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RETRACTED: The Effects of Financial Development and Pandemics Prevalence on Forests: Evidence From Asia-Pacific Region

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RETRACTED

Achieving sustainable development and the necessity to pay attention to the quality of the environment is one of the challenges of the new century. Experimental studies on deforestation determinants have focused mainly on analyzing an environmental Kuznets curve for deforestation (EKCd). The present study introduces three contributions to experimental studies using data from 15 Asia-Pacific countries over a 16-year period, from 2005 to 2020. In this regard, the effects of six financial development indexes and a new pandemic uncertainty index on forest regions have been investigated. Furthermore, the effects of the variables have been estimated through a spatial econometric model. This estimation can be used to investigate the variables of neighboring countries on the inland forest cover of countries. Diagnostic tests confirmed the spatial Durbin model. The results indicate the existence of an environmental Kuznets curve hypothesis. The trade openness variable has decreased the inland forest cover; however, the trade openness in neighboring countries has increased the inland forest cover in the countries. Besides, similar results were obtained for urbanization. Furthermore, natural resource rent is a beneficial factor dominating the improvement of forest areas. As confirmed by the results, the financial institution depth has a significant adverse effect on the forest cover of countries. The results for other reductions in financial development are meaningless. Despite the theoretically positive and negative dimensions of pandemics, the estimation results highlight its positive effects in forest regions.

Keywords: financial development, forest region, Asia-Pacific countries, spatial econometric, pandemics, kuznets curve

INTRODUCTION

Over the last 2 decades, deforestation, depletion of underground water tables, air pollution, and global warming have contributed to the worldwide environmental crisis (Elahi et al., 2018a; Peng et al., 2021; Wu et al., 2021; Zhao et al., 2021; Elahi et al., 2022a; Elahi et al., 2022b). It causes to climate change which ultimately responsible for negative impact on global society (Abid et al., 2018;

Gu et al., 2019; Van Tran et al., 2019; Gu et al., 2020b; Zhao et al., 2020; Elahi et al., 2021a). Identifying economic and non-economic factors that may cause land-use conversion (Elahi et al., 2021b) and deforestation has received interest from international and domestic policymakers (Geist and Lambin, 2002; Lambin and Meyfroidt, 2011). Historically, the environment and development have always had a sensitive dependence, and forests have always played an essential role in economic development (Williams, 2003). As satellite sources indicate, the total forest areas have globally increased (Liu et al., 2020). As is evident, we are experiencing net forest loss at a declining deforestation rate (FAO, 2020). Although the global economic expansion rate has been increased, the declining pattern of deforestation support the hypothesis of the environmental Kuznets curve for deforestation (EKCd).

The EKC hypothesis, referred to as forestry, assumes that impoverished countries have relatively low deforestation rates due to the lack of extensive forest exploitation technology (Barbier et al., 2017). Moreover, rich countries consider the environment a valuable resource, and the rate of deforestation in these countries is low. Therefore, most of the exploitation and deforestation occurs in middle-income countries. While some studies support the presence of the EKC hypothesis regarding deforestation (Antle and Heidebrink, 1995; Ehrhardt-Martinez., 1998; Motel et al., 2009; Joshi and Beck, 2016; Cuaresma et al., 2017; Andrée et al., 2019), other studies have not reached a definite conclusion in this regard (Koop and Tole, 1999; Van and Azomahou, 2007; Mills and Waite, 2009; Damette and Delacote, 2012; Leblois et al., 2017; Ogundari et al., 2017).

The financial sector development play a fundamental role in resource monitoring, savings, business transactions and mobility for economic growth (Nasreen et al., 2017). Financial development technologically and structurally affects the environment, stimulating financial channels through foreign investment, leading to R&D projects in green environmental technology (Du et al., 2012).

Financial development affects the environment through the technique, composition, and scale effects (Peng et al., 2022a; Peng et al., 2022b; Saud et al., 2020). The technique effects refer to the transfer of green technology and environmentally friendly products from financial development, increasing the quality of the environment by reducing energy consumption, improving production procedures (Peng et al., 2019b; Shen et al., 2019; Tu et al., 2019; Zheng et al., 2020), and decreasing deforestation. The scale effects through economic liberalization, the purchase of large-scale equipment, and the creation of new production deplete natural resources (Zhang et al., 2018; Peng et al., 2020b; Pazienza, 2015). On the other hand, the composition effects refer to the economic movement from an agricultural-based economy to an industry that leads to the movement of a traditional economy based on the production of primary goods towards industrial goods and a reduction in deforestation. The composition depends on the production expertise of the economy and competitive advantage (Peng et al., 2018; Peng et al., 2020a; Zhong et al., 2020; Zhong et al., 2021; Cole and Elliott, 2003). Multiple pieces of research have examined the effects of financial development on CO_2 emissions investigating the different channels of financial development impact on environmental quality (Ziaei, 2015; Abbasi and Riaz, 2016; Salahuddin et al., 2018; Charfeddine and Kahia, 2019; Gokmenoglu and Sadeghieh, 2019; Acheampong et al., 2020; Kayani et al., 2020; Zhao and Yang, 2020). However, no research has been conducted on deforestation. Accordingly, as the first contribution, the present study investigates the effects of six different components of the financial development index on the deforestation rate.

Some studies have concentrated on the consequences of COVID-19 on the quality of water (Yunus et al., 2020), and green gas emission (Muhammad, Long, and Salman, 2020; Bao and Zhang, 2020; Marlier et al., 2020). The economic downturn resulting from epidemics may decrease the growth of infrastructure projects; therefore, deforestation slows down due to reduced construction of roads, dams, and mining. On the other hand, the imposed political and commercial environments, the depreciation of the national currency, and the increased domestic and international demand for agricultural products calm the regulations and agreements on forest protection (Degnarain, 2020). Accordingly, farmers have a better chance of trading the extra yields from a larger production area and illegal foresters for obtaining land titles for invaded lands (Seymour and Harris, 2019; Brancalion et al., 2020). In this study, to understand the effects of epidemic outbreaks on deforestation, such effects have been investigated using a new index. Previous studies have used dummy variables such as morbidity/mortality to consider its effects on different economic accepts; however, in the present study, a new index, World Pandemic Uncertainty Index (WPUI), measure uncertainty related to pandemics across the globe (Ahir et al., 2020). To the best of the authors' knowledge, this is the first experimental study that examines the consequences of epidemics on deforestation change, and it is the second contribution in the article.

Several topics associated with environmental problems have spatial interdependence (Peng et al., 2019a; Sheng et al., 2019; Wang et al., 2021; Zhao et al., 2019; Lv and Li 2020). Spatial interdependence means that observations of one cross-section depend on other cross-sections. Lv and Li (2020) used a panel data spatial econometric to indicate that the financial development of its neighbors could influence a country's CO2 emissions. Therefore, the traditional panel econometric techniques give rise to biased estimations and neglecting spatial interaction dependence to get the spatial spillover effect of the independent variables of the neighboring countries on the deforestation rate of a special country (Meng and Huang, 2018; You and Lv, 2018). The third contribution of the present paper is the spatial econometric models to investigate the effects of deforestation rate determinants.

The rest of the paper is organized as follows: *Methodology and Data* defines the data sample and empirical models employed; *Emperical Results and Discussions* presents empirical results, and *Conclusion and Policy Implications* concludes the study and provides some policy implications.

METHODOLOGY AND DATA

Empirical Model

According to Maji (2017) and Nathaniel and Bekun (2020), the current study leading equation is presented as follows with some modifications. The logarithm of the forest area ($lnFOREST_{it}$) has been considered a function of some explanatory variables, including the logarithm of GDP per capita ($lnGDP$), the squared form of GDP per capita ($lnGDP^2$), natural resource rent ($lnRENT$), trade openness ($lnOPE$), urbanization ($lnURB$), world pandemic uncertainty index ($lnWPUI$), and financial development index ($lnFD$):

$$\begin{aligned} lnFOREST_{it} = \beta_1 + \beta_2 lnGDP_{it} + \beta_3 lnGDP_{it}^2 + \beta_4 lnRENT_{it} \\ + \beta_5 lnOPE_{it} + \beta_6 lnURB_{it} + \beta_7 lnWUPI_{it} \\ + \beta_8 lnFD + c_i(optional) + \alpha_t(optional) + v_{it} \end{aligned} \tag{1}$$

A developed financial sector has cheaper access to credit finance for purchasing new machinery and equipment (Sadorsky, 2010, 2011; Acheampong, 2019). As mentioned, the effects of financial development on environmental quality can be summarized in the technique, scale, and composition effects (Saud et al., 2020). Hyde (2012) and Niklitschek (2007) showed that trade and technology improvements decrease the point at which forests begin to recover. Leblois et al. (2017) demonstrated that public economic liberalization and trade openness lead to deforestation. Urbanization is another driver of deforestation as it is associated with reduced pressure on forest resources, providing better job opportunities outside the forest sector (Hyde, 2012). Moreover, the squared form of GDP per capita is considered to investigate the Environmental Kuznets Curve (EKC) hypothesis. According to this hypothesis, when economic growth is considered an independent variable, environmental quality is an inverted U-shaped (Grossman and Krueger, 1991; Lee et al., 2010). Therefore, the negative coefficient of the squared form of GDP per capita is theoretically discussed and needs to be investigated.

In the present study, spatial econometric models are used to investigate the effects of domestic determinants of forest regions and the probable spillover effects of the independent variable in neighboring units. A spatial panel model can include a lagged dependent variable, a spatially autoregressive process in the error term, or the spatially lagged independent variables (LeSage and Pace, 2009; Anselin et al., 2008). The spatial lag model is formulated as follows:

$$y_{it} = \lambda \sum_{j=1}^{N} w_{ij} y_{jt} + \varphi + x_{it}\beta + c_i(optional) + \alpha_t(optional) + v_{it} \tag{2}$$

Where y_{it} is the dependent variable for cross-sectional unit $i = 1, \ldots, N$ at time $t = 1, \ldots, T$. x_{it} is a 1×K vector of exogenous variables. The variable $\sum_{j=1}^{N} w_{ij} y_{jt}$ denotes the interaction effect of the dependent variables y_{jt} in neighboring units on the dependent variable y_{it}. w_{ij} is the $i, j-th$ element of a prespecified nonnegative $N \times N$ spatial weights matrix w. λ is the response parameter of the interaction effects. v_{it} is an independently and identically distributed error term which is assumed to be noramly distributed at zero mean value and constant variance (Elahi et al., 2017; Elahi et al., 2018b; Gu et al., 2020a; Elahi et al., 2021b; Gu et al., 2021). c_i denotes a spatial specific effect, and α_t is a time-period specific effect (Baltagi, 2005).

The spatial error model includes the error term of unit i, $u_{it} = \rho \sum_{j=1}^{N} w_{ij} u_{jt} + v_{it}$, which depends on an idiosyncratic component v_{it} and the spatial weights matrix W:

$$y_{it} = \lambda \sum_{j=1}^{N} w_{ij} y_{jt} + \varphi + x_{it}\beta + c_i(optional) + \alpha_t(optional) + u_{it} \tag{3}$$

Also, the spatial Durbin model is an extended version of the spatial lag model with spatially lagged independent variables:

$$\begin{aligned} y_{it} = \lambda \sum_{j=1}^{N} w_{ij} y_{jt} + \varphi + x_{it}\beta + \sum_{j=1}^{N} w_{ij} x_{ijt}\theta + c_i(optional) \\ + \alpha_t(optional) + v_{it} \end{aligned} \tag{4}$$

Where θ is a $K \times 1$ vector of parameters.

Data

The data from 15 East Asia and Pacific countries over a 15-year period, from 2005 to 2020, was collected to investigate the effects of forest region determinants. **Figure 1** shows a comparative observation for forest region density in the countries. All variables are in logarithms; therefore, the estimated coefficients are elasticity. A summary of the constructed variables used in the analysis and the descriptive statistics is presented in **Table 1** and **Table 2**, respectively.

EMPERICAL RESULTS AND DISCUSSIONS

Two different Likelihood Ratio (LR) tests are used to investigate the probability of the time-period fixed effects and spatial fixed effects in the models. The simultaneous spatial and time-period fixed effects are compared with the time-period fixed effects and/or the spatial fixed effects in models. If the null hypothesis is rejected, the model with simultaneous spatial and time-period fixed effects is selected, and if the alternative hypothesis is rejected, the subsequent model is selected. The LR test statistics for each model are presented in **Table 1**. The test results indicate that the LR test statistics are significant in the different models. Accordingly, the model of simultaneous spatial and time-period fixed effects is selected as the best model.

Alternatively, the inclusion of the spatial lag or the spatial error in the model is tested in **Table 1**. For this purpose, the Lagrange Multiplier (LM) is used for a spatially lagged dependent variable and spatial error autoregressive using the residuals of a non-spatial model. If the null hypothesis of the LM test is rejected,

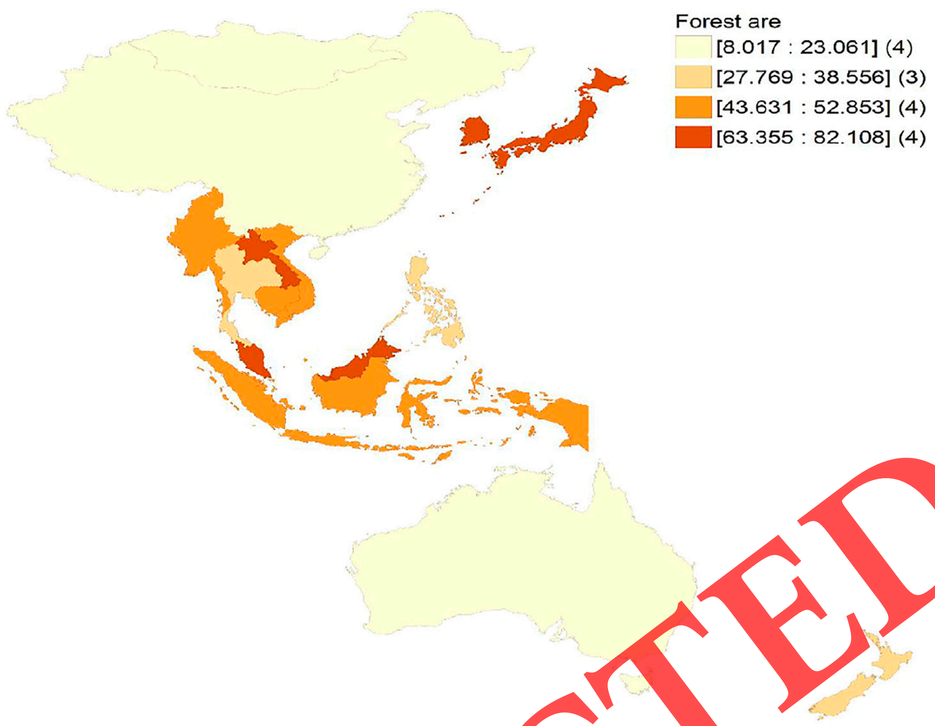

FIGURE 1 | Forest region (as a percentage of land) in the countries.

TABLE 1 | Constructed variables.

Variable	Variable constructed	Source
$lnFOREST_{it}$	$lnFOREST_{it} = log(FOREST_{it})$ $FOREST_{it}$ = Forest area (as a percentage of land area) in the country *i* in period *t*	WDI
$lnGDP_{it}$	$lnGDPP_{it} = log(GDPP_{it})$ GDP_{it} = GDP per capita in 2010 prices$	WDI
$lnRENT_{it}$	$lnRENT_{it} = log(RENT_{it})$ $RENT_{it}$ = Total natural resources rents (as a percentage of GDP)	WDI
$lnOPE_{it}$	$lnOPE_{it} = log(OPE_{it})$ OPE_{it} = Trade Openness (total exports and imports as a percentage of GDP (	WDI
$lnURB_{it}$	$lnURB_{it} = \log(URB_{it})$ URB_{it} = Urban population (as a percentage of the total population)	WDI
$lnWPUI_{it}$	$lnWPUI_{it} = log(WPUI_{it})$ $WPUI_{it}$ = World Pandemic Uncertainty Index	WDI
$lnFID_{it}$	$lnFID_{it} = \log(1 + 100 \times FID_{it})$ FID_{it} = the Development of Financial Institution depth	IMF
$lnFIA_{it}$	$lnFM_{it} = \log(1 + 100 \times FIA_{it})$ FIA_{it} = the Development of Financial Institution access	IMF
$lnFIE_{it}$	$lnFIE_{it} = \log(1 + 100 \times FIE_{it})$ FIE_{it} = the Development of Financial Institution efficiency	IMF
$lnFMD_{it}$	$lnFMD_{it} = \log(1 + 100 \times FMD_{it})$ FMD_{it} = the Development of Financial Market depth	IMF
$lnFMA_{it}$	$lnFMA_{it} = \log(1 + 100 \times FMA_{it})$ FMA_{it} = the Development of Financial Market access	IMF
$lnFME_{it}$	$lnFME_{it} = \log(1 + 100 \times FME_{it})$ FME_{it} = the Development of Financial Market efficiency	IMF

WDI, world development indicator; https://datacatalog.worldbank.org/dataset/world-development-indicators. IMF, international monetary fund; https://data.imf.org/

the presence of the spatial lagged model and the spatial error model will be confirmed.

Table 1 presents that the amount of test statistics in all models is significant at the level of one percent. Therefore, spatial lagged and spatial error effects must be entered. The presence of spatial interaction effects in the model emphasizes the requirement to consider such effects to the forest area model in experimental studies.

Furthermore, two different hypotheses of H_0: $\theta = 0$ and H_0: $\theta + \lambda\beta = 0$ are examined and presented in **Eq. 4**. If the first hypothesis is correct, the spatial Durbin model is simplified to the spatial lag model. Besides, if the second hypothesis is correct, the spatial Durbin model can be simplified to a spatial error model (Burridge, 1980). For this purpose, the LR and Wald tests have been used. As presented in **Table 2**, the statistical value of the two tests is significant for all models, and the existence of the spatial lagged independent variable is also confirmed. Therefore, the spatial Durbin model is the basis for analyzing the estimation results. Finally, the Hausman test results to examine the possibility of replacing the fixed effects model with a random-effects model is presented in **Table 4**. The null hypothesis in this test emphasizes the existence of random effects in the model. The test results show that the random-

TABLE 2 | A summary of descriptive statistics from 2005 to 2020.

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Observations
$lnFOREST_{it}$	3.598	3.776	4.408	1.985	0.624	255
$lnGDP_{it}$	8.596	8.260	10.928	5.835	1.536	255
$lnRENT_{it}$	0.285	1.227	3.819	-8.075	2.956	255
$lnOPE_{it}$	4.200	4.319	6.081	-1.787	1.307	255
$lnURB_{it}$	3.937	3.947	4.605	2.922	0.496	255
$lnWPUI_{it}$	0.462	0.000	8.639	0.000	1.705	255
$lnFID_{it}$	3.173	3.639	4.581	0.537	1.186	255
$lnFIA_{it}$	3.157	3.483	4.526	0.968	1.119	255
$lnFIE_{it}$	4.268	4.331	4.470	3.078	0.191	255
$lnFMD_{it}$	3.195	3.658	4.598	0.066	1.373	255
$lnFMA_{it}$	3.058	3.698	4.533	0.000	1.478	255
$lnFME_{it}$	2.946	3.699	4.615	0.000	1.872	255

TABLE 3 | The spatial lag or the spatial error in the spatial and time-period fixed effects model.

		Pooled OLS		Spatial fixed effects		Time-period fixed effects		Spatial and time-period fixed effects	
Model 1	LM spatial lag	20.424	(0.000***)	8.452	(0.004***)	45.358	(0.000***)	10.456	(0.001***)
	LM spatial error	33.571	(0.000***)	0.867	(0.352)	33.885	(0.000***)	8.014	(0.005***)
	LR-test			27.288	(0.054*)	1388.013	(0.000***)		
Model 2	LM spatial lag	21.855	(0.000***)	7.499	(0.006***)	45.766	(0.000***)	9.503	(0.002***)
	LM spatial error	33.73	(0.000***)	0.384	(0.535)	34.329	(0.000***)	6.985	(0.008***)
	LR-test			28.262	(0.042**)	1392.519	(0.000***)		
Model 3	LM spatial lag	19.956	(0.000***)	8.248	(0.004***)	50.608	(0.000***)	10.789	(0.001***)
	LM spatial error	33.175	(0.000***)	0.844	(0.358)	34.516	(0.000***)	8.352	(0.004***)
	LR-test			27.046	(0.057*)	1381.134	(0.000***)		
Model 4	LM spatial lag	20.159	(0.000***)	9.188	(0.002***)	44.763	(0.000***)	10.918	(0.001***)
	LM spatial error	32.186	(0.000***)	1.371	(0.242)	32.645	(0.000***)	8.493	(0.004***)
	LR-test			25.114	(0.092*)	1387.689	(0.000***)		
Model 5	LM spatial lag	29.074	(0.000***)	9.716	(0.002***)	48.527	(0.000***)	11.108	(0.001***)
	LM spatial error	38.944	(0.000***)	2.265	(0.132)	39.365	(0.000***)	8.848	(0.003***)
	LR-test			23.617	(0.13)	1388.213	(0.000***)		
Model 6	LM spatial lag	21.605	(0.000***)	7.645	(0.006***)	50.015	(0.000***)	9.794	(0.002***)
	LM spatial error	34.662	(0.000***)	0.821	(0.365)	36.925	(0.000***)	7.432	(0.006***)
	LR-test			25.428	(0.086*)	1382.887	(0.000***)		
Model 7	LM spatial lag	20.591	(0.000***)	8.595	(0.003***)	44.934	(0.000***)	10.338	(0.001***)
	LM spatial error	33.375	(0.000***)	0.995	(0.319)	33.644	(0.000***)	7.93	(0.005***)
	LR-test			27.401	(0.052*)	1388.393	(0.000***)		

*Note: p-value, ***, **, and * show significance at 1, 5, and 10% level respectively.*
Source: Authors' estimations.

effects model is confirmed at a significance level of 1% for the spatial Durbin model.

According to the estimation results of **Table 5**, each percent increase in GDP per capita leads to a significant decrease of about 0.15 percent in the forest regions of countries. The squared form of GDP per capita is also positive and significant. A positive value of about 0.01 of the coefficient indicates that with increasing GDP per capita, its effects on reducing forest cover will decrease, which confirms the existence of Kuznets hypothesis in the sample of the studied countries. Resource rent is one of the influential variables in maintaining forest cover. The coefficient of the variable is significantly about 0.024. However, the trade openness variable harms the coverage of forest regions, and each percentage of growth in it leads to a decrease of about 0.005%. Urbanization and the epidemic uncertainty index have positive effects on forest regions. Each percentage increase in the former results is about 0.16%, while the latter results are about 0.004.

The estimation results are not the same for financial development components. While the coefficient of the logarithm of the financial institution depth is significantly negative, the results are not significant for other components. The negative and significant coefficient of the variable indicates

TABLE 4 | The spatial durbin model and hausman test results.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Hausman test-statistic in spatial lag model	40.743 (0.000***)	39.668 (0.000***)	44.097 (0.000***)	44.21 (0.000***)	44.543 (0.000***)	41.328 (0.000***)	40.87 (0.000***)
Hausman test-statistic spatial Durbin model	19.513 (0.108)	14.748 (0.47)	6.009 (0.98)	22.093 (0.105)	3.602 (1)	19.397 (0.196)	2.793 (1)
fixed effects estimator							
Wald test: spatial Durbin model against spatial lag model	65.284 (0.000***)	69.358 (0.000***)	65.771 (0.000***)	67.38 (0.000***)	59.184 (0.000***)	64.397 (0.000***)	69.158 (0.000***)
Wald test: spatial Durbin model against spatial error model	73.587 (0.000***)	77.863 (0.000***)	72.843 (0.000***)	74.72 (0.000***)	65.212 (0.000***)	70.388 (0.000***)	77.874 (0.000***)
LR test: spatial Durbin model against spatial lag model	59.446 (0.000***)	61.931 (0.000***)	59.513 (0.000***)	60.273 (0.000***)	55.393 (0.000***)	58.718 (0.000***)	62.838 (0.000***)
LR test: spatial Durbin model against spatial error model	58.98 (0.000***)	62.04 (0.000***)	58.117 (0.000***)	59.422 (0.000***)	54.404 (0.000***)	58.19 (0.000***)	62.524 (0.000***)
random-effects estimator							
Wald test: spatial Durbin model against spatial lag model	58.07 (0.000***)	64.721 (0.000***)	68.011 (0.000***)	60.326 (0.000***)	54.527 (0.000***)	57.455 (0.000***)	59.344 (0.000***)
Wald test: spatial Durbin model against spatial error model	67.753 (0.000***)	74.711 (0.000***)	75.823 (0.000***)	68.688 (0.000***)	61.456 (0.000***)	63.735 (0.000***)	69.124 (0.000***)
LR test: spatial Durbin model against spatial lag model	45.402 (0.000***)	50.729 (0.000***)	49.621 (0.000***)	47.212 (0.000***)	41.662 (0.000***)	44.242 (0.000***)	45.824 (0.000***)
LR test: spatial Durbin model against spatial error model	49.866 (0.000***)	55.7 (0.000***)	53.227 (0.000***)	51.458 (0.000***)	45.446 (0.000***)	48.467 (0.000***)	50.481 (0.000***)

*Note: p-value, ***, **, and * show significance at 1, 5, and 10% level respectively. Source: Authors' estimations.*

that each percentage increase in financial institution depth development leads to a decrease of about 0.003 in the inland forest cover.

The lower part of the tables shows the weighted variables of neighboring countries. According to the results, the coefficient of forest areas in neighboring countries has a significant negative effect on inland forests, leading to increased harvests and imports of inland forests. Such results show the importance of considering spatial interactions in forest area modeling. Also, growth in GDP per capita, trade openness in neighboring countries leads to increased inland forest areas, which could be due to the export of more wood products from neighboring countries to the interior, reducing the harvest from inland forests. Urbanization in neighboring countries also reduces domestic forest cover, as urbanization leads to a reduction in deforestation in neighboring countries and greater dependence on imports from abroad. Financial development and the epidemic uncertainty index in neighboring countries do not significantly affect inland forest areas; however, increasing resource rents in neighboring countries have a significant positive effect on inland forest areas.

CONCLUSION AND POLICY IMPLICATIONS

The present study examines factors determining forest areas by using data from 15 Asia-Pacific countries over 16 years, from 2005 to 2020. The investigation of the financial development and epidemic uncertainty effects are the mai006E contributions of the present study. The diagnostic tests demonstrated a spatial interaction between domestic variables and those of the neighboring countries. Several tests emphasized the presence of spatially-lagged dependent and independent effects in the model. Therefore, the spatial Durbin model was selected to investigate the determinants of forest cover.

The estimation results showed the existence of an environmental Kuznets curve for deforestation (EKCd) in the countries. Accordingly, forests participate in economic growth, leading to increased forest exploitation and deforestation. Above this turning point in economic growth, deforestation continues at a slower rate.

Trade openness can act as a stimulus to intensify the effects of economic growth. In a more open economy, the export of wood products leads to a further reduction of forest areas. However, trade openness in the neighboring countries with adverse effects increases domestic coverage. At a glance, trade openness cannot be considered to be a decisive factor in the expansion of deforestation. Thus, positive and negative dimensions must be considered. However, the natural resource outcomes are clear, and the existence of more natural resource rents in countries has clear and direct impacts, diminishing the consumption of other natural resources, e.g., forests.

Urbanization mainly arises from inequality in development factors, including household income, access to welfare facilities, and infrastructure. Therefore, infrastructure and facilities in rural areas help reduce the increasing trend of urbanization and the associated anomalies. This can be implemented as a policy to address inequalities in countries. The results indicated that the components of such policies in countries lead to further

TABLE 5 | The estimation results for the spatial durbin model.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
lnGDP	−0.15	−0.066	−0.19	−0.143	−0.139	−0.147	−0.146
	(0.024**)	(0.356)	(0.006***)	(0.032**)	(0.047**)	(0.03**)	(0.028**)
lnGDP^2	0.011	0.006	0.014	0.011	0.01	0.011	0.011
	(0.017**)	(0.263)	(0.003***)	(0.023**)	(0.065*)	(0.023**)	(0.019**)
lnRENT	0.024	0.028	0.02	0.025	0.022	0.024	0.025
	(0.000***)	(0.000***)	(0.004***)	(0.000***)	(0.003***)	(0.001***)	(0.000***)
lnOPEN	−0.007	−0.005	−0.007	−0.007	−0.006	−0.007	−0.006
	(0.095*)	(0.245)	(0.087*)	(0.091*)	(0.11)	(0.074*)	(0.106)
lnRENT	0.165	0.184	0.175	0.152	0.166	0.155	0.161
	(0.001***)	(0.001***)	(0.019**)	(0.003***)	(0.002***)	(0.003***)	(0.002***)
lnWPUI	0.004	0.003	0.004	0.004	0.004	0.004	0.004
	(0.042**)	(0.082*)	(0.055*)	(0.036**)	(0.038**)	(0.058*)	(0.046**)
lnFID	—	−0.03	—	—	—	—	—
	—	(0.039**)		—	—	—	—
lnFIA	—	—	−0.003	—	—	—	—
	—	—	(0.829)		—	—	—
lnFIE	—	—	—	−0.031	—	—	—
	—	—	—	(0.164)	—	—	—
lnFMD	—	—	—	—	0.007	—	—
	—	—	—	—	(0.436)	—	—
lnFMA	—	—	—	—	—	0.011	—
	—	—	—	—	—	(0.397)	—
lnFME	—	—	—	—	—	—	−0.007
	—	—	—	—	—	—	(0.519)
W × lnGDP	0.642	0.645	0.396	0.6	0.62	0.634	0.679
	(0.004***)	(0.007***)	(0.117)	(0.008***)	(0.006***)	(0.005***)	(0.004***)
W × lnGDP^2	−0.022	−0.023	−0.006	−0.02	−0.024	−0.022	−0.023
	(0.054*)	(0.067*)	(0.647)	(0.083*)	(0.037**)	(0.052*)	(0.047**)
W × lnRENT	0.046	0.045	0.033	0.043	0.041	0.041	0.053
	(0.003***)	(0.004***)	(0.069*)	(0.01**)	(0.016**)	(0.02**)	(0.002***)
W × lnOPEN	0.036	0.044	0.036	0.042	0.039	0.035	0.036
	(0.02**)	(0.016**)	(0.019**)	(0.008***)	(0.02**)	(0.024**)	(0.02**)
W × lnURB	−1.181	−1.178	−0.827	−1.161	−1.108	−1.163	−1.228
	(0.000***)	(0.000***)	(0.01)	(0.000***)	(0.000***)	(0.000***)	(0.000***)
W × lnWPUI	0	0	−0.001	0	0	−0.001	0
	(0.994)	(0.9)	(0.783)	(0.994)	(0.997)	(0.883)	(0.919)
W × lnFID	—	0.016	—	—	—	—	—
	—	(0.772)	—	—	—	—	—
W × lnFIA	—	—	−0.071	—	—	—	—
	—	—	(0.31)	—	—	—	—
W × lnFIE	—	—	—	0.04	—	—	—
	—	—	—	(0.632)	—	—	—
W × lnFMD	—	—	—	—	0.03	—	—
	—	—	—	—	(0.345)	—	—
W × lnFIE	—	—	—	—	—	0.031	—
	—	—	—	—	—	(0.471)	—
W × lnFME	—	—	—	—	—	—	−0.019
	—	—	—	—	—	—	(0.498)
W × lnFOREST	−0.743	−0.721	−0.819	−0.752	−0.777	−0.756	−0.752
	(0.000***)	(0.000***)	(0.000***)	(0.000***)	(0.000***)	(0.000***)	(0.000***)
TETA	0.013	0.013	0.013	0.013	0.013	0.013	0.013
	(0.000***)	(0.000***)	(0.000***)	(0.000***)	(0.000***)	(0.000***)	(0.000***)

*Note: p-value, ***, **, and * show significance at 1, 5, and 10% level respectively. Source: Authors' estimations.*

degradation of forest cover, and the implementation of such a policy in the neighboring countries would improve inland forest cover. Therefore, it is required to regionally study the effects of urbanization on forest cover and accordingly adopt environmental policies.

In some countries, financial development encourages investment in environmentally-friendly industries. On the other hand, it leads to the expansion of polluting industries, the application of outdated technology, and the high consumption of environment-degrading fossil fuels. The results showed that the positive and negative dimensions of financial development neutralize each other for most indicators and do not seem to significantly affect forest cover. At the same time, as a critical dimension of financial development, the financial institution depth shows significant adverse effects. The oversight of the financial sector to grant higher loans to projects and industries with socially-responsible for the creation of a green environment, along with Prudent and strong environmental regulations, can provide the conditions to move toward sustainable development.

Epidemics can have positive and negative dimensions in forest areas. The positive dimensions of epidemics become dominant when economic activities reduce; however, negative dimensions and proper forest management during an epidemic cannot be ignored. In an epidemic, governments need to adopt innovative strategies to protect forests, implement environmental monitoring, and control their list of essential activities. For example, border patrols and satellite imagery can quickly trace deforestation (Finer et al., 2018). Moreover, governments require strategies that strengthen legal timber markets and supply chains to prevent opportunistic actors from gaining access to national and international markets.

DATA AVAILABILITY STATEMENT

Data used in this research can be found in the data section of the article as well as in **Table 1**. Further inquiries can be directed to the corresponding authors.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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