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To cite this article: Yi-Ling Hwong *et al* 2025 *Environ. Res.: Climate* **4** 035005

IOP Publishing Environ. Res.: Climate 4 (2025) 035005 https://doi.org/10.1088/2752-5295/adec11

ENVIRONMENTAL RESEARCH
CLIMATE

OPEN ACCESS

RECEIVED
25 October 2024

REVISED
23 June 2025

ACCEPTED FOR PUBLICATION
4 July 2025

PUBLISHED
15 July 2025

PAPER

Sustainable development key to limiting climate change-driven wildfire damages

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Keywords: wildfire, economic damage, climate change, vapor pressure deficit, shared socioeconomic pathways

Supplementary material for this article is available online

Abstract

Climate change is causing wildfires to become more frequent and intense. While predicting burned areas using bioclimatic and anthropogenic factors is an active research area, few studies have examined what drives the economic damages of wildfires. Our study aims to fill this gap by analyzing key factors influencing global economic wildfire damages and projecting future damages under three shared socioeconomic pathways (SSPs). We apply regression analyses to identify significant predictors of economic wildfire damages at country levels and use the fitted model to project future damages under SSP126, SSP245, and SSP370. Results show that the human vulnerability index (HVI), reflecting socioeconomic conditions, is the strongest predictor of historical wildfire damages, followed by water vapor pressure deficit during the fire season and population density around forested areas. We found high population density to be associated with lower damages. These findings contrast with studies of burned areas, where climate factors are more dominant. Our model projects that by 2070, average global economic wildfire damages will be three times higher under SSP370 than SSP126. Our model also shows that following SSP126 not only reduces wildfire damages but also lessens the inequalities in damage distribution across countries. This pathway's dual focus on equitable socioeconomic progress and climate action potentially enhances a country's resilience that helps mitigate wildfire damages. Our analyses also indicate that strong socioeconomic development can offset wildfire damages associated with climate hazards, although this is less certain under SSP370. SSP126's integrated approach improves both socioeconomic conditions and limits global warming, providing substantial benefits to less developed countries while still reducing damages in developed nations, despite their already low HVI scores. Our work complements existing research on burned areas and underscores the importance of sustainable development and international collaboration in reducing the economic damages of wildfires.

1. Introduction

Wildfires are an integral component of the global ecosystem (Bowman *et al* 2009, Bond and Van Wilgen 2012). They occur both naturally and as a consequence of human activities, impacting vegetation, biodiversity, infrastructures, human assets, the terrestrial carbon cycle, and atmospheric composition (Lasslop *et al* 2020, Libonati *et al* 2022). Climate change is causing fire weather—characterized by hot, dry, and windy conditions—to become more frequent, intense, persistent, and widespread (IPCC 2021), directly contributing to the increase of wildfires (Abatzoglou and Williams 2016, Sanderson and Fisher 2020, Turco *et al* 2023).

Despite challenges in disentangling the effects of the many bioclimatic and anthropogenic factors affecting wildfires (Sanderson and Fisher 2020), state-of-the-art fire models are capable of capturing the trends of fire emission and burned area when compared to satellite observations (Li *et al* 2019, Hantson *et al* 2020). However, projecting future economic damages of wildfires has received scant attention, and is the focus of the present study. Globally, insured damages due to wildfires are estimated to have increased by up to 12.4% between 2016 and 2020 (Swiss Re Institute 2021). The Australian wildfires of 2019/2020 incurred around US$75 billion in economic damages, equivalent to 6% of the country's gross domestic product (GDP) (Read and Denniss 2020). The 2020 Californian wildfires resulted in an estimated damage of US$140 billion, representing 1.5% of the state's GDP (Wang *et al* 2021). The average annual economic wildfire damage of the United States has been estimated to range between US$63–285 billion (Thomas *et al* 2017). Initial assessments indicate that the economic damages from the Los Angeles 2025 wildfires surpass US$250 billion (Qiu *et al* 2025) and a 0.48% reduction in county-level GDP (Li and Yu 2025). Wildfires can have both positive (e.g. increased demand for recovery and restoration services) and negative economic impact, though the positive impacts are generally much smaller (Diaz 2012). They also incur both direct (e.g. property damages, business interruption) and indirect (e.g. supply-chain disruption, healthcare costs) damages (Stephenson *et al* 2013, Kim and Kwon 2023).

Four key processes govern wildfire occurrence: fuel production, fuel availability, fire-weather, and fuel ignition (Archibald *et al* 2009). These processes are influenced by climatic, anthropogenic, and socioeconomic factors. Climate-related factors have been found to be the most important drivers of burned area (Jain *et al* 2022, Jones *et al* 2022, Burton *et al* 2024). The impact of climate on wildfires is mediated by fuels: in arid ecosystems where climate conditions are conducive to fire occurrence, fire is limited by fuel availability; while in wetter regions where fuel is more abundant, fire is constrained by humid conditions (Krawchuk and Moritz 2011, Pausas and Ribeiro 2013, Bedia *et al* 2015). Water vapor pressure deficit (VPD) has been found to be a robust predictor of burned areas (Williams *et al* 2019, de Dios *et al* 2021, Balch *et al* 2022), particularly when the fire season (typically summer months) VPD is used (Williams *et al* 2014, Bedia *et al* 2015, Abatzoglou *et al* 2018, Mueller *et al* 2020, Brey *et al* 2021). It is an effective proxy for fuel flammability (Williams *et al* 2014) and has been shown to be a stronger predictor of wildfires than temperature, relative humidity or precipitation alone (Williams *et al* 2019, Graff *et al* 2020, Brey *et al* 2021, Turco *et al* 2023). Precipitation is also often used to predict burned areas (Archibald *et al* 2009, Bistinas *et al* 2014, Abatzoglou *et al* 2018), although it is generally not as effective as VPD (Graff *et al* 2020, Mueller *et al* 2020, Jain *et al* 2022). Its unimodal relationship with burned area (Van der Werf *et al* 2008, Harrison *et al* 2010, Prentice *et al* 2011) means its applicability varies depending on whether the region is fuel-limited (arid, where antecedent rainfall is used) (Westerling *et al* 2002, Crimmins and Comrie 2004, Littell *et al* 2009) or moisture-limited (wetter, where concurrent precipitation is used) (Abatzoglou *et al* 2018, Holden *et al* 2018, Burton *et al* 2024). Compound indices are also employed to estimate wildfire occurrence. For instance, the Canadian fire weather index (FWI) (Quilcaille *et al* 2023a)—which accounts for the effects of temperature, humidity, precipitation, wind speed, and moisture contents of fuels—has been shown to significantly correlate with burned areas (Bedia *et al* 2015, Grillakis *et al* 2022).

Humans influence wildfire in myriad ways. They can cause wildfires, either intentionally or by accident (Russell-Smith *et al* 2007, Aldersley *et al* 2011, Ribeiro *et al* 2022), but human activities can also lower wildfire risk. Increased urbanization and landscape fragmentation, for example, can reduce vegetation flammability (Jolly *et al* 2015, Andela *et al* 2017). Controlled burning programs may also reduce burned areas (Bradstock *et al* 2012, Hiers *et al* 2020). In dynamic global vegetation models, fire ignitions generally increase with population density up to a certain threshold, beyond which they decline, while fire suppression is generally modeled to increase as population density rises (Hantson *et al* 2016, Teckentrup *et al* 2019, Ford *et al* 2021). Indeed, studies have revealed a unimodal relationship between population density and burned area (Archibald *et al* 2009, Aldersley *et al* 2011, Bistinas *et al* 2013), with recent analyses highlighting a predominant fire-suppression role of humans (Bistinas *et al* 2014, Knorr *et al* 2014, Parisien *et al* 2016, Andela *et al* 2017, Forkel *et al* 2017). However, there are significant regional variations in the correlation between human presence and burned areas, which often leads to weak global averages (Jones *et al* 2022). Socioeconomic factors have also been applied for fire projections, such as GDP (Aldersley *et al* 2011, Bistinas *et al* 2014), road density (Archibald *et al* 2009, Arndt *et al* 2013), and indices such as the night light development index (Forkel *et al* 2017), youth index (as a proxy for urbanization, e.g. Koutsias *et al* 2010), and human footprint index (Parisien *et al* 2016, Abatzoglou *et al* 2018).

Projecting future wildfires is challenging due to uncertainties in ecosystem changes and the dynamic impact of human activities on fires. Many studies have been conducted to project future burned areas using outputs of the Coupled Model Intercomparison Project (CMIP) under various warming scenarios (Williams *et al* 2014, 2019, Bedia *et al* 2015, Brey *et al* 2021, Zhang *et al* 2024). However, research focusing on the projection of the future economic damages of wildfires is limited and, when conducted, is often confined to regional scales (e.g. Stougiannidou and Zafeiriou 2021). This study aims to fill this gap. Specifically, the goals are to (1) identify key drivers of global economic damages of wildfires, and (2) project and compare future global wildfire damages under different climate and socioeconomic scenarios. Hereafter, 'damages' refers specifically to the economic damages of wildfires.

2. Methods

Our methodology uses multiple regression analysis, a common approach in wildfire modeling (Williams *et al* 2019, Graff *et al* 2020, Brey *et al* 2021, Su *et al* 2021, Meier *et al* 2023). The response variable is wildfire damages, driven by selected predictor variables to maximize the explained variance in these damages. A statistically significant predictor indicates that the predictor is associated with wildfire damages beyond random chance and after considering the effects of the other predictors. The method relies on a simple linear regression analysis and does not explore nonlinear relationships between the variables to facilitate easier and more intuitive interpretation of the model results, but also to avoid overfitting given the limited data size.

The second goal of our study is to use the fitted regression model to project future wildfire damages under the 'shared socioeconomic pathways—representative concentration pathway' framework (Van Vuuren *et al* 2014). Specifically, we focus on shared socioeconomic pathways (SSP) 1-2.6, SSP2-4.5, and SSP3-7.0, henceforth referred to as SSP126, SSP245, and SSP370 for simplicity. The values 2.6, 4.5, and 3.7 represent the projected radiative forcings in W m^{-2} by year 2100 under the different RCPs, corresponding to comparatively low, medium, and high warming pathways from the CMIP6 ScenarioMIP project (O'Neill *et al* 2016), with global mean temperature increases of around 1.5 °C–2.0 °C, 2.5 °C–3.0 °C, and 3.5 °C–4.0 °C, respectively, relative to the pre-industrial baseline (1850–1900). SSP126 emphasizes sustainable development with high levels of international cooperation and strong environmental policies; SSP245 represents a continuation of current trends with moderate levels of technological development and policy actions; SSP370 is characterized by resurgent nationalism and stalled socioeconomic development.

Note that while our main analyses use a linear model, we have also conducted preliminary analyses incorporating quadratic terms of the predictors. The cross-validation R^2 scores of these nonlinear models confirm overfitting (table S1), thus limiting their applicability to unseen data. Further, SSP projections using nonlinear predictors produce damage estimates similar to those of our linear model (figure S1). However, due to concerns about the poor generalizability of these nonlinear models, we do not recommend using the beta coefficients reported in table S1 for projections of future wildfire damages.

2.1. Wildfire damage data

The damage values of wildfires are obtained from the recorded wildfire data of the Emergency Events Database (EM-DAT) from the Center for Research on the Epidemiology of Disasters (Delforge *et al* 2023). EM-DAT compiles its data from multiple sources, including the United Nations, governmental and non-governmental organizations, insurance companies, research institutes, and media coverage. The database categorizes wildfires as forest fire, land fire (brush, bush, pasture, grassland, or other treeless natural environment), and general wildfire (EM-DAT n.d.a).

From EM-DAT, we use the inflation-adjusted country-level total damage data from 1990–2022, which includes direct and indirect damages (EM-DAT n.d.b). To address the well-known problem of missing data in EM-DAT (Jones *et al* 2023), which can bias statistical analyses and affect model reliability, we apply a regression-based imputation technique, where missing data is replaced with values predicted from a regression analysis trained on available values of the missing variable regressed on some available predictors (Jones *et al* 2023). Exploratory tests revealed that wildfire damages are correlated with the number of people affected (a separate 'affected' column in EM-DAT) and GDP. Missing damage data is imputed using a fitted regression model to predict the missing damage values based on available 'affected' and GDP values. This method leverages the relationship between 'damage', 'affected', and GDP to fill in the missing values in a way that preserves data integrity. The reliability and validity of imputed data is verified using robustness tests, by comparing regression results using subsets of the imputed data and assessing models with and without imputation.

For model fitting, we follow established methods for cross-country disaster loss comparisons (Coronese *et al* 2019, Bodenstein and Scaramucci 2025) and use GDP-normalized wildfire damages as the outcome variable, with wildfire damage values divided by each country's GDP (World Bank n.d.) to account for varying economic sizes across countries. By using GDP-normalized damages, our approach assesses *relative* rather than absolute impacts, providing a more equitable measure of the economic burden of wildfires across countries. This approach takes into account the possibility that lower-income countries—despite experiencing smaller absolute damages (due to lower values of exposed assets)—may endure disproportionately larger economic disruptions as a share of their GDP. In essence, our regression analyses aim to address the research question: if all countries had the same GDP, what factors would account for higher relative wildfire damages in some countries compared to others?

To address potential confounding between GDP and vulnerability, we conduct a supplementary analysis using absolute (un-normalized) damages with GDP included as an independent predictor. Multicollinearity diagnostics confirm no redundancy between GDP and our independent variables (variance inflation factors, VIFs < 2; table S2). We emphasize that the main focus of this manuscript remains on the analyses of relative wildfire economic impact using normalized damages, with wildfire damages expressed as a percentage of GDP (%GDP) hereafter, unless otherwise specified.

The wildfire damages are averaged across available years for each country, resulting in a single damage value per country. We use cross-sectional instead of panel data due to inconsistent data availability in EM-DAT that led to highly imbalanced country-year combinations across different countries, particularly among poorer countries. While panel regression would allow us to leverage all available country-year observations and control for unobserved heterogeneity (e.g. time-invariant country-specific characteristics and temporal trends) via fixed effects, this approach is undermined by substantial missing wildfire damage data in lower-income countries. Such missingness likely violates the missing-at-random assumption required for valid panel regression. Hence, we opt for cross-sectional analysis to examine between-country variation in wildfire damages but acknowledge that this approach reduces the number of observations and limits our ability to capture the full relationship between damages and explanatory variables. A comparison between panel and cross-sectional regression results is provided in table S3 of the supplementary information. The panel model shows low explanatory power ($R^2 = 0.29$) and large standard errors relative to coefficient magnitudes, indicating insufficient within-country variation in wildfire damage data and underscoring the limitations of a panel-based approach for our study. To assess the validity of averaging damage data across years in our cross-sectional analysis, we conduct autocorrelation and Durbin–Watson tests to confirm the independence of damages across years for each country. The final dataset consists of 62 data points, with damage values closely aligning with wildfire damages reported in Lüthi *et al* (2021).

2.2. Predictor variables

We select the predictor variables based on the following criteria: (1) minimal correlation among the predictors to avoid multicollinearity, (2) representation of the Intergovernmental Panel on Climate Change (IPCC) impact assessment framework components (hazard, exposure, and vulnerability) (Reisinger *et al* 2020), (3) availability of projection data for the SSPs considered, and (4) ability to explain high variance in wildfire damages, as evaluated by the R^2 scores of initial regression models (table S4 in the supplementary information). The final predictors chosen are the mean fire season VPD ($\mathrm{VPD_{fs}}$), population density around forested areas ($\mathrm{PD_{forest}}$), and the human vulnerability index (HVI), corresponding to hazard, exposure, and vulnerability, respectively.

$\mathrm{VPD_{fs}}$ is calculated from the gridded daily maximum temperature (*tasmax*) and near-surface relative humidity (*hurs*) outputs of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP3a) (Frieler *et al* 2024). We use the *obsclim* dataset, which has a 0.5° spatial resolution. The dataset is derived from bias-adjusted ERA5 reanalysis data and uses the GSWP3-W5E5 climate forcing data (Lange *et al* 2023). For tropical and subtropical countries, $\mathrm{VPD_{fs}}$ is averaged annually, while for temperate countries, it is averaged over the summer months (June–August for northern hemisphere; December–February for southern hemisphere). While this definition of the fire season is a simplification, it enables a globally consistent and interpretable metric suitable for country-level analysis, and is supported by studies showing strong correlations between summer fire weather and burned areas (Williams *et al* 2014, Brey *et al* 2018, 2021, Mueller *et al* 2020). Alternative metrics using annual mean, maximum, or winter months VPD yielded lower R^2 scores and weaker significance for VPD (table S4). While the EM-DAT database does not consistently record the dates of wildfire events across all entries, a manual inspection of available wildfire dates revealed that most events in temperate regions occurred during the hemispheric summer months. A potential solution could be the use of 90 days running average to assess the fire season. Nevertheless, we caution that such simple definitions may not capture the complex fire seasonality observed in many regions, where fire activity can be bimodal or follow irregular patterns (Boschetti and Roy 2008, Le Page *et al* 2010, Benali *et al* 2017). Our fixed fire season approach may therefore introduce bias in the calculation of $\mathrm{VPD_{fs}}$ for regions with such complex fire regimes. The gridded $\mathrm{VPD_{fs}}$ values are weighted based on the national land area (LA) fraction of each grid cell and then aggregated to the country level following equation (1):

$$\mathrm{VPD}_{fs,c,t} = \sum_{i\epsilon c} \mathrm{VPD}_{fs,i,t} \frac{\mathrm{LA}_i}{\sum_{i\epsilon c} \mathrm{LA}_i} \tag{1}$$

where the subscript c denotes the national scale, i the grid point, and t the year. We exclude precipitation data as including either antecedent (prior year) or concurrent precipitation does not improve model performance and sometimes worsens it.

For the anthropogenic factor, we introduce a new predictor ($\mathrm{PD_{forest}}$), which estimates population density around forested areas. It is calculated by dividing gridded population data by gridded forest area (FA) (both with 0.5° spatial resolutions). A higher population value and/or lower forest cover in a given grid point indicate greater human presence around forested areas. Only grid points with at least 5% forested areas are selected to prevent unreasonably large $\mathrm{PD_{forest}}$ values (results are not sensitive to the chosen threshold). The population data used for $\mathrm{PD_{forest}}$ is obtained from Werning (2024), which scales the gridded population projections from the original SSP (Jones and O'Neill 2016, KC and Lutz 2017) to align with the most recent SSP population projections (KC *et al* 2024). This population dataset is consistent with population data reported in previous studies (e.g. Liu and Chen 2022). For model fitting, we use the baseline population data from 2020, which has been calibrated to reflect recent observed population changes (KC *et al* 2024). We select data from SSP245, as it is closest to observed data (KC *et al* 2024). The gridded FA data is obtained from the Global Biosphere Management Model (GLOBIOM) (Havlík *et al* 2014, IBF-IIASA 2023, Frank *et al* 2024). The GLOBIOM database includes eleven land cover types (IBF-IIASA 2023), from which we select six that most closely align with the land cover categories used in the EM-DAT wildfire damage data (as exact matches between the two databases are not available): primary forest, protected primary forest, plantation forest, managed forest, natural land, and grass land. We select the FA data from 2020 and SSP245 to ensure consistency with the population data. Results are not sensitive to the choice of baseline year or SSP, with only slight differences in coefficient values while maintaining consistent signs and statistical significance. To obtain country-level $\mathrm{PD_{forest}}$ data, the gridded $\mathrm{PD_{forest}}$ values are weighted by the FA fraction of each grid cell and then aggregated to the country level:

$$\mathrm{PD}_{\mathrm{forest},c,t} = \sum_{i\epsilon c} \mathrm{PD}_{\mathrm{forest},i,t} \frac{\mathrm{FA}_i}{\sum_{i\epsilon c} \mathrm{FA}_i}. \quad (2)$$

We also evaluate an alternative predictor for the anthropogenic factor by aggregating the population only within forested grid points (applying the same 5% forest cover threshold) to approximate population around wildland urban interface (WUI). We note that this approximation is a pragmatic solution necessitated by the coarse spatial resolution (~50 km) of our population and forest cover datasets, and does not fully align with conventional WUI framework, which typically aggregates populations within a buffer zone (~1–2 km) around forested areas (Schug *et al* 2023, Gonzalez and Ghermandi 2024, Guo *et al* 2024). As a result, it may underestimate WUI populations by excluding non-forested grid points that fall within the WUI interface. The model using this predictor ($\mathrm{pop_{wui}}$) yields almost identical results to the model using $\mathrm{PD_{forest}}$, but slightly lower R^2 score and beta coefficients with reduced statistical significance. Therefore, we select the $\mathrm{PD_{forest}}$ as the predictor for all further analyses and SSP projections. Comparisons of results using $\mathrm{PD_{forest}}$ and $\mathrm{pop_{wui}}$ are presented in sections 3.1 and 3.3.2. We decided to use the ISIMIP and GLOBIOM model data for the computation of $\mathrm{VPD_{fs}}$ and $\mathrm{PD_{forest}}$ to ensure consistency with the computation of SSP projection data (where only model data are available), described in section 2.4. The GLOBIOM forest cover model data is calibrated using the Food and Agriculture Organization Global Forest Resources Assessments and uses SSP scenarios and their associated drivers (e.g. policy assumptions) to project future land use and forest cover (IBF-IIASA 2023).

For HVI, we use the complement of the Human Development Index (HDI) of the United Nations Development Programme (UNDP 2024) by calculating HVI as $(1-\mathrm{HDI})$. This adjustment maintains the index on a scale from 0 to 1 while ensuring that larger HVI values are associated with greater levels of vulnerability. We also test other indices related to governance, corruption control, rule of law, gender and income inequality but do not include them because they are either highly correlated with HVI, or result in poorer model performance (table S4). To obtain cross-sectional country-level data (i.e. a single value for each predictor per country), we average the country-level $\mathrm{VPD_{fs}}$, $\mathrm{PD_{forest}}$ and HVI values over the years for which damage data is available. Figure 1 shows a map of the response and predictor variables used for model fitting. Wildfire damages are expressed as percentages of GDP (%GDP) throughout this manuscript.

The predictors may also interact in influencing wildfire damages. For example, countries with higher HVI may suffer greater wildfire damages under the same increase in $\mathrm{VPD_{fs}}$; countries with lower HVI (reflecting more advanced socioeconomic development) and higher population density near forested areas may be better equipped to mitigate wildfire damages due to more robust infrastructure and effective emergency response. To explore these potential interactions, we conduct supplementary analyses incorporating interaction terms between HVI and $\mathrm{VPD_{fs}}$ ($\mathrm{HVI} \times \mathrm{VPD_{fs}}$), and between HVI and $\mathrm{PD_{forest}}$ ($\mathrm{HVI} \times \mathrm{PD_{forest}}$). Results show that neither interaction term is statistically significant, and their inclusion

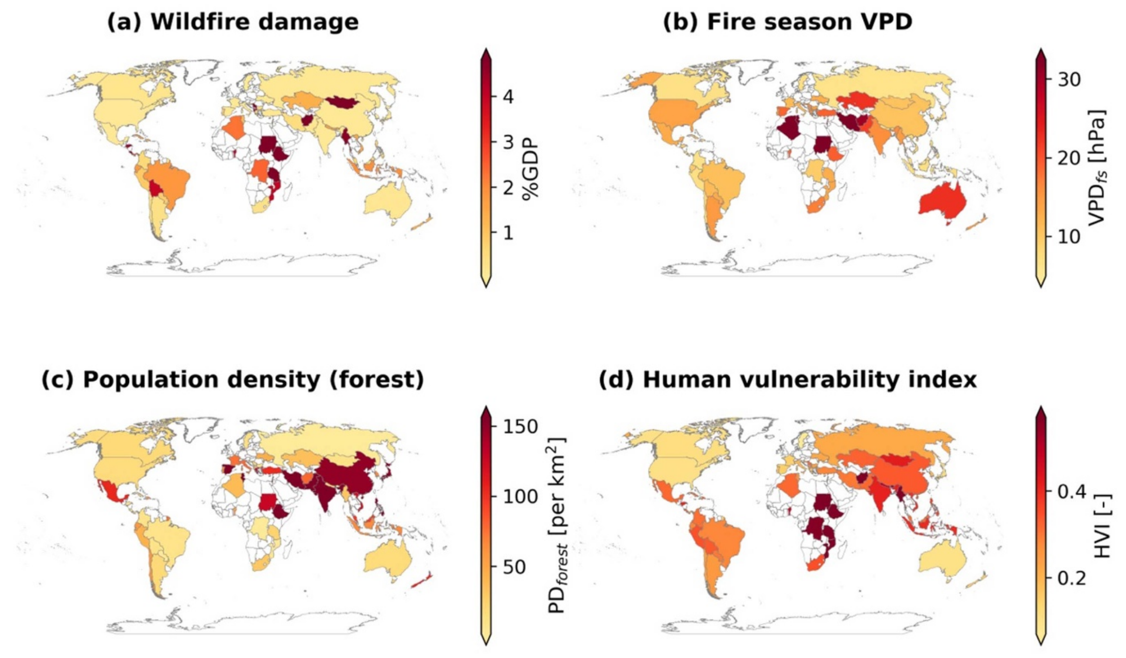

Figure 1. Maps of historical wildfire damage (EM-DAT) and predictors used to fit the regression model in this study.

does not improve overall model fit (table S5). Additionally, SSP projections with and without these interaction terms yield very similar results (figure S2). Consequently, we retain the main-effects-only model for ease of result interpretability. While our results suggest that the three predictors act additively rather than interactively in influencing wildfire damages, we acknowledge that finer-resolution data (e.g. subnational vulnerability metrics) might reveal context-specific interactions that our analyses do not capture.

2.3. Multiple linear regression

The response and predictor variables are converted from skewed to Gaussian distribution using a natural log transformation, which helps minimize the impact of outliers. To facilitate comparison of variables with different units and ranges, we standardize them by subtracting their means and then dividing by their standard deviations (SDs).

We use a generalized linear model (GLM) with a Gaussian family and an identity link function, which is equivalent to ordinary least squares regression but offers more flexibility in handling high levels of variability and uses maximum likelihood estimation instead of least squares to estimate the coefficients (McCullagh 2019). We implement the regression model using the GLM module from the Python *statsmodel* package (Seabold and Perktold 2010). The equation of the regression model in mathematical form is as follows:

$$Z_{\log(\text{damage})} = \beta_0 + \beta_1 Z_{\log(\text{VPD}_\text{fs})} + \beta_2 Z_{\log(\text{PD}_\text{forest})} + \beta_3 Z_{\log(\text{HVI})} + \epsilon \tag{3}$$

where $Z_{\log(\text{damage})}$, $Z_{\log(\text{VPD}_\text{fs})}$, $Z_{\log(\text{PD}_\text{forest})}$, and $Z_{\log(\text{HVI})}$ are the standardized log-transformed variables for wildfire damage, VPD_fs, PD_forest, and HVI, respectively, β_0 the intercept term, β_1, β_2, and β_3 the beta (standardized) coefficients, and ε the error term. The derivation of the unstandardized form of equation (3) is outlined in appendix. Since the response and predictor variables are standardized, the coefficients measure the change in the standardized log-transformed wildfire damage for one SD change in the standardized log-transformed predictors. To ease readability, the standardized log-transformed predictors are henceforth denoted as $\log(\text{VPD}_\text{fs})^*$, $\log(\text{PD}_\text{forest})^*$, and $\log(\text{HVI})^*$. Note that the log transformation applied here does not introduce nonlinearity, as both the outcome (Y) and predictor (X) variables are log-transformed. The standardization does not alter the underlying assumption of a linear relationship between Y and X's; it simply makes the beta coefficients comparable by scaling the variables to the same SD.

Our wildfire damage training data exhibit an imbalanced regional representation—a well-documented limitation of the EM-DAT and other global disaster loss and damage databases (Osuteye *et al* 2017, Mazhin *et al* 2021, Jones *et al* 2023)—which may affect the generalizability of our model. Among the 62 data points, 21 are from developed countries, 30 from developing countries, and 11 from least-developed countries, based on the IPCC Sixth Assessment Report (AR6) developmental classification. To address this imbalance, we apply sample weights when fitting the GLM model: each region group is weighted inversely proportional to its sample size, and the weights are normalized so that their total equals the number of observations. This approach helps prevent overrepresented regions from dominating the coefficient estimates, giving more balanced influence across development regions. To validate the model, we evaluate the residuals for normality using the Shapiro–Wilk test (Shapiro and Wilk 1965) and for heteroscedasticity using the Breusch–Pagan test (Breusch and Pagan 1979). We apply 5-fold cross-validation to ensure no overfitting occurs and the model generalizes well to unseen data.

2.4. Projection of future wildfire damage

For the projection of future wildfire damages using our fitted regression model, we use national GDP projections for the SSP scenarios from Koch and Leimbach (2023) and population projections from Werning (2024). Climate data projections for *tasmax* and *hurs* are obtained from the ISIMIP3b project (Lange 2019, 2021, Lange and Büchner 2022), including simulations from five Earth System Models (ESMs): the Geophysical Fluid Dynamics Laboratory ESM (GFDL-ESM4), Institut Pierre-Simon Laplace Climate Model (IPSL-CM6A-LR), Max Planck Institute for Meteorology ESM (MPI-ESM1-2-HR), Meteorological Research Institute ESM (MRI-ESM2-0), and the UK ESM (UKESM1-0-LL). The ESMs have the same 0.5° spatial resolution as the ISIMIP3a data used for fitting the regression model. To facilitate an assessment of the uncertainty in future wildfire damage projections, we use the VPD_{fs} values derived from individual ESM outputs rather than multi-model means. Forest cover projections from the same five ESMs of the GLOBIOM project are employed for the PD_{forest} calculation. The HDI projections are obtained from Cuaresma and Lutz (2015). The same data processing procedures outlined in section 2.2 are applied. Countries with less than 5% forest coverage are excluded from the projections. The resulting SSP dataset contains 129 countries.

3. Results and discussion

3.1. Regression model results

We obtain an R^2 score of 0.85 with our GLM regression model (cross-validation $\overline{R^2_{cv}} = 0.84$, $\sigma_{cv} = 0.04$). Figure 2 shows the residual plot of the overall fitted model and the partial residual plots, depicting the contribution of the individual predictors to the response variable after accounting for the effects of other predictors.

All three predictors are statistically significant at the 95% confidence level (figure 3(a)). Model-estimated damages are shown against reported damages in figures 3(b) and (c) (results of the alternative model using pop_{wui} are shown in figure S3 in the supplementary information). We assess the robustness of the coefficient estimates using bootstrap methods, resampling the data with replacement 1000 times and fitting a regression model to each sample. The VIF values of the predictors are all close to 1, indicating a very low level of multicollinearity among the predictors. The final model results and bootstrap estimates are shown in table 1.

3.2. Important drivers of historical wildfire damage

The beta (standardized) coefficients of the regression model are used to quantify the importance of the predictors, with larger coefficients indicating a stronger relationship with wildfire damages. Results show that HVI is the most important predictor, followed by VPD_{fs}, and PD_{forest}.

The dominant importance of HVI points to the possibility that strong socioeconomic development could counteract wildfire damages. This suggests that a country's adaptive capacity to cope with wildfires plays a crucial role in reducing wildfire damages. This may include factors such as improved response and management strategies, better infrastructure, effective resource assignment, and efficient containment measures to mitigate wildfire damage. Notably, the higher significance of socioeconomic factors compared to climate-related factors in predicting wildfire damage is distinctly different from findings on burned area predictions, where climate-related factors have been shown to be more important (Kelley *et al* 2019, Jain *et al* 2022, Burton *et al* 2024).

Our results demonstrate that VPD is not only an effective predictor of burned areas but also of wildfire damages. Initial experiments using precipitation, FWI, and temperature led to lower R^2 scores (table S4). High VPD is often associated with hot and dry conditions. These conditions increase the dryness of vegetations, making them more flammable and susceptible to ignition and more likely to burn intensely. Managing and suppressing large, intense wildfires requires substantial resources, including personnel and equipment. Larger fires also inflict more severe damages on infrastructures and ecosystems, leading to increased damages.

PD_{forest} is found to be the least important, albeit still statistically significant, predictor. The negative value of $\beta_{PDforest}$ indicates an inverse relationship between PD_{forest} and wildfire damage (higher PD_{forest} is associated with lower damages). This finding is consistent with the prevalent conclusions of recent studies on burned areas. People can directly intervene to extinguish fires. Human activities like wood removal and road

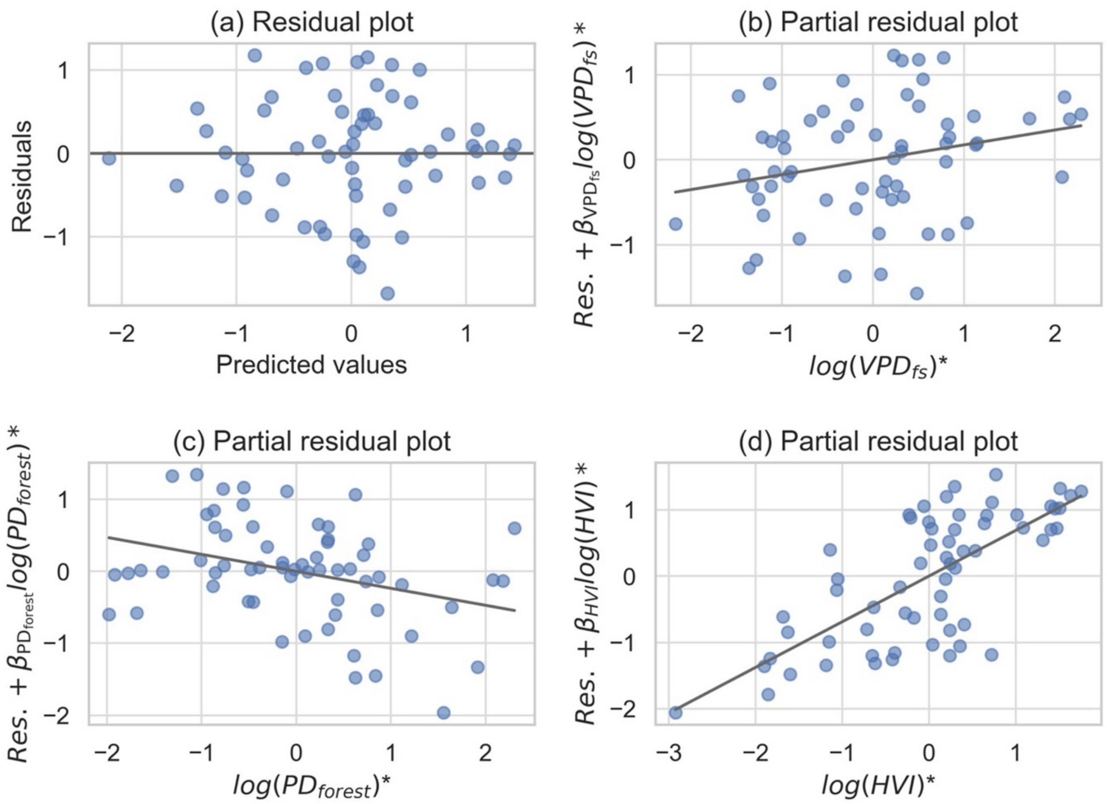

Figure 2. (a) Residual and (b)–(d) partial residual plots of the fitted regression model.

construction can also indirectly suppress fires by creating barriers that limit fire spread (Bistinas *et al* 2013, Knorr *et al* 2014, Andela *et al* 2017). However, burned area and wildfire damages are conceptually distinct, and our result requires a more nuanced interpretation. We propose two contrasting effects of human activity on wildfire damages, reflecting its dual role in forested regions. On one hand, higher population density increases potential damages due to greater asset exposure. On the other hand, human presence often correlates with improved fire management capacity (e.g. firefighting resources, land-use regulation, early warning systems) and more resilient infrastructure (e.g. fire-resistant buildings, defensible space). The negative coefficient of PD_{forest} observed in our regression model suggests that the latter effect predominates in our dataset: in densely populated forested areas, the benefits of risk mitigation and economic resilience outweigh the risks associated with higher asset exposure, leading to proportionally lower wildfire damages. This negative relationship extends the known association between human presence and reduced burned area to economic outcomes, indicating that proactive governance and robust infrastructure can substantially reduce losses despite greater exposure. Nevertheless, our model does not explicitly separate the effects of exposure from those of mitigation and resilience. Future research could address this by incorporating direct measures of governance quality or infrastructure robustness to better clarify the mechanisms underlying this relationship.

Our supplementary analyses using absolute damage as the outcome variable confirms GDP as the strongest predictor of wildfire absolute damages (table S2), while the above analyses of normalized damages highlight HVI's role in amplifying proportional damages. Notably, in the absolute-damage model, once GDP is accounted for, the relative importance of the remaining predictors—HVI, VPD_{fs}, and PD_{forest}—mirrors the ranking observed in our main normalized-damage model. Further, our panel regression analyses produce the same ranking and direction (sign) of predictor importance as our main results (table S3)—albeit with none of the predictors reaching statistical significance at the 95% confidence level—demonstrating the robustness of our findings regarding the key drivers of wildfire damages. However, caution must be applied when interpreting causality in regression analyses. While the selected predictors are strongly associated with wildfire damages, this does not necessarily imply a *direct* causal relationship. For example, although drier conditions (high VPD) are associated with higher wildfire damages, it is also possible that these regions tend to have sparse populations, which may result in reduced human capacity to manage wildfires.

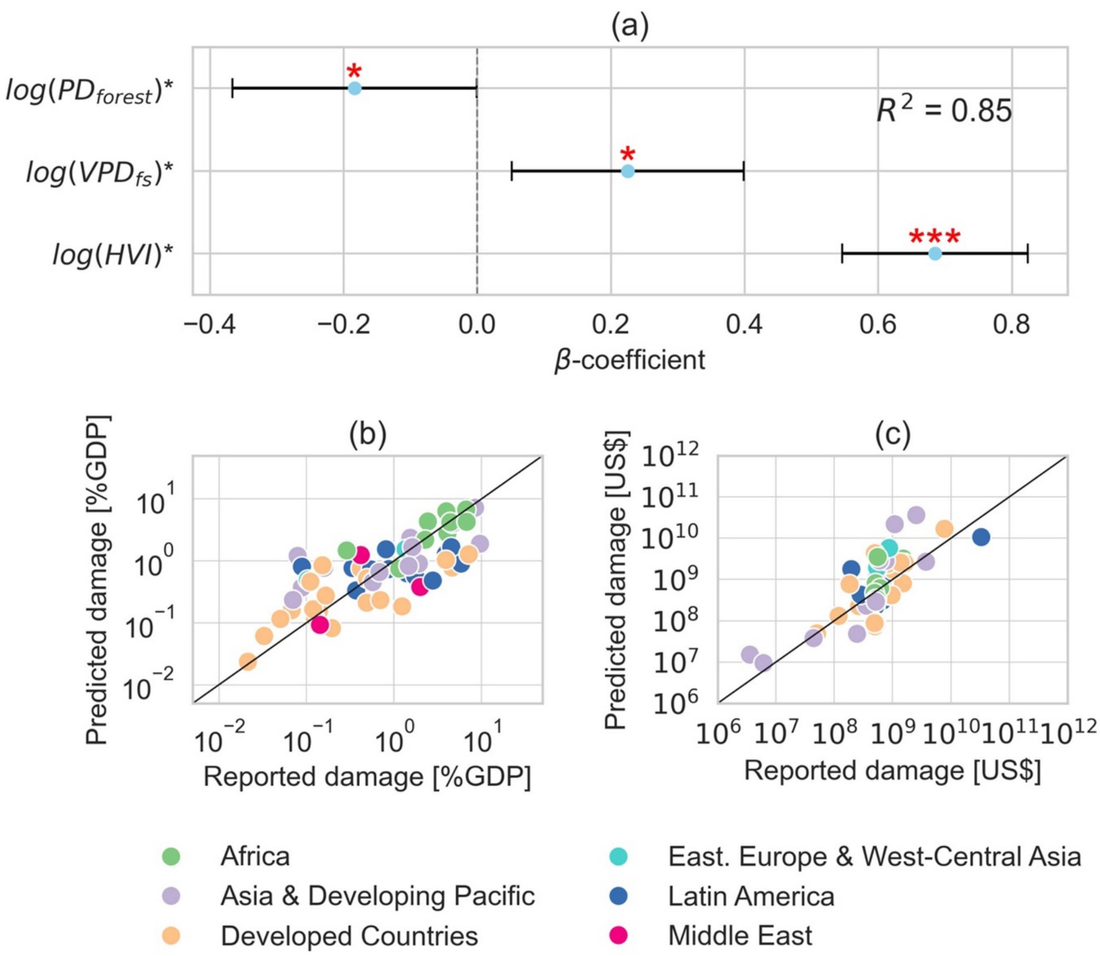

Figure 3. (a) Standardized beta coefficients of the fitted linear regression model using GDP-normalized wildfire damages (%GDP) as the outcome variable. Error bars indicate the lower and upper bounds of the 95% confidence interval. Asterisks indicate p-values: *** signifies $p < 0.001$, * signifies $p < 0.05$. Scatterplots of reported (EM-DAT) against model-estimated damages are shown for (b) GDP-normalized damages, and (c) absolute damages in US$, calculated by multiplying the model-predicted %GDP by each country's respective GDP.

Table 1. GLM and bootstrap coefficient estimates.

					Bootstrap results ($n = 1{,}000$)			
	GLM fitted model results						95% confidence interval	
Predictor	β-coef.	Std. error	p-value	VIF	Mean β-coef.	SD	Lower	Upper
$\log(\mathrm{VPD_{fs}})^*$	0.225	0.088	0.011	1.279	0.224	0.060	0.113	0.341
$\log(\mathrm{PD_{forest}})^*$	−0.184	0.093	0.048	1.288	−0.196	0.094	−0.389	−0.037
$\log(\mathrm{HVI})^*$	0.685	0.071	0.000	1.024	0.687	0.048	0.584	0.775

3.3. Projection of future wildfire damage

3.3.1. Trends in predictor evolution

Future projections of the three predictors exhibit distinct variations between the SSP scenarios. Globally averaged (figure 4), $\mathrm{VPD_{fs}}$ generally increases, with only minor differences between the scenarios until 2040. Beyond 2040, the trajectories diverge significantly, decreasing under SSP126 while increasing under SSP245 and SSP370. The differences between SSP126 and the two other scenarios (SSP245 and SSP370) become statistically significant at the 95% confidence interval by 2070, indicating that the projected changes under a sustainable pathway diverge significantly from those under more intermediate and high-emission scenarios. This indicates the effectiveness of robust climate mitigation policies under SSP126, which successfully maintain global warming at low levels. $\mathrm{PD_{forest}}$ generally grows until 2050 across all scenarios. After 2050, $\mathrm{PD_{forest}}$ growth declines under SSP126, decelerates under SSP245 and continues its growing trajectory under SSP370. Given the negative association between $\mathrm{PD_{forest}}$ and wildfire damage, higher populations under SSP370 would have a beneficial—albeit minor, given its small coefficient—impact on reducing wildfire

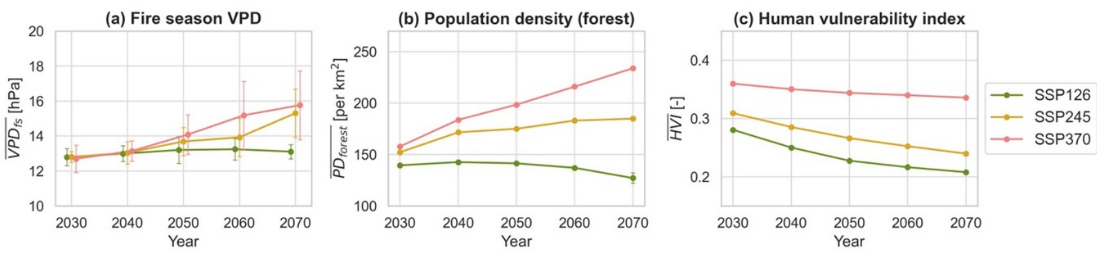

Figure 4. Time-series of the SSP projections (global means) of the predictors used in this study. Error bars represent the 95% confidence intervals, accounting for inter-model variability in the projections across different ESMs. The narrow error bars for (b) PD_{forest} indicate that the uncertainty in this predictor arises primarily from SSP population changes, which have no inter-model variation, rather than from differences in the forest cover projections across the ESMs. For (c) HVI, no error bars are shown because the projections do not come from ESMs.

damages. HVI declines across all SSPs, indicating improving socioeconomic conditions globally. However, the differences among SSPs become increasingly pronounced over time, resulting in a dramatic divergence in future damage projections across the scenarios, given that HVI is the most important predictor.

Figure 5 illustrates regional variations of the three predictors across the three SSP scenarios. Across all scenarios, VPD_{fs} increases in all regions, with particularly strong rises in North America, the Mediterranean, parts of Africa, and Australia, consistent with previous studies linking VPD increases to warming and drying trends. The magnitude of VPD_{fs} changes is generally consistent with findings of previous studies (Cook *et al* 2021, Chen *et al* 2024). VPD_{fs} rise intensifies with SSP370, especially in semi-arid and temperate regions, aligning with projections that warmer temperatures and declining relative humidity drive higher VPD levels under climate change (Ficklin and Novick 2017, Williams *et al* 2019). The trends in PD_{forest} are more nuanced, but generally align with the broader SSP population patterns in our dataset (figure S4). PD_{forest} tends to increase in regions with high projected population growth, such as Africa and parts of Asia (with the notable exception of China, where a population decline is expected). Under SSP370, high population growth coupled with forest loss drives the increase in PD_{forest} for large parts of the world, while under SSP126, slower population growth and stronger forest conservation stabilize or reduce PD_{forest}, especially for Europe, North America, and parts of South America. The trends in pop_{wui} largely follow similar patterns (figure S5). For HVI, most regions in the world—particularly in Africa, South America, and Asia—see a significant decrease in the vulnerability under SSP126, reflecting improved socioeconomic conditions. In contrast, under SSP370, socioeconomic improvements are slower across most regions, with the USA and parts of Africa even experiencing a slight increase in vulnerability.

3.3.2. Future wildfire damages

Figure 6 shows the projected global mean damages and a regional breakdown of these damages under the three SSPs (maps depicting the spatial distribution of these damages are shown in figure S6). Owing to improving socioeconomic developments, projected global wildfire damages are expected to decrease from 2030 to 2070. Damages are generally higher under SSP370 compared to SSP126. Our model predicts a global mean wildfire damage of 1.04%GDP under SSP126 and 1.75%GDP under SSP370 in 2030. This disparity widens significantly by 2070, with projected mean damages of 0.53%GDP under SSP126 and 1.64%GDP under SSP370, indicating that damages under SSP370 are three times greater than those under SSP126. The alternative model using pop_{wui} instead of PD_{forest} yields similar results (figure S7).

Our analyses suggest that following a sustainable pathway (SSP126) not only reduces wildfire damages but also ensures a more even distribution of damages globally (figures 6(a), (d) and (g)). This is primarily due to the reduced disparity in HVI between countries under SSP126, driven mainly by improving socioeconomic development amongst less developed countries (figure S8(c) in the supplementary information). Together, the strong socioeconomic development HVI and reduced climate hazards (VPD_{fs}) under SSP126 outweigh the increased wildfire damage associated with population decline (PD_{forest}). The focus of SSP126 on reducing inequality further results in a more equitable distribution of damages worldwide. Greater inequality may undermine the adaptive capacities of vulnerable communities, which are often located in rural forested areas (Commins 2004), potentially impairing their ability to effectively manage and combat wildfires.

We note that the projected damages are likely underestimated because our model does not fully explain the variability in historical wildfire damage nor does it sample the entire range of predictor values. Additionally, studies have shown a nonlinear relationship between VPD and fire activity (Williams *et al* 2019, Balch *et al* 2022). Given that both the mean and SD of VPD are projected to rise with climate change (Brey

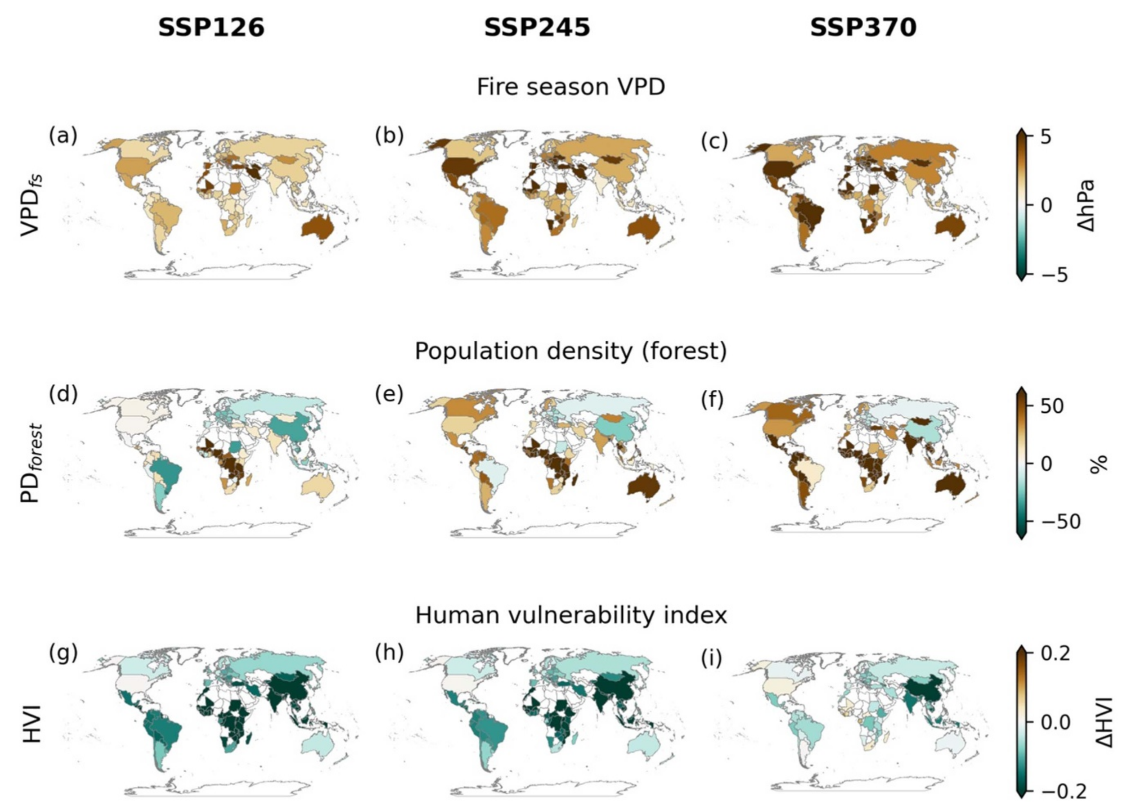

Figure 5. Maps showing changes in (a)–(c) VPD$_{fs}$, (d)–(f) PD$_{forest}$ and (g)–(i) HVI under the three SSPs. Changes are calculated as the differences between historical and future means for each SSP, averaged across the five ESMs for VPD$_{fs}$ and PD$_{forest}$. Historical periods are 1990–2000 for VPD$_{fs}$ and HVI, 2010–2020 for PD$_{forest}$; future periods are 2060–2070 for all predictors.

et al 2021), the impact of climate on wildfires is expected to increase exponentially. However, Quilcaille *et al* (2023b) shows that the Canadian FWI—a frequently used proxy for fire weather—can be parameterized with a linear relationship to global mean temperature in most regions in the world, and the FWI has been shown to correlate linearly with burned areas (Bedia *et al* 2015, Abatzoglou *et al* 2018). While these studies focused on burned areas rather than wildfire damages, they highlight the complex relationship between climate and wildfires. We recognize the importance of exploring both linear and nonlinear models to better capture the true relationship between climate and wildfire damages. However, for the sake of simplicity and interpretability, and limited by the availability of wildfire damage data, we have chosen to apply a linear model. Nevertheless, preliminary results suggest that accounting for the nonlinear effects of VPD$_{fs}$ would likely lead to higher damages than our model predicts (figure S1).

3.3.3. Predictor contributions to projected wildfire damages

To quantify the risk arising from individual predictors, we compare projected wildfire damages under scenarios where only one predictor changes while the others remain fixed at their historical values (figure 7). Under all three SSPs, damage trajectories with all predictors included closely follow those where only HVI changes, showing a downward trend. This again highlights the importance of socioeconomic development, which, under SSP126 and SSP245, is sufficient to offset the impact of worsening climate (VPD$_{fs}$). The VPD$_{fs}$-only projected damages (green curves) vary across the three scenarios: they stabilize under SSP126, grow slowly under SSP245, and increase more rapidly under SSP370. These results echo findings of projected burned areas under various SSP scenarios (e.g. Zhang *et al* 2024). Notably, the highest damage projections for all three SSPs occur when only VPD$_{fs}$ changes (green curves), indicating that climate hazard will have an outsized impact if socioeconomic development stagnates. Under SSP370, trends differ markedly from SSP126 and SSP245. Until 2040, the ability of socioeconomic developments (red curve) to offset the negative climate impact remains uncertain, owing to the sluggish pace of HVI reduction. Although the improvement in HVI after 2040 overcomes the negative climate impact, the difference between VPD$_{fs}$-only and HVI-only scenarios (red and green curves in figure 7(c)), while statistically significant at the 95% confidence interval, is much smaller than in SSP126 and SSP245. SSP370 is also the only pathway where PD$_{forest}$ growth alone results in the lowest damages (due to the negative association between PD$_{forest}$ and wildfire damage) compared to the VPD$_{fs}$-only and HVI-only scenarios (blue curve in figure 7(c)). This result underscores not

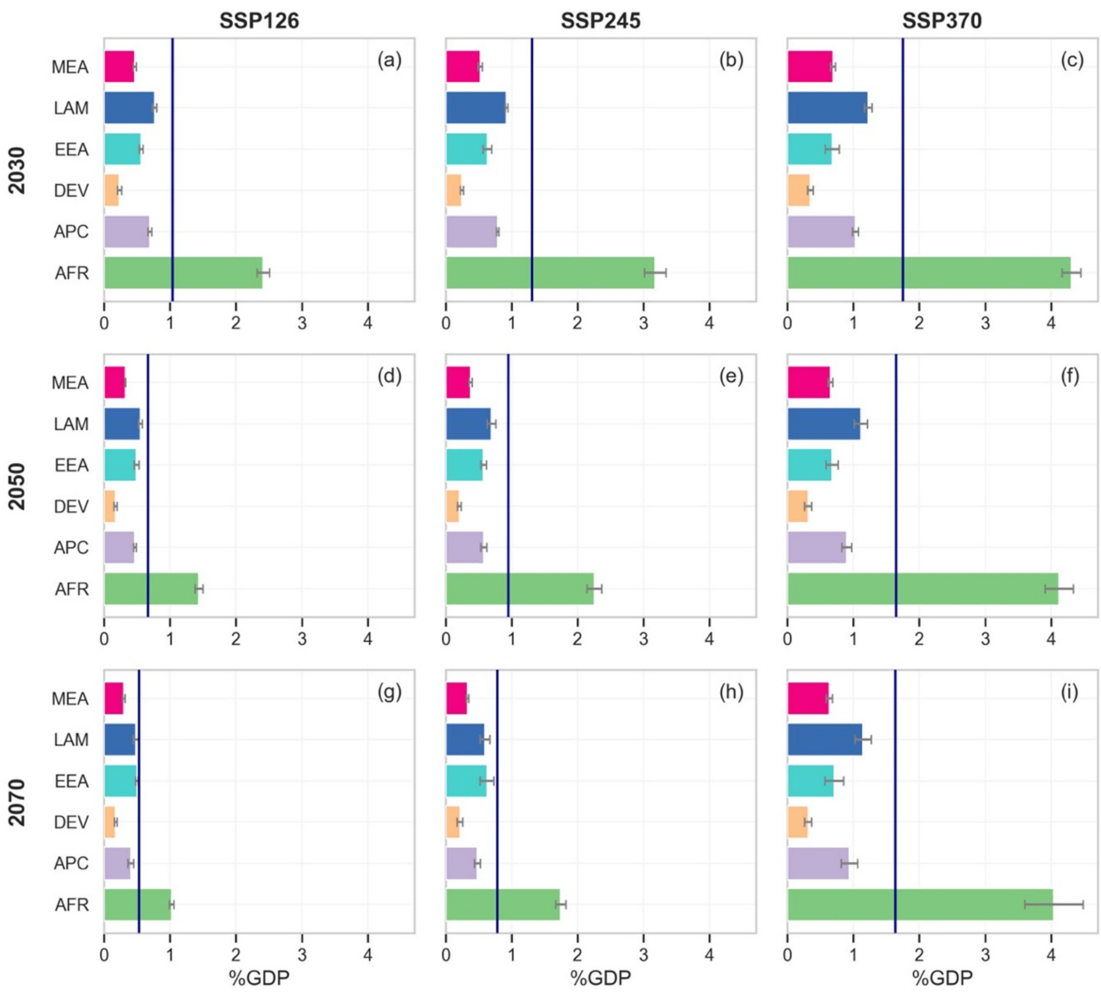

Figure 6. Mean projected wildfire damages under three SSP scenarios and for the six IPCC AR6 regions. Error bars represent the 95% confidence intervals of the mean damage projections, accounting for uncertainties in the estimates due to inter-model variability across the ESMs. Dark blue vertical lines indicate global means. The region labels are as follows: AFR (Africa), APC (Asia and Developing Pacific), DEV (Developed Countries), EEA (Eastern Europe and West-Central Asia), LAM (Latin America and the Caribbean), and MEA (Middle East).

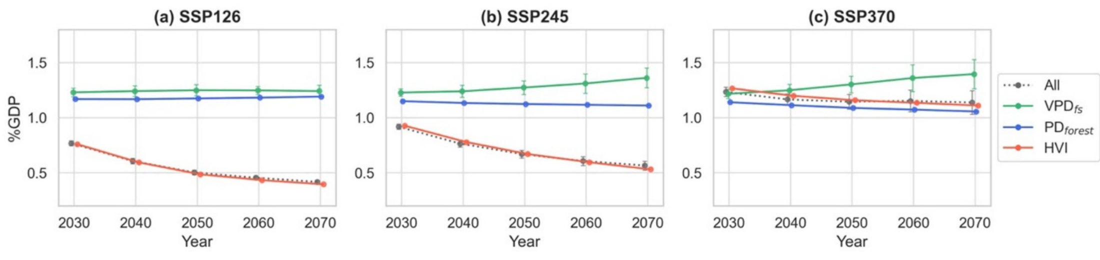

Figure 7. Comparison of global mean projected wildfire damage with all predictors changing (All), and only one predictor changing (VPD_{fs}, PD_{forest}, or HVI) while the other two remain at their historical mean values. Error bars represent the 95% confidence interval of the mean damage projections, accounting for uncertainties from the spread in projections across the ESMs. Since ESM projection uncertainty primarily affects the VPD_{fs} predictor, error bars are not shown for the HVI and PD_{forest} curves. Note that the mean values differ slightly from those in section 3.3.2 because this analysis is limited to countries in the training (historical) dataset.

the benefits of population growth under SSP370 but rather the risks posed by inadequate socioeconomic growth combined with worsening climate in a fragmented world.

3.3.4. What do countries stand to gain by following a sustainable pathway?

To assess what countries can gain from pursuing a sustainable path, we present the damage difference between SSP370 and SSP126 in figure 8, shown both as percentage of GDP (%GDP, top row) and as a

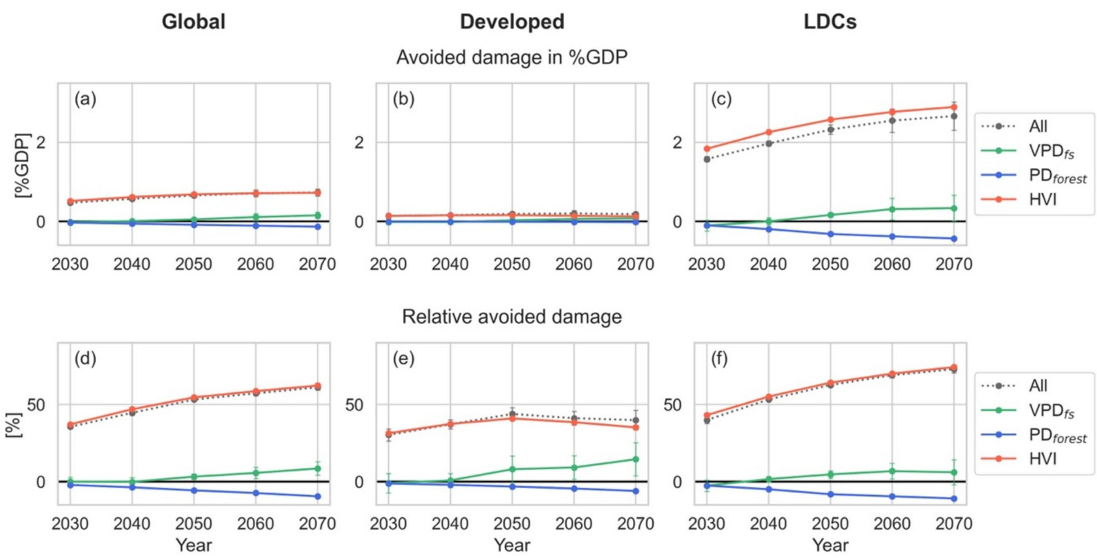

Figure 8. Mean avoided wildfire damages under SSP126 compared to SSP370. Top row shows projected damages (%GDP) in SSP370 minus those in SSP126. Bottom row shows relative avoided damages, calculated as absolute damages in SSP370 minus those in SSP126 and expressed as a percentage of SSP370 absolute damages. Absolute damages (US$) are calculated by multiplying projected %GDP by projected GDP. Results are shown for (a) and (d) all, (b) and (e) developed, and (c) and (f) least-developed countries (LDCs), based on IPCC AR6 developmental classifications. Each panel shows contributions from all predictors combined (dotted black line) and from individual predictors (VPD$_{fs}$, PD$_{forest}$, HVI). Error bars represent the 95% confidence intervals across ESMs. As ESM projection uncertainty primarily affects the VPD$_{fs}$ predictor, error bars are not shown for the HVI and PD$_{forest}$ curves.

percentage of absolute damages under SSP370 (bottom row). The latter metric directly answers the question: what percentage of SSP370 damages are avoided under SSP126? Globally, following SSP126 generally leads to reduced damages (figures 8(a) and (d)), except in the PD$_{forest}$-only scenario (blue curves) where higher population growth under SSP370 is advantageous due to the negative correlation between population and wildfire damages. However, this trend is less pronounced for developed countries, where population growth is weak or declining. Our analysis hence indicates that adopting a sustainable pathway may attenuate wildfire risks by (1) fostering stronger and more equitable socioeconomic development (red curves) and (2) enacting environmental policies that improve climate conditions (green curves).

For developed countries, SSP126 offers modest damage reductions of approximately 0.2%GDP by 2070 (figure 8(b)), though this represents a substantial relative reduction of about 40% compared to SSP370 damages (figure 8(e)). Though HVI remains the primary contributor of avoided damages, the increasing impact of climate hazard could potentially become the dominant driver of wildfire damages by century's end if socioeconomic conditions (red curve) remain stable at their current high levels while climate conditions continue to worsen (growing green curve in figure 8(e)). Least-developed countries (LDCs)—which face disproportionate exposure to anthropogenic climate change (Schleussner *et al* 2016, King and Harrington 2018, IPCC 2022)—stand to gain significantly more from following a sustainable development pathway by 2070. In relative GDP terms, their potential avoided damages exceed those of developed countries by more than a factor of ten, reaching over 2%GDP compared to just 0.2%GDP in developed nations (figure 8(c)). Similarly, relative avoided damages amount to approximately 73% of SSP370 damages in LDCs, compared to 40% in developed countries (figure 8(f)). Socioeconomic conditions again represent the primary driver of these avoided damages, which—unlike the relatively stable trends in developed countries—continue to improve in LDCs (red curves in figures 8(c) and (f)).

Overall, the picture that emerges attests to the significant advantages of adopting a sustainable pathway in mitigating the economic impact of wildfires. Strong socioeconomic development under SSP126 (Cuaresma and Lutz 2015) is envisioned to alleviate adaptation constraints to climate change, which the IPCC AR6 defines as 'factors that make it harder to plan and implement adaptation actions' (IPCC 2022). This is reflected by the HVI factor, which represents the vulnerability component of wildfire risk evaluation in our model and likely also captures the effects of institutional and regulatory mechanisms (HVI is highly correlated with other governance indices). Further, robust environmental policies under SSP126 improve overall climate conditions, which also help reduce wildfire damages (indicated by VPD$_{fs}$). For LDCs especially, prioritizing development practices that balance economic growth with ecological conservation is crucial, as these countries stand to gain the most—both in absolute and relative terms—from the reduced damages and enhanced resilience achieved under sustainable pathways.

4. Conclusions

We apply regression analyses to identify key factors influencing global (country-level) wildfire damages and use the fitted model to project future damages under three SSP scenarios. Our findings lead to three main conclusions.

First, our analyses indicate that the socioeconomic factor, measured by a HVI, is the strongest predictor of historical wildfire damages, followed by the climate factor (fire season VPD), and population density around forested areas (PD_{forest}). This differs from predictions of burned areas, where climatological factors have been found to be more important. Robust socioeconomic conditions may enable countries to develop and deploy effective management and adaptation strategies, design innovative and damage-efficient solutions to combat wildfires, which could ultimately reduce their damages. Conversely, stagnating socioeconomic conditions potentially deepen vulnerability by impeding the flow of resources and human capital needed to address wildfire damages.

Second, results suggest that following a sustainable pathway (SSP126) not only reduces wildfire damages but also results in a more balanced damage distribution across countries. Our model projects that global mean wildfire damages will be three times higher under SSP370 than SSP126 by 2070. By emphasizing international cooperation over regional rivalry, countries following SSP126 could collectively achieve higher socioeconomic development, which may help mitigate the damages of wildfires. Additionally, global adherence to climate targets under SSP126 improves climate conditions and promotes equitable socioeconomic development, possibly narrowing inequality that can heighten climate vulnerabilities. This aligns with the fulfillment of the Sustainable Development Goal 10, which aims to reduce inequalities within and among countries (UN General Assembly 2015).

Third, our results imply that robust socioeconomic development can offset wildfire damages attributable to climate hazards, but this outcome is not guaranteed under a regional rivalry scenario (SSP370). Negative climate impact can hinder socioeconomic progress, and vice versa (Hallegatte *et al* 2016, Thomas and Benjamin 2018, Tol 2018). SSP126's dual emphasis on societal welfare and environmental protection fosters a virtuous cycle that improves both areas. Our findings indicate that sustainable development can enhance the resilience of less developed countries—which often bear the brunt of climate change—leading to substantial savings in wildfire damages. While developed countries may see limited damage reductions from socioeconomic factors due to their already low HVI scores, they still benefit from SSP126's positive climate effects.

Our study has several limitations. Using a statistical model to predict future wildfire damages assumes that relationships between damages and predictors remain constant, which may not hold true, especially as adaptation strategies and climate conditions evolve (Higuera *et al* 2015, Littell *et al* 2016). Due to limited data on wildfire damages, we did not account for possible nonlinear relationships between the predictors and wildfire damages, apart from a preliminary exploration of nonlinear effects. This potentially limits the reliability and predictive power of our model. Striking a balance between avoiding overfitting and ensuring a robust representation of the factors influencing wildfire damages is a challenging task and should be a priority of future studies. While weighting underrepresented regions during model fitting partially mitigates representation bias, the generalizability of our fitted model remains constrained by the small sample sizes in least-developed countries, which may yield less reliable coefficient estimates for these countries. Our use of cross-sectional analyses helps mitigate data sparsity by averaging wildfire damage values across years, but it introduces a risk of omitted variable bias—particularly from unobserved time-varying factors such as policy changes—and prevents us from modeling within-country temporal trends, such as decadal shifts in climate. As a result, the analysis may overemphasize differences between countries while overlooking important dynamics over time. We also note that while our analysis based on the ISIMIP model ensemble provides internally consistent projections, future work incorporating the full suite of CMIP6 models and large-ensemble simulations would enable a more comprehensive assessment of the range of uncertainties associated with wildfire damage projections. The exclusion of climate feedback in the SSP framework could potentially also bias our estimations of future risks. For example, socioeconomic improvements are projected even under SSP370 (figure 4(c)), when in reality worsening climate conditions could stall or even reverse this trend. Therefore, our model projections should be viewed as useful benchmarks to assess comparative trends rather than exact wildfire damage predictions. Nonetheless, our study offers a novel contribution by applying well-established empirical methods to the relatively under-explored topic of the economic damage of wildfires, providing new insights into wildfire risks beyond just burned areas.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://doi.org/10.5281/zenodo.15409324 (Hwong *et al* 2025).

Acknowledgment

We thank Marina Andrijevic, Giacomo Falchetta, Samuel Lüthi, Caroline Muller, Carl Schleussner, and Adriano Vinca for providing useful ideas and feedback for this work. YLH is supported by funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie Grant No. 101034413. EB, MW, and YQ are supported by the European Union's Horizon Europe research and innovation programme under Grant Agreement No. 101081369 (SPARCCLE). We also thank the two anonymous reviewers for providing helpful feedback that greatly improved this manuscript.

Conflict of interest

The authors of this manuscript have no conflicts of interests to declare.

Appendix. Unstandardized regression equation

Here we outline the steps to convert the standardized form of the regression equation (equation (1)) into its unstandardized form. Assuming $\mu_{\log(\text{damage})}$ and $\sigma_{\log(\text{damage})}$ are the mean and SD of the log-transformed wildfire damage, the unstandardized log-transformed damage is:

$$\log(\text{damage}) = \sigma_{\log(\text{damage})} \cdot \left(\beta_0 + \beta_1 Z_{\log(\text{VPD}_{\text{fs}})} + \beta_2 Z_{\log(\text{PD}_{\text{forest}})} + \beta_3 Z_{\log(\text{HVI})} + \epsilon\right) + \mu_{\log(\text{damage})}. \quad \text{(A1)}$$

Reverting from logarithmic to the original scale:

$$\text{damage} = \mathrm{e}^{\left(\sigma_{\log(\text{damage})} \cdot \left(\beta_0 + \beta_1 Z_{\log(\text{VPD}_{\text{fs}})} + \beta_2 Z_{\log(\text{PD}_{\text{forest}})} + \beta_3 Z_{\log(\text{HVI})} + \epsilon\right) + \mu_{\log(\text{damage})}\right)}. \quad \text{(A2)}$$

Since $\mathrm{e}^{a+b} = \mathrm{e}^a \cdot \mathrm{e}^b$, equation (A2) can be rewritten as:

$$\text{damage} = \mathrm{e}^{\left(\sigma_{\log(\text{damage})}\beta_0\right)} \cdot \mathrm{e}^{\left(\sigma_{\log(\text{damage})}\beta_1 Z_{\log(\text{VPD}_{\text{fs}})}\right)} \cdot \mathrm{e}^{\left(\sigma_{\log(\text{damage})}\beta_2 Z_{\log(\text{PD}_{\text{forest}})}\right)} \cdot \mathrm{e}^{\left(\sigma_{\log(\text{damage})}\beta_3 Z_{\log(\text{HVI})}\right)} \cdot \mathrm{e}^{\left(\sigma_{\log(\text{damage})}\epsilon\right)} \cdot \mathrm{e}^{\mu_{\log(\text{damage})}}. \quad \text{(A3)}$$

Given $\beta_0 \approx 0$ when all predictors are standardized, the first term reduces to unity.

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