Evaluating the Impact of Climate Change on Pear Fruit Quality Using Ecotron Simulations of 2050 Conditions

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Abstract

Background: Climate change is directly impacting global food productivity. This highlights the urgent need to better understand how ecosystems respond to these changes and to assess the role they can play in mitigating and preventing further disruptions and their effects.

Objectives: This report aims to assess the effect of climate change interventions (CO_2 removal, sustainable energy production, and transportation improvements) on pear fruit quality, pear size and soil feature dynamics by using Ecotrons.

Methodology: Statistical analysis were conducted using linear and generalized mixed effects models as well as generalized estimating equations to determine the most effective intervention on the pear quality.

Results: The findings suggest that climate interventions, with the main focus on actively removing CO_2 and sustainable energy, have a significant impact on the pear quality score and lead to a decrease in pear size.

Conclusions: An improvement in pear quality scores was observed in the Conference species, where CO_2 removal and sustainability measures outperformed climate conditions without intervention, particularly in association with specific soil trends.

Key Words: Controlled Environment Facilities; Experimental design; Climate interventions; Linear Mixed Model; Generalized Mixed Effects Model;

1 Introduction

In recent decades, climate change has exerted a measurable global impact. According to the Intergovernmental Panel on Climate Change (IPCC) 2023 report, the global surface temperature during the period 2011–2020 was 1.09°C higher than in the pre-industrial era (1850–1900). Furthermore, approximately 42% of the cumulative increase in carbon dioxide (CO_2) emissions occurred between 1990 and 2019, underscoring the acceleration of anthropogenic contributions to climate change during recent decades.

Variations in atmospheric CO_2 concentrations, rising average temperatures, and other climate-related factors have directly influenced agricultural productivity and food supply chains by changing crop productivity and quality of food produced. For example, studies such as Cho et al. (2021) have demonstrated that higher temperatures can have an effect on the nutritional quality of pear fruit.

However, agriculture itself has a significant environmental impact. According to Poore and Nemecek (2018), the sector accounts for approximately 26% of global greenhouse gas emissions. Moreover, it contributes to rising global temperatures and ocean pollution. In light of these challenges, it is essential not only to consider how to ensure food security in the context of climate change, but also to explore strategies for making the agricultural sector more sustainable.

Certain drivers are already contributing significantly to global climate change. A primary example is the combustion of petroleum-derived fuels, which remains as one of the main energy sources to the transportation sector. This process is increasing the emission of greenhouse gases (Chu & Majumdar, 2012; Lee et al., 2023), directly linked to rising global temperatures. One notable consequence is olive oil production in Spain. It is estimated that the change in precipitation patterns will affect the soil and cause serious ecological changes threatening the production of olive oil, therefore impacting livelihood and national economy.

These issues led to the development of ecosystem sciences with a focus on understanding fundamental processes of ecosystem functioning (Roy et al., 2021). One of the tools used by researchers in this field is Controlled Environment Facilities (CEFs). Roy et al. define an ecotron as an experimental facility that can replicate ecosystem functioning – such as temperature and CO2 levels – enabling simulations of climate outcomes. Understanding these systems allows the design of targeted interventions to improve food quality and security. Belgium's ecotron center consists of 12 closed units located in the municipality of Maasmechelen. The main objectives are to not only understand how ecosystems function, but also their interactions with other environmental drivers.

This report examines the impact of climate change on pear production in Belgium, with an emphasis on assessing variations in pear quality under different climate scenarios and specific soil conditions. In particular, we are interested in evaluating whether certain simulated climate interventions will improve the fruit quality of two pear species when compared to the projected climate conditions of 2050 without further interventions. Additionally, we will analyze the impact of these simulated conditions on the fruit growth and, as a final step, apply multivariate methods to explore patterns in soil features.

2 Methods and Materials

2.1 Materials

The study was conducted using advanced Ecotron infrastructure designed to simulate future climate scenarios under controlled conditions. Each Ecotron unit is an enclosed ecosystem that allows precise control of three climate scenarios: CO_2 removal (Climate scenario 2), sustainable energy production (Climate scenario 3), and transportation improvements (Climate scenario 4) alongside a control scenario (Climate scenario 1). Ecotrons were located at two research facilities: UHasselt in Belgium and CNRS in France. Each Ecotron was planted with 6 pear trees. Two pear species were used, Conference which is harvested in October–early November and Doyenné du Comice harvested in late September–mid-October. The trees were planted in September of year X and exposed to controlled climate treatments from year X to X+2, at which point pears were harvested for quality assessment. Each harvested pear was evaluated individually.

2.2 Experimental Design

The experiment was conducted using 20 Ecotrons (12 in Belgium and 8 in France), each containing 6 pear trees, 3 of each species, all of which are features that make it a nested study design (Figure 1). Trees were assigned to four climate scenarios using stratified randomization based on species (Conference and Doyenné du Comice) and research location (Belgium or France), ensuring balanced allocation across treatments. The experiment followed a double-blind protocol, whereby both field caretakers and quality assessors were unaware of the climate scenario assignments. This design minimized bias and allowed for objective assessment of the effects of climate conditions on pear production, and reliable estimation of climate effects while controlling for potential confounders.

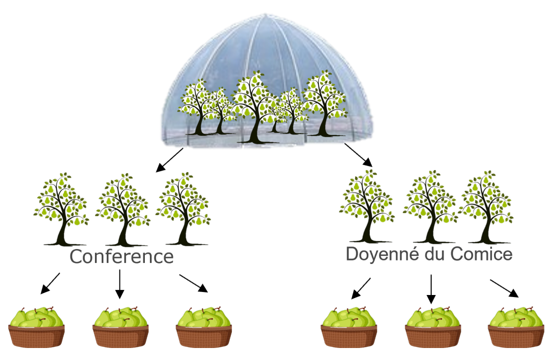

Figure 1: Nested Study Design

2.3 Sample Size Calculation

As a preliminary step, pilot data were collected from 10 trees per species under climate scenario 1. To ensure adequate statistical power for detecting differences in pear quality across climate scenarios, a sample size calculation was performed using estimates of variability obtained from pilot data. The quality index, measured on a scale from 0 to 100, was used as the primary outcome for this calculation.

Assuming a significance level of 0.05 and aiming for 80 percent power, power analysis indicated that 20 Ecotrons (8 in France and 12 in Belgium) in total across all four scenarios would be required to detect a minimum effect size of 24. With 6 trees per Ecotron, this resulted in a total of 120 trees. The sample size was justified to ensure sufficient representation of both pear species and geographic sites.

2.4 Data Collection

The quality of the pear fruit was measured at the end of the harvest season. In addition, pears were monitored weekly and their sizes were recorded throughout the growing season (repeated measures). Covariates such as species, Ecotron ID, climate scenario, and individual tree ID were also recorded to facilitate stratified analysis and are summarized in Table 1. Furthermore, 17 features of soil condition were collected at the Ecotron level to capture soil fertility, structure, and biological activity, which are known to influence fruit development and yield.

Table 1: Variable Descriptions

Variable	**Description**
Climate Scenario 1	Projected 2050 climate without interventions (worst-case scenario)
Climate Scenario 2	Climate variables set to implement active CO_2 removal
Climate Scenario 3	Climate variables set to support more sustainable energy production
Climate Scenario 4	Climate variables set to prioritize transportation improvements
Species	Doyenné du Comice or Conference
Location	Belgium or France
Quality Index	Quality of each pear measured on a scale from 0 to 100
Size	Pear size measured in cm
Time	week 0, 1, ..., 24

2.5 Ethics

The experiment was conducted at Hasselt University (Belgium) and CNRS (France) under institutional guidelines for responsible research practices. As the study involved only plant-based experimental units (pear trees) and environmental monitoring under controlled Ecotron conditions, no ethical approval was required. All procedures adhered to standard institutional protocols for environmental and agricultural research.

2.6 Statistical Analysis

In this section, we first describe three datasets collected during the study and steps taken to preprocess them. We then detail the statistical approaches used to evaluate which simulated climate conditions outperformed climate scenario 1 in terms of pear quality, to assess how those conditions influence pear size over time, and to explore patterns in soil-condition variables across the different climate scenarios. All statistical analyses were performed with the Rstudio software (The R Foundation) version 4.5.0.

2.6.1 Datasets

We used three distinct datasets for statistical analysis. The first dataset was *df final*, which contained the pear quality index measured at the end of the harvest season for each individual pear. It included covariates such as species, climate scenario, tree ID, and Ecotron ID. The second dataset, *df size* captured weekly measurements of pear size throughout the growing season. It is structured as a repeated measures dataset, enabling analysis of size development over time. It also includes species, climate scenario, and tree ID as predictors. The third dataset was *df soil*, which included 17 soil characteristics measured at the Ecotron level. These variables represented physical, chemical, and biological properties of the soil, which are expected to influence pear development and yield.

2.6.2 Processing of raw data

All three datasets were checked for completeness before analysis. No missing values were found across all the included variables in each dataset. As a result, no imputation or data exclusion procedures were required.

2.6.3 Exploratory analysis on pear quality index and pear size

This was performed to gain an initial understanding of the structure and distribution of the data, as well as to inform the choice of variables and model structure. Boxplots were used to examine the potential effect of climate scenarios on the pear quality index. These were also stratified by region and species to explore potential variation across locations and tree species. An interaction plot was used to explore whether the effect of climate scenario on pear quality differed by species. To understand the distribution of fruit samples per tree, a histogram of the number of pears per tree was generated. This helped identify any imbalance in sampling across trees. In addition, the continuous quality index was converted into a binary outcome based on a threshold of 60 to classify pears as either high or low quality. The effect of climate on this binary outcome was visualized using bar charts for the proportion of pears between the species and across the different locations. These visualizations allowed for a preliminary view of group differences. We also conducted an exploratory analysis on the weekly pear size data to understand growth patterns over time. Line plots were created to visualize how pear size evolved across weeks, stratified by species and climate scenarios. This helped in identifying trends and potential interactions between time and other covariates. The interaction between week and species was also explored visually to check if the growth rate differed across species. These exploratory steps provided preliminary evidence for including time, species, and their interaction as fixed effects, and pear ID as the clustering variable in our model.

2.6.4 Exploratory analysis on the soil characteristics

The soil dataset includes information about the bulk density, infiltration, soil porosity, soil depth, water holding capacity, and other key factors. These soil properties were analyzed by linear discriminant analysis (LDA), which maximizes the ratio of the variability between-group and within-group, given LDA performs classification in a dimension-reduced space by maximizing the separability of categories. The goal was to identify how 4 climate scenarios differ from one another in terms of soil characteristics. The categorical response variable was climate scenario, and the predictors consisted of 17 soil characteristics.

2.6.5 Primary Analysis

The primary analysis aimed to assess the effect of different climate change scenarios on pear quality, while accounting for the hierarchical structure of the data. Each ecotron housed six trees, and each tree produced several pears, leading to repeated measures within trees. To account for this nested design, the model incorporated nested random effects, capturing variability at the tree levels. Initially, random effects for ecotron were considered. However, it showed singular fits with a near-zero variance estimate and was therefore excluded from the final model. We fitted a Linear Mixed Model (LMM) using the pear quality index as the continuous outcome. The model included climate scenario, pear species, and location as fixed effects. A random intercept for tree ID was added to account for clustering and to capture the intra-tree correlation of repeated measurements. The fixed effects of the parameters yielded average effects and appropriately accounted for the dependency among observations originating from the same tree. The final model was specified as:

$$Y_{ijk} = \beta_0 + \beta_1 \text{Climate2}_i + \beta_2 \text{Climate3}_i + \beta_3 \text{Climate4}_i + \beta_4 \text{Species}_j + \beta_5 \text{Location}_i + b_{j(i)} + \varepsilon_{ijk}$$

where:

- Y_{ijk} is the quality index of the k-th pear observation from tree j, of Ecotron i.
- β_0 is the baseline effect of individual observations under climate scenario 1, of pears from the species Doyenné du Comice in the location of Belgium.
- β_1, β_2, and β_3 represent the fixed effects of climate scenarios 2, 3, and 4 of Ecotron i, respectively. The dummy variables of climate scenario take the values of 1 if they match the associated scenario, and 0 otherwise
- β_4 represents the fixed effect of the species, if the j-th tree is of the species Conference (0 if Doyenné du Comice)
- β_5 represents the fixed effect of the location, if the i-th Ecotron is located in France (0 if in Belgium)

- $b_j(i) \sim \mathcal{N}(0, \sigma_b^2)$ is the random effect of tree j (nested within Ecotron i)
- $\varepsilon_{ijk} \sim \mathcal{N}(0, \sigma^2)$ is the residual error, representing variation not explained by the fixed or random effects.

2.6.6 Secondary Analysis

We conducted secondary analysis to explore two additional outcomes related to pear quality and pear growth:

(a) Binary Pear Quality Classification

To complement the primary analysis of the continuous quality score, a binary classification of the pear quality index was performed. We dichotomized the pear quality index into a binary outcome (1 = high quality, 0 = low quality) based on a defined threshold of a quality score of 60. A GEE with a logit link function was then applied to assess the effect of different climate scenarios and other predictors on the probability of high-quality pears. Climate scenario, species and location were considered as fixed effects. The within-tree correlation was accounted for with an exchangeable correlation structure and by using the tree as the clustering element. This model estimates the average population effects of the predictors on the binary outcome. We specified the GEE model as follows:

$$\text{logit}\left(\Pr(Y_{ijk} = 1)\right) = \beta_0 + \beta_1 \text{Climate2}_i + \beta_2 \text{Climate3}_i + \beta_3 \text{Climate4}_i + \beta_4 \text{Species}_j + \beta_5 \text{Location}_i + \varepsilon_{ijk}$$

Where:

- Y_{ijk} is the binary quality value of the k-th pear observation from tree j, of ecotron i.
- β_0 is the intercept, representing the baseline log-odds of pear quality for the reference levels of climate scenario 1, of species Doyenné Du Comice in the location of Belgium.
- β_1, β_2, and β_3 represent the average log-odds ratios of pear quality associated with climate scenario 2, 3, and 4, in Ecotron i, respectively, when compared to the baseline. The dummy variables of the climate scenario take the value of 1 if they match the associated scenario, and 0 otherwise.
- β_4 represents the average log-odds ratio of the species when compared to the baseline, if the j-th tree is of the species Conference (0 if Doyenné du Comice).
- β_5 represents the average log-odds ratio of the location when compared to the baseline, if the i-th Ecotron is located in France (0 if in Belgium).
- $\varepsilon_{ijk} \sim \mathcal{N}(0, \sigma^2)$ is the residual error for observation (i, j, k).

(b) Pear Size Over Time

To investigate how pear size developed over time under different climate scenarios, we analyzed weekly measurements using a Generalized Estimating Equation (GEE) model. As diagnostic plots indicated heteroscedasticity, the model included $\sqrt{\text{size}}$ as a response. We also tested the pear size model and found that the variable *week* is highly collinear with $week^2$, which is expected given the polynomial relationship. To address this, we centered the *week* variable by subtracting its mean, which reduced the Variance Inflation Factors (VIFs) to 5 and 7, respectively. These values fall below the commonly accepted threshold of 10, indicating that multicollinearity is at an acceptable level. The primary aim was to assess the effect of climate scenario and species on pear growth patterns throughout the season. Because size measurements were collected repeatedly for the same pear weekly, we accounted for this within-subject correlation by specifying an exchangeable working-correlation structure. The model included the effects of *week*, $week^2$, climate scenario, species, and the interaction effect between week and species. This approach models both the overall trend in pear size and individual variation over time. Due to the short-term nature of the experiment and the regular, equally spaced observations, this was treated as a repeated-measures design, rather than a longitudinal one. The model was specified as:

$$\sqrt{Y_{ijkl}} = \beta_0 + \beta_1 \text{Climate2}_i + \beta_2 \text{Climate3}_i + \beta_3 \text{Climate4}_i + \beta_4 \text{Species}_j + \beta_5 \text{Week}_{kl} + \beta_6 \text{Week}_{kl}^2 + \beta_7 (\text{Week}_{kl} \times \text{Species}_j) + \varepsilon_{ijkl}$$

Where:

- $\sqrt{Y_{ijkl}}$ is the square root of the pear size for pear observation k at week l on tree j in Ecotron i.
- β_0 is the intercept term (baseline square-root size for the reference levels of climate scenario 1, Doyenné du Comice and week 12).
- $\beta_1, \beta_2, \beta_3$ represent the average effects of climate scenarios 2, 3, and 4 in Ecotron i, respectively. The dummy variables of the climate scenario take the values of 1 if they match the associated scenario, and 0 otherwise
- β_4 represents the average effect of the species, if the j-th tree is of the species Conference (0 if Doyenné du Comice)
- β_5 is the average effect of the linear term week l for pear observation k
- β_6 is the average effect of the quadratic term week l for pear observation k.

- β_7 is the interaction between week l of observation k and species of tree j.
- $\varepsilon_{ijkl} \sim \mathcal{N}(0, \sigma^2)$ — residual error for observation (i, j, k, l).

2.6.7 Statistical Inference

The study evaluated the effect of climate intervention scenarios on pear fruit quality using two types of outcomes: a continuous quality score and a binary quality classification.

For the continuous pear quality scores, the hypotheses were:

Null Hypothesis (H_0): Climate intervention scenarios do not improve the average pear quality score compared to the worst-case scenario (Scenario 1). The mean quality scores under Scenarios 2, 3, and 4 are less than or equal to Scenario 1 ($\mu_2 \leq \mu_1$, $\mu_3 \leq \mu_1$, $\mu_4 \leq \mu_1$).

Alternative Hypothesis (H_1): At least one intervention scenario results in a higher mean quality score than Scenario 1 ($\exists i \in \{2, 3, 4\}$ such that $\mu_i > \mu_1$).

A linear mixed-effects model (LMM) was used to test these hypotheses, accounting for random effects due to tree variability and fixed effects including climate scenario, species, and location. Two-sided p-values were provided in the general table of model estimates as calculated by R. Bonferroni-adjusted pairwise comparisons of estimated marginal means were conducted to explore specific differences between climate scenarios, and one-sided p-values were reported.

For the binary quality outcome (high or low quality classification), Generalized Estimating Equation (GEE) with a logit link function was applied. The corresponding one-sided hypotheses were:

Null Hypothesis (H_0). Climate intervention scenarios do not affect the odds of achieving high pear quality compared with Scenario 1, i.e. $\mathrm{OR}_2 \leq 1,\ \mathrm{OR}_3 \leq 1,\ \mathrm{OR}_4 \leq 1$.

Alternative Hypothesis (H_1). At least one intervention scenario increases the odds of high pear quality relative to Scenario 1, that is, $\exists\, i \in \{2, 3, 4\}$ such that $\mathrm{OR}_i > 1$.

In a similar fashion as previously, two-sided p-values were reported in the general table of model estimates as calculated by R. Bonferroni-adjusted pairwise comparisons of estimated marginal means were conducted to explore specific differences between climate scenarios, and one-sided p-values were reported.

To assess whether climate scenario, species, and their interaction with time influence pear size development, Generalized Estimating Equation (GEE) model was used for the repeated weekly measurements. The corresponding two-sided hypotheses were:

Null Hypothesis (H_0): There is no significant effect of climate scenarios on pear size over time.

$$\beta_1 = \beta_2 = \beta_3 = 0$$

Two-sided p-values were reported as they were directly provided by R. Bonferroni-adjusted pairwise comparisons of estimated marginal means were conducted to explore specific differences between climate scenarios, and two-sided p-values were reported.
Alternative Hypothesis (H_1): There is a significant effect of at least one of the climate scenarios 2, 3, and 4 on the growth of pear size over time:
At least one of the parameters doesn't equal to 0:

$$\beta_1 \neq 0 \text{ or } \beta_2 \neq 0 \text{ or } \beta_3 \neq 0$$

Statistical significance for all tests was determined at an alpha level of 0.05. Results from these models provided inferential evidence on the effectiveness of climate interventions on pear fruit quality under projected future conditions.

2.6.8 Model Assumptions

Before interpreting model results, we evaluated key assumptions for each model. For linear mixed-effects models (LMMs), we assessed normality of residuals using Q-Q plots and homoscedasticity through residuals vs. fitted plots. For the GEE model with a binomial distribution, we examined goodness-of-fit with Pearson's X^2/df. For the GEE model of the continuous size outcome, we assessed normality of residuals using Q-Q plots and homoscedasticity through residuals vs. fitted plots. Multicollinearity among predictors was checked using the Variance Inflation Factor (VIF), with values below 10 considered acceptable. Whenever diagnostic checks indicated collinear predictors, collinearity was reduced by centering the affected covariates on their respective means.

2.6.9 Exploratory Analysis on Soil Conditions

LDA was conducted to assess how well soil composition could distinguish between the different climate scenarios. The analysis provided linear discriminant functions, group means, and classification accuracy. An additional analysis was done to verify which variables had a more positive and negative influence on pushing the data to each discriminant function. The resulting LDA plots illustrate separation between scenarios based on soil composition.

3 Results

3.1 Assessment of the pear quality score as a continuous outcome

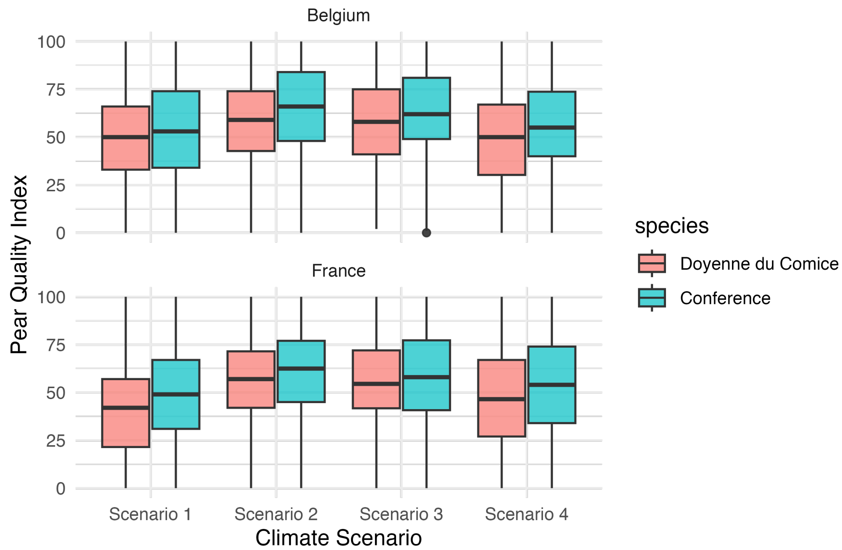

Figure 2: Quality Index among different climate scenarios and across Belgium and France

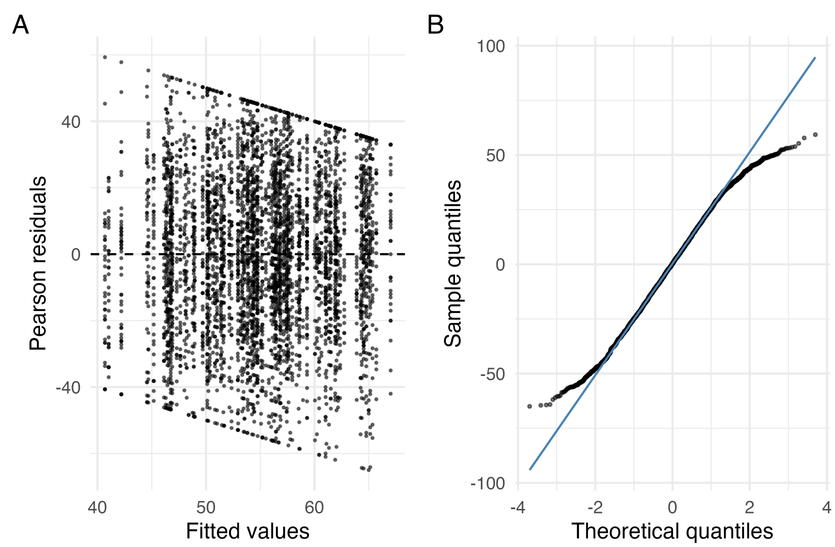

Figure 3: (A) Residuals vs Fitted values; (B) QQ Plot of Residuals;

Figure 2 exhibited that across all scenarios and locations, Conference pears showed higher quality scores compared to Doyenné du Comice. Notably, in Belgium, Scenario 2 and Scenario 3 appeared to yield the highest quality indices, particularly for Conference. In France, quality scores were generally lower, with greater variability, especially under Scenario 1.

The residuals versus fitted values plot from the linear mixed-effects model (Figure 3A) displayed a fairly random scatter, suggesting a reasonable model fit. However, slight patterns in the spread of residuals may indicate slight heteroscedasticity. The residuals are centered around zero, supporting the adequacy of the model. In contrast, the Q-Q plot (Figure 3B) revealed deviations at both tails, indicating that the residuals deviate slightly from normality. While the central portion of the distribution aligned well with expectations, the heavy tails suggest the presence of outliers or slight skewness. Despite this, linear mixed models are generally robust to such deviations, particularly with large sample sizes.

The linear mixed model, revealed that the average pear quality index for climate scenario 1 and for the species Doyenné Du Comice was estimated at 47.45 (95% CI: 42.26 to 49.45, $p < 0.001$) (Table 2). Climate scenario 2 was associated with a statistically significant average increase of 11.47 units in the quality index (95% CI: 8.97 to 13.97, $p < 0.001$), compared to climate scenario 1. Scenario 3 also showed a significant improvement, with an average increase of 9.71 units (95% CI: 7.23 to 12.19, $p < 0.001$). Scenario 4 led to a smaller but still significant increase of 2.81 units on average (95% CI: 0.38 to 5.23, $p = 0.025$). In terms of species, Doyenné du Comice pears had a significantly lower quality index compared to the Conference species, with the latter demonstrating an average increase of 5.90 units (95% CI: 2.49 to 9.69, $p < 0.001$). Regarding location, pears grown in France had, on average, a lower quality index by 3.34 units compared to Belgium (95% CI: -5.11 to -1.58, $p < 0.001$). The estimated residual variance (σ^2) was 573.53, and the variance attributable to differences between trees (τ_{00}) was 7.72, resulting in an intra-class correlation (ICC) of 0.01. The model included 120 trees and 4,613 total observations. The marginal R^2 (variance explained by fixed effects alone) was 0.052, and the conditional R^2 (variance explained by both fixed and random effects) was 0.065.

To explore the differences in pear quality across climate scenarios, pairwise comparisons (Table 3) were conducted using Bonferroni-adjusted one-sided p-values to control for multiple testing. Pear quality in scenario 2 was significantly higher than in scenario 1, with an average increase of 11.47 units ($p < .0001$). Scenario 3 also showed significantly higher pear quality than Scenario 1, with an average increase of 9.71 units ($p < .0001$). Although scenario 4 yielded pears of a higher quality than those of scenario 1 by 2.81 units, this difference was not statistically significant after Bonferroni correction ($p = 0.14$).

Table 2: Linear mixed model estimates for the pear quality index outcome.

Predictors	**Estimates**	**95% CI**	**p-value(two-sided)**
(Intercept)	47.45	[42.26, 49.45]	<**0.001*****
Climate [Scenario 2]	11.47	[8.97, 13.97]	<**0.001*****
Climate [Scenario 3]	9.71	[7.23, 12.19]	<**0.001*****
Climate [Scenario 4]	2.81	[0.38, 5.23]	**0.02548***
Species [Conference]	5.9	[2.49, 9.69]	<**0.001*****
Location [FR]	-3.34	[-5.11, -1.58]	<**0.001*****
Random Effects			
Residual variance (σ^2)	573.53		
Tree ID variance (τ_{00})	7.72		
ICC	0.01		
Observations	4613		
Marginal R^2 / Conditional R^2	0.052 / 0.065		

Table 3: Bonferroni-adjusted pairwise comparisons of estimated marginal means between climate scenarios

Contrast	**Estimate**	**SE**	**df**	**z-ratio**	**p-value(one-sided)**
Scenario 1 – Scenario 2	-11.47	1.28	Inf	-8.990	<**0.001*****
Scenario 1 – Scenario 3	-9.71	1.26	Inf	-7.680	<**0.001*****
Scenario 1 – Scenario 4	-2.81	1.24	Inf	-2.270	0.1400

3.2 Assessment of the pear quality score as a binary outcome

As shown in the barchart of Figure 4, in Belgium, climate scenarios 2 and 3 led to a higher proportion of high-quality Conference pears, in contrast to Doyenné du Comice, which yielded consistently lower quality fruits across all simulated scenarios. In France, low-quality pears remained predominant in every scenario, with the Conference species demonstrating a slight increase in high-quality output under scenario 2. Doyenné du Comice continued to underperform across all simulated scenarios.

Table 4 summarizes the log-odds ratios and significance of the logit GEE model. In terms of percent change, pears of climate scenario 2 had on average 114% higher odds (OR: $e^{0.7411} = 2.14$, 95% CI: 1.74 to 2.63, $p < 0.001$) of being of better quality than the ones from climate scenario 1. Similarly, pears of climate scenario 3 had on average 72% higher odds (OR: $e^{0.5471} = 1.72$, 95% CI: 1.37 to 2.17, $p < 0.001$) of being better quality than pears of climate scenario 1. In contrast, the fruit quality of pears of climate scenario 4 showed no significant increase in odds when compared to the baseline (OR: $e^{0.1569} = 1.17$, 95% CI:

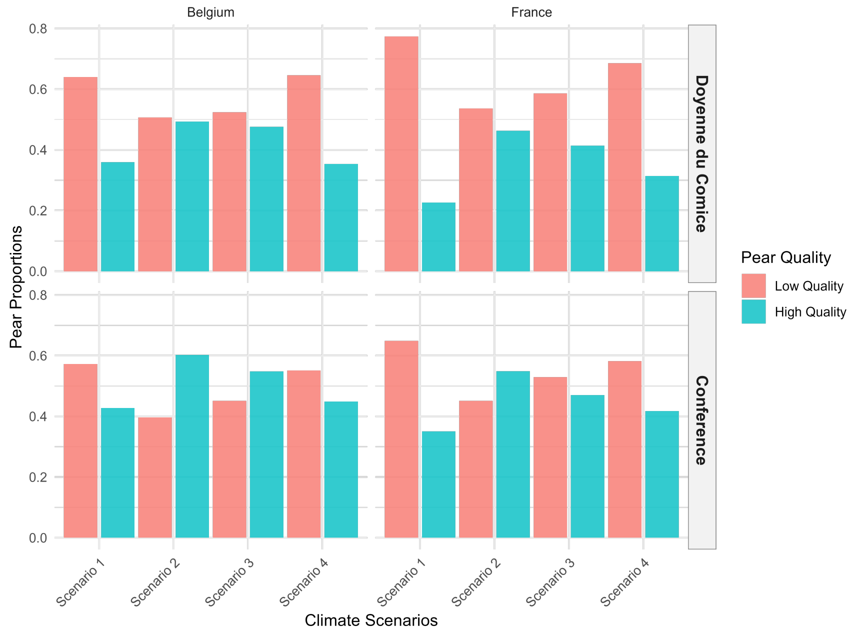

Figure 4: Comparison of low-quality (orange) and high-quality (green) pear proportions in Belgium and France under each simulated climate scenario

0.96 to 1.42, $p = 0.11$). Additionally, pears from the Conference species had 42% higher odds (OR: $e^{0.3569} = 1.42$, 95% CI: 1.23 to 1.66, $p < 0.001$) of being high-quality than those from Doyenné du Comice, while the pears from France had 23% lower odds of being high quality than those of Belgium (OR: $e^{-0.2639} = 0.768$, 95 % CI 0.6613 to 0.89, $p < 0.001$). Pearson's-based dispersion was applied, and the dispersion statistic (0.92) indicated no evidence of overdispersion in the model. Pairwise Bonferroni-adjusted comparisons of the estimated marginal means (Table 5) suggested that the odds for obtaining a high-quality pear under climate scenario 1 conditions decreased by almost 53% (OR: $e^{-0.761} = 0.467$) in pears when compared to climate scenario 2 ($p < 0.001$) and by 42% (OR: $e^{-0.547} = 0.58$) when compared to climate scenario 3 ($p < 0.001$). In contrast, the observed 15% (OR: $e^{-0.157} = 0.85$) decrease of the quality of pears of climate scenario 1 when compared to climate scenario 4 was not statistically significant (p =0.6630).

Table 4: GEE log-odds coefficients

Predictor	Estimate (Log OR)	Std. Error	95% CI	p-value (two-sided)
Intercept	-0.6947	0.0927	[-0.8763, 0.513]	<**0.001*****
Climate Scenario 2	0.7611	0.1053	[0.5547, 0.967]	<**0.001*****
Climate Scenario 3	0.5471	0.1182	[0.3155, 0.779]	<**0.001*****
Climate Scenario 4	0.1569	0.0983	[-0.0357, 0.350]	0.11037
Species (Conference)	0.3569	0.0751	[0.2096, 0.504]	<**0.001*****
Location (France)	-0.2639	0.0763	[-0.4135, -0.114]	<**0.001*****

Table 5: Bonferroni adjusted pairwise mean comparisons for log-odds ratios of the GEE model

contrast	estimate	SE	z.ratio	*p* values (one-sided)
Scenario 1 - Scenario 2	-0.761	0.1050	-7.230	<**0.001**
Scenario 1 - Scenario 3	-0.547	0.1180	-4.630	<**0.001**
Scenario 1 - Scenario 4	-0.157	0.00983	-1.600	0.6630

3.3 Assessment of the pear size

Figure 5 shows the growth of pears of both species through each collection time point. Pear growth measurements appear lowered in Ecotrons simulating conditions of climate scenario 2, in comparison to climate scenario 1 and across the weeks. The repeated measurements of 200 pears were analyzed using a GEE model, and the resulting estimates are presented in Table 6. To stabilize variance, the response was square-root transformed, and both linear and quadratic week terms were included. High collinearity between the linear and quadratic week terms was corrected by mean-centering the variable week. The intercept was estimated at 2.219 $\sqrt{\text{cm}}$. (95% CI: 2.190 to 2.248, p < 0.001), reflecting the average pear size of Doyenné du Comice under climate scenario 1 at mid-season. Climate scenarios 2 and 3 led to a significant reduction of size by 0.09 $\sqrt{\text{cm}}$ (95% CI: -0.121 to -0.050, p < 0.001) and 0.103 $\sqrt{\text{cm}}$ (95% CI: -0.136 to -0.069, p < 0.001) respectively, whereas climate scenario 4 showed no significant effect (-0.011 $\sqrt{\text{cm}}$, 95% CI: -0.04 to 0.02, p = 0.491). Additionally, pears from the species Conference were on average 0.365 $\sqrt{\text{cm}}$ larger than Doyenné du Comice (95% CI: 0.340 to 0.389, p < 0.001), and grew faster week-by-week, as indicated by the interaction term *Week* and *Conference*. Finally, the positive linear (95% CI: 0.114 to 0.119, < 0.001) and negative quadratic term (95% CI: -0.004 to -0.003, p < 0.001) for the week demonstrate a quick pear growth that slows over time. Pairwise mean comparisons with units backtransformed to the original scale (Table 7), indicated that the mean size of pears in climate scenario 1 was significantly larger than pears in climate scenarios 2 and 3 by 0.403 cm ($p < 0.001$) and 0.482 cm ($p < 0.001$), respectively. Model diagnostics showed that the Pearson residuals were symmetrically and uniformly scattered around zero (Fig. 6A) with no discernible pattern, and the QQ−plot (Fig. 6B) exhibited an approximately straight line, indicating that the normality and homoscedasticity assumptions were met.

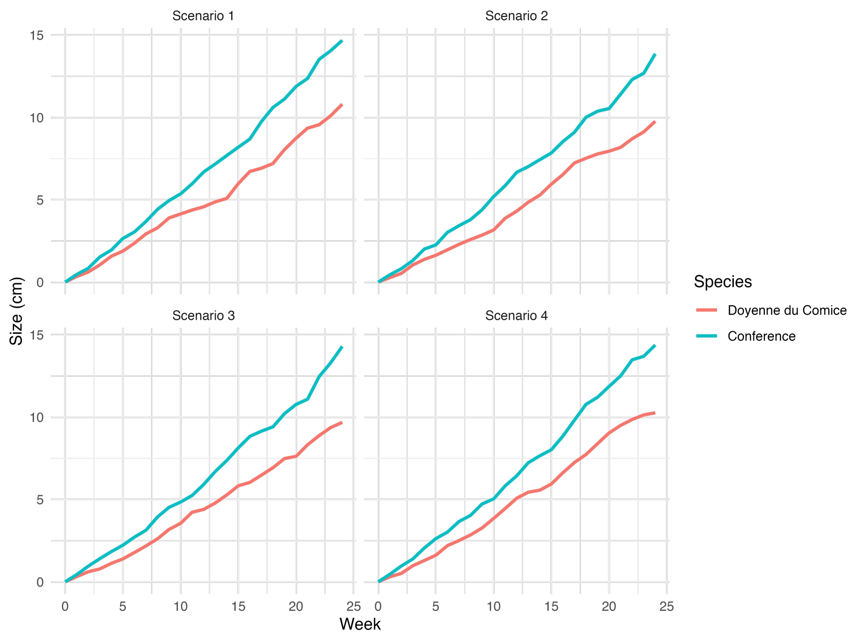

Figure 5: Changes on pear size over 24 weeks

Table 6: GEE Model Estimates for $\sqrt{\text{size}}$

Term	**Estimate**	**95% CI**	***p*-value (two-sided)**
(Intercept)	2.219	[2.190, 2.248]	< **0.001*****
climate Scenario 2	–0.085	[–0.121, –0.050]	< **0.001*****
climate Scenario 3	–0.103	[–0.136, –0.069]	< **0.001*****
climate Scenario 4	–0.011	[–0.042, 0.020]	0.491
species (Conference)	0.365	[0.340, 0.389]	< **0.001*****
week	0.116	[0.114, 0.119]	< **0.001*****
(week^2)	–0.003	[–0.004, –0.003]	< **0.001*****
species Conference × week	0.018	[0.015, 0.021]	< **0.001*****

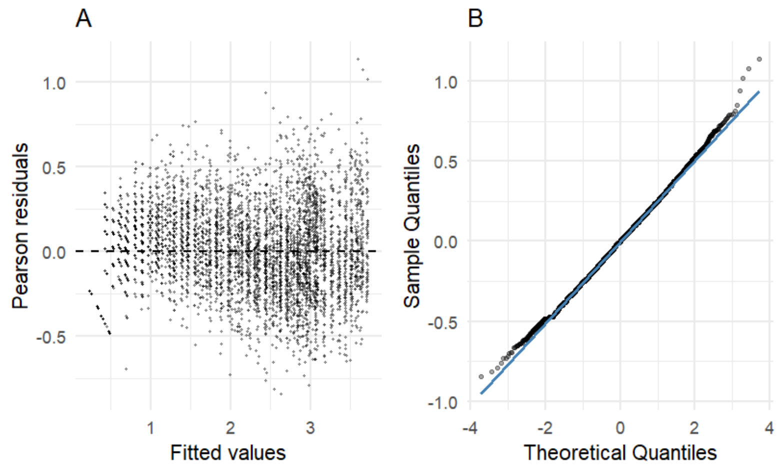

Figure 6: Diagnostic plots of GEE model. (A) Residuals vs Fitted values; (B) QQ Plot of Residuals;

Table 7: Pairwise contrasts of estimated marginal means for pear size model (GEE) back-transformed to cm

Contrast	*Estimate (cm)*	*SE*	*z.ratio*	*p.value (two-sided)*
Scenario 1 – Scenario 2	0.4030	0.0855	4.712	<**0.001***
Scenario 1 – Scenario 3	0.4818	0.0798	6.035	<**0.001***
Scenario 1 – Scenario 4	0.0522	0.0758	0.689	1.0000

3.4 Exploratory Analysis on Soil Conditions

Following the linear discriminant analysis, 3 discriminant functions were produced (LD1, LD2 and LD3) based on the soil data. Their proportion of trace, accountability between-groups variance, were 93.85%, 6.14% and 0.1% respectively. This result captured which function separates better the climate scenario groups. Based on this first result, LD1 and LD2 visualize the separation.

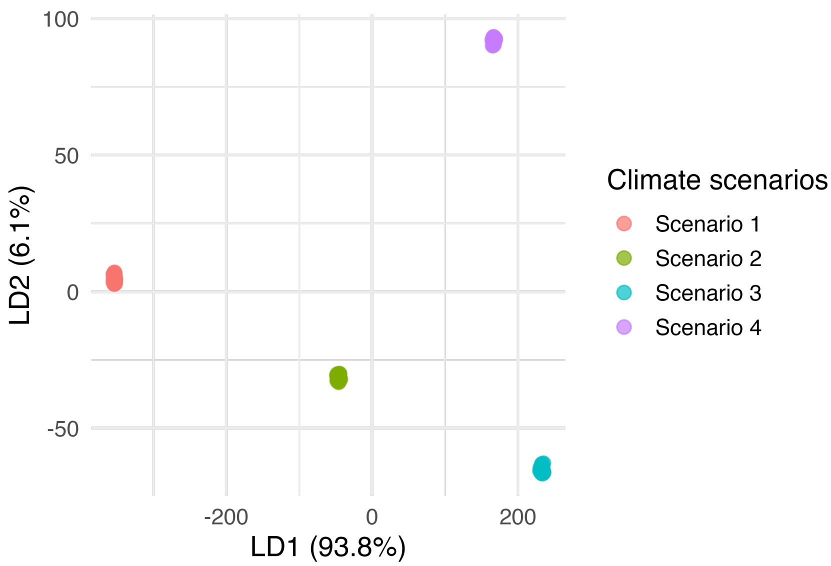

Figure 7: Scores plotted on the first two linear discriminant functions grouped by climate scenario

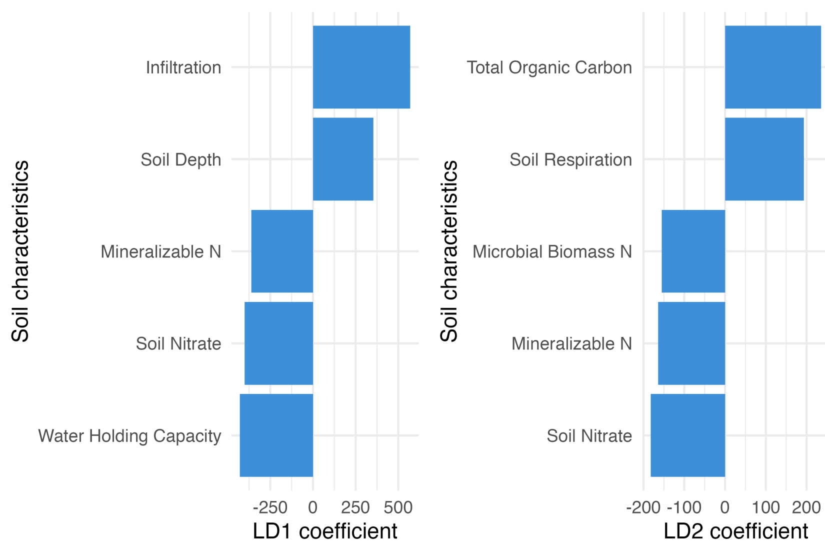

Figure 8: Five most influential soil characteristics for LD1 and L2

As presented in Figure 7, the climate scenarios are well separated, indicating that soil characteristics are effective predictors. In addition, there is no overlap between climate groups, suggesting a robust and accurate classification. Each climate group is clustered in a compact shape, implying the samples from each group are consistent. Notably, climate scenario 1 lies near zero on LD1, and scenario 2 on LD2, meaning these functions have a limited contribution to distinguishing these climates from the others. Conducting a more in-depth analysis on the LDA result, it's possible to observe which soil characteristics contributed more strongly to each function, based on the coefficients of linear discriminants. As shown in Figure 8, the top five contributors were selected based on the linear discriminant coefficients. These contributors influence group separation in opposite directions (negative and positive) to each discriminant function. For LD1, infiltration and soil depth are the factors with higher positive discriminant score, while total organic carbon and soil respiration are for LD2. Meanwhile, mineralizable nitrogen and soil nitrate are contributing in a negative direction to both functions.

4 Discussion

Both the LMM for continuous quality scores and the GEE for binary quality outcomes indicated that climate Scenario 2 (active CO_2 removal) and Scenario 3 (sustainable energy production) interventions significantly increase the proportion of high-quality fruit compared to the no-intervention baseline. Scenario 2 consistently shows the highest improvement across both models. These findings align with studies focusing on other fruit species (Sun et al., 2012), which discovered that elevated levels of CO_2 can lead to an increase in size, and sugars become diluted. Conversely, removing CO_2 can reduce fruit size and concentrate carbohydrates, improving the quality score. Scenario 4 (transportation-focused) produces a small but statistically insignificant increase in the continuous quality score and also does not significantly affect the odds of achieving high-quality status in the binary model. Furthermore, Conference pears outperform Doyenné du Comice in both models, with Conference pears producing a higher proportion of high-quality fruit than Doyenné. This is likely due to fruit-specific biochemical traits, such as more efficient carbon assimilation or other metabolic pathways, that offer greater resilience under reduced CO_2 conditions. In particular, Dizon et al. (2024) demonstrated that Doyenné du Comice pears retain significantly fewer aroma compounds when cultured under reduced CO_2 conditions, an effect that might explain the overall lower quality indices we observed for this species. Pears grown in Belgium also demonstrate higher quality than those grown in France, likely reflecting local environmental or agricultural management differences.

The statistical analysis of pear size over time shows that some climate interventions can be associated with smaller pears relative to the reference scenario. As CO_2 is the essential substrate for photosynthesis, its removal might directly limit the tree's capacity to produce the molecules that drive fruit growth through photosynthesis. Similarly, sustainable-energy measures that lower ambient CO_2 levels might lead to an indirect reduction in available carbon, explaining the observed decrease in pear size under both interventions. In contrast, interventions that focus on transportation initiatives were not associated with lower average pear sizes, likely because such a potential CO_2 reduction happens on a smaller scale without a negative effect on fruit growth. Additionally, the two different species of the study show different growth rates and sizes. Specifically, the Conference species shows an overall faster pear growth when compared to Doyenné du Comice. This difference suggests that the choice of species might be as influential as climate intervention in cases where fruit growth and size are prioritized.

Soil profiles cluster well when grouping for climate interventions, suggesting that different climate scenarios may leave an identifiable signature in soil composition, which can be nutrient, water, or carbon factors. The selection of these five influential soil characteristics translates into the key indicators of soil health, defined by Lal R., 2011 as the capacity to perform sustainable production while maintaining and improving the environment. Soils under climate conditions projected at 2050 are relatively richer in nitrates and mineralizable N compared to the overall mean, which both have been documented as playing a central role in soil fertility (Rompré et al., 2010). Yet, excessive levels of these nutrients have been associated with low fruit quality (Sete et al., 2019) and increased fruit growth (Zhang et al., 2022), patterns which were also observed in our analysis. In addition, CO_2 removal interventions show no strong increase in any of the five variables, whereas sustainability initiatives exhibit notably increased deeper soils and higher water infiltration rates, patterns of which have already been confirmed in the scientific literature by Komatsuzaki, M., & Ohta, H. (2007). Specifically, soils with improved water infiltration have been positively associated with greater fruit quality (Wang et al., 2024, Zhang et al., 2022), a relationship that our findings further support. Moreover, reductions in transportation-related emissions contribute to higher levels of soil organic carbon and respiration. Although these conditions are associated with enhanced microbial development and support the preservation of soil health by limiting the deposition of transportation-derived pollutants (De Silva et al., 2021), our findings did not reveal a significant improvement in pear quality.

Our study is considered successful, as it was possible to detect the climate scenarios that outperform climate scenario 1, with all our findings highlighting the significant influence of climate interventions on pear quality. While CO_2 removal and sustainability measures improved pear quality, they might be associated with a reduction of pear growth, likely due to limitations in photosynthesis and shifts in soil nutrient dynamics. Among the two pear species studied, Conference consistently outperforms Doyenné du Comice in terms of fruit quality under intervention scenarios, suggesting that it is better suited to future climate conditions. Moreover, the distinct soil clusters observed under different climate scenarios may indicate the indirect role of soil features on fruit quality. Overall, these findings suggest a complex interplay where climate scenarios might alter soil dynamics, which then might influence fruit size, ultimately modulating the pear sugar levels, impacting fruit quality. Our results underline that the success of climate interventions in agriculture depends not only on atmospheric management but also on species selection and the alignment of soil health strategies with climate goals.

It would be important to mention that this study comes with some limitations. Firstly, the climate scenarios that were studied were simulated in strictly controlled conditions, which might not fully capture the variability of weather conditions. Additionally, the experiments were performed in Belgium and France, countries with specific soil features that might influence both the growth and the quality of the pears. It is therefore not optimal to generalize the outcomes to other regions other than Belgium and France.

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Appendix - R code

The following R script was used to perform the linear mixed model analysis and other key statistical procedures. Due to length, the full code is not included in this report but is available as an external R Markdown file.

```
# Linear Mixed-Effects Model for the continuous outcome

model2 <- lmer(quality_index ~ climate + species + location +
                  (1|tree_id), data = G18.final.data)



# Generalized Estimating Equations (GEE) Model for the binary outcome

model3 <- geeglm(quality_score_binary ~ climate + species + location,
                  id = tree_id,
                  data = G18.final.data_binary,
                  family = binomial(link = "logit"),
                  corstr = "exchangeable")

# Generalized estimating equations model for analysis of the pear size over time

model_gee_sqrt_2 <- geeglm(
  sqrt(size) ~ climate + species +
    cweek + I(cweek^2) +
    cweek:species,
  id       = pear_id,
  family   = gaussian(link="identity"),
  corstr   = "exchangeable",
  data     = series_size_data
)


# Fit LDA model for visualization of the soil features
model_LDA <- lda(climate ~ ., data = lda_data)
```