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# Effect of climate change on potato yield and starch content

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ABSTRACT

Potato (*Solanum tuberosum* L.) ranks as the fourth most important food crop after rice, wheat, and maize. In the literature, models have been developed to predict potato yield evolution due to climate change, projecting a decrease in production across various regions. This study was conducted on field data collected over 31 years in five contrasting sites in the Western Alps, Switzerland. Results show that 24 % of yield variation can be explained by the genotype, and 50 % by the environment. Among the studied meteorological conditions influencing the yield, 1) "total precipitation from tuber initiation to tuber harvest", 2) "sum of solar irradiation from planting to maturity", 3) "average temperature from planting to maturity" and, 4) "sum of daily maximal temperature from planting to maturity", were the most important variables. The third variable exhibits a positive linear relationship with yield up to an average temperature of 16.5 °C during the growth season. Beyond this threshold, the relationship becomes negative and results in yield loss. Using this unprecedented dataset, we estimated potential yield losses in the Western Alps of Switzerland by the end of the century under three different Representative Concentration Pathway (RCP) scenarios (*i.e.* 2.6, 4.5, 8.5). In the short term, by 2035, yield losses are projected to range from 3.2 % to 15.0 % regardless of the scenarios. By 2060, RCP 4.5 and RCP 8.5 predict the highest losses, reaching 22.7–50.3 % compared to the 1990–2020 average yield. The most significant loss was predicted under the RCP 8.5 long-term scenario, by 2085, with yield losses ranging from 24.2 % to 84.6 %. These losses are attributed to an estimated precipitation decrease of 42 % compared to the average of the past 30 years and a +7.2 °C increase in average temperature during the potato growth season. Except in the case of RCP 2.6, which estimates low yield losses compared to 1990–2020, this study anticipates significant yield losses by the end of the century in Switzerland. To mitigate these losses due to climate change, potential adaptation strategies include the adoption of drought or heat-stress-resistant genotypes, enhancements in irrigation systems, adjustments of planting schedules, and relocating planting sites to higher elevations. In addition, the G x E interaction effect should be considered in breeding strategies, to cope with climate change impacts on potato yield and to grow genotypes better adapted to their environment.

## 1. Introduction

Potato (*Solanum tuberosum* L.) is the fourth most important food crop after rice, wheat and maize with 376 million tonnes of potatoes produced in 2021 (FAO, 2022) and potato demand will increase as the world's population grows (Tian et al., 2021). The growing season for potato can range from three to five months in temperate climates and during this period, 350–500 mm of rain is required to obtain a

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respectable yield (Khurana, 2003; Tang et al., 2018; Xie et al., 2012). Precipitation plays a crucial role during the tuber bulking and ripening stages, as it supports tuber growth (Djaman et al., 2021). Additionally, the amount of rainfall between planting and tuber initiation determines the number of tubers per stem. Higher precipitation during the period leads to an increase in tuber numbers (Ewing and Struik, 1992), and determines sink strength. Air temperature between 16 °C and 30 °C, corresponding to about 2000 degree-days over the growing period, is necessary to avoid photosynthesis inhibition and heat-stress (Levy and Veilleux, 2007; Struik, 2007; Timlin et al., 2006; Wang et al., 2015). However dry matter partitioning to tubers decreases above 19 °C average temperature (Marinus and Bodlaender, 1975; Kooman et al., 1996; Struik, 2007), which can impact the yield. The optimal soil temperature depends on the tuber development stages, *i.e.* tuber induction is optimal at 15 °C, initiation at 22 °C, and setting at 15 °C (Struik, 2007). Optimal growth, in terms of tuber bulking rate and final yield, is achieved with photoperiods of around 11–13 h (*i.e.*, approximately 2700 MJ $m^{-2}$ of total radiation over the growing period) (Zhao et al., 2016). However, potato growth can still occur with a minimum daily photoperiod of approximately four to six hours (Zhao et al., 2016). Conversely, potatoes can also be grown above the polar circle under very long days (Merzlaya et al., 2008), highlighting the crop's flexibility in adapting to extended daylight conditions. The expression of the genetic yield potential in terms of potato growth and development varies according to several environmental variables including the above-mentioned factors (Sood et al., 2022). Final yield also fluctuates over the years according to biotic stresses (Dupuis et al., 2019) or to agronomic practices such as tillage (Abrougui et al., 2019; Ochuodho et al., 2014) or soil nutrition (Prasad et al., 2015). The effect of all these factors: yield potential related to the genetic factors, agricultural practices or environment is linked and can be expressed as the Genotype x Environment x Management interaction (G x E x M). Climatic variables fluctuate across years and locations, inducing variations in the importance of the "environment" factor on potato yield. Consequently, the G x E x M interaction is and will continue to be a key factor to study and follow, especially with the challenges posed by both climate change and the rising global population (Cooper et al., 2021).

The last Intergovernmental Panel on Climate Change (IPCC) report underlines that the earth is warming and this warming is even greater at land level than at ocean level (CH2018, 2018) which alters important parameters for crop growth and development such as temperature and precipitation. The global average air temperature in Switzerland has risen by 2 °C since the industrial era (1871–1900) (OFEV et al., 2020; CH2018, 2018). By 2085, predictions during the summer period (*i.e.* potato growth) foresee an increase of 1.5 °C [from +0.7 °C to +2.3 °C] according to RCP 2.6, and of 5.35 °C [from +3.5 °C to +7.2 °C] according to RCP 8.5. In addition, a modification in rainfall is also expected, of -6.5 % [from +5.9 % to −18.9 %] according to RCP 2.6 and of −26.4 % [from −10.0 % to −42.8 %] according to RCP 8.5 (OFEV et al., 2020; CH2018, 2018). Changes in atmospheric carbon dioxide from 400 ppm according to RCP 2.6 up to more than 1000 ppm for the RCP 8.5 (IPCC, 2021) are also predicted. Atmospheric carbon dioxide increases have been shown to mitigate yield losses caused by climate change particularly for legumes and root crops (Ainsworth and Long, 2005; Finnan et al., 2002). For a given planting date, rising temperatures shorten the potato growth period, which decreases the final yield (Muthoni and Kabira, 2015). In some regions the potential duration of the growing season may be increased since higher temperatures allow earlier planting due to longer periods without frost, as is already seen and practised in some regions of China (Tang et al., 2022). In addition, under drought conditions, potato tubers also experience a reduction in net starch content. Nevertheless, a drought period can result in greater water loss compared to the limitations in starch biosynthesis, potentially increasing the proportion of starch content in tubers relative to their overall fresh weight (Bach et al., 2013). Starch content is a parameter of high importance as it defines the quality of potatoes at harvest. Considering the increasing threat of climate change, a better understanding of the relation between climatic variables and yield or starch content according to different phenological stages is needed to establish models able to accurately predict yield stability.

Over the years, models have been developed for potato yield prediction, such as SUBSTOR-potato and LINTUL-potato models, which are the most common potato models (Franke et al., 2013; Haverkort et al., 2013; Raymundo et al., 2014). Those models estimate yield variation according to climate data (*e.g.* atmospheric $CO_2$, air temperature or precipitation), potato growth (*e.g.* leaf, root or tuber growth), crop management, soil conditions (Haverkort and Top, 2011) or satellite data, for example, to calculate vegetation health indices (Akhand et al., 2016; Hara et al., 2021). According to most RCP scenarios from the IPCC, yield is expected to (i) decrease in almost all regions in the world (Raymundo et al., 2017a), (ii) stagnate in some parts of the word, *e.g.* Estonia, with the optimistic climate scenario (Saue and Kadaja, 2011) or (iii) increase in the coolest areas of the world (*i.e.* Canada) (Ochuodho et al., 2014; Supit et al., 2012). The present study has the advantage of being based on field data acquired in the same region. We worked on a large dataset containing potato yield (t $ha^{-1}$) and starch content (percentage) data obtained from variety trials managed under contrasting environmental conditions over a period of 31 years and five locations located in the Western Alps, Switzerland. These trials were managed according to the best recommended management practices in Switzerland, thus offering a dataset which allows identification of the effect of G x E interaction on yield and starch content without the noise introduced by management practices (M), which were homogeneous over the 31 years of study.

The effect of G x E on yield and starch content was first analysed by a Random Forest, a machine learning method used for classification or regression by using multitudes of decision trees. It allowed the selection of the most important variables explaining potato yield variations (Genuer et al., 2015; Jeong et al., 2016). Second, threshold models, graphical observations and a 2nd derivative estimation method were implemented to establish the type of relation between climatic variables and potato yield or starch content (Fong et al., 2017). Then, according to the identified relations between variables, different models were implemented to estimate the yield and starch content. Combined, these methods allowed us to implement accurate predictions of yield variation under different climate change scenarios, in short, medium and long term.

## 2. Material and methods

### 2.1. Field trials and dataset

Potato variety trials have been conducted by Agroscope since 1990, in five experimental sites located at different altitudes in Switzerland, namely: "La Fretaz" (CH-1453; 1200 m above sea level (asl)), "Les Mottes" (CH-1530; 455 m asl), "Grangeneuve" (CH-1725; 680 m asl), "Goumoëns" (CH-1376; 609 m asl), and "Changins" (CH-1260; 420 m asl). A total of 662 genotypes have been tested over the 31 years of trials (1990–2021) in the different locations (Supplementary material 1). All genotypes tested were genotype registered in the official European variety catalogue. Potatoes were planted from March to June and harvested from August to September, depending on the year and location. The soils were fertilized following the usual agricultural practices. Before potato emergence, an herbicide was applied according to the best management recommendations each year. Haulm destruction was implemented with a combination of chemicals (various products) and mechanical methods (the EnviMaxX machine from Rema environmental machinery B. V., the Netherlands). Potatoes were treated to prevent late blight (*Phytophthora infestans*) approximately once a week from emergence to haulm killing, using various fungicides. At harvest, yield (t $ha^{-1}$) was measured for each site, location, genotype and year, and the starch content measured using the densimetric method and the conversion table of Von Scheele et al. (1937), allowing the acquisition of 3723 records. For the 31 years of trials, dates of the main physiological stages of the crop (*i.e.*, planting, emergence, tuber initiation, and maturity) and dates of crop management operations (*e.g.* haulm killing and harvest) were recorded. Plant maturity refers to the physiological maturity as shown by the foliage color change from green to yellow and was considered when 80 % of plants for a given genotypes were turning yellow. Haulm killing was implemented when all genotype reached maturity. Based on these dates the following fifteen periods were defined: *planting to emergence*, *planting to tuber initiation*, *planting to haulm killing*, *planting to harvest*, *emergence to tuber initiation*, *emergence to haulm killing*, *emergence to harvest*, *tuber initiation to haulm killing*, *tuber initiation to harvest*, *haulm killing to harvest*, *planting to maturity*, *emergence to maturity*, *tuber initiation to maturity*, *maturity to haulm killing and maturity to harvest* (Visse-Mansiaux et al., 2022).

The following weather data were collected: minimal temperature (°C), average temperature (°C), maximal temperature (°C), soil temperature at 10 cm (°C), precipitation (mm), solar irradiation ($MJ.m^{-2}$) and relative humidity (%); either from Agrometeo (https://www.agrometeo.ch/, accessed 2021) or from MeteoSwiss (Federal Office of Meteorology and Climatology MeteoSwiss, Switzerland) for the 31 years of trials. The method to calculate the explanatory variables consisted of summing or averaging the weather data for each above-mentioned period. In addition, in the "Changins" site, plots were irrigated for a few growing seasons between 1990 and 2008, and then every year since 2009 except 2021 due to extreme precipitation. The other sites were not irrigated. Irrigation data were handled by adding the irrigation amounts per day to the daily precipitation data. More details on the method are available in the study of Visse-Mansiaux et al. (2022).

### 2.2. Statistical analysis

The R software version 4.2 (R Core Team, 2021) was used for data preparation and statistical analysis.

### 2.3. Factorial analysis

To identify the part of variation explained by factors genotype, year and site, and their effects on yield and starch content, an Analysis of Variance (ANOVA) was implemented using the "stats" package in R. In this study, the 31 years of trials were used, as well as the five above-mentioned locations and the 662 genotypes (Supplementary material 1). We considered as a statistical experimental unit the combination of each genotype, site and year. The ratio of the sum of squares for the considered effect of the total sum of squares was used to calculate the percentage of variability explained by each factor. In Swiss conventional variety testing trials, genotype was usually tested over two years. To check that there is no bias due to the low number of years per genotype, the same analyses were conducted on three control genotypes (Agria, Lady-Claire and Bintje) which were included in the trials for at least 20 years.

### 2.4. Variable selection

Each random forest was built using the "VSURF" package in R with yield or starch content as variables to be explained and all climatic variables as explanative variables. The analysis was run with the following parameters*: (i) ntree = 2000; (ii) nfor.thresh = 50; (iii) nmin = 1; (iv) nfor.interp = 25; (v) nsd = 1; (vi) nfor.pred = 25; (vii) nmj = 1; (viii) Rfimplem = "randomForest"; (ix) clusterType = "PSOCK"*. The VSURF package uses an approach based on performance and a stepwise selection procedure, which implements backward elimination then forward selection based on importance measures (relative importance = RI) and error rate for variable selection. More details on the method are available in the study of Genuer et al. (2015). It is implemented in three steps: (i) a thresholding step which estimates the variable importance associated with each climatic variables (*i.e.* explanatory variables); (ii) interpretation step and (iii) prediction step leading to the most important variables (Genuer et al., 2015).

### 2.5. Type of relation between selected variables and explanatory variables

To identify the type of relations (*i.e* linear or non-linear) between selected variables and yield or starch content, three methods were implemented: method 1) graphical observation of selected variables and explanatory variables using "Loess" tool from "ggplot" package in R. This allows a subjective assessment of the type of relation and potential threshold by observing the shape of the curve. Method 2) threshold regression model using segmented types with "Chngpt" package (Fong et al., 2017), which allows a threshold estimation along with its confidence interval using maximum likelihood optimisation. Method 3) threshold was estimated based on the maximum value of the second derivative of the squared-function within ranged of observed value. It allows a mathematical estimation of the threshold to estimate the type of relation. Based on the outputs of the different methods, we assessed the type of relation, and the respective effect between the selected variable and the variable to explain.

The dataset was split in a training dataset (2/3 of the dataset) and validation dataset (1/3 of the dataset). The dataset was split in such a way that each genotype was present in both sub-data sets. For both yield and starch content parameters, models were implemented by including the variables selected by the Random Forest analysis with or without the genotype effect. Then, stepwise regression was used for each model to keep only significant variables *(p-value* $< 0.05$) and two-way interactions in order to correlate meteorological data. Then, the different models were compared using cross-validation and by comparing their coefficient of determination ($R^2$), the root of the mean of the squared errors (RMSE) and the mean absolute error (MAE). The relative root mean square, *i.e.*, the ratio between the RMSE and the mean value of the yield (RMSE%) were calculated for the different models. This ratio provides a normalized measure of the prediction error, where a lower value indicates better predictive accuracy relative to the average value of the observed data.

### 2.6. Model prediction

To assess the effect of climate change in the future on potato yield and starch content, models with the highest $R^2$, the lowest MAE and RMSE for each variable to be explained (yield or starch content) were run on datasets using weather data obtained from a report on climate scenarios for Switzerland. Those reports were published by the Zurich National Centre for Climate Services, which adapt IPCC's scenarios for different regions in Switzerland. Scenarios were selected for the Western Alps region corresponding to: Representative Concentration Pathway 2.6 (RCP 2.6), Representative Concentration Pathway 4.5 (RCP 4.5) and Representative Concentration Pathway 8.5 (RCP 8.5) (CH2018 report, 2018). Each scenario includes a lower, medium and upper estimate value of the increase in global temperature and changes in precipitation by 2035, 2065 and 2085. Estimated predictions calculated in the above-mentioned report were used to estimate new predicted values for each variable included in models used in the present study. The sum of solar irradiation was integrated as the average value between 1990 and 2021 in this study. The predicted value was then compared to the average yield or starch content from 1990 to 2021 to estimate evolution in regards to climate change.

## 3. Results

### 3.1. Factors influencing yield and starch content in potato

Following the ANOVA, the year and genotype effects explained respectively, 25.47 % ($p < 0.05$) and 24.16 % ($p < 0.05$) of the yield variability, while the interaction of these two factors explained 15.02 % of the variability ($p < 0.05$) (Fig. 1.A). The average potato yield over the 31 years of trials (1990–2021) was 43.10 t ha$^{-1}$ and ranged from 31.60 t ha$^{-1}$ on average in 1995 to 57.70 t ha$^{-1}$ on average in 2011. Among the 662 genotypes studied, yield ranged from 23.50 t ha$^{-1}$ (G97TT013004 [N = 3]; N = number of records in the dataset) to 74.40 t ha$^{-1}$ (Georgina [N = 3]).

The yield variation due to the year for the three most tested genotypes, *i.e.* Agria, Bintje, and Lady-Claire is presented in Fig. 2.A. Over the 31 years, the yield of Agria ranged from 20.30 t ha$^{-1}$ to 77.30 t ha$^{-1}$ with an average of 48.80 t ha$^{-1}$ [N = 117], the yield of Bintje ranged from 22.90 t ha$^{-1}$ to 71.70 t ha$^{-1}$ with an average of 46.40 t ha$^{-1}$ [N = 158], and the yield of Lady-Claire ranged from 8.90 t ha$^{-1}$ to 64.70 t ha$^{-1}$ with an average of 37.30 t ha$^{-1}$ [N = 88] (Fig. 2.A). Among growing sites, yield varied from 41.10 t ha$^{-1}$ (Grangeneuve [N = 330]) to 48.80 t ha$^{-1}$ (Goumoëns [N = 219]), which represents 3.96 % of yield variability ($p < 0.05$) (Fig. 1.A). Agria was tested in four sites and the yield varied from 42.90 t ha$^{-1}$ (La Fretaz [N = 25]) to 56.00 t ha$^{-1}$ (Goumoëns [N = 11]). Bintje was tested in the five sites and the yield ranged from 42.50 t ha$^{-1}$ (Grangeneuve [N = 9]) to 53.10 t ha$^{-1}$ (Goumoëns [N = 9]). Finally, Lady-Claire was tested in four sites and the yield ranged from 33.60 t ha$^{-1}$ (La Fretaz [N = 23]) to 41.10 t ha$^{-1}$ (Goumoëns [N = 14]) (Fig. 2.B). The effect of the interaction between the growing site and year of trial is high as it explained 21.15 % of yield variability ($p < 0.05$) (Fig. 1.A). As an example, in 2017 the average yield at "Changins" (420 m asl) was 50.00 t ha$^{-1}$ and 50.60 t ha$^{-1}$ at "La Fretaz", the site at high altitude (1200 m asl), while in 2021 the average yield at "Changins" was 50.00 t ha$^{-1}$ and 34.50 t ha$^{-1}$ at "La Fretaz".

The genotype effect was the most important one to explain the potato starch content variability (74.54 %, $p < 0.05$), while the year and the growing site effects explained respectively 4.24 % and 0.34 % of the starch content variability ($p < 0.05$) (Fig. 1.B). The two-way interactions between year, site, and genotypes accounted for 2.99 % (genotypes * site), 6.39 % (genotypes * year), and 8.93 % (genotypes * site) of the starch content variability ($p < 0.05$) (Fig. 1.B). Potato starch content ranged from 14.19 % in 2013 to 16.91 % in 1992, with an average of 15.52 % over the 31 years of trials. Among the 662 genotypes studied, starch content varied on average from 10.37 % (Carrera [N = 3]) to 23.30 % (Assia [N = 3]). The starch content of the three most tested genotypes, *i.e.* Agria, Bintje, and Lady-Claire, ranged respectively from 12.20 % to 19.30 %, 12.10 % to 19.00 %, and 13.80 % to 23.00 % during the 31 years of trials (Fig. 2.C). Based on the growing site, the average starch content varied from 15.40 % (Grangeneuve [N = 330]) to 15.94 % (Les Mottes [N = 116]). On average, according to the site, the starch content ranged respectively from 14.50 % to 16.48 %, from 15.06 % to 15.99 %, and from 16.28 % to 19.67 %, for the genotypes Agria, Bintje and Lady-Claire (Fig. 2.D).

### 3.2. Main variables influencing yield and starch content

Among the 240 climatic variables, the random forest analysis effectively identified the key variables influencing yield and starch content variation. This process involved several selection steps and utilized the respective importance (RI) criterion to determine the most significant. Four variables were selected to explain yield variation: 1) sum of solar irradiation from planting to plant maturity (RI = 2155); 2) total precipitation from tuber initiation to harvest (RI = 1323); 3) sum of daily maximum temperatures from planting to plant maturity (RI = 586) and 4) average temperature from planting to plant maturity (RI = 575). The relationships between these variables and the yield are presented in Fig. 3. Three variables were selected to explain starch content variability: 1) average maximal temperature from plant maturity to haulm killing (RI = 0.63); 2) total precipitation from planting to haulm killing (RI = 0.23) and 3) sum of daily minimum temperatures at soil level from maturity to harvest (RI = 0.17). The relationships between these variables and the starch content are presented in Fig. 4. The variables were selected based on their RI and the correlation with other previously selected climatic variables. Variables were added only if the error decrease was larger than a specific threshold (set at default value) (Genuer et al., 2015)

### 3.3. Different types of models implemented to identify the relationship between climatic variables and yield or starch content

The first method (Fig. 3) allows graphical identification of the type of relationship between a selected climatic variable and the yield. Based on this first method, the shape of the curves indicates that the variables "total precipitation from tuber initiation to tuber harvest" and "sum of solar irradiation from planting to maturity" are linearly correlated with the yield (Fig. 3. A & D). In contrast, according to the shape of the curves, the variables "average temperature from planting to maturity" and "sum of daily maximum temperatures from planting to maturity" have a non-linear relation with the yield, with a threshold around 16.50 °C and a slope change around 2000 °C, respectively (Fig. 3. B and C). The second method, using a threshold analysis (Table 1), allows one to determine if there is a change point in the curve slope.

The outputs of the model indicate that there is a linear relationship between the variables "total precipitation from tuber initiation to tuber harvest" and the yield and, because this method determined the threshold value for three other variables, this means that there are non-linear relations between these three variables and the yield. Based on the confidence interval (CI) provided with the threshold value, it can be seen

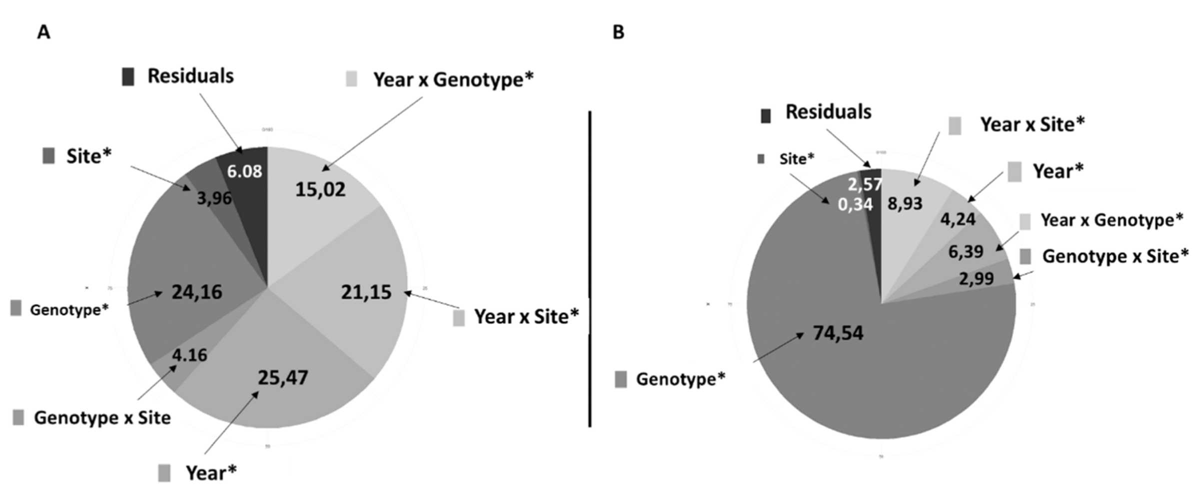


**Fig. 1.** Pie-chart representation of A: yield; B: starch content variation (percentage) explained by factors genotype, year, site, and their interactions (*: $p < 0.01$).

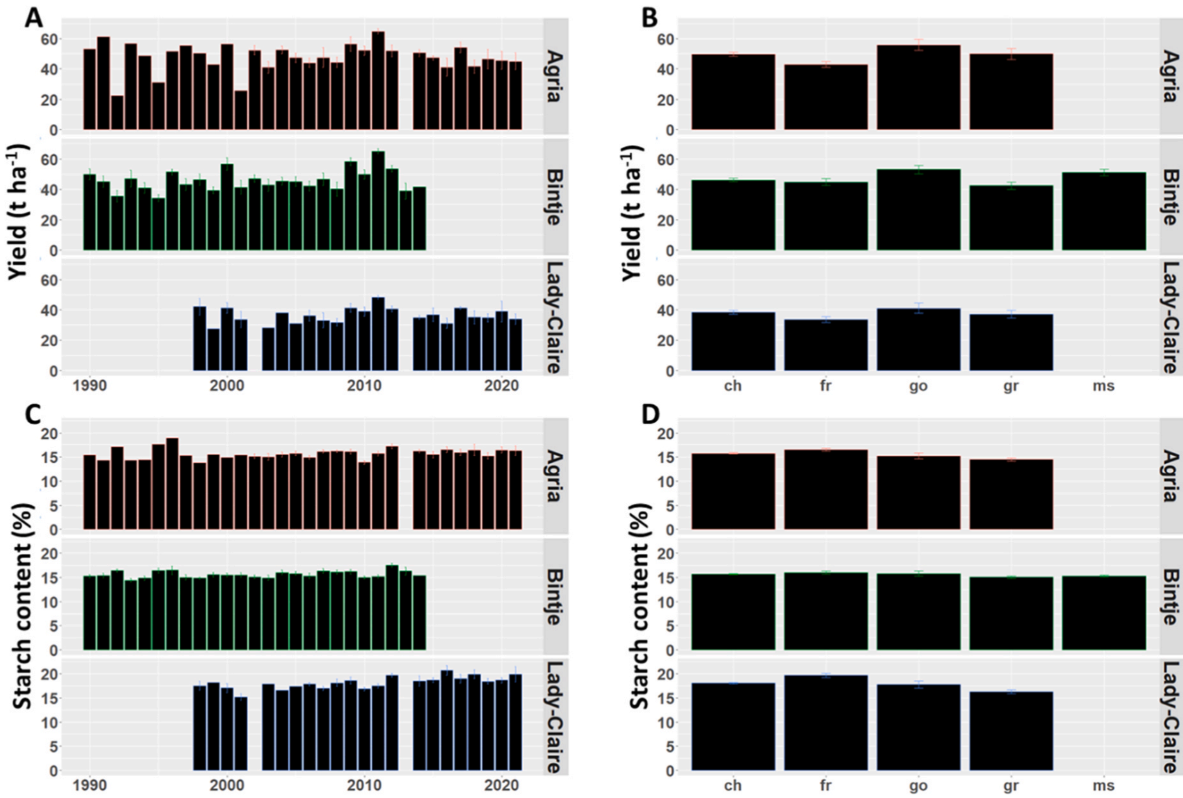


**Fig. 2.** Evolution of yield (t ha$^{-1}$) and starch content (percentage) for three potato genotypes (Agria, Bintje, Lady-Claire) from 1990–2021 (A, C) and growing sites (B, D) with their standard errors. The factor "year", explains 19.11 %, 31.5 % and 7.9 % (based on ANOVA) of yield variance (A) of Agria, Bintje and Lady-Claire, respectively, and 13.1 %, 13.1 %, and 27.5 % of starch content variance (C) of Agria, Bintje and Lady-Claire, respectively. The factor "site", explains 8.5 %, 3.8 % and 4.3 % of yield variance (B) of Agria, Bintje and Lady-Claire, respectively, and 12.0 %, 0.2 %, and 27.6 % of starch content variance (D) of Agria, Bintje and Lady-Claire, respectively.

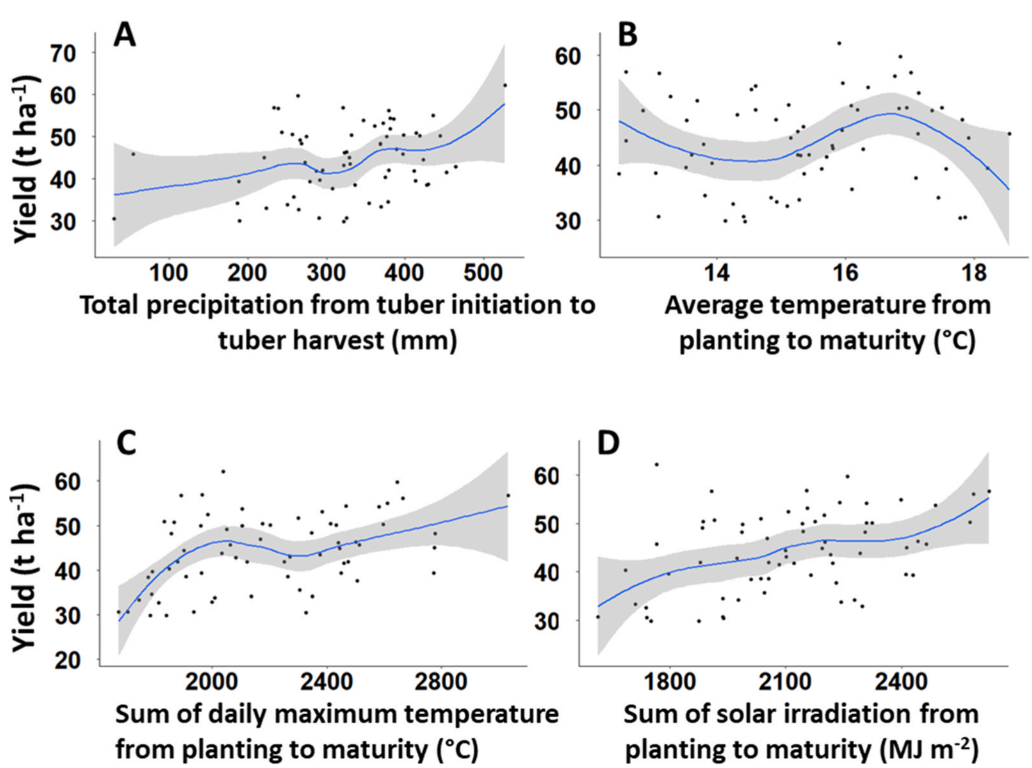


**Fig. 3.** Graphical representation of climatic variables selected by Random Forest for yield variation explanation. A. Total precipitation from tuber initiation to tuber harvest (mm). B. Average temperature from planting to maturity (°C). C. Sum of daily maximum temperatures from planting to maturity (°C). D. Sum of solar irradiation from planting to maturity (MJ m$^{-2}$).

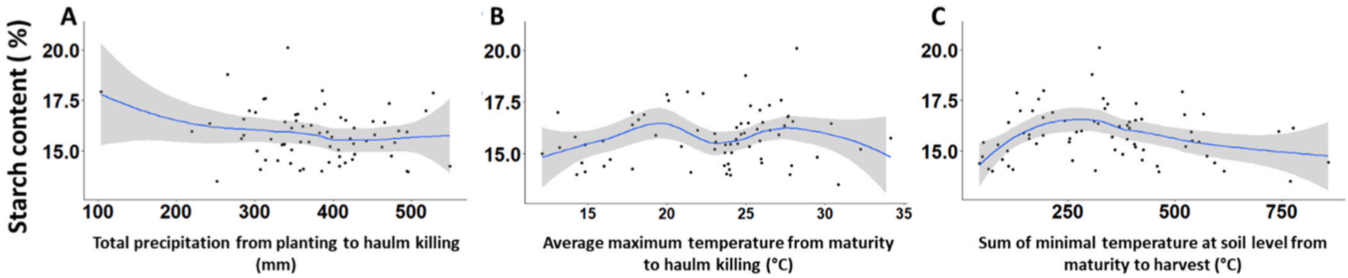


**Fig. 4.** Graphical representation of climatic variables selected by Random Forest for starch content variation explanation. A. sum of precipitation (mm) from planting to haulm killing; B. average maximum temperatures (°C) from maturity to haulm killing; C. sum of minimum temperatures (°C) at soil level from maturity to harvest.

**Table 1**
Summary of variables selected by RandomForest and threshold regression model output using segmented-type. Type of relationship: Non-linear, change point (*p value* <thinsp;0.05); Linear, no change point (*p value* > 0.05). Threshold / CI: Threshold position / Confidence Interval. Yield equation[1]: Yield[1]= intercept + estimate*variable. Yield estimation according to model output before the threshold. Yield equation[2]: Yield[2]= Yield[1]+estimate*variable. Yield estimation according to model output after the threshold. X = variable until threshold. Z = variable after threshold. ε: residual error (Chngpt package (Fong et al., 2017)).

| Variables | Relationship | Threshold / CI | Yield equation[1] | Yield equation[2] |
|---|---|---|---|---|
| **Total precipitation from tuber initiation to tuber harvest (mm)** | Linear | | y1 = 329.92 + 0.287 *x + ε | |
| **Average temperature from planting to maturity (°C)** | Non-linear | 16.76 °C / [16.76–16.83] | y1 = 50.73 + 25.80 *x + ε | y2 = y1–63.86 *y + ε |
| **Sum of daily maximum temperature from planting to maturity (°C)** | Non-linear | 1892.20 °C / [1745.40–2665.30] | y1 = −246.70 + 0.35 *x + ε | y2 = y1 + 0.082 *y + ε |
| **Sum of solar irradiation from planting to maturity (MJ m$^{-2}$)** | Non-linear | 1885.95 MJ m$^{-2}$ / [1793.32–2488.58] | y1 = −295.27 + 0.38 *x + ε | y2 = y1 + 0.09 *y + ε |

that the threshold obtained is precise for the variable "average temperature from planting to maturity" with a threshold at 16.76 °C and a [CI] at [16.76–16.83] (Table 1), but not for the variables "sum of daily maximum temperatures from planting to maturity" and "sum of solar irradiation from planting to maturity" with values and [CI] of 1892.20 °C [1745.40–2665.30] and 1885.95 MJ m$^{-2}$ [1793.32–2488.58], respectively. The third method, using the derivative methods, allows a mathematical estimation of a threshold within the observed values by obtaining the highest value of the squared-transformed variable. If the highest value is the highest observed value in the dataset it means that there is no threshold, which was the case for "total precipitation from tuber initiation to tuber harvest", "sum of solar irradiation from planting to maturity" and "sum of daily maximum temperature from planting to maturity" (Table 2). Based on the three methods, it is considered that the relationship between each of three variables: "total precipitation from tuber initiation to tuber harvest", "sum of solar irradiation from planting to maturity", and "sum of daily maximum temperatures from planting to maturity" and the yield are linear (Table 3). This was concluded as the first method showed linear curves for two of the three the variables, and the second and third methods estimated no change points, large confidence intervals or no thresholds with squared-transformed variables for the three variables. Furthermore, it is estimated that each additional millilitre of water, each MJ m$^{-2}$ of solar irradiation and each additional degree brought to the field, results in a yield increase of 0.03 t ha$^{-1}$; 0.038 t ha$^{-1}$ and 0.035 t ha$^{-1}$, respectively (within the observed values for each of the climatic variables) (Table 1). In addition, based on method 3 results, there is a threshold of 16.61 °C for the variable "average temperature from planting to maturity". This is similar to the thresholds from methods 1 and 2 and it can thus be accepted that this variable has a non-linear relationship with yield (Table 3). The threshold of this non-linear relationship is approximately 16.50 °C with two parts: 1) a positive linear relationship below 16.50 °C in which each degree gained results in an average yield increase of 2.58 t ha$^{-1}$; and 2) a negative linear relationship above 16.50 °C in which each degree causes an average decrease in yield of 6.39 t ha$^{-1}$ (Table 3).

**Table 2**
Estimated threshold value for variables selected for yield prediction using the derivative method.

| Variables | Threshold |
|---|---|
| **Total precipitation from tuber initiation to tuber harvest (mm)** | 557.49 mm |
| **Average temperature from planting to maturity (°C)** | 16.61 °C |
| **Sum of daily maximum temperature from planting to maturity (°C)** | 3032.20 °C |
| **Sum of solar irradiation from planting to maturity (MJ m$^{-2}$)** | 2627.00 MJ m$^{-2}$ |

**Table 3**
Summary of the relationship types between yield and climatic variable according to methods described in Fig. 3, Tables 1 and 2.

| **Variables** | **Relationship** | | |
|---|---|---|---|
| | **Method 1** | **Method 2** | **Method 3** |
| **Total precipitation from tuber initiation to tuber harvest (mm)** | Linear | Linear | Linear |
| **Average temperature from planting to maturity (°C)** | Non-linear | Threshold at 16.76 °C | Threshold at 16.61 °C |
| **Sum of daily maximum temperature from planting to maturity (°C)** | Non-linear | Threshold at 1892.20 °C | Linear |
| **Sum of solar irradiation from planting to maturity (MJ m$^{-2}$)** | Linear | Threshold at 1885.95 MJ m$^{-2}$ | Linear |

The types of relationships of variables with starch content were also identified. Based on the graphical analysis (method 1), the variable "total precipitation from planting to haulm killing" is linearly correlated with the starch content (Fig. 4.A). On the other hand, according to the shape of the curve, the variable: "average maximum temperature from maturity to haulm killing" is not linearly correlated with the starch content, as two optimal values at 19 °C and 27 °C were observed (Fig. 4. B). Finally, the variable "sum of minimum temperature at soil level from maturity to harvest" has a non-linear relationship with the yield with a threshold at 250 °C (Fig. 4.C). The second method indicates that there is a linear relationship between the variables "total precipitation from planting to haulm killing" and the starch content, and a non-linear relationship between the two other variables (Table 4). Based on the confidence interval (CI) provided with the threshold value, it can be observed that the threshold obtained is imprecise for "sum of minimum temperatures at soil level from maturity to harvest" with a threshold value and [CI] of 130.50 °C [130.50–181.50], and even less precise for "average maximum temperature from maturity to haulm killing" with a threshold value and [CI] of 20.00 °C [14.30–23.93]. Method 3 provides a threshold value for each of the three variables at the highest observed values (Table 5), which means that no threshold is detected by this method. Based on results from the three methods, the three variables had a linear relationship with the starch content (Table 6). The second and third methods do not estimate any change point, show large confidence intervals or no thresholds with squared transformed variable for the variables: "average maximum temperature from maturity to haulm killing" and "sum of minimum temperatures at soil level from maturity to harvest". The last variables, "sum of precipitation from planting to haulm killing" has a linear relationship with starch content according to the three methods.

**Table 5**
Estimated threshold value for variables selected for starch content prediction using the derivative method.

| Variables | Threshold |
|---|---|
| **Sum of precipitation from planting to haulm killing (mm)** | >516.26 mm |
| **Average maximum temperature from maturity to haulm killing (°C)** | >34.15 °C |
| **Sum of minimal temperature at soil level from maturity to harvest (°C)** | >857.30 °C |

**Table 6**
Summary of the decision of the relationship between starch content and climatic variables according to methods described in Fig. 4, Tables 4 and 5.

| Variables | Relationship | | |
|---|---|---|---|
| | Method 1 | Method 2 | **Method 3** |
| **Sum of precipitation from planting to haulm killing (mm)** | Linear | Linear | Linear |
| **Average maximum temperature from maturity to haulm killing (°C)** | Non-Linear | Threshold at 20.0 °C | Linear |
| **Sum of minimal temperature at soil level from maturity to harvest (°C)** | Linear | Threshold at 130.5 °C | Linear |

### 3.4. Yield prediction

Using the three or four above-mentioned climatic variables, models were developed using Random Forest, threshold model and stepwise regression output of the 31 years trial dataset. Subsequently prediction models for potato yield and starch content in the Western Alps, Switzerland, were established based on the Zurich Institute's adaptation of IPCC's climate scenarios for Switzerland (CH2018, 2018). To do so, our models were run on meteorological data prediction of climatic scenarios (*i.e.* average temperature, precipitation and sum of temperatures) for RCP 2.6, RCP 4.5 and RCP 8.5, and each of their respective upper, medium and lower estimations. However, since solar irradiance variations only occur at two scales: over the millennia at Earth scale (Vieira et al., 2011) and over the years within an 11-year cycle with an amplitude of less than 0.10 % (Solomon et al., 2007), it was considered for the prediction models that "sum of solar irradiation from planting to maturity" was equal to the average value of 1990–2020 (*i.e.*; 2125 MJ $m^{-2}$). In addition, different linear models were established, with or without interaction and genotype effect (Table 7). The first model includes selected climatic variables, the second includes selected climatic variables and the variety effect as a factor, and the third model includes climatic variables, the genotype effect as a factor and the interaction between the genotype effect and climatic variables. Models with the lowest prediction rate were used for yield and starch content prediction. The model selected in this study to explain yield variation includes the genotype factor and the four climatic variables: (i) sum of solar irradiation from planting to maturity, (ii) sum of precipitation from tuber initiation to harvest, (iii) average temperature from planting to maturity as a polynomial variable, and (iv) sum of maximum temperatures from planting to maturity, or only the four climatic variables. The model selected in this study to explain starch content variation includes the genotype factor and the three climatic variables: (i) sum of precipitation from planting to haulm killing; (ii) average maximum temperature from maturity to haulm killing and (iii) sum of minimum temperatures at soil level from maturity to harvest, or only the three climatic variables. The above-mentioned selected model for yield, explained 46 % ($R^2$) of yield variability with an RMSE of 8.15 t $ha^{-1}$ and an MAE of 6.47 t $ha^{-1}$ on the validation dataset (Table 7. A). The selected starch model explained 63 % ($R^2$) of starch content variability with an RMSE of 1.52 % and an MAE of 1.18 % on the validation dataset (Table 7. B).

According to the National Centre for Climate Services of Zurich, there could be a significant increase in average temperature and a decrease in total precipitation in Switzerland in the coming years. The yield prediction model has been used to estimate yield loss in the short, medium, and long-term. The short-term scenarios predict only slight changes (Fig. 5), with yield losses of approximately 3.20–15.00 %, 3.30–14.40 % and 3.00–16.30 % according to RCP 2.6, RCP 4.5 and RCP 8.5, respectively, in short-term compared to the average yield from 1990 to 2020. In the medium term, differences between the three scenarios are observed. The RCP 2.6 predicts a yield loss from 2.70 % to 17.50 %, while the RCP 4.5 predicts a yield loss from 5.30 % to 22.70 % and the RCP 8.5 from 8.20 % to 50.30 %. Medium and long-term predictions are similar for the RCP 2.6. However, in the long-term the RCP 4.5 and RCP 8.5 predict yield losses as high as 37.30 % and 84.60 %, respectively (Fig. 5). Among those scenarios, we observed that a significant increase in temperature coupled with a decrease in precipitation lead to the highest yield loss. Starch model prediction (Fig. 6) showed slight changes depending on the scenario and the period predicted: short,

**Table 4**
Summary of variables selected by RandomForest and threshold regression model output using segmented-type Relationship: Non-linear, change point (*p value* $< 0.05$); Linear, no change point (*p.value* $> 0.05$). Threshold / CI: Threshold position / Confidence Interval. Starch content equation before threshold: $Yield^1 = intercept + estimate*variable$: Yield estimation according to model output before the threshold. Starch content equation after threshold: $Yield^2 = Yield^1 + estimate*variable$: Yield estimation according to model output after the threshold. X = variable until threshold. Z = variable after threshold. ε: residual error. Chngpt package (Fong et al., 2017).

| Variables | Relationship | Threshold / CI | Yield equation[1] | Yield equation[2] |
|---|---|---|---|---|
| **Sum of precipitation from planting to haulm killing (mm)** | Linear | | $y1 = 18.09–0.006 *x + ε$ | |
| **Average maximum temperature from maturity to haulm killing (°C)** | Non-linear | 20.00 / [14.30 – 23.93] | $y1 = 13.65 + 0.13 *x + ε$ | $y2 = y1–0.06 *y + ε$ |
| **Sum of minimal temperature at soil level from maturity to harvest (°C)** | Non-linear | 130.50 / [130.50 – 181.50] | $y1 = 13.06 + 0.027 *x + ε$ | $y2 = y1–0.0026 *y + ε$ |

**Table 7**

Model output. (A) Yield models, (B) Starch models; $R^2$: Coefficient of determination; RMSE: root of the mean squared errors; MAE: mean absolute error; RMSE % : ratio between the RMSE and the mean value of the yield, on training and validation datasets. (i) models that include the three or four selected climatic variables, according to the variables to be explained; (ii) models that include the three or four selected climatic variables and the genotype effect as factor; (iii) models that include the three or four selected climatic variables, the genotype effect as factor and the interaction between genotype effect and climatic variables.

| (A) Yield models | R2 | | RMSE | | MAE | | Prediction error rate |
|---|---|---|---|---|---|---|---|
| | Train | Validation | Train | Validation | Train | Validation | |
| (i) Climatic variables | 0.30 | 0.31 | 8.53 | 9.17 | 6.47 | 7.27 | 0.21 |
| (ii) Climatic variables + genotype | 0.50 | 0.46 | 7.24 | 8.15 | 5.72 | 6.47 | 0.19 |
| (iii) Climatic variables + genotype + (climatic variable*genotype) | 0.54 | 0.41 | 6.89 | 8.58 | 5.41 | 6.67 | 0.20 |
| **(B) Starch models** | **R2** | | **RMSE** | | **MAE** | | **Prediction error rate** |
| | Train | Validation | Train | Validation | Train | Validation | |
| (i) Climatic variables | 0.04 | 0.06 | 2.39 | 2.42 | 1.93 | 1.95 | 0.15 |
| (ii) Climatic variables + genotype | 0.81 | 0.63 | 1.05 | 1.52 | 0.82 | 1.18 | 0.10 |
| (iii) Climatic variables + genotype + (climatic variable*genotype) | 0.90 | 0.00 | 0.77 | 19.72 | 0.46 | 3.82 | 1.24 |

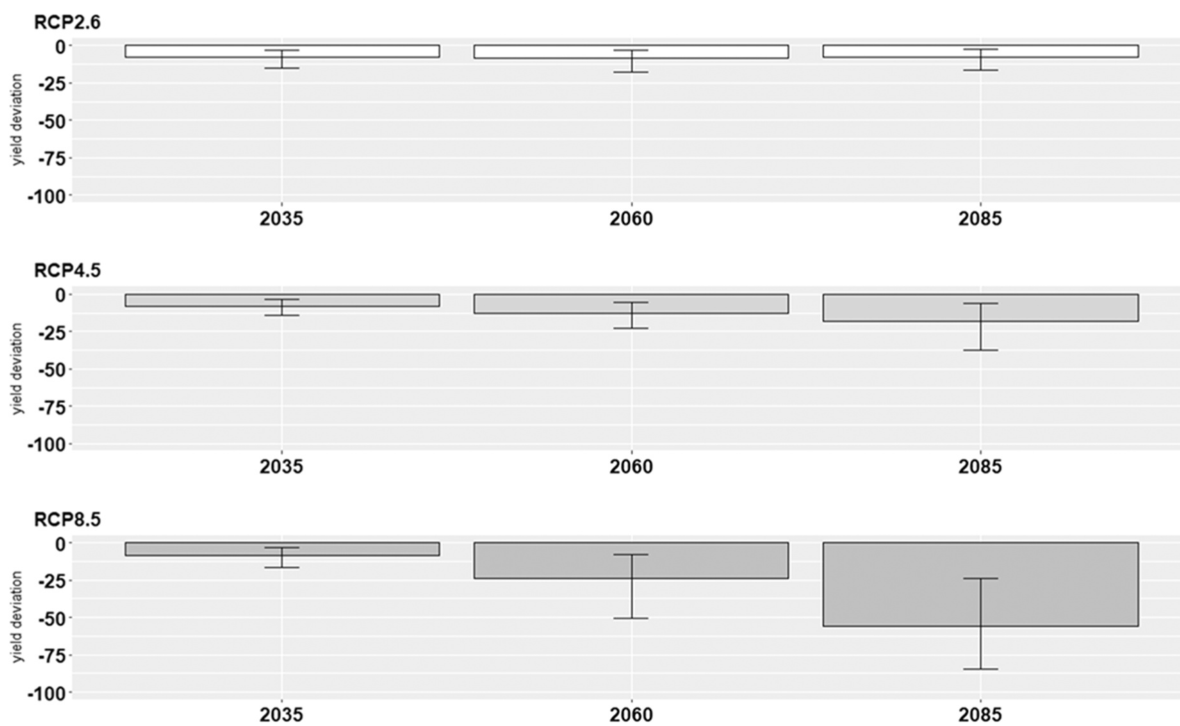


**Fig. 5.** Estimated yield loss, in short (2035), medium (2060) and long-term (2085) under three climate scenarios (RCP2.6; RCP4.5; RCP8.5), and their respective lower, medium and upper estimates.

medium or long-term. In all tested cases the observed variation in starch content ranged from −3 % to +3 %.

## 4. Discussion

### 4.1. Effect of the environment on potato yield

The environment, including year-to-year weather variations, and growing region variations explain 50 % of potato yield variability based on data collected from 1990 to 2021 in Western Alps (Switzerland) (Fig. 1.A). Contrasting years in terms of yield were observed over the 30 years of data in this study, with average yields ranging from 31.6 t $ha^{-1}$ to 57.8 t $ha^{-1}$ (data not shown). This is in line with studies conducted across various locations and altitudes in East Africa reporting an environmental effect of 54 % (Mulema et al., 2008), with a yield variation ranging from 21.7 t $ha^{-1}$ to 38.9 t $ha^{-1}$ (Kwambai et al., 2024; Mulema et al., 2008). However, the proportion of yield variation explained by the environment in our study is lower than in some other studies. For instance, Flis et al. (2014) report a yield variability caused by the environment of 72 % in a study conducted in three countries (*i.e.* Hungary, Spain and Poland) over two years and 21 genotypes. Mijic et al. (2019) report that the environment explains 78.9 % of yield variability with a yield ranging from 26.1 t $ha^{-1}$ to 44.6 t $ha^{-1}$ in their study conducted in Croatia between 2001 and 2012, across 52 genotypes, three sites and 12 years.

These differences in yield variability due to the environment among studies may stem from higher year-to-year weather variations during growing periods, or more heterogeneous growing sites, especially when data were collected across different countries, due for example to the effect of soil type on plant growth (Quan and Liang, 2017). It has been shown that year-to-year yield variability varied across world regions, especially for crops cultivated worldwide such as potatoes and wheat (Ben-Ari and Makowski, 2014). This variability is due to differences in yield potential across growing regions, year-to-year weather fluctuations that increase with climate change and also the stagnation of yields in some high average yield regions in recent years, which limits yield variability (Schauberger et al., 2018). In contrast, in our study, data were collected in one country, which could explain the low effect of the growing site on potato yield, around 4 % (Fig. 1.A), despite differences in average yield according to growing site. It ranged from 41.1 t $ha^{-1}$ for

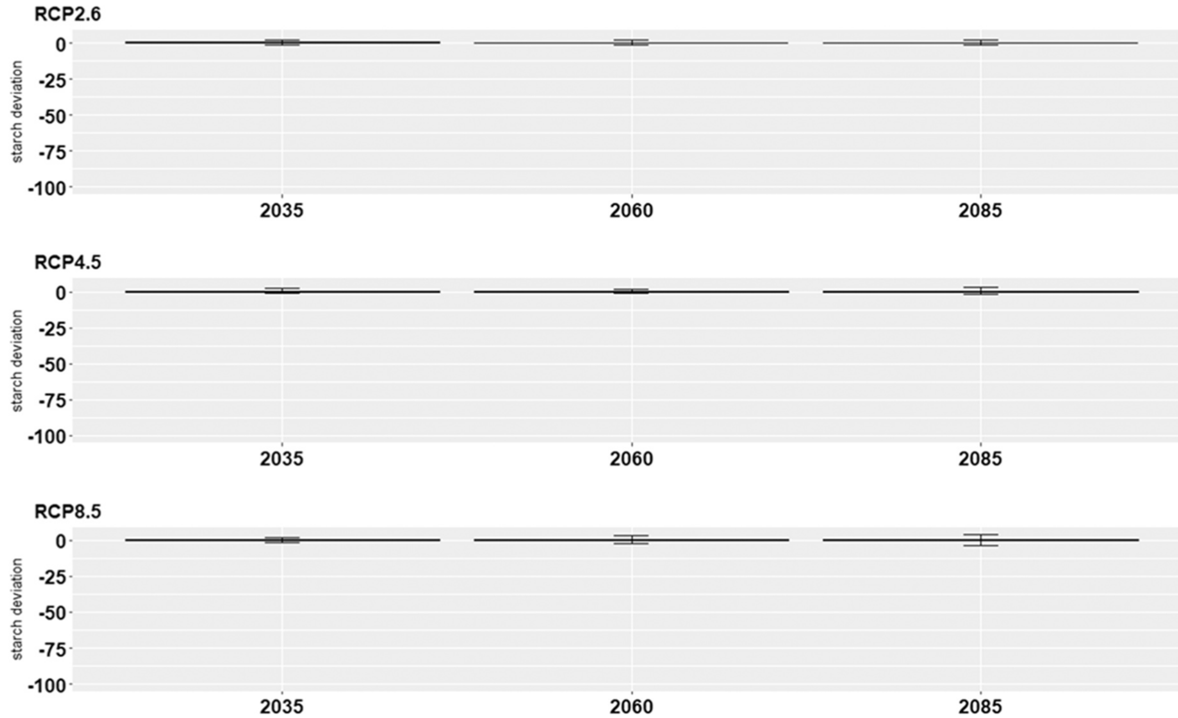


**Fig. 6.** Estimated starch change, in short (2035), medium (2060) and long-term (2085) under three climate scenarios (RCP2.6; RCP4.5; RCP8.5), and their respective lower, medium and upper estimates.

"Grangeneuve" [N = 330] to 48.8 t ha$^{-1}$ for "Goumoëns" [N = 219], with smaller differences between other sites with more trials such as "Changins" and "La Fretaz". This suggests a high homogeneity in the Western Alps climate in Switzerland over past 30 years. However, we can expect changes in the coming years with increasing climate variability through the year, as already observed in many crop trends throughout Europe (Hawkins et al., 2013, 2013; Moore and Lobell, 2015). In addition, in our study, no significant difference in yield was observed between the two sites with the most contrast in elevation, *i.e.* the site "Changins" at 420 m asl (average yield of 43.70 t ha$^{-1}$ [N = 2190]) and the site "La Fretaz" at 1200 m asl (average yield of 40.60 t ha$^{-1}$ [N = 867]). These results were surprising as a lower average temperature was observed in the site at high elevation compared to the site at low elevation. An average temperature between planting and harvest over 30 years of 13.40 °C was recorded at the site "La Fretaz" and 16.90 °C at "Changins", giving a difference of 3.50 °C. In addition, the length of the growing period from planting to harvest was shorter at the site at high elevation (*i.e.* 140 days in the site "Changins" compared to 125 days at the site "La Fretaz"). These differences were, however not statistically different.

This is in contradiction with literature describing the effect of elevation on plant growth. For example, in rice, lower yields were observed at higher altitudes due to lower temperatures and insufficient irrigation facilities (Guo et al., 2018), both of which were differences observed between our two sites. Additionally, for potato, it has been calculated that with every 1000 m asl increase in elevation, the duration of the growing period of potato is delayed by about one month (Ahmadi et al., 2019). This delay reported in the literature is linked to a reduction in physiological aging at lower temperatures observed at altitude, prolonging the length of the growing period. As we did not observe a lower yield in the site at elevation, despite a reduced growing period and a lower average temperature, the homogeneity observed in yield between those sites could be due to a beneficial effect of lower temperatures on yield by avoiding heat-stress periods. Indeed, there were 279 days with temperatures above 30 °C in the site at high altitude between 1990 and 2021, and 332 days at the site at low altitude (data not shown), giving an average 2–3 more days of heat-stress at the site at low altitude versus the site at high altitude. This can compensate for the loss in yield normally observed at lower temperatures (Minda et al., 2018). Also, altitude effect could be more pronounced at higher altitudes; Kwambai et al. (2024) showed differences in average yield and yield variability among genotypes between sites at 1837 m asl and 2915 m asl, caused by favourable weather at lower altitudes.

### 4.2. *Effect of meteorological variables on potato yield*

From this dataset, we chose and implemented a linear model that estimates potato yield variability caused by weather variation. Our model explained 30 % of yield variability (Table 7), which is in line with other studies estimating that climate variation explains a third of global crop yield variability (Ray et al., 2015). The linear relationship between the crop development and variables such as the sum of temperatures, growing degree days (Reaumur, 1735), solar radiation and biomass production has already been described by authors (Monteith, 1972). Consequently, it is important to quantify the effect of each variable on potato yield to better predict potential losses due to climate change.

In this study, rainfall had a greater effect on potato yield in the period from tuber initiation to harvest than in the other defined periods. This can be explain by the fact that drought preceding tuber initiation has been reported to inhibit the tuber formation, thus reducing the number of tubers per plant but not necessarily the final yield (Deblonde and Ledent, 2001). Furthermore, we found that within a precipitation range of 100 mm to 500 mm during the season, each decrease of 1 mm in rainfall or irrigation led to a yield decrease of 0.03 t ha$^{-1}$ (Fig. 3.A). The importance of precipitation for potato yield has been reported in the literature (Boguszewska-Mankowska et al., 2022). Fleisher et al. (2017) used models such as SUBSTOR or LINTUL (Ritchie et al., 1995; Spitters, 1990) on a dataset covering four potato production regions worldwide over 30 years. The authors estimated that each 10 % decrease in precipitation resulted in an average yield loss of 2 %. In our study, results are similar as a 10 % precipitation decrease led to losses of 1.2 t ha$^{-1}$, which is equivalent to a 2.8 % yield loss for an average yield of 43.1 t ha$^{-1}$ over the 30 years in our study. However, the average estimations in yield loss according to variation in precipitation and temperature from our study or the literature do not seem to reflect losses during years with extreme drought. Obidiegwu et al. (2015) report similar results in their study conducted in Poland and Russia, with a 30 % yield decrease observed between an irrigated condition and a drought condition, with around 150 mm less total water in the drought condition compared to the irrigated condition, corresponding to a yield loss of 4 t ha$^{-1}$ per 10 % decrease in precipitation. These results suggest a higher loss in yield in case of severe drought.

Our study also quantified the effect of temperature on potato yield, a major component of plant growth (Struik, 2007). The threshold above which temperature has a negative effect on final yield has been estimated at 16.5 °C. Each degree above this threshold led to a loss of 6.4 t. ha$^{-1}$, which corresponds to a decrease of 14.8 % in yield per degree Celsius. This can be explained by the fact that the optimal temperature for potato growth has been reported to be around 14 °C–16 °C, in field experiments conducted in Florida (USA) in the seventies (Ingram and McCloud, 1984). Our results are also in line with Fleisher et al. (2017) who studied the effect of climate change on potato yield in seven sites. In their study the average baseline temperature varied from 13.81 °C to 16.45 °C according to the site. They applied different scenarios of climate change, from −3 °C (best scenario) to +9 °C (worst scenario) of variation in temperature (*i.e.* −3, +0, +3, +6 and +9 °C) compared to the baseline temperatures to predict the change in yield. Results showed that each increase in temperature of one degree will cause a yield loss of 4.6 % over all tested scenarios. The temperature range studied in Fleisher et al. (2017), varies from 10.81 °C (13.81 °C minus the −3 °C scenario) to 25.45 °C (16.45 °C plus the +9 °C scenario), a broader range than in our study, which is from 16.50 °C to 22.80 °C. This could explain the differences in yield loss estimation per degree Celsius increase observed between our study compared to that of Fleisher et al. (2017). The negative effect of climatic variables selected in our model on potato yield, highlights the negative impact of climate change on potato grown in Switzerland, as predicted for almost all region worldwide (Raymundo et al., 2017b). This negative effect will be particularly significant for the variables "total precipitation from tuber initiation to tuber harvest" and "average temperature from planting to maturity" as those variables are more subject to climate change than the other two (CH2018, 2018). In our study we did not quantify the effect of atmospheric-$CO_2$ changes on potato yield, estimated to be positive to potato (Kimball, 2016), because changes in our dataset were too small to be considered. Climate change will continue to reinforce the negative effect of those meteorological variables on potato yield with changes in intensity and homogeneity in weather (IPCC, 2021).

### 4.3. Effect of the genotype on potato yield

After the environment, the genotype (*i.e.* variety) is the second most important factor influencing potato yield and explains 24 % of potato yield variability in our study (Fig. 1. A). Results obtained are in line with the literature, as it is reported that the yield of a genotype is determined by the genetic yield potential (Sood et al., 2022). However, the percentage of yield variability explained by the genotype in our study is different to that in other studies. Flis et al. (2014) reported that the genotype explains 8 % of yield variability among 22 genotypes studied, while Mijic et al. (2019) reported an effect of 9.30 % on 105 genotypes studied; and Mulema et al. (2008) reported a yield variability of 11 % on 12 genotypes studied. Finally, a study in Kenya, including 50 contrasting genotypes estimated that genotype explains 71.20 % of total tuber yield variation (Kwambai et al., 2024). Few parameters explain variation in genotype as a proportion of total tuber yield variation. For example (i) differences in climate, soil type, water availability and nutrient levels influence the share of yield variation due to genotype or environmental factors; (ii) G x E, with some genotypes that perform well in one environment but less in another one, for example Zarzyńska et al. (2023) showed that Polish genotypes yield higher compared to foreign genotypes in two different Polish sites; or (iii) the number of genotypes tested, with more than 600 genotypes tested in our study, while other study tested between 12 and 105 genotypes (Flis et al., 2014; Kwambai et al., 2024; Mijic et al., 2019; Mulema et al., 2008). The importance of the genotype factor on potato yield observed in our study is also explained by the focus on increasing the yield through genotype selection in past potato breeding strategies. Indeed, in the 1990s the yield in a Swiss variety trial was 40.4 t ha$^{-1}$ on average, while it was 43.6 t ha$^{-1}$ in 2000s and 44.8 t ha$^{-1}$ in the 2010s (data not shown). However, these strategies are changing and recent studies report that during the last decade the yield increase observed was mainly due to improvements in agronomic practices (39 %) and to the choice of genotypes more adapted to their environment (48 %), rather than to the genetic yield potential increase (13 %) (Rizzo et al., 2022), also observed in our study by the decrease in the decade-on-decade growth rate. Furthermore, because an increase in the genetic yield potential of a crop generally leads to a decrease in nutritional quality (Davis et al., 2004) and stability (Paget et al., 2015), it would be more relevant to focus on finding genotypes adapted to a specific climate than to search for genotypes with the highest possible yield. Besides, crop yield stability is an important factor to consider in the context of climate change, as it contributes to food security by avoiding famine in less developed countries (Thiele et al., 2010). Consequently, the effect of the environment and the G x E interaction effect on potato yield should receive greater consideration in the future since it captures almost all of the yield variation, around 85 % in our study (Fig. 1.A).

### 4.4. Effect of the environment and genotype on potato starch content

Potato starch content (in percentage of fresh weight), was primarily explained by genotype in our study as it explained 75 % of potato starch variability (Fig. 1. B). As the potato culinary type (*i.e.* potatoes for French fries, chips, or stew) is driven by starch content (Komiyama et al., 2002), our results suggest that even after a drought season, the potato quality in terms of culinary type will remain unchanged, which is of great interest for industry. It is in line with the literature as Singh et al. (2016) reported that the potato quality (*i.e.* dry matter, starch content, color and specific gravity in their study) is mainly driven by the genotype effect and not much by the environment. However, it is important to consider that drought stress may affect other quality parameters in potato, which should also be considered, such as skin quality (Jiang et al., 2022), sugar content (Eldredge et al., 1996), physiological disorders or diseases (*e.g.* scab, growth crack, hollow heart) (Musse et al., 2021), as well as dormancy duration during storage (Visse-Mansiaux et al., 2022).

The effect of climatic variables on potato starch content was less pronounced than the effect on yield. The three selected climatic variables with the greatest influence on the potato starch content through the random forest analysis were: 1) "average maximum temperature from maturity to haulm killing", 2) "sum of minimum temperatures at soil level from maturity to harvest" and 3) "total precipitation from planting to haulm killing" (Fig. 4). Those variables explain only a small part of starch content variation (4–6 %) (Fig. 1.B). Among these three climatic variables, the negative effect of "total precipitation from planting to haulm killing" on potato starch content may be explained by a higher water loss in tubers than starch biosynthesis limitation (Bach et al., 2013). In contrast, the effect of the two other variables on starch content, *i.e.* "average maximum temperature from maturity to haulm killing" and "sum of minimum temperatures at soil level from maturity to harvest" could be due to changes in starch biosynthesis after maturity. However, small changes in potato starch content (in percentage of fresh weight) may lead to changes in starch composition and quality (Haase and Plate, 1996). In addition, It has been reported that the reduction in mealiness and textural quality of processed potatoes in French fries caused by drought stress might be due to a reduction in starch content

(Searle et al., 2005).

Finally, it is possible that climatic variables had a higher impact on the starch quality than quantity in our study. Bach et al. (2013) showed that starch quality, measured by its digestibly, is more sensitive to environmental changes than total starch content. It would be of interest in future studies to evaluate the quality of starch in variety trials in addition to starch quantity to access the effect of climate change on both quality and quantity of starch in potato.

### 4.5. Evolution of potato yield under the different climate change scenarios

Short-term climatic scenarios for Switzerland (*i.e.* by 2035) predict an increase in temperature of +0.7 °C to +2.3 °C during summer. Mid-century forecasts (*i.e.* by 2050–2060) estimate a temperature increase during summer ranging from +1.4 °C to +3.0 °C according to the RCP 4.5 scenario and from +2.2 °C to +4.4 °C under the RCP 8.5 scenario. Finally, forecasts for the end of the century (*i.e.* by 2080) predict summer temperature changes ranging from +1.6 °C to +3.8 °C for RCP 4.5 and from +3.5 °C to 7.2 °C for RCP 8.5. Precipitation will also be subject to changes in the coming years. In the best-case predicted scenario, precipitation will gradually increase up to +6 % by 2085. However, in most RCP scenarios a decrease in precipitation is expected, from −0.6 % to −16 % for RCP 2.3, down to −28 % for RCP 4.5 and −42.8 % for RCP 8.5, which corresponds to 20 mm (-0.6 %) to 140 mm (-42.8 %) of water, compared to the 1990– 2021 average Swiss precipitation.

The model built in the present study, considering climatic variables and genotype effect predicts that, according to the above-mentioned climatic changes predicted by the different RCP scenarios, the average potato yield will decrease compared to the average yield observed from 1990 to 2020 (Fig. 5). A decrease in yield from 3 % to 16 % is predicted by 2035, regardless of the RCP scenario in Switzerland. By 2050–2060, yield losses are predicted from 5.4 % to 22.7 % for RCP 4.5 and from 8.2 % to 50.3 % for RCP 8.5. Finally, by the end of the century we predicted yield losses from 6 % to 37 % under RCP 4.5 scenario and from 24 % to 84 % under RCP 8.5 scenario. Our results are in line with other studies which estimate yield losses from 10 % to 25 % by 2040, 10–25 % by 2040–2069 and up to 50 % in some part of the Mediterranean rim compared to the average yields from 1961 to 1990 in Western Europe (Hijmans, 2003). In another study conducted by Raymundo et al. (2018), the authors used the SUBSTOR-Potato model to estimate worldwide potato yield changes by including the increase in atmospheric $CO_2$ concentration and pre-planting rainfall in addition to climate data during the growth period. The results of this research are more optimistic as the authors estimate yield changes of −2 % (+1.60 % to −6.80 %) for RCP 4.5, −6.0 % (from −0.80 % to −10.20 %) for RCP 8.5 by 2040– 2070, yield changes of −2 % (+2.40 % to −6.80 %) for RCP 4.5 and −26.0 % (-20.60 % to −30.60 %) for RCP 8.5 by 2071–2100, compared to the average yield during the period from 1979 to 2009. Interestingly, they estimate that in Western Europe, yield could increase from 5 % to 25 % for RCP 8.5 in 2070 compared to the average yields from 1979 to 2009. However, these optimistic results probably came from the increase in atmospheric $CO_2$ concentration considered in their study which increased the yield by 22–33 % in the “FACE (Free-Air Carbon dioxide Enrichment)” experiment (Kimball, 2016).

However, it is important to consider that the rising $CO_2$ atmospheric concentration is not necessarily beneficial and may present disadvantages for example, (i) higher atmospheric $CO_2$ leads to higher yields only in highly fertilize soil (Ainsworth and Long, 2005), (ii) an increase in $CO_2$ causes an increase in $O_3$, a gaseous toxin that cause damage to plant and decreases yield by 12 % (Feng et al., 2008) and (iii) $CO_2$ concentration also enables growth of competitors (Poorter and Navas, 2003). Consequently, our predictions could be less pessimistic by considering the atmospheric $CO_2$ concentration, and pre-planting rainfall effects in our model as in the study of Raymundo et al. (2018). However, in the future it is important to limit the increase of $CO_2$ in the atmosphere since it presents several above-mentioned disadvantages.

### 4.6. Perspectives for the future

It is necessary to implement solutions to avoid potato yield losses due to climate change predicted in our study and other studies in the short, medium, or long term. Hijmans (2003) reported that implementing different agronomic practices could limit yield losses to 10– 15 % instead of 25 % by 2040. Those agronomic practices could be: advancing the planting date to avoid some late heat-waves (Tang et al., 2018), better use of water resources using efficient irrigation as Partial Root-zone Drying (PRD) (Brocic et al., 2009), or using water conservation practices (Ochuodho et al., 2014). Research to develop agronomic genotypes more resistant to environmental stresses, particularly to heat-waves and agricultural drought is also necessary and will be important to cope with yield losses due to climate change (Sprenger et al., 2018, 2015). Finally, it would be of interest to change the geographical location of growing sites. For instance, sites with high elevation could be used as the temperatures are lower at high altitude (Ahmadi et al., 2019; Visse-Mansiaux et al., 2022). However, each of these agronomic practices has to remain practical and applicable by growers (Hopkins et al., 2007). Another solution to avoid high yield losses due to stresses caused by extremely hot and dry seasons, which will be more frequent due to climate change, could be to add a “resistance to abiotic stress” criteria in variety trials to promote genotypes resistant to drought.

To conclude, our results revealed that climate change will have a negative impact on potato crops, with a higher impact on yield than on starch content. Solutions need to be implemented to cope with a higher occurrence of extreme weather events, such as 1) consideration of the GxE interaction to select potato genotypes better adapted to their environment, 2) adapting the growing period to avoid periods of stress and 3) development of genotypes tolerant to extreme conditions.

## CRediT authorship contribution statement

**M. Gouerou:** Conceptualization, Methodology, Visualization, Investigation, Formal analysis, Writing – original draft, Validation, Writing – review & editing. **M. Visse-Mansiaux:** Conceptualization, Methodology, Visualization, Investigation, Formal analysis, Writing – original draft, Validation, Writing – review & editing. **Y. Brostaux:** Methodology, Formal analysis, Writing – review & editing. **C. Deleu:** Supervision, Validation, Writing – review & editing. **F. Val:** Supervision, Writing – review & editing. **L. Leport:** Supervision, Validation, Writing – review & editing. **B. Dupuis:** Supervision, Conceptualization, Methodology, Investigation, Project administration, Funding acquisition, Validation, Writing – review & editing.

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## Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT to check the language of the manuscript. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

## Declaration of Competing Interest

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

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## Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.fcr.2025.109951.

## Data availability

The data that has been used is confidential.

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