Disentangling Environmental and Economic Risks in Mortgage Default: A Spatio-Temporal Modelling and Stress-Testing Framework with Capital Implications

Viani B. Djeundje, Jonathan Crook, Galina Andreeva

Credit Research Centre, University of Edinburgh
29 Bucceleuch Place, Edinburgh EH8 9JS, UK

Abstract

This paper develops and empirically validates a spatio-temporal framework that integrates extreme weather events and climate-related risk drivers with conventional borrower, loan and macroeconomic variables to explain and predict mortgage default risk. We use discrete-time survival models ranging from linear specifications to flexible general additive models with P-splines, time-varying coefficients and interaction surfaces. We contribute to the literature in three ways. First, unlike existing literature we investigate the predictive efficacy of models with time-varying coefficients and with coefficients dependent on other risk drivers. Second, we explore linear effects, nonlinear effects and nonlinear interactions between a wide range of weather drivers of default and between macroeconomic drivers of default, which have not been incorporated into credit risk models before. Third, we assess the relative contribution to the required economic capital of uncertainty over weather events and uncertainty of the macroeconomy. We do this by building time series models for weather and for macroeconomic variables. The omission of weather events results in significant underestimation of the capital required, especially under joint macroeconomic and weather stress. The approach is validated using mortgage defaults and wildfires in California. Recent wildfire occurrences across the world make our methodology particularly appropriate for risk modellers in banks.

1 Introduction

The accelerating rise in global temperatures, driven largely by anthropogenic greenhouse gas emissions and land-use changes, has intensified the frequency and severity of climate-related disasters (Intergovernmental Panel on Climate Change, 2023). These events pose acute physical risks to real assets, particularly residential properties that serve as collateral in mortgage portfolios. Among these hazards, wildfires have emerged as a particularly destructive force, reshaping ecosystems, threatening communities, and imposing substantial economic costs. In recent years, there has been a surge in wildfires across the world, including the United States, with longer fire seasons, larger burn areas, and more frequent high-intensity events (Iglesias et al., 2022; Environmental Protection Agency, 2024).

Financial institutions and regulators are increasingly recognizing the material risks that wildfires and other climate hazards pose to credit portfolios. Increasing numbers of regulators are developing expectations of lenders, both at the borrower and portfolio level. For example, at obligor level, in a Supervisory Statement in December 2025 the Bank of England stated that "at the level of individual exposures banks should assess climate related risks across the complete credit life cycle and evaluate the extent to which these risks affect the borrower's overall default risk…" (Bank of England PRA, 2025). In 2020 the ECB stated "institutions are expected to form an opinion on how climate related environmental factors affect the borrower's default risk" (European Central Bank, 2022). In 2022-23 the OCC stated that management should consider climate related financial risks as part of the underwriting and ongoing monitoring of portfolios, although this specific expectation was withdrawn in October 2025 (Department of the Treasury Office of the Comptroller of the Currency et al., 2023).

Concerning portfolios, in December 2025 the Bank of England stated that "Firms [banks] should use climate scenario analysis to provide sufficient information to understand the link between climate related risks and capital" (Bank of England PRA (2025) para 4.56). In 2022 the Basel Committee set out several principles for the management and supervision of climate related financial risks (Basel Committee on Banking Supervision, 2022). In 2025 the Canadian regulator set out principles applicable to large banks for the incorporation of climate risks into its capital and liquidity calculations (Office of the Superintendent of Financial Institutions Canada, 2025). Before they were withdrawn, the Federal Reserve Regulatory Service issued climate principles for large banks which included that "management should develop processes to measure and monitor material climate related financial risks" and report these to shareholders (Department of the Treasury Office of the Comptroller of the Currency et al., 2023).

Regulators in many other countries have carried out stress tests of bank capital to climate risks and an increasing number hold, or are developing, expectations of banks concerning the implementation of such stress tests in the short and/or longer term. Some examples include Australia (Australian Prudential Regulation Authority, 2021, 2024), South Africa (South African Reserve Bank, 2025) and Denmark (Moller, Niels, F. and Oksbjerg, Martin , 2024). Yet traditional credit risk models typically overlook these environmental drivers, focussing primarily on borrower behaviour and macroeconomic indicators. This gap in risk assessment can lead to significant underestimation of default probabilities and capital requirements, particularly in regions exposed to climate extremes.

Academic literature has started to address these challenges by incorporating weather predictors and utilising flexible functional forms into borrower default probability modelling(Calabrese et al., 2024; Dombrowski and Zanin, 2025). We build upon and extend this body of work by proposing predictive probability models that include additional important weather factors, that are more dynamic in form and more comprehensive in terms of the implications for the amount of economic capital to be held than those in the existing literature.

Specifically, we develop a spatio-temporal model that incorporates multiple physical climate related risk drivers, such as wildfire occurrences, drought severity, windspeed and temperature anomalies into a predictive model of mortgage default. We separate the effects of borrower and loan factors, climate variables and macroeconomic variables which allows an understanding of their separate and interactive effects on borrower outcomes. We allow the relationships to evolve over time and we thoroughly investigate the combinations of functional form, climate and/or macroeconomic variables to be included for predictive accuracy. We show the substantial effects of omitting weather variables on economic capital for a large loan portfolio. We employ penalized splines (P-splines) and varying coefficient models to capture non-linearities and spatial-temporal heterogeneity in the relationships between predictors and mortgage default probabilities.

Recent literature relating weather events to the probability of default (PD) can be divided into two methodologies: difference-in-differences models and probability of default models. The former are used by papers that ask the question: did a particular event, in our context a wildfire or other weather event, that occurred in a particular geographic location in a particular period in the past *cause* a change in average PD? These studies do not yield models that predict PD into the future, are restricted to a specific time, location and event and typically omit some PD drivers like macroeconomic variables. However, they can inform the choice of risk drivers to be included in predictive PD models. In this paper we are concerned with predictive PD models that do not have the above restrictions.

Most papers that include weather events to predict PD use a discrete time or occasionally a continuous time survival model. Most include macroeconomic variables and include dynamic loan to value to represent a transmission channel from weather events to mortgage default.

Concerning wildfires the differences in differences literature finds that specific wildfires have caused increases in mortgage PD. Issler and Wallace (2020) found that PD increased after wildfires in California. Wong and Ho (2023) found that the Fort McMurray wildfire in Canada in 2016 increased mortgage arrears rates. Biswas and Zink (2023) found 90-day delinquency rates were substantially higher for properties damaged by wildfires in California compared to properties that were undamaged. An et al (2024) found that specific fires significantly increased mortgage delinquency rates. Elhami-Khorasani et al. (2022) proposed a conceptual probabilistic framework for wild fire risk assessment, emphasising the need to account for spatial and temporal uncertainties in loss modelling. Auer (2024) reviewed the behavioural and policy dimensions of wildfire risk and insurance, noting that shrinking insurance markets in fire prone regions exacerbate borrower vulnerability to credit risk. However there appear to be no parameterised models that predict obligor level mortgage PD using wildfires as a driver. One of the aims of this paper is to fill this gap in the literature.

There has been some progress in modelling the effects of flood and hurricane events on PD. Causal models have found that floods and cyclones have caused higher default probabilities. For example, Kousky et al. (2020) found that homeowners whose properties sustained moderate to severe damage during Hurricane Harvey were more likely to subsequently default. The study also underscores the mitigating effect of flood insurance, highlighting its role in reducing PDs. Gete and Wachter (2024) also found exposure to hurricanes Harvey and Irma in 2017 substantially increased delinquency probabilities.

Turning to predictive models, in a cross-sectional model Rossi (2021) related mortgage PD to hurricane rating to find PD was substantially higher for loans experiencing major hurricanes, but the authors adopted simplistic treatments of the covariates and this study omitted macroeconomic variables.

Perhaps the most comprehensive predictive models are those of Calabrese et al. (2024), Zanin et al. (2024) and Dombrowski and Zanin (2025). Calabrese et al. (2024) used a Cox proportional hazard generalized additive model (GAM) with P-splines to model competing risks of mortgage default and early repayment, using data for Florida. They found that tropical storms and hurricanes increased the hazards as did higher average rainfall, whilst heavy rainfall was associated with reduced likelihood of mortgage prepayment with weather variables enhancing model predictive accuracy. They used a weather scenario for 2050 from First Street Foundation to find the 99th percentile of the predicted PD distribution. Dombrowski and Zanin (2025) employed a discrete time logit survival model with a GAM specification, building on Djeundje and Crook (2019b) with a hazards function specification derived built from Bellotti and Crook (2013). They found high precipitation and windspeed were associated with higher PD. They used a nested tree specification to account for potential association between default and prepayment. Zanin et al. (2024) also used a discrete time logit survival model, but without a GAM specification. They confirmed that cyclone-induced property damages increased mortgage PD in Louisiana.

We contribute to the literature in a number of ways. First, we propose a discrete time PD survival model with time varying coefficients and models with coefficients dependent on other risk drivers. These innovations are incorporated using highly flexible P-spline estimators. We indicate the relative contributions to predictive accuracy of each of a large number of specifications. Second, we investigate a number of weather variables, including the number of wildfires in the vicinity of a property and the occurrence of a period of drought as drivers of default, in addition to more traditional loan and macroeconomic predictors. With the outbreaks of wildfires in Spain, Italy, France and California in 2026 these models would be of considerable use to institutions lending in these regions.

Our third contribution is to contribute to the rapidly increasing literature on climate related capital adequacy. Regulatory climate stress tests typically involve scenario analysis over a 10 to 30 plus year horizon (of Governors of the Federal Reserve System (2024), European Central Bank (2022) and many others) and usually include the capital implications of transition risk as well as physical risk. See DeMenno (2023) and Acharya et al. (2023) for reviews of the limitations of climate stress testing practices in banking regulation. In this paper we are interested in the short-term implications of physical climate events for economic capital, in particular acute events such as wildfires and also certain chronic physical risks such as changes in temperature, in rainfall, in windspeed and in drought severity.

There is little academic literature on the capital implications of physical climate events. Different methods have been followed. Zanin et al. (2024) estimate a survival model of mortgage default for Louisiana. They included a property damage index and measure of flood risk as covariates. Since cyclones with high windspeed are rare they use the STORM model to generate windspeed scenarios for up to 1000 years. Windspeeds with return periods from 1 in 10 years to 1 in 1000 years are predicted and consequently so are property damage, LTV and hence PD values. Calabrese et al. (2024) used a survival model to perform a scenario analysis on Florida mortgages, projecting flood exposure under a RCP 4.5 pathway for 2050. Notice that neither Calabrese nor Zanin stress macroeconomic variables at the same time as the weather variables.

A second method, exemplified by Dhima et al. (2025) follows a structural approach. The authors assume a firm's or household's real estate assets and total assets follow a Brownian motion with jumps. The jumps represent exogenous shocks such as climate events. They apply the method to flooding in Paris, making predictions for 2030. But their method appears to omit borrower characteristics. Some parameters in their model were assumed, but literature suggests historical values of these have been affected by climate change and this was not taken into account.

The above analyses have been implemented as 'bottom up', that is carried out by academics or consultants, rather than by a central bank. An example of the latter is by Caloia and Jansen (2021) who focus on flooding in the Netherlands using flood depths recommended by a Dutch government expert group for events ranging from 1-in-50 to 1-in-2000-year return periods. The effects of floods on GDP were chosen by an expert panel and consequent shocks to other macroeconomic variables incorporated. However, their PD econometric model uses only annual rather than monthly data, it is estimated using OLS rather than being a binary event survival model and it lacks a dynamic LTV driver.

We enhance the literature on assessing the capital implications of including weather events in PD models by simulating time paths for macroeconomic PD drivers and time paths for each weather variable. Hence, we can estimate the Value at Risk for the portfolio. Our findings show that omitting climate drivers from credit risk models can lead to significant under-capitalization, especially under adverse macroeconomic scenarios.

The structure of the remainder of the paper is as follows. In section two we describe the assembly of the data relating to the loans in our sample, to the weather variables and the macroeconomic series. In section three we present the spatio-temporal statistical models. In section four we show the model parameterisations and relationships between the covariates and PD. In section five we show the impact on capital requirements of omitting weather events. Section six concludes.

2 Default predictors and data

2.1 Rationale for Choosing Predictors

The choice of borrower and loan characteristics we include is motivated by the weather transmissions mechanism literature that relates weather events to PD, by the options approach to mortgage default and by the empirical mortgage default prediction literature. The transmission mechanism literature has specified several transmission mechanisms between physical weather events and the PD of mortgages. A frequently quoted list of mechnisms is presented by the NGFS (Network for Greening the Financial System, 2022). Here, acute physical risks such a wildfires and heatwaves and chronic physical risks, such as changes in temperature and changes in precipitation, have at least two effects on mortgage PD. These events may damage property, reducing its value and so, ceteris paribus, increase the loan to value ratio and the strategic incentive to default (depending on the bankruptcy punishments (White, 2006). Second, these events may disrupt an economy's production capacity and supply chains, and/or reduce human health, for example by smoke inhalation, and so result in lower household income from which to make mortgage payments. Under the option approach (for example Kau et al. (1993), Deng et al. (2000)) a borrower defaults if the value of the put option to default is in the money. Whilst we do not have access to the put option values, we represent strategic choice to default and the transmission mechanism by the current loan to value ratio. The loan to value ratio is also highlighted in Campbell and Cocco's analytic model of mortgage default (Campbell and Cocco, 2015). The predictive mortgage credit scoring literature (for example Fitzpatrick and Mues (2016), Kim et al (2016), Djeundje et al. (2025)) includes variables which have been found to be predictive of mortgage default, although the mechanism is sometimes not discussed.

We concentrate on the acute risks of wildfires and the chronic risks we have listed above: changes in temperature, wind speed and drought. We have included a number of macroeconomic variables, also found to predictive of mortgage and credit default in the literature (for example Djeundje and Crook (2019a), Calabrese et al. (2024), Dombrowski and Zanin (2025)).

2.2 Loan data and macroeconomic series

The dataset used in this paper consists of a sample of mortgage loan accounts originated in California. We chose California because it is well known for its long history of wildfire activity driven by a complex interplay of environmental and climatic factors. But focussing on California allows us to identify patterns and associations that may be specific to the region and may not necessarily be generalisable to the broader country. Our results show such customisation can enhance accuracy of default prediction and capital reserves estimation.

The dataset numbers approximately 77,000 mortgage accounts observed from 2014 through to 2024[1]. This sample is sourced from Freddie Mac's single-family loan dataset (Freddie Mac, 2025). Although we estimated a large number of models with a variety of variables, we focus our discussion in this paper on those variables that we found to be plausibly associated with risk. All variables used in the estimations are recorded monthly. Weather variables were adjusted to represent the variable's value for the 3-digit ZIP code [2] of the property. Macroeconomic variables [3] relate to the State of California because many of the variables we were interested in were not available with a geographic granularity that allowed us to plausibly convert them to 3-digit ZIP level.

The feature selection routine identified two subsets of predictive variables: static origination characteristics and time-varying drivers. The static features measured at loan inception comprise borrower attributes (credit score, first-time buyer indicator, and whether there were multiple borrowers), property characteristics (property type, geographical coordinates), and mortgage characteristics (loan purpose, unpaid balance). The time-varying features comprise loan-level evolution metrics (loan age, time to legal maturity, and dynamic loan-to-value (LTV) ratio) alongside external environmental drivers and macroeconomic variables. Specifically, the wildfire-climate predictors include monthly wildfire counts, proximity to the nearest wildfire event, maximum temperature, average wind speed, average precipitation, and a standardized drought severity index. The macroeconomic features include the unemployment rate, interest rate spread, and consumer confidence index.

The Freddie-Mac dataset did not include a dynamic LTV variable for the sample period (a time varying value for the property is omitted). To estimate a dynamic LTV we followed Dombrowski and Zanin (2025), Calabrese et al. (2024) and Zanin et al.

[1] Note that the dataset includes accounts originated between 1999 and 2024, but the observation/performance window used in this study is restricted to the period 2014-2024 in order to align with the observation period of the wildfire variables used in this analysis. Hence many accounts are left truncated when estimating the models presented in this paper.

[2] We shall denote by ZIP3 the first three digits of a postal code, and we shall use such an area as the proxy area location of the mortgaged property since the remaining digits were masked in the source database.

[3] The macroeconomic data series included in the models are those of the U.S. Bureau of Labor Statistics.

(2024) and used the following formula:

$$\text{LTV}_{i,t} = 100 \times \frac{\text{Current balance}_{i,t} \times \text{HPI}_{s,t_0}}{\text{Property value}_{i,t_0} \times \text{HPI}_{s,t}}$$

where HPI_{s,t_0} denotes the House Price Index for 3-digit ZIP code s in month t_0, and $\text{HPI}_{s,t}$ denotes the corresponding House Price Index in month t.

Essentially, the house value is assumed to inflate at the average house price inflation rate for the 3 digit zip code in which it is located.

All macroeconomic and weather/wildfire variables were lagged three months since it can take several months for their effect on defaults to take effect (Djeundje and Crook, 2019b; Calabrese et al., 2024).

2.3 Wildfire and climate data

We considered a wide range of wildfire and climate-weather related variables from multiple sources (Yavas et al., 2025; St-Denis et al., 2022; NOAA, 2025).

Wildfire occurrences

The *wildfire occurrence* variable represents the number of occurrences of wildfire events (only wildfires ≥ 10 acre are counted). These counts were constructed using the recorded spatial coordinates of individual wildfire ignition points from the CAL FIRE database. Specifically, each wildfire was assigned to its corresponding ZIP3 area and calendar month based on the latitude and longitude of the ignition location and the wildfire origination date. The resulting monthly ZIP3–level counts were then merged unto the loan dataset using the ZIP3 and calendar time fields, ensuring temporal and geographic alignment between wildfire activity and loan performance over time.

Wildfire proximity

The *wildfire proximity* variable is intended to serve as a proxy measure capturing how close wildfire activity occurs to ZIP3-code areas. It is constructed by computing, for each ZIP3 centroid, the distance between that centroid and the ignition location of every wildfire occurring in the same month. For each ZIP3–month pair, the smallest of these distances is retained, representing the distance to the nearest wildfire event. The inverse of this minimum distance is then used as the wildfire proximity measure, yielding a metric that increases as wildfires occur closer to the centroid of the ZIP3 area. This procedure is performed separately for each month, and the resulting ZIP3–month series is merged unto the loan-level dataset using the ZIP3 and calendar time fields. [4]

Drought severity

Several *drought severity* indices were considered in this work, and the Palmer Drought Severity Index (PDSI) was found to be predictive of PD. These indices are standardized measures that quantify relative dryness (Palmer, 1965).[5] The drought severity data used in this work were sourced from the U.S. National Centers for Environmental Information, originally reported as monthly observations at the county level. To use these data in our analysis, they were first transformed from county-level to ZIP3 level. Specifically, for each ZIP3-month, the drought severity value was computed as a weighted mean of the county-level observations, where the weights correspond to the area of intersection between each county and the ZIP3 region under consideration. The resulting drought severity was then merged unto the loan-level dataset using the ZIP3 and calendar-time fields. Notice that higher values of the PDSI imply wetter conditions.

Wind speed

The *wind speed* variable was constructed using the information on the east–west and the north–south components of the wind (10m above the surface) reported in the ERA5 database of Copernicus (Hersbach et al., 2018). Given the orthogonality of these two components, the starting point for calculating wind speed was to compute the Euclidien norm of these two components at the native grid resolution (30 metre grids), yielding the scalar wind-speed measure at the native grid level. The resulting wind speed series were then aggregated to monthly level by calculating, for each month, the minimum, mean, and maximum wind speeds across all hourly observations, at the native grid level, and monthly ZIP3-level values were derived as area-weighted averages. This produced a consistent ZIP3–month panel of minimum, mean, and maximum wind speeds, which were then merged unto the loan-level dataset using ZIP3 and calendar-time fields.

[4] Note that some months contain no wildfire events. In such cases, the wildfire proximity value is set to zero, reflecting the implicit assumption that the nearest wildfire during that month is very distant.

[5] By incorporating temperature inputs and a physical water balance model, the PDSI is capable of capturing potential effects of global warming on drought conditions. Other drought indices such as Palmer Hydrological Drought Index and Z-index have also been considered.

Air temperature

The *Temperature* variable was constructed from the air temperature measured 2m above ground as reported in the ERA5 dataset. Similar to the aggregation approach used for wind speed, from the original grid resolution up to the ZIP3 level-the monthly minimum, mean, and maximum temperatures were computed, and these three measures were merged unto the loan dataset using ZIP3 and calendar time fields.[6]

Precipitations (Rx5d)

The *precipitation (Rx5day)* variable was constructed from the total precipitation reported in the ERA5 database using the following standard approach. For each grid cell, the hourly total precipitation values were first extracted and converted from meters to millimeters. These hourly amounts were then aggregated to daily totals at the native grid resolution. A 5-day rolling sum was computed from the daily series, producing time-series of consecutive 5-day accumulated precipitation for each grid. For each month, the maximum (and mean) of these 5-day totals was retained, yielding the monthly Rx5day values at the grid-cell level. The resulting monthly Rx5day values were then mapped onto ZIP3 regions, and ZIP3-level values were calculated as area-weighted averages. The resulting maximum and mean Rx5day values were then merged into the loan dataset using ZIP3 and calendar-time fields.

3 Spatio-temporal models for mortgage default

To assess the potential impact of wildfire and weather-climate related drivers on mortgage defaults, we consider several model variants with spatio-temporal structures: a standard specification, a non-linear variant, a variant with varying coefficients, and a variant with more flexible interaction structures. Each variant aims to explore different aspects of the relationship between wildfire/weather related factors and mortgage risk.

To formulate these models, let us consider a portfolio of mortgages, opened at various time points and monitored over many time periods. Over their lifecycle, these accounts may progress through (or recover from) multiple stages of delinquency, ultimately resulting in either full repayment or default. Such data lend themselves naturally into the framework of survival analysis.

[6] Additionally, soil temperature level 1 (i.e., the temperature in the top soil layer) was also considered. However, its incremental predictive power - beyond that provided by air temperature - was found to be negligible.

Hence, we denote by T_i the survival time associated with account i. In practice, credit risk data are typically stored in discrete time. For example, in the datasets used in this paper, time is recorded in months. In such a context, we can define the conditional monthly default probabilities, $q_{i,t}$, by

$$q_{i,t} = Pr\left\{T_i = t \,|\, T_i > t-1\right\}, \tag{1}$$

where t is time since origination.

3.1 A standard model

To assess the impact of wildfire and weather-climate drivers on the risk of default, the first model structure that we consider is a discrete spatio-temporal model structured as follows

$$g(q_{i,t}) = \text{baseline}_{i,t} \;+\; \sum_k \beta_k Z^{\{k\}}_{i,c_i+t} \;+\; \sum_r \delta_r W^{\{r\}}_{i,c_i+t} \tag{2}$$

where $W^{\{r\}}$ and $Z^{\{k\}}$ represents the r^{th} macroeconomic variable and the k^{th} weather specific variable respectively, δ_r and β_k are the associated unknown coefficients to be estimated, c_i is the opening calendar date for account i, $g(\cdot)$ is the link function, and $\text{baseline}_{i,t}$ is a baseline term taking the form

$$\text{baseline}_{i,t} = h\left(\text{lat}_i, \text{long}_i, t\right) \;+\; \sum_j \alpha_j X^{\{j\}}_{i,t} \tag{3}$$

where $X^{\{j\}}$ are variables that are conventionally used in credit scoring models and relate to borrower-loan characteristics, α_j are the coefficients to be estimated, and $h(\cdot)$ is a 3-variate function capturing the base spatio-temporal component. More details of the structure of this base component are provided in Section 3.5 below.

In the standard model representation (2), we have explicitly separated the three components (baseline, wildfire and weather-climate, macroeconomic) because the aim of this work is not only to quantify the potential effect of wildfire and weather-climate drivers on mortgage default risk, but also to compare their impact against that of the macroeconomic variables which are typically used in credit risk survival models (Djeundje and Crook, 2019a; Bocchiio et al., 2023; Calabrese et al., 2024; Djeundje et al., 2025).

3.2 Non-linearity

The standard model in the previous section postulates a linear relationship between the probability of default (on the link scale) and wildfire-climate drivers. To scrutinize this assumption, we relax the linearity constraint and consider an alternative specification of the form:

$$g(q_{i,t}) = \text{baseline}_{i,t} \; + \; \sum_k \beta_k Z_{i,c_i+t}^{\{k\}} \; + \; \sum_r \delta_r W_{i,c_i+t}^{\{r\}} \; + \; \sum_l \mathcal{S}_{1,l}\left(U_{i,c_i+t}^{\{l\}}\right) \tag{4}$$

Here, $\mathcal{S}_{1,l}(\cdot)$ denote a set of flexible functions to be estimated, and the $U^{\{l\}}$ are those of risk drivers whose association with the default risk is non-linear (including some of the weather variables as well as some of the macroeconomic variables). To preserve regularity in the dependence structure, we impose smoothness on these functions while allowing sufficient flexibility to uncover potentially hidden aspects of the impact of weather and macroeconomic related variables on mortgage risk. Further details regarding the specification and estimation of these components are discussed in Section 3.5.

3.3 Dynamic varying coefficients for wildfire-climate drivers

The dataset used in this work comprises loan accounts that were opened and monitored over a long time frame ($\sim$ 25 years). Yet, both the standard model (2) and its non-linear extension (4) assume that the marginal effects (i.e. the coefficients) of the explanatory variables on the risk of default remain constant throughout the entire time frame. This assumption was generally made by the six US bank holding groups that responded to the Fed's Climate Scenario Analysis exercise (Federal Reserve Board (2024)). But, as the Fed argued this is a strong assumption, as numerous structural and environmental changes may occur over such an extended period, potentially altering the relationship between the candidate variables and mortgage default outcomes.

To account for this possibility, we consider a flexible model structure in which the coefficients associated with wildfire-climate drivers are allowed to vary dynamically as follows

$$g(q_{i,t}) = \text{baseline}_{i,t} \; + \; \sum_k \beta_k Z_{i,c_i+t}^{\{k\}} \; + \; \sum_r \delta_r W_{i,c_i+t}^{\{r\}} \; + \; \sum_l \mathcal{S}_{2,l}\left(V_{i,t}^{\{l\}}\right) U_{i,c_i+t}^{\{l\}} \tag{5}$$

where $\mathcal{S}_{2,l}(\cdot)$ are univariate smooth functions to be estimated, and the $V^{\{l\}}$ and $U^{\{i\}}$ are some covariates. In other words, model (5) allows the marginal effect of some variable $U^{\{r\}}$ to evolve dynamically as a function of another covariate $V^{\{r\}}$. For example, the model can accommodate situations where the marginal effect of a wildfire-climate related variable changes as a function of another covariate.[7] In particular, time-varying

[7]Similarly, the model allows the marginal effect of a macroeconomic variable to vary dynamically as a function of another covariate.

coefficients can be introduced by specifying $V_{i,t}^{\{r\}} = c_i + t$, or by modelling the coefficients as functions of survival time, as in Djeundje and Crook (2019a) in the context of credit card portfolios.

3.4 Complex interactions

We would also expect that the effects of wildfires on PD may be increased by, for example, simultaneously high wind speeds. These two simultaneous events would be expected to lead to a much greater reduction in house prices (due to damage) than if there were only very high winds. This would be incorporated in model (5) with $V^{\{r\}}$ representing windspeed. But the model structures can be further extended to capture more intricate interactions by incorporating fully flexible two-dimensional functions, as follows:

$$g(q_{i,t}) = \text{baseline}_{i,t} + \sum_k \beta_k Z_{i,c_i+t}^{\{k\}} + \sum_r \delta_r W_{i,c_i+t}^{\{r\}} + \sum_l \mathcal{S}_{3,l}\left(V_{i,t}^{\{l\}}, U_{i,t}^{\{l\}}\right) \tag{6}$$

Here, $\mathcal{S}_{3,l}(\cdot,\cdot)$ denotes a set of flexible bivariate functions to be estimated from the data, designed to capture multidimensional dependencies and joint effects between the risk drivers $U^{\{l\}}$ and $V^{\{l\}}$. This formulation allows the model to move beyond additive linear effects and account for nonlinear interactions between covariates. Hence, this extension enables a richer characterisation of mortgage risk by uncovering how combinations of factors interact in complex ways. For instance, the impact of wildfire- and climate-related variables may vary depending on their interactions, and these joint effects can be more accurately captured through the flexible surfaces defined by $\mathcal{S}_{3,r}(\cdot,\cdot)$. The estimation procedure is discussed in Section 3.5.

3.5 Inference

Each of the spatio-temporal models presented so far includes a baseline component involving a spatio-temporal function $h(\cdot,\cdot,\cdot)$ - see Eq. 3. We can express this spatio-temporal effect as an additive sum of a univariate function of time, $\mathcal{S}_{o1}(\cdot)$, and a bivariate function of latitude and longitude, $\mathcal{S}_{o2}(\cdot,\cdot)$:

$$h(\text{lat}_i, \text{lon}_i, t) = \mathcal{S}_{o1}(t) + \mathcal{S}_{o2}(\text{lat}_i, \text{lon}_i). \tag{7}$$

Hence, each spatio-temporal model introduced in previous sections involves three parts: (i) the first part consisting of linear combination of the covariates, (ii) the second part consisting of flexible univariate functions of some covariates, and (iii) the third part consisting of a sum of flexible bivariate functions of relevant covariates.

To achieve the desired flexibility for the univariate functions such as for $\mathcal{S}_{o1}(t)$ in Eq. 7 or $\mathcal{S}_{2,l}(V_{i,t}^{\{l\}})$ in Eq. 5, we employ the method of P-splines in one dimension. This consists of setting univariate B-spline basis along the relevant covariates and applying roughness penalties on adjacent B-spline coefficients to prevent overfitting and ensure smoothness of the estimated curve (Eilers and Marx, 1996; Djeundje and Crook, 2019b; Wood, 2011, 2024).

For the bivariate components, such as $\mathcal{S}_{o2}(\text{lat}_i, \text{lon}_i)$ in Eq. 7 or $\mathcal{S}(V_{i,t}^{\{r\}}, W_{i,c_i+t}^{\{r\}})$ in Eq.6, we employ a basis of two-dimensional B-splines consisting of tensor-products of marginal B-spline bases and roughness penalties are then applied to the underlying coefficients to control smoothness across both dimensions (Currie et al., 2006; Lee et al., 2013; Wood et al., 2014; Wood, 2024).

To illustrate the estimation process, consider a simplified version of Eq.4 in which we have two weather variables $U^{\{1\}}$ and $U^{\{2\}}$ on which smoothing is applied. The core model structure becomes

$$g(q_{i,t}) = \mathcal{S}_{o1}(t) + \mathcal{S}_{o2}(\text{lat}_i, \text{lon}_i) + \sum_j \alpha_j X_{i,t}^{\{j\}} + \sum_k \beta_k Z_{i,c_i+t}^{\{k\}} + \sum_r \delta_r W_{i,c_i+t}^{\{r\}} + \sum_{l=1}^{2} \mathcal{S}_{1,l}\left(U_{i,c_i+t}^{\{l\}}\right)$$

where each of the $\mathcal{S}_{o1}(\cdot)$, $\mathcal{S}_{1,1}(\cdot)$ and $\mathcal{S}_{1,2}(\cdot)$ are flexible functions expressed as linear combinations of basis of one dimensional B-splines along the axes of t, $U^{\{1\}}$ and $U^{\{2\}}$ respectively[8], and $\mathcal{S}_{o2}(\cdot,\cdot)$ is a flexible 2D tensor product B-spline surface which can be represented as follows:

$$\mathcal{S}_{o2}(\text{lat}_i, \text{lon}_i) = \sum_{l=1}^{K_1} \sum_{j=1}^{K_2} \Theta_{l,j}^{\{o\}} \times B_{1,l}(\text{lat}_i) \times B_{2,j}(\text{lon}_i)$$

where $B_{1,l}$ and $B_{2,l}$ are B-spline basis functions along the axes of latitude and longitude, respectively.

With this in place, the full set of unknown parameters to be estimated comprises the linear-coefficient vectors $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, and $\boldsymbol{\delta}$; the spline coefficient vectors $\boldsymbol{\theta}^{\{o\}}$, $\boldsymbol{\theta}^{\{1\}}$, and $\boldsymbol{\theta}^{\{2\}}$ associated with $\mathcal{S}_{o1}(\cdot)$, $\mathcal{S}_{1,1}(\cdot)$ and $\mathcal{S}_{1,2}(\cdot)$, respectively; and the $K_1 \times K_2$ matrix of spline coefficients $\boldsymbol{\Theta}^{\{o\}}$ associated with the 2D spatial surface $\mathcal{S}_{o2}(\cdot,\cdot)$. This estimation is carried out by maximising the penalised log-likelihood, ℓ_P, given by

$$\ell_P = \ell\left(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\delta}, \boldsymbol{\theta}^{\{o\}}, \boldsymbol{\theta}^{\{1\}}, \boldsymbol{\theta}^{\{2\}}, \boldsymbol{\Theta}^{\{o\}}\right) - \frac{1}{2} \sum_{j \in \{o,1,2\}} \lambda_j \mathcal{P}\left(\boldsymbol{\theta}^{\{j\}}\right) - \frac{1}{2}\lambda_{\text{lat}} \mathcal{P}_{\text{lat}}\left(\boldsymbol{\Theta}^{\{o\}}\right) - \frac{1}{2}\lambda_{\text{lon}} \mathcal{P}_{\text{lon}}\left(\boldsymbol{\Theta}^{\{o\}}\right)$$

where $\ell(\cdot)$ denotes the ordinary log-likelihood, $\mathcal{P}$ represents the marginal difference penalty operator penalizing non-smoothness along the axes of t, $U^{\{1\}}$, and $U^{\{2\}}$, respectively; $\mathcal{P}_{\text{lat}}$ and $\mathcal{P}_{\text{lon}}$ are the marginal penalty functions penalising non-smoothness of the spatial surface along the latitude and longitude directions, respectively; and λ_k ($k \in \{o, 1, 2, \text{lat}, \text{lon}\}$) are smoothing parameters controlling the degree of penalisation.

We estimate the regression parameters and spline coefficients for fixed values of the smoothing parameters using penalised iteratively re-weighted least squares and

[8] as in Djeundje and Crook (2019b).

use second order difference penalties. The values of the smoothing parameters can be chosen according to the values of the Akaike information criterion or the Bayesian Information criterion, controlling the trade-off between fidelity to the data and parsimony.

4 Impact of wildfire-climate drivers on mortgage risk

4.1 Impact in terms explainability and predictive performance

To assess the impact of wildfire-climate drivers on mortgage risk, several variants of the models presented in Section 3 were fitted to training data comprising 80% of account-level observation months from 2014 to 2023; the remaining 20% constituted the out-of-sample testing data and the monthly observations for calendar year 2024 constituted the out of time testing set. These testing data were used to assess and compare prediction performance.

4.2 Results: the standard model

Table 1 presents the fitted coefficients obtained from estimating the standard spatio-temporal model (2)[9]. The signs of the marginal effects of the covariates considered on mortgage default risk align broadly with expectations. For example, the risk of default declines as credit scores improve, whereas larger unpaid balances at origination or elevated values of the dynamic loan-to-value ratio over the life of the account are associated with higher default risk. Similarly, first-time buyers exhibit a higher likelihood of default relative to more experienced buyers, and loans with joint borrowers tend to carry lower risk compared to those with a single borrower. Additionally, loans originated for the purpose of cash-out refinancing exhibit higher default risk compared with the two other loan types present in the dataset.

Looking at the marginal effects of the macroeconomic variables, the table shows that an increase in unemployment rates or interest rate spreads is associated with heightened default risk. Rising unemployment typically signals economic distress, which can lead to income loss, reduced repayment capacity, and greater financial vulnerability among borrowers. The interest rate spread (defined as the difference between an individual mortgage loan's interest rate and the benchmark 30-year fixed-

[9]Additionally, the fitted smooth loan-age component and the spatial component that together form the spatio-temporal baseline function $h(\cdot,\cdot)$ are presented in Figure 1. Both components are found to be significantly associated with the risk of default, as reported in the lower panel of Table 1.

Linear Terms	**Coef**	**Std Error**	***p*-value**
Credit Score	-0.010	0.000	0.000
Original Unpaid Balance / 10^6	2.604	0.177	0.000
Dynmic Loan-to-Value	0.215	0.082	0.008
Time to legal Maturity	0.001	0.000	0.009
First time buyer (Yes)	0.182	0.079	0.022
Multiple_Borrowers (Yes)	-0.543	0.046	0.000
Property type (ref: Condo)			
Manufactured Housing	-0.262	0.328	0.425
PUD	-0.285	0.099	0.004
Single Family	-0.106	0.077	0.169
Loan Purpose (ref: Refinance - Cash Out)			
Refinance - No Cash Out)	-0.221	0.057	0.000
Purchase	-0.030	0.070	0.667
Unemployment Rate	0.164	0.009	0.000
Consumer Confidence	-0.023	0.002	0.000
Spread Rate	0.474	0.027	0.000
Average Wind Speed	0.058	0.057	0.308
Average Rx5d	0.001	0.000	0.000
Max Temperature	-0.021	0.005	0.000
Drought Index	0.104	0.009	0.000
Wildfire Count	0.079	0.026	0.003
Wildfire Proximity /10^5	0.769	0.880	0.382
Smooth Terms	**Estimate**	**Eff Dim**	***p*-value**
$\mathcal{S}$(Loan Age)	Figure 1	5.505	0.000
$\mathcal{S}$(Latitude, Longetude)		12.379	0.027

Table 1: Output from fitting Model (2): coefficients and baseline components.
Note: Macroeconomic and weather variables were lagged three months.

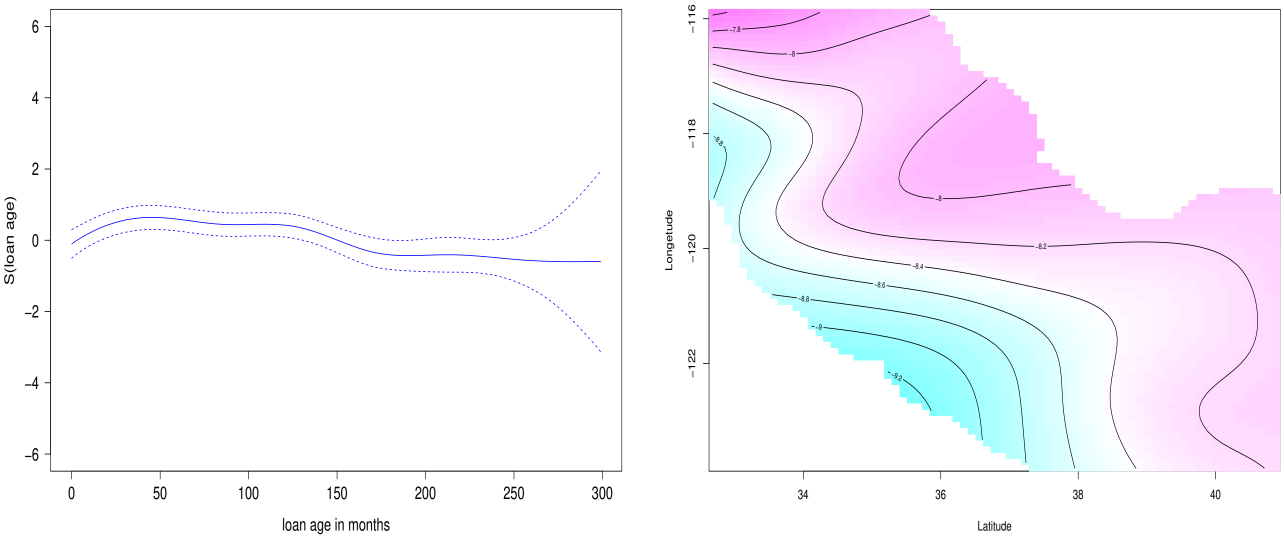

Figure 1: Components of the baseline (7) from fitting model (2).

rate mortgage) serves as a proxy for borrower-specific credit risk or market segmentation. A widening spread may reflect higher perceived risk by lenders, tighter credit conditions, or increased borrowing costs, all of which can contribute to elevated default probabilities. In contrast, higher consumer confidence is associated with reduced mortgage risk, likely reflecting improved household sentiment, financial stability, and willingness to meet debt obligations.

Turning to environmental factors, the inclusion of wildfire and climate-related drivers reveals important patterns. Increases in maximum temperatures, fire occurrences, heavy precipitations and wetter conditions (higher drought index) are all associated with increasing mortgage default risk. These variables reflect both direct and indirect stressors: wildfires can cause physical damage to properties and disrupt local economies, while prolonged high precipitation and extreme temperatures may undermine regional stability, reduce agricultural productivity, and increase financial strain on households. By capturing these effects, the model highlights the growing relevance of climate-related exposures in mortgage risk assessment.

4.3 Results: Flexible models

The results discussed in Section 4.2 are based on strong linearity assumptions, which constrain the model to capture only additive and proportionate relationships between covariates and default risk. While such assumptions offer straightforward interpretability and computational simplicity, they may overlook important nonlinear patterns and interactions present in the data. In this section, we relax those assumptions and present results from the three more flexible model structures introduced in Section 3: the non-linear model (4), the varying coefficients model (5), and the flexible 2D interaction model (6).

Linear Terms	**Coef**	**Std Error**	***p*-value**
Credit Score	-0.010	0.000	0.000
Original Unpaid Balance / 10^6	2.483	0.182	0.000
Dynmic Loan-to-Value	0.228	0.077	0.003
Time to legal Maturity	0.001	0.000	0.094
First time buyer (Yes)	0.175	0.079	0.027
Multiple_Borrowers (Yes)	-0.528	0.047	0.000
Property type (ref: Condo)			
Manufactured Housing	-0.123	0.329	0.709
PUD	-0.281	0.099	0.005
Single Family	-0.090	0.078	0.246
Loan Purpose (ref: Refinance - Cash Out)			
Refinance - No Cash Out)	-0.192	0.058	0.001
Purchase	-0.032	0.071	0.656
Smooth Terms	**Illustration**	**Eff Dim**	***p*-value**
$\mathcal{S}$(Loan Age)		5.088	0.002
$\mathcal{S}$(Latitude, Longetude)		14.570	0.000
$\mathcal{S}$(Unemployment Rate)		7.928	0.000
$\mathcal{S}$(Consumer Confidence)		8.785	0.000
$\mathcal{S}$(Spread Rate)		6.859	0.000
$\mathcal{S}$(Average Wind Speed)	Figures 2, 1	3.763	0.001
$\mathcal{S}$(Average Rx5d)		3.434	0.000
$\mathcal{S}$(Max Temperature)		6.376	0.000
$\mathcal{S}$(Drought Index)		1.000	0.006
$\mathcal{S}$(Wildfire Count)		2.490	0.009
$\mathcal{S}$(Wildfire Proximity)		1.000	0.066

Table 2: Output from fitting Model (4): coefficients, baseline components and smooth terms.

Table 2 reports the parameter estimates obtained from fitting the non-linear Model (4), along with the effective dimensions of the non-linear components. The table shows that when we allow for non-linearity, unlike the linear model and with perhaps the exception of wildfire proximity, all of the wildfire-climate variables are statistically strong. This includes average windspeed which was insignificant in the linear model. In addition, Table 2 shows with the exception of the drought index and wildfire proximity, the relationship between each macroeconomic and each wildfire-climate variable and default probability is nonlinear, as evidenced by their effective dimension in the

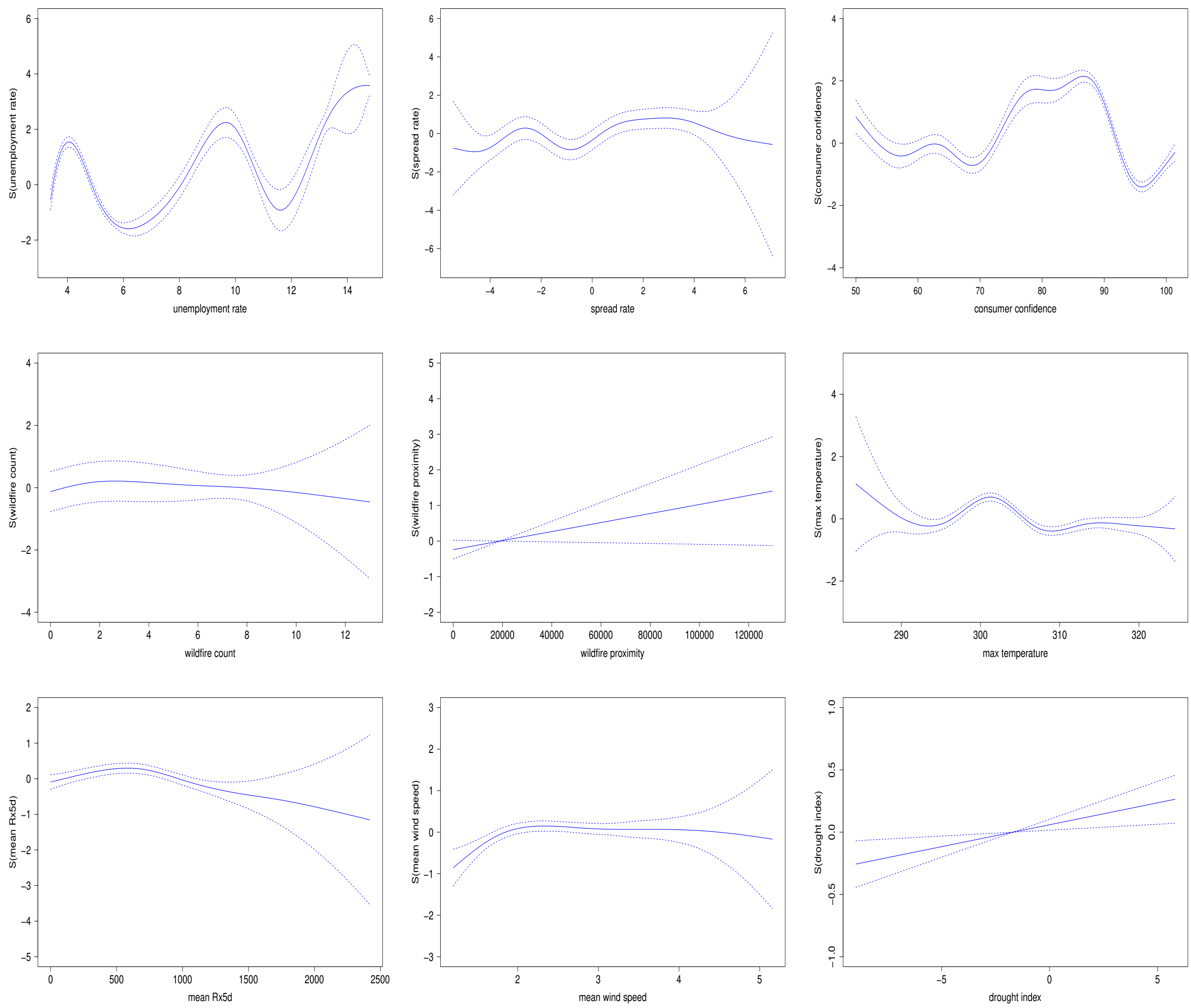

Figure 2: Marginal components of selected wildfire-climate drivers from fitting the non-linear Model (4). The list of terms included in this model can be found in in Table 2.

model. This is especially so for the macroeconomic variables and for average windspeed, precipitation and maximum temperature and slightly less so for the number of wildfires. Figure 2 illustrates some selected wildfire–climate and macroeconomic components from this model, all exhibiting pronounced nonlinear patterns. Notice that the height of the central line in the Figure shows the value of S(X) at each value of X, that is the contribution that variable makes to a predicted value of PD. The slope of each function at a value of X shows the approximate equivalent to a marginal effect in a non-smoothed function at that value of X. So for example, at higher wildfire counts the contribution to PD is positive until the number of wildfires equals 8 whereafter it becomes negative. The marginal effect is positive until the number of wildfires equals 3 then becomes negative. In contrast, at higher values of maximum temperature, up until 17C (290 K), the contribution to PD is positive, but decreasing, between 17C and 22C (295K) the contribution is negative and between 22C (295K) and 32C (305K) the contribution increases PD, though the marginal effect increases then falls. Above 32C (305K) the contribution is negative and the marginal effect is generally constant. Section 4.4 further elaborates on how these flexible shape can enhance the predictive accuracy.

Turning to the varying-coefficient specification, Table 3 again shows highly non-linear relationships between each wildfire-climate variable and PD, when each has a time varying coefficient function. This is especially so for average windspeed, precipitation and drought and slightly less so for temperature and number of wildfires. Figure 3 top panel illustrates this non-linearity for selected coefficients from the time varying coefficients model. Thus whilst the coefficient on maximum temperature is constant over the sample period, that for average windspeed is highly variable and that for the number of wildfires decreases monotonically between 2014 and 2020. Table 4 presents results for the temperature varying coefficients model. All wildfire-climate variables with these coefficients are statistically significant except for wildfire proximity. All wildfire-climate variables show considerably non-linear relationships with PD, with effective dimensions statistics over 4.5, again except for wildfire proximity. Figure 3 middle panel illustrates the non-linear relationships of selected temperature varying coefficients variables to PD. So for example we see that the coefficient on wild fire count varies with maximum temperature. At higher maximum temperatures, up to 19.9C (293K) the coefficient on wildfire count is negative but increasing. Between 19.9C and 35.9C (309K) the coefficient is positive and increasing and after 26.9C (309K) it decreases to zero. The bottom panel of the table illustrates estimated non-linear relationships for the macroeconomic variable consumer confidence index (results table available on request). In summary, Tables 2 to 4 demonstrate how the model structure is sufficiently flexible to capture complex, varying coefficients when needed, while also adapting to simpler, near-linear patterns where appropriate.

Linear Terms	**Coef**	**Std Error**	**p-value**
Credit Score	-0.011	0.000	0.000
Original Unpaid Balance	0.000	0.000	0.000
Dynmic Loan-to-Value	0.270	0.074	0.000
Time to legal Maturity	0.002	0.000	0.000
First time buyer (Yes)	0.144	0.080	0.070
Multiple_Borrowers (Yes)	-0.523	0.047	0.000
Property type (ref: Condo)			
Manufactured Housing	-0.115	0.330	0.728
PUD	-0.301	0.100	0.003
Single Family	-0.086	0.078	0.274
Loan Purpose (ref: Refinance - Cash Out)			
Refinance - No Cash Out)	-0.197	0.058	0.001
Purchase	-0.017	0.071	0.807
Unemployment Rate	-0.093	0.013	0.000
Consumer Confidence	-0.009	0.006	0.114
Spread Rate	0.257	0.035	0.000
Smooth Terms	**Illustration**	**Eff Dim**	**p-value**
$\mathcal{S}$(Loan Age)		5.713	0.000
$\mathcal{S}$(Latitude, Longitude)		20.602	0.000
Time-varying coefs for Wind Speed		9.408	0.000
Time-varying coefs for Rx5d		9.765	0.000
Time-varying coefs for Temperature	Figure 3, 1	3.979	0.000
Time-varying coefs for Drought Index		6.296	0.000
Time-varying coefs for Wildfire Count		3.304	0.022
Time-varying coefs for Wildfire Proximity		2.000	0.082

Table 3: Output from fitting Model (5) with time-varying coefficients on wildfire-climate variables.

Turning to the 2D interaction model (6), Table 5 shows the fitted model. All of the interactions terms in the model are significant. Figure 4 presents four representative interaction components. These are heat maps where redder shades indicate higher values of the coefficient function and blue colours indicate smaller values. The figures highlight the non-linear interplay between the wildfire-climate variables as well as between the macroeconomic variables. For example we can see (top left panel) that both higher wind speeds and higher maximum temperatures increase PD, whilst in the top right panel we see that, for the drought index below zero (ie drier than average conditions), a larger number of wildfires and lower drought index (i.e. drier conditions) also

Linear Terms	**Coef**	**Std Error**	***p*-value**
Credit Score	-0.010	0.000	0.000
Original Unpaid Balance	0.000	0.000	0.000
Dynmic Loan-to-Value	0.222	0.081	0.006
Time to legal Maturity	0.001	0.000	0.018
First time buyer (Yes)	0.176	0.079	0.026
Multiple_Borrowers (Yes)	-0.535	0.046	0.000
Property type (ref: Condo)			
Manufactured Housing	-0.250	0.330	0.448
PUD	-0.282	0.099	0.004
Single Family	-0.102	0.077	0.187
Loan Purpose (ref: Refinance - Cash Out)			
Refinance - No Cash Out)	-0.186	0.058	0.001
Purchase	-0.036	0.071	0.610

Smooth Terms	**Illustration**	**Eff Dim**	***p*-value**
$\mathcal{S}$(Loan Age)		5.577	0.000
$\mathcal{S}$(Latitude, Longitude)		13.118	0.002
Temperature-varying coefs for Unemployment Rate	Figures 3, 1	5.999	0.000
Temperature-varying coefs for Consumer Confidence		6.585	0.000
Temperature-varying coefs for Spread Rate		7.135	0.000
Temperature-varying coefs for Wildfire Count		5.500	0.000
Temperature-varying coefs for Average Wind Speed		4.642	0.000
Temperature-varying coefs for Average Rx5d		6.794	0.000
Temperature-varying coefs for Drought Index		6.101	0.000
Temperature-varying coefs for Wildfire Proximity		2.738	0.126

Table 4: Output from fitting Model (5) with Temperature-varying coefficients on wildfire-climate variables.

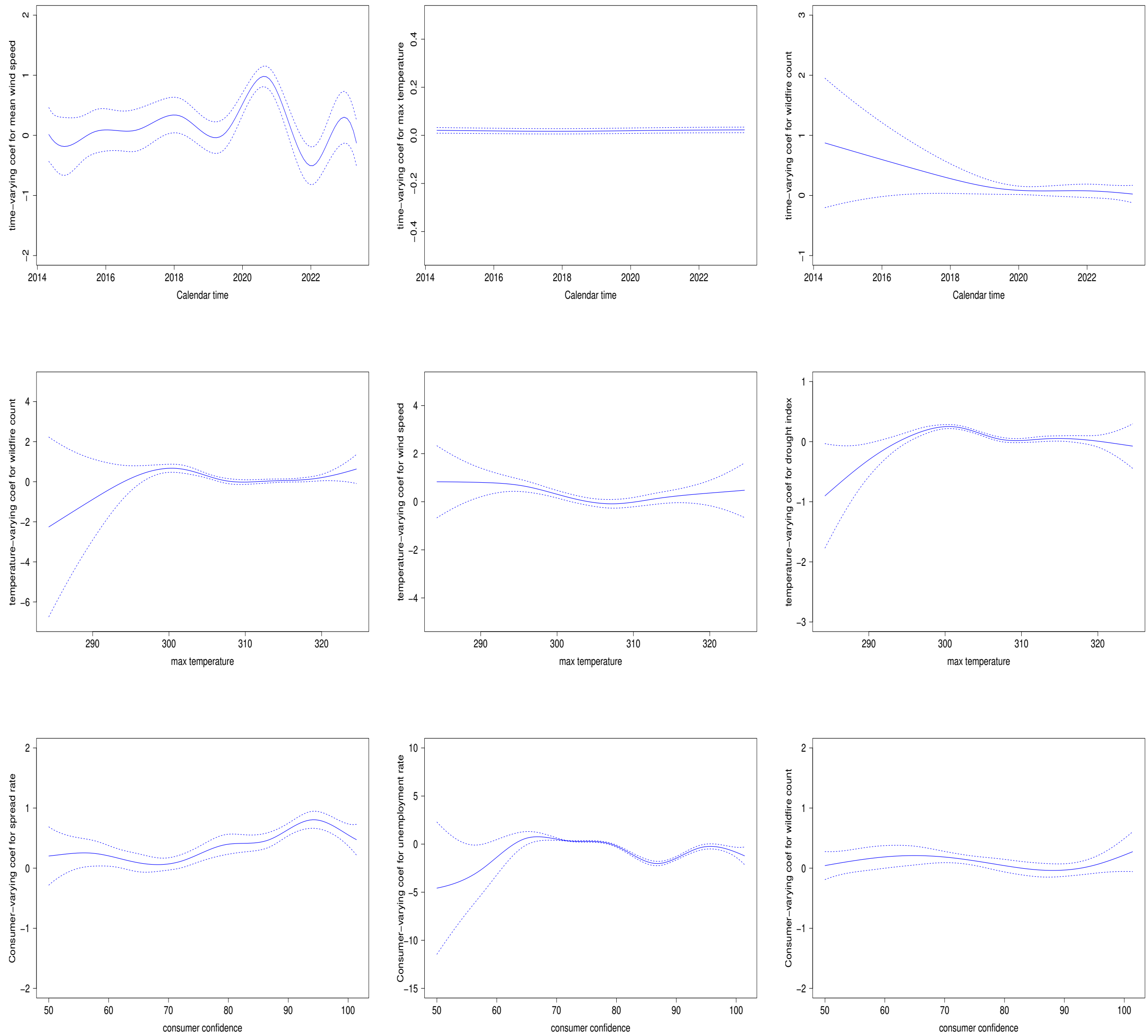

Figure 3: Selected component from fitting three variants of the varying-coefficients model (5).

Upper panels: from model with time-varying coefficients (see Table 3).

Middle panels: from model with temperature-varying coefficients (See Table 4).

Lower panels: from model with consumer confidence-varying coefficients.

Linear Terms	Coef	Std Error	p-value
Credit score	-0.010	0.000	0.000
Original unpaid balance	0.000	0.000	0.000
Loan to value	0.187	0.075	0.013
Time to legal Maturity	0.001	0.000	0.002
First time buyer (Yes)	0.143	0.062	0.020
Multiple_Borrowers (Yes)	-0.503	0.036	0.000
Property type (ref: Condo)			
Manufactured Housing	-0.066	0.259	0.799
PUD	-0.254	0.075	0.001
Single Family	-0.057	0.059	0.329
Loan Purpose (ref: Refinance - Cash Out)			
Refinance - No Cash Out)	-0.164	0.044	0.000
Purchase	-0.002	0.055	0.971
Wildfire proximity	0.000	0.000	0.025
Smooth Terms	**Illustration**	**Eff Dim**	**p-value**
$\mathcal{S}$(Loan_Age)		5.534	0.001
$\mathcal{S}$(LatitudeMeanNew,LongetudeMeanNew)		7.049	0.413
$\mathcal{S}$(Unemployment Rate, Consumer Confidence)		36.320	0.000
$\mathcal{S}$(Spread Rate, Consumer Confidence)	Figures 4, 1	15.838	0.000
$\mathcal{S}$(Wildfire Count, Drought Index)		3.001	0.017
$\mathcal{S}$(Max Wind Speed, Max Temperature)		3.525	0.000
$\mathcal{S}$(Max Wind Speed, Mean Rx5d)		3.001	0.551

Table 5: Output from fitting Model (6) with flexible 2D interactions.

increase PD. The following section delves into how incorporating such flexible interaction structures can enhance the model's ability to capture underlying dynamics and ultimately improves its predictive performance.

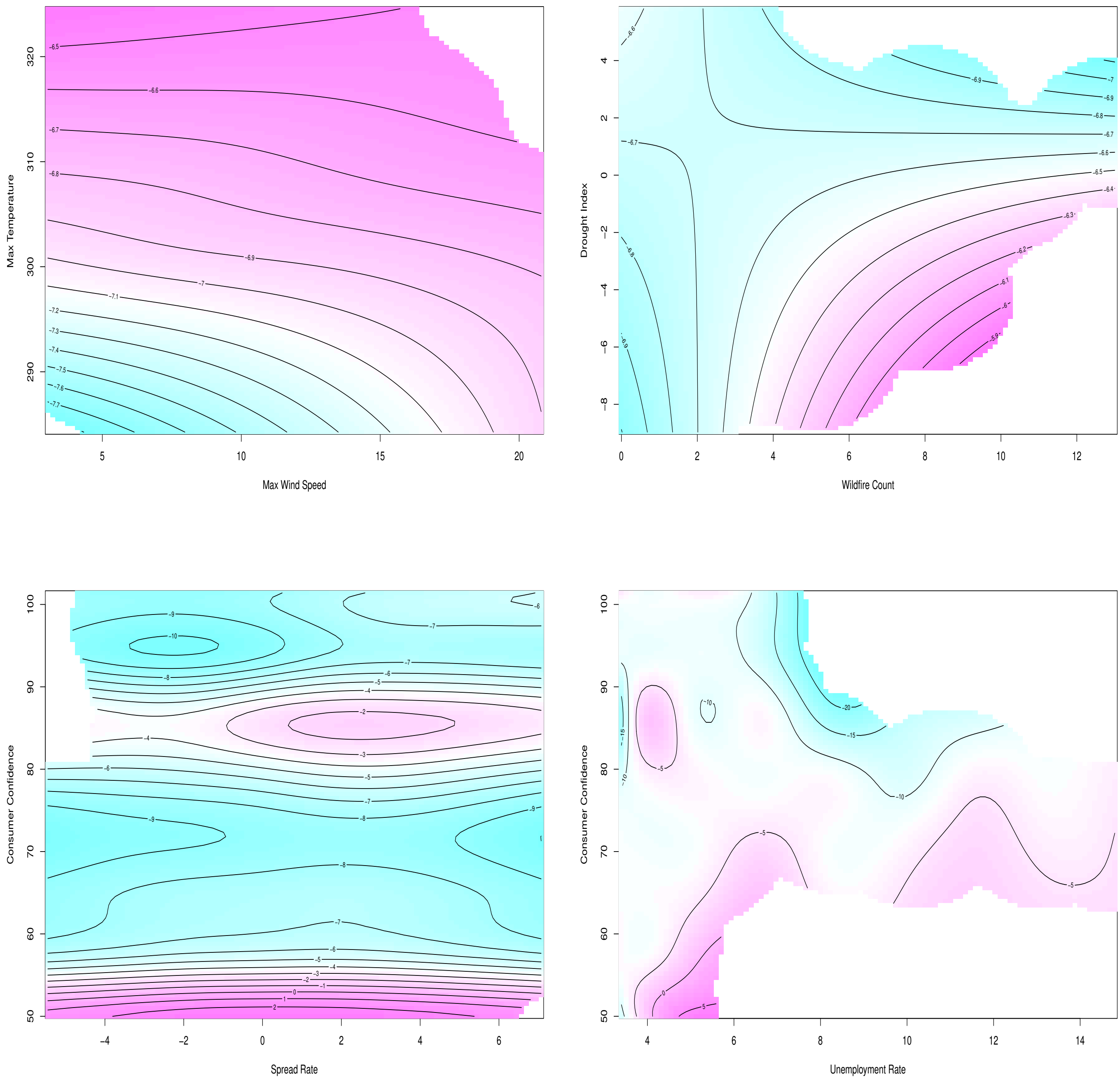

Figure 4: Selected components from fitting the flexible 2D interactions Model (6).

4.4 Results: predictive performance

This section examines and compares predictive performance, with particular emphasis on (i) the role of wildfire-climate drivers relative to macroeconomic variables, as well as (ii) the relevance of the model structure. The results are summarised in Table 6, which reports the area under the ROC curve (AUC) for various model specifications. To assess the magnitude of the differences in predictive performance presented in this table, we apply the statistical test proposed by DeLong et al. (1988), which evaluates differences between ROC curves. The corresponding results are shown in the same table.

First, Table 6 shows that augmenting the baseline model (Model 3) with either the wildfire-climate drivers or the macroeconomic variables (Model 2) improves predictive performance on both the training and test sets, with the inclusion of macroeconomic variables enhancing predictive accuracy more than the inclusion of the wildfire-climate variables. However, including both macroeconomic and wildfire-climate variables *together* yields a higher predictive performance than adding the macroeconomic variables alone.

Second, allowing for non-linear/smoothing to capture non-linear effects of wildfire-climate, as in the non-linear Model (4), gives better AIC/BIC statistics (not shown) than the linear models and statistically significant enhancement of predictive accuracy on the training and out-of-sample (OOS) test sets, but not necessarily on the test set that was both OOS and out-of time (OOT). Similarly, the time varying coefficient models (a particular specification of Model (5)) show considerable improvement in predictive performance on the OOS test set compared to the linear model, but they performed poorly on the OOS-OOT test set. In contrast, several variants of the varying coefficient model (alternative specifications of Model (5)) show substantial improvements in predictive performance for the OOS test set and, for the consumer confidence varying coefficient model, for the OOS-OOT test set as well. The precipitation-varying, maximum temperature-varying and maximum windspeed-varying coefficient models all performed better than the linear model for the OOS samples and no worse than the linear model on the OOS-OOT samples.

Turning to the 2D interactions structure specified in Model (6), we evaluated several variants. Table 6 shows that the model that included smooth 2D interactions between the macroeconomic variables and between the wildfire-climate variables, reported in Table 5 and illustrated in Figure 4, achieved the greatest predictive accuracy compared with the other specifications and did so on all three samples. Preliminary explorations (not shown) also suggest that additional improvements in predictive accuracy may be attainable - for example, by introducing flexible interaction surfaces that jointly capture the dependence between wildfire-climate drivers and macroeconomic variables.

Model 6		Models 4 & 5		Model 2		Model 2		Model 3
Baseline, macro, weather; smooths 2D interactions between macro & between weather		Baseline, macro, weather smooths on macro & weather		Baseline, macro, weather		Baseline, macro		Baseline
88.21%	>**	85.80%	>**	82.00%	>**	80.24%	>**	73.73%
87.71%	>**	84.95%	>**	81.94%	>**	79.53%	>**	74.25%
84.43%	>**	79.27%	ns	80.64%	>**	79.14%	>**	73.53%
		Baseline, macro, weather smooths on weather		Baseline, macro, weather		Baseline, weather		Baseline
		84.36%	>**	82.00%	>**	75.84%	>**	73.73%
		83.37%	>*	81.94%	>**	76.92%	>**	74.25%
		80.71%	ns	80.64%	>**	74.56%	>*	73.53%
		Baseline, macro, weather; coeffs vary by smoothed Rx5d		Baseline, macro, weather				
		83.99%	>**	82.00%				
		83.01%	> *	81.94%				
		81.20%	ns	80.64%				
Baseline, macro, weather; smooths 2D interactions between macro & between weather		Baseline, macro, weather; coeffs vary by smoothed max temp.		Baseline, macro, weather				
88.21%	>**	84.98%	>**	82.00%				
87.71%	>**	84.13%	> *	81.94%				
84.43%	>**	81.44%	ns	80.64%				
Baseline, macro, weather; smooths 2D interactions between macro & between weather		Baseline, macro, weather; coeffs vary by smoothed consum confid.		Baseline, macro, weather				
88.21%	>**	86.53%	>**	82.00%				
87.71%	>**	86.43%	> *	81.94%				
84.43%	>**	82.47%	>**	80.64%				
		Baseline, macro, weather; coeffs vary by smoothed max windspeed.		Baseline, macro, weather				
		83.13%	>**	82.00%				
		82.69%	> *	81.94%				
		80.31%	ns	80.64%				
Baseline, macro, weather; smooths 2D interactions between macro & between weather		Baseline, macro, weather; coeffs on macro vary by smoothed time		Baseline, macro, weather				
88.21%	> *	87.49%	>**	82.00%				
87.71%	> *	86.59%	>**	81.94%				
84.43%	>**	76.66%	<**	80.64%				
Baseline, macro, weather; smooths 2D interactions between macro & between weather		Baseline, macro, weather; coeffs on weather vary by smoothed time		Baseline, macro, weather				
88.21%	ns	88.64%	>**	82.00%				
87.71%	> *	86.56%	>**	81.94%				
84.43%	>**	76.84%	<**	80.64%				

Table 6: Comparative predictive performance across models.

Notes: For each specified model, the three reported values represent the AUC respectively on (i) the training set, (ii) the out-of-sample test set, and (iii) the out-of-sample and out-of-time test set. Intermediary columns compare the AUCs of adjacent models and indicate if the difference in AUC values is significant (*, **) or non significant (ns) at a significance level of 5%.

5 Impact in terms of capital requirements

So far, we have examined the effects of wildfire and weather-climate drivers on mortgage risk in terms of explanatory and predictive performance. In this section, we consider the potential capital implications of these findings in the wide context of portfolio risk management.

5.1 Method

The Federal Reserve conducts stress tests as part of its oversight framework to gauge how banks might withstand hypothetical, severe but plausible economic conditions. In this section, we explore to what extent extreme weather-climate conditions could impact required capital reserves for mortgage portfolios and compare these effects with those driven by selected macroeconomic factors alone.

Let us consider a portfolio of mortgage accounts. For a hypothetical current calendar date t_o, the expected (or prospective) loss, denoted by EL_{t_o}, over the future time horizon from t_o to $t_o + \tau$ can be expressed as:

$$\mathrm{EL}_{t_o} \;=\; \sum_i \mathrm{EAD}_{i,t_o} \times \mathrm{LGD}_{i,t_o} \times \mathrm{PD}_{i,t_o^+} \tag{8}$$

Here, EAD_{i,t_o}, LGD_{i,t_o}, and PD_{i,t_o^+} represent, respectively, the exposure at default for account i at the *current* calendar date t_o, the loss given default, and the forward-looking probability of default for account i over a specified horizon. Of these three components of the expected loss, the probability of default is the one driven by the spatio-temporal model structures discussed in previous sections[10].

In order to assess the potential impact of weather-climate drivers on capital requirements, and to compare this impact with that of macroeconomic variables, we adopt a simulation approach to predict Value-at-Risk of distributions of expected losses (Djeundje and Crook (2025); Berkowitz (1999); Ferrari and Vespio (2021); Wang (2020). We set up the following three scenarios.

S1 Baseline scenario:

We first compute the expected loss using the central forecasts of the macroeconomic variables generated by a small macro model together with the central forecasts of the climate-weather variables generated by our small weather model. The resulting expected loss is denoted by $\mathrm{EL}_{t_0}(0)$.

[10]Expected losses to a bank due to climate events consist of uninsured losses. We assume that the proportion of EAD that is uninsured is a predictor of LGD and here we model only PD.

The macroeconomic model consists of a vector autoregressive (VAR) model of the form:

$$\boldsymbol{Z}_t = \boldsymbol{a}_0 + \boldsymbol{\phi}_1 \boldsymbol{Z}_{t-1} + \boldsymbol{\phi}_2 \boldsymbol{Z}_{t-2} + \boldsymbol{\phi}_3 \boldsymbol{Z}_{t-3} + \boldsymbol{\varepsilon}_t$$

$$\text{where} \quad \boldsymbol{Z}_t = \begin{pmatrix} u_t \\ c_t \\ r_t \end{pmatrix}, \quad \boldsymbol{\phi}_j = \begin{pmatrix} v_{u,j} & v_{u,j+3} & v_{u,j+6} \\ v_{c,j} & v_{c,j+3} & v_{c,j+6} \\ v_{r,j} & v_{r,j+3} & v_{r,j+6} \end{pmatrix}, \quad \boldsymbol{\varepsilon}_t = \begin{pmatrix} \varepsilon_{u,t} \\ \varepsilon_{c,t} \\ \varepsilon_{r,t} \end{pmatrix}$$

and u_t denotes unemployment rate in month t, c_t denotes consumer confidence index, r_t denotes interest rate, ε_t denotes a vector of error terms, and $v_{(u,j)}$ denotes the coefficient to be estimated on unemployment rate in matrix ϕ_j.

This specification allows each macroeconomic variable to be influenced by and to influence each of the others without imposing a structure (apart from linearity) on the relationships. The data used is the same as was described in section 2.1. The parameters were estimated using OLS. Illustrations of the resulting forecasts are provided in Figure 5.

To forecast the climate-weather variables, we adopt a VAR approach with pooled covariance. For illustration we wish to make predictions two or three years out of time. A VAR is a plausible choice since it allows each weather characteristic to affect every other characteristic in a lagged fashion but without the need to impose structure on the relationship apart from linearity. We estimate a separate VAR model for each ZIP3 area to capture geographically local relationships. The one step ahead residuals from all area models are then pooled to give a common innovation covariance matrix, Σ. For each ZIP3 area we generate a random sample from the multivariate distribution of eta with covariance matrix, Σ and use these values together with previous values of the wildfire-climate variables and values of the parameter estimates of the VAR to generate next step values for the wildfire-climate variables. We iterate forwards and repeat for each ZIP3 area [11]. Illustrative weather forecasts are shown in Figure 6. We then insert the simulated values of the macroeconomic variables and of the weather variables into the parameterised Model (2) (see Table 1) to compute values of the expected loss.

S2 Macroeconomic uncertainty only:

We generate N joint simulations of future macroeconomic paths from the small macro model, thereby preserving the dependence structure among the macroeconomic variables. We do this by sampling from the distribution of ε_t. For each simulated path, we compute the corresponding prospective expected loss using Eq. (8), while keeping the

[11] This approach is analogous to the classical pooled-variance estimator, where several groups are assumed to share a common variance.

climate-weather variables fixed at their baseline (central forecast) values obtained in Scenario S1. The resulting sample of expected losses are henceforth denoted by

$$\mathrm{EL}_{t_0}(Z)_k, \qquad k = 1, \ldots, N.$$

S3 Joint macroeconomic and wildfire–climate uncertainty:

We generate a sample of N expected losses by combining the simulated macroeconomic paths from Scenario S2 with simulated climate-weather paths generated from the small weather model and feeding them into the expected loss formula (8). Consequently, the resulting loss sample reflects uncertainty in both the macroeconomic and weather–climate drivers. The resulting sample of expected losses shall be denoted by

$$\mathrm{EL}_{t_0}(Z, W)_k, \qquad k = 1, \ldots, N.$$

With these scenarios in place, the incremental contribution of weather–climate uncertainty to capital requirements can then be assessed by comparing the tail distributions from the samples of expected losses obtained under Scenarios S2 and S3.

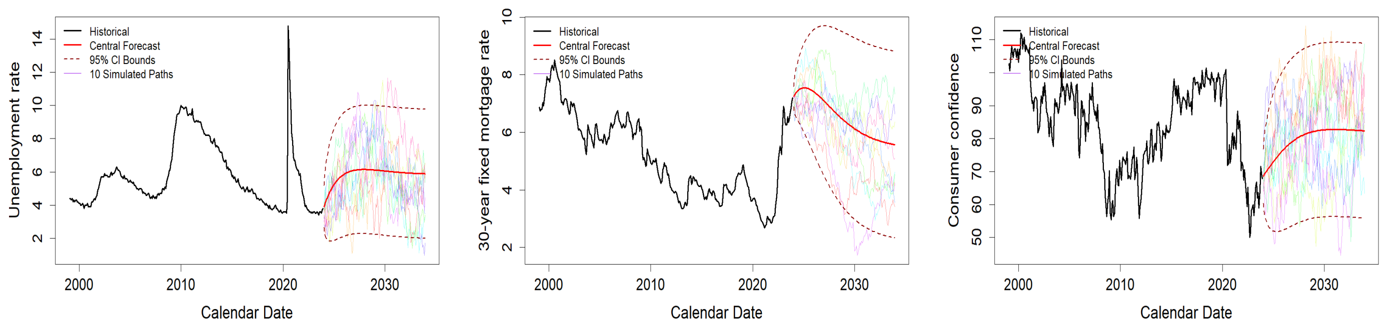

Figure 5: Forecast of the macro variables.

5.2 Results

Figure 7 compares the expected loss distributions from Scenario 2 (macroeconomic uncertainty included but climate-weather uncertainty ignored) versus Scenario 3 (both macroeconomic and climate-weather uncertainties incorporated).[12] This graphic shows that ignoring climate-weather related uncertainty leads to an understatement of the range of potential losses. In particular, looking at the 99% Value-at-Risk, it shows that ignoring wildfire-climate drivers in capital estimation (as is generally the case) in this

[12]On the horizontal axis of Figure 7, the expected losses are scaled by the baseline expected loss, $\mathrm{EL}_{t_0}(0)$, so that all results are expressed relative to the baseline scenario.

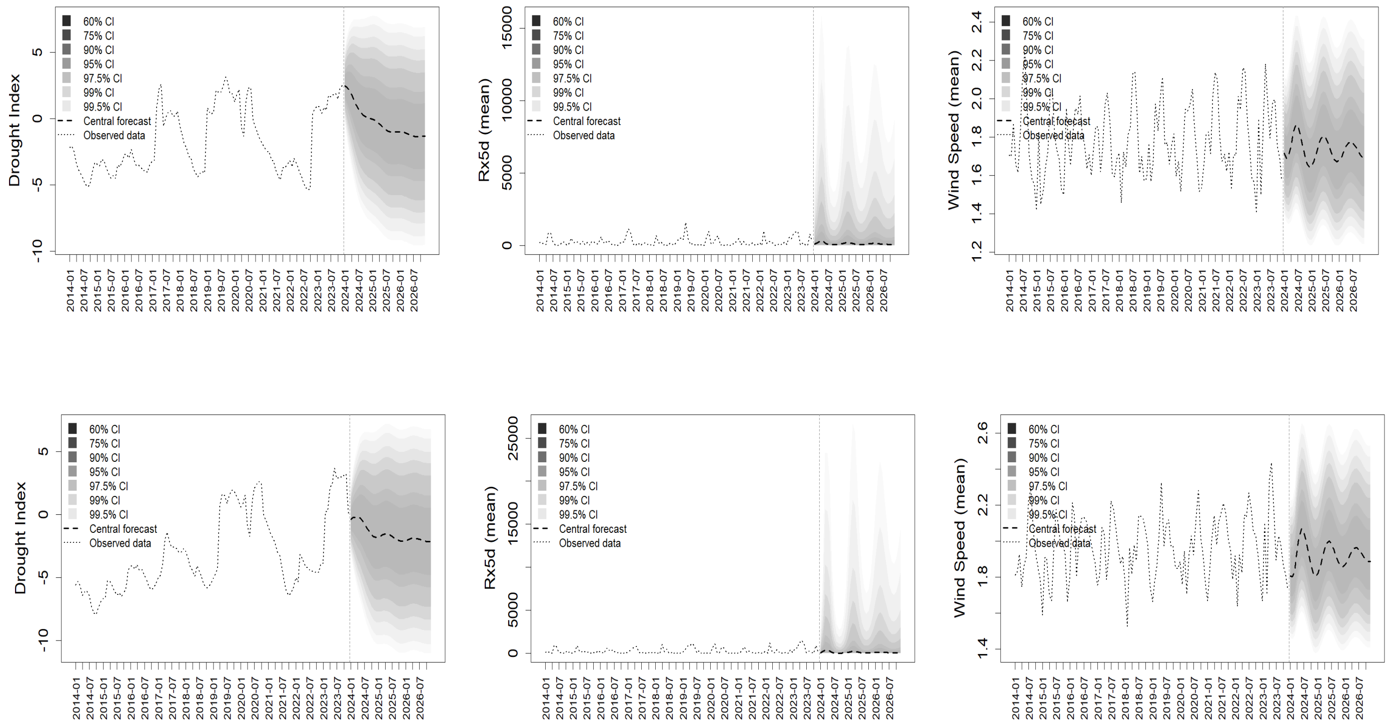

Figure 6: Forecast of a subset of three weather variables for two selected ZIP3 locations.

case leads to a material understatement of the capital required to withstand severe conditions by more than 10%.

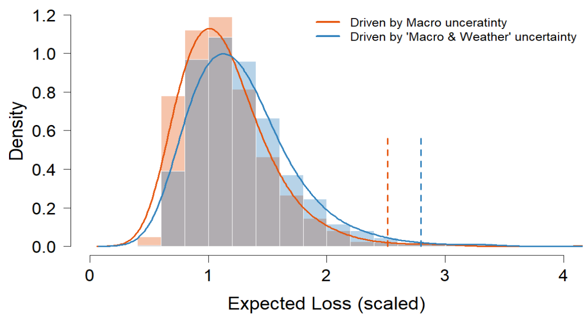

Figure 7: Expected loss distributions. The vertical dashed lines correspond to the 99th percentiles, with corresponding VaR(99%) values of 2.51 and 2.80, respectively.

This calculation used the structure of the standard model (2) when computing the probabilities of default fed into the construction of the expected loss samples. We note, however, that the magnitude of the impact of climate-weather variables on capital can vary depending on the specification of the underlying model driving the PD. Indeed, in addition to assuming the standard model when constructing the loss distribution, we also considered alternative specifications. In particular, we found that the model that delivers the best predictive performance is not necessarily the best candidate when it comes to exploring the tails of the loss distributions.

Exploring the tail of the loss distribution involves extrapolating the PD into extreme scenarios/paths of the macroeconomic and climate-weather variables beyond the ranges of their observed values. Such extrapolation can become unstable or unreasonable depending on the extrapolation method used (see for example Currie et al (2004)). In this work, for instance, we found that while the 2D flexible interaction model showed the best overall prediction performance (as discussed in section 4.4), the P-splines extrapolation of some of the 2D interaction surfaces into extreme positions of the macro and weather variables became unstable in some instances.

6 Discussion and concluding remarks

This paper develops and empirically validates a spatio-temporal stress-testing framework that integrates wildfire and climate related physical risk drivers alongside conventional borrower, loan, and macroeconomic variables to explain and forecast mortgage default risk. Across a comprehensive suite of discrete time survival specifications, ranging from a standard linear model to non-linear generalized additive models (GAMs) with P-splines, time-varying coefficients, and flexible interaction surfaces, we document four principal findings. First, many wildfire-climate variables are non-linearly related to mortgage default risk. This is especially true of maximum temperature, average precipitation and to some extent the number of wildfires in the same area as a mortgaged property. It is less true of closeness to the nearest wildfire and the degree of drought that are appear linearly and positively and linearly and negatively related to default risk, respectively. Second, jointly modelling macroeconomic indicators (e.g., unemployment and interest rate spreads) and climate wildfire drivers significantly improves accuracy beyond macroeconomic inputs alone. Third, moving beyond linear additivity to capture non-linearities and interactions yields further gains in predictive performance, with the richest interaction specification attaining the highest test AUC. Fourth, the omission of wildfire-climate variables from a credit risk model to be used for capital requirements prediction would result in significant underestimation of the capital required.

The baseline spatio-temporal model establishes expected signs for standard credit risk features (e.g., lower default risk for higher credit scores and joint borrowers; higher risk for first time buyers and larger original unpaid balances). It also confirms the role of macroeconomic conditions: rising unemployment and widening mortgage rate spread rates elevate default risk, whereas stronger consumer confidence mitigates it.

Importantly, the inclusion of wildfire-climate drivers reveals material associations: higher fire counts and precipitation are each positively related to default probabilities, whilst drought severity and maximum temperatures are negatively related to default risk.

However, relaxing linearity in credit risk models shows that relationships between wildfire-climate variables and mortgage default risk are strongly non-linear, with smooth functions uncovering thresholds and curvature that linear models obscure (Figure 2). Time varying formulations(Figure 3) indicate relatively flat temporal profiles for some drivers but reveal wildly varying profiles for windspeed and a declining relationship to reach a constant for wildfire count. This highlights the importance of modelling temporal sensitivities rather than assuming static associations. Similarly, allowing for non-linear effects of a weather variables on the marginal effects of another (Figure 3) reveals considerable nonlinearity, for example the non-linear marginal effect of wildfire count depends on maximum temperature. These would not be reflected if the interactions were assumed to be merely multiplicative. The interaction surfaces (Figure 4) depict complex joint dependencies among climate variables, demonstrating that compound hazard rates (for example high fire-count and greater drought or increased maximum windspeed and increased maximum temperature) amplify increases in default risk above the sum of their individual effects.

Out of sample comparisons underscore the practical value of climate wildfire drivers. Augmenting the baseline with macroeconomic variables improves test AUC, but adding climate wildfire drivers on top of macroeconomic inputs improves it further. Allowing smooth specifications, multiple varying coefficients, and complex interactions yields the highest test AUC with the DeLong tests confirming statistical significance of these improvements relative to simpler formulations. These results suggest that lenders and regulators who rely solely on macroeconomic conditions may under-detect pockets of climate conditioned risk; adopting flexible structures that reflect non linear and interactive climate effects can produce more robust PD estimates and ranking power.

Simulation analysis can translate PD estimates into expected loss (EL) VaR-style ratios under four scenarios: baseline; severe macro; severe wildfire climate; and combined severe. Three insights follow. First, severe macroeconomic paths or extreme wildfire climate states individually raise expected losses relative to the baseline. Second, the combined scenario produces substantially larger loss impacts than either factor alone, emphasizing the necessity of joint stressors in capital planning. Third, including uncertainty over future wildfire-climate factors can increase expected loss by over 10 per cent. Put another way, failing to incorporate climate drivers risks material under-capitalisation under adverse conditions, especially for portfolios that concentrate on high hazard exposure locations.

Methodologically, we provide a general, extensible spatio-temporal survival framework with P-splines, time-varying coefficients, and interaction surfaces that is compatible with established credit risk practice and scalable to other hazards (e.g., floods, hurricanes, heatwaves) and assets beyond mortgages. Substantively, we show that wildfire climate drivers are material to mortgage default risk in California and that their omission biases PDs and capital estimates. Practically, we outline a pathway for institutions to embed climate variables in risk quantification, bridging the gap between environmental data and portfolio management and aligning with emerging supervisory expectations on climate related financial risks. Our analysis, by design, focuses on California and employs 3 digit ZIP postal code level alignment of climate variables (aggregated monthly), which may mask micro geographic heterogeneity (e.g., parcel level exposure, defensible space, building standards). The LGD component is held constant in capital illustrations, whereas hazard conditional LGDs could vary significantly with event severity and local market conditions.

These constraints offer avenues for refinement rather than detracting from the methodological contributions and central conclusion that climate wildfire drivers matter for mortgage risk and capital. Future work should pursue higher resolution exposure modeling. Extending the framework to hazard dependent LGD/EAD modeling would enable fully climate-aware expected loss and economic capital estimation. Given evidence of regional heterogeneity, applying the framework to other U.S. states separately and climate hazards contexts would enrich our understanding of place-specific risks, since our analysis shows this is necessary for an accurate risk assessment, a generic model cannot capture a wide range of territorial diversities.

In sum, our findings demonstrate that environmental and economic drivers jointly shape mortgage default risk and that ignoring climate wildfire exposures can lead to mis-specified PDs and under-stated capital needs, particularly under adverse wildfire-climate conditions. By embedding flexible spatio-temporal structures and climate wildfire interactions into survival models, institutions can enhance predictive performance, improve stress testing fidelity, and support more resilient capital planning in the face of accelerating climate risks.

Bibliography

Australian Prudential Regulation Authority (2021). Climate vulnerability assessment. Report, Australian Prudential Regulation Authority.

Australian Prudential Regulation Authority (2024). Corporate plan 2024-25. Report, Australian Prudential Regulation Authority.

Acharya, V., Berner, Engle, R., Jung, H., Stroebel, J., Zeng, X., and Zhao, Y. (2023). Climate stress testing. *Annual Review of Financial Economics*, 15:291–326.

Auer, M. R. (2024). Wildfire risk and insurance: research directions for policy scientists. *Policy Sciences*, 57(2):459–484.

Bank of England PRA (2025). Supervisory statement 5/25-enhancing banks' and insurers' appraches to managing climate-related risks. https://www.bankofengland.co.uk/prudential-regulation/publication/2025/december/enhancing-banks-and-insurers-approaches-to-managing-climate-related-risks-ss.

Basel Committee on Banking Supervision (2022). Principles for the effective management and supervision of climate-related financial risks. https://www.bis.org/bcbs/publ/d532.htm.

Bellotti, T. and Crook, J. (2013). Forecasting and stress testing credit card default using dynamic models. *International Journal of Forecasting*, 29(4):563–574.

Berkowitz, J. (1999). A coherent framework for stress testing.

Biswas, s., H.-M. and Zink, D. (2023). California wildfires, property damage and mortgage repayment. http://dx.doi.org/10.2139/ssrn.4372320. Working Paper 23-05, Federal Reserve Bank of Philadephia.

Bocchiio, C., Crook, J., , and Andreeva, G. (2023). The impact of macroeconomic scenarios on recurrent delinquency: a stress testing framework using multi-state models for mortgages. *International Journal of Forecasting*, 39(4):1655–1677.

Calabrese, R., Dombrowski, T., Mandel, A., Pace, R. K., and Zanin, L. (2024). Impacts of extreme weather events on mortgage risks and their evolution under climate change: A case study on florida. *European Journal of Operational Research*, 314(1):377–392.

Caloia, F. and Jansen, D.-J. (2021). Flood risk and financial stability: Evidence from a stress test for the netherlands. Working Paper 730, De Nederlandsche Bank, Amsterdam, The Netherlands.

Campbell, J. Y. and Cocco, J. F. (2015). A model of mortgage default. *The Journal of Finance*, LXX(4):1495–1554.

Currie, I. D., Durban, M., and Eilers, P. H. C. (2006). Generalized linear array models with applications to multidimensional smoothing. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 68(2):259–280.

DeLong, E. R., DeLong, D. M., and Clarke-Pearson, D. L. (1988). Comparing the areas under two or more correlated receiver operating characteristic curves: a nonparametric approach. *Biometrics*.

DeMenno, M. B. (2023). Environmental sustainability and financial stability: can macroprudential stress testing measure and mitigate climate-related systemic financial risk? *Journal of Banking Regulation*, 24:445–473.

Deng, Y., Quigley, J. M., and van Order, R. (2000). Mortgage terminations, heterogeneity and the exercise of mortgage options. *Econometrica*, 68(2):275–307.

Department of the Treasury Office of the Comptroller of the Currency, Federal Reserve System, and Federal Deposit Insurance Corporation (2023). Principles for climate-related financial risk management for large financial institutions. Document ref: 2023-23844; Billing Code 4810-33-P; 6210-01-P; 6714-01-P.

Dhima, J., Ali Irvana, M., Itam, E., and Boidot-Doremieux, T. (2025). Integration of physical climate risk into banks' credit risk and capital assessment: a case study on the impact of flooding on real estate portfolios.

Djeundje, V. and Crook, J. (2025). A new method to predict economic capital for the credit risk of a lending portfolio. *Journal of the Operational Research Society*, 76(7):1432–1448.

Djeundje, V., Crook, J., and Andreeva, G. (2025). The devil is in the details: dynamic prediction of loan portfolio profitability with macroeconomic drivers through multistate modelling. *European Journal of Operational Research*, 327(2):703–715.

Djeundje, V. A. and Crook, J. (2019a). Dynamic survival models with time varying coefficients for credit risks. *European Journal of Operational Research*, 275(1):319–333.

Djeundje, V. A. and Crook, J. (2019b). Identifying hidden patterns in credit risk survival data using generalised additive models. *European Journal of Operational Research*, 277(1):366–376.

Dombrowski, T. and Zanin, L. (2025). Mortgage credit risk and extreme weather events in the united states: A flexible survival modelling framework with a nested tree structure. Working Paper 5296389, SSRN Electronic Journal.

Eilers, P. and Marx, B. (1996). Flexible smoothing with b-splines and penalties. *Statistical Science*, 11(2):89–121.

Elhami-Khorasani, N., Ebrahimian, H., Buja, L., Cutter, S. L., Kosovic, B., Lareau, N., Meacham, B. J., Rowell, E., Taciroglu, E., Thompson, M. P., and Watts, A. C. (2022). Conceptualizing a probabilistic risk and loss assessment framework for wildfires. *Natural Hazards*.

Environmental Protection Agency (2024). Climate change indicators: Wildfires. Available from EPA website.

European Central Bank (2022). 2022 climate risk stress test. Technical report, European Central Bank.

Ferrari, S., V.-P. and Vespio, C. (2021). Sensitivity of credit risk stress test results: modelling issues with an application to belgium. *Journal of Financial Stability*, 52.

Fitzpatrick, T. and Mues, C. (2016). An empirical comparison of classification algorithms for mortgage default prediction: evidence from a distressed mortgage model. *European Journal of Operational Research*, 249(1):427–439.

Gete, P., T.-A. and Wachter, S. M. (2024). Climate riskin mortgage markets: evidence from hurricanes harvey and irma. *Real Estate Economics*, 52:660–686.

Hersbach, H., Bell, B., Berrisford, P., Biavati, G., Horányi, A., and Sabater, J. M. (2018). Era5 hourly data on single levels from 1979 to present.

Iglesias, V., Balch, J. K., and Travis, W. R. (2022). U.S. fires became larger, more frequent, and more widespread in the 2000s. *Science Advances*, 8(11):eabc0020.

Intergovernmental Panel on Climate Change (2023). Climate change 2023: Synthesis report. *IPCC*.

Issler, P., S.-R. V. C. and Wallace, N. (2020). Mortgage markets with climate change risk: evidence from wildfires in california. *SSRN Electronic Journal*.

Kau, J. B., Keenan, D. C., and Kim, T. (1993). Transaction costs, suboptimal termination and default probabilities. *Journal of the American Real Estate and Urban Economics Association*, 21(3):247–263.

Kousky, C., Palim, M., and Pan, Y. (2020). Flood damage and mortgage credit risk: A case study of hurricane Harvey. *Journal of Housing Research*, 29(sup1):S86–S120.

Lee, D.-J., Durbán, M., and Eilers, P. (2013). Efficient two-dimensional smoothing with p-spline anova mixed models and nested bases. *Computational Statistics & Data Analysis*, 61:22–37.

Moller, Niels, F. and Oksbjerg, Martin (2024). The most significant financial risks from climate change and green transition. Report 6, Danmarks Nationalbank.

Network for Greening the Financial System (2022). Scenarios for central banks and supervisors. Technical report, Network for Greening the Financial System.

NOAA (2025). Climate at a glance: County time series (retrieved in february 2025 from noaa national centers for environmental information).

of Governors of the Federal Reserve System, B. (2024). Pilot climate scenario analysis exercise: Summary of participants' risk management practices and estaimtes. Technical report, Board of Goernors of the Federal Reserve System.

Office of the Superintendent of Financial Institutions Canada (2025). Climate risk management. Technical report, Office of the Superintendent of Financial Institutions Canada. Document B-15.

Palmer, W. (1965). Meteorological drought - research paper no. 45. Research paper, U.S. Department of Commerce.

Rossi, C. V. (2021). Assessing the impact of hurricane frequency and intensity on mortgage delinquency. *Journal of Risk Management in Financial Institutions*, 14(4).

South African Reserve Bank (2025). Climate change policy and regulatory framework in the national payment system. Report, South African Reserve Banks.

St-Denis, L., Short, K., McConnell, K., Cook, M., Buckland, M., and Mietkiewicz, N. (2022). All-hazards dataset mined from the us national incident management system 1999-2020.

Wang, Z., C. J. A. G. (2020). Reducing estimation risk using bayesian posterior distribution approach: application to stress testiing mortgage loan default. *European Journal of Operational Research*, 287(2):725–738.

White, M. (2006). Bankruptcy and consumer behaviour: theory and u.s. evidence. *The Economic of consumer credit*.

Wong, M. C. S. and Ho, H. M. (2023). A framework for integrating extreme weather risk, probability of default, and loss given default for residential mortgage loans. *Sustainability*, 15(15).

Wood, S. N. (2011). Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric generalized linear models. *Journal of the Royal Statistical Society (B)*, 73(1):3–36.

Wood, S. N. (2024). *mgcv: Mixed GAM Computation Vehicle with Automatic Smoothness Estimation*. R package version 1.9-1.

Wood, S. N., Goude, Y., and Shaw, S. (2014). Generalized additive models for large data sets. *Journal of the Royal Statistical Society Series C: Applied Statistics*, 64(1):139–155.

Yavas, C. E., Kadlec, C., Kim, J., and Chen, L. (2025). California weather and fire prediction dataset (1984–2025) with engineered features.

Zanin, L., Calabrese, R., and Thorburn, C. I. (2024). Climate stress testing for mortgage default probability. *International Review of Financial Analysis*, 95:103497.