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DISSERTAÇÃO

CLIMATE RISK AND AGRICULTURAL INSURANCE: A
GENERALIZED ADDITIVE MODEL APPROACH FOR
PORTUGAL

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ABSTRACT

Climate change has increased the exposure of agriculture to climatic risk, reinforcing the importance of agricultural insurance as a risk management instrument. This dissertation investigates the relationship between climatic conditions and the Portuguese agricultural insurance system through Generalized Additive Models. Using meteorological data from IPMA and agricultural insurance records from IFAP, this work examines the effects of climatic variables on insurance pricing, public support, and realized losses, while accounting for regional and crop-specific heterogeneity. The results show that GAMs effectively capture the non-linear effects of climate on public support and insurance pricing, whereas indemnities are only weakly explained by the climatic variables considered, suggesting the influence of additional non-climatic factors. The analysis also reveals substantial differences across tariff regions and crop groups, as separating vineyards from the remaining crops generally improves model performance. Overall, the findings highlight the importance of climatic conditions in shaping the Portuguese agricultural insurance system and demonstrate the suitability of GAMs for modelling complex climate–insurance relationships.

Keywords: Climate change; agricultural insurance; Generalized Additive Models; climate risk; Portugal.

RESUMO

As alterações climáticas têm aumentado a exposição da agricultura ao risco climático, reforçando a importância do seguro agrícola como instrumento de gestão do risco. Esta dissertação analisa a relação entre as condições climáticas e o sistema de seguros agrícolas em Portugal através de Modelos Aditivos Generalizados (Generalized Additive Models – GAMs). Com base em dados meteorológicos do IPMA e em registos de seguros agrícolas do IFAP, este trabalho avalia os efeitos das variáveis climáticas sobre as tarifas de seguro, a bonificação sobre o prémio comercial (BoCP) e as indemnizações, tendo em consideração a heterogeneidade entre regiões tarifárias e grupos de culturas. Os resultados mostram que os GAMs captam eficazmente os efeitos não lineares das condições climáticas sobre a tarifação dos seguros e o apoio público, enquanto as indemnizações são apenas fracamente explicadas pelas variáveis climáticas consideradas, sugerindo a influência de fatores adicionais de natureza não climática. A análise revela ainda diferenças significativas entre regiões tarifárias e grupos de culturas, verificando-se que a modelação separada das vinhas melhora, em geral, o desempenho dos modelos. De um modo geral, os resultados demonstram que as condições climáticas constituem determinantes importantes do sistema português de seguros agrícolas e confirmam a adequação dos GAMs para modelar relações complexas entre o clima e os seguros agrícolas.

Palavras-chave: alterações climáticas; seguros agrícolas; Modelos Aditivos Generalizados (GAMs); risco climático; Portugal.

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1 INTRODUCTION

Climate change refers to long-term alterations in temperature patterns and climatic conditions. Although such variations may occur naturally, resulting from factors such as changes in solar activity or major volcanic eruptions, human activities have become the primary driver since the 18th century (United Nations, 2021). In particular, the widespread combustion of fossil fuels, including coal, oil, and natural gas, has significantly contributed to the increase in greenhouse gas concentrations and, consequently, to global warming (United Nations, 2021). As a global phenomenon, climate change is a significant threat, affecting all regions of the planet. Its impacts manifest across different dimensions of society, including the environment, the economy, and social and territorial organization (European Commission, 2025).

According to the United Nations Office for Disaster Risk Reduction, the number of climate-related disasters and the associated material damage between 2000 and 2019 were approximately 1.8 times higher than those recorded in the previous two decades, reinforcing the persistent threat posed by climate-related hazards (UNDRR and CRED, 2020).

There is broad recognition of the need to act urgently, as the absence of effective measures may further intensify the severity of these effects (European Commission, 2025). In recent years, heatwaves and wildfires have become more frequent and more intense, as documented in the *European State of the Climate 2025*, which reports record-breaking heatwaves spanning from the Mediterranean region to the Arctic, together with associated glacier retreat and reductions in snow cover (Copernicus Climate Change Service (C3S) and World Meteorological Organization (WMO), 2026). In addition, extreme precipitation episodes and floods have been exacerbated by global warming, which increases the atmosphere's moisture-holding capacity by about 7% per 1°C of warming (Faranda et al., 2022). Recent research also suggests that Arctic warming may be destabilizing the polar vortex and the jet stream, allowing masses of polar air to move further south into regions such as the United States and Europe, which could result in more severe and frequent winters in the future (Woodwell Climate, 2024).

These events pose significant risks to several key sectors of the economy. For instance, driven by climate change, the redistribution of tourist flows may lead to losses of up to 0.5% of GDP in more exposed regions (Bigano et al., 2008). In addition, sea-level rise threatens critical infrastructure, with annual costs in Europe estimated at up to EUR 42.5 billion (Bigano et al., 2008). Simultaneously, the rise of a new climate economy is compelling firms to adapt their business models and production systems more flexibly in response to unprecedented volatility and disruptions in global supply chains caused by

these extreme events (Saura et al., 2023). Beyond these direct economic effects, the intensification of extreme events also has important social consequences, particularly through forced human mobility. According to International Federation of Red Cross and Red Crescent Societies (2021), approximately 98% of internal displacements caused by disasters in 2020 occurred in the context of meteorological and climate-related hazards.

In Portugal, these pressures are already manifest across several sectors, with tourism serving as a primary example of this growing exposure. Driven by rising temperatures, tourist arrivals are estimated to decrease by between 2.5% and 5.2%, a shift that could translate into losses of up to 0.40% of GDP and approximately 19,600 jobs (Pintassilgo et al., 2016). This sectoral decline is further exacerbated by a loss of national competitiveness as new destinations with milder climates emerge (Pintassilgo et al., 2016). Consequently, European assessments identify Portugal as one of the nations most vulnerable to climate change, already experiencing significant impacts in a context where global average temperatures have risen by approximately 1°C above pre-industrial levels (Schleussner et al., 2020). Taken together, these pressures reinforce the urgent need for adaptation and mitigation strategies to address climate change (Anita et al., 2010).

In recent years, the international community has witnessed an increasing instability in agri-food supply chains, reinforcing the importance of food security as a priority on the global climate agenda (Jensen and Hourdin, 2025). The Intergovernmental Panel on Climate Change (IPCC) states that climate change is already affecting food security, due to rising temperatures, changing precipitation patterns, and the increased frequency of extreme events (Mbow et al., 2019). In Europe, although the region displays relatively low levels of food insecurity in global terms compared with other parts of the world, climate change has been intensifying concerns related to economic accessibility, availability, and quality of food products. In July 2025, approximately 8% of the European population faced moderate to severe food insecurity, with the most socio-economically vulnerable groups and some Eastern European countries being the most affected. It is also estimated that climate change has already contributed to worsening the food insecurity of around 12 million Europeans (Jensen and Hourdin, 2025).

In Jensen and Hourdin (2025), climate projections indicate that, by 2070, major changes in European climate zones are likely to alter agricultural conditions across the continent. While elevated CO₂ concentrations can, in certain contexts, enhance yield through stimulation of photosynthesis and reduced water loss, these gains may be offset by declines in the nutritional quality of harvested crops, particularly in protein, zinc, and iron content. In Portugal, as noted in Assunção et al. (2018), one of the impacts of climate change on food is the increased risk of aflatoxin contamination, which consists of naturally occur-

ring mycotoxins produced by fungi. Rising temperatures and drought create favorable conditions for their proliferation, making this issue particularly relevant for food security in staple crops such as maize and wheat.

Agriculture is among the sectors most vulnerable to contemporary climatic change, as production depends heavily on climatic stability and favorable atmospheric conditions (Grigorieva et al., 2023). This vulnerability is already reflected in the empirical literature, with recent meta-analytic evidence showing that climatic instability leads to measurable declines in agricultural productivity and income (Hussen et al., 2026).

These impacts extend to the macroeconomic level, where agriculture operates as a principal channel for supply-side shocks, leading to shortages of inputs and increased volatility in food commodity prices (Batten, 2018). Temperature increases of between 3°C and 5°C could raise agricultural prices by up to 40%, while natural disasters may cause immediate losses of physical capital, infrastructure, and biological assets, sometimes resulting in a permanent reduction in GDP (Batten, 2018).

Beyond these aggregate effects, the Mediterranean region stands out as a critical hotspot, with climate projections signaling yield losses that are unprecedented within the European context (Valverde et al., 2015). It is projected that staple crops such as maize and wheat may experience yield reductions of up to 50% and 75%, respectively, due to increased climatic variability and reduced precipitation (Valverde et al., 2015). For example, in the Guadiana basin, irrigation water requirements are expected to increase by between 15% and 20% by 2050, exacerbating the imbalance between water supply and demand and threatening the economic viability of farms (Valverde et al., 2015).

This scenario is further aggravated by projected changes in thermal conditions, which indicate a general increase in heat accumulation and a significant reduction in winter chilling (Santos et al., 2017). These changes pose a major challenge for the development of species such as chestnut, apple, and cherry, with southern inland Portugal identified as the most vulnerable region, where the viability of these crops may be seriously compromised (Santos et al., 2017).

In the viticulture sector in Portugal, the earlier onset of phenological stages, driven by higher temperatures, exposes vineyards to new risks such as late frosts and extreme heatwaves during critical periods, resulting in substantial year-to-year variability in production (Fraga et al., 2017).

Climate change and the increasing severity of extreme weather events have placed unprecedented pressure on nature-dependent sectors such as agriculture. Europe has recently witnessed a critical transition: from isolated and temporary economic losses to a

structural upward trend in damages (Manescu et al., 2025). This emerging pattern is evidenced by the fact that the period between 2021 and 2023 recorded the highest annual loss values of recent decades, with cumulative damage amounting to approximately USD 162 billion, representing 22% of all losses recorded since 1980 (Manescu et al., 2025). Against this background, agricultural insurance becomes an increasingly important mechanism for managing climate-related risk. Climate change, by increasing the frequency and severity of adverse events, reinforces the fundamental role of agricultural insurance as a risk-transfer mechanism, allowing producers to replace the uncertainty of catastrophic losses with a fixed and manageable cost (Chatterjee and Oza, 2017). This tool is particularly vital given that agriculture is a high-risk activity, exposed to uncontrollable variables that can compromise the economic viability of farms (Chatterjee and Oza, 2017; Wang et al., 2011).

Among the key functions of agricultural insurance is its role in supporting farmers in maintaining economic stability through compensation mechanisms that promote continuity of production following losses (Wang et al., 2011). By providing liquid capital after a loss event, insurance helps prevent farmers from falling into a cycle of poverty, while also reducing the need for them to sell productive assets to cover damage (Alam et al., 2020). Insurance also acts as an investment promoter, since holding a policy increases the confidence of financial institutions, thereby facilitating access to formal credit (Alam et al., 2020).

In several countries, agricultural insurance systems are based on risk-sharing models between the public and private sectors, using subsidisation mechanisms aimed at increasing farmers' protection against extreme climatic events. In the United States, the Federal Crop Insurance Program operates through a public-private partnership in which the federal government covers a substantial share of premium costs, with average subsidies ranging between 60% and 65%, enabling high participation rates in the programme (Smith et al., 2016). However, this model entails high administrative costs associated with its extensive coverage.

In Spain, the system is likewise based on a mixed model involving the state, private insurance companies, and farmers' organizations. Public support for premiums is more moderate, generally ranging between 20% and 45%, reflecting a greater sharing of risk by agricultural producers (Garrido and Zilberman, 2008).

In Portugal, public support for agricultural insurance is implemented by the Institute for the Financing of Agriculture and Fisheries (IFAP) through specific schemes, namely Crop Insurance (SC) and Viticulture Crop Insurance (SVC), which progressively replaced the former Integrated Weather Protection System (SIPAC), in force between 1996 and

2013. The Portuguese support scheme is based on the partial subsidisation of insurance premiums, reducing the cost of coverage borne by farmers and increasing the resilience of the agricultural sector to adverse climatic events (IFAP – Instituto de Financiamento da Agricultura e Pescas, I. P., 2026).

Within the scope of agricultural insurance in Portugal, SC can reach up to 70% of the premium value, varying according to the type of farmer, insurance history, and policy type. This system aims to protect production against losses resulting from adverse weather events such as hail, frost, fires, tornadoes, waterspouts, and persistent rainfall, among others. In turn, SVC is exclusively intended for wine grape producers and may benefit from a subsidy of between 75% and 80% of the insurance premium when coverage includes climate risks classified as equivalent to natural disasters (IFAP – Instituto de Financiamento da Agricultura e Pescas, I. P., 2026).

Compared with other countries, the Portuguese model presents relatively high levels of subsidisation in certain cases, particularly in the viticulture sector, reflecting the economic importance of agriculture and the growing need to adapt to climate change (IFAP – Instituto de Financiamento da Agricultura e Pescas, I. P., 2026).

Manescu et al. (2025) highlight that the insurance market has often responded in a reactive and lagged manner, with variations in crop insurance premiums tending to follow losses with a delay of one to two years. This temporal gap undermines the immediate effectiveness of support systems, reinforcing the need for insurance strategies and contracts to be grounded in robust scientific evidence (Flora, 2022). Specifically, this requires moving beyond traditional models that oversimplify climate impacts and often fail to capture the complex biophysical responses and climatic tipping points that drive insurance losses (Manescu et al., 2025).

Flora (2022) corroborates the need for greater methodological sophistication by investigating the relationships between climatic variables and the agricultural insurance sector in Portugal through linear regression models. The research demonstrated that the explanatory power of these frameworks is significantly enhanced by the inclusion of non-linear components, particularly quadratic relationships. Specifically, it was shown that metrics such as insurance tariffs and the proportion of claims per contract are modeled with greater accuracy when variables like the frequency of extreme precipitation (DATRt) are included quadratically. This methodological approach led to a substantial improvement in the models' R^2 .

Given that the dependent variables under study are better represented when non-linear effects are taken into account, this work investigates the relationship between climate dynamics and the agricultural insurance sector using a modelling framework capable of

capturing such complexity. Specifically, it analyzes climatic and agricultural insurance data from Portugal to assess how recent climatic changes have influenced this line of business. This study extends Flora (2022) by adopting Generalized Additive Models (GAMs), which provide a more flexible framework for capturing the complex non-linear relationships between climate and insurance variables.

Based on the existing literature, this work presents a coherent model selection methodology using GAMs for explaining the dependent variables. The results demonstrate that these models exhibit superior performance compared to linear regression models, explaining a substantially higher proportion of the data’s variability. Specifically, the results indicate that climatic variables explain public support and tariffs in a robust and non-linear manner, whereas indemnities are less effectively explained by the climatic factors considered.

The remainder of this dissertation is organized as follows. Section 2 describes the data. Section 3 outlines the methodology. Section 4 presents and discusses the empirical results, together with an evaluation of model performance. Finally, Section 5 concludes.

2 DATA DESCRIPTION

To study how climate affects agricultural insurance outcomes, this dissertation combines meteorological records from the Portuguese Institute for Sea and Atmosphere (IPMA) with agricultural insurance data from IFAP. The climatic component of the database is based on meteorological observations collected by IPMA, the institution responsible for monitoring and disseminating weather information in Portugal.

The climatic database used in this study comprises observations from 58 automatic weather stations covering the period between 1996 and 2025, although data availability varies across stations and not all provide complete records for the entire period. The original observations were recorded at an hourly frequency and subsequently aggregated into daily climatic indicators.

For each station and day, as Flora (2022), the maximum temperature (T_{max}) was defined as the highest hourly temperature recorded within the 24-hour period, while the minimum temperature (T_{min}) corresponded to the lowest hourly temperature observation. Daily wind conditions were represented by the maximum wind speed (W_{speed}), computed as the average of the hourly maximum wind-speed measurements recorded throughout the day. Total daily precipitation (R_{total}) was calculated as the sum of hourly precipitation amounts over the corresponding 24-hour period. These variables were selected because they capture the climatic dimensions most closely linked to agricultural productivity and

insured losses (Vogel et al., 2021; Niu et al., 2016).

The resulting dataset provides a detailed record of daily weather conditions spanning up to 29 years, thereby enabling the investigation of long-term relationships between climatic variability and agricultural insurance outcomes.

Prior to the construction of the climatic indicators, a data-cleaning procedure was undertaken to ensure the quality and consistency of the observations. Values falling outside physically plausible ranges were identified, recoded as missing, and excluded from subsequent analyses. The cleaned daily series were then aggregated to derive annual climatic indicators for each weather station and year. These annual measures constitute the basis for the empirical analysis presented in the following sections.

For each climatic variable (T_{min} , T_{max} , R_{total} , and W_{speed}), three types of annual indicators were computed. First, annual extremes were obtained through the yearly minimum and maximum values. Second, the first and third quartiles of the annual distribution were calculated to describe within-year variability. Third, frequency-based indicators were defined by counting the number of days in each year in which the variable was above the annual third quartile or below the annual first quartile. In this way, the daily climate information was converted into annual measures of climatic intensity, dispersion, and extreme-event frequency.

Table I summarizes the annual climatic indicators used as independent variables in the analysis. These variables were constructed from the cleaned daily observations for each station and year.

TABLE I: Definition of the Independent Variables (adapted from Flora (2022))

Category	Variable Name	Description	Acronym
Frequency	Days_above_threshold_x	Number of days per year exceeding the third quartile of x.	DATx
	Days_under_threshold_x	Number of days per year below the first quartile of x.	DUTx
Absolute	min_x	Annual minimum value recorded for x, calculated per region and year.	Minx
	max_x	Annual maximum value recorded for x, calculated per region and year.	Maxx
Distribution	fst_qtl_x_year	First quartile of x's annual distribution within each region and year.	Fstx
	trd_qtl_x_year	Third quartile of x's annual distribution within each region and year.	Trdx

Note: The suffix x denotes the climatic dimensions R_{total} , T_{min} , T_{max} , and W_{speed} .

The dependent variables capture three complementary dimensions of the agricultural insurance market: pricing, public support, and realized losses. Specifically, Tariffs measure the premium charged by insurance companies per unit of insured capital, the bonus over commercial prize (BoCP) captures the share of the commercial prize financed by the State, and Indemnities represent the total amount paid by insurers in the event of loss. In addition, meteorological variables were introduced with a one-year lag, while tariffs remained the dependent variable in year t . This means that the climatic conditions of the previous year ($t - 1$) were used to explain the tariff level of the current year, rather than contemporaneous weather conditions. This specification reflects the assumption that insurance pricing may be influenced by recent climatic history, given that tariffs are set a priori and may incorporate information from the most recently observed meteorological period.

TABLE II: Definition of the Dependent Variables (adapted from Flora (2022))

Category	Variable Name	Description	Acronym
Pricing	Tariffs	The price per unit insured, paid to the insurance companies.	Tariffs
Public support	Bonus over Commercial Prize	The proportion of what is paid by the State as part of the total amount of Commercial Prize that the Insurance companies receive.	BoCP
Losses	Indemnities	Total amount paid by insurance companies in case of incidents.	Indemnities

The insurance component of the analysis is based on administrative records provided by IFAP. The database includes information on insurance contracts and public support, insured capital, commercial prize, applied tariffs, public subsidies, indemnities paid, and, in some cases, the causes of loss. It should be noted that the year 2018 contained incomplete information. In this year, the data were utilized only when possible. Whenever the information was insufficient to ensure the integrity of the analysis, those specific observations were excluded from the study. ¹

Following the introduction of these variables, a data cleaning and standardization process was conducted. A key concern was ensuring that all financial records were comparable across the study period. To achieve this, all monetary values were expressed in constant 2023 euros. This transformation was performed using the official conversion tool provided by the National Statistics Institute (INE)², the central authority for Portuguese official statistics. The conversion utilized the average Consumer Price Index (IPC) for Mainland Portugal, allowing for a consistent analysis that accounts for inflation and the historical transition from Escudos to Euros in older records. Furthermore, the data span different institutional settings over time, from the SIPAC framework to the later Crop Insurance and Viticulture Crop Insurance schemes, thereby reflecting the evolution of agricultural risk management policies in Portugal.

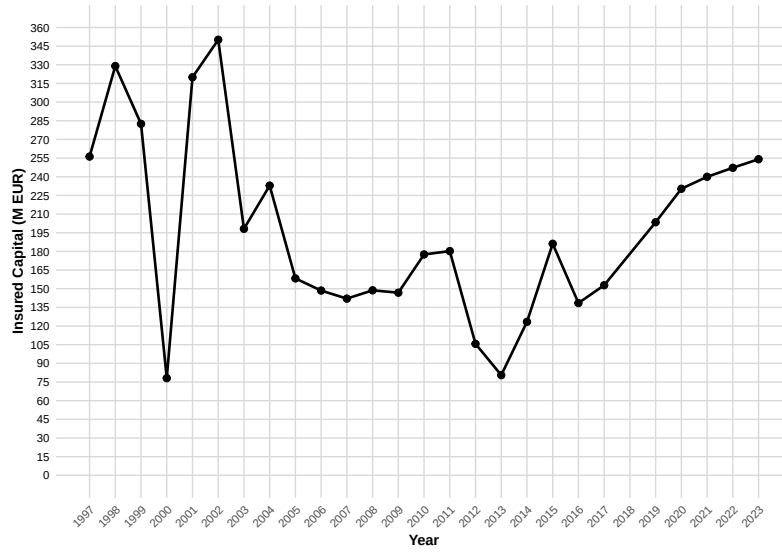
Public intervention in the Portuguese agricultural insurance market has evolved through several distinct legal frameworks, moving from the largely ineffective pre-1980 schemes to the more structured systems later co-financed by the European Union (Coelho, 2024).

¹In all graphical representations presented in this section, no aggregated value is reported for 2018. Since the data for that year are incomplete, displaying an aggregated value could be misleading.

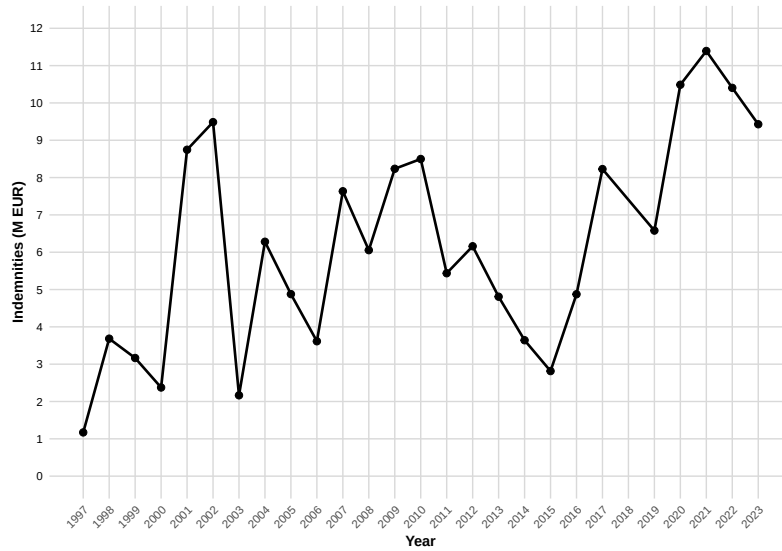
²The official INE conversion tool for the Consumer Price Index can be found at: [here](#)

In this process, SIPAC, established in 1996, marked the first major institutional reform of the sector (Coelho, 2024). It was built upon three fundamental pillars: subsidized crop insurance to encourage uptake, a calamity fund to compensate for non-insurable risks, and a public reinsurance mechanism to support insurance companies during years of excessive claims (Coelho, 2024). Exclusively funded by national budgets, SIPAC initially achieved significant success, covering 28% of the cultivated area by 1999 (Coelho, 2024). However, its effectiveness waned over time as subsidy levels decreased and the calamity fund shifted from direct compensation toward credit lines. A subsequent shift began in 2012 with the introduction of the SVC, followed by SC in 2014, marking a transition toward a more rational approach to subsidy allocation integrated into the European Union's co-financing framework (Coelho, 2024). The new framework replaced the exclusively state-funded approach with a system that conditions support on the existence of active insurance contracts and broadens coverage to include additional climate-related risks (Coelho, 2024).

The evolution of the Portuguese agricultural insurance market suggests an increasing role of insurance in the management of climatic risk. As illustrated in Figure 1a, insured capital displays a marked increase in recent years, especially after 2016, although the series remains characterized by considerable year-to-year volatility. This pattern is consistent with other European Countries, such as Spain, where insured capital has reached successive historical highs for eleven consecutive years, peaking at €19.36 billion in 2025 (Entidad Estatal de Seguros Agrarios (ENESA), 2026). After reaching relatively high levels of insured capital in the late 1990s, it declined in the early 2000s, before recovering in the following years. From 2016 onward, however, insured capital increased steadily, rising from approximately EUR 140 million to around EUR 255 million in 2023, corresponding to an increase of 82.1%. This suggests a renewed expansion in the use of insurance as part of agricultural risk management, possibly reflecting greater awareness of climate-related risks and the role of insurance as an adaptation mechanism to meteorological shocks (Roberts, 2005).



(a) Temporal Evolution of Insured Capital



(b) Temporal Evolution of Indemnities

FIGURE 1: The top panel illustrates the temporal evolution of insured capital, expressed in millions of euros, over the period 1997–2023. The bottom panel presents the temporal evolution of indemnities, also expressed in millions of euros, over the same period.

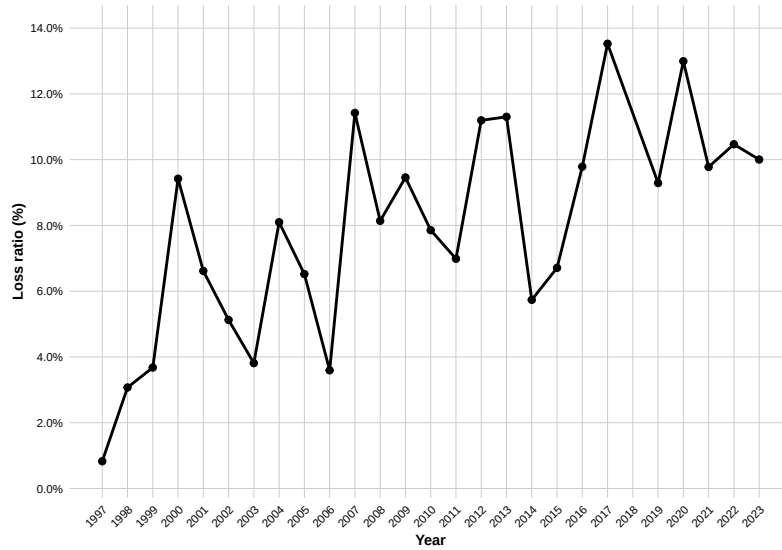


FIGURE 2: Temporal evolution of loss ratio, over the period 1997–2023.

Figure 1b shows that indemnities have increased in the period 1997-2023, although there is substantial year to year variation. Indemnities were relatively low in the late 1990s before increasing sharply to about EUR 9.5 million in 2002 and then falling again to approximately EUR 2.2 million in 2003. The series continued to fluctuate in the following years, peaking at roughly EUR 11.5 million in 2021 and finishing the series with indemnity values around 9 million. The joint evolution of insured capital and indemnities should be interpreted with caution, as it may reflect not only changes in exposure and climatic conditions, but also shifts in insurance penetration, coverage levels, and contract structure.

Figure 2 presents the loss ratio, defined as indemnities relative to insured capital. The series exhibits a clear upward trend over the period, increasing from around 1% in 1997 to approximately 10% in 2023. This increase is accompanied by substantial year-to-year volatility, with several distinct peaks, the highest occurring in 2017. This suggests that climatic losses continued to generate episodic pressure on the insurance system.

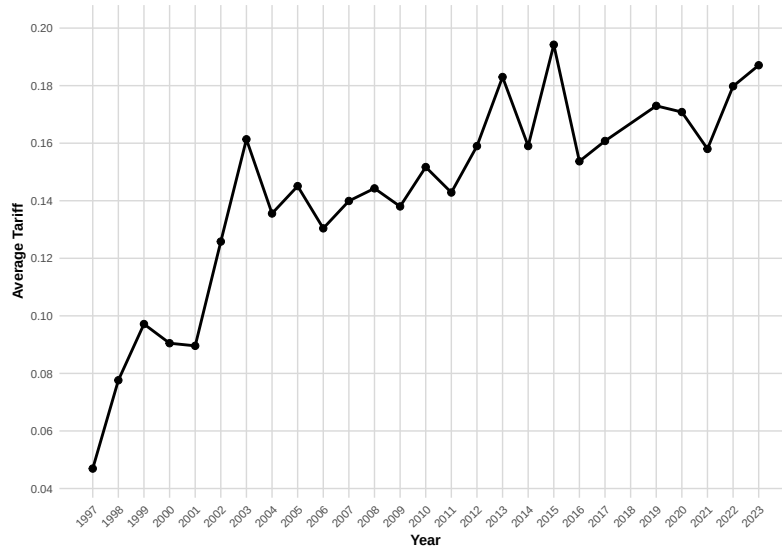
Overall, the evidence is consistent with a market that is becoming increasingly relevant for agricultural risk management, although it does not on its own show that damages have become more frequent or more severe in financial terms. Rather, the combination of rising insured capital and a volatile loss ratio suggests a sector that is expanding in coverage while still facing substantial climatic uncertainty.

Over the long term, as shown in Figure 3a, average tariffs exhibit a broad upward trajectory, indicating that insurers have progressively incorporated higher expected losses into premium calculations. In particular, average tariffs increased from approximately

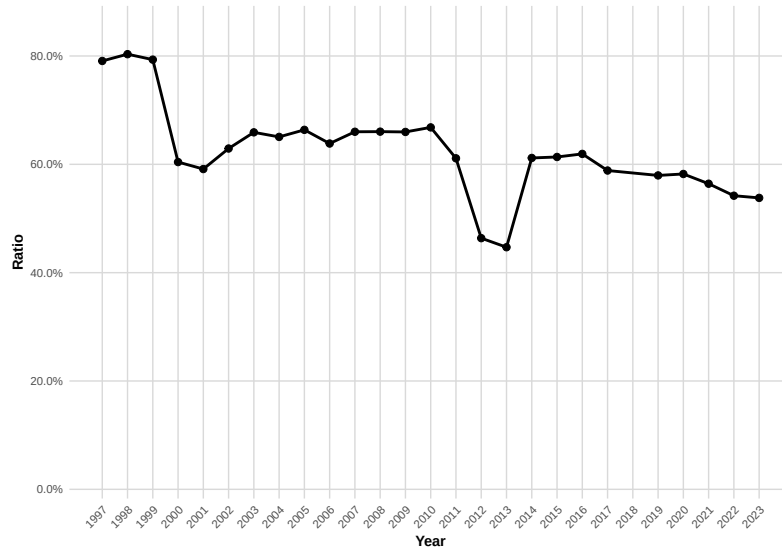
0.05 in 1997 to around 0.183 in 2023, corresponding to an increase of roughly 266% over the period, and reached their highest level in 2015 at approximately 0.195.

The functioning of the agricultural insurance market cannot be fully understood without considering the role of public intervention. Figure 3b shows that the share of insurance costs financed through public support declined from about 80% in 1997 to about 55% in 2023, a decrease of approximately 25 percentage points. This suggests a gradual reduction in the State's relative contribution to the financing of agricultural insurance contracts.

At the same time, the relatively low average tariff levels observed at the beginning of the period, together with the high share of insurance costs financed through public support, may help explain the substantial levels of insured capital recorded throughout the 1990s. As shown in Figure 3a, the average tariff in 1997 was the lowest in the entire historical series (approximately 0.05), while public support, as shown in Figure 3b, covered around 80% of insurance costs in that same year. This combination likely reduced the effective cost of coverage and encouraged early participation in the SIPAC scheme.



(a) Annual evolution of insurance tariffs



(b) Bonus over Commercial Prize

FIGURE 3: Panel (a) presents the annual evolution of insurance tariffs, represented by the average tariff by year, over the period 1997–2023. Panel (b) shows the evolution of the Bonus over Commercial Prize over the same period.

The result of this growth in average tariffs, coupled with the simultaneous decline in the insurance costs financed through public support, is reflected in farmers' payments. Figure 4 represents the evolution of the insurance payment supported by the farmers. It shows that the amount paid by farmers has increased substantially over time, with a particularly pronounced rise in the most recent years of the sample. This pattern provides direct empirical support for the view that producers are bearing a growing share of insurance costs. In this context, this greater financial burden may reduce the affordability and attractiveness of insurance coverage. Ultimately, it may also place additional pressure on

the long-term resilience of the sector, particularly for smaller producers with more limited financial capacity.

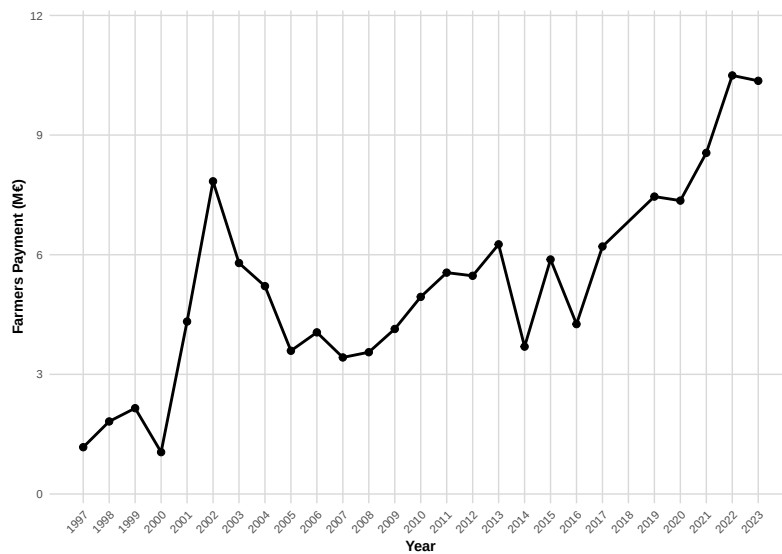


FIGURE 4: Annual evolution of farmers' payments, calculated as commercial prize minus bonus, for the period 1997–2023.

While aggregate trends provide valuable information about the evolution of the sector, understanding the nature of insured losses requires a closer examination of the specific climatic events generating claims, such as hail, frost, fire, lightning and explosion, persistent rain, sunburn or sun exposure, tornado, waterspout, poor fruit set, lightning strike and explosion, snowfall and other causes. As revealed in Figure 5, hail and frost are by far the most recurrent causes of insured losses, accounting for 1,613 and 1,571 observations, respectively. The third most frequent cause, fire, lightning and explosion, is reported far less often, with 336 observations. Therefore, the prevalence of hail and frost highlights their central role as the main drivers of insured losses in the Portuguese agricultural insurance market.

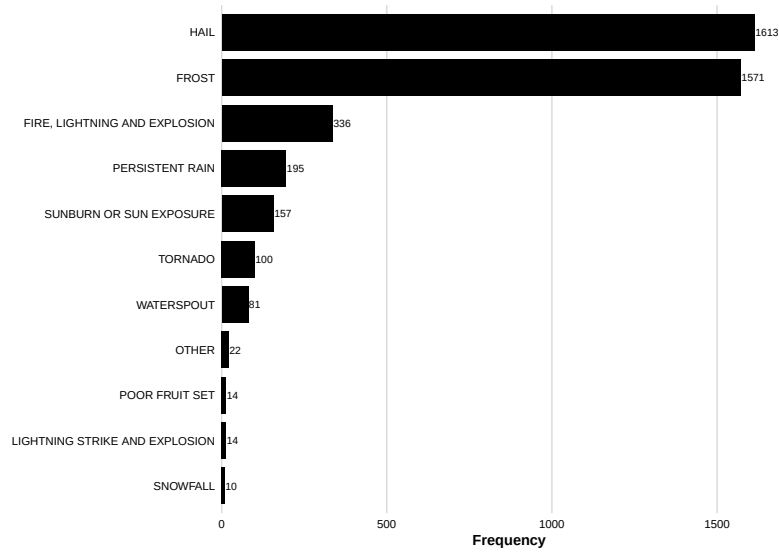


FIGURE 5: Frequency of claim causes for the period 1997–2023 across all tariff regions.

The frequency of occurrence alone does not fully capture the economic consequences of different climatic events. Some hazards occur relatively often but generate moderate losses, whereas others are less frequent yet produce substantial financial impacts when they materialize. This distinction becomes evident in Figure 6, which shows that causes such as sunburn or sun exposure and waterspout are associated with high average indemnity payments per claim. Although less frequent than hail or frost, these events can generate considerably larger losses at the individual claim level.

It is important to highlight that the frequency of sunburn or sun exposure recorded in the historical data likely reflects an administrative reporting bias rather than the true occurrence of the hazard. Until the issuance of *Ministerial Order No. 92/2025/I, dated 10 March 2025*³, SVC only provided indemnities for sunburn or sun exposure when losses exceeded 20% of the total production. As a result of this threshold, many heat-related losses were absent from official statistics because damages below the minimum level did not qualify for claims.

Consequently, the information currently observed for sunburn or sun exposure in Figure 6 is likely driven by a reporting bias introduced by the former regulation, under which only large-loss events were eligible for compensation. Future records are therefore expected to show a marked increase in the frequency of sunburn claims.

³ Available at the official Diário da República portal: [here](#)

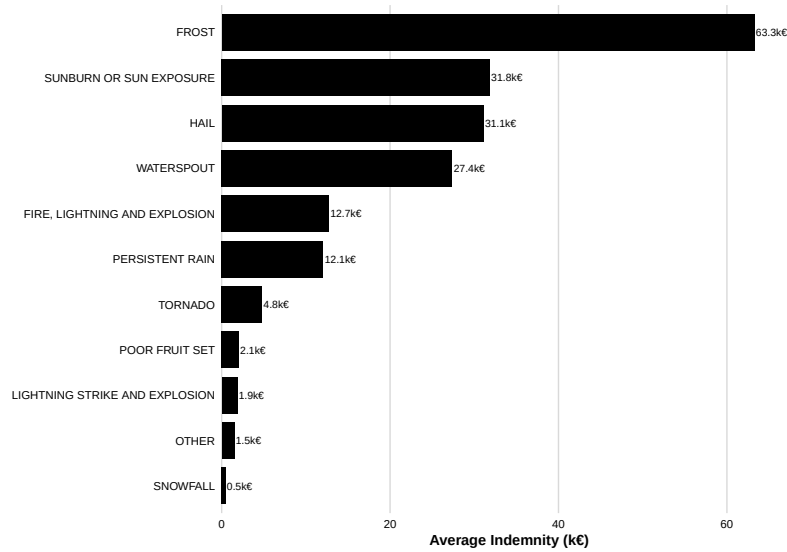


FIGURE 6: Annual average indemnity by claim cause, computed for the period 1997–2023 and across all tariff regions.

The interaction between frequency and severity is summarized in Figure 7. It shows that frost and hail stand out as the most important hazards, since they occur often and are associated with the highest indemnities. It also shows that hazards such as sunburn or sun exposure and waterspout, although less frequent, can still produce sizeable losses, confirming that low-probability events may have a major financial impact.

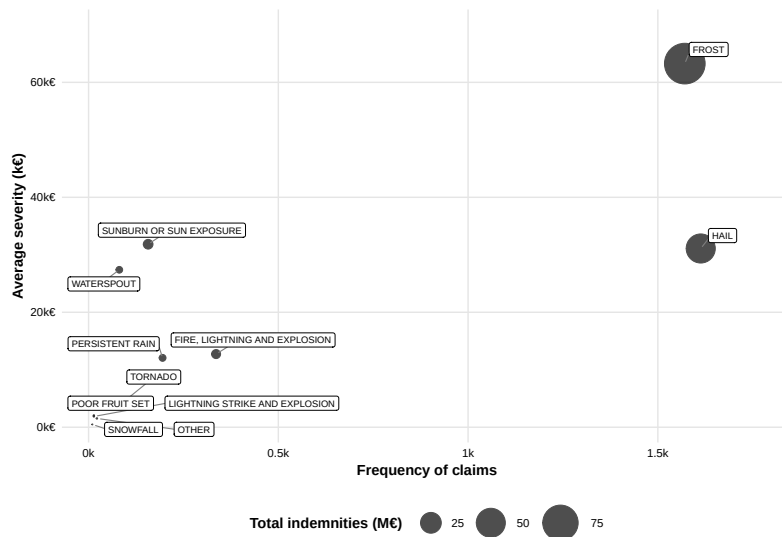


FIGURE 7: Frequency versus severity of insurance claims. The bubble size represents total indemnities.

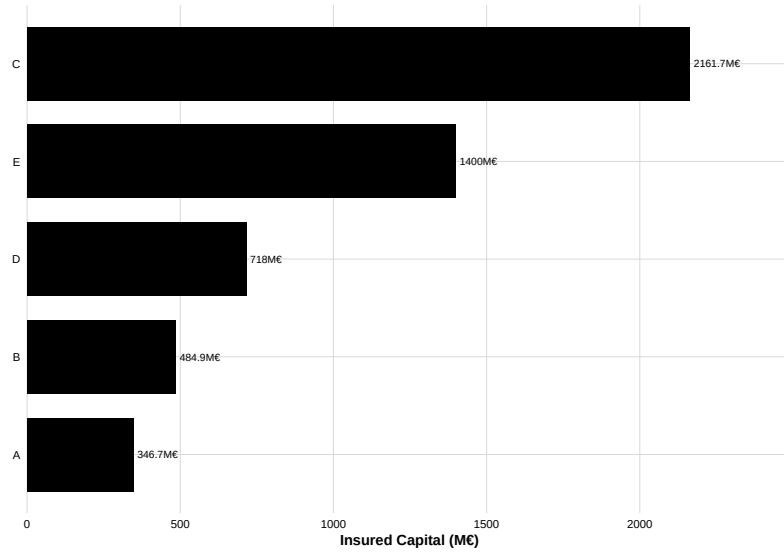
Agricultural risk is not uniformly distributed across Portugal. To account for these differences, the country is divided into five administrative tariff regions (A to E), because

official regulations recognize that the probability of loss and the degree of risk are not the same across the country, as established in *Ministerial Order No. 388/99, dated 27 May 1999*⁴. These regions follow district boundaries to reflect local risk profiles, allowing the insurance system to set specific prices and state compensation levels that match the actual risk of each zone. These tariff regions include ⁵:

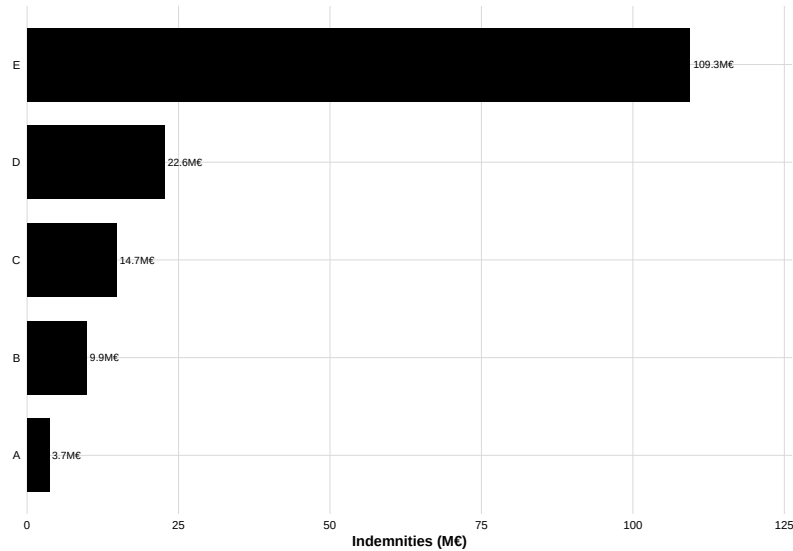
- Region A: Faro, Lisbon, and Setúbal.
- Region B: Sesimbra, Santarém, Setúbal, and Viana do Castelo.
- Region C: Setúbal and Santarém.
- Region D: Aveiro, Braga, Bragança, Castelo Branco, Coimbra, Vila Real and Viseu.
- Region E: Bragança, Guarda, Vila Real, Viseu, Castelo Branco, and Coimbra.

⁴Available at the official Diário da República portal: [here](#)

⁵Some districts appear in more than one tariff region because the classification is determined at the county level. Consequently, counties within the same district may belong to different tariff regions. An illustrative table of this distribution by county is available in Flora (2022).



(a) Total Insured Capital by Tariff Region

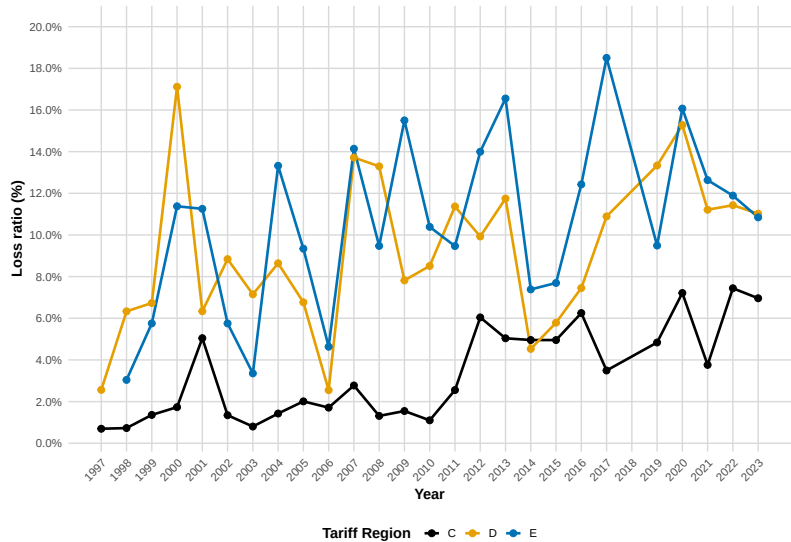


(b) Total Insurance Indemnities by Tariff Region

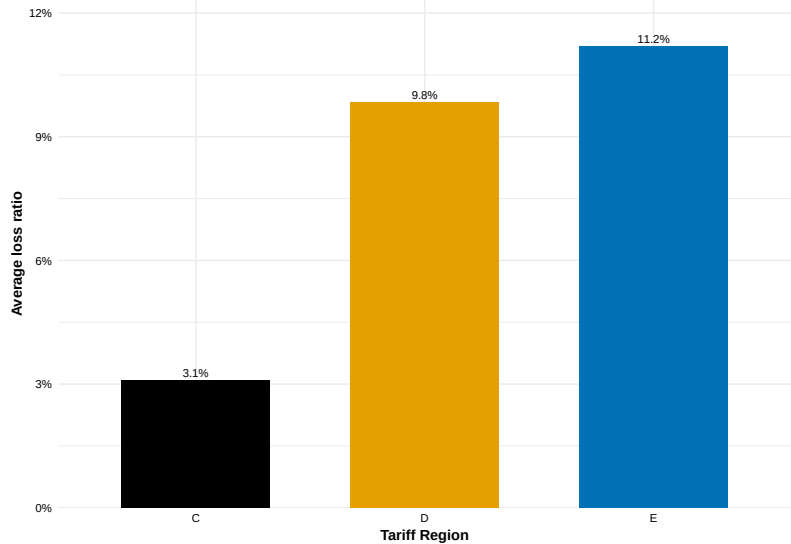
FIGURE 8: Regional aggregation of insured capital and insurance indemnities across tariff regions, 1997–2023. Panel (a) shows total insured capital accumulated over the period by tariff region, and panel (b) shows total insurance indemnities accumulated over the period by tariff region.

Figure 8 shows that the regional aggregation of insured capital differs markedly from the aggregation of indemnity payments, pointing to significant spatial variation in the relationship between exposure and losses. Although Region C accounts for the largest volume of insured capital (approximately EUR 2.16 billion), it generated only EUR 14.7 million in indemnity payments over the study period. In contrast, Region E, with a lower insured capital (EUR 1.40 billion), recorded the highest indemnities (EUR 109.3 million). Consistent with this pattern, Figure 9a shows that, despite high volatility, the three tariff

regions displayed exhibit an overall upward trend in the loss ratio over time. Figure 9b shows that Region C exhibits the lowest average loss ratio (3.1%), while Regions D and E display substantially higher values, reaching 9.8% and 11.2%, respectively. These findings suggest that the relationship between insured exposure and indemnities is highly heterogeneous across regions, reflecting differences in climatic hazard intensity, crop vulnerability, and the composition of insured agricultural production.



(a) Annual Evolution of the Loss Ratio by Selected Tariff Regions



(b) Average Loss Ratio by Selected Tariff Regions

FIGURE 9: Evolution and average level of the loss ratio across tariff regions C, D, and E over the period 1997–2023.

Overall, the descriptive evidence indicates that the agricultural sector is facing increasing climatic and financial pressures. Three main patterns support this conclusion.

First, farmers appear to be increasingly concerned about potential losses, as reflected in the expansion of insured capital, which reached record levels in recent years. Second, indemnities increased over the sample period, while the loss ratio exhibited a clear positive trend, rising from around 1% in 1997 to approximately 10% in 2023. Third, these developments occurred alongside a relative decline in public support, with the share of insurance costs financed by the State decreasing from about 80% in 1997 to approximately 55% in 2023.

3 METHODOLOGY

In this work, we use GAMs to study the relationship between insurance and public aid data on the agricultural sector and climate data. GAMs extend Generalized Linear Models (GLMs) by allowing the effects of predictors to be represented through smooth functions estimated from the data, rather than through strictly linear relationships (Wood, 2025). In this way, GAMs retain the structure of GLMs while introducing flexibility for modelling non-linear relationships (Wood, 2017, Cap. 4). As in GLMs, a link function is used to relate the mean of the dependent variable to the predictors (Baayen and Linke, 2020).

Let Y be the response variable and $X_1, \dots, X_p$ the explanatory variables. The conditional mean structure of the model is specified as Hastie and Tibshirani (1986):

$$g(E[Y \mid X_1, \dots, X_p]) = s_0 + \sum_{j=1}^p s_j(X_j), \quad (1)$$

where $g(\cdot)$ is the link function, s_0 is the intercept, and $s_j(\cdot)$ are non-parametric smooth functions. For the models estimated in this study, $g(\cdot)$ is the identity function and a Gaussian family is assumed, although GAMs can be estimated under alternative distributions. The smooth functions are represented using a basis of known functions, which can be expressed as (Wood, 2017, Cap. 4):

$$f(x) = \sum_{j=1}^k b_j(x)\beta_j, \quad (2)$$

where $b_j(x)$ are the basis functions and β_j are the parameters to be estimated. Splines (such as cubic splines or thin-plate splines) are the most commonly used basis functions because of their ability to approximate complex functions with low error (Wood, 2017, Cap. 5). In this study, thin-plate splines were used.

To prevent the function from adapting excessively to the data and thereby avoiding overfitting, we penalized the regression (Wood, 2017, Cap. 4). The objective is to minimize the function C_f , defined below, which balances goodness of fit and smoothness (Hastie and Tibshirani, 1986):

$$C_f = \sum_{i=1}^n (y_i - f(x_i))^2 + \lambda \int [f''(x)]^2 dx. \quad (3)$$

In this expression, the first term represents data fidelity, while the second term penalizes the “wiggleness” of the function, measured by the integral of the squared second derivative (Hastie and Tibshirani, 1986). The smoothing parameter λ controls the trade-off between these two components: as $\lambda \rightarrow \infty$, the penalty dominates and the resulting function approaches a straight line, when $\lambda = 0$, the penalty vanishes and the function interpolates the data (Hastie and Tibshirani, 1986). The optimal value of λ is estimated from the data using statistical criteria such as Generalized Cross-Validation (GCV) or Restricted Maximum Likelihood (REML) (Wood, 2017, Cap. 4). The GCV criterion is based on minimizing the prediction error, functioning as a computationally efficient approximation to leave-one-out cross-validation (Simpson, 2018). In contrast, REML adopts a likelihood-based approach, treating smooth functions as random effects and the smoothing parameter λ as a variance component to be estimated (Wood, 2011).

The modelling strategy was developed in two distinct stages. The first stage consisted of a diagnostic assessment aimed at evaluating the adequacy of model specification and the ability of the smooth terms to accurately represent the relationships present in the data. The second stage, described subsequently, focused on the interpretation and comparison of models that had successfully passed these diagnostic procedures.

One of the central aspects of the methodology was the evaluation of the basis dimension (k), a parameter that defines the maximum amount of flexibility available to each smooth function (Gomez-Rubio, 2018; Pedersen et al., 2019). As noted in the previous references, the choice of k does not directly determine the effective flexibility of the term but merely establishes an upper limit on that flexibility, with the actual degree of smoothness being controlled by the model’s smoothing parameters. In this sense, the basis dimension corresponds to the number of basis functions available and acts as a ceiling for the Effective Degrees of Freedom (EDF), since a smoother cannot exhibit EDF values greater than k . Thus, an appropriate choice of k ensures sufficient flexibility to capture the relationships in the data, while avoiding unnecessarily large values that may increase computational complexity and introduce unnecessary flexibility (Gomez-Rubio, 2018; Pedersen et al., 2019). For this reason, values of k were selected to be sufficiently

large to capture the structure of the data without resorting to excessively large basis dimensions (Gomez-Rubio, 2018).

To assess whether the chosen basis dimensions were adequate, the diagnostic procedures implemented in the `gam.check()` function of the `mgcv` package in R were used (Wood, 2017, Cap. 4). Among the diagnostics provided by this function, the adequacy of the basis dimensions was evaluated using the k-index test (Wood, 2017, Cap. 6). This test is based on residual analysis and assesses whether the residuals exhibit systematic structure that has not been captured by the smooth terms, which may indicate that the selected basis dimension is insufficient (Wood, 2017, Cap. 5).

In this context, a non-significant p-value ($p > 0.10$) was interpreted as evidence that the basis dimension was adequate and that increasing k was unnecessary. In contrast, a significant p-value ($p \leq 0.10$) could suggest that the flexibility assigned to the smooth term was insufficient, thereby justifying consideration of larger values of k .

For this diagnostic assessment, the models were fitted using GCV as the smoothing parameter selection criterion prior to applying the `gam.check()` procedure. The choice of GCV is relevant because the outcome of the diagnostic assessment may depend on the smoothing criterion adopted during model fitting. Compared with likelihood-based approaches such as REML, GCV generally penalizes model complexity less restrictively, allowing greater flexibility in the estimation of smooth functions (Simpson, 2018; Wood, 2017, Cap. 6). This characteristic makes GCV particularly useful during the exploratory stage, as it provides the model with greater freedom to identify potentially complex non-linear relationships in the data.

The smoothing parameter λ controls the trade-off between data fidelity and the penalty for excessive curvature, as described in Equation (3). In addition to λ , the `mgcv` package allows the use of an additional penalty factor γ , which acts as a multiplier on the smoothing penalty during the model estimation process. Increasing γ above 1 makes the smoothing selection more conservative (Wood, 2017; Gomez-Rubio, 2018). In this study, a value of $\gamma = 1.5$ was used during model estimation, following the recommendation in the literature that $\gamma = 1.5$ provides a more parsimonious model while maintaining adequate flexibility to capture non-linear patterns (Wood, 2017, Cap. 4).

However, it was observed that, in some cases, increasing k failed to improve the diagnostic results, even when k was increased to its maximum allowable value, while EDF values remained virtually unchanged. When this occurred, it was concluded that the model already possessed sufficient flexibility to represent the functional relationship under analysis. Consequently, the residual patterns observed were attributed to intrinsic characteristics of the data, namely variance heterogeneity, autocorrelation, or other forms of residual

structure not explained by the model rather than to an insufficient basis dimension (Pya and Wood, 2016; Wood, 2017, Cap. 5).

Accordingly, only variables whose smooth terms showed evidence of adequate specification in the diagnostics produced by the `gam.check()` function were considered suitable to advance to the second stage of the analysis. In this way, the initial phase served as a methodological quality-control mechanism, ensuring that only appropriately specified models with levels of flexibility compatible with the structure of the data were subsequently used for interpretation.

Following the preliminary diagnostic phase and validation of basis dimension adequacy, the final models were estimated using the REML method. The adoption of this approach followed recommendations in the literature, as REML tends to produce more stable estimates of smoothing parameters and performs well in selecting the appropriate complexity of smooth terms (Wood, 2011).

During this second stage, the basis dimension was specified at a level sufficiently high to avoid restricting the flexibility of the smooth terms. In accordance with methodological recommendations for GAMs, efforts were made to ensure that the estimated EDF values remained sufficiently below the maximum limit imposed by k , thereby avoiding situations in which EDF values approached the basis dimension too closely. Whenever necessary, progressively larger values of k were considered to ensure that the complexity of the smooth functions was determined by the smoothing parameters estimated by REML rather than by limitations imposed by the basis dimension.

Once the models had been estimated using REML, the focus of the analysis shifted to the statistical significance of the included terms. A significance level of 10% was adopted. An iterative model simplification procedure was therefore conducted, whereby non-significant terms were successively removed. After each removal, the model was re-estimated, and the model simplification procedure was repeated until a final specification containing only statistically significant variables was obtained.

After the final models had been defined, their predictive performance was evaluated using a 10-fold cross-validation procedure. This approach allowed the assessment of model performance on data not used during estimation, thereby providing a more robust measure of its generalization ability.

For this purpose, the dataset was randomly divided into ten subsets of approximately equal size. In each iteration, nine subsets were used for model estimation and the remaining subset was used for testing. This process was repeated ten times, ensuring that every observation was used once for validation and nine times for estimation.

At each iteration, the model was re-estimated using the same previously selected specification, maintaining both the REML estimation method and the parameter $\gamma = 1.5$. Predictions generated for the test subset were compared with the observed values of the response variable, and two predictive performance metrics were calculated: Mean Squared Error (MSE) and Root Mean Squared Error (RMSE).

The metrics were subsequently aggregated by taking the average of the results obtained across the ten iterations. Additionally, to facilitate interpretation of the magnitude of prediction error, a relative RMSE was calculated by dividing the RMSE by the observed range of the response variable (the difference between the maximum and minimum values). This measure was also expressed as a percentage, allowing the predictive error of the model to be evaluated relative to the total variability observed in the data.

The use of cross-validation therefore complemented the statistical evaluation of the models with an assessment of their predictive performance, providing additional evidence regarding the robustness and generalizability of the relationships identified.

4 RESULTS

In this section, we estimate the dependent variables reported in Table II, namely Tariffs, BoCP, and Indemnities, using the climatic predictors listed in Table I. As previously noted, this analysis extends the work developed by Flora (2022), applying GAMs as described in the methodology section.

The estimations were carried out using distinct initial model specifications for each dependent variable. Table III summarizes the climatic predictors included at the starting point of the modelling process. These initial specifications were defined in accordance with the modelling strategy adopted by Flora (2022).

TABLE III: Initial model specifications by dependent variable

Dependent variable	No. of predictors	Initial climatic specification
<i>Indemnities</i>	11	Frequency and extreme indicators for precipitation (<i>DAT</i> and <i>Max</i> for <i>Rtotal</i>), and frequency and extreme indicators for the remaining climatic dimensions (<i>DAT</i> , <i>Min</i> , and <i>Max</i> for <i>Tmin</i> , <i>Tmax</i> , and <i>Wspeed</i>).
<i>BoCP</i>	20	Frequency and distributional indicators for precipitation (<i>DAT</i> and <i>Trd</i> for <i>Rtotal</i>), together with frequency, extreme, and distributional indicators (<i>DAT</i> , <i>DUT</i> , <i>Min</i> , <i>Max</i> , <i>Fst</i> , and <i>Trd</i>) for <i>Tmin</i> , <i>Tmax</i> , and <i>Wspeed</i> .
<i>Tariffs</i>	14	Frequency and maximum precipitation indicators (<i>DAT</i> and <i>Max</i> for <i>Rtotal</i>), and frequency and extreme indicators (<i>DAT</i> , <i>DUT</i> , <i>Min</i> , and <i>Max</i>) for <i>Tmin</i> , <i>Tmax</i> , and <i>Wspeed</i> .

The results are organized by dependent variable and crop type, and are further disaggregated by tariff region (A–E). Table IV reports the percentage of deviance explained for each model, considering three crop classifications: all crops, vineyard, and all crops except vineyard. This structure allows for a systematic comparison of model performance across regions and crop groups.

TABLE IV: Deviance explained (%) by dependent variable, crop type, and tariff region.

Dependent Variable	Crop type	A	B	C	D	E
BoCP	All except vineyard	91.8	89.6	83.4	94.8	90.1
	Vineyard	92.1	94.0	59.7	–	76.6
	All	77.3	83.2	76.0	83.9	85.5
Tariffs	All except vineyard	90.5	65.7	16.5	–	–
	Vineyard	–	82.6	–	–	–
	All	38.2	47.9	–	–	–
Indemnities	All except vineyard	–	–	–	–	–
	Vineyard	15.5	–	–	–	–
	All	–	12.0	5.31	0.379	2.55

The absence of results for certain regions and crop types in Table IV reflects the two-stage modelling strategy adopted in this study. Initially, 45 possible models were considered, resulting from the cross-combination of the three dependent variables, three crop classifications, and five tariff regions. For regions C, D and E, the higher volume of observations and the inherent complexity may have posed significant challenges for the estimation process. This increased data volume potentially contributed to complex residual structures, which might have hindered the models' ability to pass the preliminary diagnostic phase mentioned in the methodology.

The results indicate that model performance differs across dependent variables, crop types, and tariff regions, with BoCP exhibiting higher explained deviance than Tariffs and Indemnities. Region C provides a particularly insightful case when comparing crop types within the BoCP specification. While the models estimated for all crops and all except vineyard exhibit relatively strong explanatory power (76% and 83.4%, respectively), the corresponding model for vineyard shows a weaker fit, explaining 59.7% of the deviance. This difference in performance is also reflected in model complexity, as shown by the number of statistically significant variables retained in each final model (see Figures 21-23 in Appendix A). The vineyard model includes 7 significant predictors, whereas the all crops except vineyard and all crops specifications retain 16 and 17, respectively. This suggests that, in tariff region C, BoCP in general responds to a wider set of weather conditions, while the viticulture sector appears to be also driven by additional factors not included in the model.

In contrast, the indemnity models performed poorly, suggesting that indemnity payments are only weakly associated with the climatic variables considered, as they also depend on administrative rules, insurance contracts, and payment practices. Moreover, aggregating indemnity payments across insurance companies adds heterogeneity and makes it harder to identify a clear climatic pattern. In addition to using a GAM with a Gaussian family, we fitted the GAM using a Gamma family with a log link function to assess whether a more suitable response distribution improved model performance. This specification is often more appropriate for indemnity data, as such payments are strictly positive, and typically exhibit a right-skewed distribution (Goldburd et al., 2016). Nevertheless, the results remained poor.

The high explained deviance observed for some BoCP and Tariffs specifications may suggest the presence of overfitting. To ensure the robustness of the results, different steps of the methodology were implemented. Firstly, the use of a conservative penalty term ($\gamma = 1.5$) and a 10-fold cross-validation procedure were implemented to mitigate this risk. The results presented in Table V, which reports the mean relative RMSE (%) of the

10-fold cross validation, confirm that the models exhibit limited prediction error relative to the total variability of the data. Consequently, there is no concerning evidence of overfitting.

The results of the 10-fold cross-validation are reported only for the BoCP and Tariffs models, as these specifications achieved satisfactory statistical performance. For completeness, the Appendix A and Appendix B also presents the cross-validation results for the specifications including lagged climatic variables. The reported metrics include the fold identifier (*Fold*), mean squared error (*MSE*), root mean squared error (*RMSE*), relative RMSE (*RMSE_rel*), and relative RMSE expressed as a percentage (*RMSE_rel_pct*).

TABLE V: Mean relative RMSE (%) from 10-fold cross-validation by dependent variable, crop type and tariff region.

Dependent Variable	Crop type	A	B	C	D	E
BoCP	All except Vineyard	7.27	11.59	9.33	18.26	4.15
	Vineyard	15.38	15.95	15.94	–	14.66
	All	12.25	11.77	8.24	10.89	5.37
Tariffs	All except Vineyard	6.07	10.59	–	–	–
	Vineyard	–	11.91	–	–	–
	All	13.85	10.03	–	–	–

We now look at particular BoCP models that illustrate some of the main findings of the analysis. We begin with the BoCP model for the all except vineyard crop type in region E, as it explains a high share of the variance (90.1%) and achieves the lowest mean relative RMSE (5.37%) in the 10-fold cross-validation.

```

Family: gaussian
Link function: identity

Formula:
Bonus_over_Comercial_Prize ~ s(Days_above_threshold_Rtotal, k = 12) +
  s(trd_qtl_Rtotal_year, k = 12) + s(Days_above_threshold_Tmin,
  k = 12) + s(Days_under_threshold_Tmin, k = 12) + s(min_Tmin,
  k = 12) + s(max_Tmin, k = 12) + s(fst_qtl_Tmin_year, k = 12) +
  s(trd_qtl_Tmin_year, k = 12) + s(Days_above_threshold_Tmax,
  k = 12) + s(Days_under_threshold_Tmax, k = 12) + s(min_Tmax,
  k = 12) + s(max_Tmax, k = 12) + s(trd_qtl_Tmax_year, k = 12) +
  s(Days_above_threshold_wspped, k = 12) + s(Days_under_threshold_wspped,
  k = 12) + s(min_wspped, k = 12) + s(max_wspped, k = 12) +
  s(fst_qtl_wspped_year, k = 12) + s(trd_qtl_wspped_year, k = 12)

Parametric coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.62731    0.00089   704.8   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
              edf Ref.df      F    p-value
s(Days_above_threshold_Rtotal)  7.026  7.706 24.659 < 2e-16 ***
s(trd_qtl_Rtotal_year)          8.591  9.074 17.002 < 2e-16 ***
s(Days_above_threshold_Tmin)    9.970 10.307 13.785 < 2e-16 ***
s(Days_under_threshold_Tmin)    7.460  8.070 10.393 < 2e-16 ***
s(min_Tmin)                    6.513  7.055 19.145 < 2e-16 ***
s(max_Tmin)                    7.707  8.296 16.228 < 2e-16 ***
s(fst_qtl_Tmin_year)           9.568  9.870  9.220 < 2e-16 ***
s(trd_qtl_Tmin_year)           8.946  9.370 17.955 < 2e-16 ***
s(Days_above_threshold_Tmax)    3.127  3.577  7.412 3.28e-05 ***
s(Days_under_threshold_Tmax)    7.793  8.329 14.840 < 2e-16 ***
s(min_Tmax)                    6.586  7.119 15.587 < 2e-16 ***
s(max_Tmax)                    9.733 10.116 50.474 < 2e-16 ***
s(trd_qtl_Tmax_year)           6.861  7.431  8.252 < 2e-16 ***
s(Days_above_threshold_wspped)  9.754 10.140 13.279 < 2e-16 ***
s(Days_under_threshold_wspped) 10.092 10.397 29.588 < 2e-16 ***
s(min_wspped)                  5.448  6.036 21.074 < 2e-16 ***
s(max_wspped)                  3.958  4.445  8.137 1.06e-06 ***
s(fst_qtl_wspped_year)         8.033  8.649 27.904 < 2e-16 ***
s(trd_qtl_wspped_year)         7.045  7.770  9.613 < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.889 Deviance explained = 90.1%
-REML = -1361.3 Scale est. = 0.0010661 n = 1346

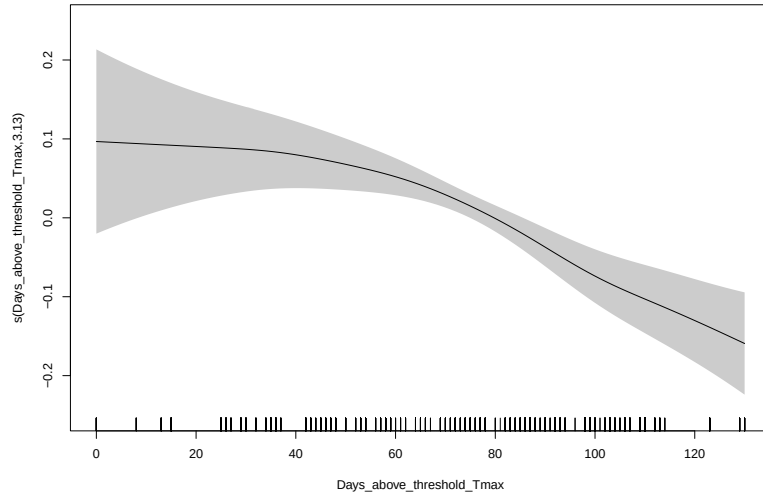
```

FIGURE 10: GAM results for the BoCP specification excluding vineyard crops in Region E.

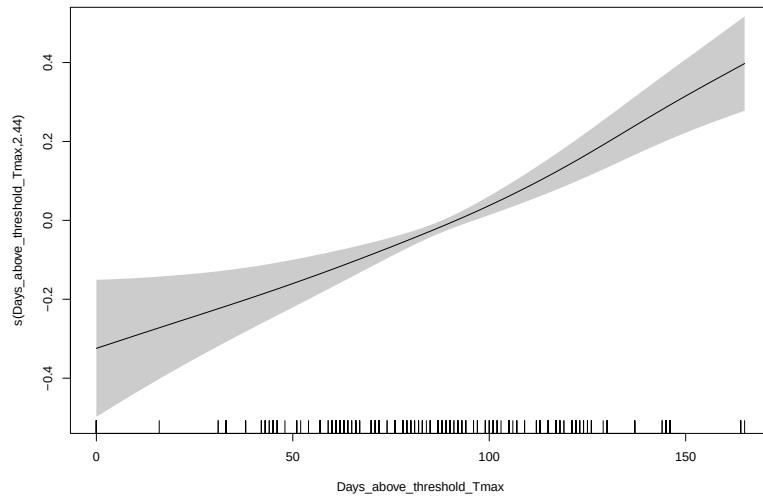
Figure 10 presents the estimated GAM results, reporting the EDF values, Reference Degrees of Freedom (Ref.df), test statistic, and p-value for each smooth term. The EDF indicates the complexity of the smooth term (EDF = 1 denotes a linear effect, whereas EDF > 1 indicates a non-linear effect), while the Ref.df is used as the reference for the significance tests. The p-values identify which terms contribute statistically to explaining BoCP. The global fit measures (R-squared and deviance explained) indicate the proportion of variability explained by the model.

As illustrated in Figure 10, nearly all variables in the initial model are statistically significant, confirming their relevance for explaining BoCP. Notably, EDF values are above one for all smooth terms, confirming the presence of markedly non-linear effects and a considerable degree of flexibility within the estimated relationships. Figure 11 shows that BoCP responds differently to the number of days with maximum temperatures above the usual level (i.e., above the third quartile of the maximum temperature distribution), and

the effect remains statistically significant in both regions. In region E, the effect follows a non-monotonic pattern, with an initial positive association that gradually levels off and becomes negative as the number of heat days increases. In contrast, region D exhibits the opposite pattern, with an initially negative effect that becomes positive at higher levels of exposure. The shaded area around the line represents the 95% confidence interval of the estimated smooth function, which tends to be narrower in regions with a higher concentration of observations, as indicated by the small vertical tick marks displayed along the lower margin of the plot.



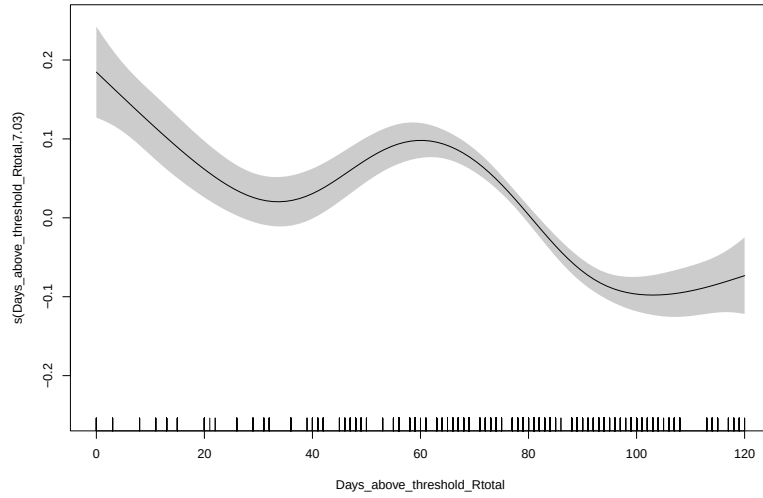
(a) Smooth Effect of Days_above_threshold_Tmax in Region E



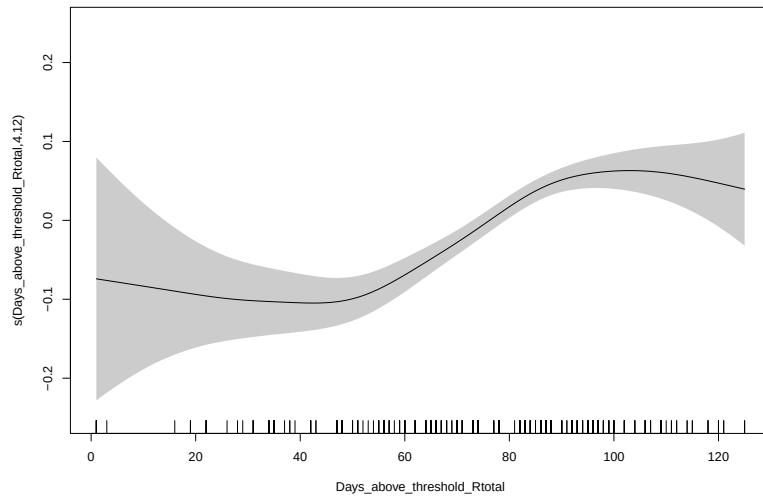
(b) Smooth Effect of Days_above_threshold_Tmax in Region D

FIGURE 11: Estimated smooth effect of Days_above_threshold_Tmax on BoCP in the *all except vineyard* specification for region E (panel (a)) and region D (panel (b)).

A similar behaviour is observed in Figure 12 for the *Days_above_threshold_Rtotal* variable. In region E, the relationship between the BoCP and the number of days with above usual rainfall is non-monotonic, initially decreasing, then increasing over intermediate values, before declining again at higher levels. In region D, the effect shows a more sustained increase across the mid-range, reaching a peak at higher values and then slightly declining towards the upper end of the distribution.



(a) Smooth Effect of Days_above_threshold_Rtotal in Region E



(b) Smooth Effect of Days_above_threshold_Rtotal in Region D

FIGURE 12: Estimated smooth effect of Days_above_threshold_Rtotal on BoCP in the *all except vineyard* specification for region E (panel(a)) and region D (panel(b)).

Tariff results are highly sensitive to crop aggregation, with model performance varying substantially across crop classifications. In tariff region A, this difference is particularly pronounced, as the deviance explained decreases by more than 50 percentage points when moving from the *all except vineyard* specification to the *all crops* specification.

Figure 13 illustrates that the inclusion of vineyard changes the set of variables in the

model. In the all crops specification, tariffs are primarily associated with the frequency of weather conditions falling outside the interquartile range, specifically the number of days that are unusually wet, cold, or hot. This pattern is also observed in Figure 14 for tariff region B in the Tariffs model, suggesting that aggregating vineyards with the other crops leads the model to retain threshold-based climatic indicators as the main explanatory variables.

```
Family: gaussian
Link function: identity

Formula:
Tariffs ~ s(max.Rtotal., k = 6) + s(Days_above_threshold_Tmin,
k = 6) + s(Days_under_threshold_Tmin, k = 6) + s(Days_above_threshold_Tmax,
k = 6) + s(Days_under_threshold_Tmax, k = 6) + s(min.Tmax.,
k = 6) + s(Days_above_threshold_wspped, k = 6) + s(Days_under_threshold_wspped,
k = 6) + s(min.wspped., k = 6) + s(max.wspped., k = 6)

Parametric coefficients:
      Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.036449   0.000273   133.5   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
              edf Ref.df      F p-value
s(max.Rtotal.)      2.483  2.918  5.826 0.001802 **
s(Days_above_threshold_Tmin) 1.000  1.000 17.068 8.90e-05 ***
s(Days_under_threshold_Tmin) 2.827  3.311 11.894 6.43e-07 ***
s(Days_above_threshold_Tmax) 1.000  1.000 21.148 1.62e-05 ***
s(Days_under_threshold_Tmax) 4.229  4.569 11.803 < 2e-16 ***
s(min.Tmax.)         1.000  1.000 15.484 0.000178 ***
s(Days_above_threshold_wspped) 3.371  3.908  7.729 4.67e-05 ***
s(Days_under_threshold_wspped) 1.000  1.000 18.129 5.69e-05 ***
s(min.wspped.)       1.149  1.246 13.652 0.000112 ***
s(max.wspped.)       3.584  4.097 12.105 < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.879   Deviance explained = 90.5%
-REML = -209.63   Scale est. = 7.6002e-06   n = 102
```

(a) All except vineyard

```
Family: gaussian
Link function: identity

Formula:
Tariffs ~ s(Days_above_threshold_Rtotal, k = 7) + s(Days_above_threshold_Tmin,
k = 7) + s(Days_under_threshold_Tmin, k = 7) + s(Days_under_threshold_Tmax,
k = 7) + s(max.wspped., k = 7)

Parametric coefficients:
      Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.0318699   0.0007188   44.34   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
              edf Ref.df      F p-value
s(Days_above_threshold_Rtotal) 2.226  2.757  6.079 0.00113 **
s(Days_above_threshold_Tmin)  1.000  1.000  7.227 0.00810 **
s(Days_under_threshold_Tmin)  1.040  1.077  3.043 0.08716 .
s(Days_under_threshold_Tmax)  1.000  1.000 10.108 0.00184 **
s(max.wspped.)               2.815  3.480  4.850 0.00209 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.344   Deviance explained = 38.2%
-REML = -274.53   Scale est. = 7.286e-05   n = 141
```

(b) All crops

FIGURE 13: GAM results for the Tariffs specification in Region A


```

Family: gaussian
Link function: identity

Formula:
Tariffs ~ s(Days_above_threshold_Rtotal, k = 7) + s(Days_under_threshold_Tmin,
k = 7) + s(min.Tmin., k = 7) + s(Days_above_threshold_Tmax,
k = 7) + s(min.Tmax., k = 7) + s(max.Tmax., k = 7) + s(Days_above_threshold_wspeak,
k = 7) + s(Days_under_threshold_wspeak, k = 7) + s(min.wspeak.,
k = 7) + s(max.wspeak., k = 7)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.0450939  0.0007292   61.84  <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
            edf Ref.df      F p-value
s(Days_above_threshold_Rtotal) 1.548  1.890 17.698 1.47e-05 ***
s(Days_under_threshold_Tmin)   1.727  2.146  6.043 0.002086 **
s(min.Tmin.)                   2.481  3.048  7.225 0.000103 ***
s(Days_above_threshold_Tmax)   4.116  4.852  5.629 7.52e-05 ***
s(min.Tmax.)                   3.524  4.214  4.862 0.001088 **
s(max.Tmax.)                   1.000  1.001 15.613 0.000104 ***
s(Days_above_threshold_wspeak) 3.902  4.493  5.105 0.000503 ***
s(Days_under_threshold_wspeak) 2.595  3.224  5.161 0.001550 **
s(min.wspeak.)                 2.141  2.577  2.508 0.087483 .
s(max.wspeak.)                 4.673  5.074  9.456  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.614 Deviance explained = 65.7%
-REML = -415.39 Scale est. = 0.0001324 n = 249

```

(a) All except vineyard

```

Family: gaussian
Link function: identity

Formula:
Tariffs ~ s(Days_above_threshold_Rtotal, k = 5) + s(Days_above_threshold_Tmax,
k = 5) + s(max.Tmax., k = 5) + s(Days_above_threshold_wspeak,
k = 5) + s(Days_under_threshold_wspeak, k = 5) + s(max.wspeak.,
k = 5)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.0428464  0.0008253   51.91  <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
            edf Ref.df      F p-value
s(Days_above_threshold_Rtotal) 2.412  2.951  4.285 0.003844 **
s(Days_above_threshold_Tmax)   3.705  3.936 15.470  < 2e-16 ***
s(max.Tmax.)                   1.552  1.885 10.360 5.82e-05 ***
s(Days_above_threshold_wspeak) 2.877  3.346  6.960 0.000306 ***
s(Days_under_threshold_wspeak) 2.392  2.913 11.918 7.02e-07 ***
s(max.wspeak.)                 1.001  1.001 10.487 0.001346 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.452 Deviance explained = 47.9%
-REML = -487.04 Scale est. = 0.00019277 n = 283

```

(b) All crops

FIGURE 14: GAM results for the Tariffs specification in Region B

Given that Tariffs are set a priori based on historical meteorological conditions, the Tariffs models are also estimated using one-year lagged climatic variables instead of contemporaneous climatic variables. This specification uses the same predictors, differing only in the one-year lag applied to the climatic variables. The use of lagged climatic information is consistent with the findings of Nadolnyak and Hartarska (2012), who show that climate variability explains most disaster payments, supporting the use of historical climate data in agricultural insurance pricing.

Table VI presents the estimation results and the corresponding 10-fold cross-validation

performance for the Tariffs models using lagged climatic variables, following the same structure adopted in Table IV and Table V.

TABLE VI: Deviance explained (%) and Mean Relative RMSE (%) from 10-fold cross-validation for the Tariffs models using lagged climatic variables.

Measure	Crop type	A	B	C	D	E
Deviance explained (%)	All except Vineyard	88.9	99.6 ⁶	–	24.7	–
	Vineyard	–	–	–	54.8	65.4
	All	75.6	96.3	41.7	–	–
Mean Relative RMSE (%)	All except Vineyard	5.89	20.68 ⁶	–	–	–
	Vineyard	–	–	–	15.36	15.14
	All	9.19	2.70	16.02	–	–

For Tariffs in tariff region A and B, under the all crops specification, the inclusion of lagged climatic variables leads to a clear improvement in model fit, suggesting that past weather conditions are more informative than contemporaneous indicators alone. Overall, tariff region A shows a similar level of complexity in the final model without lagged variables and in the final model with lagged variables, as both retain a comparable number of predictors. In both specifications, *Days_above_threshold_Tmin* and *Days_under_threshold_Tmin* are consistently selected, indicating a common climatic core associated with tariffs in this region. By contrast, tariff region B displays a clearer increase in complexity in the lagged specification, as additional variables become relevant, namely *Days_above_threshold_Tmin*, *Days_under_threshold_Tmin*, *max_Rtotal*, *min_Tmin* and *min_Tmax*. This points to a stronger role for lagged climatic effects in region B.

Having completed this analysis, a robustness check for temporal autocorrelation was conducted. Specifically, the variable *Year* was included in the set of predictors to account for any intrinsic temporal structures or long-term trends that might bias the estimated climatic effects. The estimation process was refitted for the dependent variables following the previously established methodology. The results of this analysis are described in Table VII. Furthermore, the detailed model summaries and the 10-fold cross-validation results for these specifications are reported in the Appendix C.

⁶The corresponding cross-validation results for this specific region and crop type show highly uneven performance across folds. This instability suggests that the results should be interpreted with caution, as they may indicate potential overfitting. Detailed fold-specific metrics are available in the Appendix B.

TABLE VII: Deviance explained (%) after including the variable *Year*, by dependent variable, crop type, and tariff region.

Dependent Variable	Crop type	A	B	C	D	E
BoCP	All except Vineyard	92.9	84.6	86.9	93.7	89.0
	Vineyard	–	–	77.7	–	93.4
	All	75.0	87.8	80.4	81.8	83.9
Tariffs	All except Vineyard	90.3	64.0	–	–	–
	Vineyard	–	90.5	–	–	–
	All	46.3	53.9	–	30.8	–
Tariffs (lagged)	All except Vineyard	89.8	99.6 ⁷	–	30.8	–
	Vineyard	–	–	–	59.4	61.4
	All	–	96.9	–	–	–
Indemnities	All except Vineyard	–	–	–	–	–
	Vineyard	–	–	–	–	2.36
	All	–	–	6.08	–	2.62

The results are omitted in Table VII when: (i) the model failed to pass the initial diagnostic assessment stage, or (ii) if the variable *Year* did not prove to be a statistically significant predictor. The results corroborate the main findings reported in Table IV and Table VI, indicating that the models’ explanatory power remains stable. For the BoCP and Tariffs specifications, the deviance explained exhibits only marginal changes after the inclusion of the variable *Year*. The only notable exception is in the BoCP specification for vineyard in tariff region E, where the deviance explained increases by approximately 17 percentage points. In contrast, the Indemnities models consistently demonstrate poor performance across all tables.

The similarity of these results to those reported in Table IV and Table VI suggests that no significant time-varying factors have explanatory power, indicating that the estimated climatic effects are likely not driven by unobserved temporal patterns.

⁷The corresponding cross-validation results for this specific region and crop type show highly uneven performance across folds. This instability suggests that the results should be interpreted with caution, as they may indicate potential overfitting. Detailed fold-specific metrics are available in the Appendix C.

5 CONCLUSION

This dissertation analyzed the relationship between climatic conditions and the Portuguese agricultural insurance sector using GAMs. Building on Flora (2022), it assessed whether flexible functional forms better capture the effects of climatic variables on three insurance outcomes: tariffs, the bonus over the commercial prize, and indemnities.

The descriptive analysis showed that the Portuguese agricultural insurance market has been facing increasing climatic and financial pressures. Between 1997 and 2023, insured capital expanded substantially in recent years, indemnities increased, and the loss ratio exhibited an upward trend. At the same time, the relative contribution of public support declined, implying a growing financial burden for farmers.

The empirical results confirm the relevance of non-linear climatic effects in explaining agricultural insurance outcomes and public support. Overall, the GAMs achieved high explanatory power for BoCP and, in several cases, for Tariffs, while the effects of climatic variables varied across tariff regions and crop groups. Moreover, including lagged climatic variables improved the performance of some Tariffs models, suggesting that insurance pricing incorporates information from recent climatic conditions.

In contrast, climatic variables explained indemnities substantially less well than insurance pricing and public support. BoCP and Tariffs models achieved high explained deviance and satisfactory predictive performance under 10-fold cross-validation, whereas Indemnities models consistently showed low explanatory power. These findings suggest that indemnity payments are influenced by factors beyond the climatic variables considered in this study, such as administrative rules, insurance contracts, and payment practices.

Overall, these results demonstrate that climatic conditions are important determinants of the Portuguese agricultural insurance system and that GAMs provide an effective framework for capturing their non-linear effects.

As this dissertation directly extends the research conducted by Flora (2022), a comparative analysis was performed to evaluate the gains in explanatory power provided by GAMs relative to linear regression. The results of the linear specifications, corresponding to the final GAM variables, are summarized in Table VIII.

TABLE VIII: R^2 (%) of linear regression models corresponding to the final GAM specifications, by dependent variable, crop type, and tariff region.

Dependent Variable	Crop type	A	B	C	D	E
BoCP	All except vineyard	47.26	41.90	36.31	40.59	38.23
	Vineyard	43.69	65.29	42.57	–	45.63
	All	50.75	21.70	36.56	39.98	38.26
Tariffs	All except vineyard	39.24	37.16	5.06	–	–
	Vineyard	–	36.00	–	–	–
	All	21.21	36.58	–	–	–
Tariffs (Lagged)	All except vineyard	62.27	50.56	–	13.19	–
	Vineyard	–	–	–	30.59	20.47
	All	23.82	38.68	30.63	–	–
Indemnities	All except vineyard	–	–	–	–	–
	Vineyard	0.0121	–	–	–	–
	All	–	2.06	1.145	0.03941	1.108

The comparison shows that, although the linear models lead to similar conclusions, the GAM approach consistently provides better overall performance by explaining a substantially larger proportion of the variability in the data. This improvement is particularly evident for BoCP and Tariffs, with the corresponding GAMs frequently achieving explained deviance above 80%, compared with 21.7% to 65.3% explained deviance for the respective linear models. These findings indicate that modelling the relationship between climate and the Portuguese agricultural insurance system as purely linear is not sufficient. For Indemnities, the consistently low explanatory power of both linear and GAM specifications reinforces the conclusion that indemnity payments are primarily driven by non-climatic factors.

Future research could extend this analysis by moving to a finer level of granularity, allowing the application of high-dimensional modelling techniques, such as neural networks and other machine learning methods. These approaches could better capture the complex relationships between climate and agricultural insurance, particularly when using larger and more disaggregated datasets. Furthermore, their application to predictive modelling would be of significant value for both policymakers and insurance companies, supporting more effective risk assessment and strategic decision-making. Finally, future studies could also incorporate non-climatic factors to explain the variation not captured

by climate variables alone.

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A MODELS ESTIMATION IN TABLE IV

Family: gaussian
Link function: identity

Formula:

Bonus_over_Comercial_Prize ~ s(Days_above_threshold_Rtotal, k = 5) +
s(trd_qtl_Rtotal_year, k = 5) + s(min_Tmin, k = 5) + s(fst_qtl_Tmin_year,
k = 5) + s(Days_under_threshold_Tmax, k = 5) + s(min_Tmax,
k = 5) + s(trd_qtl_Tmax_year, k = 5) + s(Days_above_threshold_wspeed,
k = 5) + s(min_wspeed, k = 5) + s(max_wspeed, k = 5) + s(trd_qtl_wspeed_year,
k = 5)

Parametric coefficients:

Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.537655 0.002274 236.4 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Days_above_threshold_Rtotal)	1.000	1.000	10.082	0.00213 **
s(trd_qtl_Rtotal_year)	2.109	2.524	10.712	0.00015 ***
s(min_Tmin)	1.000	1.000	82.539	< 2e-16 ***
s(fst_qtl_Tmin_year)	1.000	1.000	7.065	0.00949 **
s(Days_under_threshold_Tmax)	1.000	1.000	109.189	< 2e-16 ***
s(min_Tmax)	1.000	1.000	30.854	4.79e-07 ***
s(trd_qtl_Tmax_year)	3.220	3.619	12.909	3.37e-07 ***
s(Days_above_threshold_wspeed)	3.244	3.479	40.092	< 2e-16 ***
s(min_wspeed)	2.252	2.528	28.741	< 2e-16 ***
s(max_wspeed)	2.201	2.617	5.469	0.00294 **
s(trd_qtl_wspeed_year)	2.931	3.205	6.890	0.03221 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.897 Deviance explained = 91.8%
-REML = -87.431 Scale est. = 0.00052756 n = 102

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	0.0003460595	0.01860268	0.04247589	4.247589
2	2	0.0009857766	0.03139708	0.07168963	7.168963
3	3	0.0002020308	0.01421375	0.03245457	3.245457
4	4	0.0021354714	0.04621116	0.10551495	10.551495
5	5	0.0029534591	0.05434574	0.12408880	12.408880
6	6	0.0004004100	0.02001025	0.04568983	4.568983
7	7	0.0016610570	0.04075607	0.09305921	9.305921
8	8	0.0014392174	0.03793702	0.08662242	8.662242
9	9	0.0012012925	0.03465967	0.07913917	7.913917
10	10	0.0004119586	0.02029676	0.04634404	4.634404

(b)

FIGURE 15: GAM (a) and 10-fold cross-validation (b) results for the BoCP specification in tariff region A: All except vineyard.

Family: gaussian
Link function: identity

Formula:

Bonus_over_Comercial_Prize ~ s(Days_above_threshold_Rtotal, k = 3) +
s(Days_above_threshold_Tmin, k = 3) + s(Days_under_threshold_Tmin,
k = 3) + s(max_Tmin, k = 3) + s(fst_qtl_Tmin_year, k = 3) +
s(Days_above_threshold_Tmax, k = 3) + s(Days_under_threshold_Tmax,
k = 3) + s(min_Tmax, k = 3) + s(max_Tmax, k = 3) + s(trd_qtl_Tmax_year,
k = 3) + s(Days_under_threshold_wspeed, k = 3) + s(min_wspeed,
k = 3) + s(max_wspeed, k = 3)

Parametric coefficients:

Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.635795 0.006187 102.8 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Days_above_threshold_Rtotal)	1.826	1.969	15.44	5.32e-05 ***
s(Days_above_threshold_Tmin)	1.954	1.997	32.93	5.26e-07 ***
s(Days_under_threshold_Tmin)	1.000	1.000	85.46	< 2e-16 ***
s(max_Tmin)	1.000	1.000	14.28	0.000792 ***
s(fst_qtl_Tmin_year)	1.000	1.000	70.83	< 2e-16 ***
s(Days_above_threshold_Tmax)	1.000	1.000	40.43	1.78e-06 ***
s(Days_under_threshold_Tmax)	1.000	1.000	65.20	< 2e-16 ***
s(min_Tmax)	1.000	1.000	18.22	0.000218 ***
s(max_Tmax)	1.000	1.000	49.92	< 2e-16 ***
s(trd_qtl_Tmax_year)	1.000	1.000	15.82	0.000471 ***
s(Days_under_threshold_wspeed)	1.000	1.000	15.79	0.000475 ***
s(min_wspeed)	1.869	1.983	20.80	3.28e-06 ***
s(max_wspeed)	1.961	1.998	41.21	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.874 Deviance explained = 92.1%
-REML = 2.0122 Scale est. = 0.0017225 n = 45

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	0.0076434798	0.08742700	0.18762881	18.762881
2	2	0.0053715870	0.07329111	0.15729151	15.729151
3	3	0.0017773504	0.04215863	0.09047748	9.047748
4	4	0.0007309603	0.02703628	0.05802309	5.802309
5	5	0.0044068120	0.06638382	0.14246764	14.246764
6	6	0.0118091757	0.10867003	0.23321891	23.321891
7	7	0.0033085981	0.05752042	0.12344570	12.344570
8	8	0.0101943850	0.10096725	0.21668781	21.668781
9	9	0.0124459093	0.11156124	0.23942378	23.942378
10	10	0.0017244425	0.04152641	0.08912065	8.912065

(b)

FIGURE 16: GAM (a) and 10-fold cross-validation (b) results for the BoCP specification in tariff region A: Vineyard.

Family: gaussian
Link function: identity

Formula:
Bonus_over_Comercial_Prize ~ s(Days_above_threshold_Rtotal, k = 6) +
s(trd_qtl_Rtotal_year, k = 6) + s(min_Tmin, k = 6) + s(max_Tmin,
k = 6) + s(Days_above_threshold_Tmax, k = 6) + s(Days_under_threshold_Tmax,
k = 6) + s(min_Tmax, k = 6) + s(trd_qtl_Tmax_year, k = 6) +
s(Days_above_threshold_wspped, k = 6) + s(Days_under_threshold_wspped,
k = 6) + s(min_wspped, k = 6) + s(max_wspped, k = 6) + s(trd_qtl_wspped_year,
k = 6)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.561040 0.004091 137.1 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Days_above_threshold_Rtotal)	1.000	1.001	70.399	< 2e-16 ***
s(trd_qtl_Rtotal_year)	1.000	1.000	4.560	0.034758 *
s(min_Tmin)	1.527	1.868	5.900	0.002680 **
s(max_Tmin)	1.000	1.000	6.880	0.009844 **
s(Days_above_threshold_Tmax)	4.064	4.555	17.323	< 2e-16 ***
s(Days_under_threshold_Tmax)	1.000	1.000	63.331	< 2e-16 ***
s(min_Tmax)	1.000	1.000	11.496	0.000945 ***
s(trd_qtl_Tmax_year)	1.000	1.000	8.535	0.004163 **
s(Days_above_threshold_wspped)	3.234	3.831	9.022	8.48e-06 ***
s(Days_under_threshold_wspped)	1.000	1.000	7.998	0.005489 **
s(min_wspped)	1.000	1.000	44.384	< 2e-16 ***
s(max_wspped)	2.569	3.097	4.854	0.002897 **
s(trd_qtl_wspped_year)	1.000	1.000	5.289	0.023194 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.734 Deviance explained = 77.3%
-REML = -84.141 Scale est. = 0.0023597 n = 141

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	0.007779516	0.08820156	0.18025198	18.025198
2	2	0.002855876	0.05344039	0.10921277	10.921277
3	3	0.001301358	0.03607434	0.07372285	7.372285
4	4	0.003957612	0.06290955	0.12856429	12.856429
5	5	0.010361283	0.10179039	0.20802261	20.802261
6	6	0.002831490	0.05321175	0.10874550	10.874550
7	7	0.003616929	0.06014091	0.12290618	12.290618
8	8	0.001846494	0.04297085	0.08781683	8.781683
9	9	0.002121822	0.04606324	0.09413654	9.413654
10	10	0.003025161	0.05500147	0.11240304	11.240304

(b)

FIGURE 17: GAM (a) and 10-fold cross-validation (b) results for the BoCP specification in tariff region A: All crops.

Family: gaussian
Link function: identity

Formula:
Bonus_over_Comercial_Prize ~ s(Days_above_threshold_Rtotal, k = 9) +
s(trd_qtl_Rtotal_year, k = 9) + s(Days_above_threshold_Tmin, k = 9) + s(Days_under_threshold_Tmin, k = 9) + s(min_Tmin, k = 9) + s(fst_qtl_Tmin_year, k = 9) + s(trd_qtl_Tmin_year, k = 9) + s(Days_above_threshold_Tmax, k = 9) + s(Days_under_threshold_Tmax, k = 9) + s(min_Tmax, k = 9) + s(max_Tmax, k = 9) + s(fst_qtl_Tmax_year, k = 9) + s(trd_qtl_Tmax_year, k = 9) + s(Days_above_threshold_wspped, k = 9) + s(Days_under_threshold_wspped, k = 9) + s(fst_qtl_wspped_year, k = 9) + s(trd_qtl_wspped_year, k = 9)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.573994 0.002152 266.8 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Days_above_threshold_Rtotal)	3.924	4.579	8.407	1.42e-06 ***
s(trd_qtl_Rtotal_year)	2.605	3.036	12.330	8.57e-07 ***
s(Days_above_threshold_Tmin)	6.873	7.139	15.462	< 2e-16 ***
s(Days_under_threshold_Tmin)	1.000	1.000	8.108	0.00488 **
s(min_Tmin)	3.661	4.203	8.119	4.06e-06 ***
s(fst_qtl_Tmin_year)	3.613	4.130	14.784	< 2e-16 ***
s(trd_qtl_Tmin_year)	4.502	5.063	17.951	< 2e-16 ***
s(Days_above_threshold_Tmax)	1.000	1.000	7.919	0.00540 **
s(Days_under_threshold_Tmax)	3.750	4.371	12.197	< 2e-16 ***
s(min_Tmax)	5.255	5.912	16.076	< 2e-16 ***
s(max_Tmax)	5.464	6.019	7.244	5.80e-07 ***
s(fst_qtl_Tmax_year)	1.000	1.000	55.859	< 2e-16 ***
s(trd_qtl_Tmax_year)	1.000	1.000	21.893	5.74e-06 ***
s(Days_above_threshold_wspped)	5.920	6.480	8.453	< 2e-16 ***
s(Days_under_threshold_wspped)	1.000	1.000	8.276	0.00446 **
s(max_wspped)	1.000	1.000	19.578	1.62e-05 ***
s(fst_qtl_wspped_year)	2.313	2.766	15.735	9.76e-07 ***
s(trd_qtl_wspped_year)	1.000	1.000	60.838	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.867 Deviance explained = 89.6%
-REML = -169.25 Scale est. = 0.0011527 n = 249

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	0.011995746	0.10952509	0.17502637	17.502637
2	2	0.004645517	0.06815803	0.10891981	10.891981
3	3	0.001711787	0.04137375	0.06611724	6.611724
4	4	0.004059394	0.06371338	0.10181704	10.181704
5	5	0.004264641	0.06530422	0.10435929	10.435929
6	6	0.001939395	0.04403857	0.07037575	7.037575
7	7	0.003258090	0.05707968	0.09121608	9.121608
8	8	0.001416782	0.03764016	0.06015079	6.015079
9	9	0.009038022	0.09506851	0.15192406	15.192406
10	10	0.006201409	0.07874902	0.12584473	12.584473

(b)

FIGURE 18: GAM (a) and 10-fold cross-validation (b) results for the BoCP specification in tariff region B: All except vineyard.

Family: gaussian
Link function: identity

Formula:
Bonus_over_comercial_Prize ~ s(Days_above_threshold_Rtotal, k = 3) +
s(trd_qtl_Rtotal_year, k = 3) + s(Days_above_threshold_Tmin,
k = 3) + s(max_Tmin, k = 3) + s(fst_qtl_Tmin_year, k = 3) +
s(trd_qtl_Tmin_year, k = 3) + s(Days_above_threshold_Tmax,
k = 3) + s(trd_qtl_Tmax_year, k = 3) + s(Days_above_threshold_wspeerd,
k = 3) + s(Days_under_threshold_wspeerd, k = 3) + s(fst_qtl_wspeerd_year,
k = 3) + s(trd_qtl_wspeerd_year, k = 3)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.64731 0.00583 111 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Days_above_threshold_Rtotal)	1.360	1.586	30.583	1.17e-06 ***
s(trd_qtl_Rtotal_year)	1.950	1.994	22.584	3.48e-06 ***
s(Days_above_threshold_Tmin)	1.000	1.000	15.447	0.000561 ***
s(max_Tmin)	1.000	1.000	8.680	0.006706 **
s(fst_qtl_Tmin_year)	1.000	1.000	3.567	0.070142 .
s(trd_qtl_Tmin_year)	1.000	1.000	11.982	0.001871 **
s(Days_above_threshold_Tmax)	1.000	1.000	21.075	0.000100 ***
s(trd_qtl_Tmax_year)	1.000	1.000	18.273	0.000229 ***
s(Days_above_threshold_wspeerd)	1.000	1.000	28.471	1.50e-05 ***
s(Days_under_threshold_wspeerd)	1.000	1.000	33.091	5.81e-06 ***
s(fst_qtl_wspeerd_year)	1.000	1.000	32.252	6.79e-06 ***
s(trd_qtl_wspeerd_year)	1.976	1.998	45.400	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq. (adj) = 0.906 Deviance explained = 94%
-REML = -3.2789 Scale est. = 0.0013935 n = 41

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	0.0012257738	0.03501105	0.09939449	9.939449
2	2	0.0009027065	0.03004507	0.08529635	8.529635
3	3	0.0056340585	0.07506037	0.21309233	21.309233
4	4	0.0020088722	0.04482044	0.12724282	12.724282
5	5	0.0039201332	0.06261097	0.17774916	17.774916
6	6	0.0045874976	0.06773107	0.19228485	19.228485
7	7	0.0027587915	0.05252420	0.14911337	14.911337
8	8	0.0017945842	0.04236253	0.12026495	12.026495
9	9	0.0117479479	0.10838795	0.30770755	30.770755
10	10	0.0018774186	0.04332919	0.12300923	12.300923

(b)

FIGURE 19: GAM (a) and 10-fold cross-validation (b) results for the BoCP specification in tariff region B: Vineyard.

Family: gaussian
Link function: identity

Formula:
Bonus_over_comercial_Prize ~ s(Days_above_threshold_Rtotal, k = 10) +
s(trd_qtl_Rtotal_year, k = 10) + s(min_Tmin, k = 10) + s(Days_above_threshold_Tmax,
k = 10) + s(Days_under_threshold_Tmax, k = 10) + s(min_Tmax,
k = 10) + s(max_Tmax, k = 10) + s(fst_qtl_Tmax_year, k = 10) +
s(trd_qtl_Tmax_year, k = 10) + s(Days_above_threshold_wspeerd,
k = 10) + s(Days_under_threshold_wspeerd, k = 10) + s(min_wspeerd,
k = 10) + s(max_wspeerd, k = 10) + s(fst_qtl_wspeerd_year,
k = 10) + s(trd_qtl_wspeerd_year, k = 10)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.583729 0.002733 213.6 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Days_above_threshold_Rtotal)	6.635	7.464	16.698	< 2e-16 ***
s(trd_qtl_Rtotal_year)	3.726	4.343	8.769	9.61e-07 ***
s(min_Tmin)	7.109	7.781	17.589	< 2e-16 ***
s(Days_above_threshold_Tmax)	8.297	8.730	12.482	< 2e-16 ***
s(Days_under_threshold_Tmax)	2.789	3.349	5.189	0.009659 **
s(min_Tmax)	6.381	7.209	8.770	< 2e-16 ***
s(max_Tmax)	3.510	4.191	9.474	9.42e-07 ***
s(fst_qtl_Tmax_year)	1.000	1.000	12.548	0.000483 ***
s(trd_qtl_Tmax_year)	4.832	5.816	5.620	2.25e-05 ***
s(Days_above_threshold_wspeerd)	1.110	1.190	6.314	0.008780 **
s(Days_under_threshold_wspeerd)	1.000	1.000	23.459	2.68e-06 ***
s(min_wspeerd)	7.698	8.414	12.812	< 2e-16 ***
s(max_wspeerd)	1.000	1.000	3.929	0.048673 *
s(fst_qtl_wspeerd_year)	1.000	1.000	13.769	0.000261 ***
s(trd_qtl_wspeerd_year)	1.000	1.000	15.682	0.000101 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

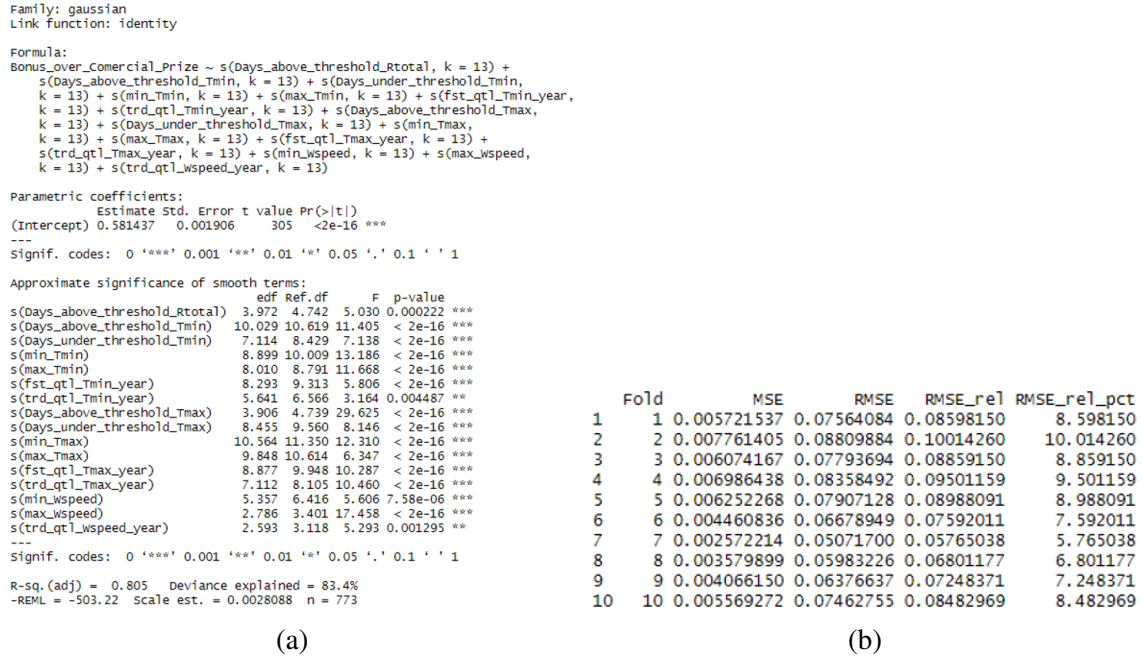
R-sq. (adj) = 0.789 Deviance explained = 83.2%
-REML = -161.17 Scale est. = 0.0021136 n = 283

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	0.002874407	0.05361350	0.08503619	8.503619
2	2	0.005182632	0.07199050	0.11418388	11.418388
3	3	0.012423271	0.11145973	0.17678589	17.678589
4	4	0.003174735	0.05634479	0.08936828	8.936828
5	5	0.005011126	0.07078931	0.11227868	11.227868
6	6	0.004381222	0.06619080	0.10498499	10.498499
7	7	0.004247775	0.06517496	0.10337378	10.337378
8	8	0.006501747	0.08063341	0.12789237	12.789237
9	9	0.011741938	0.10836022	0.17186977	17.186977
10	10	0.003314699	0.05757342	0.09131700	9.131700

(b)

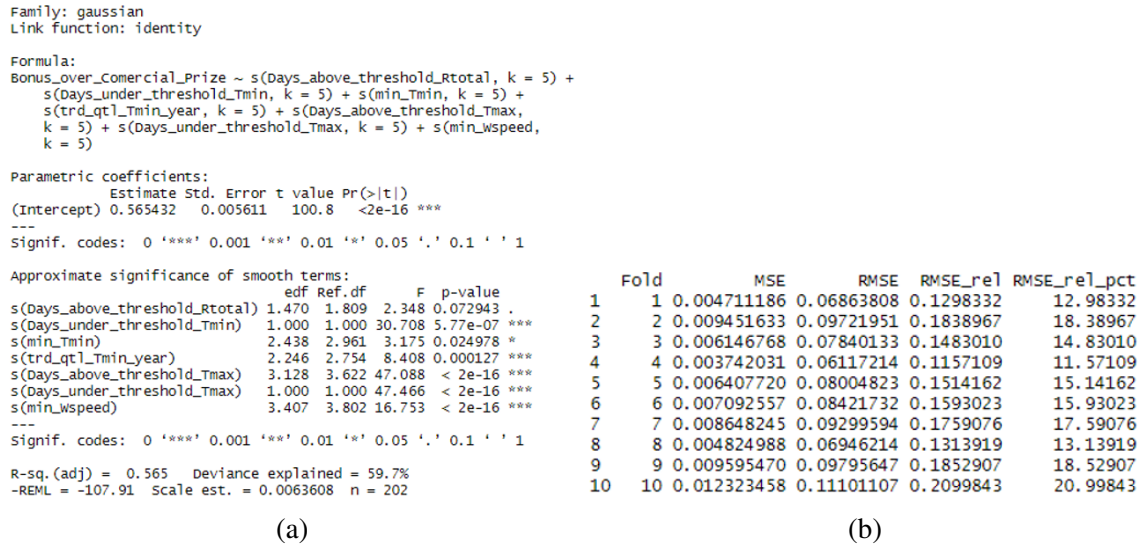
FIGURE 20: GAM (a) and 10-fold cross-validation (b) results for the BoCP specification in tariff region B: All crops.



(a)

(b)

FIGURE 21: GAM (a) and 10-fold cross-validation (b) results for the BoCP specification in tariff region C: All except vineyard.



(a)

(b)

FIGURE 22: GAM (a) and 10-fold cross-validation (b) results for the BoCP specification in tariff region C: Vineyard.

Family: gaussian
Link function: identity

Formula:
Bonus_over_comercial_Prize ~ s(Days_above_threshold_Rtotal, k = 13) +
s(Days_above_threshold_Tmin, k = 13) + s(Days_under_threshold_Tmin,
k = 13) + s(min_Tmin, k = 13) + s(max_Tmin, k = 13) + s(fst_qtl_Tmin_year,
k = 13) + s(trd_qtl_Tmin_year, k = 13) + s(Days_above_threshold_Tmax,
k = 13) + s(Days_under_threshold_Tmax, k = 13) + s(min_Tmax,
k = 13) + s(max_Tmax, k = 13) + s(fst_qtl_Tmax_year, k = 13) +
s(trd_qtl_Tmax_year, k = 13) + s(Days_above_threshold_wspped,
k = 13) + s(Days_under_threshold_wspped, k = 13) + s(min_wspped,
k = 13) + s(max_wspped, k = 13) + s(fst_qtl_wspped_year,
k = 13) + s(trd_qtl_wspped_year, k = 13)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.579311 0.002035 284.7 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Days_above_threshold_Rtotal)	7.403	8.656	5.465	5.90e-07 ***
s(Days_above_threshold_Tmin)	10.318	10.852	12.171	< 2e-16 ***
s(Days_under_threshold_Tmin)	5.348	6.607	3.935	0.000589 ***
s(min_Tmin)	8.048	9.306	6.349	< 2e-16 ***
s(max_Tmin)	6.694	7.701	3.189	5.67e-06 ***
s(fst_qtl_Tmin_year)	8.266	9.341	5.164	1.42e-06 ***
s(trd_qtl_Tmin_year)	7.423	8.466	3.632	0.001682 **
s(Days_above_threshold_Tmax)	9.364	10.239	12.101	< 2e-16 ***
s(Days_under_threshold_Tmax)	5.075	6.234	6.092	2.66e-06 ***
s(min_Tmax)	4.524	5.456	6.009	1.41e-05 ***
s(max_Tmax)	7.583	8.578	3.833	7.34e-05 ***
s(fst_qtl_Tmax_year)	7.648	8.881	7.955	< 2e-16 ***
s(trd_qtl_Tmax_year)	3.910	4.754	4.348	0.002914 **
s(Days_above_threshold_wspped)	5.522	6.647	9.378	< 2e-16 ***
s(max_wspped)	1.000	1.000	55.512	< 2e-16 ***
s(fst_qtl_wspped_year)	5.576	6.566	6.501	6.65e-07 ***
s(trd_qtl_wspped_year)	1.936	2.450	6.504	0.001139 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq. (adj) = 0.73 Deviance explained = 76%
-REML = -607.74 Scale est. = 0.0039597 n = 956

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	0.003662672	0.06052001	0.06879354	6.879354
2	2	0.005312243	0.07288514	0.08284907	8.284907
3	3	0.006736875	0.08207847	0.09329920	9.329920
4	4	0.004957963	0.07041281	0.08003875	8.003875
5	5	0.004983766	0.07059579	0.08024676	8.024676
6	6	0.004660936	0.06827105	0.07760420	7.760420
7	7	0.005950247	0.07713785	0.08768316	8.768316
8	8	0.005262306	0.07254176	0.08245875	8.245875
9	9	0.005453741	0.07384945	0.08394521	8.394521
10	10	0.005908993	0.07686997	0.08737866	8.737866

(b)

FIGURE 23: GAM (a) and 10-fold cross-validation (b) results for the BoCP specification in tariff region C: All crops.

Family: gaussian
Link function: identity

Formula:
Bonus_over_comercial_Prize ~ s(Days_above_threshold_Rtotal, k = 12) +
s(trd_qtl_Rtotal_year, k = 12) + s(Days_above_threshold_Tmin,
k = 12) + s(Days_under_threshold_Tmin, k = 12) + s(min_Tmin,
k = 12) + s(max_Tmin, k = 12) + s(fst_qtl_Tmin_year, k = 12) +
s(trd_qtl_Tmin_year, k = 12) + s(Days_above_threshold_Tmax,
k = 12) + s(Days_under_threshold_Tmax, k = 12) + s(min_Tmax,
k = 12) + s(max_Tmax, k = 12) + s(fst_qtl_Tmax_year, k = 12) +
s(trd_qtl_Tmax_year, k = 12) + s(Days_above_threshold_wspped,
k = 12) + s(Days_under_threshold_wspped, k = 12) + s(min_wspped,
k = 12) + s(max_wspped, k = 12) + s(fst_qtl_wspped_year,
k = 12) + s(trd_qtl_wspped_year, k = 12)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.620535 0.001138 545.2 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Days_above_threshold_Rtotal)	4.122	4.619	12.649	< 2e-16 ***
s(trd_qtl_Rtotal_year)	5.473	5.998	10.553	< 2e-16 ***
s(Days_above_threshold_Tmin)	9.339	9.777	21.208	< 2e-16 ***
s(Days_under_threshold_Tmin)	1.000	1.000	17.104	4.33e-05 ***
s(min_Tmin)	6.693	7.187	13.078	< 2e-16 ***
s(max_Tmin)	1.000	1.000	16.228	6.75e-05 ***
s(fst_qtl_Tmin_year)	4.804	5.363	11.819	< 2e-16 ***
s(trd_qtl_Tmin_year)	8.104	8.664	13.760	< 2e-16 ***
s(Days_above_threshold_Tmax)	2.444	2.775	14.688	< 2e-16 ***
s(Days_under_threshold_Tmax)	4.074	4.577	10.344	< 2e-16 ***
s(min_Tmax)	8.329	8.800	9.285	< 2e-16 ***
s(max_Tmax)	4.069	4.549	6.106	4.93e-05 ***
s(fst_qtl_Tmax_year)	10.134	10.401	24.659	< 2e-16 ***
s(trd_qtl_Tmax_year)	3.207	3.579	15.235	< 2e-16 ***
s(Days_above_threshold_wspped)	7.462	7.874	8.482	< 2e-16 ***
s(Days_under_threshold_wspped)	8.474	9.083	12.586	< 2e-16 ***
s(min_wspped)	9.072	9.383	19.023	< 2e-16 ***
s(max_wspped)	7.222	7.639	9.548	< 2e-16 ***
s(fst_qtl_wspped_year)	8.274	8.740	9.728	< 2e-16 ***
s(trd_qtl_wspped_year)	4.135	4.579	4.228	0.00325 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq. (adj) = 0.933 Deviance explained = 94.8%
-REML = -417.58 Scale est. = 0.00067752 n = 523

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	0.001793963	0.04235520	0.07362283	7.362283
2	2	0.001570418	0.03962850	0.06888323	6.888323
3	3	0.024600280	0.15684476	0.27263137	27.263137
4	4	0.006510346	0.08068671	0.14025160	14.025160
5	5	0.141542349	0.37622114	0.65395672	65.395672
6	6	0.001577913	0.03972295	0.06904740	6.904740
7	7	0.003587238	0.05989355	0.10410843	10.410843
8	8	0.023268432	0.15253994	0.26514862	26.514862
9	9	0.004693565	0.06850960	0.11908505	11.908505
10	10	0.001180908	0.03436435	0.05973294	5.973294

(b)

FIGURE 24: GAM (a) and 10-fold cross-validation (b) results for the BoCP specification in tariff region D: All except vineyard.

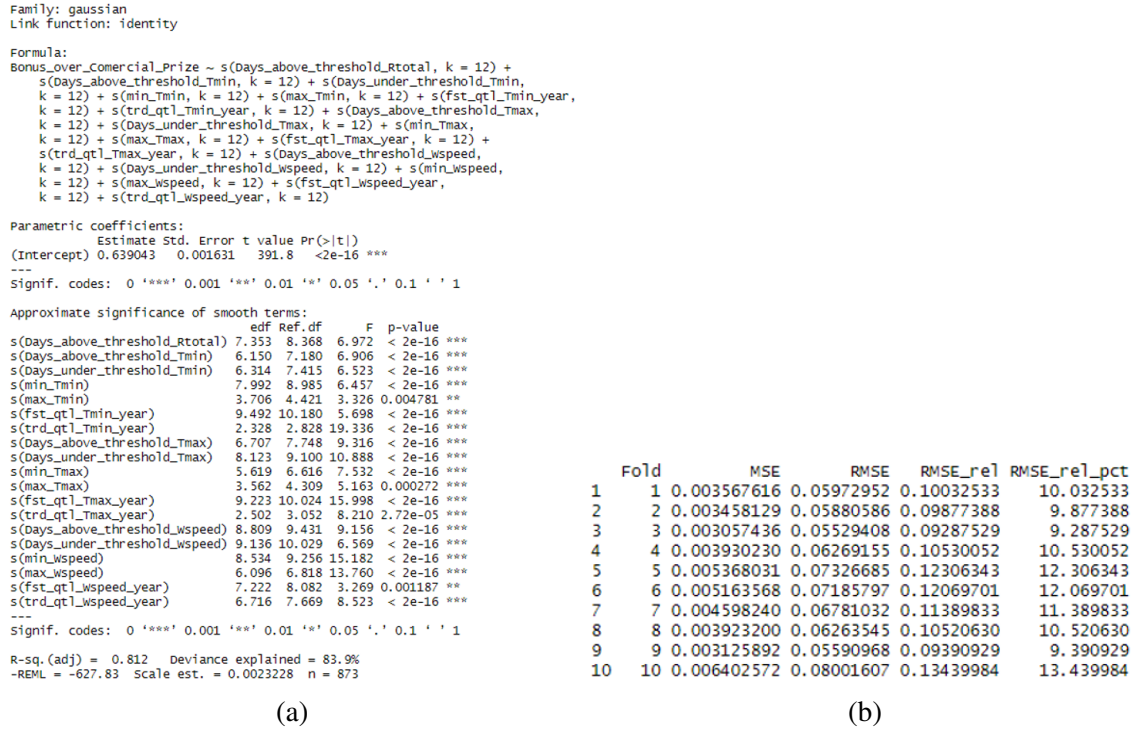


FIGURE 25: GAM (a) and 10-fold cross-validation (b) results for the BoCP specification in tariff region D: All crops.

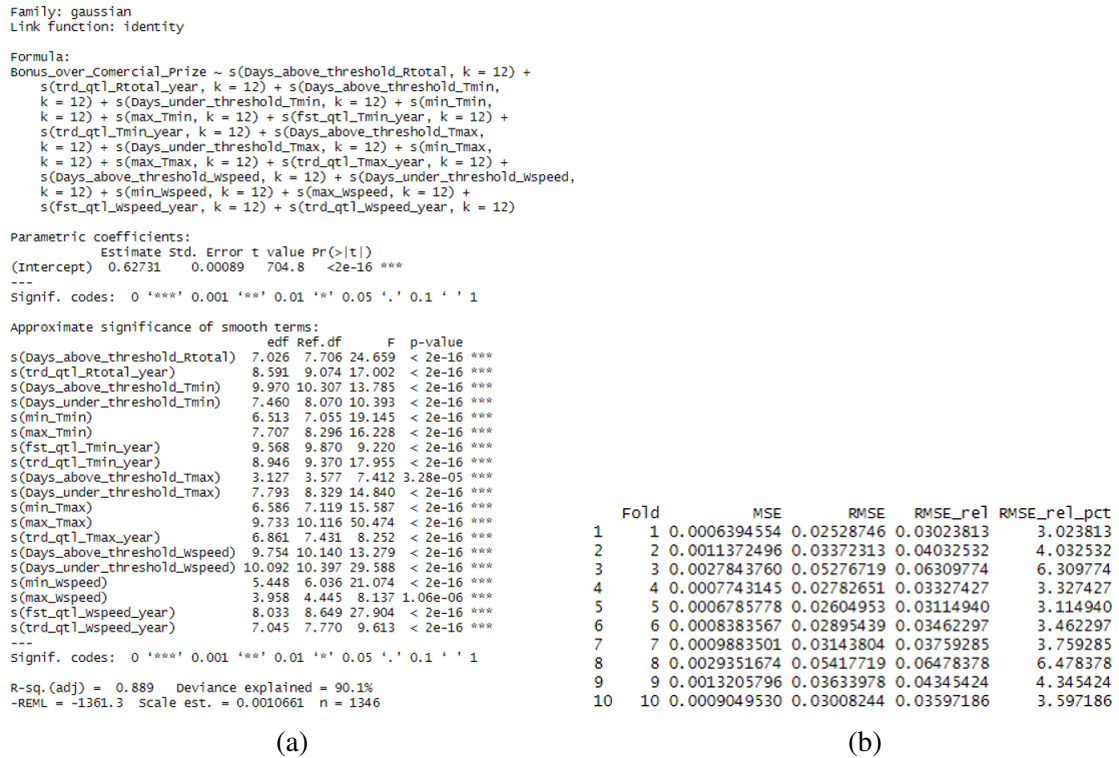


FIGURE 26: GAM (a) and 10-fold cross-validation (b) results for the BoCP specification in tariff region E: All except vineyard.

Family: gaussian
Link function: identity

Formula:

Bonus_over_comercial_Prize ~ s(Days_above_threshold_Rtotal, k = 9) +
s(trd_qtl_Rtotal_year, k = 9) + s(Days_above_threshold_Tmin,
k = 9) + s(Days_under_threshold_Tmin, k = 9) + s(min_Tmin,
k = 9) + s(max_Tmin, k = 9) + s(fst_qtl_Tmin_year, k = 9) +
s(trd_qtl_Tmin_year, k = 9) + s(Days_under_threshold_Tmax,
k = 9) + s(min_Tmax, k = 9) + s(max_Tmax, k = 9) + s(fst_qtl_Tmax_year,
k = 9) + s(trd_qtl_Tmax_year, k = 9) + s(fst_qtl_wspeed_year,
k = 9) + s(trd_qtl_wspeed_year, k = 9)

Parametric coefficients:

Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.622565 0.003015 206.5 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Days_above_threshold_Rtotal)	4.943	5.881	19.693	< 2e-16 ***
s(trd_qtl_Rtotal_year)	3.177	3.819	8.213	5.30e-06 ***
s(Days_above_threshold_Tmin)	1.000	1.000	15.878	8.11e-05 ***
s(Days_under_threshold_Tmin)	2.632	3.340	14.104	< 2e-16 ***
s(min_Tmin)	4.011	4.785	5.391	8.95e-05 ***
s(max_Tmin)	4.811	5.682	4.856	0.000478 ***
s(fst_qtl_Tmin_year)	3.550	4.343	6.271	4.37e-05 ***
s(trd_qtl_Tmin_year)	7.032	7.486	6.295	3.03e-07 ***
s(Days_under_threshold_Tmax)	5.414	6.248	11.079	< 2e-16 ***
s(min_Tmax)	1.000	1.000	79.100	< 2e-16 ***
s(max_Tmax)	4.224	5.076	8.643	< 2e-16 ***
s(fst_qtl_Tmax_year)	2.515	3.185	2.341	0.089003 .
s(trd_qtl_Tmax_year)	4.534	5.381	10.806	< 2e-16 ***
s(fst_qtl_wspeed_year)	5.775	6.663	15.758	< 2e-16 ***
s(trd_qtl_wspeed_year)	1.900	2.398	9.004	6.89e-05 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.732 Deviance explained = 76.6%
-REML = -265.73 Scale est. = 0.0040907 n = 450

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	0.003559151	0.05965862	0.1195641	11.95641
2	2	0.005101908	0.07142764	0.1431509	14.31509
3	3	0.006262673	0.07913705	0.1586016	15.86016
4	4	0.003509033	0.05923709	0.1187193	11.87193
5	5	0.005517564	0.07428031	0.1488680	14.88680
6	6	0.007599764	0.08717662	0.1747140	17.47140
7	7	0.006109981	0.07816637	0.1566562	15.66562
8	8	0.006093384	0.07806013	0.1564433	15.64433
9	9	0.004744146	0.06887776	0.1380405	13.80405
10	10	0.005687410	0.07541492	0.1511419	15.11419

(b)

FIGURE 27: GAM (a) and 10-fold cross-validation (b) results for the BoCP specification in tariff region E: Vineyard.

Family: gaussian
Link function: identity

Formula:

Bonus_over_comercial_Prize ~ s(Days_above_threshold_Rtotal, k = 15) +
s(trd_qtl_Rtotal_year, k = 15) + s(Days_above_threshold_Tmin,
k = 15) + s(min_Tmin, k = 15) + s(max_Tmin, k = 15) + s(fst_qtl_Tmin_year,
k = 15) + s(trd_qtl_Tmin_year, k = 15) + s(Days_above_threshold_Tmax,
k = 15) + s(Days_under_threshold_Tmax, k = 15) + s(min_Tmax,
k = 15) + s(max_Tmax, k = 15) + s(fst_qtl_Tmax_year, k = 15) +
s(trd_qtl_Tmax_year, k = 15) + s(Days_above_threshold_wspeed,
k = 15) + s(Days_under_threshold_wspeed, k = 15) + s(min_wspeed,
k = 15) + s(max_wspeed, k = 15) + s(fst_qtl_wspeed_year,
k = 15) + s(trd_qtl_wspeed_year, k = 15)

Parametric coefficients:

Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.6270635 0.0009904 633.1 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Days_above_threshold_Rtotal)	6.361	7.111	11.915	< 2e-16 ***
s(trd_qtl_Rtotal_year)	9.076	9.744	14.646	< 2e-16 ***
s(Days_above_threshold_Tmin)	8.800	9.614	19.597	< 2e-16 ***
s(min_Tmin)	11.838	12.336	18.419	< 2e-16 ***
s(max_Tmin)	7.357	8.063	15.406	< 2e-16 ***
s(fst_qtl_Tmin_year)	11.358	11.881	14.754	< 2e-16 ***
s(trd_qtl_Tmin_year)	1.000	1.001	10.905	0.000978 ***
s(Days_above_threshold_Tmax)	10.689	11.398	9.001	< 2e-16 ***
s(Days_under_threshold_Tmax)	10.695	11.213	15.054	< 2e-16 ***
s(min_Tmax)	8.976	9.743	11.582	< 2e-16 ***
s(max_Tmax)	11.180	11.800	26.217	< 2e-16 ***
s(fst_qtl_Tmax_year)	4.254	4.750	3.219	0.004549 **
s(trd_qtl_Tmax_year)	7.260	8.021	9.190	< 2e-16 ***
s(Days_above_threshold_wspeed)	11.318	12.011	11.727	< 2e-16 ***
s(Days_under_threshold_wspeed)	12.122	12.709	7.660	< 2e-16 ***
s(min_wspeed)	9.649	10.394	22.831	< 2e-16 ***
s(max_wspeed)	3.303	3.744	7.161	2.39e-05 ***
s(fst_qtl_wspeed_year)	7.892	8.689	12.746	< 2e-16 ***
s(trd_qtl_wspeed_year)	6.718	7.515	5.237	7.44e-06 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

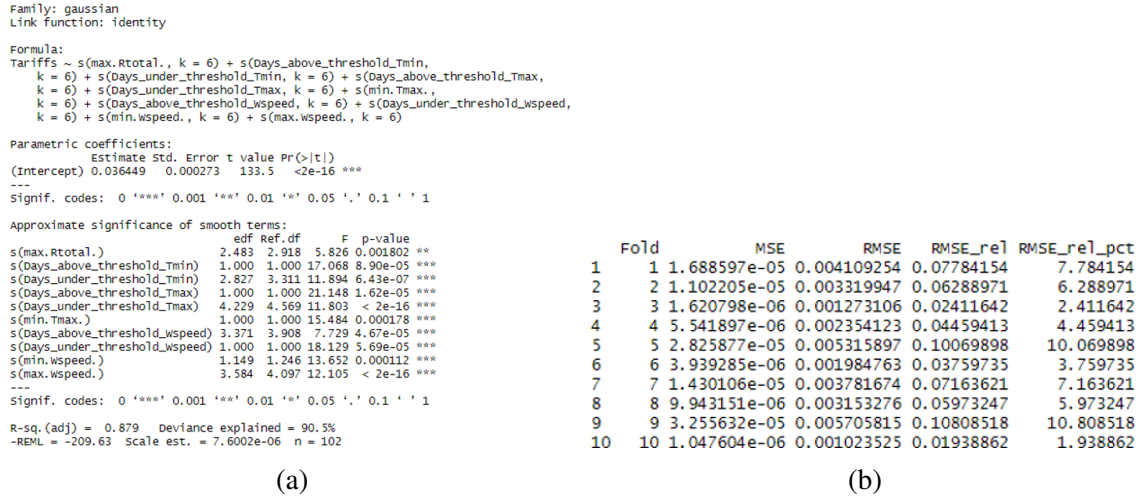
R-sq.(adj) = 0.841 Deviance explained = 85.5%
-REML = -1612.3 Scale est. = 0.0017402 n = 1774

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	0.002183544	0.04672841	0.05587672	5.587672
2	2	0.002726580	0.05221666	0.06243943	6.243943
3	3	0.001560196	0.03949932	0.04723234	4.723234
4	4	0.001577464	0.03971730	0.04749300	4.749300
5	5	0.002057539	0.04536010	0.05424052	5.424052
6	6	0.002125799	0.04610638	0.05513291	5.513291
7	7	0.001365804	0.03695679	0.04419205	4.419205
8	8	0.003293058	0.05738517	0.06861981	6.861981
9	9	0.001812639	0.04257510	0.05091029	5.091029
10	10	0.001825374	0.04272439	0.05108881	5.108881

(b)

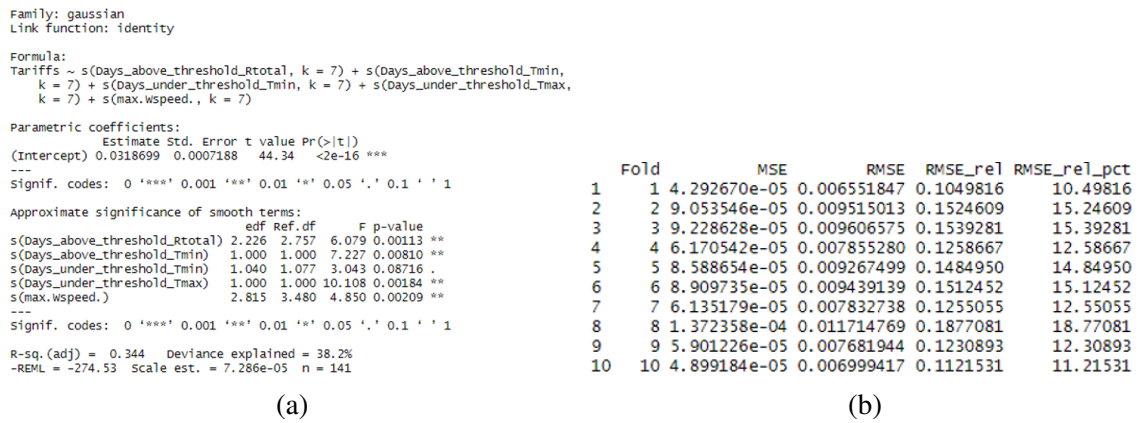
FIGURE 28: GAM (a) and 10-fold cross-validation (b) results for the BoCP specification in tariff region E: All crops.



(a)

(b)

FIGURE 29: GAM (a) and 10-fold cross-validation (b) results for the Tariffs specification in tariff region A: All except vineyard.



(a)

(b)

FIGURE 30: GAM (a) and 10-fold cross-validation (b) results for the Tariffs specification in tariff region A: All crops.

Family: gaussian
Link function: identity

Formula:
Tariffs ~ s(Days_above_threshold_Rtotal, k = 7) + s(Days_under_threshold_Tmin, k = 7) + s(min.Tmin., k = 7) + s(Days_above_threshold_Tmax, k = 7) + s(min.Tmax., k = 7) + s(max.Tmax., k = 7) + s(Days_above_threshold_wspeed, k = 7) + s(Days_under_threshold_wspeed, k = 7) + s(min.wspeed., k = 7) + s(max.wspeed., k = 7)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.0450939 0.0007292 61.84 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Days_above_threshold_Rtotal)	1.548	1.890	17.698	1.47e-05 ***
s(Days_under_threshold_Tmin)	1.727	2.146	6.043	0.002086 **
s(min.Tmin.)	2.481	3.048	7.225	0.000103 ***
s(Days_above_threshold_Tmax)	4.116	4.852	5.629	7.52e-05 ***
s(min.Tmax.)	3.524	4.214	4.862	0.001088 **
s(max.Tmax.)	1.000	1.001	15.613	0.000104 ***
s(Days_above_threshold_wspeed)	3.902	4.493	5.105	0.000503 ***
s(Days_under_threshold_wspeed)	2.595	3.224	5.161	0.001550 **
s(min.wspeed.)	2.141	2.577	2.508	0.087483 .
s(max.wspeed.)	4.673	5.074	9.456	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq. (adj) = 0.614 Deviance explained = 65.7%
-REML = -415.39 scale est. = 0.0001324 n = 249

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	8.304642e-05	0.009112981	0.06540354	6.540354
2	2	4.055237e-04	0.020137619	0.14452697	14.452697
3	3	1.693191e-04	0.013012268	0.09338858	9.338858
4	4	1.836420e-04	0.013551456	0.09725832	9.725832
5	5	1.803503e-04	0.013429456	0.09638273	9.638273
6	6	1.281100e-04	0.011318570	0.08123297	8.123297
7	7	1.011483e-04	0.010057252	0.07218054	7.218054
8	8	3.597374e-04	0.018966745	0.13612366	13.612366
9	9	6.651435e-04	0.025790377	0.18509661	18.509661
10	10	1.467394e-04	0.012113602	0.08693889	8.693889

(b)

FIGURE 31: GAM (a) and 10-fold cross-validation (b) results for the Tariffs specification in tariff region B: All except vineyard.

Family: gaussian
Link function: identity

Formula:
Tariffs ~ s(Days_above_threshold_Rtotal, k = 5) + s(Days_above_threshold_Tmax, k = 5) + s(max.Tmax., k = 5) + s(Days_above_threshold_wspeed, k = 5) + s(Days_under_threshold_wspeed, k = 5) + s(max.wspeed., k = 5)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.0428464 0.0008253 51.91 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Days_above_threshold_Rtotal)	2.412	2.951	4.285	0.003844 **
s(Days_above_threshold_Tmax)	3.705	3.936	15.470	< 2e-16 ***
s(max.Tmax.)	1.552	1.885	10.360	5.82e-05 ***
s(Days_above_threshold_wspeed)	2.877	3.346	6.960	0.000306 ***
s(Days_under_threshold_wspeed)	2.392	2.913	11.918	7.02e-07 ***
s(max.wspeed.)	1.001	1.001	10.487	0.001346 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq. (adj) = 0.452 Deviance explained = 47.9%
-REML = -487.04 scale est. = 0.00019277 n = 283

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	1.086920e-04	0.010425544	0.07482376	7.482376
2	2	1.995755e-04	0.014127119	0.10138983	10.138983
3	3	2.208943e-04	0.014862512	0.10666772	10.666772
4	4	8.689294e-05	0.009321638	0.06690106	6.690106
5	5	1.587534e-04	0.012599737	0.09042786	9.042786
6	6	1.042808e-04	0.010211795	0.07328969	7.328969
7	7	1.989669e-04	0.014105562	0.10123512	10.123512
8	8	2.420026e-04	0.015556433	0.11164797	11.164797
9	9	9.310510e-04	0.030513129	0.21899164	21.899164
10	10	6.490589e-05	0.008056419	0.05782063	5.782063

(b)

FIGURE 32: GAM (a) and 10-fold cross-validation (b) results for the Tariffs specification in tariff region B: All crops.

```

Family: gaussian
Link function: identity

Formula:
Tariffs ~ s(max.Rtotal., k = 3) + s(Days_under_threshold_Tmin,
k = 3) + s(min.Tmin., k = 3) + s(max.Tmin., k = 3) + s(Days_under_threshold_Tmax,
k = 3) + s(min.Tmax., k = 3) + s(Days_above_threshold_wspped,
k = 3) + s(Days_under_threshold_wspped, k = 3)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.025999   0.000737   35.27  <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
            edf Ref.df      F  p-value
s(max.Rtotal.)      1.536   1.781 10.067  0.001790 **
s(Days_under_threshold_Tmin) 1.000   1.000   4.355  0.045809 *
s(min.Tmin.)        1.000   1.000   7.328  0.011258 *
s(max.Tmin.)        1.842   1.972   6.264  0.003828 **
s(Days_under_threshold_Tmax) 1.000   1.000 11.192  0.002283 **
s(min.Tmax.)        1.913   1.992 13.338  0.000128 ***
s(Days_above_threshold_wspped) 1.000   1.000 18.152  0.000197 ***
s(Days_under_threshold_wspped) 1.881   1.982 14.464  5.57e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.759   Deviance explained = 82.6%
-REML = -49.658   Scale est. = 2.2273e-05   n = 41

```

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	1.592795e-04	0.012620600	0.22298011	22.298011
2	2	9.334519e-05	0.009661531	0.17069944	17.069944
3	3	1.395543e-05	0.003735697	0.06600211	6.600211
4	4	6.225626e-06	0.002495120	0.04408366	4.408366
5	5	8.680680e-05	0.009317017	0.16461257	16.461257
6	6	2.548714e-05	0.005048479	0.08919627	8.919627
7	7	4.217223e-05	0.006494015	0.11473592	11.473592
8	8	2.135723e-06	0.001461411	0.02582014	2.582014
9	9	1.161173e-04	0.010775775	0.19038584	19.038584
10	10	3.367296e-05	0.005802840	0.10252428	10.252428

(b)

FIGURE 33: GAM (a) and 10-fold cross-validation (b) results for the Tariffs specification in tariff region B: Vineyard.

```

Family: gaussian
Link function: identity

Formula:
Tariffs ~ s(min.Tmin., k = 6) + s(min.Tmax., k = 6) + s(min.wspped.,
k = 6)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.037761   0.001016   37.16  <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
            edf Ref.df      F  p-value
s(min.Tmin.)      3.637   4.295 13.22  <2e-16 ***
s(min.Tmax.)      2.794   3.423 13.30  <2e-16 ***
s(min.wspped.)    4.231   4.741 11.37  <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.153   Deviance explained = 16.5%
-REML = -1072.9   Scale est. = 0.00079815   n = 773

```

FIGURE 34: GAM results for the Tariffs specification in tariff region C: All except vineyard.

B MODELS ESTIMATION IN TABLE IV

Family: gaussian
Link function: identity

Formula:

Tariffs ~ s(max.Rtotal., k = 4) + s(Days_above_threshold_Tmin,
k = 4) + s(Days_under_threshold_Tmin, k = 4) + s(max.Tmin.,
k = 4) + s(Days_above_threshold_Tmax, k = 4) + s(max.Tmax.,
k = 4) + s(Days_above_threshold_wspped, k = 4) + s(Days_under_threshold_wspped,
k = 4) + s(max.Wspped., k = 4)

Parametric coefficients:

Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.0381956 0.0005975 63.92 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref. df	F	p-value
s(max.Rtotal.)	1.000	1.000	53.626	< 2e-16 ***
s(Days_above_threshold_Tmin)	1.000	1.000	11.005	0.00222 **
s(Days_under_threshold_Tmin)	1.000	1.000	77.108	< 2e-16 ***
s(max.Tmin.)	2.020	2.353	28.511	< 2e-16 ***
s(Days_above_threshold_Tmax)	1.666	2.004	37.572	< 2e-16 ***
s(max.Tmax.)	2.757	2.920	13.386	7.76e-06 ***
s(Days_above_threshold_wspped)	1.944	2.218	2.793	0.04491 *
s(Days_under_threshold_wspped)	1.020	1.036	33.058	1.26e-06 ***
s(max.Wspped.)	1.000	1.000	30.193	4.40e-06 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.843 deviance explained = 88.9%
-REML = -62.024 scale est. = 1.6781e-05 n = 47

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	2.883651e-05	0.005369963	0.10752699	10.752699
2	2	7.796468e-06	0.002792216	0.05591072	5.591072
3	3	1.202488e-05	0.003467691	0.06943630	6.943630
4	4	7.960875e-06	0.002821502	0.05649715	5.649715
5	5	3.358695e-06	0.001832674	0.03669708	3.669708
6	6	3.119949e-05	0.005585650	0.11184586	11.184586
7	7	1.392010e-05	0.003730964	0.07470803	7.470803
8	8	5.527134e-07	0.000743447	0.01488662	1.488662
9	9	1.700731e-06	0.001304121	0.02611343	2.611343
10	10	3.113435e-06	0.001764493	0.03533182	3.533182

(b)

FIGURE 35: GAM (a) and 10-fold cross-validation (b) results for the Tariffs with lagged climatic variables specification in tariff region A: All except vineyard.

Family: gaussian
Link function: identity

Formula:

Tariffs ~ s(max.Rtotal., k = 4) + s(Days_above_threshold_Tmin,
k = 4) + s(Days_under_threshold_Tmin, k = 4) + s(min.Tmax.,
k = 4) + s(Days_above_threshold_wspped, k = 4) + s(Days_under_threshold_wspped,
k = 4) + s(min.Wspped., k = 4)

Parametric coefficients:

Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.0345376 0.0008592 40.2 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref. df	F	p-value
s(max.Rtotal.)	1.000	1.000	8.472	0.005544 **
s(Days_above_threshold_Tmin)	2.396	2.723	8.910	0.000403 ***
s(Days_under_threshold_Tmin)	1.000	1.000	10.367	0.002354 **
s(min.Tmax.)	1.000	1.000	5.310	0.025770 *
s(Days_above_threshold_wspped)	2.670	2.875	20.780	3.56e-07 ***
s(Days_under_threshold_wspped)	2.667	2.911	13.465	2.22e-06 ***
s(min.Wspped.)	1.000	1.000	6.119	0.017129 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.694 deviance explained = 75.6%
-REML = -88.658 scale est. = 4.3555e-05 n = 59

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	1.853130e-05	0.004304800	0.07112572	7.112572
2	2	2.921606e-05	0.005405189	0.08930682	8.930682
3	3	4.390452e-05	0.006626049	0.10947839	10.947839
4	4	1.700227e-05	0.004123381	0.06812824	6.812824
5	5	2.037180e-05	0.004513513	0.07457418	7.457418
6	6	1.586103e-05	0.003982591	0.06580206	6.580206
7	7	4.167070e-05	0.006455285	0.10665695	10.665695
8	8	9.678782e-05	0.009838080	0.16254893	16.254893
9	9	1.084383e-05	0.003292996	0.05440828	5.440828
10	10	4.999590e-05	0.007070778	0.11682639	11.682639

(b)

FIGURE 36: GAM (a) and 10-fold cross-validation (b) results for the Tariffs with lagged climatic variables specification in tariff region A: All crops.

Family: gaussian
Link function: identity

Formula:
Tariffs ~ s(Days_above_threshold_Rtotal, k = 5) + s(max.Rtotal.,
k = 5) + s(Days_above_threshold_Tmin, k = 5) + s(Days_under_threshold_Tmin,
k = 5) + s(min.Tmin., k = 5) + s(max.Tmin., k = 5) + s(Days_above_threshold_Tmax,
k = 5) + s(Days_under_threshold_Tmax, k = 5) + s(min.Tmax.,
k = 5) + s(Days_above_threshold_wspped, k = 5) + s(Days_under_threshold_wspped,
k = 5) + s(min.wspped., k = 5)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.052602 0.000158 332.9 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Days_above_threshold_Rtotal)	3.905	3.959	81.37	< 2e-16 ***
s(max.Rtotal.)	3.672	3.850	62.76	< 2e-16 ***
s(Days_above_threshold_Tmin)	3.692	3.855	200.86	< 2e-16 ***
s(Days_under_threshold_Tmin)	1.000	1.000	637.13	< 2e-16 ***
s(min.Tmin.)	1.000	1.000	28.55	2.62e-06 ***
s(max.Tmin.)	3.281	3.439	146.14	< 2e-16 ***
s(Days_above_threshold_Tmax)	3.243	3.557	85.37	< 2e-16 ***
s(Days_under_threshold_Tmax)	3.756	3.826	229.02	< 2e-16 ***
s(min.Tmax.)	3.574	3.673	390.85	< 2e-16 ***
s(Days_above_threshold_wspped)	3.743	3.876	285.62	< 2e-16 ***
s(Days_under_threshold_wspped)	1.000	1.000	1424.57	< 2e-16 ***
s(min.wspped.)	1.000	1.000	58.91	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq. (adj) = 0.994 Deviance explained = 99.6%
-REML = -129.74 Scale est. = 2.0971e-06 n = 84

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	1.292749e-02	0.1136990988	0.912938062	91.2938062
2	2	3.231070e-04	0.0179751760	0.144330276	14.4330276
3	3	4.973194e-03	0.0705208762	0.566241885	56.6241885
4	4	2.439116e-04	0.0156176696	0.125400862	12.5400862
5	5	2.135259e-05	0.0046208861	0.037103045	3.7103045
6	6	4.531964e-06	0.0021288410	0.017093363	1.7093363
7	7	1.293645e-04	0.0113738512	0.091325453	9.1325453
8	8	3.569920e-04	0.0188942311	0.151709757	15.1709757
9	9	7.875306e-07	0.0008874292	0.007125544	0.7125544
10	10	3.442895e-06	0.0018555041	0.014898626	1.4898626

(b)

FIGURE 37: GAM (a) and 10-fold cross-validation (b) results for the Tariffs with lagged climatic variables specification in tariff region B: All except vineyard.

Family: gaussian
Link function: identity

Formula:
Tariffs ~ s(Days_above_threshold_Rtotal, k = 6) + s(max.Rtotal.,
k = 6) + s(Days_above_threshold_Tmin, k = 6) + s(Days_under_threshold_Tmin,
k = 6) + s(min.Tmin., k = 6) + s(max.Tmin., k = 6) + s(Days_above_threshold_Tmax,
k = 6) + s(min.Tmax., k = 6) + s(max.Tmax., k = 6) + s(Days_above_threshold_wspped,
k = 6) + s(Days_under_threshold_wspped, k = 6) + s(max.wspped.,
k = 6)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.0498277 0.0004851 102.7 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Days_above_threshold_Rtotal)	4.688	4.885	27.066	< 2e-16 ***
s(max.Rtotal.)	1.643	1.918	32.491	2.36e-07 ***
s(Days_above_threshold_Tmin)	1.000	1.000	21.739	1.79e-05 ***
s(Days_under_threshold_Tmin)	2.179	2.598	18.250	1.91e-07 ***
s(min.Tmin.)	4.341	4.598	17.484	< 2e-16 ***
s(Days_above_threshold_Tmax)	1.000	1.000	65.283	< 2e-16 ***
s(min.Tmax.)	4.132	4.404	20.595	< 2e-16 ***
s(max.Tmax.)	1.000	1.000	4.693	0.0342 *
s(Days_above_threshold_wspped)	3.473	3.904	19.869	< 2e-16 ***
s(Days_under_threshold_wspped)	3.059	3.500	27.295	< 2e-16 ***
s(max.wspped.)	3.986	4.377	17.492	8.15e-07 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq. (adj) = 0.944 Deviance explained = 96.3%
-REML = -127.5 Scale est. = 2.1888e-05 n = 93

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	1.503231e-05	0.003877152	0.03108808	3.108808
2	2	3.575063e-06	0.001890784	0.01516083	1.516083
3	3	1.777388e-05	0.004215908	0.03380432	3.380432
4	4	4.721956e-06	0.002173006	0.01742377	1.742377
5	5	7.252552e-06	0.002693056	0.02159367	2.159367
6	6	6.741641e-05	0.008210750	0.06583607	6.583607
7	7	1.004197e-05	0.003168906	0.02540917	2.540917
8	8	9.354081e-06	0.003058444	0.02452346	2.452346
9	9	7.865493e-06	0.002804549	0.02248765	2.248765
10	10	2.489105e-06	0.001577690	0.01265036	1.265036

(b)

FIGURE 38: GAM (a) and 10-fold cross-validation (b) results for the Tariffs with lagged climatic variables specification in tariff region B: All crops.

```

Family: gaussian
Link function: identity

Formula:
Tariffs ~ s(max.Tmin., k = 5) + s(max.Tmax., k = 5) + s(Days_under_threshold_wspeer,
k = 5) + s(max.wspeer., k = 5)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.040359   0.001369   29.48  <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
            edf Ref.df    F p-value
s(max.Tmin.)      3.427  3.819 44.795 < 2e-16 ***
s(max.Tmax.)      1.000  1.000   9.612  0.00211 **
s(Days_under_threshold_wspeer) 1.569  1.887  4.561  0.03771 *
s(max.wspeer.)    2.436  2.997  4.546  0.00394 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.401  Deviance explained = 41.7%
-REML = -448.77  Scale est. = 0.00058831  n = 314

```

(a)

```

Family: gaussian
Link function: identity

Formula:
Tariffs ~ s(Days_above_threshold_Rtotal, k = 6) + s(Days_under_threshold_Tmin,
k = 6) + s(Days_above_threshold_Tmax, k = 6) + s(Days_under_threshold_Tmax,
k = 6) + s(min.wspeer., k = 6) + s(max.wspeer., k = 6)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.233367   0.002551   91.5  <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
            edf Ref.df    F p-value
s(Days_above_threshold_Rtotal) 1.001  1.003   6.059  0.014359 *
s(Days_under_threshold_Tmin)  2.483  3.089   4.216  0.005309 **
s(Days_above_threshold_Tmax)  1.000  1.000   8.351  0.004133 **
s(Days_under_threshold_Tmax)  3.137  3.822   3.760  0.004789 **
s(min.wspeer.)              2.197  2.746   7.328  0.000339 ***
s(max.wspeer.)              1.000  1.000  10.498  0.001328 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.22  Deviance explained = 24.7%
-REML = -312.64  Scale est. = 0.0020427  n = 314

```

(b)

FIGURE 39: GAM results for the Tariffs with lagged climatic variables specification in tariff region C: All crops (a) and tariff region D: All except vineyard (b).

```

Family: gaussian
Link function: identity

Formula:
Tariffs ~ s(Days_above_threshold_Tmax, k = 6) + s(Days_under_threshold_Tmax,
k = 6) + s(Days_under_threshold_wspeer, k = 6)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.087196   0.001205   72.33  <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
            edf Ref.df    F p-value
s(Days_above_threshold_Tmax)  2.840  3.479 14.840 <2e-16 ***
s(Days_under_threshold_Tmax)  2.606  3.254  2.855  0.0303 *
s(Days_under_threshold_wspeer) 3.669  4.283 17.218 <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.528  Deviance explained = 54.8%
-REML = -343.67  Scale est. = 0.00031096  n = 214

```

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	0.0007003259	0.02646367	0.20221206	20.221206
2	2	0.0001778297	0.01333528	0.10189646	10.189646
3	3	0.0003900645	0.01975005	0.15091249	15.091249
4	4	0.0003878101	0.01969289	0.15047575	15.047575
5	5	0.0002442112	0.01562726	0.11940974	11.940974
6	6	0.0001171057	0.01082154	0.08268866	8.268866
7	7	0.0006918662	0.02630335	0.20098702	20.098702
8	8	0.0002556386	0.01598870	0.12217157	12.217157
9	9	0.0003461896	0.01860617	0.14217196	14.217196
10	10	0.0003512612	0.01874196	0.14320958	14.320958

(b)

FIGURE 40: GAM (a) and 10-fold cross-validation (b) results for the Tariffs with lagged climatic variables specification in tariff region D: Vineyard.

Family: gaussian
Link function: identity

Formula:
Tariffs ~ s(Days_above_threshold_Rtotal, k = 8) + s(max.Rtotal.,
k = 8) + s(Days_above_threshold_Tmin, k = 8) + s(Days_under_threshold_Tmin,
k = 8) + s(min.Tmin., k = 8) + s(Days_above_threshold_Tmax,
k = 8) + s(min.Tmax., k = 8) + s(Days_above_threshold_wspped,
k = 8) + s(Days_under_threshold_wspped, k = 8) + s(min.wspped.,
k = 8)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.135492 0.001622 83.51 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Days_above_threshold_Rtotal)	1.000	1.000	28.567	3.14e-07 ***
s(max.Rtotal.)	1.000	1.000	20.258	9.88e-06 ***
s(Days_above_threshold_Tmin)	2.064	2.613	4.658	0.003614 **
s(Days_under_threshold_Tmin)	4.554	5.359	13.769	< 2e-16 ***
s(min.Tmin.)	3.254	3.959	7.153	3.26e-05 ***
s(Days_above_threshold_Tmax)	3.221	3.999	4.905	0.000746 ***
s(min.Tmax.)	2.442	3.040	3.514	0.013991 *
s(Days_above_threshold_wspped)	3.866	4.676	21.092	< 2e-16 ***
s(Days_under_threshold_wspped)	4.963	5.834	14.063	< 2e-16 ***
s(min.wspped.)	4.885	5.724	7.041	1.43e-06 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.62 Deviance explained = 65.4%
-REML = -394.67 Scale est. = 0.00091077 n = 346

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	0.0012728521	0.03567705	0.1719885	17.19885
2	2	0.0010115497	0.03180487	0.1533219	15.33219
3	3	0.0009190804	0.03031634	0.1461461	14.61461
4	4	0.0012680830	0.03561015	0.1716660	17.16660
5	5	0.0005608024	0.02368127	0.1141604	11.41604
6	6	0.0009078035	0.03012978	0.1452467	14.52467
7	7	0.0014309017	0.03782726	0.1823540	18.23540
8	8	0.0008642485	0.02939810	0.1417196	14.17196
9	9	0.0011131002	0.03336316	0.1608339	16.08339
10	10	0.0006930923	0.02632665	0.1269130	12.69130

(b)

FIGURE 41: GAM (a) and 10-fold cross-validation (b) results for the Tariffs with lagged climatic variables specification in tariff region E: Vineyard.

C MODELS ESTIMATION IN TABLE VII

Family: gaussian
Link function: identity

Formula:
Bonus_over_Comercial_Prize ~ s(Days_above_threshold_Rtotal, k = 5) +
s(trd_qtl_Rtotal_year, k = 5) + s(Days_above_threshold_Tmin,
k = 5) + s(Days_under_threshold_Tmin, k = 5) + s(min_Tmin,
k = 5) + s(max_Tmin, k = 5) + s(fst_qtl_Tmin_year, k = 5) +
s(Days_above_threshold_Tmax, k = 5) + s(Days_under_threshold_Tmax,
k = 5) + s(min_Tmax, k = 5) + s(fst_qtl_Tmax_year, k = 5) +
s(Days_under_threshold_wspeak, k = 5) + s(min_wspeak, k = 5) +
s(fst_qtl_wspeak_year, k = 5) + s(trd_qtl_wspeak_year, k = 5) +
s(Year, k = 5)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.537655 0.002164 248.5 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Days_above_threshold_Rtotal)	1.000	1.000	107.758	< 2e-16 ***
s(trd_qtl_Rtotal_year)	1.000	1.000	25.143	3.53e-06 ***
s(Days_above_threshold_Tmin)	2.425	2.817	5.226	0.01434 *
s(Days_under_threshold_Tmin)	2.405	2.813	4.011	0.00816 **
s(min_Tmin)	3.839	3.941	35.941	< 2e-16 ***
s(max_Tmin)	1.000	1.000	48.921	< 2e-16 ***
s(fst_qtl_Tmin_year)	1.000	1.000	3.305	0.07294 .
s(Days_above_threshold_Tmax)	1.000	1.000	21.681	1.35e-05 ***
s(Days_under_threshold_Tmax)	1.000	1.000	189.077	< 2e-16 ***
s(min_Tmax)	1.000	1.000	19.469	3.33e-05 ***
s(fst_qtl_Tmax_year)	1.000	1.000	57.038	< 2e-16 ***
s(Days_under_threshold_wspeak)	2.622	3.037	16.994	< 2e-16 ***
s(min_wspeak)	1.000	1.000	78.646	< 2e-16 ***
s(fst_qtl_wspeak_year)	1.166	1.282	15.953	5.03e-05 ***
s(trd_qtl_wspeak_year)	1.000	1.000	31.518	4.25e-07 ***
s(Year)	1.382	1.591	122.567	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.907 Deviance explained = 92.9%
-REML = -73.89 Scale est. = 0.00047757 n = 102

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	0.0001843225	0.01357654	0.03099961	3.099961
2	2	0.0010183516	0.03191162	0.07286450	7.286450
3	3	0.0001937288	0.01391865	0.03178075	3.178075
4	4	0.0057826910	0.07604401	0.17363293	17.363293
5	5	0.0030246308	0.05499664	0.12557503	12.557503
6	6	0.0002855834	0.01689921	0.03858634	3.858634
7	7	0.0015114665	0.03887758	0.08877003	8.877003
8	8	0.0010621559	0.03259073	0.07441513	7.441513
9	9	0.0009120089	0.03019948	0.06895514	6.895514
10	10	0.0005096840	0.02257618	0.05154868	5.154868

(b)

FIGURE 42: GAM (a) and 10-fold cross-validation (b) results for the BoCP specification in tariff region A considering year as a predictor: All except vineyard.

Family: gaussian
Link function: identity

Formula:
Bonus_over_Comercial_Prize ~ s(Days_above_threshold_Rtotal, k = 5) +
s(min_Tmin, k = 5) + s(max_Tmin, k = 5) + s(Days_under_threshold_Tmax,
k = 5) + s(trd_qtl_Tmax_year, k = 5) + s(Days_above_threshold_wspeak,
k = 5) + s(max_wspeak, k = 5) + s(fst_qtl_wspeak_year, k = 5) +
s(Year, k = 5)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.561040 0.004202 133.5 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Days_above_threshold_Rtotal)	2.195	2.634	32.339	< 2e-16 ***
s(min_Tmin)	1.000	1.000	12.650	0.000532 ***
s(max_Tmin)	1.000	1.000	3.489	0.064123 .
s(Days_under_threshold_Tmax)	1.548	1.896	21.496	< 2e-16 ***
s(trd_qtl_Tmax_year)	3.147	3.605	4.152	0.020339 *
s(Days_above_threshold_wspeak)	1.000	1.000	17.045	6.64e-05 ***
s(max_wspeak)	1.000	1.000	7.921	0.005675 **
s(fst_qtl_wspeak_year)	1.000	1.000	14.313	0.000239 ***
s(Year)	3.451	3.808	20.047	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.72 Deviance explained = 75%
-REML = -97.522 Scale est. = 0.0024891 n = 141

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	0.003750274	0.06123948	0.12515127	12.515127
2	2	0.003177953	0.05637333	0.11520663	11.520663
3	3	0.001351278	0.03675973	0.07512354	7.512354
4	4	0.002917315	0.05401217	0.11038128	11.038128
5	5	0.004231305	0.06504849	0.13293550	13.293550
6	6	0.003529024	0.05940559	0.12140347	12.140347
7	7	0.003147874	0.05610592	0.11466013	11.466013
8	8	0.002027683	0.04502980	0.09202457	9.202457
9	9	0.001313158	0.03623752	0.07405634	7.405634
10	10	0.003571542	0.05976238	0.12213262	12.213262

(b)

FIGURE 43: GAM (a) and 10-fold cross-validation (b) results for the BoCP specification in tariff region A considering year as a predictor: All crops.

Family: gaussian
Link function: identity

Formula:
Bonus_over_comercial_Prize ~ s(trd_qtl_Rtotal_year, k = 9) +
s(Days_above_threshold_Tmin, k = 9) + s(Days_under_threshold_Tmin,
k = 9) + s(min_Tmin, k = 9) + s(fst_qtl_Tmin_year, k = 9) +
s(trd_qtl_Tmin_year, k = 9) + s(Days_under_threshold_Tmax,
k = 9) + s(min_Tmax, k = 9) + s(max_Tmax, k = 9) + s(fst_qtl_Tmax_year,
k = 9) + s(Days_above_threshold_wspped, k = 9) + s(Days_under_threshold_wspped,
k = 9) + s(max_wspped, k = 9) + s(fst_qtl_wspped_year, k = 9) +
s(year, k = 9)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.573994 0.002527 227.2 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(trd_qtl_Rtotal_year)	2.843	3.291	8.924	5.27e-06 ***
s(Days_above_threshold_Tmin)	1.000	1.000	27.239	5.55e-07 ***
s(Days_under_threshold_Tmin)	4.265	5.066	4.440	0.000586 ***
s(min_Tmin)	5.405	6.128	6.148	4.26e-06 ***
s(fst_qtl_Tmin_year)	4.737	5.511	4.763	0.000133 ***
s(trd_qtl_Tmin_year)	1.000	1.001	18.427	2.72e-05 ***
s(Days_under_threshold_Tmax)	3.982	4.727	9.728	6.30e-06 ***
s(min_Tmax)	2.877	3.541	5.068	0.001277 **
s(max_Tmax)	1.245	1.408	11.758	0.000118 ***
s(fst_qtl_Tmax_year)	1.000	1.000	4.069	0.044958 *
s(Days_above_threshold_wspped)	1.000	1.000	3.829	0.051717 .
s(Days_under_threshold_wspped)	1.000	1.000	47.763	< 2e-16 ***
s(max_wspped)	1.000	1.000	13.839	0.000257 ***
s(fst_qtl_wspped_year)	1.000	1.000	10.143	0.001671 **
s(year)	7.442	7.839	35.578	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.816 Deviance explained = 84.6%
-REML = -184.11 Scale est. = 0.0015896 n = 249

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	0.004924129	0.07017214	0.11213845	11.213845
2	2	0.003083548	0.05552971	0.08873915	8.873915
3	3	0.002577175	0.05076588	0.08112632	8.112632
4	4	0.001607442	0.04009292	0.06407042	6.407042
5	5	0.003808579	0.06171368	0.09862144	9.862144
6	6	0.001984214	0.04454452	0.07118428	7.118428
7	7	0.003400487	0.05831370	0.09318810	9.318810
8	8	0.001726742	0.04155408	0.06640542	6.640542
9	9	0.049836865	0.22324172	0.35675101	35.675101
10	10	0.003185732	0.05644229	0.09019750	9.019750

(b)

FIGURE 44: GAM (a) and 10-fold cross-validation (b) results for the BoCP specification in tariff region B considering year as a predictor: All except vineyard.

Family: gaussian
Link function: identity

Formula:
Bonus_over_comercial_Prize ~ s(trd_qtl_Rtotal_year, k = 13) +
s(Days_above_threshold_Tmin, k = 13) + s(min_Tmin, k = 13) +
s(fst_qtl_Tmin_year, k = 13) + s(trd_qtl_Tmin_year, k = 13) +
s(Days_above_threshold_Tmax, k = 13) + s(min_Tmax, k = 13) +
s(max_Tmax, k = 13) + s(fst_qtl_Tmax_year, k = 13) + s(trd_qtl_Tmax_year,
k = 13) + s(Days_above_threshold_wspped, k = 13) + s(max_wspped,
k = 13) + s(fst_qtl_wspped_year, k = 13) + s(year, k = 13)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.5837 0.0023 253.8 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(trd_qtl_Rtotal_year)	2.566	3.019	4.849	0.002417 **
s(Days_above_threshold_Tmin)	1.000	1.000	11.842	0.000687 ***
s(min_Tmin)	6.579	7.531	6.283	6.59e-07 ***
s(fst_qtl_Tmin_year)	3.651	4.396	2.847	0.015931 *
s(trd_qtl_Tmin_year)	2.036	2.482	7.582	0.000216 ***
s(Days_above_threshold_Tmax)	3.330	4.117	6.440	5.91e-05 ***
s(min_Tmax)	2.213	2.731	3.170	0.024293 *
s(max_Tmax)	1.000	1.000	33.613	< 2e-16 ***
s(fst_qtl_Tmax_year)	1.920	2.331	3.558	0.028023 *
s(trd_qtl_Tmax_year)	4.853	5.884	5.826	2.47e-05 ***
s(Days_above_threshold_wspped)	9.752	10.624	15.698	< 2e-16 ***
s(max_wspped)	1.000	1.000	8.973	0.003038 **
s(fst_qtl_wspped_year)	1.000	1.000	10.599	0.001300 **
s(year)	9.981	10.914	36.631	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.851 Deviance explained = 87.8%
-REML = -206.86 Scale est. = 0.0014966 n = 283

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	0.0005685284	0.02384383	0.03781862	3.781862
2	2	0.0015652255	0.03956293	0.06275063	6.275063
3	3	0.0011950377	0.03456932	0.05483027	5.483027
4	4	0.0017681243	0.04204907	0.06669388	6.669388
5	5	0.0013771783	0.03711035	0.05886060	5.886060
6	6	0.0006133567	0.02476604	0.03928133	3.928133
7	7	0.0004433666	0.02105627	0.03339728	3.339728
8	8	0.0021526222	0.04639636	0.07358910	7.358910
9	9	0.0014962905	0.03868191	0.06135325	6.135325
10	10	0.0010546415	0.03247524	0.05150887	5.150887

(b)

FIGURE 45: GAM (a) and 10-fold cross-validation (b) results for the BoCP specification in tariff region B considering year as a predictor: All crops.

```

Family: gaussian
Link function: identity

Formula:
Bonus_over_Comercial_Prize ~ s(Days_above_threshold_Rtotal, k = 13) +
  s(trd_qtl_Rtotal_year, k = 13) + s(Days_above_threshold_Tmin,
    k = 13) + s(min_Tmin, k = 13) + s(max_Tmin, k = 13) + s(trd_qtl_Tmin_year,
    k = 13) + s(Days_above_threshold_Tmax, k = 13) + s(Days_under_threshold_Tmax,
    k = 13) + s(min_Tmax, k = 13) + s(max_Tmax, k = 13) + s(trd_qtl_Tmax_year,
    k = 13) + s(min_wspped, k = 13) + s(max_wspped, k = 13) +
  s(Year, k = 13)

Parametric coefficients:
      Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.581437  0.001639   354.8 <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
      edf Ref.df      F p-value
s(Days_above_threshold_Rtotal) 1.292 1.499  5.355 0.008511 **
s(trd_qtl_Rtotal_year)         3.199 3.915  3.890 0.002945 **
s(Days_above_threshold_Tmin)  9.085 10.200  8.032 < 2e-16 ***
s(min_Tmin)                   2.268 2.826  9.237 1.48e-05 ***
s(max_Tmin)                   5.975 7.158  8.677 < 2e-16 ***
s(trd_qtl_Tmin_year)          2.826 3.473  5.124 0.013121 *
s(Days_above_threshold_Tmax)  1.001 1.002  8.755 0.003176 **
s(Days_under_threshold_Tmax)  9.804 10.923  7.617 < 2e-16 ***
s(min_Tmax)                   6.760 8.078  8.331 < 2e-16 ***
s(max_Tmax)                   4.058 4.882  4.243 0.000635 ***
s(trd_qtl_Tmax_year)          1.000 1.000 14.797 0.000131 ***
s(min_wspped)                 5.103 6.258  5.825 5.01e-06 ***
s(max_wspped)                 4.169 5.114  6.838 2.47e-06 ***
s(Year)                       11.195 11.772 144.926 < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.856 Deviance explained = 86.9%
-REML = -684.71 Scale est. = 0.0020755 n = 773

```

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	0.002721342	0.05216648	0.05929802	5.929802
2	2	0.003509705	0.05924277	0.06734169	6.734169
3	3	0.003991578	0.06317894	0.07181596	7.181596
4	4	0.003616161	0.06013452	0.06835535	6.835535
5	5	0.003011765	0.05487955	0.06238199	6.238199
6	6	0.002267537	0.04761866	0.05412849	5.412849
7	7	0.001332469	0.03650300	0.04149323	4.149323
8	8	0.002145331	0.04631772	0.05264969	5.264969
9	9	0.002378077	0.04876554	0.05543214	5.543214
10	10	0.003036192	0.05510165	0.06263446	6.263446

(b)

FIGURE 46: GAM (a) and 10-fold cross-validation (b) results for the BoCP specification in tariff region C considering year as a predictor: All except vineyard.

```

Family: gaussian
Link function: identity

Formula:
Bonus_over_Comercial_Prize ~ s(Days_above_threshold_Rtotal, k = 13) +
  s(trd_qtl_Rtotal_year, k = 13) + s(Days_above_threshold_Tmin,
    k = 13) + s(min_Tmin, k = 13) + s(max_Tmin, k = 13) + s(Days_above_threshold_Tmax,
    k = 13) + s(min_Tmax, k = 13) + s(max_Tmax, k = 13) + s(fst_qtl_Tmax_year,
    k = 13) + s(min_wspped, k = 13) + s(max_wspped, k = 13) +
  s(Year, k = 13)

Parametric coefficients:
      Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.579311  0.001782   325.1 <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
      edf Ref.df      F p-value
s(Days_above_threshold_Rtotal) 1.578 1.940  2.389 0.078071 .
s(trd_qtl_Rtotal_year)         1.981 2.471  2.079 0.096586 .
s(Days_above_threshold_Tmin)  9.753 10.900  6.893 < 2e-16 ***
s(min_Tmin)                   1.300 1.533  8.442 0.000754 ***
s(max_Tmin)                   5.301 6.481  5.305 7.62e-06 ***
s(Days_above_threshold_Tmax)  1.000 1.000  7.669 0.005729 **
s(min_Tmax)                   4.727 5.822  6.021 1.10e-05 ***
s(max_Tmax)                   2.409 2.965  2.508 0.058337 .
s(fst_qtl_Tmax_year)          5.566 6.783  4.067 0.000164 ***
s(min_wspped)                 4.689 5.843  5.030 7.13e-05 ***
s(max_wspped)                 1.000 1.000  9.158 0.002546 **
s(Year)                       11.402 11.884 117.327 < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.793 Deviance explained = 80.4%
-REML = -806.13 Scale est. = 0.0030358 n = 956

```

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	0.001969130	0.04437488	0.05044125	5.044125
2	2	0.002409013	0.04908170	0.05579153	5.579153
3	3	0.003361208	0.05797592	0.06590166	6.590166
4	4	0.003674690	0.06061922	0.06890631	6.890631
5	5	0.002310710	0.04806985	0.05464135	5.464135
6	6	0.002707963	0.05203809	0.05915208	5.915208
7	7	0.003227892	0.05681454	0.06458151	6.458151
8	8	0.002801777	0.05293182	0.06016798	6.016798
9	9	0.003029441	0.05504036	0.06256478	6.256478
10	10	0.003232886	0.05685848	0.06463145	6.463145

(b)

FIGURE 47: GAM (a) and 10-fold cross-validation (b) results for the BoCP specification in tariff region C considering year as a predictor: All crops.

Family: gaussian
Link function: identity

Formula:
Bonus_over_Comercial_Prize ~ s(Days_above_threshold_Rtotal, k = 10) +
s(trd_qtl_Rtotal_year, k = 10) + s(Days_above_threshold_Tmin,
k = 10) + s(Days_under_threshold_Tmin, k = 10) + s(min_Tmin,
k = 10) + s(max_Tmin, k = 10) + s(fst_qtl_Tmin_year, k = 10) +
s(Days_under_threshold_Tmax, k = 10) + s(min_Tmax, k = 10) +
s(max_Tmax, k = 10) + s(fst_qtl_Tmax_year, k = 10) + s(min_wspped,
k = 10) + s(max_wspped, k = 10) + s(Year, k = 10)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.578121 0.001877 307.9 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Days_above_threshold_Rtotal)	2.196	2.743	5.612	0.001015 ***
s(trd_qtl_Rtotal_year)	2.842	3.503	8.646	9.89e-06 ***
s(Days_above_threshold_Tmin)	6.815	7.664	5.845	5.64e-07 ***
s(Days_under_threshold_Tmin)	1.171	1.311	4.907	0.043251 *
s(min_Tmin)	1.915	2.404	4.939	0.004696 ***
s(max_Tmin)	5.203	6.186	5.131	9.26e-05 ***
s(fst_qtl_Tmin_year)	1.001	1.001	8.430	0.003773 ***
s(Days_under_threshold_Tmax)	6.538	7.571	4.213	5.03e-05 ***
s(min_Tmax)	7.006	7.975	11.432	< 2e-16 ***
s(max_Tmax)	3.956	4.760	3.707	0.002734 ***
s(fst_qtl_Tmax_year)	5.186	6.288	6.507	2.09e-06 ***
s(min_wspped)	3.665	4.562	4.451	0.001323 ***
s(max_wspped)	1.000	1.000	15.122	0.000109 ***
s(Year)	8.461	8.877	138.473	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.763 Deviance explained = 77.7%
-REML = -774.16 Scale est. = 0.0034363 n = 975

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	0.003763162	0.06134462	0.06973088	6.973088
2	2	0.004438819	0.06662446	0.07573251	7.573251
3	3	0.003154197	0.05616224	0.06384003	6.384003
4	4	0.003467744	0.05888755	0.06693791	6.693791
5	5	0.003518231	0.05931468	0.06742343	6.742343
6	6	0.002298791	0.04794571	0.05450024	5.450024
7	7	0.002789593	0.05281659	0.06003701	6.003701
8	8	0.003163397	0.05624408	0.06393306	6.393306
9	9	0.001951232	0.04417275	0.05021149	5.021149
10	10	0.002947819	0.05429382	0.06171618	6.171618

(b)

FIGURE 48: GAM (a) and 10-fold cross-validation (b) results for the BoCP specification in tariff region C considering year as a predictor: Vineyard.

Family: gaussian
Link function: identity

Formula:
Bonus_over_Comercial_Prize ~ s(Days_above_threshold_Rtotal, k = 12) +
s(trd_qtl_Rtotal_year, k = 12) + s(Days_above_threshold_Tmin,
k = 12) + s(Days_under_threshold_Tmin, k = 12) + s(min_Tmin,
k = 12) + s(max_Tmin, k = 12) + s(fst_qtl_Tmin_year, k = 12) +
s(trd_qtl_Tmin_year, k = 12) + s(Days_above_threshold_Tmax,
k = 12) + s(min_Tmax, k = 12) + s(max_Tmax, k = 12) + s(fst_qtl_Tmax_year,
k = 12) + s(Days_above_threshold_wspped, k = 12) + s(Days_under_threshold_wspped,
k = 12) + s(min_wspped, k = 12) + s(max_wspped, k = 12) +
s(fst_qtl_wspped_year, k = 12) + s(trd_qtl_wspped_year, k = 12) +
s(Year, k = 12)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.62053 0.00121 512.7 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Days_above_threshold_Rtotal)	5.847	6.746	11.102	< 2e-16 ***
s(trd_qtl_Rtotal_year)	4.831	5.541	5.503	3.30e-05 ***
s(Days_above_threshold_Tmin)	7.008	8.038	9.354	< 2e-16 ***
s(Days_under_threshold_Tmin)	1.000	1.000	23.709	1.81e-06 ***
s(min_Tmin)	5.585	6.482	7.573	< 2e-16 ***
s(max_Tmin)	1.000	1.000	4.503	0.034380 *
s(fst_qtl_Tmin_year)	1.000	1.000	6.669	0.010133 *
s(trd_qtl_Tmin_year)	6.901	7.921	10.555	< 2e-16 ***
s(Days_above_threshold_Tmax)	6.222	7.237	15.220	< 2e-16 ***
s(min_Tmax)	4.192	4.905	5.793	5.49e-05 ***
s(max_Tmax)	1.000	1.000	23.487	2.00e-06 ***
s(fst_qtl_Tmax_year)	5.700	6.656	7.187	2.68e-07 ***
s(Days_above_threshold_wspped)	1.000	1.000	17.188	4.10e-05 ***
s(Days_under_threshold_wspped)	5.027	5.980	4.475	0.000321 ***
s(min_wspped)	8.077	8.852	6.339	< 2e-16 ***
s(max_wspped)	1.824	2.060	3.327	0.03260 *
s(fst_qtl_wspped_year)	1.000	1.000	14.188	0.000188 ***
s(trd_qtl_wspped_year)	6.205	7.250	3.517	0.001696 **
s(Year)	10.618	10.869	117.376	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.924 Deviance explained = 93.7%
-REML = -525.02 Scale est. = 0.000766 n = 523

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	0.0011451257	0.03383971	0.05882100	5.882100
2	2	0.0006467539	0.02543136	0.04420540	4.420540
3	3	0.0026235138	0.05122025	0.08903228	8.903228
4	4	0.0022798640	0.04774792	0.08299660	8.299660
5	5	0.0139215315	0.11798954	0.20509228	20.509228
6	6	0.0016797332	0.04098455	0.07124034	7.124034
7	7	0.0014656689	0.03828406	0.06654627	6.654627
8	8	0.0016271009	0.04033734	0.07011534	7.011534
9	9	0.0008789021	0.02964628	0.05153189	5.153189
10	10	0.0012948749	0.03598437	0.06254890	6.254890

(b)

FIGURE 49: GAM (a) and 10-fold cross-validation (b) results for the BoCP specification in tariff region D considering year as a predictor: All except vineyard.

Family: gaussian
Link function: identity

Formula:
Bonus_over_comercial_Prize ~ s(Days_above_threshold_Rtotal, k = 12) +
s(trd_qtl_Rtotal_year, k = 12) + s(Days_above_threshold_Tmin,
k = 12) + s(Days_under_threshold_Tmin, k = 12) + s(trd_qtl_Tmin_year,
k = 12) + s(Days_under_threshold_Tmax, k = 12) + s(min_Tmax,
k = 12) + s(max_Tmax, k = 12) + s(fst_qtl_Tmax_year, k = 12) +
s(trd_qtl_Tmax_year, k = 12) + s(Days_above_threshold_wspeed,
k = 12) + s(Days_under_threshold_wspeed, k = 12) + s(min_wspeed,
k = 12) + s(max_wspeed, k = 12) + s(fst_qtl_wspeed_year,
k = 12) + s(year, k = 12)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.639043 0.001687 378.7 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Days_above_threshold_Rtotal)	7.306	8.464	9.658	< 2e-16 ***
s(trd_qtl_Rtotal_year)	4.121	4.944	12.721	< 2e-16 ***
s(Days_above_threshold_Tmin)	5.452	6.609	5.833	3.42e-06 ***
s(Days_under_threshold_Tmin)	7.990	9.187	9.124	< 2e-16 ***
s(trd_qtl_Tmin_year)	3.498	4.386	3.256	0.009224 **
s(Days_under_threshold_Tmax)	2.184	2.801	6.323	0.000545 ***
s(min_Tmax)	5.874	7.042	6.034	6.98e-07 ***
s(max_Tmax)	1.000	1.000	21.828	3.90e-06 ***
s(fst_qtl_Tmax_year)	9.441	10.317	16.149	< 2e-16 ***
s(trd_qtl_Tmax_year)	1.003	1.006	6.203	0.012788 *
s(Days_above_threshold_wspeed)	8.805	9.677	8.306	< 2e-16 ***
s(Days_under_threshold_wspeed)	4.059	4.996	5.714	3.06e-05 ***
s(min_wspeed)	6.919	8.022	8.011	< 2e-16 ***
s(max_wspeed)	1.000	1.000	4.897	0.027205 *
s(fst_qtl_wspeed_year)	5.640	6.775	2.304	0.025444 *
s(year)	9.541	10.404	58.450	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.799 Deviance explained = 81.8%
-REML = -713.58 Scale est. = 0.0024859 n = 873

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	0.003074257	0.05544598	0.09313044	9.313044
2	2	0.002908926	0.05393446	0.09059158	9.059158
3	3	0.002548845	0.05048609	0.08479949	8.479949
4	4	0.003714147	0.06094381	0.10236491	10.236491
5	5	0.004125372	0.06422906	0.10788302	10.788302
6	6	0.002913156	0.05397366	0.09065743	9.065743
7	7	0.003665588	0.06054410	0.10169353	10.169353
8	8	0.003097748	0.05565742	0.09348558	9.348558
9	9	0.003971460	0.06301952	0.10585140	10.585140
10	10	0.003426175	0.05853354	0.09831648	9.831648

(b)

FIGURE 50: GAM (a) and 10-fold cross-validation (b) results for the BoCP specification in tariff region D considering year as a predictor: All crops.

Family: gaussian
Link function: identity

Formula:
Bonus_over_comercial_Prize ~ s(Days_above_threshold_Rtotal, k = 12) +
s(trd_qtl_Rtotal_year, k = 12) + s(Days_above_threshold_Tmin,
k = 12) + s(Days_under_threshold_Tmin, k = 12) + s(min_Tmin,
k = 12) + s(max_Tmin, k = 12) + s(fst_qtl_Tmin_year, k = 12) +
s(trd_qtl_Tmin_year, k = 12) + s(Days_above_threshold_Tmax,
k = 12) + s(min_Tmax, k = 12) + s(max_Tmax, k = 12) + s(fst_qtl_Tmax_year,
k = 12) + s(trd_qtl_Tmax_year, k = 12) + s(Days_above_threshold_wspeed,
k = 12) + s(min_wspeed, k = 12) + s(fst_qtl_wspeed_year,
k = 12) + s(trd_qtl_wspeed_year, k = 12) + s(year, k = 12)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.627308 0.000914 686.3 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Days_above_threshold_Rtotal)	5.987	7.070	7.297	< 2e-16 ***
s(trd_qtl_Rtotal_year)	5.204	6.148	9.265	< 2e-16 ***
s(Days_above_threshold_Tmin)	2.621	3.225	15.614	< 2e-16 ***
s(Days_under_threshold_Tmin)	5.088	6.052	12.660	< 2e-16 ***
s(min_Tmin)	1.000	1.001	9.374	0.00224 **
s(max_Tmin)	3.808	4.581	11.506	< 2e-16 ***
s(fst_qtl_Tmin_year)	5.327	6.321	32.734	< 2e-16 ***
s(trd_qtl_Tmin_year)	2.993	3.689	5.274	0.00135 **
s(Days_above_threshold_Tmax)	7.623	8.704	7.446	< 2e-16 ***
s(min_Tmax)	5.490	6.467	5.604	5.74e-06 ***
s(max_Tmax)	1.000	1.001	52.602	< 2e-16 ***
s(fst_qtl_Tmax_year)	4.560	5.423	4.433	0.00107 **
s(trd_qtl_Tmax_year)	3.466	4.240	3.940	0.00302 **
s(Days_above_threshold_wspeed)	1.334	1.540	13.052	0.00050 ***
s(min_wspeed)	5.931	7.012	9.138	< 2e-16 ***
s(fst_qtl_wspeed_year)	3.935	4.841	9.244	< 2e-16 ***
s(trd_qtl_wspeed_year)	7.759	8.844	6.616	< 2e-16 ***
s(year)	10.862	10.967	293.189	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.883 Deviance explained = 89%
-REML = -1547.8 Scale est. = 0.0011244 n = 1346

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	0.0007670452	0.02769558	0.03311771	3.311771
2	2	0.0011427630	0.03380478	0.04042295	4.042295
3	3	0.0024969855	0.04996985	0.05975275	5.975275
4	4	0.0006871823	0.02621416	0.03134627	3.134627
5	5	0.0005888410	0.02426605	0.02901676	2.901676
6	6	0.0009909821	0.03147987	0.03764287	3.764287
7	7	0.0009651285	0.03106652	0.03714860	3.714860
8	8	0.0029243039	0.05407683	0.06466378	6.466378
9	9	0.0014104384	0.03755580	0.04490833	4.490833
10	10	0.0008184349	0.02860830	0.03420912	3.420912

(b)

FIGURE 51: GAM (a) and 10-fold cross-validation (b) results for the BoCP specification in tariff region E considering year as a predictor: All except vineyard.

```

Family: gaussian
Link function: identity

Formula:
Bonus_over_Comercial_Prize ~ s(trd_qtl_Rtotal_year, k = 17) +
  s(Days_above_threshold_Tmin, k = 17) + s(Days_under_threshold_Tmin,
  k = 17) + s(min_Tmin, k = 17) + s(max_Tmin, k = 17) + s(fst_qtl_Tmin_year,
  k = 17) + s(Days_above_threshold_Tmax, k = 17) + s(max_Tmax,
  k = 17) + s(fst_qtl_Tmax_year, k = 17) + s(Days_above_threshold_wspeerd,
  k = 17) + s(max_wspeerd, k = 17) + s(fst_qtl_wspeerd_year,
  k = 17) + s(year, k = 17)

Parametric coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.627063    0.001014   618.4 <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
              edf Ref.df      F  p-value
s(trd_qtl_Rtotal_year)  5.059  6.139   5.185 2.46e-05 ***
s(Days_above_threshold_Tmin) 1.000  1.000  31.362 < 2e-16 ***
s(Days_under_threshold_Tmin)  3.169  3.974   2.358  0.04331 *
s(min_Tmin)                1.001  1.003   9.293  0.00231 **
s(max_Tmin)                 3.583  4.453   6.692  1.29e-05 ***
s(fst_qtl_Tmin_year)        4.793  5.908   5.038  3.44e-05 ***
s(Days_above_threshold_Tmax)  8.288  9.945   8.843 < 2e-16 ***
s(max_Tmax)                 1.001  1.002  25.719 5.42e-07 ***
s(fst_qtl_Tmax_year)        4.358  5.333   3.340  0.00262 **
s(Days_above_threshold_wspeerd) 3.071  3.840   3.919  0.00564 **
s(max_wspeerd)              2.806  3.570   3.071  0.01432 *
s(fst_qtl_wspeerd_year)     6.253  7.649   3.052  0.00262 **
s(year)                     15.485 15.907  260.623 < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.834   Deviance explained = 83.9%
-REML = -1886.1   Scale est. = 0.001824   n = 1774

```

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	0.001886916	0.04343864	0.05194289	5.194289
2	2	0.002433408	0.04932959	0.05898714	5.898714
3	3	0.001623724	0.04029546	0.04818435	4.818435
4	4	0.001543453	0.03928681	0.04697823	4.697823
5	5	0.002169560	0.04657853	0.05569750	5.569750
6	6	0.001728341	0.04157332	0.04971238	4.971238
7	7	0.001333092	0.03651153	0.04365962	4.365962
8	8	0.003147188	0.05609980	0.06708280	6.708280
9	9	0.001867960	0.04321990	0.05168132	5.168132
10	10	0.001751165	0.04184692	0.05003954	5.003954

(b)

FIGURE 52: GAM (a) and 10-fold cross-validation (b) results for the BoCP specification in tariff region E considering year as a predictor: All crops.

```

Family: gaussian
Link function: identity

Formula:
Bonus_over_Comercial_Prize ~ s(Days_above_threshold_Rtotal, k = 12) +
  s(Days_above_threshold_Tmin, k = 12) + s(Days_under_threshold_Tmin,
  k = 12) + s(max_Tmin, k = 12) + s(trd_qtl_Tmin_year, k = 12) +
  s(Days_above_threshold_Tmax, k = 12) + s(Days_under_threshold_Tmax,
  k = 12) + s(fst_qtl_Tmax_year, k = 12) + s(trd_qtl_Tmax_year,
  k = 12) + s(Days_above_threshold_wspeerd, k = 12) + s(max_wspeerd,
  k = 12) + s(fst_qtl_wspeerd_year, k = 12) + s(year, k = 12)

Parametric coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.622565    0.001621   384.1 <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
              edf Ref.df      F  p-value
s(Days_above_threshold_Rtotal) 1.199  1.352  21.440 5.98e-06 ***
s(Days_above_threshold_Tmin)  4.119  5.058  13.448 < 2e-16 ***
s(Days_under_threshold_Tmin)  8.785  9.789   8.328 < 2e-16 ***
s(max_Tmin)                   6.436  7.719   6.623 < 2e-16 ***
s(trd_qtl_Tmin_year)          1.001  1.002  10.052 0.001634 **
s(Days_above_threshold_Tmax)  5.834  7.038   5.249 8.40e-06 ***
s(Days_under_threshold_Tmax)  7.723  8.928   6.472 < 2e-16 ***
s(fst_qtl_Tmax_year)          1.773  2.206   9.711 5.00e-05 ***
s(trd_qtl_Tmax_year)          3.667  4.586   4.397 0.000988 ***
s(Days_above_threshold_wspeerd) 3.398  4.269   8.326 1.69e-06 ***
s(max_wspeerd)                7.194  8.504   5.536 1.24e-06 ***
s(fst_qtl_wspeerd_year)       6.754  8.027  10.545 < 2e-16 ***
s(year)                       10.517 10.887  145.849 < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.922   Deviance explained = 93.4%
-REML = -415.53   Scale est. = 0.0011824   n = 450

```

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	0.0012341106	0.03512991	0.07040519	7.040519
2	2	0.0007960967	0.02821519	0.05654713	5.654713
3	3	0.0014558736	0.03815591	0.07646972	7.646972
4	4	0.0006886568	0.02624227	0.05259314	5.259314
5	5	0.0008413869	0.02900667	0.05813337	5.813337
6	6	0.0010592425	0.03254601	0.06522669	6.522669
7	7	0.0013559395	0.03682308	0.07379855	7.379855
8	8	0.0008587868	0.02930506	0.05873140	5.873140
9	9	0.0011169610	0.03342097	0.06698023	6.698023
10	10	0.0006803904	0.02608429	0.05227653	5.227653

(b)

FIGURE 53: GAM (a) and 10-fold cross-validation (b) results for the BoCP specification in tariff region E considering year as a predictor: Vineyard.

Family: gaussian									
Link function: identity									
Formula:									
Tariffs ~ s(Days_above_threshold_Rtotal, k = 6) + s(Days_above_threshold_Tmin, k = 6) + s(Days_under_threshold_Tmin, k = 6) + s(Days_above_threshold_Tmax, k = 6) + s(Days_under_threshold_Tmax, k = 6) + s(min.Tmax, k = 6) + s(max.Tmax, k = 6) + s(max.wspeed, k = 6) + s(Year, k = 6)									
Parametric coefficients:									
Estimate Std. Error t value Pr(> t)									
(Intercept) 0.0364485 0.0002704 134.8 <2e-16 ***									

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1									
Approximate significance of smooth terms:									
edf Ref.df F p-value									
s(Days_above_threshold_Rtotal) 1.000 1.000 15.121 0.000204 ***									
s(Days_above_threshold_Tmin) 4.466 4.798 6.773 1.95e-05 ***									
s(Days_under_threshold_Tmin) 1.000 1.000 51.397 < 2e-16 ***									
s(Days_above_threshold_Tmax) 1.000 1.000 24.352 4.36e-06 ***									
s(Days_under_threshold_Tmax) 1.000 1.000 21.602 1.30e-05 ***									
s(min.Tmax) 2.219 2.669 5.207 0.003839 **									
s(max.Tmax) 1.654 2.030 28.186 < 2e-16 ***									
s(max.wspeed) 3.517 4.068 25.397 < 2e-16 ***									
s(Year) 3.000 3.512 40.441 < 2e-16 ***									

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1									
R-sq.(adj) = 0.881 Deviance explained = 90.3%									
-REML = -219.62 Scale est. = 7.4558e-06 n = 102									
(a)					(b)				

FIGURE 54: GAM (a) and 10-fold cross-validation (b) results for the Tariffs specification in tariff region A considering year as a predictor: All except vineyard.

Family: gaussian									
Link function: identity									
Formula:									
Tariffs ~ s(Days_above_threshold_Rtotal, k = 10) + s(max.wspeed, k = 10) + s(Year, k = 10)									
Parametric coefficients:									
Estimate Std. Error t value Pr(> t)									
(Intercept) 0.0318699 0.0006673 47.76 <2e-16 ***									

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1									
Approximate significance of smooth terms:									
edf Ref.df F p-value									
s(Days_above_threshold_Rtotal) 1.000 1.001 4.572 0.0343 *									
s(max.wspeed) 3.008 3.775 10.612 8.10e-07 ***									
s(Year) 3.000 3.686 10.198 1.59e-06 ***									

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1									
R-sq.(adj) = 0.435 Deviance explained = 46.3%									
-REML = -291.69 Scale est. = 6.2785e-05 n = 141									
(a)					(b)				

FIGURE 55: GAM (a) and 10-fold cross-validation (b) results for the Tariffs specification in tariff region A considering year as a predictor: All crops.

Family: gaussian
Link function: identity

Formula:
Tariffs ~ s(Days_above_threshold_Rtotal, k = 7) + s(Days_above_threshold_Tmin, k = 7) + s(min.Tmin., k = 7) + s(Days_above_threshold_Tmax, k = 7) + s(max.Tmax., k = 7) + s(Days_above_threshold_wspped, k = 7) + s(min.wspped., k = 7) + s(max.wspped., k = 7) + s(Year, k = 7)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.0450939 0.0007393 60.99 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Days_above_threshold_Rtotal)	3.248	3.940	4.656	0.001132 **
s(Days_above_threshold_Tmin)	1.000	1.001	27.029	5.70e-07 ***
s(min.Tmin.)	1.000	1.000	14.788	0.000157 ***
s(Days_above_threshold_Tmax)	2.985	3.690	7.965	2.63e-05 ***
s(max.Tmax.)	1.000	1.000	10.613	0.001296 **
s(Days_above_threshold_wspped)	2.316	2.823	6.735	0.001535 **
s(min.wspped.)	2.443	2.926	4.795	0.005845 **
s(max.wspped.)	4.769	5.270	9.526	< 2e-16 ***
s(Year)	4.055	4.792	6.766	7.04e-06 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.603 Deviance explained = 64%
-REML = -424.43 Scale est. = 0.0001361 n = 249

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	8.304642e-05	0.009112981	0.06540354	6.540354
2	2	4.055237e-04	0.020137619	0.14452697	14.452697
3	3	1.693191e-04	0.013012268	0.09338858	9.338858
4	4	1.836420e-04	0.013551456	0.09725832	9.725832
5	5	1.803503e-04	0.013429456	0.09638273	9.638273
6	6	1.281100e-04	0.011318570	0.08123297	8.123297
7	7	1.011483e-04	0.010057252	0.07218054	7.218054
8	8	3.597374e-04	0.018966745	0.13612366	13.612366
9	9	6.651435e-04	0.025790377	0.18509661	18.509661
10	10	1.467394e-04	0.012113602	0.08693889	8.693889

(b)

FIGURE 56: GAM (a) and 10-fold cross-validation (b) results for the Tariffs specification in tariff region B considering year as a predictor: All except vineyard.

Family: gaussian
Link function: identity

Formula:
Tariffs ~ s(Days_above_threshold_Rtotal, k = 8) + s(Days_above_threshold_Tmin, k = 8) + s(Days_above_threshold_Tmax, k = 8) + s(max.Tmax., k = 8) + s(Days_under_threshold_wspped, k = 8) + s(max.wspped., k = 8) + s(Year, k = 8)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.0428464 0.0007782 55.06 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Days_above_threshold_Rtotal)	2.514	3.180	3.006	0.028655 *
s(Days_above_threshold_Tmin)	1.001	1.001	13.131	0.000347 ***
s(Days_above_threshold_Tmax)	3.913	4.808	13.281	< 2e-16 ***
s(max.Tmax.)	1.000	1.001	17.202	4.52e-05 ***
s(Days_under_threshold_wspped)	1.580	1.946	11.103	6.49e-05 ***
s(max.wspped.)	1.000	1.000	18.734	2.17e-05 ***
s(Year)	4.441	5.303	12.266	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.513 Deviance explained = 53.9%
-REML = -491.79 Scale est. = 0.00017136 n = 283

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	1.449774e-04	0.012040655	0.08641535	8.641535
2	2	1.468819e-04	0.012119484	0.08698110	8.698110
3	3	2.079023e-04	0.014418819	0.10348335	10.348335
4	4	7.367886e-05	0.008583639	0.06160447	6.160447
5	5	1.244454e-04	0.011155511	0.08006271	8.006271
6	6	8.850289e-05	0.009407597	0.06751799	6.751799
7	7	1.127749e-04	0.010619551	0.07621614	7.621614
8	8	2.417690e-04	0.015548921	0.11159405	11.159405
9	9	7.836805e-04	0.027994294	0.20091405	20.091405
10	10	9.910197e-05	0.009954997	0.07144666	7.144666

(b)

FIGURE 57: GAM (a) and 10-fold cross-validation (b) results for the Tariffs specification in tariff region B considering year as a predictor: All crops.

Family: gaussian
Link function: identity

Formula:
Tariffs ~ s(Days_above_threshold_Tmin, k = 3) + s(Days_under_threshold_Tmax,
k = 3) + s(min.Tmax., k = 3) + s(Days_under_threshold_wspped,
k = 3) + s(Year, k = 3)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.0259990 0.0005187 50.12 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
edf Ref.df F p-value
s(Days_above_threshold_Tmin) 1.918 1.993 30.550 < 2e-16 ***
s(Days_under_threshold_Tmax) 1.274 1.472 7.003 0.01651 *
s(min.Tmax.) 1.000 1.000 10.209 0.00314 **
s(Days_under_threshold_wspped) 1.932 1.995 15.559 3.13e-05 ***
s(Year) 1.953 1.997 49.639 < 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.881 Deviance explained = 90.5%
-REML = -73.418 Scale est. = 1.1032e-05 n = 41

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	8.925266e-05	0.009447362	0.16691551	16.691551
2	2	2.267042e-05	0.004761346	0.08412322	8.412322
3	3	3.943197e-06	0.001985748	0.03508410	3.508410
4	4	1.080418e-05	0.003286971	0.05807403	5.807403
5	5	9.771655e-06	0.003125965	0.05522938	5.522938
6	6	2.861738e-05	0.005349521	0.09451506	9.451506
7	7	1.221873e-05	0.003495530	0.06175885	6.175885
8	8	6.550597e-06	0.002559413	0.04521958	4.521958
9	9	5.007702e-06	0.002237789	0.03953715	3.953715
10	10	5.409670e-06	0.002325870	0.04109335	4.109335

(b)

FIGURE 58: GAM (a) and 10-fold cross-validation (b) results for the Tariffs specification in tariff region B considering year as a predictor: Vineyard.

Family: gaussian
Link function: identity

Formula:
Tariffs ~ s(Days_above_threshold_Rtotal, k = 10) + s(Days_above_threshold_Tmin,
k = 10) + s(Days_above_threshold_Tmax, k = 10) + s(Days_under_threshold_Tmax,
k = 10) + s(max.Tmax., k = 10) + s(Days_under_threshold_wspped,
k = 10) + s(Year, k = 10)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.160634 0.002405 66.8 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
edf Ref.df F p-value
s(Days_above_threshold_Rtotal) 4.365 5.396 5.449 4.97e-05 ***
s(Days_above_threshold_Tmin) 2.852 3.619 5.234 0.00857 ***
s(Days_above_threshold_Tmax) 1.000 1.000 8.542 0.003559 **
s(Days_under_threshold_Tmax) 1.000 1.001 7.834 0.005237 **
s(max.Tmax.) 2.854 3.597 3.996 0.006407 **
s(Days_under_threshold_wspped) 6.345 7.434 9.171 < 2e-16 ***
s(Year) 1.000 1.000 19.785 9.81e-06 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

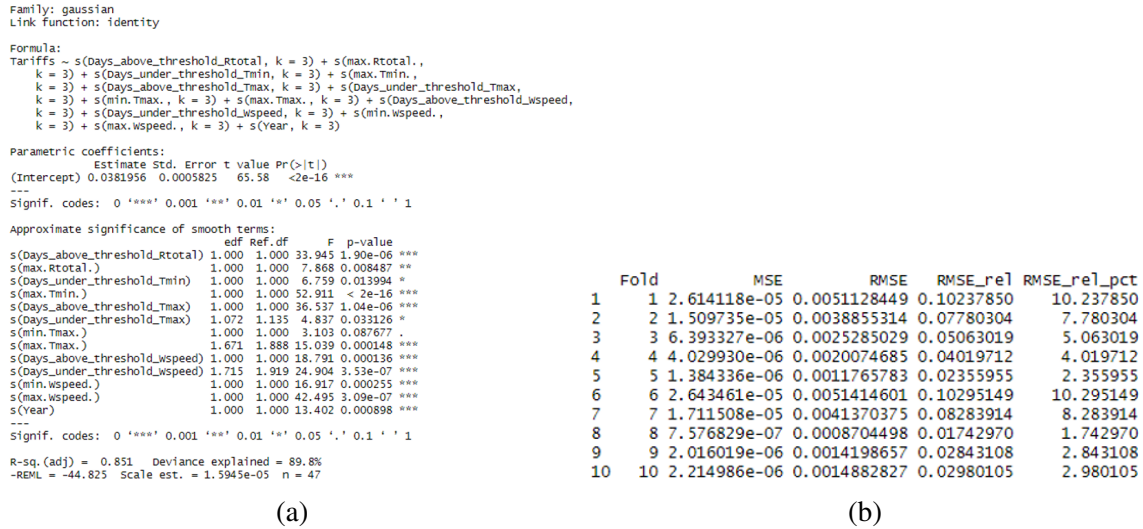
R-sq.(adj) = 0.292 Deviance explained = 30.8%
-REML = -668.31 Scale est. = 0.0051754 n = 895

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	0.005239873	0.07238697	0.2113328	21.13328
2	2	0.005573850	0.07465822	0.2179637	21.79637
3	3	0.005740190	0.07576404	0.2211922	22.11922
4	4	0.005046646	0.07103975	0.2073997	20.73997
5	5	0.005866916	0.07659580	0.2236205	22.36205
6	6	0.005206048	0.07215295	0.2106496	21.06496
7	7	0.004950958	0.07036305	0.2054240	20.54240
8	8	0.005158422	0.07182216	0.2096839	20.96839
9	9	0.005152934	0.07178394	0.2095723	20.95723
10	10	0.005102633	0.07143271	0.2085469	20.85469

(b)

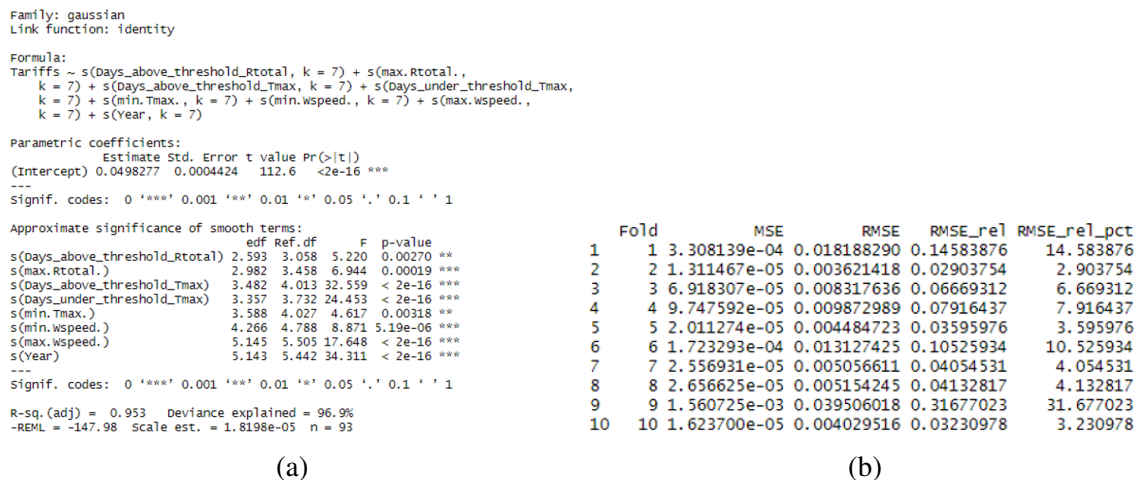
FIGURE 59: GAM (a) and 10-fold cross-validation (b) results for the Tariffs specification in tariff region D considering year as a predictor: All crops.



(a)

(b)

FIGURE 60: GAM (a) and 10-fold cross-validation (b) results for the Tariffs with lagged climatic variables specification in tariff region A considering year as a predictor: All except vineyard.



(a)

(b)

FIGURE 61: GAM (a) and 10-fold cross-validation (b) results for the Tariffs with lagged climatic variables specification in tariff region B considering year as a predictor: All crops.

Family: gaussian
Link function: identity

Formula:
Tariffs ~ s(Days_above_threshold_Rtotal, k = 4) + s(max.Rtotal, k = 4) + s(Days_above_threshold_Tmin, k = 4) + s(max.Tmin, k = 4) + s(Days_above_threshold_Tmax, k = 4) + s(Days_under_threshold_Tmax, k = 4) + s(min.Tmax, k = 4) + s(max.Tmax, k = 4) + s(Days_above_threshold_wspeak, k = 4) + s(Days_under_threshold_wspeak, k = 4) + s(max.wspeak, k = 4) + s(Year, k = 4)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.0526019 0.0001925 273.2 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Days_above_threshold_Rtotal)	2.964	2.998	219.089	<2e-16 ***
s(max.Rtotal)	1.011	1.021	6.872	0.0117 *
s(Days_above_threshold_Tmin)	1.000	1.000	109.026	<2e-16 ***
s(Days_under_threshold_Tmin)	2.898	2.983	265.552	<2e-16 ***
s(max.Tmin)	1.000	1.000	111.589	<2e-16 ***
s(Days_above_threshold_Tmax)	2.966	2.998	58.043	<2e-16 ***
s(Days_under_threshold_Tmax)	2.935	2.992	236.222	<2e-16 ***
s(min.Tmax)	2.981	2.999	241.851	<2e-16 ***
s(max.Tmax)	1.000	1.000	393.929	<2e-16 ***
s(Days_above_threshold_wspeak)	2.988	2.999	349.095	<2e-16 ***
s(Days_under_threshold_wspeak)	2.977	2.999	102.484	<2e-16 ***
s(max.wspeak)	2.903	2.986	100.549	<2e-16 ***
s(Year)	2.942	2.997	104.091	<2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.991 Deviance explained = 99.4%
-REML = -122.25 Scale est. = 3.1131e-06 n = 84

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	3.523736e-03	0.059361063	0.476635031	47.6635031
2	2	9.050059e-04	0.030083316	0.241551645	24.1551645
3	3	2.576147e-04	0.016050381	0.128875285	12.8875285
4	4	3.285521e-05	0.005731946	0.046024217	4.6024217
5	5	7.419976e-05	0.008613928	0.069164868	6.9164868
6	6	1.574308e-05	0.003967755	0.031858780	3.1858780
7	7	4.869730e-04	0.022067464	0.177188982	17.7188982
8	8	8.530015e-05	0.009235808	0.074158203	7.4158203
9	9	1.482738e-06	0.001217677	0.009777246	0.9777246
10	10	3.325937e-05	0.005767094	0.046306430	4.6306430

(b)

FIGURE 62: GAM (a) and 10-fold cross-validation (b) results for the Tariffs with lagged climatic variables specification in tariff region B considering year as a predictor: All except vineyard.

Family: gaussian
Link function: identity

Formula:
Tariffs ~ s(Days_under_threshold_Tmin, k = 9) + s(Days_under_threshold_Tmax, k = 9) + s(max.wspeak, k = 9) + s(Year, k = 9)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.233367 0.002449 95.28 <2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(Days_under_threshold_Tmin)	3.258	4.076	6.857	2.26e-05 ***
s(Days_under_threshold_Tmax)	3.666	4.503	8.764	1.15e-06 ***
s(max.wspeak)	2.771	3.456	2.793	0.0324 *
s(Year)	2.149	2.633	20.246	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.281 Deviance explained = 30.8%
-REML = -326.6 Scale est. = 0.0018836 n = 314

(a)

	Fold	MSE	RMSE	RMSE_rel	RMSE_rel_pct
1	1	0.0018181842	0.04264017	0.12900184	12.900184
2	2	0.0019638275	0.04431509	0.13406908	13.406908
3	3	0.0028403850	0.05329526	0.16123732	16.123732
4	4	0.0009925116	0.03150415	0.09531138	9.531138
5	5	0.0008359812	0.02891334	0.08747324	8.747324
6	6	0.0031607723	0.05622075	0.17008796	17.008796
7	7	0.0043093280	0.06564547	0.19860115	19.860115
8	8	0.0019153605	0.04376483	0.13240435	13.240435
9	9	0.0010847678	0.03293581	0.09964267	9.964267
10	10	0.0013841498	0.03720416	0.11255597	11.255597

(b)

FIGURE 63: GAM (a) and 10-fold cross-validation (b) results for the Tariffs with lagged climatic variables specification in tariff region D considering year as a predictor: All except vineyard.

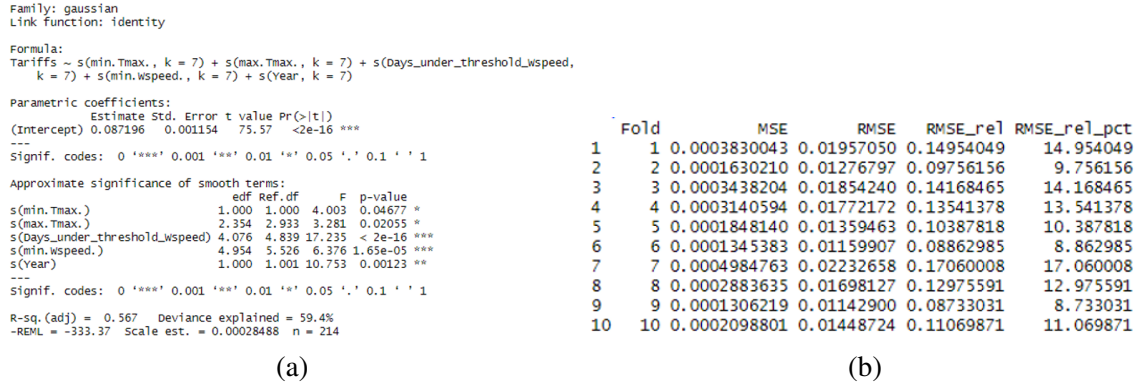


FIGURE 64: GAM (a) and 10-fold cross-validation (b) results for the Tariffs with lagged climatic variables specification in tariff region D considering year as a predictor: Vineyard.

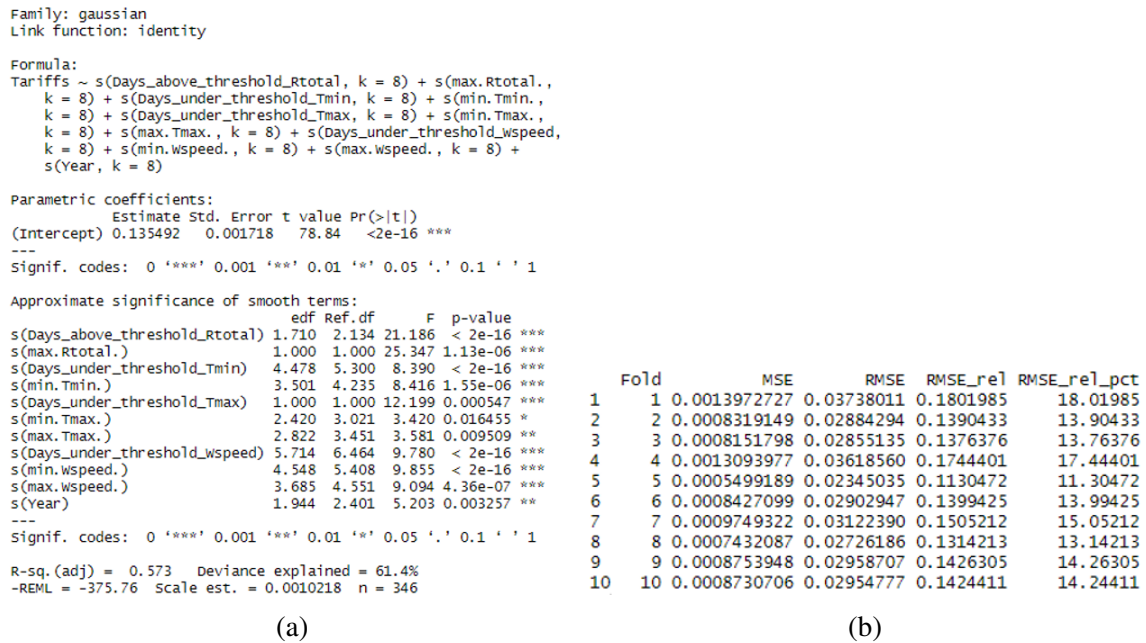


FIGURE 65: GAM (a) and 10-fold cross-validation (b) results for the Tariffs with lagged climatic variables specification in tariff region E considering year as a predictor: Vineyard.