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WORKING PAPER

A framework for wildfire prediction and loss assessment: Potential application in the financial sector—case study in Yunnan

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CONTENTS

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EXECUTIVE SUMMARY

Highlights

- This paper introduces a framework that combines remote sensing data and climate projections, presenting an alternative to traditional physical models for assessing and managing the wildfire impact on assets under future climate warming projections.
- Through showcasing the agriculture sector in Yunnan, the paper reveals changes in severity and frequency of wildfires in Yunnan and impact on five different crops under different climate scenarios.
- With extreme wildfire events accounting for 15 to 30 percent of annual losses, a single event poses significant threats to smallholder farmers, which can lead to noticeable risk for financial institutions.
- Financial institutions in Yunnan are facing complex climate-induced impacts and the challenges of limited readiness and capacity to manage risk, requiring a comprehensive solution and external empowerment.

About this paper

This working paper introduces a climate risk assessment framework utilizing remote sensing data and climate projections to improve the understanding and management of wildfire risks under a climate change background for financial institutions. The impact of climate change on wildfires is complex, and when these impacts are transmitted to agriculture, the situation becomes even more complicated, requiring a comprehensive analysis that combines the geographic distribution and lifecycle of agricultural assets. In our interactions with the financial institutions, we found that different stakeholders in the financial system exhibit varying understandings of physical climate risks. However, overall, there is a significant gap in the understanding of physical climate risks. This gap in understanding may lead to inequitable resource allocation, further exacerbating the plight of vulnerable communities. To improve the capacity to manage climate risk for financial institutions and close the gap, it is important to involve government-leading stakeholders and synergize a comprehensive approach.

Key findings

Based on the research conducted, the study draws the following conclusions regarding Yunnan Province:

- During 2011 to 2020, historical loss from wildfires in Yunnan's five target agricultural crops ranged from US$135.8 million to $254.8 million per year.
- Extreme wildfire events account for 15 to 30 percent of annual loss, posing a significant threat to smallholder farmers.
- The current framework of the wildfire loss simulation model shows good performance in most of the crops through testing, providing reliable results for practical use.
- In Yunnan Province, historical data show the highest regional mean Fire Weather Index (FWI) in March and April, but future projections shift the peak to February and March. Among the scenarios, Shared Socioeconomic Pathway (SSP)2-45 shows the highest mean FWI, followed by SSP1-26, SSP3-70, and SSP5-85, all exceeding observed values.
- Scenario analysis of wildfire loss demonstrates the complexity of the impact of wildfires on crops under climate change. We did not observe a trend where higher emissions led to greater impacts under different climate scenarios.
- Insurance companies are highly enthusiastic about integrating physical climate risk analysis to develop relevant products like catastrophe and parametric insurance. Banks prioritize using climate risk analysis tools for effective credit risk management. Stress testing for climate risks is crucial but resource intensive.

INTRODUCTION

Climate change has become an increasingly global concern, profoundly affecting ecosystems and many economic sectors of human society. The rise in global temperatures is altering weather patterns, leading to more extreme conditions and climate anomalies. This escalation in abnormal climate patterns correlates directly with the increase in natural disasters, which have become not only more frequent but also more severe. Globally, natural disasters have become five times more frequent over the past 50 years, with heightened intensity (WMO 2021). On the other hand, risks and impacts that disproportionately affect particular groups due to uneven distribution of physical climate change hazards, exposure, or vulnerability (IPCC 2023) point to the need for locally based work.

Among these disasters, wildfires have emerged as a critical hazard, posing substantial risks to both human activities and the environment. The global incidence of wildfires has doubled since 1984 (Mansoor et al. 2022). It is essential to understand and assess this heightened frequency of wildfires and the links to changing climate patterns (Mansoor et al. 2022). Extreme weather events such as droughts, heat waves, and strong winds caused by climate change increase the probability of wildfires (Westerling et al. 2006). Wildfires, on the one hand, release a large amount of carbon dioxide and other greenhouse gases, further contributing to climate change (Bowman et al. 2009). As a type of physical climate risk, wildfires also cause massive damage, including ecological, economic, and social. Ecological impacts mainly occur in the form of loss of forest, soil, and wildlife resources (Dale et al. 2001). Economic impacts include direct economic loss, such as fire suppression costs, infrastructure and property damage, and indirect economic loss, such as reduced productivity and damage to tourism (Hand et al. 2014). Social impacts are reflected in human casualties, loss of personal possessions, reduced living standards, and impaired mental health (Stephens et al. 2014).

In regard to the empirical side of climate risk and its association with the financial sector, financial institutions, including banks, insurers, and asset managers, face significant challenges from physical climate risks related to hazards such as wildfire. These risks variously affect different sectors within the financial industry (BIS 2021). In the case of banks, risks could translate into credit risks, as borrowers may struggle with loan repayments due to loss of income or damage to collateral. The United Nations Environment Programme Finance Initiative (UNEP FI) and Acclimatize find that under the 2040s 4°C scenario (RCP 8.5), the probability of default of a sample bank's loan portfolio could increase to as much as 1.5 times the probability under the business-as-usual scenario (UNEP 2018). Widespread damage could even cause market risk and threaten the stability of the financial system. Insurers face the consequences of physical climate risk through their underwriting business, as claims and loses become higher and more frequent (Mills 2009).

However, according to a survey conducted by CDP in 2020, most financial institutions underestimate their exposure to climate risk, especially credit and market risks (CDP 2022). Financial institutions face multiple challenges when managing credit risks related to climate change. First, they cannot identify and assess physical climate–related risks in a quantified and granular measurement. This is mainly due to poor data availability, complex methodology, lack of hazard-specific metrics, and damage functions (Zhou 2022). Second, financial institutions' climate risk assessments for the agriculture sector often underestimate the magnitude of its impact. Limited practices, such as insufficient climate risk disclosure and inadequate scenario analysis, have been identified in reports by major financial institutions like JPMorgan Chase (2022) and HSBC (2021). This discrepancy may stem from the relatively smaller portion of agriculture-related assets in financial portfolios compared to high-emission industrial sectors. Consequently, climate risks associated with the agriculture sector are frequently neglected. A report by the Network for Greening the Financial System highlighted that financial exposure to agriculture-related climate risks is often underrepresented in stress testing frameworks (HSBC 2021; JPMorgan Chase 2022; NGFS 2020).

Yunnan is a hot spot of wildfire hazard in Southeast Asia (Ying et al. 2021). Agriculture is not commonly thought of as being susceptible to wildfires, but certain economic crops that are grown adjacent to or intermixed with forests and shrubs can be impacted by wildfire. In Yunnan, agriculture has integrated agroforestry practices for a long historical period (Guo and Padoch 1995). Additionally, it continues to be a vital pillar of the local economy, providing both rural employment and food security (Zhu et al. 2022). In 2021, 49 percent of the total population lived in rural areas in Yunnan, much higher than the average rural population of China, which was 35.3 percent (National Bureau of Statistics 2021). Agriculture products are the largest export from Yunnan Province, contributing an important source of income (Yunnan Provincial Department of Agriculture and Rural Affairs 2021).

The agricultural sector also plays an important role in the rural financial system. For instance, agriculture-related loans accounted for 54 percent of rural commercial banks' total loan portfolios in China in 2019 (Yu 2022). In Yunnan, Fudian Bank, Yunnan's largest urban commercial bank, allocates one-fourth of its loan assets to the agriculture sector (FDB 2019). It is critical for these financial institutions to understand physical climate risks to their agricultural assets as the first step in taking effective measures, such as adjusting investment strategies, improving risk assessment models, or implementing resilience-building initiatives.

Currently, the physical climate risk assessment primarily employs scenario analysis methods, which rely on scenarios of future climate change projections based on greenhouse gas emission scenarios to evaluate the risks and opportunities for businesses. It is an effective approach for devising more flexible and robust strategic plans that cover a range of potential future scenarios. However, physical climate risk assessment in general faces several challenges, including the following:

- First, current scenario analysis methods employ a "black-box" approach extensively. This lowers transparency and credibility and limits the ability to improve, compare, and integrate different results in climate risk assessments (Arribas et al. 2022).
- Second, even though diverse climate simulation models are available, loss assessment is rarely included in the projection. Moreover, many loss analysis experts offer scant analysis of the climate itself (Ding et al. 2021), which leads to a disconnect between the tools and analytical methods covering the entire process.
- Third, while physical risks of some disasters—for example, floods—have received relatively focused attention, trustworthy assessments, evaluations, and projection models of the physical risks of most other disasters, such as wildfires, are not available. Businesses are interested in understanding the various hazards they face, but there is a gap between their needs and the information available about hazards that are not well researched.

These three issues warrant significant attention as we strive to enhance our understanding of physical climate risks and improve the accuracy, comprehensiveness, and transparency of the assessments.

There are many different methods to assess wildfire risk that consider the interaction of climate, land cover, topography, and humans at different spatial and temporal scales. Statistical wildfire models have been used for regional and global assessments since they captured the nonlinear fire-driver relationships and are able to reproduce historical wildfire patterns (Galizia et al. 2022; Turco et al. 2017). Yet, those normally require a spatial aggregation, implying a prediction with a coarse spatial resolution, which is a limitation for assessing the wildfire risk at a proprietary level. Machine learning algorithms have been increasingly used in fire science to model wildfire risk (Jain et al. 2020). Those algorithms deal very well with nonlinear relationships and present an overall good agreement with observations; however, they lack interpretability, especially when projected future climate exceeds the observed values during the historical period. Another possible approach for assessing wildfire risk is the use of fire spread models, also known as fire behavior simulations (e.g., FlamMap). These simulations explicitly consider how landscape variables affect fire behavior processes through fire spread equations, and they also account for other wildfire drivers, such as wind and fire suppression effects (Finney et al. 2011). However, this approach is better suited for local studies since this requires very fine-scale landscape data that are computationally expensive to run across continental domains. Additionally, fire spread models are mostly used to design and evaluate fuel treatments, exposure, and risk analysis (Parisien et al. 2019), but often they fail in predicting future fire activity since they rely on strong assumptions of constant weather conditions such as fire duration and wind speed during the simulations.

To address the three challenges above, we chose the CLIMADA model as a base is for our work. CLIMADA is a transparent model developed by ETH Zurich. It provides statistical models with machine learning algorithms for hazard prediction. Combined with a loss assessment function, CLIMADA presents a comprehensive framework for assessing physical climate risk.

In our study, we built and further developed a forecasting methodology framework based on CLIMADA and equipped it with scenario analysis. Empirically, we conducted a case study on agriculture portfolios in Yunnan Province. Through the assessment of the impact of wildfires on agricultural production, our objective was to examine the model and highlight the importance and practicality of physical climate risk assessment in this specific context. Meanwhile, we organized multiple informal discussions with financial institutions and experts in the area, aiming to understand the practical difficulties in implementing climate risk measures and explore solutions to address the difficulties. By building this framework and conducting a case study, this paper aims to answer the research question of how could an we build a transparent climate risk assessment framework and integrate such a framework into decision-making for financial institutions to manage climate risk and benefit people, nature, and the climate, especially for vulnerable groups (small stakeholder farmers in this case)? To answer this question, we developed this paper using the following steps:

- Methodology framework and case study
    - To introduce a methodology framework for detailed assessing and predicting economic loss caused by wildfire
    - To evaluate crop production loss caused by wildfire under a historical baseline and different climate scenarios in Yunnan Province
- Local status of climate risk measures and implementation of the framework
    - To understand the status and challenges of financial institutions in Yunnan in the context of facing physical climate risks
    - To discuss briefly how financial institutions could apply this methodology and integrate the assessment of climate risks into their businesses

METHODOLOGY

The methodology is divided into two parts. The first part introduces a framework for the assessment and prediction of economic loss from wildfires. The second part is an initial exploration with the target audience to assess the readiness and applicability of the framework, to understand the status and challenges financial institutions are facing in implementing measures against climate risk.

Framework for evaluating economic loss

We demonstrate this framework in four parts—dataset preprocessing, evaluating historical loss, predicting near-term future loss based on historical records, and predicting long-term future loss based on scenario analysis.

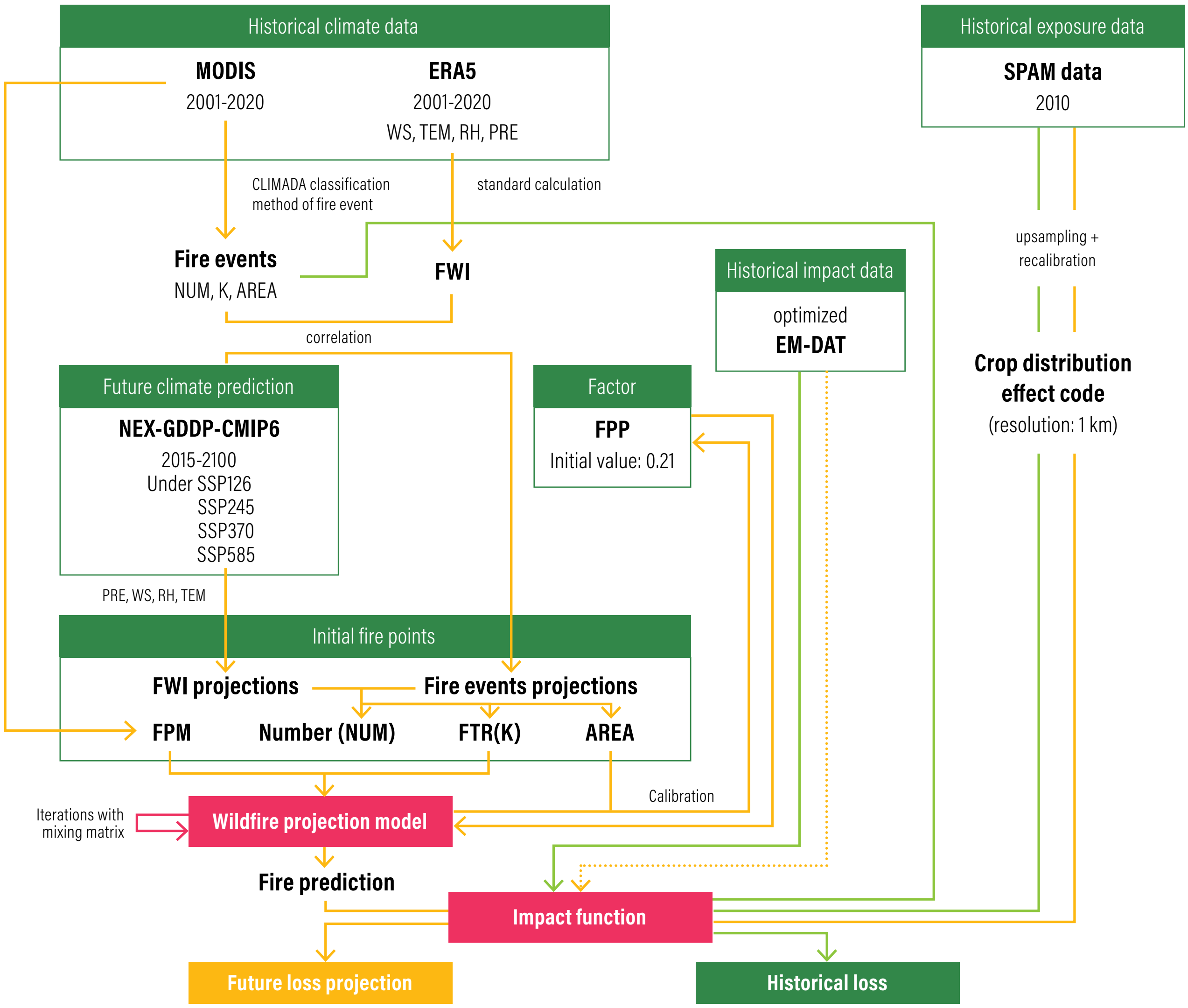
An overall structure to quantify economic loss involves four dimensions of variables—hazard, exposure, exposure's price, and vulnerability (impact function). The mathematical expression is defined as:

$$Economic\ Loss = Exposure \times f_{imp}\ (Hazard) \times Price \tag{1}$$

Where **hazard** describes weather events such as wildfire, storms, floods, droughts, or heat waves both in terms of probability of occurrence and physical intensity. In this study, hazard represents the expected intensity (calculated in brightness temperature) of wildfire. **Exposure** describes the set of assets, crops, people, livelihoods, infrastructures, and so on within an area of interest in terms of their geographic location, their value, and other characteristics. Here, exposure is the production of the crops that are exposed to wildfire. **f_{imp}(impact function)** describes a relationship between a hazard's intensity (calculated in brightness temperature) and the exposure in terms of **a percentage loss**. **Price** represents the monetary value per unit of the exposed asset.

With the basic concept above, we will explain in the following sections how to evaluate the impact of historical wildfires on crop losses, near-term future losses based on historical records, and long-term future losses based on scenario analysis. The framework is illustrated in Figure 1. The green flows represent historical loss. The framework uses historical climate data, impact function, and historical exposure data to assess historical economic loss. The orange flows present near-term future loss based on historical records and long-term future loss based on scenario

Figure 1 | **Overall framework of the methodologies for the assessment and prediction of economic loss from wildfires**



Notes: MODIS = Moderate Resolution Imaging Spectroradiometer. ERA5 = ECMWF Reanalysis v5 - Land. WS = wind speed. TEM = temperature. RH = relative humidity. PRE = precipitation. NUM = number of wildfire events in the study area. K = brightness temperature of wildfire. AREA = the average of the total area of wildfires per unit time in the study area. FWI = Fire Weather Index. NEX-GDDP-CMIP6 = NASA Earth Exchange Global Daily Downscaled Climate Projections. SSP = Shared Socioeconomic Pathway. FPP = fire propagation probability. EM-DAT = Emergency Events Database. FPM = fire probabilistic matrix. FTR = fire temperature range. SPAM = Spatial Production Allocation Model. km = kilometer.

Source: Authors.

analysis. The framework uses generated predicted climate data, impact function, and future exposure data to assess future economic loss.

Data and preprocessing

In the framework of predicting and assessing the crops' production loss caused by wildfire, different types of datasets are needed. In this working paper, we use only open source datasets and provide details of preprocessing methods to make the framework easy to use. This section shows the four key datasets and the preprocess methods.

HAZARDS: WILDFIRE

In our working paper, we use the Moderate Resolution Imaging Spectroradiometer (MODIS) fire products as our historical wildfire hazard observation. The MODIS dataset is offered by the Fire Information for Resource Management System, or FIRMS (Earthdata 2015), which is run by the National Aeronautics and Space Administration, or NASA (Appendix A-a). The datasets include latitude, longitude, acquisition date, and the brightness temperature in Kelvin (K) for each pixel identified as a fire point in one-kilometer (km) resolution. We collected the MODIS wildfire data from a 20-year period (2001–20) and transformed them into wildfire events.

We used the definition of "wildfire events" and the processing method of CLIMADA to modify the MODIS wildfire data for later use in the analysis and projection model (CLIMADA 2017). A wildfire event is defined as when the temporal and spatial distance of the burning pixel centroids is close enough. There are two parameters defining the "closeness":

- Temporal distance. If the time interval between two wildfire points is less than two days, they will be considered as one wildfire event.
- Spatial distance. If the cluster maximum distance between two center points (centroids) is 15 km, they will be considered as one wildfire event.

In addition, we chose the highest temperature in each pixel from an individual wildfire event to represent the intensity of the wildfire (CLIMADA 2017).

ASSET EXPOSURE: CROPS

Yunnan has a diverse range of agricultural products due to its climate characteristics and geographic location. However, considering that the research objectives need to include both staple grains and cash crops, due to their significance to the local economy and food security; crops' susceptibility to wildfire impacts; and data availability, we ultimately selected five agricultural products—wheat, maize, soybeans, sugarcane, and coffee—as our research targets (Appendix A-b).

To estimate the impact of wildfires on crops in the Yunnan region as accurately as possible, we needed to reconstruct exposure based on the agricultural data we have collected. There are two types of exposure data being used—crops' lifecycle and spatial distribution.

Exposure data—growing period

For the crops' lifecycle exposure data, we made a simple distinction of the time periods when crops are affected by wildfire and the time periods when crops are not affected by wildfire. To define those two periods, for short-term crops, we considered the growing period as an affected period, and the rest as an unaffected period. For perennial crops, we considered them to be constantly affected by wildfire. The lifecycle of those five crops is shown in Figure 2 (Chen Dan 2020; Hu and Zimmer 2013; Yunnan Provincial Department of Agriculture and Rural Development 2023; Jianyi 2019; Yunnan Coffee Industry Expert Group 2021). Only the affected periods are included in the loss calculation.

Exposure data—crop distribution

For the crops' spatial distribution data, we combined the Spatial Production Allocation Model (SPAM)[3] with the National Bureau of Statistics, or NBS[4], to generate (mathematical expression, Appendix A-c) our target crops' production values spatial distribution (Figure 3). The SPAM 2010 we used was spatial production values intensity distribution in tonnes of global area in 10 km in 42 types of crops. The NBS dataset is annual crop production values at the provincial level, with the units converted to tonnes.

The details of combining and generating the steps are as follows:

1. Clip the crop production data for the Yunnan region from the global 2010 SPAM dataset using boundary shapefile.
2. Upsample the SPAM 2010 from 10 km to 1 km in the Yunnan region (Appendix A-d).
3. Calibrate each pixel's production by using NBS Yunnan provincial level production dataset in 2010.

Figure 2 | **Overall framework of the methodologies for the assessment and prediction of economic loss from wildfires**

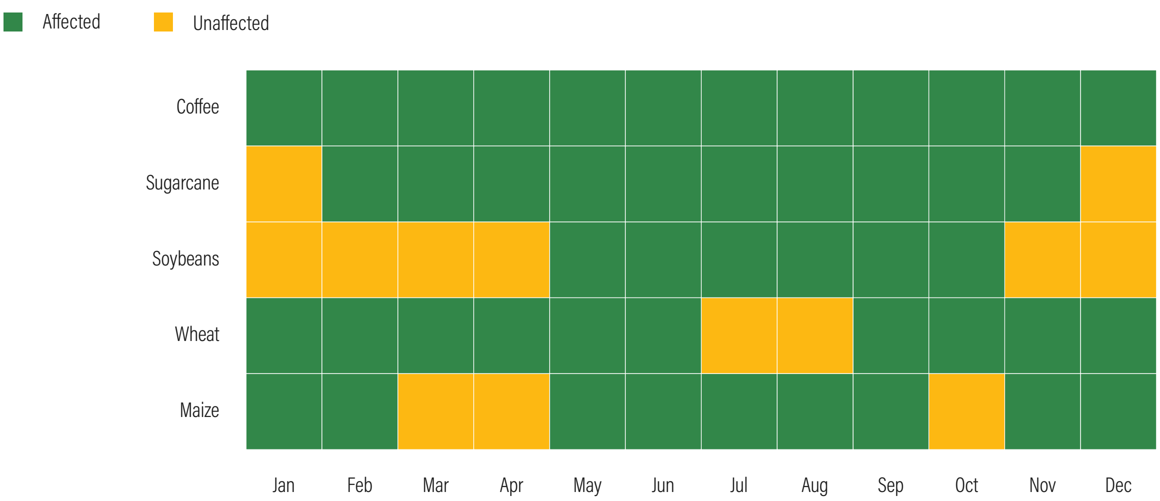
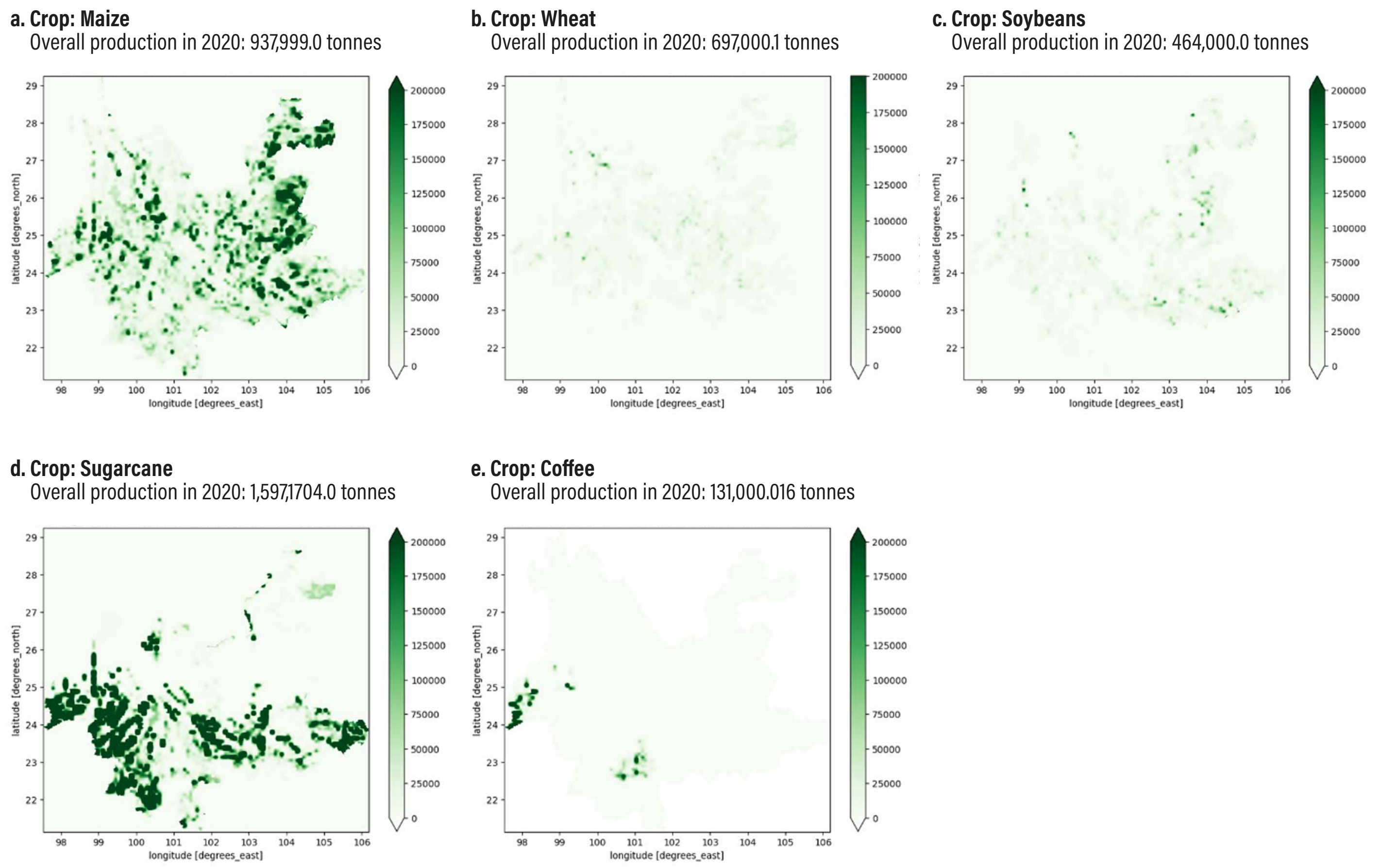


Figure 3 | **Crop production distribution in Yunnan Province, 2020**



Source: Authors.

4. Rescale the spatial dataset by using the ratio of the Yunnan provincial crops' production for the target year to the crops' production in 2010.

REANALYSIS OF METEOROLOGICAL OBSERVATION DATA: ERA5-LAND

In our research, in addition to using wildfire data and agricultural production data, we also used meteorological data. We extracted the necessary meteorological data from ERA5-Land[5], including temperature, precipitation, wind speed, and relative humidity. We used those variables to calculate the Fire Weather Index (FWI); details of how to calculate the FWI are displayed in Appendix A-e. The FWI is used to estimate the wildfire intensity (Xin 2010). The details of how we used the FWI calculated by ERA5-Land will be explained in "Near-term future wildfire economic loss on crops."

FUTURE CLIMATE PROJECTION: NEX-GDDP-CMIP6

Except for meteorological data, we also used the climate scenario dataset to predict how climate change affects wildfires, which in turn impacts agricultural production. We used the NEX-GDDP-CMIP6 (NASA Earth Exchange Global Daily Downscaled Climate Projections) as our scenario analysis dataset.

The dataset comprises global downscaled climate scenarios derived from the general circulation model (GCM) runs conducted under the Coupled Model Intercomparison Project Phase 6 (CMIP6) and across the four Tier 1 greenhouse gas emissions scenarios known as Shared Socioeconomic Pathways, or SSPs (Thrasher et al. 2024). The dataset compiles climate projections from 35 CMIP6 GCMs and four SSP scenarios (SSP2-45, SSP5-85, SSP1-26, and SSP3-70) (Appendix A-h) for 2015 to 2100, as well as the historical experiment for each model for 1950 to 2014.

In our study, we used temperature, precipitation, wind speed, and relative humidity data from NEX-GDDP-CMIP6 to calculate the FWI under four SSP scenarios.

Historical economic loss caused by wildfire

The historical economic loss refers to crop history loss by wildfire in tonnes multiplied by the corresponding year's annual price in a particular year. The historical loss is calculated based on historical hazard, historical exposure, and impact function, illustrated by the green flows in Figure 1.

Historical hazard refers to wildfire hazard, which consists of individual wildfire events defined in "Framework for valuating economic loss." Each wildfire event comprises its coordinates, time, and brightness temperature. **Coordinate** describes the locations of all pixels in one wildfire, and it can also describe the one wildfire's burning area by summing the area of all pixels in one wildfire event. **Time** is the start and end date of the wildfire. **Brightness temperature** describes the intensity of each wildfire event pixel by pixel.

Historical exposure refers to the five types of crop production spatial distribution of unit tonnes in corresponding years, demonstrated in "Asset exposure: Crops."

We used the **impact function** developed by Lüthi (Lüthi et al. 2021). This function assumes that the fire brightness temperature serves as a proxy of wildfire intensity, which is the main cause of damage to infrastructure like buildings, to forests, and to crops. We assumed that wildfire's effect on crops obeys the impact function used by Lüthi (equations 2 and 3; see Figure 4). In our study, the resolution of the hazard and exposure dataset's resolution was 1 km, so we used the impact function with 1 km resolution (Appendix A-n). We also assumed that the impact of wildfire burning on exposure, in the absence of human intervention, will continue until the exposure is completely burned out, so mean damage degree is always 100 percent, as shown in Figure 4. However, due to the limitations of satellite resolution, a single pixel represents a mixture of multiple land features. The higher the brightness temperature, the higher the proportion of wildfire in the mixed pixel, which means a higher percentage of affected assets (PAA). So, in our paper, impact function is the same curve as PAA, and the impact function is expressed as follows:

$$f = \frac{i^3}{1+i^3} \tag{2}$$

Where $i_{lat,lon}$ at a given location is defined as:

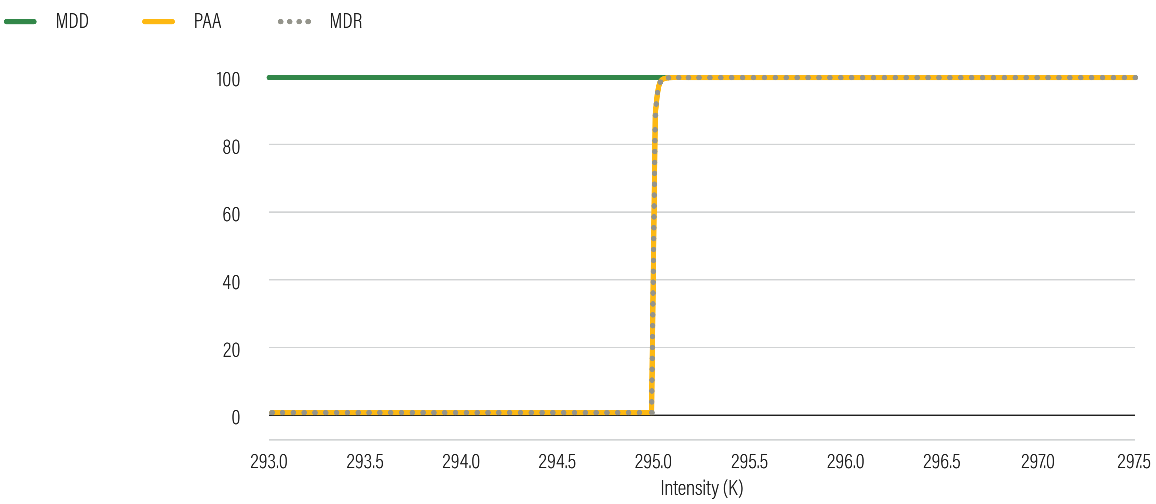
$$i_{lat,lon} = \frac{MAX\,[(I_{lat,lon} - I_{thresh})]}{I_{half} - I_{thresh}} \tag{3}$$

where i or $i_{lat,lon}$ is brightness temperature of the fire pixel measured in Kelvin, I_{half}=295.01 K, which can be seen as the steepness of the sigmoid function (equation 2); I_{thresh}=295 K, the minimum intensity where damages occur (here chosen as a constant 295 K, the minimum value of a FIRMS data point to be displayed as a fire); *MAX* means the maximum value of overlap pixel in one wildfire event.

The wildfire impact function at one-kilometer resolution was approximated as a near-binary impact equation. The impact reaches its peak as the intensity of the brightness temperature reaches 295.2 K, with an approximate 99.99 percent loss for bright temperature over 295.2 K.

To calculate a specific year's economic loss, we used the corresponding year's wildfire events observations and crop exposures with wildfire impact function, equations 2 and 3. After that, we included Food and Agriculture Organization of the United Nations (FAO) crop prices for a specific year and used the annual exchange rate (USD to CNY) to get the local currency[6] (Appendix A-k). **We calculated the historical economic loss from wildfire by averaging the loss for the 10-year period 2011–20.**

Figure 4 | **Wildfire impact function—the impact of wildfire with different intensity (one-kilometer resolution)**



Notes: MDD = mean damage degree. PAA = percentage of affected assets for each intensity. MDR = mean damage rate; MDR = MDD × PAA.

Source: Authors.

Near-term future projected economic loss caused by wildfire

Near-term future projected economic loss here focuses on short-term projection; for example, economic loss of 2021 is based on data from 2020. To assess the projected economic loss, we need the **target year's hazard simulation, target year's crop exposure,** and **impact function**. We used a wildfire model based on the Monte Carlo simulation. This model, requiring wildfire parameters as input, can simulate the occurrence of wildfires in the study area for a year. According to the characteristics of the crop growth cycle (Figure 2) and the relationship between meteorological elements and wildfire parameters (Figure 7 and Figure 8), **the input parameters have been changed from annual to monthly parameters**. We provide a detailed introduction on how wildfire is simulated in "Near future wildfire simulation" and "Near-term future wildfire economic loss on crops." As for the target year's crop exposure, we directly used the spatial distribution of crop production corresponding to those years. As for the impact function, it remained unchanged.

NEAR FUTURE WILDFIRE SIMULATION

The wildfire simulation is the most challenging part in the framework. The process for wildfire prediction is illustrated by the orange flows in Figure 1, starting from "FPM," "Number," "FTR," and "AREA," and ending at "Fire prediction." We can divide the process into three parts: how the wildfire simulation model works, how to build relationships between the FWI and wildfire simulation model's input parameters, and how to build a large number of wildfire projections by using a mixing matrix.

How the wildfire simulation model works. Before running a wildfire simulation, we have to make assumptions about factors that induce wildfire events. The cause of wildfire often varies, including climate factors, geographic factors, local policy, local culture, and so on. Changes in those factors can potentially lead to a significantly different probability. In our future prediction simulations, the future weather factors follow the relationship with the FWI and global climate simulation. We assume that other factors that can induce wildfire follow a natural historical trend based on historical data and will not change significantly. Therefore, we can run our simulation in a predictable environment.

The wildfire projection model contains four parameters and one simulation function to project wildfire, shown as in Figure 5. **Parameter 1**: the fire probabilistic matrix (FPM). **Parameter 2**: the number of wildfire events (NUM). **Parameter 3**: the overall fire propagation probability (FPP). **Parameter 4**: the fire temperature range of wildfire events (FTR). **Simulation function**: run one wildfire. For each one wildfire projection (yearly), the model combines **numbers** of "**run one wildfire**," and each "run one wildfire" will start on the FPM and propagate until it stops. The FPP and FTP as well as NUM will change according to the corresponding month of the year. The details of obtaining wildfire projection model input parameters are described in Appendix A-f.

SIMULATE CORE FUNCTION: RUN ONE WILDFIRE

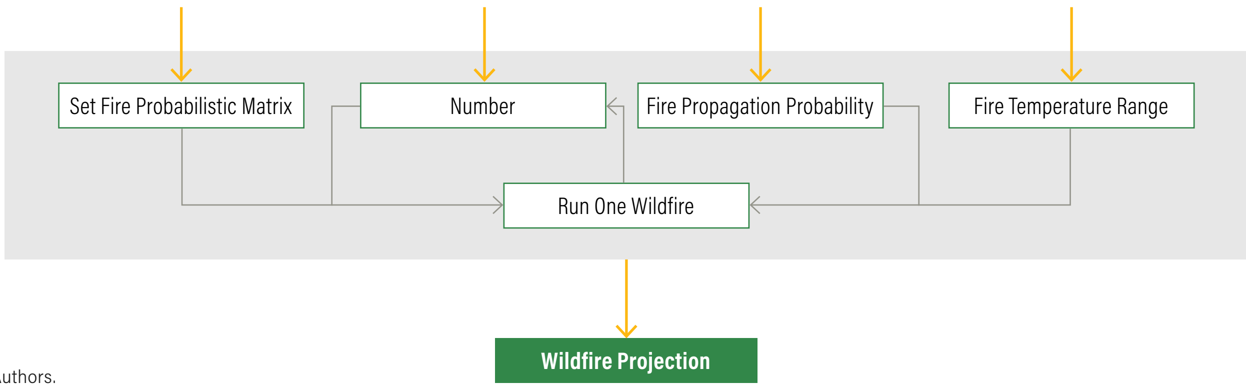
With the above four parameters input into the wildfire prediction model, the core function of "run one wildfire" is driven. "Run one wildfire" simulates the spread of a wildfire from the starting ignition to burning out and produces the final burned area and location with max brightness temperature of a wildfire event.

Run one wildfire is driven by three parameters: the FPM, FPP, and FTR.

The "run one wildfire" propagation rules are as follows:

① Select an ignition centroid **randomly based on uniform distribution** from the FPM, since a wildfire can only ignite on centroids from the FPM.

Figure 5 | **Flowchart of the wildfire projection model**



Source: Authors.

② Every adjacent (queen adjacent) centroid to the selected centroid can start burning with a probability (generated **randomly** from 0 to 1 based on **uniform distribution**, Figure 6) larger than (>) the FPP (**Parameter3**) × the centroid specific propagation probability, which is defined on the FPM (**Parameter1**). For the FPP, different months correspond to different FPPs.

③ The selected burning centroid becomes an ember centroid, which cannot start burning again and thus no longer propagates any fire.

④ Each burning centroid will give a wildfire temperature based on the FTR (**Parameter4**) in the corresponding month.

⑤ Repeat ① to ④ until the propagation stops. **Stop criteria**: the propagation stops when no centroid is burning or exceeds the iteration threshold. In this study, we set the iteration threshold as 50,000 based on historical experience (i.e., most wildfire events generally stop propagation when the iteration is less than 50,000) and consideration of the time and expense required to run the model.

⑥ After propagation stops, we get one simulated wildfire event with a burning area, burning location, and burning brightness temperature of corresponding pixels.

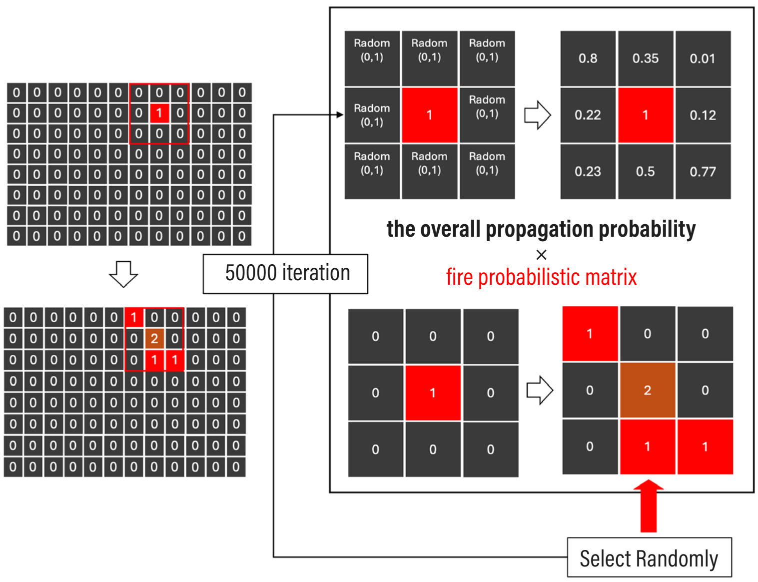
For one whole year's simulation, according to the monthly difference, we will "run one wildfire" based on the monthly wildfire events number (**Parameter** 2) with the corresponding FPP and FTR, and eventually we get one **wildfire projection model** of a year.

How to build relationships between the FWI and wildfire simulation model's input parameters. In the wildfire simulation model section, we know that the model's input parameters contain a fire probabilistic matrix, wildfire events number, fire propagation probability, and fire temperature range. And for the near-term future prediction, we know that we are using the target year's monthly FWI to predict the above parameters. According to the research (Ager et al. 2014; Ntinopoulos et al. 2022; Shumuel 2023) and experiment (Figure 7), we found that the FWI is a good parameter to build the bridge between climate/weather change and wildfire trends. The FWI indicates the historical monthly regional FWIs from 2001 to 2020, which are calculated using the following steps:

1. Extract the daily noon temperature and daily noon relative humidity, daily noon wind speed, and total precipitation in the past 24 hours from ERA5 to calculate all the pixel's daily FWIs in Yunnan Province from 2001 to 2020.
2. Average the spatial daily FWIs into spatial monthly FWIs in Yunnan Province from 2001 to 2020.
3. Calculate the zonal mean value statistic based on each spatial monthly FWI in Yunnan Province to get historical monthly regional FWIs from 2001 to 2020.

The wildfire trends indicate the monthly wildfire events number (Number) and monthly mean burning area (Area), which indicate the corresponding monthly FPP (Appendix A-j) and monthly mean brightness temperature (K) in Yunnan Province from 2001 to 2020.

Figure 6 | **Detailed illustration of one iteration of the wildfire propagation rule from 1 to 3 in the "run one wildfire"**

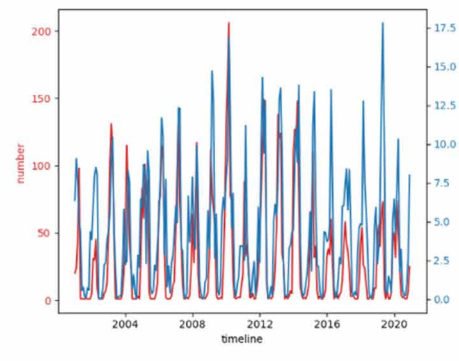


Notes: Properties from centroid burned: 0 = unburned centroid, 1 = burning centroid, 2 = ember centroid.

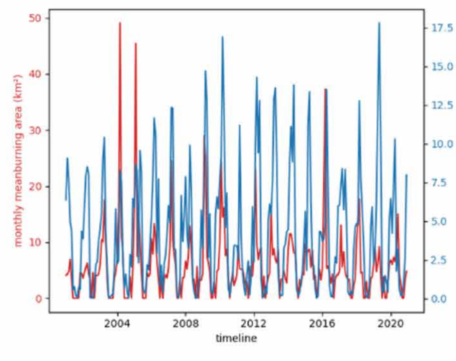
Source: Authors.

Figure 7 | **Correlation between FWI and wildfire characteristics**

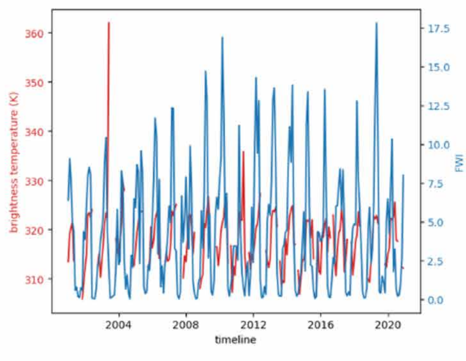
a. Correlation between FWI and Number of Wildfires



b. Correlation between FWI and Centroid Brightness Temperature



c. Correlation between FWI and Monthly Mean Burned Area

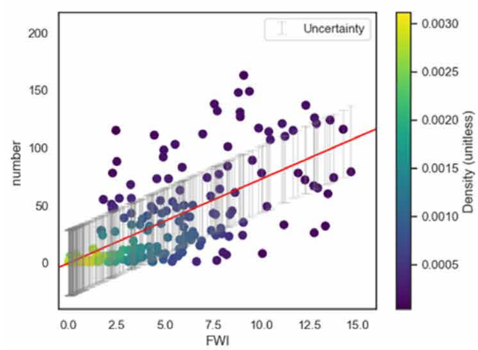


Source: Authors.

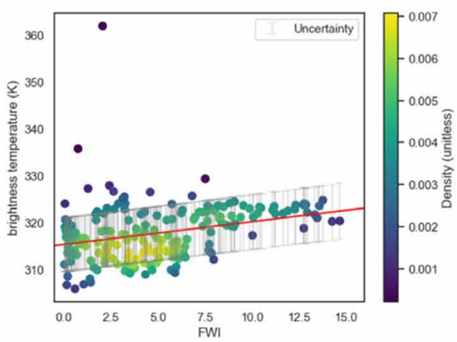
We used a Bayesian Ridge Regression to model the relationship between the FWI and the variables "Number," "K," and "Area." We identified outliers through a two-dimensional density distribution (Figure 8). To mitigate the potential adverse impact of these outliers on our model, we opted for Bayesian Ridge Regression as our initial approach to establishing relationships. One of the key advantages of Bayesian Ridge Regression is that it measures the uncertainty of a model's predictions. Also, we separated the training data (80 percent) and test data (20 percent). The values of the fitted correlation R^2 and root mean square error for test data as well as the parameter slopes and intercepts of the Bayesian Ridge Regression model are given in Table 1.

Figure 8 | **Bayesian Ridge Regression visualization for correlations between FWI and wildfire indicators**

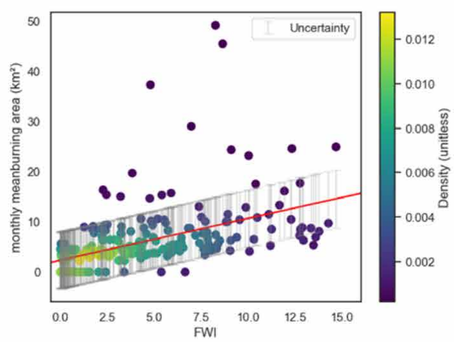
a. FWI and Wildfire Events Correlation



b. FWI and Temperature Correlation



c. FWI and Burned Area Correlation



Source: Authors.

Table 1 | **Analysis results of the fitting relationships (R^2, RMSE, slope, intercept) between each parameter influencing the fire prediction model and the FWI**

VARIABLE	R^2	RMSE	SLOPE	INTERCEPT	CORR	P-VALUE
Number	0.70	24.34	7.34	-0.702	0.7115	2.400e-38
K	0.31	5.87	0.48	315.4	0.3261	3.900e-06
Area	0.50	6.79	0.83	2.34	0.5067	4.637e-17

Notes: R^2 = R squared. RMSE = root mean square error. p = probability. K = brightness temperature.

Sources: Authors' estimate based on AidData (2023), Asia Society Policy Institute (2024), OECD (2023b), Qu (2021), and Zhou et al. (2022).

After we constructed the relationship between the monthly mean FWI and monthly "Number," monthly "K" range, and monthly mean "Area," when we predicted the future wildfire result, we only needed to know the corresponding year's monthly regional FWI.

How to build a large number of wildfire projections by using a mixing matrix. As the wildfire model is based on simulation, multiple instances of simulation are needed to get a reliable result. In our research, we simulated 500 yearly wildfire results for the target year, and then we synthesized 10,000 yearly wildfire results by using a mixing matrix. The specific method was to permute and combine the simulation results of different batches for each month. Considering the limitations of computational resources and time, we ultimately chose 10,000 simulations as the final number, thus obtaining the annual wildfire distribution.

Near-term future wildfire economic loss on crops

With the near-term future target year's wildfire simulation distribution, we first got rid of the wildfire events that did not affect each crop in Yunnan Province, then used the economic loss calculation function (equation 1) to get the final crop loss result affected by wildfire. Then we used the target year's crop spatial distribution and filter hazard and used the wildfire impact function to calculate production loss, and we used a mixing matrix to get the final loss distribution in Yunan Province.

Long-term future loss based on scenario analysis

For a long-term future' like 2030 or 2050, that is over five years, we chose scenario analysis to predict the future loss. Like the near-term future's prediction, we also needed the FWI to build the relationship between the climate scenario and wildfire simulation model inputs. As for the climate scenarios, we utilized the NEX-GDDP-CMIP6's SSP1-26, SSP2-45, SSP3-70, and SSP5-85 as our target climate projections. Considering the computational consumption, we only calculated the FWI for the year 2030 to demonstrate our predictions for four different climate scenarios.

To quantify wildfire loss under different climate scenarios, we completed the following steps:

1. We calculated the monthly regional FWI under four climate scenarios (SSP1-26, SSP2-45, SSP3-70, SSP5-85) in 2030 by using NEX-GDDP-CMIP6. The calculation process was the same as for calculating the historical monthly regional FWI. In our calculations, we selected 18 models to calculate the FWI from the 34 models available for each scenario. These 18 models (Appendix A-g) are available in every scenario and have the same time range. Then we computed the monthly average values to represent the FWI for each scenario.
2. We calculated monthly "Number," "Area," and "K" value based on corresponding linear models shown in Table 1 using the monthly FWI under different climate scenarios as input.
3. We calculated the monthly FPP based on the monthly "Area" predicted under different scenarios and the curve model shown in Figure D (Appendix A-f).
4. Based on each climate scenario's monthly FPP, monthly wildfire events number, and monthly fire temperature, as well as the FPM generated by historical wildfire observation from 2001 to 2020 input into the wildfire simulation model, we simulated annual wildfire projections in 2030 under four climate scenarios (SSP1-26, SSP2-45, SSP3-70, SSP5-85). Also, we still needed to simulate 500 projections and synthesize 10,000 projections to make the 2030 wildfire projection distribution the same as the method mentioned in "Near future wildfire simulation."
5. To get each crop production loss, we first aggregated 12 months (from January to December) of wildfire projections and excluded the unaffected months' (Figure 2) result from one final wildfire projection. We then used equation 1 to calculate the loss production based on crop production spatial distribution and impact function as well as 10,000 wildfire projections to get the production loss distribution in the corresponding four climate scenarios.
6. For the price of a specific future year (2030), we used the Organisation for Economic Co-operation and Development's (OECD 2019) long-term prediction on inflation to adjust the crop price per tonne based on the 2020 price. By multiplying the crop production loss of 2030, we got the economic loss of crops in 2030.

Assessing readiness and applicability

To authenticate the assessment findings and attain a comprehensive understanding of local stakeholders' viewpoints regarding the implementation of climate risk assessment, we targeted a diverse array of stakeholders, ranging from local governmental bodies, local financial institutions such as banks and asset management firms, local state-sponsored investors, insurance and reinsurance companies both in Yunnan and nationally, and university institutions. The principal aim underlying these interactions was to delve into the subsequent pivotal questions:

- How do the financial institutions perceive the impact of wildfires on the agriculture sector?
- How do the financial institutions currently manage and mitigate risks associated with wildfires in the agriculture sector?
- What are the major challenges faced by the financial institutions in mitigating loss?

- Which policies, products, methods, or tools would be valuable in enhancing risk management, and what gaps exist in this regard?
- What are the perspectives of financial institutions regarding integrating our methodology into their operational process?

Given travel limitations imposed by COVID-19 and the diverse perspectives represented by the stakeholders, the interactions did not follow a structured approach. Instead, they were conducted in a diverse and open-ended manner to encourage in-depth discussions. It is important to note that the information collected was qualitative in nature and primarily intended to supplement the limited information available about local financial institutions' risk management practices. The results of questions are summarized in "Discussion" to provide further insights into stakeholders' viewpoints and inform the study's overall findings.

RESULTS

Historical wildfire economic loss indicates strong threat to small farmers

Based on the 2020 annual exchange rate and the FAO's annual crop price, we calculated the total economic loss of those crops from 2001 to 2020; the amount was from $135.8 million to $254.8 million. Despite the total loss being less than 1 percent of total production, individual maximum wildfire events, accounting for 15 to 30 percent of annual loss, pose significant threats to small farmers, as small farmers can lose 100 percent of their crops in a wildfire event. The impact of wildfires on small farmers also extends to the financial sector, particularly banks that serve rural communities.

Table 2 shows the calculated historical state (2011–20) of average annual production, mean damage, percentage of damage, and maximum damage from a single wildfire event on the five crops in Yunnan Province. The average annual damage to production caused by wildfires constitutes about 0.4 to 1 percent of crop production. The impact on soybeans is only about 0.1 percent; this is primarily due to the difference in timing between the soybean growing cycle and the main wildfire season. It is worth noting that we calculated average annual maximum damage loss based on historical data from 2011 to 2020.

$$Average\ Maximum\ Damage = \frac{1}{N} \sum_{i=1}^{N} \max_{j}(D_{i,j}) \quad (4)$$

Here, $D_{i,j}$ represents the damage value in year i for event j, and N is the total number of years considered. The formula calculates the average of the maximum damage values across all years.

Wildfire is a relatively small proportion compared to other crop-impacting disasters such as regional droughts (Wang et al. 2017; Yue et al. 2022). However, it is an aspect that should not be overlooked. In rural China, the basic unit of agricultural production and management is the family farm (Jun 2019). A single wildfire event could potentially lead to a direct baseline loss of up to 939 tonnes of wheat. If we make an assumption that the per capita grain sales volume of rural residents in 2020 was three times that of 2012, and then compare this sales volume with our estimated loss historical state, we find that the loss from a single fire far exceeds the sales volume per unit. This finding clearly indicates that a single fire event could potentially result in catastrophic loss for a farmer's family. They may struggle to meet financial obligations such as loans and mortgages, which can also lead to

Table 2 | **Assessment for annual average of five crops' production loss (2011–20)**

CROP	BASELINE PRODUCTION (TONNES)	DAMAGE (PRODUCTION: TONNES)	PERCENTAGE (%)	AVERAGE ANNUAL MAXIMUM DAMAGE (TONNES)
Maize	8,452,540.05	35,028.34	0.41	9,523.97
Wheat	753,690.06	4,794.00	0.64	939.14
Soybeans	407,380.07	387.69	0.10	46.66
Sugarcane	17,053,112.30	130,993.99	0.77	33,366.69
Coffee	125,555.01	1,312.54	1.05	313.51

Source: Authors.

defaults for the bank's portfolio. The need for financial institutions to reassess the risk profile of agricultural lending and possibly to increase their reserves to cover potential loan loss can have a ripple effect on the availability of credit throughout the rural economy.

Near-term future wildfire simulations show good performance in most of the crops

For the near-term future's crop production loss prediction, we used only 2020 and 2021 as our target years to demonstrate the process of how the model simulates the loss and the model's accuracy. We used meteorological data from ERA5-Land for the years 2020 and 2021 to calculate the monthly FWI for the corresponding years. Based on the monthly FWI, we calculated the parameters (Appendix A-1) we needed: the FTR, FPP, and number of wildfire events. We then input these parameters into the wildfire prediction model. After we got the wildfire projection distribution, we calculated the loss with the corresponding five types of crops' production values' spatial distribution in tonnes.

We calculated the average of the crop losses we obtained, as well as the 95 percent confidence interval of the average. We compared these averages with observations by using relative error (RE), and we obtained the following results, shown in Tables 3 and 4: For maize, wheat, and soybeans, the RE was within 5 percent; coffee was second, with an RE of around 20 percent over two years. The worst was sugarcane, with an error exceeding 80 percent in 2020. However, it is worth noting that the magnitude of observations and predictions generally showed the same trend; that is, if observed crop losses were high, the predictions were also relatively high. Overall, the predictions were relatively accurate for maize, wheat, and soybeans.

Table 3 | **Projected mean economic loss in 2020 of five crops**

CROP	PRODUCTION 2020 (SIMULATION, TONNES)	PRODUCTION 2020 (OBSERVATION, TONNES)	RELATIVE ERROR	95% CONFIDENCE INTERVAL
Maize	16426.74	16771.582	-2.05%	16353.17~16500.3
Wheat	3966.73	4064.610	-2.4%	3957.18~3976.29
Soybeans	235.17	240.613	-2.26%	232.263~238.07
Sugarcane	70019.73	37967.838	84%	69562.60~70476.85
Coffee	397.129	338.679	17.26%	392.51~401.75

Table 4 | **Mean economic loss in 2021 of five crops**

CROP	PRODUCTION 2021 (SIMULATION, TONNES)	PRODUCTION 2021 (OBSERVATION, TONNES)	REALATIVE ERROR	95% CONFIDENCE INTERVAL
Maize	15145.278	15450.780	1.97%	15063.255~15227.30
Wheat	3285.644	3425.301	-4.07%	3274.77~ 3296.512
Soybeans	149.478	150.701	0.811%	147.661~ 151.294
Sugarcane	78475.912	62662.699	25.2%	77970.82~ 78980.99
Coffee	336.021	264.833	26.88%	331.795~ 340.24

The scenario analysis of wildfire loss demonstrates the complexity of the impact of wildfires on crops under climate change

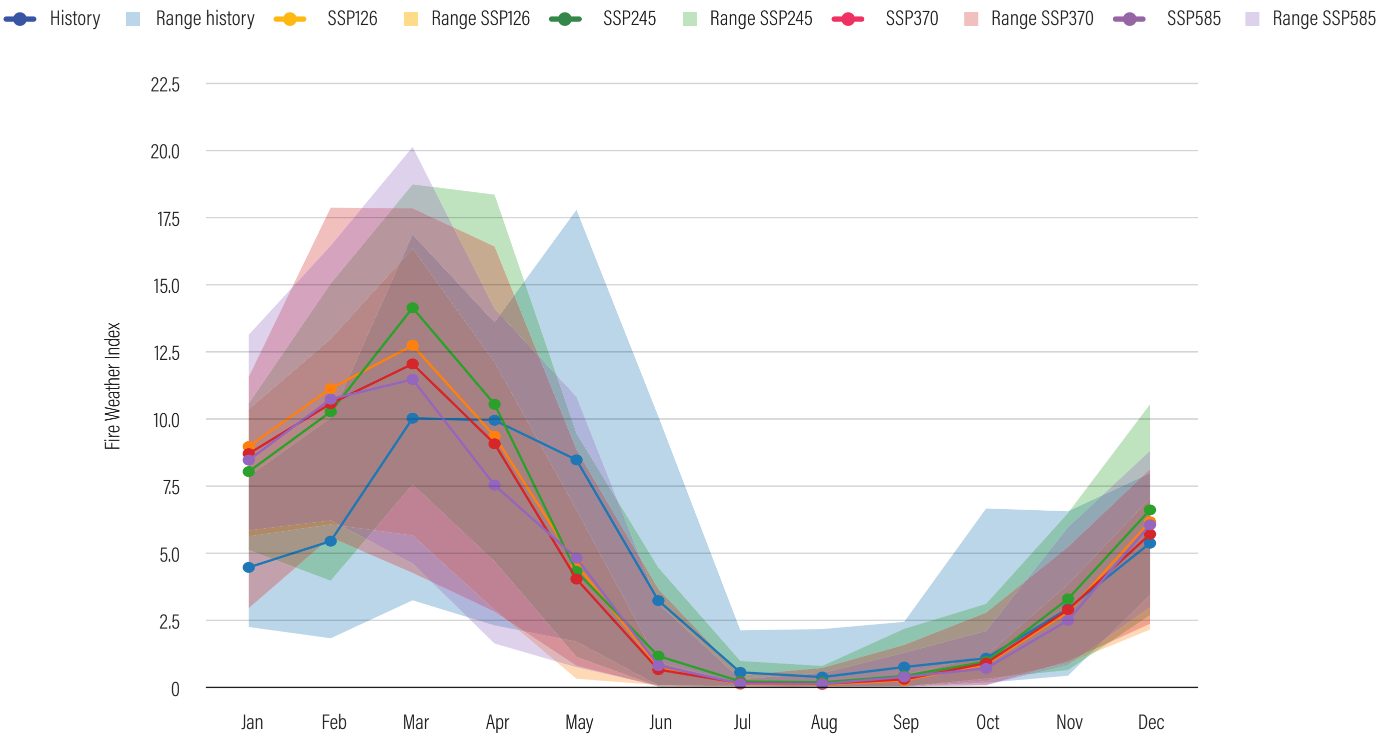
In our working paper, we explored four SSPs' (SSP1-26, SSP2-45, SSP3-70, SSP5-85) FWI, wildfire simulation, as well as damages. The results show that the impact of climate change on agricultural products through wildfires is complex and requires detailed analysis, considering scenarios as well as the spatiotemporal characteristics of agricultural products. Following are the details on how we conducted our evaluation.

Figure 9 presents the monthly average and range of the FWI based on the historical observation (2001–20) and different scenarios of 18 models (2030, Appendix A-g). For historical FWI, the range represents the monthly maximum and minimum values of the FWI from 2001 to 2020. For each SSP, the range indicates the monthly maximum and minimum of the FWI in all 18 models. The FWI was calculated by first computing daily averages through zonal statistics, then monthly averaging the daily values, and finally obtaining the monthly average by averaging each year for history and each model for projections. For Yunnan Province, the top two historical regional mean FWIs occurred in March and April; however, future projections indicate that the highest mean FWI values were concentrated in February and March, **which is a shift of the FWI peak along the time dimension. From the mean value of the FWI in different scenarios, SSP2-45 had the maximum FWI, followed by SSP1-26, SSP3-70, and SSP5-85, which were all higher than the observation.** The maximum value of the FWI range of all scenarios was in SSP5-85, which showed up in March.

According to the FWI in different scenarios (Figure 9), we calculated the wildfire projection model parameters under different scenarios (Figure 10).

We summarized the monthly "Number," "K," and "Area" in 2030 compared with the baseline. The result (Figure 11) shows that the number and area of wildfire increased in all SSPs scenarios. From all scenarios, the Number and Area in SSP2-45 increased the most; 1.23 times for Number and 1.11 times for Area compared with the baseline. This was followed by SSP1-26, 1.19 times for Number and 1.08 times for Area compared with the baseline. Next were SSP3-70 (1.13 times for Number and 1.05 times for Area) and SSP5-85 (1.1 times for Number and 1.03 times for Area). As for the temperature, there were no noticeable changes in any of the scenarios.

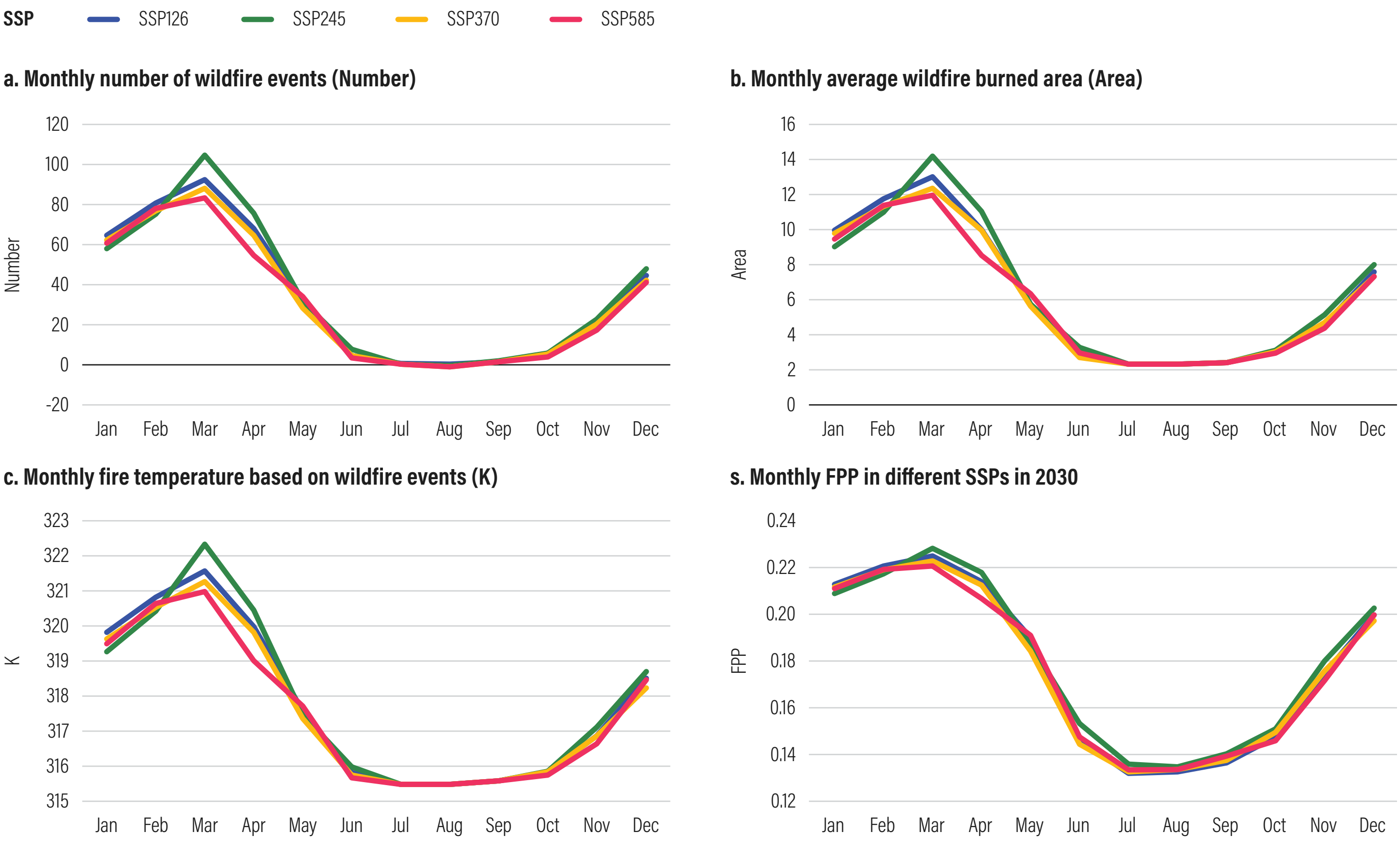
Figure 9 | **Monthly FWI, historical data and projected SSPs in 2030**



Notes: SSP = Shared Socioeconomic Pathway.

Source: Authors.

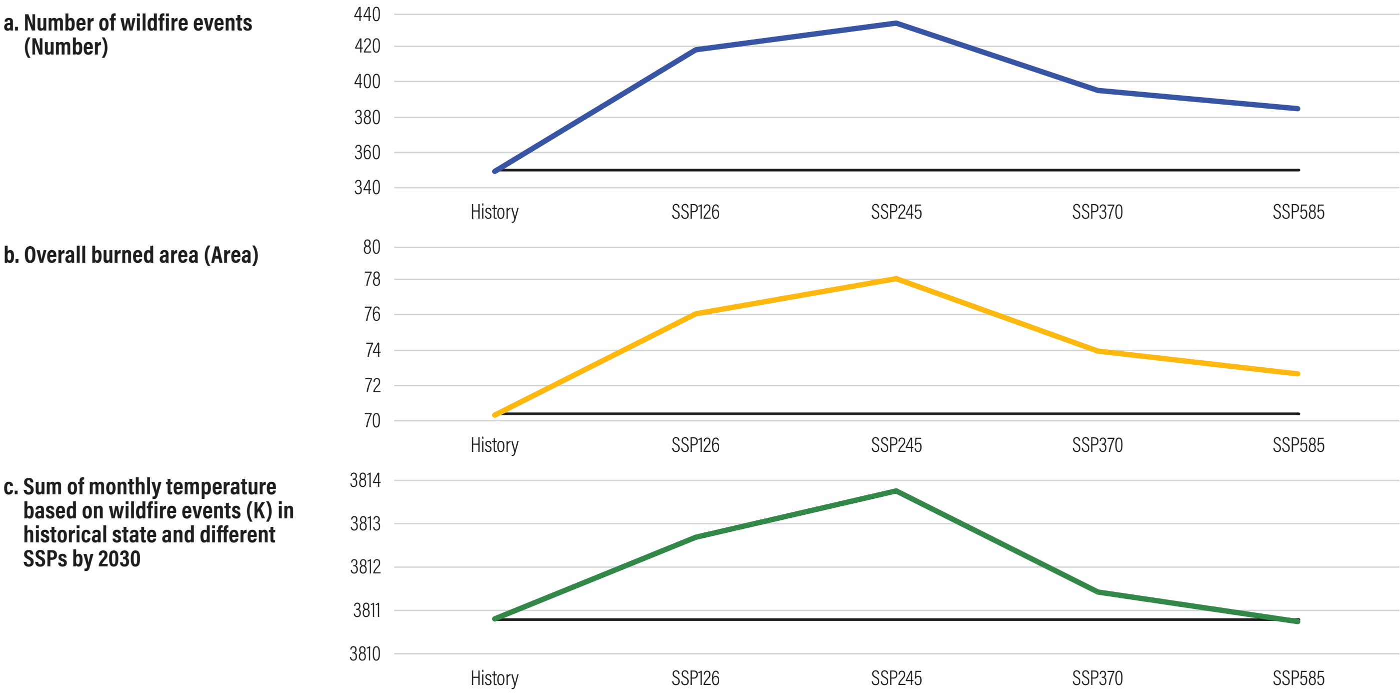
Figure 10 | Monthly statistics and analysis of wildfire events



Notes: SSP = Shared Socioeconomic Pathway.

Source: Authors.

Figure 11 | Historical and projected analysis of wildfire events and impacts by 2030



Notes: The black lines of each subplot describe the baseline of each parameter. SSP = Shared Socioeconomic Pathway.

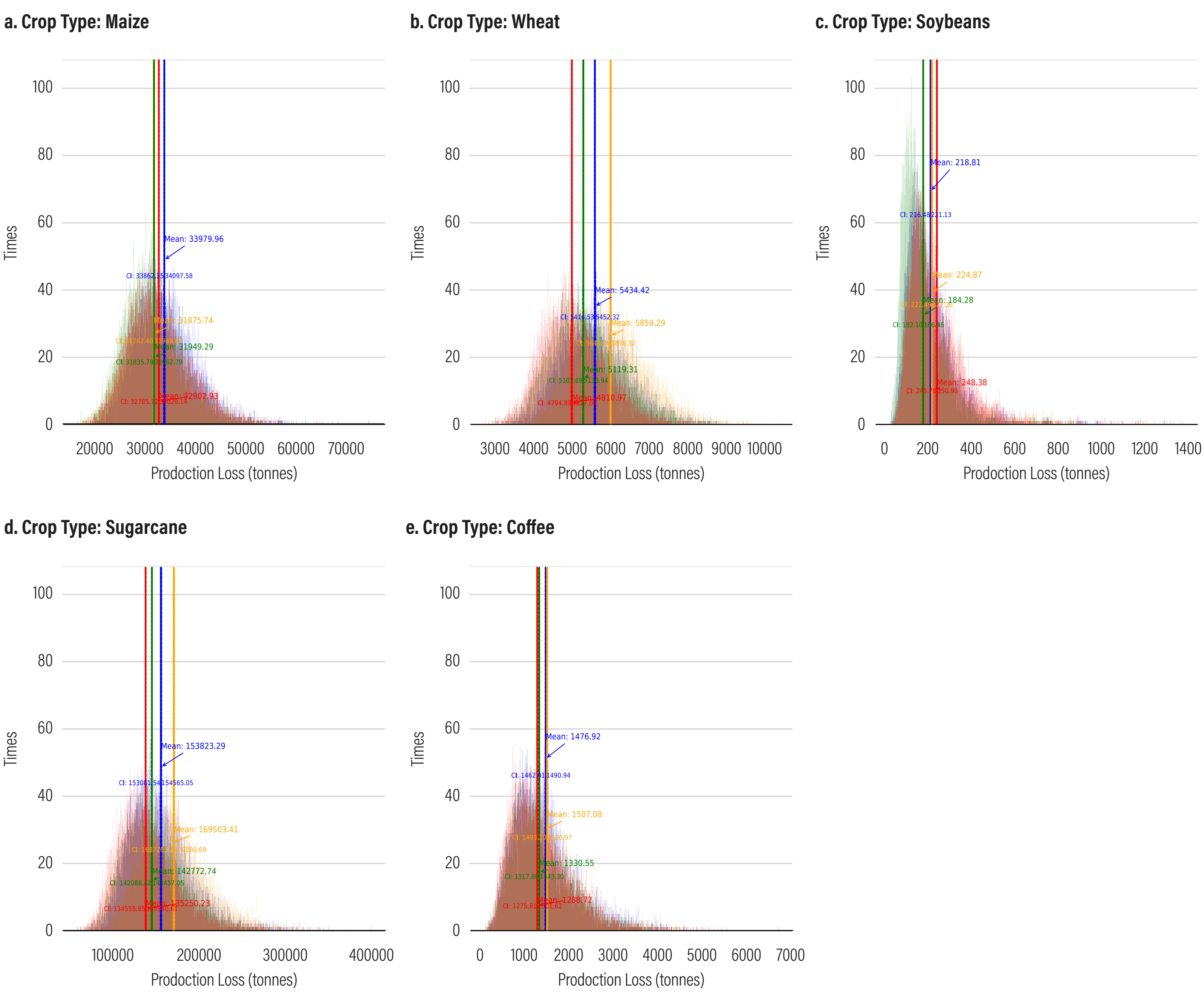
Source: Authors.

We used the monthly parameters (Figure 13) under different scenarios to input into the simulation wildfire model. For each projection, we integrated 10,000 forecast simulations (Figure 12), and in the end, we calculated the mean value and its 95 percent confidence interval. For each type of crops exposure, we did not calculate the 2030 scenario of the exposure but mainly used the average crop exposure over a 10-year period (2011–20). Figure 13 and Table 5 show the loss and change due to damage to all crops under different SSPs.

The crop production loss trend can be classified into three types: Increasing Trend: Wheat and Sugarcane show an increasing trend in losses across all scenarios, particularly under SSP2-45. This may indicate that these crops are becoming more sensitive to wildfires in the context of future climate change. Decreasing Trend: Maize shows a decreasing trend in losses across all scenarios, especially in SSP2-45 and SSP3-70. This might suggest that these crops are becoming less sensitive to wildfires due to future climate changes. Mixed Trend: The changes in losses for soybeans and coffee show a mixed trend. Soybeans exhibit an increase under SSP5-85, while coffee shows an increase under SSP1-26 and SSP2-45 but a slight decrease under SSP5-85. These projections underscore the varied impact of different socioeconomic pathways on crop production, reflecting the complex interplay between climate change, agriculture, and wildfire.

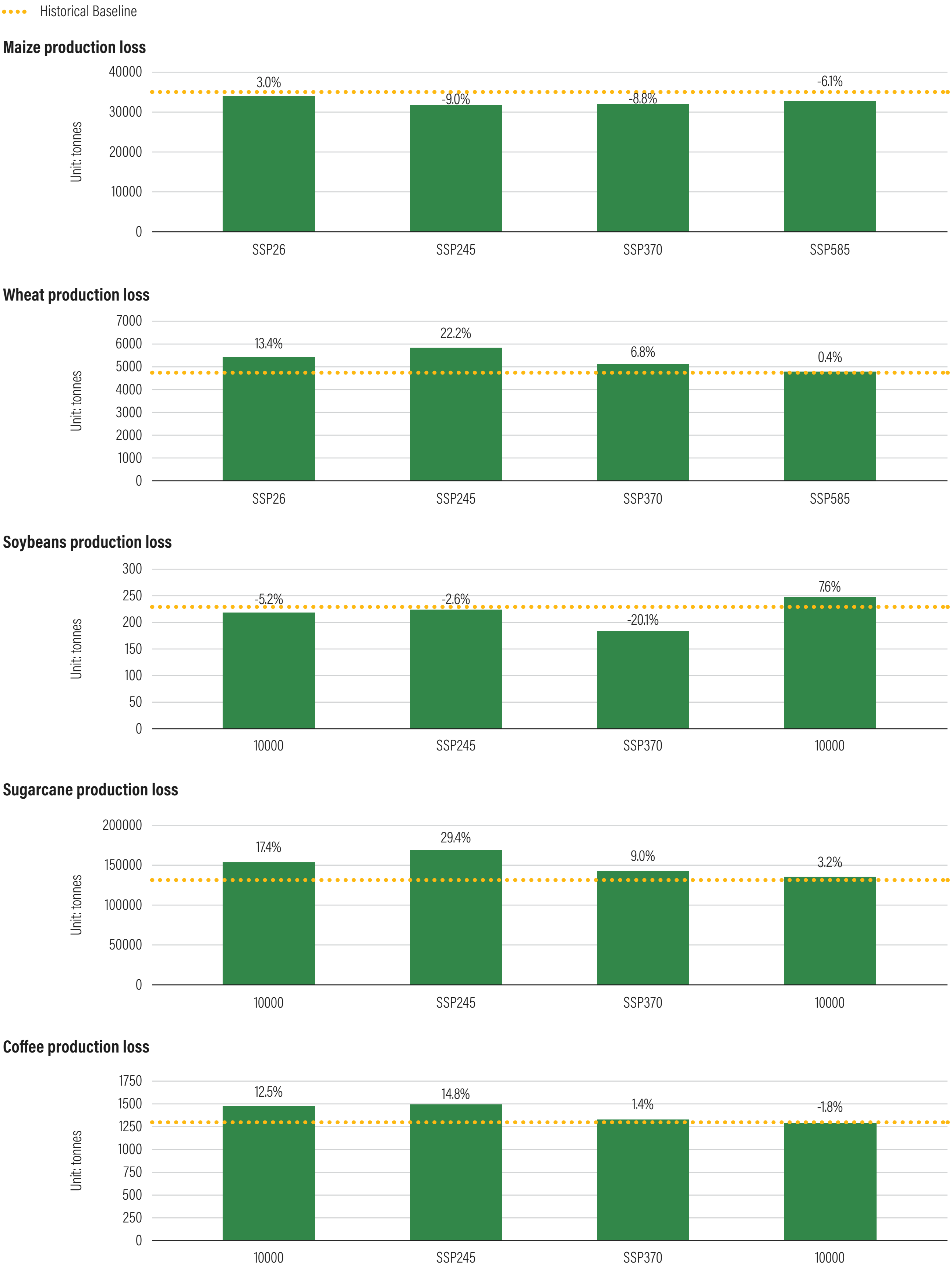
With prices multiplied into the crops production loss, we also gain the corresponding scenarios' economic loss in Table 6. Due to the introduction of the inflation rate, the economic losses for all crops under all four types of scenarios have increased compared to the historical baseline.

Figure 12 | **Loss distribution of five crops under different SSPs (tonnes)**



Source: Authors.

Figure 12 | **Loss distribution of five crops under different SSPs (tonnes) (cont.)**



Notes: SSP = Shared Socioeconomic Pathway.

Source: Authors.

Table 5 | **Change in production of five crops under different SSPs compared to the baseline (in tonnes)**

VARIABLE	MAIZE	WHEAT	SOYBEANS	SUGARCANE	COFFEE
Historical	35028.34	4794.00	230.77	130993.99	1312.54
SSP1-26	33979.96	5434.42	218.81	153823.29	1476.92
SSP2-45	31875.74	5859.29	224.87	169503.41	1507.08
SSP3-70	31949.29	5119.31	184.28	142772.74	1330.55
SSP5-85	32902.93	4810.97	248.38	135250.23	1288.72

Notes: SSP = Shared Socioeconomic Pathway.
Source: Authors.

Table 6 | **Change in economic loss of five crops under different SSPs compared to the baseline (in US$)**

SCENARIO	MAIZE	WHEAT	SOYBEANS	SUGARCANE	COFFEE
Historical	14,691,596	1,752,589	180,542	99,012,472	4,086,641
SSP1-26	19,164,482	2,671,530	230,193	156,345,509	6,183,519
SSP2-45	17,977,715	2,880,394	236,568	172,282,734	6,309,791
SSP3-70	18,019,197	2,516,624	193,867	145,113,765	5,570,702
SSP5-85	18,557,044	2,365,046	261,301	137,467,910	5,395,569

Notes: SSP = Shared Socioeconomic Pathway.
Source: Authors.

Our different scenario projections show that escalating emission does not necessarily worsen the impact of wildfire on crop production loss. Wildfire is influenced by various factors, and even the FWI is a complex measure affected by wind speed, temperature, precipitation, and relative humidity. However, this does not mean hotter scenarios are better, as climate change imposes a systemic impact on different climate hazards, and there is often a compound effect among hazards. In this case, financial institutions with diverse portfolios should consider analyzing a comprehensive effect related to their sensitive asset.

Stakeholders show eagerness to integrate climate risk analysis while facing challenges

Through interactions with relevant stakeholders, we found that financial institutions exhibited enthusiasm for assimilating physical climate risk analysis into their operational frameworks. Particularly, banks holding substantial agricultural portfolios evinced a resolute inclination to infuse this analytical approach into their evaluation and monitoring of credit risks. Their recognition of the significance of comprehending and effectively addressing climate-induced vulnerabilities within their lending undertakings was pronounced. Likewise, the ranks of interested parties encompassed a pair of insurance companies, intent on conceiving insurance products underpinned by these methodologies. Their emphasis lies in the imperative to harmonize their offerings with assessing the physical risk and using it as a base for pricing. Notably, asset management firms, too, showcased eagerness in assimilating physical climate risk analysis into their investment deliberations thereby underscoring the mounting cognizance of climate-connected perils' influence on investment yield.

However, alongside their interest, financial institutions also acknowledged several challenges. Their understanding of the specific risk posed by wildfires is limited. This highlights the need for increased awareness and knowledge-building initiatives to address this gap and enhance their risk assessment capabilities.

The feedback from stakeholders revealed significant challenges faced by financial institutions in terms of their awareness of how to effectively assess and manage physical climate risk. Many institutions currently lack a comprehensive understanding of the potential impacts that climate change could have on their operations and portfolios. This limited awareness can be attributed to various factors, including a lack of dedicated resources and expertise within these institutions, as well as a historical focus on more traditional financial risks. Consequently, financial institutions may underestimate the potential risks associated with climate-related events such as wildfires, including their frequency, intensity, and overall impact. Such lack of awareness can impede their ability to proactively identify and mitigate physical climate risk, leaving them vulnerable to financial loss.

In addition to limited awareness, financial institutions face challenges related to their capacity and technical expertise in assessing physical climate risk. Assessing physical climate risk necessitates specialized knowledge, sophisticated modeling techniques, and access to relevant data sources. However, many institutions lack the necessary tools and expertise to effectively analyze and interpret climate data or to incorporate climate risk factors into their existing risk management frameworks. Furthermore, the complexity and uncertainty inherent in climate modeling pose additional challenges for financial institutions, as they must navigate a rapidly evolving field with constantly changing methodologies and standards. These capacity constraints limit financial institutions' ability to accurately quantify and assess physical climate risks, making it difficult to incorporate these risks into their decision-making processes and adequately safeguard their portfolios.

DISCUSSION

Uncertainties in the methodology

Based on the current stage of the model and framework, uncertainty in the results of the model may come from the following factors:

- **Uncertainty from hazard input.** Currently, the prediction of input parameters is mainly based on the FWI. However, the FWI is an indicator that tells how weather impacts wildfire. Wildfire is quite complex, triggered by both climate and human activities. Although in our research we have implemented a different kind of method to remove human activities by using a high-confidence wildfire point result, clustering to get rid of individual points as long as we get rid of wildfire points from any unaffected time period of crops, weather-driven and human-driven wildfire still compound each other. Also, we use historical observation to generate the FPM; however, it still has the limitation that the land use in the future will contribute to a change in the FPM. If more precise wildfire records and more advanced algorithms can be found in future research, it would greatly enhance the accuracy of the model.
- **Crop exposure.** Current exposure data are available only at low resolution, which increases uncertainty. For example, in "Assess readiness and applicability," our study integrates SPAM with production values from the NBS to map out the distribution of crop production in Yunnan, using 2010 as a baseline and scaling the data to 2020. This approach presupposes that various crop types across the province evolve uniformly, a presumption that may seem overly simplistic due to data scarcity. The uncertainty of crop exposure data accuracy could be reduced through data replacement and algorithmic improvements.
- **Crop prices.** Crop prices are influenced by various factors such as climate change, market demand, natural disasters, policy changes, and so on. In our paper, we do not predict crop prices but simply estimate the price for 2030 based on the OECD's long-term inflation forecast. However, in practical applications, practitioners need to incorporate these price estimates into the final loss calculations to obtain the precise economic loss.
- **Impact function.** As the impact function involves the intensity threshold, which could be derived from previous projections using various methods, errors might arise from the errors in these projections. This kind of error could introduce inaccuracies in both the historical assessment results and the projections. The best method for eliminating this potential error might require higher granularity observations. The uncertainty in the percentage of affected assets in this study primarily stems from the growth cycle of the crops themselves. A more precise description of the growth cycle would reduce this uncertainty.
- **The systematic bias between reanalysis data and climate simulation data.** This part of the error mainly comes from the discrepancy between ERA5 and NEX-GDDP-CMIP6. ERA5 has far higher time and spatial resolution than NEX-GDDP-CMIP6, leading to a systematic error in the data of the research area itself. The current approach is to correct the data based on an overlapping short historical period (2000–14) through linear fitting, which only reduces the systematic error of this period. In future research, if more precise and stable algorithms are available, this part of the error would be further reduced. Alternatively, regional climate models may be employed instead of global climate models when focusing on specific regions.

Practical measures in addressing climate risks for different stakeholders

Regarding integrating climate risk assessment with different financial institutions, insurance companies exhibited more enthusiasm for integrating physical climate risk analysis. Insurance companies have a strong interest in understanding and quantifying the increased climate-related risks and in developing relevant insurance products, such as catastrophe insurance. Technically, approaches to looking into extreme situations should be applied. This can be done in various ways. One method is to use distributions that present the possible situation better, such as long tail distribution. A simpler method is to investigate upper-end percentile in the distribution, instead of only the expected estimates. In the situation of lacking capacity, upper-end percentile is possibly a better method, as using a different distribution requires rerunning the simulation process. Additionally, to build insurance products, companies require accurate data and risk estimation. In this sense, the modeling framework presented here is essential for the proper functioning of insurance products, as it supports accurate payouts, enhances reliability, and enables better risk assessment—especially for parametric insurance, which relies on predefined triggers or indices to determine payouts. Without accurate risk estimation, there is the possibility of either false positives or false negatives, leading to incorrect insurance pricing. The model developed here can be used as a reference for the annual expected loss, helping insurers define the premium and manage their overall risk exposure more effectively. Finally, integrating climate data and risk models into parametric insurance pricing systems allows insurers to continuously monitor and update pricing in response to changing climate conditions. This dynamic approach ensures that premiums accurately reflect evolving climate-related risks.

Banks, on the other hand, prioritize effective credit risk management as a crucial aspect of their business. Consequently, they are eager to utilize physical climate risk analysis tools to evaluate loan applications and conduct risk analyses throughout the credit process. Additionally, banks have a vested interest in monitoring potential risks to manage the credit risk on their loan assets. This can be integrated into credit procedures as a factor for an overall risk model or as a risk screening tool. It can also be used for after-loan management to provide capacity to increase resilience of loan portfolios. For stress testing, even though it is crucial for financial stability, it requires understanding and comparison of overall risk, as well as more intensive resources for implementation. At this stage, it is more central banks' and regulators' role to develop methodology and implement capacity building for banks.

Meanwhile, the government can play a vital role in addressing financial institutions' concerns about climate change's physical risks. Firstly, it can improve the collection and distribution of meteorological and climate data to provide financial institutions with real-time, high-quality weather information. This empowers them to make more precise assessments of climate-related risks. Secondly, the government can support collaborative risk management platforms, facilitating joint research and modeling among financial institutions and offering tools and guidelines on climate risks. Lastly, by offering incentives for proactive climate risk management and enforcing mandatory climate risk disclosure, the government can encourage financial institutions to incorporate climate-related risks into their strategies, fortifying the financial system's stability.

Regarding the potential of implementing our methodology, from a technical perspective, if relevant stakeholders are interested in integrating this framework into their assessment system, they might need or get the input/output shown in Table 7.

Table 7 | **Summary of the input, intermediate, and output of the framework/model**

FRAMEWORK/MODEL INPUT	FRAMEWORK/MODEL INTERMEDIATE PRODUCTS	FRAMEWORK/MODEL OUTPUT
• Historical wildfire satellite observation • Observation of meteorological elements • Portfolio map (crop geospatial distribution) • Damage record • Climate model output • Crop lifecycle	• Wildfire events • FWI historical/future projection • Wildfire future prediction (future 1 year) • Wildfire future projection (SSP)	• Historical loss/damage • Wildfire future prediction loss (future 1 year) • Wildfire future projection loss (SSP)

Notes: FWI = Fire Weather Index. SSP = Shared Socioeconomic Pathway.
Source: Authors.

There are several types of data involved in the areas of climatology, economic analysis, remote sensing, and finance. Interdisciplinary knowledge and capacity are required in order to implement and integrate physical risks assessment into financial institutions' work. In addition, if financial institutions intended to utilize more precise data, the cost would significantly increase. Often, smaller financial institutions lack the capacity and resources to implement such a framework. Therefore, a government-leading data platform is essential for those financial institutions.

Improvements and outlook

Going forward for this research, there are two perspectives for future improvements. On the one hand, there is still space for better model performance. This should focus on reducing the uncertainty. From a modeling perspective, a significant change could be creating a crop-tailored impact function to accurately describe the connection between hazard intensity and crop loss severity. Building a better connection between the FWI and wildfire event is also pivotal in increasing accuracy of the future prediction. Data quality is another pillar for accurate results. The next stage should also aim to increase the quality of local meteorological data and non-meteorological data, as well as update the model with future newest global climate simulations.

On the other hand, from an empirical and implementation perspective, it is crucial to conduct the pilot projects and gather feedback from financial institutions to understand empirical challenges. Meanwhile, it is also important to collaborate with multi-stakeholders to address capacity and operational difficulties. This iterative process will allow for continuous improvement of the methodology and forming an implacable tool that can be integrated into financial institutions' and other stakeholders' operation, thereby enabling its eventual widespread adoption for managing physical climate risk within the financial sector.

APPENDIX A

a.

FIRMS offers two types of satellite instruments:

1. Moderate Resolution Imaging Spectroradiometer (MODIS): Near real-time with 1 km resolution. Data available from November 2000 to present.
1. Visible Infrared Imaging Radiometer Suite (VIIRS): Near real-time data with 0.375 km resolution. Data available from January 20, 2012, to present.

Both MODIS and VIIRS datasets provide global coverage and free access online. A hybrid thresholding and contextual algorithm classifies each swat pixel as a fire point or not for MODIS data (Giglio et al. 2016) and for VIIRS data (Schroeder et al. 2014).

b.

Indicators of choosing target crops in Yunnan:

1. SPAM and NBS's crop tap are overlapped.
2. Affected by wildfire: a. The crop distribution and historical wildfire records are overlapped. b. Information from experts on what kind of crops are affected by wildfire.
3. Historically, crop production has exceeded 100,000 tonnes.
4. Data integrity: Available up to the year 2020.
5. The crop types need both staple grains and cash crops.
6. Preferably, choose characteristic agricultural products of Yunnan (e.g., coffee, sugarcane, tobacco).

c.

The mathematical expression is as follows:

$$SPAM2010_{yunnan} = C_{lip}\,(SPAM_{2010})$$

$$SPAM2010_{yunnan_{upsample}} = U_{psampling}(SPAM2010_{yunnan})$$

$$SPAM2010_{yunnan_{upsample_{calibration}}} = \frac{NBS_{2010} \times SPAM2010_{yunnan_{upsample}}}{S_{um}\,(SPAM2010_{yunnan_{upsample}})}$$

$$SPAM\{year\}_{yunnan_{upsample_{calibration}}} = \frac{NBS_{\{Year\}} \times SPAM2010_{yunnan_{upsample_{calibration}}}}{S_{um}\,(SPAM2010_{yunnan_{upsample}})}$$

C_{lip} refers to clipping the area of Yunnan from original SPAM data by using Yunnan Province's boundary.

$U_{psampling}$ refers to upsampling from 10 km resolution to 1 km resolution; the detail methodology will be displayed in section d below.

S_{um} refers to the accumulation of all the pixel values (production values in different crops) in SPAM 2010 in the region of Yunnan.

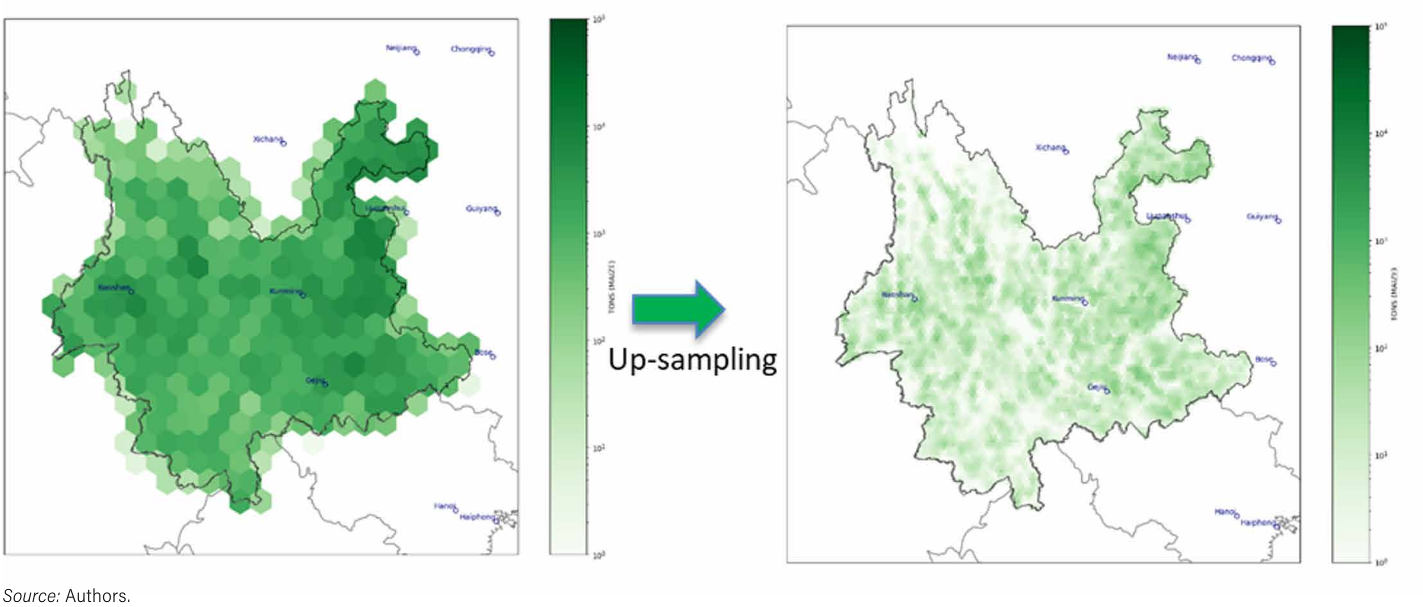
$NBS_{\{Year\}}$ refers to the total agricultural production (in tonnes) in Yunnan in the target year.

Figure A-1 | **Indicators of choosing target crops in Yunnan**

Crop (full)	Name (code)	food/non-food	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Name in raw data (万吨)	Effected by wildfire: 1.crops distribution and historical wildfire records are overlapped, 2.information from expertise	staple grains or cash crops	产量均<=10万	Data integrity : Available up to the year 2020	final_selected
wheat	whea	food	44.69	94.22	80.51	72.13	71.08	74.67	71.52	73.68	74.28	71.9	69.7	61.92	59.51	小麦	Y	1	N	Y	Y
rice	rice	food	563.5	602.13	561.88	567.76	548.33	528.62	524.08	529.23	527.7	534	524.91	491.9	464.67	稻谷	N	1	N	Y	N
maize	maiz	food	622.01	620.42	736.1	788.15	850.54	868.11	892.29	912.93	926	920	938	992.6	1026.17	玉米	Y	1	N	Y	Y
barley	barl	food	11.16	20.69	21.75	20.48	23.35	23.71	26.99	27.96	29.13					大麦	Y	0	N	N	N
pearl millet	pmil	food																			N
small millet	smil	food																			N
sorghum	sorg	food	0.63	0.75	0.77	0.77	0.94	1.01	1	0.98	0.97					高粱	Y	1	Y	N	N
other cereals	ocer	food																			N
potato	pota	food	143.07	146.36	146.31	163.52	149.62	146.31	145.4	145.35	148.7					马铃薯	Y	1	N	N	N
sweet potato	swpo	food																			N
yams	yams	food																			N
cassava	cass	food																			N
other roots	orts	food																			N
bean	bean	food	74.27	105.25	105.47	110.89	116.23	112.11	117.05	118.31	118.08	122.33	123.33	109.15	109.83	豆类	Y	0	N	Y	N
chickpea	chic	food																			N
pigeonpea	pige	food																			N
lentil	lent	food																			N
other pulses	opul	food																			N
soybean	soyb	food	30.75	28.45	32.44	39.58	43.53	40.94	43.06	43.47	43.51	46	46.4	31.61	32.23	大豆	Y	0	N	Y	Y
groundnut	grou	food	7.01	6.16	7.49	7.99	8.15	6.44	6.3	6.24	6.96	6.76	7.61	8.2	8.51	花生	Y	0	Y	Y	N
coconut	cnut	food																			N
oilpalm	oilp	non-food																			N
sunflower	sunf	non-food	0.82	1.01	0.92	1.07	0.84	0.79	0.76	0.7	0.77					葵花籽	Y	0	Y	N	N
rapeseed	rape	non-food	23.88	51.84	47.14	43.73	54.93	46.51	47.51	47.52	52.52	54.1	54.23	54.49	53.88	油菜籽	Y	0	N	Y	N
sesameseed	sesa	non-food	0.02	0.02	0.01	0.01	0.01	0.01	0.02	0.02	0.01	0.01	0.01	0.01	0.01	芝麻	Y	0	Y	Y	N
other oil crops	ooil	non-food																			N
sugarcane	sugc	non-food	1657.88	1773.51	1883.06	1950.67	1892.08	1706.93	1523.77	1516.15	1640.08	1569.69	1597.17	1583.89	1553.7	甘蔗	Y	0	N	Y	Y
sugarbeet	sugb	non-food	0.05	0	0	0	0	0	0	0	0					甜菜	Y	0	Y	N	N
cotton	cott	non-food	0.0392	0.0445	0.0703	0.0377	0.03	0.0287	0.0105	0	0.0007	0.0004	0.0003			棉花	Y	0	Y	Y	N
cotton seed	cotts	non-food																			N
other fibre crops	ofib	non-food																			N
arabica coffee	acof	non-food																			N
robusta coffee	rcof	non-food	4.94	6.51	9.18	11.66	13.71	13.91	15.84	14.5	13.73	13.415	13.1	10.87		咖啡	Y	0	N	Y	Y
cocoa	coco	non-food																			N
tea	teas	non-food																			N
tobacco	toba	non-food	99.14	105.57	115	107.55	98.35	92.12	90.74	86.23	84.47	83.54	84.3	84.75	86.25	烟叶	N	0	N	Y	N
banana	bana	food																			N
plantain	plnt	food																			N
tropical fruit	trof	food																			N
temperate fruit	temf	food																			N
vegetables	vege	food	880.66	1338.48	1470.86	1625.33	1735.26	1944.83	1968.61	2077.76	2205.71	2304.14	2507.9	2748.86	2857.92	蔬菜	Y	0	N	Y	N
rest of crops	rest	non-food																			N

Figure A-2 | **Upsampling of Yunnan maize production data from 10 km to 1 km**

Maize production distribution in Yunnan 10 km resolution **Maize production distribution in Yunnan 1 km resolution**



Source: Authors.

d.

Upsampling methodology:

The original crop production dataset's spatial resolution is around 10 km. To match the spatial resolution with MODIS wildfire data, we used bilinear interpolation to upsample the data, increasing the spatial resolution from the original 10 km to 1 km (Figure A-2). This interpolation method ensures that the total production is consistent with official statistics, and the value of each pixel at the original resolution is the same as the total value within the range of the original pixel resolution after scaling. However, since it is scaled based on a mathematical algorithm and does not take into account the actual distribution of crop production at a 1 km resolution, there is still a discrepancy between the scaled results and the actual observations.

e.

The Fire Weather Index (FWI) is a component of the Canadian Forest Fire Weather Index System. It is used to estimate fire intensity (Xin 2010). The FWI System includes six components: three fuel moisture codes (Fine Fuel Moisture Code, Duff Moisture Code, Drought Code) and three fire behavior indices (Initial Spread Index, Buildup Index, Fire Weather Index). These components are calculated from weather observations of temperature (T), relative humidity (RH), wind speed (WS), and 24-hour precipitation (PRE) (Van Wagner 1987).

Following is an explanation about coding in the FWI:

Fine Fuel Moisture Code (FFMC). This code is a numeric rating of the moisture content of litter and other cured fine fuels. This is an indicator of the relative ease of ignition and the flammability of fine fuel. FFMC is affected by temperature, relative humidity, wind speed, and 24-hour precipitation.

Duff Moisture Code (DMC). This code represents the moisture content of loosely compacted organic layers of moderate depth. It gives an indication of fuel consumption in moderate duff layers and medium-size woody material. DMC is affected by temperature, relative humidity, and 24-hour precipitation.

Drought Code (DC). This is a rating of the average moisture content of deep, compact organic layers. It is an indicator of seasonal drought effects on forest fuels and the amount of smoldering in deep duff layers and large logs. DC is affected by temperature and 24-hour precipitation.

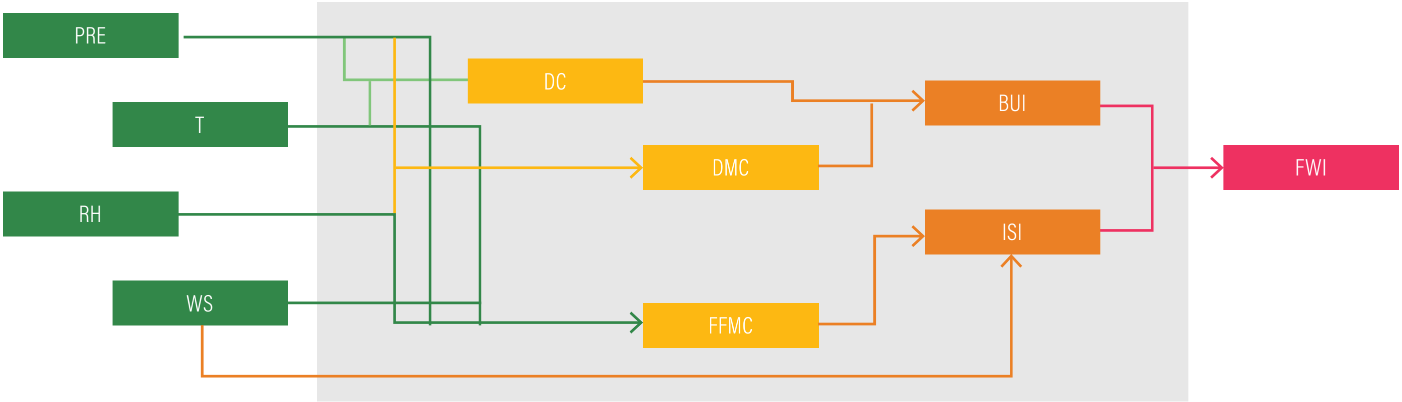
Initial Spread Index (ISI). This is a combination of the effect of fuel moisture and wind speed on the rate of spread of a fire.

Buildup Index (BUI). This is a combination of the DMC and DC. It is an indicator of the total amount of fuel available for combustion.

Fire Weather Index (FWI). This is a combination of the ISI and the BUI. It indicates the potential rate of fire spread, assuming that the fire is fueled by a mixture of fine fuel and deeper organic layers.

The relationship of these components is shown in Figure A-3.

Figure A-3 | **Framework for calculating the Fire Weather Index**



Note: PRE =precipitation. T = temperature. RH = relative humidity. WS = wind speed. DC = drought code. DMC = duff moisture code. FFMC = fine fuel moisture code. BUI = buildup index. ISI = initial spread index. FWI = Fire Weather Index.

Source: Authors.

f.

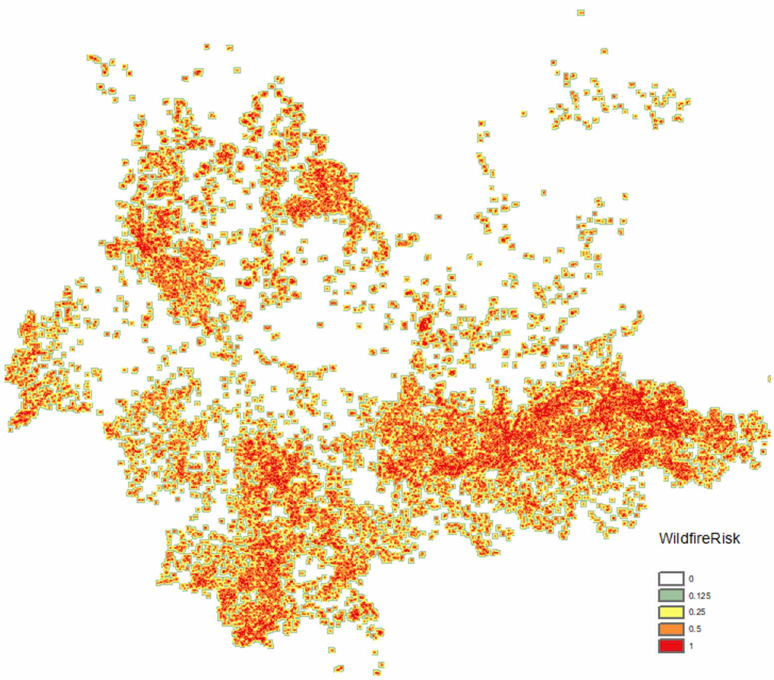
Description of simulation model input parameters

Parameter 1: Fire probabilistic matrix

The fire probabilistic matrix (FPM) was constructed using historical fires with the following steps:

1. Collecting satellite observations of wildfires over a historical period. Locations where wildfires were observed historically are defined with a probability of 1.
2. We assume that areas surrounding these historically observed wildfire points also have a probability of experiencing wildfires. However, this probability decays exponentially with distance from the wildfire occurrence point, following a 2^{-n} pattern, where n is the number of decay steps.
3. It is important to note that our MODIS data has a resolution of 1 km. Therefore, decay occurs every 1 km. We follow CLIMADA's wildfire model decay setting, applying the decay three times (i.e., n = 3). In our study, we used historical wildfire observations from 2001 to 2020 in Yunnan Province to generate the FPM. During the simulation, the wildfire can only ignite on the FPM where probability is over 0. The results are shown in Figure A-4.

Figure A-4 | **Fire probabilistic matrix**



Source: Authors.

Parameter 2: Wildfire events number

Wildfire events number (Number) refers to the count of fire events that occur within a certain temporal and spatial range. To drive wildfire simulation, the number of wildfire events for each month of the year is needed in the wildfire projection model. For the near future projection, we can predict the wildfire events using a different approach: by establishing a self-regression equation using historical wildfire events and predicting the number of wildfire events for the target year, or by establishing a relationship between the number of wildfires and a weather index and ultimately predicting the number of fire events based on the weather index. In order to maintain consistency in methodology for obtaining the number of wildfire events in the near-term future and scenarios analysis, we ultimately adopted the approach of establishing an index relationship. That is, we established a relationship using monthly data of the FWI and the number of wildfires from historical data, and then predicted the final events number by using the monthly FWI for the target year.

Parameter 3: Fire propagation probability

The fire propagation probability (FPP) is another input parameter used to describe the probability of wildfire spread and propagation. The FPP is positively correlated with monthly mean burning area. According to CLIMADA, the FPP is assigned an initial global average value of 0.21. We optimized the monthly FPP for Yunnan by scaling this value up or down to reflect local conditions. The adjusted FPP values were input into the wildfire projection model to simulate the monthly total burned area (a). We then compared this simulated burned area with the monthly total historical observed burned area (b) for the same number of wildfire events in Yunnan Province. We determined the final monthly FPP's value when the relative error between a and b is within 10 percent. According to our experiments (Figure A-5a), there is a high correlation between the monthly FPP and the monthly mean burning area (equation 5) in the same temporal and spatial range. The monthly FPP increases sharply at first, and then the curve flattens as the area reaches around 15 km^2. In our study, we determined the relationship between the monthly mean burned area in Yunnan Province and the corresponding monthly FPP by fitting a function. Based on the characteristics of the scatterplot formed by the FPP and mean burned area, we selected an exponential function, a logarithmic function, and a rational function to fit the final relationship. We separated the dataset into a training set (80 percent) and a test set (20 percent). The training set was used to fit the curve. For model evaluation, we calculated the R-square on the training and test sets independently. As shown in Figure A-5b, we fit the data with three possible models and obtained the best optimization result (R^2= 0.586, a moderate fit, implying that the model is useful but there is still room for improvement) from function $y= -0.3x^{-1/3.19}+0.36$:

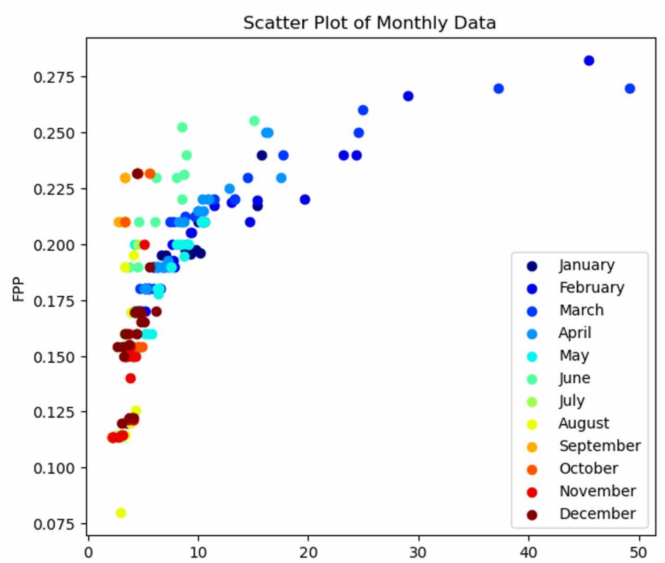
$$\textit{mean burning area} = \frac{\sum_{i=1} \textit{individual wildfire events area}}{\textit{wildfire events number}} \qquad (5)$$

where n equals the number of wildfire events in a specific month. The wildfire events number means the number of wildfire events in that month. Individual wildfire events area means the aggregate of all pixels' area in one wildfire event.

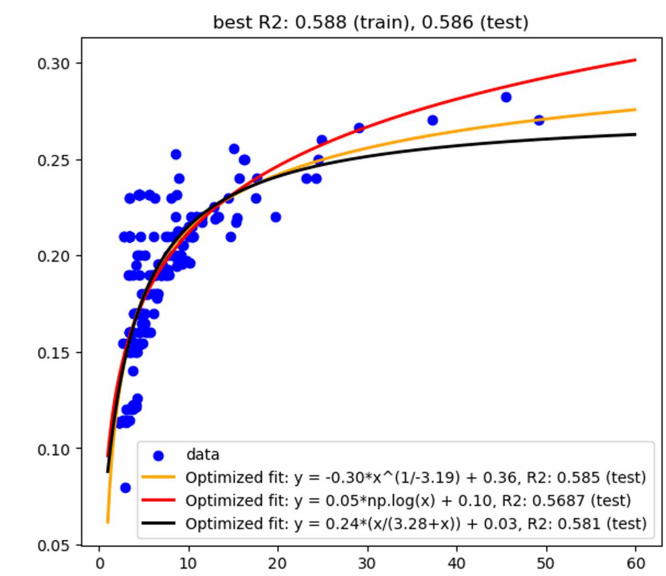
As we got the curve between the FPP and monthly mean burning area, for the near-term future prediction, as long as we know the monthly mean burning area at the target year, we know the monthly FPP inputs for the simulation model. To calculate the monthly mean burning area, we followed the same strategy by establishing a relationship between historical wildfires' monthly burning area and the FWI and use the targeted year's monthly FWI to predict the monthly burning area to get monthly FPPs in the target year.

Figure A-5 | **Correlation analysis between fire propagation probability and burned area**

a. Fire propagation probability analysis



b. Burned area analysis



Source: Authors.

Parameter 4: Fire temperature range

Except for the monthly number of wildfire events and monthly FPPs, we also need the monthly fire temperature range (FTR) as input for the wildfire projection model. Following the same rule, we also first built the historical relationship between the FTR and FWI and predicted the target year's FTR by using the target year's FWI.

g.

We mainly considered the availability and completeness of the model, and finally selected all the models from 34 GCM models that were time-complete and available in different scenarios and could be quickly downloaded from the NASA data portal at https://www.nccs.nasa.gov/services/data-collections/land-based-products/nex-gddp-cmip6.

h.

The Intergovernmental Panel on Climate Change Sixth Assessment Report assessed the projected temperature outcomes of a set of five scenarios that are based on the framework of the SSPs. The names of these scenarios consist of the SSP on which they are based (SSP1–SSP5), combined with the expected level of radiative forcing in the year 2100 (1.9 to 8.5 watts per square meter). This results in scenario names SSPx-xx listed below. And in NEX-GDDP-CMIP6, it only offers SSP1-26, SSP2-45, SSP3-70, and SSP5-85.

Table A-1 | **Model table**

Model list in CMIP6	'ACCESS-CM2', 'ACCESS-ESM1-5', 'BCC-CSM2-MR', 'CESM2', 'CESM2-WACCM', 'CMCC-CM2-SR5', 'CMCC-ESM2', 'CNRM-CM6-1', 'CNRM-ESM2-1', 'CanESM5', 'EC-Earth3', 'EC-Earth3-Veg-LR', 'FGOALS-g3', 'GFDL-CM4', 'GFDL-ESM4', 'GISS-E2-1-G', 'HadGEM3-GC31-LL', 'HadGEM3-GC31-MM', 'IITM-ESM', 'INM-CM4-8', 'INM-CM5-0', 'IPSL-CM6A-LR', 'KACE-1-0-G', 'KIOST-ESM', 'MIROC-ES2L', 'MIROC6', 'MPI-ESM1-2-HR', 'MPI-ESM1-2-LR', 'MRI-ESM2-0', 'NESM3', 'NorESM2-LM', 'NorESM2-MM', 'TaiESM1', 'UKESM1-0-LL'
Model list used in working paper	'FGOALS-g3','MRI-ESM2-0','NorESM2-LM','MPI-ESM1-2-LR','KACE-1-0-G', 'MPI-ESM1-2-HR','EC-Earth3', 'NorESM2-MM','INM-CM5-0', 'CESM2','CMCC-ESM2','CMCC-CM2-SR5','TaiESM1','GISS-E2-1-G', 'ACCESS-CM2','ACCESS-ESM1-5', 'GFDL-ESM4','IITM-ESM'

Notes: FAOSTAT = Food and Agriculture Organization Corporate Statistical Database. FAO = Food and Agriculture Organization of the United Nations. OECD = Organisation for Economic Co-operation and Development.

Source: Authors.

Table A-2 | **The projected temperature outcomes of a set of five scenarios that are based on the framework of the SSPs**

SSP	SCENARIO	ESTIMATED WARMING (2041–60)	ESTIMATED WARMING (2081–2100)	VERY LIKELY RANGE IN °C (2081–2100)
SSP1-19	Very low GHG emissions: CO_2 emissions cut to net zero around 2050	1.6°C	1.4°C	1.0–1.8
SSP1-26	Low GHG emissions: CO_2 emissions cut to net zero around 2075	1.7°C	1.8°C	1.3–2.4
SSP2-45	Intermediate GHG emissions: CO_2 emissions around current levels until 2050, then falling but not reaching net zero by 2100	2.0°C	2.7°C	2.1–3.5
SSP3-70	High GHG emissions: CO_2 emissions double by 2100	2.1°C	3.6°C	2.8–4.6
SSP5-85	Very high GHG emissions: CO_2 emissions triple by 2075	2.4°C	4.4°C	3.3–5.7

Notes: SSP = Shared Socioeconomic Pathway. GHG = greenhouse gas. CO_2 = carbon dioxide.

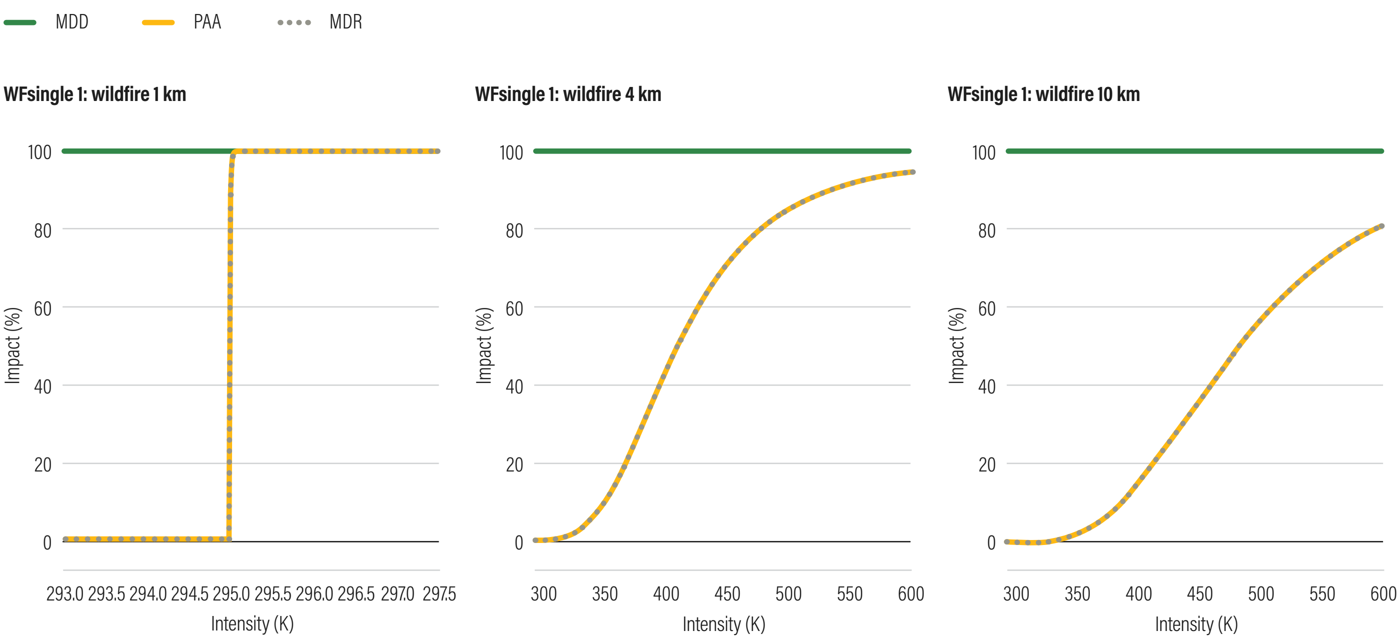
Source: Authors.

i.

Lüthi offers three types of resolution impact functions for wildfire. The details are shown in Figure A-6.

From his research, the impact function is calibrated by the Emergency Events Database (EM-DAT). Maintained by the Center for Research on the Epidemiology of Disasters, EM-DAT is a global database on natural and technological disasters. EM-DAT provides comprehensive and systematic data on the occurrence and impact of disasters worldwide from 1900 to the present. The database includes information on the affected population, human causalities, and economic costs of different types of disasters, such as earthquakes, floods, droughts, wildfires, and industrial accidents.

Figure A-6 | **Three types of resolution impact functions for wildfire**



Source: Authors.

APPENDIX B

Table B-1 | **Price of five crops**

CROP	PRICE (YUAN PER TONNE) IN 2020	SOURCE	PRICE (YUAN PER TONNE) IN 2030	SOURCE
Maize	2894	FAOSTAT of FAO	3891.5562	2020 prices multiplied by the OECD's projected inflation factors of 34.47% until 2030.
Wheat	2522.5	FAOSTAT of FAO	3392.0009	
Soybeans	5398.2	FAOSTAT of FAO	7258.94916	
Sugarcane	5215.4	FAOSTAT of FAO	7013.1383	
Coffee	21483.4	FAOSTAT of FAO	28888.68	

Notes: FAOSTAT = Food and Agriculture Organization Corporate Statistical Database. FAO = Food and Agriculture Organization of the United Nations. OECD = Organisation for Economic Co-operation and Development.

Table B-2 | **The wildfire projection model inputs for 2020 and 2021**

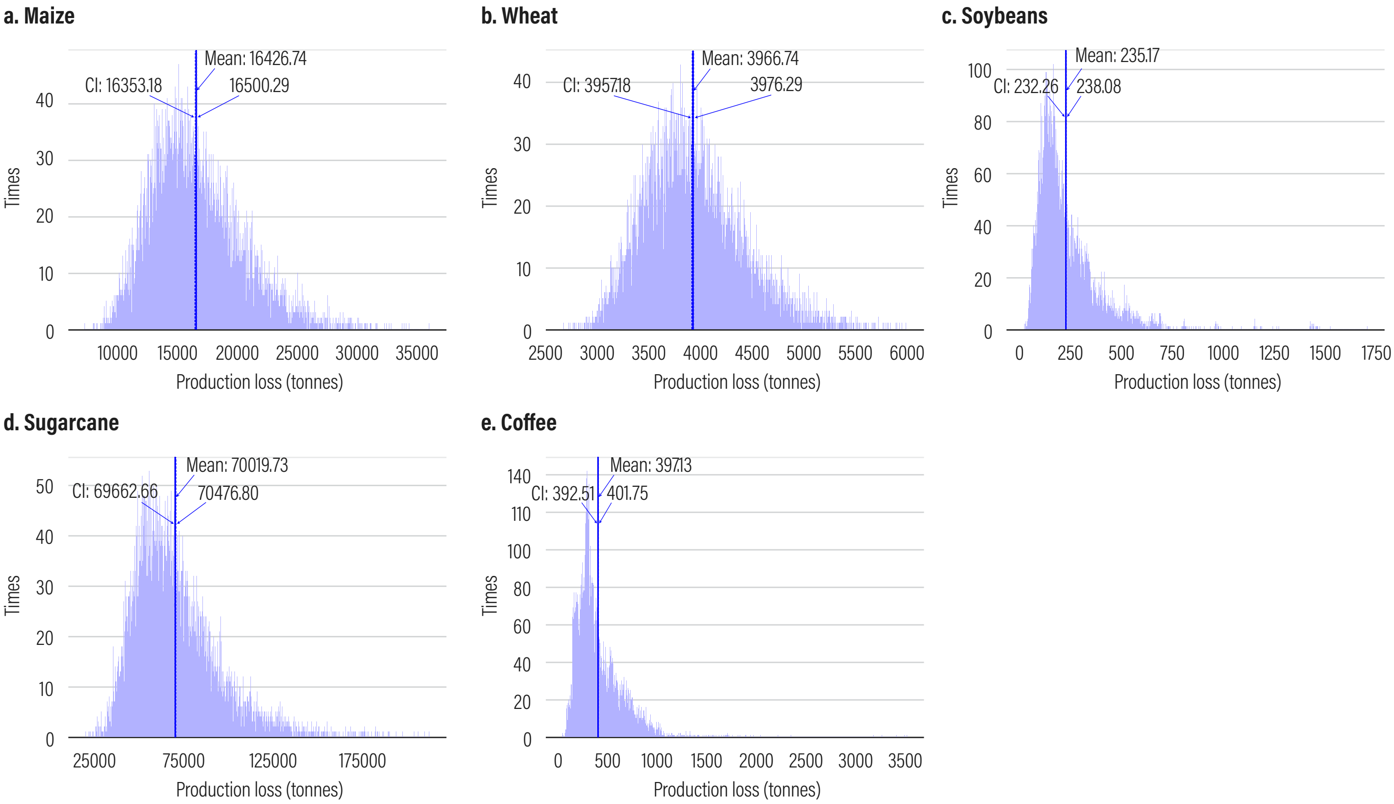
PARAMETER 2020	JAN.	FEB.	MAR.	APR.	MAY	JUN.	JUL.	AUG.	SEP.	OCT.	NOV.	DEC.
FWI	4.56	3.33	4.56	4.56	6.13	26.75	6.13	0.1	0.01	0.01	0.01	1.57
NUM	32	23	32	32	44	195	44	0	0	0	0	10
K	317.58	316.9	317.58	317.5	318.3	328.24	318.342	315.39	315.39	315.39	315.39	316.15
Area	6.12	5.10	6.121	6.12	7.428	24.54	7.428	2.33	2.334	2.33	2.33	3.645
FPP	0.19	0.18	0.19	0.19	0.20	0.25	0.20	0.13	0.13	0.13	0.13	0.16

PARAMETER 2021	JAN.	FEB.	MAR.	APR.	MAY	JUN.	JUL.	AUG.	SEP.	OCT.	NOV.	DEC.
FWI	4.26	5.13	13.18	9.65	9.53	4.7	0.13	1.26	0.01	1.26	0.55	2.96
NUM	30	36	96	70	69	33	0	8	0	8	3	21
K	317.45	317.86	321.72	320.03	319.97	317.65	315.46	316.01	315.4	316.0	315.6	316.82
Area	5.878	6.599	13.275	10.35	10.250	6.240	2.45	3.389	2.334	3.389	2.80	4.8
FPP	0.18	0.19	0.23	0.21	0.21	0.19	0.13	0.15	0.13	0.15	0.142	0.17

Notes: NUM = number of wildfire events. K = brightness temperature of wildfire. FPP = fire propagation probability. FWI = Fire Weather Index

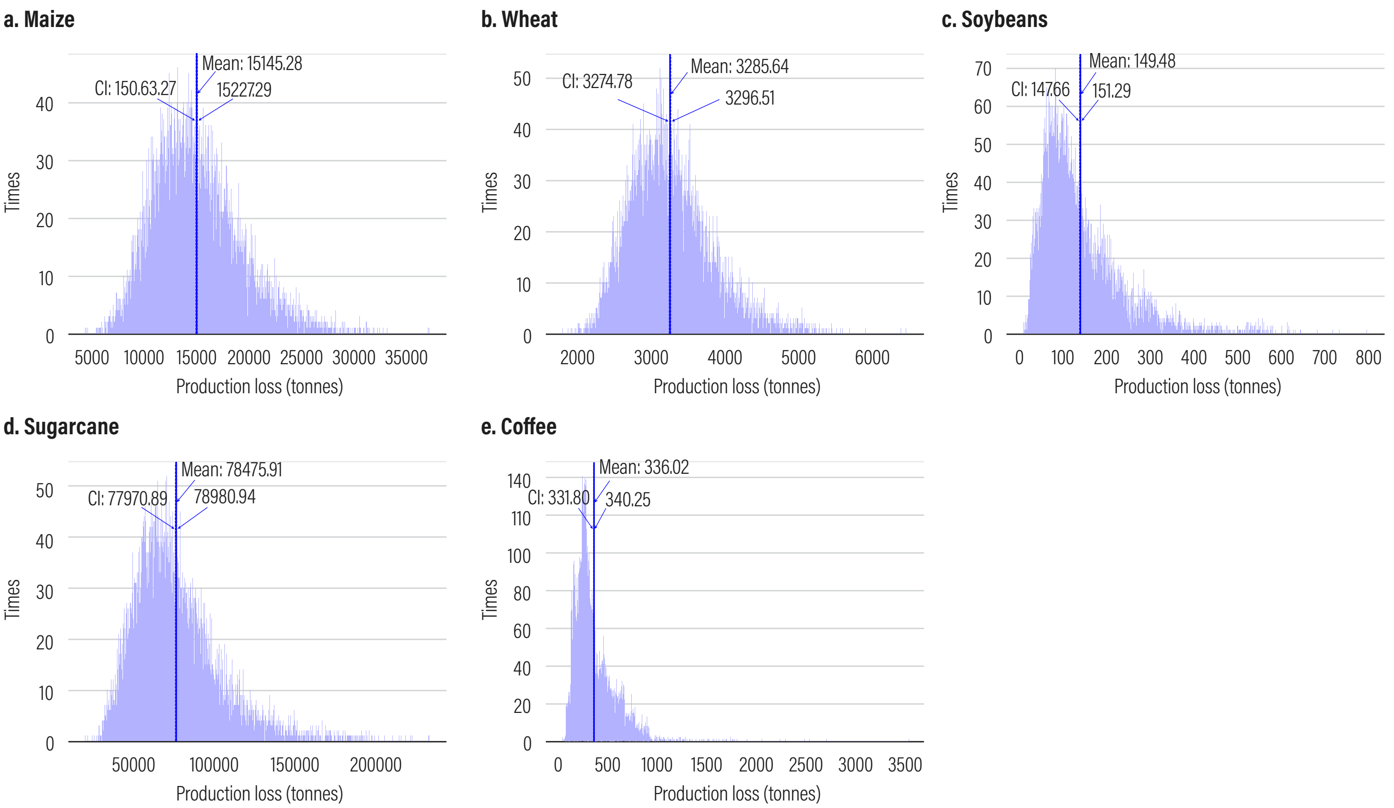
Source: Authors.

Figure B-1 | **Loss distribution of five crops in 2020**



Source: Authors.

Figure B-2 | **Loss distribution of five crops in 2021**



Source: Authors.

ENDNOTES

1. A natural disaster is the highly harmful impact on a society or community following a natural hazard event. Some examples of natural hazard events include flooding, drought, earthquake, tropical cyclone, lightning, tsunami, volcanic activity, and wildfire.

2. Brightness temperature (also referred to as BT) is a measure of the radiance of microwave radiation traveling upward from the top of Earth's atmosphere; as for MODIS, it is the channel 21/22 brightness temperature of the fire pixel measured in Kelvin (NASA 2024).

3. Global Spatially-Disaggregated Crop Production Statistics Data for 2010 Version 2.0: IFPRI HarvestChoice Dataverse (https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/PRFF8V). This database not only applies the latest global synergy cropland layers and other relevant data but also expands the estimates of crop area, yield, and production from 20 to 42 major crops under four farming systems across a global 5-arcminute grid (Yu et al. 2020).

4. The National Bureau of Statistics (https://data.stats.gov.cn/easyquery.htm?cn=E0103) provides historical province-level data sector-by-sector. We chose the dataset from 2001 to 2021 and selected the sector "农业," subsector "主要农作物产品产量," and province "云南."

5. ERA5-Land (Copernicus Climate Change Service 2017) is a global climate reanalysis dataset released by the European Centre for Medium-Range Weather Forecasts (ECMWF). It is based on advanced climate models and various weather prediction systems. It uses ground and satellite observation data to generate high spatial resolution (about 9 km) and high temporal resolution (hourly) global atmospheric, land, and ocean data from 1979 to the present. The ERA5-Land dataset includes various meteorological variables (e.g., temperature, precipitation, wind speed, humidity) and can be used in climate analysis and projecting, environmental monitoring, and weather forecasting, due to its high accuracy and wide applicability.

6. Average exchange rate (1 US$ = 6.9 yuan).

7. EM-DAT: https://www.emdat.be/

8. The initial version of this code was inspired by https://scipython.com/blog/the-forest-fire-model/.

9. Relative error = $|(a - b)/b| \times 100\%$.

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ABOUT WRI

World Resources Institute is a global research organization that turns big ideas into action at the nexus of environment, economic opportunity, and human well-being.

Our challenge

Natural resources are at the foundation of economic opportunity and human well-being. But today, we are depleting Earth's resources at rates that are not sustainable, endangering economies and people's lives. People depend on clean water, fertile land, healthy forests, and a stable climate. Livable cities and clean energy are essential for a sustainable planet. We must address these urgent, global challenges this decade.

Our vision

We envision an equitable and prosperous planet driven by the wise management of natural resources. We aspire to create a world where the actions of government, business, and communities combine to eliminate poverty and sustain the natural environment for all people.

Our approach

COUNT IT

We start with data. We conduct independent research and draw on the latest technology to develop new insights and recommendations. Our rigorous analysis identifies risks, unveils opportunities, and informs smart strategies. We focus our efforts on influential and emerging economies where the future of sustainability will be determined.

CHANGE IT

We use our research to influence government policies, business strategies, and civil society action. We test projects with communities, companies, and government agencies to build a strong evidence base. Then, we work with partners to deliver change on the ground that alleviates poverty and strengthens society. We hold ourselves accountable to ensure our outcomes will be bold and enduring.

SCALE IT

We don't think small. Once tested, we work with partners to adopt and expand our efforts regionally and globally. We engage with decision-makers to carry out our ideas and elevate our impact. We measure success through government and business actions that improve people's lives and sustain a healthy environment.