12	0.043	Var16_Var17	-0.054

**Number of daily extreme precipitation (Var2), Number of days included in Cold Spells (Var3), Number of days included in dry spells of 5 days or more (Var5), Number of days included in dry spell and warm spell (Var6), Number of days included in warm spells (Var7), Number of days included in wet spells of 5 days or more (Var8), Number of late frost days OR Number of early frost days? (Var10), Number of warm Spells (Var11), Ratio of precipitation falling during extreme event (Var14), Average temperature (Var15), Average precipitation volume per wet days (>1mm) (Var16), Total Precipitation volume (Var17)*

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