Attribution of Winter Wheat Yield Variability to Climate Drivers in Switzerland

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Abstract

Climate variability is known to impact crop yields. Studying how a crop's yield may vary in the future is important in order to allow time for agricultural adaptation measures to be developed. Winter wheat is an important crop in Switzerland and understanding how its yields may change with the climate is important for food security. This thesis used correlation analysis to study which climate indicators relate most strongly to wheat yields from 1981 to 2017, and constructed a multiple regression model to predict yield on the basis of climate variables. The model had a R^2 of 0.35 and its most important climate variables were temperature, especially summer heat and winter frost. Adverse effects of warmer winter temperatures and precipitation were also identified. Radiation was significant as well, but its role was more difficult to interpret. The model was also used to predict yield based on data 2°C and 4°C warmer. The results indicate that mean yield may not change significantly under these circumstances, but yield variability from year to year would likely increase. These results suggest that including additional variables in statistical crop models, not only temperature and precipitation, may be beneficial but not essential. Additionally, using intra-seasonal climate variables can give insight into what specific challenges crop growers may face. Future studies could help clarify relationships between climate drivers and yield across the regions of Switzerland. They may also benefit from the use of more sophisticated climate projections.

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1. Introduction

1.1 Motivation

Studies have established that climate variability contributes to crop yield variability (Hatfield & Prueger, 2015; Lobell & Field, 2007; Ray et al., 2019). Therefore, as the climate changes, yield amounts and variability are also expected to change. Studying the relationship between climate variables and yield can therefore give insight into what drives changes in yield. Climate projections can then be used to estimate changes in yield in the future. This information can in turn be used to plan an agricultural adaptation strategy for climate change, since technology and adaptation also play a role in crop yields (Lecerf et al., 2019). A crop model is one of the tools that can be used to examine yield and the variables that influence it.

This study examines winter wheat (*Triticum aestivum* L.) in Switzerland, one of the most important crops in Switzerland for direct human consumption. In Switzerland, wheat yield increased steadily from the 1960s to the 1990s, due to technological advancements such as crop breeding. However, this growth tapered off in the early 1990s due to agricultural policy changes that promoted environmental wellbeing, which included measures such as banning fungicides and insecticides (Finger, 2010). Climate suitability for winter wheat growth may have decreased in recent decades, but a yield decrease attributable to climate was not identified (Holzkämper et al., 2014).

Wheat cultivars in Europe have been carefully selected to perform under specific growing conditions. In Switzerland, these growing conditions are likely to change in the future. Without significant global action to mitigate climate change, by 2060, the country could face increased summer temperatures (+2.5 to +4.5°C) and changes in summer precipitation (-25% to +10%) compared to the reference period 1981-2010 (NCCS, 2018). Current wheat cultivars may not perform as well under these conditions (Mäkinen et al., 2018). A greater understanding of how future conditions may affect yield is necessary so that farmers can adapt. Adaptation strategies such as planting different crop varieties or developing new ones, or implementing irrigation, can be effective, but they require time to develop and implement (Semenov et al., 2014). Therefore, models are a tool that can help researchers understand how to best prepare for future conditions to preserve food security.

1.2 Context

Statistical models are based on regression equations, built from crop yield and weather data, and are relatively simple compared to process-based (numerical) models, which are built on experimental trials and require more data input (Lobell & Burke, 2010). Statistical models are useful for projecting future responses in yield, and they are more useful at broad scales than at single sites (Lobell & Burke, 2010). The performance of a statistical model differs with the response to each climate variable chosen (Lobell & Burke, 2010). The most commonly selected variables in statistical crop models are temperature, total precipitation, and annual grain yield. Temperature is usually taken as daily or monthly minimum and maximum, and sometimes average, through the growing season.

These climate variables have been shown to affect yields of various crops. Wheat, maize, and barley have a negative response in yield globally due to increased temperatures. By 2002 there were already global losses of $5 billion a year, although they were compensated by technological advancements (Lobell & Field, 2007). A study of European wheat yield found that it had a climate sensitivity of 6% decrease with a 1°C increase in temperature (Mäkinen et al., 2018).

1.2.1 Wheat Development

Winter wheat is sown in October in Switzerland, and harvested in June or July, but sometimes as late as August. As wheat grows throughout this lengthy growing season, different factors influence the plant's eventual yield. For survival and high yield, it is critical that the plant's various stages of growth are synchronized with optimal seasonal conditions (Hyles et al., 2020).

In the fall, the seed sprouts and grows a main shoot. Then tillers, or axillary shoots, grow (Hyles et al., 2020; Large, 1954). Tillers are essential for high yields, because each tiller has the potential to form one head. Each head contains spikelets, which are composed of florets. Each floret can produce one kernel of wheat. Tillers that grow in the fall are more productive in terms of yield. This is because in the spring, the plant is focused on reproductive growth instead of vegetative. The driving force behind this differentiation in growth is vernalization. Vernalization occurs in winter, when the plant experiences cold temperatures for several successive weeks. Several factors affect winter survival ("Winter Wheat Development and Growth Staging," 2018). Exposure to cold temperatures "hardens" the plant to survive freezing temperatures. Therefore, temperatures that are cold but above freezing can aid winter survival (Hyles et al., 2020). Repetitive freezing and thawing damages tissues more than a single frost event. Ice encasement or midwinter thaw and rain with flooding can both suffocate plants. Snow cover can provide protective insulation ("Winter Wheat Development and Growth Staging," 2018).

Vernalization ends when temperature warms and the wheat experiences more radiation due to longer days in spring. After these conditions are met, reproductive growth is induced, so the head begins to grow inside the stem (Hyles et al., 2020). This reproductive growth is not hardened to frost the way that the vegetative tissue was, so after vernalization is over the plant becomes vulnerable to frost ("Winter Wheat Development and Growth Staging," 2018). Warmer springs, and therefore shorter vernalization periods, can lead to fewer heads, which in turn result in lower yields (Ortiz et al., 2012) Stem elongation occurs just as the plant enters the reproductive growth stage. If this period of growth lasts longer, the spike grows longer, and therefore more florets and potentially more kernels can grow (Kronenberg et al., 2019). The heads emerge, flower, and fertilize. At this point the plant enters the grain-filling stage, where kernels grow. During the plant's reproductive growth phase, higher temperatures can accelerate the plant's life cycle, ultimately resulting in a lower yield (Fischer, 1985). The period after anthesis, or flowering, through grain-filling, is especially critical and sensitive. High temperatures during this time period can drastically reduce yield, as the grain-filling is accelerated and the kernels are much smaller at maturity (Gibson & Paulsen, 1999; Mitchell et al., 1993). Finally, the plant dries to straw and is ready for harvest. In Switzerland harvest usually occurs in June, but may be as late as August.

1.3 Research question

The objective of the master thesis is to attribute interannual variability of winter wheat yields in Switzerland to variation in climate drivers. The specific research questions addressed are:

1. Which climate indicators relate most strongly to observed winter wheat yields?
2. How do these relationships between climate drivers and yield deviate between different agroclimatic regions of Switzerland?
3. How well can yield variability be predicted on the basis of climate variables?
4. How might yield variability change under warmer conditions?

2. Data and Methods

2.1 Data

Weather data was downloaded from the Swiss Federal Office of Meteorology and Climatology's (MeteoSwiss) IDAWEB server, for the years 1981-2017. The variables downloaded were:

1. daily mean air temperature 2 meters above ground (°C),
2. daily maximum air temperature 2 meters above ground (°C),
3. daily minimum air temperature 2 meters above ground (°C),
4. calendar day precipitation (mm),
5. daily mean relative air humidity 2 meters above ground (%),
6. daily mean vapor pressure 2 meters above ground, and
7. daily mean global radiation (W/m^2).

The Farm Accountancy Data Network of Switzerland (FAT) provided annual winter wheat yield totals sampled from farms within local communities between 1981 and 2017.

2.2 Data Processing

Data processing was conducted in R (R Core Team, 2020b), generally following the outline described in Holzkämper et al. (2014). The first step was to match municipal wheat data to corresponding weather data. This was done by drawing a radius of 15 km around each weather station. When a municipality's centroid fell inside the radius, it was assigned to that station. Then, yield data was aggregated for each station. Stations with no wheat yield data were removed from further analysis, leaving 86 stations out of an original 210. For the remaining 86 stations, the yields from all the assigned municipalities were aggregated by year, and the mean, standard deviation, minimum, maximum, and median values were calculated. Fourteen stations were chosen for further analysis: Bern Zollikofen, Güttingen, Genève Cointrin, Zürich Kloten, Neuchâtel, Payerne, Pully, Zürich Affoltern, Schaffhausen, St. Gallen, Aadorf Tänikon, Vaduz, Wädenswil, and Wynau. Station names, abbreviations, coordinates, elevation, average daily temperature, and average annual precipitation are shown in Table 1. The location of each station is shown in Figure 1.

Table 1: Stations with their full names, Swiss kilometer coordinates, elevation, and average daily temperature and average annual precipitation from 1981 to 2017.

Station	Full Name	X Coordinate (km)	Y Coordinate (km)	Elevation (m)	Temperature (°C)	Precipitation (mm)
BER	Bern Zollikofen	601933	204409	552	9.2	1039
GUT	Güttingen	738421	273962	440	9.4	955
GVE	Genève Cointrin	498904	122631	410	10.7	933
KLO	Zürich Kloten	682710	259338	426	9.5	986
NEU	Neuchâtel	563086	205559	485	10.4	970
PAY	Payerne	562131	184611	490	9.5	864
PUY	Pully	540819	151510	455	11.0	955
REH	Zürich Affoltern	681432	253548	443	9.5	1027
SHA	Schaffhausen	688702	282803	438	9.6	913
STG	St. Gallen	747865	254588	775	8.4	1328
TAE	Aadorf Tänikon	710517	259824	539	8.8	1182
VAD	Vaduz	757722	221699	457	10.2	952
WAE	Wädenswil	693847	230744	485	9.7	1376
WYN	Wynau	626404	233848	422	9.2	1129

The selected stations had sufficient climate time series data and give an overview of the Swiss plateau, the relevant area for wheat harvest. Weather data was cropped to match the growing season, from sowing in October of the previous year to August, the latest possible date for harvest.

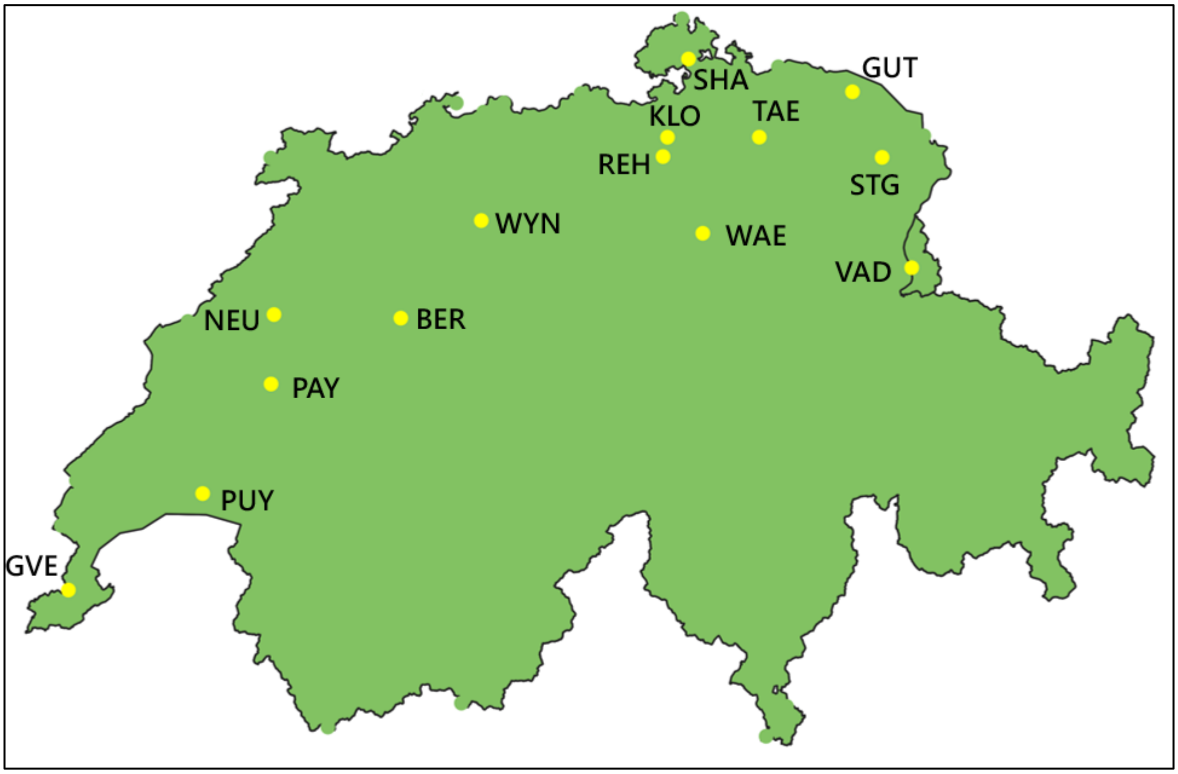

Figure 1: Locations of the 14 selected weather stations across the Swiss plateau.

The climate data were processed into indices and some derived variables were calculated. In total, nine final variables were used for analysis:

1. daily mean air temperature 2 meters above ground (°C),
2. daily maximum air temperature 2 meters above ground (°C),
3. daily minimum air temperature 2 meters above ground (°C),
4. daily maximum temperature over 25°C,
5. daily minimum temperature below 0°C,
6. calendar day precipitation (mm),

7. daily total water availability (mm),

8. daily mean vapor pressure deficit (hPa), and

9. daily mean global radiation (W/m^2).

The derived climate variables were water availability, vapor pressure deficit, mean temperature below 0°C, and mean temperature above 25°C. Water availability is equal to precipitation minus evapotranspiration (Holzkämper et al., 2014). Vapor pressure deficit was calculated from measured vapor pressure and relative humidity (Castellvi et al., 1996). Vapor pressure deficit was included rather than simply humidity (Hsiao et al., 2019). To calculate mean temperature below 0°C, days with minimum temperatures below 0°C were selected, and the average temperature was computed. This was to capture frost effects. The same procedure was done for days with maximum temperatures above 25°C, to capture heat stress effects (Acevedo et al. 2002, cited in Holzkämper et al., 2014).

To create indices, the variables were averaged for each month of the growing season (October to August), and then for seasonal aggregates. The exception is precipitation, which is measured cumulatively instead of averaged. Seven seasonal aggregates were created: October and November (ON), October through December (OND), December through February (DJF), January through March (JFM), March through May (MAM), April through June (AMJ), and June through August (JJA). The growing season was also calculated (GS).

Additional packages used in data processing are listed in the references (Hlavac, 2018; Nolan & Padilla-Parra, 2017; R Core Team, 2020a; Zarei et al., 2019a).

2.3 Data analysis

The steps of the data analysis were designed to answer the research questions of the thesis. Correlation analysis was performed to answer the question corresponding to the relationship between yield and climate variables. Station-specific correlation analysis was used to analyze possible changes in these relationship across different regions of Switzerland. A linear model was created and judged based on its ability to predict yield variability using climate variables. Finally, the model was used to predict yield density distribution with warmer temperatures.

When building linear crop models, yield is typically detrended (Nicholls, 1997; Shi et al., 2013). It is assumed that some improvements in yield production over time are due to advancements in agricultural practices such as crop variety selection and fertilizer application (Shi et al., 2013). In an attempt to remove these anthropological elements and isolate the effects of climate, the trend with time is removed. Detrending of yield was performed before the correlation analysis and linear regression, since the correlation analysis was used to choose the variables for the linear model. Each station's yield data was detrended separately using the "Detrend" function from the *SpecsVerification* package (Siegert, 2020). This function fits a linear trend to a time series and then removes it. Finally, data from all 14 stations were combined into one dataset.

2.3.1 Correlation analysis

Correlation analysis was performed to examine the relationship between yield and each of the climate variables. These results also informed the choice of variables for the linear model.

Two-sided Pearson correlation tests were performed in R. This tests for a linear relationship between paired samples, from 0 (no relationship) to 1 (equal), with a p-value used to determine statistical significance. First, the dataset with all stations was tested. Then, each station was tested individually in order to examine possible trends across the wheat-growing region of Switzerland. Some stations had insufficient data for meaningful results. Trends were examined at different stations to compare if certain climate variables had a stronger relationship with wheat in different regions. Additionally, to examine changes in trends in later years, the dataset was split in half, into earlier and later years. Correlation analysis was performed on each half so that the results could be compared.

2.3.2 Linear regression

A linear model was built using the selected climate indices as predictor variables and yield as the response variable. The objective was to answer the third research question, about how well yield variability can be predicted on the basis of climate variables.

The same dataset of combined data from all selected stations that was used in the correlation analysis was also used here. All rows with NA values were removed. The data was not split for cross-validation at this point, as automated cross-validation was performed later. The linear model was built stepwise, and then with the help of a best linear model selection function from the *bestglm* package (Kern et al., 2018; McLeod et al., 2020). First, the correlation analysis of all stations was examined. Indices with statistically significant correlations were all selected. This included many variables that correlated with each other, which can cause collinearity problems (Shi et al., 2013). To reduce this danger, correlation analysis of all the variables with each other was performed. Variables that had a correlation coefficient of |0.5| or higher (closer to positive or negative 1) with each other were identified, and only one of them was selected for the model. That selection was based on the variable having fewer covariates overall and having a stronger correlation with yield. Then all of these variables were put into the step function, which uses Akaike information criterion (AIC) to remove some variables until the final model has a good fit but avoids overfitting. This reduced the number of variables. Next, quadratic terms were added for the remaining temperature and moisture variables, to check for nonlinear effects. Then the step function was repeated. Once fewer than ten linear and nonlinear terms were remaining, the *bestglm* function was used. It selects the best subset of a linear model using an information criterion like AIC or cross-validation. In this case, cross-validation was used.

Once a satisfactory model had been created, the final step was to check its residuals. Quantile-quantile plots and the Shapiro-Wilks normality test were used to confirm that the residuals were normally distributed.

2.3.3 Predicted yield density distribution with increased temperatures

This method was designed to answer the fourth research question concerning the prediction of yield variability change under warmer conditions. This was done by perturbing the data. The temperature values were increased, but other variables were left constant. The first step was to create a histogram. Then the linear model was used to predict a density distribution without any change to the data. Next, 2°C were added to each value of each temperature column to create a new, perturbed dataset. A third dataset was created with the temperature increased a further 2°, or 4° higher than the measured data. These two new datasets were input into the prediction of the linear model, creating two more density distributions.

3. Results

3.1 Correlations

First, the results of the correlation analysis from the large dataset will be examined. Next, regional differences will be addressed. Finally, correlations from the years before and after 2000 will each be examined.

3.1.1. All Stations

Correlations for the five temperature indices can be seen in Figure 2. The eleven months of the growing season are shown on the left side, and seasonal indices are shown on the right. A few patterns are visible. First, correlations between yield and temperature are generally small. However, mean, minimum, and maximum temperatures have a strong negative correlation in December. Correlations with mean maximum temperature over 25°C are very small, less than |0.1|, and none of them are statistically significant. Mean minimum temperature below 0°C appears to have a significant, positive relationship with yield in late winter and early spring.

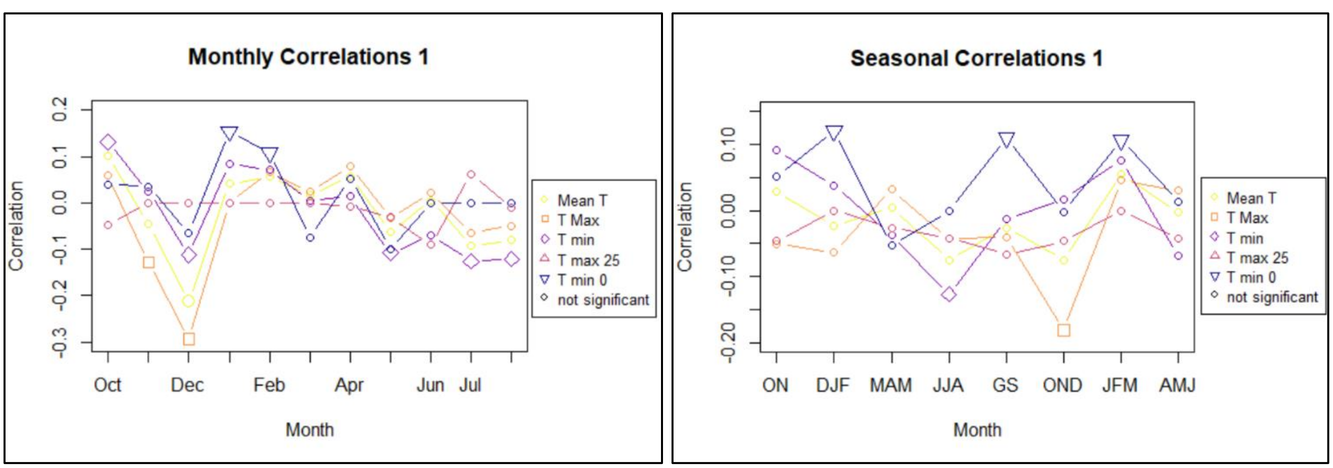

Figure 2: Monthly (left) and seasonal (right) correlations between five temperature variables and yield. Small circles indicate correlation values that are not statistically significant. Larger shapes indicate statistically significant correlations of their respective variables.

Precipitation has a negative relationship with yield. Correlations are small in the fall and early winter, and higher in late winter and spring, until July. The pattern of correlations in water availability is almost identical. The same time indices are statistically significant, and the relationship between water availability and yield is also negative. This relationship between precipitation and water availability is not surprising, because precipitation is one of the two variables used to calculate water availability. The correlations with water availability are often stronger (more negative) in the monthly aggregates than they are for precipitation. Vapor pressure deficit (VPD) is the other moisture variable, and is usually inversely related to precipitation and water availability. Vapor pressure deficit has slightly fewer significant correlations, and they are less strong. However, VPD is significant more often in the fall, October through January. Higher values of VPD indicate drier conditions, while higher values of precipitation and water availability indicate wetter conditions. When looking at all stations, correlations between yield and precipitation and yield and water availability are almost always negative. Correlations between yield and VPD are negative in the fall months and generally positive in the spring months.

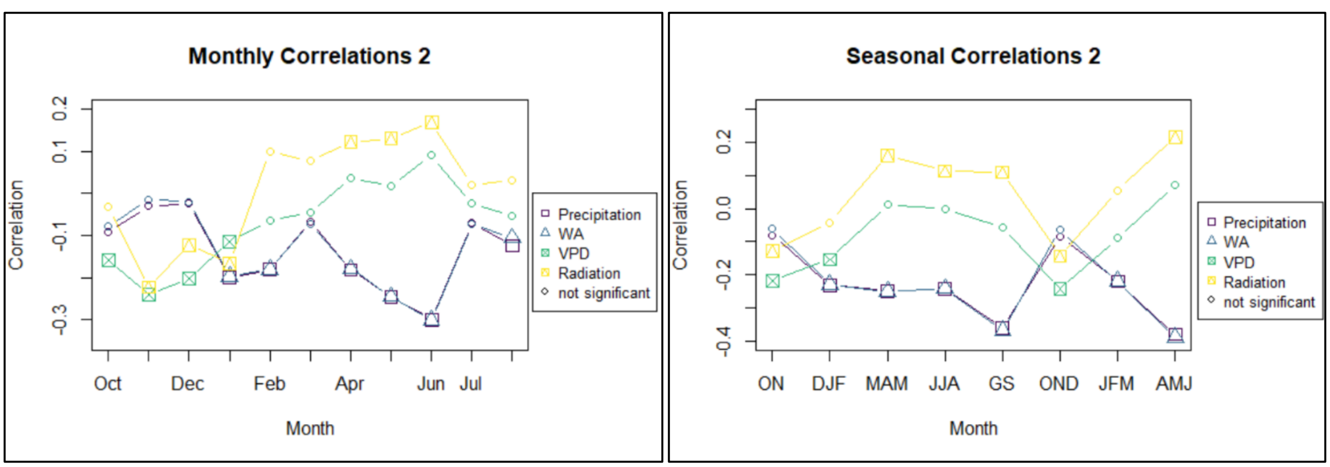

Figure 3: Monthly (left) and seasonal (right) correlations between precipitation, water availability, vapor pressure deficit, radiation, and yield. Small circles indicate correlation values that are not statistically significant. Larger shapes indicate statistically significant correlations of their respective variables.

Radiation has many statistically significant correlations. The monthly index correlations of radiation seem to be slightly similar to those of VPD. The seasonal index correlations of radiation and VPD appear very similar. In the fall and early winter, correlations are negative. From February through the remainder of the growing season, they are positive. This is reflected in the seasonal aggregates. This indicates that higher radiation in the fall is associated with lower yields, while more radiation in the early spring onwards is associated with higher yields. The strongest effect occurs in the months before harvest. This may be a cross effect rather than a direct cause.

In general, for the dataset with all stations included, negative correlations between yield and precipitation and yield and water availability can be seen. These correlations match in timing and sign but are slightly stronger for water availability. Negative correlations exist in the fall for vapor pressure deficit, but are positive by the late spring. Radiation correlations are negative until February, after which they are positive. Temperature correlations show a strong negative spike in December.

3.1.2 Regional Differences

Although variations in patterns of correlations were examined at different stations, no regional trends or distinctions could be identified. Stations with sufficient climate and yield time series were examined, nine in total. No regional patterns were visible in the relationships between climate variables and wheat. Since no conclusions could be drawn, this segment of analysis did not contribute meaningfully to the study, so their correlation estimates and p-values are shown in the appendix only.

3.1.3. Comparing Earlier and Later Years

First, temperature variables were examined. Before 2000, the only significant correlations were in minimum temperature in July (-0.46) and JJA (-0.52; Fig. 4). After 2000, the strong negative correlation with December temperatures appears for the first time (Fig. 5). Statistically significant correlations are strong and negative in December (-0.51 to -0.62). Minimum temperature below 0°C has significant negative correlations in the November indices as well. This may indicate that the negative correlation with

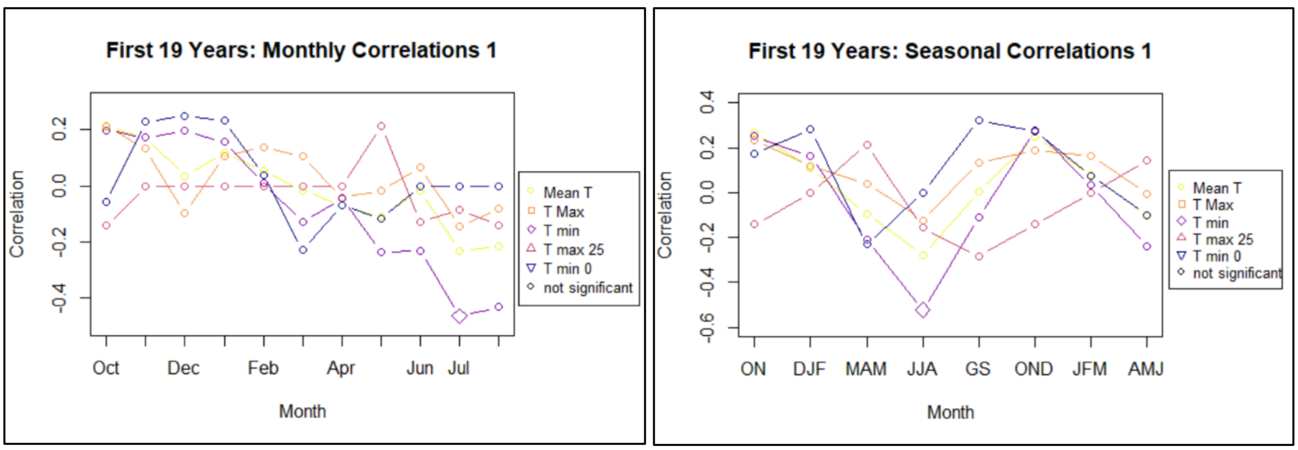

Figure 4: Monthly (left) and seasonal (right) correlations between five temperature variables and yield from 1981-1999. Small circles indicate correlation values that are not statistically significant. Larger shapes indicate a statistically significant correlation.

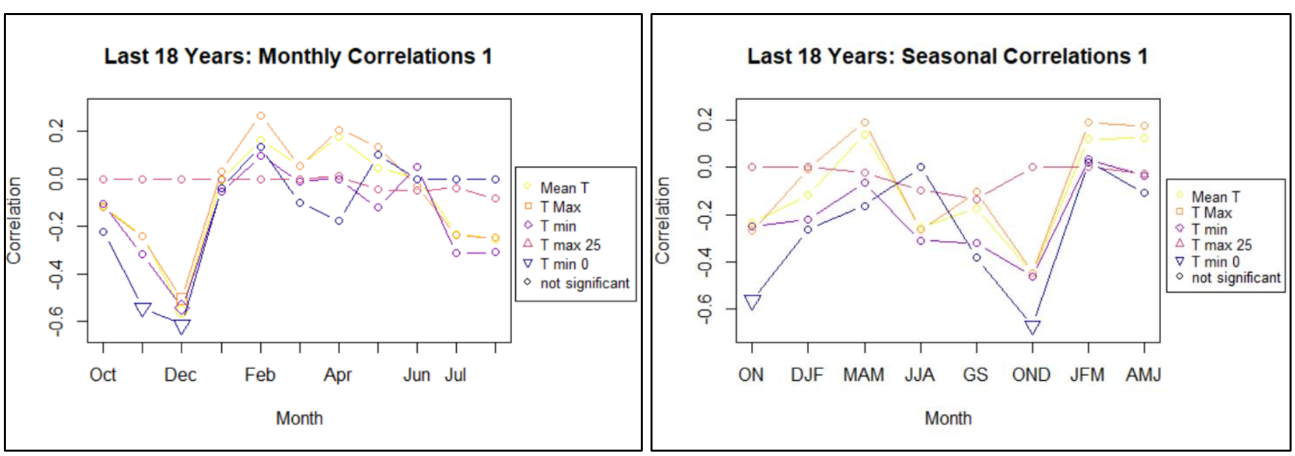

Figure 5: Monthly (left) and seasonal (right) correlations between five temperature variables and yield from 2000-2017. Small circles indicate correlation values that are not statistically significant. Larger shapes indicate a statistically significant correlation.

temperature in December that was seen in Figure 2 originated mainly in later, warmer years.

Moisture and radiation indices are shown for the years before 2000 in Fig. 6, and for the years after 2000 in Fig. 7. In the first 19 years, the significant correlations for radiation are in December (-0.48), JFM (0.52), JJA (0.47), and the growing season (0.53). For the moisture variables, water availability has significant correlations in JFM (-0.47), AMJ (-0.52), and the growing season (-0.65). Precipitation correlations are

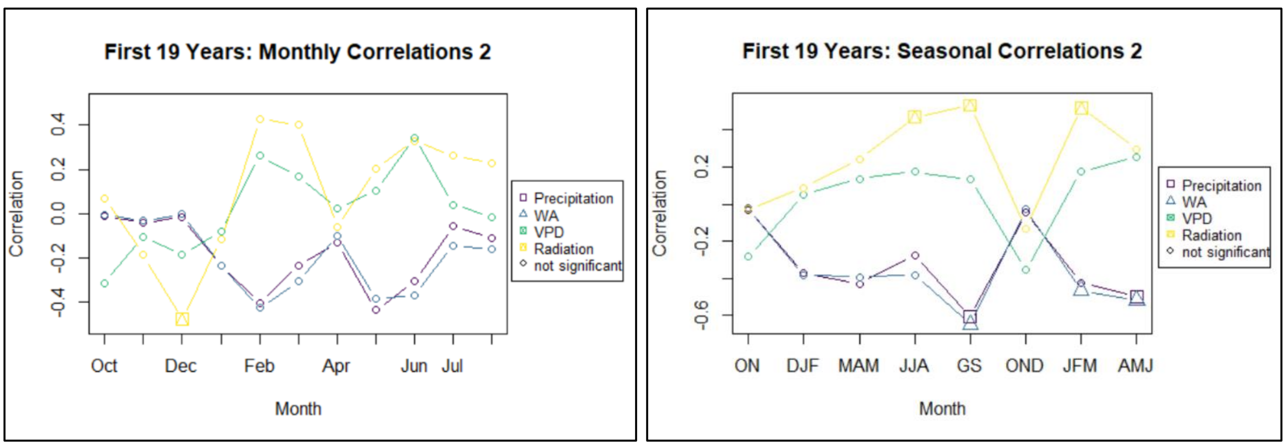

Figure 6: Monthly (left) and seasonal (right) correlations between precipitation, water availability, vapor pressure deficit, radiation, and yield from 1981-1999. Small circles indicate correlation values that are not statistically significant. Larger shapes indicate statistically significant correlations.

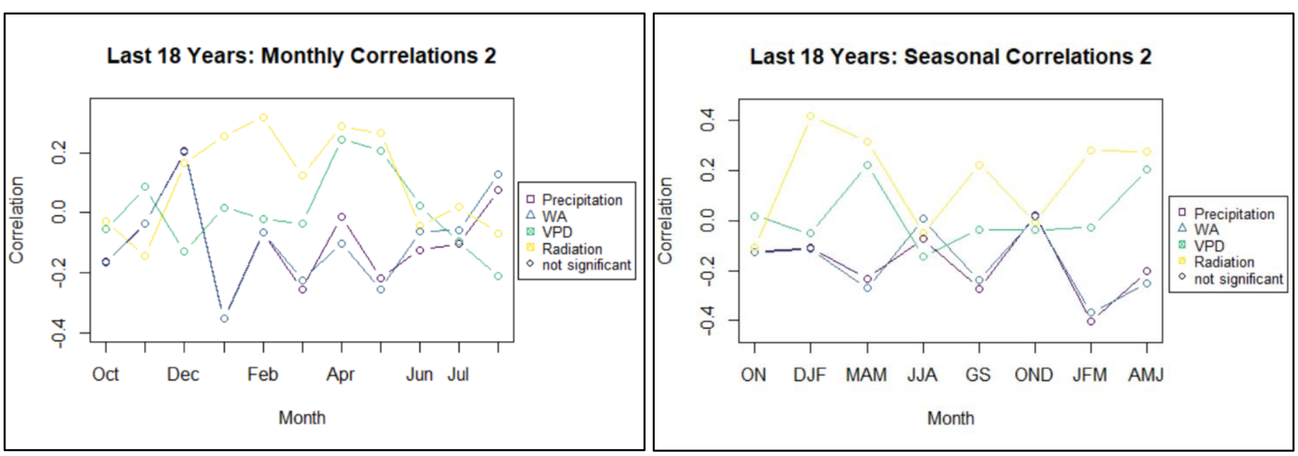

Figure 7: Monthly (left) and seasonal (right) correlations between precipitation, water availability, vapor pressure deficit, radiation, and yield from 2000-2017. Small circles indicate correlation values that are not statistically significant. Larger shapes indicate statistically significant correlations.

significant in AMJ (-0.50) and the growing season (-0.61). In general, correlations of precipitation and water availability match each other closely, while mirroring VPD, as expected. Radiation correlations seem to follow a similar pattern to VPD, especially seasonally. In the last 18 years, these patterns are not so clear, with the exception of the relationship between water availability and precipitation. There are no statistically significant correlations for radiation or moisture variables.

3.2 Linear model

The final linear model's terms and their coefficients are shown in Table 2. The model includes a quadratic term for average daily maximum temperature in December, a quadratic term for average daily minimum temperature in October, average daily minimum temperature in JJA, average daily minimum temperature below 0° in DJF, cumulative precipitation throughout the growing season, and mean daily radiation in November and AMJ. The adjusted R^2 value is 0.351.

In summary, there are four temperature variables, one moisture variable, and two radiation variables. Looking at the coefficients, this model relies more on temperature for yield prediction than on other variables. The variables with the highest coefficients are minimum temperature in JJA and minimum temperature below 0°C in DJF.

The model captures several climate effects on wheat. Winter temperatures below freezing are harmful, but so are high maximum temperatures. Warmer temperatures after sowing may be beneficial. Higher minimum temperatures in summer have a negative effect. Precipitation throughout the growing season has a weaker negative effect. Radiation has a negative effect in the fall, but a positive effect in the spring. These factors will be returned to in the discussion.

Table 2: Summary of the linear model showing the estimate for each coefficient. Standard error is indicated in parenthesis and significance level is indicated with asterisks (** $p < 0.01$; *** $p < 0.001$).

	Dependent variable:
	Yield
(Mean Daily Max Temp Dec)^2	-0.127^{***}
	(0.024)
(Mean Daily Min Temp Oct)^2	0.082^{***}
	(0.016)
Mean Daily Min Temp JJA	-1.519^{***}
	(0.316)
Mean Daily Min Temp Below 0° DJF	1.458^{***}
	(0.358)
Growing Season Precipitation	-0.010^{***}
	(0.002)
Mean Radiation AMJ	0.061^{***}
	(0.021)
Mean Radiation Nov	-0.239^{***}
	(0.039)
Constant	87.001^{***}
	(6.173)
Observations	366
R^2	0.363
Adjusted R^2	0.351
Residual Std. Error	6.116 (df = 358)
F Statistic	29.167^{***} (df = 7; 358)

3.3 Predicted yield density distribution with increased temperatures

Using the linear model, yield density distributions were predicted using a dataset with warmer temperatures. The results are illustrated in Figure 8. Summary statistics are shown in Table 3. In general, it can be seen that the mean and median yield may decrease only very slightly at higher temperatures. However, the spread increases at higher temperatures, so minimum yields are lower and maximum yields are higher.

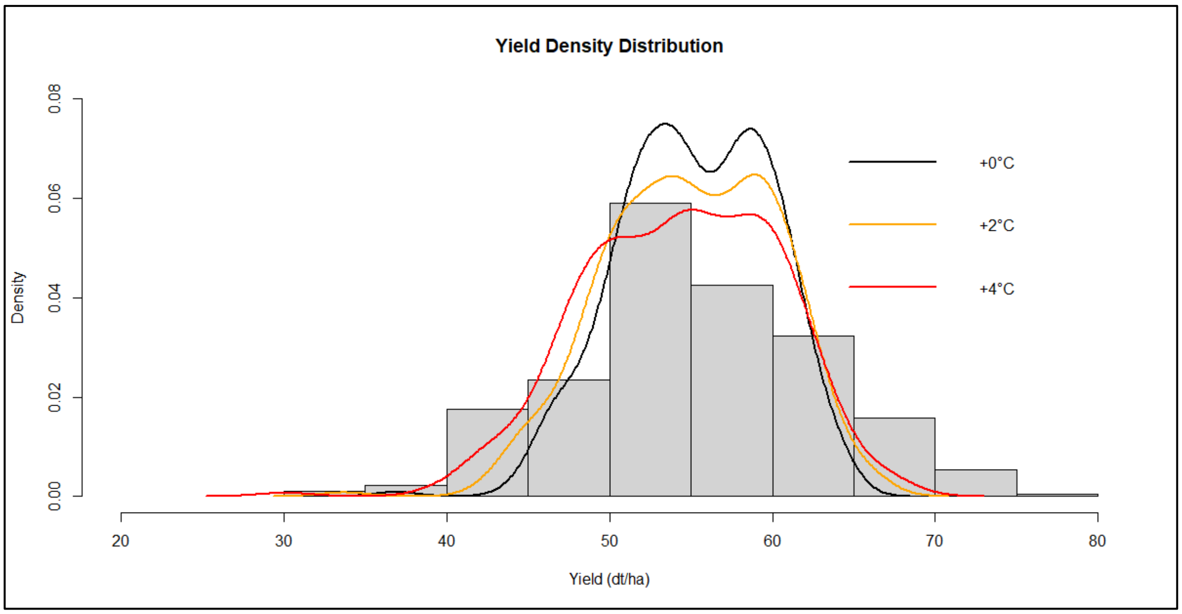

Figure 6: The histogram's gray bars represent measured yield values. The black line represents the predicted density distribution of yield based on the unaltered data and linear model. The orange line shows the predicted density distribution of yield under conditions 2°C warmer, and the red line for 4°C warmer.

Table 3: Summary statistics for the predicted density distribution of the original and perturbed datasets.

	+0°C	+2°C	+4°C
Minimum	36.85	33.65	30.08
1st Quartile	51.9	51.04	50.01
Median	55.13	54.99	54.65
Mean	55.25	54.98	54.36
3rd Quartile	58.88	59.08	59.1
Max	64.64	66.53	68.06

4. Discussion

4.1 Findings and Interpretation

4.1.1 Correlations

Some notable results of the correlation analysis will be examined in detail and put into context with other literature. First, the strong negative correlation between yield and several temperature indices in December and winter. This indicates that warmer winter temperatures are associated with lower yields. This could be related to disease. Warmer winter temperatures are associated with diseases such as rust infections later in the season, which can reduce yield (Te Beest et al., 2008) However, it could also be related to climate. Temperatures that are cold but above freezing are necessary for protective frost hardening. A warmer monthly temperature might indicate that a crop is not sufficiently hardened to survive frost, or that the field is undergoing successive periods of frost and thaw, which can be very damaging (Hyles et al., 2020; “Winter Wheat Development and Growth Staging,” 2018). These negative fall and December correlations with temperature did not appear in the earlier half of the dataset. Possibly there were not enough years with warm winter anomalies for the trend to be visible.

There is precedent for this kind of correlation in the literature. Ceglar et al. (2016) examined the relative importance of various meteorological drivers throughout different regions of France. In the wheat-growing region of France that borders Switzerland, they found a significant positive temperature anomaly in December, which contributed to a lower yield. They did find in general that significant warm temperature anomalies in the winter months had negative impacts on yield, and attributed this to reduced frost hardening and vernalization.

In January and February, positive correlations with the minimum temperature below 0°C are visible. This is related to the above points about frost and cold temperatures. Less frost is beneficial, but so are temperatures that are cold but above freezing, as they aid in vernalization and frost hardening (Hyles et al., 2020; "Winter Wheat Development and Growth Staging," 2018).

Moisture effects throughout the year were somewhat difficult to interpret. Precipitation and water availability had a negative relationship with yield throughout the growing season, indicating that drier conditions are associated with higher yields. Vapor pressure deficit was negative and significant in the fall and winter, but positive in the spring. This may be somewhat contradictory to the information from precipitation and water availability. Negative correlations with vapor pressure deficit indicate that yield is higher when VPD is lower, meaning that conditions are moister. This may indicate that in the fall, more moisture helps yield, while later in the growing season, excess moisture is detrimental. Sufficient water in the fall is necessary for germination and sprouting. Waterlogging can reduce yields, but when it occurs in midwinter or earlier in the season, the plant is often able to compensate later in the season, so that the yield is not significantly reduced (Cannell et al., 1980). However, if the waterlogging occurs later in the season, the plant may not have sufficient time to recover, and yields may be lower as a result. Additionally, higher moisture in the spring and summer can lead to vivipary, which reduces the quality of the yield (Lenton, 2001, as cited in Xia et al., 2009). However, this effect is not necessarily visible in the measured weight used here. A positive correlation with VPD could also be attributed to disease. Higher VPD indicates less moisture, and moisture is associated with disease outbreaks such as rust (Te Beest et al., 2008). This effect was visible in the correlation analysis of the first half of the dataset, but not clear in the later half.

Therefore, germination, saturation, and disease are possible explanations for the different correlations with VPD shown throughout the growing season. Precipitation and water availability only captured the effect of excess moisture. Considering that factors such as soil water saturation may be important, perhaps it would have been more beneficial to use soil moisture as a variable. This is a common variable in process-based models, but is often not included in statistical crop models, which strive for simplicity and use of readily-available variables (Lobell & Asseng, 2017).

Correlations with radiation appear to follow the same pattern as VPD correlations here, meaning that more radiation in the fall is associated with lower yields, while the opposite is true in the spring. Radiation is generally expected to have a positive relationship with yield (Fischer, 1985). Holzkämper et al. (2014) found that in Switzerland, winter wheat growth suitability regions were primarily limited by low radiation and high precipitation. Since evidence exists for this positive relationship between radiation and yield, especially in Switzerland itself, the radiation correlations here may be capturing some other effect, rather than showing a direct relationship with yield. It is possible that low values of radiation are related to precipitation events. Radiation and VPD are positively correlated with each other in the spring and summer. Likewise, precipitation and water availability are each negatively correlated with radiation in the spring and summer. Excess moisture effects on yield in the fall could be positive, as discussed above.

4.1.2 Model

In the model created here, important effects analyzed in the discussion of correlations apply as well. Temperature variables appear to be the most important for yield prediction. Excess heat in summer and frost in winter are important, as well as avoiding too-warm temperatures in winter. Precipitation in the growing season has a small negative effect. However, radiation in November, which has a relatively high negative coefficient in the model, may actually be capturing a moisture effect, as discussed above. It is not clear why one of the moisture variables was not able to perform as well in the model as radiation. Holzkämper et al. (2014) found that winter wheat growth suitability regions in Switzerland is primarily limited by excess precipitation and low radiation, and also by minimum and maximum temperature thresholds. The model generated here does include negative effects of summer heat and winter frost, but in general the temperature indices are more important than precipitation.

Many statistical crop models use monthly or growing season aggregates of daily precipitation and minimum and maximum temperature as their only climate variables (Lobell et al., 2007). This study demonstrates that other variables, such as radiation, can have a significant effect on yield, and perhaps they should be considered more often for crop models, as in (Zarei et al., 2019b). In the process of this study, models with fewer variables, and that considered only the growing season variables, did not perform as well, so in this case the R^2 was improved with the inclusion of additional variables.

However, this model's R^2 is lower than other country-specific winter wheat models in the European region. Kern et al. (2018) created a cross-validated linear crop model that was able to explain 67% of the variance in winter wheat yields in Hungary.

This included fertilizer amount (rather than detrending yield data), a remote-sensing based vegetation index in May, and minimum temperature in May. One element involved is that models that incorporate the time or technological trend as one of the variables can achieve a higher proportion of explained variance overall, because both climate and non-climate variance is being explained. Another more unusual element for a statistical model was the inclusion of the vegetation index. This contribution alone improved the model's R^2 by 0.1 (Kern et al., 2018). Another variable that could potentially benefit the model created in this thesis is soil water content, since the potential explanations for the November radiation coefficient indicated that moisture may play a role not otherwise captured in the model.

Another promising approach would be to split the climate data based on the growing phase of wheat, rather than by months or several months, resulting in a model that is focused on biological needs of the plant rather than on anthropologic conventions of time. This was demonstrated by Bönecke et al. (2020). This study conducted in Germany was able to explain 50% or more of winter wheat yield variability based on climate variability. Temperature was the most influential climate variable, with heat stress being particularly important. By isolating vulnerable stages of plant growth such as stem elongation, they were able to make a more precise model Bönecke et al. (2020).

A possible extension of this model's use would be to predict how technological trends may affect future wheat yields, and if they could compensate for potential losses from climate change. In the past, farmers have taken advantage of technological advancements and may have adapted to climate change, but future patterns of adaptation and advancement may not follow past patterns, which introduces uncertainty (Lecerf et al., 2019; Lobell & Asseng, 2017). Gammans et al. (2017) used a statistical model to predict a 21% decrease in winter wheat yields in France under RCP8.5, if technology remained constant. However, if the historical trend of yield increases due to technological advances continued at the same rate in the future, this may compensate for negative effects of warming, especially moderate warming, as in scenario RCP4.5. In the future, beneficial effects of higher carbon dioxide levels are also expected (Lobell & Asseng, 2017).

4.1.3 Predicted Yield

With warmer temperatures, the spread of the density distribution grew wider. This is likely due to the model including both positive and negative effects of temperature, so the resulting yield may vary more widely from year to year. This may indicate that in a warmer future, farmers may need to adapt in order to avoid years with large losses. (Bönecke et al., 2020) recommended several adaptations to farmers in Germany to adapt by avoiding excessive heat stress by sowing early, planting crops that can be harvested early, and considering implementing irrigation systems if drought is a concern. This would not solve the problem of warm winter temperatures negatively affecting yield. In this case, the crop may need to be protected from frost, or crop varieties will have to be planted that are more tolerant to intermittent frost.

This is clearly a rough sketch of what this model could do with more sophisticated climate projection data. (Holzkämper et al., 2015) found that statistical models could be improved if they included effects of ozone or carbon dioxide. Models that are used for the distant future or for more than 2°C of warming especially can benefit from these effects being included.

Using a linear model to predict changes can be risky if the new data extends beyond the observed values which were used to create the model. This is especially relevant for variables which may have a range with linear or quadratic response, but upon reaching certain thresholds, suddenly begin to respond differently (Asseng et al., 2011). This may be relevant in this case, as the maximum temperature above 25°C was not included as one of the variables in the model. It is possible that some nonlinear effects of increased heat stress beyond this point were not captured when the model was used with the new hotter dataset. Asseng et al. (2011) found that in Australia, temperature changes as small as 2°C could reduce wheat yield by as much as 50%. However, this is likely due to temperatures in Australia already being very hot, so a temperature increase of 2°C can result in temperatures over 34°C, and therefore plant senescence. This contributes to the idea that temperature extremes or thresholds may be more significant than linear increases.

A potential source of error in similar analysis is that evapotranspiration is affected by temperature. This would change the water availability, which would in turn affect the predicted yield density distribution if water availability was a factor in the model. This could be solved by calculating the evapotranspiration rate rather than using a measured value.

4.2 Other Limitations

In general, one limitation was the availability of wheat data. Wheat data was sampled from each municipality each year. Municipalities were assigned to the closest station, but individual wheat fields may have experienced climatic conditions differing slightly from those reported by the station.

In the variable selection, another possibility in addition to considering other variables such as soil water content would be to change the metrics for extreme temperature. It could be much more beneficial to consider the number of days with minimum (or maximum) temperatures under (or over) a temperature threshold (Asseng et al., 2011). This would capture effects like the number of frost events, which may be more meaningful than mean minimum temperature belove 0°C.

5. Conclusions and Outlook

The thesis set out to address four main research questions. The first concerned which climate indicators relate most strongly to observed winter wheat yields. In the model, temperature indices are the most important climate drivers for yield. Summer and winter heat are especially important. Winter heat began to negatively correlate with yield in the past two decades. Radiation and precipitation are also significant. The second question aimed to examine how relationships between climate drivers and yield deviate between different agroclimatic regions of Switzerland. Meaningful differences across Switzerland were not identified in these results. The third question addressed how well yield variability can be predicted on the basis of climate variables. This research produced a cross-validated model with an adjusted R^2 of 0.35. The final question referred to how yield amount and variability might change under warmer conditions. The predicted yield density distribution with 2°C and 4°C warmer temperatures indicates that the overall mean yield may not change significantly, but yield variability may increase.

Future studies may benefit from utilizing soil moisture data, where available. This may bring clarity to differences that were seen between correlations of VPD and precipitation here. Another step that would improve clarity of these results would be to make climate indices around phenological timing rather than months. One area that remained ambiguous here was possible differences in the relationships between climate drivers and yield across the different agroclimatic regions of Switzerland. A future study, perhaps with more datapoints carefully selected to represent these regions, might identify a pattern not observed in these results.

A clear extension of this study would be to input projected data from a climate model into the model created here to make a more precise prediction of yield in the future. This could include more accurate temperature projections, and would include precipitation projections, which were not included here. However, future research could also use the predictions that were made here and focus on how to adapt to prevent more highly varying yield in the future. This might include researching techniques to protect wheat from intermittent winter frost, alter planting times to avoid exposure to excessive summer heat, or develop new crop varieties that are more resilient to these factors.

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7. Appendix

7.1 Correlation Tables

The tables show the correlation estimates and their p-values. P-values of 0.05 and smaller are in red typeface, indicating that the correlation to the left is statistically significant at that level. Some tables were represented graphically in figures in the text. Tables begin on the following page.

Table 4: All Stations (appears in Figs. 2 and 3)

	Mean Temp (°C)		Mean Max Temp (°C)		Mean Min Temp (°C)		Mean Max Temp Over 25 °C		Mean Min Temp Under 0 °C	
	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value
Oct	0.137	0.0057	0.0805	0.1052	0.1597	0.0012	-0.0682	0.17	0.0325	0.5141
Nov	0.037	0.4567	-0.0578	0.245	0.0962	0.0527	0	1	0.0455	0.3604
Dec	-0.1381	0.0053	-0.2375	0	-0.039	0.4333	0	1	0.0134	0.7879
Jan	0.0867	0.0813	0.0341	0.4929	0.139	0.005	0	1	0.1977	0.0001
Feb	0.0982	0.0483	0.1011	0.0417	0.1147	0.0208	0	1	0.1548	0.0018
Mar	0.003	0.9521	0.0147	0.7683	-0.0193	0.6985	0	1	-0.0638	0.1996
Apr	0.1136	0.0223	0.1155	0.0199	0.0763	0.1249	0.0151	0.7612	0.1121	0.0239
May	0.0168	0.7366	0.0308	0.5367	-0.0288	0.5626	-0.001	0.9846	-0.0576	0.2468
Jun	0.0792	0.1117	0.0821	0.0986	0.0171	0.7313	-0.0681	0.1705	0	1
Jul	-0.0079	0.8744	0.0001	0.9982	-0.0279	0.5748	0.0781	0.1162	0	1
Aug	-0.0103	0.8365	-0.0141	0.7777	-0.0182	0.7143	-0.0058	0.907	0	1
GS	0.0738	0.1379	0.0427	0.3903	0.0749	0.1317	0.0001	0.998	0.1613	0.0011
ON	0.1044	0.0355	0.0101	0.8399	0.1527	0.002	-0.0682	0.17	0.0563	0.2574
DJF	0.0504	0.3113	-0.0018	0.9708	0.113	0.0228	0	1	0.1965	0.0001
MAM	0.056	0.2604	0.072	0.1474	0.0075	0.8802	0.008	0.8725	-0.0109	0.8264
JJA	0.0284	0.5681	0.0308	0.5356	-0.0113	0.8203	-0.019	0.7031	0	1
OND	0.0152	0.7608	-0.1044	0.0355	0.0906	0.0683	-0.0682	0.17	0.0431	0.3861
JFM	0.0929	0.0618	0.0762	0.1254	0.1141	0.0215	0	1	0.1581	0.0014
AMJ	0.0894	0.0722	0.1025	0.039	0.0241	0.6285	-0.0053	0.916	0.0855	0.0855
	Sum Precipitation (mm)		Mean Water Availability (mm)		Mean VPD (hPa)		Mean Rad (W/m^2)			
	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value		
Oct	-0.0913	0.071	-0.076	0.1329	-0.1527	0.002	0.0077	0.878		
Nov	-0.015	0.7668	0.0027	0.9579	-0.2135	0	-0.1846	0.0002		
Dec	-0.0284	0.5739	-0.0245	0.6272	-0.2039	0	-0.091	0.0707		
Jan	-0.2075	0	-0.2047	0	-0.1155	0.0202	-0.1182	0.0175		
Feb	-0.123	0.0135	-0.1234	0.0132	-0.0628	0.2081	0.1152	0.0206		
Mar	-0.1028	0.0391	-0.1079	0.0322	-0.0457	0.3597	0.1245	0.0123		
Apr	-0.139	0.0052	-0.1542	0.0019	0.0644	0.1965	0.1512	0.0023		
May	-0.2504	0	-0.2603	0	0.0618	0.2148	0.1941	0.0001		
Jun	-0.252	0	-0.2789	0	0.1129	0.0232	0.2228	0		
Jul	-0.0542	0.2803	-0.0801	0.11	0.0207	0.6785	0.0973	0.0503		
Aug	-0.0964	0.0531	-0.0857	0.0858	-0.0265	0.5939	0.0644	0.1955		
GS	-0.2613	0	-0.322	0	-0.0156	0.7545	0.0725	0.1449		
ON	0.0068	0.8908	-0.0444	0.3798	-0.2021	0	-0.0799	0.113		
DJF	-0.1654	0.0008	-0.1981	0.0001	-0.1484	0.0027	-0.0498	0.318		
MAM	-0.2317	0	-0.2606	0	0.0452	0.365	0.2241	0		
JJA	-0.1967	0.0001	-0.2289	0	0.0414	0.4052	0.1974	0.0001		
OND	0.0223	0.6548	-0.0518	0.304	-0.2276	0	-0.0945	0.0606		
JFM	-0.2203	0	-0.2216	0	-0.0871	0.0804	0.1055	0.034		
AMJ	-0.3088	0	-0.3748	0	0.1094	0.028	0.287	0		

Table 5: BER

	Mean Temp (°C)		Mean Max Temp (°C)		Mean Min Temp (°C)		Mean Max Temp Over 25 °C		Mean Min Temp Under 0 °C	
	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value
Oct	0.0654	0.7006	0.0674	0.692	0.0442	0.7951	-0.1181	0.4864	-0.1729	0.3063
Nov	0.0857	0.614	0.0331	0.8459	0.0441	0.7954	0	1	-0.2302	0.1706
Dec	-0.2037	0.2267	-0.2519	0.1326	-0.1597	0.345	0	1	-0.1686	0.3184
Jan	0.1189	0.4832	0.115	0.4981	0.1228	0.4691	0	1	0.1753	0.2994
Feb	0.1632	0.3346	0.2432	0.1469	0.0996	0.5576	0	1	0.132	0.436
Mar	0.0084	0.9607	0.0954	0.5745	-0.13	0.4431	0	1	-0.17	0.3143
Apr	0.1047	0.5375	0.1361	0.422	-0.0318	0.8519	0.0495	0.7711	-0.0495	0.7711
May	0.0252	0.8824	0.1062	0.5316	-0.1315	0.4379	0.1247	0.462	-0.0049	0.9769
Jun	0.0941	0.5794	0.0829	0.6258	0.0512	0.7636	-0.0595	0.7265	0	1
Jul	-0.1252	0.4601	-0.1235	0.4663	-0.2429	0.1475	0.0077	0.9638	0	1
Aug	-0.1788	0.2896	-0.1749	0.3005	-0.2424	0.1483	-0.0837	0.6222	0	1
GS	0.0616	0.7171	0.1234	0.4669	-0.0735	0.6655	-0.1311	0.4392	-0.003	0.9858
ON	0.1044	0.5385	0.0708	0.6773	0.059	0.7287	-0.1181	0.4864	-0.3012	0.07
DJF	0.0889	0.6006	0.1251	0.4608	0.0622	0.7148	0	1	0.1135	0.5037
MAM	0.0613	0.7187	0.1688	0.3179	-0.1585	0.3488	0.1231	0.4679	-0.1778	0.2923
JJA	-0.1021	0.5477	-0.1191	0.4824	-0.1955	0.2463	-0.1023	0.5467	0	1
OND	-0.0268	0.8748	-0.0686	0.6864	-0.0426	0.8022	-0.1181	0.4864	-0.2826	0.0901
JFM	0.1533	0.365	0.2276	0.1756	0.0694	0.683	0	1	0.0998	0.5566
AMJ	0.1021	0.5476	0.1645	0.3307	-0.0613	0.7187	0.0992	0.559	-0.0467	0.7838
	Sum Precipitation (mm)		Mean Water Availability (mm)		Mean VPD (hPa)		Mean Rad (W/m^2)			
	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value		
Oct	-0.0854	0.6205	-0.0797	0.6439	-0.2066	0.2198	0.0643	0.7096		
Nov	-0.0294	0.8648	-0.0259	0.8809	0.0112	0.9477	-0.1362	0.4285		
Dec	0.1127	0.5128	0.1161	0.5002	-0.1489	0.3791	-0.0219	0.899		
Jan	-0.3132	0.0591	-0.314	0.0584	-0.014	0.9346	0.0523	0.7585		
Feb	-0.1909	0.2577	-0.2017	0.2312	0.1685	0.3187	0.3358	0.0422		
Mar	-0.3071	0.0644	-0.3177	0.0554	0.115	0.498	0.3048	0.0666		
Apr	-0.0321	0.8504	-0.0789	0.6425	0.1543	0.3618	0.1547	0.3605		
May	-0.3854	0.0185	-0.3815	0.0198	0.1939	0.2501	0.3093	0.0625		
Jun	-0.1905	0.2587	-0.2195	0.1917	0.1803	0.2856	0.1945	0.2486		
Jul	-0.0734	0.666	-0.1091	0.5202	0.0155	0.9275	0.2359	0.1598		
Aug	0.0194	0.9094	0.0239	0.8882	-0.1362	0.4214	0.0613	0.7183		
GS	-0.344	0.0371	-0.427	0.0084	0.0973	0.5666	0.2228	0.1849		
ON	0.0292	0.8636	-0.0696	0.6865	-0.1389	0.4123	-0.0112	0.9483		
DJF	-0.1782	0.2913	-0.2261	0.1784	0.032	0.8511	0.1558	0.357		
MAM	-0.3657	0.026	-0.3792	0.0206	0.2231	0.1844	0.3472	0.0353		
JJA	-0.14	0.4087	-0.1736	0.3042	0.0195	0.9086	0.2455	0.143		
OND	0.1162	0.4933	-0.0029	0.9868	-0.1836	0.2767	-0.0171	0.9211		
JFM	-0.4406	0.0064	-0.4456	0.0057	0.1307	0.4408	0.4001	0.0141		
AMJ	-0.3467	0.0356	-0.3934	0.016	0.2605	0.1194	0.3347	0.0429		

Table 6: GUT

	Mean Temp (°C)		Mean Max Temp (°C)		Mean Min Temp (°C)		Mean Max Temp Over 25 °C		Mean Min Temp Under 0 °C	
	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value
Oct	0.1247	0.4623	0.1065	0.5303	0.1654	0.3281	0.1198	0.4801	-0.2037	0.2267
Nov	0.0898	0.5972	0.0455	0.7892	0.1075	0.5265	0	1	0.0714	0.6746
Dec	-0.2731	0.102	-0.3545	0.0313	-0.1662	0.3257	0	1	-0.1391	0.4115
Jan	0.0772	0.6498	0.0631	0.7108	0.103	0.5439	0	1	0.1805	0.2851
Feb	0.1275	0.4522	0.1675	0.3218	0.1017	0.5494	0	1	0.0231	0.8921
Mar	-0.0302	0.8593	-0.0098	0.9539	-0.0408	0.8104	0	1	-0.1168	0.4911
Apr	0.2331	0.1651	0.2254	0.1798	0.1894	0.2615	0.0873	0.6076	0.398	0.0147
May	0.0675	0.6916	0.0827	0.6264	0.0184	0.9139	0.1184	0.4852	-0.172	0.3087
Jun	0.1069	0.5289	0.1128	0.5063	0.0052	0.9754	-0.148	0.3821	0	1
Jul	-0.1086	0.5224	-0.1065	0.5304	-0.0669	0.694	-0.0571	0.7371	0	1
Aug	-0.1391	0.4117	-0.1459	0.3887	-0.1096	0.5185	-0.1546	0.3608	0	1
GS	0.0667	0.6948	0.0678	0.6902	0.0644	0.7047	-0.1756	0.2986	0.0425	0.8029
ON	0.1369	0.4191	0.0971	0.5674	0.1769	0.295	0.1198	0.4801	-0.0331	0.8458
DJF	0.0258	0.8795	0.0262	0.8776	0.0529	0.7557	0	1	0.0571	0.7373
MAM	0.115	0.4979	0.1399	0.4089	0.0598	0.7254	0.1329	0.433	0.0336	0.8437
JJA	-0.0563	0.7404	-0.0695	0.6828	-0.0656	0.6997	-0.1884	0.2642	0	1
OND	-0.0209	0.9022	-0.0953	0.5749	0.0506	0.7663	0.1198	0.4801	-0.0983	0.5626
JFM	0.0939	0.5802	0.1214	0.4743	0.0887	0.6015	0	1	0.0536	0.7527
AMJ	0.1742	0.3025	0.1981	0.2397	0.0812	0.6327	0.1245	0.4627	0.3073	0.0643
	Sum Precipitation (mm)		Mean Water Availability (mm)		Mean VPD (hPa)		Mean Rad (W/m^2)			
	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value		
Oct	-0.1429	0.4056	-0.1372	0.4248	-0.117	0.4903	0.0316	0.855		
Nov	-0.0665	0.7001	-0.0657	0.7036	-0.0231	0.8919	-0.0411	0.8118		
Dec	0.0447	0.7958	0.0429	0.8036	-0.1225	0.4703	-0.0958	0.5785		
Jan	-0.3953	0.0155	-0.3972	0.0149	0.0664	0.6961	0.03	0.86		
Feb	-0.3309	0.0454	-0.3419	0.0383	0.1768	0.2952	0.4155	0.0105		
Mar	0.0019	0.9909	-0.0403	0.8153	0.1146	0.4993	0.1327	0.4338		
Apr	-0.1678	0.321	-0.1837	0.2765	0.2382	0.1556	0.1948	0.2479		
May	-0.404	0.0145	-0.3941	0.0174	0.2311	0.1688	0.2662	0.1113		
Jun	-0.3944	0.0157	-0.3877	0.0178	0.2072	0.2185	0.1938	0.2504		
Jul	0.1267	0.4616	0.1038	0.5468	-0.1367	0.4197	-0.0137	0.936		
Aug	0.0895	0.6037	0.1188	0.4901	-0.1434	0.397	-0.0672	0.6926		
GS	-0.426	0.0086	-0.4735	0.0031	0.099	0.5598	0.1055	0.5342		
ON	-0.0431	0.8	-0.1384	0.4208	-0.0905	0.5942	0.0005	0.9977		
DJF	-0.3496	0.0339	-0.4117	0.0113	0.0707	0.6773	0.1941	0.2496		
MAM	-0.3392	0.04	-0.3649	0.0264	0.3008	0.0705	0.2955	0.0758		
JJA	-0.1831	0.2779	-0.1011	0.5515	-0.0424	0.8034	0.0683	0.6878		
OND	0.0251	0.8826	-0.0874	0.6122	-0.14	0.4084	-0.0301	0.8618		
JFM	-0.4423	0.0061	-0.4636	0.0039	0.1827	0.2792	0.282	0.0909		
AMJ	-0.5433	0.0005	-0.5697	0.0002	0.3319	0.0448	0.3364	0.0418		

Table 7: KLO

	Mean Temp (°C)		Mean Max Temp (°C)		Mean Min Temp (°C)		Mean Max Temp Over 25 °C		Mean Min Temp Under 0 °C	
	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value
Oct	0.2731	0.1019	0.2773	0.0966	0.2302	0.1706	-0.0927	0.5854	0.2608	0.119
Nov	-0.053	0.7554	-0.1344	0.4277	0.0085	0.9602	0	1	0.013	0.939
Dec	-0.1723	0.3078	-0.2862	0.0859	-0.0565	0.7398	0	1	0.0012	0.9946
Jan	0.0473	0.781	0.0307	0.857	0.0744	0.6615	0	1	0.1736	0.3041
Feb	0.1411	0.405	0.1796	0.2876	0.129	0.4468	0	1	0.1499	0.3757
Mar	0.0357	0.8336	0.0314	0.8537	0.002	0.9907	0	1	-0.162	0.338
Apr	0.1475	0.3837	0.1498	0.3761	0.0095	0.9557	0.0437	0.7972	0.1772	0.294
May	0.1778	0.2924	0.1842	0.2751	0.0589	0.7291	0.099	0.56	-0.2221	0.1865
Jun	-0.0089	0.9585	0.0346	0.8389	-0.1908	0.258	-0.3079	0.0638	0	1
Jul	-0.1078	0.5254	-0.0726	0.6692	-0.1386	0.4132	0.1416	0.4031	0	1
Aug	-0.0533	0.754	-0.032	0.8507	-0.0957	0.5733	-0.0346	0.8389	0	1
GS	0.0983	0.5628	0.0998	0.5567	0.0522	0.7588	-0.1422	0.4011	0.096	0.5721
ON	0.1263	0.4563	0.0769	0.6509	0.1546	0.361	-0.0927	0.5854	0.2025	0.2293
DJF	0.0529	0.7559	0.0368	0.8286	0.1006	0.5535	0	1	0.2039	0.226
MAM	0.1746	0.3012	0.1748	0.3008	0.0346	0.8389	0.0936	0.5816	-0.1078	0.5252
JJA	-0.0846	0.6188	-0.0348	0.8379	-0.2117	0.2085	-0.0899	0.5968	0	1
OND	0.0134	0.937	-0.0795	0.6401	0.0831	0.625	-0.0927	0.5854	0.1402	0.4077
JFM	0.1182	0.4858	0.1298	0.4439	0.1159	0.4947	0	1	0.1253	0.4599
AMJ	0.1471	0.3849	0.1772	0.294	-0.0608	0.7208	0.0747	0.6602	0.0505	0.7666
	Sum Precipitation (mm)		Mean Water Availability (mm)		Mean VPD (hPa)		Mean Rad (W/m^2)			
	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value		
Oct	-0.0855	0.62	-0.0749	0.6642	-0.0804	0.6361	0.0914	0.596		
Nov	-0.0604	0.7263	-0.0468	0.7866	-0.2764	0.0977	-0.2122	0.214		
Dec	-0.1403	0.4143	-0.1353	0.4315	-0.1487	0.3796	-0.1967	0.2502		
Jan	-0.3521	0.0326	-0.3516	0.0328	-0.0172	0.9193	-0.178	0.2918		
Feb	-0.0854	0.6153	-0.0898	0.5969	0.0478	0.7787	0.1899	0.2604		
Mar	0.1341	0.4286	0.1102	0.5221	0.0191	0.9107	0.1209	0.476		
Apr	-0.0338	0.8427	-0.0905	0.5942	0.172	0.3088	0.1849	0.2733		
May	-0.3526	0.0323	-0.3666	0.0256	0.3154	0.0572	0.3165	0.0563		
Jun	-0.2894	0.0824	-0.3297	0.0463	0.1675	0.3216	0.3179	0.0552		
Jul	0.0258	0.8793	0.0272	0.8729	-0.0291	0.8642	0.0123	0.9425		
Aug	-0.1545	0.3612	-0.1059	0.5326	-0.1051	0.5357	-0.005	0.9767		
GS	-0.3051	0.0663	-0.3843	0.0189	0.0979	0.5643	0.131	0.4396		
ON	0.0037	0.9826	-0.0865	0.6159	-0.2127	0.2062	-0.0442	0.798		
DJF	-0.3349	0.0428	-0.3787	0.0208	-0.042	0.8052	-0.0759	0.6554		
MAM	-0.1331	0.4323	-0.1935	0.2511	0.2975	0.0738	0.3089	0.0629		
JJA	-0.2189	0.193	-0.2226	0.1853	0.0086	0.9596	0.1806	0.2849		
OND	-0.0272	0.8729	-0.1562	0.3631	-0.2821	0.0907	-0.1049	0.5427		
JFM	-0.1505	0.3738	-0.1516	0.3704	0.0307	0.8568	0.1367	0.4198		
AMJ	-0.389	0.0173	-0.4601	0.0042	0.3386	0.0404	0.424	0.0089		

Table 8: NEU

	Mean Temp (°C)		Mean Max Temp (°C)		Mean Min Temp (°C)		Mean Max Temp Over 25 °C		Mean Min Temp Under 0 °C	
	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value
Oct	0.1097	0.5181	-0.0171	0.9200	0.1777	0.2926	-0.1814	0.2825	-0.2304	0.1701
Nov	0.0088	0.9589	-0.0613	0.7185	0.0397	0.8155	0.0000	1.0000	-0.1373	0.4176
Dec	-0.1390	0.4118	-0.1471	0.3850	-0.1500	0.3754	0.0000	1.0000	0.0271	0.8735
Jan	0.0454	0.7894	0.0029	0.9863	0.0652	0.7014	0.0000	1.0000	0.0919	0.5884
Feb	0.2967	0.0746	0.2696	0.1065	0.3182	0.0549	0.0000	1.0000	0.3555	0.0308
Mar	-0.0728	0.6686	-0.1144	0.5001	-0.0338	0.8428	0.0000	1.0000	0.0143	0.9329
Apr	0.1854	0.2720	0.1622	0.3375	0.1856	0.2714	-0.1701	0.3141	0.1036	0.5419
May	0.1508	0.3729	0.1527	0.3670	0.1322	0.4353	-0.0007	0.9967	0.0000	1.0000
Jun	-0.0028	0.9867	0.0296	0.8619	-0.0877	0.6058	-0.1387	0.4128	0.0000	1.0000
Jul	-0.1100	0.5169	-0.0903	0.5949	-0.1238	0.4654	-0.0919	0.5886	0.0000	1.0000
Aug	-0.0478	0.7788	-0.0936	0.5816	0.0062	0.9710	-0.0154	0.9279	0.0000	1.0000
GS	0.1112	0.5121	0.0585	0.7308	0.1232	0.4677	-0.0248	0.8843	0.3303	0.0459
ON	0.0747	0.6605	-0.0531	0.7549	0.1413	0.4041	-0.1814	0.2825	-0.2152	0.2009
DJF	0.1555	0.3580	0.1252	0.4603	0.1669	0.3235	0.0000	1.0000	0.2910	0.0806
MAM	0.1171	0.4901	0.0948	0.5769	0.1213	0.4743	-0.0929	0.5844	0.0533	0.7539
JJA	-0.0822	0.6287	-0.0785	0.6442	-0.1032	0.5432	-0.1199	0.4796	0.0000	1.0000
OND	-0.0106	0.9505	-0.1171	0.4900	0.0311	0.8548	-0.1814	0.2825	-0.1297	0.4443
JFM	0.1547	0.3605	0.1022	0.5473	0.1965	0.2438	0.0000	1.0000	0.2544	0.1286
AMJ	0.1631	0.3348	0.1788	0.2896	0.0984	0.5622	-0.1007	0.5531	0.1036	0.5419

	Sum Precipitation (mm)		Mean Water Availability (mm)		Mean VPD (hPa)		Mean Rad (W/m^2)			
	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value		
Oct	-0.0046	0.9793	0.0373	0.8317	-0.3575	0.0298	-0.1464	0.3941		
Nov	-0.0227	0.8955	-0.0228	0.8949	0.0438	0.7971	-0.0507	0.7690		
Dec	-0.2585	0.1279	-0.2687	0.1130	0.0677	0.6907	0.2889	0.0875		
Jan	-0.0792	0.6461	-0.0763	0.6582	-0.0906	0.5937	-0.1066	0.5300		
Feb	0.0977	0.5650	0.0950	0.5758	0.0852	0.6159	-0.0206	0.9037		
Mar	0.0251	0.8827	0.0227	0.8954	-0.1292	0.4458	-0.0521	0.7594		
Apr	-0.2125	0.2068	-0.1888	0.2631	0.1389	0.4124	0.1361	0.4217		
May	-0.1820	0.2811	-0.2465	0.1413	0.2798	0.0934	0.2472	0.1401		
Jun	-0.2657	0.1119	-0.3131	0.0592	0.2147	0.2020	0.2582	0.1229		
Jul	-0.0214	0.8999	-0.0128	0.9401	-0.0466	0.7841	-0.0824	0.6276		
Aug	-0.0257	0.8799	-0.0045	0.9788	-0.1012	0.5512	-0.0521	0.7595		
GS	-0.2055	0.2224	-0.2689	0.1075	0.0617	0.7167	-0.0309	0.8558		
ON	0.0861	0.6125	0.0221	0.8984	-0.2466	0.1412	-0.1430	0.4053		
DJF	-0.1505	0.3738	-0.1742	0.3023	0.0372	0.8271	-0.0525	0.7578		
MAM	-0.1746	0.3015	-0.2083	0.2160	0.1759	0.2978	0.1743	0.3021		
JJA	-0.1460	0.3886	-0.1686	0.3186	0.0156	0.9272	0.0894	0.5987		
OND	-0.0081	0.9622	-0.1193	0.4883	-0.2080	0.2167	-0.0492	0.7758		
JFM	-0.0192	0.9101	-0.0020	0.9906	-0.0831	0.6247	-0.0698	0.6814		
AMJ	-0.3757	0.0219	-0.4392	0.0065	0.3180	0.0551	0.3323	0.0445		

Table 9: PAY

	Mean Temp (°C)		Mean Max Temp (°C)		Mean Min Temp (°C)		Mean Max Temp Over 25 °C		Mean Min Temp Under 0 °C	
	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value
Oct	0.1728	0.3065	0.1739	0.3034	0.1245	0.4627	-0.0251	0.8828	0.0603	0.7231
Nov	0.087	0.6086	0.0247	0.8847	0.1159	0.4945	0	1	-0.0747	0.6602
Dec	-0.205	0.2235	-0.2099	0.2124	-0.1736	0.3041	0	1	-0.0854	0.6154
Jan	0.187	0.2678	0.1688	0.3179	0.2005	0.2342	0	1	0.2402	0.1522
Feb	0.0736	0.6649	0.1198	0.4799	0.0671	0.6932	0	1	0.1323	0.4349
Mar	0.0549	0.7469	0.1423	0.4008	-0.0543	0.7496	0	1	-0.1704	0.3133
Apr	0.2496	0.1362	0.283	0.0897	0.0634	0.7093	0.0145	0.9322	0.027	0.8741
May	-0.0314	0.8536	0.0239	0.8886	-0.1829	0.2787	-0.0519	0.7604	0.0478	0.7785
Jun	0.1517	0.3702	0.1612	0.3406	0.0463	0.7856	0.1649	0.3295	0	1
Jul	-0.1214	0.4742	-0.0771	0.6501	-0.2117	0.2085	0.09	0.5962	0	1
Aug	-0.0861	0.6125	-0.0705	0.6783	-0.1266	0.4553	-0.1214	0.4742	0	1
GS	0.116	0.4941	0.1838	0.2761	0.0075	0.9647	0.0973	0.5669	-0.0003	0.9986
ON	0.17	0.3144	0.1338	0.4299	0.1603	0.3433	-0.0251	0.8828	-0.033	0.8464
DJF	0.0698	0.6815	0.0962	0.571	0.0797	0.6391	0	1	0.1907	0.2583
MAM	0.1184	0.4851	0.2173	0.1964	-0.1077	0.5256	-0.0381	0.823	-0.1176	0.4884
JJA	-0.0212	0.9008	0.0072	0.9663	-0.1241	0.4642	0.0606	0.7215	0	1
OND	0.0262	0.8775	0.011	0.9486	0.0296	0.8621	-0.0251	0.8828	-0.0677	0.6906
JFM	0.1554	0.3583	0.2068	0.2194	0.1231	0.4679	0	1	0.1406	0.4067
AMJ	0.1641	0.3318	0.2295	0.1718	-0.0524	0.7581	-0.0253	0.8818	0.0536	0.7525
	Sum Precipitation (mm)		Mean Water Availability (mm)		Mean VPD (hPa)		Mean Rad (W/m^2)			
	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value		
Oct	0.0369	0.8309	0.0375	0.8283	-0.1288	0.4475	0.1407	0.413		
Nov	0.0469	0.7858	0.0501	0.7719	-0.093	0.5839	-0.0116	0.9463		
Dec	-0.0935	0.5877	-0.1012	0.5571	-0.0745	0.6613	0.2175	0.2026		
Jan	-0.1682	0.3196	-0.167	0.3232	0.0101	0.9527	0.0624	0.7136		
Feb	-0.1113	0.5121	-0.1199	0.4796	0.0865	0.6108	0.278	0.0957		
Mar	-0.1206	0.477	-0.1251	0.4673	0.0039	0.9819	0.3062	0.0653		
Apr	-0.1902	0.2595	-0.2168	0.1974	0.2899	0.0818	0.2812	0.0918		
May	-0.3689	0.0246	-0.3723	0.0233	0.1877	0.2659	0.3302	0.0459		
Jun	-0.1974	0.2417	-0.2553	0.1272	0.2263	0.178	0.345	0.0365		
Jul	-0.0077	0.9641	-0.0456	0.7889	0.0523	0.7585	0.1397	0.4096		
Aug	-0.1313	0.4387	-0.1	0.5558	-0.009	0.9579	0.0461	0.7862		
GS	-0.276	0.0982	-0.3747	0.0223	0.1644	0.3308	0.3245	0.0501		
ON	0.1361	0.4219	0.059	0.7325	-0.1481	0.3817	0.1022	0.5531		
DJF	-0.1673	0.3222	-0.2094	0.2136	0.0218	0.8983	0.2186	0.1938		
MAM	-0.3522	0.0325	-0.3742	0.0225	0.2469	0.1407	0.4321	0.0076		
JJA	-0.1875	0.2664	-0.2214	0.188	0.1116	0.5107	0.2939	0.0775		
OND	0.1168	0.4912	0.011	0.9491	-0.1778	0.2925	0.1559	0.3639		
JFM	-0.1916	0.256	-0.1779	0.292	0.0481	0.7772	0.3669	0.0255		
AMJ	-0.4581	0.0044	-0.5165	0.0011	0.3385	0.0404	0.5023	0.0015		

Table 10: PUY

	Mean Temp (°C)		Mean Max Temp (°C)		Mean Min Temp (°C)		Mean Max Temp Over 25 °C		Mean Min Temp Under 0 °C	
	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value
Oct	0.2316	0.1740	0.2456	0.1487	0.1947	0.2553	0.0194	0.9107	-0.1730	0.3129
Nov	0.2412	0.1564	0.1692	0.3239	0.2562	0.1315	0.0000	1.0000	0.0919	0.5938
Dec	-0.2512	0.1395	-0.2664	0.1163	-0.2475	0.1456	0.0000	1.0000	-0.1948	0.2550
Jan	0.1464	0.3944	0.1164	0.4991	0.1652	0.3356	0.0000	1.0000	0.0769	0.6557
Feb	0.0776	0.6530	0.0951	0.5811	0.0557	0.7470	0.0000	1.0000	-0.0234	0.8923
Mar	0.1027	0.5513	0.1395	0.4172	0.0595	0.7302	0.0000	1.0000	-0.1041	0.5455
Apr	0.4157	0.0117	0.4189	0.0110	0.3759	0.0239	0.2927	0.0832	0.0989	0.5659
May	0.0446	0.7962	0.0605	0.7261	-0.0078	0.9642	0.2239	0.1894	0.0000	1.0000
Jun	0.2838	0.0935	0.2355	0.1669	0.3065	0.0690	0.1613	0.3472	0.0000	1.0000
Jul	0.0276	0.8730	-0.0089	0.9588	0.0039	0.9821	-0.0233	0.8928	0.0000	1.0000
Aug	0.0748	0.6648	0.0127	0.9414	0.1012	0.5570	0.0463	0.7885	0.0000	1.0000
GS	0.2725	0.1078	0.2793	0.0991	0.2296	0.1779	0.0193	0.9111	-0.0720	0.6766
ON	0.3173	0.0593	0.2789	0.0995	0.3085	0.0672	0.0194	0.9107	0.0783	0.6498
DJF	0.0278	0.8722	0.0236	0.8914	0.0224	0.8970	0.0000	1.0000	-0.0622	0.7185
MAM	0.2569	0.1303	0.2977	0.0778	0.1860	0.2774	0.3043	0.0712	-0.0556	0.7472
JJA	0.1971	0.2493	0.1258	0.4648	0.1968	0.2499	0.0901	0.6012	0.0000	1.0000
OND	0.1170	0.4966	0.0957	0.5789	0.1003	0.5605	0.0194	0.9107	-0.1075	0.5327
JFM	0.1507	0.3804	0.1641	0.3390	0.1329	0.4399	0.0000	1.0000	-0.0083	0.9615
AMJ	0.3335	0.0469	0.3482	0.0374	0.2905	0.0857	0.3110	0.0649	0.0989	0.5659
	Sum Precipitation (mm)		Mean Water Availability (mm)		Mean VPD (hPa)		Mean Rad (W/m^2)			
	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value		
Oct	-0.1662	0.3476	-0.1794	0.3101	0.2169	0.2039	0.2838	0.0985		
Nov	0.1046	0.5498	0.1186	0.4973	-0.2720	0.1085	-0.1167	0.5043		
Dec	0.0043	0.9805	0.0004	0.9983	-0.0884	0.6082	0.1678	0.3354		
Jan	-0.2299	0.1773	-0.2313	0.1746	0.0809	0.6391	0.2955	0.0802		
Feb	-0.1238	0.4718	-0.1292	0.4526	0.0862	0.6170	0.4355	0.0079		
Mar	-0.3503	0.0362	-0.3551	0.0364	0.1494	0.3846	0.3320	0.0479		
Apr	-0.3372	0.0443	-0.3668	0.0278	0.4359	0.0079	0.4319	0.0085		
May	-0.2063	0.2274	-0.2391	0.1602	0.1399	0.4158	0.2002	0.2418		
Jun	-0.1147	0.5055	-0.1513	0.3784	0.1656	0.3345	0.1216	0.4798		
Jul	0.0115	0.9475	-0.0990	0.5714	0.0613	0.7226	0.0510	0.7677		
Aug	-0.0035	0.9841	-0.0308	0.8608	0.0187	0.9139	0.0457	0.7912		
GS	-0.3365	0.0448	-0.4056	0.0141	0.2368	0.1644	0.3555	0.0334		
ON	0.0367	0.8317	-0.0352	0.8410	0.0156	0.9280	0.1752	0.3140		
DJF	-0.1681	0.3270	-0.2159	0.2060	0.0416	0.8094	0.4210	0.0106		
MAM	-0.4442	0.0066	-0.4759	0.0034	0.3658	0.0282	0.4786	0.0032		
JJA	-0.1623	0.3444	-0.1642	0.3387	0.1082	0.5298	0.1347	0.4335		
OND	0.0651	0.7058	-0.0401	0.8193	-0.0248	0.8859	0.2093	0.2275		
JFM	-0.3664	0.0279	-0.3631	0.0295	0.1583	0.3565	0.4994	0.0019		
AMJ	-0.3714	0.0257	-0.4382	0.0075	0.3493	0.0368	0.4772	0.0033		

Table 11: SHA

	Mean Temp (°C)		Mean Max Temp (°C)		Mean Min Temp (°C)		Mean Max Temp Over 25 °C		Mean Min Temp Under 0 °C	
	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value
Oct	0.1534	0.3647	0.1454	0.3905	0.1786	0.2902	-0.1269	0.4541	-0.0576	0.7348
Nov	-0.0924	0.5865	-0.1097	0.5182	-0.0825	0.6275	0.0000	1.0000	0.0530	0.7555
Dec	-0.2269	0.1769	-0.2803	0.0929	-0.1721	0.3084	0.0000	1.0000	0.0017	0.9920
Jan	-0.0638	0.7114	-0.0782	0.6456	-0.0291	0.8640	0.0000	1.0000	0.1308	0.4403
Feb	-0.0344	0.8420	0.0143	0.9332	-0.0268	0.8748	0.0000	1.0000	0.0027	0.9872
Mar	-0.0147	0.9322	-0.0395	0.8162	0.0012	0.9942	0.0000	1.0000	-0.0918	0.5891
Apr	-0.0266	0.8776	-0.0085	0.9601	-0.0693	0.6838	-0.0169	0.9209	0.1041	0.5399
May	-0.1489	0.3860	-0.1016	0.5497	-0.2125	0.2067	-0.0953	0.5749	-0.1336	0.4305
Jun	-0.2004	0.2413	-0.1418	0.4025	-0.3321	0.0447	-0.2801	0.0932	0.0000	1.0000
Jul	-0.1256	0.4588	-0.0871	0.6082	-0.1800	0.2864	0.0126	0.9410	0.0000	1.0000
Aug	-0.2100	0.2123	-0.1449	0.3922	-0.3033	0.0680	-0.2189	0.1930	0.0000	1.0000
GS	-0.1890	0.2625	-0.1598	0.3447	-0.1891	0.2623	-0.1959	0.2451	0.0403	0.8128
ON	0.0182	0.9148	0.0070	0.9672	0.0476	0.7799	-0.1269	0.4541	0.0188	0.9123
DJF	-0.1219	0.4724	-0.1205	0.4773	-0.0964	0.5702	0.0000	1.0000	0.0848	0.6178
MAM	-0.0893	0.6045	-0.0719	0.6722	-0.1318	0.4368	-0.0706	0.6781	-0.0510	0.7643
JJA	-0.2610	0.1187	-0.1926	0.2535	-0.3567	0.0302	-0.2608	0.1191	0.0000	1.0000
OND	-0.0944	0.5783	-0.1349	0.4260	-0.0452	0.7904	-0.1269	0.4541	0.0136	0.9365
JFM	-0.0546	0.7516	-0.0442	0.7949	-0.0295	0.8625	0.0000	1.0000	0.0418	0.8060
AMJ	-0.1735	0.3115	-0.1196	0.4808	-0.2791	0.0943	-0.0853	0.6156	0.0728	0.6685
	Sum Precipitation (mm)		Mean Water Availability (mm)		Mean VPD (hPa)		Mean Rad (W/m^2)			
	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value		
Oct	-0.0298	0.8632	-0.0133	0.9387	-0.1883	0.2644	-0.0295	0.8643		
Nov	-0.0098	0.9547	-0.0034	0.9843	-0.1059	0.5328	-0.1981	0.2468		
Dec	-0.0894	0.6040	-0.0910	0.5977	-0.0389	0.8193	-0.1214	0.4806		
Jan	-0.2763	0.1082	-0.2754	0.1093	-0.1130	0.5117	-0.2915	0.0846		
Feb	-0.3062	0.0736	-0.3010	0.0790	-0.0291	0.8663	0.1405	0.4136		
Mar	-0.0188	0.9132	-0.0157	0.9285	-0.0565	0.7434	-0.0419	0.8082		
Apr	-0.1874	0.2739	-0.1597	0.3521	0.0282	0.8704	0.0341	0.8433		
May	-0.3318	0.0515	-0.2989	0.0811	0.0735	0.6700	0.1486	0.3871		
Jun	-0.1921	0.2616	-0.1940	0.2569	0.0545	0.7523	0.1646	0.3375		
Jul	0.0218	0.8998	0.0563	0.7445	-0.1576	0.3516	0.0144	0.9324		
Aug	-0.1068	0.5294	-0.0396	0.8159	-0.2056	0.2222	0.0539	0.7516		
GS	-0.3702	0.0241	-0.3304	0.0458	-0.1412	0.4043	-0.0075	0.9649		
ON	-0.0014	0.9933	-0.0115	0.9471	-0.1748	0.3008	-0.1248	0.4683		
DJF	-0.4101	0.0117	-0.4710	0.0037	-0.0628	0.7118	-0.0236	0.8913		
MAM	-0.2721	0.1033	-0.2574	0.1296	0.0384	0.8240	0.0855	0.6202		
JJA	-0.1247	0.4623	-0.1039	0.5406	-0.1627	0.3359	0.1371	0.4184		
OND	-0.0446	0.7932	-0.0706	0.6822	-0.1683	0.3195	-0.1429	0.4059		
JFM	-0.3139	0.0585	-0.3168	0.0597	-0.0886	0.6073	-0.0228	0.8951		
AMJ	-0.3560	0.0306	-0.3841	0.0207	0.0800	0.6429	0.1845	0.2813		

Table 12: STG

	Mean Temp (°C)		Mean Max Temp (°C)		Mean Min Temp (°C)		Mean Max Temp Over 25 °C		Mean Min Temp Under 0 °C	
	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value
Oct	0.3701	0.0241	0.3458	0.0360	0.3478	0.0349	0.0000	1.0000	0.2711	0.1045
Nov	-0.2657	0.1119	-0.2738	0.1011	-0.2387	0.1547	0.0000	1.0000	-0.0991	0.5594
Dec	-0.2722	0.1031	-0.2607	0.1191	-0.2649	0.1131	0.0000	1.0000	-0.1965	0.2436
Jan	0.1999	0.2354	0.2350	0.1615	0.1819	0.2813	0.0000	1.0000	0.2274	0.1758
Feb	0.1747	0.3011	0.1815	0.2825	0.1778	0.2924	0.0000	1.0000	0.2114	0.2091
Mar	0.0624	0.7137	0.0872	0.6078	0.0238	0.8890	0.0000	1.0000	0.0103	0.9517
Apr	0.0922	0.5872	0.0791	0.6418	0.1090	0.5207	-0.0711	0.6760	0.2001	0.2350
May	0.0139	0.9352	0.0181	0.9155	-0.0258	0.8794	0.0104	0.9512	-0.0106	0.9506
Jun	0.1980	0.2402	0.2237	0.1833	0.1252	0.4605	-0.2698	0.1064	0.0000	1.0000
Jul	-0.1347	0.4265	-0.1287	0.4479	-0.1459	0.3888	0.1955	0.2463	0.0000	1.0000
Aug	-0.1661	0.3258	-0.1870	0.2677	-0.1410	0.4050	-0.0209	0.9025	0.0000	1.0000
GS	0.0807	0.6350	0.0938	0.5810	0.0640	0.7067	0.0416	0.8069	0.1856	0.2714
ON	0.0155	0.9274	-0.0163	0.9238	0.0309	0.8559	0.0000	1.0000	0.0763	0.6536
DJF	0.1048	0.5371	0.1314	0.4381	0.1086	0.5224	0.0000	1.0000	0.1958	0.2454
MAM	0.0834	0.6234	0.0926	0.5859	0.0513	0.7632	-0.0114	0.9468	0.0940	0.5798
JJA	-0.0413	0.8083	-0.0444	0.7939	-0.0592	0.7279	-0.1406	0.4065	0.0000	1.0000
OND	-0.1383	0.4143	-0.1566	0.3545	-0.1180	0.4868	0.0000	1.0000	-0.0651	0.7018
JFM	0.2182	0.1945	0.2460	0.1422	0.1992	0.2373	0.0000	1.0000	0.2383	0.1556
AMJ	0.1385	0.4136	0.1459	0.3888	0.0942	0.5793	-0.1259	0.4577	0.1928	0.2530
	Sum Precipitation (mm)		Mean Water Availability (mm)		Mean VPD (hPa)		Mean Rad (W/m^2)			
	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value		
Oct	-0.3037	0.0762	-0.3072	0.0727	0.2589	0.1217	0.1802	0.2928		
Nov	0.0310	0.8596	0.0610	0.7279	-0.4351	0.0071	-0.2911	0.0850		
Dec	0.0407	0.8139	0.0531	0.7583	-0.2756	0.0988	-0.0732	0.6715		
Jan	-0.3196	0.0574	-0.3193	0.0577	0.0767	0.6566	0.1082	0.5298		
Feb	-0.3516	0.0355	-0.3556	0.0333	0.1245	0.4692	0.3307	0.0489		
Mar	-0.0929	0.5954	-0.0868	0.6199	0.1736	0.3114	0.2711	0.1098		
Apr	-0.1922	0.2615	-0.1936	0.2578	0.1448	0.3993	0.1124	0.5139		
May	-0.4122	0.0125	-0.3742	0.0245	0.1300	0.4497	0.1300	0.4497		
Jun	-0.4869	0.0026	-0.5260	0.0010	0.3312	0.0484	0.4397	0.0073		
Jul	0.2854	0.0915	0.2416	0.1558	-0.0704	0.6835	-0.1768	0.3024		
Aug	0.1933	0.2518	0.1900	0.2600	-0.1074	0.5270	-0.1638	0.3326		
GS	-0.1348	0.4265	-0.2122	0.2074	0.1489	0.3789	-0.0427	0.8020		
ON	-0.0966	0.5697	-0.1601	0.3581	-0.1455	0.3904	0.0094	0.9568		
DJF	-0.2130	0.2056	-0.3791	0.0226	0.0038	0.9823	0.2406	0.1576		
MAM	-0.2369	0.1579	-0.4027	0.0149	0.2103	0.2184	0.2384	0.1614		
JJA	0.1220	0.4718	0.0270	0.8740	0.0628	0.7119	0.1204	0.4777		
OND	-0.0373	0.8264	-0.1096	0.5247	-0.2601	0.1201	-0.0250	0.8847		
JFM	-0.2678	0.1090	-0.4743	0.0035	0.1838	0.2833	0.3998	0.0157		
AMJ	-0.3627	0.0274	-0.5933	0.0001	0.3042	0.0713	0.3503	0.0362		

Table 13: WYN

	Mean Temp (°C)		Mean Max Temp (°C)		Mean Min Temp (°C)		Mean Max Temp Over 25 °C		Mean Min Temp Under 0 °C	
	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value
Oct	0.2279	0.1750	0.1911	0.2573	0.1989	0.2379	-0.1523	0.3682	-0.1187	0.4841
Nov	0.0922	0.5874	-0.0324	0.8492	0.1107	0.5143	0.0000	1.0000	-0.0901	0.5960
Dec	-0.1806	0.2848	-0.2259	0.1788	-0.1496	0.3768	0.0000	1.0000	-0.0464	0.7853
Jan	0.0999	0.5562	0.0827	0.6264	0.1305	0.4413	0.0000	1.0000	0.2345	0.1625
Feb	0.2224	0.1858	0.2943	0.0770	0.1847	0.2737	0.0000	1.0000	0.2276	0.1754
Mar	0.1394	0.4108	0.2313	0.1684	-0.0340	0.8418	0.0000	1.0000	-0.0209	0.9021
Apr	0.2761	0.0981	0.2976	0.0736	0.0785	0.6443	0.0693	0.6838	0.2295	0.1719
May	0.2105	0.2110	0.2537	0.1297	0.0277	0.8706	0.0965	0.5699	-0.0611	0.7194
Jun	0.1589	0.3475	0.1863	0.2697	-0.0046	0.9784	-0.0706	0.6781	0.0000	1.0000
Jul	-0.0968	0.5687	-0.0886	0.6022	-0.0912	0.5912	0.0348	0.8379	0.0000	1.0000
Aug	0.0471	0.7821	0.0129	0.9395	0.1049	0.5368	0.0429	0.8010	0.0000	1.0000
GS	0.2438	0.1458	0.2963	0.0750	0.1295	0.4451	-0.0074	0.9654	0.0880	0.6044
ON	0.2025	0.2294	0.1044	0.5385	0.2041	0.2256	-0.1523	0.3682	-0.1526	0.3671
DJF	0.1242	0.4641	0.1587	0.3482	0.1245	0.4630	0.0000	1.0000	0.2628	0.1161
MAM	0.2967	0.0745	0.3846	0.0188	0.0228	0.8934	0.1118	0.5099	0.0524	0.7580
JJA	0.0546	0.7484	0.0587	0.7300	-0.0063	0.9706	0.0355	0.8348	0.0000	1.0000
OND	0.0646	0.7041	-0.0212	0.9010	0.0684	0.6873	-0.1523	0.3682	-0.1312	0.4390
JFM	0.2354	0.1608	0.3065	0.0651	0.1712	0.3111	0.0000	1.0000	0.2608	0.1189
AMJ	0.2958	0.0755	0.3629	0.0273	0.0420	0.8051	0.1056	0.5339	0.1648	0.3297

	Sum Precipitation (mm)		Mean Water Availability (mm)		Mean VPD (hPa)		Mean Rad (W/m^2)			
	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value		
Oct	-0.0916	0.5953	-0.0810	0.6386	-0.2794	0.0940	0.0970	0.5737		
Nov	-0.0316	0.8546	-0.0216	0.9005	-0.2203	0.1901	-0.1163	0.4992		
Dec	-0.0472	0.7847	-0.0455	0.7923	-0.1087	0.5217	0.0827	0.6316		
Jan	-0.4510	0.0051	-0.4499	0.0052	-0.1426	0.4000	-0.1182	0.4860		
Feb	-0.0605	0.7222	-0.0608	0.7207	0.0508	0.7654	0.2356	0.1603		
Mar	-0.1169	0.4908	-0.1389	0.4191	0.1547	0.3608	0.2993	0.0719		
Apr	-0.1577	0.3512	-0.1757	0.2982	0.1565	0.3549	0.2539	0.1295		
May	-0.3196	0.0538	-0.3554	0.0309	0.3578	0.0297	0.4305	0.0078		
Jun	-0.3075	0.0681	-0.3451	0.0393	0.1817	0.2817	0.3979	0.0147		
Jul	0.2113	0.2230	0.1703	0.3280	-0.1371	0.4184	0.0966	0.5697		
Aug	-0.0301	0.8595	-0.0056	0.9737	-0.1678	0.3208	0.0832	0.6245		
GS	-0.3625	0.0275	-0.4311	0.0077	0.0302	0.8590	0.2661	0.1114		
ON	0.0542	0.7501	-0.0709	0.6811	-0.2855	0.0867	0.0153	0.9296		
DJF	-0.2962	0.0751	-0.3485	0.0345	-0.0863	0.6114	0.0276	0.8712		
MAM	-0.3059	0.0656	-0.3501	0.0336	0.3426	0.0379	0.4696	0.0034		
JJA	-0.1738	0.3037	-0.1654	0.3280	-0.0540	0.7508	0.3320	0.0447		
OND	0.0761	0.6545	-0.0933	0.5883	-0.2754	0.0990	0.0383	0.8246		
JFM	-0.3604	0.0284	-0.3481	0.0348	0.0746	0.6609	0.3029	0.0684		
AMJ	-0.4999	0.0016	-0.5266	0.0008	0.3538	0.0317	0.5717	0.0002		

Table 14: All stations, first 19 years (appears in Figs. 4 and 6)

	Mean Temp (°C)		Mean Max Temp (°C)		Mean Min Temp (°C)		Mean Max Temp Over 25 °C		Mean Min Temp Under 0 °C	
	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value
Oct	0.2098	0.3887	0.2117	0.3843	0.1991	0.4138	-0.1418	0.5625	-0.0581	0.8131
Nov	0.1744	0.4753	0.1328	0.5879	0.1720	0.4814	0.0000	1.0000	0.2277	0.3486
Dec	0.0346	0.8883	-0.0971	0.6924	0.1976	0.4175	0.0000	1.0000	0.2506	0.3007
Jan	0.1190	0.6274	0.1047	0.6698	0.1562	0.5232	0.0000	1.0000	0.2341	0.3346
Feb	0.0556	0.8211	0.1369	0.5762	0.0110	0.9645	0.0000	1.0000	0.0398	0.8715
Mar	-0.0168	0.9456	0.1065	0.6644	-0.1288	0.5993	0.0000	1.0000	-0.2285	0.3468
Apr	-0.0699	0.7763	-0.0405	0.8692	-0.0446	0.8561	0.0000	1.0000	-0.0695	0.7775
May	-0.1091	0.6565	-0.0167	0.9458	-0.2345	0.3339	0.2126	0.3822	-0.1167	0.6343
Jun	-0.0161	0.9480	0.0653	0.7905	-0.2321	0.3389	-0.1292	0.5981	0.0000	1.0000
Jul	-0.2299	0.3438	-0.1447	0.5545	-0.4638	0.0455	-0.0856	0.7275	0.0000	1.0000
Aug	-0.2172	0.3718	-0.0788	0.7486	-0.4320	0.0647	-0.1395	0.5690	0.0000	1.0000
GS	0.0061	0.9801	0.1326	0.5884	-0.1102	0.6535	-0.2844	0.2379	0.3235	0.1768
ON	0.2663	0.2705	0.2317	0.3398	0.2508	0.3004	-0.1418	0.5625	0.1736	0.4771
DJF	0.1106	0.6523	0.1194	0.6262	0.1624	0.5064	0.0000	1.0000	0.2805	0.2448
MAM	-0.0945	0.7002	0.0394	0.8728	-0.2121	0.3834	0.2126	0.3822	-0.2307	0.3419
JJA	-0.2785	0.2483	-0.1232	0.6153	-0.5238	0.0214	-0.1574	0.5198	0.0000	1.0000
OND	0.2475	0.3070	0.1868	0.4438	0.2785	0.2483	-0.1418	0.5625	0.2720	0.2600
JFM	0.0773	0.7532	0.1640	0.5022	0.0314	0.8984	0.0000	1.0000	0.0743	0.7625
AMJ	-0.1045	0.6702	-0.0054	0.9824	-0.2409	0.3205	0.1422	0.5613	-0.0990	0.6868

	Sum Precipitation (mm)		Mean Water Availability (mm)		Mean VPD (hPa)		Mean Rad (W/m^2)			
	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value		
Oct	-0.0123	0.9601	-0.0036	0.9883	-0.3116	0.1940	0.0666	0.7864		
Nov	-0.0397	0.8716	-0.0323	0.8955	-0.1049	0.6691	-0.1863	0.4452		
Dec	-0.0165	0.9464	-0.0015	0.9950	-0.1842	0.4504	-0.4762	0.0393		
Jan	-0.2347	0.3335	-0.2322	0.3387	-0.0806	0.7429	-0.1163	0.6353		
Feb	-0.4023	0.0877	-0.4238	0.0706	0.2613	0.2799	0.4263	0.0687		
Mar	-0.2319	0.3395	-0.3057	0.2031	0.1707	0.4846	0.4011	0.0888		
Apr	-0.1310	0.5929	-0.0984	0.6887	0.0228	0.9262	-0.0607	0.8050		
May	-0.4347	0.0629	-0.3847	0.1039	0.1039	0.6722	0.2045	0.4011		
Jun	-0.3027	0.2078	-0.3682	0.1209	0.3414	0.1526	0.3293	0.1686		
Jul	-0.0539	0.8266	-0.1431	0.5590	0.0415	0.8661	0.2632	0.2764		
Aug	-0.1107	0.6518	-0.1579	0.5184	-0.0137	0.9556	0.2277	0.3485		
GS	-0.6062	0.0059	-0.6508	0.0026	0.1335	0.5859	0.5340	0.0185		
ON	-0.0338	0.8907	-0.0231	0.9251	-0.2843	0.2381	-0.0282	0.9087		
DJF	-0.3724	0.1164	-0.3854	0.1032	0.0502	0.8382	0.0877	0.7210		
MAM	-0.4298	0.0663	-0.3936	0.0955	0.1371	0.5758	0.2410	0.3203		
JJA	-0.2771	0.2507	-0.3839	0.1047	0.1745	0.4750	0.4691	0.0427		
OND	-0.0453	0.8538	-0.0263	0.9148	-0.3543	0.1366	-0.1340	0.5844		
JFM	-0.4250	0.0697	-0.4671	0.0438	0.1760	0.4712	0.5192	0.0227		
AMJ	-0.4987	0.0298	-0.5206	0.0223	0.2556	0.2909	0.2956	0.2193		

Table 15: All stations, last 18 years (appears in Figs. 5 and 7)

	Mean Temp (°C)		Mean Max Temp (°C)		Mean Min Temp (°C)		Mean Max Temp Over 25 °C		Mean Min Temp Under 0 °C	
	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value
Oct	-0.1162	0.6461	-0.1177	0.6418	-0.1064	0.6743	0.0000	1.0000	-0.2239	0.3718
Nov	-0.2408	0.3357	-0.2434	0.3304	-0.3190	0.1970	0.0000	1.0000	-0.5428	0.0199
Dec	-0.5555	0.0167	-0.5071	0.0317	-0.5421	0.0201	0.0000	1.0000	-0.6157	0.0065
Jan	-0.0034	0.9893	0.0341	0.8933	-0.0548	0.8291	0.0000	1.0000	-0.0402	0.8741
Feb	0.1636	0.5167	0.2705	0.2777	0.0976	0.7002	0.0000	1.0000	0.1376	0.5862
Mar	0.0571	0.8218	0.0547	0.8294	-0.0099	0.9689	0.0000	1.0000	-0.1004	0.6917
Apr	0.1785	0.4786	0.2089	0.4055	-0.0004	0.9987	0.0111	0.9651	-0.1750	0.4872
May	0.0466	0.8543	0.1352	0.5927	-0.1197	0.6360	-0.0454	0.8579	0.1007	0.6910
Jun	0.0012	0.9963	-0.0297	0.9068	0.0501	0.8436	-0.0500	0.8439	0.0000	1.0000
Jul	-0.2322	0.3539	-0.2381	0.3415	-0.3140	0.2045	-0.0368	0.8848	0.0000	1.0000
Aug	-0.2539	0.3094	-0.2485	0.3201	-0.3092	0.2118	-0.0822	0.7457	0.0000	1.0000
GS	-0.1737	0.4906	-0.1036	0.6824	-0.3211	0.1938	-0.1346	0.5945	-0.3825	0.1172
ON	-0.2369	0.3439	-0.2682	0.2819	-0.2474	0.3223	0.0000	1.0000	-0.5629	0.0150
DJF	-0.1147	0.6503	-0.0063	0.9801	-0.2206	0.3791	0.0000	1.0000	-0.2633	0.2912
MAM	0.1380	0.5851	0.1910	0.4478	-0.0652	0.7971	-0.0226	0.9289	-0.1625	0.5193
JJA	-0.2528	0.3115	-0.2632	0.2913	-0.3099	0.2108	-0.0964	0.7035	0.0000	1.0000
OND	-0.4468	0.0630	-0.4488	0.0617	-0.4625	0.0533	0.0000	1.0000	-0.6690	0.0024
JFM	0.1191	0.6378	0.1895	0.4515	0.0343	0.8924	0.0000	1.0000	0.0219	0.9312
AMJ	0.1221	0.6294	0.1751	0.4871	-0.0344	0.8921	-0.0253	0.9207	-0.1088	0.6675
	Sum Precipitation (mm)		Mean Water Availability (mm)		Mean VPD (hPa)		Mean Rad (W/m^2)			
	Cor	P-value	Cor	P-value	Cor	P-value	Cor	P-value		
Oct	-0.1648	0.5134	-0.1680	0.5052	-0.0565	0.8239	-0.0296	0.9071		
Nov	-0.0348	0.8911	-0.0353	0.8893	0.0847	0.7382	-0.1454	0.5649		
Dec	0.2050	0.4146	0.2001	0.4260	-0.1303	0.6062	0.1639	0.5157		
Jan	-0.3522	0.1518	-0.3548	0.1485	0.0160	0.9497	0.2545	0.3082		
Feb	-0.0650	0.7979	-0.0668	0.7922	-0.0204	0.9358	0.3180	0.1985		
Mar	-0.2553	0.3066	-0.2262	0.3667	-0.0370	0.8841	0.1239	0.6242		
Apr	-0.0152	0.9522	-0.1023	0.6861	0.2437	0.3299	0.2878	0.2468		
May	-0.2194	0.3817	-0.2569	0.3034	0.2058	0.4127	0.2638	0.2903		
Jun	-0.1249	0.6216	-0.0613	0.8092	0.0220	0.9311	-0.0444	0.8610		
Jul	-0.1045	0.6800	-0.0600	0.8129	-0.0980	0.6989	0.0184	0.9423		
Aug	0.0757	0.7652	0.1292	0.6094	-0.2116	0.3993	-0.0685	0.7871		
GS	-0.2723	0.2743	-0.2369	0.3438	-0.0359	0.8875	0.2249	0.3695		
ON	-0.1269	0.6159	-0.1276	0.6140	0.0196	0.9384	-0.1076	0.6708		
DJF	-0.1076	0.6708	-0.1141	0.6520	-0.0516	0.8388	0.4187	0.0837		
MAM	-0.2322	0.3538	-0.2693	0.2798	0.2239	0.3717	0.3165	0.2006		
JJA	-0.0732	0.7727	0.0063	0.9802	-0.1428	0.5720	-0.0510	0.8409		
OND	0.0199	0.9375	0.0154	0.9516	-0.0367	0.8849	-0.0029	0.9910		
JFM	-0.4037	0.0967	-0.3692	0.1316	-0.0255	0.9201	0.2796	0.2612		
AMJ	-0.2036	0.4179	-0.2508	0.3155	0.2045	0.4157	0.2780	0.2640		

Declaration of consent

on the basis of Article 30 of the RSL Phil.-nat. 18

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Study program: Climate Sciences

Bachelor ☐ Master ☑ Dissertation ☐

Title of the thesis: Attribution of Winter Wheat Yield Variability to Climate Drivers in Switzerland

Supervisor: PD Dr. Annelie Holzkämper
Co-supervisor Dr. Jakob Zscheischler
Advisor Dr. Dario Fossati

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