Don't rely too much on trees: Evidence from flood mitigation in China

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Abstract

Combining a popular flood disaster dataset with climate data and satellite land cover data from China, this paper estimates how forests mitigate the frequency of flooding, resulting in two major findings. First, we confirm that an increase in forest area mitigates the possibility of flood occurrence even after controlling for socioeconomic and meteorological variables and time-invariant individual effects. Second, broadleaf trees and mixed-tree forests have a flood mitigation effect, whereas coniferous trees do not; these results are robust against alternative model specifications. This paper newly corroborates the concept of ecosystem-based disaster risk reduction. While there is an emerging consensus that ecosystems can mitigate natural disasters, there is limited evidence on how ecosystems mitigate disasters. To the best of the authors' knowledge, this study is the first to show that the type of forest is critical for mitigating floods in a rigorous econometric way (survival analysis) spanning numerous areas of interest.

Keywords: flood mitigation, afforestation, forest type, China, remote sensing data, forest ecosystem service

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1 Introduction

Among all the types of natural disasters occurring worldwide, floods have occurred most frequently over the past couple of decades, accounting for 43% of all natural disasters recorded between 1998 and 2017, followed by storms and earthquakes (Wallemacq and House, 2018). During the same period, floods affected approximately two billion people and inflicted economic damage, reaching USD 656 billion. In 2018 alone, 34.2 million people were affected by flooding, and economic losses of USD 19.7 billion were incurred (CRED, 2019). Within the context of disaster risk reduction, the importance of natural ecosystems has gained considerable attention on a global scale. For example, the Millennium Ecosystem Assessment (MEA) emphasizes the use of the natural environment (e.g., mangroves, wetlands, and upland forests) as response options for flood and storm control instead of the physical structures and measures historically employed (e.g., dams and drainage channels) (MEA, 2005).

Moreover, the MEA highlights how these ecosystem services are linked to human well-being.[1] Therefore, by impacting environmental security, health, and livelihood, the degradation of ecosystem services negatively affects people's lives. In particular, the loss of forests leads to soil erosion and a

[1] Many recent studies found that forest ecosystems could affect rural livelihood (Costanza et al., 2014; Ickowitz et al., 2014; Yamamoto et al., 2019).

decrease in the capacity to retain water, thereby increasing the vulnerability of affected people and areas to floods and other natural hazards (Zong and Chen, 2000).

Over the years, China has suffered significant flooding. As a countermeasure intended to reduce flood risk, the country has dramatically increased its forest area by introducing the Grain for Green Program (GGP).[2] The GGP aims to transform steep farmlands into forests to reduce soil erosion and the risks of floods in the upper and middle reaches of the Yellow and Yangtze Rivers, constituting the world's largest payment for ecosystem services. Since the compensation scheme involves local farmers,[3] the GGP affects both the natural environment and local livelihood in several ways, including improving the livelihood of farmers (Rodríguez et al., 2016; Wu et al., 2019), protecting ecosystem services and forestland (Xu et al., 2018; Li et al., 2019; Qian et al., 2019; Fan and Xiao, 2020), decreasing water yield (Rodríguez et al., 2016; An et al., 2017; Wang et al., 2019), moderating soil erosion (Lu et al., 2013; Peng et al., 2019; Ye et al., 2019; Wu et al., 2019), and enhancing carbon stock (Song et al., 2015; Peng et al., 2019; Wu et al.,

[2]While deforestation remains an important issue throughout the world, China increased its forest area from 1.57 million hectares to 2.1 million hectares between 1990 and 2016 (FAO, 2018).

[3]Each farmer received CNY 300 (USD 43 as of November 2019) per hectare per year and in-kind compensation for 8 years (transformation to ecological forest), 5 years (to economic forest), or 2 years (to grassland) (Delang and Yuan, 2016). Thus, the total compensation payment reached CNY 78.44 billion (USD 11.26 billion) between 2002 and 2005 (Delang and Yuan, 2016).

2019).

This paper examines the effects of forest cover on flood frequency in China to confirm whether the recent promotion of forest area has contributed to the mitigation of flooding. Specifically, we focus on forest types to examine whether any particular type of forest can help mitigate the risk of floods. While there is an emerging consensus that ecosystems can mitigate natural disasters, there is limited evidence on how ecosystems mitigate flood occurrence. To the best of our knowledge, this study is the first to show that the forest type is critical for mitigating floods in a rigorous econometric way spanning numerous areas of interest. In this study, we applied survival analysis methods to investigate the effects of forest ecosystems on flood occurrence because floods can be assumed to be events occurring with a certain probability during periods. Our analysis also includes socioeconomic and meteorological characteristics as potential confounding factors that most likely affect the occurrence of floods

This study contributes to the literature on a debate among hydrological and forestry science on the role of forest ecosystems on flood mitigation.[4] One component of the literature has reported evidence of the effects of deforestation on the occurrence of floods and the corresponding damage

[4]We will discuss the hydrological mechanisms of how forests and floods are related in detail in Section 2.

caused by these events. Bradshaw et al. (2007) used cross-country panel data for 56 developing countries from 1990 to 2000 to study the relationship between forest cover and flood frequency. Their statistical analyses demonstrated that the number of flood events was associated with forest-related factors, such as forest cover, natural forest loss, and nonnatural forest cover. By incorporating forest cover attributes into models, their study ultimately found that deforestation caused floods with an increased frequency. The effect of forest cover on flood mitigation is also supported by recent empirical work. Bhattacharjee and Behera (2017, 2018) examined whether forest cover can mitigate floods in India. Their investigations revealed that areas with more forest cover were associated with less flood-related damage and highlighted the ability of forests to weaken the adverse impact of climate change incurred by extreme weather events (Bhattacharjee and Behera, 2018). In the study analyzing the impact of public policies on the occurrence of natural disasters in Brazil, Sant'Anna (2018) found that while extreme rainfall increased the frequencies of floods and landslides, negative impacts were mitigated in areas with relatively high forest cover.

While the above studies showed that forest cover can have a significant mitigating effect on flood events, others found that this conclusion does not hold (Van Dijk et al., 2009; Ferreira and Ghimire, 2012; Ferreira et al., 2013). In fact, the relationship between forests and floods is a much debated topic insomuch that the roles of forest cover in preventing floods are questioned (CIFOR, 2005). Van Dijk et al. (2009) reanalyzed the work performed by Bradshaw et al. (2007) and argued that the results of the latter are inconclusive when socioeconomic factors are not considered in the estimation; after considering the impact of population density, they found no correlation between forest cover or forest loss and the frequency of floods. The study by Bradshaw et al. (2007) was similarly challenged by Ferreira and Ghimire (2012), who found an insignificant impact of forest cover when the estimation considered other socioeconomic and institutional characteristics. They argued that these factors may be more important than deforestation as determinants of human-induced floods.

Indeed, deforestation is not the only way by which humans can impact floods. The consensus in the literature on the economic impacts of natural disasters is that the extent of disaster-related damage is associated with countries' income levels (Kahn, 2005; Noy, 2009; Kellenberg and Mobarak, 2008; Ferreira et al., 2013). In addition to income, other socioeconomic factors that most likely affect the frequency of floods and flood-induced damage include a variety of demographic and institutional factors, e.g., population, urbanization, corruption, and democracy levels (Kahn, 2005; Güneralp et al., 2015; Ferreira and Ghimire, 2012). Furthermore, geographical and meteorological characteristics are considered to be important factors that affect flood occurrence (Zong and Chen, 2000; Sant'Anna, 2018). It is also widely recognized that flood occurrence is affected by land degradation and soil erosion resulting from land use change (Zong and Chen, 2000; Bradshaw et al., 2007). Hence, in addition to forest cover, these factors should be considered when further analyzing the roles forests play in mitigating floods.

Moreover, many investigations have linked natural disasters to land use and land cover (Yin and Li, 2001; Van Westen et al., 2008; Van Dijk et al., 2009; Tan-Soo et al., 2016; Wells et al., 2016). To explore these relationships, researchers often apply spatial data to natural hazards and land use and land cover (Bradshaw et al., 2007; Van Dijk et al., 2009; Wells et al., 2016). For instance, Wells et al. (2016) incorporated interview surveys and newspaper articles to spatially analyze whether flood frequency is related to land use in Indonesian Borneo. Their results suggested that the frequency of floods tends to decrease in areas with more logged and intact forests and increase in areas with more extensive oil palm plantations.

This study aims to clarify the hypothesis that the existence of forest cover mitigates flood frequency and the mitigation effects differ by forest type. In this sense, our work is also related to ecosystem-based disaster risk reduction (Eco-DRR) or natural-based solutions because forests provide various ecosystem services that reduce hydrological risks, land degradation, and climatic risks (Keesstra et al., 2018; Albert et al., 2019; Calliari et al., 2019; Dorst et al., 2019).

2 The role of forests in water yield

The hydrological impacts of forests have been debated by researchers in the fields of forestry science and hydrology for almost a century (Bruijnzeel, 2004). On the one hand, Gentry and Lopez-Parodi (1980) found that the frequency of floods in the Amazon increased due to increased runoff caused by deforestation, although precipitation patterns remained unchanged. On the other hand, Hewlett (1982) observed that the existence of forests did not influence the quantity of water flow. Ultimately, Ferreira et al. (2013) concluded that it was difficult to identify whether forest cover was the sole factor affecting flood occurrence because forest cover changes and socioeconomic conditions both affect the frequency of flooding.

More recently, however, it has been acknowledged that the existence of forests or vegetation can contribute to the mitigation of flood risk. Bosch and Hewlett (1982) highlighted that an increase in forest cover can decrease streamflow, while enhanced deforestation leads to an increase in streamflow. Ogden et al. (2013) found that forests reduced the amount of runoff water during the heavy rainy season in Panama, while forests increased the runoff rate during the dry season. Wang et al. (2019) found that forests decreased the water yield in China and attributed this phenomenon to the increased water conservation capacity in afforestation areas. Andréassian (2004) reviewed hydrological studies that conducted experiments with paired watersheds and discovered that deforestation can increase the flood volume and flood peak; in contrast, reforestation is associated with a decreased water yield. Filoso et al. (2017) summarized 308 case studies while focusing on the hydrological impacts of reforestation and mostly found that increasing the extent of forest cover can decrease the water yield. Ellison et al. (2017) revealed that some functions of forests play significant roles in mitigating the occurrence and intensity of floods; for example, forests can disperse water by intercepting and recycling precipitation, promoting upward moisture fluxes, and recharging infiltration and groundwater.

In addition, some researchers have discovered that different types of vegetation have varying hydrological effects. Tan-Soo et al. (2016) reported that the conversion of forests into plantations (such as oil palm plantations) led to an increased likelihood of flooding in Malaysia, and Swank and Douglass (1974) observed that the clearing of coniferous forest increased the water yield in the study area more than the clearing of broadleaf forest. However, Brown et al. (2005) noted that the impacts of forest changes on water yield should be quantified based on long-term analyses and found that the effects varied according to the types of vegetation and land use. In this context, Komatsu et al. (2007) demonstrated that broadleaf forest had a greater potential to decrease the water yield in Japan than coniferous forest.

Considering the findings of the above literature, the types of vegetation, meteorological conditions, and socioeconomic factors must be considered to investigate the hydrological impacts of forests.

3 Research design

To investigate the relationship between forest cover and flood occurrence in China (focusing particularly on forest types), we employ survival (duration) analysis.[5] Our analyses are conducted at the subdistrict level from 2001 to 2018 considering the availability of relevant data. The flowchart of our estimation procedure is given in Figure 1. In section 3.1, we introduce our dataset, and in section 3.2, we show the empirical framework employed herein. QGIS 2.14.12 and Stata 14.2 were used to conduct the geographical and statistical analyses.

3.1 *Data*

The forest cover data we employ were obtained from satellite observations provided by Sulla-Menashe et al. (2019). This dataset has been updated

[5] The survival analysis treats time as a continuous variable and can be applied to investigate the repeated and sequential occurrence of events.

and is currently available for the period from 2001 to 2018. The dataset comprises global land cover grids with dimensions of 0.05×0.05 degrees based on the International Geosphere-Biosphere Programme (IGBP) classification. In particular, a pixel dominated by woody vegetation (covering over 60% of the pixel) with a tree height higher than 2 m is reported as forest. Based on an identification strategy of observing trees during an annual cycle of leaf-on and leaf-off periods, the dataset provides five forest type classifications: evergreen coniferous, evergreen broadleaf, deciduous coniferous, deciduous broadleaf, and mixed forest.[6]

The forest area in China has increased over the last two decades. The broadleaf forest area increased from 4.20 million km^2 in 2001 to 5.04 million km^2 in 2017; the coniferous forest area increased from 0.76 million km^2 to 1.22 million km^2; and the mixed forest area increased from 15.31 million km^2 to 17.77 million km^2 in the same period (Sulla-Menashe et al., 2019).[7]

To investigate the effect of each forest type on flood occurrence, we aggregate and recategorize pixels based on broadleaf, coniferous, and mixed forests at the subdistrict level. Figure 2 shows the forest gain by forest type between 2001 and 2017. In particular, broadleaf forest accounts for a large part of the forest gain in northeastern and southern China. Similarly,

[6] Mixed forest consists of a mixture of various forest types.
[7] We aggregate and recategorize the forest type into broadleaf, coniferous, and mixed forest.

Figure 3 shows the change in the forest cover rate at the subdistrict level in China between 2001 and 2017. In terms of broadleaf forest, 68.4% of subdistricts experienced forest gain during the study period. Furthermore, a large proportion of subdistricts in northeastern, central, and southern China displayed a gain in forest cover during the study period. However, the forest cover did not change in most of the subdistricts in western China.[8]

The flood data were acquired from the Global Active Archive of Large Flood Events, Dartmouth Flood Observatory (Brakenridge, 2012). This dataset has recorded the occurrence of global floods since 1985.[9] Figure 4 shows the number of floods recorded in the database in China between 2001 and 2017. Evidently, the number of floods has decreased in China in recent years, whereas the frequency and severity of floods have increased worldwide (Najibi and Devineni, 2018; Wallemacq and House, 2018).

The weather data were obtained from the Climate Prediction Center's Global Unified Precipitation dataset provided by the National Oceanic and Atmospheric Administration.[10] This dataset reports global precipitation in

[8]There are few forest areas in the western regions corresponding to the definition that a forest that covers more than 60% of each pixel with a tree height higher than 2 m.

[9]The flood events presented in the Dartmouth Flood Observatory are derived from a variety of news, governmental sources, and remote sensing sources. The dataset provides the flood event data including the location, beginning and ending days, affected areas of flood occurrence as well as the severity of the flood as the indicator of the intensity of the floods. For a more detailed description of the floods in this dataset, see http://floodobservatory.colorado.edu/index.html.

[10]The data are available at https://www.esrl.noaa.gov/psd/.

grids of 0.05×0.05 degrees. Our precipitation data refer to the values that are geographically nearest to the center of the corresponding subdistrict. The demographic data were obtained from the National Bureau of Statistics of China.[11]

Table 1 presents the descriptive statistics of our sample.[12] Our dependent variable, *flood*, is a dummy variable that takes a value of one when the flood occurred in the considered subdistrict and zero otherwise, indicating that the probability of flood occurrence is 2.8% for all subdistricts between 2001 and 2017. Table 1 also reports the areas of forest cover at the subdistrict level based on the classification of broadleaf, coniferous, and mixed forest. Broadleaf and mixed forest account for a large portion of the observed forest cover, while coniferous forest covers a relatively small area in China. Regarding precipitation, the maximum daily precipitation in a year and the annual average precipitation are also reported in Table 1.

3.2 *Model*

We adopt survival analysis with both parametric and semiparametric models to investigate the effects of forest resources on flood occurrence. For the

[11] See `http://data.stats.gov.cn/english/index.htm`.

[12] We aggregated the dataset to merge the information at the subdistrict level. Detailed information on the data source is summarized in Table S1 of supplemental material.

parametric analysis, we use the Weibull hazard function, denoted as

$$h(t|m) = \gamma m t^{m-1}, \tag{1}$$

where $\gamma > 0$ and $m > 0$ are parameters. It is common to allow $\gamma = \exp(x'\beta)$ to include regressors because this allowance guarantees that $\gamma > 0$. Thus, our hazard function is expressed as

$$h(t|x, m, \beta) = m t^{m-1} \exp(x'\beta), \tag{2}$$

where x represents the independent variables and β represents the parameters. The hazard ratio increases over time if $m > 1$, while it decreases monotonically if $m < 1$. The hazard rate is independent of time if $m = 1$.

To avoid the case in which the Weibull distribution does not provide a proper fit, we introduce a semiparametric model, called the Cox proportional hazard model. Instead of assuming the distribution of the data, the Cox model assumes that the hazard ratio is constant over time:

$$h(t|x, \beta) = h_0(t) \exp(x'\beta), \tag{3}$$

where $h_0(t)$ is the baseline hazard. Note that as long as the proportional hazard assumption is held, there is no need to know the actual distribution shape of $h_0(t)$.[13]

In the actual estimation, we extend the normal survival analysis approach in the following two aspects. First, we include time-varying covariates, while most survival analyses are based upon time-invariant covariates, such as gender. It is problematic to include time-varying variables because this approach usually destroys the exogeneity of covariates (Cameron and Trivedi, 2005). For instance, the unemployment period depends upon the job search strategy, but the job search strategy can be affected by the length of unemployment, while a variation such as seasonal cycle would have no feedback effect similar to this. Nevertheless, we believe our time-varying covariates are closer to the latter example and are sufficiently exogenous to use in the estimation. Second, as floods can be observed repeatedly, we apply a survival analysis of repeated events. Several methods can be utilized to incorporate recurrent events, but we adopt an Anderson-Gill-type recurrent event survival analysis.[14]

4 Results

In this section, we first show the overall results of how different types of forest contribute to mitigating flood occurrence using the Cox and Weibull models. We then conduct additional analyses by dividing the samples in

[13]The details of the model selection can be found in Cameron and Trivedi (2005).
[14]For more details, see Amorim and Cai (2015).

consideration of possible biases.

4.1 *Effects of forest cover on flood occurrence*

The results of the survival analysis are presented in Table 2.[15] We first show estimates for the Cox model. In Column 1, we explore the relationship between flood occurrence and each type of forest without controlling for regional demographic characteristics or precipitation levels. We then include these regional characteristics in the model in Column 2.[16] Finally, we include precipitation variables in the estimation model, as shown in Columns 3 and 4. Column 3 includes the annual average precipitation, while Column 4 includes the maximum daily precipitation. Columns 5 and 6 report the estimation results using models with the Weibull distribution corresponding to Columns 3 and 4, respectively.

The above results are further confirmed by estimating the parametric model with the assumption of a Weibull distribution. Columns 5 and 6 show the corresponding results, suggesting that broadleaf forest and mixed forest play roles in mitigating the frequency of floods. Comparing the coefficients of

[15] We also conducted similar analyses with the total forest area as an independent variable. Results similar to those of our main analyses (Table 2) were obtained. All specifications included subdistrict-fixed effects, which captured unobserved regional characteristics such as distance to the nearest river. To focus on our main objective (i.e., the effects of different forest types on flood occurrence), these results are shown in Table S2 of supplementary material.

[16] The regressions of models other than that in Column 1 of Table 2 include other land cover areas classified by the IGBP, such as grasslands, croplands, and barren land, in the subdistrict.

broadleaf forest and mixed forest, those of broadleaf forest were larger than those of mixed forest; this finding reiterates that broadleaf forest is more effective than other types of forest at mitigating the frequency of floods.

4.2 *Selection bias*

Our survival analyses suggest that an increase in forest area has an effect on flood mitigation (Table S2 of supplementary material), particularly increases in the areas of broadleaf forest and mixed forest (Table 2). However, since a gain in forest cover might not occur randomly, there is a possibility that our results suffer from a sample selection bias. For example, there is a possibility that gains in forest cover occurred only in subdistricts where the potential flood risk is low. Therefore, we test for biases by restricting the sample to areas that have a potential flood occurrence risk. Here, we apply only the Cox model, as the Weibull model shows similar results.

Table 3 shows the results. The test sample is composed of 107 subdistricts that experienced at least one flood during the study period. The coefficients for broadleaf and mixed forest were negative and statistically significant, while those for coniferous forest were not significant. These results support our findings in Table 2 that broadleaf forest and mixed forest have the potential to mitigate the occurrence of floods, and the broadleaf forest coefficients are similarly larger than the mixed forest coefficients.

4.3 *Heterogeneous effects*

Since the probability of flood occurrence increases in response to precipitation, there is a possibility that afforestation policies target high-precipitation areas for the planting of trees. In the case that the estimates suffer from unobserved bias, we test for such bias by dividing the subdistricts based on precipitation. We define high- and low-precipitation areas based on maximum daily rainfall above or below a precipitation threshold of 77 mm in a year. In other words, subdistricts that experienced daily rainfall above 77 mm (sample mean) are defined as high-precipitation areas. The explanatory variables are the same as those in our main analyses. Here, we apply only the Cox model, as the Weibull model shows similar results.

Table 4 shows the results for high-precipitation areas in Columns 1 and 2 and low-precipitation areas in Columns 3 and 4. The coefficients of broadleaf and mixed forests remained negative and statistically significant in every specification, suggesting that the hydrological effects of forests elucidated above are robust.

Similarly, there is a possibility that the flood mitigation effects are different depending on the climate. To test the heterogeneity effects among climates, we estimated the models by dividing the samples into two climate zones based on Li et al. (2013)'s definitions: tropical and monsoon areas and temperate and plateau areas (Figure S1 of supplementary material).[17] Columns 5–8 of Table 4 show the results.[18] The coefficients of *mixed forest* remain negative and statistically significant in every area. However, in temperate and plateau areas, the coefficients of *broadleaf forest* are negative but statistically insignificant. This finding suggests that the flood mitigation effects depend on the tree species and ecological characteristics.

4.4 *Different levels of severity*

In addition, there is a possibility that the tree cover effects on flood mitigation are heterogeneous depending on the intensity of floods because floods occur with multivariate processes. In fact, European Union (2007) emphasizes that a flood management plan should be based on information such as the potential size of the area affected and the depth and velocity of water because they are not independent. Using copula theory, Salvadori et al. (2016) showed the importance of the multivariate flood process in general, while Yin et al. (2018) assessed the implications of climate change in the Ganjiang River basin in China.

[17] Several areas are categorized as both monsoon and temperate. Our estimations include these mixed areas in both monsoon and temperate models. This approach has the advantage that our estimations would be more efficient in terms of sample size and degree of freedom.

[18] As the Cox model failed to achieve a convergence of the likelihood function, we apply the Weibull models.

We test for heterogeneity by applying the estimations to higher and lower intensities of flood events, which correspond to the severity classes reported in the flood dataset (Brakenridge, 2012). The severity of flood events was classified based on the flood recurrence interval: Class 1 includes large floods with reported intervals for one or two decades, and Class 2 includes extreme flood events with reported intervals greater than 100 years. The dependent variable takes the value of one if the flood is categorized as Class 2 for high-intensity estimation and Class 1 for low-intensity estimation. The explanatory variables are the same as those in our main analyses presented in Subsection 4.1. Similar to the estimations in Columns 5–8 of Table 4, the Cox model failed to achieve a convergence of the likelihood function; thus, we apply the Weibull model.

Table 5 shows the results for high-intensity flood events in Columns 1 and 2 and low-intensity flood events in Columns 3 and 4. The coefficients of the broadleaf and mixed forest had a significant negative impact on flood frequency. This finding suggests that the tree cover has mitigation effects on flood frequency, regardless of the flood intensity level.

5 Discussion

Our results are consistent with findings from previous literature on the flood mitigation effects of forest cover (Bradshaw et al., 2007; Bhattacharjee and

Behera, 2017, 2018). In addition, our results indicate that the effects on flood occurrences are different depending on the type of tree cover. Broadleaf and mixed forests have mitigation effects, while coniferous forest does not. This finding indicates that increases in the areas of broadleaf and mixed forest have the potential to mitigate the frequency of floods. Furthermore, the absolute values of the coefficients for broadleaf forest were slightly larger than those for mixed forest, suggesting that broadleaf forest is more effective than mixed forest at mitigating flood occurrence. However, increases in the area of coniferous forest are not associated with the mitigation of flood occurrence. Coniferous trees tend to have high market value due to their demand as home building materials. There may be an incentive to plant coniferous trees rather than broadleaf trees at the time of afforestation, as they have higher value when logging after a long time. This study shows that if policy makers make such decisions, they rely too much on trees.

Figures 5 helps clarify the effect of each forest type on flood occurrence. These figures illustrate the difference in forest effects between the areas with increasing and decreasing forest cover by forest type based on Nelson-Aalen cumulative hazard estimates. The results indicate that the probability of flood occurrence decreased in areas with increasing broadleaf and mixed forest cover, while this tendency was not observed for coniferous forest. These results are consistent with the findings in the field of forestry science, indicating that broadleaf forest contributes to the mitigation of underground water flow (Komatsu et al., 2007).

Other things being equal, the net precipitation (sum of throughfall and stemflow) through a forest is defined by gross precipitation minus total interception loss, which is the sum of canopy interception loss and litter interception loss. When the net precipitation per time reaching the ground exceeds a threshold, a flood occurs (Poorter, 2004). Broadleaf trees usually have more complex shapes and more leaves than coniferous trees. This characteristic enables broadleaf trees to capture more rain and reduce the peak level of net precipitation per time. Precipitation spending more time on leaves and stems increases evapotranspiration as well (Sato, 2007). Combining these two effects, broadleaf forests can reduce the possibility of exceeding the threshold. Broadleaf trees gather precipitation through stemflow, while coniferous trees tend to spread rainfall into relatively broader areas (Kume, 2007). Since soil near a tree is drier due to the consumption of water by the root of the tree, it helps to prevent too much runoff. In addition, changes in forest cover alter not only storm runoff but also base flow (mainly groundwater flow). Yin et al. (2018) discussed that deforestation can increase storm runoff but reduce base flow because the water-holding capacity of the soil decreases when the quality of the forest is degraded. Usually, broadleaf trees generate richer soil with more litter. This characteristic might be another advantage of broadleaf forest.

Columns 3 and 4 in Table 2 show the estimated results with the logarithms of the annual average and maximum daily precipitation, respectively, as the explanatory variables. The coefficients of precipitation indicate positive effects on the flood frequency. These results are intuitively reasonable and similar to the conclusions of previous analyses (see Section 2). Furthermore, the coefficients of GRP were significantly negative for all the models, meaning that increasing the economic level of a subdistrict has a flood mitigation effect.

Overall, our findings remain significant across various model specifications. Specifically, we confirmed that broadleaf trees and mixed-tree forests have effects on flood mitigation, regardless of the precipitation level, climate zones, and flood intensity. This finding suggests that the flood mitigation effects of forests are not particular to certain regions.

6 Conclusion

In this study, we examined the hydrological effects of forests on the mitigation of floods in China, focusing particularly on the effects of different forest types, by applying satellite data to forest and flood data. This study contributes to the literature by estimating how flood prevention effects differ by forest type by applying rigorous survival analysis using samples from the whole country of China. We found that, in accordance with recent hydrological and forestry research, forests moderated the occurrence of floods. We then evaluated the effects by dividing the forest areas by type and found that broadleaf forest and mixed forest contributed to flood prevention, while coniferous forest did not.

These results pose important policy implications for policymakers considering flood mitigation by promoting afforestation, which has recently received attention as Eco-DRR. While coniferous forests might not help prevent flooding, coniferous trees tend to be preferred in afforestation policy, as coniferous trees have economic value as wood resources for construction. For example, in the GGP, coniferous trees such as Chinese fir and Masson pine have been preferred (Zhou et al., 2007; Delang and Yuan, 2016). However, in terms of flood prevention, coniferous forests are not effective.

In addition, it is worth noting that forests have the potential to mitigate floods over broad areas by leveraging the functions of trees. For example, trees could moderate the yield of water in areas by capturing and recycling precipitation. Hence, considering the effects of forests as Eco-DRR solutions during conventional flood mitigation efforts, such as the construction of levees and dams, might be effective for flood management. These policy implications are applicable not only to China but also to other countries, as the mechanism of flood prevention by forest type can be applied to any country.

Finally, several limitations of this study should be mentioned. First, several landscape variations and subdistrict-level variables to control for flood occurrences were excluded from our estimates due to data limitations. Although our time-invariant fixed effects approach captured unobserved regional characteristics such as the distance to the nearest river, there was a possibility of bias due to other omitted variables. For example, we could not include regional investments in flood mitigation, such as the construction of levees and dams, because of the limited availability of data. Therefore, we cannot fully rule out the possibility of bias from unobserved explanatory characteristics on the mitigation of flood occurrence.

Second, while this study ascertained the hydrological effects of some forest types, we cannot clearly determine the mechanism underlying the mitigation of flood occurrence. As we discussed in Section 2, how forests mitigate flooding is complex and broadly debated in the fields of forestry science and hydrology. Further studies should attempt to address these issues to promote flood prevention by considering the functions of forests. Nevertheless, although these topics constitute areas of improvement, our study confirms that flood mitigation effects differ by forest type and that broadleaf and mixed forest types are particularly effective; moreover, these findings are robust to our various specifications.

Third, we cannot examine the detailed effects of different tree species and vegetation characteristics. The forest cover data we employed include broadleaf, coniferous, and mixed forest. Although there are a variety of tree species and ecological characteristics depending on climate properties, information on detailed tree species is not available. Future studies should attempt to address these issues.

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Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.
Flood	0.028	0.165	0	1
Broadleaf forest (thousand km^2)	1.337	3.495	0	28.778
Coniferous forest (thousand km^2)	0.315	1.327	0	23.243
Mixed forest (thousand km^2)	5.033	13.302	0	155.273
Maximum daily precipitation (mm)	77.355	39.933	0.194	355.831
Annual average precipitation (mm)	825.920	466.907	0.357	2731.924
GRP in the subdistrict (CNY 100 million)	16.069	16.511	0.139	89.705
Population	5328.138	2754.722	264	11169

Note: The number of observations is 5763.

Table 2: Survival analysis on flood occurrence (all samples).

	Cox model (1)	Cox model (2)	Cox model (3)	Cox model (4)	Weibull model (5)	Weibull model (6)
Broadleaf forest	-0.010^{*}	-0.044^{***}	-0.047^{***}	-0.045^{***}	-0.074^{***}	-0.072^{***}
	(0.005)	(0.011)	(0.012)	(0.011)	(0.018)	(0.017)
Coniferous forest	−0.004	0.000	−0.003	−0.003	0.011	0.008
	(0.019)	(0.017)	(0.018)	(0.018)	(0.022)	(0.020)
Mixed forest	-0.008^{*}	-0.042^{***}	-0.043^{***}	-0.042^{***}	-0.064^{***}	-0.063^{***}
	(0.005)	(0.009)	(0.009)	(0.010)	(0.015)	(0.014)
GRP (/1000)		-0.094^{***}	-0.091^{***}	-0.093^{***}	-0.184^{***}	-0.182^{***}
		(0.023)	(0.022)	(0.022)	(0.029)	(0.029)
Population		0.002^{***}	0.002^{***}	0.002^{***}	0.003^{***}	0.003^{***}
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln(*Annual average precipitation*)			2.198^{***}		1.590^{***}	
			(0.600)		(0.607)	
ln(*Maximum daily precipitation*)				0.562^{**}		0.670^{**}
				(0.277)		(0.275)
Observations	5763	5763	5763	5761	5761	5761
Log-likelihood	−833.673	−808.943	−800.318	−806.847	632.233	627.937
Wald chi-square	12568.099	72559.806	2314.732	11428.741		

Note: The dependent variable is flood occurrence.

Standard errors in parentheses are clustered at the subdistrict level.

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

All estimates include subdistrict-fixed effects.

All regressions in Columns 2–6 include other land cover areas classified by the IGBP, such as grasslands, croplands, and barren land in each subdistrict.

Table 3: Effects restricted to areas that experienced floods during the study period.

	(1)	(2)
Broadleaf forest	-2.111***	-2.012***
	(0.524)	(0.509)
Coniferous forest	-0.125	-0.112
	(0.783)	(0.804)
Mixed forest	-1.901***	-1.874***
	(0.418)	(0.427)
GRP (/1000)	-0.091***	-0.093***
	(0.022)	(0.022)
Population	0.002***	0.002***
	(0.001)	(0.001)
ln(*Annual average precipitation*)	2.198***	
	(0.602)	
ln(*Maximum daily precipitation*)		0.562**
		(0.278)
Observations	1819	1819
Log-likelihood	-800.318	-806.847
Wald chi-square	2299.880	11355.400

Note: The dependent variable is flood occurrence.

Standard errors in parentheses are clustered at the subdistrict level.

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

All estimates include subdistrict-fixed effects.

All regressions include other land cover areas classified by the IGBP, such as grasslands, croplands, and barren land in each subdistrict.

Table 4: Heterogeneous effects by dividing areas based on precipitation levels and climate zones.

	Precipitation levels				Climate zones			
	High-precipitation areas		Low-precipitation areas		Monsoon and tropical		Temperate and plateau	
	1	2	3	4	5	6	7	8
Broadleaf forest	−3.391**	−3.436**	−2.048**	−1.762*	−2.637***	−2.673***	−1.132	−1.006
	(1.620)	(1.423)	(0.994)	(1.028)	(0.776)	(0.747)	(1.252)	(1.099)
Coniferous forest	−1.124	−1.557	1.629	1.270	0.105	−0.124	−0.400	−2.374
	(2.068)	(2.078)	(1.719)	(2.011)	(1.048)	(1.004)	(11.568)	(10.642)
Mixed forest	−3.320**	−3.378**	−1.192***	−1.261**	−2.406***	−2.503***	−1.223**	−1.187**
	(1.568)	(1.403)	(0.456)	(0.541)	(0.726)	(0.712)	(0.546)	(0.541)
GRP (/1000)	−0.127***	−0.125***	−0.063	−0.065	−0.222***	−0.222***	−0.181*	−0.177
	(0.033)	(0.032)	(0.041)	(0.046)	(0.034)	(0.035)	(0.109)	(0.109)
Population	0.003***	0.002***	−0.002	−0.002	0.004***	0.004***	0.001	0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.004)	(0.004)
ln(*Annual average precipitation*)	2.280***		3.368***		2.041***		1.812*	
	(0.850)		(1.073)		(0.548)		(1.077)	
ln(*Maximum daily precipitation*)		1.340***		0.906		1.106***		1.833**
		(0.366)		(0.721)		(0.278)		(0.776)
Observations	2463	2463	3300	3300	4811	4810	2839	2839
Log-likelihood	−376.002	−376.110	−252.453	−257.655	552.236	551.717	158.379	161.169
Wald chi-square	1774.964	2483.771	2605.169	8558.731				

Note: The dependent variable is flood occurrence.

Standard errors in parentheses are clustered at the subdistrict level.

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

All estimates include subdistrict-fixed effects.

All regressions include other land cover areas classified by the IGBP, such as grasslands, croplands, and barren land in each subdistrict.

Estimates use models with the Cox distribution for Column 1–4 and Weibull distribution for Column 5–8.

Table 5: Effects on different levels of severity of floods.

	Higher intensity		Lower intensity	
	1	2	3	4
Broadleaf forest	-11.349^{**}	-11.513^{**}	-4.841^{***}	-4.396^{***}
	(4.957)	(5.265)	(1.540)	(1.566)
Coniferous forest	-10.739	-11.479	1.896	1.571
	(8.811)	(8.684)	(1.609)	(1.624)
Mixed forest	-11.764^{**}	-12.004^{**}	-3.251^{***}	-3.173^{***}
	(5.328)	(5.727)	(1.030)	(1.038)
GRP (/1000)	-0.287^{**}	-0.296^{**}	-0.343^{***}	-0.342^{***}
	(0.141)	(0.136)	(0.099)	(0.102)
Population	0.004	0.004^{*}	0.004^{***}	0.004^{***}
	(0.002)	(0.002)	(0.001)	(0.001)
ln(*Annual average precipitation*)	2.812^{*}		2.060^{***}	
	(1.567)		(0.644)	
ln(*Maximum daily precipitation*)		0.508		1.121^{***}
		(0.679)		(0.395)
Observations	5762	5760	5762	5760
Log-likelihood	93.457	91.552	390.643	390.412

Note: The dependent variables are flood occurrence, with higher severity corresponding to severity Class 2 in columns 1 and 2 and lower severity corresponding to severity Class 1 in columns 3 and 4.

Standard errors in parentheses are clustered at the subdistrict level.

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

All estimates include subdistrict-fixed effects.

All regressions include other land cover areas classified by the IGBP, such as grasslands, croplands, and barren land in each subdistrict.

All estimates use models with the Weibull distribution.

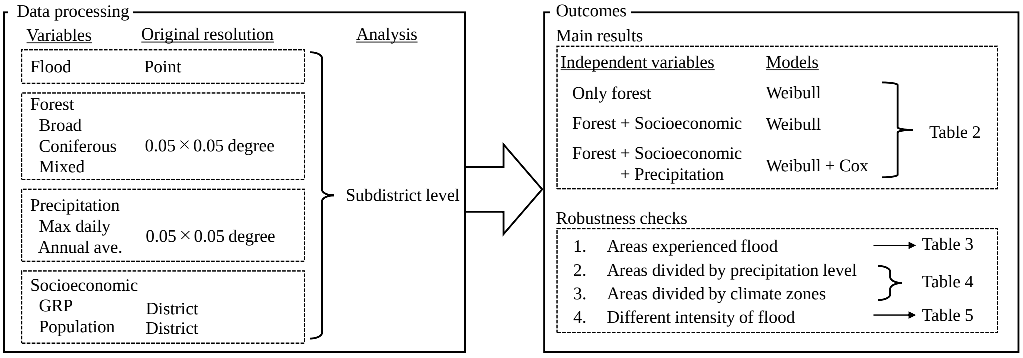

Figure 1: Flowchart of the estimation procedure.

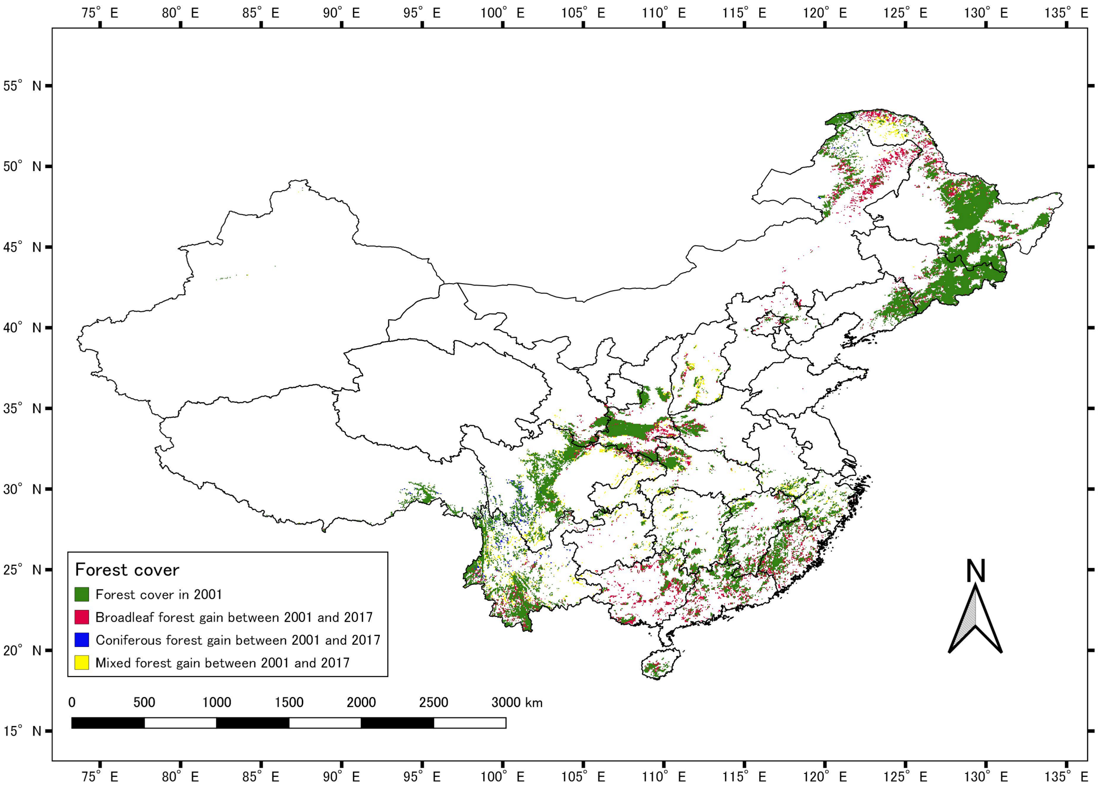

Figure 2: Forest cover and forest gain in China (grid base). *Source: Sulla-Menashe et al. (2019).*

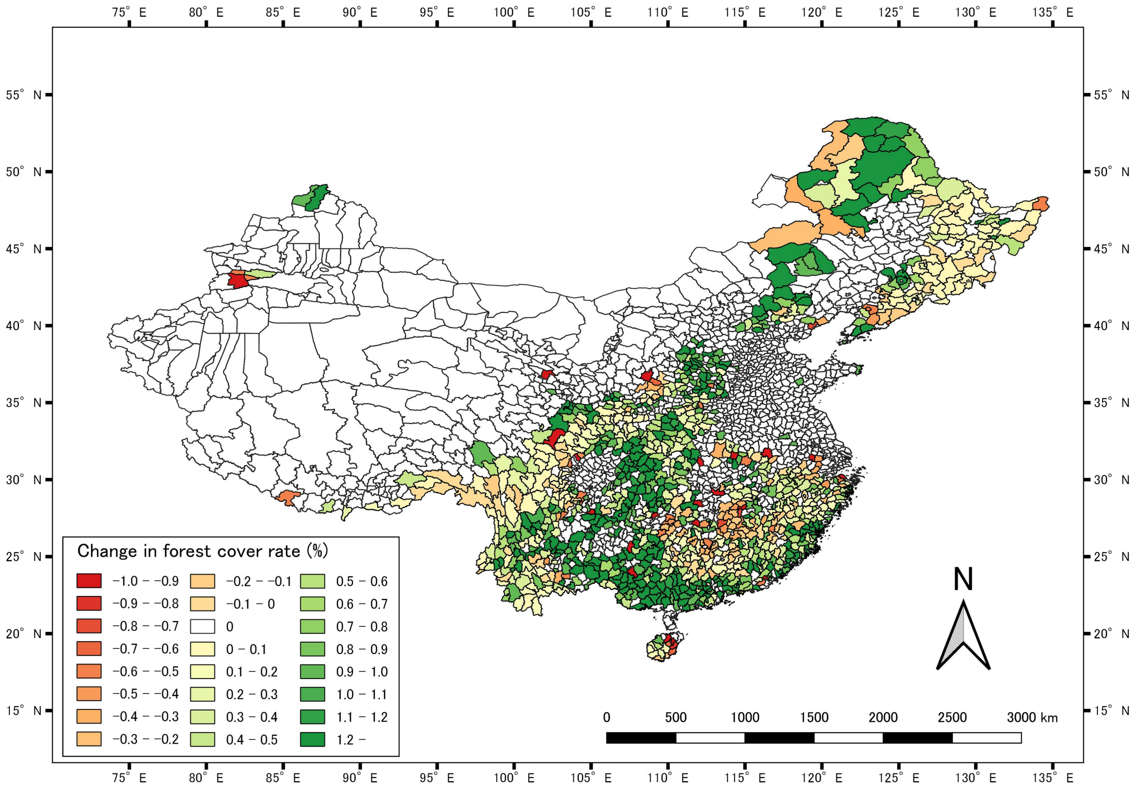

Figure 3: Percentage change in forest cover rate by subdistrict. *Source: Sulla-Menashe et al. (2019).*

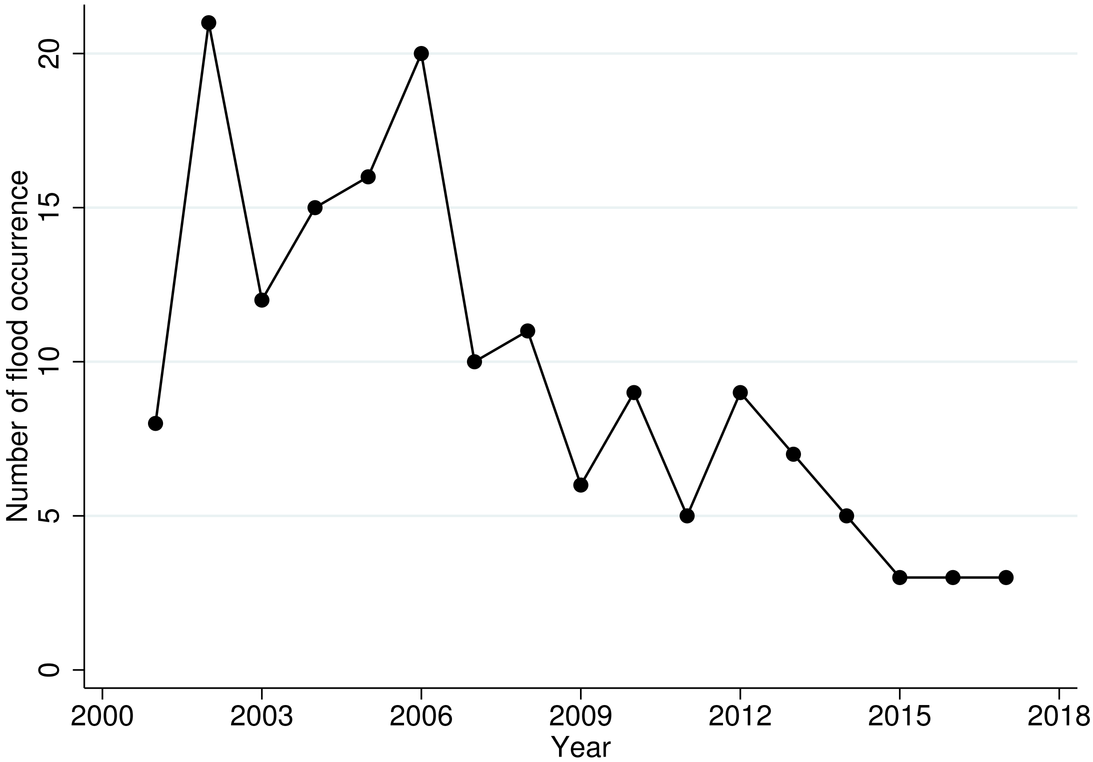

Figure 4: Number of floods that have occurred in China. *Source: Brakenridge (2012).*

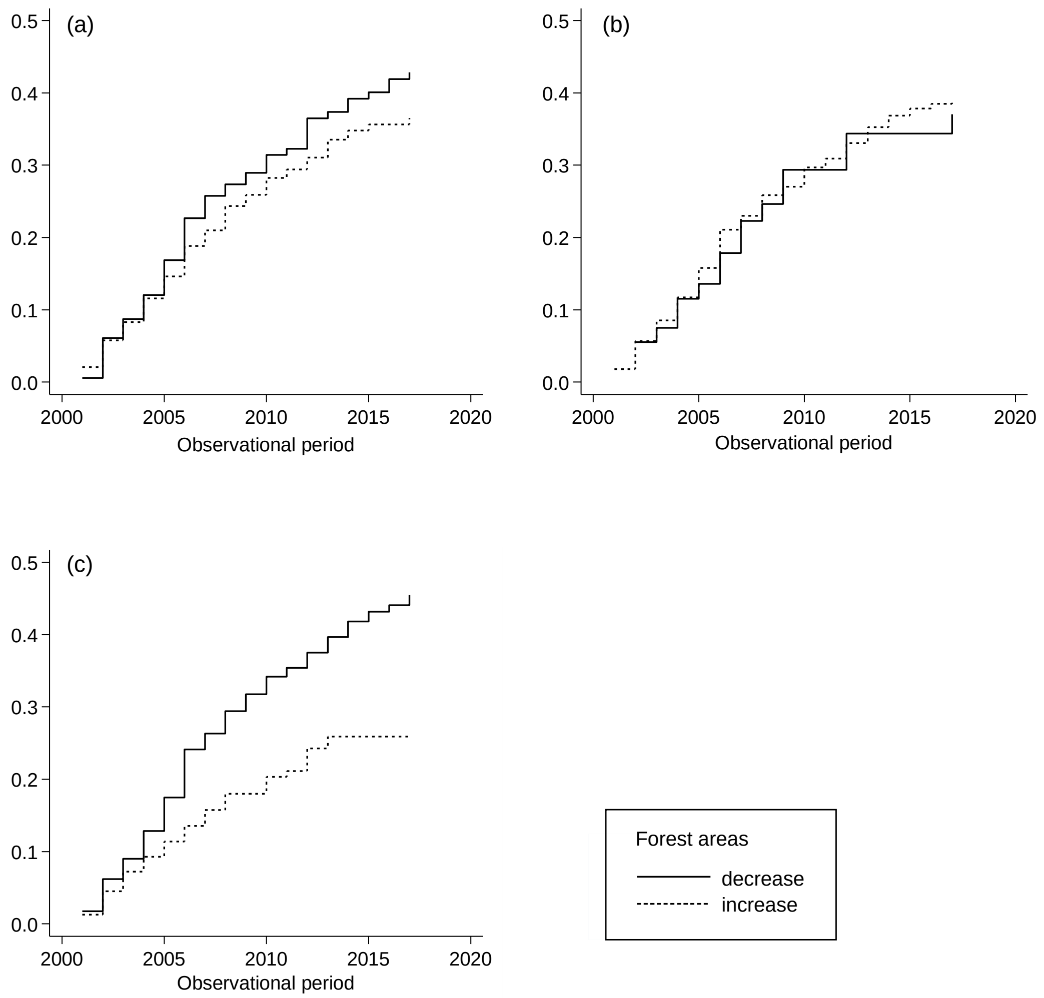

Figure 5: Nelson-Aalen cumulative hazard estimates for broadleaf forest (a), coniferous forest (b), and Mixed forest (c).

Supplementary material

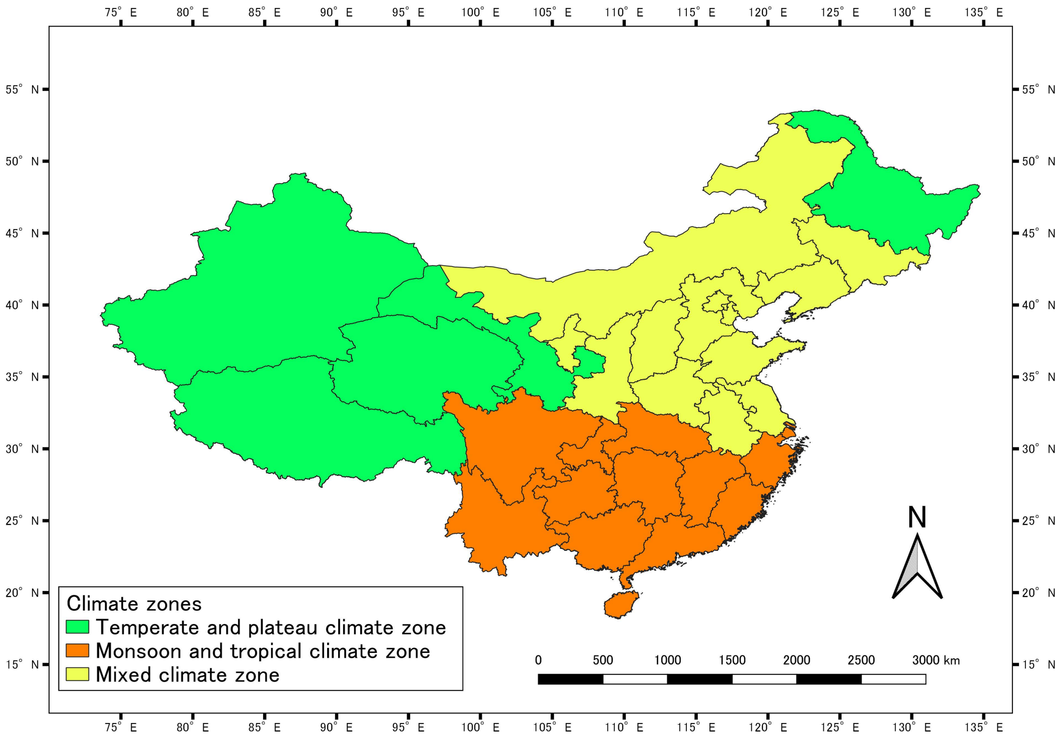

Figure S1: Climate regions in China. *Source: Li et al. (2013)*

Table S1: Variable description and data sources.

Variable	Description	Original resolution	Data source
Flood	Recorded flood events	Point data	Brakenridge (2012)
Broadleaf forest *Coniferous forest* *Mixed forest* *Total forest areas*	Forest area based on IGBP classification	0.05 × 0.05 degrees	Sulla-Menashe et al. (2019)
GRP	Gross regional product per thousand CNY	District level	National Bureau of Statistics of China
Population	Total population		
Annual average precipitation	Mean value on geographical approximate grid of subdistrict	0.05 × 0.05 degrees	Global Unified Precipitation dataset from the Climate Prediction Center
Maximum daily precipitation	Maximum value at each subdistrict and year		

Table S2: Effect of total forest area on flood occurrence.

	Cox model	Cox model	Cox model	Cox model	Weibull model	Weibull model
	(1)	(2)	(3)	(4)	(5)	(6)
Total forest area	−0.355**	−1.454***	−1.564***	−1.586***	−2.059***	−2.064***
	(0.165)	(0.286)	(0.299)	(0.306)	(0.607)	(0.536)
GRP (/1000)		−0.092***	−0.090***	−0.091***	−0.180***	−0.177***
		(0.022)	(0.022)	(0.022)	(0.027)	(0.028)
Population		0.002***	0.002***	0.002***	0.003***	0.003***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln(*Annual average precipitation*)			2.312***		1.774***	
			(0.580)		(0.502)	
ln(*Maximum daily precipitation*)				0.655**		0.728**
				(0.289)		(0.295)
Observations	5763	5763	5763	5761	5763	5761
Log-likelihood	−833.665	−810.951	−801.411	−808.182	625.035	621.650
Wald chi-square	15137.657	18777.887	12678.017	41728.748		

Note: The dependent variable is flood occurrence.

Standard errors in parentheses are clustered at the subdistrict level.

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

All estimates include subdistrict-fixed effects.

All regressions in Columns 2–6 include other land cover areas classified by the IGBP, such as grasslands, croplands, and barren land in each subdistrict.